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Using a remote sensing-based, percent tree cover map to enhance forest inventory estimation

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ABSTRACT

For most national forest inventories, the variables of primary interest to users are forest area and growing stock volume. The precision of estimates of parameters related to these variables can be increased using remotely sensed auxiliary variables, often in combination with stratified estimators. However, acquisition and processing of large amounts of remotely sensed data can be costly and laborious, and stratified estimation requires construction of strata and satisfaction of within-stratum sample size constraints. An alternative to both challenges is to use an existing remote sensing-based, spatial product with the model-assisted estimators. The latter estimators use continuous auxiliary information directly rather than their aggregation into strata and are not subject to such severe sample size constraints. The objective of the study was to compare estimates of mean proportion forest area and mean growing stock volume per unit area obtained using both stratified and model assisted estimators with a remote sensing-based percent tree canopy cover map as auxiliary information. For a study area in Minnesota, USA, the primary conclusion was that estimates obtained with both sets of estimators were acceptably precise, but that the model-assisted estimators were easier to implement and facilitated aggregation of estimates from smaller sub-areas to estimates for larger areas.

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1. Introduction

National forest inventories (NFI) typically report estimates of parameters related to forest area and growing stock volume and their changes using unbiased probability-based (design-based) estimators. The estimates are used for multiple purposes including strategic planning (USDA-FS, 2012) and reporting for an increasing number of international agreements such as the Global Forest Resources Assessment (FAO, 2010) and Annex 1 of the United Nations Framework Convention on Climate Change (UNFCCC, 2006). However, for important inventory parameters related to forest area and volume, limited sample sizes inhibit these estimators from producing sufficiently precise estimates unless the estimation process is enhanced using auxiliary information. Remote sensing-based thematic maps are increasingly used as auxiliary information to address this challenge.

The Forest Inventory and Analysis (FIA) program of the U.S. Forest Service conducts the NFI of the United States of America (USA) and has conducted extensive research on using remotely sensed data to enhance inventory estimates via stratified estimation. (Hansen and Wendt, 2000; McRoberts et al., 2002a, b, 2006, 2012; Liknes et al., 2004, 2009; Nelson et al., 2005; Westfall et al., 2011). However, for large areas such as states, provinces, and regions, the labor and costs associated with acquiring and processing large amounts of remotely sensed data inhibit this practice. For example, 10–20 Landsat scenes are required to cover individual states in the Midwestern region of the USA. An alternative is to use a readily available, remote sensing-based, spatial, thematic product such as the National Land Cover Database (NLCD) (Vogelmann et al., 2001; Homer et al., 2004, 2007). The NLCD is a 30-m $\times$ 30-m, multi-class, land cover dataset that has been widely used as a source of auxiliary information for multiple purposes. McRoberts et al. (2002a) aggregated the thematic classes of the 1992 NLCD to forest and non-forest and then constructed four related strata. These strata, when used with stratified estimators (Section 3.2.2), reduced variances of estimates of mean proportion forest area by factors as great as 3.2 for four Midwestern states. This approach was operationally implemented for at least some of the regional FIA programs in the USA. McRoberts et al. (2006) later showed that stratifications based on estimates of pixel-level probabilities of forest cover reduced variances of estimated mean proportion forest by factors as great as 5.9 and variances of estimates of mean growing stock volume per unit area by factors as great as 2.5. The similarity between the probability of forest cover

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and the percent tree canopy cover layer for the 2001 NLCD facilitated operational implementation of the latter approach to stratification.

One disadvantage of stratified estimation is that the full utility of continuous auxiliary data such as percent tree canopy cover is not realized when the data are aggregated into a small number of strata. In addition, when using continuous auxiliary information for stratification, strata boundaries must be selected, and sufficient numbers of observations per stratum must be ensured (Westfall et al., 2011). The model-assisted regression estimators are alternative estimators that more fully utilize continuous auxiliary data. These estimators calculate an initial estimate as the aggregation of estimates for individual population units and then adjust the initial estimate using differences between unit-level estimates and observations for a probability sample (Section 3.2.3). The increased availability of remotely sensed satellite and lidar data and products based on them has increased the appeal of model-assisted estimators for forest inventory applications (Baffetta et al., 2009; Gregoire et al., 2011; McRoberts, 2010, 2011; McRoberts and Walters, 2012; McRoberts et al., 2013a, b; Næsset et al., 2011, 2013a, b; Vibrans et al., 2013; Sannier et al., 2014). With these estimators, selection of strata boundaries is not necessary because the auxiliary data are used in their continuous form. In addition, although overall minimum samples sizes must be accommodated, satisfaction of a sample size criterion for each of multiple strata is not necessary.

For inventory estimation, the ultimate analytical objective is a statistical inference in the form of a confidence interval calculated as $\hat{\mu} \pm t_{1-\alpha} \cdot \sqrt{V\hat{a}r(\hat{\mu})}$ where $\hat{\mu}$ is the estimate of a mean, $V\hat{a}r(\hat{\mu})$ is an estimate of the variance of the estimated mean, and t corresponds to the confidence level. The primary objective of the study was to compare estimates of mean proportion forest area and mean forest growing stock volume per unit area using continuous NLCD tree canopy cover data as auxiliary information with three sets of statistical estimators: (1) the simple random sampling estimators, (2) the stratified estimators, and (3) the model-assisted regression estimators. A particular underlying objective was to determine if the model-assisted regression estimators circumvent the disadvantages of the stratified estimators without introducing additional disadvantages.

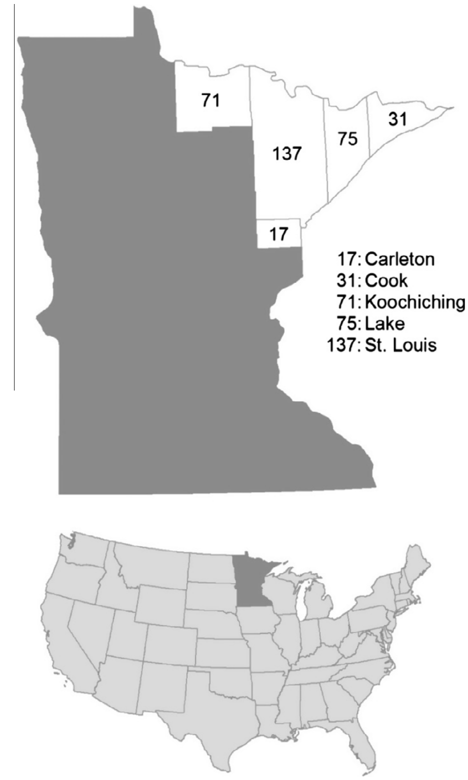

Fig. 1. Study area consisting of Minnesota FIA Unit 1 and five subordinate counties by name and U.S. Federal Information Processing Standard (FIPS) codes.

2. Data

2.1. Forest inventory field data

The study area was Minnesota FIA Inventory Unit 1 and the five counties included within the Unit (Fig. 1). Land use for the study area consists of forest land dominated by aspen-birch and spruce-fir associations, agriculture, wetlands, and water (Miles et al., 2011). The FIA program samples without replacement and has established field plot centers in permanent locations using a quasi-systematic sampling design that is regarded as producing an equal probability sample (McRoberts et al., 2010). Each FIA plot consists of four 7.32-m (24-ft) radius circular subplots that are configured as a central subplot and three peripheral subplots with centers located at distances of 36.58 m (120 ft) and azimuths of 0°, 120°, and 240° from the center of the central subplot. Field crews visually estimate the proportion of each subplot that satisfies the FIA definition of forest land: minimum area of 0.4 ha (1.0 ac); minimum canopy cover of 10%; stand width, measured as external crown-to-crown distance, of at least 36.6 m (120 ft); and forest land use. Field crews also observe species and measure diameter at-breast-height (dbh) (1.37 m, 4.5 ft) and height for all trees with dbh of at least 12.7 cm (5 in.). Volumes for individual trees are estimated using statistical models (Woodall et al., 2011), aggregated at plot-level, expressed as volume per unit area, and for inventory estimation purposes are considered to be observations without error (McRoberts and Westfall, 2014). For this study, data were used for 2681 FIA plots measured between 2008 and 2012. At the time the plots were measured, the sampling intensity in the study area was approximately one plot per 1200 ha. Two variables were considered: proportion forest area (FOR) and growing stock volume per unit area (VOL, m^3/ha).

2.2. Auxiliary data

The NLCD is a 30-m × 30-m, multi-class, Landsat-based land cover product of the Multi-Resolution Land Characteristics Consortium, a collaboration of multiple agencies of the U.S. Government (Homer et al., 2004, 2007). The NLCD is national in scope and provides spatial data for thematic classes such as urban, agriculture, and forest and separately for percent tree canopy cover. The latter data reflect land cover, not land use, and were predicted from Landsat 7 ETM + images and high resolution reference data using regression trees (Huang et al., 2001). For this study, the 2001 NLCD percent tree canopy cover (PCT) product was used as auxiliary information for both stratified and model-assisted estimation. For each FIA plot, FOR and VOL were associated with PCT for the NLCD map unit containing the plot center. Preliminary investigations indicated only negligible benefits accrued from using mean PCT for the 3 × 3 block of pixels centered on the map unit containing the plot center.

3. Methods

3.1. Assumptions

All three estimators rely on the same three underlying assumptions: (1) a finite population, U, consisting of N units in the form of square, 900-m^2 NLCD map units; (2) a sample, S, of n population units in the form of map units that contain FIA plot centers; and (3) availability of auxiliary data in the form of PCT for all map units.

3.2. Probability-based estimators

Properties of probability-based (design-based) estimators derive from the probabilities of selection of population units into the sample. Hansen et al. (1983) apparently coined the term *probability-based* to describe these estimators as an alternative to the more familiar term *design-based.* Because the basis for inference is not just a *design* for sampling, but more specifically a probability-based design, the term *probability-based* is considered by some to better characterize the basis for inference. Probability-based inference is based on three assumptions: (1) population units are selected for the sample using a probability-based randomization scheme; (2) the probability of selection for each population unit is positive and known; and (3) the observation of the response variable for each population unit is a fixed value. Estimators are derived to correspond to sampling designs and typically are unbiased, meaning that the expectation of the estimator over all samples and sample sizes that could be obtained with the sampling design is the true value of the population parameter. However, the estimate obtained with any particular sample may deviate considerably from the true value.

3.2.1. Simple random sampling estimators

The simplest approach to probability-based inference is to use the familiar simple random sampling (SRS) estimators for means and their variances,

$$\hat{\mu}_{\mathrm{SRS}} = \frac{1}{n}\sum_{i \in S} y_i \tag{1}$$

and

$$V\hat{a}r(\hat{\mu}_{\mathrm{SRS}}) = \frac{\sum_{i \in S}(y_i - \hat{\mu}_{\mathrm{SRS}})^2}{n(n-1)}, \tag{2}$$

where y_i is the observation of the response variable for the ith sample unit. The primary advantages of the SRS estimators are that they are intuitive, simple, and unbiased when used with an SRS design; the disadvantage is that variances are frequently large, particularly for highly variable populations and small sample sizes. Although $V\hat{a}r(\hat{\mu}_{\mathrm{SRS}})$ from Eq. (2) may be biased when used with systematic sampling, it is usually conservative in the sense that it over-estimates the variance (Särndal et al., 1992). For this study, finite population correction factors were ignored because of the small sampling intensity of one 672-m^2 plot per 1200 ha of land area, a sampling intensity of less than 0.0001.

3.2.2. Stratified estimators

The essence of stratified estimation is to assign map units to homogeneous groups characterized as *strata*, calculate within-stratum sample plot means and variances, and then calculate the population estimate as a weighted average of the within-stratum estimates. Stratified estimation requires accomplishment of two tasks: (1) calculation of stratum weights, and (2) assignment of each sample unit to a single stratum. The first task is accomplished by calculating the stratum weights as proportions of map units in strata. The second task is accomplished for this study by assigning the FIA plots to strata on the basis of the stratum assignments of the map units containing the plot centers.

NFIs often use permanent plots whose locations are based on systematic grids or tessellations and use sampling intensities that are constant over large geographic areas. In such cases, even though stratified sampling is not possible, increase in precision may still be achieved by using stratified estimation subsequent to the sampling, a technique characterized as post-sampling stratification or simply *post-stratification*. Post-stratified (STR) estimates of means and variances are calculated as (Cochran, 1977, p. 134),

$$\hat{\mu}_{\mathrm{STR}} = \sum_{h=1}^{H} w_h \hat{\mu}_h, \tag{3}$$

and

$$V\hat{a}r(\hat{\mu}_{\mathrm{STR}}) = \sum_{h=1}^{H}\left[w_h \frac{\hat{\sigma}_h^2}{n} + (1 - w_h) \cdot \frac{\hat{\sigma}_h^2}{n^2}\right], \tag{4}$$

where

$$\hat{\mu}_h = \frac{1}{n_h}\sum_{i \in S_h} y_i,$$

$$\hat{\sigma}_h^2 = \frac{1}{n_h - 1}\sum_{i \in S_h}(y_i - \hat{\mu}_h)^2,$$

$h = 1, \ldots, H$ indexes strata; S_h is the portion of the sample, S, in the hth stratum; w_h is the weight for the hth stratum; n is the total sample size; and $\hat{\mu}_h$ and $\hat{\sigma}_h^2$ are the sample estimates of the within-stratum mean and variance, respectively. The utility of a stratification for increasing precision is often expressed using relative efficiency (RE) calculated as,

$$\mathrm{RE} = \frac{V\hat{a}r(\hat{\mu}_{\mathrm{SRS}})}{V\hat{a}r(\hat{\mu}_{\mathrm{STR}})}, \tag{5}$$

where values of RE greater than 1.0 indicate increasing effectiveness of the stratification.

3.2.3. Model-assisted regression estimators

Model-assisted regression estimators use models based on auxiliary data to enhance inferences by increasing precision but rely on probability samples for validity. For this study, the model-assisted regression (MAR) estimators of means and variances were used (Särndal et al., 1992, Section 6.5),

$$\hat{\mu}_{\mathrm{MAR}} = \frac{1}{N}\sum_{i \in U} \hat{y}_i - \frac{1}{n}\sum_{i \in S} \varepsilon_i \tag{6}$$

and

$$V\hat{a}r(\hat{\mu}_{\mathrm{MAR}}) = \frac{1}{n(n-1)}\sum_{i \in S}(\varepsilon_i - \bar{\varepsilon})^2, \tag{7}$$

where $\hat{y}_i$ is a model prediction and $\varepsilon_i = \hat{y}_i - y_i$. The first term in Eq. (6) is simply the mean of the model predictions over all map units, and the second term is an estimate of bias calculated over the sample units and compensates for systematic model prediction errors. For the MAR estimators, RE was calculated as,

$$\mathrm{RE} = \frac{V\hat{a}r(\hat{\mu}_{\mathrm{SRS}})}{V\hat{a}r(\hat{\mu}_{\mathrm{MAR}})}. \tag{8}$$

The descriptive term *regression* is commonly used to describe the MAR estimators (Cochran, 1977; Särndal et al., 1992), probably because when they were developed models of the relationships between the response and predictor variables were most often in the form of a linear regression model. However, any prediction procedure, whether explicit or implicit, that produces replicable predictions is generally understood to be acceptable for use with these estimators. For example, Breidt and Opsomer (2000) used local polynomial regression; Lehtonen et al. (2005) used a nonlinear logistic regression model; Särndal (2007) used a calibration approach; Zheng and Little (2004) used penalized splines; Breidt and Opsomer (2009) used non-parametric and semi-parametric approaches; and Sannier et al. (2014) used visual assessments, all while still using the term *regression estimator*.

The primary advantage of the MAR estimators is that they capitalize on the relationship between the sample observations and their model predictions to reduce the variance of the estimate of the population mean. In this regard, they are potentially preferable to the STR estimators because they use the model predictions for individual population units, whereas the STR estimators use the model predictions to aggregate the population units into a small number of strata.

3.3. Analyses

3.3.1. Constructing strata

For the stratified analyses, four strata were used based on Cochran's (1977) recommendation that more than 6–8 strata produce little additional gain in precision and previous experiences with FIA data indicating that four Landsat-based strata were approximately optimal (McRoberts et al., 2002a,b, 2006; McRoberts, 2010).

The general approach to constructing strata entails dividing the range of a continuous variable, possibly in the form of model predictions, into a small number of intervals that constitute the strata. For this study, only a single auxiliary variable, PCT, was used, and only monotonic increasing models were used to represent the relationships between FOR and PCT and between VOL and PCT. Therefore, dividing the range of predictions for any monotonic model based only on PCT into strata is equivalent to dividing the range of the PCT auxiliary variable itself into strata. Therefore, all stratifications were constructed by dividing the $0 \leqslant \text{PCT} \leqslant 1$ range into intervals that satisfied selected criteria. Strata were constructed in two steps. First, the [0,1] continuum of PCT values was divided into 101 standardized classes [0,0], (0,1], ..., (99,100]. Second, adjacent standardized classes were aggregated into strata that satisfied selected criteria. Two criteria were considered: (1) minimization of $\hat{Var}(\hat{\mu}_{STR})$ and (2) maximization of $RE_{FOR} + RE_{VOL}$. The first criterion prioritizes precise estimation of mean VOL under the assumption that it will be more difficult to estimate precisely than mean FOR which is more closely related to PCT. The second criterion balances the priorities.

Stratum boundaries were selected to satisfy the criteria for the entirety of Unit 1, and then were applied to each of the five counties within the Unit (Fig. 1). All stratifications were subject to the constraint that each stratum must include at least 50 plots at the Unit level. For comparison purposes, the regional FIA program of the Northern Research Station (NRS), U.S. Forest Service, uses five strata and requires at least 10 plots per stratum per county which is equivalent to 50 plots per stratum for a 5-county unit level. Thus, the within-stratum sample size constraint used for this study was comparable to the constraint used in practice.

3.3.2. Constructing models

For the MAR estimators, each response variable must be predicted for each 30-m × 30-m map unit. For FOR, the PCT value itself was used as the prediction. For VOL, predictions were calculated using a nonlinear logistic model of the form,

$$\text{VOL} = \frac{\alpha}{1 + \exp(\beta_0 + \beta_1 \cdot \text{PCT} + \beta_2 \cdot \text{PCT}^2)} + \varepsilon \tag{9}$$

where ε is a residual with mean zero, and α and the βs are parameters to be estimated. The advantage of this model over a linear model is it that has a lower asymptote at VOL = 0 and an upper asymptote at VOL = α whose estimate is based on the sample data. Linear models have no such constraints and can produce negative and unrealistically large predictions, particularly for values of predictor variables that are beyond the ranges of those variables represented in the sample.

3.3.3. Estimation

Means and standard errors (SE) of the means were estimated for each of the five counties using the SRS estimators, the STR estimators with strata constructed to satisfy both criteria, and the MAR estimators. For each case, RE was also calculated.

The MAR estimators are not subject to selection of strata boundaries or the necessity of altering strata boundaries to accommodate a minimum number of plots per stratum. Therefore, estimation for multi-county units is much easier; in particular, basic within-county sums can be calculated and then further added to estimate multi-county means and SEs. This advantage is demonstrated for the VOL response variable.

4. Results and discussion

4.1. Accuracies

For the 2861 FIA plots with centers in the study area, the correlation between FOR and PCT was 0.68. If map units with PCT < 0.5 are classified as non-forest and maps units with PCT $\geqslant$ 0.5 are classified as forest, then for the 2461 of the 2861 plots that were completely non-forested or completely forested, the classification accuracy was 0.93.

The quality of fit of the nonlinear logistic model to the data was also assessed using pseudo-R^2 calculated as,

$$R^{2*} = \frac{\sum_{i \in S}(y_i - \bar{y})^2 - \sum_{i \in S}^{n}(y_i - \hat{y}_i)^2}{\sum_{i \in S}(y_i - \bar{y})^2}. \tag{10}$$

For the logistic model of Eq. (8), R^{2*} = 0.54 (Fig. 2). Although this is value is rather small, several factors must be considered. First, as noted in Section 2.1, the FIA plot observations reflect forest land use, not necessarily forest land cover. In particular, land with tree canopy cover that fails to satisfy the FIA definition of forest land, is characterized by FIA as having non-forest land use, whereas forest land that has recently been harvested and has no tree canopy cover is still characterized by FIA as having forest land use. Second, the relationship between VOL and PCT exhibits considerable variability.

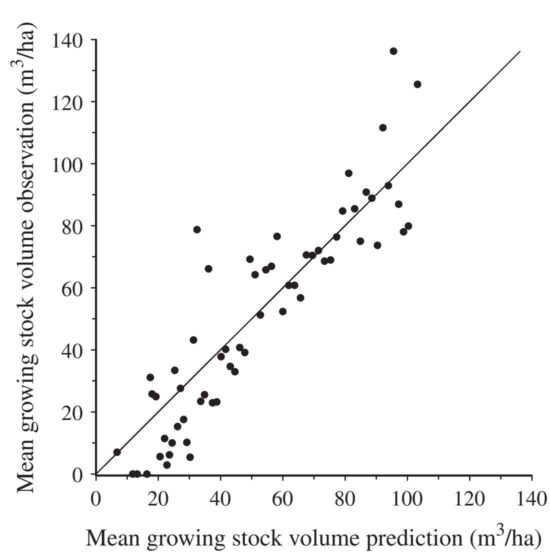

Fig. 2. Mean growing stock volume observations versus mean growing stock volume predictions for NLCD percent canopy cover classes.

For example, for PCT = 0.00, the VOL range was 0.0–289.3 m^3/ha; for PCT = 0.75, the VOL range was 0.0–236.6 m^3/ha; and for PCT = 1.00, the VOL range was 49.0–330.9 m^3/ha. The best a model can achieve is to predict exactly the VOL mean for each value of PCT. Thus, the minimum sum of squared deviations between observations and predictions, SS_{res}, that can be achieved is the sum of squared deviations between VOL observations around their means over all PCT values. In this context, the SS_{res} achieved by the model was only 2.2% greater than the minimum possible.

Multiple factors contribute to the large variability among VOL observations for particular PCT values: (1) changes on the ground between the dates of the map training and image data and the FIA plot measurements, (2) map classification and prediction errors, (3) FIA plot location errors, (4) geo-referencing errors, (5) deviations between the plot area of 672 m^2 distributed over nine or more map units and single map units of size 900 m^2, (6) differences between land cover as depicted by the map and land use as recorded for FIA plots, and (7) volume in trees with dbh < 12.7 cm (5 in) which is not included in VOL as reported by FIA. Other than minimizing errors resulting from these factors, the only other solution for increasing the quality of fit of the model to the data is to find additional predictor variables that are available for all map units and that are correlated with VOL.

4.2. Estimation

4.2.1. Stratified estimators

The strong relationship between PCT and FOR is the explanation for the success of the stratifications in reducing SEs of estimates of mean FOR (Table 1). REs for FOR ranged from 21.26 to 43.61 but, as expected, were greater when the stratifications maximized $RE_{FOR} + RE_{VOL}$ than when they minimized $V\hat{a}r(\hat{\mu}^{VOL})$.

RE_{VOL} for the stratified estimators ranged from 1.09 to 1.38 These values were considerably smaller than RE_{FOR} which was as expected because PCT is more strongly related to the canopy level forest/non-forest attribute than to the below canopy volume attribute. Of interest, minimization of $V\hat{a}r(\hat{\mu}^{VOL}_{STR})$ did not produce substantially greater REs for VOL than did maximization of $RE_{FOR} + RE_{VOL}$. Although values of RE_{VOL} were small and sometimes close to 1.0, the cost efficiency of even small values should not be ignored. For example, RE = 1.12 means that to achieve the same precision levels without use of the auxiliary information, sample sizes would have to be increased by a factor of 0.12, i.e., for this study, the sample size of 2861 would have to be increased by $0.12 \times 2861 = 343$ plots. For a 2014 measurement cost of approximately $500/plot, the cost savings from using the auxiliary information and post-stratified estimation is $171,500, a non-negligible amount, particularly for only one of the four Minnesota FIA inventory units.

4.2.2. Model-assisted regression estimators

The MAR estimators produced increases in precision for both FOR and VOL; RE_{FOR} ranged from 1.51 to 3.12, and RE_{VOL} ranged from 1.10 to 1.42. The bias adjustment component of the MAR estimator has two important features. First, it compensates for deviations between predictions and observations for sample units resulting from any of the causes described in Section 4.1. Second, it compensates for differences in relationships between the response variable and PCT for different geographical regions within the study area. In particular, the model of Eq. (9) was constructed using plot data without regard to individual counties within Unit 1. Therefore, because of different distributions of forest resources and the PCT variable, the quality of model predictions may vary by county. The bias adjustment feature preserves the unbiasedness or nearly unbiasedness feature of the MAR estimator, although a greater degree of adjustment contributes to larger variances and less precision.

4.2.3. Comparisons

The smaller SEs for mean FOR and mean VOL when using the STR and MAR estimators than when using the SRS estimators attest to the utility of the PCT auxiliary information. This result is reflected in RE > 1 for all counties using the STR and MAR estimators. As previously noted, RE_{FOR} was always greater than RE_{VOL}, regardless of the estimator or optimization criterion, as a result of the stronger relationship between FOR and PCT than between VOL and PCT.

For mean FOR, the STR estimators produced considerably smaller SEs than did the MAR estimators. For mean VOL, REs obtained using the MAR estimators were slightly smaller or comparable to REs obtained using the STR estimators. Despite the apparent superiority of the STR estimators for mean FOR, additional factors must be considered. First, operational implementation of the STR estimators is more complex because stratum boundaries must be selected, minimum within-stratum sample sizes are more difficult to achieve, and optimality criterion may have to be considered. Further, for counties with few forest resources, use of a common pan-county stratification may be problematic because subdivision

Table 1
Estimates of mean proportion forest area and mean volume per unit area (m^3/ha).

County	Sample size (n)	Simple random sampling (SRS)		Stratified (STR)						Model-assisted regression (MAR)		
				Optimal $V\hat{a}r(\hat{\mu}^{VOL}_{STR})$			Optimal $RE_{FOR} + RE_{VOL}$					
		Mean	SE[a]	Mean	SE[a]	RE[b]	Mean	SE[a]	RE[b]	Mean	SE[a]	RE[b]
Proportion forest area												
17	179	0.618	0.036	0.624	0.007	21.26	0.636	0.007	22.99	0.661	0.023	2.10
31	284	0.856	0.021	0.755	0.004	21.37	0.752	0.004	22.71	0.870	0.010	3.12
71	624	0.837	0.015	0.718	0.003	30.65	0.718	0.002	43.61	0.853	0.011	1.51
75	416	0.867	0.017	0.730	0.003	22.01	0.726	0.003	35.94	0.887	0.009	3.12
37	1358	0.730	0.012	0.656	0.002	30.94	0.659	0.002	40.76	0.756	0.007	2.27
Growing stock volume (m^3/ha)												
17	179	59.95	5.28	61.75	4.50	1.38	63.75	4.73	1.24	62.62	4.43	1.42
31	284	87.19	4.56	88.10	4.24	1.16	87.46	4.22	1.17	88.96	4.25	1.15
71	624	53.05	2.52	53.48	2.40	1.10	53.48	2.40	1.10	55.32	2.38	1.12
75	416	75.84	3.13	76.87	2.96	1.12	76.26	3.00	1.09	78.32	2.99	1.10
37	1358	52.35	1.70	53.47	1.55	1.20	53.73	1.56	1.18	55.18	1.53	1.23

[a] Standard error.
[b] Relative efficiency.

Table 2
County and Minnesota FIA Unit 1 estimates for mean growing stock volume per unit area (m^3/ha) using the model-assisted regression estimators.

County	Sums					Estimates			
	N ($\times 10^7$)	$\sum_{i=1}^{N}\hat{P}y_i$ ($\times 10^9$)	n	$\sum_{i=1}^{n}\varepsilon_i$ ($\times 10^3$)	$\sum_{i=1}^{n}\varepsilon_i^2$ ($\times 10^6$)	$\hat{\mu}_{\text{init}}$ [a]	$\hat{Bias}(\hat{\mu}_{\text{init}})$ [b]	$\hat{\mu}_{\text{MAR}}$ [c]	SE($\hat{\mu}_{\text{MAR}}$) [d]
17	0.2519	0.1426	179	−1.0773	0.6322	56.60	−6.02	62.62	4.43
31	0.4620	0.3245	284	−5.3168	1.5490	70.24	−18.72	88.96	4.25
71	0.9077	0.5870	624	5.8334	2.2516	64.67	9.35	55.32	2.38
75	0.6584	0.4299	416	−5.4179	1.6137	65.30	−13.02	78.32	2.99
137	1.9380	1.1391	1358	4.8823	4.3441	58.78	3.60	55.18	1.53
Unit 1	4.2180	2.6231	2861	−1.0962	10.3910	62.19	−0.38	62.57	1.13

[a] $\hat{\mu}_{\text{init}} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i$.
[b] $\hat{Bias}(\text{init}) = \frac{1}{n}\sum_{i\in S}\varepsilon_i$.
[c] $\hat{\mu}_{\text{MAR}} = \hat{\mu}_{\text{init}} - \hat{Bias}(\hat{\mu}_{\text{init}})$.
[d] $\text{SE}(\hat{\mu}_{\text{MA}}) = \sqrt{\frac{1}{n(n-1)}\sum_{i\in S}(\varepsilon_i - \bar{\varepsilon})^2} = \sqrt{\frac{1}{n(n-1)}\left[\sum_{i\in S}\varepsilon_i^2 - \frac{1}{n}\left(\sum_{i\in S}\varepsilon_i\right)^2\right]}$.

of small forest areas into multiple strata invariably fails to satisfy minimum sample size constraints for some strata. The result is that either fewer strata must be used or some existing strata must be combined, a laborious county-by-county task when many counties are involved. The MAR estimators avoid these problems; the only constraint is the total sample size for a county.

Second, aggregation of stratified estimates for individual counties with different stratifications to multi-county estimates is extremely complex, if not operationally infeasible. For example, if the strata for County A are [0–40] and [41–100] and the strata for County B are [0–60] and [61–100], then a method for producing an estimate for the combination of the counties that is consistent with the individual estimates for the two counties and, of necessity, preserves the county stratifications is not apparent. For most counties, the regional NRS FIA program uses five strata with PCT boundaries of [0–5], [6–50], [51–65], [66–81], and [82–100]. However, for some counties, the first three strata were combined; for other counties, the last four were combined; and in some cases all five strata were combined. As is apparent, when different stratifications are used for different counties, county estimates cannot easily be aggregated to produce multi-county estimates. This task is circumvented with the MAR estimators, because county-level sums of population sizes, sample sizes, model predictions, residuals, and residuals squared can be readily carried forward to produce estimates for aggregations of counties (Table 2).

Third, the primary disadvantage of the MAR estimators, at least for this study area, is that the precision of estimates of FOR suffers. However, in a practical sense, the larger SEs obtained with the MAR estimators may still be acceptable. The FIA program reports precision estimates as coefficients of variation scaled to compensate for varying sample sizes using the sample size corresponding to 404,694 ha (1 million ac) as a reference standard (USDA-FS, 1970). Thus, precision is expressed as,

$$\pi = \frac{\sqrt{\hat{Var}(\hat{\mu})}}{\hat{\mu}}\sqrt{\frac{A\cdot\hat{\mu}}{404,694}}, \tag{11}$$

where $\hat{\mu}$ is the estimate of mean FOR, $\hat{Var}(\hat{\mu})$ is its variance estimate, and A is the total area inventoried. The threshold for satisfying the FIA precision criterion is $\pi \leqslant 0.03$. For the estimates obtained using the MAR estimators, $\pi \leqslant 0.022$ for all counties, meaning that even though precision was not as great as obtained using the STR estimators, it still satisfied the FIA criterion. Thus, the smaller but still acceptable precision for estimates of FOR with the MAR estimators may be a reasonable price to pay for greater ease of implementation, less severe sample size constraints, and the ability to easily aggregate individual county estimates to multi-county estimates. Finally, the MAR estimators have potential for greater precision if additional predictor variables correlated with VOL can be incorporated into the model.

5. Conclusions

Three conclusions may be drawn from the study. First, as a source of auxiliary information, the NLCD percent tree canopy cover layer contributed to reducing variances and increasing the precision of parameter estimates associated with forest area and growing stock volume, the two most important and commonly reported NFI variables. Second, the model-assisted estimators produced precision for estimates of mean growing stock volume comparable to precision produced using the stratified estimators. Although precision for mean proportion forest area obtained using the model-assisted estimates was less than that obtained using the stratified estimators, the model-assisted estimates still satisfied the FIA precision criterion. Thus, no serious disadvantages with respect to required precision accrue through use of the model-assisted estimators. Third, and most importantly, multiple advantages accrue with use of the model-assisted regression estimators. In particular, they are easier to implement because selection of strata boundaries is not necessary, sample size requirements are more easily satisfied, and county-level sums may be aggregated to produce multi-county estimates which is often not possible with stratified estimators.

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