THESIS

EVALUATING MORTALITY DYNAMICS DURING A SPRUCE BEETLE EPIDEMIC IN THE SOUTHERN COLORADO ROCKY MOUNTAINS

Submitted by

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ABSTRACT

EVALUATING MORTALITY DYNAMICS DURING A SPRUCE BEETLE EPIDEMIC IN THE SOUTHERN COLORADO ROCKY MOUNTAINS

The onset of a decade-long spruce beetle (*Dendroctonus rufipennis*) epidemic in Southern Colorado has resulted in the death of thousands of acres of forests primarily dominated by Engelmann spruce (*Picea engelmannii*). To evaluate the ecological and economic impacts of this massive mortality event, researchers and land managers need the ability to actively track its progression, spread, and severity across large spatial extents. This study improves our understanding of this under researched spruce beetle epidemic in multiple ways. First, I mapped the progression and severity of this epidemic scale spruce beetle infestation using traditional remote sensing methods in new, unexplored scenarios. Working in a large (5000 km^2), persistently cloud covered study area, I successfully fused data from multiple Landsat sensors in a decision tree based modelling framework to track the progression and severity of spruce beetle induced mortality throughout peak years of infestation (2011-2015). Next, I characterized spruce stand susceptibility to attack in this outbreak event and tracked how environmental characteristics of new spruce beetle attacks changed through time. I found that sites with new spruce beetle attack had higher canopy densities, were closer to disturbance events, and further from stream environments as compared to sites that had never been attacked. As the epidemic progressed, sites with new attacks occurred at higher elevations, on less steep slopes, were further from disturbances, and had less dense canopies. Findings from this study will support implementation of future landscape scale forest monitoring efforts using remote sensing, enable more directed on-the-ground management activities following beetle infestation, and highlight the dynamic nature of spruce beetle induced mortality across large spatial extents.

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CHAPTER 1: MAPPING PROGRESSION AND SEVERITY OF A SOUTHERN COLORADO SPRUCE BEETLE EPIDEMIC IN A CLOUDY STUDY AREA

1. Introduction

Timely monitoring of forest health across large spatial extents is a historically complex and resource intensive endeavor (Olsen *et al*., 1999, Wulder *et al.*, 2005). In the wake of a changing climate, multi-year drought conditions, and severe insect and disease activity, the complexity of monitoring and understanding change across vast expanses of public and privately owned forestlands in the western United States has only increased (Dale *et al.*, 2001). In southern Colorado, the onset of a decade-long spruce beetle (*Dendroctonus rufipennis*) epidemic has resulted in mortality across thousands of acres of forests primarily dominated by Engelmann spruce (*Picea engelmannii*) (Andrus *et al.*, 2016).

The spruce beetle is one of the most damaging agents in mature spruce stands in Colorado. A native insect, the spruce beetle primarily attacks Engelmann spruce, but can infest any spruce species found within the Colorado subalpine zone (Holsten *et al.* 1999). Spruce beetles generally have a two-year life cycle; however one to three-year life cycles have been recorded (Holsten *et al.*, 1999; Jenkins *et al.*, 2014). Adult female spruce beetles bore into a tree and create galleries for their eggs in the tree's phloem tissue. Once the eggs hatch, the larvae overwinter in the galleries and eventually tunnel out of the tree, feeding on phloem tissue as they create additional galleries. These feeding galleries inhibit the flow of nutrients throughout the tree, weakening and eventually killing the tree (CSFS, 2014). Following infestation, the tree's needles slowly fade from green to yellowish-green until entering the gray phase where they ultimately drop. The entirety of this process typically takes less than two years (Schmid and Frye, 1977; Jenkins *et al.*, 2014). The beetles can be present at both endemic and epidemic population levels (Holsten *et al.* 1999). Outbreaks typically begin in areas that have experienced disturbances, often at sites affected by blowdown events or where woody debris have accumulated (Schmid & Frye 1977). At endemic levels, adult beetles attack downed woody material and debris. At epidemic levels, beetles will attack trees of all sizes; although usually large (>40cm DBH) spruce trees are attacked first, trees of any size, including saplings can serve as suitable hosts as outbreak progresses (CSFS, 2014). As beetle pressure on hosts increases, the majority of suitable host trees within a stand can be killed (Holsten *et al.* 1999, De Rose & Long, 2007).

While spruce beetles are native to the Southern Colorado Rocky Mountains, epidemics will likely occur more frequently and with greater severity than in the past (Temperli *et al.,* 2015) with an increased prevalence of drought and changing climate, and the long term impacts of this modified recurrence interval on the environmental benefits offered by spruce/fir forests are unknown. Spruce/fir forests offer many ecological services, such as providing habitat for wildlife and filtering and improving water quality (Eyre, 1980). They also maintain an important role in carbon storage, with more carbon being stored within spruce/fir forests and associated understory plant and soil communities than most other types of conifer forests found in the United States (Birdsey, 1992). They also provide important habitats for wildlife (Uchytil 1991), offering forage opportunities and cover for many species, including ungulates such as moose (*Alces alces*), mule deer (*Odocoileus hemionus*), elk (*Cervus canadensis*), Canada lynx (*Lynx canadensis*) and snowshoe hare (*Lepus americanus*). Lumber created from spruce/fir forests also represents an important economic commodity, providing high quality lumber products used in boards and plywood (CSFS, 2008). With spruce/fir forest types representing approximately 20% of statewide forest cover (CSFS, 2014) and encompassing the largest number of forested acres under public ownership within the state (Benson & Green, 1987), monitoring and management of these forests is a top priority for both public and private land managers and owners.

Resource managers currently rely on annual forest monitoring programs, such as the United States Forest Service (USFS) Aerial Detection Survey (ADS), to plan and implement forest management projects (Fettig *et al.*, 2007), monitor forest carbon dynamics (Hicke *et al.*, 2013) and to help keep the public informed on the status and health of spruce/fir forest resources (Lockwood & Lujan, 2016). The USFS has conducted aerial surveys to remotely detect insect and disease spread on an annual basis since the 1990s, but the use of aerial surveys to monitor United States forests goes back as far 1925 (McConnell *et al.*, 2000). Surveys are completed using fixed wing aircraft and canopy mortality or damage is visually interpreted and hand sketched on to a map within a GIS, which is subsequently compared to data from previous years (Johnson & Ross 2008). Results are then reported annually and provide information such as identifying new areas of impact as well as number of acres experiencing pest damage (Johnson & Wittwer 2008). While this program has been a successful and important component in monitoring forest health in the United States, it is a costly program and measurements of insect-induced mortality, particularly the spatial extent, are not highly accurate and report on mortality intensity at coarse spatial scales (Johnson & Ross 2008). As such, researchers have attempted to supplement and expand upon information provided by the USFS ADS program by remotely sensing bark beetle induced tree mortality using moderate ($30m^2$) and high resolution (<$5m^2$) satellite imagery in combination with modelling (Wulder *et al.*, 2006).

Remote sensing has long been shown to be an effective method to detect mortality in coniferous forests (Franklin *et al.*, 2003; Meddens *et al.*, 2012), and has expanded the ability of researchers and land managers to track the progression, spread, and magnitude of bark beetle induced mortality events. Many studies have attempted to employ moderate resolution satellite imagery ($30m^2$), such as Landsat, to map insect induced tree mortality (Macomber & Woodcok 1994; Meigs *et al,.* 2011; Meddens *et al., 2014*). While employing satellite imagery to map the presence and absence of canopy mortality is a relatively efficient and cost effective method when compared to collecting similar data via aerial survey (Wulder *et al.*, 2005), a presence/absence map of mortality does not fully provide resource managers with enough information to accurately quantify spread, intensity, or distribution of an infestation.

Recent research has resulted in improved methodologies for detecting mortality severity at the stand and even single tree level (Hart & Veblen, 2015) using remotely sensed imagery. Long and Lawrence (2016) focused upon detecting mountain pine beetle (*Dendroctonus ponderosae)* induced tree mortality in Montana and demonstrated that it is possible to accurately detect and map the percentage of a pixel with dead canopy present (referred to as "mortality severity"). This method integrates ocular estimates of canopy mortality using National Agricultural Imagery Program (NAIP) orthoimagery with spatial modelling using Landsat imagery, making the data collection and modelling process very cost effective. Mapping percent canopy mortality within a Landsat pixel ($30\ m^2$) rather than mapping only presence and absence allows for the improved quantification of intensity, spread, and distribution of bark beetles (Long & Lawrence 2016). This method offers a promising opportunity for researchers to supplement information provided by aerial detection surveys with remotely sensed maps of canopy mortality severity, which may offer higher precision in estimating severity of attack. Still, the use of remote sensing and Landsat in quantification of spruce beetle induced mortality comes with its own set of complications and caveats, particularly when attempting to examine outbreaks across large study areas and at multiple time steps.

When working with remotely sensed data, researchers must consider their research objective and weigh the advantages and disadvantages of each available remotely sensed data product's spectral, temporal, and spatial resolution (Wulder *et al*., 2006*)*. Landsat TM, ETM+ and OLI's spatial resolution of 30 m^2 has been shown to be of sufficient resolution for resource managers to explore spatial patterns and trends of bark beetle outbreaks across landscape extents (Meddens & Hicke, 2014). Although Landsat's spectral resolution has been shown in many cases to be sufficient for use in predictive detection models of bark beetle attack, changing sensor properties through time (TM to ETM+ to OLI within the study period) complicates image selection and differencing and can result in spectral mismatches between neighboring image collections. Additionally, Landsat's temporal resolution of 16 days can complicate the implementation of gray stage mortality mapping at larger spatial scales because of limited image availability, especially in persistently cloudy areas such as Colorado's subalpine zone.

Approximately 55% of the earth's land surface is covered by clouds at any given time (King *et al.,* 2013). With Landsat 8 OLI collections occurring less than two times each month at any given location and the Landsat 7 ETM+ scan line corrector failure (Kovalskyy *et al.,* 2013) further limiting image availability, in some seasons it is possible that little or no cloud or scan line free Landsat imagery is available for a particular study areas of interest (Sano *et al.,* 2007). In many scenarios, this can be easily and acceptably rectified by selecting imagery that contain clouds only partially obscuring a study area of interest and excluding affected areas with a cloud mask. While this process is necessary in some applications, doing so when attempting to conduct landscape-scale forest monitoring has the potential to leave some stands unmonitored (Wulder *et al.,* 2005), which limits the applicability and transfer of methods from small study areas to larger study regions, completely limiting the ability to monitor the progression of outbreaks in these cloud masked areas through time.

A proposed method to overcome these challenges is to conduct image compositing and spectral harmonization of multiple image sets collected throughout a growing season. This method is a combined approach that offers an alternative to cloud masking, selecting a single sensor collection when multiple are available, or having spectral mismatches between sensor types across time. Image compositing and harmonization is a multi-step process that involves collecting all available Landsat imagery for a specified time period across multiple sensors and employing spectral harmonization by modelling spectral relationships between indices to ensure spectral alignment across sensors (Pflugmacher *et al.*, 2011). The tasseled cap transformation is a particularly powerful transformation that can be employed in compositing and spectral harmonization procedures because of its reported spectral consistency through time and cross-sensor application (Crist and Kauth, 1986). Once an index of interest, like tasseled cap, is applied to available satellite collections, all available pixels are composited by taking the mean or median of all overlapping cloud and shadow free observations (Braaten, 2015; Pflugmacher *et al.*, 2011). The resulting product is a spectrally aligned composited image or set of composited indices that creates the largest study area extent possible. Since the detection of spruce beetle canopy mortality hinges upon identifying gray stage spruce trees, which is relatively spectrally static and does not rely on phenology, we believe compositing is a relevant way to increase area sampled while concurrently maintaining the spectral information required to detect gray stage spruce canopy mortality.

The long existing and spatially extensive spruce beetle outbreak in Southern Colorado (*See Appendix 1/2*) provides a unique opportunity for us to explore the application of methods to detect bark beetle mortality severity in new, unexplored scenarios. The region selected for this study is in an area often flanked by clouds, is spatially expansive, and the study period integrates multiple years and Landsat sensor types. The objectives of this study were to describe and improve understanding of the spruce beetle outbreak event occurring in southern Colorado spruce/fir forests by testing and expanding upon existing remote sensing methods in new scenarios. Namely, we sought to test the application of composited imagery to enhance our ability to monitor large, cloud covered study areas with remote sensing and to test the effectiveness of using composited Landsat indices as predictive data structures in detecting gray stage spruce beetle induced outbreak severity at multiple time steps, using random forest regression models. Existing methods to detect bark beetle canopy mortality severity at the Landsat pixel scale are thought to be untested in these particular scenarios.

2. Materials and Methods

2.1 Study Area

We selected a *c.* 5000 km^2 study region (Figure 1) composed principally of Engelmann spruce and subalpine fir located within and around the Rio Grande and San Juan National Forests in the southern Colorado Rocky Mountains. The study area was restricted to spruce/fir forest types using the publicly available LANDFIRE existing vegetation type layer (LANDFIRE, 2012). Burned areas were excluded from sampling using Monitoring Trends in Burn Severity (Eidenshink *et al.,* 2007) fire history records. Elevations in the study area range between ~1,800 m and ~4,000 m. While average temperatures and rainfall are quite variable in the study region, Elliot & Baker (2004) averaged conditions reported at three nearby weather stations and found mean temperatures to be between -5.9 °C and 12.4 °C and a mean annual precipitation of 50.8 cm. Most of the study region is managed by the USFS for multiple-use objectives, including conservation of public lands, recreational activities, timber and resource extraction, as well as cattle grazing.

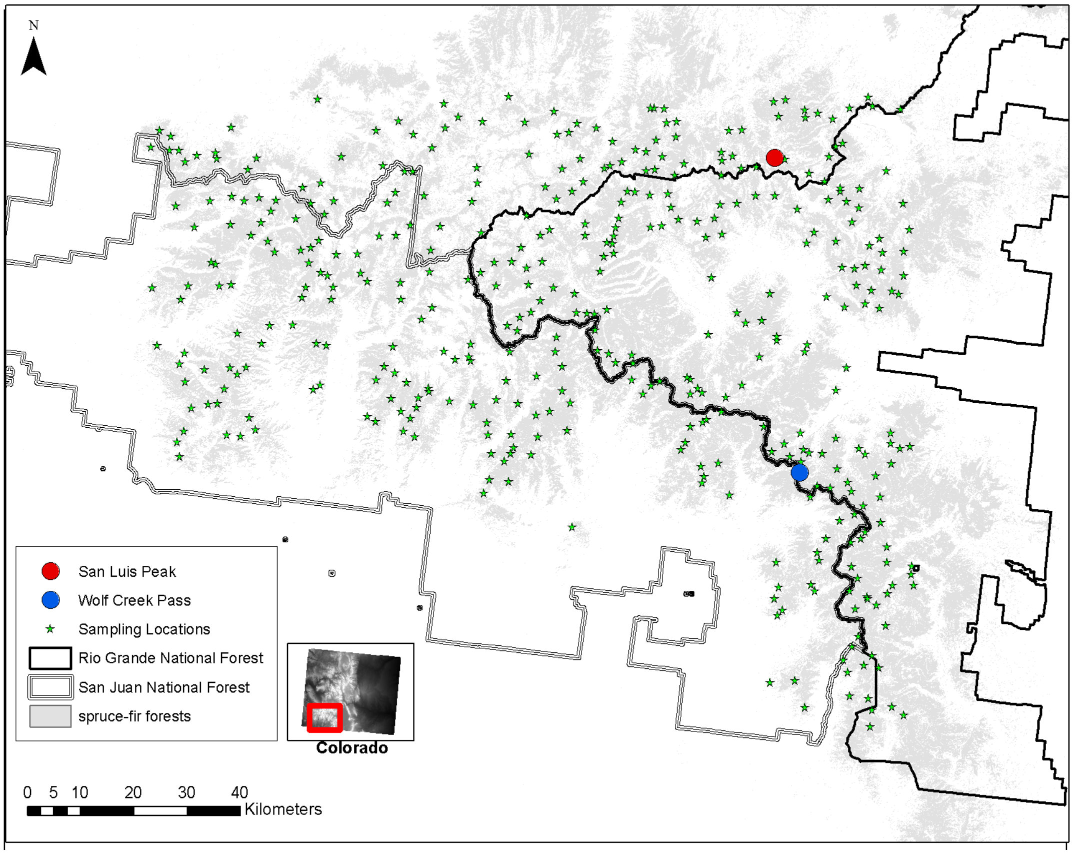

Figure 1: The study area located in and around San Juan and Rio Grande National Forests. Spruce fir forests were delineated using the LANDFIRE Existing Vegetation Type Layer.

Aerial detection surveys show that spruce/fir forest types in the study region experienced varying levels of spruce beetle caused tree mortality over the past decade, which was reported at outbreak levels beginning in 2004, later intensifying to epidemic proportions across the landscape between 2010 and 2015 (*See Appendix 1/2*). In addition to being an area of ecological interest because of the recent and intense nature of spruce beetle induced tree mortality, we selected this study region to emulate challenges encountered when researchers use satellite data collections to model ecological phenomena at the landscape level: 1) cloud cover obstructing areas of scientific interest, and 2) date and sensor mismatches between neighboring satellite collection paths causing spectral inconsistency between available imagery. As such, the study area and period covered portions of two Landsat WRS-2 path/rows (P/R), including P034, R034 and P035, R034 across sensor periods (TM/ETM+ to OLI) and was distributed across high elevation spruce/fir forests that are often cloud covered.

2.2 Data Collection

We randomly distributed 410 sampling locations within the study area to facilitate ocular estimation of canopy mortality using high resolution (1 m^2) National Agricultural Imagery Program (NAIP) imagery for 2011 and 2015. We extracted 30 m^2 Landsat pixel boundaries at the locations where the 410 sampling points were distributed and overlaid a 10x10 sampling grid to aid in ocular estimation of 4 categories: percent gray stage canopy mortality, live canopy, other live vegetation, and "other" within each of the plots. The sampling strategy was designed so that estimations of percent canopy mortality would coincide with the pixel-level spectral values that can be extracted from Landsat imagery (Savage & Lawrence 2016, Long & Lawrence 2016). While both NAIP and Landsat are not geolocated with perfect precision, their geolocation accuracies have been shown to be sufficient to have a minimal effect on sampling accuracy (Long & Lawrence 2016). All ocular estimation of canopy mortality using NAIP imagery was conducted within Google Earth Engine's API (Google Earth Engine Team, 2015) using a scripted interface that allowed for near instant mosaicking and display of NAIP orthorectified quarter quad tiles for all years of interest (*See Appendix 3*). Ocular estimation was carried out by two calibrated image interpreters with multiple years of experience working together to conduct image interpretation. We classified tree mortality as "mortality" only if the tree was characteristic of spruce beetle induced mortality in the gray stage. Other types of disturbance that were seen in the study area (i.e. windthrow, management activities) were not included in estimates of canopy mortality to ensure our estimates were characteristic only of those resulting from spruce beetle attack.

2.3 Remotely Sensed Data

To derive predictors of spruce beetle outbreak severity, we obtained all available Landsat imagery that overlapped with mortality sampling periods for three sensors (TM, ETM+, and OLI) across two primary study periods: 2011 (Jul - Aug) and 2015 (Jul – Aug). To facilitate differencing of imagery to capture pre-, mid- and post-outbreak characteristics in the spatial models, we also obtained all available imagery for the same months in 2000 (pre-outbreak) and 2007 (mid-outbreak). All products were obtained pre-processed to surface reflectance through the USGS Earth Resources Observation and Science (EROS) Center Science Processing Architecture (ESPA) On Demand Interface (Jenkerson 2013). Imagery was selected without consideration for cloud cover, but the study period was restricted to these two peak summer months to ensure the high elevation study area was free of snow and ice and deciduous vegetation was leaf-on. Landsat imagery has a spatial resolution of $30m^2$ and temporal resolution of 16 days, and all imagery was obtained in the Albers equal-area conic projection (Snyder, 1982).

The predictive indices of focus in this study were Landsat derived tasseled cap transformations (Kauth & Thomas, 1976; Crist & Cicone, 1984) and derivations thereof. The tasseled cap transformation uses spectral information from the six reflective Landsat bands to concentrate into three interpretable bands directly associated with landscape and vegetative characteristics, including brightness (which represents soil and image brightness), greenness (which represents vegetative greenness) and wetness (which represents soil and vegetation wetness) (Kauth and Tomas, 1976). We selected tasseled cap transformations as the primary set of predictive indices because of their reported spectral consistency through time and their cross-sensor application (Crist and Kauth, 1986), both of which are important when compositing multiple images. In addition, tasseled cap transformations have strong experimental precedence as robust predictors of forest disturbances and change in canopy characteristics (Cohen *et al.*, 2002; Jin, 2005; Masek *et al.*, 2008).

We processed all imagery using LandsatLinkr (Braaten *et al*., 2015), an R package, to obtain near cloud free tasseled cap brightness, greenness, and wetness (BGW) indices that were used as predictors of spruce beetle induced tree mortality for both 2011 and 2015 (Table 1). LandsatLinkr applies reflectance based tasseled cap transformations (Crist & Cicone, 1984) to all provided image sets, masks all cloud covered pixels within a Landsat scene, and then composites cloud-free portions of the imagery using a mean of the pixel values that overlap for all images available in the year (Braaten, 2017). Sensor to sensor differences (TM/ETM+ to OLI) are normalized by applying an offset of Landsat 8 OLI values scaled to ETM+ space to ensure spectral consistency across sensors (Braaten, 2016; Pflugmacher *et al.*, 2011). The resulting products are single composites of tasseled cap BGW indices for each year (hereafter referred to as *compositeTCAP* products).

To generate additional indices for the final spruce/fir mortality models for 2011 and 2015, we differenced the 2011 and 2015 BGW *compositeTCAP* with previous years (2015 - 2011, 2011 - 2007, and 2015/2011 - 2000) BGW *compositeTCAP* products. This allowed for the creation of additional indices that capture changes in TCAP values between pre-, mid-, and post-spruce beetle outbreak conditions, a practice commonly employed in land and forest change studies (Vorster *et al.*, 2017). Finally, to capture the potential influence of topography on spruce beetle mortality characteristics, we derived elevation, slope, and aspect from the 1 arc-second Shuttle Radar Topography Mission v2.0 digital elevation model product, which was projected to Albers equal area conic and snapped in a GIS to spatially align with the Landsat based rasters. After all processing was completed, 12 individual predictive data layers were available for both 2011 and 2015 (Table 1).

Table 1: A summary of all predictive layers produced for each year (2011 and 2015) using Landsat derived tasseled cap transformations. Each predictor was included in the final RF predictive models of % canopy mortality.

Predictor(s)	**Data Sources**
2015 and 2011 TCAP Brightness Composites	TM/ETM+ (2011), TM, ETM+, OLI (2015)
2015 and 2011 TCAP Greenness Composites	
2015 and 2011 TCAP Wetness Composites	
2015-2011 and 2011-2007 Brightness	TM-ETM+ (2011 - 2007), TM, ETM+, OLI (2015 - 2011)
2015-2011 and 2011-2007 Greenness	
2015- 2011 and 2011-2007 Wetness	
2015- 2000 and 2011-2000 Brightness	TM-ETM+ (2011 - 2000), TM, ETM+, OLI (2015 - 2000)
2015-2000 and 2011-2000 Greenness	
2015-2000 and 2011-2000 Wetness	
Elevation, Slope, Aspect	Shuttle Radar Topography Mission v2.0

Finally, to test the robustness and application of *compositeTCAP*, which used 16 individual image collections versus single image date tasseled cap derived indices, we created one additional set of TCAP BGW indices for 2015 that used only one image date per scene. The two scenes with the lowest cloud cover for the study period were downloaded pre-processed to surface reflectance, transformed to TCAP indices using coefficients specifically created for Landsat 8 OLI (Baig *et al.*, 2013), and mosaicked the images for analysis and comparison to the *compositeTCAP* product (hereafter, this product is referred to as *singleTCAP).*

2.4 Mapping Spruce Mortality Severity in 2011 and 2015

We used a combination of the mortality severity data collected at plots in 2011 and 2015 and extracted associated spectral values from the twelve predictor variables (Table 1) to build two random forest models of spruce mortality severity. Random forests are a robust decision tree based prediction algorithm that can be used in both classification and regression based problems (Breiman, 2001). Random forests are a particularly powerful tool for remote sensing based analyses (Pal, 2005) because they are non-parametric and difficult to overfit (Breiman, 2001; Liaw & Wiener, 2002). Random forests also facilitate simple evaluation of model performance without the use of separate testing data because the model is built with a randomly selected subset of the predictors and training data, resulting in "built in" cross validation in each model run (Belgiu and Dragut, 2016).

Both models were tested and built in the R statistical software using the *randomForest* package (Liaw & Wiener, 2002) using *ntree= 2000* decision trees and the remainder of parameters left at default. We conducted model selection using the rfUtilities package model selection function (Evans and Murphy, 2017) to achieve a balance of model parsimony and predictive power. We evaluated the performance of each model using variance explained, root mean squared error, and mean absolute error. After selecting the best performing models in 2011 and 2015, we applied the models using the predict() function within R to generate spatial predictions of mortality severity across the entire study area.

2.5 Effectiveness of Composited TCAP Indices

To perform an initial test as to whether *compositeTCAP* BGW were an effective substitute for traditional *singleTCAP* BGW in modelling spruce beetle induced tree mortality, we compared them in two ways. First, we compared the proportion of the total study area size that remained following cloud and cloud shadow masking. This was completed by simply tabulating within a GIS the number of pixels remaining following completion of both processing types.

Table 2: Characteristics of the two predictive layer stacks that were used in the initial comparison of composited predictors versus single image date predictors.

Description	# of Collections/Sensors Applied	Response	Associated Predictors
2015 Tasseled Cap July/August Composite (*compositeTCAP*)	16 collection dates, ETM+ and OLI	% Mortality	TCAP Brightness, Greenness, Wetness
2015 Tasseled Cap July/August 2 scene mosaic (*singleTCAP*)	2 collection dates, OLI only	% Mortality	TCAP Brightness, Greenness, Wetness

Next, we built a simplistic random forest model for each image type and compared evaluation metrics. The models used the same number of plots in the same geographic location with the same response variable. The only difference in model preparation was the image processing type used in predictor variables creation within each model (Table 2). We extracted values of the BGW predictors at the 342 plots (out of 410 original plots) that were still present after cloud masking in both the *singleTCAP* and *compositeTCAP* products and built a random forest model for each dataset, with parameters set to default except the number of trees (*ntree= 2000*). We then compared model evaluation metrics including RMSE and MAE to determine if composited products were an effective substitute for single date tasseled cap products in this application.

3. Results and Discussion

3.1 Comparison of Composited TCAP Indices with Single Scene TCAP Indices

The use of *multipleTCAP* indices, which composited 16 separate sets of tasseled cap transformed predictor layers of BGW from all available July and August Landsat imagery from 2015, increased the spruce/fir area that was unobstructed by clouds and available for a landscape scale analysis. The comparative use of the two lowest cloud cover available single image dates that were mosaicked and masked for cloud cover in the same area and time period (Table 3) reduced the study area size by 16%, as single date cloud free imagery was not available for the study region or study period. This is, of course, a snapshot in time and serves only as an example of the power that compositing imagery can have to expand a study area in a situation where cloud free imagery is simply unavailable. While many studies are forced to select image dates that are not optimal for their application or to significantly reduce their study area size because of cloud coverage, compositing allowed us to expand the area of analysis to cover nearly all (99.5%) spruce/fir forests within the study region, while maintaining the optimal time period of interest in the peak summer months.

Table 3: Number of cloud free pixels remaining in each product following the two processing schemes.

Image Product	**Cloud Free Pixels (*% of Total Study Area*)**
compositeTCAP	5,416,792 (99.5%)
singleTCAP	4,544,057 (83.5%)

Each of the random forest models performed similarly, with *singleTCAP* slightly outperforming *compositeTCAP*. Since both models used the same set of observations and are based upon the same scale, we can directly compare the two model's evaluation metrics. Root mean square error (RMSE), a measure of the differences between the observed and predicted values of the model, was similar for both at 14.9 (18%) for *compositeTCAP* and 13.9 (17%) for *singleTCAP*. Mean absolute error (MAE), a measure similar to RMSE except that it does not weigh differences in prediction error, was 10.9 (13.4%) and 10.4 (12.8%) for *composite* and *single* TCAP, respectively. Since these models were built and evaluated only as an initial test of image effectiveness using three predictors, predictive maps were not produced.

This initial test gave us confidence in the use of *compositeTCAP* products in the more expansive and refined modelling techniques employed in the final models of spruce mortality, which used an expanded set of predictors and training dataset. While the *compositeTCAP* products performed similarly, albeit slightly worse than *singleTCAP* indices in this test, we were satisfied by the increase in study area size (16%) produced through compositing and the relatively minor reduction in model performance. Expanded analyses that look at many sets of imagery in different regions and with different applications would be required to conclude that composited imagery is appropriate to use in additional modelling scenarios. It is important to note that gray stage spruce trees are likely spectrally stagnant within a summer season, so if composited imagery was to be used in an evaluation that depended upon phenological variation of vegetation throughout a growing season, we would suggest that additional testing be conducted to ensure composited imagery or indices are relevant in those applications.

3.2 Final Models of Spruce/Fir Mortality Severity in 2011/2015

In 2011, TCAP brightness and the differenced (2011-2000) TCAP wetness were the two most important predictors, followed by differenced indices for wetness and brightness, and finally TCAP greenness and wetness. The inclusion of topographic indices provided no additional

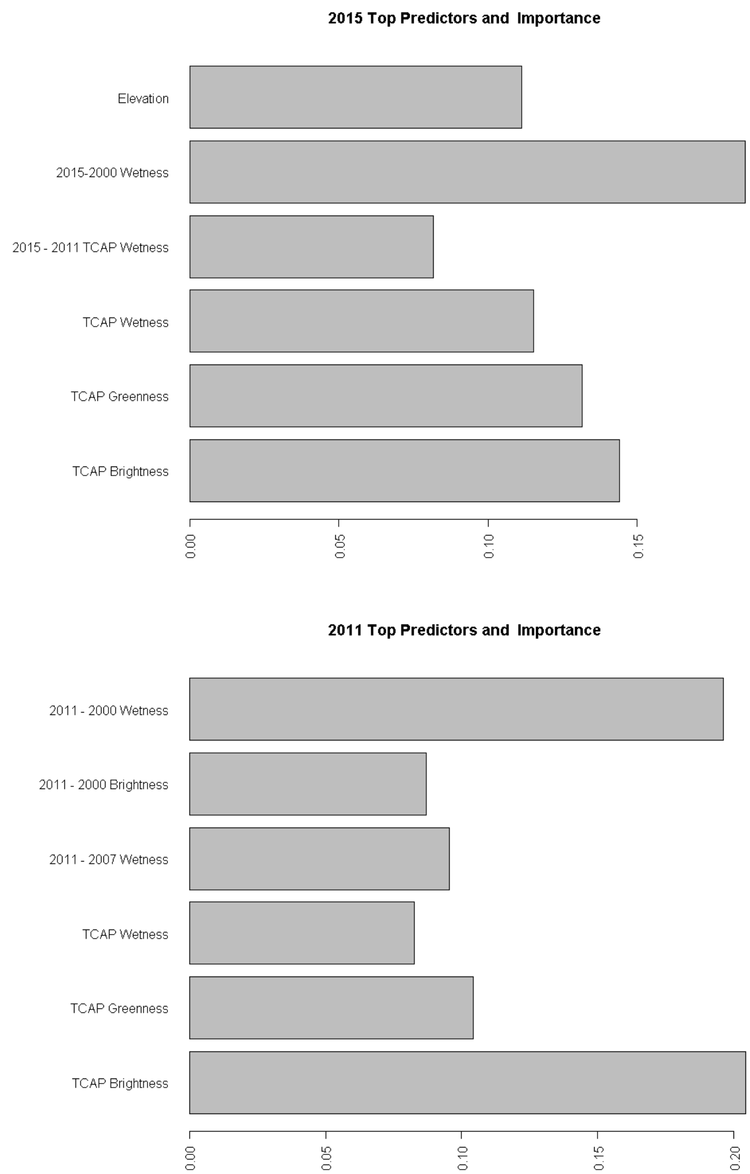

Figure 2: Top predictors and relative importance for 2011 and 2015 models

predictive power to the model in 2011. In 2015, the differenced outbreak (2015 -2000) TCAP wetness and TCAP brightness were also the top two predictors, followed closely by TCAP greenness, wetness, and the 2015-2011 differenced wetness. Interestingly, site elevation was found to increase predictive power of the model for 2015.

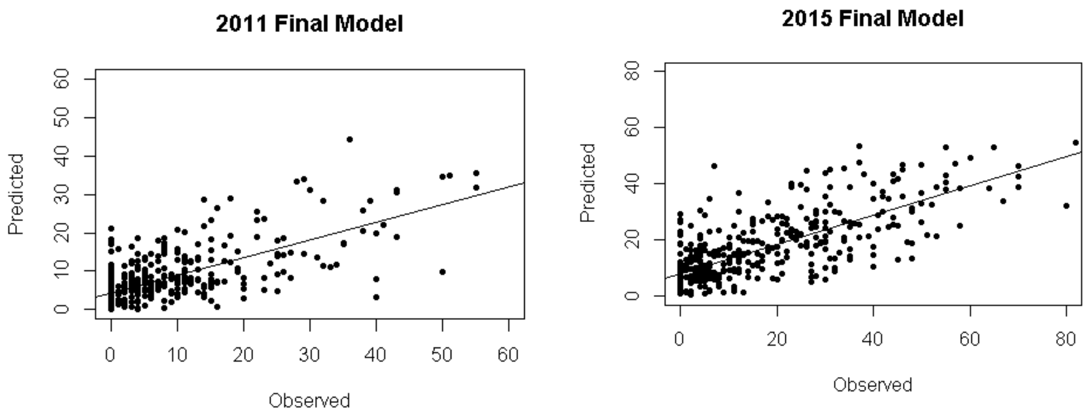

Figure 3: Plots of predicted and observed values for the final 2011 and 2015 models of spruce mortality.

Visual inspection of the 2011 spatial prediction of spruce mortality shows the main epicenter and highest severity outbreaks were located in the northeast corner of the study area, between San Luis Peak and Wolf Creek Pass (Figure 4). Other low severity outbreaks were detected across fairly small spatial extents, but the vast majority of the study region appeared to have been unaffected or affected at low levels of severity (10 – 20% dead) in 2011. Between the 2011 and 2015 study periods, spruce beetle activity in and around the San Juan and Rio Grande National Forests became more severe, with a much wider spatial distribution of outbreak events.

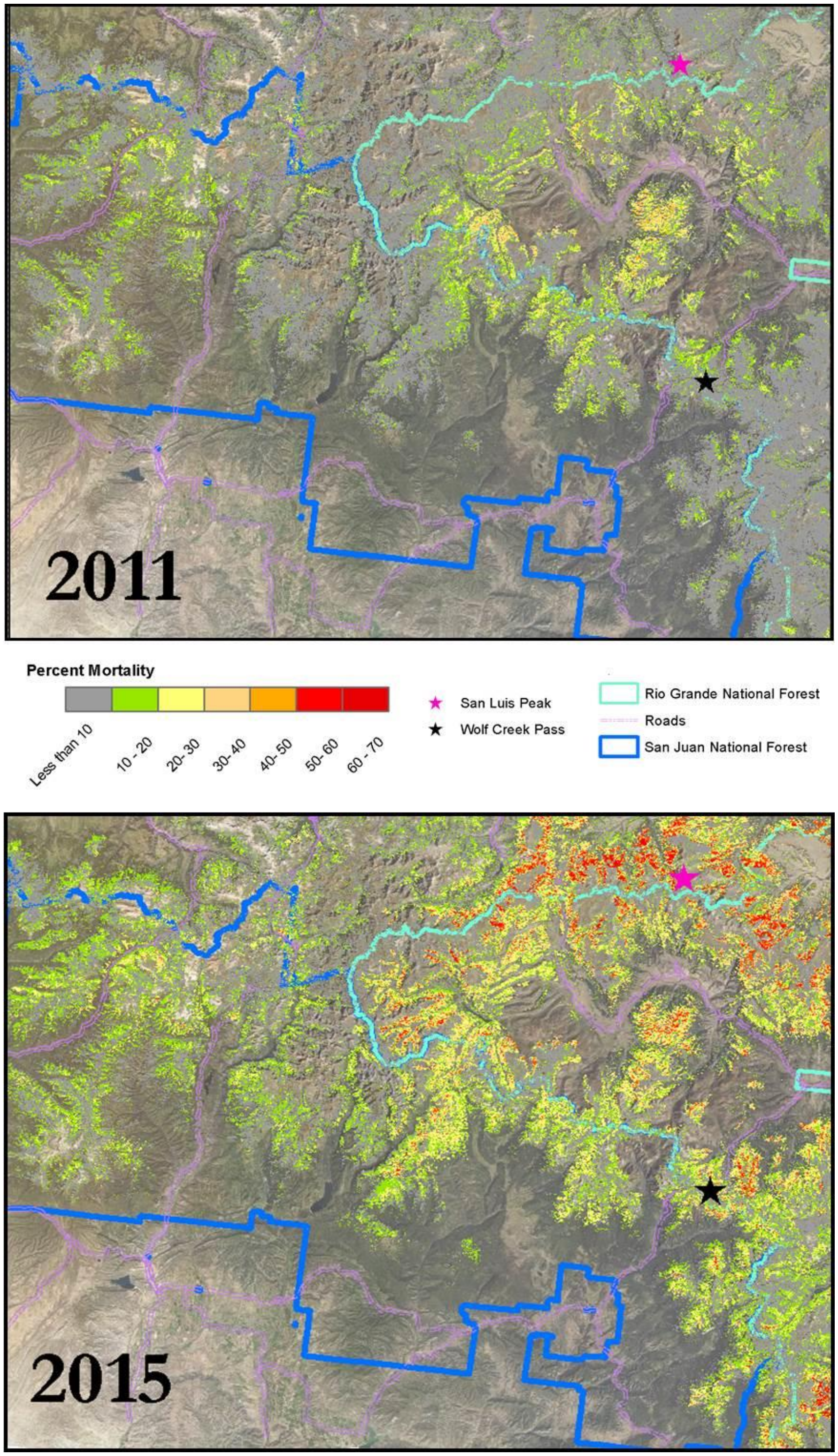

Figure 4: Final predictions of percent gray stage canopy mortality in and around Rio Grande and San Juan National Forests in 2011 and 2015.

Spruce beetle attack seemed to expand northward from the epicenter seen in 2011, with areas along the northern border of the Rio Grande National Forest being attacked very severely (50-70% dead). The outbreak occurring near Wolf Creek Pass increased in severity, and an additional high severity mortality pocket appeared in the southeast portion of the study area. Overall, by 2015, very little of the study region had been left unaffected by spruce beetle attack. These maps are consistent with the broad patterns of new attacks conveyed through the USFS Aerial Detection Survey (*Appendix 1/2*). This lends credence to the concept that maps produced through similar modelling techniques as those in this study could be combined with ADS data to provide an enhanced product that more clearly and precisely conveys information on the severity and distribution of insect and disease activity than current ADS products can facilitate.

This study has shown that multiyear, cross Landsat sensor monitoring of spruce beetle attack is an effective way to monitor a large, persistently cloudy study area. While many studies have focused upon a single year of monitoring, we have displayed the progression and severity of attack across a five year period is possible using multi-sensor tasseled cap composites. We further show that the methods employed in the modelling framework are applicable and effective across spatially expansive ($5000\ km^2$) study regions, a larger size than explored in previous literature using similar methods (Long and Lawrence, 2016). In addition, the results show that the use of composited tasseled cap indices is effective in detecting subtle, slow moving and potentially less severe disturbances. While similar predictive structures have been used in studies exploring deforestation (Muller et. al 2016), bark beetle induced disturbances are often considered more difficult to detect than more severe and fast moving disturbances (Meigs *et al.*, 2011), such as fire or forest harvest, when using moderate resolution imagery like Landsat.

Final results suggest that composited tasseled cap indices and their derivatives are effective predictors of gray stage spruce mortality when applied within a regression tree based modeling framework. The variable selection procedure highlighted the important role that differencing indices from different stages of an outbreak can play in detecting changes in vegetation through time, a finding that is consistent with similar studies (Vorster *et al.*, 2017). While the models both seemed to slightly overpredict low levels of mortality and underpredict more severe levels of mortality (Figure 3), we believe the RMSE is within an acceptable range for the models to be valuable tools to be applied in forest management and planning and a significant improvement over products that display only presence/absence of canopy mortality.

4. Additional Considerations

The study period included only the height of the spruce beetle epidemic (2011 – 2015) occurring in the region. To understand the full history and progression of spruce beetle activity within this epidemic, additional sampling from previous years would be required, although this comes with an additional caveat. This method is successful because we have a wide range of mortality severity occurring across the landscape. Modelling mortality severity at the beginning of the outbreak could be less successful because a randomly distributed dataset would contain mostly absence values, which may be better suited for a classification modelling approach.

The next consideration is image processing and index selection. The approach employed in LandsatLinkr to spectrally harmonize tasseled cap transformations through time is based upon approaches that have been published (Pflugmacher *et al.*, 2011), but the tool itself has not been reported in scientific literature. At the time of writing, a publication outlining and testing the tool is being drafted by its authors. Next, we chose to apply only tasseled cap transformations and topographic predictors within the models because we were concerned that other indices may not provide the spectral consistency required to facilitate compositing and differencing of indices through time. While both models performed reasonably well, inclusion of additional spectral information (i.e. Landsat bands, SAVI, NDVI) does have potential to improve model performance and predictive power.

Finally, while we took care to exclude disturbances that were not caused by spruce beetle in sampling and initial pre-processing steps (such as excluding areas affected by fire and by restricting the study area to the spruce/fir vegetation class) we are almost certainly capturing disturbances in the final maps that are not induced by spruce beetle. While forest canopies in the area were observed to be almost entirely green in scans of pre-outbreak imagery, other insects, tree diseases, and disturbances are present in the area, which may be classified by the model as gray stage spruce mortality. Because of the massive extent of the ongoing outbreak, we believe it is reasonable to assume that the vast majority of predicted mortality was the result of spruce beetle attack.

5. Conclusions

This study displayed an effective methodology for detecting gray stage spruce mortality in a large, cloudy, multiple Landsat scene study region. We have shown that 1) multi-image date and multi-sensor tasseled cap composites are a powerful tool when working in a cloudy study area and serve as an effective predictor of gray stage spruce mortality severity across time and in large study regions; 2) differencing images from multiple time steps is important when attempting to detect long, slow moving disturbances like spruce beetle outbreaks, and 3) data produced through models like those in this study can serve as a potential supplement to existing forest management and monitoring programs, such as the USFS Aerial Detection Survey. Finally, we created a spatially extensive map of an ongoing outbreak event that supports a better understanding of outbreak progression, spread, and intensity for this particular spruce beetle epidemic.

CHAPTER 2: A RESEARCH NOTE CHARACTERIZING STAND SUSCEPTIBILITY AND PROGRESSION OF SPRUCE BEETLE INFESTATION DURING A SOUTHERN COLORADO EPIDEMIC

1. Introduction

Forest managers have long attempted to characterize how spruce beetle (*Dendroctonus rufipennis)* outbreaks progress across a landscape and why some stands are more susceptible than others to attack. These characterizations have ranged from simplistic evaluations that rate site susceptibility characteristics (Schmid and Frye, 1976) to complex, multi-scale evaluations of susceptibility and outbreak progression that integrate field measurements and remote sensing (Simard, *et al.,* 2012). While similar conclusions have been made in many studies with regard to environmental site characteristics that can drive spruce beetle attack, outbreaks are dynamic across space and time (Raffa *et al.,* 2008) and very few studies have been conducted to explore how environmental conditions of spruce beetle attack change as an outbreak progresses.

A spruce beetle outbreak that began in the Southern Colorado Rocky Mountains in 2004 and progressed to epidemic proportions between 2011 and 2015 (*See Appendix 1/2*) offers a unique opportunity to further explore how spruce stand characteristics, topography, and other environmental covariates may have influenced susceptibility to spruce beetle attack in this particular epidemic. There are many examples of past research that have conducted expansive reviews of spruce beetle ecology and the general characteristics that influence stand level spruce beetle susceptibility (Schmid and Frye, 1977; Reynolds *et al.,* 1994; Jenkins *et al.,* 2014). While there is variability in the characteristics used to describe susceptibility and progression of an outbreak, studies have reported that climatic conditions, particularly drought, topographic conditions, such as elevation and slope, and stand characteristics, such as size of tree, amongst others, can describe an outbreak's progression and the susceptibility of trees to spruce beetle attack. Here, we have collected a sampling of publicly available datasets that are similar to noted sources of susceptibility and that have been used to describe outbreak progression (Table 4) to explore their application in describing this particular epidemic, which is active at the time of writing.

The impetus for this research is twofold: 1) to create a general understanding of site characteristics that have influenced progression and susceptibility to spruce beetle attack in this particular Southern Colorado epidemic, and 2) to highlight the vast amount of information that can be extracted from free, public datasets regarding forest health and site characteristics that can be applied in future, more expansive studies of dynamics of spruce beetle attack. Our research questions are as follows:

1. Can publicly available datasets be used to effectively determine significant differences between sites that are attacked versus those that have never been attacked, thereby characterizing site susceptibility to spruce beetle?
2. Are there distinguishable and significant differences between sites that were attacked early in the epidemic (2009 -2011) versus sites that were attacked later in the epidemic (2012- 2015)?

2. Methods

2.1 Study Area

Our study area covers a *c.* 5000 km^2 region composed principally of Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa)* located within and around the Rio Grande and San Juan National Forests in the Southern Colorado Rocky Mountains. Elevations range between 1,800 m to ~4,000 m. Average temperatures and rainfall are quite variable in the study region because of its large size and intense topographic diversity, but Elliot & Baker (2004) averaged conditions reported at three nearby weather stations and found mean temperatures to be between -5.9 °C and 12.4 °C, with a mean annual average of 3.2 °C, and a mean annual precipitation of 50.83 cm. The majority of the study region is managed by the USFS for multiple-use objectives, including conservation of public lands, recreational activities, timber and resource extraction, and cattle grazing.

2.2 Forest Monitoring and Outbreak Detection

We used an existing dataset that monitored 356 forested plots designated as spruce/fir forest type (Landfire, 2012) using high resolution (1 m^2) National Agricultural Imagery Program orthorectified quarter quad tiles from 2009, 2011, and 2015. Plots were 30 m^2 in size and distributed randomly across the study area within a GIS using a minimum distance of 600 m between plots. Two trained and calibrated interpreters ocularly observed the plots and looked for signs of gray stage canopy mortality characteristic of spruce beetle, noting absence (<5% mortality) and presence (>5% mortality) of spruce beetle attack at each of the sites in each year of sampling.

Some outbreaks started within the study area prior to monitoring efforts (*See Appendix 1/2*), so 2009 sampling data were used as a baseline to determine which sites had never experienced spruce beetle attack to avoid characterizing sites as new outbreaks that may have died years before. Plots that showed signs of previous spruce beetle attack in 2009 imagery were removed, resulting in 268 plots that had never experienced mortality. These 268 plots were then "revisited" using imagery from 2011 and 2015 to track presence of new spruce beetle attack through time. In 2011 and 2015, 86 and 84 sites experienced new spruce beetle attack, respectively, while 98 of the sites never saw signs of spruce beetle attack in our sampling. To explore two primary research questions, these observations were distributed into two datasets: 1) categorized by sites that experienced new spruce beetle attacks versus sites that never experienced attack and 2) categorized by sites that experienced new attack 2009 - 2011 versus sites that experienced new attacks 2012 - 2015. Environmental covariates described as potential factors associated with stand susceptibility to spruce beetle (*See Table 4*) were then extracted at these sites in preparation for statistical analyses.

2.3 Environmental Covariates

We obtained 10 datasets from publicly available data sources that can be used to describe site characteristics and susceptibility of sites to spruce beetle attack (Table 4). Datasets that were obtained "analysis ready" were simply clipped and extracted within a GIS to match the spatial extent of our study area. For datasets that were described with distance (i.e. distance to stream), we calculated distance within a GIS using the geodesic method.

Some data required more extensive processing or preparation. Topographic data were derived using a GIS using the Shuttle Radar Topography Mission Digital Elevation Model v2.0 product (NASA JPL, 2013). Our "distance to disturbance" dataset was obtained from a reconstruction of disturbances in the area using LandTrendr (Kennedy *et al.,* 2010), which can currently be derived using publicly available Landsat data but will also be available soon as a distributed product. In an attempt to characterize true disturbance events occurring before our observed outbreaks, we used a filtered LandTrendr product that had a minimum patch size for disturbances of 11 pixels and was run with LandTrendr defaults using the tasseled cap wetness index for segmentation and no cover model (See Kennedy *et al.*, 2010 for a full description of the LandTrendr algorithm).

The use of some environmental covariates that relied on the USFS Field Sampled Vegetation (FSVeg) spatial database (*See Table 4*) required a reduction of the overall sample size in all categorical tests because our study region expanded beyond the boundaries of the national forest datasets and some sites were characterized as being dominated by non-forest (but were verified to be forested at the plot scale). Following completion of data preparation, we extracted values for all of our environmental variables at our plot locations in preparation for our statistical analyses.

Table 4: A summary of the environmental attributes extracted at every sample site.

Environmental Attribute	Description and Source	Data Type	Hypothesized Relationship
Elevation	Elevation in meters, SRTM DEM v2	Continuous	Sites unattacked are at lower elevations, sites attacked in 2015 were lower in elevation than 2011
Slope	Slope in degrees, derived from SRTM DEM v2	Continuous	Sites with steeper slopes more susceptible because of wind and water stress, less steep slopes attacked in 2015 as outbreaks progress
Aspect	Aspect, derived from SRTM DEM v2	Continuous	Drier sites on south slopes more susceptible, attacked earlier in outbreak
Compound Topographic Index	Describes soil wetness, derived from SRTM DEM v2	Continuous	Drier sites more susceptible to attack, attacked earlier in outbreak
Percent Canopy Cover	Percent of plot that is canopy covered, recorded using NAIP Imagery	Continuous	Dense canopies more susceptible as greater host stock, lower densities attacked through time
Tree Size Class	Dominant size class of stand compacted into 3 categories, extracted from the USFS FSVeg Database	Categorical	Larger tree sizes more susceptible to attack, tree size class reduces through time
Dominant Tree Species	Dominant tree species of stand, extracted from the USFS FSVeg Database	Categorical	Stands with spruce dominant most susceptible, unexpected to change through time at this stage of the outbreak
Vegetation Layering	Vertical structure of the stand, extracted from the USFS FSVeg Database	Categorical	Stands with less canopy diversity more susceptible, unexpected to change through time at this stage of the outbreak
Distance to Streams	Distance to nearest stream, extracted from USGS Hydrography Dataset	Continuous	Stands closer to streams less susceptible because of water availability, sites closer to streams attacked as outbreak progresses
Distance to Nearest Pre-Outbreak Disturbance	Distance to nearest pre-outbreak disturbance event, extracted from a LandTrendr Disturbance History	Continuous	Stands closer to disturbance more susceptible, less important as outbreaks take hold

2.4 Statistical Analyses

We selected one of two statistical test types depending on the variable of interest (categorical versus continuous). For continuous variables, we used two-tailed Wilcoxon Rank Sum Tests. The Wilcoxon Rank Sum Test was selected because it is a non-parametric test that works well with relatively small sample sizes, and because the test has been used in similar applications of outbreak characterization (Klutsch *et al.*, 2009). For our limited number of categorical variables, we used the Chi Squared test of independence, which tests independence of categories (i.e. outbreak vs. no outbreak) based upon proportions of observations (Zibran, 2007). Results are reported at the 95% confidence level.

3. Results

3.1 Susceptibility of Sites to Spruce Beetle Attack

We found that some tested environmental characteristics were significantly different in sites that experienced new spruce beetle attack during our study period when compared to those

Table 5: A comparison of sites that never experienced infestation versus those that saw an infestation for the first time between 2009 and 2015.

Variable	No Spruce Beetle Activity *n=98*	New Spruce Beetle Attack *n= 170*	*P*
Elevation (m)	3279	3303	0.431
Slope (%)	18	20	0.066
Aspect (Degrees)	186	192	0.671
Compound Topographic Index	.69	.72	0.220
Distance to Pre Outbreak Disturbance (m)	73	35	**0.024
Distance to Streams (m)	172	227	**0.031
Canopy Cover (%)	40	52	**<0.001
Tree Size Class (S, M, L, VL)^	-	-	0.577
Dominant Tree Species (Spruce, Fir, Other)^	-	-	0.109
Canopy Layering (Single, Multiple)^	-	-	0.226

Summary of datasets by mean. **Statistically significant at α= 0.95. Continuous variables were tested with a Wilcoxon rank sum test and categorical with a Chi squared test of independence. ^Categorical variables had a reduced sample size: No activity; n = 52 New Outbreaks; n = 100.

that had never been attacked by the beetle (Table 5). Sites attacked by spruce beetle had significantly higher levels of percent canopy cover than sites that had never been attacked (Wilcoxon rank sum test, *p=<.001*). Attacked sites were also seen to be significantly closer to previous disturbance events than sites that had never been attacked (*p=.024)* and were farther away from streams (*p=.031*). No significant differences were present in topographic (elevation, slope, aspect, CTI) or stand characteristics (size, dominant species, canopy layering) of sites that had been attacked versus unattacked.

3.2 Distinguishing Site Characteristics as an Outbreak Progresses

As the Southern Colorado spruce beetle epidemic progressed across the landscape and through time, some site characteristics of outbreaks changed significantly between 2011 and 2015 plot sampling. Sites attacked in 2015 were significantly higher in elevation than sites

Table 6: A comparison of sites that experienced infestation between 2009 and 2011 versus those that saw an infestation for the first time between 2012 and 2015.

Variable	**2011** *n= 86*	**2015** *n= 84*	***P***
Elevation (m)	3263	3345	**0.008
Slope (%)	20	16	**0.007
Aspect (Degrees)	198	187	0.417
Compound Topographic Index	.73	.78	0.3001
Distance to Pre Outbreak Disturbance (m)	25	47	**0.021
Distance to Streams (m)	212	242	0.777
Canopy Cover (%)	55	49	**0.025
Tree Size Class (S, M, L, VL)^	-	-	0.7592
Dominant Tree Species (Spruce, Fir, Other)^	-	-	0.975
Canopy Layering (Single, Multiple)^	-	-	0.641

Summary of datasets by mean. **Statistically significant at α= 0.95. Continuous variables were tested with a Wilcoxon rank sum test and categorical with a Chi squared test. ^Categorical variables had a reduced sample size: 2011; n = 56 , 2015; n = 46.

attacked in 2011 (Wilcoxon rank sum test, *p=<.008*), and were located on significantly steeper slopes (*p=<.007).* Additionally, spruce beetles attacked sites with significantly lower canopy densities (*p=<.025)* that were farther away from disturbance events in 2015 (*p= .021*) than in 2011.

4. Discussion

4.1 Susceptibility of Sites to Spruce Beetle Attack

Our results agree with the long-held explanation that previously occurring disturbance events drive new spruce beetle attacks to occur in nearby spruce stands (Jenkins *et al.*, 2014). This further reinforces that active management of disturbed areas may be a particularly important step in preventing endemic spruce beetle populations from expanding to epidemics (Fettig *et al.*, 2007). Our finding of dense canopies being more susceptible to attack than stands with more open canopies is intuitive, as a greater host stock is likely available, and has been reported as a characteristic of susceptibility for decades (Schmid and Frye, 1976). Similarly, spruce beetle attacked sites being further from stream environments is a logical outcome. With our study area being in a state of drought during nearly our entire study period, we hypothesized that weak, drought stressed trees further away from the moist environments that creeks, rivers, and streams create would be more likely to be attacked.

We had hypothesized that sites with higher elevations, steeper slopes, and south facing aspects would have been more susceptible to spruce beetle attack than sites that were not, all of which must be rejected. We believe that this may be explained by our large study area size and the fact that multiple, distinct outbreak events and epicenters are occurring simultaneously within our study area at different topographic positions. Additionally, there was little or no value in using topographic predictors in detection of mortality in the research presented in the first chapter of this thesis, further supporting that attack was not constrained by topographic characteristics. Finally, our findings that showed no differences in tree size class, canopy layering, or dominant species type can likely be explained by two factors. First, while the scale of this epidemic is massive, there are likely still many suitable host tree species of all sizes remaining on the landscape and limited dispersal distances may drive beetles to attack trees of any suitable size in epidemic conditions. Next, our categorical data, which is subjectively categorized by the USFS, may not be of an adequate scale to appropriately detect differences between unattacked and attacked sites.

4.2 Distinguishing Site Characteristics as an Outbreak Progresses

We were surprised to see that new sites attacked by spruce beetle in 2015 were significantly higher in elevation than in 2011. While this initially had us perplexed, as bark beetle outbreaks are often characterized as starting at higher elevations and moving lower through time (Johnson, 1967; Hebertson & Jenkins, 2008), reports from the 2015 Aerial Detection Survey agree with our results that spruce beetle activity did move to higher elevations in 2015 (Lockwood & Johnson, 2016), a phenomenon that may be driven by climatic differences between our sampling years. Steeper slopes being attacked between 2009 and 2011 versus 2012 to 2015 agrees with our hypothesized outcome. Since disturbances are more likely to occur, particularly windthrow, on steeper slopes than less steep slopes (Ulanova, 2009), steep slopes seem particularly susceptible to initial attack early in the outbreak event. As the outbreak progresses, the beetles may disperse away from these disturbances to areas that still have sufficient host tree stocks. Our findings of distance to pre-outbreak disturbance increasing and significantly lower canopy covers being attacked as the epidemic progressed are both intuitive. As an outbreak continues, available host stocks with dense canopies around an outbreak epicenter also likely decrease, and as populations of beetles rise, dispersal distance away from an original disturbance event that may have triggered the original outbreak will also likely increase.

4.3 Caveats

First, no ground sampled field data was included in these analyses. While care was taken in sampling to ensure mortality observed was characteristic of spruce beetle attack, this study could be more robust with field verification of mortality events. Next, our stand characteristics (size class, canopy layering, and dominant species) were categorical and broadly characterized. If resources are available, we certainly suggest that future research integrates stand characteristics measured at the plot level (DBH, stand density, etc), even though some studies report landscape scale metrics being the most important when characterizing spruce stand susceptibility to beetle attack (Simard, *et al.,* 2012). Next, we did not explicitly check for characteristics of spatial autocorrelation, but instead insured there was a 600 m buffer between our plots, a distance greater than those used in studies with similar environmental covariates that found no issue with spatial autocorrelation (Klutsch *et al.,* 2009, Simard, *et al.*, 2012). Finally, we tested only a limited set of variables. Many additional environmental covariates could be explored and may have greater explanatory power than the variables we tested. The obvious gap in this analysis is related to the lack of climatic data, which likely has a great impact on spruce susceptibility to outbreak. Unfortunately, our study design and short study period prevented exploration in this area.

5. Conclusions

We successfully described stand level susceptibility characteristics to spruce beetle outbreak and outbreak progression through time using public datasets for the ongoing Southern Colorado epidemic. Sites attacked by spruce beetle were closer to disturbances in areas of dense canopy cover and were further from streams when compared to sites that were uninfested. As the epidemic progressed, spruce beetle infested sites moved up in elevation, were on less steep slopes, further from disturbances, and had less dense canopies than those sites attacked earlier in the outbreak. The results display the power and application of the use of public datasets in creating a better understanding of spruce beetle movement and stand susceptibility throughout an ongoing outbreak event, and highlight the dynamic nature of spruce beetle induced mortality at large spatial scales and through time.

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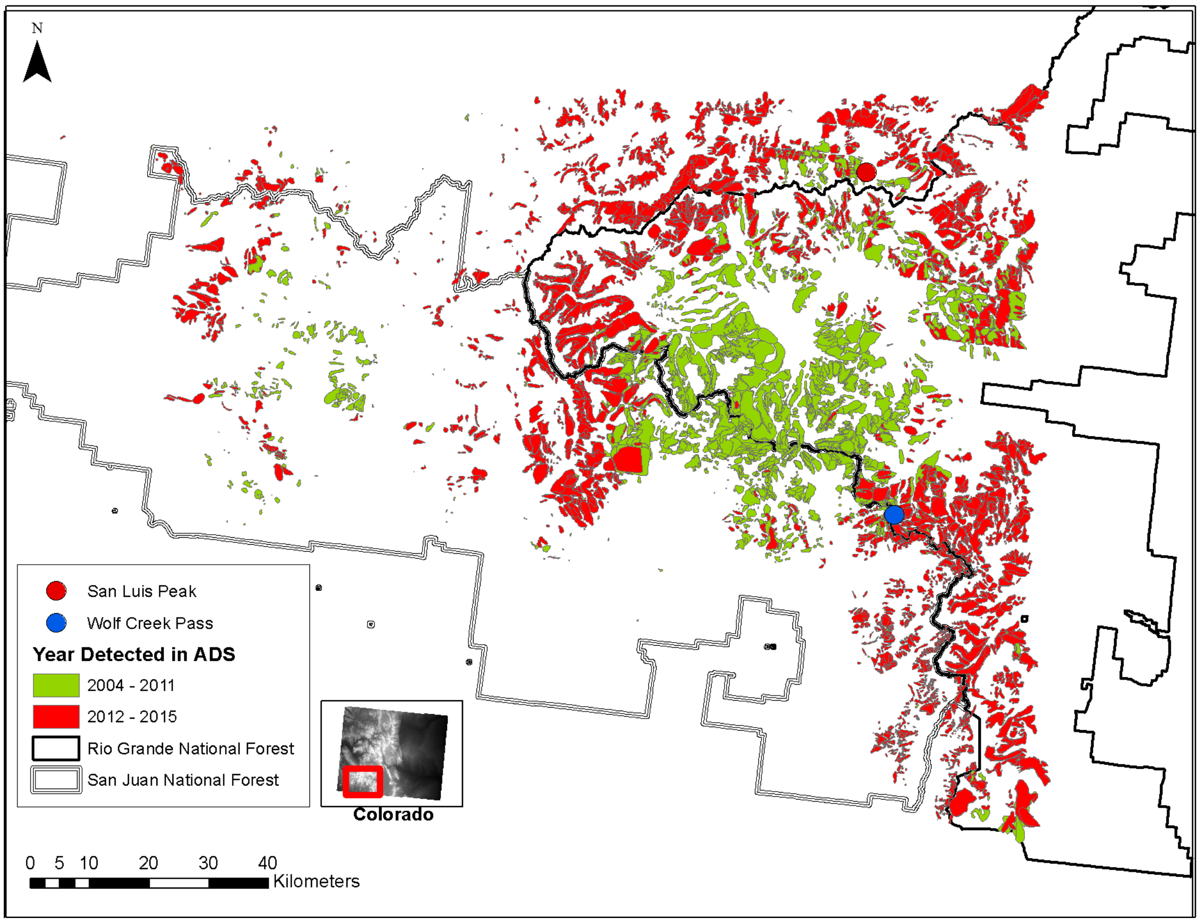
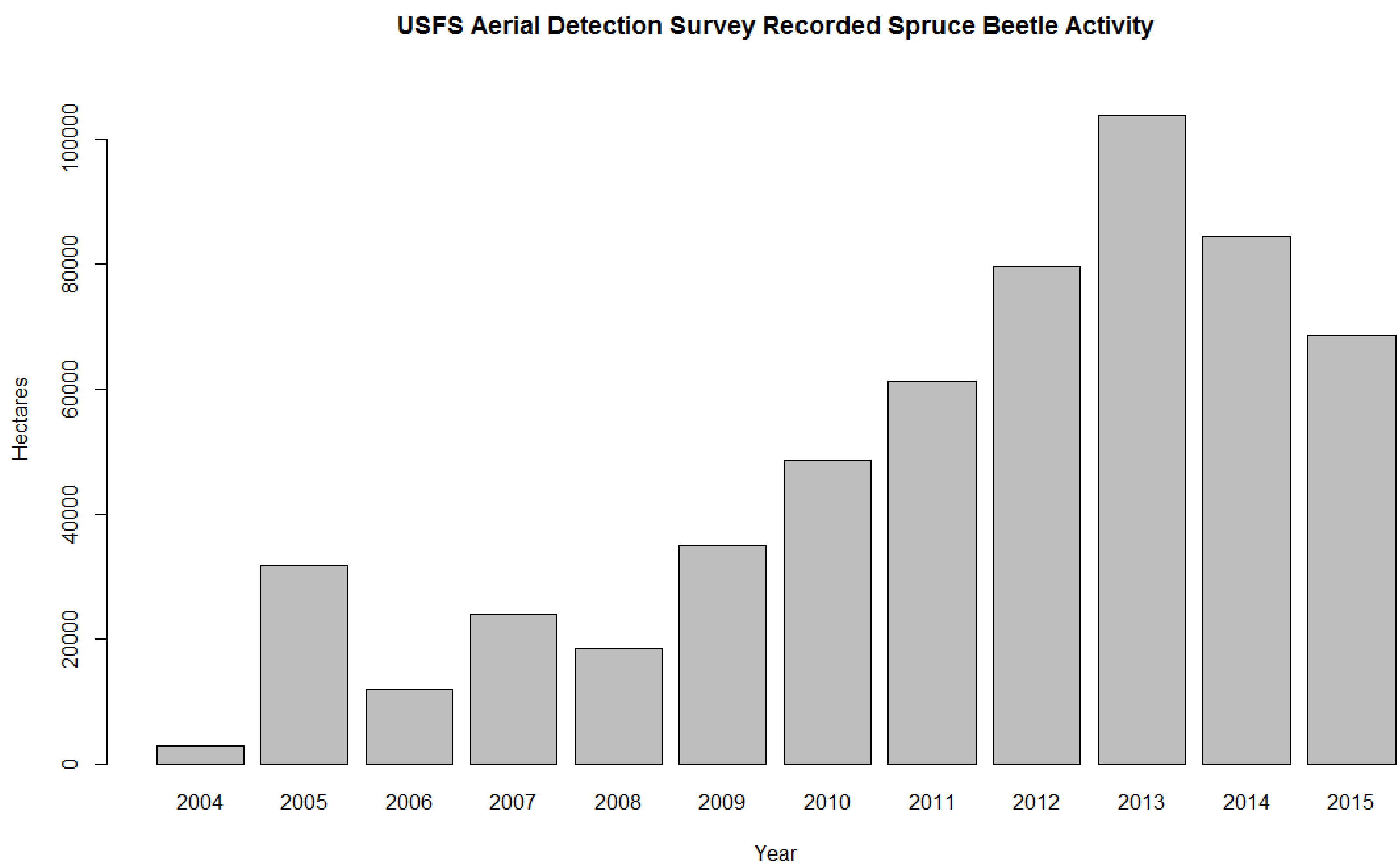
APPENDICES



Appendix 1: Aerial detection survey polygons for 2004 – 2015 showing spruce beetle activity within our study area. Visual comparison of ADS data with our modelled results show very similar extents and areas of activity.



Appendix 2: Spruce beetle activity recorded in the USFS Aerial Detection Program, 2004 – 2015 within the study region.

```
Google Earth Engine Code to conduct NAIP Sampling
// Load 2015 NAIP quarter quads
var naip2015 = ee.ImageCollection('USDA/NAIP/DOQQ')
  .filterBounds(ee.Geometry.Rectangle(-108.9679, 38.1557, -106.0236, 37.1029)) //This is your
study area extent
  .filterDate('2015-01-01', '2015-12-31'); //This is where you select the year of NAIP imagery you
would like to use. You can add as many years as you want by copying and pasting this and the
following sections and changing the dates.

// Spatially mosaic the images in the collection and display.
var mosaic = naip2015.mosaic();
Map.setCenter(-107.4847, 37.5576, 9); //Set map center
Map.addLayer(mosaic, {}, 'NAIP Mosaic 2015');
Map.addLayer(mosaic, {bands: 'N,B,G'}, 'NAIP Mosaic 2015 False'); //Add false color image. You
can change the image "stretch" in the layers tab.


// Load a FeatureCollection from a Fusion Table.
var fromFT = ee.FeatureCollection('ft:1NoIp3TXzzTy9mf3CHPsa9Zu-
wHN4SvndrNrC7c2V'); //Once you have your plots generated, you'll need to upload your outline
shapefile/points into a a KML, then a fusion table. This can be done through Google Drive.

// Print and display the FeatureCollection.
print(fromFT);
Map.addLayer(fromFT, {}, 'From Fusion Table'); //This adds your points/polygons to the map. You
can set transparency via the layers tab.

// Make a drop down menu to zoom to plot locations
var places = {
1 :[-107.643703,37.656711  ],
2 :[-107.842758,37.74372  ] //Add all of your plot center coordinates here. This just creates a drop
down menu that allows you to zoom directly into a plot. I have truncated it here, but this would
usually have a few hundred plot coordinates.

var select = ui.Select({
  items: Object.keys(places),
  onChange: function(key) {
    Map.setCenter(places[key][0], places[key][1],25);
  }
});

// Set a place holder.
select.setPlaceholder('Choose a location...');

print(select);
```

Appendix 3: Abbreviated code to use Google Earth Engine for National Agricultural Imagery Program Plot Sampling