RESEARCH ARTICLE

SPATIAL VARIATION IN POSTFIRE CHEATGRASS: DINOSAUR NATIONAL MONUMENT, USA

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ABSTRACT

A major environmental problem in semi-arid landscapes of western North America is the invasion of native vegetation by cheatgrass (*Bromus tectorum* L.), an annual Eurasian grass that covers >40 million ha of range and woodland in the western US. Cheatgrass can be especially problematic after fire—either prescribed fire or wildfire. Although cheatgrass is known to generally thrive in regions of moderate temperatures, dry summers, and reliable winter precipitation, the spatial patterns of postfire cheatgrass invasion are not well characterized at finer spatial scales (e.g., within most individual landscapes). We used boosted regression trees to develop a spatial model of cheatgrass abundance 0 yr to 19 yr postfire in an 8000 km^2 semiarid landscape centered on Dinosaur National Monument (Colorado and Utah, USA). Elevation, a deterministic variable, was the strongest single predictor, with higher cheatgrass cover occurring below 1600 meters. Two other contingent variables, fire severity and climatic conditions in the year after the fire, increased the model's predictive power. The influence of fire severity differed with the scale of analysis. Across the landscape as a whole (including extensive areas at moderate to high elevation), a greater likelihood of high postfire cheatgrass cover (≥10 %) was associated with lower fire severity. Focusing only on low-elevation areas (<1600 m), higher fire severity was associated with greater likelihood of high cheatgrass cover. Low precipitation in the year after fire was associated with greater probability of high cheatgrass cover in all areas.

Keywords: Boosted regression tree, *Bromus tectorum*, cheatgrass, Dinosaur National Monument, fire severity, invasive species, land management, spatial modeling

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INTRODUCTION

Invasion of native vegetation by non-native plant species is a major environmental problem in semi-arid landscapes of western North America. An invasive species of particular concern is cheatgrass (*Bromus tectorum* L.), an annual Eurasian grass that first appeared in western North America in the late 1800s (Morrow and Stahlman 1984) and has since spread over 40 million ha (Whisenant 1990). Cheatgrass is now the dominant plant species over much of the western US. (Knapp 1996, Bradley and Mustard 2005).

Cheatgrass domination typically leads to several undesirable changes in biodiversity and community composition (Anderson and Inouye 2001, Ponzetti *et al*. 2007, Ostoja and Schupp 2009). Water and nutrient cycling are altered when cheatgrass becomes a dominant ecosystem component (Evans *et al*. 2001), and cheatgrass is generally considered poorer forage for livestock than native grasses (Young *et al*. 1987, Ganskopp and Bohnert 2001; but see Young and Allen 1997). Increased cover of dry cheatgrass creates a continuous "flashy" fuel that can carry fire over large areas, increasing fire risk (Link 2006). In areas of high cheatgrass cover, recent fire intervals have been much shorter than was typical before the arrival of cheatgrass (Billings 1990, Whisenant 1990). Many native plant species cannot tolerate such frequent fire and have become reduced in abundance or locally extirpated; in contrast, cheatgrass is well adapted to recurrent disturbance, and frequent fire promotes increasing cheatgrass dominance, which leads to more fire in a process of positive feedback (Melgoza and Nowack 1991, D'Antonio and Vitousek 1992).

The cheatgrass threat generally is greatest in regions of moderate temperatures, dry summers, and reliable winter precipitation (Bradford and Lauenroth 2006, Chambers *et al*. 2007, Bradley 2009, Condon *et al*. 2011), conditions that apply to much of the semi-arid shrublands and woodlands in western North America. However, local postfire cheatgrass presence and abundance typically vary substantially within an individual landscape. The spatial patterns of postfire cheatgrass invasion are not well characterized at the landscape scale, nor are the ecological factors controlling local invasion potential, especially after fire. Research to date indicates that a combination of local environmental characteristics, climate (before, after, and in the year of the fire), and propagule availability can influence the occurrence and magnitude of postfire cheatgrass invasion, but results are limited and not always consistent (Rew and Johnson 2010). On the Uncompahgre Plateau in western Colorado, USA, Shinneman and Baker (2009) reported higher postfire cheatgrass cover in sagebrush-grassland than in piñon-juniper woodland, on sites having higher pre-fire cover of annual forbs and lower cover of biological soil crust, in burns occurring after a year of lower precipitation or followed by years of higher precipitation, and with increasing time since fire. Slope, elevation, aspect, and geologic substrate were not significant predictors in that study, nor were distance to edge of burn or to roads (Shinneman and Baker 2009). In contrast, other studies have indicated that vulnerability to cheatgrass invasion is greater on sites with higher solar radiation (e.g., on south-facing slopes) (Billings 1990, Condon *et al*. 2011), on sites located closer to paved roads (Gelbard and Belnap 2003, Anacker *et al*. 2010) or to the edge of a burned patch (Getz and Baker 2008), and in places where perennial herbaceous cover is lower (Chambers *et al*. 2007, Condon *et al*. 2011).

Prescribed fire is increasingly used as a management tool for wildlands. However, if a cheatgrass seed bank is present, prescribed fire may increase cheatgrass cover, often to the detriment of the restoration objective (Keeley and McGinnis 2007). Application of seed or mulch after wildfire can facilitate cheatgrass invasion if contaminated sources are used (Robichaud *et al*. 2000, Beyers 2004, Keeley 2006). Therefore, a better understanding of the specific places in a landscape that are most vulnerable to postfire cheatgrass invasion would aid managers in planning prescribed burns and in setting priorities for seeding and other postfire rehabilitation treatments.

The objective of this study was to identify specific areas at greatest risk of postfire cheatgrass invasion, as well as other variables that further influence cheatgrass invasion potential. The study area was centered on Dinosaur National Monument (DINO) in northwestern Colorado, USA—a large, heterogeneous, semiarid landscape where numerous wildfires have occurred recently and where manager-ignited prescribed burning is being conducted.

We used regression tree and boosted regression tree methods (BRT) to develop a model of vulnerability to cheatgrass invasion in the DINO study area. These techniques are relatively new statistical methods for drawing out meaningful ecological patterns from complex and often nonlinear, interacting datasets, and then using these patterns to make predictions (De'ath 2007, Elith *et al*. 2008). Traditional regression tree modeling approaches develop a single model, whereas BRT modeling uses boosting to facilitate the combination and assessment of large numbers of simple classification trees in an iterative manner to optimize predictive performance (Elith *et al*. 2006, Elith *et al*. 2008). Using a combination of classification tree methods to make model groups and boosting techniques to test many combinations of models, BRT modeling is able to achieve both robust explanation and prediction (De'ath 2007). The BRT method and similar methods have been used recently to understand and predict a remarkably wide variety of spatial patterns related to, for instance, the distribution of threatened bird species (Tanneberger *et al*. 2010), periglacial features (Hjort *et al*. 2010), coral diseases (Williams *et al*. 2010), and mosquito malaria vectors (Sinka *et al*. 2010). Of particular interest to our study, these methods have predicted places most vulnerable to invasion by a non-native ant species (Roura-Pascual *et al*. 2009) and by an estuarine crab (Compton *et al*. 2010). Anacker *et al*. (2010) used BRT to identify specific locations in the Lake Tahoe basin that were most vulnerable to cheatgrass invasion under current and projected climate conditions. However, the Anacker *et al.* study did not focus on fire, as we have done in this study.

METHODS

Study Area

Dinosaur National Monument (DINO) is located in northwestern Colorado and adjacent northeastern Utah (Figure 1). Dinosaur National Monument is 850 km^2 in size, and ranges in elevation from 1450 m to 2740 m; average annual precipitation ranges from 280 mm at the lowest elevations to 508 mm at the highest elevations; and average temperatures range from −18 °C to −1 °C in January, to 10 °C to 38 °C in July (Fertig 2009). The geology is complex, with 23 major geologic formations (Precambrian through Holocene) exposed within the monument; topography is equally diverse, with deep canyons, cliffs, and rolling uplands. Five major upland plant communities are found: (1) desert shrublands at low elevations; (2) piñon-juniper at middle elevations; (3) montane shrublands, also at middle elevations; (4) montane woodlands at the highest elevations; and (5) riparian vegetation along streams, springs, and seeps (Fertig 2009).

Historical fire regimes in the DINO landscape (before Euro-American settlement in the late nineteenth century) have not been characterized locally, but probably were dominated by infrequent, high-severity fires occurring during dry summers (Baker 2009). Fire rotations probably were ≥400 yr in piñon-juniper woodlands (persistent woodland *sensu* Romme *et al*. 2009), 150 yr to 300 yr in higher-elevation shrublands with mountain big sagebrush

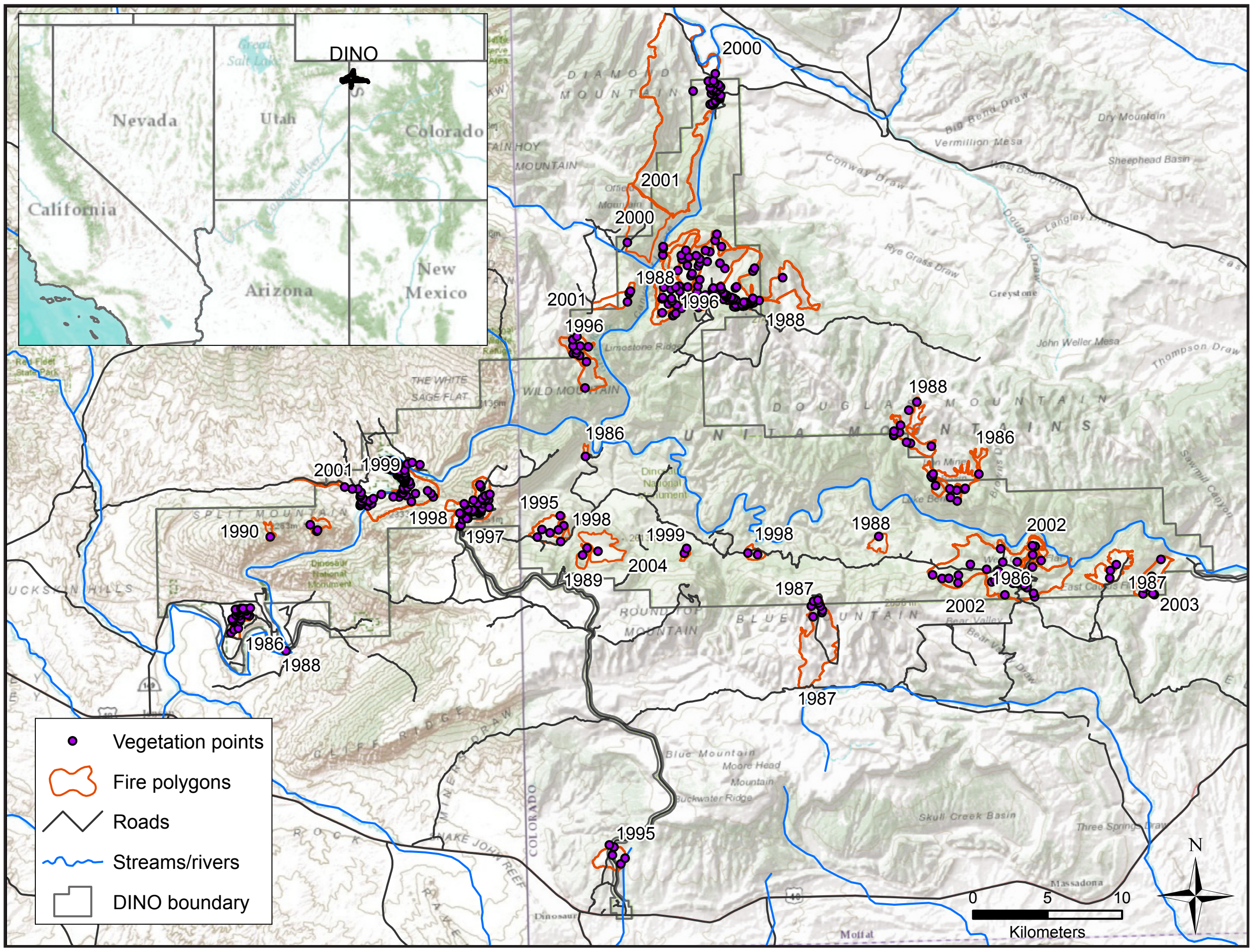

Figure 1. Study area, Dinosaur National Monument in northwestern Colorado and northeastern Utah. Vegetation plots that were coincident with fire polygons are depicted, along with the year of the fire. The larger 8000 km[2] landscape that was modeled extends beyond the edges of this map; see Figure 5 for its full extent.

(*Artemisia tridentata* Nutt. ssp. *vaseyana* [Rydb.] Beetle), and 200 yr to >500 yr in lower-elevation shrublands with Wyoming big sagebrush (*Artemisia tridentata* Nutt. var. *wyomingensis* Beetle & Young) (Baker 2009). Livestock grazing began in the late nineteenth century and has continued to be the major land use in all areas outside the national monument, which today are a mix of private lands and lands administered by the US Bureau of Land Management. Dinosaur National Monument was established in 1915 and expanded to its present size in 1978 (Fertig 2009); recreation is now a major use within the monument.

Because the topography, geology, climate, and vegetation of surrounding lands is generally similar to DINO, and because postfire cheatgrass invasion is also a major management concern in these areas, we also created an expanded study area centered on DINO but encompassing a total area of ~8000 km^2. Our models predicting cheatgrass abundance were developed using data only from DINO (Coles *et al*. 2008), but the final maps were generated for the larger 8000 km^2 study area.

Data Sources

The vegetation map of DINO, developed from 727 sampling plots distributed in a stratified random manner (Coles *et al*. 2008), was the source of vegetation data for this study.

Plot sizes were 100 m^2 (herbaceous vegetation) or 400 m^2 (forest, woodland, and shrubland). Percent cover of all vascular plant species (including cheatgrass) was estimated in each plot in 2003 to 2005. Fire events since 1943 were obtained from the DINO GIS fire database, which consists of fire polygons digitized from DINO hard copy fire atlas maps. All vegetation plots sampled by Coles *et al*. (2008) that fell within areas burned after 1984 were used in our analysis; the 1984 cutoff reflected the earliest availability of Landsat imagery, which was used to derive explanatory variables in the model. This resulted in the selection of 354 vegetation plot samples, which were spatially coincident with 33 fire events. These 354 vegetation plots were sampled by Coles *et al*. (2008) from 0 yr to 19 yr after the most recent fire at that site.

We identified five groups of potential explanatory variables for abundance (Table 1), based on the literature and our experience, and each was mapped using GIS and numerous geospatial data sources. Biogeophysical variables were related to soil characteristics and topographic position. Soil characteristics were derived from Natural Resources Conservation Service (NRCS 2010) Soil Survey Geographic Databases (SSURGO) for areas outside of DINO, and from National Park Service (NPS) SSURGO (2009) data for areas within DINO. We used a Digital Elevation Model (USGS 2010) with a 10 m spatial resolution to derive elevation, slope and topographic position. We derived topographic position using the Landscape Connectivity and Pattern tools for ArcGIS, Topographic Position Index tool (Theobald 2007).

Disturbance history and propagule source variables represented proximity to potential cheatgrass seed sources, notably distance from previously burned areas and roads. The road network was obtained from the local DINO GIS roads database. Climatic variables included local maximum and minimum temperature and mean precipitation, and weather conditions in the first year after the fire. Temperature and precipitation variables were obtained from PRISM (Parameter-elevation Regressions on Independent Slopes Model) climatic data, which have a 4 km spatial resolution. To attain postfire (next growing season) measures of soil moisture availability, tasseled cap index (Crist and Cicone 1984), brightness, greenness, and wetness mean values around a 150 m buffer per fire were derived from Landsat imagery. We evaluated one fire variable, the fire severity index dNBR (differenced Normalized Burn Ratio, Eidenshink *et. al.* 2007), which was obtained from Landsat imagery one year prior and one year after a fire event (Appendix 1). Lastly, data quality variables included years since last fire at the time the plot was sampled, and winter and summer precipitation in the year before the vegetation survey was conducted (from PRISM data).

Statistical Analyses

Two primary analyses were performed. The first entailed using traditional classification tree analysis to classify cheatgrass cover in a variable reduction manner to identify significant explanatory variables to be used in subsequent analysis. Using the resulting significant explanatory variables from five categories, we performed Boosted Regression Tree (BRT) modeling to facilitate interpretation of postfire cheatgrass dynamics and subsequent spatial modeling scenarios of postfire cheatgrass susceptibility.

Step 1: Variable Reduction—Classification Trees. A perusal of the plot data revealed that cheatgrass was present in three quarters of the plots used in our analysis, but often in only trace amounts. Although this widespread occurrence is noteworthy, managers are particularly concerned about identifying places where cheatgrass is abundant enough to strongly influence vegetation structure and dynamics. We selected 10 % cheatgrass cover as a threshold

Table 1. Initial potential explanatory variables by regression group and data sources. Single asterisks (*) indicate explanatory variables retained after classification tree variable reduction. Double asterisks (**) indicate variables also retained for subsequent BRT and spatial modeling.

Model group - Variable description
Biogeophysical
Percent silt, clay, and sand 1 cm to 100 cm weighted average - NRCS and NPS soil surveys
Available water capacity 1 cm to 100 cm weighted average - NRCS and NPS soil surveys
Soil pH 1 cm to 60 cm weighted average - NRCS SSURGO and NPS soil surveys
Cation-exchange capacity 1 cm to 100 cm weighted average - NRCS and NPS soil surveys
**Elevation (10 m) - National Elevation Dataset
Slope (degrees) (10 m) - Derived from National Elevation Dataset
Topographic Position Index (10 m) - Derived from National Elevation Dataset
Disturbance history - cheatgrass propagule sources
Fire by decade, 1940s to 2000s (10 m) - DINO fire and roads database
Distance to roads (10 m) - DINO roads database
Distance to polygon fire boundary (within fire) (10 m) - DINO fire database
Distance to all fire disturbances across all years (10 m) - DINO fire database
Distance to fire disturbance by decade: 1940s, 1950s, 1960s, 1970s*, 1980s*, 1990s, 2000s (10 m) (Includes both polygon and points) - DINO fire database
Number of fires (polygons and points) - DINO fire database
Climatic
Mean minimum annual temperature 30 yr means (4 km) - PRISM
*Mean maximum annual temperature 30 yr means (4 km) - PRISM
Mean annual precipitation 30 yr means (4 km) - PRISM
Mean maximum and minimum annual temperature 1 yr postfire (4 km) - PRISM
Mean annual precipitation 1 yr postfire fire (4 km) - PRISM group data
Mean minimum winter temperature 1 yr postfire (Dec, Jan, Feb) (4 km) - PRISM
Mean maximum winter temperature 1 yr postfire (Dec, Jan, Feb) (4 km) - PRISM
Mean spring precipitation (Mar, Apr, May) 1 yr postfire (4 km) - PRISM
Mean summer precipitation (Jun, Jul, Aug, Sep) 1 yr postfire (4 km) - PRISM
TasselCap brightness by 1 yr postfire 150 meter mean buffer values (30 m) - Landsat
TasselCap greenness by 1 yr postfire 150 meter mean buffer values (30 m) - Landsat
**TasselCap wetness by 1 yr postfire 150 meter mean buffer values (30 m) - Landsat
Fire properties
**Fire severity – differenced Normalized Burn Ratio per fire (dNBR = NBR postfire – NBR prefire). Increased dNBR = increased fire severity (30 m) - Landsat
Data quality
**Years since last fire at the time of vegetation sampling (polygon)
**Winter precipitation (Dec to Apr) year of vegetation survey (2002, 2003, 2005) (4 km) - PRISM
Winter precipitation (Dec to Apr) year before vegetation survey (2001, 2002, 2004) (4 km) - PRISM
*Summer precipitation (Jun to Oct) year of vegetation survey (2002, 2003, 2005) (4 km) - PRISM
Summer precipitation (Jun to Oct) year before vegetation survey (2001, 2002, 2004) (4 km) - PRISM

of ecologically significant cheatgrass abundance because we had adequate sample sizes of plots with ≥10% and <10% cheatgrass cover, and because a local population with ≥10% cover is visually conspicuous and likely has the potential to increase rapidly under favorable conditions. Thus, we performed the variable reduction analyses using models that distinguish between ≥10% and <10% cheatgrass cover.

We used classification trees to identify significant variables in each explanatory group (Table 1) as determined by the final pruned classification tree. To avoid over-fitting the classification trees, we used the cross validation cv.tree function (http://www.r-project.org; Ripley 2010). The cv.tree function identifies the pruned tree size and associated explanatory variables that minimize cross-validation deviance in the classification tree. The variables retained (i.e., not pruned) in the final pruned tree were considered significant. We used R statistical software (to perform variable reduction classification tree analyses using the tree package).

Significant variables within an individual predictor group can be highly correlated with one or more variables from a different predictor group, a problem that is not automatically accounted for in the individual classification trees. We computed Pearson's correlation coefficient among all of the significant variables resulting from the initial variable reduction procedure. Highly correlated variables ($r > 0.7$) were evaluated and excluded in order to avoid inclusion of highly correlated variables in the final BRT analysis.

Step 2: Boosted Regression Tree (BRT) Modeling. We performed BRT analysis in R using the Generalized Boosted Regression Models (GBM) package (Ridgeway 2010) and the gbm.step function in the BRT script functions in the online tutorial appendix of Elith *et al.* (2008). Categorical cheatgrass abundance was modeled in a Bernoulli (binary) fashion: cheatgrass cover ≥10% vs. <10% (referred to hereafter as the 10% model). BRT modeling was performed using the significant variables identified in the classification tree variable reduction process (summarized in Table 1). The BRT model training was performed using 254 randomly selected vegetation plots, with the remaining 100 plots set aside for accuracy assessment of the developed BRT models. Three different randomly selected sets of training and accuracy assessment plots were modeled to test for any influence of random plot selection on model performance.

When working with small data sets in BRT modeling, it is optimal to set the learning rate (lr) and tree complexity parameters (tc) in an iterative manner until one achieves ~1000 trees (Elith *et al*. 2008). The lr is the shrinkage parameter and determines the contribution of each tree to the growing model, while tc controls whether interactions are fitted. In general, decreasing tc yields an increase in the number of trees. The BRT modeling was performed using a tc value of 3, and an lr value of 0.004, which achieved a tree size of 850.

Accuracy Assessment and Model Performance

Output from the gbm.step function when using a Bernoulli model is the probability of a positive value (i.e., 1) per modeled point. Rather than use a traditional split of 0.5 (i.e., ≥0.50 = 1 and <0.50 = 0), we performed a cross validation procedure to find the probability threshold that gave the highest number of correctly predicted values in the training set. This identified threshold value was subsequently applied to the accuracy assessment values when evaluating model predictive ability. After model development and identification of the optimal threshold value, the predictive ability of the model sets was tested using the predict.gbm function (GBM) on the 100 random vegetation plots that were set aside from model training.

Variable Trends

Relationships between the explanatory variables and cheatgrass response within the BRT model were evaluated using three diagnostic tools:

1) Relative influence (Friedman and Meulman 2003) of explanatory variables across all BRT models was measured using Ridgeway's (http://www.r-project.org) summary function.
2) Partial dependence functions (gbm.plot; http://www.r-project.org, G. Ridgeway 2010) were used to plot the effect of the explanatory variable on the response variable. Partial dependence functions show the effect of a variable on the response after accounting for effects from the other explanatory variables in the model (Elith *et al*. 2008).
3) Three-dimensional plots (gbm.perspec; Elith *et al*. 2008 appendix) of cheatgrass abundance were developed and interpreted.

RESULTS

Variable Reduction—Classification Trees

Elevation was the most significant biogeophysical explanatory variable. Cheatgrass cover was significantly greater at lower elevations (ANOVA, $F_{1, 353}$), with mean cover of 25.7% below 1600 m vs. 2.5% above 1600 m. Soil characteristics including texture, water-holding capacity, pH, and cation exchange capacity did not add significant explanatory power. Distance to fires in the 1960s, 1970s, and 1980s was also significant. Both 30 yr mean maximum temperature and moisture conditions for the first postfire year were significant climatic variables. Fire severity, winter and summer precipitation for the year of the vegetation survey, and years since last fire were also significant variables (Table 1).

Examination of Pearson's correlation values between the variables identified as significant (asterisked in Table 1) revealed that 30 yr mean maximum temperature and summer precipitation for the year of the vegetation survey were both highly ($r > 0.7$) and significantly correlated with elevation (−0.976 and 0.726, $P < 0.05$, respectively); thus, they were removed from subsequent analysis. None of the other variables identified in the initial classification trees were highly and significantly correlated (Appendix 2), so they were retained for preliminary BRT analyses.

A different kind of problem emerged after preliminary classification tree analyses. The disturbance variables (distance to nearest previous burn in the 1960s, 1970s, and 1980s) gave results that did not make sense ecologically: at some regression splits, greater distances to burned areas were modeled to have higher likelihood of high cheatgrass cover (≥10%), not lower cover, as would be expected if the previously burned areas were functioning as seed sources. The reason for these results are not obvious, but probably reflect the non-random spatial pattern of previous fires in DINO, and the fact that at least some cheatgrass is present almost everywhere in DINO. We determined that inclusion of these disturbance variables in the final BRT models would obscure rather than enhance the actual patterns of postfire cheatgrass dynamics, and so they were deleted before the final BRT runs.

BRT Training Model Performance

The optimal probability threshold value for the 10% model was 0.565. Error matrices were used to test the predictive performance of the BRT models, with calculation of overall accuracy, Cohen's Kappa, and users and producers accuracies (Table 2). Overall predictive accuracy for the three 10% models ranged from a low of 0.88 to a high of 0.89, with Cohen's Kappa values ranging from 0.58 to 0.68. Users accuracy values ranged from 0.50 to 0.71 for the ≥10% class, and from 0.95 to 0.97

Table 2. Error matrix for the accuracy assessment plots for the best predictive cheatgrass model out of three that were developed for the Dinosaur National Monument landscape.

	Model/Set	Observed		Total	Users	Overall accuracy	Cohen's accuracy
Predicted	Set 2	0 (<10%)	1 (≥10%)				
	0 (<10%)	72	4	76	0.95	0.89	0.68
	1 (≥10%)	7	17	24	0.71		
	Total	79	21				
	Producers	0.91	0.81				

for the <10% class. Comparable producer accuracies ranged from 0.81 to 0.92 for the ≥10% class, and from 0.88 to 0.91 for the <10% class.

The best randomly drawn 10% model had a cross validation deviance value of 0.59 using the final set of potential explanatory variables (summarized in Table 1). Estimated probability values and density plots for the best 10% model are shown in Figure 2. Each model's respective class (e.g., ≥10% vs. <10%) has differing density signatures indicative of the model's ability to distinguish between classes.

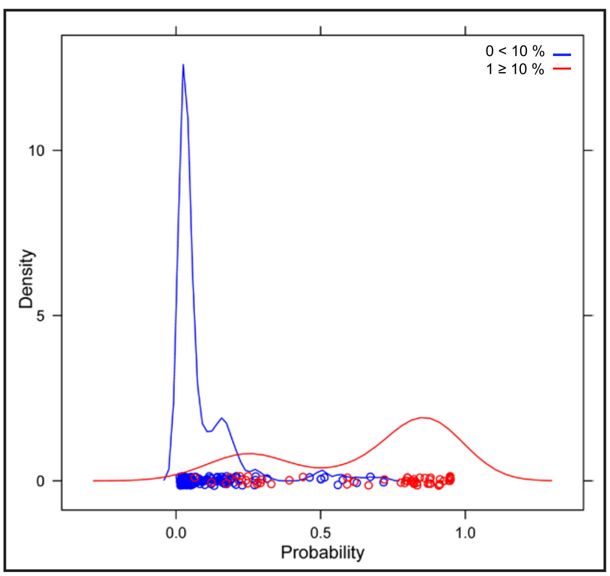

Figure 2. Estimated probability values and density plots by categorical class (>10% vs. <10% cover) for a postfire cheatgrass spatial model based on three variables: elevation, fire severity, and soil moisture in the year after fire.

Variable Trends

The biophysical variable elevation was most influential, with a relative influence value of 60.5. The partial dependence function graphs (Figure 3) show elevation as the best predictor of cheatgrass abundance. Cheatgrass cover ≥10% was most likely to be seen at elevations below 1600 m. Soil moisture in the first year postfire and fire severity were the second and third most influential variables, with relative influences of 12.9 and 11.3, respectively. The probability of ≥10% cheatgrass cover was reduced somewhat where time since fire at the time of sampling was longer than about 8 years. Winter precipitation in the year of sampling showed little relationship with the cheatgrass response.

To further explore cheatgrass invasion potential at lower elevations, where cheatgrass tends to be more abundant regardless of other factors, the results of the 10% models were plotted as functions of burn severity and moisture conditions the first year postfire at an elevation of 1460 m (an elevation at which all of the BRT models predicted the highest probabilities of cheatgrass cover) at 1 yr, 2 yr, 5 yr, and 10 yr postfire. The resulting surfaces (Figure 4) revealed a positive relationship of cheatgrass cover with burn severity, and a negative relationship with moisture conditions the first year postfire. Overall, at an elevation of 1460 m, probability of ≥10% cheatgrass cover was greatest in more severely burned areas in which the first year postfire was dry. The plotted surfaces changed slightly with increasing

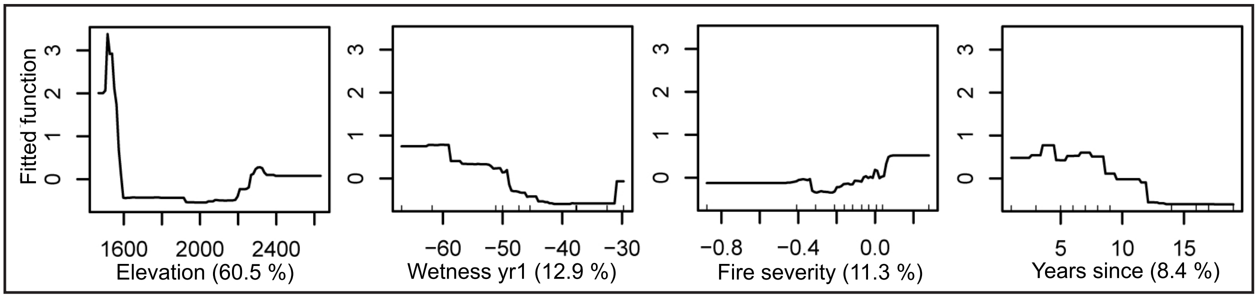

Figure 3. Partial dependence functions for >10 % vs. <10 % cheatgrass cover with relative influence values for the variables elevation, fire severity, soil moisture in the year after fire, and years since last fire at the time of sampling.

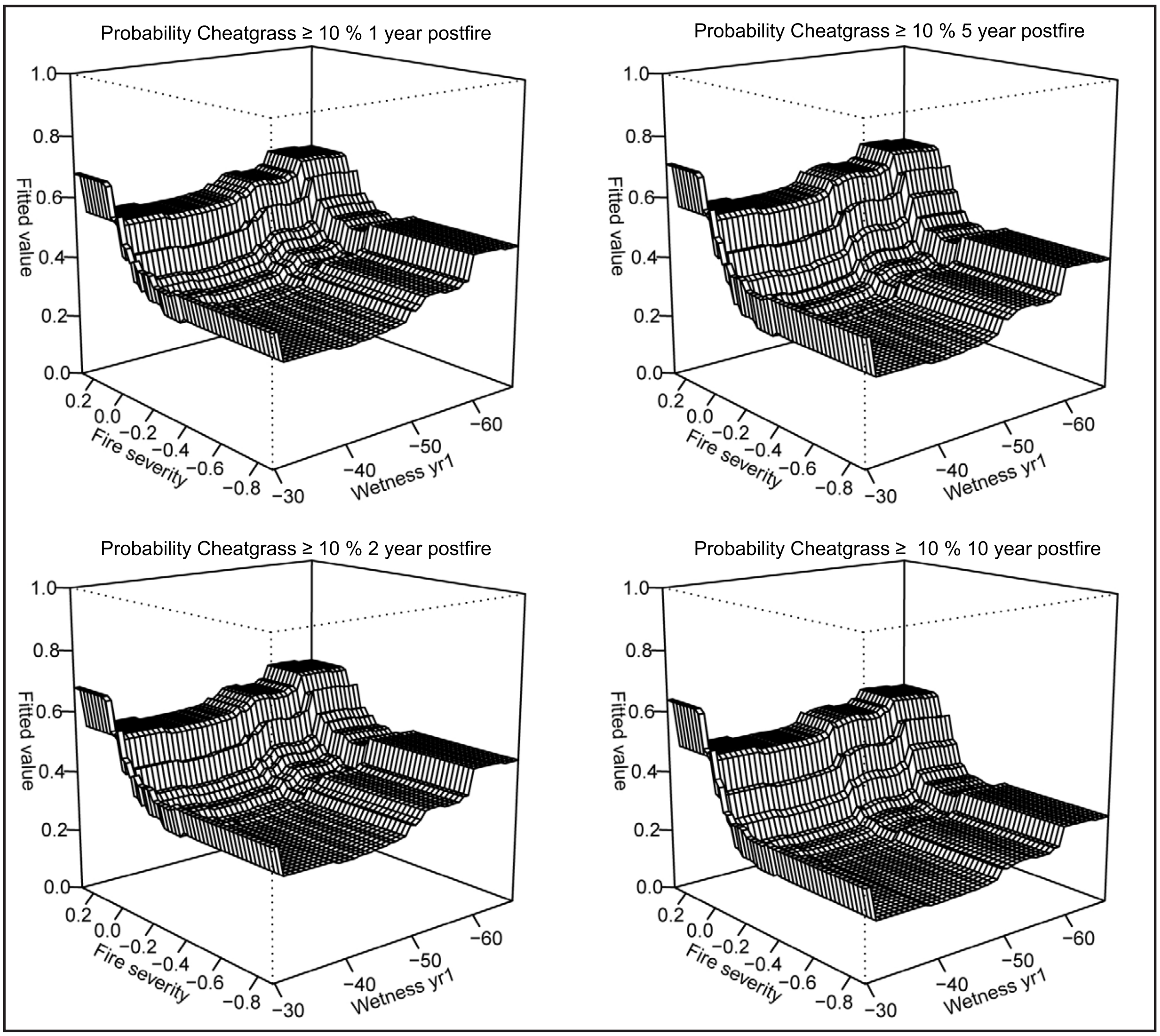

Figure 4. Three-dimensional partial dependence plots of fire severity and one year postfire precipitation for the 10 % models at an elevation of 1460 m, at 1 yr, 2 yr, 5 yr, and 10 yr postfire.

time since fire, but the overall patterns remained constant for at least 10 yr postfire (Figure 4).

Fire Severity and Precipitation Scenarios across the Landscape

The BRT modeling identified elevation, fire severity, and moisture conditions the first year postfire as the most important controls on cheatgrass invasion of burned areas in DINO. To display these interacting influences, we applied the 10% model across the 8000 km^2 DINO landscape in a GIS environment, using true elevation values, 10% (low severity) and 90% (high severity) values for the fire severity variable, 10% (dry) and 90% (wet) moisture conditions for the first year postfire variable, a constant 50% value for the PRISM winter precipitation variable, and a constant 1 yr postfire value for the years since last fire variable. This yielded four fire severity and postfire moisture scenarios: (1) high fire severity/dry postfire year (high/dry), (2) high fire severity/wet postfire year (high/wet), (3) low fire severity/dry postfire year (low/dry), and (4) low fire severity/wet postfire year (low/wet).

In the resulting spatial models, lower fire severity and drier postfire conditions generally were associated with the highest probabilities for cheatgrass cover ≥10% across the DINO landscape as a whole (Figure 5). The same kinds of models were also developed for just the low-elevation (<1600 m) portion of the landscape (not shown). Patterns were very similar to those for the entire landscape, except that the highest probabilities of postfire cheatgrass cover ≥10% at low elevations were associated with higher fire severity and drier postfire conditions.

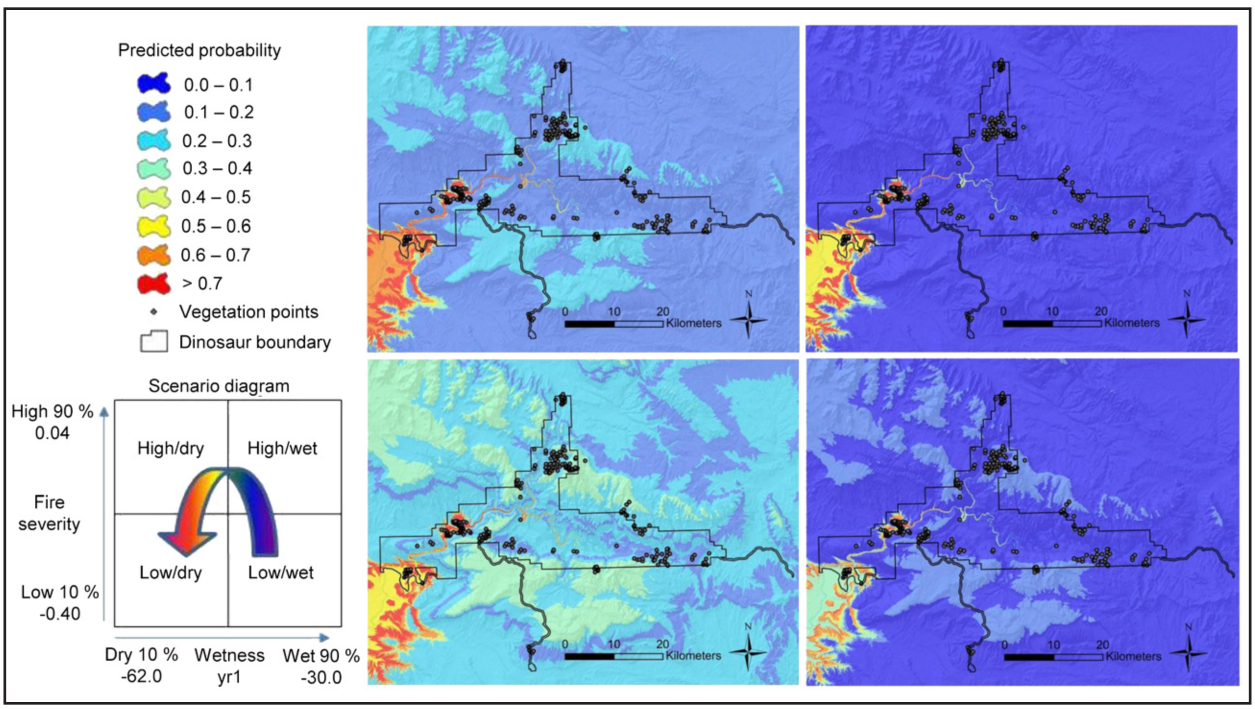

Figure 5. Modeled probability values of >10% vs. <10% cheatgrass cover for four fire severity and postfire precipitation scenarios: (1) high fire severity/dry postfire (high/dry) (upper left), (2) high fire severity/wet postfire (high/wet) (upper right), (3) low fire severity/dry postfire (low/dry) (lower left), and (4) low fire severity/wet postfire (low/wet) (lower right). The cheatgrass suitability arrow in the scenario diagram starts at the least likely (blue) and progresses sequentially in order of likelihood to the most likely (red arrowhead) set of conditions for postfire cheatgrass cover >10% across the Dinosaur National Monument landscape.

DISCUSSION

Three predictor variables—elevation, fire severity, and one-year postfire soil moisture—were the most important determinants of cheatgrass invasion of burned areas across the DINO landscape. The first and most influential predictor was elevation: lower elevations (<1600 m) had the highest probability of cheatgrass cover ≥10% after fire. The mechanism driving this pattern is not elevation *per se*, of course, but the other climatic and biophysical variables that are highly correlated with elevation and thereby subsumed in the model under the variable elevation, notably mean maximum temperature (Pearson's $r = -0.976$). Previous studies have consistently reported greater cheatgrass abundance in areas of lower elevation and higher temperatures, except where inadequate moisture availability limits cheatgrass (Bradford and Lauenroth 2006, Chambers *et al*. 2007, Bradley 2009, Anacker *et al*. 2010, Banks and Baker 2011).

After accounting for elevation, a deterministic variable that does not vary with individual fire events, predictive ability was increased by adding fire severity and postfire moisture conditions—contingent variables that do vary with individual fire events. Drier conditions the year after a fire were consistently associated with a greater probability of cheatgrass cover ≥10%. However, the direction of the fire severity effect was different depending on the scale of analysis. When modeled over the entire study area (DINO plus the surrounding landscape, including extensive areas at moderate to high elevation), lower fire severity was associated with greater likelihood of cheatgrass cover ≥10%. However, when looking only at the lower elevations (<1600 m), where cheatgrass is most likely to be abundant after fire regardless of the two contingent variables, higher fire severity was associated with greater likelihood of postfire cheatgrass cover ≥10%. These opposing influences of fire severity suggest that different ecological mechanisms are operating at lower vs. higher elevations. It was beyond the scope of this statistical study to evaluate those mechanisms, but we have suggested possible explanations.

The greater likelihood of high cheatgrass cover following high-severity fire at lower elevations (<1600 m) may be primarily a reflection of competition between cheatgrass and native perennial plants. Cheatgrass can have a large soil seed bank that is poised to germinate and grow rapidly after fire (Mack and Pyke 1983), whereas soil seed banks of the native perennial herbaceous species tend to be relatively small (Chambers *et al*. 2007). Thus, postfire cheatgrass seedlings would be subjected to less competition from the native flora after high-severity fire than after low-severity fire. An experimental study in the Great Basin (Chambers *et al*. 2007) found that removal of perennial herbaceous species, even without associated burning, led to a two- to three-fold increase in cheatgrass biomass and seed production, with even greater increases following a combination of removal and burning. Surveys of recently burned areas also have reported a negative relationship between cover of cheatgrass and native perennials (e.g., Condon *et al*. 2011). Dry conditions in the year after a fire also may have a stronger negative effect on growth of native seedlings and surviving perennials than on cheatgrass. Cheatgrass begins taking up soil moisture very early in the season, and may deplete the soil moisture accumulated over the winter before the native species have begun to grow, especially in a dry year (Chambers *et al*. 2007).

The opposite pattern is seen for the DINO landscape as a whole, where a greater likelihood of postfire cheatgrass cover ≥10% is associated with low-severity fire. Because most of the study area is above 1600 m elevation, this pattern apparently reflects environmental conditions and processes at higher elevations, which result in a different response of cheatgrass to fire severity than is observed at lower elevations. At higher elevations, where cheatgrass is less abundant overall and its soil seed banks probably are smaller than at lower elevations, fire-caused mortality in the cheatgrass soil seed bank may lead to substantially lower cheatgrass density and cover after a high-severity fire than after a low-severity fire. Getz and Baker (2008), in a relatively high-elevation landscape in western Colorado (1900 m to 2300 m), reported lower cheatgrass cover in the centers of burned patches and higher cheatgrass cover near the edges of patches where the fire was about to go out and heat release was presumably reduced.

A spatial model of the kind developed here, which predicts the locations and conditions most likely to be associated with postfire cheatgrass invasion, can be useful to managers planning prescribed burns and developing postfire rehabilitation plans after wildfires in DINO or similar landscapes. Of the three most influential variables documented in DINO, elevation is likely most useful to managers because it is deterministic (unvarying) and is readily available in almost any GIS database. Fire severity and one-year postfire soil moisture variables may be more difficult to use for planning purposes because of their inherent unpredictability until the fire actually occurs. Nevertheless, the patterns associated with these variables can also be useful. For example, fire severity can be largely controlled in prescribed burning by igniting the fire during appropriate weather and fuel moisture conditions. If burning is to be done at a lower elevation, a relatively low-severity burn may be preferable, since high-severity burns are associated with a greater likelihood of high postfire cheatgrass cover at lower elevations. At higher elevations, however, a high-severity burn (e.g., to reduce fuels or to remove expanding trees or shrubs), might be less worrisome. This is because postfire cheatgrass tends to be less abundant at higher elevations in DINO regardless of fire severity or moisture conditions, and our model predicts that cheatgrass cover actually may be less after a high-severity burn at higher elevations. In the aftermath of a wildfire, a high-severity burn at lower elevations may require more vigorous mitigation treatments against cheatgrass than a low-severity burn in the same area or a burn of any fire severity at higher elevations. As for postfire moisture conditions, long-range weather forecasts can provide a manager with at least a general idea of what to expect the year after a fire. If the forecast is for above-average precipitation, then the current year might be a good time for a prescribed burn, since the risk of high cheatgrass cover is reduced in wet postfire years; but if the forecast calls for below-average precipitation, then it may be wise to postpone the burn until a year of average or wet conditions. Of course, numerous other considerations come into play in planning a prescribed fire or responding to a wildfire—fuel conditions, threats to life and infrastructure, fire management capacity, etc.—but postfire cheatgrass risk often is one of the elements incorporated in planning.

The spatial patterns and contingent influences we documented in this study provide a baseline model of late twentieth century cheatgrass invasion potential in the DINO landscape. However, climate models predict warmer average temperatures, longer fire seasons, and increased fire frequency and fire size in coming decades (IPCC 2007, Flannigan *et al*. 2009, Westerling *et al*. 2011). These changes could permit cheatgrass to become more abundant after fires at higher elevations than we documented in this study because cheatgrass appears to be limited by low temperatures (Bradford and Lauenroth 2006, Chambers *et al*. 2007, Bradley 2009, Anacker *et al*. 2010, Banks and Baker 2011). If effective precipitation decreases and native plants are unable to compensate for moisture deficits via enhanced water use efficiency or other mechanisms, then competition between cheatgrass and native species may become more intense and may facilitate greater expansion of cheatgrass into higher elevations. Comparing the effects of future fires to the baseline model developed here will permit early detection of fundamental changes in ecological processes that may occur as a consequence of climate change.

With any modeling study, an important consideration is in recognizing the spatial domain over which the modeled projection space is appropriate. In this model of postfire cheatgrass invasion, the projection space is likely constrained to landscapes having diverse topography, which in turn influences temperature and precipitation patterns in particular. At a more general level, we expect our model results and observed relationships to be appropriate for a semi-arid Intermountain West landscape with a similar elevation range, where temperature and precipitation vary strongly with elevation and strongly influence fire occurrence, fire severity, and postfire vegetative responses.

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Appendix 1. By fire event, Landsat imagery dates for prefire dNBR, postfire dNBR and Tasseled Cap index.

Fire name	Fire year	Prefire dNBR	Postfire dNBR / Tasseled Cap
Finally	1986	14 June 1985	4 June 1987
West Cactus	1986	17 June 1986	4 June 1987
Long/Pocket	1986	14 June 1985	4 June 1987
Triple C	1986	17 June 1986	4 June 1987
East Cactus	1987	4 June 1987	22 June 1988
Tank	1987	4 June 1987	22 June 1988
1988	1988	22 June 1988	13 August 1989
Bower 2	1988	22 June 1988	13 August 1989
Bogan	1988	4 June 1987	13 August 1989
Gr Slope	1988	22 June 1988	13 August 1989
Placer	1988	22 June 1988	13 August 1989
Zenobia	1988	22 June 1988	13 August 1989
Pearl Park	1989	22 June 1988	13 August 1989
Split	1990	27 May 1990	15 June 1991
Dinosaur	1995	12 July 1995	14 July 1996
Ironspring #3	1995	12 July 1995	14 July 1996
L.D. Falls	1996	12 July 1995	1 July 1997
Zenobia 2	1996	12 July 1995	1 July 1997
Persistent	1996	14 July 1996	1 July 1997
Chewbasin	1997	1 July 1997	20 July 1998
Rainbow	1998	1 July 1997	7 July 1999
Johnson	1998	1 July 1997	7 July 1999
Ironspring	1998	1 July 1997	7 July 1999
Red Rock	1999	20 July 1998	23 June 2000
Rupleranch	1999	20 July 1998	23 June 2000
Busterflat	2000	23 June 2000	10 June 2001
Split #2	2001	23 June 2000	15 July 2002
Jack Springs	2001	10 June 2001	15 July 2002
Ecklund	2001	23 June 2000	15 July 2002
Pearl Park	2001	10 June 2001	15 July 2002
Bear	2002	10 June 2001	2 July 2003
Disappointment	2003	15 July 2002	6 September 2004
Pearl Park	2004	2 July 2003	7 July 2005

Appendix 2. Pearson's correlation values and significance for the variables identified in first classification tree analysis step as significant by explanatory group.

Pearson's	**ELEV**	**DIST 60**	**DIST 70**	**DIST 80**	**TMAX_ MN**	**WET_ YR1**	**dNBR_ CONT**	**WPPT_ YR0**	**SUMPPT_ YR0**	**YEARS SINCE**
ELEV	1.00									
DIST60	0.04	1.00								
DIST70	–0.23*	–0.04	1.00							
DIST80	–0.34*	–0.16	0.22	1.00						
MN_TMAX	–0.98*	0.04	0.19	0.33	1.00					
WET_YR1	–0.04	0.05	–0.37	0.13	0.07	1.00				
dNBR_CONT	–0.55*	–0.22	0.28	0.29	0.53	0.01	1.00			
WPPT_YR0	0.25*	0.14*	–0.07	0.00	–0.26*	0.09	–0.27*	1.00		
SUMPPT_YR0	0.73*	0.05	–0.09	–0.20*	–0.73*	–0.09	–0.44*	0.55*	1.00	
YEARSSINCE	0.31*	0.00	–0.13*	–0.71*	–0.34*	–0.17*	–0.35*	0.21*	0.30*	1.00

* $P < 0.05$