INTEGRATING REMOTE SENSING, GIS, AND SPATIAL STATISTICS: A CASE STUDY OF INVASIVE PLANTS AND WILDFIRE ON THE CERRO GRANDE FIRE, LOS ALAMOS, NEW MEXICO

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ABSTRACT

Investigating spatial relationships among fuels, wildfire severity, and post-fire invasion by exotic plant species through linkage of multiphase sampling design and multiscale nested sampling field plots, pre- and post-fire, can be accomplished by integrating spatial information with spatial statistical models. This technique provides useful information and tools for describing ecological and environmental characteristics, including landscape-scale fire regimes, invasive plants, and hotspots of diversity (native and exotic plants) for the Cerro Grande fire site, Los Alamos, New Mexico. To predict the distribution, presence, and patterns of native and exotic species, we used modeling of large- and small-scale variability by integrating field data and spatial information (eight bands of Landsat Thematic Mapper [TM] data, six derived vegetation indices, six bands of tasseled cap transformations, elevation, slope, aspect) and spatial statistics. We present the results of trend surface models that describe the large-scale spatial variability using stepwise multiple regressions based on the Ordinary Least Squares (OLS) method. Models with small variance were selected. In addition, the residuals from the trend surface model based on the OLS estimates were modeled using ordinary kriging for modeling small-scale variability based on a Gaussian semi-variogram. The final surfaces were obtained by combining two models (the trend surface based on the OLS and the kriging surface of residuals). All models were selected based on the lowest values of standard errors, modified Akaike's Information Criterion (AICC) statistics, and high R^2. For large-scale spatial variability models using the OLS procedure, R^2 values ranged from 10.04% to 58.6% and all variables were significant at $\alpha < 0.05$ level. When the kriging model was added with the OLS model, R^2 values ranged from 60% to 84%. This new technique will help natural resource management teams to identify areas vulnerable to invasion by exotic plant species and predict their consequent potential for wildfire.

keywords: Cerro Grande fire, invasive plants, fire severity, kriging, multiphase design, multiscale sampling, Ordinary Least Squares method, New Mexico, spatial information, spatial statistics, trend surface, variogram.

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INTRODUCTION

Synergistic interactions and positive feedbacks among fuels, extreme wildfire behavior, and exotic species invasions are increasingly recognized as major threats to the structure and function of natural ecosystems (Mack and D'Antonio 1998). We are investigating spatial relationships among fuels, wildfire severity, post-fire invasion by exotic plant species, and other ecological–environmental characteristics through the linkage of multiphase design (Figure 1), multiscale field plots (Modified-Whittaker; Stohlgren et al. 1995, 1998) (Figure 2), and pre- and post-fire remote sensing imagery using spatial models (Kalkhan et al. 1998, 2001; Kalkhan and Stohlgren 2000). The integration of spatial information (remote sensing data, Geographic Information Systems [GIS]) using spatial statistics provides useful tools for assessing landscape-scale structure of forest and rangelands (Kalkhan et al. 2000, 2001; Chong et al. 2001). In addition, the ability to model the small-scale variability in landscape characteristics requires the generation of full-coverage maps depicting characteristics measured in the field (Gown et al. 1994). Gown et al. (1994) point out that, while many spatial data sets describing land characteristics have proven reliable for macro-scale ecological monitoring, these relatively coarse-scale data fall short in providing the precision required by more refined ecosystem resource models.

Reich et al. (1999) described a model based on the process using stepwise regression, trend surface anal-

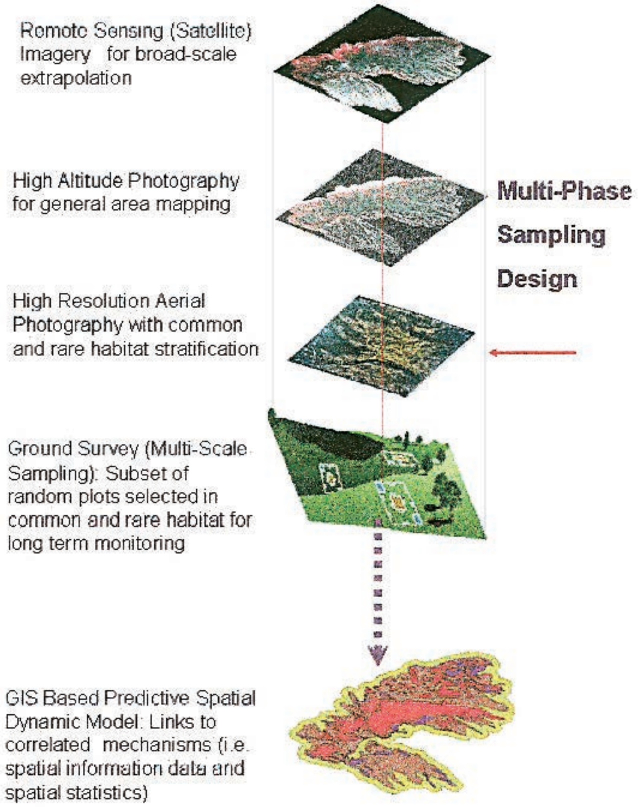

Figure 1. Multiphase sampling design (modified from Kalkhan et al. 1998).

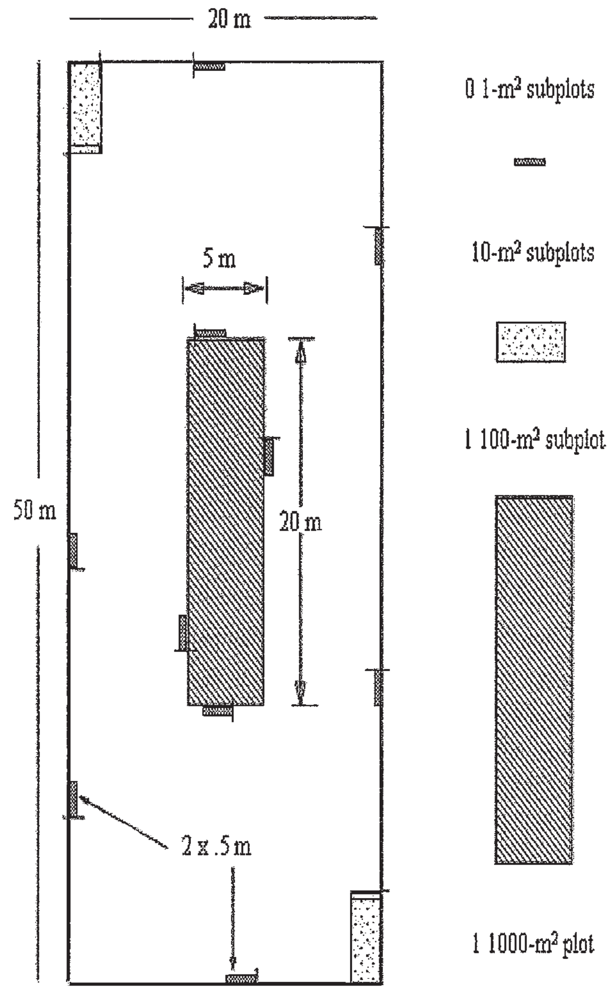

Figure 2. Modified-Whittaker nested sampling design (modified from Stohlgren et al. 1995, 1998).

ysis of geographical variables (e.g., elevation, slope, and aspect), and measures of local taxa to evaluate large-scale spatial variability. This model, described by Reich and Bravo (1999), was used in this study and is defined as:

$$\Phi_0 = \sum_{i+j}^{p} \sum_{\le p}^{p} \beta_{ij} \, x_{10}^{i} \, x_{20}^{j} + \sum_{k=1}^{q} \gamma_k \, y_{k0} + \eta_0, \qquad (1)$$

where β_{ij} are the regression coefficients associated with the trend surface component of the model, γ_k are the regression coefficients associated with the q auxiliary variables, y_{k0}, are available as a coverage in the GIS database, and η_0 is the error term which may or may not be spatially correlated with its neighbors (Kallas 1997, Metzger 1997).

Spatial statistics and spatial information provide a means to develop spatial models that can be used to correlate coarse-scale geographical data with field measurements of biotic variables. Here we present our spatial modeling process and preliminary predictive models of native and exotic plant distributions for the 2000 Cerro Grande fire, Los Alamos, New Mexico.

Our research program objectives included the interpolation of plot-level information to the landscape-scale with generalized predictive spatial statistical models derived from remotely sensed data, GIS, and field data, allowing broad examination and conclusions regarding the interactions among fuels, wildfire, and exotic plants. The uniqueness of this approach is the combination of multiphase sampling design (i.e., double sampling; Figure 1) (Kalkhan et al. 1998) and multiscale nested plot designs (Modified-Whittaker; Stohlgren et al. 1995, 1998). The main plot dimension was 20 × 50 m (1,000 m^2) with ten 0.5 × 2-m (1-m^2) subplots, two 2 × 5-m (10-m^2) subplots in opposite corners, and a 5 × 20-m (100-m^2) subplot in the plot center (Figure 2). Both approaches allow us to perform intensive unbiased sampling surveys at certain plot levels which can help to reduce the cost of sampling surveys and improve the efficiency of sampling design. The specific objective of this paper is to develop a predictive spatial statistical model for describing large- and small-scale variability of plant species richness (native and exotic species) in relation to the Cerro Grande fire.

Table 1. Summary statistics for all variables used in developing spatial statistical models for the Cerro Grande fire, Los Alamos, New Mexico, 2001.

Variable	Minimum	Median	Mean	Maximum
Total plant species	14	44	51	78
Native plant species	8	31	40	57
Exotic plant species	0	4	4.1	9
Native cover (%)	4.2	22.3	25.9	76.3
Exotic cover (%)	0	0.6	1.3	7.9
Elevation	1972	2266	2356	3023
Slope	1.4	10.02	12.46	32.5
Absolute aspect	5.2	80	86.9	180
Thematic Mapper band				
1	60	80	81.3	116
2	45	65	66.3	106
3	38	71	73.5	131
4	29	48	49.9	111
5	43	100	98.9	168
6	112	188	185.1	222
7	26	92	92.2	169
8	34	47	49.2	85
Band ratio				
(5/4)	63	127	133.5	191
(4/3)	1	1	1.038	2
(3/1)	85	85	88.2	170
(4–3)	22	42	54.9	184
NDVI[a]	0	1	0.620	1
TNDVI[b]	0	0	0.4975	115
Tassel Cap				
Band 1	111	168	173.4	265
Band 2	–80	–53	–49.8	3
Band 3	–83	–41	38.7	7
Band 4	19	27	26.7	34
Band 5	–71	–39	–37.7	–12
Band 6	–20	–15	–15.2	–11

[a] NDVI = Normalized Difference Vegetation Index.
[b] TNDVI = Transformed Normalized Difference Vegetation Index.

STUDY SITE

The Cerro Grande fire site is located near Los Alamos, New Mexico. Elevation ranges from 1,932 m to 3,200 m. The fire site was well suited for our study because it included multiple fuel types, exhibited a wide range of burn severities, and involved pre-fire fuel treatments. In addition, existing digital spatial information was abundant and available, and there was potential for cooperation with other research groups that have complementary interests.We completed field sampling for our study site in August 2001. The Cerro Grande fire began as a prescribed fuel treatment by Bandelier National Monument, Los Alamos, New Mexico, on 4 May 2000. The fire escaped control and was declared a wildfire on 5 May 2000. The fire was contained on 24 May after burning about 19,300 ha of lands managed by seven different agencies, including the town of Los Alamos. However, 60% of the fire area burned 10–11 May 2000, and 60% of the fire was on the Española District of the Santa Fe National Forest (Burned Area Emergency Rehabilitation [BAER] Team 2000). Initial remotely sensed estimates of burn severity were classified as high (35%), moderate (9%), and low (56%). Elevations in sampled areas ranged from 2,000 m to 3,000 m and included pinyon–juniper woodlands, ponderosa pine (*Pinus ponderosa*) forests, and mixed-conifer forests.

METHODS

Sampling Design

We employed a stratified random sampling design to locate 66 multiscale nested plots (Modified-Whittaker; Stohlgren et al. 1995, 1998) (Figure 2) within areas burned on 10–11 May 2000 in the Santa Fe National

Forest, and an additional 13 unburned plots within 300 m of the fire perimeter. Burned-area strata included vegetation type (pinyon–juniper woodland, ponderosa pine forest, and mixed-conifer forest), BAER fire severity classification (high, low, moderate), aspect (north, south), and pre-fire fuel treatment (untreated, prescribed burn, thin only, thin followed by prescribed burn). Unburned strata included aspect (north, south) and elevation (<2,500 m; >2,500 m). At least 3 plots were randomly located in each stratum.

Data Analysis

Data collected from each plot included measurements related to pre-fire stand condition, refined estimates of fire severity, plant species cover and richness, and measurements related to post-fire fuel flammability. For the vegetation data, we used the Modified-Whittaker multiscale nested plots design (Figure 2). The Global Positioning System was used to document the locations of the plots and incorporate the field data directly into the GIS. Five soil samples (depth 10–20 cm) were taken and pooled from each 20 × 50-m vegetation plot. These five samples were located in each of the corners of each Modified-Whittaker plot, as well as in the plot center. Samples were used for total carbon (C), nitrogen (N), and soil texture analyses. Data used in modeling included eight bands of Landsat TM Data, six different vegetation indices, six bands of transformed tasseled cap indices (using IMAGINE 8.4 [ERDAS 2000]), topographic derived data (elevation, slope, aspect; ArcInfo 7.4 [ESRI 2000]), and vegetation data (total number of plant species, number of native plant species, number of exotic plant species, and percent cover for total, native, and exotic species). All spatial information from remotely sensed data and GIS layers were converted to a grid using ArcInfo 7.4 (ESRI 2000), and a program written in ARC Macro Language (ESRI 2000) was used to extract the 79 data points (field plot locations) with respect to their Universal Transverse Mercator *X*- and *Y*-coordinates within the study area. All data were then used for the development of the spatial models using S-Plus software (MathSoft 2000). Soil data were collected but are not discussed here.

Spatial Analysis

In this paper we used the same approach by Kalkhan and Stohlgren (2000) by using the cross-correlation statistic to test the null hypothesis of no spatial cross-correlation among all pairwise combinations of vegetation variables and topographic characteristics (Table 1). In calculating the cross-correlation statistic (I_{YZ}), we used the inverse distance between sample plots as a weighting factor to give more weight to values in the closest sample plots and less to those in plots that are farthest away. The null hypotheses of no spatial cross-correlation were rejected at $P < 0.05$. Moran's *I*, which is a special case of the cross-correlation statistic I_{YZ} (Czaplewski and Reich 1993), was used to calculate the spatial auto-correlation associated with each of the variables used in this study (Table 1). Cliff and Ord (1981) showed that I_{YZ} ranges from –1 to +1, although it can exceed these limits with certain types of spatial matrices. Data distributions that were strongly skewed were transformed prior to analysis. Aspect data were transformed using the absolute value from due south (180°; high solar radiation) (Kalkhan and Stohlgren 2000).

Spatial Modeling

Stepwise multiple regression analysis was used first to identify the best linear combination of independent variables. It also allows us to explore the variation in predicting total, exotic, and native plant species richness as a function of the eight TM bands, six derived vegetation indices, six tasseled cap transformation indices, slope, aspect, and elevation. The selected independent variables were used in the OLS procedure to describe large-scale variability estimates.

OLS estimators were used to fit the model if the variable of interest had a linear relationship with the geographical coordinates of the sample plots, the digital number value of any of the Landsat TM bands, and the topographic data. In addition, the least squares method fits a continuous, univariate response as a linear function of the predicted variable. This trend surface model represented continuous first-order spatial variation. AIC (Brockwell and Davis 1991, Akaike 1997) was used as a guide in selecting the number of model parameters to include in the regression model, where

$$\text{AIC} = -2(\text{max log likelihood}) + 2(\text{number of parameters}) \quad (2)$$

When maximum likelihood is used as a criterion for selecting between models of different orders, there is the possibility of finding another model with equal or greater likelihood by increasing the number of parameters (Metzger 1997). Therefore, the AIC allows for a penalty for each increase in the number of parameters. Using this criterion, we considered a model with a smaller AIC to have a better fit. While the model was kept as simplistic as possible, a more complex model could be used if warranted. In this paper, we used the AICC, which is a modification model of AIC (Reich et al. 1999).

Table 2. Summary statistics for large- and small-scale variability models for predicting total, native, and exotic plant species richness and their percent cover within the Cerro Grande fire, Los Alamos, New Mexico, 2001.

	Large-scale variability (OLS model)[a]			Large- and small-scale variability (OLS and kriging–variogram model)[b]		
Variable	R^2 (%)	SE	AICC[c]	Model	R^2 (%)	SE
Total plant species	14.1	11.1	610.3	Gaussian	63.9	7.0
Native plant species	43.7	8.6	571.6	Gaussian	60.0	7.0
Exotic plant species	58.2	1.6	309.5	Gaussian	60.9	1.5
Probability of exotic species	58.6	1.97	342.1	No spatial auto-correlation with residuals		
Total plant cover (%)	43.6	13.3	639.6	Gaussian	81.6	7.3
Native plant cover (%)	46.2	13.3	639.9	Gaussian	84.4	6.9
Exotic plant cover (%)	10.1	0.5	125.2	No spatial auto-correlation with residuals		

[a] P significant at $\alpha < 0.05$ for the OLS (Ordinary Least Squares) models.
[b] P significant at $\alpha < 0.01$ for the variogram models.
[c] AICC = Modified Akaike's Information Criterion.

In the next stage of the model building process, the residuals from the trend surface models were analyzed for spatial dependencies. This was accomplished using spatial auto-correlation and cross-correlation statistics. If the residuals were cross-correlated with other variables, we could use co-kriging to interpolate the residuals. However, if the residuals were not cross-correlated, we used ordinary kriging. Finally, the weights associated with the kriging and co-kriging models were estimated as a function of the spatial continuity of the data (Isaaks and Srivastiva 1989). This estimation can be accomplished using a sample variogram to describe spatial continuity. With spatial data, the variation of the samples generally changes with distance. In other words, the variogram is a measure of how the variance changes with distance. The variogram and cross-variogram models used in this analysis were considered "basic" models, meaning they are simple and isotropic (Reich et al. 1999). They include Gaussian, spherical, and exponential models (see Isaaks and Srivastiva 1989). Prior to estimating the sample variogram and cross-variogram, the data were rescaled by dividing the individual variables and the residuals by their respective maximum values. This was necessary to maintain numerical stability (Isaaks and Srivastiva 1989) by eliminating any differences in the magnitude of the variables without altering the solution. Although this was not necessary for kriging, it was important in co-kriging (Isaaks and Srivastiva 1989, Metzger 1997).

RESULTS

We used 79 data points (based on Modified-Whittaker nested plots of 1,000 m^2) to represent different variables that were extracted from Landsat TM data, topographic data, and vegetation characteristics (Table 1). Total plant species richness, including species of unknown origin and taxa that could not be identified, ranged from 14 to 78 per plot. Typically, nonnative species represented >10% of the total species at a site and about 5% of the foliar cover (Table 1).

Spatial Relationships

The preliminary results for our field data using Moran's *I* (Moran 1948, Mantel 1967) and the bivariate cross correlation-statistic, I_{YZ} (Czaplewski and Reich 1993, Bonham et al. 1995) to test for spatial auto-correlation and cross-correlation with residuals suggested that, at large-scales, the probabilities of presence and absence of exotic plant species and their percent cover were spatially independent throughout the study site (Table 2). That is, the spatial relationships were not statistically significant. Native species richness was not independent (Kalkhan and Stohlgren 2000). However, these results may be different for individual plant species (Kalkhan et al. 2000). In general, large-scale patterns of species distribution were controlled by topographic factors such as elevation, aspect, and slope with complex spatial patterns. This may explain why negative spatial auto-correlation and cross-correlation resulted when large-scale plots were used (Kalkhan et al. 2000). These results may have been different if individual native or exotic plant species had been used in the analysis (Kalkhan et al. 2000).

Spatial Statistical Model

The results of modeling the large-scale and small-scale variability in predicting total, native, and exotic

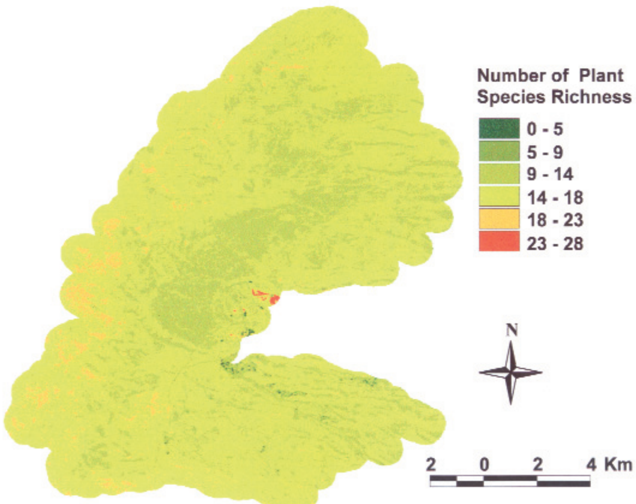

Figure 3. Predicted spatial statistical map (based on 30-m resolution) for total plant species richness (based on 1,000 m^2/plot) for the Cerro Grande fire, Los Alamos, New Mexico, 2001. Model significant variables: elevation, slope, vegetation index (Transformed Normalized Difference Vegetation Index), and tasseled cap band 1 with R^2 = 64%.

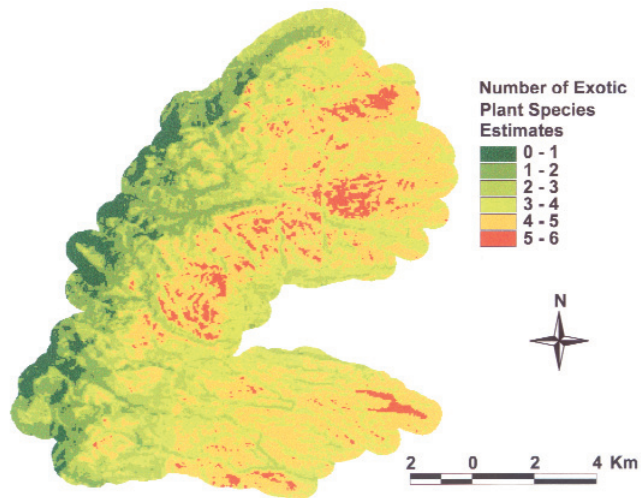

Figure 4. Predicted spatial statistical map (based on 30-m resolution) for exotic plant species richness (based on 1,000 m^2/plot) for the Cerro Grande fire, Los Alamos, New Mexico, 2001. Model significant variables: Universal Transverse Mercator (UTM)-*X*, UTM-*Y*, number of native plants, vegetation indices (band ratio 5/4, 4/3, and Normalized Difference Vegetation Index), tasseled cap band 5 with R^2 = 58%.

species richness and percent cover of exotic and native plant species within the Cerro Grande fire site are shown in Table 2. Models were developed for large-scale variability of the total number of plants (both native and exotic species) and percent plant cover (total, native, and exotic). The trend surface models identified in this study used stepwise multiple regressions that had R^2 values ranging from 10.04% to 58.6% and all variables were significant at $\alpha < 0.05$.

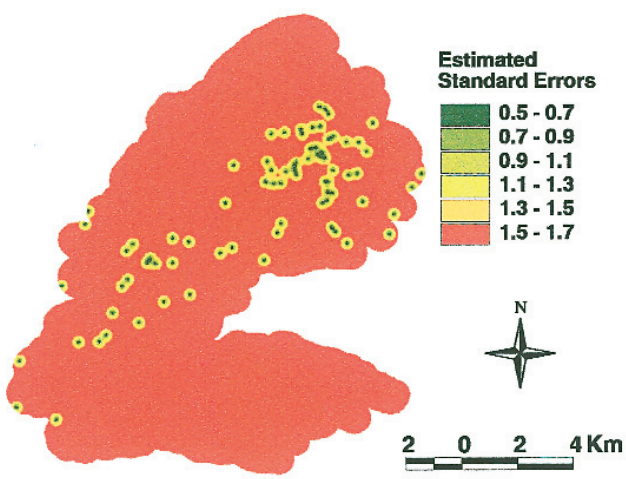

Figure 5. Predicted standard errors (uncertainty) map (based on 30-m resolution) for exotic plant species richness (based on 1,000 m^2/plot) for the Cerro Grande fire, Los Alamos, New Mexico, 2001. Model significant variables: Universal Transverse Mercator (UTM)-*X*, UTM-*Y*, number of native plants, vegetation indices (band ratio 5/4, 4/3, and Normalized Difference Vegetation Index), tasseled cap band 5 with R^2 = 58%.

Small-scale variability models were used to examine the spatial continuity of variability and were developed using ordinary kriging based on the Gaussian semi-variogram model which was based on the AICC (Table 2). Model parameters were estimated using weighted least squares (Cressie 1985). The residuals were also analyzed for spatial auto-correlation and cross-correlation (Czaplewski and Reich 1993, Reich et al. 1995) with the geographical variables (e.g., elevation, slope, other). Inverse distance weighting was used to define the spatial weights matrix. The kriging models were cross-validated to assess the variability in the prediction errors. The cross-validation included deleting one observation from the data set and predicting the deleted observation using the remaining observations (Reich et al. 1999). This process was repeated for all observations in the data set. The final models (trend surface plus the kriged residuals) had R^2 values ranging from 60% to 84%. In addition, the accuracies of the kriging models were assessed using the relative mean squared error suggested by Havesi et al. (1992).

Figures 3 and 4 represent examples of predictive spatial statistical maps based on the trend surface model (OLS) and kriging (variogram) on total species richness distributions for total plant species and exotic plant species within the Cerro Grande fire site. The information gained from integration of remotely sensed data, GIS, and field data is used to produce spatial statistical maps of total plant diversity, in particular, of invasive species richness. Integrating spatial information technology permits predictive modeling on multiple scales with more focused and unbiased sampling designs (thus reducing cost). Consequently, natural resource management teams can utilize this as a cost-effective tool in identifying areas vulnerable to exotic plant species invasion and increased potential for wildfire. The spatial map of one variable (e.g., number of native plants) can be used to predict additional spatial models (e.g., number of exotic plants) if there is a significant spatial cross-correlation. Figure 5 is an example of the standard errors associated with predicting exotic plant species richness (map of uncertainty). The figure shows that standard errors increased with distance from the sample points, as would be expected. The standard errors indicated significant utility of the map of exotic plant species richness for directing future management activities. This technique of spatial mapping provides a unique way to describe landscape-scale wildfire patterns and may contribute to better management decisions. Adding more sampling points and examining ecological relationships (e.g., between vegetation and soil) may help to improve predictive spatial statistical models and their accuracy (i.e., error reductions).

DISCUSSION

Spatial relationships among fuels, wildfire severity, and post-fire invasion of exotic plant species can be investigated through linkage of multiphase sampling designs and multiscale nested sampling field plots, pre- and post-fire, and can be accomplished by integrating remotely sensed data and GIS, with spatial statistical models. This technique provided useful information and tools for describing landscape-scale patterns of plant diversity within the Cerro Grande fire site. Current fire behavior models such as BEHAVE (Andrews 1986) and *FARSITE* (Finney 1998) were used to aid in predicting fire and subsequent mapping of probable scenarios of fire spread during a given time period. These models do not take advantage of remotely sensed data and utilized only forest stand parameters, fire behavior, a fuel model, and topographic (i.e., elevation, aspect, and slope) characteristics. Using remote sensing data allows us to easily develop these layers and their characteristics. Satellite data and aerial photographs have been used to map vegetation characteristics and then assign fuel models to various vegetation classes (Kourtz 1977, Miller and Johnston 1985, Wilson et al. 1994, Mark et al. 1995). The disadvantage of this approach is that the various components of vegetation (i.e., forest structure) are not always correlated with existing vegetation characteristics because of past management activities and random disturbance in the form of individual tree or plant mortality (R.M. Reich, Colorado State University, personal communication). Thus, collecting intensive fuel data and vegetation measurements using unbiased multiscale sampling within the forest landscape provide an excellent data source and input to spatial models similar to the one used in this paper. These spatial models provide unbiased estimates of the various components of forest fuels as well as estimates of the prediction variance associated with individual estimates. Also, the estimating spatial models are relatively more precise and accurate in terms of statistical components and properties than currently available fuel models, and are thus more useful to the forest decision-makers. Models covering such areas as the Cerro Grande site enable the spatial integration of fuel loading estimates to a wide range of spatial scales, along with estimates of the level of uncertainty. Finally, these types of models can help natural resource management teams to minimize field assessment through use of multiphase sampling designs and multiscale nested plot designs.

CONCLUSIONS

The integration of remotely sensed data and GIS using spatial statistics provides useful information for describing large- and small-scale variability of landscape, as demonstrated at the Cerro Grande fire site. We used spatial statistical predictive models based on large- and small-scale variability to predict plant species richness of both native and exotic plant species (hot spots of diversity) and patterns of exotic plant invasions. The predicted standard errors for exotic species richness (Figure 5) are <40% of the mean number of exotic species per plot, even at the farthest distance from a sampled point. This indicates significant utility of the map of exotic species richness for directing management activities because the error is relatively low. This error could be reduced when soil data, for example, become available and could add to future predictive models.

Future research will use data (including additional variables of soil and vegetation) collected from small subplots (i.e., 1 m^2). This will improve the accuracy of model predictions as well as advance the investigations of spatial auto-correlation and cross-correlation statistical patterns in landscape-scale assessments, which are essential for the development of spatial statistical models for relations between vegetation and environmental variables (e.g., soil characteristics), fuel data, and wildfire severity at different levels. This will also help us to understand their spatial relationships with respect to remotely sensed data at different scales of plot sizes (e.g., 1 m^2, 10 m^2, 100 m^2, and 1,000 m^2) and improve the spatial model, since we will be able to capture more information about landscape-scale patterns and variability. Finally, this new technique will help natural resource management teams to identify areas vulnerable to invasion by exotic plant species (hotspots of plant diversity) and predict their consequent potential for wildfire.

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