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Predicting Post-Fire Change in West Virginia, USA from Remotely-Sensed Data

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Abstract

Prescribed burning is used in West Virginia, USA to return the important disturbance process of fire to oak and oak-pine forests. Species composition and structure are often the main goals for re-establishing fire with less emphasis on fuel reduction or reducing catastrophic wildfire. In planning prescribed fires land managers could benefit from the ability to predict mortality to overstory trees. In this study, wildfires and prescribed fires in West Virginia were examined to determine if specific landscape and terrain characteristics were associated with patches of high/moderate post-fire change. Using the ensemble machine learning approach of Random Forest, we determined that linear aspect was the most important variable associated with high/moderate post-fire change patches, followed by hillshade, aspect as class, heat load index, slope/aspect ratio (sine transformed), average roughness, and slope in degrees. These findings were then applied to a statewide spatial model for predicting post-fire change. Our results will help land managers contemplating the use of prescribed fire to spatially target landscape planning and restoration sites and better estimate potential post-fire effects.

Keywords: spatial analysis, terrain characteristics, prediction, prescribed fire, wildfire

Introduction

Fire, human-caused or otherwise, has been a disturbance factor in the forests of the eastern United States for thousands of years (Delcourt and Delcourt 1998, Delcourt et al. 1998). Where there are people there is fire (Guyette et al. 2002); it is well established that Native Americans influenced the forest through intentional and unintentional use of fire (DeVivo 1991, Delcourt and Delcourt 1998). Fire can be thought of as an herbivore (Bond and Keeley 2005) that has impacted vegetation and evolution since at least the late Cretaceous period (Keeley et al. 2011). The suppression of fire in eastern forests has revealed unintended consequences to species composition, generally the increase in importance of fire-sensitive species and replacement of fire-tolerant species (Nowacki and

Abrams 2008) in both managed and unmanaged forests (Abrams and Downs 1990; Abrams 1998; Fei and Steiner 2007; Fei et al. 2011).

The use of fire as a management tool in eastern hardwood forests has increased as the role of fire in many ecosystems is understood and prescribed fires are implemented. Prescribed fire is used to create and maintain wildlife habitat and to promote the regeneration of oak (*Quercus spp*.) and some pine (*Pinus spp*.) species. In most cases, repeated burning is needed to achieve objectives. National Forest land managers have a mandate for restoration of species composition, forest structure, and ecosystem functions on the lands they manage. Returning fire as a disturbance regime may be considered in restoration plans and is often accomplished through prescribed fires.

In using prescribed fire, concerns over the spatial variability in severity (as defined by overstory mortality) have been raised. While variability in burn severity is likely in fires covering larger areas and occurring on diverse topography, the ability to predict the potential spatial patterns of burn severity before fire is applied would aid in the determination of potential negative impacts from the prescribed fire in ecologically, biologically, or socially sensitive areas. This information also would be useful in selecting areas where overstory mortality from prescribed fire could create or maintain habitat for specific species.

Previous studies have mapped burn severity using remote sensing techniques to identify changes in spectral signatures for western wildfires post-burn (van Wagtendonk et al. 2004, Brewer et al. 2005, Cocke et al. 2005, Epting et al. 2005, Chuvieco et al. 2006). Others have combined remotely sensed severity maps with topographic variables to predict future burn severity (Wimberly and Reilly 2007, Holden et al. 2009). A test of seven image processing techniques in mapping fire scars (visibly blackened land surface left after bushfires burn vegetation and leaf litter) for the oak-dominated forests of eastern Kentucky found the most useful bands for mapping burned and unburned sites were the ETM+3, ETM+4, and ETM+7 bands (Maingi 2005). Two of these bands (4 and 7) are used in the calculation of the normalized burn ratio (NBR) as part of the national fire effects monitoring protocol FIREMON (Key and Benson 2006). These same spectral bands were used in an analysis of a large wildfire in North Carolina, which showed a predictable relationship between a composite burn index (CBI) and the change in normalized burn ratio (dNBR) obtained from satellite imagery (Wimberly and Reilly 2007). This relationship then allows for CBI to be predicted from topographic and vegetative variables (Wimberly and Reilly 2007).

If similar relationships exist for prescribed fire on similar landscapes across the Central Appalachians, the ability to predict burn severity before burning would allow for better assessments of direct and indirect effects. As prescribed fire is applied in larger blocks, variety in topography and vegetation increases the variability of fire intensity and severity. The ability to predict this patchiness would be useful to land managers.

While the use of prescribed fire is increasing across the Central Appalachians, the total area burned in the past few years still represents a small percentage of the total. In order to develop a predictive model of post-fire change, information from many fires across the Central Appalachian region would be more useful than the smaller set of just prescribed fires. The objectives of this research were to 1) use remotely sensed data from wildfires and prescribed fires in West Virginia to determine which topographic variables were associated with post-fire change and then 2) apply those findings to the entire state to develop a predictive model for post-fire change.

Methodology

Monitoring Trends in Burn Severity Data

In an effort to monitor the effectiveness of the National Fire Plan and the Healthy Forest Restoration Act, the Wildland Fire Leadership Council sponsored the Monitoring Trends in Burn Severity (MTBS) project, to map and assess burn severity for all large (greater than 202 ha) current and historical fires in the United States. In the MTBS dataset, burn severity is defined as visible changes in living and non-living vegetation, combustion by-products (scorch, char, ash), and soil exposure within one growing season of the fire (Eidenshink et al. 2007). Burn severity products are calculated from Landsat imagery; the normalized burn ratio (NBR) is calculated using Landsat imagery as described by Key and Benson (2006), the change in NBR (dNBR) is calculated by subtracting post-fire NBR from pre-fire NBR (Key and Benson 2006), a relativized dNBR (RdNBR) is calculated based on the methods of Miller and Thode (2007). The creation of all three of these ratios is a straightforward process, then the RdNBR and dNBR are evaluated by an analyst to determine thresholds in the data to assign severity classes (Eidenshink et al. 2007). A categorical thematic burn severity is then created with six classes: unburned/low (1), low (2), moderate (3), high (4), increased greenness (5), and no data/masked areas (6).

These thresholds have been criticized as subjective, highly variable, and ecologically invalid (Kolden et al. 2015). No field verification of the burn severity classes created by the MTBS group has taken place for fires in the hardwood forests of eastern United Sates. However a test of MTBS methods with field determination of the composite burn index (CBI) in oak woodlands in Oklahoma determined that the accuracies of various models were comparable to the MTBS classification (Stambaugh et al. 2015). Because of these concerns with the thematic burn severity classes, we propose to use the MTBS class data as an index of post-fire change since the basis for the classes is either dNBR or RdNBR, representing a change in reflectance between pre- and post-fire.

We queried the MTBS dataset for all fires partly or completely within the state boundary of West Virginia (Table 1). Spatial grids of thematic burn severity for 92 fires, both wild and prescribed, from 1994 to 2012 (for some years, no fires of sufficient size occurred) were obtained from the MTSB website (http://www.mtbs.gov/index.html). Figure 1 shows the study area location and the fires used as inputs in this study.

Table 1. Fires included in the model by ecological subsection and year.

Subsection **year**	**Number of fires**	**Area (ha)**
Eastern Allegheny Mountain and Valley		
2010	1	556
Eastern Coal Fields	13	8,253
2000	2	842
2001	8	6,452
2008	1	274
2009	1	446
2012	1	240
Northern High Allegheny Mountain		
2010	1	413
Northern Ridge and Valley		
2001	1	210
Ridge and Valley	4	1,191
1994	1	281
2000	1	427
2001	1	195
2012	1	287
Teays Plateau	9	1,984
2000	2	556
2001	7	1,429
Western Allegheny Mountain and Valley		
2001	1	280
Western Coal Fields	68	27,176
1999	1	316
2000	13	1,831
2001	39	18,085
2005	2	1,041
2006	1	391
2007	1	187
2009	1	264
2010	8	3,865
2012	2	1,196
Grand Total	92	40,064

[1]Number of fires will not match grand total of number of fires as six fires are split between subsections.

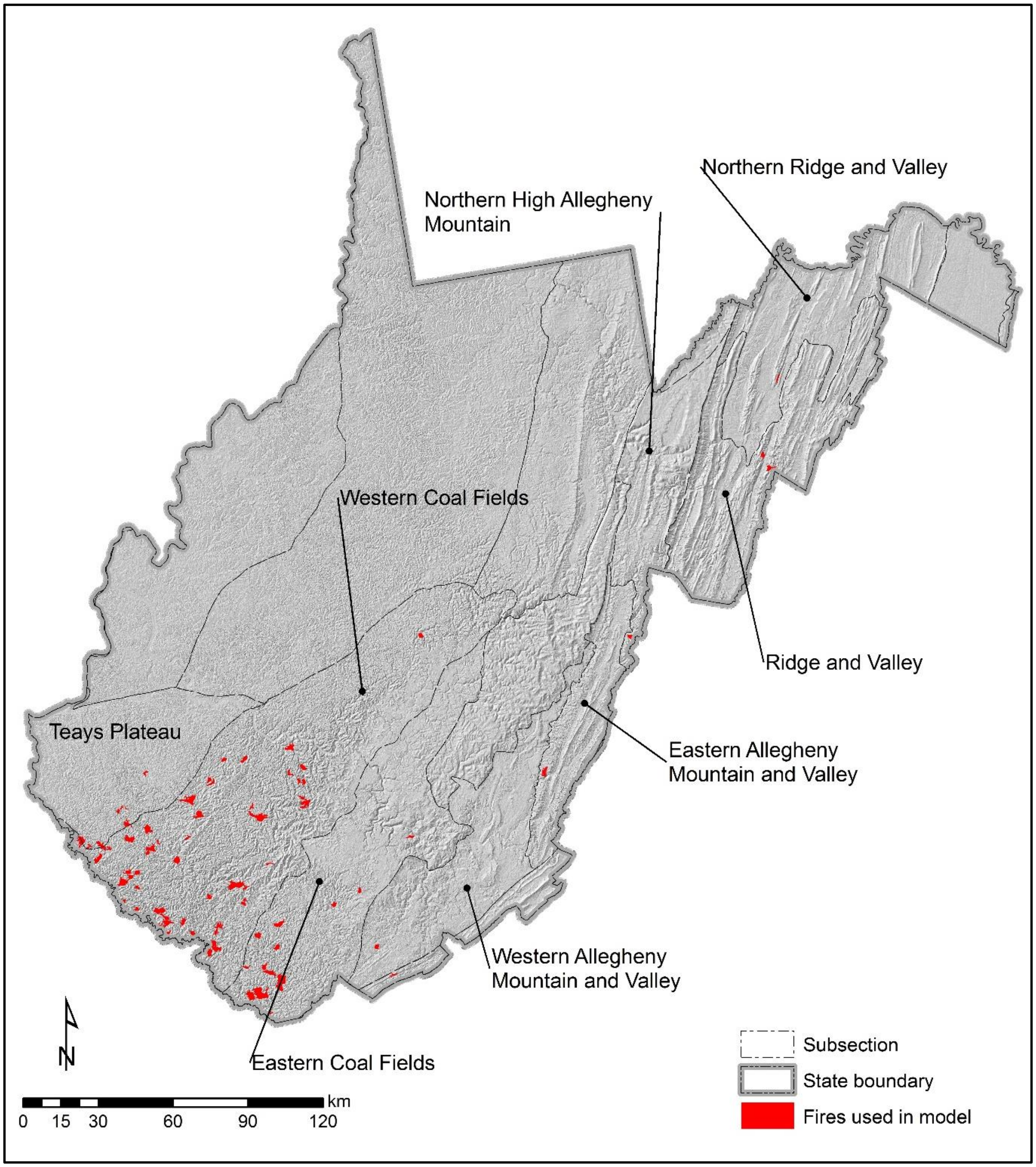

Figure 1. Study area and locations of fires used to create predictive model.

Topographic Variables

To create the predictive model of post-fire change, topographic variables were derived from a 3m digital elevation model resampled to 30 meter squared grids using cubic convolution with the Spatial Analyst Extension in ArcMap (ESRI, 2013). Variables created with this extension include: aspect (asp), slope (in degrees; slp_deg), and hillshade (using the default settings; hs). Twenty-nine other variables were created using the Geomorphometry and Gradient Metrics Toolbox (Evans et al. 2014) and are listed in Table 2. These variables included measurements of curvature, dissection, roughness, slope position, and surface relief ratio using three levels of search (1, 2, or 3 pixels from center) plus an average value. Forest cover values were derived from land use and land cover (NRAC, 2012) resulting in four classes: non-forest, deciduous forest, evergreen forest, and mixed forest.

Table 2. Topographic variables.

Variable	**Definition**
asp	aspect as discrete classes
asp_lin	transformed circular aspect to linear variable
cos	slope/aspect transformation using cosine
cti	compound topographic moisture index
curv_1	curvature using circular window with offset of 1 pixel
curv_2	curvature using circular window with offset of 2 pixel
curv_3	curvature using circular window with offset of 3 pixel
curv_a	average of three curvature grids
diss_1	dissection using circular window with offset of 1 pixel
diss_2	dissection using circular window with offset of 2 pixel
diss_3	dissection using circular window with offset of 3 pixel
diss_a	average of three dissection grids
hli	heat load index (latitude value set to 38.9537 degrees)
rough_1	roughness using circular window with offset of 1 pixel
rough_2	roughness using circular window with offset of 2 pixel
rough_3	roughness using circular window with offset of 3 pixel
rough_a	average of three roughness grids
sar	surface/area ratio
sin	slope/aspect transformation using sine
slp_der	slope second derivative
slope_deg	slope measured in degrees
sp_1	slope position using circular window with offset of 1 pixel
sp_2	slope position using circular window with offset of 2 pixel
sp_3	slope position using circular window with offset of 3 pixel
sp_a	average of three slope position grids
srr_1	surface relief ratio using circular window with offset of 1 pixel
srr_2	surface relief ratio using circular window with offset of 2 pixel
srr_3	surface relief ratio using circular window with offset of 3 pixel
srr_a	average of three surface relief ratio grids
trasp	slope/aspect transformation – N-NE = 0, S-SW = 1

Predictive Modeling

To perform the predictive modeling to estimate post-fire change probability for each of the cells we used the Random Forest algorithm (Breiman 2001). The Random Forests algorithm offers many advantages in that it does not adhere to parametric assumptions, can utilize mixed data type with different scales, handles high dimensional data, is robust to outliers and noise, is not sensitive to autocorrelation, quantifies importance of the predictor variables, and requires minimal parameterization (Cutler et al. 2007, Evans and Cushman 2009, Beyer 2012, Evans and Murphy 2014, Strager et al. 2015, Breiman 2001).

A response variable was created where presence was defined as a post-fire change class of moderate (3) or high (4) and absence was defined as unburned. We used the 30 meters squared cells with burn severity class 3 or 4 within the fire perimeters from the MTBS dataset for the presence observations. The fires for our prediction model came from eight ecological subsections – Eastern Allegheny Mountain and Valley, Eastern Coal Fields, Northern High Allegheny Mountain, Northern Ridge and Valley, Ridge and Valley, Teays Plateau, Western Allegheny Mountain and Valley, and Western Coal Fields (Cleland et al. 2007).

To ensure that statistical and spatial variability was represented without introducing a zero-inflation issue (Cutler et al. 2007), we created five sets of pseudo-absence data by creating random points selected from within the state boundary of West Virginia and then removing observations occurring within 1 km of a fire perimeter. For each training subset, we used an equal number of presence and absence observations, with the same presence data used in each subset. The independent variables (topographic and forest cover parameters) were appended to the points, from the corresponding raster cell(s), using the software tool Geospatial Modeling Environment (Beyer 2012).

Using the compiled training data we specified five Random Forests models, representing each random subset, using the Random Forests (Liaw 2001) package in R (R Core Team 2014). We tested models by removing low-performing parameters and observed a decrease in model performance as compared to the full model. Model error converged in fewer than 1,000 bootstrap replicates however, since variable interactions stabilize at a slower rate than error, we fixed the number of bootstrap replicated at n = 1,000. Because Random Forests is an ensemble approach, as long as the parameter space remains fixed, independent models can be combined into a single ensemble- model (Evans and Murphy 2014). Using only consistently selected parameters in the model selection, we fit the final models for each random-subset and combined them into a final ensemble-model. Model significance was evaluated using a permutated (n = 999) randomization procedure and an iterative 10% withhold cross-validation using the rfUtilties R package (Hijmans 2014). Once the significant independent variables were identified from the Random Forest models, the probability of the presence class (post-fire change class of 3 or 4) was predicted using the scaled posterior distribution of the common observation plurality (Evans and Murphy, 2014) with the R raster package (R Core Team 2014) across the entire state of West Virginia.

Results

The best fitting model with an out-of-bag error rate of 8.2% or 92% accuracy occurred when post-fire change classes of moderate and high were combined and compared to the unburned class. The analyses performed by Random Forest identified linear aspect as the most important variable in describing burned patches compared to unburned patches, followed by hillshade, aspect (as class), heat load index, slope/aspect ratio (sine transformed), average roughness, and slope in degrees (Figure 2). Our model shows high/moderate post-fire change rating associated with southwest and western aspects, and with increasing heat load index, slope/aspect ratio, average roughness, and slope.

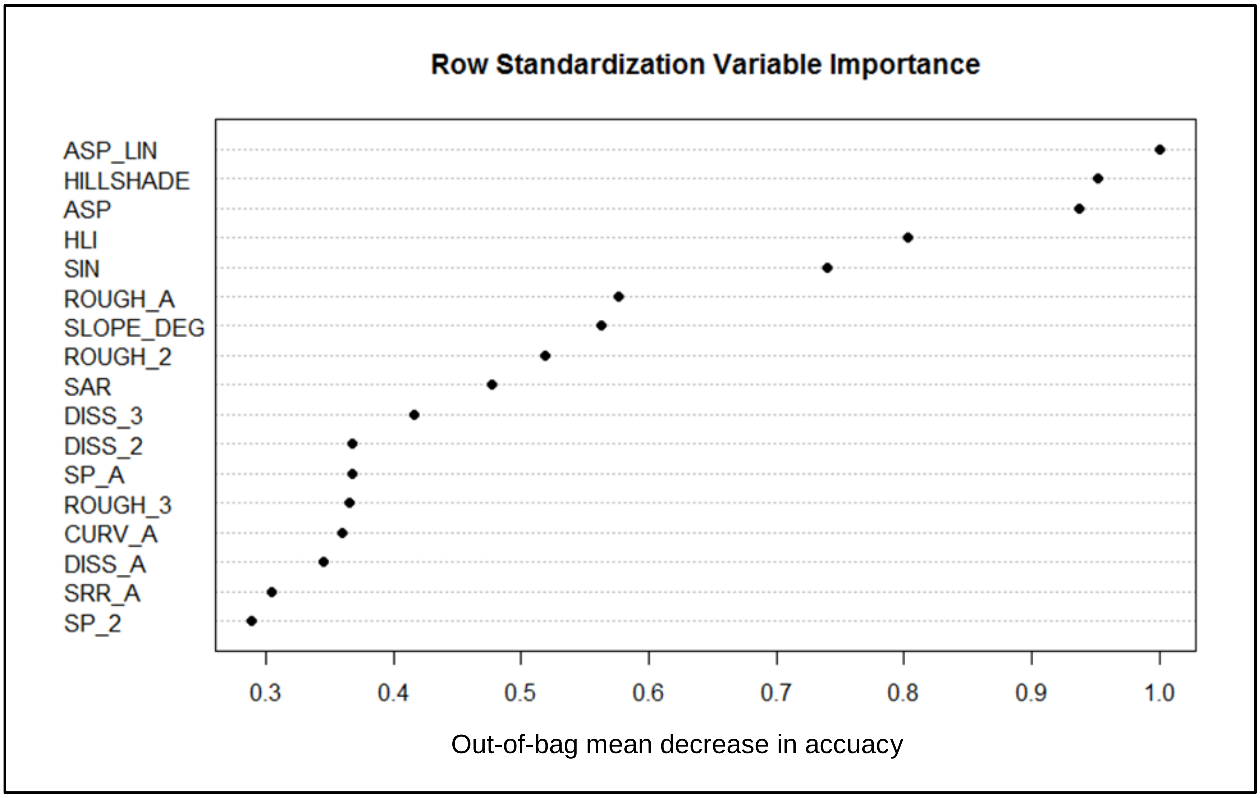

Figure 2. Relative importance of topographic variables in the predictive model of post-fire change using mean decrease in accuracy.

When these variables were then used in a predictive model for the entire state, much of the state has a low probability of high/moderate post-fire change (Figure 3; Table 3). On 59% of the area in West Virginia, the probability of a fire causing high or moderate post-fire change is predicted to be 0-10%. Relatively little area is predicted to have greater than a 50% probability of a post-fire change rating of high or moderate; approximately 27,805.5 ha (68,710 acres) or about 0.5% of West Virginia.

Our predictive model was based on binary input, post-fire change class of moderate/high or unburned, while the output is a continuous probability (0-1). Given the skewed nature of the data (Table 3), the modeled probabilities were converted to three classes based on natural breaks in the data (Jenks method in ArcMap). This resulted in classes of low, moderate, and high probability of a high/moderate post-fire change patch occurring (Figure 4; Table 3). These classes may be more useful for land managers than the original modeled continuous probabilities.

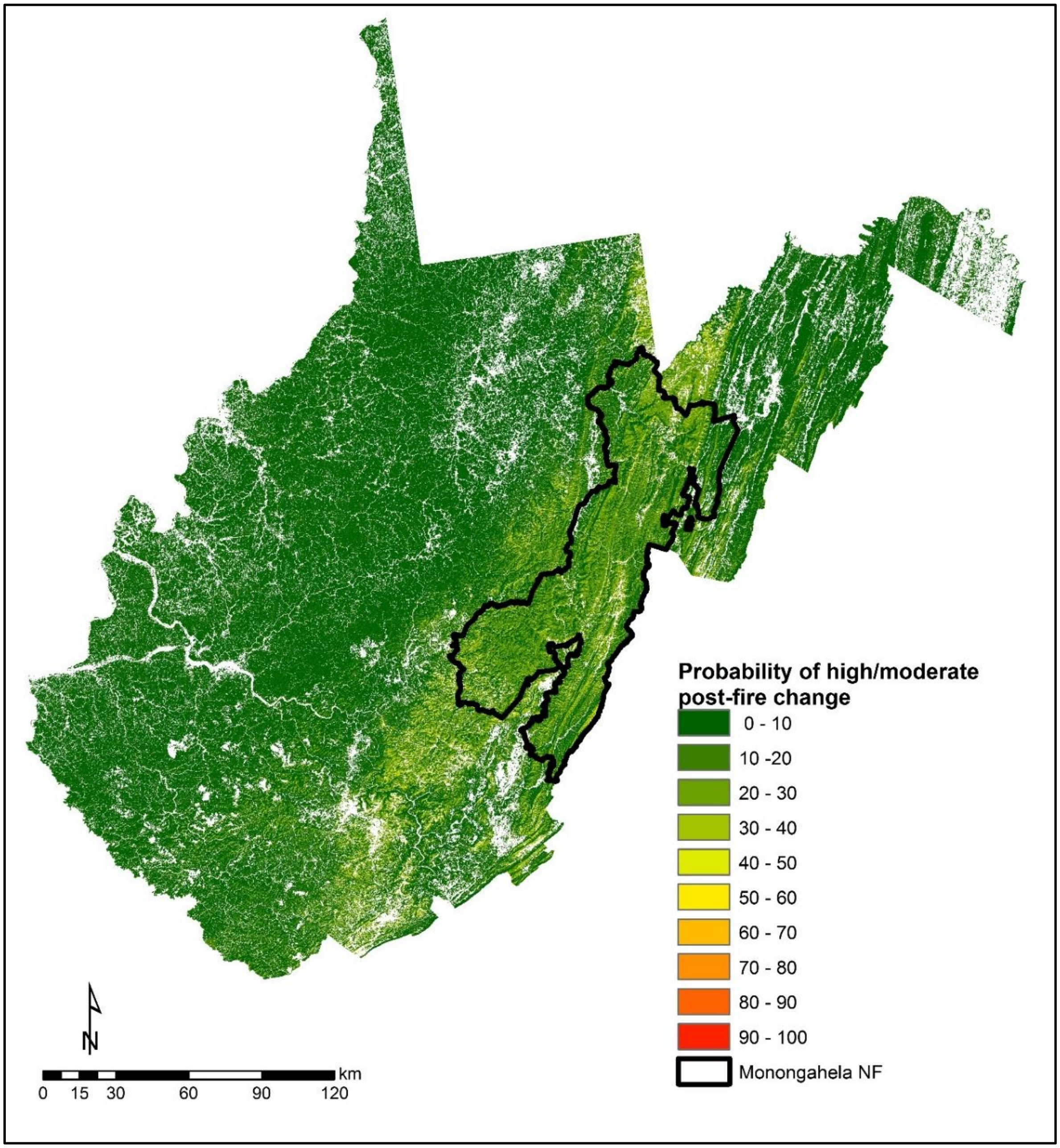

Figure 3. Results of the predictive model of high/moderate post-fire change for West Virginia.

Table 3. The probability of high/moderate post-fire change class across West Virginia as both percent probability and as three re-classified categories.

Probability of high/moderate post-fire change (%)	**Area (ha)**	**Percent of total**
0-10	3,491,755	59
11-20	1,705,763	29
21-30	420,521	7
31-40	173,490	3
41-50	61,456	1
51-60	22,298	0
61-70	5,247	0
71-80	253	0
81-90	7	0
91-100	>1	0
total	5,880,790	
Probability class		
Low (0-10)	3,491,755	59
Moderate (11-25)	2,000,809	34
High (26+)	388,226	7

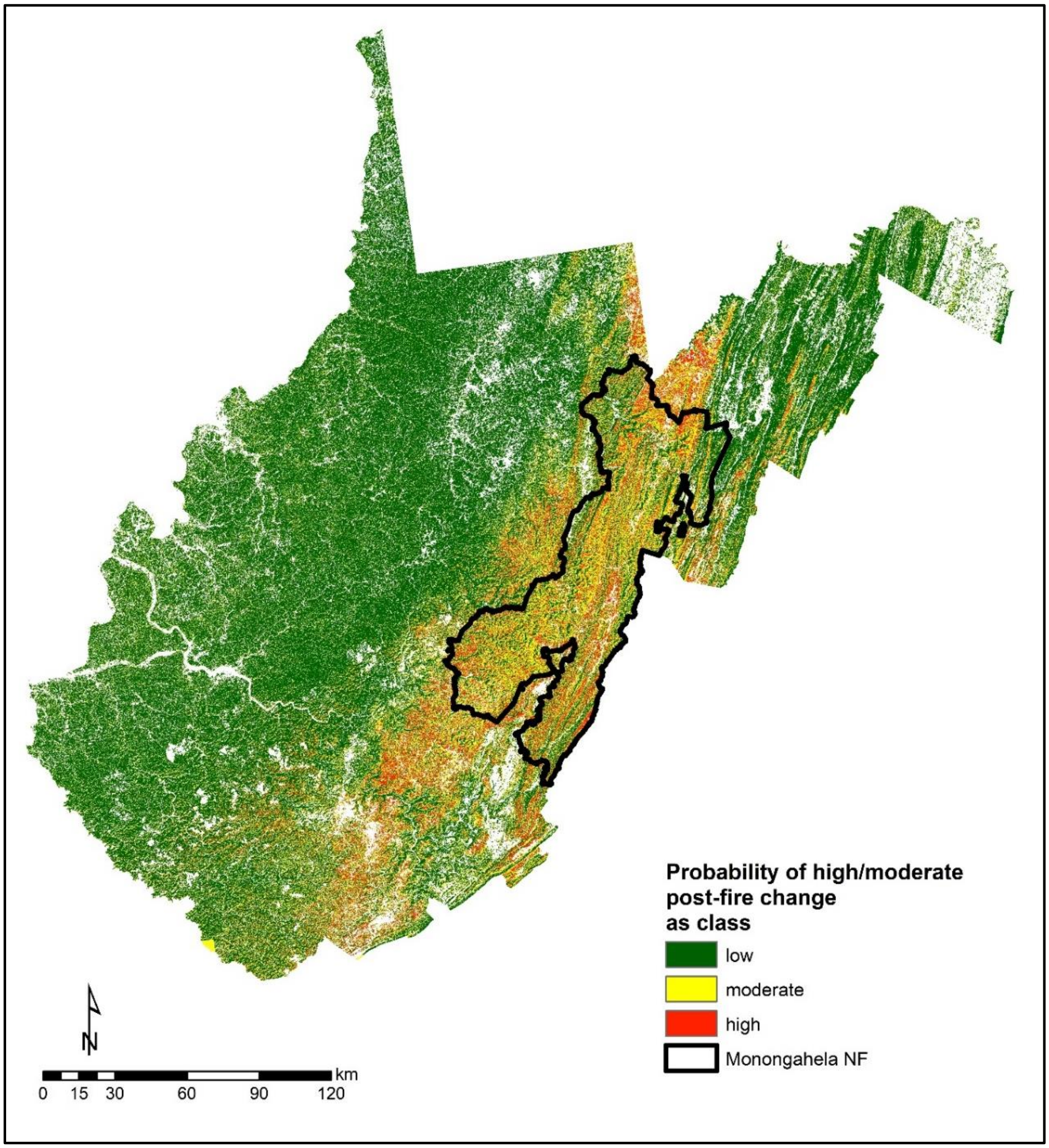

Figure 4. Model results of probability of high/moderate post-fire change reclassified as categorical post-fire change for West Virginia.

For the moderate and high probability classes that were mapped, the linear aspect, hillshade, aspect as class, and heat load index were the main terrain variables found in the study area for those probability classes. This was not surprising since many of these terrain characteristics correspond with areas of drier and warmer landscape positions. In study areas with terrain such as West Virginia which has a high degree of terrain relief, local variation, and landform, these driving factors as noted in Figure 2 help to identify patches of high/moderate post-fire change.

While 92 fires were used to determine important variables for the final probability model, only 399 square kilometers of the state was classed as high or moderate burn severity by MTBS analysts. In our model, cells used as observations of absence of high/moderate post-fire change were selected outside of fire perimeters. This allows our model to be independent of ignition patterns and the influences of adjacency.

Conclusions

The use of the MTBS classified data in our model was partly based on the use of similar spectral bands to map fire scars in mixed-oak forests in eastern Kentucky (Maingi 2005). Fires in eastern Kentucky are very similar to those in West Virginia, being largely surface fires occurring in dormant seasons and where leaf litter is the main fuel consumed. These fire scars result in blacked areas that do not persist on the landscape as they are rapidly covered up by annual leaf fall. To map these first-order fire effects, leaf-off imagery is required. While the MTBS methods and definitions of burn severity classes are based on western fire behavior – higher severity fires where overstory is consumed directly – the results may still be applicable to eastern hardwood forests. However, the classes may no longer represent burn severity (as defined as overstory mortality), instead they represent an index of post-fire change. What is needed is for these burn severity classes to be field-verified by measuring CBI on recent wildfires in eastern hardwood forests. In the absence of field-verified severity classes, we contend that our model predicts areas where post-fire change may be expected and where greater fire effects may be found. In North Carolina, the relationship between observed CBI and dNBR was used to predict CBI in un-observed areas (Wimberly and Reilly 2007). Predicted CBI was found to be highest on southwest and west aspect and higher in pine-dominated patches, and increased with higher heat load index, and decreased as topographic wetness increased (Wimberly and Reilly 2007). Our model resulted in similar findings for the topographic variables in common – increase probability of a high/moderate post-fire change patch on southwest and west aspects, and increasing probability in areas with increasing heat load index. Elevation was found to have an important effect on burn severity in North Carolina (Wimberly and Reilly 2007). One significant difference between the North Carolina study and our analysis is spatial extent; the North Carolina study assessed burn severity and its relationship to topographic variables on one large fire as compared to our approach of combining many fires and predicting post-fire change across an entire state.

In boreal forests of China, burn severity in small fires was found mainly to be controlled by vegetation while in large fires, topography influenced burn severity (Wu et al. 2014). Small fires were defined as less than 100 ha and large fires as greater than 1,000 ha. These relationships make ecological sense considering ignition patterns and factors that constrain fire spread. Fire ignition largely depends on local vegetation characteristics such as fuel type, fuel moisture, and spatial arrangement of fuels (Falk et al. 2011). Ignitions may occur but not all fires spread or cause overstory mortality. After ignition, burn severity is controlled by topography (Falk et al. 2007). This relationship is illustrated by our model results on the Monongahela National Forest. Since our model was based on many fires, over time, and across a large area, the relationships modeled are essentially those of large fires where topographic characteristics control burn severity. The categorical class model for the Monongahela National Forest shows higher probabilities of post-fire change across the complex terrain regardless of forest type (Figure 5). While an ignition is unlikely in the high elevation and moist red spruce forests found at the highest elevations, if a fire did occur, post-fire change could be high as controlled by topography. This did occur in the history of many of these high elevation forests during the exploitative logging era (Allard and Leonard 1952). One refinement that could be made to our model is the forest cover type parameter. The results presented here are based on four simple forest cover types and none were found to be important in describing the occurrence of high/moderate post-fire change patches.

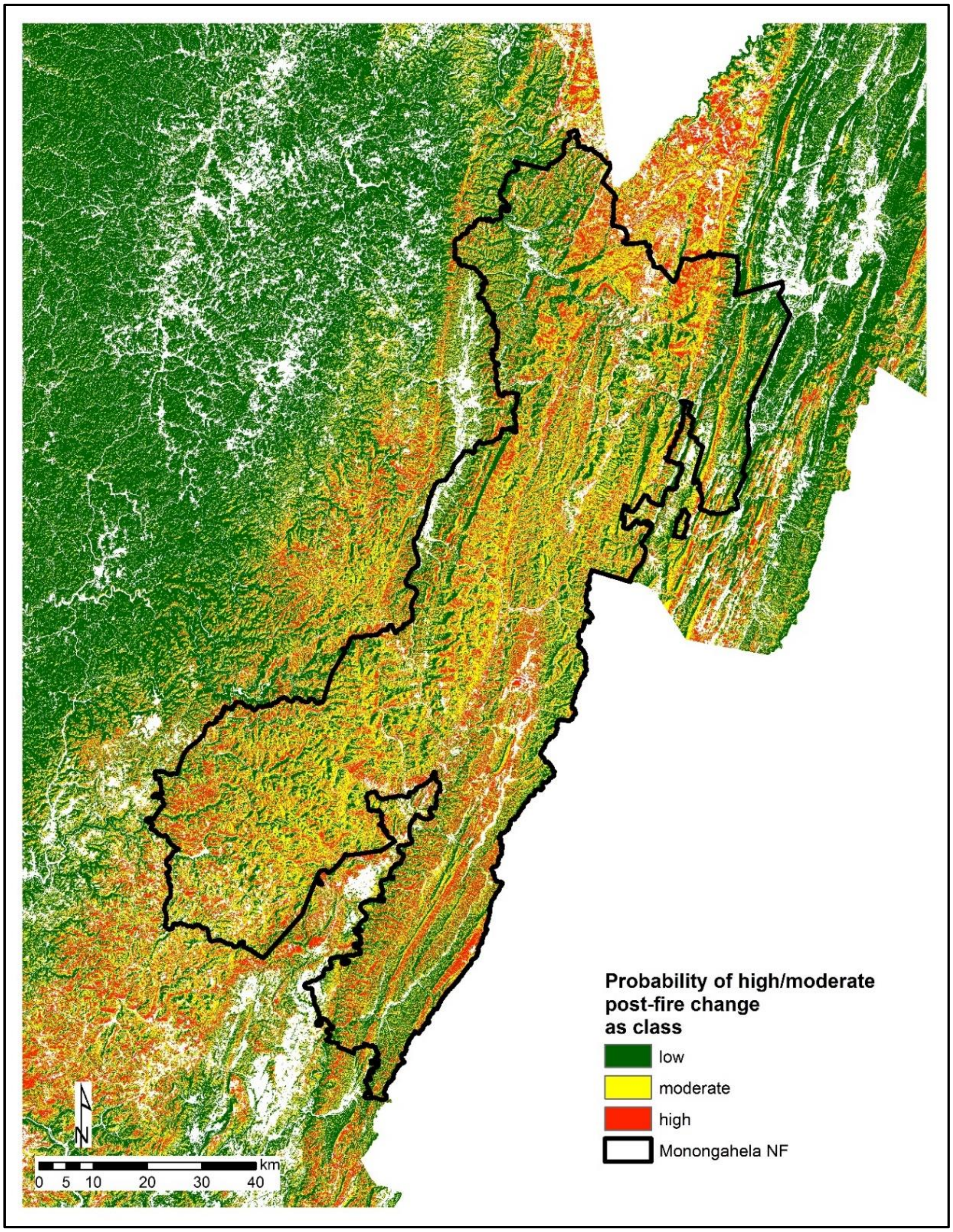

Figure 5. Model results of probability of high/moderate post-fire change reclassified as categorical post-fire change for the Monongahela National Forest.

As others have done for individual fires, our model may be improved by calculating CBI on a recent fire and comparing the observed CBI to dNBR and burn severity classes created from satellite imagery. The class breaks used to create the burn severity categories in the MTBS dataset are made based on remotely sensed data only. There may be delayed canopy mortality after wildfires and prescribed fires in eastern forests as has been documented in Ohio four years after a prescribed fire (Yaussy and Waldrop 2009). Post-fire imagery collected and used within one year of a fire may not represent the entire range of fire impacts. The MTBS methodology was developed to capture immediate, first-order fire effects, which may vary greatly between western and eastern forests.

Our model for West Virginia should be useful for land managers in planning prescribed fires and estimating effects to resources such as canopy cover, rare plant communities, and associated wildlife habitat. Model results could be used in conjunction with site visits to identify areas where post-fire change may be higher than anticipated or desired. Burn units and firing patterns may be modified to avoid or minimize these potential effects. In contrast, higher burn severity may be a desired outcome of prescribed fire for regeneration of certain plant species such as Table Mountain pine (*Pinus pungens Lamb*.) or for creating woodland or savannah habitat and our model may be useful in identifying those areas.

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