TITLE: Detection of spruce beetle-induced tree mortality using high- and medium-resolution
remotely sensed imagery

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ABSTRACT

Outbreaks of bark beetles cause widespread tree mortality, which have important consequences for wildlife, forest composition and structure, timber production, and water resources. Recent severe, extensive, and synchronous bark beetle outbreaks have motivated research into methods for surveying the location, extent, and attack stage of outbreak using remotely sensed data. In this paper, we adapt methods for classing mountain pine beetle-induced tree mortality to detect spruce beetle-induced tree mortality from single-date high-resolution imagery and multi-date moderate-resolution data. We use freely available aerial imagery from the National Agriculture Imagery Program (NAIP) to produce a tree-scale map of gray-stage spruce beetle kill across a broad spatial extent. This map was then used to train a stand-scale classification of spruce beetle outbreak from Landsat Climate Data Record (CDR) data. Gray-stage spruce beetle outbreak was characterized by higher values of the red-green index (RGI) at the tree-level. At the stand-level, gray stands were associated with high values of a Disturbance Index (DI) and low values of the Normalized Difference Vegetation Index (NDVI). Both tree- and stand-scale classifiers of spruce beetle-attributed tree mortality were highly accurate (overall accuracy and user's accuracy for gray trees/stands greater than 88%). Stand-level classification improved with post-classification correction, which removed high-frequency year-to-year variability in forest condition. Comparison of high-resolution and moderate-resolution classified imagery revealed variable amounts of tree mortality occur in areas of landscape-scale spruce beetle outbreak. Our results highlight the utility of both ecologically informed post-classification correction and coupling fine-scale and moderate-scale resolution imagery for mapping and studying spruce beetle outbreaks.

KEYWORDS – bark beetle, Landsat, NAIP, aerial imagery, support vector machine

1. INTRODUCTION

During the late 20th and early 21st centuries, severe and extensive bark beetle outbreaks have caused dramatic tree mortality from Alaska to the Southwestern US (Bentz et al., 2009; Meddens, Hicke, & Ferguson, 2012). Across the western US, tree mortality and damage is currently assessed by the United States Forest Service using Aerial Detection Surveys (ADS). ADS data provides a rough estimate of bark beetle-induced tree mortality at a broad-scale (minimum mapping unit 5 ha) for select areas of National Forest land (Johnson & Wittwer, 2008). Spatiotemporal gaps in ADS data, relatively high data collection costs (\$0.25/ha; E. W. Johnson & Wittwer, 2008), and only moderate agreement between ADS data and ground reference data (68% agreement with a 50 m spatial tolerance; Johnson & Ross, 2008) are among the key limitations of relying on ADS data to assess bark beetle outbreaks. These limitations in conjunction with the severity, broad spatial extent and synchrony of recent outbreaks has promoted research into methods for surveying the location, extent, and attack stage of bark beetle outbreak using remotely sensed data (Coops, Johnson, Wulder, & White, 2006; DeRose, Long, & Ramsey, 2011; Franklin, Wulder, Skakun, & Carroll, 2003; Meddens, Hicke, Vierling, & Hudak, 2013; Skakun, Wulder, & Franklin, 2003; White, Wulder, Brooks, Reich, & Wheate, 2005; M. A. Wulder, White, Bentz, Alvarez, & Coops, 2006; M. A. Wulder, White, et al., 2006).

Across the Southern Rocky Mountains, mountain pine beetle (*Dendroctonus ponderosae*) and the spruce beetle (*Dendroctonus rufipennis*) have caused most of the bark beetle-related damage (Ciesla, 2013). While remote sensing of mountain pine beetle-induced tree mortality has proven successful particularly in lodgepole pine-dominated forests (Goodwin et al., 2008; White et al., 2005), remote sensing studies of spruce beetle-caused tree mortality are relatively limited and there is no consensus on the most effective detection methods (DeRose et al., 2011;

Johnson, Greenfield, & Munson, 1997; Makoto, Tani, & Kamata, 2013). Further, from 2009 through 2014, the area affected by spruce beetle in Colorado grew rapidly (46,000 ha in 2009 and 196,000 ha in 2014; Ciesla, 2011; USFS, 2015). Thus there is an increased need for developing methods for remote sensing of spruce beetle-induced tree mortality, which may allow scientists and managers to better study the causes and consequences of spruce beetle outbreak.

The spruce beetle is one of the most damaging forest insects in North America, where it can lead to mortality of greater than >90% of mature spruce within a stand (DeRose & Long, 2007; Hopkins, 1909). Spruce beetles predominantly feed upon Engelmann spruce (*Picea engelmannii*), white spruce (*Picea glauca*), Sitka spruce (*Picea sitchensis*), and Lutz spruce (*Picea X lutzii*) (Bentz et al., 2009). In the Southern Rocky Mountains (i.e. southern Wyoming to northern New Mexico), spruce beetles are found in high elevation Engelmann spruce and subalpine fir (*Abies lasiocarpa*) forests. The spruce beetle inhabits the inner bark and feeds on the tree's phloem tissues. Heavy colonization and reproduction within the inner bark interrupts the flow of water and nutrients throughout the tree and typically causes tree death. Endemic populations typically live in recently downed and weakened trees. Outbreaks occur as beetle populations grow and start attacking seemingly healthy spruce (Massey & Wygant, 1954; Schmid & Frye, 1977).

While methods for remotely sensing mountain pine beetle-induced tree mortality may inform methods for mapping spruce beetle-induced mortality, species-specific differences in the spectral signatures that accompany tree death and forest structure and composition require these methods to be adapted and tested. Several knowledge gaps exist that limit our ability to use satellite imagery to study spruce beetle-induced tree mortality. First, limited information is available about the spectral signature of spruce beetle killed trees and affected stands. Like other

bark beetle-affected trees, the spectral signature of spruce beetle-killed trees is expected to change with increasing time since initial infestation (M.A. Wulder, Dymond, White, Leckie, & Carroll, 2006). Analogous to mountain pine beetle infestation, in the initial stages of spruce beetle-infestation there are no visual signs of infestation (i.e. needles remain green, “green stage”). During this initial stage of infestation, foliar moisture content declines in both mountain pine beetle and spruce beetle-affected trees (Page & Jenkins, 2007; Jolly et al., 2012). This leads to decreased reflection in near infrared (NIR) wavelengths and increased reflection in shortwave infrared (SWIR) wavelengths (Cheng, Rivard, Sánchez-Azofeifa, Feng, & Calvo-Polanco, 2010; Wulder et al., 2006). Following initial infestation, the needle color of attacked spruce beetle-attacked trees slowly fades from green to yellow-green over the course of one year (Johnson et al., 1997). This is in stark contrast to mountain pine beetle-attacked trees, which turn red one year following infestation (“red stage”; Wulder et al., 2006). About two years following attack, spruce beetle-killed trees drop their needles and twigs become exposed in the upper crown, giving the tree a reddish-gray color, (“gray stage”; Schmid & Frye, 1977). Most remote sensing studies of mountain pine beetle infestation have focused on identifying red-stage infestation, not the gray stage, limiting the transfer of methods for remotely sensing mountain pine beetle killed-trees to spruce beetle-killed trees. At the stand-scale, subalpine forests of lodgepole pine typically consist of a single tree species forming homogeneous patches of similarly aged trees across large areas (Sibold, Veblen, & González, 2006). In contrast, spruce beetle affected forests typically consist of two or more dominant tree species usually represented by multi-aged and multi-sized populations (Veblen, Hadley, Reid, & Rebertus, 1991). Thus spectral signature of spruce beetle infestation at moderate resolutions may be more diluted by an abundance of young and non-host trees.

Second, spruce beetle-induced tree mortality occurs at three distinct spatial scales: tree (square meters), forest stands (hectares), and landscapes (square kilometers) (Raffa et al., 2008). These distinct spatial scales arise from complex interactions between spruce beetle and tree host populations. Transitions among scales arise from complex tree-to-beetle, beetle-to-tree and beetle-to-beetle interactions resulting in amplifying positive feedbacks (Raffa et al., 2008). Forest stand-scale mortality may transition to a landscape-scale outbreak when a combination of factors are present: 1) abundant susceptible large host trees (Schmid & Frye, 1977), 2) high beetle population density (Raffa et al., 2008), 3) warm and dry weather (Berg, David Henry, Fastie, De Volder, & Matsuoka, 2006; DeRose & Long, 2012; Hart, Veblen, Eisenhart, Jarvis, & Kulakowski, 2014; Hebertson & Jenkins, 2008), and 4) low beetle predation (Berryman, 1982). Thus the appropriate spatial grain and extent for detecting spruce beetle kill depends on the spatiotemporal state of infestation. However, detailed information about the spatiotemporal progression spruce beetle infestation is extremely limited.

Previous efforts to detect spruce beetle-induced tree mortality have used a high (2.4 m; Makoto et al., 2013) or moderate (30 m; DeRose et al., 2011) spatial resolution. High resolution imagery (< 5 m) provides spatial detail at the tree-scale, which can provide important information on tree-scale infestation patterns and severity of outbreak (e.g. mortality/survivorship of individual trees; Coops et al., 2006; Meddens, Hicke, & Vierling, 2011). However, high resolution imagery often yields more variable reflectance values within one cover type (Dennison, Brunelle, & Carter, 2010; M.A. Wulder, Dymond, et al., 2006), and rarely covers a broad area (Wulder et al., 2006). In addition, the time period of record is often short and imagery may not be regularly repeated (Jensen, 2007). In contrast, remotely sensed data collected at a moderate resolution (ca. 30 m) is typically multispectral, publically available, frequently

repeated, and broad in spatial extent (Cohen & Goward, 2008). Regularly repeated imagery can be used to identifying changes in reflectance that indicate vegetation has been removed or died, which may improve classification accuracy of bark beetle infestation where the spectral signature of infestation may be diluted by uninfested host trees and non-host cover. Further post-classification correction informed by the ecological process of interest (here tree mortality) can be used to improve classification accuracy (Wulder, Dymond, et al., 2006).

Given the importance of cross-scale interactions in spruce beetle outbreak dynamics (Raffa et al., 2008), coupled high tree-scale (high resolution) and stand-scale (moderate resolution) maps of outbreak have the potential to offer important insights into the spatial and temporal patterns of spruce beetle infestation. Better understanding of the spatial and temporal patterns of spruce beetle infestation is key to understanding and predicting the transitions between different states of spruce beetle infestation. Moreover, to our knowledge, high and moderate resolution patterns of spruce beetle activity have not been compared.

To address the most critical of these knowledge gaps, we explore the use of a machine learning pixel-based classifier to detect spruce beetle-induced tree mortality from single-date high-resolution imagery and multi-date moderate-resolution data. Our objectives are (1) to adapt methods for classifying mountain pine beetle-infested trees for classifying spruce beetle-infested trees from freely available high-resolution aerial imagery; (2) to adapt methods for classifying red stage mountain pine beetle-infested stands for classifying gray stage spruce beetle-infested stands from multi-date Landsat imagery; and (3) analyze spatial and temporal patterns of spruce beetle-induced tree mortality using the high-resolution and moderate-resolution maps of spruce beetle infestation created in objectives one and two.

2. METHODS

2.1 Study Area

The study area was located in southwestern Colorado (Fig. 1). The area was chosen because it is the location of a landscape-scale spruce beetle outbreak, which began in the early 2000s (Lewis, Wardle, Leatherman, & Duda, 2003). Specifically, the study area is the spruce-fir zone of eastern San Juan Mountains and extends from ca. 38.1 to 37.4 °N and 106.6 to 107.6 °W. Elevation across the study area ranges from 2170 to 4283 m with 68% of the study area located between 3070 and 3490 m asl. The climate record (1981-2010) at Wolf Creek Pass (3243 m), which is located in the center of the study area (Fig. 1), lists total annual precipitation as 116 cm and average monthly temperatures as 11.7 C and 8 C for July and January, respectively (<http://www.ncdc.noaa.gov>). Aerial Detection Survey data indicates that 45% of spruce-fir forest in the study area was mapped as affected by spruce beetles over the period from 1998-2013 (USFS and its partners, 2013).

2.2 Ground control data collection

In the summer of 2013, we sampled 20 spruce-fir stands across the study area (Fig. 1). Sample sites were located in areas of live/green-phase (n=10) and gray phase (n=10) spruce-fir forest (Table A1). Locations for each plot were recorded with a GPS sensor accurate to 3m. At each site we sampled all trees >4 cm diameter at breast height (DBH) within a 20 x 20 m plot. For all trees we recorded the DBH, species, canopy width, and status (live, green stage, gray stage, or dead from other causes). We then calculated the proportion of the basal area of spruce in green, live, and gray stages of spruce beetle attack.

We found the mean canopy width of a canopy dominant spruce was 2.2 m (sd = 1.2). This value was used to inform the appropriate spatial grain for mapping tree-scale mortality. The total basal area of surveyed stands ranged from 30 to 114 m²/ha (Table A1). In general, stands

were dominated by spruce (spruce accounted for $85 \pm 22\%$ of the total basal area; Table A1).
Subalpine fir was present in 14 of 20 stands.

2.3 Aerial imagery

2.3.1 Data preparation of aerial imagery

We obtained multispectral aerial imagery (spatial resolution 1 x 1 m) for the study area from the National Agriculture Imagery Program (NAIP; Aerial Photography Field Office (AFPO), 2012). NAIP imagery is collected using precision digital cameras (Leica ADS40, Vexcel UltraCam, and Z/I DMC systems), which collect spectral data in visible wavelengths (Table 1). NAIP imagery is repeated every 2 to 5 years. Prior to distribution, the USDA Aerial Photography Field Office (APFO) preprocesses all imagery. First, the dynamic range of each image is adjusted to use the full range of values. Next, images are balanced for contrast and color. Then images are orthorectified using digital elevation models from the National Elevation Dataset (NED; Gesch et al., 2002). Finally images are orthomosaicked from multiple flight paths (25 for the study area) to create county mosaics (Aerial Photography Field Office (AFPO), 2012). NAIP data is horizontally accurate to within 6 meters of photo-identifiable ground control points (Aerial Photography Field Office (AFPO), 2012)

To produce a tree-scale map we aligned the NAIP data with Landsat data and aggregated the NAIP data to 3m (Bright, Hicke, & Hudak, 2012; Meddens et al., 2011) (Fig. 2). We then limited our study area to the spruce-fir zone by masking out all non-spruce-fir cover using an existing vegetation type layer interpreted from 1 m aerial imagery and produced by the USFS in 2003 (USFS, 2003) (Fig. 2).

Finally we calculated spectral indices to reduce effects of topography, viewing angle, sun angle, and radiometric consistency between flight paths (Jensen, 2007). Specifically we

calculated the red-green index (RGI; Table 2), an index useful for mapping tree mortality (Coops et al., 2006) and a blue-red index (BR; Table 2).

2.3.2 *Classification of aerial imagery*

To classify the aerial imagery, we first manually digitized 200 points for each of the four dominant classes present within the spruce-fir area of the NAIP image (shadow, non-forest cover, green trees, and gray trees). Points were randomly positioned across the image and then moved to the nearest pixel characteristic of the desired class. To determine the spectral characteristics of gray trees useful for distinguishing gray trees from other classes, we then graphically examined the spectral signatures of each class and selected the spectral indices that yielded adequate class separation.

Next, we first portioned our dataset of manually-interpreted class and NAIP index values using a randomized split-sample approach to partition our data into separate training (65% of observations) and validation (35 % of observations) datasets (Fig. 2). We then classified the NAIP imagery (shadows, non-forest, green trees, and gray trees) using a pixel-based nonparametric Support Vector Machines (SVM) classifier. SVMs attempt to find the optimal separating hyperplane between classes by focusing on the training cases that lie at the edges of class distributions (i.e. *support vectors*). The SVM approach assumes that only the cases on the class boundaries are useful for discriminating between classes (Cortes & Vapnik, 1995). As such, SVM is particularly adept at dealing with small training samples while still achieving high generalization performance (Foody & Mathur, 2004).

SVM classification was performed in R using the interface to LIBSVM (Chang & Lin, 2011) available in package e1071 (Meyer, Dimitriadou, Hornik, Weingessel, & Leisch, 2014). Here, a hyperplane is defined by the equation $\omega \cdot x + b = 0$, where x is a point on the

hyperplane, ω is normal to the hyper-plane, and b is the bias. In the simplest case of two linearly separable classes (y_i), a separating hyperplane can be defined as $\omega \cdot x + b \geq +1$ (for $y_i = +1$) and $\omega \cdot x + b \leq -1$ (for $y_i = -1$). The support vectors of the two classes lie on two hyperplanes parallel to the optimal separating hyperplane and are defined as $\omega \cdot x_i + b = \pm 1$. The margin between the two hyperplanes can be defined as $2/(\|\omega\|)$, with $\|\omega\|$ the Euclidean norm of ω (Chang & Lin, 2011). We performed a C-classification (C-SVM), which minimizes the error function:

$$\frac{\|\omega\|^2}{2} + C \sum_{i=1}^N \zeta_i \quad [11]$$

subject to:

$$y_i(\omega \cdot \phi(x_i) + b) \geq 1 - \zeta_i \text{ and } \zeta_i \geq 0, i = 1, \dots, N$$

Where ζ_i represents parameters for handling non-separable data and indicates the distance of incorrectly classified points from the optimal hyperplane (Foody & Mathur, 2004). The cost coefficient C controls the magnitude of the penalty associated with incorrectly classified points; higher values of C minimize misclassification rates thereby increasing overfitting. We set C to 1 after performing a cross-validated grid search of suitable values. Because land over class is often not linearly separable, we used a radial kernel, Φ , to transform the data to a non-linear feature space. The radial kernel has been shown to be particularly effective in remote sensing applications (Foody & Mathur, 2004; Pal & Mather, 2005) and is defined by:

$$\phi = e^{-\gamma \|x - x_i\|^2} \quad [12]$$

Where γ is adjustable parameter that determines the width of the kernel, here set to 0.1 after performing a cross-validated grid search of suitable values.

While SVM was originally designed for binary classification (Cortes & Vapnik, 1995), it can be extended to multiclass classifications. For multiclass classification with k levels, LIBSVM uses a ‘one-against-one’ approach, where $k(k-1)/2$ binary classifiers and the appropriate class is found by voting (Chang & Lin, 2011).

We evaluated model accuracy both visually and quantitatively with cross-validated confusion matrices. We randomly partitioned our data into separate training and validation datasets 10 times and calculated 10 cross-validated confusion matrices. We report the mean overall accuracy, quantity disagreement (Q), allocation disagreement (A) and producer’s and user’s accuracies for each class. The user’s accuracy indicates the probability that a classified case represents what is found on the ground. The producer’s accuracy indicates the probability that ground reference data is classified correctly (Jensen, 2005). The quantity disagreement describes the amount of disagreement between the classified map and the reference map due to an imperfect match in the quantity of each class. The remainder of the total disagreement is termed the allocation disagreement, which reflects the amount of disagreement due to an imperfect spatial allocation of classes (Pontius & Millones 2011).

2.4 Landsat imagery

2.4.1 Data preparation of Landsat imagery

We obtained late summer (July – September) Landsat Climate Data Record (CDR) images for path 34, row 34 for the time period 1995-2013 (Table 1). Landsat CDR is a high-level surface reflectance product for land change studies, which consists of surface reflectance, brightness temperature, and masks for clouds, cloud shadows, and water. Landsat CDR data are generated from specialized software called the Landsat Ecosystem Disturbance Adaptive Processing System. For each image we masked out cloud cover using the Landsat CDR cloud

mask (Fig. 2), which is based on methods outlined in Zhu and Woodcock (2012). We then masked out non-spruce forest using the R2Veg dataset (Fig. 2) (USFS, 2003). Using Landsat CDR surface reflectance values, we calculated eight vegetation indices (DI, NDMI, NDVI, RGI, RVI, TCBRI, TCGRE, and TCWET) that have been used in previous studies of bark beetle outbreaks (Table 2).

2.4.2 *Classification of Landsat imagery*

At the stand-scale, the classes of interest were gray stands, green stands, and non-forest cover. To determine the spectral characteristics of gray stands useful for distinguishing gray stands from other classes, we first aggregated the classified NAIP data to the Landsat-scale to produce proportions (i.e. the percentage of each class within a 30-m pixel; Meddens et al., 2013). Next, we randomly selected 200 cells of each class where at least 75% of the pixel was occupied by the desired class. We then graphically examined the spectral signatures of each class and selected the indices most useful for separating the classes.

To classify the Landsat imagery, we next determined a pre-disturbance baseline for each vegetation index. To calculate the undisturbed baseline, we iteratively calculated a multi-date (i.e. across all years) standard deviation for the entire study area and removed all values more than one standard deviation away from the mean in the expected direction of disturbance (e.g. for NDVI we removed all values less than 1 standard deviation from the mean). We also removed all outliers, values greater or less than 4 standard deviations away from the mean. We then calculated the multi-date anomaly, the deviation from the baseline for each year's image. Our approach follows methods described in Meddens et al. (2013), however we define one pre-disturbance baseline for the entire study area whereas Meddens et al. (2013) calculate a pre-disturbance baseline for each pixel within their study area. Given the number of values for any

given pixel is limited by the time period of record, our approach allows for a robust estimate of the pre-disturbance mean and standard deviation for each vegetation index.

Rasters of multi-date anomalies were classified using a C-classification radial kernel SVM classifier ($C=1$; $\gamma=0.01$) using the R packages e1071 (Meyer et al., 2014). We evaluated model accuracy both visually and quantitatively with cross-validated confusion matrices. We randomly selected 10 datasets composed of 200 cells of each class where at least 75% of the pixel was occupied by the desired class, as determined from aggregating the classified NAIP data. Each dataset was randomly partitioned into separate training (65% of cases) and validation (35% cases) and we calculated 10 cross-validated confusion matrices. We report the mean overall accuracy, quantity disagreement (Q), allocation disagreement (A) and producer's and user's accuracies for each class.

Following classification, we performed an ecologically informed post-classification correction on the multi-date classified data. Post-classification correction was performed to remove high frequency year-to-year variability and preserve low frequency variability, indicative of tree mortality. We removed spruce beetle-kill false-positives, defined here as pixels classified as gray-stage in the current year but not in the either previous or subsequent year (c.f. Meddens et al., 2013). We also removed false-negatives, defined here as pixels classified as green stands in the current year, but gray-stage in the previous and subsequent years. It was outside the scope of this paper to evaluate the efficacy of post-classification correction across multiple models, so model accuracy was assessed using a single confusion matrix that included the overall accuracy, quantity disagreement (Q), allocation disagreement (A) and producer's and user's accuracies for each class.

To further assess the accuracy of the Landsat imagery classifier, we compared the classified area of gray stand cover with two independent datasets of spruce beetle infestation. First, we compared our field estimates of spruce beetle activity with predicted spruce beetle presence. Because our field data do not consider time since attack, we compared field estimates with the cumulative area mapped as gray-stage outbreak during the 1996 -2012 period. Field plots did not align perfectly with Landsat grids, so we calculated the proportion of pixels affected within 100 m of our plot center. If the percent of affected pixels was greater than 50%, we assigned gray-stage as the predicted class.

Second, we compared temporal trends in classified Landsat imagery with ADS data (USDA Forest Service, 2013). We obtained annual ADS polygons depicting the presence of spruce beetle outbreak from the US Forest Service (USFS and its partners, 2013). Annual ADS data was then converted to a 30 x 30 m grid and clipped to the study area. During the initial stages of spruce beetle infestation (2000-2005), ADS data was only collected for a subset of the study area. For each year we calculated the area of ADS-detected spruce beetle outbreak within the study area and compared it with the area of remotely sensed gray stand cover.

2.5 Coupling high-resolution and moderate-resolution classifications to gain insights into spruce beetle ecology

Finally we compared high-resolution and moderate-resolution classifiers to gain insight into the severity of gray stage mortality within grid cells with a 30-m cell spatial resolution. High-resolution maps of gray trees were compared with the best classifier of gray stands, which was selected after evaluating the classifiers with independent data sources. Given that the number of infested trees within a stand may change with time, we also compared the proportion of trees within pixels newly infested (i.e. pixels identified for the first time in a given year) and

older infestation (i.e. pixels classified as infested in two or more years). Severity in new and old infestation was compared graphically and statistically using a nonparametric Kruskal-Wallis test.

3. RESULTS

3.1 High-resolution classification of spruce beetle-affected forests

Using NAIP imagery aggregated to 3-m, we found that classes could be differentiated effectively using the RGI and BR indices (Fig. 3). As expected, gray trees were characterized by higher RGI values than green trees. Non-forest cover was characterized by higher values of the BR than dead or live trees. Shadows were characterized by low values of the RGI and BR (Fig. 3).

The SVM classification of 3-m aggregated NAIP imagery from RGI and RI resulted in an average cross-validated classification accuracy of 90% (Table 3). Most individual class user's accuracies were close to or above 90%, except for non-forest cover (user's accuracy of 82%; Table 3). Gray stands were most commonly confused for the non-forest class.

3.2 Multi-date moderate-resolution classification

Using 30-m Landsat imagery, we found that gray stands (>75% gray trees by area) could be distinguished from green stands (>75% green trees by area) using the DI, NDVI and all three indices produced from the Tasseled Cap Transformation (Fig. 4). Because the DI is a linear function of all three Tasseled Cap indices, we selected just the DI for classifying spruce beetle outbreak. Additionally, the DI allowed for good separation between gray and green trees, while NDVI allowed for good separation between non-forest cover and trees (Fig. 4).

Prior to post-classification correction, the average classification accuracy of the multi-date Landsat imagery using cross-validation was 90% (Table 5). All individual class user's accuracies were similar to or above 90% (Table 5). Gray stands were misclassified as both green

stands and non-forest cover. After post-classification correction, the classification accuracy of the multi-date Landsat imagery classifier increased to 93%. Notably, the user's accuracy of gray stands improved from 88% to 93% (Table 5 and 6).

Prior to post-classification correction, 58% of the study area was estimated to have experienced stand-scale spruce beetle infestation (1996-2012), as indicated by gray-stand cover. By removing high frequency year-year variability, post-classification resulted in a dramatically lower percent area of cumulative gray-stand cover (27%). In comparison, ADS data indicates that 45% of the study area was mapped as affected by spruce beetles over the same period (USFS and its partners, 2013). Post-classification correction resulted in a smaller area of spruce beetle infestation for all years (Fig. 5).

Time series of the percentage of the study area mapped as gray-stage spruce beetle kill in classified Landsat imagery closely track the independent time series of spruce beetle activity derived from ADS data (Fig. 5). However, remotely sensed datasets illustrate increased tree mortality earlier in time than ADS data (2000 for remotely sensed estimates and 2005 for ADS data; Fig. 5). The post-classification corrected time series illustrates a smoother trend with notably less spruce beetle activity in 2006 than the multi-date classification without post-classification correction.

In comparison to 2013 field data, the multi-date classifier without post-classification correction did not accurately predict the stand-level presence/absence of gray-stage spruce beetle outbreak ($> 50\%$ of spruce basal area classified as gray stage; Table A1). Only 42% of field plots were correctly classified. Notably 80% of green stands were classified as gray stands (producer's accuracy of green stands = 20%). In contrast the post-classification corrected multi-date classifier achieved an overall accuracy of 70% with user's accuracies of 71% and 62%, for gray

stands and green stands, respectively. All green stands misclassified as gray stage were experiencing high levels of initial attack (>66% of the spruce basal area attacked). This suggests that stands in the early stages of attack may exhibit similar spectral signatures to gray stands. Of the gray stands that were misclassified as green, all stands were located in areas where gaps in data existed due to clouds or failure of the Landsat 7 ETM+ scan line corrector. Our post-classification correction relies on pixels values in the current year, prior year, and subsequent year to generate class predictions, which likely generated a higher false positive rate.

3.3 Coupling high-resolution and moderate-resolution classifications to gain insights into spruce beetle ecology

The 30-m raster of gray tree presence, which was created by aggregating the 2011 NAIP 3-m classification, revealed varying levels of tree mortality across the study area. This high variability of tree mortality within a 30 x 30 m was found within both green and gray stands, which were classified in post-classification corrected multi-date SVM approach (Fig. 6a). Of the stands with less than 40% gray trees, 76% were classified as greens stands. Of the stands with more than 60% gray trees, 81% were classified as gray stands. Stands composed of mixed gray and green trees (40-60% gray trees) were classified as gray stands in 51% of cases (Fig. 6a).

Within gray stands, newly infested pixels (i.e. pixels identified as infested for the first time in 2011) were characterized by less severe infestation than old infestation (i.e. pixels that had experienced two or more years of infestation) (Fig. 6b). Median severity of old infestation was only 4% greater than new infestation (median infestation 41% and 45% in new and old infestation, respectively). Despite this relatively small difference the severity of infestation in new and old infestation was significantly different ($K = 12577$, $p < 0.001$).

4. DISCUSSION

Consistent with previous research, spruce beetle killed-trees can be classified from both high- and moderate-resolution remotely sensed imagery (DeRose et al., 2011, Makoto et al., 2013). Although NAIP offers only a few spectral bands, it can be used to accurately classify spruce beetle-affected forest across broad spatial extents (here ca. 1,800 km²) (overall agreement = 90% and user's accuracy for gray trees = 89%). Previous high-resolution studies of bark beetle outbreaks have been conducted using commercial remote sensing data (e.g. Quickbird, Coops et al., 2006; Makoto et al., 2013; Geoeye-1, Dennison et al., 2010), characterized by smaller spatial extents but more spectral information. Our study area is considerably larger than in previous tree-scale studies of bark beetle-induced tree mortality (36 km² in Coops et al., 2006; 225 km² in Dennison et al., 2010; and 94 km² Meddens et al., 2011). Our results also confirm that stand-level bark beetle outbreak can be detected with Landsat-scale data (DeRose et al., 2011; Goodwin et al., 2010; Meddens et al., 2013; Meigs, Kennedy, & Cohen, 2011; Skakun et al., 2003), here with overall accuracies and user's accuracy for gray-stage stands greater than 90%. This represents an improvement from DeRose et al.'s (2011) existing Landsat classifier of spruce beetle-killed trees, which is characterized by a maximum user's accuracy for spruce beetle-affected stands of 71% (user's accuracies varied by year).

While USFS ADS data indicate that spruce beetle outbreak is the leading cause of tree mortality in our study area (Fig. 1), a notable limitation to our study is that gray trees and stands do not necessarily correspond to spruce beetle-induced tree mortality. Trees that died from other causes will be included in the classification and thus incorrectly attributed to spruce beetle disturbance. More research, such as the application of time series approaches, is needed to separate out different types of disturbance (e.g. Meigs et al., 2011).

Our research adds to a growing understanding of the spectral signature of spruce beetle-

killed trees. Similar to the results of high-resolution studies of mountain pine beetle outbreaks (Coops et al., 2006), we found that gray trees could be differentiated from green trees using the RGI. As chlorophyll concentration declines with tree death, trees stop absorbing red wavelengths and the RGI increases allowing for identification of dead trees. Unlike at the tree-scale, the RGI was not identified as a useful indicator of stand-level spruce beetle-kill in contrast to moderate-resolution Landsat classifiers of the recent mountain pine beetle infestation (Meddens et al., 2013). Since the canopies of spruce beetle-infested trees do not turn red, like mountain pine beetle-infested trees, this finding is not surprising. Thus while accurate high-resolution classifiers of spruce beetle-infested trees may be created with RGI, it is likely that tree-scale classifiers of gray-stage spruce beetle infestation would be improved by the inclusion of more wavelengths.

At the stand-scale, we identified the DI and NDVI as useful predictors of gray-stage spruce beetle outbreak. Previous work by DeRose et al. (2011) in Utah also identified the DI as an indicator of spruce beetle killed-trees. Spruce beetle outbreaks reduce canopy foliage and evapotranspiration, leading to lower TCGRE and TCWET values and higher TCBRI values. These changes create dramatic differences in unaffected spruce-fir forest (>75% green tree cover by area) and gray stage spruce-fir forest (>75% gray tree cover by area). In our study, we also identified NDVI as a useful vegetation index for distinguishing between gray-stage spruce beetle outbreak and non-forest. This finding is consistent with previous work, which used NDVI to distinguish between forest and non-forest classes in area of mountain pine beetle outbreak (Meddens et al., 2011). Here we show that vegetation indices that incorporate NIR and SWIR wavelengths, rather than just visible wavelengths (e.g. RGI), can improve estimates of gray-stage spruce beetle outbreak.

This study builds upon previous work using machine-learning techniques to classify

remotely sensed imagery (Arora & Foody, 1997; Huang, Davis, & Townshend, 2002; Pal & Mather, 2005; Peddle, Foody, Zhang, Franklin, & LeDrew, 1994; Rogan, Franklin, & Roberts, 2002). To our knowledge, this is the first application of the SVM classifier to either bark beetle-induced tree mortality from high-resolution NAIP imagery or moderate-resolution Landsat imagery. SVM classification offers a number of advantages that should be explored in subsequent efforts to remotely sensing of bark-beetle induced mortality. First, SVM classifiers are nonparametric and thus are insensitive to multi-collinearity between predictors. This trait was particularly important for our classification of high-resolution NAIP imagery, where our predictor indices (RGI and BR) were highly correlated ($r=-0.90$, $p<0.001$). Second, SVMs have been shown to be relatively insensitive to noise (Dalponte, Bruzzone, Vescovo, & Gianelle, 2009) and useful for small training datasets (Foody & Mathur, 2004). Our results highlight the utility of SVM classification for pixel-based classifications of forest mortality.

We found post-classification informed by ecological process, here the mortality of spruce within mixed spruce-fir stands, can markedly improve the accuracy of forest classifiers. Specifically, post-classified multi-date estimates of gray-stage outbreak more accurately represented temporal variation in spruce beetle outbreak documented in ADS datasets and agreed more strongly with field measurements of spruce beetle outbreak. A notable limitation of post-classification correction is the dependency of a pixel in a given year on values from three consecutive years. Here, we attribute missing values to lead to increased rates of false-negative gray stands.

Our study shows that coupling high-resolution and moderate-resolution imagery can improve our understanding of tree mortality at the landscape-scale. First, we find that NAIP data can be used to train a classification of spruce beetle activity from Landsat CDR imagery. This

approach allowed for substantially more training points to be used than could be obtained with field data alone (Meddens et al., 2013; Michael A. Wulder et al., 2012). By using both NAIP and Landsat data, we combined the advantages of high-resolution imagery, most importantly tree-scale information, with the advantages of Landsat imagery, specifically broader spatial extents, quicker computation times, and a longer period of record.

Finally we suggest that remote sensing may prove to be a valuable tool for studying the causes and consequences of spruce beetle outbreak. In our study, remote-sensing classifiers identified increased tree mortality prior to ADS data (2000 for remotely sensed estimates and 2005 for ADS data; Fig. 5). We note that this increase in tree mortality was observed in a portion of the study area not surveyed in ADS surveys until 2005. Such spatiotemporal gaps in ADS data often exist in wilderness areas and National Parks (Meddens et al., 2012), which are less frequently surveyed. In the Southern Rockies, 8930 km² of spruce-fir forest exist in wilderness areas alone. Thus other important spatiotemporal gaps likely exist in ADS datasets of spruce beetle infestation across the Southern Rockies. As such, we argue that remotely sensed data can provide valuable insight into spatiotemporal analyses of spruce beetle infestation.

Within a landscape-scale spruce beetle outbreak a broad range of spruce beetle-induced tree mortality may occur within any given 30 x 30 m area. This broad range of mortality is consistent with field observations of both 2000s spruce beetle infestation in the San Juan Mountains (Scott, 2013) and 1940s infestation in northwestern Colorado (Veblen et al., 2001). With increased time since initial infestation, the severity of tree mortality increased slightly. This relatively small increase may be a result of synchronous tree mortality within a 30 x 30 m pixel, which may occur because at a 30 x 30 m scale infestation is more likely to be detected once significant tree mortality has occurred. Additionally, the small change in tree mortality between

new and old infestation is likely due to the removal of tree-scale constraints on infestation during landscape-scale infestation (Raffa et al., 2008).

While severe infestation occurred in the San Juan Mountains, moderate severity infestation (35% – 55% of trees dead within a pixel) was far more common. Field observations in the study area indicate similar infestation severity (e.g. reduction in live basal area by about 45%; Andrus, Veblen, Harvey, & Hart, in prep). Similar studies of mountain pine beetle infestation have documented higher levels of infestation (Meddens et al. 2013). This predominance of lower severity infestation in spruce beetle outbreak is likely a result of the heterogeneous species composition and age structure that characterizes spruce-fir forests.

5. CONCLUSION

In this paper we showed that methods for classifying mountain pine beetle-induced mortality could be extended to classifying spruce beetle-induced mortality. We found gray-stage tree mortality can be distinguished from undisturbed forest and non-forest classes using freely available high-resolution aerial imagery from NAIP, and that a tree-level map of spruce beetle infestation can be used to produce stand-level maps of high severity gray-stage outbreak from Landsat CDR data. Gray-stage spruce beetle outbreak was characterized by higher RGI values at the tree-level and higher DI and lower NDVI at the stand-level. These vegetation indices have been identified in previous remote sensing studies of bark beetle kill (Coops et al., 2006; DeRose et al., 2011; Meddens et al., 2011; Walter & Platt, 2013) and are likely indicative of beetle kill in forests in other regions too. Additionally our results demonstrate the utility of machine learning techniques and in particular SVM, in classifying forest disturbance. Finally, a machine-learning technique coupled with a time-series of images may be used to create highly accurate maps of spruce beetle kill.

We found that moderate spruce beetle infestation characterized most 30 x 30 m pixels and that infestation severity increased slightly with time since initial detection. This spatially explicit information on the severity of tree mortality from spruce beetle infestation can provide important information for forest management. Notably insights into the spatial dynamics of tree mortality can greatly inform our understanding of the consequences of bark beetle outbreak on regional carbon balances (Ghimire et al., 2015), resistance and resilience to subsequent disturbance (Hart, Veblen, Mietkiewicz, & Kulakowski, Accepted; Harvey, Donato, & Turner, 2014), and water quantity (Bearup, Maxwell, Clow, & McCray, 2014) and quality (Rhoades et al., 2013).

Our methods inform efforts to map spruce beetle mortality across broad landscapes. The final products are tree- and stand-scale classified imagery that are both highly accurate. The classified imagery produced here will be useful for landscape-scale analyses of the causes and consequences of spruce beetle outbreak. In addition, our results on the spectral, spatial, and temporal dynamics of tree mortality in areas of active spruce beetle outbreak can inform future studies that aim to distinguish between different types of tree mortality in subalpine forests.

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7. REFERENCES

542 Aerial Photography Field Office (AFPO). (2012). Imagery Programs: National Agriculture
 543 Imagery Program (NAIP). Retrieved from
 544 <http://fsa.usda.gov/FSA/apfoapp?area=home&subject=prog&topic=naip>

545 Andrus, R. A., Veblen, T. T., Harvey, B. J., & Hart, S. J. (in prep). An active spruce beetle
 546 outbreak did not affect fire severity in spruce-fir forests in southern Colorado.

547 Arora, M. K., & Foody, G. M. (1997). Log-linear modelling for the evaluation of the variables
 548 affecting the accuracy of probabilistic, fuzzy and neural network classifications.
 549 *International Journal of Remote Sensing*, 18(4), 785–798.
 550 doi:10.1080/014311697218755

551 Bearup, L. A., Maxwell, R. M., Clow, D. W., & McCray, J. E. (2014). Hydrological effects of
 552 forest transpiration loss in bark beetle-impacted watersheds. *Nature Climate Change*,
 553 *advance online publication*. doi:10.1038/nclimate2198

554 Bentz, B., Logan, J., MacMahon, J., Allen, C., Hansen, M., Hicke, J., ... Wood, D. L. (2009).
 555 Bark beetle outbreaks in western North America: Causes and consequences. In *Bark*
 556 *Beetle Symposium*. Snowbird, Utah: Distributed by University of Utah Press.

557 Berg, E. E., David Henry, J., Fastie, C. L., De Volder, A. D., & Matsuoka, S. M. (2006). Spruce
 558 beetle outbreaks on the Kenai Peninsula, Alaska, and Kluane National Park and Reserve,
 559 Yukon Territory: Relationship to summer temperatures and regional differences in
 560 disturbance regimes. *Forest Ecology and Management*, 227(3), 219–232.

561 Berryman, A. A. (1982). Biological control, thresholds, and pest outbreaks. *Environmental*
 562 *Entomology*, 11(3), 544–549.

563 Bright, B. C., Hicke, J. A., & Hudak, A. T. (2012). Estimating aboveground carbon stocks of a
 564 forest affected by mountain pine beetle in Idaho using LiDAR and multispectral imagery.
 565 *Remote Sensing of Environment*, 124, 270–281.

566 Chang, C.-C., & Lin, C.-J. (2011). LIBSVM: A Library for Support Vector Machines. *ACM*
 567 *Trans. Intell. Syst. Technol.*, 2(3), 27:1–27:27. doi:10.1145/1961189.1961199

568 Chapman, T. B., Veblen, T. T., & Schoennagel, T. (2012). Spatiotemporal patterns of mountain
 569 pine beetle activity in the southern Rocky Mountains. *Ecology*, 93(10), 2175–2185.
 570 doi:10.1890/11-1055.1

571 Cheng, T., Rivard, B., Sánchez-Azofeifa, G. A., Feng, J., & Calvo-Polanco, M. (2010).
 572 Continuous wavelet analysis for the detection of green attack damage due to mountain
 573 pine beetle infestation. *Remote Sensing of Environment*, 114(4), 899–910.
 574 doi:10.1016/j.rse.2009.12.005

575 Ciesla, W. (2011). *2010 report on the health of Colorado's forests* (pp. 1–40). Fort Collins, CO:
 576 Colorado State Forest Service.

577 Cohen, W. B., & Goward, S. B. (2008). Landsat's role in ecological applications of remote
 578 sensing. *BioScience*, 54(6), 535–545. doi:10.1641/0006-
 579 3568(2004)054[0535:LRIEAO]2.0.CO;2

580 Cohen, W. B., Spies, T. A., Alig, R. J., Oetter, D. R., Maersperger, T. K., & Fiorella, M. (2002).
 581 Characterizing 23 years (1972–95) of stand replacement disturbance in western Oregon
 582 forests with Landsat imagery. *Ecosystems*, 5(2), 122–137.

583 Coops, N. C., Johnson, M., Wulder, M. A., & White, J. C. (2006). Assessment of QuickBird high
 584 spatial resolution imagery to detect red attack damage due to mountain pine beetle
 585 infestation. *Remote Sensing of Environment*, 103(1), 67–80.

586 Coppin, P. R., & Bauer, M. E. (1996). Digital change detection in forest ecosystems with remote
587 sensing imagery. *Remote Sensing Reviews*, 13(3-4), 207–234.

588 Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297.

589 Crist, E. P. (1985). A TM tasseled cap equivalent transformation for reflectance factor data.
590 *Remote Sensing of Environment*, 17(3), 301–306.

591 Dalponte, M., Bruzzone, L., Vescovo, L., & Gianelle, D. (2009). The role of spectral resolution
592 and classifier complexity in the analysis of hyperspectral images of forest areas. *Remote*
593 *Sensing of Environment*, 113(11), 2345–2355. doi:10.1016/j.rse.2009.06.013

594 Dennison, P. E., Brunelle, A. R., & Carter, V. A. (2010). Assessing canopy mortality during a
595 mountain pine beetle outbreak using GeoEye-1 high spatial resolution satellite data.
596 *Remote Sensing of Environment*, 114(11), 2431–2435.

597 DeRose, R. J., & Long, J. N. (2007). Disturbance, structure, and composition: Spruce beetle and
598 Engelmann spruce forests on the Markagunt Plateau, Utah. *Forest Ecology and*
599 *Management*, 244(1-3), 16–23. doi:10.1016/j.foreco.2007.03.065

600 DeRose, R. J., & Long, J. N. (2012). Drought-driven disturbance history characterizes a southern
601 Rocky Mountain subalpine forest. *Canadian Journal of Forest Research*, 42(9), 1649–
602 1660.

603 DeRose, R. J., Long, J. N., & Ramsey, R. D. (2011). Combining dendrochronological data and
604 the disturbance index to assess Engelmann spruce mortality caused by a spruce beetle
605 outbreak in southern Utah, USA. *Remote Sensing of Environment*, 115(9), 2342–2349.
606 doi:10.1016/j.rse.2011.04.034

607 Foody, G. M., & Mathur, A. (2004). A relative evaluation of multiclass image classification by
608 support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, 42(6),
609 1335–1343. doi:10.1109/TGRS.2004.827257

610 Franklin, S., Wulder, M., Skakun, R., & Carroll, A. (2003). Mountain pine beetle red-attack
611 forest damage classification using stratified Landsat TM data in British Columbia,
612 Canada. *Photogrammetric Engineering and Remote Sensing*, 69(3), 283–288.

613 Gao, B. (1996). NDWI—A normalized difference water index for remote sensing of vegetation
614 liquid water from space. *Remote Sensing of Environment*, 58(3), 257–266.
615 doi:10.1016/S0034-4257(96)00067-3

616 Gesch, D., Oimoen, M., Greenlee, S., Nelson, C., Steuck, M., & Tyler, D. (2002). The national
617 elevation dataset. *Photogrammetric Engineering and Remote Sensing*, 68(1), 5–32.

618 Ghimire, B., Williams, C. A., Collatz, G. J., Vanderhoof, M., Rogan, J., Kulakowski, D., &
619 Masek, J. G. (2015). Large carbon release legacy from bark Beetle outbreaks across
620 Western United States. *Global Change Biology*. doi.org/10.1111/gcb.12933

621 Goodwin, N. R., Coops, N. C., Wulder, M. A., Gillanders, S., Schroeder, T. A., & Nelson, T.
622 (2008). Estimation of insect infestation dynamics using a temporal sequence of Landsat
623 data. *Remote Sensing of Environment*, 112(9), 3680–3689. doi:10.1016/j.rse.2008.05.005

624 Goodwin, N. R., Magnussen, S., Coops, N. C., & Wulder, M. A. (2010). Curve fitting of time-
625 series Landsat imagery for characterizing a mountain pine beetle infestation.
626 *International Journal of Remote Sensing*, 31(12), 3263–3271.

627 Hart, S. J., Veblen, T. T., Eisenhart, K. S., Jarvis, D., & Kulakowski, D. (2014). Drought induces
628 spruce beetle (*Dendroctonus rufipennis*) outbreaks across northwestern Colorado.
629 *Ecology*, 95(4), 930–939. doi:10.1890/13-0230.1

630 Hart, S. J., Veblen, T. T., Mietkiewicz, N., & Kulakowski, D. (Accepted). Negative feedbacks on
631 bark beetle outbreaks: Widespread and severe spruce beetle infestation restricts
632 subsequent infestation. *PLOS ONE*.

633 Harvey, B. J., Donato, D. C., & Turner, M. G. (2014). Recent mountain pine beetle outbreaks,
634 wildfire severity, and postfire tree regeneration in the US Northern Rockies. *Proceedings*
635 *of the National Academy of Sciences*, 111(42), 15120–15125.
636 doi:10.1073/pnas.1411346111

637 Healey, S. P., Cohen, W. B., Zhiqiang, Y., & Krankina, O. N. (2005). Comparison of Tasseled
638 Cap-based Landsat data structures for use in forest disturbance detection. *Remote Sensing*
639 *of Environment*, 97(3), 301–310.

640 Hebertson, E. G., & Jenkins, M. J. (2008). Climate factors associated with historic spruce beetle
641 (Coleoptera: Curculionidae) outbreaks in Utah and Colorado. *Environmental*
642 *Entomology*, 37(2), 281–292. doi:10.1603/0046-225X(2008)37[281:CFAWHS]2.0.CO;2

643 Hilker, T., Wulder, M. A., Coops, N. C., Linke, J., McDermid, G., Masek, J. G., ... White, J. C.
644 (2009). A new data fusion model for high spatial- and temporal-resolution mapping of
645 forest disturbance based on Landsat and MODIS. *Remote Sensing of Environment*,
646 113(8), 1613–1627. doi:10.1016/j.rse.2009.03.007

647 Hopkins, A. D. (1909). *Practical information on the scolytid beetles of North American forests*.
648 *I. Bark beetles of the genus Dendroctonus*. Govt. print. off.

649 Huang, C., Davis, L. S., & Townshend, J. R. G. (2002). An assessment of support vector
650 machines for land cover classification. *International Journal of Remote Sensing*, 23(4),
651 725–749. doi:10.1080/01431160110040323

652 Jensen, J. R. (2005). *Introductory digital image processing: a remote sensing perspective* (3rd
653 ed). Upper Saddle River, N.J: Prentice Hall.

654 Jensen, J. R. (2007). *Remote sensing of the environment: an earth resource perspective* (2nd
655 Edition). Pearson Prentice Hall.

656 Johnson, E. W., & Ross, J. (2008). Quantifying error in aerial survey data. *Australian Forestry*,
657 71(3), 216–222.

658 Johnson, E. W., & Wittwer, D. (2008). Aerial detection surveys in the United States. *Australian*
659 *Forestry*, 71(3), 212–215. doi:10.1080/00049158.2008.10675037

660 Johnson, J., Greenfield, P., & Munson, A. S. (1997). *An evaluation of the utility of sub-pixel*
661 *analysis of thematic mapper imagery for the spruce beetle outbreak on the Manti-LaSal*
662 *National Forest-Final Report*. Ogden, Utah: USDA Forest Service, RSAC, Salt Lake
663 City, Utah, and Intermountain Region.

664 Jolly, W. M., Parsons, R. A., Hadlow, A. M., Cohn, G. M., McAllister, S. S., Popp, J. B., ...
665 Negron, J. F. (2012). Relationships between moisture, chemistry, and ignition of *Pinus*
666 *contorta* needles during the early stages of mountain pine beetle attack. *Forest Ecology*
667 *and Management*, 269, 52–59. doi:10.1016/j.foreco.2011.12.022

668 Lewis, P., Wardle, T., Leatherman, D., & Duda, J. (2003). *2002 Report on the Health of*
669 *Colorado's Forests* (p. 28). Fort Collins, CO: Colorado State Forest Service. Retrieved
670 from <http://csfs.colostate.edu/pdfs/02fhr.pdf>

671 Makoto, K., Tani, H., & Kamata, N. (2013). High-resolution multispectral satellite image and a
672 postfire ground survey reveal prefire beetle damage on snags in Southern Alaska.
673 *Scandinavian Journal of Forest Research*, 28(6), 581–585.
674 doi:10.1080/02827581.2013.793387

675 Massey, C., & Wygant, N. (1954). *Biology and control of the Engelmann spruce beetle in*
676 *Colorado* (No. Circular no. 944). Washington, D.C.: USDA Forest Service.

677 Meddens, A. J. H., Hicke, J. A., & Vierling, L. A. (2011). Evaluating the potential of
678 multispectral imagery to map multiple stages of tree mortality. *Remote Sensing of*
679 *Environment*, 115(7), 1632–1642. doi:10.1016/j.rse.2011.02.018

680 Meddens, A. J. H., Hicke, J. A., Vierling, L. A., & Hudak, A. T. (2013). Evaluating methods to
681 detect bark beetle-caused tree mortality using single-date and multi-date Landsat
682 imagery. *Remote Sensing of Environment*, 132, 49–58. doi:10.1016/j.rse.2013.01.002

683 Meddens, A. J. H., Hicke, J., & Ferguson, C. A. (2012). Spatial and temporal patterns of
684 observed bark beetle-caused tree mortality in British Columbia and the western US.
685 *Ecological Applications*. doi:10.1890/11-1785.1

686 Meigs, G. W., Kennedy, R. E., & Cohen, W. B. (2011). A Landsat time series approach to
687 characterize bark beetle and defoliator impacts on tree mortality and surface fuels in
688 conifer forests. *Remote Sensing of Environment*, 115(12), 3707–3718.
689 doi:10.1016/j.rse.2011.09.009

690 Meyer, D., Dimitriadou, E., Hornik, K., Weingessel, A., & Leisch, F. (2014). *e1071: Misc*
691 *functions of the Department of Statistics (e1071), TU Wien*. Retrieved from
692 <http://CRAN.R-project.org/package=e1071>

693 Page, W., & Jenkins, M. J. (2007). Mountain pine beetle-induced changes to selected lodgepole
694 pine fuel complexes within the Intermountain Region. *Forest Science*, 53(4), 507–518.

695 Pal, M., & Mather, P. M. (2005). Support vector machines for classification in remote sensing.
696 *International Journal of Remote Sensing*, 26(5), 1007–1011.

697 Pearson, R. L., & Miller, L. D. (1972). Remote mapping of standard crop biomass for estimation
 698 of the productivity of the shortgrass prairie, Pawnee National Grasslands, Colorado.
 699 *Proceedings of the 8th International Symposium on Remote Sensing of the Environment*,
 700 *II*, 1355–1379.

701 Peddle, D. R., Foody, G. M., Zhang, A., Franklin, S. E., & LeDrew, E. F. (1994). Multi-source
 702 image classification. II: An empirical comparison of evidential reasoning and neural
 703 network approaches. *Canadian Journal of Remote Sensing*, 20(4), 396–407.

704 Pontius RG, Jr., & Millones M. (2011). Death to Kappa: birth of quantity disagreement and
 705 allocation disagreement for accuracy assessment. *International Journal of Remote*
 706 *Sensing*, 32, 4407–4429.

707 Preisler, H. K., Hicke, J. A., Ager, A. A., & Hayes, J. L. (2012). Climate and weather influences
 708 on spatial temporal patterns of mountain pine beetle populations in Washington and
 709 Oregon. *Ecology*, 93(11), 2421–2434.

710 Raffa, K. F., Aukema, B. H., Bentz, B. J., Carroll, A. L., Hicke, J. a, Turner, M. G., & Romme,
 711 W. H. (2008). Cross-scale drivers of natural disturbances prone to anthropogenic
 712 amplification: The dynamics of bark beetle eruptions. *BioScience*, 58(6), 501–517.
 713 doi:10.1641/B580607

714 Rhoades, C. C., McCutchan, J. H., Cooper, L. A., Clow, D., Detmer, T. M., Briggs, J. S., ...
 715 Lewis, W. M. (2013). Biogeochemistry of beetle-killed forests: Explaining a weak nitrate
 716 response. *Proceedings of the National Academy of Sciences*.
 717 doi:10.1073/pnas.1221029110
 718

719 Rogan, J., Franklin, J., & Roberts, D. A. (2002). A comparison of methods for monitoring
720 multitemporal vegetation change using Thematic Mapper imagery. *Remote Sensing of*
721 *Environment*, 80(1), 143–156.

722 Schmid, J. M., & Frye, R. H. (1977). *Spruce beetle in the Rockies*. Fort Collins, CO: USDA
723 Forest Service, Rocky Mountain Forest and Range Experiment Station.

724

725 Scott, D. K. (2013, April). *Spruce beetle in the San Juans: spatial patterns and observations*
726 *from 2012*. Presented at the San Juan Bark Beetles and Watersheds Workshop: What are
727 the effects of beetle infestations on water supply and water quality?, Durango, Colorado.
728 Retrieved from <http://www.colorado.edu/events/workshops/beetle-water-Durango.html>

729 Sibold, J. S., Veblen, T. T., & González, M. E. (2006). Spatial and temporal variation in historic
730 fire regimes in subalpine forests across the Colorado Front Range in Rocky Mountain
731 National Park, Colorado, USA. *Journal of Biogeography*, 33(4), 631–647.
732 doi:10.1111/j.1365-2699.2005.01404.x

733 Skakun, R. S., Wulder, M. A., & Franklin, S. E. (2003). Sensitivity of the thematic mapper
734 enhanced wetness difference index to detect mountain pine beetle red-attack damage.
735 *Remote Sensing of Environment*, 86(4), 433–443.

736 Skole, D., & Tucker, C. (1993). Tropical deforestation and habitat fragmentation in the Amazon:
737 Satellite data from 1978 to 1988. *Science*, 260(5116), 1905–1910.
738 doi:10.1126/science.260.5116.1905

739 Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring
740 vegetation. *Remote Sensing of Environment*, 8(2), 127–150. doi:10.1016/0034-
741 4257(79)90013-0

742 USFS. (2003). *R2VEG. USDA Forest Service Region 2 Integrated Resource Inventory*. Retrieved
 743 from [http://www.fs.usda.gov/ detail/r2/landmanagement/gis/?cid%4stelpdb519523](http://www.fs.usda.gov/detail/r2/landmanagement/gis/?cid%4stelpdb519523)
 744 USFS. (2015). *Aerial Survey Highlights for Colorado 2014*. Retrieved from
 745 http://www.fs.usda.gov/Internet/FSE_DOCUMENTS/stelpdb3828662.pdf
 746 USFS and its partners. (2013). USDA Forest Service - Aerial Survey Data Download.
 747 USGS. (2013). *Landsat Climate Data Record (CDR) Surface Reflectance* (Product Guide).
 748 Department of the Interior, U.S. Geological Survey.
 749 Veblen, T. T., Hadley, K. S., Reid, M., & Rebertus, A. J. (1991). The response of subalpine
 750 forests to spruce beetle outbreak in Colorado. *Ecology*, 72(1), 213–231.
 751 Walter, J. A., & Platt, R. V. (2013). Multi-temporal analysis reveals that predictors of mountain
 752 pine beetle infestation change during outbreak cycles. *Forest Ecology and Management*,
 753 302, 308–318. doi:10.1016/j.foreco.2013.03.038
 754 White, J. C., Wulder, M. A., Brooks, D., Reich, R., & Wheate, R. D. (2005). Detection of red
 755 attack stage mountain pine beetle infestation with high spatial resolution satellite
 756 imagery. *Remote Sensing of Environment*, 96(3), 340–351.
 757 Wulder, M. A., Dymond, C. C., White, J. C., Leckie, D. G., & Carroll, A. L. (2006). Surveying
 758 mountain pine beetle damage of forests: A review of remote sensing opportunities. *Forest*
 759 *Ecology and Management*, 221(1-3), 27–41. doi:10.1016/j.foreco.2005.09.021
 760 Wulder, M. A., White, J. C., Bentz, B., Alvarez, M. F., & Coops, N. C. (2006). Estimating the
 761 probability of mountain pine beetle red-attack damage. *Remote Sensing of Environment*,
 762 101(2), 150–166. doi:10.1016/j.rse.2005.12.010
 763 Wulder, M. A., White, J. C., Coggins, S., Ortlepp, S. M., Coops, N. C., Heath, J., & Mora, B.
 764 (2012). Digital high spatial resolution aerial imagery to support forest health monitoring:

765 the mountain pine beetle context. *Journal of Applied Remote Sensing*, 6(1), 062527.
766 doi:10.1117/1.JRS.6.062527
767 Zhu, Z., & Woodcock, C. E. (2012). Object-based cloud and cloud shadow detection in Landsat
768 imagery. *Remote Sensing of Environment*, 118, 83–94. doi:10.1016/j.rse.2011.10.028
769

770 Table 1: A description of the aerial imagery and Landsat imagery used to classify spruce beetle
771 activity.

Data	Dates	Spectral resolution	Spatial resolution	Source
National Agriculture Imagery Program (NAIP)	Aug. 6-9, 2011	Band 1 (0.40 – 0.58 μm)	1 x 1m	AFPO (2012)
		Band 2 (0.50 – 0.65 μm)		
		Band 3 (0.59 – 0.68 μm)		
Landsat Climate Data Records (LDCR)	Sept. 15, 1995			
	Aug. 17, 1996			
	Jul. 2, 1997			
	Sept. 25, 1998			
	Sept. 26-2009			
	Sept. 13, 2000	Band 1 (0.45 – 0.52 μm)	30 x 30 m (Bands 1 – 5 & 7)	
	Aug. 15, 2001	Band 2 (0.52 – 0.60 μm)		
	Jul. 16, 2002	Band 3 (0.63 – 0.69 μm)		
	Sept. 22, 2003	Band 4 (0.76 – 0.90 ± 0.01 μm)		
	Sept. 20, 2004	Band 5 (1.55 – 1.75 μm)	120 x 120 m (Band 6)	USGS (2013)
	Sept. 10, 2005	Band 6 (10.40 – 12.50 μm)	15 x 15 m (Band 8)	
	Sept. 29, 2006	Band 7 (2.08 – 2.35 μm)		
	Jul. 5, 2007	0.01 μm)		
	Aug. 4, 2008			
	Aug. 21, 2009			
	Sept. 25, 2010			
	Sept. 28, 2011			
	Sept. 22, 2012			
	Sept. 25, 2013			

807 Table 2: Spectral indices used to classify spruce beetle affected forest (bands (B) refer to
808 Landsat TM band order).

Index	Abbrev	Formula	Reference	Application
Red-green index	RGI	$RGI = \frac{B3}{B2}$	Coops et al. (2006)	Indicator of red-stage mountain pine beetle-induced tree mortality (Coops et al., 2006)
Blue-red index	BR	$BR = \frac{B1}{B3}$	this study	Indicator of bare ground in aerial imagery (this study)
Normalized Difference Vegetation Index	NDVI	$NDVI = \frac{B4 - B3}{B4 + B3}$	Tucker (1979)	Useful for identifying different stages of mountain pine beetle attack (Meddens et al., 2011; Walter & Platt, 2013)
Ratio Vegetation Index	RVI	$RVI = \frac{B4}{B3}$	Pearson and Miller (1972)	Indicator of vegetation stress due to mountain pine beetle (Hilker et al., 2009)
Normalized Difference Moisture Index	NDMI	$NDMI = \frac{B4 - B5}{B4 + B5}$	Gao (1996)	Useful for identifying different red-stage mountain pine beetle attack from single and multi-date imagery (Goodwin, Magnussen, Coops, & Wulder, 2010; Meddens et al., 2013; Skakun et al., 2003)
Tasseled Cap Wetness	TCWET	$TCWET = B1*0.0315 + B2* 2.021 + B3* 0.3102 + B4* 0.1594 + B5* 0.6806 - B7*0.6109$	Crist (1985)	
Tasseled Cap Greenness	TCGRE	$TCGRE = B1*-0.1603 - B2*0.281 - B3*0.4934 - B4*0.7940 + B5*0.0002 - B7*0.1444$	Crist (1985)	Useful for identifying different red-stage mountain pine beetle attack from multi-date imagery (Meddens et al., 2013)
Tasseled Cap Brightness	TCBRI	$TCBRI = B1*0.2043 + B2* 0.458 + B3* 0.5524 + B4*0.5741 + B5*0.3124 + B7*0.2303$	Crist (1985)	
Disturbance Index	DI	$DI = TCBRI - TCWET - TCGRE$	Healey et (2005)	Indicator of gray-stage spruce beetle attack (DeRose et al., 2011)

809

810 Table 3: Average confusion matrix of the Support Vector Machine (SVM) classification of the
811 aggregated 3-m National Agriculture Imaging Program (NAIP) imagery (numbers of pixels and
812 standard deviations). Accuracies and quantity disagreement (Q) and allocation disagreement (A))
813 statistics are means of ten cross-validated classifications.

		Manually interpreted				Total	User's Acc. (%)
		Green tree	Gray tree	Non- forest	Shadow		
NAIP SVM Classifier	Green tree	63.9 (0.99)	1.1 (1.10)	0 (0)	0 (1.10)	65.0	98 (1.64)
	Gray tree	1.5 (0.85)	52.9 (2.81)	2.9 (1.14)	1.8 (1.10)	59.4	89 (1.65)
	Non-forest	1.7 (1.16)	12.4 (2.91)	67.1 (1.14)	0.3 (1.10)	81.2	82 (3.24)
	Shadow	2.9 (1.53)	3.6 (1.96)	0 (0)	67.9 (1.10)	74.4	91 (3.70)
	Total	70	70	70	70	O. Acc. = 90%	
Producer's Acc. (%)		91 (1.42)	76 (4.00)	95 (1.62)	97 (1.71)	Q = 0.05 A = 0.05	

814

815

816 Table 4: Average confusion matrix of the Support Vector Machine (SVM) classification of the
817 30-m multi-date Landsat 2011 imagery (numbers of pixels). Accuracies and quantity
818 disagreement (Q) and allocation disagreement (A)) statistics are means of ten cross-validated
819 classifications.

820

		NAIP classified			Total	User's Acc. (%)
		Green stand	Gray stand	Non-forest		
Landsat SVM multi- date classifier	Green stand	62.5 (3.17)	2.4 (2.27)	2.3 (1.49)	67.2	93 (4.41)
	Gray stand	3.4 (1.95)	64.9 (2.73)	5.8 (2.49)	74.1	88 (4.06)
	Non-forests	4.1 (2.23)	2.7 (1.64)	61.9 (2.29)	68.7	90 (3.51)
	Total	70	70	70	O. Acc. = 90%	
	Producer's Acc. (%)	89 (4.53)	92 (3.89)	88 (3.26)	Q = 0.03 A = 0.07	

821

822 Table 5: Confusion matrix of the post-classification correction of multi-date Landsat 2011 SVM
 823 classifier (numbers of pixels).

824

		NAIP classified			Total	User's Acc. (%)
		Green stand	Gray stand	Non-forest		
Post- classification corrected Landsat SVM multi-date classifier	Green stand	61	2	1	64	95
	Gray stand	3	67	2	72	93
	Non-forests	6	1	67	74	91
	Total	70	70	70	O. Acc. = 93%	
	Producer's Acc. (%)	87	95	95	Q = 0.03 A = 0.03	

825

826

Fig. 1: The study area located in southwestern Colorado, which has experienced significant spruce beetle-induced tree mortality over the time period from 2002-2013, as determined from United States Forest Service Aerial Detection Surveys. The distribution of spruce-fir forest across the region was determined using United States Forest Service Region 2 vegetation databases (USFS, 2003). The dashed black rectangle indicates Landsat Path 34 and Row 34.

Fig. 2: Flowchart of the products and operations used to classify NAIP and Landsat imagery. a) classification for NAIP imagery. b) classification of Landsat Climate Data Record (LCDR) imagery. Solid line boxes indicate products; dashed-line boxes indicate operations.

840

841 Fig. 3: Boxplots displaying the spectral characteristics of four classes in spruce-fir forest. RGI
842 indicates the Red/Green Index calculated by dividing reflectance in red wavelength by
843 reflectance in green wavelengths from NAIP data; BR indicates the Blue/Red index calculated
844 by dividing reflectance in blue wavelength by reflectance in Red wavelengths from NAIP data.
845 The bottom and top limits of each box are the lower and upper quartiles, respectively; the thick
846 black line within the box is the median; error bars equal ± 1.5 times the interquartile range;
847 and empty circles denote outliers, values outside ± 1.5 times the interquartile range.

848

Fig. 4: Boxplots displaying the spectral characteristics of three major classes in spruce-fir forest. DI indicates the Disturbance Index, NDMI indicates the Normalized Differenced Moisture Index, NDVI is the Normalized Differenced Vegetation Index, RGI indicates the Red/Green Index, RVI is the Ratio Vegetation Index, TCBRI is the Tasseled Cap Brightness, TCGRE is the Tasseled Cap Greenness, TCWET is the Tasseled Cap Wetness (for more description of selected vegetation indices see Table 2). For visual comparison, all indices were standardized by first subtracting the mean value and then dividing by the standard deviation. For each box, the bottom and top limits of each box are the lower and upper quartiles, respectively; the thick black line

858 within the box is the median; error bars equal ± 1.5 times the interquartile range; and empty

859 circles denote outliers, values outside ± 1.5 times the interquartile range.

860

862

863 Fig. 5: Time series plots illustrating the percentage of the study area (i.e. the spruce-fir zone)
 864 inferred to be affected by spruce beetles (gray stand). The solid gray line indicates gray stage
 865 pixels classified using the SVM multi-date classifier (without post-classification correction)
 866 produced from moderate-resolution Landsat imagery. The dotted gray line indicates the post-
 867 classification corrected SVM multi-date classifier, where misclassified gray pixels were
 868 identified by examining the stage of the pixel in the previous and subsequent year. The solid
 869 black line indicates USFS Aerial Detection Surveys (ADS), which were flown for the entire
 870 study area beginning in the year 2005.

871

872 Fig. 6: Frequency distribution of the severity of tree mortality within 30-m grid resolution pixels

873 for (a) gray and live stands and (b) new and old infestation. Infestation severity was calculated

874 from classified 3-m aggregated 2011 NAIP imagery for the study area. Moderate resolution 30-m

875 pixels where classified as either gray (dark gray) or green (light gray) stands from 2011 Landsat

876 imagery using a multi-date classifier with post-classification correction to remove false-positives

877 gray stands. New infestation indicates Landsat pixels identified for the first time in 2011. Old

878 infestation indicates Landsat pixels classified as infested in two or more years. Break points

879 indicate the midpoint of the class interval.