MODELING LARGE-SCALE FIRE EFFECTS:
CONCEPTS AND APPLICATIONS

by

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Abstract

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Climatic changes anticipated for the next century are expected to alter the effects of fire on large-scale vegetation patterns. It is unlikely that future interactions between fire and vegetation can be predicted from knowledge of current and historic patterns. Thus, there is a need for simulation models that will produce realistic large-scale projections. Three topics were addressed in this paper: 1) the difficulties in applying current fine-scale models across coarse scales, 2) qualitative modeling at continental scales, and 3) semi-qualitative modeling at regional scales.

A review of extrapolation problems revealed that a variety of methods have been developed by modelers; each has its advantages and disadvantages. A continental-scale model of vegetation changes expected from increased fire frequency suggested the large-scale patterns would be more homogeneous as a result of new dominant vegetation in fire-sensitive ecosystems. A regional-scale model that predicted fire frequency from environmental variables and vegetation types produced GIS coverages of mean fire return intervals at 1 km resolution for the Interior Columbia River Basin, and demonstrated a semi-qualitiative method that can be used in the absence of fully quantitative data.

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DEDICATION

This dissertation is dedicated to Susan and Kira McKenzie

INTRODUCTION

Understanding and predicting the effect of disturbances, particularly fire, on large-scale vegetation patterns is a challenge for scientists and resource managers. The climatic changes anticipated for the next century are expected to have a substantial effect on fire regimes (Price and Rind 1994, Qu and Omi 1994). In turn, changes in fire frequency and severity are expected to affect successional pathways, particularly in forested ecosystems (Cattelino et al. 1979, Agee 1993). Depending on life history traits and specific adaptive strategies (Rowe 1981), changes in fire regime may alter species composition at particular stages of succession or alter successional trajectories entirely. For example, increased fire frequency favors seral species in the Pacific Northwest (Agee and Huff 1987, Barrett 1988, Keane et al. 1989), the northern boreal forest (Morneau and Payette 1989, Payette 1992), and the eastern spruce-fir forests (Furyaev et al. 1983, St. Pierre et al. 1991). Conversely, fire exclusion, leading to longer fire return intervals, promotes later-successional species (Kauffman and Martin 1987, Reed and Sugihara 1987) or allows tree encroachment into shrublands or prairies (Bragg and Hurlbert 1976, Anderson and Bailey 1980, Fischer and Clayton 1983), or into subalpine meadows (Agee and Smith 1984, Butler 1986).

Because climatic changes are expected to occur much more rapidly than the historical average (Schneider 1989), it is unlikely that future interactions between fire and vegetation can be predicted from knowledge of current and historical patterns (Brubaker 1988, Payette et al. 1989). Thus, there is a need for simulation models that will produce realistic large-scale projections to assist resource managers, and society at large, in understanding the long-term effects of current policies and decisions. Fire scientists have concluded that the "ideal" simulation model of fire effects on vegetation would be (Schmoldt et al. 1998):

- process-based, rather than statistically-based
- spatially explicit
- applicable over broad and fine scales
- modular, integrating fire behavior, fire effects, and succession
- capable of incorporating climatic variability

In most cases, practical and theoretical considerations preclude the attainment of this ideal. For example, no current mechanistic model of fire behavior (e.g. Finney 1995) is applicable over broad geographic areas, primarily because the requisite data for initialization are lacking. Similarly, there are theoretical issues involved in applying models built at fine scales across spatially heterogeneous landscapes (King et al. 1991, Rastetter et al. 1992). Decisions will continue to be made based on existing information and techniques, however, and "compromise" models will be used that are subject to different types of error magnification when they are applied at broad scales. Understanding the limitations of these models is a key to assessing the reliability of their predictions and to estimating confidence intervals around them.

There are three key questions whose answers can guide both the development of broad-scale models of fire effects on vegetation and an accurate assessment of their limitations:

1. What are the difficulties/dangers in applying current fine-scale models across coarse scales? How can the appropriate level of aggregation of data and model algorithms be determined?

2. Can methods be developed for modeling at continental scales? Are they necessarily qualitative or subjective?
3. What are the broadest scales at which quantitative methods can be used effectively? Can they be integrated with qualitative methods to improve predictions?

In the following chapters, I address each of these questions in turn. Chapter One examines current strategies for "scaling up" fire-effects models. I develop a classification of existing strategies, suggest potential sources of error in each, and propose an adaptive strategy for applying models to meet specific objectives. Chapter Two describes a continental-scale, rule-based model for predicting transitions between vegetation types in response to altered fire frequency. I use the fire-effects literature as a source of expert knowledge for building the model. Chapter Three describes a regional-scale model to predict fire frequency in forested areas of the Interior Columbia River Basin. I use disparate databases, developed at different scales, to develop a model that integrates statistical methods and expert knowledge. I conclude by evaluating how the partial answers given to these questions can help to refine existing models and to suggest future directions for modeling the interactions of fire and vegetation.

CHAPTER 1: EXTRAPOLATION PROBLEMS IN MODELING FIRE EFFECTS AT LARGE SPATIAL SCALES

SUMMARY

Models of vegetation change in response to global warming need to incorporate the effects of disturbance at broad spatial scales. Process-based predictive models, whether for fire behavior or fire effects on vegetation, assume homogeneity of crucial inputs over the spatial scale to which they are applied. Landscape disturbance models predict final burning patterns, but either do not model mechanistic behavior and explicit spread rates, or require large amounts of data to initialize simulations and predict ecological effects. Empirical data on the ecological effects of fire are not generally available at these scales, and conclusions are often extrapolated upward from stand-level data. Three methods for extrapolating ecological effects of fire across spatial scales and the sources of error associated with each were identified: (1) extrapolating fire behavior models directly to larger spatial scales; (2) integrating fire behavior and fire effects models with successional models at the stand level, then extrapolating upward; and (3) aggregating model inputs to the scale of interest. Extreme fire events present a challenging problem for modelers, regardless of which extrapolation method is employed. No single approach to modeling fire effects is inherently superior; modeling objectives and the characteristics of specific systems will determine the best strategy for each situation.

INTRODUCTION

Large-scale shifts in vegetation are anticipated for the next century due to an unprecedented rate of global warming, 10-50 times that of the historical average (Schneider 1989). Large-scale vegetation change is constrained primarily by climate (Woodward 1987, Woodward and McKee 1991), thus simulation models used to predict vegetation change are driven by climatological variables (Neilson 1992, Running and Hunt 1993). These models must address broad spatial scales, while incorporating processes of vegetation change at the scales at which those processes can be quantified (King et al. 1990, Ehleringer and Field 1993).

Models of vegetation change in response to global warming also need to incorporate the effects of disturbance, particularly fire, at broad spatial scales, because fire often provides critical constraints on vegetation type (Fosberg et al. 1992, Neilson 1995, McKenzie et al. 1996a). However, data on the ecological effects of fire are not generally available at these scales. Most process-based predictive models, whether for fire behavior or fire effects on vegetation, have been built at small scales, usually the stand level, and assume homogeneity of crucial inputs over the spatial scale to which they are applied (Rothermel 1972; van Wagner 1977, 1993; Kercher and Axelrod 1984, Peterson and Ryan 1986; Keane et al. 1989; Keane et al. 1994). The spatially explicit mechanistic models that do exist require large amounts of empirical data as inputs (Finney 1995, Keane et al. 1996a), and are sensitive to the scale of resolution to which the raw data are aggregated.

Simple aggregation techniques based on a mean response are insufficient for accurate large-scale predictions in heterogeneous environments, in which nonlinear relationships produce biased estimation of means (O'Neill 1979, King et al. 1991). For example, the severity and extent of fire effects may be complex functions of topography, microclimate, and fuel loadings, and subject to error from spatial autocorrelation at any scale of resolution. Spatial heterogeneity is a significant element in predicting disturbance spread (Green 1989, Turner and Romme 1994), fire severity (Kessell 1976, Baker 1989), and aspects of landscape pattern (Green 1989, Turner and Romme 1994, Mladenoff et al. 1996). Nevertheless, aggregation of fine scale components for broad scale predictions is necessary, not only for computational efficiency, but also to avoid the cumulative error when each of the multiple components in complex models requires the estimation of separate parameters (O'Neill 1973, Rastetter et al. 1992). Each aggregation technique carries its own sources of error and its analytical and computational difficulties (King 1991, Rastetter et al. 1992). In addition, each ecological process presents unique difficulties, because each process "perceives" heterogeneity in a unique way, and because its functional representation may change as one moves to larger spatial scales (King et al. 1991).

Fire behavior and the subsequent effects of fire on vegetation vary with abiotic factors such as microclimate and topography and with patterns of vegetation structure and composition at different spatial scales. Predictive models of vegetation change need to account for this variability.

In this chapter, I explore the problem of spatial scale extrapolation as it applies specifically to modeling fire effects as a component of large-scale vegetation change. The principal objectives are to: (1) enumerate the spatial scales at which data relevant to fire effects are available, (2) present a conceptual overview of the process by which predictive models can be scaled up, specifying potential sources of error in each method of aggregation, and (3) suggest applications for and limitations to scale extrapolation methods.

SPATIAL SCALES OF FIRE EFFECTS DATA

Fire effects data may be collected at varying scales, ranging from a single point (e.g., taking cross-sections or increment cores from fire-scarred trees; Arno and Sneck [1977], Barrett and Arno [1988] or collecting macrofossils; Desponts and Payette [1993]), to the landscape (e.g., examination of aerial photographs or satellite imagery; Gruell [1983]). Data are frequently used to suggest conclusions and justify applications at different scales and with respect to various ecological criteria (Allen and Hoekstra 1993). For example, Desponts and Payette (1993) used macrofossils collected at 8 sites along the Great Whale River, Quebec (Canada), to estimate regional-scale fire patterns. Guerin (1993), Weber (1987), and Borchert (1989) used stand level data to address community succession, ecosystem processes, and population dynamics, respectively.

Description and analysis of landscape-scale fire effects are often scale dependent, and also dependent on the appropriateness of the "landscape criterion" (Allen and Hoekstra 1993), which explicitly involves spatial relationships, for the data. For example, if one wanted to examine the connectivity of patches of highly flammable forest in a large-scale forest mosaic, amassing continuous data over the scale of interest would be obligatory. Point or stand level data would be inadequate. Satellite imagery or aerial photographs, accompanied by selective ground-truthing, could be a valuable source of data.

I suspected that there were substantial discrepancies between the spatial scales of data collection and model predictions. In order to estimate the proportions of fire effects data collected at different spatial scales, I randomly selected 100 papers from the 1984-94 AGRICOLA database, using the keywords "fire," "ecology," and "forest." Six of these references could not be located, but I examined the remaining 94 for the type of data collected, the spatial scale of the data, and the spatial scale of conclusions or suggested applications. Because these spatial scales could not generally be quantified precisely, I divided them into the following categories: individual plant (10 m^2), microsite/sub-stand (10^2 - 10^3 m^2, stand/community (10^{-1} - 10^1 km^2), landscape (10^1 - 10^4 km^2), and region (10^4 - 10^6 km^2). Each of these scales roughly corresponds to perceptual categories of data (Simard 1991). Figure 1.1 exemplifies how some of these categories change with increasing spatial scale (left-hand side), or with increasing levels of aggregation of biological attributes (right-hand side). Each step in the aggregation of data presents potential sources of error, from either the loss of quantitative information in the averaging process or the lack of precise equivalences when perceptual categories change.

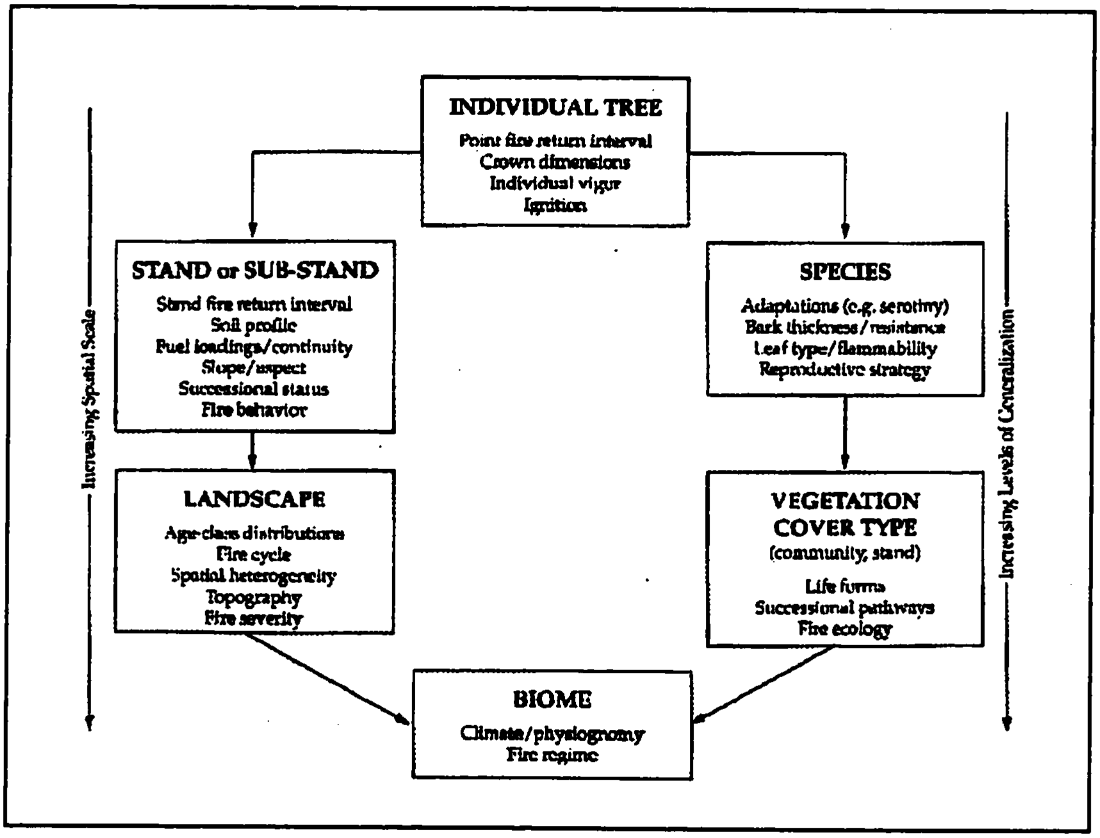


Figure 1.1: Two paths for aggregating data for modeling large-scale vegetation changes. Both spatial resolution and taxonomic resolution are lost in the aggregation process.

RESULTS AND IMPLICATIONS

The majority of studies I examined were in the stand category (above). The landscape category was the second most common, and the only significant extrapolation upward of conclusions was from stand to landscape.

In a spatially heterogeneous landscape, the range of variation displayed by a random sample of a fixed size is not necessarily an accurate estimate of landscape variance (O'Neill 1979). Extrapolating conclusions upward in scale without accounting for landscape pattern assumes either that individual stands are representative of the landscape as a whole, or that summing across the landscape and calculating mean values of statistics accurately represent the data at the landscape scale (King 1991). However, when functions describing processes at the stand level are nonlinear, simple averaging produces biased estimates of results at larger scales, and this bias is worse when there is spatial heterogeneity in a system (O'Neill 1979, King et al 1991, Rastetter et al. 1992).

The spatial extent of many ecological studies may reflect an implicit scaling on the part of researchers who associate certain taxa with certain concepts or organizational criteria (Hoekstra et al. 1991). The stand scale is familiar to most scientists studying fire effects on forest communities, but the need for accurate landscape, regional, and biome scale predictions is increasing in response to anticipated changes in climatic and fire regimes. Although stand level data will continue to be a critical input to larger scale predictions, an extrapolation approach is needed that can incorporate spatial heterogeneity and non-linearities in vegetation response.

SCALING UP PREDICTIVE MODELS -- A CONCEPTUAL APPROACH

Interactions between climate and vegetation, and between disturbance and vegetation, are bi-directional. Vegetation composition affects atmospheric moisture and microclimate, and although fire initiation is a stochastic function of climate, fuels, and human impacts, vegetation influences fuel loading and fire severity. Existing models for predicting the effects of fire on vegetation fall into three categories: (1) stand-level mechanistic fire behavior models and first-order fire effects models, (2) stand-level successional models incorporating fire stochastically, and (3) landscape scale models of disturbance. These three types operate on different spatial and temporal scales (Figure 1.2), although output from types (1) and (2) is frequently aggregated to larger scales.

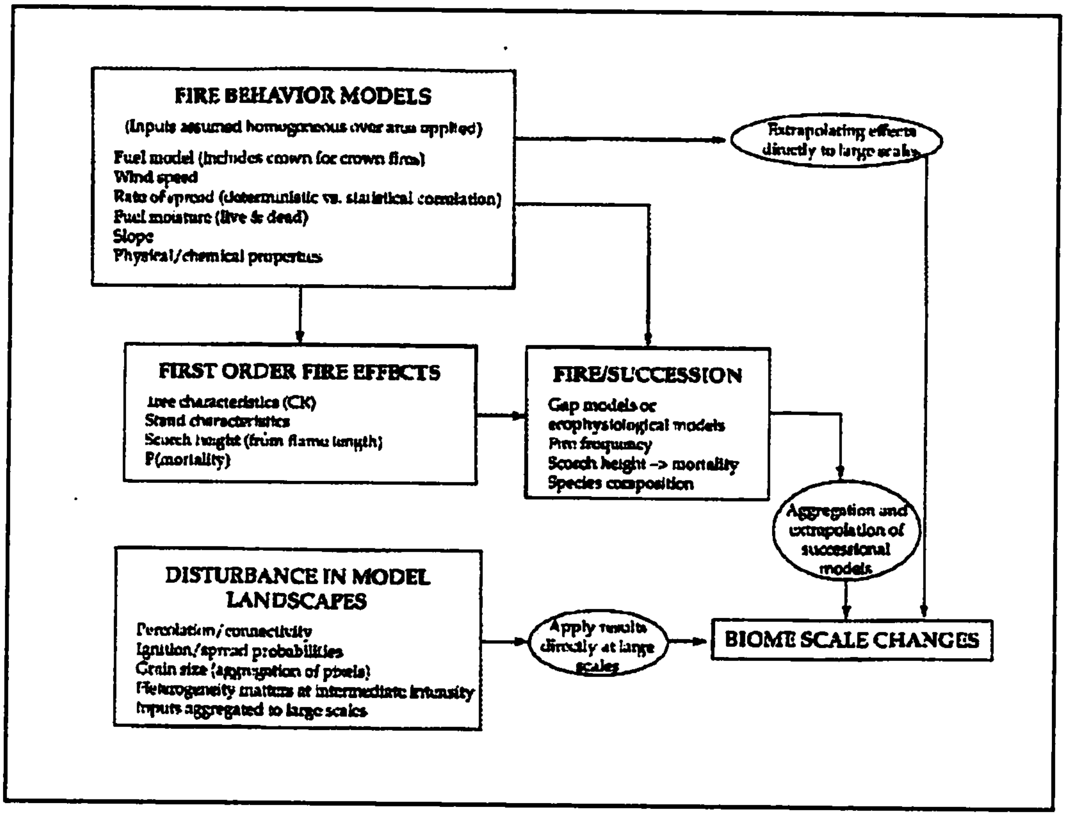


Figure 1.2: Translating fire effects predictions to the biome scale: two distinct pathways originate from a mechanistic approach, a third arises from aggregating inputs to large scales and applying methods derived from modeling abstract landscapes.

FIRE BEHAVIOR AND FIRST-ORDER FIRE EFFECTS

Mechanistic models of fire behavior calculate, for a single fire, flame length, fireline intensity and scorch height from measures of fuel loading, fuel moisture levels, and wind speed (Rothermel 1972, 1991; Andrews 1986). In combination with fire effects models (e.g., Peterson and Ryan 1986, Ryan and Reinhardt 1988, Keane et al. 1994), they predict stand structure and composition resulting from fire given specific initial conditions (e.g., leaf area index, species composition by percent basal area, crown heights). However, they do not project ecological effects into the future. They need to be linked to projections of stand development in order to drive a transient or dynamic predictive model.

Fire and succession

Fire succession models simulate structural and compositional changes in vegetation over time on a fixed-size plot, incorporating fire initiation as a stochastic element (Kercher and Axelrod 1984, Keane et al. 1989). They are based on the JABOWA-FORET class of "gap" models (Shugart and Prentice 1992, Botkin 1993), which project individual tree growth deterministically as a function of a species-specific maximum growth rate modified by reduced light levels from shading and by departures from species-specific optima for environmental variables. In contrast to empirical growth models, the structure of successional models allows for incorporation of the effects of climatic change on succession (Urban et al. 1993). The fire subroutines employ a mechanistic fire behavior model that operates by reducing stand basal area and fuel loadings, thus altering relative species dominance and susceptibility of the stand to damage from the next fire. Model outputs suggest that changes in fire frequency will strongly affect successional pathways (Keane et al. 1989). These models are limited in spatial scale by: (1) the assumption of homogeneity of the input variables to the fire behavior module, (2) the restriction of the explicit modeling of the light environment to the size of a forest canopy gap, and (3) variation in microclimate across a landscape.

Landscape disturbance models

Although fire behavior models can predict fire spread across a heterogeneous landscape (Finney 1995), calculations assume homogeneity of input parameters such as windspeed, slope, and fuel loadings, at the scale of resolution at which they are applied. Spatial patterns of these parameters will not exactly coincide, thus fire behavior models cannot explicitly account for the influence of spatial heterogeneity, or landscape pattern, on the propagation of disturbance. The effect of pattern on disturbance spread has been simulated on abstract landscapes (e.g., Turner et al. 1989, Turner and Romme 1994). In abstract models, disturbance is initiated at individual pixels stochastically, its likelihood a function of time since last disturbance or "site vulnerability." Spatial extent is usually a function of initial intensity and the vulnerability of adjacent cells, and final burning patterns are emphasized rather than mechanistic behavior or explicit spread rates (Green 1989, Turner and Romme 1994). Connectivity of landscapes and resulting constraints on disturbance can be characterized with concepts from percolation theory (Stauffer 1985).

Landscape disturbance intensity and effects have been simulated at broad spatial extents by aggregating input parameters and sacrificing the mechanistic elements of current fire behavior models (Baker 1989, Mladenoff et al. 1996). Disturbance is normally characterized by generic variables such as frequency, intensity, extent and shape, and duration. For example, landscape disturbance has been linked to successional changes in northern Lakes States (USA) forests (Mladenoff et al. 1996), with the compositional attributes of landscape units (pixels) approximated by presence/absence of 10-year age classes, and disturbances initiated based on empirical distributions derived from local data. See Kessell (1976), however, for an early attempt to link mechanistic fire behavior models and landscape pattern.

LINKING METHODOLOGIES TO PREDICT LARGE-SCALE VEGETATION PATTERNS

Which path from the micro scale (true scale of applicability of fire behavior models) to larger scales (landscape to biome scale, at which predictions are sought) is the least prone to error? Errors propagate through the system quantitatively, but scale extrapolations also often require qualitative changes in perceptual categories (Simard 1991). Perceptual categories can be critical to model building, especially in the establishment of decision criteria for rule-based models (Neilson 1992).

Three general approaches have been used in previous studies to extrapolate fire effects predictions to large spatial scales (Figure 1.2). Each has its advantages and disadvantages (Table 1).

Table 1.1: Advantages and disadvantages of methods for extrapolating fire effects to large spatial scales.

Method	Advantages	Disadvantages
Extrapolating fire behavior models directly to biome scale.	Closed form mathematical expression available, amenable to existing methodologies.	No transient component, and major temporal scale incompatibilities.
	Straightforward translation into raster images.	Aspects of stand development and succession simulated in large homogeneous units.
Extrapolating up from fire/succession models.	Combines fire behavior with ecological processes (succession).	No closed form mathematical expression possible.
	Can accommodate variability among individual organisms (individual-based model).	Spatial scale is restricted to sub-stand, and extrapolations require heavy computation, statistical modeling, or data-intensive calibration.
Aggregation of model inputs (landscape succession and disturbance models).	Models operate explicitly at scale of interest, because inputs rather than outputs are aggregated.	Aggregated inputs assume homogeneous responses at that scale. Predictions are very sensitive to scale of resolution.

Scaling up fire behavior models

Fire behavior models can be applied directly at the landscape level, and a first-order fire effects model can be applied uniformly across each unit of vegetation being modeled (Kessell 1976, Neilson et al. 1995). This method is appropriate for equilibrium predictions, but not for modeling dynamic processes such as continuous vegetation change under altered fire regimes. Input variables to the fire behavior model are also constrained to be homogeneous at the model's scale of resolution. This scale can be the entire landscape, in which case initial conditions for fire effects and fire behavior are homogeneous across the landscape, or it can be a subunit(s) of the landscape for which data are available. In the latter case, outputs can be averaged, or a more sophisticated analytical method may be used to produce landscape scale results (see example in next section). Output from fire behavior models that produce a raster image or grid (Finney 1995) presents the intriguing possibility of using image analysis techniques (Besag 1989) to model the distribution and range of first-order fire effects outputs.

Integrating different models

Fire behavior and fire effects models can be incorporated into successional simulation models at the stand or sub-stand level (e.g., Kercher and Axelrod 1984, Keane et al. 1989). The output from the successional model then needs to be aggregated at the landscape scale. This process is no longer amenable to the more complex methods discussed in King (1991) or Rastetter et al. (1992) that apply to mathematical models with closed functional forms. The remaining options are: (1) an additive approach in which many plots covering the entire landscape or a "representative" sample are simulated individually and the results averaged, (2) a statistical approach in which model outputs are aggregated based on the statistical distributions of key biotic features of the landscape, such as stand age, species composition, and leaf area index, and (3) a mechanistic approach in which growth, regeneration, and natural mortality depend on biogeochemical processes that can be simulated at broad scales (e.g., Running and Hunt 1993), and disturbance initiation and spread are simulated in a separate model (e.g., Hargrove 1994, Finney 1995).

The statistical approach avoids the computational burdens of the additive approach, but entails theoretical difficulties in modeling discrete distributions of biotic features and the transitions between "states" occupied by different proportions of stands in the landscape. For example, a Markov transitional model operating in the state space of species, function, and vertical structure, has been used to extrapolate the gap model ZELIG (Urban 1990) to broad spatial scales (Acevedo et al. 1995). A mechanistic approach avoids the theoretical statistical difficulties, but presents formidable problems of calibration, needing massive amounts of data when applied at broad scales.

Aggregating model inputs

Inputs to models can be aggregated, rather than the more common process of aggregating outputs. Examples of this type are landscape succession and disturbance models (e.g., Marsden 1983, Mladenoff et al. 1996), in which input data are lumped into broad categories (e.g., individual trees are combined into age classes, or species composition data are combined into dominant cover types), and disturbance initiation and spread no longer have the mechanistic elements of fire behavior models. No aggregation of outputs is needed because the model operates explicitly at the scale of interest. Aggregated inputs can be precisely tuned to the ecological system of interest to minimize loss of information. For example, in a forest type with two conifer species that respond similarly to fire, and a number of deciduous species that are either susceptible or resistant to fire, three cover types may suffice: conifer, deciduous and susceptible, and deciduous and resistant. Likewise, in a forest that is a mosaic of even-aged stands initiated by fire (such as much of the Northern boreal forest), a few distinct age-classes might convey most of the useful information about stand age and resulting vulnerability to disturbance.

A significant source of error for these models is the assumption that vegetation will respond homogeneously to disturbance at the spatial scale of the aggregated inputs. The flaw in this assumption is exemplified by large forest fires, which create a mosaic of burned and unburned (or lightly burned) areas (Romme and Despain 1989) under conditions that would probably be modeled as homogeneous vegetation, fuels, and fire weather. The error magnitude should be positively correlated with the scale of resolution, or "grain," of the model. Because measurements of spatial heterogeneity in a landscape also depend on the grain size (Baker 1989), the output of a landscape disturbance simulator when modeling real landscapes will be very sensitive to the choice of cell size. For each ecological system and process being modeled, there may be a threshold grain size, below which aggregated data could be considered homogeneous, and above which these data might be better defined by statistical distributions of different aggregated types. For example, in Pacific Northwest (North America) subalpine forests, characterized by large-scale, stand replacing fires (Agee 1993), this grain size might be quite large, because large areas will respond relatively homogeneously to fire (by being completely burned). In contrast, in the low to mid-elevation forests of the Oregon (USA) Cascade Range, characterized by variable intensity fires burning unevenly (Morrison and Swanson 1990), even relatively small areas, or pixels, might be better characterized by a statistical distribution of cover types or stand ages.

EXAMPLE: SCALING UP A FIRE BEHAVIOR MODEL

King (1991) presents several methods for upward scale extrapolation of models that can be expressed in a closed form (i.e., model output is an analytic function of input variables). Here I suggest how one of these methods, extrapolation by expected value, might be applied to a generic fire behavior model. I use the Rothermel (1972) model as a general guide.

Suppose we wish to estimate immediate fire effects at a large spatial scale as a function of crown scorch height, as part of a simulation of vegetation change in response to altered fire regimes. Let scorch height H_s be written as a function of fireline intensity I, which in turn is a function of fuel level F, ambient temperature T, windspeed W, and fuel moisture M_F:

$$H_s = f(I) = f(F,T,W,M_F) \qquad (1)$$

We wish to estimate H_s over a landscape that is spatially heterogeneous in the variables F, T, W and M_F. The expectation of the value of f(), $E\{H_s\}$, will be an unbiased estimator of H_s on a landscape where F, T, W, and M_F are random variables, and have a joint probability density $g(F,T,W,M_F)$. If the four variables are independent, g() is the product of the individual densities. Thus

$$E[H_S] = \int\int\int\int f(F,T,W,M_F)\, g(F,T,W,M_F)\, dF\, dT\, dW\, dM_F \qquad (2)$$

where the integral is over all values of F, T, W, and M_F. This method requires more information than simple averaging, because the density functions of the independent variables must be known or approximated. They will generally not be known, and the fuel loading will be particularly troublesome because although it is a continuous variable, most fire behavior predictions use discretely valued fuel models. If these difficulties can be overcome, however, perhaps by fitting one or more density functions g() from local data, or deriving an empirical distribution function from resampling methods (Efron and Tibshirani 1993), and Equation 2 can be solved analytically or numerically, then an estimate of H_s for a particular fire event on a particular landscape (or pixel) may be obtained. This estimate may then be used to predict mortality on that pixel, either as an average (e.g., percentage of leaf area index; Neilson 1992), or for individual species or even individual trees. For a steady-state, or equilibrium model, a new vegetation configuration may be described by whatever criterion is relevant, including life-forms, cover classes, and relative dominance of individual species. As noted earlier, a transient model must track stand development forward from the new vegetation configuration.

MAKING LARGE-SCALE PREDICTIONS MORE ACCURATE

The majority of existing data on the effects of fire on forest vegetation, and the best understanding of fire behavior and its effects on succession, are at the stand scale. I have outlined some of the intrinsic difficulties in extrapolating fire effects to large spatial scales. In addition, extreme events such as the Sundance fire that burned across northern Idaho (USA) in 1967 (Anderson 1968) and the Yellowstone (USA) region fires in 1988 (Romme and Despain 1989), are not only the most difficult to model but also have the greatest impact in terms of ecological effects, economic impacts (Strauss et al. 1989), and long-term, large-scale successional patterns. Methods of extrapolation that do not account for extreme events will ultimately result in inaccurate predictions of fire effects, but it is not clear how to assess the statistical properties of these events so that they may be included in dynamic predictive models. One potential approach is to select a fire size distribution empirically from historical observations (Mladenoff et al. 1996). However, observations in the tail of the distribution (maximum fire size) have a large variance, and model outputs will be very sensitive to this variance. Additionally, rapid climatic changes may cause these size distributions to change in unforseen ways. A compromise solution might be to acknowledge this variance and incorporate a stochastic element in management scenarios (e.g., Bratten 1982). In that case, steady-state model predictions would be ranges rather than means, while transient model predictions would vary over time and could be means or ranges.

THE PROBLEM OF AUTOCORRELATION

Fire is a "contagion" process. At most spatial scales of interest, fire spread and intensity at one site, or pixel, depend on characteristics of surrounding pixels. Thus, predictive models of vegetation change resulting from fire must account for spatial autocorrelation (Cliff and Ord 1981). For example, spatial contiguity of burned polygons had significant explanatory power in an empirical model of fire distribution in mixed chaparral and pine forests (Chou et al. 1990). This explanatory power can be deceptive, however, if the grain size in a spatial model is much smaller than the average extent of the fire, because the majority of pixels in either burned or unburned areas will always be contiguous to similar pixels. To correct this, the pixel size, or grain, could be linked to fire size, but this choice in turn would mask spatial heterogeneity of fuels, topography, and microclimate on any scale smaller than that of the average fire size.

Future attempts to incorporate spatial autocorrelation might: (1) model fire spread as a stochastic process (Guttorp 1995), generalizing existing fire behavior models to include spatial dependency based on empirical distributions of key parameters such as fuels and weather, or (2) build specific algorithms for dealing with contagion into large-scale mechanistic, or "process" modeling of fire effects and succession (e.g., Keane et al. 1996a). Rule-based models on abstract landscapes (e.g., Turner et al. 1989) may provide fertile territory for a detailed exploration of contagion properties, and may suggest what types of empirical data will be most useful to test the effectiveness of real-world models in incorporating spatial dependency. Collaboration among modelers, ecologists, statisticians, and managers is needed to address this difficult problem.

TEMPORAL SCALES

Anticipated climatic changes limit the applicability of empirically-based models to future conditions (Dixon et al. 1990), but empirical data are essential for the calibration and testing of predictive models and for assessing the precision of alternate methods of scale extrapolation. Modeling efforts in which parameters are estimated from empirical data may involve trade-offs among degrees of precision at different temporal scales. When predicting large-scale vegetation patterns, there will be a trade-off between the cumulative error from frequent re-estimation and the larger increments of estimation error that should be expected when climatic conditions change continuously.

For example, extrapolating a fire behavior model and its resultant first-order fire effects to large scales (procedure #1 above) directly requires empirical data to estimate the density functions for input parameters that are heterogeneous at the landscape scale. Suppose these empirical data are output from a stand development model, and the density functions combine these data with regression coefficients estimated under a particular climatic scenario. Variability in large-scale vegetation patterns will be sensitive to the time step for linkages between fire behavior and stand development. This time step (or distribution of time steps) will be tightly linked to the expected temporal pattern of ignitions. A longer time step, corresponding to a lower fire frequency, would reduce the number of linkages between fire behavior and succession, and thus the number of times that the input parameters for the fire behavior model had to be estimated. This would increase the potential error when a linkage was made, assuming that the regression coefficients change monotonically with climatic change. As a result, qualitatively different error correction procedures could be necessary for different fire regimes. Exhaustive testing of the model might reveal patterns in predictive errors that would suggest how to incorporate correction procedures into the model.

Extrapolating successional models that incorporate fire subroutines involves either an additive approach, which presents a huge computational burden in long-term simulations without major simplifications, or a statistical approach to the distribution of key biotic features. Assuming that techniques are developed for the latter, these distributions will change over successional time. Although fire frequency is not part of the trade-off, a balance still must be reached between the error associated with frequent re-estimation of the statistical properties of a landscape (small time steps) and the error resulting from the persistence of uncorrected properties (large time steps). For example, suppose that a "scaled-up" successional model uses 30 of the 300 simulated plots in a landscape to define the statistical properties of the landscape at each time step. If these properties were re-estimated every 5 time steps, the cumulative error (in representing biotic features as accurately as if all 300 plots had been projected individually) might actually be greater than the error from "letting the model go" for 25 time steps. The estimated landscape could diverge more and more from the "true" landscape, particularly when the estimation process entails nonlinear functions (O'Neill 1973, Rastetter et al. 1992).

A mechanistic approach (e.g., Keane et al. 1996a) circumvents some of the above difficulties but creates problems of its own. Aggregation of biogeochemical processes, such as nutrient uptake and carbon allocation, originally modeled at the stand level may mask nonlinear relationships between these processes. It is also difficult to reconcile: (1) the spatial scales at which each process is homogeneous, and (2) the time step appropriate to ecophysiological processes with the time step appropriate for successional models (Ehleringer and Field 1993).

When model inputs have been aggregated to the landscape scale, heterogeneity of vegetation response to disturbance at that scale will be a persistent source of error. If the temporal scale of resolution that minimizes this error could be determined, it would define the optimal time step for a simulation model. On a very large spatial scale, such as a General Circulation Model grid cell ($3x10^5$ km^2), error propagation could be particularly large. This would necessitate careful selection of an appropriate time step, which might differ from the appropriate time step for smaller scales. Depending on the exact objectives of the modeling effort, a shift in biome boundaries might be more relevant--and appear more homogeneous on a temporal scale--than maintaining internal heterogeneity of species distribution, stand structure, and fuels.

In simulation models, the choice of time step depends on the critical temporal units of the processes of interest. Unfortunately, there can be major incompatibilities of time scale between interacting components of models. Fire behavior and fire spread models and ecophysiological process models operate on scales from hours to days (Running and Hunt 1993; Finney 1995), whereas successional models and landscape scale disturbance models commonly use an annual time step (Urban 1990; Mladenoff et al. 1993). I have concentrated on spatial extrapolation problems in this review, but error propagation in aggregating temporally scaled processes may be just as severe, and may confound an otherwise efficient technique for spatial scale extrapolation. For example, in the fire behavior example above,Isuggested calculating the empirical distributions of the four variables, F, T, W, and M_F over space in order to estimate fire behavior over a large spatial scale. Two of these variables, windspeed and ambient temperature, may be highly variable over time. The intractability of long-term weather predictions will compromise the direct integration of current fire behavior models into simulations of fire effects over long time periods.

The difficulties of scale extrapolation, and the stochastic nature of fire, may necessitate an adaptive approach (Walters 1986). Specific examples for modeling fire effects and vegetation change include examining varying time steps in conjunction with varying levels of spatial resolution, or even dynamically specifying time increments depending on feedbacks from the system in question. These feedbacks can be specified internally, particularly in rule-based models, when any variable reaches a user-specified value.

MODELING FIRE EFFECTS: TOWARD GENERAL PRINCIPLES

Incorporating extreme fire events in dynamic predictive models is a challenging problem for fire scientists and modelers. Much fire modeling has focused on the use of fuel models, which can be configured both spatially and temporally (Burgan and Rothermel 1984, Finney 1995) to quantify fire hazard and ultimately fire intensity and rates of spread. Fuel models are a useful component of fire effects modeling (Keane et al. 1989, 1994), resource management planning (Deeming et al. 1977, Mills and Bratten 1982), and operational applications such as fire suppression and prescribed burning (Albini 1992, Agee 1994). However, empirical data from subalpine forests in the northern Rocky Mountains (Alberta, Canada) suggest that under extreme weather conditions fuel conditions may not have much explanatory power for predicting the effects of large, intense fires (Bessie and Johnson 1995), although fuels will always have some influence on spatial patterns of residual vegetation (Eberhart and Woodard 1987). Crown fires can spread through mixed conifer forest in California under hot, dry conditions even if surface fuel loadings are low (van Wagtendonk 1985). Intense fires driven by high winds and low humidity can also propagate in chaparral with minimal accumulation of dead fuels (Dunn 1989). There is apparently a diversity of vegetation types in which extreme fire events may remain unpredictable because of the unpredictability of extreme fire weather.

No single approach to modeling fire effects on vegetation is inherently superior for predicting the impacts of climatic change or of other environmental factors. Some aggregation and reduction in heterogeneity are necessary in order to produce tractable mathematical relationships. The specific objectives of modeling determine: (1) what can be averaged, (2) which approach is most accurate, and (3) how error can be minimized in the process of extrapolation to other systems and scales. There may also be limits to the orders of magnitude of spatial and temporal scale across which models can be extrapolated (Ehleringer and Field 1993). For example, extrapolating fire behavior models driven by hourly wind and temperature to the temporal scales required for modeling climatic change may be fruitless because of the chaotic dynamics of long and short term weather patterns.

Identifying appropriate spatial resolution is particularly critical in developing models that incorporate or predict fire effects on vegetation. The "grain size" of spatial heterogeneity being modeled should be stated explicitly, although the optimal model grain size for a particular system may change with disturbance. The spatial and temporal resolution of empirical data or other information used to represent fire effects should also be stated clearly, as well as potential sources of error associated with scaling up. Some assessment of data quality and confidence in major algorithms should be included in model documentation in order to guide model users and point out areas of potential improvement. Individual units or cells can be represented homogeneously or statistically (e.g., by a probability distribution); the specific application of the model may determine which approach is more appropriate.

Climatic change during the next century may alter disturbance regimes, particularly the frequency, size, and spatial distribution of fires. Fire is the primary natural disturbance in many temperate ecosystems and has profound impacts on vegetation dynamics, biogeochemical cycling, and carbon flux. The uncertainty of how fire regimes might change in the future presents a significant obstacle to accurately predicting how large-scale vegetation patterns may be affected by changes in the atmospheric environment (Price and Rind 1994, Qu and Omi 1994). We clearly need better approaches to testing large-scale predictive models. We also need more fire effects research at the landscape and regional level, so that empirical data will be more compatible with the scale of application in large-scale modeling of fire effects and other disturbances (Jensen and Bourgeron 1994; Keane et al. 1996b). For example, we need to understand how the spatial patterns created by fire change with increasing scale (Levin 1992). We also need to understand changes in the variability of these patterns, because this is critical for aggregation procedures in modeling. Geostatistical techniques (Rossi et al. 1992) and fractal methods, which quantify self-similarity of patterns with increasing scale (Milne 1991), may prove useful. Remote sensing also offers some promising approaches for data collection and model validation at large spatial scales and at different points in time (Lillesand and Kiefer 1994), as improved techniques of image classification delineate finer differences between successional and structural stages of forests (Moffett and Besag 1996).

An alternative to either landscape-scale models with aggregated inputs or to simultaneous use of several computationally intensive models (e.g., Bevins and Andrews 1994) is meta-analysis (Hunter 1990). For example, in modeling fire effects, a meta-model at the landscape scale could be built from the statistical properties of repeated simulations of: 1) a stochastic model of fire ignitions, 2) a spatially explicit model of fire spread (e.g., Finney 1995), and 3) a large-scale model of fire effects and succession (e.g., Keane et al. 1996a). The distributional properties of meta-model parameters would be known, having been derived empirically (through multiple simulations of processes that are understood mechanistically). The meta-model would operate similarly to mechanistic models that use empirically-derived parameters in the processes they simulate, except that its spatial and temporal scales of resolution would be greater. Meta-analysis may minimize error extrapolation when there are extreme scale incompatibilities, but this assertion needs to be examined carefully in each situation.

Finally, it will be important to identify those physical and biological phenomena relevant to fire effects for which no modeling strategy is currently available (Rothermel 1991, Albini 1992, van Wagner 1993), or are evidently governed by chaotic dynamical systems (Drazin 1992). Because these phenomena are so difficult to represent mathematically, it will be more productive to focus efforts on model components for which data collection and improvements in logic will result in better predictive capability.

CHAPTER 2: LARGE-SCALE VEGETATION PATTERNS IN NORTH AMERICA

SUMMARY

Potential vegetation types are constrained by many factors, including climate. Driving variables for regional- or biome-scale simulators of vegetation change are climatological. A disturbance such as fire, however, may preclude the realization of this potential by periodically returning vegetation to an earlier successional stage. Thus, models of vegetation change in response to global warming need to incorporate the effects of disturbance at broad spatial scales. The purpose of this paper is to aid development of the Mapped Atmospheric Plant Soil System (MAPSS) model by suggesting transitions between natural vegetation types resulting from the ecological effects of fire.

A biome-scale classification of natural vegetation was developed by condensing the Küchler (1964) potential natural vegetation types into "aggregated Küchler types" that were relatively homogeneous with respect to fire regime. Based on a synthesis of fire-effects literature considered applicable to the spatial scale of biomes, transition rules were developed to predict potential changes from one biome type to another resulting from increased fire frequency.

Vegetation currently associated with warmer or drier climates could replace existing vegetation in most biomes. Exceptions are subalpine forests and woodlands at the northern Arctic treeline, which are predicted to become treeless. In some cases, transitions correspond closely to potential transitions between the physiognomic vegetation types used in the MAPSS model. In other cases, where phenology or leaf type

was predicted to change without a reduction in leaf area index, no correspondence existed between transitions developed in this paper and potential transitions between MAPSS biome types.

The transition rules provide an ecological perspective on possible new vegetation configurations and a set of constraints for the steady-state version of MAPSS. They also can be used to calibrate dynamic models of biome-scale vegetation change.

INTRODUCTION

The rapid climatic changes anticipated for the 21st century may produce large-scale shifts in vegetation. Because of the unprecedented rate of temperature change, 10 to 50 times that of the global historical average (Schneider 1989), knowledge of current and historical patterns, although instructive, will be inadequate to predict future patterns (Brubaker 1988, Payette and others 1989). Simulation models will therefore be essential for realistic projections. These models must both address broad spatial scales and incorporate the driving processes of vegetation change at scales at which those processes can be quantified (Ehleringer and Field 1993, King and others 1990).

Potential vegetation types are constrained by many factors, including climate (Woodward 1987, Woodward and McKee 1991). Regional- or biome-scale simulators of vegetation change are driven by climatological variables, and may incorporate data from general circulation models (Neilson 1992, Running and Hunt 1993). A disturbance such as fire, however, may preclude the realization of this potential by periodically returning vegetation to an earlier successional stage. Therefore, simulation models of vegetation change, at any spatial scale, should project a different vegetation physiognomy in the absence of disturbance than in its presence (for example, Keane and others 1989, Mladenoff and others 1993, Neilson 1992).

Interactions between climate and vegetation, and disturbance and vegetation are bidirectional. Vegetation composition influences atmospheric moisture and microclimate, and although fire initiation is a stochastic function of climate, vegetation also can influence fuel loading and fire severity. Existing models for predicting the effects of fire on vegetation fall into three categories: (1) mechanistic fire behavior models, (2) successional models incorporating fire stochastically, and (3) landscape scale models of disturbance. Models in these three categories operate on different temporal and spatial scales.

MODELING FIRE BEHAVIOR, FIRE EFFECTS, AND SUCCESSION

Mechanistic models of fire behavior calculate, for a single fire, output variables such as flame length, fireline intensity, and scorch height from measures of fuel loading, fuel moisture levels, and wind speed (Andrews 1986, Rothermel 1972, 1991). In combination with fire effects models (for example, Keane and others 1994, Peterson and Ryan 1986, Ryan and Reinhardt 1988), fire behavior models predict stand structure and composition resulting from fire, given specific initial conditions (for example, leaf area index, species composition by percentage of basal area, and crown heights), but do not project ecological effects into the future.

Fire succession models simulate structural and compositional changes in vegetation over time on a fixed-size plot, incorporating fire initiation as a stochastic element (Keane and others 1989, Kercher and Axelrod 1984). Based on the JABOWA-FORET class of "gap" models (Botkin and others 1972, Shugart and Prentice 1992), successional models project individual tree growth deterministically, incorporating a mechanistic fire-behavior model that operates by reducing stand basal area and fuel loadings. Model outputs suggest that changes in fire frequency will strongly affect successional pathways (Keane and others 1989).

LANDSCAPE-SCALE DISTURBANCE MODELS

Although fire-behavior models predict fire spread, they do not account for the influence of spatial heterogeneity, or landscape pattern, on the propagation of disturbance. The effect of landscape pattern on disturbance spread has been simulated on abstract and real landscapes (Baker 1989, Marsden 1983, Mladenoff and others 1993, Turner and Romme 1994). Disturbance is initiated at individual pixels stochastically, with its likelihood a function of time since last disturbance or site "vulnerability." Spatial extent is usually a function of initial intensity and the vulnerability of adjacent pixels. In these broad-scale models, final burning patterns are emphasized rather than mechanistic behavior or explicit spread rates (Green 1989, Turner and Romme 1994). Connectivity of landscapes, and resulting constraints on disturbance, can be characterized by using concepts from percolation theory (Stauffer 1985).

In these broad-scale models, disturbance intensity and effects have not been simulated mechanistically at the resolution of current fire-behavior models. Rather, disturbance is characterized by generic variables such as frequency, intensity, extent, and duration. See Kessell (1976), however, for an early attempt to link fire-behavior models and landscape gradients.

BIOME-SCALE DISTURBANCE -- THE MAPSS MODEL AND FIRE EFFECTS

The Mapped Atmosphere Plant Soil System (MAPSS) simulates potential biosphere impacts from climate change by characterizing the dominant phenology and leaf type at a site, and then calculating the maximum leaf area that could be supported, within the constraints of the abiotic environment (Neilson 1992). Vegetation types are considered to be homogeneous over broad spatial scales.

Comparison of MAPSS output with the distribution of potential vegetation in the United States, as envisioned by Küchler (1964), produced the greatest discrepancy for the Prairie Peninsula (Neilson 1992). Application of the current MAPSS fire rule in simulations reduced this difference, thereby suggesting that fire effects can be modeled successfully at the biome scale. The current fire rule in MAPSS reduces leaf area index (LAI) based on the results of three calculations:

1. Fuel moisture and loading
2. Application of the Rothermel (1972) fire behavior model
3. Estimated crown and cambial kill (Peterson and Ryan, 1986) from this output

Ecological considerations provide constraints on the vegetation transitions produced by these reductions of LAI, and additional insight into successional dynamics and changes in species composition. For example, fire can cause changes in the dominant plant phenology or leaf type in a biome without obligatory changes in LAI. Understanding how ecological effects preset the initial conditions to which fire behavior models are applied will be a key step in integrating biotic and abiotic processes, to effectively model the mechanisms of change at the biome scale.

This chapter presents research that aids the development of the MAPSS model by suggesting transitions between natural vegetation types resulting from the ecological effects of fire. Rationale for the transitions comes from literature on fire effects which is relevant to broad spatial scales. These transitions are applicable to a steady-state, or equilibrium version of MAPSS, in which successional dynamics are not modeled explicitly. Specifically, the objectives are to:

1. Develop a biome-scale vegetation classification for North America, delineated by geography, dominant vegetation, and distinct characteristics of fire regime. This classification is based on an existing classification and condensed to provide a rough correspondence to MAPSS categories. Condensation is based on similarities in fire ecology among vegetation types in the existing classification.
2. Suggest possible transitions among these modified types resulting from predicted changes in fire regimes under global warming scenarios and qualitatively assess the strength of the supporting evidence for the proposed transitions. It is assumed that fire frequency will increase with warmer global temperatures (Price and Rind 1994). Logic for the transitions is based on a synthesis of available literature.
3. Apply one set of transition rules to the natural vegetation of the coterminous United States.

APPROACH

Many vegetation classifications exist for the coterminous United States (for example, Eyre 1980, Küchler 1964). I chose the Küchler (1964) classification of potential natural vegetation, because it is currently used as a basis for comparison to MAPSS output (Neilson 1992).

AGGREGATED KÜCHLER TYPES

There are 116 potential natural vegetation types in Küchler's classification, too many, in my opinion, for establishing transition rules. In addition, many of these types are geographic variants of the same or similar dominant types. For example there are five variants of the ponderosa pine[1] type, ranging from the American Southwest to the Black

[1] Scientific names of species are given in the appendix (table 2.8).

Hills, and several forest and savanna types in which oak (*Quercus*) species are dominant. Küchler also described many geographic variants of short, tall, and mixed-grass prairie, and of mesquite savanna. If current fire regimes were similar within each group of variants, all members of the group were condensed into an aggregated Küchler type.

A secondary rationale for aggregating vegetation types was similarities in fire regime among types not necessarily homogeneous in composition of dominant species. Geographically disjunct Küchler types often have similar fire regimes, particularly in the Western states, depending on congruences of elevation or broad-scale topography. Disjunct types were combined if they were expected to respond similarly to anticipated changes in fire regime. Examples include the new aggregated types: Southeast wetlands, Western oakwoods and Eastern deciduous forest (appendix Table 7).

TRANSITION RULES

Characterization of a fire regime must consider fire severity, fire frequency, the variability of both of these, and the importance of anomalous events (for example, crown fires in a system that usually experiences surface fires). Including all possible fire regime changes in the development of transition rules would be too complex, making the results inherently subjective. Fire frequency is therefore the driving factor in predicted transitions. Although the concept of fire frequency does not directly apply to a steady-state model, such as the current version of MAPSS, it facilitates links among fire, climate, and vegetation because (1) there is better documentation for vegetation change resulting from changes in fire frequency than for other aspects of fire regime, and (2) global warming scenarios have been more strongly linked to changes in fire frequency than to other fire characteristics, although the strongest evidence for this link comes from individual systems, and may not be applicable at the continental scale (Price and Rind 1994, Qu and Omi 1994). See also Bergeron and Archambault (1993) for opposing evidence. These transitions are intended primarily as constraints, as opposed to driving elements, in the current MAPSS fire subroutine.

Potential transitions were considered if the target vegetation type was geographically proximate to the initial type. This boundary condition was established to set limits on speculation and to keep the task manageable. When subsets of the initial type were spatially disjunct, target types were required to be proximate to only one subset of the initial type. No potential transition was rejected, however, solely because of geographical distance. For each potential transition remaining after this first step, the following questions about changes in vegetation were considered sequentially to ascertain the level of confidence with which regional or biome-scale changes might be predicted:

1. Are changes in vegetation due to increased fire frequency documented? If so, are the processes involved applicable to the spatial scale of biomes?
2. Does fire regularly reset succession? If so, and dominant cover types change through succession, is it appropriate to assume that the physiognomy resulting from increased fire frequency will be a cross section from an earlier stage of succession? Are fire-adapted species a crucial factor in analyzing this interrupted succession? Will specific fire adaptations become more important with increased fire? Will fire-induced changes in nutrient cycles or other indirect effects determine the new dominants?
3. Are the fire effects reversible, or does an entirely new successional pathway develop that is different from what would exist in the absence of fire? This is particularly important when considering ecotones. In some cases, transitions can be hysteretic, that is, decreased fire frequency would not necessarily move the transition in reverse. This is crucial for transitions, such as a change from Douglas-fir to oak woodlands in the West, that are assumed to be likely because the reverse has occurred with fire

exclusion.

4. Can transitions be inferred from data on similar systems or from more general considerations? The supporting literature is often anecdotal or suggestive of possible changes, rather than rigorously documenting changes. Can possible transitions be deduced from individual species' response to more frequent fires? For example, do fire resistance or sprouting ability change significantly with age?

APPLICATION OF TRANSITION RULES

To demonstrate the procedure and the resolution level of the analysis, fire transition rules were applied to the vegetation of the coterminous United States. A geographic information system (ARC-INFO) was used to combine a vector coverage of the original Küchler (1964) types into the aggregated Küchler types described in this paper (table 1). One-step transitions were applied to each of the resulting polygons to provide a geographical display of potential changes from increased fire frequency. When more than one target type was possible, the most likely transition for each polygon was determined from local, or smaller scale, considerations.

VEGETATION TRANSITIONS

The process described above produced 40 aggregated Küchler types (table 1). In some cases, there was a one-to-one correspondence between aggregated and original types, although in others, mainly nonforested types, as many as 10 Küchler types were condensed into one type. In addition, four entirely new types were created, covering some vegetation types of Canada and Alaska at a coarse scale of resolution.

Correspondences among these modified Küchler types, MAPSS types, and Society of American Foresters types (Eyre 1980) are in the appendix. Forty-four transitions are predicted as a result of increased fire frequency (tables 2-4). Most transitions are from forested vegetation types to types with either less tree cover or dominance by earlier seral species. No transitions are predicted away from any of the grassland or desert-tundra types, although fire is definitely a factor in these systems (see discussion of transitions). Each transition is assigned a mnemonic code, to identify the type of evidence used to justify it and a numeric code (1-3), to indicate the relative strength of the evidence supporting the transition (1 = strongest).

In the text that follows, initial vegetation types are assigned one of the following categories:

1. Forest (F)
2. Tree Savanna (TS)
3. Shrubland (S)
4. Grassland (G)
5. Desert or tundra (DT)

Each transition is identified by its modified Küchler type and by a unique letter and number code, with letters taken from the five categories above. Tables 2-4 summarize the transitions, the logic used, and the level of confidence for each. Figure 1 is a graphic representation of the transitions.

Not all transitions in descriptive classes necessarily lead to a transition in MAPSS vegetation classes, and in some cases, there are more than one MAPSS transition. For example, the transition spruce-hemlock → hemlock-Douglas-fir (transition F1) does not entail a change in MAPSS biome classification, whereas the transition ponderosa pine (MAPSS tree-savanna-evergreen-needle) → w. oakwoods (transition F12) results in the possibility of MAPSS classes tree-savanna-mixed-warm or tree-savanna-deciduous-broadleaf.

Table 2.1: Aggregated Küchler types and corresponding original Küchler types. Canadian types had no corresponding Küchler type.

Vegetation type	Küchler identification
Spruce-hemlock	1
Hemlock-Douglas-fir	2
Silver fir/Douglas-fir	3
Western fir-spruce	4 7 15 20 21
Mixed conifer	5 29
Redwood	6
Lodgepole pine	8
Pine-cypress	9
Ponderosa pine	10 11 16 17 18 19
Douglas-fir	12 14
Cedar-hemlock-pine	13
Great Basin pine	22
Pinyon-juniper	23 24
Alder-ash	25
Western oakwoods	26 28 30
Mesquite savanna	27 60 61 62 85 87
Oak-juniper(cypress)	31 32 83 86
Chaparral	33 34 35 36 37
Great Basin shrubland	38 39 40 55 56 57
Desert shrubland	41 42 70 71
Desert grassland	43 44 45 58 59
Tallgrass prairie	67 72 74 75 76 77
Mixed-grass prairie	47 48 50 51 53 66 68 69 72 79
Shortgrass prairie	54 63 64 65
Grassland-wetland	49 73 78 80 92
Oak savanna	81 82 84 88 90
Blackbelt (oak-gum-cypress)	89
SE wetland (forested)	91 105 113 114
Eastern spruce-fir	93 96 97
Conifer bog (tamarack-spruce)	94
White-red-jack pine	95
Northern floodplain	98
Eastern deciduous forest	99 101 102 103
Northern conifer-hardwoods	106 107 108 109
Oak-hickory	100 104
Oak-pine	110 111
Southern Mixed forest	112
Southeast pine	115 116
Alpine-arctic tundra	52
Desert	46

Table 2.2: Potential transitions from western forest vegetation types due to increased fire frequency.

Start Type	End Type	Code[a]	Conf[b]	Key References
Spruce-hemlock	Hemlock/ Douglas-fir	Doc	2	Huff (1984), Agee & Huff (1987)
Spruce-hemlock	Alder-ash	Succ	3	Franklin (1988)
Silver fir/Douglas-fir	Douglas-fir	Oth	1	Agee (1993)
Hemlock/Douglas-fir	Douglas-fir	Doc	1	Agee and Huff (1987), Huff (1984)
Douglas-fir	Ponderosa pine	Succ	2	Keane and others (1989), Barrett (1988)
Redwood	Douglas-fir	Oth	1	Finney and Martin (1992)
Cedar-hemlock-pine	Ponderosa pine or Douglas-fir	Succ	1	Fischer and Bradley (1987)
MIxed conifer	Ponderosa pine	Oth	1	van Wagtendonk (1985), Kercher and Axelrod (1984)
Douglas-fir	W. oakwoods	Doc	1	Agee and Dunwiddie (1984), Kauffman and Martin (1987)
Douglas-fir	Shortgrass prairie	Succ	2	Fischer and Clayton (1983)
Ponderosa pine	Shortgrass or mixed-grass prairie	Oth	2	Bock and Bock (1984)
Great Basin pine	Alpine tundra	Oth	2	Bradley and others (1992a, 1992b)
Great Basin pine	Great Basin shrub or shortgrass prairie	Succ	1	Bradley and others (1992a, 1992b), Fischer and Clayton (1983)
Pine-cypress	W. oakwoods	Oth	3	–
Fir-spruce	Lodgepole pine	Succ	1	Muir (1993), Bradley and others (1992b),Marsden (1983), Woodard (1994)
Fir-spruce	Alpine tundra	Doc	1	Little and Peterson (1991), Billings (1969), Vale (1981), Agee and Smith (1984)

a Doc = documented change with fire or change in fire return interval
Succ = assumption of a resulting earlier successional stage
Oth = other rationale, for example, inference from knowledge of similar transitions
b Conf = measure of confidence in transition logic (1 = strongest)

Table 2.3: Potential transitions from eastern and Canadian forest vegetation types due to increased fire frequency.

Start Type	End Type	Code[a]	Conf[b]	Key References
Boreal forest	White-red-jack or Lodgepole pine	Doc	1	Payette (1992), Carleton and Maycock (1978)
Boreal forest	Boreal woodland	Doc	1	Morneau and Payette (1989), Sirois and Payette (1991), Foster (1985), Sirois (1992)
Boreal forest	Aspen-birch or Aspen parkland	Succ Doc	1	Payette (1992), Anderson and Bailey (1980)
E. spruce-fir	White-red-jack pine or Conifer-hardwoods	Succ	1	Payette (1992), Heinselman (1981), Pastor and Mladenoff (1992), Heinselman (1981)
Conifer-hardwoods	White-red-jack pine or Aspen-birch	Succ	1	Pastor and Mladenoff (1992), Heinselman (1981)
E. deciduous (Midwest)	Oak savanna	Doc	1	Grimm (1984), Abrams (1992), Clark (1990)
E. deciduous (East)	Oak-pine or Oak-hickory	Doc	1	Abrams and Nowacki (1992), Lorimer (1985)
Conifer bog	Aspen-birch	Succ	2	Pastor and Mladenoff (1992)
S. mixed forest	Oak-pine or SE pine	Doc	1	Hartnett and Krofta (1989), Vose and others (1994), Myers (1985), Cain and Shelton (1994)
SE wetland	Grassland-wetland	Succ	2	Christensen (1988)
Blackbelt	Oak-juniper	Oth	3	
Blackbelt	Tallgrass prairie	Succ	1	
Oak-pine	SE pine	Doc	2	Boerner and others (1988), Buchholz (1983)
Oak-hickory	Oak-pine	Doc	1	Hartnett and Krofta (1989)
Oak-hickory	Oak savanna	Doc	1	Anderson and Brown (1986)

a Doc = documented change with fire or change in fire return interval
Succ = assumption of a resulting earlier successional stage
Oth = other rationale, for example, inference from knowledge of similar transitions

b Conf = measure of confidence in transition logic (1 = strongest)

Table 2.4: Potential transitions from savanna and shrubland types due to increased fire frequency.

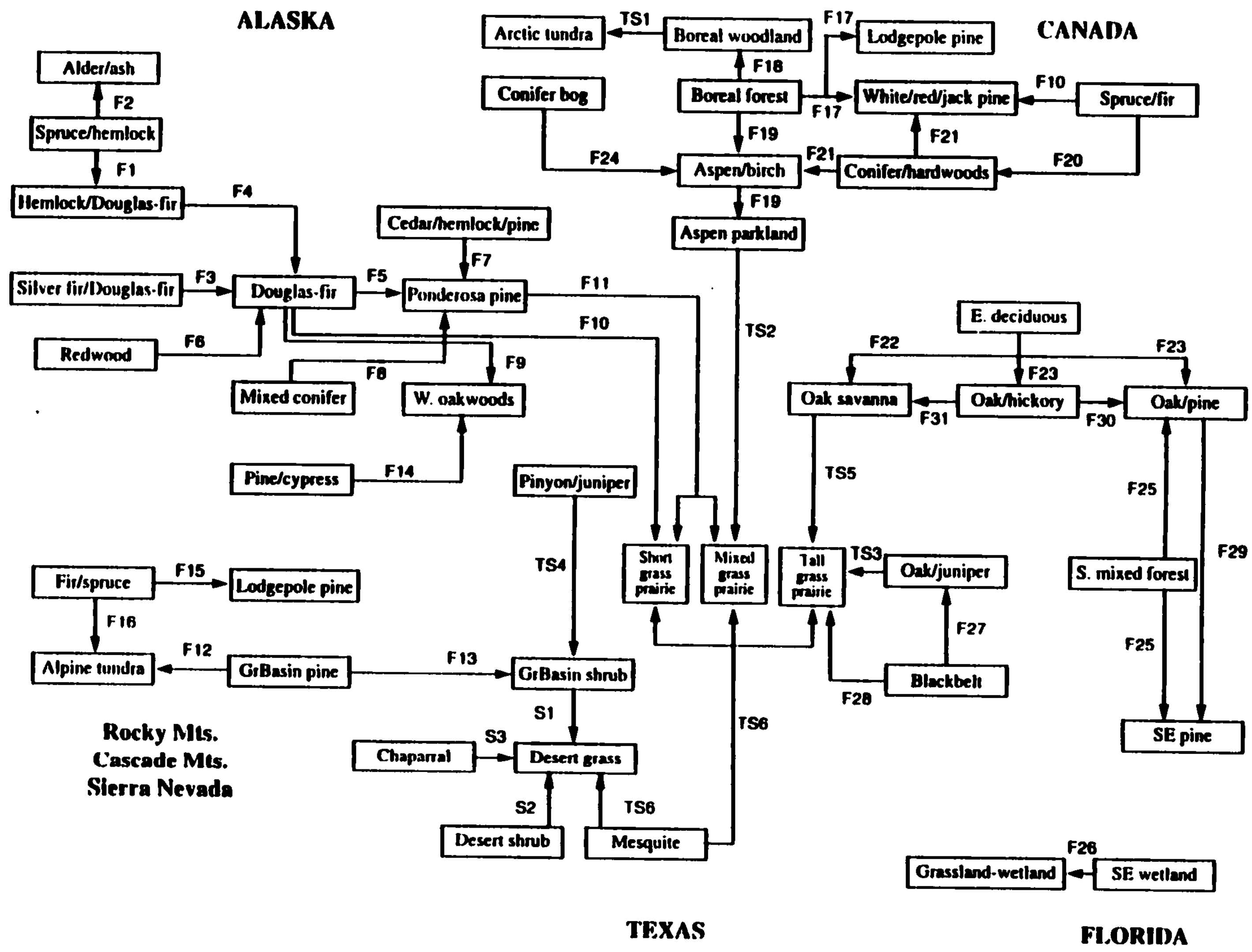
Start Type	End Type	Code[a]	Conf[b]	Key References
Boreal woodland	Arctic tundra	Doc	1	Sirois and Payette (1991),
Aspen parkland	Mixed grass prairie	Doc	1	Anderson and Bailey (1980)
Oak-juniper	Tallgrass or Mixed grass prairie	Doc	1	Abrams (1986,1992)
Pinyon-juniper	Great Basin shrub or Desert grassland	Doc	1	Jameson (1987), Everett (1987)
Oak savanna	Tallgrass prairie	Doc	1	Abrams (1986,1992)
Mesquite	Desert grassland or Prairie (3 types)	Succ	2	Martin (1975), Wright and Bailey (1982)
Great Basin shrub	Desert grassland	Doc	2	Humphrey (1974)
Desert shrub	Desert grassland	Doc	2	Humphrey (1974)
Chaparral	Desert grassland	Doc	2	Keeley and Keeley (1981,1988)

a Doc = documented change with fire or change in fire return interval
Succ = assumption of a resulting earlier successional stage
Oth = other rationale, for example, inference from knowledge of similar transitions
b Conf = measure of confidence in transition logic (1 = strongest)

INITIAL TYPE: FOREST

Transitions are possible from one forest type to another, or to a system with fewer trees, for example, savanna or woodland-parkland. Forest → forest transitions usually involve shifts in species composition from less to more fire-adapted species, which may or may not entail significant reductions in LAI. Forest → nonforest transitions entail significant reductions in density or LAI as well.

Figure 2.1: Transition flowchart - potential changes in natural vegetation resulting from increased fire frequency. Letter/number codes correspond to transitions discussed in text. Letter codes are as follows: F = forest, TS = tree savanna, and S = shrub.


ALASKA
CANADA
Alder/ash
F2
Spruce/hemlock
F1
Hemlock/Douglas-fir
F4
Silver fir/Douglas-fir
F3
Douglas-fir
Redwood
F6
F5
Ponderosa pine
Cedar/hemlock/pine
F7
Mixed conifer
F8
F9
W. oakwoods
Pine/cypress
F14
F10
F11
Arctic tundra
TS1
Boreal woodland
F18
Boreal forest
F17
Lodgepole pine
White/red/jack pine
F10
Spruce/fir
Conifer bog
F24
F19
Aspen/birch
F21
Conifer/hardwoods
F20
Aspen parkland
TS2
E. deciduous
F22
F23
Oak savanna
F31
Oak/hickory
F30
Oak/pine
TS5
F25
F29
S. mixed forest
SE pine
Pinyon/juniper
TS4
Short grass prairie
Mixed grass prairie
Tall grass prairie
TS3
Oak/juniper
F27
Blackbelt
F28
Fir/spruce
F15
Lodgepole pine
F16
Alpine tundra
F12
GrBasin pine
F13
GrBasin shrub
S1
Chaparral
S3
Desert grass
S2
Desert shrub
TS6
Mesquite
Rocky Mts.
Cascade Mts.
Sierra Nevada
F26
Grassland-wetland
SE wetland
TEXAS
FLORIDA

Thick bark, open crowns, deep roots and large buds (Brown and Davis 1973) characterize fire-resistant trees. Many pine species have these traits, as well as adaptations such as cone serotiny or superior post-fire regeneration. Some other conifers, notably Douglas-fir and western larch, become as fire resistant as pines only with age, as bark thickness increases. Thus, increased fire frequency in conifer systems may shift dominance away from late successional species toward pines. The most fire-adapted hardwoods are oaks and aspen. The same trend away from shade-tolerant species to "early successional" species is predicted for hardwood-dominated systems with increased fire frequency. Relative dominance of pines and oaks at the endpoint of transitional pathways in forested systems may depend on local conditions such as nutrient availability after fire (Boerner and others 1988) and the ability of particular species to colonize burned sites.

F1: SPRUCE-HEMLOCK → HEMLOCK-DOUGLAS-FIR

Fire is generally not a factor in dynamics of the coastal Sitka spruce-western hemlock forest. Windthrow is the principal disturbance, and acts at small spatial scales. The presence of Sitka spruce and absence of Douglas-fir indicate a fire return interval longer than the age of most stands, whereas presence of Douglas-fir suggests the increased importance of fire in stand dynamics (Agee and Huff 1987, Fahnestock and Agee 1983, Huff 1984). Increased presence of Douglas-fir in old growth stands in the Hemlock-Douglas-fir zone is related to increased fire frequency (Huff 1984).

F2: SPRUCE-HEMLOCK → ALDER-ASH

The Küchler alder-ash type is associated with riparian areas. In upland disturbed sites in the spruce-hemlock zone in the Pacific Northwest, alder is a strong colonizer that becomes more dominant with frequent disturbance (Franklin 1988), although this would probably require a greater increase in fire frequency than the transition to hemlock-Douglas-fir. See also F3 and F4.

F3: SILVER FIR/DOUGLAS-FIR → DOUGLAS-FIR

Western white pine is a successful colonizer on burned sites and may increase in Pacific silver fir zones in the Pacific Northwest with more frequent fires (Agee 1993). It is unlikely that it could dominate stands, so the transition is assumed to be to another fire-adapted species, Douglas-fir, that has this potential.

F4: HEMLOCK-DOUGLAS-FIR → DOUGLAS-FIR

The percentage of Douglas-fir in stands in the western slope of the Cascade Range and Olympic Mountains is related to time since fire, with shorter fire-return intervals associated with greater percentages of Douglas-fir (Agee and Huff 1987, Huff 1984).

F5: DOUGLAS-FIR → PONDEROSA PINE

The percentage of ponderosa pine in many forests of the Cascade Range and Rocky Mountains is related to increased fire frequency (Agee 1993, Barrett 1988, Keane and others 1989). When a seed source for ponderosa pine exists, increased fire in mixed species stands will produce a transition to a pine-dominated system (Keane and others 1989).

F6: REDWOOD → DOUGLAS-FIR

Some coastal redwood stands have endured frequent, low-intensity fires, whereas others have endured moderate severity, less frequent fires. A transition in the coastal redwood zone to forests with more dominance by Douglas-fir is possible, although moisture may be more of a factor in such a transition than any change in fire frequency (Agee 1993). Unusually short fire return intervals in redwood forests could lead to dominance by other species already present in the region (Finney and Martin 1992).

F7: CEDAR-HEMLOCK-PINE → PONDEROSA PINE OR DOUGLAS-FIR

Succession in forests on the western slope of the Rocky Mountains is reversed to various degrees depending on the intensity of fires (Fischer and Bradley 1987). Ponderosa pine and Douglas-fir are dominant seral species in these forests, and increased fire frequency could reset the successional process before the "climax" stage (cedar-hemlock) is reached.

F8: MIXED CONIFER → PONDEROSA PINE

The relative dominance of ponderosa pine in western mixed conifer forests is positively correlated with fire frequency (Kercher and Axelrod 1984), and reduced fire frequency in these forests permits late-successional species such as white fir to increase (van Wagtendonk 1985).

F9: DOUGLAS-FIR → WESTERN OAKWOODS

The principal evidence to support this transition also comes from the reverse condition: fire exclusion in the oak savannas of Oregon and Washington has led to invasion of conifer species, particularly Douglas-fir (Agee 1993, Agee and Dunwiddie 1984, Kauffman and Martin 1987, Reed and Sugihara 1987). Thus, if a seed source for oak (particularly Oregon white oak) exists, oaks may be expected to reestablish on sites that have been invaded and dominated by Douglas-fir.

F10: DOUGLAS-FIR → SHORTGRASS PRAIRIE

On the eastern slope of the Rocky Mountains in Montana, Douglas-fir forests form an ecotone with shortgrass prairie and invade the grasslands during atypically long fire-free intervals (Fischer and Clayton 1983).

F11: PONDEROSA PINE → SHORTGRASS PRAIRIE OR MIXED-GRASS PRAIRIE

Ponderosa pine is adapted to surface fire, but a crown fire could kill an overstory (Bock and Bock 1984, Fischer and Clayton 1983), thereby converting a stand to grassland. The treeless condition would be maintained by increased fire frequency because ponderosa pine saplings would not have developed sufficient fire resistance by the time fire returned. This transition should be applied only to the ponderosa pine systems where it is documented (Black Hills and Utah woodlands). It also incorporates known variability of fire intensity into the prediction.

F12: GREAT BASIN PINE → ALPINE TUNDRA

At high elevations, bristlecone pine and limber pine systems could become treeless, as the subalpine meadows in the Pacific Northwest have, when more frequent fires prevent reestablishment (Fischer and Clayton 1983). This would be more likely with increased fire intensity (Keown 1977).

F13: GREAT BASIN PINE → GREAT BASIN SHRUB OR SHORTGRASS PRAIRIE

At low elevations, the same logic applies as for F12, but with different replacement species (Fischer and Clayton 1983).

F14: PINE-CYPRESS → WESTERN OAKWOODS

This is a potential, but speculative, transition that is based on the fact that California oaks have greater geographic continuity and more fire adaptations than do coastal California pine and cypress. The coastal pine species are serotinous, however, and a transition might be possible only if fire intensity continues to be high[2].

F15: WESTERN FIR-SPRUCE → LODGEPOLE PINE

Spruce-fir forests in the Rocky Mountains, Cascade Range and high elevations in the

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[2] Personal communication. 1995. J. Agee, Professor of forest ecology, College of Forest Resources, University of Washington, Seattle, WA 98195.

Southwest could be replaced by lodgepole pine with an increase in fire frequency, because this pine species is shade intolerant, fire-adapted (serotinous cones), and an early colonizer on burned sites (Agee 1993, Bradley and others 1992a,1992b, Muir 1993). In areas currently dominated by red fir, however, more frequent, moderate-intensity fires could favor the more resistant red fir over lodgepole pine (Chappell 1991, Taylor 1993). In the southern Rocky Mountains, stands of aspen occur under various environmental conditions (Peet 1981). AlthoughIexpect an increase in aspen stands with increased fire frequency, the spatial scale of the modeling effort and the need to retain the Küchler system, precluded consideration of an aspen endtype.

F16: WESTERN FIR-SPRUCE → ALPINE (MEADOW-TUNDRA)

Fires are infrequent in the subalpine zone, but damage usually is severe (Agee 1993). Reestablishment of trees after fire may be slow, particularly on sites with no seed source for lodgepole pine, with treeless areas created by fire remaining as meadows for many years, and timberline remaining below the physiological limits for tree growth (Agee and Smith 1984, Arno and Hammerly 1984, Billings 1969, Little and others 1994, Vale 1981).

F17: BOREAL CLOSED FOREST → PINE (WHITE, RED OR JACK PINE -- LODGEPOLE PINE IN THE WEST)

Increased fire in a mixed-boreal forest will favor fire-adapted early successional species, such as jack pine (Payette 1992 and references therein).

F18: BOREAL CLOSED FOREST → BOREAL WOODLAND

Fire may negatively affect the productivity, and thus the potential tree density, of forests at the northern boreal ecotone, partly by providing an opportunity for lichen mat colonization and exclusion of seedlings (Morneau and Payette 1989). This is a case (see also transition F32) in which closed forest at an ecotone with nonforest is potentially unstable.

F19: BOREAL CLOSED FOREST → ASPEN-BIRCH OR ASPEN PARKLAND

The aspen parkland forms an ecotone between the boreal forest and the northern prairie in Canada. Aspen is one of the least shade-tolerant boreal species and one of the most fire tolerant due to its sprouting ability. Conifer invasion of stands pioneered by aspen results from fire exclusion (Wright and Bailey 1982 and references therein). This suggests that increased fire frequency could convert southern boreal forest in central Canada to open aspen parkland or to a forest dominated by early successional hardwoods (Payette 1992).

F20: EASTERN SPRUCE-FIR → WHITE-RED-JACK PINE OR CONIFER-HARDWOODS

This transition uses the same logic as F16. Spruce-fir forests have long fire-return intervals, thereby enabling shade tolerant species such as balsam fir to establish. More fires would produce a transition to pines or mixed spruce-fir and hardwoods (Furyaev and others 1983, Heinselman 1981, Payette 1992, St. Pierre and others 1991).

F21: CONIFER-HARDWOODS → WHITE-RED-JACK PINE OR ASPEN-BIRCH

The conifer-hardwood zone, sometimes referred to as the "North Woods", is a broad ecotone between the closed boreal forest to the north and the eastern deciduous forest to the south (Pastor and Mladenoff 1992). Increased fire in this region would favor fire-adapted boreal forest species such as jack pine and quaking aspen, possibly narrowing the ecotone by moving its northern edge south (Carleton and Maycock 1978, Heinselman 1973).

F22: EASTERN DECIDUOUS (MIDWEST) → OAK SAVANNA

Mature deciduous forest burns infrequently. The principal late-successional species (for example maple, basswood, elm, and eastern hemlock) are not fire-adapted and likely would be replaced by colonizers such as oak, pine, and aspen with more frequent fires (Abrams 1992, Grimm 1984, Host and others 1987, Lorimer 1985).

F23: EASTERN DECIDUOUS (EAST) → OAK-HICKORY OR OAK-PINE

Species composition in the pine-oak-hickory forest in the East and Southeast is directly related to the frequency of fire, with hickory (*Carya* spp.) being less well-adapted than the other two dominant species (Abrams 1992, Bryant and others 1993, Lorimer 1985, Nowacki and others 1990, Orwig and Abrams 1994). Thus, there may be a gradual transition from the more diverse Eastern deciduous forest to a forest increasingly dominated by pine or oak, or both, with increasing fires. Transitions F22 and F23 correspond to different climatic regimes, and different available colonizers in the prairie-forest ecotone in the Midwest than in the deciduous-pine/hardwoods ecotone in the East.

F24: CONIFER BOG → ASPEN-BIRCH

This transition is inferred from the combination of the tolerance of aspen for wet sites with its superior colonization abilities, and its preeminence, along with paper birch as an early successional species in the conifer-hardwoods zone (Pastor and Mladenoff 1992).

F25: SOUTHERN MIXED FOREST → OAK-PINE OR SOUTHEAST PINE

There is substantial documentation on the relations between fire frequency and dominant species in the Southeast (for example Cain and Shelton 1994, Hartnett and Krofta 1989, Vose and others 1994). Systems with the most frequent fires tend to be dominated by pines, whereas those with infrequent fires support diverse forests dominated by late successional species. Oak forests are intermediate. The logic of this transition also is applied to F29, F30, and F31.

F26: SOUTHEAST WETLAND (FORESTED) → GRASSLAND-WETLAND

Fire resets succession in the pocosins (Christensen 1988), one of the subsets of the Southeast forested wetland type. A similar potential is assumed to exist in mangroves and cypress swamps.

F27: BLACKBELT → OAK-JUNIPER

This system, unique to Alabama and Mississippi, has increased in forest cover in the last century, presumably after cessation of burning by natives and Euro-Americans (Rostlund 1957). With increased fire, it could become open savanna, with oaks, pines, or cypress (juniper) dominating.

F28: BLACKBELT → TALLGRASS PRAIRIE

This transition is another possibility. Tall grass prairie fragments are part of this type. The transition type (F27 or F28) could depend on the amount fire frequency is increased.

F29: OAK-PINE → SOUTHEAST PINE

This transition uses the same logic as in F25. See also Buchholz (1983) and Myers (1985), but Boerner and others (1988) for a more complex interpretation.

F30: OAK-HICKORY → OAK-PINE

This transition uses the same logic as F25. See also Quaterman and Keever (1962) and Tester (1989).

F31: OAK-HICKORY → OAK SAVANNA

Oak forests may be less stable than oak savannas, thus increased fire could stabilize these oak-dominated hardwood forests at lower tree densities (Anderson and Brown 1986).

INITIAL TYPE: TREE SAVANNA

Tree savannas are distinguished from forests by a lack of canopy closure at the mature stage. The distinctions between forest and savanna in MAPSS were retained for the aggregated Küchler types presented here. Tree savannas include parklands and woodlands at both the upper and lower latitudinal or elevational treelines. Transitions to grassland or shrubland at the southern or lower elevational ecotone may occur due to fire, even if moisture stress does not preclude tree establishment. The dynamics are complicated at the northern limit. Regeneration may be impossible even if survival of mature trees is unaffected, so fire may reduce or eliminate the time lag in the response of vegetation to climate change.

TS1: Boreal woodland → Arctic tundra

At the northern extreme of treeline, stands may not be able to reestablish after a stand-replacing fire, even though climatic conditions are unchanged (Cwynar and Speer 1991, Desponts and Payette 1993, Landhäusser and Wien 1993, Sirois and Payette 1991, Payette 1993). Thus increased fire frequency could move the northern treeline to the south, partially offsetting any northward movement due to climatic warming (Rochefort and others 1994).

TS2: Aspen parkland → Mixed grass prairie

Prescribed fire has been used successfully to control the invasion of grasslands by aspen (Anderson and Bailey 1980). As in other tree savannas, increased fire frequency is expected to produce a transition to grassland with or without shrubs, which may or may not persist in the presence of frequent fire.

TS3: Oak-juniper → Tallgrass prairie or mixed-grass prairie

The logic for this transition, as for oak savanna, is that more frequent fires will prevent savanna trees from regenerating in grassland, even where climatic conditions are favorable. Sites colonized by oaks because of fire suppression, or because the fire return interval has been long enough to allow trees to reach a less vulnerable stage of development, will revert to a treeless condition with increased fire frequency (Abrams 1986, 1992). Grassland types will depend on geographic proximity of individual species. Many species of oak are fire tolerant, so the transition is less clear for stands dominated by oaks than for stands dominated by juniper.

TS4: PINYON-JUNIPER → GREAT BASIN SHRUB OR DESERT GRASSLAND

Under some conditions, usually on more mesic sites, pinyon-juniper woodlands will recover from fire (Bunting 1987, Everett 1987). On more xeric sites, recovery is not automatic, and increases in fire frequency could cause a transition to either grassland or low shrubs (Miller and Weigand 1994). Local conditions determine which pathway this would take (Jameson 1987).

TS5: OAK SAVANNA → TALLGRASS PRAIRIE

Similar dynamics are expected for oak-grassland ecotones as for pinyon-juniper-grassland or oak-juniper/grassland (Abrams 1986, 1992, Tester 1989). Pinyon-juniper or oak invasions occur with fire exclusion in areas where the moisture is adequate to support woody vegetation. The logic is the same as in TS3.

TS6: MESQUITE SAVANNA → DESERT GRASSLAND OR PRAIRIE (SHORT, MIXED, AND TALL GRASS)

Mesquite has become established on former grasslands whose fine fuels have been depleted by overgrazing (Martin 1975, Wright and others 1976). Depending on location of mesquite types (27, 60, 61, 62, 85, 87 in Küchler), the transition could be to desert or to any of the more mesic grasslands, but might depend on restoration of native grasses (Wright and Bailey 1982).

INITIAL TYPE: SHRUBLAND

Shrub-chaparral generally is fire adapted, and increased fire frequency might change community structure but not necessarily cause a transition to another type, because species composition may be more strongly determined by climate and evolutionary history, and a shift from seeding to sprouting species might stabilize the type in the presence of more frequent fire. In some systems with large shrubs that provide a substantial fuel source, increased fire may move the system toward smaller shrubs or even grasses. Particularly intense fires or short intervals between fires may result in dominance by herbaceous species with compositional changes over several decades (Christensen 1985, Zedler and others 1983). On the other hand, fire exclusion may allow competing shrubs to dominate a stand and restrict overstory regeneration (Vose and others 1994), thereby suggesting that increased fire in certain shrub systems might allow reestablishment of fire tolerant tree species, and a possible reversal of the expected transition "arrow" in certain systems. The fire effects literature for North America generally does not distinguish among the many shrub classes in Küchler in terms of possible succession from one type to another. Geographic restrictions may preclude the need to infer shrub -> shrub transitions.

S1: GREAT BASIN SHRUB → DESERT GRASSLAND

In dry shrubland systems in which the vegetation is still continuous enough for fire spread, grasses may gain a competitive advantage under increased fire frequency (Humphrey 1974), and woody shrubs could disappear.

S2: DESERT SHRUB → DESERT GRASSLAND

This transition uses the same logic as S1 and is possible only with enough continuous vegetation.

S3: CHAPARRAL → DESERT GRASSLAND

This is a possible transition, although chaparral is generally fire-adapted and burns more completely after a few years dead fuel accumulation (Callaway and Davis 1993, Keeley and Keeley 1988, Wright and Bailey 1982). Thus, the growth cycle of chaparral controls fire frequency. More frequent fires might only burn a lower percentage of biomass but maintain the system as chaparral.

INITIAL TYPE: GRASSLAND

Grasslands generally are fire-adapted. The main changes here will be in community composition, particularly in the relative abundance of C_3 and C_4 grasses in response to seasonal timing of fires (Collins and Gibson 1990, Gibson and Hulbert 1987, Howe 1994). In general, fires are more frequent in moist grasslands, whereas they do proportionally more damage in xeric grasslands (Risser 1990). It is not clear how increased fire frequency by itself might change grassland types. Transitions to desert types would more likely be driven by increased temperature or decreased moisture, or both.

INITIAL TYPE: DESERT-TUNDRA

Desert fuels are sparse. Although fire does occur, changes in desert types are driven principally by temperature and available moisture.

APPLICATION OF TRANSITIONS TO THE COTERMINOUS UNITED STATES

I implemented one-step transitions for all the vegetation types in the coterminous United States (Figures 2.2 and 2.3), thereby replacing the total area of the initial type. If more than one transition was possible, or there was a high probability of no transition, I selected the most likely transition based on known ecological conditions or geographic proximity. For example, Western fir-spruce polygons were transformed to either alpine tundra (Olympic Peninsula and western Washington Cascade Range) or lodgepole pine (Oregon Cascade Range and central Rocky Mountains). Likewise the Eastern deciduous polygons were transformed to oak-savanna, oak-hickory, or oak-pine, depending on geographical proximity.

The most striking results of these transitions are the expansion of treeless areas at the upper treeline and the homogenization of forested types. For example, at the upper treeline in Washington west of the crest of the Cascade Range, the amount of alpine tundra is predicted to increase with the conversion of subalpine forests and parkland (transition F16). In coniferous forests west of the Cascade Range, the percentage of Douglas-fir is predicted to increase, as forests dominated by Pacific silver fir and western hemlock are converted to Douglas-fir (transitions F3 and F4) and the spruce-hemlock type is converted to hemlock-Douglas-fir (transition F1). The Douglas-fir forests in northeastern Washington and Oregon, which have significant amounts of grand fir, are predicted to become ponderosa pine forests. Table 2.5 shows how a particular subset, the aggregated types in Washington and Oregon, was homogenized by the one-step transitions.

DISCUSSION

GEOGRAPHIC AND ELEVATIONAL TRENDS

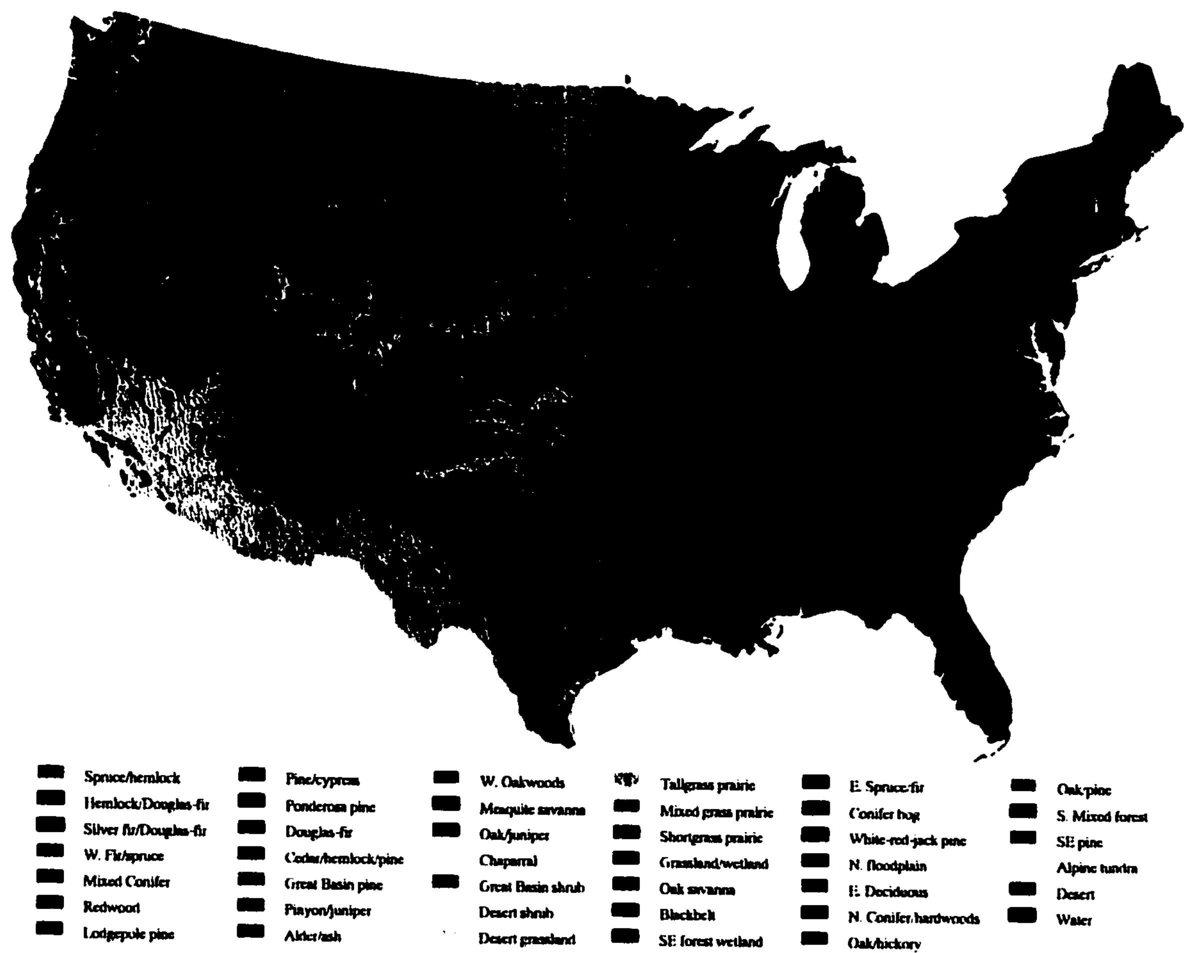
Vegetation transitions generally were characterized by vegetation types being replaced by a new type from a more southerly, warmer or drier zone, or from a lower elevation (Tables 2.2-2.4 and Figure 2.1). Precipitation generally decreases from north to south, and from west to east in western North America, and from east to west in eastern North America. Although Figure 2.1 suggests only geographical trends and could be misleading for types such as ponderosa pine that have widely dispersed subsets, it indicates that patterns will be more complex and less broadly defined in the West. This concurs with results expected from the greater topographic complexity of Western biomes.

Transitions at the highest elevations (fir-spruce → alpine tundra or Great Basin pine → alpine tundra) and most northern latitudes (boreal woodland → Arctic tundra) are exceptions to the general trends. Regeneration is slow in these systems. An increase in fire frequency would reduce the window of opportunity for the establishment of late successional or slow-growing species such as subalpine fir and black spruce. Burned sites might also be less conducive to growth and survival (Sirois and Payette 1991). If no seed source exists for a fire-adapted species, such as lodgepole pine, increased fire frequency could cause these marginal sites to revert to tundra, although the picture is complicated by predicted temperature increases that could encourage growth. Outcomes could be very sensitive to local conditions, thereby rendering predictions at broad spatial scales particularly uncertain (O'Neill and others 1989, Slatyer and Noble 1992).

CORRESPONDENCES TO CURRENT MAPSS FIRE RULE

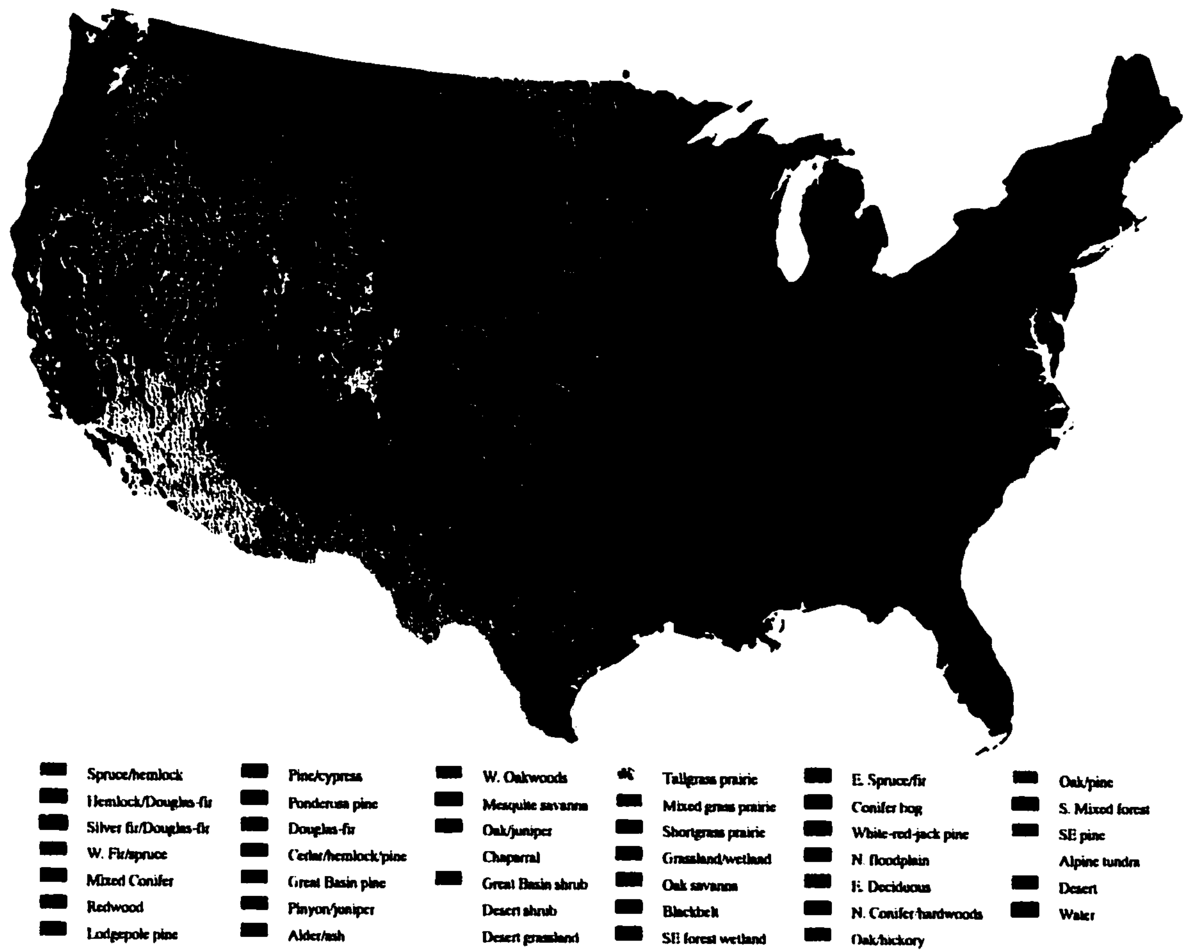
Fire transitions predicted by a model that produces changes in LAI, but not successional changes, can concur with transitions predicted from ecological effects only when these effects do not involve changes in phenology or leaf type. For example, the transition oak-hickory → oak savanna has an exact parallel, forest-deciduous-broadleaf → tree-savanna-deciduous-broadleaf, in MAPSS (Table 2.7). In both cases, leaf type and phenology are unchanged, but LAI is reduced. Transitions such as Douglas-fir → w. oakwoods or spruce-hemlock → alder-ash have no direct equivalent in MAPSS because they entail changes in phenology and leaf type along with substantial decreases in LAI.

Figure 2.2: Aggregated Küchler types in the coterminous United States before transitions were applied.



Spruce/hemlock
Hemlock/Douglas-fir
Silver fir/Douglas-fir
W. Fir/spruce
Mixed Conifer
Redwood
Lodgepole pine
Pine/cypress
Ponderosa pine
Douglas-fir
Cedar/hemlock/pine
Great Basin pine
Pinyon/juniper
Alder/ash
W. Oakwoods
Mesquite savanna
Oak/juniper
Chaparral
Great Basin shrub
Desert shrub
Desert grassland
Tallgrass prairie
Mixed grass prairie
Shortgrass prairie
Grassland/wetland
Oak savanna
Blackbelt
SE forest wetland
E. Spruce-fir
Conifer bog
White-red-jack pine
N. floodplain
E. Deciduous
N. Conifer/hardwoods
Oak/hickory
Oak/pine
S. Mixed forest
SE pine
Alpine tundra
Desert
Water

Figure 2.3: Aggregated Küchler types in the coterminous United States after transitions were applied.


Spruce/hemlock
Hemlock/Douglas-fir
Silver fir/Douglas-fir
W. Fir/spruce
Mixed Conifer
Redwood
Lodgepole pine
Pine/cypress
Ponderosa pine
Douglas-fir
Cedar/hemlock/pine
Great Basin pine
Pinyon/juniper
Alder/ash
W. Oakwoods
Mesquite savanna
Oak/juniper
Chaparral
Great Basin shrub
Desert shrub
Desert grassland
Tallgrass prairie
Mixed grass prairie
Shortgrass prairie
Grassland/wetland
Oak savanna
Blackbelt
SE forest wetland
E. Spruce/fir
Conifer bog
White-red-jack pine
N. floodplain
E. Deciduous
N. Conifer/hardwoods
Oak/hickory
Oak/pine
S. Mixed forest
SE pine
Alpine tundra
Desert
Water

Other transitions could produce an increase in LAI. A late successional boreal forest dominated by black spruce generally will have lower productivity and less biomass than earlier stages in which trees grow more vigorously and decomposition is faster (Bonan and Shugart 1989). The transitions boreal forest → white-red-jack pine or aspen-birch will in all likelihood increase LAI. Similarly, increased fire frequency in systems currently dominated by tall, rapidly growing shrubs that have established as a result of fire exclusion might allow fire resistant trees to reestablish, thus increasing LAI (Vose and others 1994). I am not predicting any specific transitions of this latter type, however.

Table 2.5: Transitions applied to the aggregated Kuchler types in Washington and Oregon

Initial type	Final type
Spruce/hemlock/cedar	Hemlock/Douglas-fir
Hemlock/cedar/Douglas-fir	Douglas-fir
Silver fir/Douglas-fir	Douglas-fir
Douglas-fir	Ponderosa pine
Redwood	Douglas-fir
Cedar/hemlock/pine	Douglas-fir
Mixed conifer	Ponderosa pine
Fir/spruce (Washington west)	Alpine tundra
Fir/spruce (Oregon and Washington east)	Lodgepole pine
Great Basin shrub	Desert grassland

A fourth type of transition entails only a compositional change, as a result of interrupted succession, and may have no counterpart in the current version of MAPSS. Although MAPSS allows fire-induced reductions in LAI to change phenology or leaf type, it has no explicit rules for succession of lifeforms. Examples are (1) spruce-hemlock → hemlock-Douglas-fir (2) Western Fir-spruce → lodgepole pine and (3) Eastern spruce-fir → white-red-jack pine.

Additional Factors Affecting Vegetation Transitions

Although I used increased fire frequency in this paper to determine possible transitions, other aspects of fire regime clearly interact with frequency and could be either antagonistic to or synergistic with the effects of changes in frequency. Three of these additional factors are (1) season of burning, (2) variability in fire frequency, and (3) fire severity and associated anomalous events.

Season of burning

In systems with more than one potential dominant plant type, the timing of fires may control which plants are most successful. In mixed-grass prairie where both C_3 and C_4 grasses occur, the relative abundance differs depending on seasonal timing of fires (Collins 1992, Collins and Gibson 1990, Ewing and Engle 1988, Howe 1994). Although most lightning ignitions occur in July and August, prescribed burns usually are conducted in the spring and may be artificially maintaining a tallgrass prairie of big bluestem, a C_4 species, in what otherwise would be a more diverse, mixed-grass prairie (Howe 1994). For similar reasons, the return of fire frequencies similar to those of the 19th century or earlier in eastern Washington and Oregon, and restoration of certain plant assemblages, will depend on seasonal timing of prescribed burns (Agee 1994).

Variability of fire frequency

In Western conifer forests, the dynamics of succession in relation to fire frequency are complex, and variation in fire-return interval may be more important than its mean (Agee 1993). For example, pathways of succession may be altered for decades in lodgepole pine-western larch forests, when variable fire-return intervals accentuate different dispersal abilities, maturation ages, and fire resistance of these species (Cattelino and others 1979). In general, in forests in which fire resistance of a potential dominant species increases dramatically with age, a single unusually long fire-free interval may have the same ecological effect over the lifetime of one cohort as an equivalent mean fire-return interval.

Fire severity and anomalous events

Infrequent severe fires, particularly in systems characterized by frequent, low-intensity fires, cause a disproportionate share of total damage (Strauss and others 1989). Crown fires have qualitatively different dynamics (Rothermel 1991), and crown-fire ecosystems have different large-scale spatial patterns (Turner and Romme 1994). Fires in these systems are often precipitated by anomalous weather events, such as the combination of high easterly winds and drop in moisture levels associated with severe fires in the Pacific Northwest (Agee 1993). Some forests are more appropriately characterized at larger spatial scales by variability in intensity than by mean frequency (Morrison and Swanson 1990). If a critical threshold of intensity exists, below which late-successional species can survive once established (for example, Harmon 1984), changes in intensity may be more important ecologically than changes in frequency. In some systems in which low-intensity fires are the norm, the ecological effect of changes in frequency of low-intensity fires may need to be catalyzed by a high-intensity fire. For example, a high-intensity fire in a woodland may kill even fire-resistant dominant trees. If the fire-free interval is subsequently reduced, saplings may not survive to a fire-resistant stage (for example, Bock and Bock 1984).

Human activities

This study uses the natural vegetation types of Küchler (1964) as a basis for vegetation distribution, but in reality, much of this vegetation has been altered by humans (Klopatek and others 1979). Agricultural and urban landscapes can be presumed "lost" from the modeling database for biome-scale vegetation change, but there are many systems in which natural vegetation patterns and fire regimes coexist with human-caused disturbance.

Known effects of fire exclusion have been used above to predict reverse transitions due to increased fire frequency. These predictions can be problematic even in natural systems with no additional significant disturbance (for example, Jameson 1987). Predictions are further confounded by the presence of invading exotic species in the understory and by changes in understory composition and fuel loads due to livestock grazing (D'Antonio and Vitousek 1992, Fleischner 1994, Mack 1981). Particularly in rangelands, grazing may alter successional pathways, thereby creating a new set of successional stages distinct from those previously maintained by fire (Westoby and others 1989), and may actively disperse exotic species, which respond in various ways to increased fire frequency (Agee 1994, D'Antonio and Vitousek 1992). Grazing also reduces the fuel load of flammable grasses, and therefore the potential for frequent, low-intensity fires that preclude the establishment of shrubs in grasslands or open woodlands (Wright and Bailey 1982). It is uncertain whether predicted increases in fire frequency will overcome the inertia established and maintained by the ecological effects of grazing.

LIMITATIONS OF MODELING AT LARGE SPATIAL SCALES

Small-scale details are lost when modeling at larger scales. O'Neill and others (1989) note two problems that make scaling upward particularly difficult: (1) higher level properties are not necessarily sums of lower level averages (the "aggregation" problem), and spatial correlations in responses by small-scale units confound unbiased estimation of averages; and (2) even if finer scales can be ignored when a system behaves in a stable manner, instabilities in low-level dynamics (for example crown fires) break the constraints imposed by larger scale properties, thereby leading to unpredictable behavior. I have tried to minimize these difficulties by aggregating systems that are relatively homogeneous with respect to fire ecology, and by modeling changes in a variable (fire frequency) that has relatively stable dynamics at the smaller scale. The "averaging" required to produce the aggregated Küchler types and the transition rules has some limitations, however.

In a steady-state model, simultaneous changes occur over areas larger than the extent of the largest fires (Figures 2.2 and 2.3). The amount of time required to accomplish this change incrementally in the real world is more commensurate with the rate of shifts in past climatic patterns than the rate of human-induced climatic changes predicted for the future. By that time, additional transitions in portions of each region or biome would be expected in response to new climatic conditions.

Distinct subsystems within the original Küchler types have been lost in the aggregation process. These subsystems are not necessarily more homogeneous than the original Küchler types combined in each of our aggregated types. For example, the lodgepole pine forests of the central Oregon Cascade Range do not appear in the Pacific Northwest in the pretransition classification (Figure 2.2). It is assumed that the relative homogeneity of aggregated types will persist through predicted ecological changes, but it is also reasonable to assume that biome boundaries will shift, and new patterns of homogeneity will form. Once again, the temporal scale of this process is probably shorter than that required for complete biome transitions in a steady-state model.

In transitions driven by smaller scale events, additional state variables like landscape pattern affect the process at intermediate scales. For example, fire-interval distributions are constrained by landscape heterogeneity and the spatial scale of aggregations of age classes (Baker 1989). Thus, the influence of spatial pattern confounds predictions of the effects of increased fire frequency. As noted above, adjacent smaller scale events will be correlated. This combination of intermediate-level constraints with theoretical problems in estimation magnifies the uncertainty of predictions for large spatial and temporal scales.

These limitations need to be addressed by a dynamic model that simulates the critical mechanisms or constraints at each distinct scale in the aggregation process. The transition rules developed in this paper provide an ecological perspective on possible new biome configurations and a set of constraints for large scale, steady-state vegetation models, such as the current version of MAPSS. They also can augment the conceptual framework for monitoring changes in vegetation composition and serve as tools for the calibration of dynamic models of biome-scale vegetation change.

Table 2.6: Descriptions and key species for aggregated Küchler types.

Küchler type	Description	Key species
Spruce-hemlock	Southeast Alaska to north Oregon coast - fire currently not a major agent of disturbance.	*Picea sitchensis, Tsuga heterophylla, Thuja plicata*
Hemlock/Douglas -fir	West Cascades or western slope Rockies, infrequent fires, but severe. Low to mid elevations	*Pseudotsuga menziesii, Tsuga heterophylla, Thuja plicata*
Silver fir/Douglas-fir	Mid to upper elevations in the Cascade Range and Olympics between subalpine and hemlock/Douglas-fir.	*Abies amabilis, Pseudotsuga menziesii*
W. Fir-spruce	High elevation forests. Decreasing moisture-successional gradient from west to east in the Pacific Northwest, corresponding to increased fire frequency.	*Abies lasiocarpa, Tsuga mertensiana, Pinus albicaulis, P. contorta, Picea englemannii, A. magnifica*
Mixed conifer	Includes the Sierra Nevada, and northern California coast range into Oregon, and high elevation in southern California.	*Abies concolor, Pinus lambertiana, P. ponderosa, Pseudotsuga menziesii,Arbutus menziesii, Quercus chrysolepis*
Redwood	California coast and southern Sierra Nevada - forests dominated by coast redwood.	*Sequoia sempervirens, Pseudotsuga menziesii*
Lodgepole pine	Inland, Rocky Mountains, Oregon Cascade Range at high elevations in western United States. Severe stand replacing fires.	*Pinus contorta, Abies lasiocarpa, Picea engelmannii*
Pine-cypress	Narrow range along California coast from Monterey to San Diego. Many isolated stands.	*Cupressus goveniana, Pinus contorta var. contorta*
Ponderosa pine	SW Oregon, California mountains, East Cascade Range. Also Rocky Mountains, Black Hills, Arizona mountains. Low severity, high frequency fire.	*Pinus ponderosa*
Douglas-fir	Cascade Range and inland mountains. Drier than hemlock/Douglas-fir, can include grand fir or other conifers, either as seral or potential climax species.	*Pseudotsuga menziesii, Abies grandis,Picea pungens* (inland states)
Cedar-hemlock-pine	Northern Rocky Mountains western slope.	*Thuja plicata, Tsuga heterophylla, Pinus monticola, Pseudotsuga menziesii, Pinus ponderosa* (low elevations)
Great Basin pine	Bristlecone and limber pine systems, spanning lower-treeline elevations, in Great Basin mountain ranges. High elevation ecotone with alpine tundra, lower with sage-steppe.	*Pinus aristata, P. flexilis*

Table 2.6: Descriptions and key species for aggregated Küchler types (continued)

Küchler type	Description	Key species
Pinyon-juniper	Dry western United States, below oak woodlands, fire adapted somewhat, can coexist with frequent fire in more mesic systems, fire will exclude in drier systems.	*Pinus edulis, Juniperus occidentalis, Artemisia tridentata*
Alder-ash	MAPSS has this as wetland, but could be pioneering vegetation on Spruce-hemlock sites after disturbance. In Pacific Northwest, much in Willamette Valley.	*Alnus rubra, Fraxinus latifolia, Populus trichocarpa*
W. oakwoods	Oak woodlands in Oregon and California. Fire exclusion leads to invasion and dominance by conifers.	*Quercus garryana, Q. agrifolia, Q. chrysolepis*
Mesquite savanna	Warm and dry-mesic, where mesquite is important shrub. Southern Arizona, Texas and Oklahoma.	*Prosopis juliflora*
Oak-juniper	Warm regions in southern United States, somewhat adapted to fire.	*Juniperus ashei, Quercus virginiana, J. virginiana, Q. stellata, Andropogon scoparius (E). J. deppeana, Q. emoryi (W)*
Chaparral	Mainly in California. Includes some oaks, also montane chaparral in Utah and Colorado.	*Arctostaphylos* spp., *Ceanothus* spp., *Cercocarpus ledifolius, Quercus gambelii*
Great Basin shrubland	Sagebrush, blackbrush, "shrub-steppe" in Intermountain West.	*Artemisia tridentata, Coleogyne ramossisima, Sarcobatus vermiculatus*
Desert shrubland	Sparse shrubs, and not much grass. Similar to desert grasslands and chaparral in California and Southwest in being fire adapted.	*Larrea divaricata, Andropogon scoparius*
Desert grassland	Very dry grasslands -- not enough continuous shrubs to burn. Southwest including west Texas.	*Larrea divaricata, Cercidium microphyllum, Bouteloua eriopoda*
Shortgrass prairie Mixed-grass prairie Tallgrass prairie	Tall and short grass prairies in central and western United States, adapted to frequent fires, without which trees will invade at ecotones. Short -> tall grasses predominate as moisture increases west to east.	*Andropogon gerardii* (tallgrass), *Agropyron spicatum* and *Festuca idahoensis* (mixed), *Bouteloua gracilis* (shortgrass)
Grassland-wetland	Non-forested wetlands in Southwest and Southeast, including Tule marshes, cordgrass and Everglades.	*Carex* spp., *Gerardia maritima, Mariscus jamaicensis*
Oak savanna	Prairie borders in the eastern Great Plains, also eastern and gulf states. Fire adapted, fire exclusion leads to invasion of shade tolerant deciduous forest species.	*Quercus macrocarpa, Q. virginiana, Andropogon gerardii, A. scoparius*

Table 2.6: Descriptions and key species for aggregated Küchler types (continued)

Küchler type	Description	Key species
Blackbelt (oak-gum-cypress)	Oak-gum-cypress forest-savanna, with some tallgrass prairie, in Alabama and Mississippi.	*Juniperus virginiana, Liquidambar styraciflua, Quercus stellata*
SE wetland (forested)	Cypress savanna (Florida), mangrove, southern floodplains and pocosins.	*Aristida* spp., *Avicennia nitida, Nyssa aquatica, Pinus serotina*
E Spruce-fir	High elevation forests in Southeastern United States and conifer forests of Eastern Canada and Maine. Fires are infrequent.	*Abies fraseri* and *Picea rubens (SE), Abies balsamea and Picea rubens (NE)*
Conifer bog	Tamarack-black spruce dominated bogs in south central Canada and Lake states.	*Picea mariana, Larix laricina, Thuja occidentalis*
White-red-jack pine	Küchler category Great Lakes pine. Pine is early successional but dominates on these sites due to frequent fires.	*Pinus banksiana, P. resinosa, P. strobus*
N. floodplain	Elm-ash-cotton bottomland forests in central United States	*Populus deltoides, Salix nigra, Ulmus americana*
E. deciduous	Eastern United States, late successional deciduous species, resistant to fire once trees are mature and the canopy is closed (for example, Minnesota Big Woods). Includes "mixed mesophytic" forest in central Eastern United States	*Acer saccharum, Fagus grandifolia, Tilia americana, Quercus rubra, Carya* spp.
Conifer-hardwoods	Transition between boreal forest and E. deciduous, complex successional dynamics, mediated by fire and herbivory. Southern Central Canada, upper Great Lakes states, in north woods in Maine these forests are spruce-fir mixed with hardwoods.	*Acer saccharum, Fagus grandifolia, Picea rubens, Tsuga canadensis, Abies balsamea, Betula alleghenensis*
Oak-hickory	Central eastern United States, south of E. deciduous forest and more adapted to frequent fire.	*Quercus* spp., *Carya* spp.
Oak-pine	Eastern US down to subtropical zone in Florida. Pines are fire adapted, and percentage of pine is related to importance of fire.	*Pinus rigida (NE), P. taeda* and *P. echinata (SE)*
S. mixed forest	Beech, gum, pine and oak in Southeast. Succession proceeds from pine to hardwoods, reversed by fire.	*Fagus grandifolia, Liquidambar styraciflua, Pinus elliottii, Quercus alba*
SE pine	Originally longleaf pine, many of these forests have been cut and planted with loblolly and slash pine. The system is fire driven.	*Pinus* spp.

Table 2.6: Descriptions and key species for aggregated Küchler types (continued)

Küchler type	Description	Key species
Arctic-alpine tundra	Northern Canada and Alaska north of treeline , and elevations above treeline in Cascade Range, Rocky Mountains, and Sierra Nevada. Meadows are invaded by subalpine tree species in favorable conditions.	*Lupinus* spp., *Carex* spp., *Festuca* spp.
Desert	United States Great Basin and Southwest. Not much fire, little to burn. Moisture-temperature driven though Great Basin high shrubland will burn. In extreme desert (for example, Mojave) fires cannot spread.	*Opuntia* spp.
Boreal woodland	South of Arctic tundra, north of continuous forest line, lichen-black spruce woodlands, peat bogs.	*Picea mariana*
Boreal forest	Stretching across Canada, increasing moisture gradient from west to east. Stand replacing fires are common.	*Pinus banksiana, Picea glauca, P. mariana, Abies balsamea, Populus tremuloides, Betula papyrifera*
Aspen-birch	Within the conifer-hardwoods zone, site dominated by aspen and birch.	*Populus tremuloides, Betula papyrifera*
Aspen parkland	Ecotone between boreal forest and northern prairie. Increasing fire and warmth along gradient north to south.	*Populus tremuloides*

Table 2.7: Correspondences among aggregated Küchler, MAPSS, and SAF types

Küchler type	MAPSS type	SAF type (type numbers in parenthesis)
Spruce-hemlock	Forest mixed warm (evergreen)	Sitka spruce (223), western hemlock (224), western hemlock-Sitka spruce (225), western redcedar (228)
Hemlock/Douglas -fir	Forest mixed warm (evergreen)	Pacific Douglas-fir (229), Douglas-fir - western hemlock (230), Port Orford cedar (231)
Silver fir/Douglas-fir	Forest evergreen needle	Coastal true fir-hemlock (226)
W. Fir-spruce	Forest evergreen needle-Tree savanna evergreen needle	Mountain hemlock (205), Engelmann spruce-subalpine fir (206), red fir (207), whitebark pine (208), California mixed subalpine (256), aspen (217)
MIxed conifer	Forest evergreen needle-Tree savanna mixed warm	Sierra Nevada mixed conifer (243), Pacific ponderosa pine-Douglas-fir (245), Jeffrey pine (247), Knobcone pine (248), white fir (211)
Redwood	Forest mixed warm (evergreen)	Redwood (232)
Lodgepole pine	Forest evergreen needle	Lodgepole pine (218)
Pine-cypress	Forest mixed warm (evergreen)	(no corresponding type)
Ponderosa pine	Tree savanna evergreen needle	Pacific ponderosa pine (245), interior ponderosa pine (237)
Douglas-fir	Forest evergreen needle	Interior Douglas-fir (210), Douglas-fir - tanoak - Pacific madrone (234), grand fir (213), blue spruce (216), western larch (212)
Cedar-hemlock-pine	Forest evergreen needle	Western redcedar-western hemlock (227), western white pine (215)
Great Basin pine	Tree savanna evergreen needle	Bristlecone pine (209), limber pine (219)
Pinyon-juniper	Tree savanna evergreen needle	Rocky mountain juniper (220), pinyon-juniper (239), western juniper (238), Arizona cypress (240)
Alder-ash	Wetland	Red alder (221), black cottonwood-willow (222)
W. oakwoods-oak savanna	Tree savanna deciduous broadleaf-Tree savanna mixed warm	Oregon white oak (233), western live oak (241), California black oak (246), canyon live oak (249), blue oak-digger pine (250), California coast live oak (255), post oak-blackjack oak (40), bur oak (42), live oak (89)

Table 2.7: Correspondences among aggregated Küchler, MAPSS, and SAF types (continued)

Küchler type	MAPSS type	SAF type (type numbers in parenthesis)
Mesquite	Shrub savanna mixed warm	Mesquite
Oak-juniper	Tree savanna mixed warm	(no corresponding type)
Chaparral	Chaparral	–
Great Basin shrubland	Shrub savanna evergreen needle	–
Blackbelt (oak-gum-cypress)	Tree savanna mixed warm	Swamp chestnut oak-cherrybark oak (91), sweetgum-willow oak (92), live oak (89), willow oak-water oak-diamondleaf oak (88)
SE wetland (forested)	Wetland	Baldcypress (101), Baldcypress-tupelo (102), Water tupelo-swamp tupelo (103), sweetbay-swamp tupelo-redbay (104), Atlantic white cedar (97), pondcypress (100), mangrove (106), tropical hardwoods (105), pond pine (98)
E spruce-fir	Forest evergreen needle	Red spruce (32), red spruce-balsam fir (33), red spruce-Fraser fir (34), red spruce-yellow birch (30), paper birch-red spruce-balsam fir (35), northern white cedar (37)
Conifer bog	Forest evergreen needle	Black spruce-tamarack (13), tamarack (38)
White-red-jack pine	Forest evergreen needle	Jack pine (1), red pine (15), eastern white pine (21), white pine-northern red oak-red maple (20), white pine-chestnut oak (51)
N. floodplain	Wetland	Black ash-American elm-red maple (39), river birch-sycamore (61), silver maple-American elm (62), cottonwood (63), pin oak-sweetgum (65), sugarberry-American elm-green ash (93), sycamore-sweetgum-American elm (94), black willow (95), overcup oak-water hickory (96)
E. deciduous	Forest hardwood cool	Sugar maple (27), sugar maple-beech-yellow birch (25), sugar maple-basswood (26), black cherry-maple (28), red spruce-sugar maple-beech (31), yellow poplar (57), yellow poplar-eastern hemlock (58), beech-sugar maple (60), red maple (108), hawthorn (109)
N. conifer-hardwoods	Forest mixed cool	White pine-hemlock (22), eastern hemlock (23), hemlock-yellow birch (24)
Oak-hickory	Forest deciduous broadleaf	Post oak-blackjack oak (40), bur oak (42), bear oak (43), chestnut oak (44), white oak-black oak-northern red oak (52), white oak (53), black oak (110), norhtern red oak (55), black locust (50), yellow poplar-white oak-northern red oak (59), sassafras-persimmon (64), eastern red cedar (46), shortleaf pine (75)

Table 2.7: Correspondences among aggregated Küchler, MAPSS, and SAF types (continued)

Küchler type	MAPSS type	SAF type (type numbers in parenthesis)
Oak-pine	Forest deciduous broadleaf	Pitch pine (45), longleaf pine-scrub oak (71), shortleaf pine-oak (76), Virginia pine-oak (78), loblolly pine-hardwood (82), slash pine-hardwood (85), Virginia pine (79)
S. mixed forest	Forest mixed warm (deciduous)	Sweetgum-yellow poplar (87) note mixed forests are difficult to categorize by cover type classifications
SE pine	Forest savanna dry tropical	Sand pine (69), longleaf pine (70), longleaf pine-slash pine (83), loblolly pine (81), loblolly pine-shortleaf pine (80), slash pine (84), S. Florida slash pine (111)
Boreal forest	Forest evergreen needle (taiga)	Balsam fir (5), black spruce (12), white spruce (107)
Aspen-birch	Forest hardwood cool	Aspen (16), pin cherry (17), paper birch (18), gray birch-red maple (19)
Boreal woodland	Taiga tundra	Non-forested types, not included in SAF classification
Arctic-alpine tundra	Tundra	–
Desert	Desert extreme	–
Shortgrass prairie	Grass prairie short	–
Mixed-grass prairie	Grass prairie mixed	–
Tallgrass prairie	Grass prairie tall	–
Desert grassland	Semidesert grassland	–
Desert shrubland	Shrub savanna mixed warm	–

Table 2.8: List of species mentioned in the text

Common name	Scientific name
Ponderosa pine	Pinus ponderosa Dougl. ex Laws.
Douglas-fir	Pseudotsuga menziesii (Mirb.) Franco
Western larch	Larix occidentalis Nutt.
Sitka spruce	Picea sitchensis (Bong.) Carr.
Western hemlock	Tsuga heterophylla (Raf.) Sarg.
Pacific silver fir	Abies amabilis Dougl. ex Forbes
Western white pine	Pinus monticola Dougl. ex D. Don
Coast redwood	Sequoia sempervirens (D. Don) Endl.
White fir	Abies concolor (Gord. & Glend.) Lindl. ex Hildebr.
Oregon white oak	Quercus garryana Dougl.
Bristlecone pine	Pinus aristata Engelm.
Limber pine	Pinus flexilis James
Lodgepole pine	Pinus contorta Dougl. ex Loud.
Red fir	Abies magnifica A. Murr.
Quaking aspen	Populus tremuloides Michx.
Eastern white pine	Pinus strobus Dougl. ex D. Don
Red pine	Pinus resinosa Ait.
Jack pine	Pinus banksiana Lamb.
Balsam fir	Abies balsamea (L.) Mill
Paper birch	Betula papyrifera Marsh.
Grand fir	Abies grandis (Dougl. ex D. Don) Lindl.
Subalpine fir	Abies lasiocarpa (Hook.) Nutt.
Black spruce	Picea mariana (Mill) B.S.P.
Big bluestem	Andropogon gerardii Vitman.

CHAPTER 3: FIRE FREQUENCY IN THE COLUMBIA RIVER BASIN

SUMMARY

Fire frequency and severity affect vegetation composition and successional pathways, thus understanding fire regimes is essential for successful broad-scale ecosystem management. Fire history data are expensive to collect, and data are lacking for many regions for which fire management decisions are being made, thus models are needed to predict fire frequency where local data are not available. A multiple regression model and a tree-based model (a clustering method based on reduction in deviance via likelihood criterion) were developed to predict fire return intervals across the Interior Columbia River Basin at 1-km resolution, using a fire history database and disparate geographic databases. The models combined semi-qualitative methods and rigorous statistics. The regression model predicted fire return intervals from 1 to 161 years for forested areas, whereas the tree-based model predicted a range of 10 to 138 years. Both models predicted latitudinal and elevational gradients of increasing fire return intervals. Internal validation suggested that both models are robust to prediction error. Examination of regional-scale output suggested that although the tree-based model explained more of the variation in the original data, the regression model was more robust to extrapolation error. Thus, the models serve complementary purposes in elucidating the relationships among fire frequency, the predictor variables, and spatial scale. The models can provide local managers with quantitative information, and provide data to initialize coarse-scale fire-effects models. They also demonstrate that qualitative and quantitative methods can be integrated when requisite data for fully quantitative models are unavailable.

INTRODUCTION

Predicting the occurrence and the effects of large-scale disturbances, particularly fires, will be an important challenge for scientists and resource managers in coming decades. Significant changes in fire severity and fire size are predicted for many ecosystems as a result of land use changes, climatic changes, and fire exclusion (Green 1989, Turner et al. 1989, Agee 1994, Habeck 1994, Baker 1995). Although large-scale vegetation change is constrained primarily by climate (Woodward 1987, Woodward and McKee 1991), changes in fire regimes could significantly alter vegetation patterns, because fire often provides critical constraints on vegetation (Fosberg et al. 1992, Baker 1995, Neilson 1995, McKenzie et al. 1996a). Thus, simulation models used to predict large-scale vegetation change need to incorporate the effects of fire. Data on the ecological effects of fire are not generally available at large scales because most empirical research has been conducted on individual stands. Nevertheless, conclusions are often extrapolated to larger scales (McKenzie et al. 1996b).

Mechanistic, or process-based, models are typically used for simulating fire effects (Schmoldt et al. 1998). Most of these have been constructed to represent stand-level processes, and assume homogeneity of crucial inputs over the spatial scale to which they are applied (Rothermel 1972, van Wagner 1977, 1993, Kercher and Axelrod 1984, Peterson and Ryan 1986, Keane et al. 1989, 1994). Spatially explicit mechanistic models that are applied at larger scales require large amounts of empirical data as inputs (e.g., Finney 1995, Keane et al. 1996a), and are sensitive to the scale of resolution to which the raw data are aggregated. Error propagation rapidly becomes problematic in complex natural systems (Cale 1995, Pahl-Wostl 1995), and no strategy for large-scale fire modeling is optimal for all situations.

Research questions are being asked, and management decisions are being made, across larger spatial scales than have been addressed by mechanistic models (McKenzie et al. 1996b, Schmoldt et al. 1998). Whereas process-based models may be preferable when the extent and quality of empirical data are adequate, coarse-scale modeling may require semi-qualitative methods (Puccia and Levins 1985, Keane et al. 1996b, McKenzie 1998). A knowledge-based approach, using qualitative models as precursors to quantitative ones, may be appropriate for poorly understood problems and where insufficient data are available (Schmoldt and Rauscher 1995). In particular, reliable methods are needed for predicting fire effects at regional and continental scales -- scales at which requisite data for mechanistic models are not available. Methods are also needed for minimizing the errors associated with 1) extrapolation of known algorithms for fire spread and fire effects on vegetation, and 2) aggregation of fuels and vegetation data to these scales. Additionally, coarse-scale modeling requires integrating multiple databases that are often in different forms, so that modelers have access to the maximum amount of relevant information.

Fire frequency is a basic parameter in simulation models of fire effects on vegetation. It may be fixed at the beginning of model runs (Kercher and Axelrod 1984, Keane et al. 1989), or sampled at random from a probability distribution (Baker 1995, Boychuk et al. 1997). Fire frequency modeling generally involves assessing the goodness of fit of a sequence of fire return intervals from fire history reconstructions to the negative exponential, two-parameter Weibull, or other right-skewed distributions (Johnson and Gutsell 1994). Reconstructions provide *local* information, and models that use them as baseline data assume homogeneity of fire frequency over the geographic range to which they are applied.

Fire history data are expensive and time-consuming to collect. There are several methods for establishing mean or median fire return intervals, and each has a different expected value for the same raw data (Agee 1993, Johnson and Gutsell 1994). The method of choice usually is determined by specific local objectives. Thus, there is a lack of consistency of methods and quality among fire history studies, and the grain and extent of studies vary significantly (Heyerdahl et al. 1995).

The dominant vegetation in forest ecosystems is often very sensitive to changes in the mean, variance, and distribution of fire return intervals. For example, different successional pathways ensue in response to different sequences of time-since-fire (Cattelino et al. 1979, Frelich and Reich 1995, Clark 1996). Thus *local* information about fire frequency distributions is critical for dynamic fire modeling. It is difficult to associate fire regimes closely with particular vegetation types in forest classifications, because historical reconstructions have demonstrated significant within-type variability in fire frequency and severity. However, broad-scale differences in fire frequency are evidently associated with different geographic areas and distinct environmental conditions. A multi-dimensional view of the influences on fire frequency should reduce the amount of unexplained variation in fire frequency models from that produced by examining only direct relationships with vegetation types or specific environmental variables.

In this chapter, I present semi-qualitative empirical models for predicting coarse-scale patterns of fire frequency in the Interior Columbia River Basin (ICRB). These models were developed from disparate databases. At some stages in the modeling process, the quality and quantity of data permitted the use of rigorous statistical methods; at other points in the process a heuristic, qualitative approach was necessary to reconcile classifications with numeric variables. My objectives were to develop a fire frequency coverage for forested areas of the ICRB, and to examine the effectiveness of different modeling strategies for extrapolating model results to broad spatial scales. I discuss the applicability of these models to the problem of modeling coarse-scale fire effects.

STUDY AREA

Quigley et al. (1996) have defined the ICRB as those portions of the Columbia River Basin inside the United States east of the crest of the Cascade Mountains in Washington and Oregon, and portions of the Klamath River Basin and the Great

Basin in Oregon. The ICRB covers more than 58 million ha, 46% of which is in forested vegetation. Elevations of the forested types ranges from 50 to 3700 m, and mean annual precipitation ranges from 130 to 3500 mm.

METHODS

GEOGRAPHIC DATABASES

The ICRB Integrated Assessment (Quigley et al. 1996) and simulation modeling efforts to predict future vegetation (Keane et al. 1996b) produced a wealth of GIS coverages, both at coarse (entire ICRB) and smaller scales (watersheds within national forests). The coarse-scale coverages provided a geographic template for our model predictions, and a source of predictor variables.

The response variable was fire frequency, expressed as mean fire return interval (FRI). Using a fire history database for the western United States (Heyerdahl et al. 1995), I extracted the following variables for 191 fire history sites within the ICRB: 1) mean fire return interval (response variable: mean = 50.7 years, range = 6-419 years), and 2) elevation and Albers projection geographic coordinates (predictor variables).

Although there are other potentially useful variables in the fire history database, I extracted only those for which there are concomitant variables in the ICRB geographic databases because I was using the model to make predictions for the entire ICRB. I then created a point coverage in ARC-INFO of the fire history site locations in the ICRB, using the Albers projection (Figure 3.1).

Other predictors were taken from the following databases (hereafter referred to as databases 1-3):

1. Three types of vegetation coverages (ARC-INFO, GRID module - 1 km resolution) produced for the ICRB coarse-scale simulation effort (Keane et al. 1996b): i)

historical *potential* vegetation (current potential vegetation is being rebuilt by the ICRB team) derived from biophysical parameters including topography, climate, and geomorphology, and ii) historical and iii) current *dominant cover* types, derived from the Society of American Foresters classification (Eyre 1980). Each coverage contains both forested and non-forested vegetation types, but I applied model predictions only to the former (Table 3.1), because the reconstructions in the fire history database were from forested sites only.

2. Mean annual precipitation over the years 1961-1990 (4 km resolution GRID coverage) for the continental United States produced by the PRISM model (Daly et al. 1994).

3. Lightning strike occurrences (4 km ARC/GRID coverage) for the years 1986-1990 in the ICRB (property of USDA Forest Service).

To extract predictors from database 1, I overlaid each vegetation coverage on the fire history point coverage, and assigned each fire history site the vegetation type of the pixel into which it fell. For database 2 (precipitation), because the pixel values are discrete approximations of a continuous surface, I used the LATTICESPOT command in ARC/GRID to obtain a distance-weighted average for each site of the pixel it was in plus the four adjacent pixels. Values in database 3 represent the number of lightning strikes within each pixel; these values were assigned to any fire history site that fell within the pixel.

QUANTIFYING VEGETATION TYPES

The model matrix now comprised a mix of qualitative and quantitative data (Table 3.2). Vegetation types could be modeled as factors, but this would eliminate the possibility of extrapolating the model to forested sites in the ICRB that had vegetation types not represented in the model database. I expected the vegetation types to be important determinants of fire frequency, and therefore developed the following method to assign numerical values to them, based on the type of fire regime I expected to be associated with each.

Table 3.1: Forested vegetation types in the Interior Columbia River Basin. Aggregated Küchler types were determined by combining cover types according to McKenzie et al. (1996a).

Potential natural vegetation types	Cover types	Aggregated Küchler types
Interior ponderosa pine	Interior ponderosa pine	Ponderosa pine
Dry Douglas-fir w/ ponderosa pine	Pacific ponderosa pine	Mixed conifer
Dry Douglas-fir w/o ponderosa pine	Sierra mixed conifer	Western oakwoods
Pacific pine /Sierra mixed conifer	Oregon white oak	Great Basin pine
Dry grand fir	Limber pine	Lodgepole pine
Oregon white oak	Mixed conifer woodland	Douglas-fir
Limber pine	Douglas-fir	Cedar/hemlock/pine
Moist Douglas-fir	Grand fir/white fir	Silver fir/Douglas-fir
Grand fir E. Cascades	Western larch	Western fir/spruce
Grand fir inland	Lodgepole pine	
Lodgepole pine Oregon	Aspen	
Mountain hemlock/Shasta red fir	Western white pine	
Aspen	Shasta red fir	
Cedar/hemlock E. Cascades	Western hemlock/western redcedar	
Cedar/hemlock inland	Pacific silver fir	
Pacific silver fir	Mountain hemlock	
Mountain hemlock E. Cascades	Engelmann spruce/subalpine fir	
Mountain hemlock inland	Whitebark pine	
Lodgepole pine Yellowstone	Whitebark pine/subalpine larch	
Spruce-fir w/aspen		
Spruce-fir w/o aspen		
Spruce-fir wet		
Spruce-fir WBP>LPP[1]		
Spruce-fir LPP>WBP[2]		
Whitebark pine/subalpine larch north		
Whitebark pine/subalpine larch south		

1 = more whitebark pine than lodgepole pine
2 = more lodgepole pine than whitebark pine

Figure 3.1: Location of fire history sites in the Interior Columbia River Basin.

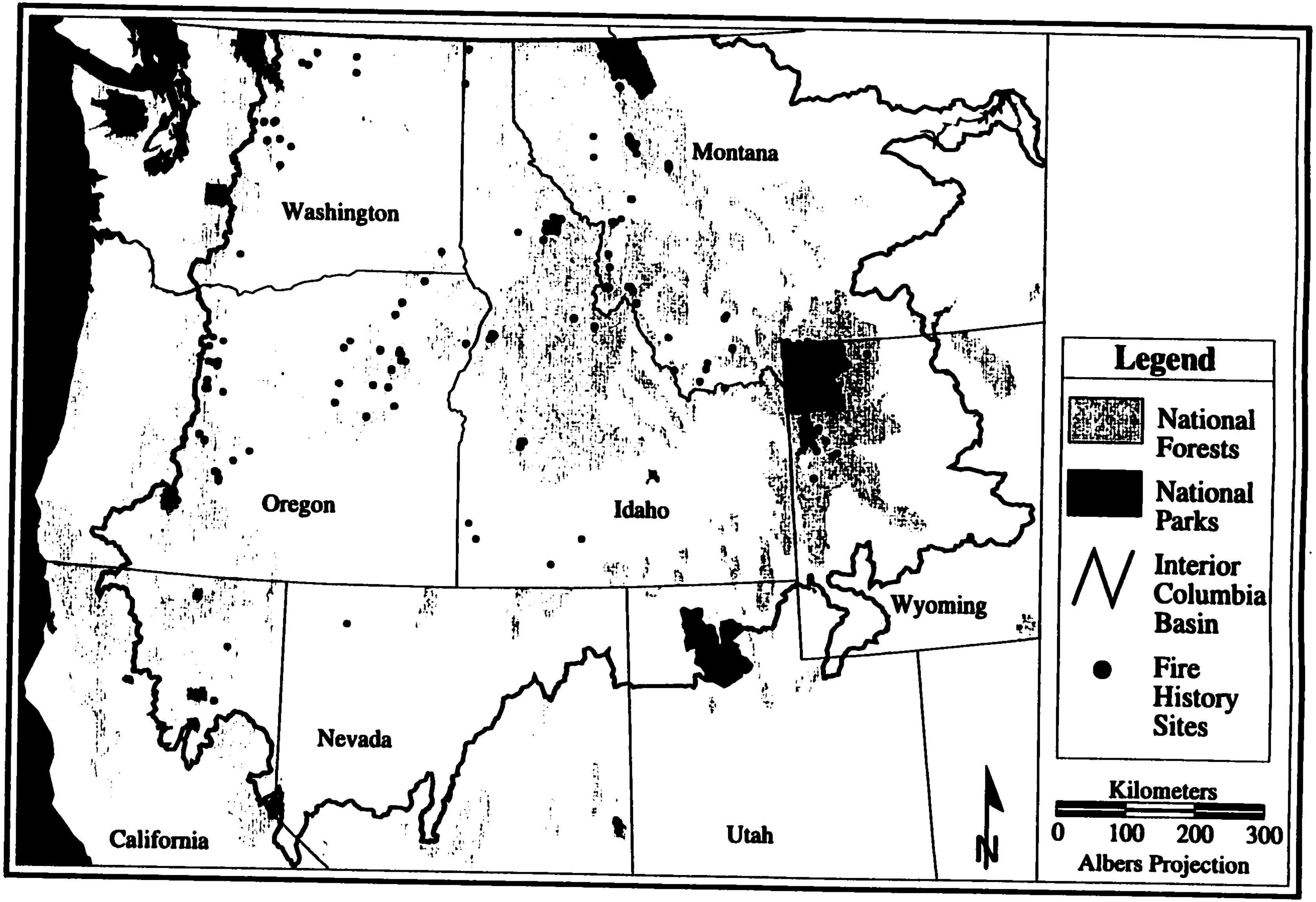

Legend
National Forests
National Parks
Interior Columbia Basin
Fire History Sites
Kilometers
0 100 200 300
Albers Projection
N
Washington
Oregon
Idaho
Montana
Wyoming
California
Nevada
Utah

Table 3.2: Predictor variables examined for the fire frequency models.

Variable	Variable description
Elevation (ELEV)	Elevation (meters) of fire history sites.
Precipitation (PPT)	30-year mean annual precipitation (1961-1990), from PRISM (Daly et al. 1994).
Lightning strike occurrence (STRIKES)	#lightning strikes within the 4-km^2 pixel containing a fire history site (years 1986-1990 and 5-year mean).
Albers east coordinate (ALBERS-E)	East coordinate from Albers projection
Albers north coordinate (ALBERS-N)	North coordinate from Albers projection
Historical potential vegetation (PVTH)	Classification of site based on ICRB coverage – qualitative.
Historical cover type (COVH)	Classification of site based on ICRB coverage – qualitative.
Current cover type (COVC)	Classification of site based on ICRB coverage – qualitative.

I created dendrograms, representing qualitatively the ecological distances, with respect to fire regime, among each of the potential vegetation types (PVTs) and cover types (COVs) in the ICRB (Figures 3.2 and 3.3). Beginning at the top of the dendrogram, each type (represented as the leaves of the dendrogram) was assigned a integral value based on its vertical distance (number of leaves) in the dendrogram from the previous type (Tables 3.3 and 3.4). As the level of aggregation increased (moving from left to right in the dendrogram), each type had a different integral value – these values became closer together as more types were clumped. At completion of this process, three vegetation types in the model matrix (historical PVT [PVTH] and historical and current COV [COVH and COVC]) had either three or four numerical vectors associated with them (Tables 3.3 and 3.4). Although I assigned only integer values for each vegetation type, I explored non-linear transformations of them during the modeling process (see below) to optimize their predictive power.

Model development

I used Splus, version 3.3 for Windows and version 3.4 for UNIX (Mathsoft 1994), including the S+ Spatial Stats module and libraries contributed by Brian Ripley, for the statistical modeling. My goal was to produce a model(s) with optimal fit, relative simplicity, ease of interpretation, and applicability to all forested areas in the ICRB.

Because fire is a contagious process, fires that affect one location (pixel) are likely to affect nearby pixels. Thus with enough data points, one would expect some autocorrelation structure to be evident when examining mean FRIs at fire history sites. I therefore examined local clusters of data points (evident in Figure 3.1) hoping to create local GIS coverages using spatial interpolation by ordinary Kriging (Isaaks and Srivastava 1989). Although this method could not be used outside clusters, local response surfaces within clusters could be compared to predictions from models that assumed independence in the response variable. However, variogram analysis showed that the covariance structure within data clusters could not be parameterized in ways suitable for spatial interpolation, due to the spatial clustering at all scales and the high variability in FRI between neighboring points. I therefore abandoned the attempt to model spatial autocorrelation directly, and searched for an optimal model of each of: 1) a multiple regression of FRI on predictor variables, and 2) a regression tree model of FRI on predictor variables.

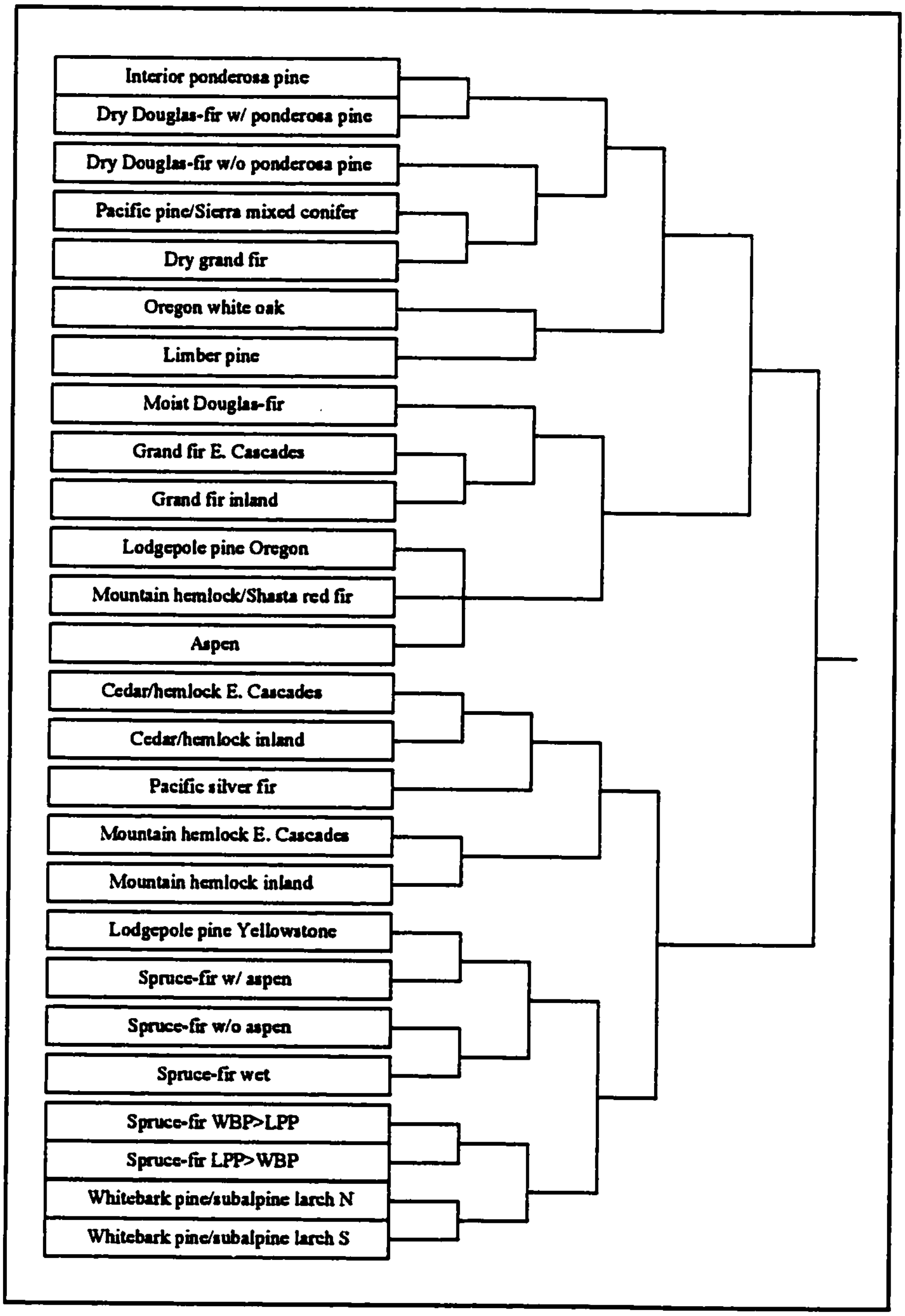


Figure 3.2: Dendrogram of forested potential vegetation types (PVTs) in the Interior Columbia River Basin, arranged so that proximity of types in the dendrogram represents similarities in fire regime.

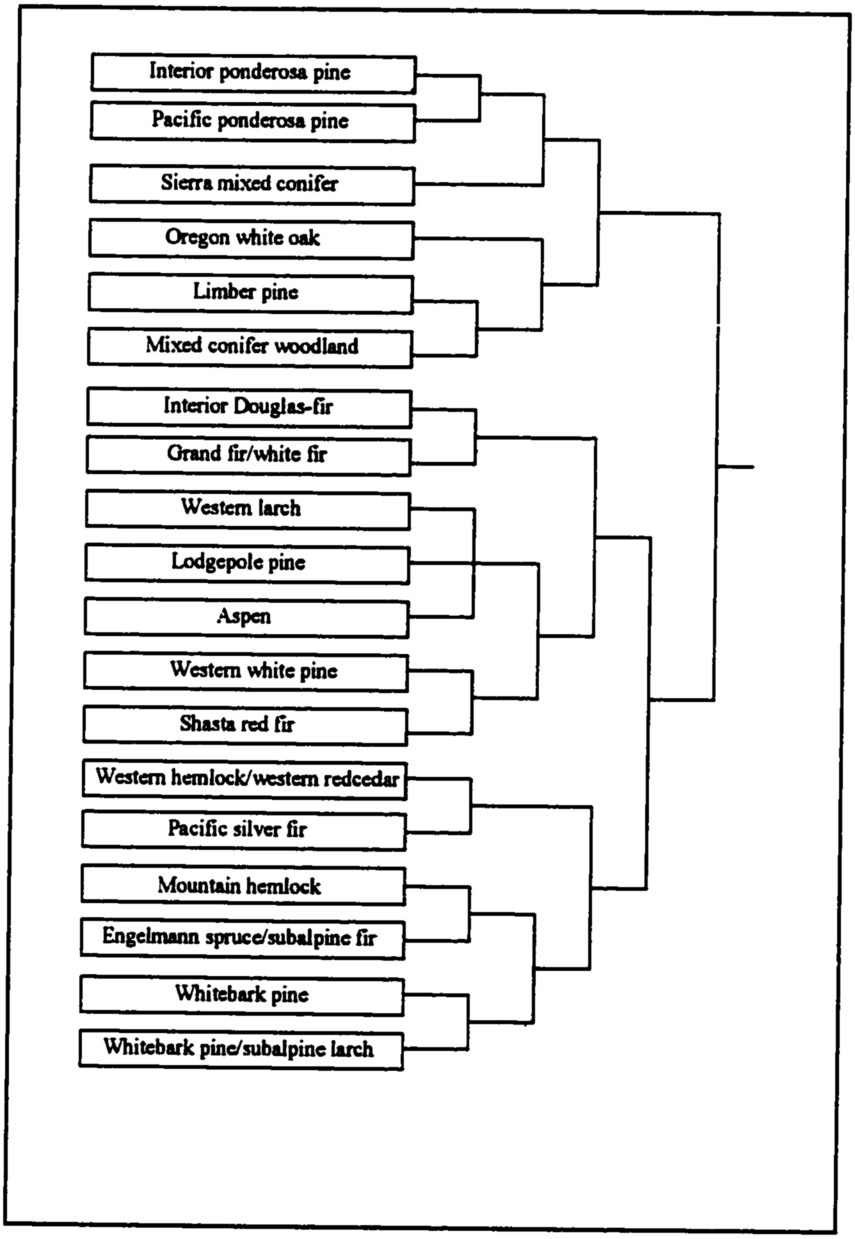


Figure 3.3: Dendrogram of forested cover vegetation types (COVs) in the Interior Columbia River Basin, arranged so that proximity of types in the dendrogram represents similarities in fire regime.

Table 3.3: Numerical values at four levels of aggregation for potential vegetation types. Based on the dendrogram in Figure 3.2.

Potential Vegetation type	None	One	Two	Three
Interior ponderosa pine	1	1	1	1
Dry Douglas-fir w/ ponderosa pine	2	1	1	1
Dry Douglas-fir w/o ponderosa pine	5	3	2	1
Pacific pine /Sierra mixed conifer	7	4	2	1
Dry grand fir	8	4	2	1
Oregon white oak	12	7	4	2
Limber pine	14	8	4	2
Moist Douglas-fir	19	12	7	4
Grand fir E. Cascades	21	13	7	4
Grand fir inland	22	13	7	4
Lodgepole pine Oregon	25	15	8	4
Mountain hemlock/Shasta red fir	26	15	8	4
Aspen	27	15	8	4
Cedar/hemlock E. Cascades	33	20	12	7
Cedar/hemlock inland	34	20	12	7
Pacific silver fir	36	21	12	7
Mountain hemlock E. Cascades	39	23	13	7
Mountain hemlock inland	40	23	13	7
Lodgepole pine Yellowstone	44	27	15	8
Spruce-fir w/ aspen	45	27	15	8
Spruce-fir w/o aspen	47	28	15	8
Spruce-fir wet	48	28	15	8
Spruce-fir WBP>LPP[1]	51	30	16	8
Spruce-fir LPP>WBP[2]	52	30	16	8
Whitebark pine/subalpine larch north	54	31	16	8
Whitebark pine/subalpine larch south	55	31	16	8

1 = more whitebark pine than lodgepole pine
2 = more lodgepole pine than whitebark pine

Table 3.4: Numerical values at three levels of aggregation for cover types. Based on the dendrogram in Figure 3.3.

Cover type	None	One	Two
Interior ponderosa pine	1	1	1
Pacific ponderosa pine	2	1	1
Sierra mixed conifer	4	2	1
Oregon white oak	7	4	2
Limber pine	9	5	2
Mixed conifer woodland	10	5	2
Interior Douglas-fir	15	9	5
Grand fir/white fir	16	9	5
Western larch	19	11	6
Lodgepole pine	20	11	6
Aspen	21	11	6
Western white pine	23	12	6
Shasta red fir	24	12	6
Western hemlock/western redcedar	28	15	8
Pacific silver fir	29	15	8
Mountain hemlock	32	17	9
Engelmann spruce/subalpine fir	33	17	9
Whitebark pine	35	18	9
Whitebark pine/subalpine larch	36	18	9

Multiple regression of FRI on predictors in the model matrix

Using the high-level programming capabilities of Splus, I developed an exhaustive procedure that tested combinations of the environmental variables (Table 3.2) with each numerical vector (corresponding to a level of aggregation in the dendrogram) for the three ICRB vegetation classifications. I then used backward elimination (Neter et al. 1990) to remove predictors that did not contribute significantly (α = 0.05) to the reduction in variance. The response variable was transformed logarithmically to meet the normality assumptions of regression, and a Cook's distance plot was used to identify and remove significant outliers. Once a model was selected, I compared the output from a robust procedure (the *rlm()* function in Ripley's library "mass") to that from ordinary regression. The intercept term was also corrected for logarithmic bias (Flewelling and Pienaar 1981).

To find the optimal transformation of the numerical values for vegetation types, I compared a log transform to fitted exponents for the vegetation variables. I used partially linear least squares (Bates and Lindstrom 1986) to obtain the extra coefficient. For example, a possible model form would be:

$$\log(FRI) = \beta_0 + \ldots + \beta_k COVH^{\beta_{k+1}} + \ldots \tag{3.1}$$

where all coefficients are linear except β_{k+1}.

I also examined multiple regression models in which the predictor variables were the principal components of a model matrix consisting of the five abiotic variables (Table 3.2 -- first 5 rows) and two vegetation variables. These two represented the best predictor in the "raw variable" regression of each of the levels of aggregation of PVTH and COVH (Tables 3.3 and 3.4). Each of these predictors was first scaled to have variance equal to 1, so that the magnitude and variance of individual predictors would not unduly influence the principal components. The assumption behind this method was that "similar" sites would have similar fire regimes, so that the position of a site on principal components axes might have a strong relationship to its fire return interval. Models of this type are, however, more difficult to interpret than models using raw variables.

Regression tree model of FRI on predictors in the model matrix

Tree-based models are a non-parametric alternative to linear models for regression problems (Breiman et al 1984). They are fit by binary recursive partitioning, in which a dataset is successively split into increasingly homogeneous subsets, using a likelihood criterion to maximize the reduction in deviance produced by each partition (Clark and Pregibon 1992). Although they are often used as an exploratory technique for revealing structure in data, they can also be used for prediction when predictors in a new database fall within the range of predictors in the modeling database. A particular advantage of tree-based models is that they can capture non-additive behavior and complex interactions between variables, whereas standard linear models are limited to prespecified multiplicative interactions (Clark and Pregibon 1992). Response variables that are factors produce *classification trees*, whereas numerical response variables produce *regression trees.*

The tree-based model used the same predictors as the regression model. I used an adaptive estimation method (Breiman et al. 1984) to minimize the complexity of the model (number of branches and nodes) without sacrificing goodness-of-fit. I first fit an overly large tree, using two criteria for deciding when a node should not be split: 1) if node deviance was less than 1% of the root node deviance, or 2) if the node had fewer than 10 observations. This choice is more robust against the "fooling" of early splits than a "forward selection" algorithm (Clark and Pregibon 1992). I then used a cost-complexity measure derived by Breiman et al. (1984) to prune the tree:

$$D_\alpha(T_i) = D(T_i) + \alpha(\text{size}(T_i)) \tag{3.2}$$

where $D(T_i)$ is the deviance of subtree T_i

$\text{size}(T_i)$ = the number of terminal nodes of T_i

α = a cost-complexity parameter

For a specified α, the cost-complexity pruning implemented in Splus minimizes $D_\alpha(T_i)$ for all subtrees of tree T. I determined α graphically by using the *plot(prune.tree())* option in Splus to plot deviance against number of nodes as a step function. The value of the cost-complexity parameter corresponding to the flattening of this step function was inserted in Equation 3.2. Each subtree was pruned, beginning at its terminal nodes, until the cost-complexity measured was minimized. Predictor variables on which there were no partitions in the final pruned model were thus eliminated.

Large-scale application of the models

For each variable in the final (tree-based or regression) models, I created a grid (1 km resolution) with data values at forested pixels and NODATA at other pixels. A pixel was considered forested if both its corresponding pixels in the coverages of historical potential vegetation and of dominant cover type coincided with the vegetation types in Table 3.1. I exported these GRIDs as one-dimensional vectors to Splus and used the *predict()* methods for tree-based and linear regression models to produce vectors of predicted values of fire return interval for each model, given the new data. I then imported the vectors of predicted values into ARC-INFO as GRIDs, creating two GRIDs of predicted fire return intervals. Because tree-based models are inaccurate when extrapolated beyond the range of model databases, I eliminated pixels from the tree-based GRID that corresponded to values of environmental variables outside those in the fire history databases (elevation > 2550 m and annual precipitation > 2000 mm).

Model evaluation

The evaluation of any statistical model typically addresses the following questions:

1. How well does the model fit the data and meet the assumptions of regression?

2. How well does the model predict new observations?

I addressed Question 1 with standard diagnostics. The fire history database was small (191 sites in the ICRB) and very heterogeneous, so I did not create a subset of the database for testing. Instead, to answer Question 2, I calculated a refined bootstrap estimate of prediction error (Efron and Tibshirani 1993) for the regression model, and compared it to the model's error sum of squares (SSE). For the regression tree model I used 10-fold cross-validation to assess graphically the degree of pruning that I applied to the model tree (Venables and Ripley 1994). Because the purpose of the model was to extrapolate local relationships to the regional scale, however, there were two other questions I needed to address:

3. How well does the model database (point information) represent the entire region?

4. How are model behavior and concomitant errors propagated in the extrapolation process?

To answer Question 3, I compared the distributions of predictor variables in the model database to those in the regional database. For example, predictions for a cover type that was abundantly represented in the region, but only sparsely represented in, or absent from, the model database, could be suspect. Conversely, predictions for a pixel whose environmental variables were well within the range of the model database, and whose cover type was abundantly represented therein, could be accepted with more confidence. This procedure also revealed sites that were likely candidates for future fire history studies by virtue of being under-represented in the model database.

To answer questions 2 (at larger scales) and 4, I produced statistical and graphical summaries of model predictions at the 1 km scale, using two different levels of aggregation of vegetation types: 1) historical cover types, and 2) aggregated Küchler types (McKenzie et al. 1996a and Table 3.1). I examined the distribution of predicted FRIs from both models for obvious anomalies or over- or under-predictions, using the output maps and histograms of FRIs for each vegetation type. For example, I expected that predicted FRI distributions for vegetation types would be unimodal and right-skewed, as distribution from individual fire history studies often are. I also expected differences between types in mean and range. Additionally, I expected FRIs to be positively correlated with latitude and elevation.

This procedure suggested which of the models would be more robust to extrapolation. I then calculated empirical variograms of two 60 x 60 km subsets from the output map of the more robust model, one from the Blue Mountains, Oregon, and the other from the western Rocky Mountains, Montana, to see if spatial autocorrelation was evident in the regional-scale predictions.

RESULTS

The best multiple regression model uses three predictor variables (Table 3.5), is highly significant ($p < 0.0001$), and has reasonable explanatory power ($R^2 = .38$). Standard diagnostic procedures revealed no violation of regression assumptions, and coefficients from the robust procedure are virtually identical to those from ordinary regression. The range of fitted values for FRI is 11.2-91.0 years. The bootstrap estimate of prediction error (from 100 replicates) produced a 6.5% error inflation above SSE for the model. Regression of log(FRI) on the principal components of the model matrix produced a slightly inferior fit ($R^2 = .34$), so I applied only the regression model using raw variables to the regional scale.

Table 3.5: Parameter estimates for the regression model. COVH1 refers to level of aggregation "One" in Table 3.4.

Coefficient	Value	Standard Error	t value	Pr(>|t|)
Intercept	-4.4810	1.5454	-2.8996	0.004
Log(elevation)	0.8910	0.2042	4.3636	<0.0001
AlbersN	$2.1315*10^{-6}$	$3.0498*10^{-7}$	6.9889	<0.0001
Log(COVH1)	0.2141	0.0482	4.4385	<0.0001

The tree-based model, after pruning, produced 20 distinct predicted values (Figure 3.4), ranging from 10.1 to 137.8 years after exponential transformation. Proportional reduction in deviance from the model (roughly equivalent to R^2) is .73; hence, it has almost twice the explanatory power of the regression model. The tree-based model uses four variables (the three in Table 3.5 plus albersE); a fifth (precipitation) was lost in the pruning process. The primary partition was on COVH1 (level one of aggregation of COVH), but this variable was not used again; most subsequent partitions were on elevation and albersN (Figure 3.4). The number of sites represented by terminal nodes ranges from 5 to 18. Cross-validation indicated that a more severe pruning might also be acceptable, but I wanted to retain as broad a range, and as great a variety, of fitted values as possible because of the number of predictions I was making from the model. Thus I retained all the nodes remaining after the cost-complexity pruning.

MODEL BEHAVIOR

The total number of regional-scale predictions from the models is three orders of magnitude greater than the number of sample sites (Table 3.6). The regional predictions cover a larger elevational range (49-3713 m) than the model database (727-2550 m).

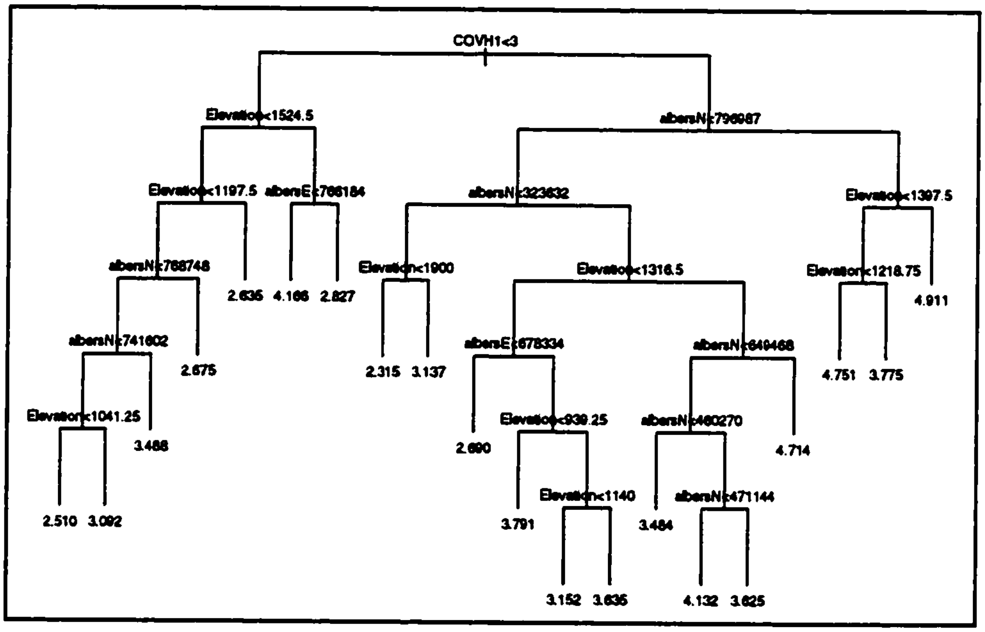


Figure 3.4: The final pruned regression tree, containing 20 distinct terminal nodes. Values at nodes are the logarithms of predicted fire return intervals. Predictions for a new site are obtained by moving down the tree, branching left at a split if the site meets the rule, or branching right otherwise. COVH1 refers to the first level of aggregation of COVH (Table 3.4), corresponding only to interior ponderosa pine in the model database, and to the first three rows of Table 3.4 in the regional database.

Table 3.6: Cover types (COVH) in the model database vs. the ICRB coarse-scale vegetation coverage.

Cover type	Number of sites in fire history database	Number of pixels in ICRB (1 km) coverage
Interior ponderosa pine	64	97762
Pacific ponderosa pine	0	2539
Sierra mixed conifer	0	872
Oregon white oak	0	481
Limber pine	0	263
Interior Douglas-fir	12	49786
Grand fir/white fir	7	4210
Western larch	32	21338
Lodgepole pine	42	67347
Aspen	6	8888
Western white pine	7	10477
Shasta red fir	1	10
Western hemlock/western redcedar	1	404
Pacific silver fir	0	123
Mountain hemlock	0	824
Engelmann spruce/subalpine fir	19	30655
Whitebark pine	0	15120
Whitebark pine/subalpine larch	0	2108
Total	191	313207

Because COVH1 was the vegetation variable represented in both models, I used COVH types to organize summary statistics for the models. Predictions from the tree-based model are restricted to the 20 discrete values at the nodes of the tree (Table 3.8). There are eight COVH types in the regional (forested) coverage that were not represented in the model database, although these account for fewer than 4% of the total pixels (Table 3.6). Predictions of FRI from the regression model range from 1.39 to 160.9 years at the regional scale (Table 3.7).

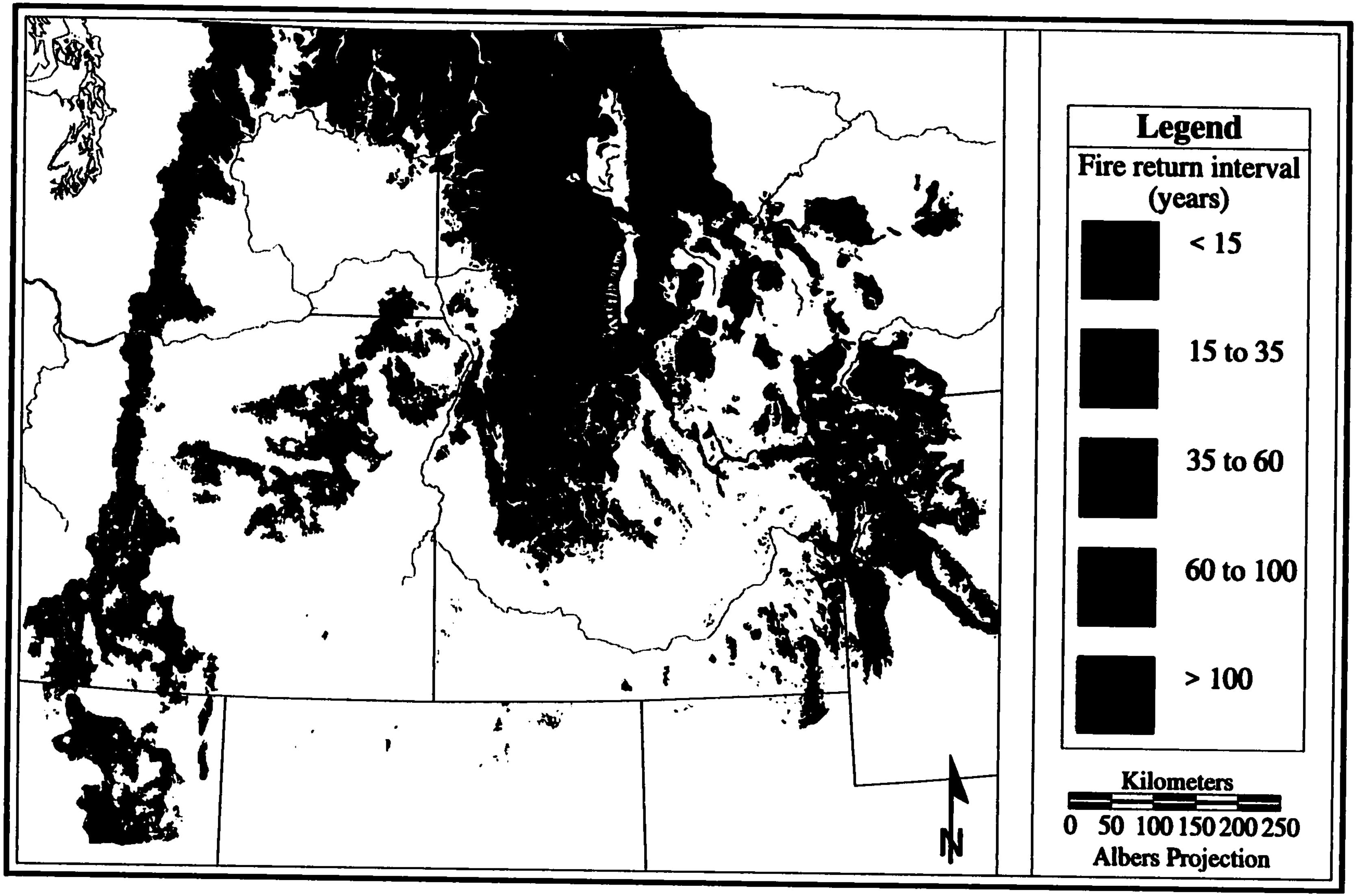
Viewed regionally, predictions from the regression model reveal a latitudinal gradient (Figure 3.5), while predictions from the tree-based model display distinct horizontal bands in addition to this gradient (Figure 3.6). These bands do not correspond to known biotic or abiotic gradients, and are probably an artifact of the model. When separated by COVH type, most distributions of predictions from the regression model are unimodal and right-skewed (examples in Figure 3.7), whereas predictions from the tree-based model are distinctly bimodal, often with wide separations between modes (examples in Figure 3.8). These patterns were retained even when COVH types were aggregated into Küchler types (see Table 3.1). Variograms of the 60 x 60 km subsets of the output maps show decreasing spatial autocorrelation out to about 24 km in the Montana subset and 32 km in the Oregon subset (Figure 3.9).

DISCUSSION

The two models reveal highly significant relationships between fire frequency and the predictor variables. Because estimates of fire frequency are necessary for modeling fire effects and succession, the output maps represent a wealth of quantitative data to assist coarse-scale modeling efforts in the ICRB. Internal validation showed the models to be robust to prediction errors at the scale at which they were developed. The significance and signs of coefficients suggested that commonly held beliefs about the relationships between fire regimes and environmental or geographic gradients could be validated quantitatively with existing data.

I expected the regression model to predict increasing FRIs along both elevational (low-high) and latitudinal (south-north) gradients. This was confirmed by examination of the output maps.

Figure 3.5: Output map of predicted fire return intervals from the regression model. Proportional area of the coverage in each category: <15 years = 12%, 15-35 years = 31%, 35-60 years = 37%, 60-100 years = 18%, >100 years = 2%.


Legend
Fire return interval (years)
< 15
15 to 35
35 to 60
60 to 100
> 100
Kilometers
0 50 100 150 200 250
Albers Projection
N

The tree-based model does not predict monotonic relationships, but partitions on albersN and elevation generally assign higher predicted FRIs to higher values of these variables (Figure 3.4). I also expected a significant positive correlation between FRI and precipitation, given the obvious link between fuel moisture and flammability and extensive documentation of longer FRIs in more mesic systems.

It is probable that precipitation dropped out of both models because both albersN and COVH are effective surrogates. (When these predictors are not included in the model, precipitation is marginally significant, but has low explanatory power). Also, the resolution of the PRISM coverage (4 km) may be too coarse to capture fine-scale fluctuations in precipitation that could have significant differential effects on fuels, and 30-year means from the late 20th century probably do not accurately represent the last several centuries. Historical reconstructions of climate from tree-ring data (e.g., Fritts et al. 1979) may provide better predictors when they become available at broad spatial scales.

Because vegetation composition affects atmospheric moisture and microclimate, and therefore fuel loading and fire severity, existing vegetation should reflect the fire regime more accurately than does potential vegetation. I therefore expected that of the three vegetation variables, COVH would be correlated most strongly with FRI, because it represents vegetation presumed to be present during the period covered by the reconstructions in the fire history database. COVH1 is the best predictor of the vegetation types and also has the strongest simple correlation with FRI (Pearson's $R = .43$, $p < 0.0001$), suggesting that fire regimes in the ICRB can be classified by vegetation types into ten levels of fire frequency, corresponding to the unique values in Table 3.4, column 3 (but see also Morgan et al. 1996).

Figure 3.6: Output map of predicted fire return intervals from the tree-based model. Proportional area of the coverage in each category: <15 years = 23%, 15-35 years = 30%, 35-60 years = 18%, 60-100 years = 9%, >100 years = 20%.

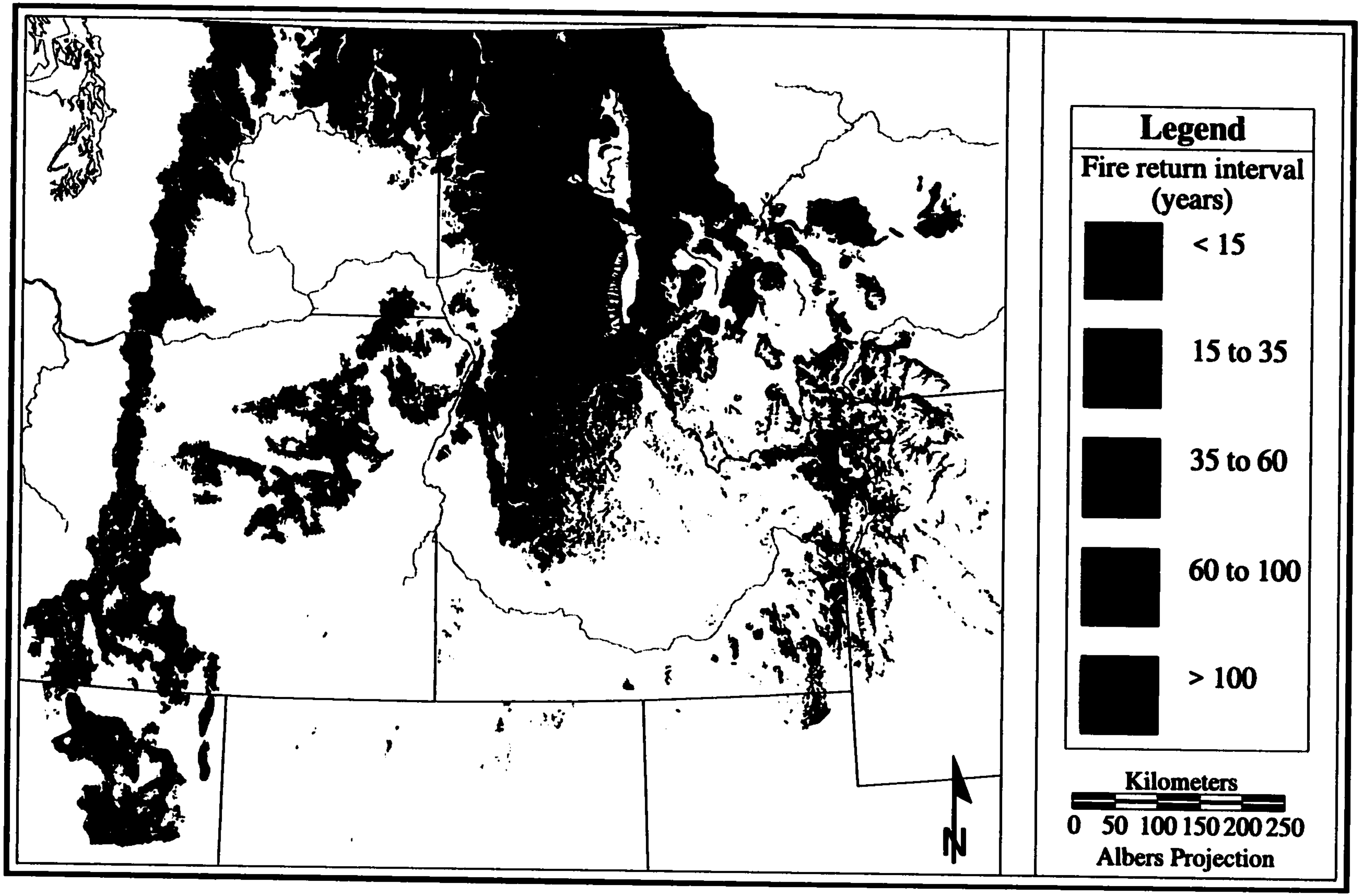

Legend
Fire return interval (years)
< 15
15 to 35
35 to 60
60 to 100
> 100
Kilometers
0 50 100 150 200 250
Albers Projection
N

Table 3.7: Summary statistics for predicted fire return intervals from the regression model for ICRB forested cover types (COVH).

Cover type	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
Interior ponderosa pine	1	13	18	19	25	70
Pacific ponderosa pine	4	7	8	10	11	33
Sierra mixed conifer	5	10	11	12	14	40
Oregon white oak	4	6	7	7	8	20
Limber pine	27	33	36	39	39	79
Interior Douglas-fir	2	34	43	44	53	126
Grand fir/white fir	10	18	32	33	41	105
Western larch	18	48	57	58	67	119
Lodgepole pine	14	41	52	54	64	141
Aspen	5	24	29	32	36	100
Western white pine	19	41	48	50	57	112
Shasta red fir	18	21	22	22	23	24
Western hemlock/western redcedar	6	29	36	42	55	108
Pacific silver fir	22	49	63	69	94	119
Mountain hemlock	22	31	52	50	61	126
Engelmann spruce/subalpine fir	15	47	56	62	76	153
Whitebark pine	22	54	62	67	75	161
Whitebark pine/subalpine larch	32	58	90	85	104	153

The two models were developed using different quantitative methods and cannot be meaningfully combined into one model. Instead, they serve complementary purposes in understanding the relationships among FRI and the predictor variables. Results of the tree-based model suggests that by exploring complex interactions and dependencies among variables that could not be captured by an ordinary regression model one could explain most of the variation in the response. However, when extrapolated to 1-km resolution, the model produces anomalous results – bimodal distributions of FRIs -- that are difficult to justify ecologically. They are probably an artifact of the sequential nature

Table 3.8: Summary statistics for predicted fire return intervals from the tree-based model for ICRB forested cover types (COVH).

Cover type	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
Interior ponderosa pine	12	14	15	27	33	64
Pacific ponderosa pine	12	14	22	35	64	64
Sierra mixed conifer	12	14	14	33	64	64
Oregon white oak	10	10	10	11	10	15
Limber pine	23	33	33	44	33	136
Interior Douglas-fir	10	23	38	51	62	136
Grand fir/white fir	10	15	33	34	38	136
Western larch	10	38	112	83	116	136
Lodgepole pine	10	33	38	59	112	136
Aspen	10	23	23	26	33	136
Western white pine	15	38	44	66	112	136
Shasta red fir	23	23	23	23	23	23
Western hemlock/western redcedar	10	15	33	42	38	136
Pacific silver fir	10	38	112	79	112	136
Mountain hemlock	10	15	23	48	112	136
Engelmann spruce/subalpine fir	10	33	38	71	112	136
Whitebark pine	10	33	38	71	112	136
Whitebark pine/subalpine larch	15	112	112	104	136	136

of the prediction process, in which once a node has been passed, new partitions on predictor variables are limited to those variables further down the branch. They may also be due to the heterogeneity of vegetation and topography within pixels (see below). Conversely, the regression model, although it has weaker explanatory power at the scale of the model database, provides a simple and robust method of prediction that reproduces expected patterns of FRI for different cover types when applied at the regional scale. Thus, the tree-based model is a better model with respect to explanatory power, whereas the regression model is better with respect to broad-scale predictions.

AGGREGATION ERROR, SPATIAL HETEROGENEITY, AND THE RELIABILITY OF THE MODELS

Applying the tree-based model at coarse scales introduces a common form of error in data aggregation. When relationships among variables are nonlinear, characterization of data by simple means will produce consistent errors when relationships are extrapolated across scales (O'Neill 1979, King et al 1991, Rastetter et al. 1992, Cale 1995, O'Neill 1998). The tree-partitioning process equates predicted values of the response to its mean over increasingly homogeneous subsets of the predictors (Clark and Pregibon 1992). This retains features of the raw data at the scale of modeling, but the discontinuities are magnified such that the proportion of extreme values is exaggerated at the scale of prediction because "mistakes" at any split are propagated down through the tree (Figures 3.4 and 3.8). The regression model provides a rougher approximation of patterns in the original data, but as a linear function, is more robust to aggregation error. The distributions of predictions from this model will have errors associated with them, but their smoothness suggests a lack of interference from model artifacts in the extrapolation process.

Patterns of spatial heterogeneity affect the connectivity of landscapes with respect to fire, and thus introduce biases into estimates of fire frequency (Lertzman et al. 1998). The 1-km vegetation classifications and DEM mask considerable spatial heterogeneity in vegetation and topography. Applying the models at this scale implicitly produces a mean FRI over 1 km^2, but the patterns of landforms and vegetation within the pixel exert considerable influence on fire severity and spread, resultant fire size, and thus expected FRI (Agee 1998). For example, local cold-air drainages can favor vegetation characteristic of higher elevations in a matrix of Douglas-fir (*Pseudotsuga menziesii*) (Agee et al. 1990). Depending on the connectivity of the landscape, FRIs of the two vegetation types in this context may be identical, or at least more similar than could be expected if they were spatially disjunct. Predictions of short FRIs in vegetation types known to support low frequency/high severity fire regimes may be reflecting this process "unintentionally," although only a detailed examination of within-pixel heterogeneity could ascertain this.

Spatial autocorrelation is clearly a factor in the geographic distribution of FRIs. I expected that patterns of autocorrelation would exist in the ICRB at multiple scales. Their extent should be correlated with the connectivity of landscapes with respect to fire spread, which is a function of biophysical parameters and disturbance history. After failing to ascertain any such patterns in the model database, I assumed independence in the models. However, the two 60 x 60 km subsets of the output map from the regression model display a definite autocorrelation structure (Figure 3.9).

Not surprisingly, a linear function of the predictor variables captures the correlations among their values at adjacent pixels and therefore their correlated effects on the response variable, perhaps more accurately than would a more complex model that attempted to incorporate spatial dependence from the outset.

Both models could be improved by additional fire history information for the ICRB. Because of the time and expense involved in collecting these data, efforts should be concentrated in systems that are currently under-represented in the model database vs. the regional database – high elevation forests (other than lodgepole pine systems) supporting low frequency/high severity fire regimes. Indirect methods, such as estimation of the time required for the buildup of fuels capable of supporting crown fire, may be needed in some ecosystems (Romme 1982). More data from these systems would likely increase the range in regional-scale predictions from the regression model for subalpine cover types (Table 3.7).

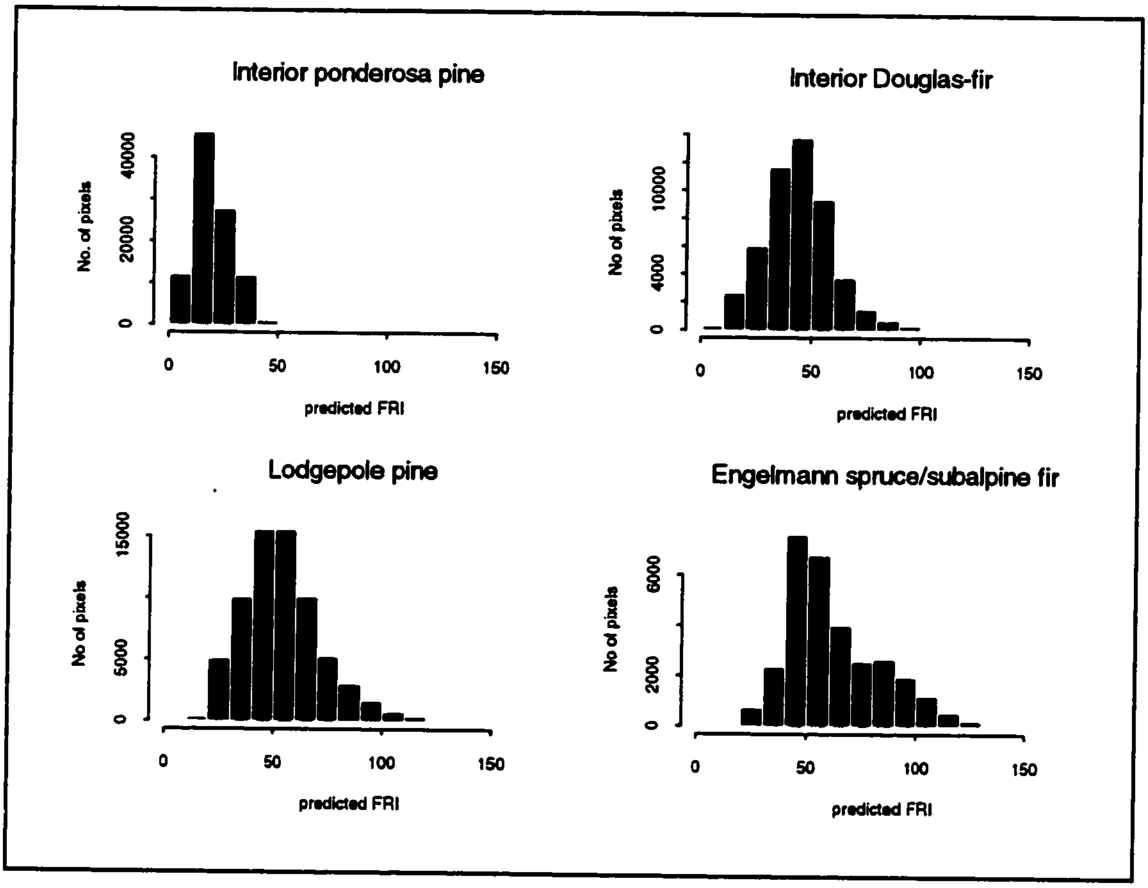


Figure 3.7: Examples of distributions of regional-scale predictions from the regression model for the four historical cover types (COVHs) most abundantly represented in the model database and the regional coverage (see Table 3.6).

MODEL APPLICATIONS

The regression model is evidently more robust than the tree-based model to extrapolation errors. I envision three applications for the current model, while recognizing that it needs to be continually revised as more fire history data are made available.

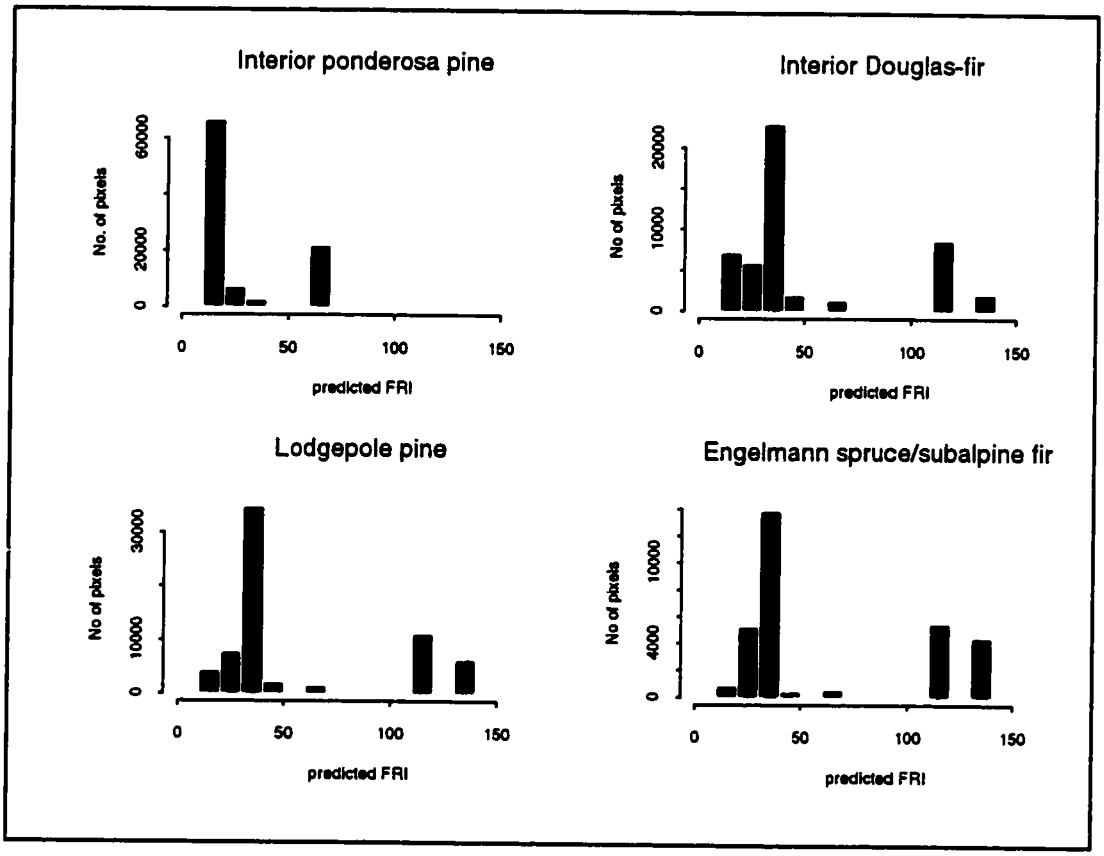


Figure 3.8: Examples of distributions of regional-scale predictions from the tree-based model for the four historical cover types (COVHs) most abundantly represented in the model database and the regional coverage (see Table 3.6).

First, it provides quantitative information where none existed previously. Most cells on the output map have no associated fire history data. Local managers will be able to integrate model predictions with local qualitative data and knowledge about systems similar to theirs to better estimate the historical natural range of variability of fire regimes. Model predictions can also be added to broader ecological inventories designed

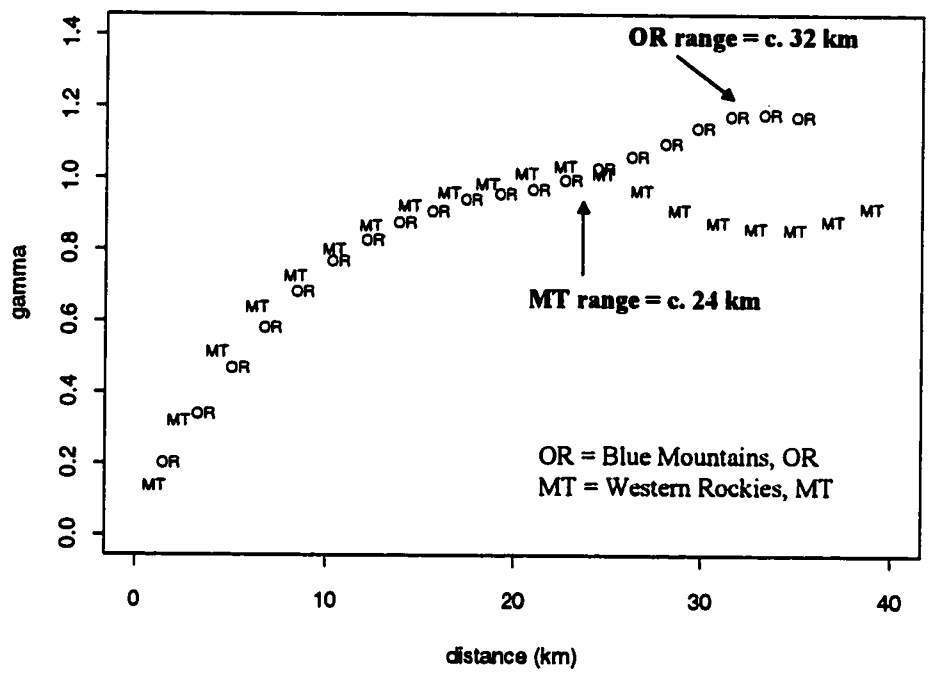


Figure 3.9: Variograms of FRI in two 60 x 60 km subsets of the output map from the regression model. MT = western Rocky Mountains, Montana. OR = Blue Mountains, Oregon. The ranges (24 km and 32 km, respectively) and the decrease beyond 24 km in MT probably reflect the scale of topographic variation in each landscape.

to assist ecosystem management (Keane et al. 1996c).

Second, it provides data to initialize spatially explicit, coarse-scale simulation models of fire behavior, fire effects, and succession. In mechanistic models (e.g., Keane et al. 1996a), predicted FRI values at each pixel could be used directly, or they could be taken as means of candidate distributions such as the Weibull (Johnson and Gutsell 1994) from which input FRIs could be chosen randomly. In cell-based models of disturbance on abstract landscapes (e.g., Turner et al. 1989, Turner and Romme 1994), patterns of FRIs taken from the regional map could be incorporated into measures of landscape connectivity and how that connectivity changes over time. The cell-based model could then be calibrated to real landscapes. For example, if each cell had the attribute "time-since-fire," its value could be derived from real data. Simulation output could be compared to that from model runs in which the time-since-fire was assigned randomly or according to formal rules.

Third, it demonstrates a methodology for integrating existing data and making coarse-scale predictions that, while not perfect, are relatively robust to aggregation error. Coarse-scale modeling will probably need to incorporate semi-qualitative elements for the foreseeable future (Keane and Long 1998, McKenzie 1998). The results suggest that heuristic, knowledge-based methods (quantifying vegetation types) and rigorous statistical methods can be successfully combined.

Finally, although the tree-based model probably should not be applied directly to broad-scale predictions, the model suggests that a quantitative understanding of how variables interact differently in different parts of their ranges should improve the explanatory power of models. For example, elevation affects the response of ponderosa pine more than does latitude (Figure 3.4 – left branch), whereas the opposite is true for other cover types in the model database. North of a certain latitude, differences in response are determined by elevation only (Figure 3.4 – right branch, right), whereas south of it, the response is determined by interactions of latitude and elevation (Figure 3.4 – right branch, left).

FUTURE DIRECTIONS

The models have implications for local fire management, simulation modeling, and ecological scale concepts. The output maps provide a coarse-scale component to local databases, and can be helpful in estimating characteristics of local fire regimes, particularly in the absence of local fire history information. For example, in forests that historically experienced high frequency, low severity fires, maps of historical mean fire return intervals can inform decadal-scale planning of prescribed burns and complementary silvicultural treatments. Similarly, in forests that experienced low frequency, high severity fires, the maps, in combination with records of fire sizes, can suggest the minimum dynamic area (Pickett and Thompson 1978) and appropriate temporal scales for management plans. Additions to the fire history database of stand reconstructions in this type of forest, for which there is currently a paucity of data, would undoubtedly make model predictions more accurate.

In coarse-scale modeling for which there are not adequate data to take a fully quantitative approach, the success of qualitative methods depends on the robustness of a heuristic, or knowledge-based approach (Schmoldt and Rauscher 1995). For example, Keane et al. (1996b) used a set of transition rules, based on expert knowledge, to model potential successional pathways in a regional-scale simulation model. Similarly, I used a qualitative clustering method to approximate the numerical contribution of vegetation types to estimates of FRI (Figures 3.3 and 3.4). Theoretical approaches exist for assessing the robustness of qualitative models (e.g., D'Ambrosio 1989); these methods need to be accessible to ecological modelers, because there may never be enough data to fully parameterize regional-scale models. Sensitivity analysis can also be performed for qualitative models (Puccia and Levins 1985), although it is likely to be more difficult to interpret.

Improvements in vegetation databases might allow models like ours to be fully quantitative. Vegetation classifications are frequently subjective or based on broad qualitative rules (Holdridge 1947, Küchler 1964, Eyre 1980, Bailey 1996). However, if the factors determining broad-scale vegetation patterns were known and could be mapped at the same scale as desired for vegetation maps, a vegetation type could be represented by a hypervolume in the multi-dimensional space of the determining factors, instead of by a heuristic rule. For example, Hargrove and Luxmoore (1998) developed a continental scale map of ecoregions at 1-km resolution. Each ecoregion is defined by a cluster of observations (pixels) in the three-dimensional space of the first three principal components of nine factors expected to determine potential vegetation. Such a classification is empirical, and its correlation to fire frequency can be numerically optimized.

An empirical classification could also be expressed probabilistically, in terms of fuzzy set membership. Doing so could alleviate the worst aspects of the aggregation problem. For example, a pixel that is classified as "Pacific silver fir" at the 1-km scale would be expected to have a different fire history if it were composed of 100% Pacific silver fir versus 60% Pacific silver fir and 40% Douglas-fir (Agee et al. 1990). In the latter case, its membership, at the species level, would be .6 in "Pacific silver fir", and .4 in "Douglas-fir". Two such pixels would not be adjacent in the multidimensional space described above, and the spatial aggregation to 1 km would not mask their differences or the different fire regimes associated with each.

The extent to which the contagious nature of fire can be incorporated into a coarse-scale fire frequency model is unknown. Landscape heterogeneity, including topography and the patchiness of vegetation and fuels, constrains fire sizes and therefore the expected extent of spatial autocorrelation of FRIs (Turner and Romme 1994, Agee 1998, Lertzman et al. 1998). I was unable to discern spatial autocorrelation among the sites in the existing fire history database, but new sampling designs for fire history reconstructions might address this problem. For example, if grids were established to measure point FRIs in different systems, autocorrelation structure could be more easily determined, and interpolated values could be compared to predictions from a model that assumes independence. This relationship, conditioned on suitable indices of landscape pattern, could estimate the extent of spatial autocorrelation expected in output maps, and thus provide a check on the reliability of models like those described in this chapter.

Ecosystem management is being applied under hierarchical frameworks at multiple spatial scales. Informed decisions are needed at increasingly broad spatial scales, but in most cases, detailed quantitative data are not, and may never be, available. Integration of existing databases, complementary use of qualitative and quantitative methods, resolution of scale incompatibilities in spatial data (Quattrochi and Goodchild 1997), and more efficient approaches to data collection will ensure the greatest improvement in our understanding of broad-scale interactions among fire, vegetation, and the physical environment.

CONCLUSIONS

No optimal strategy exists for modeling large-scale fire effects because of: 1) scale incompatibilities between input and output data, 2) uncertainties about aggregation error in extrapolating across spatial and temporal scales, 3) uncertainties about how to include the contagion properties of fire in modeling real landscapes, and 4) the stochastic nature of extreme events, which have unpredictable effects on vegetation at broad-scales. Scale incompatibilities have led to different strategies for extrapolation (Chapter 1), but quantification of error propagation in model aggregation is not a straightforward analytical process, except in the simplest linear systems (Cale 1995). Although there are reasons for preferring mechanistic models in modeling fire behavior and fire effects (Keane et al. 1996a, Schmoldt et al. 1998), the mechanisms that give rise to pattern usually change across scales (Levin 1992). Thus it is critical to understand the spatial and temporal across which mechanisms apply (Schneider 1998). The appropriateness of mechanistic models vs. statistical models, meta-models, or semi-qualitative models (Chapter 3) to answer particular questions depends on the quality and resolution of input data, the heterogeneity of the landscape on which models are applied (Lertzman et al. 1998), and on specific modeling objectives. Caution should be used in calibrating models that involve significant extrapolations in scale, because unrealistic projections from uncalibrated models at broad scales may be useful for revealing sources of aggregation error.

The effect of pattern on process in fire regimes of western North America is scale-dependent (Agee 1998). Thus, the contagion properties of landscapes, and how they change across scales and with different levels of fire severity, need to be understood more fully (Turner and Romme 1994). Various approaches have been used to model contagion, including mechanistic fire behavior models (Finney 1995, Coleman and

Sullivan 1997), percolation and fractal models on abstract landscapes (Beer and Enting 1990, Clarke et al. 1994), and stochastic cellular models on real landscapes (Vasconcelos and Guertin 1992, Turner and Romme 1994, Gardner et al. 1996). Coarse-scale models can be very sensitive to the extent and degree of contagion included in them (Keane and Long 1998). More evaluation of alternative approaches is needed before we can say whether, for example, a mechanistic fire-spread model, even with adequate data at large scales, is more accurate than stochastic modeling of statistical aggregates using a meta-model (McKenzie 1998).

Collaboration is needed between scientists and resource managers, and among fire scientists in different disciplines, to bring multidisciplinary expertise to scaling problems (Schmoldt et al. 1998). An unsolved problem is how to model extreme fire events, which affect vegetation structure and composition at scales that differ from those of ordinary events by orders of magnitude in time and space. Their intractability is typical of "middle-number" problems (Allen and Hoekstra 1992). Individually, they are stochastic, although clearly associated with extreme weather (Bessie and Johnson 1995). The time required to accumulate enough events to address their statistical properties (thousands of years) is outside the range for which there are adequate data on climate or fire extent.

The continental-scale qualitative model (Chapter 2) suggests that as fire becomes a more dominant factor in succession, large-scale vegetation patterns will become more homogeneous. Increased fire frequency can reset succession so that some stages are never reached. Model development revealed the wealth of information that can be gleaned from the fire-effects literature, but also the need for better continental-scale data. Empirically based approaches to classification (e.g., Hargrove and Luxmoore 1998) could provide a better basis for modeling than the aggregated Küchler types, or other partly subjective approaches (e.g., Holdridge 1947, Eyre 1980, Bailey 1996). Other aspects of fire regimes, such as the interaction of frequency with severity, and other disturbances such as human influences, need to be incorporated.

In coarse-scale applications, transition rules could be a fruitful alternative to mechanistic modeling of vegetation change with respect to fire. Transition thresholds would need to be quantified. For example, what change in fire return interval, fire frequency distribution, or mean fire "severity," precipitates a change in vegetation? A formal knowledge-based approach (Schmoldt and Rauscher 1995) could provide a model structure of manageable complexity. For example, the response of upper and lower treelines to changes in fire frequency, in conjunction with other limiting factors, might best be approached qualitatively. Depending on spatial resolution, multiple transition pathways would be needed in systems for which multiple successional pathways have been documented (e.g., Cattelino et al. 1979, Frelich and Reich 1995). Maps of fire return intervals (e.g., Chapter 3) associated with vegetation may provide an empirical basis for estimating possible transitions.

The regional scale model (Chapter 3) demonstrates the possibility of successful integration of quantitative and qualitative techniques when data are in different forms and not adequate to parameterize fully quantitative models. To ensure ongoing improvements in the quality of coarse-scale data, broad-scale objectives should determine some priorities for study areas. For example, some fire history studies should be initiated specifically to improve regional scale models – that is, with non-local objectives. A sparse grid of fire history sites, while not providing detailed local information, would cover more vegetation types and be capable of detecting spatial autocorrelation at broad scales. High-severity fire regimes may need creative methods for reconstructions going back through several fire cycles, because of the extreme variability likely in those systems (Romme 1982). Models that are successful at the point scale may not be applicable at a broad scale due to nonlinearities and discontinuities in extrapolation (e.g., the sequential prediction process in the tree-based model from Chapter 3). The models in Chapter 3 provide a simple, concrete example of the error propagation predicted by mathematical models (O'Neill 1979, Rastetter et al. 1992).

We need to understand how interactions between fire and vegetation change across scales, either mechanistically or stochastically. For example, life history strategies and response to variation in fire frequency distributions are important not only at small spatial scales, but also over long temporal scales (Clark 1996). How can vegetation be aggregated (e.g., Figure 1.1) from a small scale without losing components that are correlated with changes in fire regimes? For example, is dominant cover type (COVH, Chapter 3) really the best variable to associate with mean fire return intervals? Is mean fire return interval the appropriate scale-defined "mechanism" (sensu Levin 1992) at the "level" of cover type?

Coarse-scale fire-effects modeling needs to draw on other disciplines for new ideas and methods. Some of these approaches include:

1. Knowledge-based systems, providing a formal logic for modeling trends in qualitative data when quantitative data are not adequate (Schmoldt and Rauscher 1995).
2. Complex adaptive systems, providing a framework for modeling bi-directional or multi-directional effects, such as the interactions of fire and vegetation (Green 1994).
3. Meta-analysis, providing a framework for assimilating detailed models of fire behavior, fire initiation, fire effects, and contagion into meta-models (Hunter 1990).
4. Stochastic modeling, providing a sophisticated mathematical framework for integrating non-deterministic models (Guttorp 1995).
5. Meso-scale climatic modeling, providing a basis for regional-scale, long-range simulations of climatic data (Hsie 1987, Pielke et al. 1992).

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Zedler, P.H., C.R. Gautier, and G.S. McMaster. 1983. Vegetation change in response to extreme events: the effects of a short interval between fires in California chaparral and coastal shrub. Ecology. 64:809-818.

VITA

Don McKenzie
University of Washington
1998

EDUCATION

University of Washington, College of Forest Resources, Seattle, WA
Ph.D., Landscape Ecology, June 1998
Thesis title: Modeling large-scale fire effects: concepts and applications

M.S., Forest Biometrics, December 1994
Thesis title: Diameter growth equations and growth simulations for multi-cohort stands

University of California, Los Angeles, Los Angeles, CA
M.F.A., Music, June 1979

University of California, Berkeley, Berkeley, CA
B.A., Anthropology and Psychology, June 1974

RESEARCH EXPERIENCE

Graduate Research Assistant, University of Washington, 1992-1998

Modeling large-scale fire effects: Evaluated current approaches to extrapolating stand-level fire models to the broad spatial scales being addressed by management. Developed a qualitative rule-based approach to predicting vegetation changes at continental scales in response to altered fire regimes. Developed a GIS-based empirical model for predicting fire frequency for forested areas of the Interior Columbia River Basin.

Modeling understory shrub distributions: Developed generalized linear models for the distribution of common understory shrub species in the Pacific Northwest using an inventory database that spans three national forests in the Cascade Mountains. Using graphical analysis and resampling techniques, confirmed that certain species show unimodal responses to environmental gradients and demonstrated the scale-dependence of optimal predictive models.

A landscape-level simulation model of forest hydrology: Developed a simulation model, using the C language and raster-modeling routines in ARC-INFO, GRID module, to predict the differential effects of dispersed vs. aggregated logging patterns on debris-flow in a mountain watershed in western Washington.

RESEARCH EXPERIENCE (CONTINUED)

Growth modeling of Pacific Northwest conifer species: Built linear and non-linear models to predict diameter growth, height to live crown, and maximum stand density for four conifer species in old-growth and multi-cohort stands. Modified a simulation model to predict the effects on stand growth of varying levels of green-tree retention.

Modeling crown dynamics in silvicultural plantations: Developed non-linear regression models for predicting crown recession in Douglas-fir plantations in response to stand density, tree position (dominant vs. understory), and current crown dimensions.

Programming support: Developed code in the C and S languages, to assist research projects. These have included an analysis of productivity and diversity in Southeast Alaska, analysis of species-area relations in a large-scale silvicultural experiment in the Cascade Mountains, and a spatial analysis of the relationship of slope stability to logging patterns.

TEACHING EXPERIENCE

University of Washington, instructor, 1998
Co-teaching graduate seminar, "Ecological scale: theory and applications".

University of Washington, teaching assistant, 1996-1997
Graduate core course, "Forest ecosystem dynamics." Duties included grading papers and exams, lecturing, preparing course readings, organizing multi-day field trips.

Colorado College (Colorado Springs, CO) music faculty, 1979-1985

TECHNICAL AND COMPUTING SKILLS

Analysis: ecological scale concepts, geostatistics, spatial point patterns, ordination in community ecology, GIS modeling, nonlinear regression, classification and regression trees.

Programming languages: C, C++, S, Arc Macro Language, UNIX shell, HTML

Specialized software: ARC-INFO, ArcView, Splus, CANOCO

PUBLICATIONS

McKenzie, D. 1998. Fire, vegetation, and scale: toward optimal models for the Pacific Northwest. Northwest Science (*in press*).

McKenzie, D. and C.B. Halpern. 1998. Modeling understory shrub distributions in Pacific Northwest forests. Forest Ecology and Management (*in press*).

Schmoldt, D.L., D.L. Peterson, R.E. Keane, J.M. Lenihan, D. McKenzie, D.R. Weise, and D.V. Sandberg. 1998. Assessing the effects of fire disturbance on ecosystems: a scientific agenda for research and management. USDA Forest Service Gen. Tech. Rep. (*in press*).

Halpern, C.B., S.A. Evans, C.R. Nelson, D. McKenzie, D. Liguori, D.E. Hibbs, E.K. Zenner, and M.G. Halaj. Response of forest vegetation to varying levels and patterns of green-tree retention: an overview of a long-term experiment. Northwest Science (*in press*)

McKenzie, D., D.L. Peterson and E. Alvarado. 1996. Predicting the effect of fire on large-scale vegetation patterns in North America. USDA Forest Service Res. Pap. PNW-489, Pacific Northwest Research Station, Portland, Oregon.

McKenzie, D., D.L. Peterson and E. Alvarado. 1996. Extrapolation problems in modeling fire effects at large spatial scales: a review. International Journal of Wildland Fire 6(4): 165-176.

Maguire, D.A., J.L.F. Batista and D. McKenzie. 1993. Horizontal structure of uneven-aged mixed-species forests modeled as an inhomogeneous Poisson process. Proceedings of the IUFRO conference on Spatial Stochastic Processes in Forestry.

PRESENTATIONS

International Association for Landscape Ecology, annual meeting, Lansing MI, 1998
Spatial models of fire frequency for the Columbia River Basin: extrapolating local reconstructions to the regional scale.

Northwest Scientific Association, annual meeting, Olympia WA, 1998
Influences of vegetation and environmental factors on broad-scale patterns of fire frequency.

North American Forest Ecology Workshop, Raleigh NC, 1997
Predicting understory shrub distributions in Pacific Northwest forests.

Ecological Society of America, annual meeting, Providence RI, 1996
Modeling understory distributions on the Willamette National Forest, WA

Ecological Society of America, annual meeting, Snowbird UT, 1995
Predicting the effects of fire on large-scale vegetation patterns in North America.

PROFESSIONAL MEMBERSHIPS

Ecological Society of America
International Association for Landscape Ecology
Society for Conservation Biology
Natural Areas Association

REFERENCES

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Phone (206) 543- 2789 Fax (206) 543-3254
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