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Assessing fuel treatment effectiveness using satellite imagery and spatial statistics

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Abstract. Understanding the influences of forest management practices on wildfire severity is critical in fire-prone ecosystems of the western United States. Newly available geospatial data sets characterizing vegetation, fuels, topography, and burn severity offer new opportunities for studying fuel treatment effectiveness at regional to national scales. In this study, we used ordinary least-squares (OLS) regression and sequential autoregression (SAR) to analyze fuel treatment effects on burn severity for three recent wildfires: the Camp 32 fire in western Montana, the School fire in southeastern Washington, and the Warm fire in northern Arizona. Burn severity was measured using differenced normalized burn ratio (dNBR) maps developed by the Monitoring Trends in Burn Severity project. Geospatial data sets from the LANDFIRE project were used to control for prefire variability in canopy cover, fuels, and topography. Across all three fires, treatments that incorporated prescribed burning were more effective than thinning alone. Treatment effect sizes were lower, and standard errors were higher in the SAR models than in the OLS models. Spatial error terms in the SAR models indirectly controlled for confounding variables not captured in the LANDFIRE data, including spatiotemporal variability in fire weather and landscape-level effects of reduced fire severity outside the treated areas. This research demonstrates the feasibility of carrying out assessments of fuel treatment effectiveness using geospatial data sets and highlights the potential for using spatial autoregression to control for unmeasured confounding factors.

Key words: burn severity; differenced normalized burn ratio (dNBR); fire behavior; fire weather; fuel treatments; spatial autoregression.

Introduction

Fuels management has emerged as the cornerstone of efforts to mitigate the impacts of large, destructive wildfires in the western United States. Fuels are of particular interest from a management standpoint because, unlike topography and weather, they can be modified through management activities. Various types of fuel treatments are currently being applied in western forests. In particular, thinning of overstory and subcanopy trees has been proposed as a technique to reduce horizontal and vertical continuity of the forest canopy and thus decrease the hazard of fast-moving and destructive crown fires (Agee and Skinner 2005). Other treatments such as burning, piling, mastication, and compaction can alter the amount, size distribution, and spatial arrangement of surface fuels, reducing the spread rate and intensity of surface fires (Kalabokidis and Omi 1998, Jerman et al. 2004, Stephens and Moghaddas 2005). Fuel treatments have the potential to reduce tree mortality and other fire effects at a local level (Ritchie et al. 2007), limit the rate of fire growth across broader landscapes (Finney 2001), and increase the effectiveness of fire suppression activities (Moghaddas and Craggs 2007). However, despite the widespread application of fuel treatments, there is only limited information available about their actual effectiveness in modifying wildfire effects.

Most empirical studies of fuel treatment effectiveness have been case studies focusing on one or a few wildfires. Not surprisingly, studies conducted in a variety of forest ecosystems using different methodologies have produced a range of conflicting results. For example, an analysis of four wildfires in Montana, Washington, California, and Arizona found that thinning alone, prescribed burning alone, or thinning followed by prescribed burning all reduced fire severity compared to untreated areas (Pollet and Omi 2002). In contrast, on the Cone fire in northern

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California, tree mortality was lower in stands treated with thinning and prescribed fire, but not in stands treated with thinning alone, compared to untreated areas (Ritchie et al. 2007). On the Biscuit fire in southwestern Oregon, fire severity was higher in stands subjected to thinning and salvage logging than in untreated areas (Raymond and Peterson 2005, Thompson et al. 2007). To enhance fuels management efforts, an understanding of the conditions under which various types of fuel treatments reduce fire severity is needed. In particular, there is a need to analyze large numbers of fuel treatments across multiple fires and forest types to draw conclusions at regional to national levels.

The availability of data from several national projects now provides an opportunity for carrying out this type of assessment. LANDFIRE is a multi-agency project that is producing geospatial data sets of vegetation, fuels, and fire regimes across the entire United States (Rollins and Frame 2006). The Monitoring Trends in Burn Severity (MTBS) project is another multi-agency effort using satellite imagery to map burn severity for all large wildfires occurring in the United States between 1984 and 2010 (Eidenshink et al. 2007). Both of these projects produce spatial data sets at a 30-m resolution that can be used to study burn severity patterns within individual fires. Although a comprehensive national database of geolocated treatments does not currently exist, GIS data on recent fuel treatments is widely available from various public land management agencies. However, integrating these data to study fuel treatment effectiveness requires a consistent analytical strategy that can be applied to multiple fires across a variety of ecosystems.

There are several methodological challenges associated with using geospatial data sets to assess treatment effectiveness. One issue is that fuel treatments are not randomly located within fires, and are therefore usually confounded with other environmental variables. A treated stand with fire severity lower than an untreated stand may result from the treatment itself, or from differences in topography and vegetation characteristics between the treated and untreated areas. For this reason, simple overlays of treatment polygons onto burn severity maps can result in misleading conclusions about the effectiveness of treatments. Regression analysis is frequently used in observational studies to make inferences about treatment effects conditional on the effects of one or more confounding variables (Gelman and Hill 2007). However, not all confounding variables are measurable. For example, spatial and temporal variability in temperature, wind speeds, and fuel moisture all influence fire behavior as the flaming front moves across the landscape. With geospatial data sets, one approach to this missing variable problem is to utilize spatial autoregressive models, in which unmeasured but spatially structured environmental variables can be modeled indirectly using a spatial error term (Haining 1990). Although several studies have used spatial autogression and related techniques to analyze fire severity patterns (Finney et al. 2005, Thompson et al. 2007, Wimberly and Reilly 2007), none has explicitly examined the information captured by the spatial error term.

The main goals of this research were to develop a methodology for combining data from LANDFIRE and MTBS with spatial data on fuel treatment locations to quantify treatment effects on burn severity, and to apply this method in a case study to assess fuel treatments on three fires occurring in different ecosystems. Specific research objectives were to assess the effectiveness of LANDFIRE data in controlling for the influences of fuels, vegetation, and topography on burn severity patterns; and to determine whether spatial autoregression can be used to capture spatiotemporal variability in fire weather, landscape-level treatment interactions, and other confounding factors not accounted for in the LANDFIRE data set.

Methods

Data sources

Our study focused on three recent wildfires in the western United States that burned through a variety of fuel treatments: the Camp 32 fire in the Rocky Mountains of northwestern Montana (372 ha), the School fire in the Blue Mountains of southeastern Washington (19 871 ha), and the Warm fire on the Kaibab Plateau in northern Arizona (23 490 ha). Additional site descriptions and fire narratives are provided in Appendix A. Maps of the differenced normalized burn ratio (dNBR) were obtained from the Monitoring Trends in Burn Severity (MTBS) project as 30-m raster GIS layers (Fig. 1). The normalized burn ratio (NBR) was computed from pre- and postfire Landsat images using bands 4 and 7, and dNBR was computed as the difference between the pre- and postfire images (Key and Benson 2005). The dNBR index has been shown to correspond well to field-based measurements of fire severity in a variety of ecosystems and to compare favorably with other remotely sensed burn severity indices (Van Wagtendonk et al. 2004, Cocke et al. 2005, Epting et al. 2005, Wimberly and Reilly 2007).

Canopy cover, fuel model, elevation, slope angle, and slope aspect data sets were obtained from the LANDFIRE project as 30-m raster GIS layers. Aspect was transformed via a cosine function into a heat load index that was highest on southwest aspects and lowest on northeast aspects. Fuel models were from the expanded set of 40 standard fire behavior fuel models (Scott and Burgan 2005), and were coded using treatment contrasts. For each fire, the fuel model covering the largest area was selected as the baseline class, and the other fuel models were represented as indicator variables.

Maps of recent fuel treatments were obtained as shape files from the Kootenai National Forest (Camp 32 fire) the Umatilla National Forest (School fire), and the Kaibab National Forest (Warm fire). These maps were

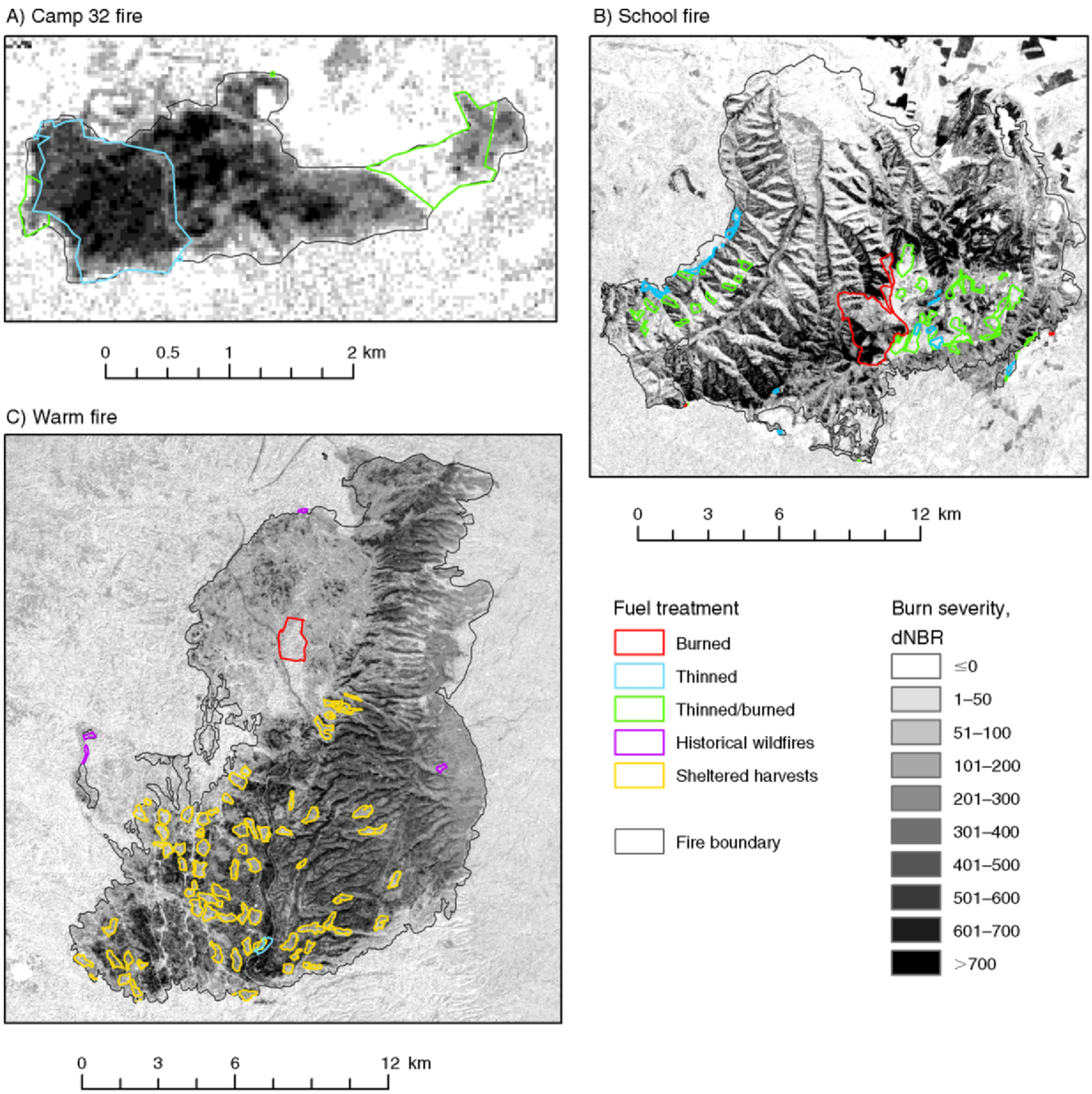

FIG. 1. Differenced normalized burn ratio (dNBR) maps of the Camp 32 (western Montana), School (southeastern Washington), and Warm (northern Arizona) fires with fuel treatment polygons.

converted to 30-m raster GIS layers. We did not attempt to map all of the historical management activities within the fire boundaries. Instead, we focused on specific activities that are currently being applied for treating forest fuels, and that were recent enough for us to acquire accurate spatial data on treatment locations. Fuel treatments in the areas burned by the three fires included thinning alone, thinning followed by prescribed burning, and prescribed burning alone (Fig. 1, Appendix A). On the Warm fire, the effects of historical shelter-wood harvests and historical wildfires were also examined. Treatments were coded as indicator variables with untreated areas as the baseline class.

Fire progression maps were obtained for School and Warm fires (Appendix A). There was no fire progression map for the Camp 32 fire because it burned for less than one day. These maps consisted of polygons, each of which encompassed the area burned during a particular time period. Most polygons represented the area burned during a single day of fire spread, although there was some variability in the temporal resolution. The fire progression polygons were coded as indicator variables with one time period set as the baseline class (5–6 August for the School fire and 25–26 July for the Warm fire). The rate of spread was computed for each polygon as the ratio of the polygon area to the length of time represented by the polygon.

TABLE 1. Regression models of differenced normalized burn ratio (dNBR) for three wildfires.

Fire and model	n	AIC	R^2
Camp 32			
1) OLS	1033	13 641	0.46
3) SAR	1033	13 026	0.75
School			
1) OLS	53 631	718 755	0.43
2) OLS with fire progression	53 631	714 433	0.47
3) SAR	53 631	679 434	0.77
4) SAR with fire progression	53 631	679 378	0.77
Warm			
1) OLS	58 726	756 377	0.22
2) OLS with fire progression	58 726	740 952	0.40
3) SAR	58 726	699 278	0.75
4) SAR with fire progression	58 726	699 134	0.75

Note: Abbreviations are: OLS, ordinary least-squares regression; SAR, sequential autoregression; AIC, Akaike information criterion; n, sample size for each model.

Analysis methods

The analyses were carried out on a 25% subsample of the 30-m pixels, with the sample of pixels distributed on a 60×60 m square lattice. All analyses were carried out in the R statistical analysis environment (R Development Core Team 2008). Four types of statistical models were examined, with dNBR as the continuous dependent variable for each model: (1) ordinary least-squares (OLS) regression with independent variables characterizing topography, fuels, vegetation, and fuel treatments; (2) OLS with date of burning added to the independent variables from model 1; (3) simultaneous autoregression (SAR) with independent variables characterizing topography, fuels, vegetation, and fuel treatments; (4) SAR with date of burning added to the independent variables from model 3. The spatial autoregressive models were fitted using the *spautolm* function from the spdep spatial analysis package in R (Bivand 2002). Sample R code for computing the spatial weights and fitting the models is provided in the Supplement.

The SAR models explicitly accounted for spatial autocorrelation by incorporating a spatial term into the standard regression model:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \lambda\mathbf{W}(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}) + \boldsymbol{\varepsilon}$$

where $\mathbf{Y}$ is a vector of dependent variables, $\mathbf{X}$ is a matrix of independent variables, $\boldsymbol{\beta}$ is a vector of parameters, λ is the autoregressive parameter that captures the degree of spatial autocorrelation among neighboring observations, $\mathbf{W}$ is a spatial weights matrix, and $\boldsymbol{\varepsilon}$ is a vector of uncorrelated errors. The spatial trend, $\mathbf{X}\boldsymbol{\beta}$, reflected the spatial variability in burn severity that was predicted by LANDFIRE variables as well as treatment effects. The spatial signal, $\lambda\mathbf{W}(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})$, captured spatially autocorrelated deviations from the trend that were modeled as an autoregressive function of deviations in neighboring sites. The noise term, $\boldsymbol{\varepsilon}$, captured deviations from the trend that were not spatially autocorrelated. The spatial weights matrix, $\mathbf{W}$, was based on an inverse distance rule in which the 12 nearest neighbors were assigned weights based on $1/d_{ij}$, where d_{ij} was the distance from the focal cell i to neighbor j.

The four statistical models for each fire were ranked in terms of their fit to the dNBR data using the AIC statistic (Burnham and Anderson 2002). We also computed pseudo-R^2 statistics for each model as the squared correlation between the observed dNBR values and the fitted values (Zheng and Agresti 2000). The fitted values of the SAR models (Eq. 1) were decomposed into maps of the spatial trend, spatial signal, and noise components (Haining 1990). These maps were derived from model 3, the SAR model without fire progression. Maps of the signal terms were examined visually to search for patterns of any important driving variables that were not captured in the trend component. For the School and Warm fires, the signal maps were overlain on the fire progression maps and Pearson correlation coefficients between mean signal values and the rate of burning for each fire progression period were calculated to test the hypothesis that the spatial error captures spatiotemporal variability in fire weather and the resulting rates of fire spread.

RESULTS

For all three fires, the OLS models without fire progression had the weakest fit as quantified by high AIC values and low R^2 values (Table 1). Adding the fire progression variables to the OLS models for the School and Warm fires improved fit slightly. The SAR models without fire progression improved model fit considerably compared to the OLS models. The SAR models with fire progression improved model fit slightly compared to the SAR models without fire progression. The model coefficients, standard errors, and the results of statistical tests on the coefficients were similar for the SAR models fitted with and without fire progression variables (Appendix B). These results demonstrated that (1) the spatial error term in the SAR models accounted for nearly all of the variability in fire severity that was captured by the fire progression maps, and (2) the decision to include or exclude the fire progression variables in the SAR models had a minimal influence on inferences about treatment effects on burn severity.

In most cases, the treatment effects in the SAR models were lower than in the comparable OLS models (Table 2). On the School fire, the positive effect of prescribed burning was higher in the SAR model than in the OLS model, although the effect was not statistically significant in either model. For all fuel treatments on all three fires, the standard errors of the treatment effects were higher in the SAR models than in the OLS models. Thus, inferences about treatment effectiveness based on OLS overestimated both the effect size and statistical significance of fuel treatments. We therefore based our analysis of treatment effects on the SAR models without fire progression variables for the Camp 32 fire, and the

TABLE 2. Treatment effects from ordinary least-squares and sequential autoregression models of dNBR for three wildfires.

Fire and treatment†	Ordinary least squares			Sequential autoregression		
	β	SE	*P*	β	SE	*P*
Camp 32‡						
Thinning	96.12	13.26	<0.001	57.41	25.53	0.025
Thinning/prescribed burn	−178.48	22.13	<0.001	−77.50	35.04	0.027
School§						
Prescribed burn	1.48	5.15	0.774	11.46	12.08	0.343
Thinning	−110.39	10.40	<0.001	−26.81	12.93	0.038
Thinning/prescribed burn	−145.10	5.42	<0.001	−27.43	6.76	<0.001
Warm§						
Shelterwood	−20.70	2.75	<0.001	−14.11	3.35	<0.001
Prescribed burn	−40.54	7.05	<0.001	−43.14	15.56	0.006
Thinning	204.47	22.82	<0.001	69.23	24.87	0.005
Historical wildfire	−39.25	16.95	0.021	−26.53	23.02	0.249

† Coded as indicator variables with untreated as the baseline class.
‡ The OLS and SAR models for the Camp 32 fire did not include fire progression variables (models 1 and 3 in *Methods: Analysis methods* and Table 1).
§ The OLS and SAR models for the School and Warm fires included fire progression variables (models 2 and 4 in *Methods: Analysis methods* and Table 1).

SAR models with fire progression variables for the School and Warm fires.

For the Camp 32 fire (Table 2), thinning alone increased burn severity, whereas the combination of thinning and prescribed burning decreased burn severity. For the School fire, the combination of thinning and prescribed burning resulted in lower burn severity than untreated areas, and thinning alone also decreased burn severity. The effect of prescribed burning alone was not statistically significant. For the Warm fire (Table 2), prescribed burning alone and shelterwood harvesting resulted in lower burn severities than untreated areas. In contrast, thinning alone increased burn severity over untreated areas. The small negative effect of previous wildfires was not statistically significant. Canopy cover, one or more topographic variables, and one or more fuel models were statistically significant in all three fires (Appendix B). Most of the fire progression variables were also statistically significant in the School and Warm fires, reflecting higher fire severity during days with extreme fire weather at the beginning of the School fire, and at the end of the Warm fire (Appendix B).

In the SAR model for the Camp 32 fire, the spatial signal was generally highest in the central portion of the burn and lowest at the edges (Fig. 2a). These signal patterns likely represented temporal variability in weather and fire behavior throughout the course of the day, and may have also captured treatment heterogeneity within the thinned and burned areas. The mean spatial signal from the SAR model without fire progression variables (model 3) was positively correlated with the mean rate of fire spread for each fire progression polygon for both the School fire ($r = 0.70$, $P = 0.05$) and the Warm fire ($r = 0.75$, $P = 0.005$). These relationships indicated that the spatial signal was associated with spatiotemporal patterns of fire weather and the resulting fire behavior. This relationship was particularly evident in the Warm fire (Fig. 2c), in which high spatial signal values were concentrated in the eastern and southern portions of the burn. This is the area where plume-dominated fire behavior drove rapid spread toward the southwest from 25 June to 26 June. The School fire exhibited a distinctive zone of low spatial signal values in the southeastern portion of the burned area (Fig. 2b). The boundaries of this zone did not correspond with the fire progression map, but were instead associated with an area where there was a high density of fuel treatments. This pattern provided evidence of a landscape-level treatment effect, in which influences of fuel treatments on fire behavior reduced burn severity outside of the fuel treatment boundaries.

DISCUSSION

Results of these analyses support the assertion that treatment of surface fuels is critical for fire severity reduction (Agee and Skinner 2005). In particular, prescribed burning has been argued to be the most effective treatment for reducing the fine surface fuel loadings that have a major influence of fire behavior and fire effects. In our study, combined thinning and prescribed burning reduced burn severity on the Camp 32 and School fires, and prescribed burning alone reduced burn severity on the Warm fire. In contrast, thinning without treatment of the resulting slash actually increased burn severity on the Camp 32 and Warm fires. This result corroborates studies of the Biscuit fire in southwestern Oregon which found higher fire severity in areas with recent forest management activities than in unmanaged areas (Raymond and Peterson 2005, Thompson et al. 2007). The situation in the thinned areas on the Camp 32 and Warm fires treatments represent a worst-case scenario in which a wildfire occurred before the thinning treatment was completed and loadings of surface fuels were therefore

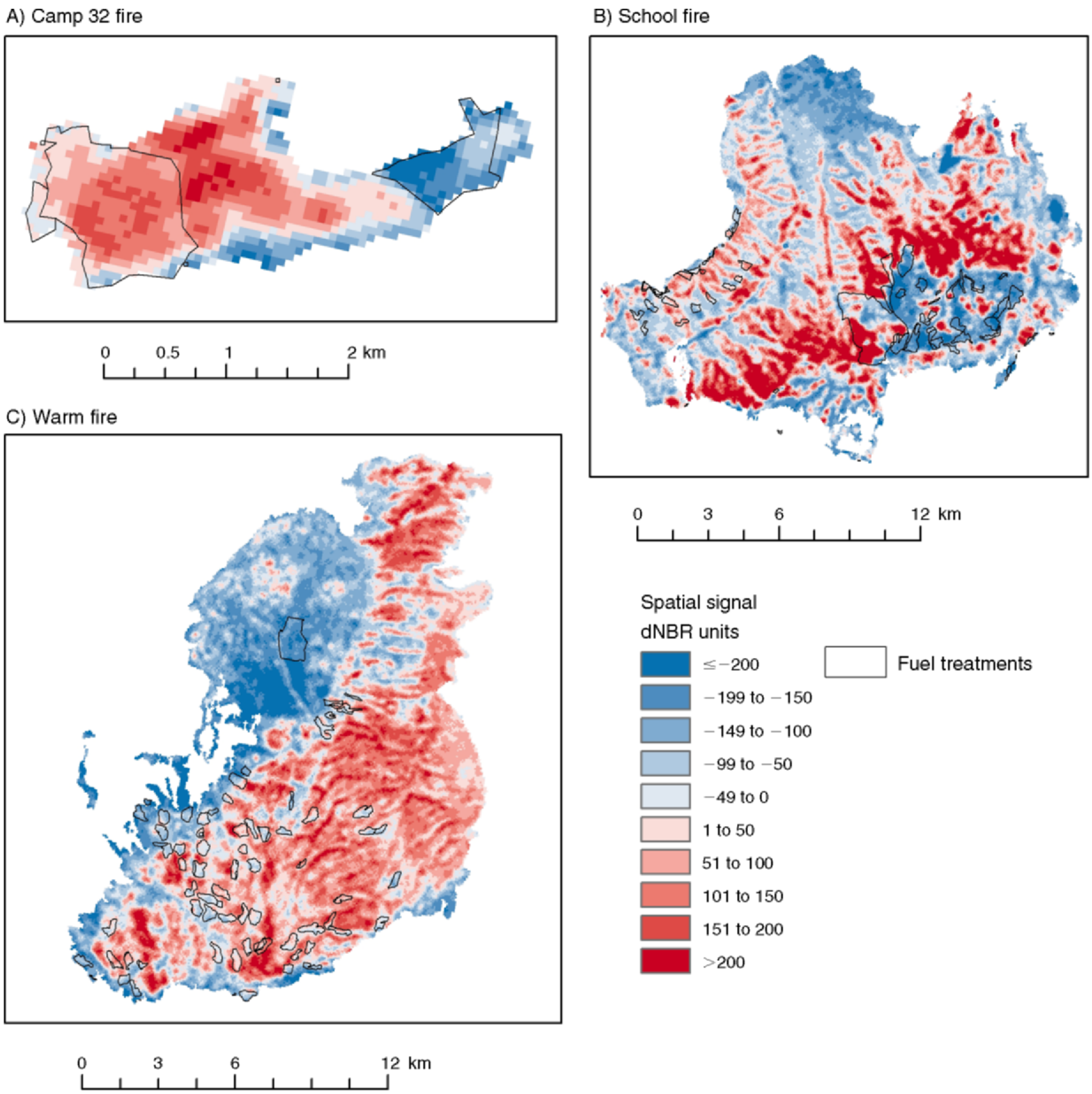

FIG. 2. Spatial signal maps of the Camp 32, School, and Warm fires with fuel treatment polygons.

particularly high. In contrast, four-year-old thinning treatments on the School fire and 14–18-year-old shelterwood harvests on the Warm fire reduced burn severity compared to untreated areas.

Empirical assessments of fuel treatment effectiveness are by necessity based on retrospective, observational studies of wildfires that have burned over one or more fuel treatments. Therefore, it is not possible to randomize treatment locations with respect to vegetation, topography, weather, and other factors that affect burn severity; and comparisons of the average burn severity among treatments are typically confounded by these other factors. Regression analysis can be used to control for these effects if all confounding variables are included in the model, and if the model is correctly specified (Gelman and Hill 2007). For all three fires that we analyzed, canopy cover and at least one topographic variable and fuel model had a statistically significant relationship with burn severity, emphasizing the importance of including these variables in assessments of fuel treatments effects. However, these analyses can still be confounded by omitted or "lurking" variables, particularly those related to fire weather. Although there have been attempts to incorporate fire progression maps and weather data into spatial analyses of fire severity (e.g., Collins et al. 2007), they have only been partially successful because of the coarse scale of fire progression polygons and the large differences between conditions at the flaming front and weather data collected at the nearest stations.

Spatial regression analysis provides an approach for incorporating information about fire weather and other omitted variables. The phenomenon of spatial autocorrelation can be framed as a missing variables problem, in which the pattern of model errors represents one or more spatially structured independent variables that are missing from the regression model (Ver Hoef et al. 2001). In the case of the SAR model, these unmeasured variables are modeled indirectly by a spatial signal term that can be computed and mapped for each pixel. We found that signal values were highest in the portions of the fires that burned most rapidly, indicating that burn severity was highest during periods of rapid fire spread and extreme fire behavior. Even when indicator variables for the fire progression polygons are included as independent variables, SAR models substantially improved the fit compared to the OLS models. This finding reflects the ability of the SAR models to capture the influences of weather variability at finer spatial and temporal scales than fire progression maps, in which each polygon typically encompasses one to three days of fire growth.

Spatial regression modeling can also provide insights into other missing variables and processes affecting patterns of burn severity. On the School fire, a large cluster of low signal values was associated with an area that had a high density of fuel treatments. We interpreted this pattern as evidence of a landscape-level treatment effect, in which the combined influences of fire interactions with the treated areas reduced burn severity even in nearby areas that were outside the treated units. These types of landscape-level effects have been demonstrated in simulation modeling studies (Finney 2001), and have been observed in the burn severity patterns resulting from the 2002 Rodeo and Chediski fires (Finney et al. 2005). In the present analysis, mapping the spatial signal allows spatially structured patterns of burn severity to be separated from patterns related to vegetation, fuels, and topography, and from the uncorrelated error term. Thus, it is possible to verify that the observed cluster of low burn severity is not an artifact of one or more confounding variables, but instead likely represents a true landscape-level effect resulting from the interaction of fire spread and the high density of fuel treatments.

Although the present study addressed only three wildfires occurring in ponderosa pine forests of the western United States, the approach could be adapted and applied in a variety of ecosystems. We focused on dNBR as a burn severity metric because of its widespread use and acceptance in the fire management and forestry communities. However, the same modeling approach could be used with relative versions of dNBR (Miller and Thode 2007) or with any other continuous burn severity metric. Different sets of confounding variables will likely be important in different regions, and various types of model-selection methods (e.g., Burnham and Anderson 2002) could be applied to select a parsimonious set of covariates. Different spatial regression modeling approaches, such as generalized least squares (Thompson et al. 2007) could also be applied. Although GLS and related methods allow for more precise modeling of spatial autocorrelation via a semivariogram, we chose spatial autoregression for analyzing fuel treatment effectiveness because of the potential for spatial analysis of large data sets ($>$50 000 samples for the School and Warm fires) using the sparse matrix algorithms available in R. Conditional autoregression (CAR) could also be used (Finney et al. 2005), although we used the SAR model in this application because its specification allows for a more straightforward decomposition of the response into spatial trend and spatial signal components (Haining 1990).

In conclusion, LANDFIRE and similar data products can be used to control for at least some of the confounding effects of vegetation, topography, and other environmental variables in assessments of treatment effectiveness. However, obtaining accurate measurements of other potential confounders such as fire weather still presents a challenge. Spatial autoregression can be used to indirectly control for these unmeasured variables by modeling them via the spatial signal term. The spatial signal can also be used to visualize other unmeasured effects, such as landscape level effects resulting from the interaction of fire spread with multiple treatments.

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Literature Cited

Agee, J. K., and C. N. Skinner. 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management 211:83–96.

Bivand, R. 2002. Spatial econometrics functions in R: classes and methods. Journal of Geographic Systems 4:405–421.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer-Verlag, New York, New York, USA.

Cocke, A. E., P. Z. Fule, and J. E. Crouse. 2005. Comparison of burn severity assessments using differenced normalized burn ratio and ground data. International Journal of Wildland Fire 14:189–198.

Collins, B. M., M. Kelly, J. W. van Wagtendonk, and S. L. Stephens. 2007. Spatial patterns of large natural fires in Sierra Nevada wilderness areas. Landscape Ecology 22:545–557.

Eidenshink, J., B. Schwind, K. Brewer, Z. L. Zhu, B. Quayle, and S. Howard. 2007. A project for monitoring trends in burn severity. Fire Ecology 3:3–21.

Epting, J., D. Verbyla, and B. Sorbel. 2005. Evaluation of remotely sensed indices for assessing burn severity in interior Alaska using Landsat TM and ETM+. Remote Sensing of Environment 96:328–339.

Finney, M. A. 2001. Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. Forest Science 47:219–228.

Communications

Finney, M. A., C. W. McHugh, and I. C. Grenfell. 2005. Stand- and landscape-level effects of prescribed burning on two Arizona wildfires. Canadian Journal of Forest Research 35: 1714–1722.

Gelman, A., and J. Hill. 2007. Data analysis using regression and multilevel/hierarchical models. Cambridge University Press, New York, New York, USA.

Haining, R. 1990. Spatial data analysis in the social and environmental sciences. Cambridge University Press, Cambridge, UK.

Jerman, J. L., P. J. Gould, and P. Z. Fule. 2004. Slash compression treatment reduced tree mortality from prescribed fire in southwestern ponderosa pine. Western Journal of Applied Forestry 19:149–153.

Kalabokidis, K. D., and P. N. Omi. 1998. Reduction of fire hazard through thinning residue disposal in the urban interface. International Journal of Wildland Fire 8:29–35.

Key, C. H., and N. C. Benson. 2005. Landscape assessment: ground measure of severity, the composite burn index, and remote sensing of severity, the normalized burn ratio. Pages LA-1–LA-51 *in* D. C. Lutes, R. E. Keane, J. F. Carattei, C. H. Key, N. C. Benson, S. Sutherland, and L. J. Gangi, editors. FIREMON: fire effects monitoring and inventory system. CD-ROM. RMRS-GTR-146CD. USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, USA.

Miller, J. D., and A. E. Thode. 2007. Quantifying burn severity in a heterogeneous landscape with a relative version of the delta normalized burn ratio (dNBR). Remote Sensing of Environment 109:66–80.

Moghaddas, J. J., and L. Craggs. 2007. A fuel treatment reduces fire severity and increases suppression efficiency in a mixed conifer forest. International Journal of Wildland Fire 16:673–678.

Pollet, J., and P. N. Omi. 2002. Effect of thinning and prescribed burning on crown fire severity in ponderosa pine forests. International Journal of Wildland Fire 11:1–10.

R Development Core Team. 2008. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Raymond, C. L., and D. L. Peterson. 2005. Fuel treatments alter the effects of wildfire in a mixed-evergreen forest, Oregon, USA. Canadian Journal of Forest Research 35: 2981–2995.

Ritchie, M. W., C. N. Skinner, and T. A. Hamilton. 2007. Probability of tree survival after wildfire in an interior pine forest of northern California: effects of thinning and prescribed fire. Forest Ecology and Management 247:200–208.

Rollins, M. G., and C. K. Frame. 2006. The LANDFIRE prototype project: nationally consistent and locally relevant geospatial data for wildland fire management. General technical report RMRS-GTR-175. USDA Forest Service Rocky Mountain Research Station, Fort Collins, Colorado, USA.

Scott, J. H., and R. E. Burgan. 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermal's surface fire spread model. RMRS-GTR-153. USDA Forest Service, Rocky Mountain Research Station, Fort Collins, Colorado, USA.

Stephens, S. L., and J. J. Moghaddas. 2005. Experimental fuel treatment impacts on forest structure, potential fire behavior, and predicted tree mortality in a California mixed conifer forest. Forest Ecology and Management 215:21–36.

Thompson, J. R., T. A. Spies, and L. M. Ganio. 2007. Reburn severity in managed and unmanaged vegetation in a large wildfire. Proceedings of the National Academy of Sciences (USA) 104:10743–10748.

Van Wagtendonk, J. W., R. R. Root, and C. H. Key. 2004. Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. Remote Sensing of Environment 92:397–408.

Ver Hoef, J. M., N. Cressie, R. N. Fisher, and T. J. Case. 2001. Uncertainty and spatial linear models for ecological data. Pages 214–237 *in* C. T. Hunsaker, M. F. Goodchild, M. A. Friedl, and T. J. Case, editors. Spatial uncertainty in ecology: implications for remote sensing and GIS applications. Springer, New York, New York, USA.

Wimberly, M. C., and M. J. Reilly. 2007. Assessment of fire severity and species diversity in the southern Appalachians using Landsat TM and ETM+ imagery. Remote Sensing of Environment 108:189–197.

Zheng, B. Y., and A. Agresti. 2000. Summarizing the predictive power of a generalized linear model. Statistics in Medicine 19:1771–1781.

APPENDIX A

Site descriptions and wildfire narratives for the Camp 32, School, and Warm fires (*Ecological Archives* A019-057-A1).

APPENDIX B

Tables of coefficients, standard errors, and *P* values for the ordinary least-squares and sequential autoregression models (*Ecological Archives* A019-057-A2).

SUPPLEMENT

Sample R script and data for analyzing fuel treatment effects on burn severity using ordinary least-squares regression and sequential autoregression (*Ecological Archives* A019-057-S1).