The Pennsylvania State University

The Graduate School

College of Earth and Mineral Sciences

USING NEUTRAL MODELS TO EVALUATE THE EFFECT OF TOPOGRAPHY ON

LANDSCAPE PATTERNS OF FIRE SEVERITY: A CASE STUDY OF LASSEN

VOLCANIC NATIONAL PARK

A Dissertation in

Geography

by

Andrew D. Pierce

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

August 2011

The dissertation of Andrew D. Pierce was reviewed and approved* by the following:

Alan H. Taylor
E. Willard and Ruby S. Miller Professor of Geography
Dissertation Adviser
Chair of Committee

Erica A. H. Smithwick
Assistant Professor of Geography

Douglas A. Miller
Associate Professor of Geography

Kenneth J. Davis
Professor of Meteorology

Karl S. Zimmerer
Professor of Geography
Head of the Department of Geography

*Signatures are on file in the Graduate School

Abstract

Fire is the most important disturbance process in forests of the American west. At the finest scales, its immediate effects on vegetation include killing of live vegetation and the consumption of dead organic debris. At the scale of one to many hectares, it drives variability in vegetation composition and structure. Heterogeneity in fire behavior and effects are not driven solely by the vegetation itself. Fire interacts with weather, climate and climate teleconnections, past human management of forested landscapes, and with topography. The effect of topography on heterogeneity in fire behavior and effects is not well knows, and some evidence is contradictory. I employ a neutral modeling approach generate an examine landscape scale patterns of fire intensity and fire effects. Broadly, I address three main research questions: 1) what is the distribution of surface and canopy fuels in LVNP, and how do they vary with topography? 2) what is the effect of topography on landscape level heterogeneity in neutral models of fireline intensity and fire type? 3) Is topography able to explain heterogeneity in the observed severity of historic and contemporary fires and is it able to explain heterogeneity in modeled fireline intensity? I accomplish this in stages. I use plot level data from 223 plots and 669 hemispherical photographs to assess the effect of topography—elevation, slope, and aspect—on the distribution of both surface and canopy fuels. Then I develop ten remotely sensed variables from Landast imagery and five topographic variables—elevation, slope, aspect, local topographic position, and landscape position—from the National Elevation Dataset. I use a Random Forest algorithm to model and then predictively map canopy fuels. In the second part, I model fire burning through homogenously distributed fuels at the 80th, 90th, and 97th percentile fuel moisture conditions and for a range of wind scenarios. This set of simulations forms the base of our neutral model expectations and is analyzed for the effect of topography. Finally, we map historic patches of

high intensity fire effects from geo-referenced aerial photographs and extract severity data from remotely sensed images of recent fires. We compare the topographic conditions of these real high severity patches with information on high intensity fire from the neutral model approach to assess how important topography is in explaining the distribution of different severities. Our results show that slope angle is the most important variable for determining modeled fireline intensity, but that elevation and local topographic position are the most important variables for explaining the distribution of observed locations of high severity fire. These result support our conclusion that some patches of vegetation may be 'fixed in space' through the interaction of fire with topography and fuels.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my parents, Robert and Frances Pierce, for always inspiring me and pushing me to be the best I could be. I'd like to thank my brother, Josh, for also being supportive and also being someone who is great to talk to about anything. Many of the other members of my extended family have been great inspirations. Poppop Roberts most of all for all of the interest he always took in my studies and for the example he provided by the way he lives. Many of the other Robertses too; coming from a family of teachers had provided much of the inspiration and motivation that I have needed and wanted. I would also like to thank my advisor, Dr. Alan Taylor, for all the support, encouragement, and advice that he has provided since I have been here at Penn State. All of the people in the Vegetation Dynamics Lab have been great friends and colleagues. I would like to thank my committee, Erica Smithwick, Doug Miller, and Ken Davis for their great advice throughout my work. Finally, all the people at the Park and Forest Service who have been helpful to me in the field including: Tom Rickman, Tom Garcia, Eric Hensel, and Calvin Farris. Thanks also to Carl Skinner for periodic advice.

Chapter 1—Introduction:

The Interaction of Pattern and Process, Known Relations between Topography and Fire Severity, Modeling Approaches to Biogeographic Questions, and the Need for High Quality Fuels Maps

Pattern and Process

Fire is a process that has the potential to alter vegetation development pathways for hundreds to thousands of years (Miller 2007; He and Mladenoff 1999; Baker 1992). This potential can be realized in both low severity dominated fire regimes (Fulé et al. 1997) or in high severity dominated fire regimes (Turner et al. 1994). The best understood of these relationships is the high frequency, low severity fire regime that typically kept ponderosa pine ecosystems of the southwestern US open and composed of large diameter, fire resistant stems (Fulé et al. 1997). In these systems, open areas between large trees grew grasses that formed a continuous fuel bed in a matter of a few years. Once a drier than average year occurred, this continuous fuel bed became highly flammable. When ignited, the fuel bed would burn at low intensity, but could potentially burn hundreds to thousands of acres leaving most large trees healthy or minimally scarred but also killing seedlings and leaving the forest open (Fulé et al. 1997). The interaction of fire regime and vegetation in this example produced a more or less stable, fire dependent ecosystem (Fulé et al. 1997; Allen et al. 2002). In boreal and sub-alpine forests, even when abundant fuels are present, droughts of the necessary length and severity to make these fuels flammable are rare. In these systems, the interaction of fuels and climate is a limiting factor that drives long-interval, high severity fires. Here, static age patterns that result from large patches of severely burned vegetation are the hallmark of this fire regime and can be mapped on the landscape (Johnson et al. 2001; Romme 1982).

Other factors that influence the variation in fire severity that are also well understood include time-since-last-fire (Odion et al. 2004), fire suppression and its consequential accumulation of fuels and infilling of fire intolerant species (Beaty and Taylor 2001; Safford et al. 2008), logging and subsequent management action or non-action (Weatherspoon and Skinner 1995; Thompson

2

et al. 2007), climate, climate change, and climate teleconnections (Norman and Taylor 2003, Schoennagel et al. 2007; Westerling et al. 2006), vegetation composition (Collins and Stephens 2010; Odion et al. 2010), and patchiness of vegetation (Collins and Stephens 2010). Each has been identified as an important driver of fire regimes and fire severity change over the course of the 20th century.

In the 20th century, a federal policy of fire suppression has altered the structure of many forests (Agee 1993; Fulé et al. 1997; Taylor 2000). Prior to 1910, there was a significant debate among foresters and other land managers about the role of 'light burning'—an agricultural and forestry practice of the south and west akin to modern prescribed burning—and the proper role of fire in forested ecosystems. However, the extensive fires of 1910 pushed the advocates of complete elimination of fire to an ideological victory. Following the 'Great Fires' of 1910, all fires were outlawed including 'light burning' (Pyne 2008). Thus the culture of suppression and the view of fire as a primarily destructive force became the dominant paradigm. In this paradigm, all high intensity forest fire is abnormal (Pyne 2008). By suppressing fires, we had successfully reduced the amount of area burned per year, and thus reduced the area burned at high intensity each year. But by removing high intensity fire as a structuring process from the landscape, some high-fire-intensity dependent brushfield communities (e.g. Collins and Stephens 2010; Odion et al. 2010)—which add structural and habitat diversity to the landscape—are at risk of loss because of succession to conifer forest (Nagel and Taylor 2005). Furthermore, there has been growing recognition of the importance of the high severity component of fire regimes in mixed-conifer forests (Taylor and Skinner 1998; Taylor and Beaty 2005; Collins and Stephens 2010).

Low to moderate elevation, dry pine ecosystems with extensive grass understories have likely been impacted the most by the policy of fire suppression causing an increase in surface fuels,

seedling, sapling, and tree density, and fire severity (Fulé et al. 1997; Allen et al. 2002). On the other hand, sub-alpine and boreal forests have likely not been affected by fire suppression to the degree that their structure and composition have been significantly altered because of their historically long fire return intervals (Johnson et al. 2001). Nevertheless, large portions of the mixed-conifer zone of the US west in general, and California in particular, now show the increases in fire severity predicted by critics of the full-fire-suppression paradigm (Miller et al. 2009b). This increase in the severity of recent wildfires has become one of the main concerns of fire managers (Fulé et al. 2004), resource managers (Fried et al. 2004; Miller et al. 2009b), and land use planners in California (Syphard et al. 2007; Syphard et al. 2008). Their concern reflects the fact that high severity fire is potentially the type of fire most likely to result in long-term changes in vegetation structure (Pierce and Taylor 2011) and the type most likely to have the longest-lasting effects on vegetation function (Kashian et al. 2006).

High severity fire creates a pattern of patches on the landscape. The arrangement of these patches is just one realization of the stochastic process of fire burning through a heterogeneous fuel, vegetation, and topographic environment that is subject to human management (*sensu* O'Sullivan and Unwin 2003). The characteristic scales of spatial and temporal variations in these patches range over many orders of magnitude (Krawchuk et al. 2009; Agee 1998). At the landscape scale, the dominant type of fire (low, moderate or high severity) is an important driver of variability in patch metrics. At the scale of an individual fire, Collins et al. (2007) and Thompson et al. (2007) showed that weather is the primary driver of fire severity patchiness. While a single fire may be dominated by short-term controls, weather is essentially a stochastic process because of its wide range of variability and its rate of change relative to the time scale of a single fire. Further, the combination of fuel, weather, and topographic conditions that occur

during any one fire are not necessarily comparable to the combination of conditions during other fires.   Because the number of fires studied by Collins et al. (2007) and Thompson et al. (2007) is small and fire severity is strongly influenced by the stochastic process of weather and environmental heterogeneity, these studies cannot be repeated in order to identify a set of expected topographic influences on fire severity.

In Lassen Volcanic National Park (LVNP), high severity, low frequency fire regimes in some topographic positions may result in stable, fire dependent brushfield communities. In addition, there is evidence that burns are becoming more intense and more severe (Miller et al. 2009b) and that climate change is increasing the length of the fire season (Westerling et al. 2006). What is less clear, however, is the role that topography plays in determining patterns of fire severity patches. These are all motivating factors for the study of topography and its relation to high severity fire regimes.

Approaches to High Severity and Topography

Historic and Landscape Vegetation Structure Methods

Topography is a driver of variations in fire severity, and its influence on fire regimes is known generally in broad strokes through fire history studies. Quantifying these historic fire regimes and their topographic controls is typically done through the analysis of fire scarred wood extracted from living and dead trees (Swetnam 1993; Taylor 2000; Stephens et al. 2003). This method is excellent for calculating the frequency and seasonality of fires, and strong inferences can be made about fire size. In the Cascade Range and in southern British Columbia, fire return intervals lengthen as elevation increases because winter snowpack lasts longer at these elevations (Beaty and Taylor 2001; Heyerdahl et al. 2001; Heyerdahl et al. 2007) and fire return intervals

5

are shorter on south-facing slopes because they slopes dry more quickly than other aspects (Heyerdahl et al. 2001; Taylor and Skinner 2003; Heyerdahl et al. 2007). Frequency relationships vary geographically, however. Rollins et al. (2002) compared wilderness areas in Montana and New Mexico and found that in Montana, south and southwestern aspects burned more often because they were subject to increased insolation which dried fuels more quickly. In contrast, northeastern aspects in New Mexico burned more often because their moisture regimes allowed for more rapid accumulation and connectivity of fuels (Rollins et al. 2002). In the nearby Klamath Range, the influence of topography (ridges, rocky outcrops, cliffs, and roads) on the inhibition of fire spread is recognized (Taylor and Skinner 2003).

The fire scar method has been used to infer topographic controls on fire frequency and size patterns, but these methods are limited by their inherent assumptions which lead to the conclusions about historic severity. Also, direct quantification of the magnitude of topographic effects on fire severity in relation to other factors that are known to control severity is much more difficult. Fire severity can be driven by the structure and arrangement of fuels (Odion et al. 2004; Thompson et al. 2007), daily meteorological conditions (Collins et al. 2007), or vegetation type (Collins and Stephens 2010). Additionally, high intensity fires often destroy scarred trees which leaves fire scar based inferences about severity suspect because the evidence is missing. Despite this, topography has been broadly inferred to affect severity in the nearby Klamath Range where historical studies suggest west facing upper slopes burn more severely (Taylor and Skinner 1998). Additionally, slope was shown to be positively associated with fire severity measures in Sequoia National Park (Knapp and Keeley 2006). In contrast, in the specific case of the Big Bar complex and the Quartz fire of the Klamath Range, Alexander et al. (2006) found evidence that higher elevations burned less severely than lower elevations. Using the recently

developed Relative differenced Normalized Burn Ratio (RdNBR; Miller et al. 2009a) several studies have shown that slope aspect can be a determinant of the location of high severity fire (Collins et al. 2007; Thompson et al 2007). In most of these cases, however, daily meteorological conditions overshadowed topographic conditions in explaining spatial variation in fire severity (Collins et al. 2007; Thompson et al 2007).

In the absence of other evidence, vegetation size structure, age structure, and composition have been used as indicators of past fire regimes. Vegetation structure has been used to infer the presence of low-severity fire regimes (e.g. Taylor 2000), mixed-severity fire regimes (e.g. Hessburg et al. 2007), and high-severity fire regimes (e.g. Nagel and Taylor 2005). Taylor (2000) used age-structure interpretation, stand composition, and fire scar analysis to show a distinct shift in fire frequency following the onset of fire suppression policies in Lassen Volcanic National Park. Hessburg et al. (2007) used aerial photograph interpretation of stand structure to determine the proportion of the landscape that was represented by low-, mixed-, and high-fire severity patches. Nagel and Taylor (2005) used cross-dating of trees and shrubs to show that brushfield communities in the Lake Tahoe Basin experienced long-interval, high severity fire. Additionally, patches of vegetation on the landscape can themselves be important drivers of within-fire variability in severity (Collins and Stephens 2010, Odion et al. 2010). In particular, Collins and Stephens (2010) identified vegetation types that can be easily identified *a priori* from aerial photographs. Moreover, vegetation effects on fire severity can be self-reinforcing such that highly pyrogenic vegetation tends to promote fire behavior that results in its own persistence (Odion et al. 2010).

Simulation Models and Neutral Models

To investigate real landscapes against hypotheses, biogeographers and landscape ecologists use neutral models (Caswell 1976; Turner et al. 2001) or simulation models built on some combination of physical, statistical, probabilistic, or empirical approaches (Turner et al. 2001). Conceptually, neutral models work by first assuming that ecological processes are independent and that the patterns observed in natural systems can be explained by simpler means. When a neutral model is used, it often produces a baseline against which observed patterns can be evaluated (Gardner et al. 1987; Gardner and Urban 2007).

Because real fires burn through highly heterogeneous conditions and are affected by stochastic processes, and because single fires suffer from the statistically small sample size problem, modeling approaches are a warranted and necessary route for investigating the various combinations of topography and fuels. Simulation models have been employed to investigate many aspects of fire behavior, fire effects, and fire regimes, often at quite broad scales. The Boundary Waters Canoe Area and the effects of Euro-American settlement and fire suppression on its landscape characteristics was the focus of an investigation by Baker (1992) who found that some landscape metrics increase quickly with shifting fire regimes while others lagged by decades to centuries. Simulation models for mapping fire return intervals were compared to statistical models by Keane et al. (2003) who found that while simulation models generally performed poorly when explicitly mapping those intervals, they were nonetheless useful because of their wide flexibility and general ability to 'burn' the same landscape under different conditions many times and over very long time periods. Large patches were important for the persistence of fire sensitive species in Mediterranean climates in the face of altered fire regimes (Pausas 2006).

Neutral models are often implemented to create baseline scenarios against which observations can be tested (Caswell 1976; Gardner et al. 1987; Gardner and Urban 2007). A neutral model approach by McKenzie et al. (2006) examined the effect of sampling intensity and completeness on estimates of fire regime parameters (average size, mean fire return interval) where all of the factors deemed important to determining fire regimes were decoupled in the modeling approach. In this work, we use model generated evidence on expected distribution of fire behavior as it relates to topography and examine how that evidence is similar to or differs from observational evidence.

Need for Fuels Mapping to Understand High Severity Fire

At the national level, maps of forest fuels have become an important part of resource managers' toolbox, especially in the context of both planning fuels treatments and assessing potential fire behavior. Even with allowances for 'natural' fires in recent decades (Collins and Stephens 2007), a federal policy of fire suppression in the US west over the 20th century has induced wide spread changes in fuel loads (Parsons and DeBenedetti 1979, Agee 1993) and fire severity (Safford et al. 2008; Miller et al. 2009b). However, fire suppression induced changes in both fuels and fire behavior and effects are highly variable, due primarily to heterogeneity in vegetation communities' responses to fire exclusion. Sub-alpine and boreal forests have likely been affected very little by fuel load changes caused by fire suppression because of their naturally long fire-return intervals as well as their tendency to burn at high severity when fire does return (Schoennagel et al. 2004; Johnson et al. 2001). Low elevation semi-arid ponderosa pine forests, on the other hand, likely have been greatly impacted by fuel build up due to fire suppression (Schoennagel et al. 2004; Fulé et al. 2001). Furthermore, some mixed-conifer forests of the montane zone have fire regimes where fire behavior is predominantly controlled by

9

interannual climate variations (Schoennagel et al. 2004; Westerling et al. 2006; Collins et al. 2007).

At the landscape level, fuels mapping is directed towards displaying variation in fuel loads that have potential to influence fire behavior under specific weather conditions and in support of specific management objectives. Recent efforts directed at Stewardship and Fireshed Assessment (SFA) are fuels-data intensive, necessitating highly accurate fuel maps (Bahro et al. 2006). Canopy fuel characteristics in particular are needed to accurately assess potential fire behavior at this level because they largely determine the potential for fires to transition from surface or ground fires to torching or crown fires and because small changes can have large impacts on potential fire behavior (Fulé et al. 2001). Canopy fuels information has been developed at a national scale and is appropriate for national or regional long term fire management plans (Rollins and Frame 2006), but the data needed for specific management objectives often needs to be focused on particular landscapes, especially at the National Park or Forest level. Here, a single Park or Forest may contain many vegetation types primarily due to strong co-variation with topography (elevation, slope, and aspect). Thus, due to high variability at the Park or Forest level, intensive sampling of fuels characteristics across vegetation types and topographic settings is needed to accurately capture fuels heterogeneity in support of sound fire management.

Critical canopy fuel parameters are needed for comprehensive fire behavior models. Fuel structure and arrangement is the most directly related variable to fire severity because it is the physical complex that interacts with the combustion process to produce heat, consume vegetation, and kill vegetation. Measures of fire severity in forests are often related directly to the amount of canopy consumed or killed by fire (Miller and Thode 2007; Miller et al. 2009a).

Thus, canopy fuel variables are critical components in modeling potential fire behavior. The four most widely used variables are Canopy Bulk Density (CBD), Canopy Cover (CC), Canopy Base Height (CBH), and Canopy Height (HT). As a measure of the total amount of above-ground-surface fuel that is available to wildfires, CBD typically includes foliage and up to one half of the smallest branchwood (0-6.4 mm) and is measured in units of kg m^{-3}. CC is the horizontal fraction of the ground that has canopy above it and is measured as a percentage of total area. The lower threshold above which there is sufficient fuel for a crown fire to be self-sustaining is quantified by CBH and is measured in m. Lower CBH values indicate that canopy fuel is closer to the ground and hence could act to transition surface fire into the crown. Finally, HT is the average height of the dominant stratum of tree cover and affects modeled fuel moistures and is measured in m.

Introduction to the Rest of the Work

Our approach to the investigation of high severity and high intensity fire and the role that topography plays in the variability of high intensity and high severity fire across the landscape is based on two assumptions. First, high intensity fire will often destroy past physical evidence of fire regimes. This assumption necessitates the utilization of alternative methods of investigating high intensity fire effects. Second, within-fire variability in intensity and severity is high, and weather and vegetation effects tend to be more important drivers of variability within each fire (e.g. Collins et al. 2007). Given this, the investigation of one or a few fires is unlikely to reveal the correspondence between topography and fire intensity and high severity fire. With these two assumptions in mind, we approach the analysis of high intensity fire and topography from two directions. First, we use simulation modeling to generate an expected distribution of high intensity fire as it is related to topographic variation. This base of expectations forms the core of

our neutral model approach. Second, we map patches of high severity fire effects from the historic and contemporary record. This also allows for a comparison between the expected and observed topographic characteristics of the locations of these high severity and high intensity fire patterns.

Comparison to historic patches of high severity fire will be conducted with Lassen Volcanic National Park as a case study. Inside the perimeter of the park, high intensity fires from the historic period are being mapped from 1941 aerial photographs. The topographic characteristics of historic high severity fires will be compared to the results of our neutral simulation modeling. To assess current patterns of fire severity patches, remotely sensed maps of fire severity derived from the dNBR methodology will be analyzing in comparison to the model results.

In chapter 2, we apply Random Forest (RF, Breiman 2001; Prasad et al. 2006) regression to plot level field data of canopy fuel loads and predict canopy fuel values over the full extent of Lassen Volcanic National Park, California, USA using Landsat data and topographic characteristics as predictor variables. We first model and predictively map 2010 canopy fuels characteristics using plot level data from 2009 and 2010. We then use the same approach to predictively map canopy fuels in 2003. Finally, we integrate our estimates of canopy fuels from 2003 with a contemporary surface fuel map to predict potential fire behavior within the perimeter of the 2004 Bluff fire and compare our results with other estimates of fire severity. We will demonstrate that intensive fuels mapping provides information that makes the prediction of fire type more accurate.

In Chapter 3, we use simulation models to generate an expected distribution of fire behavior as it relates to topography. We use many surface fuel models which will be distributed uniformly

across the landscape, independent of their typical structuring forces. Additionally, we use our predicted canopy fuels to create a homogenous load across the landscape. We burn these homogenous assemblages of fuel under 80th, 90th and 97th percentile fire weather for a range of wind scenarios to create the base of expectations for our neutral model. The results of this set of simulation models will then be used to assess the pattern of high intensity fires on real landscapes. We investigate differences in fireline intensity and fire type across these weather and wind scenarios for each of the homogenous surface fuels cases. We are specifically interested in comparing our set of simulations and their predictions of the spatial distribution of high intensity fire with knowledge about the real distributions of known patches of high severity fire across the landscape of Lassen Volcanic National Park.

In chapter 4, we develop and then use historic, contemporary, and model generated evidence regarding the expected and observed locations of high severity fire effects with respect primarily to its topographic setting. Inside the perimeter of LVNP, we map high intensity fire effects from 1941 aerial photographs. To assess current patterns of fire severity patches, remotely sensed maps of fire severity derived from the dNBR methodology will be analyzed in comparison to the model results. We use fire behavior simulation models to generate expected locations of high intensity fire. We compare the topographic characteristics of the historic and contemporary high severity fires with the results of the simulation modeling to assess how observed fire severity is related to topography in real fires *vis-á-vis* the effect of topography on fire intensity in simulated fires.

Works Cited

Agee, J. K. (1993). *Fire Ecology of Pacific Northwest Forests.* Washington, D.C. and Covelo, CA: Island Press. 493p.

Agee, J. K. (1998). The landscape ecology of western forest fire regimes. *Northwest Science* 72: 24-34.

Alexander, J. D., N. E. Seavy, C. J. Ralph and B. Hogoboom (2006). Vegetation and topographical correlates of fire severity from two fires in the Klamath-Siskiyou region of Oregon and California. *International Journal of Wildland Fire* 15: 237-245.

Allen, C. D., M. Savage, D. A. Falk, K. F. Suckling, T. W. Swetnam, T. Schulke, P. B. Stacey, P. Morgan, M. Hoffman, and J. T. Klingel (2002). Ecological restoration of southwestern ponderosa pine ecosystems: a broad perspective. *Ecological Applications* 12(5): 1418-1433.

Bahro, B., K. H. Barber, J. W. Sherlock, and D. A. Yasuda (2006). Stewardship and fireshed assessment: a process for designing a landscape fuel treatment strategy. In Robert F. Power (tech. ed.) *Restoring Fire-Adapted Ecosystems: Proceedings of the 2005 National Silviculture Workshop.* Gen. Tech. Rep. PSW-GTR-203. Albany, CA: United States Department of Agriculture, Forest Service, Pacific Southwest Research Station. 306p.

Baker, W.L. (1992). Effects of settlement and fire suppression on landscape structure. *Ecology* 73(5): 1879-1887.

Beaty, R. M. and A. H. Taylor (2001). Spatial and temporal variation of fire regimes in a mixed conifer landscape, Southern Cascades, California, USA. *Journal of Biogeography* 28: 955-966.

Breiman, L. (2001). Random forests. *Machine Learning* 45: 5-32.

Caswell, H. (1976). Community structure: a neutral model analysis. *Ecological Monographs.* 46(3): 327-354.

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

Collins, B. M. and S. L. Stephens (2010). Stand-replacing patches within a 'mixed severity' fire regime: quantitative characterization using recent fires in a long-established natural fire area. *Landscape Ecology* 25: 927-939

Collins, B.M. and S.L. Stephens (2007). Managing Natural Fires in Sierra Nevada Wilderness Areas. Frontiers in Ecology and the Environment 5(10): 523-52

Fried, J. S., M. S. Torn and E. Mills (2004). The impact of climate change on wildfire severity: a regional forecast for northern California. *Climatic Change* 64: 169-191.

Fulé, P. Z., W. W. Covington, and M. M. Moore (1997). Determining reference conditions for ecosystem management of southwestern ponderosa pine. *Ecological Applications* 7(3): 895-908.

Fulé, P. Z., J. E. Crouse, A.E. Cocke, M. M. Moore, and W. W.Covington (2004). Changes in canopy fuels and potential fire behavior 1880-2040: Grand Canyon, Arizona. *Ecological Modelling* 175: 231-248.

Fulé, P. Z., A.E. M. Waltz, W. W. Covington, and T. A. Heinlein (2001). Measuring forest
restoration effectiveness in reducing hazardous fuels. *Journal of Forestry*. 99(11): 24-29.

Gardner, R. H., B. T. Miller, M. G. Turner, and R. V. O'Neill (1987). Neutral models for the
analysis of broad-scale landscape pattern. *Landscape Ecology* 1(1): 19-28.

Gardner, R. H. and D. L. Urban (2007). Neutral models for testing landscape hypotheses.
Landscape Ecology 22(1): 15-29.

He, H. S. and D. J. Mladenoff (1999). Spatially explicit and stochastic simulation of forest-
landscape fire disturbance and succession. *Ecology* 80(1): 81-99.

Hessburg, P. F., R. B. Salter, and K. M. James (2007). Re-examining fire severity relations in
pre-management era mixed conifer forests: inferences from landscape patterns of forest
structure. *Landscape Ecology* 22: 5-24.

Heyerdahl, E. K., L. B. Brubaker and J. K. Agee (2001). Spatial controls of historical fire
regimes: a multiscale example from the interior west, USA. *Ecology* 82(3): 660-678.

Heyerdahl, E. K., K. P. Lertzman and S. Karpuk (2007). Local-scale controls of a low-severity
fire regime (1750-1950), southern British Columbia, Canada. *Ecoscience* 14(1): 40-47.

Johnson, E. A., K. Miyanishi, and S. R. J. Bridge (2001). Wildfire regime in the boreal forest
and the idea of suppression and fuel buildup. *Conservation Biology* 15(6): 1554-1557.

Kashian, D. M., W.H. Romme, D. B. Tinker, M. G. Turner, and M. G. Ryan (2006). Carbon
storage on landscapes with stand-replacing fires. *BioScience* 56(7): 598-606.

Keane, R. E., G. J. Cary, and R. Parsons (2003). Using simulation to map fire regimes: an

    evaluation of approaches, strategies, and limitations. *International Journal of Wildland*

    Fire 12: 309-322.

Knapp, E. A., and J. E. Keeley (2006). Heterogeneity in fire severity within early season and late

    season prescribed burns in a mixed-conifer forest. *International Journal of Wildland*

    Fire 15: 37-45.

Krawchuk, M. A., M. A. Moritz, M.-A. Parisien, J. Van Dorn, and K. Hayhoe (2009). Global

    pyrogeography: the current and future distribution of wildfire. *PlOS ONE* 4(4): e5102

McKenzie, D., A. E. Hessl, and L.-K. B. Kellogg (2006). Using neutral models to identify

    constraints on low-severity fire regimes. *Landscape Ecology* 21:139-152.

Miller, C. (2007). Simulation of the consequences of different fire regimes to support Wildland

    Fire Use decisions. *Fire Ecology* 3(2): 83-102.

Miller, J. D. and A. E. Thode (2007). Quantifying burn severity in a heterogeneous landscape

    with a relative version of the delta Normalized Burn Ration (dNBR). *Remote Sensing of*

    the Environment 109: 66-80.

Miller, J. D., E. E. Knapp, C. H. Key, C. N. Skinner, C. J. Isbell, R. M. Creasy, and J. W.

    Sherlock (2009a). Calibration and validation of the relative differenced Normalized Burn

    Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath

    Mountains, California, USA. *Remote Sensing of Environment* 113: 645-656.

Miller, J. D., H. D. Safford, M. Crimmins, and A. E. Thode (2009b). Quantitative evidence for increasing forest fire severity in the Sierra Nevada and Southern Cascade Mountains, California and Nevada, USA. *Ecosystems* 12: 16-32.

Nagel, T. A. and A. H. Taylor (2005). Fire and persistence of montane chaparral in mixed conifer forest landscapes in the northern Sierra Nevada, Lake Tahoe Basin, California, USA. *Journal of the Torrey Botanical Society* 132(3): 442-457.

Norman, S. P. and A. H. Taylor (2003). Tropical and north Pacific teleconnections influence fire regimes in pine-dominated forests of north-eastern California, USA. *Journal of Biogeography* 30: 1081-1092.

Odion, D. C., E. J. Frost, J. R. Strittholt, H. Jiang, D. A. Dellasalla and M. A. Moritz (2004). Patterns of fire severity and forest conditions in the western Klamath Mountains, California. *Conservation Biology* 18(4): 927-936.

Odion, D. C., M.A. Moritz, and D. A. DellaSalla (2010). Alternative community states maintained by fire in the Klamath Mountains, USA. *Journal of Ecology* 98: 69-105.

O'Sullivan, D. and D. Unwin (2003). *Geographic Information Analysis*. Hoboken, NJ: John Wiley and Sons, Inc.

Parsons, David J. and Steven H. DeBenedetti (1979). Impact of fire suppression on a mixed-conifer forest. *Forest Ecology and Management* 2:21-33.

Pausas, J. G. (2006). Simulating Mediterranean landscape pattern and vegetation dynamics under different fire regimes. *Plant Ecology* 187: 249-259.

Pierce, A. D. and A. H. Taylor (2011). Fire severity and seed source influence lodgepole pine
(*Pinus contorta* var. *murrayana*) regeneration in the southern Cascades, Lassen Volcanic
National Park, California. *Landscape Ecology* 26(2): 225-237.

Prasad, A. M., L. R. Iverson, and A. Liaw (2006). Newer classification and regression tree
techniques: bagging and random forests for ecological prediction. *Ecosystems* 9: 181-
199.

Pyne, S. J. (2008). *Year of the Fires: The Story of the Great Fires of 1910.* Missoula, MT:
Mountain Press Publishing Company.

Rollins, M. G. and C. K. Frame, tech. eds. (2006). *The LANDFIRE Prototype Project: nationally
consistent and locally relevant geospatial data for wildland fire management*. Gen. Tech.
Rep. RMRS-GTR-175. Fort Collins, CO: U.S. Department of Agriculture, Forest Service,
Rocky Mountain Research Station. 416 p.

Rollins, M. G., P. Morgan, and T. Swetnam (2002). Landscape-scale controls over 20th century
fire occurrences in two large Rocky Mountain (USA) wilderness areas. *Landscape
Ecology* 17: 539-557.

Romme, W. H. (1982). Fire and landscape diversity in subalpine forests of Yellowstone National
Park. *Ecological Monographs* 52(2): 199-221.

Safford, H. D., J. Miller, D. Schmidt, B. Roath, and A. Parsons (2008). BAER soil burn severity
maps do not measure fire effects to vegetation: a comment on Odion and Hanson (2006).
Ecosystems 11: 1-11.

Schoennagel, T., T. T. Veblen, and W.H. Romme (2004). The interaction of fire, fuels, and

    climate across Rocky Mountain Forests. *BioScience* 54(7): 661-676.

Schoennagel, T., T. T. Veblen, W. H. Romme, J. S. Sibold, and E. R. Cook (2007). ENSO and

    PDO variability affect drought-induced fire occurrence in Rocky Mountain subalpine

    forests. *Ecological Applications* 15(6): 2000-2014.

Stephens, S. L., C. N. Skinner, and S. J. Gill (2003). Dendrochronology-based fire history of

    Jeffrey pine-mixed conifer forests in the Sierra San Pedro Martir, Mexico. *Canadian*

    Journal of Forest Research 33: 1090-1101.

Swetnam, T. W. (1993). Fire history and climate change in giant sequoia groves. *Science*

    262(5135): 885-889.

Syphard, A. D., V. C. Radeloff, J. E. Keeley, T. J. Hawbaker, M. K. Clayton, S. I. Stewart and R.

    B. Hammer (2007). Human influence on California fire regimes. *Ecological Applications*

    17(5): 1388-1402.

Syphard, A. D., V. C. Radeloff, N. S. Keuler, R. S. Taylor, T. J. Hawbaker, S. I. Stewart and M.

    K. Clayton (2008). Predicting spatial patterns of fire on a southern California landscape.

    International Journal of Wildland Fire 17: 602-613.

Taylor, A. H. (2000). Fire regimes and forest changes in mid and upper montane forests of the

    southern Cascades, Lassen Volcanic National Park, California, USA. *Journal of*

    Biogeography 27: 87-104.

Taylor, A, H. and R. M. Beaty (2005). Climatic influences on fire regimes in the northern Sierra Nevada mountains, Lake Tahoe Basin, Nevada, USA. *Journal of Biogeography* 32: 425-438.

Taylor, A. H. and C. N. Skinner (1998). Fire history and landscape dynamics in a late-successional reserve, Klamath Mountains, California, USA. *Forest Ecology and Management* 111: 285-301.

Taylor, A. H. and C. N. Skinner (2003). Spatial patterns and controls on historical fire regimes and forest structure in the Klamath mountains. *Ecological Applications* 13(3): 704-719.

Thompson, J. R., T. A. Spies and L. M. Ganio (2007). Reburn severity in managed and unmanaged vegetation in a large wildfire. *Proceedings of the National Academy of Sciences* 104(25): 10743-10748.

Turner, M. G., R. H. Gardner and R. V. O'Neill (2001). *Landscape Ecology in Theory and Practice: Pattern and Process*. New York, NY: Springer Verlag.

Turner, M. G., W. W. Hargrove, R. H. Gardner, and W.H. Romme (1994). Effects of fire on landscape heterogeneity in Yellowstone National Park, Wyoming. *Journal of Vegetation Science* 5: 731-742.

Weatherspoon, C. P. and C. N. Skinner (1995). An assessment of factors associated with damage to tree crowns from the 1987 wildfires in northern California. *Forest Science* 41(3): 430-451.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam (2006). Warming and earlier spring increase western U.S. forest wildfire activity. *Science* 313: 940-943.

Chapter 2:

Use of Random Forest for Modeling and Mapping Forest Canopy Fuels for Fire Behavior

Analysis in Lassen Volcanic National Park, California, USA

Abstract

Fire managers often need data that is spatially explicit at a fine scale (30 m) but is also laborious and time consuming to collect. This study integrates Landsat 5 imagery and topographic information with plot and tree based measures of key canopy fuels variables. We sampled 223 plots of 500 m^2 each in Lassen Volcanic National Park**.** Within each plot we recorded every tree by species, diameter, condition, and canopy position. Additionally, we measured each tree's height, height to live crown base and height to dead crown base. Finally, we took three hemispherical photographs of the forest canopy above each plot. The plot data and the hemispherical photographs were used to compute four critical canopy fuels characteristics: Canopy Bulk Density (CBD), Canopy Cover (CC), Canopy Base Height (CBH), and canopy Height (HT). We developed five topographic variables—elevation, slope, aspect, and two measures of topographic position—and used Landsat 5 spectral bands 1-5, and 7 as well as the Normalized Difference Vegetation Index (NDVI) and the Tasseled Cap Greenness, Brightness, and Wetness to model and then predict these canopy fuels variables for both 2009 and 2003 across LVNP. RF models relating predictor variables to canopy fuels characteristics had pseudo-r^2 values ranging from 0.55 - 0.68. To demonstrate the potential utility of our mapping procedure, we used our 2003 canopy fuels map along with a contemporary surface fuels map and the fire behavior modeling program FlamMap® to relate predicted fire behavior of our fuels maps with fire severity from the Monitoring Trends in Burn Severity (MTBS) dataset for the Bluff (2004) fire.

23

Introduction:

At the national level, forest fuels mapping has become an important part of resource managers'
toolbox, especially in the context of both planning fuels treatments and assessing potential fire
behavior. Even with growing recognition of the beneficial effects of fire in forested ecosystems
and the establishment of large, natural fire areas (Collins et al. 2007), fire suppression policies in
the US west over the 20th century have induced wide spread changes in fuel loads (Parsons and
DeBenedetti 1979, Agee 1993) and fire severity (Safford et al. 2008; Miller et al. 2009b).
However, fire suppression induced changes in both fuels and fire behavior and effects are highly
variable, due primarily to heterogeneity in vegetation communities' responses to fire exclusion.
Sub-alpine and boreal forests have likely been affected very little by fuel load changes caused by
fire suppression because of their naturally long fire-return intervals as well as their tendency to
burn at high severity when fire does return (Schoennagel et al. 2004; Johnson et al. 2001). Low
elevation semi-arid ponderosa pine forests that once burned frequently, on the other hand, likely
have been greatly impacted by fuel build up due to fire suppression (Schoennagel et al. 2004;
Fulé et al. 2001). Furthermore, some mixed-conifer forests of the montane zone have mixed fire
regimes where fire occurrence is predominantly controlled by interannual climate variations
(Schoennagel et al. 2004; Hessburg et al. 2007).

At the landscape level, fuels mapping is directed towards displaying variation in fuel loads that
have potential to influence fire behavior under specific weather conditions and in support of
specific management objectives. Recent efforts directed at Stewardship and Fireshed
Assessment (SFA) are fuels-data intensive, necessitating highly accurate fuel maps This
program enables many stakeholders (Federal, State, County and private) to work together to
develop comprehensive fire and fuels management plans in recognition of the potential for

widespread, intense fire that threatens both natural resources and human infrastructure (Bahro et al. 2006). Canopy fuel characteristics in particular are needed to accurately assess potential fire behavior at this level because they largely determine the potential for fires to transition from surface or ground fires to torching or crown fires and because small changes can have large impacts on potential fire behavior (Fulé et al. 2001). Canopy fuels maps have been developed at a national scale and are appropriate for national or regional long term fire management plans (Rollins and Frame 2006), but the maps and data are insufficient to evaluate potential fire behavior and specific management objectives in particular landscapes, especially at the National Park or Forest level. A single Park or Forest may contain many vegetation types primarily due to the strong co-variation with topography (elevation, slope, and aspect). Thus, approaches are needed to capture within Park heterogeneity in support of sound fire management at the Park or Forest level (e.g. Krasnow et al. 2009),

Critical canopy fuel parameters needed to estimate potential fire behavior are Canopy Bulk Density (CBD), Canopy Cover (CC), Canopy Base Height (CBH), and Canopy Height (HT). This suite of variables determines if forest canopy characteristics could sustain a crown fire. CBD is a measure of the total amount of above-ground-surface fuel that is available to wildfires; typically including foliage and up to one half of the smallest branchwood (0-6.4 mm). CBD is measured in units of kg m^{-3}. CC is the horizontal fraction of the ground covered by the forest canopy and is measured as a percentage of total area. CBH is a measure of the vertical continuity of fuels and expresses the lowest point of the crown above the forest floor and is measured in m. Lower CBH values indicate that canopy fuel is closer to the ground and hence could act to transition surface fire into the crown. Finally, HT is the average height of the dominant stratum of tree cover and affects modeled fuel moistures and is measured in m.

Random Forests (RF; Breiman 2001) offer a particularly powerful new approach for classification and regression of ecological data that in turn can be readily applied to generating maps of ecological attributes (Prasad et al. 2006; Cutler et al. 2007). RF is an extension of the Classification and Regression Tree (CART; De'ath and Fabricius 2000) methodology. RF algorithms generally outperform CART methods at both classification (Cutler et al. 2007) and regression (Prasad et al. 2006). These methodologies have the additional advantage that they are robust to missing data, non-normal data, and data with many zeroes. While CART has been used to map forest canopy fuels at the national level (Rollins and Frame 2006) and at the local level (Poulos et al. 2007), RF have not yet been applied to the mapping of forest canopy fuels. RF has, however, been applied to predict plot level forest basal area and density using LiDAR (Hudak et al. 2008), identify landcover classes using airborne hyperspectral data from Probe-1 (Lawrence et al. 2006), and to identify landcover classes using AVIRIS and EO-1 data (Ham et al. 2005).

This study quantifies plot level canopy fuel loads and predicts canopy fuels characteristic across the entirety of Lassen Volcanic National Park (LVNP), California, USA using RF regression, Landsat data and topographic characteristics as predictor variables. Our research is focused on 1) quantifying surface and canopy fuel loads across LVNP and identifying how they vary according to topography and vegetation type; 2) comparing our assessment of canopy fuels with other datasets on canopy fuels; 3) using our maps of canopy fuels to predict fire behavior and comparing our predictions with observed fire severity within the perimeter of a 1382 ha Wildfire Use fire that burned in 2004 (Bluff Fire).

Methods

Study Area

LVNP lies at the southern end of the Cascade Range, a volcanic plateau punctuated by high

volcanic peaks (Figure 2-1). Elevation ranges from 1,609 to 3,187 m and the Park's total area is

42,900 ha. Dominant vegetation communities covary with elevation (Taylor 1990, 2000; Parker

1991; Schoenherr 1992). The lowest elevation forests are dominated by ponderosa pine (*Pinus*

ponderosa) and Jeffery pine (*P. jeffreyi*). Mixed conifer forests of Jeffrey pine (*P. jeffreyi*) and

white fir (*Abies concolor*) dominate the lower montane forests. Upper montane forests are

composed of red fir (*A. magnifica* var. *magnifica*), white fir (*A. concolor*), and western white

pine (*P. monticola*). Lodgepole pine (*P. contorta* spp. *murrayana*) occupies low lying

depressions where cold air drainage is a dominant part of the regeneration climate. High

elevation forests are dominated by mountain hemlock (*Tsuga mertensiana*) and whitebark pine

(*Pinus albicaulis*). The climate is Mediterranean and is characterized by hot, dry summers and

cold, wet winters. Average monthly temperatures at Manzanita Lake, California (in LVNP,

elevation 1802 m), range from -6.6 °C minimum and 5.0 °C maximum in January to 7.5 °C and

26.1 °C in July (WRCC 2009). Annual average precipitation is 104 cm, but inter-annual

variability is high. Most precipitation (>80%) falls as snow between November and April and

annual maximum snowpack depth from the Lower Lassen Peak Snow Course (usually in April or

May) ranges from 1.63 to 8.41 m with an average of 4.63 m (NOHRSC 2010).

Field Data Collection

To quantify canopy fuel characteristics field sampling was conducted in Lassen Volcanic

National Park in the summer of 2009 and 2010. We selected 223 plots from a set of 340 surface

fuel sampling plots established in 1998-99 (C. Farris, 2009, personal communication) by grouping plots by their dominant species and then proportionally sampling from each group (Table 2-1). The plots in the larger set were located to map surface fuels during the summers of 1998 and 1999 by clustering NDVI values from Landsat imagery using ISODATA, an unsupervised distance to mean algorithm (ERDAS 1997). The clusters produced by ISODATA were used to assign initial surface fuel models (Anderson 1982). Field plots were used to support the surface fuels mapping. Detailed fuels information was collected at these plots including surface quantity fuel loading using Brown's planar intercept method (Brown 1973), overstory, understory, and shrub species composition, surface and litter fuel characteristics, canopy and understory height, and photographs for comparison with fuel load photoseries (e.g Blonski and Schramel 1981). The center of each plot was permanently marked with a steel stake. Additional plots were located in ambiguous or highly heterogeneous spectral clusters and stratified based on topographic and compositional characteristics to assign final fuel models. Once the final surface fuels map was created, 122 accuracy assessment plots were laid out and visited to ensure validity of the mapping process (C. Farris, unpublished report).

At each of the 223 plots we established a 500 m^2 circular plot centered on the permanent stake. We re-recorded the plot's geographic position using a GPS and also measured its slope, elevation, aspect, topographic position, and topographic configuration. Topographic position was recorded in one of five categories: ridge top, upper slope, middle slope, lower slope, or valley bottom. Topographic configuration was also recorded in one of five categories: convex, convex-straight, straight, concave-straight, or concave. For each tree (> 5 cm diameter at breast height [DBH]) we measured DBH (cm), height (m), status (live or dead), and visually estimated live crown fraction to the nearest 5%. We rated each tree's relative crown position using the

following categories and criteria: Suppressed— <25% of main canopy height; Intermediate—
>25% but < 75% of main canopy height; Co-dominant—part of the main canopy, but receiving
top shading from other canopy trees; Dominant—part of the main canopy and only receiving
side-shading from other trees; Emergent—trees with crowns above the main canopy that are not
receiving significant side-shading from any trees. We recorded the Height to Live (Dead) Crown
Base as the height above the ground of the lowest live (dead) limb longer than 60 cm (Fulé et al.
2001; Skinner 2005). To aid in determining canopy fuels characteristics, we took three upward
facing hemispherical photographs per plot with a digital camera mounted with a full hemispheric
lens and leveled with a bubble level at 2 m above the ground. We estimated dead woody fuels in
1-hr (0.0 – 0.64 cm diameter), 10-hr (0.64 – 2.54 cm), 100-hr (2.54 – 7.62 cm), 1000-hr (7.62 –
22.86 cm) classes as well as total load using photo series interpretations and recorded our
observations in tons per acre (t/ac) which were later converted to metric tons per hectare (t/ha).

Plot Analysis

We characterized stand structure in each plot by computing each species' density and basal area
on a per hectare basis. We also computed species relative Importance Values (IV) for basal area
and density (maximum 200) (Taylor 2000). To facilitate comparison among plots we first
grouped and set aside grass and shrub dominated plots. Then we grouped the remaining forested
plots according to the species with the highest IV. Each group was denoted by its dominant
species.

Canopy fuels characteristics (CBD, CC, CBH, and HT) values were estimated from the data
gathered on individual trees and from the hemispherical photographs. We computed gap fraction
and CC from 669 hemispherical photographs (3 per plot) using GLA software (Frazer et al.

1999). GLA software computes gap fraction as the percent of open sky as seen from beneath

the forest canopy (Frazer et al. 1999). Gap fraction was then transformed to CBD using the

methods described in Keane et al. (2005, eq. 5). To calculate CBH, we combined each plots'

values of Height to Live Crown Base and Height to Dead Crown Base. Because low CBH are

most important for the transition to crown fire, we used the 1st quartile CBH as the estimate for

each plot (Fulé et al. 2001; Skinner 2005). To compute HT, we averaged the heights of the live

trees in the canopy in each plot (typically the Co-dominant and Dominant trees, but also

Emergent trees if they were present).

We quantified the effect of vegetation type, elevation, slope, and aspect on both surface and

canopy fuel parameters. We used the same nine vegetation types for the fuels analysis that we

used in the stand structure descriptions. We created five categories for each topographic

variable. Elevation classes were 1600-1800 m, 1800-2000 m, 2000-2200 m, 2200-2400 m, and

2400+ m. Aspect classes were North (315° - 45°), East (45° - 135°), South (135° - 225°), West

(225° - 315°), and Flat. Slope classes were 0°- 3°, 3°- 8°, 8°- 15°, 15° - 25°, and 25°+. For each

class we computed means, standard errors, and ranges. We used ANOVA to test for the effect of

each topographic variable on the mean of each fuels variable by class.

Random Forest Modeling and Fuels Upscaling

To scale data from the plot to the landscape level, we developed a dataset consisting of the point

locations of the 223 plots plus 29 additional points representing barren and water areas (n = 252

total points). The 29 additional plots were selected based on the proportion of area in LVNP

covered by barren (9.7% n = 25 plots) or water areas (1.8%, n = 4). These 29 additional points

were initialized with zero values for each of the canopy fuels characteristics. We refer to this as the Full Dataset.

To test the efficacy of our canopy fuels mapping procedure, we also sought to build a model of canopy fuels for the pre-fire conditions of the 2004 Bluff fire and then use these predicted fuels to simulate fire behavior. To this end, we reduced the dataset of 223 field plots by removing 39 plots that fell within areas burned since 2003. To compensate on a proportional basis, we also removed 1 barren plot and 1 water plot, each selected at random. The final dataset for 2003 predictive fuels mapping totaled 211 points. We refer to this as the Reduced Dataset.

Because vegetation structure and composition in LVNP co-varies strongly with topographic variables including elevation, slope aspect, and potential soil moisture (Taylor 1990, 2000; Parker 1991) we derived a set of topographic variables related to vegetation type from a 30 m x 30 m resolution digital elevation model (USGS 2010). The National Elevation dataset for LVNP was used to obtain elevation, slope, aspect, and two measures of topographic position for each pixel in the park. These two measures of topographic position—Topo_Pos_150 and Topo_Pos_450—are the difference between the focal pixel's elevation with the average elevation of pixels within 150 m and 450 m respectively (Poulos et al. 2007; Poulos 2009).

To facilitate the scaling of plot level data to the landscape level, we used Landsat 5 imagery of LVNP for July 10, 2009 and August 11, 2003. The raw Landsat scenes were converted to at-satellite reflectances for 6 bands (1-5 and 7). These reflectances were then used to compute the Normalized Differenced Vegetation Index (NDVI) and the Tasseled Cap transformations for Greenness, Brightness, and Wetness (Kauth and Thomas 1976). We used NDVI as a general measure of the amount of vegetation in each pixel while the Tasseled Cap transformations

provide information to separate forest from both other vegetation types and from barren or water areas. All resulting rasters were exported for analysis in ArcGIS® (ESRI 2010). Satellite imagery was processed using ENVI® (ITT 2010).

Each of the points in the Full and Reduced Datasets were intersected with the rasters representing topographic position, slope, aspect, elevation and the remotely sensed reflectance values and derived vegetation indices in ArcGIS (ESRI 2010). This yielded two datasets with 25 explanatory variables (independent variables) for each of the four canopy fuels variables (dependent variables). Both of the datasets contained at-satellite reflectances for bands 1-5 and band 7, NDVI, and Tasseled Cap Brightness, Greenness, and Wetness for July 10, 2009 and August 11, 2003 for a total of 20 remotely sensed variables in each.

We used a Random Forest algorithm in R (Breimen 2001; Liaw and Wiener 2002; R Development Core Team 2010) to model and the scale up the plot level estimates of each canopy fuel variable to the entire landscape. This resulted in four RF models and four predicted maps for each of the two time periods. We developed the predicted maps in three steps. First we used the Full Dataset and the Landsat derived variables from 2009 to model and predictively map canopy fuels characteristics for 2009. Second, we used the Reduced Dataset and the Landsat derived variables from 2003 to model and predict 2009 canopy fuels characteristics. Finally we used the model developed from the Reduced Dataset to predictively map 2003 canopy fuels by applying it to all 15 of the potential explanatory variables across the entirety of our study area on a pixel by pixel basis within the randomForest R package (Liaw and Weiner 2002). In every case, the RF algorithm was run to iteratively grow 4,000 trees with 5 of the 15 explanatory variables randomly selected at each node as potential variables to base the split on. A large number of trees is recommended when using RF algorithms to stabilize the Mean

Squared Error (MSE) over many iterations. We used the pseudo-r^2 and the MSE statistic to evaluate model performance. The pseudo-r^2 statistic is calculated as:

$$1 - \frac{\text{MSE}}{\text{var(y)}}$$

The pseudo-r^2 statistic is calculated identically to the r^2 statistic for standard linear regression, and is called pseudo because the predicted values used to calculate the MSE come from the random forest, and not from a linear regression (Liaw and Wiener 2002).

To identify the relative strength of each predictor variable on each of the response variables, we used importance plots. Importance plots assess the strength of each variable by reporting the percentage increase in the model's MSE if that predictor variable's values are randomized across the sample. We compared each model's output using Pearson product-moment correlations.

We compared the results of our canopy fuels mapping with two independent datasets to assess the accuracy of our RF model of 2009 canopy fuels. First we retrieved landscape scale maps of all four canopy fuels variables (CBD, CC, CBH, and HT) available from the LANDFIRE online database (Rollins and Frame 2006). We also created plot level estimates of CBD and CBH from the Fire and Fuels Extension of the Forest Vegetation Simulator (FFE-FVS; Reinhardt and Crookston 2003). We compared each canopy fuel variables' calculated values, predicted 2009 values, and predicted 2003 values with the LANDFIRE value and the value derived from FFE-FVS at the plot level using Pearson's product moment correlations.

Fire Models and Comparisons with the Bluff (2004) Fire

To test the effectiveness of our modeling approach, we modeled fire behavior inside the perimeter of the 2004 Bluff fire. We used FlamMap® to create an expected fire behavior

pattern. FlamMap was initialized with the same elevation, slope, and aspect information used in

the RF models as well as our predicted maps of 2003 values of CBD, CC, CBH, and HT, and the

2000 surface fuels map. We used Fire Family Plus® to derive fire weather parameters (1-hr, 10-

hr, 100-hr, live herbaceous, and live woody fuel moistures) as well as dominant wind speeds and

directions for the summer of 2004 at the 80th, 90th, and 97th percentiles. We used WindNinja® to

translate wind speeds and directions into gridded wind vectors that take into account topography.

We ran FlamMap® using the gridded winds and under the 80th, 90th, and 97th fuel-moisture

scenarios. Our outputs were fireline intensity (kW/m) and fire type index (0-no fire; 1-surface

fire; 2-torching fire; 3-crown fire). We averaged fireline intensity over the twelve runs. We

compared our modeling results with Relative difference Normalized Burn Ratio (NBR, RdNBR)

classed and unclassed data downloaded from the Monitoring Trends in Burn Severity

(Eidenshink et al. 2007) project. The MTBS program uses a spectral processing algorithm on

Landsat spectral data to assess the severity of wildfires and is presented as the difference

between pre- and post-fire NBR and then normalized by the pre-fire NBR. RdNBR ranges from

roughly -4000 to 4000 with the bulk of analyzed pixel lying between -250 to 2000 (Miller and

Thode 2007). MTBS also classifies RdNBR images into fire severity categories: 1-Unburned to

Low; 2-Low; 3-Moderate; 4-High; 5-Increased Greenness; 6-Cloud/Water mask. Category 5

represents pixels whose RdNBR value is negative, which indicates that the pixel was not only

unburned, but that the post-fire pixel was also more green than in the pre-fire image. To

compare our modeled fire type categories, we kept the three classes from FlamMap; we also

combined MTBS categories 1 and 2 and denoted it a "surface" fire category, we denoted MTBS

category 3 as a "torching" fire category, and we denoted MTBS category 4 as a "crown" fire

category. While MTBS does not strictly map fire types, our categorization is based on a

comparison of the Composite Burn Index (CBI; Miller et al. 2009a) with the expected effects of

surface, torching, and crown fire predictions of FlamMap. We used a RF approach to explain

RdNBR values using our 5 derived topographic variables as well as 2003 predictions of CBD,

CC, CBH, and HT, surface fuel model, and modeled average fireline intensity.

Results and Discussion

We quantified stand structure for each plot by computing each species' basal area (Table 2-2)

and density (Table 2-3) on a per hectare basis for each plot. We identified 9 vegetation

groupings according to computed IVs. Seven of these types are forested types, one is a chaparral

type and one is a meadow type. Each is denoted by the dominant species. The vegetation types

are: ARNE-ARPA (*Arctostaphylos nevadensis – A. patula*); Mixed-Other (catch all for

Calocedrus decurrens—Pseudotsuga menziesii—Pinus lambertiana dominated plots); Grass;

PIJE/PIPO (*P. jeffreyi—P. ponderosa*); PICO (*P. latifolia* var. *murrayana*); TSME (*Tsuga

mertensiana*); ABMA (*Abies magnifica*); ABCO (*A. concolor*); and PIMO (*P. monticola*).

Landscape Scale Variation in Fuels

We tested the effect of vegetation type, elevation, slope, and aspect on plot level surface and

canopy fuel parameters using ANOVA. Of the four categorical variables, vegetation type had

the strongest effect on the largest number of fuel-model parameters (Table 2-4). The Grass

vegetation type had the lowest fuel loads in all categories. The ABCO vegetation type had the

highest surface fuel loads for all categories except 1000-hr fuels, where the ARNE-ARPA

vegetation type had the highest load and ABCO had the second highest load. In addition,

ABMA had high fuel loads across all categories. Both the ABCO and AMBA vegetation types

are extensive throughout LVNP and occupy cooler and wetter sites which simultaneously

35

increases moisture availability and decreases decomposition rates. The high elevation TSME and PIMO vegetation types had lower fuel loads because, in these forest types, cold, high elevation environments limit primary biomass production. CBH was highest in PIJE/PIPO forests. CBD and CC were highest and CBH lowest in ABCO forests. The combination of high surface fuel loads, high CBD and low CBH in the ABCO vegetation type describes a fuel complex that is susceptible to intense and potentially severe fire. Fir forests in other parts of the west are also known to have higher fuels loads than other forest types under similar environmental conditions (van Wagtendonk et al. 1998).

Of the three topographic variables, aspect had the strongest effects on the most number of fuel model parameters (Table 2-5). Flat aspects, where the Grass vegetation type dominates, had the lowest coarse woody fuel loads. 1-, 10-, 100-, and 1000- hr fuels were the lowest on less productive south facing aspects. This is due to primarily to two factors. First, south facing slopes are less productive and more likely to burn and these two conditions interact to maintain low levels of coarse woody debris (Rollins et al. 2002). Secondly, the ARNE-ARPA vegetation type has a generally low 1-, 10-, and 100-hr fuel load (Blonski and Schramel 1981). Fuel loads were generally highest on west and north slopes where moisture stress is reduced. These aspects support higher primary productivity, and therefore more coarse woody fuels production.

Elevation had a small effect on a few of the fuel model components. Fuels were generally highest at middle (1800-2000 m and 2000-2200 m) elevations and lowest at the highest (2400+ m) elevation (Table 2-6). Though this pattern holds across most of the fuel model characteristics examined here, only 10-hr, 1000-hr and Dead Woody Total fuel loads were significantly different between elevation classes. This general pattern of fuel loads has been noted in other parts of the Sierra Nevada (van Wagtendonk et al. 1998).

Slope angle had the smallest effect on measured fuels parameters. Only CBD varied significantly between slope angle classes, and was highest on intermediate (15°-25°) slopes (Table 2-7).

Canopy Fuels

Canopy Fuels Quantification, Modeling, and Mapping

We computed four critical canopy fuels parameters (CBD, CBH, CC, and HT) from the field plot data described above and scaled our estimates up to the landscape level using RF regression and prediction. Each were quantified from some combination of the plot level data and the data derived from the hemispherical photographs and are summarized here (Table 2-8). We built two models of each computed canopy fuels parameter; one using the Full Dataset, the topographic variables and the 2009 spectral data, and one using the Reduced Dataset, the topographic variables and the 2003 spectral data. The results of the RF algorithm were consistently strong for CBD, CC, and HT, but weak for CBH (Table 2-9). Overall, topographic variables were largely unimportant in modeling and mapping the 2009 or 2003 canopy fuels parameters but vegetation indices and several at-satellite Landsat spectral bands were important (Figure 2-2, 2-3). NDVI, an important vegetation index for many types of landscape-scale and larger studies, was the most important predictor for most canopy fuel variables in both the Full and Reduced datasets case. NDVI is generally well correlated with within-pixel canopy coverage and density (Pettorelli et al. 2005). Hence, its importance as a variable- is not surprising. NDVI is also known to be a significant predictor of canopy fuels characteristics in the northern Rockies (Rollins et al. 2004). Tasseled Cap transformations were also important predictor variables for each of the canopy characteristics, but were particularly important for CC and CBD. The Brightness transformation

is useful for distinguishing bare soil area from vegetated pixels which is perhaps why it is important in predicting CC. The Greenness transformation increases as canopy cover and green vegetation increase and can be useful in distinguishing forest from other vegetation. The last transformation, Wetness, contrasts sharply with Brightness (Kauth and Thomas 1976). These transformations have be used previously to map landscape-scale fuel patterns (Poulos et al. 2007), but have not, to our knowledge, been applied to RF mapping of fuels in the Pacific northwest. The at-satellite reflectances of the infrared bands were generally more important than the visible bands in predicting canopy fuels. Bands 4 and 5 were almost always the most important of the spectral bands. Band 4 detects near-infrared wavelengths and is able to detect the difference between water and vegetated land. Band 5 is highly sensitive to moisture and is useful for assessing vegetation vigor (Avery and Berlin 1992) A subset of LVNP with maps of each of the four canopy fuels variables as well as a comparison to aerial imagery shows strong correspondence with CBD, CC, and HT as well as weak correspondence with CBH (Figure 2-4).

There was little difference between our two RF models. We used the measured values from 2009 as our dependent variables in the model building stage of our analysis, but built models using either the 2009 or the 2003 spectral data. When predicting the 2009 values from the 2003 spectral data, the results were similar to the values predicted using the 2009 spectral data.

Comparison of Models for 2009 and 2003 Canopy Fuels

We compared our predicted values for CBD, CC, CBH, and HT for the models built using 2009 spectral data and 2003 spectral data using Pearson's Product-Moment correlation test in order to show that predicting canopy fuels at some point in the recent past is a viable way to examine observed fire severity patterns. Regardless of the time period of Landsat data that we used to

predict 2009 canopy fuels, our measured and modeled values were always highly correlated (Table 2-10). Furthermore, our measured and predicted values were highly correlated with the FFE-FVS predictions for both CBD ($r^2 = 0.57$, $P < 0.001$, $n = 252$) and CBH ($r^2 = 0.64$, $P < 0.001$, $n = 252$). Our empirical methods for both CBD and CBH differ fundamentally from the biologically based allometric approach taken by FFE-FVS. FFE-FVS calculates CBD based on allometric equations for foliage and branchwood weight for each species and further calculates CBH as the threshold height above which there is sufficient canopy fuel for crown fire to be sustained (Reinhardt and Crookston 2003). This differs from our empirical approach based on hemispherical photographs and *in situ* measurements of limb height. That these two approaches agree so strongly is perhaps testament to both the 'correctness' of either method, and to the fact that Sierra Nevada forests are well studied. The data from the LANDFIRE database was the most poorly correlated to the four canopy fuels characteristics data. The LANDFIRE project is a national level mapping project that relies on breadth to supply the entire nation with baseline fuels inputs (Rollins and Frame 2006). LANDFIRE used a very similar biophysical modeling approach to our approach, but employed Classification and Regression Trees (CART) in its implementation. RF have been shown to outperform CART in both classification and regression (Cutler et al. 2007; Prasad et al. 2006). Furthermore, our data and model come from and are applied to a smaller area; this allows us to have a much higher sampling density for the landscape of interest. While LANDFIRE is mapping the entirety of the Cascade range with one model, our more focused approach allows us to capture more of the within park heterogeneity in fuels and vegetation.

Canopy Bulk Density

Computed CBD ranged from 0.000 to 0.306 kg m^{-3} (Table 2-8). The method that we used was developed for the northern Rocky Mountains using several of the same species that are present in LVNP. Our estimates of CBD were comparable to other estimates. In dry ponderosa-pine systems of northern Arizona, Fulé et al. (2004) predicted maximum values of 0.26 kg m^{-3}. In the northern Rocky Mountains, Keane et al. (2005) described stands of with a maximum CBD of nearly 0.30 kg m^{-3} (Keane et al. 2005, Figure 6). Finally, Keane et al. (2000) predicted values of 0.25 kg m^{-3} in the Gila National Forest in New Mexico. Our maximum predicted value of 0.238 kg m^{-3} comes from forests that more closely match those found in the northern Rocky Mountain (Keane et al. 2005). The Arizona (Fulé et al. 2004) and New Mexico (Keane et al. 2000) estimates are from forests that experience more moisture stress than ours, and are consequently less productive.

FFE-FVS derived estimates of CBD were highly correlated with our computed CBD estimates (Table 2-10) even though the two algorithms use a fundamentally different approach. The FFE-FVS method uses allometric equations based on tree species, diameter and height to compute foliage and branchwood weight while the Keane et al. (2005) method is based on observable canopy gaps and hemispherical photography. We find that the Keane et al. (2005) method is the simplest to apply at the landscape scale because of the rapidity with which data can be gathered. Also, this approach is more directly comparable to a remotely sensed approach because it relates incoming visible light with CBD. Perhaps the best comparison is this: the hemispherical photograph is capturing the degree to which a sensor like Landsat will observe an area as being bare or occluded by canopy, and thus Landsat bands and derived vegetation indices will be able to describe the forest canopy in that area accurately. On the other hand the FFE-FVS method,

while biologically the most accurate, is not based in any part on either incoming or reflected radiation.

Canopy Cover

Computed values of Canopy Cover (CC) ranged from 0 to 87.8% (Table 2-8). Our RF model achieved the best results with this variable with a pseudo-r^2 of 0.663 and an MSE of 189.9. Furthermore, the model replicated the range of CC values across the landscape, and correctly identified barren and water areas as having no CC. Our CC values were also highly correlated (r^2 = 0.698, P < 0.001, n = 252) with the values from the LANDFIRE database (Rollins and Frame 2006). This is expected because of the use of Landsat data and a similar predictive method by both our study (RF) and by the LANDFIRE study (CART).

Canopy Height

The distributions of measured canopy heights across the landscape were wide: from 0.0 m to 42.3 m; however, more than 50% of plots were between 20 m and 30 m tall (113 of 223 plots). Our predicted values ranged from 0.0 to 31.8 m with a pseudo-r^2 of 0.59 an MSE of 39.25 (Tables 2-8 and 2-9). Predicting canopy height from satellite data can be difficult (Hyyppä et al. 2000). However, using only Landsat and Landsat derived spectral characteristics along with topographic information gave us a RF model that outperforms other types of models including neural networks (Hyyppä et al. 2000). Additionally, while LiDAR has the potential to increase the accuracy of canopy height estimation (Hudak et al. 2002) LiDAR data were unavailable for our study area and are often expensive to obtain on a per-project basis.

<u>Canopy Base Height</u>

CBH values ranged from 0 to 11.9 m with a mean of 0.7 m. The data is extremely skewed to the right, and the mode is 0. Our models faithfully reproduced the mean and minimum of the dataset, but were unable to capture the high end of the range (Table 2-9). High values of CBH will limit the chance for surface fire to transition to torching or crown fire, and under-predicting CBH values may lead to an over-prediction of torching or crowning behavior.

Mapping CBH across the landscape was challenging. The model results were poor (Table 2-9), but our estimates were highly correlated with the FFE-FVS estimates of CBH (Table 2-10). Our empirical method differs fundamentally from the allometric equation based method implemented by both FFE-FVS and the LANDFIRE database (Rollins and Frame 2006). Also, our method of using topographic and remotely sensed spectral data is not well suited to mapping a variable like CBH because it is inherently hidden by forest canopies. CBH in general, even with measurements can be a challenging variable to predict or map (Fulé et al. 2004).

Modeled and Observed Fire Behavior and Severity for the Bluff Fire

We used our derived canopy fuels layers for 2003 (CBD, CC, CBH, and HT) along with a contemporary surface fuels map to model fireline intensity and fire type inside the perimeter of the Bluff 2004 fire. Fireline intensity varied over 5 orders of magnitude (Figure 2-5) and visually did not seem to match the RdNBR data downloaded from the MTBS website. FlamMap predicted 72% of pixels to burn with a surface fire while the categories 1 and 2 of the MTBS severity categorization combined for 83% of pixels (Table 2-11; Figure 2-6). FlamMap predicted the remaining 28% of the area to burn with torching behavior, with a negligible amount of crown fire. MTBS rated 13.7% of the pixels as intermediate severity and 2.8% as high

severity. The Bluff fire generally produced a lower amount of intermediate and high severity effects than other recently analyzed fires in Sierra Nevadan mixed-conifer forests (Collins et al. 2007).

It is important to differentiate between predicted behavior and assessed severity. Depending on the scale of torching, effects may be severe or intermediate. FlamMap does not differentiate between the torching of a single tree—which a program like MTBS would likely classify as 'low' if it picked up the damage at all—and torching of a large patch of trees—which MTBS would likely classify as 'moderate' or 'high'. Furthermore, even though we used raster themes with a resolution of 30 m for FlamMap to match the resolution of the MTBS data, the internal calculations for fire type classification do not take the pixel size into account—they are in a sense point calculations that are in turn assigned to pixels of a given size. Therefore, heterogeneity in measured fire severity patterns may be due to a fine scale variation in fuels that a program like FlamMap—or an approach like ours—is unable to capture.

The similar proportions of fire types predicted by FlamMap and the MTBS severity data is encouraging in the sense that fire modeling programs are able to predict the relative proportions of fire types given accurate fuels maps. Accurate, site specific fuels maps have been used in preference to sources like LANDFIRE in the Colorado Front Range (Krasnow et al. 2009). Here, locally developed fuels maps were shown to increase the accuracy of fire modeling predictions of area burned. What we have shown, is that more accurate fuels information along with fire perimeters are able to predict the relative amounts of different types of fires. While our under-prediction of CBH may have lead to an over-prediction of the proportion of torching fire in the specific case of the Bluff fire, the over-prediction of torching or crowning can be important from a safety standpoint. These are important contributions because fire managers are

43

often focused on ecological or natural resource outcomes when deciding whether or not to initiate prescribed burns or whether or not to allow naturally occurring fires to burn.

Conclusions

Localization of fuels mapping projects is an important part of fire management planning at the National Park and National Forest level, especially in support of specific management actions or fire suppression activities. The Stewardship and Fireshed Assessment program, in particular, is an intensive user of high resolution surface and canopy fuels information. Integrating hemispherical photographs, plot level data, remotely sensed vegetation data, and topographic information with Random Forest models is an effective and efficient way to support canopy fuels mapping at the spatial scale of a single Park or Forest.

Works Cited

Agee, J. K. (1993). *Fire Ecology of Pacific Northwest Forests.* Washington, D.C. and Covelo,
    CA: Island Press. 493p.

Anderson, H. E. (1982). *Aids to determining fuels models for estimating fire behavior.* Gen.
    Tech. Rep. GTR-INT-122. Ogden, UT: United States Department of Agriculture, Forest
    Service, Intermountain Research Station. 28p.

Avery, T. E. and G. L. Berlin (1992). *Fundamentals of Remote Sensing and Air Photo
    Interpretation.* New York, NY: Macmillan. 472 p.

Bahro, B., K. H. Barber, J. W. Sherlock, and D. A. Yasuda (2006). Stewardship and fireshed
    assessment: a process for designing a landscape fuel treatment strategy. In Robert F.
    Powers (tech. ed.) *Restoring Fire-Adapted Ecosystems: Proceedings of the 2005 National
    Silviculture Workshop.* Gen. Tech. Rep. PSW-GTR-203. Albany, CA: United States
    Department of Agriculture, Forest Service, Pacific Southwest Research Station. 306p.

Blonski, K. S. and J. L. Schramel (1981). *Photo Series for Quantifying Natural Forest Residues:
    southern Cascades, northern Sierra Nevada.* Gen. Tech. Rep. GTR-PSW-056. Berkeley,
    CA: United States Department of Agriculture, Forest Service, Pacific Southwest Forest
    and Ranges Experiment Station. 154 p.

Breiman, L. (2001). Random forests. *Machine Learning* 45: 5-32.

Brown, J. K. (1973). A planar intersect method for sampling fuel volume and surface area.
    Forest Science 17: 96-102.

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

Cutler, D. R., T. C. Edwards, Jr., K. H. Beard, A. Cutler, K. T. Hess, J. Gibson, and J. J. Lawler (2007). Random forests for classification in ecology. *Ecology* 88(11): 2783-2792.

De'ath, G. and K. E. Fabricius (2000). Classification and regression trees: a powerful yet simple technique for ecological data analysis. *Ecology* 81(11): 3178-3192.

Eidenshink, J., B. Schwind, K. Brewer, Z.-L. Zhu, B. Quayle, and S. Howard (2007). A project for monitoring trends in burn severity. *Fire Ecology* 3(1): 3-21.

ERDAS® (1997). ERDAS® Field Guide, Field Edition. Atlanta, GA: ERDAS® Inc. 655 p.

ESRI (2010). ArcEditor, Educational Version 9.3.1. Redlands, CA: Environmental Systems Research Institute.

Farris, C. (unpublished report). Preliminary fuels mapping methodology for Lassen Volcanic National Park.

Frazer, G. W., C. D. Canham, and K. P. Lertzmann (1999). Gap Light Analyzer (GLA), Version 2.0: Imaging software to extract canopy structure and gap light transmission indices from true-colour fisheye photographs, users manual and program documentation. Copyright © 1999: Simon Fraser University, Burnaby, British Columbia, and the Institute of Ecosystem Studies, Millbrook, New York.

Fulé, P. Z., J. E. Crouse, A. E. Cocke, M. M. Moore, and W. W.Covington (2004). Changes in canopy fuels and potential fire behavior 1880-2040: Grand Canyon, Arizona. *Ecological Modelling* 175: 231-248.

Fulé, P. Z., A.E. M. Waltz, W. W. Covington, and T. A. Heinlein (2001). Measuring forest

    restoration effectiveness in reducing hazardous fuels. *Journal of Forestry.* 99(11): 24-29.

Ham, J., Y. Chen, M. M. Crawford and J. Ghosh (2005). Investigation of the Random Forest

    framework for classification of hyperspectral data. *IEEE Transactions on Geoscience and*

    Remote Sensing 43(3): 492-501.

Hessburg, P. F., R. B. Salter, and K. M. James (2007). Re-examining fire severity relations in

    pre-management era mixed conifer forests: inferences from landscape patterns of forest

    structure. *Landscape Ecology* 22: 5-24.

Hudak, A. T., N. L. Crookston, J. S. Evans, D. E. Hall and M. J. Falkowski (2008). Nearest

    neighbor imputation of species-level, plot-scale forest structure attributes from LiDAR

    data. *Remote Sensing of Environment* 112: 2232-2245.

Hyyppä, J., H. Hyyppä, M. Inkinen, M. Engdahl, S. Linko, and Y.-H. Zhu (2000). Accuracy

    comparison of various remote sensing data sources in the retrieval of forest stand

    attributes. *Forest Ecology and Management* 128: 109-120.

ITT (2010). ENVI + IDL. Boulder, CO: ITT Visual Information Solutions.

Johnson, E. A., K. Miyanishi, and S. R. J. Bridge (2001). Wildfire regime in the boreal forest

    and the idea of suppression and fuel buildup. *Conservation Biology* 15(6): 1554-1557.

Kauth, R. J., and G. S. Thomas (1976). "The Tasselled Cap – A Graphic Description of the

    Spectral-Temporal Development of Agricultural Crops as Seen by LANDSAT."

    Laboratory for Applications of Remote Sensing Symposia. Paper 159.

    http;//docs.lib.purdue.edu/lars_symp/159. Accessed 4/25/11.

Keane, R.E., S.A. Mincemoyer, K.M. Schmidt, D.G. Long, and J.L. Garner, (2000). *Mapping Vegetation and Fuels for Fire Management on the Gila National Forest Complex, New Mexico*. USDA Forest Service General Technical Report RMRS-GTR-46-CD, Fort Collins.

Keane, R. E., E. D. Reinhardt, J. Scott, K. Gray and J. Reardon (2005). Estimating forest canopy bulk density using six indirect methods. *Canadian Journal of Forest Research* 35: 724-739.

Krasnow, K., T. Schoennagel, and T. T. Veblen (2009). Forest fuel mapping and evaluation of LANDFIRE fuel maps in Boulder County, Colorado, USA. *Forest Ecology and Management* 257: 1603-1612.

Lawrence, R. L., S. D. Wood and R. L. Sheley (2006). Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). *Remote Sensing of Environment* 100: 356-362.

Liaw, A. and M. Wiener (2002). Classification and Regression by randomForest. *R News* (2)3: 18-22.

Miller, J. D., E. E. Knapp, C. H. Key, C. N. Skinner, C. J. Isbell, R. M. Creasy, and J. W. Sherlock (2009a). Calibration and validation of the relative difference Normalized Burn Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA. *Remote Sensing of Environment* 113: 645-656.

Miller, J. D., H. D. Safford, M. Crimmins, and A. E. Thode (2009b). Quantitative evidence for

increasing forest fire severity in the Sierra Nevada and Southern Cascade mountains,

California and Nevada, USA. *Ecosystems* 12: 16-32.

Miller, J. D. and A. E. Thode (2007). Quantifying burn severity in a heterogeneous landscape

with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of

Environment* 109: 66-80.

NOHRSC (2010). National Operational Hydrologic Remote Sensing Center *Snow Data

Assimilation System (SNODAS) data products at NSIDC*. Boulder, CO: National Snow

and Ice Data Center.

Parker, A. J. (1991). Forest/environment relationships in Lassen Volcanic National Park,

California, USA. *Journal of Biogeography* 18: 543-552.

Parsons, D. J. and S. H. DeBenedetti (1979). Impact of fire suppression on a mixed-conifer

forest. *Forest Ecology and Management* 2:21-33.

Pettorelli, N., J. O. Vik, A. Mysterud, J.-M. Gaillard, C. J. Tucker, N. C. Stenseth (2005). Using

the satellite-derived NDVI to assess ecological responses to environmental change.

TRENDS in Ecology and Evolution. 20(9): 503-510.

Poulos, H. M. (2009). Mapping fuels in the Chihuahuan Desert borderlands using remote

sensing, geographic information systems, and biophysical modeling. *Canadian Journal

of Forest Research* 39: 1917-1927.

Poulos, H. M., A. E. Camp, R. G. Gatewood, and L. Loomis (2007). A hierarchical approach for scaling forest inventory and fuels data from local to landscape scales in the Davis Mountains, Texas, USA. *Forest Ecology and Management* 244: 1-15.

Prasad, A. M., L. R. Iverson, and A. Liaw (2006). Newer classification and regression tree techniques: bagging and random forests for ecological prediction. *Ecosystems* 9: 181-199.

R Development Core Team (2010). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Reinhardt, E., and N. L. Crookston, tech. eds. (2003). *The Fire and Fuels Extension to the Forest Vegetation Simulator.* Gen. Tech. Rep. RMRS-GTR-116. Odgen, UT: United States Department of Agriculture, Forest Service, Rocky Mountain Research Station. 209 p.

Rollins, M. G. and C. K. Frame, tech. eds. (2006). *The LANDFIRE Prototype Project: nationally consistent and locally relevant geospatial data for wildland fire management*. Gen. Tech. Rep. RMRS-GTR-175. Fort Collins: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 416 p.

Rollins, M. G., R. E. Keane, and R. A. Parsons (2004). Mapping fuels and fire regimes using remote sensing, ecosystem simulation and gradient modeling. *Ecological Applications* 14(1): 75-95.

Safford, H. D., J. Miller, D. Schmidt, B. Roath, and A. Parsons (2008). BAER soil burn severity maps do not measure fire effects to vegetation: a comment on Odion and Hanson (2006). *Ecosystems* 11: 1-11.

Schoenherr, A. A. (1995). *A Natural History of California.* Berkeley, CA: University of California Press.

Schoennagel, T., T. T. Veblen, and W. H. Romme (2004). The interaction of fire, fuels, and climate across Rocky Mountain Forests. *BioScience* 54(7): 661-676.

Skinner, C. N. (2005). Reintroducing fire into the Blacks Mountain Research Natural Area: effects on fire hazard. in *Proceedings of the Symposium on Ponderosa Pine: Issues, Trends, and Management*. October 18-21, 2004, Klamath Falls, OR. Gen. Tech. Rep. PSW-GTR-198. Berkeley, CA: United States Department of Agriculture, Forest Service, Pacific Southwest Research Station.

Taylor, A. H. (1990). Habitat segregation and regeneration of red fir and mountain hemlock in ecotonal forests of Lassen Volcanic National Park, California. *Physical Geography* 8:35-49.

Taylor, A. H. (2000). Fire regimes and forest changes in mid and upper montane forests of the southern Cascades, Lassen Volcanic National Park, California, USA. *Journal of Biogeography* 27: 87-104.

USGS (2009). "National Elevation Dataset." Washington, D.C.: United States Department of the Interior, Unites States Geological Survey.

van Wagtendonk, J., J. M. Benedict, and W. M. Sydoriak (1998). Fuel bed characteristics of

    Sierra Nevada conifers. *Western Journal of Applied Forestry* 13(3): 73-84.

WRCC—Western Regional Climate Center (2009). Manzanita Lake, California, Period of

    Record. Accessed 12/09 at http://www.wrcc.dri.edu/cgi-bin/cliMAIN.pl?ca5311.

Table 2-1: Distribution of Sampling
Plots by Dominant Species

Dominant Species	Original Plot Set	Subsampled Plot Set
ABCO	86	80
ABMA	68	28
Mixed-Other*	9	12
ARNE-ARPA	21**	8
Grass		9
PICO	64	33
PIMO	19	5
PIPO/PIJE	51	36
TSME	22	12
total***	340	223

Table 2-1: Histogram of number of fuel sampling plots by dominant species. Abbreviations are as follows: ABCO—*Abies concolor;* ABMA—*A. magnifica*; ARNE—*Arctostaphylos nevadensis*; ARPA—*A. patula*; PICO—*Pinus contorta* var. *murrayana*; PIMO—*P. monticola*; PIPO—*P. ponderosa*; PIJE—P. jeffreyi; TSME—*Tsuga mertensiana.* *The mixed-other group contains plots dominated by *Calocedrus decurrens* (CADE), *P. albicaulis* (PIAL), *P. lambertiana* (PILA), and *Pseudotsuga menzesii* (PSME). **This group contains plots dominated by both grasses and shrubs but were not broken out in the original data. For the ANOVA analysis, the ARNE-ARPA plots and the Grass plots were lumped into one category representing 17 plots. ***The distribution of frequencies of dominant species were not statistically different using ANOVA (P = 0.29; df = 1, 14; F = 1.25).

												Grand
Veg. Type	Status	ABCO	ABMA	CADE	PIAL	PICO	PIJE	PILA	PIMO	PIPO	PSME	TSME	Total
ABCO	L	9.77	0.73	0.32		0.28	0.79	0.08	0.12	0.10	0.04	0.03	12.26
n = 80	D	1.71	0.39	0.00		0.10	0.37	0.00	0.00	0.18	0.00	0.00	2.75
ABMA	L	0.46	13.88			0.68	0.61	0.00	0.94			0.35	16.92
n = 28	D	0.03	2.03			0.15	0.01	0.00	0.03			0.07	2.32
Mixed-Other	L	1.76	0.12	5.16		0.34	2.03	2.63		0.55	1.40		13.99
n = 12	D	1.36	0.00	0.07		0.00	0.50	0.43		0.10	0.22		2.68
ARNE-ARPA	L	1.93					0.57		0.67				3.16
n = 7													
Grass	L	0.00				1.95	0.00						1.95
n = 4	D	0.72				0.00	1.79						2.51
PICO	L	0.84	1.02			5.45	0.04	0.06	0.33	0.00		0.00	7.73
n = 33	D	0.24	0.83			1.47	0.00	0.00	0.01	0.00		0.14	2.71
PIMO	L	0.07	1.91			0.68	0.59		4.72			0.04	8.01
n = 5	D	0.00	2.89			0.09	0.00		0.01				2.98
PIPO/PIJE	L	1.17	0.07	0.14		0.45	5.46	0.24	0.09	1.07			8.69
n = 36	D	0.43	0.01	0.01		0.15	1.14	0.02	0.00	0.30			2.06
TSME	L	0.49			0.68							16.45	17.62
n = 12	D	1.07			0.04							2.06	3.17

Table 2-2: Average Basal Area (m^2) of tree species by vegetation type on a per hectare basis. The status column breaks down each vegetation type into the Live (L) and Dead (D) component of each type. Vegetation types are described in the text. Abbreviations in column headings are as in Table 2-1.

Table 2-3: Average Tree Stem Density per Hectare (stems ha^{-1})

Veg. Type	Status	ABCO	ABMA	CADE	PIAL	PICO	PIJE	PILA	PIMO	PIPO	PSME	TSME	Grand Total
ABCO	L	497.25	46.25	5.50		23.75	35.50	1.75	3.00	4.50	1.75		619.25
n = 80	D	95.25	11.75	0.75		4.75	11.00	0.00	0.00	3.00	0.00		126.50
ABMA	L	14.81	497.04			58.52	9.63	1.48	35.56			26.67	643.70
n = 28	D	2.22	61.48			6.67	0.74	0.00	0.74			0.74	72.59
Mixed-Other	L	185.45	9.09	121.82		20.00	58.18	25.45		27.27	27.27		474.55
n = 12	D	27.27	0.00	9.09		0.00	7.27	5.45		12.73	3.64		40.00
ARNE-ARPA	L	142.86					45.71		2.86				191.43
n = 9													
Grass	L	0.00				273.33	0.00						273.33
n = 8	D	33.33				0.00	20.00						53.33
PICO	L	69.09	181.21			384.85	7.27	4.24	20.61	0.00		1.21	668.48
n = 33	D	8.48	22.42			116.97	0.00	1.21	1.82	0.61		1.21	152.73
PIMO	L	28.00	88.00			52.00	16.00		212.00			8.00	404.00
n = 5	D	0.00	80.00			4.00	0.00		4.00			0.00	88.00
PIPO/PIJE	L	71.11	7.78	7.78		43.33	160.56	2.78	7.22	33.33			333.89
n = 36	D	37.22	1.67	0.56		19.44	28.33	1.67	0.00	11.11			100.00
TSME	L	30.00			31.67							421.67	483.33
n = 12	D	10.00			5.00							36.67	51.67

Table 2-3: Average density of tree species by vegetation type on a per hectare basis. The status column breaks down each vegetation type into the Live (L) and Dead (D) component of each type. Vegetation types are described in the text. Four letter species abbreviations are as in Table 2-1.

Table 2-4: Fuel Loads by Vegetation Type

Vegetation Type	1-hr***	10-hr***	100-hr***	1 to 100 hr total***	1000 hr***	Coarse Woody Total***,†	CBD***	CC***	Ht***	CBH***	N
ABCO	1.21 ± 0.09	3.9 ± 0.22	5.16 ± 0.29	10.11 ± 0.47	9.62 ± 0.85	42.15 ± 2.91	0.13 ± 0	57.3 ± 1.8	23.4 ± 0.7	0.47 ± 0.05	80
range	0.18 - 4.48	0.67 - 10.09	0.45 - 12.56	1.57 - 20.63	0 - 33.18	10.76 - 112.77	0.04 - 0.25	10.2 - 87.8	2.4 - 43.9	0 - 1.85	
AMBA	0.87 ± 0.11	3.56 ± 0.4	4.89 ± 0.7	9.33 ± 1.14	5.61 ± 1.43	31.39 ± 4.71	0.11 ± 0.01	48.1 ± 3.3	22.6 ± 1.6	0.77 ± 0.17	28
range	0 - 2.02	0.22 - 8.97	0.22 - 17.04	0.45 - 28.03	0.67 - 35.42	3.36 - 88.56	0.06 - 0.21	0 - 73	0 - 35.7	0 - 3.85	
Mixed-Other	0.81 ± 0.18	2.35 ± 0.47	2.47 ± 0.58	5.63 ± 1.08	5.54 ± 1.19	31.84 ± 8.07	0.12 ± 0.02	55.2 ± 7.2	23.5 ± 2.6	0.69 ± 0.2	12
range	0 - 1.57	0 - 4.71	0 - 6.5	0 - 11.43	0 - 15.25	0 - 84.3	0 - 0.31	0 - 85.8	0 - 32.7	0 - 2.4	
ARNE-ARPA	0.52 ± 0.22	1.97 ± 0.61	1.7 ± 0.81	4.17 ± 1.61	20.27 ± 3.21	66.14 ± 12.33	0.06 ± 0.01	15 ± 4.7	12.3 ± 2.7	0.52 ± 0.26	8
range	0.22 - 2.02	0.9 - 5.61	0.67 - 7.17	1.79 - 14.8	3.36 - 25.11	9.19 - 95.51	0.04 - 0.1	0 - 41.4	0 - 25	0 - 2.28	
Grass	0.09 ± 0.04	0.13 ± 0.07	0.38 ± 0.25	0.58 ± 0.34	1.59 ± 1.23	10.76 ± 8.97	0.04 ± 0.01	7.8 ± 5.1	6.4 ± 2.6	0.02 ± 0.02	9
range	0 - 0.22	0 - 0.45	0 - 2.24	0 - 2.91	0 - 10.99	0 - 81.61	0 - 0.14	0 - 46.9	0 - 17	0 - 0.18	
PICO	0.52 ± 0.07	1.91 ± 0.31	2.91 ± 0.52	5.34 ± 0.83	9.21 ± 1.59	24.89 ± 3.81	0.1 ± 0.01	41.9 ± 3.3	20.3 ± 1	0.54 ± 0.1	33
range	0.11 - 2.02	0 - 6.5	0 - 12.11	0.22 - 19.51	0 - 35.42	0.22 - 74.21	0.03 - 0.17	0 - 71.7	2.5 - 31.6	0 - 2	
PIMO	0.63 ± 0.27	2.74 ± 0.72	2.11 ± 0.63	5.47 ± 1.41	5.07 ± 1.7	23.32 ± 8.52	0.07 ± 0.01	30.1 ± 6.7	20 ± 1.2	0.72 ± 0.25	5
range	0.22 - 1.57	0.9 - 4.71	0.45 - 3.81	1.57 - 8.52	1.57 - 10.54	3.14 - 46.86	0.05 - 0.1	12.7 - 47.1	17.3 - 23.8	0.3 - 1.7	
PIPO/PIJE	0.49 ± 0.09	1.91 ± 0.22	2.24 ± 0.34	4.57 ± 0.56	4.01 ± 0.78	22.42 ± 3.59	0.09 ± 0.01	38.9 ± 2.6	23.2 ± 1.4	1.6 ± 0.42	36
range	0.02 - 2.24	0.22 - 4.71	0.22 - 10.99	0.47 - 16.14	0.22 - 27.58	1.12 - 84.3	0.03 - 0.19	5.4 - 65.2	9.3 - 36.7	0 - 11.9	
TSME	0.47 ± 0.07	0.9 ± 0.13	1.88 ± 0.22	3.25 ± 0.38	2.06 ± 0.18	20.85 ± 3.14	0.11 ± 0.01	37.9 ± 3.3	17.5 ± 1.4	0.58 ± 0.28	12
range	0.22 - 0.67	0.22 - 1.35	0.45 - 2.47	0.9 - 4.48	1.12 - 2.47	6.95 - 31.84	0.05 - 0.17	20.6 - 59.3	12 - 28.2	0 - 3.45	
total	0.81 ± 0.04	2.74 ± 0.13	3.61 ± 0.2	7.11 ± 0.34	7.49 ± 0.52	32.51 ± 1.79	0.11 ± 0	45.6 ± 1.4	21.3 ± 0.5	0.71 ± 0.08	223
range	0 - 4.48	0 - 10.09	0 - 17.04	0 - 28.03	0 - 35.42	0 - 112.77	0 - 0.31	0 - 87.8	0 - 43.9	0 - 11.9	

Table 2-4: Means ± standard errors and ranges for fuel loads in LVNP by vegetation type. Columns 1-hr, 10-hr, 100-hr, 1- to 100-hr total, 1000-hr and Dead Woody Total are in units of t/ha; CBD is in units of kg/m^3; CC is in %; Ht is in m, and CBH is in m. N is the number of plots in each vegetation type. Vegetation types are described in the text. Means were tested for significant differences by ANOVA: *P < 0.05; **P < 0.01; ***P < 0.001. †Dead Woody Total includes fuels larger than 1000-hr (i.e. 22.9 cm in diameter).

Table 2-5: Fuel Loads by Aspect Class

Aspect	1-hr*	10-hr	100-hr*	1 to 100 hr total*	1000 hr*	Dead Woody Total**,†	CBD	CC	Ht	CBH	N
North 315-45	0.78 ± 0.09	2.8 ± 0.29	3.92 ± 0.45	7.51 ± 0.74	8.72 ± 1.1	32.06 ± 3.36	0.11 ± 0.01	46.8 ± 2.7	21.3 ± 1.1	0.65 ± 0.09	62
range	0 - 2.24	0 - 10.09	0 - 17.04	0 - 28.03	0 - 35.42	0 - 112.77	0 - 0.24	0 - 85.05	0 - 43.9	0 - 4.2	
East 45-135	0.85 ± 0.09	3.14 ± 0.29	4.17 ± 0.43	8.09 ± 0.72	8.79 ± 1.19	37.44 ± 3.59	0.11 ± 0.01	45 ± 3	20.4 ± 1.1	0.73 ± 0.16	57
range	0 - 2.24	0 - 10.09	0 - 12.56	0 - 20.4	0 - 35.42	0 - 86.77	0.03 - 0.25	0 - 87.78	0 - 36.7	0 - 7.8	
South 135-225	0.63 ± 0.09	2.22 ± 0.22	2.51 ± 0.27	5.34 ± 0.52	4.35 ± 0.58	22.42 ± 2.91	0.1 ± 0.01	42.7 ± 3	22.5 ± 1.1	1.04 ± 0.31	45
range	0 - 2.24	0 - 5.61	0 - 7.4	0 - 14.8	0 - 15.25	0 - 91.03	0 - 0.17	0 - 72.58	0 - 37.6	0 - 11.9	
West 225-315	1.01 ± 0.11	2.94 ± 0.27	3.92 ± 0.38	7.65 ± 0.65	7.42 ± 1.01	39.01 ± 4.04	0.12 ± 0.01	49.8 ± 2.5	22.2 ± 0.8	0.53 ± 0.09	49
range	0.11 - 4.48	0.22 - 8.52	0.22 - 11.66	0.67 - 19.73	0.45 - 29.37	1.12 - 111.88	0.05 - 0.31	18.15 - 85.82	11.6 - 34.2	0 - 3.5	
Flat	0.49 ± 0.18	1.5 ± 0.61	2.06 ± 0.76	4.08 ± 1.5	6.7 ± 2.98	20.85 ± 8.07	0.08 ± 0.01	33.6 ± 7.8	17.3 ± 3	0.37 ± 0.19	10
range	0 - 2.02	0 - 6.5	0 - 7.62	0 - 16.14	0 - 25.11	0 - 74.21	0 - 0.12	0 - 59.8	0 - 27.2	0 - 2	
Total	0.81 ± 0.04	2.74 ± 0.13	3.61 ± 0.2	7.11 ± 0.34	7.49 ± 0.52	32.51 ± 1.79	0.11 ± 0	45.6 ± 1.4	21.3 ± 0.5	0.71 ± 0.08	223

Table 2-5: Means ± standard errors and ranges for fuel loads in LVNP by aspect classes. Columns 1-hr, 10-hr, 100-hr, 1- to 100-hr total, 1000-hr and Dead Woody Total are in units of t/ha; CBD is in units of kg/m^3; CC is in %; Ht is in m, and CBH is in m. N is the number of plots in each aspect class. Aspects are measured in degrees with 0° at North. Means were tested for significant differences by ANOVA: *$P < 0.05$; **$P < 0.01$. †Dead Woody Total includes fuels larger than 1000-hr (i.e. 22.9 cm in diameter).

Table 2-6: Fuel Loads by Elevation Range

Elevation	1-hr	10-hr*	100-hr	1- to 100-hr total	1000-hr**	Dead Woody Total*[†]	CBD	CC	Ht	CBH	N
1600 – 1800	0.74 ± 0.13	2.2 ± 0.34	2.96 ± 0.47	5.9 ± 0.87	8.59 ± 1.66	30.27 ± 5.16	0.1 ± 0.01	44.8 ± 3.8	20.5 ± 1.7	0.54 ± 0.11	32
range	0 - 2.24	0 - 8.3	0 - 10.09	0 - 20.63	0 - 33.18	0 - 86.77	0 - 0.18	0 - 82.6	0 - 38.5	0 - 2.4	
1800-2000	0.83 ± 0.07	2.89 ± 0.18	3.92 ± 0.27	7.53 ± 0.45	8.47 ± 0.67	37.44 ± 2.47	0.11 ± 0	47.9 ± 2	21.9 ± 0.7	0.81 ± 0.14	119
range	0 - 2.24	0 - 10.09	0 - 12.56	0.22 - 20.4	0 - 29.37	0.22 - 112.77	0.03 - 0.31	0 - 87.8	0 - 43.9	0 - 11.9	
2000-2200	0.9 ± 0.11	3.14 ± 0.34	3.81 ± 0.49	7.85 ± 0.85	6.84 ± 1.21	27.58 ± 3.36	0.1 ± 0.01	44.8 ± 2.5	21.6 ± 1	0.5 ± 0.06	49
range	0 - 4.48	0 - 10.09	0 - 17.04	0 - 28.03	0 - 35.42	0 - 88.56	0 - 0.21	0 - 70.2	0 - 35.7	0 - 1.8	
2200-2400	0.56 ± 0.13	2.24 ± 0.58	2.87 ± 0.67	5.67 ± 1.3	2.11 ± 0.43	18.61 ± 5.38	0.08 ± 0.01	35.1 ± 6.7	20.8 ± 2.8	1.03 ± 0.36	13
range	0 - 2.02	0 - 6.95	0 - 7.17	0 - 15.69	0 - 4.93	0 - 58.74	0 - 0.16	0 - 73	0 - 32.8	0 - 3.85	
2400+	0.54 ± 0.07	1.32 ± 0.4	2.06 ± 0.25	3.92 ± 0.63	2.35 ± 0.2	23.09 ± 3.14	0.11 ± 0.01	38.1 ± 2.8	16.4 ± 1.3	0.57 ± 0.33	10
range	0.22 - 0.9	0.22 - 4.71	0.45 - 2.69	0.9 - 8.3	1.12 - 3.59	7.4 - 31.84	0.06 - 0.17	24.2 - 52.9	12 - 24	0 - 3.45	
Total	0.81 ± 0.04	2.74 ± 0.13	3.61 ± 0.2	7.11 ± 0.34	7.49 ± 0.52	32.51 ± 1.79	0.11 ± 0	45.6 ± 1.4	21.3 ± 0.5	0.71 ± 0.08	223

Table 2-6: Means ± standard errors and ranges for fuel loads in LVNP by elevation range. Columns 1-hr, 10-hr, 100-hr, 1- to 100-hr total, 1000-hr and Dead Woody Total are in units of t/ha; CBD is in units of kg/m^3; CC is in %; Ht is in m, and CBH is in m. N is the number of plots in each elevation range. Elevations are in meters above sea level. Means were tested for significant differences by ANOVA: *$P < 0.05$; **$P < 0.01$. [†]Dead Woody Total includes fuels larger than 1000-hr (i.e. 22.9 cm in diameter).

Table 2-7: Fuel Loads by Slope Class

Slope Angle	1-hr	10-hr	100-hr	1 to 100 hr total	1000 hr	Dead Woody Total[†]	CBD*	CC	Ht	CBH	N
0°-3°	0.58 ± 0.05	2.15 ± 0.18	3.09 ± 0.27	5.74 ± 0.47	9.93 ± 0.96	32.28 ± 2.7	0.08 ± 0.01	34.8 ± 4.7	17.9 ± 1.7	0.41 ± 0.09	25
range	0 - 2.02	0 - 6.5	0 - 12.11	0 - 19.51	0 - 35.42	0 - 91.03	0 - 0.16	0 - 68.2	0 - 30.6	0 - 2	
3°-8°	0.72 ± 0.04	2.67 ± 0.13	3.81 ± 0.21	7.06 ± 0.35	7.2 ± 0.42	35.65 ± 1.9	0.1 ± 0	44.5 ± 2.1	21.8 ± 0.8	0.78 ± 0.16	54
range	0.18 - 2.24	0.22 - 8.97	0.22 - 17.04	0.67 - 28.03	0 - 27.58	1.12 - 112.77	0.05 - 0.19	15.1 - 76	9.3 - 36.7	0 - 7.8	
8°-15°	0.81 ± 0.03	2.76 ± 0.1	3.81 ± 0.15	7.33 ± 0.24	7.47 ± 0.4	33.41 ± 1.2	0.11 ± 0	48 ± 2.3	22.4 ± 0.9	0.85 ± 0.17	84
range	0 - 2.24	0 - 10.09	0 - 12.56	0 - 20.4	0 - 35.42	0 - 88.56	0 - 0.24	0 - 84	0 - 43.9	0 - 11.9	
15°-25°	1.01 ± 0.06	3.03 ± 0.14	3.54 ± 0.17	7.56 ± 0.3	6.75 ± 0.45	28.92 ± 1.5	0.12 ± 0.01	47.4 ± 3.4	21.6 ± 1.1	0.59 ± 0.14	42
range	0.02 - 4.48	0.22 - 8.3	0.22 - 10.09	0.47 - 19.73	0 - 25.11	1.35 - 84.3	0.03 - 0.31	0 - 87.4	0 - 35.7	0 - 5.5	
25°+	0.87 ± 0.07	3.05 ± 0.29	3.05 ± 0.25	6.95 ± 0.57	6.7 ± 0.75	28.03 ± 2.6	0.12 ± 0.01	48.2 ± 6.1	19.3 ± 1.9	0.52 ± 0.19	18
range	0 - 2.24	0 - 10.09	0 - 7.4	0 - 18.16	0 - 29.37	0 - 87.21	0.03 - 0.25	0 - 87.8	0 - 28.5	0 - 3.45	
Total	0.81 ± 0.3	2.74 ± 0.93	3.61 ± 1.33	7.11 ± 2.27	7.49 ± 3.48	32.51 ± 11.9	0.11 ± 0.05	45.6 ± 20.8	21.3 ± 7.8	0.71 ± 1.21	223

Table 2-7: Means ± standard errors and ranges for fuel loads in LVNP by slope classes. Columns 1-hr, 10-hr, 100-hr, 1- to 100-hr total, 1000-hr and Dead Woody Total are in units of t/ha; CBD is in units of kg/m^3; CC is in %; Ht is in m, and CBH is in m. N is the number of plots in each slope class. Slope angles are measured in degrees. Means were tested for significant differences by ANOVA: *$P < 0.05$; **$P < 0.01$. [†]Dead Woody Total includes fuels larger than 1000-hr (i.e. 22.9 cm in diameter).

Table 2-8: Canopy Fuels Summary Statistics				
	CBD (kg m^{-3})	CC (%)	CBH (m)	HT (m)
min	0.0	0.0	0.0	0.0
max	0.306	87.8	11.9	43.9
mean ± s.e.	0.105 ± 0.003	45.6 ± 1.40	0.71 ± 0.08	21.3 ± 0.52
SD	0.178	20.848	1.211	7.815

Table 2-8: Summary statistics of canopy fuels characteristics across all sampled plots computed from the analysis of each plot's digital hemispherical photographs and tree level data. Abbreviations are CBD-Canopy Bulk Density; CC-Canopy Cover; CBH-Canopy Base Height; HT-Canopy Height.

Table 2-9: Random Forest Model Statistics					
Model		CBD	CC	CBH	Ht
Full	pseudo r^2	0.55	0.67	-0.02	0.59
	MSE	0.0014	196.6	1.37	40.9
Reduced	pseudo r^2	0.63	0.68	0.08	0.59
	MSE	0.0012	192.4	0.727	41.9

Table 2-9: Summary of model fit statistics (pseudo-r^2 and mean-squared error [MSE]). Abbreviations are as in Table 2-8.

Table 2-10: Model Comparisons and Comparisons to Other Datasets

CBD	FVS	LANDFIRE	2009 Model	2003 Model
Measured	0.570***	0.359***	0.903***	0.898***
FVS		0.313***	0.576***	0.558***
LANDFIRE			0.459***	0.417***
2009 Model				0.929***
CC				
Measured		0.698***	0.910***	0.910***
LANDFIRE			0.763***	0.733***
2009 Model				0.926***
CBH				
Measured	0.637***	0.059	0.607***	0.659***
FVS		0.056	0.519***	0.432***
LANDFIRE			0.194**	0.193**
2009 Model				0.733***
HT				
Measured		0.441***	0.869***	0.896***
LANDFIRE			0.570***	0.507***
2009 Model				0.936***

Table 2-10: Pearson product-moment correlations between measured canopy fuels characteristics, modeled values for those characteristics, and two other data sources for all field plots plus water or barren ground cover plots. Columns and rows are labeled as follows: Measured: the value of the characteristic from field measurements. FFE-FVS: the value of the characteristic derived from the Fire and Fuels Extension for the Forest Vegetation Simulator (FFE-FVS). LANDFIRE: the value of the characteristic obtained from the LANDFIRE dataset. 2009 Model: the value of the characteristic based on the model built with Landsat data from 2009, and used to predict the characteristic from 2009 values. 2003 Model: the value of the characteristic based on the model built with Landsat data from 2003, and used to predict the characteristic from 2003 values. *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

	MTBS		FlamMap
Table 2-11: Comparisons of Pixel Counts: MTBS and FlamMap			
Unburned to Low	7008	Surface	132576
Low	5735		
Moderate	2084	Torching	51573
High	426	Crown	27

Table 2-11: A comparison of pixel counts between the MTBS fire severity categorization and FlamMap's fire activity index.

Figure 2-1: Map showing the location of Lassen Volcanic National Park in northeastern California, USA.

Canopy Bulk Density 2009

NDVI
TC Greenness
TC Brightness
TM Band 5
TM Band 7
TM Band 4
TC Wetness
TM Band 3
TM Band 2
TM Band 1
TP 150
TP 450
Elevation
Aspect
Slope

0 10 20 30 40 50 60

%IncMSE

Canopy Cover 2009

TC Greenness
NDVI
TC Brightness
TM Band 5
TM Band 4
TC Wetness
TM Band 7
TM Band 2
TM Band 3
TM Band 1
Elevation
TP 150
Slope
TP 450
Aspect

10 20 30 40 50 60

%IncMSE

Canopy Base Height 2009

TC Wetness
TC Brightness
NDVI
TM Band 5
TM Band 1
TM Band 7
TM Band 2
TM Band 3
TC Greenness
Elevation
TM Band 4
Slope
TP 450
TP 150
Aspect

0 5 10 15 20

%IncMSE

Canopy Height 2009

NDVI
TC Greenness
TC Brightness
TM Band 4
TM Band 2
TM Band 5
TM Band 7
TM Band 3
TC Wetness
TM Band 1
TP 450
Elevation
Slope
TP 150
Aspect

0 20 40 60

%IncMSE

Figure 2-2: Variable importance plot showing rank orders of variable importance for all four RF models using the Full Dataset and the spectral data from 2009 to predict the measured values of the canopy fuels parameters. The most important variables are at the top of the y-axis in each plot, and variables decrease in importance as one moves down the y-axis. The x-axis gives the mean percentage decrease in MSE for each variable. Abbreviations are: TC Bright—Tasseled Cap Brightness; TC Green—Tasseled Cap Greenness; TC Wet—Tasseled Cap Wetness; TM Band 1-5, TM Band 7 from Landsat 5, Aug. 11, 2009; Slope—Slope of each plot in degrees; Aspect—Aspect of each plot in degrees from north; Elevation—Elevation of each plot; TP 150—Topographic Position of each plot relative to points within 150 m; TP 450—Topographic Position of each plot relative to points within 450 m. See the text for more details on each variable.

Figure 2-3: Variable importance plot showing rank orders of variable importance for all four RF models using the Reduced Dataset and the spectral data from 2003 to predict the measured values of the canopy fuels parameters. The most important variables are at the top of the y-axis in each plot, and variables decrease in importance as one moves down the y-axis. The x-axis gives the mean percentage decrease in MSE for each variable. Abbreviations are: TC Bright—Tasseled Cap Brightness; TC Green—Tasseled Cap Greenness; TC Wet—Tasseled Cap Wetness; TM Band 1-5, TM Band 7 from Landsat 5, Aug. 11, 2009; Slope—Slope of each plot in degrees; Aspect—Aspect of each plot in degrees from north; Elevation—Elevation of each plot; TP 150—Topographic Position of each plot relative to points within 150 m; TP 450—Topographic Position of each plot relative to points within 450 m. See the text for more details on each variable.

Figure 2-4: Map of a subsection of LVNP showing predicted values of canopy fuels parameters from 2009 using RF algorithm. The dark patch on the map consists of Butte Lake, the Fantastic Lava Beds, and Snag Lake (from north to south) within LVNP.

67
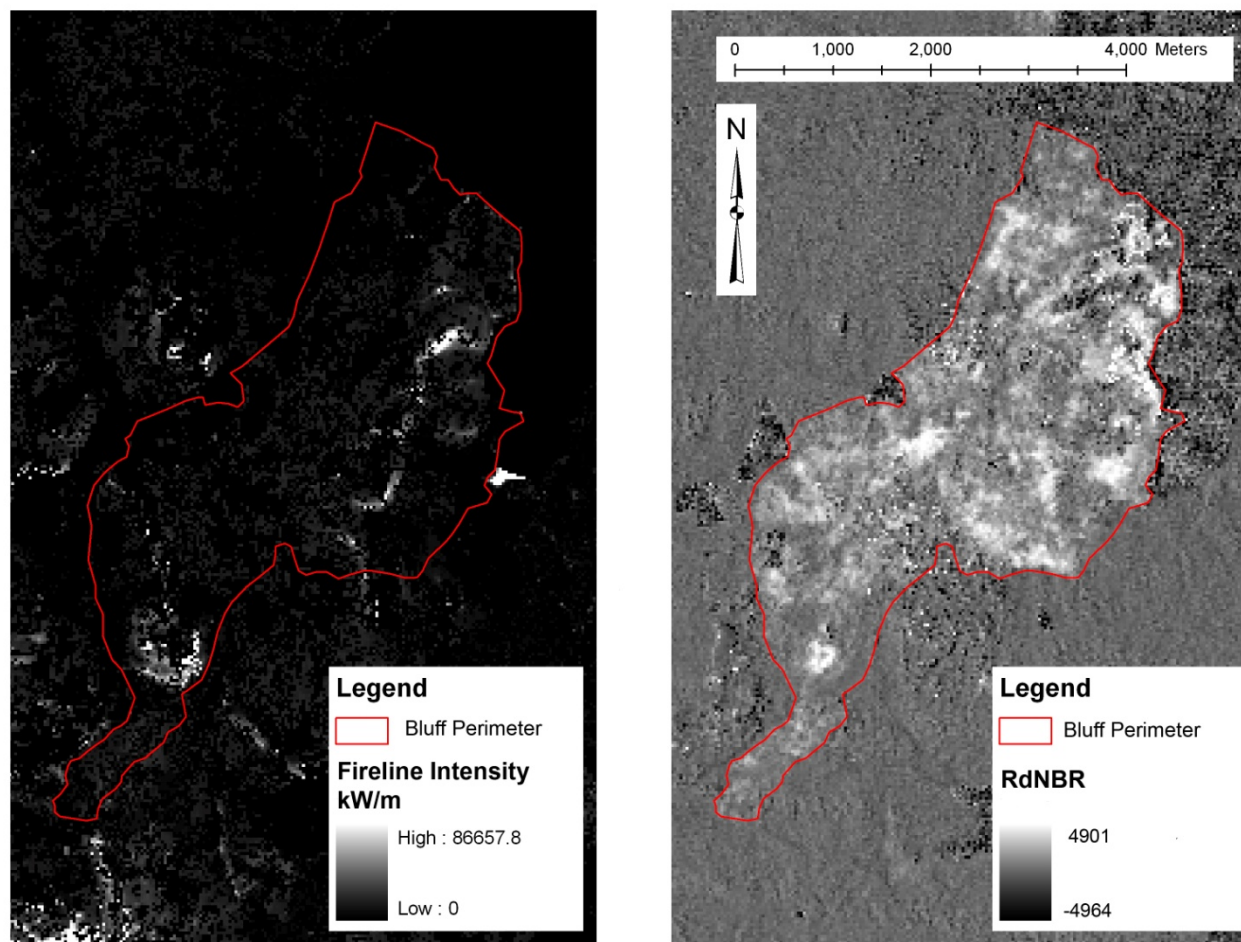
Figure 2-5: Visual comparison of modeled Fireline Intensities (left) with remotely sensed RdNBR values (right) for the Bluff 2004 fire inside LVNP.
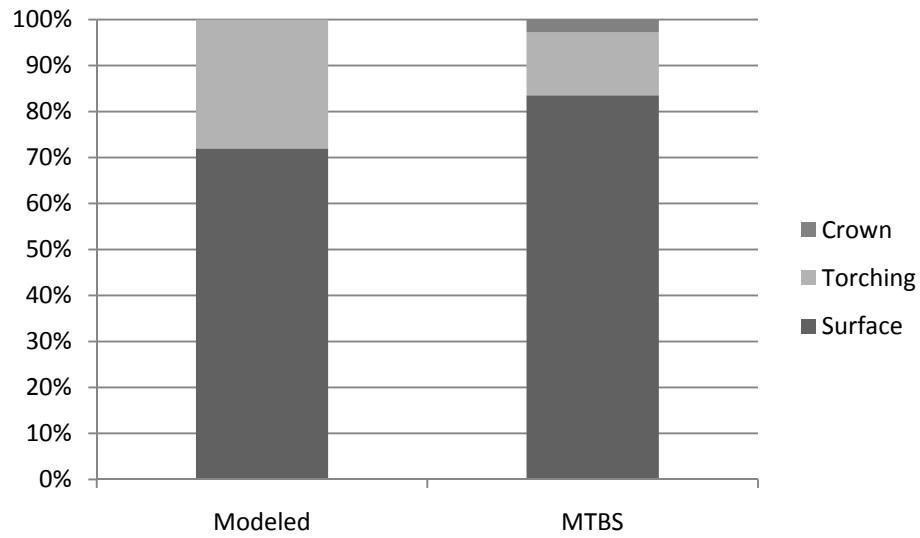
Figure 2-6: Comparison between modeled fire type (Surface, Torching or Crown) with MTBS rated severity. The MTBS uses 5 categories of severity. We grouped categories 1 (Unburned to Low) and 2 (Low) together for this plot and denoted them surface fires to match FlamMap output. We denoted MTBS category 3 (Intermediate) as a torching fire to match FlamMap. We denoted MTBS category 4 (High) as a crown fire to match FlamMap. We ignored pixels with MTBS category 5 (increased greenness).

Chapter 3:

A Neutral Model Approach for Evaluating the Influence of Topography and Fuels on

Expected Fire Behavior in a Forested Landscape, Southern Cascades, USA

Abstract

The effect of topography is recognized as an important driver of variation in fire behavior and fire severity. Direct analysis of this effect has been limited because fire severity within a single fire is often driven by variation in fuels or weather and because fire-scar methodologies have difficulty assessing severity. We use the fire behavior modeling program FlamMap in a neutral model framework to assess the effect of topography on the distribution of variations in fireline intensity and fire type in a diverse 400 km^2 forest landscape. In our approach, we systematically vary fuel moisture and wind scenarios while simultaneously holding canopy fuels variables (Canopy Bulk Density, Canopy Cover, Canopy Base Height, and Canopy Height) constant and uniformly distributing surface fuel models across the landscape. We explain the variation observed in our results by employing a Random Forest algorithm and use elevation, slope, aspect and two measures of topographic position as explanatory variables. Our results indicate that slope is the most important driver of variation in the model output however, the greatest differences in expected fire behavior occur when comparing across fuel models. Additionally, our results support the general expectation that upper slope positions tend to burn more severely and expand this general notion by providing explicit evidence on the locations of expected high intensity fire across the landscape.

Key Words: fire intensity, fire severity, FlamMap, neutral models, topography, simulation models, Lassen Volcanic National Park, elevation, slope, aspect

Introduction

Over the course of centuries, the repeated burning of an ecosystem can potentially create a distinctive relationship between fire regimes and vegetation structure and composition. Perhaps the best understood of these relationships is the effect the high frequency, low severity fire regime that typically kept ponderosa pine ecosystems of the southwestern US open and composed of large diameter, fire resistant stems (Fulé et al. 1997). In these forests, open areas between large trees grew grasses that formed a continuous fuel bed in a matter of a few years. Once a drier than average year occurred, this continuous fuel bed became highly flammable. When ignited, the fuel bed would burn at low intensity, but could potentially burn hundreds to thousands of acres leaving most large trees healthy or minimally scarred but also killing seedlings and leaving the forest open (Fulé et al. 1997). The interaction of fire regime and vegetation in this example produced a more or less stable, fire dependent ecosystem that is now subject to alteration by human use of fire suppression (Fulé et al. 1997; Allen et al. 2002). Boreal and sub-alpine forests have likely not been affected by fire suppression to the degree that their structure and composition have been significantly altered (Johnson et al. 2001). Yet even in these boreal and sub-alpine forests dominated by long-interval, high severity fires, static age patterns that are the evidence of high severity fires can be mapped on the landscape (Johnson et al. 2001; Romme 1982). In Lassen Volcanic National Park, relatively high severity, low frequency fire regimes in some topographic positions may result in stable, fire dependent brushfield communities. By removing high intensity fire as a structuring process from the landscape, these communities—which add structural and habitat diversity to the landscape—are at risk of loss due to a century of fire suppression efforts (Nagel and Taylor 2005).

Quantifying topographic effects on fire intensity and severity is typically done through the analysis of fire scarred wood extracted from living and dead trees (Swetnam 1993; Taylor 2000; Stephens et al. 2003) or through the analysis of age structure patterns of tree populations (Taylor 2000; Nagel and Taylor 2005). This method is excellent for calculating the frequency and seasonality of fires, and strong inferences can be made about size. In the Cascade Range and in southern British Columbia, fire return intervals lengthen as elevation increases because winter snowpack lasts longer at these elevations (Beaty and Taylor 2001; Heyerdahl et al. 2001; Heyerdahl et al. 2007) and fire return intervals are shorter on south-facing slopes because these slopes dry more quickly than other aspects (Heyerdahl et al. 2001; Taylor and Skinner 2003; Heyerdahl et al. 2007). Frequency relationships vary geographically, however. Rollins et al. (2002) compared wilderness areas in Montana and New Mexico and found that in Montana, south and southwestern aspects burned more often because they were subject to increased insolation which dried fuels more quickly. In contrast, northeastern aspects in New Mexico burned more often because their moisture regimes allowed for more rapid accumulation and connectivity of fuels (Rollins et al. 2002). In the nearby Klamath Range, the influence of topography (ridges, rocky outcrops, cliffs, and roads) on the inhibition of fire spread is recognized (Taylor and Skinner 2003). Additionally, high severity fires predated a large pulse of establishment of chaparral fields followed by infilling of fire intolerant tree species in the northern Sierra Nevada (Nagel and Taylor 2005).

Direct quantification of the magnitude of topographic effects on fire severity in relation to other factors that are known to control severity is much more difficult. Fire severity can be driven by the structure and arrangement of fuels (Odion et al. 2004; Thompson et al. 2007), daily meteorological conditions (Collins et al. 2007), or vegetation type. Additionally, high intensity

fires often destroy scarred trees which leaves fire scar based inferences about severity suspect because the evidence is missing. Despite this, topography has been broadly inferred to affect severity in the nearby Klamath Range where historical studies suggest west facing upper slopes burn more severely (Taylor and Skinner 1998). Forest stand age structures have been used to identify spatial variation in fire return intervals and fire severity in the southern Cascades (Beaty and Taylor 2001) and the northern Sierra Nevada (Beaty and Taylor 2008). Additionally, slope was shown to be positively associated with fire severity measures in Sequoia National Park (Knapp and Keeley 2006). In contrast, in the specific case of the Big Bar complex and the Quartz fire of the Klamath Range, Alexander et al. (2006) found evidence that higher elevations burned less severely than lower elevations. Using the recently developed Relative differenced Normalized Burn Ratio (RdNBR) for recent fires several studies have shown that aspect can be a determinant of the location of high severity fire (Collins et al. 2007; Thompson et al 2007). In the few studies that have taken this approach, however, daily meteorological conditions overshadowed topographic conditions in explaining spatial variation in fire severity (Collins et al. 2007; Thompson et al 2007).

The arrangement of fire severity patches on the landscape is just one realization of the stochastic process of fire burning through heterogeneous fuels, vegetation, and terrain that is also subject to human management (*sensu* O'Sullivan and Unwin 2003). Collins et al. (2007) and Thompson et al. (2007) showed that for individual fires weather is the primary driver of fire severity. However, weather is essentially a stochastic process because of its wide range of variability and its rate of change relative to the time scale of a single fire. Further, the combination of fuel, weather, and topographic conditions that occur during any one fire are not necessarily comparable to the combination of conditions during other fires. Because the number of fires

studied by Collins et al. (2007) and Thompson et al. (2007) is small and fire severity is strongly influenced by the stochastic process of weather and environmental heterogeneity, these studies cannot be repeated in order to identify a set of expected patterns of fire severity for complex terrain.

In order to investigate real landscapes against hypotheses, biogeographers and landscape ecologists use neutral and simulation models built on some combination of physical, statistical, or empirical approaches (Turner et al. 2001). Neutral models have been advocated for the development of baseline patterns against which to test observations of real landscape (Gardner et al. 1993; Gardner and Urban 2007). Simulation models have been employed to investigate many aspects of fire behavior, fire effects, and fire regimes. The effects of Euro-American settlement and fire suppression on the landscape characteristics of the Boundary Waters Canoe Area were investigated by Baker (1992) who found that some landscape measures increase quickly with shifting fire regimes while others lagged by decades to centuries. Simulation models were compared to statistical models for the mapping of fire return intervals by Keane et al. (2003) who found that while simulation models generally performed poorly when explicitly mapping those intervals, they were nonetheless useful because of their wide flexibility and general ability to 'burn' the same landscape under different conditions many times and over very long time periods. The question of vegetation persistence in the face of altered fire regimes was investigated by Pausas (2006). This study found that large patches were important for retaining fire sensitive species in Mediterranean climates. Finally, the effect of sampling intensity and completeness on estimates of fire regime parameters (average size, mean fire return interval) was investigated by McKenzie et al. (2006) using a neutral model approach where all of the factors deemed important to determining fire regimes were decoupled in the modeling approach.

In this study, we employ the fire behavior simulation model FlamMap in a neutral framework to examine the landscape scale distribution of expected fire behavior as it relates to topography. FlamMap is a landscape-scale, raster based model for predicting fire behavior (Finney 2006). FlamMap uses raster grid themes of topographic, surface fuels, and canopy fuels variables to predict fire behavior characteristics independently for each location on a gridded landscape. FlamMap is the most appropriate model because it was developed primarily for "mapping *how* a fire might burn a given area" (Stratton 2006, p. 13, emphasis in original) and fire behavior calculations are rapid. The implementation of FlamMap calculates fire parameters (fireline intensity, crown fire activity etc.) for each grid cell independently of other grid cells. FlamMap is commonly used to estimate landscape scale fire behavior for different fuel and weather conditions (Stratton 2004) and is parameterized so that many combinations of fuels and weather can be burned across the same physical template without the need for excessive computing power (Finney 2006). FlamMap can handle raster data of any resolution, provided all datasets are of the same resolution and extent and cover the same geographic area (Finney 2006).

Our neutral framework is based on a homogenous distribution of many surface fuel models and canopy fuels parameters across the landscape, independent of their typical structuring forces. We burn these homogenous assemblages of fuel under 80th, 90th and 97th percentile fire weather for a range of wind scenarios. This systematic variation in fire weather will then be used as the basis for an exploration of the role of topography on patches of high intensity fire. We investigate differences in fireline intensity and fire type across these weather and wind scenarios for each of the homogenous surface fuels cases. The results of this set of simulation models will then be used to assess the pattern of high intensity fires on real landscapes. We are specifically interested in comparing our set of simulations and their predictions of the spatial distribution of

high intensity fire with knowledge about the real distributions of known patches of high severity fire across the landscape of Lassen Volcanic National Park.

Study Area

LVNP lies at the southern end of the Cascade Range, a volcanic plateau punctuated by high volcanic peaks (Figure 3-1). Elevation ranges from 1,609 to 3,187 m and the Park's total area is 42,900 ha. Dominant vegetation communities co-vary with elevation (Taylor 1990, 2000; Parker 1991; Schoenherr 1995). The lowest elevation forests are dominated by ponderosa pine (*Pinus ponderosa*) and Jeffery pine (*P. jeffreyi*). Mixed conifer forests of Jeffrey pine (*P. jeffreyi*) and white fir (*Abies concolor*) dominate the lower montane forests. Upper montane forests are composed of red fir (*A. magnifica* var. *magnifica*), white fir (*A. concolor*), and western white pine (*P. monticola*). Lodgepole pine (*P. contorta* spp. *murrayana*) occupies low lying depressions where cold air drainage is a dominant part of the regeneration climate. High elevation forests are dominated by mountain hemlock (*Tsuga mertensiana*) and whitebark pine (*Pinus albicaulis*). LVNP is dominated by gentle to moderate slopes and the average slope angle is 10.8°. Less than 0.5% (110 ha) of LVNP occupy slopes greater than 45°. The climate is Mediterranean and is characterized by hot, dry summers and cold, wet winters. Average monthly temperatures at Manzanita Lake, California (elevation 1802 m in LVNP), range from -6.6 °C minimum and 5.0 °C maximum in January to 7.5 °C and 26.1 °C in July (WRCC 2009). Annual average precipitation is 104 cm, but inter-annual variability is high. Most precipitation (>80%) falls as snow between November and April and annual maximum snowpack depth from the Lower Lassen Peak Snow Course (usually in April or May) ranges from 1.63 to 8.41 m with an average of 4.63 m (NOHRSC 2010).

Methods

Field Data Collection

Our modeling approach calls for constant values for four critical canopy fuels components: Canopy Bulk Density (CBD), Canopy Cover (CC), Canopy Base Height (CBH), and Canopy Height (HT). CBD is a measure of the total amount of above-ground-surface fuel that is available to wildfires; typically including foliage and up to one half of the smallest branchwood (0-6.4 mm) and is measured in units of kg m^{-3}. CC is the horizontal fraction of the ground that has canopy above it and is measured as a percentage of total area. CBH is a measure of the vertical continuity of fuels and expresses the lower threshold above which there is sufficient fuel for a crown fire to be self-sustaining and is measured in m. Lower CBH values indicate that canopy fuel is closer to the ground and hence could act to transition surface fire into the crown. Finally, HT is the average height of the dominant stratum of tree cover and affects modeled fuel moistures and is measured in m. To determine appropriate values for these variables across the LVNP landscape, we collected field data in the summers of 2009 and 2010 in LVNP. We selected 223 plots from a set of 340 surface fuel sampling plots established in 1998-99 (C. Farris, 2009, personal communication) by grouping plots by their dominant species and then proportionally sampling from each group. Dominant species in each plot were estimated in the field, and were measured as the percentage of live vegetation (i.e. all plots have 100% total values for each strata). The plots in the larger set were located to map surface fuels during the summers of 1998 and 1999 by clustering NDVI values from Landsat imagery using an unsupervised distance to mean algorithm (ERDAS 1997). Detailed fuels information was collected at these plots including surface fuel loading using Brown's planar intercept method (Brown 1973), overstory, understory, and shrub species composition, surface and litter fuel

78

characteristics, canopy and understory height, and photographs for comparison with fuel load photo series (e.g. Blonksi and Schramel 1981). The center of each plot was permanently marked with a steel stake. These data were used to assign each plot an initial fuel model (Anderson 1982). These fuel models were then assigned to the results of the spectral clustering algorithm. Additional plots were located in ambiguous or highly heterogeneous spectral clusters and stratified based on topographic and compositional characteristics to assign final fuel models. Once the final surface fuels map was created, 122 accuracy assessment plots were laid out and visited to ensure validity of the mapping process (C. Farris, unpublished report).

We located the 223 plots by navigating to them with GPS. We established a 500 m^2 circular plot centered on the permanent stake. We recorded the plot's geographic position from the GPS and also measured its slope, elevation, aspect, topographic position, and topographic configuration. Topographic position was recorded in one of five categories: ridge top, upper slope, middle slope, lower slope, or valley bottom. Topographic configuration was also recorded in one of five categories: convex, convex-straight, straight, concave-straight, or concave. For each tree (> 5 cm diameter at breast height [DBH]) we measured DBH (cm), height (m), status (live or dead), and visually estimated live crown fraction to the nearest 5%. We rated each tree's relative crown position using the following categories and criteria: Suppressed— <25% of main canopy height; Intermediate— >25% but < 75% of main canopy height; Co-dominant—part of the main canopy, but receiving top shading from other canopy trees; Dominant—part of the main canopy and only receiving side-shading from other trees; Emergent—trees with crowns above the main canopy that are not receiving significant side-shading from any trees. We recorded the Height to Live (Dead) Crown Base as the height above the ground of the lowest live (dead) limb longer than 60 cm (Fulé et al. 2001; Skinner 2005). To aid in determining canopy fuels characteristics, we took

three upward facing hemispherical photographs per plot with a digital camera mounted with a

full hemispheric lens and leveled with a bubble level at 2 m above the ground.

Canopy Fuels

Canopy fuels characteristics (CBD, CC, CBH, and HT) values were estimated from the data

gathered on individual trees and from the hemispherical photographs. We computed gap fraction

and CC from 669 hemispherical photographs (3 per plot) using GLA software (Frazer et al.

1999). Gap fraction was then transformed to CBD using the methods described in Keane et al.

(2005, eq. 5). To calculate CBH, we combined each plots' values of Height to Live Crown Base

and Height to Dead Crown Base. Because low CBH are most important for the transition to

crown fire, we used the 1st quartile CBH as the estimate for each plot (Fulé et al. 2001; Skinner

2005). To compute HT, we averaged the heights of the live trees in the canopy in each plot

(typically the Co-dominant and Dominant trees, but also Emergent trees if they were present).

We created constant raster layers representing CBD, CC, CBH, and HT from these values. We

computed the average of CBD, CC, and HT across all plots to create the first three constant

rasters. We also computed the average of the 1st quartile CBH values across the landscape and

created a constant raster containing this value. Constant rasters were created in ArcGIS software

(ESRI 2010).

Surface Fuels

Surface fuel models are idealized assemblages of fuel characteristics (Anderson 1982) that

produce an expected fire behavior under a given set of weather and topographic characteristics.

We selected 7 idealized fuel models to use as homogenous fuels in LVNP. These selections

represent a wide range of possible fuel models for the park and also represent some extremes and

come from the set described by Albini (1976) (Table 3-1). The seven models we chose are Short

Grass (Fuel Model 1 [FM1]), Timber Grass and Understory (FM2), Brush (FM5), Dormant

Brush (FM6), Compact Timber Litter (FM8), Hardwood Litter (FM9), and Timber Understory

(FM10) (Scott and Burgan 2005). We further investigated a fuel type that is common in LVNP

by using 6 of the 9 Timber-Litter (TL) models from Scott and Burgan (2005). Each was designed

to supplement the original set by presenting gradations and common variations of the original

models (Scott and Burgan 2005). We included in our analysis TL 1, 3, 4, 5, 7, and 8. Each of

these models is designed to represent dry-climate conifer forests with various levels of fuel

loads. TL 1 is for "Low Load Compact Conifer Litter" and represents recently burned, open

forests or low density, old fir forests. TL 3 is for "Moderate Load Conifer Litter" which adds a

low load of coarse woody fuels to the previous model. The TL 4 is for "Small Downed Logs"

and can represent either stands damaged by heavy snows or ice or stands with numerous small

dead trees. TL 5 is a "High Load Conifer Litter" model and represents a conifer litter surface

with a high coarse woody load. TL 7 is for "Large Downed Logs" and can be used to represent

stands that have been severely damaged by insects or areas of blowdown from storms. TL 8 is a

model for "Long Needle Litter" (pine) forests and can have a variable load of coarse woody fuels

(Scott and Burgan 2005). We did not include TL 2, 6, or 9 in our modeling analysis because

these models represent broadleaf forests, which are not found in any abundance in LVNP.

Examples of each of the other models can be found in the park.

Fire Weather

We computed dead woody fuel moistures and wind speeds for the 80th, 90th, and 97th percentile

condition with FireFamily Plus (Bradshaw and Tirmenstein 2010) using weather data from the

Manzanita Lake weather station (FAM Web 2011). Fuel moisture calculations were limited to

the fire season of June 1 through October 31 but used the entire Manzanita Lake record which

extends from 1962 to 2010. I computed fuel moistures for 5 fuel components: 0 – 0.64 cm, 0.64

– 2.54 cm, and 2.54 – 7.62 cm diameter dead woody fuels, as well as Live Herbaceous and Live

Woody fuels to use as input to FlamMap. 0 – 0.64 cm, 0.64 – 2.54 cm, and 2.54 – 7.62 cm

diameter dead woody fuels are often referred to by the terms 1-hr, 10-hr, and 100-hr fuels. This

convention refers to the amount of time required for a fuel particle to reach 63% of the difference

between its initial moisture content and a final moisture content that is in equilibrium with

changed atmospheric conditions (Pyne et al. 1996). Fuel moistures are given in percentages and

interpreted as the amount of water in a particular fuel particle as a percentage of that particle's

oven-dry weight. For all 5 classes of fuel moistures, percentages range from 0 (oven-dry) up to

300 (fresh grass and herbaceous cover). We also computed 6.2 m wind speeds for the 80th, 90th

and 97th percentile conditions. This is the speed of the wind at 6.2 m above the forest canopy.

FlamMap uses the given grid of canopy cover to calculate an attenuated 6.2 m wind speed at the

site of (simulated) surface combustion. Lastly, we used this data to calculate the dominant

direction of daytime winds.

Wind Scenarios

We applied 4 different wind scenarios for each combination of surface fuel model and fuel

moisture condition. Wind is an important factor that controls both rates of fire spread and fire

intensity. Wind is addressed in FlamMap in three ways (Finney 2006). Depending on the

moisture profile (80th, 90th, or 97th) we simulated winds as: 1) calm (no wind); 2) blowing uphill

at their 80th, 90th and 97th percentile speeds, respectively; 3) blowing at a constant direction and

speed at their 80th, 90th and 97th percentile speeds, and 4) blowing at variable speeds and

directions based on the model WindNinja ® at their 80th, 90th and 97th percentile speeds,

respectively. WindNinja® calculates surface wind speed and direction for a grid of arbitrary resolution based on the topographic interference that a constant wind would encounter. Winds gridded in this way have been shown to increase the accuracy of predictions (Finney 2006; Stratton 2006).

Simulation Approach

We used FlamMap to generate expected fire behavior at the landscape scale for LVNP. The fire behavior outputs we calculated fireline intensity (kW/m) and fire activity type (0 = no fire, 1 = surface fire, 2 = torching fire, or 3 = crown fire categorical index) (Finney 2006). We simulated fire behavior for each possible combination for fuels, wind, and weather. Fire behavior outputs for each run were fireline intensity and crown fire activity. Fireline intensity is measured in kilowatts per meter (kW m^{-1}) and is related to both flame length and crown fire activity (Agee 1993). Crown fire activity is rated on a scale of 0-3: 0) no fire activity; 1) ground fire only; 2) passive crown fire (torching); and 3) active crown fire. FlamMap's calculations are set up so that each successively higher class of fire activity (class 0-3) requires activity at the previous class, e.g. passive crown fire (class 2) can only occur in a location if there is a ground fire (class 1) (Finney 2006). This experimental design produced 156 raster maps each for fireline intensity and crown fire activity index. To simplify the dataset of landscape scale maps, we randomly selected 1% of the vegetated pixels inside LVNP (n = 4259, Table 3-2). This 1% subsample was used to extract fireline intensity, crown fire activity indices, and all of the topographic information across all of LVNP by intersecting each point's location with each raster map representing fireline intensity and crown fire index and all five topographic variables' raster maps in a GIS.

Relative Importance of Variables on Fire Behavior

We used a Random Forest approach (Breiman 2001) to quantify the effect of elevation, slope, aspect, and two measures of landscape position on fireline intensity. The five topographic variables related to the distribution of vegetation were developed from a 30 m x 30 m resolution digital elevation model (USGS 2010). A section of the National Elevation dataset representing LVNP was used to obtain elevation data and derive four additional topographic variables: slope, aspect, and two measures of topographic position. These two measures of topographic position—Topo_Pos_150 and Topo_Pos_450—are the difference between the focal pixel's elevation with the average elevation of pixels within 150 m and 450 m respectively (Poulos et al. 2007; Poulos 2010). In every case, the RF algorithm was run to iteratively grow 500 trees with 1 of the 5 explanatory variables randomly selected at each node as potential variables to base the split on. A large number of trees is recommended when using RF algorithms to stabilize the Mean Squared Error (MSE) over many iterations. We used the pseudo-r^2 and the MSE statistic to evaluate model performance. The pseudo-r^2 statistic is calculated as:

$$1 - \frac{\text{MSE}}{\text{var(y)}}$$

The pseudo-r^2 statistic is calculated identically to the r^2 statistic for standard linear regression, and is called pseudo because the predicted values used to calculate the MSE come from the random forest, and not from a linear regression (Liaw and Wiener 2002). We used importance plots to show rank orders of variables in terms of their ability to reduce the MSE.

To further simplify our dataset, we combined data in the following ways. For each surface fuel model, we averaged the crown fire index and the fireline intensity at each pixel over all moisture

and wind scenarios. This approach yielded 2 maps for each fuel model for a total of 26 maps. To

visualize differences between fuel models, moisture scenarios, and wind scenarios, we plotted

log transformed fireline intensities in rank order and frequencies of crown fire indices. Finally,

we partitioned our 1% subset of pixels by their mapped surface fuel model and examined each by

its frequency of surface, torching and crown fires. From this, we created a bar plot that depicts

the frequency of each type of fire by fuel model.

We compared the range of variation in predicted fire behavior for the TL series of models by

adopting a similar approach. For each point in the 1% subset, we extracted the average fireline

intensity and the frequencies of each of the values of the crown fire index. TL models are not on

the mapped surface fuel map that we used for our study. They do, however, represent variations

on common conifer dominated vegetation types, which are nearly ubiquitous within LVNP. We

compared fuel models 5, 8, and 10 with the TL series of fuel models from Scott and Burgan

(2005). Model 8 (Compact Timber Litter) is the most common fuel model used in LVNP and the

most similar to the TL series (Scott and Burgan 2005). Model 5 (Brush) is the second most

common fuel model in LVNP and has a high potential for intense behavior (torching). Model 10

(Timber Understory) is the likely type to which Model 8 would transition if coarse woody fuels

increased through time and is used here to book-end the comparison of the TL series of models

with Model 8.

Results

Field Plots and Canopy Fuels Characteristics

We used field data from 223 plots and 669 hemispherical photographs to compute plot level

CBD, CC, CBH, and HT estimates. Because our aim in this study was to model potential fire

behavior across the landscape using homogenous fuels, we used the means of CBD, CC, and HT

and the mean of the lower quartile of CBH across all plots for every pixel on the landscape. Our

CBD values ranged from 0.00 to 0.31 kg/m^3 with an average of 0.11 kg/m^3. CC ranged from 0 to

87.8% with a mean of 45.6%. CBH lower quartiles ranged from 0.0 to 11.9 m with an average

of 0.71 m. HT ranged from 0.0 to 43.9 m with an average of 21.3 m. Our constant rasters,

therefore, were 0.11 kg/m^3 CBD, 45.6% CC, 0.71 m CBH, and 21.3 m HT.

Fuel Moisture and Wind Scenarios

Fuel moistures and 6.2 m wind speeds for the 80th, 90th, and 97th percentile conditions were

computed with FireFamilyPlus (Bradshaw and Tirmenstein 2010) using the Manzanita Lake

weather station data (FAM Web 2011). Fuel moistures for 1-, 10-, and 100-hr fuels were

typically low, ranging from 4%, 5%, and 10% respectively at the 80th percentile condition and

declining to 2%, 3%, and 7% respectively at the 97th percentile condition (Table 3-3). Wind

speeds at 6.2 m increased from 16.1 kph at the 80th percentile condition to 22.5 kph at the 97th

percentile condition. Live herbaceous and live woody fuel moistures declined steadily from 74%

and 102% respectively at the 80th percentile condition to 40% and 79% respectively at the 97th

percentile condition.

Gridded winds were computed from WindNinja® for 6.4 m wind speeds of 16.1, 19.3, and 22.5

km/h from a direction of 247° (west-southwest). All three models had minimum winds speeds

somewhere in the grid of near 0 km/h (Table 3-4). Maximum wind speeds for the three models

ranged from 41.7 km/h at the 80th percentile to 58.4 km/h at the 97th percentile. Mean values for

the gridded wind predictions were all close to their respective input speeds.

Fireline Intensities and Crown Fire Indices

We plotted rank order $\log_{10}$ transformed fireline intensities and crown fire activity index histograms for each fuel model, wind and weather condition to visualize the differences in expected fire behavior. Within each fuel model, 97th percentile conditions produced the highest frequency of crown fire while 80th percentile conditions produced the lowest frequency. However, the greatest variation in the frequency distributions of crown fire index was related to the wind scenario. The No Wind scenario always produced the least potential for crown fire. The Uphill Wind scenario always produced the greatest potential for crown fire. The Gridded Wind scenario produced a potential for crown fire intermediate to the two previously stated extreme scenarios, but the potential for crown fire here was closer to the Uphill Wind than the No Wind scenario (see figures 3-2, 3-4, 3-6, 3-8, 3-10, 3-12, and 3-14). For all of the models except 8—Compact Timber Litter—fuel moisture and winds had little overall effect on the range of fireline intensities. The fuel models all had ranges between 2 and 5 (10^2 and 10^5 kW/m). Fuel model 8 had a small range (1-2) and low overall values (~10^0 to 10^2).

We also partitioned our 1% subsample by existing surface fuel model to examine the proportion of instances of surface, torching and crown fire (Figure 3-16 and 3-17). Overall, torching was the most common type of fire, and was especially common in surface fuel models representing Timber Grass and Understory (Fuel Model 2), Brush (5), Dormant Brush (6), and Timber Understory (10) where it accounted for more than half of the predicted fires by type. Surface fires were also common, and occurred predominantly in surface fuel models representing Compact Timber Litter (8) and Hardwood Litter (9). Crown Fire was the least predicted of the fire types, occurring just under 12% of the time in Dormant Brush (Fuel Model 6). Crown fire was predicted in Short Grass (1), Timber Grass and Understory (2), Brush (5), and Dormant

Brush (6) between 3% and 12%. In Hardwood Litter (9) and Timber Understory (10) crown fire was predicted less than 1% of the time, and in Compact Timber Litter (8), it was not predicted at all. The Short Grass (1) model produced the most even split between surface (~50% of fires) and torching (~45% of fires) with the remainder being crown fires.

We compared fuel models 2, 8, and 10 with the TL series of fuel models from Scott and Burgan (2005). While model 8 was dominated by surface fires and model 10 by torching fires, the TL series of models were expected to burn intermediately to these two. TL1, TL3, and TL4 were expected to behave very similarly to model 8; TL5 and TL7 were expected to add a small amount of torching fires; TL8 was the only one of the TL series of models tested here to produce a majority of torching fires. Model 10 was expected to produce more torching than any of the TL models. In this comparison, only models 10 and 2 were expected to produce crown fires.

Topographic Effects as Assessed by Random Forests

We used a RF regression to assess the importance of topographic characteristics on the variability of fireline intensity. Results for the subset of Albini's (1976) surface fuel models showed that slope was by far the most important variable for predicting fireline intensity (Figure 3-18). Trees in which Slope was not included had between 55% and 145% higher MSE values. Other topographic variables were much weaker in their explanatory power. Of the remaining, Aspect and TP450 were able to explain approximately 5% to 15% of MSE. Results for the TL series of fuel models from (Scott and Burgan 2005) were similarly clear (Figure 3-19). Slope was again the most important of the variables for reducing model MSE; trees not including Slope had between 40% and 120% higher MSE values.

Discussion

Overall, wind and weather scenarios had little effect on some fuel models but a large effect on other models. Fuel models 8 and 10 showed little effect of wind and weather on both fireline intensity and on crown fire index frequencies (Figures 3-10, 3-11, 3-14, 3-15). In other cases where there was a more drastic difference between moisture and/or wind scenarios, it is likely that the driving factor in these differences was not moisture or wind scenario per se, but these scenarios' effect on fireline intensity that induced a threshold behavior towards an increase in the predicted amounts of torching or crown fire. The threshold nature of canopy fuels variables has been noted in other studies where linear increases in canopy biomass result in non-linear increases in torching and crown fire probabilities (Fulé et al. 2004). In our study, we used a single value for each of the four canopy fuels variables—CBD, CBH, CC, and HT—throughout the entire process. In some cases, our values were never enough to create the conditions under which FlamMap would predict crown fire (e.g. Fuel Model 8, Figure 3-10). In other cases, decreasing fuel moistures was sufficient to induce a change in the dominant type of predicted fire without the need to change winds or canopy fuel parameters (e.g. Fuel Model 5, Figure 3-6, No Winds scenario). Finally, in other situations, changing the wind scenario had a very strong effect on the proportion of fire types without varying moisture or canopy fuels (e.g. Fuel Model 9, Figure 3-12, 97th percentile fuel moistures). Each of these examples serves to highlight the fact that many variables are important in determining fire behavior.

Slope was a dominant factor in determining fireline intensity. Our RF regression separated slope out as the most important topographic variable; it reduced the MSE the most. Slope has an important effect on fire behavior because fires burning upslope can preheat and dry upslope fuels, before combustion occurs. This tendency for slope to affect fire intensity and severity is

noted in the study of real fires (Knapp and Keeley 2006). While slope is hard-coded into a model like FlamMap, the variation in slope and its effect on fireline intensity is not enough to explain the great variation in fire types predicted by FlamMap. For example, there was no burning scenario with fireline intensities sufficient to create either torching or crowning in fuel model 8, Compact Timber Litter. On the other hand, even under the 80th percentile fuel moisture conditions, fuel models 5 and 6 (Brush and Dormant Brush) tended to exhibit torching behavior. Across all burning scenarios, the differences between fuel models are indeed drastic. This highlights the fundamental effect of fuel load and fuel structure on potential fire behavior. The other topographic variables are unused in my scenarios FlamMap, which renders there apparent contribution to fireline intensity spurious. FlamMap does use aspect and elevation during pre-burning calculations to modify initial fuel moisture; however, we did not utilize these routines because we wanted to control for fuel moisture while examining the others.

The TL series of models (Scott and Burgan 2005) were burned under identical conditions to the models from Albini's (1976) set of 13. The TL models were predicted to have proportions of surface, torching and crown fire intermediate between Albini (1976) models 2, 8 and 10. That this is the case is unsurprising as the TL series was developed to represent common variations and gradations of the original set (Scott and Burgan 2005). What is most interesting about these models is that TL1, 3, and 4 all produced the same expectation of uniform surface fire no matter what the fuel moisture, wind scenario, or slope. We could employ more severe weather and wind conditions to examine when these models would produce increased fire intensity and more extreme behavior, however these conditions would likely be unrealistic (i.e. physically impossible wind speeds or temperatures). Producing different fire types largely relies on changing the fuel model to one that more often produces other types. It is in this aspect of fire

modeling that the limitations of the modeling approach become most clear. In order to produce the most likely or most realistic fire behavior, a fuel model could be chosen that might not necessarily accurately represent the fuel conditions of a given pixel. This practice generally reflects the reality that fuels do interact with other environmental conditions to produce fire behavior and that choosing a fuel model on the basis of expected fire behavior underscores the limitations of fire models to completely capture the burning process.

The neutral model framework (Caswell 1976) offers a conceptual frame for studies like this one. Caswell's (1976) original intent was to produce a model of species distributions that did not depend on inter-species interactions—it was neutral to these interactions. In this sense, FlamMap is a neutral model of topographic effects on fire behavior because its topographic inputs do not interact. By further restricting the model by feeding it homogenous fuels, we reduce the variability in the output to that which is readily attributable to topography, weather, or wind. This approach is conceptually similar to the neutral model approach which advocates for the use of models that decouple processes of interest to create baselines against which observations can be tested (Gardner et al. 1993; Gardner and Urban 2007). We find that slope is the most important predictor of fireline intensity. Whether that fireline intensity translates into a fast moving grass fire, a surface fire, or a torching fire depends more on the quantity and arrangement of fuels present.

The goal of studies like these and like ours is not the explicit prediction of fire behavior or effects, but the generation of patterns against which to judge evidence. In using a model to assess landscape scale variations in expected fire behavior, we note that our approach is different because we systematically vary fuel models, winds, and fuel moistures. Baker (1992) used a model based on the fire regime parameters size and frequency to examine how Euro-American

91

settlement and fire suppression altered patch metrics in the Boundary Waters Canoe Area. Krasnow et al. (2009) used pixel level modeling to predict the area burned by two wildfires in the Colorado Front Range and found that local level mapping improved predictions of area burned. Stratton (2004) showed that fuel treatments were effective in reducing potential fire behavior in a southern Utah fuels treatment. Pausas (2006) demonstrated that fire sensitive species are retained longer when they occupy large patches in a Mediterranean landscape with altered fire regimes. Ager et al. (2010) used fire behavior and fire severity models in concert with carbon accounting procedures to assess the impact of prescribed fire and other fuels treatments on the capacity of the landscape to store carbon. These types of analyses use specific landscapes as the template on which to conduct their modeling exercises and as a guide to examine how the patterns generated by the model vary across that space. Our approach shows how a neutral approach can be used to generate expectations of fire intensity. Ager's et al. (2010) approach is the most similar to ours, and was developed to map carbon emission or sequestration across a forested landscape given a large number of simulated fire ignition locations.

At the landscape scale, we predicted fireline intensities to be greatest on steep slopes. Our systematic exploration of the landscape scale patterns using a model approach is very different from observational studies of the effect of topography on fire behavior. In the Klamath Mountains, upper slopes were found to have burned with higher severity (Taylor and Skinner 2003). In contrast, upper slope positions in the Klamath Mountains were found to burn with comparatively lower severity by Alexander et al. (2006). These empirical results are valuable in the sense that they provide specific evidence of the effects of fire on the landscape in relation to topography, but they are limited because of their use of historic fire scar data (Taylor and

Skinner 2003) or their analysis of a small number of fires (Alexander et al. 2006). Furthermore, single fires may be dominated by the effects of weather and wind (Collins et al. 2007) and historical, fire-scar based studies are limited because high intensity fire can destroy evidence of fire and because sampling intensity and completeness can influence conclusions made from fire-scar evidence regarding fire regimes (McKenzie et al. 2006). Systematically building a set of fireline expectations across an entire landscape gives information against which empirical studies can be compared.

A systematic prediction of the locations of high intensity fire can also be useful to managers. The inclusion of topography as a management consideration is gaining acceptance as a broad heuristic under which to plan fuels treatments (North et al. 2009). Topography is a strong driver of vegetation composition, and recognizing that influence means that fuels treatments will differ based on the location of the stand and its relative topographic position. Our study further informs this approach by giving managers an explicit way of assessing topographic influence on fireline intensity such that stand locations can be compared with locations of potential high intensity fire in order that fuel treatment decisions are optimized.

Conclusions

Our findings support the general conclusion that upper slopes or steeper slopes burn with higher potential fireline intensity. By varying wind and weather, we are further able to examine the proportion of fire predicted for each fuel model. Furthermore, we find that the differences in expected fire behavior are greatest when comparing across fuel models. These results also show that in addition to the indirect effect of topography on fire behavior generated by its control of

vegetation composition, topography has a direct control on fire behavior through upslope heating

of fuels.

Works Cited

Agee, J. K. (1993). *Fire Ecology of Pacific Northwest Forests.* Washington, D.C. and Covelo, CA: Island Press. 493p.

Ager, A. A., M. A. Finney, A. McMahan, and J. Cathcart (2010). Measuring the effect of fuel treatments on forest carbon using landscape risk analysis. *Natural Hazards and Earth System Sciences* 10: 2515-2526.

Albini, F. A. (1976). *Estimating Wildfire Behavior and Effects.* Gen. Tech. Rep. INT-GTR-30. Ogden, UT: United States Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 100 p.

Alexander, J. D., N. E. Seavy, C. J. Ralph and B. Hogoboom (2006). Vegetation and topographical correlates of fire severity from two fires in the Klamath-Siskiyou region of Oregon and California. *International Journal of Wildland Fire* 15: 237-245.

Allen, C. D., M. Savage, D. A. Falk, K. F. Suckling, T. W. Swetnam, T. Schulke, P. B. Stacey, P. Morgan, M. Hoffman, and J. T. Klingel (2002). Ecological restoration of southwestern ponderosa pine ecosystems: a broad perspective. *Ecological Applications* 12(5): 1418-1433.

Anderson, H. E. (1982). *Aids to determining fuels models for estimating fire behavior.* Gen. Tech. Rep. GTR-INT-122. Ogden, UT: United States Department of Agriculture, Forest Service, Intermountain Research Station. 28p.

Baker, W. L. (1992). Effects of settlement and fire suppression on landscape structure. *Ecology* 73(5): 1879-1887.

Beaty, R. M. and A. H. Taylor (2001). Spatial and temporal variation of fire regimes in a mixed conifer landscape, Southern Cascades, California, USA. *Journal of Biogeography* 28: 955-966.

Beaty, R. M. and A. H. Taylor (2008). Fire disturbance and forest structure in old-growth mixed conifer forests in the northern Sierra Nevada, California. *Journal of Vegetation Science* 18:879-890.

Blonski, K. S. and J. L. Schramel (1981). *Photo Series for Quantifying Natural Forest Residues: southern Cascades, northern Sierra Nevada.* Gen. Tech. Rep. GTR-PSW-056. Berkeley, CA: United States Department of Agriculture, Forest Service, Pacific Southwest Forest and Ranges Experiment Station. 154 p.

Bradshaw, L.S. and D. Tirmenstein (2010). FireFamilyPlus user's guide, version 4.1. Boise, ID: United States Department of Agriculture, Forest Service, National Fire and Aviation Management Information Systems Team. 282 p.

Breiman, L. (2001). Random forests. *Machine Learning* 45: 5-32.

Brown, J. K. (1973). A planar intersect method for sampling fuel volume and surface area. *Forest Science* 17: 96-102.

Caswell, H. (1976). Community structure: a neutral model analysis. *Ecological Monographs.* 46(3): 327-354.

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

ERDAS® (1997). ERDAS® Field Guide, Field Edition. Atlanta, GA: ERDAS® Inc. 655 p.

ESRI (2010). ArcEditor, Educational Version 9.3.1. Redlands, CA: Environmental Systems Research Institute.

FAM (Fire and Aviation Management) Web (2011). *Fire and Weather Data: California.* Accessed 1/15/2011 at http://fam.nwcg.gov/fam-web/weatherfirecd/state_data.htm.

Farris, C. (unpublished report). Preliminary fuels mapping methodology for Lassen Volcanic National Park.

Finney, M. A. (2006). An overview of FlamMap fire modeling capabilities. In P. L. Andrews and B. W. Butler (eds.): *Fuels Management-How to Measure Success*: Conference Proceedings, March 28-30, 2006, Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Frazer, G. W., C. D. Canham, and K. P. Lertzmann (1999). Gap Light Analyzer (GLA), Version 2.0: Imaging software to extract canopy structure and gap light transmission indices from true-colour fisheye photographs, users manual and program documentation. Copyright © 1999: Simon Fraser University, Burnaby, British Columbia, and the Institute of Ecosystem Studies, Millbrook, New York.

Fulé, P. Z., W. W. Covington, and M. M. Moore (1997). Determining reference conditions for ecosystem management of southwestern ponderosa pine. *Ecological Applications* 7(3): 895-908.

Fulé, P. Z., J. E. Crouse, A.E. Cocke, M. M. Moore, and W. W.Covington (2004). Changes in canopy fuels and potential fire behavior 1880-2040: Grand Canyon, Arizona. *Ecological Modelling* 175: 231-248.

Fulé, P. Z., A.E. M. Waltz, W. W. Covington, and T. A. Heinlein (2001). Measuring forest
restoration effectiveness in reducing hazardous fuels. *Journal of Forestry.* 99(11): 24-29.

Gardner, R. H., B. T. Miller, M. G. Turner, and R. V. O'Neill (1987). Neutral models for the
analysis of broad-scale landscape pattern. *Landscape Ecology* 1(1): 19-28.

Gardner, R. H. and D. L. Urban (2007). Neutral models for testing landscape hypotheses.
Landscape Ecology 22(1): 15-29.

Heyerdahl, E. K., L. B. Brubaker and J. K. Agee (2001). Spatial controls of historical fire
regimes: a multiscale example from the interior west, USA. *Ecology* 82(3): 660-678.

Heyerdahl, E. K., K. P. Lertzman and S. Karpuk (2007). Local-scale controls of a low-severity
fire regime (1750-1950), southern British Columbia, Canada. *Ecoscience* 14(1): 40-47.

Johnson, E. A., K. Miyanishi, and S. R. J. Bridge (2001). Wildfire regime in the boreal forest
and the idea of suppression and fuel buildup. *Conservation Biology* 15(6): 1554-1557.

Keane, R. E., G. J. Cary, and R. Parsons (2003). Using simulation to map fire regimes: an
evaluation of approaches, strategies, and limitations. *International Journal of Wildland
Fire* 12: 309-322.

Keane, R. E., E. D. Reinhardt, J. Scott, K. Gray and J. Reardon (2005). Estimating forest canopy
bulk density using six indirect methods. *Canadian Journal of Forest Research* 35: 724-
739.

Knapp, E. A., and J. E. Keeley (2006). Heterogeneity in fire severity within early season and late
season prescirbed burns in a mixed-conifer forest. *International Journal of Wildland
Fire* 15: 37-45.

Krasnow, K., T. Schoennagel, and T. T. Veblen (2009). Forest fuel mapping and evaluation of

LANDFIRE fuel maps in Boulder County, Colorado, USA. *Forest Ecology and

Management* 257: 1603-1612.

Liaw, A. and M. Wiener (2002). Classification and Regression by randomForest. *R News* (2)3:

18-22.

McKenzie, D., A. E. Hessl, and L.-K. B. Kellogg (2006). Using neutral models to identify

constraints on low-severity fire regimes. *Landscape Ecology* 21:139-152.

O'Sullivan, D. and D. Unwin (2003). *Geographic Information Analysis*. Hoboken, NJ: John

Wiley and Sons, Inc.

Odion, D. C., E. J. Frost, J. R. Strittholt, H. Jiang, D. A. Dellasalla and M. A. Moritz (2004).

Patterns of fire severity and forest conditions in the western Klamath Mountains,

California. *Conservation Biology* 18(4): 927-936.

Odion, D. C. and C. T. Hanson (2008). Fire severity in the Sierra Nevada revisited: conclusions

robust to further analysis. *Ecosystems* 11: 12-15.

Nagel, T. A. and A. H. Taylor (2005). Fire and persistence of montane chaparral in mixed

conifer forest landscapes in the northern Sierra Nevada, Lake Tahoe Basin, California,

USA. *Journal of the Torrey Botanical Society* 132(3): 442-457.

NED (2010). *National Elevation Dataset.* Washington, D.C.: United States Department of the

Interior, United States Geological Survey. Available online at http://ned.usgs.gov/.

NOHRSC (2010). National Operational Hydrologic Remote Sensing Center *Snow Data Assimilation System (SNODAS) data products at NSIDC*. Boulder, CO: National Snow and Ice Data Center.

North, M., P. Stine, K. O'Hara, W. Zielinski, and S. Stephesn (2009). *An Ecosystem Management Strategy for Sierran Mixed-Conifer Forests*. Gen. Tech. Rep. PSW-GTR-220. Albany, CA: United States Department of Agriculture, Forest Service, Pacific Southwest Research Station. 49 p.

Parker, A. J. (1991). Forest/environment relationships in Lassen Volcanic National Park, California, USA. *Journal of Biogeography* 18: 543-552.

Pausas, J. G. (2006). Simulating Mediterranean landscape pattern and vegetation dynamics under different fire regimes. *Plant Ecology* 187: 249-259.

Poulos, H. M. (2009). Mapping fuels in the Chihuahuan Desert borderlands using remote sensing, geographic information systems, and biophysical modeling. *Canadian Journal of Forest Research* 39: 1917-1927.

Poulos, H. M., A. E. Camp, R. G. Gatewood, and L. Loomis (2007). A hierarchical approach for scaling forest inventory and fuels data from local to landscape scales in the Davis Mountains, Texas, USA. *Forest Ecology and Management* 244: 1-15.

Pyne, S. J., P. L. Andrews, and R. D. Laven (1996). *Introduction to Wildland Fire*. New York: Wiley.

Rollins, M. G., P. Morgan and T. W. Swetnam (2002). Landscape-scale controls over 20th
century fire occurrence in two large Rocky Mountain (USA) wilderness areas. *Landscape Ecology* 17: 539-557.

Romme, W. H. (1982). Fire and landscape diversity in subalpine forests of Yellowstone National
Park. *Ecological Monographs* 52(2): 199-221.

Schoenherr, A. A. (1995). *A Natural History of California.* Berkeley, CA: University of
California Press.

Scott, J. H. and R. E. Burgan (2005). *Standard fire behavior fuel models: A comprehensive set
for use with Rothermel's surface fire spread model.* Gen. Tech. Rep. RMRS-GTR-153.
Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain
Research Station. 72p.

Skinner, C. N. (2005). Reintroducing fire into the Blacks Mountain Research Natural Area:
effects on fire hazard. in *Proceedings of the Symposium on Ponderosa Pine: Issues,
Trends, and Management.* October 18-21, 2004, Klamath Falls, OR. Gen. Tech. Rep.
PSW-GTR-198. Berkeley, CA: United States Department of Agriculture, Forest Service,
Pacific Southwest Research Station.

Stephens, S. L., C. N. Skinner, and S. J. Gill (2003). Dendrochronology-based fire history of
Jeffrey pine-mixed conifer forests in the Sierra San Pedro Martir, Mexico. *Canadian
Journal of Forest Research* 33: 1090-1101.

Stratton, R. D. (2004). Assessing the effectiveness of landscape fuel treatments on fire growth
and behavior. *Journal of Forestry* 102(7): 32-40.

Stratton, R. D. (2006). *Guidance on Spatial Wildland Fire Analysis: Models, Tools, and Techniques*. Gen. Tech. Rep. RMRS-GTR-183. Fort Collins, CO: US Department of Agriculture, Forest Service.

Swetnam, T. W. (1993). Fire history and climate change in giant sequoia groves. *Science* 262(5135): 885-889.

Taylor, A. H. (1990). Habitat segregation and regeneration of red fir and mountain hemlock in ecotonal forests of Lassen Volcanic National Park, California. *Physical Geography* 8:35-49.

Taylor, A. H. (2000). Fire regimes and forest changes in mid and upper montane forests of the southern Cascades, Lassen Volcanic National Park, California, USA. *Journal of Biogeography.* 27: 87-104.

Taylor, A. H. and C. N. Skinner (1998). Fire history and landscape dynamics in a late-successional reserve, Klamath Mountains, California, USA. *Forest Ecology and Management* 111: 285-301.

Taylor, A. H. and C. N. Skinner (2003). Spatial patterns and controls on historical fire regimes and forest structure in the Klamath mountains. *Ecological Applications* 13(3): 704-719.

Thompson, J. R., T. A. Spies and L. M. Ganio (2007). Reburn severity in managed and unmanaged vegetation in a large wildfire. *Proceedings of the National Academy of Sciences* 104(25): 10743-10748.

Turner, M. G., R. H. Gardner and R. V. O'Neill (2001). *Landscape Ecology in Theory and Practice: Pattern and Process*. New York: Springer Verlag.

WRCC—Western Regional Climate Center (2009). Manzanita Lake, California, Period of

Record. Accessed 12/09 at http://www.wrcc.dri.edu/cgi-bin/cliMAIN.pl?ca5311.

Fuel Model	1-hr (t/ha)	10-hr (t/ha)	100-hr (t/ha)	Live Herbaceous (t/ha)	Live Woody (t/ha)	Fuelbed Depth (m)	Dead Fuel moisture of extinction (%)
							Table 3-1: Fuel Model Parameters
1*	1.66	0	0	0	[†]	0.31	12
2*	4.48	2.24	.45	1.12	[†]	0.31	15
5*	2.24	1.12	0	4.48	[†]	0.62	20
6*	3.36	5.61	4.48	0	[†]	0.76	25
8*	3.36	2.24	5.61	0	[†]	0.06	30
9*	6.54	0.92	0.34	0	[†]	0.06	25
10*	6.74	4.45	11.23	4.48	[†]	0.31	25
TL1	2.24	4.93	8.07	0	0	0.06	30
TL3	1.12	4.93	6.28	0	0	0.09	20
TL4	1.12	3.36	9.42	0	0	0.12	25
TL5	2.58	5.61	9.86	0	0	0.18	25
TL7	0.67	3.14	18.16	0	0	0.12	25
TL8	13.00	3.14	3.14	0	0	0.09	35

Table 3-1: Fuel Model Parameters for the fuel models used in this study. *Models from Albini (1976); all other models are from Scott and Burgan (2005). [†]These parameters were not specified in the original models.

Table 3-2: Average Topographic Characteristics of 1% Subsample (n = 4259)					
	Elevation	Slope	Aspect	TP150	TP450
Average ± s.e.	2071 ± 2.7	158.5 ± 1.6	10.2 ± 0.1	0.14 ± 0.09	-0.01 ± 0.3

Table 3-2: Average topographic conditions in the 1% subsample used in this study. See text for description of variables.

Fire Weather Percentile	1-hr Fuel Moisture	10-hr Fuel Moisture	100-hr Fuel Moisture	Live Herbaceous Fuel Moisture	Live Woody Fuel Moisture	6.2 m Wind Speed (km h^{-1})
80th	4	5	10	74	102	16.1
90th	3	4	8	54	90	19.3
97th	2	3	7	40	79	22.5

Table 3-3: Fire Weather Inputs for FlamMap

Table 3-3: Initial fuel moistures and 6.2 m wind speeds for the 80th, 90th and 97th fire weather percentiles for use in FlamMap. The fuel moisture columns are in units of percent of oven-dry weight. 6.2 m wind speeds represent the wind speed at 6.2 m above the top of the forest canopy.

Table 3-4: Gridded Winds Output Summary			
	Initial 6.2 Meter Wind Speed (km h^{-1})		
	16.1	19.3	22.5
Range	0.6-41.7	0.6-50.1	0.7-58.4
Mean	15.9	19.2	22.2
Standard Deviation	4.5	5.3	6.3

Table 3-4: Summary of the gridded wind datasets. All winds were simulated as blowing from 247 degrees (west southwest).
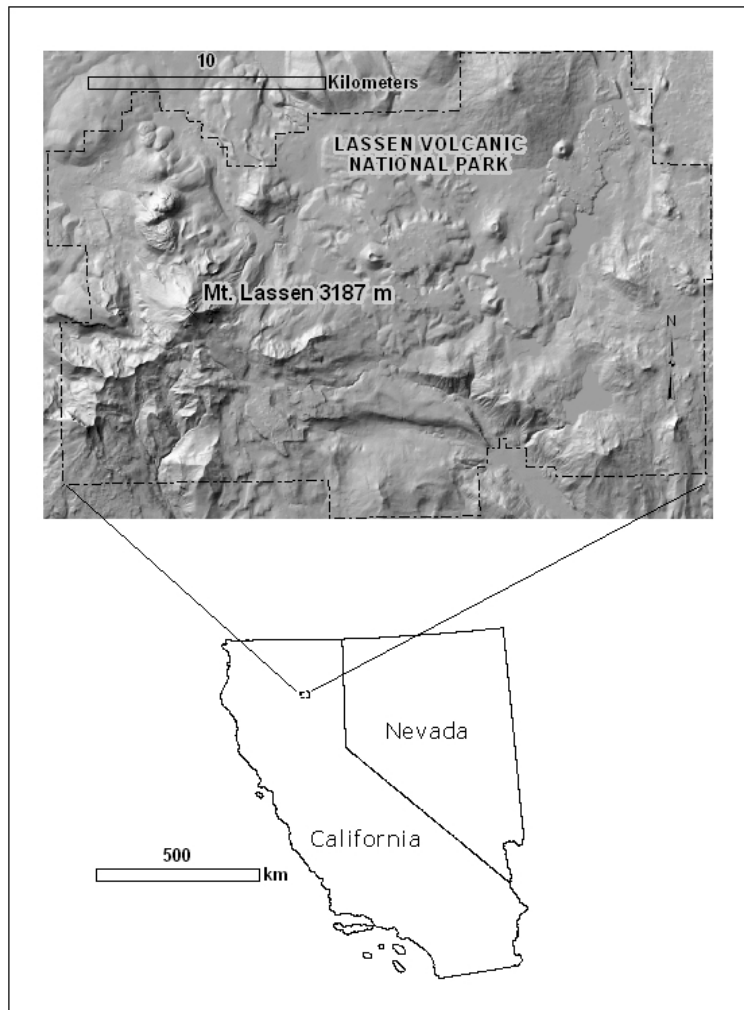
Figure 3-1: Shaded relief map of Lassen Volcanic National Park and its location in northeastern California, USA.
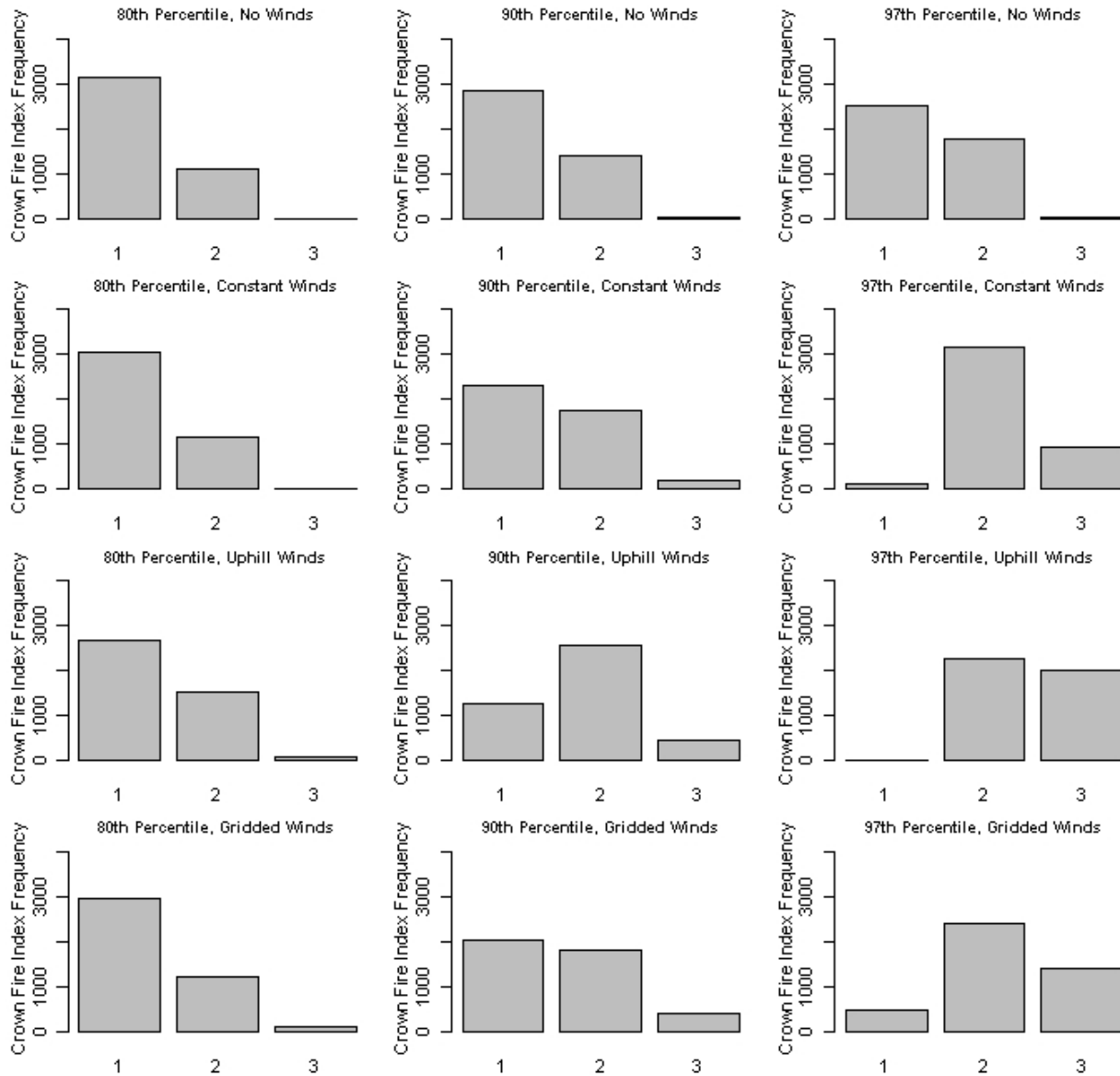
Figure 3-2: Crown Fire Activity Index histograms for Fuel Model 1 by weather and wind scenario. Categories are 1 – Surface Fire; 2 – Surface Fire with Torching; 3 – Crown Fire. N = 4259.
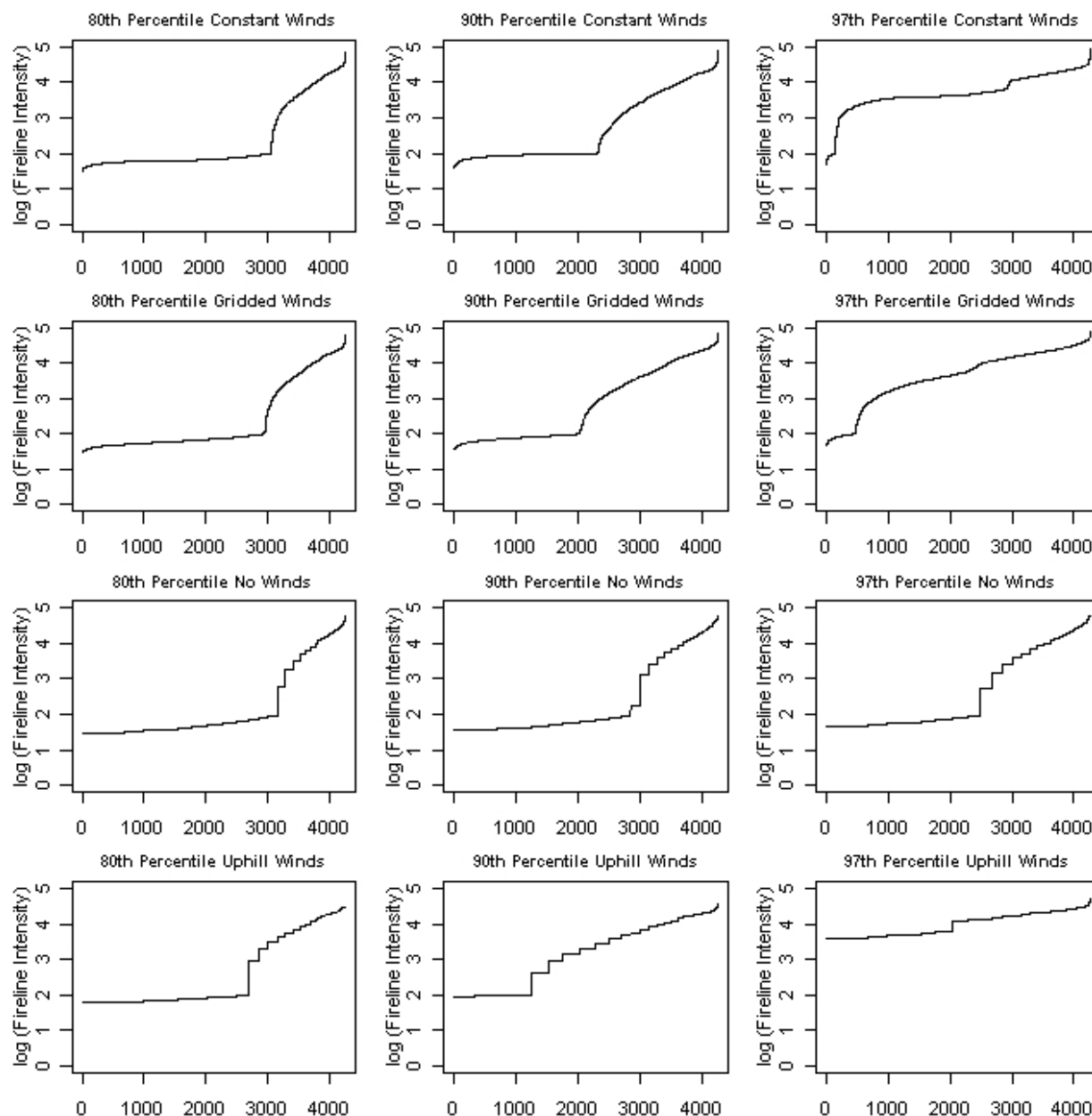
Figure 3-3: Log$_{10}$ of Fireline Intensity for Fuel Model 1 by wind and weather scenario. X-axis is in units of rank order. Fireline Intensity is reported in units of kilowatts per meter (kW/m). N = 4259.
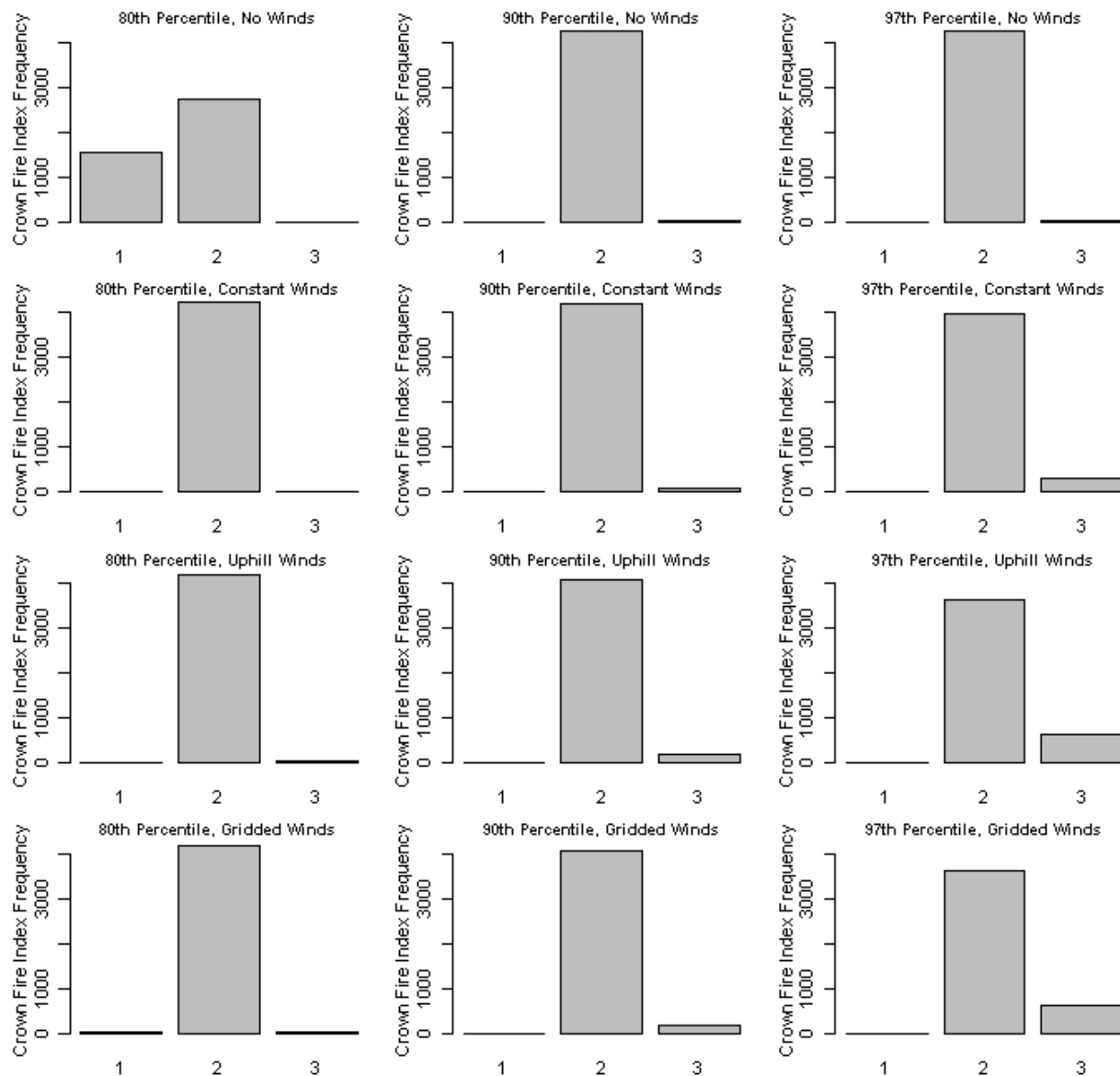
Figure 3-4: Crown Fire Activity Index histograms for Fuel Model 2 by weather and wind scenario. Categories are 1 – Surface Fire; 2 – Surface Fire with Torching; 3 – Crown Fire. N = 4259.
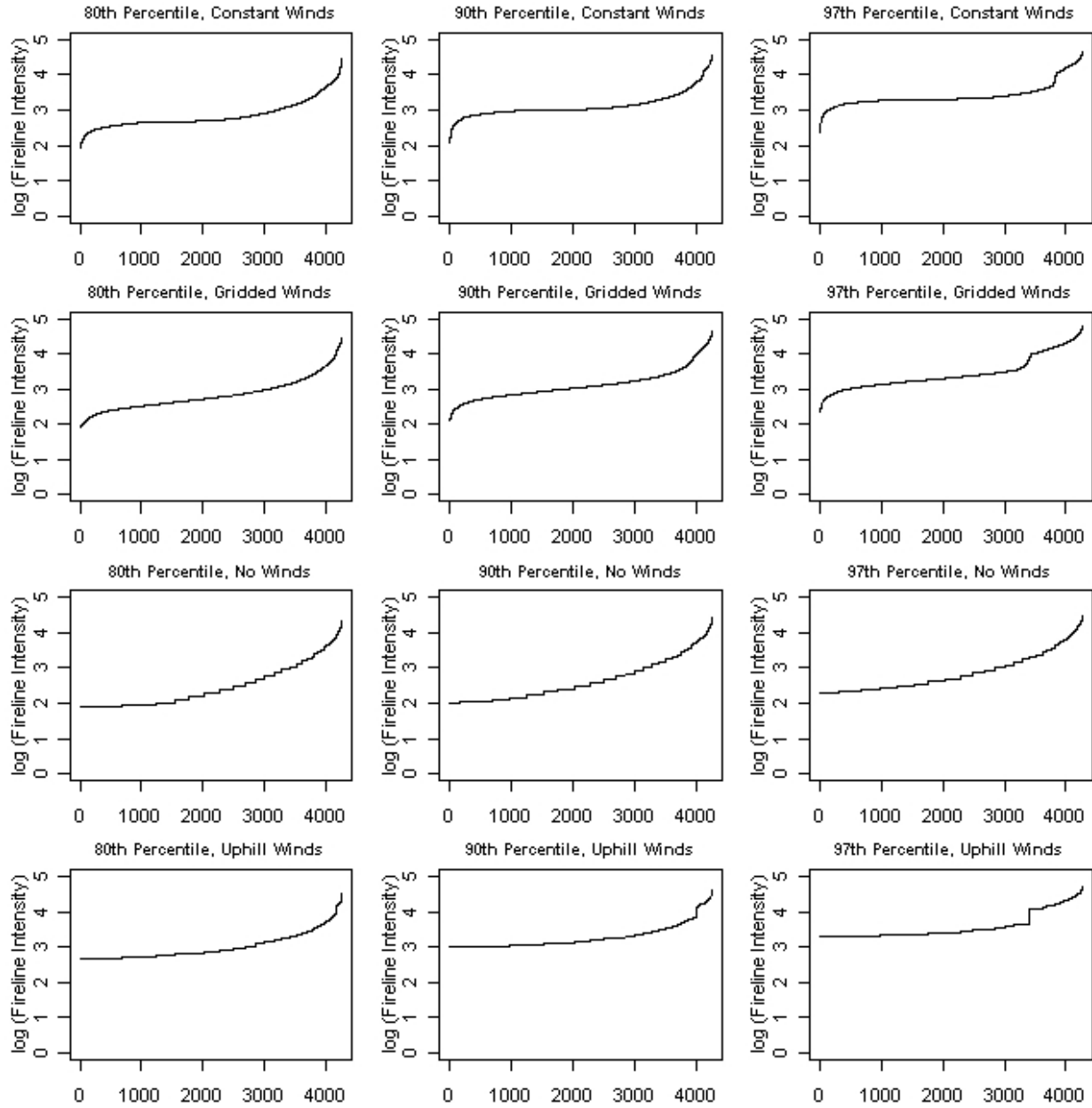
Figure 3-5: Log$_{10}$ of Fireline Intensity for Fuel Model 2 by wind and weather scenario.X-axis is in units of rank order. Fireline Intensity is reported in units of kilowatts per meter (kW/m). N = 4259.
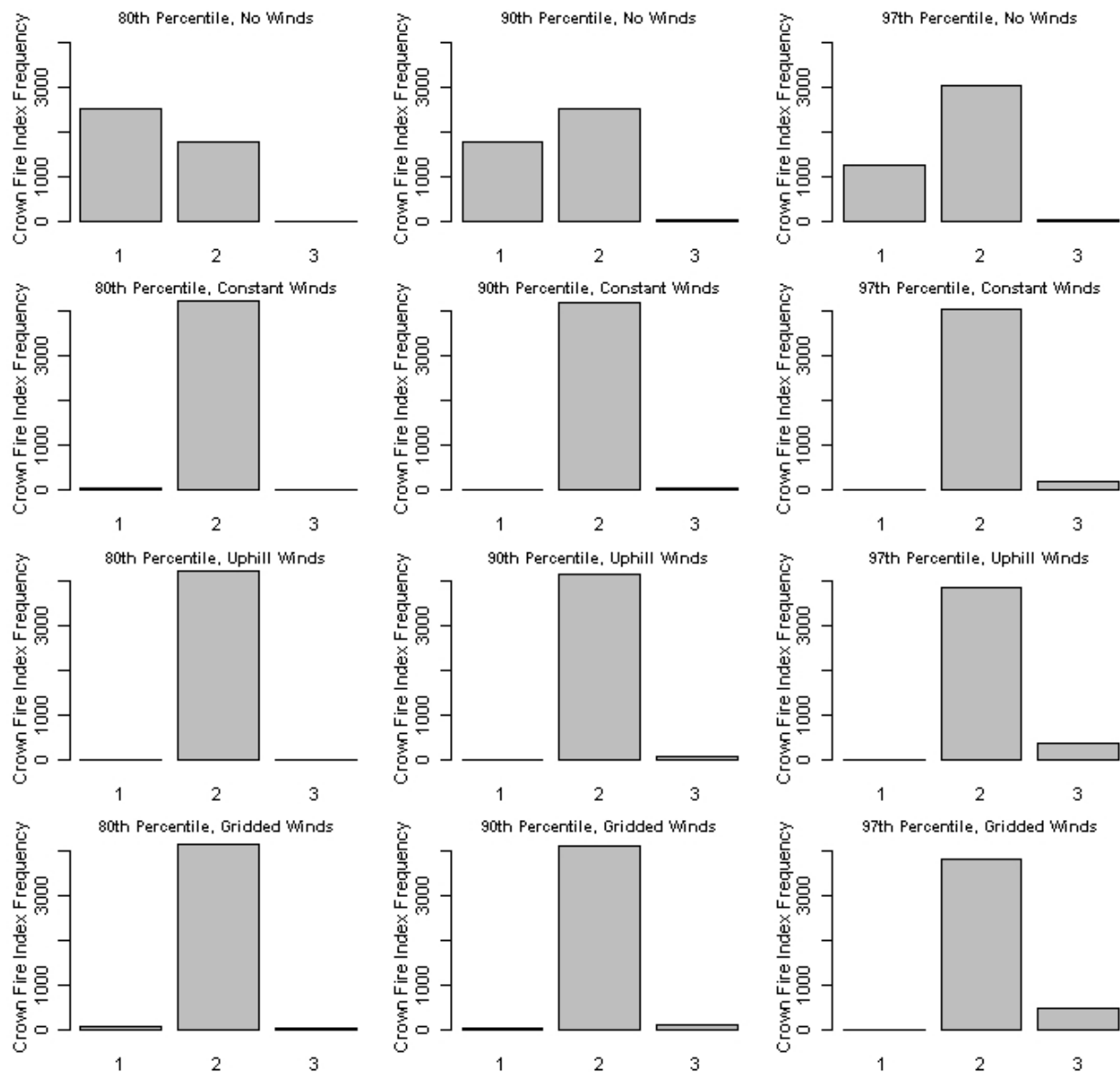
Figure 3-6: Crown Fire Activity Index histograms for Fuel Model 5 by weather and wind scenario. Categories are 1 – Surface Fire; 2 – Surface Fire with Torching; 3 – Crown Fire. N = 4259.
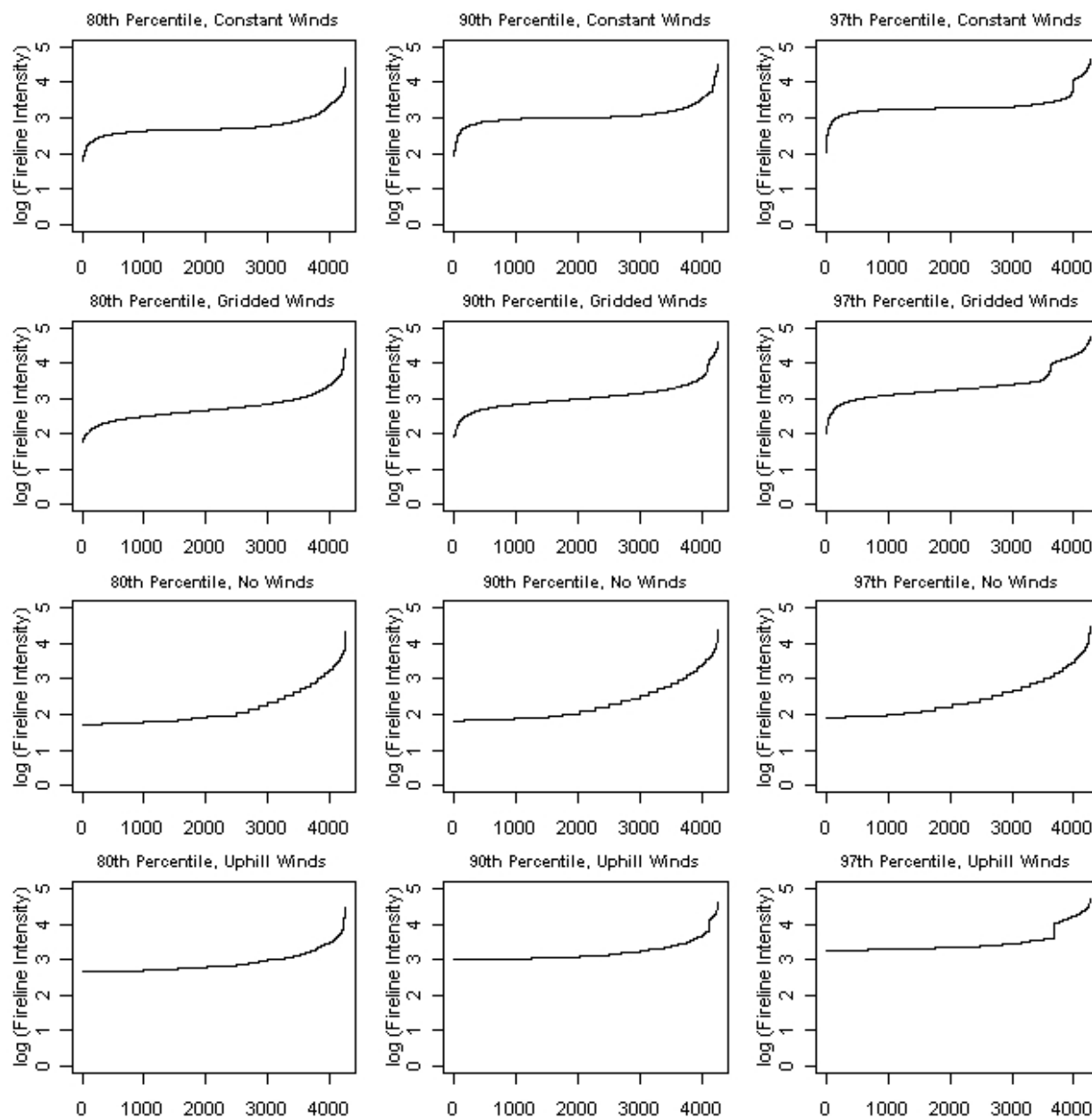
Figure 3-7: Log$_{10}$ of Fireline Intensity for Fuel Model 5 by wind and weather scenario. X-axis is in units of rank order. N = 4259. Fireline Intensity is reported in units of kilowatts per meter (kW/m).
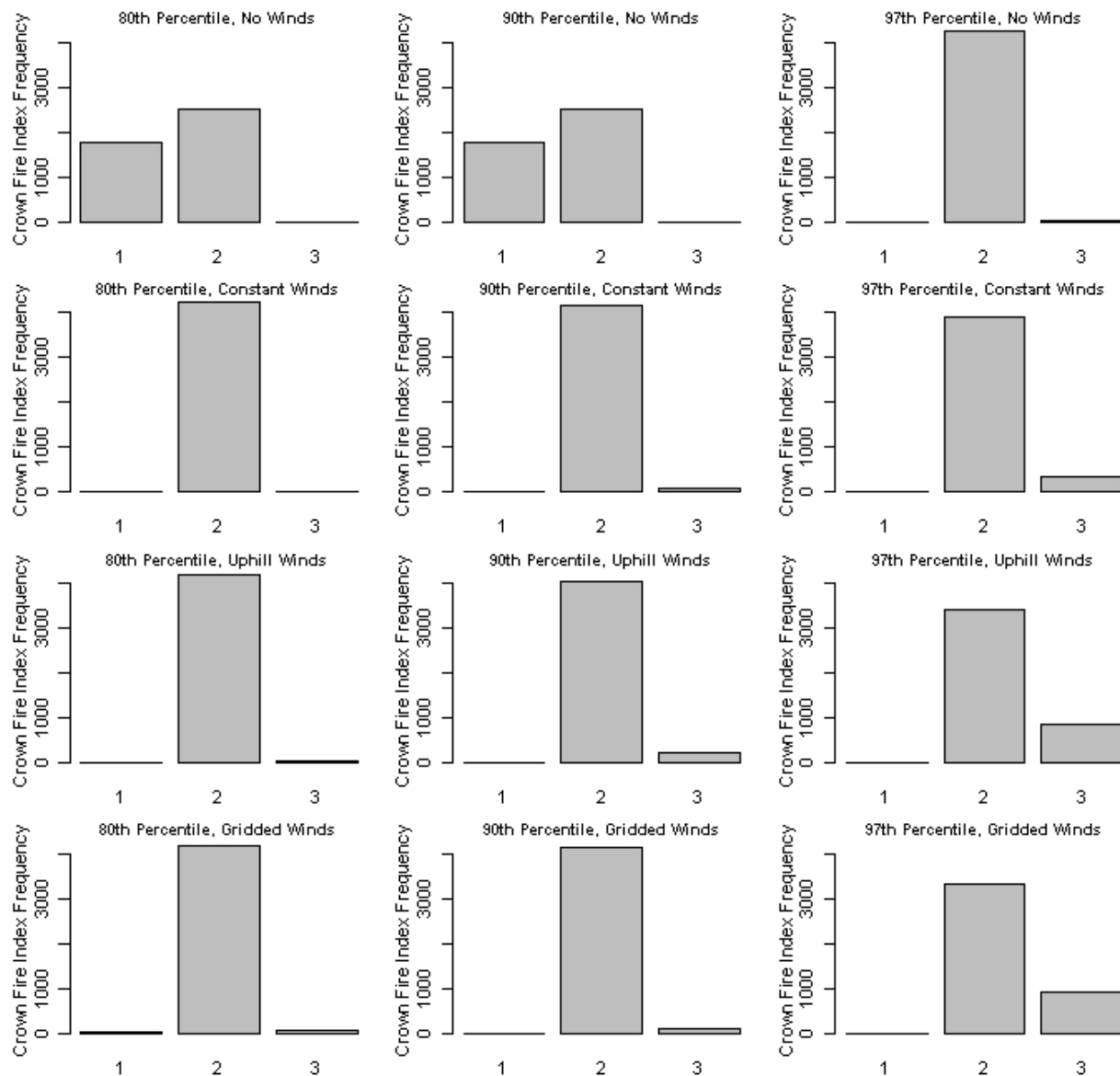
Figure 3-8: Crown Fire Activity Index histograms for Fuel Model 6 by weather and wind scenario. Categories are 1 – Surface Fire; 2 – Surface Fire with Torching; 3 – Crown Fire. N = 4259.
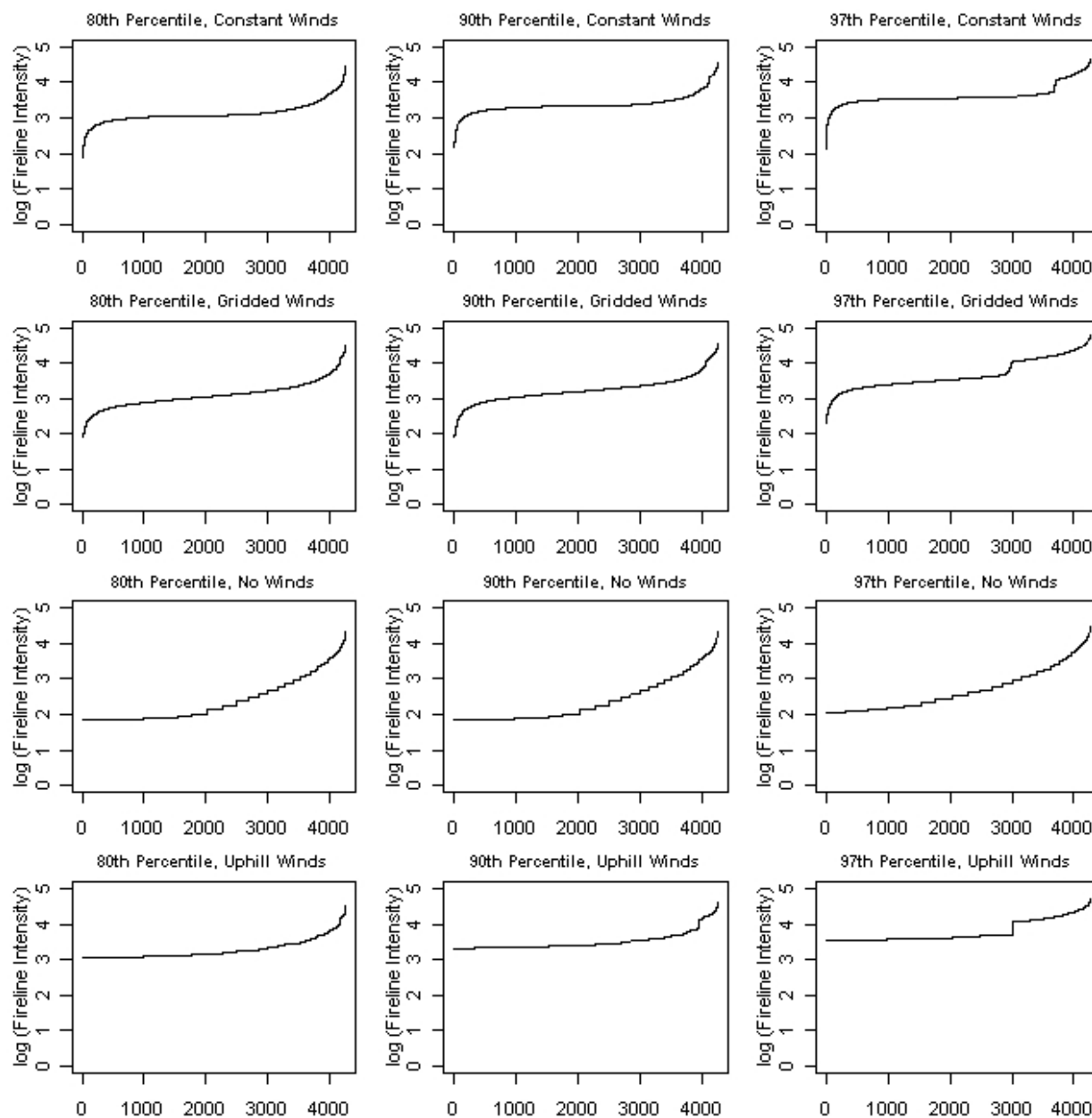
Figure 3-9: Log$_{10}$ of Fireline Intensity for Fuel Model 6 by wind and weather scenario. X-axis is in units of rank order. Fireline Intensity is reported in units of kilowatts per meter (kW/m). N = 4259.
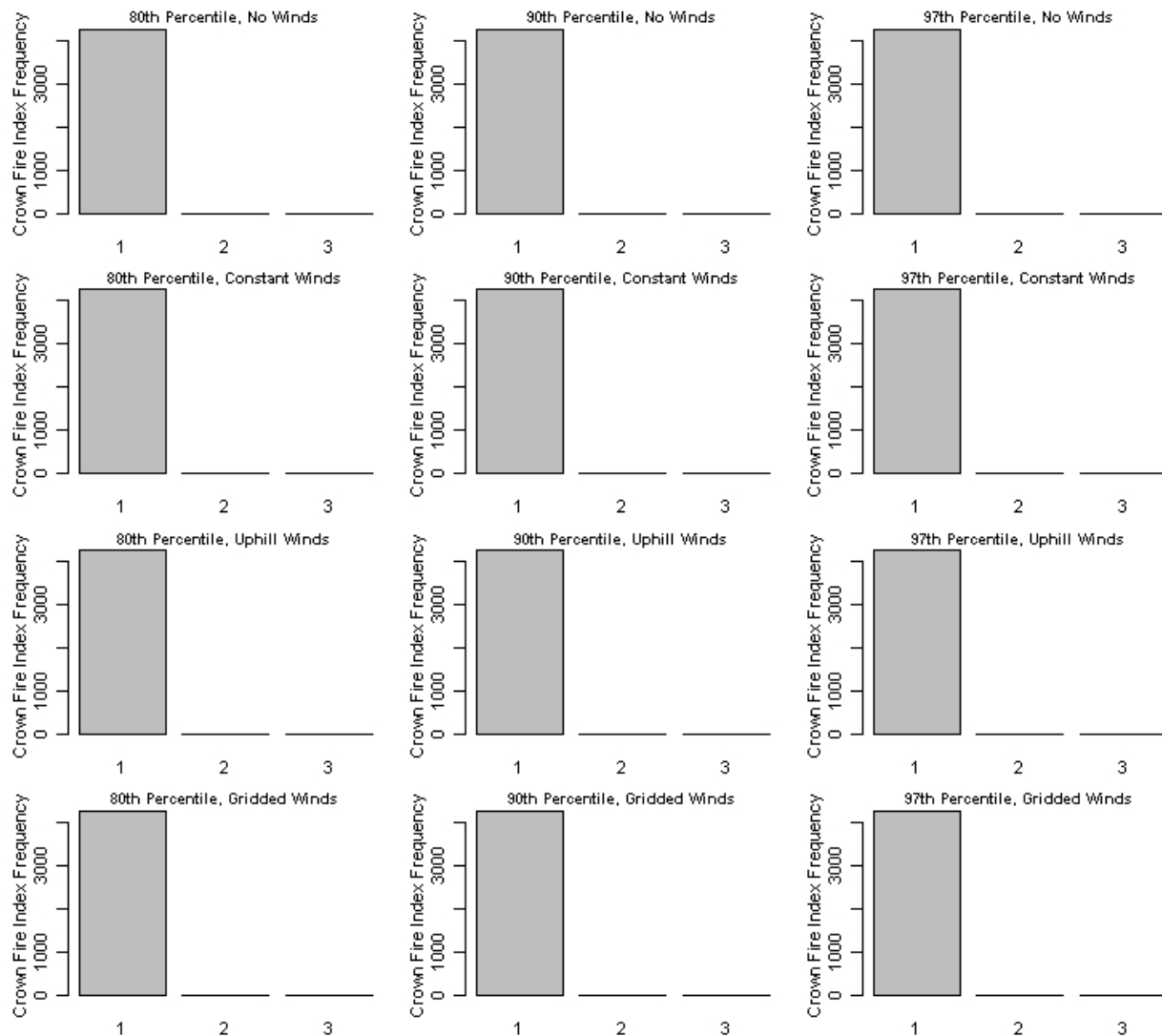
Figure 3-10: Crown Fire Activity Index histograms for Fuel Model 8 by weather and wind scenario. Categories are 1 – Surface Fire; 2 – Surface Fire with Torching; 3 – Crown Fire. N = 4259.
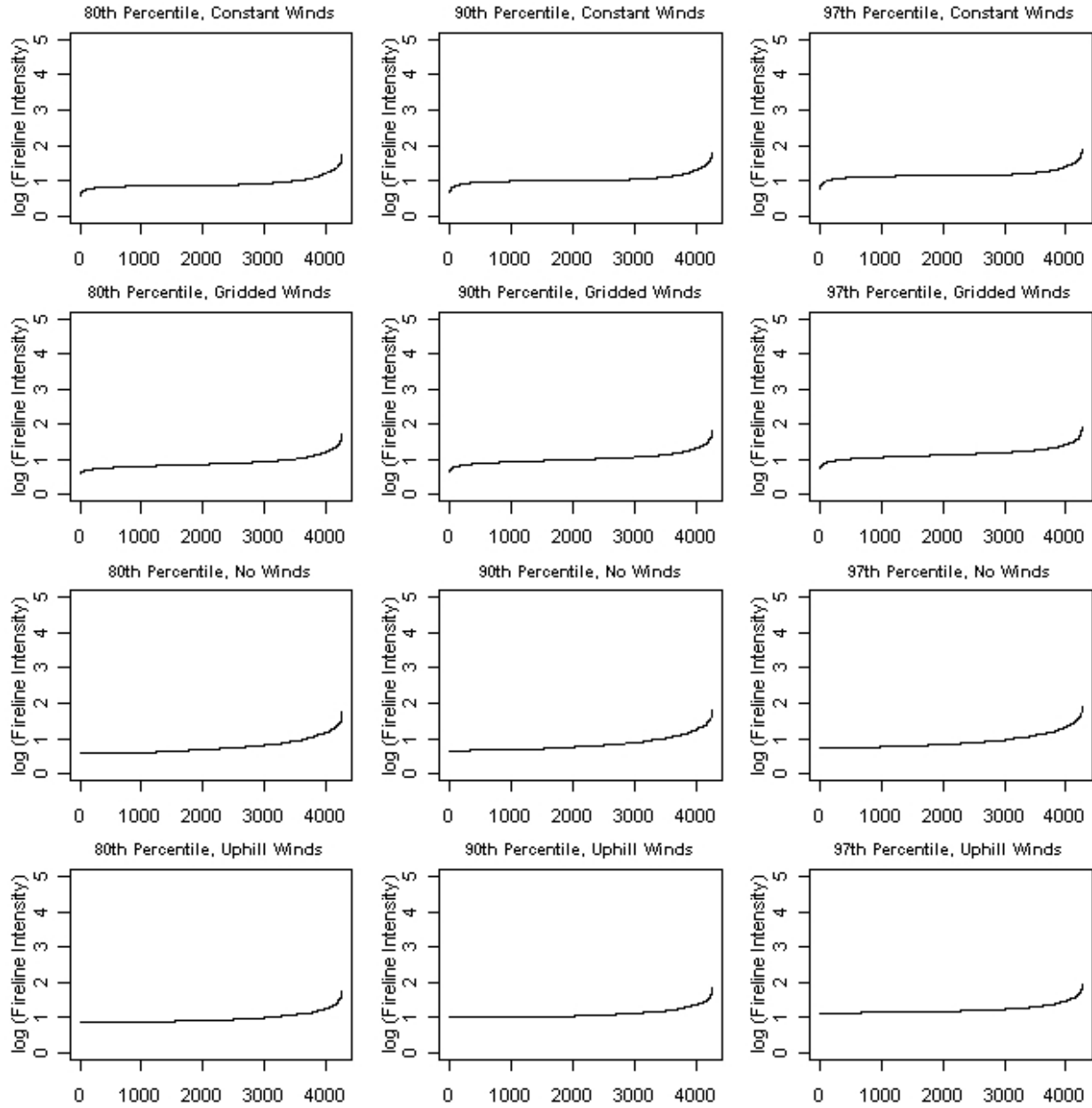
Figure 3-11: Log$_{10}$ of Fireline Intensity for Fuel Model 8 by wind and weather scenario. X-axis is in units of rank order. Fireline Intensity is reported in units of kilowatts per meter (kW/m). N = 4259.
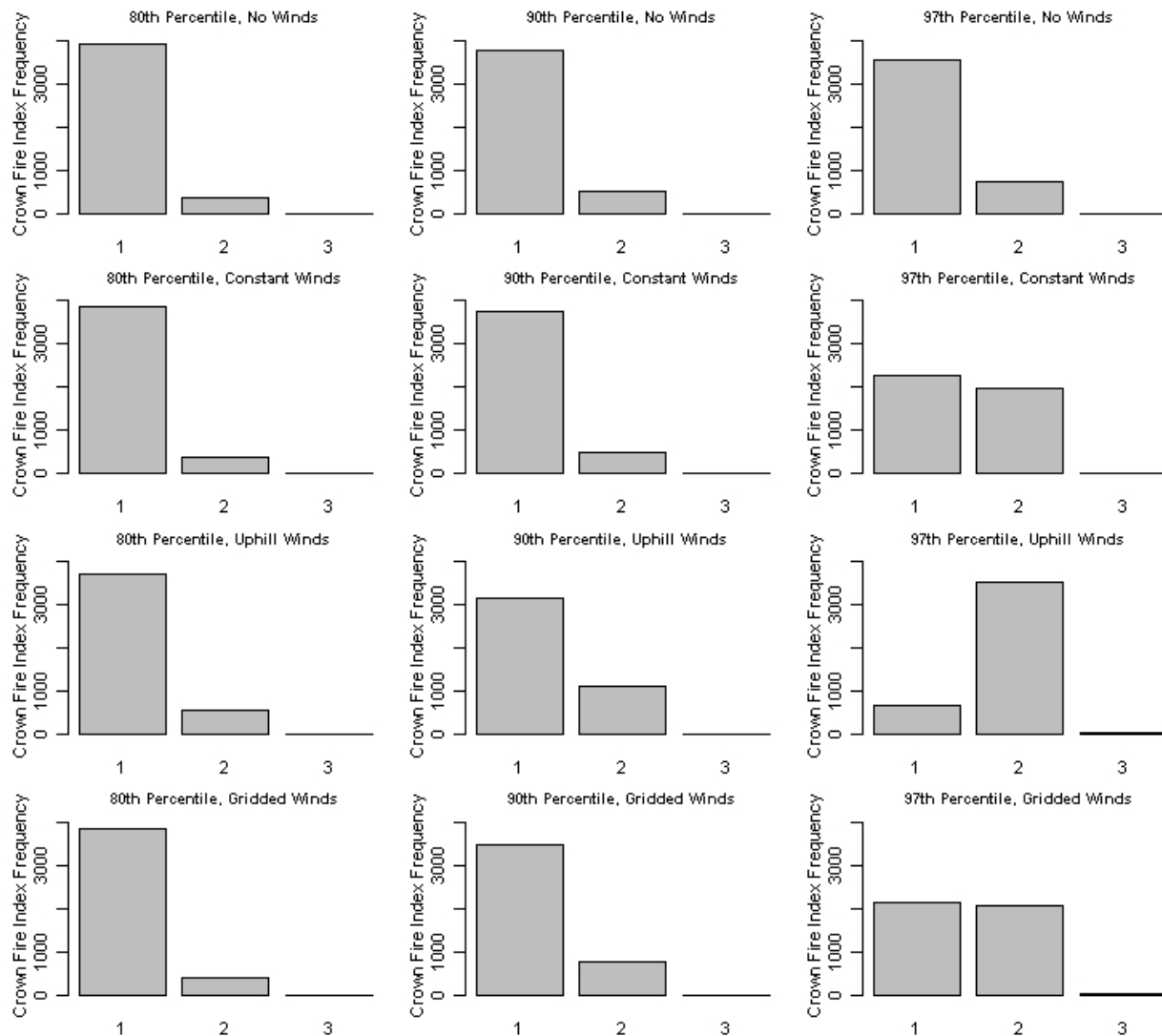
Figure 3-12: Crown Fire Activity Index histograms for Fuel Model 9 by weather and wind scenario. Categories are 1 – Surface Fire; 2 – Surface Fire with Torching; 3 – Crown Fire. N = 4259.
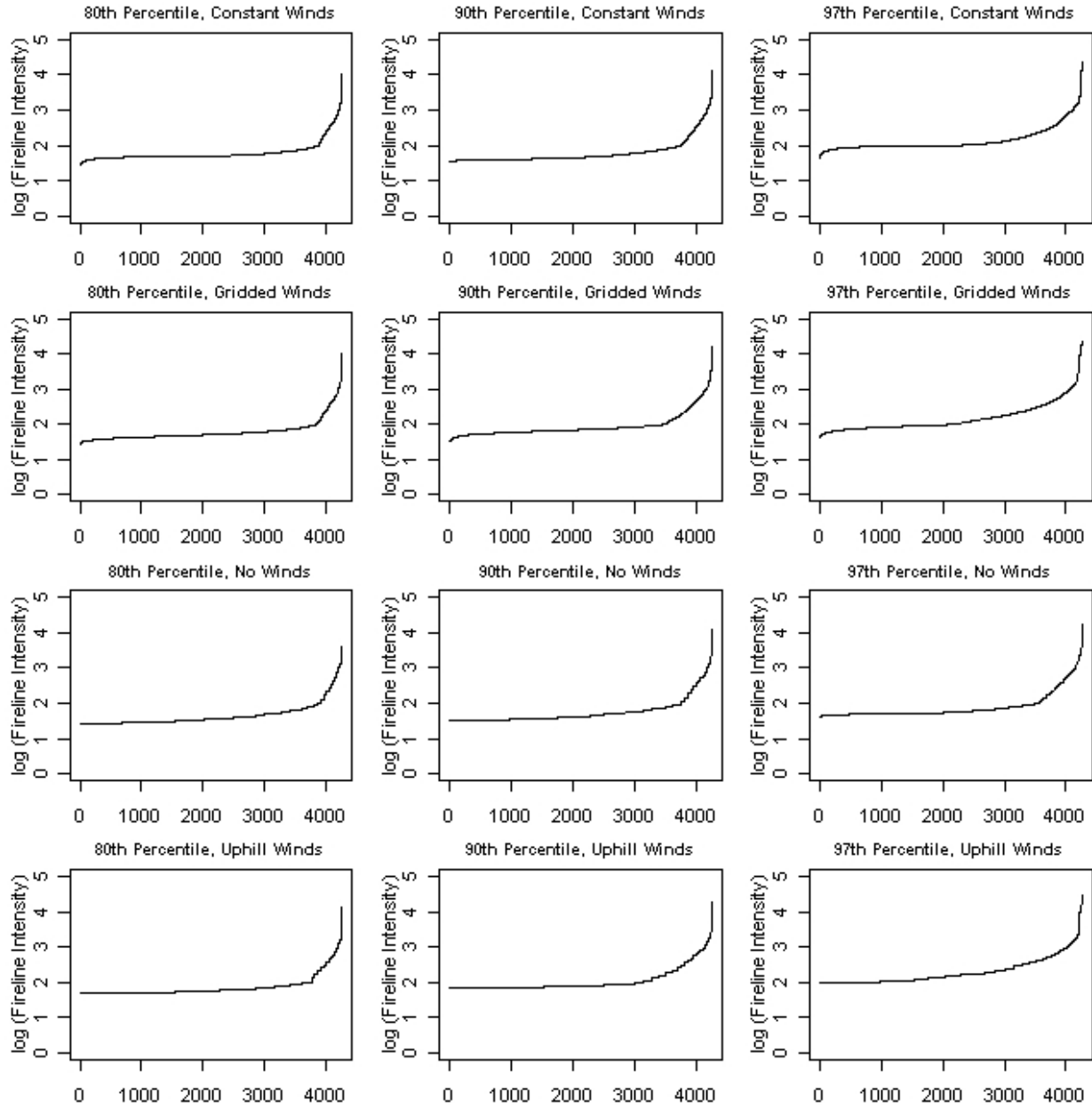
Figure 3-13: Log$_{10}$ of Fireline Intensity for Fuel Model 9 by wind and weather scenario. X-axis is in units of rank order. Fireline Intensity is reported in units of kilowatts per meter (kW/m). N = 4259.
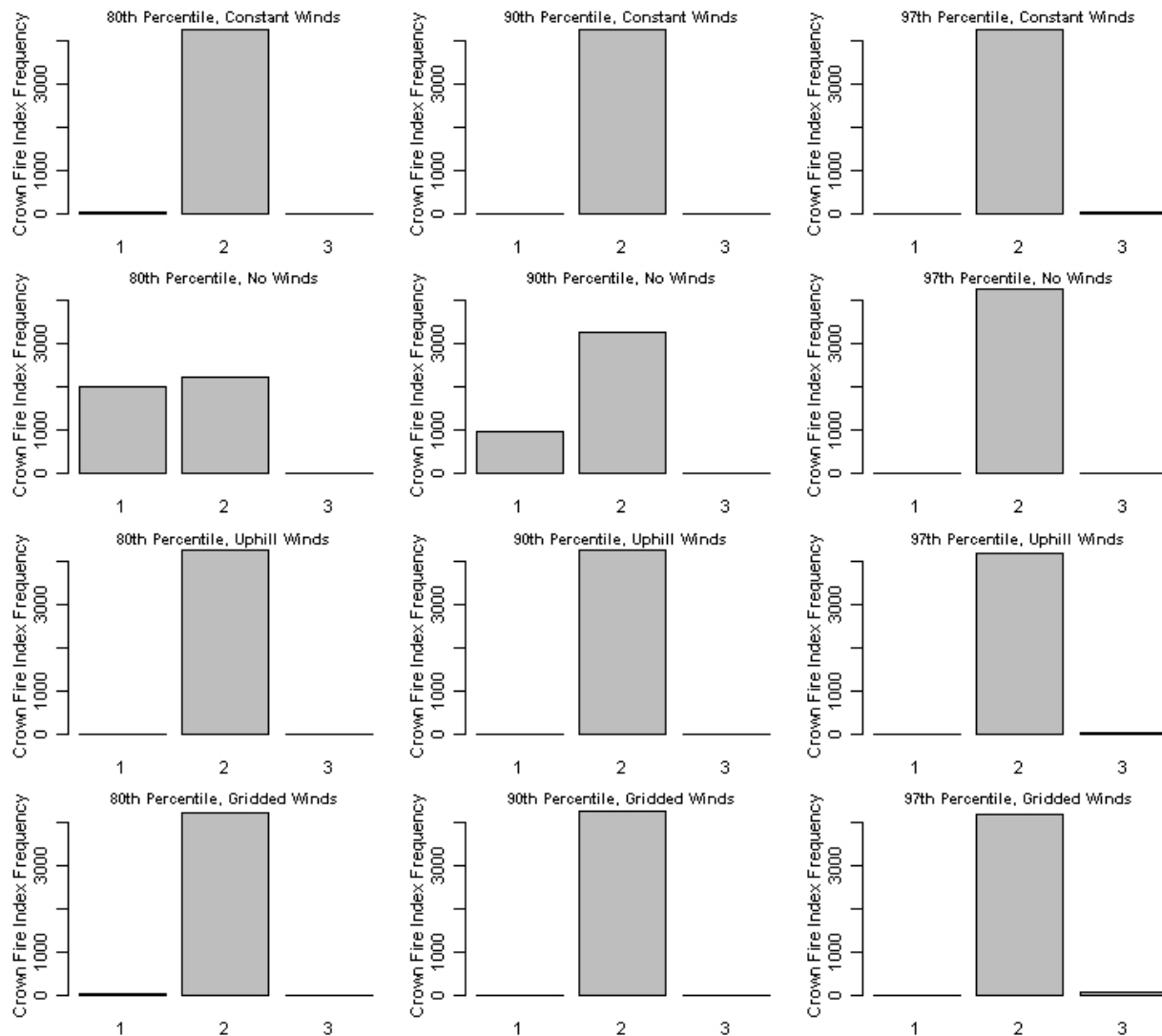
Figure 3-14: Crown Fire Activity Index histograms for Fuel Model 10 by weather and wind scenario. Categories are 1 – Surface Fire; 2 – Surface Fire with Torching; 3 – Crown Fire. N = 4259.
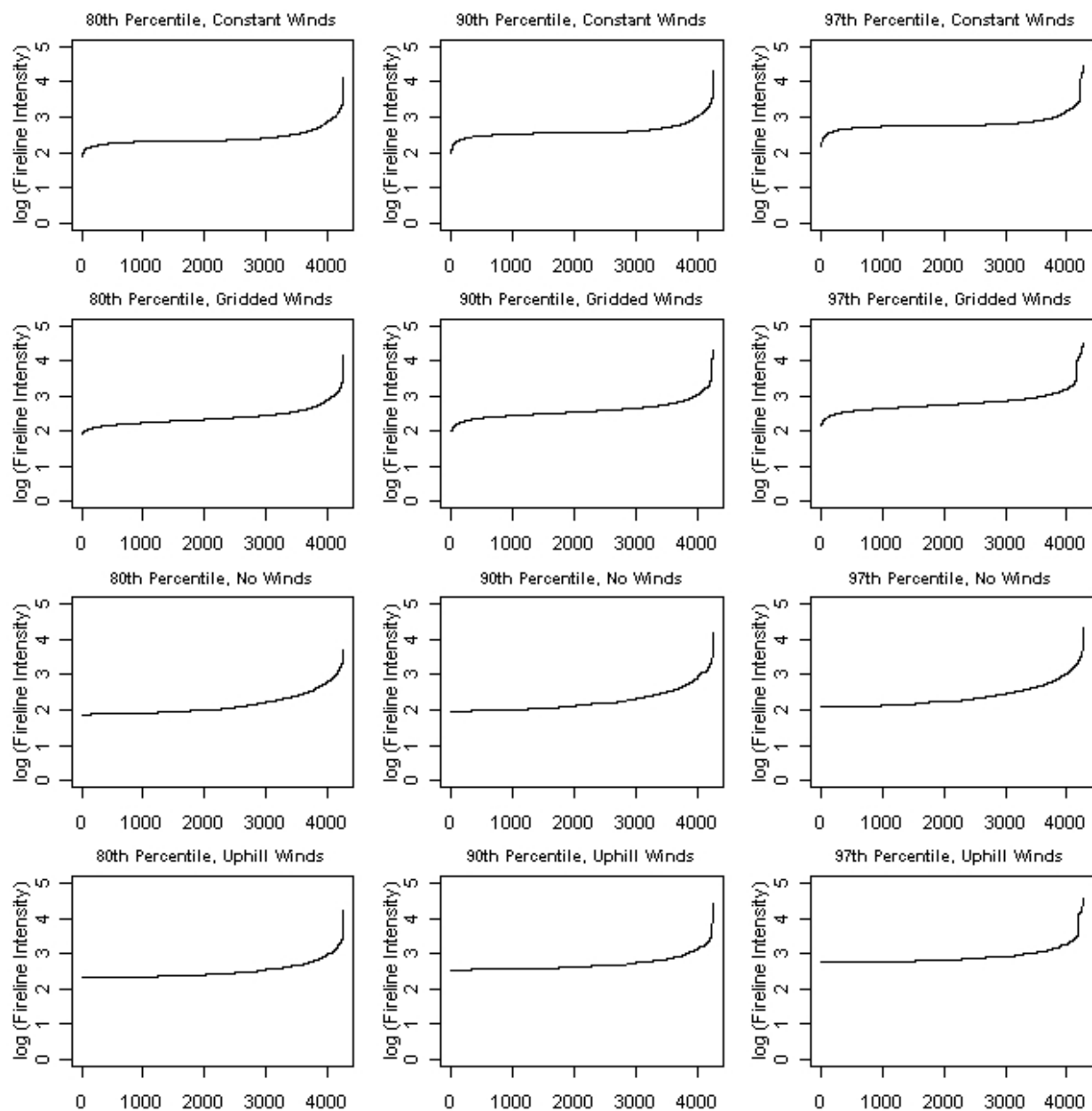
Figure 3-15: Log$_{10}$ of Fireline Intensity for Fuel Model 10 by wind and weather scenario. X-axis is in units of rank order. Fireline Intensity is reported in units of kilowatts per meter (kW/m). N = 4259.
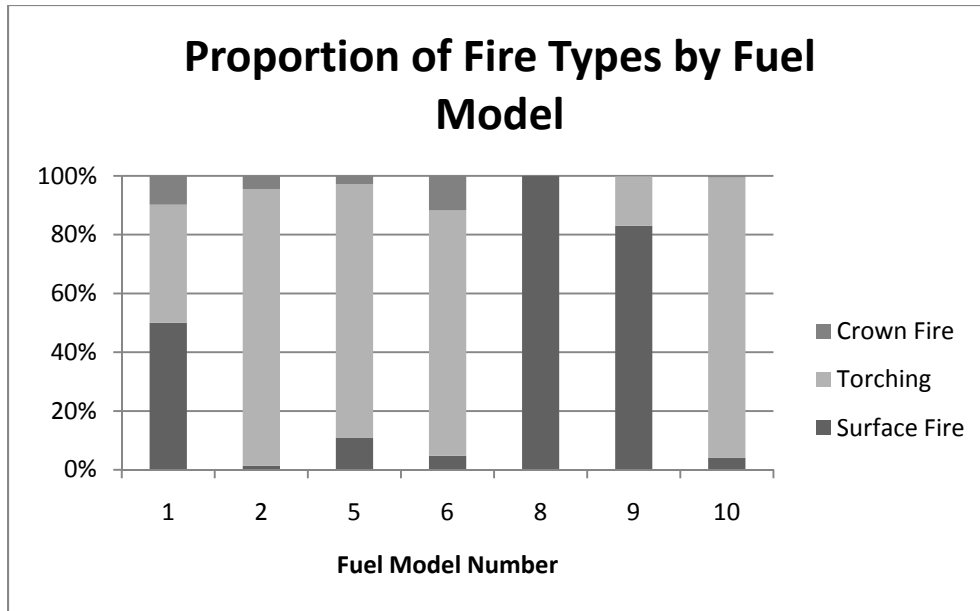
Figure 3-16: Proportion of fire types by fuel model. Fuel models 1, 2, 5, 6, 8, 9, and 10 come from Albini's (1976) set of 13. See the text for a description of the fuel models.
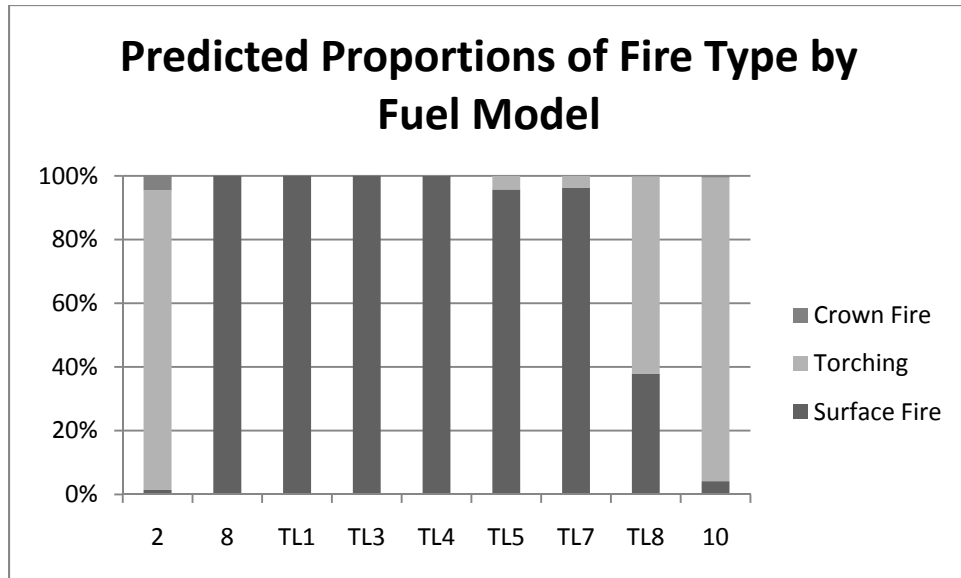
Figure 3-17: Comparison of expected proportion of fire types for Albini's (1976) fuel models (2, 8, 10) and Scott and Burgan's (2005) fuel models (TL1, TL3, TL4, TL5, TL7, TL8) for common fuel types in LVNP. See text for a description of the fuel models.
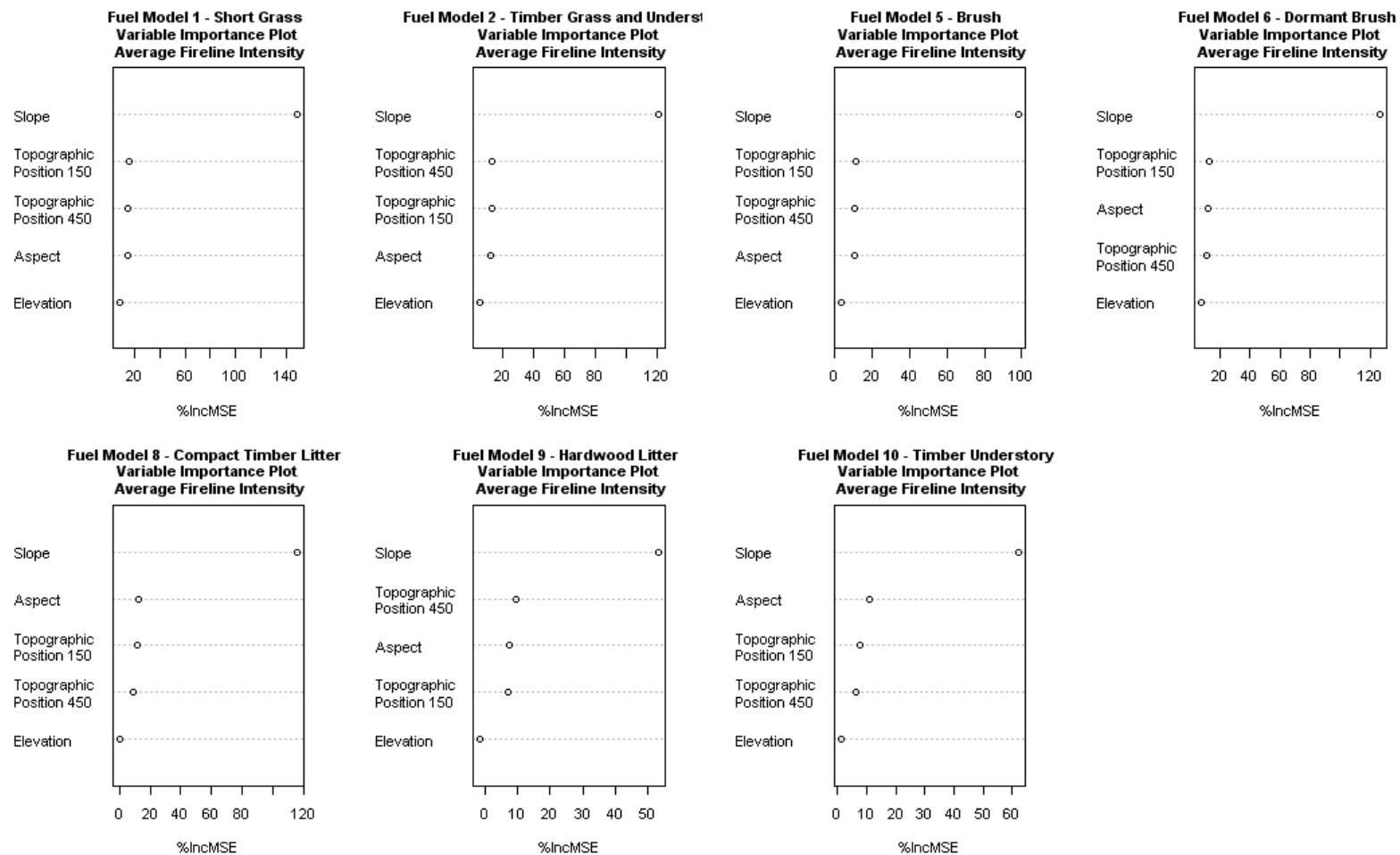
Figure 3-18: Variable importance plots for fuel models 1, 2, 5, 6, 8, 9, and 10 from Albini's (1976) set of 13. Variables on the y-axis are explanatory variables with the most important listed at the top and the least important listed at the bottom. The x-axis shows the change in MSE associated with each variable when it is absent from the model.
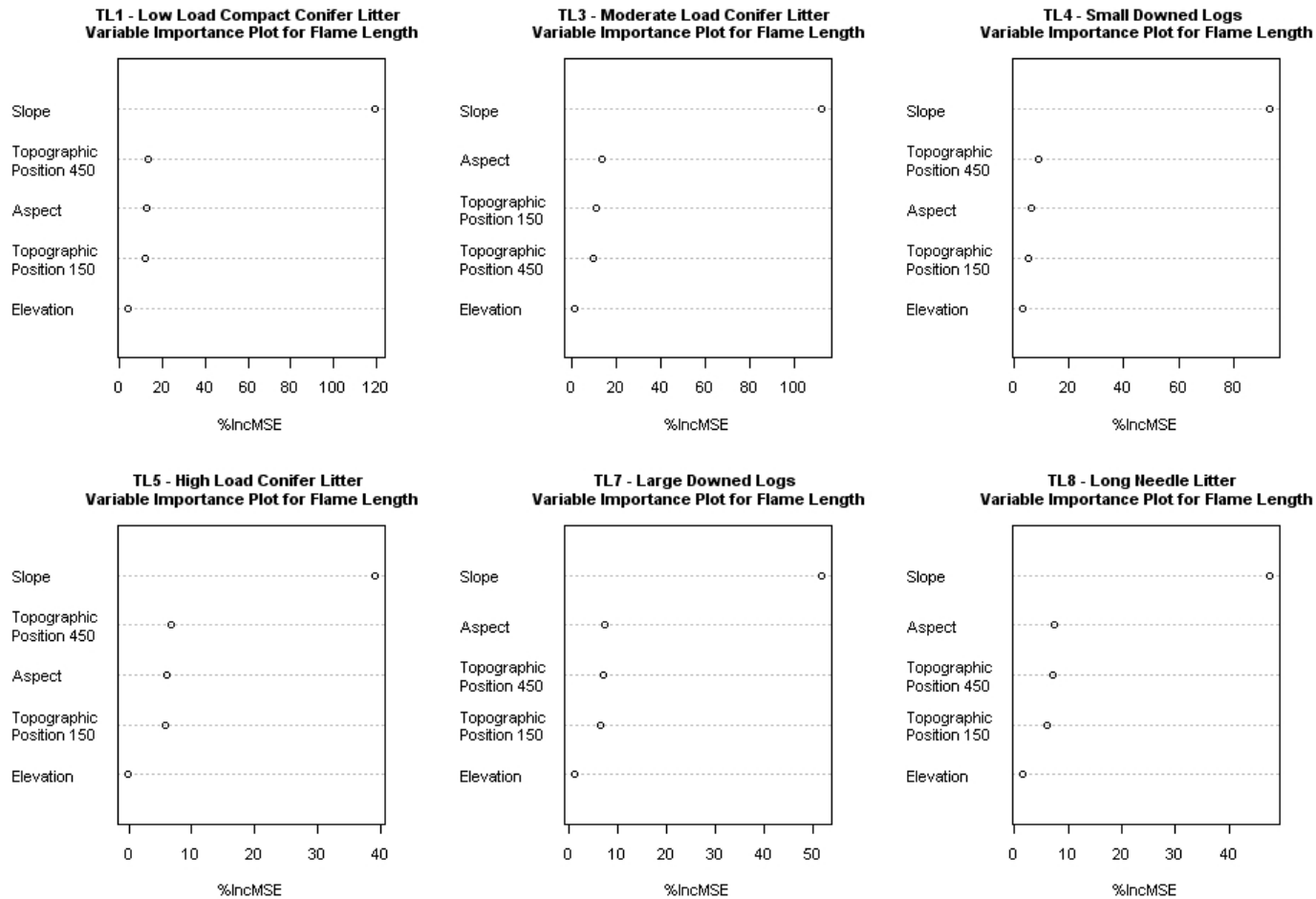
Figure 3-19: Variable importance plots for fuel models TL1, TL3, TL4, TL5, TL7, and TL8 from Scott and Burgan (2005). Variables on the y-axis are explanatory variables with the most important listed at the top and the least important listed at the bottom. The x-axis shows the change in MSE associated with each variable when it is absent from the model.

Chapter 4:

Comparing Historic and Contemporary Measures of Fire Severity with Modeled Fire Behavior to Assess Topographic Controls of Within-Fire Heterogeneity

Abstract

Fire is one of the dominant disturbance processes in forests of the Pacific northwest. It interacts with topography, vegetation, fuel abundance and arrangement, and legacies of human use. In this study, we examine how topography may influence within fire heterogeneity of observed fire severity and predicted fire behavior. To accomplish this, we analyze historic aerial photographs of Lassen Volcanic National Park (LVNP) for evidence of high severity fire effects. We also utilize Relative difference Normalized Burn Ratio (RdNBR) data for six fires that burned in the satellite era. Finally, we model fireline intensity and fire type (surface, torching fire, or crown fire) with realistic surface and canopy fuels burned under the 80th, 90th, and 97th percentile fuel moisture conditions using the fire behavior simulation model FlamMap. To attempt to explain the observed and modeled variation in fire severity and fire behavior, we develop five topographic variables—elevation, slope, aspect, local topographic position, and landscape position. We also develop forest structure and composition variables for conditions prior to burning. We apply a Random Forest algorithm to assess the relative importance of our predictor variables in explaining the variation in RdNBR values. Our results show that historic and contemporary high severity fires in LVNP occurred predominantly at lower elevations and on exposed topographic positions. The strength of the explanatory power of topography for some fires supports our conclusion that some highly pyrogenic vegetation patches may be 'fixed in space' through the interaction of topography, fuels, and the burning process.

Key Words: fire severity, Lassen Volcanic National Park, Relative differenced Normalized Burn Ratio, elevation, slope, aspect, topographic position, Random Forest

Introduction

Fire is a process that has the potential to structure vegetation communities for hundreds to thousands of years (Miller 2007; He and Mladenoff 1999; Baker 1992). This potential can be realized in ecosystems with both low severity dominated regimes (Fulé et al. 1997) and high severity dominated regimes (Turner et al.1994; Turner in press). Some of the well understood factors that influence the variation in fire severity are time-since-last-fire (Odion et al. 2004; Collins and Stephens 2010), fire suppression and its consequential accumulation of fuels and infilling of fire intolerant species (Beaty and Taylor 2001; Safford et al. 2008), logging and subsequent management action or non-action (Weatherspoon and Skinner 1995; Thompson et al. 2007), climate, climate change, and climate teleconnections (Norman and Taylor 2003, Schoennagel et al. 2007; Westerling et al. 2006), vegetation composition (Collins and Stephens 2010; Odion et al. 2010), and patchiness of vegetation (Collins and Stephens 2010). Each of these have been identified as important drivers of fire regime and fire severity change over the course of the 20th century.

Topography is a determinant of variations in fire severity as well, and its influence on fire regimes is known generally in broad strokes through fire history studies. In the Cascade Range, upper slopes tended to burn at longer intervals and at higher severity than other topographic settings (Beaty and Taylor 2001). Similarly, in the Klamath Range, upper slopes tend to burn with higher severity (Taylor and Skinner 2003). In contrast, in the specific case of the Big Bar complex and the Quartz fire of the Klamath Range, Alexander et al. (2006) found evidence that higher elevation forests burned less severely than forests at lower elevations. Heyerdahl et al. (2001) describe forests in the Cascades of eastern Oregon and southeastern Washington where fire severity was high on north and east slopes and low on south and west slopes. Rollins et al.

(2002) compared wilderness areas in Montana and New Mexico and found that in Montana,

south and southwestern aspects burned more often because they were subject to increased

insolation which dried fuels more quickly. In contrast, northeastern aspects in New Mexico

burned more often because their moisture regimes allowed for more rapid accumulation and

connectivity of fuels (Rollins et al. 2002). Topography had no effect on fires studied by Baker

and Kipfmueller (2001) in the northern Rocky Mountains. These sub-alpine forests are likely

dominated by long-interval, high intensity fires driven by extreme weather such that topographic

effects on fire behavior and severity are overpowered (Baker and Kipfmueller 2001). In southern

Arizona forests, historic fires were more widespread on low-relief portions of the landscape

while strongly dissected landscapes inhibited fire spread (Iniguez et al. 2009). Holden et al.

(2009) used topographic variables to predict the locations of high severity fires and found that

elevation was the single most important predictor of high v. other fire severities.

In the absence of other evidence, vegetation size structure, age structure, and composition have

been used as indicators of past fire regimes. Vegetation structure has been used to infer the

presence of low-severity fire regimes (e.g. Taylor 2000), mixed-severity fire regimes (e.g.

Hessburg et al. 2007), and high-severity fire regimes (e.g. Nagel and Taylor 2005). Patches of

vegetation on the landscape can also be important drivers of within-fire variability in severity

(Collins and Stephens 2010, Odion et al. 2010). Moreover, vegetation effects on fire severity

can be self-reinforcing such that highly pyrogenic vegetation tends to promote fire behavior that

results in its own persistence (Odion et al. 2010).

Recently, remotely sensed pre- and post-fire imagery has enabled the development of the

differenced Normalized Burn Ratio (dNBR) method of mapping fire severity patches (Miller and

Thode 2007; Miller et al. 2009). This method was developed from Landsat TM data and allows

a pixel by pixel classification of fire severity patches (Miller and Thode 2007). While the RdNBR methodology has been criticized by some because it is a measure of the decrease in the greenness of a pixel and inferring fire severity from this measure is an inexact science (Odion and Hanson 2008). In Canadian boreal forests, RdNBR and dNBR may capture the same types of pre- and post-fire differences (Wulder et al. 2009) but also may not be as proficient as other methods for determining fire severity (Soverel et al. 2010). However, the forest types for which RdNBR was originally calibrated are very similar to the types of forests that occur in our study area, and we use RdNBR values because they are a comparable, repeatable measure across fires (Miller and Thode 2007). Collins et al. (2007) and Thompson et al. (2007) utilize dNBR data to examine slope, aspect, and elevation, among other variables, as predictors of fire severity and find that aspect is a somewhat important predictor of fire severity. In general, however, topographic controls were overshadowed by other variables that drive fire severity such as daily meteorological condition and time since last fire (Collins et al. 2007) or stand level fuel structure and type (Thompson et al. 2007).

Fuel structure and arrangement is the variable most directly related to fire severity because it is the physical complex that interacts with the combustion process to produce heat, consume vegetation, and kill vegetation. Measures of fire severity in forests are often related directly to the amount of canopy consumed or killed by fire (Miller and Thode 2007). Thus, canopy fuel variables are critical components in modeling potential fire behavior. The four most widely used variables are Canopy Bulk Density (CBD), Canopy Cover (CC), Canopy Base Height (CBH), and Canopy Height (HT). CBD is a measure of the total amount of above-ground-surface fuel that is available to wildfires; typically including foliage and up to one half of the smallest branchwood (0-6.4 mm) and is measured in units of kg m^{-3}. CC is the horizontal fraction of the

131

ground that has canopy above it and is measured as a percentage of total area. CBH is a measure of the vertical continuity of fuels and expresses the lower threshold above which there is sufficient fuel for a crown fire to be self-sustaining and is measured in m. Lower CBH values indicate that canopy fuel is closer to the ground and hence could act to transition surface fire into the crown. Finally, HT is the average height of the dominant stratum of tree cover and affects modeled fuel moistures and is measured in m.

In Lassen Volcanic National Park (LVNP), high severity, low frequency fire regimes in some topographic positions may result in stable, fire dependent brushfield communities. The arrangement of these patches is just one realization of the stochastic process of fire burning through a heterogeneous fuel, vegetation, and topographic environment that is subject to human management (sensu O'Sullivan and Unwin 2003). While a single fire may be dominated by short-term controls, weather is essentially a stochastic process because of its wide range of variability and its rate of change relative to the time scale of a single fire. Further, the combination of fuel, weather, and topographic conditions that occur during any one fire are not necessarily comparable to the combination of conditions during other fires.

We investigate the effect of topography on the location of high severity and high intensity fire using historic, contemporary, and model generated evidence regarding the expected and known locations of high severity fire effects. Our null hypothesis is that topography (elevation, slope, aspect, and topographic position) do not affect observed fire effects or predicted fire intensity. Our alternative hypothesis is that topography does affect the spatial distribution of fire effects and behavior. We conducted our study with LVNP as a case study. Inside the perimeter of the park, we mapped high intensity fire effects from 1941 aerial photographs. To assess current patterns of fire severity patches, remotely sensed maps of fire severity derived from the dNBR

132

methodology were analyzed in comparison to the model results. We used the fire behavior simulation model FlamMap® to generate expectations of the locations of high intensity fire. We compared the topographic characteristics of the historic and contemporary high severity fires with the results of the simulation modeling. We are interested primarily in those locations where fire intensity and severity are strongly controlled by topography because it is in these places that the composition of vegetation communities will most likely reflect the interaction between fire and topography. Comparisons made between expected fire intensity and historic and contemporary fire severity can then give natural resource and fire managers guidance on fuel treatments and fire suppression efforts.

Study Area

LVNP lies at the southern end of the Cascade Range, a volcanic plateau punctuated by high volcanic peaks (Figure 4-1). Elevation ranges from 1,609 to 3,187 m and the Park's total area is 42,900 ha. Dominant vegetation communities covary with elevation (Taylor 1990, 2000; Parker 1991; Schoenherr 1996). The lowest elevation forests are dominated by ponderosa pine (*Pinus ponderosa*) and Jeffery pine (*P. jeffreyi*). Mixed conifer forests of Jeffrey pine (*Pinus jeffreyi*) and white fir (*Abies concolor*) dominate the lower montane forests. Upper montane forests are composed of red fir (*A. magnifica* var. *magnifica*), white fir (*A. concolor*), and western white pine (*P. monticola*). Lodgepole pine (*P. contorta* spp. *murrayana*) occupies low lying depressions where cold air drainage is a dominant part of the regeneration climate. High elevation forests are dominated by mountain hemlock (*Tsuga mertensiana*) and whitebark pine (*Pinus albicaulis*). The climate is Mediterranean and is characterized by hot, dry summers and cold, wet winters. Average monthly temperatures at Manzanita Lake, California (in LVNP, elevation 1802 m), range from -6.6 °C minimum and 5.0 °C maximum in January to 7.5 °C and

26.1 °C in July (WRCC 2009). Annual average precipitation is 104 cm, but inter-annual

variability is high. Most precipitation (>80%) falls as snow between November and April and

annual maximum snowpack depth from the Lower Lassen Peak Snow Course (usually in April or

May) ranges from 1.63 to 8.41 m with an average of 4.63 m (NOHRSC 2010).

Methods

Contemporary Fire Severity Data

To analyze the locations of contemporary high severity fire effects, we downloaded mapped fire

severity patterns from the Monitoring Trends in Burn Severity website (MTBS 2008). This

website is a clearinghouse for fire severity data on all fire that originate on federal lands

(including National Parks, National Forests, and Bureau of Land Management lands). We

downloaded the fire severity data for 6 fires that occurred inside LVNP since the beginning of

the MTBS record in 1984. They are the Badger (1984), Huffer (1997), Fantastic (1998), Bluff

(2004), Prospect Peak (2005), and Horseshoe (2005) fires. Each of these fires burned more than

405 hectares (1000 acres). The Prospect Peak fire was an intentionally lit, prescribed fire that

escaped control and the Horseshoe fire was Wildland Fire Use fire that burned under conditions

that favored low intensity burning. The other four fires are all classified as wildfire (MTBS

2008). We utilized MTBS records for relative differenced NBR (RdNBR), a thematic

classification of burn severity, and a fire perimeter based on the dNBR data (Eidenshink et al.

2007). We chose to analyze RdNBR because it is the most comparable between fires (Miller and

Thode 2007). RdNBR is computed as:

$$\frac{\mathrm{PreFireNBR} - \mathrm{PostFireNBR}}{\sqrt{|\mathrm{PreFireNBR}/1000|}}$$

where NBR is calculated from LandSat images as:

$$\frac{\text{band } 4 - \text{band } 7}{\text{band } 4 + \text{band } 7}$$

RdNBR is positive for pixels that have decreased vegetation cover and higher values indicate greater decreases. Negative values are possible as well and interpreted as 'unburned to low' severity (values very close to zero) or as 'increased greenness' (negative values further from zero; Miller and Thode 2007). MTBS categorical fire severity rankings are based on dNBR and guided by analysts (MTBS 2008). Its 6 categories are: 1—unburned to low; 2—low; 3—moderate; 4—high; 5—increased greenness; and 6—water/barren/cloud mask.

Historic Severity Data

We were also interested in locating historic patches of high severity fire on the landscape and analyzing their relationship with topography. To accomplish this, we georeferenced 57 aerial photographs of LVNP from 1941. We used these as the basis on which to map the location of patches of vegetation that are associated with high severity fire. Vegetation types assumed to be associated with high severity fire included brushfields and patches of even-aged forests. These patches were recognized by their relatively smooth texture on the aerial photographs and were also compared against a contemporaneous vegetation type map. Many of these vegetation patches were visited during field work in LVNP to confirm their structure as either brushfields or even aged forests. We mapped these across the entirety of LVNP with a minimum patch size of 2 ha (5 acres).

Simulation Approach

We used FlamMap to generate expected fire behavior at the landscape scale for LVNP. FlamMap is a landscape-scale, raster based model for predicting fire behavior (Finney 2006). FlamMap uses raster grid themes of slope, aspect, elevation, surface fuel model, CC, CH, CBH, and CBD to predict fire behavior characteristics independently for each location on the gridded landscape. Fire behavior outputs include, but are not limited to, fireline intensity (kW/m) and crown fire activity (0, 1, 2 or 3 categorical index) (Finney 2006). FlamMap is the most appropriate model because it was developed primarily for "mapping *how* a fire might burn a given area" (Stratton 2006, p. 13, emphasis in original) and fire behavior calculations are rapid. The implementation of FlamMap calculates fire parameters (fireline intensity, crown fire activity etc.) for each grid cell independently of other grid cells. FlamMap is commonly used to estimate landscape scale fire behavior for different fuel and weather conditions (Stratton 2004) and is parameterized so that many combinations of fuels and weather can be burned across the same physical template without the need for excessive computing power (Finney 2006). FlamMap can handle raster data of any resolution, provided all datasets are of the same resolution and extent and cover the same geographic area (Finney 2006).

Surface and Canopy Fuels

A map of surface fuels for LVNP was developed from a set of 340 surface fuel sampling plots established in 1998-99 by C. Farris (C. Farris, 2009, unpublished report). The plots were located by clustering NDVI values from Landsat imagery using ISODATA, an unsupervised distance to mean algorithm (ERDAS 1997). The clusters produced by ISODATA were used to assign initial surface fuel models (Anderson 1982). Field plots were used to support the surface fuels mapping. Detailed fuels information was collected at these plots including surface fuel loading using Brown's planar intercept method (Brown 1973), overstory, understory, and shrub species

composition, surface and litter fuel characteristics, canopy and understory height, and photographs for comparison with fuel load photo series (e.g. Blonksi and Schramel 1981). The center of each plot was permanently marked with a steel stake. Additional plots were located in ambiguous or highly heterogeneous spectral clusters and stratified based on topographic and compositional characteristics to assign final fuel models. Once the final surface fuels map was created, 122 accuracy assessment plots were laid out and visited to ensure validity of the mapping process (C. Farris, unpublished report).

Our fire behavior modeling approach calls for realistic current values for CBD, CC, CBH, and HT. To determine these values we collected field data in the summers of 2009 and 2010 in LVNP. We located a 223 plot subset of the above 462 plots by navigating to them with GPS and we established a 500 m^2 circular plot centered on the permanent stake. We recorded the plot's geographic position from the GPS and also measured its slope, elevation, aspect, topographic position, and topographic configuration. Topographic position was recorded in one of five categories: ridge top, upper slope, middle slope, lower slope, or valley bottom. Topographic configuration was also recorded in one of five categories: convex, convex-straight, straight, concave-straight, or concave. For each tree (> 5 cm diameter at breast height [DBH]) we measured DBH (cm), height (m), status (live or dead), and visually estimated live crown fraction to the nearest 5%. We rated each tree's relative crown position using the following categories and criteria: Suppressed— <25% of main canopy height; Intermediate— >25% but < 75% of main canopy height; Co-dominant—part of the main canopy, but receiving top shading from other canopy trees; Dominant—part of the main canopy and only receiving side-shading from other trees; Emergent—trees with crowns above the main canopy that are not receiving significant side-shading from any trees. We recorded the Height to Live (Dead) Crown Base as

the height above the ground of the lowest live (dead) limb longer than 60 cm (Fulé et al. 2001; Skinner 2005). To aid in determining canopy fuels characteristics, we took three upward facing hemispherical photographs per plot with a digital camera mounted with a full hemispheric lens and leveled with a bubble level at 2 m above the ground.

Because vegetation composition in LVNP co-varies strongly with topographic variables including elevation, slope, aspect, and potential soil moisture (Taylor 1990, 2000; Parker 1991) we derived a set of topographic variables related to vegetation type from a 30 m x 30 m resolution digital elevation model under the assumption that, through its strong covariation with vegetation, topography can potentially explain variation in RdNBR (USGS 2010). The National Elevation dataset for LVNP was used to obtain elevation, slope, aspect, and two measures of topographic position for each pixel in the park. These two measures of topographic position—Topographic Position 150 (TP150) and Topographic Position 450 (TP450)—are the difference between the focal pixel's elevation with the average elevation of pixels within 150 m and 450 m respectively (Poulos et al. 2007; Poulos 2009). We used this set of topographic variables for mapping canopy fuels as well as in our later analyses of high severity or high intensity fire.

Canopy fuels characteristics (CBD, CC, CBH, and HT) values were estimated from the data gathered on individual trees and from the hemispherical photographs. We computed gap fraction and CC from 669 hemispherical photographs (3 per plot) using GLA software (Frazer et al. 1999). Gap fraction was then transformed to CBD using the methods described in Keane et al. (2005, eq. 5). To calculate CBH, we combined each plots' values of Height to Live Crown Base and Height to Dead Crown Base. Because low CBH are most important for the transition to crown fire, we used the 1st quartile CBH as the estimate for each plot (Fulé et al. 2001; Skinner 2005). To compute HT, we averaged the heights of the live trees in the canopy in each plot

(typically the Co-dominant and Dominant trees, but also Emergent trees if they were present).

We created constant raster layers representing CBD, CC, CBH, and HT from these values. We computed the average of CBD, CC, and HT across all plots to create the first three constant rasters. We also computed the average of the 1st quartile CBH values across the landscape and created a constant raster containing this value. Constant rasters were created in ArcGIS software (ESRI 2010). To facilitate the scaling of plot level data to the landscape level, we used Landsat 5 imagery of LVNP for August 11, 2009. The raw Landsat scene was converted to at-satellite reflectances for 6 bands (1-5 and 7). These reflectances were then used to compute the Normalized Differenced Vegetation Index (NDVI) and the Tasseled Cap transformations for Greenness, Brightness, and Wetness (Kauth and Thomas 1976). All resulting rasters were exported for analysis in ArcGIS® (ESRI 2010). Satellite imagery was processed using ENVI® (ITT 2010).

We used a Random Forest algorithm in R (Breimen 2001; Liaw and Wiener 2002; R Development Core Team 2010) to model the plot level estimates of each canopy fuel variable and to predict canopy fuels values across the entire landscape on a pixel by pixel basis. In every case, the RF algorithm was run to iteratively grow 4,000 trees with 5 of the 15 explanatory variables randomly selected at each node as potential variables to base the split on. A large number of trees is recommended when using RF algorithms to stabilize the Mean Squared Error (MSE) over many iterations. We used the pseudo-r^2 and the MSE statistic to evaluate model performance. The pseudo-r^2 statistic is calculated as:

$$1 - \frac{\text{MSE}}{\text{var(y)}}$$

The pseudo-r^2 statistic is calculated identically to the r^2 statistic for standard linear regression, and is called pseudo because the predicted values used to calculate the MSE come from the random forest, and not from a linear regression (Liaw and Wiener 2002).

Fire Weather and Fuel Moisture

We computed dead woody fuel moistures and wind speeds for the 80th, 90th, and 97th percentile condition with FireFamily Plus (Bradshaw and Tirmenstein 2010) using weather data from the Manzanita Lake weather station (FAM Web 2011). Fuel moisture calculations were limited to the fire season of June 1 through October 31 but used the entire Manzanita Lake record which extends from 1962 to 2010. I computed fuel moistures for 5 fuel components: 0 – 0.64 cm (0 – 0.25"), 0.64 – 2.54 cm (0.25" – 1.0"), and 2.54 – 7.62 cm (1.0" – 3") diameter dead woody fuels, as well as Live Herbaceous and Live Woody fuels to use as input to FlamMap. 0 – 0.64 cm, 0.64 – 2.54 cm, and 2.54 – 7.62 cm diameter dead woody fuels are often referred to by the terms 1-hr, 10-hr, and 100-hr fuels. This convention relates to the amount of time required for a fuel particle of the given diameter to reach 63% of the difference between its initial moisture content and a final moisture content that is in equilibrium with changed atmospheric conditions (Pyne et al. 1996). Fuel moistures are given in percentages and interpreted as the amount of water in a particular fuel particle as a percentage of that particle's oven-dry weight. For all 5 classes of fuel moistures, percentages range from 0 (oven-dry) up to 300 (fresh grass and herbaceous cover). We also computed 6.5 m (20') wind speeds for the 80th, 90th and 97th percentile conditions. This is the speed of the wind at 6.5 m above the forest canopy. FlamMap uses the given grid of canopy cover to calculate an attenuated 6.5 m wind speed at the site of (simulated) surface combustion. Lastly, we used this data to calculate the dominant direction of daytime winds.

Wind Scenarios

We applied 4 different wind scenarios for each combination of surface fuel model and fuel moisture condition. Wind is an important factor that controls both rates of fire spread and fire intensity. Wind is addressed in FlamMap in three ways (Finney 2006). Depending on the moisture profile (80th, 90th, or 97th) we simulated winds as: 1) calm (no wind); 2) blowing uphill at their 80th, 90th and 97th percentile speeds, respectively; 3) blowing at a constant direction and speed at their 80th, 90th and 97th percentile speeds, and 4) blowing at variable speeds and directions based on the model WindNinja ® at their 80th, 90th and 97th percentile speeds, respectively. WindNinja® calculates surface wind speed and direction for a grid of arbitrary resolution based on the topographic interference that a constant wind would encounter. Winds gridded in this way have been shown to increase the accuracy of predictions (Finney 2006; Stratton 2006).

Simulating Fire Behavior

We simulated fire behavior for each possible combination of wind scenario and fuel moisture. Fire behavior outputs for each run were fireline intensity and crown fire activity. Fireline intensity is measured in kilowatts per meter (kW/m) and is related to both flame length and crown fire activity (Agee 1993). Crown fire activity is rated on a scale of 0-3: 0) no fire activity; 1) ground fire only; 2) passive crown fire (torching); and 3) active crown fire. FlamMap's calculations require that each successively higher class of fire activity (class 0-3) requires activity at the previous class, e.g. torching fires (class 2) can only occur in a location if there is a ground fire (class 1) (Finney 2006). This experimental design produced 12 raster maps each for fireline intensity and fire activity index. To simplify this dataset, we averaged the fireline

intensity of each pixel over all 12 rasters. We also produced a pixel by pixel count of the frequency of each of the fire activity index values.

Vegetation Structure Data

We added a vegetation component to our dataset of MTBS downloaded fires (1984 and later) to assess how antecedent vegetation cover might impact observed fire severities. To accomplish this we geo-referenced a map of vegetation patches from the 1960s which was created by vegetation type mapping utilizing the interpretation of aerial photography and field reconnaissance of vegetation composition. Once we georeferenced the map, we digitized the boundaries of the vegetation patches and added their attribute data. The attribute data consisted of 4 overstory and understory density classes (1: 1-9% of available canopy space; 2: 10-39%; 3: 40-69%; and 4: 70-100%); up to 5 canopy tree species with their relative cover expressed as a percentage; up to 3 ground cover species with their total cover as a percentage, and the species and density of any seedlings (if present). From this dataset we extracted the overstory and understory density classes (denoted Overstory and Understory in figures and tables), and up to the first 2 canopy species (denoted Canopy 1 and Canopy 2 in figures and tables).

Analysis of High Severity and High Intensity Fire Locations

For the collection of mapped patches of historic high severity fire, we created a point sample inside the boundary of each patch at a density of 1 per 5 ha. For the remainder of LVNP, we created another random point sample with the same total number of points but excluding the areas deemed water or barren. We extracted the elevation, slope, aspect, TP150, and TP 450 values for each point. We then compared the mean values of each of the topographic variables to

each of the two samples to examine if the mapped patches of historic high severity fire were located in significantly different topographic settings.

To examine how measured contemporary fire severity and modeled fire intensity varied relative to topography, we set up a regular grid of points at a 30 m interval inside each of the 6 fire perimeter layers downloaded from the MTBS website. To each point, we added the values of each of the 5 topographic variables, the four vegetation variables, the surface fuel model, the 2003 predicted value of CBD, CC, CBH, and HT, the RdNBR value, the MTBS rated severity, the average fireline intensity and the fire activity index frequencies.

We used an RF algorithm to model RdNBR as a function of topography to assess which topographic variables explained the largest amount of variation. Likewise, we used an RF algorithm to attempt to explain model derived predictions of fireline intensity as a function of topography. We used several discrete sets of variables and iteratively increased the number of variables in our model to examine how each set explained variability individually, and how that contribution might change given other variables. First, we used only our 5 topographic variables to try to explain RdNBR (Model Scenario A). In Model Scenario B, we added vegetation data from our historic vegetation map. In Model Scenario C, we further added mapped surface and canopy fuels for the Bluff, Horseshoe, and Prospect fires only because these were the only three of the six fires that post-dated the production of the surface fuels map. Finally, Model Scenario D attempted to explain variability in modeled fireline intensity using either the variables from Model Scenario B (Badger, Huffer, and Fantastic fires) or the variables from Model Scenario C (Bluff, Horseshoe, and Prospect fires) To compare between the two datasets, we examined each variable's relative importance and its contribution to reducing the Mean Square Error of the final tree and each model's total variance explained.

We compared the locations of high severity fire across our different lines of evidence. Because it was the most limited, we based our comparisons on the data available for the high severity patches mapped from the 1941 aerial photographs. Each point inside these polygons had elevation, slope, aspect, and topographic position information appended to it. To develop the high severity portion of the other two lines of evidence we first pooled all of the data from the 6 fires that we investigated. Then, we selected points using the following procedures. For the MTBS data, we used only those pixels with a mapped MTBS categorical severity rating of 4 (high). For the FlamMap derived estimates of fire behavior, we chose only those pixels with a fire type index of 2 (torching fire) or 3 (crown fire) on at least 6 of the 12 burning scenarios Because the FlamMap® derived dataset was so large, we selected a random subset that was intermediate in size to the MTBS dataset and the Brushfield dataset. These three datasets were all compared against the sample of topographic variables for LVNP that was described above. We calculated means and standard deviations for elevation, slope, aspect, TP150, and TP450 for each dataset and compared between them with a two-sample Student's t-test. Because we were making multiple comparisons between datasets, we used an alpha level of 0.05 and a Bonferroni correction (n = 6 comparisons).

Results

MTBS Fire Severity Data

The six fires we downloaded from the MTBS website were the Badger, Huffer, Fantastic, Bluff, Prospect Peak, and Horseshoe (Table 4-1). These fires burned between 1984 and 2005. Fires burned a low of 450 hecatres (Badger 1984) to a high of 1382.4 ha (Bluff 2004). RdNBR ranges were large, but average RdNBR were indicative of overall distribution of area designated to the

severity classes. The Horseshoe fire had the lowest overall RdNBR average—most mapped pixels were only somewhat less green after the fire—and this fire burned only at Low severity. In contrast, the Badger fire had the highest overall average RdNBR which is indicative of its overall large proportion of hectares burned at moderate to high severity; the high RdNBR values indicate that there was a large change in vegetation cover when comparing pre- and post-fire imagery. Proportionally, most of the area of all six fires was categorized as either 'unburned to low' (category 1) or 'low' (category 2) (Figure 4-2). The Badger and Huffer fires had the largest proportions of 'moderate' (category 3) and 'high' (category 4) severity effects.

FlamMap® Fire Intensity

We used FlamMap® to obtain expected fireline intensity and fire type inside the perimeters of these six fires. Proportionally, FlamMap® almost never predicted active crown fire on the landscape (Figure 4-3). Surface fire was the most common type of fire predicted. In the case of the Badger fire, almost 50% of fire activity was predicted to be torching fires, but within all of the other fire perimeters, the proportion of torching fire was smaller.

Canopy and Surface Fuels

We measured CBD, CC, CBH, and HT at 223 plots across LVNP and mapped these variables for the entire extent of LVNP using a Random Forest approach. Measured CBD values ranged from 0.0 to 0.306 kg/m^3. CC ranged from 0 to 87.8%. CBH ranged from 0 to 11.9 m and HT varied from 0 to 43.9 m (Table 4-2). Our RF models were generally able to explain CBD, CC, and HT well, but CBH could not be modeled effectively (Table 4-3). For CBD, CC, and HT, our models' had pseudo-r^2 values of 0.55, 0.67, and 0.59 resprectively (Table 4-3).

Mapping Historic High Severity Effects

We mapped historic high severity effects on 57 aerial photographs that were georeferenced to an accuracy of 7.9 m Root Mean Square Error (RMSE). We identified 119 of patches of high severity effects with a mean area of 47.8 ha (range 2.12 – 626.84) and a total area of 5686.3 ha. The mean elevation of all sample points inside patches mapped as exhibiting high severity effects was 1995 m, the mean slope was 13.1°, and the mean aspect was 162.5°.

Random Forests

We used a random forest approach to analyze RdNBR fire severity data for 6 contemporary fires from the MTBS dataset in relation to several combinations of variables. When we used only our 5 topographic variables (Model Scenario A), Elevation was the most important variable for reducing MSE of the model explanation of RdNBR (Figure 4-4). It reduced MSE by up to 134% for the Huffer fire but only 25.5% for the Bluff fire. Pseudo-r^2 values ranged from a low of 0.12 for the Horseshoe fire up to a high of 0.53 for the Badger fire (Table 4-4). Elevation was the most important variable in reducing MSE in 5 out of 6 cases, and second most important in the 6th case. Aspect and topographic position were also important. Slope was somewhat important (Table 4-5).

When we added information on the historic vegetation structure to our RF approach (Model Scenario B), topographic variables were still the most important (Figure 4-5). Overstory density and Canopy species also contributed to reducing MSE. Overstory density was able to reduce MSE by 69.1% for the RF model of Huffer fire RdNBR (Figure 4-5). The addition of vegetation data was able to increase the pseudo-r^2 of all of our models (Table 4-4). The largest increase was for the Huffer fire, where the addition of vegetation information increased pseudo-r^2 to 0.69 from

0.44. When we examined the ranked importance of the explanatory variables, there was little overall change in the order as compared to Model Scenario A (Table 4-5).

In Model Scenario C, we added mapped surface and canopy fuels information for three recent fires—the Bluff, Horseshoe, and Prospect fires. These fires occurred in 2004 (Bluff) and 2005 (Horseshoe and Prospect) which post-dates our surface fuels map. The results for this Model Scenario were somewhat different from the first two. While one of the topographic variables was always the most important, some of the mapped fuels data were among the most important. For the Horseshoe fire, CC, HT, and CBD were the 2nd, 3rd, and 4th most important variables, respectively, and were able to reduce MSE by 25.1%, 23.8%, and 13.4%, respectively (Figure 4-6). This information also was able to further increase the pseudo-r^2 for the models for each fire's RdNBR (Table 4-4).

We also sought to compare modeled fireline intensity with RdNBR, and with our variables' ability to explain variation in fireline intensity compared to RdNBR. In Model Scenario D, we examined modeled fireline intensity within the perimeter of each of the six fires. For three fires, the Badger, Huffer, and Fantastic, we did not have surface or canopy fuels information because these fires pre-date our fuels information. For the other three fires, the Bluff, Horseshoe, and Prospect, we were able to use surface and canopy fuels information in our RF models. For these models, fuels information was important in reducing model MSE, and by up to 45.8% in the case of Surface Fuel model for the Prospect fire perimeter (Figure 4-7).

Topographic Comparisons Among Datasets

We compared the topographic variables of elevation, slope, aspect, TP150, and TP450 between 4 different dataset in order to understand how drivers of fire severity might vary between fires

(Table 4-6). Our datasets were all the pixels denoted by the MTBS fire severity category 4 (high severity effects; n = 1832), a sample of all pixels predicted by FlamMap® to burn with torching or crowning behavior in at least 6 out of 12 of our scenarios (n = 1169), a sample of 1 point per 5 ha of historic mapped high severity patches (n = 1082), and a random sample of points in LVNP—excluding water and barren areas—with the same number of points as the historic mapped high severity patches (n = 1082). We denote these datasets MTBS, FlamMap®, brushfield, and Park, respectively. With the exception of aspect, the topographic variables differed significantly between most or all of the datasets. Elevation averages ranged from a low of 1995 m in the brushfield dataset to a high of 2063 m for the Park as a whole. Brushfields also occupied the steepest average slopes (13.1°), while high fire intensity effects predicted by FlamMap® occupied the lowest average slopes (9.7°). Brushfields were also found in areas with generally high TP150 and TP450 values, indicating that they tend to exist higher on slopes. This is in contrast to the Park as a whole where the values of TP150 and TP450 were close to zero. The high severity effects seen in the MTBS dataset occupied the highest topographic positions as compared to all other datasets.

Discussion

The topographic variation of high severity and high intensity fire was noteworthy. The pixels mapped as high severity by MTBS and the Brushfield sample occupied significantly lower, steeper, and more exposed slopes than the Park as a whole. This combination of topographic characteristics is strong evidence for topographic controls on fire severity beyond those implemented by fire modeling programs which primarily use slope and aspect to modify fire behavior (J. Scott, personal communication, 2011). While a program like FlamMap® uses elevation to adjust fuel moistures based on adiabatic lapse rates, we did not utilize that portion of

148

the FlamMap® routine. Furthermore, because individual pixels in FlamMap® do not interact with their neighbors, relative differences in topographic position are not taken into account. That a RF model using only Elevation, Slope, Aspect, TP150, and TP450 was able to explain almost 55% of the variance in RdNBR values in the Badger fire and 46% of the variance in RdNBR values in the Huffer fire shows that topographic drivers of fire severity can be extremely important. However, lower percentages of explained variance in the other fires (14% to 28.9%) indicate that the explanatory power of topography might be limited to certain cases.

Topographic characteristics retained much of the explanatory power even when considered alongside other, more commonly implicated, drivers of observed fire severity like pre-existing vegetation (Canopy 1, Canopy 2) and mapped fuels values (Surface Fuel model, CBD). In fact, the addition of these other potential explanatory variables only marginally increased the pseudo-r^2 values of several models (Bluff, Fantastic, Horseshoe, and Prospect). These variables had a much larger impact—though still not as large as topography—on the models for the Badger and Huffer fires. Interestingly, it was these two latter fires that had the highest proportions of 'moderate' and 'high' severity MTBS rankings. Coupling these results to the results using only the topographic variables, is it plausible that topography is the dominant driver of some fires while not of others. In the Klamath Mountains, Alexander et al. (2006) found that higher elevations—upper slope positions—burned primarily with low severity but south aspects and those plots dominated by intermediate sized trees (33 cm to 43.5 cm dbh) burned with high severity. In contrast, Taylor and Skinner (2003) found that upper slope positions tended to burn with high severity in other parts of the Klamath Mountains. These contrasting results for the same mountain range echo our findings that drivers of fire severity may be heterogenous not only within fires, but also between fires in the same forest types. Whereas topography was an

extremely important driver of severity in the case of the Badger and Huffer fires, it was not as strong in the other four fires. Extrapolating this implies that a single position on the landscape, over the course of many years and multiple fires, will burn with different severities at different times due to different drivers. Our results show that these different severities are related to topography such that certain combinations of topographic characteristics (low elevations, and steep exposed slopes) tend to produce more high severity fire than other combinations of topographic characteristics.

The most surprising of the results here is that historic vegetation maps and surface and canopy fuels information did little to improve model fit. This is in contrast to Collins and Stephens (2010) who found that many patches of high severity fire were significantly associated with highly pyrogenic vegetation. Similarly, Odion et al. (2010) demonstrated that highly pyrogenic sclerophyll vegetation and dense stands of young conifers burned with higher average severity than other types of vegetation. These studies confirm the extent to which vegetation can be a predictor of high severity fire. One limitation of our own vegetation map is its relative coarseness. For our historic vegetation information, we relied on a hand-drawn map from c.1960. This map, while impressive for its detail in its own day, is nonetheless limited in the amount of information it can carry forward to the present. However, even absent vegetation information, topography was a strong driver in some fires. When compared with the previously mentioned studies, our evidence allows for the interpretation that while fire severity may be driven by vegetation in some cases, topography may overwhelm its effect in other cases. If this is true, it means that high intensity fire with high severity effects is more common in some locations which in turn implies that some patches of fire dependent vegetation may be 'fixed in space.' This notion underlies the research of Holden et al. (2009) who find that topography can

be used to predict the locations of high severity fire. The idea of vegetation patches being 'fixed in space' also has implications for the steady-state shifting mosaic paradigm which posits that when viewed over a large enough spatial frame and a long enough temporal frame, disturbance prone ecosystems exhibit a relatively static proportion of vegetation types and structural stages, although their specific locations are random (Bormann and Likens 1979; Turner et al 1993; Perry 2002). In contrast, we suggest that while the proportion of the landscape occupied by a specific vegetation type or structural stage might be in relative equilibrium, the locations of those patches could be 'fixed in place' through the interaction of the disturbance process itself—here fire—and the topography.

When comparing modeled measures of fire type from FlamMap® with the MTBS categories of severity, there are two evident patterns. First, if we lump together the MTBS categories of 'moderate' with 'severe', and we lump 'unburned to low' with 'low' (Figure 4-8), then the FlamMap® predictions of proportions of fire type are very similar to the proportions of severity effects as categorized by the MTBS project. FlamMap® appears to be potentially overestimating the proportion of torching fires—which would certainly fall in the MTBS 'moderate' category— but this conservative estimate of fire severity suits the application of FlamMap® well. If federal agencies are to continue to use FlamMap® as a planning tool, then it behooves those agencies, in the interest of safety, to over-estimate the proportion of torching fires on the landscape. Second, we ran FlamMap® with 12 different combinations of fuel moisture and wind scenario, which includes the most intense 97th percentile fuel moistures with uphill winds. In contrast, the MTBS severity data reflects the effects of real fires that often did not burn under such extreme conditions. Especially in the case of the Horseshoe fire, at least part of the over-prediction of torching fires is due to this fact. Finally, there is also the consideration that FlamMap, while a

spatial model of fire behavior in the sense that it computes fire behavior for each pixel on the landscape, is ignorant of the effects of pixel size. A single FlamMap calculation is the basis for the fire type prediction assigned to a pixel, and essentially takes place at a point. Thus, a 'torching' fire predicted by FlamMap may correspond to a pixel mapped by MTBS as 'low' severity when that MTBS pixel could have sustained one or a few trees worth of torching behavior.

Conclusions

Our study has shown that more exposed topographic positions tended to burn with higher severity. In forests of the nearby Klamath Mountains, upper slope positions may burn with higher severity (Taylor and Skinner 2003) or lower severity (Alexander et al. 2006). The contrasting results presented in these two studies may be due to the use of fire scar and tree ring evidence only (Taylor and Skinner 2003) or due to small sample size (Alexander et al. 2006). Across all of the fires that we studied, topography was able to explain much of the variation in RdNBR. We also find that our results corroborate the findings from other parts of the southern Cascades where upper slope positions and positions higher in the watershed burned with higher severity when compared with lower slopes or positions lower in the watershed (Beaty and Taylor 2001). The results presented here lend weight to the idea that some types of highly pyrogenic vegetation patches (here brushfields) exist where they do on the landscape because those landscape positions tend to be associated with high fire intensity and high fire severity. Therefore, certain vegetation assemblages can be 'fixed in space' by their topographic settings through a mutual association with high severity fire. This has implications for the management of forested ecosystems wherein a single type of fire regime (e.g. low-severity v. high-severity) is posited for all instances of a vegetation type (e.g. mixed conifer) when in fact different fire

regimes may be associated with a single vegetation type through the interaction of fuels,

topography, and the burning process.

Works Cited

Agee, J. K. (1993). *Fire Ecology of Pacific Northwest Forests.* Washington, D.C. and Covelo, CA: Island Press. 493p.

Alexander, J. D., N. E. Seavy, C. J. Ralph and B. Hogoboom (2006). Vegetation and topographical correlates of fire severity from two fires in the Klamath-Siskiyou region of Oregon and California. *International Journal of Wildland Fire* 15: 237-245.

Anderson, H. E. (1982). *Aids to determining fuels models for estimating fire behavior.* Gen. Tech. Rep. GTR-INT-122. Ogden, UT: United States Department of Agriculture, Forest Service, Intermountain Research Station. 28p.

Baker, W. L. (1992). Effects of settlement and fire suppression on landscape structure. *Ecology* 73(5): 1879-1887.

Baker, W. L. and K. F. Kipfmueller (2001). Spatial ecology of pre-Euro-American fires in a southern Rocky Mountain subalpine forest landscape. *Professional Geographer* 53(2): 248-262.

Beaty, R. M. and A. H. Taylor (2001). Spatial and temporal variation of fire regimes in a mixed conifer landscape, Southern Cascades, California, USA. *Journal of Biogeography* 28: 955-966.

Bormann, F. H., and G. E. Likens (1979). *Pattern and Process in a Forested Ecosystem.* New York, NY: Springer-Verlag.

Blonski, K. S. and J. L. Schramel (1981). *Photo Series for Quantifying Natural Forest Residues: southern Cascades, northern Sierra Nevada.* Gen. Tech. Rep. GTR-PSW-056. Berkeley,

CA: United States Department of Agriculture, Forest Service, Pacific Southwest Forest and Ranges Experiment Station. 154 p.

Bradshaw, L.S. and D. Tirmenstein (2010). FireFamilyPlus user's guide, version 4.1. Boise, ID: United States Department of Agriculture, Forest Service, National Fire and Aviation Management Information Systems Team. 282 p.

Breiman, L. (2001). Random forests. *Machine Learning* 45: 5-32.

Brown, J. K. (1973). A planar intersect method for sampling fuel volume and surface area. *Forest Science* 17: 96-102.

Collins, B. M. and S. L. Stephens (2010). Stand-replacing patches within a mixed severity fire regimes: quantitative characterization using recent fires in a long-established natural fire area. *Landscape Ecology* 25: 927-939.

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

Eidenshink, J., B. Schwind, K. Brewer, Z.-L. Zhu, B. Quayle, and S. Howard (2007). A project for monitoring trends in burn severity. *Fire Ecology* 3(1): 3-21.

ERDAS® (1997). ERDAS® Field Guide, Field Edition. Atlanta, GA: ERDAS® Inc. 655 p.

ESRI (2010). ArcEditor, Educational Version 9.3.1. Redlands, CA: Environmental Systems Research Institute.

FAM (Fire and Aviation Management) Web (2011). *Fire and Weather Data: California.* Accessed 1/15/2011 at http://fam.nwcg.gov/fam-web/weatherfirecd/state_data.htm.

Farris, C. (unpublished report). Preliminary fuels mapping methodology for Lassen Volcanic National Park.

Finney, M. A. (2006). An overview of FlamMap fire modeling capabilities. In P. L. Andrews and B. W. Butler: *Fuels Management-How to Measure Success*: Conference Proceedings, (March 28-30, 2006, Portland OR). Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. Proceedings RMRS-P-41.

Frazer, G. W., C. D. Canham, and K. P. Lertzmann (1999). Gap Light Analyzer (GLA), Version 2.0: Imaging software to extract canopy structure and gap light transmission indices from true-colour fisheye photographs, users manual and program documentation. Copyright © 1999: Simon Fraser University, Burnaby, British Columbia, and the Institute of Ecosystem Studies, Millbrook, New York.

Fulé, P. Z., W. W. Covington, and M. M. Moore (1997). Determining reference conditions for ecosystem management of southwestern ponderosa pine. *Ecological Applications* 7(3): 895-908.

Fulé, P. Z., A.E. M. Waltz, W. W. Covington, and T. A. Heinlein (2001). Measuring forest restoration effectiveness in reducing hazardous fuels. *Journal of Forestry.* 99(11): 24-29.

He, H. S. and D. J. Mladenoff (1999). Spatially explicit and stochastic simulation of forest-landscape fire disturbance and succession. *Ecology* 80(1): 81-99.

Hessburg, P. F., R. B. Salter, and K. M. James (2007). Re-examining fire severity relations in pre-management era mixed conifer forests: inferences from landscape patterns of forest structure. *Landscape Ecology* 22: 5-24Heyerdahl, E. K., L. B. Brubaker and J. K. Agee

(2001). Spatial controls of historical fire regimes: a multiscale example from the interior west, USA. *Ecology* 82(3): 660-678.

Heyerdahl, E. K., K. P. Lertzman and S. Karpuk (2007). Local-scale controls of a low-severity fire regime (1750-1950), southern British Columbia, Canada. *Ecoscience* 14(1): 40-47.

Holden, Z. A., P. Morgan, and J. S. Evans (2009) A predictive model of burn severity based on 20-year satellite-inferred burn severity data in a large southwestern US wilderness area. *Forest Ecology and Management* 258(11): 2399-2406.

Iniguez, J. M., T. W. Swetnam, and S. R. Yool (2009). Topography affected landscape fire history patterns in southern Arizona, USA. *Forest Ecology and Management* 256: 295-303.

ITT (2010). ENVI + IDL. Boulder, CO: ITT Visual Information Solutions.

Kauth, R. J., and G. S. Thomas (1976). "The Tasselled Cap – A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by LANDSAT." Laboratory for Applications of Remote Sensing Symposia. Paper 159. http;//docs.lib.purdue.edu/lars_symp/159. Accessed 4/25/11.

Keane, R. E., E. D. Reinhardt, J. Scott, K. Gray and J. Reardon (2005). Estimating forest canopy bulk density using six indirect methods. *Canadian Journal of Forest Research* 35: 724-739.

Liaw, A. and M. Wiener (2002). Classification and Regression by randomForest. *R News* (2)3: 18-22.

Miller, C. (2007). Simulation of the consequences of different fire regimes to support Wildland Fire Use decisions. *Fire Ecology* 3(2): 83-102.

Miller, J. D., H. D. Safford, M. Crimmins, and A. E. Thode (2009). Quantitative evidence for increasing forest fire severity in the Sierra Nevada and Southern Cascade mountains, California and Nevada, USA. *Ecosystems* 12: 16-32.

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

MTBS (Monitoring Trends in Burn Severity) (2008). *MTBS Data Search and Distribution Tools.* Available online at http://www.mtbs.gov/index.html. Accessed 9/1/2010.

Nagel, T. A. and A. H. Taylor (2005). Fire and persistence of montane chaparral in mixed conifer forest landscapes in the northern Sierra Nevada, Lake Tahoe Basin, California, USA. *Journal of the Torrey Botanical Society* 132(3): 442-457.

NOHRSC (2010). National Operational Hydrologic Remote Sensing Center. *Snow Data Assimilation System (SNODAS) data products at NSIDC*. Boulder, CO: National Snow and Ice Data Center.

Norman, S. P. and A. H. Taylor (2003). Tropical and north Pacific teleconnections influence fire regimes in pine-dominated forests of north-eastern California, USA. *Journal of Biogeography* 30: 1081-1092.

Odion, D. C., E. J. Frost, J. R. Strittholt, H. Jiang, D. A. Dellasalla and M. A. Moritz (2004). Patterns of fire severity and forest conditions in the western Klamath Mountains, California. *Conservation Biology* 18(4): 927-936.

Odion, D. C., M.A. Moritz, and D. A. DellaSalla (2010). Alternative community states maintained by fire in the Klamath Mountains, USA. *Journal of Ecology* 98: 69-105.

O'Sullivan, D. and D. Unwin (2003). *Geographic Information Analysis*. Hoboken, NJ: John Wiley and Sons, Inc.

Parker, A. J. (1991). Forest/environment relationships in Lassen Volcanic National Park, California, USA. *Journal of Biogeography* 18: 543-552.

Perry, G. L. W. (2002). Landscapes, space and equilibrium: shifting viewpoints. *Progress in Physical Geography* 26(3): 339-359.

Poulos, H. M. (2009). Mapping fuels in the Chihuahuan Desert borderlands using remote sensing, geographic information systems, and biophysical modeling. *Canadian Journal of Forest Research* 39: 1917-1927.

Poulos, H. M., A. E. Camp, R. G. Gatewood, and L. Loomis (2007). A hierarchical approach for scaling forest inventory and fuels data from local to landscape scales in the Davis Mountains, Texas, USA. *Forest Ecology and Management* 244: 1-15.

R Development Core Team (2010). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Rollins, M. G., P. Morgan, and T. Swetnam (2002). Landscape-scale controls over 20th century

    fire occurrences in two large Rocky Mountain (USA) wilderness areas. *Landscape*

    Ecology 17: 539-557.

Safford, H. D., J. Miller, D. Schmidt, B. Roath, and A. Parsons (2008). BAER soil burn severity

    maps do not measure fire effects to vegetation: a comment on Odion and Hanson (2006).

    Ecosystems 11: 1-11.

Schoenherr, A. A. (1995). *A Natural History of California.* Berkeley, CA: University of

    California Press.

Schoennagel, T., T. T. Veblen, W. H. Romme, J. S. Sibold, and E. R. Cook (2007). ENSO and

    PDO variability affect drought-induced fire occurrence in Rocky Mountain subalpine

    forests. *Ecological Applications* 15(6): 2000-2014.

Skinner, C. N. (2005). Reintroducing fire into the Blacks Mountain Research Natural Area:

    effects on fire hazard. in *Proceedings of the Symposium on Ponderosa Pine: Issues,*

    Trends, and Management. October 18-21, 2004, Klamath Falls, OR. Gen. Tech. Rep.

    PSW-GTR-198. Berkeley, CA: United States Department of Agriculture, Forest Service,

    Pacific Southwest Research Station.

Soverel N. O., D. D. B. Perrakis, and N. C. Coops (2010). Estimating burn severity from Landsat

    dNBR and RdNBR indices across western Canada. *Remote Sensing of Environment*

    114:1896-1909.

Stratton, R. D. (2004). Assessing the effectiveness of landscape fuel treatments on fire growth

    and behavior. *Journal of Forestry* **102**(7): 32-40.

Stratton, R. D. (2006). Guidance on Spatial Wildland Fire Analysis: Models, Tools, and

      Techniques. US Department of Agriculture, Forest Service, Gen. Tech. Rep. RMRS-

      GTR-183, Fort Collins, CO.

Taylor, A. H. (1990). Habitat segregation and regeneration of red fir and mountain hemlock in

      ecotonal forests of Lassen Volcanic National Park, California. *Physical Geography* 8:35-

      49.

Taylor, A. H. (2000). Fire regimes and forest changes in mid and upper montane forests of the

      southern Cascades, Lassen Volcanic National Park, California, USA. *Journal of*

      Biogeography 27: 87-104.

Taylor, A. H. and C. N. Skinner (2003). Spatial patterns and controls on historical fire regimes

      and forest structure in the Klamath mountains. *Ecological Applications* 13(3): 704-719.

Thompson, J. R., T. A. Spies and L. M. Ganio (2007). Reburn severity in managed and

      unmanaged vegetation in a large wildfire. *Proceedings of the National Academy of*

      Sciences 104(25): 10743-10748.

Turner, M. G. (in press). Disturbance and landscape dynamics in a changing world. *Ecology.*

Turner, M. G., W. H. Romme, and R. H. Gardner (1994). Landscape disturbance models and the

      long-term dynamics of natural areas. *Natural Areas Journal* 14: 3-11.

Turner, M. G., W. H. Romme, R. H. Gardner, R. V. O'Neill, and T. K. Kratz (1993). A revised

      concept of landscape equilibrium: disturbance and stability on scaled landscapes.

      Landscape Ecology 8(3): 213-227.

Weatherspoon, C. P. and C. N. Skinner (1995). An assessment of factors associated with damage to tree crowns from the 1987 wildfires in northern California. *Forest Science* 41(3): 430-451.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam (2006). Warming and earlier spring increase western U.S. forest wildfire activity. Science 313: 940-943.

WRCC—Western Regional Climate Center (2009). Manzanita Lake, California, Period of Record. Accessed 12/09 at http://www.wrcc.dri.edu/cgi-bin/cliMAIN.pl?ca5311.

Wulder, M. A., J. C. White, F. Alvarez, T. Han, J. Rogan, and B. Hawkes (2009). Characterizing boreal forest wildfire with multi-temporal Landsat and LIDAR data. *Remote Sensing of Environment* 113:1540-1555.

MTBS Category Severity	Badger (1984)	Bluff (2004)	Fantastic (1998)	Horseshoe (2005)	Huffer (2004)	Prospect (2005)
Table 4-1: MTBS Fire Severity Hectares Burned and RdNBR Summary						
1 - Unburned to Low	124.2	634.5	372.7	565.8	357.3	1125.8
2 - Low	201.5	515.2	205.6	46.5	293.8	160.3
3 - Moderate	80.5	187.4	46.1	0	164.7	59.5
4 - High	43.3	38.4	5.7	0	64.7	14.2
5 - Increased Greenness	0.4	6.9	0.4	5.3	0.8	2.4
6 - Water or Barren Mask	0	0	0	3.6	39.3	0
total hectares	450	1382.4	629.7	621.2	920.7	1362.2
RdNBR average	386	256	203	91	376	46
RdNBR range	-762 - 1223	-13344 - 5059	-13408 - 6989	-5122 - 6883	-3193 - 9833	-6482 - 2624

Table 4-1: Summary of fires downloaded from the MTBS website and analyzed in this study. The top section of the table shows the number of hectares classified into each burn severity class by the MTBS analysis. The bottom section shows the average and range of RdNBR values from the MTBS analysis.

	CBD (kg m^{-3})	CC (%)	CBH (m)	HT (m)
min	0.0	0.0	0.0	0.0
max	0.306	87.8	11.9	43.9
mean $\pm$ s.e.	0.105 ± 0.003	45.6 ± 1.40	0.71 ± 0.08	21.3 ± 0.52
SD	0.178	20.848	1.211	7.815

Table 4-2: Canopy Fuels Summary Statistics

Table 4-2: Summary statistics of canopy fuels characteristics across all sampled plots computed from the analysis of each plot's digital hemispherical photographs and tree level data. Abbreviations are CBD-Canopy Bulk Density; CC-Canopy Cover; CBH-Canopy Base Height; HT-Canopy Height.

Table 4-3:Random Forest Model Statistics				
	CBD	CC	CBH	Ht
pseudo r^2	0.55	0.67	-0.02	0.59
MSE	0.0014	196.6	1.37	40.9

Table 4-3: Summary of model fit statistics (pseudo-r^2 and mean-squared error [MSE]). Abbreviations are as in Table 4-2.

Scenario		Badger	Bluff	Fantastic	Horseshoe	Huffer	Prospect
				Table 4-4: Summary of RF Models of RdNBR and Modeled Fireline Intensity			
A	pseudo-r^2	0.53	0.17	0.27	0.12	0.44	0.26
	% Variance Explained	54.8	18.3	28.9	14.0	46.0	27.8
	Mean of Square Residuals	40991	119895	35024	51612	59800	30360
B	pseudo-r^2	0.64	0.22	0.34	0.13	0.69	0.29
	% Variance Explained	65.3	24.4	35.2	14.9	69.8	30.8
	Mean of Square Residuals	31469	110987	31899	51031	33415	29098
C	pseudo-r^2		0.24		0.16		0.32
	% Variance Explained		26.6		18.3		33.5
	Mean of Square Residuals		110082		49019		27982
D	pseudo-r^2	0.44	0.16	0.26	0.15	0.19	0.15
	% Variance Explained	46.0	18.8	27.0	17.5	20.1	17.2
	Mean of Square Residuals	78232	258571	12970	52507	134314	44522

Table 4-4: Summary of model fit statistics for our RF models of RdNBR and modeled fireline intensity. Scenarios A, B, and C are models of remotely sensed values of RdNBR. Scenario D are models of fireline intensity for the area enclosed by the perimeters of the 6 fires analyzed here. Scenario A includes only topographic variables. Scenario B adds historic vegetation data. Scenario C (Bluff, Horseshoe, and Prospect fires only) adds mapped surface and canopy fuel variables. Scenario D uses modeled fireline intensity as the dependent variable.

Table 4-5: Summary of Variable Importance Ranks

	Badger				Bluff				Fantastic				Horseshoe				Huffer				Prospect			
Modeling Scenario:	A	B	C*	D†	A	B	C	D	A	B	C*	D†	A	B	C	D	A	B	C*	D†	A	B	C	D
Elevation	2	2	-	3	1	1	2		1	1	-	1	1	1	1	3	1	1	-		1	1	2	3
Aspect	1	1	-	1	4		4	1	4	5	-	3	2	2		4	2	3	-	5	5	5	4	1
Slope	4	5	-	2	3	2		5	3	3	-	2	3	4		1	3	2	-	1	4			
TP150	5	3	-		2	5	3		5	4	-		5		5		5	5	-	3	2	2	1	
TP450	3	4	-	4	5		1		2	2	-	4	4	3		5	4		-	2	3	3		5
Overstory						3	5																	
Understory						4																		
Canopy 1				5																4				
Canopy 2												5		5				4				4		
Surface Fuel																2								2
CBD								4							4									
CC								2							2								5	
CBH																								4
HT								3							3								3	

Table 4-5: A summary of ranked variable importance for Modeling Scenarios A through D. Each Modeling Scenario builds on the previous scenario. Variables listed on the left hand side are described in the text. Model Scenarios A, B, and C use RdNBR values as the dependent variable. Model Scenario D uses modeled fireline intensity as the dependent variable. *Model Scenario C was not run for these fires because these fires pre-date the surface and canopy fuels estimates. †For scenario D, these models do not include surface and canopy fuels because these fires pre-date the fuels estimates.

Table 4-6: Summary of Topographic Variables					
Dataset	Elevation	Slope	Aspect	TP150	TP450
MTBS	2024	11.4	199.6	1.9	8.08
SD	73.7	6.5	105.4	5.97	20.25
FlamMap®	2052	9.7	164.8*	1.03*	3.8*
SD	127.2	6.9	101.1	5.21	17.27
Park	2063	10.4	158*	-0.11	-0.95
SD	178.5	7.8	103.9	5.67	18.92
Brushfields	1995	13.1	162.5*	1.05*	5.78*
SD	144.9	8.5	102.3	6.28	21.27

Table 4-6: Summary of topographic characteristics from random samples of high severity or high intensity fire locations and a comparison to a random sample of topographic variables from LVNP. Dataset are: MTBS—all pixels mapped as experiencing high severity fire effects (category 4) by the MTBS program; FlamMap®--a subset of pixels predicted by FlamMap® to burn with torching or crowning behavior in at least 6 out of the 12 scenarios under which we ran FlamMap®; Park—a sample of pixels from across all of LVNP, excluding water and barren areas; and Brushfields—a sample taken at 1 point per 5 ha of all patches mapped as exhibiting high severity effects from geo-referenced aerial photographs of LVNP from the year 1941. Column variables are Elevation (m), Slope (°), Aspect (°), TP150 (unitless), and TP450 (unitless). All values in the columns are different at alpha level of 0.05 using a Bonferroni's correction for n = 6 Student's two-sample t-test comparisons except those marked by an asterisk (*).
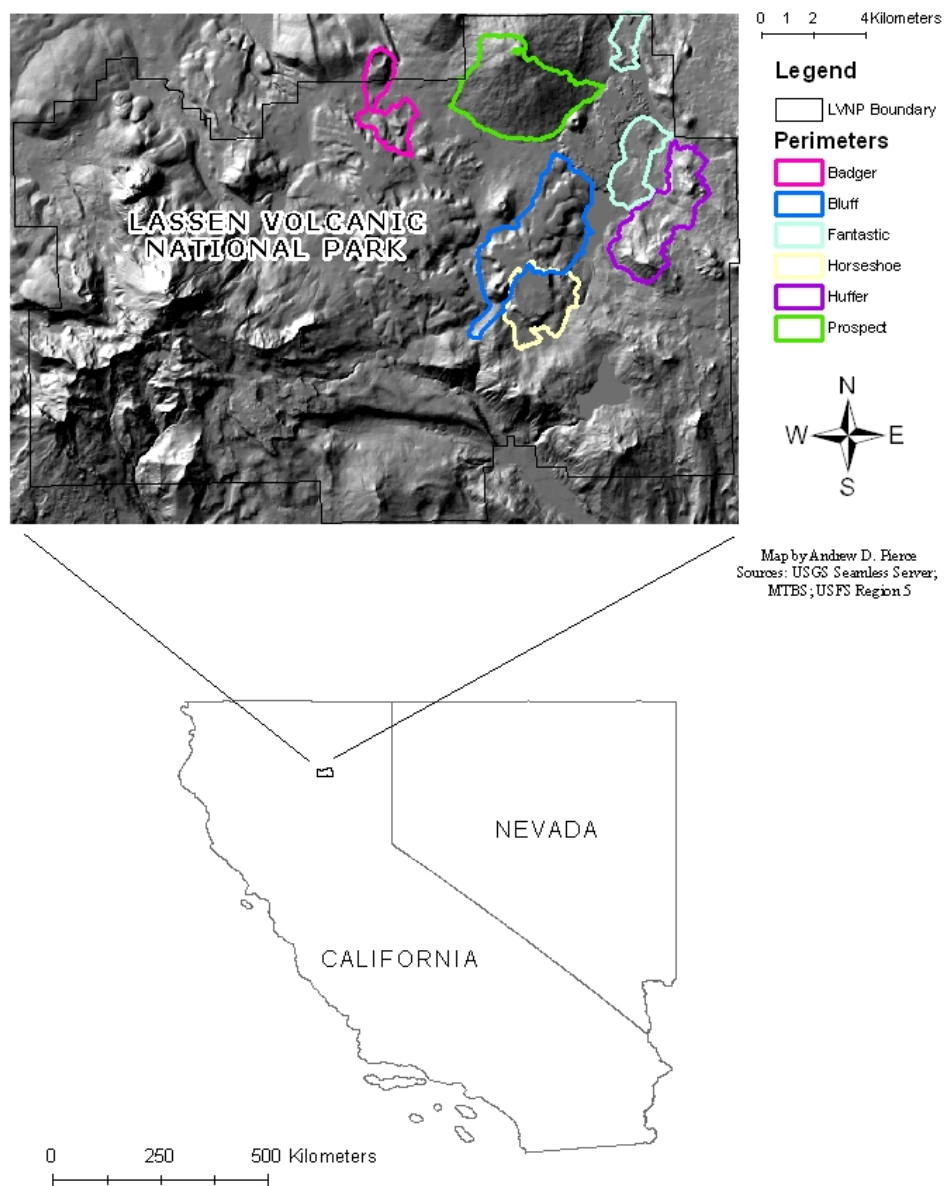
Figure 4-1: Study area map showing Lassen Volcanic National Park in northeastern California as well as the fire perimeters of the 6 contemporary fires analyzed in this study.
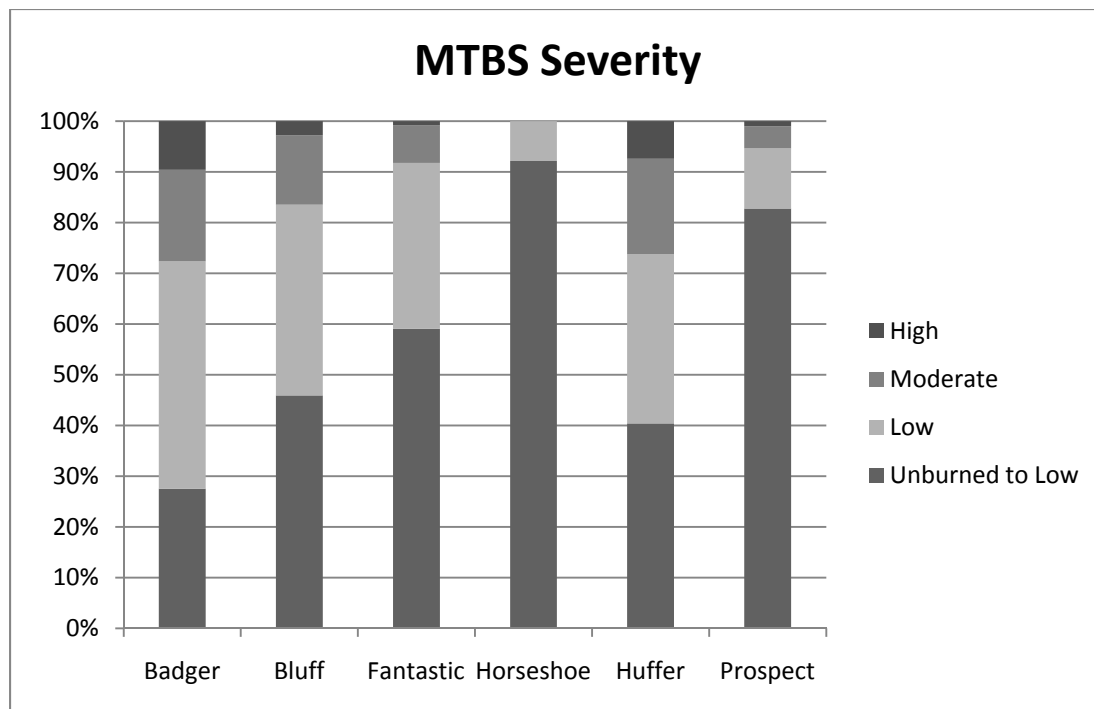
Figure 4-2: A proportional plot of the amount of area of each fire that was categorized by MTBS as exhibiting different levels of fire effects.
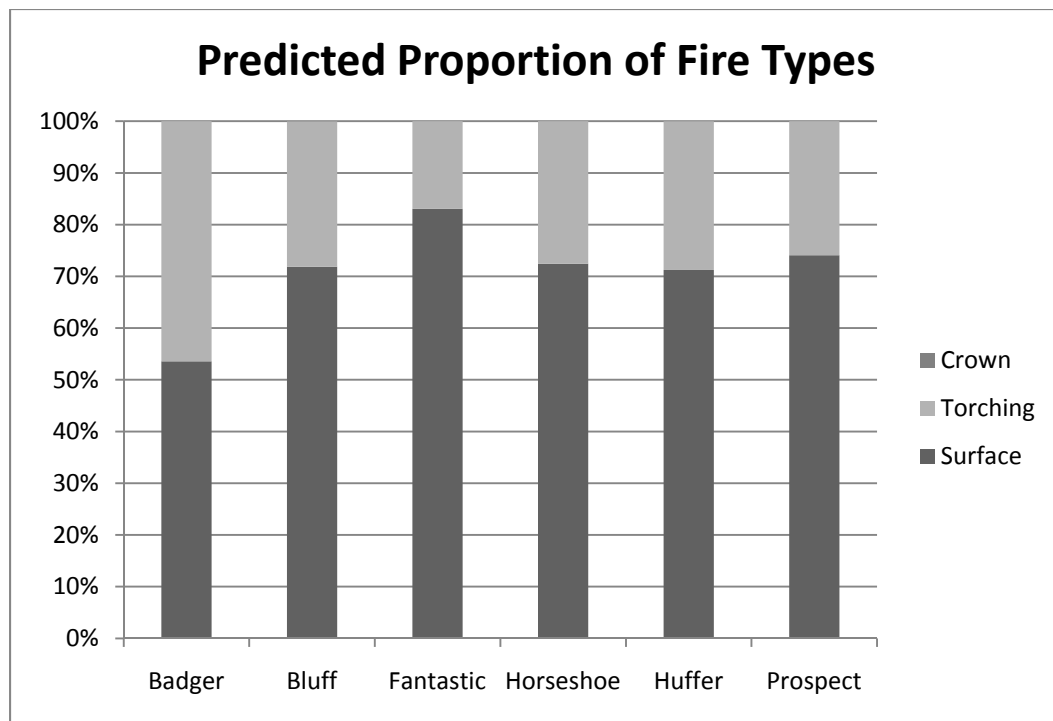
Figure 4-3: A proportional chart of the frequency of different fire behavior types as predicted by FlamMap®.

Figure 4-4: Variable Importance Plots for RF explanation of RdNBR fire severity values for 6 contemporary fires. These RF models used topographic variables only. Variables one the y-axis are listed with the most important at the top. The x-axis shows the percentage increase in MSE when the variable is excluded from the RF.
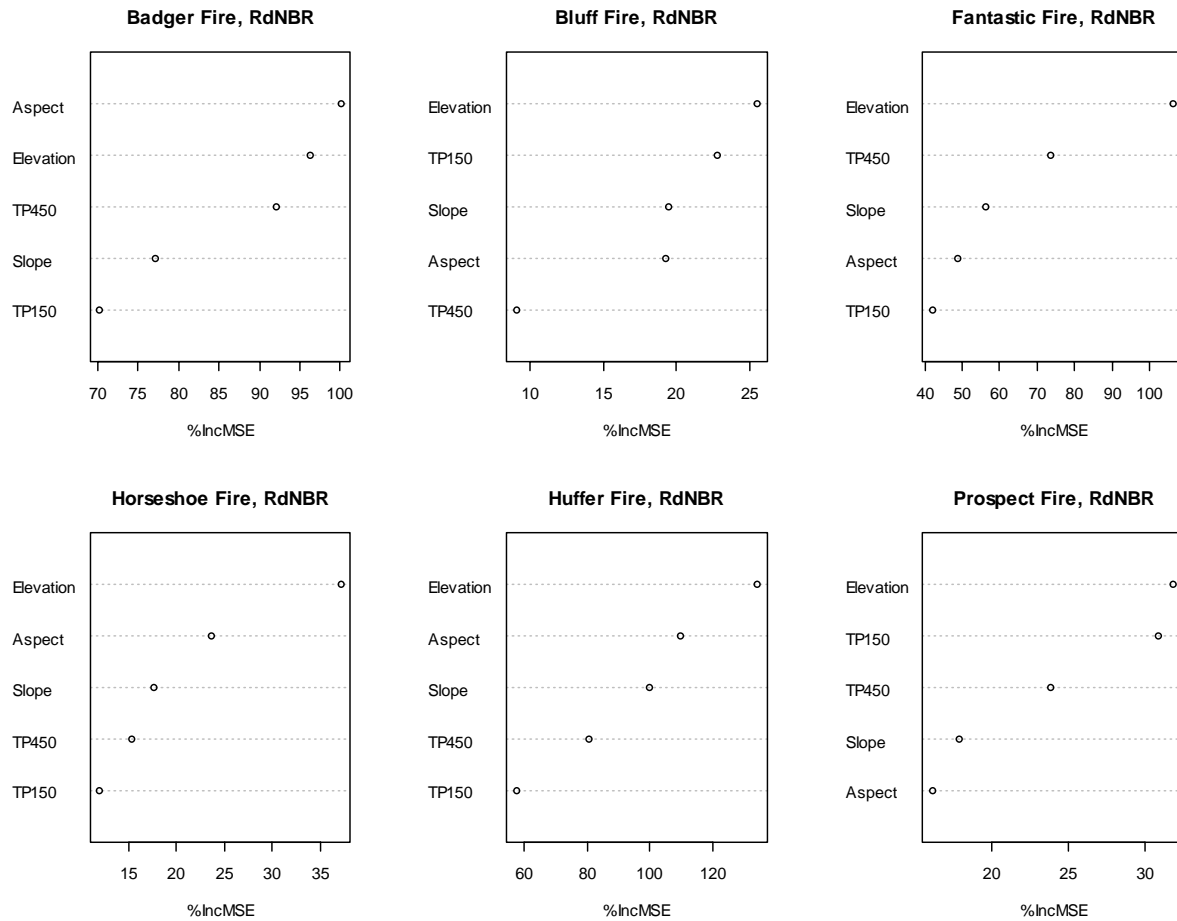
Figure 4-5: Variable Importance Plots for RF explanation of RdNBR fire severity values for 6 contemporary fires. These RF models used topographic variables and historic vegetation data. Variables on the y-axis are listed with the most important at the top. The x-axis shows the percentage increase in MSE when the variable is excluded from the RF.

Figure 4-6: Variable Importance Plots for RF explanation of RdNBR fire severity values for 3 contemporary fires. These RF models used topographic variables, historic vegetation data, and mapped surface and canopy fuels data. Variables one the y-axis are listed with the most important at the top. The x-axis shows the percentage increase in MSE when the variable is excluded from the RF.
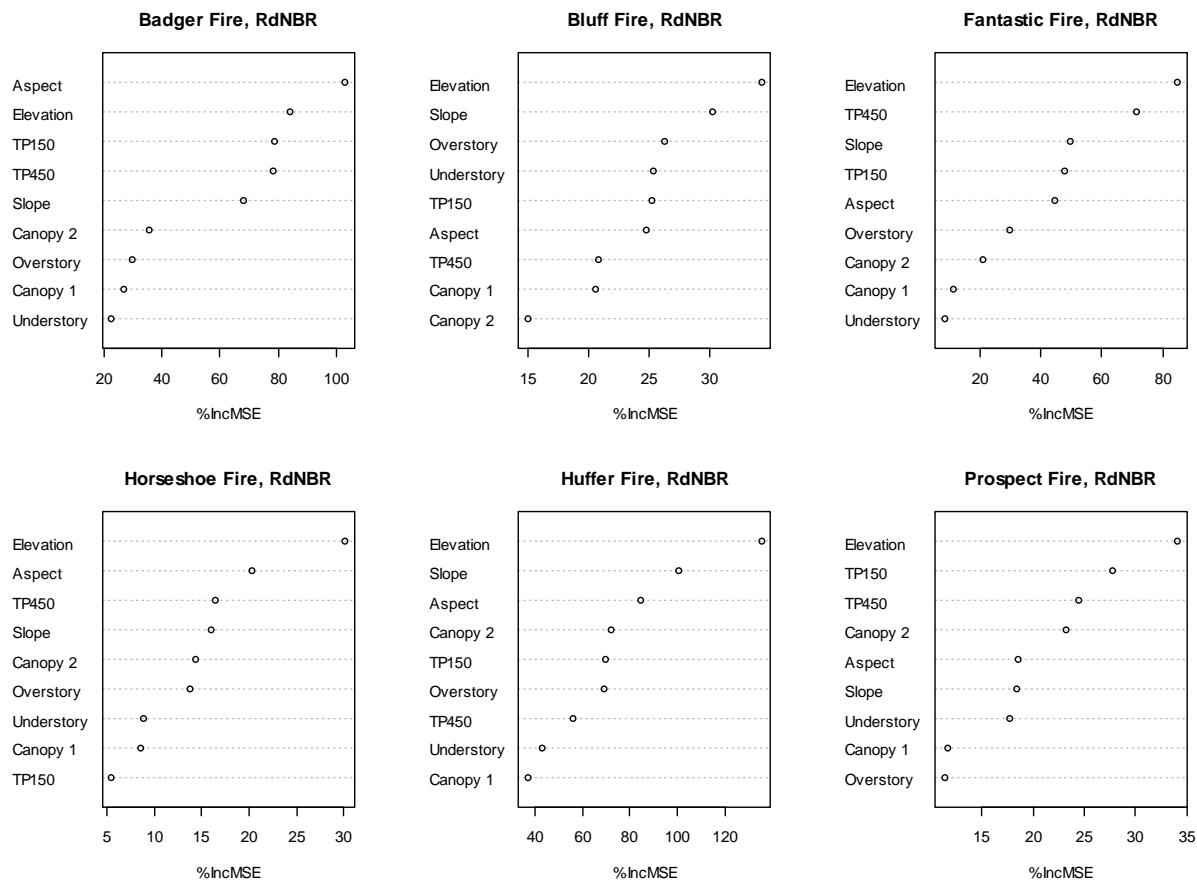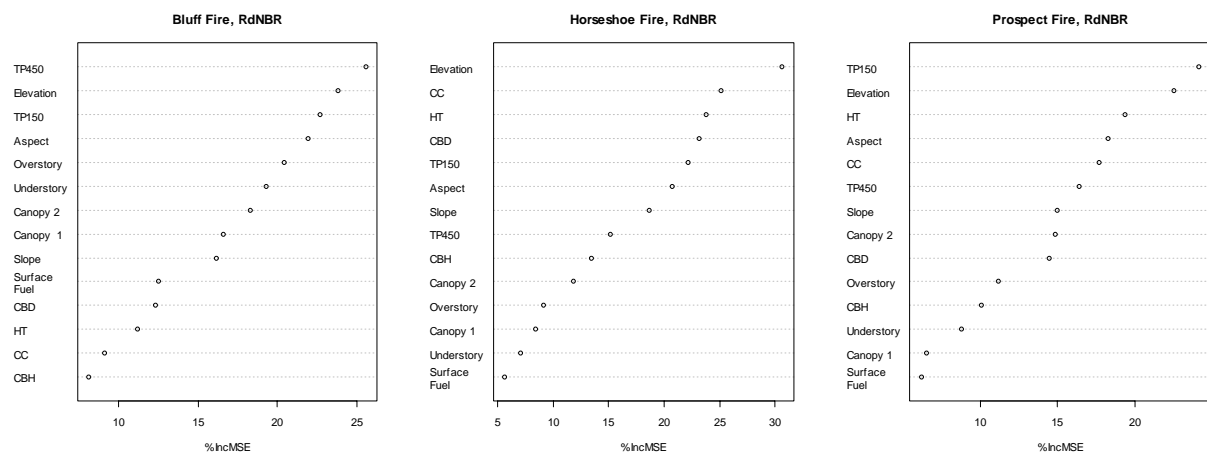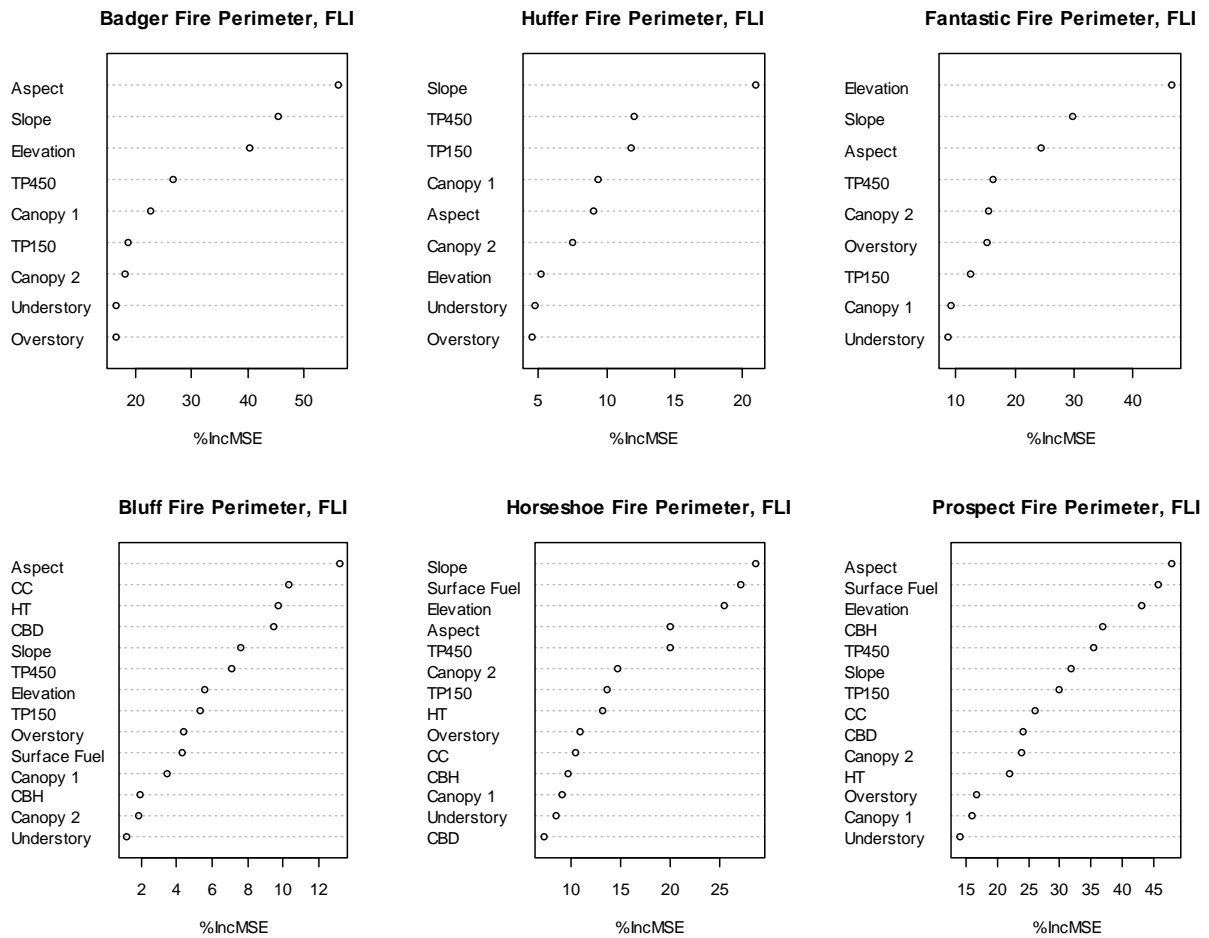
Figure 4-7: Variable Importance Plots for RF explanation of fireline intensity values modeled inside the perimeters of 6 contemporary fires. These RF models used topographic variables, historic vegetation data, and mapped surface and canopy fuels data. Variables on the y-axis are listed with the most important at the top. The x-axis shows the percentage increase in MSE when the variable is excluded from the RF.

Figure 4-8: A proportional chart of the proportions of pixels mapped by MTBS as experiencing different fire severity levels. This chart uses the same data as Figure 4-6 but lumps 'unburned to low' with 'low' and 'moderate' with 'high' for comparison purposes with Figure 4-7.

Chapter 5—Conclusions

Implications for Management and Future Directions

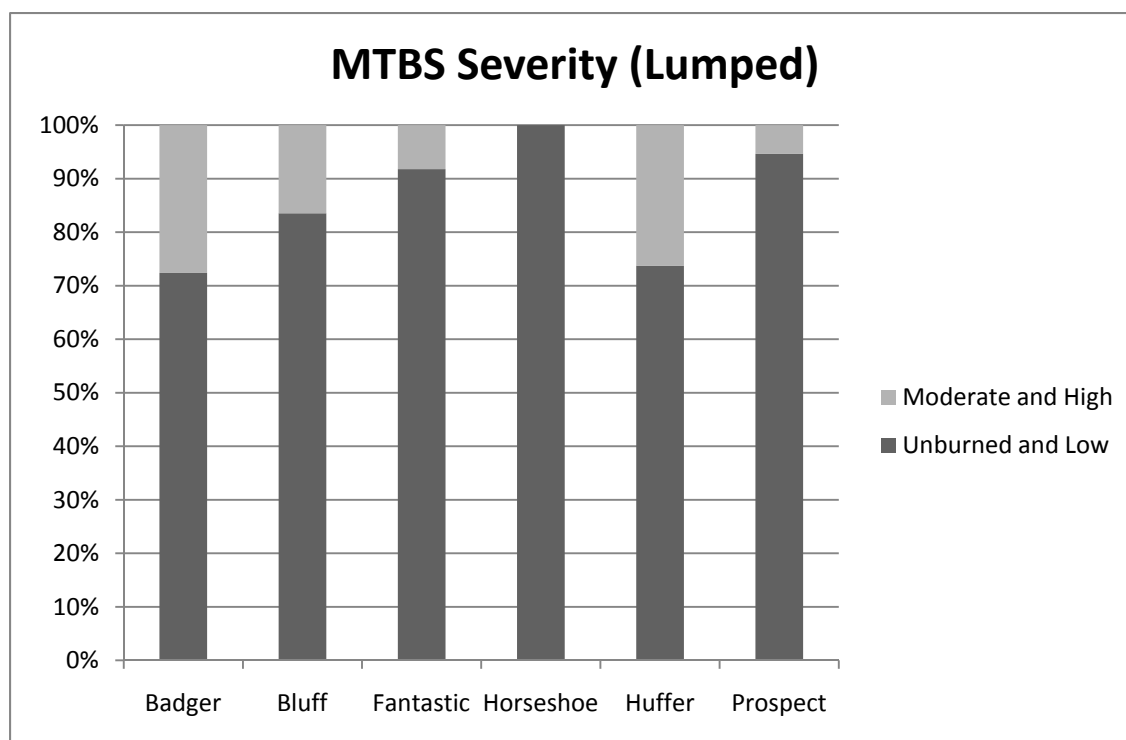*Implications for Management*

Topography is a factor that is well recognized for its potential to impact to fire behavior and fire effects. This research has shown how to develop fire behavior expectation across the landscape as they relate to topography. It has also shown that topographic variables can potentially explain up to half or more of the observed variance of quantitative measures of fire severity. Elevation was a very strong explanatory variable in our study. Also, our measure of local topographic position—Topographic Position 150, or the difference between the elevation of a focal pixel and the average elevation of all pixels within 150 meters—was very important. Managers recognize the importance of topography, especially its impact on controlling the spread of wildfires through the arrangement of rivers, lakes, and barren areas. In a more explicit sense, North et al. (2009) support the use of topography as a guide for restoration treatments. The use of strategically placed area treatments (SPLATs; Finney 2001) reduces the amount of area that needs to be treated to reduce overall landscape level extreme fire behavior (Schmidt et al. 2008). The combination of these two approaches to managing landscapes for resilience in the face of potentially severe fire is, we hope, great. We have shown that more exposed topographic settings on the landscape deserve special consideration when developing fire management plans. In Lassen Volcanic National Park, lower elevation slopes that were comparatively higher in elevation in relation to the slopes around them—and therefore more exposed—were associated with high severity fire. These topographic settings that have a tendency to burn at higher severity than other settings are also associated with historic, observed evidence of high severity fire.

We have also shown that the combination of pyrogenic vegetation and exposed slopes can 'fix in place' some patches of high intensity burning on the landscape. Although embedded—in our

178

case study—in a mixed conifer forest that typically experiences low- to moderate-severity fire, these vegetation communities exist because of high severity fire, they promote high severity fire, and they exist in locations that increase the chances for high severity fire. In the Sierra Nevada and the southern Cascades, brushfield communities are declining in area because of fire suppression activities and have been invaded by conifers in the modern era (Nagel and Taylor 2005). Historically, upper slope positions and higher elevations tended to burn with high severity as well (Beaty and Taylor 2001; Bekker and Taylor 2001). Vegetation patches that are 'fixed in space' have implications for the steady-state shifting mosaic paradigm. This paradigm posits that when viewed over a large enough spatial frame and a long enough temporal frame, disturbance prone ecosystems exhibit a relatively static proportion of vegetation types and structural stages, although their specific locations are random (Bormann and Likens 1979; Turner et al 1993; Perry 2002). In contrast, we suggest that while the proportion of the landscape occupied by a specific vegetation type or structural stage might be in relative equilibrium, the locations of those patches could be 'fixed in place' through the interaction of the disturbance process itself—here fire—and the topography.

Future Directions

The research presented here has inspired my own new perspective on the drivers of variations in fire severity. These drivers fall into the broad categories of Weather, Climate, Vegetation, Management, and Topography (Figure 1). Specifically, Weather includes temperature, wind speed and direction, and humidity; Climate include annual and interannual variations as well as climate teleconnections; Vegetation includes vegetation type, the amount and arrangement of

179

fuels, and changes in vegetation type; Management includes development, logging, fire suppression, fragmentation, and all other human impacts; and Topography includes elevation, slope, aspect, topographic position, and topographic configuration. Their overlapping or non-overlapping realms of spatial and temporal influence on fire severity necessitate different investigative approaches. For example, an investigation of the effects of weather on fire severity requires detailed day-to-day weather observations and daily to sub-weekly maps of fire spread (e.g. Collins et al. 2007). Examining the effects of management requires data on multiple fires over a larger area and over a longer time frame (e.g. Thompson et al. 2007). The analysis of climatic effects on fire regimes often requires long-term fire records accessible only through paleoecological methods (e.g. Taylor 2000). The effects of fire on different vegetation types in the large landscape often must be dealt with in abstractions through the use of models (He and Mladenoff 1999), but 'natural experiments' allow for the examination of the differential effects of vegetation treatments (Agee and Skinner 2005) and differential topographies (Iniguez et al. 2009) on fire behavior and effects. These approaches all take topography into account only in so far as it is the physical template on which the other drivers of fire severity interact. I am not advocating for the use of geomorphological models to enhance our understanding of the effect of topography on fire severity. However, the recognition that models may be the only way to study certain aspects of fire regimes has proven to be a fruitful approach in the past and should continue to have a prominent place in fire ecology.

Finally, climate change has the potential to impact most of the above identified drivers of fire severity and also to drive changes in fire regimes themselves. Already, it has affected weather by increasing minimum temperatures (Breshears et al. 2005) while concurrently lengthening the fire season by inducing earlier snowmelt (Westerling et al. 2006). Climate change also makes

more likely the emergence of no-analog climates and novel ecosystems that can potentially bring with them novel fire regimes (Williams and Jackson 2007). The seemingly stable forest ecosystems that exist today may be assemblages of species that established under different climate regimes at different points in the past such that their transience on the landscape is only evident on the time scale of centuries to millennia (Millar and Woolfenden 1999). In this work, we have shown that the potential exists on the landscape for some topographic positions to produce more high intensity and high severity fire than other positions. As vegetation communities are broadly impacted further by climate change through migration, compositional changes, or structural changes, landscape heterogeneity in vegetation composition will continue to be driven by spatially discrete drivers of fire intensity and severity.

Works Cited

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

Beaty, R. M. and A. H. Taylor (2001). Spatial and temporal variation of fire regimes in a mixed conifer landscape, Southern Cascades, California, USA. *Journal of Biogeography* 28: 955-966.

Bekker, M. F. and A. H. Taylor (2001). Gradient analysis of fire regimes in montane forests of the southern Cascade Range, Thousand Lakes Wilderness, California, USA. *Plant Ecology* 155: 15-28.

Bormann, F. H., & G. E. Likens (1979). *Pattern and Process in a Forested Ecosystem.* New York, NY: Springer-Verlag.

Breshears, D. D., N. S. Cobb, P. M. Rich, K. P. Price, C. D. Allen, R. G. Balice, W. H. Romme, J. H. Kastens, M. L. Floyd, J. Belnap, J. J. Anderson, O. B. Myers, and C. W. Meyer (2005). Regional vegetation die-off in response to global-change-type drought. *Proceeding of the National Academy of Sciences* 102(42): 15144-15148.

Collins, B.M. and S.L. Stephens (2007). Managing natural fires in Sierra Nevada wilderness areas. *Frontiers in Ecology and the Environment* 5(10): 523-52

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

He, H. S. and D. J. Mladenoff (1999). Spatially explicit and stochastic simulation of forest-landscape fire disturbance and succession. *Ecology* 80(1): 81-99.

Iniguez, J. M., T. W. Swetnam, and S. R. Yool (2009). Topography affected landscape fire
history patterns in southern Arizona, USA. *Forest Ecology and Management* 256: 295-
303.

Millar, C. I. and W. B. Woolfenden (1999). The role of climate change in interpreting historical
variability. *Ecological Applications* 9(4): 1207-1216.

Nagel, T. A. and A. H. Taylor (2005). Fire and persistence of montane chaparral in mixed
conifer forest landscapes in the northern Sierra Nevada, Lake Tahoe Basin, California,
USA. *Journal of the Torrey Botanical Society* 132(2): 442-457.

North, M., P. Stine, K. O'Hara, W. Zielinski, and S. Stephens (2009). *An Ecosystem
Management Strategy for Sierran Mixed-Conifer Forests.* Gen. Tech. Rep. PSW-GTR-
220. Albany, CA: United States Department of Agriculture, Forest Service, Pacific
Southwest Research Station. 49 p.

Perry, G. L. W. (2002). Landscapes, space and equilibrium: shifting viewpoints. *Progress in
Physical Geography* 26(3): 339-359.

Schmidt, D. A., A. H. Taylor, and C. N. Skinner (2008). The influence of fuels treatment and
landscape arrangement on simulated fire behavior, Southern Cascade range, California.
Forest Ecology and Management 255: 3170-3184.

Taylor, A. H. (2000). Fire regimes and forest changes in mid and upper montane forests of the
southern Cascades, Lassen Volcanic National Park, California, USA. *Journal of
Biogeography* 27: 87-104.

Thompson, J. R., T. A. Spies and L. M. Ganio (2007). Reburn severity in managed and

   unmanaged vegetation in a large wildfire. *Proceedings of the National Academy of*

   Sciences 104(25): 10743-10748.

Turner, M. G., W. H. Romme, R. H. Gardner, R. V. O'Neill, & T. K. Kratz (1993). A revised

   concept of landscape equilibrium: disturbance and stability on scaled landscapes.

   Landscape Ecology 8(3): 213-227.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, & T. W. Swetnam (2006). Warming and earlier

   spring increase western U.S. forest wildfire activity. *Science* 313: 940-943

Williams, J. W. and S. T. Jackson (2007). Novel climates, no-analog communities, and

   ecological surprises. *Frontiers in Ecology and the Environment* 5(9): 475-482.
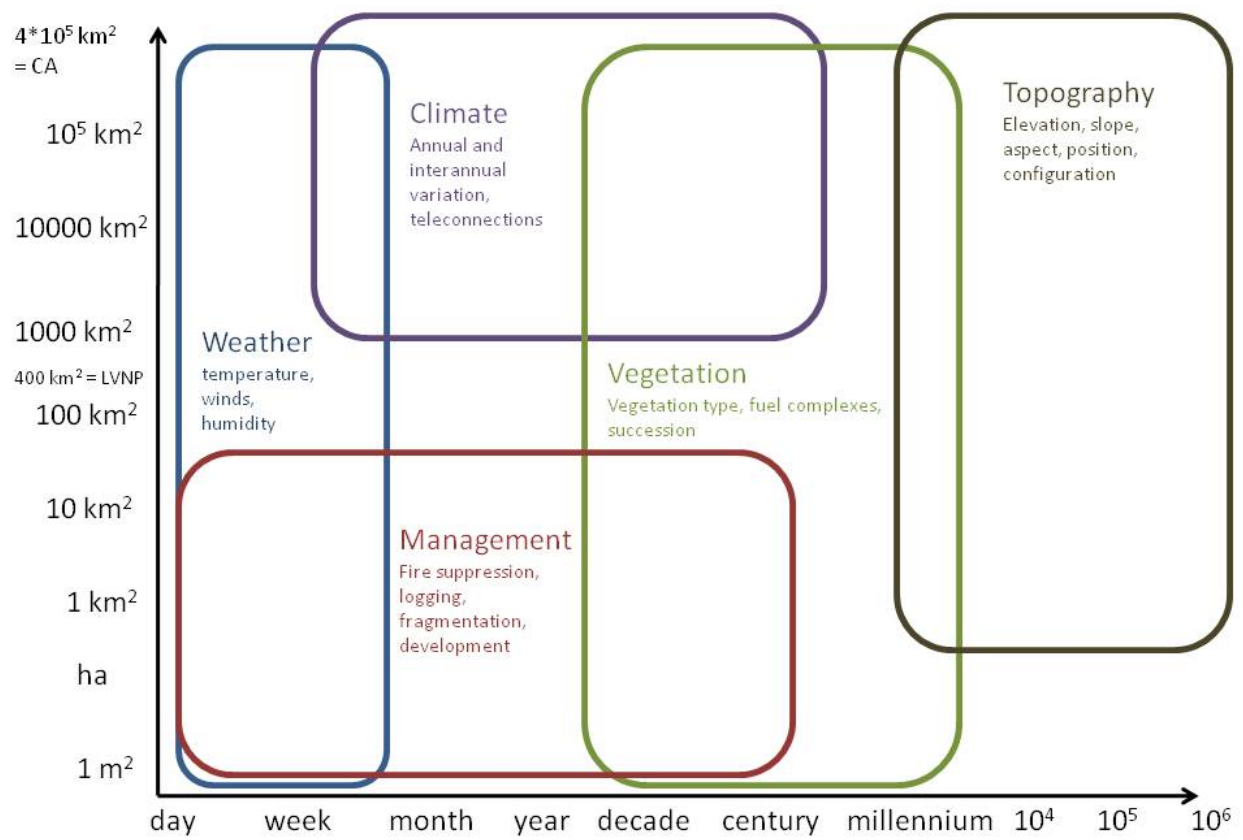
Figure 5-1: A log-log plot of the drivers of fire severity and their characteristic scales of spatial and temporal variation.

Curriculum Vitae   Department of Geography
Andrew D. Pierce   Pennsylvania State University
                                                    304 Walker Building
                                                    University Park, PA 16802

Education
2011 PhD, Geography, Pennsylvania State University
2007 MS, Geography, Pennsylvania State University
2002 BA, Mathematics, Dartmouth College

Professional Experience
2005 – 2008; 2009 – 2010 Research Assistant, Vegetation Dynamics Laboratory, Pennsylvania
        State University, Dr. Alan Taylor, Director.
2009 Environmental Scholars Fellowship, Earth and Environmental Systems Institute,
        Pennsylvania State University
2008 – 2009 Water-Land-Ecosystem Geography Fellow, Department of Geography,
        Pennsylvania State University.

Teaching Experience
Spring, 2011 Teaching Assistant, Geography 363: Geographic Information Systems
Fall, 2010 Instructor, Geography 010: Introduction to Physical Geography.
Summer, 2010 Instructor, Geography 010: Introduction to Physical Geography.
Summer, 2006; 2008-2010. Field Research Supervisor. Train and supervise interns during a
        field summer in Lassen Volcanic National Park.
Spring, 2007 Teaching Assistant, Geography 464: Spatial Analysis II

Publications
Peer Reviewed:
Pierce, Andrew D. & Alan H. Taylor (2011). Fire severity and seed source influence lodgepole
        pine (*Pinus contorta* var. *murrayana*) regeneration in the southern Cascades, Lassen
        Volcanic National Park, California. *Landscape Ecology* **26**(2): 225-237.
Pierce, Andrew D. & Alan H. Taylor (2010).   Competition and regeneration in quaking aspen-
        white fir (*Populus tremuloides-Abies concolor*) forests in the Northern Sierra Nevada,
        USA. *Journal of Vegetation Science* **21**(5): 507-519.

Awards
2011 Geography Alumni Scholars Graduate Student Award, Department of Geography,
        Pennsylvania State University
2011 E. Willard Miller Award, Ph.D. Paper; Department of Geography, Pennsylvania State
        University
2009 – 2010 Outstanding Graduate Research Assistant, Department of Geography, Pennsylvania
        State University
2005 – 2006 Anne C. Wilson Graduate Research Award, College of Earth and Mineral Sciences,
        Pennsylvania State University

Grants Received
"Mapping Canopy Fuel Characteristics to Assess Potential Fire Behavior, Lassen Volcanic
        National Park" (Co-PI). United States Department of Interior, National Park Service.
        ($35,333)
"Doctoral Dissertation Research: Using Neutral Models to Evaluate the Effect of Topography on
        Landscape Patterns of Fire Severity: A Case Study of Lassen Volcanic National Park"
        (Co-PI). National Science Foundation, Doctoral Dissertation Research Improvement
        Grant. ($11,900)