SPATIOTEMPORAL MAPPING OF MOUNTAIN PINE BEETLE INFESTATION
SEVERITY AND PROBABILITY OF NEW INFESTATION IN
THE CENTRAL U.S. ROCKY MOUNTAINS

by

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Synchronous, widespread, and severe mountain pine beetle (MPB; *Dendroctonus ponderosae*) outbreaks impacted forests of western North America at unprecedented levels in recent decades. Severe MPB epidemics can degrade ecosystem services and socio-economic assets. Mapping outbreak progression informs mitigation efforts and enables analysis of MPB attack processes on a landscape scale. Existing time-series methods for mapping disturbance focus on extent rather than severity. Infestation severity, expressed as within-pixel mortality percentage, is more robust for answering a variety of ecological questions. Our objectives were to: (1) map infestation severity from 2005-2015 using a time-series regression; and (2) analyze MPB attack processes by modeling new infestation probability using spatial and environmental variables in the central U.S. Rocky Mountains. We used spectral data from all available Landsat images, topographic data, and data from U.S. Forest Service aerial detection survey (ADS) polygons to model infestation severity. We collected reference data by interpreting National Agricultural Imagery Program images. We then employed logistic regression model-based recursive partitioning (MOB) to determine: (a) to what degree nearby infestation severity increased probability of new infestation; (b) the degree of variation in probability across space and time with respect to other spatial and environmental risk factors; and (c) the extent to which these effects were directional relative to prevailing winds. Validation of our infestation severity model against a randomly selected subset of the data resulted in no statistical difference between predicted and observed severity. Our raster maps allowed us to identify lower severity infestation not recorded by the ADS. The final MOB model obtained 72.1% accuracy in predicting new infestation. Nearby infestation severity strongly influenced the probability of new infestations. This effect varied with elevation, aspect, temperature, phase of the outbreak, and spatial location. Variation in probability of infestation was highest when surrounding infestation severity was low. Use of wind-informed directional effects did not improve the model. This analysis establishes the efficacy of mapping an infestation severity time series and demonstrates that severity maps facilitate novel analyses of MPB attack processes. The processes developed here can support management decisions with timely maps of MPB infestation severity and probability of new infestation.
CHAPTER ONE

INTRODUCTION

Bark beetle infestations have disturbed vast forested areas across North America in recent years. Tree mortality is ubiquitous across 18 million hectares in British Columbia, Canada and 4 million hectares in the Rocky Mountains of the U.S. (Corbett et al., 2016; USDA Forest Service, 2015). Future intensification of outbreaks is likely due to the climate-driven increase in temperatures in this region (Mitton and Ferrenberg, 2012; Safranyik et al., 2010). The trees killed by these bark beetles are comprised of woody biomass suitable for transformation into biofuel and biochar (BANR, 2018). Use of dead tree biomass circumnavigates issues associated with other sources of biomass because those sources require use of land and resources for cultivation that could otherwise be used for food production.

Beetle-killed biomass presents its own challenges, however. Infestations of sufficient density and accessibility are difficult to locate in a timely manner and the cost of extraction and transportation of the biomass from rugged and remote areas is prohibitive (BANR, 2018). Additionally, the social and environmental logistics of logging beetle-killed trees require further investigation.

Cool Planet Energy Systems has developed a process to produce liquid biofuel feedstock and biochar co-products on-site. This means of production minimizes many of the transportation and extraction challenges. The Bioenergy Alliance Network of the Rockies (BANR) is a coordinated agricultural project funded by the USDA National
Institute of Food and Agriculture (BANR, 2018). BANR is comprised of many scientists, educators, and government and university extension specialists working to address the obstacles limiting the production of beetle-killed biomass products. BANR has partnered with Cool Planet to address the remaining technical, environmental, economic, and social barriers to the beetle-killed biomass industry.

BANR focuses on five overarching tasks: (1) feedstock supply; (2) harvesting and logistics processing; (3) system performance and sustainability; (4) education; and (5) extension, outreach and health and safety. The objective of the feedstock supply task is to analyze field and aerial reference data with satellite imagery and a variety of geospatial layers to determine the location, timing, and biomass of beetle-kill tree mortality. The harvest and logistics processing task involves determination of needed quality and preparation procedures for feedstock. The harvest and transport process is modeled to determine the most efficient and cost effective system. The system performance and sustainability task requires investigation of the impacts of beetle-killed biomass harvest on the ecosystem and to greenhouse gas emissions. This task is focused on evaluating the viability of both a biofuel product and biochar co-product from beetle-killed biomass. Viability is assessed from a financial, social, and policy standpoint to produce a web-based decision support system. The education task involves development of K-12, undergraduate, and graduate level education materials and coursework to promote bioenergy literacy. The extension, outreach, and health and safety task provides information to surrounding communities and stakeholder groups to inform, discuss, and address concerns over the health and safety of the beetle-killed biomass industry.
The methods described in this manuscript contribute to the feedstock supply task and focus on timely identification and mapping of beetle infestation over eleven years of outbreak. A subsequent study will combine information from these infestation maps and a total biomass map to obtain an estimate of the beetle-kill biomass available after infestation. The infestation maps must provide a continuous measure of infestation severity in order to effectively combine them with the biomass maps. Areas with high quantities of beetle-killed biomass will provide more efficient and economical harvesting. Harvesting must also be timely to preserve the value of the beetle-killed biomass.

Research supporting the harvesting and logistics task indicates that downed trees considerably limit the efficiency and safety of harvesting systems (Kim et al., 2017). A study measuring lodgepole pine fall rates in central Oregon found that snags begin to fall five years after death, 50% of trees fall after nine years, and 90% of trees fall after 14 years in unthinned stands (Mitchell and Preisler, 1998). The expense of harvesting beetle-killed stands increases each year salvage logging is postponed. It is imperative to the economic feasibility of the BANR project that infested stands are identified as quickly as possible so that the age of mortality is known for harvest planning. This also allows permitting and implementation of salvage logging to be carried out expediently.

This study used remotely sensed data to map a time series of tree mortality severity during a major outbreak. We then analyzed these maps to identify factors influencing the likelihood of new infestation. Chapter two of this manuscript provides a review of the relevant literature, including MPB processes, forest disturbance mapping techniques, and methods for determining the probability of new infestation. Chapter three
describes the development and analysis of time-series infestation severity maps. The fourth chapter investigates an application of the maps developed in chapter three. We assess the effects of weather, spatial geography, and MPB dispersal on the likelihood of observing new infestation in the following year of outbreak. The fifth chapter offers a summary of the findings. It concludes by considering improvements to this research and describing future applications.
CHAPTER TWO

LITERATURE REVIEW

Mountain Pine Beetle Processes

Niche

The mountain pine beetle (MPB; *Dendroctonus ponderosae*) is a parasitic insect native to western North America. MPBs feed on a number of host pine species, including lodgepole, white bark, ponderosa, limber, bristlecone, and pinon pines (USFS Rocky Mountain Research Station, 2005). MPBs, like other insects and diseases, are agents of healthy forest disturbance that remove old and sick trees and foster diversity in forest age and structure (Roe and Amman, 1970). MPBs are predominantly present at low population levels, but are capable of massive irruptions in population that infest entire forest landscapes (Raffa et al., 2008).

Lifecycle

A univoltine, or one-year, life cycle of a MPB begins when an adult MPB lays its eggs in a new host tree (Safranyik and Carroll, 2006). These eggs hatch into larvae and overwinter inside the tree’s phloem. The larvae feed off the phloem, killing the tree by infecting it with various strains of blue stain fungi that interrupt the exchange of water and nutrients between its roots and needles. Many larvae die in the freezing temperatures of consistently cold winters. Surviving larvae transition into pupae in the spring and then
hatch as adults in early summer. The adults emerge from the tree to mate and find a new host tree in which to lay their eggs.

Dispersal and range of MPB when finding a new host can be highly variable due to the effect of wind on flight and pheromone diffusion. MPBs emit pheromones that attract nearby beetles to initiate mass attacks on suitable hosts and overcome the host tree defenses (Pitman et al., 1969; Raffa and Berryman, 1983; Safranyik et al., 1974b). Pheromone concentration declines exponentially with distance from the beetles, however, and effective range is estimated to be only tens of meters (Byers et al., 1989). MPB are weak fliers and are likely to travel short distances to find a host (less than 30 m), however several studies have documented that they can be caught in convection currents and transported more than 100 km in upper wind currents (Chapman, 1967; Furniss and Furniss, 1972; Robertson et al., 2007; Simard et al., 2012).

Tree Defenses and Environmental Controls

Trees have a number of physical and chemical defenses against insect attack (Franceschi et al., 2005). Their thick bark creates a physical barrier that MPBs must bore through. Trees use chemicals to repel insects and make their bark more difficult to digest. Tree sap physically pushes MPBs out of the bark in a process called “pitching out.” The sap also contains toxic chemicals that further hinder the attackers. These defenses are supported by tree health. A study in eastern Oregon found that trees with more vigor had increased resistance to beetle attack (Mitchell et al., 1983). Vigor is defined as the current growth (grams of stemwood produced) per square meter of crown leaf surface.
Forest composition and structure build the framework for a MPB outbreak. An abundant source of hosts in the immediate vicinity is an obvious contributing factor. MPBs are known to target larger diameter trees. A study in British Columbia found that MPB beetles did not attack trees with a diameter less than 10 cm and that the rate of tree mortality increased 1.5-4% with each centimeter increase in diameter (Safranyik et al., 1974). Trees with thicker phloem and larger surface area provide more room for beetle tunnels, called galleries, and more phloem resources to each larva. A laboratory study on lodgepole pine found that numbers of emerging adults increased linearly with phloem thickness when food supply limited production and that numbers of emerging brood adults increased exponentially with an increase in inches of egg gallery when food supply did not limit production (Amman, 1972). Preference in host size varies with MPB population size, however. Research indicates that MPBs attack smaller diameter trees when the MPB population is small because they do not have large enough numbers to overwhelm the defenses of large trees (Safranyik and Carroll, 2006).

Stand density is also an important aspect of forest composition that affects the success and dispersal of attacking MPBs. Intraspecific competition for resources, including nitrogen, water, and light, can affect trees’ ability to produce defense compounds, making them more susceptible to MPB attack (Waring and Pitman, 1985). Dense stands also facilitate MPB dispersal by providing short travel distances for MPBs to find a new host. Reducing stand density through logging has been demonstrated to be an effective method for increasing tree resistance to MPB attack (Mitchell et al., 1983).
Climate and weather influence outbreaks by changing MPB survivorship and altering tree susceptibility to attack. Temperature can inhibit MPB outbreak through cold induced-mortality and extension of reproductive cycles. Temperature regulates timing of MPB life cycles by affecting how MPBs develop, how quickly they reproduce, and how long they live. A study in Grand Teton National Park examined the effect of temperature on a MPB life cycle period by comparing the length of the cycle across a range of elevations. They found that MPBs in the warmer lower elevations, were univoltine, requiring only one year to complete a lifecycle. Beetles at high elevations, where winters are colder and warm periods are shorter, were predominantly semivoltine, requiring two years to complete a cycle (Amman, 1973). Seasonal variation in susceptibility to cold is an important consideration as well. Cold snaps in the spring and fall might be more deadly to larvae than consistently cold winter temperatures because MPBs are more cold-hardened with cryoprotectants in the middle of winter than at the beginning and end of the season (Bentz and Mullins, 1999). Drought is another important climatic consideration. Tree defenses can be weakened when trees are drought-stressed (Raffa and Berryman, 1983). Drought has been found to coincide with increases in infestation-caused tree mortality, but is not necessary to maintain an outbreak (Creeden et al., 2014; Powell and Bentz, 2009). The effects of drought are not uniform, however. A study comparing susceptibility of juvenile loblolly pines (Pinus taeda) to the southern pine beetle (Dendroctonus frontalis) in drought-stressed and irrigated conditions found that the attacks on the drought-stressed pines were more successful, but they were attacked
less often and suffered less constructed gallery area than the irrigated pines (Dunn and Lorio, 1993).

Spatial factors form complicated interactions with climate, tree defenses, and MPB survivorship that influence MPB infestation on a landscape scale. Topographic characteristics, including slope, aspect, and elevation, create local variability in temperature and moisture (Geiger, 1956; Oke, 1987). Warmer and drier slopes, on southerly aspects and at low elevations, might provide reduced defense against attack compared to colder and wetter slopes, on northerly aspects and at high elevations (Nelson et al., 2007; Wulder et al., 2006). Geographic features can also influence tree susceptibility to attack. Limited host availability above tree line, for example, might act as a barrier to, or produce directionality in, the spread of MPB infestations. The northern Rocky Mountains in British Columbia were a geoclimatic barrier to MPB infestation until 2002, when infestation was discovered east of the divide, a region not historically considered part of their distribution (de la Giroday et al., 2012). Extreme cold in geographically northern latitudes can also limit the spread of MPBs (Safranyik, 1978). The historically cold winters and short summers in northern latitudes have restrained MPBs from spreading north to jack pine (Pinus banksiana Lamb.), a potential new host (Carroll et al., 2004; Safranyik et al., 2010). Environmental and spatial factors, in conjunction with forest composition and structure, influence MPB infestations and enable or repress irruptive MPB outbreaks.
Progression of Attack and Phases of Outbreak

Trees that succumb to MPB attack take several years to fully exhibit the effects. Initial symptoms of attack include boring dust (frass) and pitch tubes comprised of boring dust and tree resin surrounding beetle entry holes. Tree bark flaked away by woodpeckers looking for larvae, galleries excavated under the tree bark, and emergence holes from new beetles indicate that beetles have resided within the tree (Figure 2.1). These symptoms require close inspection on the ground (Safranyik and Carroll, 2006).

Figure 2.1: Images of beetle attack symptoms. From left to right: a MPB beetle (within white circle) with a mechanical pencil for scale, gray stage tree trunk that has lost all its bark, MPB lodged within a gallery on the underside of a piece of tree bark.

Change of the needle coloration is a more prominent symptom of attack. An initial yellowing of the needles is called the “green stage.” The tree needles dry out and turn red over the course of a year or more, reaching what is referred to as the “red stage” of tree mortality. The “gray stage” occurs after the needles drop, three to five years from initial infestation (Safranyik and Carroll, 2006). These canopy color changes allow
remote observation of an infestation, so long as there is certainty that the tree mortality is caused by MPB and not another factor (Wulder et al., 2005). The red and gray stages are most pronounced and provide a clearer remote indication of infestation than the green stage. The initial MPB attack begins the year before trees exhibit the characteristic red needles. Climatic variables from one year or several years prior to observed tree mortality are thus, more apt to explain beetle behavior and attack processes than those of the year in which the attack is observed (Chapman et al., 2012; Jewett et al., 2011).

MPB infestations are controlled by a series of thresholds and move cyclically through four major phases of outbreak. Multiple researchers have coined terms and definitions for these phases, however they largely agree in quantity and criteria of phases (Lundquist and Reich, 2014; Raffa et al., 2008; Safranyik and Carroll, 2006). The phases are regulated by environmental and spatial controls. The relationships between MPB infestation and influential variables can change as infestation thresholds are crossed. The initial factors that provoked an outbreak might not be needed to sustain it (Raffa et al., 2008).

The predominant phase is the endemic phase in which MPB infestation occurs across the landscape at low densities, which are difficult to detect. This is followed by the stand-level incipient outbreak phase, characterized by clusters of attacked stands at short and long ranges from dispersing beetles (Lundquist and Reich, 2014). This phase occurs when stand composition and structure, herbivory, and other tree ailments compromise tree resistance or favor MPB proliferation (Raffa et al., 2008, 2005). The infested stands overlap and grow into a traveling wave in the landscape-level outbreak phase (Lundquist
and Reich, 2014). This phase results when weather and climate, landscape composition and structure, and MPB dispersal further compromise tree resistance or favor MPB proliferation (Raffa et al., 2008). The infestation declines to endemic levels in the outbreak collapse phase, when the available hosts become scarce or environmental factors limit population growth (Lundquist and Reich, 2014). A fifth phase, called regime shift, is possible when outbreak exceeds historical extents, frequencies, severities, or locations (Raffa et al., 2008). Outbreak levels in a regime shift break the cycle of the previous four phases. MPBs that cause a regime shift exceed the forest system’s capacity for resilience, resulting in lasting changes to the system’s function, structure and feedbacks.

Climate Change

The increase in average temperature in northwest North America has impacted MPB behavior and processes. MPB flight season on the Colorado Front Range begins more than one month earlier and lasts about twice as long compared to the historical season (Mitton and Ferrenberg, 2012). Life cycle frequency has also increased in some broods, shifting from univoltine to multivoltine beetles which produce two generations in one year (Mitton and Ferrenberg, 2012). Warmer temperatures have enabled the MPB to attack trees at higher elevations and latitudes than previously recorded (Aukema et al., 2006; Carroll et al., 2004; Robertson et al., 2009). The synchronicity and extent of recent outbreaks are also unprecedented, occurring across forests from northwestern Canada to the southwestern boarder of the United States (Logan and Powell, 2001). Past climate change has affected MPB attack processes, and the attacked trees will in turn change the
future climate. Carbon dioxide, released into the atmosphere as the trees decompose or burn, will further warm North America (Kurz et al., 2008).

It is important to understand how MPBs affect forests because outbreaks profoundly impact many aspects of forest ecosystem function and services. In addition to affecting carbon storage, MPBs affect forest hydrology. A two-year study of snowpack dynamics in northcentral Colorado found that snowpack depletion occurred earlier under red and gray stage stands than under uninfested stands, due to decreased surface albedo from falling needles under red stage stands and increased solar transmission through the canopy of gray stage stands. Gray stage stands experienced 15% greater accumulation of snow than green and red stage stands (Pugh and Small, 2011). Evidence of MPB-caused alterations to soil nitrogen cycling were found in Arizona where nitrogen rich needles, dropped by infested ponderosa pine forests, sent a pulse of nitrogen into the forest soils (Morehouse et al., 2008). Changes in forest structure caused by MPB infestation can alter wildlife habitat, creating a spike in resources for woodpeckers and other insectivorous species, negatively impacting species that depend on forest cover as trees drop their needles, and benefiting species that prosper in open stand conditions as the dead trees fall (Chan-McLeod, 2006). Wide expanses of dead trees raise concerns over increased risk of forest fire, however a review of the literature found that some characteristics of fuels and fire are enhanced following outbreaks and others are unchanged or diminished (Hicke et al., 2012). The primary factor determining susceptibility to forest fire is the amount of time since the outbreak. MPB outbreaks can also contribute to air pollution as the defense compounds, emitted by trees in high concentrations when under attack, form secondary
organic aerosols in the atmosphere (Amin et al., 2012). The social and economic effect of MPB outbreak is felt though perceived degradation of scenic and recreation value of forests and by threatened timber stocks (Safranyik et al., 1974). These impacts present many challenges to managers and policy makers.

Mapping Forest Disturbance

Understanding where MPB outbreaks are occurring and the processes that influence them allows managers to develop timely mitigation efforts, sanitation logging plans, and meaningful forest management strategies (Wulder et al., 2005). An outbreak map locates and quantifies the affected area. Repeated mapping can provide indications of how infestation moves across a landscape and what factors hinder and facilitate its spread.

Aerial Detection Survey

The U.S. Forest Service aerial detection surveys (ADS) are the longest running form of presence-absence disturbance monitoring (USDA Forest Service and Forest Health Protection and its partners, 2005). Some regions have conducted ADS for more than 60 years, while others made their programs active in the last decade. Trained interpreters fly over forests in airplanes on an annual basis to locate infested trees and digitize polygons around the corresponding area on a map. These surveys provide much needed information, but have several shortcomings. Interpreters must draw absolute lines to differentiate disturbed and undisturbed forest, when in reality these outbreaks are very heterogeneous in both presence and degree of disturbance (Meddens et al., 2011). Human
interpretations are also subjective and can vary in accuracy depending on the experience
and skill of the interpreter, which complicates statistical analyses (White et al., 2005).
Surveying is costly in terms of time and resources and aviation work is hazardous. Most
areas are surveyed every two years, but some are missed. Wilderness areas and national
parks in particular are not surveyed regularly (Coops et al., 2006; Hicke and Logan,
2009). A 2012 study found that U.S. aerial surveys underestimate tree mortality by a
factor ranging from 3-20 (Meddens et al., 2012). ADS is valued for its widespread data
collection and long historical precedence, but the dataset’s inconsistencies, exclusions,
risks, and costs make it challenging to analyze and maintain.

**Satellite Mapping**

Satellite imagery offers many advantages over the ADS for monitoring forest
disturbance. Satellite imagery is available at fine temporal and spatial scales. It enables
repeatable assessments of disturbance with relatively little investment in terms of time
and human resources. Imagery is spatially explicit, encompasses large geographic areas,
and is available at temporal resolutions coinciding with MPB lifecycles (Senf et al.,
2017). Collection of satellite imagery is automated and does not pose safety risks to
interpreters.

Disturbances are mapped by satellites at the pixel level. Extent mapping defines
pixels as either *presence* or *absence* of disturbance using band values and indices, or
change in band values and indices across time. Severity mapping measures the *percent* of
each pixel disturbed. Another important consideration is the temporal type of analysis. A
single-date study uses only one date of imagery to produce a forest disturbance map,
while a multitemporal analysis uses more than one, often many, dates of imagery (Table 2.1).

Models identify forest disturbance by discerning ways that disturbed areas differ from their surroundings in the electromagnetic spectrum. A review of studies existing before 2017 found that 47% of studies mapping bark beetle disturbance use multispectral bands (Senf et al., 2017). The same review found that 29% of the studies use a single spectral index. The most frequently used index is the difference in Tasseled Cap Wetness component between two observations called the enhanced wetness difference index (EWDI; Campbell and Wynne, 2011). The tasseled cap wetness component identifies areas of moisture. Disturbed areas often experience vegetation loss and thus a loss in surface moisture. The normalized burn ratio (NBR) and normalized difference vegetation index (NDVI) are also commonly used indices, which leverage the high reflectance of vegetation in the near infrared (NIR) portion of the electromagnetic spectrum (Campbell and Wynne, 2011).

Disturbance mapping techniques have employed bands and indices across a variety of imagery types and resolutions. Studies have successfully identified MPB

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Table 2.1: Temporality and precision of response create four unique types of infestation mapping techniques.
infestation with spatial resolutions ranging from 30 cm to 30 m. Accuracy comparisons between spatial resolutions suggest that, when mapping infestation as an extent of tree mortality, resolutions that match the crown size of the trees have the highest accuracy. A study comparing tasseled cap component classification of Landsat imagery (30-m pixels) to IKONOS imagery (4-m pixels) found that overall accuracy in classifying infested pixels was 59% for Landsat imagery and 79% for IKONOS imagery (Bentz and Endreson, 2003). Another study classified infestation in imagery with 30-cm pixels using green radiation, RGI, and NDVI and compared its accuracy to that of pixels from the same image resampled to 1.2 m, 2.4 m, and 4.2 m. They found that 2.4-m pixels produced the highest overall accuracy at 90%, which was an increase of 3% from the 30-cm pixel image (Meddens et al., 2011). A spatial resolution that matches tree crowns can be especially important in rugged terrain where slope angles and shadows can complicate an analysis. Classification of whitebark pine in the White Cloud Peaks of Idaho using RGI and green reflectance at 2.4-m pixel size obtained 86% overall accuracy.

It is also important to match the spatial and spectral resolution of imagery with the phase of outbreak when mapping the extent of an infestation. A pixel’s spectral response is an amalgamation of the land cover within that spatial extent. MPB infestations at the endemic level require high-resolution imagery because single trees, or only small groups of trees, are infested, and their signatures are overcome by the healthy trees represented in the pixel (Figure 2.2). Moderate-resolution imagery can be sufficient at the stand level and landscape level outbreak phase because groups of infested trees dominate the pixel response even in larger sized pixels (Wulder et al., 2005). High-spectral resolution is
helpful when attempting to identify the earliest stages of attack. Classification of hyperspectral imagery using classification and regression tree analysis obtained 63% accuracy in identifying green stage Douglas-fir trees attacked by the Douglas-fir beetle (Lawrence and Labus, 2003).

Landsat Imagery. The pixel size of moderate-resolution imagery (5-30 m) is much larger than the crown of a single tree, but it is a common and practical choice for infestation classifications. Landsat imagery provides a balance between cost, precision,
accuracy, and repeatability. The Landsat archive was made freely available in 2008. Two
Landsat satellites have been concurrently in operation for the last two decades, each with
a return time of 16 days, making a new image available over a given study area every 8
days on average.

One study in British Columbia using all seven bands of Landsat imagery obtained
72.3% overall accuracy in identifying red-attack damage (Franklin et al., 2003). Another
study mapping extent of infestation using tasseled cap components from Landsat imagery
obtained 91% overall accuracy (Meddens et al., 2013). Both of the mentioned Landsat
studies mapped the extent of tree mortality as presence or absence of infestation in each
pixel. A third study used Landsat imagery to map the presence of mortality and then
quantified the percent mortality within the pixels identified as having mortality present.
All of the models assessed in this study obtained < 3% difference between predicted and
observed pseudomedian mortality and < 18% root mean square error (RMSE), which
they deemed acceptable accuracy for management (Long and Lawrence, 2016).

Severity maps provide several advantages over extent. Mapping outbreak as a
severity overcomes the challenge of matching the outbreak level with the spatial
resolution of the imagery because low levels of tree mortality are detectable as a within-
pixel percentage (Long and Lawrence, 2016). Severity maps also offer a better indication
of the ecological effects of a disturbance within a single-date analysis. A low severity
infestation, for example, might have limited effects on forest habitat, while a high
severity infestation might affect forest structure enough to alter processes that regulate
ecosystem communities (Menge and Sutherland, 1987). Severity maps can provide a
more representative view of the ecological impact of an infestation by combining them with a variety of other forest metrics, such as percent tree cover and biomass. A study in the southern Colorado Rockies mapping percent canopy cover combined several percent canopy cover maps of the top four tree species in their study area for a holistic measure of canopy composition (Savage et al., 2017).

**Temporal Breadth.** The temporal breadth of an infestation mapping technique is also an important consideration. The studies mentioned previously were all single-date analyses, which used a single-date of imagery to map mortality. Single-date approaches lend themselves to incorporation of many indices and bands because the analysis is performed only once. These approaches offer a snapshot of beetle activity by producing models well fitted to the data, but do not provide accurate predictions of other dates and thus do not lend themselves to continued monitoring.

Multitemporal analyses use multiple dates of imagery to map disturbance. These analyses often leverage change in an index or band from one year to the next to represent disturbance. An early multitemporal study used EWDI generated from Landsat Imagery to identify changed pixels in an infested region one and two years apart in date with an overall accuracy of 74% (Skakun et al., 2003). Free access to the Landsat archive fostered a plethora of multitemporal studies that employ many dates of imagery. A 2013 study used 20 images from 1996-2011 to identify presence of infestation. They achieved 89.6% overall accuracy by measuring changes in the red/NIR ratio of each pixel from a base year (Meddens et al., 2013).
Multitemporal change detection techniques are common for all types of forest disturbance. A review of the prominent, Landsat-based changed detection techniques compared seven different algorithms that use higher volumes of Landsat data (Cohen et al., 2017). The Vegetation Change Tracker (VCT) uses a forest z-score, integrated forest z-score, and a normalized burn ratio (NBR) to identify departure from the previous year in an annual time series. VCT is designed to identify discrete disturbance events and obtained around 80% overall accuracy in the authors’ original study (Huang et al., 2010).

The Multi-Index Integrate Change Analysis (MIICA) is also designed to identify discrete events between two images of any date, but the authors did not report an overall accuracy in their original study. MIICA uses NBR, NDVI, change vector, and relative change vector indices (Jin et al., 2013). Image Trends from Regression Analysis (ITRA) utilizes NDVI to classify gradual trends in the slope of annual multi-year time series (Vogelmann et al., 2012). The authors also did not report an overall accuracy in their original study.

Landsat-based Detection of Trends in Disturbance and Recovery (LandTrendr) identifies both discrete events and gradual trends using an annual NBR time series. LandTrendr obtained over 86% accuracy for reported model types in the authors’ original study (Kennedy et al., 2010). Vegetation Regeneration and Disturbance Estimates through Time (VeRDET) is another technique measuring both discrete events and gradual trends. VeRDET utilizes an annual time series of normalized difference moisture index (NDMI) and obtained 85% overall accuracy in the authors’ original study (Hughes, 2014).
The final two reviewed change detections are “massively multitemporal,” using every clear pixel from every date of imagery within their study periods. Continuous Change Detection and Classification (CCDC) is best tailored for discrete disturbance events and uses hundreds of images to obtain every clear pixel over a multi-year period. CCDC identifies departures from a sinusoidal model of each pixel’s phenology by employing the blue, green, red, NIR, and SWIR 1 and 2, and thermal bands. The authors’ achieved 90% overall accuracy in their original study (Zhu and Woodcock, 2014). Exponentially Weighted Moving Average Change Detection (EWMACD) used tasseled cap angle index to measure departures in a multi-year phenology model. EWMACD obtained 85% accuracy identifying disturbance in the author’s original study (Brooks et al., 2014).

These high-volume multi-date approaches can identify anomalies and trends in the data to minimize challenges associated with cloud masking, phenology, sun angle differences, and other exogenous factors. Additionally, most of these approaches have the ability to provide disturbance information for every image released. Many of these techniques use a single index rather than several individual bands, which might be due to the large amount of data involved with analyzing many dates of imagery.

A comparison between all seven of these high-volume change detection methods used each method to detect change in the same images (Cohen et al., 2017). It should be noted that some of the bands and indices used for each method differed from those of the authors’ original studies, but that the overall methodologies were the same. The comparison found that LandTrendr had the lowest rate of disturbance omission, but one
of the highest rates of commission. CCDC had the lowest rate of disturbance commission, but one of the highest rates of omission. All of the methods varied widely in both the overall extent of disturbed area identified and the physical locations of that disturbance (Cohen et al., 2017). This incongruity is partially due to differing definitions of disturbance, which incorporate thresholds tailored to their respective study questions and applications (Cohen et al., 2017). Different algorithms are incompatible on a pixel-by-pixel basis and can produce complications when applying an algorithm developed for one application to another.

All of the above multitemporal forest disturbance algorithms classify disturbance by extent rather than severity. Multitemporal severity approaches are valuable, because they quantify infestation extensification (the change in infestation extent from one period to another) as well as intensification (the change in severity within the same extent from one period to another). Measuring intensification allows for continued observation of affected pixels where extent maps cannot because the infestation severity of a single pixel can increase over time while the extent remains the same. Mapping severity additionally bypasses the complications from tailoring a change detection threshold to a specific study question by avoiding the need to define a threshold altogether.

There is a dearth of published literature describing studies that use multitemporal approaches for mapping severity of forest disturbance. One study mapped red attack as a probability of presence or absence using Landsat derived EWDI, which allowed the users to define their own threshold but did not offer a direct measure of the severity of infestation (Wulder et al., 2006). An article mapping defoliation events using CCDC
indicated that magnitude of deviations from the base trend could be leveraged to provide defoliation severity (Pasquarella et al., 2017). An abstract from a 2018 conference indicates that a study utilizing a CCDC approach to classify categories of infestation severity is underway (Pasquarella and Orwig, 2018).

Substantial progress has been made in providing estimates of infestation extensification. The high-volume multitemporal techniques offer many advantages over single-date analysis, including frequency of predictions, removal of image artifacts, and high accuracy. These single-date and multitemporal extent maps do not address aspects of intensification, however, and are difficult to combine with other ecosystem metrics. Severity mapping is relatively underdeveloped, despite the ability for time-series severity maps to provide valuable insights into processes and drivers of MPB outbreaks. Multitemporal severity maps are conspicuously absent from the literature.

**Probability of New Infestation**

The widespread MPB outbreaks across western North America create timber and recreation management challenges. Rating the susceptibility of forests to MPB attack can inform stand management strategies that reduce the risk of infestation and can anticipate how recreational campgrounds and scenic corridors might be affected. Some of the first means of rating MPB infestation risk were developed empirically for ponderosa pine on the Colorado Plateau. A 1980 rating used forest stand metrics to classify areas into low, moderate, and high potential for outbreak. The rating used the metrics of basal area, average diameter at breast height (dbh), and stand structure (Stevens et al., 1980). A 1995
rating developed for the same region added proportion of ponderosa pine in the canopy and number of trees infested per acre in place of the stand structure metric in the 1980 rating system (Munson and Anhold, 1995).

A subsequent study used logistic regression to estimate the probability of attack at 45 study sites across the Colorado Plateau and measured the agreement between its ratings and those of the 1980 and 1995 methods (Chojnacky et al., 2000). The authors provided the model with around 50 variables of stand characteristics at the tree, plot, and site level. Stepwise variable selection found that significant variables were: plot level stand density, tree dbh, plot level basal area, quadratic mean diameter, and a tree competition rank ($p$-value $\leq 0.0002$). The final model obtained an $R^2$ of 0.47 and agreed most closely with the 1995 rating system. The authors recommended including weather and MPB population dynamics into future models. A similar study also identified probability of infestation in ponderosa pine using stand characteristics, but instead applied a classification tree model (Negrón and Popp, 2004). This study found that, for 35 locations in the Arapaho-Roosevelt National Forest in north-central Colorado between 1998 and 2000, dbh, stand density, and basal area were defining factors in probability of infestation. The model achieved 70% overall accuracy.

Predicting probability of attack with logistic regression has been applied to remotely sensed data as well. These studies incorporate weather and MPB population dynamics to map probability of new infestation continuously across wide spatial extents. An analysis spanning from 1972–1986 in British Columbia used ADS previous infestation, ADS neighboring infestation, a variety of temperature metrics, and elevation
in a logistic regression to model the probability of new infestation (Aukema et al., 2008). They achieved 78% accuracy for a one-year forecast in their 12-km pixels. Another study predicting new infestation in lodgepole pine of Washington and Oregon used 1-km ADS pixels as the response (Preisler et al., 2012). Their covariates included nearby beetle pressure in the previous year, cumulative number of trees killed over previous five years, longitude and latitude of the center of the cell, several precipitation and soil moisture variables, mean temperature variables for the fall and summer, minimum winter temperature, climate suitability, and 27-year averages for all weather variables. Their analysis ranged in time from 1980-2006 and predicted probability of infestation in three classes of outbreak level. The final map demonstrated good spatial agreement with observed outbreak, but no quantitative measure of accuracy was obtained.

The known methods for assessing susceptibility to attack either use forest stand metrics applied to individual sites or apply wide ranging weather, climate, and MPB infestation information to predict probability of infestation across wide spatial extents. Logistic regression is a common means of modeling probability of infestation, however classification trees have also been utilized with comparable accuracy. The models mapping probability across wide extents used large pixel sizes (1 and 12 km) due to the coarseness of the ADS reference data. A finer-scale analysis might reveal more nuanced relationships between weather, climate, and MPB population dynamics. A model incorporating forest metrics with climate, weather, and past MPB infestation would likely be superior to all the above methods, however stand characteristics at the accuracy needed are not currently available across wide spatial extents.
CHAPTER THREE

A TIME-SERIES APPROACH FOR MAPPING MOUNTAIN PINE BEETLE INFESTATION EXTENT AND SEVERITY

Introduction

Mountain pine beetles (MPB; *Dendroctonus ponderosae*) are native to the forests of western North America and, like other insects and diseases, are typically agents of healthy forest disturbance that remove old and sick trees and foster diversity in forest age and structure (Roe and Amman, 1970). In recent decades, however, infestations have become more severe, frequent, and widespread than historic levels (Colorado State Forest Service, 2017). Epidemic MPB events profoundly impact forests and the services they provide. High severity disturbance can impair ecosystem function, degrade wildlife habitat, and hinder ecosystem services such as carbon storage, watershed quality, recreation, and timber (Chan-McLeod, 2006; Kurz et al., 2008; McGregor, 1985; Morehouse et al., 2008; Pugh and Small, 2011). Severe outbreaks can also pose risk to public health and safety due to the hazard of falling dead trees, increased air pollution, and changing susceptibility to wildfires (Amin et al., 2012; Hicke et al., 2012; Safranyik et al., 1974). These impacts present challenges to managers and policy makers.

MPB infestations are controlled by a series of thresholds and move cyclically through four major stages of outbreak (Lundquist and Reich, 2014; Raffa et al., 2008). The predominant phase is the “endemic phase” in which MPB infestation occurs across the landscape at low densities that are difficult to detect. This is followed by the stand-
level incipient outbreak phase characterized by clusters of attacked stands at short and long ranges from dispersing beetles (Lundquist and Reich, 2014). This phase occurs when stand composition and structure (Raffa and A. Berryman, 1987; Safranyik and Carroll, 2006), herbivory, and other tree ailments compromise tree resistance or favor MPB proliferation (Raffa et al., 2008, 2005). The infested stands overlap and grow into a traveling wave in the landscape-level outbreak phase (Lundquist and Reich, 2014). This phase results when weather and climate, landscape composition and structure, and MPB dispersal further compromise tree resistance or favor MPB proliferation (Raffa et al., 2008). The infestation returns to endemic levels in the outbreak collapse phase, when the available hosts become scarce or environmental factors limit population growth (Lundquist and Reich, 2014). The relationships between MPB infestation and influential variables can change as infestation thresholds are crossed. The initial factors that provoked an outbreak might not be needed to sustain it (Raffa et al., 2008).

Infested trees present visible color changes as they die, which are observable with remote sensing technology (Wulder et al., 2005). An initial yellowing of the needles is called the “green stage.” The tree needles dry out and turn red over the course of a year or more, reaching what is referred to as the “red stage” of tree mortality. The “gray stage” tree occurs after the needles drop, three to five years from initial infestation. The red and gray stages are pronounced, providing a clearer remote indication of infestation than green stage trees.

The U.S. Forest Service aerial detection surveys (ADS) are the longest running form of presence-absence disturbance monitoring (USDA Forest Service and Forest
Health Protection and its partners, 2005). Some regions have conducted ADS for more than 60 years, while others made their programs active in the last decade. Trained interpreters fly over forests in airplanes on an annual basis to locate infested trees and digitize polygons around the corresponding area on a map. These surveys provide much needed information, but have several shortcomings. Interpreters must draw absolute lines to differentiate disturbed and undisturbed forest, when in reality these outbreaks are very heterogeneous in both presence and degree of disturbance (Meddens et al., 2011). Human interpretations are also subjective and can vary in accuracy depending on the experience and skill of the interpreter, complicating statistical analyses (White et al., 2005).

Surveying is costly in terms of time and resources and aviation work is hazardous. Most areas are surveyed every two years, but some are missed. Wilderness areas and national parks in particular are not surveyed regularly (Coops et al., 2006; Hicke and Logan, 2009). US. A 2012 study found that US aerial surveys underestimate tree mortality by a factor ranging from 3-20 (Meddens et al., 2012). ADS is valued for its widespread data collection and long historical precedence, but the dataset’s inconsistencies, exclusions, risks, and costs make it challenging to analyze and maintain.

Satellite imagery offers many advantages over the ADS for monitoring forest disturbance. Satellite imagery is available at fine temporal and spatial scales. It enables repeatable assessments of disturbance with relatively little investment in terms of time and human resources. Imagery is spatially explicit, encompasses large geographic areas, and is available at temporal resolutions coinciding with MPB lifecycles (Senf et al.,
Collection of satellite imagery is automated and does not pose safety risks to interpreters.

Forest disturbances mapped with satellite imagery are defined by their extent or their severity. Extent mapping defines pixels as either presence or absence of disturbance using band values and indices, or change in band values and indices across time (Bentz and Endreson, 2003; Lawrence and Labus, 2003; Meddens et al., 2011; Skakun et al., 2003). Severity mapping measures the percent of each pixel disturbed (Long and Lawrence, 2016; Savage et al., 2015). Severity maps provide several advantages over extent. Severity offers a better indication of the ecological effects of a disturbance within a single date analysis. A low severity infestation, for example, might have limited effects on forest habitat, while a high severity infestation might affect forest structure enough to alter processes that regulate ecosystems (Menge and Sutherland, 1987; Pfeifer et al., 2011). Severity maps can provide a more representative view of the ecological impact of an infestation by combining them with a variety of other forest metrics, such as percent tree cover and biomass (Savage et al., 2017).

The temporal breadth of an infestation mapping technique is also an important consideration. Single date analyses use one or more dates of imagery to map mortality for a single time period. Single date analyses have employed a variety of explanatory variables to map various stages of MPB attack at numerous image resolutions (Bentz and Endreson, 2003; Coops et al., 2006; Hicke and Logan, 2009; Lawrence and Labus, 2003; Meddens et al., 2011; Skakun et al., 2003; White et al., 2005; Wulder et al., 2006). Single date approaches lend themselves to incorporation of many indices and bands because the
analysis is only performed once. These approaches offer a snapshot of beetle activity by producing models well fitted to the data, but do not provide accurate predictions of other dates and thus do not lend themselves to continued monitoring.

Multitemporal analyses use many dates of imagery to map disturbances. Moderate spatial resolution imagery, such as Landsat, is commonly used to map forest disturbances because it provides the best balance between precision, accuracy, and cost (Bentz and Endreson, 2003). Access to the Landsat archive, made freely available in 2008, fostered a variety of multitemporal time-series techniques for mapping forest disturbance that make use of every date of available imagery. A review of the published Landsat forest disturbance algorithms summarized the overarching approach of the following techniques (Cohen et al., 2017). Vegetation Change Tracker (VCT), Exponentially Weighted Moving Average Change Detection (EWMACD), Multi-index Integrated Change Analysis (MIICA), and Continuous Change Detection and Classification (CCDC) identify abrupt changes within a time period, from a base year, or from a modeled phenology (Brooks et al., 2014; Huang et al., 2010; Jin et al., 2013; Kennedy et al., 2010; Zhu et al., 2015; Zhu and Woodcock, 2014). Image Trends from Regression Analysis (ITRA) identifies gradual trends (Vogelmann et al., 2012). Only Landsat-based detection of Trends in disturbance recovery (LandTrendr) and vegetation regeneration and disturbance estimates through time (VeRDET) monitor both abrupt changes and gradual trends (Hughes 2014, Kennedy et al., 2010).

Multitemporal approaches to mapping forest disturbance can provide improved accuracy by using trends to identify changes due to clouds, phenology, and other
exogenous factors rather than real forest change. Additionally, most of these approaches have the ability to provide disturbance information for every image released (every eight days for Landsat). These techniques are limited, however, in two ways: (1) many of these techniques use a single index, which might remove valuable information present in multiple bands and result in lower model accuracy (Lawrence and Ripple, 1998; Maynard et al., 2007), and (2) all of the reviewed forest disturbance algorithms classify extent of disturbance rather than by severity. These techniques agree well in their predictions of overall proportion of forest area disturbed, but one study comparing multiple methods revealed that they can have vastly different pixel-by-pixel estimates (Cohen et al., 2017). This incongruity is partially due to differing definitions of disturbance, which incorporate thresholds tailored to their respective study questions and applications (Cohen et al., 2017). Different algorithms are incompatible on a pixel-by-pixel basis and can produce complications when applying an algorithm developed for one application to another. Mapping severity bypasses these complications by avoiding the need to define a threshold altogether.

Multitemporal severity maps can offer more detailed information in an ongoing infestation than maps of extent. Multitemporal severity approaches quantify infestation extensification (the change in infestation extent from one period to another) as well as intensification (the change in severity within the same extent from one period to another). Measuring intensification allows for continued observation of affected pixels where extent maps cannot because the infestation severity of a single pixel can increase over
time while the extent remains the same. Unfortunately, we are unaware of published studies offering multitemporal approaches for mapping severity of forest disturbance.

Substantial progress has been made in providing estimates of infestation extensification. Extent maps do not address aspects of intensification, however, and are difficult to combine with other ecosystem metrics. Severity mapping is relatively underdeveloped despite the ability for time-series severity maps to provide valuable insights into processes and drivers of MPB outbreaks. In this study, we evaluated the ability to map infestation severity during a MPB epidemic outbreak in the Central U.S. Rocky Mountains. Our objective was to develop and evaluate one multitemporal model of infestation severity that would be robust in its applicability over an 11-year study period. Accuracy of such a model will enable evaluation of the progress of an epidemic outbreak in terms of both extensification and intensification and allow users to set a threshold for presence or absence of mortality that is tailored to their study question or application.

**Methods**

**Study Area**

The study area for our analysis was comprised of the forested regions of a single Landsat scene, path 34 row 32, in northern Colorado and southern Wyoming (Figure 3.1). We restricted this analysis to conifer forests only where pixels were greater than or equal to 10% forested in the LANDFIRE data set (USGS, 2008). The study area excluded areas logged during the time-series period (Woodward et al., 2017), areas within city boundaries (U.S. Department of Commerce et al., 2013), highways (Colorado
Department of Transportation, 2011; Wyoming Department of Transportation, 2005), high density housing (Radeloff V. C. et al., 2005), agriculture, and developed open space (U.S. Geological Survey, 2014). The resulting area included approximately 1.5 million ha of land the Medicine Bow, Routt, Arapaho, Roosevelt, White River, and Pike National Forests as well at the Colorado State Forest State Park and the Rocky Mountain National

![Figure 3.1: Study area map of the forested land in the Central U.S. Rocky Mountains](image-url)
Park (RMNP). The elevation ranged from 1,636 m to 4,124 m. A stand-level incipient outbreak began in this area in 2003 and grew to a landscape-level outbreak over the next several years (Chapman et al., 2012). Predominant host species in the study area included lodgepole pine (*Pinus contorta* var. *latifolia*), ponderosa pine (*Pinus ponderosa*), and limber pine (*Pinus flexilis*) (Chapman et al., 2012). We defined tree mortality as any red stage or grey stage tree as well as any tree that died from any other disease or physical trauma. It was not possible to exclude trees that died from other diseases or physical traumas if they also displayed red or gray stage characteristics.

**Reference Data**

Reference data for the analysis was collected by manual interpretation of National Agricultural Imagery Program (NAIP) imagery. There were 7 years of NAIP imagery available with a resolution of one meter or finer (Colorado NAIP from years 2005, 2009, 2011, 2013, and 2015 and Wyoming NAIP from years 2006, 2009, 2012, and 2015). We created 10 x 10 (100 point) grids with points spaced three meters apart to coincide with 30-m pixels of Landsat imagery. We placed 26 grids at random locations for each year of available NAIP imagery for a total of 182 grids. A sample size test determined an appropriate sample size. A sample test for a desired margin of error of 0.06 required 82 observations, based on the sample standard deviation (Ramsey and Schafer, 2012). We interpreted the land cover at each of the 100 points per location. Higher resolution Google Earth imagery was viewed for additional context, but never for final interpretation. Grid points over dead trees (red or grey stage) were summed and converted to a percent mortality of all 100 observed points for each location. This method
of interpretation of fine-scale imagery is an acceptable substitute for ground reference data of tree mortality (Hicke and Logan, 2009; Long and Lawrence, 2016; Meddens et al., 2013; White et al., 2005).

The percent mortality observations were divided into a training and validation dataset using a stratified random sampling method. The method was stratified by the year of observation and the severity of mortality observed in order to obtain similar ranges of mortality and representation from each observed year in both datasets. Three of the observed locations were discarded due to alignment issues between the different footprints of Landsat sensors (training dataset n = 90 and validation dataset n = 89).

Digital Data Acquisition and Pre-Processing

Spectral data were extracted at the individual pixel level for each of the 179 sampled locations from a variety of digital imagery (Table 3.1). All available dates of Landsat surface reflectance imagery were compiled using the Google Earth Engine (GEE). We calculated median pixel values from cloud free pixels for the blue, green, red, near infrared (NIR), and shortwave infrared (SWIR) 1 and 2 bands across Landsat TM, ETM+, and OLI sensors for a pre-outbreak year (2001) and for each year of the time series (2005 - 2015). Cloud free pixels were identified using F-mask (Zhu and Woodcock, 2012). We acquired a normalized difference vegetation index (NDVI) layer for each year by determining the single greatest NDVI value for each pixel across all sensors. NDVI is a prominent index used for identifying live vegetation and is calculated using the red and NIR bands (Xie et al., 2008). The highest NDVI values are cloud free and represent similar phenology across years. To study the effects of the outbreak, we
subtracted the outbreak variables from the corresponding pre-outbreak variables (Table 3.1). We also extracted information from several ancillary datasets. Elevation, slope, and aspect were derived from a digital elevation model acquired from the U.S. Geological Survey National Elevation Dataset (U.S. Geological Survey, 2015, 2013). Aspect was grouped into 8 classes: N, NE, E, SE, S, SW, W, NW. Flat pixels were merged into the S group because there were not enough of them to properly train and validate the model.

We included a variable specifying the year of observation for the percent mortality for each sample. We also included the cumulative extent of infested area identified by the ADS from 2001 (what we consider the beginning of the outbreak) to the year of observation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent mortality*</td>
<td>Reference Data</td>
</tr>
<tr>
<td>Pre-outbreak median annual spectral response</td>
<td>Landsat</td>
</tr>
<tr>
<td>Pre-outbreak annual maximum NDVI</td>
<td>Landsat</td>
</tr>
<tr>
<td>Outbreak median annual spectral response</td>
<td>Landsat</td>
</tr>
<tr>
<td>Outbreak NDVI</td>
<td>Landsat</td>
</tr>
<tr>
<td>Difference in median annual spectral responses</td>
<td>Landsat</td>
</tr>
<tr>
<td>Difference in annual maximum NDVI</td>
<td>Landsat</td>
</tr>
<tr>
<td>Cumulative ADS**</td>
<td>U.S. Forest Service</td>
</tr>
<tr>
<td>Year of Observation</td>
<td>Reference Data</td>
</tr>
<tr>
<td>Slope</td>
<td>U.S. Geological Data</td>
</tr>
<tr>
<td>Aspect (N, NE, E, SE, S, SW, W, NW)**</td>
<td>U.S. Geological Survey</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>U.S. Geological Survey</td>
</tr>
</tbody>
</table>

Note that median annual spectral responses are for the blue, green, red, near infrared (NIR), short wave infrared (SWIR) 1, and SWIR 2 bands of the Landsat TM, ETM+, and OLI sensors. In total, there were 26 variables available to explain infestation severity in the time series. *Response. **Categorical variable
Data Analysis

We built a regression model using the aforementioned extracted data. We employed an agnostic approach to model selection, whereby several promising model types are tested with an external validation dataset and the best performing model type is selected by validation on withheld data (Lawrence et al., 2017). We conducted the analysis using the statistical programming language R version 3.1.4 (R Core Team, 2017). The following models were included in the selection process, based on previous use with remotely sensed imagery (Lawrence et al., 2017): general linear model (GLM) with step AIC, cubist, random forest, support vector machine (SVM) with linear and radial kernels, multivariate adaptive regression splines, and extreme gradient boosting trees. Each of these models was trained with the reference dataset, model parameters were tuned with ten-fold cross validation using the caret package in R, and then assessed for accuracy using the validation dataset. Our sample size determined that the model’s minimum detectible difference in ability to discern infestation severity was plus or minus 6%, or 12% total. Our models, therefore, could not be expected to reliably detect the difference between 6% and 0%. Long and Lawrence, 2016). Thus, all predictions less than 6% severity were reassigned to zero before validation.

The model with the best accuracy was then used to predict the values of all pixels in the study area for each year of the time series. We measured accuracy with Wilcoxon pseudomedians with 95% confidence intervals, Wilcoxon p-values, mean absolute deviation (MAD), and root mean square error (RMSE). The Wilcoxon pseudomedian assessed the difference between the observed and predicted infestation severity values.
The Wilcoxon p-value assessed if the predicted mortality values were significantly different at a 0.05 alpha level from the observed values. MAD measured the average deviation between the predicted and observed values and provided an indication of how much variation there was in the accuracy of the model predictions. RMSE, a variation of MAD that takes the square root of the sum squared deviations, was used to measure less frequent but larger errors in predictions.

We controlled for occasional large errors in the predictions by smoothing the data temporally with a centered moving average (Makridakis et al., 1997). The value of a prediction for a given year was averaged with the predictions for that pixel in the previous year and the following year. An asymmetric filter was applied to the ends of the time series by giving the end years double weight and averaging them with the value of that pixel in the single year closest in time. The model predictions were further transformed to reflect expected fall rates of beetle-killed trees and increasing severity of infestation. The natural fall rate of beetle-killed standing dead trees varies by factors including climate, soil type, tree species, tree size, and occurrence of high winds. Beetle-killed ponderosa pine in the Front Range typically remain standing for two years following infestation and then fall at a rate of 3-5% per year (Schmid et al., 1985). We thus expect 24-40% of the trees killed in 2005 to have fallen by 2015 and none of the trees from 2013-2015 to have fallen by 2015. It is likely that few trees killed in the middle and end of our study period fell and that proportionally more from the earlier years fell during our study period. Thus, accurate predictions of the severity of infestation within a pixel should not decrease substantially within our time series.
We limited the severity predictions of each pixel to be equal to, or less than, the severity prediction of the year following that pixel. The correction was applied from the most recent to the oldest imagery because both the Landsat imagery and the reference NAIP imagery at the end of the time series were of superior quality than the earlier imagery and were likely to provide superior interpretations and model predictions. We implemented this step starting in 2014 because the asymmetrical smoothing of the 2015 year at the end of the time series was likely to provide slightly less accurate predictions. The 2015 predictions were limited to be equal to or greater than the 2014 predictions. A second accuracy assessment, using the validation dataset, determined the final accuracy of the mapped percent tree mortality.

We then compared our raster maps to the ADS maps for each year of the time series. We summed the total extent of outbreak area identified by each dataset. A paired, one-sided t-test of the mean prediction value of the raster map pixels that overlapped with the ADS outbreak areas and those that did not in each year enabled an evaluation of the differences between our methods and the ADS with respect to differences in minimum mapping units. The finer spatial resolution of Landsat data offers opportunities to reveal uninfested locations within ADS polygons, as well as map small outbreaks outside of ADS polygons.

**Results**

The reference data for interpreted percent mortality of the 179 random plots ranged from zero to 53%. The mean non-zero response over all observed years was 19%
infested. The mortality estimates might seem low given that this area experienced landscape-scale epidemic outbreak. However, other land cover types within the pixel, such as bare ground and understory vegetation, lowered the overall pixel mortality percentage even when 100% of the conifer trees in a pixel were dead. The reference data were used to train seven potential model types. The Wilcoxon medians of all seven model predictions were not statistically different from the observed values except for the predictions from the SVM radial model (Table 3.2). From the remaining models, GLM with step AIC produced the lowest RMSE (10.5%), while SVM linear produced the lowest MAD (7.5%). We selected RMSE as the more important metric for our analysis because of its ability to amplify occasional large errors, which could be more troublesome to decision-makers than small errors.

Table 3.2: Accuracy statistics for the seven models considered.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAD (%)</th>
<th>RMSE (%)</th>
<th>Wilcoxon Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLM Step AIC</td>
<td>7.7</td>
<td>10.5</td>
<td>0.5 -2.7 to 3.3</td>
</tr>
<tr>
<td>SVM Linear</td>
<td>7.5</td>
<td>11.1</td>
<td>-2.2 -6.1 to 1.3</td>
</tr>
<tr>
<td>Cubist</td>
<td>8.2</td>
<td>12.1</td>
<td>-3.2 -6.7 to 0.7</td>
</tr>
<tr>
<td>SVM Radial</td>
<td>7.6</td>
<td>12.2</td>
<td>-6.0 -9.5 to -2.5</td>
</tr>
<tr>
<td>Random Forest</td>
<td>9.3</td>
<td>12.2</td>
<td>0.6 -3.4 to 4.7</td>
</tr>
<tr>
<td>Multivariate Adaptive</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regression Splines</td>
<td>11.0</td>
<td>14.1</td>
<td>2.4 -1.5 to 5.1</td>
</tr>
<tr>
<td>Extreme Gradient Boosting Tree</td>
<td>11.4</td>
<td>14.8</td>
<td>2.0 -2.5 to 6.2</td>
</tr>
</tbody>
</table>

The GLM model with step AIC was the best model for our application because it had a comparable MAD (7.7%) and the lowest RMSE. We recognized that the observed differences between the models were not statistically different, however, these metrics
provided a reasonable basis for the determination of a best model. The step AIC process removed three quarters of the available explanatory variables (Table 3.3). The remaining variables were all median annual spectral responses from the outbreak and pre-outbreak years. None of the median difference bands or ancillary variables were utilized.

Smoothing the mortality predictions from the GLM model resulted in a lower RMSE (10.1%) and an identical MAD statistic (7.7%; Table 3.4). The limiting post-processing step produced an even lower RMSE and MAD of 9.9% and 7.2%, respectively (Table 3.4). These predictions tended to overestimate low levels of mortality and underestimate high levels of infestation (Figure 3.2). The final version of the raster maps displayed extensification and intensification of tree mortality across the time series (Figure 3.3). The average severity of affected pixels was 9.4% in 2005 and 17.6% in 2015, with a maximum severity that increased from 49.7% to 58.8% over the same period.

Table 3.3: The final model from the GLM Step AIC model selection process included 7 variables.

<table>
<thead>
<tr>
<th>Final GLM</th>
<th>Band</th>
<th>Estimate</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td></td>
<td>3.1 x 10^2</td>
<td>---</td>
</tr>
<tr>
<td>Pre-outbreak median annual spectral response</td>
<td>Blue</td>
<td>-8.0 x 10^-2</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>Green</td>
<td>1.3 x 10^1</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>Red</td>
<td>-7.3 x 10^-2</td>
<td>0.03</td>
</tr>
<tr>
<td>Outbreak median annual spectral response</td>
<td>Blue</td>
<td>5.2 x 10^-2</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>Green</td>
<td>-8.9 x 10^-2</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>NIR</td>
<td>-1.3 x 10^-2</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>SWIR 1</td>
<td>2.4 x 10^-2</td>
<td>&lt; 0.01</td>
</tr>
</tbody>
</table>
We compared the severity and cumulative extent of tree mortality in our raster maps to the ADS maps for each year from 2005 to 2015 (Figure 3.4). The observed extent of tree mortality in the ADS maps was lower than our raster maps in all years of

![Scatterplot of the reference tree mortality versus the GLM step AIC predicted mortality for the validation dataset with a 1:1 line. Note that the model tended to overestimate low levels of mortality and underestimate high levels of mortality.](image)

Table 3.4: Accuracy statistics for the original, smoothed, and limited versions of the final GLM Step AIC model. Each step of post processing improved the RMSE. The median differences between the predicted and observed mortality rates are small with tight confidence intervals. Note that large p-values indicate no statistical difference between the predicted and observed mortality levels.

<table>
<thead>
<tr>
<th>Validation Dataset</th>
<th>MAD (%)</th>
<th>RMSE (%)</th>
<th>Wilcoxon Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Median (%)</td>
</tr>
<tr>
<td>Raw predictions</td>
<td>7.7</td>
<td>10.5</td>
<td>0.6</td>
</tr>
<tr>
<td>Smoothed predictions</td>
<td>7.7</td>
<td>10.1</td>
<td>1.5</td>
</tr>
<tr>
<td>Limited predictions</td>
<td>7.2</td>
<td>9.9</td>
<td>0.3</td>
</tr>
</tbody>
</table>
Figure 3.3: Percent tree mortality for a section of the Medicine Bow National Forest in each year of the time series.
the time series by an average of 131,538 ha. The ADS and raster maps indicate that 27.9% and 42.4%, respectively, of the approximately 1.5 million-ha study area was infested in 2005. The infested area climbed to 71.2% and 78.7%, respectively by 2015. The rate of extensification decreased over time in both datasets, nearing zero in 2011 and thereafter, while the severity of infestation continued to intensify. There was strong evidence against the null hypothesis that there was no difference, on average, between the percent mortality of the pixels that both datasets identified and those that only our raster maps identified (paired t-test, t = 17.514 with a one-sided p-value < 0.001 on 10 df). We estimated that the infestation severity of the pixels that only our raster maps identified as infestation was 7.2% less, on average, than

Figure 3.4: Average severity and annual cumulative extent of infestation in our raster maps compared to ADS extent. The ADS and raster maps indicate that 27.9% and 42.4%, respectively, of the 1,559,000 ha study area was affected in 2005. The affected area climbed to 71.2% and 78.7%, respectively.
the pixels identified by both datasets as infestation with an associated 95% confidence interval of 6.3% to 8.1% (Fig 3.5).

Discussion

We mapped the progression of tree mortality severity during a major epidemic outbreak in the Central U.S. Rocky Mountains. We developed and evaluated a robust multitemporal model of percent tree mortality over an 11-year period of study. Our time-series analysis provided visual and quantitative measures of both extensification and

Figure 3.5: Raster map severity v. ADS extent of infestation. The pixels identified as infested by only our raster maps were lower, on average, than those that both the ADS and our raster maps identified as infested.
intensification of MPB infestation (Figure 3.3, Figure 3.4). This approach to mapping infestation is the first to our knowledge to predict severity from a time-series analysis. This approach enabled us to predict infestation in years for which reference data were not available, although we were not able to validate the results for those years. Mapping MPB outbreaks in terms of severity overcomes complications with defining a threshold for what is considered an affected pixel and instead allows the user to decide a level most fitting for their application. Furthermore, maps of severity can be combined with other continuous forest metrics such as percent forest cover and pre-mortality biomass, for example, to provide estimates of dead biomass.

We found that the best predictive model of tree mortality was the simplest one. GLM’s basic structure allowed for interpretation of the predictor variables and their coefficients compared to prominent model types like random forest that often make interpretation impractical. We used Landsat surface reflectance values, which standardized the values of spectral data and enabled an evaluation of which variables have the largest relative weighted coefficients. The two variables with the greatest impacts were the annual median green bands for pre-outbreak and outbreak years. The contrasting signs of the coefficients for these variables (positive for pre-outbreak, negative for during the outbreak) has the effect of building the change in green reflectance into the model and seems to use the drastic change in green reflectance from tree death to identify tree mortality. The red and NIR bands are a logical inclusion in the model for their usefulness in many vegetation indices. The presence of the blue bands is surprising because the blue portion of the electromagnetic spectrum contains the most
atmospheric effect and is rarely incorporated into vegetation indices. The absence of NDVI and the median differences provides an argument for multispectral tree mortality analyses over those using a single index (Lawrence and Ripple, 1998; Maynard et al., 2007). The absence of slope, aspect, and elevation variables suggests that, at an epidemic level of outbreak, topography might not have a notable influence on beetle attack.

Visual inspection of the raster maps indicated that the outbreak both extensified and intensified from 2005 to 2011, then maintained a relatively constant extent while intensifying further from 2013 to 2015 (Figure 3.3). This observed trend is representative of the incipient outbreak phase and outbreak phase of MPB infestation (Lundquist and Reich, 2014). This trend also points to an important advantage of mapping a time series of severity rather than extent. Evident in the contrast with ADS, extent mapping data failed to reveal the progress of the epidemic after 2012, whereas our raster maps showed intensification of the outbreak.

The accuracy of the final smoothed and limited maps met and exceeded that of previously reported single-date within-pixel forest analyses (Long and Lawrence, 2016; Savage et al., 2017, 2015). The model overestimated low mortality values and underestimated high mortality values. This trend is consistent with other within-pixel analyses (Long and Lawrence, 2016; Savage et al., 2015). We cannot directly compare our maps to the other time-series disturbance methods, however because those methods use classifications with varying thresholds for disturbance.

The predictions agree closely with the ADS maps on a regional scale with both datasets conveying similar trends of increasing extent of mortality throughout the time
series. Our raster maps did identify a greater extent of mortality overall compared to the ADS maps. This is likely because our pixel-based analysis identified single affected pixels within stands of unaffected pixels that were too small for human interpreters of the ADS to identify or that areas were simply missed by the ADS surveys. This latter possibility might be especially true with respect to areas such as Rocky Mountain National Park, which is not surveyed as frequently. We found that the pixels that were not identified as infected by the ADS but that our raster maps did identify had considerably lower levels of mortality. This indicates that our raster maps identified widespread, lower severity infestation not recorded in the ADS dataset (Figure 3.5). Detecting these low levels of infestation might improve mitigation efforts by allowing managers to address new infestations before they become more severe.

This methodology produced one mortality map per year for the period within the training data. Annual maps are sufficient when beetle life cycles take one or more years. MPBs have been known to complete more than one cycle a year in warming climates (Mitton and Ferrenberg, 2012). This analysis could be altered to analyze a spring and fall time series by using seasonal median spectral responses as the explanatory variables. The efficacy of using the established time-series model to extrapolate beyond the study period is untested. Year of outbreak was an available explanatory variable not selected for use in the final model, suggesting that temporal trends were not necessary to accurately map the infestation. Spectral response alone might provide enough information to map infestation in extrapolated years, allowing users to set up a model using a few base years of imagery and then continue to map infestation as new imagery becomes available.
This analysis demonstrates the efficacy and advantages of mapping time series of within-pixel disturbance. Our raster maps achieved a high overall accuracy and were able to identify widespread, lower severity infestation absent from the ADS. This technique can improve mitigation efforts by allowing managers to: address low severity infestations before they intensify, monitor intensifying infestations within previously identified outbreak extents, and combine infestation severity with other forest metrics. Land cover information formatted as a measure of severity provides flexibility in data applications. The advancement of spectral, radiometric, and temporal resolution of Landsat-scale imagery will further enable analysis of continuous land cover responses. The raster maps created in this study offer a wealth of information that can be tailored to explore a wide range of forest health questions.
CHAPTER FOUR

PROBABILITY OF NEW BARK-BEETLE INFESTATION:
A MODEL-BASED RECURSIVE PARTITIONING APPROACH

Introduction

The mountain pine beetle (MPB; *Dendroctonus ponderosae*) is a parasitic insect native to western North America. MPBs feed on a number of host pine species, including lodgepole, white bark, ponderosa, limber, bristlecone, and pinon pines (USFS Rocky Mountain Research Station, 2005). MPB outbreaks are historically agents of healthy forest disturbance, which maintain diversity in forest age and structure (Raffa et al., 2009). The intense MPB outbreaks of the recent decades impact forest structure in ways that degrade wildlife habitat, carbon storage, and watershed quality while threatening timber stocks, recreation, air quality and scenic value (Amin et al., 2012; McGregor, 1985; Safranyik et al., 1974; USFS Rocky Mountain Research Station, 2005). Individual tree and beetle behavior occupy a prominent space in MPB research. Researchers can make inferences on the wider effect of these behaviors, but cannot account for interactions caused by many beetles, trees, and varying ecologic factors at the landscape scale (Lundquist and Reich, 2014). Mass behavior of MPB attack has not been extensively researched, particularly in relation to dispersal distance and directionality (Aukema et al., 2006; Chapman et al., 2012; de la Giroday et al., 2012). Isolated effects of climate and topography on beetle fecundity and proliferation have been examined, but the interactions between these variables and their effect at different stages of an outbreak
are poorly understood. Techniques in use for managing MPB at a landscape scale are preventative, rather than responsive, and include thinning and prescribe fire (National Park Service, 2005; Safranyik et al., 1974). Thus it is essential to predict where new outbreak might occur and treat those regions in advance of an infestation. An improved understanding of MPB behavior at the landscape scale will allow managers to accurately identify high-risk regions and more effectively mitigate impacts to those areas during an outbreak.

The life cycle of a MPB reveals how individual environmental factors might affect beetle fecundity and success in finding a new host. A univoltine, or one year life cycle of a MPB beetle begins when an adult pine beetle lays its eggs in a new host tree. These eggs hatch into larvae and overwinter inside the tree’s phloem. The larvae feed off the phloem, killing the tree by infecting it with various strains of blue stain fungi that interrupt the exchange of water and nutrients between its roots and needles. Many larvae die in the freezing temperatures of consistently cold winters. Surviving larvae transition into pupae in the spring and then hatch as adults in early summer. The adults leave the tree in which they developed to mate and find a new host tree in which to lay their eggs (Safranyik and Carroll, 2006).

Perhaps the most obvious potential risk factors for the spread of MPB to a new location are an abundant source of both adequate hosts and MPB adults in the immediate vicinity. MPBs are known to target larger diameter trees due to their thicker phloem and larger surface area, however their preference in host size changes with the phase of outbreak, making definitive behavior elusive (Amman, 1972; De la Mata et al., 2017).
High tree density can also influence host susceptibility to MPB attack by competition-limited access to resources, such as nitrogen and light, which affect the tree’s ability to produce defense compounds (Waring and Pitman, 1985). Dense trees also facilitate MPB proliferation by providing short distances for MPB dispersal to a new host.

Dispersal and range of MPB when finding a new host can be highly variable due to the effect of wind on flight and pheromone diffusion. MPBs emit pheromones to attract nearby beetles and initiate mass attacks on suitable hosts to overcome the host tree defenses (Pitman et al., 1969; Raffa and Berryman, 1983; Safranyik et al., 1974). Pheromone concentration declines exponentially with distance from the beetles, however, and effective range is estimated to be only tens of meters (Byers et al., 1989). MPBs fly downwind when dispersing from the expended host tree until they encounter an active pheromone plume, then fly upwind to the source (Gray et al., 1972). MPB are weak fliers and are likely to travel short distances to find a host (less than 30 m), however they can be caught in convection currents and transported more than 100 km in upper wind currents (Chapman, 1967; Furniss and Furniss, 1972; Robertson et al., 2007; Simard et al., 2012). The impact of MPB source infestations might be directional (anisotropic), with greater risk of infestation occurring downwind from infestation sources. Directionality (anisotropy) in autocorrelation would indicate that an environmental vector, such as wind, is a conduit for MPB dispersal.

Trees have a number of physical and chemical defenses against insect attack (Franceschi et al., 2005). Their thick bark creates a physical barrier that MPBs must bore through. Trees use chemicals to repel insects and make their bark more difficult to digest.
Tree sap physically pushes MPBs out of the bark in a process called pitching out. The sap also contains toxic chemicals that further hinder the attackers. These defenses can be weakened when trees are stressed, such as by extreme drought, although there is evidence that trees can make internal adjustments to fortify defenses during these times (Dunn and Lorio, 1993; Powell and Bentz, 2009).

Environmental and spatial factors form complicated interactions with tree defenses and MPB survivorship that influence MPB infestation on a landscape scale. Topographic characteristics, including slope, aspect, and elevation, create local variability in temperature and moisture (Geiger, 1956; Oke, 1987). Warmer and drier slopes, on southerly aspects and at low elevations, might provide reduced defense against attack compared to colder and wetter slopes, on northerly aspects and at high elevations (Nelson et al., 2007; Wulder et al., 2006). Seasonal variation in susceptibility to cold is an important consideration as well. Cold snaps in the spring and fall might be more deadly to larvae than consistently cold winter temperatures because MPBs are more cold-hardened with cryoprotectants in the middle of winter, than on the tail ends of the season (Bentz and Mullins, 1999). Geographic locations and features can also influence tree susceptibility to attack. Limited host availability above tree line, for example, might act as a barrier to, or produce directionality in, the spread of MPB infestations (de la Giroday et al., 2012). Extreme cold in geographically northern latitudes can also limit the spread of MPBs (Safranyik, 1978). All of these environmental and spatial factors can have an influential in role in eruptive MPB infestations.
Trees that succumb to MPB attack take several years to fully exhibit the effects, transitioning from green needles (green stage) to red needles (red stage). The tree has reached gray stage once all needles have dropped (Safranyik and Carroll, 2006). The initial attack begins the year before trees exhibit the characteristic red needles. Climatic variables from one year or several years prior to observed tree mortality are thus more apt to explain beetle behavior than those of the year in which the attack is observed (Chapman et al., 2012; Jewett et al., 2011).

MPB infestations are controlled by a series of thresholds and move cyclically through four major stages of outbreak (Lundquist and Reich, 2014; Raffa et al., 2008). The predominant phase is the “endemic phase” in which MPB infestation occurs across the landscape at low densities that are difficult to detect. This is followed by the stand-level incipient outbreak phase characterized by clusters of attacked stands at short and long ranges from dispersing beetles (Lundquist and Reich, 2014). This phase occurs when stand composition and structure herbivory, and other tree ailments compromise tree resistance or favor MPB proliferation (Raffa et al., 2008, 2005). The infested stands begin to overlap and grow into a traveling wave in the landscape-level outbreak phase (Lundquist and Reich, 2014). This phase results when weather and climate, landscape composition and structure, and MPB dispersal further compromise tree resistance or favor MPB proliferation (Raffa et al., 2008). The infestation returns to endemic levels in the outbreak collapse phase, when the available hosts become scarce or environmental factors limit population growth (Lundquist and Reich, 2014). The relationships between MPB infestation and controlling variables can change as infestation thresholds are
crossed. The initial controlling factors that provoked an outbreak might not be needed to sustain it (Raffa et al., 2008).

Modeling the risk of infestation is complicated by the existence of multiple thresholds. One model cannot adequately explain the relationship between MPB infestation and environmental covariates at every phase of the outbreak. Model-based recursive partitioning (MOB) using logistic regression is suitable for identifying the risk of incipient MPB attack because this technique can produce a unique logistic model for each spatial and temporal threshold that identifies the importance of the main effects in each situation. Model-based recursive partitioning (MOB) fits a parametric model to a dataset using main effect variables and then splits the data set using a second group of parameters, called partitioning variables, to produce local models on each subset of the dataset. The MOB splits the dataset where there is the most instability in the model parameters with respect to the partitioning variables and then produces a refined model for each split, called a node. This process repeats for all nodes until variable instability is adequately managed (Zeileis et al., 2008).

We employed a logistic regression based MOB to model the likelihood of incipient infestation throughout nine years of an outbreak in the Central U.S. Rocky Mountains. Our specific objectives were to identify: (1) to what degree severity (characterized by percent mortality) of nearby infestations increased probability of new infestations; (2) the degree to which this effect varied across space and time with respect to other factors that have been noted to constitute risk factors, specifically topographic and climatic variability; and (3) the extent to which this effect was directional
(anisotropic) relative to prevailing winds. Identifying how primary risk factors for MPB infestation vary across environmental gradients and quantifying their effects has the potential to reveal actionable tools for mitigating and responding to MPB epidemics. Characterizing relationships between MPB proliferation and environmental variables will give managers and scientists insight for future outbreaks and their effect on anthropogenic and natural systems.

**Methods**

**Study Area**

The study area for our analysis was comprised of the forested regions of a single Landsat scene, path 34 row 32, in northern Colorado and southern Wyoming (Figure 3.1). We restricted this analysis to conifer forests only where pixels were greater than or equal to 10% forested in the LANDFIRE data set (USGS, 2008). The study area excluded areas logged during the time-series period (Woodward et al., 2017), areas within city boundaries (U.S. Department of Commerce et al., 2013), highways (Colorado Department of Transportation, 2011; Wyoming Department of Transportation, 2005), high density housing (Radeloff V. C. et al., 2005), agriculture, and developed open space (U.S. Geological Survey, 2014). The resulting area included approximately 1.5 million ha of land the Medicine Bow, Routt, Arapaho, Roosevelt, White River, and Pike National Forests as well at the Colorado State Forest State Park and the Rocky Mountain National Park (RMNP). The elevation ranged from 1,636 m to 4,124 m. A stand-level incipient outbreak began in this area in 2003 and grew to a landscape-level outbreak over the next
several years (Chapman et al., 2012). Predominant host species in the study area included lodgepole pine (Pinus contorta var. latifolia), ponderosa pine (Pinus ponderosa), and limber pine (Pinus flexilis) (Chapman et al., 2012). We defined tree mortality as any red stage or grey stage tree as well as any tree that died from any other disease or physical

Figure 4.1: Study area map of the forested land in the Central U.S. Rocky Mountains.
trauma. It was not possible to exclude trees that died from other diseases or physical traumas if they also displayed red or gray stage characteristics.

**Reference Data**

Our analysis modeled the probability that each 30-m pixel within the study area experienced new infestation or remained uninfested from one year to the next. We determined new infestation using the eleven raster maps of severity of infestation, as percent land cover of tree mortality, from 2005 to 2015 that were created in the previous chapter. We defined infestation as detectible tree mortality within these raster maps. Pixels newly infested with MPB were identified for each year from 2006 to 2015 by identifying each pixel that had 0% infestation in one year and > 0% infestation in the immediately succeeding year. The 2005 raster map was the earliest date available, thus it was not possible to identify newly infested pixels in 2005 and there were no newly infested pixels in 2015. We therefore analyzed patterns of outbreak in years 2006-2014. Uninfested pixels were identified in the same manner, singling out those pixels with 0% infestation in one year that remained 0% infested the following year.

A stratified random sampling design selected 10,000 training points in each year, 5,000 points of new infestation and 5,000 points where pixels remained uninfested in the year of observation (n = 90,000). We selected an additional 2,500 validation points for each year using the same stratified design (n = 22,500). The response, the main effects, and the partitioning variables were extracted at all of the training and validation points.
Digital Data Acquisition and Pre-Processing

Our analysis explored an array of possible spatial autocorrelation terms representing proximity to source beetle infestations as main effects and several additional environmental risk factors as partitioning variables, which enabled us to determine whether the main effects varied spatially based on these partitioning variables (Zeileis et al., 2008). We averaged percent tree mortality from the raster maps of infestation severity at potential MPB dispersal distances (30, 60, 90 m and 120 m radii; Figure 4.2) surrounding the pixel of interest using a moving window to represent proximity to source infestations of varying intensities (Gray et al., 1972; Jewett et al., 2011; Robertson et al., 2007). Additionally, we created directional windows to the northwest, west, and

![Figure 4.2: Neighborhoods for autocorrelation partitioning variables calculated by averaging the infestation severity in the light gray pixels surrounding the dark gray pixel. Above are isotropic patterns at each radii and anisotropic patterns at 90 m only. There were sixteen autocorrelation terms in total: four isotropic variables and twelve anisotropic variables (four radii in the NW, W, and SW directions).](image-url)
southwest at each radius to test for the effects of prevailing westerly winds present for the study area (Hansen et al., 1978). Each year of new infestation was paired with the surrounding infestation data from the previous year based on the precept that these infestations would be the likely sources of tree mortality detectable in the ensuing year. Sixteen infestation source autocorrelation terms in total were considered as main effects in this analysis, 4 non-directional (isotropic) and 12 directional (anisotropic). We included partitioning variables to account for variation in outbreak phase, weather, topography, and geographic space. We defined two outbreak phases using our raster maps, which displayed an obvious change in the rate of extensification (increase in the total extent of infestation over time) when comparing years 2006 through 2010 to years 2011 through 2014 (Figure 4.3).

Our MOB models included several partitioning variables to account for potential variation in the relationship between probability of a new infestation and MPB source infestations across the landscape (Table 4.1). We created a variable to differentiate the two phases of the outbreak, recognizing that if the MPBs surpassed a threshold, the statistical relationships might change as well. We obtained annual precipitation and several temperature covariates at a spatial resolution of 0.0416 decimal degrees latitude and longitude corresponding to approximately 4-km cells (PRISM Climate Group, 2005). The temperature partitioning variables included average minimum daily temperature in early winter (October-November; AMDT-A), deep winter (December-February: AMDT-B), and late winter (March-April: AMDT-C). The early and late winter averages were combined to form a tail-season average minimum daily temperature (AMDT-D).
Table 4.1: Variables included in the MOB and their respective sources.

<table>
<thead>
<tr>
<th>Variable</th>
<th># of Variables</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incipient infestation</td>
<td>1*</td>
<td>Reference Data</td>
</tr>
<tr>
<td>Isotropic surrounding infestation severity (30, 60, 90, and 120 m radii)</td>
<td>4**</td>
<td></td>
</tr>
<tr>
<td>Anisotropic infestation severity in the NW, W, and SW directions (30, 60, 90, and 120 m radii)</td>
<td>12**</td>
<td></td>
</tr>
<tr>
<td>Outbreak phase</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>UTM coordinates (x, y)</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Average min. daily temperature (early winter, deep winter, late winter, and tail season average) one and two years prior</td>
<td>8</td>
<td>PRISM</td>
</tr>
<tr>
<td>Average annual precipitation one and two years prior</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>1</td>
<td>US Geological Survey</td>
</tr>
<tr>
<td>Aspect (N, NE, E, SE, S, SW, W, NW, Flat)</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

*response variable, **main effects, all others are partitioning variables.

Figure 4.3: Annual cumulative extent of infestation in our raster maps from 2005 to 2015. The rate of extensification (increase in the total extent of infestation over time) changes from the earlier years in the time series (2005-2010) to the later years of the time series (2011-2015).
We matched each year of new infestation with the weather covariate from one and two years prior because the first sign of MPB attack visible to satellite imagery, which is the basis of the raster maps, presents as red stage infestation a year after attack. We derived three topographic partitioning variables, slope, aspect, and elevation, from a 30-m digital elevation model (U.S. Geological Survey, 2015, 2013). We calculated slope as a percent and classified aspect into nine classes: north, northeast, east, southeast, south, southwest, west, northwest, and flat. The final partitioning variables included were the x and y coordinates of the pixel centroids. All covariates and partitioning variables were resampled to 30-m pixel size using nearest neighbor resampling when necessary.

Data Analysis

We implemented several MOB models with logistic regression using the glmtree function in R (Hothorn and Zeileis, 2015; R Core Team, 2017). We first inspected an initial MOB of the four isotropic main effects and all the partitioning variables. We compared the correlation coefficients of each radius at each terminal node of the resulting MOB to determine which radius achieved the greatest correlation with the response. Correlation coefficients were deemed preferable over analysis of slope coefficients because high multicollinearity between the main effect variables made slope coefficients unreliable. We then ran a secondary MOB with only this best main effect and all the partitioning variables. We assessed the potential for prevailing wind driven dispersal by repeating the above process for a MOB model with all anisotropic variables and a MOB model with only the most correlated anisotropic variables. All MOB models were pruned with AICs and constrained to only include splits with a Bonferroni corrected $p$-value.
below 0.05 and a minimum bin size of \( n = 6,750 \). We chose a minimum bin size that consistently produced MOB trees of interpretable sizes without overfitting. We assessed the MOB models by their overall accuracy in predicting new infestation in the validation dataset. The resulting MOB models consisted of binary trees that subdivided land study area based on the selected partitioning variables with a separate logistic regression model applied to each division of the landscape. The MOB predictions from these logistic regression models predicted log-odds for each pixel within the study area, which were in turn converted to probabilities by exponentiation. These probabilities were converted to predicted new infestation or uninfested pixels using a 50% probability threshold (e.g., a pixel with a < 50% probability of incipient infestation for a given year was predicted to remain uninfested).

**Results**

The MOB model with all isotropic variables produced nine nodes with an overall accuracy for validation data of 71.2%. We calculated the correlation coefficients between the isotropic main effects and the binary response of new infestation or remaining uninfested at each node (Table 4.2). The 30-m isotropic variable was most highly correlated in every node except the third node where it was only 0.01 less correlated than the other isotropic variables. We ran a second MOB model with only the 30-m isotropic variable as a main effect. This reduced model produced ten nodes with an overall accuracy of 72.6%. The 30-m isotropic main effect was statistically significant (\( p \)-value < 0.01) for all ten terminal MOB nodes. This indicated that nearby severity of infestation
strongly influenced the probability of incipient infestation.

Table 4.2: Correlation coefficients for all isotropic variables at each node with the binary response of new infestation or uninfested.

<table>
<thead>
<tr>
<th>Node</th>
<th>30 m</th>
<th>60 m</th>
<th>90 m</th>
<th>120 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.48</td>
<td>-0.47</td>
<td>-0.46</td>
<td>-0.44</td>
</tr>
<tr>
<td>2</td>
<td>-0.44</td>
<td>-0.43</td>
<td>-0.42</td>
<td>-0.40</td>
</tr>
<tr>
<td>3</td>
<td>-0.43</td>
<td>-0.44</td>
<td>-0.44</td>
<td>-0.44</td>
</tr>
<tr>
<td>4</td>
<td>-0.33</td>
<td>-0.32</td>
<td>-0.32</td>
<td>-0.31</td>
</tr>
<tr>
<td>5</td>
<td>-0.37</td>
<td>-0.36</td>
<td>-0.35</td>
<td>-0.33</td>
</tr>
<tr>
<td>6</td>
<td>-0.35</td>
<td>-0.33</td>
<td>-0.31</td>
<td>-0.29</td>
</tr>
<tr>
<td>7</td>
<td>-0.28</td>
<td>-0.26</td>
<td>-0.25</td>
<td>-0.23</td>
</tr>
<tr>
<td>8</td>
<td>-0.29</td>
<td>-0.26</td>
<td>-0.24</td>
<td>-0.22</td>
</tr>
<tr>
<td>9</td>
<td>-0.19</td>
<td>-0.15</td>
<td>-0.12</td>
<td>-0.09</td>
</tr>
</tbody>
</table>

The reduced MOB model used elevation, the x and y coordinates of pixel centroids, aspect, late winter minimum average temperature, and outbreak phase for partitioning variables. Elevation, y, and aspect were most prominent in the MOB (Figure 4.4). New infestation was more likely at higher elevations, in more northern latitudes, on northerly, flat and east aspects, after warmer late winter temperatures, in the earlier years of the outbreak (2006-2010), and in more eastern longitudes. The likelihood of new infestation varied across terminal nodes and severity of surrounding infestation. We examined how the equations for each node performed by inserting 0-10% surrounding infestation severity into the equations in 1% increments. Node 9 was the only node to have a probability of infestation above 50% at its intercept (Figure 4.5). Probability of infestation exceeded 50% in all nodes at a surrounding infestation severity of only 3% and reached a logarithmic asymptote in most nodes by 10% surrounding infestation.
Figure 4.4: MOB tree for the model using only 30-m isotropic severity of infestation in the year prior as a main effect. The model information at each terminal node is summarized below the node heading. Note that the intercept and slope coefficients are in log odds. AMDT-C1 stands for average daily minimum temperature March through April one year prior. *p-value < 0.05. All others are < 0.0001.
Nodes 1, 2, and 3 had small intercepts but the largest slope coefficients, meaning that they were most susceptible to surrounding infestation.

We then examined what our MOB model would have predicted for each node given the average infestation severity observed at that node for each year of the time series (Figure 4.6). Our MOB model predicted that nodes 7, 8, 9, and 10 had, on average, greater than 50% probability of new infestation across all years of the time series. Nodes

Figure 4.5: Conceptual comparison of nodes across increasing severity of surrounding infestation. We calculated these probabilities using the output from a MOB model using only isotropic infestation severity at 30 m as a main effect. The black dotted line represents the threshold by which we classified predictions as new infestation or not infested.
4 and 6 crossed the threshold in 2009 and persisted above it thereafter. Nodes 1, 2, 3, and 5 remained below the 50% threshold for all years of the time series except for node 3 in 2012, which spiked abruptly before falling back below the threshold in 2013. Pixels meeting requirements for each node coalesced spatially (Figure 4.7). The nodes with the highest probability of infestation were in the north central section of the study area, while the nodes with the lowest probability of infestation were found in the southeast and southwest sections of the study area. Elevation, x, and y partitioning variables dominated

Figure 4.6: The predicted probability of infestation within each node based on the average surrounding infestation severity at 30 m at that node for each year of the time series. Note that Nodes eight and nine end early and node 10 starts late because these nodes are dependent on the two outbreak phase (2006-2010 and 2011-2014).
Figure 4.7: The ten nodes from the best MOB model coalesced spatially. Vertical and horizontal lines represent the effects of the x and y coordinates respectively. Variation within the green and blue colored nodes is due to differences in aspect while the delineation between these modes is due to differences in elevation. Purple colored nodes are also delineated from orange nodes using elevation. Note that the orange nodes (nodes 8 and 9) merge to form node ten in the second phase (2011-2014).
a visual representation of the nodes with aspect and temperature having more nuanced effects.

The MOB model with all anisotropic variables produced nine nodes with an overall accuracy of 71.6%. We calculated the correlation coefficients between the anisotropic main effects and the binary response of new infestation or remaining uninfested at each node (Table 4.3). The three 30-m anisotropic variables were most highly correlated in every node except the third node for the southwest anisotropic variable where it was only 0.01 less correlated than at the other southwest distances. We ran a final MOB model with only the three 30-m anisotropic variables as main effects. This reduced model produced ten nodes with an overall accuracy of 71.1%. Both versions of the anisotropic MOBs achieved a lower accuracy than the reduced isotropic MOB

Discussion

Impact of Outbreak Severity on New Infestations

Nearby infestation severity strongly influenced the probability of new infestation. Isotropic severity of infestation in the year prior was statistically significant ($p$-value < 0.01) for all four radii. The effect was most highly correlated at 30 m, suggesting that MPB dispersal takes place more strongly at 30 m or less (Table 4.2). The MOB accuracy improved from 71.2% to 72.6% when the 60, 90, and 120 m isotropic main effects were removed. This more parsimonious model performed just as well, if not better than the model with all radii, further supporting that dispersal from source infestations was dominated by shorter distances, with distances greater than 30 m causing increased error
Table 4.3: Correlation coefficients for all anisotropic variables with the binary response of new infestation or uninfested. Shaded columns represent most correlated terms across all nodes.

<table>
<thead>
<tr>
<th>Node</th>
<th>NW 30</th>
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<th>NW 90</th>
<th>NW 120</th>
<th>W 30</th>
<th>W 60</th>
<th>W 90</th>
<th>W 120</th>
<th>SW 30</th>
<th>SW 60</th>
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<td>-0.33</td>
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<td>-0.35</td>
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</table>
in the model. Elevation was the most important partitioning variable for the final isotropic model, followed by y coordinate and aspect, which were utilized in both branches from elevation. AMDT-C from the year prior, phase, and x coordinate were helpful, although less prominent, partitioning variables.

The trend observed that the AMDT-C partitioning variable aligned with expectations of cooler areas possessing superior environmental protection from MPB attack. Locations with lower late winter temperatures (below an average of 4.6°C) on average had reduced probability of experiencing new infestations. This result was consistent with the documented negative effects of low temperatures on MPB survival and greater vulnerability to low temperatures in the spring and fall when MPBs have seasonally lower concentrations of cryoprotectants (Bentz and Mullins, 1999; Jewett et al., 2011; Régnière and Bentz, 2007). The phase and x partitioning variables indicated that host availability influenced probability of new infestation. New infestation was more likely in the earlier phase from 2006 to 2010. Widespread infestation during this phase might have consumed available hosts making new infestation in the following phase less likely. This result is consistent with previous research documenting an inverse relationship with new infestation and host depletion (Jewett et al., 2011).

The trends observed in the elevation and aspect partitioning variables were counter to expectation. We expected the colder high elevations and colder and wetter northerly aspects to be less likely to suffer new infestations, but they displayed a higher probability of new infestation within our study area. The study area demonstrated the expected trend of higher elevations suffering less infestation, earlier in the outbreak, from
1996 to 2001 (Chapman et al., 2012). Inspection of our reference data also supported this trend, revealing that in 2005 and 2006 mean infestation severity was 5.2% more severe at low elevations than at high elevations (2890 m boundary; \( t = 2.7 \), two-sided \( p \)-value = 0.01, on 27 df; 95% CI: 1.3 - 9.2%). The observed severity of infestation at lower elevations indicated that the host might have been depleted, or at least been widely infested in the low elevations by 2006. New infestation would thus be less likely at those low elevations and more likely in the uninfested higher elevations in the later years of the study period. The trend of range expansion to higher elevations is also consistent with range expansion due to changing climate (Carroll et al., 2004).

We also investigated the relationship between infestation severity and aspect. We found no evidence of a difference in mean infestation severity on northerly and southerly aspects (\( t = 0.5 \), \( p \)-value = 0.62, on 155 df). Northerly aspects did, however comprise a greater portion of the study area (63% northerly aspects). Tree density can influence host susceptibility to MPB attack (Chapman et al., 2012; Chojnacky et al., 2000; USFS Rocky Mountain Research Station, 2005). We did not use percent forest cover as a partitioning variable because these data were not available for the entire study area; however, we interpreted percent forest cover from NAIP imagery for 182 locations. We found that the mean percent forest cover within the study was 7.9% higher on northerly aspects than on southerly aspects (\( t = 2.7 \) two sided \( p \)-value 0.007 on 136 df; 95% CI: 2.2 - 13.6%). Aspect might have served as a proxy for percent forest cover in our MOB. We posit that the denser northerly aspects were more prone to infestation because the trees were closer together and more susceptible to dispersing beetles.
Notable absences to the selected partitioning variables included the AMDT-A and AMDT-B variables as well as all temperature variables from two years prior. Cold snaps in the spring evidently had a stronger influence on cold induced beetle mortality than late fall and deep winter periods of cold. Previous research identified cold snaps in both the spring and fall to be influential, while our MOB only identified cold spring temperatures as a valuable factor (Bentz and Mullins, 1999; Jewett et al., 2011). Furthermore, MPBs were most influenced by temperature one year prior to detectible signs of tree mortality, which is consistent with field evidence of univoltine MPB lifecycles (Bentz and Schen-Langenheim, 2006; Safranyik and Carroll, 2006).

Another notable absence to the selected partitioning variables are both of the precipitation variables. This suggests that, within our study area and time period, variation in tree moisture was not sufficient to create a distinguishing impact on defense against MPB infestation. This could be due in part to the drought conditions before our study period in 1994 and 2001-2002, which then returned to average or above average PPT from 2004-2011 with a brief drought in 2012 followed by normal conditions in 2013 (PRISM Climate Group, 2005). The droughts in earlier years might have created conditions conducive to MPB populations crossing a threshold past which drought conditions were not necessary to sustain the outbreak (Chapman et al., 2012; Raffa et al., 2008).

Spatial Variation in the Effect of MPB Outbreak Severity on New Infestations

Spatial variation in probability of new infestation in the north-south latitudes also defied expectation. We expected colder northern latitudes to be more resistant to
infestation when in fact they demonstrated a higher probability of new infestation. There was evidence that the relationship between infestation severity and y-coordinate was influenced by tree density. There was no evidence of a difference in mean infestation severity in northern and southern latitudes in 2005 and 2006, the earliest years of our study period \((t = 0.6, \ p\text{-value} = 0.55\), on 17 df\), demonstrating that the high probability of new infestation in northern latitudes was not due to higher levels of infestation in the south that then moved north in later years of outbreak. We found that mean percent forest cover within the study was 6.9% denser in northern latitudes than in southern ones \((t = 2.2, \ \text{two sided } p\text{-value} = 0.03\) on 102 df; 95% CI: 0.6 - 13.2%). The northern latitudes had more dense tree cover and were, therefore, potentially more susceptible to dispersing MPBs. The trend of range expansion to more northern latitudes is also consistent with range expansion due to changing climate (Carroll et al., 2004).

The x partitioning variable revealed that new infestation was more likely in the east. The delineating boundary fell across the Central U.S. Rocky Mountains (Figure 7). Inspection of our reference data found the average infestation severity of western pixels was 4.8% more severe than eastern pixels for the early years for which we had reference data, 2005, 2006, and 2009 \((t = 2.18\) two sided \(p\text{-value} = 0.03\) on 74 df; 95% CI: 0.4 - 9.4%). The Rocky Mountains were likely a barrier to spread of the infestation, a result congruous with the northern Rocky Mountain geoclimatic barrier to MPB infestation (de la Giroday et al., 2012). New infestation might have been more likely to the east in the first phase because the west was already disproportionally infested. This east-west
deferential did not play a role in the second phase, suggesting that the infestation successfully crossed the Rocky Mountain crest.

Our spatial partitioning variables created broad variation in the probability of new infestation, particularly when surrounding infestation severity was low. Node 8 conditions (spatially west) were 20% less likely to be infested than node 9 conditions (spatially east), when surrounding infestation severity was 0-2% (Figure 5). Similarly, Node 1 and 2 conditions (spatially south) were 16% and 19% less likely to experience new infestation than their northern counterparts, nodes 3 and 4 (spatially north), when surrounding infestation severity was 0-2%. The combination of these factors along with elevation, phase, and aspect resulted in node 1 conditions being 3.5 times less likely to experience new infestation than node 9 conditions, when surrounding infestation severity was 0-2%. There was almost no difference between nodes 1, 2, 3, 4, 8, and 9 once infestation severity increased to above 7% (Figure 5).

Effect of Directionality on New MPB Infestations

The anisotropic infestation severity main effects performed slightly worse than the isotropic main effects. The best MOB model used only the isotropic 30-m main effect. We did not find compelling evidence of infestation severity in the westerly directions influencing probability of new infestation more than isotropic infestation severity. This result demonstrates that, at the scale detectable with our data (30 m or more), predominant winds were not a key factor in the probability of new infestations compared to the overall severity of infestation surrounding a site. MPB dispersion has been documented in previous studies to be wind aided (Chapman, 1967; Furniss and
Furniss, 1972; Robertson et al., 2007; Simard et al., 2012). The absence of compelling evidence of this effect in our study could be the result of the effects primarily occurring at shorter distances or that these effects are less prevalent during epidemic phases of an outbreak. The MPB tendency to fly downwind of a host tree and then turn back and fly upwind to the tree might also mask these effects at the spatial distances we examined (Gray et al., 1972).

**Implications for Management**

The node characterizations are helpful tools for understanding the processes affecting new MPB infestation. The study area employed for this analysis is much larger than a typical management unit, however, and managers would likely find replicating this technique over smaller spatial extents to be more applicable. The MOB model serves a dual purpose of understanding processes driving MPB attack and predicting where new infestation might occur. The model can apply infestation severity from the current year to predict probability of new infestation in the following year. This predictive functionality demonstrates how areas with similar amounts of mortality can have widely differing probability of new infestation due to the effects of environmental and spatial factors (Figure 4.8). The predictive power of this technique could be advantageous for informing mitigation efforts and to get a head start on completing the proper protocol for salvage logging. Forest managers might focus treatments reducing tree density in areas of high probability of infestation. Low probability areas could be most efficiently protected by reducing the probability of attack in nearby high probability regions.
Figure 4.8: The probability of new infestation for 2008 calculated with 2007 data. Inset maps A and B demonstrate that areas with similar amounts of surrounding severity of infestation have differing probability of new infestation due to differences in environmental and spatial factors.
Conclusions

Our specific objectives were to identify: (1) to what degree severity (characterized by percent mortality) of nearby infestations increased probability of new infestations; (2) the degree to which this effect varied across space and time with respect to other factors that have been noted to constitute risk factors, specifically topographic and climatic variability; and (3) the extent to which this effect was directional (anisotropic) relative to prevailing winds. We determined that severity of nearby infestations highly influenced the probability of new infestations. A 30-m radius best captured the effect of surrounding infestation severity on new infestation within our study area. The effect of nearby infestation was exacerbated at higher elevations and on northerly, flat and east aspects. This heightened probability of infestation was also evident after warmer late winter temperatures and in the earlier years of the outbreak (2006-2010). We found that nearby infestation created a higher probability of attack in more northern latitudes and in more eastern longitudes. The interaction of these environmental and spatial factors resulted in the highest probability of new infestation in the north central section of the study area, while the southern low elevation regions experienced the lowest probability of new infestation (Figures 4.6 and 4.7), which is consistent with climate-driven range expansion (Carroll et al., 2004). There was not strong evidence that direction of surrounding infestation, relative to prevailing winds, explain new infestations better than isotropic effects.

MOBs are an effective way to model the probability of infestation across different spatial and environmental thresholds. The best MOB model preformed remarkably well,
able to predict new infestation with 72.6% accuracy. The resulting node characterizations and maps provide actionable information for land managers to apply to MPB infestation in their management region by identifying the most impactful risk factors in differing spatial and environmental regions. The detailed node characterizations and annual predictive capability of our MOB allow managers to identify high priority sites for MPB mitigation (Figures 4.5-4.8). We determined that, in our study area and time period, even very low levels of surrounding infestation created high probability of new infestation. The differences between nodes, and thus the value in the node descriptions, were most prominent when surrounding infestation severity was low (0-2%; Figure 4.5). The probability of new infestation became indistinguishable between nodes as surrounding infestation severity increased.
CHAPTER FIVE

CONCLUSION

This research had two overarching objectives in support of the task one of the BANR project: to create a time series of infestation severity maps for a portion of the Central U.S. Rocky Mountains and then to apply those maps to explore what influences the probability that healthy trees will become infested. We successfully mapped tree mortality severity with a multitemporal model that met and exceeded the accuracy of similar single-date analyses (Long and Lawrence, 2016; Savage et al., 2017, 2015). This approach to mapping infestation identifies where outbreaks occur and how long the beetle killed trees in those areas have been dead. Furthermore, these maps of infestation severity can be combined with other forest metrics, such as biomass, to determine ideal locations to obtain large quantities of viable feedstock (BANR, 2018). This information will aid the beetle-killed biomass industry in finding feedstocks of sufficient quality and quantity for financially viable conversion to biomass products. This information will also aid forest managers. The maps allow for monitoring of intensifying infestations within previously identified outbreak extents. Managers could use this information to determine the optimal time and location for salvage logging or preemptive methods of stand management including thinning or prescribed fire.

Our investigation of factors influencing the probability of infestation could further prepare the beetle-kill biomass industry and inform forest managers. The probability models revealed that severity of nearby infestation was the most influential factor.
Elevation, aspect, minimum average temperature over March and April, phase of outbreak, and geographic location also affected the likelihood of new infestation, but were only consequential when surrounding infestation was minimal.

The infestation severity maps could be further validated by obtaining infestation data for the years not used to train the regression model. NAIP imagery was not available for 2007, 2008, 2010, and 2014. The ability of the regression model to interpolate by identifying infestation in years within the study period, but not directly included in the reference data, is untested. Extrapolation capabilities, identifying infestation before or after the study period, have also not been assessed. We expect that extrapolated infestation severity would be less accurate than the modeled infestation within our study period.

We used the annual median of every pixel value for each band to overcome differences in phenology from year to year and to mitigate the effects of exogenous factors, such as sun angle and atmospheric effects. It is possible that averages of shorter time periods, biannual or quarterly, could be sufficient to minimize these sources of error. Near real-time information is not needed for management of the MPB due to their typically univoltine lifecycle and the slower pace of management decisions, permitting, and implementation of mitigation efforts. More frequent iterations of this technique could be helpful as rising temperatures increase the prominence of multivoltine beetles (Mitton and Ferrenberg, 2012). Other forest metrics to which this technique could be applied might also change on a biannual or quarterly timeframe, such as percent canopy cover in regrowth after a fire.
Land cover information formatted as a measure of severity provides flexibility in data applications. The advancement of spectral, radiometric, and temporal resolution of Landsat-scale imagery will further enable analysis of continuous land cover responses. The severity maps created in this study offer information that can be tailored to explore a wide range of forest health questions. MPB infestations are known to influence fire, hydrology, soil nitrogen cycling, wildlife habitat, and air pollution (Amin et al., 2012; Chan-McLeod, 2006; Hicke et al., 2012; Morehouse et al., 2008; Pugh and Small, 2011). Our annual infestation severity maps could be used to investigate and further quantify these effects. They could also be employed to determine the degree of success past mitigation efforts have had, including salvage logging, preemptive thinning, and controlled burns.

Models predicting the probability of infestation could be improved by incorporation of stand characteristics. Tree species, density, and diameter at breast height are prominent variables in infestation risk ratings (Chojnacky et al., 2000; Munson and Anhold, 1995; Stevens et al., 1980). The U.S. Forest Service maintains a database that stores information about trees, fuels, down woody material, surface cover, and understory vegetation called Field Sampled Vegetation (FSVeg; USDA Forest Service and Natural Resource Manager, 2018). The accuracy of this dataset is variable within and between forests and is updated irregularly. Improvement of this dataset would provide a resource for broad application to forest disturbance modeling.

The probability models provided insights into MPB processes and how they interact with environmental and spatial factors. We examined the probability of new
infestation as a presence or absence response. Investigation of the probability of intensification could provide further insights. The probability maps can show which trees are at high risk of attack, but they cannot forecast which trees will be attacked next. The reference data we used to train the probability model included information from every year of the time period. A forecast uses no information from the year for which it is modeling. We anticipate that a successful forecast model would require forest stand characteristics, past infestation history, active MPB population size and location, phase of the outbreak, projected temperature and moisture, and topography.

There are many possible refinements to both the infestation severity and probability models. Continued climate change is expected to increase forest disturbance effects, including MPB outbreaks, during the next century. The importance of advancing research that supports our understanding, monitoring, and forecasting of these events will continue to increase as climatic factors exacerbate the effects of MPB outbreaks on environmental processes and social and financial assets.
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