Donald McKenzie, University of Washington Field Station for Protected Area Research. College of Forest Resources. Box 352100, Seattle, Washington 98195-2100

Fire, Vegetation, and Scale: Toward Optimal Models for the Pacific Northwest

Abstract

There is great variability in frequency, severity, and spatial scales of fire in the Pacific Northwest. Because of steep gradients in elevation and precipitation in mountainous regions, fire regimes change rapidly with geographic distance. Coarse-scale fire models must account for internal spatial heterogeneity of fire behavior and fire effects. Most research on the effects of fire on vegetation has been conducted at small spatial scales; thus large-scale models must address the problem of aggregation, or scale extrapolation. Theoretical work has shown that, even within deterministic systems, there is persistent error associated with model aggregation unless model components are entirely homogeneous, but error minimization is relatively straightforward. When model components include stochastic elements, decision rules based on expert opinion, and qualitative elements such as vegetation classifications, errors propagate through the system in complex ways, and no single approach to scale extrapolation is inherently superior. I review the types and quality of empirical data available for large-scale fire modeling, and present a classification of strategies for extrapolating models to broad scales. An example is given of developing a spatial model of fire frequency in the Columbia River Basin from fire history databases and large-scale vegetation classifications.

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 and fire exclusion (Habeck 1985, Green 1989, Turner et al. 1989, Agee 1994, Baker 1995). In the past, extreme events, associated with anomalous weather patterns that increase landscape connectivity, have accounted for most of the area burned by fires (Pickford et al. 1980, Strauss et al. 1989, Johnson and Wowchuk 1993, Bessie and Johnson 1995). Extreme events are highly synchronous in time and space, and cause abrupt, large-scale changes in vegetation patterns.

Additionally, long-term 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). 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 (Fosberg et al. 1992, Baker 1995, Neilson 1995, McKenzie et al. 1996a). Simulation models used to predict large-scale vegetation change are driven by climatological variables (Neilson 1992, Running and Hunt 1993), but also need to incorporate the effects of fire, because fire often imposes critical constraints on vegetation. To date, continental-scale ecosystem process models have not successfully incorporated disturbance (Fosberg et al. 1992, Schimel et al. 1997). Data on the ecological effects of fire are not generally available at these scales, and most empirical research has been conducted at the forest stand level, although conclusions are often extrapolated to larger scales (McKenzie et al. 1996b). Similarly, most process-based fire-effects models have been built at 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). Spatially explicit mechanistic models that are applied at larger scales 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. 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.

The problem of extrapolation, or aggregation error, is substantial in heterogeneous environments, in which nonlinear relationships produce biased estimation of means (O'Neill 1979, King et al. 1990). Thus simple aggregation techniques based on a mean response are insufficient for accurate predictions. Some progress has been made in quantifying and minimizing extrapolation error in model ecosystems driven by differential equations (Cale et al. 1983, Iwasa et al. 1987, Gard 1988), but error propagation rapidly becomes problematic in complex natural systems (Cale 1995, Pahl-Wostl 1995). 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 source of aggregation error, and is related to 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).

Aggregation of fine scale components for broad scale predictions is necessary, however, 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. 1990).

The Pacific Northwest exemplifies the difficulties of extrapolating fire effects to large spatial scales. Steep gradients in elevation, precipitation, and temperature exist across multiple scales. The diversity of climatic conditions, topography and elevations supports a variety of ecosystem types, including coastal temperate rainforest, subalpine parkland and alpine meadows, drier mixed conifer forests, and semi-arid shrublands and grasslands (Daubenmire 1978, Lassoie et al. 1985). It also produces a variety of fire regimes (Agee 1993), including large, stand-replacing fires (Agee and Smith 1984, Huff 1984, Henderson et al. 1989), mixed severity, medium frequency fires (Morrison and Swanson 1990, Taylor and Halpern 1991), and non-lethal (to trees), high frequency fires (Bork 1985, Kertis 1986). It is difficult to associate fire regimes closely with particular forested vegetation types, because historical reconstructions have demonstrated significant within-type variability. However, broad-scale differences in fire frequency are evidently associated with different geographic areas and distinct environmental conditions (Table 1).

Is it possible to develop a conceptual framework for large-scale fire modeling applicable to the diverse ecosystems of the Pacific Northwest? Fire researchers have agreed that the "ideal" fire effects model would have the following attributes (Schmoldt et al. 1998):

- Be process-based, rather than statistically-based
- Be spatially explicit
- Be applicable over broad and fine scales

TABLE 1. Mean fire return interval (FRI) at selected geographic areas in the Pacific Northwest.

Location (dominant vegetation)	Mean FRI (years)	Source(s)
Eastern Cascade Range, Oregon (Ponderosa pine)	21	Multiple sources cited in Heyerdahl et al. (1995)
Wenatchee Mts., Washington (Douglas-fir/grand fir)	28	Wischnofske & Anderson (1983), Wright (1996)
Blue Mts., Oregon and Washington (multiple)	50	Bork (1984), Maruoka (1994)
Bitterroot Mts., Idaho & Montana (Subalpine fir/Douglas-fir)	92	Arno (1976, 1981)
East-north Cascade Range, Washington (Pacific silver fir/Douglas-fir)	146	Agee et al. (1990)
Mt. Rainier, Washington (Pacific silver fir)	407	Hemstrom and Franklin (1982)

- Be as modular as possible, while integrating fire behavior, fire effects, and succession
- Incorporate changing climate

In most cases, practical and theoretical considerations preclude the attainment of this ideal. For example, if a mechanistic model has been built locally with high-quality measurements of vegetation and climate, lack of empirical data for other geographic areas may preclude application of the model to other areas. As a result, "missing values" would confound aggregation methods.

In this paper, I examine the characteristics of three types of empirical data as they pertain to the aggregation problem. I refine a classification of extrapolation strategies for fire-effects modeling presented in McKenzie et al. (1996b), and suggest conditions under which each might be an effective strategy for minimizing errors. Choices are driven by the type and quality of available empirical data, and by modeling objectives. I provide an example of one strategy from ongoing research to develop a spatial model of fire frequency for the Interior Columbia River Basin.

Empirical Data for Fire-effects Models

Most fire-effects databases cover short time periods and small spatial scales, and have not been effectively integrated at a regional level (Schmoldt et al. 1998), although large-scale assessments have begun (Quigley et al. 1996, Sierra Nevada Ecosystem Project 1996). Often different types of data within a database are collected at different spatial and temporal scales. For example, weather data often are collected hourly, whereas successional data are collected at intervals of five years, or more. Thus, the *extent* and *resolution* of empirical data are important considerations. Additionally, the *spatial pattern* of sampled data may not reflect the spatial pattern of variability in the landscape being modeled. For example, when viewed at large spatial scales, data points will often be clustered, due to the local nature of most data collection (e.g., Figure 1). In such cases it is easy to underestimate the intrinsic variability of the data, and difficult to discern its autocorrelation structure (Rossi et al. 1992).

Empirical data that form the basis for fire/vegetation models are of three types: 1) climate data; 2) fire history reconstructions; and 3) vegetation, fuels, and topography data. Each entails key questions regarding extent, resolution, and spatial pattern, and presents key problems affecting the quality of data and its usefulness for modeling (Table 2).

Climate Data

Some fire-effects models rely on climate or weather data as basic drivers, either directly or indirectly. For example, fire spread models use hourly weather information (Finney 1995). In contrast, some successional models that incorporate fire use monthly means of temperature and precipitation to predict resulting species-specific growth responses. Tree growth is then used to predict stand structures and available fuels (Keane et al. 1989). Estimating climatic parameters at appropriate scales in the complex terrain of the Pacific Northwest is difficult, and current general circulation models have too broad a resolution to be applicable, although mesoscale models may help to bridge the gap (Hsie 1987, Pielke et al. 1992). Available methods for interpolation from weather stations are constrained to particular temporal scales (Hungerford et al. 1989, Daly et al. 1994). Statistical weather generators rely on time series from weather stations, and are subject to the same constraints as raw data (Schmoldt et al. 1998).

Projections of future climate need to be incorporated into predictions of future disturbance regimes, because future ignition patterns are expected to change with altered climates (Price and Rind 1994, Qu and Omi 1994). Interpolated predictions of current climatic parameters must provide baseline data for future projections for specific localities. Total error for future projections will be a function of error associated with extrapolation down in scale from regional climate models, and error associated with current interpolations.

Fire History Reconstructions

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).

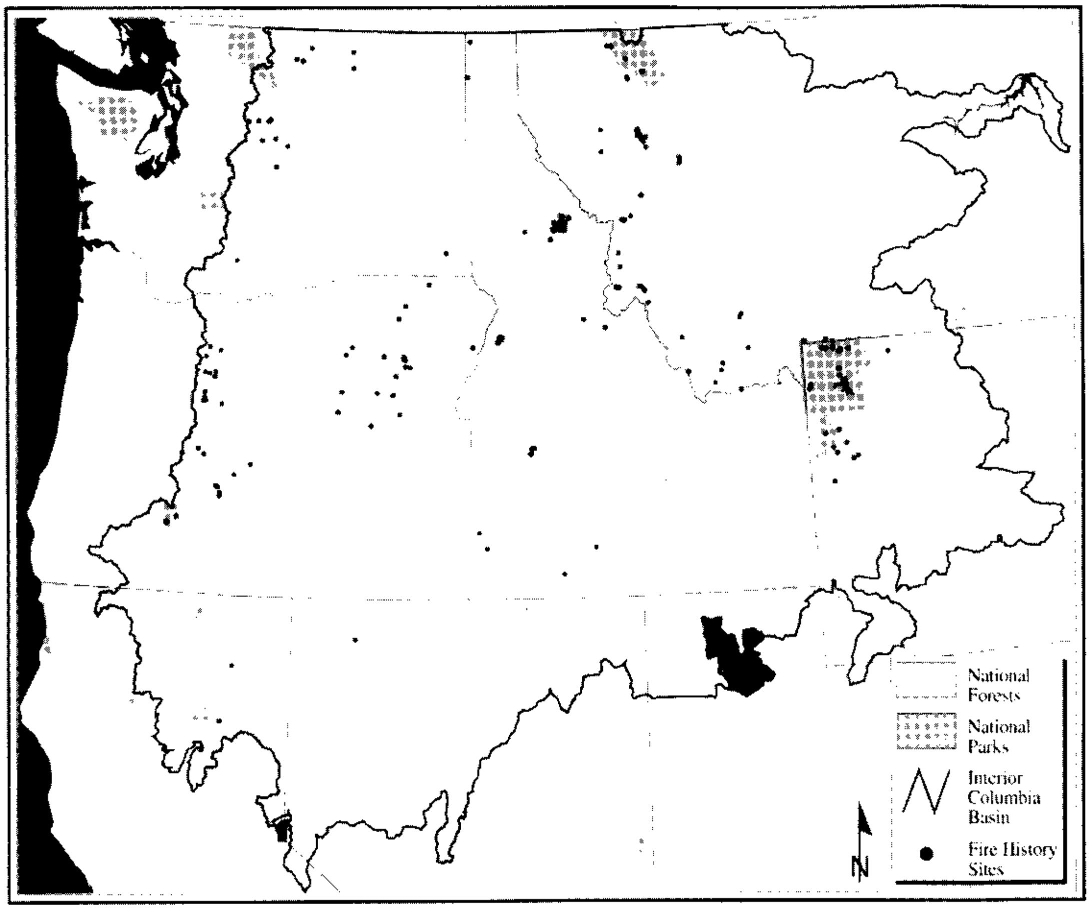

Figure 1. Locations of fire history sites (from Heyerdahl et al. 1995) in the Interior Columbia River Basin.

Reconstructions provide *local* information; models that use them as baseline data assume homogeneity of fire frequency over the geographic range that 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. In the Pacific Northwest, data points are clustered, and the extent and resolution 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. In particular, different successional pathways ensue in response to different sequences of time-since-fire (Cattelino et al. 1979, Frelich and Reich 1995, Clark 1996). Fire-effects models that are applied at broad scales will need to address this sensitivity by validating the choices of fire return intervals used in simulations.

Vegetation, Fuels, and Topography

There are a number of GIS-based vegetation classifications for the Pacific Northwest (Pacific Meridian Resources 1991, 1996, Morrison 1994, Quigley et al. 1996). Because of different objectives and methods (Adams et al. 1995, Moffett and Besag 1996), classifications even of the same area may be drastically different (Norheim 1996). Most fuel inventories are stand-based (Schmoldt et al. 1998), although large-scale databases are being developed (Loveland et al. 1991, Hardy et

TABLE 2. Characteristics of empirical data (resolution, extent, and spatial pattern) affecting the success of large-scale fire modeling, and key problems presented by each type of data.

Characteristic	Climate data	Fire history	Vegetation/fuels & topography
Resolution	Resolution of raw data (e.g. weather stations) vs. resolution of simulated input data for models (e.g. interpolated grids).	Sampling intensity may not be enough to capture small-scale variation.	Spatial resolution of remotely sensed data. Types are not all mapped with equal taxonomic resolution.
Extent	Raw climate data does not span the range of variability of modeled climate.	Fire history sites do not span the range of environmental variability of modeled sites.	Raw data do not span the range of variability of modeled data.
Spatial pattern	Placement of weather stations in complex terrain vs. regularity of gridded simulated data.	Heterogeneity of burn patterns vs. sampling pattern.	Patchy discontinuous fuels, and heterogeneous age-structures of vegetation.
Key problems	Interpolation or extrapolation in complex terrain. Time-step differences in raw data or statistical weather generators vs. models.	Fire scars not crossdated. Data points clustered, so difficult to interpolate. Costly and time-consuming. Difficult to assess stand histories.	Classification errors in remotely sensed data. Heterogeneity at scales critical for fire modeling is not captured. Data are often qualitative vs. quantitative, and site effects (biophysical factors) often not incorporated.

al. 1997). Classifications also exist for forest structural stage classes (Quigley et al. 1996) and fire regimes (Morgan et al. 1996). Digital elevation models are available at a variety of resolutions. The interactions of vegetation composition and structure with fuels and topography are critical for predicting fire effects.

Most of these large-scale classifications are qualitative, and therefore of limited use for quantitative models. Given the inconsistency of results and varying methodologies, attempts to derive quantitative data for process-based modeling from these coverages would be subject to significant biases. In some cases it may be preferable to make use of qualitative information as is, rather than transforming it to quantitative layers of questionable accuracy (see below).

Conceptual Approaches to Scaling Up Predictive Models

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. I have previously classified models for predicting the effects of fire on vegetation 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 (McKenzie et al. 1996b). Output from types (1) and (2) is frequently aggregated to larger scales, whereas in type (3) input data are often aggregated to the scale at which the model is applied. A fourth type of model may be useful at the ecoregional, or biome scale, for predicting aspects of fire regime or long-term effects of fire on vegetation. I will call these models semi-qualitative; they are often based partially, out of necessity, on expert opinion or subjective classifications instead of quantitative empirical research. Examples of these are fire regime classifications (Morgan et al. 1996),

TABLE 3. Advantages and disadvantages of methods for extrapolating fire effects to large spatial scales.

Method	Description	Advantages	Disadvantages
Extrapolating fire behavior models directly.	Extrapolating fire behavior models directly to biome scale before calculating fire effects.	Closed form mathematical expression available, amenable to existing methodologies. Straightforward translation into raster images.	No transient component, and major temporal scale incompatibilities. Developed at fine spatial scales incompatible with current ecosystem models.
Integrating models	Extrapolating up from fire/succession models. Additive, statistical, or process-based approach (see text).	Combines fire behavior with ecological processes (succession). Can accommodate variability among individual organisms (individual-based model).	No closed form mathematical expression possible. Spatial scale is restricted to sub-stand, and extrapolations require heavy computation, statistical modeling, or data-intensive calibration.
Landscape disturbance models	Aggregation of model inputs (landscape succession and disturbance models, including cellular automaton 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.
Semi-qualitative models	Qualitative rules and expert judgement built into model structure	Accepts wider range of inputs. Valuable when empirical data are not adequate for more quantitative methods.	Most difficult to calibrate, validate, test. Subjective choices involved that may not be repeatable.

successional pathway models based on decision rules (Fischer and Clayton 1983, Fischer and Bradley 1987, Bradley et al. 1992), large-scale successional models driven by such decision rules (Keane et al. 1996b, Keane and Long 1998), and rule-based models of transitions in vegetation types in response to changes in fire regimes (McKenzie et al. 1996a).

No single approach to coarse-scale modeling of fire effects is inherently superior; modeling objectives, computer resources, and the characteristics of specific systems determine the best strategy for each situation (McKenzie et al. 1996b). Each of the strategies outlined below has its advantages and disadvantages (Table 3), and each must address the loss of fine-scale heterogeneity and resulting increases in landscape connectivity and altered rates of fire spread (Agee 1998). Because fire is a "contagion" process, simulated fire spread and intensity at one site, or pixel, depend on characteristics of surrounding pixels. But as spatial resolution increases, adjacent pixels become more similar, thus artificially inflating the connectivity of landscapes. Similarity of adjacent pixels is scale-dependent, and this is a source of aggregation error for any modeling strategy that uses algorithms developed at smaller scales than those at which they are being applied.

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; Burgan and Rothermel 1984, Andrews 1986). In combination with fire effects models (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), but do not project ecological effects into the future. In order to drive a transient or dynamic predictive model, they need to be linked to projections of stand development.

Fire behavior models can be applied directly at any spatial scale, and a first-order fire effects model can be applied uniformly across each unit of vegetation being modeled (Kessell 1976, Neilson 1995). Input variables to the fire behavior model are 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 additive, or a more sophisticated analytical method may be used to produce landscape scale results (McKenzie et al. 1996b). Raster images from fire behavior models (Finney 1995) could be coupled with image analysis (Besag 1989) to model the distribution and range of first-order fire effects. This method is appropriate for equilibrium predictions, but not for modeling dynamic processes such as continuous vegetation change under altered fire regimes. It can be very useful, however, for demonstrating the need to incorporate disturbance into continental-scale models of vegetation distribution (Neilson 1995).

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). Most 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. More detailed biogeochemical modeling, however, may replace the individual tree-based growth algorithms in future successional models (Running and Hunt 1993, Keane et al. 1996a). 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.

Output from the successional model then needs to be aggregated to the spatial scale for which predictions are needed. This process is not amenable to the analytic methods that apply to mathematical models with closed functional forms (King 1991, Rastetter et al. 1992, Cale 1995). 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 (Hargrove 1994, Finney 1995, Gardner et al. 1996).

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 (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 (Keane et al. 1996a). Thus the mechanistic approach is preferable for large-scale application when data are available for initialization, but the magnitude of error will be difficult to determine when data are not available. In contrast, a statistical approach assumes some aggregation error, but error magnitude is controlled if distributions of biotic features on the landscape have been correctly parameterized (Acevedo et al. 1995).

Landscape Disturbance Models

Continuing advances in computer technology have made the computational burdens of spatially explicit models less formidable, thus much recent work has incorporated interactions between fire effects on vegetation and landscape pattern (Green 1989, Antonovski et al. 1992, Turner and Romme 1994, Baker 1995, Ratz 1995, Fall and Fall 1996, Gardner et al. 1996, Mladenoff et al. 1996). 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.

More abstract approaches that sacrifice the mechanistic elements of fire behavior models are useful for simulating the effect of landscape pattern on the spread of disturbance (Hogweg 1988, Green 1989, Turner et al. 1989, Turner and Romme 1994). In abstract models, disturbance is initiated at individual pixels stochastically, and its likelihood is 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, and final burning patterns are emphasized rather than mechanistic behavior or explicit spread rates (Green 1989, Turner and Romme 1994). Connectivity of landscapes and other constraints on the spread of disturbance can change drastically as a function of land use changes and altered disturbance regimes (Baker 1995), and model landscapes can be used to explore a wide range of possibilities.

In models using real landscapes, input data are often aggregated into broad categories (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 (e.g., Marsden 1983, Mladenoff et al. 1996). 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/susceptible, and deciduous/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 pixel size. For each ecological system and process being modeled, there may be a threshold grain size, below which it would be advantageous to consider aggregated data to be homogeneous, and above which these data might be better defined by statistical distributions of different aggregated types. For example, in subalpine forests of the Pacific Northwest, characterized by large-scale, stand replacing fires (Agee 1993), this grain size might be quite large, because large areas (pixels) 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.

This strategy is useful when spatially explicit outputs are desired (e.g., spatial patterns of age classes, or cover types), and therefore when the interaction of landscape patterns with fire is being specifically addressed (Agee 1998). What is lost by eschewing the mechanistic approach may be offset if spatial autocorrelation can be intergrated more directly into fire-effects models. The scale-dependence of inter-pixel similarity will confound attempts to implement mechanistic models at coarse scales, unless contagion properties within large pixels (that are aggregates of heterogeneous smaller units) can be represented statistically.

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, (2) build specific algorithms for dealing with contagion into large-scale mechanistic, or "process" modeling of fire effects and succession (Keane and Long 1998), or (3) include contagion implicitly by modeling fire severity (which is a function of abrupt changes in landscape connectivity) directly (Lenihan et al. 1998). Rule-based models on abstract landscapes (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. They can also test exhaustively the relationship between spatial scale and contagion in both neutral models (Gardner and O'Neill 1991) and models based on patterns of spatial heterogeneity found in real landscapes.

Semi-qualitative Models

There are no algorithms for minimizing error propagation in complex natural systems (Cale 1995). Errors propagate through systems 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). In many cases, statistical aggregates provide more information than detailed measurements at smaller scales (Levin 1992), and ecological patterns can be linked to ecosystem processes such as succession only at discrete scales (Bradshaw 1998). Thus, at some spatial scales quantitative aggregation rules may lead to an erroneous characterization of model input or output. In these situations combinations of quantitative and qualitative information may be required to optimize models.

Problems of Temporal Scale

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 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. A balance 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). Thus, it will be difficult to specify an ideal timestep for a particular spatial scale, because for each spatial scale, the processes being modeled will have disparate optimal timesteps.

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). Error propagation in aggregating temporally scaled processes may confound an otherwise efficient technique for spatial scale extrapolation. For example, 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.

Example: A Semi-qualitative Model of Broad-scale Fire Frequency

Fire frequency models for forest ecosystems depend on reconstructions of fire history (Johnson and Gutsell 1994), but fire history data are intensive rather than extensive. When viewed at broad spatial scales, data points are clustered, thereby exacerbating the difficulties of modeling. The spatial autocorrelation structure will be particularly hard to discern with clustered data (Isaaks and Srivastava 1989).

The Columbia River Basin scientific assessment includes a qualitative classification of fire regimes, both for frequency and severity (Morgan et al. 1996). GIS coverages for both these classifications exist. However, a quantitative coverage would be more useful for models of vegetation change that incorporate disturbance. The fire history database compiled by Heyerdahl et al. (1995) contains 211 data points inside the Interior Columbia River Basin (ICRB - Figure 1). The database includes mean fire return interval (FRI), elevation, and geographic coordinates. In addition, I have extracted the mean annual precipitation for each site from PRISM coverages (Daly et al. 1994), and associated each site with vegetation types from other GIS coverages, including four coverages from the Columbia River Basin assessment (Table 4). Thus each site in the fire history database has quantitative environmental data and qualitative vegetation data associated with it.

I have explored two quantitative methods for extrapolating from known data points to a fire frequency coverage for forested areas of the ICRB (McKenzie et al. 1997):

1. Multiple regression of fire return interval on mean annual precipitation and elevation. A good fit would suggest that the regression equation could be applied to any site whose biotic and abiotic characteristics were in the range of the sample data. This model had mixed results ($p < 0.001$, but $R^2 = 0.17$), and graphical analysis suggested that fire return intervals were underpredicted in the northeast of the ICRB and in Yellowstone National Park (Figure 2).

TABLE 4. Vegetation types from three classifications represented by sites in the fire history database for the Columbia River Basin.

Historical and current potential vegetation types (Keane et al. 1996b)	Historical and current cover types (Keane et al. 1996b)	Aggregated Küchler types (McKenzie et al. 1996a)
Alpine Shrub-Herbaceous	Alpine Tundra	Western Fir-spruce
Aspen	Aspen	Ponderosa Pine
Barren	Barren	Douglas-fir
Big Sage-Warm	Big Sagebrush	Great Basin Shrubland
Cedar/Hemlock East Cascades	Engelmann Spruce/Subalpine Fir	Mixed-grass Prairie
Cedar/Hemlock Inland	Fescue-Bunchgrass	Shortgrass Prairie
Dry Douglas-fir with Ponderosa pine	Grand Fir/White Fir	
Dry Douglas-fir without Ponderosa pine	Interior Douglas-fir	
Dry GrandFir/WhiteFir	Interior Ponderosa Pine	
Fescue Grassland with Conifer	Lodgepole Pine	
Grand Fir/White Fir East Cascades	Mixed Conifer Woodlands	
Grand Fir/White Fir Inland	Shrub or Herb/Tree Regeneration	
Interior Ponderosa Pine	Western Larch	
Moist Douglas-fir	Western Redcedar/Western Hemlock	
Mountain Big Sage-Mesic-East with Conifer	Western White Pine	
Pacific Silver Fir		
Spruce-Fir(LPP>WBP)[1]		
Spruce-Fir(WBP>LPP)		
Spruce-Fir Dry with Aspen		
Spruce-Fir Dry without Aspen		
Spruce-Fir Wet		

(1) LPP = Lodgepole pine. WBP = Whitebark pine

2. Spatial interpolation within clusters of points, using ordinary Kriging (Isaaks and Srivastava 1989). Although this method could not be used outside clusters, local response surfaces within clusters could be converted to GIS coverages. Variograms (not shown) 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 between neighboring points.

Given that no satisfactory quantitative method could be developed to predict fire frequency at new locations as a function of site variables, I am developing a semi-qualitative method, based on the idea that a multidimensional view of the influences on fire frequency, incorporating all available empirical data, should reduce the amount of unexplained variation exhibited by the simple regression model. Both qualitative and quantitative information will be synthesized to establish an overall measure of similarity among sites, under the assumption that because vegetation, climate, and disturbance are related, similar sites will have similar disturbance regimes. Thus a reasonable estimator of the fire frequency at one site is a weighted average of that at other sites, where the weights are intersite similarities.

Consider the vegetation classifications from Table 4. Similarity rankings of the types in each classification can be established, and represented numerically (J.K. Agee, *pers. comm.*). The similarity rankings can be based on expert opinion, as successional pathway models have been in previous applications (Bradley et al. 1992, Keane et al. 1996b). Thus each site in the fire history database will have a rank associated with it for each vegetation type, in addition to climatic factors (elevation and precipitation) and geographic coordinates.

These variables will constitute the columns of a data matrix whose dimensions can reduced by principal components analysis (Rencher 1996). Intersite distances in principal components space will provide a measure of similarity between sites for which the fire frequency is known. If a row vector of information (vegetation type rankings plus environmental variables) from a new site (any pixel in the ICRB) is added to the data matrix, a

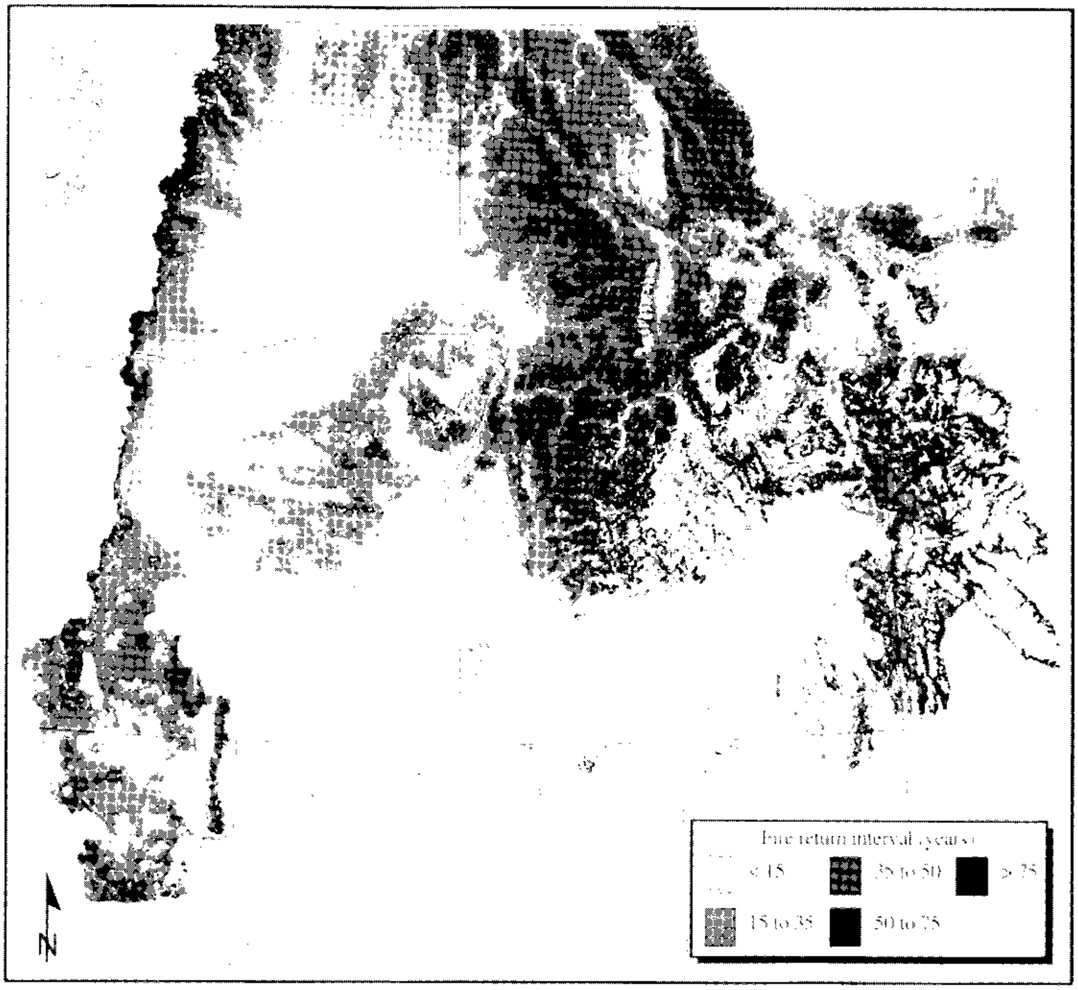

Figure 2. Estimated fire return intervals (FRIs) from the regression model for forested areas of the Interior Columbia River Basin. FRIs were only predicted for sites under 3000 m elevation and with less than 2700 mm annual precipitation.

new analysis will place that new site "nearby" similar sites in principal components space, and its fire frequency can be estimated as a weighted average of known sites.

Indirect methods to provide input data may be required as broad-scale fire-effects models are developed and refined. Fire frequency is only one of many inputs to models, but exemplifies the inadequacy of current databases for use in process-based or even rigorous statistical models. Methods such as the above can provide useful approximations when empirical data for initializing simulations at particular locales are lacking. In turn, a flexible semi-qualitative method can be refined as new empirical data are collected.

Conclusions

No strategy for large-scale fire modeling is superior for all situations. Process-based models may be preferable when the extent and quality of empirical data are adequate. Although much progress has been made in building databases, future modeling efforts will depend on filling gaps in theory, methodology, and empirical data (Schmoldt et al. 1998). In particular, fire history data are lacking for much of the Pacific Northwest, and methods and quality are inconsistent among completed studies. Changes in conceptual framework may be necessary as modeling moves to larger scales (Simard 1991). For example, more direct modeling of fire severity as a central element in large-scale vegetation composition may be required for proactive management (Strauss et al. 1989, Lenihan et al. 1998, Schmoldt et al. 1998). Also, since fire is a dominant factor in vegetation succession in much of the Northwest, fire may need to play a more central role in future successional models. Successional pathways are sensitive to small differences in fire regimes (e.g., variability, timing of severe events), life history strategies that respond to these differences (Clark 1996), and the spatial scale at which vegetation is modeled (Frelich and Reich 1995). Better linkages are needed between disturbance spread models and forest growth and succession models (but see Bevins and Andrews 1994, Keane et al. 1996a for initial efforts).

Spatial autocorrelation also needs to be integrated into fire-effects models. When contagion properties are added to coarse-scale models, burn patterns and subsequent age structures on the landscape are more realistic (Keane and Long 1998). A modeling approach that combines mechanistic algorithms that were developed at small scales with stochastic methods that operate on statistical aggregates of mechanistic results may prove fruitful. For example, statistical properties of multiple outputs of fire spread models (Finney 1995) or cellular automata (Hogweg 1988) may be used to parameterize coarse-scale stochastic models (R.E. Keane *pers comm*). Similarly, a metamodel 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, and 3) a coarse-scale model of fire effects and succession (McKenzie et al. 1996b).

In the Pacific Northwest, topography and environmental complexity magnify the errors in data aggregation. Better methods for assessing the statistical properties of data as they vary over heterogeneous landscapes will reduce extrapolation errors, and make large-scale predictions more accurate. Improved accuracy in the classification of satellite imagery will aid the validation of aggregation methods. It may also be possible to link satellite imagery with ground-based parameterization of basic ecosystem processes such as photosynthesis and evapotranspiration to quantify predictions of fire regimes at coarse scales (Keane et al. 1996c).

Finally, we need to make optimal use of data that currently exist. Because data exist in many forms (e.g., qualitative classifications vs. quantitative climate data), we need to continually refine the process of integrating different types of information. No rigorous method exists for quantifying aggregation errors in complex natural systems. Qualitative information, including expert opinion, will probably always play a part in large-scale models, even though it should be supplanted by quantitative methods as they are developed, and by empirical data as they become available.

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