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Exploratory modeling of forest disturbance scenarios in central Oregon using computational experiments in GIS

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ABSTRACT

Exploratory modeling is an approach used when process and/or parameter uncertainties are such that modeling attempts at realistic prediction are not appropriate. Exploratory modeling makes use of computational experimentation to test how varying model scenarios drive model outcome. The goal of exploratory modeling is to better understand the system of interest through delineation of plausible boundaries, description of patterns within multidimensional model space, and to the extent possible, quantification of the likelihood of occurrence of different model outcomes. This study makes use of exploratory modeling in GIS to delineate boundaries of likely and plausible variability in past Oregon forests due to natural fire disturbance processes interacting with climate change, and compares those with current forests modified by harvest disturbance and with a hypothetical forest scenario. The implications of different forest landscapes for biodiversity are quantified, using a rule base constructed from empirical data describing forest age class, elevation, and heterogeneity requirements by species. Results show: 1) a wide range of natural forest structure plausibly existed in the past, 2) portions of the current forest are outside of the most liberal models of the natural range of forest variability, and 3) large changes in forest structure produce relatively small changes in biodiversity indicators. These findings suggest that disturbance processes (natural or human) that retain forested land cover but alter forest age class structure do not have a strong impact on biodiversity. As an exploratory exercise, the findings are not the end objective; rather, they serve as a basis for dialogue about which forest landscape factors are most important for assessment of biodiversity impacts.

1. Introduction

Models are uncertain, and the only certainty we have is that the output from a model is wrong in at least some aspect, and perhaps in many aspects. Types and characteristics of model uncertainty have been extensively studied (Rotmans and Van Asselt, 2001; Regan et al., 2002; Bredehoeft, 2005; Scheller and Mladenoff, 2007) along with methods for quantification of uncertainty (Clark et al., 2001; O'Neill, 2005). The most common approach places probabilistic estimates on various sources of uncertainty and integrates them into an overall output uncertainty. In that approach, the goal is to predict the most likely system response and provide accurate error estimates.

The above approach assumes that we have enough information to make predictions with at least some certainty. While this is true in many cases, there are numerous cases where either the theory or the empirical data are insufficient to make "likely" predictions (Swart et al., 2004). For example, any integrated assessment of human–environmental systems may have well understood theory behind the physical processes but is unlikely to have well-developed theory or data about social inputs. Model output validity has little meaning in this context.

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Modeling efforts that contain a high degree of uncertainty will become increasingly necessary with increasing multidisciplinary research in complex systems with high societal relevance. In this context, new approaches to modeling uncertain systems are necessary (Swart et al., 2004). An approach called "exploratory modeling" has had some success in modeling climate change (Bankes, 1993; Lempert et al., 1996). Exploratory modeling is an extreme form of scenario analysis that emerged in the 1980s and is becoming popular in many decision-making arenas when confronted with many future uncertainties (Wack, 1985; Schoemaker, 1995; Carpenter, 2002; Bennett et al., 2003; Nassauer and Corry, 2004; Swart et al., 2004; Zegras et al., 2004; Butler et al., 2005; Dessai et al., 2005; O'Neill, 2005). In this paper, I describe exploratory modeling, illustrate the approach with an example from ecology, and highlight the opportunities and challenges associated with this method.

The illustration is taken from a retrospective analysis of forests in the Oregon Cascades that makes use of the natural range of variability concept (Pennington, 2002). The approach asserts that managed forest landscapes that are within the range of natural variability are likely to better sustain ecological processes than those that are not within that range. This concept emerged in the 1990s as a reference point for assessing current forested landscapes (Hunter et al., 1988; Hunter, 1993; Swanson et al., 1993; Morgan et al., 1994; Landres et al., 1999; Perera et al., 2004). Numerous studies have predicted the range of past forest conditions from models of wildfire disturbance and have compared them with current forest landscapes (Agee, 2003; Wimberly et al., 2000; Nonaka et al., in press). Scientists and land managers continue to explore the usefulness of the concept in managing for multiple objectives, such as wildlife (Bunnell, 1995), and fire and fuels (Cleland et al., 2004).

All of these studies modeled the most likely past forest landscapes using wildfire probability distributions constructed from limited field information regarding fire regimes. In this paper, I use an exploratory modeling approach to analyze the range and variability of plausible past conditions, characterizing the uncertainty of past forest landscapes. Current forest landscapes are compared to the range of plausible past landscapes, and a targeted analysis of the effect of divergent landscapes on biodiversity is considered.

First, this paper presents a brief description of exploratory modeling since it may be a new approach to many readers. Then the case study is presented. Lastly, I discuss challenges and opportunities associated with exploratory modeling.

1.1. *Primer on exploratory modeling*

Computational simulation and modeling have been applied within the sciences for decades and have enjoyed much success in assisting our understanding of real-world processes. In computational science, a model run is considered a form of experimentation. In a computational experiment, a hypothesis is devised regarding how the model will behave with a change in specification of the system. The model can be run twice, once without the change (control model) and a second time with the change (treated model). The test is a comparison of the control and treated model. However, in a computational experiment the object being tested is the model of reality, not reality itself. Therefore the inference that is made is not about reality; rather one makes inferences about the behavior of the model, and the relevance of that behavior to reality must be argued from theory. Therefore, we could construct a model with many parameters and run it many times varying a given parameter to measure its effect on the model outcome, and we have "tested" the effect of the parameter on the model. This approach is often done in a sensitivity analysis, where each parameter is varied independently in order to gauge how uncertainty in each input parameter impacts model outcome, yielding information about the sensitivity of the model to various parameters.

There are many approaches in computational simulation and modeling. These can be roughly divided into those models that try to package our best understanding of all aspects of reality, and those that try to explore hypotheses about the implications of one or a few aspects of reality (Scheller and Mladenoff, 2007). Clark et al. (2001) referred to the former as models of systems that are "forecastable." Bankes (1993) referred to the latter as "exploratory" models. In consolidative modeling, the objective is to develop a detailed understanding of present day processes and make projections in time (forecasting) and/or space. The goal of consolidated modeling is to achieve the best prediction possible. Therefore, the consolidated modeling process is much concerned with model validation and with accurate parameterization (Ryliel, 1996). A useful consolidated model depends on having well-developed theory from which to construct the model and sufficient empirical data from which to derive the parameters.

In contradistinction, the goal of exploratory modeling is not accurate, realistic prediction; it is computational experimentation to achieve better understanding of the system in question. Exploratory modeling is typically used when there are large uncertainties in theoretical understanding such that constructing a consolidated model is not possible, and/or a lack of empirical data from which to derive parameters. Often these two concerns go together. An investigation that has a sufficiently well-developed theoretical base usually also has sufficient empirical information for parameterization. For complex systems one may have a great deal of empirical data yet not have very well-developed theory (Pickett et al., 1999; Cumming et al., 2005). It is in these situations, when theory and/or data are lacking, that exploratory modeling plays an important role.

There is a continuum between consolidated and exploratory modeling. The most reliable mechanistic models contain some predictive uncertainty because they are by design simplifications of a scientist's incomplete understanding of reality. Most consolidated models capture some parts of the system quite well while other parts are underspecified. The distinction between consolidated and exploratory modeling is in large part a distinction between goals of the investigation.

Exploratory modeling is a search through spaces of many computational experiments that manipulate factors through informed guessing that is known from the outset to be highly uncertain. The goal is not prediction of the real system; the goal is achieving some understanding of how the guesses impact the model, from which inferences may be made about theoretical behavior of the real system. Exploratory modeling attempts to capture major theoretical uncertainties in a set of model runs that investigate the implications of different models and/or parameterizations in order to:

- Investigate the credibility of each model,
- Explore the magnitude of possible changes across models,
- Highlight issues that may have a significant impact,
- Discover regions in model space that are robust across models, and/or
- Discover thresholds that divide robust regions from those that deviate.

The result of exploratory modeling is a set of outcomes that explore how key drivers push the model in different directions. It highlights elements of the system that are relatively stable and predictable as opposed to those that are not, and draws attention to significant aspects of competing scientific theories. The problem in exploratory modeling is how to "cleverly select a finite number of models and cases to examine from the infinite set of possibilities" (Bankes and Gillogly, 1994). The usefulness of exploratory modeling lies in the skill of the modeler to construct a strategic ensemble of model outcomes that enable new insight for theoretical discourse.

In exploratory modeling, one does not validate the model, one validates the strategy (Bankes, 1993). A valid exploratory modeling investigation is one that is informative about some aspect of the uncertain system, providing some perspective that was previously unknown. Exploratory modeling has been used extensively by theoreticians; however, the approach can be useful to empirical scientists as well. For instance Lempert and others have employed the approach extensively in the context of IPCC climate change modeling, to find solutions that are robust across many different future scenarios (Lempert, 2002). He argues that "under conditions of deep uncertainty, an ensemble of plausible models, rather than any single model, best represents the available information about the future and refers to the process as "Computer Assisted Reasoning (Lempert, 2002)." Here, I illustrate the usefulness of exploratory modeling in a very different context: modeling of uncertain past environments.

2. Case study: natural range of variability in forest cover in the Oregon Cascades

Many factors produce spatial and temporal variability in forest age classes. Forest wildfire regimes in the Pacific Northwest, for example, vary spatially due to topography, elevation, and – since European settlement – land ownership and associated forest management practices. Fire regimes during the Holocene (past 10,000 years; Whitlock et al., 2003) were more variable than those of the historical fire record reconstructed from dendrochronology (usually <500 years) (Weisberg and Swanson, 2003), which in turn are different from those prevailing since European settlement and fire suppression. Therefore, the historical range of variability of a portion of a forest landscape depends on the spatial and temporal scale chosen for analysis.

The study area occupies 15,670 km^2 in the central western Cascades of Oregon, containing four major public and private landowner categories (Fig. 1) overprinted on spatially and temporally variable fire regimes. This area has useful properties for study—it spans a steep environmental gradient from the western foothills to the eastern alpine treeline in the Cascade Range and diverse land use types and intensities, ranging from industrial forestry to legislated wilderness. Land ownership and land use categories co-vary with elevation in the study area. The western, low-elevation (<400 m) portion of the study area is predominantly private industrial forest land, or "checkerboard" land consisting of alternating square mile sections in public ownership (BLM) and private industrial forest company lands, hereafter "BLM/private checkerboard". The central, northern, and southern portions of the study area at intermediate (400–1200 m) elevations are predominantly "general forest", which are lands of the Willamette, Mount Hood, and Umpqua National Forests subjected to dispersed patch clearcutting over about 25 to 30% of their area in ca. 1950–1990. The eastern portion of the study area above 1200 m elevation is predominantly legislated wilderness, managed by the USDA Forest Service.

Climate varies with elevation and also varies more subtly along a north–south gradient. The central western Cascades (center and east of the study area) are highly dissected; forest vegetation is dominated by Douglas-fir (*Pseudotsuga menziesii*), western hemlock (*Tsuga heterophylla*) and western red cedar (*Thuja plicata*) (Franklin and Dyrness, 1988). In the southern portion of the study area topography is more gentle than the central portion; forests are mixed evergreen dominated by Douglas-fir with a variety of evergreen hardwoods including tanoak (*Lithocarpus densiflorus*), madrone (*Arbutus menziesii*), chinkapin (*Castanopsis chrysophylla*) and canyon live oak (*Quercus chrysolepis*) (Franklin and Dyrness, 1988). The eastern portion of the study area runs along the crest of the Cascades; forest vegetation is sub-alpine forest dominated by mountain hemlock (*Tsuga mertensiana*), sub-alpine fire (*Abies lasiocarpa*) and Pacific silver fir (*A. amabilis*) (Franklin and Dyrness, 1988). The northern portion of the study area includes the western Cascades and the western slope of Mount Hood, where forest vegetation is Douglas-fir/western hemlock at lower elevations and sub-alpine forest above 1000–1200 m.

The case study investigates: 1) what are the plausible bounds of variability in past forest landscapes, 2) how do current forest landscapes compare to those, and 3) how do differences between past and future forest landscapes impact biodiversity? Exploratory modeling is used to address these questions.

2.1. *Exploratory modeling of plausible bounds of variability*

Exploratory modeling begins with identification of the key variables controlling model output. Wildfire studies typically characterize fire frequency, fire severity, and fire size (Agee, 1993; Weisberg, 1998). Fire frequency is measured by the fire return interval, which may be standardized as the natural fire rotation (NFR), a measure of the time required to burn an accumulated area equal to the size of the whole landscape. Some studies report the mean fire return interval (MFRI), the mean number of years between fires at a given study site, without reference to the area burned. Fire severity is a measure of tree mortality, usually reported as the percentage

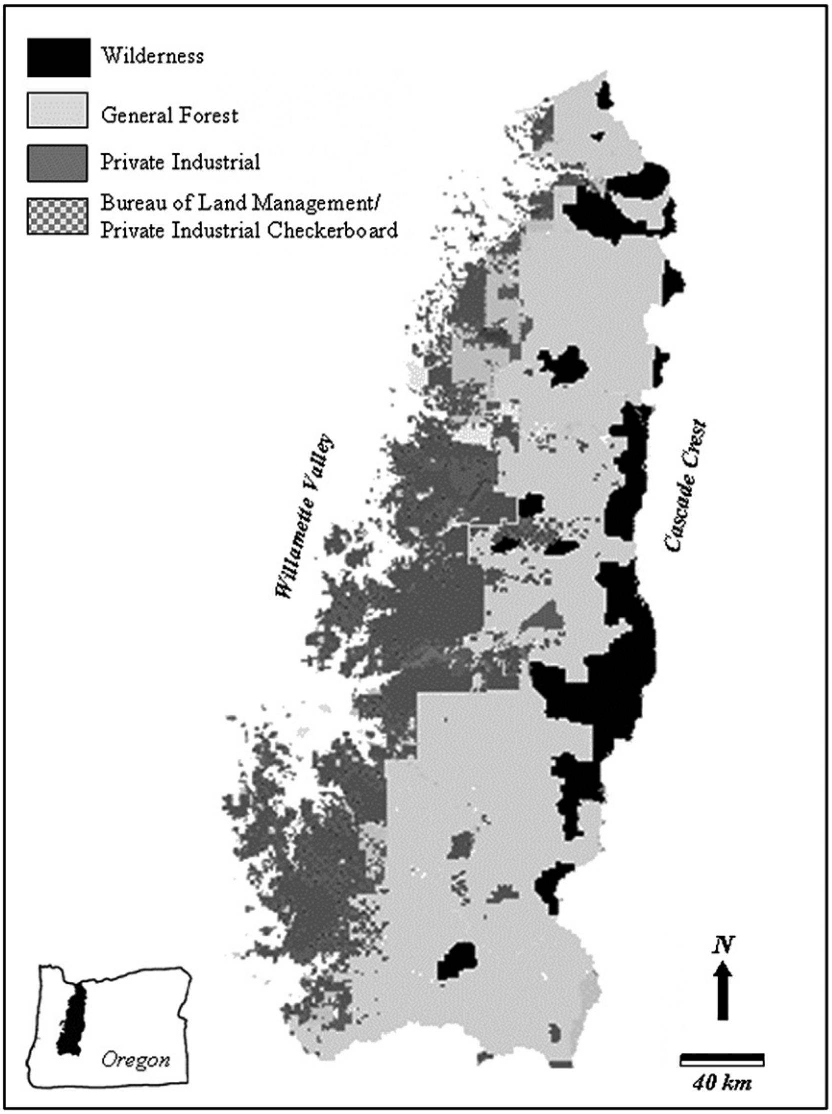

Fig. 1 – The study area occupies 15,670 km^2 in the western Cascades of Oregon.

of trees killed. Fire extent is determined by correlation of fire events between sample sites, and is most accurate if cross-correlation techniques are used (Weisberg, 1998). In practice, fire frequency, severity and size parameters are very difficult to establish for historical times due to limited evidence of low severity fires, erasure of evidence by subsequent fires and the continuous variation in parameters related to ongoing climatic change (Weisberg and Swanson, 2003; Long et al., 1998). Fire frequency measures are generally believed to be more accurate than severity and size measures (Weisberg, 1998). Fire size, in particular, may be difficult to determine.

In the study area, fire frequency generally increases, fire severity is more variable, and fire size decreases and becomes more variable from high elevation (east) to low elevation (west) and from north to south of the study area (Fig. 2) (Weisberg, 1997a,b, 1998; Van Norman, 1998; Cissel et al., 1999; Agee and Krusemark, 2001). The empirical data show considerable variability and represent only a small portion of the landscape. Additionally, the data represent a narrow range of climatic conditions over the past 300–500 years, insufficient to assess the natural range of variability under which local biota evolved and to which they are presumably robust.

An exploratory modeling approach was adopted for this analysis because of both high uncertainty in the key drivers of wildfire and high uncertainty in appropriate parameterization. The goal of the modeling was to illustrate both likely landscape conditions in the recent past based on the limited evidence available and also the plausible set of landscape conditions that could have occurred over the past few millennia, given the uncertainty in the relationship between fire frequency, severity and size parameters and longer-term climate change. The empirical data from the past 500 years were used to produce a set of landscapes representing the likely range of landscapes from the past 500 years (the historical range of variability (HRV)). The empirical data were then used as a reference for postulating a range of parameter values that might have occurred under more variable climate conditions (the "plausible" set from the natural range of variability (NRV)). Parameterization of the model for the plausible set was based on assumptions constructed from wildfire theory, constrained by the empirical fire data.

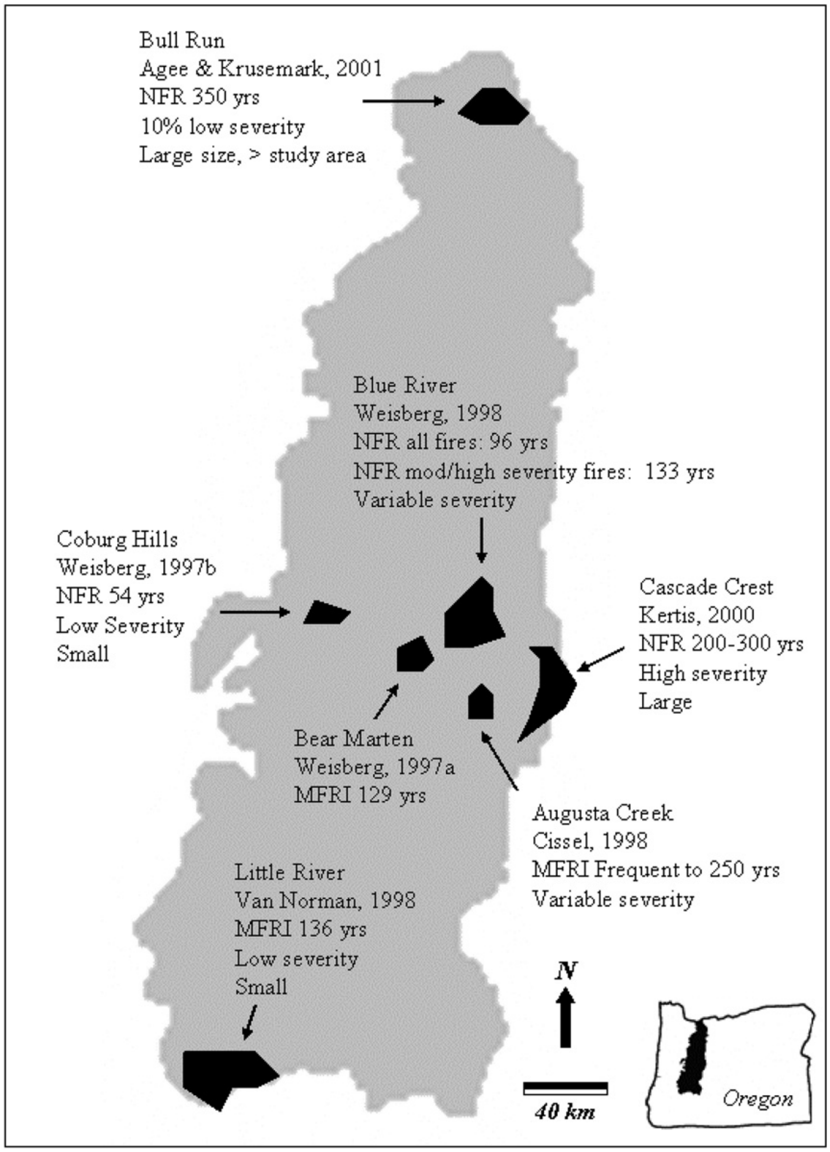

Fig. 2 – Locations and major findings from dendrochronologic fire history studies in the study area. Fire frequency is reported as natural fire rotation (NFR) or mean fire return interval (MFRI). This image was derived from Berkley (2000).

Assumptions included:

A1 Fire frequency at a given site varies through time related to changing climate.
A2 Fire frequency varies through space related to topography and latitude.
A3 Fire severity and size increase with decreasing fire frequency.

Landscape conditions in the study area were simulated using a spatially explicit wildfire simulation model (Landscape Age-class Demographics Simulator, or LADS) developed by Wimberly et al. (2000) and applied in the Oregon Coast Range (Wimberly, 2002; Nonaka et al., in press). The LADS model simulates the spread of randomly initiated fire across the study area and tracks the resultant distribution of vegetation classes over time. The user specifies parameters for fire frequency, extent, and severity; these variables are modeled as independent random variables. Fire extent is expressed as mean fire size. Fire frequency (the interval between successive fires at a point) was represented as the mean number of fires per year on the landscape, calculated by dividing the study area by the product of mean fire size and the natural fire rotation (NFR). The mean number of fires per year was modeled as a Poisson random variable, implying that fire occurrence is a process with no memory. Fire severity was modeled as a Bernoulli (0,1) random variable with parameter k to determine if a given cell experienced high or low/moderate severity fire; values of k determined the percent of fires that were high severity. High severity fires were defined as those with greater than 70% mortality of overstory tree canopy (Morrison and Swanson, 1990). Fire size was modeled as a geometric random variable (Wimberly et al., 2000). The spatial resolution of model runs was 200 m. For each 200-m cell, the LADS model tracks the length of time since 1) the last fire of any kind, and 2) the last high severity fire. When a cell

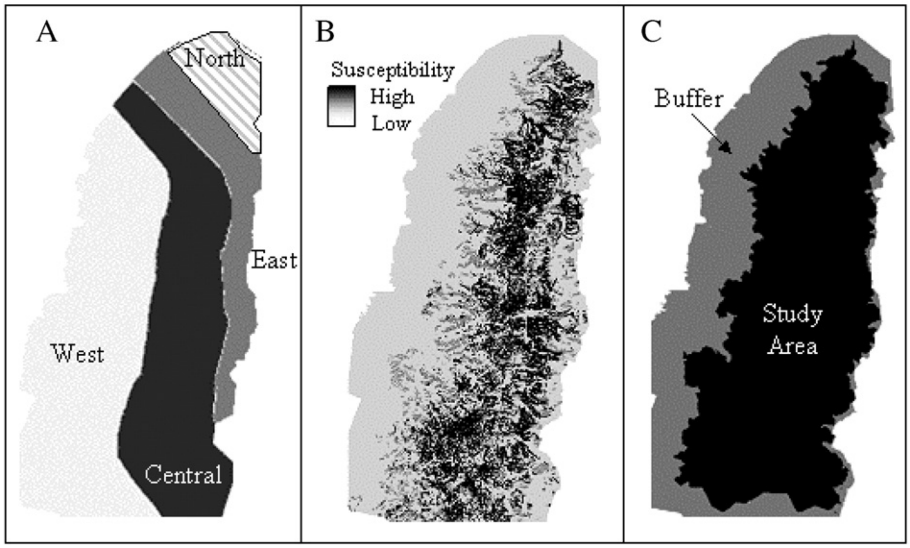

Fig. 3 – Input layers for the LADS fire model for the study area in the western Cascades of Oregon. A) Four fire regimes specify fire frequency and severity characteristics. B) Fire susceptibility layer incorporates topographic effects. Darker areas are more susceptible to fire. C) Area of analysis and surrounding buffer zone.

experiences a high severity fire both values are reset to zero; when it experiences a low to moderate severity fire only the first value is reset. Therefore, simulated landscape conditions in this analysis were based on the age of the oldest possible cohort of trees in the stand, which was the time since the last high severity fire.

The LADS model requires three input data layers: 1) a fire regime layer, 2) a fire susceptibility layer, and 3) a study area buffer zone (Fig. 3). The fire regime layer (Fig. 3A) designates portions of the study area with similar fire sizes and frequencies. Fires are assigned characteristics based on the regime in which they initiate, but may spread into adjacent areas with different fire regimes. The locations of four fire regimes (North, East, Central, and West) were defined from fire history reconstructions (Weisberg, 1997a,b, 1998; Van Norman, 1998; Agee and Krusemark, 2001; J. Kertis, Siuslaw National Forest, Corvallis, OR, unpublished; see Fig. 2). Fire regime boundaries were interpolated between fire history studies based on elevation and latitude (Pennington, 2002).

The fire susceptibility layer (Fig. 3B) was constructed by extrapolating a statistical model of maximum fire interval from a dendrochronology-based reconstruction of fire history since 1500 AD in the central portion of the study area (Weisberg, 1998) to the entire study area, and grouping continuous maximum fire intervals predicted from the model into three categories (Pennington, 2002). Maximum fire interval was used

Table 1 – Fire size, frequency, and severity parameters by fire regime area (Fig. 3A) for each of the five scenarios modeled using the LADS model in the western Cascades of Oregon

	Fire regime scenarios				
	Scenario 1 fire history	Scenario 2 very infrequent	Scenario 3 infrequent	Scenario 4 moderately frequent	Scenario 5 frequent
Fire size (ha)					
High severity	20,000	100,000	77,500	55,000	32,500
Low–moderate severity	50	1000	775	550	325
Fire frequency (years)					
North	450	1000	562	300	178
East	250	700	394	221	124
Central	125	400	225	126	71
West	75	100	56	32	18
Percent of fires that are high severity					
North	85	100	87	75	63
East	75	80	68	59	43
Central	50	65	53	42	27
West	25	50	37	25	12

as a surrogate for susceptibility to fire in the LADS model because areas with longer fire intervals are more likely to be protected from fire. In the LADS model runs, steep, highly dissected terrain in the central part of the Cascades had higher fire susceptibility than the gentler slopes of the High Cascades and western foothills, consistent with some field observations (Weisberg, 1997a,b, 1998; J. Kertis, Siuslaw National Forest, Corvallis, OR, personal communication).

The buffer zone allows fires to burn outside of the area of analysis, preventing unnatural edges. The constructed buffer zone was wide on the west side of the study area allowing fires to burn outside of the forest area into adjacent grasslands, but narrow along the east side where the Cascade crest acts as an edge and natural barrier to wildfire (Fig. 3C).

Five scenarios were defined based on fire size, frequency, and severity parameters, which vary by fire regime (Table 1). A historical fire scenario was defined from dendrochronology-based reconstructions of fire history since 1500 AD in the study area (Fig. 2). Fire frequency ranged from 450 to 75 years and fire size ranged from 50 to 20,000 ha in the historical fire scenario (Table 1). Four alternative scenarios (very infrequent fire, infrequent fire, moderately frequent fire, and frequent fire) were constructed to represent hypothetical variation in fire regimes over the Holocene. Fire frequency in these scenarios ranged from 1000 to 18 years and fire size ranged from 325 to 100,000 ha. The average fire frequency across all four fire regimes ranged from 550 years for the very infrequent fire scenario to 98 years for the frequent fire scenario, comparable to the range of fire intervals (330 to 100 years) inferred from charcoal in a 9000 year sediment core from Little Lake in the Oregon Coast Range (Long et al., 1998). Although the Little Lake site is in the Coast Range to the west, we believe that it may be representative in relative terms of the variability of fire frequency in our study area over the Holocene. We based the fire scenario parameters on results of the fire history studies and recognition of their limitations. Fire history studies have limited spatial and temporal extent, leading to probable underestimation of maximum fire sizes, so the Holocene scenarios were adjusted to compensate.

Each scenario comprised a 3000 year run of the LADS model preceded by a 500 year burn-in period that was not included in the analysis. Model outputs were sampled at 50-year intervals, producing 60 samples of landscape conditions for each of five simulations (Fig. 4). Four forest age classes were defined consistent with a commonly used age class scheme based on known forest succession pathways and rates that has been used in prior studies of wildfire (Wimberly et al., 2000; Wimberly, 2002; Nonaka et al., in press) in the Pacific Northwest. Forest age classes were: early seral (0–30 years), young (31–80 years), mature (81–200 years) and old (over 200 years) (Franklin et al., 2002). Predicted proportions of the four age classes were calculated for each landscape.

The predicted mean percents of the whole landscape in various forest age classes based on the spatially explicit simulation model varied according to scenario (Table 2). In the historical fire simulations, old forest occupied twice the area of early seral vegetation. Old forest and early seral vegetation proportions varied widely and inversely among the other scenarios constructed to represent Holocene fire regime variability. Old forest occupied six times more area than early seral vegetation in the very infrequent fire simulation, but only two-thirds in the frequent fire simulation. Mean amounts of early seral vegetation and young forest decreased and mean amounts of old forest increased with longer fire return periods, while mean amounts of mature forest remained fairly consistent among scenarios.

Proportions of the study area occupied by the four age classes varied markedly over time within each scenario (Table 3).

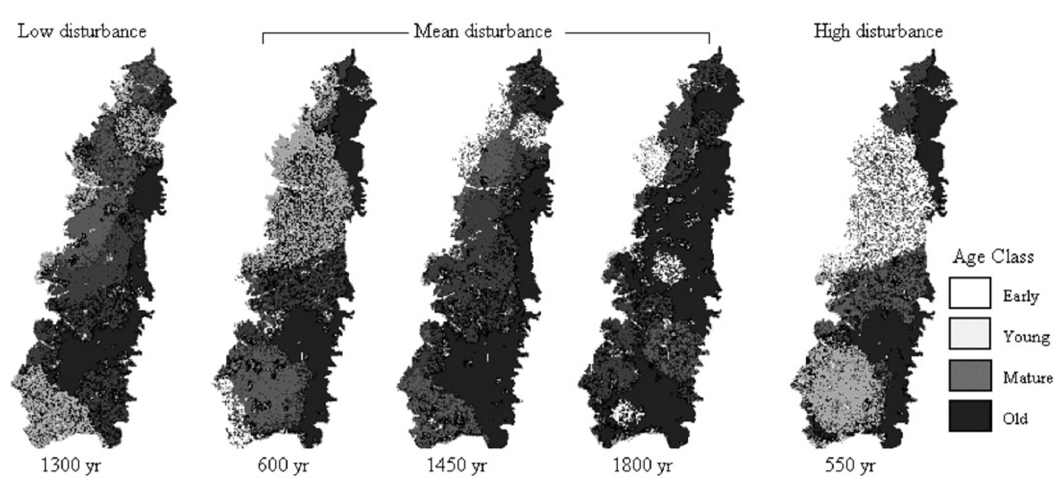

Fig. 4 – Five samples of landscape conditions from the very infrequent fire simulation. Model output like these were used to estimate landscape conditions for the study area as a whole (n = 60 for each scenario) and by landowner categories (n = 5 for each scenario) to produce values in Tables 3 and 4 and Figs. 5, 6, 7, and 8. In each scenario, 5 simulated landscapes were selected for analysis by landowner category. Three of the five were randomly selected from landscapes having average amounts of early seral vegetation, compared to the 60 landscapes sampled for the that scenario, while the remaining two contained proportions of early seral vegetation consistent with the 5- and 95-percentiles of the proportion of the landscape in early seral vegetation calculated from the 60 sampled landscapes. The landscapes illustrated in this figure were used for analysis of the very infrequent fire scenario by landowner category.

Table 2 – Predicted percent of study area by forest age class according to mean values from 60 sampled landscapes in each of 5 scenarios, based on LADS fire simulation model

	Fire regime scenarios					
	Historical	Very infrequent	Infrequent	Moderately frequent	Frequent	1995
Mean fire return period (years)	225	550	310	170	55	–
Mean % of landscape						
0–30 years	19	11	17	26	36	29
31–80 years	21	13	18	24	25	16
81–200 years	17	16	16	15	13	29
>200 years	43	60	49	35	26	26
Min–max %						
0–30 years	14–31	4–31	9–34	16–42	29–46	–
31–80 years	15–31	3–42	6–38	12–35	19–34	–
81–200 years	9–27	0–55	4–34	4–31	3–23	–
>200 years	32–54	33–78	31–63	20–50	18–33	–
Standard deviation of landscape %						
0–30 years	3	7	6	6	4	–
31–80 years	4	8	6	6	4	–
81–200 years	4	10	7	6	4	–
>200 years	5	12	9	7	4	–
5th percentile						
0–30 years	14	4	9	18	31	–
31–80 years	16	4	11	14	20	–
81–200 years	11	4	8	5	6	–
>200 years	34	38	35	23	20	–
95th percentile						
0–30 years	25	26	31	39	45	–
31–80 years	28	33	30	34	33	–
81–200 years	25	38	30	27	20	–
>200 years	52	76	62	47	33	–

Landscape conditions were least variable in the historical fire and the frequent fire scenarios, but even so the proportions of the landscape occupied by each age class varied by 20% of landscape area over the 3000-year simulated period in each scenario. In the very infrequent fire scenario, the proportions of the landscape occupied by old-growth and mature forest varied by as much as 45 to 55% of landscape area over the 3000-year simulation.

Table 3 – Percent of landscape in four forest age classes by land owner type in the study area in 1995

Owner	Total		Percent by forest age class				
	(ha)	As % of total	Early seral (0–30 years)	Young forest (31–80 years)	Mature forest (81–200 years)	Old-growth forest (>200 years)	All
Wilderness	87,408	6	3	9	49	39	100
General forest	862,592	55	23	9	31	37	100
Private industrial	335,704	21	50	26	18	6	100
BLM/private checkerboard [a]	223,820	14	34	25	27	12	100
State [b]	28,113	2	–	–	–	–	–
Private non-industrial, miscellaneous [b]	29,047	2	–	–	–	–	–
Total	1,567,124	100	29	16	29	26	100

Landowner allocations were determined by aggregating categories in an ownership survey created using tax records and county plat information, current as of 1991 (Atterbury Consultants, Inc., Beaverton, Oregon, under contract to Oregon Department of Forestry).

[a] Bureau of Land Management lands were combined with adjacent private industrial checkerboard tracts to create a Bureau of Land Management/private industrial checkerboard owner type.

[b] State, private non industrial, and other land owners occupied about 4% of the study area, but these lands were subsumed into the four land owner categories in analyses of land owner effects.

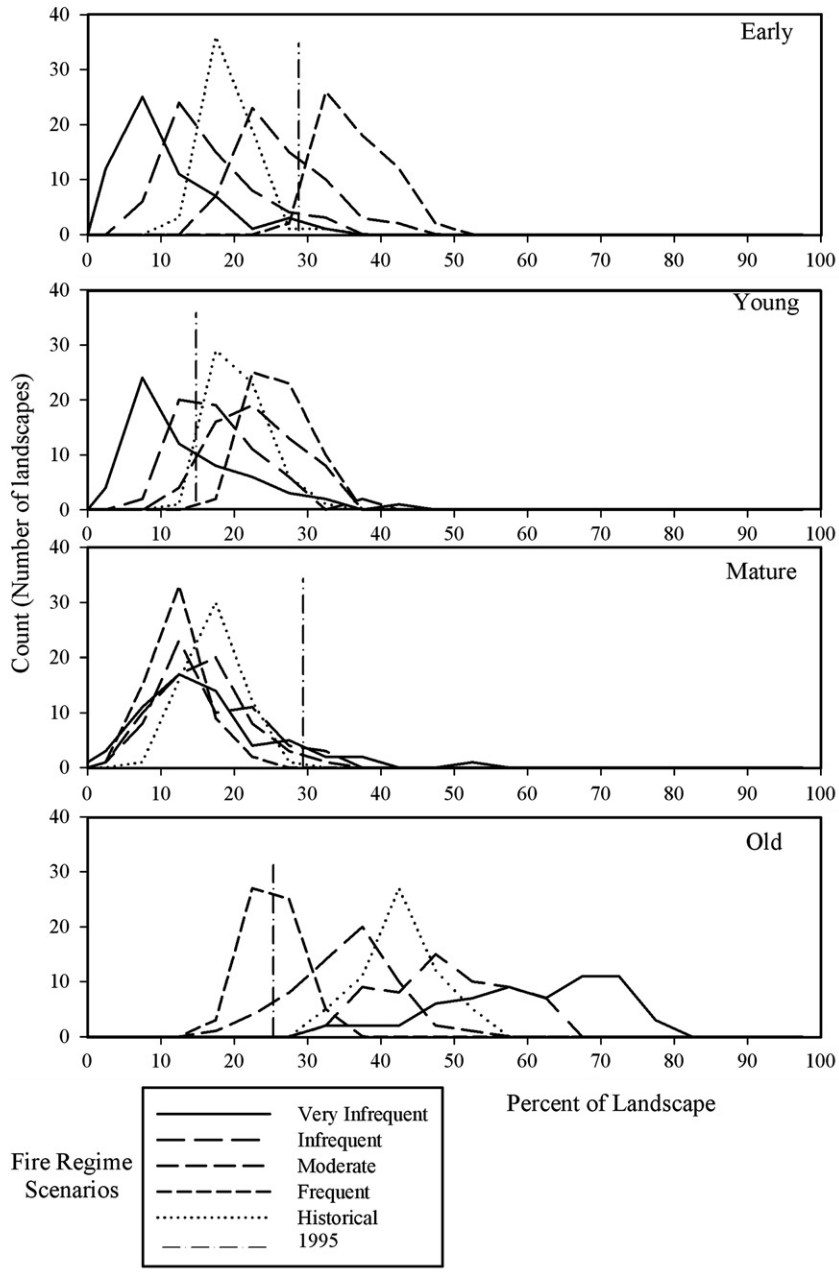

Fig. 5 – Simulated versus observed landscape conditions by forest age classes. Simulated landscape conditions are shown as frequency distributions in 5-percent bins for four age classes (early seral, young, mature, and old forest) from 60 simulated landscapes for each of five climate scenarios. The proportions of forest age classes in a 1995 classified composite satellite image are shown as vertical lines. Four of the simulation runs represent hypothetical conditions under a range of fire frequency scenarios, while one represents fire frequencies from the past 500 years interpreted from field studies of fire history shown in Fig. 2.

2.2. *Comparison with current forest landscapes*

Observed landscape conditions in the study area were determined from a 1995 image of forest age classes derived by combining base maps of classified 30 m Thematic Mapper remotely sensed imagery from (Cohen et al., 1995a,b, 1998). By 1995, forests in the study area had been shaped by histories of wildfire, anthropogenic fire and grazing, fire suppression, and forest harvest, but each land owner and use category was influenced by a unique set of factors. Spies et al. (1994) demonstrated that landscape patterns in a portion of the central western Cascades varied among land ownership categories, as a result of these contrasting histories. We summarized age class extent as a proportion of the whole landscape and by land owner and use category for comparison with the modeled landscapes.

Age class proportions in 1995 were defined as outside the range of variability with respect to a given wildfire scenario if the observed proportions of the area in that age class in 1995 fell outside the range of values predicted from the spatial simulation for that scenario. For each age class and scenario, a predicted frequency distribution was created from the 60 estimates of the proportions of that age class in the sampled simulation output and compared to the observed proportion of that age class in the 1995 image, for the study area as a whole and by land owner and use category. The probability of an observed proportion falling outside the predicted frequency distribution was 0.016.

In 1995, according to classified satellite imagery, the study area as a whole was roughly one-fourth early seral vegetation, mature forest, and old-growth forest, with slightly less young forest (Table 3). Early seral vegetation occupied nearly half of private industrial land area, but only 3% of Forest Service wilderness lands (Table 3). Mature and old forest combined occupied roughly 90% of Forest Service wilderness, and 70% of Forest Service general forest. Old-growth forest occupied only 6% of the area of private industrial lands but more than a third of wilderness and general forest.

Compared to the historical fire scenario, proportions of early seral vegetation and young forest aggregated across all land ownership categories in 1995 were near the upper margin of the predicted range of variability, and proportions of mature and old-growth forest were below the predicted historical ranges of variability (Table 2, Fig. 5). In 1995, 10% more of the landscape was in early seral vegetation, and 17% less of the landscape was in old forest, than predicted from the historical fire scenario. Also in 1995, 5% less of the landscape was in young forest, and 12% more of the landscape was in mature forest, than predicted from the historical fire scenario.

Five sets of simulated landscape conditions for each wildfire scenario were selected for land owner and use category comparison, rather than the 60 sets per scenario used for the whole study area comparison. These five sets of landscape conditions were selected from each scenario to represent the average, and also span a wide range, of landscape conditions from the 3000-year model run (Fig. 4).

Proportions of forest age classes varied by landowner and land use category in the historical fire scenario (Table 4). In the historical fire simulation, old forest was most abundant in wilderness, while early seral vegetation was most abundant on BLM/private checkerboard and private industrial lands. Predicted amounts of young and mature forest did not differ by more than 5% among landowner types in the historical fire scenario.

In 1995, some landowner categories were within the range of variability predicted by the historical fire scenario, but others were outside of the range (Fig. 6). On wilderness lands in 1995, early seral and young forest age classes were less abundant, and mature forest was much more abundant, than predicted by the historical fire scenario. On general forest lands, young forest was less abundant and mature forest was slightly more abundant than predicted by the historical fire scenario. On private industrial and BLM/private checkerboard lands, early seral vegetation and young forest were more abundant, and old forest was much less abundant, than predicted by the historical fire scenario. Certain key age class and landowner combinations in 1995 were outside the ranges of variability predicted by all the fire regime scenarios considered (Fig. 6). Wilderness lands had more area in mature forest, and private industrial forestlands had less old forest than any scenario.

2.3. Computational experiments of biodiversity effects

The differences identified above were used to generate hypotheses about key ways in which forest landscape differences might affect biodiversity. Although the 1995 age class amounts across the whole study area were comparable to those from the model, there was a change in spatial distribution with more mature and old forest at high elevations and more open young forest at low elevations. In addition to changing the dominant elevation range in which each age class occurred, this led to relative homogenization of the landscape with both low and high elevations heavily dominated by two age classes each (early seral/young forest and mature/old forest, respectively) rather than all portions of the landscape having a heterogeneous mixture of all four age classes. Computational experiments were designed to test the effects of both changes (elevation and homogenization) on biodiversity.

Twenty seven landscapes were used during this analysis: the twenty five wildfire simulation landscapes, the 1995 landscape, and one hypothetical landscape. The hypothetical landscape was constructed in order to assess the effect of

Table 4 – Mean and range of percents of study area in four forest age classes by land owner and land use category according to the historical fire scenario of the LADS simulation model

Owner	Percent by forest age class				
	Early seral (0–30 years)	Young forest (31–80 years)	Mature forest (81–200 years)	Old-growth forest (>200 years)	All
Mean (%)					
USFS wilderness	12	16	19	53	100
USFS General forest	16	21	19	44	100
Private industrial	21	18	23	38	100
BLM/private checkerboard	23	18	20	39	100
Min–max (%)					
USFS wilderness	8–16	12–25	12–30	38–64	
USFS General forest	8–26	16–29	11–31	35–55	
Private industrial	14–28	15–21	5–26	27–51	
BLM/private checkerboard	21–26	16–21	9–25	31–44	

Percents are means of 5 sampled landscapes for each land owner and use category.

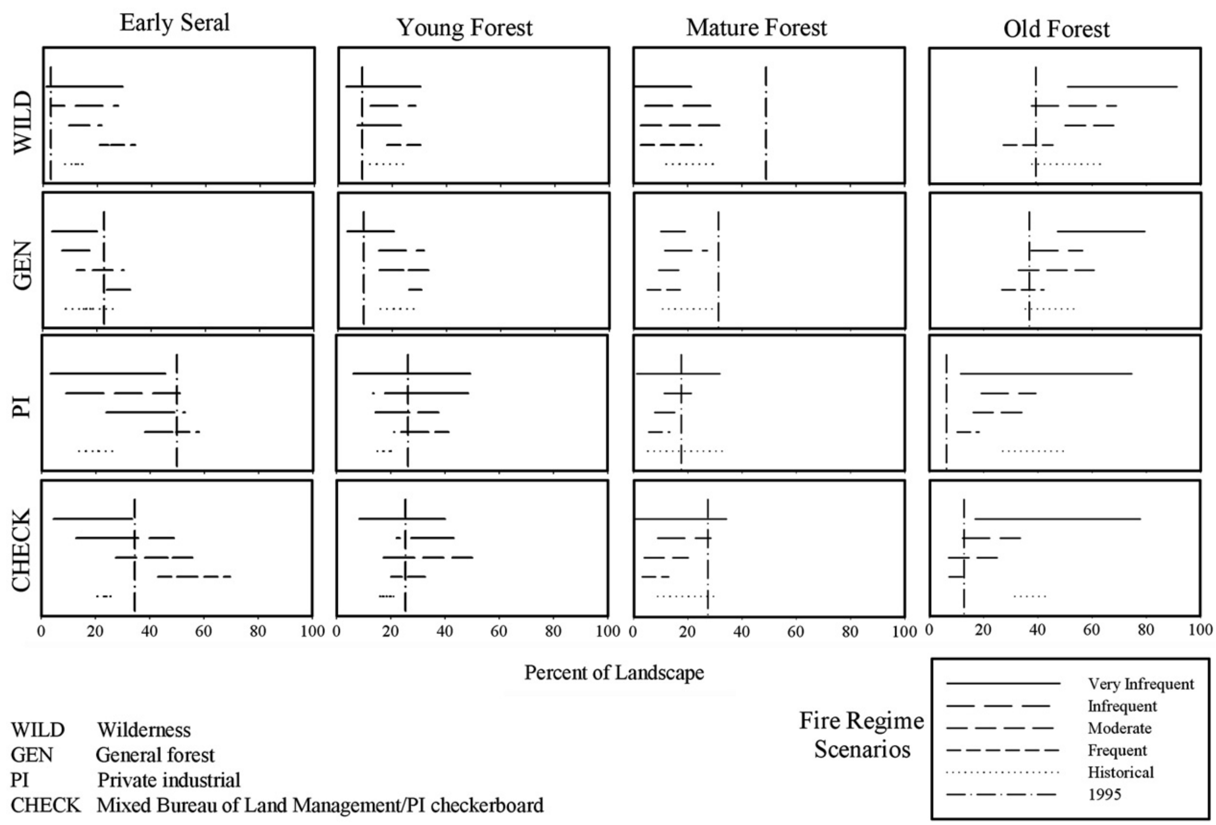

Fig. 6 – Simulated versus observed landscape conditions by forest age classes and land owner category. Horizontal lines are ranges of the proportions of the study area in each forest age classes by landowner category for 25 fire simulated landscapes. Vertical lines depict the proportions of these forest age classes in the 1995 composite satellite image.

landscape changes in the extreme case that all forest in the upper elevation wilderness area were converted to old forest and all forest in the lower elevation private industrial area were converted to early seral vegetation and young forest in proportions corresponding to a precise 40 year harvest rotation (75% early seral, 25% young forest). General forest and checkerboard lands were assigned forest age classes in proportions corresponding to a precise 80 year harvest rotation (38% early seral, 62% young forest) except for riparian buffer zones along streams which were assigned to the old forest age class. The hypothetical landscape represented the landscape structure under the most extreme conditions plausible for the key drivers identified in this analysis, to assess the resultant effect on biodiversity.

Bird and mammal species occurrence data in this locale were compiled from Johnson and O'Neill (2001). Data included a list of species, the forest habitats in which they are found, closely associated habitats that they require during some portion of their life cycle, their elevation range, and their areal range. Habitat was converted to probable forest age class using heuristics developed through examination of the data.

For each cell in each landscape, a species was counted as potentially present or absent using two rules: 1) species is associated with this forest age class and the cell location is within elevation constraints of the species, and 2) other closely associated age classes occur within the range of the species (proximity analysis). For instance, some birds are most closely associated with early seral conditions where they hunt and breed, but they can occur in any other forest conditions. These bird species would be counted as potentially present for a given cell of any age class under rule one if the cell is within the specie's elevation range, and counted as potentially present under rule two only if rule one is satisfied and a given number of early seral cells (closely associated habitat) occur within an area centered on the cell defined by the average range of an individual of that species. The required percentages of area of closely associated age class were arbitrarily defined, since these requirements are unknown, and were higher for species with small ranges (25% of range area) compared with far ranging species (10% of range area; see Pennington, 2002 for details). The purpose of this approach was to isolate the effect of the factors of interest (elevation and age class homogenization) from each other.

For each landscape and rule set species richness, or the number of species potentially present at cell location, was calculated and output to maps. Due to its computational intensity, the third rule set (closely associated age class proximity) was conducted on only seven landscapes: an average landscape from each of the wildfire simulation scenarios, the 1995 landscape, and the hypothetical landscape. The cell values for each map were averaged by landscape and by land owner and use category. The resulting values were compared.

In 1995, according to age class and elevation (rule set 1), an average of 121 bird species and 71 mammal species were

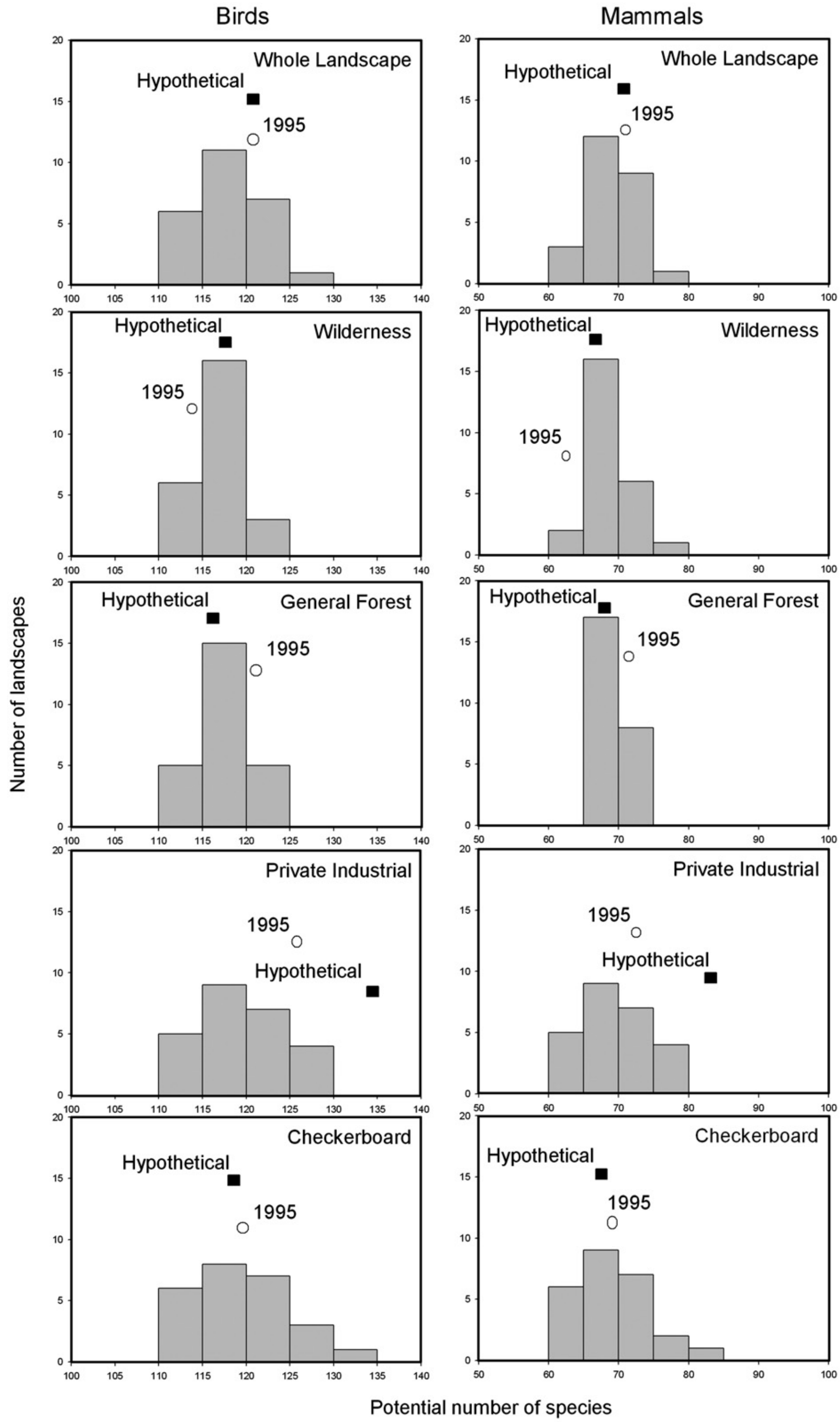

Fig. 7 – Potential species richness based on age class and elevation for the 1995 (open circle) and hypothetical landscape (solid square) compared with histograms of potential species richness for twenty five simulated wildfire landscapes, by landowner category.

potentially present across the whole landscape (Fig. 7). The lowest average number was potentially present on high elevation wilderness lands (114 and 65, respectively) and the highest average number was potentially present on low elevation private industrial lands (125 and 76, respectively). General forest and checkerboard areas were intermediate in average values.

Compared with the wildfire simulation landscapes, potential species richness for all landowner categories were within the simulated range of natural variability in potential species richness (Fig. 7). The lowest comparative values were on wilderness lands where the average number of mammal species in 1995 was comparable to the lowest histogram category consisting of values from only two wildfire simulation landscapes. The hypothetical landscape also showed potential species richness for all landowner categories within the simulated range of natural variability in potential species richness with the exception of private industrial lands, which showed very high average potential species richness for both birds (135 species) and mammals (84 species).

When proximity of closely associated age classes in included in the analysis (rule set 2), the 1995 landscape as a whole is still within the simulated natural range of variability from the five analyzed wildfire landscapes (Fig. 8). All of the landowner categories were also within the simulated natural range of variability with two exceptions. First, average number of mammals on wilderness lands in 1995 (49 species) is less than observed on the simulated wildfire landscapes (51 to 59 species). Second, average number of birds on checkerboard lands in 1995 (83 species) is less than observed on the simulated wildfire landscapes (85 to 106 species). However, these five simulated wildfire landscapes represented average conditions — the range of variability in conditions for each wildfire scenario was not analyzed therefore these results are only suggestive of possible differences between the 1995 landscape and the natural range of variability. Results from the hypothetical landscape were very similar to results from the 1995 landscape as a whole and by most landowner categories. The exception is on private industrial lands. Compared with the 1995 landscape private industrial lands on the hypothetical landscape showed a large increase in the potential number of both birds (from 93 to 107 species) and mammals (from 62 to 71 species), in both cases more than the averages observed in the five wildfire simulation landscapes.

The number of bird species lost on the wildfire simulated landscapes due solely to restrictions on the proximity of closely associated age classes ranged from 19 on private industrial lands to 40 on checkerboard lands (Fig. 9). Losses on the 1995 and hypothetical landscape were within this range, though generally towards the high end of the range. Wilderness was the only landowner category on which losses in the 1995 and hypothetical landscapes exceeded those of the wildfire simulated landscapes. The number of mammal species lost on the wildfire simulated landscapes due solely to restrictions on the proximity of closely associated age classes ranged from 6 on checkerboard lands to 16 on wilderness lands. Losses on the 1995 landscape were generally towards the high end of that range but did not exceed that range. The hypothetical landscape exceeded that range on wilderness lands by one additional species lost.

Number of bird and mammal species lost increased with decreasing levels of disturbance on the wildfire simulated landscapes (Fig. 9). The 1995 and hypothetical landscapes generally showed more species lost for the proportion of disturbance in the landscape than would be predicted by the wildfire simulation landscapes. This is true in the general forest lands and especially in private industrial lands.

3. Lessons learned from the case study

The conclusions that could be drawn from this case study include:

- The 1995 forest landscape as a whole across this study area is well within the plausible natural range of variability of the past few millennia, though outside of the historical range of variability of the past 500 years.
- Key structural deviations are two: 1) conversion of low elevation private industrial forest to homogenous early seral and young forest; and 2) conversion of high elevation wilderness to homogenous mature and old forest.
- The change in proportion of age classes in a given elevation range has little impact on the potential richness of bird and mammal species over and above impacts observed in the past, and where that impact could occur it is positive, producing increased species richness.
- The reduction of heterogeneity could, possibly, result in reduction in potential richness of bird and mammal species that exceeds those in the past, in some portions of the landscape. The landscape as a whole, however, should support comparable numbers of species. The primary impact of homogenization is to decrease richness below what might be expected for the same level of disturbance in a natural landscape. This effect is more pronounced in private industrial lands.

Implications of these findings for general ecological theory are:

- One could infer from these results that in order to impact species richness at a magnitude greater than past impacts, the landscape would have to undergo wholesale conversion from forest to other land cover types such as agricultural or suburban.
- It follows, then, that observed declines in biodiversity worldwide are more likely the result of forest conversion to non-forest, with little impact from forest arrangement.

Are these results and conclusions valid? In a consolidation modeling approach one would attempt to test how well the landscapes produced by the wildfire simulation model predict reality. However, there are no past landscapes in existence to validate against. Additionally, a century of fire suppression, grazing, and harvest disturbance preclude any opportunity to validate the model against current landscapes. The theories used to construct the model are generally accepted within the wildfire modeling community as valid for this particular scale of analysis but there are other models that might yield different results. Model assumptions and mechanics are highly simplified due to the uncertain nature of our understanding. Therefore, the validity of model outcome is also uncertain. Consolidation modeling approaches have found this forest landscape to be outside of the historical range of variability, but because of the high uncertainty in outcome those findings do not necessarily provide convincing evidence in the realm of decision-making and stakeholder dialogue where model uncertainties are difficult to convey (Clark et al., 2001; Rose

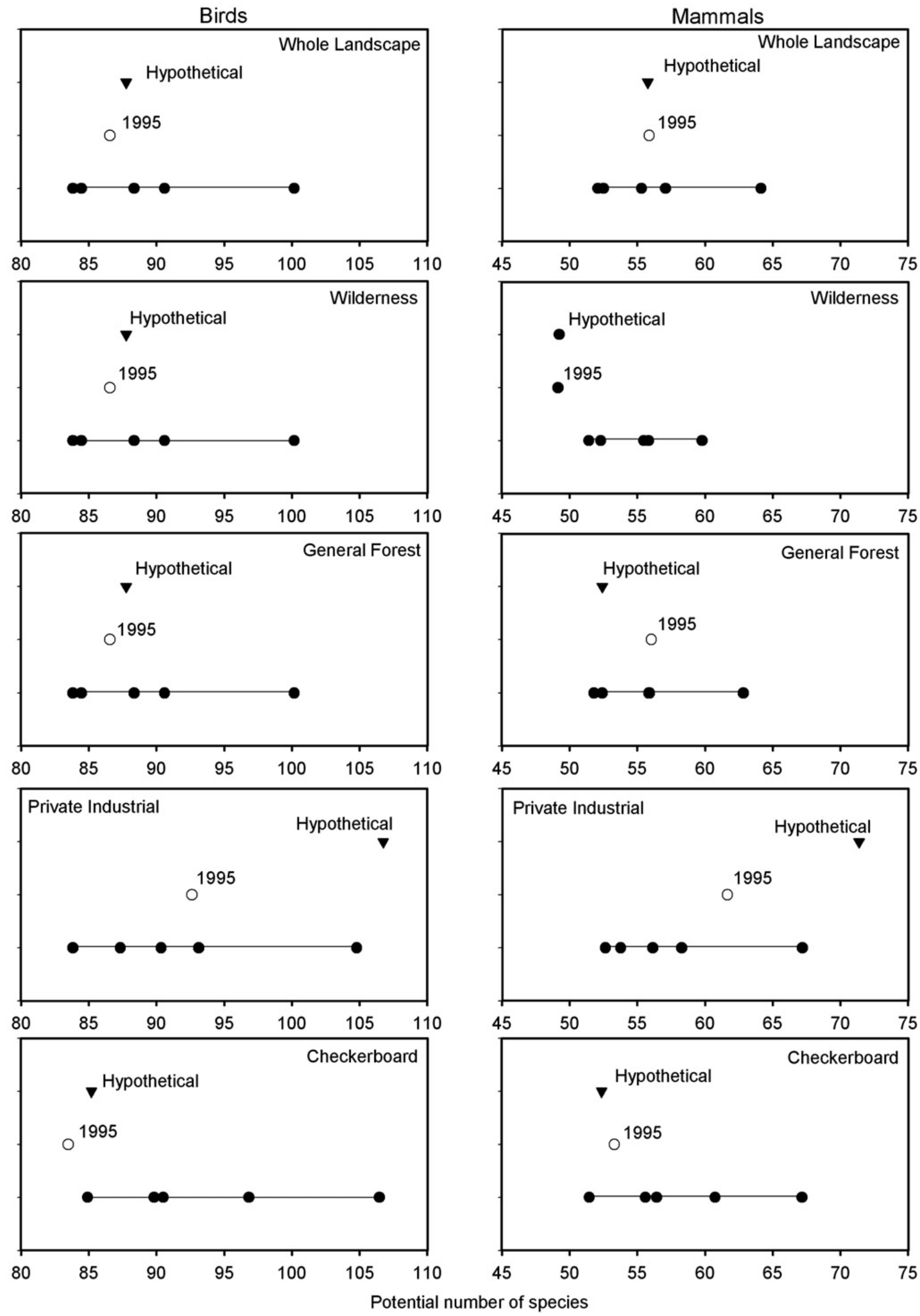

Fig. 8 – Potential species richness based on age class, elevation, and closely associated age class proximity for the 1995 (open circle) and hypothetical landscape (solid triangle) compared with the range of potential species richness for five simulated wildfire landscapes (solid circles), by landowner category.

and Cowan, 2003). In the exploratory modeling approach, one does not attempt to validate any particular model outcome—one validates the exploratory modeling strategy. In this case, the strategy was to model the widest plausible range of drivers to produce the most divergent landscapes that the model is capable of producing given that range. There is no point in arguing that any of the landscapes are valid representations of the past. The point is that certain key combinations of land owner and forest age class are outside the entire range of plausible conditions that could have existed given the most liberal interpretation of the range of natural variability. It lends compelling evidence that current forest structure does indeed diverge from the natural range of variability.

Given the high confidence in the above finding, the remaining strategy to validate is the experimental approach

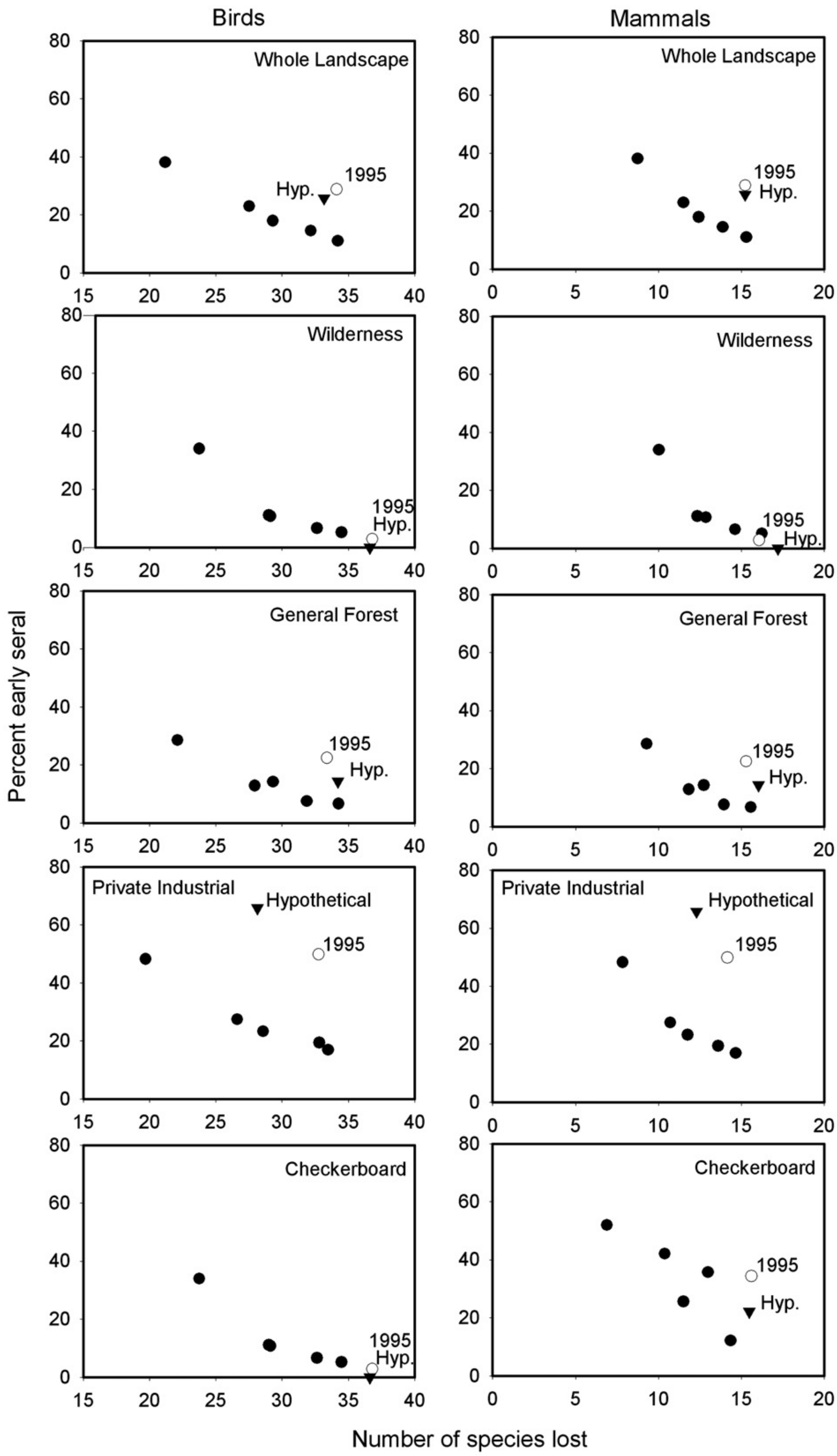

Fig. 9 – Number of species lost due to restrictions on age class, elevation and proximity of closely associated age classes, compared with level of landscape disturbance as measured by proportion of early seral vegetation, by landowner category for five simulated wildfire landscapes (solid circles), the 1995 (open circle), and hypothetical landscape (solid triangle).

used in the biodiversity analysis. The very strategy that made the argument convincing above makes these findings less convincing. If the range of simulated past conditions is intentionally more divergent than is likely to have occurred in the past, showing that 1995 richness effects are within that range does not provide convincing argumentation that the effects are within the true range of natural variability. If we were able to simulate the true range, some of the observations on the 1995 and hypothetical landscape may very well have fallen outside of that range. Additionally, since some of the analysis was conducted on only a single average landscape from each wildfire scenario (five landscapes total), the analysis most certainly does not capture the full range. What can be concluded, though, is that the effect of redistributing and homogenizing age classes together is relatively small compared with an average wildfire landscape, typically an additional loss of less than five bird and five mammal species. Given the total number of species in the area (approximately 140 birds and 90 mammals), this is insufficient to infer statistically significant loss of biodiversity due to these forest structural changes.

However, the changes considered by this analysis are not the only possible changes. In a consolidation modeling approach, one would have to fully simulate every process that could impact the occurrence of every species to validate the outcome, a hopelessly futile endeavor. In this example, the strategy was to identify the few key structural changes and run simple computational experiments as indicators of the degree to which those changes could potentially impact biodiversity. The assumption is made that if these major drivers are insufficient to produce significant declines in biodiversity, less prominent changes are highly unlikely to produce significant changes. The validity of that strategy depends on whether or not this analysis was truly able to identify the major drivers of forest change at this scale. Other changes not identified in this analysis could potentially be important. The approach is analogous to solving a complex mathematical equation. By comparing the various terms of the equation one can conclude that certain terms are very small relative to others and can be safely ignored, while others drive the result. The difference is that in ecological modeling, we don't have the equation fully expressed, therefore it's difficult to be certain that the major terms that are under consideration are the only major terms of importance. However, this kind of exploratory modeling can be a starting point for framing a discussion about which details are essential to include in the analysis (Levin, 1992). The appropriate use of this kind of approach is to conduct multiple iterations of analysis, adding in a single component each time until outcomes are stable and discussants are satisfied that the major terms have indeed been incorporated. In that case, the results can inform both theory and practice in a meaningful way. In the case study presented here, the analytical outcome of the biodiversity computational experiment should be a starting point not an ending point.

4. Conclusion

Exploratory modeling can be a very useful approach in situation when the system being modeled is very uncertain. It can provide compelling evidence that is lacking through standard modeling approaches. It should not be a one-off exercise, though. The greatest benefit gained through exploratory modeling is by continually developing and applying scenarios as a tool to learn about the system through a deeper understanding of the major driving forces. It provides an opportunity to brainstorm drivers of change using explicit representations of outcomes related to those drivers as a basis for strategic debate.

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REFERENCES

Agee, J.K., 1993. Fire Ecology of Pacific Northwest Forests. Island Press, Washington, DC. 493 pp.

Agee, J.K., 2003. Historical range of variability in eastern Cascades forests, Washington, USA. Landscape Ecology 18, 725–740.

Agee, J.K., Krusemark, R., 2001. Forest fire regime of the Bull Run watershed, Oregon. Northwest Science 75, 292–306.

Bankes, S., 1993. Exploratory modeling for policy analysis. Operations Research 41 (3), 435–449.

Bankes, S.C., Gillogly, J., 1994. Validation of exploratory modeling. In: Tentner, A. (Ed.), High Performance Computing: Grand Challenges in Computer Simulation. The Society for Computer Simulation, San Diego, CA, pp. 382–387.

Bennett, E.M., Carpenter, S.R., Peterson, G.D., Cumming, G.S., Zurek, M., Pingali, P., 2003. Why global scenarios need ecology. Frontiers in Ecology and the Environment 1 (6), 322–329.

Bredehoeft, J., 2005. The conceptualization model problem — surprise. Journal of Hydrogeology 13, 37–46.

Bunnell, F.L., 1995. Forest-dwelling vertebrate faunas and natural fire regimes in British Columbia: patterns and implications for conservation. Conservation Biology 9, 636–644.

Butler, C.D., Corvalan, C.F., Koren, H.S., 2005. Human health, well-being, and global ecological scenarios. Ecosystems 8, 153–162.

Carpenter, S.R., 2002. Ecological futures: building an ecology of the long now. Ecology 83 (8), 2069–2083.

Cissel, J.H., Swanson, F.J., Weisberg, P.J., 1999. Landscape management using historical fire regimes: Blue River, Oregon. Ecological Applications 9, 1217–1231.

Clark, J.S., Carpenter, S.R., Barber, M., Collins, S., Dobson, A., Foley, J.A., Lodge, D.M, Pascual, M., Pielke Jr., R., Pizer, W., Pringle, C., Reid, W.V., Rose, K.A., Sala, O., Schlesinger, W.H., Wall, D.H., Wear, D., 2001. Ecological forecasts: an emerging imperative. Science 293 (5530), 657–661.

Cleland, D.T., Saunders, S.C., Crow, T.R., Dickmann, D.I., Maclean, A.L., Jordan, J.K., Watson, R.L., Sloan, A.M., 2004. Characterizing historical and modern fire regimes in the lake states: a landscape ecosystem approach. Landscape Ecology 19, 311–325.

Cohen, W.B., Spies, T.A., Fiorella, M., 1995a. Estimating the age and structure of forests in a multi-ownership landscape of western

Oregon, U.S.A. International Journal of Remote Sensing 16, 721–746.
Cohen, W.B., Spies, T.A., Swanson, F.J., 1995b. Land cover on the western slopes of the central Oregon Cascade Range. International Journal of Remote Sensing 16, 595–596.
Cohen, W.B., Fiorella, M., Gray, J., Helmer, E., Anderson, K., 1998. An efficient and accurate method for mapping forest clearcuts in the Pacific Northwest using Landsat imagery. Photogrammetric Engineering and Remote Sensing 64, 293–300.
Cumming, G.S., Barnes, G., Perz, S., Schmink, M., Sieving, K.E., Southworth, J., Binford, M., Holt, R.D., Stickler, C., Van Holt, T., 2005. An exploratory framework for the empirical measurement of resilience. Ecosystems 8, 975–987.
Dessai, S., Lu, X., Risbey, J.S., 2005. On the role of climate scenarios for adaptation planning. Global Environmental Change 15, 87–97.
Franklin, J., Dyrness, C.T., 1988. Natural Vegetation of Oregon and Washington. Oregon State University Press, Corvallis, OR.
Franklin, J.F., Spies, T.A., Van Pelt, R., Carey, A.B., Thornburgh, D.A., Bert, D.R., Lindenbayer, D.B., Harmon, M.E., Keeton, W.S., Shaw, D.C., Bible, K., Chen, J., 2002. Disturbances and structural development of natural forest ecosystems with silvicultural implications, using Douglas-fir forests as an example. Forest Ecology and Management 155, 399–423.
Hunter, M.L.J., 1993. Natural fire regimes as spatial models for managing boreal forests. Biological Conservation 65, 115–120.
Hunter, M.L.J., Jacobson, G., Webb, T., 1988. Paleoecology and the coarse-filter approach to maintaining biological diversity. Conservation Biology 1, 375–385.
Landres, P.B., Morganm, P., Swanson, F.J., 1999. Overview of the use of natural variability concepts in managing ecological systems. Ecological Applications 9, 1179–1188.
Lempert, R.J., 2002. A new decision sciences for complex systems. PNAS 99 (3), 7309–7313.
Lempert, R.J., Schlesinger, M.E., Bankes, S.C., 1996. When we don't know the costs or the benefits: adaptive strategies for abating climate change. Climate Change 33, 235–274.
Levin, S.A., 1992. The problem of pattern and scale in ecology. Ecology 73 (6), 1067–1943.
Long, C.J., Whitlock, C., Bartlein, P.J., Millspaugh, S.H., 1998. A 9000-year fire history from the Oregon Coast Range, based on a high-resolution charcoal study. Canadian Journal of Forest Research 28, 774–787.
Morgan, P., Aplet, G.H., H.J.B., Humphries, H.C., Moore, M.M., Wilson, W.D., 1994. Historical range of variability: a useful tool for evaluating ecosystem change. Journal of Sustainable Forestry 2, 87–111.
Morrison, P.H., Swanson, F.J., 1990. Fire history and pattern in a Cascade Range landscape. U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station, Corvallis, OR. General Technical Report PNW-GTR-254, p. 77.
Nonaka, E., Spies, T.A., Wimberly, M.C., Ohmann, J.L., in press. Historical range of variability in live and dead wood biomass: a simulation study in the Coast Range of Oregon, USA. Canadian Journal of Forest Research.
Nassauer, J.I., Corry, R.C., 2004. Using normative scenarios in landscape ecology. Landscape Ecology 19, 343–356.
O'Neill, B.C., 2005. Population scenarios based on probabilistic projections: an application for the Millennium Ecosystem Assessment. Population and Environment 26 (3), 229–254.
Pennington, D., 2002. Structural and functional comparison of human-impacted and natural forest landscapes in the western Cascades of Oregon. Geography. Oregon State University, Corvallis, p. 263.
Pickett, S.T.A., Burch Jr., W.R., Grove, J.M., 1999. Interdisciplinary research: maintaining the constructive impulse in a culture of criticism. Ecosystems 2, 302–307.
Perera, A.H., Buse, L.J., Weber, M.G. (Eds.), 2004. Emulating Natural Forest Landscape Disturbances: Concepts and Applications. Columbia University Press, New York, NY.
Regan, H.M., Colyvan, M., Burgman, M.A., 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological Applications 12 (2), 618–628.
Rose, K.A., Cowan Jr., J.H., 2003. Data, models, and decisions in U.S. marine fisheries management: lessons for ecologists. Annual Review of Ecology and Systematics 34, 127–151.
Rotmans, J., Van Asselt, M.B.A., 2001. Uncertainty management in integrated assessment modeling: towards a pluralistic approach. Environmental Monitoring and Assessment 69, 101–130.
Ryliel, E.J., 1996. Testing ecological models: the meaning of validation. Ecological Modelling 90, 229–244.
Scheller, R.M., Mladenoff, D.J., 2007. An ecological classification of forest landscape simulation models: tools and strategies for understanding broad-scale forested ecosystems. Landscape Ecology 22 (4), 491–505.
Schoemaker, P.J.H., 1995. Scenario planning: a tool for strategic thinking. Sloan Management Review 36 (2), 25–40.
Spies, T.A., Ripple, W.J., Bradshaw, G.A., 1994. Dynamics and pattern of a managed coniferous forest landscape in Oregon. Ecological Applications 4, 555–568.
Swanson, F.J., Jones, J.A., Wallin, D.O., Cissel, J.H., 1993. Natural variability-implications for ecosystem management. Eastside Forest Ecosystem Health Assessment-Volume II: Ecosystem management: principles and applications. M.E. Jensen and P.S. Bourgeron. Portland, Oregon, USDA Forest Service. Pacific Northwest Research Station 2, 89–103.
Swart, R.J., Raskin, P., Robinson, J., 2004. The problem of the future: sustainability science and scenario analysis. Global Environmental Change 14, 137–146.
Van Norman, K.J., 1998. Historical fire regime in the little river watershed, southwestern Oregon. Forest Science. Oregon State University, Corvallis, p. 102.
Wack, P., 1985. Scenarios: uncharted waters ahead. Harvard Business Review 63 (5).
Weisberg, P.J., 1997a. Fire history and fire regimes of the Bear-Marten watershed. Oregon State University, Corvallis, OR. Final Report to the Bureau of Land Management: Eugene District, p. 30.
Weisberg, P.J., 1997b. Fire History in the Coburg Hills. Corvallis, Oregon (unpublished document).
Weisberg, P.J., 1998. Fire history, fire regimes, and development of forest structure in the central western Oregon Cascades. Forest Science. Oregon State University, Corvallis, OR, p. 256.
Weisberg, P.J., Swanson, F.J., 2003. Regional synchronicity in changing fire regime patterns of the Western Cascades, U.S.A. Forest Ecology and Management 172, 17–28.
Whitlock, C., Shafer, S.L., Marlon, J., 2003. The role of climate and vegetation change in shaping past and future fire regimes in the northwestern US and the implications for ecosystem management. Forest Ecology and Management 178, 5–21.
Wimberly, M.C., 2002. Spatial simulation of historical landscape patterns in coastal forests of the Pacific Northwest. Canadian Journal of Forest Research 32, 1316–1328.
Wimberly, M.C., Spies, T.A., Long, C.J., Whitlock, C., 2000. Simulating historical variability in the amount of old forests in the Oregon Coast Range. Conservation Biology 14, 167–180.
Zegras, C., Sussman, J., Conklin, C., 2004. Scenario planning for strategic regional transportation planning. Journal of Urban Planning and Development 130 (1), 2–13.