INTERACTIONS BETWEEN FOREST INSECT ACTIVITY AND WILDFIRE SEVERITY IN THE BOOTH AND BEAR COMPLEX FIRES, OREGON

by

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THESIS ABSTRACT

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This study investigates how two major groups of forest pests in North America, defoliating insects and bark beetles, influenced subsequent wildfire severity in the Booth and Bear Complex Fires. A secondary goal is to ascertain whether high-resolution plot-based vegetation data are better predictors of fire severity than lower resolution historical vegetation data. General Additive Models were used with an information-theoretic approach to determine the importance of forest insect outbreaks as predictors of fire severity. The models indicate that pest outbreaks were not significant predictors of fire severity and that high-resolution plot-based vegetation data are not superior to lower resolution historical vegetation data. Elevation and weather conditions were the most important controls of severity, while low-resolution vegetation data, slope and topographic position were of secondary importance. These results suggest defoliating insect outbreaks do not appreciably increase fire severity, though this finding should be verified in the context provided by other fires.

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Dedicated to my Dad

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CHAPTER I

INTRODUCTION

The structure, species composition and successional stages of contemporary forests are largely the result of environmental constraints on the growth and reproductive success of tree species and disturbance regimes over varying spatial and temporal scales. While it is well known that disturbances have the capacity to alter forest structure and composition (Chadwick 1980; Sousa 1984; Picket & White 1985), interactions between types of disturbances have received much less attention. In the western forests of North America two of the most influential types of disturbance are forest insect outbreaks and wildfires. Both of these forms of disturbance directly impact forested landscapes by causing tree stress and/or mortality, but they also can influence each other. Fire directly affects insect populations through mortality and by changing stand level structure and tree densities, while insect outbreaks have the capacity to alter the fuel characteristics of a landscape and therefore fire behavior (Bepi et al. 2003; Hummel & Agee 2003; Bigler et al. 2005; Cunningham et al. 2005; Breece et al. 2008; Jenkins et al. 2008).

The aim of this study is to assess how two of the major groups of forest insects in North America, defoliators and bark beetles, influence fire severity. These two groups of forest insects differ in their feeding and reproductive strategies and with respect to their host mortality rates (reviewed below). In particular, bark beetles often result in complete mortality of host trees, while defoliators reduce leaf area and vigor of trees, typically causing only partial dieback. Therefore, one might expect fuels and subsequent fire severity to differ between the two insect groups.

In this study forest insect outbreak-fire interactions were investigated for the 2003 Bear and Booth (B&B) Fire in central Oregon. This fire occurred over approximately 365 km^2 and produced a range of fire severity across a variety of forest types and previous levels of insect outbreak. There are two broad goals of this research. The primary goal was to assess the relationships between insect outbreaks and subsequent wildfire severity. These relationships were explored by investigating the ability of insect outbreak covariates to explain the residual variation of fire severity remaining from statistical models built using fuel, weather and topography covariates. A secondary goal of the research was to compare the ability of coarse resolution vegetation data to predict fire severity relative to high resolution survey-based vegetation data. This comparison was made between vegetation data interpreted from public land survey records and vegetation data from a detailed survey of species composition and fuel loads carried out 12 years before the 2003 B&B Fire.

The study addresses the following three questions using free, publically available data: 1) Did antecedent defoliator outbreaks measurably increase the severity of the B&B Fire? 2) Did antecedent bark-beetle outbreaks measurably increase the severity of the B&B Fire? 3) Is the prediction of fire severity in the B&B Fire significantly improved by including plot-level pre-fire vegetation and fuel data relative to a model based only on coarse-resolution vegetation data?

CHAPTER II

BACKGROUND

2.1. Current Trends in Wildfires and Forest Insect Outbreaks

Trends in wildfire frequency, extent and ecological severity are important to many stakeholders, including land management agencies, wildland conservationists, property owners, and private industry. Both wildfire and large scale insect outbreaks are important factors in determining the biodiversity of North American forests as well as the storage and emission of carbon and the loss of merchantable timber (McCullough et al. 1998; Meigs 2009; Kurz et al. 2008). The importance of fire and insect outbreak disturbance regimes in North American forests is accentuated by recent studies that suggest that wildfires in western North America may be increasing in both geographic extent and frequency over the last several decades despite no apparent increase in natural ignition events (Stephens 2005; Westerling et al. 2006; Littell et al. 2009). Additional studies suggest that while modern fire suppression practices may be effectively reducing the area burned by low severity fires, high severity fires may actually be increasing in size and frequency, in part due to greater fuel loads related to those fire suppression practices (Covington & Moore 1994; McKelvey et al. 1996; Miller et al. 2009).

The degree to which fire regimes have been affected by climatic change or fire suppression depends on geographic context (elevation, dominant vegetation, etc.) and scale. In addition, forest types that historically experienced frequent, low-severity fires have a greater opportunity to have missed fire cycles due to modern suppression efforts than those forest types that typically experience infrequent but high severity and stand replacing fires (Agee 1993). Safford et al. (2006) found that departure from mean fire return interval is correlated with fire severity in coniferous forests. However, Odion & Hanson (2008) contest that departure from mean fire return intervals due to fire suppression in the western U.S. is not a sound predictor of contemporary fire severity patterns.

Insect outbreaks in North American forests may also be increasing in frequency and/or severity due to changing climate and forest composition. Increased forest insect outbreak activity over the past century is likely related to rising minimum winter temperatures in areas that historically experienced winters cold enough to reduce reproductive rates of forest insects, as well as fluctuations in precipitation rates that can result in water stress for host trees (Logan & Bentz 1999, Ayers and Lombardera 2000; Williams & Liebhold 2002; Logan and Powell 2009). Increases in forest insect outbreaks may also in part be due to more than 50 years of attempted fire exclusion from most federal and state lands, which has increased the density of late-succession tree species. The high density of these late-successional stands makes them more susceptible to attack by insects (Hessburg et al. 1994; Swetnam et al. 1995).

An improved understanding of how forest insect outbreaks contribute to the controls that regulate wildfire behavior is vital to producing strategies that encourage the maintenance of healthy forests and which satisfy management goals. Despite the fact that insect outbreaks cause damage over expansive areas that may then burn at high severities (Schmid & Frye 1977; Baker and Veblen 1990), few studies have analyzed these interactions over the scale of tens of thousands of hectares.

2.2. Controls of Wildfire Behavior

Fire behavior at the landscape scale can be considered a function of the 'fire behavior triangle'. The three contributing factors or legs of this triangle are weather, topography and fuels (Rothermel 1972; Chandler et al. 1983; Agee 1993). Most aspects of fire behavior, including spread rates and flame lengths are dependent on these three components. For example, as wind speed and slope increase, the flame length and rate of spread increase. Similarly, wind speed affects the minimum fuel-packing ratio, which in turn affects the maximum fuel moisture required for ignition (Rothermel 1972; Rothermel 1983). Important fuel load characteristics include the moisture and structure of the fuel. Fuel diameter is important because small diameter wood has a much greater surface area to volume ratio, allowing the center of fine fuel to dry quickly and reach combustion temperatures during a fire. Generally, smaller diameter and drier wood is easier to combust than larger diameter and wetter wood.

Fuel load characteristics, climatic conditions and tree species adaptations combine to form the fire regime of a forest. Fire regimes can be conceptualized as existing along a spectrum ranging from frequent low severity fires on one side to infrequent high severity fires on the other. The two extremes of this spectrum are well represented by forest types dominated by two species common to the area of the B&B Fire: ponderosa pine (*Pinus ponderosa*) and lodgepole pine (*Pinus contorta*).

The short fire return intervals for ponderosa pine forests are made possible by a combination of factors including limited annual precipitation, an abundance of fine fuels in the form of irregularly stacked long needles dropped in profusion by pure ponderosa stands, a lack of large diameter fuel buildup on the forest floor, a lack ladder fuels, and a large ground-to-lower-crown distance. A typical low severity fire burning in a ponderosa pine stand spreads in the form of a ground fire with short flame lengths traveling though grasses and small saplings (Weaver 1951). These fires are usually relatively cool and are unable to burn through ponderosa pine's thick, fire resistant bark. Short flame lengths often prevent fire from reaching the relatively high bottom branches of mature trees and so stop fire from climbing through a ladder of fuels and into the crown. By avoiding crown fires that can quickly transition from one tree to another, ponderosa pine stands are often able to thrive for hundreds of years through dozens of fire events that would consume stands of less fire resistant species.

Although ponderosa pines usually promote the low severity fires which help perpetuate their dominance on the landscape, high severity, stand replacing events occur infrequently. These high severity fires can result from several compounding factors, including the prevailing weather conditions, the periodicity between fires, and the degree of fuel accumulation that has taken place during those periods.

Lodgepole pine is also an example of a fire adapted tree species. However, in contrast to ponderosa pine, lodgepole pine is thin barked and often grows in crowded, spatially homogenous stands through which fire spreads easily. Consequently lodgepole pine is usually killed in infrequent, stand-replacing fire events of moderate to high severity. The tree's serotinous cones help to ensure that future generations of lodgepole pine will be the first tree species to establish in the post-burned site (Agee 1993). The cones release their seeds in response to the high temperatures generated by the fire, which melts the sticky resin that holds their scales closed.

2.3. Challenges to Modeling Wildfire Behavior

The primary challenges to modeling fire behavior are acquiring extensive data sets representative of the weather, topography and fuel inputs and appraising their accuracy (Rothermel 1983). These inputs are associated with varying levels of uncertainty. Weather is generally considered the least predictable and most stochastic of the three because weather models are only able to predict conditions reliably for one or two days into the future. Beyond that, stochastic events controlling weather conditions reduce the accuracy of predictions enough to render them largely irrelevant in the context of making sound, long term, fire-based management decisions. In addition to the inherent difficulties in predicting weather variables, weather observations are typically acquired as point data from fixed weather stations or by individuals with portable equipment, while spatially continuous data would be required for optimal model construction.

Topography on the other hand can be accurately measured and modeled using a variety of methods, including, airborne and satellite based sensors utilizing such technologies as RADAR and LIDAR. These data are becoming both cheaply and widely available and are useful tools in studying wildfires and developing wildland management strategies.

Fuel type and loading density are not as temporally variable or stochastically sensitive as weather, but are more difficult to measure and accurately describe than topography. Forest insect outbreaks may change the size-distribution and abundance of fuels; the interactions between insect outbreaks and wildfire behavior primarily take place through the fuels component of the fire behavior triangle.

2.4. Insect Outbreak-Fire Interactions

The relationships between fire and forest insect outbreaks are complex with feedbacks potentially operating in both directions, i.e. fires have the capacity to alter the course of insect outbreaks, while insect outbreaks have the potential to alter the course of fire events. The most obvious influence insect outbreaks exercise on fuels is their potential to kill large numbers of trees over expansive and spatially contiguous areas, with the potential to transform a moist, green forest into a dense assemblage of standing, dead, dry snags and large woody debris. Pandemic populations of forest insects (geographically extensive at high densities) may significantly influence the severity of subsequent fires by altering the fuel characteristics on the landscape (Flemming et al. 2002). This has been observed in lodgepole pine dominated forests under attack by mountain pine beetle (*Dendroctonus ponderosae*) throughout Colorado, Wyoming and much of the western US in recent years (McCambridge et al. 1982; Logan & Powell 2009).

However, tree death is only one way insect outbreaks can affect forest structure and fuel characteristics in a forest. Changes in fuel load and structure due to branch dieback and the dropping of leaves and needles are also potential results of insect outbreaks. These changes in fuel loading can be complex and temporally dependent. Fuel loads on the forest floor may initially increase as dead needles and twigs are shed from the trees, but with the first few years after the outbreak this fine fuel decomposes and ground-level fine fuel loads may be quite low. If mortality after an outbreak is high there may then be an increase in large woody debris as dead trees begin to topple. The time scale of this process is likely dependent on environmental variables that influence decomposition rates such as temperature and humidity.

Fire can also have a significant impact on forest insects by killing them during fire events or by setting a forest on a successional pathway that is either conducive or adverse to future outbreaks (Bebi et al. 2003; Jenkins et al. 2008). Much of these interactions depend on the climate, weather, tree species and insect species involved. While dozens of insect species affect North American forests, comparatively few are responsible for the majority of the damage caused during outbreaks and most of those fit into the categories of defoliators or bark beetles.

Bark beetles and defoliators have different survival and reproduction strategies, that influence their effect on forest structure, fuels and potential fire behavior/severity. Bark beetles bore through the bark and into the vascular tissue of living trees where they create galleries as they feed. Most defoliators are part of the Lepidoptera family, characterized by their voracious caterpillar larval stage. Defoliators consume foliage but do not bore into the tree. Defoliation does not typically kill the tree unless it occurs for several seasons sequentially or the tree is otherwise stressed such as through drought, temperature, disease or mechanical damage. After an outbreak, caterpillars may fall to the understory and occur in high numbers on small trees, often completely defoliating them. Small trees are more susceptible to defoliation than larger tree and can be killed; these can be important fuel for wildfires. Bark beetles on the other hand typically must kill their host in order to successfully reproduce, or else the host tree's immune system will flush the insects out of their galleries with a profusion of resinous sap (Flamm et al. 1988; Williams & Liebhold 2002). Because these two groups of forest insects operate so differently, it makes sense to address the two groups separately in this study.

2.4.1. Beetle-Wildfire Interactions

Bark beetles cause extensive outbreaks in North American forests. There are several species of bark beetles but most belong to the *Dendroctonus* (meaning tree killers) genus. Individual species of *Dendroctonus* have their own preferred host tree species. For example spruce beetle (*Dendroctonus rufipennis*) prefers spruce (*Picea*) but also attacks true firs (*Abies*), while the mountain pine beetle (*Dendroctonus ponderosae*) is often found in tremendous numbers in dense lodgepole pine stands, but will attack many species of *Pinus* (including *ponderosa*) and even Douglas-fir (*Pseudotsuga*), true firs (*Abies*) and spruce (*Picea*).

Bark-beetles typically exist among their hosts in an endemic phase, where their population level is more or less constant and relatively small. Occasionally beetle populations experience outbreak-events when their numbers increase dramatically for a relatively short period of time before quickly declining again. During endemic population phases *Dendtroctonus* species typically only attack trees that have ideal physical characteristics for successful reproduction, such as sufficient trunk diameter and phloem depth. *Dendtroctonus* also preferably attack trees which are already stressed to some degree, often choosing trees which have been charred by fire, weekend by disease or partially uprooted by wind throw (Goheen & Hansen 1993; Cunningham et al. 2005). The triggers that initiate outbreaks of *Dendroctonus* species are not well understood, but it is likely that a combination of ideal climatic conditions and various forms of disturbance preceding the outbreak are contributing factors (Schmid & Frye 1977). Fire is one type of disturbance which can help initiate outbreak scenarios. *Dendroctonus* species are known to attack ponderosa pine with greater success following fire damage to their host trees (McHugh et al. 2003; Breece et al. 2008). In turn, trees injured or killed by insects may be more likely to support crown fire and therefore contribute to higher severity fires in the future. However, the relationship between fire events and beetle outbreaks is likely variable over the time scale of several decades. A study on the relationship between spruce beetles and fire in subalpine Rocky Mountain forest suggested that forests which burned in 1879 were less susceptible to a widespread beetle outbreak in 1940 than older forests were (Bebi et al. 2003).

When bark beetle outbreaks do occur they can be very large in geographic extent, covering several hundred thousand hectares, and are often characterized by mortality rates approaching 100% (Schmid & Frye 1977; Baker and Veblen 1990). Mortality rates reach high levels because the beetles become less selective of their hosts and often begin to attack less optimum host trees as resources dwindle.

Unlike fire, which typically results in complete mortality of the understory tree layer and often in the establishment of early-successional even-aged stands of trees, Dendroctonus outbreaks may accelerate the process of succession. This is because *Dendtroctonus* beetles prefer larger trees of a more advanced age class to younger, slimmer trees which have thinner layers of the vascular tissue (phloem) on which they feed. Canopy tree mortality results in the release of previously suppressed understory or sub-canopy trees. Because understory trees are often more shade tolerant species that established over long periods of time, post-outbreak stands tend to have a more diverse age class distribution than stands affected by severe fires (Veblen et al. 1991).

Severe *Dendroctonus* outbreaks can result in notable changes to the volume and distribution of available fuel (Schmid & Frye 1977; Bigler et al. 2005). The alteration to fuels following beetle outbreaks also changes dramatically through time. Initially there is a large increase in the volume of available fine fuels, mostly needles, as dead and dying trees first retain dead and desiccated needles before they drop and contribute to duff and litter. The volume of this litter reduces quickly as the fine needles and twigs decompose and become compacted. During a beetle outbreak-event coarse woody debris levels may be relatively low, but after 2-3 years the volume of coarse woody debris increases dramatically as dead tree tops and limbs fall to the ground (Page & Jenkins 2007; Jenkins et al. 2008). Branches and dead tree tops tangled in lower branches provide ladder fuels that encourage the transition from ground fires to crown fires (Stocks 1987).

About a decade after a *Dendroctonus* outbreak, the rate of tree-fall of beetle-killed trees increases (Ohmann 2002). The exact length of this interval is dependent on tree species as well as local climatic and weather conditions. An accumulation of dead trees on the forest floor is likely to continue for at least 20 years following an outbreak, again dependant on species and local conditions (Mielke 1950). As dead snags gradually fall to the ground the forest structure becomes increasingly open and the reduced canopy cover allows for more insolation to reach the ground, thus reducing the moisture content of the small diameter fuels that are critical in the rapid spread of wildfires. The opening up of the forest structure caused by widespread dieback can also contribute to higher wind speeds at the forest floor, further increasing desiccation rates of fuels and contributing to greater flame lengths during fire events (Rothermel 1991; Jenkins et al. 2008).

Though concerns over the impact of large scale beetle outbreaks on subsequent fire severity are common, there are relatively few studies that attempt to quantitatively describe the relationship between the two. However, the Rocky Mountains have been comparatively well studied in this respect (Veblen et al. 1994; Kulakowski & Veblen 2002; Bebi et al. 2003). Notably, a study on the relationship between a severe spruce beetle outbreak in the Rocky Mountains that occurred during the 1940s and the 17,000 acre Big Fish Lake fire that burned in 2002 failed to show significant levels of correlation between beetle outbreaks and fire severity (Bigler et al. 2005). A second study on the Big Fish Lake fire investigated the relationship between beetle outbreaks five years prior to the fire and subsequent fire severity also found no significant correlation between beetle outbreaks and fire severity (Kulakowski & Veblin 2007).

2.4.2. Defoliator-Wildfire Interactions

Defoliators consume foliage, reducing the photosynthetic capacity of the host tree. In general, evergreen trees are considered fairly susceptible to defoliation-induced stress because they are not physiologically well adapted to rapidly re-grow a large percentage of their crown (Krause & Raffa 1996). In contrast deciduous trees have a inherent resiliance to defoliation events because they typically replace their entire leaf area each year (Krause & Raffa 1996). Even so, most evergreen trees can survive one or more partial-defoliation events without significant risk of mortality, though continued defoliation over several years can stress a tree enough to kill it or predispose it to other diseases (Krause & Raffa 1996; Edmonds et al. 2000; Cooke et al. 2007). In any case, defoliation events may persist for up to a decade and result in widespread crown dieback and mortality (Powell 1994).

Defoliators can have significant impacts on the structure and fuel load of forests. Unlike bark beetles, defoliators reduce the availability of fine fuels during outbreaks by consuming their hosts' foliage. However, by consuming foliage defoliators also open the canopy and allow both more insolation and air movement to reach the forest floor (Fleming et al. 2002). Thus, defoliation will lead to more rapid drying of what fuel already exists on the forest floor and increases the likelihood of fire ignition. These same conditions also increase the potential for fire to spread through the understory. Sustained defoliation can also lead to branch die back as the tree reallocates resources away from defoliated regions in order to maintain vital physiological functions in the rest of the tree (Ferguson 1988). A potential repercussion of branch die back is an increase in ladder fuels as bits and pieces of dead branches and tree top are caught on lower branches (McCullough et al. 1998). This increase in accumulation of ladder fuels translates to an increase in risk of ground fires transitioning into crown fires (Stocks 1985, Stocks 1987).

Western spruce budworm (*Choristoneura occidentalis*) is the most widespread and arguably the most important insect defoliator in North American conifer forests (Swetnam & Lynch 1993). Spruce budworms are known to attack many species of trees including species in the *Picea*, *Abies*, *Pinus*, *Tsuga* and *Pseudotsuga* genera. In addition to consuming foliage, spruce budworms are also known to consume staminate flowers and developing cones, which can result in reduced reproductive success in their hosts following outbreak events (Nealis & Régnière 2004). In stands of trees with mixed age class structures spruce budworm larva can drop out of the canopy of mature trees onto young understory saplings below. In contrast to mature trees which have some level of resistance to defoliation events, young saplings have relatively few needles in relation to their size which makes them particularly susceptible to defoliation, serious injury and death.

In an extensive study on the relationship between spruce budworm and wildfire carried out in central Canada (Fleming et al. 2002) between 1941 and 1996 less than 10% of the total area defoliated by spruce budworm experienced wildfire events. It is important to realize however that in central Canada and much of the western U.S. periodic defoliation by spruce budworm is generally far more geographically expansive than the annual area burned. Therefore, one should not expect the percentage of overlapping area between fires and outbreak events to be particularly high even if there is a positive correlation between the two.

Evidence from Fleming's central Canadian study on budworm outbreaks and wildfire events suggests that there is a three to nine year window after defoliation during which fire has a small but significant and disproportionately high rate of occurrence (Fleming et al. 2002). The increased rate of fire occurrence is partially dependent on regional and climatic variations. In wet areas, the temporal window of increased likelihood for wildfire closes relatively early, while in drier areas that window is wider and ends several years later. The primary factor that influences the length of this window is the decay rates of coarse woody debris in wet vs. dry climatic conditions.

Hummell & Agee (2003) examined the impact of defoliator outbreaks between 1992 and 2000 on fuel loads, canopy structure and potential fire behavior at 21 sample locations near Smith Butte in the Washington Cascades. Immediately following eight years of defoliation, the canopy cover was significantly reduced and course woody debris on the forest floor significantly increased. Potential flame lengths were predicted using the TSTMDL program of BEHAVE (Burgan & Rothermel 1984). Predicted flame lengths significantly increased after defoliation, but flame lengths did not increase enough for torching potential (the likelihood of transitioning from surface fire to crown fire) to increase significantly (Hummell & Agee 2003).

2.5. Quantifying Wildfire Severity Remotely

Conventionally, fire severity represents the degree to which an ecosystem or plant community has been ecologically affected by a fire event, e.g. the proportion of trees and other organisms killed, though depending on the subject of inquiry fire severity can relate to a wide range of ecological parameters. In quantitative analyses a fire severity index is commonly used to represent fire severity.

Fire severity may be mapped using field-based methods. The Composite Burn Index (CBI) is a field based methodology of quantifying fire severity that was developed by the U.S. Forest Service to parallel remote sensing based techniques. It is considered a comprehensive method of determining fire severity because it takes into account fire effects in the soil, understory and over-story strata (Key & Benson 2006). However, the CBI methodology requires highly trained field technicians, is costly and time consuming. It is also subject to inconsistencies in data interpretation between individual field technicians. A major component of the CBI is the percent tree mortality, but tree mortality is often deceivingly difficult to determine, even with careful observations made by an experienced field technician. In contrast, remote sensing provides a method to quantitatively map large areas of fire severity regardless of terrain and other issues affecting site accessibility.

The Differenced Normalized Burn Ratio (dNBR) is currently the most commonly used fire-severity index in the U.S. (Cocke et al. 2005). It is generated by differencing two Normalized Burn Ratio scenes. The Normalized Burn Ratio is calculated using imagery from Landsat's multispectral Thematic Mapper (TM) and Thematic MapperPlus (TM+) sensors. NBR is calculated as 1000 * (TM4 – TM7) / (TM4 + TM7), where TM4 and TM7 are reflectance of Landsat bands 4 and 7. TM band 4 is in the near-infrared wavelengths (0.76-0.90 μm) that reflects strongly from vegetation and therefore decreases after fire, while TM band 7 is in the shortwave-infrared (2.08-2.35 μm) that reflects strongly from soil and rock, and therefore increases after fire. The differenced Normalized Burn Ratio is generated from Landsat images acquired just prior to and just after the fire, where the values of the post-fire image are subtracted from the values of the pre-fire image. A dNBR value of zero represents no change on the landscape while a positive value of dNBR represents an overall loss of vegetation. A negative dNBR value usually represents an overall increase in vegetation, which can often occur in low severity fires after an adequate period of time has elapsed to allow for basal-sprouting of existing vegetation and/or colonization of new vegetation. The dNBR index has been demonstrated to have high levels of agreement with ground based measurements of wildfire severity characteristics (Brewer et al. 2005; Cocke et al. 2005; Epting et al. 2005; Holden et al. 2005; Roy et al. 2006) and has been successfully used in a number of fire severity and disturbance related studies (Bigler et al. 2005; Epting & Verbyla 2005; Miller & Fites 2006; Thomspson et al. 2007).

A recent critique of dNBR is that it is overly influenced by the NBR values of the pre-fire image (Miller & Thode 2007). For example, consider a scenario where two patches of forest burn in an ecologically high severity fire, where all individual trees die, but where one patch starts out more lush and green before the fire event than the other. Both patches suffer 100% mortality but the patch which started out greener and moister will have a higher dNBR. This is relevant when assessing fire severity where some patches of forest are unaffected by insect outbreaks (more green) and other patches are affected by insect outbreaks (less green).

To cope with this issue, a relatively new fire severity index has been developed called the Relativized Differenced Normalized Burn Ratio (RdNBR). The RdNBR is relativized to the pre-fire image and to reduce the influence of differences among the pre-fire images. The RdNBR is relatively new and has not been used as extensively as dNBR, but it is gaining acceptance in the fire science community (Soverel et al. 2010). The RdNBR data have been shown to have stronger correlations to CBI plot data than dNBR in some western ecosystems (Miller et al. 2009).

CHAPTER III

STUDY SITE

3.1. Forest Types, Management History and Land Ownership

The B&B Complex fire burned approximately 90,000 acres of forest over diverse topography surrounding Santiam Pass in the central Oregon Cascades, east of the city of Sisters (Fig. 1; all figures are in Appendix A). The B&B Fire began as two separate fires that were both independently detected on Aug 19th, 14 days after their probable lightning ignitions. On September 4th the two fires merged and the combined fire was dubbed the B&B Complex Fire (Fig.2). The majority of the 2003 B&B Fire occurred in non-wilderness designated areas within the Deschutes National Forest (approx. 42,000 acres) and in the Mt. Jefferson Wilderness (approx. 40,000 acres) inside the boundaries of both the Willamette and Deschutes National Forests. The remaining 8,000 acres of fire affected land belonging to the Warm Springs Confederated Tribes, non-wilderness Willamette National Forest, state land and private in-holdings within the National Forest. While National Forest lands in this area have not been subject to large scale logging since the early part of the century, salvage logging (the practice of felling and removing fire-damaged trees to offset financial loss after fires) has been implemented more recently (Bork 1984). Historic logging in the non-wilderness portions of the fire probably resulted in greater patchiness of older trees and in the coverage of younger, denser stands over what would otherwise be expected in an ecologically equivalent unlogged forest.

The landscape across which the B&B Fire burned during its two and a half week run is typical of that found in the central Oregon Cascades. This landscape is dominated by a range of forest types that reflect the climatic transition found between the western Cascades and the shrub steppe of eastern Oregon. This transition spans one of the steepest precipitation gradients found in western North America (Daly et al. 2002). Forest types within the fire area include ponderosa pine (*Pinus ponderosa*), grand fir (*Abies grandis*), Pacific silver fir (*Abies amablis*), subalpine fir (*Abies lasiocarpa*), Douglas-fir (*Pseudotsuga menziesii*), lodgepole pine (*Pinus contorta*), mountain hemlock (*Tsuga mertensiana*) and mixed conifer (i.e., a mixture of pines and short-needled species).

3.2. Historical Fire Regimes in the Study Site

The forest types affected by the B&B Fire are associated with various fire return intervals, fuel loading, and historical wildfire fire severities (Agee 1993). One can consider forests with assemblages of these species to exist on a continuum or gradient between those forest types that typically experience infrequent but high severity fire (example: mountain hemlock) and those that typically experience frequent but low severity fire (example: ponderosa pine). Some forest types exist at the ends of this spectrum while others experience a much wider range of fire regimes.

In regions that typically experience frequent, low-severity surface fires, trees with thick, fire-resistant bark are generally strong competitors. In the western U.S. these species include ponderosa pine, western larch (*Larix occidentalis*) and mature Douglas-fir (Arno et al. 1985; Agee 1993). Within the Mount Jefferson Wilderness ponderosa pine is the most common tree in areas characterized by short fire return intervals. It is a fire-adapted species with thick bark, protected buds, and high height to lower crown. It frequently exists in single species, or nearly single species stands, which tend to encourage conditions that help to perpetuate their dominance on the landscape. Ponderosa pine generally exists in relatively dry sites at lower elevations on the east side of the central Oregon Cascades.

Ponderosa pine is one of the most widely distributed conifers in the Pacific Northwest and is often cited as the poster child for low severity, high frequency fire regimes (Agee 1993). The earliest work on the fire histories of ponderosa pines was spearheaded by Harold Weaver in the American southwest where typical fire return intervals were found to be four to 12 years (Weaver 1951). Weaver expanded his studies to the Warm Springs area of Oregon were he found slightly longer fire return intervals for ponderosa pine of 11to 16 years (Weaver 1959). More recent research by Joyce Bork found fire return intervals for east central Oregon ponderosa pine in the range of four to 24 years for three geographically disparate study sites across a steep precipitation gradient (Bork 1984). Even more recently, mean fire return intervals for ponderosa pine within the Deschutes National Forest were estimated to be approximately 5 years for the period between 1458 and 2001(Arabas et al. 2006).

Within the Mt. Jefferson Wilderness at higher elevations (>4000 ft), ponderosa pine transitions through a narrow band of mixed confer stands (with Douglas-fir and grand fir) to subalpine forests of lodgepole pine and subalpine fir. Though lodgepole pine is often successful at re-colonizing after fire events it is considered more of a seral species than a climax species in the area of the B&B Fire, as it can also be replaced by several late-successional species (Simon 1991). These forests are characterized by high tree densities, biomass and fuel loads, and are marked by an infrequent but high severity fire regime. However, mature stands may also have more mixed fire regimes consisting of both high and low severity fires. At higher elevations, subalpine fir, pacific silver fir and mountain hemlock become more common. These species have thin bark and normally burn infrequently and at high severity in stand-replacing events.

Because high mortality is often characteristic of fires in the subalpine zone, fire scars in these regions are rare (Agee 1993). Consequently the historic fire regimes of this zone have not been studied as extensively as forest types which experience more frequent and lower severity fires. Fire regimes in the subalpine zone of the study site are likely typical of the tree species that dominate the region, which include subalpine fir, pacific silver fir and mountain hemlock. In a study on the fire regimes of subalpine forests in Wyoming (ecologically similar to those found in Oregon) fire return interval of approximately 300 years have been reported (Romme & Knight 1981), determined by estimating the age class distribution of trees in several contiguous stands. Another study produced similar results for subalpine sites with similar species compositions in Colorado (Clagg 1975).

In a 1991 report to the Deschutes National Forest Fire Staff, Steven Simon reconstructed a fire history of the Mount Jefferson Wilderness area using an updated methodology by Barrett and Arno (Barrett & Arno 1989). Simon determined mean fire intervals in the subalpine zones of the Jefferson Wilderness Area typically ranged between 100 and 200 years (Simon 1991). High-resolution charcoal and pollen analyses in Tumalo Lake (44°02.27′N, 121°54.11′W) suggest average fire return intervals in the mid to upper elevations of the Central Cascades at approximately 115 years (Long et al. 2011).

CHAPTER IV

METHODS

4.1. Overview of Modeling Approach

To investigate the relationship between local forest insect outbreaks and the severity of the 2003 B&B Fire (questions 1 and 2) I compared the results of best fit models built using covariates known to be controls of fire behavior with models that included the same covariates with the addition of insect outbreak variables. Several models of best fit were constructed that predict the fire-severity indices of dNBR and RdNBR. These models were fit to 500 sample points within the B&B Fire perimeter. The sample points were randomly located and spaced by > 300 meters to reduce spatial autocorrelation among sample points. Generalized additive models (GAMs) were used in order to account for linear, curvi-linear & categorical relationships between predictors and fire severity. The set of covariates (excluding insect outbreak variables) that created the best-fit model was determined using an information-theoretic approach (Burnham and Anderson 2002). In order to determine if antecedent defoliator and bark-beetle outbreaks measurably increased the severity of the B&B Fire, insect outbreak variables were assessed for their ability to predict residual variation in the fire-severity indices. Maps of the model outputs and model residuals were also compared to maps of the observed dNBR and RdNBR values in order to further investigate the models' accuracy in capturing variation in the data.

To determine if the accuracy of fire severity predictions significantly improved when including plot-level pre-fire vegetation and fuel data versus only coarse-resolution vegetation type data (question 3), I used vegetation and fuel data collected in 160 plots in 1990 by Steven Simon (Simon 1991). The methods used to address question (3) are the same as used to address questions (1) and (2) with the exception that the covariates of interest are *tons of down/woody fuel* and *plot-based vegetation* type instead of *defoliator* and *beetle severity.* The data set used to address question (3) is based on sample plots published in Steven Simon's fire history report, which are limited to the Mount Jefferson Wilderness. These plots provided measurements of the fuel load and vegetation type.

The data layers used in this study are based on a variety of data types from several sources. Data include weather station data, the daily fire progression map, a 10-m digital elevation model, coarse resolution vegetation classification, aerial surveys of forest insect outbreaks, and plot-based vegetation and fuel load data. All data used in this study were obtained at zero cost and are freely available to the public. The following are brief explanations of these data and their sources. Unlike the other covariates used in this study the data from the pre-fire survey plots are not available as spatially continuous data layers because they were recorded only at individual sample locations.

4.2. Data Layers & Sources for the Entire Burn Area

Fire severity maps: dNBR and RdNBR maps of the B&B Fire were sourced from the Monitoring Trends in Burn Severity program (MTBS, 2009). MTBS is sponsored by the Wildland Fire Leadership Council (WFLC) and has mapped wildfire severity and perimeters for all fires larger than 1000 acres in the western United States and fires larger than 500 acres in the eastern U.S. from 1984 to the present. The data packages available through MTBS usually include the original multi-spectral Landsat images taken before and after the wildfire, wildfire severity indices generated from the differences between those two images (dNBR and RdNBR) and fire perimeter maps.

Digital Elevation Model: The DEM is a Shuttle Radar Topography Mission (SRTM, 2009) data-set at 10-meter resolution. The DEM was used as the elevation covariate and was also used to produce data layers for slope, topographic position index and insolation covariates.

Insolation: The insolation data layer represents the amount of incoming insolation received at the surface. The values for this data layer were calculated using a solar radiation algorithm (r.sun in GRASS GIS) that uses the DEM, sun path, hillshading, and aspect to compute direct-beam and diffuse solar radiation. To account for the greater desiccation capacity of insolation during warm afternoon hours the aspect of slopes were adjusted to reflect maximum insolation in the southwest rather than directly south. Insolation values are represented by an index calibrated to be relative to the insolation received by a flat, horizontal surface at sea level. A value of zero represents no insolation; a value of one is equivalent to insolation received on a flat plane at sea level and a value of 1.18 (the highest value observed in this study) represents 1.18 times the insolation found on a flat plane at sea level (See Appendix B).

Slope: The slope data layer was calculated from the DEM and represents how steep or shallow the terrain is over the area of the fire. Slope is represented in this data layer in degrees, where a value of zero represents a horizontal surface and a value of ninety represents a vertical surface. The initial slope data layer was smoothed using a 5x5 smoothing window function to ensure that the slope is represented at a scale relevant to a fire behavior analysis.

Topographic Position: Topographic position was calculated from the DEM and is a measure of the elevation at a given point on the landscape in relation to the elevation of an area surrounding that point. In essence it is a numerical representation of where the sample point exists on a continuum that ranges from valleys, to flat ground, to slopes, to ridges, to peaks. I followed the example of Thompson et al. (2007) and defined our measure of topographic position as the elevation of the sample point divided by the mean elevation of a surrounding annulus spanning 150-300m surrounding the sample point.

Historic Potential Natural Vegetation: This layer was sourced from the Oregon Natural Heritage Information Center (ORNHIC, 2010) and represents the climax communities of historic forests in Oregon. This layer is based primarily on interpretation of public land survey records of the federal government's General Land Office (GLO). The data reflects historical vegetation classes and boundaries. The effects of contemporary land use practices on species distributions are not shown in this layer.

Forest Insect Outbreak Data: The original forest insect outbreak data sets used in this study were sourced from the national Forest Health Protection Pacific Northwest Region (FHPPNR, 2009). These data sets were then used to produce several measures of outbreak severity for both bark beetles and defoliators. Aerial surveys are an economical and effective means of evaluating the health of large forested areas (Wear & Buckhorn 1955). The Forest Service started carrying out aerial forest insect outbreak surveys in the 1950s but only data from 1980 to present was available to the public at the time of this study. These aerial surveys are carried out from small aircraft flying at approximately 1,000-3,000 ft. above ground level along transects covering forested land throughout the Pacific Northwest. Trained sketch-mappers on either side of these small aircraft observe and map insect outbreaks during flights. Traditionally these hand drawn maps were digitized after the flight. Contemporary sketch-mapping is carried out using electronic tablets loaded with Geographic Information System software, which allows the real-time creation of geographically meaningful digital data without any subsequent digitizing. See section 4.5 for a more complete description and the quantitative treatment of these data.

Fire Progression Map: The perimeter of the B&B Complex was recorded at nearly daily intervals. The fire perimeter was recorded at night for most (but not all) evenings of the fire, typically just prior to or just after midnight. A fire progression map was created and posted online by the U.S. Forest Service (USFS, 2004) and modified for use in this study (see Fig.2). In this study polygons derived from these semi-daily fire perimeters were reclassified with daily fire weather data obtained from a nearby Remote Automated

Weather Station (RAWS) in order to produce spatially continuous fire weather data layers (see Fire Weather Data section below).

Fire Weather Data: Several components of weather are important for fire behavior, including temperature, humidity, and wind speed. Fire fighters frequently take these measurements in the field but the data is irregularly distributed in time and space and is infrequently digitally archived or made accessible to the public. I used fire weather data from the Remote Automated Weather Station (RAWS, 2010) in Colgate, Oregon (44°18'57"N, 121°36'20"W, Elev. 1000m, NWS ID: 352620). RAWS reports data include several fire weather indices and components based on temperature, relative humidity, wind speed, precipitation and fuel models. The two RAWS components assessed in this study are the Spread Component (SC) and the Energy Release Component (ERC). The Spread Component is a function of the wind speed, live fuel moisture and the fuel model. The Energy Release Component (ERC) is a function of the dead and live fuel moisture and the fuel model. The data from each component is reported on a scale from 0-100. The Burning Index (BI) is also produced by RAWS and represents the potential difficulty in wildfire containment. It is based on the outputs of the Energy Release Component, Spread Component and an Ignition Component; it is also reported on a scale from 0 (low difficulty) to 100 (high difficulty). RAWS also reports Keetch-Bryram Drought Index (KBDI) values which range from 0 (wet) to 800 (dry) and are dependent on daily precipitation. Fire weather data from the Colgate RAWS station (the only station near the

B&B Fire) was assigned to fire perimeter data layers in order to produce fire weather data layers at a near daily temporal resolution.

4.3. Pre-Wildfire Plot Measurements

To address whether plot-level information on fuels and forest types improved predictions of fire severity (question 3), plot data were obtained from a 1991 report on the on the fire history and plant communities of the Mount Jefferson Wilderness area (Simon 1991).

The major objective of Steven Simon's study was to "supply basic data for use in developing a fire management plan for the Wilderness" (Simon 1991). Simon performed comprehensive vegetation surveys in 1989 and 1990, noted any obvious signs of previous fires and estimated fuel loads at over 200 site locations in the area. One hundred and twenty four of these field sites were within the perimeter of the 2003 B&B Fire and were used as sample locations for our model construction process. Because the Mount Jefferson Wilderness is located along the Cascade Crest, which mainly burned at high severity, the models used to address question (3) predict a relatively small range of the variation of fire severity in the B&B Fire compared to the models used to address questions (1) and (2). However, there is still value in using these field study locations to generate models for comparison and data exploration purposes. The vegetation survey data from Steven Simon's report is presumably superior to the statewide historic vegetation data set used in the models used to address questions (1) and (2) because it is based on systematic observations rather than interpreted from historical land survey records. Additionally, the pre-fire fuel load data from Steven Simon's report represents an opportunity to assess the controls of fire severity within a forest type prone to stand-replacing fire.

4.3.1. Defining Plot-Based Vegetation Types

The plot data from Steven Simon's 1991 fire history report includes detailed information on the number of individuals and species of trees found at each sample location. Vegetation classes defined from these data were used as the *plot-based vegetation* covariate during model construction. Non-metric multi-dimensional scaling based on the Bray-Curtis index was used to identify four vegetation classes, or clusters, in ecological space (Appendix B). The Bray-Curtis distance has been shown to be a robust measure of compositional dissimilarity and ecological distance between sites (Faith et al. 1987; Minchin 1987). Our initial classification of vegetation plots into four groups was improved by removing the effect of very uncommon species (which was defined as species occurring in fewer than 10% of plots) and by removing plots with very few trees (i.e. non-forested locations).

4.4. Data Projection

Because the data analysis used geographically explicit methods where spatial relationships between covariates and observed values is important, it is necessary for all the spatial data to be projected in the same format and for an appropriate projection to be used. The single most important criteria for an appropriate projection in this study was for it to be representative of equal area. A Lambert Conic Conformal projection adopted by the U.S. Geologic Survey (USGS) in the NAD83 datum was used.

4.5. Quantifying Forest Insect Outbreaks

Forest insect outbreak data for the study site was sourced from the national Forest Health Protection Pacific Northwest Region (FHPPNR 2009). The FHPPNR data sets include outbreak perimeters, damage vectors, and severity ratings unique to the vector type. Beetle outbreak severity was typically reported in the number of dead trees per acre at the time of the survey, while defoliator severity was reported on a scale from one (little apparent defoliation in the canopy) to four (mostly defoliated canopies).

Records of defoliator outbreaks and bark beetle outbreaks were extracted from the complete data sets and treated as separate covariates for the purpose of model construction. Three indices representing insect outbreak severity were constructed for this study; two for defoliators and one for bark beetles. Defoliator outbreak severity is represented by both its persistence on the landscape from year to year (*defoliator persistence index*; DPI) and by a weighted, cumulative measure of average crown defoliation (*weighted defoliator severity index*; WDSI). Bark-Beetle outbreak severity is represented by the *beetle severity index* (BSI) and is based on the number of trees killed per acre.

In order to construct the DPI, features from vector data layers for each year were first converted to raster. Cells were assigned a value of '1' if an outbreak was present in a given cell and '0' if absent. The raster calculator in ARC GIS was then used to sum the values of all cells for all available years (1980-2003), resulting in a measurement of persistence on the landscape with values ranging from zero to nine for defoliator outbreaks. A value of zero represents the total absence of any defoliators between 1980 and 2003 while a value of anything greater than zero represents the presence of an outbreak for that number of years. For reasons further explained in section **5.1.1** the WDSI was ultimately favored over DPI as a predictor variable of fire severity.

The WDSI was constructed to approximate the cumulative impact of defoliation, and weighted such that more recent defoliation is considered more important than defoliation that occurred several years ago. The WDSI is based on the damage classes provided in the FHPPNR data set, which ranges from one (little to no defoliation) to four (total defoliation). The WDSI is calculated as the sum of damage classes for the years prior to the B&B Fire, using a weighting scheme such that weights decrease linearly to zero over a 20 year period before the fire, and are scaled such that the sum of the weights equals one (Fig.5).

BSI had to be computed differently from the defoliator indices because sketch-mappers are trained to only report beetle outbreaks that are new during the year of the aerial survey. The FHPPNR reports beetle outbreaks as number of dead trees per acre. Therefore, the BSI was calculated as the most severe mortality that occurred for all years between 1980 and 2003 (Fig.6).

4.6. Statistical Modeling of Wildfire Severity

Four reference models were created in this study, one each to represent dNBR and RdNBR from the two data sets (one used to address questions (1) and (2) and the other used to address question (3)). Reference models were constructed in the MGCV package in R. Goodness-of-fit was reported as 'percent deviance explained' (D^2), which is conceptually similar to r^2. D^2 is calculated using the model residuals relative to a null model. If a covariate's associated p-value was marginally significant (ca. 0.1) and it improved other measures of model validity such as D^2 and ΔAIC_C those covariates were considered for retention in the final model.

Initially, all covariates were included in model construction, but AICC values were generally high and most covariates had insignificant P-values (Appendix B). Subsequent models were constructed using a manual step-wise process based on the three components of the 'fire triangle'. Components were added to the model in order of most to least easily measured (topography first, then fuel, then weather) to favor the highest quality data. First, a model was constructed using all topography related covariates including *slope, insolation* and *topographic position.* The p-values of each covariate in the model were then compared; most covariates with insignificant p-values were removed one at a time until removing additional variables was not warranted as determined by the Akaike Information Criteria (AIC_C) of the model. Once a best-fit model was constructed using only topography related covariates, fuel covariates were added to the model (*vegetation* and *elevation*), and the same process of removing insignificant covariates was carried out. This process was then repeated for weather related covariates (including *bi*, *erc*, *sc*, and *kbdi*). In the end, all models with a ΔAIC_C of less than two (compared to the "best" model with the smallest AIC_C) were retained for discussion (Burnham and Anderson 2002). Finally, the outbreak severity or vegetation and fuel covariates were added to the reference model and the ΔAIC_C was used to assess their contribution to predicting fire severity.

4.7. Predicted Severity and Residuals Maps

To produce the predicted severity and residuals maps the original covariate data layers were exported from GRASS GIS into R statistical environment were the values were input to each of the models to predicted fire severity. Once predicted values were generated in R they were imported back into GRASS GIS with their associated geographic coordinates to construct predicted fire severity maps. Maps of the residuals were generated by subtracting the predicted fire severity values from observed values. Maps generated with the models used to address question (3) were restricted to a 5000 ft. elevation contour and above in order to avoid extrapolation of results to lower elevations located far from the plot locations.

CHAPTER V

RESULTS

The observed dNBR and RdNBR images (Fig.3 & 4) illustrate that the B&B Fire was of mixed severity, with the highest severity areas west of the Cascade crest, a gradient of less severe fire on the relatively gentle eastern slopes, and patches of very low severity spread throughout. Both observed dNBR and RdNBR severity images show that some areas experienced a 'positive vegetation response'. This response is due to an increase in greenness and water content of vegetation between the two images used to generate the fire severity indices.

5.1. Reference Models Used to Address Questions (1) and (2)

Models developed to predict dNBR and RdNBR, in which insect defoliation variables were withheld, explained 35.5% and 35.7% of the deviation in fire severity respectively (Table 1; all tables are in Appendix C). Both models were identical in the composition of their covariates with the exception that topographic position was included in the dNBR model and not in the RdNBR model. Notably, elevation and the energy release component (ERC) were highly significant ($p < 0.001$) in both models. ERC was the only fire-weather variable included in either reference model. The slope covariate had less significant p-values than *elevation* or *erc* but they were still less than 0.05 for both reference dNBR and RdNBR models. In both models smoothing of the elevation and slope variables produced better results than a linear function, implying non-linear relationships with fire severity (Fig. 7 & 8). No single vegetation type was significant but models that included the vegetation covariate always produced a lower ΔAIC_C and explained a greater percentage of variation in the data than models without the vegetation covariate. Therefore, vegetation was retained in both reference models.

Overall, the reference dNBR and RdNBR models were remarkably similar in their ability to predict fire severity. There were only small variations in p-values and correlation coefficients for some predictor variables between the two reference models.

5.1.1. Question (1): Defoliator Outbreaks and Wildfire Severity

While neither the weighted defoliator-severity index (WDSI) nor the defoliator-persistence index (DPI) greatly improved model fit, WDSI consistently produced superior models compared to DPI. The introduction of the WDSI to the reference models increased D^2 by only 0.3% for dNBR and 0.1% for RdNBR models, and the ΔAIC for the models indicate the insect variables did not substantially improve the model fit (Table 1). The coefficient for WDSI was negative in both dNBR and RdNBR models, implying that where defoliation outbreaks occurred, subsequent fire severity was lower than where outbreaks did not occur (Table 1). The scatter plot of residual values of the reference models (i.e., dNBR adjusted for covariates) plotted against the WDSI (Fig. 9) did not indicate a relationship between outbreak-events and subsequent fire severity.

Though the regression coefficients imply a negative relationship between defoliator severity and subsequent fire severity, the p-values of the defoliator covariate and the ΔAIC_C values for the models were not significant in either the defoliator dNBR or

RdNBR models. Therefore the hypothesis that defoliator outbreaks are an important predictor for subsequent fire severity in the B&B Fire is not supported.

5.1.2. Question (2): Bark-Beetle Outbreaks and Wildfire Severity

Bark beetle outbreaks in the Mount Jefferson Wilderness area during the decades immediately prior to the B&B Fire tended to be localized in geographic extent and usually did not persist for more than one or two years. There were also some years between 1980 and 2003 when no beetle outbreaks were recorded within the study area. Additionally, the longest lasting and most geographically extensive outbreaks of bark beetles near the vicinity of the study area occurred outside of the B&B Fire perimeter (Fig. 6). Mortality rates inside the study area reached six trees/acre outside the fire perimeter, five trees/acre within the fire perimeter, and only three trees/acre at any sample location. Relatively few of the sample points exhibited any beetle outbreak activity. Therefore, the results of models that include the beetle-severity index (BSI) should be considered with caution.

Unlike the defoliator models, which exhibited only small increases in percent of explained variation, the inclusion of BSI did not improve the reference models and the ΔAIC_C scores increased notably for the RdNBR model (ΔAIC_C =1.85) and significantly for the dNBR model (ΔAIC_C = 2.72; Table 1). Additionally, the scatter plot of residual values of the reference models plotted against BSI (Fig. 9) did not indicate a relationship between outbreak-events and subsequent fire severity. The results of this study do not support the hypothesis that bark beetle outbreaks were a significant predictor of fire severity in the 2003 B&B Fire and the null hypothesis cannot be rejected.

5.2. Question (3): Pre-fire Survey Data and Model Performance

Reference models predicting fire severity at the sample plots, in which the plot-based variables (*tons of down/woody fuel* and *plot-based vegetation*) were withheld, had D^2 values of 16.0% and 11.7% respectively (Table 2).

The inclusion of *tons of down/woody fuel* to the reference dNBR and RdNBR models increased the percentage of explained variation in the data by 0.3% each, while the inclusion of the *plot-based vegetation* covariate to the reference dNBR and RdNBR models increased the percentage of explained variation in the data by 2.1% and 1.2% respectively. However, it is possible for an improvement of this level to be expected from including a covariate consisting of random values and these variables are not significant. Introducing *tons of down/woody fuel* to the models resulted in ΔAIC_C scores approaching two while introducing *plot-based vegetation* to the models resulted in ΔAIC_C scores of greater than four (Table 2). Scatter plots of the residuals from the reference dNBR and RdNBR models vs. the *tons of down/woody fuel* and *survey-based vegetation* covariates conveyed no pattern, indicating no relationship between covariate and dependent variable (Fig. 10). These results do not support the hypothesis that either *tons of down/woody fuel* or *survey-based vegetation* significantly improved model performance and the null hypothesis cannot be rejected.

CHAPTER VI

DISCUSSION

6.1. Reference Models Used to Address Questions (1) and (2)

D^2 values of 35% may not seem to indicate robust reference models were constructed in this study. However, because fire severity is difficult to quantify even from a detailed plot resurvey, D^2 value approaching 100% would be highly unlikely even for a particularly robust model. For example, studies have shown that linear models used to predict dNBR from the Composite Burn Index (CBI, a ground-based index) have typically resulted in r^2 values of between 0.1-0.6, roughly equivalent to D^2 values of 10%-60% (Miller & Thode 2007; Hoy et al. 2008; Murphy et al. 2008). This is despite the fact that CBI was specifically designed to be a field-based ground-truthing estimate of dNBR. With this in mind, a D^2 value of 35% for a model predicting a fire severity index indicates the model is robust.

A comparison of the observed dNBR and RdNBR images with the predicted severity maps provides an alternative means to assess the models and the influence of covariates on model outputs. The predicted severity maps (Figs. 11 & 12) reproduced the general trend of the fire severity fairly well but they do diverge from the observed values in some notable instance. The areas with the greatest divergence between observed and predicted values are most easily identified using the predicted severity residuals maps (Figs. 13 & 14). There is no readily apparent systematic pattern in the residuals maps, which is a good indication that the models do not lack important geographic covariates. Both residuals maps indicate some areas where the models strongly diverged from the observed values. Where predictions and observations diverged the models most often over-predicted fire severity rather than under-predict it. Further investigation revealed some possibilities as to why these variations in the data were not captured by the models.

Two locations where models predicted burn severity poorly are readily explicable by local factors. In the first location, the residuals maps show a patch of forest approximately 120 hectares in extent just north of the prominent peak Three Fingered Jack where the models over predicted fire severity. The DEM and LANDSAT images suggest this site occupies a drainage area surrounding Jorn and Bowerman Lakes (44° 31.06'N, 121° 52'W; 44° 31.08' N, 121° 51.48' W respectively). The local humidity, moisture content of plants and soil as well as its low topographic position likely all helped to prevent the fire from reaching higher severities in this location.

Second, there are several 5-15 acres patches of forest along the northeastern edge of the fire where the models over predict fire severity. The DEM and Landsat images reveal that these areas experienced logging at some point in their history prior to the 2003 B&B Fire, resulting in relatively low fuel loads compared to the surrounding area and subsequently lower fire severity.

Nine covariates were assessed during model construction. The best-supported models used 5 (reference dNBR model) and 4 (reference RdNBR model) covariates respectively. The retained covariates included *elevation, energy release component* (*erc*), *topographic position* (dNBR only), *slope* and *vegetation*. The four potential covariates that were not used for any of the reference models included three fire weather covariates (*burn index* (*bi*), *spread component* (*sc*), *Keetch-Byram Drought Index* (*kbdi*)) and the *solar index*. It seems reasonable that the inclusion of more than one fire weather index would not significantly improve the results of a given model, especially considering that each of the four fire weather indices are based on several fire weather components, some of which may be shared between indices. Similarly it is not surprising that the *solar index* did not improve model results because both the *slope* and *topographic position* capture some of the variation in the *solar index*.

A smoothing of the *elevation* and *slope* predictor variables produced superior models relative to un-smoothed variables, suggesting nonlinear relationships between these covariates and fire severity (Fig. 7 & 8). The smoothed form of the *slope* covariate may also help explain why the inclusion of the *solar index* did not significantly improve model performance. It is apparent that the positive relationship between fire severity and slope becomes weaker at angles greater than approximately 35 or 40 degrees (Fig. 8). This might reflect the fact that the steepest slopes are usually less vegetated than more moderate slopes and so receive more direct sunlight. It is also possible that insolation would actually decline for surfaces at very steep angles in comparison to surfaces at moderate angles, which provide a more perpendicular orientation toward the sun at mid latitudes and experience more evaporation.

The smoothed function of the *elevation* covariate also displays an interesting relationship with fire severity. It is often assumed that fire severity increases with elevation as forest type transitions from those which experience high frequency, low severity fire regimes into forest types which typically experience infrequent, high severity fire regimes. The relationship between elevation and fire severity described in (Fig. 7) however becomes weak above approximately 5,200 ft. This may represent the effect of more alpine vegetation, where fire severity and flame length would necessarily reduce due to lack of fuel. However there is also a notable ‘dip’ in the relationship between elevation and fire severity between approximately 3,500 and 4,500 ft (Fig. 8). It is not obvious why the relationship between elevation and fire severity expresses this behavior but it may be the result of stochastic weather conditions present during when the fire burned through these mid altitude regions.

Both RdNBR and dNBR were included as response variables in this study because there have been some recent concerns over dNBR's tendency to overemphasize the importance of the pre-fire image. Although it would not be appropriate to compare ΔAIC_C values between two models predicting different response variables the fact that their D^2 values were nearly identical implies that neither dNBR nor RdNBR was clearly the better of the two indices at predicting fire severity.

6.1.1. Question (1): Defoliator Outbreaks and Wildfire Severity

The absence of correlation between defoliation outbreak events and subsequent fire severity found in this study are in accord with the findings of Fleming et al. (2002), where a positive correlation between defoliation events and subsequent fire severity was only evident during a three to nine year window after defoliator outbreaks. The most pandemic defoliation outbreaks in the area of the B&B fire occurred in the mid to late 1980s, several years beyond the temporal window described by Flemming et al. (2002).

Because the relationship between defoliation and fire severity is likely most strongly related to fuel loading conditions, it is reasonable to expect the relationship between defoliation events and fire events to change as fuel load conditions change over time. Any relationship between defoliation outbreaks and subsequent fire severity is likely strongest soon after the defoliation events, before the trees are able to fully leaf-out in the following spring. It is during this period when fine fuels have been mostly consumed and when there is likely an increase in the amount of insolation reaching the forest floor. If the defoliation outbreaks are relatively short-lived then one might expect the effect of the outbreaks on fire severity to be negligible after a single or very few growing seasons. If outbreaks are persistent and occur sequentially over several years one might expect longer lasting alterations to fuel loads as trees experience dieback of their branches and tops. The rate at which fuel conditions return to 'normal' is dependent on local climatic, environmental and biotic conditions, such as temperature, humidity, seedling establishment rates and sapling growth rates. In the case of this study, the signature of defoliator outbreaks at the time of the 2003 B&B wildfire was not strong enough to make claims about the relationship between defoliator outbreaks and fire severity with a high degree of confidence.

6.1.2. Question (2): Bark-Beetle Outbreaks and Wildfire Severity

In models predicting both dNBR and RdNBR the presence of beetle damage was positively correlated with fire severity. However, p-values for the *beetle* covariate were insignificant in both the dNBR and RdNBR beetle models. The ΔAIC_C score for the dNBR beetle model was significantly greater than the reference model (Table 1). The ΔAIC_C score for the RdNBR beetle model was not significantly higher than the reference models but did approach two. The insignificant p-values for the *beetle* covariate, relatively high ΔAIC_C scores and small regression coefficients (especially in the RdNBR model) indicate that the presence of beetle outbreaks in the B&B Fire was not a significant determining factor in subsequent fire severity.

Like defoliator outbreaks, any potential effect of beetle outbreaks on the severity of subsequent wildfires is likely related to fuel load characteristics. As such, the relationship between beetle outbreaks and fire severity is also likely a temporally sensitive relationship. Unlike defoliator outbreaks though, the effect of beetle outbreaks on the landscape are relatively long-lived, since beetles tend to kill their hosts rather than just defoliate them. Recently killed trees, still retaining their dead needles, would likely have an increased tenancy to support high severity crown fires due to an abundance of dry high surface-area to volume ratio fuels. However, most trees will not retain dead needles for more than a year or two, especially if the tree itself is dead. The fuel characteristics of a standing dead tree which that retains its needles are markedly different from those of a standing dead tree that has dropped its needles. This is because large diameter woody fuel is capable of supporting high severity fires but is relatively difficult to ignite without small diameter fuels to help raise the temperature of the fuel. Therefore, even if a positive relationship between beetle outbreaks and subsequent fire severity exists immediately following epidemic outbreak-events that relationship may not be evident after a few years. Antecedent beetle outbreaks within the perimeter of the B&B

Fire were not extensive or varied enough in severity to make claims about the relationship between beetle outbreaks and fire severity with a high degree of confidence.

6.2. Reference Models Used to Address Question (3)

It is immediately apparent that the reference models used to address question (3) explain much less variation in the data than the reference models fit to the entire fire area for questions (1) and (2). However, it is not appropriate to directly compare these sets of models because they are based on separate data sets compiled from independent sample locations. Also, it is expected that models based on this data set would have lower measures of goodness-of-fit compared to models used to address questions (1) and (2), considering that the sample points of this data set represent a much smaller proportion of the total fire area than the 500 sample locations used to address questions (1) and (2). Because there are relatively few sample points in this data set the models are being used to predict a smaller proportion of the total range of fire severity values. Typically, a model will perform better when predicting a wide range of values for the dependent variable than when predicting a narrow range of values for the dependent variable. Even so, the goodness of fit for these reference models were quite low by most standards, implying that even the best models based on this data set did not do a particularly good of a job of predicting fire severity (Table 2).

Of the eight potential covariates that could have been included in the reference dNBR model only three were retained: *elevation*, *slope* and *KBDI*. Like all other reference models in this study the retained elevation covariate for the reference dNBR model was smoothed, suggesting a non-linear relationship between elevation and fire severity. Unlike the models used to address question (1) and (2) where there were very large variations between average fire severity at mid and high elevations, the smoothed relationship between elevation and fire severity for this reference dNBR model is more subtle (Fig. 7). Considering the smaller range in elevation values in this data set compared to the data set used to address questions (1) and (2) this more subtle curvi-linear relationship is expected. Unlike any of the other reference models in this study the elevation covariate does not have a significant p-value. However, the inclusion of the elevation covariate did significantly reduce the AIC_C score of the model, so it was retained.

Similarly slope was retained in the reference model despite not having a significant p-value, because the inclusion of the covariate significantly reduced the overall AIC_C score for the model. The p-values associated with the slope covariate did approach significance in some iterations of the model (Table 2). While the coefficient of the slope covariate is positive, the relationship is not particularly strong. It is not clear why a linear relationship between *slope* and fire severity produced better model results than a smoothed relationship as was the case for all models based used to address questions (1) and (2).

The covariate with the most significant associated p-value included in the reference dNBR model was *kbdi*. Drought conditions (*kbdi*) helped to predict more variation in the data than the other fire weather covariates such as *energy release component (erc)*, which was highly significant in the models used to address questions

(1) and (2). However, it reasonable that the models would vary in their inclusion of the *erc* and *kbdi* covariates when one considers that there is a great deal of overlap between the covariates in what they represent. Both *kbdi* and *erc* are essentially measures of droughtiness. The primary difference between the two is that *erc* is also a function of a regional fuel model and predicted fuel moisture levels, while *kbdi* is calculated only from daily precipitation and humidity levels. It might be that the regional fuel model used in the calculation of *erc* does not closely approximate the actual fuel loads found at the relatively high elevation sample locations found in this data set.

It also was unexpected that the best model built to predict RdNBR included only a single covariate. The inclusion of the *slope* and *kbdi* covariates did not improve the measures of goodness-of-fit for the reference RdNBR model like they did for the reference dNBR model (Table 2). This is especially unexpected because there is relatively little variation in the *elevation* covariate for the sample points from this data set. The *elevation* covariate did have a similarly smoothed relationship with fire severity to that observed in the reference dNBR model. The poor measures of goodness-of-fit associated with the RdNBR model may suggest that the RdNBR fire severity index did not do a good job of representing the actual fire severity realized on the landscape at the sample locations (Table 2).

It is unclear why the inclusion of any covariate other than *elevation* would reduce the AIC_C score of this model. Models predicting RdNBR for questions (1) and (2) also have fewer covariates than their equivalent models predicting dNBR but the exclusion of all but a single covariate suggests a relatively weak model.

6.2.1. Question (3): Pre-fire Survey Data and Model Performance

Neither the inclusion of the *survey-based vegetation* or the *tons of down/woody fuel* covariates improved the ΔAIC_C scores of the reference dNBR & RdNBR models. The absence of both these variables in the final models is somewhat surprising. Because wildfire behavior is at least partially dependent on the species of trees present in the fire perimeter I would have expected that the high-resolution vegetation survey data would capture some variation in the fire severity data. The fact that the addition of this *survey-based vegetation covariate* did not improve model predictions implies that the signatures of other covariates (such as elevation and fire weather variables) dominated any potential signature of vegetation type in our study.

The exclusion of the *fuel load covariate* is surprising because the presence of large woody fuel is typically considered a sign of increased fire risk conditions (Arno 2000, Brown et al. 2003). The absence of the *fuel load covariate* in the final models indicate that other variables in the study likely also captured some of the variation in the data that might be associated with fuel loads, such as *elevation* and *insolation.* This is because elevation and insolation both influence which plant communities will be competitive at a given site, and these plant communities may in turn be correlated with broad-scale patterns in fuel characteristics.

CHAPTER VII

IMPLICATIONS

The lack of association between forest insect outbreaks and subsequent fire severity in the B&B fire comply with the notion that relationships between antecedent insect outbreaks and wildfire behavior are likely temporally variable in their nature. This variability is probably based on local decay rates and on the process by which fuel transitions from voluminous standing dead wood to horizontal compact wood on the forest floor. More severe forest insect outbreaks do not inevitably lead to more expansive and severe wildfires.

A secondary line of inquiry from this study was to determine the relative value of coarse-resolution historical vegetation survey data in comparison to modern high-resolution plot-based vegetation data. The results support the notion that coarse-resolution historical vegetation data sets do not measurably differ in their ability to predict fire severity from high resolution plot-based vegetation data sets. However, all of the models used to address this question had poor fits to the observed data compared to the models used to address the insect related questions. This suggests that fire severity was easier to predict when using a large number of evenly and fully distributed sample points than fewer, highly localized sample points.

Although evaluating the predictive power of both the dNBR and RdNBR indices was not a primary goal of this study, models predicting both of these indices were produced and provide ground to make some generalized comments. Models predicting dNBR and RdNBR were very similar in both their composition and their ability to predict the observed fire severity values. RdNBR and dNBR are correlated with each other so similar results are somewhat expected. The results suggest the dNBR and RdNBR indices are probably both adequate measures of fire severity, even after moderate defoliation and beetle outbreak events.

In addition to expanding on the discourse over interaction between forest-insects and wildfire severity this study shows that it is possible to produce models capable of predicting coarse-grained trends in wildfire severity using only publicly and freely available data sets. These kinds of models have some clear limitations in predicting future fire events because fire-weather variables proved to be such important predictors and because these models required a defined fire perimeter. Even so, such models could be used by to predict fire behavior and potentially assess risk in defined geographies during weather conditions of particular interest.

APPENDIX A

FIGURES

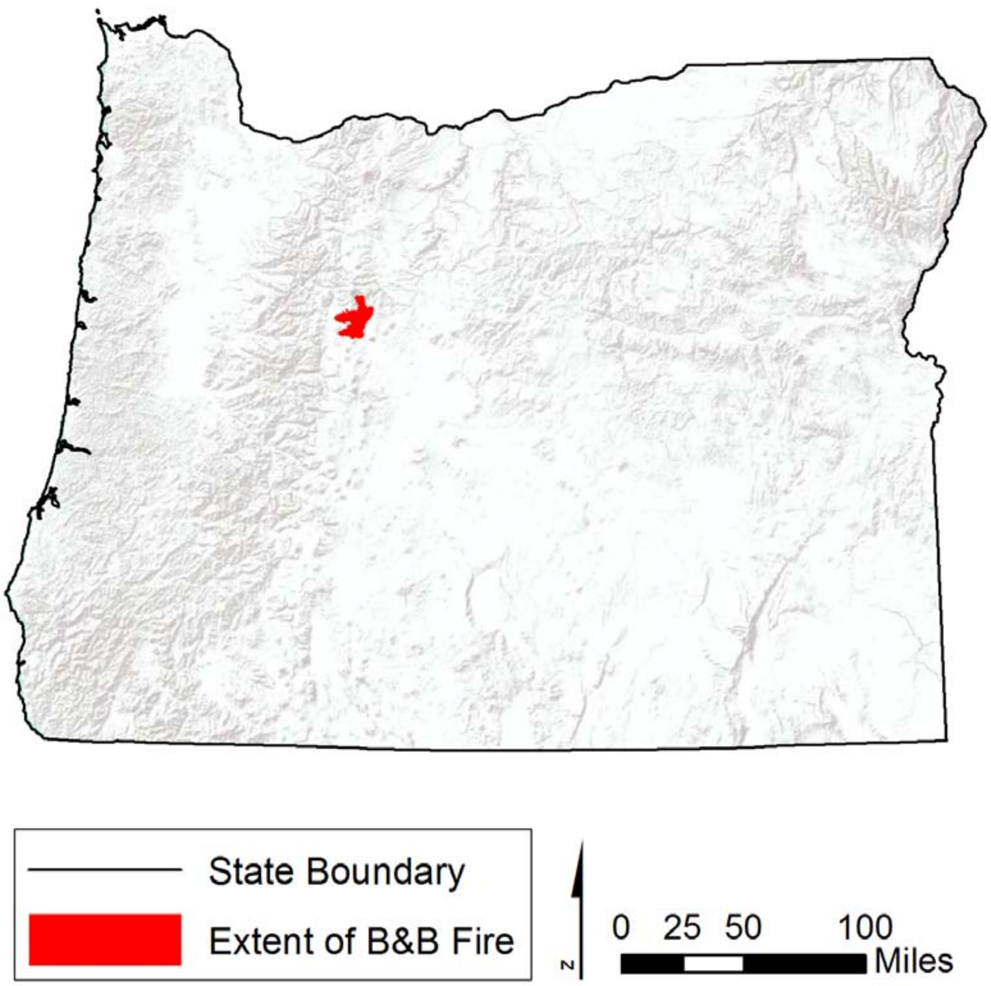

Figure 1. Location and Extent of the B & B Complex Fire in Relation to State of Oregon

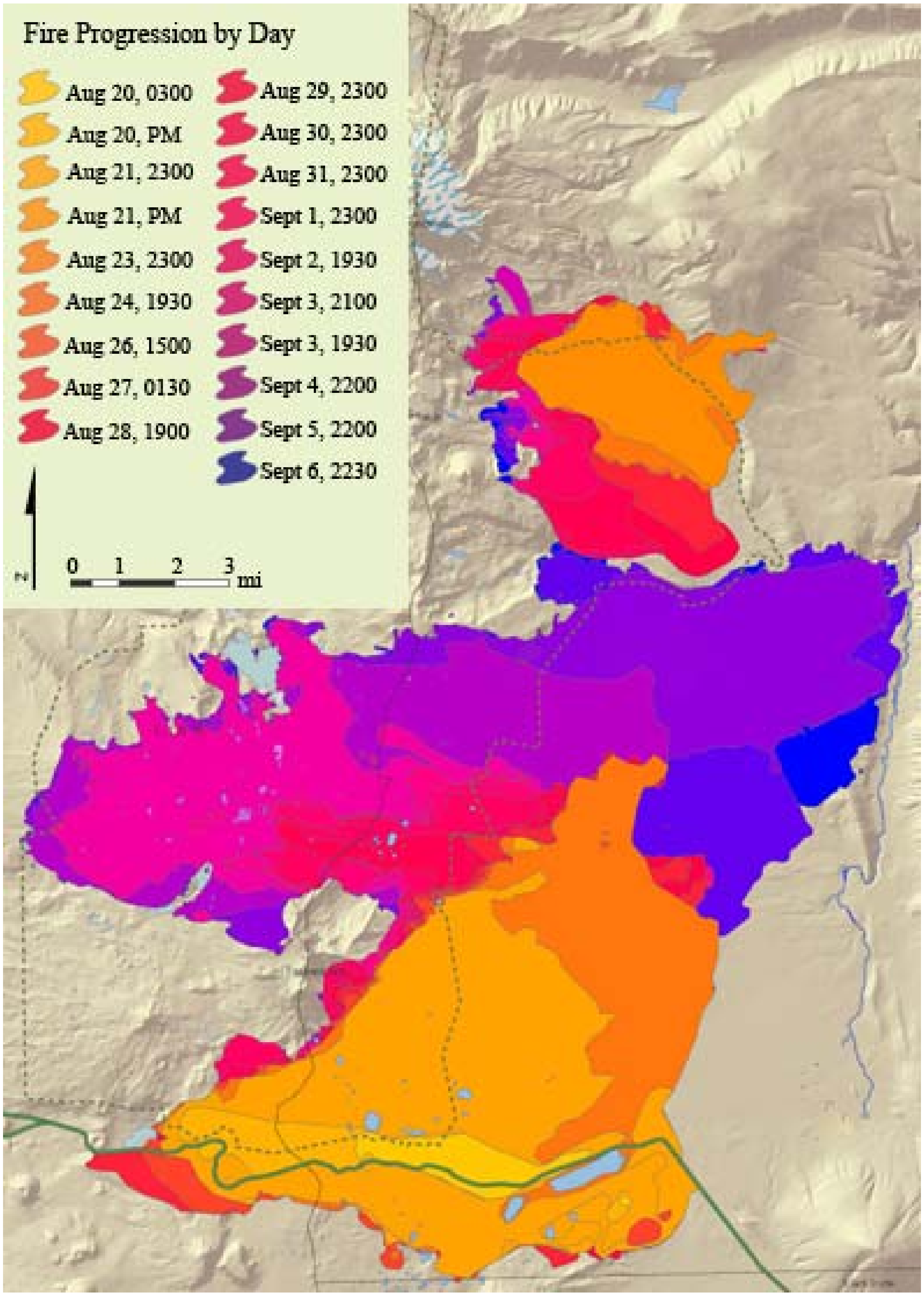

Figure 2. Progression of B&B Complex Fire
This map is modified from the U.S. Forest Service original (2004).

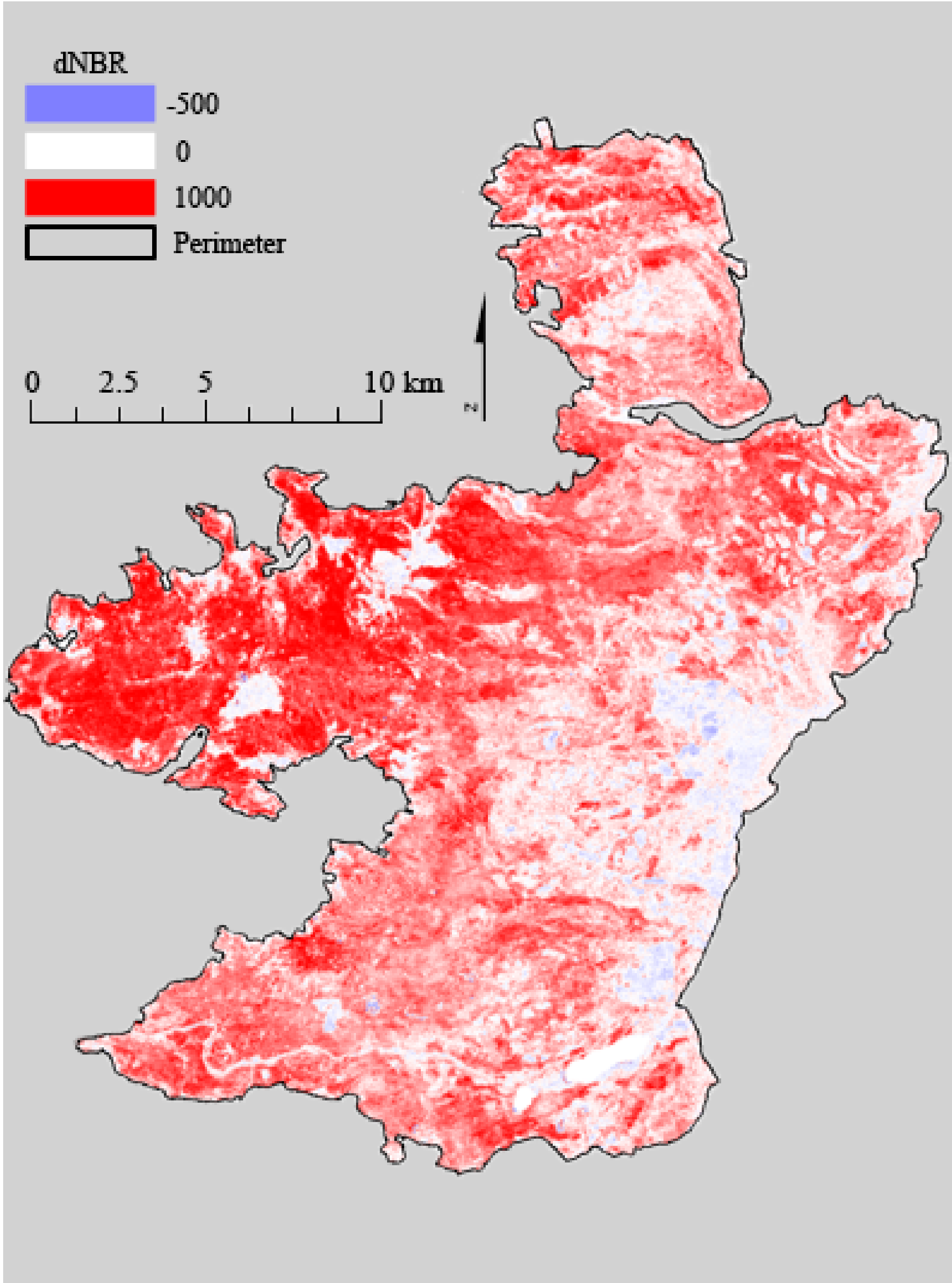

Figure 3. Fire Severity Estimated by the dNBR Index
The black line indicates the fire perimeter.

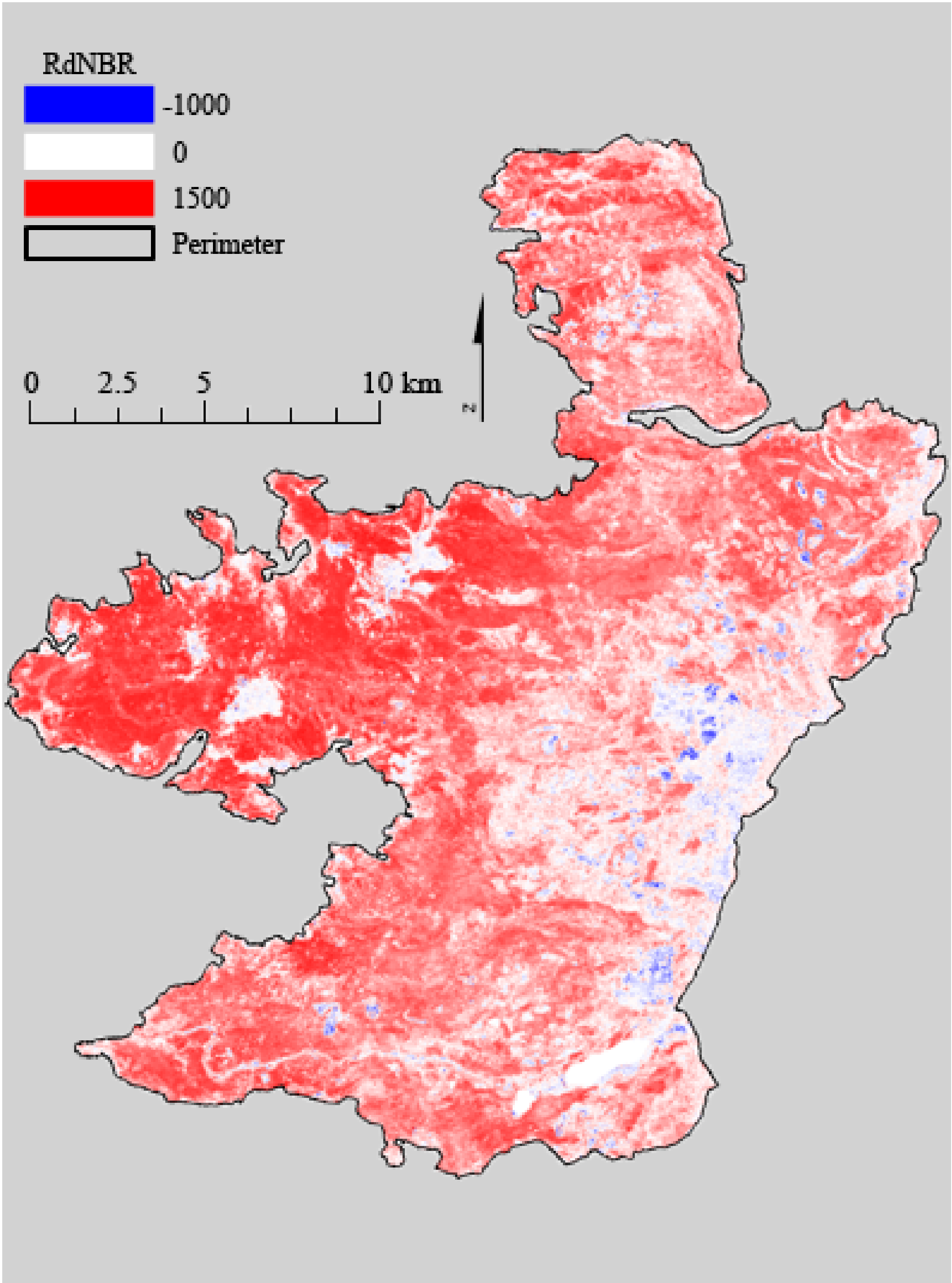

Figure 4. Fire Severity Estimated by the RdNBR Index
The black line indicates the fire perimeter.

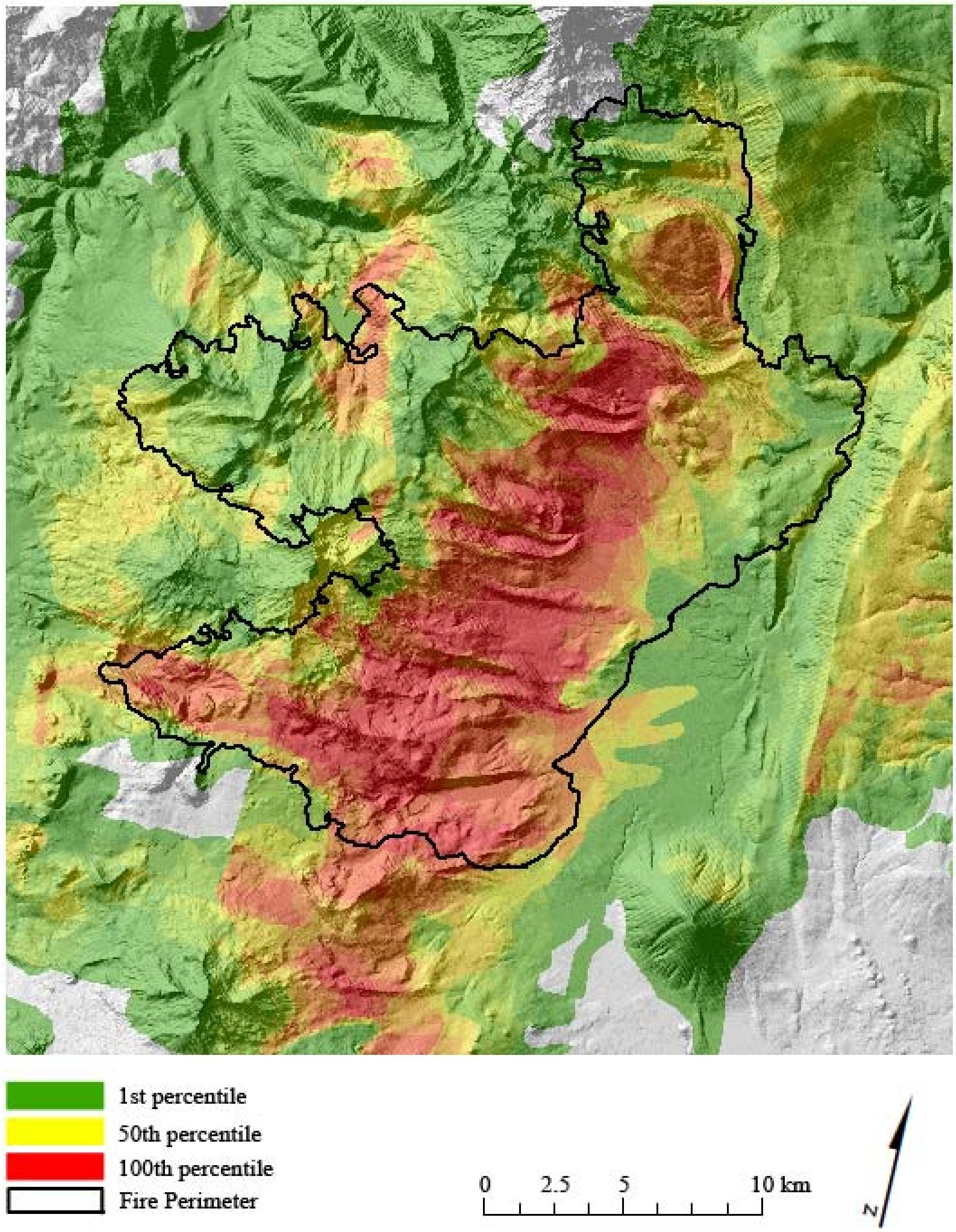

Figure 5. Weighted Defoliator Severity Index (WDSI)
This map indicates defoliator outbreaks in the study area for the 20-year period prior to the B & B Fire. WDSI values are classified by quantile. The black line indicates the fire perimeter.

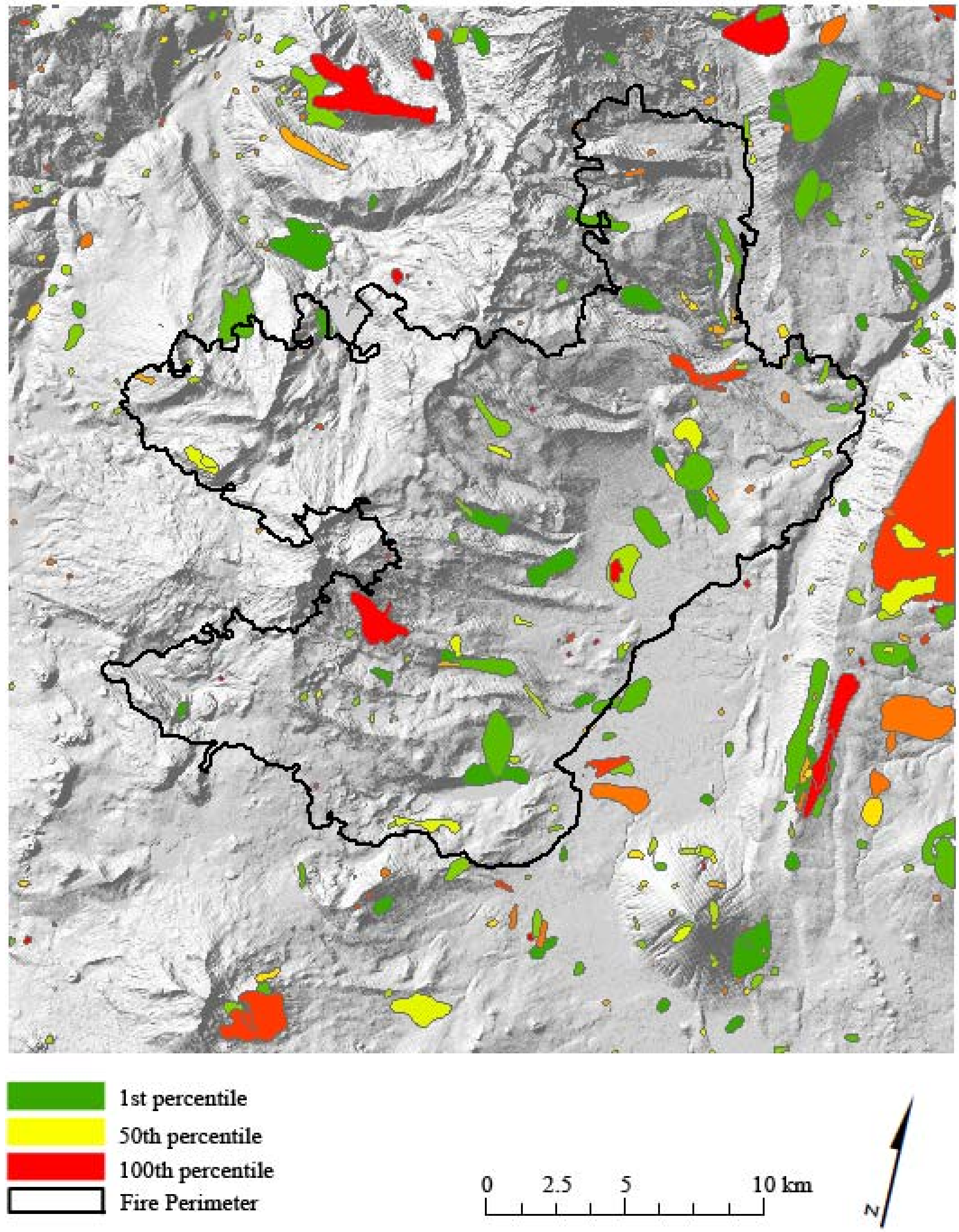

Figure 6. Beetle Severity Index (BSI)
This map indicates the highest mortality due to beetle outbreaks in the 20 year period prior to the B & B fire. BSI values are classified by quantile. The black line indicates the fire perimeter.

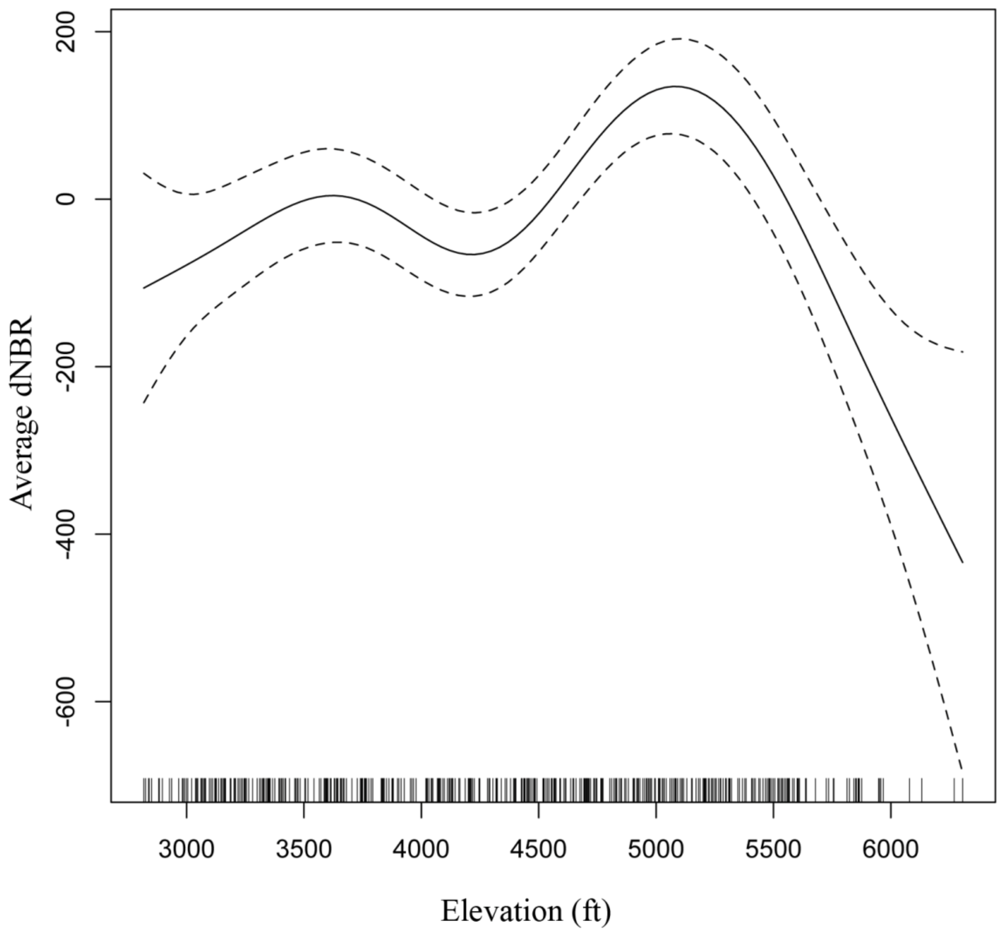

Figure 7. Smoothed Elevation Function Estimated by the GAM model (dNBR)

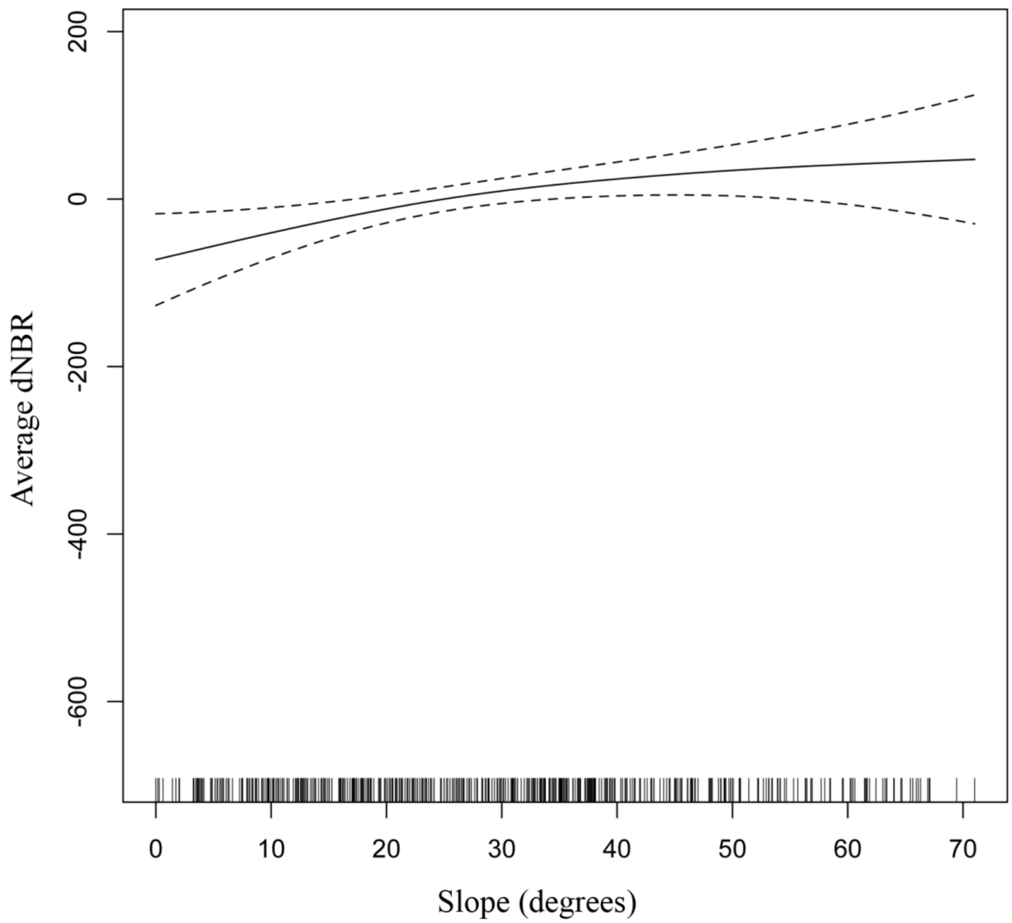

Figure 8. Smoothed Slope Function Estimated by the GAM model (dNBR)

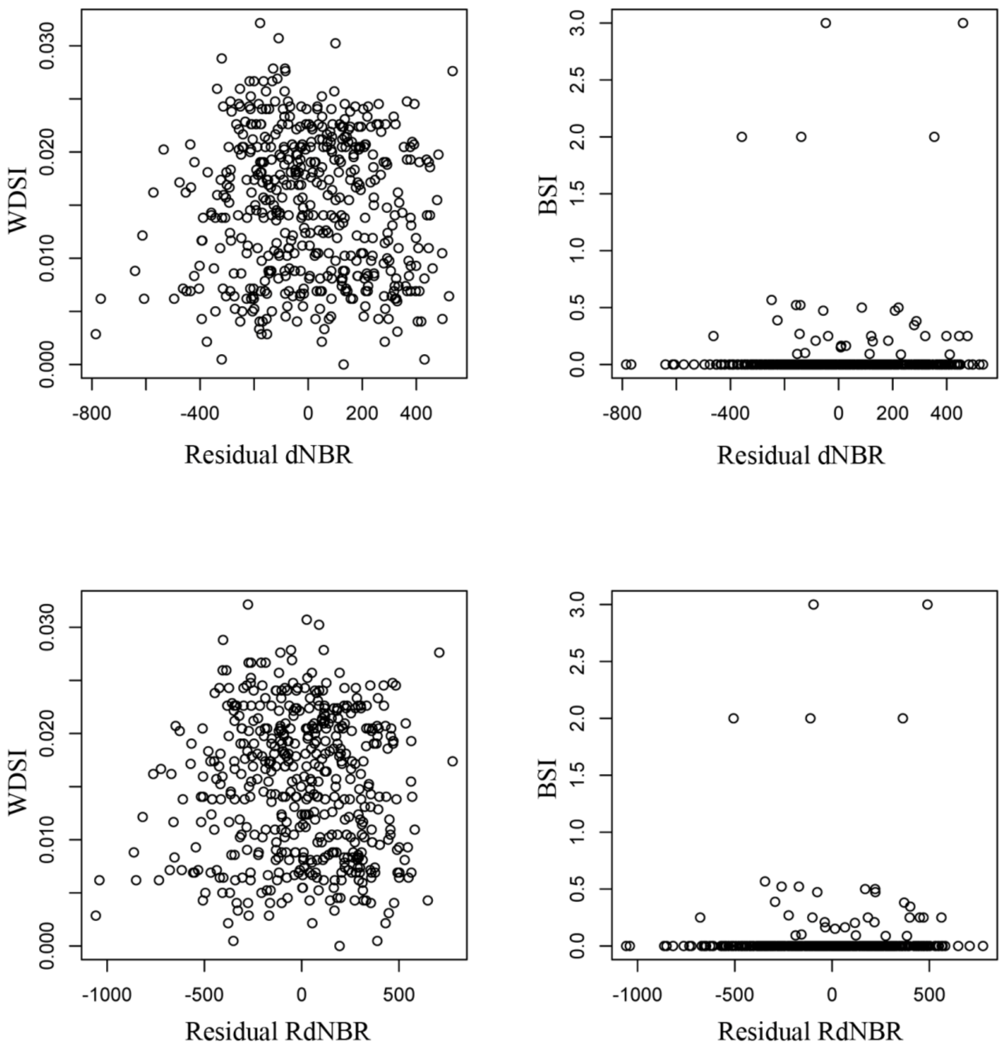

Figure 9. Insect Outbreak Severity Variables (WDSI & BSI) Plotted Against Model Residuals (dNBR & RdNBR)

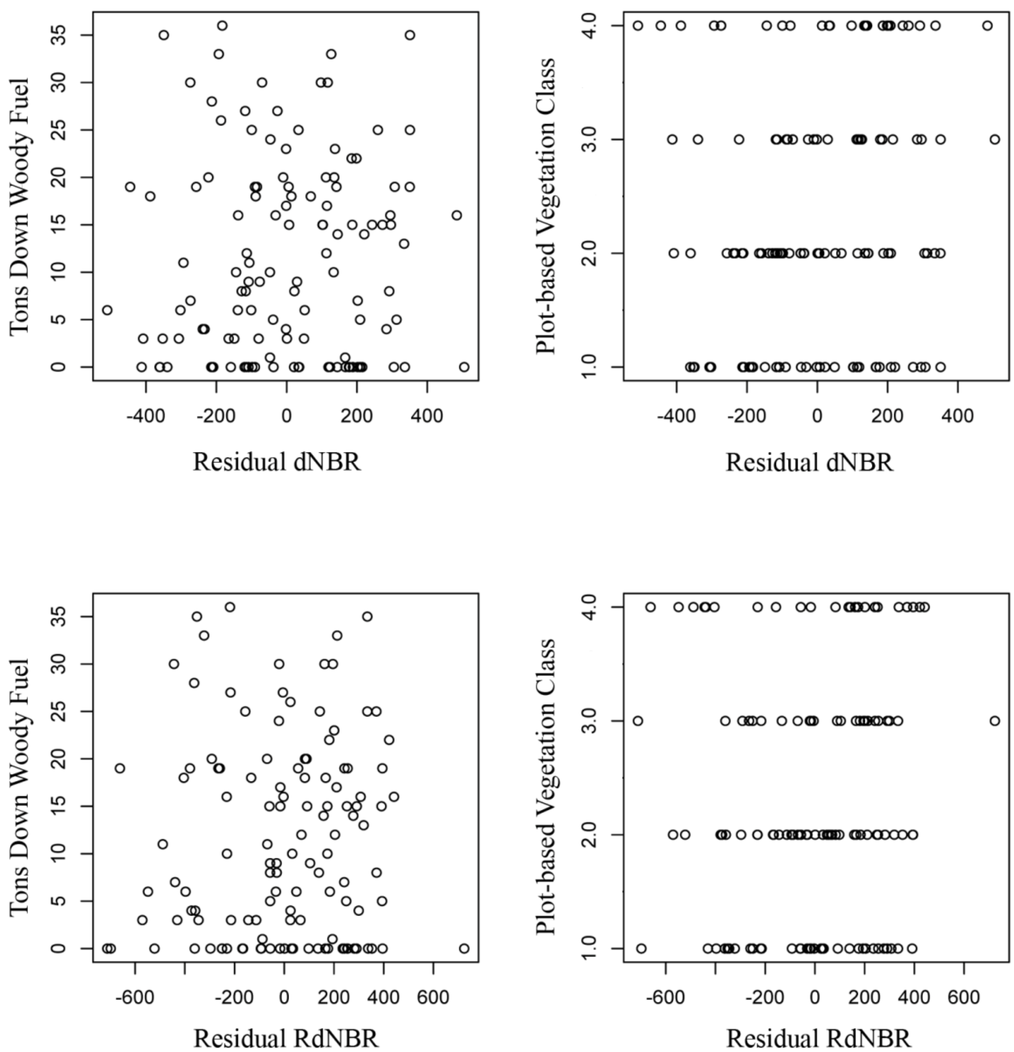

Figure 10. Pre-fire Survey Variables (Plot-based Vegetation Class & Tons of Downed Woody Fuel) Plotted Against Model Residuals (dNBR & RdNBR)

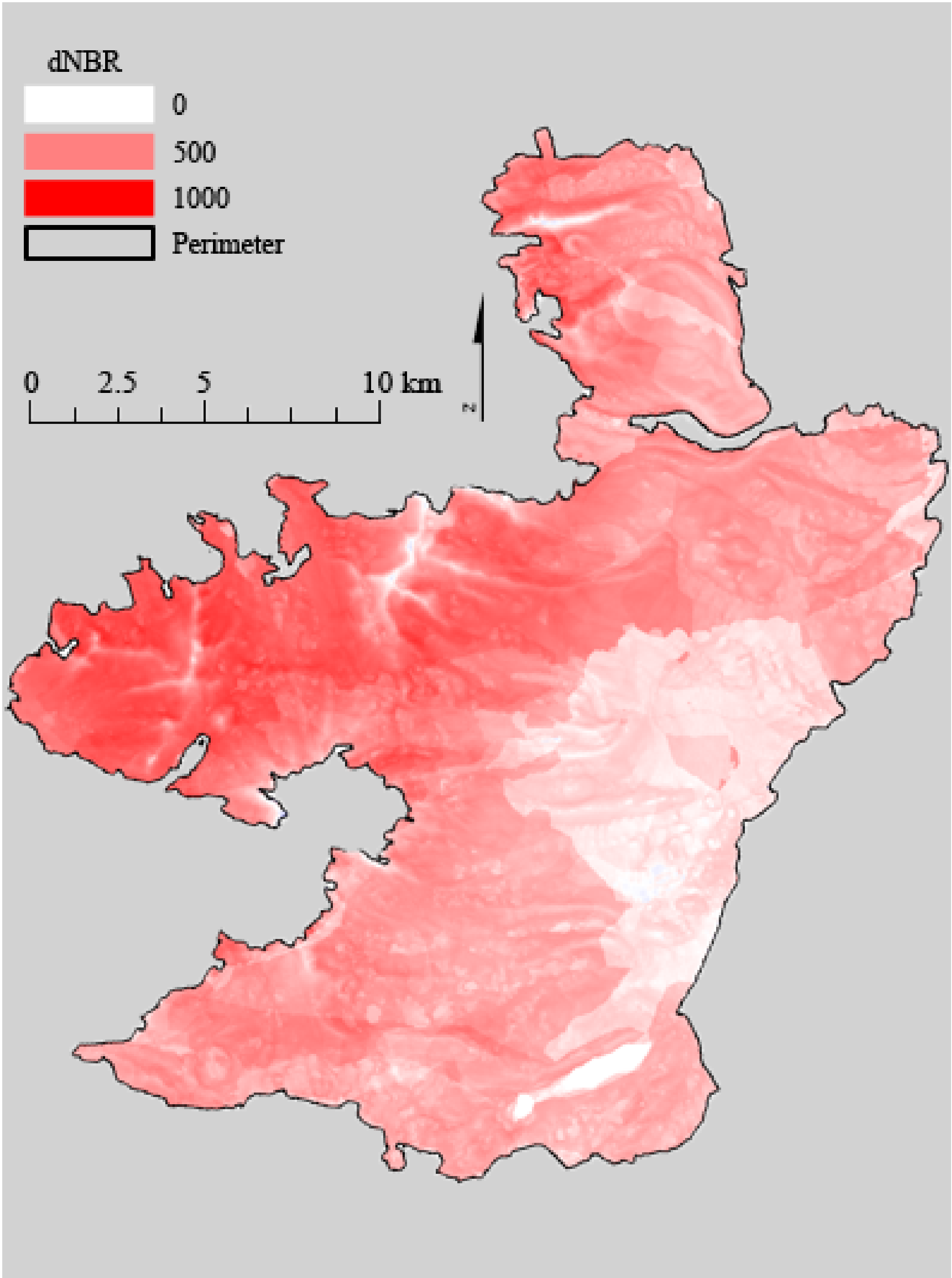

Figure 11. Predicted Fire Severity (dNBR) From the Reference GAM Model in Table 1

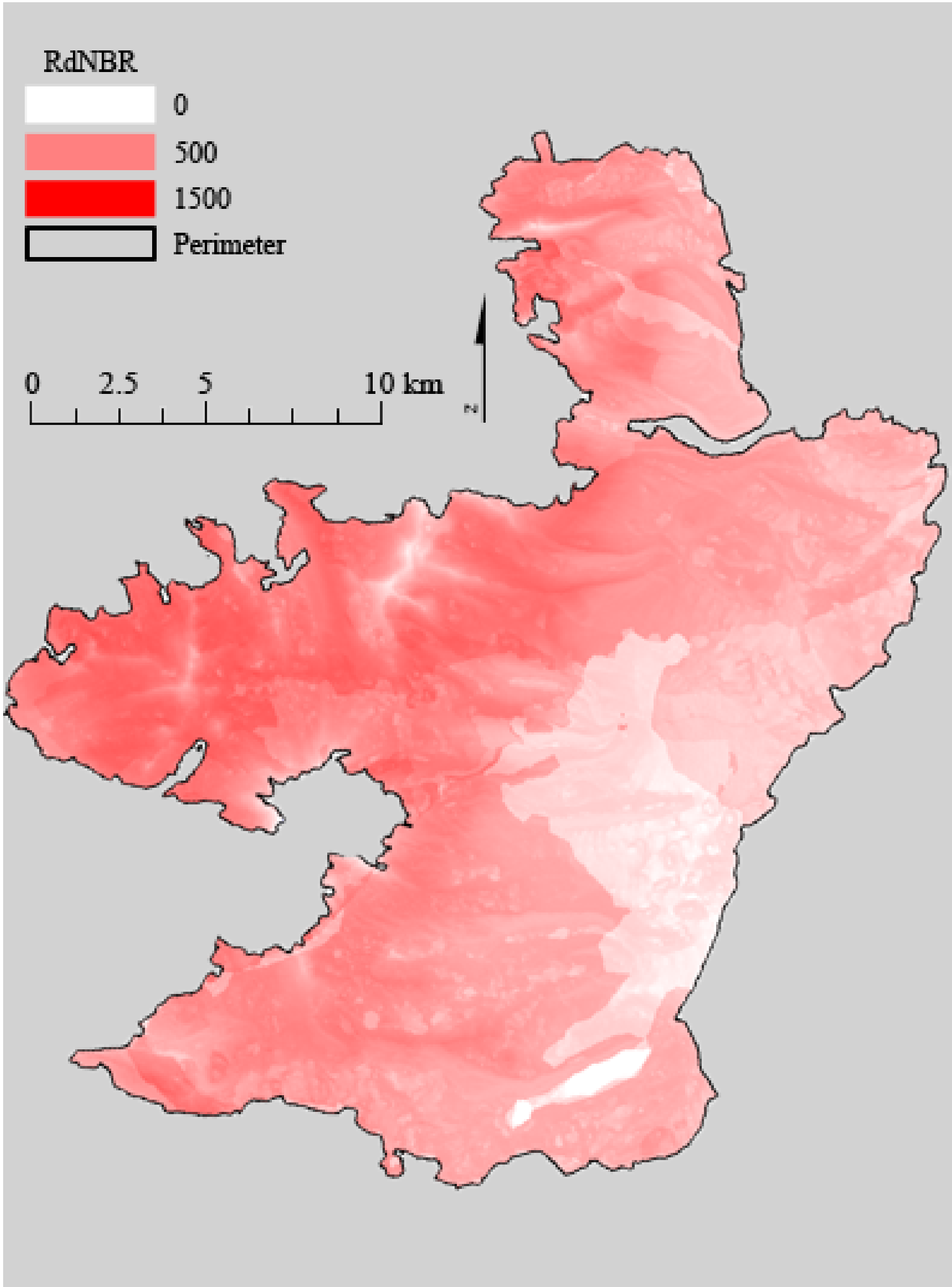

Figure 12. Predicted Fire Severity (RdNBR) From the Reference GAM Model in Table 1

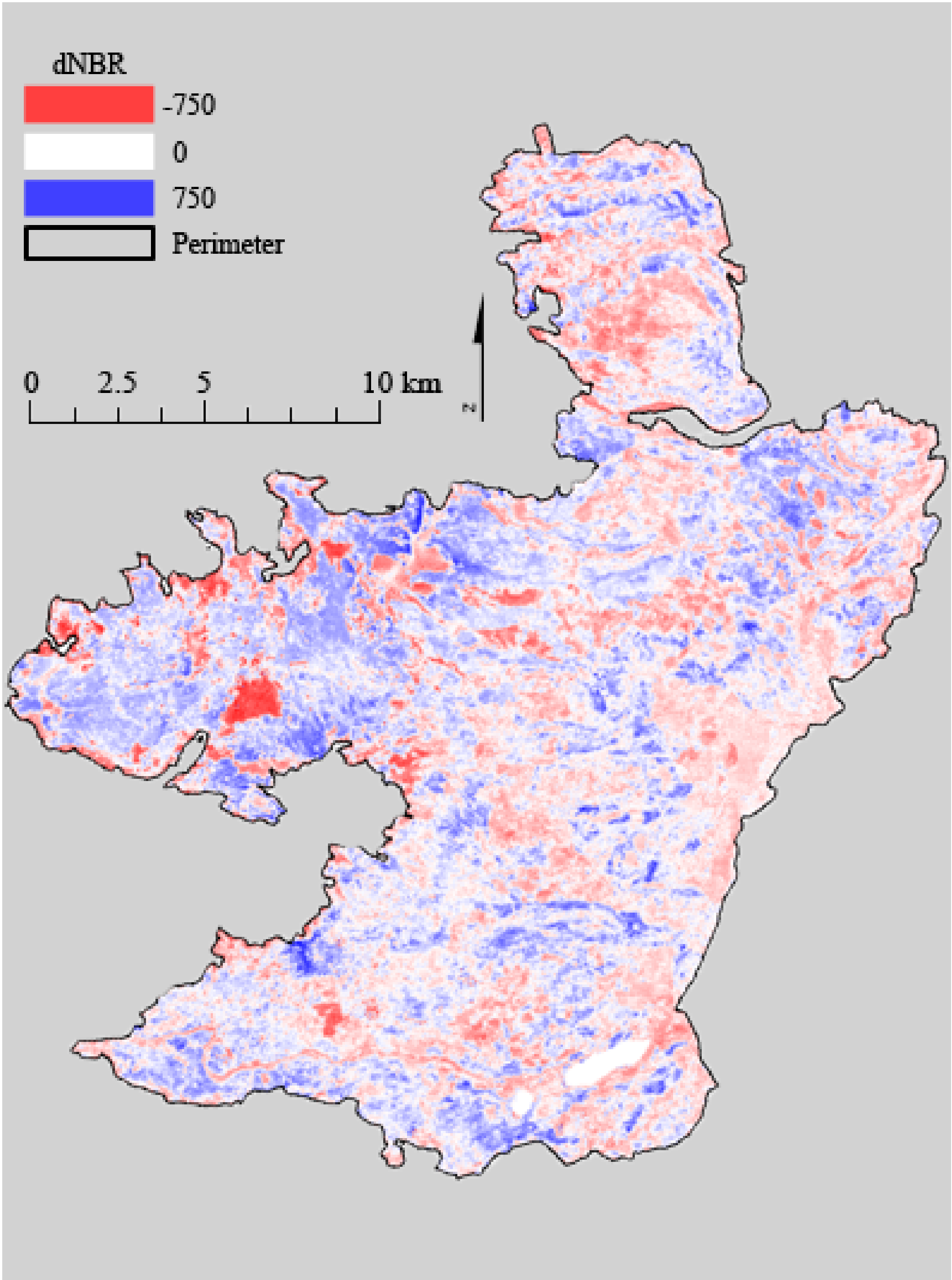

Figure 13. Model Residuals (dNBR) From the Reference GAM Model in Table 1

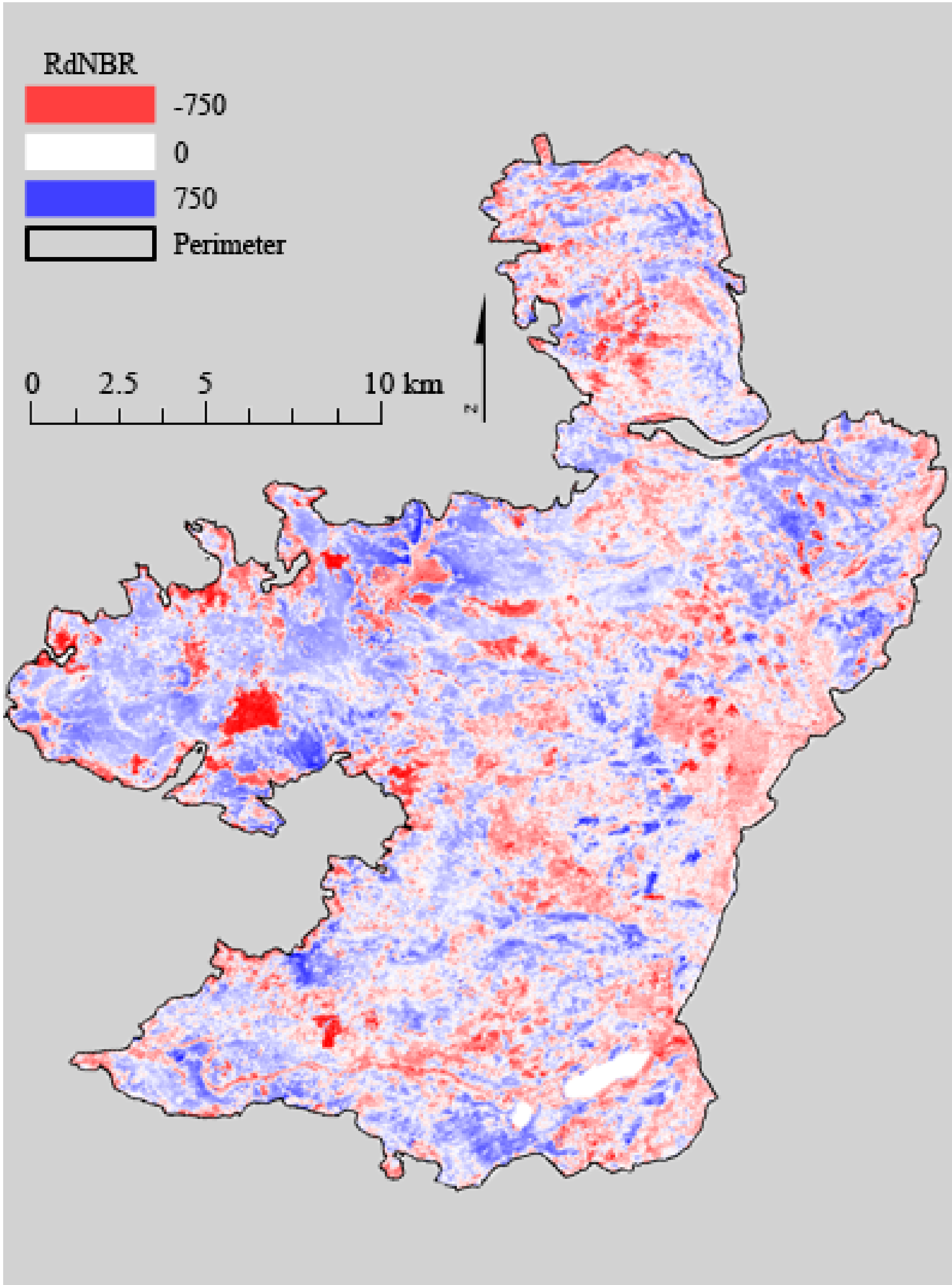

Figure 14. Model Residuals (RdNBR) From the Reference GAM Model in Table 1

APPENDIX B

CODE EXAMPLES

This appendix contains examples of code used in GRASS GIS and R statistical environment. Code segments are indented. Annotations to code are preceded with two pound symbols “##”.

Insolation Code: Example of GRASS GIS code used to generate insolation data using r.sun function.

```
## Designates digital elevation model and calculates slope and aspect.
r.slope.aspect elevation=dem10 aspect=dem10.aspect slope=dem10.slope

## Modifies aspect values to account for greater solar heating potential of SW facing slopes.
r.mapcalc
mapcalc> dem10.aspect.modified=if(dem10.aspect==0,0,if(dem10.aspect>315,dem10.aspect+45-
360,dem10.aspect+45))
mapcalc> end


## Sets date and time-step perimeters for r.sun function
r.sun -s elevin=dem10 aspin=dem10.aspect.modified slopein=dem10.slope day=233 step=0.5
beam_rad=beam_aug20 diff_rad=diff_aug20

r.mapcalc
mapcalc> zero=0
mapcalc> end


## Runs r.sun function for flat surface at sea level
r.sun elevin=zero aspin=zero slopein=zero day=233 step=0.5 beam_rad=beam_zero
diff_rad=diff_zero


## Represents insolation as a fraction relative to insolation of flat terrain at sea level.
r.mapcalc
mapcalc> solar.index=(beam_aug20 + diff_aug20)/( beam_zero+ diff_zero)
mapcalc> end

r.mapcalc
mapcalc> solar.index.1000=int(solar.index*1000)
mapcalc> end
```

Vegetation Classification Code: Example of R code used to classify vegetation according to Nonmetric Multidimensional Scaling (NMDS) and K-Means clustering.

```
library(vegan)
library(MASS)

## Reads the .csv file and makes a matrix objectplots <- read.csv(file="plotid_species.csv",
header=TRUE)

## Take out column 1, use it for row names
rownames(plots) <- plots[,1]

plots2 <- plots[,2:14]
## Remove column 1

## Calculates Bray-Curtis dissimilarity matrix
plots2.dis <- vegdist(plots2)

## NMDS from MASS package
plots2.mds0 <- isoMDS(plots2.dis)

## Compares ordination and observed distances
stressplot(plots2.mds0,plots2.dis)

## Plots the object created by isoMDS
ordiplot(plots2.mds0,type="t")

## K-means clustering into 4 categories
plots2.kmeans<-kmeans(plots2.dis, centers=4)

## Plots the mds plot
plot(plots2.mds0$points,col=plots2.kmeans$cluster)

## Correlation coefficients between mds axis 1 and species
colors=cluster categories
cor(plots2[,1],plots2.mds0$points[,1])

## Calculates the mean of within-group sum of squares for the i clusters
kmss<-array(NA,10)
for(i in 2:11){
kmss[(i-1)]<-mean(kmeans(plots2.dis,centers=i,nstart=25)$withinss)
}
```

General Additive Model (GAM) Construction: Example of R code used to Construct General Additive Models (GAM) using all potential covariates.

```
## Creates a GAM model using all variables.
> gam.object<-gam(rdnbr~veg_class + elev + slope_5 + solar + topo_fine + erc + bi +sc + kbdi +
weighted_def + years_def + beetle_dam)

## Use a stepwise procedure to select variables for a best-fit model.
> random.step.gam<-step.gam(gam.object,
scope=list("veg_class"=~1+veg_class,"elev"=~1+elev+s(elev),"slope_5"=~1+slope_5+s(slope_5),
"solar"=~1+solar+s(solar),"topo_fine"=~1+topo_fine+s(topo_fine),"erc"=~1+erc+s(erc),"bi"=~1+
bi+s(bi),"sc"=~1+sc+s(sc),"kbdi"=~1+kbdi+s(kbdi),"weighted_def"=~1+weighted_def+s(weighte
d_def),"years_def"=~1+years_def+s(years_def) ,"beetle_dam"=~1+beetle_dam+s(beetle_dam)
))
```

General Additive Model (GAM) predictions and residuals: Example of fire severity prediction and residuals maps generated running R statistical environment through the GRASS command interface.

```
## Starts R statistics environment in GRASS GIS command prompt
R

Library(rgdal)
Library(spgrass6)
Library(gam)
library(mgcv)

Load(rdata2.r)

## Gets data into R from grass
G<-gmeta6()

## Puts all data values retrieved from GRASS into “full” object
full<-
readRAST6(c("veg","elev","slope","kbdi","beetle","solar","weighted_def","dnbr","rdnbr","topo_fi
ne","erc","bi","cum_defol"))

## Binds columns to make matrix in dataframe
newdata=as.data.frame(cbind(full$veg,full$elev,full$slope,full$kbdi,full$beetle,full$solar,full$wei
ghted_def,full$topo_fine,full$erc,full$bi)

## Names variables
names(newdata)<-
c("veg","elev","slope","kbdi","beetle","solar","weighted_def","topo_fine","erc","bi")

## Names variables
names(random)<-
c("fire_day","veg","beetle","elev","slope","solar","dnbr","rdnbr","ave_rdnbr","norm_rdnbr","weig
hted_def","years_def","x","y","topo_fine","erc","bi","sc","kbdi","rdnbr_dev")

## Treats ‘veg’ as a factor
random$veg<-as.factor(random$veg)
```

```
## Activates data set for use
attach(random)

## Attaches model output from derived from selected variables to object
random.gam.dnbr<-gam(dnbr~s(elev)    +slope+topo_fine+erc+weighted_def,method="ML")

## Saves model into full
full$random.dnbr.predicted<-predict(random.gam.dnbr,newdata=newdata)

Predicted.residuals<-observed.values-predicted.values #observed severity – predicted severity =
residuals

## Creates AICC values
> aicc<-function(obj){
+ n<-obj$df.null+1
+ k<-n-obj$df.residual+1
+ aicc.out<-obj$aic+(2*k*(k+1))/(n-k-1)
+ return(aicc.out)
+ }

## Produces predicted severity map
WriteRAST6(full,"predicted.values",zcol="predicted.values")

## Produces residuals maps
WriteRAST6(full,"predicted.residuals",zcol="predicted.residuals")

## quits R
Q()
```

APPENDIX C

TABLES

Table 1.1. Generalized Additive Model Results for Questions (1) & (2) Fit to Predict dNBR in the B&B Fire

model	**reference**	**defoliator**	**beetle**	**defoliator & beetle**
elevation	s****	s****	s****	s****
erc	+***	+***	+***	+***
topographic position	-**	-**	-**	-**
slope	s*	s	s*	s*
vegetation	c	c	c	c
defoliator (WDSI)	ø	-	ø	-
beetle (BSI)	ø	ø	+	+
% deviation explained	35.5	35.8	35.3	35.5
ΔAIC_C	0	0.382	2.718	3.278

Table 1.2. Generalized Additive Model Results for Questions (1) & (2) Fit to Predict RdNBR in the B&B Fire

model	**reference**	**defoliator**	**beetle**	**defoliator & beetle**
elevation	s****	s****	s****	s****
energy release component (ERC)	+****	+****	+****	+****
slope	s**	s**	s**	s**
vegetaion	c	c	c	c
weighted defoliation severity index (WDSI)	ø	-	ø	-
beetle severity index (BSI)	ø	ø	+	+
% deviation explained	35.7	35.8	35.7	36.0
ΔAIC_C	0	1.645	1.854	3.536

legend

+	positive correlation
-	negative correlation
s	covariate smoothed
ø	covariate not included
c	categorical covariate
*	p value = 0.1-0.05
**	p value = 0.05-0.01
***	p value = 0.01-0.001
****	p value = 0.001-0

Table 2.1. Generalized Additive Model Results for Question (3) Fit to Predict dNBR in the B&B Fire

model	**reference**	**tons fuel**	**vegetation**	**tons fuel & vegetation**
elevation	s	s	s*	s*
keetch-byram drought index (KBDI)	+***	+***	+***	+***
slope	+*	+*	+	+
tons downed woody fuel	ø	+	ø	+
plot-based vegetation	ø	ø	c	c
% deviation explained	16	16.3	18.1	18.1
ΔAIC_C	0	1.886	4.051	6.447

Table 2.2. Generalized Additive Model Results for Question (3) Fit to Predict RdNBR in the B&B Fire

model	**reference**	**tons fuel**	**vegetation**	**tons fuel & vegetation**
elevation	s**	s**	s	s
tons fuel	ø	+	ø	+
plot-based vegetation	ø	ø	c	c
% deviation explained	11.7	12	12.9	13
ΔAIC_C	0	1.816	4.895	7.194

legend

+	positive correlation
-	negative correlation
s	covariate smoothed
ø	covariate not included
c	categorical covariate
*	p value = 0.1-0.05
**	p value = 0.05-0.01
***	p value = 0.01-0.001
****	p value = 0.001-0

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