PRACTICES AND APPLICATIONS

NEGLIGIBLE INFLUENCE OF SPATIAL AUTOCORRELATION IN THE ASSESSMENT OF FIRE EFFECTS IN A MIXED CONIFER FOREST

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ABSTRACT

Fire is an important feature of many forest ecosystems, although the quantification of its effects is compromised by the large scale at which fire occurs and its inherent unpredictability. A recurring problem is the use of subsamples collected within individual burns, potentially resulting in spatially autocorrelated data. Using subsamples from six different fires (and three unburned control areas) we show little evidence for strong spatial autocorrelation either before or after burning for eight measures of forest conditions (both fuels and vegetation). Additionally, including a term for spatially autocorrelated errors provided little improvement for simple linear models contrasting the effects of early versus late season burning. While the effects of spatial autocorrelation should always be examined, it may not always greatly influence assessments of fire effects. If high patch scale variability is common in Sierra Nevada mixed conifer forests, even following more than a century of fire exclusion, treatments designed to encourage further heterogeneity in forest conditions prior to the reintroduction of fire will likely be unnecessary.

Keywords: forest restoration, prescribed fire, pseudoreplication, Sierra Nevada, statistics

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INTRODUCTION

Fire is fundamental in shaping most terrestrial ecosystems (Bond and Keeley 2005). However, understanding fire effects remains elusive in part because fires are typically unplanned, not normally under experimental control, and occur at spatial scales of hundreds to thousands of hectares; these features are at odds with classical experimental design and analysis. Experimental burning in forests, where it has been attempted, is constrained by the logistical and financial resources needed to conduct the fires, limiting the size, intensity and number of replicated burning treatments (Fulé *et al*. 2004, Stephens and Moghaddas 2005, Fulé *et al*. 2006, North *et al*. 2007, Schwilk *et al*. 2009). Opportunistic studies of fire effects frequently rely on data collected from subsamples within a single burned area. These subsamples may be correlated both spatially and temporally, and when subjected to standard statistical testing provide reduced estimates of variation (error), increasing the likelihood of committing a Type I error (the chance of detecting a significant effect of fire when no meaningful effect has occurred). That is, the subsampled data underlying these tests are pseudoreplicated (Hurlbert 1984).

Interpreting pseudoreplicated fire effects data will always present challenges (van Mantgem *et al*. 2001), but some of these difficulties could be mitigated by estimating spatial autocorrelation (the correspondence of nearby sampling units) and temporal autocorrelation (the similarity of samples measured repeatedly over time), and controlling for these relationships in analyses of fire effects (Legendre 1993, Legendre and Legendre 1998, Fortin and Dale 2005, Bataineh *et al*. 2006). It is unclear; however, to what degree the consideration of autocorrelation, particularly spatial autocorrelation, would improve our understanding of fire effects. Small scale heterogeneity in fire effects may be common as daily and seasonal differences in fire weather and fuel moisture interact with variability in topography, fuel loading, and vegetation during burning (Kilgore 1973, Knapp and Keeley 2006).

The degree of spatial heterogeneity also has implications for an ongoing debate concerning the need for mechanical thinning prior to the reintroduction of prescribed fire in Sierran mixed conifer forests. Arguments in favor of pre-fire thinning are based on the notion that a century of fire exclusion has led to the homogenization of previously heterogeneous stands, and the application of fire without preceding silvicultural treatments will perpetuate these changes in forest structure (Bonnicksen and Stone 1981, 1982; Bonnicksen 1989). Here we show that there is only weak evidence for pervasive spatial autocorrelation both before and after prescription burning for measures of fire effects relevant to managers, and that spatial autocorrelation had trivial effects when comparing the outcomes of early versus late season burning in a Sierra Nevada mixed conifer forest.

METHODS

Study Site

We conducted the study in an old growth mixed conifer forest within the Giant Forest region of Sequoia National Park, California, USA. The sites have never been logged. Frequent fires characterized the forests prior to Euro-American settlement, but the area containing the study plots has not burned since the late 1800s (Swetnam *et al*. 1992). The climate is Mediterranean, with hot, dry summers and cool, wet winters, with about half of annual precipitation falling as snow (Stephenson 1988). Soils are relatively young (mostly inceptisols) and derived from granitic parent material.

Burning Treatments

We compared the effects of early season burning, late season burning and no burning across nine experimental units using data from the southern Sierra Nevada node of the Fire and Fire Surrogate network (Schwilk *et al*. 2009) (Figure 1). The experimental units were each 15 ha to 20 ha in size and were located within larger burn areas on west to northwest facing aspects of variable slope at elevations ranging from 1900 m to 2150 m. Burning treatments were applied using a completely

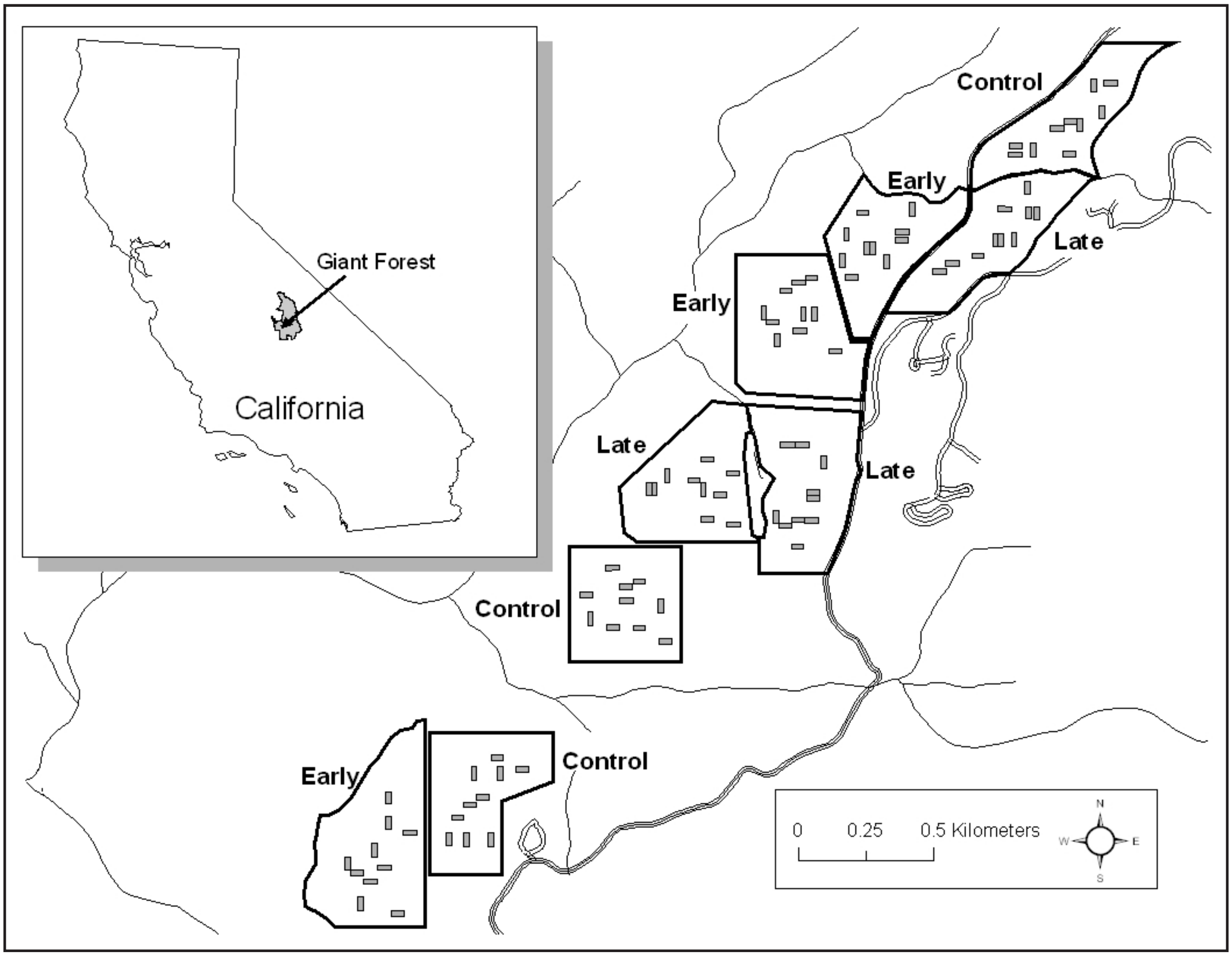

Figure 1. Location of the Giant Forest area within Sequoia National Park, California. Magnified area shows the plot layout for the Sequoia National Park site of the National Fire and Fire Surrogate study. Plot labels designate treatment (early season burning, late season burning, or unburned control), while rectangles within the plots represent randomly located 0.1 ha subplots where fire effects data were collected.

randomized design with three replicates per treatment.

Early season burns were conducted on 20 and 27 June 2002. Late season burns were conducted on 28 September, and on 17 and 28 October 2001. Burns were ignited with strip head fires started at the highest point in the unit, and designed to burn at low to moderate intensities. The burns were surface fires, with a few cases of individual trees torching. Weather and fuel conditions at the time of the burns are provided in Knapp *et al*. (2005).

Sampling

We took all pre- and post-treatment data in plots referenced to a 50 m grid in the interior of each unit. To minimize edge effects, the grid system was surrounded by a 50 m to 100 m buffer that was also treated. We averaged fuels data (total fuels [Mg ha^{-1}] and large fuels [woody fuels >76 mm diameter, Mg ha^{-1}]) from two transects at each of 36 grid points per experimental unit. Forest structure data (stand density [trees >1.37 m in height ha^{-1}], basal area [m^2 ha^{-1}]) were taken from ten 0.1 ha subplots at each experimental unit. We took community composition data (forb cover, graminoid cover, shrub cover) at the same ten 0.1 ha subplots at each experimental unit, while understory species richness data were averaged from nine 1 m^2 quadrats at each 0.1 ha subplot. We measured fuels before and one year following burning. We measured trees, shrubs, and herbaceous vegetation before and three years following burning.

Statistical Tests

We used the Mantel test to measure spatial dependence among samples (Legendre 1993, Legendre and Legendre 1998, Fortin and Dale 2005). The Mantel test compares two or more distance matrices, one matrix ($\boldsymbol{A}_{ij}$) being differences in the variable of interest (e.g., fuel loading, stand density, etc.), with the other matrix ($\boldsymbol{B}_{ij}$) being the distance between the sampling units. The Mantel test computes the correlation between the two distance matrices, with the formula:

$$z = \sum_{i=1}^{n} \sum_{j=1}^{n} A_j B_j \text{ , for i} \neq \text{j}$$

The z statistic is usually normalized (r):

$$r = \frac{1}{(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{(A_j - \overline{A})}{s_A} \frac{(B_j - \overline{B})}{s_B}$$

where n is the number of elements in the distance matrix and s_A and s_B are standard deviations of the elements of the A_{ij} and B_{ij} matrices. The normalized statistic behaves similar to the Pearson correlation coefficient, varying between −1 and +1, so that coefficients can be compared to other variables at the same site or to similar variables at other sites. We determined the overall significance of spatial relationships by permutation testing (standard tests are unreliable because the distances in the matrices are not independent [Goslee and Urban 2007]).

We assessed spatial correlations among subplots within each experimental unit before and after burning for measures of fire effects that are relevant for resource managers, including total surface fuels, large fuels, stand density, stand basal area, herbaceous vegetation cover, graminoid vegetation cover, shrub cover, and understory species richness. We subjected each of these measures within each experimental unit to a Mantel test using Euclidean distances, with 10 000 permutations used to establish significance ($\alpha = 0.05$). Although the large number of tests we performed would argue for an adjustment of the critical value, we wanted these tests to be as liberal as possible to search for evidence of significant spatial autocorrelation (e.g., if we used a Bonferroni correction for our 144 tests, we would have a critical value of $\alpha = 0.05 \div 144 = 0.00035$, (a value not surpassed by any of our tests). For both the pre-fire and post-fire intervals we calculated the ratio of significant Mantel tests versus the total number of tests conducted, and created 95 % confidence intervals for this ratio from 10 000 bootstrapped samples.

To determine the effects of spatial autocorrelation on an assessment of fire effects, we contrasted the results of tests that compared early versus late season burning using ordinary least-squares regression (OLS) and a spatial generalized least squares regression (GLS). The OLS model assumes no spatial autocorrelation among samples, potentially leading to excessive reductions in standard errors of the parameter estimates (and thereby inflating the probability of Type I errors), while the GLS model included spatial structure into the error term of the regression (Pinheiro and Bates 2000). For the GLS model, we used a spherical spatial error structure, with the inclusion of a nugget effect where needed (Cressie 1993). Our response variables were the change in a forest attribute (e.g., paired differences of stem $\text{density}_{\text{pre-fire}} - \text{stem density}_{\text{post-fire}}$) as predicted by season of burning. Season of burning contrasts are presented relative to early season burning. Parameters were estimated using maximum likelihood and model comparisons were performed using *AICc*, the Akaike information criterion corrected for sample size (Burnham and Anderson 2002). Model selection is typically done by referencing the model with the lowest *AICc* value. Here, to emphasize the inclusion of spatially autocorrelated errors, we made our selection relative to the GLS model ($\Delta\ AICc_{GLS} = AICc_{OLS} - AICc_{GLS}$), with evidence to include spatial autocorrelation when $\Delta\ AICc_{GLS} > 2$, and evidence not to include spatial autocorrelation when $\Delta\ AICc_{GLS} < -2$. Strong evidence to include or exclude spatial autocorrelations is present when the absolute value of $\Delta\ AICc_{GLS} > 10$. Mantel tests were conducted using the "ecodist" package, and regression tests used the "nlme" package written for the R language (R Foundation for Statistical Computing, Vienna, Austria).

Table 1a. Normalized Mantel test statistics for pre-fire and post-fire measurements of fuels. Mantel test statistics in bold signify significant spatial correlations within experimental units at $\alpha = 0.05$.

		Mantel r	
Observation	**Treatment**	**Total fuels ($Mg\ ha^{-1}$)**	**Large fuels ($Mg\ ha^{-1}$)**
Pre-fire	early	0.0961	0.0832
	early	**0.1681**	0.1061
	early	0.0142	0.0003
	late	0.0651	0.0380
	late	-0.0053	0.0524
	late	**0.1694**	**0.1787**
	unburned	-0.0222	0.0364
	unburned	-0.0191	-0.0424
	unburned	-0.0050	0.0375
Post-fire	early	0.0815	0.1294
	early	0.0640	0.0763
	early	-0.0250	-0.0281
	late	0.0193	0.0957
	late	-0.0430	-0.0690
	late	-0.0032	0.0190
	unburned	0.1186	**0.1746**
	unburned	0.0629	0.0227
	unburned	0.0494	0.0583

RESULTS

The Mantel tests did not show evidence for widespread spatial autocorrelation either before or after burning for fuels (Table 1a) or vegetation (Table 1b). The pre-fire interval had nine significant Mantel tests out of 72 tests (ratio of significant tests = 0.13; 95% CI = 0.06 to 0.22), which is only marginally greater than the frequency of significant tests expected by chance alone (i.e., 1 out of 20, or 0.05). The post-fire interval had even fewer significant Mantel tests, with the 95% CI overlapping the number of significant tests expected by chance (seven out of 72 significant tests, ratio of significant tests = 0.10; 95% CI = 0.03 to 0.17). There was no obvious pattern of significant results in any measure of fire effects either before or after burning, with each measure of fire effects averaging only a single significant Mantel test during both the pre- and post-fire interval (average ratio of significant tests = 0.11; range = 0.00 to 0.33).

The lack of evidence for significant spatial autocorrelation was also reflected in our comparisons of the OLS and spatial GLS models (Table 2). In only three of eight tests (changes in stand density, forb cover, and species richness) was the inclusion of spatial autocorrelation justified by *AICc*. In four of eight tests, the inclusion of spatial autocorrelation was not justified ($\Delta\ AICc_{GLS} < -2$), with one test (change in basal area) giving essentially equal evidence for the OLS and GLS models. In only one test (change in forb cover) was the absolute difference in *AICc* > 10, suggesting that for most measures of fire effects there was approximately equivalent evidence for the OLS and GLS models. In only a single instance could

Table 1b. Normalized Mantel test statistics for pre-fire and post-fire measurements of forest structure and understory community composition. Mantel test statistics in bold signify significant spatial correlations within experimental units at α = 0.05.

		Mantel r					
Observation	**Treatment**	**Stand density (stems ha^{-1})**	**Basal area (m^2 ha^{-1})**	**Forb cover (%)**	**Graminoid cover (%)**	**Shrub cover (%)**	**Species richness (m^2)**
Pre-fire	early	-0.0214	0.0046	-0.0574	0.1624	-0.1282	-0.1241
	early	0.0664	0.0454	0.2591	-0.0434	**0.4878**	**0.4589**
	early	0.0459	0.0297	0.0781	0.0021	0.0961	0.1743
	late	0.1907	0.0830	-0.0162	-0.2049	-0.1395	-0.2009
	late	**0.3339**	-0.1076	-0.0544	**0.3857**	-0.0753	0.2311
	late	0.0156	0.1366	-0.0358	0.0495	0.2654	-0.1754
	unburned	0.1313	0.1064	**0.4808**	0.1083	0.2900	0.2333
	unburned	**0.4008**	0.3319	-0.1771	0.1789	-0.1207	-0.1056
	unburned	-0.0372	-0.1592	0.0045	0.1470	-0.0513	-0.0950
Post-fire	early	**0.4763**	-0.0393	0.0168	-0.0029	0.2973	-0.0155
	early	-0.2356	0.0397	0.1430	-0.0480	-0.0185	0.2230
	early	0.2779	-0.0373	0.0191	0.0564	-0.2011	0.0013
	late	-0.0844	-0.2104	-0.1105	-0.0790	-0.0584	-0.1062
	late	0.1009	0.0935	0.0673	-0.0742	-0.1050	-0.0010
	late	**0.4551**	0.2165	0.0049	-0.0055	0.1364	0.1905
	unburned	0.2032	0.1414	**0.5612**	**0.3111**	0.2978	0.1827
	unburned	**0.3826**	**0.3597**	-0.0660	0.1680	-0.0039	-0.1181
	unburned	-0.0320	-0.1168	0.1633	-0.0147	0.1916	-0.1625

Table 2. Coefficients for changes following fire as determined by season of burning using ordinary least-squares regression (OLS) and spatial generalized least squares regression (GLS). Regression parameters (β) describe the difference of late season burning relative to early season burning. *AICc* values of OLS and GLS models are compared relative to the GLS model ($\Delta AICc_{GLS}$).

	OLS			GLS			
Post-fire change	**β ± SE**	***P***	***AICc***	**β ± SE**	***P***	***AICc***	**$\Delta AICc_{GLS}$**
Total fuels (Mg ha^{-1})	35.16 ± 10.43	0.001	2497.7	35.06 ± 10.98	0.002	2506.2	-8.4
Large fuels (Mg ha^{-1})	9.4 ± 7.61	0.218	2361.6	9.76 ± 7.92	0.219	2365.2	-3.6
Stand density (stems ha^{-1})	27.96 ± 32.42	0.392	761.3	17.96 ± 44.55	0.688	752.3	9.1
Basal area (m^2 ha^{-1})	0.93 ± 3.59	0.796	497.3	-0.61 ± 4.22	0.885	496.1	1.1
Forb cover (%)	6.11 ± 3.16	0.058	482.1	6.18 ± 4.6	0.184	467.6	14.5
Graminoid cover (%)	-0.54 ± 0.26	0.040	181.1	-0.54 ± 0.26	0.041	186.1	-5.0
Shrub cover (%)	5.85 ± 2.05	0.006	429.7	5.62 ± 2.24	0.015	434.7	-5.0
Species richness (m^2)	0.28 ± 0.27	0.309	186.5	0.27 ± 0.33	0.405	181.4	5.1

the inclusion of spatial autocorrelation conceivably give rise to a different interpretation of the results when comparing P values (critical value $\alpha = 0.05$, change in forb cover: OLS $P = 0.058$, GLS $P = 0.184$).

The parameter estimates for the OLS and GLS models were generally similar. As expected, the standard errors of these estimates were consistently smaller in the OLS models relative to the GLS models (paired permutation test, $P = 0.016$), although the magnitude of these differences were slight (average standard error reduction in the OLS models = 13.6 %), suggesting that the OLS estimates did not greatly inflate the risks of Type I errors. Note that some of these tests imply differences in the effects of early versus late season prescribed burning, with late season burning resulting in the greater consumption of total fuels (in agreement with Knapp *et al*. [2005]), lesser reductions in graminoid cover and greater reductions in shrub cover.

DISCUSSION

It appears, at least in the mixed conifer forests of the Sierra Nevada, that there is little evidence for pervasive significant spatial autocorrelation for many of the measures of fire effects important to managers (e.g., fuels, forest structure, understory community structure). We do not, however, take this as evidence that spatial autocorrelation should be ignored in statistical tests of fire effects. The ratio of significant Mantel tests was above 5 % both in the pre-fire and post-fire intervals, and some tests were highly significant. In addition, comparing linear models with and without spatial autocorrelation (OLS versus GLS models), there were a minority of tests that supported the inclusion of spatial autocorrelation (though the effects of spatial autocorrelation was minor and did not influence model interpretation). The infrequent presence of significant spatial autocorrelation precludes the creation of simple rules concerning the presence or absence of spatial autocorrelation for fire effects studies. These findings underscore the idea that the effects of spatial autocorrelation should be routinely checked in ecological studies (Legendre 1993, Legendre and Legendre 1998), although it may not often prove to be pivotal in the assessment of fire effects. As a cautionary note, Diniz-Filho *et al*. (2003) found that including a term for spatial autocorrelation when its effects are weak may lead to subtle biases in model interpretation (i.e., a reduced emphasis on predictors that operate at small spatial scales). If subsampled data are used as independent replicates in fire effect studies, other problems arising from pseudoreplication still remain (e.g., temporal autocorrelation, non-representative samples), though spatial autocorrelation may not heavily influence the results.

Our results imply that forest conditions before and after burning have a high degree of small, patch scale spatial heterogeneity. Knapp and Keeley (2006) also found evidence for high patch scale heterogeneity in fire severity, as measured by scorch heights and area burned, which they attributed to variation in topography, fuel characteristics and forest structure (including pre-burn species composition), and sometimes, as in our study, season of burning. Higher fuel moistures in early season burns likely inhibit effective fuel continuity, thereby increasing small scale differences in fire severity. High patch scale heterogeneity is similar to the high levels of heterogeneity in fire severity commonly observed at the landscape scale in the Sierra Nevada (Collins *et al*. 2007) and in other forest systems (e.g., Turner *et al*. 1994). We suspect that small scale heterogeneity is a general feature of fire effects, particularly in forest types that burn at low to moderate intensity (in contrast to crown fire systems that may have lower patch scale heterogeneity [Turner and Romme 1994]).

The presence of high patch scale variability in pre- and post-fire stand conditions has important consequences for the management of Sierra Nevada forests. Bonnicksen and Stone (1981, 1982) and Bonnicksen (1989) have argued that fire exclusion has resulted in the homogenization of historically heterogeneous forests, and application of prescribed fire without prior silvicultural treatment would maintain unnaturally uniform forest conditions. This view has been challenged on several accounts (e.g., imprecise knowledge of historic forest conditions [Stephenson 1999]), and our results also demonstrate that even following a century of fire exclusion, forest conditions are far from homogeneous either before or after prescription fire. Thus, the application of treatments prior to prescribed burning to encourage further stand heterogeneity either in fuels or vegetation is likely unnecessary in Sierra Nevada mixed conifer forests.

The lack of strong spatial autocorrelation also has implications for the interpretation and analysis of fire effects monitoring data. If spatial autocorrelation is generally weak, it is doubtful that one or even several small monitoring plots within a burned area will provide a general description of overall effects of a given fire. Currently, a national plot-based fire effects monitoring program (FFI, http://frames.nbii.gov/ffi) measures fuels and forest structure within small-scale plots (≤0.1 ha), usually with only a single plot established within each burned area (Paul Reeberg, National Park Service, personal communication). Besides its potential to support satellite-based observations of fire effects (Key 2006), these data might be best used when individual plot data are assembled together across a particular vegetation type to offer a broad picture of fire effects (e.g., Keifer 1998).

We conclude that the conditions and response of forests to fire are complex, and are certainly more variable than is sometimes supposed. It is an overgeneralization to consider an area as simply burned or unburned, as conditions prior to, during and following fires combine to create heterogeneous conditions. We do not, however, possess a mechanistic understanding of what drives this complexity. Some factors are obvious, such as variation in slope or vegetation types within a burned area. Other factors are surprising (e.g., pre-burn species composition [Knapp and Keeley 2006]), or will probably remain elusive (e.g., small changes in fire weather during burning), and it is likely that many of these factors interact in unexpected ways. Understanding these mechanisms is becoming increasingly important in an era where forest and fire conditions are rapidly changing (Westerling *et al*. 2006, van Mantgem *et al*. 2009), obviating simple predictions of fire effects.

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