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RESEARCH ARTICLE

Spatial models for inferring topographic controls on historical low-severity fire in the eastern Cascade Range of Washington, USA

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Abstract Fire regimes are complex systems that represent an aggregate of spatial and temporal events whose statistical properties are scale dependent. Despite the breadth of research regarding the spatial controls on fire regime variability, few datasets are available with sufficient resolution to test spatially explicit hypotheses. We used a spatially distributed network of georeferenced fire-scarred trees to investigate the spatial structure of fire occurrence at multiple scales. Mantel's tests and geostatistical analysis of fire-occurrence time series led to inferences about the mechanisms that generated spatial patterns of historical fire synchrony (multiple trees recording fire in a single year) in eastern Washington, USA. The spatial autocorrelation structure of historical fire regimes varied within and among sites, with clearer patterns in the complex rugged terrain of the Cascade Range than in more open and rolling terrain further north and east. Results illustrate that the statistical spatial characteristics of fire regimes change with landform characteristics within a forest type, suggesting that simple relationships between fire frequency, fire synchrony, and forest type do not exist. Quantifying the spatial structures in fire occurrence associated with topographic variation showed that fire regime variability depends on both landscape structure and the scale of measurement. Spatially explicit fire-scar data open new possibilities for analysis and interpretation, potentially informing the design and application of fire management on landscapes, including hazardous fuel treatments and the use of fire for ecosystem restoration.

Keywords Topographic controls · Historical fire regimes · Spatial statistics · Eastern Washington · Scale dependence

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Introduction

Large severe fires over the last decade remind us that wildfire may be the most important ecological disturbance in western North America. Forest managers are using both wildfire and prescribed fire to restore forests after the adverse effects of fire exclusion, giving priority to forests with low-severity fire regimes (ca. 25 million ha in the western US). Only a fraction of this area can be treated, so methods are needed to identify high-priority areas for prescribed fire. To integrate wildfire effectively into managed landscapes it will be imperative to identify the scales at which fire phenomena are relevant for different ecosystem types and locations.

Fire regimes are associated with specific geographic areas and usually summarized by frequency, severity, seasonality, extent, and spatial distribution (Agee 1993; Johnson and Gutsell 1994). Identifying the spatial and temporal characteristics of fire regimes has proven difficult, however, and there is no consensus on how fire regime statistics should be calculated because means and variances of most metrics change with the temporal and spatial scales of analysis (McKenzie et al. 2006a, Falk et al. 2007).

Climate, fuels, and topography control fire regimes at different temporal and spatial scales. The relative influences of these three controls can be classified as top-down or bottom-up (Lertzman and Fall 1998). Climate provides top-down controls on fire at large spatial scales, whereas topography and fuels are typically viewed as bottom-up controls influencing fire at smaller scales (Heyerdahl et al. 2001). Climate controls on fire regimes vary throughout western North America. For example, fire frequency in ponderosa pine (*Pinus ponderosa*) forests in the American Southwest is strongly associated with El Niño Southern Oscillation (ENSO) cycles (Swetnam and Betancourt 1999; Veblen et al. 2000), whereas the relations in the mixed-conifer forests of the Northwest are less clear (Heyerdahl et al. 2001; Hessl et al. 2004; Gedalof et al. 2005). Fuels exert bottom-up influences on fire regimes at fine spatial scales, also with regional variation in strength. For example, at fine scales, fuel type, quantity, and spatial configuration influence fire regimes in Southwestern ponderosa pine forests (Allen et al. 2002). In similar forest types in the Northwest, microclimate exerts bottom-up controls on fire regimes by affecting fuel moisture (Tande 1979; Taylor and Skinner 1998; Heyerdahl et al. 2001; Hessl et al. 2004). Climate and fuels are linked with topography as the common denominator that acts at multiple scales to mediate the interaction between coarser and finer scale processes influencing fire regimes (Lertzman and Fall 1998).

Many ecological processes are spatially and temporally dependent (Cliff and Ord 1981; Legendre and Legendre 1998). For example, fire history research in low-severity fire regimes typically begins in the field with point measurements. Sample data become increasingly spatially autocorrelated with finer-grained observations, because the temporal pattern of fires for one recorder tree will be most similar to those on nearby recorder trees (Dutilleul 1998). Fire-history data are often treated with standard parametric statistics, but they violate assumptions of independence (Dorner et al. 2002).

Fire scarring is best modeled as a stochastic process in which each tree or group of trees that records fire represents a random sample from a population that has a probability distribution (Lertzman and Fall 1998; McKenzie et al. 2006a; Falk et al. 2007). The time series of fires associated with each recorder tree is one of many possible realizations. Statistical theory allows us to treat each observation as a random variable with a mean, variance, and cumulative distribution. The underlying distributions of fire regime metrics are scale dependent because a fire regime is an aggregate of temporal events that overlap in space (Falk et al. 2007). By observing the properties of multiple fire events in space and time, we can detect patterns that may not be discernible for individual fires or at single points. Quantifying both spatial structures and scale dependence will bring us closer to estimating fire regime metrics that are comparable across landscapes and regions (Baker 1989; Falk et al. 2007).

The statistical theory of random processes allow us to model the spatial dependence associated with fire regimes. Spatial and multivariate statistical methods (particularly variogram analysis and Mantel's tests) have been applied to spatially autocorrelated ecological data to quantify spatial dependence (Legendre and Troussellier 1988; Wagner 2003), epidemiology (Cliff and Ord 1981), soil sciences (Isaaks and Srivastava 1989), and genetics (Smouse et al. 1986; Oden and Sokal 1992). To date, however, no such analyses have been used to quantify the spatial structures associated with fire regimes, partly because of the dearth of fire-history datasets with adequate spatial resolution or extent.

In this study, we took advantage of the largest existing spatially explicit fire-history dataset (Everett et al. 2000) to investigate the spatial structure in low-severity fire regimes associated with lower-elevation ponderosa pine-dominated forests in eastern Washington State, USA (Table 1). We analyzed both global and multi-scale spatial structure using geostatistical methods. We hypothesized that fire occurrence in

Table 1 Location, analysis area, and sample sizes with temporal record of fire-scarred trees at each of the seven sites from northeast to southwest

Site	Location			Fire Scars			
	Lat. (N)	Lon. (W)	Study site (ha)	Trees (n)	No. fire scars	First scar	Last scar
South Deep	48° 45′	117° 40′	15,597	168	680	1,399	1,986
Quartzite	48° 17′	117° 37′	7,228	142	1,300	1,384	1,989
Frosty Creek	48° 34′	119° 00′	47,793	420	4,461	1,343	1,994
Twenty Mile	48° 36′	120° 17′	5,313	409	2,946	1,342	1,990
Entiat	47° 48′	120° 20′	17,575	490	3,904	1,530	1,988
Swauk Creek	47° 15′	120° 38′	21,654	665	7,048	1,257	1,942
Nile Creek	46° 52′	121° 05′	39,979	234	2,314	1,367	1,970
Total			155,139	2,528	22,653		

each site was controlled to varying degrees by topography, with stronger controls in sites with complex rugged terrain and weaker controls in areas with gentle terrain. The objectives of this study were to: (1) take advantage of the spatially explicit fire record to examine fire occurrence at multiple spatial scales; (2) identify spatial controls on fire regimes and infer the limits to these controls; and (3) identify future research and management opportunities associated with spatially explicit fire-history data.

Methods

Study area

Fire history data were collected by Everett et al. (2000) from seven study sites located along a 300-km distance from the Colville National Forest in the Okanogan Highlands in NE Washington to the Okanogan-Wenatchee National Forest in central Washington, in the eastern Cascade Range (Fig. 1). Topography in the study sites becomes increasingly complex and rugged along the gradient from NE to SW, reflecting dominant influences of continental Pleistocene glaciers in the NE versus primarily mountain glaciers in the SW. East of the crest of the Cascade Mountains, forest ecosystems are dominated by conifer species, with mixtures of ponderosa pine, grand fir (*Abies grandis*), and Douglas-fir (*Pseudotsuga menziesii*). Ponderosa pine, grand fir, and Douglas-fir occupy a wide elevational range in the Pacific Northwest; ponderosa pine dominates at low and middle elevations, with Douglas-fir and grand fir increasing in abundance with elevation (Franklin and Dyrness 1988).

Data collection

Everett et al. (2000) selected sites to capture the heterogeneity of the eastern Cascade landscape and span the range of ponderosa pine-dominated ecosystems. The size, sampling intensity, and fire record varied at each study site (Table 1), as did climate, geomorphology, landform, and species composition. Within each study site, aerial photographs and topographic maps were used to identify and map *aspect polygons*, delineated by aspect (northerly or southerly) and slope (flat, moderate, or steep). Sizes of aspect polygons ranged from 32 to 1,700 ha, and the number of polygons within each site ranged from 2 to 21. Polygons were internally stratified into four to five sub-polygons to ensure that fire scar samples were spatially segregated in the polygon. All fire-scarred trees within each sub-polygon were mapped, and between 2 and 23 "high quality" trees (with a large number of scars) were sampled. Sections were cut from live trees (Arno and Sneck 1977), and cross-sections were collected from stumps, snags and logs.

Fire scars collected from both living and dead trees were prepared using standard procedures (Arno and Sneck 1977). All samples were then crossdated against an independent master tree-ring chronology developed from 20–50 climatically sensitive trees (without fire scars) within each sampling area. The year of each fire scar was determined by the position

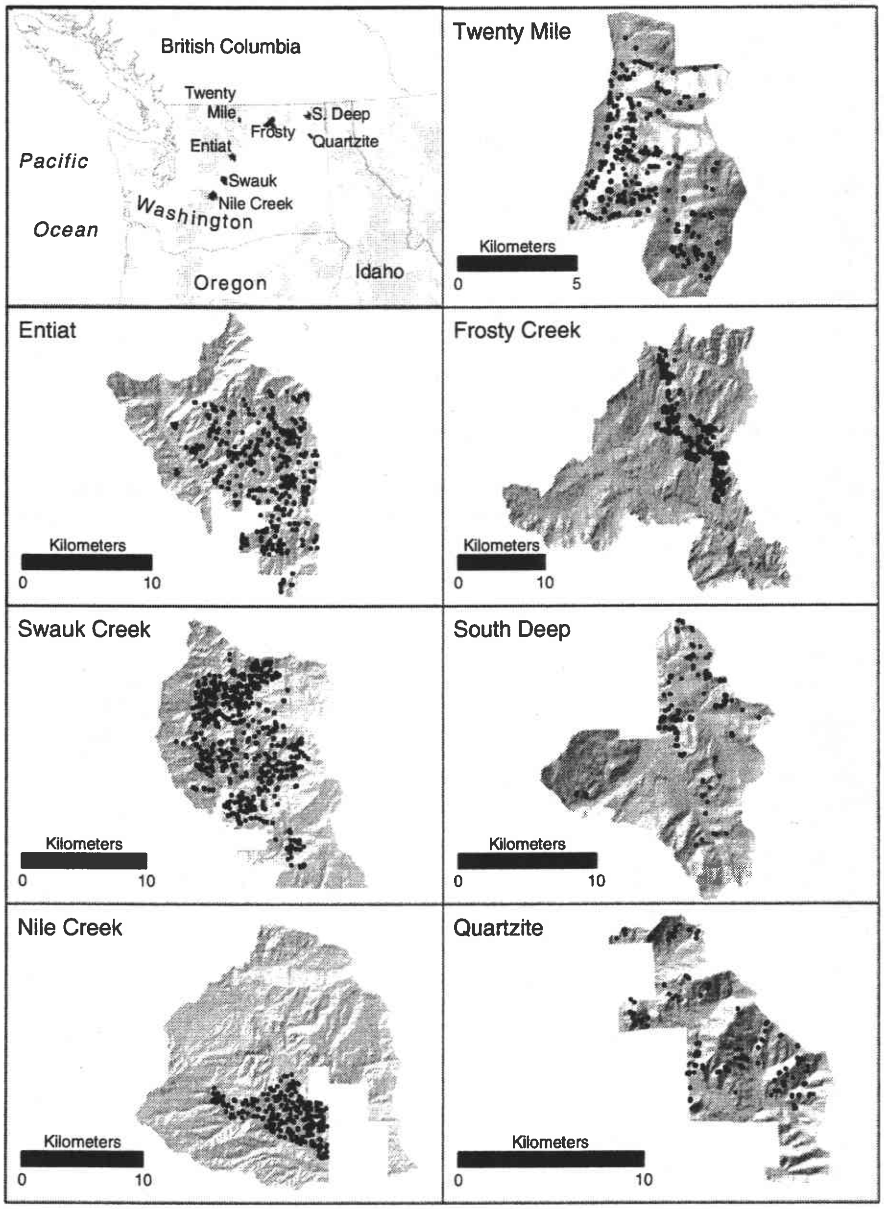

Fig. 1 Fire history study sites, east of the crest of the Cascade Mountains, Washington, USA. From northeast to southwest: South Deep, Quartzite, Frosty Creek, Twenty Mile, Entiat, Swauk Creek, and Nile Creek. Inserts display *hill shaded* topography (ESRI 2006) with dots representing the locations of recorder trees. Total areas of study sites are given in Table 1

of the scar relative to the dated sequence of annual rings in the cross-section (Dieterich and Swetnam 1984). Based on the pattern of late season fires (July–October) in the modern record, dormant season fires were always assigned to the calendar year of the previous ring (representing a fall fire), rather than the following ring (representing a spring fire). For a complete description of the methodology see Everett et al. (2000) or Hessl et al. (2004). Topographic data were derived from 30 m x 30 m resolution USGS digital elevation models (DEM).

Topographic analysis

To quantify topographic complexity, we calculated Hurst exponents (H) (Feder 1988) in order to compute the fractal dimension (D) for each of the seven sites (Turcotte 1989). Using DEMs, the average standard deviation of elevation (σ) is calculated over varying window lengths (τ). Window lengths (τ) are increased from a minimum step size of 2 (60m), and increased by a factor of 2 to a maximum of one half the distance across the study site using a 'moving window' method. The Hurst exponent (H) (Feder 1988) is the slope (β) from log (σ) regressed on log (τ). H is directly related to the fractal dimension (D) as:

$$D = 2 - H \tag{1}$$

Average standard deviation (σ) over window sizes captures local relief in smaller windows and landscape roughness in larger window sizes, thereby defining topographic relief across scales. Because of the limitations of raster modeling, windows were expanded linearly by rows and columns in the topographic grid rather than omni-directionally (as expanding circles). Besides its significance as the slope parameter in a log-log regression, the Hurst exponent value is open to other interpretations. A Hurst exponent of $H = 0.5$ suggests a random process or no autocorrelation, whereas $0.5 < H < 1$ suggests long-range dependence and positive autocorrelation, and $0 < H < 0.5$ suggests negative autocorrelation.

Spatial analysis

We quantified synchrony among temporal patterns of fire occurrence within the study sites, as reflected in fire-scar dates for individual recorder trees, using Sorensen's measure of dissimilarity (Sorensen 1948, Legendre and Legendre 1998), hereafter "Sorensen's distance". The binary (0,1) time series of fire occurrence for recorder trees in each site were combined into matrices where rows were years and columns were recorder trees. Fire-occurrence distance matrices were then created where each cell was calculated as:

$$d_{ij} = 1 - \frac{\sum_{k=1}^{n} |x_{ik}x_{jk}|}{\sum_{k=1}^{n} [(x_{ik} + x_{jk}) - x_{ik}x_{jk}]} \tag{2}$$

where d_{ij} is the entry in the ith row and jth column of the distance matrix, the values of k correspond to the years in the fire record, and the x_{ik} and x_{jk} are either 1 or 0, depending on whether a fire occurred in year k in the ith and jth recorder trees.

This measure is bounded by [0, 1], where years in which no fires were recorded by either tree are considered to have no information. We assumed that if any two trees recorded the same fire year that it was the same fire. Fire-occurrence distance matrices for each study site were used as multivariate responses in Mantel's tests and variogram models. Analyses used a combination of ARCGIS 9.0 (ESRI 2006) and Splus 2000 for Windows (Insightful 2000).

We used Mantel's tests (Mantel 1967) to test the null hypothesis that there was no spatial dependence of synchronous fire occurrence in each study area: fire-occurrence time series were no more similar to those at nearby recorder trees than to those more distant. Mantel's correlations were computed using Sorensen's distance matrices as the dependent variable (y) and Euclidean distance as the independent variable (x). The cross-product of the matrices (X,Y) is standardized by first subtracting means ($\bar{x}$,$\bar{y}$) and dividing by standard deviations (S_X ,S_Y), then dividing the double summation by the effective degrees of freedom (d−1) where d = the number of distances in the upper triangle of each matrix (n[n−1]/2) (Eq. 3). The correlation coefficients are thereby bounded on [−1, 1] (Legendre and Legendre 1998).

$$r_M = \frac{1}{d-1} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \left[\frac{X_{ij} - \bar{X}}{S_x}\right] \left[\frac{Y - \bar{Y}}{S_y}\right] \tag{3}$$

where i and j are row and column indices of the Sorensen's distance matrix **X** and the Euclidean distance matrix **Y**, respectively.

Significance of correlations (r_M) was evaluated via a weak-restricted randomization procedure in which the rows (i) and columns (j) of the distance matrices (X,Y) are randomly rearranged, and the correlation statistic is computed over 10,000 iterations to create a reference distribution (Legendre and Legendre 1998; Fortin and Payette 2002).

The Mantel statistic provides a global metric for the dependence of similarity between fire records on geographic distance, but it does not quantify how Sorensen's distance changes over increasing geographic distance. Semivariance (γ) measures were used to decompose spatial variability among distance classes to detect finer scales and gradients of spatial dependence.

A standard semivariance (γ) for a univariate statistic is

$$\gamma(d) = \frac{1}{2W} \sum_{h=1}^{n-1} \sum_{i=n+1}^{n} w_{hi}(y_h - y_i)^2, \text{for } h \neq 1 \tag{4}$$

Semivariance at distance d (γ(d)) is a measure of the average degree of similarity (squared difference) between pairs of observations (y_h, y_i), possibly weighted (w_{hi}) as a function of distance and direction where membership in a distance class is determined by the sum of weights (W_{hi}) (Legendre and Fortin 1989). Semivariance values are standardized covariance measures and the range is theoretically $[0,\infty]$, representing complete spatial dependence to no spatial dependence, although most observational data will have a finite variance.

We used Sorensen's distance (Eq. 2) in place of the squared-distance term in Eq. 4. The semivariance of a distance class (γ(d)) is thereby represented as the mean Sorensen's distance between pairs of observations. We constructed omni-directional variograms of Sorensen's distance (hereafter "Sorensen variograms"). Spherical variogram models (Eq. 5) were fit using a weighted, non-linear least squares method (Cressie 1985).

$$\gamma(h) = C_o + C\left[1.5\left(\frac{h}{A_o}\right) - 0.5\left(\frac{h}{A_o}\right)^3\right],\ h \leq A_o \quad (5)$$
$$\text{and}\ \gamma(h) = C_o + C,\ h > A_o$$

where C_o is the nugget, C is the sill effect, and A_o is the range. We used the model parameters individually or in combination to interpret how spatial dependence changes across scale (Goovaerts 1997; Legendre and Legendre 1998; Webster and Oliver 2001).

Variogram patterns were considered robust for distance classes containing greater than 1% of the total possible pairs of points from the sample (Legendre and Fortin 1989). Spatial dependence was quantified by the ratio (sill/(sill + nugget)), where the nugget represents variance that is unrelated to the distance between observations (Wang et al. 2002). We use this ratio as a surrogate for R^2, or percentage variance explained, in that we are quantifying how much of the change in Sorensen's distance (analogous to the "Y" is a classic regression) can be explained by lag distance (the "X").

Last, we wanted to be able to infer relationships between topographic structure and spatial autocorrelation structure, to quantify the degree of topographic control on fire across sites. As a direct link between variogram models and topographic complexity, we used simple linear regression to model variogram range (the distance beyond which between-tree dissimilarity does not increase further) as a function of the fractal dimensions calculated in the topographic structure analysis. This regression, combined with qualitative comparisons of both the Mantel statistics and Sorensen variograms with topographic complexity, guided our inferences about the strength of topographic controls on fire.

Results

Fractal dimensions ranged from approximately 1.2–1.4 (Table 2). Regressions from roughness length calculations produced all positive ($0.5 < H < 1$), significant slopes (H) at $P < 0.005$ (Table 2). The rank of the seven study sites, from gentle to complex, is Twenty Mile, Frosty Creek, South Deep, Entiat, Nile Creek, Quartzite and Swauk Creek, reflecting anomalies in the gentle-to-complex topographic gradient commonly assumed from NE to SW in eastern Washington.

The null hypothesis tested with a Mantel's test, that fire synchrony was independent of geographic distance, was rejected for all seven study sites. Euclidean distances were positively and significantly correlated with fire synchrony (Table 3). The strongest dependence was in Nile Creek, Twenty Mile, and Swauk Creek (r = 0.50, 0.51, and 0.54), with moderate dependence present in the Entiat and Frosty Creek (r = 0.34 and 0.35), and weaker dependence in the Quartzite and South Deep (r = 0.29 and 0.19).

Mean Sorensen's distance monotonically increased over geographic distance in all study sites (Fig. 2). Empirical variograms fit a spherical model (Eq. 5) over varying numbers of lags and maximum distances (Table 4). Percentage of variance in historical fire

Table 2 Results of topographic structure analysis on the 7 study sites—fractal dimensions, Hurst exponents and correlations from roughness-length regressions

Site	Fractal dimension	Hurst exponent	R^2
South Deep	1.26	.74	.88*
Quartzite	1.35	.65	.88*
Frosty Creek	1.25	.75	.86*
Twenty Mile	1.20	.80	.84*
Entiat	1.30	.70	.79*
Swauk Creek	1.40	.60	.86*
Nile Creek	1.33	.67	.85*

* Significant at $P < 0.005$. Study sites listed from northeast to southwest

Table 3 Spatial statistics of fire synchrony represented by Mantel correlations and Sorensen variograms fit to spherical models. Mantel's correlations were all significant ($P < 0.01$). Spherical model parameters of Sorensen variograms are range, nugget, sill, proportion of spatial dependence explained (sill/(sill + nugget)), and approximate extent (area of a circle with the range as radius), which serves as a surrogate for modal fire size (see text). Nugget + sill, and therefore one or the other separately, are bounded on [0,1] by definition. Study sites are listed from northeast to southwest

Site	Mantel correlation	Range (m)	Nugget (C_o)	Sill[a] (C)	Spatial dependence %	Extent (ha)
South Deep	0.19	2,480	.71	.17	19	1,932
Quartzite	0.29	3,856	.67	.21	24	4,671
Frosty Creek	0.35	5,674	.73	.13	15	10,114
Twenty Mile	0.51	5,519	.51	.33	37	9,569
Entiat	0.34	4,178	.65	.14	18	5,484
Swauk Creek	0.54	3,080	.60	.26	30	2,980
Nile Creek	0.50	3,104	.62	.23	27	3,027

[a] Here the sill is the difference between the nugget (Sorensen's distance at lag = 0) and the maximum Sorensen's distance for any lag distance, observed at the range. In the ecological literature "sill" is sometimes equated with this maximum

synchrony explained by the variograms ranged from 15% in Frosty Creek to 37% in Twenty Mile (Table 3). The range parameter from the spherical models indicated that fire was synchronous over fairly long distances, from approximately 2.5 km in South Deep to 5.7 km in Frosty Creek (Table 3). From these ranges we infer the extent (ha) of fire synchrony for the study sites, which we refer to as "effective fire size", or range of influence of the average fire, conditional on the nugget and sill parameters (Table 3). Because the sill in no cases reaches 1.0 (complete disagreement in fire synchrony among pairs of trees), at least one fire scarred two of the most widely separated trees in every site.

The regression relationship between fractal dimension and Sorensen variogram range was significant ($P < 0.01$, $R^2 = 0.91$), but only after a very significant outlier (South Deep) was removed (Fig. 3). We considered outlier removal valid because South Deep is anomalous in many ways, including having by far

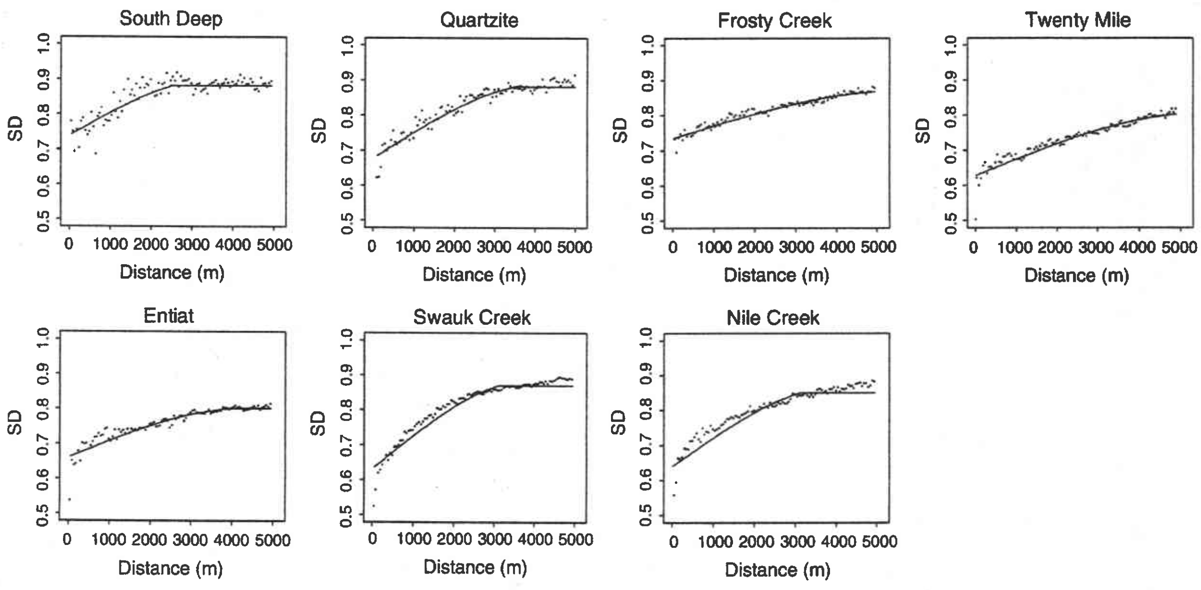

Fig. 2 Empirical Sorensen variograms (points) and theoretical variograms, using the spherical model (lines), as a function of distance (m) at the 7 sites, presented in row-major order from NE to SW. The spherical model becomes flat at the range (Table 3, Equation 5). "SD" on the Y axes indicates Sorensen's distance

Table 4 Total sample size, lag (meters), and maximum distance (meters) used for constructing Sorensen variograms. The minimum, maximum, and mean number of pairs used for the mean Sorenson's Dissimilarity Index at each lag distance are followed by the minimum, maximum, and mean distances (meters) between observations by site. Study sites are listed from northeast to southwest

Site	n	(m)		No. of pairs			Distance (m) between pairs		
		Lag	Max (d)	Min	Max	Mean	Min	Max	Mean
South Deep	680	50	9,000	29	111	65	16	17,100	6,300
Quartzite	142	50	5,000	7	14	40	30	13,950	5,215
Frosty Creek	420	50	9,000	13	566	426	17	18,500	5,850
Twenty Mile	409	200	5,000	153	929	668	11	10,445	3,307
Entiat	490	50	9,000	83	764	564	11	17,650	6,080
Swauk Creek	665	50	9,000	172	1,352	974	15	17,955	5,760
Nile Creek	234	200	5,000	9	315	213	4	10,900	3,490

the fewest fire scars (which are widely separated), the weakest variogram model (suggesting large uncertainty in the range estimate), the weakest Mantel correlation, and a qualitatively different fire regime (see Discussion). An outlier in such a small sample (7) does of course call into question the robustness of the model for extrapolation to other regions. Nevertheless, we see a strong negative relationship between fractal dimension and Sorensen variogram range (Fig. 3).

Discussion

This study demonstrates the importance of understanding spatial pattern and spatial autocorrelation, at multiple scales, in low-severity fire regimes. It further shows that spatially explicit intensive sampling of fire-scarred trees is necessary to enable such understanding. Our analyses highlight the importance of topography as a fine-scale control on historical surface fires.

We compared seven sites with varying complexity of topography by quantifying the spatial autocorrelation structure of fire synchrony—how common fire years between recorder trees are associated with the trees' proximity in space—within each. We used two statistical methods, the Mantel's test and Sorensen variogram models, analogous to correlation and regression approaches, respectively, but explicitly incorporating spatial autocorrelation.

Combining the numerical results for spatial structures in fire synchrony (Table 4) with the fractal characteristics of surface topography (Table 2), we infer three distinct patterns of spatial dependence across our seven sites.

1. Strong spatial dependence, reflected in Mantel's test statistics, percentage of spatial dependence explained and shorter ranges in variograms, and higher fractal dimensions (Swauk Creek, Quartzite, and Nile Creek).
2. Equivocal spatial dependence, strong globally (Mantel's test) but unclear in multi-scale analysis, with longer variogram ranges, varying percentage of spatial dependence, and lower fractal dimensions (Twenty Mile, Frosty Creek, Entiat).
3. Weak spatial dependence associated with lower fractal dimensions (South Deep), albeit with an anomalously short variogram range.

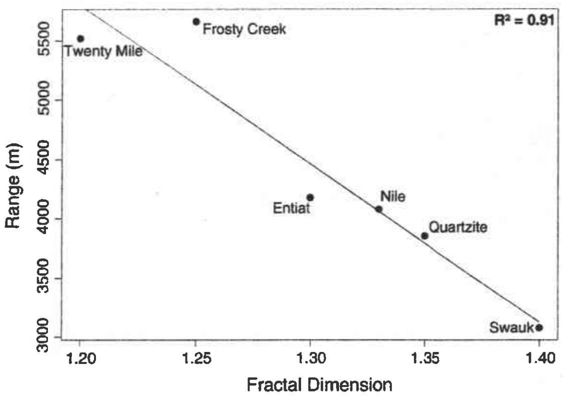

Fig. 3 Relationship between ranges from Sorensen variogram models and topographic complexity measured by fractal dimension. The South Deep was removed as a significant outlier from the model, and would have appeared below the lower left of the graph. Fractal dimension is a unitless measure

The farthest northeast site, South Deep, showed weak spatial dependence in fire occurrence. The short range in fire synchrony was disproportionate to the fractal characteristics of the site. This suggests little within-site control on the fire regime. In each instance, South Deep was an anomaly in the study; not only a statistical outlier in the regression, but also physically and ecologically different from the other sites. Topography in the Okanogan Highlands is gently rolling, with broad U-shaped valleys, and the climate is cooler and wetter than in the other sites, with a greater proportion of rain falling in summer than along the Cascade crest (Daly et al. 1994). South Deep also lies in the Northern Rocky Mountain eco-province and is more aligned with the Selkirk Mountains than the Cascade Range (Bailey 1996). On average, fires in South Deep are larger and less frequent than the other sites (Hessl et al. 2004). In contrast, the topographically complex Quartzite showed strong multi-scale dependence in fire synchrony with a relatively short range (3856 m).

At the southernmost sites, Nile Creek and Swauk Creek, historical fire regimes showed moderate to strong spatial dependence in fire occurrence (Table 4) with high fractal dimension (Table 2), suggesting that their spatial variability was controlled by topography. Landscapes in both Nile and Swauk Creek have complex topography that is deeply incised with steep V-shaped valleys. The spatial patterns of recorder trees at both sites are relatively dispersed across topographic barriers, further contributing to precision in estimates of spatial dependence. For example, dispersed recorder trees provide less biased surrogates for fire size than clustered trees because the greatest interpolation errors are associated with large gaps between points of reference, i.e., recorder trees (Hessl et al. 2007).

At the middle latitude sites, Entiat, Frosty Creek and Twenty Mile, global dependence in fire synchrony is moderate, but the relatively long variogram ranges (4178–5674 m) in conjunction with the fractal characteristics of the sites (Table 2), suggest that topography has less control of the spatial variability of fire occurrence. Recorder trees are slightly more clustered within topographic structures in these sites when compared to Swauk Creek and Nile Creek, increasing uncertainty in the statistics.

The relative strength of global and multi-scale spatial dependence in fire synchrony within the sites provides a framework for inferring which controls (top-down or bottom-up) are influencing fire regime variability (Lertzman and Fall 1998). We distinguish here between the amount of fire synchrony per se, reflecting a global interannual effect (Hessl et al. 2004, Kitzberger et al. 2006, Heyerdahl et al. in press), and the spatial dependence of fire synchrony. The former reflects top-down controls, whereas the latter reflects bottom-up control. Spatial dependence of fire synchrony reflects topographic controls in that (1) global relationships (Mantel statistic) suggest on-the-ground impediments to fire spread, causing decline in synchrony over space, and (2) the range of synchrony will decline more rapidly (Sorensen variograms) if fire sizes are small and constrained by topographic barriers.

When strong spatial dependence in fire synchrony coincides with relatively high fractal dimensions and relatively short variogram ranges, we therefore infer that the primary control on the fire regime is exerted from the bottom up, i.e., likely controlled by within-site variability in topography or possibly spatial heterogeneity in fuels (McKenzie et al. 2006a). Conversely, when weak spatial dependence in fire occurrence coincides with low fractal dimensions and longer ranges, we infer the controls originate from top-down influences such as annual to decadal climatic variability. For example, imagine climatically controlled "big fire" years, in which ignitions are randomly located in space. There will be synchronous fires, but no relationship to geographic distance.

Working with the same data, McKenzie et al. (2006a) found stronger fine-scale controls on fire occurrence in the more topographically complex sites, and inferred that spatial heterogeneity in fuels (from past fires or other disturbances, e.g., grazing), possibly accentuated by topographic barriers, was the likely cause. Hessl et al. (2004) analyzed fire-climate associations on the same sites and found no significant differences among topographically complex versus simple sites in the strength of climatic controls. Further analysis is certainly needed, therefore, to establish quantitatively the relative strength of top-down and bottom-up controls. We emphasize that these inferences are preliminary and await further analysis and interpretation (see Future Research).

We hypothesize that two sets of processes control the spatial structure of fire synchrony within sites: (1)

topography directly controls fire sizes by creating barriers to fire spread, and (2) a complex set of processes generates spatial patterns of recorder trees, including local environmental controls on flammability and fuel continuity and the stochastic process of seedling establishment and survival, which in turn depends on microscale patterns of substrates (Swezy and Agee 1991; Brown and Smith 2000). We cannot assess here the relative importance of the two or the direct effect of spatial patterns on the strength of modeled spatial structures; this analysis would require replication of the process of recorder-tree establishment, perhaps with neutral fire-history simulations (sensu McKenzie et al. 2006a).

Limitations to the analysis

Clearly we have not explained all the sources of variation in spatial structures of fire occurrence. Maximum correlation for Mantel tests is 0.54 (Swauk Creek), and maximum percentage variance explained in the variogram models is 0.37. There is a general pattern of sites with more complex topography having shorter variogram ranges, higher fractal dimensions, and stronger spatial structure, but no perfect association among these three criteria.

One major confounding factor may be Native American burning, clearly an ignition source prior to the major population and cultural changes of the early 1900's. Archeological evidence indicates that Native Americans first settled the inland Pacific Northwest approximately 13,000 years ago (Robbins 1999). Documentary and anecdotal evidence describes the Entiat, Methow, and Spokane people burning low elevation ponderosa pine forest and grasslands in the region (Robbins and Wolf 1994, Robbins 1999). Other native groups, such as the Okanogan, Colville, Yakima, and Salishan, may have also set fires, although evidence is lacking.

Natives may have set fires to remove undergrowth, stimulate new growth of species important for game, reduce the likelihood of more destructive fires, or enhance growth of food-producing species (Barrett 1980). These fires would have been smaller on average than wildfires, being partially controlled, and possibly repeated at regular intervals over the same terrain, as opposed to wildfires, which were less likely to occur in quick succession in the same locations (McKenzie et al. 2006a). The possible effects of this burning, presumably not controlled as directly by topography as wildfire, are not entirely clear, but we would expect variograms to be affected in that nuggets would be lower (more similarity at small scales) but ranges might be longer (no big fires to limit variance at large scales). One net effect (observed above) would be to decouple variogram ranges from percentage variance explained (sill/sill + nugget) and topographic complexity (e.g., fractal dimension).

Fractal dimension, like the Mantel statistic, is a global metric of scale dependence, but does not capture spatial patterns of topographic variability within sites, which are implicitly reflected in our Mantel correlations and Sorensen variograms. A multi-scale analysis similar to variogram modeling would likely reveal more subtleties in topographic complexity, whose effect on this analysis, particularly the regression of Sorensen variogram range on a topographic metric, is presently unclear.[1]

Future research

Fire regimes are complex systems that represent an aggregate of spatial and temporal properties. Statistically considering fire regimes in their aggregate form may elucidate more meaningful results than the reconstruction of properties surrounding a single fire event. Very recent fire history research (Moritz et al. 2005; McKenzie et al. 2006a; Falk et al. 2007) has focused on the aggregate properties of fire regimes across scales. Falk et al. (2007) suggest that cross-scale analyses of fire-scar records can bring us closer to unifying principles surrounding landscape fires by considering the central role of fire-size distributions in understanding multi-scale properties of fire regimes. Jordan et al. (2005) approached fire sizes from a different but complementary perspective, demonstrating that the uncertainty associated with individual fire sizes can be quantified using a fuzzy-set approach, which eliminates much of the subjectivity of estimating fire perimeters from fire-scar data.

[1] High resolution graphics of topographic complexity for the seven sites are available from the corresponding author. These provide a point of departure, albeit qualitative, for such a multi-scale analysis.

McKenzie et al. (2006b) began to explore the estimation of fire-size distributions—as opposed to individual fire events—from geostatistical methods similar to those we use in this paper. Quantifying historical fire sizes would be a major step toward direct comparisons between the historical and modern record. We therefore suggest the following specific topics to pursue in future work:

- Examine other variogram models for fire synchrony using Sorensen's distance as the distance measure. Particularly useful might be models that can be mathematically linked to power–law relationships that (1) are present in fire-size distributions (Malamud et al. 1998, Moritz et al. 2005), and (2) characterize the self-similar geomorphology of landscapes with complex topography. A method to link fire size distributions mathematically to topographic controls would be a major breakthrough (McKenzie et al. 2006b).
- Deconstruct fire synchrony over direction so that it can be related to anisotropy in topographic variance. Just as representing fire perimeters as circles is unrealistic, so too is invoking omnidirectional topographic controls on fire size.
- Compare fire synchrony among pairs of composite fire records (CFRs) at different scales (McKenzie et al. 2006a) or within groups of trees which record a similar fire occurrence time series. Because most existing fire-history data comprise CFRs at single sites instead of individual recorder trees, analysis at the CFR scale might be extrapolated with more confidence to sites without spatially explicit data.
- Compare models of fire synchrony in topographically controlled sites with neutral fire history models (McKenzie et al. 2006a). Similarly, compare fire size distributions from (1) geostatistical models of fire synchrony (McKenzie et al. 2006b), (2) probabilistic analysis of the cumulative distribution of individual fires (Jordan et al. 2005), and (3) standard interpolation methods such as Kriging or inverse distance weighting (Hessl et al. 2007).

Implications for management

As the land management paradigm in arid mountain forests of western North America shifts away from fire suppression and towards use of fire to achieve ecosystem restoration, management prescriptions can take advantage of spatially explicit fire data and analysis. For example, the current template for many decisions relies on estimates of historical fire frequency from composite fire records, ignoring how fire frequency appears different at different scales and is associated with different drivers (McKenzie et al. 2006a; Falk et al. 2007). Coarse-scale analyses have identified areas with large departures from the historical range of variability in fire frequency as the highest priorities for treatment (e.g. fire regime condition class 3 [FRCC3], Schmidt et al. 2002, Hann and Strohm 2003). However, these landscape classifications lack information regarding spatial controls on fire occurrence at the finer scales relevant for management, mainly because spatially explicit analyses like ours were not available, not necessarily because the FRCC process is incapable of incorporating them. According to our analysis, fire regimes are scale dependent and variable within a single ecosystem type (ponderosa pine) in eastern Washington, suggesting that an alternative approach to classifying and prioritizing treatment areas is needed. This alternative also must go beyond simply mapping fire regimes to forest types or potential vegetation, which ignores the issue of spatial dependence in fire occurrence.

A better understanding of the spatial structures in fire regimes may inform decisions about whether to use prescribed fire or Wildland Fire Use (WFU)—allowing wildfires to burn to realize management benefits. The largest historical fire sizes in this area suggested by our analysis were probably at most ca. 5,000–10,000 ha, suggesting that WFU may be the most appropriate option for restoring historical fire regimes (if indeed this is possible at all in a rapidly warming world—McKenzie et al. 2004). Individual fire-size reconstructions from the Pacific Northwest indicate that although large fires did occur in the past, they were typically not comparable in size to the large fires that have occurred in the past few decades. For example, in the Entiat River drainage, exceptionally large wildfires burned in 1970 (24,685 ha), and again in 1994 (38,445 ha) (Agee 1994). The even larger Tripod Fire of 2006 burned over 80,000 ha in the Okanogan Highlands; much of it was very high-severity fire. These complexes of wildfires that burned tens of thousands of hectares clearly overcame any topographic constraints such as those we have suggested for historical fires.

By identifying spatial structure in fire regimes at multiple scales, we can match the fire regime to the inherent scales of the controlling factors (i.e. topography, fuels, climate) with greater precision, thereby enhancing our ability to evaluate their co-varying relationship and assess how the current regime is deviating from its historic pattern. For example, Taylor and Skinner (2003) found that spatial and temporal variations for fire regimes in the Klamath Mountains prior to effective fire suppression (ca. 1,940) were consistent with the tactical approach by land managers to use topographic features as fire boundaries when setting prescribed fires in highly complex terrain.

Scaling relations of fire regimes may also be useful for prioritizing restoration efforts. If current fire size exceeds the boundaries of topographic units, we may infer that a control is no longer in effect. These locations become likely candidates for treatments that at least partially restore historic controls; for example, reducing fuel connectivity such that topographic units once more function as fire boundaries (Agee and Skinner 2005).

Conclusions

This study takes advantage of a unique fire-history database to apply geostatistical techniques in a way that is new to fire history, though well established in other branches of ecological research. Geospatial analyses revealed spatial autocorrelation structure at multiple scales, suggesting varying strengths of topographic controls on fire occurrence and fire size while revealing considerable unexplained variation that is likely due to other historical controls such as Native-American burning and the intrinsic variability of other drivers such as climate, ignitions, and patterns of vegetation. Our results suggest possibilities for future research when more spatially explicit data become available, and a preliminary understanding of how spatially explicit analyses might be incorporated into landscape management.

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