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Pushing Boundaries: New Directions in Inventory Techniques & Applications; Forest Inventory and Analysis (FIA) Symposium 2015

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Pushing Boundaries: New Directions in Inventory Techniques & Applications; Forest Inventory and Analysis (FIA) Symposium 2015

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Portland, Oregon

Compiled by Sharon M. Stanton and Glenn A. Christensen

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Abstract

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These proceedings report invited presentations and contributions to the 2015 Forest Inventory and Analysis (FIA) Symposium, which was hosted by the Research and Development branch of the U.S. Forest Service. As the only comprehensive and continuous census of the forests in the United States, FIA provides strategic information needed to evaluate sustainability of current forest management practices across all ownerships. Papers and abstracts included in the publication have been sorted into general topic areas, including forest carbon accounting, change detection, and techniques development. Symposium papers cover high priority and timely issue-based topics including climate change, carbon flux, wildlife, disturbance, bioenergy, geo-spatial extensions, change monitoring, and integrating remote sensing and GIS applications.

Keywords: statistics, estimation, sampling, modeling, remote sensing, forest health, data integrity, environmental monitoring, cover estimation, international forest monitoring.

Preface

The twelfth Forest Inventory and Analysis Symposium was held December 8-10, 2015, in Portland, Oregon. The symposium brought together almost 200 inventory and forest scientists from across the United States and four foreign countries. There were 145 presentations and 12 posters emphasizing the development of innovative approaches to incorporating non-traditional approaches and uses of inventory information. The goal of the symposium is to provide a forum for international forest scientists, managers, and stakeholders to share insights on a wide variety of topics, including contemporary issues, science policy, mensuration, geospatial products, and inventory methods.

The symposium organizers thank all participants and presenters, especially those who submitted papers for these proceedings. We would like to convey special thanks and acknowledgement to the late Paul Van Deusen, Principal Research Scientist of National Council for Air and Stream Improvement. Paul was an accomplished biometrician and enthusiastic collaborator with FIA, including actively participating in the organization of the symposia—his contributions will be greatly missed.

Steering Committee

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Paul Van Deusen

Contents

A TRIBUTE TO
DR. PAUL VAN DEUSEN

THE RESEARCH CONTRIBUTIONS OF DR. PAUL VAN DEUSEN

Thomas B. Lynch, Francis A. Roesch, John Paul McTague, Jeffrey H. Gove, Gregory A. Reams, and Aaron R. Weiskittel[1]

Abstract—Dr. Paul Van Deusen's recent passing concluded a rich 30+-year research career dedicated to development and implementation of quantitative methods for forestry and natural resources. Since the early part of his career as a biometrician with the USDA Forest Service Southern Research Station in the 1980s-1990s and continuing with his later employment at NCASI, Dr. Van Deusen has made many research contributions that have been directly or indirectly important for the implementation of FIA data collection methods and for the analysis and interpretation of FIA data. We have attempted to summarize highlights of Dr. Van Deusen's contributions to FIA and to forestry, as well as natural resources in general.

On August 21, 2015 the forestry profession lost Dr. Paul Van Deusen, a generational science leader in applying quantitative sciences to the contemporary issues of each decade of his career. Paul's knowledge and practical applications of forest biometrics were uniquely multi-dimensional as this paper chronicles. In the mid-to-late 1990s Paul worked with the Forest Service's Forest Inventory and Analysis (FIA) program, and inventory experts and users of FIA's partner and user community in defining the statistical design and estimation techniques for FIA's annual forest inventory. Paul was a rare combination of theory and practicality and an ardent student of Occam's razor or 'law of parsimony' and the current annual FIA panel design is a direct reflection of this principle. Dr. Van Deusen was a founding member of the first FIA science symposium held in November of 1999 in San Antonio, Texas. He continued to work closely with the FIA science and user community and was a member of the planning committee for this symposium, the 12th FIA science symposium. He also worked tirelessly with the organizing committee of each and every Annual National FIA User's Group Meeting sponsored by the Society of American Foresters over the last two decades. We dedicate this symposium to Dr. Paul Van Deusen and invite you to read this tribute to Paul's research contributions.

EARLY YEARS AND THE SOUTHERN STATION

Dr. Paul Van Deusen received his Ph.D. from the University of California, Berkeley under the direction of Dr. Gregory Biging, where he also interacted with Dr. Lee Wensel who was then developing the CACTOS growth model for California forests. Paul's doctoral work contributed to the stand generator for CACTOS (Van Deusen 1984; Van Deusen and Biging 1984; Biging et al. 1994). Previously, he received an M.S. from Mississippi State University working with Drs. Thomas Matney and Al Sullivan, where among other projects they published early south-wide individual tree volume equations for loblolly pine (Van Deusen et al. 1981) and a system of equations for predicting volume and diameter of sweetgum trees to any height (Van Deusen et al. 1982). Prior to his M.S., Paul earned a B.S. in forest management from the University of Massachusetts. After leaving

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Berkeley, Paul was employed by the Institute of Quantitative Studies unit in the USDA Forest Service Southern Research Station at New Orleans, LA headed by Project Leader Dr. Tommy Dell. The unit in those days had responsibility for technical aspects of the southern FIA (then termed Forest Survey) and Dr. Van Deusen developed a keen interest in forest sampling problems.

Dr. Van Deusen was one of the early contributors to the application of Monte Carlo Integration to forest sampling problems. With Dr. Walter Meerschaert, he published a paper proving that critical height sampling was unbiased for any tree taper function using the framework provided by the cylindrical shells integral (Van Deusen and Meershaert, 1986). By remarkable coincidence, Lynch (1986) published a paper in a different journal taking a very similar approach to critical height sampling independently of Dr. Van Deusen's work. With Lynch, Dr. Van Deusen was the first to apply the variance reduction technique of antithetic variates to obtain unbiased estimates of tree volume (Van Deusen and Lynch 1987), combining the technique with importance sampling that had previously been introduced into forestry by Gregoire et al. shortly prior (Gregoire et al. 1985, 1986; and Furnival et al. 1986). Importance sampling was originally developed to reduce the number of computer operations needed in Monte Carlo analyses (Kahn and Marshall, 1953). Dr. Van Deusen (1987a, 1990a) was also the first to apply the control variates technique often used for variance reduction in Monte Carlo integration to the unbiased estimation of tree stem volume. At about the same time, Van Deusen (1987c) discussed design versus model-based estimates in reference to 3-P sampling and Van Deusen (1988) investigated simultaneous estimation with a squared error loss function. Dr. Van Deusen (1995a) later proposed difference sampling as an alternative to importance sampling. Since that time antithetic variates and control variates have had other applications in forest sampling and promise to remain part of the "tool kit" in forest sampling for the foreseeable future.

During the 1980s, the potential effects of acid rain on forest growth became an issue of interest, and Dr. Van Deusen made several contributions in this area. He made a pioneering application of the Kalman filter in dendrochronology by applying it to increment core data, which were being used to study possible effects of acid rain on tree growth (Van Deusen 1987b, 1988, 1989a, 1990b,c). Although Visser (1986) published an application of the Kalman filter to tree ring data slightly earlier, Van Deusen (1987b, 1988) had formulated it independently before the Visser (1986) paper was published. While at Berkley he had taken a course from Dr. Andrew Harvey, econometrician and expert on Kalman filtering. Dr. Van Deusen also supervised work on a project to study increment cores obtained with probability proportional to size sampling on point samples, which in that era were used by the southern FIA (formerly called "Forest Survey"). As part of that project, Drs. Juha Lappi and Robert Bailey quantified bias in growth estimates due to collection of increment cores on point samples (Lappi and Bailey 1987). Due to the sampling method, trees with cores showing faster growth also had larger inclusion zones and were more likely to be sampled than other trees of a given initial size a fixed number of years previous. Lynch also worked on the project and proposed ratio estimators to correct the problems, testing these in simulations (Lynch and Huebschmann 1992). Dr. Van Deusen (1986) also obtained likelihood equations for fitting tree diameter distributions (e.g, the Weibull distribution) when sample trees were selected from point samples. Another contribution to point sampling research included estimators for point clusters (Van Deusen and Grender 1989). Van Deusen and Baldwin (1993) proposed methods of sampling and predicting tree dry weight. Van Deusen (1992) discussed growth dynamics for naturally-occurring loblolly pine in the south. The recurrence of slash pine blight was analyzed by Van Duesen and Snow (1991). In an extension of his tree-ring research, Dr. Van Deusen collaborated on the use of data to detect large-scale disturbances in Reams and Van Deusen (1993), the standardization of tree-ring data in Van Deusen and Reams (1993), and on historic climatic variation in Reams and Van Deusen (1998).

Obtaining compatible estimates of the components for forest growth from remeasured point samples or from partial replacement sampling was an issue of interest during Dr. Van Deusen's tenure with the Southern Station, especially since the FIA plots at the time were point samples. Dr. Van Deusen made several contributions in this area. Significant papers by Dr. Van Deusen that focused on improved estimation included Van Deusen et al. (1986), Van Deusen (1993, 1996a, 1999a), and Roesch and Van Deusen (1993). As indicated above, Dr. Van Deusen had taken econometrics coursework at Berkeley during his Ph.D. studies and was aware of generalized least squares as used by econometricians. He realized that generalized least squares could be applied to the forest inventory problem of obtaining compatible estimates of forest growth from remeasured point samples and partial replacement data. He developed a framework that included partial replacement sampling and achieved partial compatibility for estimates of the components of growth using remeasured point or plot sample data (Van Deusen 1989b). Subsequently, Lynch (1995) applied restricted generalized least squares in a similar framework to achieve exact equality between growth component estimators. Van Deusen later applied generalized least squares to obtain one of the early estimators for the annual FIA system, which was new at that time (the mid or later 1990s). This estimator allowed specification of a restriction that could be varied in strength from exact to approximate. The generalized least squares framework remains an important approach to the analysis of FIA and other large forest inventory datasets.

In 1997, Dr. Van Deusen proposed the technique of multiple imputation for annual forest inventory applications, which had previously been used by statisticians working in other fields. Since then, the method has been widely used to supply missing data in forestry datasets and to develop tree lists for forest growth simulators among other applications. Although single imputation had been applied in the Swedish National Survey (Holm et al. 1979, Ranneby et al. 1987) and the Finnish forest survey (Poso 1978), and Moeur and Stage (1995) had proposed nearest neighbor methods, Van Deusen's (1997) application of multiple imputation to natural resource data was pioneering.

NCASI AND LATER CAREER

After working for the USDA Forest Service Southern Station for a 10 year period, Dr. Van Deusen worked as a biometrician for the National Council for Air and Stream Improvement (NCASI), where his interest in forest sampling and FIA continued. He also developed software for harvest scheduling, among many other endeavors. In the early 1990s, Dr. Van Deusen, focused his research effort into building a multi-objective harvest scheduling program called HABPLAN. HABPLAN can be described as a Model I harvest schedule with an integer formulation that permits the user to obtain solutions that are spatially compliant with adjacency constraints. Paul elected to achieve optimality using the Metropolis heuristic in a methodology that is best described as simulated annealing. Dr. Van Deusen collaborated with others later to use the HABPLAN harvest scheduler for landscape-scale analysis of forestry guidelines using bird habitat models in Loehle et al. (2006). He also constructed an ingenious matrix generator program called HABGEN, and wrote both applications in JAVA. Some of his publications in this area include Van Deusen (1999b) concerning multiple solution harvest scheduling, Van Deusen (2001a) which relates to harvest scheduling with spatial constraints, and Van Deusen (1996b) which applied Bayesian concepts to habitat and harvest scheduling. His collaborations and contributions in habitat modeling and ecology also appear in Wigley et al. (2001), Mitchell et al. (2008), Loehle et al. (2009), Miller et al. (2011), Irwin et al. (2015), Van Deusen and Irwin (2012), Van Deusen et al. (1998) and Van Deusen (2002a). Van Deusen (2010) discussed the evaluation of the option of carbon storage in forests.

In the late 1990's, Dr. Van Deusen was part of a group of scientists and professionals who were a key influence on changing the FIA to the current national annual design from the various regional periodic designs. The implementation of annual inventories by the Forest Inventory and Analysis (FIA) program in the United States initiated entirely new threads of estimation-focused research. It was immediately obvious that the traditional way of thinking about and analyzing remeasured samples was inadequate for the panelized annual sample design. One of the earliest papers on the subject was Van Deusen (1997). The significant implications of the design were discussed in Van Deusen (2000a, 2000b) and Van Deusen et al. (1999). Additional significant research is found in Van Deusen (2001b, 2002b, 2004), on alternative designs and estimators for annual inventories. Spinney et al. (2006) unveiled one of at least three comprehensive on-line estimation tools for FIA data (SOLE). The other two tools are COLE (Proctor et al., 2002; Spinney et al., 2005) and GForest (Spinney and Van Deusen, 2007). With respect to this sample design, many papers offered interesting perspectives on improved estimation. Van Deusen (2005), in an attempt to nudge FIA into choosing more efficient estimation methods, gave an alternative view of some of the issues that led to the existing procedures. Van Deusen (2007a, 2007b) then showed an alternative way for FIA to achieve the long-standing goal of ensuring compatible marginal totals in tables using weighted estimators. Van Deusen and Heath (2010) proposed weighted analysis methods for mapped forest inventory data. The need for estimators that consider the specific timing of the observations from this design was recognized in these and the later publications of Van Deusen and Roesch (2007, 2009a, 2009b, 2013), Roesch and Van Deusen (2010a,b, 2012, 2013), and Van Deusen et al. (2013).

Until his passing, Dr. Van Deusen continued to investigate alternative designs and estimators for special problems in forestry. A notable collaboration with Dr. Jeff Gove started with the problem of sampling downed woody debris and resulted in the “sausage method” of estimation in Gove and Van Deusen (2011) and a general spoked transect discussion in Van Deusen and Gove (2011). Dr. Van Deusen also contributed to the three-dimensional jigsaw-puzzle view of forest monitoring in Roesch and Van Deusen (2013). The utility of the simple systematic well- dispersed sample design, currently used by FIA, that Paul was very instrumental in effecting, is being discovered by many investigators for use in highly specialized studies. Finally, Dr. Van Deusen considered alternate ways of sampling and estimating tree volume, biomass and carbon, which is an issue on which FIA is still working (Van Deusen and Roesch, 2011).

Like many of his contemporaries, Paul also contributed to improving the integration of remotely sensed data and forest inventories. Van Deusen (1994, 1995b) discussed the correction of bias in change estimates from thematic maps. Roesch, Van Deusen, and Zhu (1995) investigated estimators for updating forest area coverage using AVHRR and forest inventory data, while Van Deusen (1996c) gave unbiased estimates of class proportions from thematic maps.

Most biometricians have some talent with and affinity towards computers and the programming thereof. Dr. Van Deusen was no exception in this area; on the contrary he was quite exceptional. He was an early adopter of *nix (i.e., Unix, Linux) computational platforms and was instrumental in converting several colleagues from proprietary systems to Linux. In the nineties, when most people were using PCs or Macs, Dr. Van Deusen was working on Sun Microsystems SPARC-based workstations running Solaris Unix as the operating system. Eventually, in the late 1990s Dr. Van Deusen was drawn to Linux, an open source alternative to Unix, and began building his own computers running Red Hat (and later Fedora) Linux. Dr. Van Deusen was comfortable with a diverse array of programming languages, both closed (on SPARC) and open-source (on Linux). His “Dynaclim” Kalman filtering system (Van Deusen and Kortez, 1988) was written in the Gauss (Aptech Systems) matrix language. The online applications like COLE (Proctor et. al, 2002) developed by Dr. Van Deusen and his staff (at various times including: John Beebe, Patrick Proctor, Mike Spinney, and Rei Hayashi) employed a variety of different open-source languages including perl, Java, JavaScript, Grass, Povray (a ray tracing program, used in GForest for 3D views of individual plots), mySQL (later MariaDB), R, LaTeX (for automated report generation through Sweave in

R) and, of course, HTML. Dr. Van Deusen was an advocate for the Linux and open-source development model (Proctor et. al, 2003) and would often comment that it would have been much more difficult to develop similar online tools on other (i.e., closed) platforms. Dr. Van Deusen's preferred software for everyday work on Linux was a combination of R for analysis and LaTeX for manuscripts. He would joke that he did not know how to use a spreadsheet program.

CONCLUSIONS

The tools mentioned above give testimony to Paul's contributions as a "complete biometrician." Although many of us tend to prefer the theoretical developments of our craft, a complete biometrician gets an idea, develops the theory to express the idea, and then packages the results into a product that is usable by others. Paul was not only adept at simplifying complex ideas to the point where they were understandable to any reader of his publications, he was also extremely adept at developing user-friendly systems to implement those ideas, and he did that in every area of his research.

Unfortunately, Paul passed away on August 21, 2015, but he has left a rich legacy to the forest biometrics community. Dr. Van Deusen remained an active and vibrant scientist until his death, as will be evidenced by his posthumous publications. So far, we know of Roesch et al. (2015). Given the many areas that he had an interest in, we suspect that there are other manuscripts still in process.

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ADVANCES IN TREE BIOMASS PREDICTION FOR U.S. FORESTS

ADDITIVITY AND MAXIMUM LIKELIHOOD ESTIMATION OF NONLINEAR COMPONENT BIOMASS MODELS

David L.R. Affleck[1]

Abstract—Since Parresol's (2001) seminal paper on the subject, it has become common practice to develop nonlinear tree biomass equations so as to ensure compatibility among total and component predictions and to fit equations jointly using multi-step least squares (MSLS) methods. In particular, many researchers have specified total tree biomass models by aggregating the expectations of nonlinear component equations. More recently, an alternative approach has been used wherein compatibility is ensured by specifying a total biomass equation plus one or more component disaggregation functions. Yet calibration of such equations typically has not recognized the additivity of the biomass data or the implied stochastic constraints necessary for development of a valid probability model. For model selection based on information criteria, stochastic simulation, Bayesian inference, or estimation with missing data, it is important to base estimation and inference on probabilistic models. Thus, we show how to specify valid stochastic models for nonlinear biomass equation systems and how to estimate parameters using maximum likelihood (ML). We also explain how ML procedures can accommodate unobserved or aggregated component biomass data. We use Parresol's slash pine data set to contrast model forms and demonstrate Gaussian ML from complete and missing data using open-source software.

Forest inventory programs commonly report estimates of total aboveground biomass and carbon in live trees. The estimates are often obtained from individual tree equations that also furnish estimates for foliage, branches, stems, and other tree components. For many purposes, compatibility among component and total tree biomass models is important. As pointed out by Parresol (2001) this compatibility should, at a minimum, ensure that component biomass or carbon estimates do not exceed estimates of whole-tree biomass or carbon, and that component estimates sum to the estimates of the totals. Yet this level of compatibility is insufficient for analytical and estimation procedures such as mixed-effects modeling, stochastic simulation, and Bayesian inference. These techniques require that the additive nature of tree biomass measurements be recognized and that valid probabilistic models be formulated.

The objectives of this research were to synthesize alternative approaches to nonlinear biomass equation specification within a probabilistic modeling framework, and demonstrate how the models and ML algorithms can be extended to accommodate missing component biomoass observations.

ADDITIVITY OF BIOMASS COMPONENTS

Let $Y_1,Y_2,\ldots,Y_M$ denote M biomass components of a tree and Y_t the total of interest. A fundamental identity is $Y_t = \Sigma_m Y_m$. This identity holds when the symbols represent unobserved tree biomass quantities and is often desired of biomass estimates. Yet it also generally holds when the symbols represent biomass measurements. This is because total tree biomass typically goes unmeasured and is obtained instead by summing the component biomass estimates gathered in the field. From the identity stems the result that, given a set of predictors x, the joint probability law for a set of random variables $Y_1,Y_2,\ldots,Y_M$ and Y_t is

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That is, the joint probability model for $Y_1, Y_2, \ldots, Y_M$ and Y_t is a simple multiplicative function of the model for $Y_1, Y_2, \ldots, Y_M$ with the multiplier being independent of any model parameters or predictors. As such, the ML estimators of the parameters governing the former model can be obtained by maximizing only the latter model. Given the biomass components and their additivity there is no additional information in the biomass totals.

SYSTEMS OF NONLINEAR BIOMASS EQUATIONS

Parresol (2001) noted that in the nonlinear setting, additivity of component estimates can be guaranteed only by restricting the total biomass equation to be the sum of the component biomass equations. He advocated direct specification of individual component equations $E(Y_m) = g_m(x_m; \beta_m)$, deriving the equation for the total (and/or subtotals) through aggregation $E(Y_t) = \Sigma_m g_m(x_m; \beta_m)$, and completing a statistical model

$$Y_m = g_m(x_m; \beta_m) + \varepsilon_m \qquad m = 1,2,\ldots,M$$
$$Y_t = \Sigma_m g_m(x_m; \beta_m) + \varepsilon_t$$

allowing for non-constant variance as well as cross-correlations on the error terms $\varepsilon_{\bullet}$. Parresol further recommended joint estimation of the parameters of this system by MSLS using observations of component and total biomass.

An alternative approach, developed initially in the Chinese literature (Tang et al. 2000; see also Dong et al. 2015), is to specify first an equation for the total, then use multiplicative disaggregation functions to yield component equations. For example,

$$Y_t = g_t(x_t; \beta_t) + \varepsilon_t$$

$$Y_c = g_t(x_t; \beta_t)\, g_{cs}(x_{cs}; \beta_{cs}) + \varepsilon_c$$

$$Y_w = g_t(x_t; \beta_t)\, [1 - g_{cs}(x_{cs}; \beta_{cs})]\, g_{wb}(x_{wb}; \beta_{wb}) + \varepsilon_w$$

$$Y_b = g_t(x_t; \beta_t)\, [1 - g_{cs}(x_{cs}; \beta_{cs})]\, [1 - g_{wb}(x_{wb}; \beta_{wb})] + \varepsilon_b$$

where Y_c, Y_w, and Y_b denote respectively crown, stem-wood, and stem-bark biomass; and $g_{cs}(\cdot)$ and $g_{wb}(\cdot)$ are functions bounded by 0 and 1 that disaggregate, respectively, the total into crown and stem fractions, and the stem fraction into wood and bark fractions. Tang and Wang (2002) describe a MSLS approach for this system that accounts for non-constant error variance and cross-correlations among errors.

While guaranteeing additivity of estimates, neither of the above systems recognizes the additivity of the data and thus neither represents a valid probability model. It follows that the associated MSLS strategies are not ML procedures. Essentially, $Y_t = \Sigma_m Y_m$ together with $g_t(x_t; \beta_t) = \Sigma_m g_m(x_m; \beta_m)$ implies $\varepsilon_t = \Sigma_m \varepsilon_m$, meaning that the variance function and cross-correlations of ε_t are constrained. The MSLS procedures do not recognize these constraints, so using the observed totals in estimation amounts to specifying an internally inconsistent system and estimators with inscrutable properties. The simplest way to align the above equation systems with probabilistic models is to strike the submodels for biomass totals. With component variance and cross-correlation structures otherwise preserved the reduced systems are valid probability models; parameters can be estimated by ML and information criteria such as AIC can be used in model selection. The models can then also be extended to accommodate mixed-effects or Bayesian specifications, or used for stochastic simulation.

MISSING BIOMASS DATA

A further advantage of specifying a valid probabilistic component biomass model is that missing data patterns can be accommodated. In particular, if the missingness mechanism is uninformative (Little & Rubin 1987, ch.1) then the complete data likelihood for impacted trees can be integrated to yield an observed data likelihood for ML estimation.

With component biomass data, there are two important forms of missingness. The first results when individual components (and thus biomass totals) go unobserved. For example, if crown material is lost and only stem biomass components are observed then the likelihood for the tree in question reduces to

A second form of missingness is when all components are represented (and thus the total is computable), but some are known only in aggregate. For example, if crown biomass and overall stem biomass (but not bark and wood biomass) are available for a certain tree, then its contribution to the overall likelihood is

Both integrals are complex in the general case, but easily obtained for Gaussian models.

CASE STUDY: PARRESOL'S (2001) SLASH PINE DATA

Parresol (2001) presented biomass data for 40 slash pine (*Pinus elliottii*) grown in Louisiana, USA. Table 1 reproduces the data and identifies observations masked from missing data analyses.

To the complete and simulated-incomplete data were fit Parresol's (2001) aggregative system of equations with variance functions

$var(Y_m) = \theta_{m1}(d.b.h.)$

and unstructured cross-correlations between crown, bark, and wood biomass observations from the same tree. With the same variance and cross-correlation structures, a disaggregation-based system of equations was also fit with

$$g_t(x_t; \beta_t) = \exp[\ \beta_{t1} + \beta_{t2}\ \ln(d.b.h.) + \beta_{t2}\ \ln(h)\ ]$$

$$g_{cs}(x_{cs}; \beta_{cs}) = (1 + \exp[\ \beta_{cs1} + \beta_{cs2}\ \ln(d.b.h.) + \beta_{cs2}\ \ln(h)\ ])^{-1}$$

$$g_{wb}(x_{wb}; \beta_{wb}) = (1 + \exp[\ \beta_{wb1} + \beta_{wb2}\ \ln(d.b.h.) + \beta_{wb2}\ \ln(h)\ ])^{-1}$$

where h is tree height.

The models were fit by Gaussian ML using the *gnls* function of the *nlme* package (Pinheiro et al. 2014) in R (R Core Team 2014). To do so, a symmetric covariance structure was coded from the basic *gnls* correlation structure; this allowed for reduction of the covariance matrix to account for missing or aggregated components.

Model fit statistics are in Table 2. The systems provide comparable predictive models, and the patterns of missingness shown in Table 1 only slightly degrade model-data agreement. The models are also similar to the two-stage and three-stage least squares models presented in Parresol (2001) but, as they constitute valid probability models, they can be extended to include random effects (e.g., to express dependence among trees within plots) or prior information on parameters (using Bayesian techniques).

Table 1—Slash pine biomass data from Parresol (2001) with tree diameter at breast height (d.b.h.) and total height (h). Shaded cells identify data masked from some analyses; within these cells component values printed in white are assumed missing (i.e. unknown along with the tree total) while those printed in black are assumed known only in aggregate (i.e. stem mass known but not wood or bark separately).

Tree	d.b.h. (cm)	height (m)	Green mass (kg) Wood	Bark	Crown	Total
1	5.6	7.9	6.5	2.3	1.0	9.8
2	6.4	8.5	7.4	2.6	2.1	12.1
3	8.1	10.7	17.6	4.5	2.3	24.4
4	8.4	11.3	18.5	4.3	4.2	27.0
5	9.1	11.0	22.6	5.4	5.6	33.6
6	9.9	13.1	30.6	7.4	5.5	43.5
7	10.4	14.3	32.9	6.7	6.4	46.0
8	11.2	14.6	40.6	9.3	6.2	56.1
9	11.7	14.3	46.0	10.7	7.7	64.4
10	12.2	14.9	51.6	13.1	6.1	70.8
11	11.9	16.8	60.4	10.1	5.4	75.9
12	13.2	13.7	62.8	15.2	10.7	88.7
13	12.2	15.8	67.5	12.9	15.3	95.7
14	13.7	18.0	81.2	12.5	8.7	102.4
15	14.2	16.5	94.3	18.2	11.2	123.7
16	15.0	20.1	123.4	16.5	7.7	147.6
17	15.7	16.8	107.3	21.5	19.7	148.5
18	16.5	17.1	123.8	22.1	28.9	174.8
19	16.5	17.1	151.6	24.6	16.8	193.0
20	19.6	13.7	140.4	25.1	46.2	211.7
21	17.5	19.2	170.4	27.4	16.8	214.6
22	17.8	18.3	169.6	31.7	24.0	225.3
23	18.5	17.7	160.3	36.9	47.5	244.7
24	19.6	19.8	199.8	38.7	19.7	258.2
25	18.5	22.9	231.6	29.6	24.6	285.8
26	19.8	18.6	217.9	33.9	45.8	297.6
27	20.6	17.4	216.0	32.6	61.2	309.8
28	21.6	17.7	200.6	40.2	75.4	316.2
29	19.8	18.9	217.5	38.5	62.0	318.0
30	22.9	19.8	314.8	43.1	43.2	401.1
31	23.6	18.3	287.1	63.4	51.7	402.2
32	23.1	18.9	290.9	44.3	76.7	411.9
33	24.1	21.3	320.1	50.6	75.6	446.3
34	26.4	19.2	308.6	65.7	116.0	490.3
35	24.6	25.0	403.0	49.8	69.8	522.6
36	25.1	19.8	390.4	48.8	83.5	522.7
37	29.0	20.4	445.2	60.4	88.0	593.6
38	28.4	26.8	736.4	84.0	79.9	900.3
39	31.8	27.4	770.9	93.8	170.2	1034.9
40	33.0	27.7	921.3	108.0	169.2	1198.5

Table 2—Component root mean squared error (RMSE) and corrected Akaike's information criterion (AICc) for alternative models, parameter estimation routines, and data.

			RMSE[a] (kg)				
Model	**Estimation**	**Data**	**Crown**	**Bark**	**Wood**	**Total**	**AICc[b]**
Aggregative	ML	complete	13.3	5.1	26.9	30.4	784.6
	ML	incomplete	13.2	5.2	26.9	30.7	786.4
	2SLS[c]	complete	13.9	5.0	26.7	31.4	795.6
	3SLS[c]	complete	12.8	5.0	26.7	29.8	808.5
Disaggregation	ML	complete	13.4	4.8	26.2	29.6	789.1
	ML	incomplete	13.4	5.4	26.2	30.3	792.8

[a] Based on the complete data without weight functions or degrees of freedom adjustments.
[b] Based on the complete data and a joint Gaussian model for crown, bark, and wood biomass.
[c] From coefficients published in Parresol (2001).

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BUILDING GENERALIZED TREE MASS / VOLUME COMPONENT MODELS FOR IMPROVED ESTIMATION OF FOREST STOCKS AND UTILIZATION POTENTIAL

David W. MacFarlane[1]

Abstract— Accurately assessing forest biomass potential is contingent upon having accurate tree biomass models to translate data from forest inventories. Building generality into these models is especially important when they are to be applied over large spatial domains, such as regional, national and international scales. Here, new, generalized whole-tree mass / volume component models are discussed and tested. The models integrate principles of tree branching architecture and stem taper into compatible equation systems for estimating whole-tree mass or volume components across a range of species and site conditions. The models were tested using data collected in Michigan, USA, as part of a national effort by the Forest Inventory and Analysis (FIA) Program of the US Department of Agriculture to improve estimation of tree mass components, including the merchantable mass of the tree.

The results suggest that the new variable-form variable-density models will provide superior predictions of tree mass components and whole-tree mass, as compared to standard allometric models, across a range of tree species and forest conditions, even when tree density is held constant within the tree and derived from published values. Whole-tree volume and stem taper models, derived from the biomass equation system, could provide flexible characterization of whole-tree mass utilization potential under different local, regional or national merchantability standards for industrial round wood production. The generality of the model system, in terms of accommodating a wide range of tree forms, might also allow it to be used across many forest types and growing conditions, including urban forests, agroforestry systems and plantation forests.

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METHODS FOR ESTIMATING ABOVEGROUND BIOMASS AND ITS COMPONENTS FOR FIVE PACIFIC NORTHWEST TREE SPECIES

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Abstract—Performance of three groups of methods to estimate total and/or component aboveground biomass was evaluated using the data collected from destructively sampled trees in different parts of Oregon. First group of methods used analytical approach to estimate total and component biomass using existing equations, and produced biased estimates for our dataset. The second group used a system of equations fitted with seemingly unrelated regression (SUR), and was superior to group I methods. The third group of methods predicted the proportions of biomass in each component using beta, Dirichlet, and multinomial logistic regression (MLR). The MLR approach produced smaller root mean squared error (RMSE) compared to the SUR approaches except for grand fir branch biomass while the beta and Dirichlet regressions provided smaller RMSE compared to the SUR approaches for 85 percent of the species-component combinations.

Forest carbon reporting requires information on tree measurements, forest area estimates, and methods to estimate forest biomass. Tree measurements and forest area estimates for the official U.S. forest carbon reporting are obtained from the U.S. Forest Service's Forest Inventory and Analysis (FIA). Forest biomass estimates until 2009 were based on the equations developed by Jenkins and others (2003) but after 2009 these estimates are obtained using the component ratio method of the FIA (FIA-CRM). These methods were developed for national scale application but are commonly used to estimate biomass at the local scale. Therefore these methods may be biased at the local scale if there is spatial variation in the tree form due to one or more unknown predictors in the sub-region or subarea.

DATA

A detailed biomass data collection was carried out by destructively sampling 90 trees in different forests within the state of Oregon. The 90 trees belonged to five different species: Douglas-fir (*Pseudotsuga menziesii* (Mirbel) Franco), Grand fir (*Abies grandis* (Dougl. ex D. Don) Lindl.), lodgepole pine (*Pinus contorta)*, western hemlock (*Tsuga heterophylla)*, and red alder (*Alnus rubra).* Efforts were made to select trees to give an approximately equal representation across a range of size class while avoiding the trees with severe defects and close to stand edges. Trees that were forked below breast height and with damaged tops were also not included in sampling. The average D.B.H. ranged from 24.6 cm to 54.9 cm and average height ranged from 17 m to 33 m. Volume of 5.18 m bole sections was converted into biomass by multiplying it by the average density of the disks taken from two ends. Total bole biomass was obtained by summing section masses. Individual branch wood and foliage biomass was obtained by fitting species specific log linear regression as a function of branch diameter.

METHODS

Methods for estimating aboveground biomass (AGB) used in this study belonged to three major groups. The first group of methods used analytical approach based on existing equations. The analytical methods are the FIA-CRM, the equations used by the FIA-PNW and the equations developed by Jenkins and others (2003). The equations used in FIA-CRM and FIA-PNW methods can be found in Woodall and others (2011)

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and Zhou and Hemstrom (2010), respectively. The second group is the locally fitted systems of equations using a seemingly unrelated regression. We fitted two systems of equations: a DBH based single entry system (simple SUR) and a multiple entry system that included DBH and other explanatory variables (extended SUR) to estimate component and total AGB. The systems were constrained such that the sum of the predicted biomass from component equations is equal to the total AGB obtained from the equation for total AGB. Third group of methods predicted proportion of total AGB in different components using beta, Dirichlet, and multinomial logistic regression (MLR). The predicted proportions were then multiplied by observed total AGB to obtain predicted biomass estimates in different components. These generalized regression models assume that the errors of component biomass equations are beta, Dirichlet, and multinomial distributed, respectively. The beta and Dirichlet regressions have been described by Ferrari and Cribari-Neto (2004) and Maier (2010), respectively. Performance of all the methods was evaluated based on bias and root mean squared error (RMSE).

RESULTS AND DISCUSSION

The FIA-CRM, FIA-PNW, and the Jenkins methods were biased and produced the highest RMSE values among the methods used in the study. The average bias and RMSE produced by these methods are given in Table 1. These methods produced similar estimates for total AGB except for Douglas-fir. The Jenkins method for Douglas-fir produced total AGB that was respectively 18.4 and 23.7 percent higher than the estimates provided by the FIA-PNW and FIA-CRM methods. Despite their similar predictions for total AGB, these methods showed inconsistent discrepancies in component biomass estimates (Fig. 1).

It is important to note, however, that the component biomass estimates obtained from these methods were similar for lodgepole pine and red alder, trees with smaller D.B.H. in our study. Indeed, these methods were more sensitive to tree size compared to other methods. For example, in Douglas-fir, the RMSE percent for total AGB dropped from 57.7 to 11.1 percent, 10.2 to 7.1 percent, and 16.3 to 8.5 percent when Jenkins, FIA-CRM, and FIA-PNW equations, respectively, were applied to trees with less than 94 cm D.B.H.

The average bias and RMSE produced by simple and extended SUR approaches are shown in Figure 2. These methods consistently provided smaller RMSE compared to FIA-CRM, FIA-PNW, and Jenkins methods. Including additional explanatory variables than just D.B.H. in the SUR models resulted in the decrease in RMSE percent from 10.7 to 8.3 for Douglas-fir, 4.7 to 4.3 for grand fir, 22.8 to 20.5 for lodgepole pine, 10.7 to 1.9 for western hemlock, and 14.0 to 8.0 for red alder total AGB respectively. The RMSE for bole biomass estimation was reduced by 2.3, 0.2, 6.9, 10.1, and 2.0 percent for Douglas-fir, grand fir, lodgepole pine, western hemlock, and red alder respectively by using the extended SUR approach instead of the simple SUR. It is logical because one would, for example, expect differences, at least, in the bole biomass for a tree with same D.B.H. but different height which would not be accounted for by D.B.H. only models.

However, it should be noted that even though the RMSE for total AGB is decreased by using the extended SUR, the RMSE for some component biomass increased (Fig. 2). This could have been avoided by not constraining the extended SUR models i.e. fitting independent component models rather than fitting a system of equations which in turn would have affected the additivity of the component models.

The beta, Dirichlet, and MLR unbiasedly predicted the proportions of biomass in different components. These methods consistently produced smaller values for bias and RMSE compared to the FIA-CRM, FIA-PNW, and Jenkins methods but there were some exceptions when these methods were compared against the simple and extended SUR methods (Table 2). There was no clear winner within this group of methods.

The beta regression produced smaller RMSEs compared to the simple SUR models except for grand fir foliage and bark biomass and Douglas-fir branch

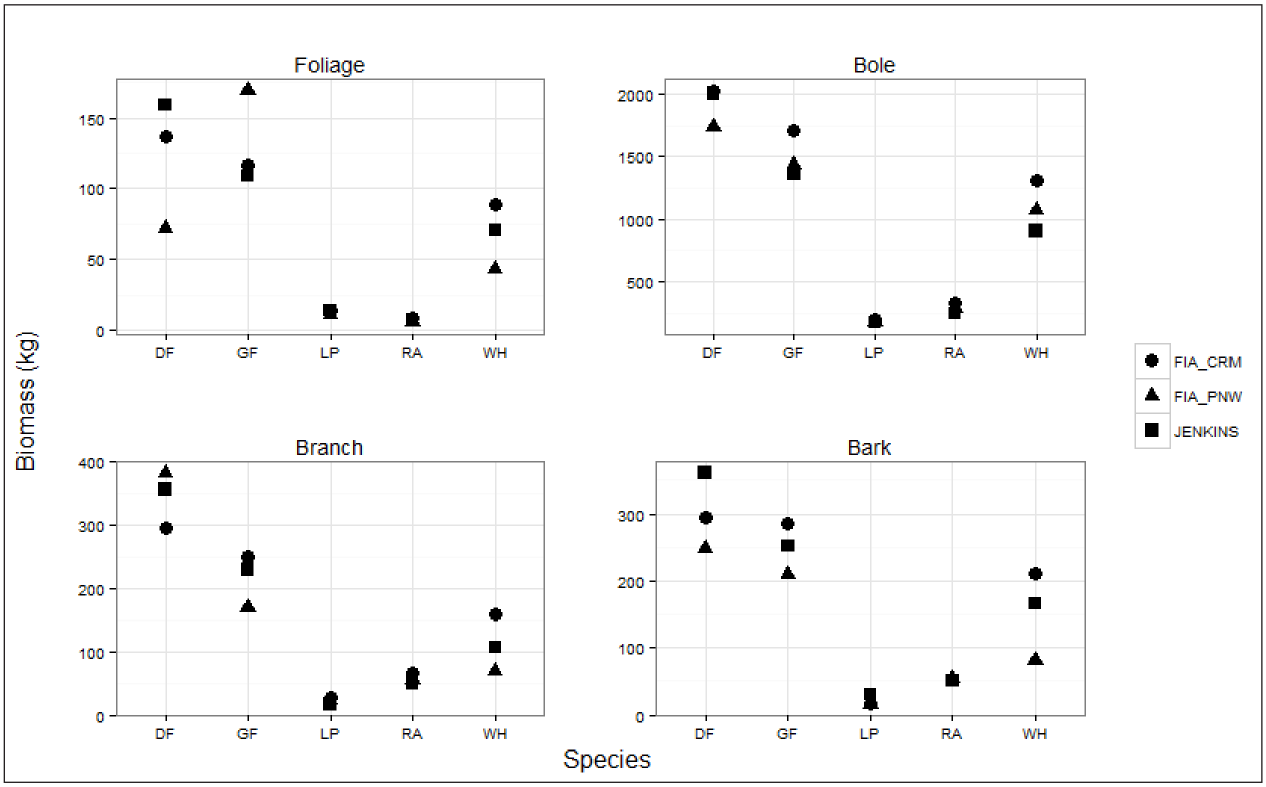

Figure 1—Average component biomass estimates produced by the FIA-CRM, FIA-PNW, and Jenkins methods in different species (Species are DF = Douglas-fir; GF = Grand Fir; LP = Lodgepole Pine; RA = Red Alder; WH = Western Hemlock).

biomass while it produced smaller RMSEs than the extended SUR models except for grand fir foliage, bark, and branch biomass. It is unclear whether the poor performance of beta regression in grand fir component proportion estimation is due to smaller sample size (n=9) because it performed better than both SUR methods for bole mass and better than the simple SUR for branch biomass for this species. In case of other species-component combinations, beta regression produced up to 24.6 and 17.7 percent lower RMSE for conifers and up to 46.8 and 40.9 percent lower RMSE for red alder compared to the simple and extended SUR methods respectively.

The Dirichlet regression also produced smaller RMSEs compared to SUR methods with some exceptions. It specifically performed poorly for red alder producing up to 32.1 and 22.3 percent higher RMSE compared to simple and extended SUR methods respectively. In the case of conifers, it produced smaller RMSEs compared to simple SUR except for Douglas-fir branch biomass while it performed better than extended SUR except for western hemlock bark and grand fir branch biomass estimation.

The MLR consistently produced smaller RMSEs compared to simple SUR methods for all species and all components. It also produced smaller RMSEs compared to the extended SUR for all species and components except for grand fir branch biomass for which it produced 2.7 percent higher RMSE compared to the extended SUR method. Once again, one of the reasons for this could have been smaller sample size (n=9) for grand fir. In a simulation study, Peduzzi and others (1996) showed that with less than 10 events per predictive variables, the logistic regression model produced biased coefficients in both positive and negative directions. However, this method provided better estimates (up to 4.4 and 6.8 percent smaller RMSE compared to simple and extended SUR approaches respectively) for other components even for grand fir.

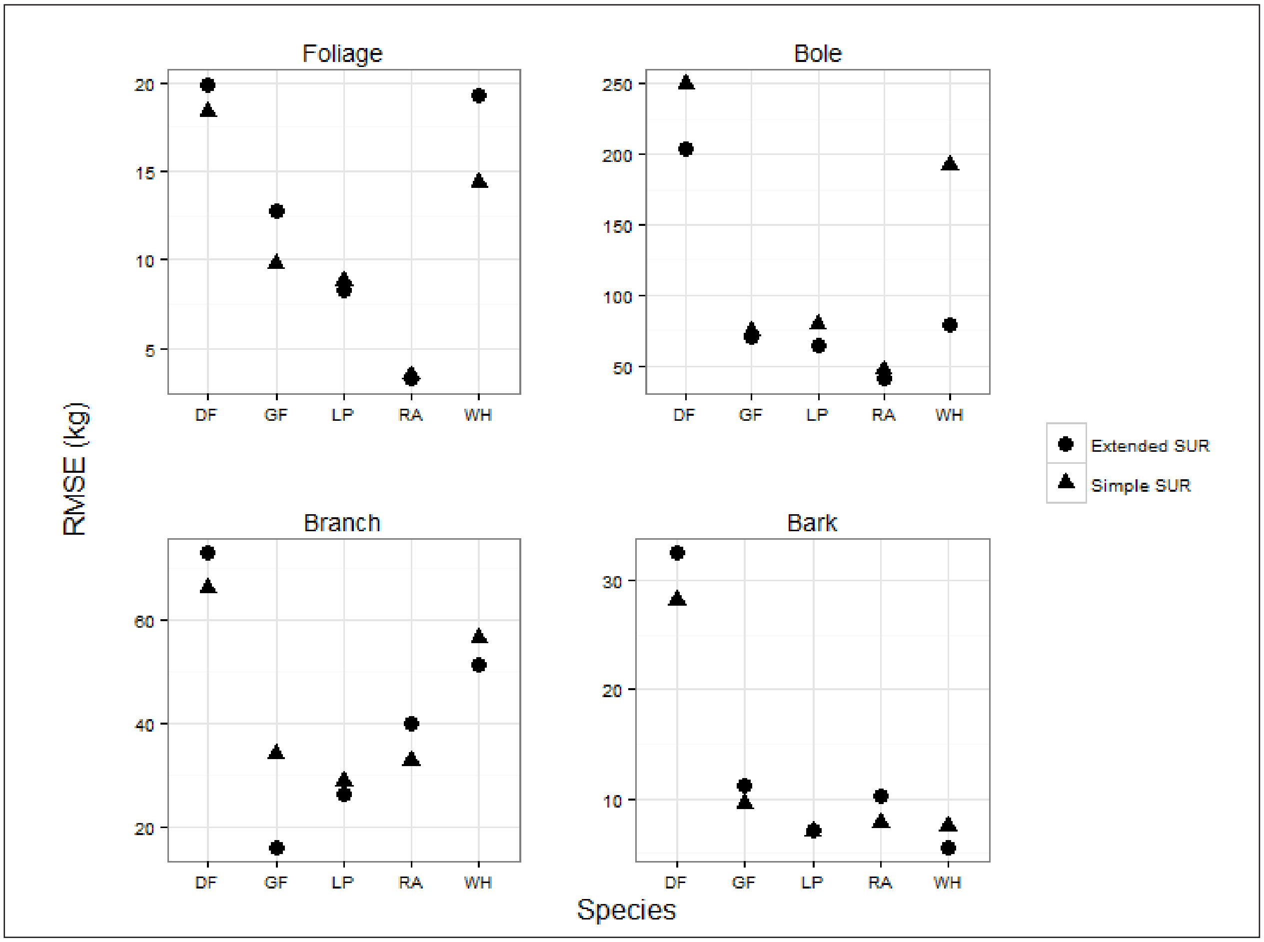

Figure 2—RMSE produced by simple and extended SUR approaches in estimating component biomass for different species (Species are DF = Douglas-fir; GF = Grand Fir; LP = Lodgepole Pine; RA = Red Alder; WH = Western Hemlock).

Even though the methods or models that are capable of predicting biomass at large scale are desired, the use of such models without local calibration could lead to serious bias due to the differences in scale of development and application of such models. Findings of this study provide information on the efficiency of selected methods in quantifying component and total AGB. Methods to predict proportions are promising to apportion total AGB to different components. One advantage of using Dirichlet regression and MLR over beta regression is that these regressions allow simultaneous fitting of the component proportions and therefore the predicted proportions sum to 1. Application of the methods to predict component proportions for other species and locations and with the larger dataset would further validate their accuracy.

ACKNOWLEDGMENT

The authors thank Drs. Lisa Madsen and Glen Murphy, both professors at Oregon State University and Dr. Andrew Gray, Research Ecologist at USDA Forest Service, Pacific Northwest Research Station for their comments and suggestions during the manuscript preparation.

Table 1—Average bias and RMSE for component and total aboveground biomass produced by the FIA-CRM, FIA-PNW, and Jenkins approaches (Species are DF = Douglas-fir; GF = Grand Fir; LP = Lodgepole Pine; RA = Red Alder; WH = Western Hemlock).

Method	Species	Bias (kg)					RMSE (kg)				
		Foliage	Bark	Branch	Bole	Total	Foliage	Bark	Branch	Bole	Total
FIA-CRM	DF	-79.6	-189.6	-73.3	-109.7	-32.5	126.0	281.1	136.8	289.8	234.5
	GF	-14.4	-208.7	105.4	-161.2	107.3	24.9	270.6	166.8	255.6	281.0
	LP	3.2	-4.8	19.4	25.1	72.4	12.7	12.5	37.9	70.5	101.8
	WH	-11.2	-148.8	77.7	-184.0	17.6	20.9	184.1	154.3	240.2	88.3
	RA	-4.8	-29.4	3.5	-27.7	-2.5	6.4	41.2	79.6	53.8	87.7
FIA-PNW	DF	-14.9	-143.2	-161.2	182.8	-136.6	37.7	232.5	280.3	311.7	376.1
	GF	-67.0	-132.4	185.4	114.6	100.7	88.4	175.1	263.6	229.8	265.7
	LP	6.6	-3.9	22.7	38.8	64.2	12.0	9.4	40.6	78.7	99.7
	WH	34.5	-19.6	166.4	45.0	226.4	49.4	26.9	237.3	81.8	305.7
	RA	-1.8	-29.6	13.8	19.6	2.1	2.5	41.9	71.0	35.8	71.5
Jenkins	DF	-102.1	-255.5	-134.8	-93.8	-586.2	176.0	418.7	246.5	597.6	1327.7
	GF	-7.0	-174.7	125.9	180.0	124.2	16.3	228.5	188.1	249.4	203.9
	LP	3.5	-18.7	29.7	49.1	63.6	9.9	26.7	44.6	102.5	104.2
	WH	7.0	-103.8	128.9	216.8	248.9	13.6	136.2	185.0	305.8	323.9
	RA	-3.6	-26.8	17.5	61.0	48.2	5.0	38.8	81.3	80.3	105.6

Table 2—Average bias and RMSE of component biomass produced by the beta, multinomial logistic, and Dirichlet regression approaches (Species are DF = Douglas-fir; GF = Grand Fir; LP = Lodgepole Pine; RA = Red Alder; WH = Western Hemlock). Predicted component biomass was obtained by applying predicted proportions to the observed total aboveground biomass.

		Bias (kg)				RMSE (kg)			
Method	**Species**	**Foliage**	**Bark**	**Branch**	**Bole**	**Foliage**	**Bark**	**Branch**	**Bole**
Beta	DF	-0.218	-2.619	-1.221	2.994	15.3	20.0	72.5	79.8
	GF	1.109	-0.392	-0.152	-0.320	13.7	14.3	24.3	36.0
	LP	-0.122	0.105	-0.111	-0.766	5.9	6.6	22.2	25.5
	WH	0.811	-0.386	1.330	-1.567	13.6	5.4	32.8	43.2
	RA	0.350	-0.258	3.801	-3.230	1.9	4.2	22.4	20.8
MLR	DF	0.001	-0.005	-0.004	-0.083	17.2	23.2	63.7	74.3
	GF	-0.002	0.000	0.001	0.001	9.4	6.1	25.7	35.4
	LP	-0.007	-0.006	-0.025	-0.114	7.0	6.5	21.6	27.9
	WH	0.009	0.008	0.042	0.108	11.4	5.1	29.8	40.8
	RA	-0.001	-0.017	-0.023	-0.173	1.1	2.6	13.6	12.9
Dirichlet	DF	-1.948	-2.971	6.807	-1.979	17.5	24.3	70.8	83.0
	GF	-0.832	0.177	-0.312	0.968	9.4	6.0	24.7	33.5
	LP	-1.515	-1.356	0.729	1.990	7.5	7.0	21.7	28.6
	WH	1.473	-2.130	5.325	-4.501	13.3	7.1	34.9	45.7
	RA	-0.859	-5.289	15.286	-9.353	1.6	15.8	51.6	35.6

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LEGACY TREE DATA: A NATIONAL DATABASE OF DETAILED TREE MEASUREMENTS FOR VOLUME, WEIGHT, AND PHYSICAL PROPERTIES

P.J. Radtke, D.M. Walker, A.R. Weiskittel, J. Frank, J.W. Coulston, J.A. Westfall[1]

Abstract—Forest mensurationists in the United States have expended considerable effort over the past century making detailed observations of trees' dimensions. In recent decades efforts have focused increasingly on weights and physical properties. Work is underway to compile original measurements from past volume, taper, and weight or biomass studies for North American tree species. To date, taper records have been recovered from over 150,000 trees, and biomass records from another 22,000. Upon completion the database will serve many purposes including the development and testing of taper, volume, and biomass estimators for about thirty U.S. tree species that comprise roughly two-thirds of the Nation's growing stock. The work is going very well, especially for eastern species that currently make up a majority of the collection to-date. Work will continue in the East, but a major emphasis going forward will be the collection of data sets from western species.

INTRODUCTION

Forest mensurationists in the United States have expended considerable effort over the past century making detailed observations of trees' dimensions and physical properties. Many studies involved felling trees to make dimensional measurements of main stem attributes including: scaling diameters and lengths of merchantable logs (Allen, 1902; Kenety, 1917); determination of cubic foot volumes, taper, bark thickness, and internal defects (Hornibrook, 1950; Pemberton, 1924); and tree-ring analysis for reconstructing height and diameter growth over time (Bishop et al., 1958). Stem wood and bark physical properties have been carefully studied in felled-tree studies, including extensive efforts carried out by the Forest Service to characterize wood specific gravity in commercially important species (Maeglin and Wahlgren, 1972; Mitchell, 1964).

Interest in estimating biomass yields and production have necessitated studies involving the green and dry weight contents of felled trees, including branch and foliage components together with stem wood and bark, and roots (Whittaker and Woodwell, 1968). The collection of felled tree data has continued to the present time, with measurement protocols varying to suit underlying research goals. Often the goals involve the measurement of stem dimensions along with weights and basic physical properties of aboveground components (Saucier and Clark, 1985). Studies primarily concerned with outside-bark stem dimensions have successfully relied on nondestructive techniques including the use of optical dendrometers or direct measurement with the use of ladders or climbing ropes (Reed, 1926; Westfall and Scott, 2010).

Despite shifting interests and research goals over time, researchers have recognized the value of incorporating information from past studies into new analyses and tools. Often summary results such as tables or equations are used in place of original measurements because the original data are not available (Jenkins et al., 2003). Challenges with standardizing

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measurements collected using different protocols or instruments have also been noted to be problematic (Wiemann and Williamson, 2012). Despite these challenges, many original data sets listing detailed tree measurements are known to exist, and methods exist for standardizing or "harmonizing" data collected using different tools and methods (Stahl et al., 2012). The goal of this work is to compile a comprehensive set of detailed field and laboratory measurements for use in developing estimators of standing tree volume, weight, and carbon contents. A further goal is to develop a sharable repository to facilitate long-term archival and re-use of legacy tree data for a wide range of research or management applications.

APPROACH

Facilities and individuals affiliated with the U.S. Forest Service, universities, private companies, and various other institutions were identified as potential points of contact for acquiring legacy data. An initial review of published research articles, written reports, and theses and dissertations was conducted to find data sets directly incorporated into written materials. When only available as paper copies, print materials were scanned to digital image format, primarily as multi-page portable document format (PDF) files. Optical character recognition (OCR) software was used to extract tabular data from PDF files or other digital images into ASCII text. Other printed lists of tree-related measurements such as unpublished computer printouts were also digitized using OCR when original digital files could not be found.

Many electronic files were obtained and processed using a range of hardware and software tools to compile measurement data into ASCII text files that could be easily shared and transferred to other computer software for management, analysis, and public distribution where allowed by data set owners. Non-print media obtained with viable data sets included punched cards, reel- and cartridge-type magnetic tape, floppy disks, CD-rom optical disks, hard disk drives, and portable media such as USB thumb drives or files transmitted over the Internet. A range of binary file formats were encountered including several from electronic spreadsheet, database management, and statistical analysis software. Data originated from various operating systems including VAX/VMS®, MS-DOS®, Microsoft Windows®, Unix®, Linux®, and Apple® O/S versions spanning over thirty years of change in mainstream computer technology.

Hand-written paper forms were also common, including field-tally sheets, Forest Service 558a forms, keypunch forms, and various notebooks containing field and laboratory records. These data were entered manually since OCR was ineffective at digitizing hand-written entries. It was also necessary to manually enter data from some printouts of fixed-width computer files, since OCR has only limited ability to determine the number of blank spaces strung together in a sequence. Scatterplot digitization software was used to efficiently extract stem taper diameter and height coordinate pairs from 558a forms (p. 71; Chapman and Demeritt, 1936).

Legacy Tree Database

A relational database schema was developed to accommodate the range of attributes and study designs represented in legacy data sets. The public view of the database contains roughly 575 attributes, including key fields, arranged into seven basic tables (Table 1—Legacy database relational tables and selected attributes in each table. Relational keys not shown.). With few exceptions, the tree was the basic unit of observation in the database. A few studies were added to the compilation that collected specimens or samples deemed useful for the development of biomass estimators even if no tree-level data were available. An example was a set of wood and bark moisture content measurements collected from quaking bolts upon delivery to a mill.A number of primary and secondary keys link relevant observations among tables and provide flexibility to add measurements to the database without restructuring the underlying database structure. Widely-used and freely-available software tools, such as PostgreSQL, Apache Server, and PHP were used as much as possible to promote accessibility and encourage adoption of the database structure or its contents over the WWW.

Figure 1—Examples of print and electronic media containing legacy tree data records.

Table 1—Legacy database relational tables and selected attributes in each table. Relational keys not shown.

Table	No. Attributes	Typical Attributes
LOCATION	30	Source; LAT/LON; Study design;
TREE	400	Size; Component; Weight; Volume; MC; SG; Protocol
STEM	10	Taper
SECTION	35	Dimensions; Weight
DISK	50	MC; SG; Bark; Wood
BRANCH	35	Position; Dimensions; Component; Weight
CORE	15	SG

STATUS AND DISCUSSION

To-date, 220 distinct data sets containing 174,115 individual trees have been fully incorporated into the database format, with many others not yet fully digitized or formatted to match the legacy database structure. Over 151,000 trees having stem taper measurements are included, along with about 22,000 and 11,000 trees having dry weights and green weights, respectively (Table 2—Number of Legacy trees having dry and green weight records and taper measurements for selected species.). Mainly just those species represented by 100 or more trees measured for stem taper are shown in Table 2—Number of Legacy trees having dry and green weight records and taper measurements for selected species., except for a few commercially important western species that are currently underrepresented in the collection and others that have stem forms not conducive to taper measurements.

Tree records from the Southern Region make up the largest subset of legacy data to-date, with 45% of all taper data being from the four major southern yellow pines, sweetgum, and yellow-poplar. The high proportion of data from southern species is a result of several factors: 1) that the work was aided by a small number of individuals who were able to assist us in obtaining large collections of tree biomass and taper data from the Southeast; 2) that our search began with southern and eastern locales, and only recently has been expanded to find comparable data sets further north and west; and 3) that many northern and western studies of stem volumes were conducted decades earlier than southern studies, especially in southern pines which have been intensively managed only since about 1950 (Fox et al., 2007).

Efforts to recover legacy data will continue under the auspices of this work for some time, with increased attention given to the recovery of data sets in all geographic regions of the United States. Significant collections of Central American and Canadian legacy data have been identified that may be suitable to include with the legacy tree database as well (Navar et al., 2013; Ung et al., 2008). Including trees outside of U.S. borders may aid in developing models for species whose ranges are not limited to the contiguous 48 states. The database design includes tools for continuously adding legacy records so that ongoing work or newly recovered data may be added to the compilation; further, as field researchers and practitioners gain familiarity with standardized sampling protocols, measurement attributes, and the existence of public data repositories like this one, the number of contributions is expected to grow.

Table 2—Number of Legacy trees having dry and green weight records and taper measurements for selected species.

Common_Name	SPCD	No. Legacy Trees Dry wt.	Green wt.	Taper
balsam fir	12	271	23	1,459
white fir	15	12	30	941
subalpine fir	19	169	-	217
Alaska yellow-cedar	42	4	-	737
Atlantic white-cedar	43	-	-	259
eastern redcedar	68	655	17	894
tamarack (native)	71	26	-	167
western larch	73	77	-	15
Engelmann spruce	93	107	-	600
white spruce	94	340	57	1,277
black spruce	95	415	9	1,148
red spruce	97	155	48	450
Sitka spruce	98	-	-	224
jack pine	105	224	-	3,080
sand pine	107	138	-	652
lodgepole pine	108	505	19	204
shortleaf pine	110	481	397	6,470
slash pine	111	991	833	14,208
spruce pine	115	75	1	182
sugar pine	117	4	-	217
western white pine	119	96	-	36
longleaf pine	121	751	787	6,088
ponderosa pine	122	543	254	2,890
Table Mountain pine	123	100	-	151
red pine	125	129	-	2,665
pitch pine	126	117	-	553
pond pine	128	118	18	1,157
eastern white pine	129	236	77	2,642
loblolly pine	131	3,450	2,950	31,146
Virginia pine	132	190	216	3,121
singleleaf pinyon	133	102	76	-
Austrian pine	136	-	-	285
Douglas-fir	202	548	18	1,349
baldcypress	221	28	28	290
pondcypress	222	93	83	696
northern white-cedar	241	20	-	273
western redcedar	242	66	-	540
hemlock spp.	260	-	-	216
eastern hemlock	261	58	32	623
western hemlock	263	91	-	615
red maple	316	709	391	3,864
silver maple	317	14	14	211
sugar maple	318	568	92	1,861
buckeye spp.	330	-	-	113
birch spp.	370	95	69	469
yellow birch	371	466	20	773
sweet birch	372	38	32	145
paper birch	375	304	-	1,562
hickory spp.	400	281	199	2,993
pecan	404	8	-	101
shagbark hickory	407	-	-	128

Common_Name	SPCD	No. Legacy Trees Dry wt.	Green wt.	Taper
hackberry spp.	460	16	14	242
flowering dogwood	491	140	60	290
common persimmon	521	11	6	104
American beech	531	339	10	1,077
ash spp.	540	467	279	686
white ash	541	161	71	388
black ash	543	-	-	163
green ash	544	43	43	164
loblolly-bay	555	-	-	134
American holly	591	22	13	129
black walnut	602	1	1	299
Arizona walnut	606	190	-	-
sweetgum	611	780	771	5,810
yellow-poplar	621	440	416	4,767
magnolia spp.	650	175	-	37
cucumbertree	651	1	1	157
sweetbay Magnolia	653	17	8	417
water tupelo	691	202	203	348
blackgum	693	137	32	1,189
swamp tupelo	694	184	203	1,655
bay spp.	720	188	-	-
American sycamore	731	41	40	430
poplar spp.	740	170	142	286
balsam poplar	741	21	16	215
eastern cottonwood	742	72	-	176
bigtooth aspen	743	85	-	566
quaking aspen	746	535	12	2,517
black cherry	762	145	78	825
oak spp.	800	113	6	707
white oak	802	491	380	5,284
scarlet oak	806	159	142	1,700
northern pin oak	809	-	-	127
southern red oak	812	92	84	1,900
cherrybark oak	813	19	19	414
laurel oak	820	48	48	1,187
overcup oak	822	4	4	183
swamp chestnut oak	825	1	1	244
water oak	827	218	234	2,126
Texas red oak	828	-	-	107
willow oak	831	72	72	520
chestnut oak	832	156	150	2,512
northern red oak	833	332	162	2,371
post oak	835	37	30	1,163
black oak	837	128	139	1,923
live oak	838	-	-	238
black locust	901	29	21	514
basswood spp.	950	32	32	360
American basswood	951	31	-	510
elm spp.	970	68	56	820
American elm	972	133	-	241
unknown/other tree	999	573	46	855
All species		22,373	11,164	151,139

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GAPS IN SAMPLING AND LIMITATIONS TO TREE BIOMASS ESTIMATION: A REVIEW OF PAST SAMPLING EFFORTS OVER THE PAST 50 YEARS

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Abstract—Tree biomass models are widely used but differ due to variation in the quality and quantity of data used in their development. We reviewed over 250 biomass studies and categorized them by species, location, sampled diameter distribution, and sample size. Overall, less than half of the tree species in Forest Inventory and Analysis database (FIADB) are without a published biomass model and most of the sampled trees are less than 13 inches diameter at breast height (d.b.h.). Although some species are well represented with biomass sampled, most focus on the aboveground components and as a result, there are important spatial gaps in their sampling as there was general divergence between the observed and sampled biomass centroids. In addition, most studies we analyzed did not sample trees of poor form or vigor, which means the models may not be representative of the larger population. Currently, this information is being used to address existing biomass sampling gaps in order to develop more robust prediction models.

Tree-level biomass models are generally derived by destructively sampling a subset of trees, drying and weighing their components, and using allometry to relate some easily measured metric (e.g., diameter) to the whole tree or component dry weight. Due to high costs, most biomass studies sample a small number of trees over a limited area, thus making extrapolation to different locations or larger areas difficult due to differences in climate, site characteristics, management practices, tree form, and other properties across the landscape. As such, those seeking to derive stand- and landscape-level biomass estimates generally rely on geographically generalized allometric models that use data from multiple studies and locations to refit models to a larger area (e.g., Schmitt and Grigal 1981) or use pseudo-data (Jenkins et al. 2003, Pastor et al. 1984).

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In addition, many biomass studies group species to ensure an adequate sample size for model fitting. For example, the ratio estimators of Jenkins et al. (2003) were generalized for 10 species groups across the United States. In theory, generalized models should perform well at the scale for which they are developed, however, when applied to a single site or region or a particular species, errors could be high.

With the assumption that gaps in previous sampling efforts could cause generalized model bias, we formally examined the existing body of biomass literature. Our objectives were to document existing studies' coverage in terms of: 1) geography; 2) species; 3) components measured; 4) size and diameter distribution; and 5) sample size. We utilized USDA Forest Service FIA database (FIADB; O'Connell et al. 2014) for comparisons to a substantial compilation of destructively sampled "legacy" trees to assess gaps.

METHODS

For each published biomass study, we recorded the author, year, species, and location. All studies we examined were conducted in the United States. Sample size, average, minimum, and maximum tree diameter, and sampled components by location and species were noted. We examined each article to determine if tree sampling restrictions were imposed as evidenced by avoiding trees of poor form (e.g., low forks or broken tops), poor health (e.g., high risk of mortality, lacking vigor, or diseased).

Generally, we could estimate the geographic coordinates within 0.05°. However, for some articles, the coordinate precision was considerably lower because the location description was too general or area sampled too large. To assess whether the sampled biomass represented the biomass distribution across a species' range, we developed maps showing past biomass study locations for the 20 most voluminous eastern species and 10 most voluminous western species with FIA derived biomass per acre. The observed aboveground FIA biomass centroid and the derived legacy biomass centroid were also plotted.

The number of trees sampled was summarized by five specific geographic regions: 1) Northeast (NE); 2) Southeast (SE); 3) Inter-mountain West (IMW), 4) Pacific Northwest (PNW) and 5) North Central (NORCEN).

Although Wang (2014) identifies 47 different biomass component classes, eight major component groups were summarized in this analysis, which included: 1) stem wood; 2) stem bark; 3) total stem (wood & bark); 4) branch wood and bark; 5) total aboveground wood and bark (excluding foliage); 6) total aboveground (including foliage); 7) foliage; and 8) root biomass. As a metric for balancing the number of trees sampled (n_legacy) and the percentage of biomass across the landscape (pct_bio), we calculated a sampling completeness value (SCV) as n_legacy/pct_bio/10

RESULTS

We examined 262 studies with 43,006 trees. Thirty studies contained nearly 62 percent of these trees with the work of Clark et al. (1986) contributing nearly 5,000 trees and a comprehensive sampling across the SE. Young et al. (1980) sampled over 900 trees in Maine, while Perala and Alban (1980) sampled extensively across the Great Lakes region. To date, we have compiled original data from over 150 studies with over 15,000 trees.

There are models or legacy data for 166 of the 346 tree species in the Forest Inventory and Analysis database (FIADB). Preliminary estimates suggest that the top 20 species by volume comprise nearly 85 percent of the biomass in the FIADB and 47 percent of the trees destructively sampled in the literature. Though 95 percent of the trees are less than 13 inches diameter at breast height (d.b.h) (Fig. 1), 95 percent of the hardwood and conifer biomass in FIADB is contained in trees less than 26 inches and 43 inches d.b.h., respectively.

Of the 262 studies, we could not discern whether 175 studies (25,372 trees) sampled with restrictions. We determined that 42 studies (4,291 trees) imposed sampling restrictions while 45 studies (10,820 trees) were random in their selection methods. Generally, the restrictions were evidenced in methodologies that avoided trees that were open-grown, heavily defoliated, broken at the top, low-forked, diseased, or otherwise distorted.

Maps for four example species indicate a general divergence between the observed and sampled centroids (Fig. 2). The Allegheny Plateau was an observed center of species biomass. Only eight trees were sampled for red maple (*Acer rubrum* L.) in this area (Wood 1971) and none of the trees were over 11.8 inches d.b.h.

With regard to biomass components, we identified 24,412 trees that have been destructively sampled for above stump (≥ 0 inches) biomass across the United States (Table 1). Most of these trees (19,862) measured stem biomass, while 16,559 and 12,961 provided estimates of wood and bark, respectively. Branch and foliage biomass were estimated for 19,431 and 21,510 trees, respectively. A smaller number of trees contain estimates for total aboveground biomass (AGB)

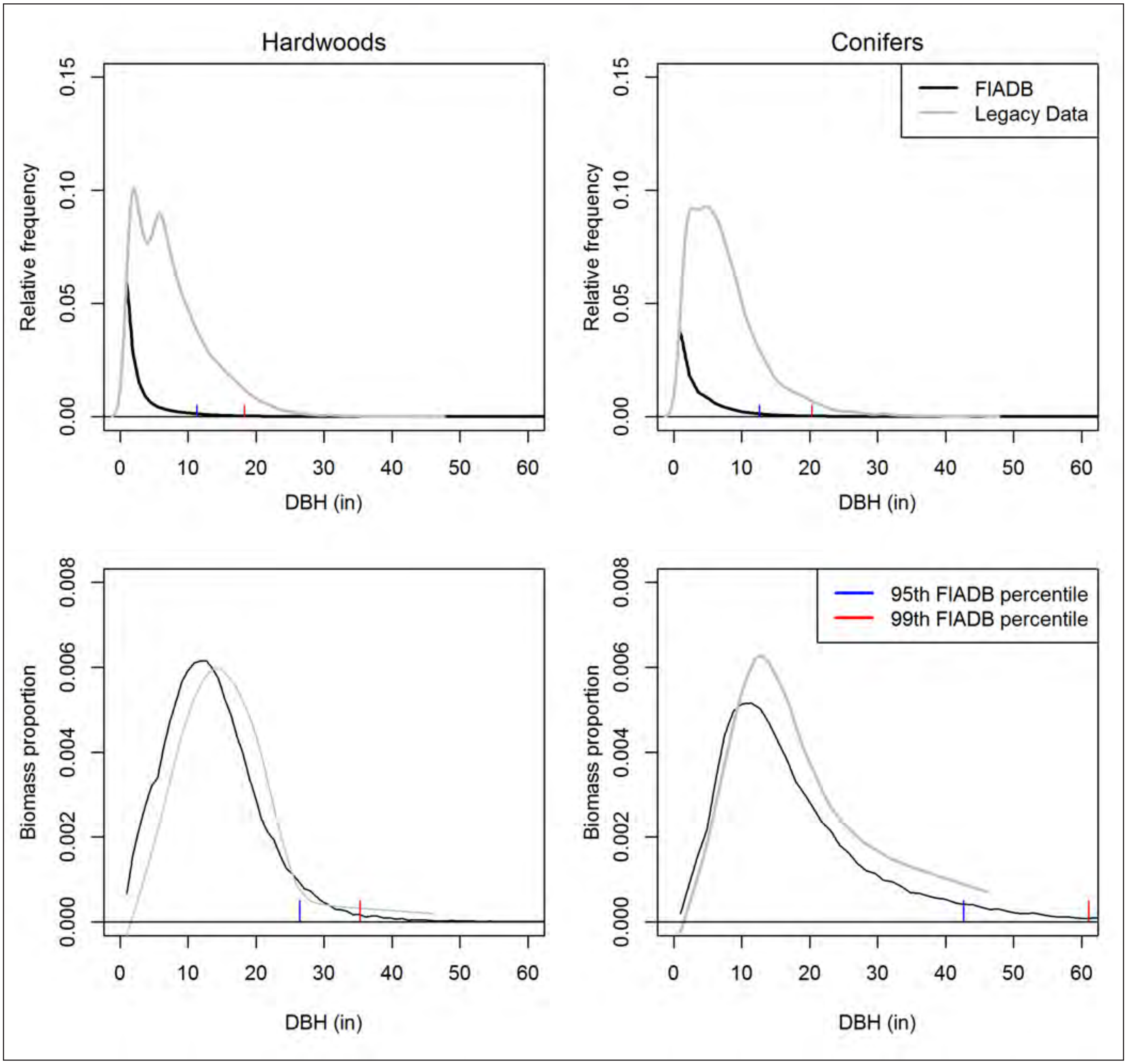

Figure 1—Comparison between the frequency of trees by diameter in the Forest Inventory and Analysis (FIA) database and legacy databases (top panels) for hardwoods and conifers. Bottom panels show the proportion of biomass by diameter in the FIA database.

leaving the stump component poorly represented. Although root biomass contain 17 percent of the whole tree (FIADB), it is largely under-sampled as only 3,834 trees had root biomass measurements.

Table 2 shows the FIADB proportion by species, region, and diameter class compared to the number of legacy trees sampled for aboveground wood and bark biomass. This summary is an estimation of biomass using the trees measured in the FIADB without accounting for the density of plots. Representation is good for the top 20 percent of biomass, but there is an obvious gap in large Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) trees. Certain hardwoods, such as sugar maple (*Acer saccharum* Marsh.) and northern red oak (*Querus rubra* L.) in the North Central region, and 10-20 inch d.b.h. red maple, and northern red oak in the Northeast, are relatively undersampled. SCVs indicate good representation for major species in the SE.

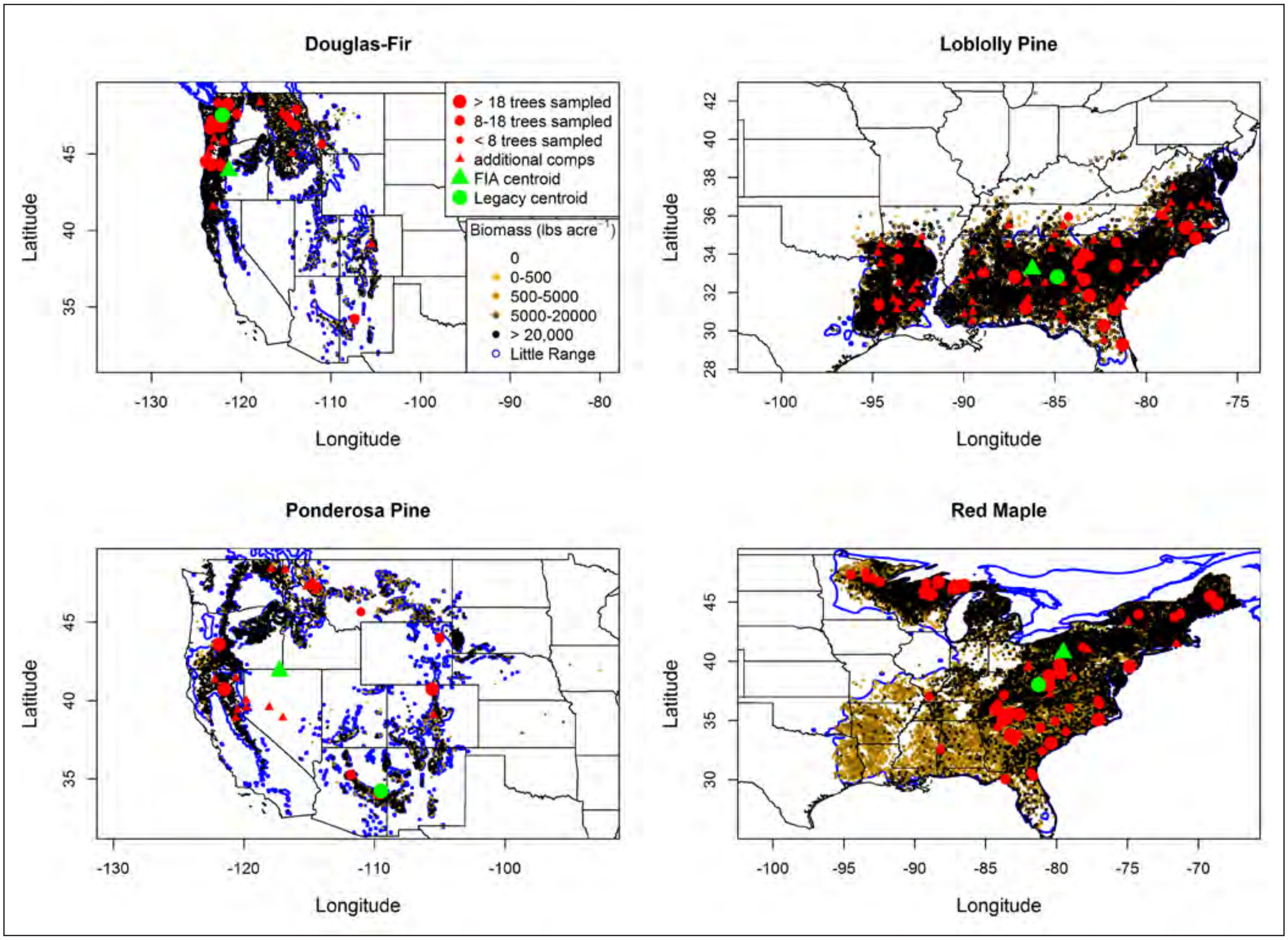

Figure 2—Known biomass study locations and maximum sample size sampled for the four most prevalent species by volume across the United States plotted over biomass per acre as estimated from the FIA database. Centroids are calculated only for studies with actual data.

DISCUSSION

Three primary sampling gaps were observed in this assessment: 1) larger diameter classes (>25 inches d.b.h.); 2) root biomass; and 3) spatial gaps. Examining the top four species by volume in the United States, we observed gaps in the southern Cascades in Douglas-fir. Sampling here would pull the legacy biomass centroid towards the FIA biomass centroid. Red maple studies were largely absent in the Allegheny Plateau and northern Michigan, while ponderosa pine observations were largely absent in eastern Oregon.

We present SCV to assess whether sampling intensity is sufficient. The largest gaps had a high percentage of biomass in the FIADB and low number of trees sampled. Consequently, the lower the SCV value the bigger the gap. Since funding poses a serious limitation for this type of research, we might set an SCV goal of 1 and assess how many trees, by grouping, need sampled. Where the SCV exceeds the SCV goal we would have a sufficient sample under this scenario. Otherwise we would prioritize trees with the lowest SCV (e.g., large Douglas-fir trees in the PNW, red oak in the NORCEN, and eastern white pine *(Pinus strobus* L.) in the NE).

Nearly half of the studies likely imposed some sort of sampling restriction. While the CRM method applies a cull volume deduction to the stem, most generalized biomass models do not obviously account for this and may overestimate for poorly formed unhealthy trees. We recommend that future studies examine how variation in tree form and health influences biomass and carbon content estimation.

FIA is currently sampling trees across the United States to fill in current species-, spatial-, and size-related gaps. Emphasis is on sampling large trees and recent work has been conducted in Pennsylvania, Oregon, and Michigan. The costs associated with destructively sampling trees can be incredibly high. As such, university partners are seeking additional collaborators to share resources and knowledge to achieve common goals.

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RATIO EQUATIONS FOR LOBLOLLY PINE TREES

Dehai Zhao, Michael Kane, Daniel Markewitz, Robert Teskey[1]

Abstract—The conversion factors (CFs) or expansion factors (EFs) are often used to convert volume to green or dry weight, or from one component biomass to estimate total biomass or other component biomass. These factors might be inferred from the previously developed biomass and volume equations with or without destructive sampling data. However, how the factors are related to tree size such as DBH, height or tree volume had not been examined. Using the tape and biomass measurement data of about 2000 destructively sampled loblolly pine trees, we developed several nonlinear equations to relate ratios between stem green/dry weights and stem volume to DBH and height, or tree volume. We also developed tree fractional biomass component equations with the Dirichlet regression and logratio regression approaches. These two approaches guarantee all component proportions sum to 1, and have almost the same performance. The ratios are functions of tree size and can be better estimated by DBH and HT than by stem volume.

The conversion factors (CFs) and expansion factors (EFs) are commonly used to convert tree volume to green and dry weights or from one component or total biomass to other components. These factors are usually derived from previously developed biomass and/or volume equations. How the factors are related to tree size had not been formally tested. Traditionally, separate tree fractional biomass component equations were developed, but this approach cannot hold the constraint that all component proportions sum to one. Using loblolly pine expanded datasets and new modeling approaches, in the study we developed a series of ratio equations for: (1) ratio of stem total green weight to total outside volume, (2) ratio of stem-wood dry weight to total outside volume, (3) proportions of stem-wood and bark in stem biomass, and (4) proportions of stem-wood, bark, branch, and foliage components in total tree aboveground biomass. We also compared two new modeling approaches.

DATA AND METHODS

Data are from (1) 1280 trees with taper measurements and green weight of cut-bolts, from which tree stem outside volume and stem green weight with bark were calculated; (2) 274 trees with taper measurements, green weights of disks, and dry weight without bark, from which tree stem outside volume, stem green weight with bark, and dry weight of stem without bark were calculated; (3) 481 new destructively sampled trees with taper measurements, green weights of cut-bolts and branch with foliage, green weights of disks, subsampled branch with foliage, dry weights of disk wood, bark, branch and foliage. For the new sampled trees, stem green weight, dry weight of stem without bark (stem-wood), dry weight of bark, dry weight of branches, and dry weight of foliage were calculated for each tree. Stem volume for each tree was obtained using Bailey's (1995) over-lapping-bolts method.

For the ratio of stem weight to volume, the ratio equations were fitted in a system of stem volume, stem green or dry weight, and ratio equations with NSUR approach following Zhao et al. (2015) 4-step fitting strategies. The ratio equations were also directly fitted to stem volume using the OLS.

The Dirichlet regression Model (DRM) and log-ratio regression OLS Model (LGRM) approaches were used to model stem biomass composition and total aboveground biomass composition.

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RESULTS

The ratio of stem green weight to volume ($R_{gw/v}$) and ratio of stem dry weight to volume ($R_{dw/v}$) can be estimated by tree diameter at breast height (DBH, cm) and total height (HT, m) or stem outside volume (VOL, m^3):

$$R_{gw/v} = 547.648993 DBH^{0.026656} HT^{0.42614} \text{, or} \qquad R_{gw/v} = 950.0 VOL^{0.0504}$$

$$R_{dw/v} = 152.455601 DBH^{0.040590} HT^{0.259236} \qquad R_{dw/v} = 432.447 VOL^{0.10692} e^{-0.08677 VOL}$$

Proportions of stem-wood and bark in stem biomass can be estimated with the following equations:

$$P_{stemwood} = \frac{87.8561 DBH^{-0.3584} HT^{0.8903}}{87.8561 DBH^{-0.3584} HT^{0.8903} + 149.6651 DBH^{-0.4311}} \text{, or}$$

$$P_{stemwood} = \frac{1}{1 + 1.60724 DBH^{-0.06283} HT^{0.88325}} \text{, or}$$

$$P_{stemwood} = \frac{544.7898 V^{0.32036} e^{-0.28403V}}{33.824 + 544.7898 V^{0.32036} e^{-0.28403V}}$$

$$P_{stembark} = 1 - P_{stemwood}$$

Biomass allocation in total tree aboveground biomass can be estimated by DBH and HT using either DRM or LGRM:

$$\begin{aligned} a_0 = {} & 7.829 + 1.5964 DBH^{-1.2763} HT^{2.9237} \\ & + 2.6327 DBH^{-1.3144} HT^{2.0156} + 1.6966 HT^{0.9634} \end{aligned}$$

$$P_{wood} = 1.5964 DBH^{-1.2763} HT^{2.9237} / a_0$$

$$P_{bark} = 2.6327 DBH^{-1.3144} HT^{2.0156} / a_0$$

$$P_{branch} = 1.6966 HT^{0.9634} / a_0$$

$$P_{foliage} = 7.829 / a_0$$

, or

$$\begin{aligned} c_0 = {} & 1 + 1.60724 DBH^{-0.06283} HT^{0.88325} + DBH^{1.28554} HT^{-1.95407} \\ & + 4.66716 DBH^{1.28151} HT^{-2.93341} \end{aligned}$$

$$P_{wood} = 1 / c_0$$

$$P_{bark} = 1.60724 DBH^{-0.06283} HT^{0.88325} / c_0$$

$$P_{branch} = DBH^{1.28554} HT^{-1.95407} / c_0$$

$$P_{foliage} = 4.66716 DBH^{1.28151} HT^{-2.93341} / c_0$$

DISCUSSION AND CONCLUSIONS

Both the Dirichlet regression and log-ratio regression approaches can be used to model biomass allocation, with almost the same performance. The approaches guarantee all components sum to one. The models based on DBH and HT perform better than the model based on stem volume only.

ACKNOWLEDGMENT

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FIA IN THE BOREAL FORESTS OF ALASKA: HIGHLIGHTS OF THE 2014 TANANA PILOT AND THE KENAI PENINSULA

THE 2014 TANANA INVENTORY PILOT: A USFS-NASA PARTNERSHIP TO LEVERAGE ADVANCED REMOTE SENSING TECHNOLOGIES FOR FOREST INVENTORY

Hans-Erik Andersen[1], Chad Babcock[2], Robert Pattison[3], Bruce Cook[4], Doug Morton[4], and Andrew Finley[5]

Abstract—Interior Alaska (approx. 112 million forested acres in size) is the last remaining forested area within the United States where the Forest Inventory and Analysis (FIA) program is not currently implemented. A joint NASA-FIA inventory pilot project was carried out in 2014 to increase familiarity with interior Alaska logistics and evaluate the utility of state-of-the-art high-resolution remote sensing (lidar+hyperspectral+thermal airborne imaging) to support an FIA inventory of interior Alaska.

DATA DESCRIPTION

In the 2014 Tanana inventory pilot project, FIA plots were established at a 1:4 intensity (or 1 plot per 24,000 acres) on a regular (i.e. systematic) hexagonal grid across both Tanana Valley State Forest and Tetlin National Wildlife Refuge, within the Tanana valley of interior Alaska. The relatively sparse FIA field plot sample described was augmented with sampled airborne remotely-sensed data acquired with the G-LiHT (Goddard-Lidar/Hyperspectral/Thermal) system to increase the precision of inventory parameter estimates. G-LiHT is a portable, airborne imaging system, developed at NASA-Goddard Space Flight Center, that simultaneously maps the composition, structure, and function of terrestrial ecosystems using lidar, imaging spectroscopy, and thermal imaging. G-LiHT provides high-resolution (~1 m) data that is well suited for studying tree-level ecosystem dynamics, including assessment of forest health and productivity of forest stands and individual trees. In addition G-LiHT data support local-scale mapping and regional-scale sampling of plant biomass, photosynthesis, and disturbance. The data is accurately georeferenced and can be matched very precisely with field plot data that are georeferenced using high-accuracy (dual-frequency, GLONASS-enabled) GPS. G-LiHT data was acquired in July-August, 2014 along single swaths (250 meters wide) spaced 9.3 km apart over the entire Tanana inventory unit (135,000 sq.km). Standard (design-unbiased, plot-based) FIA estimation approaches are compared with model-assisted (i.e. approximately design-unbiased) and model-based (spec. Bayesian hierarchical) approaches which utilize relationships between field measurements and G-LiHT-derived structural and spectral metrics.

Several modified FIA field measurement protocols were used to provide additional information on boreal forest conditions, including: 1) Ground cover measurements to quantify biomass/carbon of lichens and mosses, 2) Soil core sampling to quantify soil carbon content , 3) Two microplots to increase sample of small (1”-5”) diameter trees , and 4) High-precision GPS to enable accurate registration of field plots to airborne remote sensing data. Preliminary analyses indicate a strong relationship between

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lidar-derived variables and forest inventory metrics and also suggest that the addition of a second microplot at subplot locations further improves model fit for biomass prediction in the boreal forestes of interior Alaska.

ANALYSIS METHODS

In this study three different approaches were used to estimate forest inventory variables of interest; with particular emphasis on estimation and mapping of aboveground carbon. The three estimation procedures include 1) the standard, design-based approach currently used by the annual FIA inventory for estimation of inventory parameters within the contiguous US, 2) a model-assisted technique where sample collections of remote sensing data can be incorporated into the estimation procedure to potentially decrease uncertainty while still being approximately design-unbiased; and 3) a Bayesian multilevel hierarchical modeling approach. We plan to assess the accuracy and bias of the three approaches experimentally via simulation and application within the Tanana Valley State Forest and Tetlin National Wildlife Refuge, using the field and remote sensing data collected during the 2014 Tanana Inventory Pilot project.

CONCLUDING REMARKS

Given the remoteness (i.e. lack of transportation infrastructure) and size of interior Alaska, it is prohibitively expensive to implement a FIA inventory at the same sampling intensity as the lower 48 (1 plot per 6000 acres). It is also expected that remote sensing (both airborne and spaceborne) will be heavily relied-upon to achieve acceptable levels of precision for inventory estimates in interior Alaska (i.e. levels that will provide a clear picture of present status and important trends in forest resource conditions). By comparing design and modelbased approaches we will gain understanding about how model bias influences forest inventory estimates for interior Alaska and determine if it is possible to obtain approximately design-unbiased inventory estimates while leveraging the flexibility of model-based approaches.

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A BAYESIAN HIERARCHICAL MODEL FOR SPATIO-TEMPORAL PREDICTION AND UNCERTAINTY ASSESSMENT USING REPEAT LIDAR ACQUISITIONS FOR THE KENAI PENINSULA, AK, USA

Chad Babcock[1], Hans-Erik Andersen[2], Andrew O. Finley[3], and Bruce D. Cook[4]

Abstract—Models leveraging repeat LiDAR and field collection campaigns may be one possible mechanism to monitor carbon flux in remote forested regions. Here, we look to the spatio-temporally data-rich Kenai Peninsula in Alaska, USA to examine the potential for Bayesian spatio-temporal mapping of terrestrial forest carbon storage and uncertainty.

INTRODUCTION AND MOTIVATIONS

Models leveraging repeat LiDAR and field collection campaigns may be one possible mechanism to monitor carbon flux in remote forested regions. Hopkinson et al. (2008) showed that it is possible to detect growth using repeated LiDAR collections for a pine plantation in Ontario, Canada. Plot-level field measures of forest height increment paralleled corresponding changes in LiDAR height, indicating that it may be possible to track forest growth by monitoring change in LiDAR metrics from year to year. Yu et al. (2008) constructed difference metrics by subtracting LiDAR variables derived from repeat LiDAR collections. Using these as predictor variables in a linear regression, they showed that forest height and volume increment can be predicted moderately well in a boreal forest in Finland. Hudak et al. (2012) developed biomass maps for two LiDAR acquisitions over a mixed conifer forest in Idaho, USA and showed that, even when LiDAR point densities differed dramatically between the datasets, it was possible to estimate change in biomass by subtracting the two predicted maps.

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Considering the demonstrated ability of multi-temporal LiDAR to estimate forest growth, it is not surprising that there is great interest in developing forest carbon monitoring strategies that rely on repeated LiDAR acquisitions for remote areas. Allowing for sparser field campaigns, LiDAR stands to make monitoring forest carbon cheaper and more efficient than field-only sampling procedures. There are issues concerning the few procedures currently proposed to assess growth, and subsequently carbon flux, using multi-temporal LiDAR though. Most linear regression approaches implicitly assume that remote sensing and field data are collected in the same season, which is problematic for most large-area field inventory campaigns. To increase spatial field sampling coverage without incurring extra cost, typically, only portions of the network of permanent sample plots are remeasured each year. Since the LiDAR and field data need to be coincident for proper calibration, the researcher is forced to discard all inventory data from other years or otherwise assume temporal misalignments to be negligible. We need methods capable of using temporally disjointed data appropriately. Further, subtracting maps of separately predicted forest biomass does not allow for prediction uncertainty to be properly carried through to the estimation of carbon flux. Without an accurate and useful assessment of carbon flux uncertainty, we have no way of understanding if predicted values are reliable.

Here, we look to the spatio-temporally data-rich Kenai Peninsula in Alaska, USA to examine the potential for Bayesian spatio-temporal mapping of terrestrial forest carbon storage and uncertainty. The modeling framework explored here can predict forest carbon through space and time, while formally propagating uncertainty through to prediction. Bayesian spatio-temporal models are flexible frameworks allowing for forest growth processes to be formally integrated into the model. By incorporating a mechanism for growth---using temporally repeated field and LiDAR data---we can more fully exploit the information-rich field inventory network to improve prediction accuracy.

MOTIVATING DATASET DESCRIPTION

LiDAR data for the Kenai Peninsula has been collected on four different occasions---spatially coincident LiDAR strip samples in 2004, 09 and 14, along with a wall-to-wall collection in 2008 (Table 1). There were 436 inventory locations measured at least twice between 2002 and 2014 (Figure 1). Plot locations exhibit a clustered configuration of up to 4 plots within a cluster (Figure 1, inset). Inventory data was collected according to the US Forest Service Forest Inventory Analysis plot design (Bechtold & Patterson, 2005). LiDAR information was acquired at least once over most of the inventory plots with many having LiDAR collected during 2, 3 or 4 different campaigns.

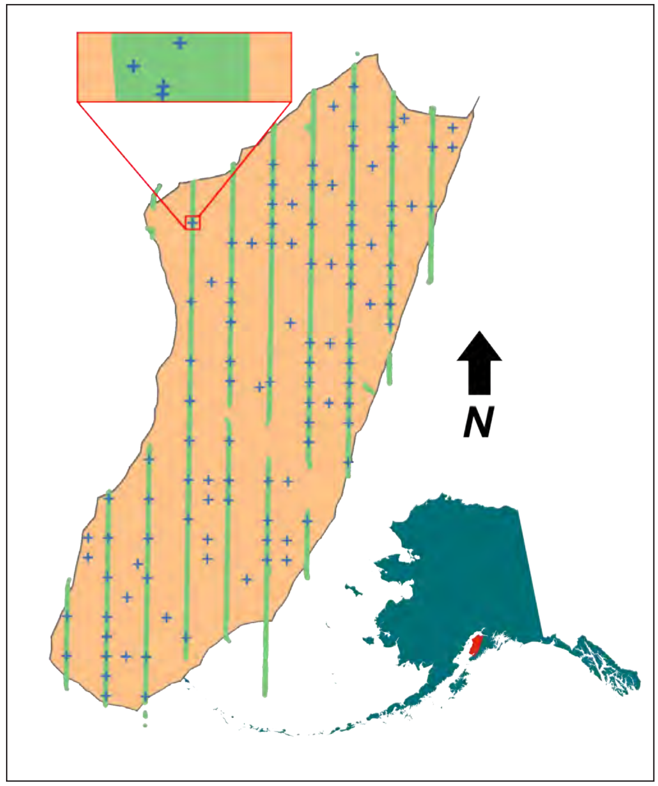

Figure 1—Kenai Peninsula study area. The orange region represents the coverage area for the 2008 wall-to-wall LiDAR dataset. The green areas represent the 2014 LiDAR strip dataset coverage. The 2004 and 2009 LiDAR datasets closely (but not completely) spatially coincide with the 2014 LiDAR dataset. The purple cross hairs locate the inventory plot locations (FUZZED). The inset map in the top left area of the figure zooms in on one cluster of plot locations. The Alaska state boundary map in the lower shows the location of the Kenai Peninsula in red.

Table 1—LiDAR acquisitions

Acquisition year	Strip sampling / wall to wall	Strip spacing, strip width	Average point density
2004	strip sampling	10 km, 300 m	7.88 points/m^2
2008	wall to wall	NA	1.81 points/m^2
2009	strip sampling	10 km, 300 m	4.13 points/m^2
2014	strip sampling	10 km, 300 m	7.38 points/m^2

MODEL FRAMEWORK

Bayesian hierarchical spatio-temporal modeling frameworks offer a useful solution to the problems of temporally misaligned data and uncertainty assessment (Cressie & Wikle, 2011). Here, we explore this class of models to develop a unified statistical framework capable of coupling the temporally misaligned and repeated measures of field inventory and LiDAR data for the Kenai Peninsula. This framework is able to predict forest carbon through space and time, while formally propagating uncertainty through to prediction. Bayesian spatio-temporal models are flexible frameworks allowing for forest growth processes to be formally integrated into the model. By incorporating a mechanism for growth—using temporally repeated field and LiDAR data—we can more fully exploit the information-rich field inventory network to improve prediction accuracy (Babcock et al., In Review). These frameworks also provide access to spatially and temporally explicit posterior predictive distributions useful for summarizing uncertainty. Because predictions of forest carbon for each year result from the same model in a spatio-temporal framework, it is possible to probabilistically assess uncertainty of carbon flux by summarizing posterior predictive distributions appropriately.

CONCLUDING REMARKS

Results from this research will impact how forests are inventoried. It is too expensive to monitor terrestrial carbon flux using field-only sampling and estimation strategies and currently proposed model-based techniques leveraging LiDAR lack the ability to properly utilize temporally misaligned data---we need new and innovative methods to track forest carbon dynamics in remote regions. Bayesian hierarchical spatio-temporal modeling frameworks offer a solution to these shortcomings and, further, easily allow for formal predictive error assessment. which is useful decision making about the certainty of our estimates and about when and where to collect future field and LiDAR data to best improve prediction accuracy.

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DOWN WOODY MATERIAL, SOIL AND TREE CORE COLLECTION AND ANALYSIS FROM THE 2014 TANANA PILOT PLOTS

Robert R. Pattison, Andrew N. Gray, Patrick F. Sullivan, and Kristen L. Manies[1]

Abstract—In the summer of 2014 the US Forest Service's Forest Inventory and Analysis (FIA) Program of the Pacific Northwest (PNW) Research Station in conjunction with NASA Goddard carried out a pilot inventory of the forests of interior Alaska. This inventory was conducted on the State of Alaska's Tanana Valley State Forest and on the Tetlin National Wildlife Refuge. As part of the field protocols that were implemented, field crews measured Down Woody Material (DWM), sampled soils and collected tree cores. The DWM protocols were based on standard FIA protocols. The soil sampling included a modified protocol based on the US Geological Survey's (USGS) protocols for the boreal forests of the region. The tree core measurements were made on cores collected from site and age trees of FIA plots. The results of these data collection efforts will provide insights into carbon content in these forests and into trends in tree growth rates. In addition, because it was a pilot inventory the goals were to improve field sampling methods prior to a full scale inventory of the interior forests of Alaska.

INTRODUCTION

Interior Alaska has experienced some of the greatest increases in temperature globally and this trend is predicted to continue. The results of this warming trend appear to manifest in large scale changes in the region, leading some to suggest that a "biome shift" is underway (Beck et al. 2010, Juday et al. 2015). Such a shift could have dramatic impacts on local communities, which are dependent on wildlife and forest resources. In addition, as boreal forests worldwide contain to up 30% of terrestrial carbon, warming trends may impact global carbon cycles (Tarnocia et al. 2009).

Interior Alaska contains an estimated 15% of the forested lands in the US but does not have an FIA or other large scale inventory. The 2014 inventory in the Tanana Valley State Forest and Tetlin National Wildlife Refuge in interior Alaska was the first large scale systematic inventory in the region since the early 1980s. This inventory sought to test new field protocols to provide critical insights into current conditions in the region. Of particular interest are the carbon stores in soils and in trends in tree growth for these forested plots.

Downed woody material and soils properties are poorly understood for much of interior Alaska. Knowledge of DWM and soil carbon can improve insights into carbon storage and fire dynamics of these ecosystems (Gould et al. 2008, Beck et al. 2011).

STUDY AREA

The Tanana Valley is located in Interior Alaska, north of the Alaska Range, following the Tanana River. A systematic sample of 98 plots was measured within the Tanana Valley State Forest and the Tetlin National Wildlife Refuge (NWR). These plots represent a ¼ sample of the standard FIA grid.

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METHODS

The crews used a standard P2 DWM protocols for sampling the DWM and a modified soils protocol developed by the USGS that included the use of a soil corer (Nadler and Wein 1998) and tile probes. Tile probe measurements were made to sample the depth of the active thaw layer. Soils sampling was limited to a depth of 40” because of the logistical constraints of packing excesses materials. Tree cores were collected from the field and analyzed for growth trends in a tree core analysis lab.

RESULTS AND DISCUSSION

There were 95 field plots that were sampled for soils. Of these 51 (54 percent) had frozen soils present at depths < 40”. The depths of the frozen layer ranged from < 1” to 37” (Fig. 1). There were 21 plots in which crews tallied gravel and did not hit frozen soils and 14 plots in which soil probes reached > 40”. There were 7 plots where the substrate was classified as unknown (neither rock or nor frozen). In many boreal forest ecosystems (e.g., black spruce dominated forests) the maximum thaw of the soils occurs in the September or October (Hollingsworth et al. 2008) - well after the optimal time to inventory the above ground forested conditions (June- mid August). As a result the soil sampling efforts used in this study are likely to not be capturing the maximum thaw depth of the soils and therefore not sampling full available soil carbon pool in these forest soils. The FIA program is currently considering alternative methods to sample soil carbon pools more effectively. These methods include using more robust soil sampling methods that require the use of gas powered augers.

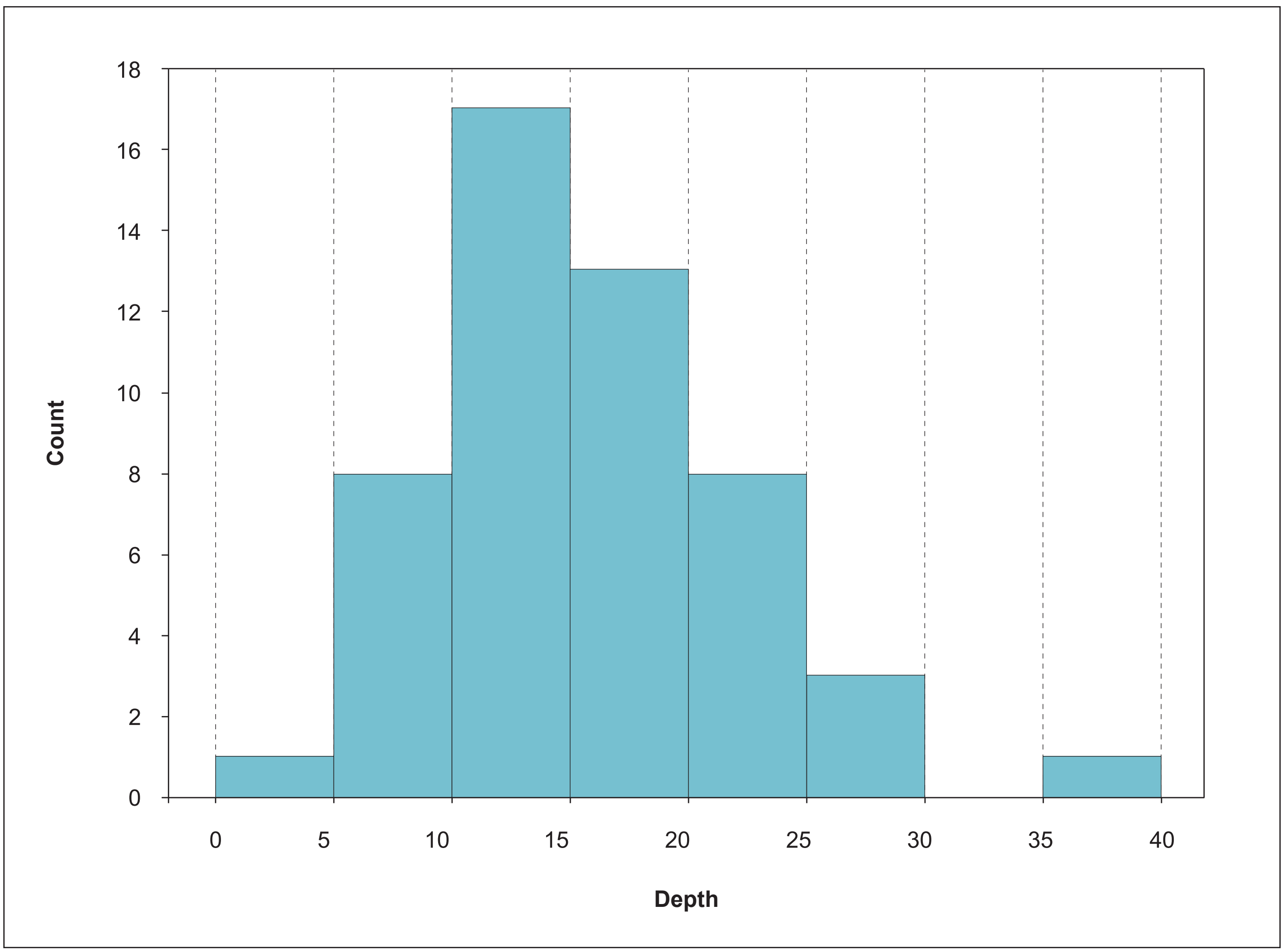

Figure 1—Distribution of depth to frozen layer on the 51 plots that had frozen soils.

Unlike the soils, the DWM protocols were generally not constrained by frozen soil conditions. One exception was the presence of frozen duff on several plots which prevented crews from obtaining accurate measurements of duff depth. Duff measurements can be useful in providing insights into fuel properties of forests.

Accurate aging of trees is important to determine stand age and site quality. In order to account for the time it takes for trees to reach breast height a set value is typically added to the counted rings on cores. However black spruce trees can take 50 + years to reach breast height. In order to account for this long period of time changes to core collection location such as collection cores at the base of trees are being considered. The preliminary results of the trends in tree growth rates across all of the field plots suggests that both black and white (Picea glauca) spruce have seen increases in tree growth. The greatest increases in growth occurred from 1920- 1950. From 1950 to the present tree growth rates showed stable to slight increases in growth. These trends are counter to recent studies suggesting that tree growth rates are declining in interior boreal forests (Juday et al. 2015).

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CHARACTERIZING FOREST VEGETATION OF THE TANANA VALLEY: WHAT CAN FOREST INVENTORY AND ANALYSIS DELIVER?

Bethany Schulz[1]

Abstract—Vegetation profile data were collected as part of a forest inventory project in the Tanana Valley in interior Alaska, providing a means of characterizing the forest vegetation. The black spruce forest type was most common, followed by Alaska paper birch, and white spruce, quaking aspen, and balsam poplar. For individual tree species, black spruce was recorded on 68 percent of all plots, birch was recorded on 67 percent and white spruce on 58 percent. The distribution of growth habits in horizontal layers varied by forest type. There was a higher percentage tree cover in hardwood forest types. Shrubs were prominent in all forest types, dominating in the lowest horizontal layer in black spruce forests and mid layers in other forest types. The most common species recorded include (in descending order) lingonberry, black spruce, Alaska paper birch, bog Labrador tea, white spruce, green alder, bog blueberry, and prickly rose all recorded on at least 35 percent of all plots. A full census of vascular plants on 25 subplots accumulated almost 2.5 times as many species as the Vegetation profile protocol on 101 subplots on the same set of plots.

INTRODUCTION

Understanding the existing distribution and abundance of plant species in ecosystems is important for monitoring the effects of a changing climate on natural ecosystems. In Alaska, changing distribution and composition of vegetation have been observed as shrubs encroach into tundra (Dial and others 2007); hardwoods replace spruce in some areas (Rupp 2011); and white spruce forests are expanding in others (Roland and others 2013). At the same time, new pest outbreaks are being observed that could further influence shifts in vegetation composition (USDA Forest Service 2015). These changes can effect biomass accumulation and greenhouse gas emissions (Rupp 2011). Vegetation data collected on the ground is relatively scarce in Alaska, but is needed to aid the interpretation of the remotely sensed-data that managers depend on with increasing frequency. The Forest Inventory and Analysis (FIA) 2014 project in interior Alaska provides a systematic sample of 98 plots within the Tanana River Valley, in part to estimate biomass. Documenting vegetation characteristics now is essential for monitoring vegetation change over time. Using data generated from FIA's Vegetation Profile (VEG profile) protocol, I characterize the vegetation in the different forested conditions sampled, and demonstrate what can be reported using this new set of measurements.

STUDY AREA

The Tanana Valley is located in Interior Alaska, north of the Alaska Range, following the Tanana River. Systematic samples of 71 plots within the Tanana Valley State Forest and 27 plots on the Tetlin National Wildlife Refuge (TNWR) were collected from June through August, 2014.

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METHODS

The FIA Core-Optional VEG profile, level of detail 3 protocol was implemented on all plots (USDA Forest Service 2014). Both forest and non-forest conditions were sampled if accessible. Data were collected on each subplot and included the distribution of plant growth habit cover by layer. Layer 1 is between the ground and 2 feet, Layer 2 is between 2 and 6 feet, Layer 3 is between 6 and 16 feet, Layer 4 is 16 feet and higher. Up to four of the most abundant species per growth habit, if present with at least 3-percent subplot cover, were also recorded with percentage of subplot cover. In addition, a full census of all vascular plants on subplot 1 was implemented on the plots within the TNWR. These data were summarized by averaging subplot cover measurements to either plot or domain, and determining the percentage of plots where species were recorded for various domains.

RESULTS

Conditions

Of the 98 sampled plots, 73 were intact (100 percent single condition), 11 were fully forested but with multiple conditions, and 14 plots included some non-forest land cover class (Table 1). Black spruce (see Appendix Table 1 for list of common and scientific names) forest type was most the common, with 38 intact plots, and occurring on seven samples with multiples condition and eight edge plots. Alaska paper birch (birch) was the second most common with 20 intact plots; white spruce was third with eight intact plots. All of the non-forest land cover classes sampled were natural vegetation types, with shrubland being most common. Full descriptions of forested conditions sampled are included in Table 1.

Structure

Data from the intact forest condition plots were used to characterize structure overall and by forest type. Total tree cover on 73 intact plots included 23 plots with cover greater than 60 percent, 42 plots with greater than 40, and four with less than 10 percent. There were 27 plots with the highest percent tree cover in Layer 4. Twelve of these plots had average tree cover of 60 percent or more and 14 had cover between 25 and 60 percent. There were 16 plots where the maximum tree cover was in Layer 2 and Layer 3. The maximum tally tree cover was recorded in Layer 1 on 13 plots. Non-tally trees (a growth habit to describe species growing as trees but not included in standard tree measurements) were recorded on10 plots, three plots had an average of more than10 percent subplot cover.

Average shrub cover exceeded tree cover on 40 plots. Overall, average subplot shrub cover exceeded 10 percent in Layer 3 on16 plots and in Layer 4 on 19 plots. Grasses and forbs contributed to cover primarily in Layer 1. The average overall grass cover was 4 percent, recorded on all but two plots, and 22 plots had grass cover of 10 percent or more. Forbs had an average cover 13 percent, cover greater than 10 percent on 24 plots.

Structure was quite different between forest types. Average subplot cover of growth habits by layer for stands of the three main forest types that were at least 35 years old are shown in Figure 1. Shrubs were important in all types but varied by height.

Most abundant species

A total of 105 species were recorded using VEG Profile protocols. Tree and shrub species dominated the most abundant species collected (Table 2) and most forest types had several top species in common. The hardwood types with only a few sample plots had a few unique species. Although forb and grass growth habit cover were recorded on most plots as structure, only a few species exceeded the 3-percent threshold for recording (blue-joint reed grass, field horsetail, and fireweed).

Tree species distributions were examined by size across forest types. Large trees (LT) were 5 inch or greater in diameter, and small trees (SD) were less than 5 inch diameter (USDA Forest Service 2014). Black spruce and birch forest types are tied for number of other tree species found on single condition plots, but white spruce and birch trees are found on more forest types and condition combinations than black spruce trees (Table 1). Non-tally tree species were recorded as either large or small trees on seven plots, and included Bebb willow, green alder, and Scouler's willow.

Table 1—Number of plots by forested condition and percentage of plots with records of large (LT) and small (SD) trees by species

		Tree species										
		Black spruce		Alaska paper birch		White spruce		Quaking aspen		Balsam poplar		Tamarack
Condition and Forest Type Description	Plot Count	LT	SD	LT	SD	LT	SD	LT	SD	LT	SD	SD
Single condition:	*Number*	*Percentage of plots where recorded*										
Black spruce	38	47	100	21	50	21	0	8	8	0	0	8
Paper birch	20	20	45	80	90	55	60	5	25	5	5	0
White spruce	8	0	0	75	50	100	88	25	25	13	0	0
Aspen	3	0	33	33	67	67	67	67	67	0	0	0
Balsam poplar	3	0	0	0	0	33	67	0	0	100	100	0
Non-stocked	1	0	0	0	0	0	0	0	0	0	0	0
Multiple condition:												
Black spruce/ Paper birch	4	75	100	100	100	50	100	0	0	0	0	0
Black spruce / Multi age	3	33	100	0	100	67	100	0	0	0	0	0
White spruce/ Multi age	2	0	0	0	0	100	100	0	0	50	0	0
Paper birch/ Multi age	1	0	0	100	100	100	100	0	0	0	0	0
White spruce / Paper birch	1	0	100	100	100	100	100	0	0	0	0	0
Some non-forest:												
Black spruce/ Shrubland	3	33	100	0	33	0	0	0	0	0	0	33
Black spruce/ Mixed Veg	2	50	100	50	0	50	100	0	50	0	0	0
White spruce/ Shrubland	2	0	0	100	50	100	50	0	0	0	0	0
Black spruce/ Shrubland/Mixed Veg	1	100	100	100	0	100	100	0	0	0	0	0
Black spruce/ Non-vascular	1	100	100	0	100	0	0	0	0	0	0	0
White spruce/ Mixed Veg	1	100	100	0	100	100	100	0	0	0	0	0
Paper birch / Shrubland	1	0	0	0	0	0	0	0	0	0	0	0
Paper birch /Non-vascular	1	0	100	0	100	0	0	0	0	0	0	0
Paper birch / Mixed Veg	1	100	100	0	100	100	0	0	0	0	0	0
White spruce/Non-vascular	1	100	0	0	0	0	100	0	0	0	0	0

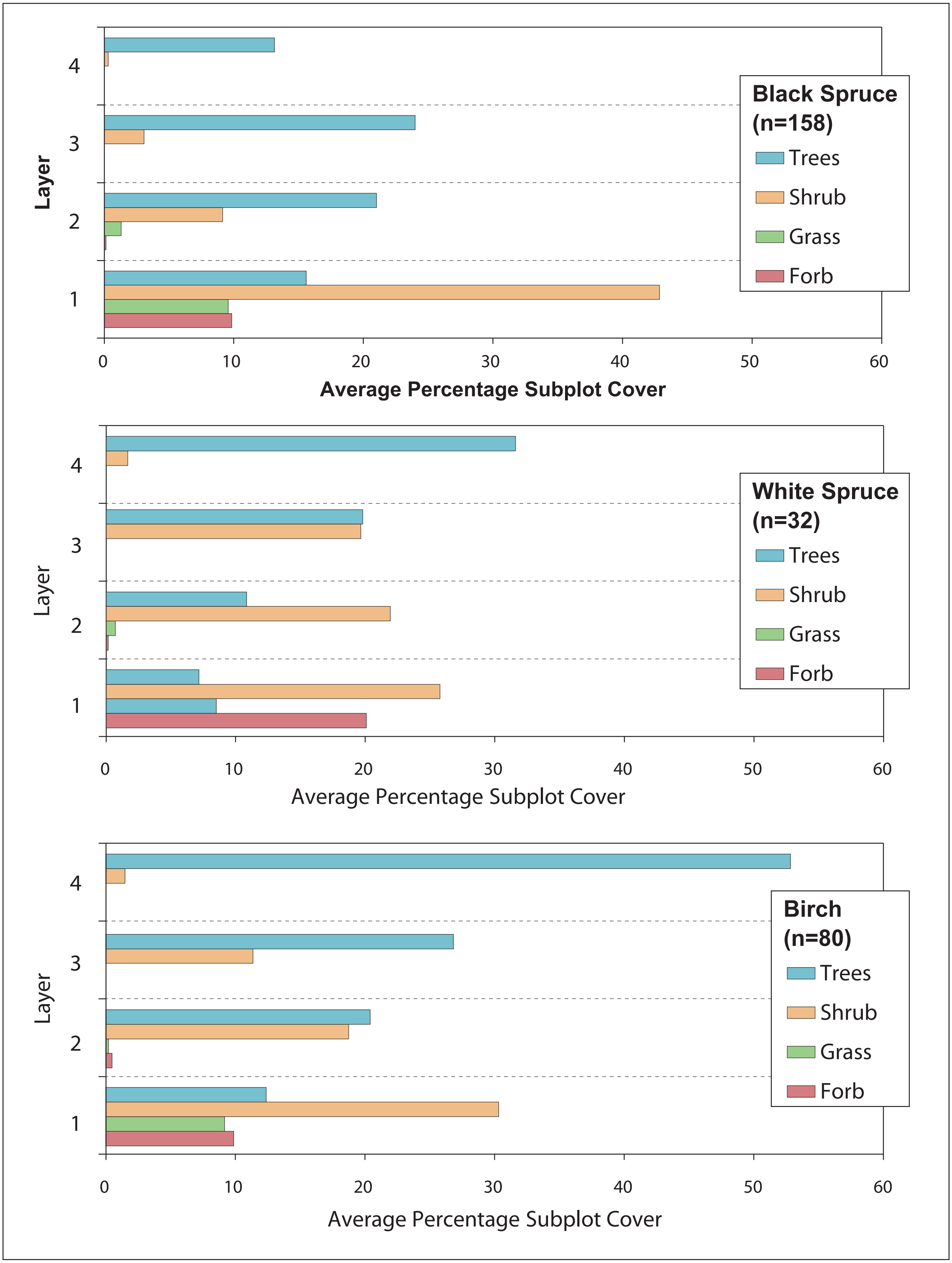

Figure 1—Average subplot percentage of cover by growth habit by layer for three predominant forest types in interior Alaska

Table 2—Most common abundant species and percentage of plots where recorded overall and by forest type; superscripts indicate the rank of the five most common species within each forest type

		Forest type					
Species common name	All Plots (n=98)	Black spruce (n=38)	Paper birch (n=20)	White spruce (n=8)	Balsam poplar (n=3)	Aspen (n=3)	Other (n=25)
		Percentage of plots where recorded					
Lingonberry	72^{1}	84^{3}	65^{4}	38	0	33	88
Black spruce	68^{2}	100^{1}	45	0	0	33	76
Alaskapaperbirch	67^{3}	53^{4}	100^{1}	88^{2}	0	67^{2}	68
Bog Labrador tea	62^{4}	87^{2}	55^{5}	0	0	33	64
White spruce	58^{5}	34	70^{3}	100^{1}	67^{2}	67^{2}	72
Green alder	53^{6}	40	75^{2}	63^{3}	0	67^{2}	60
Bog blueberry	38^{7}	53^{4}	25	0	0	33	44
Prickly rose	36^{8}	8	70^{3}	88^{2}	67^{2}	33	32
Bluejoint	28^{9}	13	40	38	67^{2}	67^{2}	28
Dwarf birch	24^{10}	42^{5}	5	0	0	0	24
Field horsetail	16	11	20	63^{3}	67^{2}	33	16
Quaking aspen	16	11	30	25	0	100^{1}	4
Fireweed	12	3	25	13	33	67^{2}	8
Thinleaf alder	8	0	5	38	100^{1}	0	4
Balsam poplar	6	0	5	13	100^{1}	0	4
Redosier dogwood	2	0	0	0	67^{2}	0	0

n = number of plots

The two most commonly recorded shrub species, lingonberry and bog Labrador tea, made up the majority of shrub cover in Layer 1 in black spruce forest types. Alder and willow species were common and provided cover in the mid layers of most other conditions sampled. An alder species was recorded on 58 of 98 plots, and on 30 of those plots, the average subplot cover was greater than15 percent. There were 54 plots with one to three species of willow, and 32 plots with willow species that may be encountered either as shrubs or trees (USDA NRCS 2015, Viereck and Little 2007).

TNWR full census

A complete census on 25 subplots accumulated 135 species, whereas the VEG Profile method recorded only 55 species on a total of 101 subplots on the same Tetlin plots (some subplots were inaccessible). There were 82 species recorded on the full census that were not captured and only nine species recorded with VEG Profile not in the full census. Of those species present on 50 percent of sampled subplots for each effort, the lists matched except for four species recorded on the full census trial (dwarf scouring rush, field horsetail, red fruit bearberry, and prickly rose).

DISCUSSION

The VEG Profile provides important information about the arrangement of all vascular plants in the forest stands sampled. Structure characterization is important for fire behavior models/maps of vegetation types. Data on the distribution of large and small trees support the observations that black spruce types seem to be increasingly replaced by hardwoods rather than regenerating black spruce (Rupp 2011). Although VEG Profile captures the presence of large shrubs and non-tally trees with cover and height layer, the only allometric equations for calculating biomass of large shrubs are based on stem diameters (Chojnacky and Milton 2008). Stem diameter measures for large woody shrubs and non-tally tree species should be considered in the future for inclusion into biomass estimations.

ACKNOWLEDGMENTS

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APPENDIX TABLE 1 – COMMON AND SCIENTIFIC NAMES

Common name	Scientific name
Alaska paper birch	*Betula neoalaskana* Sarg.
Balsam poplar	*Populus balsamifera* L.
Black spruce	*Picea mariana* (Mill.) Britton, Sterns & Poggen.
Blue joint	*Calamagrostis canadensis* (Michx.) P. Beauv.
Bog blueberry	*Vaccinium uliginosum* L.
Bog Labrador tea	*Ledum groenlandicum* Oeder
Dwarf birch	*Betula nana* L.
Dwarf scouring rush	*Equisetum scripoides* Michx.
Field horsetail	*Equisetum arvense* L.
Fireweed	*Chamerion angustifolium* (L.) Holub ssp. *angustifolium*
Green alder	*Alnus viridis* (Chaix) DC.
Lingonberry	*Vaccinium vitis-idaea* L.
Prickly rose	*Rosa acicularis* Lindl.
Quaking aspen	*Populus tremuloides* Michx.
Red fruit bearberry	*Arctostaphylos rubra* (Rehder & Wilson) Fernald
Red osier dogwood	*Cornus sericea* ssp. *sericea*
Tamarack	*Larix larcinia* (Du Roi) K.Koch)
Thin leaf alder	*Alnus incana* (L.) Moench ssp. *tenuifolia* (Nutt.) Breitung
White spruce	*Picea glauca* (Moench) Voss

EVALUATING CARBON STORES AT THE EARTH-ATMOSPHERE INTERFACE: MOSS AND LICHEN MATS OF SUBARCTIC ALASKA

Robert J. Smith[1], Sarah Jovan[2], Bruce McCune[3]

Abstract—A fundamental goal of the forest inventory in interior Alaska is to accurately estimate carbon pools in a way that sheds light on the feedbacks between forests and climate. In boreal forests, moss and lichen mats often serve as the interface between soils and the atmosphere, therefore characterizing the biomass and composition of mats is essential for understanding how forest carbon exchange might interact with shifting climatic regimes. Previous estimation approaches did not permit volumetric estimates of moss mats and were based on inconsistent definitions distinguishing between soil, duff, and moss layers. We confronted these challenges by implementing a novel, non-destructive technique centered on three research questions. First, what is the pattern of biomass and carbon distribution for moss/lichen ground layers in subarctic, interior Alaska? Second, how do climatic and stand-level factors drive these patterns? Third, what are the functional consequences and ecosystem effects of moss/lichen ground layers? Moss and lichen species were assigned to functional groups based on the capacity to fix nitrogen, serve as wildlife forage, indicate disturbance, alter hydrology, or signal eutrophic conditions (among other ecosystem functions). Among 99 sites located in the Tanana River valley of interior Alaska, biomass averaged 12 934 kg ha^{-1} (SD: 8546), of which carbon was an estimated 5456 (3778) kg ha^{-1}. Biomass had a weakly negative relationship with plant litter depth, to which topoedaphic and climatic factors also contributed. On average there were 7.2 functional groups per site – most frequent and abundant were nitrogen-fixing mosses, which commonly formed extensive, thick carpets. Together, these findings imply that moss and lichen mats in the Tanana River area can contribute substantially to both forest nitrogen stores and organic carbon sequestration.

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ANALYSIS TECHNIQUES

AN EVALUATION OF FIA'S STAND AGE VARIABLE

John D. Shaw[1]

Abstract—The Forest Inventory and Analysis Database (FIADB) includes a large number of measured and computed variables. The definitions of measured variables are usually well-documented in FIA field and database manuals. Some computed variables, such as live basal area of the condition, are equally straightforward. Other computed variables, such as individual tree volume, require a more in-depth understanding of the FIA compilation system, such as how equations are selected based on species and plot location. For other computed variables, their derivation and meaning might not be clear to many users based on readily-available documentation. As a result, users may be prone to making their own assumptions about the meaning of these variables. This can be the case for users of the data and those who evaluate the use of FIA data, such as in the peer review process, where the value of certain variable can be debated. FIA stand age is one variable that is commonly used, but for which there is apparently disagreement about its meaning and usefulness. The "controversy" over this variable even exists with the FIA program, partly due to small differences in the way it is computed regionally or user experience with the variable in analysis. In this paper, the relationship between FIA stand age and other stand-level descriptors, such as composition, structure, and stand origin are explored. Some guidelines for the use of the variable, such as when it is appropriate to use it "straight", and when other factors should be considered in analyses, will be presented.

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ANALYSIS ISSUES DUE TO MAPPED CONDITIONS CHANGING OVER TIME

Paul Van Deusen[1]

Abstract—Plot mapping is one of the innovations that were implemented when FIA moved to the annual forest inventory system. Mapped plots can improve the precision of estimates if the mapped conditions are carefully chosen and used judiciously. However, after plots are remeasured multiple times, it can be difficult to properly track changes in conditions and incorporate this into the analysis. Early discussions about plot mapping considered 2 mapping options: 1) full mapping and 2) fuzzed mapping. Full mapping is what FIA adopted. Fuzzed mapping (fuzzing) was felt to provide less precision, since it would assign a single condition to each subplot. However, fuzzing would never allow a condition proportion to be less than 0.25 and would be much easier to track over time than full mapping. These issues are elaborated and some comparisons based on FIA data are presented.

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ARE OBSERVED TRENDS IN HARDWOOD TREE GRADE DUE TO RESOURCE CHANGES OR DATA ANOMALIES?

Thomas Brandeis, Christopher Oswalt, Jeffery Stringer, and Stan Zarnoch[1]

Abstract—Preliminary analyses show decreasing amounts of higher grade tree volumes in the east-central United States, suggesting degradation in the hardwood saw-log resource. While there were indications of trend, the quality and repeatability of the tree grade data themselves has been questioned, questions that Quality Control data could not answer. While the quantification of tree grade on Forest Inventory and Analysis plots has potential value, subjectivity and inconsistency limits the variable's usefulness.

The temperate broadleaf and mixed broadleaf/conifer forests of the east-central United States are an important ecological and economic resource. Preliminary analyses and anecdotal evidence have shown decreasing prevalence of higher quality trees as defined by their tree grade, suggesting degradation in the hardwood saw-log resource. If true, such trends could indicate forest management shortcomings or large-scale demographic changes. The indepth analysis of volume across tree grades required to assess this situation, however, also requires careful scrutiny and understanding of the methods used to grade a tree. Tree grading is one of the most subjective evaluations made on a Forest Inventory and Analysis (FIA) plot and requires that field crews have considerable training and experience before accuracy and repeatability is achieved.

We investigated trends in the proportion of volume in each tree grade from 2001 to 2013 in Kentucky (KY) and Tennessee (TN) for a selection of high-value timber species. Additionally, we examined the Quality Assurance/Quality Control (QA/QC) data collected during this period.

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METHODS

Forest Inventory and Tree Grading Procedures

Volume of the saw-log portion (FIA variable VOLCSNET) (Woudenberg and others 2010, Oswalt and Conner 2011) of the tree is estimated for sawtimber-sized trees that meet certain minimum requirements. Trees that meet sawtimber size requirements are graded for tree quality. Tree grades 1 through 4 are in descending order of quality. A tree grade 1 tree is larger, with a minimum diameter at breast height (d.b.h.) of 16 inches, and has more clear wood free of defects within the saw log. Grades 2, 3, and 4 are of smaller d.b.h. or have less clear wood in the saw log. Tree grade 5 is different. These trees do not meet the requirements of tree grades 1-4 but have a saw log located somewhere in the tree other than the butt portion, e.g., upper stem or branch, or have at least two noncontiguous 8-foot long logs.

Data Queried from the FIA Database

We queried the FIA Database (FIADB) to extract data on selected sawtimber-size hardwood trees measured in KY and TN from 2001 to 2013. Both States are on 5-year remeasurement cycles. The response variable chosen was the proportion volume in each tree grade on each plot. Values of zero were generated so that each tree grade had a value on every plot. Comparisons were made among the proportions of volume in each tree grade to evaluate whether there were changes over time. Several hardwood species were chosen for inclusion in the query based on expert knowledge of the resource and demand by forest industry. We also queried the database for older data from the periodic forest inventories by tree grade, filtering on the same hardwood species. Percentages of volume by tree grade were calculated by dividing the volume in each tree grade by the total volume for that inventory. Blind and cold-check QA/QC data for tree grade were extracted for these same States. Field data collection in both KY and TN was done by Forest Service, U.S. Department of Agriculture personnel during the periodic inventories. However, with the implementation of annualized inventories starting in 2001, State natural resource agency personnel have collected the data.

Statistical Methods

We tested for differences between individual years of data, not between the averages of multiple years. For example, we compared 2001 to 2002, 2002 to 2003, etc., but not the average for the cycle ending 2004 to the average for the cycle ending 2009. This was done for two reasons. First, we are interested in differences in tree data from specific measurement years. Second, we treat individual years of data as independent from one another except when comparing one year to its remeasured value five years later, e.g., comparing 2002 to 2007. Comparing averages for a full cycle of panels or remeasured years would violate the assumption of sample independence, and other methods must then be used to assess statistical differences (Westfall and others 2013). Estimates and standard errors were computed for each tree grade and year using a ratio of means estimator, then compared using the overlapping confidence interval method.

The accuracy and repeatability of tree grade by the field crew and QA/QC foresters were assessed using matrices of frequency distributions. It was assumed that the more experienced, highly trained QA/QC foresters provided a truer assessment of tree grade against which the field crew calls were judged. While variation around the relatively subjective tree grade assessment is to be expected, we focused our examination on whether field crews showed any consistent bias toward over- or under-estimating the tree grade.

RESULTS

The numbers of trees extracted from FIADB ranged from a high of 591 trees in TN in 2013 to a low of 353 trees in KY in 2002. In an average year for TN and KY combined, there were 40.1 grade 1, 107.8 grade 2, 178.7 grade 3, 99.7 grade 4 and 23.7 grade 5 trees.

In KY, the mean plot volume percentage in tree grade 1 reached a high value in 2002 then decreased significantly to 2004 (Fig. 1). In TN, mean tree-grade-1 plot volume percentage was stable until 2005, when it decreased significantly from 2006 and then began increasing until 2013 (Fig. 2). For tree grade 2, the percentages in KY held relatively stable with some fluctuations across the study period. In TN, however, tree grade 2 decreased from 2005 to 2006, recovered, and then decreased again. Volume percentages in tree grades 3 and 5 remained relatively stable in both States, while tree grade 4 percentages behaved erratically.

Periodic inventory results for KY show that percentages of volume remained relatively stable except for tree grade 1. Tree grade 1 in KY was 13.4 percent of the volume in 1988, while in 2004 (moving average of annualized data from 2001 to 2004) it was 24.2 percent (Table 1). Tree grade 1 also showed volatility in TN (Table 1). Tree grade 4 in TN displayed a decrease from 1989 to 1999, low values through 2004, then an increase that continued through 2009 and 2012. In KY, tree grade 2 values from 1998 were comparable to those found in the KY 2004 annualized moving average.

QA/QC Results

Of the field plots that were revisited by QA/QC foresters to conduct blind checks on field crew measurements, a total of 440 trees were assessed during both visits in Kentucky from 2001 to 2013 (Table 2). On average across all years, there was a 66.0-percent agreement on the tree's grade. In Tennessee there were 224 trees graded with 64.6-percent agreement. Notable in the QA/QC data were the small number of trees that were blind-checked in some years and how variable the numbers of checked trees were from year to year. Extremes ranged from only 7 trees blind-checked in TN in 2002 and 2012 to 104 trees in KY in 2005.

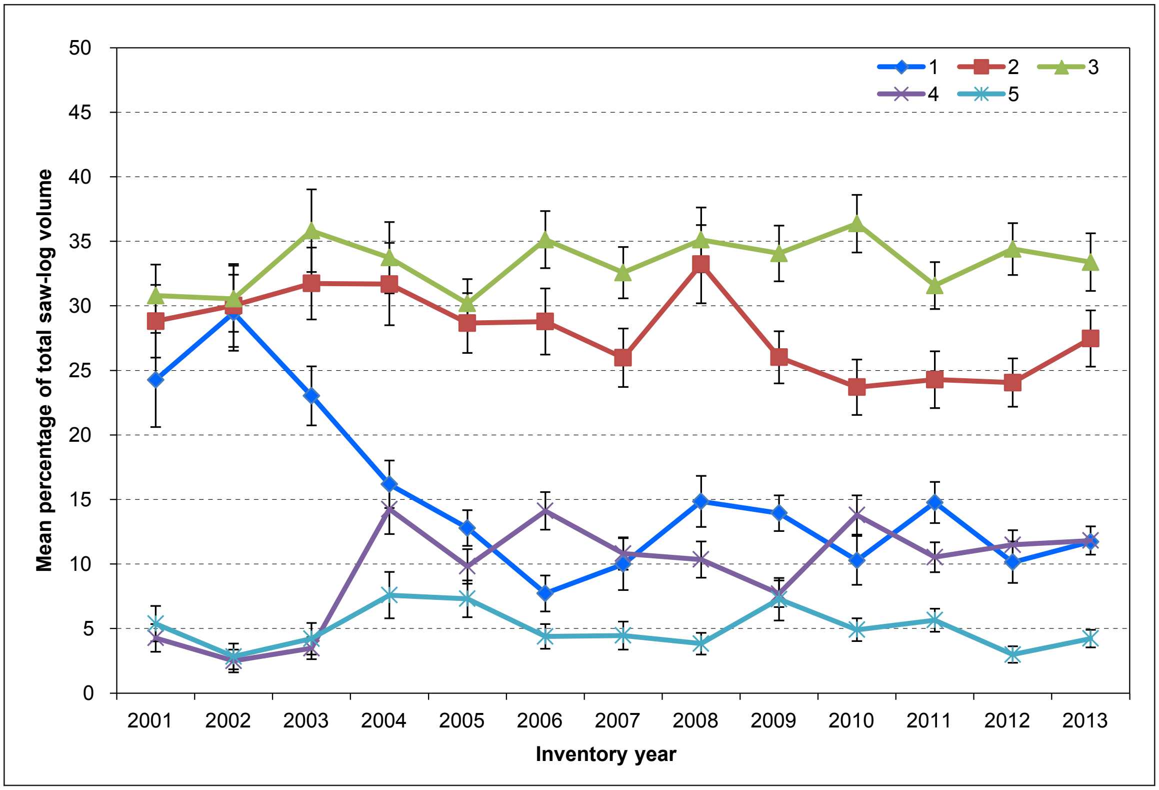

Figure 1—Mean percentage of plot net saw-log volume per plot by tree grade with standard errors of the mean, Kentucky, 2001-2013.

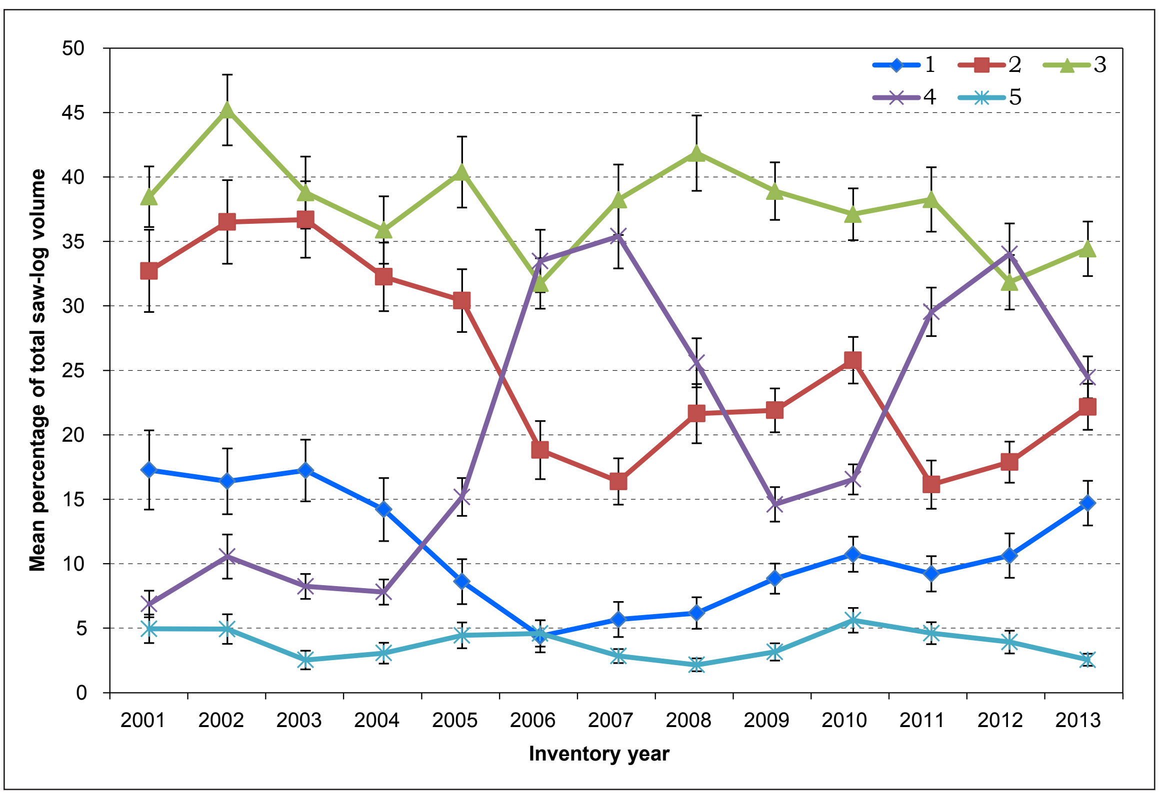

Figure 2—Mean percentage of plot net saw-log volume per plot by tree grade with standard errors of the mean, Tennessee, 2001-2013.

Table 1—Percentage of net volume (cubic feet) of saw-log portion of sawtimber trees on timberland by hardwood tree grade for Kentucky and Tennessee for periodic inventories (KY 1988, TN 1989, TN 1999) and annualized moving averages (2004, 2009, 2012).

	Inventory year—Kentucky				Inventory year—Tennessee				
Grade	1988	2004	2009	2012	1989	1999	2004	2009	2012
1	13.4	24.2	13.0	13.8	8.6	22.7	16.2	6.9	9.5
2	30.4	31.5	31.2	29.3	20.6	29.7	33.5	23.3	21.7
3	37.3	33.2	37.9	39.0	46.6	35.6	38.2	40.2	39.0
4	11.4	5.6	11.5	12.2	18.9	7.2	8.0	25.6	25.2
5	7.4	5.4	6.4	5.7	5.4	4.7	4.1	4.0	4.6

Table 2—Numbers of trees graded on plots visited by both field crew and Quality Assurance/Quality Control foresters with numbers and percentage of tree grade agreements for Kentucky and Tennessee, 2002 to 2013.

	Kentucky				Tennessee			
Measurement year	Total trees graded by either field or QA/QC	Total trees with both field and QA/QC grades	Number with matching grades	Percent trees with matching grades	Total trees graded by either field or QA/QC	Total trees with both field and QA/QC grades	Number with matching grades	Percent trees with matching grades
2002	9	8	7	87.5	7	7	4	57.1
2003	36	33	23	69.7	9	8	4	50.0
2004	39	38	26	68.4	11	9	5	55.6
2005	104	98	61	62.2	68	61	35	57.4
2006	34	33	18	54.5	28	25	20	80.0
2007	19	19	8	42.1	13	11	4	36.4
2008	15	15	12	80.0	0	0	-	-
2009	11	11	7	63.6	28	28	24	85.7
2010	54	54	33	61.1	10	10	7	70.0
2011	24	24	17	70.8	10	10	8	80.0
2012	25	25	17	68.0	7	7	4	57.1
2013	70	70	45	64.3	33	33	27	81.8
Total	440	428	274	66.0	224	209	142	64.6

Frequency distributions of tree grade agreement and disagreement were examined. All possible combinations of field crew and QA/QC tree grade calls were put in matrices by State and year. Based on a visual examination of these sparse data, there may have been a slight trend toward field crews calling tree grades higher than QA/QC foresters when they were in disagreement. Overall, however, this possible trend was weak and based on too few instances to judge adequately.

DISCUSSION

While there were indications of trend over time from 2001 to 2013, the quality and repeatability of the tree grade data themselves has been called into question. Zarnoch and Turner (2005) questioned the validity of the 2001 tree grade data from KY based on values observed in the preceding periodic forest inventories. They cited amounts of tree grade 1 volume that were twice as great in 2001 as they were in the periodic inventory of 1988 (Zarnoch and Turner 2005). They postulated that changes in the training of KY field crews on tree grading resulted in assigning too many trees to tree grade 1 when compared to past inventories. However, there has been no documentation or studies to indicate the possibility of a similar bias in the TN data, where a decrease in tree grade 1 volume was also observed. The TN field crews operated and were trained independently of the KY field crews.

While we can postulate management or biological reasons for steady decreases or increases in certain grades of volume over time, it is harder to do so for the seemingly abrupt changes seen in tree grade 4. There, we must consider that observed trends might be due to training inconsistencies or field crew turnover. The QA/QC data did not provide satisfactory answers to these questions, primarily due to the paucity of data for specific grades during any given year. Perhaps with a larger QA/QC sample, patterns would have emerged. While the quantification of tree grade on FIA plots has potential value, the subjectivity and inconsistency of the variable limits its usefulness in TN and KY.

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ASSESSMENT OF NATIONAL BIOMASS IN COMPLEX FORESTS AND TECHNICAL CAPACITY SCENARIOS

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Abstract—Understanding forest ecosystems is paramount for their sustainable management and for the livelihoods and ecosystem services which depend on them. However, the complexity and diversity of these systems poses a challenge to interpreting data patterns. The availability and accessibility of data and tools often determine the method selected for forest assessment. Capacity building is fundamental to ensure that sampling methods, data analysis and use of tools are efficiently and sustainably appropriated. FAO has trained people from over 30 countries to develop tools and databases to improve forest resource assessment. In highly diverse inventory plots in the tropics, the use of one single pantropical allometric equation (models for the estimation of forest elements such as biomass and carbon stock) for all trees inventoried is the norm in many countries. However these equations present large biases and/or uncertainties for several tropical regions of the world, due to their compositional and structural complexity, and their limited representation in the original datasets used to build the pantropical model. In order to contribute to the elimination of bias and increasing accuracy, we propose a combined approach to stand biomass estimation following statistical methods that depends on both the availability of equations and/or destructive data, and the existing capacities in the country. We illustrate the methods through different scenarios of existing technical capabilities and data availability, taking GlobAllomeTree as a source for allometric equations. GlobAllomeTree provides access to existing available allometric equations and relevant documentation, supports the development of new models and builds a network of national experts for data-sharing and collaboration. The different alternative approaches proposed present a realistic roadmap towards the reduction of uncertainties and biases in reporting national stocks.

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USING FOREST INVENTORY AND ANALYSIS DATA TO UNDERSTAND BIOTIC RESISTANCE TO PLANT INVASIONS ACROSS THE EASTERN UNITED STATES

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Abstract—Biological invasions and their impacts are likely to increase with the expansion of global commerce, making the need to identify key drivers and regulators of invasion perhaps greater than ever. One of the most enduring, and tested, hypotheses for explaining invasions is the "biotic resistance hypothesis." Broadly, this hypothesis states that communities having greater biodiversity have fewer unfilled niches, making them less invasible. Using data from 46,071 Forest Inventory and Analysis plots located across the forests of the Eastern United States, we tested for associations between native trees and invasive plants that would suggest the presence of biotic resistance. For both invasive species richness and cover, we determined: 1) if accounting for the spatial heterogeneity nested within a large geographic area improves models of biotic resistance, 2) if the direction, magnitude, and spatial variability of associations pertaining to biotic resistance differ based on how biotic resistance is measured, and 3) if the direction and magnitude of associations pertaining to biotic resistance vary with either scale or location. These determinations will provide clarity regarding the role of biotic resistance in regulating invasion patterns across large geographic areas. We found that accounting for heterogeneity allowed for better models of biotic resistance, and that both invasion measures were negatively associated with native tree biomass and evolutionary diversity, but positively associated with native tree species richness. A few sub-regions, however, exhibited opposite associations. Association size tended to be greatest for evolutionary diversity. Strong negative associations were aggregated within and near the Appalachian Mountains. Finally, association size and direction were affected by both scale and location, although location seemed more influential. As forests and the services they provide are increasingly harmed by invasive plants, particularly in our study region, the findings of this investigation will have implications for both invasive species management and policy.

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SEEING THE FOREST FOR THE TREES: UTILIZING MODIFIED RANDOM FORESTS IMPUTATION OF FOREST PLOT DATA FOR LANDSCAPE-LEVEL ANALYSES

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Abstract—Mapping the number, size, and species of trees in forests across the western United States has utility for a number of research endeavors, ranging from estimation of terrestrial carbon resources to tree mortality following wildfires. For landscape fire and forest simulations that use the Forest Vegetation Simulator (FVS), a tree-level dataset, or "tree list", is a necessity. FVS is widely used at the stand level for simulating fire effects on tree mortality, carbon, and biomass, but uses at the landscape level are limited by availability of forest inventory data for large contiguous areas. Detailed mapping of trees for large areas is not feasible with current technologies, but statistical methods for matching forest plot data with biophysical characteristics of the landscape offers a practical means to populate landscapes with a limited set of forest plot inventory data. We used a modified Random Forests approach with Landfire vegetation and biophysical predictors to impute plot data from the U.S. Forest Service's Forest Inventory Analysis (FIA). This method imputes the plot with the best statistical match, according to a "forest" of decision trees, to each pixel of gridded landscape data. Landfire data was used in this project because it is publicly available, offers seamless coverage of variables needed for fire models, and is consistent with other datasets, including burn probabilities and flame length probabilities generated for the continental U.S. by Fire Program Analysis (FPA). We used the imputed inventory data to generate maps of forest cover, forest height, and existing vegetation group at 30-meter resolution for the entire western U.S. The results showed good correspondence between the target Landfire data and the imputed plot data. In future work, we plan to use the imputed grid of inventory data for landscape simulation studies to analyze a wide range of fuel management problems.

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DEVELOPMENT OF FOREST REGENERATION IMPUTATION MODELS USING PERMANENT PLOTS IN OREGON AND WASHINGTON

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Abstract—Imputation models were developed and tested to estimate tree regeneration on Forest Service land in Oregon and Washington. The models were based on Forest Inventory and Analysis and Pacific Northwest Regional NFS Monitoring data. The data was processed into sets of tables containing estimates of regeneration by broad plant associations and spanning a large variety in forest cover conditions. The output tables were organized to facilitate their use within variants of FVS commonly used in the Pacific Northwest region. The methods were implemented in a highly reproducible fashion to ensure future model adaptability.

INTRODUCTION

Growth and yield models are an important tool for foresters and land managers. They are often used to assess the impacts of different management actions on tree growth and mortality through time. The Pacific Northwest Region of the National Forest System uses the Forest Vegetation Simulator (FVS) growth and yield model to analyze information at multiple scales, from stands of a few acres in size to entire watersheds. Currently FVS requires users to specify forest regeneration densities for all variants applicable in Oregon and Washington. A need exists to have forest regeneration models that are standardized and can be easily incorporated into FVS.

An alternative to traditional predictive model-based methods for estimating regeneration is imputation. Imputation involves replacing missing measurements with realistic measurements from one or more stands with similar characteristics (Ek and others 1997, Hassani and others 2004). Imputation approaches offer advantages over traditional modeling approaches in that they can easily provide estimates of multiple species simultaneously and are not subject to parametric assumptions regarding the distributions of response variables.

STUDY AREA

The study area is all National Forest System lands in Oregon and Washington. Coastal and dry inland effects combine with the topographic effect of numerous mountain ranges and valleys to produce a wide range of climatic zones and vegetation types. This highly diverse region contains seven distinct ecological variants, over 850 plant associations and totals just over 25.0 million acres of NFS land (U.S. Department of Agriculture, Forest Service 2014). The majority of Oregon and Washington's forests are dominated by coniferous forest types, predominantly Douglas-fir (*Pseudotsuga menziesii*), western hemlock (*Tsuga heterophylla*), ponderosa pine (*Pinus ponderosa*), and lodgepole pine (*Pinus contorta*).

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METHODS

Forest Inventory and Analysis and Pacific Northwest Regional NFS Monitoring plot data from Oregon and Washington were combined into a single data set. The data were then subset based on a list of criteria in preparation for imputation. Subplots sampled after 2001 on Forest Service lands were targeted to ensure sampling protocols were standardized. Additional criteria included natural origin with no evidence of artificial seeding, planting, or site preparation and each microplot associated with a subplot need to be dominated by a single condition class. If a subplot was sampled between 2001 and 2003 and was remeasured in the next measurement period (2011 to 2013) then both subplots were only included in the final data set if there was evidence of a significant disturbance 5 to 10 years prior to the most recent measurement; otherwise only the recent remeasurement was included.

Plot and tree data were used to calculate subplot level attributes including estimates of tree density, forest canopy, and fuels. Due to the high number of plant associations and variants, plant associations were grouped resulting in 402 distinct plant association-variant combinations (VPAG). Based on these VPAGs, the data were further subset to ensure an adequate sample size for the development of imputation models, resulting in 64 VPAGs. Although the resulting 64 VPAGs were only 16 percent of the original VPAGs, they represent 78 percent of the subplots in that original data.

Lastly, and to aid in validating our models, the data were split into two groups: a “training” data (75 percent) and a “testing” data (25 percent). The training data was treated as a complete set and used to develop models, whereas the testing data was treated as missing regeneration measurements, candidates for imputation, and utilized as a validation data set.

Empirical knowledge along with generalized linear model procedures and correlation analysis were used in preliminary analysis to determine the attributes most related to regeneration. Based on the resulting important attributes, tabular imputation tables were compiled and validated. Additionally, performance and predictive capability of the tabular imputation model was compared with results using various nearest neighbor approaches.

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EFFECTS OF HEIGHT AND LIVE CROWN RATIO IMPUTATION STRATEGIES ON STAND BIOMASS ESTIMATION

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Abstract—The effects of subsample design and imputation of total height (ht) and live crown ratio (cr) on the accuracy of stand-level estimates of component and total aboveground biomass are not well investigated in the current body of literature. To assess this gap in research, this study uses a data set of 3,454 Douglas-fir trees obtained from 102 stands in southwestern Oregon to simulate different combinations of subsample designs and imputation methods. The predictive ability of the regional ht and cr imputation methods on estimates of component and total aboveground biomass for a range of subsample sizes (n = 0,…, 15) and subsample designs (simple random selection, largest trees by diameter at breast height (d), smallest trees by d, trees grouped about the median by d, and several combinations of the latter three designs) is evaluated using the leave-one-out cross validation technique. The best methods for imputing ht and cr independently are identified which are then used to simultaneously impute ht and cr across the range of subsample sizes and designs. Methods to impute cr include the current methods used in the southern Oregon variant of the USFS Forest Vegetation Simulator (SO-FVS) and in the southwestern Oregon variant of the ORGANON growth and yield model (SWO-ORGANON) from Oregon State University as well as subsample-calibrated versions of both. Methods to impute ht include the current methods used in SO-FVS, SWO-ORGANON, and a collection of equations developed by Temesgen et al. (2008) as well as subsample-calibrated versions of each. The findings of this study should be beneficial in identifying the most accurate ht and cr imputation method to estimate component and total aboveground biomass for each subsample size and selection method.

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FIA DATA AND SPECIES DIVERSITY - SUCCESSES AND FAILURES USING MULTIVARIATE ANALYSIS TECHNIQUES, SPATIAL LAG AND ERROR MODELS AND HOT-SPOT ANALYSIS

Andrew J. Hartsell[1]

Abstract—This study will investigate how global and local predictors differ with varying spatial scale in relation to species evenness and richness in the gulf coastal plain. Particularly, all-live trees >= one-inch d.b.h. Forest Inventory and Analysis (FIA) data was used as the basis for the study. Watersheds are defined by the USGS 12 digit hydrologic units. The dataset includes various environmental data such as temperature, rainfall, frost free days, soil productivity, stand age, latitude, longitude, average elevation, and land use fragmentation or disturbance indicators. Multivariate analysis techniques such as nonmetric multidimensional scaling (NMS) and multi-response permutation procedures (MRPP) were performed using the software package PC-ORD to identify patterns within the data. Spatial lag and error models where created using the freeware GeaDa. These models reveal how various predictors of tree diversity (Shannon's, Simpson's and species richness) differ not only from each other, but change as spatial scale varies.

Preliminary results indicate that global variables such as climate and productivity have a greater impact on diversity indicators than more local variables such as disturbance and land use. However, this changes as spatial scale decreases, where land-use and disturbance play a larger role in predicting tree diversity in southern forests. Additionally, the presence of southern pine plantations has a profound impact on diversity indicators at certain scales. However, the impact varies depending on the indicator. At certain scales, the presence of plantations has a negative effect on evenness indicators and a positive effect on species richness. MRPP analysis proved to be futile, while only one watershed size yielded a solution of greater than one axis using NMS. NMS on HUC10 watersheds yielded a three axis solution that proved to be insightful.

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WHEN DOES BIODIVERSITY MATTER? ASSESSING ECOSYSTEM SERVICES ACROSS BROAD REGIONS USING FOREST INVENTORY AND ANALYSIS DATA

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Abstract—Biodiversity is expected to convey numerous functional benefits to forested ecosystems, including increased productivity and resilience. When assessing biodiversity, however, statistics that account for evolutionary relationships among species may be more ecologically meaningful than traditional measures such as species richness. In three broad-scale studies, we applied evolutionary diversity metrics to assess the relationship between biodiversity and forest function across broad U.S. regions, using Forest Inventory and Analysis (FIA) data. In one study, we assessed trends in live aboveground tree biomass (LAGB) in relation to tree biodiversity on 79,000 FIA plots across the United States, controlling for site productivity and live tree stocking. Biodiversity was more closely associated with greater LAGB on low-productivity sites with low tree stocking. This is consistent with the expectation that the coexistence of functionally different species increases forest productivity in less productive and more stressful environments, while dominant and highly productive species are able to competitively dominate in more productive habitats. In a second study, we assessed the associations between tree diversity metrics and invasive species diversity and cover on 39,000 FIA plots across the Southeast. Region-wide, tree biodiversity was higher on plots that also had invasive plants, and plot-level "invadedness" was positively correlated with evolutionary biodiversity. Among the biodiversity metrics, plot invadedness was most strongly correlated with phylogenetic diversity. The results suggest that forest tree biodiversity in parts of the Southeast may actually indicate the presence of better environmental conditions for invasive plants. In a third study, we tracked regional changes in forest community biodiversity separately for trees and seedlings on FIA plots across broad regions of the eastern United States. We detected broad-scale patterns of forest evolutionary diversity change that are consistent with expected early effects of climate change. Such changes could alter the ecological functions of forest communities.

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FIESTA – AN R ESTIMATION TOOL FOR FIA ANALYSTS

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Abstract—FIESTA (Forest Inventory ESTimation for Analysis) is a user-friendly R package that was originally developed to support the production of estimates consistent with current tools available for the Forest Inventory and Analysis (FIA) National Program, such as FIDO (Forest Inventory Data Online) and EVALIDator. FIESTA provides an alternative data retrieval and reporting tool that is functional within the R environment, allowing customized applications and compatibility with other R-based analyses. Over the last few years, the tool has expanded to include new modules that accommodate nonresponse, photo-based estimators, two-phase regression estimators for inclusion of temporal remote sensing data, as well as small area estimates. Here, we describe these new modules and illustrate with FIA applications in the Interior West.

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USING SMALL AREA ESTIMATION AND LIDAR-DERIVED VARIABLES FOR MULTIVARIATE PREDICTION OF FOREST ATTRIBUTES

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Abstract— Small area estimation (SAE) techniques have been successfully applied in forest inventories to provide reliable estimates for domains where the sample size is small (i.e. small areas). Previous studies have explored the use of either Area Level or Unit Level Empirical Best Linear Unbiased Predictors (EBLUPs) in a univariate framework, modeling each variable of interest at a time, and not considering their potential correlation. Yet most forest inventory variables such as basal area (G) and volume (V) are strongly correlated. In this situation, EBLUPs for multivariate responses can improve the quality of the estimates. In this study, we apply multivariate SAE techniques in a LiDAR assisted forest inventory. We compare the resulting estimates to those obtained using traditional univariate SAE techniques and other synthetic estimates widely used in forest inventories. The study area is a set of Bureau of Land Management (BLM) and Bureau of Indian Affairs (BIA) owned forest lands in Southwestern Oregon. The small areas are the subsets of the BLM\BIA lands in the study area contained in each 12 level Hydrologic Unit Codes (HUC12). Variables of interest were G and V. A total of 899, 0.125 acre plots were measured in the field. Univariate and multivariate fixed effects and mixed effects regression models were developed. Preliminary results show that correlation between HUC12 level random effects for different variables is moderate while residuals for different variables are highly correlated.

Forest planning needs information about forest structure, available stock, health status and other variables at different scales in order to make informed and better management decisions. This information is usually obtained through sampling and is therefore subject to certain amount of uncertainty. Increasing the sample size of field surveys is a possibility to reduce the uncertainty of the estimates, but this solution may not be affordable. A large variety of techniques have been developed to use of inexpensive or easier to obtain auxiliary information to increase sampling efficiency. These techniques can be either design based such as stratification (Hawbaker et al., 2009), ratio/regression estimators, generalized regression estimators (GREG) (Breidenbach and Astrup, 2012), or model based, such as synthetic prediction (Breidenbach and Astrup, 2012; Næsset et al., 2011; Næsset, 2002)2012; N\\uc0\\u230{}sset et al., 2011; N\\uc0\\u230{}sset, 2002. In general, these methods provide accurate estimates for large populations.

However, in addition to estimates of means and totals for the whole population, where sample sizes are usually large, estimates are needed for subpopulations where the sample size is reduced. Depending on the context, these subpopulations can be stands, counties, species or other units, and they are usually referred to as small areas. Design based and model assisted estimators are, in general, unbiased or nearly so for these small areas. Unfortunately, these estimators are unreliable for small areas because of their large variances when the sample size is small. On the other hand, model based synthetic estimators for subpopulations may not suffer the abovementioned problem of high variance, but they assume that all small areas follow a model that is common for the whole population. If there is significant variability

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among small areas, then there may be a high risk of obtaining biased estimates for subpopulations. For those cases, Empirical Best Linear Unbiased Predictors (EBLUP's), based on linear mixed models, have been proposed (Rao and Molina, 2015) as one of the main alternatives to gain efficiency by using auxiliary information and correct both the high variance of design based estimators and the bias of model based synthetic estimators

The need for suitable methods to provide estimates for small subpopulations has been recognized by Næsset, et al. (2011 p. 3612) and different studies have explored the use of EBLUPs in forest inventories assisted by remote sensing auxiliary information. Area level EBLUPs were used by Goerndt et al., (2011), and unit level EBLUPs have been tested by Breidenbach and Astrup, 2012; Goerndt et al., 2013; Magnussen et al., 20142012; Goerndt et al., 2013; Magnussen et al., 2014. In those studies, EBLUP's were derived from univariate linear mixed models where only one response variable was considered at each time. Certain results from the SAE literature show that, when the residuals and small area random effects for different variables of interest are correlated, an additional gain in efficiency can be obtained if the EBLUP's are based on multivariate models (i.e Multivariate EBLUP's MEBLUP's), that correctly account for those correlations (Datta et al., 1999; Molina, 2009). Certain attributes of interest for forest inventories such as basal areas (G) and volumes (V) might be highly to moderately correlated, so that potential gains in efficiency can be expected if estimates for these variables are based on MEBLUP's. No study to the date has analyzed this potential improvement in forest inventories.

This paper explores with a case study how estimated means for G and V can be improved when using MEBLUP's instead of univariate EBLUP's (UEBLUP's hereafter), based on LiDAR auxiliary information.

STUDY AREA

The study area is the set of Bureau of Land Management (BLM) and Bureau of Indian Affairs (BIA) owned lands covered by the DOGAMI LiDAR survey carried out in Southwestern Oregon. Approximately 1,630,000 acres were covered by the LiDAR flight, of which 254,389 acres are managed by BLM and BIA. Coastal coniferous forest with variable degree of species mixing is prevalent, being Douglas fir (Pseudotsuga Menziesii (Mirb) Franco) the dominant species. Other softwoods such as western hemlock (Tsuga hetorphila (Raf.) Sarg.), sitka spruce (Picea sitchensis (Bong.) Carr.) and red cedar (Thuja plicata Donn ex D.Don) are relatively frequent. The most frequent hardwoods species are red alder (Alnus rubra Bong.), bigleaf maple (Acer macrophyllum Pursh), Oregon myrtille (Umbellularia californica (Hook. & Arn.) Nutt.) and tanoak (Notholithocarpus densiflorus (Hook. & Arn.) Manos, Cannon & S.H.Oh). In general, hardwood species are frequent in the understory and play a secondary role in the upperstory, where conifers are by far more abundant.

LIDAR DATA

LiDAR data were collected during the spring and summer of 2008 and 2009 using a Leica ALS Phase II laser. The average return density was 0.761returns/ft^2. Flight and laser sensor specifications are provided in Table 1.

Table 1—Flight parameters and sensor specification

	Description
Sensor	Leica ALS50 Phase II
Flying altitude	3000 ft above ground level
Field of view	28° (±14° from nadir*)
Pulse rate	> 105 kHz
Pulse mode	Single
Mirror scan rate	52.5 Hz
Overlap	100 % (50% side-lap)

A grid was overlaid on the study area and traditional LiDAR height covariates, including extreme values, percentiles, and fractions of pulses above different thresholds were computed for each pixel using FUSION (Mc Gaughey, 2010). The pixel size was 0.125 acres (75 ft side). Only returns with heights of at least 3.28 ft above the ground were used to compute LiDAR covariates. The return threshold for computing cover covariates was set at a height of 6.56 ft. Pixels where the 80th percentile of the LiDAR returns was higher than 9.85 ft and where more than 2% of the first returns were above 19.69 ft were regarded as forested and pixels that did not meet these criteria were removed. This forest mask was visually assessed to ensure that omission and commission errors were low. Total area of the BLM\BIA owned lands classified as forest according to those criteria was 251,000 ac (≈2 million pixels).

GROUND INVENTORY AND VARIABLES OF INTEREST

Forested areas were stratified based on two LiDAR metrics (80th percentile and standard deviation of the LiDAR heights). A total of 30 strata were defined and, within each one, a random sample of 30 pixels was selected to be measured in the field. Field crews visited all the selected locations except one and measured a total of 899 circular plots of approximately the same area as the pixels.

The diameter at breast height (DBH), height and species of every tree larger than 5.5 in were recorded. Trees smaller than 5.5 in were measured only in concentric plots of 0.02 ac. Standing volume for each tree was computed using regional species specific volume equations included in the US National Volume Estimator Library. Tree volumes were aggregated at plot level and then converted to per acre values applying the corresponding expansion factors to large (DBH≥ 5.5 in) and small trees (DBH< 5.5 in). Basal area per acre was similarly computed for each plot.

SUBPOPULATIONS OF INTEREST

The study area was divided in smaller subpopulations using the 12 level Hydrologic Unit Codes (HUC12). The BLM and BIA owned lands included in each HUC12 estimates were considered as small areas, and mean per hectare values of V and G, were obtained for each one. The study area, forest mask and HUC12 used to define subpopulations are shown in Figure 1.

MODEL SELECTION

Univariate Models

A method similar to the one described in Goerndt et al., (2011), based on fitting linear fixed effects models, was applied to select the LiDAR predictors for each response variable. Once the auxiliary variables were selected, linear mixed effects models with the same LiDAR predictors and random intercepts for each HUC12 were obtained. Significance of HUC12 level random effects was tested for each model.

Multivariate Models

The LiDAR predictors associated with each variable of interest were not modified and correlation between HUC12 random effects associated to V and G were considered in the multivariate model. The plot or pixel levels random effects for different variables were considered independent for this analysis.
In addition, multivariate fixed effects models considering the correlation between residuals for different variables were fit.

RESULTS AND CONCLUSION

In both univariate and models the HUC12 random effects were significant. When modelled together, the correlation between the HUC12 random effects for each variable was moderate and negative (-0.155). Multivariate fixed effects models showed that the correlation between residuals for G and V was strong and positive (0.952). Further analyses will develop models that include both the correlation between random effects for each variable within the HUC12 and the correlations between residuals for different variables.

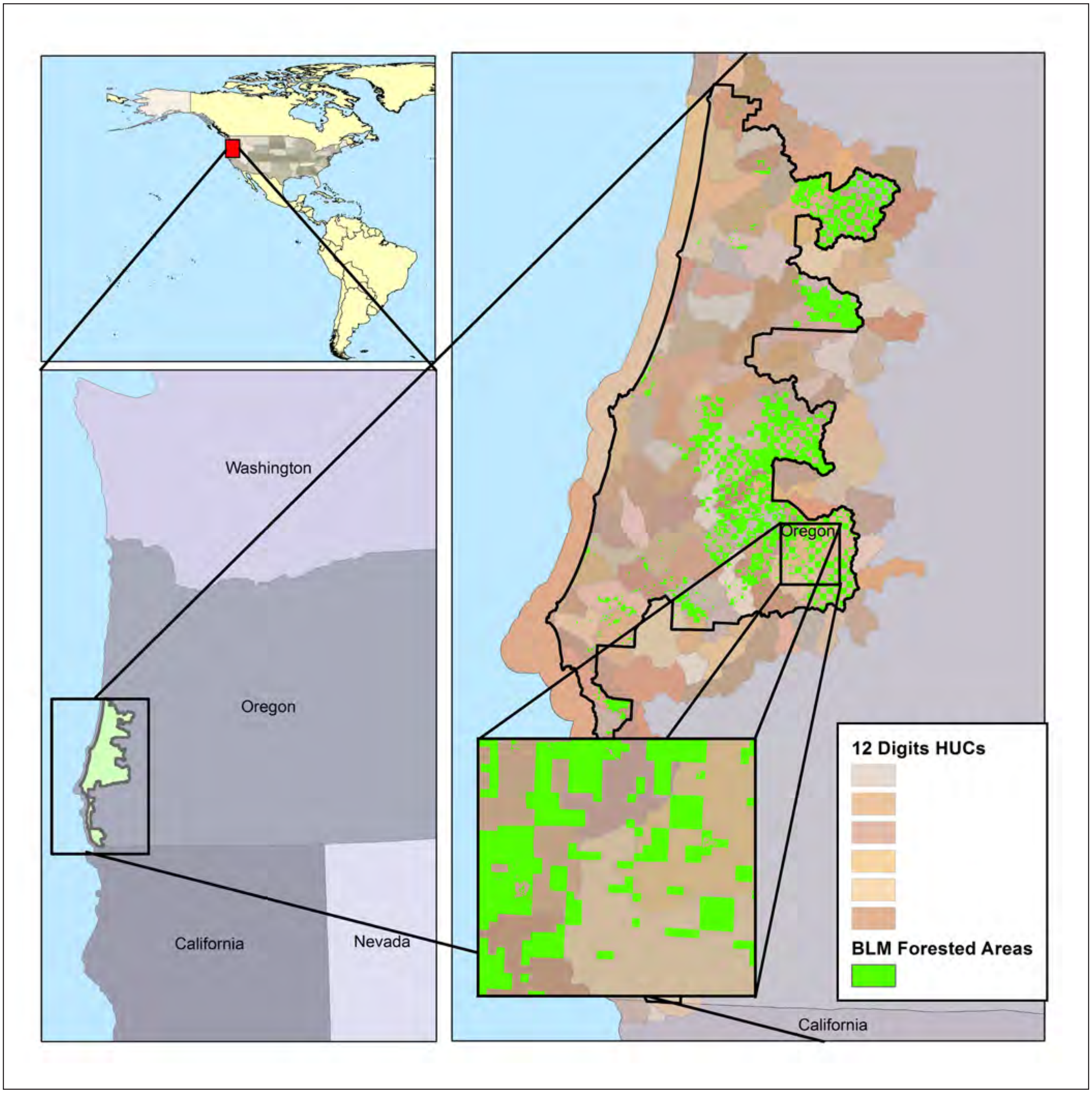

Figure 1—Study area. BLM\BIA owned forest lands (green) and HUC12 employed to define subpopulations of interest.

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BATCH REPORTING OF FOREST INVENTORY STATISTICS USING THE EVALIDATOR

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Abstract—The EVALIDator Web application, developed in 2007, provides estimates and sampling errors of forest statistics (e.g., forest area, number of trees, tree biomass) from data stored in the Forest Inventory and Analysis database. In response to user demand, new features have been added to the EVALIDator. The most recent additions are 1) the ability to generate multiple reports in a single retrieval (batch reporting); 2) the flexibility to report change components (growth, removals, and mortality) by stand and/or tree classification values as recorded at the time of the first or second measurement; and 3) the ability to generate reports of ratio estimates that have pages, rows, and columns. Information on the data and methods used is provided along with sample output from a query that demonstrates the new batch feature.

INTRODUCTION

The EVALIDator Web-application was designed to simplify the generation of population estimates—and their associated sampling errors—from data in the Forest Inventory and Analysis database (FIADB) (USDA Forest Service 2015). The EVALIDator guides the user, via a graphical user interface (GUI), to select 1) the desired attribute estimate; 2) the area of interest; 3) the page, row, and column classifiers; and 4) additional filtering. The user can generate desired output in as few as seven mouse clicks. Depending on the type of retrieval and the size of the geographic area queried, the output will be generated in from several seconds to several minutes. Over 50,000 retrievals were completed using this method in 2014.

The EVALIDator GUI was designed to prevent users from obtaining estimates that are not possible given the underlying data set. For example, forest land volume estimates for inventories collected prior to the annual inventory design (Bechtold and Patterson 2005) may not be available because tree measurements were often not collected on reserved and unproductive forest land. Therefore, if the user selects volume on forest land as the estimate of interest using the EVALIDator GUI, the user will be presented with only a list of those inventories where this estimate is appropriate (usually only on annual inventories completed after 1998).

There are situations in which a user might need to run hundreds or thousands of retrievals for an analysis. The siting of a mill, for example, may require a “wood basket” analysis where several estimates would be needed for several hundred possible mill locations. The analysis might also include a sensitivity analysis where the radius of the wood basket may vary from 50 to 100 miles from the prospective mill locations. A different approach is required for this type of analysis. Users cannot be expected to use the EVALIDator GUI interface thousands of times waiting from seconds to minutes after each run to save the output for future use. Thus an application programming interface (API) was developed for the EVALIDator web-application. This API can be integrated into an MS-Excel® macro-enabled spreadsheet to enable batch processing of these estimates.

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Because the EVALIDator API bypasses the EVALIDator's GUI, there is an increased likelihood that the user will produce forest statistics that are not supported by the data. For example, the user could try to produce an estimate of the volume on forest land for the 1977 inventory of Minnesota. However, the 1977 Minnesota inventory predates the annual inventory implementation, so tree measurements would not have been taken on reserved and unproductive forest land. The estimate returned would be based only on productive nonreserved forest land, thereby underreporting the desired number. It is suggested that a trial run of the EVALIDator GUI be used to verify that an estimate is supported by the data.

METHODS

The EVALIDator API requires 16 parameters (Table 1). Figure 1 shows how this information can be used to invoke the EVALIDator Web application. This example contains the URL (first line) and the parameters (subsequent lines) necessary to generate an estimate of the "Area of timberland, in acres" by "Stand-size class", and "Ownership group – Major", within "50" miles of latitude "45" degrees North, and "-93" degrees West.

Copying and pasting a series of URLs containing these 16 parameters would be awkward and time consuming. An MS-Excel macro was created to demonstrate how URLs and parameters could

```
http://apps.fs.fed.us/Evalidator/batcheval.jsp?
reptype=Circle
&lat=45.0
&lon=-93.0
&radius=50
&snum=Area of timberland, in acres
&sdenom=No denominator - just produce estimate.
&wc=272014,552014
&pselected=None
&rselected=Stand-size class
&cselected=Ownership group - Major
&ptime=Current
&rtime=Current
&ctime=Current
&wf=
&wnum=
&wnumdenom=
```

Figure 1. Example parameters for the EVALIDator API. Note: all this information would be on a single line and copied to the browser address line.

Table 1. EVALIDator API input parameters.

Parameter	Valid values
reptype	"State", "Circle"
lat	0.0000 to 90.0000 (decimal degrees NAD83)
lon	-180.0000 to 180.0000 (decimal degrees NAD83)
radius	0.0 to 1000.0 (units are in miles)
snum	See values of attribute_descr variable in ref_pop_attribute FIADB table
sdenom	If not performing a ratio estimate then enter "No denominator - just produce estimate." For ratio estimates see values of attribute_descr variable in ref_pop_attribute FIADB table.
wc	See values of eval_grp variable in pop_eval_grp FIADB table. When more than one evaluation group is selected the evaluation group numbers should be separated by a comma.
pselected	See values of label_var variable in evalidator_variable_library table where page_list='Y'. If pages breakdowns are not desired enter "None"
rselected	See values of label_var variable in evalidator_variable_library table where row_list='Y'.
cselected	See values of label_var variable in evalidator_variable_library table where col_list='Y'.
ptime	"Accounting", "Previous", "Current", "Previous if available else current", "Current if available else previous" Note: Always use "Current" unless generating growth, removals or mortality estimates.
rtime	"Accounting", "Previous", "Current", "Previous if available else current", "Current if available else previous" Note: Always use "Current" unless generating growth, removals or mortality estimates.
ctime	"Accounting", "Previous", "Current", "Previous if available else current", "Current if available else previous" Note: Always use Current unless generating growth, removals or mortality estimates.
wf	SQL clause filter used for non-ratio estimates.
wnum	SQL clause filter - only applied to numerator in a ratio estimate .
wnumdenom	SQL clause filter - applied to both numerator and denominator in a ratio estimate.

be submitted as a batch retrieval. An MS-Excel workbook named "BatchInternetEvalidator.xlsm" containing this macro can be downloaded from a link on the FIA Data and Tools page (http://www.fia.fs.fed.us/tools-data/default.asp).

When the workbook is downloaded and opened, a worksheet named "Sheet1" will appear (Fig. 2). On this worksheet, there is a button labeled "QueryEvalidatorWeb-application". Clicking this button will result in the execution of the macro named "getMillLocationEstimate," which will then create nine html pages (there are three mill locations listed on Sheet1 and three estimates will be created for each mill) that are each automatically opened and displayed in MS-Excel. Users can modify the code in the macro to generate additional estimates.

The MS-Excel macro "getMillLocationEstimate", as currently written, will read information for up to 1000 mill locations[1] from the MS-Excel worksheet labeled "Sheet 1." Mill location information is contained in the columns labeled "Latitude" and "Longitude." The radius in miles of the circular area is contained in the column labeled "Radius." The column labeled "EvaluationGroups" identifies the inventories to be used in this retrieval. In this example 272013 refers to the Minnesota (Federal Information Processing Standards state code = 27) 2013 inventory and 552013 refers to the Wisconsin 2013 inventory. For each mill location, the macro will generate three population estimate reports. The first report is for the "Area of timberland, in acres" (see line 12 in appendix) by "Forest type" (see line 38 in appendix) and by "Ownership group – Major" (see line 39 in appendix). The second report is for the "Net volume of live trees (at least 5 inches d.b.h./d.r.c.), in cubic feet, on timberland" (see lines 13 and 14 in appendix). The third report is a ratio report. It reports the "Average annual net growth of live trees (at least 5 inches d.b.h./d.r.c.), in cubic feet, on timberland" divided by the "Average annual removals of live trees (at least 5 inches d.b.h./d.r.c.), in cubic feet, on timberland." It should be noted that this is for the area that was timberland at both the time of the current and previous inventories as this provides a more realistic ratio estimates of the actual removals that have occurred on lands that remained in the timberland base. The code is executed by left-clicking on the "QueryEvalidatorWeb-application" button on Sheet1 with the computer's mouse device. The output from this example is stored in nine html files. The filenames consist of the MillName combined with the estimate number.

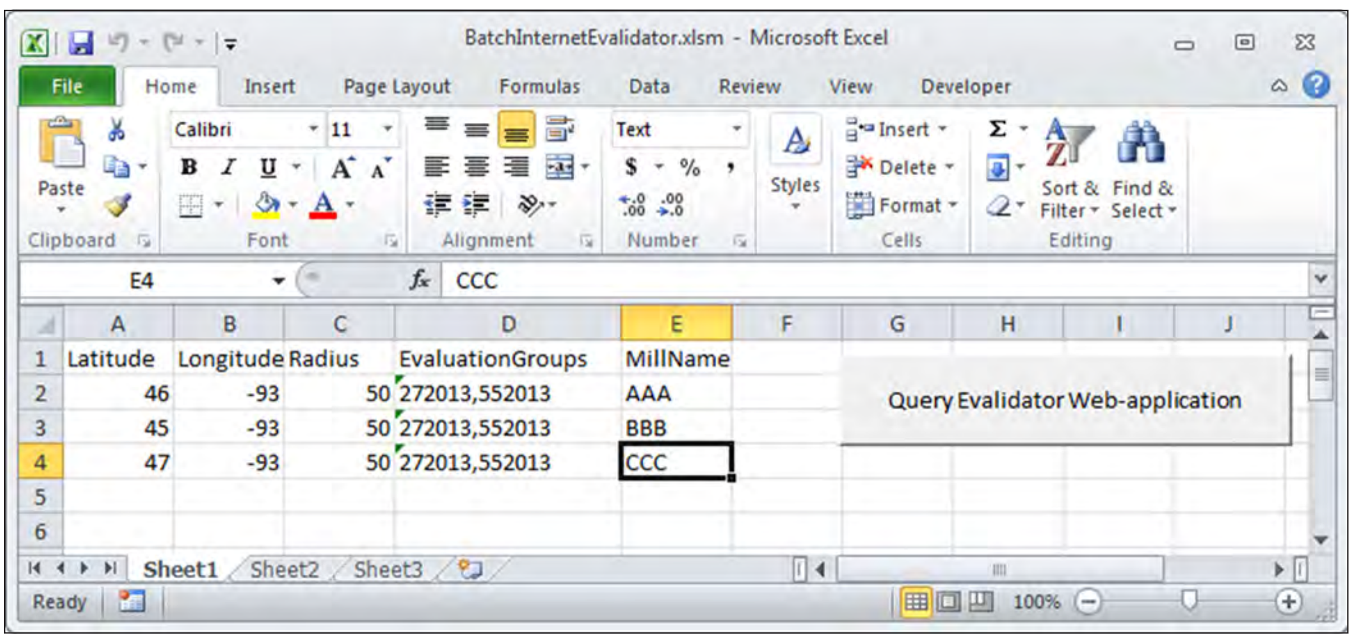

Figure 2. MS-Excel Workbook "BatchInternetEvalidator.xlsm" Sheet1 with "QueryEvalidatorWeb-application" button to initiate EVALIDator batch runs.

RESULTS

The code in Figure 1, when entered into a browser's address line, will return an html page that can be copied and pasted into an MS-Excel worksheet. The output from this query is depicted in Table 2. The total area of timberland within 50 miles of a site located at 45 degrees North and -93 degrees West is 1.0 million acres. The sampling error for this estimate, based on one standard deviation, is 4.8 percent or +/- 50,000 acres. This estimate is based on 445 FIA timberland plots.

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APPENDIX

Workbook BatchInternetEvalidator.xlsm macro getMillLocationEstimate is triggered by clicking on the "QueryEvalidatorWeb-application" button. The code for the macro is provided below.

```
Sub getMillLocationEstimate()

    Dim mill_lat As Double

    Dim mill_lon As Double

    Dim mill_radius As Double

    Dim evalGroups As String

    Dim mill_id As String
```

Table 2. Results from running query depicted in Figure 1.

Numerator type Area of timberland, in acres
Statecd/EVALID(s):
Wisconsin 552014
Minnesota 272014
Page variable=None (based on values from the Current inventory).
Row variable=Stand-size class (based on values from the Current inventory).
Column variable=Ownership group - Major (based on values from the Current inventory).
Circle retrieval centered at 45.0 degrees north and -93.0 degrees west with a radius of 50 miles.
Filtering clause(s):

Estimate:

	Ownership group - Major		
Stand-size class	**Total**	**Public**	**Private**
Total	1,040,428	90,646	949,782
Large diameter	566,608	39,853	526,755
Medium diameter	290,017	18,116	271,901
Small diameter	168,573	32,676	135,897
Nonstocked	15,230	-	15,230

Sampling error percent:

	Ownership group - Major		
Stand-size class	**Total**	**Public**	**Private**
Total	4.8	16.99	5.02
Large diameter	6.51	24.82	6.76
Medium diameter	8.96	34.37	9.29
Small diameter	12.29	27.5	13.69
Nonstocked	31.95	-	31.95

Number of non-zero plots in estimate:

	Ownership group - Major		
Stand-size class	**Total**	**Public**	**Private**
Total	445	39	409
Large diameter	252	20	232
Medium diameter	150	10	140
Small diameter	76	15	62
Nonstocked	11	-	11

```
    Dim sURL As String
    Dim sResult As String
    Dim urlStr As String
    Dim numerator(3) As String
    Dim denominator(3) As String
    numerator(1) = “Area of timberland, in acres”
    numerator(2) = “Net volume of live trees (at least 5 inches d.b.h./d.r.c.), in cubic feet, on timberland”
    numerator(3) = “Average annual net growth of live trees (at least 5 inches d.b.h./d.r.c.), in cubic feet, on timberland”
    denominator(1) = “No denominator - just produce estimate.”
    denominator(2) = “No denominator - just produce estimate.”
    denominator(3) = “Average annual removals of live trees (at least 5 inches d.b.h./d.r.c.), in cubic feet, on timberland”
    For i = 2 To 1001 ‘maximum number of mills is set to 1000
        For j = 1 To 3
        mill_lat = ThisWorkbook.Sheets(“sheet1”).Range(“a” + LTrim(Str(i)))
        mill_lon = ThisWorkbook.Sheets(“sheet1”).Range(“b” + LTrim(Str(i)))
        mill_radius = ThisWorkbook.Sheets(“sheet1”).Range(“c” + LTrim(Str(i)))
        evalGroups = ThisWorkbook.Sheets(“sheet1”).Range(“d” + LTrim(Str(i)))
        mill_id = ThisWorkbook.Sheets(“sheet1”).Range(“e” + LTrim(Str(i)))
        If mill_id <> “” Then
        urlStr = “http://apps.fs.fed.us/Evalidator/batcheval.jsp?”
        urlStr = urlStr + “reptype=Circle”
        urlStr = urlStr + “&lat=” + Str(mill_lat)
        urlStr = urlStr + “&lon=” + Str(mill_lon)
        urlStr = urlStr + “&radius=” + Str(mill_radius)
        urlStr = urlStr + “&snum=” + numerator(j)
        urlStr = urlStr + “&sdenom=” + denominator(j)
        urlStr = urlStr + “&wc=” + evalGroups
        urlStr = urlStr + “&pselected=None”
        urlStr = urlStr + “&rselected=Forest type”
        urlStr = urlStr + “&cselected=Ownership group - Major”
        urlStr = urlStr + “&ptime=Current”
        urlStr = urlStr + “&rtime=Current”
        urlStr = urlStr + “&ctime=Current”
        urlStr = urlStr + “&wf=”
        urlStr = urlStr + “&wnum=”
        urlStr = urlStr + “&wnumdenom=”
        sResult = GetHTTPResult(urlStr)
        Call OpenTextFile(mill_id + “_” + Format(Str(j), “00”), sResult)
        End If
        Next j
    Next i
End Sub
Function GetHTTPResult(sURL As String) As String
    Dim XMLHTTP As Variant, sResult As String
```

```
    Set XMLHTTP = CreateObject("WinHttp.
WinHttpRequest.5.1")

    XMLHTTP.SetTimeouts "300000", "300000",
"300000", "300000" 'timeout= 300 seconds

    XMLHTTP.Open "GET", sURL, False

    XMLHTTP.Send

    'Debug.Print "Status: " & XMLHTTP.Status & " - "
& XMLHTTP.StatusText

    sResult = XMLHTTP.ResponseText

    'Debug.Print "Length of response: " & Len(sResult)

    Set XMLHTTP = Nothing

    GetHTTPResult = sResult

End Function

Sub OpenTextFile(mill_id As String, sResult As
String)

Dim File_Path As String, folder_path As String

File_Path = Application.ActiveWorkbook.Path + "\" +
mill_id + ".html"

Open File_Path For Output As #1

Write #1, sResult

Close #1

    ChDir _

        Application.ActiveWorkbook.Path

    Workbooks.Open Filename:= _

        Application.ActiveWorkbook.Path + "\" + mill_id
+ ".html"

End Sub
```

APPLICATIONS IN FOREST HEALTH

PROJECT CAPTURE: USING FOREST INVENTORY AND ANALYSIS DATA TO PRIORITIZE TREE SPECIES FOR CONSERVATION, MANAGEMENT, AND RESTORATION

Kevin M. Potter[1], Barbara S. Crane[2], William W. Hargrove[3]

Abstract—A variety of threats, most importantly climate change and insect and disease infestation, will increase the likelihood that forest tree species could experience population-level extirpation or species-level extinction during the next century. Project CAPTURE (Conservation Assessment and Prioritization of Forest Trees Under Risk of Extirpation) is a cooperative effort across the three Forest Service deputy areas to establish a framework for conservation priority-setting assessments of forest tree species across the entire United States. Forest Inventory and Analysis (FIA) data represent an unmatched resource for conducting broad-scale, spatially explicit assessments of the risk posed by climate change and other threats to the genetic integrity of forest tree populations and species. Project CAPTURE uses FIA data, along with life history trait and pest and pathogen threat information from other sources, to categorize and prioritize nearly 400 tree species for conservation, monitoring, management and restoration across all forested lands in the contiguous United States and Alaska. Specifically, we used FIA data to (1) generate 4-km2 resolution maps predicting the genetic pressure that could be imposed by climate change on forest tree species and to (2) compile information about the biological attributes and genetic diversity of individual species. This assessment tool should be valuable for scientists and managers attempting to determine which species and populations to target for monitoring efforts and for pro-active gene conservation and management activities.

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DEVELOPMENT OF FULL REGENERATION ESTABLISHMENT MODELS FOR THE FOREST VEGETATION SIMULATOR

John D. Shaw[1]

Abstract—For most simulation modeling efforts, the goal of model developers is to produce simulations that are the best representations of realism as possible. Achieving this goal commonly requires a considerable amount of data to set the initial parameters, followed by validation and model improvement – both of which require even more data. The Forest Vegetation Simulator (FVS) is a widely-used, distance-independent forest growth simulator that can be used to model a wide variety of forest conditions and silvicultural treatments. Extensions to FVS include modules for simulating fire effects and the impacts of insects and disease. Being an important silvicultural tool, the incorporation of realistic tree regeneration, with or without the occurrence of treatments, is a desirable component. Regeneration is implemented in FVS using two kinds of models – full establishment models, which are calibrated to automatically regenerate seedlings (including root and stump sprouts) in response to stand conditions and treatments, and partial establishment models, in which the establishment of new trees is largely under the control of the user. Although establishment models have been part of FVS since the 1980s in its predecessor, Prognosis, only a few of the 19 FVS variants currently in use have full establishment models. While user demand has been high for full establishment models to be added to more variants, the accessibility to sufficient regeneration data has been a barrier to implementation. As a wide-ranging data source, the Forest Inventory and Analysis (FIA) program has potential to assist with development of full establishment models in variants that are currently lacking them. FIA has formed a partnership with other parts of Forest Service Research and Development, National Forest Systems, and other researchers who have an interest in, or are currently working on forest regeneration modeling. The goal of the partnership will be universal implementation of full establishment models within FVS.

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MODELING URBAN HOST TREE DISTRIBUTIONS FOR INVASIVE FOREST INSECTS USING A TWO-STEP APPROACH

Mark J. Ambrose, Frank H. Koch, Denys Yemshanov, and P. Eric Wiseman[1]

Abstract – Many alien insect species currently impacting forested ecosystems in North America first appeared in urban forests. Unfortunately, despite serving as critical gateways for the human-mediated spread of these and other forest pests, urban forests remain less well documented than their "natural" forest counterparts. While Forest Inventory and Analysis (FIA) data provide good information about the composition of natural forests, only a small percentage of the more than 26,000 communities in the US and Canada have completed any sort of urban forest inventory, and these inventories have commonly been restricted to street trees. We devised a two-step approach that utilizes the available local inventory data to comprehensively model urban host tree distributions at a regional scale. We illustrate the approach for three tree genera – ash (*Fraxinus*), maple (Acer), and oak (*Quercus*) – that are associated with high-profile insect pests. Available inventory data include 60 sample-based inventories of entire cities (i-Tree Eco inventories) and 475 street tree inventories. First, based on existing inventories, we use a suite of explanatory spatial variables to model the proportion of the total basal area (as a proxy for forest volume) occupied by each genus. Second, we apply a similar suite of spatial variables to estimate the total basal area of these communities. These estimates will be combined to estimate basal area of each genus in non-inventoried communities and to construct region-wide urban distribution maps for each genus. By merging these maps with similar data on natural forests (e.g., distribution maps developed from FIA plot data), we are able to provide a more complete host setting for spread modeling efforts. Urban FIA projects promise to provide information about the composition of urban forests, but it will be some time before most US urban areas have been inventoried intensely. This modeling approach provides a use for urban FIA data as they become available to better understand urban forests at larger spatial scales.

INTRODUCTION

Many alien insect species currently impacting forested ecosystems in North America first appeared in urban forests. Unfortunately, despite serving as critical gateways for the human-mediated spread of these and other forest pests, urban forests remain less well documented than their "natural" forest counterparts. Forest Inventory and Analysis (FIA) plot data are an excellent resource for estimating host species distributions, since they provide a nationwide, systematic, and fairly intensive sample. However, FIA data generally do not depict conditions in urban forests (with the exception of the limited amount of Urban FIA data that are just coming on-line). This results in a major data gap with respect to forest pests, in terms of both the early detection of new pests as well as the modeling of pest spread, including spread via human-mediated pathways (U.S. Government Accountability Office 2006).

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Many communities have some sort of independent urban inventory, but they are piecemeal and have a variety of formats and sample densities. This makes it challenging to apply such data for broad-scale analyses (such as a pest risk map). Our objective is to compile such available urban forest inventory data, and use them as basis for models to estimate presence of host trees of interest in non-sampled communities throughout study region (Eastern US). We focus on key host genera for three prominent invasive forest insect pests in Eastern US, maple (*Acer*), ash (*Fraxinus*), and oak (*Quercus*).

DATA AND METHODS

Data

We acquired urban forest inventory data from over 700 communities across the United States and Canada. Data are from two basic types of inventories: (1) sample-based whole-city (e.g., i-Tree ECO, formerly known as UFORE; Nowak and Crane 2000; Nowak et al. 2008) inventories; (2) street tree/public tree inventories. Of these datasets, the vast majority were from street/public tree inventories.

The street tree inventory data, usually lacked information needed to determine the absolute dominance (i.e., in terms of BA per hectare) of our genera of interest. Therefore, we used relative basal area (BA) as our measure of the importance of each genus in urban forests. For each inventory dataset we calculated the proportion of BA represented by each of the three genera.

Step 1: Modeling relative basal area

Our interest was in the overall urban forest tree population, but most of our data came from street/public tree inventories. So our first step was to model the relationship between street tree and whole-city populations using data from cities where both types of inventory had been conducted. We had data of both types from 41 cities across the US and Canada, but these cities were spatially imbalanced; clustered in certain states (MN, VA). To address this imbalance, we used geographically weighted regression (GWR) (ESRI 2012), where the dependent variable was relative BA for each genus from whole-city inventory and the independent variable was the relative BA from street tree inventory. In GWR, an individual regression runs for each observation, using an adaptive kernel to determine neighborhood for each model.

We then applied the GWR models to adjust the BA proportions in the 464 Eastern US cities having only street tree inventories and combined those data with the 60 cities that had whole-city inventories that did not require adjustment.

Next, we constructed models to estimate BA proportion for each host genus from the adjusted data set. We used boosted decision trees (Sherrod 2014) with a 20% validation (random) sample. Our explanatory variables included the following:

- Geographic: latitude, longitude, elevation
- Demographic: population (2010 Census)
- Climatic: annual extreme minimum temperature, summer maximum temperature, precipitation, growing degree days, last freeze, annual number of wet days, moisture index
- Land cover: proportion natural, agriculture, developed, forested; road density

Step 2: Modeling total urban forest basal area

Total urban forest BA per hectare estimates were available from i-Tree Eco output for 78 cities across continental US. Our aim was to relate total urban forest BA (all species) to canopy cover. Canopy cover estimates were derived from 2011 National Land Cover Database (NLCD). The canopy cover map product (30-m spatial resolution) was developed in cooperation with USFS.

We again used GWR, with an adaptive kernel to determine modeling neighborhood for each observation. The primary explanatory variable was the estimate of each city's total canopy cover; this measure combines canopy density measure with city's total land area. Population density served as an additional explanatory variable

RESULTS AND DISCUSION

Our models of relative BA fit rather well for all three genera. The model explained 0.67 of the variation in relative BA of maple. The fit was not quite as good for oak, explaining only 0.59 of the variation. For ash, we needed to remove to outlying cities (Minot and Grand Forks, ND) to achieve a good fit. With those cities dropped from the data set, our model explained about 0.67 of the variation (Fig. 1).

Initial results of modeling total BA from canopy cover are encouraging. We achieved a good fit overall (r^2= 0.79), but the BA of a few cities was significantly under-predicted (Fig. 2). We aim to refine this model. We plan to seek additional data to expand the set of cities used for this portion of the model. We also will explore using additional explanatory variables.

We intend to combine our model of relative BA for our genera of interest with our total BA model to estimate the total BA for each genus in each city. Then we will apply the combined model steps to estimate amount of oak, ash, maple in all populated places across Eastern US. Ultimately, we hope to extend the models to the Western US and Canada.

A

B

C

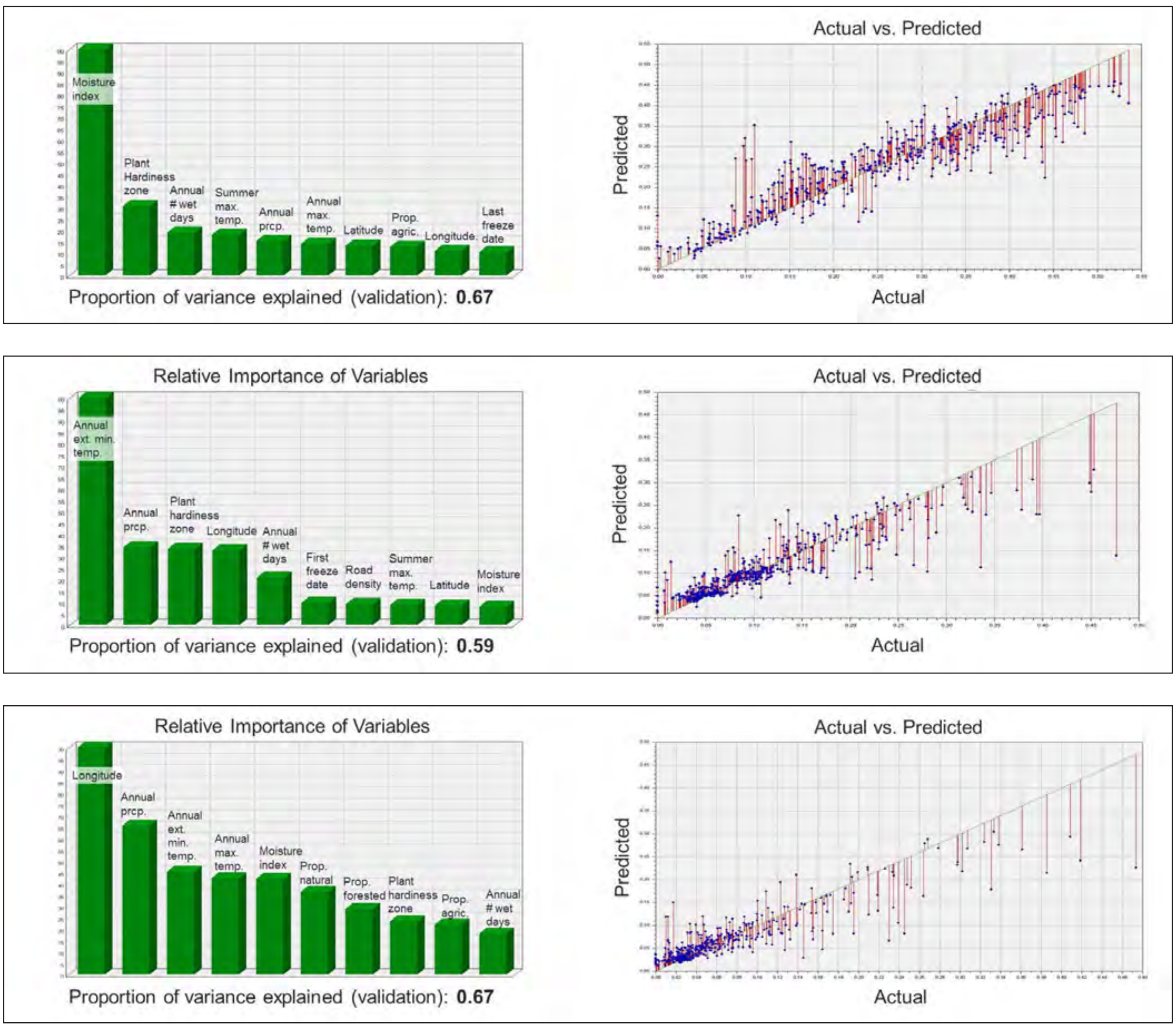

Figure 1—Results of boosted decision tree model for relative basal area of (a) maple, (b) oak, and (c) ash.

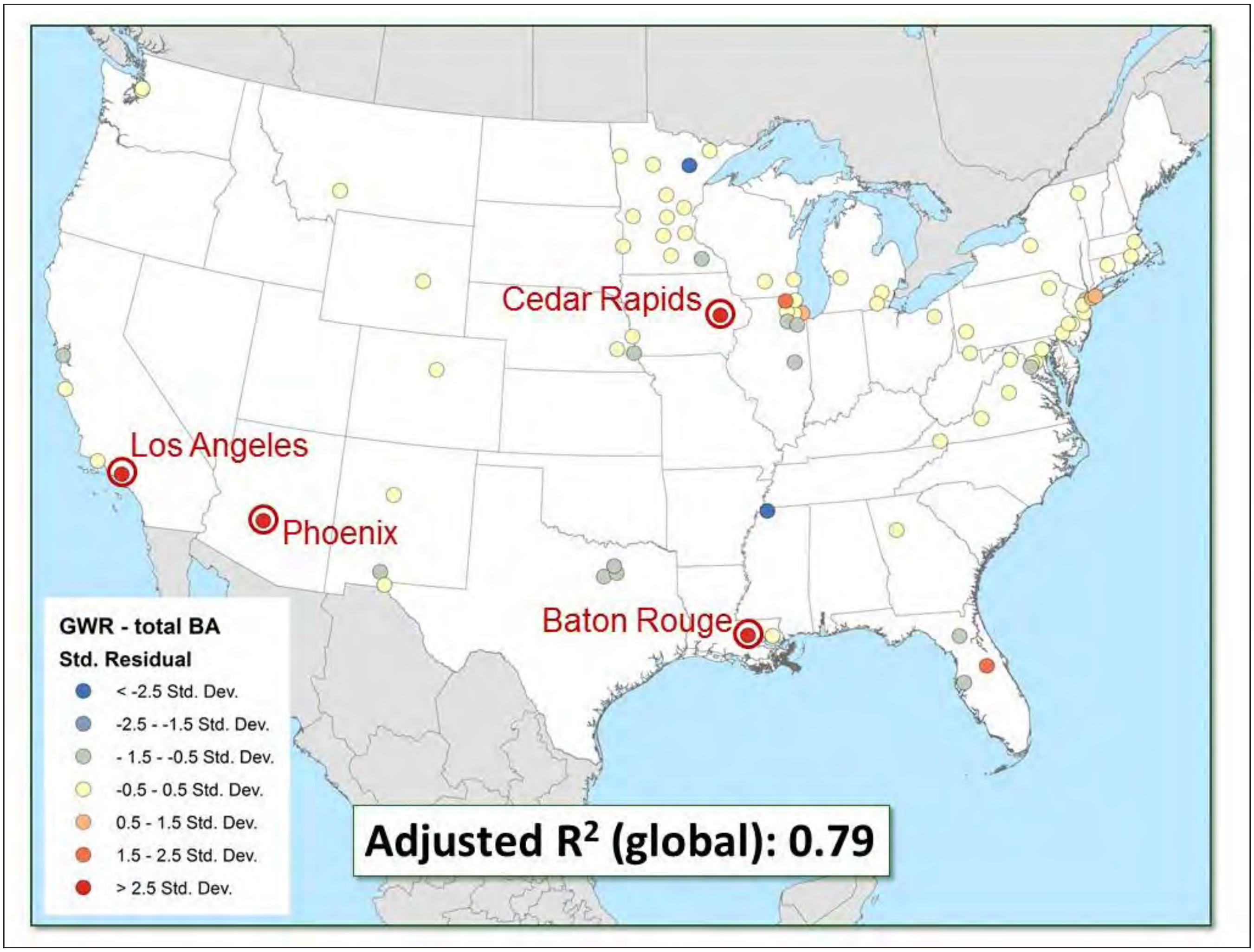

Figure 2—Results of geographically weighted regression of total urban forest basal area on city canopy cover. Cities where the model strongly under-predicts the basal area are circled in red.

By merging these maps with similar data on natural forests (e.g., distribution maps developed from Forest Inventory and Analysis plot data), we are able to provide a more complete host setting for spread modeling efforts. Urban FIA projects promise to provide information about the composition of urban forests, but it will be some time before most US urban areas have been inventoried intensely. This modeling approach provides a use for urban FIA data as they become available to better understand urban forests at larger spatial scales. It may be useful to consider FIA urban inventories as potential input to models such as these when determining where to implement future urban FIA i-Tree Eco inventories.

ACKNOWLEDGMENTS

Space does not allow us to name them all, but we are indebted to literally hundreds of municipal foresters, State urban forestry coordinators, foresters working in the US Forest Service Urban and Community Forestry Program, staffs of urban forestry-related NGOs, and university researchers who supplied us with data. Without their cooperation, this research would have been impossible. Special thanks go to Dave Nowak, Research Forester, US Forest Service, Northern Research Station and the other researchers in the Urban Forest Research Work Unit for their aid in obtaining key datasets and their valuable comments on this work.

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UNDERSTANDING MACROSCALE INVASION PATTERNS AND PROCESSES WITH FIA DATA

Songlin Fei, Basil V. Iannone III, Christopher M. Oswalt, Qinfeng Guo, Kevin M. Potter, Sonja N. Oswalt, Bryan C. Pijanowski, Gabriela C. Nunez-Mir[1]

Abstract—Using empirical data from FIA, we modeled invasion richness and invasion prevalence as functions of 22 factors reflective of propagule pressure and/or habitat invasibility across the continental US. Our statistical models suggest that both propagule pressure and habitat invasibility contribute to macroscale patterns of forest plant invasions. Our investigation provides insight into sub-continental invasion patterns and processes, confirming the utility of accounting for multiple invasion measures and sub-regional heterogeneity.

Biological invasions are a major component of global change, resulting in significant impacts. Despite the vast number of smaller-scale investigations, these studies cannot provide comprehensive insight into the complexities of invasions at macroscales. Stronger inferences about biological invasions may be obtained when accounting for multiple invasion measures and the spatial heterogeneity occurring across large geographic areas. We pursued this inquiry by utilizing a multi-measure, multi-regional framework to investigate forest plant invasions at a sub-continental scale.

METHODS

We mapped invasion richness and invasion prevalence across the contiguous 48 states of the USA based on FIA invasive plants dataset. To determine the extent to which different invasion measures and spatial heterogeneity affect factors most associated with invasion patterns, we modeled each invasion measure separately for eastern and western forests as a function of 22 variables reflecting propagule pressure and habitat invasibility using simultaneous autoregressive error models (SARerr).

INVASION SPATIAL PATTERNS AND DRIVERS

Eastern forests were more invaded than western forests. The invasion richness per county was twice more in the East than the West (6.1 ± 0.1 and 3.2 ± 0.2, respectively). Invasive prevalence was 48 ± 1% in the East and 10 ± 1% in the West. Invasion patterns were spatially heterogeneous both for the East and West.

Both propagule pressure and habitat invasibility contribute to macroscale patterns of forest plant invasions.

Population density, distance to the nearest port, and years since annexation by the USA were positively related to invasion richness and prevalence. We also found that human-caused forest fragmentation, along with native tree live biomass, species richness, and phylogenetic richness, was associated with the observed invasion patterns.

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DISCUSSIONS

Our investigation provides insight into sub-continental invasion patterns and processes. By accounting for spatial heterogeneity, we detected a declining effect of propagule pressure on macroscale invasion patterns. Our analyses suggest that eastern and western forests as a whole are at different stages of invasion and are influenced by different drivers, indicating a need for considering spatial heterogeneity when prescribing invasive plant management and policy.

ACKNOWLEDGMENT

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EARLY-SERAL STAND AGE AND FOREST STRUCTURAL CHANGES IN PUBLIC AND PRIVATE FORESTLANDS IN WESTERN OREGON AND WASHINGTON

Robert L Deal*, Sharon Stanton[1], Matthew Betts[2] and Zhiqiang Yang[2]

Abstract—Federal forests in the Pacific Northwest region have undergone exceptional changes in management over the past 20 years, and these changes have led to a reduction in regional timber production and significant changes in the management and current age structure of forests. Public lands include large areas of older forests with relatively little younger early-seral forests. In contrast, private lands include large areas of younger forests and little land in older forests. The lack of early-seral forests on federal lands is an important and distinguishing characteristic of these forests and there is concern about the amount and type of early-seral wildlife habitat available in the region. Reductions in timber harvests in federal forests in the PNW region in recent years may lead to significant changes in forest age class structure between public and private lands. Lack of regeneration harvests may also reduce early-seral forest habitat on federal lands and this loss of early-seral habitat is a conservation concern for wildlife species that depend on this type of forest habitat. Conversely, the amount and intensity of management in industrial private lands have has increased with a greater proportion of private forests in relatively young stands less than 20 years old.

We assess changes in forest stand age, forest structure and vegetation in public and private lands using both USFS Forest Inventory and Analysis and LANDSAT data to compare differences among forestland owners since the Northwest Forest Plan was implemented. Findings show significant differences in stand age and forest structure between federal, state and private forestlands in the Northwest Forest Plan area. We are conducting analyses of forest stand and understory data to assess potential differences between public and private landowners and relate to quality of wildlife habitat for ungulates and birds. We will report results with implications for forest management and wildlife habitat in the PNW region.

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AN EARLY LOOK AT FOREST REGENERATION INDICATOR RESULTS FOR THE MIDWEST AND NORTHEAST UNITED STATES

William H. McWilliams and James A. Westfall[1]

Abstract—Interacting regeneration stressors create challenges for policy makers and managers who are tasked with making decisions for restoring forest following major disturbances, such as harvest or catastrophic mortality. Concern over an aging forest, dwindling young forest habitat, and restoration of native forests in the midwest and northeast United States has resulted in the development of the regeneration indicator (RI), a new ecological health indicator derived from 25 years of measuring advance regeneration in Pennsylvania. The RI protocols were added to the Northern Research Station (NRS), Forest Inventory and Analysis (FIA) program sample plot design in 2012. Two case studies are presented that exemplify the scope of possible inferences from the existing data. The examples use two key variables—numbers of seedlings and browse impact—to highlight potential applications of this metric. Future research should focus on identifying issue-oriented geographic hot spots, further development of regeneration adequacy analytics, and integration with other publicly available geographic datasets.

INTRODUCTION

Multiple interacting regeneration stressors challenge wide-ranging policy and management decisions for restoring native forest ecosystems following major disturbances, such as harvest or catastrophic mortality. Some of the more complicated stressors are invasive plants, herbivory, and changing climate. Although it has been accepted as fact that tree regeneration determines future forest composition, structure, and health following stand replacement events, regeneration studies for subcontinental-scale forest landscapes are rare.

Concern over an aging forest, dwindling young forest habitat, and restoration of native forests in the midwest and northeast United States has resulted in the development of the regeneration indicator (RI), a new ecological health indicator derived from 25 years of experience measuring advance regeneration in Pennsylvania (McWilliams et al. 2012). The RI protocols include a suite of tree-seedling and browse impact measurements that were added to Northern Research Station (NRS), Forest Inventory and Analysis (FIA) program sample plot design in 2012 (McWilliams et al. 2015).

The goal of this paper is to demonstrate decisions for making inferences and observations using the RI data with examples that range from the substate to subcontinental scale. Only general guidance is offered because the of many prospective uses, sample sizes, and options for geographic applications preclude more complete recommendations in this short paper.

METHODS

In 2012, the NRS-FIA program began taking measurements for a suite of ecosystem health indicators collected during the leaf-on season. A 12-percent subsample of the core Phase 2 sample was selected randomly within estimation strata; the subsample plots are referred to as “Phase 2-plus.” Each RI sample is coincident with Phase 2 and other Phase 2-plus indicator samples, including down woody material, vegetation structure, and soils.

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The vegetation structure measurements are collected on forested conditions and comprised of a vegetation profile, an invasive plant survey, and the RI. The vegetation profile includes estimates of percent cover by growth habit for four height classes and an aerial view of the subplot. The invasive plant survey is made up of percent cover estimates for 43 invasive plant species encountered on the subplot. The RI measurements are collected on microplots within the subplot and include a tally of all established tree seedlings at least 2-inches in length (or height) by species, assignment of each seedling to one of six height classes, and an assessment of root-collar diameter for large-seeded species. A browse impact code is also recorded based on conditions surrounding the sample plot. Details of plot, subplot, and microplot design are provided in USDA Forest Service 2012.

Two case studies exemplify the scope of possible inferences for data that range from small to large scales and to illustrate opportunities and limitations of analyzing results. The case studies use two key variables—numbers of seedlings and browse impact—to highlight reporting and research products.

The first case study presents estimates of seedlings in West Virginia. The estimates are based on 83 forested Phase 2-plus samples collected in 2012-2013. Population estimates for the six seedling-height classes were combined into three to take advantage of lower sampling errors associated with larger sample sizes of the wider range of heights. These traditional FIA sampling errors represent one standard error or a 68-percent confidence level.

The second case study is a geographic evaluation of browse impact comparing results for a variety of scales. The visualization includes RI data for 2012-2013 for Delaware (four samples), Maryland (19), and New Jersey (17) to represent minimum reporting options. These results are compared to the NRS-FIA region-wide data for 2012-2013 (1,711) and the full baseline data set for Pennsylvania (292) to provide context. Statistical confidence intervals for population estimates are used to suggest bounds for deriving logical conclusions from the results.

RESULTS

In the Midwest and Northeast, large blocks of forest land are aging and subject to a plethora of stressors, which means stand-replacement disturbances will likely become more common. Estimates of the number of seedlings by height class, species, and spatial extent provide information for predicting future forest composition and prospective regeneration management challenges (Fig. 1a-c). Sampling errors for species and species groups range from 20 percent for the number of red maple seedlings to 70 percent for boxelder (see Appendix Table 1 for list of common and scientific names). The sampling errors exceed 25 percent for all species that comprise 3 percent or less of the total number of seedlings, suggesting a possible limit for taxa-specific inferences at these sample sizes. It is apparent that with only two inventory panels complete, nearly all of the estimates for species by height class lack statistical confidence needed for making inferences. The visualization of seedlings per acre across West Virginia clarifies spatial patterns of seedling development. The seedlings per-acre classes can be adjusted as needed for species, forest types, and regions of interest, subject to statistical confidence limitations.

Results displayed in a geographic context can facilitate the understanding of how and where deer browse has the most impact. The distribution of samples by browse impact for the NRS-FIA region provides a first look at general patterns of high versus low browse impact, e.g., Maine compared to central Pennsylvania (Fig. 2a). Figure 2b shows three states with relatively small sample sizes combined with the full baseline data set for Pennsylvania. Even though low sample sizes prevent rigorous spatial analysis for the three small states, including the Pennsylvania samples and the ecological province boundaries assists in observing broad browse impact patterns. For example, samples for western Maryland appear to follow the relatively nondescript patterns of the Central Appalachian Broadleaf Province. Combining the Outer Coastal Mixed province portions of the three small states suggests careful monitoring is needed because of the abundance of high browse impact samples.

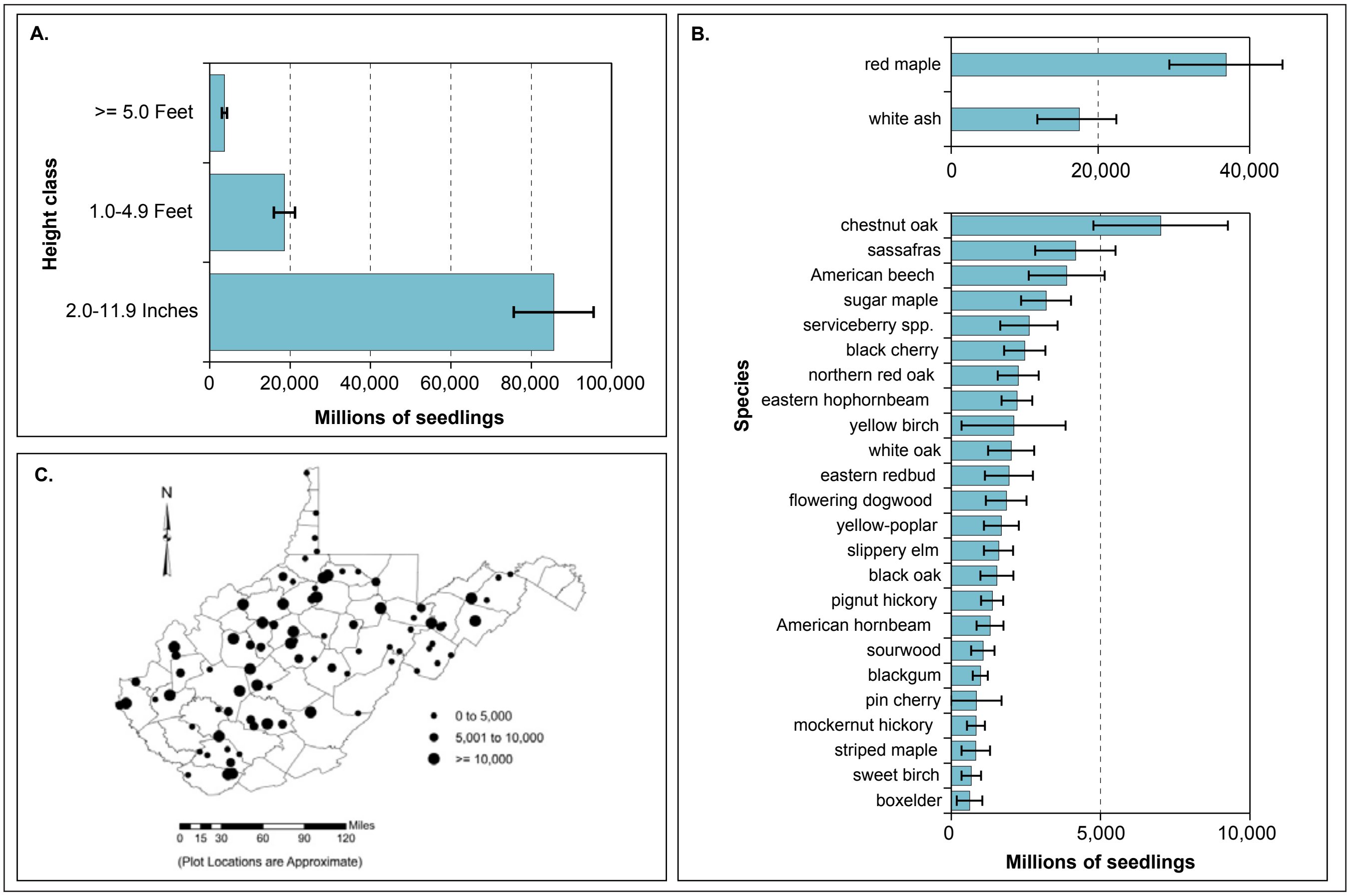

Figure 1—a) Number of seedlings by height class; b) Number of seedlings ranked by species for species with at least 1 percent of the total number of seedlings; and c) distribution of forested Phase 2-plus samples by the average number of seedlings per acre, West Virginia 2012-2013. Error bars represent 1 standard error or a 68-percent confidence interval.

DISCUSSION

The RI results provide meaningful insight into the character and abundance of the seedling component for the NRS-FIA region; however, it is clear that caution is needed for making inferences. The relatively small sample size at the regional level means that some states, study regions, and variables have sample sizes that limit the ability to make inferences. Consequently, reporting templates for West Virginia and Maryland would be quite different because analyses need to be tailored to fit statistical limitations. Presenting the results with error bars and geographic distributions for the major variables of interest provides insights for the smaller states. It becomes obvious that more information is needed for taxa-specific abundance (numbers of seedlings) and structure (seedling height). These attributes are critical for understanding the future status of forest ecosystems following stand-replacement disturbance.

These results reflect only two of the seven panels of measurements that will eventually comprise the first full baseline data set for the RI. Completion of the baseline data set in 2018 will improve the level of statistical confidence in the estimates and facilitate more detailed studies.

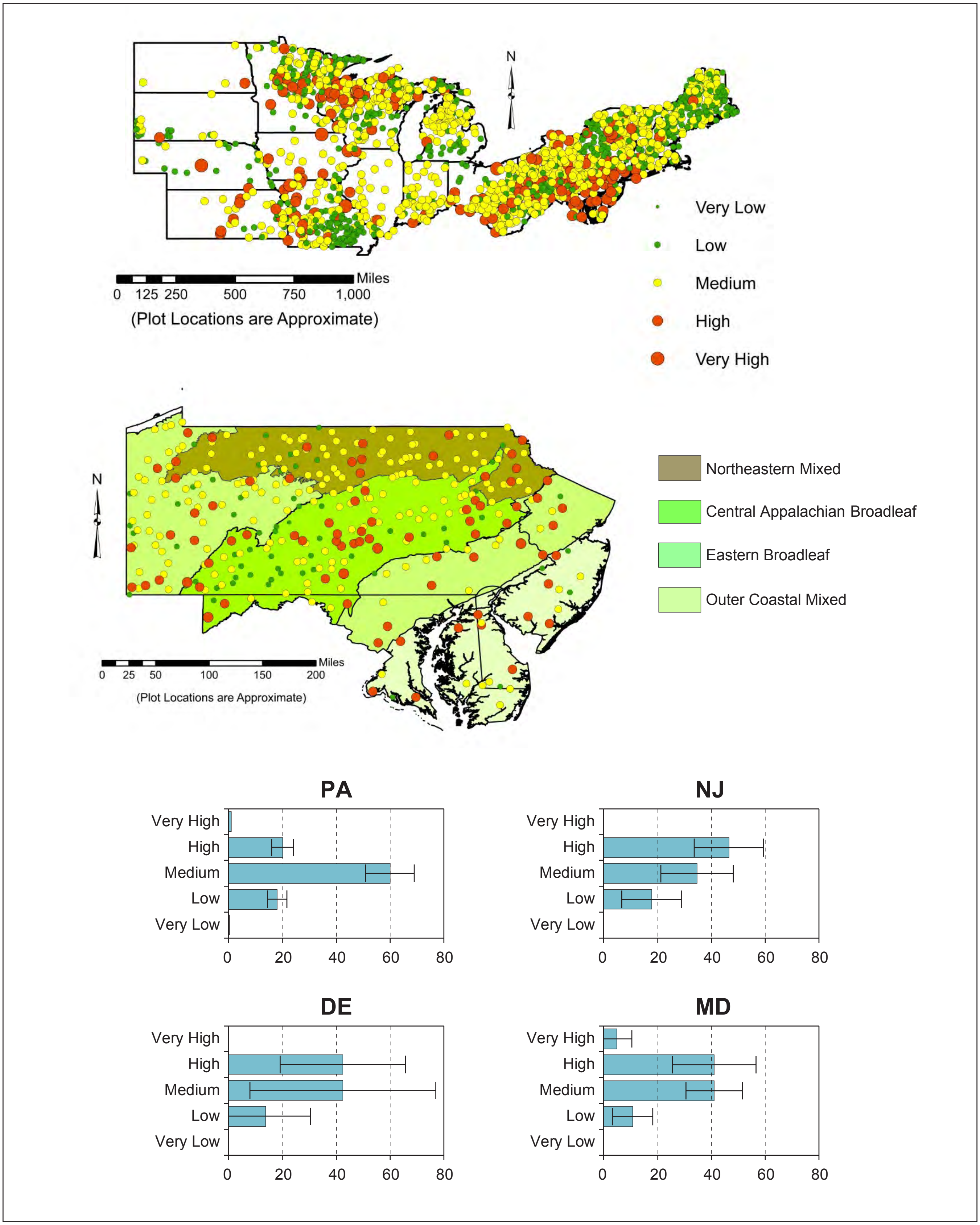

Figure 2—a) Distribution of forested Phase 2-plus samples on forest land by browse impact, b) distribution of forested phase 2-plus samples and by browse impact and ecological province (Cleland et. al. 2007), NRS-FIA states, US, 2012-2014. Error bars represent 1 standard error or a 68-percent confidence interval. (Note: results for Pennsylvania are for 2010-2014).

FUTURE WORK

As with any new ecological health indicator, there are numerous research extensions and applications to enhance the utility of science products. Future research should focus on an analysis of composition and structure of the seedling component as the data set expands and a geospatial analyses to identify high-risk areas, such as forest types with poor regeneration or areas with high browse impact.

Research is also needed to address the viability, or adequacy, of the regeneration process. While analytics that adjust existing regeneration guidelines to reflect browse impact have been applied for the mid-Atlantic States (McWilliams et al. 1995), similar analytics for the Central, Lake, and New England States are needed. Once complete, such metrics will facilitate a seamless and transparent assessment of regeneration adequacy for the major forest types of the Northeast and Midwest. This is a critical need due the aging of mixed oak and northern hardwood forests of the region and regeneration stress factors that interact to make regeneration difficult.

Modern resource questions often require multivariate studies that combine geographic data to better understand complex relationships. There are many research opportunities to integrate the RI data with other publicly available geographic datasets. For example, tree-species migration studies would benefit from including soils (USDA Natural Resource Conservation Service 2015), climate (NOAA National Weather Service 2015), and disturbance (USDI Geological Survey 2015).

The RI was designed to supplement NRS-FIA's vegetation profile and invasive plant survey information. Combining results from these three components of the vegetation structure measurements provides a fuller appraisal of the forest understory that will better address emerging issues, e.g., the status and condition of new forest communities (Royo and Carson 2006). In turn, this should improve our ability to evaluate sustainability of future forest values in the Midwest and Northeast.

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APPENDIX

Table 1—Common and scientific names of FIA tree species.

Species Common name	Scientific name[1]
American beech	*Fagus grandifolia*
American hornbeam	*Carprinus caroliniana*
black cherry	*Prunus serotina*
black oak	*Quercus velutina*
blackgum	*Nyssa silvatica*
boxelder	*Acer negundo*
chestnut oak	*Quercus prinus*
eastern hophornbeam	*Ostrya virginiana*
eastern redbud	*Cercis canadensis*
flowering dogwood	*Cornus florida*
mockernut hickory	*Carya alba*
northern red oak	*Quercus rubra*
pignut hickory	*Carya glabra*
pin cherry	*Prunus pensylvanica*
red maple	*Acer rubrum*
sassafras	*Sassafras albidum*
serviceberry spp.	*Amelanchier spp.*
slippery elm	*Ulmus rubra*
sourwood	*Oxydendron arboreum*
striped maple	*Acer pensylvanicum*
sugar maple	*Acer saccharum*
sweet birch	*Betula lenta*
white ash	*Fraxinus americana*
white oak	*Quercus alba*
yellow birch	*Betula alleghaniensis*
yellow-poplar	*Liriodendron tulipifera*

[1] USDA Natural Resources Conservation Service, 2014.

FOREST DISTURBANCES TRIGGER EROSION CONTROLLED FLUXES OF NITROGEN, PHOSPHORUS AND DISSOLVED CARBON

Marek Matyjasik[1], Gretchen Moisen[2], Todd A. Schroeder[2], Tracy Frescino[2], Michael Hernandez[1]

Abstract—The initial phase of the research that addressed correlation between annual forest disturbance maps produced from LANDSAT images and water quality and flow data indicate that forest disturbances in conjunction with intense atmospheric precipitation commonly trigger fluxes of several chemical constituents, such as nitrogen, phosphorus carbon. These fluxes appear to be correlated with intense soil erosion. While concentration on N, P and dissolved C do not significantly fluctuate, their total fluxes vary by five to twenty times when flow volumes increase by on order of magnitude during peak flow rates. These large fluxes of N, P and dissolved C are transferred to downstream watersheds affecting effectively environmental ecosystems of upstream and downstream areas. These fluxes are also highly correlated with wild fire triggered erosion. Erosion has been modeled using ERMiT: Erosion Risk Management Tool, developed specifically for post-fire assessments that predicts the probability associated with a given amount of single-storm soil erosion in tons/acre for a given hillslope topography in each of five years following forest wildfire. Erosion modeling allows changing vegetation cover as the function of severity of forest disturbances. Input data in erosion modeling include types of soils, types of vegetation cover, slope angle, burn severity level, and hydrologic conditions for the modeled area. Niitrogen fluxes from two study area have been correlated with ERMiT modeled erosion. Both areas display high correlation between erosion and nitrogen fluxes, with correlation coefficients higher than 0.7.

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FOREST CARBON ACCOUNTING

INTEGRATING FIELD PLOTS, LIDAR, AND LANDSAT TIME SERIES TO PROVIDE TEMPORALLY CONSISTENT ANNUAL ESTIMATES OF BIOMASS FROM 1990 TO PRESENT

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Abstract—We are developing a system that provides temporally consistent biomass estimates for national greenhouse gas inventory reporting to the United Nations Framework Convention on Climate Change. Our model-assisted estimation framework relies on remote sensing to scale from plot measurements to lidar strip samples, to Landsat time series-based maps. As a demonstration, new field plots are strategically located across six diverse Landsat scenes within the major forested regions of the US. To distribute the plots across structure and cover gradients within each scene, we use forest structure metrics derived from recent lidar acquisitions. Landsat time series are used to derive disturbance and recovery history metrics that, when linked to the plots and the lidar strip samples, facilitate improved mapping of current biomass. Because the mapping model is based on Landsat history metrics it can be walked back in time to 1990, using Landsat data acquired since 1972. This provides a temporally consistent approach for mapping biomass at an annual time-step, using a model that has well characterized errors from diagnostics associated with the plots and lidar strip samples from the current period.

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USING LANDSAT TIME-SERIES AND LIDAR TO INFORM ABOVEGROUND CARBON BASELINE ESTIMATION IN MINNESOTA

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Abstract—Landsat data has long been used to support forest monitoring and management decisions despite the limited success of passive optical remote sensing for accurate estimation of structural attributes such as aboveground biomass. The archive of publicly available Landsat images dating back to the 1970s can be used to predict historic forest biomass dynamics. In addition, increasing regional scale availability and high sensitivity of LiDAR for biomass mapping also needs exploration of its utility in back-projection modeling. This study has combined recent national forest inventory (NFI) data (2007-2011) with the Landsat data from 1986-2011 and a regional LiDAR dataset acquired by the Minnesota Department of Natural Resources (DNR) to assess the potential of the remote sensing data in predicting aboveground forest biomass back to the 1990 baseline used in the United Nations Framework Convention on Climate Change reporting in the US. Since obtaining cloud-free Landsat images at required seasons for a regional or national study is unlikely, pixel level polynomial models were fitted to a suite of time-series predictors obtained from cloud-free Landsat data of a single scene in Minnesota such that each predictor represented only one growing season between 1986 and 2011. Similarly, selected LiDAR variables were back-projected using Landsat metrics as explanatory variables. The rational for this effort was to obtain a wall-to-wall inventory for any target year that does not have remote sensing data by combining a set of projected predictors and current NFI data. Several candidate models were developed to produce biomass maps for the year 2000 to compare the outputs with the extant map of National Biomass and Carbon Dataset (NBCD) circa 2000 and annual NFI plot measurements. We found that the model including back-projected LiDAR metrics did not significantly improve the prediction accuracy as compared to the model based only on projected Landsat metrics. As the polynomial-projected Landsat-based model provided accuracy similar to the NBCD model, the former may be used for reference mapping back to 1990.

INTRODUCTION

Regional scale, spatially explicit and periodic quantification of aboveground biomass (AGB) is critical for forest carbon accounting and analysis of growth dynamics (Powell et al., 2010). Additionally, a back-in-time biomass baseline is necessary to evaluate national efforts (e.g., forestry-based) on greenhouse gas (GHG) emissions reduction implemented within the United Nations Framework Convention on Climate Change (UNFCCC). Any spatial inventory of forest AGB for the past that lacked sufficient field samples can most reliably apply historic satellite imagery (Huang et al., 2010). Landsat remotely sensed data has long been used to support forest inventory despite limited success of the passive optical data for accurate estimation of AGB. The archive of publicly available Landsat data dating back to the 1970s can be integrated with available standard national

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forest inventory (NFI) data to predict biomass in a temporally consistent approach. The NFI system in the US, implemented by the Forest Inventory and Analysis (FIA) program of the USDA Forest Service, has evolved over time with a nationally consistent design adopted since1999. It has been documented that resource estimates based on the current annual design compared to previous periodic designs produce inconsistent results (Goeking et al., 2015).

LiDAR technology has been found to provide the most sensitive remote sensing metrics (e.g., height distribution, strata density, canopy cover) to characterize forest structural attributes. Several studies have highlighted the strengths of LiDAR for landscape scale forest inventory and mapping, and such applications are receiving increasing attention, especially when regional scale LiDAR acquisitions are publicly available (e.g., MN High Resolution Elevation Mapping Project; see http://arcgis.dnr.state.mn.us/maps/mntopo/). This provides an opportunity to combine one-time LiDAR data with the time-series Landsat data for back-projection modeling of AGB.

This study was initially designed to combine a recent cycle (2007-2011) of FIA data with time-series Landsat data from 1986-2011 to assess the efficacy of the optical remote sensing data in back-projecting AGB to the 1990 baseline used in the US for national GHG inventory (NGHGI) reporting to the UNFCCC. An additional goal was to evaluate the inclusion of back-projected LiDAR metrics (as predictors in the modeling frames) from the recently acquired dataset with anticipation of improving the prediction accuracy of AGB for the reference year.

METHODS

FIA Data

Aboveground biomass data for the annual NFI plots measured in 2000 and 2007 to 2011 in northeastern Minnesota were obtained from the FIA program. The data were processed at the FIA, Northern Research Station to comply with the privacy requirements of actual plot locations. The plot biomass data scaled to tons per ha were based on nationally consistent allometric equations (Jenkins et al. 2003) applied to the records of all subplots and micro-plots in each NFI plot.

Remote Sensing Data

We acquired a time-series (1986-2011) of near-anniversary date Landsat-5 Thematic Mapper (TM) surface reflectance data for a single scene in Minnesota (WRS-2 path 27, row 27) from the USGS Climate Data Record (CDR, http://espa.cr.usgs.gov/ordering/new). The acquired images were radiometrically and atmospherically preprocessed at the source via LEDAPS software (http://landsat.usgs.gov/CDR_LSR.php). The time-series collection contained one cloud-free image per peak leaf-on season between mid-July and mid-September when consistent landscape conditions and phenology can be expected due to similar solar geometry; however, only 17 of the 26 seasons contained cloud-free images with a maximum gap of 2 years. The CDR products included surface reflectance-derived spectral indices (http://landsat.usgs.gov/-CDR_ECV.php) as well as individual bands for each acquisition. Six spatial predictors from Landsat data were considered for AGB modeling: Band-5, NDVI (normalized difference vegetation index), NBR (normalized burn ratio), IFZ (integrated forest z-score), TCA (tasseled cap angle), and DI (disturbance index). Band-5, NDVI, and NBR were obtained directly from CDR while IFZ, TCA, and DI were derived as described in Huang et al. (2010), Pflugmacher et al. (2012) and Healey et al. (2005) respectively.

A highly accurate LiDAR dataset (5 cm vertical error), acquired in spring 2011 (May, 3-26) with 1-1.5 m pulse spacing, is publicly available for over 75 percent coverage of the target Landsat scene to the northeastern side called the Arrowhead region. The raw LiDAR data were downloaded from the MnGeo web-portal (http://www.mngeo.state.mn.us/chouse/elevation/-lidar.html#data) and processed to obtain 30 grid-metrics representing canopy cover, elevation distributions, and proportion of returns in vertical strata following Falkowski et al. (2010). The analysis for spatial inventory was focused only to the Arrowhead region of Minnesota.

Modeling Approach

Since obtaining cloud-free Landsat images at nominal intervals for a regional or national study was unlikely, a pixel-level polynomial (3rd degree) curve fit (De Jager and Fox, 2013) was applied to each of the six time-series predictors obtained from the Landsat time-series (17 images between 1986-2011) for the target scene (WRS-2 path-27, row-27). The rationale for this approach was to obtain a wall-to-wall inventory for any target year that does not have cloud-free satellite images by combining a set of projected predictors from polynomial models and current FIA data. The FIA plot data was attached to the Landsat and LiDAR predictors to obtain a reference frame for modelling. The collinear spatial variables were pruned and then best-subset and Random Forest (RF)-based variable selection approach was followed to develop robust and parsimonious spatial models for predicting AGB (Falkowski et al., 2009, 2010). Several AGB models were formulated using the RF-based *k*-Nearest Neighbor (*k*-NN) imputation approach (Crookston and Finley, 2008). The candidate models were dependent on different combinations of Landsat and LiDAR derived spatial predictors, number of observations (plots within years) used in the reference frame and number of

Table 1—Fitted models for aboveground biomass and accuracy statistics for the Arrowhead region in northeastern Minnesota

Model	Predictors and reference years for the model frame	No. of plots	Value of k	% variance explained	Plot-level validation with FIA data in 2000 (n= 262)		Polygon-level validation with NBCD 2000 (n= 110)	
					Bias %	RMSE (mt/ha)	Bias %	RMSE (mt)
1	6 actual TM metrics[ψ] from 2007, 08, 10 & 11	1347	1	19.27	-2.2432	61.9552	-13.4873	1421.7299
2	6 projected TM metrics from 2007-2011	1661	1	25.79	-1.3484	63.6090	-9.7693	1236.7107
3	TM band-5 and 3 LiDAR[£] metrics from 2011 only	253	1	62.82	-2.1143	61.8594	-13.0971	1417.8929
4	6 projected TM metrics from 2011 only	327	1	24.71	3.5179	58.5749	5.1847	1237.4841
5	6 actual TM metrics from 2007, 08, 10 & 11	1347	3	18.95	-3.1665	61.4549	-13.4693	1427.2498
6	6 projected TM metrics from 2007-2011	1661	3	26.03	-2.7252	63.5456	-10.2685	1263.1804
7	TM band-5 and 3 LiDAR metrics from 2011 only	253	3	62.86	-1.2213	61.5482	-12.9604	1412.8583
8	6 projected TM metrics from 2011 only	327	3	24.83	4.3745	58.0422	4.9054	1237.3781
9	6 actual TM metrics from 2007, 08, 10 & 11	1347	5	19.16	-2.1723	62.3220	-12.9010	1397.7346
10	6 projected TM metrics from 2007-2011	1661	5	25.87	-3.2511	63.8337	-10.0981	1252.0701
11	TM band-5 and 3 LiDAR metrics from 2011 only	253	5	62.8	-1.8642	61.6539	-13.0042	1415.1248
12	6 projected TM metrics from 2011 only	327	5	24.88	4.8440	58.6628	5.5991	1249.3276
NBCD Model					5.0480	43.0694		

ψ 6 TM metrics: Band-5, DI, NBR, IFZ, TCA, and NDVI.
£ 3 LiDAR metrics: Maximum elevn, average elevn, and canopy cover based on percentage of all returns above 2 m.

nearest neighbors (*k*) considered for the imputation (Table 1). For LiDAR dependent models obtained from the plot data and coinciding LiDAR metrics of the acquisition year, only the selected LiDAR metrics were back-projected for a target year via Landsat variables. The selected LiDAR metrics were projected using the RF-based *k*-NN imputation models fitted to a frame obtained from 5000 arbitrary points across the target area where both LiDAR metrics as response and Landsat metrics as predictors were extracted in a GIS environment. The accuracy of model predictions for the year 2000 was evaluated at plot-level using the FIA data of 2000 and also at 110 arbitrary polygon-level (~10 - 133 ha) using an extant AGB map circa 2000 from the National Biomass and Carbon Dataset (NBCD, http://whrc.org/mapping/nbcd/). The performance of AGB models was assessed using statistical measures of bias (predicted - observed) and root mean square error (RMSE), to select the most suitable model for spatial inventory in 1990.

RESULTS AND DISCUSSION

Polynomial curve-fitting to the time-series actual Landsat-derived metrics revealed a better coefficient of determination (R^2) (i.e., temporal consistency) with band-5 where almost 50% of pixels in the target area attained an $R^2 > 0.40$; DI, IFZ, NBR, NDVI and TCA had 37.17%, 32.86%, 31.43%, 17.20% and 4.20% of their respective pixels with $R^2 > 0.40$. The RF-based variable selection algorithm for Landsat dependent models did not identify any collinear metrics but identified only three prime metrics for the LiDAR dependent model. When spatial models of the selected LiDAR metrics dependent on Landsat metrics were developed, reasonable R^2 values were obtained (0.56, 0.49 and 0.65 for ElevMax, ElevAv and Cover-above-2 m, respectively) with the fitting dataset for the year 2011. However, performance of these models when applied for back-projection using the Landsat metrics for the year 2000, were not tested in absence of data.

The plot level validation of AGB prediction using FIA measurements from the inventory year 2000 showed that the model including LiDAR metrics and the projected TM band-5, yield least bias with *k* = 3 NN in the imputation. Further, the bias of the model including LiDAR was very close to the model dependent on polynomial-projected TM metrics. However, the inspection of RMSE infers that the model based on projected TM predictors from the year 2011 with only 327 plots provided the least error. Additionally, the models based on LiDAR metrics have similar RMSE as the models based only on actual TM derived predictors. Although the LiDAR model performed well when applied in the same year from which it was built, the back-projection was impaired because ultimately it relied on TM predictors which become insensitive in high biomass areas. All the models provided negative bias, except the projected TM only model with fewer plots, suggesting that the imputation models result in under predictions of AGB. This fact of under prediction and the range of observed RMSE are also highlighted in Powell et al. (2013). An interesting finding is that the NBCD model provided the highest bias (but least RMSE) at plot-level compared to all the models formulated in this study. A comparison of polygon-level total estimates by the models evaluated in this study at *k*= 3 against the NBCD are shown in Figure 1.

CONCLUSIONS

Including current LiDAR data for back-projection of AGB did not improve prediction accuracy. The model based only on back-projected TM, or based on back-projected LiDAR provided similar estimates and hence either could be used. That said, it may be more efficient to just apply projected Landsat metrics rather than exploring many LiDAR metrics and conducting their back projection using Landsat variables. Rather than applying back-projected LiDAR explained by TM variables, it may be better to directly use back-projected TM variables in the model to minimize bias.

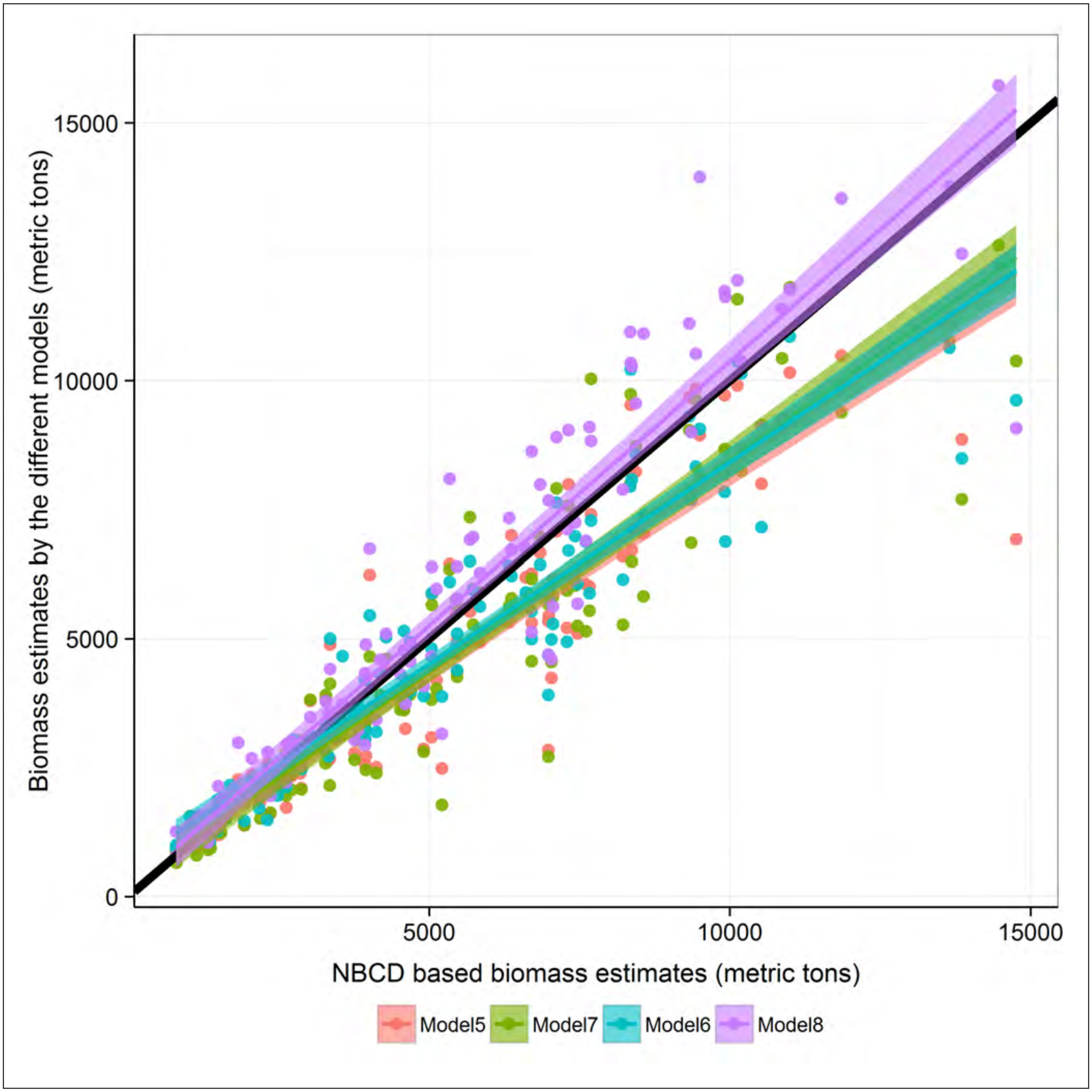

Figure 1—Polygon-level total aboveground biomass estimates for different models (see Table 1) compared with NBCD model estimates for the Arrowhead region in northeastern Minnesota.

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THE NEW FOREST CARBON ACCOUNTING FRAMEWORK FOR THE UNITED STATES

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Abstract—The forest carbon accounting system used in recent National Greenhouse Gas Inventories (NGHGI) was developed more than a decade ago when the USDA Forest Service, Forest Inventory and Analysis annual inventory system was in its infancy and contemporary questions regarding the terrestrial sink (e.g., attribution) did not exist. The time has come to develop a new framework that can quickly address new questions, enables forest carbon analytics, and uses all the inventory information (e.g., disturbances and land use change) while having the flexibility to engage a wider breadth of stakeholders and partner agencies. The Forest Carbon Accounting Framework (FCAF) is comprised of a forest dynamics module and a land use dynamics module. Together these modules produce data-driven estimates of carbon stocks and stock changes in forest ecosystems that are sensitive to carbon sequestration, forest aging, and disturbance effects as well as carbon stock transfers associated with afforestation and deforestation. The new accounting system was used in the 2016 NGHGI report and research is currently underway to incorporate emerging non-live tree carbon pool data, remotely sensed information, and auxiliary data (e.g., climate data) into the FCAF.

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FUTURE FOREST CARBON ACCOUNTING CHALLENGES: THE QUESTION OF REGIONALIZATION

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Abstract—Forest carbon accounting techniques are changing. This year, a new accounting system is making its debut with the production of forest carbon data for EPA's National Greenhouse Gas Inventory. The Forest Service's annualized inventory system is being more fully integrated into estimates of forest carbon at the national and state levels both for the present and the recent past. With the advent of this new accounting system, however, a need persists for information at smaller scales. For example, National Forest managers are being asked to incorporate carbon management into Forest planning. Local government agencies often request a need for estimates of carbon in their jurisdictions. Production of carbon estimates at small scales has always presented major challenges. The quality and coverage of U.S. forest inventories has varied over time and among different parts of the country. The full incorporation of FIA's uniform annualized inventory into carbon accounting offers new opportunities to overcome these challenges.

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THE GREAT CARBON PUSH-PULL: WHERE SCIENCE IS PUSHING AND POLICY IS PULLING THE OFFICIAL FOREST CARBON INVENTORY OF THE US

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Abstract—A national system of field inventory plots (FIA) is the primary data source for the annual assessment of US forest carbon (C) stocks and stock-change to meet reporting requirements under the United Nations Framework Convention on Climate Change (UNFCCC). The inventory data and their role in national carbon reporting continue to evolve. The framework of the previous C accounting system (up through 2015) was developed more than a decade ago when FIA's annual inventory system was just being implemented and contemporary questions regarding the terrestrial C sink (e.g., attribution) did not exist. The time has come to develop a new framework that can quickly address new questions, enables C analytics, and uses all the inventory information (e.g., disturbances and land use change) while having the flexibility to engage a wider breadth of stakeholders and partner agencies. The current and future status of the science and framework of the US' official C inventory will be discussed in the context of UNFCCC reporting and future C commitments.

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DETERMINING FOREST CARBON STOCK LOSSES DUE TO WILDFIRE DISTURBANCE IN THE WESTERN UNITED STATES

John M. Zobel[1] and John W. Coulston[2]

Abstract—Quantifying carbon stock losses after wildfire events is challenging due to the lack of detailed information before and after the disturbance. We propose to use the extensive Western FIA database (including periodic and annual inventories) to recreate pre- and post-fire conditions to better estimate actual carbon losses. Methods include using remeasurement date where available, growth models for forecasting and backcasting, and wildfire data and mapping from the United States Geological Survey. We will discuss the results and provide specific examples to demonstrate the proposed modeling system.

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HIERARCHICAL MODELS FOR INFORMING GENERAL BIOMASS EQUATIONS WITH FELLED TREE DATA

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Abstract— We present a hierarchical framework that uses a large multispecies felled tree database to inform a set of general models for predicting tree foliage biomass, with accompanying uncertainty, within the FIA database. Results suggest significant prediction uncertainty for individual trees and reveal higher errors when predicting foliage biomass for larger trees and for conifers. Consequently, we found large uncertainties when applying the fitted models to predict plot-scale foliage biomass for FIA data within Minnesota. These results suggest that applying general equations with fixed parameters may ignore significant error when used to estimate foliage biomass within the FIA database.

INTRODUCTION

The National Greenhouse Gas Inventory (NGHGI) requires that forest biomass component pools are quantified at the national scale, and within FIA this is accomplished by aggregating biomass estimates calculated for individual trees (Woodall et al., 2011). Currently these are derived from a set of equations with fixed parameters (Jenkins et al., 2003), which fail to account for uncertainty when estimating biomass pools at the tree scale (Wayson et al., 2014; Weiskittel et al., 2015). This limitation may be particularly problematic when estimating variable and dynamic biomass components such as tree foliage. Recently a large felled-tree database has been compiled by the USFS Volume Biomass Project, providing the opportunity to inform uncertainty surrounding biomass models with field-measured data for many North American tree species. We used these data to address two specific objectives: (1) assess the expected uncertainty range of foliage biomass at the tree-scale; and (2) quantify the effect of these errors on plot-level estimates of foliage biomass within a set of FIA data.

STUDY AREA

The felled tree data, which were compiled from many previously published and unpublished studies (hereafter referred to as “legacy data”), come from 130 unique locations spanning the United States and Canada. Models fitted to these data were applied to estimate foliage biomass and associated uncertainty across the state of Minnesota, United States.

METHODS

Data

The legacy data we utilized consist of 5690 observations of foliage biomass (kg), total biomass (kg), and diameter at breast height (dbh; cm). These data cover a range of tree sizes (1.0-115.4 cm) and represent 99 species spread across all 10 species groups used by Jenkins et al. (2003). For prediction, we utilized the most recent cycle (2009-2013) of FIA measurements for Minnesota (N=174,883 across 6,144 plots). We included both adult trees and saplings in this set and filtered the data to remove dead trees.

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Model

Our empirical model follows a "component ratio" approach (Chojnacky et al., 2013; Domke et al., 2012) where:`

$$\ln(BM_{total}) = \beta_0 + \beta_1 \ln(dbh) + \varepsilon, \quad [1]$$
$$\ln(FR) = \alpha_0 + \alpha_1 \ln(dbh) + \tau, \quad [2]$$
$$BM_{fol} = BM_{total} * FR, \quad [3]$$

where BM_{total} is total aboveground biomass (kg), FR is a foliage component ratio, BM_{fol} is foliage biomass (kg), dbh is diameter-at-breast height (cm), and the remaining terms are model parameters. Note that while our target is foliage biomass, the component ratio approach requires fitting a model for total biomass as well. Observed foliage ratios (FR) were calculated as observed foliage biomass (kg)/observed total aboveground biomass (kg).

Model Fitting

Models [1] and [2] were fit to the legacy data using a hierarchical Bayes approach. We used weakly informative normal prior distributions (i.e.,~N(0,20)) on the regression coefficients (β_0, β_1, α_0, α_1). Model variances were specified with vague gamma priors (i.e., $\sigma^2 \sim$ Gamma(0.001, 0.001)). In addition, we placed vague "hyper-prior" distributions on the priors of the regression coefficients, allowing the model parameters from all groups to arise from a set of common distributions. Models were fit via Markov chain Monte Carlo (MCMC) methods using Stan, called from R via the RStan package (Stan Development Team, 2014). Our program generated posterior predictions from [1], [2], and [3] simultaneously, which allows us to assess prediction uncertainty in foliage biomass at both tree and plot scales.

Assessing tree-scale uncertainty

We characterized the range of tree-scale uncertainty within our model by performing Bayesian posterior predictive checks (Gelman et al., 1996). We generated 1,000 simulated datasets, of the same dimensions as the legacy data, by taking draws from the posterior predictive distribution, resulting in a marginal posterior distribution for every tree within the dataset. We compared the simulated means, as well as tree-scale 95% uncertainty ranges, to observed foliage biomass from the legacy data.

Application to FIA data

The fitted hierarchical model was then applied to generate posterior predictive distributions, based on 500 simulations, for every tree within the Minnesota FIA data. These were aggregated into plot estimates by multiplying predicted foliage biomass with an adjustment factor to standardize biomass estimates on a per hectare basis and summing this product within plots. This procedure resulted in a distribution of predicted foliage biomass stock (kg*ha^{-1}) at each plot, which we summarized by its mean and 95% uncertainty interval range.

RESULTS

For individual trees within the legacy data, overall mean posterior predicted foliage biomass was 13.3 kg for conifers and 5.5 kg for hardwoods. The corresponding mean uncertainty bounds (95% credible intervals from the posterior simulations) were ±47.12 kg and ±19.44 kg respectively. These uncertainties are large relative to the mean, but for both groups there is much higher error around predicted foliage biomass for large trees than for smaller individuals (Figure 1). In general, uncertainty is higher for conifers than for hardwoods within the legacy data, though hardwoods in these data generally had less foliage biomass.

When applied to predict foliage biomass for FIA data, the fitted models resulted in an overall mean of 3932.2 kg*ha^{-1} across all plots. The large tree-scale uncertainties noted in our first analysis led to considerable error at the plot level, with an average uncertainty interval of 3492.4 kg*ha^{-1}. The distributions of both the plot-scale means and uncertainties are skewed to the left (Figure 2), with most plots predicted to have relatively little foliage biomass, and a smaller number of plots possessing larger stocks with accompanying large error bounds.

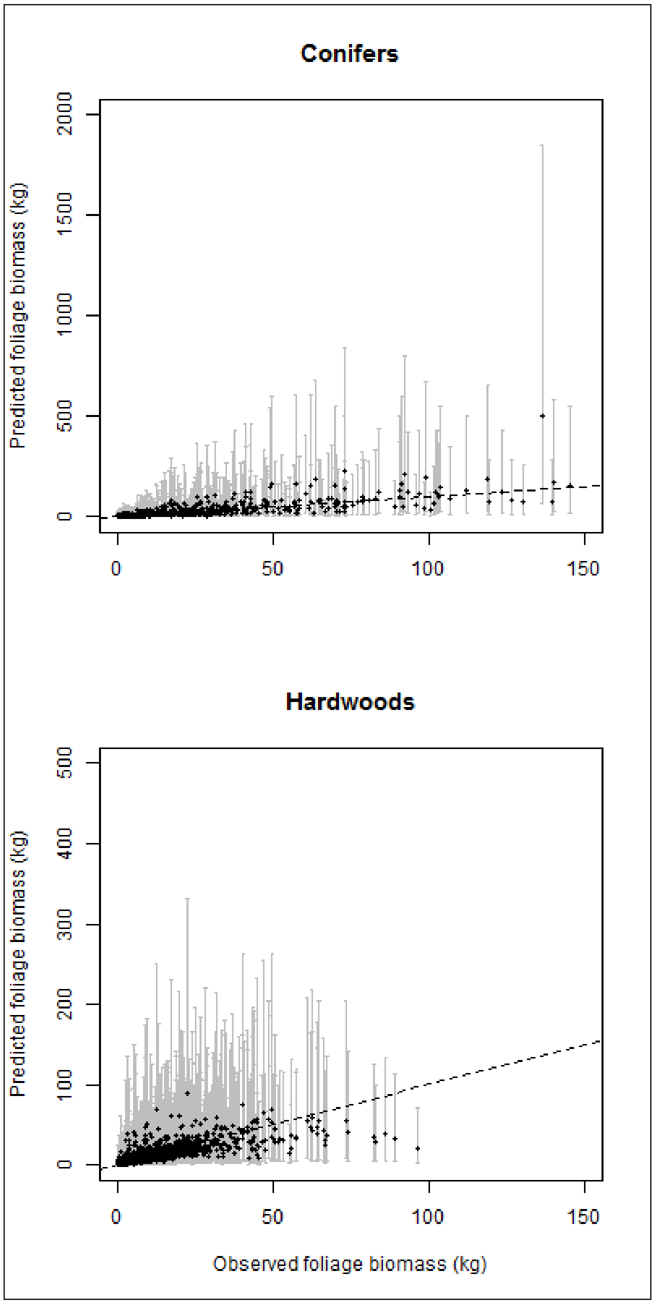

Figure 1—Observed vs. predicted foliage biomass for the legacy data. Error bars represents the 95% uncertainty intervals resulting from the posterior predictive checks we performed.

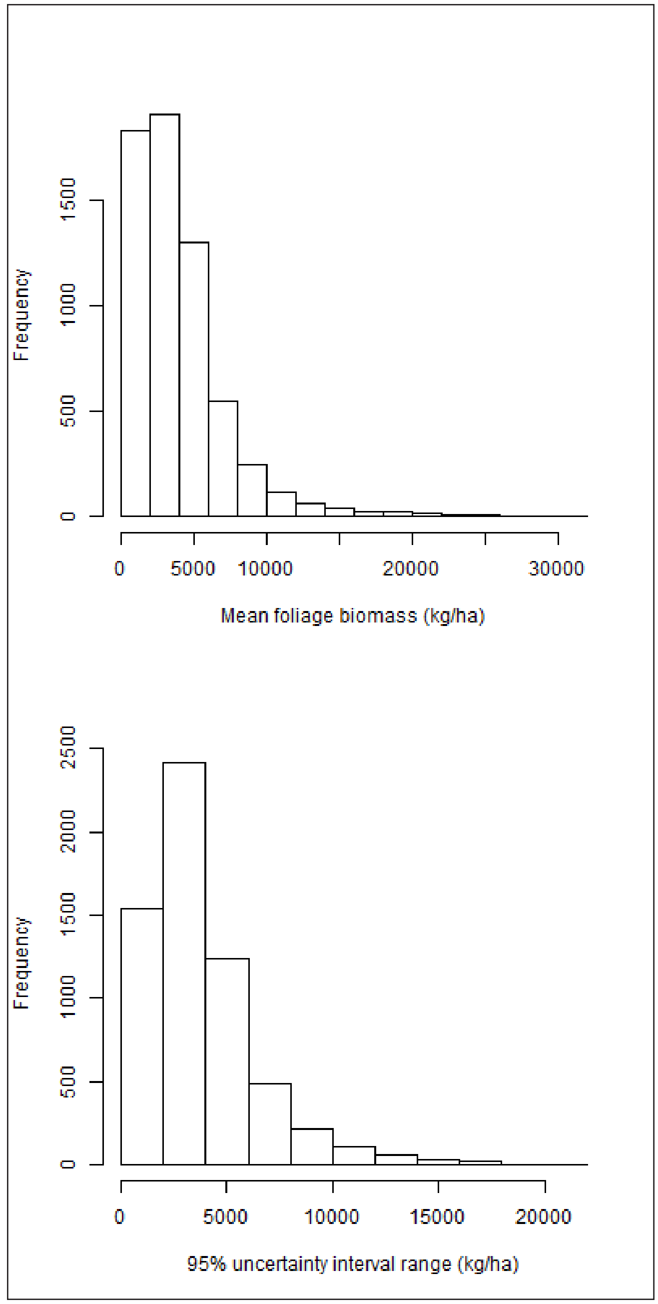

Figure 2—Predicted means and 95% uncertainty intervals of plot-scale foliage biomass (kg*ha-1) for 6,115 FIA plots within Minnesota.

DISCUSSION

Per reporting guidelines for NGHGIs outlined by the United Nations' Framework Convention on Climate Change, the United States is required to provide quantitative estimates of uncertainties surrounding standing forest carbon stocks (IPCC, 2006). In order to best support development of international policy and decision-making, all nations should aim for these error estimates to be both reasonable and all-inclusive. Our results suggest that the current approach, where biomass pools are estimated via equations with fixed parameters, ignores substantial uncertainties associated with allometric functions for estimating foliage biomass.

A hierarchical framework such as we use here provides an ideal approach for capturing this error. While non-hierarchical simulation-based approaches have been proposed (e.g., Wayson et al., 2014)"type" : "article-journal" }, "uris" : ["http://www.mendeley.com/documents/?uuid=8beb78c2-5742-41c0-8282-826aabf09cae"] }], "mendeley" : { "formattedCitation" : "(Wayson et al., 2014, these require *a priori* decisions about the distributions underlying model parameters. In a hierarchical model, the dimensions of these distributions are determined by the fitting data (Green et al., 1999). Further, when a Bayesian approach is employed, uncertainties in both model parameters and data are seamlessly integrated into predicted estimates. Of course fitting a hierarchical model requires felled-tree data, so projects that aim to compile and enhance existing datasets, such as the USFS Volume Biomass Project, are integral to this approach.

While the uncertainties found by our analysis are large, these results do carry some important caveats. First, the legacy data are sparse relative to the study area, and provide varying coverage across species groups. Ongoing work aims to fill gaps in these data, in order to provide a more representative dataset for the whole United States. Second, while we found large prediction errors in the foliage biomass pool, the extent to which this impacts overall uncertainty in the forest carbon pool remains unclear. Future work will assess whether similar error bounds can be expected for other, larger biomass components (i.e. roots, which are similarly dynamic), as well as for total aboveground biomass.

CONCLUSIONS

By using a hierarchical model fit to a large felled-tree database, we reveal large uncertainty from allometric functions for predicting foliage biomass. Given the need for complete and accurate error estimates to support decision making related to the management of greenhouse gas emissions, these results may have important implications for national and international policy related to climate change. A hierarchical approach and the availability of the legacy data were important in uncovering these uncertainties, and we argue that such a framework should be adopted by future NGHGIs. That said more research is required to assess if the scale of uncertainty we found for foliage biomass is particular to this component, or if it will have a large impact on the estimation of the overall forest carbon pool.

ACKNOWLEDGMENTS

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LITTER CARBON STOCKS IN FORESTS OF THE US ARE MARKEDLY SMALLER THAN PREVIOUSLY REPORTED

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Abstract—Forest ecosystems are the largest terrestrial carbon sink on earth with more than half of their net primary production moving to the soil via the decomposition of litter biomass. Therefore, changes in the litter carbon pool have important implications for global carbon budgets and carbon emissions reduction targets and negotiations. Litter accounts for an estimated 5 percent of all forest ecosystem carbon stocks worldwide. Given the cost and time required to measure litter attributes, many nations that are signatories to the United Nations Framework Convention on Climate Change (UNFCCC) report estimates of litter carbon stocks and stock changes using default values from the Intergovernmental Panel on Climate Change (IPCC) or country-specific models. Here we present, for the first time, estimates of litter carbon obtained using more than 5,000 field measurements from the national forest inventory of the United States. These field-based estimates mark a 44% reduction (2,081±77 Tg) in litter carbon stocks nationally when compared to country-specific model predictions reported in previous UNFCCC submissions. Our work suggests that IPCC defaults and country-specific models used to estimate litter carbon in temperate forest ecosystems may grossly overestimate the contribution of this pool in national carbon budgets.

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INCORPORATING CLIMATE INTO BELOWGROUND CARBON ESTIMATES IN THE NATIONAL GREENHOUSE GAS INVENTORY

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Abstract— Refined estimation of carbon (C) stocks within forest ecosystems is a critical component of efforts to reduce greenhouse gas emissions and mitigate the effects of projected climate change through forest C management. Recent evidence has pointed to the importance of climate as a driver of belowground C stocks. This study describes an approach for adjusting allometric models of belowground C with climate-derived predictions of belowground C stocks and quantifies the change in reported belowground C stocks applied to the US National Greenhouse Gas Inventory (NGHGI). Climate-adjusted predictions varied by region and forest type, but represented a 6.4% increase at the national scale when compared to current estimates. By combining allometric equations with trends in temperature, we conclude that climate variables can be used to adjust the US NGHGI estimates of belowground C stocks. Such strategies can also be used to determine the effects of future global change scenarios within a biomass and C accounting framework.

INTRODUCTION

The logistical and methodological constraints associated with estimating forest carbon (C) in belowground pools have created a need for refined modeling approaches to quantify belowground C stocks. Although allometric equations are designed to account for a large portion of the apparent variability associated with belowground biomass (Litton and others, 2003), there are some drawbacks to this approach. Allometric equations lack the flexibility to incorporate climate information that integrates differences in ecosystem productivity and allows for evaluations of future climate change scenarios on global C cycles. Highlighting this concern, Reich and others (2014) recently compiled a global dataset and concluded that forest biomass found in coarse roots was inversely related to mean annual temperature, suggesting that climate may act as a driver of belowground C allocation.

The objective of this project is to adjust belowground C estimation procedures for reporting in the US National Greenhouse Gas Inventory (NGHGI) through integrating climate information. Specific objectives are to (1) adjust estimates of belowground C by combining allometric and climate-derived approaches using current and projected climate attributes and (2) quantify the effect of the adjusted estimation approach on belowground forest C in the US NGHGI.

METHODS

FIA Data

All data were obtained from the publically-available Forest Inventory and Analysis (FIA) database (Woudenberg and others 2010; http://apps.fs.fed.us/fiadb-downloads/datamart.html). These data were accessed and compiled in May 2014. Publicly available data from the FIA database are regularly updated when data collection and/or processing anomalies are found and corrected. Additionally, new

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data are added regularly which may be reflected by small changes in the past or current estimates. If an FIA plot was remeasured at any point, only the most recent measurement was used in this analysis.

Belowground Carbon in the US National Greenhouse Gas Inventory (BGC_{NGHGI})

Here, as in the NGHGI, live belowground C is defined as all coarse living roots greater than 2 mm diameter (Smith and others 2013). In the current NGHGI, belowground carbon stocks are estimated in two stages. First, total aboveground biomass is estimated using allometric equations (Jenkins and others 2003; their Table 4). Second, a ratio of coarse root to total aboveground biomass is calculated (Jenkins and others 2003 [their Table 6]; Smith and others 2013), dependent on whether the species is a hardwood or conifer. As observations of belowground tree biomass and C are often limited (Zianis and others 2005), relying on allometric equations has been necessary to obtain estimates from national-scale forest inventories such as FIA's.

As outlined in Jenkins and others (2003), parameters indicate that the belowground ratio will decrease for larger diameter trees. For a fixed d.b.h., the belowground ratio will be larger for conifers compared to hardwood species. Belowground biomass was estimated for all FIA plots in the lower 48 states and coastal Alaska using the most recent inventory measurement by performing current NGHGI estimation strategies. Biomass was converted to C by multiplying by 0.5, assuming 50% of biomass is C. Estimates of belowground C were scaled to the plot level and are hereby abbreviated as BGC_{NGHGI}.

Climate-adjusted Models of Belowground Carbon ($BGC_{ClimAdj}$)

Belowground C modeling approaches that incorporate climatic attributes may be used both to adjust our estimates of coarse root C stocks at the national scale (i.e., application in the US NGHGI) and to enhance evaluations of future climate change scenarios on forest C cycles. We estimated climate-sensitive predictions of belowground biomass (BGB_{Clim}) for all FIA plots as a linear function of the following explanatory variables: mean annual temperature, natural or planted stand, hardwood- or conifer-dominated stand, and stem biomass of live trees (Reich and others 2014). We assigned the hardwood/conifer variable using the FIA forest type code by separating conifer-dominated forest type codes (i.e., FORTYPCD <= 409) with hardwood-dominated codes (FORTYPCD >= 500). Values for BGB_{Clim} were converted to belowground carbon (BGC_{Clim}) by multiplying by 0.5.

Adjustment factors were estimated to align allometric- and climate-derived estimates:

$$\text{AdjFactor} = BGC_{Clim}/BGC_{NGHGI}, \qquad [1]$$

where AdjFactor is the ratio of climate- to allometric-derived belowground C for a specific forest type found in a given geographic region. New climate-adjusted estimates of belowground C ($BGC_{ClimAdj}$) are then:

$$BGC_{ClimAdj} = BGC_{NGHGI} * \text{AdjFactor} \qquad [2]$$

RESULTS AND DISCUSSION

Estimates of belowground carbon from the approaches currently employed in the US NGHGI suggest that C stocks are dependent on geographic region and forest type. Mean BGC_{NGHGI} was largest in hemlock-Sitka spruce forests in the Pacific Northwest (40.76±0.96 Mg ha^{-1} [mean±SE]) and redwood forests in the Pacific Southwest (59.27±7.06 Mg ha^{-1}). Climate-derived stock estimates of belowground C (BGC_{Clim}) were slightly smaller in magnitude when compared to BGC_{NGHGI} estimates (e.g., hemlock-Sitka spruce [33.82±0.80 Mg ha^{-1}] and redwood forests [45.64±5.44 Mg ha^{-1}]) and generally showed decreasing C at lower latitudes (Figure 1). On average, BGC_{Clim} estimates were 0.60 Mg ha^{-1} greater than current BGC_{NGHGI} models when considering all forest types.

The adjustment factors ranged from 0.77 to 1.60 with little variability within a region of interest. Compared to current NGHGI models, model differences showed greater belowground C stocks occurring in the Appalachian Mountain region and areas where northern hardwood forests are common, e.g., in the upper Midwest and northeastern US states.

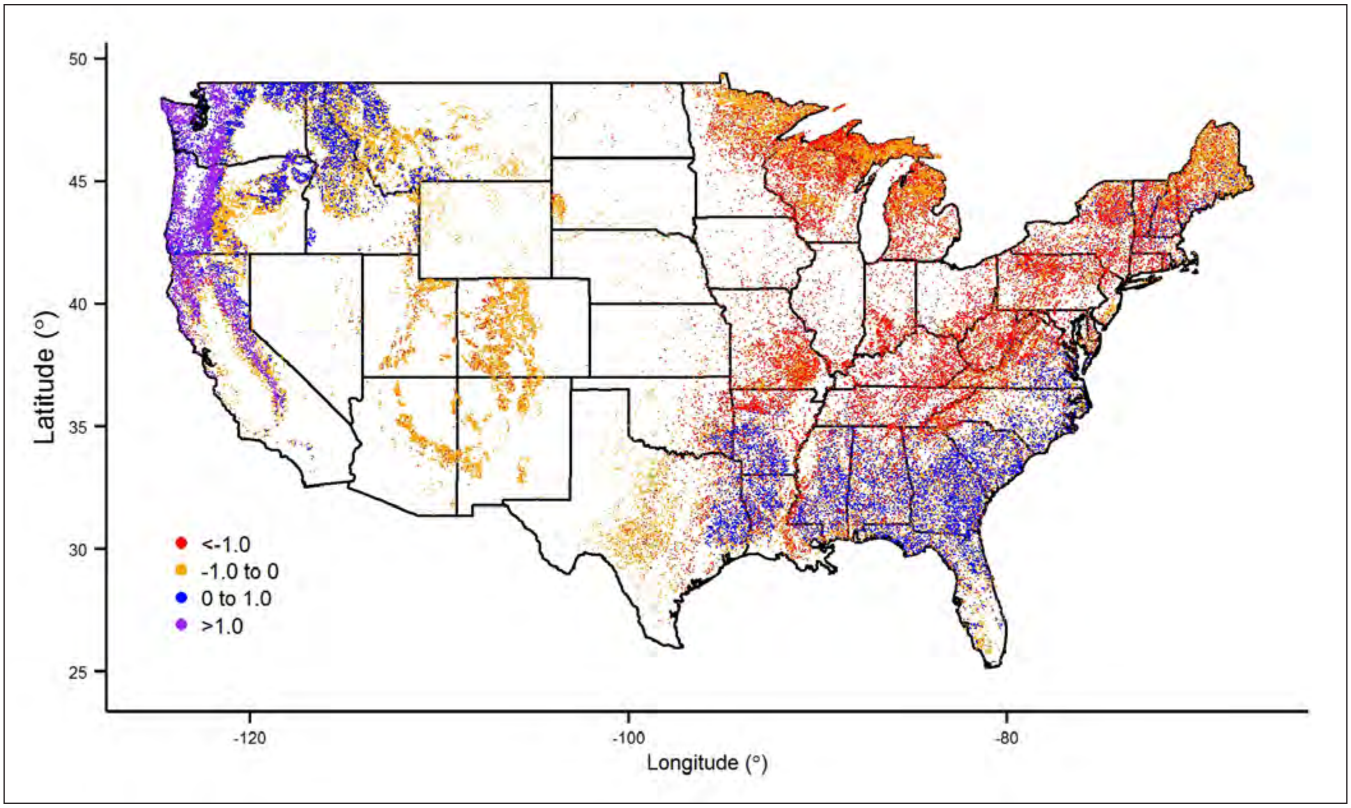

Figure 1—Distribution of differences between live-tree belowground C estimates from the National Greenhouse Gas Inventory and climate-adjusted estimates (BGCNGHGI - BGCClimAdj; Mg ha-1). Red colors indicate higher estimated belowground C and purple colors less belowground C.

Conversely, areas of smaller belowground C stocks were identified across the Pacific Northwest and Southeast US (Figure 1). The states of Oregon and Washington were predicted to display the largest negative mean difference in belowground C stocks (-10.6% and -10.7%, respectively). Comparatively, this region contains the largest belowground C stocks in the US, quantified using model imputation strategies (Wilson and others 2013). Conversely, the largest mean positive difference in belowground C stocks was in the states of Kentucky, Tennessee, and Oklahoma (28.0%, 26.7%, and 22.6%, respectively). Ultimately, this represented a total estimated increase of 368.87 Tg of belowground C across the US, or a 6.4% increase when compared to currently implemented NGHGI models (Table 1).

Table 1—Largest mean percent differences of belowground C by state for current US National Greenhouse Gas Inventory (BGCNGHGI) and climate-adjusted estimates (BGCClimAdj).

State	BGC_{NGHGI} (SE)	$BGC_{ClimAdj}$ (SE)	Mean % difference
	Population-level belowground C (Tg)		
Washington	410.46 (1.29)	366.61 (1.26)	-10.70%
Oregon	478.52 (1.03)	427.63 (0.99)	-10.60%
California	456.22 (1.37)	428.69 (1.27)	-6.00%
Oklahoma	47.62 (2.54)	58.36 (2.54)	22.60%
Tennessee	160.47 (1.27)	203.39 (1.29)	26.70%
Kentucky	109.67 (1.83)	140.42 (1.84)	28.00%
All states	5798.84	6167.71	6.40%

The majority of forest types displayed negative mean differences between current NGHGI and climate-adjusted models, indicating greater live tree belowground C stocks when using the adjusted models. The larger stocks in climate-adjusted models are partially a reflection of the ability of this framework to account for temperature-related shifts in patterns of belowground allocation within a species; a relationship held constant in current NGHGI models.

CONCLUSIONS

A number of findings emerged from our investigation of incorporating climate variables into the estimation of belowground C stocks. First, climate variables can be used to adjust the US NGHGI estimates of belowground C stocks. Specifically, adjustment factors were specified to amend current coarse root C stocks estimated from allometric equations by incorporating mean annual temperature at various locations across the US. Second, for the US NGHGI, incorporating mean annual temperature increased national belowground C stocks by 6.4%. Future work that integrates both climate and stand conditions (e.g., stand origin and forest type) will increase our ability to predict belowground C stocks across regions containing a mixture of management and climate regimes. Finally, as a means of refining NGHGIs, climate-adjusted models depicting belowground C stocks can be adopted to incorporate the impacts of future global change and management scenarios on C sequestration patterns and stocks. Adjusting current models so that they are sensitive to climate variables will aid modelers seeking to forecast forest C stocks by incorporating projected changes in climate variables such as temperature and precipitation.

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LEVERAGING FIA DATA FOR ANALYSIS BEYOND FOREST REPORTS: EXAMPLES FROM THE WORLD OF CARBON

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Abstract—The Forest Inventory and Analysis program of the USDA Forest Service is the go-to source for data to estimate carbon stocks and stock changes for the annual national greenhouse gas inventory (NGHGI) of the United States. However, the different pools of forest carbon have not always been estimated directly from FIA measurements. As part of the new forest carbon accounting framework, pools historically estimated from models based upon the literature, and lacking FIA data, are getting updated with fresh models utilizing empirical data on the forest floor, soils, and down dead wood collected since 2000. We will demonstrate how we constructed custom datasets to inform model development, along with how we integrated ancillary geospatial data. We will also discuss potential future uses of FIA and ancillary data to inform carbon estimates as well as exploring new ways to communicate carbon reporting to the public.

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ADVANCING INDIVIDUAL TREE BIOMASS PREDICTION: ASSESSMENT AND ALTERNATIVES TO THE COMPONENT RATIO METHOD

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Abstract—Prediction of forest biomass and carbon is becoming important issues in the United States. However, estimating forest biomass and carbon is difficult and relies on empirically-derived regression equations. Based on recent findings from a national gap analysis and comprehensive assessment of the USDA Forest Service Forest Inventory and Analysis (USFS-FIA) component ratio method (CRM) for estimating both biomass and carbon using historical individual tree biomass data, alternative approaches for predicting forest biomass and carbon were evaluated. The different CRM approaches tested included: 1) development and use of a unified stem taper equation to estimate stem volume; 2) updated model forms and parameters for predicting biomass components; and 3) comparison of alternative wood density values. Overall, these modifications show the potential to improve estimates of forest biomass and carbon, but additional testing is required before implementation.

Estimation of national forest biomass and carbon in the United States is increasingly desirable for many reasons. Recent studies evaluated nationally-prominent (Domke et al. 2012) and regionally-prominent (Westfall 2012) biomass estimation methods and found significantly disparate results, instigating research into current estimation methods. However, assessing biomass estimation methods and developing new methods are difficult due to the requisite for independent empirical data. A national biomass estimation research project currently is acquiring the necessary data for improving biomass estimation.

Currently, the USDA Forest Service Forest Inventory and Analysis (USFS-FIA) uses the component ratio method (CRM) to estimate biomass. This method relies on sound wood volume estimates, component ratio estimators (Jenkins et al. 2003), and bark and wood density values (Miles and Smith 2009). These ratio estimators are generalized across the United States into two broad groups (hardwoods and softwoods) and a fixed species-level value is assumed for bark ratios and densities. In contrast, over 25 different species-level volume forms are used across over 20 different regions. These models are largely delineated across state lines (see Fig. 1 in Woodall et al, 2011), though it may be more appropriate to group across ecologically delineated spatial units.

Estimation of different components at different taxonomic and geographic levels may be appropriate because of large observed variation in these relationships. However, to our knowledge this assumption has not been formally examined. For instance, using hardwood and softwood ratio estimators at the national level may lead to errors when estimating at a regional or state level. With regard to bole estimation, separate volume equations of varying form may be overly complex, whereas a single model form could simplify implementation while improving estimation at varying scales. In this analysis, we evaluate alternative approaches to volume and component estimation within the context of the CRM method.

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The primary objectives are:

1. Develop and test a unified bole volume model
2. Examine variation in wood specific gravity
3. Provide an improved component ratio model
4. Compare these modifications to the current CRM method on trees with observed biomass

Considering that one objective is to estimate volume at varying scales (nationally, regionally, and perhaps statewide), a formal examination of these factors at the national level warrants a unified approach, while allowing for methods to examine how different taxonomic groupings and geographical specifications influence estimates. Mixed-effects modeling allows for such an approach. Using all available tree data across the United States and incorporating taxonomic and regional random effects provide a flexible framework to formally examine what groupings are most appropriate.

METHODS

We compiled a volume and biomass "legacy" data set of over 100,000 trees with stem taper profiles and over 3,000 trees with aboveground biomass (AGB), bole, top, and foliage biomass observations. For each component we estimated biomass using 1) the original component ratio method (CRM); 2) a refit CRM where we generated new coefficients using CRM/Jenkins model forms and species groupings (CRM1); and 3) a modified CRM using species-specific parameters derived from non-linear mixed-effects models (CRM2). The Jenkins model and CRM impose a merchantability limit from 1-foot stump to a 4-inch top. For the modified CRM, we remove these limits and estimate bole biomass from ground line to a 0 inch top. Aside from merchantability limits and how parameters were estimated, the methods follow Woodall et al. (2011).

We chose the Kozak (2004) taper model form and incorporated a mixed-effects structure (Li et al. 2012). While results from previous work (Li and Weiskittel 2010) suggest that a segmented taper model (e.g., Clark et al. 1991) may offer small gains in estimation accuracy, we thought that the variable exponent equation of Kozak (2004) offered a more flexible model form that can ease the estimation and updating of parameters with minimal reduction in accuracy.

The form of the Kozak (2004) model with random effects is:

$$dob = (\propto_0 + Gp_0/\boldsymbol{Sp_0})\, D^{\propto_1} H^{\propto_2} X^{\left(\mathrm{B}_1 z^4 + \mathrm{B}_2\left(1/e^{D/H}\right) + (\beta_3 + Gp_0/\boldsymbol{Sp_0})X^{0.1} + \beta_4(1/D) + \beta_5 \mathrm{H}^{\mathrm{Q}} + \beta_6 \mathrm{X}\right)}$$

where $X = 1 - z^{1/3} / 1 - p^{1/3}$, $Q = 1 - z^{1/3}$, dob = diameter outside bark, H = total tree height, D = diameter at breast height (d.b.h.), h = section height from ground, p = 1.3/H (relative breast height), and z = h/H (relative height from ground). We generated models separately for hardwoods and softwoods and modified the original Kozak (2004) function by adding nested random effects coefficients for Jenkins species groups and species (Gp_0/Sp_0 and Gp_3/Sp_3). For the modified CRM, rather than generate new coefficients using existing species-level-regional volume models, we estimate volume using the Jenkins species groups (CRM1), while we used species as the random effect for the modified estimate (CRM2). To convert from outside bark diameter to inside bark diameter (dib), we used the following equation: dib = (a + Spa) * $dob^{(b+Spb)}$.

We derived new coefficients for AGB and ratio estimators (CRM1) using equation forms and broad species groupings (Jenkins et al. 2003). In the second formulation (CRM2) for AGB, we used a simple non-linear model form: $(a + Spa) * DBH^{(b+Spb)}$. We also estimated parameters using a mixed-effects Chapman-Richards formulation with species as a random effect on all parameters (CRM2). The Jenkins et al. (2003) ratio model is below:

$$component\ ratio = e^{\left(\beta_0 + \frac{\beta_1}{DBH}\right)}.$$

The mixed-effects Chapman-Richards model is specified as follows:

$$CR\ component\ ratio = (a+Spa)\left[1 - e^{-(b+Spb)*DBH}\right]^{(C+Spc)}$$

Using data from the legacy database, we calculated mean wood specific gravity and 95percent confidence interval for 12 species that had a sample size of at least 30 observations. We compared this to the value presented in Miles and Smith (2009).

RESULTS

Model performance was strong with no clear trend in the residuals for any given species (Fig. 1). By species, whole tree volume percent root mean square error ranged from 8.6 to 24.4 percent (Table 1), which was comparable and in some cases better than the regional volume equations.

There was considerable regional variation in wood specific gravity for a given species and these values were generally significantly different than the value reported by Miles and Smith (2009) (Fig. 2). For example, mean specific gravity values for sugar maple (*Acer saccharum* Marsh.) ranged from 0.61 inches the northeast to 0.65 inches the north-central region, while Miles and Smith (2009) reports 0.56 inches.

CRM underestimated stem biomass by 5.0 ± 20.2 percent (mean ± SD) overall, while top biomass was underestimated by 43.3 ± 108.2 percent. Using the unified taper function for species groups (CRM1) and species-specific (CRM2), we found stem biomass error estimates of 1.5 ± 19.0 percent and 0.8 ± 19.3 percent, respectively. Since the Miles and Smith (2009) specific gravity values were used throughout the analysis, some improvement over the current regional volume equations was indicated. Likewise, improved accuracy with the newly generated AGB and ratio estimators (CRM1) as well as additional improvement using the mixed-effect AGB and Chapman-Richards formulation (CRM2) were observed (Table 2).

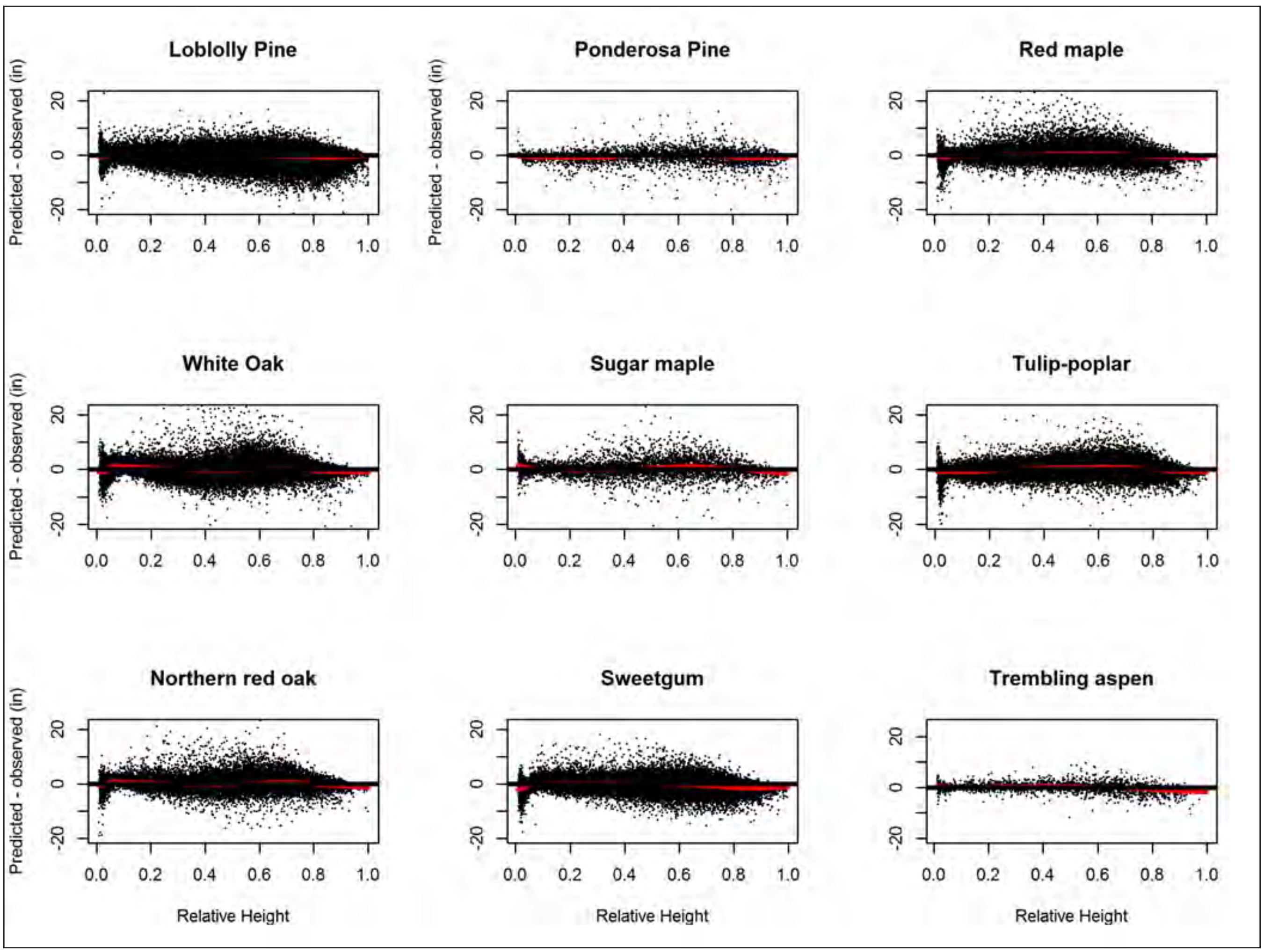

Figure 1—Prediction errors (predicted – observed) for diameter outside bark (d.o.b in inches) over relative height (disc height divided by total height) using the unified taper equation for nine prominent species with a lowess regression trend line (red).

Table 1—Summary statistics and errors associated with volume estimates for a species-level unified taper equation.

Common name	SPCD	n	Min d.b.h. (in)	Mean d.b.h. (in)	Max d.b.h. (in)	Outside bark volume (ft^3)	Outside bark volume error (ft^3)	Outside bark volume RMSE (ft^3)	Inside bark volume (ft^3)	Inside bark volume error (ft^3)	Inside bark volume RMSE (ft^3)
Loblolly pine	131	10664	5.0	11.1	38.3	27.88	-1.27	4.72	22.75	-1.27	5.01
Ponderosa pine	122	360	5.0	15.9	38.9	61.03	-6.29	14.70	48.96	-6.06	15.44
Red maple	316	1540	5.0	10.8	41.8	22.43	0.59	5.48	19.59	0.61	5.12
White oak	802	2604	5.0	12.1	44.4	30.91	0.25	6.12	25.66	0.32	5.54
Sugar maple	318	92	5.1	11.3	29.7	23.91	0.95	4.83	20.88	0.75	4.38
Yellow-poplar	621	2378	5.0	13.1	39.5	42.93	0.07	4.82	34.78	0.02	4.25
Northern red oak	833	1010	5.0	13.7	34.4	39.88	1.15	7.08	33.56	0.91	6.36
Sweetgum	611	2300	5.0	11.7	32.6	31.81	-0.57	5.14	26.41	-0.35	4.55
Quaking aspen	746	154	5.1	8.2	15.4	11.35	-0.12	1.46	9.56	-0.04	1.06
Engelmann spruce	93	100	5.0	8.1	17.8	10.77	-0.05	2.00	9.47	-0.10	1.99
Shortleaf pine	110	4435	5.0	11.0	26.1	26.82	-0.94	3.85	21.99	-0.94	4.02
White fir	15	596	5.1	17.3	48.7	68.91	-0.06	10.70	51.85	-0.45	9.83
Eastern white pine	129	1597	5.0	13.1	32.8	40.77	-0.22	5.56	35.01	-0.39	5.41
Black oak	837	1004	5.0	13.0	28.7	35.17	0.82	4.67	28.07	0.70	3.81
Chestnut oak	832	1464	5.0	12.3	34.0	30.46	0.10	4.59	24.19	-0.53	4.01
Slash pine	111	5513	5.0	9.0	23.8	16.68	-0.31	2.03	12.74	-0.50	2.24
American beech	531	402	5.1	13.6	35.0	35.73	1.57	6.41	32.36	2.08	6.53
Eastern hemlock	261	189	5.8	14.2	30.4	48.25	0.48	6.33	40.13	0.63	4.77
White ash	541	183	5.0	13.5	26.5	45.12	-0.75	5.97	37.02	-0.30	4.93
Water oak	827	691	5.0	11.8	30.1	27.38	0.12	3.57	23.67	-0.01	3.30
Black cherry	762	176	5.0	12.7	31.9	41.23	-0.50	5.94	36.66	-0.19	5.69
Hickory spp.	400	1711	5.0	12.1	33.8	31.54	0.04	5.20	25.46	-0.25	4.28
Virginia pine	132	1739	5.0	9.0	21.6	14.63	-0.50	1.82	12.77	-0.24	1.89
Post oak	835	578	5.0	11.6	25.3	23.26	0.24	2.95	18.74	0.00	2.58
Scarlet oak	806	1022	5.0	11.9	31.1	29.35	0.65	5.16	24.43	0.61	4.35
Southern red oak	812	893	5.0	12.4	48.9	29.43	0.64	5.95	23.92	0.20	4.63
Swamp tupelo	694	886	5.0	11.7	32.7	28.35	0.63	5.31	22.74	0.97	5.12
Paper birch	375	339	5.0	8.6	19.4	10.34	-0.08	1.77	9.14	-0.13	1.66
Northern white-ce	241	66	7.2	9.2	11.7	9.42	0.07	0.75	8.00	0.04	0.69
Balsam fir	12	494	5.0	8.4	18.9	11.89	0.09	1.56	10.61	0.03	1.42
All	All	61535	5.0	11.3	48.9	27.83	-0.32	4.79	22.91	-0.39	4.57

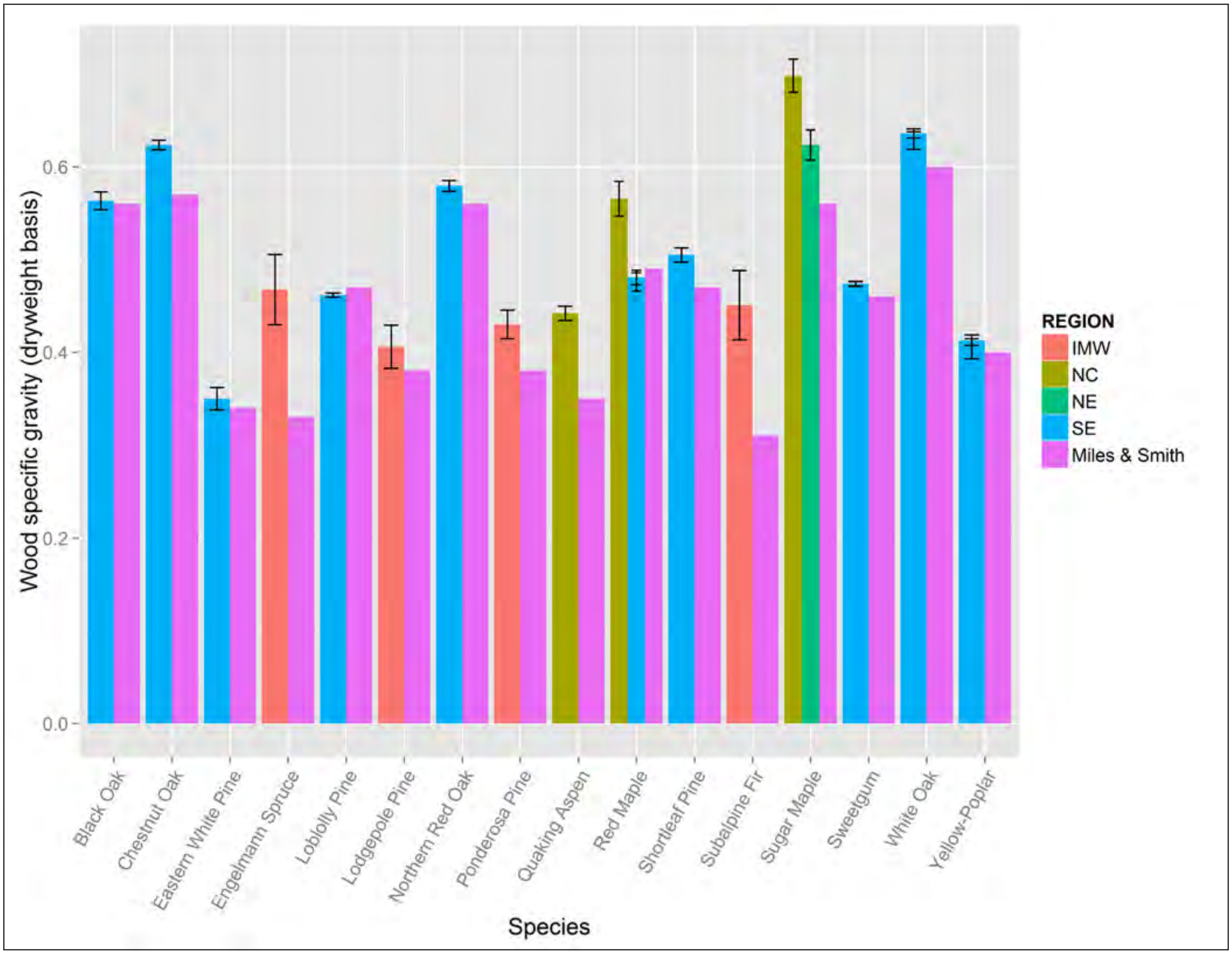

Figure 2—Comparison between average regional specific gravity and Miles and Smith (2009) reported specific gravity. Error bars are presented for the 95 percent confidence interval.

Table 2—Summary statistics and mean errors (standard deviation in parentheses) for all observations and four common eastern species between the current component ratio method (CRM), CRM with refitted parameters (CRM1) and modified CRM with species-specific parameters and updated model forms (CRM2). Error was estimated as predicted – observed. Mean CRM estimated error is derived from mean observed biomass with merchantability limits, while estimated error for CRM1 and CRM2 are derived from mean observed biomass without merchantability limits. Bole and Top are CRM estimates, while Above-ground and Foliage are Jenkins (2003) estimates.

Component	Common Name	No. of trees	Min. d.b.h. (in)	Mean d.b.h. (in)	Max. d.b.h. (in)	Mean observed biomass (lbs) (with merch. limit)	Mean observed biomass (lbs) (without merch. limit)	Mean CRM estimated error (lbs)	Mean CRM1 estimated error (lbs)	Mean CRM2 estimated error (lbs)
Above-ground	Loblolly pine	645	5.0	11.8	24.0	1088.6	1088.6	-245.4 [277.7]	58.5 [217.6]	5.2 [214.8]
Above-ground	Red maple	148	5.0	8.7	33.7	624.9	624.9	10.4 [125.0]	37.8 [115.3]	-8.6 [105.8]
Above-ground	Yellow-poplar	71	5.2	11.6	20.3	1117.2	1117.2	-68.2 [198.0]	-23.9 [196.2]	9.8 [193.1]
Above-ground	White oak	155	5.0	9.4	29.7	1011.5	1011.5	-39.8 [360.3]	0.2 [331.7]	-31 [324.9]
Above-ground	All	3154	5.0	10.5	33.7	968.7	968.7	-159.7 [326.4]	-9.3 [256.0]	1.3 [209.7]
Bole	Loblolly pine	645	5.0	11.8	24.0	849.3	916.8	-33.2 [126.5]	-7.9 [128.9]	-34 [133.0]
Bole	Red maple	148	5.0	8.7	33.7	403.8	461.4	-18.8 [128.3]	24 [211.2]	15.6 [201.6]
Bole	Yellow-poplar	71	5.2	11.6	20.3	863.8	929.4	-129.6 [167.5]	-76.4 [165.4]	-87 [168.9]
Bole	White oak	155	5.0	9.4	29.7	614.9	694.2	12.0 [89.8]	-16.8 [87.0]	7.5 [103.2]
Bole	All	3154	5.0	10.5	33.7	701.0	770.7	-34.8 [141.6]	-11.3 [146.7]	-6.5 [148.6]
Foliage	Loblolly pine	645	5.0	11.8	24.0	40.1	40.1	9.6 [15.2]	4.4 [12.4]	-6.3 [15.3]
Foliage	Red maple	148	5.0	8.7	33.7	13.8	13.8	-0.4 [11.0]	2.2 [13.9]	-1.8 [10.2]
Foliage	Yellow-poplar	71	5.2	11.6	20.3	15.3	15.3	5.6 [8.5]	10.3 [11.8]	2.2 [6.8]
Foliage	White oak	155	5.0	9.4	29.7	30.3	30.3	-10.5 [20.8]	-6.3 [20.0]	-8.5 [19.8]
Foliage	All	3154	5.0	10.5	33.7	28.2	28.2	2.8 [18.0]	2.4 [16.4]	-3.4 [15.3]
Top	Loblolly pine	645	5.0	11.8	24.0	199.2	131.7	-67.3 [86.2]	-1.3 [82.0]	4.3 [75.9]
Top	Red maple	148	5.0	8.7	33.7	213.3	155.7	-103.2 [566.2]	-54 [507.4]	-62 [506.6]
Top	Yellow-poplar	71	5.2	11.6	20.3	238.2	172.5	-60.0 [175.2]	6.3 [149.7]	-40 [161.5]
Top	White oak	155	5.0	9.4	29.7	366.4	287.1	-204.9 [522.4]	-138 [433.0]	-89 [357.7]
Top	All	3153	5.0	10.5	33.7	239.9	170.2	-104.3 [259.5]	-33.8 [220.3]	-22 [194.9]

DISCUSSION

This analysis indicates that a unified, nationally-consistent taper equation has potential to improve upon regional, species-specific volume equations. The taper equation has the advantage of estimating compatible total and merchantable volume when compared to existing approaches used by the FIA. Continuing efforts will focus on acquiring additional stem taper data.

The mixed-effects modeling framework that we propose here has the potential to examine species groupings by assessing the magnitude of the random effect and grouping by influential species traits. The similar performance between the species group volume/biomass model and the species model suggests that grouping species may be appropriate. Examining the branch component, we see improvement by first removing merchantability restraints and refitting coefficients (CRM1) and additional improvement by fitting a more flexible model form that allows for variation between species (CRM2). We present results from our most robust model with random effects on all coefficients. Future analyses will examine simplifying by species groups, removing parameters as appropriate, and grouping by geographical units to address local variability. This subject is not well understood, but recent work (Westfall 2015) suggests that local bias issues need to be addressed as part of the model development process.

Our examination of species-level wood specific gravity suggests that there can be considerable differences as regional estimates were generally statistically different than what is currently being used by the FIA CRM method. Previous efforts have suggested strong spatial patterns in wood specific gravity and this may need to be accounted for. In addition, other analyses have suggested that localized specific gravity estimates can improve stem biomass estimates.

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REDUCING UNCERTAINTY AND INCREASING CONSISTENCY: TECHNICAL IMPROVEMENTS TO FOREST CARBON POOL ESTIMATION USING THE NATIONAL FOREST INVENTORY OF THE US

[1]Woodall, C.W., Domke, G.M., Coulston, J., Russell, M.B. Smith, J.A., Perry, C.H., Ogle, S.M., Healey, S., Gray, A.

Abstract—The FIA program does not directly measure forest C stocks. Instead, a combination of empirically derived C estimates (e.g., standing live and dead trees) and models (e.g., understory C stocks related to stand age and forest type) are used to estimate forest C stocks. A series of recent refinements in FIA estimation procedures have sought to reduce the uncertainty associated with the national C inventory by: 1) refining forest floor C estimates with in situ data, 2) updating the live belowground and understory C pools modeling approaches, 3) refining objective delineations between woodland and forest land uses, and 4) revising managed land delineations. The results of these studies in the context of forest C accounting and future refinements are discussed in the context of UNFCCC reporting.

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DEAD WOOD INVENTORY AND ASSESSMENT IN SOUTH KOREA

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Abstract—Dead wood (DW) plays a critical role not only in maintaining biodiversity but also in stocking carbon under UNFCCC. From the 5th national forest inventory (NFI5; 2006-2010) in South Korea, field data relevant to the DW including standing and downed dead trees by four decay class, *etc.* were collected. Based on the NFI5 data, the average volume of DW over the country is estimated to be 12.3m^3/ha of which the total carbon stock accounts for 10.9 Tg C. Recently, NFI6 (2011-2015) has been implemented into monitoring and assessing forest resources including DW over time. We are to analyze relationship between DW and stand structure for sustainable forest management.

INTRODUCTION

From an economic point of view, dead wood means natural loss for timber production. Since 1996, the dead wood has been recognized as one of carbon pools under UNFCCC (IPCC, 2000) and has played a crucial role in maintaining biodiversity. From the 5th national forest inventory (NFI5) of South Korea (Kim et al., 2010), field data relevant to the dead wood including standing and downed dead trees have been collected. Additionally, to assess Greenhouse gas Inventory in forest sector, biomass conversion/expansion factors for biomass and dead organic matter at a national level have been developed. The objectives of this research are to estimate tree mortality with annual inventory system and to assess carbon stock for dead wood with developed carbon factors by decay classes.

MATERIAL AND METHODS

In South Korea, national forest inventory system has been changed to support sustainable forest management at the national level and to report national forest resources to international institutes including the FAO, UNFCCC, *etc*. The first new inventory was conducted during 2006-2010. In this study, field data from the 5th NFI was used to assess tree mortality and carbon stock with developed carbon factors by decay classes.

Dead wood inventory

Sampling design

With the NFI5 design, a systematic sampling with clusters was adopted. As shown in Fig. 1, the total of 4,000 sample clusters was systematically distributed with a square grid of 4km and 20% of the clusters were surveyed each year (Kim *et al*., 2010).

Plot design

In this inventory system, a cluster plot having 4 subplots was applied. Each subplot consists of the three concentric circles for collecting stand variables (Fig. 1). Dead wood inventory was implemented at the center subplot with a plot size of 400 m^2. On each center subplot, forest variables were collected relevant to dead wood (standing and downed trees) such as tree species, diameter (DBH or DCH), length or height, decay classes by 4 classes, dead cause, *etc*.

In order to convert mortality into carbon stock, biomass conversion factors (BCF) and carbon factors (CF) by forest groups and decay classes were developed (Yoon, *et al*., 2011; KFRI, 2014) as shown in the Table 1. In the case of BCFs, those of non-conifer tree species were slightly higher than those of conifer tree species, whereas CFs of conifer tree species were higher.

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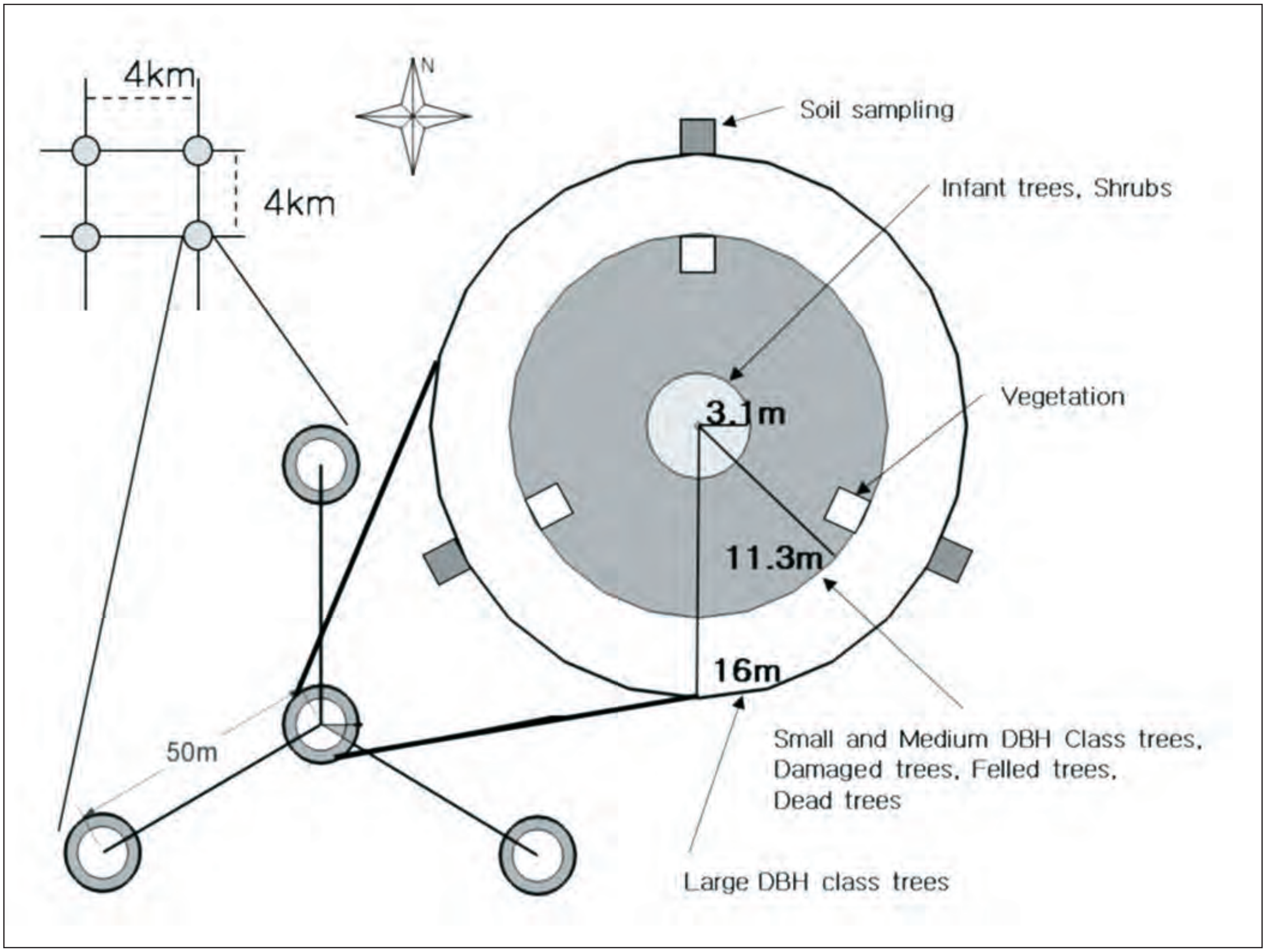

Figure 1—Sampling and plot design for the 5th National Forest Inventory in South Korea.

Table 1—Carbon conversion factors of dead wood by decay classes and tree groups.

	Biomass conversion factors (g/cm3)				Carbon factors (percent)			
Classification	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Conifer	0.38	0.34	0.26	0.15	49.5	50.2	50.2	51.6
Non-conifer	0.48	0.37	0.29	0.16	48.6	48.6	48.6	48.3

Dead wood assessment

Mortality estimation at the subplot level

In order to estimate growing stock volumes for each standing dead tree and felled dead wood, there are two equations that are similar to equations for standing trees. The mortality at a subplot level was estimated by Eq. (2).

$$m_s = f(dbh, height), \quad m_f = f(dch, length) \qquad \text{Eq. (1)}$$

$$y_i = \frac{\sum_{s=1}^{n_s} m_s + \sum_{f=1}^{n_f} m_f}{a_i^{'}} \qquad \text{Eq. (2)}$$

where m_s : the mortality of standing dead tree *s*,
m_f : the mortality of felled dead tree *f*,
n_s, n_f : the number of standing dead tree (*s*) and felled dead wood (*f*) per subplot *i*,
y_i : total mortality per subplot *i* , and actual plot size at a subplot *i*.

Carbon stock estimation at the subplot level

In this study, estimating carbon stock for each dead wood was done with the following equation:

$$c_s = m_s \times cf_s, \; c_f = m_f \times cf_f \qquad \text{Eq. (3)}$$

where c_s, c_f : carbon stock of standing dead tree *s* and felled dead tree *f*, cf : carbon factor by decay class and tree group

The total carbon stock at the subplot can be estimated by Eq. (2).

Combining of annual estimates

As mentioned above, field data were annually collected. To combine annual data, we assumed that field data are collected at a same period which is so-called Temporally Indifferent Method (Kangas, 1993; Bechtold and Patterson, 2005; Yim *et al*., 2012). The estimators for simple random sampling were applied (Cochran, 1977).

$$\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}, \quad \hat{\mathrm{var}}(\bar{y}) = \frac{s^2}{n} \quad \text{where} \quad s^2 = \frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n-1} \qquad \text{Eq. (4)}$$

RESULTS AND DISCUSSION

Mortality by tree groups

As most forests in South Korea were reforested during in 1970-1980s, current forest areas by age classes are included in 40-50 years (KFS, 2011). The stand density is relatively high accounting for 1,305 trees per hectare on average. Based on NFI5, the average volume of DW over the country is estimated to be 12.3 m^3/ha as shown in Table 2. The total mortality accounts for about 75 million m^3 and the mean mortality is about 12.3 m^3/ha. Mortality could be divided into standing dead tree and felled wood, of which were 3.5 m^3/ha and 8.8 m^3/ha, respectively. As most forests in South Korea were reforested during in 1970-1980s. Recently, numerous trees felled by "the Forest tending project (2004-2008)", however the felled trees left in the forest due to a low forest road density.

Carbon stock in dead wood

The observed total number of DWs accounts for about 50,457 trees. When decay classes divided, the three and four classes comprised about 70 percent of the total DW. Especially, felled woods were about 70 percent. For this reason, the total carbon stock in DW at 2010 year is estimated to be 10.9 Tg C (Table 2). Regard to decay classes, the classification is not clear, that is overly dependent on surveyor's subjective decisions. There is necessary for more clear definitions of decay classes for field survey.

Recently, the NFI6 (2011-2015) has been implemented for monitoring and assessing forest resources including the DW over time and we aim to analyze relationship between DW and stand structure for sustainable forest management from a economic point of view. In order to improve uncertainty of DW carbon pool under UNFCCC, wood density and carbon conversion factors by decay classes for each tree species at the national level should be developed.

ACKNOWLEDGMENT

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Table 2—Tree mortality and carbon stock for dead wood in South Korea.

Mortality			Carbon stock in dead wood		
Mean (m3/ha)	SE (m3/ha)	Total(103m3)	Mean (Mg C/ha)	SE (Mg C/ha)	Total (Tg C)
12.3	±0.30	75,654	1.76	±0.04	10.9

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USING FIA AND LANDSAT OBSERVATIONS TO IMPROVE THE SPATIAL AND TEMPORAL RESOLUTION OF FOREST CARBON ESTIMATES

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Abstract—For nearly a decade, the USFS FIA, NASA, and the University of Maryland have collaborated on the NASA/NACP funded North American Forest Dynamics (NAFD) project, and developed new approaches for annual mapping of CONUS forest dynamics (1984-2011). Building on this foundation of empirical research and results, the collaboration will continue with a new Carbon Cycle Science Synthesis Research effort to improve the spatial and temporal estimation of forest related carbon emissions. This newly funded study will 1) produce annual age and biomass maps and 2) use these national products to advance estimates from a Carbon Bookkeeping model. The work will allow the model to calculate carbon fluxes from forest disturbances and post-disturbance recovery processes with unprecedented spatial and temporal details. Using NAFD disturbance maps and spectral trajectories from Landsat time-series stacks, forest areas can be separated into three broad age categories. "Young" forests had stand-clearing disturbance occurring with known year between 1985 and 2013. "Middle-aged" forests are areas recovering to forest include pixels that were not identified as forest (spectrally) in 1984 but became forested in later years, or forests that grew substantially over 30 years as indicated by trends in the 30-year Landsat surface reflectance record. "Old" forests include locations that remained forested between 1984 and 2014 and showed no obvious trend in the 30-year Landsat record. During this presentation, the three- tiered approach to model per pixel estimates of age and biomass using NAFD products and FIA plot data will be discussed along with results from prototype studies and updates to the bookkeeping model.

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THE FUTURE OF THE U.S. FOREST CARBON SINK

Richard Birdsey[1], Yude Pan[2], Fangmin Zhang[3]

Abstract—For more than a decade, the U.S. forest carbon sink including carbon in harvested wood products has been persistently removing more than 200 million tons of carbon from the atmosphere, enough to offset 16% of CO_2 emissions from fossil fuel use. Maintaining or increasing this valuable benefit of forests is an important element of the U.S. strategy to reduce net greenhouse gas emissions as part of the national commitment to the next global climate accord. Yet, doubts have been raised about the future of the U.S. forest carbon sink which is threatened by deforestation, increasing demand for bioenergy, aging forests, natural disturbances, and climate change. Resources Planning Act (RPA) projections, which reflect mainly the first 3 factors, suggest a rapidly decreasing carbon sink. In contrast, projections from an ecosystem process model that reflect mainly the last 3 factors plus CO_2 fertilization and N deposition, indicate that the forest carbon sink may persist for many more decades before saturating. On top of these contrasting baselines, there are opportunities for land management changes to help sustain or increase the U.S. forest carbon sink. Here we analyze the influence of past drivers of change in U.S. forest carbon stocks, compare future baselines from different modeling approaches, and assess the prospects of land management to change the projected baselines. All of the results presented are based on modeling and analysis tools that are well calibrated to FIA standards and reported historical estimates, so that this information can be readily assimilated into policy considerations. Suggestions for improving analysis capabilities in future assessments are included.

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DEVELOPMENT OF CARBON RESPONSE TRAJECTORIES USING FIA PLOT DATA AND FVS GROWTH SIMULATOR: CHALLENGES OF A LARGE SCALE SIMULATION PROJECT

James B. McCarter[1] and Sean Healey[2]

Abstract— The Forest Carbon Management Framework (ForCaMF) integrates Forest Inventory and Analysis (FIA) plot inventory data, disturbance histories, and carbon response trajectories to develop estimates of disturbance and management effects on carbon pools for the National Forest System. All appropriate FIA inventory plots are simulated using the Forest Vegetation Simulator (FVS) growth model to develop the carbon response trajectories for undisturbed, managed, and disturbance from fire, pests, and in some regions wind. The challenges presented by the number of plots, number of FVS variants, selection of localization variables, growth calibration, regeneration, and disturbance magnitude calibration will be presented. The carbon response curve fitting process will also be presented. These response curves developed by forest type, disturbance type, initial carbon bin, and disturbance magnitude are then used in a stochastic simulation process that combines the annual disturbance maps over a 20 year period to determine a forest by forest realization of carbon changes at the forest level in response to observed disturbance patterns. The resulting response curves can also be used to develop estimates of potential carbon response under alternative management or disturbance scenarios.

INTRODUCTION

The National Forest System (NFS) plays a critical role in mitigating greenhouse gas emissions in the U.S. Various efforts are underway to access current conditions and potential trends of C on the forest of the NFS. One of these efforts, looking at the effects of disturbance on C accumulation is the Forest Carbon Management Framework (ForCaMF). ForCaMF combines Forest Inventory and Analysis plot information, Forest Vegetation Simulator (FVS) growth and carbon estimates, and Landsat-derived disturbance histories to provide forest level C stocks over a 20 year time frame.

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STUDY AREA/DATA SOURCES

The U.S. Forest Inventory and Analysis (FIA) program provides a national-consistent and statistically-valid sample documenting trends in forest extent, status, condition, and resources (Bechtold and Patterson 2005). For each FIA plot on NFS lands, variables useful for C estimation are collected on the ground such as forest type, tree species, tree size, stand age, and recent disturbance. The FIA database (O'Connell et al 2014) is queried for appropriate plots for each state to calculate tree volume, biomass, and C stocks via allometric equations based on the inventory information for each plot. Over 71,000 plots are being assessed and simulated for this and subsequent analyses. Table 1 shows the breakdown of plots by region and state.

Table 1—Number of FIA inventory plots by region and state. Note: WY is listed for both R2 and R3 but only counted once in the total.

Region	State	FS Plots
R1	ID	5285
	MT	4949
	SD	591
	WA	3940
R2	CO	2017
	KS	0
	NE	40
	SD	480
	WY	832
R3	AZ	2667
	NM	2290
R4	ID	4512
	NV	1001
	UT	2586
	WY	832
R5	CA	4639
R6	OR	4945
	WA	2362
R8	AL	772
	AR	2046
	FL	1786
	GA	886
	KY	409
	LA	548
	MS	1159
	NC	1331
	OK	210
	SC	916
	TN	600
	TX	661
	VA	1795
R9	CT	0
	DE	0
	IA	0
	MA	0
	MD	0
	NL	0
	RI	0
	IL	415
	IN	303
	ME	32
	MI	3845
	MN	3293
	MO	1358
	HM	437
	NY	7
	OH	128
	PA	423
	VT	332
	WI	1848
	WV	697
R10	AK	1716
	Total	71089

MODELING FRAMEWORK

The Forest Carbon Management Framework (ForCaMF, Healey et al 2014, Raymond et al. 2015) was developed to leverage Landsat imagery, FIA plot data, and forest growth models in combination. Each FIA plots is simulated using the appropriate FVS (Crookston and Dixon 2005, Dixon 2002, Stage 1973) variant under a range of disturbances (undisturbed, management, fire, insect, and wind) customized for each region. The resulting C numbers are provided by the Fire and Fuels Extension (FFE) to FVS (Rebain 2010). For each region the FIA plots are grouped by forest type (Table 2), initial carbon bin (defined by 25, 50, 75, and 100% quartiles of initial C by region), disturbance type, and disturbance magnitude ((25, 50, 75, and 100% canopy disturbance). Each of these bins has a mean trend line fit to all FIA plot trajectories using generalized estimation equations (GEE, Hardin and Hilbe 2003) using the geeglm() function in the R statistical software package (R Core Team 2015). See Raymond et. al. (2015) for additional details on the fit process. These resulting trajectories for each combination of forest type, initial carbon, disturbance type, and disturbance magnitude are then combined with disturbance maps in a stochastic simulation framework (Healey et al. 2014) to arrive at estimates for each national forest.

Table 2—Forest types by region. R1 used defined dominance types. R2-10 use FIA forest types groups.

R1
ABLA
HMIX
IMIX
PICO
PIPO
PSME
TMIX

R2
spruce/fir
other softwoods
pinyon/juniper
douglas-fir
ponderosa pine
fir/spruce/mountain hemlock
lodgepole pine
other western softwoods
oak/hickory
elm/ash/cottonwood
aspen/birch
other hardoods
woodland hardwoods

R3
pinyon/juniper
douglas- fir
ponderosa pine
fir/spruce/mountain hemlock
other western softwoods
elm/ash/cottonwood
aspen/birch
woodland hardwoods

R4
pinyon/juniper
douglas-fir
ponderosa pine
western white pine
fir/spruce/mountain hemlock
lodgepole pine
hemlock/sitka spruce
western larch
other western softwoods
oak/hickory
elm/ash/cottonwood
aspen/birch
woodland hardwoods

R5
pinyon/juniper
douglas-fir
ponderosa pine
western white pine
fir/spruce/mountain hemlock
lodgepole pine
redwood
other western softwoods
california mixed conifer
aspen/birch
alder/maple
western oaks
tanoak/laurel
other hardoods
woodland hardwoods

R6
pinyon/juniper
douglas-fir
ponderosa pine
western white pine
fir/spruce/mountain
lodgepole pine
hemlock/sitka spruce
western larch
other western softwoods
elm/ash/cottonwood
aspen/birch
alder/maple
western oaks
tanoak/laurel
other hardoods
woodland hardwoods

R8
white/red/jack pine
spruce/fir
longleaf/slash pine
loblolly/shortleaf pine
other eastern softwoods
oak/pine
oak/hickory
oak/gum/cypress
elm/ash/cottonwood
maple/beech/birch
aspen/birch
other hardwoods
tropical hardwoods

R9
white/red/jack pine
spruce/fir
loblolly/shortleaf pine
other eastern softwoods
hemlock exotic softwoods
oak/pine
oak/hickory
oak/gum/cypress
elm/ash/cottonwood
maple/beech/birch
aspen/birch
other hardoods

R10
spruce/fir
fir/spruce hemlock
lodgepole pine
hemlock/sitka spruce
elm/ash/cottonwood
aspen/birch
alder/maple

RESULTS AND DISCUSSION

R8 Case Study

The FVS growth results are grouped by forest type, initial carbon, disturbance type, and disturbance magnitude. Individual plot trajectories are shown for loblolly/shortleaf plots for undisturbed (Figure 1a), management (1b), and fire (1c) for carbon bin 2, disturbance magnitude 1 (number of plots that ended up grouped in each respective bin). The resulting fit trajectories for loblolly/shortleaf pine plots are shown for undisturbed (Figure1d) across the 4 initial carbon bins and management, carbon bin 2, and 4 disturbance magnitudes (Figure 1e). The 4 trajectories in 1e start at the same initial C level as the red line in 1d, but because the management simulation are targeted to remove 25, 50, 75, and 100% of the cover each management scenario starts below the initial starting point for cb=2 in 1d. The results show that for this forest type/disturbance type/initial carbon bin

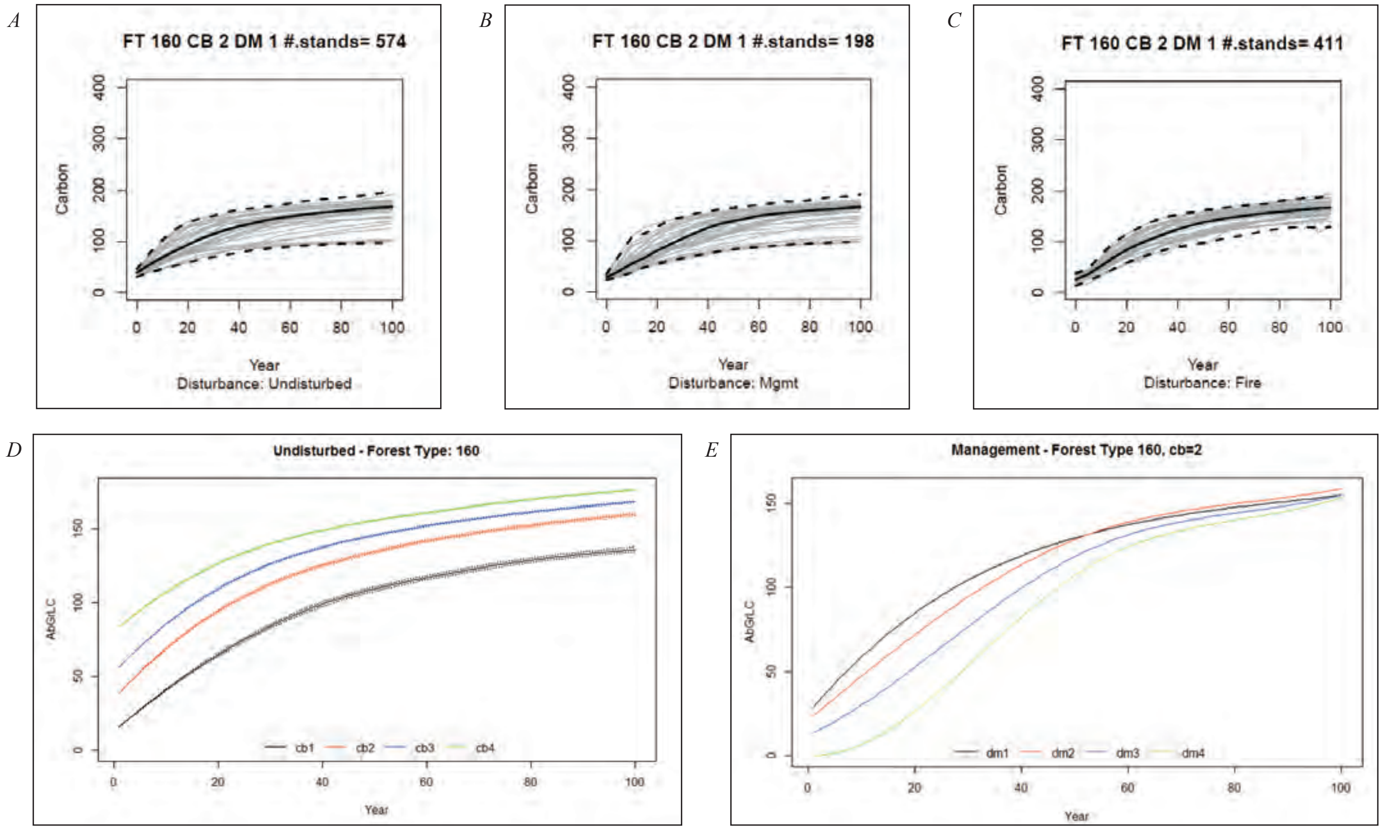

Figure 1—Individual growth trajectories for R8, forest type 160 (loblolly/shortleaf pine), carbon bin 2, disturbance magnitude 1 for undisturbed (a), management (b), and fire (c). The fit results for all 4 carbon bins are show for undisturbed (d) and for a single initial carbon bin (2) and the 4 disturbance magnitudes for the management (e) scenarios.

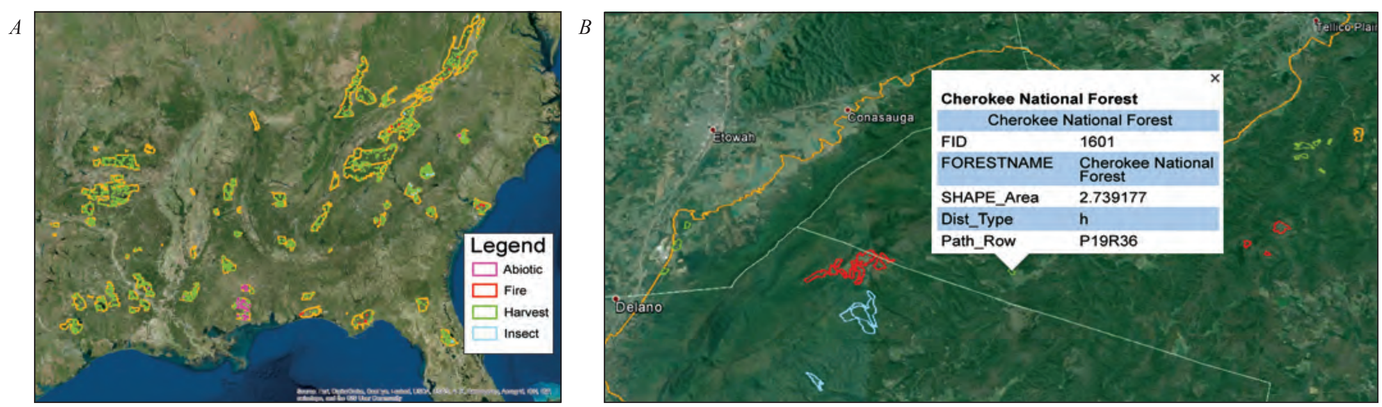

Figure 2—Composite disturbance map for R8 (a.), all years combined to show scope of impacts of disturbance across area. Orange outline are NFS lands, disturbances are as indicated in legend. Disturbance map zoomed in (b.) to show specific detail on an individual disturbance on the Cherokee NF.

combination each disturbance magnitude recovers, although at different rates over the 100-year simulation and achieve about the same level of C as the undisturbed plot. These fit trajectories are developed for all forest type, initial carbon bin, disturbance type, and disturbance magnitude combinations.

Landsat derived disturbance maps are developed for the 1999-2001 time frame (Figure 2) for each region. The disturbance maps are then combined with the individual trajectories in a stochastic simulation framework (Healey et al. 2014) for estimates of C for individual national forests. The simulations for R8 are currently running at the time of writing of this abstract.

Modeling Other Regions

R8, while having a large number of states, only uses a single FVS variant. For most western regions multiple FVS variants are required for each state (e.g. CA – 5 variants, OR – 7 variants, WA – 5 variants). This complicates the process of running the simulations because each variant has minor differences that need to be dealt with. The simulation and analysis framework has been taught to automatically separate FIA plots by variant to run the simulations and then to combine the results back together for the next steps in the analysis process.

In addition each region has preliminary simulations run so that existing calibration data in the FIA databases can be used to develop regional calibration statistics. These preliminary simulations are also used to establish initial carbon and cover values for the plots that are used as part of the disturbance map creation. The regional calibration statistics are developed to adjust FVS growth rates based on growth data from the databases. All plots have regional calibration adjustments applied. This has the effect of increasing growth for some species but may decrease growth for others. In addition to the regional calibration adjustments, plots that have sufficient increment data for that individual plots also are further adjusted using the plot specific increment information. This approach ensures that plots that contribute to the regional calibration statistics use their own plot specific information, but plots that do not include increment information are calibrated using the regional average information.

Challenges

R1 simulations had the advantage of a complete establishment model in the Inland Empire variant used for the region. Other regions, R8 for example, do not have the full establishment model and therefore regeneration assumptions have be developed separately from the FVS growth model. For all other regions a regeneration model was developed using the SEEDING table and management history information contained in the FIA database. For each state all plots that contain seedling records are classified by forest type, overstory condition, and time since observed management to create a population of potential inventory records for any plots that need regeneration. When a regeneration event occurs in a simulation (management or disturbance activity) the pool of candidate stands for the matching forest type and management type is used to randomly select a plot. If the existing plot has seedling records its own seedling records are used for regeneration. If the current plot does not have seedling records a sample population from the seedling database is created, expanding age as needed to have a sufficient sample pool (>30) and a plot is selected to provide species composition and number of individuals by species for the regeneration event. The size of individual seedling records introduced into the simulation is scaled by type and intensity of the disturbance.

Running multiple simulations for 70,000+ plots results in the use of considerable disk space so all results are stored in ZIP files to reduce storage use. The simulation results for all simulations run so far (800,000 and counting) now takes over 106 GB of disk space.

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UTILIZING FOREST INVENTORY AND ANALYSIS DATA, REMOTE SENSING, AND ECOSYSTEM MODELS FOR NATIONAL FOREST SYSTEM CARBON ASSESSMENTS

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Abstract—Forested lands, representing the largest terrestrial carbon sink in the United States, offset 16% of total U.S. carbon dioxide emissions through carbon sequestration. Meanwhile, this carbon sink is threatened by deforestation, climate change and natural disturbances. As a result, U.S. Forest Service policies require that National Forests assess baseline carbon stocks and influences of disturbance and management activities on carbon stocks and trends, with the goal of incorporating carbon stewardship into management activities. To accomplish these objectives, we utilize Forest Inventory and Analysis datasets and remote sensing-based disturbance histories within a carbon modeling framework to estimate past and present carbon stocks and trends for each national forest. We integrate three forest carbon models: 1) Carbon Calculation Tool, 2) Forest Carbon Management Framework, and 3) Integrated Terrestrial Ecosystem Carbon model, to calculate baseline carbon stocks and the relative impacts of disturbance and non-disturbance factors on forest carbon stocks and flux. Results of the assessments ultimately help forest managers quantify carbon consequences of broad forest management strategies and project-level decisions. A case study from Flathead National Forest shows that disturbances, primarily fire and disease, have had the largest effect on forest carbon stocks.

INTRODUCTION

Containing approximately a quarter of the total carbon (C) stored in U.S. forests, the National Forest System can play a critical role in mitigating greenhouse gas emissions through C sequestration. Climate change along with natural and anthropogenic disturbances may threaten or in some cases enhance forest C stocks. The effects of climate change and disturbances on forest C are both spatially and temporally complex, further complicating forest C management. Few studies have examined in detail the drivers of C stocks and trends at landscape-management scales, such as across individual National Forests. Forest C assessments including a full attribution of natural and anthropogenic causes of observed change at the scale at which management decisions are made are needed.

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Recognizing this, both international and national policies have been enacted with the goal of managing and sustaining these valuable forest resources. By signing the United National Framework Convention on Climate Change (UNFCCC), the U.S. agreed to report annual C stores and changes, including those on forested lands, as part of a complete greenhouse gas inventory. Furthermore, the U.S. Forest Service Climate Change Response Strategy and Performance Scorecard requires management units (i.e., National Forests) to report baseline C stocks and changes over time due to disturbance and management, and in the future, it is likely that management guidelines will incorporate C stewardship among other objectives.

To address these mandates, we integrated remotely sensed and field-sampled data sources within a C modeling framework to develop a comprehensive assessment of forest C stocks and dynamics within each U.S. National Forest. Specifically we estimated the following: 1) baseline C stocks via the Carbon Calculation Tool (CCT), 2) effects of disturbances on C accumulation using the Forest Carbon Management Framework (ForCaMF), and 3) long-term relative effects of disturbance and non-disturbance factors (climate and atmospheric chemistry) on C stocks and flux using the Integrated Terrestrial Ecosystem Carbon model (InTEC).

DATA SOURCES

Fundamental to the assessment of forest C stocks is a thorough inventory of all forested lands. The U.S. Forest Inventory and Analysis (FIA) program provides a nationally-consistent and statistically-valid sample documenting trends in forest extent, status, condition, and resources. Within each FIA plot, variables useful to C accounting are collected such as forest type, tree species, tree size, stand age, and recent disturbances (Bechtold and Patterson 2005). FIA datasets can be utilized to directly calculate tree volume, biomass, and C stocks via allometric equations (e.g., Woodall and others 2011). Along with FIA forested area measurements, C density and total C stocks in component pools can be estimated for an area of interest, such as a National Forest (e.g., Woodall and others 2013). FIA data is also suitable for deriving other C modeling inputs such as stand age and forest type maps (Zhang and others 2012), and growth and yield functions (Raymond and others 2015). Utilizing inventory-based, on-the-ground measurements enhances model confidence and facilitates comparisons across forests.

Along with other forest characteristics, disturbances, including their timing, types, and magnitudes, regulate the amount of C present in a forest and how that C may fluctuate overtime. Although inventory data is useful for tracking total C and net changes, and can reveal the effects of harvesting and mortality, it is less suited for tracking effects of specific disturbances and intensities on C stocks, and cannot assess the impact of climate change and atmospheric chemistry. Therefore, high-resolution disturbance and atmospheric data is also needed to model C dynamics with attribution to specific causes of change. Landsat satellite imagery and manual verification are used to detect annual changes in forest cover, and assign disturbance types (e.g., fire, insect, harvest) and magnitudes at 30-m resolution from 1990-2011 (Healey and others 2014). High-resolution, measurement-based datasets (e.g. PRISM Climate Group) enable us to investigate growth enhancements and reductions due to climatic variability, CO_2 fertilization, and nitrogen deposition.

MODELING FRAMEWORK

For this project we use CCT (Smith and others 2010) to provide baseline C stocks and trends from 1990-2013 on forested lands in National Forests. Annual C stocks are calculated by linear interpolation between at least two complete FIA surveys conducted since 1990, and extrapolation to recent years after the last available inventory. C stocks within FIA plots are calculated using regional and forest-type specific conversion factors and coefficients within sets of equations (e.g., Woodall and others 2011). To estimate total C for each national forest, the C per hectare at the plot location is multiplied by the total area that the plot represents, and then these totals are summed. CCT accounts for changes in forest area reflected in the FIA data, thus also reports annual C density (Woodall and others 2013).

ForCaMF builds upon CCT by utilizing FIA data along with Landsat-derived disturbance histories to estimate the relative impacts of disturbances and management activities on C stored in forested ecosystems from 1990-2011 (Healey and others 2014). FIA plots are used as inputs to the Forest Vegetation Simulator (FVS) model (Crookston and Dixon 2005) to simulate C trajectories for non-soil C pools in 10-year intervals over a 100-year span (Raymond and others 2014). These trajectories are then used to track C storage change on the national forest over time as they are applied across Landsat-based maps of forest structure and disturbance. The relative impacts of disturbances are quantified based on the direct export of C to the atmosphere or other pools and prevented sequestration (Healey and others 2014, Raymond and others 2015).

Lastly, InTEC (Chen and others 2000, Zhang and others 2012) expands upon both CCT and ForCaMF by attributing C stocks and flux to non-disturbance and disturbance factors. InTEC is a process-based, biogeochemical model calibrated with FIA-derived inputs including stand age, forest type, and net primary productivity-stand age relationships that drive forest growth (Zhang and others 2012). InTEC estimates the impacts of Landsat disturbances and stand age (time-since-disturbance) by calculating C emissions, transfers between live and dead pools, and accumulation. Fluctuations in non-disturbance factors including climate (i.e., temperature, precipitation), nitrogen deposition and atmospheric CO_2 concentrations, which influence growth rates, guide forest C dynamics. A series of differential equations along with scalars and coefficients of allocation, turnover, decomposition, and C loss controls how disturbance and non-disturbance factors affect total net biome productivity and component C pools since 1950.

RESULTS AND DISCUSSION

A Case Study: Flathead National Forest

Flathead National Forest (FNF) in Northwestern Montana, contains predominately subalpine fir (*Abies lasiocarpa*) and Douglas fir (*Pseudotsuga menziesii*) forests and about 10% of the forests are <10 years old (Fig. 1). Results of CCT in FNF indicate that from 1990-2013 C density remained relatively stable around 155 Mg ha^{-1} C (Fig. 2a), with aboveground live tree and soil C pools containing most forest C (Fig. 2b). ForCaMF results show that since 1990, there has been an increase in disturbance effects, with disease and fire having the greatest relative impacts (Fig. 3a). By 2011, disturbances emitted or prevented the sequestration of 4.8 Tg C, with considerable emissions in 2004 and 2007 due to fires (Fig. 3a). Increased disturbances may explain the subtle decline in C density in aboveground and belowground live pools and subsequent increase in dead down, standing dead, and forest floor pools from 1990-2013 (Fig. 2b). InTEC outputs reveal that since the 1950s FNF fluctuated between a small C sink and source, but from 2000-2009 it remained a C source (Fig. 3b) due to both negative disturbance/aging and climatic effects (i.e., warmer, drier) (Figs. 3c-d). In 2010 FNF became a C sink again (Figs. 2b-c) as forests began recovering from recent disturbances (Fig. 3a) shown by the pulse of newly established stands (Fig. 1). The positive impacts of nitrogen deposition and CO_2 fertilization were generally overshadowed by the much stronger, mostly negative disturbance and climate effects, cumulatively causing a loss in C over time (Figs. 3b-d).

These C assessments can help inform management decisions. Results from FNF suggest that despite increased disturbances, C density has been stable (Fig. 1a). However, if the goal is to increase C storage, it may be most effective to focus on mitigating disturbance effects, specifically disease and fire, which have had the most negative impacts on C trends (Fig. 2a). It is important that national forest managers place C management within a broader context of long-term sustainable management. These forests are diverse, multi-use landscapes and C management adds another very complex dimension to already complicated strategies.

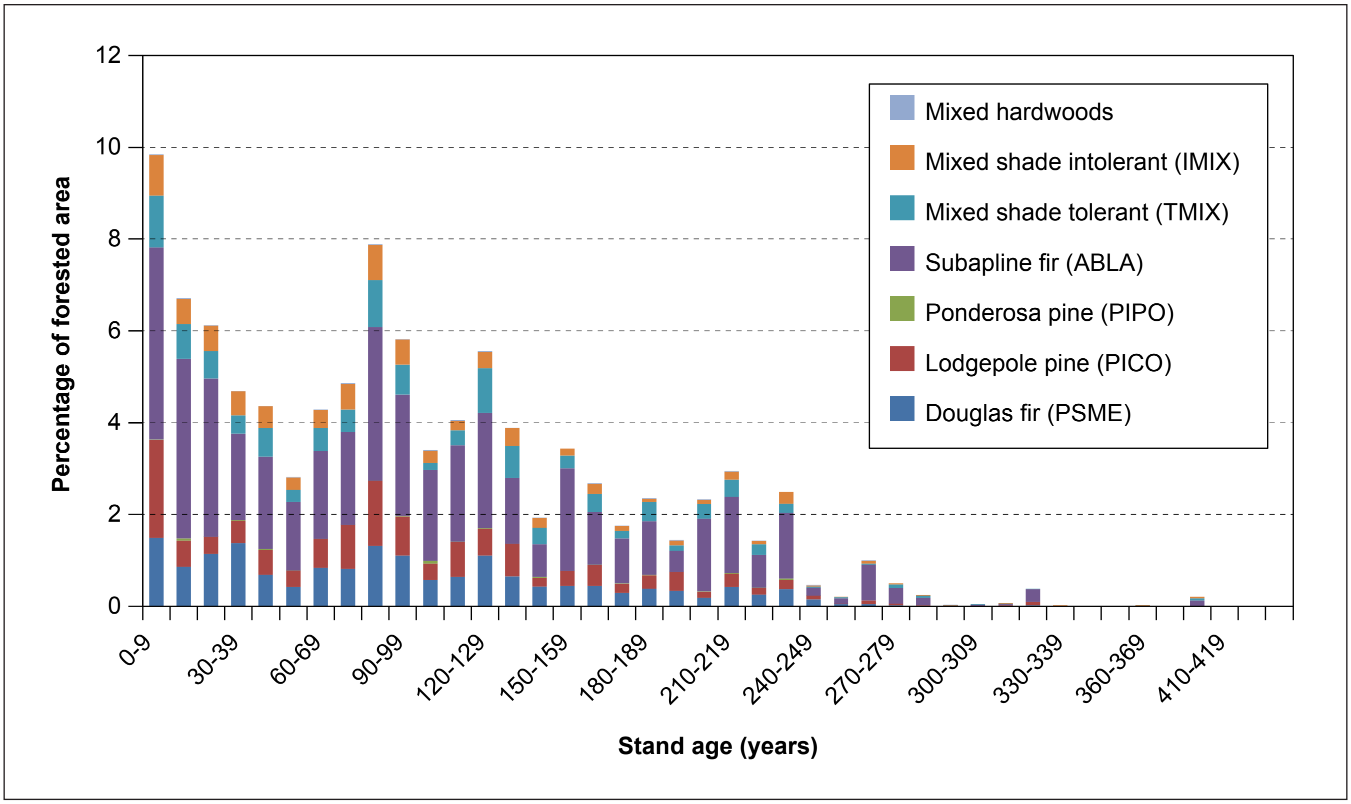

Figure 1—Age-class distribution displaying the percentage of forested area of each forest dominance type in 10-year age classes, derived from Forest Inventory and Analysis data.

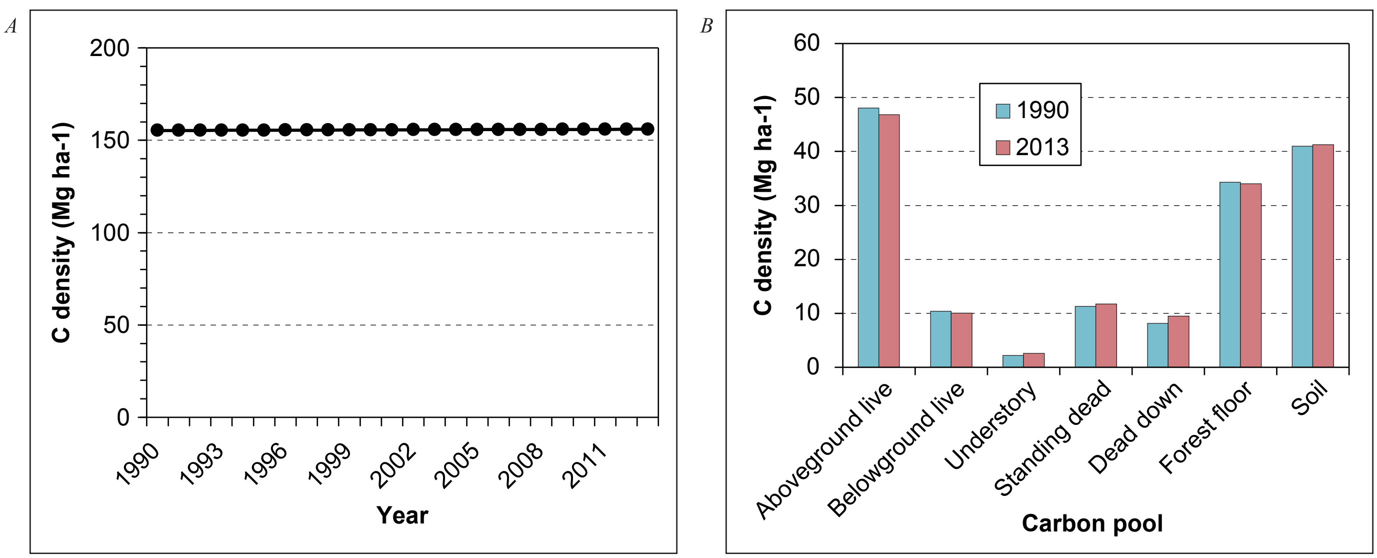

Figure 2—Carbon Calculation Tool outputs for Flathead National Forest showing carbon density (Mg C ha-1) for (a) all ecosystem carbon pools combined from 1990-2013 and (b) each individual carbon pool in 1990 and 2013.

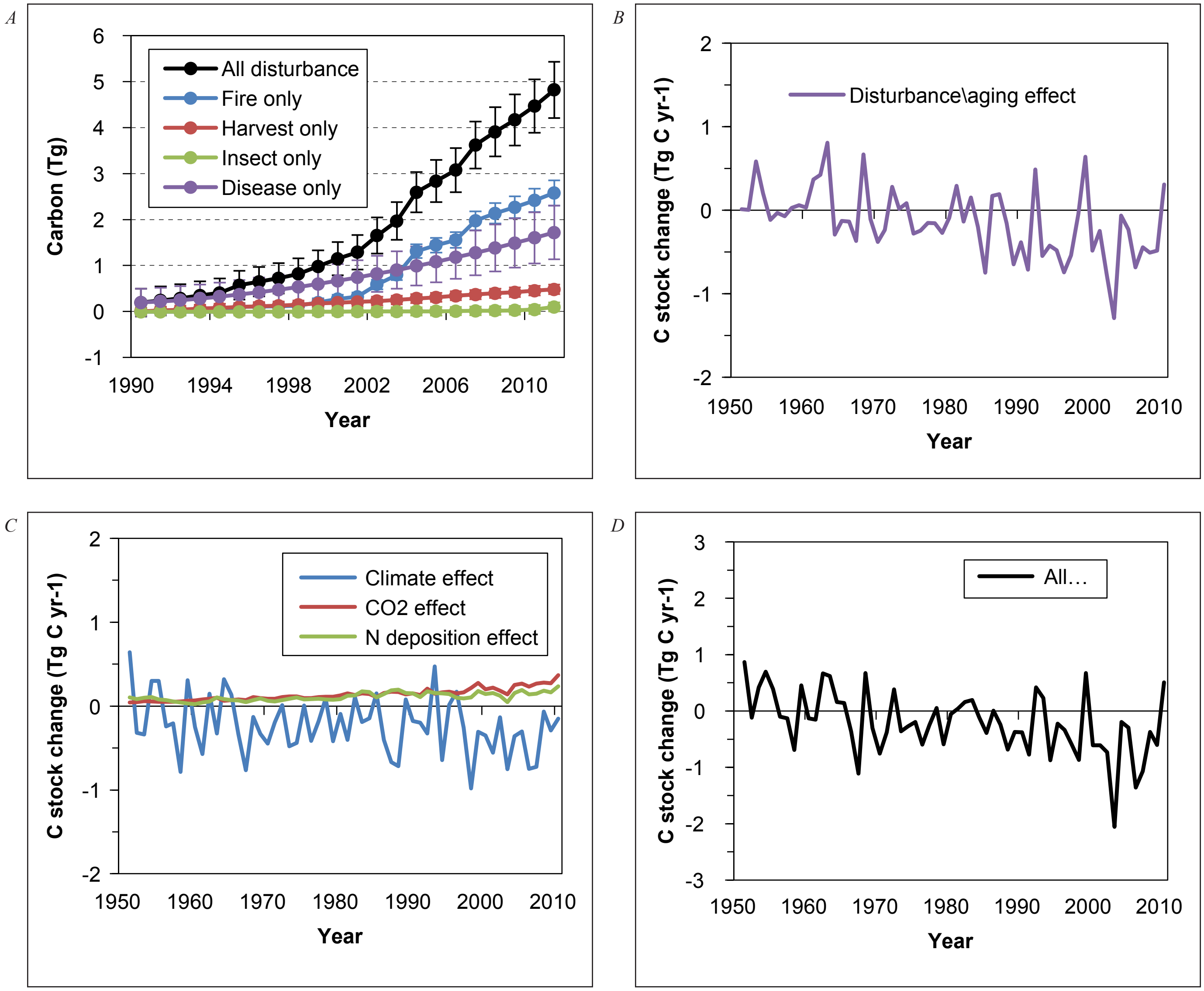

Figure 3—Model outputs for Flathead National Forest showing the relative effects of disturbance and non-disturbance factors on forest carbon trends. (a) Output from the Forest Carbon Management Framework showing impacts of management and disturbances occuring from 1990 and 2011 on non-soil C storage. Error bars specify the standard error of 500 error simulations. InTEC outputs showing the changes in total ecosystem C stocks from 1951-2010 due to: (b) disturbances including fire, harvests, insects, and disease and subsequent regrowth with stand age, (c) non-disturbance factors including climatic variability, nitrogen deposition, and atmospheric CO2 concentrations, and (d) all disturbance/aging and non-disturbance factors combined. Positive values indicate the forest is a C sink from the atmosphere whereas negative values indicates a C source to the atmosphere.

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THE ROLE OF OLD FORESTS AND BIG TREES IN FOREST CARBON SEQUESTRATION IN THE PACIFIC NORTHWEST

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Abstract—Forest ecosystems are an important component of the global carbon (C) cycle. Recent research has indicated that large trees in general, and old-growth forests in particular, sequester substantial amounts of C annually. C sequestration rates are thought to peak and decline with stand age but the timing and controls are not well-understood. The objectives of this study were to determine how the balance of tree growth, mortality, and dead wood decay vary by plant community type, site productivity, and stand age. We compiled remeasured tree and dead wood estimates from 8,767 inventory plots on Pacific Northwest Region National Forest lands and assessed changes by climax plant association zones (PAZs) and site productivity estimates of mean annual increment at culmination (MAI). Estimated maximum C density for old-growth stands (≥300 years old) varied significantly by MAI class within PAZ, but on average stands accumulated 66% of maximum stores by age 100. We did not see a decline in live tree production in older stands in moderate and low MAI classes, but a 33% reduction in high MAI classes. We found that mortality in undisturbed stands increased with stand age such that the net growth in live tree biomass, and the change in total C, was not significantly different from zero in stands over age 400 (0.15 ± 0.64 Mg/ha/yr for total C, 95% confidence interval). Mortality of large trees (>100 cm diameter) exceeded growth, but trees were growing into the larger size classes at a high-enough rate that a net increase in large tree C was seen across the region. Even though large trees accumulated C at a faster rate than small trees on an individual basis, their contribution to C sequestration was smaller on an area basis, and their importance relative to small trees declined in older stands compared to younger stands.

Forest ecosystems play a major role in the global carbon cycle because they can attain high levels of carbon storage, and can gain or lose carbon relatively rapidly (McKinley et al. 2011). Understanding the magnitude and drivers of C flux between forests and the atmosphere has been a focus of research given concerns about the effects of rising levels of atmospheric carbon dioxide on climate change (IPCC Core Writing Team 2007). The rate at which different forests store and release C through growth and decomposition is determined by available resources, environmental conditions, and their seasonal distribution. Some of this variation is reflected in the species composition of the plant community.

The net rate of C sequestration also changes with forest age and successional stage. During forest development after disturbance, after an initial period of loss from decomposition, the net rate at which C accumulates in forest stands tends to peak early in stand development, and then declines as stands age. The timing of the loss phase, peak, and the relative speed of the decline are related to the balance between gross growth, or creation of new organic material, and mortality of living material (with the difference referred to as "net growth").

Old-growth forests store large amounts of C per unit area, but change in their stocks is sensitive to the balance of tree growth and mortality. Recent studies suggests that substantial rates of positive growth in old-growth forests may be more common than previously thought (Luyssaert et al. 2008). The characteristic rates and net effects of gross growth and

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mortality of different tree sizes for C accumulation as stands age are not clear.

The objectives of this study were to assess the role of stand age, plant community type, and productivity on forest C stocks (excluding C in mineral soil) and their net changes as well as net sequestration rates over a diverse range of forest conditions. We conducted the study with inventory data from a systematic sample of National Forests in the Pacific Northwest, USA, with repeat measurements of most aboveground C pools.

METHODS

We assessed C stocks and their change on the 22.5 million ac of forested federal land administered by the Pacific Northwest (PNW) Region of the National Forest System (NFS). These lands are found primarily in the states of Oregon and Washington as well as parts of California and Idaho, U.S.A. NFS lands in this region occur in a great variety of conditions. We grouped individual plots into ten Plant Association Zones (PAZ; Table 1) designated by the climax tree species as classified by field crews using local NFS guides (Hall 1998). The data and compilation methods we used for this study are similar to those used in Gray and Whittier (2014).

There were 8,767 grid points ("plots") within NFS lands that had forested conditions measured 3 or more years apart. We grouped points of the same land class and measurement status on a plot into condition classes and assigned values for stand age, site index, and forest type based on the subsequent compilation of the FIA sample of the same plot location. We

Table 1—Area and environmental characteristics of forested plots on Pacific Northwest national forests by climax Plant Association Zones (PAZ) . Values are means. Listed most common species make up ≥80% of the live tree carbon in a PAZ. PAZs are sorted from lowest estimated mean carbon density (Mg/ha) to highest.

Plant Association Zone (PAZ)	Code	Area (1000 ha)	Annual Precipitation (cm)	Annual temperature (C)	Most common species (ranked)*
Juniperus occidentalis	JUOC	97	48	6.7	JUOC, PIPO
Pinus ponderosa	PIPO	1,102	61	6.1	PIPO
Pinus contorta	PICO	416	84	4.8	PICO, PIPO, LAOC
Pseudotsuga menziesii	PSME	1,212	82	6.1	PSME, PIPO
Abies lasiocarpa	ABLA	776	105	2.2	PSME, ABLA, PIEN, PICO
Abies concolor & *A. grandis*	ABCOGR	1,669	91	5.3	PSME, ABCOGR, PIPO
Tsuga mertensiana & subalpine parkland	TSMEpark	924	183	3.6	TSME, ABAM, ABMAS, ABLA, PSME
Lithocarpus densiflorus	LIDE3	229	210	9.8	PSME, LIDE3, ARME
Tsuga heterophylla & *Picea sitchensis*	TSHEPISI	1,742	188	7.8	PSME, TSHE
Abies amabilis	ABAM	910	222	5.4	ABAM, TSHE, PSME

* In addition to the species names and codes shown in the first two columns, LAOC = *Larix occidentalis*, PIEN = *Picea engelmanii*, ABMAS = *Abies magnifica* var. *shastensis*, ARME = *Arbutus menziesii*

grouped FIA site class codes into three "MAI classes" (<50, 50-120, >120 $ft^3/ac/yr$). Estimates of above- and below-ground live tree and standing dead tree woody C used the regional equations of merchantable bole volume, national FIA equations of stump and bark volume, species-specific wood- and bark-density parameters, and ratios of top and branch biomass to merchantable bole biomass documented in Woodall et al. (2011).

Statistical estimates used standard double-sampling for post-stratification (Scott et al. 2005), with strata defined by national forest boundaries, Wilderness boundaries, and classified Landsat satellite imagery (Dunham et al. 2002). However, a model was used to estimate maximum C density from stand age for each PAZ*MAI class group using a cumulative two-parameter Weibull model:

allCdens = exp(a0 + a1*(stdage**a2))

where allCdens was total C density (Mg/ha) and stdage was stand age (yrs). Modeling was done using proc NLIN in SAS and datasets were restricted to stand age 300 (150 for the PICO PAZs) to avoid problems with extrapolation of models into regions of sparse data.

RESULTS & DISCUSSION

The maximum mean "total" C density (live and dead woody pools, tree foliage, understory vegetation, and forest floor combined) and the apparent rate at which it was reached varied by plant association zone (PAZ) and productivity (MAI) class. The Weibull model results identified significant differences in the maximum C density attainable by PAZ*MAI class (Table 2). Maximum C density was greater in more productive MAI classes than in less productive MAI classes within most of the PAZs, and also differed among PAZs. The apparent rate of C accumulation (i.e., the steepness of the curve) also differed among PAZs, with TSMEpark and ABCOGR showing the oldest stand age to attain 75% of maximum total C, and PIPO and JUOC the youngest. The mean stand age required to reach the 75% level across PAZs was 125 years.

Sequestration rates varied significantly with stand age and MAI class. Gross growth increased to a plateau at the 80-100 year age class on low MAI sites, rose more quickly to plateau in the 20-40 year class on medium MAI sites, and peaked in the 20-60 year ages and fell by ~33% in older stands on high MAI sites (Fig. 1). Mortality rates for the medium and high MAI classes increased slowly but steadily as stand age increased, eventually matching the rates for gross growth. Consequently, net growth was not significantly different from zero for stands over 250 years old for these two groups. For the low MAI class group, the effect of the rate of C change due to mortality was more variable, with net growth not significantly different from zero for most stand age classes over 175 years old.

Table 2—Predicted maximum total carbon density at stand age 300 (150 for PICO) by plant association zone (PAZ; see Table 1) and MAI class (and 95% confidence intervals). All major pools were included except mineral soil.

	MAI class (m3/ha/yr)		
PAZ	**Low (<3.5)**	**Medium (3.5-8.4)**	**High (>8.4)**
JUOC	26 (9)	—	—
PIPO	77 (5)	100 (12)	66 (27)
PICO	88 (6)	124 (14)	—
PSME	123 (13)	237 (23)	221 (69)
ABLA	149 (17)	187 (16)	201 (81)
ABCOGR	162 (16)	246 (16)	382 (50)
TSMEpark	219 (23)	307 (35)	348 (55)
LIDE3	206 (80)	289 (44)	382 (65)
TSHEPISI	232 (44)	376 (24)	457 (24)
ABAM	271 (43)	381 (29)	425 (33)

Most of the accumulation of C in undisturbed stands across the study region was in small trees, with trees <20 in DBH at time 1 accounting for 69% of the gross growth and 87% of the net growth. Growth of the largest-diameter trees was offset by mortality, with net growth significantly <0 for trees 40-60 in DBH at time 1 (Z=3.86, P<0.001), and not different from zero for

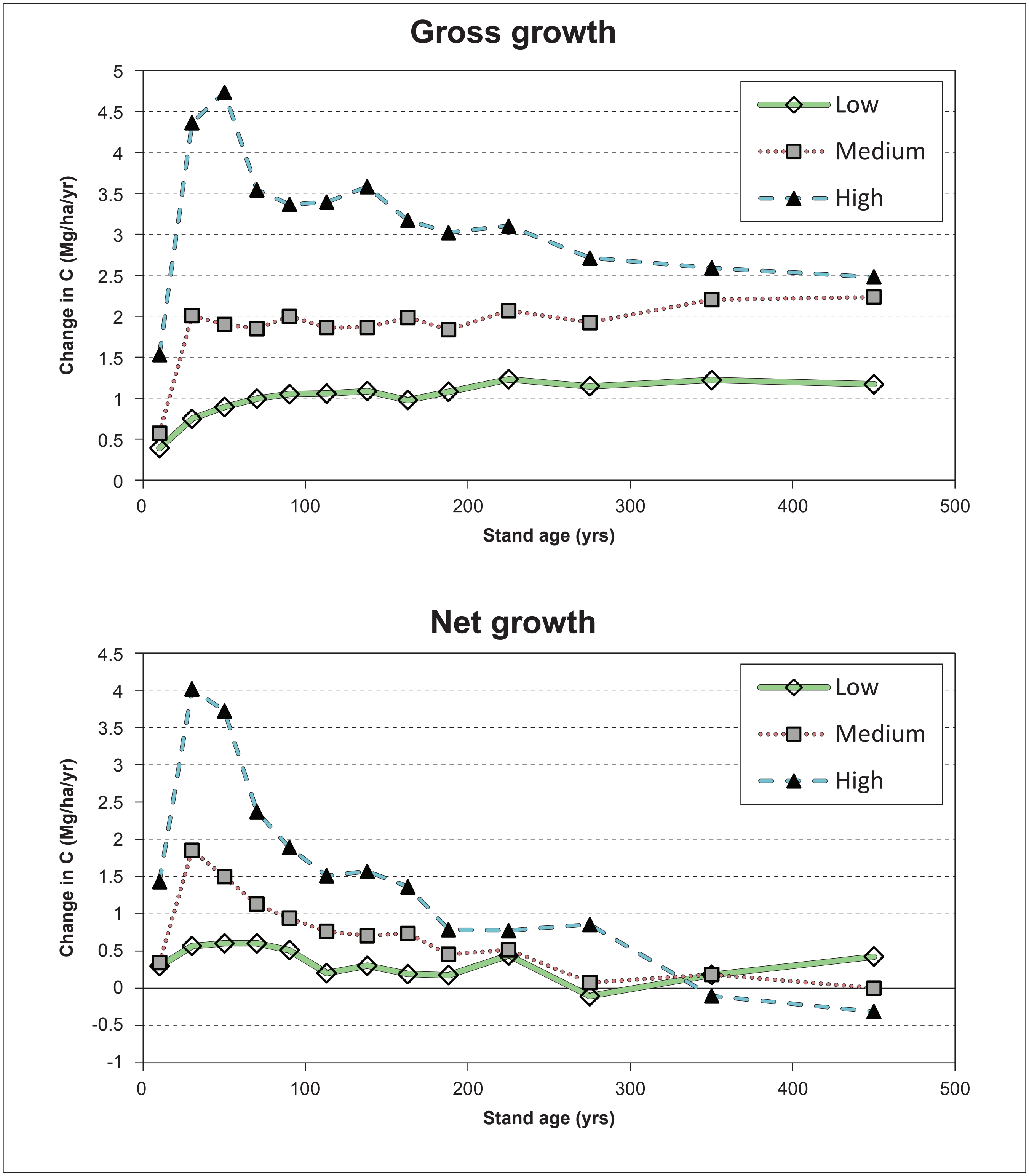

Figure 1—Annual changes in carbon in undisturbed stands by MAI class and stand age., showing gross growth on the top, and net growth (growth - mortality) on the bottom.

trees >60 in DBH (Fig. 2). Nevertheless, the density of C in large trees (and all trees >10 in DBH) increased overall in undisturbed stands due to recruitment from smaller size classes ($P<0.05$). The increase in C density in large trees also held true when disturbed stands were included ($P<0.05$), although increases for all sizes were proportionately lower, particularly in the smaller tree sizes.

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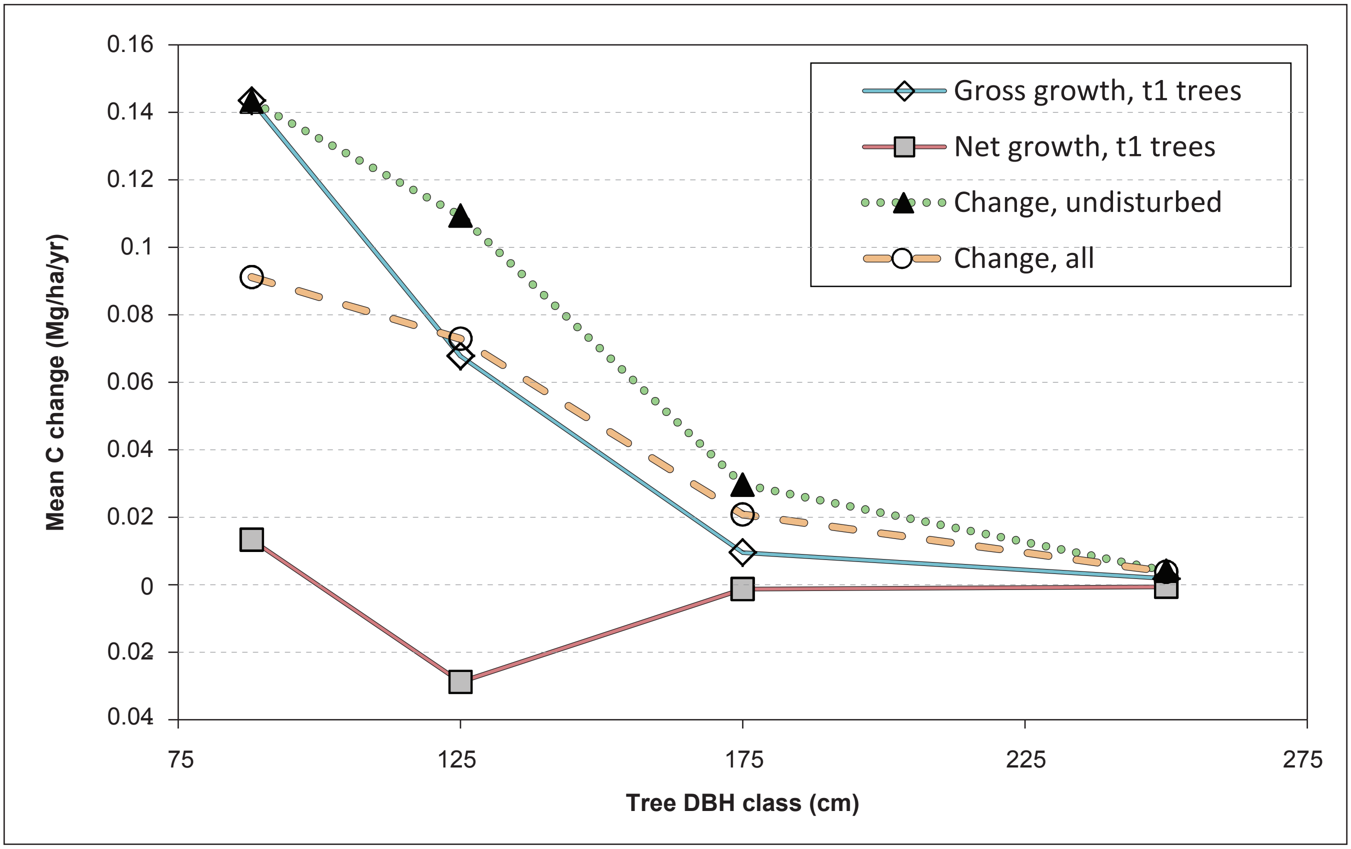

Figure 2—Change in mean live tree carbon by tree size class, showing gross growth and net growth (growth - mortality) of trees in the class at time 1, and net change (growth into and out of a class plus net growth) for undisturbed stands and for all stands.

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CHANGE DETECTION FOR SOIL CARBON IN THE FOREST INVENTORY AND ANALYSIS

An-Min Wu, Edward A. Nater, Charles H. Perry, Brent J. Dalzell, and Barry T. Wilson[1]

Abstract—Estimates of carbon stocks and stock changes in the U.S. Department of Agriculture Forest Service's Forest Inventory and Analysis (FIA) Program are reported as the official United States submission to the UN Framework Convention on Climate Change. Soil, as a critical component of the forest carbon stocks, has been sampled in about 10-year intervals in FIA with the re-measurement underway. However, the magnitude of detectable change in soil organic carbon (SOC) with the current sampling scheme is unknown. We aim to identify SOC variability and to best determine minimum detectable changes in SOC under the current sampling scheme. The project seeks to: identify statistical relationships between SOC and environmental covariates; normalize SOC data for main forest-type groups (FTGs) using identified covariates; and determine the minimum detectable change in the normalized SOC using power analysis. We investigated SOC variability for 8 FTGs: Oak-Hickory, Maple-Beech-Birch, Pinyon-Juniper, Loblolly-Shortleaf Pine, Aspen-Birch, Douglas-Fir, Fir-Spruce-Mountain Hemlock and Woodland Hardwoods. Relationships between SOC and environmental covariates (biomass/soil properties in FIA, PRISM climate data, and DEM-derived terrain attributes) are determined by multiple linear regression and are used to normalize SOC variability. The results showed that terrain attributes were not significant in explaining SOC in the FIA dataset and climate data were only significant in certain FTGs locations. Except for Oak-Hickory, Maple-Beech-Birch and Pinyon-Juniper groups, sample numbers are insufficient to detect a change in SOC less than 10 percent (%) of the mean. To guide future sampling efforts, we will continue our study on detecting minimal change in SOC and to explore sample number and sampling frequency scenarios to inform future soil sampling protocols.

The U.S. Department of Agriculture Forest Service's Forest Inventory and Analysis (FIA) Program assesses nationwide forest resources to ensure sustainable management and to report critical status and trends (Smith, 2002). One of the critical reports from the FIA is an estimate of forest carbon stocks in biomass and soil as a part of the official United States submission to the United Nations Framework Convention on Climate Change (Smith et al., 2013). Although soil is the critical component in the forest carbon system, the magnitude of detectable change in soil organic carbon (SOC) in FIA is still unknown for current sampling density and time intervals (soils are sampled at roughly 10-yr or longer intervals; Woodall et al., 2010). In order to ensure wise investment on sampling efforts, it is essential to determine which levels of SOC change are statistically meaningful.

In this study, our goals are to identify SOC variability in FIA and to determine the minimum SOC change that can be detected. Our specific objectives are to 1) identify relationships between SOC and environmental covariates, 2) reduce environment-affected SOC variability by data normalization, and 3) determine detectable SOC change using power analysis.

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MATERIALS

Mineral soils in FIA are sampled in 0-10cm and 10-20cm depth intervals and in a 10-year or longer time interval. The current FIA database, measured between 1999 –2011, contains 2783 unique plot samples with SOC measurements available in both depths. We used the latest sampling data from sites in the conterminous US; 5 coastal sites lacking elevation coverage in our terrain model were eliminated. A total of 2763 samples were used for the analysis.

We applied the resampled 250-m Elevation Derivatives for National Applications(EDNA) for terrain attributes and the 800-m long-term climate norms from the PRISM data for climate parameters.

METHODS

We calculated composite SOC density in the top 20 cm of soil and investigated its variability within forest-type groups (FTGs) at the sampling sites. Statistical analyses were stratified by FTGs to reduce variability in environmental and management conditions. FTGs selected for analyses were Oak-Hickory, Maple-Beech-Birch, Pinyon-Juniper, Loblolly-Shortleaf Pine, Aspen-Birch, Douglas-Fir, Fir-Spruce-Mountain Hemlock and Woodland Hardwoods.

We used multiple linear regression to build a best-fit SOC model for each FTG using readily available environmental covariates such as topographic attributes, climate variables, and biomass and soil properties. Forest biomass C pools (e.g., understory aboveground & belowground, dead, standing dead, and litter; litter and forest floor thickness) and soil properties (ECEC, pH, total water, total N, coarse fragments, and texture layers) are available in the FIA database. We derived topographic attributes, including elevation, slope, aspect, plan/profile curvature, and contributing area, from the EDNA dataset. We obtained 30-year averaged annual precipitation and temperature (minimum, mean, and maximum) estimates from PRISM. Environmental covariates in best-fit regression models were selected for data normalization.

To make SOC comparable across various environmental conditions in the US, we normalized the distribution to the means of the identified covariates before SOC change detection. We adjusted SOC density by off-setting the distance of covariate values to the means of the covariates with proportions using the partial regression coefficients of the SOC model. Mean, standard deviation, and coefficient of variation (CV) of SOC density in each FTG before and after data normalization were examined.

We then ran power analysis to determine the minimum detectable change in SOC using current sample numbers. We calculated the required sample sizes needed to detect specific levels of change. Power analysis provides the perspectives of statistical significance (Cohen, 1969). Its 4 components – sample size (n), effect size (Cohen's d), a significance level (Type I error, or α) and power (=1-Type II error) – allow us to determine the sample size required or an experimental effect when giving constraints to the other components. We defaulted the significance level to be 0.05 with a power of 0.8 to estimate the required sample size for a given effect, or vice versa.

RESULTS: SOC RELATIONSHIPS

Overall, SOC variability across all sites is high. SOC density for all sites has a mean of 5.08 kg m^{-2} with a coefficient of variation (CV) of 0.64. The SOC distribution varies by FTGs. The means of SOC range from 3.18 kg m^{-2} for the Loblolly-Shortleaf pine group to 6.97 kg m^{-2} for the Maple-Beech-Birch group (Table 1).

Preliminary analyses showed no significant relationships between SOC and terrain attributes, and only a few FTGs displayed significant relationships with climate. SOC models are mainly associated with biomass and soil properties (e.g. litter thickness or carbon, ECEC, coarse fragments). Besides these properties, SOC in Woodland Hardwoods, Pinyon-Juniper, and Oak-Hickory groups is also driven by precipitation and/or temperature.

RESULTS: DATA NORMALIZATION

Based on relationships between SOC and covariates identified in SOC models, data normalization reduces SOC variability for all FTGs. Data normalization adjusted diverse site environments to the means of covariates and improved CV by from 14 to 49.8 percent (%), depending on FTGs (Table 1).

RESULTS: POWER ANALYSIS

Comparing SOC detectable changes before and after normalization, the effect sizes for all FTGs increase with data normalization. Hence, the number of samples required for detecting change in SOC decreases. For example, Oak-Hickory (n=584), Maple-Beech-Birch (n=292) and Pinyon-Juniper (n=279) groups have sufficient sampling sites to detect SOC change ≤10 percent (%) of the mean, but other FTGs require more samples for such detection (Table 1). The Douglas-fir group, which currently has 174 sample sites, would need 406 samples to detect a 10 percent (%) change.

DISCUSSION

Terrain attributes were surprisingly not significant in building SOC models. Terrain attributes are typically a strong driver in SOC formation (Wu, 2014), but our results suggest that topography is not a major factor in driving SOC in forests at the national extent, possibly due to regional variations in ecological processes or terrain data resolution (Cao et al., 2012, Minasny et al., 2013).

Soil properties used to build SOC models are soil texture, particle size and related properties (e.g. ECEC, coarse fragments, and total water), suggesting texture as an important factor to further investigate C stocks and stock changes. Future sampling effort might also focus in collecting more detailed soil texture information.

Using covariate relationships, data normalization reduces sample numbers required in a given effect size. Data normalization, therefore, is effective for planning sampling efforts when study sites are located across a large area with diverse environmental conditions.

Except for Oak-Hickory, Maple-Beech-Birch and Pinyon-Juniper groups, current FIA sample numbers are insufficient to detect changes in SOC stocks ≤10 percent (%) of the mean. While re-measurements may allow us to detect SOC stock changes, our ability to do so is limited by the current number of sampling sites for most FTGs.

ACKNOWLEDGMENT

The authors thank the US Forest Service Northern Research Station for the funding support.

Table 1—Data normalization effect on variability and detectable change of soil organic carbon.

		SOC density, 0-20 cm (kg m-2)						Detectable change of the means					
		Original			Normalized			Effect size	Original		Normalized		Improvement
Forest-type groups	n	Mean	SD	CV	Mean	SD	CV	Cohen's d	(kg m-2)	(%)	(kg m-2)	(%)	(%)
Oak-Hickory	584	5.11	3.16	0.62	5.20	2.71	0.52	0.16	0.52	10.2	0.44	8.5	15.8
Maple-Beech-Birch	292	6.97	3.50	0.50	6.97	3.01	0.43	0.23	0.81	11.7	0.70	10.0	14.0
Pinyon-Juniper	279	3.48	2.11	0.61	3.48	1.25	0.36	0.24	0.50	14.4	0.30	8.6	40.5
Douglas-Fir	174	6.19	3.78	0.61	6.19	3.14	0.51	0.30	1.14	18.4	0.95	15.3	16.9
Aspen-Birch	174	5.72	2.87	0.50	5.72	1.98	0.35	0.30	0.86	15.1	0.59	10.4	31.2
Woodland hardwood	137	3.97	2.36	0.59	3.97	1.18	0.30	0.34	0.80	20.2	0.40	10.1	49.8
Fir-Spruce-Mountain hemlock	136	5.92	3.49	0.59	5.92	2.17	0.37	0.34	1.19	20.1	0.74	12.5	37.8
Loblolly-Shortleaf pine	133	3.18	2.48	0.78	3.18	1.65	0.52	0.34	0.86	26.9	0.57	17.8	33.6

Abbreviations are as follows: SOC = soil organic carbon, SD = standard deviation, CV = coefficient of variation.

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EXTRAPOLATING EXISTING SOIL ORGANIC CARBON DATA TO ESTIMATE SOIL ORGANIC CARBON STOCKS BELOW 20 CM

Edward A. Nater, Cinzia Fissore, Charles H. Perry, An-Min Wu, Brent Dalzell, and Barry T. Wilson[1]

Abstract—Estimates of forest soil organic carbon stocks across the US are currently developed from expert opinion in STATSGO/SSURGO and linked to forest type. The results are reported to the US EPA as the official United States submission to the UN Framework Convention on Climate Change. Beginning in 2015, however, estimates of soil organic carbon (SOC) stocks will be based on SOC data from soil cores collected in the field (0-10 and 10-20 cm depth). In addition, the Intergovernmental Panel on Climate Change (IPCC) Good Practice Guidance suggests these estimates extend to at least 30 cm for all forested lands. This study reports the results of that extrapolation effort. Data for this effort were obtained from the International Soil Carbon Network (ISCN) database, from analyses of more than 500 150 cm deep cores collected from forested sites across the Upper Midwest, and from cores taken at several US Forest Service Experimental Forests. SOC contents were adjusted to 0-10, 10-20, and 20-50 cm depth increments by a weighted average estimation technique if needed. Multiple linear regression modeling was used to predict the percent SOC of the 20 to 50 cm depth layer from the percent SOC of the 0-10 and 10-20 cm depth layers. Additional covariates included climatic data, latitude and longitude. Preliminary analyses show a best fit prediction $R^2 > 0.6$ for all data.

INTRODUCTION

The Forest Inventory Analysis (FIA) program has established a systematic measurement approach to provide statistically valid measures of a wide array of forest parameters, such as aboveground living tree biomass, dead and down biomass, woody shrub biomass, and others at thousands of forested sites across the United States. Soils are sampled at 0-10 and 10-20 cm depths at a subset (1 of 16) of sites and analyzed for soil organic carbon, pH, extractable metals, and other properties.

Currently, estimates of forest soil organic carbon (SOC) stocks across the US are developed from expert opinion in STATSGO/SSURGO and linked to forest type. Results are reported to the US EPA as the official US submission to the UN Framework Convention on Climate Change. Starting in 2015, however, estimates of SOC stocks will be based on SOC data from soil cores (0-10 and 10-20 cm depth) collected in the field by FIA. In addition, the IPCC Good Practice Guidance suggests these estimates extend to at least 30 cm for all forested lands.

Because FIA has not collected soils data below 20 cm, the SOC content of these deeper horizons must be estimated by statistical modeling. Further, this pedometric model can only utilize data currently in the FIA database and environmental data that can be readily obtained from other established sources.

Our objectives are to 1) develop predictive statistical relationships for deep (20-50 cm) percent SOC from percent SOC in the 0-10 and 10-20 cm depth increments and from environmental variables that can be estimated for forested sites across the US; and 2) combine these new percent SOC estimates with bulk density data to estimate SOC stocks for soils below 20 cm.

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MATERIALS AND METHODS

Mineral soil SOC data for US forests were obtained from three sources: 1) the International Soil Carbon Network (ISCN) database (International Soil Carbon Network, 2012), 2) a study we (Nater and Fissore) conducted where more than 500 deep (150cm) cores were collected from forested sites in Minnesota, Michigan, and Wisconsin, and 3) data from deep soil cores collected on several USFS Experimental Forests. Because the cores in the ISCN and the Experimental Forests were collected by multiple investigators using different protocols, sample depth increments varied widely. In order to make this model applicable to existing FIA soils data, we had to standardize the data to 0-10 and 10-20 cm depth increments as per FIA protocols, and the 20-50 cm depth increment we sought to model. We estimated the percent SOC of the three depth increments by a weighted average method. The datasets were carefully examined before and after production of the estimate to eliminate cores <50 cm deep, cores having missing SOC values, or cores that had SOC values > 12 percent (generally indicating forest floor or an organic soil horizon) or ≤ 0 percent. The initial combined dataset had 3,700 cores; more than 2800 remained after data validation.

All cores had geospatial (latitude and longitude) data, which allowed us to obtain environmental data that could be used as covariates in our regression modeling. We obtained 30-year annual precipitation, minimum temperature, mean temperature, and maximum temperature for all sites (excluding sites in Alaska, Hawaii, and Puerto Rico, where estimates are unavailable) from PRISM (PRISM Climate Group, 2015.

Stepwise multiple regression analyses were conducted in the statistical package R, v. 0.98.953 (R Development Core Team, 2011)

RESULTS

Not surprisingly, percent SOC values were not normally distributed and were normalized by a log transform. The dependent variable, $\text{Log(PercentC)}_{35}$, is the log of the percent SOC in the 20-50 cm depth increment (35 cm is the midpoint of the increment). Independent variables used in the regression modeling included:

- Log(PercentC)_{5} = log of PercentC in the 0-10 cm depth increment,
- $\text{Log(PercentC)}_{15}$ = log of PercentC in the 10-20 cm depth increment,
- Precip = the 30-year average precipitation (mm) obtained from PRISM,
- Tmin = the minimum temperature (C) obtained from PRISM,
- Lat = latitude in degrees, and
- Long = longitude in degrees.

Stepwise multiple regression modeling to predict $\text{Log(PercentC)}_{35}$ for the entire US produced the following model:

$$\text{Log(PercentC)}_{35} = -0.636 + 0.679*\text{Log(PercentC)}_{15} -0.0039*\text{Long} + 0.103*\text{Log(PercentC)}_{5} - 0.0086*\text{Tmin} + 0.000064*\text{Precip} = 0.0029*\text{Lat}$$

Adjusted $R^2 = 0.63$, df = 2817, F = 809.3, and $p < 2.2e\text{-}16$. With the exception of latitude, all variables in the regression were significant to $p<0.001$.

The strong relationship observed with longitude suggested that a better fit might be obtained by regionalizing the dataset and separately analyzing individual regions. We split the dataset into three regions based on longitude: an Eastern Region (longitude > -105°, which is roughly in central Nebraska), a Western Region (longitude < -105° and > -128°), and a Far West Region (longitude < 128°, that only included Alaska and Hawaii). Because PRISM climate data are not available for Alaska or Hawaii, they would be removed from any analysis using Precip or Tmin; consequently, we felt it best to put them in their own, albeit small, region.

Individual analyses of the three regions follows:

Eastern Region

The best fit model for the Eastern Region was:

$\text{Log(PercentC)}_{35} = -0.364 + 0.609*\text{Log(PercentC)}_{15} + 0.119*\ \text{Log(PercentC)}_{5} - 0.006*\text{Tmin}$

Adjusted $R^2 = 0.49$, df = 1971, F = 834.6, and $p < 2.2e\text{-}16$. All variables in the regression were significant to $p<0.001$.

Western Region

The best fit model for the Western Region was:

$\text{Log(PercentC)}_{35} = -0.00312 + 0.855*\text{Log(PercentC)}_{15} + 0.000047*\ \text{Precip} - 0.006*\text{Lat}$

Adjusted $R^2 = 0.74$, df = 846, F = 825, and $p < 2.2e\text{-}16$. All variables in the regression were significant to $p<0.001$.

Far West Region

The best fit model for the Far West Region was:

$\text{Log(PercentC)}_{35} = -0.00312 + 0.855*\text{Log(PercentC)}_{15}$

Adjusted $R^2 = 0.79$, df = 40, F = 156.7, and $p = 2.05e\text{-}15$. $\text{Log(PercentC)}_{15}$ was significant to $p<0.001$; no other variables were significant.

DISCUSSION

Overall, the regression models provide a good estimate of the percent SOC in the 20-50 cm depth increment. This is particularly true in the Western Region, less so in the Eastern Region. This east-west disparity may be due to a longer history of forest soil disturbance in the eastern US, which could alter these relationships, or it may be due to the higher occurrence of poorly drained soils in the east, which tend to have much higher SOC contents than well-drained soils. Improvements to the model fit may be possible with the inclusion of soil textural data (estimated from NRCS Soil Survey data) and/or elevation data.

Estimates of soil bulk density will be required in order to calculate SOC stocks at depth. FIA has no bulk density data for depths below 20 cm; therefore these data will have to be estimated, most likely from the USDA NRCS Soil Survey database for locations where data are present, and from other pedometric models for other locations (Sequeira et al. 2014).

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IMPROVING ESTIMATION OF GROWTH, REMOVALS, AND MORTALITY

ADDING NET GROWTH, REMOVALS, AND MORTALITY ESTIMATES FOR BIOMASS AND CARBON IN FIADB

Jeffery A. Turner[1]

Abstract—Traditional growth, removals, and mortality (GRM) estimates produced from Forest Inventory and Analysis (FIA) periodic inventories were limited to changes in volume on timberland. Estimates on forestland were added in the east as the first installment of annual inventory plots was remeasured. The western FIA units have begun annual remeasurement, precipitating the need to produce GRM estimates on the macroplot and for woodland species. In addition, FIA faces increased demand to produce biomass and carbon GRM estimates. Recent accomplishments that meet the need for expanded GRM estimation for carbon and biomass, as well as meeting the specific needs of the western FIA units, will be presented. The provided solution offers new challenges to the FIA on-line tools and our external users.

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IMPLEMENTING A NATIONAL PROCESS FOR ESTIMATING GROWTH, REMOVALS, AND MORTALITY AT THE PACIFIC NORTHWEST'S FOREST INVENTORY AND ANALYSIS'S REGION: MODELING DIAMETER GROWTH

Olaf Kuegler[1]

Abstract— The Pacific Northwest Research Station's Forest Inventory and Analysis Unit began remeasurement of permanently located FIA plots under the annualized design in 2011. With remeasurement has come the need to implement the national FIA system for compiling estimates of forest growth, removals, and mortality. The national system requires regional diameter-growth models to estimate diameters on trees in situations where the initial or terminal diameter is not known at the beginning or end of a measurement interval. Examples of such trees are those classified as alive at the beginning of the measurement interval and subsequently died (mortality) or have been harvested (removal). This presentation provides an overview of how we adapted regionally specific models of diameter growth into FIA's national compilation system.

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A DIAMETER GROWTH MODEL FOR SINGLE-STEM GROWTH FORMS FOR THE INTERIOR WEST FOREST INVENTORY AND ANALYSIS'S REGION

Michael T. Thompson[1]

Abstract—The Interior West Forest Inventory and Analysis Unit (IWFIA) will soon transition from a regional system to a national FIA system for compiling estimates of forest growth, removals, and mortality. The national system requires regional diameter-growth models to estimate diameters on trees in situations where the initial or terminal diameter is not known at the beginning or end of a measurement interval. Examples of such trees are those classified as alive at the beginning of the measurement interval and subsequently died (mortality) or have been harvested (removal). Only single-stem growth forms measured at either diameter at breast height (dbh) or diameter at root collar (drc) were used to build the model. The annual diameter growth rate was selected as the response variable and several potential predictor variables were tested for significance. After testing several regression equation forms, a non-linear model was chosen and the predictor variable selected was previous diameter.

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A DIAMETER GROWTH MODEL FOR THE SRS FIA

David Gartner[1]

Abstract—Changes in the national Forest Inventory and Analysis (FIA) processing system required the Southern Research Station's FIA unit to create a diameter growth model to estimate the growth of trees that could not be measured at both ends of a measurement interval. Examples of such trees are trees that have died or been harvested, and trees that grow over the minimum diameter threshold. I used a form of the Chapman-Richards function to model the growth. A function containing crown ratio, condition basal area, amount of basal area in larger trees, latitude, longitude, elevation, site class, tree mortality, and being on a plantation is used to modify the rate that a tree moves along the Chapman-Richard's curve. The model was first fit using ordinary least squares, then this set of parameters were used to estimate the errors, and then the parameters were refit using a mixed effects model. The variables used to model the variance were remeasurement period and initial predicted growth.

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EVERYTHING YOU EVER WANTED TO KNOW ABOUT GRM* (*BUT WERE AFRAID TO ASK)

Jeffery A. Turner[1]

Abstract—Querying the Forest Inventory and Analysis Database (FIADB) for growth, removals, and mortality (GRM) estimates can certainly be a conundrum. Providing the flexibility necessary to produce a wide array of GRM estimates has the unfortunate side effect of added complexity. This presentation seeks to answer some recurring questions related to GRM and how our new system can be leveraged to meet our needs.

Questions addressed include:

- What is the difference between the accounting and other methods of summarizing GRM estimates?
- Why do GRM estimates for an eastern evaluation include plots that are 10 years old?
- What happens when a tree:
- Is determined to be extraneous or missed at time 1?
- Species code differs between time1 and time 2?
- Is recorded as standing dead at time 1 but live at time 2?
- How can the same tree be a diversion in one estimate and a survivor tree different estimate?
- What is the difference between Beers/Miller and Van Deusen methodology?

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CHANGE DETECTION

HURRICANE IMPACTS ON FOREST RESOURCES IN THE EASTERN UNITED STATES: A POST-SANDY ASSESSMENT

Greg C. Liknes, Susan J. Crocker, Randall S. Morin, and Brian F. Walters[1]

Abstract—Extreme weather events play a role in shaping the composition and structure of forests. Responding to and mitigating a storm event in a forested environment requires information about the location and severity of tree damage. However, this information can be difficult to obtain immediately following an event. Post-storm assessments using regularly collected forest information from the Forest Inventory and Analysis (FIA) program of the USDA Forest Service can help inform response to future storm events. We analyzed data from the FIA program for an area along the Atlantic Coast directly in the path of Hurricane Sandy in October 2012 as well as an area in West Virginia that received heavy snowfall coincident with the hurricane. The ratio of damaged trees to all live trees was not substantially different between the pre- and post-storm observations at field sites. However, the ratio of trees with broken tops to all live trees increased in the path of the storm from 0.025 to 0.041 and from 0.019 to 0.040 in the heavy snowfall area. Hardwoods experienced an increase in broken tops in both areas, while for softwoods, an increase occurred only in the heavy snowfall area.

Extreme weather events act upon forests with outcomes ranging from minor changes in forest structure to major compositional shifts with long-term ecological consequences. Impacts on forests have been documented using diverse methodologies, including satellite remote sensing and field studies, for multiple types of severe weather such as ice storms (Bragg et al. 2003, Irland 2000), wind storms (Everham and Brokaw 1996, Nelson et al. 2009, Stueve et al. 2010), tornadoes (Peterson 2000), and hurricanes (Boose et al. 1994, Boutet and Weishampel 2003). Because of the sudden and dramatic implications of these major disturbance events, land managers and policy makers need rapid assessments of the impacts to forests. Gathering this type of information using remote sensing is often complicated by cloud cover that accompanies weather events, and logistical and safety challenges can impede immediate in situ data collection. As such, each new weather event is an opportunity to inform responses to future events. The Forest Inventory and Analysis (FIA) program of the USDA Forest Service collects forest data on a network of field plots across the United States on a recurring basis. Our objective was to use FIA data to assess changes in the condition of forest resources following a major hurricane which made landfall in the eastern United States.

Hurricane Sandy battered the Atlantic Coast of the United States in late October 2012, resulting in saltwater inundation from storm surges, rain-induced flooding, property damage estimated in the billions of dollars, and loss of life. Farther inland, a co-occurring cold weather system deposited nearly 1 meter of snow in the mountains of West Virginia and Maryland as well as heavy snow in five other states over the course of 2 days.

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METHODS

We identified FIA plots for two storm-damaged areas: the Atlantic Coast, which experienced high winds in the direct path of the storm in parts of several states (for this analysis, Connecticut, Delaware, Maryland, New Jersey, New York, Pennsylvania, and Rhode Island); and the Appalachian Mountains of West Virginia, which received heavy snowfall (Fig. 1).

In the Atlantic region, areas of probable high winds (25.7 – 32.9 m sec-1) were identified using wind swath data from the National Hurricane Center. Areas of high snowfall (≥50 mm snow water equivalent) in the West Virginia Appalachians were identified using data from the National Operational Hydrologic Remote Sensing Center Snow Data Assimilation System (NOAA 2004). For both regions, we selected FIA plots that were visited after the storm in either 2012 or 2013 and compared them to their previous plot visit, which occurred 5 to 7 years earlier (Atlantic Coast: n=195; West Virginia: n=193). Using standard FIA estimation procedures (Bechtold and Patterson 2005), we examined the ratio of trees damaged by weather events to all live trees for trees greater than 12.7 cm d.b.h. for both the pre- and post-storm conditions. Damage was assessed with regard to both damage agent codes recorded by field staff as well as those trees for which a broken top was recorded. This ratio was estimated for all trees as well as separately for select hardwoods and softwoods common in each area, and also by genus.

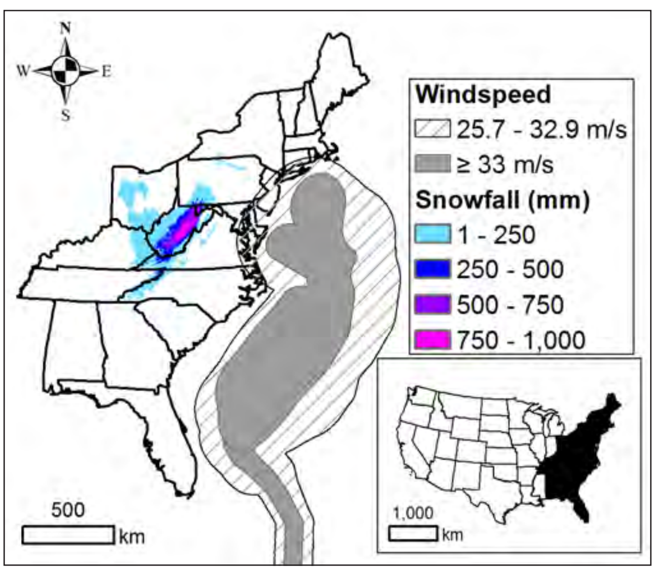

Figure 1.— Areas impacted by Hurricane Sandy in 2012. Both areas of high snowfall in the mid-Atlantic states and areas of probable high winds in the direct path of the storm are shown.

We note that for a damage code to be recorded for an individual tree, a threshold must be met. For example, the threshold for wind damage is as follows:

Any damage to the terminal leader; damage = 20 percent of the roots or boles with >20 percent of the circumference affected; damage >20 percent of the multiple-stems (on multi-stemmed woodland species) with >20 percent of the circumference affected; >20 percent of the branches affected; damage = 20 percent of the foliage with > 50 percent of the leaf/needle affected (USDA Forest Service 2010).

Broken tops are recorded for live trees if completely detached from the bole.

RESULTS

The ratio of weather-damaged trees to all trees was very low in both the path of the hurricane and in the heavy snowfall area in West Virginia and was not substantially different prior to Hurricane Sandy (Table 1). There is some variation between hardwoods and softwoods and by genus, although we note that high standard errors limit interpretation at the genus level. The impact is more apparent with regard to broken tops. In the coastal area, the broken top ratio increased from 0.025 to 0.041. The West Virginia snowfall area experienced a similar increase from 0.019 to 0.040. The ratio of broken tops for softwoods increased tenfold in the heavy snowfall area with most of the change occurring in eastern hemlock (Tsuga canadensis). Broken tops nearly doubled in hardwoods for the West Virginia study area with most tree species experiencing some increase.

In the coastal hurricane path, softwoods showed a slight, but unsubstantial decrease (Table 1). The hardwood broken top ratio increased from 0.033 to 0.057 with every genus experiencing some increase (although changes for some species are not substantial). Both Nyssa and Liquidambar (primarily tupelo and sweetgum species) had broken tops on more than 11 percent of all live trees after the storm.

Table 1—Ratio of trees damaged by weather to all trees and ratio of trees with broken tops to all trees. The sample size of live trees used in each ratio estimate is provided, as well as the lower and upper bounds of the 95 percent confidence interval (95% C.I.). Estimates are provided for all species combined, for common hardwoods/softwoods, and by genus for common species. Estimates are provided for an area affected by high winds in the path of Hurricane Sandy and for an area in West Virginia that received more than 50 mm snow water equivalent in a single storm event.

	Ratio of weather damage		Ratio of broken tree tops		n (live trees)	
	Pre-storm (95% C.I.)	**Post-storm (95% C.I.)**	**Pre-storm (95% C.I.)**	**Post-storm (95% C.I.)**	**Pre-storm**	**Post-storm**
Hurricane Path						
Overall (Total)	0.005 (0.0004, 0.0096)	0.008 (0.0034, 0.0126)	0.025 (0.0181, 0.0319)	0.041 (0.0320, 0.0500)	4236	4888
Common Softwoods	0.001 (0.00, 0.0031)	0.002 (0.00, 0.0047)	0.010 (0.0034, 0.0166)	0.008 (0.0022, 0.0138)	1197	1379
Chamaecyparis	0.000 (N/A)	0.016 (0.0013, 0.0307)	0.030 (0.0109, 0.0491)	0.017 (0.00, 0.0354)	70	64
Pinus	0.001 (0.00, 0.0031)	0.001 (0.00, 0.0029)	0.006 (0.0013, 0.0107)	0.005 (0.0004, 0.0096)	1127	1315
Common Hardwoods	0.007 (0.0003, 0.0137)	0.011 (0.0044, 0.0176)	0.033 (0.0237, 0.0423)	0.057 (0.0449, 0.0691)	2611	2970
Acer	0.005 (0.00, 0.0106)	0.017 (0.0019, 0.0321)	0.028 (0.0115, 0.0445)	0.051 (0.0330, 0.0690)	804	958
Fagus	0.000 (N/A)	0.020 (0.00, 0.0609)	0.027 (0.00, 0.0791)	0.032 (0.00, 0.0757)	58	69
Ilex	0.000 (N/A)	0.006 (0.00, 0.0185)	0.013 (0.00, 0.0419)	0.074 (0.0122, 0.1358)	136	185
Liquidambar	0.027 (0.00, 0.0797)	0.009 (0.00, 0.0212)	0.073 (0.0288, 0.1172)	0.114 (0.0598, 0.1682)	354	391
Liriodendron	0.017 (0.00, 0.0437)	0.000 (N/A)	0.029 (0.00, 0.0617)	0.065 (0.00, 0.1348)	108	111
Nyssa	0.000 (N/A)	0.013 (0.00, 0.0321)	0.082 (0.0371, 0.1269)	0.113 (0.0711, 0.1549)	200	228
Prunus	0.014 (0.00, 0.0428)	0.007 (0.00, 0.0209)	0.031 (0.00, 0.0677)	0.064 (0.0094, 0.1186)	116	123
Quercus	0.000 (N/A)	0.009 (0.0008, 0.0172)	0.019 (0.0084, 0.0296)	0.025 (0.0088, 0.0412)	768	833
Sassafras	0.027 (0.00, 0.0826)	0.000 (N/A)	0.050 (0.00, 0.1176)	0.083 (0.00, 0.1687)	67	72

Table 1—Ratio of trees damaged by weather to all trees and ratio of trees with broken tops to all trees. The sample size of live trees used in each ratio estimate is provided, as well as the lower and upper bounds of the 95 percent confidence interval (95% C.I.). Estimates are provided for all species combined, for common hardwoods/softwoods, and by genus for common species. Estimates are provided for an area affected by high winds in the path of Hurricane Sandy and for an area in West Virginia that received more than 50 mm snow water equivalent in a single storm event. (continued)

	Ratio of weather damage		Ratio of broken tree tops		n (live trees)	
	Pre-storm (95% C.I.)	Post-storm (95% C.I.)	Pre-storm (95% C.I.)	Post-storm (95% C.I.)	Pre-storm	Post-storm
Snowfall (WV)						
Overall (Total)	0.013 (0.0082, 0.0178)	0.012 (0.0070, 0.0170)	0.019 (0.0134, 0.0246)	0.040 (0.0300, 0.0500)	5360	4778
Common Softwoods	0.002 (0.00, 0.0057)	0.017 (0.0024, 0.0316)	0.005 (0.00, 0.0115)	0.050 (0.0145, 0.0855)	392	376
Picea	0.000 (N/A)	0.025 (0.00, 0.0647)	0.00 (N/A)	0.0 (N/A)	158	160
Tsuga	0.003 (0.00, 0.0087)	0.018 (0.00,0.0369)	0.00 (N/A)	0.067 (0.0183, 0.1157)	234	216
Common Hardwoods	0.014 (0.0087, 0.0193)	0.012 (0.0066, 0.0174)	0.021 (0.0147, 0.0273)	0.039 (0.0290, 0.0490)	3770	3358
Acer	0.017 (0.0080, 0.0260)	0.008 (0.0023, 0.0137)	0.017 (0.0090, 0.0250)	0.036 (0.0209, 0.0511)	1627	1412
Betula	0.004 (0.00, 0.0096)	0.009 (0.00, 0.0194)	0.009 (0.00, 0.0202)	0.017 (0.0032, 0.0308)	544	493
Fagus	0.013 (0.0001, 0.0259)	0.012 (0.00, 0.0242)	0.041 (0.0025, 0.0795)	0.090 (0.0379, 0.1421)	333	329
Fraxinus	0.026 (0.00, 0.0572)	0.033 (0.00, 0.0787)	0.000 (N/A)	0.089 (0.0055, 0.1725)	85	75
Oxydendrum	0.010 (0.00, 0.0288)	0.010 (0.00, 0.0296)	0.046 (0.0125, 0.0795)	0.052 (0.0126, 0.0914)	133	123
Prunus	0.006 (0.00, 0.0175)	0.019 (0.00, 0.0440)	0.027 (0.0031, 0.0509)	0.023 (0.00, 0.0509)	243	249
Quercus	0.006 (0.0000, 0.0120)	0.006 (0.00, 0.0128)	0.015 (0.0050, 0.0250)	0.012 (0.0039, 0.0201)	673	567
Tilia	0.026 (0.00, 0.0766)	0.012 (0.00, 0.0349)	0.035 (0.00, 0.0870)	0.064 (0.0128, 0.1152)	132	110

DISCUSSION

While overall reported estimates of damage were relatively low, this assessment provides an initial indication of the impacts of Hurricane Sandy on forests in the eastern United States. Analysis was influenced by several factors. First, a large-scale, long-lived wind storm (i.e., a derecho) swept through West Virginia on June 29, 2012, just 4 months before the snowfall associated with Hurricane Sandy. Anecdotal reports indicated many trees in the state experienced weather-related damage due to wind gusts up to 44 m sec^{-1}, and it is difficult to separate trees damaged by wind in June and those damaged in the snowstorm in late October when damage observations occurred after both events. In addition, the FIA damage codes used in the region through 2012 were generic and included a single code for weather. As a result, wind damage and heavy snowfall damage could both be labeled as "weather" damage. Beginning with the 2013 inventory year, more detailed codes were implemented. Finally, the amount of FIA data available for the post-storm period was limited at the time of this analysis. Damage appears to be sporadic and patchy with some plots having up to 25 percent of all trees impacted by weather. Yet, a large number of plots in the storm areas had little or no weather-related damage that rose to the threshold described previously. As additional FIA observations become available, we will also examine mortality and down woody materials and should be better able to fully assess the impact on forest resources, in both the direct path of Hurricane Sandy and the associated snowstorm.

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CLOUD-BASED COMPUTATION FOR ACCELERATING VEGETATION MAPPING AND CHANGE DETECTION AT REGIONAL TO NATIONAL SCALES

Matthew J. Gregory[1], Zhiqiang Yang[2], David M. Bell[3], Warren B. Cohen[4], Sean Healey[5], Janet L. Ohmann[6], and Heather M. Roberts[7]

Abstract—Mapping vegetation and landscape change at fine spatial scales is needed to inform natural resource and conservation planning, but such maps are expensive and time-consuming to produce. For Landsat-based methodologies, mapping efforts are hampered by the daunting task of manipulating multivariate data for millions to billions of pixels. The advent of cloud-based geospatial computing platforms, such as the Google Earth Engine (GEE), enables a solution to big data problems by providing an environment for massively parallel processing of simple to complex algorithms. In addition to the obvious processing benefits, GEE supplies access to petabytes of remote sensing, topographic, and climatological data, including the entire Landsat archive. As a proof of concept, we will demonstrate the utility of GEE in vegetation change detection and mapping at both regional and national scales. We showcase two current projects utilizing GEE: 1) a random-forest based ensemble model incorporating information from leading change detection algorithms and 2) a nearest neighbors model combining forest inventory plots and spatial predictors to produce regional to national forest vegetation maps. Our early results suggest that this programming approach is ideal for rapid prototyping of change detection and forest vegetation modeling, including flexibility in specifying model forms and spatial covariates. We envision that this type of computing system could support many of FIA's national data products.

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LAND-USE CHANGE AND NEW HOUSES ON FORESTLAND: CONTRASTING TRENDS OVER 30 YEARS IN OREGON AND WASHINGTON

Andrew N. Gray, Joel L. Thompson, and Gary J. Lettman[1]

Abstract—Conversion of forest, range, and agricultural resource lands to residential and commercial uses affects the available land base, management practices on remaining resource lands, habitat quality, and ecosystem services. The Forest Inventory and Analysis program (FIA) mandate includes monitoring changes in the land area in forest use, and this has proved valuable for policy-makers interested in the effectiveness of laws regulating changes in local land-use. A variety of semi-automated approaches have been used to identify land-use change with imagery, but distinguishing changes in land cover from changes in land use has proven difficult in many vegetation types. We mapped land-use zones across Oregon and Washington and identified houses in 33 ha circles around 81,556 photo-points distributed across non-federal ownerships. Interpretations were done using high-resolution digital NAIP imagery and earlier photography, with summaries and spatial analyses done in GIS. We found that the area of nonfederal land in resource land uses (forest, range, and agriculture) declined by 2 percent between 1974 and 2009 in Oregon and by 4 percent between 1976 and 2006 in Washington. After land-use plan implementation in Oregon, nonfederal land converted from resource land uses decreased from 0.37 to 0.10 ha per new resident. In Washington, the loss remained constant at 0.18 ha per new resident. For lands remaining forestland in both states, housing density approximately doubled over a 30-year period. A substantial portion of the increased housing density on forestlands was in close proximity to public lands, suggesting an attraction of development in rural areas to amenities on public forestland. The Oregon Board of Forestry is using this ongoing study to assess the effectiveness of state conservation policies, establish metrics and indicators for use in limiting of productive forestland, and evaluate proposals to modify land-use laws and plans.

How urban and residential areas develop to accommodate population growth can have varying effects on forest and agricultural resource lands. A common concern with current land use change in the United States is with the expansion of housing and its effects on traditional economic production from rural lands (Kline et al. 2004, Wear et al. 1999) and on natural habitats and the ecosystem services they provide. In response to these concerns, some states in the Western United States have established planning programs to develop and update land use plans, often at the county or multicounty level, to guide the location and nature of development. Consideration in these plans is usually given to maintaining resource land uses while allowing development in appropriate areas.

In Washington State, the Growth Management Act of 1990 required counties to adopt comprehensive plans and regulations to plan for and address the impacts of growth. Oregon enacted the Land Conservation and Development Act in 1973, which was fully implemented statewide by the mid-1980s. Both laws were intended to limit conversion of highly productive resource lands and to plan for the conversion of forest and agricultural lands to urban uses where appropriate.

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One of the goals of the Forest Inventory and Analysis (FIA) program is to track changes in the area of forest land, which has been a key part of inventory reports since the 1930s. However, given the low rate of land-use change in most regions of the country (<0.5%/yr), the current density of one plot per 2,400 hectares results in imprecise estimates at sub-state levels. A procedure based on photo-interpretation of FIA Phase 1 points has proved useful for assessing change in relation to geography and landscape context (MacLean and Bolsinger 1997). The objective of this paper is to synthesize results of recent applications of that technique in the states of Oregon and Washington.

METHODS

The study area consisted of all Oregon and Washington counties, but most of the analyses excluded large federal landowners whose mandate is to maintain natural land cover (namely, National Forest Systems, National Park Service, and Bureau of Land Management). All other lands are referred to as "nonfederal" for convenience. Land use classes were defined by a combination of land cover, density and spatial pattern of human structures, road density, and the amount of area in contrasting, contiguous land uses. The minimum mapping unit of resource land uses (either pure or mixed combinations of forest, range, or agriculture) was 260 ha (640 acres). Low-density residential and urban areas could be any size, but had to have at least nine houses in a clumped or dense pattern. The term "house" is meant to represent individual dwellings, thus multiple associated buildings (e.g., barns and sheds) would all count as a single house.

Aerial photographic imagery was used for this study, which was either captured digitally or digitized and georeferenced. The most recent imagery was obtained from USDA's National Agricultural Imagery Program (NAIP), which is collecting data across the conterminous US on a 3-year cycle. Land use class polygons were delineated in a GIS over displayed imagery for different dates. Land use calls were assigned to a systematic-random grid of photointerpretation points with a density of one point per 187 ha. Structures were counted in 32-ha circles around each nonurban grid point, in effect sampling 17 percent of the nonurban classes. Houses were individually recorded in a GIS. These photo interpretation procedures were repeated for several dates of imagery.

RESULTS & DISCUSSION

Nonfederal land in resource land uses (forestry, range, and agriculture) declined by 249,000 ha in Oregon (2%), and by 470,000 ha in Washington (4%) from 1976 to 2006. Losses were greatest on the west sides of each state, and the proportional losses of agricultural and mixed forest/agriculture land uses were greater than those of wildland forest (Fig. 1). As might be expected, areas that were converted to urban and residential uses tended to be at lower elevations and more moderate slopes than average (Gray et al. 2013), reflecting that a significant portion of forestland is simply not readily developable.

Land use change in the West is driven by population increases, largely from migration from other areas. While the loss of forestland in western Washington has been greater than that of western Oregon, the number of new residents has been greater as well. Over the 30-year period of the study, the area of development per new resident has been lower in western Washington than in western Oregon (Table 1). In Oregon the rate (area per person) changed dramatically before and after the 1990s from 0.37 to 0.10 ha per new resident, while in Washington, the loss remained at 0.18 ha per new resident (Lettman et al. 2013). Most of the development occurred on the west sides of each state, where the rate over the full 30-year period was remarkably similar at 0.14 ha per new resident (Table 1). It's not clear whether a big pulse of development occurred in Oregon in anticipation of the new laws, or if the geography and economy were more conducive to dispersed development prior to implementation of land-use laws.

Land classified as wildland forest does contain dispersed housing at low densities. The mean density of dispersed housing on forestland increased significantly in both states. The greatest increases were found in eastern Oregon, although overall densities

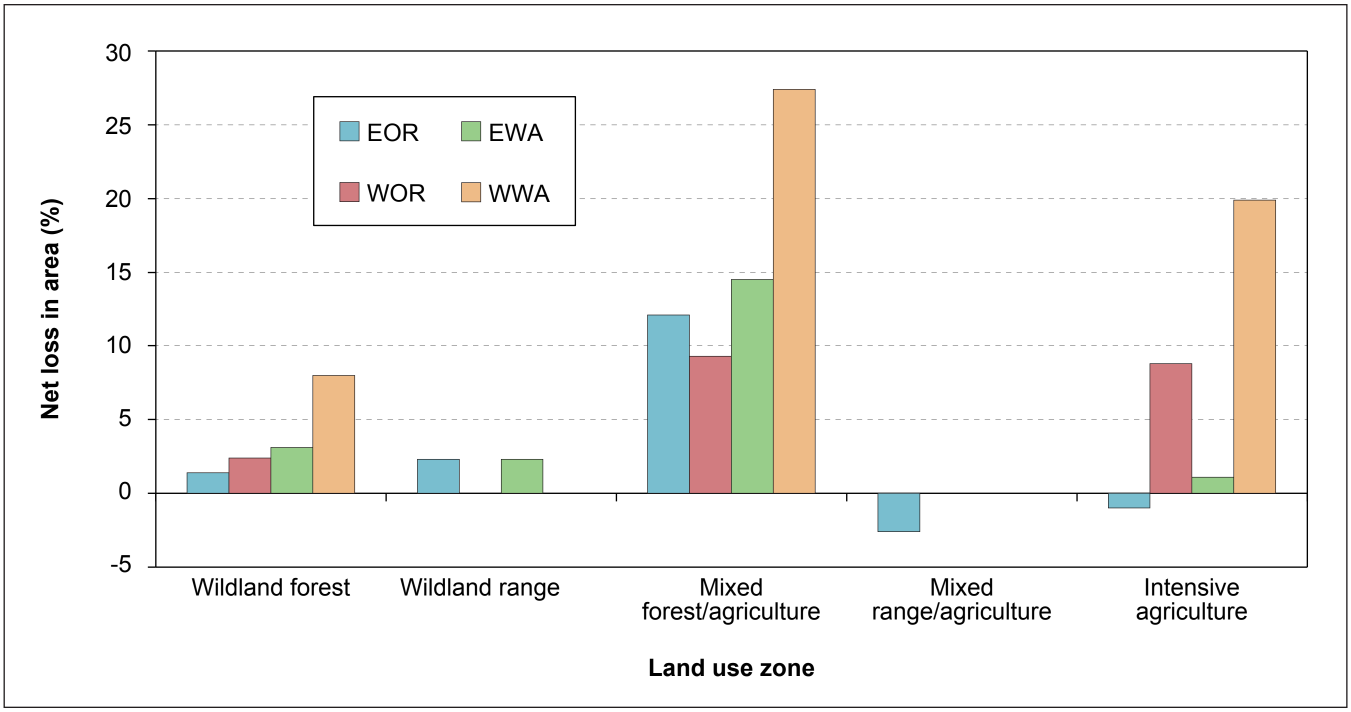

Figure 1—Net loss in area in resource land uses in Oregon and Washington from 1976 to 2006, by East and West side of state.

Table 1—Change in area in resource land uses (forest and agriculture) and change in population, 1976-2006, western Oregon and Washington.

	WOR	WWA
Change in resource land use (ha)	-158,238	-306,389
Change in number of people (N)	1,148,631	2,193,304
Area of change in resource land per new person in state (ha/N)	-0.14	-0.14

Table 2—Change in density of houses in 32-ha circles around points in wildland forest use on nonfederal land in Oregon and Washington, by East and West side of state.

	Number per km²			Change
Area	1976	1994	2006	1976-2006
EOR	0.08	0.19	0.23	300%
WOR	0.39	0.66	0.89	230%
EWA	0.40	0.63	0.83	208%
WWA	1.37	1.93	2.59	189%

were still relatively low (Table 2). Rates of increase were comparable in the other portions of the two states, but the highest house densities throughout the study were found in western Washington. Dispersed development can have important implications for land management. For example, it becomes more difficult and more expensive to try to protect houses from forest fires (Stein et al. 2013). A study of the metropolitan area around Portland (1 county in Washington and 3 in Oregon) found that state-mandated urban growth boundaries did have an effect at constraining development, but the amount of dispersed development varied considerably among counties (Kline et al. 2014).

Federal and state land management can also be affected by development on private lands, because people are often attracted to the amenity values of public lands (Azuma et al. 2013). Over the 30 year period, the density of houses within 1 km of public lands increased in both states, with the greatest increases found near Washington state lands (Fig. 2). State lands in Washington tend to be more dispersed and intermingled with other ownership classes than the other public ownerships are.

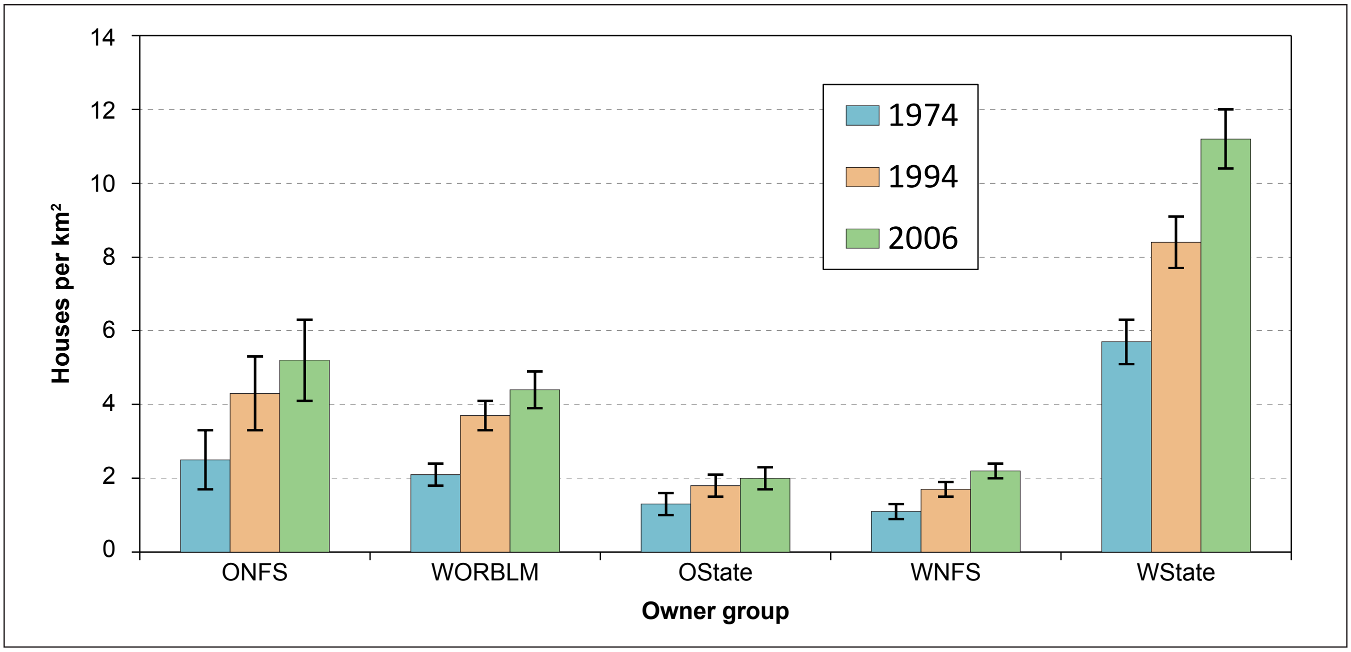

Figure 2—Change in the mean number of houses per square kilometer on private land less than 1 km from public owners in Oregon and Washington (O and W prefixes for National Forest System [NFS] and State land; WORBLM refers to Bureau of Land Management lands in western Oregon).

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EXAMINING *PSEUDOTSUGA MENZIESII* BIOMASS CHANGE DYNAMICS THROUGH SUCCESSION USING A REGIONAL FOREST INVENTORY SYSTEM

David M. Bell[1], Andrew N. Gray[2],

Abstract—Models of forest succession provide an appealing conceptual framework for understanding forest dynamics, but uncertainty in the degree to which patterns are regionally consistent might limit the application of successional theory in forest management. Remeasurements of forest inventory networks provide an opportunity to assess this consistency, improving our understanding of forest dynamics through succession at regional scales. In this study, we examined the responses of proportional *Pseudotsuga menziesii* biomass change to successional status, relative abundance, resource availability, and canopy cover change across an elevational and longitudinal gradient in the Cascade Mountains of Oregon and Washington, USA. Our objective was to assess the consistency (i.e., equivalence between climax vegetation types) of proportional biomass change responses in the dominant species, *P. menziesii*, across the region using repeated measurements of 9700 Current Vegetation Survey (CVS) forest inventory plots. Our results indicated that proportional biomass change for *P. menziesii* responses to successional status (i.e., stand age, mean tree biomass, and canopy cover), canopy cover change, and abiotic environmental conditions varied regionally. Biomass losses associated with reductions in canopy cover were mostly observed in drier regions. These results imply that individual mortality may be a particularly important driver of biomass loss in dry ecosystems while *P. menziesii* in wetter ecosystems may be more capable of taking advantage a competitor's death, offsetting ecosystem level biomass losses. Our analysis of proportional biomass change in a regionally dominant conifer tree species (*P. menziesii*) emphasizes the importance of forest successional status and small-scale changes in forest structure on ecosystem productivity.

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REMEASURED FIA PLOTS REVEAL TREE-LEVEL DIAMETER GROWTH AND TREE MORTALITY IMPACTS OF NITROGEN DEPOSITION ON CALIFORNIA'S FORESTS

Mark E. Fenn, Jeremy S. Fried, Haiganoush K. Preisler, Andrzej Bytnerowicz, Susan Schilling, Sarah Jovan, and Olaf Kuegler[1]

Abstract—The air in California's forests spans a broad range of purity, from virtually no locally generated pollutants to highly elevated levels of pollutants in forests downwind of urban and agricultural source areas. Ten-year remeasurement data from Forest Inventory and Analysis (FIA) plots in California were used in combination with modelled atmospheric nitrogen (N) deposition to evaluate tree diameter growth and mortality responses across the state. After controlling for tree size, site productivity, climate attributes, stand density, and competition experienced by each tallied tree, we found significant N deposition effects on tree bole growth when N deposition exceeded a threshold of approximately 15 kg/ha/yr. Increased tree mortality for all 14 species combined appears to increase when N deposition exceeds 10 kg/ha/yr, although the confidence intervals on the response curve are large. Preliminary analyses suggest ozone modifies the growth response, particularly at lower N deposition levels.

Long term N deposition and ambient ozone are the two major pollutants impacting forests in California, USA. Little is known of the dose-response relationships for tree growth and mortality to the combined exposure to these two pollutants in the Mediterranean climate of California. In contrast to the spatially extensive field survey on which this study is based, controlled experiments with N generally involve N fertilization additions which cannot replicate the chronic atmospheric inputs of N to forest canopies as deposition in dry (gaseous and particulate), cloud-water, and wet forms. Likewise, many ozone studies are based on fumigation chamber experiments with seedlings or saplings or Free-Air Controlled Exposure studies using a limited number of tree species. We present a preliminary analysis of tree basal area growth and mortality in response to these pollutants for 14 major tree species, most of them widely distributed across California, using data from the US Forest Service, Forest Inventory and Analysis (FIA) program.

METHODS

A statewide growth, removals, and mortality dataset containing ten-year remeasurement data from 1706 FIA plots (33,091 trees) in California forests provided the basis for evaluating the growth and mortality implications of atmospheric nitrogen deposition and ozone exposure for 14 tree species commonly encountered in California's forests. Nitrogen deposition ranges were limited for individual tree species so we analyzed N deposition effects for two broad species groups---conifers and hardwoods. We relied on measurements in the FIA dataset of trees, greater than 12.7 cm diameter breast height (d.b.h.) at the initial visit, conducted between 1/16/2001 and 10/26/2004 (Time 1) and that were remeasured approximately 10 years later, between 4/6/2011 – 11/12/2013 (Time 2). Relative basal area increment (BAI_{rel}) was calculated as the mean annual change in tree basal area between time 1 and time 2, scaled by the basal area at time 1:

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$Y = BAI_{rel} = 100*(BA2 – BA1)/(BA1xDt)$

Where BA1 and BA2 are, respectively, tree basal area at time 1 and 2, and Dt is the remeasurement interval in years.

In order to estimate effects of various factors on BAI_{rel} we used the following Generalized Additive Model (GAM) with a multiplicative log-normal error term:
Y = Site effect x Tree effect x Climate x Nitrogen x error

Variables [and variable type] included in these model terms are as follows:

Site Effect:

- Crown ratio (cr1 and cr2), [continuous]
- mean annual increment (derived from site index), [continuous]
- basal area of trees larger than the subject tree, [continuous]
- BurnCode, (5 levels of effect of fire during the remeasurement interval on stand basal area) [categorical]
- Harvest, (5 levels of effect of harvest during the remeasurement interval on stand basal area) [categorical]
- Other disturbance, insect, disease [categorical]

Tree Effect:

- Diameter at time 1 [continuous]; tree species [categorical]

Climate Effect:

- Mean annual temperature & precipitation [continuous]
- moisture deficit [continuous]
- frost-free days [continuous]

Nitrogen:

- Total N based on the EPA CMAQ model with output adjusted based on throughfall N deposition data (Fig. 1; Fenn et al. 2010) [continuous].

Tree mortality response was evaluated with a logistic model. We have plans to more fully utilize two-week average ozone concentration data from passive sampler networks after developing a more biologically relevant ozone exposure index from the data. As supportive information, soil C and N data from the FIA P3 plots were also used to evaluate relationships between N deposition and N fertility of the soils in the P3 plots.

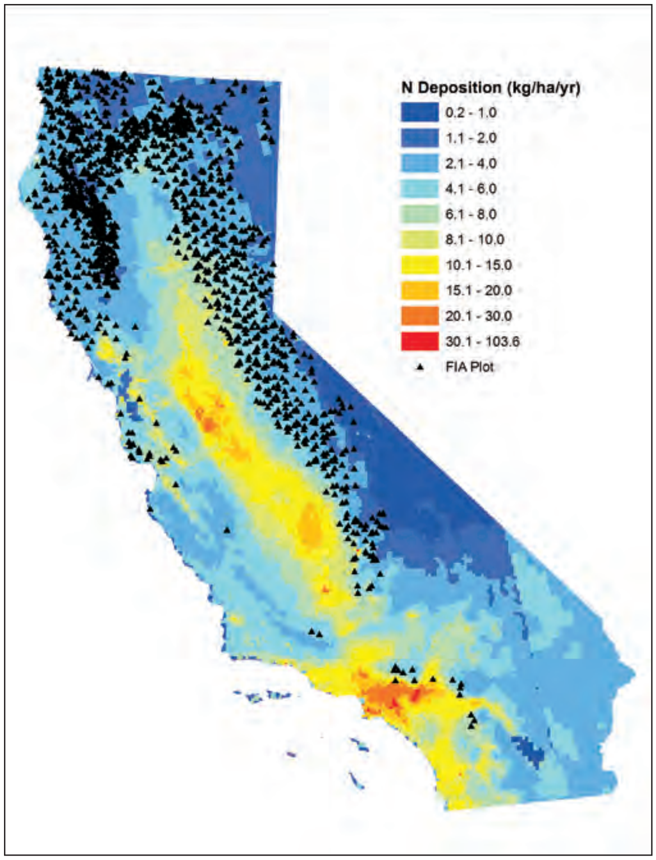

Figure 1—*Modeled, annual N Deposition* in California and locations of FIA plots used to estimate N deposition effects on tree growth.

RESULTS

Above an N deposition threshold of ca. 15 kg/hr/yr, tree diameter growth appears to increase in response to increasing atmospheric N deposition. This is true for conifers and hardwoods, although we were not able to test the growth or mortality responses of individual species. In a model with no species effect other than diameter, growth also increased with increasing N deposition (Fig. 2). When a model with two species categories (conifer and hardwood) was employed, growth for the conifer species increased above N deposition of ca. 15 kg/ha/yr (Fig. 3a). However, at N deposition rates below this threshold, a bimodal response was evident, with potentially reduced growth

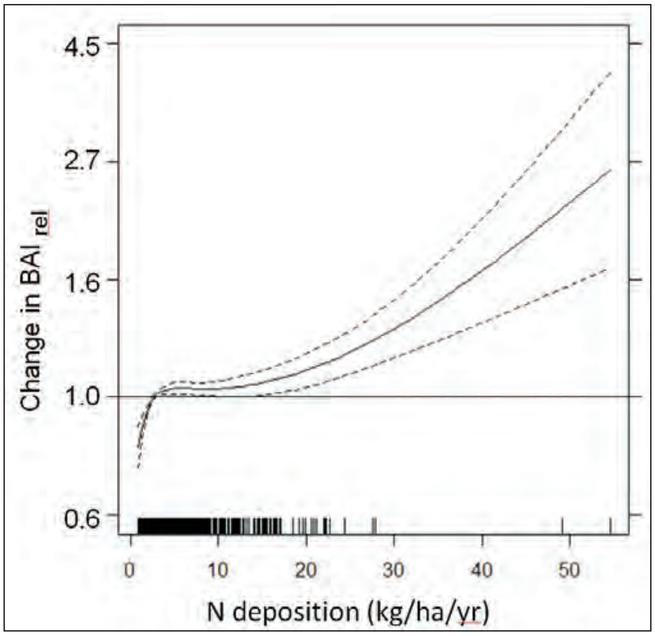

Figure 2—Estimated effect of total N deposition on relative basal area increment (BAI_{rel}) relative to BAI_{rel} at average N deposition, over full range of N deposition, for all 14 species combined. Values on the y-axis represent multiplicative change in BAI_{rel} relative to BAI_{rel} at average Ndep, which is ca. 4 kg/ha/yr. Dashed lines are 95 percent confidence bounds.

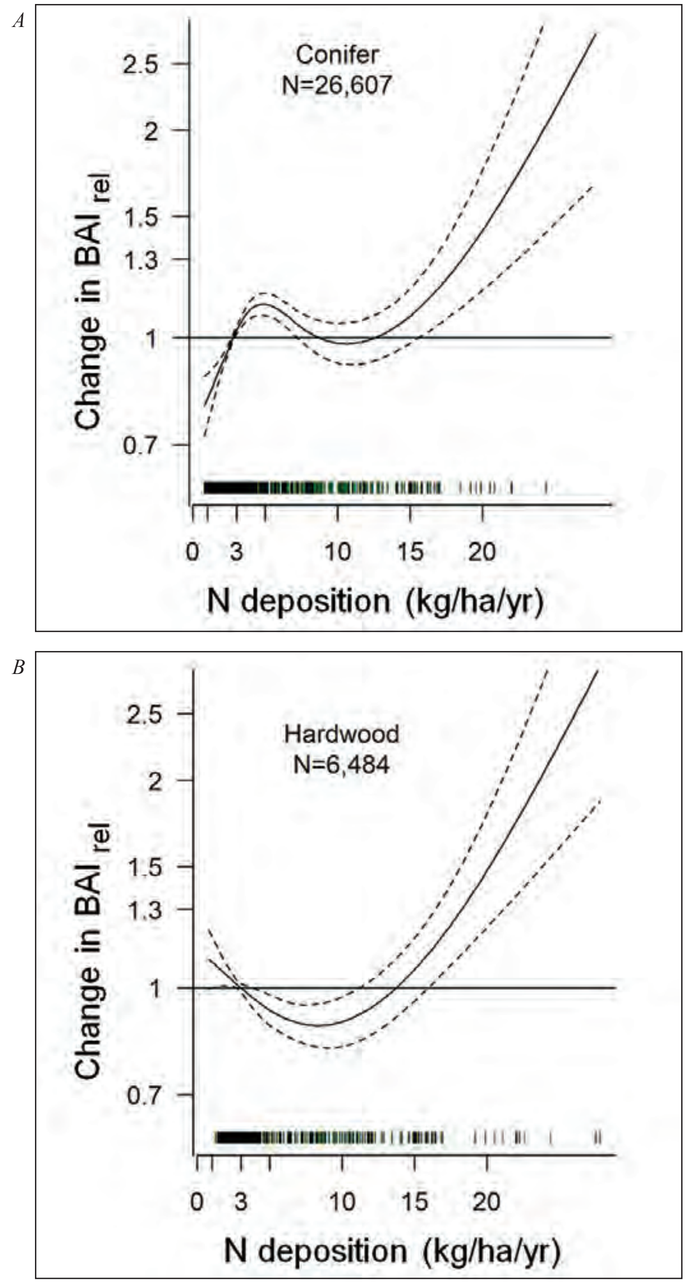

Figure 3—Estimated effect of total N deposition on relative basal area increment (BAI_{rel}) relative to BAI_{rel} at average N deposition, for a) conifers, and b) hardwoods, excluding the few plots where modeled N deposition exceeds 40.

at low N deposition, followed by an increase over the range of 3-9 kg/ha/yr, and then another reduction, over the range 9-15, before steadily increasing at N deposition values greater than 15 kg/ha/yr. Similarly, with the lumped hardwood species, growth appears to decrease as N deposition goes from 1-10 kg/ha/yr, before increasing (Fig. 3b).

Tree mortality did not increase in response to N deposition until a threshold of ca. 10 kg/ha/yr at which point it steadily increased (Fig. 4). The probability of a tree dying over the ten-year period increased from 11 percent at the average level of N deposition (4.3 kg N/ha/yr) to 14 percent at 20 kg/ha/yr and 17 percent at 28 kg N/ha/yr.

Evidence of soil enrichment with N was seen in data on C:N ratios of the forest floor and mineral soil horizons (0-10 and 10-20 cm depths). Correlation coefficients were low (0.06 – 0.09) because of scatter in the data at the many sites where N deposition was low. C:N in the forest floor decreased from 45 to 25 as N deposition increased from 1 to 35 kg/ha/yr (data not shown). Over the same range of N deposition, C:N in mineral soil decreased from 24 to 10 and from 22 to 10 in the top two layers of the mineral soil.

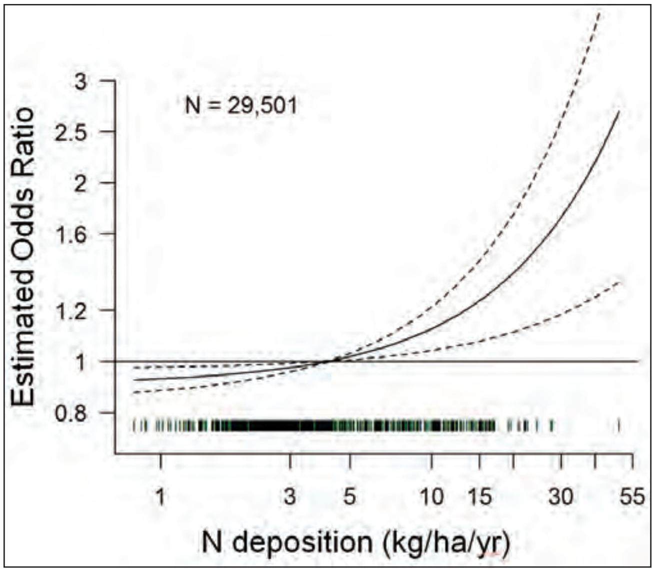

Figure 4—Estimated effect of total N deposition on tree mortality (odds relative to the odds at the average value of N deposition), for all 14 species combined.

DISCUSSION

Many studies have shown increased forest growth with increasing N deposition. In Italy, diameter growth increased steadily as N deposition levels increased beyond the lowest level of ca. 7 kg N/ha/yr (Ferretti et al. 2014). While it isn't entirely clear why we did not see an increase in growth until N deposition exceeded 15 kg/ha/yr, preliminary analyses suggest exposure to ozone may be muting the N deposition response at low N deposition in California. Above 15 kg N/ha/yr, we found consistent growth increases whether hardwoods and conifers were considered separately, or together. This does not mean that the growth response of every species will be positive, given that species responses to N deposition can differ greatly (Thomas et al. 2010).

Although tree growth appears to increase with N deposition, tree mortality also showed an increase with a threshold of ca. 10 kg/ha/yr. Future analysis plans include estimating effects of N deposition on stand level C increment and consideration of more biologically relevant ozone exposure indices (e.g., W126) and possible responses to N dep. of pests and diseases.

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US FORESTS ARE SHOWING INCREASED RATES OF DECLINE IN RESPONSE TO A CHANGING CLIMATE

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Abstract—How vulnerable are US forest to a changing climate? We answer this question using Landsat time series data and a unique interpretation approach, TimeSync, a plot-based Landsat visualization and data collection tool. Original analyses were based on a stratified two-stage cluster sample design that included interpretation of 3858 forested plots. From these data, we derived annual plot-based estimates (with uncertainties) of rates of forest decline from 1985-2012. Noted was a dramatic national-level increase in rates from the mid-90s (<1% of total forest per year) to 2000 (nearly 3% per year), with these elevated rates persisting for most of the past decade. Although forest decline was observed in eastern forests, the overwhelming proportion was in western forests, where rates reached as high as 8% per year. Increases in observed rates of decline exhibited a strong statistical relationship with the coupling of increasing summertime temperatures and decreasing precipitation beginning in the mid-90s. Using a statistical model, we developed a predictive relationship between forest decline and climate that allowed us to project the likelihood of forest decline forward to 2100 using expected climate projections. This analysis revealed that, even under reduced carbon emission scenarios, US forests are likely to be increasingly vulnerable to climate change. We are currently collecting more TimeSync interpretations (~10,000) and developing improved modeling strategies, and will present results from this more recent analysis.

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A SPACE-TIME LOOK AT TWO-PHASE ESTIMATION FOR IMPROVED ANNUAL INVENTORY ESTIMATES

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Abstract—Over the past several years, three sets of new temporal remote sensing data have become available improving FIA's ability to detect, characterize and forecast land cover changes. First, historic Landsat data has been processed for the conterminous US to provide disturbance history, agents of change, and fitted spectral trajectories annually over the last 30+ years at 30 m resolution. Second, the collection of TimeSync data is becoming more widespread and allows image interpreters to capture three decades of forest disturbance and recovery on FIA plots in a consistent and repeatable fashion. Third, the Image-based Change Estimation (ICE) project is gaining momentum and involves collecting detailed land-use land-cover change information on FIA plots using two or more dates of NAIP imagery. Here we present a two-phase estimation approach to combine wall-to-wall landsat-based products, TimeSync observations, and FIA plot data in space and time, improving annual estimates of forest attributes. We illustrate this approach using data collected in the state of Utah. We also discuss potential for integrating ICE data under this framework.

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REPEATED MEASURES FROM FIA DATA FACILITATES ANALYSIS ACROSS SPATIAL SCALES OF TREE GROWTH RESPONSES TO NITROGEN DEPOSITION FROM INDIVIDUAL TREES TO WHOLE ECOREGIONS

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Abstract—The abundance of temporally and spatially consistent Forest Inventory and Analysis data facilitates hierarchical/multilevel analysis to investigate factors affecting tree growth, scaling from plot-level to continental scales. Herein we use FIA tree and soil inventories in conjunction with various spatial climate and soils data to estimate species-specific responses of tree growth to nitrogen (N) deposition across the contiguous United States. Plot-level analyses have shown that N deposition affects tree growth but not uniformly. Increases in bio-available N can stimulate tree growth rates but also impair soil fertility, increase plant susceptibility to pathogen infection, and alter competition between plant species. How these effects scale to regional landscapes will in part determine the trajectory of forest composition and health. We use the repeated measures in FIA data to calculate growth rates of thousands of individual trees nationwide and then compare them to other available spatial data for climate and soil and deposition chemistry. Specifically, we address the following questions: 1) What are the species-specific growth responses to N deposition? and 2) What are the variances of these responses with respect to scales of individual tree, FIA plot, and ecoregion? Tree growth responses were nonuniform across the more than 100 species examined. Growth rates varied across the range of N deposition to include continuous increases in growth, continuous decreases in growth and threshold responses among the different species. Important covariates affecting tree growth in addition to N deposition from FIA data include canopy position and various soil characteristics. We hypothesize that large variances across individual tree, FIA plot, and ecoregion scales will indicate scale-dependent covariates and regional sensitivity of forests to N deposition.

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FIELD VISION: FOREST MONITORING COLLABORATIONS FROM A DATA COLLECTION PERSPECTIVE

BRIDGING THE GAP BETWEEN DATA ANALYSIS AND DATA COLLECTION IN FIA AND FOREST MONITORING GLOBALLY: SUCCESSES, RESEARCH FINDINGS, AND LESSONS LEARNED FROM THE WESTERN US AND SOUTHEAST ASIA

Leif Mortenson[1]

Abstract—Globally, national forest inventories (NFI) require a large work force typically consisting of multiple teams spread across multiple locations in order to successfully capture a given nation's forest resources. This is true of the Forest Inventory and Analysis (FIA) program in the US and in many inventories in developing countries that are supported by USFS International Programs. As such, communication between teams, especially analytical staff in central offices and "boots on the ground" field staff collecting the data in dispersed locations is paramount to a robust data set. This inter-team communication and collaboration is also crucial for generating key scientific findings from FIA/NFI data sets. This is because there is often not the luxury of a single scientist, or team being able to make observations and generate findings based both from data analysis and significant time in the field, that there are in smaller scale research projects. Fortunately, in FIA, the quality assurance/quality control program helps keep data quality at targeted levels, fosters inter-team communication and offers a great framework for similar programs in developing countries. Additional collaborations between data collection and data analysis occur in FIA and successful examples are presented. Additionally, several specific forest health research findings and lessons learned from working with both data collection and data analysis in forest monitoring systems are presented from the western U.S. and Southeast Asia.

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CENTRAL AFRICAN DETAIL EXPERIENCE: WHAT US FIA FIELD STAFF CAN TEACH AND LEARN THROUGH SHORT TERM ASSIGNMENTS – DEMOCRATIC REPUBLIC OF CONGO AND CAMEROON

Josh Feinberg[1]

Abstract—REDD+, Reduction of Emissions from Deforestation and Forest Degradation is a United Nations initiative targeted to combat atmospheric carbon dioxide and global warming by providing monetary incentives to developing countries to preserve their forested land as effective carbon sinks. In order for these countries to receive this monetary benefit, they must develop and implement forest monitoring, reporting and validation (MRV) programs that effectively quantify the amount and change of "forested" land, the "health" of the forests, and estimate the amount of carbon in these forests. The USFS International Programs is involved in REDD+ by assisting these developing countries in the development of these MRV programs by facilitating technical exchanges with experts from the United States. Not only do countries benefit from this technical expertise, but awareness within all parties being part of a global community is raised, as well as the importance of effective across border communication. Despite vast personal differences, cultural differences, differences in governments and how policies are made and implemented, relationships are built around a shared human commonality. Central Africa is home to some of the most significant forests in the world both in terms of biodiversity and carbon sequestration. Democratic Republic of Congo (DRC) and Cameroon are two countries that are presently engaged in the REDD+ process and are in varying stages of MRV development. I've had the opportunity to be involved in two different short-term assignments first to DRC and then to Cameroon over the past two years. While I was able to share some of what I have learned from my years working for FIA, I gained a greater appreciation for the global importance of our work, and a greater appreciation for the importance of open communication, cultural sensitivity, and patience.

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FOREST INVENTORY AND ANALYSIS PROGRAM IN THE WESTERN U.S. AFFILIATED PACIFIC ISLANDS: PERSPECTIVES FROM WORKING IN ISLAND ECOSYSTEMS AND BUILDING CROSS CULTURAL PARTNERSHIPS

Ashley Lehman[1]

Abstract—The Pacific Northwest (PNW) Research Station's Forest Inventory and Analysis (FIA) program of the USDA Forest Service monitors and reports on the status and trends of the Pacific Island's forest resources and ecosystem services. Since 2001 the FIA program has partnered with State and Private Forestry's, Region 5 and the local governments in the U.S. Affiliated Western Pacific Islands to implement a nationally-standardized plot sampling design on a periodic basis. Permanent monitoring plots are measured on a 10 year periodic cycle across the island nations of American Samoa, Guam, Palau, The Commonwealth of the Northern Mariana Islands, The Federated States of Micronesia and The Republic of the Marshall Islands. To date we are conducting our second measurement of the region and have successfully completed two thirds of the inventory. Forest health changes over 10 years have been drastic on some island ecosystems. Further, collaboration with other agencies, NGO's and other state governments has been a successful approach to build local partnerships and maximize data use. Monitoring efforts are important for local land managers and communities because inventories provide detailed information on forest health issues and provide insights to long term trends in forest change.

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LAVA, VOG, AND TROPICAL FORESTS: WORKING WITH THE FIA PROGRAM IN HAWAII

Thomas McGinley[1], **Ashley Lehman**[2]

Abstract—In the winter of 2009, the Pacific Northwest Research Station initiated the ground implementation of their Forest Inventory and Analysis (FIA) program on the Hawaiian Islands. In the Pacific, people from the indigenous to the transplanted, hold intrinsic and utilitarian values of their forests that often differ considerably from values of mainstream mainland USA. These values need to be thoroughly respected in order to obtain the trust needed to collect forestry data in these regions, and the Hawaiian Islands proved to be a challenging place to earn sufficient trust to establish permanent research plots. Establishing partnerships with local land management entities such as state land management departments and non-governmental organizations was vital. Additionally, the ability of FIA field crews to fit the measurement anomalies and unconventional growth habits of tropical trees and understory vegetation to standard FIA protocols was paramount to successful FIA implementation. As such, local crews from Hawaii were assembled and trained by mainland FIA crews from the PNW Research Station. Hawaiian crews provided local knowledge of local flora identification, access to remote and rugged areas, and remaining safe by avoiding locations that shouldn't be accessed due to unknown lava tubes and potential SO^2 exposure. Unconventional vegetative growth common to the tropics, in combination with new field hazards including wild pigs, VOG (volcanic air pollution consisting primarily of SO^2), and lava tubes were the norm and not the exception in Hawaii FIA plots.

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COLLABORATING FOR SUCCESS: IMPLEMENTATION OF THE INTERIOR ALASKA INVENTORY

Brendt Mueller[1], Dan Irvine[2]

Abstract—Interior Alaska's boreal forests are approximately 112 million acres in size, or 15 percent of the United States forest land. This is currently a very dynamic region with rising temperatures, melting permafrost, changes in vegetation, fire, carbon, and water cycles due to a warming climate. This is the last forested area in the United States where the national Forest Inventory and Analysis (FIA) program has not been implemented largely due to its remoteness, size, lack of infrastructure, complex logistics, and cost. A pilot study was conducted in the Tanana Valley in 2014 aimed at testing a cost-effective inventory design that utilized a combination of field plots containing new protocols in conjunction with the latest airborne, remote sensing technology. In addition to the national FIA protocols, some interior specific variables tested were: a modified P3 soils protocol (carbon, permafrost), ground cover (mosses and lichens), tree cores (ring analysis), a modified P3 down wood protocol (carbon), and a second microplot (to better characterize small diameter trees). The success of the pilot can be attributed to developing cooperative partnerships between the US Forest Service (USFS), NASA, US Fish and Wildlife Service, State of Alaska-Division of Forestry (DOF), and the University of Alaska-Fairbanks (UAF). Plans for initial phases of implementation beginning in 2016 are moving forward with joint venture agreements between the USFS, DOF, and UAF to continue installing FIA plots in the Tanana Valley. Developing additional partnerships with organizations like the National Park Service, Bureau of Land Management and Native Corporations will be critical for implementation of the interior Alaska inventory. The long term goal is full implementation with a 1/5 intensity FIA grid, approximately 4600 plots over 10-12 years, divided into five inventory units, including a large aviation component, with an estimated average annual budget of $2.5 million per year.

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REGIONAL BIOMASS STORES AND DYNAMICS IN FORESTS OF COASTAL ALASKA

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Abstract—Coastal Alaska is a vast forested region (6.2 million ha) with the potential to store large amounts of carbon in live and dead biomass thus influencing continental and global carbon dynamics. The main objectives of this study were to assess regional biomass stores, examine the biomass partitioning between live and dead pools, and evaluate the effect of disturbance on live and dead biomass pools. Data collected by the Forest Inventory and Analysis program between 1995 and 2003 across all ownerships in Coastal Alaska were used to estimate live tree, snag, and log biomass pools in forest types, and ecoregions (Boreal versus Temperate). The regional average combined (live and dead) biomass was 76.7±3.8 Mg/ha in the Boreal ecoregion and 277.5±5.4 Mg/ha in the Temperate ecoregion. Biomass of snags and logs comprising Coarse Woody Debris (CWD) pool was 35.1±3.1 Mg/ha in the Boreal ecoregion and 58.6±2.1 Mg/ha in the Temperate ecoregion. Total regional biomass was 45.4±3.0 Tg and 1001.9±20.6 Tg, whereas CWD biomass was 20.8±2.1 Tg and 211.4±7.7 Tg for the Boreal and the Temperate ecoregions, respectively. In the Boreal ecoregion, the recent spruce bark beetle outbreaks greatly increased CWD stores, with damaged stands containing 82% of total CWD biomass. Decomposition rate-constants for beetle-killed spruce in the Boreal ecoregion were 0.02 yr^{-1} (from chronosequence) and 0.04 yr^{-1} (from decomposition-vectors) for logs and 0.001 yr^{-1} for snags. The complexity of temporal pattern of C stores and fluxes was influenced by the form of mortality (snags vs. logs). In the Temperate ecoregion, undisturbed stands contained 76% of total CWD, indicating disturbance had less impact on CWD stores. In Coastal Alaska, average live biomass (194.0±4.1 Mg/ha) was 4-23 percent higher and average snag biomass (29.5±1.0 Mg/ha) was approximately twice as high as that found in Washington and Oregon, states considered to have high biomass stores.

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LANDSCAPE CHANGE MONITORING

HARMONIC ANALYSIS OF DENSE TIME SERIES OF LANDSAT IMAGERY FOR MODELING CHANGE IN FOREST CONDITIONS

Barry Tyler Wilson[1]

Abstract—This study examined the utility of dense time series of Landsat imagery for small area estimation and mapping of change in forest conditions over time. The study area was a region in north central Wisconsin for which Landsat 7 ETM+ imagery and field measurements from the Forest Inventory and Analysis program are available for the decade of 2003 to 2012. For the periods 2003-2007 and 2008-2012, the monthly imagery was processed using harmonic analysis in order to capture seasonal trends in reflectance across spectral bands. A nonparametric modeling approach was used with predictor variables and field measurements at two points in time to predict change in live tree basal area. Predictions for individual plots poorly matched observations of change, however the resultant maps of change compared favorably to a purposive sample of locations of high predicted relative change, based on multi-date, high-resolution aerial photography. This suggests the need for a larger sample of plots or further tuning of the model.

INTRODUCTION

While the national forest inventory (NFI) conducted by the USDA Forest Service, Forest Inventory and Analysis (FIA) program is intended to address strategic-level questions about the forest resources across large geographic areas under a design-based mode of inference (Bechtold and Patterson 2005), there is increasing interest in using this information for reporting on and monitoring change in forest conditions over time for smaller areas within the population (McRoberts et al. 2010). By using auxiliary variables from data collected for all population units, such as those obtained from remote sensors, and shifting to a model-based mode of inference, dramatic gains in the precision of estimates can be achieved, though possibly at the expense of the unbiasedness assumption for the estimators (Gregoire 1998). Here we evaluate the use of dense time series of satellite imagery for predicting change in forest conditions by an examination of the linear regression of observed versus predicted values and a comparison of a purposive sample of areas on the map of predicted change to multi-date aerial photos.

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STUDY AREA

The study area was approximately 5.56 million acres in north central Wisconsin, corresponding to Web-enabled Landsat Data (WELD) tile H20V05 and described in the next section (Roy et al. 2010). The landscape includes a variety of land covers and uses, from agriculture in the south and southwest, deciduous and evergreen forest in the north and northeast, developed land around the city of Wausau in the central portion, as well as scattered wetlands, lakes, and rivers. The study area experienced a severe weather-related disturbance event in June of 2007, when a tornado traced a ½ mile-wide swath through part of Menominee County.

METHODS

The auxiliary data used in the study were dense Landsat time series images from the WELD project. WELD imagery are composites of the highest fidelity data, determined on a pixel-by-pixel basis, from all Landsat 7 ETM+ scenes collected over a compositing period. These composite images have been processed for the contiguous United States and Alaska over the decade of 2003-2012. The composite scenes have been orthorectified, transformed to top-of-atmosphere reflectance, and mosaicked into 5,000-by-5,000 pixel tiles.

NFI data from 1,446 plots were used in the study, including both forested and nonforested plots. Each of these plots was measured and then remeasured during the decade of 2003-2012, spanning two 5-year FIA measurement cycles in Wisconsin, a state that has a sampling intensity twice the base level of roughly 1 plot per 6,000 acres. Remeasurement of sample plots provides information about change in forest conditions in the population over the remeasurement period.

Since satellite-based sensors, such as Landsat 7's ETM+ instrument, detect reflectance from the Earth's surface, these data are expected to be closely correlated with land cover. Of the attributes measured on NFI plots, live tree basal area is considered to be one of those most correlated with tree canopy cover (Jennings et al. 1999). Therefore, the live tree basal area condition-level attribute was used as the attribute of interest. These summary values were calculated on all plots for both 5-year periods: measurements during 2003-2007 and remeasurements during 2008-2012. Nonforested conditions were assigned a value of 0. The plot-level data were calculated by multiplying each condition's plot proportion by its corresponding basal area value, then summing across all conditions. Differences in live tree basal area were computed for each plot by subtracting the summary value at the earlier time period from the summary value at the later time period.

The WELD monthly composites for the entire decade of 2003-2012 for tile H20V05 were used for the study. For each monthly composite, the reflectance values from ETM+ were transformed to the first three Tasseled Cap (TC) components: brightness, greenness, and wetness (Huang et al. 2002). The monthly TC components were then compiled into individual stacks, by TC component and time period, resulting in six separate stacks. To account for the seasonality of the TC components, harmonic analysis was conducted separately on each stack fitting a Fourier series with two harmonics individually to each pixel in the stack via least squares regression (Sellers et al. 1996). To compensate for missing data in the time series due to clouds or the scan line corrector (SLC) failure, weighted regression was used, with the weight for each observation calculated as the inverse of the total number of observations over each respective 5-year period for the month of the given observation.

The Fourier coefficients calculated for each of the TC components for each of the time periods were bundled together to form a 30-layer stack of auxiliary variables for each pixel in the tile. To reduce dimensionality, principal components analysis (PCA) was conducted on the stack. Only the first eight principal components (PCs) were kept, accounting for roughly 93 percent of the original variance. Finally, because of the spatial mismatch in the size of the FIA plot relative to the size of the ETM+ pixel, a 3-by-3 pixel moving window was used to compute the focal mean for each of the PCs.

The 8-layer stack of focal means was used as the feature space with the k-nearest neighbors (kNN) estimator. The kNN estimator has been widely used with NFI and remote sensing data (Eskelson et al. 2009). It provides an estimate for each unsampled unit in the population as a weighted average of the observed response variable for the k-nearest sample units in the feature space.

Because the focus of this study was the utility of dense time series of satellite imagery for modeling change in forest conditions, the only tuning of the kNN estimator was to objectively determine the optimal value of *k* to minimize the root mean square error (RMSE) using the 1,446 observations of change. For this optimization a leave-one-out procedure was used, whereby the k-nearest neighbors for a given plot were found by holding the given plot out of the list of possible neighbors. Using this criterion, the optimal value of *k* was determined to be 9, resulting in a minimum RMSE of approximately 19.2 square feet per acre.

RESULTS

Scatterplots of observed versus predicted live tree basal area for all 1,446 remeasured plots show strong agreement for both time periods. Figure 1 depicts the results for period 2, with similar results for period 1 (not shown). However, a scatterplot of observed versus predicted change indicates poor agreement, as shown in Figure 2 (Piñeiro et al. 2008).

After masking out areas that were nonforested in the first time period (less than 10 square feet per acre of live tree basal area), comparisons of the map of relative change in live tree basal area (i.e., relative to the basal area in the first time period), shown in Figure 3, to multi-date aerial photography collected over the same period indicate strong agreement for a purposive sample of areas of high predicted relative change, an example of which is shown in Figure 4. The multi-date aerial photography was collected from online property tax information systems for two counties in the study area: Langlade County (2003, 2008, and 2010) and Price County (2005, 2006, 2008, 2010, and 2011).

DISCUSSION

The uncertainty in the individual estimates of live tree basal area for each period results in even greater uncertainty in their difference. Furthermore, the results shown in the scatterplots, combined with the strong agreement between the predicted map and aerial photography for the purposive sample, suggest that the issue may be related to the size and frequency of areas of change. Small relative increases in live tree basal are commonplace across the study area, corresponding to forest growth. Large relative decreases are much less common and are highly localized in extent, corresponding to forest disturbance events such as harvests, wildfires, and blow-down due to weather events.

This suggests that the sample of 1,446 remeasured plots may not be large enough to adequately characterize such rare disturbance events. One possible solution is to use a larger sample of plots, perhaps by including sample units from neighboring WELD tiles in the kNN estimation. Another option would be to adjust the value of *k* according to the unsampled target unit's location in feature space, with units in the interior having a larger value of *k* than those closer to the convex hull enclosing all sample units.

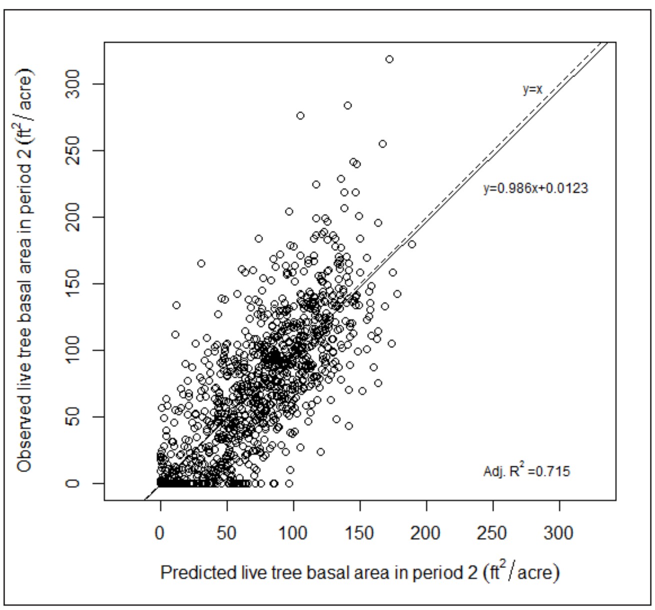

Figure 1—Scatterplot of observed vs. predicted live tree basal area for 1,446 plots in the second time period. The solid line is the linear regression of the data. The dashed line is the line y=x.

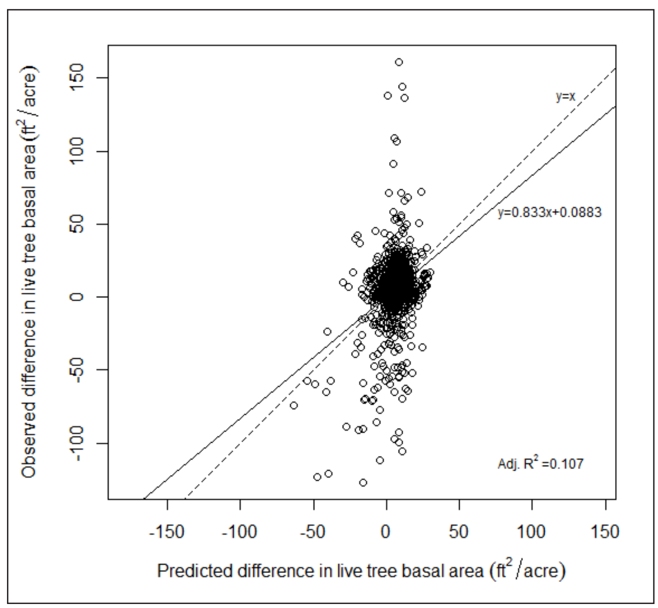

Figure 2—Scatterplot of observed vs. predicted difference in live tree basal area between time periods, for 1,446 remeasured plots. The solid line is the linear regression of the data. The dashed line is the line y=x.

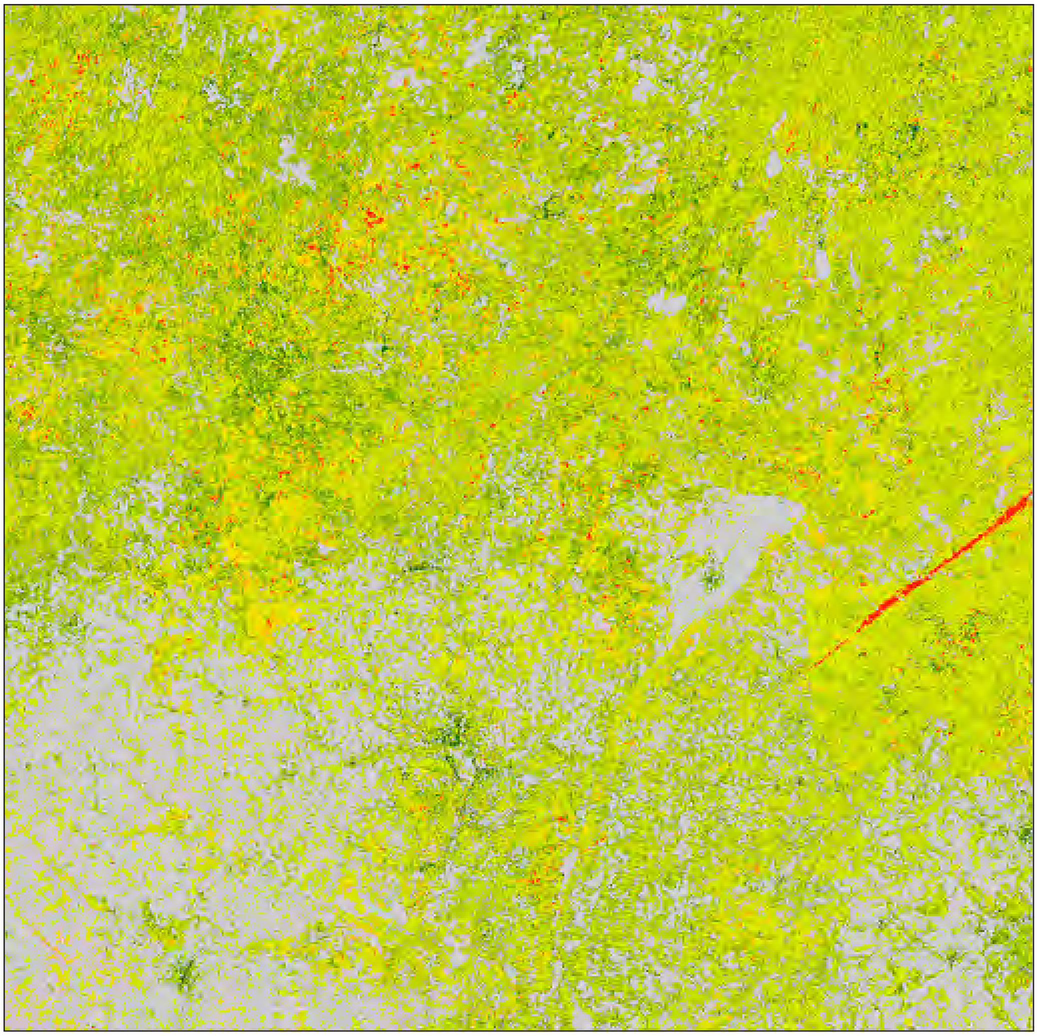

Figure 3—Map of the study area of predicted relative difference in live tree basal area, in percent of the predicted total for the first time period. Nonforest land (less than 10 square feet per acre of live tree basal area in the first time period) is gray, relative gain is green, relative loss is red, and no change is yellow. Darker shades of green and red indicate larger relative gains or losses than lighter tints.

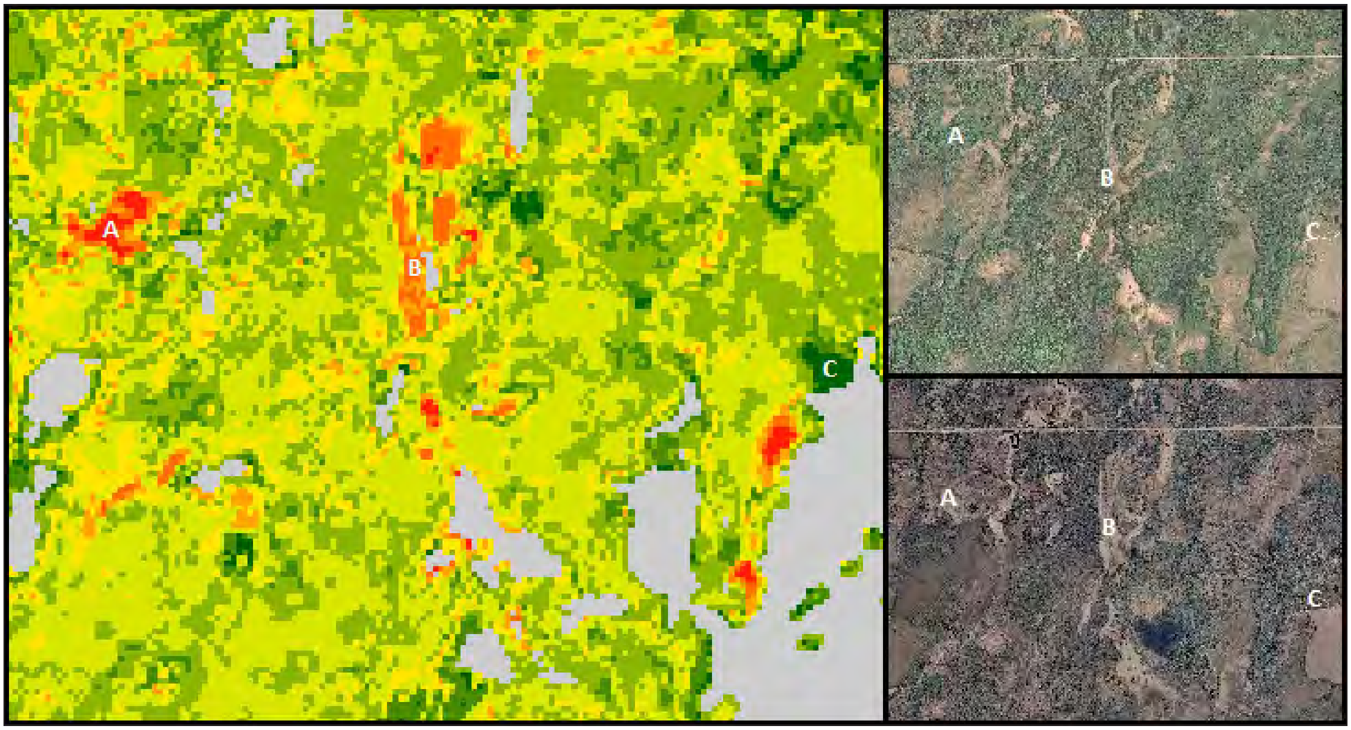

Figure 4—Detail from Figure 3 (left) and aerial photos from 2005 (top right) and 2010 (bottom right) of an area in Price County with patches of large relative gains and losses. Patch A was harvested earlier in the second time period than patch B. Patch C shows regrowth of an area harvested prior to the first time period.

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MAPPING TIMING, EXTENT, TYPE AND MAGNITUDE OF DISTURBANCES ACROSS THE NATIONAL FOREST SYSTEM, 1990 - 2011

Alexander Hernandez[1], Sean P. Healey[2], Chenquan Huang[3], R. Douglas Ramsey[1]

Abstract—As part of the U.S. Forest Service (USFS), National Forest System (NFS) comprehensive plan for carbon monitoring, a detailed temporal mapping of forest disturbances across all National Forests in the United States has been conducted. A long-term annual time series of data layers that show the timing, extent, type, and magnitude of disturbance beginning in 1990 and ending in 2011 is available for all the USFS Regions. Our mapping approach starts with an automated initial detection of annual disturbances using imagery captured within the growing season from the Landsat archive. Through a meticulous process, the initial detections were visually inspected, manually corrected and labeled using various USFS ancillary datasets (Monitoring Trends in Burn Severity (MTBS), Aerial Detection Surveys (ADS), and Forest Activities (FACTS), and Google Earth high-resolution historic imagery. For each National Forest we produced disturbance history composites containing all the possible disturbance pathways that a single pixel can have. We have mapped how many years a pixel was undisturbed, and also in what years and what type of disturbance (i.e. fires, harvest, insects) said pixel was affected. The magnitude of change was obtained by fitting multitemporal models of percent canopy cover that were calibrated with extensive field data from the USFS Forest Inventory and Analysis Program (FIA). By applying these models to pre- and post-event Landsat images at the site of known disturbances, we develop maps showing first-order estimates of disturbance magnitude on the basis of cover removal. This effort provides a universally-interpretable, biophysically- based estimate of disturbance effects across all of the nation's national forests with an unprecedented detail. Major trends are highlighted by USFS region, and by major forest ecosystem. The local-scale interpretability that can be extracted out of these data improves our understanding of disturbance processes affecting US forests over the last two decades.

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SHAPESELECTFOREST: A NEW R PACKAGE FOR MODELING LANDSAT TIME SERIES

Mary Meyer[1], Xiyue Liao[2], Gretchen Moisen[3], Elizabeth Freeman[4]

Abstract—We present a new R package called ShapeSelectForest recently posted to the Comprehensive R Archival Network. The package was developed to fit nonparametric shape-restricted regression splines to time series of Landsat imagery for the purpose of modeling, mapping, and monitoring annual forest disturbance dynamics over nearly three decades. For each pixel and spectral band or index of choice in temporal Landsat data, the package delivers an optimally smoothed rendition of the trajectory constrained to behave in an ecologically sensible manner, assuming one of seven possible "shapes". It also provides parameters summarizing the temporal pattern including year(s) of inflection, magnitude of change, and pre- and post- inflection rates of growth or recovery. In addition, the package contains functions for deriving annual predictions of forest disturbance, as well as graphical displays of the shape fits.

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A NOVEL STATISTICAL METHODOLOGY TO OVERCOME SAMPLING IRREGULARITIES IN THE FOREST INVENTORY DATA AND TO MODEL FOREST CHANGES UNDER DYNAMIC DISTURBANCE REGIMES

Nikolay Strigul, Jean Lienard[1]

Abstract— Forest inventory datasets offer unprecedented opportunities to model forest dynamics under evolving environmental conditions but they are analytically challenging due to irregular sampling time intervals of the same plot, across the years. We propose here a novel method to model dynamic changes in forest biomass and basal area using forest inventory data. Our methodology involves the following steps: 1) parameterize transition matrices for biomass using Gibbs sampling, 2) incorporate dynamic disturbance and forest growth scenarios and 3) simulate transient dynamics and stationary states using Markov chain model. We extend this method to further include changes in natural disturbance regimes and land-use practices, to predict the impact of changing climate and forest management practices. We apply this methodology on North American forests. We first assess the predictive power of the methodology, without including changing disturbance regimes, in two independent ways: (a) the first years of the dataset are used to predict the later years, and (b) the long-term predictions of two random partitions are compared. The model predicts consistent short-term increases in biomass. We then investigate the consequences of global warming scenarios including changes in forest fire rate in hardwood forests as well as possible growth enhancements due to increasing CO2 and temperature. We conclude that ongoing increasing biomass trends are relatively unaffected in the short term by changing disturbances regimes. Overall, our original data-intensive methodology provides both descriptions of the short-term dynamics as well as predictions of forest development on a longer timescale.

INTRODUCTION

Existing national forest inventory programs collect a large number of individual tree records on permanent plots and sample forested ecosystems uniformly across the landscape. These databases provide unique opportunities to quantify and examine forest disturbances using a data intensive approach that involves data mining and the development of stochastic models (Lienard et al., 2015a, 2015b). In particular, one approach relying on Markov chain models has recently been developed to capture stand level dynamics from forest inventories (Strigul et al., 2012). These models operate with probabilities of forest state transitions. Markov chain models can be naturally linked with forest inventory data by considering every forest permanent plot as an independent realization of the underlying Markov chain process.

We propose here a novel approach to model stand biomass based on forest inventory data using inhomogeneous Markov Chain processes. We first develop a methodology to estimate the transition matrices based on survey data collected at irregular intervals. We then study how progressive dynamic changes in forest biomass resulting from variations in natural disturbance regimes and land-use practices.

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METHODS

Transition matrix estimation

We consider here an estimated 3-year transition matrix obtained using Gibbs sampling. This matrix is entirely deduced from empirical data and its shape is not constrained by any prior knowledge. Specifically, the matrix is estimated using the following methodology (explained in details in Lienard et al., 2015b):

1. Construct temporal sequences of uncorrelated characteristics depending on forest survey dates.
2. Use Gibbs sampling to infer the transition matrix. This algorithm consists of random initialization of missing values followed by iteration of parameter estimation (a) and data augmentation (b):
   a. Parameter estimation: Compute the transition matrix using the (augmented) sequences of plot transitions.
   b. Data augmentation: Draw new sequences conditional on the new transition matrix.

Dynamic changes of growth and disturbance

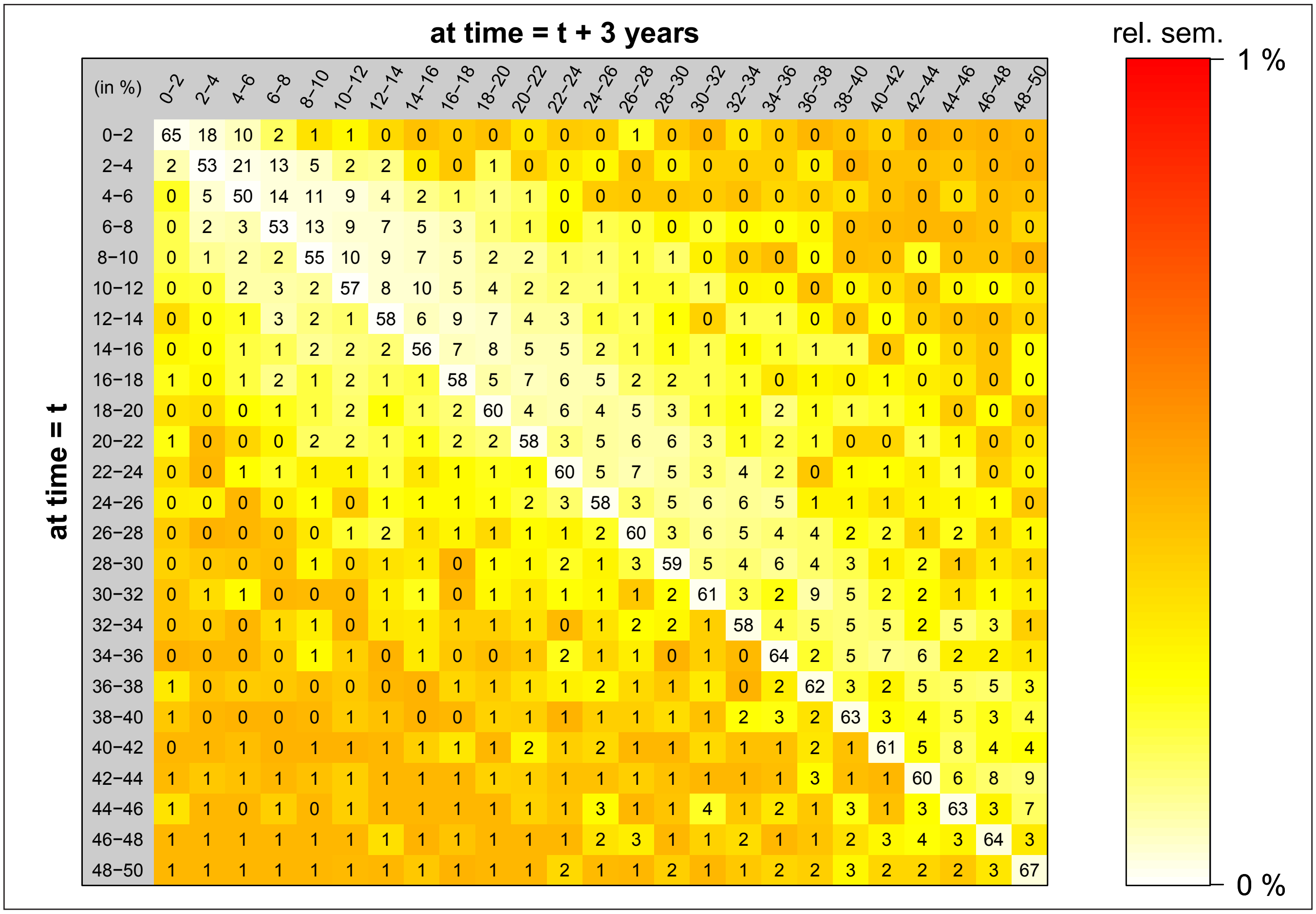
We further model hypothetical, dynamic changes of growth and disturbance probabilities with the inclusion of time-dependent terms within the biomass transition matrix (inhomogeneous Markov Chain model). We employ these terms to model forecasted changes in forest fire frequency caused by global warming, and the possible enhanced growth effect resulting from the greater temperature and greater availability of atmospheric. Specifically, we derive lower and upper bounds among the published predictions of forest from the study of Bergeron et al. (2005) and Drever et al. (2009). In accordance with meta-analyses of data gathered in Free-Air CO_2 Enrichment (FACE) experiments and to avoid over-estimation of boosted growth, we settled for a rather conservative growth enhancement of 20 percents until the $3xCO_2$ concentration is reached, around 2090. Figure 2a summarizes the scenarios used in this study.

RESULTS

Estimation of transition matrices

The methodology is able to estimate transition matrices even with irregular survey intervals (e.g. when the time between two successive measurements varies along the years due). In the biomass transition matrix shown in Figure 1, each value at row i and column j corresponds to the probability of transition from state i into state j after 3 years. By definition, rows sum to 100%. This transition matrix is dominated by its diagonal elements, which is expected because few plots show large changes in a given 3-year period. The values below the diagonal correspond to transitions to a lower state (hence, they can be interpreted as the probabilities of disturbance), while values above the diagonal correspond to transitions to a higher state (i.e., growth). The transitions in the first column of the matrix correspond to major disturbances, where the stand transitions to a very low biomass condition. As the probabilities above the diagonal are larger than below the diagonal, the overall 3-year prediction is of an increase in biomass. This matrix also shows that plots with a biomass larger than 40,000 kg/ha have a roughly uniform 10% probability of ending with a biomass of less than 20,000 kg/ha 3 years later, which is interpreted as the probability of high-biomass stand to go through a moderate to high disturbance.

We performed a cross-validations of our methodology by estimating the transition matrix with data from 1970 to 1988, and then used the model to predict forest for the period corresponding to 1989 to 2007. The comparison of the predicted dynamics with the aggregated distribution of the second half of the dataset shows accurate predictions, with R^2 coefficients ranging from 0.8 to 0.95. This indicates that the second half of the dataset is overall predictable with a Markov chain model based solely on the first half.



(in %)	0–2	2–4	4–6	6–8	8–10	10–12	12–14	14–16	16–18	18–20	20–22	22–24	24–26	26–28	28–30	30–32	32–34	34–36	36–38	38–40	40–42	42–44	44–46	46–48	48–50
0–2	65	18	10	2	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2–4	2	53	21	13	5	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4–6	0	5	50	14	11	9	4	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6–8	0	2	3	53	13	9	7	5	3	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
8–10	0	1	2	2	55	10	9	7	5	2	2	1	1	1	1	0	0	0	0	0	0	0	0	0	0
10–12	0	0	2	3	2	57	8	10	5	4	2	2	1	1	1	1	0	0	0	0	0	0	0	0	0
12–14	0	0	1	3	2	1	58	6	9	7	4	3	1	1	1	0	1	1	0	0	0	0	0	0	0
14–16	0	0	1	1	2	2	2	56	7	8	5	5	2	1	1	1	1	1	1	1	0	0	0	0	0
16–18	1	0	1	2	1	2	1	1	58	5	7	6	5	2	2	1	1	0	1	0	1	0	0	0	0
18–20	0	0	0	1	1	2	1	1	2	60	4	6	4	5	3	1	1	2	1	1	1	1	0	0	0
20–22	1	0	0	0	2	2	1	1	2	2	58	3	5	6	6	3	1	2	1	0	0	1	1	0	0
22–24	0	0	1	1	1	1	1	1	1	1	1	60	5	7	5	3	4	2	0	1	1	1	1	0	0
24–26	0	0	0	0	1	0	1	1	1	1	2	3	58	3	5	6	6	5	1	1	1	1	1	1	0
26–28	0	0	0	0	0	1	2	1	1	1	1	1	2	60	3	6	5	4	4	2	2	1	2	1	1
28–30	0	0	0	0	1	0	1	1	0	1	1	2	1	3	59	5	4	6	4	3	1	2	1	1	1
30–32	0	1	1	0	0	0	1	1	0	1	1	1	1	1	2	61	3	2	9	5	2	2	1	1	1
32–34	0	0	0	1	1	0	1	1	1	1	1	0	1	2	2	1	58	4	5	5	5	2	5	3	1
34–36	0	0	0	0	1	1	0	1	0	0	1	2	1	1	0	1	0	64	2	5	7	6	2	2	1
36–38	1	0	0	0	0	0	0	0	1	1	1	1	2	1	1	1	0	2	62	3	2	5	5	5	3
38–40	1	0	0	0	0	1	1	0	0	1	1	1	1	1	1	1	2	3	2	63	3	4	5	3	4
40–42	0	1	1	0	1	1	1	1	1	1	2	1	2	1	1	1	1	1	2	1	61	5	8	4	4
42–44	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	60	6	8	9
44–46	1	1	0	1	0	1	1	1	1	1	1	1	3	1	1	4	1	2	1	3	1	3	63	3	7
46–48	1	1	1	1	1	1	1	1	1	1	1	1	2	3	1	1	2	1	1	2	3	4	3	64	3
48–50	1	1	1	1	1	1	1	1	1	1	1	2	1	1	2	1	1	2	2	3	2	2	2	3	67

Figure 1—3-year transition matrix for the biomass. The states are the biomass ranges in 10^3 kg/ha, spanning from 0-2 to 48-50 10^3 kg/ha, and represented here on the left and on top of the matrix. The values M(i,j) inside the matrix correspond to the rounded probability of transition from state i to state j, in percents. The color represents the relative standard error of the mean and indicates the uncertainty in the matrix coefficients.

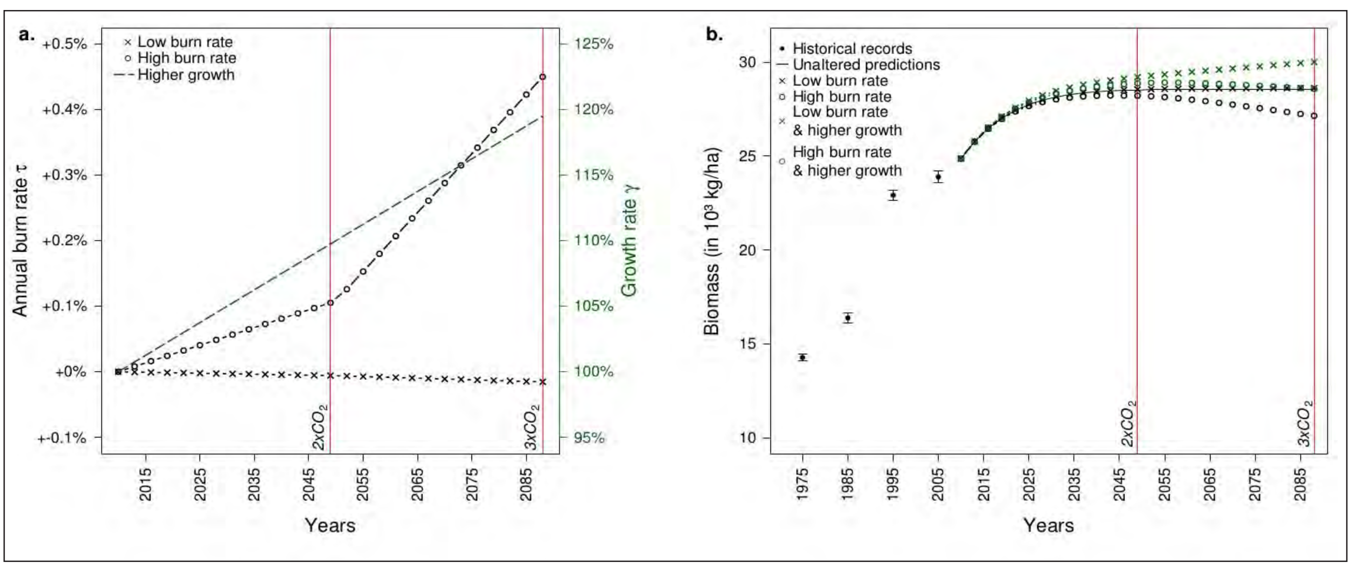


Figure 2—climate-change scenarios and predicted average biomass changes. Panel a: forest fires scenarios (black, left y-axis) and possible growth enhancement (green, right y-axis) in hardwood forests. The two burn rate scenarios were derived from Bergeron et al. (2006); Drever et al. (2009) (see methods for details). Panel b: average biomass predicted with no change in current disturbance regime (solid line) and in the two future burn rate scenarios computed with or without the addition of enhanced growth. Historical biomass records from the forest inventory are displayed in 10-year bins with standard error of the mean.

Climate change scenarios

The average biomass in Quebec hardwood forests displays distinct trajectories and dynamics under the different scenarios (Figure 1b). The unaltered projections show a continuous increase of biomass until 2050, consistent with the trend observed in the database (historical records in Figure 1b). In the "low burn rate" scenario, the average biomass is almost not discernible from the unaltered predictions; the slight decrease of burn rate considered in this scenario does not significantly affect the average biomass dynamics. In the "high burn rate" scenario, a departing from the unaltered predictions is apparent after reaching the $2xCO_2$ threshold. The addition of the "higher growth" condition changed substantially the dynamics with a marked increase in both scenarios. In the "low burn rate" scenario the boosted growth is able to sustain an increasing trend until 2090, while in the "high burn rate" scenario the boosted growth negates the effects of increased burn rate for the average biomass.

DISCUSSION

In this work we have developed an inhomogeneous Markov chain approach to model forest changes under nonstationary environmental conditions. This approach integrates mechanistic models of growth and disturbance into empirically-derived transition models. Its practical realization involves three consecutive steps: 1) biomass transition matrices are estimated from forest inventory data using data mining and Bayesian methods, 2) different scenarios of disturbance and forest growth are formulated according to climate change projections, 3) biomass forecasts are obtained via time-dependent alterations of the transition matrices according to these scenarios.

Markov chain models have a rich history of application in ecology, and, in particular, in forest modeling. This modeling framework has been employed in particular to describe forest transitions at different scales with various focal variables, for example, succession models defined on the species and forest type level, gap mosaic transition models, or biomass transition models. The Bayesian methodology proposed in this study allows to extend the scope of transition matrices by allowing their computation directly from forest inventory data.

On well-known limitation of Markov chain models is the time-homogeneity (stationarity) assumption, meaning that transitional probabilities remain the same over the focal time horizon (Usher, 1979, Waggoner and Stephens, 1980). While this assumption is often justified on small and intermediate time scales that span from years to decades, time-homogeneous Markov chains will likely provide unrealistic predictions in case disturbance or growth regimes change substantially over longer time horizons (decades to centuries). With the inclusion of time-dependent growth and mortality terms in the transition matrices, we relax this assumption and extend the scope of application of Markov chain biomass models.

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EXTRAPOLATING INTENSIFIED FOREST INVENTORY DATA TO THE SURROUNDING LANDSCAPE USING LANDSAT

Evan B. Brooks, John W. Coulston, Valerie A. Thomas, and Randolph H. Wynne[1]

Abstract—In 2011, a collection of spatially intensified plots was established on three of the Experimental Forests and Ranges (EFRs) sites with the intent of facilitating FIA program objectives for regional extrapolation. Characteristic coefficients from harmonic regression (HR) analysis of associated Landsat stacks are used as inputs into a conditional random forests model to form predictive models of key forest biophysical parameters for use in making wall-to-wall maps.

In 2011, the FIA program established intensified plots in several of the Experimental Forests and Ranges (EFRs). These plots resemble standard FIA phase 2 plots as described in Bechtold et al. (2005), but they are much denser per unit area, with roughly 50 plots in each EFR. The motivation behind the intensified sampling was to facilitate the FIA mission by having a large number of plots on representative sections of the nation's forests, enabling the extrapolation of forest biophysical parameter estimates into the areas around the forests.

The Landsat collection of satellite imagery is a common choice for regional extrapolation of point forest data, primarily because it has the spatial resolution to monitor individual stands and has a decades-long record to compare with historical FIA plot measurements. Multitemporal approaches are not subject to issues resulting from the choice of a single image for analysis, but they must contend with missing or poor-quality data due to striping from the scan line corrector failure on Landsat 7 in 2003, as well as clouds, shadows, and other obscuring factors.

Harmonic regression (HR; Brooks et al., 2012) is an algorithm designed to interpolate missing data in large multitemporal image stacks. HR fits curves based on the superposition of sinusoidal curves of different frequencies (harmonics), independently to each pixel. Each HR curve is characterized by a collection of data-driven coefficients. While these coefficients are generally used to generate simulated Landsat-scale images, they have value in their own right. In addition to straightforward applications like land cover/land use classification, the coefficients have also been used to improve the precision of forest parameter estimation (Brooks et al., 2015). Thus, given training data in the form of spatially explicit FIA plot measurements, it is our contention that they may also be used as predictors in a model for forest biophysical variables. Additionally, because the coefficients are not specific to any one image, we expect that once trained, models based on them may be applied to Landsat data from other years as well.

STUDY AREA

Our study focused on three EFRs which formed an approximate line, covering roughly the range of elevation in the southeastern US. (Fig. 1) Specifically, we looked at the Coweeta Hydrologic Laboratory in southwestern North Carolina, the Calhoun Experimental Forest in north-central South Carolina, and the Santee Experimental Forest in South Carolina, near the Atlantic coast. Each of these EFRs has approximately 50 intensified FIA plots, all established so as to avoid overlapping other ongoing experiments in the EFRs. The plots were measured in 2011, the measurements being a slight subset of the biophysical metrics commonly found in FIA

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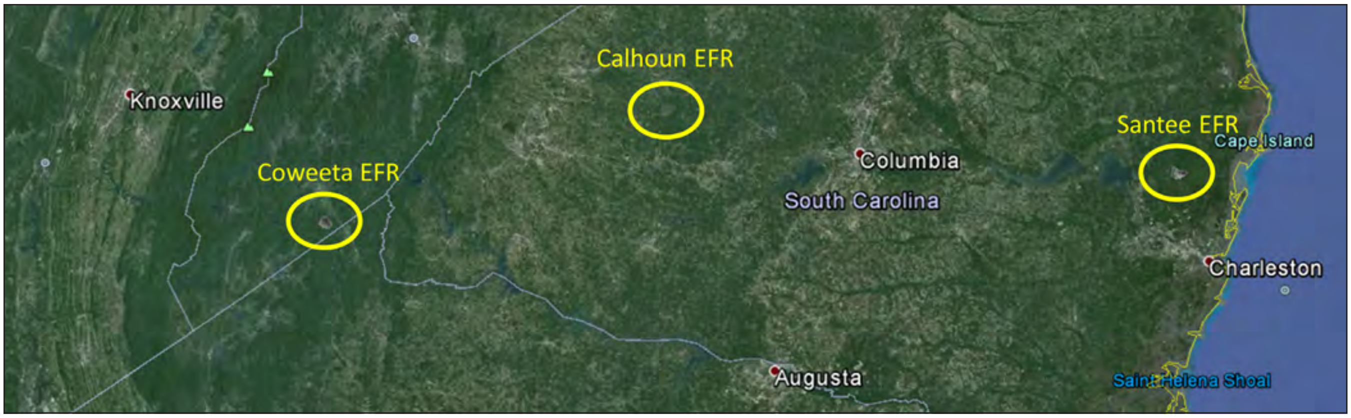

Figure 1—Overall study area, representing a rough transect from the Piedmont to the Atlantic coast. The three experimental forests are named and circled.

phase 2 plots. Note that the term "intensified" refers to the increased spatial density of the plots, not to the degree of measurements taken within the plots. Table 1 lists some of the variables measured in the intensified plots.

Table 1—Selected biophysical variables and parameters in the intensified FIA plot data.

Condition table variables	Tree table variables
Owner, forest type, stand age, site index, stocking, disturbance type	Species, species group, DBH, height, age, volume, biomass

In order to extrapolate the information contained within the EFRs' intensified plots to the broader landscape, we used Landsat thematic mapper (TM) and enhanced thematic mapper plus (ETM+) images, covering the transect with data from WRS-2 path/row combinations 18/36, 17/36, 17/37, and 16/37. We acquired every available image from 2010 and 2011, regardless of image quality, choosing images that were already processed to L1T standards and also corrected to surface reflectance via the Landsat Ecosystem Disturbance Adaptive Processing System. (LEDAPS, Masek et al. 2006)

We then obtained spatial subsets corresponding to the three EFR boundaries for model training, using FMask (Zhu and Woodcock, 2012) from the post-LEDAPS product to filter out the majority of cloud and shadow-related pixels. Subsequently, we filled in the missing data gaps within the resulting images with window regression. (WR, de Oliveira et al., 2014)

Because the spatial size of the FIA plots is larger than a single 30m Landsat pixel, we took the additional step of computing 3x3 pixel window averages, by layer, to ensure that each pixel reflected the immediate neighborhood that would comprise an FIA plot. We then used these stacks as inputs into HR, thus obtaining characteristic coefficient rasters for each subset.

We treated each of the seven spectral bands separately, obtaining a collection of coefficient rasters for each band in addition to a raster for normalized difference vegetation index. (NDVI, Tucker, 1979) For each band and index, we fitted the data to a two-harmonic curve, obtaining five coefficients (constant, sin(t), sin(2t), cos(t), and cos(2t)) in each case, resulting in 40 coefficient layers total for each EFR. Preprocessing was done using R (R Core Team, 2014), with emphasis on the spatial.tools package and its dependencies. (Greenberg, 2014)

METHODS

We treated the HR coefficients as predictors of the measured values from the intensified plots in the EFRs boundaries. Thus, we first joined the plot measurements to the associated pixels in the HR coefficient stacks by the spatial location of the plot, in each case using the pixel which corresponded to the recorded location. Due to the correlated nature of many of the original Landsat spectral bands and the inclusion of NDVI-based coefficients as potential predictors, we used conditional random forests from the party package as the basis for our model-fitting. (Strobl et al., 2008)

After a final predictive model is derived, we will apply that model to the HR coefficients obtained by applying HR across the full extent of the study area. Where possible, the resulting predictions will be compared with FIA Phase 2 plot data from the study area.

RESULTS

Currently, processing and preliminary model-fitting are complete for the EFRs subset stacks. These results show R^2 values for quantitative variables such as height, Carbon above ground, and age on the order of 55 to 64 percent. Similarly, the misclassification rate for the species group is 22.3 percent. These values seem promising when one considers that the only predictors used were products derived from multitemporal satellite data. Further comparison with FIA Phase 2 plots across the study area is planned, pending calculation of HR coefficients across the region.

DISCUSSION

The spatially dense nature of the intensified plots made computation of the HR coefficients simpler. While we will utilize broad coverage from all four input scenes, the ability to crop out the subsets around the EFRs made the processing and model training much more efficient. This in its own right is computationally valuable, and when coupling this fact with the public availability of the exact spatial coordinates of the plots, it makes the intensified plots in the EFRs convenient for this sort of extrapolation effort.

While the HR coefficients were trained on the 2010-2011 period, the coefficients themselves are simply characteristic of the corresponding curves. If such curves represent commonly occurring phenologies, then it reasonable to assume that one may use the models from this study with HR coefficients from different years. This possibility makes the intensified plots that much more potentially valuable.

Complications may arise, however, from the choice of intensified plot locations within the EFRs. The locations of intensified plots were chosen to avoid intersecting with other experiments currently being conducted in the EFRs. As a result, the models we built were fitted to forests that were undisturbed after the establishment of the EFRs. Accordingly, we expect comparisons of model predictions with the more general Phase 2 plots to have a considerable amount of disagreement. In order to extend the effectiveness of the models, additional intensified plots, covering a broader range of treatments, would be helpful.

ACKNOWLEDGMENTS

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NEXT-GENERATION FOREST CHANGE MAPPING ACROSS THE UNITED STATES: THE LANDSCAPE CHANGE MONITORING SYSTEM (LCMS)

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Abstract—Forest change information is critical in forest planning, ecosystem modeling, and in updating forest condition maps. The Landsat satellite platform has provided consistent observations of the world's ecosystems since 1972. A number of innovative change detection algorithms have been developed to use the Landsat archive to identify and characterize forest change. The inter-agency Landscape Change Monitoring System (LCMS) has been launched to engage these cutting edge methodologies in a national-scale, sustained change monitoring operation. A Science Team supporting LCMS has evaluated the relative strengths of several leading algorithms in identifying different types of forest change across a variety of ecosystems. Additionally, a machine-learning approach has been developed that uses an ensemble of algorithm outputs to predict a surface which best matches independently collected reference data. This ensemble technique integrates the strengths of each individual algorithm in different situations, and has been shown to reduce overall error in LCMS trials. The LCMS Science Team has also, in collaboration with Google, overcome significant data processing hurdles associated with analyzing tens of thousands of large images. Following Science Team recommendations, LCMS is quickly moving toward production and maintenance of validated, nationally consistent maps of the causes and timing of historical forest change.

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IMAGE-BASED CHANGE ESTIMATION (ICE): MONITORING LAND USE, LAND COVER AND AGENT OF CHANGE INFORMATION FOR ALL LANDS

Kevin Megown[1], Andy Lister[2], Paul Patterson[3], Tracey Frescino[4], Dennis Jacobs[5], Jeremy Webb[6], Nicholas Daniels[7], Mark Finco[8]

Abstract—The Image-based Change Estimation (ICE) protocols have been designed to respond to several Agency and Department information requirements. These include provisions set forth by the 2014 Farm Bill, the Forest Service Action Plan and Strategic Plan, the 2012 Planning Rule, and the 2015 Planning Directives. ICE outputs support the information needs by providing estimates of land use and land cover area and change, together with agent of change.

ICE data is collected by interpreting two years of NAIP imagery and identifying areas of land cover and land use change (LCLUC). Forest Inventory and Analysis (FIA) plot locations are used for the sample design, and LCLUC is quantified using dot grids over each FIA plot. When no change occurs on a plot, land cover and land use are attributed on a subset of the dot grid. When change occurs, however, a denser grid of dots is attributed and agent of change is also interpreted. Currently, the states of Colorado, Georgia, Washington, Texas, Utah, Nebraska, Maryland, Vermont and New Hampshire are being interpreted to support ICE objectives.

Estimation procedures have been developed to analyze the ICE data. These statistical summaries result in tables, graphs, or matrices to support State and National Forest land area and change estimates. This presentation will provide information about the ICE data collection and estimation methods, and a sample of estimation outputs.

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LCMS LANDSCAPE CHANGE MONITORING SYSTEM – RESULTS FROM AN INFORMATION NEEDS ASSESSMENT

Kevin Megown[1], Brian Schwind[2], Don Evans[3], Mark Finco[3]

Abstract—Understanding changes in land use and land cover over space and time provides an important means to evaluate complex interactions between human and biophysical systems, to project future conditions, and to design mitigation and adaptive management strategies. Assessing and monitoring landscape change is evolving into a foundational element of climate change adaptation, ecological restoration, and resource sustainability. Landscape change data are core to Forest Service functions including: land management planning, restoration analysis, carbon accounting, greenhouse gas emission reporting, biomass and bioenergy assessments, hydrologic function assessments, fire and fuels planning and management, and forest and rangeland health assessments.

The Forest Service is collaborating with federal and academic scientists to evaluate the status of existing landscape change information systems, assess gaps in information content, and implement science and information system efforts aimed at improving our ability to understand and monitor landscape changes through time. Promising research for enhanced landscape change detection techniques will enable resource managers to attain a more complete and precise understanding of how, why, and to what extent the landscape is changing.

In order to support strategic investment decisions on information resources, the Forest Service Geospatial Management Office has distributed a voluntary information needs survey to a broad audience of Agency resource and information management professionals to assess current and projected requirements for landscape change information. The survey, in conjunction with a technical assessment of existing landscape change information products, will enable the Agency and our partners to prioritize efforts that develop and maintain needed information assets, and results from the survey will be used to help define requirements for future landscape level change products.

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LAND COVER CHANGE MAP COMPARISONS USING OPEN SOURCE WEB MAPPING TECHNOLOGIES

Erik Lindblom[1], Ian Housman[2], Tony Guay[3], Mark Finco[4], Kevin Megown[5]

Abstract—The USDA Forest Service is evaluating the status of current landscape change maps and assessing gaps in their information content. These activities have been occurring under the auspices of the Landscape Change Monitoring System (LCMS) project, which is a joint effort between USFS Research, USFS Remote Sensing Applications Center (RSAC), USGS Earth Resources Observation and Science (EROS) Center, and academic partners. One of the early needs identified was a system that facilitated the visual comparison of several change maps in a common visualization framework. The application presented here is the result of this need.

The LCMS landscape change viewer is a web-based platform that allows users to interact with the various change data layers and visually identify areas of overlap and uniqueness. In addition to the zoom and pan functions that are expected in a web map, features of the application include user configurable:

- Order of comparison in the map table of contents
- Turning on and off individual years for each of the change data sources
- Year selection based on a user defined range of years
- Adjusting the transparency for each change data source
- Selection of color for each of the change data sources

These functions are made possible through the following technologies:

- Tilemill that produces static data tiles for viewing on a web map
- Leaflet.js to render the maps
- A custom Leaflet layer developed at RSAC that allows the browser to render tiles in a color and opacity as specified by a user

Together, these technologies eliminate the need for a GIS server and allow most basic GIS viewing operations to occur on the client's browser.

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SILVICULTURAL AND ECOLOGICAL INSIGHTS FROM REMEASURED INVENTORY PLOTS

FOREST DYNAMICS IN THE TEMPERATE RAINFORESTS OF ALASKA: FROM INDIVIDUAL TREE TO REGIONAL SCALES

Tara M. Barrett

Abstract—Analysis of remeasurement data from 1079 Forest Inventory and Analysis (FIA) plots revealed multi-scale change occurring in the temperate rainforests of southeast Alaska. In the western half of the region, including Prince William Sound, aboveground live tree biomass and carbon are increasing at a rate of 8 (± 2) percent per decade, driven by an increase in Sitka spruce. In the Alexander Archipelago, western red cedar is increasing, as is overall biomass on gentler slopes and in higher latitudes. These increases, which occurred during a warmer period of the Pacific Decadal Oscillation, correspond well with regional predictions of forest change in a warming climate. In the 180 thousand ha of managed forests on the Tongass National Forest, aboveground live tree carbon was found to be stable between the two inventory periods. And at the regional level, analysis of FIA data showed no significant change in the yellow-cedar population, despite widespread publicity for a 'decline' in this species. While FIA remeasurement data provides insight at a variety of scales, alterations in forest definition and other inventory methods complicated analysis.

Northern latitudes are expected to have the largest temperature increases from global climate change (IPCC 2014). With fire absent or extremely rare, fire suppression has had almost no impact on the forests of southeast Alaska, and timber harvesting or other forms of vegetation manipulation have also been absent from large expanses of the forest. Thus these forests provide an ideal environment for monitoring early detection of change associated with climate.

To examine whether changes were occurring, a combination of forest inventory and remote sensing data was used to examine growth, mortality, and net change in southeast Alaska's temperate rainforest.

METHODS

The study area included the whole temperate rainforest region of Alaska (figure 1), with the exception of national forest wilderness and Glacier Bay National Park. Plots were initially installed between 1995 and 2003, and then remeasured between 2004 and 2010. Stratification with remote sensing data (NLCD) and other spatial information was used to account for different sampling intensity on Kodiak Island, population boundaries that varied between inventories, and missing data (inaccessible plots) that occurred primarily on forested land. Individual tree data were reconciled to Time 1 measurements, with analysis limited to subplots that were fully forested at both measurements due to a change in definition of 'forest' that occurred between inventories. Growth and mortality were converted to average annual values and then compiled to population level estimates using standard national methods (Bechtold and Patterson 2005). Detailed description of methods can be found in Barrett (2014).

RESULTS

Within-forest live tree biomass is increasing in the western portion of the Alaska temperate rainforest, where the Chugach National Forest is found. Estimated rate of change was an average annual increase of 0.8 ± 0.2 percent (p-value < 0.001). This change is primarily driven by an average annual increase in Sitka spruce live tree biomass of 0.9 ± 0.3 percent. Increases also occurred in paper birch and cottonwood in that region.

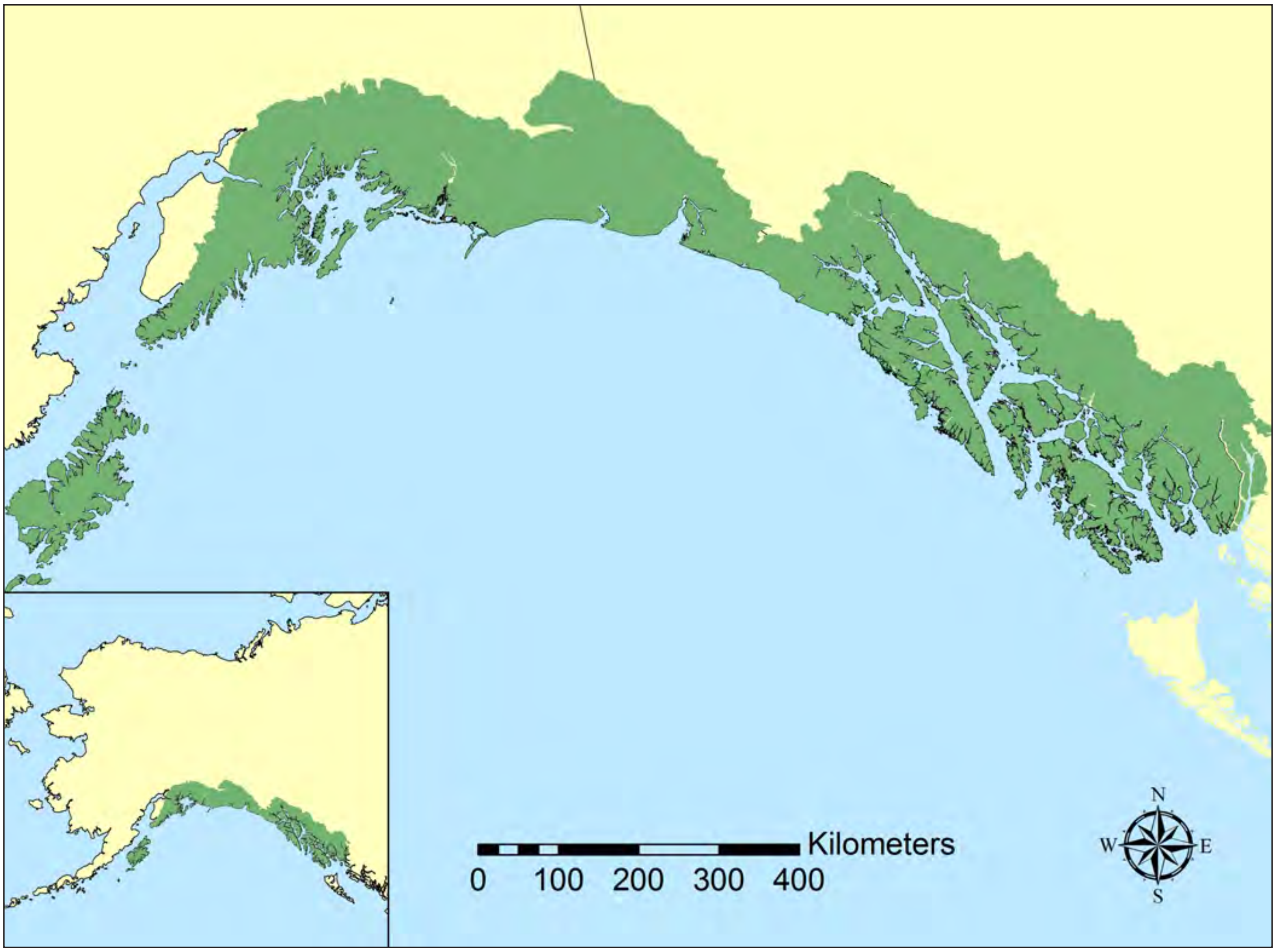

Figure 1—The study area included the temperate rainforest region of Alaska.

In the eastern region of the temperate rainforest, including the Alexander Archipelago, western redcedar is increasing in biomass (average annual increase of 0.6 ± 0.1 percent) and there is some evidence for a decrease in shore pine live tree biomass (-0.31 ± 0.19 percent). Although substantial research has focused on yellow cedar decline, the population outside of wilderness areas appears to be stable overall; the 95 percent confidence interval for live yellow-cedar average annual biomass change was from -0.04 percent to +0.29 percent of initial biomass.

Shifts in species composition and carbon storage and flux differed between managed and unmanaged forest. Areas of the Tongass National Forest that had past silvicultural treatments ("managed" forest) had higher log density and lower live tree and snag density than unmanaged forest (Figure 2a). Managed forest also had greater carbon turnover (Figure 2b) than did areas of unmanaged forest.

DISCUSSION

Procedural changes between the two inventories greatly complicated analysis. Procedural changes included a shift in forest definition from tree cover to tree stocking, alterations in which species were considered trees, the exclusion of Krumholtz forest in the first inventory, altered rules used to decide whether a tree was in or out of a subplot, shifting boundaries for the non-inventoried national forest wilderness, different sampling intensities, altered interpretation

A

B

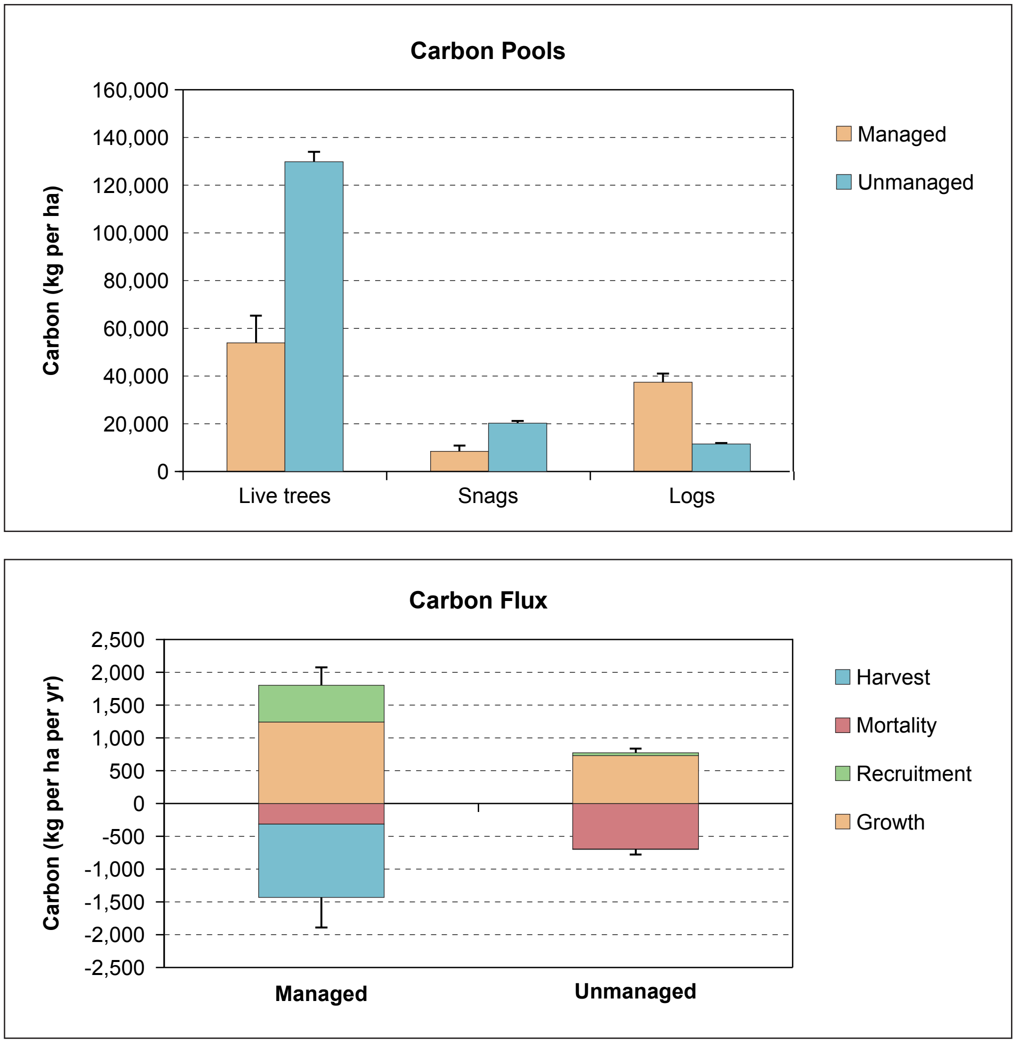

Figure 2—Aboveground tree carbon (a) density and (b) flux in managed (180,000 ha) and unmanaged (2,547,000 ha) forest of the Tongass National Forest. (Does not include forest in wilderness areas.)

of decay classes and crown classes, and a variety of other changes. The impact of the procedural changes is greater than actual change in many cases, with the result that unsuspecting users of the two data sets from the national web site are likely to make erroneous conclusions from a *prima facie* comparison.

While the change in forest definition prevented reliable estimates of deforestation or afforestation, using an approach based on remote sensing data suggests gains are outpacing losses, with forest increasing in northerly aspects, lower elevations, and higher latitudes (Buma and Barrett 2015).

Given the absence of fire and other large disturbances, the changes observed in the unmanaged portions of the temperate rainforest seem likely to be associated with climate or atmospheric changes. The remeasurement period largely coincided with a warmer period of the Pacific Decadal Oscilliation, and so may be an earlier indicator of trends under climate change. Future monitoring will help to detect whether the observed changes continue into the future.

ACKNOWLEDGMENTS

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OBSERVED AND PROJECTED C CHANGE IN THE SOUTHEASTERN US

John Coulston[1], David Wear[2], and Jim Vose[3]

Abstract—Over the past century forest regrowth in Europe and North America expanded forest carbon (C) sinks and offset C emissions but future C accumulation is uncertain due to the effects of land use changes, management, disturbance, and climate change. Policy makers need insights into forest C dynamics as they anticipate emissions futures and goals. Using a completely remeasured land use and forest inventory we show that forests in the southeastern United States yielded a net sink of C over a 5 year period (2007-2012) because of net land use change (+6.48 TgC yr^{-1}) and net forest accumulation (+75.4 TgC yr^{-1}). Forests disturbed by weather, insect/disease, and fire show positive forest C changes (+1.56, +1.4, +5.48 TgC yr^{-1}, respectively). Forest cutting was the only disturbance causing net decreases in C (-76.7 TgC yr^{-1}) but was offset by forest accumulation (+143.77 TgC yr^{-1}). Projected C stock changes indicate a gradual slowing of carbon accumulation with forest aging (a reduction of 9.5% over the next five years) but was highly sensitive to land use.

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MODELING POST-FIRE WOODY CARBON DYNAMICS WITH DATA FROM REMEASURED INVENTORY PLOTS

Bianca N.I. Eskelson[1], J.S. Fried[2], and V.J. Monleon[3].

Abstract—In California, the Forest Inventory and Analysis (FIA) plots within large fires were visited one year after the fire occurred resulting in a time series of measurements before and after fire. During this additional plot visit, the standard inventory measurements were augmented for these burned plots to assess fire effects. One example of the additional measurements is the post fire index (PFI), which is a fire severity classification based on post-fire crown observations. Stands that showed presence or no evidence of residual green crowns were assigned to PFI classes Alive and Dead respectively. The repeated measurements of 109 burned FIA plots allowed us to quantify gains and losses in dead and life woody carbon pools in the first five years following a wildfire. We used a mixed model to estimate the change in each woody carbon pool as a function of PFI, years since fire, and pre-fire woody carbon. Most of the 109 plots in this study burned with low to moderate severity and the post-fire carbon trajectories by pool differed from those observed for the stands that burned with high severity. This study showcases how large-scale inventory data can be supplemented with additional re-measurements to answer disturbance related research questions and hypotheses.

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REDRAWING THE BASELINE: A METHOD FOR ADJUSTING BIASED HISTORICAL FOREST ESTIMATES USING A SPATIAL AND TEMPORALLY REPRESENTATIVE PLOT NETWORK

Sara A. Goeking and Paul L. Patterson[1]

Abstract—Users of Forest Inventory and Analysis (FIA) data sometimes compare historic and current forest inventory estimates, despite warnings that such comparisons may be tenuous. The purpose of this study was to demonstrate a method for obtaining a more accurate and representative reference dataset using data collected at co-located plots (i.e., plots that were measured during both periodic and annual inventories). The approach described here uses co-located plot-level data to build linear regression models that relate annual inventory measurements to periodic inventory measurements. Separate models were constructed within each state, and wherever possible, for domains defined by factors that may affect forest attributes over time and that also affected the intensity of the periodic inventories (i.e., timber versus woodland forest types). We used these regressions to simulate periodic-era, plot-level response variables, on a per-acre basis, for annual plot locations that were not sampled during the periodic inventories. Because the extent of the resulting dataset coincides with the annual plot grid, the post-stratification procedures used to produce broad-scale annual inventory estimates can be applied to the simulated periodic dataset to produce periodic-era estimates of forest attributes. Construction of this simulated periodic-era dataset allows investigation of broad-scale trends in forest attributes, particularly as they vary across ownership group, reserved status, and forest type group due to disturbance and land management history.

In the eastern U.S., the Forest Inventory and Analysis (FIA) program has completed multiple inventory cycles and therefore provides assessments of trends in forest attributes such as volume, growth, mortality, biomass, and carbon over time. However, in the western U.S., the 10-year cycle length precludes long-term evaluations in states where only one cycle of data has been collected. In these areas, many users of FIA data rely on historical, periodic inventory estimates to serve as temporal reference conditions, and then directly compare them to annual estimates to quantify forest trends. Because the periodic plots did not representatively sample all forested locations, directly comparing the periodic and annual estimates can lead to erroneous conclusions (Goeking 2015). The purpose of this paper is to describe a methodological framework for obtaining a more accurate and representative reference dataset using data collected at co-located plots, or plots that were measured during both periodic and annual inventories, in states where direct comparisons of multiple inventories over time are tenuous.

STUDY AREA

The methods described below were applied to the eight states within the Interior West FIA region: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. The analysis was restricted to periodic plot measurements collected from 1993-2002 and annual plot measurements collected from 2004-2013.

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METHODS

The response variables presented here include net volume of live trees, net volume of dead trees, and above-ground tree biomass at time 1 (periodic inventory), where the predictors are the values of these variables at time 2 (annual inventory). Tree-level volumes were obtained as the variable VOLCFNET in FIADB (O'Connell et al. 2015) and related to tree status (live or dead) to permit separate calculations of live and dead net volume. Biomass was queried from several variables that constitute the component ratio method, as described in O'Connell et al. (2015), and summed to a single above-ground metric. Because differences in periodic versus annual inventory plot designs preclude direct comparisons of total plot-level tree volume, these variables were calculated on a per-acre basis as described by Goeking (2015).

Based on the linear relationships evident between time 1 and time 2 plot-level volumes (Fig. 1), we adopted the approach of developing linear regression models where time 1 values were predicted based on time 2 values. Although this is contrary to typical regression modeling that seeks to predict future values based on current or previous measurements, in this situation the time 2 dataset is more complete and representative than any of the time 1 datasets.

Prior to building regression models, we identified domains for the purpose of developing separate regression models. Individual states formed the primary division into domains. Within each state, we considered that timber and woodland forest types might require separate regression models because their attributes may experience different rates of change, and also because this distinction undoubtedly affected the intensity of the periodic inventories (Goeking 2015). Thus, within each state, we tested whether timber and woodland forest types qualified as separate domains versus a single domain for the state. To qualify as a single domain, the regression models for timber and woodland plots within each state had to have slopes and intercepts that were not statistically different. We followed the procedure described by Zar (1996) for comparing two or more regression equations, which first tests for equal slopes and then if the slopes are not statistically different, tests for equal intercepts. Each response variable was considered separately, so the tests for equal slopes and intercepts were repeated for live and dead volume. An alpha of 0.05 was used to reject the null hypotheses that slopes and intercepts were equal between timber and woodland models.

Based on the results of the comparisons of slopes and intercepts in each state, we established domain-specific linear regression models relating the estimates made with the annual and periodic data at co-located plots. We used these relationships to estimate periodic-era, plot-level response variables for annual plot locations that were not sampled during the periodic inventory. Using plot-specific expansion factors obtained from the annual post-stratification estimation process, we then produced estimates of live volume, dead volume, and biomass.

RESULTS

Table 1 presents the results of tests for equal slopes and intercepts between regression models for timber and woodland plots within each state. Based on these results, timber and woodland domains were modeled separately in most states. Exceptions included Colorado, where a single model was used for each response variable (live volume, dead volume, and biomass); and Arizona and Wyoming, where each state had one model for biomass.

The relationships between above-ground biomass per acre at co-located plots, as measured at time 1 and time 2, for each modeling domain are shown in Figure 1. Adjusted r^2 values were generally lower for woodland models than for timber models.

Ongoing research and future papers will present the detailed calculation of statewide estimates based on the modeling approach described here and investigate trends in forest attributes such as volume, biomass, growth and mortality, particularly as they vary across ownership group, reserved status, and forest type group due to potential differences in disturbance and land management history. This plot-based approach will allow evaluation of changes in volume and

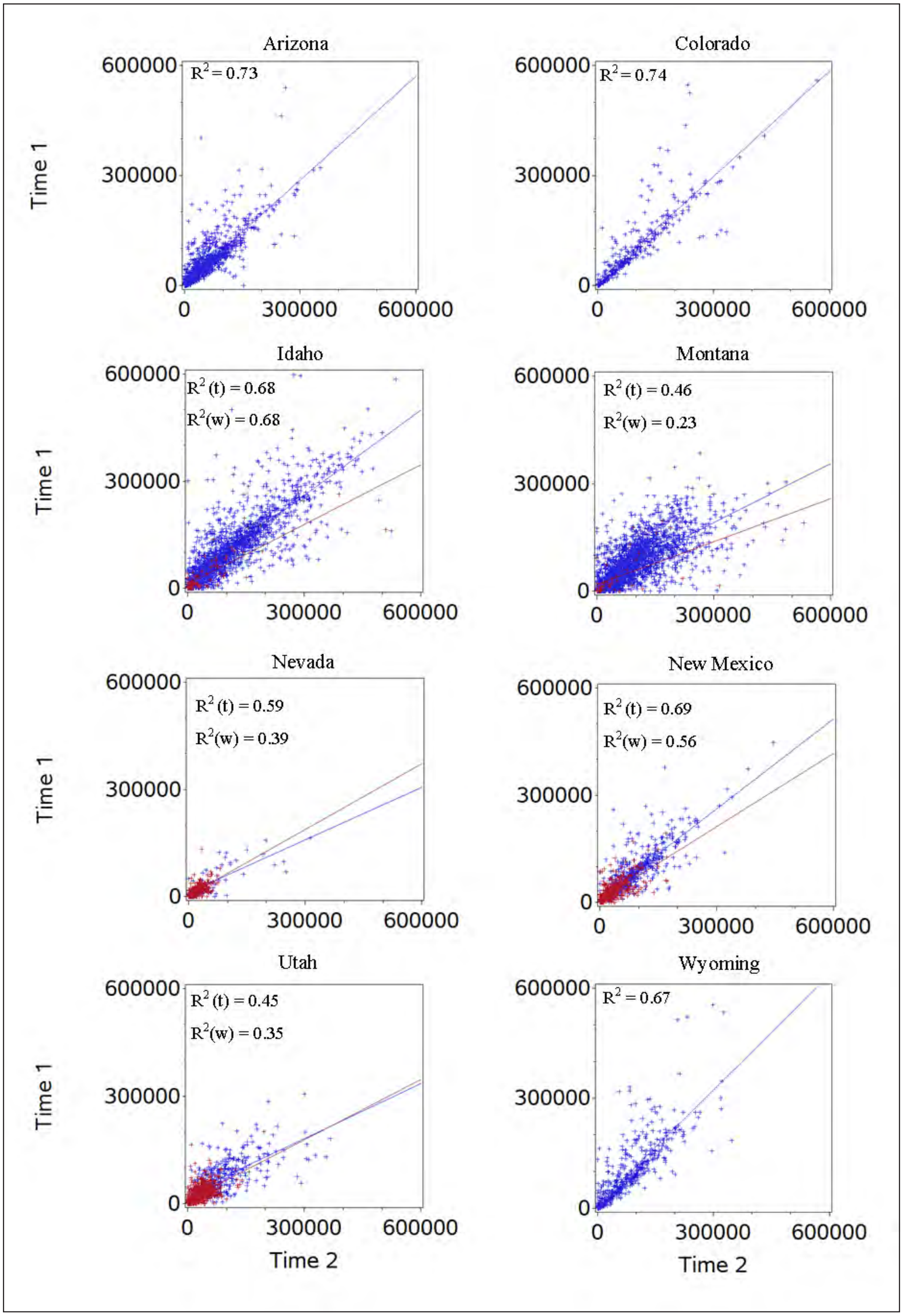

Figure 1—Scatter plots of time 1 (periodic) versus time 2 (annual) above-ground tree biomass, in dry tons per acre, by state. Within each state, each line represents a domain, where a regression model was developed for each domain. Five of the 8 states had separate domains for timber (blue markers) and woodland (red markers). In Arizona, Colorado, and Wyoming, timber and woodland were grouped into a single domain. Domains were defined based on the results of tests for equal slopes and intercepts of the timber and woodland regressions. Adjusted r2 values are shown for each modeling domain, where t indicates timber domains and w indicates woodland domains.

Table 1—Results of tests used for identifying domains for regression models, by state. Tests for equal slopes and equal intercepts follow Zar's (1996) methods for comparing two or more regression equations. Where "Number of domains"=2, timber and woodland domains were modeled separately.

		Test for equal slopes	Test for equal intercepts			Number of domains
State	Variable	p-value[a]	t[b]	df[b]	t*	
Arizona	Live volume	0.003	3.064	1635	1.962	2
	Dead volume	<.0001	4.606	1635	1.962	2
	Biomass	0.169	0.373	1635	1.962	1
Colorado	Live volume	0.365	1.589	333	1.968	1
	Dead volume	0.105	1.159	333	1.968	1
	Biomass	0.337	1.445	333	1.968	1
Idaho	Live volume	0.197	4.889	1760	1.962	2
	Dead volume	0.037	1.755	1760	1.962	2
	Biomass	0.008	4.109	1760	1.962	2
Montana	Live volume	0.437	2.264	2118	1.962	2
	Dead volume	0.665	2.068	2118	1.962	2
	Biomass	0.195	2.389	2118	1.962	2
Nevada	Live volume	<.0001	4.777	449	1.962	2
	Dead volume	0.073	2.791	449	1.962	2
	Biomass	<.0001	3.925	449	1.962	2
New Mexico	Live volume	0.015	1.420	1372	1.966	2
	Dead volume	0.732	4.438	1372	1.966	2
	Biomass	0.034	1.276	1372	1.966	2
Utah	Live volume	0.042	9.421	1218	1.962	2
	Dead volume	0.001	7.388	1218	1.962	2
	Biomass	0.258	6.037	1218	1.962	2
Wyoming	Live volume	0.383	3.302	509	1.965	2
	Dead volume	0.017	1.938	509	1.965	2
	Biomass	0.303	1.359	509	1.965	1

[a]P-values for tests of equal slopes were produced using a contrast statement in Proc GLM (SAS Institute, Inc. 2009).
[b]Values of t-statistics and df (degrees of freedom) were calculated as prescribed by Zar (1996) for testing equal elevations of regression models, and compared to critical values (t*). Where values of t are greater than t*, the null hypothesis that the intercepts are equal was rejected.

biomass by categories such as ownership group and reserved status, and the estimated variance of our volume and biomass estimates; the estimated variance will need to include the error associated with the simulated periodic dataset.

DISCUSSION

The modeling approach described here generates a spatially balanced dataset of periodic-era plot-level variables, to which the annual inventory's post-stratification estimation process can be applied to produce broad-scale periodic-era estimates. The fundamental advantage of FIA's annual inventory design over previous periodic inventories is that it provides spatially and temporally representative estimates of forest attributes (Bechtold and Patterson 2005). This advantage is especially pronounced in regions such as the Interior West, where periodic inventories were decidedly non-representative not only throughout space and time, but also relative to tabular attributes such as ownership and forest type. This paper describes an approach for using co-located plot data to produce more representative baseline estimates for the periodic inventories of the 1990s. Although the development of this approach is focused on the Interior West, it could be applied to other states or regions where (a) periodic datasets are known to be incongruous with annual inventory datasets, and (b) sufficient co-located plots exist to build regression models that allow prediction of time 1 (periodic inventory) values based on time 2 (annual inventory) values.

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A REGIONAL ASSESSMENT OF EMERALD ASH BORER IMPACTS IN THE EASTERN UNITED STATES: ASH MORTALITY AND ABUNDANCE TRENDS IN TIME AND SPACE

Randall S. Morin, Scott A. Pugh, Andrew M. Liebhold, and Susan J. Crocker[1]

Abstract—The nonnative insect, emerald ash borer (*Agrilus plannipennis* Fairmaire), has caused extensive mortality of ash tree species (*Fraxinus* spp.) in the eastern United States. As of 2012, the pest had been detected in about 15 percent of the counties in the 37 states that comprise the natural range of ash in forests of the eastern United States. Here we use regional forest inventory data from the USDA Forest Service Forest Inventory and Analysis program to quantify ash mortality, volume, and standing dead tree abundance relative to the year of initial emerald ash borer detection. Results from remeasured plots indicate that the annual ash mortality rate increases dramatically over the background level several years after initial invasion of the pest into a county. The corresponding decrease in ash volume and increase in standing dead trees continues for several more years until the live ash resource is reduced to very low levels in local areas.

INTRODUCTION

The nonnative insect, emerald ash borer (EAB; *Agrilus plannipennis* Fairmaire), was initially detected in Michigan and Ontario in 2002 although it had probably established in the early 1990s (Siegert et al. 2014). As of 2012, EAB had been discovered in about 15 percent of the counties in the 37 states that comprise the natural range of ash species (*Fraxinus* spp.) in forests of the eastern United States (Figs. 1,2). As it continues to spread, EAB has the potential to functionally extirpate ash with extensive economic and ecological impacts. An essential part of the management for any invasive pest is measuring the extent of its impacts over time and space (Parker et al. 1999). Here, we use remeasured regional forest conditions using inventory data from the USDA Forest Service Forest Inventory and Analysis (FIA) program to quantify changes in live ash volume, ash mortality, and ratio of standing dead to live tree abundance, relative to the historical spread of EAB.

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METHODS

The study area includes counties in the 14 states where EAB had been detected as of 2012. This area includes: Illinois, Indiana, Kentucky, Maryland, Michigan, Minnesota, Missouri, New York, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and Wisconsin (Fig. 1). Forest conditions of grouped counties were estimated from the 2005 to 2012 inventory years by the year of first EAB detection.

Two metrics were employed to assess the impact of EAB on regional dynamics of all ash species in the study area: annual mortality rate and annual volume change. Annual mortality rate was computed as the proportion of annual mortality to initial live volume. Annual volume change was calculated as the difference between annual volume estimates as a percentage of the first estimate.

RESULTS

The background annual mortality, computed as annual mortality as a fraction of initial volume, for ash species across all counties (invaded and non-invaded) in the 14-state study area as computed for 2005 was 0.5 percent. Results from remeasured plots indicate that

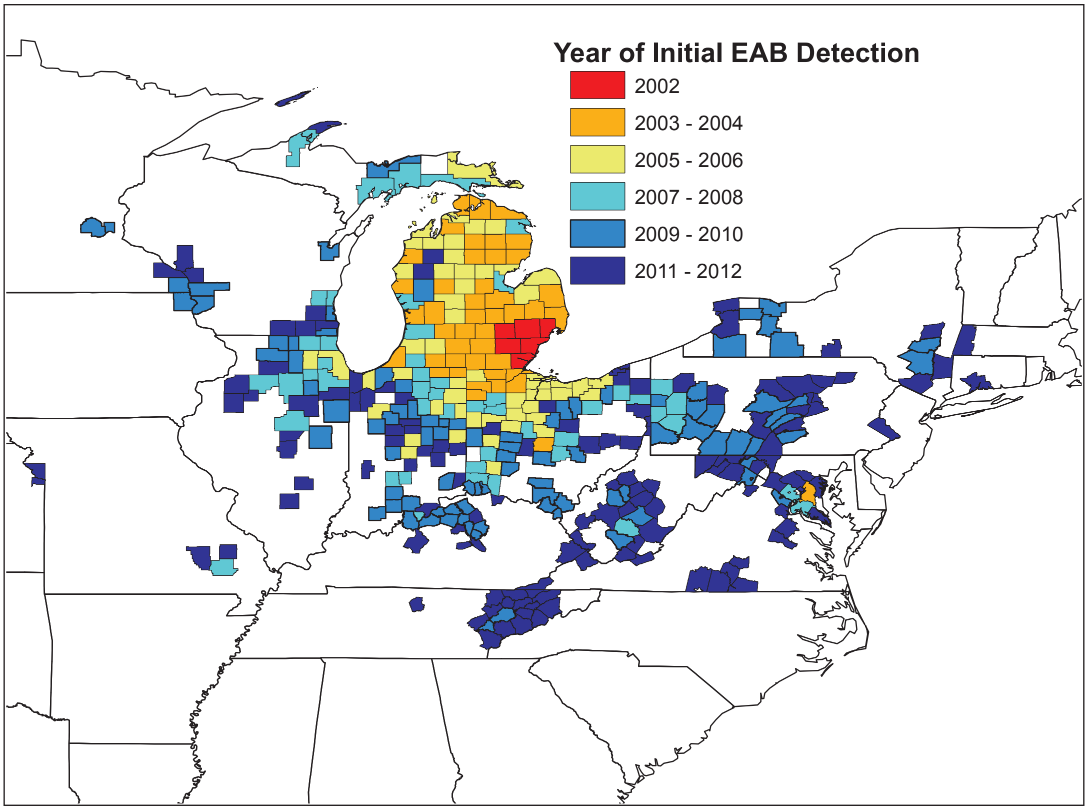

Figure 1—Year of initial EAB detection by county, 2013.

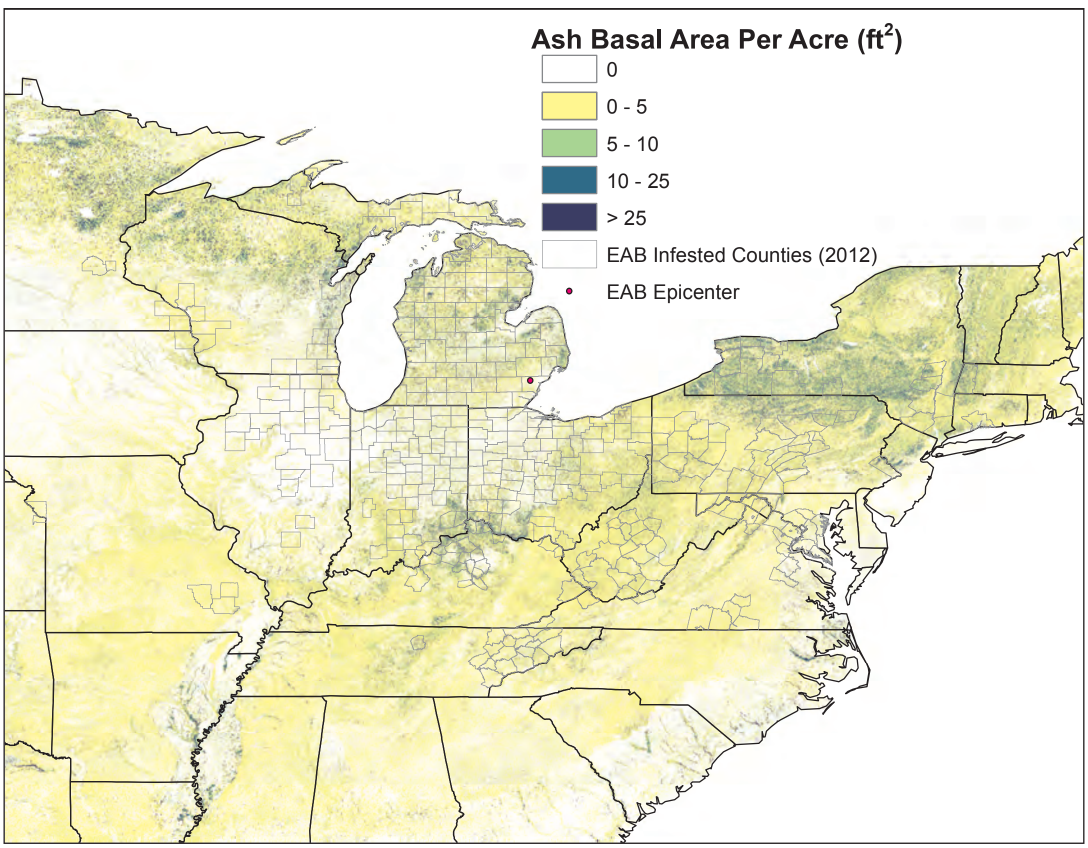

Figure 2—Spatial distribution of ash basal area per acre in the eastern United States, 2009.

annual ash mortality rates increase dramatically over the background level in the fourth to seventh inventory year after initial invasion of the pest into a county (Table 1). The exception is the 2002 invasion category where EAB has likely been present since the early to mid-1990s (Siegert et al. 2014).

This lag between initial invasion and mortality is also reflected in the change in ash volume over time. Volume generally continues to increase after EAB invasion for 3 to 4 inventory years before beginning to decrease (Table 1). Large decreases in volume of 5 percent or more appear to have a longer lag period of nearly a decade.

Some of the areas with the highest ash density have yet to be invaded by EAB. For example, northern Minnesota, northern Wisconsin, northern Pennsylvania, and southern New York (Fig. 2).

DISCUSSION

The impact of EAB on ash mortality has been demonstrated in localized (Ghandi et al. 2008) as well as regional studies (Pugh et al. 2011). As EAB continues to spread across the range of ash in the United States, FIA data can be used to quantify subsequent mortality across time and space. The annual mortality rate has been used in pest impact assessments with FIA data (Morin and Liebhold 2015) because it can be compared to background mortality levels to quantify the level of increase due to a particular disturbance agent. This metric is most useful for understanding the ecological impacts of pest invasion because it quantifies mortality as a function of the resource that was present prior to establishment. Our analyses indicate that the annual mortality rate doubles after approximately 4 to 7 years and then continues to rise. The rate is as high as 20 percent in the areas that have been invaded the longest (Fig. 1; Table 1).

Similarly, annual volume change is valuable for assessing resource loss over time. Although volume generally continues to increase for 3 to 4 inventory years after invasion by EAB, once volumes begin to decrease the losses can be dramatic because the amount of live volume available is further reduced over time. For example, the areas invaded by EAB since 2003-2004 were gaining ash volume at 3 to 4 percent annually before and immediately after invasion, but 5 to 6 years after invasion, volume began to decrease. By 2012, ash volume was decreasing

Table 1—Regional trends in annual mortality rate and annual volume change by inventory year and EAB invasion year for the county groups shown in Figure 1A.

	Inventory year							
EAB invasion year	2005	2006	2007	2008	2009	2010	2011	2012
	Annual mortality rate (%)							
2002	19.7	11.5	8.3	8.2	9.6	9.9	14.8	19.7
2003-2004	1.2	1.0	1.0	1.3	1.3	2.3	3.1	4.7
2005-2006	0.6	0.6	1.3	1.5	1.3	1.7	2.1	3.4
2007-2008	1.4	1.5	1.0	1.4	1.6	1.6	1.6	2.2
2009-2010	1.7	0.9	1.0	1.3	1.0	1.0	1.3	1.6
2011-2012	1.0	1.4	1.4	1.3	1.2	1.1	1.1	1.2
	Annual volume change (%)							
2002	-	-2.4	-13.2	-13.1	-22.7	-2.1	-41.9	-77.7
2003-2004	-	3.0	3.0	3.8	-2.6	0.0	-2.2	-7.5
2005-2006	-	4.9	1.6	1.9	-0.5	1.8	1.7	-4.3
2007-2008	-	4.8	1.5	3.0	-2.3	2.9	-0.4	2.7
2009-2010	-	3.7	1.3	2.1	0.7	1.6	2.7	-0.9
2011-2012	-	1.2	6.7	2.2	2.6	1.1	2.6	2.2

at nearly 8 percent per year. The lag period between initial invasion and the onset of ash volume decrease can be attributed in part to the nature of the scale of historical invasion data; a county is considered invaded once EAB is found reproducing in any location but it may take several years for the insect to invade the entire county.

Two factors that complicate the interpretation of the results of these analyses are the 5-year remeasurement period for plots and the annual comparison of full-cycle estimates. For example, the lag for all the metrics in this analysis is likely to be highly correlated with the 5-year cycle of remeasurements. Additionally, each estimate shares approximately 80 percent of observations with previous and subsequent estimates so a full set of new observations is only available after 5 years.

CONCLUSIONS

FIA remeasurement data can provide powerful information to quantify the impacts of an invasive pest by estimating mortality rates and volume trends across time and space. However, due to confounding factors addressed above, an analysis of estimates by measurement year may provide more information about the timing of impacts after invasion providing enough samples are available annually.

The increase in ash mortality and the corresponding decrease in ash volume typically begin 3 to 7 years after a county is designated as EAB invaded and continues for several more years until the live ash resource is reduced to very low levels in local areas. As EAB continues to spread, it has the potential to functionally extirpate a large fraction of the ash component with potentially devastating economic and ecological impacts. Further monitoring and analysis will be needed to quantify the timing and magnitude of EAB impacts as its range expands across the eastern United States.

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LANDSCAPE-SCALE MAPPING

ON THE ROAD TO NATIONAL MAPPING AND ATTRIBUTION OF THE PROCESSES UNDERLYING U.S. FOREST CHANGES

Karen Schleeweis[1], Gretchen G. Moisen[1], Todd A. Schroeder[1], Chris Toney[2], and Elizabeth A. Freeman[1]

Abstract—Questions regarding the impact of natural and anthropogenic forest change events (temporary and persisting) on energy, water and nutrient cycling, forest sustainability and resilience, and ecosystem services call for a full suite of information on the spatial and temporal trends of forest dynamics. Temporal and spatial patterns of change along with their magnitude and cause are all equally important when weaving together the full story of our forests' history. National statistical estimation and mapping of land use and cover changes have been progressing for decades. However, especially in the case of forest cover changes, attributing the magnitude and underlying causal processes to areas of change are newly developing endeavors. The NASA/NACP funded North American Forest Dynamics (NAFD) project has conducted nearly a decade of research in mapping U.S. forest dynamics using Landsat imagery. One part of this research is an empirical and rule-based modeling approach to attribute the casual processes underlying temporary forest changes from wind, fire, insects/stress, harvest and persisting change from land cover conversion. In this presentation we address model matters including the utility of using the outputs (temporal, spatial and magnitude) from multiple forest disturbance algorithms as predictors to reduce commission and omission among response classes, insufficient and imbalanced training data, model and map accuracy, as well as initial results from these maps of CONUS forest change causal processes over two and a half decades.

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USING AN EMPIRICAL AND RULE-BASED MODELING APPROACH TO MAP CAUSE OF DISTURBANCE IN U.S. FORESTS: RESULTS AND INSIGHTS FROM THE NORTH AMERICAN FOREST DYNAMICS (NAFD) PROJECT

Todd A. Schroeder[1], Gretchen G. Moisen[1], Karen Schleeweis[1], Chris Toney[2], Warren B. Cohen[3], Zhiqiang Yang[4], and Elizabeth A. Freeman[1]

Abstract—Recently completing over a decade of research, the NASA/NACP funded North American Forest Dynamics (NAFD) project has led to several important advancements in the way U.S. forest disturbance dynamics are mapped at regional and continental scales. One major contribution has been the development of an empirical and rule-based modeling approach which addresses two of the major challenges associated with mapping forest disturbance. The first challenge is that no single spectral band or index responds consistently to all disturbance types. To overcome this challenge we use a new, non-parametric shape-fitting algorithm to derive pixel-level temporal change metrics (e.g. timing, magnitude, duration) from four different types of Landsat trajectories. By incorporating both shortwave-infrared data (e.g. Landsat band 5) and near-infrared-based vegetation indices (e.g. NDVI, NBR) we increase capture of subtle changes which alter forest structure and/or canopy leaf area. The second challenge is that certain types of disturbance are influenced by topographic and biophysical factors which are not inherently captured by optical remote sensing data. To overcome this challenge we use Random Forest models to integrate multiple spectral and non-spectral predictor variables to map fires, harvests, wind damage, as well as stress brought on by insect/disease outbreaks and land use conversion resulting in permanent forest cover loss. In this presentation we show results from 10 Landsat scenes representing a diverse array of causal agents, forest types, and forest prevalence levels found across the country. Using these example scenes we discuss the construction and importance of various predictor variables, as well as examine how model prediction accuracy varies as a function of geographic location, forest type and input training data. Lastly, we discuss how these initial results are being used to guide development of a nationwide map aimed at improving quantification of continental scale disturbance rates occurring over the last two decades.

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NATIONWIDE DISTURBANCE ATTRIBUTION ON NASA'S EARTH EXCHANGE: EXPERIENCES IN A HIGH-END COMPUTING ENVIRONMENT

J. Chris Toney[1], Karen G. Schleeweis[2], Jennifer Dungan[3], Andrew Michaelis[3], Todd Schroeder[2], Gretchen G. Moisen[2]

Abstract—The North American Forest Dynamics (NAFD) project's Attribution Team is completing nationwide processing of historic Landsat data to provide a comprehensive annual, wall-to-wall analysis of US disturbance history, with attribution, over the last 25+ years. Per-pixel time series analysis based on a new nonparametric curve fitting algorithm yields several metrics useful for elucidating causal processes underlying forest disturbance dynamics but requires CPU-intensive computation across large data sets (>4 billion pixels classified as forest in 434 Landsat scenes covering the conterminous US). FIA has worked collaboratively with NASA to conduct all processing for this project in NASA's Earth Exchange (NEX) which includes the Pleiades supercomputer providing 210,336 CPU cores, 719 TB total memory, and 15 PB of disk storage. In this presentation, we describe the NEX computing environment, outline our processing steps for the NAFD attribution work, identify computing needs for this application, and present results from efficiency trials under different parallel processing strategies.

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FOREST SERVICE CONTRIBUTIONS TO THE NATIONAL LAND COVER DATABASE (NLCD): TREE CANOPY COVER PRODUCTION

Bonnie Ruefenacht, Robert Benton, Vicky Johnson, Tanushree Biswas, Craig Baker, Mark Finco, Kevin Megown, John Coulston, Ken Winterberger, Mark Riley[1]

Abstract—A tree canopy cover (TCC) layer is one of three elements in the National Land Cover Database (NLCD) 2011 suite of nationwide geospatial data layers. In 2010, the USDA Forest Service (USFS) committed to creating the TCC layer as a member of the Multi-Resolution Land Cover (MRLC) consortium. A general methodology for creating the TCC layer was reported at the 2012 FIA Symposium in Knoxville, Tennessee by several USFS researchers. Since that time, remote sensing specialists at the USFS Remote Sensing Applications Center (RSAC) have translated those methods into a process capable of being implemented over the Contiguous United States, Coastal Alaska, Hawaii, Puerto Rico, and the US Virgin Islands.

This paper describes the products produced by the NLCD 2011 TCC team, the challenges encountered, and the solutions devised while creating this Landsat grained map over the entire nation. The NLCD TCC 2011 was produced in two forms. The first is called the analytical dataset and is intended primarily for purposes of research and analysis. This dataset has two data layers, which are a per pixel estimate of tree canopy cover and a per pixel estimate of standard error. The second form of NCLD TCC 2011 is called the cartographic dataset and is intended primarily as an image backdrop or map display. This dataset consists of a single layer – tree canopy cover – that is a statistically masked version of the analytical dataset. Both versions of the NLCD TCC dataset are distributed through the MRLC NLCD website (http://www.mrlc.gov).

INTRODUCTION

The first NLCD products were prepared by the Earth Observation and Science (EROS) Center. The latest version of the NLCD percent canopy cover dataset was prepared by the USDA Forest Service (USFS) and the Remote Sensing Applications Center (RSAC). The NLCD products are available for free at http://www.mrlc.gov/ (last accessed 6 Jul 2015) and are downloaded more than 400 times per month.

METHODS

There are 456 Landsat WRS2 path/rows for the conterminous United States (CONUS), 51 for coastal Alaska (AK), 10 for Hawaii (HI), and 6 for Puerto Rico (PR) and the United States Virgin Islands (USVI). For all these path/rows except for HI, PR, and USVI, all Landsat 5 images with less than 70 percent cloud cover acquired during the growing season for the years 2009-2011 were downloaded from glovis.usgs.gov (last accessed: 6 Jul 2015). For HI, PR, and USVI, Landsat 8 images for the

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2013-2015 growing season were used. The individual Landsat scenes for each path/row were combined into a single median composite for each path/row.

For each of the Landsat median composites, NDMI (normalized difference moisture index), NDVI (normalized difference vegetation index), and Tassel Cap (Baig and others 2014, Crist and Cicone 1984) images were created to use as explanatory variables. Other explanatory variables available for modeling but not necessarily used included elevation data, elevation derivatives, ecoregions, NLCD 2001 land cover, NLCD 2001 TCC, pixel coordinates, soils data, climate data, and geology data. Using 3 by 3 windows, focal standard deviation images were created for the Landsat data, Landsat derivatives, elevation data, and elevation derivatives.

There were 63,010 (CONUS), 1,884 (coastal AK), 737 (PR and USVI), and 1,385 (HI) USDA Forest Service Inventory and Analysis (FIA) plot locations used to collect the response data. A circle with a radius of 43.9 m was placed over each FIA plot center. Each circle contained a 109-dot grid, which was oriented 15 degrees east of true north, with each dot separated by 8 m. Photo-interpreters evaluated each dot as being either tree or not tree. For each plot, percent TCC was calculated from these dot counts.

Because the spatial resolution of the response data was approximately 90 m, focal means using 3 by 3 windows were created for all of the 30 m explanatory variables except for the focal standard deviation images, large-scale images, and thematic datasets, which included ecoregions, NLCD 2001 land cover, pixel coordinates, soils data, climate data, and geology data. For thematic datasets that were not large-scale such as NLCD 2001 land cover, focal majority algorithms using 3 by 3 windows were used.

The algorithm used to model TCC was random forest as implemented in R 3.02 (Liaw and Wiener 2002, R Core Team 2013). Selected explanatory variables along with the response data were used to train the random forest model. The random forest model was applied to the original datasets.

The number of trees used in the random forest algorithm was 500, which means for every pixel, 500 TCC predictions were generated. The final TCC estimate for each pixel was the mean of these 500 predictions. Standard errors for each pixel were derived from these 500 predictions.

To create the cartographic NLCD 2011 TCC dataset, 500 random forest models were created using a portion of the data that was used to create the TCC dataset. The portion of the data not used was applied to the random forest models to obtained predicted TCC values, which were used to derive t-values: (predicted TCC – observed TCC)/standard error. The derived t-values were multiplied by the standard errors of the NLCD 2011 TCC dataset. If the TCC value was less than this product, the TCC value was forced to 0.

RESULTS AND DISCUSSION

There were many challenges and learning experiences encountered while creating the NLCD 2011 TCC product. One of the first challenges was to efficiently process over 7,000 Landsat scenes. Elements of this challenge included how to remove clouds and shadows, how to deal with banding effects caused by Landsat 7 SLC-off gaps, and how to condense individual Landsat scenes for a path/row into a single image for a path/row. FMASK (Zhu and Woodcock 2012), a cloud and shadow masking program for Landsat, was released in January 2012, which helped with the cloud and shadow removal problem. FMASK, is not perfect and there were occasions when manual editing of clouds and shadows was necessary especially in coastal Alaska and the mountain regions of the southwest US. The Landsat 7 SLC-off gap banding problem was solved by not using Landsat 7. We developed a median composite technique (Ruefenacht in review) to condense the individual Landsat scenes into a single image. Additionally, an automatic processing system was developed, which was instrumental in being able to process the volume of data in a timely manner.

Another challenge was the shifting of Landsat scenes between path/rows. We built a national grid system based upon the NLCD 2001 TCC layer and anchored all Landsat scenes to this national grid.

Originally, all of the explanatory data were used for the TCC modeling. However, some of the explanatory data, such as ecoregions and the focal standard deviation images, caused artificial boundaries in the TCC product. Thus, we carefully selected a subset of the explanatory variables for use in the TCC modeling.

There were other challenges encountered in creating the NLCD 2011 TCC dataset that were not solvable. For instance, we did our best to select and process Landsat scenes to avoid visible boundaries or seamlines between overlapping Landsat path/rows. Some seamlines are visible in the TCC data, but they are not prevalent. The influence of terrain shadowing can also be observed in the TCC data. Finally, in Alaska, clear-cut areas quickly regenerate into extremely thick stands of trees with 100 percent canopy cover. These areas were difficult to represent accurately.

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RESEARCH ACTIVITIES IN SUPPORT OF HIGH-RESOLUTION LAND COVER MAPPING IN THE NORTH CENTRAL UNITED STATES

Dacia M. Meneguzzo[1] and Greg C. Liknes[2]

Abstract—The USDA Agroforestry Strategic Framework and the 2014 Farm Bill call for inventory and monitoring of agroforestry practices; however, collecting such data over very large non-forested areas is costly. The Forest Inventory and Analysis (FIA) program at the Northern Research Station has addressed this challenge by forming a targeted task team whose primary purpose is to conduct an image-based inventory of tree cover in the heavily agricultural north central United States. The team conducts applied research and performs operational mapping of treed lands and other land cover using high-resolution imagery from the National Agriculture Imagery Program (NAIP). The imagery is available at no cost to the user and acquired at a spatial resolution capable of locating individual trees. Spatial pattern analysis is then applied to the resulting high-resolution maps to discern forest from other wooded lands, including agroforestry practices. We present a variety of applied research activities that have supported this effort including, 1) advancements in object-based image analysis, 2) implementation of shape-based thematic classification to distinguish other wooded lands from traditional forest land, and 3) the creation of value-added geospatial products describing functions provided by nonforest trees. We discuss challenges associated with mapping over large areas including imagery, software, and hardware considerations. Finally, we present high-resolution maps of tree cover and their functions, examples of summary statistics derived from those maps, and a proposal for reporting tree resources in these expansive landscapes.

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GLOBAL ECOSYSTEM DYNAMICS INVESTIGATION (GEDI) LIDAR SAMPLING STRATEGY

Paul L. Patterson[1], Sean Healey[2]

Abstract—Global Ecosystem Dynamics Investigation (GEDI) Lidar was selected by NASA for funding under its Earth Venture Instrument-2 program. A full-waveform lidar instrument will be attached to the International Space Station (ISS) and will provide unprecedented detail about the structure of the world's forest between 52°S and 52°N (the area covered by the ISS ground track). One of GEDI's science objectives is to quantify the distribution of above-ground forest biomass at fine spatial resolution, i.e., at the 500x500 meter pixel level. We will present the sampling design and estimators for average above ground live tree biomass (tons per ha), along with uncertainty, for each 500x500 meter pixel. The GEDI data is collected in linear tracks of lidar "shots", or plots with a 25m footprint and 60m posting. The first step is to build a model for predicting biomass for a single GEDI lidar shot. The estimate for each 500x500 pixel is a design based estimate, where the sample locations are the location of the GEDI lidar shots and the "observed" quantities are the predicted biomass. We propose to treat the tracks of lidar as clusters and treat the sample design as a combination of two single stage cluster samples. The estimated variance will take into account the uncertainty in the biomass prediction as well as uncertainty due to the sample design. Where auxiliary data is available, e.g., Landsat, we extend the methods to a model-assisted regression estimator to reduce the uncertainty in the estimated average biomass in theses near- global 500x500 meter pixels.

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DEVELOPMENT OF A REGIONAL LIDAR FIELD PLOT STRATEGY FOR OREGON AND WASHINGTON

Dr. Arvind Bhuta and Dr. Leah Rathbun[1]

Abstract—The National Forest System (NFS) Pacific Northwest Region (R6) has been flying LiDAR on a per project basis. Additional field data was also collected in situ to many of these LiDAR projects to aid in the development of predictive models and estimate values which are unattainable through LiDAR data alone (e.g. species composition, tree volume, and downed woody material). Until now, the protocols for collecting vegetation field data within LiDAR project areas have varied from project to project, leading to the inability to share, use, or analyze data across multiple project areas. The R6 Regional Office in conjunction with staff from the National Forests, the Pacific Northwest and Southwest Research Stations, and other collaborators, has developed a regional strategy for standardized field data collection in LiDAR project areas. The strategy includes the modification of Forest Inventory and Analysis (FIA) plots for field data collection. This allows for the opportunity to maintain consistency across the region and to leverage information from the existing FIA and Regional Monitoring data at no additional costs. This presentation will outline the strategy and discuss its implementation within a pilot project area located in the Blue Mountains.

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REFINING FIA PLOT LOCATIONS USING LIDAR POINT CLOUDS

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Abstract—Forest Inventory and Analysis (FIA) plot location coordinate precision is often insufficient for use with high resolution remotely sensed data, thereby limiting the use of these plots for geospatial applications and reducing the validity of models that assume the locations are precise. A practical and efficient method is needed to improve coordinate precision. To address this need, the USDA Forest Service's Remote Sensing Steering Committee has funded an applied research project to evaluate alternative methods that capitalize on lidar data availability to improve plot location precision. We are exploring two methods to improve plot location precision—a manual interpretation technique and a 3D surface model matching routine using FIA tree data and lidar collected in northeastern Minnesota.

The Forest Inventory and Analysis (FIA) program of the USDA Forest Service maintains an extensive network of field plots. Data collected on these plots at regular time intervals are used to provide unbiased statistical estimates of forest resources across the USA and US territories. The established sample plot density was designed to produce estimates for county- or multi-county areas, and to support informed decision-making at the strategic level with prescribed levels of precision. Tactical decision-making by forest managers and ecological analyses by landscape scientists necessitate that plot-level data be combined with high-resolution ancillary data in support of small-area estimation techniques (e.g., Goerndt and others 2013). However, creating accurate linkages between plot-level data and high-resolution data requires precise plot locations, or, minimally, accurate co-registration between datasets.

FIA plot coordinates have been obtained using several methods depending upon the technology available at the time of the field visit and available funding. Methods have evolved over time, including location of plots by pin-pricking aerial photos and transferring to corresponding digital ortho quads, use of early GPS units with "Selective Availability" (intentional degradation of public GPS signals by the U.S. Department of Defense), and, lately, recreation grade and survey grade GPS units. These coordinates have been used primarily to efficiently relocate plots during return visits.

Recreational grade equipment has been deemed sufficient for navigational purposes to and from plots. GPS methods vary substantially in their horizontal (locational) precision and also vary with location, terrain, and canopy cover conditions. In many states (e.g., Minnesota), recreation grade GPS receivers are believed to produce horizontal accuracies within 8–10 m RMSE in medium to heavy canopy (USDA Forest Service 2015), which are inadequate for co-registration with high resolution imagery.

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In the absence of highly precise (i.e., survey grade GPS) coordinates, there is a need to enhance the precision of existing forest inventory plot location coordinates to better correlate with digital imagery and other geospatial data (Gobakken and Nasset 2009).

Although efforts are underway to upgrade plot coordinates to survey grade precision for selected states and special study areas, a nationwide implementation is not under consideration. Except for the Pacific Northwest FIA region, acquiring plot coordinates with survey- or even mapping-grade receivers has not been made a priority for the FIA program. To address the need for higher precision FIA plot locations, the Forest Service's Remote Sensing Steering Committee has funded an applied research project in which lidar (light detection and ranging) point clouds will be used in an attempt to enhance the precision of FIA plot locations in northeastern Minnesota.

The State of Minnesota has complete statewide lidar coverage with acquisition dates ranging from 2008 to 2012. The primary use of these data is terrain mapping with a focus on hydrologic applications. Considering that lidar point clouds have planar coordinate registration errors consistently below 1 m, the coordinates of landscape objects, such as dominant trees identified from the lidar data are more precise than those calculated by the aforementioned methods.

We are evaluating two methods for improving FIA plot location coordinate precision—a manual approach based on human cognition, and a 3D surface matching process developed by Gatziolis (2012)—using Minnesota's statewide low density (approximately 1 return per m^2) lidar data. Additionally we are testing these methods using a moderate density (approximately 4 returns per m^2) lidar dataset collected in support of the NASA Carbon Monitoring System (CMS; Cohen and others 2013).

METHODS

Our study area extends north of Duluth and is roughly coincident with the boundary of St. Louis County. This area was selected because it is also the lidar data acquisition area for the NASA CMS study. The methods are as follows:

1. Surface model matching method (Gatziolis 2012). This method was developed using FIA data and high density lidar data with a return density of approximately 9 returns per m^2 in forests of the Pacific Northwest, USA. This project will assess the feasibility of and results obtained from using FIA plot data and lower density lidar data in Minnesota, USA.
2. Manual interpretation of FIA plot stem maps and corresponding lidar point data. Brian Wing Research Forester, U.S. Forest Service Pacific Southwest Research Station) has developed a method of repositioning a plot's location by manually interpreting tree locations from the lidar point clouds and shifting the location of the plot to match the field stem map data.

The surface model matching method compares 3D canopy surface models derived from the lidar data and the FIA plot data (Fig. 1). The lidar surface model is held stationary while the FIA model is iteratively shifted in two horizontal dimensions. For each shift a weighted correlation between the two surfaces is calculated, with weight values determined dynamically from the vegetation structure present on the plot. A pronounced maximum in the correlation raster indicates that the actual plot location has been determined. Multiple weak correlation maxima suggest that the precise plot location remains elusive (Gatziolis 2012). The inputs required by the surface matching model include FIA-collected tree location and dimensionality (e.g., crown size and shape) data, either field-measured or model-derived, and lidar data and derivatives (Table 1).

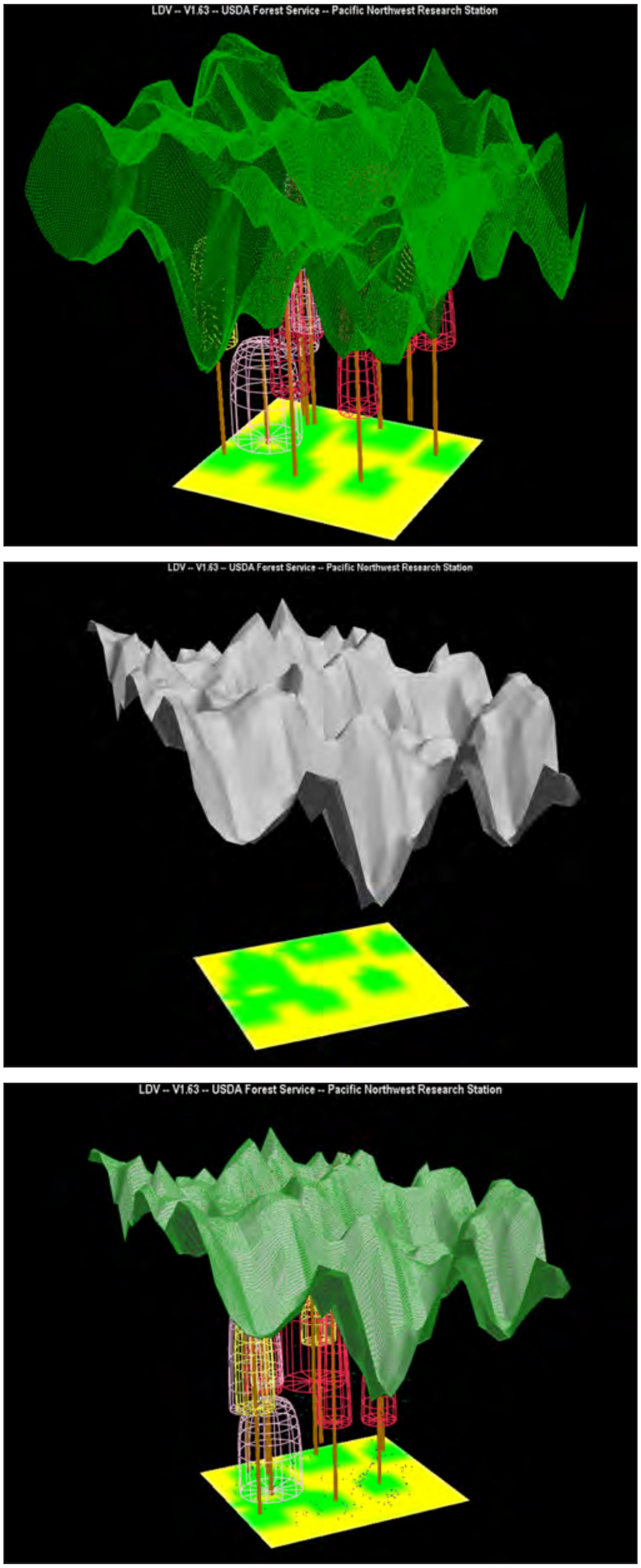

Figure 1—Conceptual representation of surface model matching method (Gatziolis 2012). A field-derived canopy height model (CHM) (1a) is iteratively shifted relative to a lidar-derived canopy surface height model (1b) until a satisfactory fit is achieved (1c). After fitting, new plot center coordinates are recorded from the shifted CHM.

Tree crowns that intersect a subplot but do not have a stem inside the subplot must be accounted for in the surface model matching method. This required delineation of tree crown boundaries in an area slightly larger than each subplot via a process called image segmentation. Using canopy height surface models derived from the lidar point cloud we compared segmentation results from eCognition software (Trimble Corporation; Sunnyvale, CA) and a tree crown segmentation program in FUSION (McGaughey and Carson 2003) called TreeSeg. TreeSeg is currently in development and is expected to be released in January 2016. The input canopy models were built using CanopyModel in FUSION with a 3x3 smoothing filter, with no preservation of minimum and maximum, at a 1 m cell output and with a normalized lidar LAS file as the input. The LAS files were normalized using the vendor-supplied digital elevation model (DEM). After several iterations of adjusting program settings to achieve suitable segments, both approaches produced comparable results and we elected to use segments produced by TreeSeg. The output from TreeSeg provides both a raster segmentation file and a maximum height point shapefile for each segment.

The manual interpretation method involves generating a tree stem map from the plot data using ArcMap v. 10.2.2 software (ESRI; Redlands, CA) and then overlaying the uncorrected position of the plot center with the lidar point cloud. Point clouds are visualized in the FUSION or other point cloud visualization software package. The interpreter then matches the tree stem map pattern with the trees identified in the lidar point cloud returns representing trees and shifts the plot location accordingly (Fig. 2). Manual interpretation focuses on visual cues such as the relative positioning of trees, tree heights, species-specific crown sizes and shapes, and the presence of snags.

This method was developed using a larger plot size (16.9 m radius) than the FIA subplots (7.3 m radius) and with all stems mapped, whereas in FIA subplots only trees larger than 12.7 cm d.b.h were tallied. Additionally this method has been used with higher density lidar (8–12 returns per m^2) than the data in this

Table 1—Inputs that are required by a program that attempts to match lidar point clouds to field-collected stem map data (Gatziolis 2012). An explanation of each input and how it was collected or derived is provided.

Data source	Input	Description and source
FIA tree data	Tree diameter	d.b.h. directly from FIA database
	Tree height	FIA variable 'actual height' which is a measure of a tree's length. The length and height differ depending on the amount of tree lean.
	Crown diameter	Modeled from tree diameter, crown ratio, and Hopkins Index using Forest Vegetation Simulator (FVS) Lakes States Variant equations (Dixon and Keyser 2008).
	x,y	Location of tree base relative to subplot center. Calculated from FIA measurements of distance and azimuth and corrected for declination using an online web application from NOAA's National Centers for Environmental Information.
	Crown shape	Shape on an ellipsoidal to conical gradient by tree species. Assignments of shapes were based on a majority opinion of three field-experienced foresters with regional knowledge.
	Crown base height	Height to bottom of crown. Approximated using Height – (Compacted Crown Ratio x Height). Uncompacted crown ratio would be a more appropriate choice, but it is only available on a subset of plots. As with tree heights, crown base will be impacted by tree lean.
Lidar/lidar derivatives	Lidar point cloud	LAS file containing lidar point data.
	Bare earth elevation	Vendor-delivered digital elevation model.
	Crown segments	2-D delineation of individual crown segments for each plot including some buffer space around the plot footprint. This is used to identify stems that fall outside the plot but that have crowns that would intersect the plot area. Segmentation rasters were produced by the TreeSeg function in FUSION software.

study (0.5–1 returns per m^2 for the statewide MN data, 4 returns per m^2 for the NASA CMS data). Identifying trees on this lower density data may be problematic. Using all FIA subplots in the interpretive process may compensate to a degree for the lower lidar data density.

Relative precision of plot location coordinates resulting from the two methods will be determined by comparing locations to survey- or mapping-grade GPS locations. In addition, we will evaluate the impact of refined locations on models of biomass created from FIA plot data and derivatives modeled from the lidar data. The goal is <=3 m RMSE horizontal precision for at least 80 percent of the sample plots assessed using survey-grade GPS data, and an improvement in biomass model fit using a plot-based response variable and lidar-derived predictor variables. We recognize that the success of these methods may be dependent on the canopy structure characteristics present in the plot. To help define the relationship between plot canopy structure and successful interpolation of new plot coordinates, precision metrics are being calculated for multiple plot stand structure and composition strata.

DISCUSSION

A number of challenges need to be overcome in order to generate required input data for the surface model matching program. Many tree inputs are not directly collected by FIA but can be derived from FIA data (Table 1). This requires a mix of approaches. For example, crown shapes were assigned to the species present in the study area by field foresters with regional knowledge using a combination of experience and consultation with silvicultural reference materials. FIA does not measure crown width or crown base height in the study area, but these were modeled using existing equations or by approximating from another FIA variable (e.g., using compacted crown ratio).

Statewide lidar collections are becoming more common (US IEI: http://coast.noaa.gov/inventory/#) but many are collected using pulse density that is

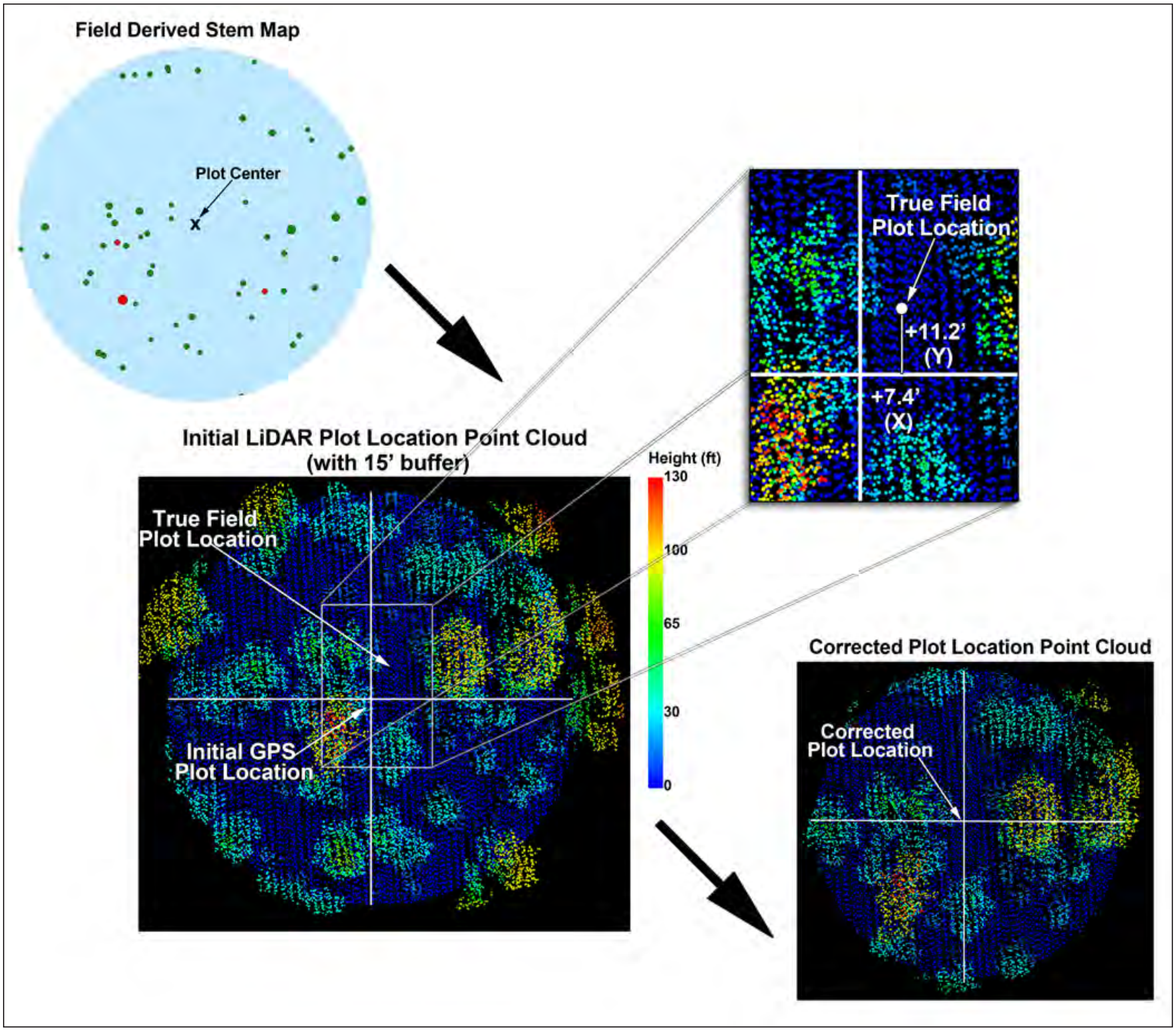

Figure 2—Methodology of repositioning plot center location using lidar point cloud data and a field derived plot stem map.

less than optimal for forestry applications (Gatziolis and Andersen 2008). This project seeks to determine whether lower pulse density lidar (i.e. 1-2 returns per m^2) has utility for improving coordinate precision of FIA plots. The lessons learned in working with lower pulse density lidar data have implications for future FIA projects that may require lidar coverage over broad-scale areas. In the case of the Minnesota statewide lidar collection, we discovered some additional challenges, such as highly variable pulse density and high variability in sidelap between adjacent flight lines. The implications of these irregularities for this project are still being explored.

The ability of these methods to improve plot locations will undoubtedly vary with canopy heterogeneity and perhaps composition. Improved precision on a subset of plots would still be valuable for remote sensing-based operation and analyses, especially if that subset is representative of the larger forest population or for plots with heterogeneous composition or structure for which improvement in location coordinates provides more benefit.

In summary, we are providing a status report on an applied project that is exploring one automated and one manual method for co-registering field plot locations with lidar data. Finding good matches between in situ and lidar data holds promise for improving the precision of field plot locations—if technical limitations can be overcome. In addition to testing two methods, we will be replicating the study with a higher-pulse density lidar collection and then validating the results against high-precision GPS coordinates and exploring the impact of improved co-registration on biophysical models. We aspire to provide recommendations for future lidar acquisitions and GPS coordinate data collection to improve the precision of FIA plot locations.

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FOREST INVENTORY WITH LIDAR AND STEREO DSM ON WASHINGTON DEPARTMENT OF NATURAL RESOURCES LANDS

Jacob L Strunk[1] and Peter J Gould[2]

Abstract—DNR's forest inventory group has completed its first version of a new remote-sensing based forest inventory system covering 1.4 million acres of DNR forest lands. We use a combination of field plots, lidar, NAIP, and a NAIP-derived canopy surface DSM. Given that height drives many key inventory variables (e.g. height, volume, biomass, carbon), remote-sensing derived height information provides a powerful tool to make fine scale inference about height related forest attributes. Predictions can also be aggregated to sub-stand, stand, or strata levels. Remote-sensing derived forest attributes can also be used to automate stand delineation, a capability that we incorporated into our inventory system following object-oriented segmentation with eCognition software.

Our sampling design is closely related to the FIA plot design (paneled hexagonal grid), with slight modifications to the plot and grid layouts to accommodate remote sensing auxiliary variables, and to provide greater flexibility in adapting to changes in funding for field measurements. Modifications include (e.g.) using 1/5 acre fixed plots, survey-grade plot positioning with Javad GNNS units, and providing extra panels in each hex grid cell.

Our presentation will provide greater detail about our new inventory system, while describing key technical hurdles we overcame in moving a technology out of a (mostly) research mode and into an operational framework. Examples include merging a patchwork of remote sensing data, processing and managing tens of terabytes of point clouds, and distributing final products to our users. We also discuss hurdles that we have not yet overcome in an effort to motivate discussions which will benefit us and others who work to operationalize remote-sensing based methods.

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MODELING AND FUTURING

ANALYSIS OF THE U.S. FOREST TOLERANCE PATTERNS DEPENDING ON CURRENT AND FUTURE TEMPERATURE AND PRECIPITATION

Jean Lienard, John Harrison, Nikolay Strigul[1]

Abstract— Forested ecosystems are shaped by climate, soil and biotic interactions, resulting in constrained spatial distribution of species and biomes. Tolerance traits of species determine their fundamental ecological niche, while biotic interactions narrow tree distributions to the realized niche. In particular, shade, drought and waterlogging tolerances have been well-characterized at the species level in the Northern hemisphere tree species. Species distribution models explore fundamental niches and current geographic distributions with respect to environmental factors, but their ability to capture and predict the community-level patterns is limited. Here, we analyze the Forest Inventory and Analysis Database and show that the tolerances of forest stands are directly linked with annual temperature, precipitations, and soil features in mainland USA. Using temperature and precipitation as two major predictors, we developed a model of tolerance distributions at forest patch-mosaic level, that we call the Tolerance Distribution Model (TDM). Using 17 climate change models from CMIP5, we delineate forested ecosystems vulnerable to drought, and we show that high elevation areas, and Midwest as well as Northeast US are at a high risk under future climate. We also predict changes of forest type over much of the land surface along the Southern and Western borders of the conterminous US. Our TDM provides a scaling of species tolerances to the community level and improves our understanding of how terrestrial ecosystems develop over large spatial scales shaped by climate. In particular, the direct connection we elucidate between temperature, precipitation and stand-level tolerances provides a new tool to quantitatively assess the impact of climatic changes in forested ecosystems.

INTRODUCTION

Understanding and predicting how forest distributions will respond to ongoing and anticipated climate change is a challenge with great ecological, economic, and cultural implications (Levin, 1999). It is well established that environmental stressors increase mortality of intolerant trees (e.g. Hanson and Weltzin, 2000, Lienard et al. 2015a). However, our ability to scale up individual plant traits such as growth/mortality characteristics to the ecosystem level has been limited due to ecosystem biocomplexity, including numerous non-linear functional relationships and feedback loops between different organisms (Strigul, 2012).

Although it is widely recognized that climate change will require a major spatial reorganization of forests on the landscape, our ability to predict what this will look like has been quite limited. Current modeling efforts to predict future distribution of forested ecosystems as a function of climate include species distribution models (for precise, local scale predictions) and potential vegetation climate envelope models (for coarse-grained, large scale predictions). In this work we bridge these approaches by considering an intermediate level of complexity, using stand-level tolerances.

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METHODS

The USDA Forest Inventory and Analysis database was used to compute the tolerance indices of current US forests. The connection between soil moisture and waterlogging tolerance was investigated using the FIADB and USFWS National Wetlands Database. Two independent databases were employed to link vegetation patterns and climate: Worldclim (using a spatial resolution of 30 seconds) and PRISM (using a spatial resolution of 800 meters). The 17 climate change models from CMIP5 were bias-corrected with a baseline extracted from the Worldclim dataset.

To establish the drought tolerance model, annual temperatures and precipitations occurring in forested plots were gridded into cells of 0.5 °C and 60 mm/month. To validate the model, we compared the drought tolerance index computed from the FIADB (i.e. current forest) with the model's predictions based on current temperature and precipitations. To extrapolate expected values of drought tolerance index to future climate, we computed the model's prediction over the conterminous US, with a spatial resolution of 30 seconds. We relied on projected climatic data using two representative concentration pathways adopted on the Fifth Assessment Report from the Intergovernmental Panel on Climate Change: moderate forcing (RCP4.5) and severe forcing (RCP8.5).

RESULTS

Shade, drought and waterlogging tolerance indices show distinct landscape level patterns (Fig. 1A), demonstrating that these stand-level indicators can effectively describe forests in the US (Lienard et al, 2015a, 2015b, Lienard and Strigul, 2015). Waterlogging tolerant plots are located mainly on hydric soils (Fig. 1B), along the Mississippi river or its tributaries, and along the Southwestern US coast (Fig. 1A). Spatial distributions of shade and drought tolerance were strongly correlated with mean annual temperature and precipitation (Fig. 1C-D), while waterlogging tolerance displayed no clear relationship with climate parameters except for demonstrating very low values when the mean annual temperature was higher than 20°C (Fig. 1E). The shade tolerance index demonstrated fully opposite climate response to the drought tolerance index (Fig. 1C-D), and good correlation with basal area (Fig. 1C,F).

We focused our modeling efforts on drought tolerance, for which the link with global warming impacts is straightforward and develop the drought TDM for the continental US. The TDM predicts forest drought tolerance as a function of temperature and precipitation (Fig. 1C). The drought TDM is able to reproduce the current overall drought tolerance patterns in the continental US (excluding wetland areas). In particular, a detailed inspection of drought tolerance patterns across geographical features shows that the model has a high accuracy, with the exception of the lower Mississippi river, which is the most noticeable wetland area. The TDM ignores history of stochastic disturbances associated with plots as it takes only climate variables as input. This results throughout the US in the prediction of smooth patterns compared to the realized drought tolerance. An analysis of errors further reveal a symmetric, non-skewed profile that follows an exponential decrease around the mean, consistent with a high predictive power of the TDM.

Because annual precipitation and the mean annual temperature are both expected to change over the coming century, we anticipate that the geographic distribution of drought tolerance will need to shift to accommodate this change. Projected climate trajectories for forested plots in climate space can be coupled with the drought tolerance model to provide the drought tolerance expected to be resilient to future projected conditions. Extrapolation of the model to future conditions using an ensemble of 17 climate models revealed a progression toward greater required drought tolerance. This progression was geographically ubiquitous and consistent across forcing scenarios (from RCP4.5 to RCP8.5). Furthermore, we identify a number of regions where major shifts in drought tolerance will be required. Northeastern US and Northern Great Plains are at high risk, as well as, to a lower extent, higher elevation areas in the Rocky mountains. Vulnerable forests are

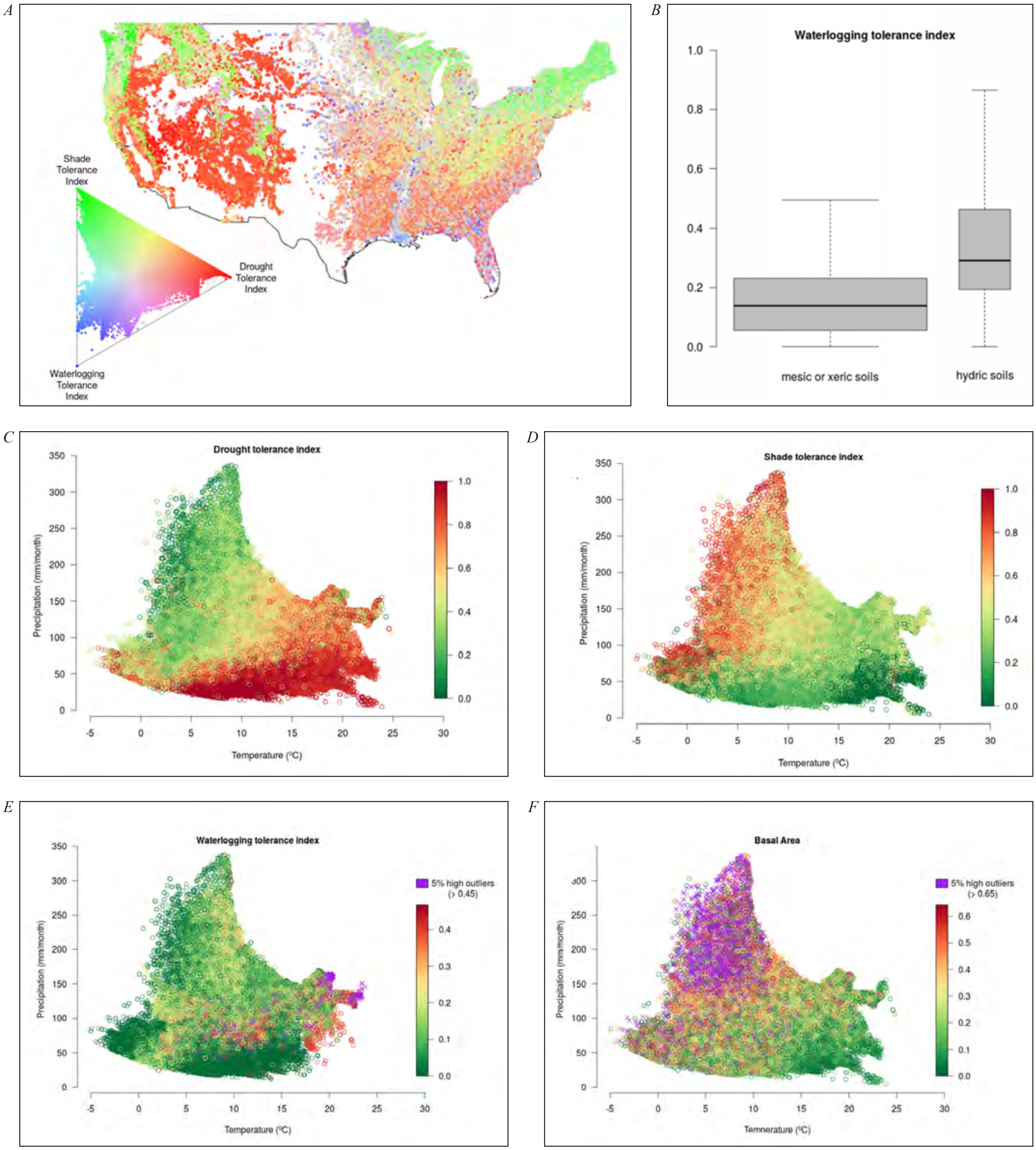

Figure 1—Overview of the tolerance indices in the conterminous US. A. Visualization of the tolerance index values in the US mapped onto the hue-saturation-value color space. In the color triangle key, plots where the shade tolerance (*respectively* drought tolerance and waterlogging tolerance) is high while all other tolerances are low are shown in green (*respectively* red and blue). Intermediate colors indicate plots with mixed tolerances (for example, yellow indicate plots resilient to both shade and drought). B. Waterlogging tolerance index as a function of soil moisture (boxplot widths are proportional to the number of plots, overall n=61,3275 total different locations are considered, two-tailed t-test is significant with p<0.001). C. to F., macroscopic variables describing forest stands plotted in the climatic system of mean annual temperature (x axis) and mean annual precipitation (y axis). The 5% high outliers for waterlogging tolerance index are represented by purple crosses.

overall evenly distributed in private, corporate, federal and state ownership. In the northeastern US, where the risks are the most pronounced, at-risk forest types include Maple/Beech/Birch, Spruce/Fir and White/Red/Jack Pine combination. Red pines (Pinus resinosa) and trembling aspens (Populus tremuloides), which are species with low to medium resistance to drought, have distributions overlapping the most vulnerable areas identified and are already considered to be endangered species. The predictions are robust with respect to the source of current climatic data (two databases used, Worldclim and PRISM) and to the climate change model choice (17 models considered).

DISCUSSION

One approach to predicting how vegetation distributions will change with climate is to associate certain biomes with certain climate envelopes (Olson et al., 2001) and assume that vegetation will migrate to fill potential vegetation niches. To a degree this approach is appealing as biome spatial distributions are strongly correlated with climatic variables, particularly temperature and precipitation (Olson et al., 2001). However, the discrete biome approach defines biomes into discrete entities at the landscape scale, which limits its ability to represent ecosystem transitions across space and time (Moncrieff et al., 2015). Alternatively, Species Distribution Models, SDMs also have been employed to study how plant communities respond to climate, albeit generally to examine plant presence or absence across environmental gradients, most often at small scales (Elith and Graham, 2009). The well-known shortcoming of SDMs is that they ignore biocomplexity and species interaction effects. In fact, species distributions depend not only on climatic factors, but also on biotic interactions within plant communities, disturbances and dispersal (Elith and Graham, 2009). Furthermore, upscaling the SDM approach is not possible as it requires too many predictors to model the large number of species present at continental or global scales (e.g. 38 environmental variables are used to predict the distribution of 134 tree species across Eastern USA in Iverson et al., 2008). Although the TDM approach provides a new insight over climate envelope models and SDMs, it shares a limitation with those models, which is an inability to predict rate of vegetation changes. Despite this limitation, the presented work substantially extends available tools for potential vegetation mapping as it offers a simple mechanistic explanation on how climatic variables affect landscape scale vegetation patterns.

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APPLYING MANAGEMENT MODELING TO ASSESS THE FEASIBILITY OF ACCELERATING LANDSCAPE RESTORATION ON FEDERAL FORESTS IN EASTERN OREGON

Sara Loreno, Jeremy S. Fried, and Andrew Yost[1]

Abstract—The state of Oregon recently invested in exploring options for increasing the extent of forest restoration activity. This initiative aims to reduce the incidence, effects, and expense of catastrophic fire events and restore economic stability to rural communities by enhancing the supply of raw materials for wood processing facilities and wood-based, renewable energy producers, particularly in the comparatively xeric, eastern two-thirds of the State. Collaborating with PNW-FIA and Portland State University, the Oregon Department of Forestry evaluated current levels of fire hazard as embodied in multiple metrics, assessed the effectiveness of a broad suite of fuel treatment-focused silvicultural prescriptions in achieving resilient forest stands, assessed the wood production potential of landscape restoration, and assessed treatment longevity for northeast Oregon, especially on federal forests. We developed a four-decade simulation, using BioSum 5 (dynamic), with 1,365 forested FIA plots in the northeastern corner of the state and 32 multi-decade sequences of silvicultural prescriptions applied, via FVS-FFE, to all plots where applicable. We estimated treatment costs using the R-based OpCost model, and treatment effectiveness based on multiple stand metrics selected to represent different dimensions of forest resilience, including crown fire potential, predicted mortality and fire intensity. The policy-relevant findings and technical insights developed via this modeling effort are presented.

The Oregon Department of Forestry sought a better understanding of the potential for increased forest restoration activity in eastern Oregon, and the impacts of such efforts on fire hazard, stand resilience, and economic benefits to rural communities that have traditionally relied on economic activity generated by timber production. A combination of active management via appropriate thinning and prescribed fire, if applied across the forested landscape, offers the potential to increase the prevalence of open, resilient stands, and to decrease the incidence of catastrophic fires resulting from an abundance of overly dense forests. We applied a modeling framework to evaluate current fire hazard in the Blue Mountain region of eastern Oregon, and to understand the effectiveness of several kinds of commonly applied silvicultural treatments for fire hazard reduction. We estimated treatment costs, including both the on-site costs of harvest and surface fuel reduction and the costs of hauling harvested wood for milling and energy generation, and the potential revenue from sales of such wood.

STUDY AREA

In a previous study by the Federal Forest Advisory Committee, an economic assessment of increased restoration activity on Oregon's eastern National Forests was conducted with the intent of accelerating restoration on federal forestlands (Federal Forest Advisory Committee 2012). We analyzed the effectiveness and feasibility of alternative silvicultural prescriptions in the Blue Mountains region, where a mix of private and public land ownership exists among three of eastern Oregon's national forests.

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Stretching from east of Pendleton to the Snake River on the Oregon-Idaho border, the Blue Mountains comprise 21 percent of eastern Oregon's land area, containing over 2.8 million acres. (Campbell and others 2003). Many forests in the Blue Mountains are overstocked, resulting from an extended period of fire suppression and a history of harvests that primarily removed large trees.

FIA plots within the Blue Mountain region provide a representative sample of this forested landscape. We selected a subset of these plots to include only those containing forests classified as Doug fir, Grand Fir, Ponderosa Pine, or Lodgepole pine – the dominant forest types in this region (Fig.1). Plots on reserved lands were excluded from this analysis, leaving a total of 1,085 plots (full or partial), referenced hereafter

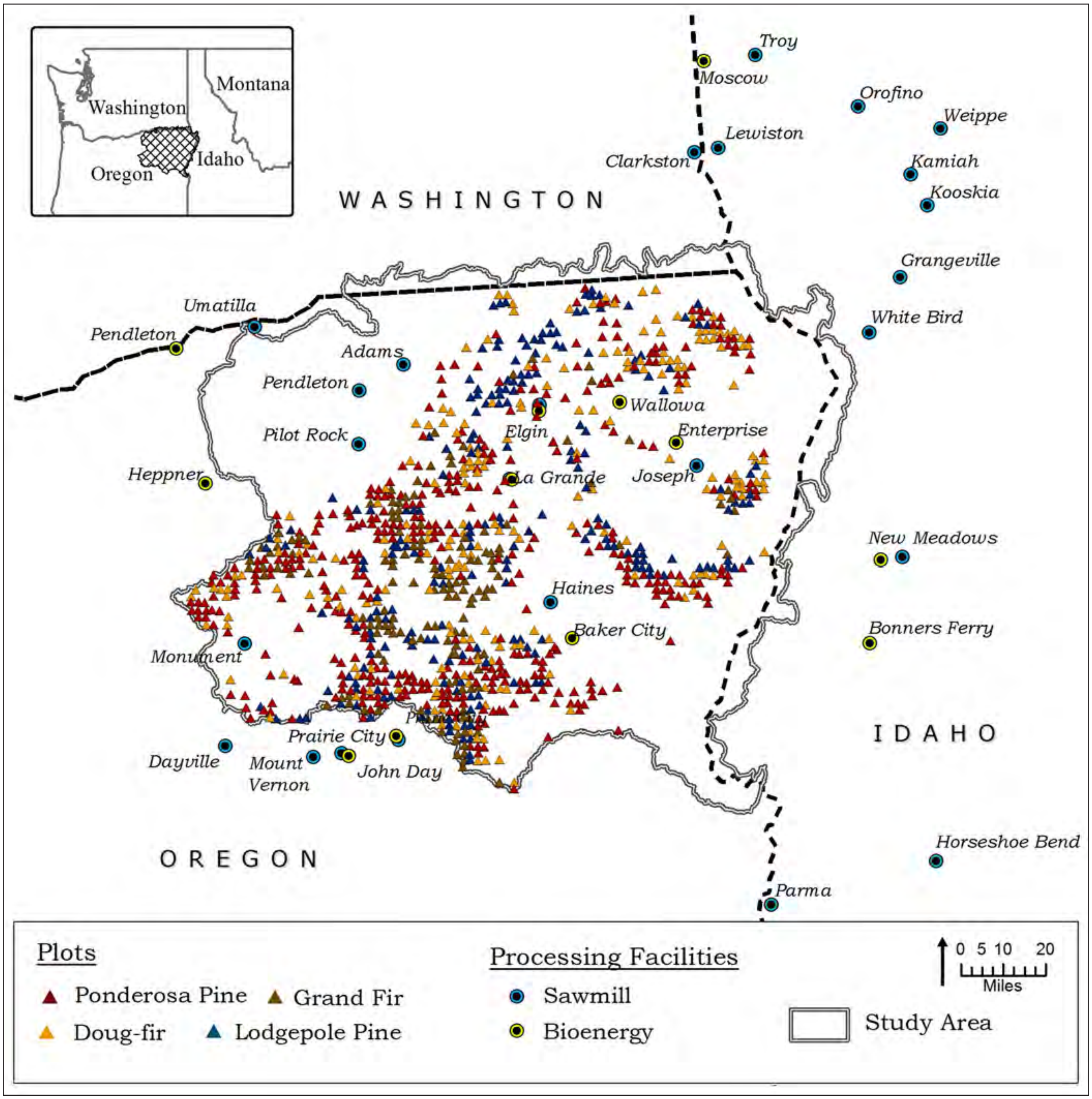

Figure1—Location of FIA plots and processing facilities within the Blue Mountain study area.

as stands, that represent 2.19 million forested acres. Most stands are located on national forest system land (NFS), with nearly all of the remainder on private land (Table 1). Due to the limited sample size of stands on state and other federal lands, we only discuss results for NFS and private lands.

METHODS

We used the Forest Inventory and Analysis (FIA) BIOSUM 5 analysis framework to assess the effectiveness, costs, and potential revenue resulting from implementing 32 generic fuel treatment-driven silvicultural sequences that reflect management prescriptions common in this region. Over the past decade, the PNW FIA Program developed BIOSUM (Fried et al. 2004) for bioregional inventory-oriented management simulation. BIOSUM integrates FIA data, wood processing facility locations, and GIS representations of transportation infrastructure with a workflow management system that:

1. Organizes data flow to and from multiple computer programs that are components of the analysis framework.
2. Audits inputs and outputs.
3. Evaluates alternative landscape-scale silvicultural treatments in terms of user-defined indicators of effectiveness and management objectives.

BIOSUM 5 integrates the following specific components:

1. Systematic forest inventory (FIA) data.
2. A dynamic forest stand model (FVS) for summarizing current conditions and predicting potential stand conditions at decadal intervals under various management alternatives (Dixon 2002).
3. An R-based treatment cost model (Bell and Keefe 2014).
4. A haul cost estimation model.
5. User-guided effectiveness heuristics for selecting the best silvicultural sequence of decadal treatment activities for each stand.

Table 1—Area of forest and number of stands modeled by owner group and forest type.

Owner	Forest Type	Area (1000 acres)	Area (percent of total)	Stands
National Forest	Douglas fir	316	14.4	200
	ponderosa pine	585	26.7	368
	grand fir	327	14.9	208
	lodgepole pine	231	10.5	160
	total	1459	66.6	936
Other Federal	Douglas fir	7	0.3	3
	ponderosa pine	22	1.0	4
	total	29	1.3	7
State and Local	Douglas fir	7	0.3	1
	ponderosa pine	16	0.7	3
	grand fir	2	0.1	2
	total	25	0.8	6
Private	Douglas fir	143	6.5	28
	lodgepole pine	379	17.3	78
	grand fir	113	5.1	19
	lodgepole pine	43	2.0	11
	total	679	31.0	136
Total		2192	100	1085

We devised 32 silvicultural sequences in consultation with specialists from the Oregon Department of Forestry, representing the full spectrum of treatments commonly implemented on federal lands in the study area.

To evaluate current levels of fire hazard and to assess the effectiveness of the selected silvicultural sequences in reducing fire hazard over time, we relied on four descriptors of stand-level fire hazard at a point in time (Jain and others 2012). These thresholds, which when exceeded indicate hazard, are: probability of torching (Ptorch) >20 percent, Torching Index (TI) <20 mph, Surface Flame Length (SFL) >4 feet, and Mortality Volume as a Percent (of pre-treatment stand volume) (MVP) >30 percent. A stand's hazard score, at a point in time such as before, or after, initiating a treatment activity at the beginning, or at any decadal interval within, a silviculural sequence, is calculated as the number of descriptors for which the threshold is exceeded. Thus, hazard score has a maximum value of 4, which occurs when all descriptor thresholds are exceeded. We defined effective treatments as those that reduce initial hazard score when assessed one year post treatment. The costs and revenues from wood production determined the economic feasibility of each silvicultural sequence.

When applied to a given stand, any one of the 32 silvicultral sequences may result in treatment activity occurring as often as every decade. Treatments were designed to follow one of two styles: thin from below or thin across diameter classes, and had residual basal area targets of 25 to 135 ft^2/acre. Many of the silvicultural sequences included reduction of surface fuels following thinning, via prescribed fire or lopping and scattering all harvested wood below merchantable size. Silvicultural sequences simulated harvest via either cut-to-length or whole tree logging systems.

RESULTS

Current Conditions

None of the 2.19 million forested acres represented by the FIA plot data are currently rated resilient with respect to all aspects of fire hazard considered in this study. All stands have at least one hazard element—the hazard indicator for MVP was present in all but 1 percent of the represented acres—and 32 percent have all four (Table 2). More than half, 66 percent, of the represented acres have a hazard score of 3 or greater.

Table 2—Area and area fraction (percent) of forest, before any simulated treatment activities, rated hazardous (+) or not hazardous (-) by combination of hazard descriptors. A "+" indicates as follows, for each hazard descriptor: Probability of Torching (PTorch) > 20 percent, Torching Index (TI) <20 mph, Surface Flame Length (SFL) >4 feet, and Mortality Volume Percent (MVP) > 30 percent.

Ptorch	TI	SFL	MVP	Area (1000 acres)	Area (percent of total)
+	+	+	+	711	32.4
+	+	-	+	437	19.9
-	+	-	+	410	18.7
-	+	+	+	252	11.5
-	-	-	+	171	7.8
+	-	-	+	157	7.2
+	-	+	+	28	1.3
+	-	+	-	10	0.4
+	+	+	-	10	0.4
-	-	+	+	7	0.3
-	-	-	-	0	0

Treatment Effectiveness

In our simulations, over 35 percent of stands, representing 775,000 acres, were effectively treated at first entry, i.e., their hazard score was reduced when evaluated one year post-treatment, by one or more of the 32 silvicultural sequences. For most stands, BIOSUM selected sequences composed of thin-from-below style treatments as the most effective, and more frequently selected those with lower residual basal area targets. Of the 775,000 treatable acres, 52 percent achieved a post-treatment hazard score of zero and 42 percent, a hazard score of one; 17 percent remained fully resilient (hazard score=0) at the end of 40 years (Fig.2).

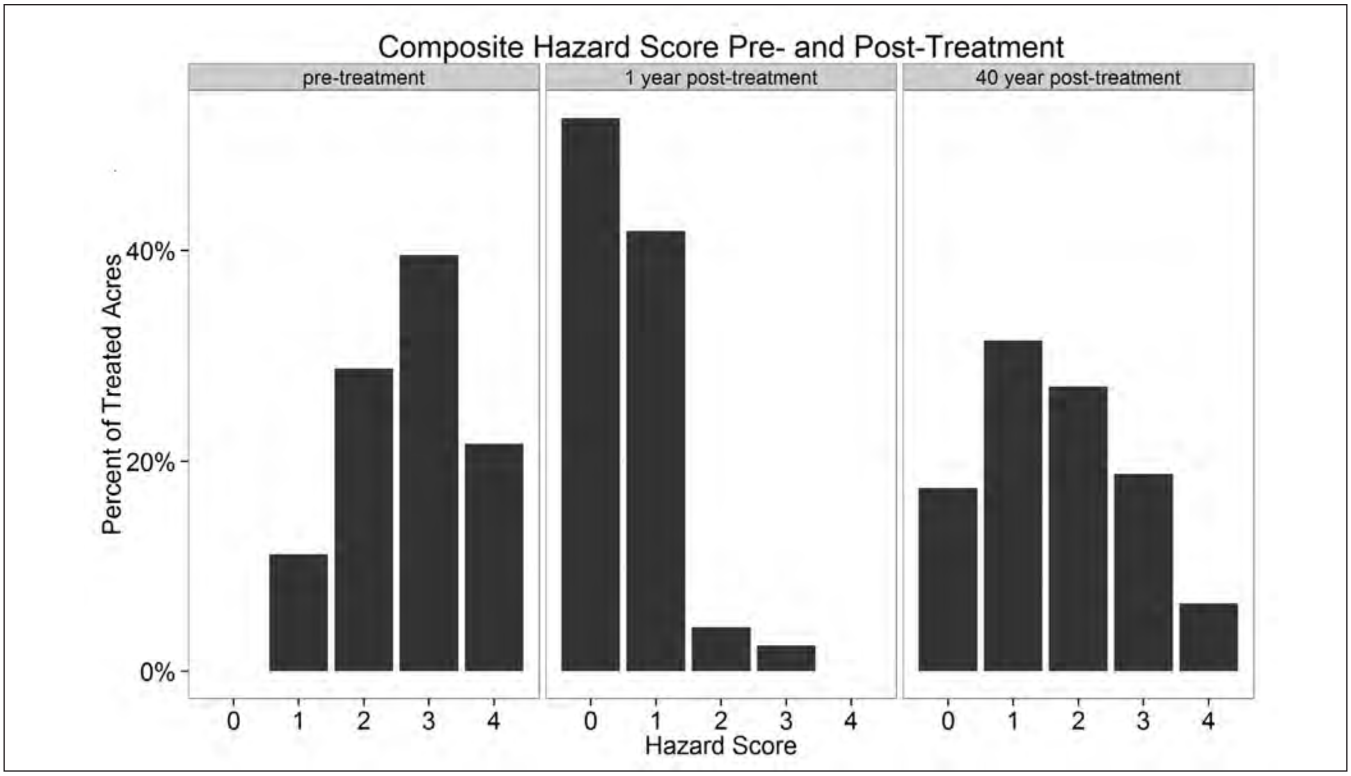

Figure 2— Distribution of area by hazard score for stands amenable to effective treatment (1) before treatment, (2) one year after treatment, and (3) 40 years after treatment.

Costs and Revenues

On most (85 percent) of the treatable acres, treatment costs could be fully financed by sales of merchantable wood and bioenergy feedstock. Private lands had the highest average dollar per acre net revenue, netting over five times more revenue per acre than National Forest land (Table 3). In all cases, the collection, transport, and sale of wood for bioenergy (collectable harvest residues such as sub-merchantable trees and the tops and limbs of merchantable trees) increased the overall maximum net revenue compared to on-site disposal of such residues in an air-curtain destructor.

Wood products obtained during harvest would notably increase the flow of wood to eastern Oregon processing facilities. By directing woody materials to a facility based on proximity to harvest site, centrally located facilities with bioenergy capabilities—Elgin, Prairie City, and Haines—would see a potential increase in merchantable wood exceeding 300 million cubic feet a year (Table 4). The increased yield of

Table 3—Predicted average, per acre yields of merchantable and energy wood and associated value, costs, net revenue and landscape-wide net revenue, by owner group with application of the most effective treatment for acres where effective treatment is possible.

Owner	Area (1000)	Merch Yield tons/ac	Chip Yield tons/ac	Merch $/ac	Chip $/ac	Harvest Cost $/ac	Haul $/ac	Merch / Chip Net $/ac	Total Net $ (1000)
National Forest	618	31	14	3,238	299	2,719	286	531	328,633
Other Federal	6	18	14	1,587	309	1,583	332	-20	-109
State and Local	14	24	12	2,511	273	1,014	349	1,420	19,583
Private	146	28	14	2,910	303	1,149	251	1,813	265,254
All	196	25	13	2561	296	1616	305	936	613,361

energy wood harvested via thin-from-below treatments would also send over 3 million green tons of bioenergy feedstock to each of these three sites.

Table 4—Predicted mean annual quantities of merchantable wood and bioenergy feedstock that fuel treatment could make available to processing facilities in the Blue Mountains region.

Processing Facility	Merchantable wood	Bioenergy feedstock
	MCF(mil)/yr	gt (1000)/yr
Elgin	378	3,405
Prairie City	358	3,639
Haines	321	3,360
Joseph	194	2,040
La Grande	193	2,076
Monument	152	1,625
Pilot Rock	119	1,261
Adams	41	395
Dayville	19	205
Mount Vernon	15	146

DISCUSSION

Our analysis of forest inventory plot data suggests that forests in the Blue Mountain Region are at high risk of experiencing stand-replacing fire and that implementing a silvicultural sequence of restoration treatments aimed at fire hazard reduction would reduce hazard on over a third of the forested area. Results of the simulation analysis support the assertion that increased forest restoration can reduce fire hazard through the harvest and processing of merchantable and energy wood while generating revenue sufficient to offset the costs of implementing treatments in most forests in this study area. Naturally, these conclusions are contingent on the hazard criteria devised for this study, the assumptions and parameters relied upon to estimate harvest and haul costs, and the value of harvested wood. These findings support the assertion that increased forest restoration can reduce fire hazard and stimulate market development through the harvest and processing of merchantable and energy wood.

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LARGE-AREA FOREST INVENTORY REGRESSION MODELING: SPATIAL SCALE CONSIDERATIONS

James A. Westfall[1]

Abstract—In many forest inventories, statistical models are employed to predict values for attributes that are difficult and/or time-consuming to measure. In some applications, models are applied across a large geographic area, which assumes the relationship between the response variable and predictors is ubiquitously invariable within the area. The extent to which this assumption holds for a tree height prediction model was evaluated at regional, ecoprovince, and ecosection spatial scales in the Northeastern United States. Two nonlinear regression models were tested, a spatially-ambiguous model that utilized tree and stand-level predictors, and a spatially-explicit model that incorporated latitude, longitude, and elevation as predictors. Regional-scale models evaluated at the state level showed considerable bias for some states, which suggests the statistical significance of spatial predictor variables does not translate into effective accounting for spatial variability. Similar results were obtained when fitting the models to an ecoprovince and evaluating bias within ecosections. Finally, fitting the models to ecosections within the ecoprovince provided a moderate level of local robustness as assessed by Moran's I statistic; however there are cases where local biases may still exist. The results suggest that models should be developed and applied at small spatial scales to reduce local biases when model predictions are aggregated to larger geographic domains. However, small spatial scales often equate to relatively small sample sizes that can present problems in model fitting and result in increased model uncertainty. Therefore, modelers need to carefully balance the minimizing of spatial extent and obtaining acceptable sample size.

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AN APPRAISAL OF THE CLASSIC FOREST SUCCESSION PARADIGM WITH THE SHADE TOLERANCE INDEX

Jean Lienard, Ionut Florescu, Nikolay Strigul[1]

Abstract— We revisit the classic theory of forest succession that relates shade tolerance and species replacement and assess its validity to understand patch-mosaic patterns of forested ecosystems of the USA. We introduce a macroscopic parameter called the "shade tolerance index" and compare it to the classic continuum index in southern Wisconsin forests. We exemplify shade tolerance driven succession in White Pine–Eastern Hemlock forests using computer simulations and analyzing approximated chronosequence data from the USDA FIA forest inventory. We describe this parameter across the last 50 years in the ecoregions of mainland USA, and demonstrate that it does not correlate with the usual macroscopic characteristics of stand age, biomass, basal area, and biodiversity measures. We characterize the dynamics of shade tolerance index using transition matrices and delimit geographical areas based on the relevance of shade tolerance to explain forest succession. We conclude that shade tolerance driven succession is linked to climatic variables and can be considered as a primary driving factor of forest dynamics mostly in central-north and northeastern areas in the USA. Overall, the shade tolerance index constitutes a new quantitative approach that can be used to understand and predict succession of forested ecosystems and biogeographic patterns.

INTRODUCTION

The classic succession paradigm has been formulated based on observations of temperate forest patterns in Wisconsin, Michigan and New England (e.g., Cowles, 1911, Curtis and McIntosh, 1951) and in northern and Central Europe. In this type of forest the gap dynamics and shade tolerance driven succession are most noticeable and easy to observe. In a broad range of plant ecology literature, including in major textbooks, shade tolerance is considered as a primary factor underlying forest successional dynamics. North-American tree species can also independently be classified as early and late successional species based on their life history and physiological traits (Niinemets and Valladares, 2006). In the classic shade tolerance succession paradigm, species that are shade intolerant and tolerant are analogous to early and late successional species, respectively. The goal of our research is to develop a quantitative approach that can be used to appraise succession of forested ecosystems.

METHODS

According to the classic paradigm, the proportion of shade tolerant versus intolerant trees is linked to the forest succession stage. We propose a quantitative parameter, the shade tolerance index, δ , to characterize stand successional stages as follows:

1. The shade tolerance of every tree species is quantified by a number from an interval ρ in [0,1] where the range spans very intolerant to tolerant species. We will call the number ρ the shade tolerance rank of a tree species. Specifically, we quantify the species as following: very intolerant = 0, intolerant = 0.25, intermediate = 0.5, tolerant = 0.75, and very tolerant = 1, according to [29, 36, 50].

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2. The shade tolerance index of the stand, δ, is defined as a weighted sum of the species abundance on their shade tolerance ranks defined as:

$$\delta = \sum_{j=1}^{k} \rho_j \alpha_j$$

In this formula α_j is a measure of relative abundance of a species *j* in the stand, is a shade tolerance rank of the species *j*, and the index *j* runs through all *k* tree species present in the stand. The relative abundance parameter α_j is estimated using the formula:

$$\alpha_j = \frac{\Omega_j}{\sum_{i=1}^{k} \Omega_i}$$

where Ω_j is a measure of abundance of the tree species in the stand. The shade tolerance index δ, is a number from [0, 1]. Specifically, δ is equal to 0 if all the trees in the stand are very shade intolerant and equal to 1 if all trees are shade tolerant.

RESULTS

Comparison with the forest continuum index

The classic forest succession paradigm was historically developed under a strong influence of the studies conducted in the Lake States (MI, WI and MN). In particular, Curtis and McIntosh (1951) have developed the classic continuum index to describe successional patterns in southern Wisconsin, in a collection of 95 forest stands. Using tree dominance data, these stands were positioned along the continuum line representing a forest succession sequence. According to this continuum index axis, Curtis and McIntosh (1951) assigned numerical values to the tree species within the stands called the climax adaptation numbers.

The original data used in this classic study is not available, and we reproduced a similar analysis using the FIA data. We have calculated the same statistical characteristics using a sample of 7017 FIA plots on mesic soils corresponding to the same geographic area as the original article. Our extension of the analysis of Curtis and McIntosh (1951) to a wider range of plots resulted in a much more diverse species composition. Despite this, our results are in good agreement with the original results (Figure 1 here vs Figures 5, 6, 7 in Curtis in McIntosh, 1951). Our results are also in agreement with the work of Rogers et al. (2008) who re-sampled the same sites as Curtis and McIntosh (1951) some 50 years later. In particular, we notice that the relative importance value of red oak (*Quercus rubra*), black oak (*Quercus velutina*) and secondarily white oak (*Quercus alba*) have decreased compared to sugar maple (*Acer saccharum*). Overall, our analysis shows that the successional pattern observed in Southern Wisconsin can be measured with the shade tolerance index. In addition, our study shows that these patterns did not change substantially over the several decades, and that the original plot sampling restrictions did not affect them substantially (Lienard et al., 2015a).

Successional dynamics

The forest stand dynamics theory states that after a major disturbance stand development follows four consecutive stages: initiation, stem exclusion, understory reinitiation, and old-growth. The stand initiation stage marks the onset of succession by regeneration of open space from seed, sprouts and advance regeneration, and lasts until the canopy closes. Different disturbances leave various types of biological legacies providing highly variable initial species composition. In the second stage of stem exclusion, the light-driven competition becomes the major determinant of survival, resulting in a domination of fast-growing early successional species. The third stage, understory reinitiation, is characterized by the selective recruitment of understory trees in the canopy through gap-dynamics. The final stage, the old-growth corresponds to the climax state of the forest, where the species composition is stable.

We compared the results of computer simulations with the statistical analysis of White Pine – Eastern Hemlock forest stands from the FIA database,

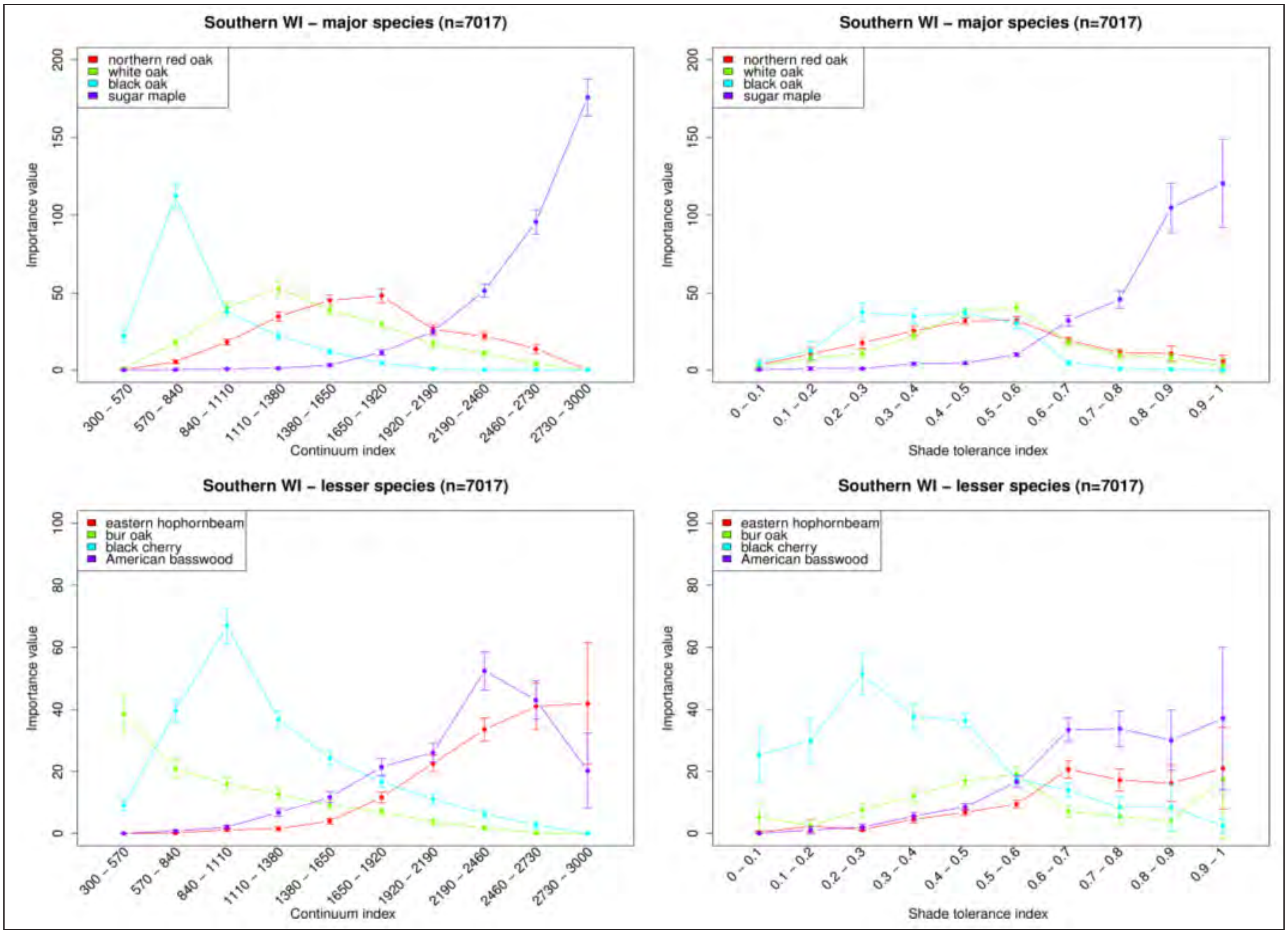

Figure 1—Comparison of the continuum index (left) and shade tolerance index (right) in southern Wisconsin. Similarly to the original study of Curtis and McIntosh (1951), the species were split in two groups: major (top) and lesser (bottom) species. Bars indicate the standard error of the mean.

using the shade tolerance index. We consider here approximate chronosequences, as the plots are ordinated relatively to the average age of trees, the time since last disturbance being not available (Strigul et al., 2012). The stands are observed throughout northeastern parts of the US. We isolated all plots in the database with more than 75% of cumulative basal area composed by these two species, resulting in a pool of 1375 plots. The comparison of these with computer simulations reveal striking qualitative similarities. Specifically, the initial distribution of seedling shade tolerance index decreases in the early years as the faster growing pioneering species start to dominate the canopy. The shade tolerance index then reaches high values as shade tolerant species eventually dominate the early successional species. These trends observed both in FIA database and in the computer simulations demonstrate the capacity of the shade tolerance index to model temporal dynamics of forest succession.

Spatiotemporal patterns of US forests

We analyzed forest stand mosaic in the whole mainland US, using the FIA dataset. Our goal is to understand statistical relationships between forest characteristics and patch mosaic patterns related to shade tolerance. The analysis of correlation patterns indicates that the shade tolerance index displays weak correlations in the range of 0.12—0.26 with the other macroscopic characteristics studied:

biomass, basal area, Gini-Simpson diversity index, species richness and average age of trees (Figure 2). However, some of the other measures are correlated: biomass with basal area (confirming the previous study by Strigul et al., 2012), and Gini-Simpson diversity with species richness. Correlation matrices have been further calculated separately for all provinces in mainland USA and all inventory years with more than 500 plots recorded from 1968 to 2012. Correlations between different variables were virtually identical for all the inventory years and different ecoregions. This result is similar to what we obtained by analyzing another dataset for Eastern Canada forests (Lienard et al., 2015b). The fact that shade tolerance index has been repeatedly shown to be uncorrelated with other macroscopic characteristics demonstrates its usefulness in the statistical description of the mosaic of forest patches.

DISCUSSION

The shade tolerance index introduced in this work is designed as a quantitative measure of forest succession according to the classic theory based on gap dynamics and replacement of shade intolerant by shade tolerant species. This study shows that this index can be utilized to understand the forest stand dynamics in ecoregions where the classic theory is validated, as it represents forest succession scale. In particular, our results demonstrate that this index is in agreement with the continuum index developed by Curtis and McIntosh (1951) as well as with gap model simulation (Strigul et al., 2008). Applications of the shade tolerance index include statistical analyses of the relationship between shade tolerance and soil moisture (Lienard and Strigul, 2015), data-intensive modeling of forested ecosystems (Lienard et al., 2015b), and the classification of U.S. ecoregions with respect to the temporal dynamics of their shade tolerance index (Lienard et al., 2015a).

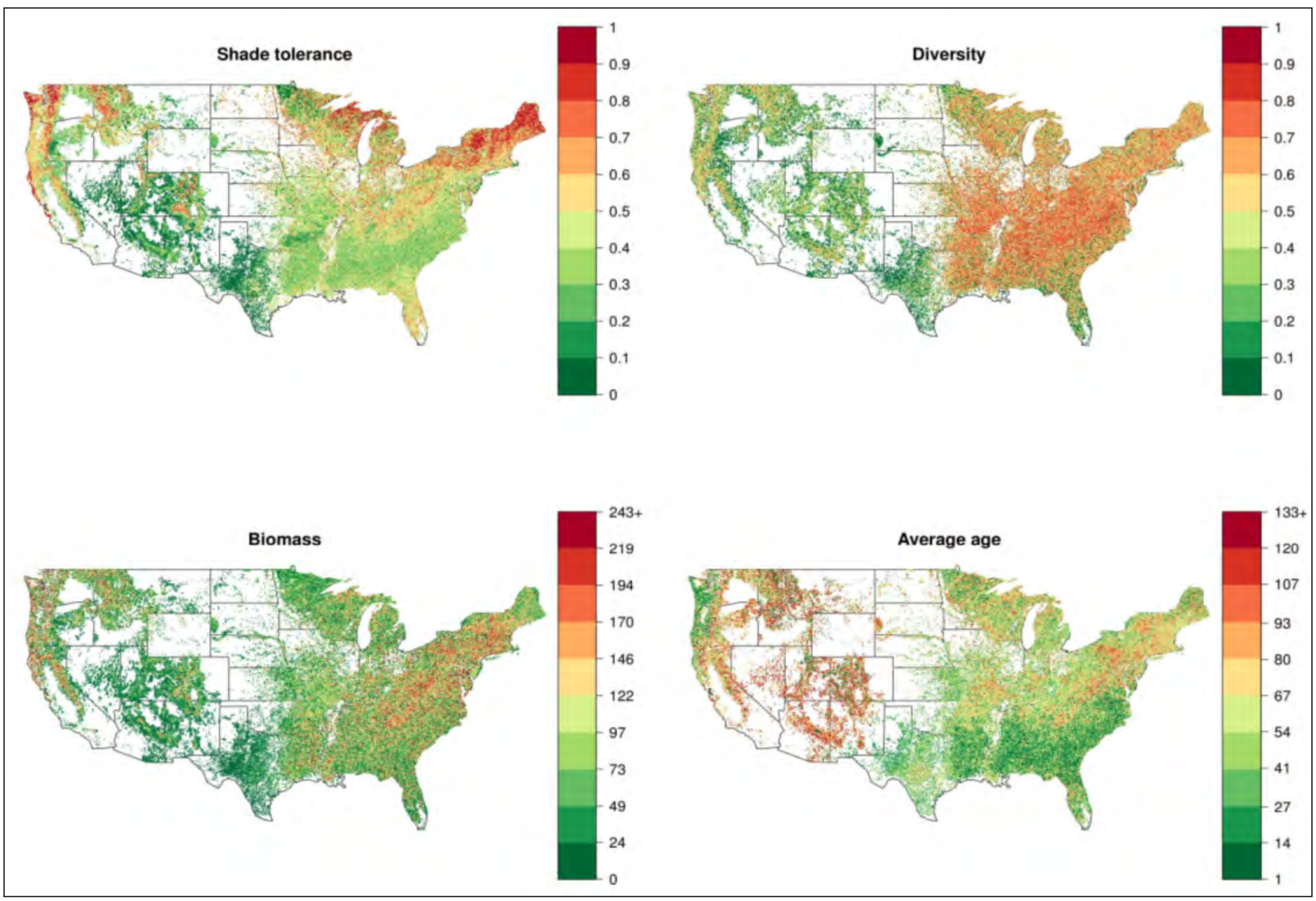

Figure 2—The stand-level characteristics of plots for all years demonstrate very heterogeneous forest types in the US, with no obvious common distribution pattern between indicators.

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SOCIO-ECONOMIC DIMENSIONS OF FOREST INVENTORY

PRIVATE FOREST LANDOWNERS' HARVEST AND REGENERATION DECISIONS- EFFECT OF PROXIMITY TO PRIMARY WOOD-USING MILLS

Consuelo Brandeis[1]

Abstract—Ownership of the U.S. southern timberland rests largely on private forest landowners' hands. As such, their harvest and regeneration choices can significantly impact the region's roundwood supply. In most cases, private forest landowners do not consider timber production among the top reasons for holding their lands. However, most research indicates that favorable timber markets (high demand of wood reflecting in high stumpage prices) can motivate landowners' participation. It follows then that landowners with access to strong timber markets (strength indicated by the number of primary mills and the volume consumed) will be more likely to engage in harvest and regeneration. To examine this assumption we develop an econometric analysis of the supply behavior of timberland owners given proximity to primary mills. We use FIA forest inventory and primary mill survey time-series data for the state of South Carolina, covering 1999 to 2011. Results reveal a weak response to mill proximity, particularly for regeneration, suggesting the need for tools other than timber markets to ensure continued regeneration efforts.

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LOGGING UTILIZATION RESEARCH IN THE PACIFIC NORTHWEST: RESIDUE PREDICTION AND UNIQUE RESEARCH CHALLENGES

Erik C. Berg, Todd A. Morgan, Eric A. Simmons, Stanley J. Zarnoch[1]

Abstract—Logging utilization research results have informed land managers of changes in utilization of forest growing stock for more than 40 years. The logging utilization residue ratio- growing stock residue volume/mill delivered volume- can be applied to historic or projected timber harvest volumes to predict woody residue volumes at varied spatial scales. Researchers at the University of Montana's Bureau of Business and Economic Research and USFS Southern Research Station are investigating variability in residue ratios across Montana, Idaho, Oregon, and Washington. This project has presented unique sample design challenges. The primary sampling unit is the logging site where trees are felled and removed from the forest. However, it is not possible to know in advance the total population of logging sites and it is therefore impossible to identify the sampling frame and conduct probabilistic design-based sampling. To meet this challenge, the authors designed a model-based sampling protocol that is yielding regional predictions of the residue ratio.

INTRODUCTION

The U.S.D.A. Forest Service's Forest Inventory and Analysis (FIA) Program provides information on the condition and changes in the timber resource throughout the western United States. The components of forest inventory change (i.e., growth, mortality, and removals) are captured by the FIA plot network. However, only through timber product output (TPO) mill surveys and logging utilization studies can removals for timber products be quantified and distinguished from inventory removals that are left in the forest or at the landing as logging residue (i.e., material that is cut or killed during commercial harvest but not utilized). TPO logging utilization studies are an effective and relatively simple way to make estimates of logging residue whether for potential biomass supply or as a component of removals.

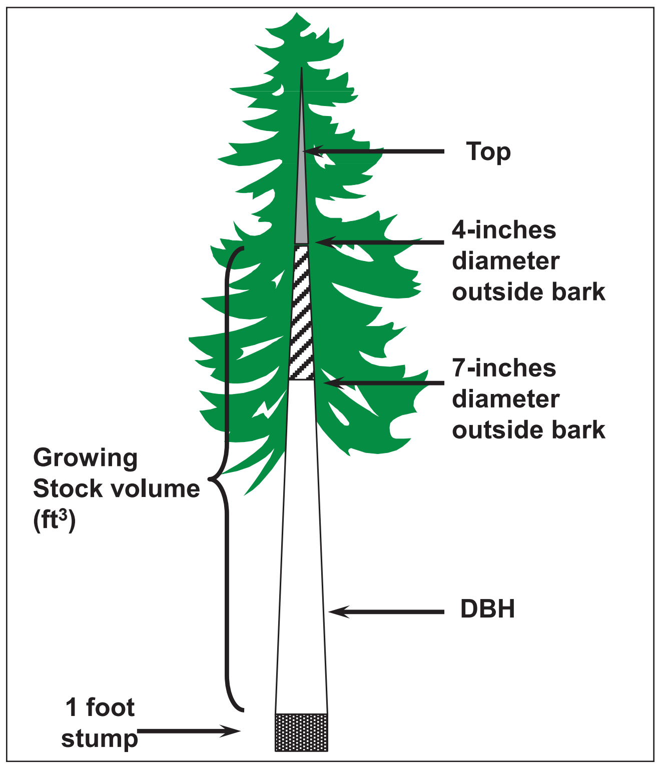

Figure 1—Individual tree growing stock. Growing stock includes live tree sections from the one-foot stump to the 4 inch outside bark top diameter.

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[2] Live trees ≥ 5 inches diameter breast height [d.b.h.]; 4.5 feet above ground on the uphill side, measured from a 1-foot stump height to a 4 inch diameter top outside bark [dob].

Logging utilization studies provide estimates of tree bole residue volumes without the need for detailed tree-level inventories (Morgan and Spoelma 2008). Study results include calculation of the growing-stock[1] (Fig. 1) residue ratio -- growing-stock logging residue volume divided by mill-delivered timber volume. The residue ratio can be used to quickly estimate growing-stock residue volumes by applying timber harvest volumes at stand, landscape, or state-levels (Morgan and Spoelma 2008). Bole, branch, and foliar biomass (i.e., non-growing stock portions of logging residue) can then be estimated with allometric equations. The residue ratio is used in the calculation of logging residue volumes published in the Timber Products Output (RPA-TPO) database (USDA FS 2015).

To answer land manager needs for updated information on logging residue production the authors investigated logging utilization in Montana, Idaho, Washington, and Oregon from 2008 through 2013. The study objective was to calculate the growing-stock logging residue factor as the ratio of means (Zarnoch et al. 2004) for the 4-state project area. Ratio values could be used to update county-level residue information in the RPA-TPO database.

METHODS

The authors sought a sample protocol that would provide data needed to estimate the growing stock residue ratio for major Pacific Northwest regions. Because lists of all active logging sites (the primary sampling unit) did not exist researchers could not identify the sampling frame and compute regional values of the residue ratio with probabilistic design-based sampling (Lohr 2009). Model-based sampling offered alternative means of obtaining parameter estimates in lieu of design-based sampling and was used in the current study (Chambers and Clark 2012). The authors also compared design (without the use of a comprehensive list of logging sites) and model-based sampling outcomes.

Sterba (2009) outlined the need to stratify the population and adjust for disproportionate sample selection when conducting model-based sampling. These provisions were accounted for in the current study:

1. Stratification. The project area was stratified into 4 regions.
   a. Inland Empire. Northeastern Washington, northern Idaho, and western Montana.
   b. Blue Mountains. South-central Idaho, eastern Oregon, and southeastern Washington.
   c. Western Washington (west of the Cascade crest).
   d. Western Oregon (west of the Cascade crest).

2. Disproportionate sample selection. The authors corrected for over and under-sampling within strata by weighting the sample.

Stratified sampling, specifically sites stratified by region, was adopted as the sampling protocol**.** Numbers of sample logging sites per region were selected proportional to the 5-year timber harvest volume of each region (Table 1) (BBER 2015).

Table 1—Number of logging sites and trees sampled; 5 year timber harvest volume by region (BBER 2015); and sample weighting factors by region.

Region	Number of logging sites sampled	Number of trees sampled	5 year timber harvest volume -Scribner board foot	Weighting factors
Blue Mountains	7	173	2,855,205	0.087
Inland Empire	53	1324	6,400,383	0.194
Western Oregon	21	519	12,638,795	0.384
Western Washington	20	486	11,060,569	0.336
TOTAL	101	2502	32,954,952	

Researchers asked timberland managers to identify logging sites where live (i.e., growing-stock) trees were being harvested for commercial products and field crews could safely measure felled trees. Sample sites were selected without regard for logging systems employed, topography, tree species, or other attributes. Twenty to 32 live felled sample trees were measured at each of 101 logging sites. Field crews selected felled trees with a systematic sampling grid using randomized starting points. Species was recorded, outside bark diameter and section length measurements were taken at the cut stump height, at one foot above ground level (uphill side of the tree), at DBH, at the 4.0-inch diameter outside bark (DOB) point, and at the end-of-utilization. Each tree had diameter outside bark and section length measurements taken along the bole at intervals corresponding to the appropriate log lengths with a maximum section length of 16 feet. The percent cubic cull for each section was recorded and each bole section was identified as utilized (delivered to the mill) or unutilized (logging residue). Individual tree section cubic foot volumes were calculated using Smalian's formula and section volumes were summed for each tree by category (e.g., utilized vs. unutilized stump, bole, and upper stem sections of the trees); the residue ratio was calculated for each site as the sum of all growing stock residue cubic foot volume divided by total mill-delivered cubic foot volume for that site.

Design-based residue ratios of means and standard errors were computed using SAS PROC SURVEYMEANS (SAS 2013) (Table 2). Sample weights were derived from the five-year timber harvest volumes (Table 1). Ratios of means were also computed with SAS PROC GENMOD (SAS 2013) in a multilevel linear mixed model incorporating sample weights. Logging sites were nested within regions.

Because sample logging sites were not chosen at random from a comprehensive list of sites for design-based computations, a true "head to head" comparison of sampling methods was not possible. The authors created a simulated residue ratio of means population (1,000 replications using a mixed binomial and exponential distribution) to analyze potential bias created by not randomly selecting sample logging sites from a comprehensive list. Samples of 100 sites were repeatedly drawn from this simulated pseudo-population and analyzed with PROC SURVEYMEANS and GENMOD.

RESULTS

Residue ratios of means and standard errors were essentially identical for SURVEYMEANS and GENMOD using either simulated or real data. Bias (the project as a whole "true" simulated parameter estimate minus the "real" data parameter estimate) was less than 0.5 percent for both methods. The real data residue ratio distribution was skewed to the right with many observations less than 0.010 (Fig. 2). The project as a whole residue ratio of means equaled 0.027 or 27 cubic feet of growing stock residue per 1,000 cubic feet of mill-delivered volume (Table 2). Residue ratios of means varied little across regions with Blue Mountain (ratio = 0.032) and western Oregon (ratio = 0.030) sites exhibiting slightly higher values (Table 2).

Table 2—Design-based and model-based ratios of means and standard errors by region.

Region	Design-based F3 ratio of means	Design-based F3 ratio of means standard error	Model-based F3 ratio of means	Model-based F3 ratio of means standard error
Blue Mountains	0.032	0.005	0.032	0.004
Inland Empire	0.024	0.003	0.025	0.003
Western Oregon	0.029	0.005	0.030	0.005
Western Washington	0.029	0.003	0.027	0.004
Total project area	0.029	0.003	0.027	0.002

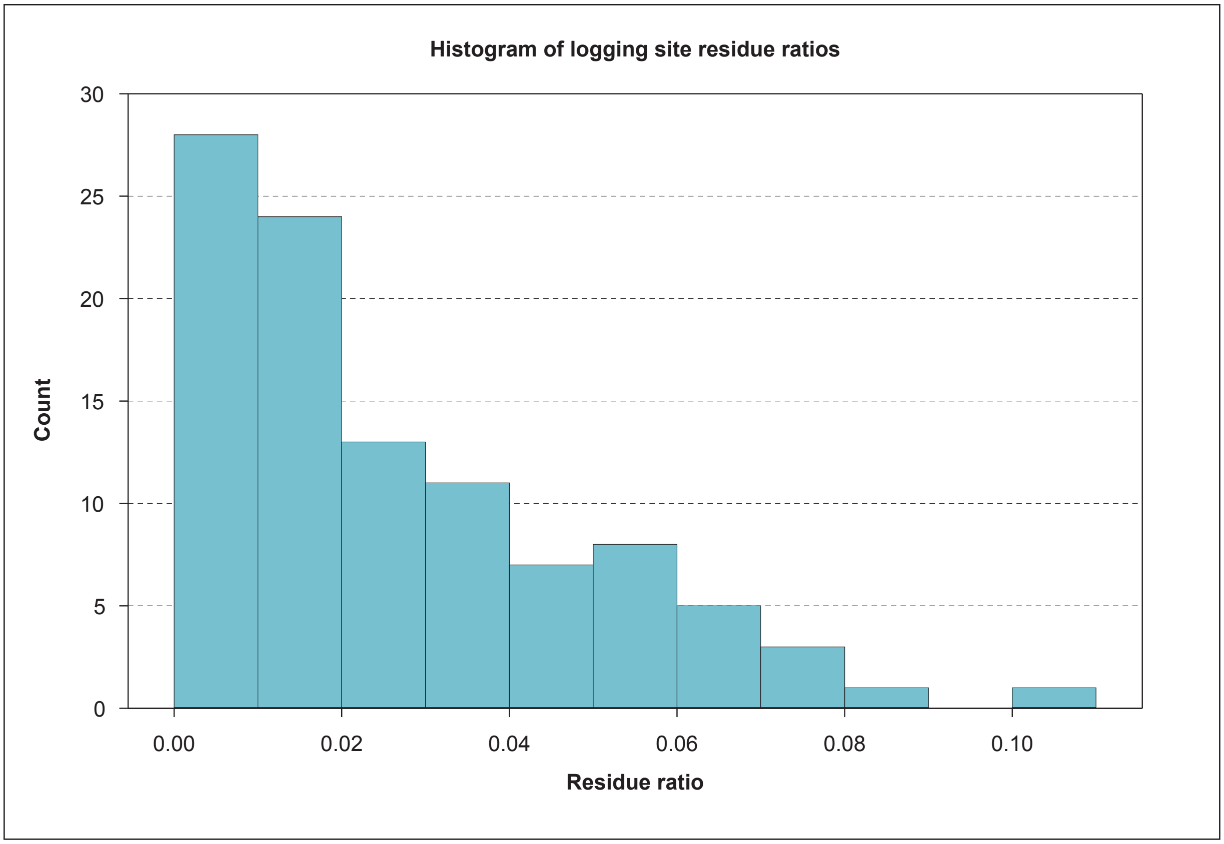

Figure 2—Histogram of logging site residue ratios (growing stock residue cubic foot volume/mill delivered cubic foot volume).

DISCUSSION AND CONCLUSIONS

Study findings concurred with other contemporary logging utilization research results: the residue ratio is now less than 4 percent of mill delivered volume. For example, Simmons et al. (2014) found that Idaho state (represented by the Inland Empire and Blue Mountain regions) ratio declined from 0.123 in 1965 to 0.024 in 2011. Because no similar Oregon or Washington pre-yarding (felled-trees measured before logs were yarded to a landing) studies were found, direct comparisons of this study's results to previous research in those states were not possible.

The lack of variability in residue ratios among Pacific Northwest regions (Table 2) was surprising. This finding likely stemmed from loggers employing similar utilization standards and harvesting systems within most logging sites regardless of location. Also, felled trees sampled in this study were consistently second or third growth timber with little defect.

Design and model-based sampling differ in statistical underpinnings and mathematical computation. However, design and model-based residue ratios and standard errors were found to be essentially identical. The authors suggest that researchers of future logging utilization studies could judiciously use either method to obtain estimates of the residue ratio. But statisticians disagree on the validity of model-based sampling (Lohr 2009). Having comprehensive lists of logging sites is clearly desirable, and if they are available scientists should use them in design-based sampling.

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USING TPO DATA TO ESTIMATE TIMBER DEMAND IN SUPPORT OF PLANNING ON THE TONGASS NATIONAL FOREST

Jean M. Daniels[1], Michael D. Paruszkiewicz[2], Susan J. Alexander[3]

Abstract—Projections of Alaska timber products output, the derived demand for logs, lumber, residues, and niche products, and timber harvest by owner are developed by using a trend-based analysis. This is the fifth such analysis performed since 1990 to assist planners in meeting statutory requirements for estimating planning cycle demand for timber from the Tongass National Forest. Results reflect the consequences of recent changes in the Alaska forest sector and trends in markets for Alaska products. Demand for Alaska national forest timber currently depends on markets for sawn wood and exports of softwood logs. Three scenarios are presented that display a range of possible future market conditions. The model was most sensitive to changes in Pacific Rim log demand. Areas of uncertainty include the prospect of continuing changes in markets and competition, the impact of the young growth transition, and the rates of investment in manufacturing in Alaska.

INTRODUCTION

The Tongass Timber Reform Act (TTRA, 1990) states that the Secretary of Agriculture will "… seek to provide a supply of timber from the Tongass National Forest which (1) meets the annual market demand for timber from such forest and (2) meets the market demand for timber from such forest for each planning cycle." Although all national forests are required to estimate demand for timber during forest planning efforts, the "seek to meet" requirement is unique to the Tongass. The Pacific Northwest Research Station has been asked to assist planners in meeting the TTRA requirement for estimating planning cycle demand for timber from the Tongass National Forest. Current efforts were initiated by evolving USDA policy encouraging the harvest of younger second-growth forest stands. The Pacific Northwest Research Station has published four previous studies in support of Tongass Land Management planning efforts. Brooks and Haynes (1990), Brooks and Haynes (1994), Brooks and Haynes (1997), and Brackley et al. (2006) all estimated demand for forest products from Southeast Alaska and projected the volume of timber required to satisfy that demand given harvest by other owners and assumptions about future market conditions. In the past, a dearth of reliable published data for the forest sector in Alaska meant that results were highly uncertain. However, two FIA Timber Products Output reports for the Alaska wood processing industry have been published since the last analysis (Halbrook et al. 2005, Berg et al. 2014). These provided data on the relationship between timber harvest and end markets not available for previous studies. Results will be used by the Alaska Region (R10) as an input in calculations of annual demand for Tongass timber, and to inform efforts to amend the Tongass Land Management Plan.

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STUDY AREA

The study area is Southeast Alaska, defined as the boroughs of Haines, Skagway-Hoonah-Angoon, Juneau, Sitka, Wrangell-Petersburg, Ketchikan Gateway, and Prince of Wales-Outer Ketchikan.

METHODS

Estimates of derived demand for Tongass National Forest timber were developed in four stages: (1) historic estimates of Southeast Alaska timber products output (by product market and destination) are gathered and projected to the year 2030; (2) the raw material requirements necessary to support this output are calculated by using explicit product recovery and conversion factors; (3) the timber harvest equivalent is calculated and allocated by timber owner; and (4) the analysis is repeated to estimate the impact on harvest from a baseline and three hypothesized alternative management scenarios.

After assembling the historic data sets necessary to represent SE AK timber markets, we developed a baseline model based on projections and market shares for each market served by SEAK producers for the period 2015-2030. The baseline model was used to construct three management scenarios representing alternative futures for timber harvest in Southeast Alaska. The first scenario (S1) establishes a timeline for the young growth transition that reflects the current state of knowledge of regional forest managers. The second scenario retains the assumptions from S1, but builds in an expansion of demand for mill residue and utility logs for growing wood energy markets. Scenario 3 also retains the young growth transition assumptions from S1, but adds the recovery of the housing industry in the United States with corresponding increased demand for logs and lumber for construction.

RESULTS

Table 1 shows the timber harvest volume from the Tongass National Forest necessary to meet projected demand for each management scenario. Incorporating the young growth transition caused harvest to decline in 2025 in all scenarios. Scenario 2, which calls for a rapid

Table 1—Projected harvest from the Tongass National Forest, 2015 to 2030, for three potential management scenarios (mbf, log scale).

Year	Baseline scenario	Scenario 1: young growth transition (YGT)	Scenario 2: YGT + wood energy expansion	Scenario 3: YGT + US housing expansion
2015	40,858	40,858	40,858	40,784
2016	41,592	41,592	41,592	41,625
2017	42,325	42,325	43,382	42,466
2018	43,059	43,059	46,301	43,308
2019	43,792	43,792	49,220	44,149
2020	44,526	44,526	52,138	44,990
2021	45,259	45,259	55,057	45,831
2022	45,993	45,993	57,976	46,673
2023	46,726	46,726	60,894	47,514
2024	47,460	47,460	63,813	48,355
2025	48,193	44,034	62,980	45,037
2026	48,927	44,508	65,665	45,619
2027	49,661	44,983	68,350	46,201
2028	50,394	45,457	71,035	46,784
2029	51,128	45,932	73,720	47,366
2030	51,861	46,406	76,405	47,948

expansion of wood energy demand for space heating, results in the greatest increase in harvest, reaching almost 25 million board feet over the baseline. Scenarios 1 and 3 have nearly the same impact on harvest, suggesting that demand from expanding housing markets in the US may not offset the losses from the young growth transition relative to the baseline.

DISCUSSION

Three different scenarios display alternative futures for Southeast Alaska and all incorporated the young growth transition on the Tongass National Forest. Taking these changes into account, our projections of the average demand for Tongass timber over the next 15 years (2015 to 2030) range from 46 to 76 million board feet. Whether Alaskan products will remain competitive during the young growth transition will depend on a variety of factors. The emergence of bioenergy markets could increase the profitability of operations owing to increased utilization of low quality material, especially utility grade logs and mill residues. Although economic feasibility will depend on capital investment and product prices, Southeast Alaska producers may find it difficult to compete with British Columbia in international markets. In addition, transportation challenges make it difficult for Southeast producers to ship material within Alaska itself. There is tremendous interest in developing markets for value added niche products. Whether demand for these products could be sufficient to sustain a timber industry in Southeast Alaska will likely be the subject of debate for many years to come.

The greatest challenge to this analysis was locating data on the Alaska forest products sector. In many cases, the most recent data were from 2011. Disclosure and confidentiality issues abound, owing to an industry structure characterized by a small number of producers. Traditional sources of international trade data were of little use because of confounding problems with transshipments, conversion factors, and that trade data showed that export volume exceeded reported harvest volume by a significant amount. TPO reports are invaluable to understanding trends in forest industry across the western United States and were crucial to completing the 2015 Tongass timber demand analysis.

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ECOSYSTEM SERVICES: A NEW NRS-FIA ANALYTICAL SCIENCE INITIATIVE

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Abstract—Forest ecosystem services (ES) are linked to sustaining human well-being. Recognizing an inappropriate economic valuation of ecosystem properties and processes, many ecologists, economists, and political scientists have pushed for an increasing awareness and appreciation of ES. Many definitions of ES include both direct and indirect benefits humans derive from ecosystem properties or processes. The Millennium Ecosystem Assessment (MA) typology classifies ES into four categories: provisioning, regulating, cultural, and supporting services; this framework enables linkages between Northern Research Station Forest Inventory and Analysis (NRS-FIA) research activities and specific services within MA categories.. A subset of those ES for which additional information is needed will be addressed in a proposed NRS-FIA ES science team.

Forest ecosystem services (ES) are linked to sustaining human well-being (Bonan 2008, Millennium Ecosystem Assessment 2005). By the mid to late 1990s, many lines of evidence suggested that the scope of human enterprise had grown large enough to begin seriously impairing ecological processes crucial to human existence. Acknowledged problems ranged from depleted fisheries to large-scale changes in climate due to the burning of fossil fuels. Many ecologists, economists, and political scientists recognized that these problems resulted from an inappropriate economic valuation of ecosystem properties and processes (Costanza and others 1997, Daily 1997). Consequently, researchers from across these fields pushed for an increasing awareness and appreciation of ES. They also called for development of valuation techniques that would better account for ES in economic decisions.

The phrase "ecosystem services" (or a variation thereof) has been independently defined several times (see definitions below) by ecological researchers and economists. From the perspective of raising public awareness, early and still widely cited definitions effectively capture the importance and pervasiveness of ES (Costanza and others 1997, Daily 1997, Millennium Ecosystem Assessment 2005). Broadly, these definitions characterize ES as the direct and indirect benefits humans derive from ecosystem properties or processes. This definition encompasses such widely varying phenomena as the aesthetic experiences natural areas provide to the importance of forest in acting as carbon sinks to buffer against climate change. Stated simply, ecosystem services are the benefits people obtain from ecosystems.

Given the wide variety of ecosystem properties and processes that qualify as ES, this definition is accompanied by a classification framework that helps clarify and highlight the types of benefits humans derive from ecosystems (de Groot and others 2002, Ekins 2003, Millennium Ecosystem Assessment 2005). One commonly cited typology was provided by the Millennium Ecosystem Assessment (MA). The MA recognized four types of ES: provisioning, regulating, cultural, and supporting (Table 1). Provisioning services refer to products (or "goods") people acquire from ecosystems, such as fiber and food. Regulating services stem from the regulation of

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Table 1.—Ecosystem services (ES) associated with forest ecosystems, adapted from a figure in Vernegaard and others (2010). Each service is assigned to a category in the ecosystem services classification framework presented in the Millennium Ecosystem Assessment (2005); see text for definitions of categories. Citations associating each service with forested ecosystems are numbered, with full references listed in the Literature Cited section. [1,2,3,4,5,6,7,8,9,10,11,12]One or more NRS-FIA product lines are associated with each ES.

ES category	Ecosystem services	Relevant citations	FIA product lines
Provisioning	wood products – timber, biomass/ biofuel, fuelwood	[1-10]	timber products output (TPO), biomass, economics
	biodiversity – genetic information, pharmaceuticals	[1-5, 8, 10-12]	Criteria & indicators (C&I) – biodiversity, Northern Forest Futures Project (NFFP), National Sustainability Report
	food – wildlife, nuts, berries, etc.	[1-4, 6, 8, 9]	nontimber forest products (NTFP)
	clean air	[2-5, 8]	ozone, lichens
	clean water	[1-3, 5-12]	water quality – Great Lakes Restoration Initiative (GLRI), NFFP
Regulating	climate regulation – carbon sequestration	[1-4, 6, 7, 9-12]	carbon
	air quality regulation – sequestration of pollutants	[2-5, 8]	ozone
	water regulation – flood control, erosion control, maintenance of water quality	[1-12]	water quantity – NFFP
	regulation of disease and pests	[2, 6, 12]	forest health
Cultural	aesthetic	[2-4, 6, 8, 10]	National Woodland Owner Survey (NWOS), urban
	spiritual/religious	[1-4, 10]	tribal
	recreational	[1-8, 11]	NWOS, NFFP
	educational	[2, 5]	NRS-FIA Techniques Team 1, New York Research Map (RMAP) of tree species distribution (Riemann et al. 2014)
	historical	[1, 2]	Trend analyses, historical map of woodland density (Liknes et al. 2013)
Supporting	biodiversity maintenance – promotes ecosystem resistance, resilience, productivity	[1-5, 8, 10, 12]	Wildlife and fish habitats, landscape structure and function, fragmentation
	nutrient cycling	[2, 3, 8]	soils, carbon, down woody
	soil formation	[2-5]	soils
	primary production	[2, 4]	soils, forest site productivity

[1] Millennium Ecosystem Assessment 2005
[2] Vernegaard and others 2010
[3] Chiabai and others 2011
[4] Cóndor and others 2008
[5] Gaodi and others 2010
[6] Nasi and others 2002
[7] Notman and others 2006
[8] Pattanayak and Butry 2003
[9] Smail and Lewis 2009
[10] Watson 2008
[11] Ghani, n.d.
[12] Myers 1997

ecological processes and include, for example, climate regulation and disease control. Cultural services refer to intangible benefits people derive from their natural surroundings, e.g., spiritual experiences and aesthetic vistas. Supporting ecosystems services make all other types of services possible. They are fundamental processes, such as primary productivity, that allow for the existence and persistence of ecosystems.

ASSESSING FOREST ES WITH FIA

A complex combination of factors affects the extent to which forest ES are realized; some of these factors include the forest characteristics of composition, structure, spatial pattern, and cultural context (Matthews and others 2014). The Forest Inventory and Analysis (FIA) program produces and distributes a wealth of data, information, and knowledge on these forest characteristics. FIA has evolved from a timber survey to a forest inventory and is moving toward a treed-lands inventory that can address a broad array of forest ES.

Each forest resource can be associated with one or more ES. Consider the ES associated with wildlife, for example. One could make a strong case for including wildlife in all four of the ES categories listed in Table 1: (1) Provisioning – food/meat; (2) Regulating - regulation of disease and pests, e.g., bird controls on forest insect pests; (3) Cultural Services – recreation: birding, hunting, etc.; and (4) Supporting Services – maintenance of biodiversity. And, additional wildlife supporting services could be added to this list: pollination, seed dispersal, and scavenging.

FIA provides indicators or proxies for important ecosystem processes or end products. For example, with regards to sustaining wildlife populations, the end product could be viewed as the number of individuals of a particular wildlife species supported within a given forest. Using only forest inventory data sets and habitat models, we cannot estimate actual populations of wildlife. However, such data sets can be used to assess the suitability of wildlife habitat and estimate trends in suitable habitat abundance, thereby defining the upper potential for wildlife population numbers (i.e., carrying capacity).

NORTHERN RESEARCH STATIONFIA ES SCIENCE TEAM

ES provides a framework or structure for understanding and linking Northern Research Station (NRS) FIA activities. The authors adopted the ES classification system outlined by the MA for use by the NRS-FIA Ecosystem Services Science Team. The mission statement proposed for this Science Team is to: use scientific methods and research to produce data, information, and knowledge that informs wise management decisions about forest ecosystem services in the midwestern and northeastern United States of the Northern Research Station.

The NRS-FIA ES Science Team – established by the authors of this paper, is intended to facilitate collaboration and product delivery of forest ES research and reporting. The ES Science Team would leverage existing experience and expertise of NRS-FIA staff and would include cooperators from other Forest Service research units and other agencies and organizations. This team is prioritizing research projects and products, based on the following context.

The definition of ES is comprehensive, and includes many disciplines, existing efforts, and topics already covered by major research initiatives: i.e., timber, biomass/biofuel, fuelwood (provisioning service), and carbon accounting (regulating service). Table 1 includes a crosswalk between ES and FIA research activities. This framework reveals that the full breadth of NRS-FIA research activities is included within ES, including the traditional notion of both "goods" and "services." The framework highlights current successes in addressing some ES via well-established FIA "product lines", while revealing emerging opportunities for better serving other ES. We emphasize ES topics that are less well represented by existing FIA research efforts, e.g., water, wildlife, fish, nontimber forest products, and those ES associated with landscape pattern (fragmentation) and land use/land cover dynamics. Examples from two specific projects are described below.

Example of Potential ES Study – "Monitoring Past Trends, Current Conditions, and Future Projections of Habitats for Forest-associated Wildlife Species"

The goal of this project is to integrate wildlife species-habitat relationships with forest inventory data and geospatial data sets to inventory, monitor, and manage forest wildlife habitat condition across northeastern and midwestern forests of NRS. We presume that 1) the FIA database (FIADB; http://apps.fs.fed.us/fiadb-downloads/datamart.html) provides a wealth of data, information, and knowledge that can be used to inform estimates of habitat abundance; 2) species-habitat relationships, like those provided by U.S. Geological Survey (USGS) Gap Analysis Program (GAP) provide a means for associating many wildlife species with specific habitat characteristics; 3) the national vegetation classification (NVC) system provides a consistent system for GAP and other species-habitat relationships, such as NatureServe Explorer and the NatureServe Northeastern Terrestrial Wildlife Habitat Classification; 4) the addition of NVC attributes to FIADB will enable consistent linkage between FIA and databases such as GAP; and 5) new attributes and techniques are needed to establish such linkages and producing estimates of habitat abundance. This ES project is designed to address these needs.

Example of Potential ES Study – "Estimating and mapping change in both land use and land cover."

The objective of this study is to develop and implement tabular and geospatial products that include attributes of both forest cover and forest use. Land use and land cover are terms often used interchangeably. Although they may be identical in some places and at some times, they differ substantially in others. Remote sensing-based maps, like the USGS National Land Cover Database (NLCD), typically are considered to portray land cover, while FIA data typically are described as representing land use. Both characterizations are oversimplifications—representing a false dichotomy—of actual definitions, thereby discouraging more comprehensive understanding and integration of various information products. The FIA image-based change estimation (ICE) project, conducted in partnership with the Forest Service Remote Sensing Applications Center (RSAC), is designed to produce statistical estimates of change in both land use and land cover. ICE requires manual photo-interpretation of aerial imagery (NAIP) in the vicinity of FIA plot locations. Concurrently, FIA and RSAC are collaborating on a project to model geospatial data sets of 1) tree canopy cover, 2) forest cover, 3) forest use, and 4) subcategories of FIA forest land (timberland, reserved forest, other forest).

CONCLUSION

The FIA program already assesses many benefits that people obtain from forest ecosystems, including provisioning, regulating, cultural, and supporting services. The MA ES framework provides a comprehensive approach for describing FIA research activities and product lines; these relationships are presented in Table 1. The NRS-FIA's proposed ES Science Team is poised to better understand those ES that have been so far inadequately studied.

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REACHING USERS AT LOCAL SCALES: INSIGHTS INTO THE VALUE OF FOREST INVENTORY INFORMATION FOR EDUCATION AND OUTREACH AND THE POTENTIAL FOR AN EFFECTIVE PARTNERSHIP BETWEEN FIA, COOPERATIVE EXTENSION, AND STATE AND NATIONAL CONSERVATION EDUCATION PARTNERS

Rachel Riemann[1]

Abstract—Forest information is desired for broader applications than we typically serve. Among those underserved users are the education and outreach communities. These groups are actively trying to engage and teach both youth and adults in areas such as GIS/spatial analysis, natural resource education, general math/science, invasive species, climate change, water quality, and forest management, via a variety of venues including classroom instruction, Master Forester workshops, Woods walks, specific issue-based workshops, and citizen science training sessions. The advent of modeled geospatial datasets of forest characteristics makes FIA data accessible to these users in a way that it wasn't before. And for most of these users, there usually isn't another source of current information about our forestlands, and certainly not one of similar quality and consistency. Reaching these users would increase awareness of forests in general, and of the USFS and FIA as a good source of information about those forests, amongst a large new eager, and often young, user group, and would improve the effectiveness of their work. We (FIA) cannot effectively reach all these users ourselves (individual schools, local forest landowner groups, conservation educators, Master Foresters and Gardeners). Fortunately several potential partners exist who serve those users – Cooperative Extension, and specific user-group partners such as State Conservation Education Departments and National Project Learning Tree – partners who could provide the essential bridging role necessary for FIA to reach them. A good webpage with readily accessible and downloadable geospatial datasets will definitely take us part of the way, but combining that critical online accessibility with direct outreach to these more local partners (e.g. Cooperative Extension) and/or specific user-group partners (State Conservation Education, National Project Learning Tree) will increase the effectiveness and use of both. In this paper we will describe our experience accessing these communities in New York, and share some recommendations for reaching these communities in other areas.

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THE NEW FACE OF AMERICA'S FAMILY FOREST OWNERS: RESULTS FROM THE 2011-2013 USDA FOREST SERVICE, NATIONAL WOODLAND OWNER SURVEY

Brett J. Butler[1], Jake H. Hewes[2], Sarah M. Butler[3], Marla Lindsay[4], and David B. Kittredge[5]

Abstract—Family forest owners rule! Across the United States, no other groups owns more forestland than families, individuals, trusts, and estates – collectively referred to as family forest owners. In total this group owns 117 million hectares of forestland, or 36% of the US forestland. Understanding the attitudes, behaviors, and general characteristics of this group of owners is necessary for understanding not just the current state of the forests, but also its future. This information is also important for designing effective programs and programs to meet the need of current and future owners. Data from the latest (2011-2013) iteration of the USDA Forest Service's National Woodland Owner Survey (NWOS; www.fia.fs.fed.us/nwos) will be used to explore differences between new and established forest ownerships in the US. Nearly 20% of America's forest owners have acquired their land within the past 10 years. These new owners have a number of factors that are similar to the more established owners, but also a number of factors that are different and these will be explored during this presentation.

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AMERICA'S FEMALE FAMILY FOREST OWNERS

Emily Silver[1], Sarah M. Butler[2], Brett J. Butler[3]

Abstract—According to the latest data from the US Forest Service National Woodland Owner Survey, there are an estimated 4 million family forest ownerships (with 10+ acres) across the U.S. Approximately 20% of these ownerships have a woman as the primary owner. A great percentage of the other ownerships are owned by a couple where the second owner is a woman and, given normal mortality patterns with woman outliving men, many more women will eventually become the primary decision makers. There has been increasing interest in establishing programs aimed specifically at female forest owners, but there has been relatively few studies looking at this important group. This presentation will explore the characteristics of female forest ownerships in the U.S. and highlight differences (and similarities) as compared to their male counterparts using data from the National Woodland Owner Survey.

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MOSS AS BIO-INDICATORS OF HUMAN EXPOSURE TO POLYCYCLIC AROMATIC HYDROCARBONS IN PORTLAND, OR

Geoffrey H. Donovan[1], Sarah E. Jovan[2], Demetrios Gatziolis[3], Vicente J. Monleon[4]

Abstract—Polycyclic aromatic hydrocarbons (PAHs) are a class of air pollutants linked to a wide range of adverse health outcomes, including asthma, cancers, cardiovascular disease, and fetal growth impairment. PAHs are emitted by combustion of organic matter (e.g. fossil fuels, plant biomass) and can accumulate in plant and animal tissues over time. Compared to criteria pollutants, such as O_3 or NO_2, less is known about PAHs in air inhaled by the general population because PAH monitoring is more technically challenging and costly (in Portland, for example, PAHs are measured by only one monitor). One cost-effective alternative is including bio-indicators in urban forest inventories to estimate how human exposure to PAHs varies across an area. Bio-indicators are less costly to collect and can integrate air pollutants over a long period of time, making them well suited to measuring chronic low-levels of air pollution that aren't detected by conventional air-quality monitors. We collected 347 moss samples (*Orthotrichum spp.*) across Portland, Oregon in December 2013 and tested each sample for the 16 PAHs identified by EPA as priority pollutants. For pyrene, benzo[a]pyrene, and naphthalene, we estimated regression models of moss PAH controlling for road density, vegetation, elevation, residential wood combustion, and weather that accounted for spatial autocorrelation among residuals. In addition, we used Bayesian multiple imputation to address non-detects. Road density and secondary wood burning (fireplaces) were associated with higher PAH levels, whereas tree cover and grass-and-shrubs were associated with lower PAH levels. Vegetation cover appears to be at least as important as road density in determining PAH concentrations. Other factors associated with PAHs in moss include elevation, daily temperature, humidity, and whether the sampled tree was in a tree genus with narrow crowns. We used the regression models to make fine-scaled maps of PAH concentrations across Portland.

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"LICHENS LITE?" CHEMICAL ANALYSIS OF LICHENS FOR TRACKING 26 POLLUTANTS

Sarah Jovan[1], Susan Will-Wolf[2], Michael Amacher[3]

Abstract—Lichen chemistry can be used to estimate concentrations of environmental contaminants, ranging from heavy metals and fertilizers to polycyclic aromatic hydrocarbons, dioxins, pesticides, herbicides, and flame retardants. We conducted a pilot looking at 26 metals and nutrient anions in 5 widespread lichen species across the upper Midwest, including: As, Al, Ba, Ca, Cd, Co, Cr, Cu, Fe, Hg, K, Mg, Mn, Mo, N, Na, Ni, P, Pb, S, Se, Si, Sr, and Zn. FIA crews collected 135 lichen samples from 75 plots across IL, IN, IA, MI, MN, WI and an expert collected 128 additional samples near 11 air monitors. Elements were measured in lichens using C, N, S, and Hg combustion analyzers and ICP-AES. Crews trained for 6 hours. Field time required per lichen sample ranged from 0.5 to 2 hrs, depending on target species. Contractors prepped samples for chemical analysis for an average of 30 to 45 minutes. The small but widespread species, *Physcia aipolia/stellaris*, took 1.5 hr/sample. Lichen concentrations of only 6 elements were below the detection limit or considered too variable to be of use (CV > 25%; Mo, B, Ba, Si, As, Se). No lichen species is found everywhere and species may accumulate pollutants at different rates. We used regression or univariate GLM between some species pairs to create conversion factors for some elements. Compared to the Phase3 Lichen Communities Indicator (LCI), advantages of chemical analysis are lower costs, less field time, and ability to map a broader range of pollutants. However, a key benefit of LCI is that it quantifies species gains and losses, which is an ecosystem response to air quality. Chemical content of lichens is not ecologically meaningful on its own, serving more as a mapping tool. Nonetheless, critical loads (pollutant thresholds known to be associated with ecosystem responses) may be used as reference points in lichen maps.

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SPECIAL STUDIES / RARE ECOSYSTEMS

EXPANDING THE FIA INVENTORY TO UNDERSTAND PLANT DIVERSITY IN PALAU'S CONSERVATION AREAS

Matthew O'Driscoll[1], Ashley Lehman[2], Mikhail Yatskov[3]

Abstract—Palau is well known as an area of high plant diversity; indeed, it is considered the most species rich island group within Micronesia (Kitalong et al., 2008). The Palauan archipelago covers only about 535 km² of land area and yet contains an estimated 730 native plants, including 151 endemic species (Kitalong et al., 2008). Broader scientific interest in Palauan forest health and biodiversity is mirrored locally by residents and land managers who seek baseline information to inform resource management decisions. With these concerns in mind, the Data Collection Team at the Pacific Northwest Research Station proposed a small pilot project to assess the feasibility of conducting more detailed vegetation surveys in Palau as well as the value of the information gained by more intensive sampling. In this survey we documented about 25% of the known plant species of Palau on the 15 subplots sampled, a total area of about 0.0025 km^2 or 0.62 acre. In summary, this pilot work demonstrates that detailed vegetation sampling (i.e., censuses) on FIA plots in the Pacific Islands is technically feasible, yields a wealth of information on plant diversity, and is potentially interesting on many levels to local communities, land managers, and the broader scientific community.

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USING LANDSCAPE-LEVEL FOREST MONITORING DATA TO DRAW A REPRESENTATIVE PICTURE OF AN ICONIC SUBALPINE TREE SPECIES

Sara A. Goeking and Deborah K. Izlar[1]

Abstract—Whitebark pine (*Pinus albicaulis*) is an ecologically important species in high-altitude, mid-latitude areas of western North America due to the habitat and food source it provides for many wildlife species. Recent concerns about the long-term viability of whitebark pine stands have arisen in the face of high mortality due to a combination of fire suppression, white pine blister rust, and mountain pine beetle outbreaks. Most previous studies of whitebark pine have focused on pure stands, yet the spatially representative Forest Inventory and Analysis (FIA) dataset shows that whitebark pine is more widespread in other forest types than in pure stands. Because previous studies have focused on iconic, pure whitebark pine stands, managers may not be aware of the potential for ecological restoration of whitebark pine in other forest types. The purpose of this study was to use FIA's spatially representative sample grid to assess whitebark pine stands in a variety of environments in the Rocky Mountains, and to compare the structure and composition of pure versus mixed-species stands where whitebark pine is present. The results illustrate that metrics of whitebark pine viability, namely regeneration and mortality, may be comparable in the understory of other forest types to those observed within pure stands. Finally, this study demonstrates that the FIA dataset permits spatially representative evaluations of populations that tend to be studied purposively rather than strategically.

Whitebark pine (*Pinus albicaulis*) is a keystone species found in high-elevation ecosystems of western North America. It is specialized for dispersal by the Clark's nutcracker (Hutchins and Lanner 1982) and serves as a food source for many species of birds and small mammals, as well as black bears (*Ursus Americanus*) and threatened grizzly bears (*Ursus arctos horribilis*) (Keane and Arno 1993). Whitebark pine is frequently considered to be a pioneer species that is maintained on more productive sites by stand replacing fire (Keane et al. 2012).

Whitebark populations are declining range-wide and in 2011 whitebark pine was found scientifically warranted for protection under the Endangered Species Act due to a combination of mortality-causing factors (United States Fish and Wildlife Service 2011). Recent large-scale outbreaks of mountain pine beetle (*Dendroctonus ponderosae*) have caused mortality of mature whitebark pine trees at higher rates and over larger areas than has been historically observed (Keane et al. 2012; Raffa et al. 2008). Ongoing infection by the exotic white pine blister rust (*Cronartium ribicola*) has impacted whitebark pine's regeneration strategy at all life stages, causing rapid mortality in young seedlings, nearly eliminating cone production in mature trees, and causing mature tree mortality (McKinney and Tomback 2007). Following a severe mortality event, seed sources for post-outbreak recruitment of whitebark pine may be limited, and as a consequence, survivorship patterns of mature trees, saplings and seedlings may be the most important determinants of future forest development (McCaughey et al. 2009).

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To assess the outlook for whitebark populations, it is of primary importance to establish the extent and amount of whitebark pine regeneration and mortality across the landscape. The specific objectives of this project were to: (1) characterize whitebark pine seedling density at all plots in the Rocky Mountains with a whitebark pine component, and (2) compare the distribution of whitebark pine size classes, for both live and mortality trees, in the forest types that most commonly contain whitebark pine.

METHODS

The study area for this project is the range of whitebark pine in the U.S. Rocky Mountains. The analysis was constrained to all FIA plots in the states of Idaho, Montana, and Wyoming that contained at least one of the following: a live or dead whitebark pine tree (diameter at breast height, or d.b.h., of 5.0 inches or larger); a live whitebark pine sapling (d.b.h. between 1.0 and 4.9 inches); or a whitebark pine seedling (d.b.h. less than 1.0 inch and length of at least 6 inches). For all plots that met at least one of these criteria, data were obtained from the seedling, tree, and condition tables in FIADB (O'Connell et al. 2013).

Density of whitebark pine seedlings was queried directly from the variable TPA_UNADJ in the seedling table in the FIA database (FIADB), where TPA_UNADJ for seedlings of each species on each subplot is equal to the number of seedlings tallied times the seedling expansion factor (O'Connell et al. 2013); this variable was then summed to the plot level. Density of mortality trees and density of live trees and saplings were calculated by summing tree-level expansion factors for each condition and then for each plot, by 2-inch diameter class. The intermediate condition-level step was used to identify forest types that most frequently contained a whitebark pine component. Plot-level stem densities were adjusted by the proportion of the plot that was forested, as described in O'Connell et al. (2013).

RESULTS

In the Rocky Mountains, 1,036 FIA plots surveyed between 2003 and 2012 contained a component of whitebark pine (Fig. 1). Seedling density at these plots ranged from zero to over 6,000 seedlings per acre, with a mean density of 312 seedlings per acre and a median density of 150 seedlings per acre. Whitebark pine seedlings were present on 719 plots; about 18 percent of these plots occurred within the whitebark pine forest type (Table 1). Similarly, about 18 percent of the 938 plots with whitebark pine trees or saplings occurred in the whitebark pine forest type (Table 1). Both lodgepole pine and spruce-fir forest types contained more plots with whitebark pine components than pure whitebark pine stands.

Figure 2 shows the size-class distribution of live whitebark pine stems and whitebark pine mortality trees by forest type. Live whitebark pine densities in all diameter classes are highest in pure whitebark stands (Fig. 2a). The density of seedlings in the lodgepole pine forest type is nearly as high as that within pure whitebark pine stands, but in larger diameter classes there is a greater disparity between lodgepole pine and pure whitebark pine stands. However, the presence of whitebark pines in all diameter classes in lodgepole pine and spruce-fir forest types may represent a much larger areal distribution of whitebark pine than acknowledged in previous studies.

The whitebark pine forest type exhibited not only higher densities of live stems but also higher densities of whitebark pine mortality trees, in all size classes (Fig. 2b). Qualitative comparison of the densities of mortality trees (Fig. 2b) to live trees (Fig. 2a) in each size class suggests that lodgepole pine and spruce-fir forest types that contain whitebark pine components did not experience mortality any more severe, and possibly less severe, than the mortality observed in pure whitebark pine stands.

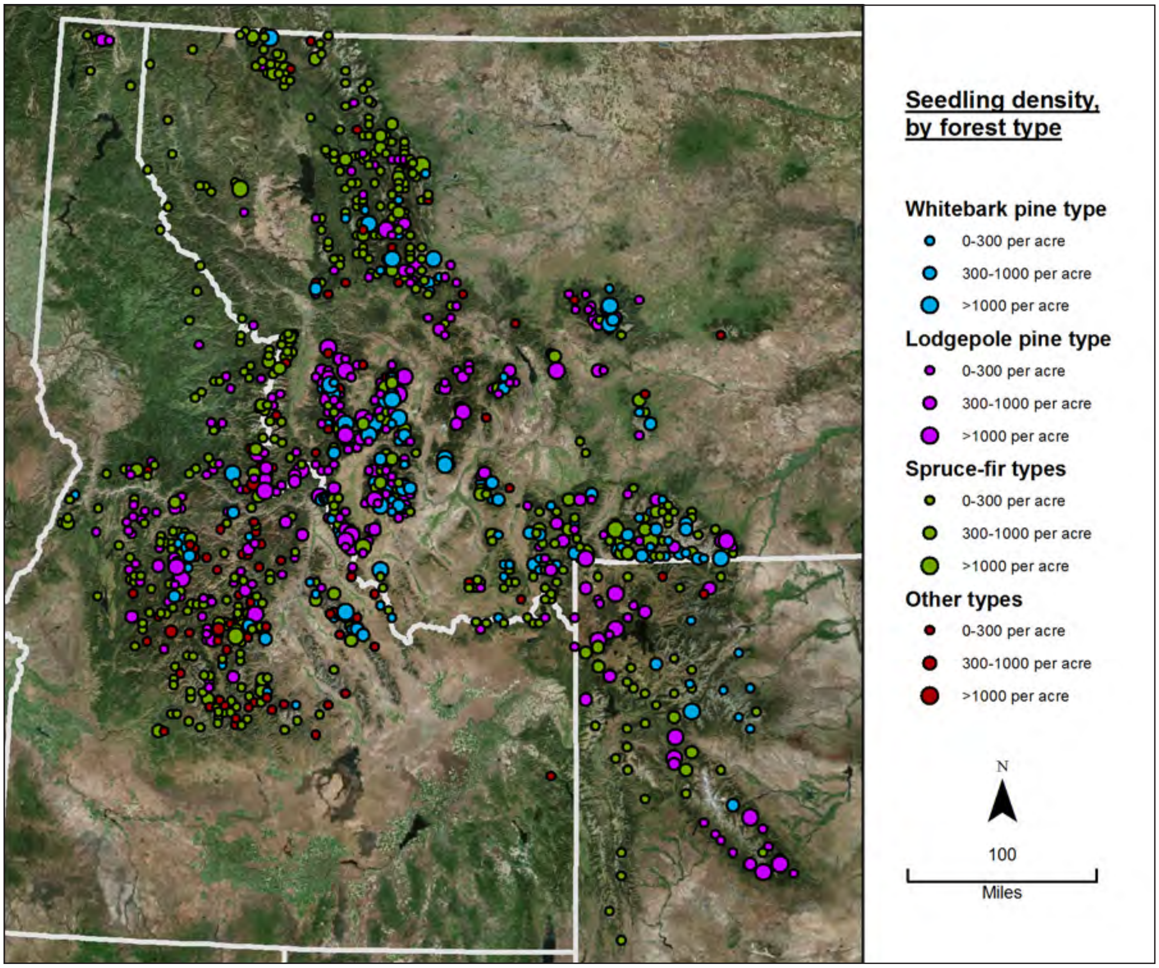

Figure 1—Map showing 1,036 FIA plots in the northern Rocky Mountains with a whitebark pine component, 2003-2012, by forest type and whitebark pine seedling density class. Plot locations are approximate.

Table 1—Number of plots, by forest type, that contain whitebark pine (WBP) trees (d.b.h. at least 5.0 inches) or saplings (d.b.h. 1.0 to 4.9) and number of conditions that contain WBP seedlings. Total are less than the total number of plots with a WBP component because some plots contain only seedlings and no trees or saplings, and others contain trees or saplings but no seedlings.

Forest type	Number of plots with WBP trees or saplings	Number of plots with WBP seedlings
Whitebark pine	172	131
Lodgepole pine	188	243
Spruce-fir types[1]	451	282
Douglas-fir	87	50
Other types	40	13
All types	938	719

[1] FIA's forest type classification includes several individual spruce-fir forest types, with four different spruce-fir types represented in this dataset. Because more than 95 percent of the plots in this dataset occur within the Engelmann spruce/subalpine fir type and the subalpine fir type, and because both types were present in nearly equal proportions and showed very similar densities of whitebark pine stems at all size classes, all spruce-fir types are aggregated here for simplicity.

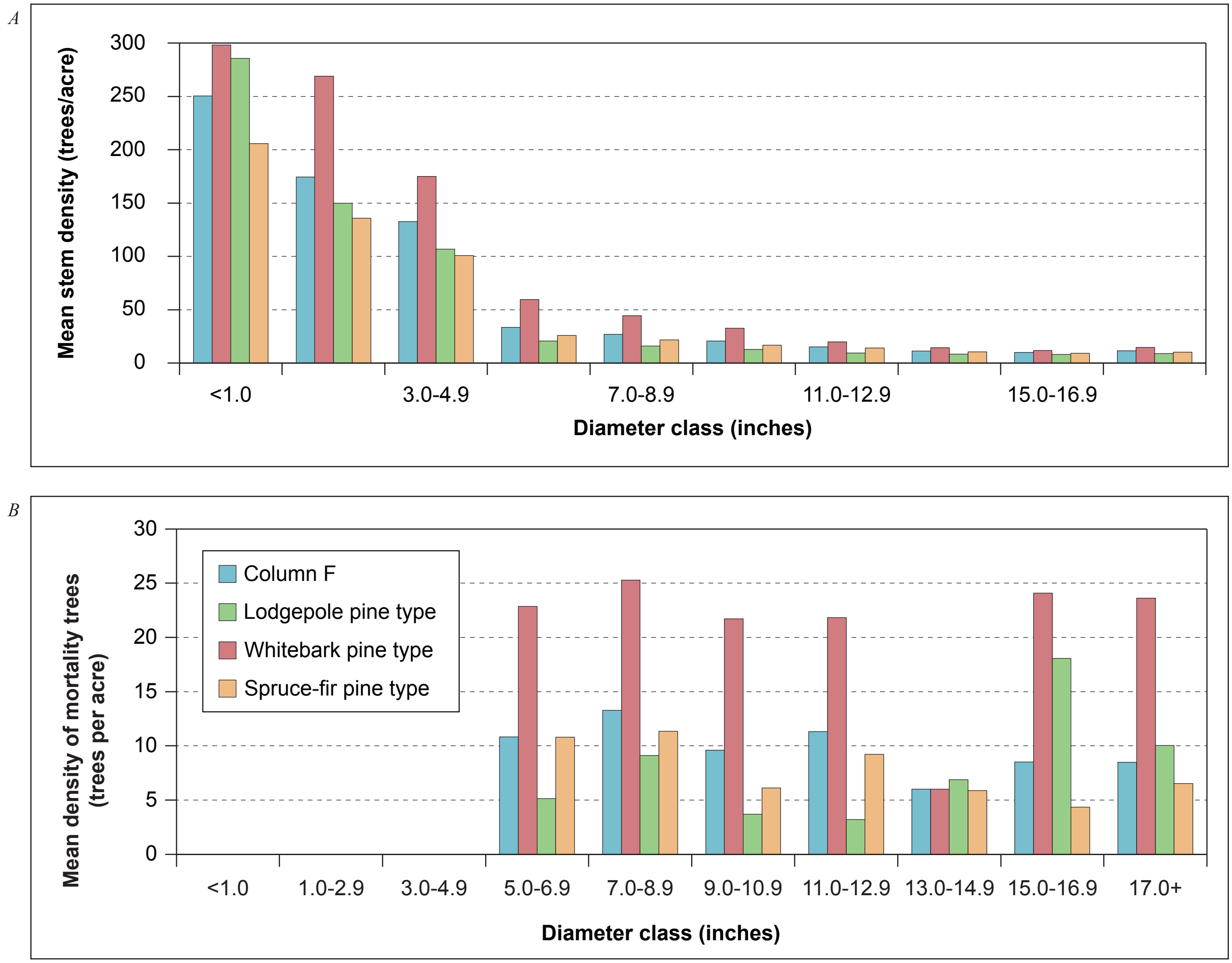

Figure 2—Mean density of live whitebark pines (A) and mean density of whitebark pine mortality trees (B), by diameter class, for the three forest types where whitebark pine is most abundant in the Rocky Mountains, 2003-2012. Estimates of mortality trees per acre were not available for trees smaller than 5.0 inches d.b.h.

DISCUSSION

The advantage of using FIA data for this type of analysis is that the FIA plot grid represents a spatially representative sample (Bechtold and Patterson 2005) across the landscape, rather than a purposive or targeted sample of sites with specific intrinsic characteristics, such as an overstory predominated by whitebark pine and/or signs of recent severe mortality. This analysis found that although the whitebark pine forest type contains the highest densities of seedlings, saplings, and trees, other forest types also have appreciable densities of whitebark pine stems in all diameter classes. Similarly, densities of whitebark pine mortality trees were higher in pure whitebark pine stands than in other forest types. However, other forest types occupy far more area than the pure whitebark pine forest type, as represented by the number of FIA plots that met the criteria for inclusion in this analysis. In particular, whitebark pine stems of all size classes occurred within lodgepole pine and spruce-fir forest types more frequently, although at lower densities, than in pure whitebark pine forests. Seedling densities in lodgepole pine forests were almost as high as those in pure whitebark pine forests, so further study is needed to identify the factors that affect recruitment into larger size classes.

To make this information useful to managers, future research should identify site factors that differentiate lodgepole pine and spruce-fir stands that contain a whitebark pine component from those that do not. Sites with a whitebark pine component may represent potential recruitment sites, either via future recruitment or competitive release of understory trees following overstory disturbances such as the mountain pine beetle epidemic. Campbell and Antos (2003) found that even small whitebark pine trees and saplings can respond favorably to disturbance-induced canopy gaps, and exhibit competitive release after growing slowly for 150-200 years. Although ecological succession from whitebark pine to subalpine fir is thought to be one cause of whitebark pine's decline (Keane and Arno 1993), it is possible that whitebark pine is not entirely seral in other forest types, and some spruce-fir and lodgepole pine stands may offer opportunities for managing for competitive release of whitebark pines in the understory.

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USING ADJUNCT FOREST INVENTORY METHODOLOGY TO QUANTIFY PINYON JAY HABITAT IN THE GREAT BASIN

Chris Witt[1]

Abstract—Pinyon jays (*Gymnorhinus cyanocephalus*) are the principal dispersal agent for pinyon pine seeds in the Great Basin region of the Intermountain West. However, Pinyon jays have exhibited significant population declines over much their range in recent decades, even as pinyon-juniper woodlands appear to have been expanding over the past 150 years. In order to identify and quantify habitat preferences for nesting, seed caching, and general foraging within the woodlands of the Great Basin, we measured stand and tree parameters of Pinyon jay nest, forage and cache sites in Idaho and Nevada using U.S. Forest Service Forest Inventory and Analysis (FIA) survey methodology. We then compared mean values of site characteristics to data collected from standard Forest Inventory plots in order to quantify habitat across Nevada, which contains most of the Great Basin land area. Sites differed in physical structure, with caching sites having lower canopy cover and higher snag basal area than other sites, and foraging sites having higher shrub cover than other sites. About 26 percent of Nevada's pinyon-juniper woodlands resemble the caching habitat preferences of the birds in our study, and about 32 percent resemble nest site preferences. However, only about seven percent of the woodlands meet general foraging habitat used in our study. This research identifies a potential limiting resource for pinyon jays in the Great Basin while also showing the utility of adjunct inventory using FIA methodology.

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ESTIMATING MANGROVE IN FLORIDA: TRIALS MONITORING RARE ECOSYSTEMS

Mark J. Brown[1]

Abstract—Mangrove species are keystone components in coastal ecosystems and are the interface between forest land and sea. Yet, estimates of their area have varied widely. Forest Inventory and Analysis (FIA) data from ground-based sample plots provide one estimate of the resource. Initial FIA estimates of the mangrove resource in Florida varied dramatically from those compiled by other sources. Estimates of mangrove forest in Florida ranged from FIA's less than 100,000 acres to nearly 600,000 acres elsewhere. FIA discovered inherent measurement difficulties, accessibility constraints, and adverse working conditions affecting accurate sampling and estimation of the resource. Reconciliation of these issues produced improved estimates. However, disparity with other estimates remains. FIA concluded that accurate assessment of peripheral margin-like resources, such as mangrove, must include methods used to sample any spatially limited resource of interest. Current FIA estimates show 238,000 acres of mangrove forest type in Florida with a sampling error of 15.48 percent.

Since Forest Inventory and Analysis (FIA) first inventoried the forests of Florida in 1936, mangroves were treated as noncommercial species and considered unproductive forest land. This designation carried through the 1949, 1959, 1970, 1980, 1987, and 1995 inventories of the State. However, FIA revised the inventory for the new millennium and switched from periodic inventory measurement to collecting field data on an annualized basis. In Florida, this process began in 2001. One important aspect of the new inventory was that mangrove species were now tallied as trees and incorporated into the inventory data. Thus, for the first time, as the inventory progressed, data were available to describe Florida's mangrove resource. In Florida, four species of mangrove were measured: red mangrove (*Rhizophora mangle)*, black mangrove (*Avicennia germinans)*, white mangrove (*Laguncularia racemosa)*, and buttonwood mangrove (*Conocarpus erectus)*. Many differences between the individual mangrove species exist; for example, the reds are generally most seaward and the buttonwoods most landward. However, for the purposes of this research, they are considered collectively.

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Analysis of early mangrove data revealed dramatic disparities with estimates from other sources. The 2004 and 2007 (Fig. 1) FIA estimates of less than 100,000 acres statewide versus other estimates approaching 600,000 acres (Florida Fish and Wildlife Conservation Commission Fish and Wildlife Research Institute 2009, Department of Environmental Protection Florida Marine Research Institute 2002, Johnston and others 1995) prompted questions regarding potential differences in sampling methods as well as forest type definition. The 2004 estimates were based on 60 percent of the sample design plots being captured and, despite algorithmic expansions, produced the lowest mangrove estimates. By 2007, the entire plot sample had been measured, but the improved estimates were still far below those from other sources. Evidently, the high proportion of probable mangrove samples not visited due to access denial and adverse condition field calls were not represented in the data output. FIA methods were largely ground-based samples with expansion factors, whereas other sources were largely aerial photography and satellite imagery based. Furthermore, the FIA forest land definition required a minimum of 1 acre in size with a minimum width of 120 feet to meet the threshold to be classified as forest, precluding small pockets or narrow strips of trees from the estimate.

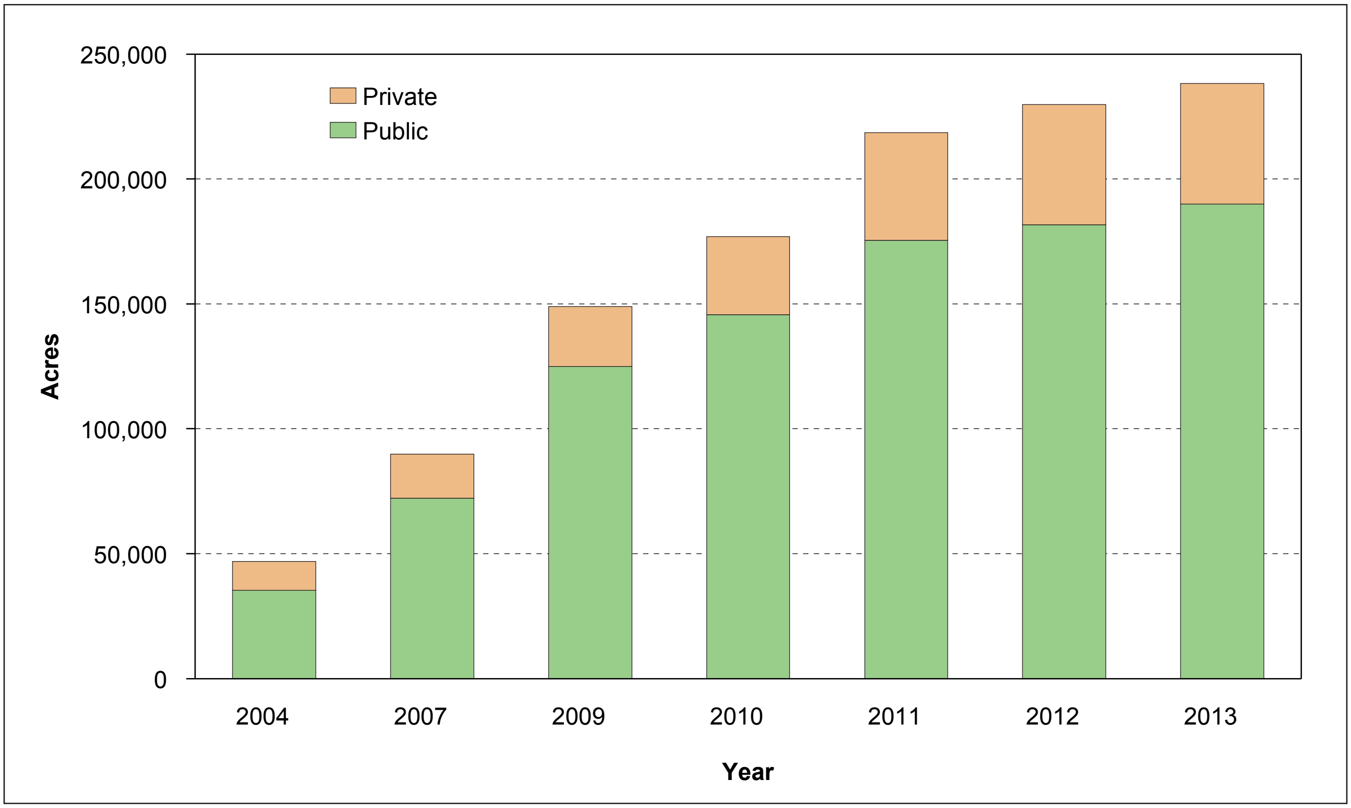

Figure 1—Area of mangrove forest type on forest land in Florida by major ownership group and year.

However, these explanations were insufficient to resolve the entire gap in mangrove area estimates. Subsequent internal investigation discovered shortcomings in the FIA sampling methods. Since the mangrove forest type typically occurs at sea level and within tidal zones, the resulting peripheral distribution along coastlines and tidally influenced drainages presented inherent difficulties to accurate sampling and estimation of the resource. Issues involving accessibility and adverse conditions encountered actually inhibited and prevented measuring many of the sample plots. Many were reported as hazardous or access denied. Having a large percentage of nonsampled plots is known to potentially lead to underestimation of forest attributes (Patterson and others 2012).

FIA evaluated the equipment used by field personnel to access mangrove forests and found the traditional watercraft used to be inadequate to reach these shallow, tidal influenced zones. Acquisition of a kayak for these purposes immediately improved accessibility and permitted the measurement of additional samples previously unmeasured.

Since many of the mangrove forests exist on public lands classified as reserved, reinforced memorandums of understanding (MOUs) were acquired to permit access across sensitive lands administered by other agencies. This added cooperation permitted the measurement of additional samples as well.

Although addressing these issues remains a work in progress, partial reconciliation of the unmeasured samples produced increased estimates of the mangrove resource evident beginning with year 2009 and forward (Fig. 1). Also evident is the increase in the mangrove estimate each year as additional annual inventories remeasured the 2007 plot design and eventually recaptured the full sample by 2013. Since 2007, the FIA estimate of mangrove in Florida has more than doubled. Mangroves can be a fragile resource regarding impacts from hurricanes and coastal urbanization, and they are not known for rapid growth or colonization; therefore, most of the increase in the FIA estimates can be attributed to the changes in sampling methods and reduction of the nonsampled rate. In 2013, 80 percent of the mangrove area existed on publicly owned lands. Although the mangrove area estimate was enhanced on both public and private lands between 2007 and 2013, it is clear that most of the apparent gain was accomplished on public land, where efforts to improve cooperation through MOUs with other agencies contributed.

The subtropical trait of the mangrove forests generally restricts their occurrence to the southern end of the Florida peninsula. Table 1 shows the distribution of the mangrove forest type by survey unit. This table corroborates that 85 percent of Florida's mangrove forest type does exist in the South survey unit of the State. Enhancements in the FIA sampling methods improved estimates to the largest extent in the South survey unit, where large public holdings exist. Noteworthy is the 2010 and onward capture of mangrove forest in the Northeast survey unit. If this measurement were for a more prevalent tree species, this could be construed as evidence of species range extension. However, it is most likely evidence of results from improvements to the FIA sampling methods for mangrove.

Estimating the population of mangrove trees independently of area estimates was done to gain another perspective on the mangrove resource. Population estimates capture mangroves from all forest conditions, including those not classified as mangrove forest type (Fig. 2). The changes in the population of mangrove trees actually emulated those of the area of mangrove forest type. Again, the estimates more than doubled from 2007 to 2013. The tracking similarity of the population estimates with that of the area estimates stems from the tendency of mangroves to occur in homogenous stands due to the wet and brackish to saline conditions not tolerated by many other tree species.

Table 1—Area of mangrove forest-type on forest land in Florida by survey unit, major ownership group, and year

Survey unit and major ownership group	2004	2007	2009	2010	2011	2012	2013
				acres			
Northwest							
Public	0	0	0	0	0	0	0
Private	0	0	0	0	0	0	0
All	0	0	0	0			
Northeast							
Public	0	0	0	9,118	9,118	9,406	9,453
Private	0	0	0	0	0	0	0
All	0	0	0	9,118	9,118	9,406	9,453
Central							
Public	19,018	13,109	20,146	20,088	19,922	19,572	19,656
Private	0	0	0	0	6,169	5,989	6,019
All	19,018	13,109	20,146	20,088	26,091	25,561	25,675
South							
Public	16,270	59,050	104,756	116,430	146,398	152,725	160,893
Private	11,568	17,700	24,109	31,246	36,911	42,095	42,161
All	27,838	76,750	128,865	147,676	183,309	194,820	203,054
State							
Public	35,288	72,159	124,902	145,636	175,438	181,703	190,002
Private	11,568	17700	24,109	31,246	43,080	48,084	48,180
All	46,856	89,859	149,011	176,882	218,518	229,787	238,182

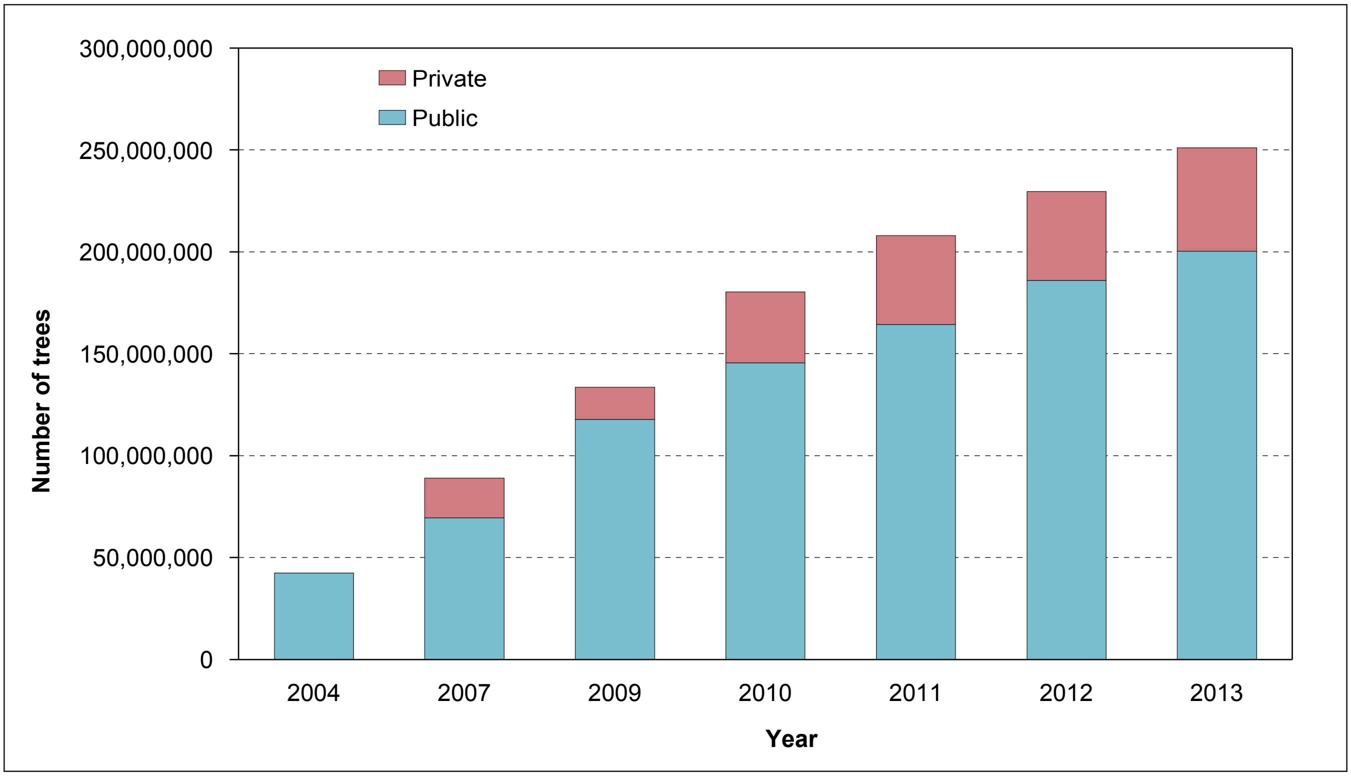

Figure 2—Number of live mangrove trees at least 1 inch d.b.h. on forest land in Florida by major ownership group and year.

The population of mangrove trees by survey unit closely tracks that of the forest type distribution (Table 2). In 2013, the South survey unit accounted for 83 percent of the State's mangrove trees. Similar to forest type, mangrove trees were measured in the Northeast survey unit beginning in 2010 and onward.

Figure 3 reveals the weaknesses and the progress FIA has made in improving estimates of the occurrence and distribution of mangrove trees in Florida. The map shows the location of samples that recorded one or more mangrove trees present. From the 2001 inception of mangroves recorded as trees, the 2004 map (Fig. 3A) shows the weakness of a partial sample and the flaws in accessibility issues affecting the data. The 2007 map (Fig. 3B) shows the full sample measured, but accessibility issues left the estimate inadequate. By 2010 (Fig. 3C), the map shows the impact of improved access methods and a better picture of the mangrove resource. By the full remeasurement of the 2007 sample in 2013 (Fig. 3D), the map shows an improved distribution. However, some gaps still appear in known areas of mangrove, such as those around Cape Canaveral and within Everglades National Park. The fact that these areas appear to remain undersampled indicates that mangroves are still being underestimated.

The gains in achieving a more accurate estimation of the mangrove resource in Florida have primarily resulted from improved access methods. The percentage increases between survey years shown in both figures and both tables appear to be diminishing. Considering the remaining disparity with other estimates leads to the premise that either other sources have overestimated the mangrove resource or FIA has to further refine the sampling method for this rare ecosystem. Ultimately, FIA has learned that other issues regarding spatially restricted resources need to be addressed to further improve its estimation. Solutions identified involve sample intensification and strata development for mangrove. FIA has concluded that more accurate assessment of the mangrove resource must include sampling methods like those employed for estimates of individual islands, singular ownerships like national forest, inclusions, and any spatially limited resource of interest.

Table 2—Number of live mangrove trees at least 1 inch d.b.h. on forest land in Florida by survey unit, major ownership group, and year.

Survey unit and major ownership group	2004	2007	2009	2010	2011	2012	2013
				number			
Northwest							
Public	0	0	0	0	0	0	0
Private	0	0	0	0	0	0	0
All	0	0	0	0	0	0	0
Northeast							
Public	0	0	0	11,391,626	11,391,626	11,751,546	11,810,674
Private	0	0	0	0	0	0	0
All	0	0	0	11,391,626	11,391,626	11,751,546	11,810,674
Central							
Public	17,995,717	13,425,064	24,967,830	23,083,166	22,825,838	22,301,343	22,046,632
Private	0	0	0	0	10,284,787	9,984,987	10,036,005
All	17,995,717	13,425,064	24,967,830	23,083,166	33,110,625	32,286,330	32,082,637
South							
Public	24,369,169	56,099,499	92,832,692	111,036,320	130,110,212	151,918,301	166,330,362
Private	69,617	19,457,355	15,796,261	34,752,196	33,343,348	33,655,103	40,784,461
All	24,438,786	75,556,854	108,628,953	145,788,516	163,453,560	185,573,404	207,114,823
State							
Public	42,364,886	69,524,563	117,800,522	145,511,112	164,327,676	185,971,190	200,187,668
Private	69,617	19,457,355	15,796,261	34,752,196	43,628,135	43,640,090	50,820,466
All	42,434,503	88,981,918	133,596,783	180,263,308	207,955,811	229,611,280	251,008,134

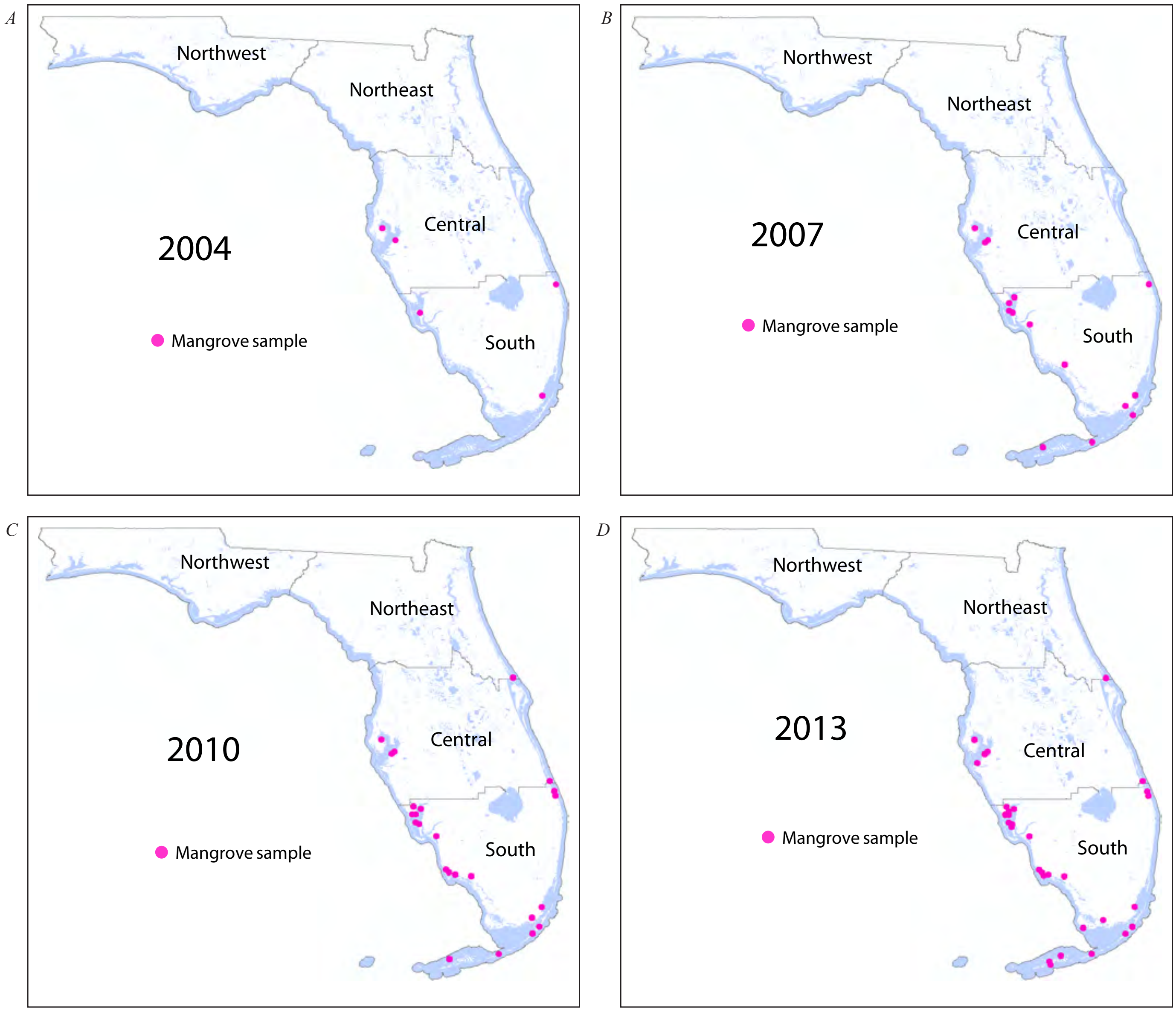

Figure 3—Mangrove sample locations and year (A) 2004, (B) 2007, (C) 2010, (D) 2013, Florida.

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A BASELINE ASSESSMENT OF FOREST COMPOSITION, STRUCTURE, AND HEALTH IN THE HAWAI'I EXPERIMENTAL TROPICAL FORESTS

Robert R. Pattison, Andrew N. Gray, and Lori Tango[1]

Abstract—The US Forest Service's Forest Inventory and Analysis (FIA) Program of the Pacific Northwest (PNW) Research Station has been working in the Hawaiian islands since 2010. During this time they have installed a base grid of field plots across all of the Hawaiian Islands and an intensified sample of two experimental forests, the Laupāhoehoe and Pu‘u Wa‘awa‘a units of the Hawaii Experimental Tropical Forests (HETF). These intensified plots used the standard P3 FIA plot design but included a number of additional measurements that were designed to address forest health issues specific to Hawai›i›s forests. Preliminary analysis of all of the data provides important insights into the structure and composition of the forests including tree damages, regeneration (seedling recruitment), understory composition, and the presence of invasive species. Results of this initial inventory effort and a preliminary analysis will be presented. Highlights include key differences in the extent of invasive species and ungulate damage across plots in these different forests.

INTRODUCTION

In 2010 the FIA program of the Pacific Northwest Research Station started the first inventory of the state of Hawai'i. This inventory is set to be completed in the fall of 2015. In addition to the establishment of a 1x grid, the FIA program installed two panels of 2x plots on Hawaii Island and installed an intensified grid on the experimental forest units of Laupāhoehoe and Pu‘u Wa‘awa‘a. The results of these initial insights into the forested conditions on the experimental forests of Hawaii will be discussed.

STUDY AREA

The Laupāhoehoe experimental forest is located on the northern end of the island of Hawaii. The forest is 12,387 acres in size and ranges from 1,700 feet elevation to 6,100 feet. The average annual precipitation in this forest is 160 inches per year in the lower regions of the forest and 60 to 100 inches at higher elevations. The Pu‘u Wa‘awa‘a experimental forest unit is located on the leeward side of Hawaii island and is 38,885 acres in size. The average annual precipitation is near sea level is 10 inches increasing to 47 inches at higher elevations. This experimental forest unit ranges from sea level feet to 6,100 feet.

METHODS

An intensified sampling of the two experimental forest units was conducted with a total of 69 plots proposed to be visited - 32 plots in the Laupāhoehoe Unit and 37 plots in the Pu‘u Wa‘awa‘a Unit. All installed plots had standard P3 protocols with modifications made to include a macro plot for trees > 24”, a comprehensive tree species list, additional branching, rooting, and crown measurements, and the inclusion of special interest species ranging from invasive plants, pathogens, and feral pig damage.

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RESULTS AND DISCUSSION

Of the 69 planned plots, a combined total of 66 plots were installed. Three plots in the Laupāhoehoe HETF were not measured due to remoteness (*i.e.*, crew was unable to safely access plots). All of the proposed 37 plots at Pu‘u Wa‘awa‘a HETF were installed and measured. Twenty of the 37 plots were considered accessible forest land, and the remaining 17 plots were considered non-forest.

A total of 4,082 and 1,764 live and dead trees and saplings were measured on FIA plots in the Laupāhoehoe and Pu‘u Wa‘awa‘a HETF units, respectively. The native species ‘ōhi‘a (*Metrosideros polymorpha*) was the most abundant species on both of these forest units.

Forests at the Laupāhoehoe HETF tended to be dominated by moderate-sized trees with approximately 54% of all trees ranging in DBH from 5.0 to 9.9 inches. The average sapling height was 23 ft, the average tree heights from subplot trees was 34 feet. The tallest tree on an FIA plot in this Unit was a 131 ft tall ‘ōhi‘a (*M. polymorpha*) with a DBH of 72.3 inches. Forest stands at the Pu‘u Wa‘awa‘a HETF were dominated by moderate-sized trees with approximately 63% of all trees measured on plots falling into the 5.0 to 9.9 inches in diameter size class. There were no trees with diameters larger than 40.0 inches in the Pu‘u Wa‘awa‘a Unit. For the Pu‘u Wa‘awa‘a Unit the average sapling and tree heights were 15 ft, and 35 ft respectively. The tallest tree on an FIA plot in this unit was a 95 ft tall ‘ōhi‘a (*M. polymorpha*) with a DBH of 21.1 inches.

Most live tress in the Laupāhoehoe HETF supported light to heavy epiphyte loading, while only a few species of live trees in the Pu‘u Wa‘awa‘a HETF supported epiphytes. Light epiphyte loading included trees that had epiphytes present but occupied less than 50 percent of branches or bole and heavy epiphyte loading included trees that had greater than 50 percent of the branches or bole loaded with epiphytes.

Approximately nine percent of trees measured in the Laupāhoehoe HETF had some form of visible damage. The primary damage types observed here were broken branches, dead tops, and open wounds. At the Pu‘u Wa‘awa‘a HETF approximately 18 percent of trees measured had some form of visible damage. The primary damage types reported here were broken or dead branches, dead tops, and vines in the crown.

In the Laupāhoehoe HETF, 19 different seedling species were tallied on plots. The invasive strawberry guava (*Psidium cattleianum*) was by far the most abundant seedling tallied in the Laupāhoehoe HETF with four low elevation (2100 to 2800 ft) FIA plots in the Natural Area Reserve containing at least 50 seedlings on each plot. In the Pu‘u Wa‘awa‘a HETF, six different seedling species were tallied on plots. The native ‘ōhi‘a (*M. polymorpha*) and māmane (*Sophora chrysophylla*) were the most abundant seedlings in the Pu‘u Wa‘awa‘a HETF.

Common understory seedling and sapling sized tree species by estimated cover were the native tree fern hāpu‘u pulu (*Cibotium glaucum*), ‘ōhi‘a (*M. polymorpha*), ‘ōlapa (*C. trigynum*), kolokolo mokihana (*Melicope clusiifolia*), and the non-native shamel ash (*Fraxinus uhdei*). There were 19 different fern, forb, graminoid, shrub, and vine species in the understory on plots in the Laupāhoehoe HETF. In the Pu‘u Wa‘awa‘a HETF, six species of seedling and sapling sized trees (excluding invasive species) were tallied. The common understory seedling and sapling sized tree species by estimated cover area in the Pu‘u Wa‘awa‘a HETF were all native: ‘ōhi‘a (*M. polymorpha*), māmane (*S. chrysophylla*), and koa (*Acacia koa*). naio (*Myoporum sandwicense*), and lama (*Diospyros sandwicensis)*. Twenty one fern, forb, graminoid, and shrub species were found in the Pu‘u Wa‘awa‘a HETF. Common non-tree understory species included non-native grasses: meadow rice grass (*E. stipoides*), kikuyu grass (*Pennisetum clandestinum*), and velvet grass (*Holcus lanatus*).

A list of priority invasive species for Hawai'i was generated through consultations with local experts. The percent cover of these species on each subplot was tallied separately. There were eight priority invasive species tallied on the Laupāhoehoe HETF. Strawberry guava (*P. cattleianum*), Koster's curse (*Clidemia hirta*), and kahili ginger (*Hedychium gardnerianum*) were among the most common species. There were five priority invasive species tallied on Puʻu Waʻawaʻa HETF. Fountain grass (*Pennisetum setaceum*), lantana (*Lantana camara*), and banana poka (*Passiflora mollissima*) were the most common invasive species on the Puʻu Waʻawaʻa HETF.

Noticeable pig damage to the ground (wallows) and/or ground vegetation (rubbing) on plot was estimated as a percent of each subplot. Pig damage was observed on 29 plots in the Laupāhoehoe HETF with an average area of impact of 8%. Pig damage was observed on 19 plots in the Puʻu Waʻawaʻa HETF; with an average area of impact of only 1-2%.

STATE-OF-THE-ART VISUALIZATIONS AND STORYTELLING USING FIA DATA

DIY VISUALIZATIONS: OPPORTUNITIES FOR STORY-TELLING WITH ESRI TOOLS

Charles H. Perry[1]* and Barry T. Wilson[1]

Abstarct—The Forest Service and Esri recently entered into a partnership: (1) to distribute FIA and other Forest Service data with the public and stakeholders through ArcGIS Online, and (2) to facilitate the application of the ArcGIS platform within the Forest Service to develop forest management and landscape management plans, and support their scientific research activities. This partnership (in combination with the Agency's master agreement with Esri) includes access to ArcGIS Online, the GeoPlanner, story maps, map journals, and business intelligence tools. In this presentation, we review the vision developed collaboratively by the Forest service and Esri to implement these tools more widely in analysis and reporting, discuss the development of appropriate digital infrastructure to support these activities, and highlight straight-forward applications of several Esri tools for digital story-telling. Additionally, we demonstrate how application of these tools fulfill aspects of FIA's mission while simultaneously accomplishing the Obama Administration's goal of sharing geospatial data with the public.

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VISUAL ANALYSIS OF FOREST HEALTH USING STORY MAPS: A TALE OF TWO FOREST INSECT PESTS

Susan J. Crocker[1], Brian F. Walters[2], Randall S. Morin[3]

Abstract—Historically, results of surveys conducted by the Forest Inventory and Analysis (FIA) program of the USDA Forest Service were conveyed in printed reports, featuring text, tables and static figures. Since the advent of the Internet and with the ubiquity of mobile smart devices, technology has changed how people consume information, as well as how they experience and interact with the world. Web applications, such as the ESRI Story Map Journal© which serves as a confluence for embedded text, maps, images and other dynamic content, provide a platform from which a user can point and click to interact and engage in in-depth analysis. Here, forest inventory data is used to assess landscape-scale risks and impacts resulting from the outbreaks of two North American insect pests, the native eastern larch beetle and the exotic emerald ash borer, using the ESRI Story Map Journal© builder. A series of journal entries, or sections linking maps, interactive graphics, and other content with text was built to enhance the storytelling ability of these two pest outbreaks and the science behind it. Exploring new ways to visualize and convey forest resource information in a technical world will ensure that we continue to meet the needs of current FIA data consumers for years to come and attract new audiences and users.

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UTILIZING ONLINE TECHNOLOGY TO INCREASE THE DATA REACH OF THE FOREST INVENTORY AND ANALYSIS PROGRAM; EXAMPLES FROM THE SOUTHERN UNITED STATES

Christopher M. Oswalt[1] and Ted R. Ridley[2]

Abstract—Benjamin Franklin once said "Tell me and I forget. Teach me and I remember. Involve me and I learn." It is with that in mind that the Southern Research Station (SRS) Forest Inventory and Analysis (FIA) Program jumps feet first into exploring alternative methods of communicating the knowledge that is discovered through broad-scale data collection of the forest resources of the Unite States. One major aspect of our current explorations is the utilization of the esri ArcGIS Online (AGOL) platform and the numerous tools found therein. We describe the efforts of the SRS-FIA program to generate added-value from AGOL by based on the forest products industry of the southern United States and invasive plant data collected across southern forests. In addition, using the AGOL Operations Dashboard, we have developed a pilot project that could prove useful in helping manage our collection of quality assurance (QA) plots as part of a recently updated QA protocol in the SRS-FIA program. As the national FIA program moves forward, our attempts to reach new audiences must include new methods of communication. The FIA program stands to broaden the reach of the data it collects with these new easy-to-use methods, while maintaining the strong support that has been developed over many years of cooperation.

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IMPLEMENTING DASHBOARDS AS A BUSINESS INTELLIGENCE TOOL IN THE FOREST INVENTORY AND ANALYSIS PROGRAM

Scott A. Pugh, Randall S. Morin, and Barb A. Johnson[1]

Abstract—Today is the era of "big data" where businesses have access to enormous amounts of often complex and sometimes unwieldy data. Businesses are using business intelligence (BI) systems to transform this data into useful information for management decisions. BI systems integrate applications, processes, data, and people to deliver prompt and robust analyses. A number of successful organizations such the New England Patriots and Google are capitalizing on BI systems. Prototype dashboards have been developed by the Forest Inventory and Analysis program of the Northern Research Station (NRS-FIA) to facilitate delivery of data, mining for trends, and an analysis of a particular natural resource issue. Further development of FIA analytical applications tied to data visualization tools should increase the speed and ability to identify emerging and monitor existing natural resource trends. Though BI systems of many organizations are often internal, FIA has the potential to offer these powerful tools to the public. With an ever-growing demand from users to access information through digital media, BI tools can provide the public with natural resource information via a variety of digital devices in simple, dynamic, and interactive graphical user interfaces. As we explore these opportunities we need to address the unique challenges posed when catering to various clients.

Today is the era of "big data" where businesses have access to enormous amounts of often complex and sometimes unwieldy data (e.g., petabytes of data often streaming in real time) resulting from advances in technology and the increase in mobile and online computing. Businesses are using business intelligence (BI) systems to transform this data into useful information for management decisions.

BI systems integrate applications, processes, data, and people to deliver prompt and robust analyses. In a simple scenario, data residing in tools from spreadsheets to transactional databases are extracted, transformed, and loaded into a repository such as a data warehouse. Next, data are accessed by analytical and presentation tools such as dashboards with interactive graphs, tables, and maps. This scenario is guided by a defined set of processes and rules.

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Powerful analytics including statistics and online analytical processors that optimize queries are one major advantage offered by BI systems. Furthermore, advancements in hardware and presentation tools assist in relatively quick analyses of large and complex data sets. A number of successful organizations such the New England Patriots and Google are capitalizing on BI systems (Davenport and Harris 2007).

Precursors to BI systems focused on monitoring inventory and transactions in business (e.g., enterprise resource planning and point-of-sale systems) and lacked many of the visual and statistical analytical tools for making management decisions (Davenport and Harris 2007). Today's systems offer information to a wide range of users through dashboards with simple, dynamic, and interactive graphical user interfaces.

With an ever-growing demand from the public to access information through digital media, FIA has the potential to provide natural resource information through user-friendly dashboards. FIA has hundreds of gigabytes of complex forest inventory data requiring analysis and periodic dissemination to the public. Furthermore, 46 percent of USDA Forest Service Research and Development customers are requesting more and improved access to data and information via the Internet (CFI Group 2015).

Implementing BI tools in a public agency poses unique challenges. Most BI systems are developed by private businesses and used internally by specific clients with known devices. In contrast, FIA has a variety of public and private clients using an array of digital devices. FIA is thus confronted with many options. In general, it can produce multiple tools optimized by device or produce a less optimized tool that works on all or most devices.

In addition, public agencies can have data governance and information technology constraints not present within private agencies. For example, USDA Forest Service applications must be compliant with Section 508 of the Rehabilitation Act (29 U.S.C. 794d), as amended by the Workforce Investment Act of 1998 (P.L. 105-220), August 7, 1998 (http://www.section508.gov/Section-508-Of-The-Rehabilitation-Act). Every feature in a compliant application must be accessible using a keyboard. To date, we have found no off-the-shelf BI tool that meets this requirement without applying custom programming. Oracle®, Tableau Software®, Microsoft®, QlikTech®, Logi Analytics®, Pentaho®, Targit®, Birst®, Bitam®, IBM®, SAS®, MicroStrategy®, Tibco®, GoodData®, Information Builders®, SAP®, Actuate®, and ESRI® are a sample of companies offering off-the-shelf BI solutions.

As a program within a public agency, the primary focus of FIA is providing user-friendly BI tools such as dashboards for public consumption but analysts within FIA will also benefit from BI implementation. Similar to methods employed in many other organizations, FIA analysts use spreadsheets, custom computer code, structured query language, and statistical packages for analysis and decision-making. Applying these tools, often on an ad hoc basis, can result in errors (Panko 1998) and can require days of custom programming or spreadsheet development. Interactive dashboards connected directly to the data and integrated with off-the-shelf and/or custom analytical tools afford a more robust environment while also increasing the speed and ability to identify emerging and monitor existing trends.

METHODS

We extracted, transformed, and loaded public FIA data from Oracle into Tableau Software tools (http://www.tableau.com/) creating dashboards. The data was from the most recent and select previous inventories of the FIA Northern Research Station (NRS-FIA, http://www.nrs.fs.fed.us/fia/). Prior to loading data into Tableau Software, the data were summarized in Oracle as new summary tables and views optimized for performance in dashboards. Oracle has been the standard transactional database used to store and maintain FIA data for decades.

In the fall of 2013, several BI tools and vendors were investigated to facilitate development of dashboards. In 2014, Tableau Desktop Professional (http://www.tableau.com/products/desktop) and Tableau Public (http://www.tableau.com/products/public) were chosen for developing and hosting dashboards. As an alternative to Tableau Software, investigations into IBM Cognos (http://www.ndm.net/bi/ibm-cognos?gclid=CIXumdCfusUCFQqDfgodSKgAig) and ESRI Maps for IBM Cognos (http://www.ndm.net/bi/ibm-cognos?gclid=CIXumdCfusUCFQqDfgodSKgAig) have been ongoing since early 2015.

RESULTS

Three dashboards were developed and have been maintained as new data become available. The dashboards allow users to create custom summaries in interactive tables, graphs, and maps and also offer downloads of the underlying data. Figure 1 shows page one of "Forests of the Northern Forest Inventory & Analysis Program," which focuses on data mining for trends and delivery of the latest information from the broad state to detailed condition-species level (https://public.tableau.com/views/NRS-FIAAnnualReport/

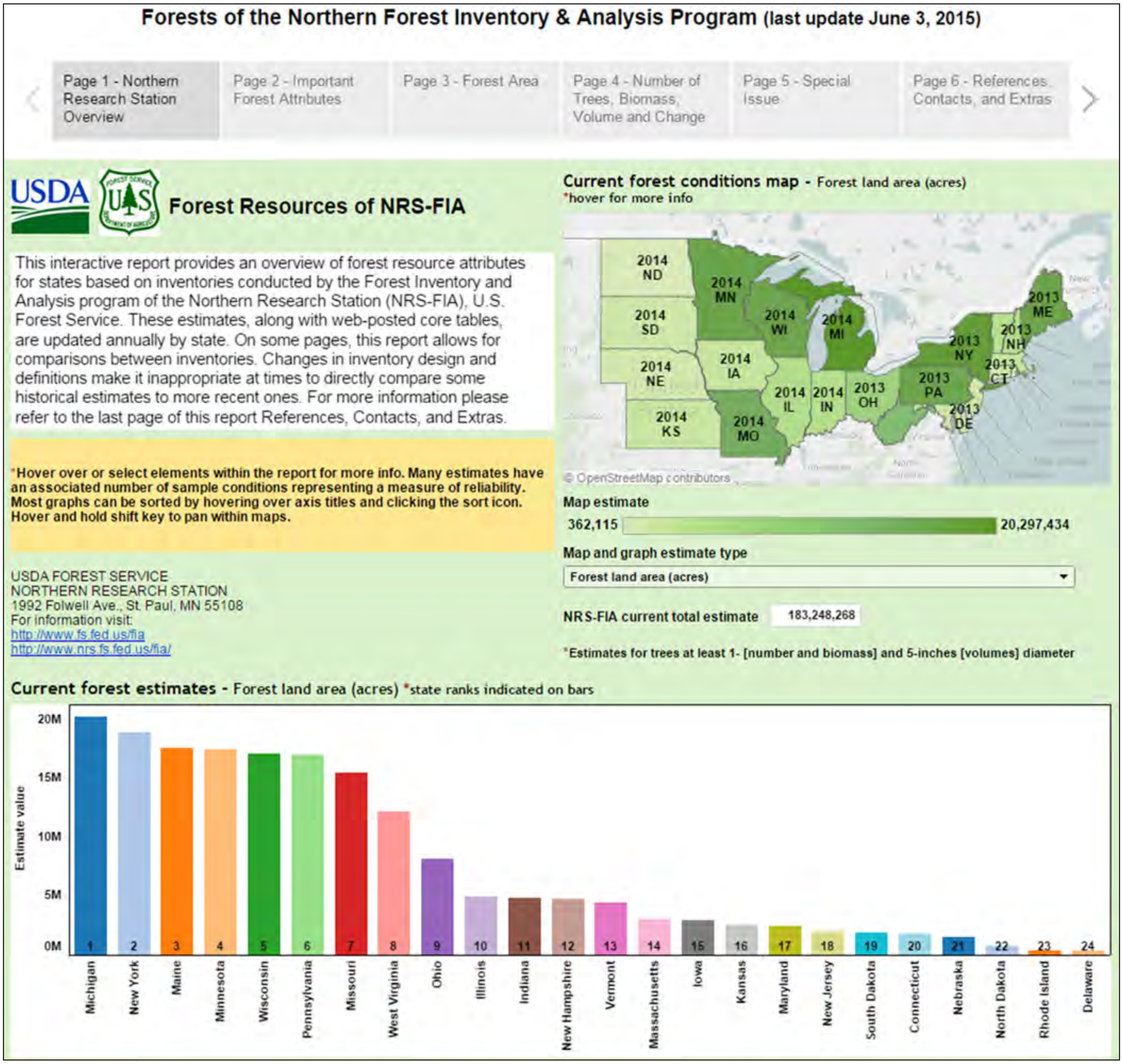

Figure 1.—Dashboard view of Forests of the Northern Forest Inventory and Analysis Program.

Story1?:showVizHome=no#1). "FIA Emerald Ash Borer Impacts Explorer" is an interactive story exploring the status of ash tree species (*Fraxinus* spp.) in the eastern United States in relation to the spread of the non-native insect emerald ash borer (EAB), *Agrilus planipennis* Fairmaire (https://public.tableau.com/views/eab_story/eab_story?:showVizHome=no#1). The story answers a number of questions using interactive graphs and maps.

- Where is EAB in relation to the ash resource?
- How is ash fairing in the non-infested area?
- How much live ash remains after mortality increases?
- How long does it take for mortality to increase substantially?
- Where are hot spots for future EAB infestations?

"Invasive Species Distribution" focuses on data mining and delivery of the latest information for invasive plant species at the county level (https://public.tableau.com/views/InvasivePlantSpecies-revised/Invasive?:showVizHome=no#1).

DISCUSSION

The dashboards created in this study are working examples of online interactive tools used for delivery of data, mining for trends, and analysis of natural resource issues. These examples are a step forward offering more and improved access to FIA information via the Internet. Story-telling dashboards have been popular for a number of years and are increasingly expected by FIA users. Moreover, dashboards can offer more engaging, robust, and up-to-date information at less cost than static reports. Traditionally, NRS-FIA has created static annual reports for each State often requiring 3 or more days of composition per report. At this time using a dashboard, one person can update all 24 state annual reports for NRS-FIA in 2 days.

Much has been accomplished with the relatively easy-to-use Tableau Software but the BI system and dashboards require further development. The future dashboards require integration of more diverse spatial information and compliance with Section 508. At this time, the dashboards are limited to using counties as a spatial unit and are not fully compliant. Continued training in dashboard development and advances in BI systems will help us meet these challenges. In addition, the user experience will improve as dashboard design advances. Currently, pop-up messages and video tutorials are being added as built-in help. As we move forward, many important stories will be pulled from FIA data and communicated through dashboards.

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TELLING THE STORY OF TREE SPECIES' RANGE SHIFTS IN A COMPLEX LANDSCAPE

Sharon M. Stanton[1], Vicente J. Monleon[2], Heather E. Lintz[3], Joel Thompson[4]

Abstract – The Forest Inventory and Analysis Program is the unrivaled source for long-term, spatially balanced, publicly available data. FIA will continue to be providers of data, but the program is growing and adapting, including a shift in how we communicate information and knowledge derived from those data. Online applications, interactive mapping, and infographics provide broader appeal to a wider audience compared to state reports or peer-reviewed journal articles. This presentation uses ArcGIS Online applications to tell the story of how tree species distributions are shifting in response to climate change,. Evidence supports that species are changing in latitude and elevation, but estimating the magnitude of the change and attributing cause can be difficult. The strength of evidence increases as the geographic area, number of species, and length of time examined increases. This study took advantage of the large geographic scale of FIA data collection to compare the distribution of seedlings and mature trees for all but the rarest tree species in California, Oregon, and Washington. Across all species and despite individual species idiosyncratic responses, there is a significant shift in the distributions of seedlings towards colder environments, relative to the distribution of mature trees. The broad geographic scale and environmental diversity of the study area, the large number of systematically sampled trees, and the direct causal relationship between the response the hypothesized cause provide strong evidence to attribute those shifts to climate change. The research was published recently - *Monleon and Lintz, PLoS ONE 10(1), 2015* – and now we are exploring ways to share that story with a wider audience through different visualization applications.

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INTEGRATING NON-TIMBER FOREST PRODUCTS INTO THE FIA PROGRAM

THE VOLUMES AND VALUE OF NON-TIMBER FOREST PRODUCTS HARVESTED IN THE UNITED STATES

James L. Chamberlain[1]

Abstract—Non-timber forest products [NTFPs] originate from plants and fungi that are harvested from natural, manipulated or disturbed forests. NTFPs may include fungi, moss, lichen, herbs, vines, shrubs, or trees. People harvest the products for many reasons, including personal, recreational and spiritual uses, as well as commercial gain. The assessment of volumes and values is based on reports of permitted harvests of NTFPs by the US Forest Service and the Bureau of Land Management. These "sales" are assumed to be for commercial use but stating definitively that they are is speculative at best. The annual harvest of non-timber forest products is estimated for a number of product categories over five regions of the United States. The total value of the receipts from the issuance of permits to harvest non-timber forest products from federal lands is estimated. The wholesale value of these products is extrapolated, as well. The data presented illustrates that non-timber forest products represent significant contribution to the country's economy. Challenges with reporting the full volumes and value of non-timber forest products are identified and a role for FIA to improve the reporting of this information is discussed.

Non-timber forest products (NTFPs) come from plant material and fungi harvested from forests and may include wood-based products that are not of timber size. The products are collected for personal and commercial use, and from public and private lands. Determining how much is harvested for personal use versus commercial gain, is speculative at best. Determining how much is harvested from private lands is next to impossible. The US Forest Service (National Forests) and the Bureau of Land Management issue permits for the harvest of NTFPs, which are 'assumed to be for commercial use" though they are likely to include personal consumption, as well (Alexander et al. 2011).

The 2010 National Report on Sustainable Forests (USDA FS 2011) and supporting documentation (Alexander et al. 2011) provides evidence of the volume and value of NTFP harvest in the United States. In developing the supporting documentation, Alexander et al. (2011) crafted an approach to analyze the volume of NTFPs harvested from US forests and estimate the overall value of these products to the Nation. The analysis presented here follows that approach and provides further evidence of a vibrant industry. This analysis focuses on the entire US that is covered by national forests and Bureau of Land Management.

METHODS

The primary sources of data for this analysis were the 'cut and sold' reports of the US Forest Service (National Forests) and the Timber Sale Information System and Special Forest Products databases of the Bureau of Land Management (BLM). The National Forests report cut and sold data for convertible and non-convertible products (USDA Forest Service 2014). Non-convertible products are those products (i.e., NTFPs) whose units of measure (e.g., gallons, pounds, linear feet) cannot be converted to units consistent with timber products. Data from each agency was collected independently and then combined to report amounts and values for the different categories of NTFPs.

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USFS and BLM data are 'permitted' harvest amounts which may differ from actual harvest quantities. Regular monitoring of actual harvest volumes is lacking in most location on public lands, and there are no records of harvest volumes from private lands. The permitted harvest volumes are the best available data of the amount of NTFPs being removed from federal forest lands.

Value estimations are based on the approach used by Alexander et al. (2011) in reporting for the 2010 National Report on Sustainable Forests (USDA FS 2011). Estimates of the first point-of-sale values are based on assumptions that receipts are 10 percent of first point-of-sales, and that FS sales represent 20-30 percent of total supply, while BLM receipts are 2-15 percent of total supply. The estimated wholesale value of wild-harvested non-timber forest products is based on assumptions that USFS and BLM receipts are 10 percent of first point-of-sale, and that first point-of-sale value is 40 percent of wholesale price. The assumptions also imply that USFS harvest volumes are 20-30 percent of the total, while BLM harvest volumes at 2-15 percent of the total supply.

RESULTS

Table 1 summarizes the volumes of products permitted harvest from National Forests and BLM lands in 2013. The two agencies report harvest volumes for ten categories of non-timber forest products. Non-convertible products are reported in more than a dozen units of measure. All regions report the permitted harvest of NTFPs, although the products and volumes vary among regions. The West and Rocky Mountain regions have by far the most amount of product harvested, across all categories. The West had the vast majority of products harvested in 12 of the 29 line items. Federal forests in Alaska reported very little permitted harvest, although the state embraces subsistence collection of NTFPs. The Northern region reported the most taps of trees for sap, while the South reported the most permitted harvest of nursery and landscape products.

The US Forest Service and BLM generated close to \$79 million from NTFPs for the ten years covering 2004 through 2013 (Table 2). Overall receipts increased on average about 2 percent per annum. Total annual fluctuations in receipts varied significantly from the mean (μ = \$7.79 million, σ = \$630 thousand) in three years. In the years 2004 through 2007, reporting of grass and forage production may have included beargrass, a plant harvested for the floral and craft industries. Receipts for the harvest of fuelwood accounted for more than half of all NTFP revenues.

The estimated average annual wholesale value of NTFPs harvested in the United States was approximately \$900 million, based on data from the National Forests and Bureau of Land Management (Table 3). In 2013, almost 85 percent of the wholesale value of NTFPs came from crafts and floral products (18%), Christmas trees (12%) and fuelwood (54%). Edible and medicinal forest products comprised approximately 8 percent of total wholesale value.

DISCUSSION

There are large volumes of plants and fungi harvested from US forests that contribute substantial value to the economy of this country. There are challenges that need to be addressed to fully account for the volumes of materials being harvested. From a demand perspective (i.e., harvest volumes), the lack of standard units of measure makes summarizing data and regional comparisons difficult. For example, products collected for the use in 'arts and crafts' are recorded with seven units of measure. Some units of measure could easily be combined; the units of measure for Christmas trees could be consolidated into one unit (e.g., pieces) which would simplify the reporting of this product.

Determining which "product category" to place products is challenging, though not overwhelming. For example, beargrass harvests may have been reported as 'grass and forage' although they should have been reported under 'arts, crafts, and floral' category. Misplacing product volumes does not impact estimates of total volumes or values, but does misrepresent assessments of specific segments.

Table 1—Permitted Harvest Volumes of Non-Timber Forest Products from Forest Service and Bureau of Land Management Forests in 2013.

Product category	Unit of Measure	Alaska	North	Rocky Mt.	South	West	All United States
Arts, crafts, and floral	Bunches	0	0	100	0	0	100
	Bushel	0	180	450	100	71,093	71,823
	Cords	0	0	5	0	93	98
	Feet^3	0	75	220	348	22	665
	Number	0	0	1,000	0	0	1,000
	Pounds	150	5,630	116,743	201,506	5,321,503	5,645,532
	Ton	0	663	281	65	6,716	7,725
Christmas trees	Each	0	7,277	128,978	249	76,240	212,744
	Linear Feet	0	0	1,566	0	175	1,741
Edible fruits, nuts, berries, and sap	Gallon	0	0	890	0	302,858	303,748
	Pounds[1]	200	400	226,868	30	443,228	670,726
	Taps	0	18,430	0	0	0	18,430
Grass and forage	Pounds	0	104	10	0	4,120,869	4,120,983
	Ton	0	295	3	8	830	1,136
Fuelwood	CCF	244	23,659	349,436	18,397	219,759	611,496
Medicinal	Pounds	0	856	12,148	14,936	14,710	42,650
Non-convertible	Acre	0	0	0	28	0	28
	Bushel	0	0	6	100	0	106
	Feet^3	0	0	500	750	450	1,700
	Each	0	1,104	50	1,829	2,772	5,755
	Piece	0	2,500	200	640	3,357	6,697
	Pounds	3,000	0	0	4,320	56,776	64,096
	Ton	0	0	43	0	1	44
Nursery and landscape	Each	600	852	9,179	24,942	10,926	46,499
	Ton	0	0	1	0	0	1
Posts and poles	CCF	0	12,367	6,570	97	16,369	35,403
	Linear Feet	0	0	0	0	2,140	2,140
	Number	0	100	22,253	0	6,547	28,900
Regeneration and silviculture	Bushel	0	10	2,183	0	3,513	5,706
	Pounds	0	0	316,744	0	17,037	333,781

[*] Units were maintained for all categories except Fuelwood, and Posts and Poles. These categories were converted to ccf (100 cubic feet) when possible.

[1] A large portion of the pounds listed as Grass and Forage is Beargrass (Xerophyllum tenax), a plant harvested to make baskets and other crafts, and in fact isn't an actual grass. The USFS categorized it as grass due to its misleading common name.

Table 2—Receipts for non-timber forest products from U.S. Forest Service and Bureau of Land Management, 2004 through 2013.

Product category	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
					Thousand 2013 U.S. Dollars					
Landscaping	257	226	225	220	177	41	84	72	59	61
Crafts and floral	1,091	907	1,759	2,059	817	785	1,166	1,141	1,134	1,518
Regeneration and seed	26	48	37	25	80	96	40	82	52	108
Edible / Culinary	629	327	415	428	733	397	626	489	546	676
Grass and forage	257	330	288	270	217	67	221	185	196	237
Herbs and medicinals	22	17	16	27	53	27	38	44	46	37
Posts and Poles	435	301	331	268	212	203	186	184	252	206
Christmas Trees	1,655	1,727	321	1,344	1,175	376	1,519	1,113	1,090	1,049
Fuelwood	3,449	3,263	3,681	3,879	4,388	4,964	5,030	4,924	4,553	4,579
Other Non-convertible	105	214	272	159	64	23	41	70	7	7
Total[a]	7,926	7,362	7,346	8,679	7,918	6,979	8,951	8,303	7,935	8,477

[a] Totals may be off due to rounding

Table 3—Estimated wholesale values of permitted NTFP harvests from Forest Service and Bureau of Land Management forests, in 2013 dollars.

Product category	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
					Million 2013 U.S. Dollars					
Landscaping	29.2	25.7	25.6	25.0	20.1	4.7	9.6	8.2	6.7	6.9
Crafts and floral	124.0	103.1	199.9	234.0	92.8	89.2	132.5	129.6	128.9	172.5
Regeneration and seed	3.0	5.4	4.2	2.8	9.1	11.0	4.5	9.3	5.9	12.3
Edible / Culinary	71.4	37.2	47.2	48.7	83.3	45.1	71.1	55.5	62.1	76.8
Grass and forage	29.2	37.5	32.8	30.7	24.7	7.7	25.1	21.0	22.3	26.9
Herbs and medicinals	2.5	1.9	1.9	3.0	6.0	3.0	4.3	5.0	5.2	4.2
Posts and Poles	49.5	34.3	37.6	30.5	24.1	23.1	21.2	20.9	28.6	23.4
Christmas Trees	188.1	196.3	36.5	152.8	133.5	42.7	172.6	126.5	123.9	119.2
Fuelwood	391.9	370.8	418.3	440.7	498.7	564.1	571.6	559.5	517.4	520.3
Other Non-convertible	11.9	24.4	30.9	18.1	7.3	2.7	4.7	8.0	0.8	0.8
Total[a]	900.6	836.6	834.8	986.2	899.7	793.1	1,017.1	943.5	901.7	963.3

[a] Totals may be off due to rounding

The estimated values of NTFPs are based on permitted harvest volumes from Forest Service and BLM lands. In western US this may not present a serious challenge, as these two agencies manage a large proportion of the forest lands. But, in eastern US, private forest lands dominate, and much of the harvest of NTFPs may be coming from non-federal forests. As example, Chamberlain et al (2013) reported the value of American ginseng as $27 million, while receipts and estimated wholesale value of 'herbs and medicinals' are much less, 37 thousand and $4.2 million, respectively. American ginseng and many other medicinal forest products are harvested primarily from eastern US hardwood forests. The overall value of NTFPs would be much larger if the volumes of private forest lands were determined.

The values would be much greater if other non-timber forest products were included, as well. Fuelwood, which is integral to the definition of non-timber forest products, dominates the value estimates. These values would increase considerably if bioenergy fuels were included. These products originate from wood that is not timber-based, which is consistent with the accepted definition of non-timber forest products.

These and other challenges could be addressed through processes similar to the FIA timber products output assessments. By building partnerships with NTFP industry representatives, FIA could streamline and improve the reporting of harvest volumes from all forests. Through collaborative dialogue such partnerships could advance the valuation estimates of NTFPs and provide better insights into the total valuation of our forests. Such efforts would have serious implications for the management and policies that affect non-timber forest resources and concomitant products.

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NON-TIMBER FOREST PRODUCTS IN HAWAII

Katie Kamelamela[1], James B. Friday[2], Tamara Ticktin[3], Ashley Lehman[4]

Abstract—Hawaiian forests provide a wide array of non-timber forest products for both traditional and modern uses. Flowers, vines, and ferns are collected for creating garlands or lei for hula dances and parades. Lei made from materials gathered in the forest are made for personal use and sold, especially during graduation times. Bamboo is harvested for structures and for making traditional Japanese New Year's ornaments or kadomatsu. Firewood is collected for traditional earth ovens. While some local gathering might impact local resources, little is known about amounts of non-timber forest products collected or locations where NTFPs are harvested. We will survey sellers and users of non-timber products at cultural festivals and analyze state collection permit records to assess amounts, economic and cultural value, and locations for non-timber products collected in Hawaii. Our data will shed light in importance of NTFPs in Hawaii and highlight management needs.

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USING FIA INVENTORY PLOT DATA TO ASSESS NTFP PRODUCTION POSSIBILITIES

Jobriath Kauffman[1], James Chamberlain[2], and Stephen Prisley[3]

Abstract—The US Forest Service, Forest Inventory and Analysis (FIA) program collects data on a wealth of variables related to trees and understory species in forests. Some of these trees and plants produce non-timber forest products (NTFPs; e.g., seeds, fruit, bark, sap, roots) that are harvested for their culinary and medicinal values. As example, the cones of *Pinus edulis* and *P. monophylla* are collected for the edible pine nuts. The bark of more than a dozen tree species that are inventoried by FIA is collected for medicinal, decorative, and construction purposes. Slippery elm (*Ulmus rubra*) bark has been used for its medicinal values for more than a generation. However, despite widespread use of non-timber forest products, little quantitative information about abundance, distribution, and harvest is available to support sustainable management of NTFPs. This project examines the use of the FIA inventory database to assess the effectiveness of plot data to monitor and explain the situation regarding selected non-timber forest products. The focus is on using FIA data to assess for: (1) geographic distribution, (2) abundance (numbers of live trees), (3) applicable metrics (e.g., square feet of bark for trees from which bark is harvested), and (4) trends in abundance and spatial distribution over time. An in-depth analysis of slippery elm bark will be presented along with examples of metrics for quantifying other types of products including sap, nuts/fruit, and understory species.

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NEW METHODS FOR ESTIMATING NON-TIMBER FOREST PRODUCT OUTPUT: AN APPALACHIAN CASE STUDY

Steve Kruger and James Chamberlain[1]

Abstract—Assessing the size and structure of non-timber forest product (NTFP) markets is difficult due to a lack of knowledge about NTFP supply chains. Harvesting ginseng and other wild medicinal plants has long provided a source of income and cultural identity in Appalachian communities in the eastern United States. With the exception of ginseng, the extent of the harvest of medicinal forest products is unknown. Surveys with ginseng dealers about other NTFPs generate data on the trade volume for a variety of other products, and the geographic distribution of their harvest. A multi-method approach is required to fully utilize and contextualize these data. Socio-economic data on the study area integrated with FIA data can help explain harvest distribution. Interviews with buyers put the data in the context of the practice of the trade and a complex fluctuating market.

INTRODUCTION

Ginseng (*Panax quinquefolius)* is the most iconic and valuable Appalachian non-timber forest product (NTFP) but dozens of other medicinal plant species are commercially harvested in the region, entering a global supply chain dating to at least the middle of the 19th century. Traditionally, harvesting medicinal forest products has helped generate supplemental income for agricultural workers in the offseason and in unstable economies reliant on coal and timber. Harvesters sell to local buyers who often operate other associated businesses such as fur buying, scrap metal/recycling, sporting goods, and convenience stores. Regional aggregators purchase from local buyers and sell to manufacturers. Most of the products leave the region as raw commodities and are manufactured into supplements, tinctures, teas and other consumer goods elsewhere. Today harvesting these other roots, barks and foliage continues to be an important resource in economically marginalized communities (Newfont 2012). It is also a meaningful practice that transmits values, and helps form cultural and family identity.

Ginseng has a limited harvest season and mandated reporting of volume and origin due to its inclusion in the 1973 Council on the International Trade in Endangered Species (CITES) treaty. Other more common medicinal plants collected in the region are not tracked, and are harvested throughout the year. Apart from industry estimates for a few species, there is no periodic estimate for regional output that includes where plants are harvested. This lack of reliable data on product output is a problem in most NTFP economies. It leads to increased instability and risk for people who trade them. It creates a barrier for private and public landholders interested in managing for or cultivating them, and is one reason the effect of harvesting on wild populations is not well understood (Vaughan and others 2013).

METHODS

This ongoing study seeks to create a voluntary, replicable mechanism for assessing the variety, volume and origin of commercially traded Appalachian NTFP species. The models for the study include other NTFP

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surveys (Schlosser and Blatner 1995), the US Forest Service's Timber Product Output Program (TPO), qualitative surveys of non-timber forest product markets (Greenfield and Davis 2003) and ethnographic work with NTFP harvesters and buyers (Emery and others 2003). A multi-method approach is used to gather data. Using the "Tailored Design Method (Dillman 2000)," surveys are distributed to ginseng buyers, who are required by law to be registered. Ginseng buyers were asked about the volume and origin of 12 other forest products purchased from harvesters. Data on harvest location were reported by FIA zone rather than county to preserve confidentiality and enable correlation with other inventory programs. In addition to the surveys, interviews are being conducted with medicinal forest product buyers to contextualize the data, get feedback on the project, improve response rates and identify trends, challenges and opportunities in the regional NTFP market.

STUDY AREA

The study area comprises states that permit ginseng harvest with territory falling within the Appalachian Regional Commission's definition of Appalachia (Appalachian Regional Commission 2015). In 2013 Virginia and North Carolina were surveyed for the 2012 harvest year. The 2014 survey included all Appalachian states in the USFS Southern Region with ginseng programs: Alabama, Georgia, North Carolina, Tennessee and Virginia. In the summer of 2015 the survey is extended to include Maryland, Ohio, New York, Pennsylvania and West Virginia for the 2014 harvest year.

RESULTS

The Products

In 2013, 61 percent of the Southeastern ginseng buyers who responded reported purchasing other products. Of the 12 species surveyed, the most commonly purchased were goldenseal (*Hydrastis canadensis)*, purchased by 50 percent of respondents, bloodroot *(Sanguinaria canadensis)* purchased by 36 percent and black cohosh (*Acteae racemosa)*, purchased by 31 percent. While the survey asked for total weight purchased for each product, uncertainty about nonresponse bias and the amount of horizontal trading prevented a total estimate of output for 2013. It was possible to determine relative harvest volume by comparing each species to the total adjusted dry weight (Fig 1). Black cohosh, slippery elm bark *(Ulmus rubra)* and goldenseal had the highest volume of trade at 47 percent, 34 percent and 8 percent respectively. Data collection is still ongoing for the 2014 harvest year. Aided by respondent input, this year's data collection will account for horizontal trading, and will also include product value.

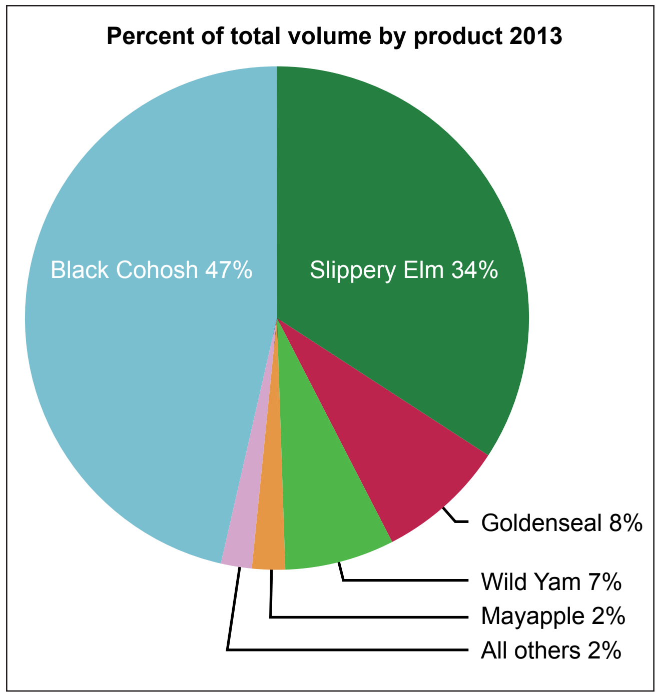

Figure 1—Percent of total reported 2013 medicinal forest product harvest in Southern Region by adjusted dry pounds.

Harvest Distribution

In 2013 harvests occurred throughout the products' ranges in the Southern region, but were concentrated in eastern Kentucky and southwest Virginia. For example, see the distribution of the harvest for black cohosh (Fig. 2). Preliminary results indicate that West Virginia is also an important source, and is included in the next round of data collection.

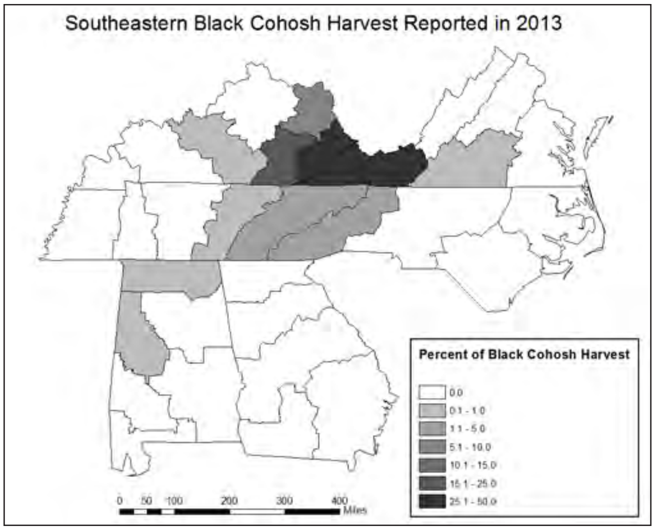

Figure 2—Percent of Black Cohosh Harvest in the Southern Region in 2013 by FIA Zone

DISCUSSION

Ginseng buyers are purchasing other medicinal forest products and can serve as a sample frame for assessing those product’s harvest. Generating an estimate for total regional output is not possible at present while data collection is ongoing, but using this method provides new data on which medicinal plants are most commonly traded, the percentage of total trade volume by species and where the products are harvested. A knowledge of the products is necessary to interpret these numbers, as the plants vary in size, abundance and value. The study is designed to be replicated, which is necessary to due to yearly fluctuations in value and output evidenced seen in some previous industry surveys (AHPA 2012).

In interviews, participants gave a number of explanations for the reported geographic distribution including presence of plant habitat, access to forests, a stronger tradition of wildcrafting and socioeconomic factors such as higher unemployment. Past NTFP Studies use socioeconomic data (Bailey 1999) and FIA data on forest composition and timber harvest (Chamberlain and others 2013) to analyze NTFP harvests. After an additional year of data collection, it will be possible to incorporate both FIA and socioeconomic data to test these explanations by ranking zones by forest cover and composition, presence of ideal site conditions, land ownership (public, private, absentee), population distribution, and socioeconomic indicators like unemployment and income. While FIA does not currently include understory plants in monitoring programs, the potential to correlate harvest and market data collected using these methods with data on plant populations is possible, and presents an opportunity to better understand the effect of NTFP harvesting and other human and environmental factors on plant populations. This integration of data sources and methods and engaging NTFP stakeholders directly is key to improved estimates for non-timber forest product output in Appalachia and beyond.

ACKNOWLEDGMENT

The authors would like to thank the people who participated in this study, especially those who took the time to sit down for interviews. This project is being conducted at Virginia Tech, and made possible through a grant from the US Forest Service, US Department of Agriculture grant number 11-JV-11330152-104.

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HOW MIGHT FIA DELIVER MORE INFORMATION ON STATUS AND TRENDS OF NON-TIMBER FOREST PRODUCTS?

Stephen P. Prisley[1]

Abstract—Data from the Forest Inventory and Analysis program (including the Timber Products Output portion) are critical for assessing the sustainability of US timber production. Private sector users of this information rely on it for strategic planning, and their strong support of the FIA program has helped to ensure funding and program viability. Non-timber forest products harvested from US forests also play a critical economic and social role, yet much less is known about their abundance, spatial distribution, and trends. Recent research has demonstrated that FIA data can provide important insights into the status of NTFPs from trees measured in Phase II plots. However, there are several shortcomings that prevent the widespread use of FIA data for evaluation of many other NTFPs. These shortcomings include: (1) lack of data on non-tree (typically understory) species of importance, (2) traditional forest inventory measurements that are unrelated to non-timber products (roots, sap, seeds and cones, bark, boughs, etc.), (3) lack of data on harvest and trade of non-timber forest products. Efforts to overcome these challenges in order to enhance the value of information for NTFP assessment might include: (1) identifying minor alterations to data collection protocols (perhaps on phase III plots), (2) conduct research that relates production of NTFPs to tree/plant measurements (e.g., estimation of bark or nut yield based on tree or plot measurements), (3) collecting data on NTFP abundance and distribution that would support modeling of likely occurrence, (4) extending the TPO data collection to survey non-timber forest product markets. We suggest that considering the costs and benefits of these and other options is the first step in expanding the value of the FIA program for NTFP assessment.

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TECHNIQUES DEVELOPMENT

SPATIOTEMPORAL PATTERNS OF RING-WIDTH VARIABILITY IN THE NORTHERN INTERIOR WEST

R. Justin DeRose, John D. Shaw and James N. Long[1]

Abstract—A fundamental goal of forest biogeography is to understand the factors that drive spatiotemporal variability in forest growth across large areas (e.g., states or regions). The ancillary collection of increment cores as part of the IW FIA Program represents an important non-traditional role for the development of unprecedented data sets. Individual-tree growth data from increment cores were paired with plot-level variables from the inventory to investigate the spatiotemporal growth patterns for Douglas-fir, ponderosa pine, common pinyon, and limber pine over the northern portion of the Interior West (Idaho, Montana, Wyoming, Utah, and Colorado). Based on dendrochronological theory proposed over 50 years ago, we tested three hypotheses that variability in ring-width increment (calculated as the Gini Coefficient): 1) would decrease as latitude increased; 2) would increase as continentality increases (i.e., west to east); and would decrease as elevation increased. The large range of observations (from 37° to 49° latitude, and from -117° to -104° longitude) were sufficient to test the first two hypotheses, but made it difficult to directly test hypothesis three (elevation). Generally, we did not confirm hypothesis one, except for common pinyon, which inhabits only a portion of the area examined. Hypothesis two was confirmed for the entire dataset, and the results were clearly driven by Douglas-fir and ponderosa pine. Hypothesis three was not supported for Douglas-fir or ponderosa pine, but was supported for common pinyon and limber pine. However, because the sample area encompasses such a huge range of latitude and longitude, which covary with elevation, we developed a corrected elevation. No significant relationships were found between ring-width variability and corrected elevation.

INTRODUCTION

A fundamental goal of forest biogeography is to understand the factors that drive spatiotemporal variability in forest growth across large areas (e.g., states or regions). The ancillary collection of increment cores as part of the IW FIA Program represents an important non-traditional dataset that can be used to ask general biogeography questions. Individual-tree growth data from increment cores were paired with plot-level location variables from the inventory to investigate the spatiotemporal growth patterns for interior Douglas-fir (*Pseudotsuga menziessii*), ponderosa pine (*Pinus ponderosa*), limber pine (*Pinus flexilis*), and common pinyon (*Pinus edulis*).

Historically, the most common way to measure variability in tree-ring growth is referred to as 'mean sensitivity' (Holmes 1983). Unfortunately, mean sensitivity covaries with first-order autoregressive properties and the coefficient of variation, making it undesirable for comparison between species and sites (Bunn et al. 2013). To avoid these issues we elected to use the Gini coefficient (G) to evaluate variability. The original use for G was as a statistic to compare the difference between samples without using the mean (Biondi and Quedan 2008). The Gini coefficient is robust to time-series that have variability in autoregressive properties or changes in mean values over time (i.e., nonstationarity) (Biondi and Quedan 2008). Therefore, we assumed that G would be appropriate to compare between increment cores collected across a large region.

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We chose Douglas-fir, ponderosa pine, limber pine, and common pinyon because these species generally exhibited a strong relationship to water-year precipitation, and typically occur in relatively lower elevation forests across the West. We examine a wide geographic gradient, the northern portion of the Interior West (Idaho, Montana, Wyoming, Utah, and Colorado). Based on dendrochronological theory proposed over 50 years ago (Schulman 1956), we tested three hypotheses related to the variability in ring-width increment: 1) it would decrease as latitude increased; 2) it would increase with longitude (i.e., west to east); and that it would decrease as elevation increased.

METHODS

Measurements of annual ring width variability used in this study came from individual tree increment cores collected from Interior West FIA phase 2 plots during both the periodic and annual inventories (Table 1). All increment cores were mounted, sanded, polished before viewing under a microscope. Increment cores were crossdated to ensure calendar year resolution, measured on a sliding stage to 1 or 10 micron. Digital ring width data were verified using program COFECHA and locally available chronologies available from the International Tree-Ring Data Bank or unpublished chronologies available from individual researchers.

Once digitized, the tree-ring data were paired with plot-level data from the database (e.g., latitude, longitude, elevation). Trends of sensitivity over latitude, longitude, and elevation were examined graphically and with Pearson's correlations for the entire dataset and as species-specific groups.

RESULTS

Over the entire dataset (n=2,949, Fig. 1), and contrary to our hypothesis, there was no relationship between G and latitude (r=-0.01) or elevation (r=-0.05). However, the relationship between G and longitude was significant (r=0.27, p<0.001), occurred in the predicted direction (west to east). Because of strong inherent relationships between latitude and longitude (r=-0.37), latitude and elevation (r=-0.77), and longitude and elevation (r=0.28), we calculated a corrected elevation. Multiple linear regression using latitude and longitude and a polynomial term for each was fitted (R^2=0.61). The relationship between G and corrected elevation was not significant (r=0.001).

Species-specific relationships between G and latitude were variable, with a negative relationship for common pinyon (r=-0.13, p<0.001), and Douglas-fir (Fig. 1a). Positive, but not significant relationships were found for limber pine (r=0.10) and ponderosa pine (r=0.07). The relationship between G and longitude was positive for all species but limber pine (r=-0.05). Ponderosa pine had the strongest relationship to longitude (r=0.32, p<0.001), followed by Douglas-fir (r=0.21, p<0.001). The relationship for common pinyon was not significant (r=0.08). The relationships between G and elevation were negative, as hypothesized, for all species except Douglas-fir (r=0.06). Common pinyon (r=-0.30, p<0.001), limber pine (r=-0.32, p<0.001), and ponderosa pine (r=-0.11, p<0.001) all exhibited significant relationships. When evaluated over corrected elevation, no significant patterns were found (common pinyon: r=-0.04, Douglas-fir: r=0.07, limber pine: r=-0.09, ponderosa pine: r=-0.07).

Table 1—Sample size, mean ring width (mm) and standard deviation, mean number of rings, mean Gini coefficient, and range (minimum to maximum) of Gini coefficient by species for the study data

Species	Common pinyon	Limber pine	Ponderosa pine	Douglas-fir
Sample size (n)	413	53	972	1511
Mean ring width (SD)	0.828 (0.345)	1.375 (0.538)	1.884 (0.836)	1.821 (0.722)
Mean number rings	107	67	73	84
Mean Gini coefficient	0.234	0.222	0.253	0.230
Range of Gini coefficient	(0.08 – 0.48)	(0.12 – 0.34)	(0.10 - 0.53)	(0.06 – 0.56)

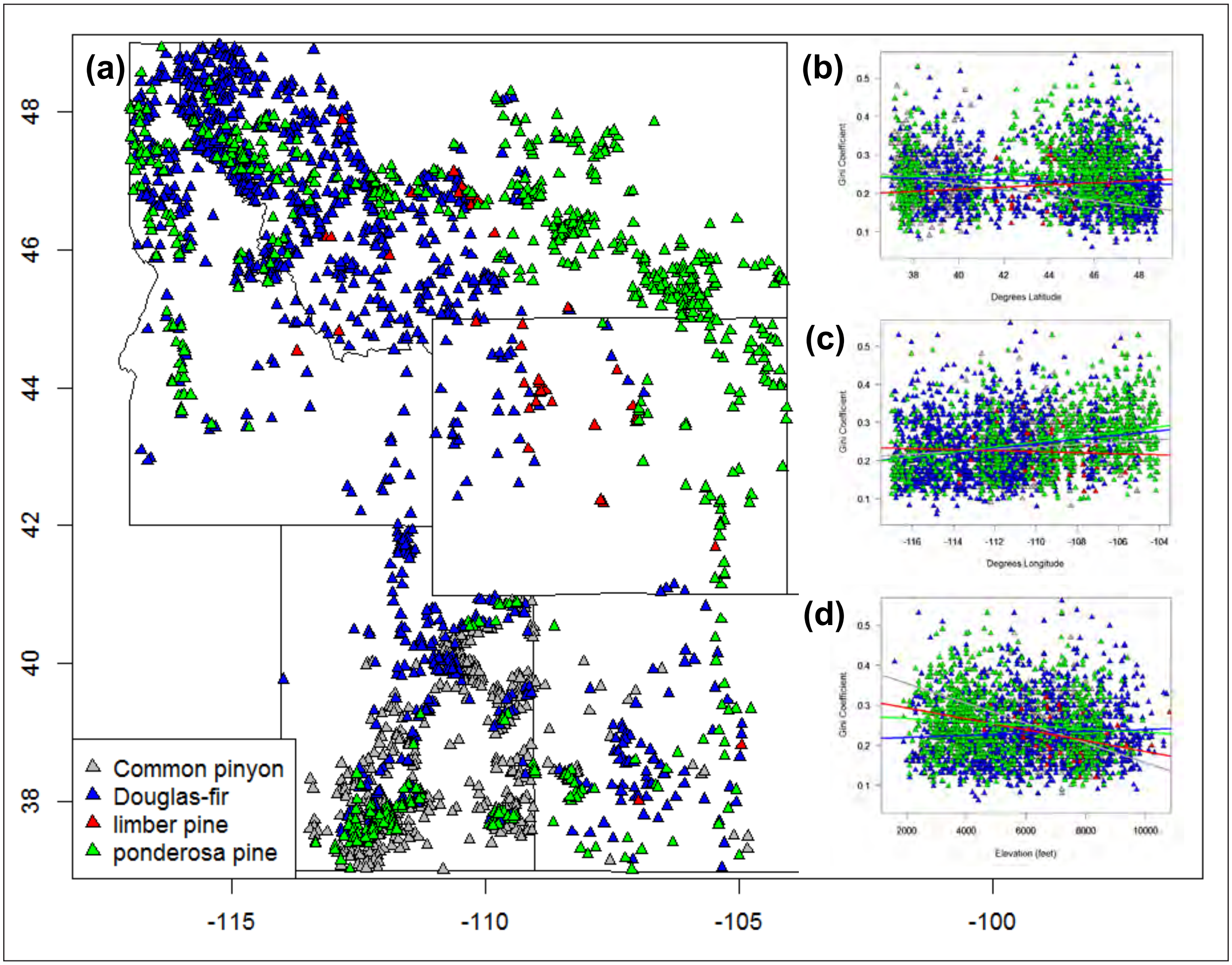

Figure 1—(a) Northern Interior West map with tree-ring locations by species, (b) relationship between Gini coefficient and latitude by species, (c) relationship between Gini coefficient and longitude, (d) relationship between Gini coefficient and elevation. Lines are linear regression models. Colors match species-specific designations.

DISCUSSION

The large range of observations (from 37° to 49° latitude, and from -117° to -104° longitude) of independently sampled tree-ring series were appropriate to test patterns in *G* long thought to vary in space and elevation (i.e., western North America) presumably due to climate variation and relative availability of water prior to and during the growing season (Schulman 1956, Fritts 1976).

Generally, we failed to confirm hypothesis one that *G* decreases with latitude. The negative relationship found for common pinyon might indicate a more regional affect, given that the species is limited to the Colorado Plateau (Fig. 1a). A great deal of dendroclimatological research relies on the desirable water-year signal inherent to common pinyon, and a relatively narrow focus on it might be at least partially a basis for the original hypothesis. It is also possible that the relationship between *G* and latitude become more pronounced once trees from lower latitudes (i.e., Arizona and New Mexico) are included.

Interestingly, hypothesis two has no basis in the published literature, therefore we can only speculate as to why we found such a strong relationship from west to east in ring-width variability (i.e., longitude). Common pinyon and limber pine were represented by fewer samples, and also covered a smaller portion of the study area, which might explain why their relationship with longitude was not significant. Douglas-fir and ponderosa pine were the most widespread of the species examined, and they likely drove the relationship for the dataset overall. We speculate that the increase in *G* (west to east) might indicate a general decrease in moisture, at the continental scale, from the prevailing westerly Pacific storms, likely indicating continentality. Further explanation of the relationship between *G* and longitude could be bolstered if tree-ring data from the Pacific Northwest were available, allowing examination of the full longitudinal range of many western tree species.

The hypothesis that ring-width variability ought to decrease with increasing elevation is based on the observation that lower elevation trees receive less growing season moisture compared to high elevation trees and, as a result, have higher *G*. Because the elevation range suitable for tree species occurrence changes markedly over the range of latitude examined here, the hypothesized relationship is not straightforward. Regardless, we failed to confirm hypothesis three for the two most widespread species, Douglas-fir and ponderosa pine. Interestingly, the relationships for elevation held for common pinyon and limber pine. We suspect the relatively narrow region in which common pinyon occurs help accentuate that relationship. Limber pine, on the other hand, had limited observations ($n = 53$), so further analysis is necessary before confirming such a strong pattern across the considerable range of limber pine.

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ESTIMATING FIA PLOT CHARACTERISTICS USING NAIP IMAGERY, FUNCTION MODELING, AND THE RMRS RASTER UTILITY CODING LIBRARY

John S. Hogland & Nathaniel M. Anderson[1]

Abstract—Raster modeling is an integral component of spatial analysis. However, conventional raster modeling techniques can require a substantial amount of processing time and storage space, often limiting the types of analyses that can be performed. To address this issue, we have developed Function Modeling. Function Modeling is a new modeling framework that streamlines the raster modeling process by utilizing delayed reading methods. Using this approach, we have successfully characterized the impacts of fuel treatments on soil erosion, estimated basal area, trees, and tons of above ground biomass per acre, identified locations in need of forest management, calculated forest residuals given multiple management prescriptions, and developed forest residual delivery cost models all in a fraction of the time and storage space it would take to perform similar analysis using conventional methods. To facilitate the use of Function Modeling, we have built an object oriented .NET library called RMRS Raster Utility. RMRS Raster Utility is free, readily available, and has an intuitive user interface that directly plugs into Environmental Science Research Institute (ESRI)'s software. In this paper we will discuss the basic concepts behind Function Modeling and present some our recent findings related to using this technique to estimate FIA plot characteristics from NAIP imagery.

INTRODUCTION

Raster modeling is vital to performing remote sensing and spatial analysis. Combined with classical statistic and machine learning algorithms, it has been used to address a wide range of questions in a broad array of disciplines (e.g. Patenaude et al. 2005; Reynolds-Hogland et al. 2006). However, the traditional workflow used to integrate statistical and machine learning algorithms and process raster models within a geographic information system (GIS) can limit the types of analyses performed and outputs created. In a recent study, Hogland and Anderson (2014) demonstrated that Function Modeling (Hogland et al. 2013) can streamline manipulating raster surfaces, building predictive models, and creating predictive raster outputs while substantially reducing processing time and digital storage requirements. Using the concept of Function Modeling (FM), they built a publicly available coding library that facilitates a wide range of tabular, spatial, statistical, and machine learning analyses (RMRS 2012a). To simplify the use of these procedures and concepts, they built an intuitive user interface packaged as an Environmental Systems Research Institute (ESRI) toolbar add-in called RMRS Raster Utility that works directly with ESRI's ArcMap versions 10.0 through 10.3 (RMRS 2012b).

One of the key benefits of FM is a reduction in the number of input/output operations performed within complex spatial modeling tasks. From a programming perspective, this can be achieved using strategies such as delayed reading and overloading the functionality of existing classes that support reading data from disk (Van Roy and Haridi 2004). In practice, these coding

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techniques take advantage of the fact that we rarely need to view, process, or use all spatial data at once and that the speed of computer processing units are significantly faster than the transfer speeds of data from disk to computer memory. Taking advantage of these types of efficiencies, we have successfully related Forest Inventory Analysis (FIA) program plot information to fine grained National Agriculture Imagery Program (NAIP) imagery and have built predictive surfaces for the extent of a national forest in Colorado (Hogland et al., 2014) and are now in the process of expanding these types of analyses across multiple forests that include both public and private lands in Montana.

METHODS

The study area is a 100 mile radius around Helena, MT. Within this area, forest community characteristics are estimated by creating statistical and machine learning relationships between FIA plot summaries (the response) and fine grained NAIP imagery, National Elevation Dataset (NED) digital elevation models (DEM), and textural and topographical derivative of those dataset (explanatory variables). Using the spatial locations of the FIA plot, explanatory variable values are extracted and related to the response to create a predictive model. The resulting predictive model is then applied to the explanatory variable values to produce a surface of forest characteristics across the landscape.

We used this approach to estimate basal area per acre (BAA), trees per acre (TPA), and tons of above ground biomass per acre (AGB) based on commonly used allometric equations (Jenkins et. al. 2003) for all tree species. The sample included 1652 FIA field plots, of which 1097 plots were randomly chosen to calibrate each model and the remaining 555 plots were used to independently evaluate each model. Imagery for the area surrounding Helena was collected, preprocessed, and mosaicked by NAIP at a spatial resolution of 10.76 feet and a geometric accuracy of + 3 pixels (McGlone et al. 2006). FIA plot summaries were related to visually interpreted patterns of 2013 NAIP color infrared imagery (CIR) using a two stage classification and estimation approach (Hogland et al., 2014).

The first stage of this approach results in a probabilistic classification of visually identifiable patterns (Table 1) such as live and dead tree crowns using RMRS Raster Utility's Soft-max neural network algorithm, derivatives of NAIP spectral reflectance, and second order Gray Level Co-occurrence Matrix (GLCM; Haralick 1973) texture values of those spectral derivatives. Training samples for the probabilistic classification consisted of 1000 random locations across the study area. Outputs from the first stage classification were summarized using the focal mean function within the RMRS Raster Utility toolbar for the approximate extent of a 1/10 acre field plot (window size of 21 x 21 NAIP pixels). Raster cells with mean percent tree canopy cover greater than 10 percent were classified as Forested. Forested areas were then used to partition FIA training plots and mask BAA, TPA, and AGB outputs.

Table 1—Visually identifiable patterns and associated labels used to estimate Forested areas.

Name	Description	Label
Green Grass	Vigorously growing grass that has a strong green spectral signature.	GG
Brown Grass	Sensed grass that does not have a strong green spectral signature.	BG
Green Crown	Live crowns for needle leaf tree species	GC
Brown Crown	Dead crowns for needle leaf tree species	BC
Tree Shadow	Shadows created by trees	TS
Green Deciduous	Live crowns for broad leaf tree species	GD
Bare Soil	Bare ground with no vegetation.	BS
Rock Pavement Building	Rock, Pavement, and Buildings	RPB
Snow Bright	Snow highly reflective materials	SB
Water	Water	W

The second stage of our estimation procedure relates FIA plot summaries to spectral, textural, elevation, and topographical derivatives using the spatial coordinates of each FIA plot, a focal window of 78 x 70 cells, and the random forest regression tree tool within the RMRS Raster Utility toolbar. Spectral, textural, elevation, and topographic variables include first order mean and standard deviation textural metrics of NAIP CIR, natural difference vegetation index (NDVI) derived from NAIP imagery, and elevation and topographic derivatives, along with second order horizontal contrast GLCM metrics values of NAIP CIR spectral bands.

RESULTS

The first stage of our approach had a maximum likelihood classification accuracy of 65 percent and accounted for 84.56 percent of the information in the data (). Using the extent of a FIA plot, the focal mean function within RMRS Raster Utility toolbar, and the probability surfaces of live and dead crowns, we created a Forested mask and attributed each FIA plot as either forested or non-forested (Fig. 1). In all, 660 and 992 FIA plots were located within and outside of Forested areas, respectively, and were used to train or validate the second stage of our classification and estimation process.

The second stage of our procedure generated a series of regression tree models that had a mean out of bag (OOB) root mean square error (RMSE) of 47.26 for BAA, TPA, and AGB (Table 2). Comparing observed plot summaries to estimated BAA, TPA, and AGB for our independent validation sample, we found that RMSE calculated from the independent sample was similar to OOB RMSE of our models. Using our regression tree models, the RMRS Raster Utility tool "Build Raster from Models", and the explanatory variable surfaces, we created a series of raster surfaces that predicted FIA plot BAA, TPA, and AGB summaries for every 32.81 ft across the study area (Fig. 2).

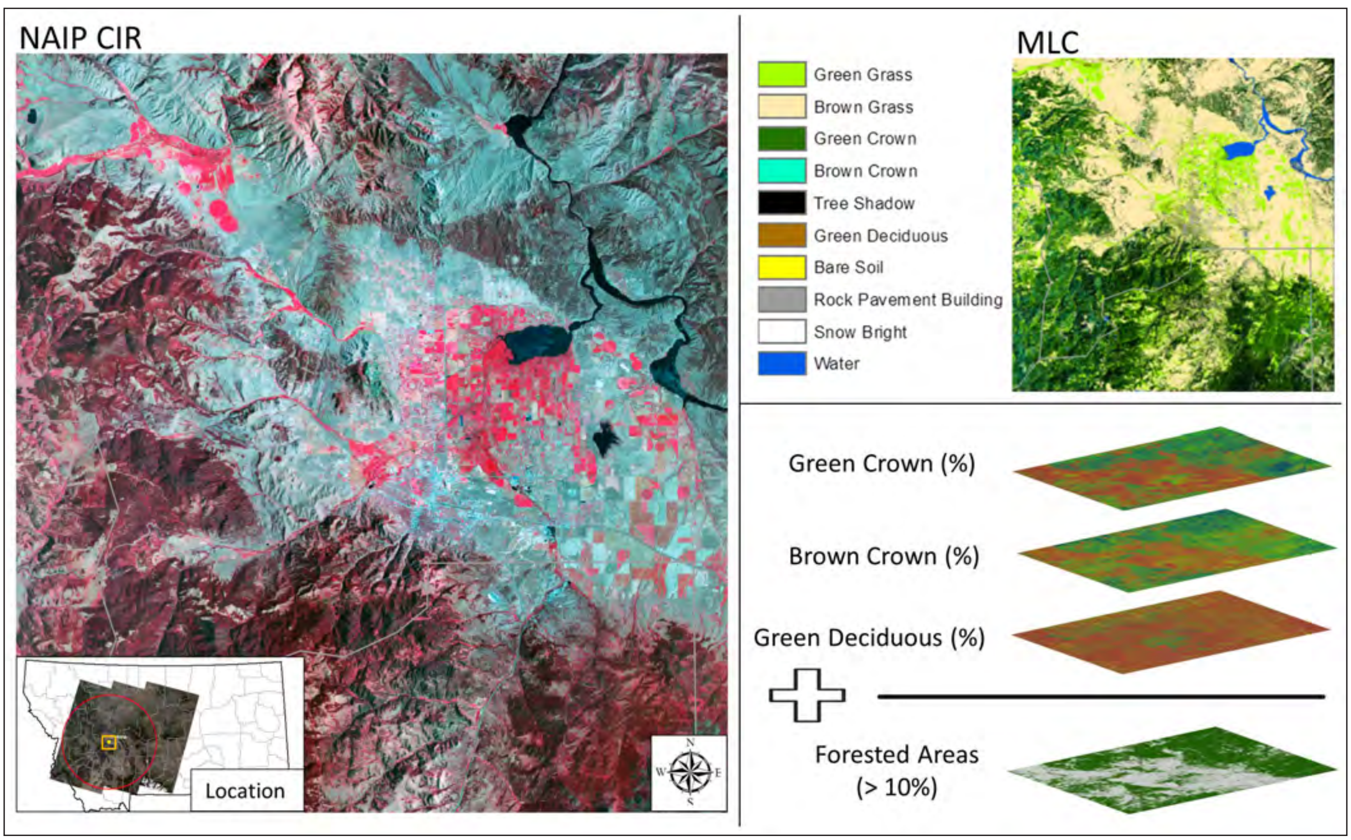

Figure 1—A close up illustration of the outputs from the first stage of our classification and estimation methodology. The extent of the close up covers 2,200 square miles around Helena, Montana and is denoted by the yellow square in the lower left Location map. Most Likely Class (MLC), Green Crown, Brown Crown, and Green Deciduous probabilistic outputs, and Forested Areas raster surfaces were derived from visually identified point locations, a Soft-max Neural Network, and NAIP CIR spectral and textural metrics.

Table 2—Fit statistics for BAA, TPA, and AGB models.

Characteristic	OOB RMSE	OOB R	Validated RMSE	Validated R
BAA	37.23	0.66	36.82	0.71
TPA	82.13	0.68	94.58	0.68
AGB	22.43	0.60	21.07	0.65

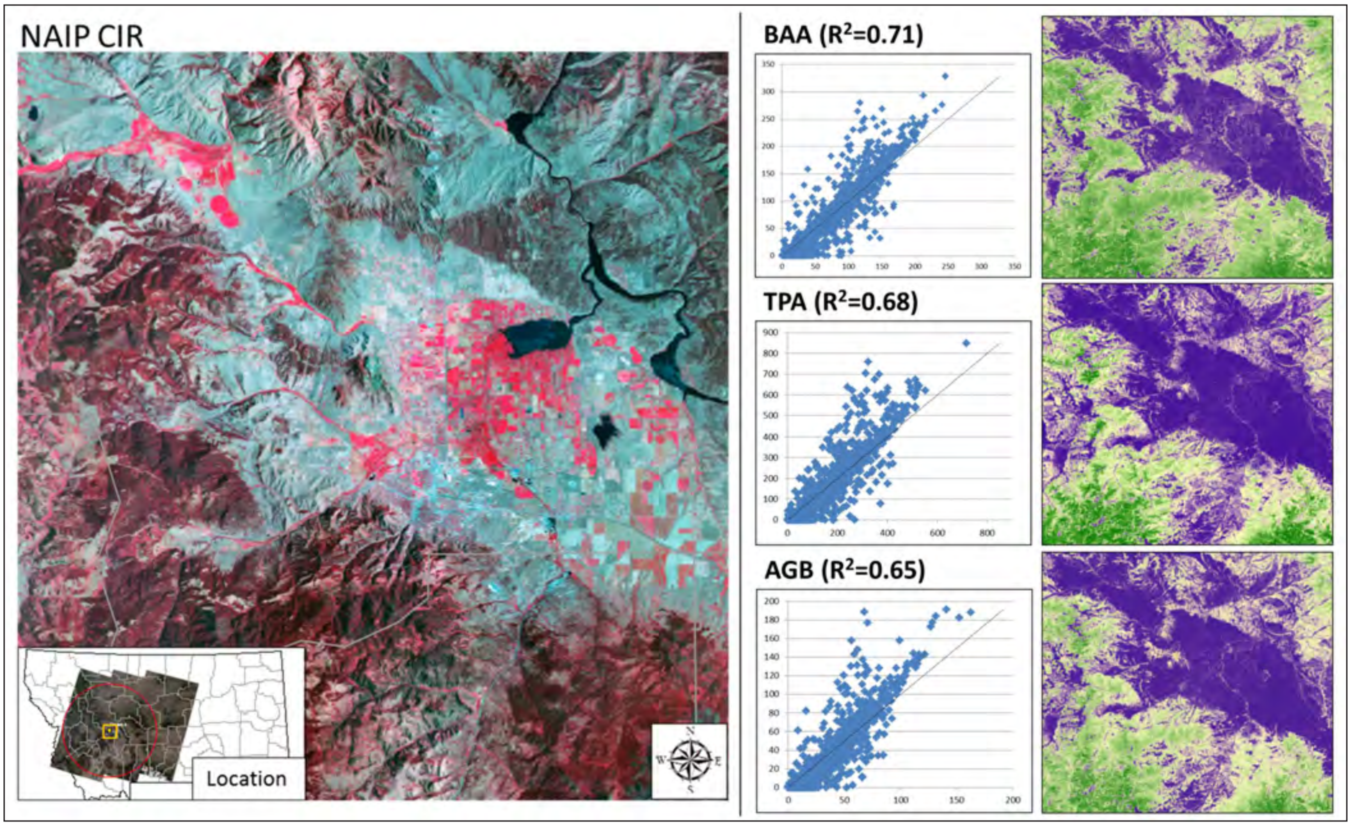

Figure 2—A close up illustration of the outputs from the second stage of our classification and estimation methodology. The extent of the close up covers 2,200 square miles around Helena, Montana and is denoted by the yellow square in the lower left Location map. Basal area per acres (BAA), trees per acre (TPA), and tons of above ground biomass per acre (AGB) were derived from FIA plot data, NAIP imagery, NED DEM, and multiple random forest algorithms. The right portion of the figure depicts the independently assessed relationships between response and explanatory variables and spatially illustrates increases in BAA, TPA, and AGB as color transitions from purple to green.

DISCUSSION

Our two stage classification and estimation approach successfully depicts mean forest characteristics for every 32.81 ft within 100 mile radius of Helena, MT. The relationships in these models are derived in explanatory variable space, as opposed to being spatial aggregations of plot characteristics, and are based on the correlative strength between the explanatory variables and FIA plot characteristics. Given that explanatory variables have been inventoried across the study area, we can use these relationships to depict forest characteristics at the resolution of each raster cell (Fig. 2). These types of outputs are extremely useful and can be aggregated across multiple geographic boundaries at many different spatial scales without losing accuracy or precision. Using our newly developed RMRS Raster Utility toolbar and coding libraries, these depictions can be easily manipulated within a GIS to address a wide range of management related questions at regional, landscape, and project extents.

ACKNOWLEDGMENTS

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EVALUATING THE POTENTIAL OF STRUCTURE FROM MOTION TECHNOLOGY FOR FOREST INVENTORY DATA COLLECTION

Demetrios Gatziolis[1]

Abstract—Since the inception of its annual plot design, the Forest Inventory and Analysis (FIA) Program of the USDA Forest Service has integrated into its data collection operations elements of digital technology, including data loggers, laser distance recorders and clinometers, and GPS devices. Data collected with the assistance of this technology during a typical plot visit comprise measurements of object dimensionality and location, as well as ocular assessments of inventory parameters of interest, all organized in a tabular form. Unlike the wealth of tabular data collected every year on FIA plots, digital images have been acquired only in the course of special projects (e.g. fire plots). Although small in number and acquired usually only along the cardinal directions, these images are nevertheless regarded as snapshots of plot conditions in time, and well-suited to retrospective resolution of an occasional ambiguity present in the tabular data. Owing to recent advancements in digital imagery technology and the field of computer vision, sets of numerous images acquired on an FIA plot with large spatial overlap among successive frames can be used to initially generate three-dimensional representations of structural plot elements in the form of a point cloud. Further processing of the cloud with algorithms originally developed for terrestrial LiDAR data leads to the identification of individual objects and quantification of their dimensionality. Variants of this process, usually known as vision structure from motion, have been used for digital reconstructions of man-made objects in urban settings. The adaptation of the process to on-plot settings and ground-based, under canopy imagery, presented with substantial challenges due to the intense variability in solar illumination conditions within a plot and the absence of planar surfaces separated by distinct edges. Algorithmic customizations have resolved many of these limitations. The modified process has been tested with inexpensive, off-the-shelf, all-weather, pinhole motion cameras weighing less than 150 grams, secured on the helmet of a field crew member. Initial results underline the method's potential for automated tree stem mapping, derivation of ground surfaces, comprehensive assessment of coarse woody debris volume and distribution, tree-specific measurements of crown base and ladder fuels, as well as for counting and assessing the height of seedlings in microplots.

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COMPLEMENTING FOREST INVENTORY DATA WITH INFORMATION FROM UNMANNED AERIAL VEHICLE IMAGERY AND PHOTOGRAMMETRY

Nikolay S. Strigul, Demetrios Gatziolis, Jean F. Liénard, Andre Vogs[1]

Abstract—Although a prerequisite for an accurate assessment of tree competition, growth, and morphological plasticity, measurements conducive to three-dimensional (3D) representations of individual trees are seldom part of forest inventory operations. This is in part because until recently our ability to measure the dimensionality, spatial arrangement, and shape of trees and tree components precisely has been constrained by technological and logistical limitations and cost. Active remote sensing technologies such as airborne LiDAR provide only partial crown reconstructions, while the use of terrestrial LiDAR is laborious and has portability limitations and high cost. In this work we capitalized on recent improvements in the capabilities and availability of small unmanned aerial vehicles (UAVs) and light and inexpensive cameras, and developed an affordable method for obtaining precise and comprehensive 3D models of trees and small groups of trees. The method employs slow-moving UAVs that acquire images along predefined trajectories near and around targeted trees and computer vision-based approaches that process the images to obtain detailed tree reconstructions. We present a step-by-step workflow which utilizes open source programs and original software. We anticipate that further refinement and development of our method can render it a valuable source of tree dimensionality information, complementary to the data recorded in traditional forest inventory field operations.

INTRODUCTION

To date, precise tree crown dimensionality and location data supportive of a rigorous modeling of individual tree growth has been inhibited by feasibility, logistics, and cost. Measuring crown characteristics by using established inventory methods is very time consuming and hardly affordable outside special projects. Existing remote sensing methods of measuring tree crowns provide only partial crown reconstructions. Airborne LiDAR data acquisitions require prolonged planning and are costly. Recently, unmanned aerial vehicles (UAVs) equipped with inexpensive, off-the-shelf panchromatic cameras have emerged as a flexible, economic alternative data source that supports the retrieval of tree dimensionality and location information. Flying at low altitude above the trees and with the camera oriented at a nadir view, UAVs acquire high-resolution images with a high degree of spatial overlap. In such conditions, a point on the surface of a tree crown or a small object on exposed ground is visible from many positions along the UAV trajectory and is depicted in multiple images. Automated photogrammetric systems based on computer Vision Structure from Motion (VSfM) algorithms (Snavely et al., 2008) explore this redundancy to retrieve the camera location the moment an image was acquired, calculate an

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orthographic rendition of each original image, and ultimately produce a precise 3D point cloud that represents objects. These acquisitions with nadir-oriented cameras onboard UAVs, however, face the same issues as airborne imagery; the great majority of points in derived clouds are positioned near or at the very top of tree crowns. The representation of crown sides tends to be sparse and contains sizeable gaps, especially lower in the crown, a potentially serious limitation in efforts to quantify lateral crown competition for space and resources, as in the periphery of canopy openings.

In this study, we extend UAV-based image acquisition configurations to include oblique and horizontal camera views and UAV trajectories around trees or tree groups at variable above-ground heights to achieve comprehensive, gap-free representations of trees. To overcome the challenges imposed by these alternative UAV/camera configurations, we evaluated many UAV platforms and open-source VSfM software options, and developed original, supplementary programs.

METHODS

UAV Platform

After a preliminary evaluation of several commercially available UAV platforms, we focused on an APM:Copter, a hexacopter rotorcraft, because of its easily modifiable architecture and open source software for flight control. We also used a commercial IRIS quadcopter developed by 3DRobotics. The components of the customized hexacopter sum to a total cost of approximately 1,000$. Both systems feature gyroscopes and GPS receivers. Compared to systems available in the market, our hexacopter is an inexpensive but versatile configuration whose component acquisition cost is expected to drop substantially in the future as UAV technology evolves and its popularity continues to increase.

Both UAVs used in this study can be operated either autonomously along a predefined trajectory or manually. The manual flight control requires expertise and continuous line of sight between the system and the operator. Maintaining nearly constant planar and vertical speed and orientation of the onboard camera towards the target is challenging, even for operators with years of experience. Experimentation confirmed that imagery acquired with manual flight control exhibits variable rates of overlap between frames captured sequentially. Smaller components of the targets are sometimes depicted in too few frames or are missing completely, while others appear in an excessive number of frames. For these reasons, it was decided to rely on autonomous flights configured by prior mission planning, and reserve the manual mode only for intervention in the event of an emergency.

We conducted extended trials with several cameras, including the sport GOPRO 3+ Black Edition, Ilook Walkera and Canon PowerShot. The evaluations involved all operating modes offered by each camera, including normal, wide, and wide zoom settings, as well as acquiring video and then extracting individual frames with post-processing.

3D reconstruction procedure

The procedure that uses a set of images exhibiting substantial spatial overlap to obtain a point cloud representing the objects present in the images contains three main steps: feature detection, bundle adjustment, and dense reconstruction. To implement this procedure, we have carefully examined a variety of software available for image processing. The workflow presented below was found by experimentation to be the most efficient for our project. We employed a sequence of computer programs, most of which are available as freeware or provide free licenses to academic institutions. The software used includes OpenCV libraries, VisualSFM, CMVS, SURE, OpenGL, and Mission Planner.

The sparse and dense reconstructions obtained from a set of overlapping images are configured in the same internal coordinate system and scale. Conversion to real-world orientation and coordinate system is a prerequisite for meaningful measurements of reconstructed objects or for comparisons with ancillary spatial data. Such conversions can be performed manually on the reconstructed scene, assuming reference *in-situ* measurements of object dimensionality are available. In this study, we used an alternative, automated approach. The latitude, longitude, and elevation of camera locations recorded by a recreational-grade GPS device onboard the UAV were converted to orthographic Universal Transverse Mercator (UTM) coordinates using a GDAL reprojection function. The rotation/ translation matrix linking the UTM and sparse model coordinates of the camera positions was then calculated via maximum likelihood, and applied to convert the sparse model coordinates system to UTM. All subsequent processing by CMVS and SURE were performed on the UTM version of the sparse model.

RESULTS

We used simulation and synthetic images to evaluate the robustness of our standard workflow to the idiosyncrasies of lateral tree imagery described above. We relied on terrestrial LiDAR data representing a collection of free-standing trees, each scanned from multiple near-ground locations. The scanning was performed in high-density mode with the laser beams distributed in fine horizontal and vertical angular increments (0.4 mrad). Details on the data acquisition are available in Gatziolis et al. (2010). The original Terrestrial LiDAR and dense reconstruction point clouds for each tree were compared in voxel space (Popescu & Zhao, 2008; Gatziolis, 2012). With sufficient field-of-view overlap between two consecutive synthetic images, the 3D model obtained using our photogrammetry workflow showed excellent agreement with the reference LiDAR model (more than 95% voxel co-localization between the two models).

Our typical setup uses a location positioned in the middle of an open area for both the start and end of the flight. The UAV would initially ascend vertically above its starting location to a pre-specified height, then move horizontally to the beginning of the trajectory, complete it, and finally return to the starting location (Figure 1). In the present development state of our system, it is the user's responsibility to ensure that the designed flight path is free of other objects, an easy to achieve requirement considering the wealth of georeferenced, high resolution, publicly available aerial photographs.

Most UAV flights produced complete tree reconstructions (Figure 2). In the absence of detailed crown dimensionality measurements, we relied on ocular assessment of reconstruction accuracy and precision. The typical examples shown on Figure 2, obtained with the spiral UAV trajectory (Figure 1c), among our most reliable for complete target reconstruction, shows that even the shaded components of the tree crown interior are represented.

DISCUSSION

Rapid developments in UAV technology and enhancements in structure from motion software have enabled detailed representation of manmade objects. In this work and in Gatziolis et al. (2015), we describe how this technology can inexpensively be extended to representations of natural objects, such as trees or groups of trees. After extensive experimentation that involved several UAV platforms, cameras, mission planning alternatives, processing software, and numerous procedural modifications and adjustments, our workflow has been proven capable of handling most conditions encountered in practice to deliver detailed reconstruction of trees. In addition to robust performance, our imaging system can be employed rapidly in support of time-sensitive monitoring operations as, for instance, the assessment of forest fire damage or progress of forest recovery from disturbance. It is also well suited to providing tree dimensionality data through time, a prerequisite for improved models of tree growth and for an accurate assessment of tree competition and morphological plasticity.

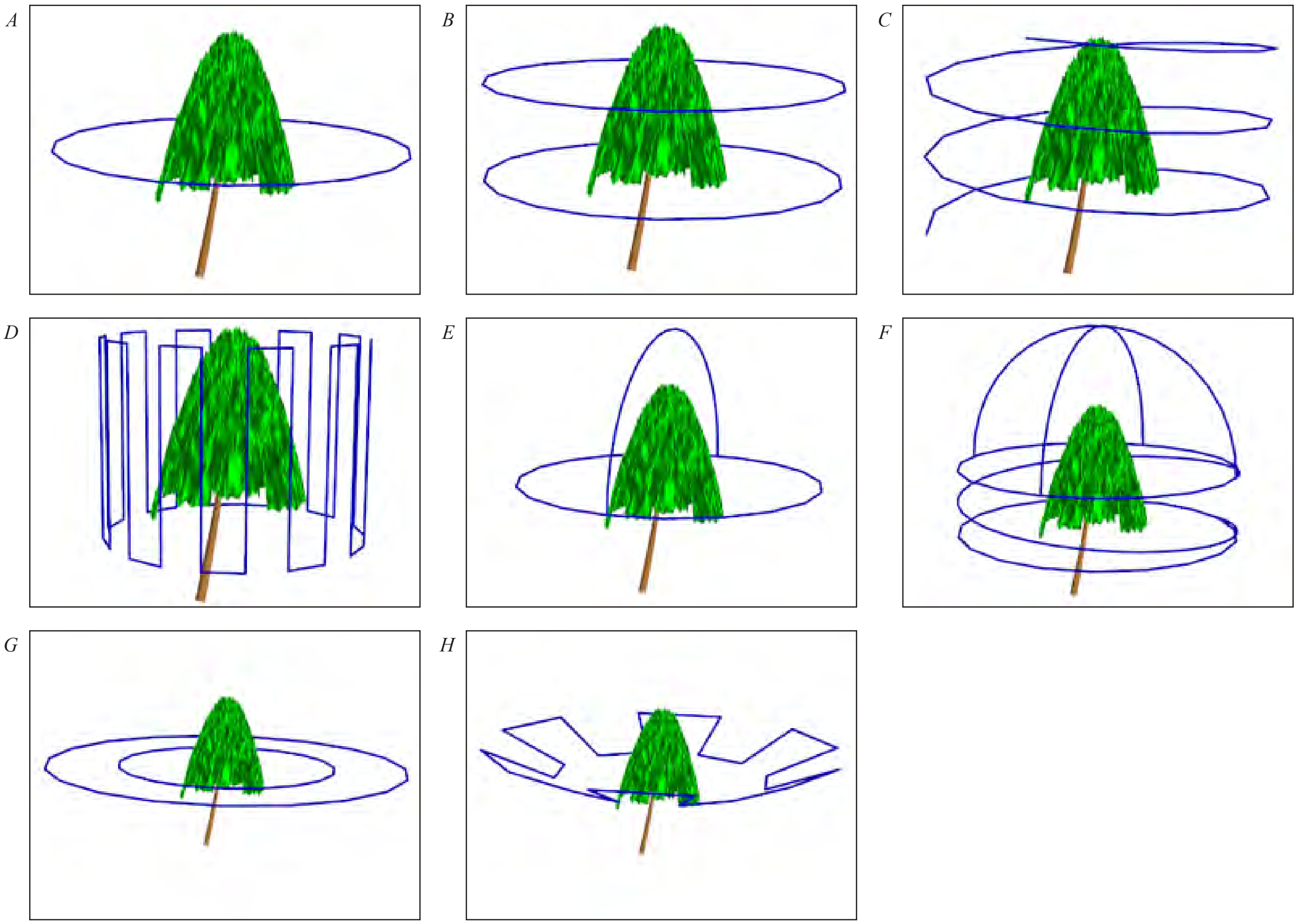

Figure 1—Different UAV trajectories tested for image acquisition. a. circular, at constant height; b. 'stacked circles', each at different above-ground height, for tall trees (height more than 20 m); c. spiral, for trees with complex geometry; d. vertical meandering, targeting tree sectors; e. clover, for trees with wide, ellipsoidal tree crowns; f. 'spring-hemisphere', designed for trees with flat-top, asymmetrical crowns; g. 'nested circles', centered on the tree; and h. 'jagged saucer', designed for trees with dense foliage but low crown compaction ratio.

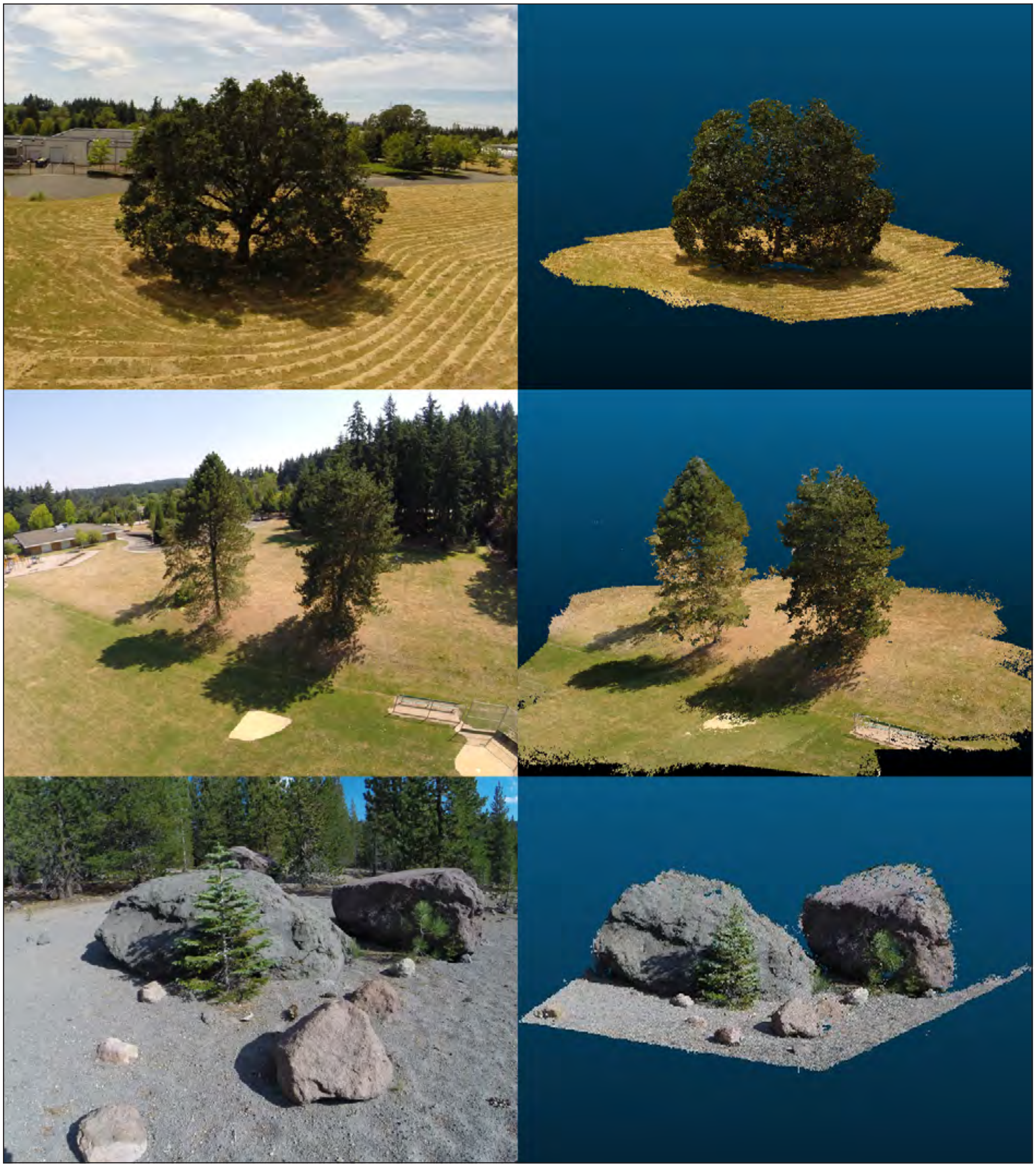

Figure 2—Illustration of comprehensive tree reconstructions (right column) and reference UAV-based images (left column).

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WHAT'S GOING ON WITH URBAN FIA?

URBAN FIA: WHERE WE HAVE BEEN, WHERE WE ARE, AND WHERE WE ARE GOING

Mark Majewsky[1]

Abstract—The FIA program has been inventorying the Nation's forestland since the 1930s. The focus of the CORE FIA program is to capture trees that meet the FIA definition of forestland, in doing so it excludes trees that do not. Leadership recognized the need to fill this gap and the 2014 Farm Bill has instructed FIA to "Implement an annualized inventory of trees in urban settings, including the status and trends of trees and forests, and assessments of their ecosystem services, values, health, and risk to pests and diseases". The objective of the Urban FIA program is to meet this mandate by not restricting the sample methods to defined forestland within Census-defined urban areas. We will use the FIA sampling frame to annually monitor the urban forests of the Nation with special emphasis in the largest (iconic) cities of America. This is not the first time the FIA program has ventured into urban areas; there were numerous pilot studies completed as far back as the mid-1990s. With the pilots behind us FIA has now partnered with the Urban and Community Forestry Unit's i-Tree program. This synergy, in addition to lessons learned from the pilots, has led to the development of the current Urban FIA protocols. The program is currently active in the Baltimore, MD and Austin, TX metro areas, and will add Houston, TX; Madison, WI; Milwaukee, WI; Providence, RI; Des Moines, IA and likely St Louis, MO metro areas during the 2015 field season. In this session, we will present a very brief history of past FIA urban pilots, why we are moving to the Urban FIA approach, and how we plan to implement the program across the Nation.

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AUSTIN'S URBAN FIA: SEAMLESS RURAL TO URBAN RESOURCE MONITORING IN TEXAS

Chris Edgar[1], Burl Carraway[2]

Abstract—In 2014 Urban Forest Inventory and Analysis (Urban-FIA) was implemented for the first time ever in Austin, Texas. Work was accelerated and a full complement of plots in the city was measured in six months. In 2015 results are to be released in an FIA report and data made available in a publicly accessible database. In this presentation we discuss the importance of seamless rural to urban monitoring in a state where 85 percent of the population lives in urban areas. We highlight major findings from the Austin analysis and report. We discuss how the data strengthen urban forest management and advocacy efforts. Our online application My City's Trees will be presented. We conclude the presentation with observations on the status and future direction of Urban-FIA in the state.

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GOING PUBLIC: ACCESSING URBAN DATA AND PRODUCING POPULATION ESTIMATES USING THE URBAN FIA DATABASE

Chris Edgar[1], Mark Hatfield[2]

Abstract—In this presentation we describe the urban forest inventory database (U-FIADB) and demonstrate how to use the database to produce population estimates. Examples from the recently completed City of Austin inventory will be used to demonstrate the capabilities of the database. We will identify several features of U-FIADB that are different from the FIA database (FIADB) and discuss whether the differences are out of necessity or by design. Urban forest inventory is a melding of two different inventory systems and approaches, FIA and i-Tree, both of which are well-established and successful in their own right. They each have their own tradition and can provide fresh perspective. Integration of the two systems will take time and the database will necessarily evolve. We conclude the presentation with observations and comments on future direction and development.

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THE URBAN FIA INVENTORY: PLOT DESIGN, DATA COLLECTION, DATA FLOW AND PROCESSING

Tonya Lister[1], Mark Majewsky[2], Mark Hatfield[3], Angie Rowe[4], Bill Dunning[5], Chris Edgar[6], Tom Brandeis[7]

Abstract—More than 80 percent of the U.S. population lives in urban areas and tree cover in these areas offers a wide range of environmental benefits including the provision of wildlife habitat, aesthetic appeal and visual barriers, microclimate control, water quality improvement, and air and noise pollution control. Recognizing the importance of urban forests, and with direction from the 2014 Farm Bill to include urban forest monitoring in its strategic plan, FIA has initiated an annualized urban inventory program. Urban FIA Inventory methods include a blending of elements from the core FIA program and from the i-Tree Eco program, along with several new urban field variables. Under the Urban FIA Inventory protocol, unique nonforest land uses are mapped and tree measurement data are collected across all land uses using a fixed radius, single subplot plot design. In this session, we will present an overview of FIA's urban inventory methods, including sample plot design and data collection methods. We will also discuss lessons learned based on the first field season of data collection and future improvements and additions to the Urban FIA methodology.

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I-TREE AND URBAN FIA—WHAT'S THE CONNECTION?

David J. Nowak[1]

Abstract—The i-Tree program (www.itreetools.org) was developed to assess ecosystem services and values from trees and forests based on measured forest data. The i-Tree program is currently being integrated with FIA data to assess various ecosystem services and values from urban FIA data. This presentation will overview the history and use of i-Tree; the various tools of i-Tree and how i-Tree assesses ecosystem services and values.

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THE EVOLUTION OF WISCONSIN'S URBAN FIA PROGRAM – YESTERDAY TODAY AND TOMORROW

Stoltman, Andrew M.[1], Rideout, Richard B.[2]

Abstract—In 2002, Wisconsin was part of two pilot projects in cooperation with the US Forest Service. The first was a street tree assessment, and the second was an urban FIA project. The data generated by these pilots changed the way that Wisconsin DNRs' Urban Forestry Program conducts its business. Although there have been several urban FIA pilot projects throughout the U.S., in 2012, Wisconsin became the first state where those pilot FIA plots were re-measured. The results of this re-measurement demonstrate how urban foresters in Wisconsin have altered their tactics in recent years due to several factors, including the emergence of emerald ash borer. In recognition that good data leads to more effective management, the Wisconsin Department of Natural Resources Division of Forestry recommended a major expansion of urban inventory data to better guide urban forest managers. This initiative is being implemented in 2015, and includes statewide continuous urban FIA plots, a repeatable remotely sensed urban tree canopy assessment, and the aggregation of existing inventories such as municipal street or park tree inventories.

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POSTER SESSION

NLCD TREE CANOPY COVER (TCC) MAPS OF THE CONTIGUOUS UNITED STATES AND COASTAL ALASKA

Robert Benton[1], Bonnie Ruefenacht[2], Vicky Johnson[3], Tanushree Biswas[4], Craig Baker[5], Mark Finco[6], Kevin Megown[7], John Coulston[8], Ken Winterberger[9], Mark Riley[10]

Abstract—A tree canopy cover (TCC) map is one of three elements in the National Land Cover Database (NLCD) 2011 suite of nationwide geospatial data layers. In 2010, the USDA Forest Service (USFS) committed to creating the TCC layer as a member of the Multi-Resolution Land Cover (MRLC) consortium. A general methodology for creating the TCC layer was reported at the 2012 FIA Symposium in Knoxville, Tennessee by several USFS researchers. Since that time, remote sensing specialists at the USFS Remote Sensing Application Center (RSAC) have translated those general methods into a process capable of being implemented over the Contiguous United States and Coastal Alaska and produced the TCC 2011 layers.

This poster presents the products produced by the NLCD TCC 2011 team in graphical form and is a companion to a presentation on the same topic. Both versions of the NLCD TCC dataset are distributed through the MRLC NLCD website at http://www.mrlc.gov.

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ESTIMATING CARBON IN FOREST SOILS OF THE UNITED STATES USING THE NATIONAL FOREST INVENTORY

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Abstract—Soil organic carbon (SOC) is the largest terrestrial carbon (C) sink on earth and management of this pool is a critical component of global efforts to mitigate atmospheric C concentrations. Soil organic carbon is also a key indicator of soil quality as it affects essential biological, chemical, and physical soil functions such as nutrient cycling, water retention, and soil structure maintenance. Much of the SOC on earth is found in forest ecosystems and is thought to be relatively stable. That said, there are a growing number of studies documenting the sensitivity of SOC to global change drivers, particularly in the northern circumpolar region where approximately 50% of the global SOC is stored. In the United States (US), SOC in forests is monitored by the national forest inventory (NFI) conducted by the Forest Inventory and Analysis (FIA) program within the United States Department of Agriculture, Forest Service. The FIA program currently uses SOC predictions based on SSURGO/STATSGO data to populate the national forest inventory. Most of the point samples used to obtain estimates of SOC in forests from the SSURGO/STATSGO data are from non-forested sites. The FIA program has been consistently measuring soil attributes as part of the NFI since 2001 and has recently amassed a nearly complete inventory of SOC in forests in the conterminous US and coastal Alaska. As an initial step towards developing a map of SOC in forests of the US we will 1) describe the inventory of soil variables in the NFI, 2) compare model predictions of SOC density with estimates from the NFI, 3) evaluate new estimation approaches to replace existing model predictions, and 4) describe next steps towards the development of data-driven visualization products that rely on existing and emerging remotely sensed data products, NFI measurements, and auxiliary environmental data sources.

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AN APPLICATION OF QUANTILE RANDOM FORESTS FOR PREDICTIVE MAPPING OF FOREST ATTRIBUTES

E.A. Freeman[1] and G.G . Moisen[2]

Abstract—Increasingly, random forest models are used in predictive mapping of forest attributes. Traditional random forests output the mean prediction from the random trees. Quantile regression forests (QRF) is an extension of random forests developed by Nicolai Meinshausen that provides non-parametric estimates of the median predicted value as well as prediction quantiles. It therefore allows spatially explicit non-parametric estimates of model uncertainty. Here, we illustrate how to use QRF in predictive mapping of continuous forest attributes such as tree canopy cover and biomass. Using FIA plot data as our response, we model the forest attributes as functions of landsat and other predictor variables through the quantregForest R package. We predict the 5th, 50th, and 95th quantiles and map the distributions over a mountainous region in the Interior West. We demonstrate how to produce prediction intervals, explore causal relationships, and detect outliers using this method, then make user-friendly code available through the extensions to the ModelMap R package.

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MAPPING FOREST CANOPY DISTURBANCE IN THE UPPER GREAT LAKES, USA

James D. Garner, Mark D. Nelson, Brian G. Tavernia, Charles H. Perry, and Ian W. Housman[1]

Abstract—A map of forest canopy disturbance was generated for Michigan, Wisconsin, and most of Minnesota using 42 Landsat time series stacks (LTSS) and a vegetation change tracker (VCTw) algorithm. Corresponding winter imagery was used to reduce commission errors of forest disturbance by identifying areas of persistent snow cover. The resulting disturbance age map was classed into 5-year age classes and then used to attribute age to forested pixels within the National Land Cover Database of 2011. Overall map classification accuracy was 84.9 percent when using Forest Inventory and Analysis data as reference. User's and producer's accuracies were high for persistent forest, nonforest, and water, but low for disturbed forest 5-year age classes, likely due to rarity of forest canopy disturbance on the landscape and confusion among 5-year age classes in both map and reference data sets.

Forest canopy disturbance is defined in this study as any event, natural or anthropogenic, that reduces tree canopy cover to the extent that there is a change in the dominant age cohort. Such disturbance events, or lack thereof, provide both benefits and challenges to a variety of forest ecosystem functions. Forest disturbance provides important habitat for early successional forest-associated wildlife species such as American woodcock (*Scolopax minor*), Kirtland's warbler (*Septophaga kirtlandii*), white-tailed deer (*Odocoileus virginianus*), and many other species. In contrast, increased water turbidity and phosphorous have been linked to increased forest canopy disturbance (Seilheimer et al. 2013). Forest canopy disturbance also provides inroads for invasive plant species, especially following timber harvesting activities if proper care is not taken to eliminate seeds and spores from logging equipment and subsequent vehicle traffic.

The USDA Forest Service, Forest Inventory and Analysis (FIA) program produces data, information, and knowledge on many characteristics of forest composition and structure. FIA attributes affected by or indicative of forest canopy disturbance include condition-level attributes of stand age, disturbance, treatment, and stand-size (tree diameter) class; and tree-level attributes of damage, mortality, and removal. These FIA attributes provide area estimates of forest canopy disturbance and stand age class, but do not fully meet the needs for spatially explicit land management information. Existing upper Great Lakes geospatial data sets also do not allow regionally consistent assessment of amount and configuration of forest canopy disturbance across a wide range of spatial scales.

METHODS

We analyzed spectral-temporal data within several Landsat time series stacks (LTSS) to identify spatially explicit forest canopy disturbance. The vegetation change tracker (VCT) algorithm (Huang et al. 2010) was employed to track spectral data of individual pixel locations throughout these LTSS. VCT identifies trajectories in these data and flags departures from stable forest as disturbance events. The USDA Forest Service Northern Research Station (NRS)

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in collaboration with the agency's Remote Sensing Applications Center adapted VCT by incorporating winter Landsat imagery of seasonally persistent snow-cover to reduce commission errors of forest disturbance (VCTw) (Stueve et al. 2011). We applied VCTw to Landsat Thematic Mapper and Enhanced Thematic Mapper Plus imagery dating from 1987 to 2010 to map forest canopy disturbance across 42 Landsat scenes encompassing the intersection of Minnesota, Wisconsin, and Michigan with Bird Conservation Regions (BCR) 12 and 23 (Fig. 1). These scenes were then mosaicked together following a procedure which assigns precedence in overlapping areas based on the consistency of each scene with neighboring scenes (Nelson et al., in prep.[2]). The resulting forest canopy disturbance map was relabeled into 5-year forest age classes based on year of disturbance (1990-1994, 1995-1999, 2000-2004, 2005-2009) plus one class of persisting forest (no disturbance since 1990) (Fig. 2).

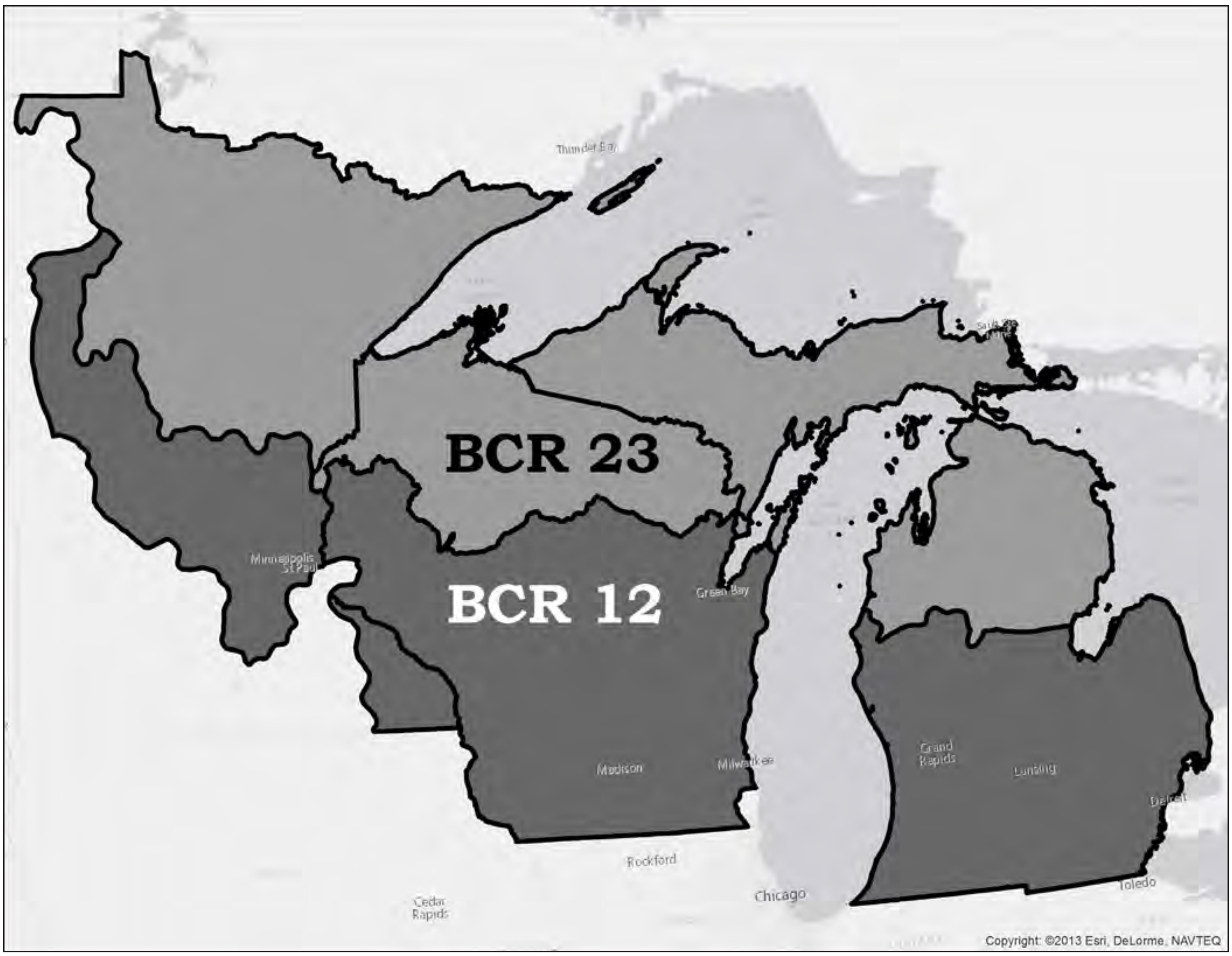

Figure 1.—Study area, consisting of the intersection of Michigan, Minnesota, and Wisconsin, with Bird Conservation Regions (BCRs) 12 and 23. Data sources: North American Bird Conservation Initiative (BCRs, with revisions), Esri (state boundaries, basemap).

[2] Nelson, M.D.; Houseman, I.W.; Stueve, K.M.; Perry, C.H. In preparation. Effects of satellite image mosaic precedence on consistency and accuracy of forest canopy disturbance mapping.

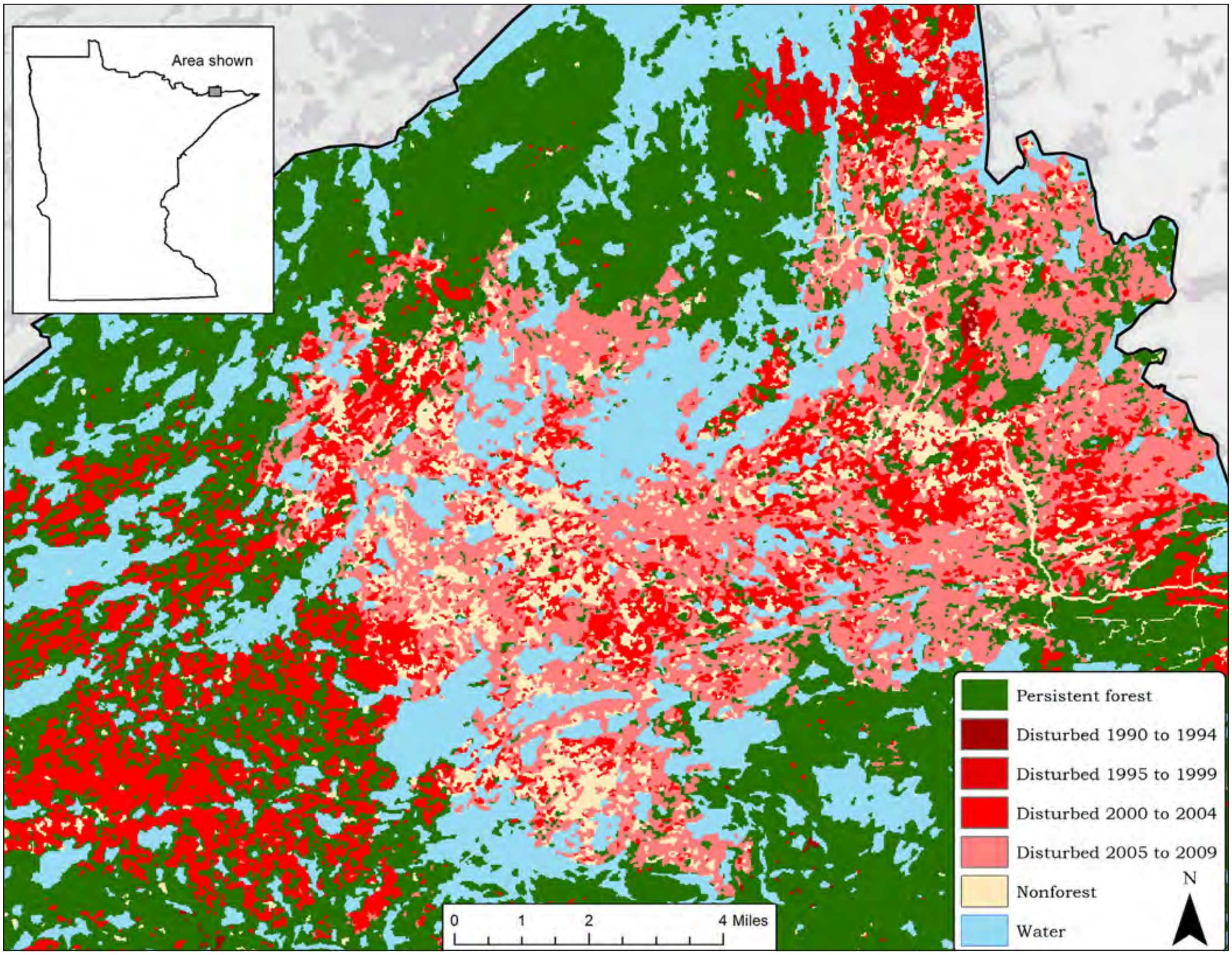

Figure 2.—Map subset shows a portion of the Boundary Waters Canoe Area Wilderness in northern Minnesota illustrating widespread canopy disturbance caused by a severe storm event on 4 July 1999, followed by the Cavity and Ham Lakes fires of 2006 and 2007. Data sources: Nelson et al. (in prep.; land cover and forest age classes), Esri (state boundaries, basemap).

To allow for the inclusion of forest type in subsequent analyses, VCTw-based forest age classes were assigned to deciduous, evergreen, and mixed forest, and woody wetlands pixels in the 2011 National Land Cover Database (NLCD2011) (Homer et al. 2015). Despite the inclusion of winter imagery in VCTw, preliminary analysis indicated that NLCD2011 provides better accuracies of persistent general land use classes (forest, nonforest, water). As such, NLCD2011 forest pixels that were not associated with VCTw age data were labeled as forest of persisting age class.

A subset of shrub/scrub and grassland/herbaceous pixels in NLCD2011 were reclassed as forest when corresponding VCTw pixels were classed as young forest (0-20 years of age); these pixels were labeled as 'other' forest type and were assigned to their corresponding VCTw-based age class. Co-registration disagreement between the NLCD and VCTw maps occasionally resulted in age class assignment to only a portion of an NLCD2011 forest patch, creating a thin strip having no age class along the NLCD2011 forest edge. Areas less than two pixels wide within these strips were assigned to the age class of the largest neighboring NLCD2011 forest patch. Finally, all patches smaller than four pixels were aggregated into their nearest neighbor, resulting in a four pixel minimum mapping unit (MMU) for the dataset. This MMU (0.36 ha) is similar to the minimum patch size required to meet FIA's definition of forest land (0.4047 ha).

The accuracy of the resulting raster data set was assessed by comparing the mapped age classes to 27,219 FIA plots located within the study area, and following "good practices" prescribed in Olofsson et al. (2014). To avoid complications involved with assigning classes to mixed condition plots and mixed pixel samples, only FIA single condition central subplots were co-located with individual pixels (Chen and Stow 2002). The percentage of FIA plots omitted for not having single condition central subplots was 2.7, 4.2, and 4.5 percent in Minnesota, Michigan, and Wisconsin, respectively. Mapped age classes were subsequently compared with corresponding FIA field age following methods described in Nelson et al.[3] Results were used to populate confusion matrices with proportion estimates weighted by proportion of area mapped in each class (Olofsson et al. 2014; Table 1), from which metrics of accuracy were estimated. Post-stratified area estimates and corresponding 95 percent confidence intervals were produced from the FIA field data using the map classes as strata, per Olofsson et al. (2014).

RESULTS

Overall classification accuracy for the study-wide assessment was 84.9 percent (±0.42 percent, based on 95 percent confidence intervals; Table 1). Overall accuracy was 89.54 percent (±0.36 percent) after aggregating forest into a single class (forest, nonforest, water; confusion matrix not shown).

We estimated 216,563 (±1,532) km^2 of forest land area, and 26,635 (±1,134) km^2 of forest canopy disturbance within the 20-year window (1990-2009). About 12 percent of forest area was disturbed between 1990 and 2009; 8.5 percent in Michigan, 10.9 percent in Wisconsin, and 16.2 percent in the Minnesota portion of the study region.

[3] Nelson, M.D.; Tavernia, B.G.; Garner, J.D.; and Perry, C.H. In preparation. Geospatial modeling and validation of recent forest canopy disturbance in the Upper Great Lakes, USA.

In general, producer's accuracies tended to decrease and user's accuracies tended to increase with decreasing proportion of the respective class on the landscape and with time since disturbance. Each of the 5-year increment disturbed forest classes occupied less than 1 percent of the study area, and their corresponding accuracies were low, ranging from 15-31 percent for producer's accuracies and 39-45 percent for user's accuracies.

DISCUSSION AND CONCLUSION

We applied the VCTw forest canopy disturbance algorithm to several Landsat LTSS and NLCD2011 data to map forest canopy disturbance, persisting forest, nonforest, and water within Minnesota, Wisconsin, and Michigan portions of BCRs 12 and 23 in the western Great Lakes. The proportion of forest area experiencing canopy disturbance within the past 20 years varied among states. Using FIA data for validation, the resulting map had relatively high overall accuracy when including all seven classes, but low producer's and user's accuracies for the 5-year age classes (Table 1), which were rare on the landscape and subject to confusion with other 5-year age classes. There was a discernable trend in both the user's and producer's accuracy of the disturbed forest classes, with accuracy tending to decrease as time since disturbance increases. This may be attributable to varying rates of recovery following disturbance, creating difficulty for FIA field crew assignment of field age to older forest conditions, thus affecting the veracity of the FIA plot data set used for map validation. Additional details on mapping, validation methods, and results by various subareas are reported in Nelson et al.[2]

ACKNOWLEDGMENTS

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Table 1. Confusion matrix and estimates of classification accuracy (overall, user's, producer's) for forest disturbance age classes, persistent forest, nonforest, and water. Matrix cell values are presented as estimated area proportions weighted by the proportion of area mapped in each class, as recommended in Olofsson et al. (2014).

Map categories	Reference categories								
	Persistent forest	Forest disturbed 1990 to 1994	Forest disturbed 1995 to 1999	Forest disturbed 2000 to 2004	Forest disturbed 2005 to 2009	Nonforest	Water	Total	User's Accuracy
Persistent forest	0.401	0.010	0.009	0.007	0.005	0.051	0.003	0.486	0.824
Forest disturbed 1990 to 1994	0.002	0.003	0.001	0.000	0.000	0.000	0.000	0.006	0.426
Forest disturbed 1995 to 1999	0.002	0.001	0.003	0.001	0.000	0.001	0.000	0.008	0.446
Forest disturbed 2000 to 2004	0.002	0.000	0.001	0.004	0.001	0.001	0.000	0.009	0.408
Forest disturbed 2005 to 2009	0.003	0.000	0.000	0.001	0.003	0.001	0.000	0.008	0.388
Nonforest	0.028	0.002	0.004	0.003	0.002	0.393	0.003	0.435	0.904
Water	0.001	0.000	0.000	0.000	0.000	0.004	0.043	0.048	0.895
Total	0.439	0.016	0.018	0.016	0.011	0.451	0.049	1.000	
Producer's accuracy	0.915	0.150	0.172	0.239	0.306	0.870	0.874		0.849

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NATIONAL FOREST CHANGE MONITORING SYSTEM IN SOUTH KOREA: AN ANALYSIS OF FOREST TREE SPECIES DISTRIBUTION SHIFTS

Eun-Sook Kim, Cheol-Min Kim, Jisun Lee and Jong-Su Yim

Abstract—Since 1971, South Korea has implemented national forest inventory (NFI) in pursuance of understanding current state and change trend of national forest resources. NFI1 (1971~1975), NFI2 (1978~1981), NFI3 (1986~1992) and NFI4 (1996~2005) were implemented in order to produce national forest resources statistics. However, since the early 1990s, international conventions and organizations started to require diverse forest information for the sustainable forest management and periodic monitoring of forest resources. Following these requirement, South Korea reformed total national forest inventory system. Starting from NFI5 (2006~2010), national forest resources inventory was implemented on the basis of the new system. These time series NFI data can be used to understand the long-term transition of forest and predict the future of forest condition in national scale.

In this study, two analyses were performed to identify forest distribution change using the long-term NFI data. First, area change and distribution change by forest types (coniferous forest, mixed forest, deciduous forest) were compared using time series forest type maps. Second, density change of *Pinus densiflora* and *Quercus* spp. using time series NFI data. As results, coniferous forest were reduced overall, but deciduous forests show evident increasing trend. The change of tree density appeared differently based on the topographic characteristics. While tree density of *Pinus densiflora* has rapidly decreased in regions with low altitude and gentle slope, tree density of *Quercus* spp. has sharply increased in regions with high altitude and steep slope. As for the tree density of *Pinus densiflora*, the northern slope showed more decreasing trend than southern slope. Time series National Forest Inventory data is the most extensive forest survey information in South Korea. We could analyze the long-term changing trend of forest stand based on these data.

Keywords: national forest inventory, forest change monitoring, distribution shifts

INTRODUCTION

Since 1971, South Korea has periodically conducted national forest inventory (NFI) to calculate the statistics of national forest resource. NFI was carried out with field surveys on sampling plots placed throughout the country in parallel with the production of forest type maps to classify and to map forest types using aerial photographs. In addition, starting in the fifth NFI, the forest monitoring system has been reformed with the aim of sustainable forest management and production of forest statistics at international standard (Table 1). Especially since the fifth NFI, sampling plots placed throughout the country became permanent and repeated survey has been conducted. Therefore, the base for monitoring changes in the same plots has been provided, and monitoring survey is now being conducted as the sixth NFI (2011~2015).

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Table 1. National Forest Inventory system for plot survey and forest type map

Phase	Years	Sample Design	Number of plots	Plot form	Forest Type Map production
NFI1	1971~1975	Stratified Systemic Sampling	7,051	Circular sample plot (0.01ha)	First Forest Type Map (1:25,000)
NFI2	1978~1981		4,839		Second Forest Type Map (1:25,000)
NFI3	1986~1992		14,474	Cluster plot (0.05ha)	Third Forest Type Map (1:25,000)
NFI4	1996~2005		2,788		Fourth Forest Type Map (1:25,000)
NFI5	2006~2010	Systematic Sampling	14,164	Cluster and multiplex circular plots (0.04ha, basic plot)	1:5,000 Forest Type Map (Separate from NFI)

These data can be used to understand the transition of forest and predict the future of forest condition in national scale. Hernandez et al.(2014) studied the change of spatial distribution for *Pinus sylverstris* and *Fagus sylvatica* using time series NFI data. Bechage et al.(2008) analyzed the distribution shifts of hardwood-boreal ecotone from 1964 to 2004 based on elevation transect survey. The aims of this study are to understand the entirely changing trends of forest type and to draw main factors of distribution shifts for *Pinus densiflora* and *Quercus* spp.

STUDY SITE AND DATA

In this study, an analysis on a pilot area was conducted using the long-term National Forest Inventory (NFI) data to develop an analysis method for forest distribution change. Study areas are located in the temperate Midwest region of South Korea and cover the Chungcheongnam-do, Chungcheongbuk-do and Daejeon Metropolitan City with the total area of 1,660,000 hectare. The study area consists of forest area of 964 hectare which is 58% of the total land. Within the Chungcheong region, as Chungcheongnam-do is adjoined the Yellow Sea and Chungcheongbuk-do includes forested areas with east high and west low characteristics, showing different forest characteristics. For forest distribution change analysis, time series forest type maps and NFI data created over 40 years were used. Forest type maps used for analysis were the first forest type map (1972~1974), the third forest type map (1991), and 1:5,000 forest type map (2009), and NFI data used in this study are the first NFI (1975, 889 plots), the third NFI (in 1991, 1,493 plots), and the fifth NFI (2006~2010, 1,662 plots).

METHODS

Two analyses were performed to identify forest distribution change using the long-term NFI data. First, area change and distribution change by forest types (coniferous forest, mixed forest, deciduous forest) were compared using time series forest type maps. Second, density change of *Pinus densiflora* and *Quercus* spp. using time series NFI data. For each sampling plot, the number of *Pinus densiflora* and *Quercus* spp. (*Quercus mongolica*, *Quercus acutissima*, *Quercus serrata*, *Quercus variabilis, Quercus aliena*, *Quercus dentata*) per hectare were calculated to obtain tree density of each sampling plot. And, we compared the time series changes of tree density and topographic factors (elevation, slope, and aspect). Tree density analysis of *Pinus densiflora* and *Quercus* spp. were carried out only on natural forest sampling plots.

RESULTS

In the analysis of area changes of forest types using the time series forest type maps, coniferous forest and mixed forest were reduced overall, but deciduous forests show evident increasing trend. In comparing the data of 1970s and today, the area of coniferous forest has declined 35% and mixed forest 68%. Whereas, deciduous forest has significantly increased from 41,109 ha to 453,596 ha, and the increasing trend is mainly found in Chungcheongbuk-do region (eastern part of study area).

Table 2. Area changes of forest types by year (hectare)

Forest type	1972~1974	1991	2009
Total	884,088	893,712	885,270
Coniferous Forest	493,048	378,930	320,654
Mixed Forest	349,931	246,308	111,020
Deciduous Forest	41,109	268,474	453,596

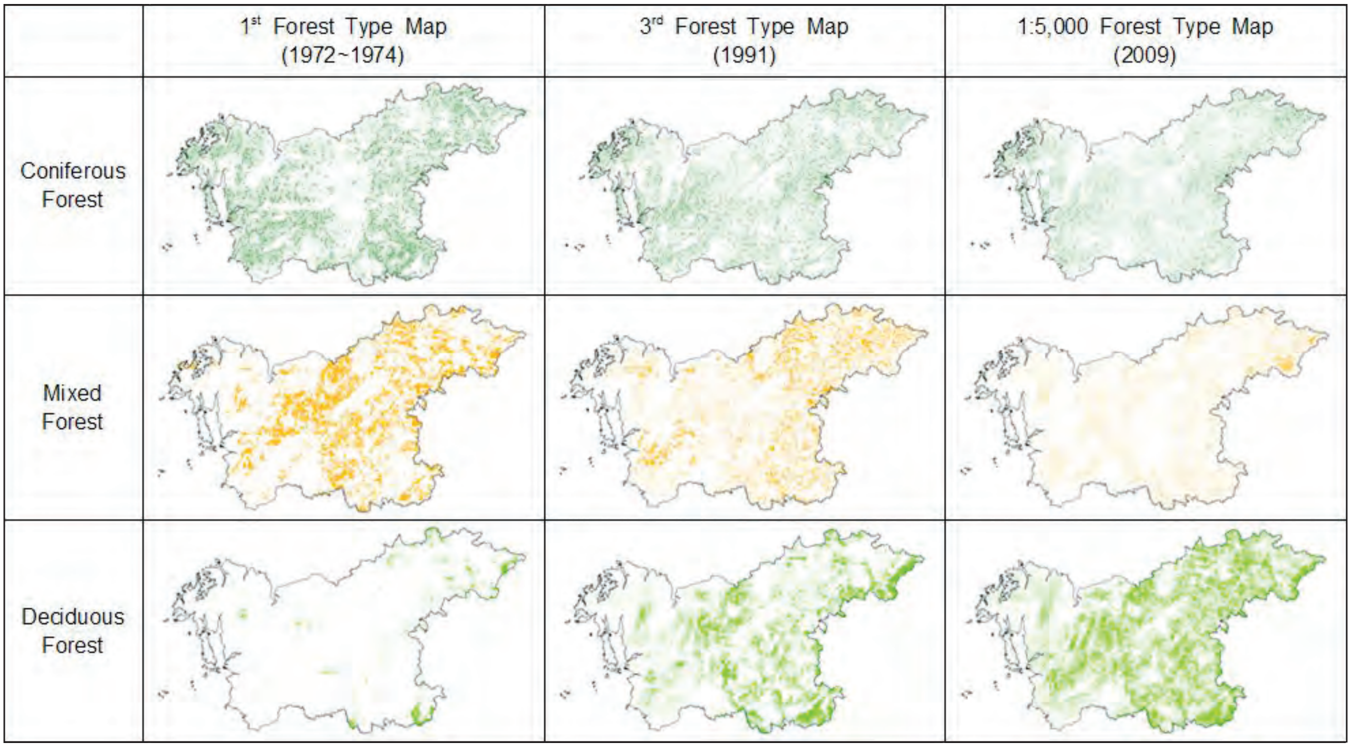

Figure 1—Forest type distribution change based on time series forest type maps

When comparing the natural change of tree density by tree species using the survey data of time series NFI sample plots, density of *Pinus densiflora* has reduced overall and particularly a notable decrease is found in the Chungcheongnam-do (western part of study area) region. Also, the tree density of *Quercus* spp. has rapidly rose entering the fifth NFI, and a significant increase was observed in the mountainous region of Chungcheongbuk-do (eastern part of study area).

The change of tree density appeared differently based on the topographic characteristics. While tree density of *Pinus densiflora* has rapidly decreased in regions with low altitude and gentle slope, tree density of *Quercus* spp. has sharply increased in regions with high altitude and steep slope. As for the tree density of *Pinus densiflora*, the northern slope showed more decreasing trend than southern slope.

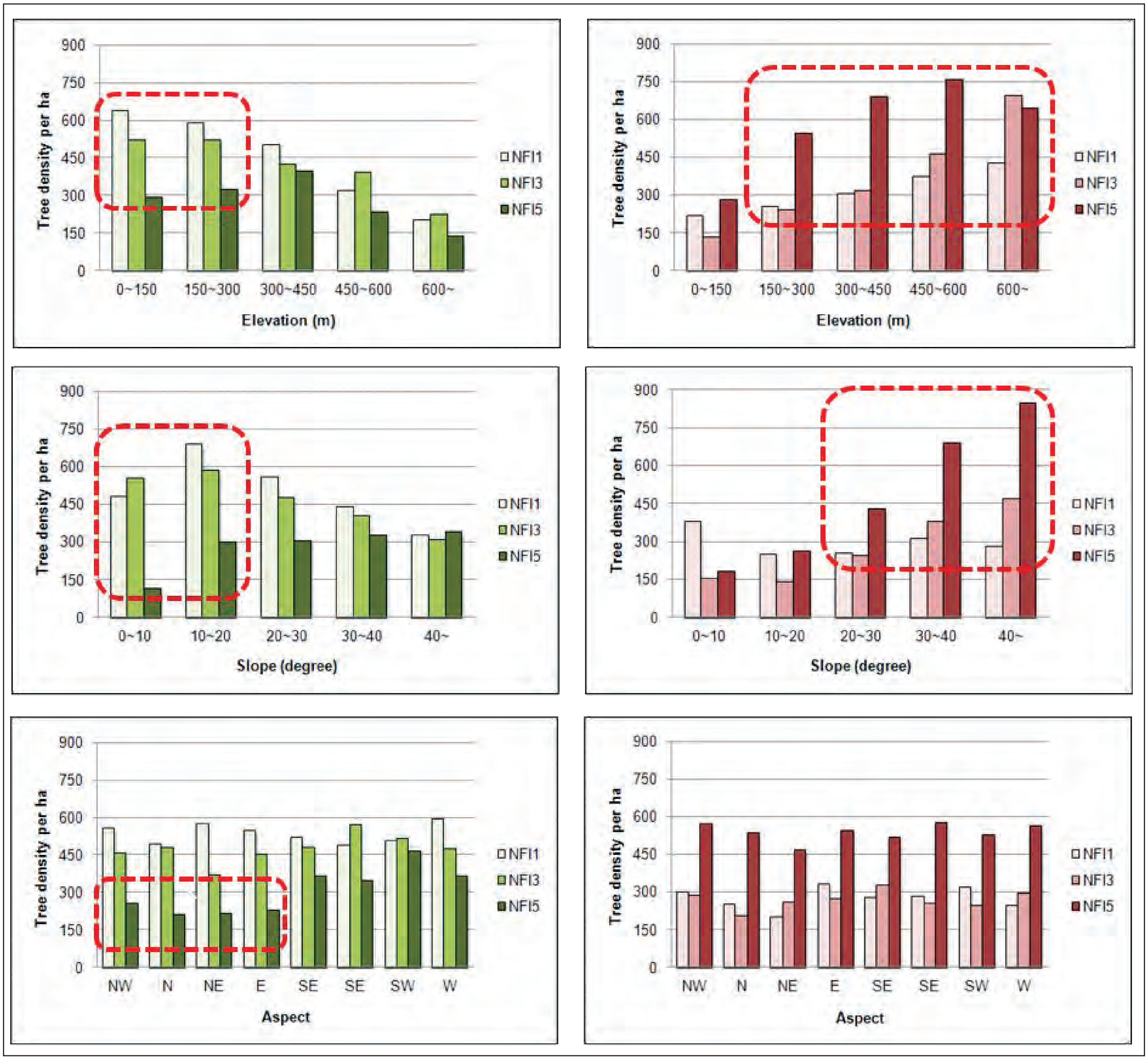

Figure 2—Change analysis in tree density of *Pinus densiflora* and *Quercus* spp. depending on the terrain conditions using time series NFI data

DISCUSSION

In this study, coniferous forest were reduced overall, but deciduous forests showed evident increasing trend. Similarly, tree density of *Pinus densiflora* has reduced and that of *Quercus* spp. has increased. This phenomenon can be understood as the general trends caused by temperature increase of climate change. Tree density of *Pinus densiflora* has rapidly decreased in regions with low altitude and gentle slope and these results shows that optimal habitat region of this species is changing. Also, decline trends of *Pinus densiflora* in northern slope region contained the good moisture conditions is the result of completion between other tree species.

Time series National Forest Inventory data is the most extensive forest survey information in South Korea. We could analyze the long-term changing trend of forest stand based on these data. We have the plans of an intensive analysis for interrelationships of climate change and forest change using NFI data and long-term climate data.

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FOREST INVENTORY AND ANALYSIS PROGRAM IN THE WESTERN U.S. AFFILIATED PACIFIC ISLANDS: PERSPECTIVES FROM WORKING IN ISLAND ECOSYSTEMS AND BUILDING CROSS CULTURAL PARTNERSHIPS

Ashley Lehman[1]

Abstract—The Pacific Northwest (PNW) Research Station's Forest Inventory and Analysis (FIA) program of the USDA Forest Service monitors and reports on the status and trends of the Pacific Island's forest resources and ecosystem services. Since 2001 the FIA program has partnered with State and Private Forestry's, Region 5 and the local governments in the U.S. Affiliated Western Pacific Islands to implement a nationally-standardized plot sampling design on a periodic basis. Permanent monitoring plots are measured on a 10 year periodic cycle across the island nations of American Samoa, Guam, Palau, The Commonwealth of the Northern Mariana Islands, The Federated States of Micronesia and The Republic of the Marshall Islands. To date we are conducting our second measurement of the region and have successfully completed two thirds of the inventory. Forest health changes over 10 years have been drastic on some island ecosystems. Further, collaboration with other agencies, NGO's and other state governments has been a successful approach to build local partnerships and maximize data use. Monitoring efforts are important for local land managers and communities because inventories provide detailed information on forest health issues and provide insights to long term trends in forest change.

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WOODY ENCROACHMENT IN THE CENTRAL UNITED STATES

Greg C. Liknes, Dacia M. Meneguzzo, and Kevin Nimerfro

Abstract—The landscape of the central United States is dominated by cropland and rangeland mixed with remnants of short- and tall-grass prairies that were once prevalent. Since the last ice age, these areas had sparse tree cover due to cyclical severe droughts, intentional fires used by indigenous people as a land management tool, and natural fires caused by lightning. More recently, tree cover is suppressed by tillage or grazing. However, the combination of fire suppression and idling of farmland due to conservation programs and periodic downturns in the agricultural economy allows woody species to take hold where they were historically absent. As a result, woody encroachment is a topic of concern in these primarily nonforest areas. Using data from the Forest Inventory and Analysis program, we examine the expansion of eastern redcedar (*Juniperus virginiana*), as well as several other prevalent woody species, in the central United States. We compare the change over time for these woody species with respect to area, density, volume, and seedling abundance at both county- and state-levels. In addition, we examine the corresponding plot-level tree diversity in the presence and absence of these species over a range of densities. Our analysis shows the expansion is widespread but highly varied across the region in terms of rate, prevalence, and dominant species. Woody species are having an impact on the region's ecosystems and will likely play an increasing role if current trends continue.

NATIONAL REPORT ON SUSTAINABLE FORESTS—2015: CONSERVATION OF BIOLOGICAL DIVERSITY

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Abstract—The National Report on Sustainable Forests—2015 relies on Montréal Process Criteria and Indicators (C&I) for Forest Sustainability to organize and present data relevant to U.S. forests. The 2015 report addresses seven criteria, the first of which is Conservation of Biological Diversity, which is organized into nine indicators that address three sub-criteria: ecosystem diversity, species diversity, and genetic diversity. Selected highlights from the report include the following. Total forest land area increased by 14 million acres since the previous report. Area of timberland increased by 7 million acres, with a 14 million acre increase in large diameter size class and a 7 million acre decrease in medium and small diameter size class. Woodlands (41%) and forest (31%) are more protected than other types of natural vegetation (16%). Between 2001 and 2011, net loss of interior forest was between 7.0 and 20.0 percent, varying with landscape scale. Greatest proportion of numbers of forest bird species with increasing population trends compared to the number of species with decreasing trends occurred in mixed wooded plains of the eastern Great Lakes and scattered valley and plains systems in the West; greatest proportion of species with decreasing trends compared to those with increasing trends occurred in oak forests of the southern Appalachians, pine and northern hardwood forests of the upper Midwest and Great Lakes, and montane and arid high plains systems in the intermountain West.

Between 1966 and 2011, about 19% of forest-associated bird species increased in populations and 20% decreased. Decliners include species associated with early successional or wetland habitats. Some generalist bird species and some that favor dead trees as foraging and nesting substrates have increased. Results for all nine indicators are presented in the poster.

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CONSEQUENCES OF DATA REDUCTION IN THE FIA DATABASE: A CASE STUDY WITH SOUTHERN YELLOW PINE

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ABSTRACT.--The Forest Inventory and Analysis Program strives to make its data publicly available in a format that is easy to use and understand most commonly accessed through online tools such as EVALIDator and Forest Inventory Data Online. This requires a certain amount of data reduction. Using a common data request concerning the resource of southern yellow pine (SYP), we demonstrate how results may vary depending on the particular data reduction approach employed. We used the loblolly-shortleaf pine forest-type group (FTG) and the longleaf-slash pine FTG as surrogates for SYP. The volume of our four target species (loblolly pine, shortleaf pine, slash pine, and longleaf pine) in these two FTGs was 98.2 billion cubic feet, but this was only 84 percent of the total volume for the target species in all FTGs. In addition, many unwanted species were included by using total volume in the two FTGs as a surrogate for SYP.

The Forest Inventory and Analysis (FIA) Database represents measurements made on a large number of sample unit variables. The FIA Program strives to make these data publicly available in a format that is easy to use and understand most commonly accessed through online tools such as EVALIDator and Forest Inventory Data Online (FIDO). This requires a certain amount of data reduction (collapsing data into understandable formats; examples are forest type and species groups). However, users may not be aware of the precise data reduction algorithms in these online tools, and this may result in output that falls short of what the user needed or expected, many times without their knowledge. In addition, the actual query a user wants may not be available, forcing them to use a surrogate that may or may not reflect what is desired. An example of this would be the use of forest type as a surrogate to determine the spatial extent of a species.

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Issues in data reduction also arise from definition confusion. Forestry terms are sometimes informal, vague, or change over time, and this causes problems when applied in a precise manner. For example, the term southern yellow pine (SYP) has evolved over the last 100 years from originally meaning only slow-growing (ring-width restricted) longleaf pine (*Pinus palustris* Mill.) to various combinations of southern pines (USDA Forest Service 1936). Furthermore, formal definitions for commercial lumber are set by the American Society for Testing and Materials and may change in reaction to market conditions. Adding to the confusion is the fact that commercial timber definitions may not coincide with botanical descriptors such as forest type. Therefore, it is important that these definitions are documented for users. Using a common data request concerning the resource of SYP, we demonstrate how results may vary depending on the particular approach used with the data.

METHODS

Our target species for SYP were loblolly pine (*P. taeda* L.), slash pine (*P. elliottii* Engelm.), shortleaf pine (*P. echinata* Mill.), and longleaf pine. Because spatial extent of an individual species is not currently an option in the online tools, we assessed the area and volume of SYP in the 13 Southern States using the loblolly-shortleaf pine forest-type group (FTG) and the longleaf-slash pine FTG as surrogates for SYP. In order to duplicate the choices and selections available to and made by many users of FIA data in FIDO or EVALIDator, we made the following assumptions for this analysis: 1 – some users would accept that all the volume in the two FTGs was SYP volume, and 2 – some users would further filter the results from the two FTGs to only include volume for the target species. The loblolly-shortleaf pine FTG includes the following detailed forest types: loblolly pine, shortleaf pine, Virginia pine, sand pine, Table Mountain pine, pond pine, pitch pine, and spruce pine. The longleaf-slash pine FTG includes the following detailed forest types: longleaf pine and slash pine. Forest type is a classification of forest land based upon and named for the tree species that forms the plurality of live-tree stocking. Forest-type groups are combinations of forest types that share closely associated species or site requirements.

RESULTS AND DISCUSSION

Area and volume for the loblolly-shortleaf pine FTG and the longleaf-slash pine FTG together in the South was 70.4 million acres of forest land, and 115.5 billion cubic feet of volume (regardless of species) (Table 1). Volume per acre for these two FTGs averaged 1,641.6 cubic feet per acre and ranged from a low of 1,152.1 cubic feet per acre in Florida to a high of 2,033.5 cubic feet per acre in Virginia. Georgia, Alabama, and Mississippi ranked as the top three States in the South for both area and volume of the two FTGs combined (Table 1). Rankings changed slightly when the FTGs were considered separately. Florida ranked first for area and volume of the longleaf-slash FTG, the majority of which was accounted for by slash pine. Our target species (loblolly pine, slash pine, shortleaf pine, and longleaf pine) were, not surprisingly, the top four species for volume in the two FTGs. They accounted for 98.2 billion cubic feet (85 percent of the total) (75.6, 11.8, 6.7, and 4.1 billion cubic feet, respectively)

Table 1.—Area and volume of all-live trees in the loblolly-shortleaf pine and the longleaf-slash pine forest-type groups (as surrogates for southern yellow pine) by State and forest-type group, 2012

			Forest-type group			
	Both groups		Longleaf-slash pine		Loblolly-shortleaf pine	
State	Forest land	Volume	Forest land	Volume	Forest land	Volume
	thousand acres	*million cubic feet*	*thousand acres*	*million cubic feet*	*thousand acres*	*million cubic feet*
Alabama	9,639.8	14,496.5	1,055.8	1,593.8	8,584.0	12,902.7
Arkansas	5,668.0	9,902.3	—	—	5,668.0	9,902.3
Florida	7,478.3	8,615.7	5,800.7	6,510.2	1,677.6	2,105.5
Georgia	11,114.9	18,407.8	3,691.8	5,055.5	7,423.1	13,352.3
Kentucky	191.2	320.2	—	—	191.2	320.2
Louisiana	5,927.6	9,580.3	812.7	1,192.9	5,114.9	8,387.4
Mississippi	8,080.6	13,692.6	822.2	1,413.0	7,258.3	12,279.6
North Carolina	5,825.0	10,489.5	323.6	519.4	5,501.4	9,970.1
Oklahoma (east)	1,102.8	1,437.3	—	—	1,102.8	1,437.3
South Carolina	6,067.9	11,184.5	549.7	701.7	5,518.2	10,482.9
Tennessee	973.2	1,546.5	—	—	973.2	1,546.5
Texas (east)	5,350.6	9,849.0	144.2	270.6	5,206.5	9,578.4
Virginia	2,950.2	5,999.2	—	—	2,950.2	5,999.2
All States	70,369.9	115,521.5	13,200.7	17,257.0	57,169.2	98,264.5

— = no value for the cell.

Table 2.—Volume of live trees (≥5.0 inches diameter at breast height; where total volume ≥100.0 million cubic feet) in the loblolly-shortleaf pine and the longleaf-slash pine forest-type groups by species and State, 2012

Species	All States	AL	AR	FL	GA	KY	LA	MS	NC	east OK	SC	TN	east TX	VA
							million cubic feet							
All species	115,521.5	14,496.5	9,902.3	8,615.7	18,407.8	320.2	9,580.3	13,692.6	10,489.5	1,437.3	11,184.5	1,546.5	9,849.0	5,999.2
Loblolly pine	75,565.7	10,593.5	6,278.6	1,123.4	11,008.2	89.1	7,159.4	10,228.6	7,224.3	625.8	8,891.3	829.4	7,329.7	4,184.5
Slash pine	11,769.2	653.4	—	5,075.1	4,133.2	—	658.0	774.3	110.4	—	144.7	—	220.3	—
Shortleaf pine	6,715.8	440.7	2,601.3	24.1	383.3	16.7	272.3	585.5	276.8	656.6	146.5	147.2	1,034.3	130.7
Longleaf pine	4,135.5	743.8	—	909.1	543.2	—	453.5	444.9	445.0	—	548.2	—	47.7	—
Sweetgum	2,882.4	407.4	231.0	30.7	424.7	6.0	276.2	356.5	350.4	8.2	286.3	30.0	322.7	152.3
Virginia pine	2,338.5	330.5	—	—	291.0	108.5	—	0.2	547.4	—	169.2	245.7	—	646.2
Water oak	1,333.1	219.2	41.3	73.4	268.6	—	142.7	174.3	68.2	3.2	168.6	—	166.4	7.2
Yellow-poplar	1,127.4	193.1	—	3.3	187.6	23.9	7.2	141.3	222.0	—	79.2	47.1	—	222.7
Southern red oak	881.8	111.3	74.8	9.1	114.1	1.4	127.0	140.1	45.1	3.8	49.2	23.5	127.6	54.7
White oak	867.7	81.9	201.7	—	86.3	10.8	73.5	106.4	76.5	19.4	55.5	26.1	59.9	69.5
Red maple	742.2	71.5	30.1	15.5	110.8	6.1	30.1	47.7	202.4	3.0	69.3	27.0	21.4	107.3
Pond pine	730.5	—	—	86.2	94.2	—	—	—	432.6	—	114.9	—	—	2.6
Sand pine	726.1	—	—	719.1	7.0	—	—	—	—	—	—	—	—	—
Post oak	586.1	51.8	101.3	1.2	33.8	0.7	67.7	79.3	22.2	65.9	25.2	8.1	120.1	8.9
Blackgum	420.7	51.4	38.2	13.2	43.0	0.7	56.6	87.1	17.5	3.4	32.2	5.8	56.7	15.1
Eastern redcedar	307.1	36.0	36.7	5.0	31.4	9.7	3.2	25.6	30.1	5.8	48.0	23.2	16.3	36.1
Laurel oak	305.9	55.8	0.4	87.4	73.5	—	4.6	21.6	9.0	—	33.7	—	19.6	0.5
Winged elm	263.0	23.5	32.5	1.0	38.9	0.6	19.2	35.6	9.6	5.2	30.8	4.9	57.2	4.0
Black cherry	260.9	37.3	17.3	14.4	44.3	3.7	16.0	42.7	26.7	0.2	26.5	8.3	5.5	18.0
Swamp tupelo	209.6	12.8	—	48.8	82.1	—	1.2	12.4	12.2	—	38.9	—	—	1.0
Willow oak	204.9	13.2	20.6	0.5	16.1	—	15.2	30.0	17.4	0.2	32.7	0.5	26.3	32.2
Cherrybark oak	202.0	15.4	21.4	0.2	2.1	0.1	33.0	31.5	12.6	—	22.3	0.2	59.6	3.7
Mockernut hickory	174.8	23.9	20.1	1.9	19.5	1.6	18.8	19.9	12.6	5.5	21.5	8.3	12.8	8.3
Sweetbay	173.4	33.6	6.2	50.2	10.5	—	9.6	52.5	3.2	—	0.5	—	6.5	0.6
Spruce pine	159.3	36.6	—	34.0	17.4	—	28.2	41.7	—	—	1.5	—	—	—
Pond cypress	131.6	1.0	—	68.7	52.8	—	2.3	3.9	0.2	—	2.8	—	—	—
Loblolly bay	122.1	—	—	37.9	22.3	—	—	—	56.0	—	5.9	—	—	—
Scarlet oak	118.2	13.8	—	—	23.0	0.1	—	2.0	22.1	—	9.8	16.3	—	31.1
Northern red oak	113.9	10.6	41.6	—	11.0	0.4	—	5.7	16.4	10.8	5.6	0.5	—	11.2
Pitch pine	111.5	—	—	—	8.6	19.6	—	—	36.5	—	0.1	3.4	—	43.3
Live oak	111.2	3.9	—	61.5	31.9	—	1.4	2.4	0.7	—	9.3	—	0.1	—
Pignut hickory	109.5	26.1	0.2	0.9	27.9	3.3	2.0	13.8	10.5	0.1	6.6	10.2	0.3	7.7
Black oak	106.5	13.7	18.2	—	7.0	—	4.3	7.0	11.1	3.2	6.2	6.3	1.5	28.0
Sourwood	104.8	18.9	—	—	23.3	1.2	0.8	16.9	21.7	—	5.7	6.0	—	10.4

— = no value for the cell.

of the volume in the two FTGs (Table 2). Mostly nonpine species accounted for the remaining volume, especially sweetgum (*Liquidambar styraciflua* L.) and water oak (*Quercus nigra* L.). There were a total of 130 species (not including unknowns) tallied in these two FTGs across the South. Virginia pine (*P. virginiana* Mill.) accounted for a significant percentage of the volume in the two FTGs in southeastern States like Tennessee, Virginia, North Carolina, and Kentucky. In addition, using the total volume in the two FTGs as a surrogate for SYP overestimated the volume of the four target species in several States and underestimated it in other States (compare totals in Table 1 to totals in Table 3). Kentucky had the highest percentage overestimate. Volume of SYP in Kentucky was estimated at 320.2 million cubic feet (Table 1) using the FTG method. However, the actual total volume of the four target species, regardless of FTG, was only 215.3 million cubic feet in that State (Table 3). This is primarily due to the amount of Virginia pine and yellow-poplar included in the FTGs.

While the four target species accounted for 85 percent of the volume in these two FTGs, this was only 84 percent of the total volume for these four species in the South (Table 3). So, while using the two FTGs as a surrogate for SYP resulted in the inclusion of unwanted species, it also resulted in the exclusion of 16 percent of the total volume for the species of interest. And in States like Kentucky, Tennessee, and east Oklahoma, a significant percentage of the volume of loblolly and shortleaf pine (no slash or longleaf pine were recorded in these States) was excluded (51, 30, and 25 percent, respectively) by using the FTG method. This is most likely due to these species occurring in mixed oak-pine stands.

While we recognize that for the Southern States as a whole the estimate of SYP volume using the FTG method was very close to the actual volume for the four species of interest regardless of FTG (115.5 (estimated) – Table 1 versus 116.5 (actual) billion cubic feet – Table 3) this does not take into account the inaccuracies at the State level, especially for States like Kentucky. In addition, while total volume

Table 3.—Actual volume of loblolly pine, shortleaf pine, slash pine, and longleaf pine by State and forest-type group, 2012

State	All groups	Forest-type group		
		Longleaf-slash pine	Loblolly-shortleaf pine	All other groups
		million cubic feet		
Alabama	15,082.2	1,375.5	11,055.9	2,650.8
Arkansas	10,881.4	—	8,879.8	2,001.5
Florida	8,514.2	5,981.2	1,150.5	1,382.5
Georgia	18,761.8	4,650.6	11,417.2	2,694.0
Kentucky	215.3	—	105.7	109.6
Louisiana	9,767.9	1,132.4	7,410.7	1,224.8
Mississippi	13,968.6	1,206.6	10,826.7	1,935.2
North Carolina	9,704.8	493.8	7,562.7	1,648.3
Oklahoma (east)	1,719.9	—	1,282.4	437.5
South Carolina	11,319.3	635.7	9,094.9	1,588.6
Tennessee	1,400.7	—	976.7	424.0
Texas (east)	9,862.6	247.7	8,384.3	1,230.6
Virginia	5,265.9	—	4,315.2	950.8
All States	116,464.6	15,723.5	82,462.8	18,278.4

— = no value for the cell.

may not be terribly overestimated or underestimated using this method in many States, other analyses may be significantly (and negatively) affected. For example, including a large amount of Virginia pine in an analysis of SYP may negatively impact growth and removal estimates or detailed diameter-class analyses.

One option for a slightly more accurate assessment of SYP using online tools would be to use detailed forest types rather than FTGs. This would (hopefully) eliminate some of the unwanted species (like Virginia pine). Further analyses into this issue will include an examination of the actual spatial extent of the four target species. This is accomplished through the creation of a specialized pseudoforest type by the user (in a programming language like Oracle) based upon the user's specifications, as well as by an investigation of the effect of including unwanted species on the resulting detailed analysis of SYP in the South.

The most accurate assessment would be for the user to select the species to include in what they perceive as the SYP group. However, current capacity of the online tools often eliminates that prospect because an estimate of forest area is usually needed along with volume. This often forces the user to rely on the SYP volume in the loblolly-shortleaf and longleaf-slash pine FTGs. Users need to be aware of the intricacies that exist and the inaccuracies introduced when forest type (or FTG) is used as a surrogate for species. The FIA Program needs to clearly document the definitions of the tool algorithms and encourage increased flexibility in online capabilities so users can accurately retrieve the information they need.

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MODELING ASPEN COVER TYPE DIAMETER DISTRIBUTIONS IN MINNESOTA

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Abstract—An attempt was made to model diameter distributions of aspen (*Populus* spp) stands. The aspen (1,020,150 acres) cover type has the greatest acreage on DNR lands and it contains a variety of hardwood and softwood species. Aspen is a valuable pulpwood species, annually comprising around 50 percent of total timber harvest on DNR lands.

Modeling distributions of this cover type has been minimal; stands often contain a variety of tree sizes and species, making modeling difficult, particularly given a disproportionate amount of smaller trees. For this analysis, a three-parameter Weibull-based modeling approach was used, where the parameters are predicted using the 0, 25th, 50th, and 95th estimated percentiles of the distribution. The percentiles are predicted as functions of quadratic mean diameter and stand/plot age. Currently, species compositions were ignored.

Data used in model fitting were obtained from the Forest Inventory and Analysis (FIA) database and from all regions of the state.

Prediction errors are rather large for smaller diameter classes and onset of merchantability (e.g. 4 to 6 inches). When looking at the average error across all diameter classes at a particular site, each diameter class within a site had an average error of 20 trees per acre (smaller diameters generally had larger absolute tree per acre errors).

For common merchantable rotations (e.g. 40 to 50 years), total errors (total across all diameter classes) are less relative to younger and older ages. However, for diameter classes of most interest (6 to 12 inches), prediction errors are generally larger for these rotation ages relative to younger stands.

INTRODUCTION

As part of a project determining optimal economic rotation ages of aspen (*Populus* spp) cover types on Minnesota DNR lands for harvest scheduling analyses, it was attempted to model diameter distributions of these stands. By far the aspen (1,020,150 acres) cover type has the greatest acreage on DNR lands. Although some stands are dominated by aspen, a variety of species can be found including ash (*Fraxinus* spp), balsam poplar (*Populus balsamifera* L), birch (*Betula* spp), elm (*Ulmus* spp), maple (*Acer* spp), oak (*Quercus* spp), balsam fir (*Abies balsamea* (L.) Mill.), pine (*Pinus* spp), and spruce (*Picea* spp). Aspen is a valuable pulpwood species, recently averaging around $30 per cord, and in 2012 it comprised 63 percent of the pulpwood harvest and 50 percent of the total timber harvest.

Knowing the likely diameter distribution within a stand can provide more precise economic assessments since stumpage values are often related to diameter class. For example, the pulpwood and bolt class which usually occurs for d.b.h.s ranging from 8 to 11 inches, generally results in higher stumpage relative to merchandizing trees as pulpwood only (e.g. 8 inches and less), stumpage values can increase by nearly 60 percent. Currently, species compositions were ignored, but if

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future analyses are conducted they should concentrate on developing separate distributions by species.

Modeling distributions of this cover type has been minimal; stands often contain a variety of tree sizes and species, making modeling difficult, particularly given a disproportionate amount of smaller trees. Previous modeling has concentrated on estimating either total stand yields or has used an individual tree approach. For this analysis, a three-parameter Weibull-based modeling approach was used, where the parameters are predicted using the 0, 25th, 50th, and 95th estimated percentiles of the diameter distribution. The percentiles are predicted as functions of quadratic mean diameter and stand/plot age.

METHODS

Data used in model fitting were obtained from the Forest Inventory and Analysis (FIA) database. Survey data were obtained from all regions of the state, only plots measured from 2003 to 2007 (EVAL_GRP = 272007), and 2008 to 2012 (EVAL_GRP = 272012) were used (FORTYPCD = 901), and all four subplots within a plot had to have the same condition class. Since only a point in time distribution estimate is desired, temporal correlation when using data from the same plot was ignored.

Plots are clusters of four points arranged such that point 1 is central, with points 2 through 4 located 120 feet from point 1 at azimuths of 0, 120, and 240 degrees. Each cluster point is surrounded by a 24.0 foot fixed-radius subplot where trees 5.0 inches d.b.h. and larger are measured. Combined, the four subplots total approximately 1/6th acre. Each subplot contains a 6.8 foot fixed-radius microplot where saplings 1.0 to 4.9 inches are measured. The four microplots total approximately 1/75th acre. Blow-up factors associated with these different plot sizes could impact modeling ability. Condition classes are assigned to differentiate conditions occurring on a plot, a subplot can have more than one condition class. A condition class differentiates stand conditions given variables that FIA monitors, such as cover type, ownership, and stand density.

A percentile-based, parameter recovery, three-parameter Weibull distribution procedure was used to model diameter distributions (Brooks and others 1992). Due to correlation among residuals of the equations, parameters were estimated using seemingly unrelated regression (SUR). The following system of equations was estimated:

$$\text{Min}(D0) = a + b * Dq + c * Age \quad [1]$$
$$D25 = d + e * Dq \quad [2]$$
$$D50 = g + h * Dq + i * Age \quad [3]$$
$$D95 = j + k * Dq + l * Age \quad [4]$$

Where:

Min (D0) – minimum d.b.h. (inches) within a plot,
Di – predicted value for the d.b.h. (inches) at which the ith percentile occurs,
Dq – quadratic mean diameter (inches), and
Age – stand age.
The percentiles were then used to estimate parameters of the Weibull distribution:

$$a\ (\text{Location}) = (n^{1/3}D0 - D50)/(n^{1/3} - 1) \quad [5]$$
$$c\ (\text{Shape}) = 2.343088/(\ln(D95-a)-\ln(D25-a)) \quad [6]$$
$$b\ (\text{Scale}) = -(a\Gamma\_1)/\Gamma\_2 + \sqrt{((a/\Gamma\_2)2(\Gamma\_12-\Gamma\_2) + Dq2/\Gamma\_2)} \quad [7]$$

Where:

$\Gamma\_1 = \Gamma[1+(1/c)]$,
$\Gamma\_2 = \Gamma[1+(2/c)]$, and
Γ = gamma function.

For the observations used to fit equations [1] to [4], the average age of plots was 39 ranging from 0 to 116 years, trees per acre ranged from 6 to 4,585 and averaged 1,039, basal area per acre averaged 76 ranging from 0.4 to 234 square feet, quadratic mean diameter ranged from 1.0 to 13.1 inches and averaged 4.4 inches, and site index (base age 50) averaged 63 feet and ranged from 2 to 112 feet.

RESULTS AND DISCUSSION

Parameter estimates for equations [1] to [4] are presented in Table 1. Perhaps future analyses can attempt to separate species.

Table 1.—Parameter estimates for equations [1] to [4]. Sample size was 1,876 plots.

Aspen	Intercept	Dq	Age
D0	0.328	0.472	-0.021
D25	-0.190	0.910	-
D50	0.238	0.911	0.029
D95	3.604	0.874	0.080

Table 2 presents verification results by diameter class. For all FIA plots used in model fitting, number of trees were predicted by diameter class using the Weibull distribution, the difference from the FIA observed was calculated, squared (to eliminate negative and positive errors), square rooted to produce the original units (trees per acre), and then averaged. Analyzing prediction errors by diameter class will help to identify if errors are greater at certain ranges of diameter classes – for example, perhaps the Weibull distribution is not flexible enough to model Aspen distributions across the entire range of stand conditions.

Prediction errors are rather large for smaller diameter classes and near the beginning of merchantability (e.g. 4 to 6 inches). Figure 1 shows in some cases there is an inability to model smaller diameter classes of merchantable rotation age Aspen stands – all plots have a site index of 65 feet. For distributions depicted in the figure plot ages ranged from 37 to 47 years.

Table 2.—Verification results for equations [1] to [4] by diameter class. Number of plots was 1,864. The number of plots is less relative to model fitting because some plots had too few trees to estimate Weibull parameters.

Diameter class (inches)	Error in Trees Per Acre
1	143.3
2	127.4
3	93.0
4	76.4
5	51.9
6	29.6
7	19.2
8	12.3
9	8.5
10	6.3
11	5.0
12	3.8
13	3.1
14	2.4
15	1.8
16	1.2
17	0.7
18	0.5
19	0.4
20	0.2
21	0.1
22	0.1
23	0.0
24	0.1
25	0.0
26	0.0
27	0.0
28	0.0
29	0.0
30	0.0

When looking at the average error across all diameter classes at an individual site, each diameter class within a site had an average error of 20 trees per acre (smaller diameters generally had larger absolute tree per acre errors). Average error across all diameter classes within a site was 585 (ranging from 13 to 3,379 trees per acre) – hence on average 585 trees were placed into the wrong diameter class at each site.

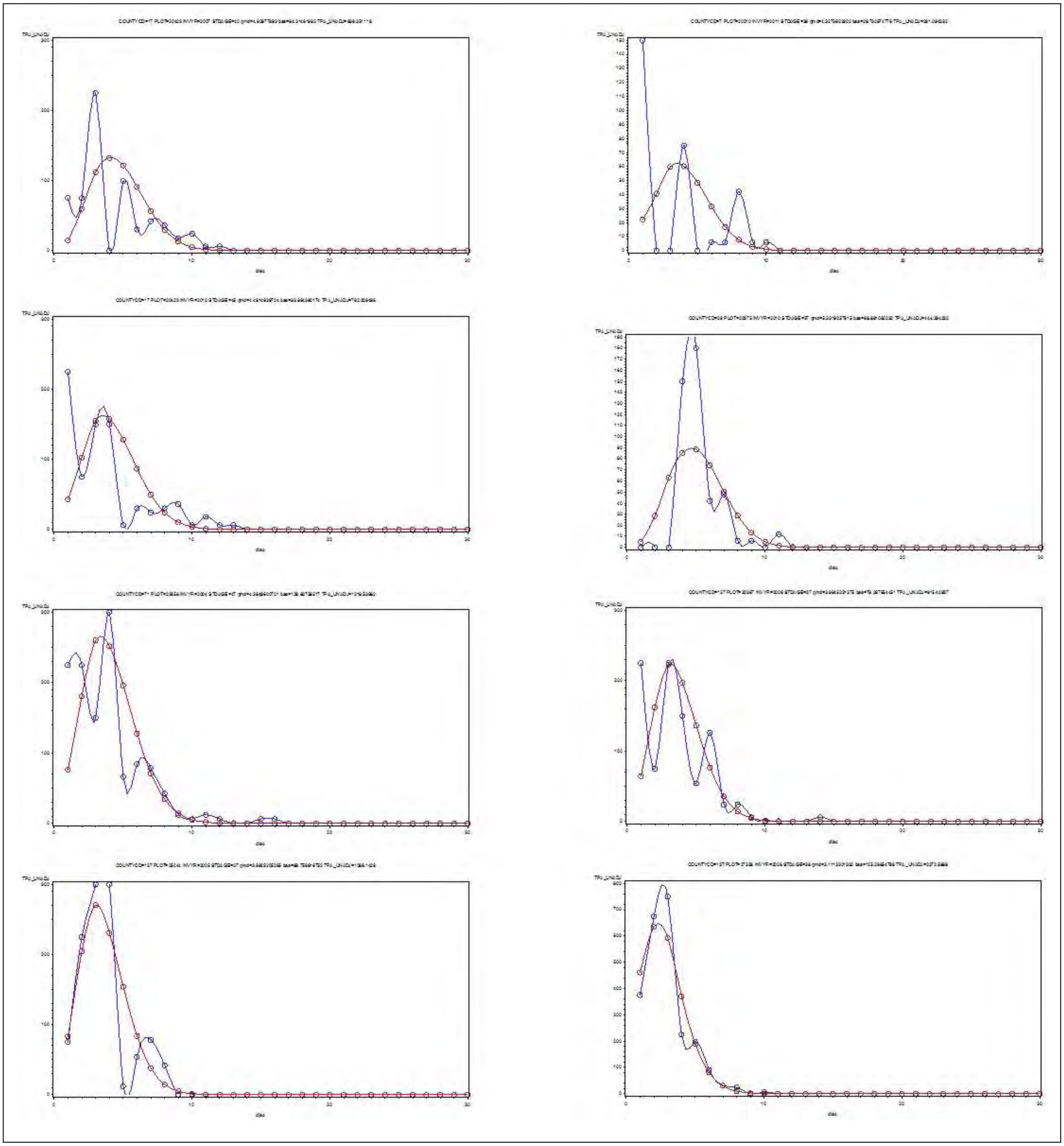

Figure 1—Observed Aspen forest type (FORTYPCD = 901) diameter distributions (from FIA – blue line) and those predicted using equations [1] to [4] for the Weibull distribution (red line), all plots have a site index (base age 50) of 65 feet, and range in age from 37 to 47 years.

Based on Table 2, it would be expected that younger stands, because of a larger number of smaller trees, would have larger prediction errors. To see if prediction errors varied by age, stands were separated into 10 year age-classes, and greater than 50 years old (Table 3). For common merchantable rotation ages (e.g. 40 to 50 years), total errors are less relative to younger and older ages. However, for diameter classes of most interest (6 to 12 inches), prediction errors are generally larger for these rotation ages relative to younger stands – absolute errors are based on number of trees per acre within a diameter class, since these ages have more trees in this range relative to younger ages, absolute errors are greater – hence absolute errors are likely a function of trees per acre (which is likely correlated with age, yes); but not directly related to age.

Table 3—Verification results for equations [1] to [4] by age-class and diameter class. Where n is number of plots within an age group.

	Age Group					
Diameter class (inches)	< 10.1	> 10 and < 20.1	> 20 and < 30.1	> 30 and < 40.1	> 40 and < 50.1	> 50.1
1	200.4	222.4	148.1	96.3	98.7	117.7
2	153.9	219.2	128.5	88.7	86.8	102.7
3	92.0	139.8	130.0	86.8	65.1	68.0
4	41.5	83.5	99.8	86.8	72.3	73.0
5	18.5	38.4	56.5	62.1	56.1	62.7
6	8.4	11.4	23.5	27.4	36.0	46.4
7	5.3	5.5	12.7	16.6	22.4	32.9
8	3.8	4.2	7.4	12.6	14.2	20.4
9	2.4	3.0	4.5	7.6	11.3	14.0
10	1.9	2.0	2.7	5.2	9.2	10.6
11	1.3	1.5	2.4	3.6	6.9	8.7
12	0.6	0.9	1.2	2.5	5.0	7.2
13	0.8	0.5	0.9	1.4	4.3	6.2
14	0.3	0.3	0.7	1.3	2.6	5.1
15	0.4	0.2	0.5	0.8	1.9	3.9
16	0.2	0.2	0.2	0.4	1.1	2.8
17	0.2	0.1	0.1	0.3	0.8	1.4
18	0.1	0.1	0.0	0.1	0.4	1.2
19	0.1	0.1	0.1	0.1	0.3	0.8
20	0.0	0.0	0.0	0.1	0.2	0.4
21	0.0	0.0	0.0	0.0	0.1	0.2
22	0.0	0.0	0.0	0.1	0.1	0.2
23	0.0	0.0	0.0	0.0	0.0	0.1
24	0.0	0.0	0.0	0.0	0.0	0.1
25	0.0	0.0	0.0	0.0	0.0	0.1
26	0.0	0.0	0.0	0.0	0.0	0.0
27	0.0	0.0	0.0	0.0	0.0	0.0
28	0.0	0.0	0.0	0.0	0.0	0.0
29	0.0	0.0	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0	0.0	0.0
N	215	304	258	226	225	636

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ALTERNATIVES TO ESTIMATE STATEWIDE CHANGES IN ASPEN COVER TYPE VOLUMES

Curtis L. VanderSchaaf[1]

Abstract—For Minnesota, the only data available to conduct regional or state-wide level assessments across all ownerships is the Forest Inventory and Analysis Program (FIA). Some of the many alternatives available to estimate regional changes in standing volume are referred to here as 1.) FIA alternative, 2.) a commonly applied growth and yield system referred to as Walters and Ek, 3.) a calibrated Walters and Ek alternative, 4.) a different calibrated Walters and Ek alternative, and 5.) Forest Vegetation Simulator (FVS) estimates. The purpose of this study is to quantify the ability of these alternatives to estimate standing merchantable volume five years into the future of unmanaged aspen cover/forest types, particularly to see whether FVS provides reliable estimates. Aspen forests are by far the dominant cover type in the state.

FIA data from 1999 and 2004 were used to calibrate models, and in some cases to project data. Projections were compared to 2009 plot data, considered to be the true values.

If large-scale, strategic, short term projections are needed, the FIA alternative (1) or the Walters and Ek Alternative Two (4) will be superior. However, for long-term planning, the FVS (5) or either the uncalibrated Walters and Ek alternative (2) or, if calibration can be easily calculated, Alternative One (3) will likely be best.

INTRODUCTION

Regional growth rate estimates are important for many natural resource analyses including silvicultural assessment, harvest scheduling, and resource planning. For Minnesota, the only statewide data available to conduct regional or statewide level assessments across all ownerships is the Forest Inventory and Analysis Program (FIA).

Of the 15.9 million acres of timberland within Minnesota, 4.8 million (or 30%) is classified as aspen forest type. Total cubic foot volume on aspen forest types of trees greater in diameter than 5 inches is estimated to be 4.3 billion (around 55 million cords), or 25% of the 17.2 billion cubic feet of volume on Minnesota timberland. Aspen volume occurs throughout the state, most heavily concentrated in northcentral and northeastern Minnesota.

Several alternatives exist to estimate regional changes in standing volume, some based more on the subject data than others. The purpose of this study is to quantify the ability of different alternatives to estimate standing merchantable volume five years into the future of unmanaged aspen cover/forest types.

METHODS

Data used in model development were obtained statewide from USDA FIA annual surveys completed between 1999 and 2009. Due to time, only the plots remeasured during 2009 were analyzed in this study (hence, an initial measurement, a second measurement, and then a third measurement in 2009).

For comparison purposes, the dependent variable is the volume of trees of d.b.h. 5.0 inches and greater from a 1-foot stump to a 4-inch top d.o.b. (essentially trees merchantable for pulpwood, sawtimber, veneer, etc.).

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Within FIADB, the variables VOLCFNET and TPA_UNADJ are used to estimate individual tree volume on a plot.

Estimate of Volume Five Years Into the Future

For this study, the true or known volume for a particular plot (i) is assumed to be the observed standing volume in 2009 obtained from FIADB, further referred to as [VT09i]. In a way, each individual FIA plot can be assumed to provide a statewide estimate of change in aspen volume.

Estimation Alternatives

A few of the more practical alternatives to estimate changes in the aspen forest type resource are compared in this paper.

FIA Alternative

An estimate of the standing volume for the plots measured in 2009 can be obtained by adding the change in standing volume for a FIA plot from 1999 to 2004 to the 2004 FIA plot volume.

[VFIA09i] = [VT04i] + ([VT04i] – [VT99i]) [1]

Where:

[VFIA09i] -- is the estimate of volume for plot i in 2009 using this alternative,

[VT04i] -- is the observed volume obtained from FIADB for a particular plot in 2004, and

[VT99i] -- is the observed volume from FIADB for a particular plot in 1999.

Walters and Ek (1993)

Walters and Ek (1993) presented plot level equations to predict cover type yield (merchantable volume) using FIA data from the 1977-1978 Minnesota survey (plots actually measured from 1974 to 1980). For this alternative, site index is an external variable obtained from the 2004 FIA plot measurement – site index is assumed to be the same in 2009 as the value from 2004.

The estimate of standing volume for this alternative is further referred to as [VW09i].

Walters and Ek (1993) Alternative One

A second approach using the Walters and Ek models was examined (Alan Ek, 2012, personal communication 02/05/2012). A calibration approach included taking the ratio between the observed 2004 FIA volume for a plot and an estimate using Walters and Ek for 2004, and then multiplying this ratio times the Walters and Ek estimate for 2009.

Estimates of merchantable volume in 2004 (V2004m) and 2009 (V2009m) were obtained using the model system presented in Walters and Ek (1993).

This alternative is obtained using the following ratio:

[VWOne09i] = [V2009m] ([VT04i] / [V2004m]) [2]

Walters and Ek (1993) Alternative Two

A third approach using Walters and Ek (1993) involves estimating volumes for both 2004 and 2009 using their models, calculating the difference, and then adding this difference to the 2004 observed FIA data (Alan Ek, 2012, personal communication 02/05/2012):

[VWTwo09i] = [VT04i] + ([V2009m] – [V2004m]) [3]

Forest Vegetation Simulator (FVS)

The Forest Vegetation Simulator (FVS) is an individual tree based, distance independent growth and yield model fit in large part to individual tree growth data. The FVS variant used in this analysis is referred to as the Lake States variant (Dixon and Keyser 2013). Within FVS, to be as consistent as possible with the definition of volume used by FIA, the minimum merchantable d.b.h. was set to 5 inches, and the stump height was maintained at 1 foot. The form class was maintained at the default value of 80 and the National Volume Estimator library equations were used.

The estimate of standing volume for this alternative is further referred to as [VF09i].

Statistical Measures of Estimation

Since estimates are obtained on a plot by plot basis, estimates of variance and bias can be obtained and used to obtain an estimate of Mean Square Error (MSE):

$$[VErrorki] = [VT09i] – [Vk09i] \quad [4]$$

Where:

[VErrorki]--is the difference between the true standing volume in 2009 of plot i obtained from FIADB [VT09i] and its estimated value for 2009 using one of the five alternatives (k), and

[Vk09i] -- is the estimate of standing volume in 2009 using one of the five alternatives for a particular plot.

Using values from equation [4], estimates of bias (average error), variance, and MSE for the five alternatives (k) were obtained using the following formulas:

$$[\text{Bias}k] = \sum_{i=1}^{n} V_{\text{Error}ki}/n \quad [5]$$

$$[\text{Variance}k] = \left[\sum_{i=1}^{n} (V_{\text{Error}ki} - \text{Bias}_k)^2\right]/(n-1) \quad [6]$$

$$[\text{MSE}k] = [\text{Bias}k^2] + [\text{Variance}k] \quad [7]$$

Where:

n -- number of plots (n = 56).

Plot Removal

Due to a variety of reasons, plots were excluded from the analysis. Plots/subplots that had any type of disturbance from 1999 to 2004 or from 2004 to 2009 were removed (e.g. harvesting [REMVCFAL > 0 for any tree in the plot], beaver/deer/disease/insect/wind damage, etc. – DSTRBCD and TRTCD). Plots were also removed if in 2004 or 2009 their cover/forest types changed from aspen. Some plots were actually measured during 2003 (even though the nominal year was 2004), for simplicity, these plots were removed from the analysis because FVS first estimated volume for 2003 to 2004, and then estimated volume from 2004 to 2009 – hence an extra year of estimation was included for the FVS alternative. Additionally, within FVS, for a particular FIA plot, those condition classes not classified as an aspen forest type were grouped with the condition classes defined to be an aspen forest type – thus, these plots were removed as well.

After plot removal, a total of 56 plots were included in the analysis (Table 1).

Table 1.--Summary statistics of the 56 aspen forest type plots included in the analysis across the three inventory years (1999, 2004, and 2009). Mean is defined as net volume of wood in the central stem of trees 5.0 inches in diameter or larger, from a 1-foot stump to a minimum 4-inch top d.o.b. (VOLCFNET within FIADB).

Species Group	Number of FIA plots	Mean (cubic feet/acre)	Std Dev
Aspen (bigtooth and quaking)	56	767	738
Other hardwoods		220	264
Conifers		186	316

RESULTS AND DISCUSSION

Excluding the calibration approaches, the FIA alternative had the best statistical properties (Table 2 and Figure 1). The Walters and Ek (1993) alternative produced the largest Mean Square Error, but less bias than the FVS Alternative. Of the three basic approaches, it is not surprising that the FIA alternative produced the best results. The 2009 estimate is highly correlated with the 1999 and 2004 estimates, thus highly correlated with the growth rate used from 2004 to 2009.

Although independent data was used to fit the FVS models (e.g. mortality, height, volume, etc.), actual plot data from 2004 was used to, in a sense, calibrate the FVS model for that individual plot. Obviously, the 2009 FVS estimate is correlated with the 2004 FIA estimate because tree data from 2004 is used to project forward to 2009, despite the use of independent tree growth equations within FVS.

Table 2—Bias, Variance, and Mean Square Error (MSE) estimates for the five alternatives.

Alternative	Number of FIA plots	Bias	Variance	MSE
FIA	56	15	121,850	122,071
FVS		-185	142,951	177,302
Walters and Ek (1993)		-151	459,298	482,122
Walters and Ek Cali One		6	128,528	128,561
Walters and Ek Cali Two		-7	73,316	73,366

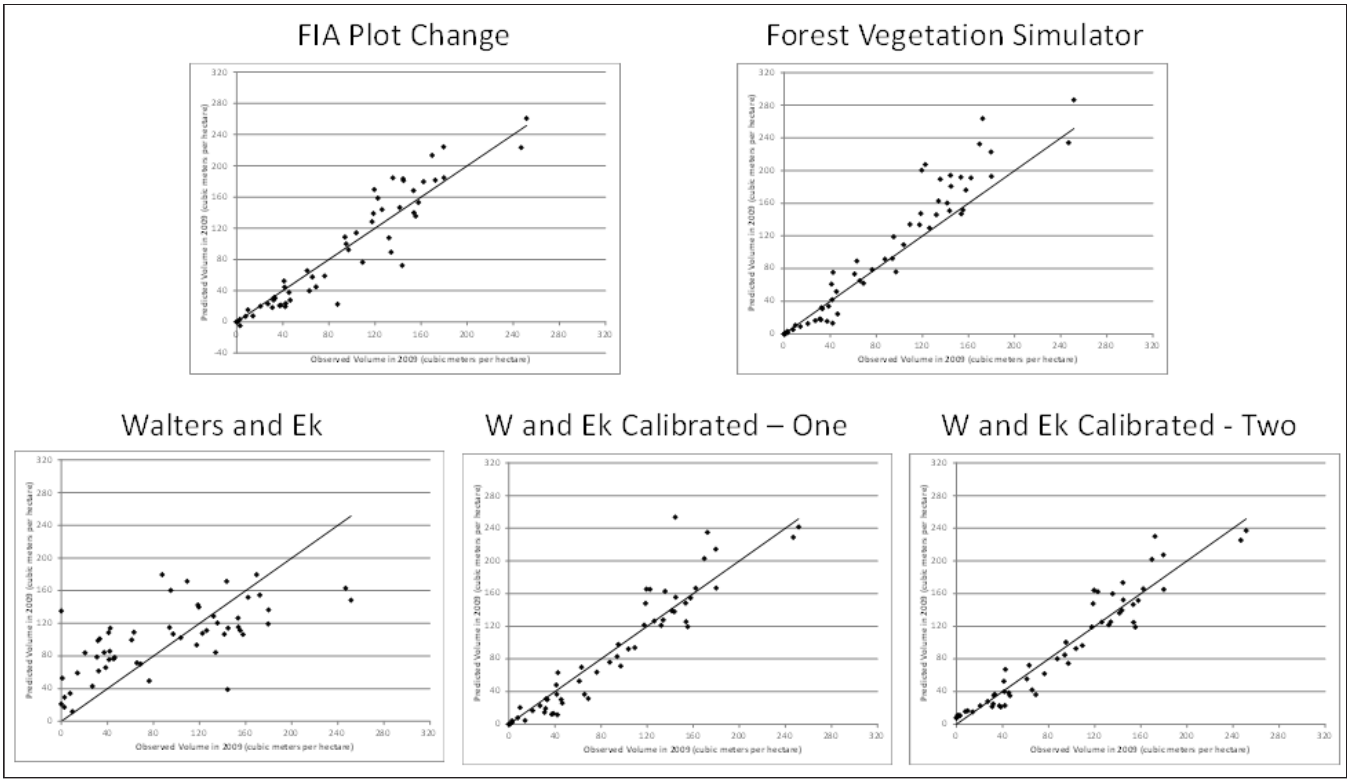

Figure 1—Predicted versus observed total volume (cubic meters per ha - VOLCFNET) in 2009 for the five alternatives. The black line is observed versus observed volume. n = 56 plots.

The Walters and Ek (1993) alternative produced the most variable results. This is most likely due to low correlations between the equations presented in Walters and Ek and the 2004 and 2009 FIA data. The calibration of the Walters and Ek model approaches produced substantial improvements.

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COMPETITION ALTERS TREE GROWTH RESPONSES TO CLIMATE AT INDIVIDUAL AND STAND SCALES

Kevin R. Ford[1], Ian K. Breckheimer[2], Jerry F. Franklin[3], James A. Freund[3], Steve J. Kroiss[2], Andrew J. Larson[4], Elinore J. Theobald[2], Janneke HilleRisLambers[2]

Abstract—Understanding how climate affects tree growth is essential for assessing climate change impacts on forests, but is complicated by the effects of competition, which strongly influences growth and could alter how forests respond to climate change. We characterized the joint effects of climate and competition on diameter growth in the mountain forests of Mount Rainier National Park, Washington State, USA using long-term (32-year) forest monitoring data from permanent sample plots in mature and old-growth stands. To analyze the data, we adapted the diameter growth function from ORGANON (a proven forest simulation model), to explicitly include climate, and fit the model using hierarchical Bayesian methods to facilitate error propagation for projections of climate change impacts on individual- and stand-level growth. Individual growth was sensitive to climate under low but not high competition, likely because tree ability to increase growth under more favorable climate (in this case, greater energy availability) is constrained by competition. We found this pattern for all focal species (*Abies amabilis*, *Tsuga heterophylla*, *Pseudotsuga menziesii* and *Thuja plicata*), but with some important variations. Therefore, warming will likely increase individual growth most in low-density stands where there is little competition. However, higher denisty stands have more and/or larger trees, conferring greater capacity for stand-level growth increases. Our results imply that stand-level growth responses to climate change will be greater at medium density than low density, due to greater capacity for increases, but similar at high and medium densities, due to greater competition counteracting greater growth increase capacity. Thus, competition will likely mediate the impacts of climate change on tree growth in important but complex ways at the individual and stand scales. This work highlights the value of combining long-term forest monitoring data with advanced statistical modeling to assess the impacts of climate change on forests.

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