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Estimating variation in a landscape simulation of forest structure

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Abstract

Modern technology makes it easy to show how forested landscapes might change with time but it remains difficult to estimate how sampling error affects landscape simulation results. To address this problem we used two methods to project the area in late-seral forest (LSF) structure for the same 6070 hectare (ha) study site over 30 years. The site was stratified into patches by using aerial photos and data were collected on sample plots within the stratum. Our two methods differed in how the initial forest conditions in unsampled patches were attributed. Using method 1, we randomly assigned empirical plot data from sampled patches to unsampled patches within the same stratum; with method 2 we bootstrapped the plot data to identify a probability distribution of LSF structure for a sampled patch and then randomly assigned these probabilities to unsampled patches within the same stratum. Both methods used an individual tree growth model to project changes in forest structure. In the first decade, the 'assignment' method produced an estimate of 2489 ha of LSF structure, an amount lying at the upper tail of the projection interval created by using the bootstrapped or 'probabilistic' method. The probabilistic method identified the variation in LSF structure within landscape stratum, the strata most likely to contribute to LSF structure, the projected mean area in LSF structure each decade, and the variation in hectares associated with the projections. Data maps from both methods, together with projection intervals from the probabilistic method, offer enhanced ways to communicate the potential variation in landscape simulation.

Keywords: Bootstrap sampling; Forest dynamics; Forest Vegetation Simulator; Monte Carlo simulation; Probabilistic method

1. Introduction

Forest vegetation creates patchworks of patterns and textures that look different depending on how they are viewed. When forest management occurs on scales larger or longer than human perception, computer models are sometimes used to aid in understanding and visualizing vegetation dynamics. Several models can portray current forest conditions and simulate future conditions over extensive, heterogeneous land areas (landscapes) (Monserud, 2003). In combination with satellite imagery and mapping software, the models make it easy to simulate and display how a particular forested landscape might change over time and space (landscape simulation) (Fassnacht et al., 2006). It remains difficult, however, to estimate the error in landscape simulation, which hampers evaluating the reliability and potential significance of projected changes (Hess and Bay, 1997). Disclosing the uncertainty associated with landscape simulation is important because land use or public policy decisions might rely on the results.

Contemporary uses of landscape simulation include managerial, scientific, and political applications. For example, in the Pacific Northwestern United States (PNW), federal and state foresters use simulation models to describe the current and expected future condition of areas within their jurisdiction, to plan activities designed to achieve desired conditions, and to communicate the plans to interested citizens (e.g., Cissel et al., 1999; Busing and Garman, 2002). Scientists use landscape simulation to investigate disturbance effects when it is difficult or impossible to apply silvicultural treatments because of physical, legal, or other limitations (e.g., Klenner et al., 2000; Gustafson et al., 2004; Hayes et al., 2004). State and regional government agencies rely on projections of land use changes to estimate effects on water and air quality and to make decisions about permits.

The established use of landscape simulation has spurred development of some common analysis methods. A landscape simulation usually begins with a description of existing conditions, often by using photo interpretation, field sampling,

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satellite imagery, inventory plots (or some combination thereof) to identify "patches", or homogeneous units, and to populate them with vegetation data (e.g. Keane et al., 2002). Units lacking empirical data are often assigned data with methods that include imputation (Ohmann and Gregory, 2002; Temesgen et al., 2003), most similar neighbor (Moeur and Stage, 1995) and forest management classes (Maffei and Tandy, 2002). The units, together with their associated data or model predictions, are then organized in a spatially explicit, geographic information system (GIS) database. Next, a computer model is used to simulate changes for a variable of interest, or "metric", through time in each unit. Selection of a simulation model depends on the questions being asked and the metrics involved. Simulation models can be broadly classified as either empirical or process-based depending on their objectives and construction. Empirical models seek to improve the predicted values of measured variables by fitting data while process models aim to improve understanding of forest dynamics by describing underlying ecological processes (Zeide, 2003). Mladenoff (2004) describes some trade-offs in spatial resolution and extent between simulation models in these two classes. In general, individual tree growth models can provide high resolution, or detail, at the expense of landscape extent, or size, and patch models can optimize extent by giving up detail. Data maps are the summary documents often produced by landscape simulation, regardless what model is used. Data maps display the conditions for a metric in each unit through time.

Consensus does not yet exist on how data maps should communicate the results of landscape simulation or what they should include (Smith et al., 2003). These are important considerations because visual impressions of such "patch" maps can be affected by human perceptions of geographic boundaries, areas, shapes, and colors (Tufte, 1983, p. 20). Further, it is rare for products of landscape simulation to disclose information on the precision of projected outcomes because estimating variance is difficult for the results of simulation. Instead, conclusions about projected conditions are often drawn by considering singular predictions obtained from multiple simulations (Parysow and Gertner, 1999). A problem with this approach arises with the desire to test hypotheses by using multiple simulations; the important question is not if the projected conditions are different but if the differences are significant. Progress made on estimating the uncertainty in landscape simulation will address this problem. Simulation results can be affected by several sources of uncertainty, including classification error (Congalton, 1991) and variation in the sample data used to characterize initial landscape conditions. We focus on the latter.

This paper highlights the potential effects of variation in sample data on a landscape simulation of forest structure and begins to develop ways for communicating these effects. We used an existing vegetation classification system for a PNW study landscape, empirical sample data, an individual tree growth model, and GIS. We compared the results of simulations run using two methods that differed in how initial forest structure was attributed to unsampled landscape patches: either by (1) randomly assigning empirical data from sampled patches to unsampled patches within the same stratum or (2) bootstrapping the data to identify a probability distribution of LSF structure for a sampled patch and then randomly assigning these probabilities to unsampled patches within the same stratum. Accordingly, we refer to the first method as an "assignment method" and to the second as a "probabilistic method". In the following sections we present our two methods, then describe how we applied them to our study landscape, and compare the results.

Our metric of interest is the area of late-seral forest (LSF) structure in the study landscape over three decades. This metric relates directly to the management objective for the study landscape, which is a late-successional forest reserve. The study reserve was established in 1994, following the adoption of a regional conservation plan (Plan), which created a network of similar reserves throughout the Plan area (USDA and USDI, 1994). The federal forestland in reserves was withdrawn from timber production and landscape management objectives shifted to non-commodity values. Specifically, the Plan anticipated that reserves would provide habitat for species like the northern spotted owl (spotted owl) (*Strix occidentalis caurina*), which are associated with later stages of forest development (USDA and USDI, 1994).

2. Methods

2.1. Study area

Our study area is a 6070 ha forest reserve located on the eastern slope of the Cascade Range in southern Washington State (description in Hummel et al., 2001 and Hummel and Calkin, 2005). Vegetation differs by aspect and elevation, but most of the area resembles the grand fir/creeping snowberry/vanillaleaf (*Abies grandis/Symphoricarpos mollis/Achlys triphylla*) or grand fir/big huckleberry (*A. grandis/Vaccinium membranaceum*) associations described in Franklin and Dyrness (1988) and Topik (1989). Increased tree mortality and down wood associated with persistent, elevated levels of western spruce budworm (*Choristoneura occidentalis*) are altering forest structure (Hummel and Agee, 2003; Willhite, 1999) and declines in nest occupancy and reproductive success of spotted owls have occurred at six nest sites in the reserve (Mendez-Treneman, 2002). A territorial competitor, the barred owl (*Strix varia varia*), has been documented in the area (Harke, 2003).

Land managers responsible for the study reserve are concerned that future forest conditions may not support Plan objectives for spotted owl habitat (USDA Forest Service, 2003). Our landscape simulation goals were therefore to estimate the mean area of LSF structure in the reserve over three decades and to calculate the uncertainty associated with the estimates in each decade. We focus on forest structure, or the arrangement and variety of living and dead forest vegetation, as a proxy for habitat because it can be

Table 1
Late-seral forest (LSF) structure definition

Basal area (BA) at least 55.2 m^2/ha
BA of trees greater than 61.0 cm dbh $\geq$ 8.3 m^2/ha
BA of trees greater than 35.6 cm dbh $\geq$ 33.1 m^2/ha
BA of trees greater than 35.6 cm dbh $\geq$ 8.3 m^2/ha

Source: Hummel and Calkin (2005).

measured and is physically and biologically relevant to reserve objectives. Our LSF structure definition includes a minimum basal area per hectare allocated among specific tree diameter classes (Table 1). The terms "study reserve" and "study landscape" are synonymous for the remainder of this paper.

2.2. *Landscape stratification and sampling*

We relied on vegetation classification methods developed for a regional assessment of federal forestland in the PNW (Hessburg et al., 1999a). The methods used interpretation of aerial photos (1:12,000) to generate a GIS data base of landscape patches and their vegetation attributes (Hessburg et al., 1999b). A matrix based on two of the attributes, structure class (SC) and potential vegetation type (PVT) was created to stratify the landscape patches in our study reserve (Hummel et al., 2001). Together, these two attributes describe the current forest vegetation in a patch and the environmental conditions influencing its growth dynamics (Tables 2 and 3). In our analysis each SC $\times$ PVT cell in the matrix represented a landscape stratum. To measure forest conditions within the strata, we selected patches randomly with probability proportional to size. Stand exam protocols from the Pacific Northwest Region of the USDA Forest Service were followed for summer field sampling of vegetation in 2000 and 2001. The number of variable radius sample plots comprising an exam depended on the size of the patch. Large patches (>200 ha) were further sub-stratified to reduce within-patch variability based on tree species composition (details in Calkin et al. (2005)). We assumed that the process of stratifying the landscape into patches and then substratifying patches into units resulted in similar within-unit conditions. Each unit retained the features of its original patch and stratum in the GIS database. These landscape units became our unit of analysis for forest structural dynamics.

Table 3
Potential vegetation type (PVT) definitions

10	Warm/dry; Douglas-fir/grand fir (*Pseudotsuga menziesii/Abies grandis*)
11	Cool/moist; Douglas-fir/grand fir *P. menziesii/A. grandis*)
13	Cool/moist; Engelmann spruce/subalpine fir (*Picea engelmannii/Abies lasiocarpa*)
18	Cool/moist; western redcedar/western hemlock (*Thuja plicata/Tsuga heterophylla*)

Source: adapted from Hessburg et al. (1999b).

2.3. *Vegetation simulation model*

We opted for using an individual tree growth model because forest structure emerges from the dimensions and arrangement of living and dead trees. The Forest Vegetation Simulator (FVS) (Stage, 1973), a model created and maintained by staff of the USDA Forest Service, is frequently used for planning on federal public forests, and 20 regional variants of FVS have been developed to cover much of the United States and parts of Canada (Monserud, 2003, p. 147). The model and its variants are documented, the source code is public, and descriptions of its structure are widely available (http://www.fs.fed.us/fmsc/fvs). In addition to a mortality model, FVS includes three tree growth components. Disturbance processes can be simulated via modules that include forest insects, diseases, and fire. Data on the number, species, and sizes of trees measured on multiple sample plots within a unit are pooled to create the input files for FVS, which are known as tree lists (Dixon, 2003). A tree list thus represents a composite profile of conditions in a unit. FVS is not spatially explicit but can be linked with GIS (McMahan et al., 2002) to leverage high model resolution with spatial extent.

2.4. *Method 1: assignment*

For our first method, we randomly assigned the FVS tree lists from sampled units to unsampled units within the same landscape stratum by using each unique tree list number and a random number table. After all units had a tree list, growth was simulated over three, 10-year periods. At the end of each decade, the conditions in each unit were classified by FVS according to the LSF structure definition (Table 1). If a unit met the definition it was assigned a value of 1, otherwise it was assigned a value of 0.

Table 2
Structure class (SC) definitions

Structure class	Definition
Stand initiation (SI)	Forest growing space is reoccupied by young trees following a stand-replacing disturbance
Stem exclusion, open canopy (SEOC)	Occurrence of new trees is excluded (moisture-limited); the forest canopy is broken and tree crowns are open-growing
Stem exclusion, closed canopy (SECC)	Occurrence of new trees is excluded (light-limited); the forest canopy is closed and tree crowns are abrading
Understory reinitiation (UR)	A new age group of trees establishes under the mortality-induced openings of the older overstory
Young forest, multistory (YFMS)	Several age groups are established; large trees are generally absent
Old forest multistory (OFMS)	Diverse horizontal and vertical distributions of tree sizes occur; with large trees also present and significant in the overstory

Source: adapted from O'Hara et al. (1996) and USDA Forest Service (1996).

The unit value was then multiplied by the total area of the unit (in hectares). The total area of LSF structure in the study landscape for each decade was then calculated by summing the results for all units. All units projected to meet the definition each decade were coded in the GIS database so that the patch dynamics of LSF structure could be mapped.

2.5. Method 2: probabilistic

Because tree data vary among the sample plots within a unit, its FVS tree list is affected by this source of variation. Mensuration techniques exist for calculating the error associated with forest sampling but they are of limited use for our purposes. After all, the issue is with the effect of sample variation not just on initial conditions but on the projected conditions in each unit and, ultimately, on the collection of units in the landscape. To address this issue we turned to bootstrap sampling (bootstrapping) and Monte Carlo simulation for our second method. A Monte Carlo method is one that solves a problem by generating random numbers and observing the fraction of the numbers obeying some property. Sometimes the underlying sampling distribution is unknown and non-parametric methods like the bootstrap are useful. The two are similar, but in Monte Carlo a new sample is drawn each time, whereas in the bootstrap, resampling is done from a single sample.

2.6. Bootstrapping

The statistical theory underlying bootstrapping dates back to the 1930s, but the huge computational capacity needed to use it in landscape simulation is new. It is a computer-intensive method of statistical inference that is gaining popularity among scientists working with problems for which estimating standard error and confidence intervals is difficult or impossible using classical statistical methods (Efron, 1979; Efron and Tibshirani, 1993; Chernick, 1999). Bootstrap sampling advances the concept that sampling data itself approximates the sampling variations which produced the data in the first place (Efron and LePage, 1992). In landscape analysis, bootstrapping has been used to explore classification error in land cover data (Hess and Bay, 1997). We used bootstrapping to identify the distribution of the mean area in LSF structure in our study landscape.

We built bootstrapped FVS tree lists for all of the landscape patches for which we had empirical plot data. A computer program called FVSBoot (Gregg and Hummel, 2002) made it possible to create bootstrapped FVS tree lists quickly by automating the data re-sampling process. Whereas FVS allows users to examine stochastic variation by running multiple simulations with the same initial tree list, FVSBoot adds the capability for users to examine variation associated with sampling by running multiple simulations using different initial tree lists all built from the same sample data. The FVSBoot program used our original sample of a patch (n) to generate a bootstrap sample also of size n by re-sampling the tree records of the original plots with replacement. Next, it computed a bootstrap mean from the bootstrap sample for LSF structure. By repeating this process, FVSBoot generated an empirical distribution of the bootstrap mean for the area of LSF structure in each sampled patch. Using the bootstrap re-sampling method thus allowed us to evaluate not only whether a patch was in LSF structure but also the probability of this condition. The FVSBoot program output includes intervals around a set of FVS projections. The intervals are created from the distribution of model outcomes using the percentile method. One interval is based on variation from the parameters and model forms of FVS while another also includes variation associated with sampling error (Gregg and Hummel, 2002).

2.7. Monte Carlo simulation

Randomly assigning FVS tree lists to unsampled units, as in the assignment method, generates one estimate of the area of LSF structure in the study reserve from among several that are possible. If users rely on only one FVS projection of a tree list to characterize forest development, then other outcomes possible from different combinations of sample data are not considered. We think it is useful to characterize "extreme" outcomes as well as "average" projected outcomes for a landscape metric of interest because analyses that consider the likelihood of different outcomes are more informative than analyses that do not. We were curious how the one estimate resulting from the assignment method would compare to the range of estimates that were possible given our sample of forest vegetation in the study landscape. To address this, we used the bootstrapped probabilities as input for a Monte Carlo simulation. A random selection and assignment of probabilities was repeated using thousands of iterations of Monte Carlo simulation for each stratum in each decade using SAS® (Fan et al., 2002). In unsampled patches, for which no LSF structure probabilities were bootstrapped, we randomly assigned probabilities from patches for which probabilities were available. Using the probabilities, the simulation created binary random variables to determine if units were in LSF structure (1) or not (0) for each decade. Probabilities were assigned within each stratum. Because units that were not sampled did not have estimated probabilities of transition to LSF structure, probabilities were randomly assigned to them from the possible probabilities of sampled units within each stratum. Assignments were completely random, with no probability more likely to be assigned to any unit than any other probability.

Once a unit was in LSF structure it remained so until the end of that iteration of the simulation. The unit value was then multiplied by the total area of the unit (in hectares). After all strata and decades had been simulated we aggregated the simulation results by decade to estimate the area of LSF structure in the study landscape each decade. For the strata and decades for which no positive probability of LSF structure existed, we ran no Monte Carlo simulations.

3. Analysis

Using 1995 aerial photos, the study reserve was stratified into 159 vegetation patches, ranging in size from 2 to 837 ha with an average of 40 ha. These patches were organized into 15

Potential vegetation (PVT)	SI	SEOC	SECC	UR	YFMS	OFMS
18	Ø	Ø	0.05% **1** *0*	Ø	Ø	Ø
13	0.07% **1** *0*	2.3% **1** *0*	1.83% **5** *1*	21% **19** *2*	0.25% **3** *0*	Ø
11	Ø	Ø	0.32% **1** *0*	4.3% **12** *1*	0.3% **3** *1*	Ø
10	7.4% **61** *3*	2.3% **12** *5*	4.6 % **18** *4*	50% **173** *21*	2.3% **16** *2*	3.4% **13** *2*

Structure class (SC)

Fig. 1. Matrix of landscape strata; refer to Table 2 for column definitions (SC) and to Table 3 for row definitions (PVT). The SC × PVT cells report strata not present in the 6070 ha study landscape (Ø). For the 15 strata present each cell reports, from top-to-bottom, its percent (%) of the landscape area, then its number of patches (bold), and the number of sample exams made (italic). See Hummel et al. (2001) for details.

strata (Fig. 1). Substratifying the large patches (>200 ha) resulted in 330 smaller units, which averaged 18 ha and ranged in size from 0.8 to 464 ha (details in Hummel and Calkin (2005)). Thirty-five patches were sampled with 327 stand exams, covering 10 strata that together represent about 98% of the study landscape (Fig. 1). Plots per exam ranged from 4 to 72, with an average of 19. Sample data were used to create a FVS tree list for that patch following standard FVS procedures (Dixon, 2003).

3.1. Method 1: estimating area in LSF structure with FVS simulation alone

We randomly assigned an FVS tree list to any unsampled patches within the same landscape stratum for our first method. All units thus had data, either measured directly or assigned based on strata affiliation. Each unit received a FVS tree list associated with its original patch but individual unit growth trajectories could differ based on stochastic variation within the model. Once each unit was associated with an input file we used the East Cascades variant of FVS (Johnson, 1990) to compare its structural conditions with the LSF structure definition. Because forest development is influenced by root diseases throughout the study landscape (Filip, 1980), each stratum was also assigned a root disease severity rating (Goheen, 1997). The severity and relative importance of the three main root diseases present in the study reserve (*Armillaria ostoyae*, *Phellinus weirii*, and *Heterobasidion annosum* (S-type)) vary by site; our rating system identified effects at a scale appropriate for the Western Root Disease Model (WRDM) (Goheen, 1997; Frankel, 1998) FVS extension.

We brought all exams to common year (2001), modified the large-tree diameter growth equation based on calibration statistics from local samples, and simulated tree regeneration according to the potential vegetation type by using FVS keywords (Van Dyck, 2000; Hummel and Calkin, 2005). We chose a 30-year analysis period by considering fire return intervals for mixed-conifer forests in the region (Agee, 1993) and Plan objectives for reserves east of the Cascade Range (USDA and USDI, 1994). Stochastic variation in forest growth was included by using the WRDM and the RANNSEED keyword in FVS (Dixon, 2003), but other potential sources of variation such as from fire, insect or climatic episodes were not simulated.

In each decade, we compared the new conditions in each unit to the LSF structure definition. The unit value (0 or 1) was then multiplied by the total area of the unit (in hectares). By summing the results for all units, we calculated the total area of LSF structure in the study landscape. The area of LSF structure in each stratum was summed to calculate the total area of the study reserve projected to be in this structural condition for each decade. A unit could lose its designation as LSF structure if the simulated conditions did not meet those in the definition. We linked FVS output files with ArcView® shape files using EMAP software (McMahan et al., 2002) to display the spatial arrangement of units whose conditions met the definition for LSF structure in the first decade.

3.2. Method 2: estimating LSF structure with bootstrapped FVS tree lists and Monte Carlo simulation

For the second method, we bootstrap sampled the original FVS tree lists to create 500 new files. The vegetation associated with each bootstrap sample was classified as LSF structure or not according to the definition (Table 1). By calculating the number of times out of 500 the conditions in a tree list met our LSF structure definition, we derived a probability of LSF structure for each sampled patch. In unsampled patches for which no probabilities were generated, we randomly assigned probabilities from sampled patches. After probabilities were randomly assigned to each unit, a single Bernoulli trial was performed on each unit within a stratum using the fixed or assigned probability to determine if a unit would make the transition to LSF during the simulation. The area for each unit within a stratum was then multiplied by the indicator variable generated by the trial for that unit to obtain the number of hectares in each unit that transitioned to LSF for the decade. The areas for all units within each stratum were then summed to obtain the total number of hectares for each stratum for each decade of the simulation.

This random selection and assignment of probabilities was repeated for each stratum, in each decade, by using 5000 iterations of Monte Carlo simulation in SAS®, to generate a probability distribution of LSF structure in each stratum and its associated patches (Table 4). After completing the iterative process, the simulation next used the results to evaluate the probability that an individual unit was in LSF structure for any given decade. We aggregated the results by strata, decade, and unit. By summing the results for all units, we calculated the total area of LSF structure projected to occupy the study landscape.

Table 4
Probability of late-seral forest (LSF) structure for each decade in each landscape stratum (SC × PVT) resulting from the probabilistic method

Stratum[a,b]	Decade 1[c]	Decade 2	Decade 3
SI10	0 (0)	0 (0)	0 (0)
SEOC10	0 (28.7)	0 (28.7)	0 (0.4–41.5)
SEOC13	0 (0)	0 (0)	0 (0.2)
SECC10	0 (0–29.7)	0 (0–29.7)	0 (0–21.2)
	1 (59.5–99.8)	1 (56.9–99.5)	1 (56.7–95.9)
UR10	0 (3.6–46.5)	0 (0–34.5)	0 (0.4–33.7)
	1 (36.9–99.8)	1 (86–100)	1 (42.3–100)
UR11	0 (3.4)	1 (60.5)	1 (95.6)
UR13	0 (14.8)	1 (77.2)	1 (95.4)
YFMS10	0 (0)	0 (0)	0 (1)
OFMS10	0 (13.2)	0 (4.8)	0 (14.2)

[a] See Tables 1 and 2 for definitions.
[b] Strata covering less than 2% of the landscape are not included in this table (SECC18).
[c] $x(y)$ when x = mean LSF value and 0 = not LSF and 1 = LSF and y = percent of 500 bootstrapped samples >0 (probability of LSF). A range for y indicates differences in probabilities for units within a stratum.

4. Results

Results for the first method suggest that the area of LSF structure in the study landscape fluctuated within a few hundred hectares over 30 years. In contrast, results for the second method reveal a trend of increasing area in LSF structure over the same period (Fig. 2). The average area predicted to be in LSF structure was greater when probability estimates were included in the simulation than when they were omitted.

4.1. Method 1

The estimate of the area of LSF structure in the first decade obtained by using the assignment method was 2489 ha (41% of the study landscape) (Figs. 2 and 3a). By the second decade, the estimate was 2060 ha, whereas in the third decade it was 2429 ha (Fig. 2).

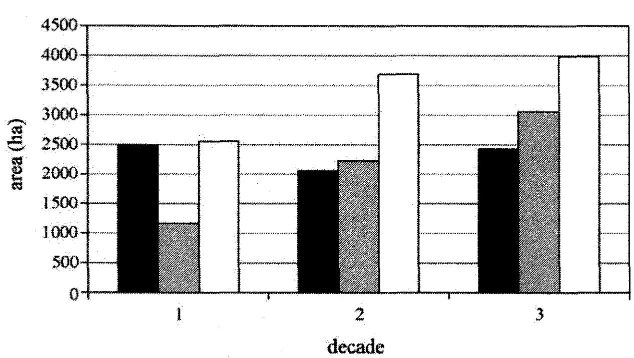

Fig. 2. Area of late-seral forest (LSF) structure (ha) projected for the 6070 ha study landscape over three decades using method 1 (assignment) (black is LSF structure area) and method 2 (probabilistic) (grey is minimum LSF structure area while white is maximum LSF structure area).

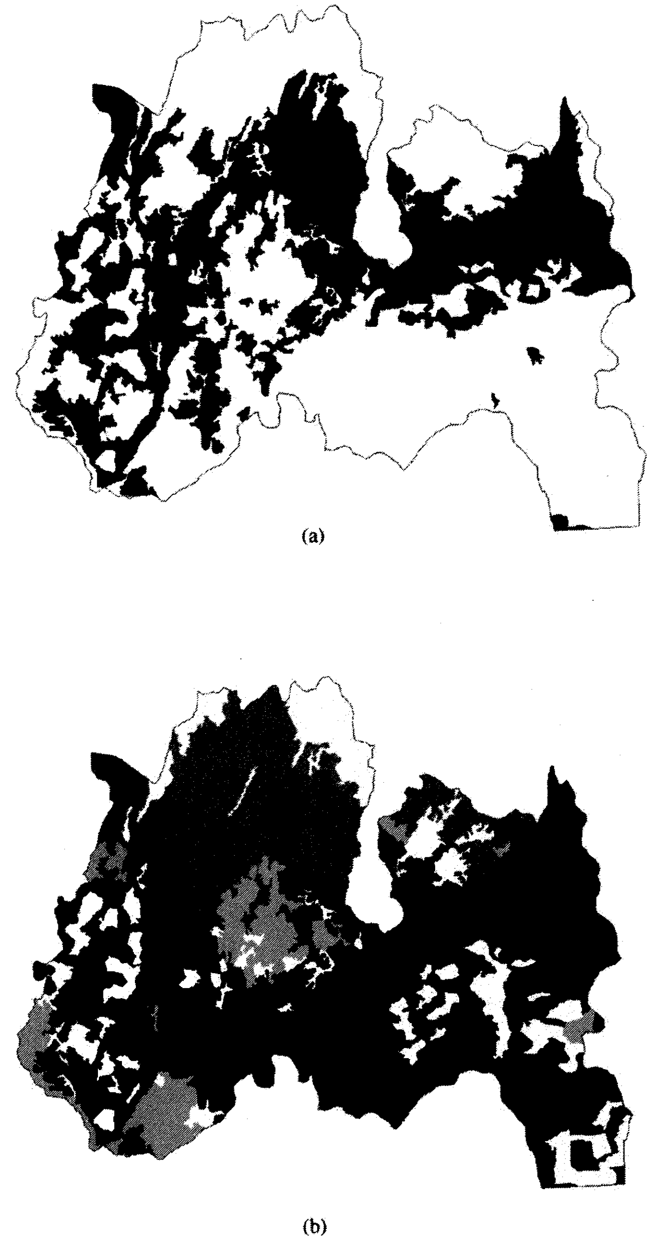

Fig. 3. Late-seral forest (LSF) structure in the 6070 ha study landscape in 2001. (a) Data map produced by method 1 (assignment). Black areas are LSF structure, white areas are non-LSF structure. (b) Probability map produced by method 2 (probabilistic). Black areas represent the highest probability of LSF structure and white areas represent the lowest, with shades of grey denoting intermediate values.

4.2. Method 2

Results obtained by using the probabilistic method indicate that, on average, 1690 ha were in LSF structure in the first decade (Fig. 4a), and 78% (1317 ha) of this metric was associated with just one stratum (UR10) (Table 5). This estimate, which has a standard error (S.E.) of 233.2 ha, represents 28% of the study landscape. By the second decade, an average of 3115 ha were projected to be in LSF structure

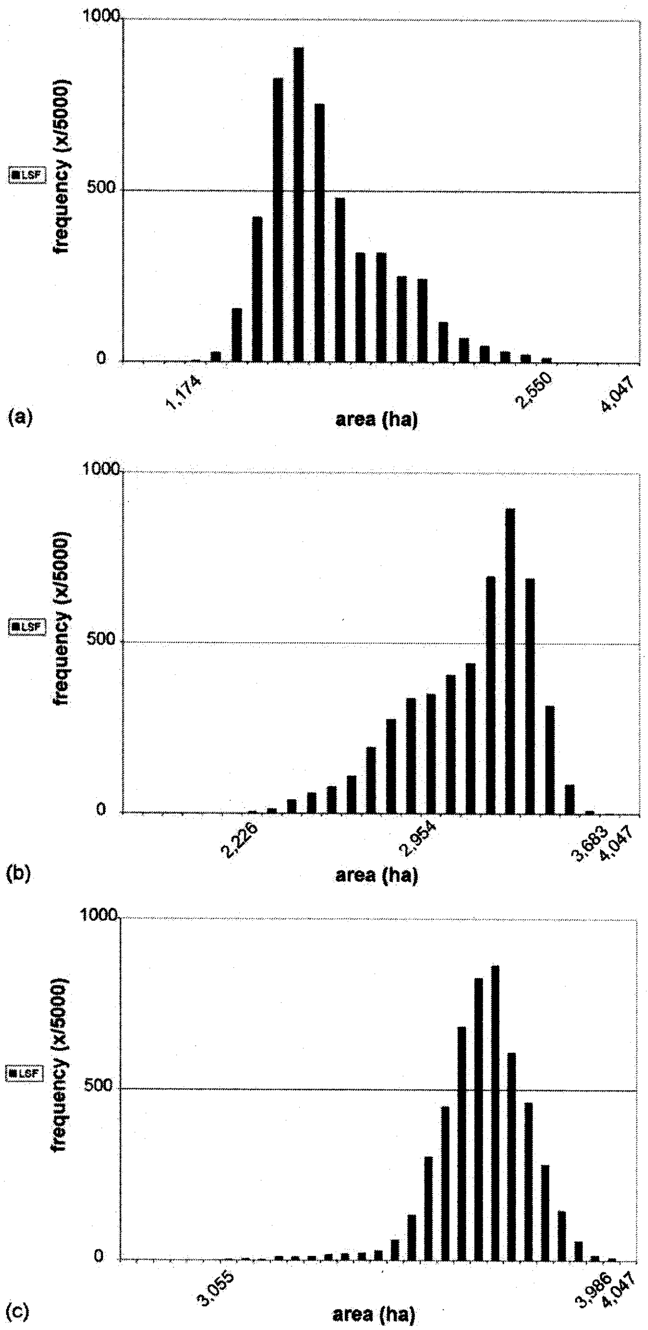

Fig. 4. Frequency distributions for the area (ha) in late-seral forest (LSF) structure in the 6070 ha study landscape using method 2 (probabilistic) over 5000 Monte Carlo simulations in decade 1 (a), decade 2 (b), and decade 3 (c).

(S.E. of 251.5 ha, Table 5, Fig. 4b) and most of this area (54% or 1671 ha) was associated with the same stratum as it was in the first decade. By the end of the third decade an average of 3674 ha were projected to be in LSF structure (S.E. of 109.1 ha) (Table 5). The projection interval associated with this estimate ranges from 3055 to 3896 ha (50–66% of the area of the study reserve, respectively) (Fig. 4c). Of the average number of hectares in LSF structure by the end of the third decade, half still came from the UR10 stratum (Table 5).

Table 5
Mean area and standard deviation (ha) of late-seral forest (LSF) per stratum by decade

Stratum[a]	Decade 1		Decade 2		Decade 3	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
SI10	0.0	0.0	0.0	0.0	0.0	0.0
SEOC10	5.6	8.0	10.0	9.3	22.3	9.5
SEOC13	0.0	0.0	0.0	0.0	0.3	6.3
SECC10	148.0	36.3	206.6	31.2	236.5	23.7
UR10	1317.7	95.8	1671.5	78.6	1832.1	82.7
UR11	9.0	17.1	162.1	47.2	259.2	12.6
UR13	182.5	205.5	1029.3	230.2	1258.1	57.4
YFMS10	0.0	0.0	0.0	0.0	0.6	3.4
YFMS11	0.0	0.0	0.0	0.0	4.6	5.2
OFMS10	27.1	23.4	35.6	25.9	60.4	31.2
Total[b]	1689.9		3115.0		3674.1	

[a] See Tables 1 and 2 for definitions.
[b] Total is the mean area of LSF structure (ha) projected for a 6070 ha forest reserve using the probabilistic method.

The probability of LSF structure in the study landscape in the first decade is conveyed by the shading in Fig. 3b, in which the lighter the color the lower the probability. The darkest shade represents a 50% likelihood of LSF structure. This happens in strata SECC10 and UR10 (Table 4) when the mean LSF structure value was sometimes 0 and sometimes 1. Despite this structural variation (or perhaps because of it) these two strata, together with UR13, are projected to contain the majority of LSF structure in the study landscape over time (Table 5). In contrast, very few if any of the samples in the stem initiation (SI), young forest multi-story (YFMS), or old forest multi-story (OFMS) structure classes are projected to meet the definition for LSF structure over time (Table 4).

The assignment method resulted in an outcome (41% of study landscape) at the upper tail of the projection interval (19–42%) generated by using the probabilistic method in the first decade (Fig. 4a). In the second and third decades, the area estimate of LSF structure resulting from the assignment method did not lie within the projection interval for this metric identified by the probabilistic method (Figs. 2 and 4b and c.). Reasons for this might lie with the FVS model: the random number seed used or differing simulation interval lengths, for example; or with the data and the particular random assignment of tree lists.

5. Discussion

Data maps are useful for displaying the current condition of landscape metrics but are less so for communicating simulated projections of their future conditions. Particularly when a landscape metric is dynamic, identifying the probability of its future occurrence could be more informative than its location. The value of such information depends on the objectives of landscape simulation. If there are questions about the persistence of endangered species, for example, or about the likelihood of rare events then information on the probabilities associated with specific metrics would be useful.

The difference between our estimates of the area in LSF structure obtained by using an assignment method versus a probabilistic method highlights the potential effect of variation in sample data on landscape simulation. The assignment method is one example of a prevailing analysis approach, in that it incorporated the stochastic variation of a simulation model but not the variation within the sample data used to describe initial landscape conditions. In contrast, the probabilistic method used the sample data, first to estimate within-stratum variation of LSF structure and then to assess how this variation affected landscape simulation results with time.

The data map associated with the assignment method offers one pattern for LSF structure in the study landscape. It is a product both of the random assignment of sample data to units within the same stratum that were not sampled and of the way the FVS model creates initial conditions based on a composite of sample data. Thus, Fig. 3a, while not inaccurate, is limited by the models and approach we used. The assignment method relies on the assumption that within-stratum variation in forest structure is lower than among-stratum variation and the results emphasize average structural conditions. Different assignments would reveal pattern dynamics of LSF structure arising from stochastic variation in the simulation model but would not yield an estimate of uncertainty in the model projections stemming from the variability in sampled vegetation.

The probabilistic method provides additional information about our landscape simulation results by including the variation within our sample data as a source of uncertainty. This method revealed that within the range of possible outcomes associated with our sample, the simulation results obtained in the assignment method are relatively uncommon. It also identified the strata most likely to contribute to LSF structure, the projected mean area in LSF structure each decade in the study landscape, and the variation in hectares associated with the projection. At the scale of individual stratum, the probabilistic method offered a glimpse at trends in the likelihood of the stratum contributing to LSF structure over time. For example, the UR13 stratum covers about 21% of the study reserve (Fig. 1). In the first decade the mean LSF structure value for this stratum is zero, which in the assignment method would mean the stratum did not contribute to LSF structure. However, based on the field sample of the stratum and the bootstrapped sample data, there was an approximately 15% likelihood that it could be in LSF structure (Table 4). Thus, in the probabilistic method the UR13 stratum did contribute to the total mean area in the LSF structure class in decade 1 (Table 5). By decade 2 both the probability and the total area contributed by this stratum were projected to increase. The assignment method obscured the potential contribution of this stratum to the area of LSF structure in the landscape. A similar story exists with the SEOC10 stratum. In this case, the probability of FVS tree lists growing into LSF structure in the first two decades was almost 30% but the mean condition did not meet the LSF structure definition (Table 4). Under the assignment method, this stratum would never contribute to the area of LSF structure in the landscape total. Even under the probabilistic method, its total contribution is small (Table 5) because the stratum represents only about 2.3% of the total land area.

Despite offering some advances over the assignment method, the probabilistic method also has limitations. It did not isolate the effects of all potential sources of uncertainty in our landscape simulation. Some stochastic variation associated with the FVS model is still included in our simulation results and we did not address specific sources of error in our sample. In addition, the probabilistic method relies on empirical data and some landscape simulations use model predictions instead. Importantly, the outcomes of landscape simulation are related to the metrics chosen and our analysis focused on just one.

Landscape simulation gives us a wide angle lens through which to view portions of our world. By combining the power of computer technology and graphic design with statistics and landscape ecology, new ways to calculate and display the variation in landscape metrics will continue to emerge. We used frequency distributions to convey information about the range of area projected to be in LSF structure in the study landscape over time and the shape of its distribution. We created a probability map by using different shades of the same color to emphasize areas with more or less certainty attached to the simulation results. Creating probability maps from landscape simulation is not new (e.g. Gustafson et al., 2004), but a new step is deriving probabilities by applying bootstrap resampling and Monte Carlo simulation to the sample data used in an individual tree growth model.

A probabilistic method could reduce the tradeoffs between spatial resolution and extent in landscape simulation. As technology continues to create opportunities for complex analyses, it might yet become possible to test for the significance of differences between simulated treatment effects. Clearly, bootstrapping does not compensate for poor sample design, but it does offer promise for improving landscape simulations done with empirical sample data. For example, an estimate of variability within landscape stratum and its effect on the precision of resulting simulations could be used to obtain more samples if needed to meet desired error levels. In this way, bootstrapping could inform sample design for landscape simulation by highlighting the conditions in which variation is high and knowledge is least certain. Analysis of empirical sample data, such as we report, can add to the information offered by classification error matrices. The wisdom of dedicating resources to this effort depends on the intent of landscape simulation. Aerial photo interpretation, remotely sensed data, or low-density inventory plots might be sufficient for some landscape metrics, whereas for others finer-scale, more expensive data might be necessary to meet landscape simulation objectives.

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