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A Spatially-Explicit Reconstruction of Historical Fire Occurrence in the Ponderosa Pine Zone of the Colorado Front Range

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Abstract

A key issue in ecosystem management in the western U.S. is the determination of the historic range of variability of fire and its ecological significance prior to major land-use changes associated with Euro-American settlement. The present study relates spatial variation in historical fire occurrence to variation in abiotic and biotic predictors of fire frequency and severity across the elevational range of ponderosa pine in northern Colorado. Logistic regression was used to relate fire frequency to environmental predictors and to derive a probability surface for mapping purposes. These results indicate that less than 20% of the ponderosa pine zone had an historic fire regime (pre-1915) of relatively frequent fires (mean fire intervals, MFI, <30 years). More than 80% is reconstructed to have had a lower frequency (MFI ≥ 30 years), more variable severity fire regime. High fire frequency is clearly associated with low elevations. Lower and more variable fire frequencies, associated with high and moderate severities, occur across a broad range of elevation and are related to variations in other environmental variables. Only a small part of the ponderosa pine zone fits the widespread view that the historic fire regime was characterized mainly by frequent, low-severity that maintained open conditions. Management attempts to restore historic forest structures and/or fire conditions must recognize that infrequent severe fires were an important component of the historic fire regime in this cover type in northern Colorado.

Key words: fire history; ponderosa pine; *Pinus ponderosa*; geographic information system; Colorado Front Range; fire regime.

Introduction

A key issue in ecosystem management in the western U.S. is the determination of the historic range of variability of fire and its ecological significance prior to major land-use changes associated with Euro-American settlement. Although broad generalizations have been made about the effects of fire suppression on current forest structures and recent fire behavior in the West (for example, see Covington 2000; Healthy Forest Restoration Act—HFRA 2003), historic fire regimes varied substantially in frequency and severity across the West (Gutsell and others 2001; Veblen 2003a). Even for different areas of the ponderosa pine (*Pinus ponderosa*) cover type there is considerable debate about the pre-1900 fire regime and the ecological consequences of modern fire exclusion

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(Covington and others 1997; Shinneman and Baker 1997; Baker and Ehle 2001; Allen and others 2002).

A widespread viewpoint is that fire exclusion in the U.S. West during the past circa 100 years has dramatically reduced the occurrence of formerly frequent low-severity fires which in turn has promoted an unnatural increase in forest density and the risk of high-severity fires (Covington 2000; HFRA 2003). Much of the supporting information for this fire exclusion-fuels buildup model comes from studies in the dry ponderosa pine ecosystems of the Southwest (Swetnam and Baisan 1996; Fule and others 1997; Mast and others 1999). In ponderosa pine forests in the Southwest and elsewhere (for example, dry ponderosa pine forests in western Montana; Gruell 1983; Arno and others 1995) where the goals of ecological restoration and fuels reduction have been shown to converge, management to reduce wildfire risk can also restore forest stands to historic conditions. However, geographic variations in climate, topography, site productivity, and land-use history across the widely distributed ponderosa pine cover type provide ample reason for conducting site-specific research to evaluate the fire exclusion-fuels buildup model.

In the Colorado Front Range, it is well established that both low- and high-severity fires played significant roles in the shaping of historic ponderosa pine forests (Veblen and Lorenz 1986; Brown and others 1999; Kaufmann and others 2000; Ehle and Baker 2003). Evidence of pre-twentieth century (that is, prior to any effects of fire exclusion) high-severity fires in the ponderosa pine zone includes historical photographs, as well as tree age structures, and dendroecological reconstructions of past stand conditions (Veblen and Lorenz 1986, 1991; Mast and others 1998; Kaufmann and others 2000; Ehle and Baker 2003; Sherriff and Veblen 2006). Yet, how past fires varied in severity spatially over the montane zone of ponderosa pine-dominated forests (circa 1,800–3,000 m) is uncertain. Recent studies in the Front Range have documented the occurrence of mixed-severity fire regimes, including inferences of the relative importance of low- and high-severity fire, in ponderosa pine-dominated ecosystems over relatively narrow gradients of elevation and topographic variation (Brown and others 1999; Kaufmann and others 2000; Ehle and Baker 2003). Despite these advances towards a more spatially explicit understanding of historic fire regimes, broad-scale patterns of historic fire regime type across the full range of ponderosa pine-dominated forests have not been examined.

The goal of this research is to map patterns in historical fire occurrence across the ponderosa pine zone in the northern Front Range by developing an empirical predictive model of past fire frequency classes from tree-ring fire history descriptors and spatial associations of parameters determined from digital terrain data. Although the primary quantitative criterion used in this analysis is fire frequency, we also have related fire frequency to fire severity by examining tree population age structures to show that where fire frequency is high, fire severity is low (Sherriff 2004; Sherriff and Veblen 2006). In the context of fuels management and ecological restoration, our primary goal is to distinguish between areas formerly characterized by relatively frequent low-severity fires and those where less frequent high- or moderate-severity fires were important. In the former areas, surface fires killed mostly juvenile trees and maintained relatively open stands. In the latter, stands were initially dense and higher severity fires killed high percentages of crown trees within a fire perimeter. Our working hypothesis is that broad classes of past fire frequency can be predicted from the same types of abiotic factors successfully used in predicting spatial variation in local vegetation patterns (for example, see Miller and Franklin 2002). For a 60,875-ha area in the ponderosa pine zone of Arapaho-Roosevelt National Forest (ARNF) on the eastern slope of the Front Range (Figure 1), we reconstruct, or ‘‘retrodict’’, the habitats characterized by different historic fire frequency classes. The objectives are to: (1) characterize fire frequency across the elevational range of ponderosa pine; (2) identify environmental conditions associated with different fire frequency classes; and (3) create and evaluate spatial models of fire frequency classes based on environmental conditions for the ponderosa pine zone of ARNF.

Study Area

The vegetation pattern in the Front Range varies along environmental gradients of elevation and moisture (Peet 1981). The montane zone extends from approximately 1,800–3,000 m; it is characterized primarily by forests but also includes limited areas of grasslands and shrublands (Marr 1961). Forest vegetation of the montane zone varies from open park-like stands of ponderosa pine at the plains-grassland ecotone to dense stands mixed with Douglas-fir (*Pseudotsuga menziesii*) in more mesic sites and north-facing slopes. In the upper montane zone, topographic position becomes increasingly important with dense stands of pon-

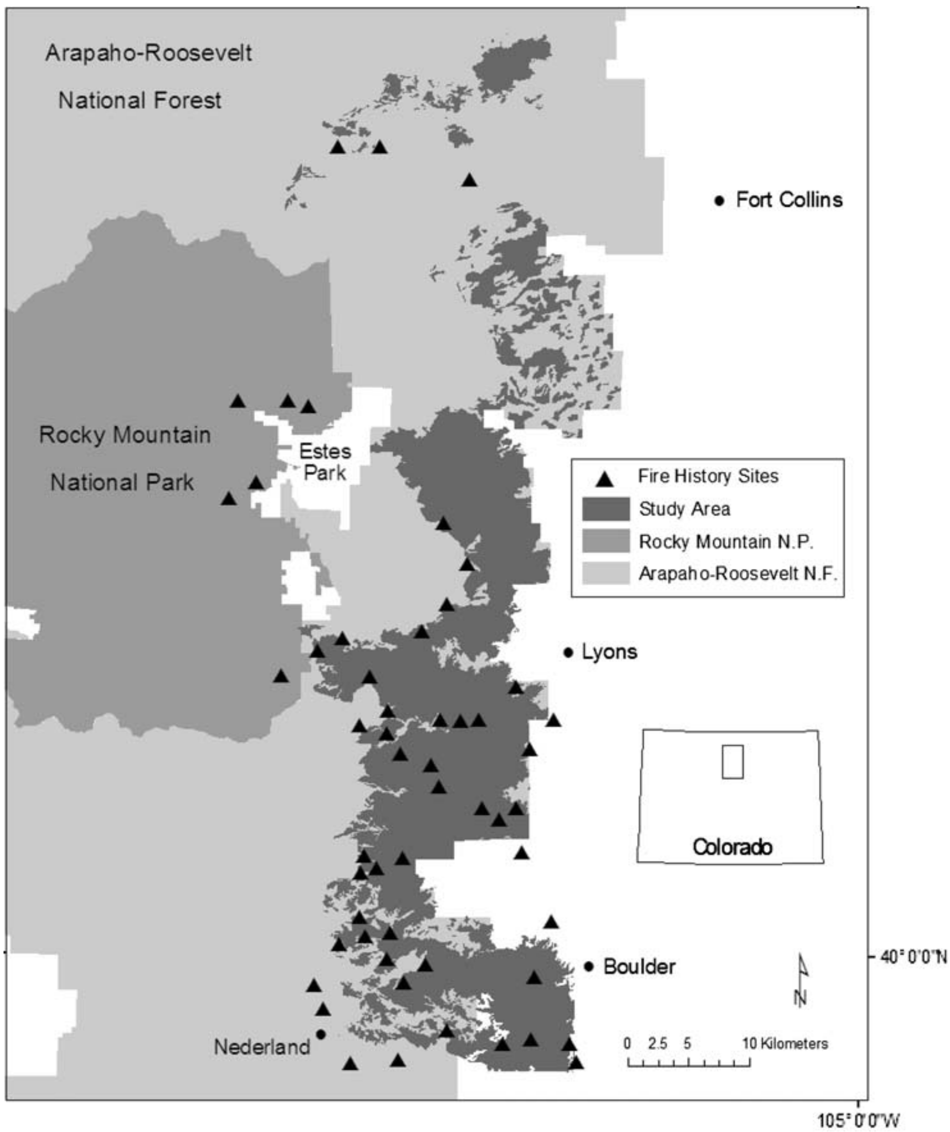

Figure 1. Location of 54 sites sampled for fire history throughout the ponderosa pine zone of the northern Colorado Front Range. For the predictive habitat mapping of fire frequency classes, the 60,875 ha study area was delineated from the Forest Service Integrated Resource Inventory (*IRI*) vegetation cover maps of the Arapaho-Roosevelt National Forest (*ARNF*) contained within the larger fire history sampling area.

derosa pine-Douglas-fir on north-facing slopes and more open ponderosa pine woodlands on south-facing slopes. Aspen (*Populus tremuloides*), limber pine (*Pinus flexilis*) and lodgepole pine (*Pinus contorta*) often co-occur with ponderosa pine and Douglas-fir at higher elevations in the montane zone.

To characterize environmental attributes associated with different fire frequencies, we used fire history data from 37 sites previously described by Veblen and others (2000) and 17 new sites (Sherriff 2004) extending across the full elevation range of ponderosa pine in the northern Colorado Front Range on lands that belong to the City of Boulder and Boulder County Open Space, Arapaho-Roosevelt National Forest, and Rocky Mountain National Park (Figure 1). For the predictive habitat mapping of fire frequency classes, the study area was delineated from the U.S.D.A. Forest Service Integrated Resource Inventory (IRI) vegetation cover maps of nine watersheds in the ARNF contained within the larger fire history sampling area. The IRI vegetation data are cover type maps that have been field checked by the Forest Service and derived from the Resource Inventory System (RIS). In the context of this study, the ponderosa pine zone includes areas mapped as ponderosa pine (28.7%), ponderosa pine-Douglas-fir (25.4%), Douglas-fir-ponderosa pine (9.7%), and mixed conifer (36.2%) cover types. Within the mixed conifer cover type ponderosa pine dominates 20.8% of the study area, Douglas-fir 4.6%, lodgepole pine 8.0%, and aspen 2.8%. Thus, the 60,875-ha ARNF study area includes all cover types where ponderosa pine is a dominant or co-dominant species; it is mapped as dominant in approximately 75% of this area.

Methods

Response Variables: Fire Frequency Classes

Methods for sampling fire history for the 37 previously published sites are given in Veblen and others (2000). The new sites added for this study followed the same protocol for sampling fire scars (Sherriff 2004). General areas for sampling were subjectively located to maximize the elevation range of sites where ponderosa pine dominated the vegetation and to eliminate areas that showed significant signs of logging. Relationships between each fire frequency class and fire severity were established by examining tree age structures (Sherriff 2004; see Figure 2 for examples), tree-ring growth releases on remnant trees, and episodes of fire-caused mortality of mature trees (data presented in Sherriff 2004; Sherriff and Veblen 2006). Tree establishment dates were determined by coring 38–164 trees with diameters at breast height (dbh) larger than 4 cm (median = 123; total > 3,000 trees) in multiple transects at 24 of the 54 fire history sites. Coring height was approximately 20 cm and establishment dates were determined by adding median ages of seedlings around 20-cm tall (n = 252 for all species) that were destructively sampled at the same site or a similar site (see Sherriff 2004 for details).

A total of 54 fire history sites (Veblen and others 2000; Sherriff 2004) were used to define two classes of higher frequency-lower fire severity and lower frequency-variable fire severity fires and to examine their relationships with environmental variables. Forty-eight of the 54 sites had a minimum of ten fire-scarred trees and six sites had seven to nine fire-scarred trees. A total of 779 fire-scarred partial cross-sections collected from live and dead trees were crossdated at the 54 sites (506 samples from Veblen and others 2000; 273 samples from Sherriff 2004).

The most objective criteria for delimiting fire history classes were the total number of fire events (each recorded by ≥2 trees scarred per site) between 1700 and 1915, MFI (all fires) before Euro-American influence (1700–1860), and numbers of trees with multiple fire-scars (Table 1). Although the number of fire-scarred trees (sample depth) is low at most sites prior to the 1800s (mean of 3.5 fire dates and 4.6 samples per site before 1800), only seven sites record no evidence of fire (no fire scars) prior to 1800 (for detailed fire histories by site see Veblen and others 1996; Sherriff 2004). For sites recording relatively few fires prior to 1800 we used stand age structure evidence to evaluate if the scarcity of fire scars was likely due to destruction of evidence by more recent severe fires which is an inherent feature of a mixed-severity fire regime. Taking into account the many limitations of fire scars as proxies of past fire occurrence (Baker and Ehle 2001; Veblen 2003b), two broad classes of fire frequencies and fire effects were recognized as an 'index' of different fire regimes based on multi-

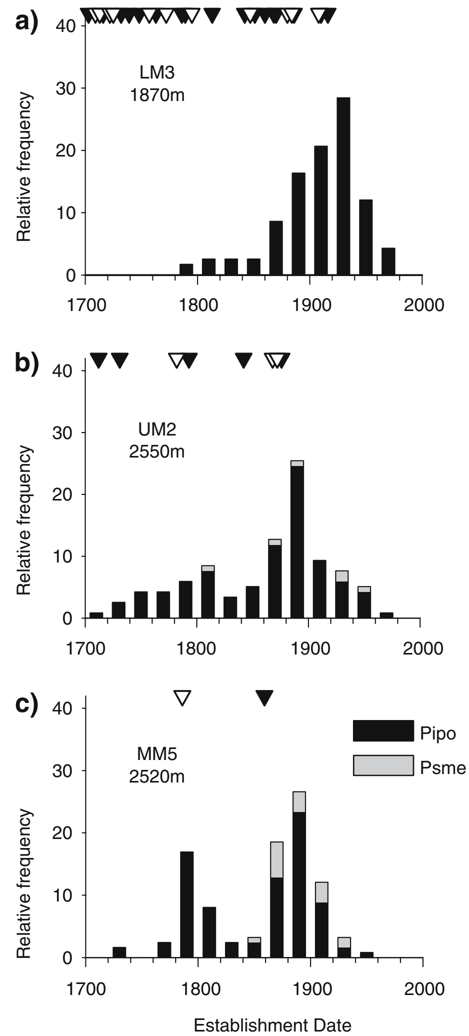

Figure 2. Examples of typical patterns of fire intervals and tree age structures for the **A** high frequency fire class, **B** variable frequency fire class, and **C** low frequency fire class. In this study, the low and variable fire frequency classes are combined for analysis. The relative frequency (%) of all aged trees (>4 cm dbh) is given in 20-year establishment classes. Numbers of tree ages are 118, 123, and 124 in **A**, **B**, and **C**, respectively. Species are ponderosa pine (*Pipo*) and Douglas-fir (*Psme*). *Empty triangles* represent local fires (single tree scarred) and *black triangles* represent more widespread fires (more than one tree scarred).

Table 1. Criteria used to Classify Fire Frequency Classes at 54 Fire History Sites

Fire frequency class	No. sites	Criteria (1700–1915)
High	9	Six or more fire years (recorded by at least two scarred trees/fire) or MFI $<$ 30 years for all fires from 1700 to 1860 More than 50% of the fire-scarred trees have multiple fire scars Three or more trees with at least three fire scars
Low and variable	35	Four or fewer fire years (recorded by at least two scarred trees/fire) or MFI $\geq$ 30 years for all fires from 1700 to 1860 Fewer than 50% of the fire-scarred trees have multiple fire scars Two or fewer trees with at least three fire scars

Fire history from 1700 to 1915 was considered at each site because of potential effects of fire suppression after approximately 1915. Mean fire interval (MFI) was calculated only

variate criteria (Table 1; Figure 2). Sites in the high fire frequency class include numerous short (<30 years) fire return intervals as expected for low-severity fires that are not dependent on the regrowth of woody fuels. This classification of the high fire frequency class was chosen because of a consistent pattern of stands sampled for age structure that historically had frequent (six or more), low-severity fires and no evidence of large post-fire cohort ages prior to the twentieth century (Figure 2A; Sherriff 2004; Sherriff and Veblen 2006). In addition, these fire history sites had less temporal variability in fire intervals compared to sites with fewer fire return intervals (Figure 2B; Sherriff 2004; Sherriff and Veblen 2006). In contrast, the fire-scar evidence for the lower, more variable fire frequency class exhibited four or fewer fire years (recorded by at least two trees scarred) between 1700 and 1915 with fire intervals of 30 to more than 100 years and clear evidence of post-fire cohort ages initiating prior to the 1900s (Figure 2B, C). The lower, more variable fire frequency sites predominantly had trees with single fire scars and fire-scar evidence in clustered areas of the stand.

For predictively mapping fire frequency classes, 40 of the 54 fire history sites were randomly selected for model development (training), and the remaining 14 sites were used for model evaluation (Test1). In addition to the 14 sites (Test1) originally sampled for fire history, 50 additional sites were sampled for model evaluation (Test2) using a less intensive procedure that did not require cutting of fire-scar samples. The criteria used to identify fire frequency classes for the 50 additional sites were derived from the results of the more intensive sampling of fire history and forest structure conducted at the 54 fire history sites where fire scars were cut (Table 2). A 1-km point grid of the ARNF study area was delineated and 50 points were randomly selected for field sampling in plots of 100×300 m. Any sites with abundant logging or other human disturbances were rejected and an adjacent point was sampled. At each random point, the number of fire-scarred trees and number of fire scars on each tree were counted and forest structure was documented in a 100×300 m plot using criteria in Table 2. Additionally, three to ten cores were taken for tree ages and estimation of the last fire date in each plot (Barrett and Arno 1988). The data from these 50 less intensively sampled sites were used independently in model evaluation (Test2), and also were combined with the 14 fire history sites (Test1) to provide an assessment of model accuracy based on all 64 test sites.

Predictor Variables: Environmental Conditions

Potential predictor variables of fire frequency classes were derived from two sources: (1) terrain variables from a 30-m digital elevation model (DEM); and (2) cover type from digital vegetation maps of the ARNF Integrated Resource Inventory (IRI) and of Rocky Mountain National Park. Elevation, slope steepness, aspect and slope curvature were all derived from the 30-m DEM. To transform aspect from a circular to a linear value, an arcsine transformation was used to create an index of −1 to +1 (''southness'' to ''northness''). Slope curvature (concavity to convexity) and hillslope position are related to soil depth, texture and potential soil moisture and represent proxy measures of soil texture (Wilson and Gallant 2000). Ravine drainages were delineated from the 30-m DEM using Arc GRID (ESRI 2002) hydrologic terrain modeling (see Jenson and Domingue 1988) and distance to ravine drainage was calculated. Forested areas adjacent to grasslands may have fire regimes that are influenced by a different fire frequency and behavior in grasslands; thus, distance-to-grassland was also

Table 2. Multi-Variate Criteria used to Identify a Specific Fire Frequency Class at Each of the 50 Random Points throughout the ARNF Study Area where Fire Scars were not Cut

Fire frequency class	Observation criteria
High	Multiple and single fire scars on trees Three or more trees with at least three fire scars/tree Multi-aged stands with a patchy spatial pattern Abundant trees <10 cm dbh Abundant grass and understory vegetation
Low and variable	Primarily single fire scars on trees Four or fewer trees with more than two fires scars/tree Single or multiple cohort ages Moderate to very low numbers of trees <10 cm dbh and <1.3 m height Self-thinning Uniform spatial pattern

The number of fire-scarred trees and number of fire scars on each tree were counted and forest structure was documented in plots of 100 × 300 m.

used as a predictor variable. Proximity to grassland was calculated as the distance to the edge of grassland areas of at least 0.1 ha. Environmental conditions at each site were classified in terms of the mean elevation, slope steepness, aspect, proximity to grassland, distance to ravine and the associated fire frequency class. Transformations of predictor variables were also examined (for example, Log distance-to-grassland) to optimize predictive power. Other environmental (abiotic) variables such as geology and soils were not available at the resolution required for analysis.

As an exploratory step in assessing the spatial variation in fire frequency classes, we used a three-class cover type classification as a predictor variable (pure ponderosa pine, ponderosa pine-Douglas-fir, and mixed conifer) to identify possible cover types associated with the two fire frequency classes. The cover types of the 54 fire history sites sampled are representative of the cover types in the ARNF study area. Field observations delineated 32 of the 54 fire history sites in ponderosa pine stands, eight in the ponderosa pine-Douglas-fir cover type, and 14 in the mixed conifer cover type with ponderosa pine as the dominant or co-dominant species.

Analytical Methods

General Linear Models (GLMs) have been used extensively in ecological modeling research (for example, see Franklin 1995; Guisan and Zimmermann 2000). Logistic regression is the suitable GLM to use when the dependent variable is binary (presence or absence). Logistic regression uses a logit link to define the relationship between the dependent and the sum of the predictor variables (Hosmer and Lemeshow 2000). An advantage to using a probability surface is that the probability values can be used as an 'index' of habitat suitability (Franklin 1995).

In this study, environmental variables were used to predict the presence or absence of the high fire frequency class and the lower, more variable fire frequency class at the site level (n = 40 sites) using logistic regression (SPSS for Windows 10.0 software 1999). A combination of stepwise and iterative procedures was used to examine environmental variables and each fire frequency class. Variables that did not contribute significantly ($P < 0.05$) to reduce variance were excluded with a backward elimination procedure. Collinearity among predictor variables can be problematic with multiple regression, however none of the predictor variables in this study were highly correlated. Only the coefficients of statistically significant ($P < 0.05$) predictor variables associated with the dependent variable (fire frequency class) were used for predicting the probability of two fire frequency classes across the 60,875-ha ARNF study area. In ArcGIS, each predictor variable was multiplied by its coefficient and summed to produce a linear predictor for the fire frequency class (Miller and Franklin 2002). A logistic transformation was used to generate probability values between 0 and 1:

$$\text{Probability (fire frequency class)} = e^{\text{FFC}}/(1 + e^{\text{FFC}}) \quad (1)$$

The results yielded a map depicting a probability surface (suitability) of the presence of each fire frequency class (FFC). For predictive purposes, a decision has to be made on the probabilities that represent class presence. Consequently, a threshold is needed to transform the probability map into class presence data (Fieldling and Bell 1997; Manel and others 2001; Liu and others 2005). Although 0.5 is a common threshold used to differentiate between binary states, alternative threshold values are often chosen to minimize the number of omission and commission errors and provide the best agreement between predicted and observed values in the training dataset (Fieldling and Bell 1997; Franklin 1998; Guisan and Zimmerman 2000; Liu and others 2005). There has been much discussion in the literature on how best to evaluate the predictions of these types of models and chose an appropriate threshold. To date, there is no uniform agreement on the most appropriate methods.

Two elements commonly identified as important for defining the appropriate threshold include (1) the relative cost of false positives and false negative errors, although assigning values to these costs is subjective and dependent upon the context within which the classification rule will be used, and (2) the prevalence of positive cases (for examples, see Zweig and Campbell 1993; Fieldling and Bell 1997; Manel and others 2001; Liu and others 2005). For instance, a lower probability threshold can considerably reduce omission errors, particularly when the dependent variable may be uncommon or when the prevalence of presence or absence is unequal (Fieldling and Bell 1997; Franklin 1998). Unequal prevalence of class sizes can also influence the scores of logistic regression and many other classifiers, and produce scores biased towards the larger class (Fieldling and Bell 1997; Hosmer and Lemeshow 2000). In the current study, the presence of high fire frequency is uncommon in comparison to the alternative (lower and more variable fire frequency) and the prevalence of sites of high fire frequency presence is unequal in comparison to the alternative. Our approach follows a protocol of choosing a probability threshold to reduce omission errors (false negatives of high fire frequency sites), but also to minimize the overall error rate by representing a balance (minimum) of omission and commission errors in the training dataset for each fire type. We used a threshold to transform the probability map into areas delineated as either high fire frequency or the alternative, and assess model performance using a matrix of correctly and incorrectly classified class predictions. Thus, our approach includes several considerations besides the fit of the GLM, which allows us to address our primary goal of producing a model that best estimates the area that historically had a relatively high frequency of fire return intervals in the range of 10–30 years. The presence/absence of a predicted fire frequency type for each site was delineated based on the majority of cells in one of the two fire frequency classes using zonal statistics in ArcGIS. All modeling and map compilations were raster based and conducted at the finest resolution (30×30 m) permitted by the data. This approach does not formally consider spatial autocorrelation; however, the sites are widely spaced throughout the study area and only three sites are within one kilometer of each other (Figure 1).

Model Evaluation

Accuracy measures were derived from a matrix of correctly and incorrectly classified fire frequency class predictions to assess omission versus commission errors for the prediction of the training dataset. The number of sites correctly predicted for the training and test sites was the primary criterion used to assess the accuracy of each predictive model. Additionally, accuracy measures of both omission and commission errors are presented for the combined evaluation datasets of Test1 and Test2. These measures include the correct classification rate (CCR) and the Kappa K statistic. CCR represents the proportion of omission and commission errors. The Kappa K statistic indicates the overall agreement between the prediction and the model evaluation dataset as opposed to random chance. Fieldling and Bell (1997) indicate values less than 40% have poor agreement, 40–70% have good agreement and values greater than 70% represent excellent agreement.

Results

There were no significant relationships of the fire frequency classes with cover type (ponderosa pine compared to ponderosa pine-Douglas-fir and mixed conifer) for the 54 fire history sample sites. Among the nine sites classified as high fire frequency sites, seven are in ponderosa pine stands and two are in ponderosa pine-Douglas-fir stands. The sites classified as lower, more variable fire frequency occurred across all three cover types. Consequently, the focus of the fire frequency modeling was on abiotic predictors of fire frequency classes, rather than cover type predictors, throughout the ARNF study area and cover type was excluded from the stepwise regression.

Fire Frequency Model

Elevation is the only significant predictor variable of the high fire frequency class (Table 3). High fire frequency sites tend to occur at lower elevations. A

Table 3. Logistic Regression Model of High Fire Frequency Developed from 40 Fire History Training Sites and the Probability Threshold for Balancing Omission and Commission Errors of the Training Dataset

Fire frequency class	Predictor variables	Coefficient	SE	*P*	Lower 95% CI	Upper 95% CI	Prediction threshold
High frequency	Elevation	−0.007	0.002	0.006	−0.003	−0.011	0.3
	Constant	13.396	5.298	0.011			

Only significant coefficients (P < 0.05) were used in the analysis.

value of 0.3 was chosen as the probability threshold to distinguish between fire type classes because it minimizes the overall error rate for the training dataset. With a probability threshold of 0.5, the logistic regression predicted four of the six training sites of high fire frequency correctly, but when the threshold was adjusted to 0.3 the accuracy increased to five of six sites (Table 4). Evaluation of the 64 test sites yields similar results (Table 4; Figure 3). Only six of 64 test sites and five of 40 training sites range between the 0.3 and 0.5 thresholds, all other values fall closer to their optimal values of 1 or 0, which also suggests a better fit of the entire dataset (particularly high fire frequency sites) by using the 0.3 threshold than the standard 0.5 threshold (Figure 3; only the test sites are presented). Using the 0.3 threshold, nine of the ten high fire frequency test sites were correctly predicted (Table 4; Figure 3). The overall CCR of omission and commission error for the combined datasets of Test1 and Test2 is 95.3%. The Kappa value is 82.9%, indicating excellent predictive agreement with the test dataset. The high prediction accuracy indicates that elevation by itself is a good predictor of high fire frequency areas.

The low and variable fire frequency sites tend to be at higher elevation than high fire frequency sites. Fifty-two of 54 test sites (Figure 3) and 31 of 34 training sites were predicted accurately (Table 4). The overall CCR of omission and commission error is 95.3%. The Kappa value is 82.9%, which demonstrates excellent prediction agreement with test datasets.

In the ponderosa pine zone of the ARNF, lower elevations below approximately 2,100 m are more favorable to high fire frequency than higher elevation areas (Figure 4B, C). Using the 0.3 threshold for defining class presence, the logistic regression model predicts 18.7% of the study area as high fire frequency (Figure 4C). In contrast to high fire frequency sites that are restricted to lower elevations, low and variable fire frequency sites occur across a broad range of the study area at higher elevation than the high fire frequency sites. Most of the study area is predicted to have a low and variable fire frequency in which 81.3% of the area is predicted to be in this fire frequency class (Figure 4C).

Discussion

The main goal of our study was to roughly estimate the area of the ponderosa pine zone of the northern Front Range that conforms to the general viewpoint that modern stand structures and fuel conditions are primarily a consequence of reduction in low-severity fires during the twentieth century. Our results indicate that less than 20% of the study area of ponderosa pine zone historically had a relatively high frequency of fire return intervals in the range of 10–30 years (Figure 4). More than 80% of the study area was reconstructed to have had lower and more variable fire frequencies with only a few fire years (recorded by at least two scarred trees) occurring over the last few centuries (Figure 4). Thus, forest structure over most of the ponderosa pine zone was molded by infrequent fires (fire intervals of 30 to over 100 years) rather than frequent surface fires. Years of widespread fire events in association with extreme weather are recorded by fire scars on many trees dispersed throughout the ponderosa pine zone (Veblen and others 2000). Many post-fire cohorts (for example, see Figure 2C) and tree-growth releases (indicating competitive suppression in closed stands prior to burning) date from a few years after the dates of widespread fire (Veblen and Lorenz 1986; Goldblum and Veblen 1992; Sherriff 2004; Sherriff and Veblen 2006). We interpret this evidence to mean that over most of the ponderosa pine zone, forest structures were shaped primarily by infrequent severe fires that killed large percentages of canopy trees promoting dense post-fire cohort ages in the northern Front Range.

According to the logistic regression analysis applied here, the high fire frequency class was clearly delimited by elevation (below circa 2,100 m). Highly similar results were obtained with classification tree models (CART; De'ath and Fabricius

Table 4. Number of Sites Classified Correctly for Each Fire Frequency Class Prediction for the Training, Test1 and Test2 Sites

	Training	Test1	Test2
HF sites correctly classified as HF	5	3	6
HF sites incorrectly classified as LF	1	0	1
LF sites correctly classified as LF	31	11	41
LF sites incorrectly classified as HF	3	0	2
Total number of sites	40	14	50

HF indicates high fire frequency and LF indicates low and variable fire frequency.

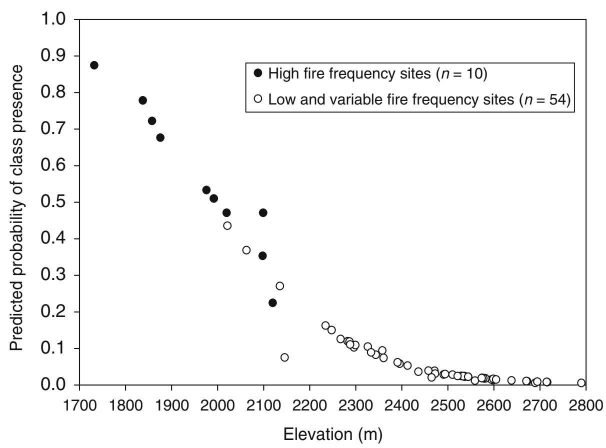

Figure 3. Predicted probabilities of class presence versus elevation for each of the evaluation sites. The optimal probability is 1.0 for high fire frequency and 0 for low and variable fire frequency. Sites of high (low and variable) fire frequency were considered to be accurately predicted if the observed probability ranged between 0.3 and 1 (<0.3).

2000) that were applied to the same fire frequency and environmental data sets (Sherriff 2004) but are not redundantly presented here. Elevation may be a proxy for other factors such as proximity to grasslands, given that the lowest elevations are adjacent to the plains-grassland ecotone, where the highest fire frequencies occur. Due to the overriding influence of low elevation, other factors such as topographic position may be inconsequential for determining fire frequency in areas adjacent to the plains-grassland ecotone. If a training dataset larger than 40 had been used, distance-to-grasslands would have been a statistically significant predictor of fire frequency areas, given that there is a clear pattern when all 54 fire history sites are analyzed (data not shown, $P = 0.035$, logistic regression). Greater proximity to grassland in lower elevation areas probably promotes more frequent fire because of a greater abundance of fine, herbaceous fuels. The lower and more variable fire frequency class occurs across a broad range of elevation in relation to other environmental conditions such as aspect, slope steepness and distance to ravines (Sherriff 2004). Mesic north-facing aspects are important for the lowest fire frequency class, and these areas tend to be on steep slopes and generally far from ravines and grassland areas (Sherriff 2004). At increasing distance from ravines and grasslands, lower amounts of fine fuel may hinder frequent fire occurrence. Across the ponderosa pine zone, a gradient exists with increasing elevation towards less frequent and higher severity fires (Sherriff 2004); however additional sites are needed to clarify these trends.

The fire frequency criteria used in the current analyses are subject to general limitations of tree-ring based fire history methodologies (see Swetnam and Baisan 1996; Baker and Ehle 2001; Veblen 2003b). In the present study, we minimized limitations of these methodologies by identifying two broad classes of past fire occurrence that were defined by a combination of fire scars, tree age structures, stand densities, tree death dates, and growth releases (Figure 2; Sherriff 2004; Sherriff and Veblen 2006). These converging lines of evidence clearly distinguished areas of mainly frequent low-severity fires from areas of less frequent and higher-severity fires.

Another limitation of the current analysis is the limited number of sites relatively undisturbed by recent anthropogenic activities available for model development relative to the spatial heterogeneity within the ponderosa pine zone. In particular, logging and residential development has greatly reduced the number of suitable sample sites at low elevations. These disturbances also limited sampling at the upper elevation range (2,000–2,100 m) of the high fire frequency regime to only a few sites. The distribution and prevalence of sites would have influenced the coefficient of the predictor variable (elevation) in the logistic regression by limiting the range for high fire frequency, which is why the 0.3 threshold better represents the overall

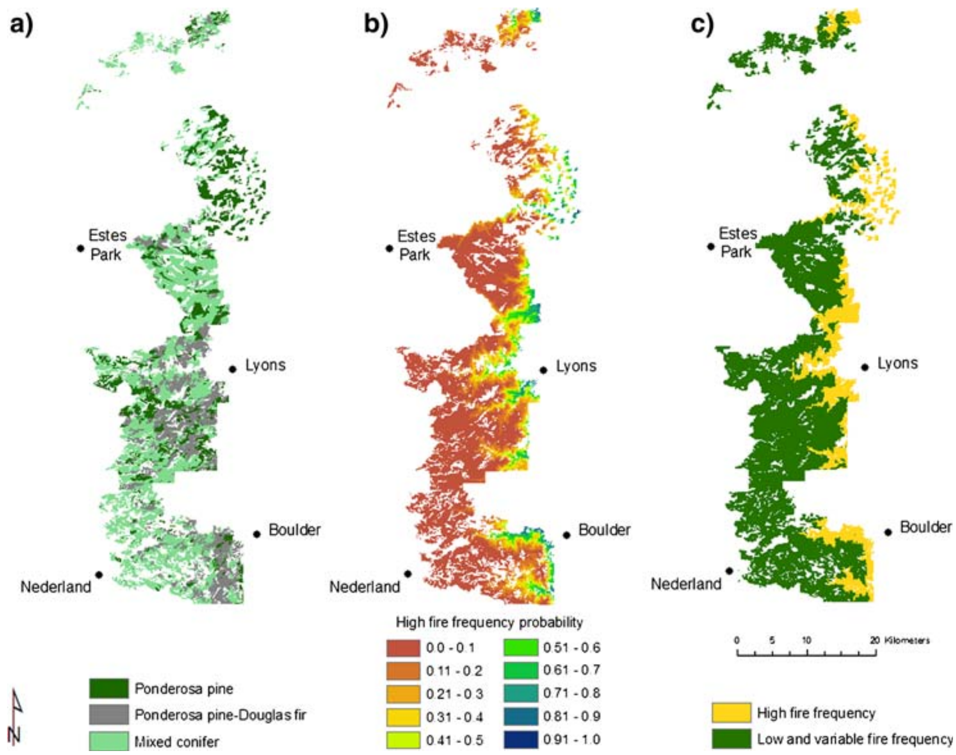

Figure 4. Cover type map and high fire frequency prediction of the Arapaho-Roosevelt National Forest study area (60,875-ha): **A** cover type includes pure ponderosa pine forest (*dark green*), ponderosa pine-Douglas-fir forest (*grey*) and mixed conifer forest (*light green*), which includes Douglas-fir-ponderosa pine based from the Forest Service IRI vegetation data; **B** the probability map of the high fire frequency prediction; and **C** the fire frequency map shows the 18.7% (*yellow*) area predicted as high fire frequency below circa 2,100 m, and the 81.3% area predicted as low and variable fire frequency (*green*).

distribution of the fire history sites than the standard 0.5 threshold. Additional sites would probably allow for a better prediction of environmental conditions associated with different fire frequency classes. Nevertheless, this initial assessment of a predictive fire frequency model clearly identifies elevation associated with fire frequency classes in ponderosa pine forests of the northern Front Range. Furthermore, in comparison with published fire history studies in other ponderosa pine ecosystems, the current dataset stands out as one of the largest in terms of numbers of sites and fire-scarred trees sampled (Baker and Ehle 2001).

A major problem in the use of tree-ring based fire history methodologies is uncertainty about the spatial extent to which fire-scar data may be extrapolated from one or a few sample points to a larger, spatially heterogeneous landscape (Swetnam and Baisan 1996; Baker and Ehle 2001; Veblen 2003b). Our results indicate that within the ponderosa pine zone there is substantial spatial variation in historic fire regimes, and also indicate the degree of uncertainty in classifying a site as having a frequent, low-severity fire regime or a lower, higher-severity fire regime. Indication of uncertainty in class membership is a key advantage of using a logistic regression model in the mapping procedure (Franklin 1995). The current results imply that for other ponderosa pine ecosystems, substantial research efforts based on large numbers of fire history sites across the full range of environmental conditions in spatially heterogeneous environments will be required to obtain a better understanding of the spatial variability in historic fire regimes.

Management Implications

The most important management implication of this study is both simple and robust: only a small fraction of the ponderosa pine zone of the northern Front Range fits the widespread notion that the historic fire regime was characterized mainly by frequent (that is, return intervals < 30 years) low-severity fires that maintained open woodlands. This is a critically important finding, because much of the current fuels reduction management in this landscape is based on the belief that thinning of stands throughout the ponderosa pine zone would both reduce fire hazard and restore the vegetation to an open structure formerly maintained by relatively frequent fires (for example, Front Range Fuels Treatment Partnership Strategy 2003). Such a perception is in fact valid only for the lowest elevations of ponderosa pine, especially those close to the plains-grassland ecotone such as the City of Boulder Open Space lands (Forest Ecosystem Management Plan, Boulder Open Space and Mountain Parks 1999). Frequent fires, presumably of low severity, would have killed mostly juvenile trees, resulting in low densities of mature trees.

The perception that the decline in fire frequency over the past circa 80 years has led to substantial increases in stand density at many sites is supported in our study area only for the lowest elevations of ponderosa pine (Veblen and Lorenz 1986; Sherriff 2004; Sherriff and Veblen 2006). Even in this low elevation sector, however, some sites had historic fire regimes dominated by infrequent rather than frequent fires (for example, steep and north-facing slopes; Sherriff 2004). These infrequent fires, inferred to be high-severity fires from age structure data, killed high percentages of trees within a fire perimeter, and promoted the establishment of naturally dense forest patches (Veblen and Lorenz 1986; Sherriff 2004; Sherriff and Veblen 2006). Nevertheless, at a coarse-scale for sites below approximately 2,100 m there is a convergence between the management objectives of fuels reduction through thinning and of landscape restoration to conditions that existed prior to fire exclusion.

Across the montane zone of the Front Range, there has been a dramatic decline in fire frequency that began in the early twentieth century (Veblen and others 2000). In comparison with the late nineteenth century which was a time of widespread burning in association with climatic conditions favorable to fire (Veblen and others 2000), the decline in fire occurrence may reflect active suppression of natural and human-caused fires, fewer ignitions by humans, fine-fuel reduction by livestock grazing, and/or climatic conditions less favorable to widespread fire. However, this study suggests that, except for the low elevation areas, widespread surface fires were not the primary fire type shaping forest structures in the pre-twentieth century in the northern Colorado Front Range. The fires that occurred in the nineteenth century and earlier at higher elevations (but still including some areas of relatively pure ponderosa pine forest), included infrequent high-severity fires that shaped the relatively dense, post-fire stands of the modern landscape. The high tree densities at higher elevations are primarily a legacy of nineteenth century severe fires rather than a consequence of any suppression of low-severity fires. Thus, management efforts to create large areas of open woodlands in the higher elevation areas of the ponderosa pine zone of ARNF would not be consistent with historic fire regimes and stand structures.

We caution that the fire frequency model presented in this study was empirically derived from the specific fire history and site conditions of the northern Colorado Front Range, and that it is unknown how well it would apply to other ponderosa pine ecosystems. Clearly, this model indicates ecologically significant variation in fire regimes in relation to topography and elevation within the ponderosa pine zone. The research design and results of the present study, however, suggest that a similar empirical modeling approach would improve our understanding of the spatial variability of fire regimes in other ponderosa pine ecosystems.

A clear delineation of the spatial extent of past fire regime types is a major concern for ecosystem managers in the context of wildfire risk and ecological restoration in the areas wildland–urban interface. At low elevations in our study area the historic fire regime of more frequent and low-severity fires implies that the goals of ecological restoration and wildland fire hazard mitigation converge. In contrast, in areas naturally characterized by low frequencies of mixed- to high-severity fires, the goals of ecological restoration and fire hazard mitigation often diverge. The potential for extreme fire behavior may largely be explained by extreme weather conditions (for example, high winds and low humidity during severe acute drought) rather than fuel conditions (Schoennagel and others 2004). This is illustrated by the 2002 Hayman fire (55,915 ha) in Colorado in which more than 24,000 ha burned at high severity throughout ponderosa pine and mixed-conifer forests in a single day (Finney and others 2003). In such areas forest thinning will not achieve restoration goals and is of questionable effectiveness in preventing severe wildfires.

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