NORTHERN ARIZONA UNIVERSITY

Lab of Landscape Ecology and Conservation Biology

FINAL REPORT

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For project **task (#1)** entitled:

Rapid Plot Monitoring Design for the Kaibab National Forest

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Submitted to:

The Kaibab National Forest

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Project overview

As part of an existing cost reimbursable agreement between the Kaibab National Forest (KNF) and the Lab of Landscape Ecology and Conservation Biology at Northern Arizona University, this report encompasses the proposed design and placement of rapid monitoring plots across the three Ranger Districts of the KNF. The objective of this 'rapid plot' design is to provide a transparent method of data collection to track changes in major vegetation types through time in a financially and time-efficient manner. As specified in Chapter 5 of the KNF Draft Land and Resource Management Plan (hereafter Forest Plan), the rapid plot approach is meant to complement, not replace, project level monitoring. The design offers flexibility to add plots within project boundaries as treatments continue to be planned and completed or as specific questions arise. This report is accompanied by a guide to statistical analyses (Appendix A).

This rapid plot monitoring approach aims to capture parameters of interest that will inform progress toward, or attainment of, desired conditions related to vegetation structure, function, and composition. The variables to be measured were chosen to maximize sampling efficiency and ensure that the goals and priorities in the KNF Forest Plan will be addressed. An initial array of plots was located randomly across the KNF in each of seven broad vegetation classes, and in numbers proportional to the area encompassed by each class. Our design identified 380 plots, which we determined would provide the necessary amount of information to detect a 2-6% annual change at an 80% power level in variables related to understory conditions (e.g., shrub cover, herbaceous cover), forest structure and regeneration (e.g., sapling density, tree size class), wildfire fuels, and non-native invasive species. This level of change is equivalent to a 10-25% change between 5-year sampling intervals, a range reasonably expected to be consistent with a forest treatment prescription.

The rapid plot design employs a multi-scale approach to include sampling subunits designed to maximize efficiency and coverage of the plot area. Plot locations will be permanently and precisely geo-referenced to facilitate possible future integration with various remote sensing platforms (e.g., Landsat, SPOT, WorldView, or LiDAR). To meet the monitoring goals described in the Forest Plan the systematic sampling framework will support data that are collected at the project level and aggregated with other project-level data to make inferences at the forest scale. Project-specific questions could be accommodated by adding more plots within project areas; however, such an approach is beyond the scope of this report.

I. Variable selection

Monitoring data collected in an efficient rapid plot design can include relatively simple measures of forest conditions. Simple measurements ensure the "efficiency, accountability, comparability of data, and the ability to better leverage monetary resources" as directed in the KNF Forest Plan (Chapter 5, Monitoring Strategies). Relatively rare ecosystem elements such as aspen (*Populus tremuloides*; hereafter aspen), oak (*Quercus gambelii*; hereafter oak), snags, large trees and understory components (e.g., dominant ground cover, regeneration) at mid to fine spatial scales tend to be unevenly distributed across the landscape, necessitating a design that is spatially extensive, while requiring a relatively small investment in time spent at a given plot to reduce cost. The diversity of vegetation cover types within KNF also dictates that the type of data collected in each cover type will vary.

In consultation with KNF staff, we omitted direct measurement of several attributes of forest structure to maintain the rapid nature of plot measurements. For example, crown-base height is not directly measured as diameter distributions can be combined in allometric equations to provide a 'height class distribution' describing local fuel structure and/or be used in conjunction with a remotely sensed estimate of crown-base height to predict wildlife response across broader spatial extents (e.g., Dickson et al. in review). We also omitted a more intensive sampling of the understory as species- and community-specific questions are often better addressed through more intensive, targeted approaches. Lastly, we omitted a more comprehensive characterization of understory fuels as measurement of these attributes is currently addressed by existing USFS Brown's transect survey efforts. If necessary, our rapid plot design could be modified to accommodate greater understory fuels sampling efforts with the recognition of the additional time required to collect more detailed attributes.

We chose variables to be measured in the rapid plots that were representative of the seven following monitoring components. These variables were reviewed and ranked by the KNF to facilitate the decision of directing and allocating sampling efforts in a rapid design framework. Table 1 shows the specific variables to be measured in each cover type:

1. *Diameter distribution of all live trees*: The KNF Plan states that treatment prescriptions “should generally retain” mature trees (Chapter 2, Guidelines for Vegetation Management in All Forested Communities). In this monitoring design, all trees in the rapid plot ≥ 10 cm diameter at breast height (dbh) will be counted with the “large” diameter class defined as trees ≥ 40 cm dbh. Additionally, large trees as described by Keen (1943) class 4 will be noted to provide an estimate of old or mature trees (See KNF Plan, Appendix C) Forest restoration treatments, fire, and disease outbreak are likely to alter the forest tree structure (Mast et al. 1999; Fulé et al. 2002, 2007). Estimation of these changes across large spatial extents will be critical as forest restoration activities increase in pace and scale on the KNF. Further, the use of diameter distributions in conjunction with remotely sensed estimates of canopy height (Dickson et al. 2011) and allometric equations of canopy fuel characteristics allows characterization of the effects of forest management on a number of fire behavior attributes (Reinhardt & Scott 2006). Lastly, relationships with diameter distribution (e.g., large tree density, mid-story density, density of oak, etc.) can be used to assess wildlife habitat conditions (e.g., Block et al. 2005; Dickson et al. 2009; Kalies et al. 2010, 2012) for a variety of species including some listed as threatened, endangered or regionally sensitive.

2. *Diameter distribution of snags*: Snags provide nesting, roosting, and feeding habitat for many wildlife species, including the threatened Mexican spotted owl (*Strix occidentalis lucida*) and their prey (Bagne et al. 2008; Kalies et al. 2012). The Desired Future Conditions in the Mexican spotted owl recovery plan list specific snag densities in all cover types present in owl habitat (US Fish and Wildlife Service 2011). The KNF Plan similarly specifies desired conditions in which snags are an important forest component in most cover types (Chapter 2). Snag distribution and abundance is likely to change as a result of forest

management activities, especially increased use of prescribed fire (Hessburg et al. 2010).

3. *Understory community*: KNF Plan monitoring questions focus on "effective ground cover," i.e., an understory comprised of diverse native grasses and forbs (*Danthonia* spp., *Festuca* spp., *Muhlenbergia* spp., *Bouteloua* spp., *Achnatherum* spp., *Aristida* spp., or *Hesperostipa* spp., etc.), shrubs (*Atriplex* spp., *Artemisia* spp., *Arctostaphylos* spp., *Cercocarpus* spp., *Coleogyne* spp., *Ephedra* spp., *Grayia* spp., *Chrysothamnus* spp., *Ericameria* spp., etc.), and saplings provide soil stability and a microclimate with improved nutrient cycling and higher soil moisture, in addition to providing food and cover for wildlife. Cover (both foliar and basal), production, and frequency of understory species or functional groups are the most commonly selected metrics; however, between-year and between-season climatic fluctuations often confound the ability to determine trend from cover and production estimates (Smith et al. 1987). As compared to measurements of cover, frequency (as a function of density) is not as sensitive to changes in weather conditions or species composition, especially for perennial plants. Frequency data therefore allows trend detection while still being sensitive to changes in the landscape (Smith et al. 1986).

   We note that questions related to understory vegetation attributes would likely benefit from a different sampling design, as species- and community-specific questions are often better addressed through more intensive, targeted approaches.

4. *Amount and distribution of coarse woody debris (CWD)*: Coarse woody debris (namely dead and down logs) is an important structural component of forest ecosystems, providing wildlife habitat and soil stability. It also facilitates tree regeneration by providing seedling establishment sites and plays a role in

nutrient cycling (Woldendorp et al. 2004). In addition, CWD is a key component of surface fuel loads in many forested systems (Brown 1971, 1981).

5. *Fine fuels*: in conjunction with the CWD estimates described above, fine fuels (i.e., 1 h, 10 h, and 100 h) provide key information for predicting fire behavior and effects (Brown 1974). For example, fine fuel loads are combined with fuel moisture estimates in spatial models to predict fire risk (e.g., FIREHARM; Keane et al. 2010) and fire spread trajectory (e.g., FARSITE/FlamMap and BehavePlus; Stratton 2006).

6. *Encroachment on aspen, grasslands and oak*: Desired conditions and objectives in the KNF Plan establish the goal of reversing the decline of aspen (Chapter 2, Objectives for Restoring Aspen) and grassland (Chapter 2, Objectives for Restoring Grasslands) systems, and maintaining oak-dominated hardwood stands (Chapter 2, Gambel Oak Shrublands). The presence (or absence) of encroachment on these forest systems by conifers, defined as conifer sapling establishment at the patch edge and/or conifer overstory cover > 10%, will be noted in this monitoring design.

7. *Soil disturbance and non-native invasive species*: soils that have been disturbed by natural (i.e., lightning-caused fire) or mechanical means can be quickly colonized by opportunistic non-native invasive species such as cheatgrass (*Bromus tectorum*), knapweed (*Centaurea* spp.), non-native thistle (*Salsola* and *Cirsium spp.;* hereafter thistle), and Dalmatian toadflax (*Linaria dalmatica*; hereafter toadflax) (Dodge et al. 2008). As non-native invasive plants quickly outcompete native species, ecosystem function becomes impaired (KNF Plan, Chapter 2, Non-native Invasive Species). Frequent monitoring for disturbed soils and non-native invasive species is recommended to increase the chances of early detection and treatment.

Table 1. Variables to be assessed using the Rapid Plot design and their associated sampling approach and effort. Variables were selected to address key monitoring questions as noted above and in Chapter 5 of the Draft Kaibab National Forest Plan. The approach for measuring each variable is categorical (C), qualitative (QL) or quantitative (QN).

Variable	Method	Survey effort	Monitoring questions[1]
General Plot Character (QL)	Photo	1 photo/plot	7
Soil disturbance (C)	Presence/Absence	1/plot	4
Shrub Cover (QN)	Line Intercept (1m)	2 transects/plot	3
Oak and aspen Cover (QN)	Stem count	2 quadrants/plot count in size classes	12, 46
Understory Cover (QN)	Line Intercept (1m)	2 transects/plot	3, 19
Overtopping/encroachment (C)	Presence/Absence	1/plot	12, 13
Non-native invasive Species (C)	Presence/Absence	1/plot	6, 23
Seedling Density (QN)	Stem count	4 4m x 12.5m belt transects	7
Sapling Density (QN)	Stem count	4 4m x 12.5m belt transects	7
Density of large trees (QN)	Stem count	Full plot stem count	1, 7
Density of mature trees (QN)[2]	Stem count	Full plot stem count	1, 7
Tree size class distribution (QN)	Stem count	Full plot count in size classes	1, 7, 9
Snags (QN)	Stem count	Full plot stem count	1
Downed Logs (QN)	Stem count	Full plot stem count	1, 2
Fuels count (QN)	PHOTOLOAD	4 PHOTOLOAD photos/plot	8
Woody debris (QN)	Length and decay class	2 transects/plot	1, 2
Litter and duff (QN)	Depth at line intercept (5m)	4 points/plot	2, 8

[1]Question numbers are from Chapter 5, Table 5 of the KNF Plan: Matrix for the Kaibab NF Monitoring Plan
[2]According to the Keen age classes 4A and B, as illustrated in the KNF Plan, Appendix C

II. Plot placement strategy

Our objective in plot placement is to monitor multiple attributes for each vegetation cover type present on the KNF. By overlaying KNF stand data, 0.3-m resolution 2010 aerial imagery from the ESRI World Imagery map service (http://www.esri.com/data/imagery), and Landfire Project (www.landfire.gov) Existing Vegetation Type (EVT; a mid-scale classification of terrestrial ecological systems based on plant community associations and environmental gradients) data, we assigned a dominant cover type to each KNF stand using broad vegetation classes of aspen, grassland, mixed conifer, oak, pinyon-juniper, ponderosa pine (*Pinus pondersa*), and spruce-fir.

We distributed the total number of projected plots in each vegetation class proportionally with the cube root of the area of KNF covered by that class. Using the cube root of the relative areas has the effect of moving plots from cover types that are over-represented (e.g., ponderosa pine) to those that are under-represented (e.g., aspen) if plots were distributed according to the untransformed relative areas.

Because strict effectiveness monitoring was not an explicit objective of this forest-wide rapid plot design, we did not restrict or stratify plot locations by forest treatment types or project boundaries. However, randomly-placed plots, stratified by vegetation type, could be located within the boundaries of planned or ongoing treatment projects, if desirable. When a specific need arises for more intensive effectiveness monitoring in a particular project area, new rapid plots can be added to the design. These project area-specific plots could be located prior to treatment and paired with control plots within the project boundary, or near existing rapid plots, so as to monitor in a manner similar to a before-after-control-impact (or BACI) study design. Additional project plots could be located, for example, according to priorities identified in the Kaibab Forest Health Focus (KFHF) and Four Forest Restoration Initiative (4FRI) in order to leverage the results of recent collaborative planning processes.

To ensure accessibility for field crews, we restricted plot locations to < 1.5 km of maintained roads and slopes < 15% (Figure 1). Slope was computed from a 30-m resolution USGS digital elevation model that was corrected for terracing artifacts with a weighted low-pass filter (see Dickson et al. 2011). We accessed the USFS Region 3 Geospatial Data website (http://www.fs.usda.gov/detail/r3/landmanagement/gis/) for the most recent spatial data on road networks. On the Tusayan and Williams Ranger Districts, all roads included in the Motor Vehicle Use Map (MVUM) dataset were considered accessible. On the North Kaibab Ranger District, we used a more detailed roads layer, selecting only roads that were classified as “arterial,” “collector,” or “local” (i.e., we excluded roads that were decommissioned, not open to the public, or only existed as unmaintained logging roads). Because designated wilderness areas (Kanab Creek, Kendrick Mountain, Saddle Mountain, and Sycamore Canyon) are roadless, only the edges of wilderness can potentially be sampled given road access restrictions. Wilderness areas may be sampled more intensively using trails for access if the need arises.

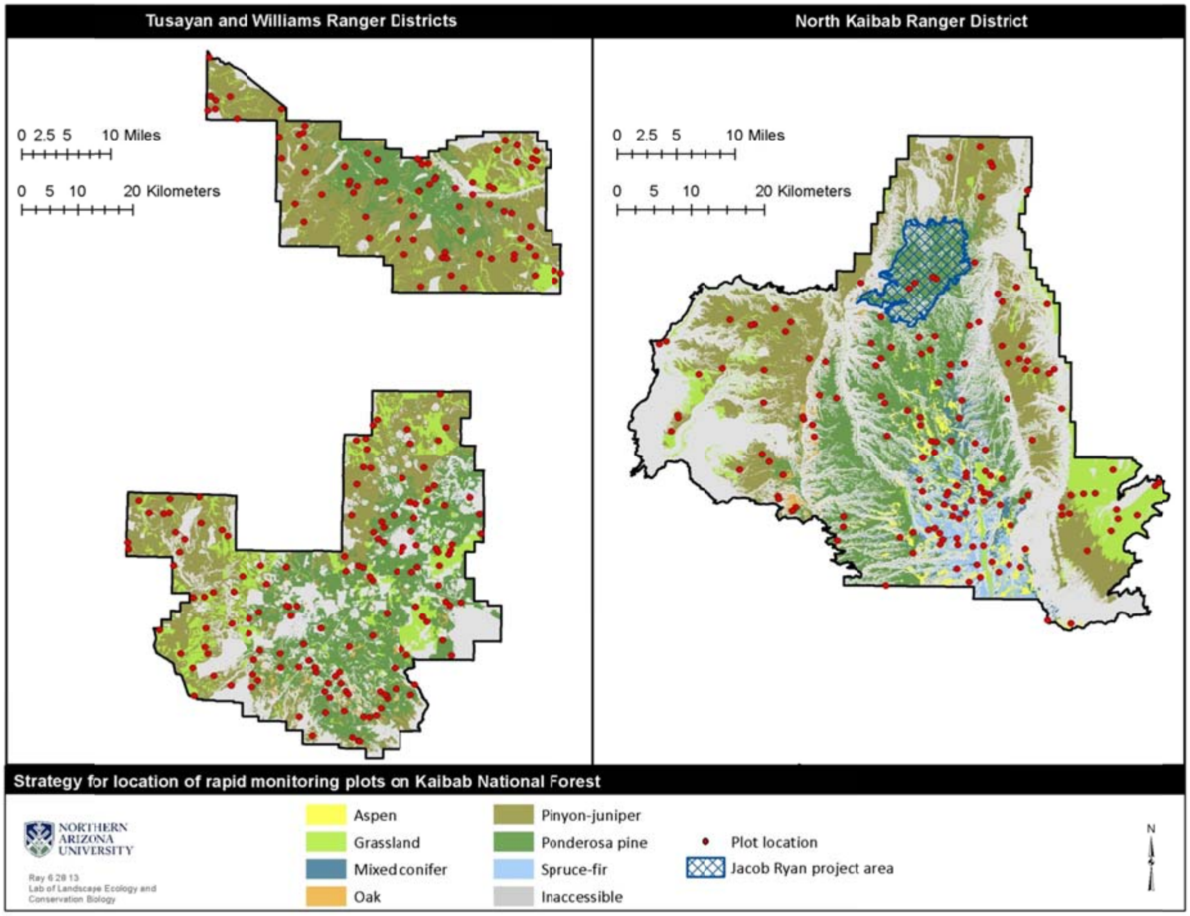

Figure 1. Map of Kaibab National Forest showing 380 rapid monitoring plot locations, randomly located and proportionally distributed across seven major cover types. Areas >1.5 km from roads and/or >15% slopes were considered inaccessible to field crews and are shown in gray color. Plots were not restricted to particular project boundaries, but the Jacob Ryan project area is shown in blue crosshatch to illustrate how randomly located plots may fall within treatments. Wilderness areas are not heavily sampled in this design due to the roadless nature of designated wilderness and our accessibility criteria.

III. STATISTICAL POWER ANALYSIS FOR MINIMUM SAMPLE SIZE

The number and configuration of samples in a study are critical components of a sound sampling method (Legendre & Legendre 1998) and can be precisely determined using a power analysis. Power analysis typically refers to simulation-based tests of statistical power – the probability that a null hypothesis will be rejected when the alternative hypothesis is “true” (Bolker 2011). In other words, statistical power reflects our ability to refine or “prove” our expectations from a given dataset. However, this traditional frequentist definition suffers from too strong of a focus on *p*-values and the "truth" of particular null hypotheses (for reasons described at length by Burnham & Anderson 2002, as well as by Bolker 2011). Therefore, we employ the term 'power analysis' when referring to questions about how the quality and quantity of data enhance our understanding of the true properties of the ecological system.

We conducted a power analysis to determine the number of plots necessary in each vegetation type to detect 2-6% annual change (i.e., effect size) in the variables of interest at an 80% power level. This degree of annual change equates to a 10-25% change between sampling at a 5-year interval, a range consistent with that of a forest treatment prescription. Since variations in the sampling design might limit our ability to answer key management questions with confidence, we performed the power analysis for several hypothetical sampling designs, e.g., accounting for differences in number of years, number of plots, and sampling frequency. Specifically, we generated a simulated dataset (Gelman & Hill 2006) using empirical estimates of the central tendency and variability of key monitoring variables based on a review of recent literature describing contemporary forest conditions. The variables used in the power analysis include: proportion of total basal area in oak (Fulé et al. 2002), percent ground cover of grasses, forbs, shrubs, and non-native invasive species (C. Albano et al., unpublished data), density of large snags (Ganey 1999, Ganey & Vojta 2012), density of pre-settlement trees (Beier & Drennan 1997), diameter distribution of pinyon pines, and mortality of pinyon and juniper (Mueller et al. 2005). We implemented all power-related simulations and analyses in the R statistical environment (R Development Core Team 2012).

We evaluated effect sizes of 2%, 4%, and 6% annual change, and conducted the power analysis at 2- and 5-year (simulated) sampling intervals. Detecting statistically significant changes through time in a given variable is more difficult for smaller effect sizes than for larger effect sizes. It is also more difficult to detect change in a single two-year sampling interval as compared to the five-year interval, although the 80% power threshold is approached faster in time using the shorter interval (due to multiple samples). For the purposes of the power analysis, we investigated an initial total sample size of 380 plots. We assessed the first power analysis to determine how many plots per cover type were necessary to detect 4% annual change after a maximum of 10 years of monitoring (i.e., two 5-year sampling intervals) at 80%

power in all monitoring variables. We then iterated the power analysis with 2%, 4%, and 6% annual changes through 25 years of monitoring to determine the minimum sample size necessary in each cover type to meet 80% power in the shortest time. For most variables, we esimated that KNF will be able to detect a 4% annual change five years into monitoring program, although detecting a smaller change (e.g., 2%) will be possible for only a few variables, such as relatively rapidly changing variables (understory cover). Table 2 presents the final minimum sample sizes for each cover type. Plot centers were located randomly proportional to the area in each ranger district and, within each district, proportion to the cube root of the area in each cover type.

Table 2. Number of plots for a rapid plot monitoring design, by cover type and ranger district, on the Kaibab National Forest.

	Ranger district			
Cover type	North Kaibab	Tusayan	Williams	TOTAL
Aspen	17	-	5	39
Grassland	25	17	33	58
Mixed conifer	16	-	6	22
Oak	10	7	15	32
Pinyon-juniper	35	33	43	111
Ponderosa pine	34	22	43	99
Spruce-fir	18	-	1	19
TOTAL	155	79	146	380

IV. Plot layout, sampling design, and data sheet

Overall plot design description

Developing a rapid plot design that is capable of monitoring a variety of forest structural components requires that all variables (and associated methodologies) included in the design meet several key criteria specified by the KNF. Namely, all variables should: 1) address multiple Forest Plan monitoring questions, 2) complement existing remotely sensed forest structural metrics, and 3) allow for efficient and consistent field measurements by novice technicians. To develop a sampling design that is simple to implement, time efficient, and capable of meeting the above criteria, we employ a design that relies on a series of spatially co-located measurements collected within subunits of various size to provide information at the plot, cover type, and landscape scale.

Sampling strategies based on multiple co-located subplots of varying size have been used extensively to characterize wildlife habitat (e.g., Noon 1981; Kalies et al. 2012), plant community composition (e.g., Stohlgren et al. 1995; Kalkhan et al. 2007a), and the effects of fire on vegetation (e.g., Key & Benson 2006). This design typically relies on a spatially consistent arrangement of subplots or other sampling units within a larger plot to allow accurate, time-efficient sampling conditions within the plot (Barnett & Stohlgren 2003). Here we use a circular plot design as they are often more efficient to deploy in the field and reduce "edge effects" due to perimeter: area ratios resulting in comparatively lower variance than square or rectangular plots (Bonham 1989). The combination of consistent geometric orientation and precisely geo-referenced plot centers allows data collected on these plots to also be related to data available through a number of remote sensing platforms (e.g., Landsat TM, IKONOS, SPOT5, Worldview2, etc.) and characterize ecological conditions at multiple spatial extents (Kalkhan et al. 2007b).

Each randomly stratified circular plot will have a 15-m radius (~707 m^2) (Figure 2). This plot size was determined based on previous rapid plot sampling experiences in southern Arizona and Montana that a plot ≤ 800 m^2 could be sampled in < 1 hour. The design combines qualitative, quantitative, and categorical measurements of the variables listed in Table 1. Overall plot condition will be documented using a single photo taken from the southern endpoint of the north-south transect. This replaces traditional photo-point methods to allow rapid photo plot documentation. Because this rapid plot design does not aim to address species-level questions except for a few focal species (e.g., aspen and oak) and target non-native invasive species (e.g., cheatgrass), we focus on documenting the frequency, density and size distribution of different vegetation components to maintain measurement expediency. We summarize stem counts, cover estimates, and diameter class distributions at the plot level to provide quantitative information about understory structure (including tree regeneration), fuel composition, tree density and size, and abundance of large trees (> 40 cm dbh), snags (> 45 cm dbh), and downed logs (> 30 cm dbh).

FIELD PROCEDURES

Appendix B provides a list of required field gear. A two-person field crew will be given the coordinates of the plot and corresponding plot ID. Once the crew has arrived at the plot center a new waypoint-averaged GPS location will be taken and the center marked (on the first plot visit) with a permanent metal stake (e.g., rebar with aluminum cap and permanent label).

Two perpendicular 30-m transects (one north-south, the other east-west) are placed through the plot center. Four 1 m x 1 m quadrats are placed on the north, south, east and west side of each transect at 2.5 m from the plot center (Figure 2).

The crew will begin by taking a photo of the blank data sheet (with plot ID already recorded, see Appendix C) and a photo of the plot from the southern end of the north-south transect. The crew will then take a photo of each 1-m quadrat for estimating fine fuels using the PHOTOLOAD technique (Keane & Dickinson 2007). The crew will then note the quadrant number (Figure 2) and presence of 1) overtopping/encroachment, 2) soil disturbance (e.g., burning, compaction, displacement, and 'other') feature with a footprint > 0.5 m^2, and 3) target non-native species including cheatgrass, knapweed, thistles, and toadflax (Appendix C).

Frequency of life forms and land features (e.g., annual and perennial grasses, forbs, fern, shrubs, litter, bare soil, and rock) will be recorded using the line-point intercept method (Elzinga et al. 2001; Herrick et al. 2009) (Figure 2). Using a pin flag, observers will record the life form or land feature of the first object encountered at each meter mark on both the north-south and east-west transects (a total of 59 estimates).

Due to the clumped or clonal nature of young conifers as well as aspen and oak, crews will use a series of four belt transects to estimate density of these attributes and to minimize measurement time. Density of seedlings (< 10 cm dbh and < 1.5 m height) and saplings (< 10 cm dbh and ≥ 1.5 height) of all species will be estimated using a series of four 4 m x 12.5 m (50 m^2) belt transects. Beginning at 2.5 m from the plot center and using a 2-m pole, one crew member will remain positioned at the transect center while the other tallies the number of individual trees in each of the aforementioned categories on each side of the four transects noting the species and size class.

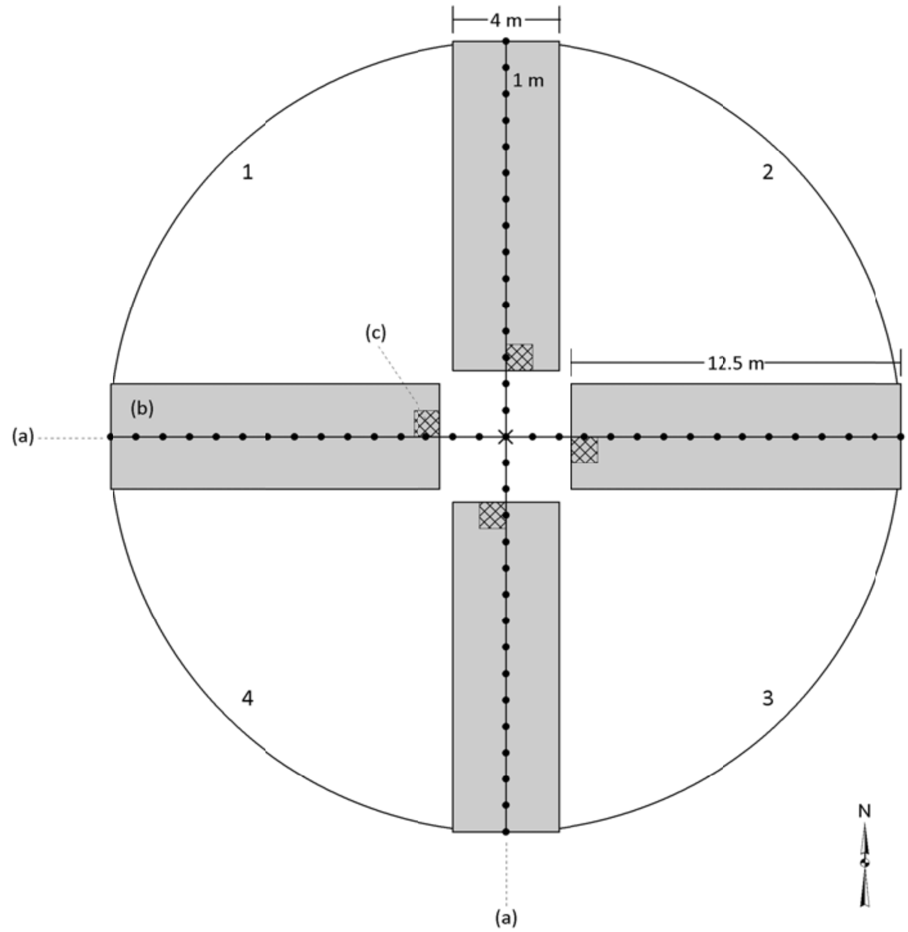

Figure 2. The 30-m diameter circular rapid plot design. The plot is divided into four 177-m^2 quadrants, numbered clockwise starting from the northwest side. Two 30-m perpendicular point-intercept transects (a) are placed through the center. Variables to be monitored using the point-intercept method will be measured at 1-m increments along these transects. Four 4 m X 12.5 m (50m^2) belt transects (b-shaded in gray) are located along the point-intercept transects. Four 1 m^2 quadrats (c-crosshatch) are placed within the belts, 2.5 m from the plot center.

All trees ≥ 10 cm in dbh, downed logs, and snags will be recorded within the entire plot using a “go/no go” board (the go/no go board is adapted from a commonly used tool for estimating fine fuels; see the USFS Region 3 Common Non-Forested Vegetation Sampling Protocol (CNVSP)) (Figure 3). Trees will be identified to species, counted and assigned to size classes in dbh of 10-20 cm, 20-30 cm, 30-40 cm, and > 40 cm. For trees >40cm, observers will count the number of those individuals that meet the Keen description of ‘over mature’ (classes 4A and B, KNF Plan Appendix C).

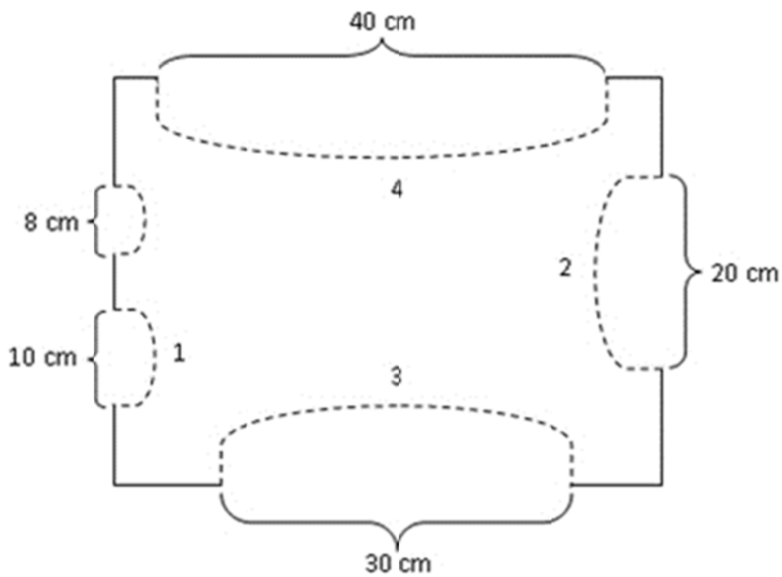

Figure 3. Example of a “go-no go” board (approximately 50 cm X 40 cm) for determining diameter distribution of live and dead trees, as well as downed logs. Boles or logs will be given the diameter class associated with the smallest cut-out on the board (dashed lines) in which they fit.

Assessing coarse woody debris using perpendicular transects avoids potential bias due to non-random orientation of tree-fall in areas of steeper slopes (Woldendorp et al. 2004). Coarse woody debris will be measured using an adaptation of the line intersect method for forest fuels (van Wagner 1968) using the two transects (Figure 2). All logs > 8 cm diameter will be measured at the point that they intersect the transect using the go-no go board. Length measurements will be taken along the entire length of the north-south transect and along the eastern-most 14 m and western-most 14 m of the east-west transect (1 m on each side of the plot center is omitted from the east-west transect to avoid bias due to double-counting downed logs). Each log will also be assigned a decay class following Brown (1974) (Appendix C). Although line intersect approaches may take slightly longer than strip-plot methods, their performance is relatively similar and the intersect approach is more familiar to managers who are experienced with Brown’s transects (Bate et al. 2004). Depth of litter and duff will be measured 5 m from the plot center on each transect. These measurements, in conjunction with the PHOTOLOAD estimates, will provide a comprehensive depiction of fuel loading within the plot.

V. Potential use of remotely sensed data

Various attributes of forest structure (e.g., basal area, canopy cover, canopy height) can be predicted consistently across broad spatial scales using remote sensing-derived metrics (Dickson et al. 2011). Remotely sensed images from diverse satellite platforms have been used to derive multiple vegetation and site condition indices based on the reflectance ratio and amplitude among different spectral bands (Table 2) (Poulin et al. 2010, Eckert 2012). These indices can be used to characterize phenological patterns to predict non-native invasive plant presence, predict fire risk and hazard, or identify species distributions. In addition, estimates of forest structure that are informed by ground-based inventory data and derived using remotely sensed imagery at fine-medium spatial, temporal, and spectral resolutions can aid in the predictive modeling of other unmeasured attributes (Falkowski et al. 2009).

In order to precisely relate ground data to aerial or satellite imagery, including images obtained from the Landsat, SPOT-5, and WorldView-2 platforms (Table 2), a plot design needs to be adaptable in a way that measurements can be appropriately linked to a given platform for future model training and testing. For the rapid plot design we propose, results from simple manipulations of satellite images (e.g., using resampling methods) can be related to ground-based measurements of forest attributes using precisely georeferenced plot locations (Kalkhan et al. 2007a). Notably, previous forest inventory studies have suggested that remote sensing imagery to be used for linking ground forest inventory data should have a pixel size ≤ 25 m (Tomppo et al. 2008). However, this threshold pixel size may be suitable for particular attributes in certain ecosystems, but not others. Thus, the optimal spatial resolution (or pixel size) of the remotely sensed data source should be evaluated based on the relationship between field and spectral attributes using robust statistical methods, such as average local variances, variograms, or linear regression (Nijland et al. 2009). Resampling coarse pixels to finer resolution tends to result in erroneous data. Although it results in some loss of detail, more fine-resolution data can be resampled to a coarser pixel size (e.g., resample 10-m pixels to

30-m pixels) that matches other data in the analysis or otherwise better fits the model, needs, or questions.

Table 2. Commonly used remote sensing vegetation and site condition indices that can be derived from images of the previously acquired Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper (ETM+), new Landsat 8 (L8), SPOT-5, or WorldView-2 (Poulin et al. 2010, Eckert 2012). Pixel size for each platform is shown in parenthesis. NIR: near-infrared band; R: visible red band; B: visible blue band; SWIR: short-wave infrared band; G: visible green band.

Index	Equation	TM/ETM+ (30m)	L8 (30m)	SPOT-5 (2.5-20m)	WorldView2 (2m)
Ratio Vegetation Index	NIR/R	3, 4	4, 5	2, 3	5, 7
Infrared Percentage Vegetation Index	NIR/(NIR+R)	3, 4	4, 5	2, 3	5, 7
Normalized Difference Vegetation Index	(NIR-R)/(NIR+R)	3, 4	4, 5	2, 3	5, 7
Enhanced Vegetation Index	2.5*((NIR − R)/ (NIR+6*R−7.5*B+1))	1, 3, 4	2, 4, 5	N/A	2, 5, 7
Soil Adjusted Vegetation Index (SAVI)	1.5*(NIR-R)/ (NIR+R+0.5)	3, 4	4, 5	2, 3	5, 7
Optimized SAVI	(NIR-R)/ (NIR+R+0.16)	3, 4	4, 5	2, 3	5, 7
Normalized Difference Water Index (NDWI)	(NIR-SWIR)/ (NIR+SWIR)	4, 5	5, 6	3, 4	N/A
Modified NDWI	(G-SWIR)/(G+SWIR)	2, 5	3, 6	1, 4	N/A
Moisture Stress Index	SWIR/NIR	4, 5	5, 6	3, 4	N/A

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APPENDIX A: GUIDE TO STATISTICAL ANALYSES

(23 October 2013)

For project **task (#1)** entitled:

Rapid Plot Monitoring Design for the Kaibab National Forest

USFS-NAU Agreement # 09-CR-11030700-019 Mod 3

Submitted to:

The Kaibab National Forest

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INTRODUCTION

This guide is intended to assist the Kaibab National Forest (KNF) staff with statistical analyses of data collected under the forest-wide rapid plot monitoring plan. This guide specifies the most appropriate parametric or nonparametric tests and articulates the assumptions of each test we propose. The guide suggests diagnostics that can be used to evaluate whether key statistical assumptions are being met, including normality of data. Using the techniques described in this guide, the KNF will be able to assess trends in forest resources by detecting statistically significant patterns in variables being monitored. We assume that the user of this guide has an understanding of basic concepts related to data distributions, sampling variability, and statistical analytical methods. Before using any statistical software to assess monitoring data, analysts should review this guide to familiarize themselves with the recommended statistical techniques, while also referencing comprehensive guide books for methods to analyze natural resources data (e.g., Helsel and Hirsch 2002), where appropriate.

I. STATISTICAL SOFTWARE

We recommend using the open source, freely available software R combined with the R-commander graphical user interface package (hereafter Rcmdr, http://www.rcommander.com/). Numerous introductory tutorials for R and Rcmdr, including screen shots of the package interface as well as sample data and codes, are available online (e.g., Gutermuth 2010, Karp 2010, Larson-Hall 2010, and http://people.ysu.edu/~gchang/r/R_Instructions.htm). R software allows raw data to be entered in another program and then imported into the R interface. We recommend the raw data from data sheets to be entered into a spreadsheet format that can be organized and summarized easily using R. Data entry will be the most efficient when spreadsheets are separated according to the data collection units of interest (e.g., Ranger District, cover type, year) and data are summarized by variable at the plot level. The data fields and rows should be in a template that allows the entry and summary of data collected over multiple years.

II. Data summary: descriptive statistics

The following variable measurements will be summarized at the plot level prior to importing them into Rcmdr. The analyst can then generate descriptive statistics based on the scale of interest (e.g., cover type, ranger district, etc.):

1. Presence/absence of target invasive species in different soil disturbance types;
2. Presence/absence of overtopping/encroachment in different cover types;
3. Shrub and understory percentage cover (number of hits at line intercepts/total number of line intercepts X 100) in districts and in different cover types;
4. Oak and aspen stem density (stem count in belt transects/total area of the transects in dbh < 10 cm, 10-20 cm, 20-30 cm, 30-40 cm, and > 40 cm) in districts and in different cover types;
5. Seedling density (stems count in bell transects/total area of the transects) in districts and in different cover types;
6. Sapling density (stems count in belt transects/total area of the transects) in districts and in different cover types;
7. Density of old trees, snags, and downed logs (stem count in plot/total area of the plot) in districts and in different cover types;
8. Tree size distribution (stem count in plot in dbh < 10 cm, 10-20 cm, 20-30 cm, 30-40 cm, and > 40 cm as well as dbh distribution for large trees) in districts and in different cover types;
9. Fuels counts (length, dbh, and decay class along transects) in districts and in different cover types;
10. Litter and duff loading estimates in districts and in different cover types.

Analysis Instructions:

Click Statistics→ Summaries→ Active data set in Rcmdr. R will produce descriptive summary, including minimum and maximum values, the first and third quartiles, the median, the mean, and the number of missing values for the numerical variables. For categorical variables, R will also produce the number of observations at each level of the factor. Similarly, clicking

Statistics→ Summaries→ Numerical Summaries will produce the mean, standard deviation (sd), and interquartile range (IQR) of the variable, along with quantiles (percentiles) corresponding to the minimum, the first quartile, the median, the third quartile, and the maximum of the variable. The Numerical Summaries function will also provide summaries within groups defined by the levels of a factor. Clicking on the Summarize by Groups button will provide options to summarize the variable measurements in different years, vegetation types, treatments types, or Ranger Districts.

III. DATA EVALUATION USING VISUAL EXAMINATIONS AND STATISTICS

Exploratory plots are recommended to identify the data distribution and visually examine any deviation from an assumed normal distribution. The Graph→Histogram function will produce a histogram in a graphical display of tabulated frequencies, shown as bars. A histogram informs what proportion of samples fall into each group. A Q-Q plot ("Q" stands for quantile) is a probability plot that uses a graphical method to compare two probability distributions by plotting their quantiles against each other (Karp 2010). A normal Q-Q plot (Graph->Quantile-comparison plot->Select normal distribution) will compare the data distribution against a theoretically normal distribution. In addition, two graphic plug-ins of HH and KMggplot2 can be loaded into Rcmdr to enhance graphic capacity for further explorations (Tools→Load Rcmdr plug-in(s)→Select RcmdrPlugin.HH or Rcmdrplugin.KMggplot2 from the dropdown menu).

A normality test also should be performed to test the assumption that the data are normally distributed. Clicking Statistics-> Summaries -> Shapiro-Wilk test of normality will produce a *p*-value that can be compared against a commonly used significance threshold (typically alpha = 0.05) (Razali and Wah 2011). If the *p*-value falls below the significance threshold, then the null hypothesis is rejected and the alternative hypothesis that the data are not normally distributed is supported. For data that do not have a normal distribution, the user may decide to transform the original data values or use non-parametric statistical approaches .

Many statistical tests also assume equal variance among samples (often referred to as homogeneity of variance or homoscedasticity). This assumption can be tested with a Levene's test that examines the null hypothesis that the variances are equal (Statistics->Variances-

>Levene's test). If the resulting *p*-value resulting from Levene's test is less than the significance threshold, then the null hypothesis of equal variances is rejected and a difference between the variances among samples is concluded (Levene 1960). Performing a data transformation is recommended to ensure homoscedasticity.

IV. Questions, hypotheses, and statistics

Analyses that address monitoring questions

We recommend the following statistical analyses to address particular questions listed in the Draft Land and Resource Management Plan for the Kaibab National Forest (hereafter Forest Plan) (2012; Table 5, pp. 113-115) and their corresponding hypotheses. The questions and hypotheses in this section are not appropriate for testing for significant differences among, for example, cover types. The following section (**V. Additional Analyses**) includes recommended analyses for examining differences among soil disturbance or cover types. Questions addressing desired habitat conditions for Mexican spotted owl (based on Table C. 2 and C.3 in Appendix C of the Mexican Spotted Owl Recovery Plan (2012; hereafter MSO plan)), as well as the desired conditions of old-growth vegetation specified in the Forest Plan, are not discussed in this guide. Rather, we aim to assess, characterize, and quantify the thresholds for these desired conditions in further discussions once preliminary data have been collected.

Question 1

Are snags, coarse woody debris (CWD), downed logs, and large trees at desired levels at the mid-scale (100 – 1,000 acre average)?

Hypothesis 1a: the density of snags >18" dbh is at the desired level of 2/acre; the density of downed logs >12" dbh and >8' long is at the desired level of 3/acre.

<u>*Analysis Instructions*</u>

The data should be summarized and evaluated at the mid-scale level in 'per acre' units. We recommend implementing a one-tailed t-test (Statistics->Means->Single-sample t-test) to evaluate the null hypothesis there is no difference between mean snag or log density or the desired density of 2/acre and 3/acre, respectively (H_o: $\mu_{snag\ density} = 2$; $\mu_{log\ density} = 3$). A t-test assumes a normal distribution and equal variance in the dependent variable (Field et al. 2012). Therefore, the data evaluation methods described above are necessary to assess the data distribution prior to running t-test (i.e., a Shapiro-Wilk test for normality and a Levene's test for homogeneity of variance). Alternatively, a non-parametric one-sample Wilcoxon signed rank test can be performed if the data are assumed to not belong to any particular distribution (click Statistics->Nonparametric tests->Paired sample Wilcoxon test, then choose the first variable as the measured density and second variable as the density value in desired condition).

Hypothesis 1b: CWD ranges from 3 – 10 tons/acre in ponderosa pine; CWD ranges from 5-15 tons/acre in mixed conifer.

Analysis Instructions

Brown et al. (1982) provides instructions to calculate loadings of CWD that can be converted to tons/acre and summarized by cover type. Summary statistics (see above) should be performed to calculate the mean and 95% confidence interval to determine whether or not CWD is within the respective desired range in ponderosa pine and mixed conifer.

Question 2

What is the percentage effective ground cover?

Hypothesis 2: Cover of perennial grasses, forbs or shrubs, or total effective ground cover is increasing across the KNF.

Analysis Instructions

The mean cover of perennial grasses (PG), forbs (F) and shrubs (S), and the mean total cover (TEG) (i.e., grasses, forbs, shrubs, litter, and rock) per sample period can be represented as the percentage of number of point intercept occurrences of different growth forms divided by total transect points per plot (n = 59). A simple linear regression of the response variable Y (i.e., cover of PG, F, S, or TEG) on sample period (t) should be implemented to test the null hypothesis that there is no linear trend in cover over time (H_o: $\beta_1 = 0$ for $Y = \beta_0 + \beta_1 t + \varepsilon$; where β_0 = regression intercept, β_1 = regression slope and ε = error term). If the null hypothesis is rejected based on the significance threshold, then it can be concluded that the cover is not static over time. In Rmdr, clicking Statistics->Linear regression will perform the simplest regression with a single response and explanatory variable. A simple linear regression assumes that Y is linearly related to t, residuals are normally distributed and independent, and variance of residuals is constant (Field et al. 2012). Using Models->Graphs->Basic diagnostic plots will generate four commonly used residual diagnostic plots including residuals versus fitted values, normal Q-Q plot for the residuals, scale-location plot, and residuals versus leverage plot. A residuals versus fitted plot examines the independence, whereas a normal Q-Q plot examine the normality of residuals. A scale-location plot verifies constant variance of the residuals and a residuals versus leverage plot detects influence of extreme values and regression outliers (Gray 1986). Quick (2009) and Kabacoff (2012a) also provided sample data and codes for various regression diagnostic tools in R. Log transformation of the data may be necessary to meet these assumptions. Alternatively, a nonparametric regression can be performed by loading the package Rsafd into Rcmdr (see codes provided by Carmona 2010).

Question 3

What is the proportion of live and dead understory vegetation, bare ground, and rock?

Hypothesis 3: The proportion of ground cover contributed by live vegetation is increasing across the KNF.

<u>*Analysis Instructions*</u>

The proportion of live and dead understory vegetation, bare ground, and rock per sample period can be represented as the percentage of number of point intercept occurrences of different growth forms divided by total transect points per plot (*n* = 59). A simple linear regression of the response variable Y (i.e., cover of live vegetation) on sample period (t) should be implemented to test the null hypothesis that there is no linear trend in cover over time (Ho: β1 = 0 for Y = β0+ β1t + ε; β0 = regression intercept, β1 = regression slope and ε = error term).

See instructions above for performing the simple linear regression, exploring regression assumptions, and conducting a nonparametric regression.

Question 4

Are the effects of forest management resulting in changes to the productivity of the soils (evidenced by erosion pedestaling of rocks/plants, rills or gullies, and exposed light-colored soil horizons)?

Hypothesis 4: The number of sample locations with visible soil disturbance is decreasing.

<u>*Analysis Instructions*</u>

A frequency of disturbance value for each plot should be summarized as total number of quadrants per plot (*n*) with presence of any soil disturbance type per sample period. A simple linear regression of the response variable Y on sample period (t) should be implemented to test the null hypothesis that there is no linear trend in frequency over time (Ho: $\beta1 = 0$ for $Y = \beta0 + \beta1t + \varepsilon$; $\beta0$ = regression intercept, $\beta1$ = regression slope and ε = error term). See instructions above for performing the simple linear regression, diagnosing regression assumptions, and conducting nonparametric regression.

Question 5

What is the percent cover of noxious weeds by species?

Hypothesis 5: The incidence of each noxious weed species is decreasing.

<u>*Analysis Instructions*</u>

A frequency of invasion value for each plot should be summarized as total number of quadrants per plot (*n*) with presence of any target invasive plant species per sample period. A simple linear regression of the response variable Y on sample period (t) should be implemented to test the null hypothesis that there is no linear trend in frequency over time (Ho: $\beta1 = 0$ for $Y = \beta0 + \beta1t + \varepsilon$; where $\beta0$ = regression intercept, $\beta1$ = regression slope and ε = error term). See instructions above for performing the simple linear regression, diagnosing regression assumptions, and conducting nonparametric regression.

V. Additional Analyses

We recommend the following analyses to address questions that are not specific to the Forest Plan but could be of ecological importance, given the KNF's interests.

Question 6

Is the presence/absence of invasive species associated with soil disturbance type? Is there association between the presence/absence of overtopping/encroachment of aspen and oak with cover types?

<u>*Analysis Instructions*</u>

A logistic regression model should be implemented to examine the association between the binary (i.e., presence/absence) response variable versus the categorical explanatory variable (i.e., soil disturbance or cover types). Rcmdr provides this analysis under Statistics→Fit models→General linear model. Set Family to binomial and the Link function to logit. Logistic regression requires each observation to be independent, i.e., data points should not come from any dependent sampling design such as before-after measurements or matched pairings (Field et al. 2012). Since logistic regression predicts the probabilistic outcome of the response variable based on a given set of predictor variables, model goodness of fit is assumed. A graphic examination of predicted versus observed probabilities provides visual assessment of the model fitness (Eckel 2007; see sample codes in Everitt and Hothorn 2010). A Hosmer-Lemeshow chi-square test (available in R and R package ResourceSelection) should be performed to test the null hypothesis that the model fits the observed data well (Eckel 2007; see sample codes in Ken Kleinman 2010 and Lele et al. 2013). In addition, the lrm and residuals.lrm functions from R package rms also perform logistic regression and test model goodness of fit (see sample codes from Harrell 2013).

Question 7

Do 1) count of oak/aspen in different size classes; 2) count of all trees in different size classes; 3) count of seedlings, saplings, downed logs, and snags; 4) understory cover; and 5) debris length/dbh/ decay class, and litter/duff loading estimate differ among cover types over time?

Analysis of variance (ANOVA) in Rcmdr should be used for only examining differences in measured variables among cover types (click Statistics→Means→One-way or Multi-way ANOVA). Parametric ANOVA assumes a normal data distribution and homogeneity of variance for the residuals (Field et al. 2012). The norm Q-Q plot and Shapiro-Wilk test describe above should be used for evaluating data normality. A Barlett's test should be used to examine the homogeneity of variances (click Statistics→Variances→Bartlett's test). Data transformation may be necessary to meet ANOVA assumptions. Alternatively, a nonparametric Kruskal-Wallis test may be used for data that violate these assumptions (click Statistics→Nonparametric tests→Kruskal-Wallis test). Kabacoff (2012b) provide sample codes for methods to explore assumptions in the ANOVA framework.

For examining differences in measured variables among cover types over time, we recommend implementing a repeated measures ANOVA. The R package ez can be loaded into Rcmdr to perform repeated measures ANOVA (tutorial available in O'connor 2007). In addition, using the R package car will produce one-way or multi-way repeated measure ANOVA (Fox et al. 2013; see sample data and codes in Quick 2011a, b). A repeated measures ANOVA assumes normality in the data distribution and homogeneity of variance, which can be evaluated using the graphic assessment and statistical test described above. Repeated measures ANOVA also assumes data sphericity, i.e., the variances and the correlations among repeated measures are equal (Field et al. 2012). The R packages described above will also produce statistical test of sphericity. Alternatively, a non-parametric Friedman test may be performed for one-way repeated measures by ranks. This test is available in Rcmdr by clicking Statistics→Nonparametric tests→Friedman rank sum test.

Another more flexible approach is to employ a mixed effects model that allows both fixed (e.g., cover types) and random (e.g., plot, quadrant, subplot, or transect) effect factors to be considered. A repeated measure ANOVA emphasizes the quantitative between-group differences between time points, whereas a mixed model emphasizes patterns of change and individual differences. Furthermore, the mixed model does not assume a normal distribution of data (Krueger and Tian 2004). Other advantages of a mixed effects model include the ability to accommodate missing data and treat time as a continuous variable (Grace-Martin 2009). The R package lme4 can be used to perform a mixed effects model that allows using variables that are not normally distributed and multiple random effect factors (Bates 2010; see sample data and codes in Bates 2010 and Bates et al. 2013).

For monitoring the chronic trend of variables and testing the null hypothesis that there is no significant trend over time, we recommend more sophisticated nonparametric trend analysis methods (Hirsch et al. 1991, Helsel and Hirsch 2002). A non-parametric Mann-Kendall test should be performed for detecting the presence of positive or negative trends in the measured variables (Mustapha 2013). This test does not assume any particular data distribution and allows irregular sampling intervals and missing data (Gilbert 1987). Subsequently, a Sen Slope estimator (also known as Theil-Sen estimator or Kendall robust line fit) should be conducted to estimate the magnitude of any significant trend found in the Mann-Kendall's trend analysis (Mustapha 2013). This is a nonparametric estimator of linear regression coefficients between two continuous variables. The slope of the regression line is calculated as the median of all possible pairwise slopes between sampling points (Granato 2006). The Sen Slope method estimates value and confidence interval for the slope, allows missing data, and makes no assumption on data distribution (Sen 1968). Both wq and rkt packages for R perform Mann-Kendall test and Sen Slope estimator (Jassby and Cloern 2013, Marchetto 2013). Alternatively, the Kendall-Theil Robust Line software (KTRLine—version 1.0) developed by the US Geological Survey can work as a stand-alone module to produce estimates of regression statistics and graphical-display interface (Granato 2006; downloadable online: http://webdmamrl.er.usgs.gov/g1/ggranato/software/KTRLine.html).

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Appendix B. Rapid plot gear list.

Item	Quantity
Rebar stake, aluminum tag with stamped plot ID, mallet	1 each (first visit only)
Data sheet	1/plot x plots/day
Clip board, pencil	1
Digital camera	1
Handheld GPS	1
30-m tape	2
1 x 1 m PVC quadrat	1
Pin flags	5
2 m PVC pole	1
Go/no go board	1
Keen's tree class guide	1
Brown's decay class guide	1
Invasive spp guide	1

Appendix C. Rapid plot data sheet.

Date:		**Plot ID:**		**Data collectors:**			
X coordinate:				**Y coordinate:**			
Veg type	Aspen	Oak	Ponderosa	Mixed confier	Grassland	PJ	Other
Circle quadrant where present:							
Platy, yellow, furrowed, or sloughing bark of old trees:				Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
Overtopping/encroachment:				Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
Soil disturbance (record quadrant ID of presence)							
Burning				Compaction			
Displacement				Other			
Non-native species (record quadrant ID of presence)							
BRTE		CESP		SASP			
CISP		LIDA		Other	(sp. code)		
Count of trees (dbh in cm) including oak, aspen, and other species							
Species	1 (10-20)	2 (20-30)	3 (30-40)	4 (> 40)		Downed log (> 30)	Snag (> 45)
Species	Diameter of large trees (dbh > 40 cm)					Count of Keen Class 4 trees	
Count of oak and aspen < 10 cm dbh, other tree saplings, and seedlings							
Belt transect	Oak	Aspen	Tree saplings	Seedlings			
W->E							
N->S							

Record the ID of the first hit: S=shrub, F=forb, G=grass, FE=fern, C=crust, B=bare soil, R=rock; indicate live (L) or dead (D)							
Transect W->E	1	2	3	4	5	6	7
	8	9	10	11	12	13	14
	15	16	17	18	19	20	21
	22	23	24	25	26	27	28
	29	30	Notes				
Transect N->S	1	2	3	4	5	6	7
	8	9	10	11	12	13	14
	15	16	17	18	19	20	21
	22	23	24	25	26	27	28
	29	30	Notes				

Woody debris (> 8cm diameter) length (cm) and Brown's transect decay class (1, 2, 3, 4, 5)							
Transect W->E	Length						
	dbh						
	Decay class						
Transect W->E	Length						
	dbh						
	Decay class						
Transect W->E	Length						
	dbh						
	Decay class						
Transect N->S	Length						
	dbh						
	Decay class						
Transect N->S	Length						
	dbh						
	Decay class						
Transect N->S	Length						
	dbh						
	Decay class						

Depth of litter and duff (cm)							
Transect W->E	Litter	5m-W	5m-E				
	Duff	5m-W	5m-E				
Transect N->S	Litter	5m-N	5m-S				
	Duff	5m-N	5m-S				