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MAPPING FUELS AND FIRE REGIMES USING REMOTE SENSING, ECOSYSTEM SIMULATION, AND GRADIENT MODELING

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Abstract. Maps of fuels and fire regimes are essential for understanding ecological relationships between wildland fire and landscape structure, composition, and function, and for managing wildland fire hazard and risk with an ecosystem perspective. While critical for successful wildland fire management, there are no standard methods for creating these maps, and spatial data representing these important characteristics of wildland fire are lacking in many areas. We present an integrated approach for mapping fuels and fire regimes using extensive field sampling, remote sensing, ecosystem simulation, and biophysical gradient modeling to create predictive landscape maps of fuels and fire regimes. A main objective was to develop a standardized, repeatable system for creating these maps using spatial data describing important landscape gradients along with straightforward statistical methods. We developed a hierarchical approach to stratifying field sampling to ensure that samples represented variability in a wide variety of ecosystem processes. We used existing and derived spatial layers to develop a modeling database within a Geographic Information System that included 38 mapped variables describing gradients of physiography, spectral characteristics, weather, and biogeochemical cycles for a 5830-km^2 study area in northwestern Montana. Using general linear models, discriminant analysis, classification and regression trees, and logistic regression, we created maps of fuel load, fuel model, fire interval, and fire severity based on spatial predictive variables and response variables measured in the field. Independently evaluated accuracies ranged from 51 to 80%. Direct gradient modeling improved map accuracy significantly compared to maps based solely on indirect gradients. By focusing efforts on direct as opposed to indirect gradient modeling, our approach is easily adaptable to mapping potential future conditions under a range of possible management actions or climate scenarios. Our methods are an example of a standard yet flexible approach for mapping fuels and fire regimes over broad areas and at multiple scales. The resulting maps provide fine-grained, broad-scale information to spatially assess both ecosystem integrity and the hazards and risks of wildland fire when making decisions about how best to restore forests of the western United States to within historical ranges and variability.

Key words: ecosystem simulation; fire ecology; fire regimes; fuels; Geographic Information Systems; gradient modeling; predictive mapping; remote sensing.

INTRODUCTION

Wildland fire is a keystone ecosystem process affecting many landscapes of the western United States. It regulates succession by selecting and regenerating plants, maintains biodiversity, and entrains ecosystem and biogeochemical processes at multiple scales (Johnson 1992, Crutzen and Goldammer 1993, Swetnam and Betancourt 1998). Fire regimes describe the historical role of wildland fire in an ecosystem and integrate the frequency, severity, and spatial distribution of fires for specific landscapes over time (Mooney et al. 1981, Agee 1993, Morgan et al. 2001). Since the late 19th century, many forests in the interior western United States have been altered by the systematic and comprehensive exclusion of wildland fire (Covington et al. 1994, Leenhouts 1998). This legacy of fire exclusion has perturbed natural fire regimes and resulted in excessive accumulations of forest fuels, as vegetation that would have previously been consumed by fire remains unburned (Arno 1976, Habeck 1985, Allen et al. 2002, Keane et al. 2002*a*).

Wildland fire managers require spatially explicit, comprehensive information on fuels and fire regimes for long-term planning focused on restoring fuel and fire regime condition in high-risk areas to within pre-20th century ranges. Maps of fuels and fire regimes based on gradient modeling can provide information on the climatic or landscape variables and the potentially complex interactions between these variables that determine fire regimes at broad scales. While maps of fuels and fire regimes provide key information for effective fire management and ecological restoration, they exist for only a few areas, and standardized methods for economically and efficiently creating these maps do not exist (Keane et al. 2001, Morgan et al.

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2001). Mapping fuels and fire regime at landscape scales (1000s to 10 000s of km^2) generally requires advanced Geographic Information System (GIS) techniques and complex statistical analyses (Keane et al. 2001, Morgan et al. 2001). The difficulty of creating these maps is compounded by the complex spatial and temporal dynamics of wildland fire. A combined approach integrating extensive field databases, multiple sources of fire history information, remote sensing, and biophysical modeling to map fuels and fire regimes is recommended (Keane et al. 2001, Morgan et al. 2001).

Wildland fuels represent the biomass available for fire ignition and combustion in wildland fires and are the one parameter affecting wildland fire that humans can control (Rothermel 1972). ''Fuels'' are defined as the characteristics of live and dead biomass (e.g., mass and density) that contribute to the spread and intensity of wildland fire (Burgan and Rothermel 1984). Often, the term ''fuel load'' is used to describe the composition and physical characteristics of fuel for an area. However, adequate depiction of the fuel load is difficult and often a generalized description of fuel properties (the ''fuel model'') is used (Anderson 1982, Sandberg et al. 2001). Fuel models represent the typical fire behavior or fuel condition for a specific site. Current fuel models are limited to the prediction of fire behavior because they do not include sufficiently detailed information on fuel loadings or fuel moistures needed for fire effects calculations.

Most attempts at mapping fuels focus on mapping fuel models (or some other comprehensive description of fuels) using classifications of vegetation and biophysical setting (indices that integrate weather, topography, and site characteristics; Burgan 1996, Keane et al. 2001, Sandberg et al. 2001). There are many factors that limit the ability to map fuels. Most passive remotely sensed data (e.g., Landsat-TM, AVHRR, MODIS) are unable to detect surface fuels because these sensors generally cannot penetrate forest canopies (Lachowski et al. 1995). Even if airborne sensors could penetrate the canopy, it is difficult to distinguish between surface and canopy fuel sizes and categories using standard image processing techniques (Keane et al. 2001). Accurate fuel mapping is also confounded by the high spatial and temporal variability of fuels (Agee and Huff 1987). Fuel maps (fuel loadings or fuel models) represent single instances in a physical template affecting the spread and intensity of wildland fire that changes constantly over time.

The ''fire regime'' of an area represents the temporal variability in the physical characteristics and subsequent effects of wildland fire. Fire regimes are usually defined in terms of fire frequency, severity, size, and pattern. A fire regime is a general description of the role of fire for a specific area or ecosystem; it refers to the ''nature of fires occurring over an extended period of time'' (Brown 1995, Morgan et al. 2001). Fire regimes integrate complex interactions of fire, vegetation, climate, and topography (Agee 1993). The fire regime for a specific landscape influences the structure and abundance of fuel, thereby affecting fire behavior and fire effects over time. In this paper, fire regimes are described by fire interval and fire severity over the last 100–400 years. These descriptors of fire regimes are most important for predicting fire effects on landscapes and have been used in the majority of studies evaluating fire regimes (e.g., Barrett et al. 1991, Brown et al. 1994, Swetnam and Baisan 1996, Agee and Krusemark 2001, Morgan et al. 2001). Mean fire interval, the average number of years between fires for an area, is often used to quantify the frequency of fire for a landscape. Mean fire interval is a main focus of most research evaluating fire regimes because repeated fires are important determinants of the successional status of ecosystems and biogeochemical dynamics, and it is possible to reconstruct long fire histories for many ecosystems (e.g., Heinselman 1973, Arno 1980, Baisan and Swetnam 1990, Niklasson and Granström 2000, Heyerdahl et al. 2001).

Maps of historical fire intervals provide a temporal context for current conditions. Current landscapes with departures of one or more fire intervals have been used to (1) identify areas of low ecosystem integrity (Swetnam et al. 1999, Quigley et al. 2001), (2) identify areas with accumulating fuels (Brown et al. 1994, Hardy et al. 2001), (3) develop strategic fire management plans (Hardy et al. 2001, Morgan et al. 2001), and (4) prioritize areas for ecological restoration (Hardy and Arno 1996, Allen et al. 2002). Maps of fire intervals are also valuable for calibrating, parameterizing, and validating landscape–fire models that focus on how changing climate or management strategies will affect fire regimes and vegetation dynamics (vanWagtendonk 1985, Keane et al. 1996, Schmoldt et al. 1999).

Many efforts at mapping fire intervals across landscapes have involved expert systems that assign aggregated point estimates of fire frequency (e.g., from fire-scarred trees) to mapped vegetation types (Barrett et al. 1991, Brown et al. 1994, Swetnam and Baisan 1996). Uncertainties and biases that result from opportunistic sampling and fires that fail to scar trees limit the utility of some point-based data for extrapolating results over broad areas or entire vegetation types (Baker and Ehle 2001). There are a few recent, notable exceptions to this heuristic method for mapping landscape-scale fire history using point samples (McKenzie et al. 2000, Niklasson and Granström 2000, Heyerdahl et al. 2001, Falk 2003). Area frequencies or rotation periods are an expression of fire interval for a specific area and incorporate observed or reconstructed spatial patterns of fires. Fire rotation periods are usually estimated using stand age analysis (Johnson 1992, Agee 1993), remote sensing (Minnich 1983, Chou and Minnich 1990), or archival fire occurrence databases (McKelvey and Busse 1996, Rollins et al. 2001). The accuracy of mapped rotation periods is limited by the

difficulty of reconstructing old fire perimeters; the quality, extent, and difficulty of analyzing remotely sensed data; and the spatial and temporal precision and accuracy of fire occurrence databases (Morgan et al. 2001, Rollins et al. 2001).

In order to make inferences about how repeated fires affect ecosystems, it is important to know about ''fire severity'': the relative effects of an individual fire on an ecosystem. Fire severity has been evaluated in terms of a myriad of fire effects, including post-fire change in vegetation, soils, or hydrology (Wells et al. 1979, Ryan and Noste 1985, Lenihan et al. 1998, Robichaud 2000). Direct effects of fire severity include fuel consumption, crown scorch, soil heating, and bole charring (Reinhardt et al. 1997). The indirect effects of fire severity include tree mortality, change in landscape composition, and change in forest structure. These effects are influenced by a host of external factors, such as antecedent plant stresses, topography, soil properties, and disturbance history. In most cases, fire severity is quantified as the degree of vegetation mortality after a wildland fire (Agee 1993). For example, nonlethal fires burn in surface fuels without killing the overstory; $>$70% of the stand basal area and/or $>$90% of the overstory canopy cover remain after the fire (Morgan et al. 1996). Stand-replacing burns kill the majority of overstory vegetation and include lethal surface fires and active crown fires. In stand-replacement fires, $<$20% of the stand basal area and $\leq$10% of the canopy cover of overstory vegetation remain after the fire (Morgan et al. 1996). Mixed-severity fires include combinations of nonlethal and stand-replacement fires mixed in space and time. Passive crown fires (i.e., occasional torching of individual or groups of trees) and underburns are common in mixed severity burns. Typically, mixed-severity fire regimes are used to describe areas that experience fires of different severities over time (e.g., a stand-replacement fire followed by a nonlethal fire; Agee 1993, Morgan et al. 1996).

Most approaches for mapping fire severity after wildland fires use remotely sensed imagery (e.g., aerial photographs or satellite imagery) to assess vegetation mortality or landscape effects resulting from the heterogeneity of fire patterns (White et al. 1996, Medler and Yool 1997; C. H. Key and N. C. Benson, unpublished manuscript [''The normalized burn ratio (NBR)''; available online][2]). Mapping potential fire severity is more difficult, as it requires spatially explicit maps of weather and fuels (Burgan 1996, Bradshaw and Andrews 1997, Andrews and Williams 1998). Many models of potential fire severity involve coarse classifications of fire environment (e.g., fuel characteristics, weather, and topography), characteristics (e.g., ignition, spread, intensity, and extinction), and potential effects of fire (Bradshaw and Andrews 1997, Andrews and Williams 1998, Andrews and Queen 2001). Data quality, methods for spatially extrapolating data from networks of weather stations, and the low spatial resolution of satellite imagery for distinguishing fuel characteristics have limited efforts to map potential fire severity for fire management or ecological applications (e.g., fuels mitigation or ecosystem restoration; Andrews and Queen 2001). Together, mapped fire interval and potential fire severity represent an integration of factors that determine wildland fire regimes.

In this paper, we describe an approach that integrates extensive ecological field sampling, remote sensing, ecosystem simulation, and biophysical gradient modeling to map fuels and fire regimes across a large (5830 km^2) study area in northwestern Montana, USA. Our objectives are to evaluate the effectiveness of using indirect, direct, resource, and functional gradient modeling (Austin and Smith 1989, Müller 1998) along with a variety of multivariate statistical techniques for mapping fuel load (in kilograms per square meter), fuel model (Anderson 1982), fire interval (years), and potential fire severity (nonlethal, mixed, and stand replacement). Direct gradients, such as temperature and humidity, have direct physiological impact but are not ''consumed,'' by vegetation (Austin and Smith 1989). On the other hand, indirect gradients such as slope, aspect, and elevation have no direct physiological influence on plant dynamics (Austin and Smith 1989). The energy and matter used or consumed by plants, such as light, water, and nutrients, define resource gradients. Functional gradients describe the response of the biota to indirect, direct, and resource gradient types (Müller 1998). Included in this gradient category would be biomass and leaf area index (Müller 1998). The main strengths of our mapping approach include: (1) a standardized, repeatable method for sampling and database development for fuel and fire regime mapping; (2) a combination of remote sensing, ecosystem simulation, and gradient modeling to create predictive landscape models of fuels and fire regimes; (3) a robust, straightforward, statistical approach and accuracy assessment; and (4) the use of indirect, direct, resource, and functional gradient analysis for mapping fuels and fire regimes.

METHODS

Study area

The 5830-km^2 Kootenai River Basin (KRB) in northwestern Montana is bounded by Canada to the north, the Whitefish Range to the east, the Yaak River watershed to the west, and the Clark Fork River watershed to the south (Fig. 1). Climate is mostly modified maritime with mild, wet winters and warm, dry summers (Finklin 1987). The study area is a very productive northern Rocky Mountain landscape containing western hemlock (*Tsuga heterophylla*) and western red cedar (*Thuja plicata*) at low elevations on moist to wet sites (northerly aspects and stream bottoms). Mixed

[2] URL: ⟨http://www.nrmsc.usgs.gov/research/ndbr.htm⟩

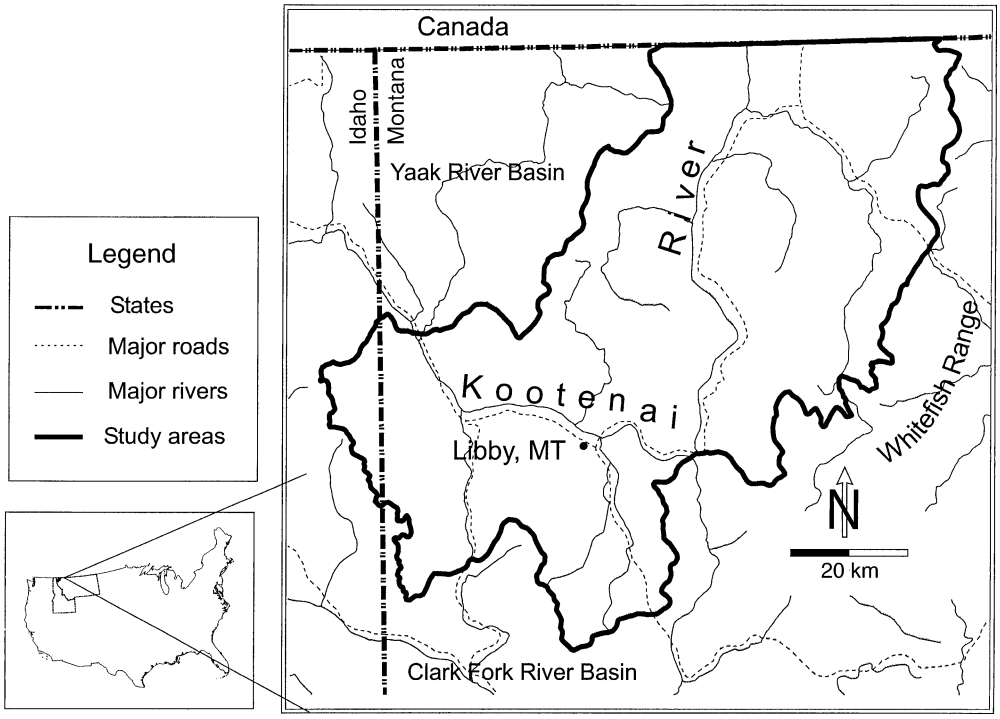

FIG. 1. The 5830-km^2 Kootenai River Basin study area in northwestern Montana, USA.

conifer forests of Douglas-fir (*Pseudotsuga* menziesii), western larch (*Larix occidentalis*), lodgepole pine (*Pinus contorta*), grand fir (*Abies grandis*) and, to some extent, western white pine (*Pinus monticola*) dominate the productive midelevation zones. Lower subalpine areas usually consist of subalpine fir (*Abies lasiocarpa*), spruce (*Picea engelmannii* and *Picea glauca*), mountain hemlock (*Tsuga mertensiana*), and lodgepole pine. Upper subalpine forests are mostly whitebark pine (*Pinus albicaulis*), subalpine fir, spruce, and small amounts of alpine larch (*Larix lyalli*). Permanent shrub and herblands are present at the highest elevations (>2000 m). A great portion of forested lands (~40%) in the Kootenai study area has been logged in the recent past (1950 to the present). Historically, fires were most frequent in dry valley bottoms in the northeastern half of the study area characterized by mixed Douglas-fir/ponderosa pine forests (Leavell 2000). Fires were least frequent in low, mesic forests comprised of western red cedar and western hemlock in the western portion of the KRB and high-elevation lodgepole pine/subalpine fir/spruce forests in the Cabinet and Yaak Mountains (Leavell 2000). Large, stand-replacement fires occurred infrequently in the KRB prior to European settlement (Arno 1980).

Sampling methods

A hierarchically structured, relevé-based sampling design was developed to inventory important ecosystem characteristics across the study area (Jensen et al. 1993; Fig. 2). Replicated, systematic sampling techniques were not employed in this study because the objective was to characterize ecological gradients for mapping purposes rather than to quantitatively describe plant composition for comparison or monitoring purposes. The field database was developed for five main objectives, (1) to serve as reference data for the classification of satellite imagery, (2) to provide initialization and parameterization data for simulation models, (3) to represent direct measurements of predictor variables along a range of environmental gradients, (4) to serve as response variables in predictive landscape models, and (5) to provide reference data for accuracy assessment of input data layers and resulting maps. Detailed description of this hierarchical sampling strategy may be found in Keane et al. (2002*b*).

Sampling locations were based on distributions of ecosystem processes across the KRB at multiple spatial scales (Gillison and Brewer 1985; Fig. 2). Landscape composition and function were represented using a set of environmental surrogates (elevation, mean annual precipitation, mean annual temperature, existing vegetation, and habitat type) mapped prior to sampling and easily identified in the field. Spatial data describing these surrogates were created using ecosystem simulation, GIS modeling, and expert systems (Quigley et al. 1996). We assumed that the surrogate variables selected for landscape stratification in this study would adequately represent the myriad of other ecological processes (e.g., carbon budget, hydrological cycle, nitrogen cycle) that potentially influence the spatial distribution of fuels and fire regimes.

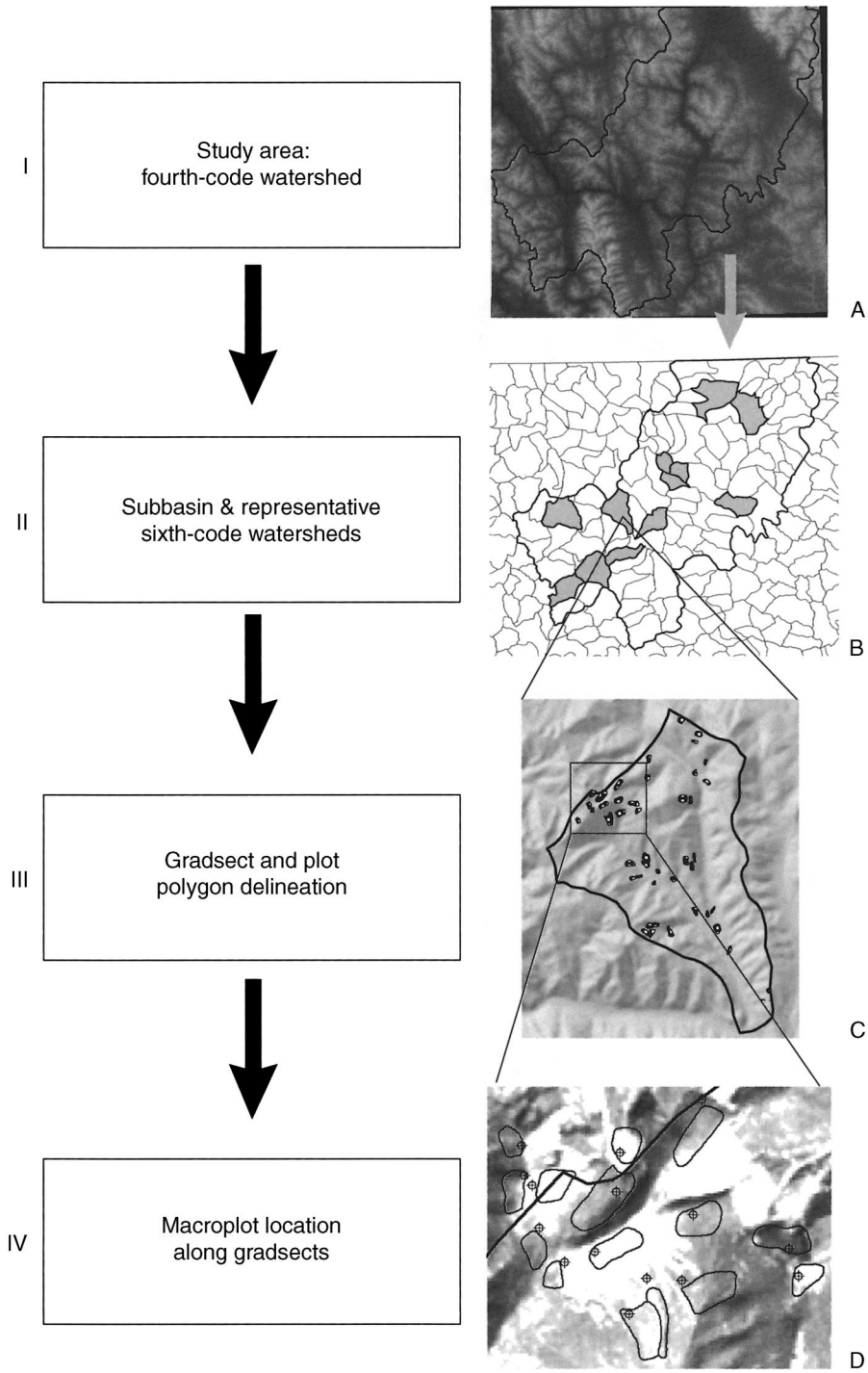

FIG. 2. Levels in the hierarchical sampling stratification used along biophysical gradients in the Kootenai River Basin. Fourth-code and sixth-code refer to Hydrologic Unit Codes, a nested classification of watersheds and subbasins. Sixth-code watersheds are nested within fourth-code watersheds. Subbasins were selected for sampling based on climate and physiography data from the Interior Columbia River Basin Ecosystem Management project. Plot polygons were delineated using aerial photography, and matrix worksheets were used to assure that plots represented the variability within subbasins.

The KRB was divided into ''subbasins'' based on watersheds delineated at the sixth-code level (Fig. 2). Fourth-code and sixth-code refer to Hydrologic Unit Codes, a nested classification of watersheds and subbasins (Quigley et al. 1996). Sixth-code watersheds are nested within fourth-code watersheds. Subbasins were selected for sampling based on climate, physiography, and accessibility. Mean annual precipitation and temperature maps (1-km^2 resolution) represented climate for determining the subbasins to sample (Quigley et al. 1996; Fig. 3). Physiography was mapped using regional delineations of subsections (Bailey 1995), land type associations (J. A. Nesser and G. L. Ford, *unpublished manuscript*), and STATSGO soil data layers (Soil Conservation Service 1991). Accessibility was assessed from digital road and trail data obtained from the Kootenai National Forest Headquarters (Libby, Montana, USA). Combinations of climate and physiographic data served as surrogates for approximating the distribution of ecosystem processes related to landscape composition, structure, and function (Booth et al. 1989, Stephenson 1998). Twelve subbasins were selected for sampling based on these criteria (Fig. 2).

The next level in the hierarchical sampling scheme was the delineation of ''plot polygons'' along gradsects within subbasins. ''Gradsects'' are transects that traverse diverse environmental conditions (Gillison and Brewer 1985, Bourgeron et al. 1994; Fig. 2). Plot polygons, defined as areas with homogeneous ecological conditions (Fig. 2), were selected to represent important ecosystem processes (e.g., productivity) within the selected subbasins, and they guided the process of plot location in the field. Aerial photos, digital orthophoto quadrangles, and 7.5-minute topographical maps were used to detect areas of similar elevation, aspect, existing vegetation, and structural stage along each gradsect within the subbasins selected for sampling. Matrix worksheets and field maps of sample plots by elevation, aspect class, existing vegetation, and structural stage were used to balance plot polygon sample locations across major biophysical and disturbance gradients within each sampled subbasin.

Georeferenced ''macroplots,'' the finest sampling units, were established within each delineated plot polygon to evaluate stand characteristics (Fig. 2). It was assumed that ecological conditions within a macroplot were representative of ecological conditions of the entire plot polygon (Mueller-Dombois and Ellenburg 1974). These circular, 0.04-ha macroplots were established $\geq$50 m from any edge that represented a distinct boundary between cover types or structural stages. Modified and standardized ECODATA methods were used to sample ecological characteristics within the macroplot. ECODATA consists of a wide variety of sampling methods, plot forms, databases, and analysis programs that may be integrated to design specific inventory and analysis application (Keane et al. 1990, Jensen et al. 1993).

Details of the sampling procedures are presented in the ECODATA handbook (Keane et al. 1990, Jensen et al. 1993) and only an overview will be discussed here (Table 1). Variables measured at each plot included elevation, aspect, slope, soil characteristics, and habitat type (Pfister et al. 1977). Geographical position was recorded using a global positioning system. Cover and height of all vascular and nonvascular (mosses and lichens) plant species were estimated using plant composition methods (Keane et al. 1990, Jensen et al. 1993). Fuels were described using the ECODATA procedures recording fuel loadings, Anderson fuel model (Anderson 1982), and live fuel, dead fuel, duff, and litter depths. Ecophysiological measurements were taken using specialized methods developed for this study. These data included leaf area index, leaf longevity by tree species, soil water holding capacity, and fire regime classification. Eight crews of two people each collected data on 372 plots during four 10-day field campaigns. Measurements requiring extensive expertise such as fire regime and soil characterization were performed by two highly trained people to ensure consistency in estimations.

ECODATA disturbance history methods (Keane et al. 1990, Jensen et al. 1993) were used to estimate fire interval for three general fire severity classes: nonlethal surface fire, mixed-severity fire, and stand-replacement fire. An experienced fire ecologist determined fire intervals at each plot to insure consistency of estimations. Fire intervals were estimated for each plot based on age structure and other historical evidence of fire (e.g., fire scars, charred woody debris, etc.). Fire intervals were estimated for nonlethal fire regimes by searching the plot polygon and surrounding areas for fire scarred trees. Where available, fire scars were sampled using a chain saw and fire interval estimated using ring counts (Arno and Sneck 1977). For areas with mixed-severity fire regimes, fire return intervals were based on age structure within each stand. Fire intervals for both mixed-severity and stand-replacement fire regimes were estimated by evaluating age differences between tree cohorts using increment cores and tree-ring counts (Arno and Sneck 1977). The period of record for these estimates varied depending on disturbance or land use history of each plot. In many cases, previous disturbances or land use practices had consumed all but the most recent evidence of past fires. In these cases, fire intervals were estimated based on evidence of historical fire on stump surfaces, stand successional status, tree ages in adjacent stands, and nearby evidence of past fires. Estimated fire intervals were assumed to represent fire regimes in the study area over the last 100–400 years.

Spatial and ECODATA field databases

Predictive landscape modeling requires high quality spatial data to serve as predictor variables over the entire study area (Franklin 1995). For this study, a GIS

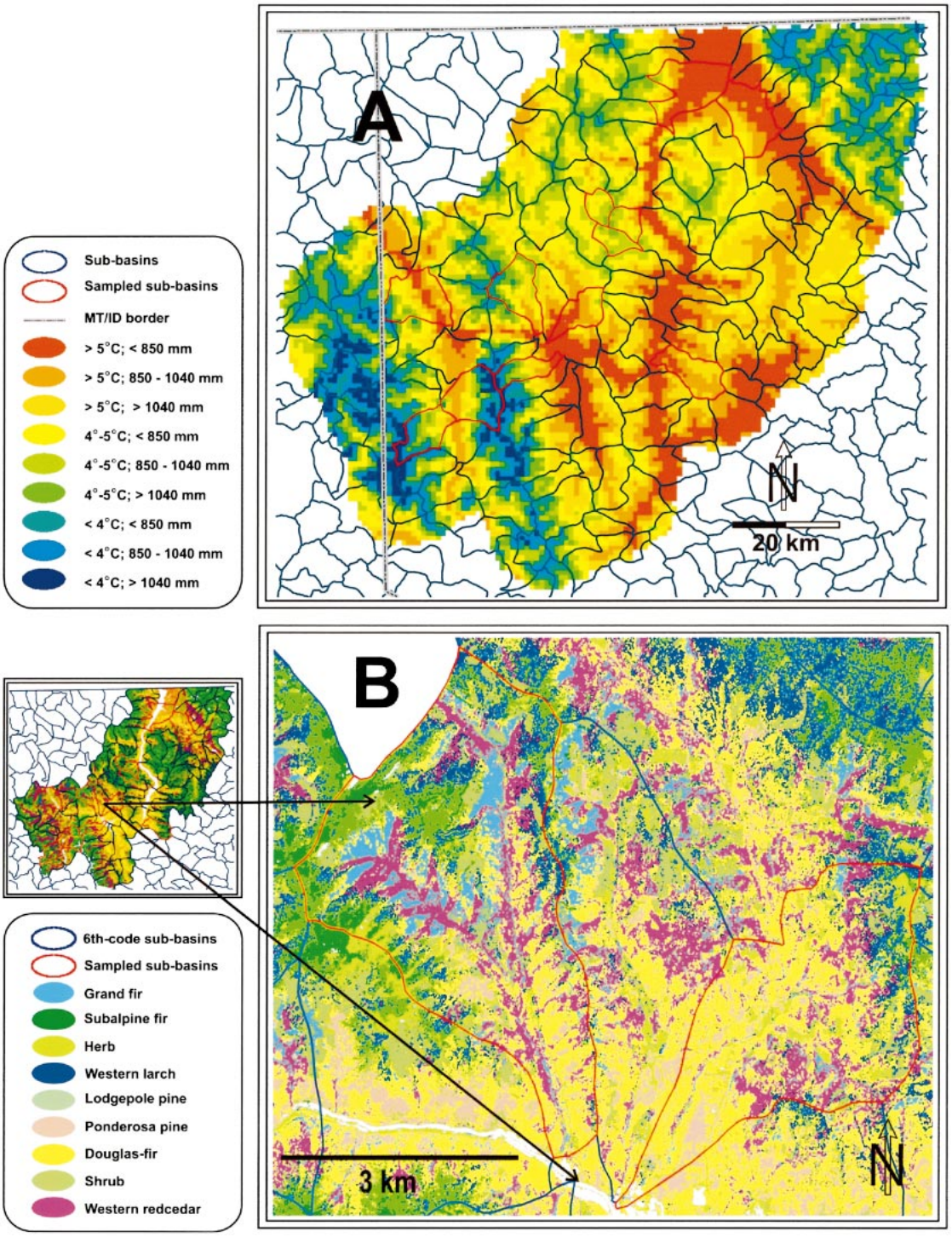

FIG. 3. Panel A: Climate data used for selecting subbasins for sampling. Colors represent different permutations of mean annual temperature and precipitation. Panel B: Landscape polygons used for extrapolating simulation output across the entire Kootenai River Basin. Classes were based on cluster analysis of plot data using percent cover of dominant tree species. Developed areas, snow and ice, and areas covered in cloud were removed from consideration and masked from the final maps. Polygons were delineated using fuzzy classification techniques.

TABLE 1. List of measured, summarized, and simulated data in the ECODATA field database.

Data level	Database name	Description	Reliability
Field data	location linkage	geographical information	highest
	general data	general site and vegetation information	
	disturbance history	record of all disturbance events	
	plant composition	species cover and height by size class	
	downed woody	fuel information	
	tree data	individual tree measurements	
	disease and insects	insect and pathogen information	
	optional data	ecosystem and biophysical information	
Summarized data	fuels	computed fuel loadings	highest
	tree and stand data	computed stand and tree characteristics	
Parameter data	GMRS-BGC parameters	ecophysiological parameters for Gradient Modeling Remote Sensing–Biological Geochemical Cycles (GMRS-BGC)	moderate
	BGC initialization WX-GMRS initialization	initializations for GMRS-BGC inputs and parameters for Weather–Gradient Modeling Remote Sensing (WX-GMRS) program	
Simulated data	GMRS-BGC output file	mean annual output from GMRS-BGC	lowest
	WX-GMRS output file	summarized simulated weather from WX-GRMS	

Notes: Information reliability is a qualitative assessment based on how far the data are removed from measured data. GMRS-BGC and WX-GMRS are mechanistic biogeochemical and weather models used for mapping direct and resource gradients.

containing 38 data layers describing physiographic, spectral, weather, and ecophysiological gradients was compiled to serve as landscape-scale variables in statistical models predicting fuels and fire regimes over the KRB (Table 2). These 38 variables were selected to represent important ecological gradients that either influence or are affected by different fuel assemblages and fire regimes based on a preliminary analysis of the field data. Examples include the effects of aspect (azimuth) and slope (percentage) because they relate to the transfer of heat energy from flaming fronts, and precipitation and temperature effects on fuel assemblages and antecedent moistures. Spectral gradients can provide information about the biomass available for combustion. Each spatial data layer in this study was compiled as an Arc/Info grid in the UTM projection (zone 11), using the NAD1927 datum (Arc/Info version 7.2.2, Environmental Systems Research Institute, Redlands, California, USA).

The physiographic gradient layers (Table 2) of elevation (in meters), aspect (azimuth), slope (percentage), profile curvature (curvature along the direction of the slope), and planform curvature (curvature perpendicular to the direction of the slope) were derived from Digital Elevation Models (DEMs) obtained from the National Elevation Database (available online).[3] Soil depth and soil texture data (percentages of sand, silt, and clay used in simulation modeling) were derived from field data, DEMs, STATSGO soil data, and hydrological modeling (Beven and Kirkby 1979, Soil Conservation Service 1991, Zheng et al. 1996).

We used Landsat-Thematic Mapper 5 (TM5) satellite imagery obtained from the Earth Resources Observation Systems (EROS) Data Center in August of 1995 to represent spectral gradients in the Kootenai River Basin in two ways (Table 2). First, the TM5 scene was used to derive raw reflectance, spectral transformations, and ancillary parameters as spatial predictor variables for mapping fuels and fire regimes. At-sensor reflectance (REFLC1-REFLC7), spectral principle components (PCA1, PCA2, and PCA3), Kauth-Thomas transformations (BRIGHT, GREEN, WET), Modified Normalized Difference Vegetation Index (MNDVI), and Leaf Area Index (LAI) were derived from the imagery and used as predictor variables in models of fuels and fire regime (Kauth and Thomas 1976, Markham and Barker 1986, Nemani et al. 1993).

The TM5 imagery was used to delineate ''landscape polygons,'' an additional landscape unit that was used to spatially extrapolate many mechanistically simulated weather and biogeochemical variables across the entire study area (Fig. 3). In this regard, landscape polygons represented a simulation unit, rather than a sampling unit (plot polygons). There is one-to-one correspondence between macroplots and plot polygons and one-to-many correspondence between macroplots and landscape polygons. To delineate landscape polygons, macroplots were clustered into nine ecologically distinct classes (Fig. 3). Macroplots representing each class were used as a spectral signature database, along with the satellite imagery, elevation, and aspect in a supervised classification routine based on fuzzy algorithms within the Earth Resource Data Analysis System (ERDAS) Imagine image processing software (version 8.4, Earth Resource Data Analysis System, Atlanta, Georgia, USA; Fahsi et al. 2000; Fig. 3). Accuracy for the resultant landscape polygon classification for extrapolation of simulation results was 67% ($\hat{K} = 0.56$).

Three mechanistic ecosystem models were used to simulate weather and ecophysiological gradients for each landscape polygon over the entire KRB landscape.

[3] URL: ⟨http://edcnts12.cr.usgs.gov/ned/default.asp⟩

TABLE 2. Spatial data layers representing physiographic, spectral, weather, and biogeochemical variables used to map fuels and fire regimes over the entire Kootenai River Basin.

Layer type Layer name	Description	Source
Physiographic		
DEM	digital elevation model	USGS†
SLOPE	slope, in percent, derived from DEM	USGS†
ASPECT	direction of exposure in azimuths	USGS†
CURVE	relative concavity/convexity	derived‡
PLAN_CURVE	curvature in the direction of slope	derived‡
PSAND*	percent of sand in soil	Soil Conservation Service (1991)
PSILT*	percent of silt in soil	Soil Conservation Service (1991)
PCLAY*	percent of clay in soil	Soil Conservation Service (1991)
SDEPTH	depth to bedrock	derived (Zheng et al. 1996)
Spectral		
REFLC1	TM5 At-sensor reflectance, band 1	derived (Markham and Barker 1986)
REFLC2	TM5 At-sensor reflectance, band 2	derived (Markham and Barker 1986)
REFLC3	TM5 At-sensor reflectance, band 3	derived (Markham and Barker 1986)
REFLC4	TM5 At-sensor reflectance, band 4	derived (Markham and Barker 1986)
REFLC5	TM5 At-sensor reflectance, band 5	derived (Markham and Barker 1986)
REFLC7	TM5 At-sensor reflectance, band 7	derived (Markham and Barker 1986)
PCA1	principal component #1 of TM5 bands	derived§
PCA2	principal component #2 of TM5 bands	derived§
PCA3	principal component #3 of TM5 bands	derived§
BRIGHT	Kauth-Thomas transform of TM5 bands	derived (Kauth and Thomas 1976)
GREEN	Kauth-Thomas transform of TM5 bands	derived (Kauth and Thomas 1976)
WET	Kauth-Thomas transform of TM5 bands	derived (Kauth and Thomas 1976)
LAI	leaf area index (m^2/m^2)	derived (Nemani et al. 1993)
MNDVI	modified normalized difference vegetation index	derived (Nemani et al. 1993)
Weather		
PET	mean annual potential evapotranspiration (m)	derived (WX-GMRS)
PPT	mean annual precipitation (cm/yr)	derived (WX-GMRS)
SRAD	mean annual daily solar radiation (kJ m^{-2} day^{-1})	derived (WX-GMRS)
TAVE	mean annual average temp. (°C)	derived (WX-GMRS)
TDEW	mean annual dewpoint temp. (°C)	derived (WX-GMRS)
TMIN	mean annual minimum temp. (°C)	derived (WX-GMRS)
TMAX	mean annual maximum temp. (°C)	derived (WX-GMRS)
TSOIL	mean annual soil temp. (°C)	derived (WX-GMRS)
VPD	mean annual vapor pressure deficit (mbar)	derived (WX-GMRS)
Ecophysiological		
NPP	net primary productivity (kg C/m^2)	derived (GMRS-BGC)
NEP	net ecosystem production (kg C/m^2)	derived (GMRS-BGC)
ER	ecosystem respiration (kg C/m^2)	derived (GMRS-BGC)
AR	autotrophic respiration (kg C/m^2)	derived (GMRS-BGC)
MR	maintenance respiration (kg C/m^2)	derived (GMRS-BGC)
OUTFL	outflow (kg H_2O/m^2)	derived (GMRS-BGC)

Notes: Data were either obtained from existing sources or derived using GIS, image processing software, or ecosystem simulation programs. WX-GMRS indicates Weather–Gradient Modeling Remote Sensing, and GMRS-BGC indicates Gradient Modeling Remote Sensing–Biological Geochemical Cycles.

† Available online, URL: ⟨http://edcnts12.cr.usgs.gov/ned/default.asp⟩.

‡Derived using Arc/Info, version 7.2.2 (Environmental Systems Research Institute, Redlands, California, USA).

§ Derived using Imagine, version 8.4 (Earth Resource Data Analysis System, Atlanta, Georgia, USA).

These models were: DAYMET (Thornton et al. 1997), WX-GMRS (Weather–Gradient Modeling Remote Sensing; Keane et al. 2002*b*), and GMRS-BGC (Gradient Modeling Remote Sensing–Biological Geochemical Cycles; Running and Hunt 1993, Keane et al. 2002*b*). Each simulation model was parameterized using data representing site characteristics and ecophysiological rates and constants, the majority of which were taken directly from the ECODATA field database. Model parameters that were not sampled during the field campaigns were taken from the literature or existing databases (see Keane et al. 1996). Each landscape polygon was assigned a parameter list for initialization of each simulation model (DAYMET, WX-GMRS, and GMRS-BGC).

Weather was computed for each landscape polygon using the DAYMET program developed by Thornton et al. (1997). Daily weather values of maximum and minimum temperature, relative humidity, precipitation, and solar radiation (TMAX, TMIN, RH, precipitation, and SRAD) are calculated across each study area using physiographic relationships and adiabatic lapse rates to extrapolate 20 years of weather data from eight weather stations located in and around the study area. Outputs

from DAYMET were used as input for WX-GMRS and GMRS-BGC to create other spatial databases. WX-GMRS was used to summarize daily weather sequences computed by DAYMET into integrated measures of local weather and climate (e.g., mean temperature, precipitation, and vapor pressure deficit) for each landscape polygon for the duration of the fire season in northwestern Montana (May–October). WX-GMRS summaries represent potentially useful predictive direct gradients, such as potential evapotranspiration, soil water potential, and vapor pressure deficit.

Important ecophysiological gradients were simulated using GMRS-BGC, a modification of BIOME-BGC, developed by Running and Hunt (1993) and Thornton (1998). GMRS-BGC simulates fluxes of carbon, nitrogen, and water at the stand level using mechanistic biogeochemical functions. GMRS-BGC was executed for 250–350 years to allow conditions in the model to equilibrate with input weather data (cycled every 20 years) and 100 more years to obtain mean annual output. Output from WX-GMRS (May–October) and GMRS-BGC (entire year) were summarized for each landscape polygon, then compiled as separate spatial data layers (raster grids). These layers served as predictive variables in the process of mapping fuels and fire regimes. For example, DAYMET calculated daily precipitation, temperature, and relative humidity for each landscape polygon from 20 years of daily weather data. WX-GMRS summarized these daily data to values of precipitation, minimum and maximum temperature, and relative humidity for the May–October fire season. In another example, mean annual net primary productivity for each landscape polygon was calculated from GMRS-BGC using input data derived from the ECODATA field database and DAYMET weather simulations for each KBR landscape polygon. These simulated variables represent important landscape-scale gradients used to predict spatial landscape characteristics across each study area.

A hierarchically structured database was designed to organize the complex information and different types of data used to map fuels and fire regimes in this study (Tables 1 and 2). Data collected in the field occupy the top of the database structure, and (1) are actual measurements of ecosystem characteristics, (2) represent the most accurate and defensible data in the database, and (3) provide the foundation of the predictive landscape modeling of fuels and fire regimes. Summaries of the ECODATA field database occupy the next level of the database; these are data generated from field measurements that summarize characteristics of each macroplot. For example, fuel loads (in kilograms per square meter) are synthesized from the downed woody inventories stored in the raw ECODATA field database. Simulation model input and parameter data occupy the third level in the database structure. These data were computed from the field and from summary databases to quantify the input parameters and initialization files required by the set of three simulation models described previously. The last and lowest level in the database contains simulated spatial databases, which are summarized outputs from these three simulation models.

Predictive gradient modeling

Our approach to mapping fuels and fire regimes consisted of multiple integrated analyses and data sources (Figs. 3 and 4). Fuel and fire regime information from the ECODATA field database (macroplots) provided information to be used as dependent or response variables. Values from each of the 38 spatial predictor variables (Table 2) were extracted for each macroplot using a GIS; and, along with measured variables for historical mean fire interval, general fire severity, fuel loads, and fuel models, these data were compiled as a separate model-building database.

To account for the effect of different units among predictor variables and to facilitate extrapolation across the study area landscape, we standardized macroplot values for 38 spatial predictor variables to Z scores with respect to the population mean and standard deviation. This procedure removed the weighting that results from differences in units and magnitudes between predictor variables (Johnson 1998). Preliminary exploration of the data with classification and regression trees (CART; Breiman et al. 1984), scatterplots, and histograms provided insights into the correlation and covariance structure. This was helpful for identifying erroneous values, statistical outliers, influential points, and potential relationships. After removing 12 plots due to erroneous data and grouping plots into fire interval and fuel load categories, the model database was partitioned into two parts: a model development set and an independent validation set (Johnson 1998). We used 75% of the data for model development and 25% of the data as a validation set for evaluating model performance and determining the degree to which model predictions could be extrapolated over the entire Kootenai River Basin.

We used general linear models (GLM), discriminant analysis, CART, and logistic regression to map fuel loads, fuel models, historical fire interval, and fire severity (Table 3). A GLM is a flexible statistical technique for predicting continuous response (dependent) variables based on a collection of continuous predictor (independent) variables (Johnson 1998). Discriminant analysis classifies records into discrete groups by developing a quadratic function of the predictor variables that captures the essential differences between groups (Johnson 1998). The CART procedure, used as an analog for regression, begins with the entire data set, proceeds by sorting all of the n cases for each predictor, and examines all $n - 1$ ways to split the data in two. For every possible split of each predictor variable, the within-cluster sum of squares about the mean of the cluster on the response variable is calculated. The predictor defines a split at a point that yields the smallest

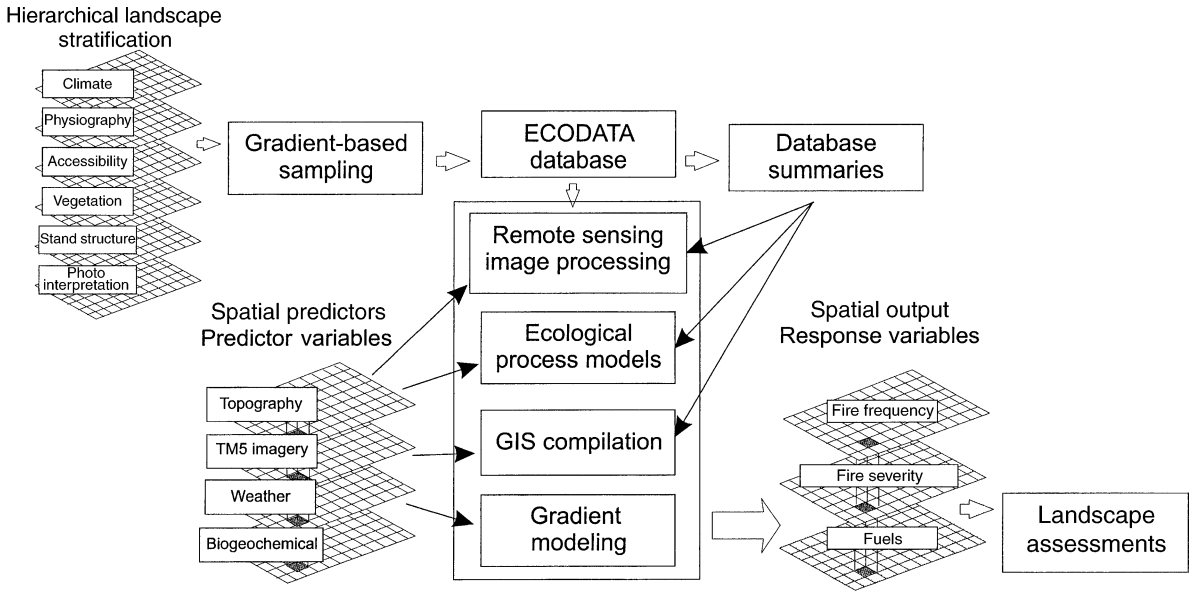

FIG. 4. Overview of the approach used to map fuels and fire regimes. Existing spatial data were used to stratify the study area for field sampling. An extensive field database served as training data for image processing and was used to derive spatial data layers and to parameterize ecosystem models; it also was the source of response variables for predictive landscape models. Discriminant analysis along with 38 predictor variables was used to map fuels and fire regimes for the Kootenai River Basin. Accuracy was assessed independently using a 25% holdout data set.

overall within-cluster sum of squares (Breiman et al. 1984). Logistic regression relates a binomial response variable to several predictor variables that can be either continuous or discrete (Christensen 1997). Logistic regression transforms the response variable into a logit variable (the natural log of the odds of the response occurring or not) and applies maximum likelihood estimation. In this way, logistic regression estimates the probability of specific events occurring.

Since fire interval and fuel loads were recorded at each plot as continuous variables, they were the only two response variables used in GLM. We used hierarchical cluster analysis to identify natural groupings and assign classes for fuel loads and fire interval. We then analyzed these variables using discriminant (discrete response), CART (discrete response), and logistic regression models. We created a separate logistic model for each fuel model. Single logistic models (binomial response) were applied to fuel loads (low or high), fire interval (short or long), and fire severity (nonlethal and stand replacement; Table 3). We created two sets of models for each statistical technique to evaluate the degree to which the incorporation of direct, resource, and functional gradients improved map accuracy over

TABLE 3. Mapped components of fuels and fire regimes, along with corresponding statistical methods, response variable classes, and important variables for developing each map component.

Map layer	Statistical method	Response type	Significant variables
Fuel loads (kg/m^2)	GLM	continuous	NDVI GREEN, SRAD, OUTFL, PET
	discriminant	discrete (L, low; M, medium; H, high)	
	CART	discrete (L, low; M, medium; H, high)	
	logistic	binomial (L, low; H, high)	
Anderson fuel model	discriminant	discrete (5, 8, 10)	REFLC4, TDEW, TMIN, ELEV
	CART	discrete (5, 8, 10)	
	logistic	binomial (separate model for each)	
Fire interval (yr)	GLM	continuous	OUTFL, PPT, REFLC4, PCLAY
	discriminant	discrete (short, medium, long)	
	CART	discrete (short, medium, long)	
	logistic	binomial (short, long)	
Fire severity	discriminant	discrete (nonlethal, mixed, stand replacement)	PPT, CURVE, OUTFL, ELEV
	CART	discrete (nonlethal, mixed, stand replacement)	
	logistic	binomial (nonlethal, stand replacement)	

Note: Anderson fuel models 5, 8, and 10 indicated different predicted fire behavior characteristics (Anderson 1982).

TABLE 4. Independently evaluated accuracies for models of fuels and fire regimes based purely on indirect variables (physiography) and models based on the entire database.

	Accuracy							
	Models based on physiography (indirect) variables							
	Discriminant		CART		Logistic		GLM	
Map layer	%	$\hat{K}$	%	$\hat{K}$	%	$\hat{K}$	R^2	P
Fuel loads	34.5	0	52.0	0.20	62.6	0.28	0.07	<0.01
Fuel model	43.4	0.44	53.9	0.27	64.6	0.32	†	†
Fire interval	57.9	0.34	59.8	0.35	70.1	0.24	0.11	<0.01
Fire severity	52.9	0.26	61.7	0.41	70.2	0.40	†	†

Notes: Maps based on discriminant, CART, and logistic regression were evaluated based on overall accuracy and the $\hat{K}$ statistic. Accuracy for maps based on GLMs were evaluated based on R^2 and P values. In all cases, accuracy assessment was based on a 25% random holdout database. Overall accuracy for discriminant, CART, and logistic analyses is computed as the percentage of total observations correctly classified (class 1 as class 1, class 2 as class 2, etc.). See *Methods: Accuracy assessment* for more information.

† Accuracy not evaluated for this layer using this method.

models based purely on indirect gradients. Our hypothesis was that models incorporating these gradients representing ecosystem processes and biophysical settings would improve mapping accuracy over models based purely on topography.

Accuracy assessment

We assessed model accuracy by classifying the validation database with statistical functions developed using the model development database. Classification accuracy was quantified for each spatial data layer with two measures: the overall accuracy and the Kappa statistic ($\hat{K}$), which measures the improvement in classification over that of pure chance by accounting for omission and commission error (Congalton and Green 1998). Overall accuracy is computed as the sum of the number of observations correctly classified (class 1 as class 1, class 2 as class 2, etc.) divided by the total number of observations (Story and Congalton 1986). This is equivalent to the ''diagonal'' of a square contingency table matrix divided by the total number of observations described in that contingency table (Story and Congalton 1986). Overall accuracy does not account for commission and omission errors (Congalton and Green 1998). Thus, it is possible to have a high overall accuracy, but also to have a high probability of false negatives or false positives. The Kappa statistic ($\hat{K}$) incorporates errors of omission and commission in classified data. It has been suggested to group continuous data for evaluating accuracy; however, this would be counter to our goal of representing fuel loads and fire intervals continuously over the landscape. Because of a small sample size, McKenzie et al. (2000) evaluated how well GLM predicted fire intervals using a bootstrap estimate of prediction error. Our model database was large; therefore, we evaluated accuracy of the continuous models of fire interval and fuel load maps by regressing measured and predicted fire frequency values for the validation database.

RESULTS AND DISCUSSION

Predictive landscape mapping

Continuous maps of fuel loads based on GLM had low accuracies (Table 4). However, general linear models predicted continuous fire interval reasonably well (Fig. 5). In general, discrete vs. continuous maps have more utility for developing management options for specific parts of a landscape (Aronoff 1989). Discrete ranges of fuel load classes and fire return intervals are more reasonable targets for landscape restoration or hazard reduction relative to individual, specific values of fire interval or fuel load which vary widely at landscape scales. This, in addition to expense and time constraints, is the main reason fire scars were not crossdated. The high temporal precision provided by detailed crossdating was not warranted because it is unnecessary to treat fire interval as a continuous variable for most land and fire management planning. Overall accuracies for discrete maps of fuel loadings, fuel model, fire interval, and fire severity varied from 51% to 81%, and $\hat{K}$ varied from 0.20 to 0.54 (Table 4, Fig. 6). Fire interval was mapped most accurately. Mean fire season precipitation, mean annual outflow (i.e., the amount of water available for runoff from a site), near infrared reflectance, and clay content in soils were the most important variables for discriminating between short, medium, and long interval classes. Fuel loadings were mapped least accurately (51%) with spectral derivatives, mean annual outflow, and topographic curvature being the most important for discriminating between areas with high, medium, and low amounts of fuel. Overall, accuracies were reasonable although the low accuracy of the maps, and the fuel maps in particular, may limit the utility of our specific approach for future applications. Despite low accuracies, the work presented in this paper represents a significant step in the search for standard methods for mapping fuels and fire regimes at high resolutions over broad areas. It is important to note that a rigorous accuracy

TABLE 4. Extended.

Accuracy							
Models based on all variables							
Discriminant		CART		Logistic		GLM	
%	$\hat{K}$	%	$\hat{K}$	%	$\hat{K}$	R^2	P
51.3	0.28	51.4	0.20	63.7	0.28	0.12	<0.001
55.1	0.30	56.4	0.34	69.2	0.38	†	†
63.2	0.43	66.4	0.44	80.7	0.54	0.41	<0.001
71.7	0.52	61.7	0.41	72.0	0.44	†	†

assessment is one of the strengths of our approach. Many attempts at mapping fuels and fire regimes lack quantitative accuracy assessment; therefore, it is difficult to evaluate our maps with regard to previous research (Morgan et al. 1996, Keane et al. 2001, Morgan et al. 2001).

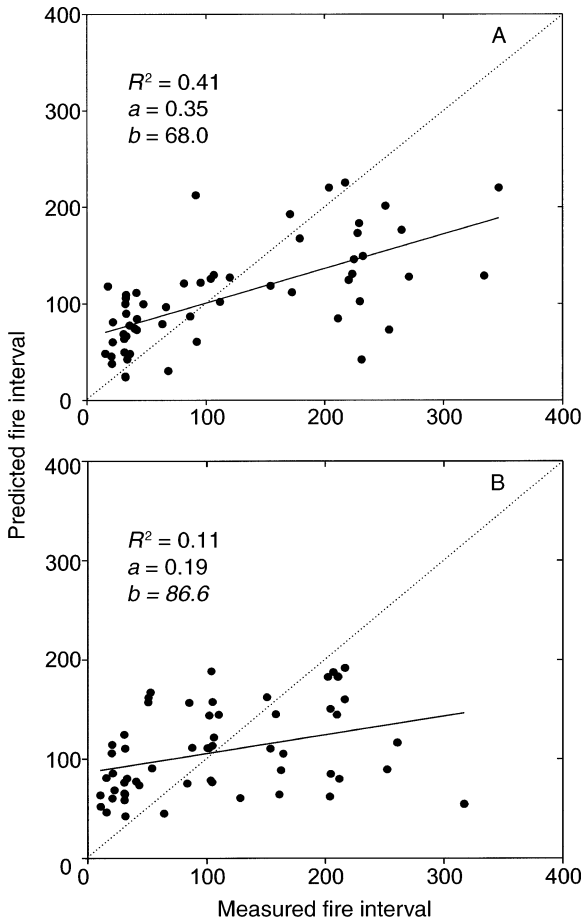

FIG. 5. Predicted vs. observed fire intervals (in years). General linear models tended to overpredict short intervals and underpredict long fire intervals. Panel A is based on all predictor variables, and panel B is based solely on physiographic variables; a is the slope of the regression line, and b is the y intercept.

Stratification and sampling strategies emphasized the collection of data that represented gradients of landscape patterns and ecosystem processes across each of these broad study areas. We feel that the main goals of the sampling efforts were achieved. A main limitation to the relevé approach used in this study was that plot locations were subjectively determined at the time of sampling. This is at least partially mitigated, however, because the study area was stratified twice prior to macroplot location using existing spatial biophysical data. The effectiveness of this stratification was largely based on the availability and quality of pre-existing data for the study area. The limited availability of broad-scale biophysical data could limit the utility of our approach in future applications; however, many comprehensive biophysical data sets exist, and more are becoming available yearly.

Overall, each statistical technique performed well for mapping fuels and fire regimes; no single statistical technique consistently outperformed the others (Table 4). Many additional statistical techniques have been applied to predictive landscape mapping. These include general additive models, neural networks, Bayesian modeling, and expert systems approaches. However, none of these approaches have shown superior mapping performance (Franklin 1995). It appears from our analyses that, in future implementations of our approach, researchers or landscape managers need not agonize over selecting an appropriate statistical technique. Rather, they should focus resources and efforts on assuring that: (1) field databases are sufficiently representative of the landscape; (2) the gradients that comprise landscapes are represented by carefully compiled, accurate spatial data; and (3) validation data are independent from the model development database.

Biophysical gradient modeling

Derivatives of satellite imagery that represented functional gradients (gradients that describe the response of the biota to other biophysical gradient types) including MNDVI, near infrared reflectance, and Kauth-Thomas Greenness, were important predictors of fuel loads, fuel model, and fuel moisture (Table 5). This indicates that an approach that integrates remote

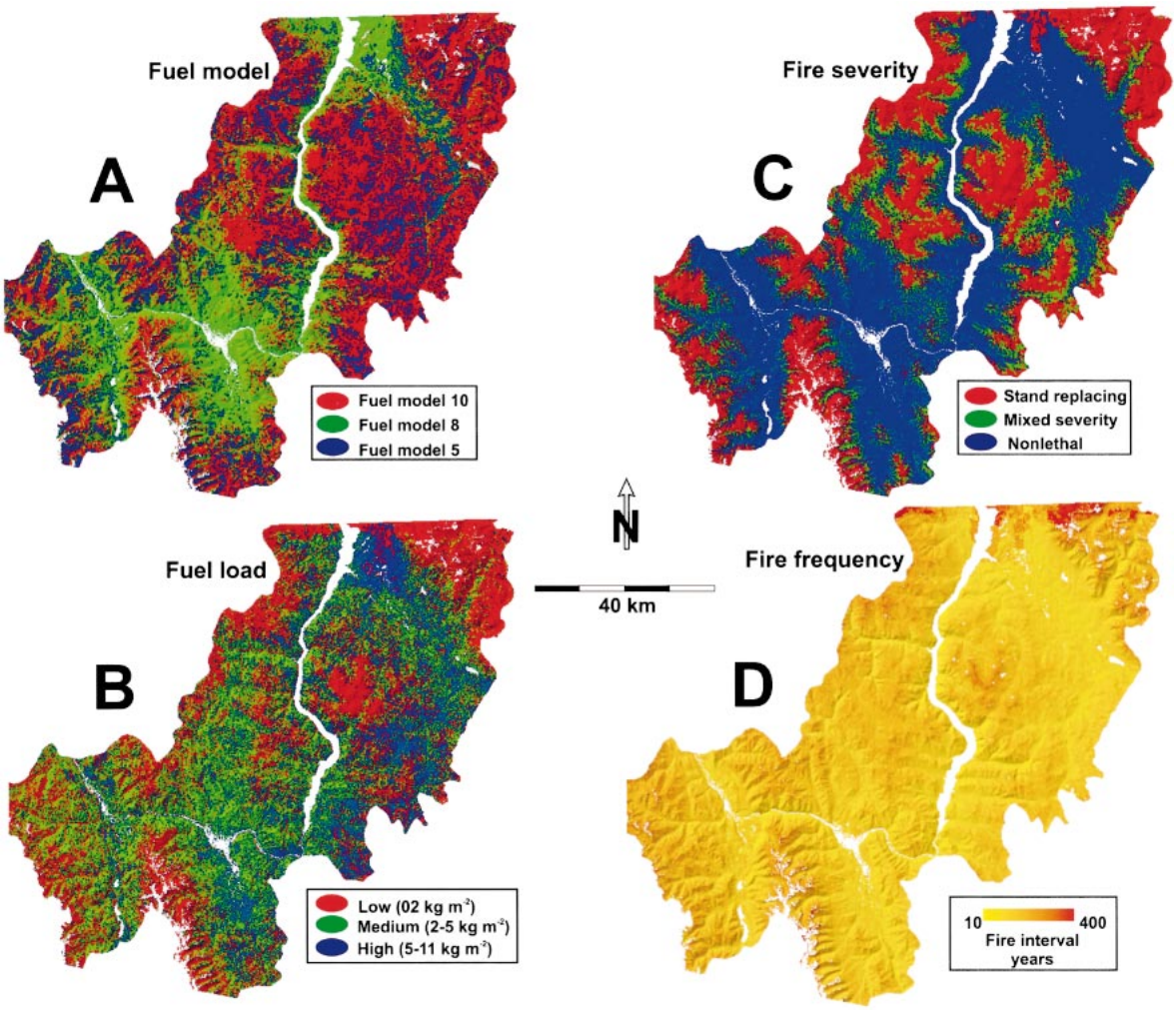

FIG. 6. Fuel model (panel A), fuel load (panel B), fire severity (panel C), and fire interval (panel D) over the entire Kootenai River Basin. Panels A, B, and C were based on discriminant analysis and were 55.1%, 51.4%, and 71.7% accurate, respectively, based on comparisons with independent field measurements. Panel D (fire interval) is portrayed as a continuous variable and was based on a general linear model with $R^2 = 0.41$ and $P < 0.001$.

sensing and gradient modeling is a significant improvement over standard remote sensing techniques using passive sensors for mapping characteristics of wildland fire. Mechanistic ecosystem models were used to spatially simulate weather and biogeochemical processes known to govern fuel and fire regime dynamics. The empirical/mechanistic DAYMET and WX-GMRS models described the spatial distribution of important fire weather variables based on a network of weather stations arrayed across the KRB at a variety of elevations. Mean fire season precipitation and temperature were the most important weather variables for mapping fuels and fire regimes.

A simulation approach characterized subtle changes in mean fire season weather conditions that an indirect modeling approach may fail to recognize. In an indirect approach, latitude and elevation are often used as surrogates representing gradients in precipitation and temperature, which are assumed to change uniformly with regard to these variables. In contrast, a simulation approach based on a large sample of real weather data is much more likely to characterize unique weather characteristics of a landscape such as rain shadows or storm tracks. The most important biogeochemical variable in predictive landscape models was outflow. This indicates that water status is an important resource gradient for discriminating fuels and fire regimes across landscapes (Clark 1989, Stephenson 1998). Ecosystem respiration and net primary productivity were also important predictors, indicating that fuels and fire regimes are directly related to the rates of carbon cycle processes (Olsen 1981, Ryan 1991, Price and Rind 1994). A simulation approach adds information about direct, resource, and functional gradients to predictive modeling of landscape characteristics and, relative to models based purely on indirect gradients, more accurately

TABLE 5. Important physiographic, spectral, weather, and biogeochemical variables for mapping fuels and fire regimes. See Table 2 for variable definitions.

Physiographic	Spectral	Weather	Biogeochemical
ELEV	REFLC4	PPT	OUTFL
SLOPE	REFLC2	TMAX	ER
CURVE	GREEN	SRAD	AR
SDEPTH	NDVI	TMIN	MR

represents the environmental factors that control landscape scale distributions of fuels and fire regimes.

Overall, the resource gradients precipitation and outflow and the functional gradients MNDVI and near-infrared reflectance (both descriptions of plant biomass) were the most important variables for mapping fuels and fire regimes across the Kootenai River Basin. It is well known that fuel loads and fire regime characteristics are functions of site water status and productivity (Clark 1989, Agee 1993, McKelvey and Busse 1996, Stephenson 1998, Li 2000, Turner et al. 2001). Therefore, accurate spatial data representing these direct gradients should be powerful predictors for mapping landscape scale fuels and fire regimes. In addition, and as expected, spectral gradients representing biomass were important functional gradients describing the spatial distribution of fuels and fire regimes because information derived from satellite imagery is directly related to vegetation composition and biomass. In future mapping efforts, we recommend an ecosystem simulation approach focused on energy budget, hydrology, and carbon cycles.

Without exception, all predictive landscape models were improved by the inclusion of direct, functional, and resource gradient variables. Overall accuracy for the maps based purely on indirect gradients was lower than accuracies for maps based on the full set of predictive landscape variables (Table 4). This supports our assertion that inclusion of predictor variables directly related to fuels and fire regimes improves mapping accuracies. We expected that elevation would be less important than the direct and resource gradients that it traditionally represents in indirect gradient modeling. This was true in most cases, but elevation was common as a secondary or tertiary variable in most models, particularly models of fire severity. This is likely due to the high accuracy of mapped elevation relative to the more moderate accuracy of simulated direct, functional, and resource gradients. Ecosystem simulation models have improved over the last decade for application from regional to local spatial scales. As simulation models improve, better spatial representation of these important direct and functional gradients will be possible. We expect that this will improve the accuracies of maps of fuels and fire regimes based on biophysical gradient modeling. Comparisons of maps based on statistical models containing only indirect gradients and maps based on models that include direct, resource, and functional gradients highlight the importance of variables representing ecosystem processes in predicting the spatial distribution of fuels and fire regimes.

Potential vs. existing conditions

Predictive landscape maps based solely on gradients represent potential conditions. Maps that incorporate functional gradients (e.g., remotely sensed biomass or vegetation structure) help narrow in on existing conditions by incorporating data for realized landscape composition, structure, and function. In the maps presented here, direct, resource, and functional gradients for mapping fuels and fire regimes were based on the previous 20 years of weather data and derivatives from single-date satellite imagery. Fire intervals represented existing conditions to the extent that the previous 100–400 years represented the stand history that led to the existing stand condition. From an ecological perspective, fire regimes often evoke a much longer time period (i.e., thousands of years); however the temporal extent of most proxy fire history data (e.g., fire scars and age structure) usually only extend back in time for a few centuries. Mapped fuels and fire regimes represented both existing and potential conditions based on the combination of indirect, direct, resource, and functional gradient types in our approach. If fire regimes for a given period of record are desired in future applications of our mapping framework, then it is necessary to limit estimates of fire interval to that period of record. For example, if a map of pre-20th century conditions is desired, then fire history evidence used for fire interval estimates should be limited to pre-1900 data.

The generally low accuracy of maps of fuel loads may result from expressions of both existing and potential fuels loads in our final predictive landscape models. Large discrepancies between potential and existing are possible in areas where landscape condition has been affected by land use and fire exclusion. Predictive maps of fuel models were more accurate, probably because general descriptions of fuel models are more static temporally than actual fuel loads. We mapped existing and potential fuels together as proof of concept for this paper. However, the integrated approach presented here could easily be modified to map purely existing or potential conditions. Existing conditions could be mapped by extracting date-specific information about direct, resource, and functional gradients from ecosystem simulations. Potential conditions could be mapped by accumulating time-series spectral information from imagery spanning a specific period of record to describe a general expression of functional gradients for the study area. If maps of purely potential conditions are desired, predictor variables describing functional gradients should be excluded. Series of maps of potential fuels and fire regimes based

on alternative weather scenarios could be produced to investigate changes under different climate scenarios.

Mapping fuels and fire regimes

Many strategies have been applied to creating maps of fire regimes, including classification, simulation, and statistical modeling. Classification involves assigning a fire regime description based on some expression of fire history and different permutations of vegetation, topography, and/or climate (e.g., Barrett et al. 1991, Brown et al. 1994, Morgan et al. 1996). The simplicity of applying the classification strategy to large areas is the major strength of the classification approach. Classification fails to account for the spatial relationships between areas with different potentials for burning (e.g., ecotones). An additional limitation is that fire regimes are sometimes not congruous with vegetation classifications. Existing patterns of vegetation integrate site characteristics and disturbance interactions, and may not adequately represent the patterns of past fires.

Simulating fire regimes involves models that simulate fire behavior and effects over an extended period of time. Outputs are summarized to generate maps of fire regimes (e.g., Baker 1995, Li 2000). The major strength of fire regime simulation is the integration of all factors that determine fire regimes into one modeling application. Models may be run many times to evaluate a range of possible conditions or to assess sensitivity by systematically changing one or more vital attributes such as climate. The major drawback to simulation modeling is that models are often oversimplifications of reality and fail to represent the complex ecological processes and landscape patterns that determine fire regimes. For example, fire occurrence and spread may not simulate realistic fire patterns because of lack of hourly weather or fine-scale fuels data. In addition, imbedded succession pathways or competitive hierarchies may fail to accurately represent the changes in plant composition and structure after fires.

Statistical modeling is the most common approach to mapping fire regimes. It most often involves the summary of fire history databases (e.g., fire scar collections, age structure data, and/or fire atlases), documenting the date and extent of past fires into representations of fire interval and severity (Arno 1976, Niklasson and Granström 2000, Heyerdahl et al. 2001, Rollins et al. 2001). This usually involves fitting distributions of fire occurrence from a specific area to a statistical distribution such as Poisson or Weibull (Grissino-Mayer 1999, Reed 2000). This method is spatially explicit; however, uncertainties exist based on data quality and the appropriate spatial and temporal resolution for ecological inference (Baker and Ehle 2001, Rollins et al. 2001). Compiling fire history databases requires a high degree of expertise, and can be very expensive. The statistical strategy is simple, efficient, and the most accurate because it is ultimately based on real field data; however, it is less comprehensive in capabilities for exploring interactions between causal factors than simulation modeling. Predictive models are possible and examples include stochastic simulation (He and Mladenoff 1999) and the incorporation of ecosystem process variables as predictor variables (McKenzie et al. 2000). Fire regime mapping based purely on statistics is limited by the cost of extensive field sampling, database quality, and difficulty of untangling correlations from causality.

Our fire regime maps are based on an integrated approach that incorporates field data, remotely sensed data, and biophysical modeling. Classifications of fire interval and fire severity are based on evaluations of stand age and structure at each macroplot. Cost was prohibitive in terms of time and money to compile a detailed fire history reconstruction for the entire Kootenai River Basin. Classification of fire severity is based on an expert opinion of the general fire severity for a wildland fire for every macroplot. Maps represent potential fire regime characteristics to the extent that current stand conditions at each macroplot represent the effects of past fires. Although fire regime classifications are subject to bias based on subjective sampling and semiqualitative evaluations of fire interval and fire severity, these maps provide an effective means for wildland fire managers to evaluate the spatial distribution of fire regimes at broad scales and for specific areas. Our approach demonstrates the utility of using extensive field inventories along with fire regime classifications, ecosystem simulation, and a relatively straightforward statistical approach to mapping fire regimes with respectable, independently assessed accuracies. The process described in this paper provides more information than rule-based or expert system approaches because it is both data driven and incorporates direct, functional, and resource gradient modeling. However, our approach provides less detailed information (e.g., time series of landscape change) than approaches based purely on simulation modeling (Keane et al. 1996, He and Mladenoff 1999).

Application of maps of fuels and fire regimes in fire and land management

Applications of fuel and fire regime maps in fire management are numerous. For example, fuel load or fuel model maps could be cross tabulated with potential fire behavior, historical condition class, or vegetation maps to make strategic decisions about fire suppression resources or to prioritize specific areas for ecosystem restoration or fuel mitigation. Fire interval maps could be compared with maps of recent fires to determine appropriate areas for prescribed burning. These data may be evaluated individually, as with plans for a specific prescribed burning operation, or with other data as part of a comprehensive landscape assessment, such as revisions of a National Forest Plan. Our approach provides landscape managers with the best available scientific information about existing or potential fuels

and fire regimes for addressing current issues in wildland fire management. Ecologists and fire managers must carefully consider the spatial and temporal context of naturally ignited fires, management-ignited fires, and mechanical vegetation treatments to effectively address issues related to managing wildland fire. This type of enlightened, ecologically based management of wildland fire requires comprehensive maps of fuels and fire regimes over broad areas. The science of restoration ecology and the practice of ecological restoration are evolving rapidly. As restoration efforts increase, spatial information about the status of landscapes with regard to their historical conditions are important for locating and prioritizing the expenditure of a limited amount of resources.

These spatial inventories are critical for assessing the risks to public safety and to ecosystem integrity involved with wildland fire in a constantly changing landscape. A consistent, standardized approach to database development and mapping is requisite for effective communication and coordination of wildland fire management information within and between both government and nongovernment institutions.

Although the mapped fuels and fire regimes presented in this paper are not ideal, they effectively represent differences in fuels and fire regimes between areas, and the spatial pattern of those relative differences is of great utility to fire managers and ecologists. Our approach allows flexibility in gradient model development, the potential for application at multiple scales, and the ability to build predictive maps, but possibly at the cost of limited implementation. Development of the empirical predictive algorithms requires expertise in statistical analysis, ecological interrelationships, and database management, so implementation of this approach in other areas may require specialized personnel. However, these protocols can be easily adjusted or formulated to generate new predictive equations for new areas or new applications, and they may be refined and modified as additional field data or gradient GIS layers become available and they may be easily implemented in standard statistical software so that local statistical experts are not needed.

The need for comprehensive spatial data for fire and land management

A legacy of fire exclusion, land use practices, and widespread exotic species invasions has altered fire regimes, fuel loads, and landscape composition, structure, and function (Pyne 1982, Swetnam and Baisan 1996, Rollins et al. 2001, Allen et al. 2002). As a result, wildfire characteristics have changed significantly from historical conditions (U.S. GAO 1999), sometimes with catastrophic consequences. Recent examples of this include the Cerro Grande fire of 2000 that burned over 235 homes in Los Alamos, New Mexico, and the 2000 and 2002 fire seasons where nearly 8 million hectares burned across the western United States with unprecedented suppression expenditures approaching $2 billion. In response to these conditions, the United States Department of Agriculture (USDA) and the United States Department of the Interior (USDI) have implemented the National Fire Plan, a long-term program to protect communities, ecosystems, and the lives of firefighters and the public. Hardy et al. (2001) developed coarse scale maps of fire regime condition class in 1999. These maps have been subjected to several revisions leading to widely varying estimates of the total area at risk of catastrophic fire.

The USDA and USDI address the following issues regarding implementation of the National Fire Plan (USDA and USDI 2002): (1) Improving the resilience and sustainability of forest and grasslands at risk; (2) conserving priority watersheds, species, and biodiversity; (3) reducing wildland fire costs, losses, and damages; and (4) ensuring public and firefighter safety. The United States General Accounting Office (GAO), in a report evaluating the USDA and USDI strategies for implementing the National Fire Plan, found that government agencies lack adequate data for making informed decisions and measuring agencies' progress in reducing fuels and restoring ecosystems (U.S. GAO 2002). This report highlighted the need for consistent, comparable data and emphasized three main spatial data needs: (1) Data for prioritizing wildland–urban interface communities within the vicinity of federal lands that are at high risk from wildland fires; (2) collection and compilation of adequate data to expedite the project planning process; and (3) data to evaluate the effectiveness of treatments to reduce accumulated fuels to decrease the reduce the risk of severe wildland fire (U.S. GAO 2002). Prioritizing landscapes for treatments is a unifying theme in the potential application of maps of fuels and fire regimes to ecological restoration or hazardous fuels mitigation. The work presented in this paper forms the foundation for a standardized, comprehensive suite of methods for developing broad-scale, high-resolution spatial data for evaluating ecosystem status, conserving watersheds and biodiversity, and ensuring public and firefighter safety. Information about current interagency efforts toward broad-scale mapping of fuels and fire regimes for the United Stated is available online.[4]

In the near future, broad-scale data will be available that may replace some or all of the advanced spatial data derivation and ecosystem simulation that was necessary for this study. The launch of the US government's Terra satellite has ushered in a new era for natural resource mapping. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on the Terra satellite is linked to complex software that will generate global maps of ecosystem variables such as net primary production and evapotranspiration every day and over the course of a growing season at 1-km^2 resolution.

[4] URL: ⟨www.landfire.gov⟩

The National Elevation Database provides standardized 30-m digital elevation models for the entire United States, and an updated version of STATSGO (state soil geographic database) soil texture and soil depth data will be available nationwide by 2002.[5] The DAYMET database, now available, provides summaries of an 18-year daily record of temperature, precipitation, and solar radiation (along with confidence intervals) at 1-km^2 resolution for the continental United States.[6] The MODIS, STATSGO, and DAYMET products provide excellent information for broad-scale landscape characterization, and could potentially replace most of the complex ecosystem simulation modeling used in this study.

Conclusions

Integration of remote sensing, simulation modeling, and gradient analysis proved to be an efficient, successful approach for mapping broad-scale fuel and fire regime characteristics. The ability of remote sensing and ecosystem simulation to portray spatial distributions of direct, resource, and functional gradients enables the efficient construction of reasonably accurate maps that are critical for both fire managers and ecologists. No single statistical approach proved superior for predictive landscape mapping. The maps created improve our ability to compare fire regimes between regions and facilitate communication between fire managers and fire ecologists. A gradient-based approach to mapping fuels and fire regimes enables the simulation of potential changes in these factors and facilitates comparison of past fire regimes with current conditions, providing valuable information for evaluating the extent and rates of ecosystem change. The findings of this study provide a framework for development of an standardized, automated system that creates maps of fuels and fire regimes for any area using combinations of field inventories, remotely sensed data, biophysical data, and multivariate statistical approaches. This approach is appropriate for local to regional applications and over a wide variety of ecosystems because maps are based on predictive variables representing important ecosystem processes that determine fuels and fire regimes across multiple scales. Resulting maps provide information to evaluate landscape and quantify the hazards and risks of wildland fire when making decisions about how best to restore forests of the western United States to within historical ranges and variability.

Maps of fuels and fire regimes are critical for managing broad-scale fire hazard that has resulted from nearly a century of fire exclusion in the United States and elsewhere. In recent years, the number of large, severe wildfires has grown dramatically in the western United States, increasing the risk of permanently and comprehensively changing ecosystem dynamics and decreasing public and firefighter safety. It is estimated that 73 562 393 ha of forested lands in the interior Western United States are at risk of catastrophic wildfire (Schmidt et al. 2002). This historically unprecedented level of fire hazard has precipitated the realization that a lack of comprehensive spatial data hinders the evaluation of fuels and fire regimes at landscape to regional scales.

The methods presented in this paper provide a basis for creating a standardized, interagency approach to comprehensively and consistently mapping the characteristics of wildland fire in almost any ecosystem at broad scales. Existing vegetation communities represent a dynamic equilibrium with the frequency, severity, and spatial patterns of past wildland fires. The role of wildland fire as a disturbance process is entrained by climate, and complex feedbacks between vegetation and fire processes make wildland fire an important mediator of climate–vegetation relationships. Fire managers must consider climate variability, a legacy of fire exclusion, and the hazards and risks of management action when making decisions about how best to restore forests of the western United States to within historical ranges of variation.

[5] URL: ⟨www.ftw.nrcs.usda.gov/stat_data.html⟩
[6] URL: ⟨www.daymet.org⟩

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