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MAPPING ALPINE TREELINE WITH HIGH RESOLUTION IMAGERY AND LIDAR DATA IN NORTH CASCADES NATIONAL PARK, WASHINGTON

By

Cathi Jones Winings

Accepted in Partial Completion Of the Requirements for the Degree Master of Science

Kathleen L. Kitto, Dean of the Graduate School

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MASTER'S THESIS

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Cathi Jones Winings May 10, 2013

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A Thesis Presented to The Faculty of Western Washington University

In Partial Fulfillment Of the Requirements for the Degree Master of Science

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Abstract

We evaluated several approaches for the automated detection and mapping of trees and treeline in an alpine environment. Using multiple remote sensing platforms and software programs, we evaluated both pixel-based and object-based classification approaches in combination with highresolution multispectral imagery and LiDAR-derived tree height data. The study area in North Cascades National Park included over 10,000 hectares of some of the most rugged terrain in the conterminous U.S. Through the use of the Normalized Difference Vegetation Index (NDVI), differences in illumination conditions created by steep slopes and tall trees were minimized. Data fusion of the multispectral imagery, NDVI, and LiDAR-derived tree height data produced the highest percent accuracies using both the pixel-based (88.4%) and the object-based classifications (92.9%). These results demonstrate that either method will produce an acceptable level of accuracy, and that the availability of a near-infrared band to calculate NDVI is extremely important. The NDVI used in conjunction with the multispectral imagery helped to minimize issues with shadows caused by rugged terrain. Furthermore, LiDAR-derived tree heights were used to augment classification routines to achieve even greater accuracy; where shadows were too dark to produce meaningful NDVI values, the LiDAR-derived tree height data was instrumental in helping to distinguish trees from other land cover types. Both the pixel-based and the object-based approaches hold considerable promise for automated mapping and monitoring of the treeline ecotone; however, the pixel-based approach may be superior because it is more straightforward and easily replicable compared to the object-based approach. These treeline mapping efforts will enhance future ecological treeline research by producing more accurate detections of trees and estimations of treeline position, and will be instrumental in building time series of imagery for future scientists conducting change detection studies at treeline.

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1. INTRODUCTION

Unequivocal warming of the climate system (IPCC, 2007) is a concern for both society and the natural environment that we depend on. Indeed, terrestrial biological systems are responding rapidly to recent warming (see IPCC 2007 for a review). For example, upward shifts in ranges of plant species, both latitudinal and altitudinal, are occurring as a result of warmer temperatures and longer growing seasons (Kullman , 2002; Walther et al., 2005). Shifts in some species ranges may be particularly noticeable within ecotones, or regions of transition between two biological communities (Risser, 1995). The alpine treeline ecotone (hereafter, treeline) is a transition zone between the tall closed forest at lower elevations and alpine tundra at higher elevations (Holtmeier & Broll, 2005; Malanson, et al., 2007). Advancing treelines can create both positive and negative climate feedbacks such as decreasing albedo in former tundra and serving as a carbon sink, respectively, and are of utmost importance because of the potential they have to influence climate (Betts, 2000).

Linkages between climate and treeline altitudinal positions have been made for some time. An early reference to treelines shifting upwards in alpine environments in response to warming temperatures can be found in Griggs (1937), and later Brink (1959) links the shift to decreasing snowpack. Franklin et al. (1971), note a, "massive invasion into subalpine meadows by a variety of tree species (p. 215)" in the Washington and Oregon Cascades, attributing it to natural climatic fluxes that occurred in the 19th century and extending into the 1940s following the Little Ice Age. More recent shifts in treeline species ranges are well documented (Rochefort et al., 1994; Munroe, 2003; Kullman & Oberg, 2009). In a recent global meta-analysis, Harsch (2009) found that over half of 166 treelines (polar and alpine) have advanced upslope, while only 2% have receded. Holtmeier and Broll (2007) describe climatically-driven treeline advance in the northern hemisphere as ubiquitous; however, other studies document no upslope movement of treeline species (summarized in Holtmeier & Broll, 2007).

Although climate is important, a multitude of interacting factors influence the position of treeline (Holtmeier & Broll, 2005). In fact, some treelines will not respond to a changing climate because they are not sensitive to changing environmental conditions. For example, treelines that are controlled by orographic features, such as steep rock walls, talus slopes, and avalanche chutes, will not advance as long as these features are present to prevent forest establishment (Holtmeier & Broll, 2005). Treeline heterogeneity between different regions or landscapes explains why all treelines are not moving upslope in step with rising temperatures. Several researchers (Holtmeier & Broll, 2007; Stueve et al., 2009) are already warning of the many confounding variables that may prevent making a direct connection between climate and treeline change. This presents a formidable challenge for researchers who are trying to identify and explain the relative importance of each variable in the hopes of using treeline as an indicator of climate change. The spatially explicit delineation of mountain vegetation is therefore a key research need that will enhance treeline-related research (Diaz-Varela et al., 2010; Ørka et al., 2012). Holtmeier and Broll (2007) further emphasize the need by urging that documentation of treeline spatial patterns is an "indispensable step in future treeline research (p. 20)."

Remote sensing is an efficient and practical tool for mapping and monitoring treeline at landscape scales (Kral, 2009). In this context, the process of remote sensing involves the use of a sensor, such as a camera, attached to an aerial platform, such as aircraft, to collect information about a subject from some distance (Jensen, 2005). Because remotely sensed data is obtained systematically over an area, larger extents can be mapped with less human subjectivity than fieldbased sampling (Baker et al., 1995). Additionally, mountainous areas with rugged terrain can prevent access to sampling areas. The bird's eye view that remote sensing provides is invaluable to treeline mapping efforts because it isn't limited by access or by size of the area to be mapped.

To extract information from remotely sensed data, some form of classification is often used, the objective of which is to assign image pixels to land cover classes (Lillesand et al., 2004). Traditional pixel-based classification is a method that considers each pixel individually and assigns it to a class based on the values in its spectral bands (Campbell, 2007). Classification using this method can be problematic, because most imagery contains texture (smoothness or coarseness), which is often neglected with the traditional approach (Blaschke et al., 2000). Valuable context can be lost by not considering the relationships between each pixel and its neighbors, especially when using data with high spatial resolution (i.e., $\leq 1 \times 1$ m pixel size). Additionally, in a complex alpine treeline environment, this can be especially problematic due to the unevenness of reflectance values across an image when shadows exist from trees and topography. For example, Stueve et al. (2011) resorted to manual classification of imagery due to their inability to efficiently and adequately identify land cover in shade, and Allen and Walsh (1996) manually corrected cliffs on north-facing slopes that were misclassified as forested scree or water due to shadows.

An alternative to pixel-based classification is object-oriented, or object-based classification. This method segments the image into homogenous regions (or objects) based on both spectral and spatial information, and then classifies the regions (Campbell, 2007). Additional information can be extracted from the objects, such as mean and standard deviation from the pixels that compose the object, as well as object size, shape, and context (Chubey et al., 2006). This technique can be especially useful for high-resolution imagery, where the objects of interest (i.e., trees) are often multi-pixel objects. Image segmentation allows these objects to be grouped into regions and processed as a single observation (Franklin et al., 2003). Texture, which is often neglected in pixelbased classifications, is a key feature in image segmentation. Another advantage of this method is that it doesn't result in the salt and pepper effect typical of pixel-based methods. Because it generates homogenous regions that are then classified, the object-based method does not require subsequent filtering (Blaschke et al., 2000).

In addition to the use of different classification techniques to improve information extraction, data fusion of complementary technologies, such as remotely sensed imagery and LiDAR (Light Detection and Ranging), can be used (Hall, 2003; Walter, 2004; Kral, 2009; Ørka et al., 2012). Unlike most optical sensors, which only provide information about horizontal vegetation distribution, LiDAR is a remote sensing technology that provides both horizontal and vertical information. LiDAR has been used to derive highly accurate estimates of vegetation height, cover, and canopy structure, as well as leaf area index and aboveground biomass (Lefsky et al., 2002). In object-based classification, LiDAR is useful because it can be added as another "band," such as canopy height, to multispectral data. In areas such as the treeline ecotone, where it may be difficult to split spectral reflectances of trees, shrubs, and areas in shadow, forest structure attributes derived from LiDAR data can yield enhanced contrast between classes.

2. RESEARCH QUESTIONS

The purpose of this research was to develop improved and more automated methods to map treeline. Specifically, this research addressed the following questions:

- 1) Is pixel-based or object-based classification more appropriate for identifying the presence or absence of trees within the alpine treeline ecotone?
- 2) Does a LiDAR-derived tree height dataset, when included as an additional band, improve either of the classifications?

4

To address these questions, we used various combinations of high spatial resolution (1 m x 1 m) multispectral orthoimagery and LiDAR-derived tree height data in several pixel-based and objectbased classifications. First we created a Normalized Difference Vegetation Index (NDVI) image using the 1 m imagery. The NDVI image was used alone and in combination with the 1 m imagery to create several pixel-based output images. The inputs that were used to achieve the highest percent accuracies in the pixel-based classifications were then classified using object-based classification. Then the classifications were performed again with the addition of the LiDAR-derived tree height data. The classification outputs were compared in an accuracy assessment, which revealed that the object-based classification of a combination of the imagery, NDVI image, and tree height dataset produced the highest percent accuracy. Since it had the highest percent accuracy, this object-based classification result was used to estimate canopy cover, which was then used to delineate treeline according to percent thresholds of canopy cover.

The final products include a spatially explicit binary dataset that contains the classes "tree" and "non-tree," a map that delineates treeline within the study area, and a description of treeline characteristics. The binary dataset can be used by others to delineate elements of the treeline ecotone, such as forest line (or timberline), treeline, and/or tree limit, based on their own definitions. Descriptive characteristics include average, minimum, and maximum elevations of treeline, as well as the range of treeline elevations.

The techniques that we chose to use were selected because they are most accessible and practical to analysts in the field. More complex techniques, such as machine learning algorithms or regression analysis, are less likely to be used by land managers interested in mapping treeline because they either require specialized software that often isn't feasible to obtain within budget constraints, or they are considered academic pursuits that are less practical for the field analyst. This research demonstrates an efficient and defensible approach to mapping treeline. The results augment ecological treeline research and aid in decision-making by providing a spatially explicit method for the delineation of treeline. The techniques used in this research can be replicated in other mountainous regions where shadows present unique problems during classification of remotely sensed data. Issues caused by shadows due to low sun angles and mountainous terrain were minimized by the use of the NDVI and tree height data derived from a LiDAR dataset. Although we did not measure treeline change over time, this study established a reliable baseline for the current altitudinal position of treeline within a large drainage in North Cascades National Park. The methods can be used to determine treeline position in other areas of the park (depending on the availability of remotely sensed datasets, especially LiDAR), and results can be used to detect future treeline change. This approach shows promise as an efficient and accurate means to obtain treeline position information and to eventually quantify landscape change in other areas.

3. BACKGROUND AND LITERATURE REVIEW

3.1. DEFINITION AND CHARACTERISTICS OF TREELINE

Treeline is defined as the transition zone from forest line, or the upper limit of contiguous closed forest, to scrub line, or the upper limit of krummholz (Franklin & Dyrness, 1988). This transition area, or ecotone, can be narrow or wide or sometimes an abrupt line. Oregon and Washington treelines are described as subalpine parklands consisting of a mosaic of tree patches and meadow communities (Franklin & Dyrness, 1988). In this zone, tree patches reduce in size and height with increasing elevation. Meadow-forest mosaics in the Pacific Northwest are extensively developed, and are probably the result of deep, late-melting snowpacks (Franklin & Dyrness, 1988). As a consequence, the treeline ecotone occupies an extensive elevational band of 300 to 400 m or more (Franklin & Dyrness, 1988).

Numerous more specific definitions of treeline exist, most of which are based on minimum tree height or minimum forest cover. In his recently published book on mountain timberlines, Holtmeier (2009) summarizes the various definitions that have been published throughout the 20th century; he concludes that the critical minimum heights range from 2 to 8 m and minimum cover ranges from 30% to 40%. Treeline canopy cover in Oregon and Washington typically ranges between 10 to 30% (Martin, 2001). Since LiDAR has been found to successfully identify trees as short as 1 m (Næsset & Nelson, 2007), this shorter value will be used in contrast to some of Holtmeier's findings. Therefore, for the purpose of this study, treeline encompasses all trees taller than 1 m with a canopy cover of 30% or less located above the contiguous closed forest.

A number of interacting scale-dependent factors influence the specific altitudinal position of treeline. At the global scale, treeline correlates well with temperature. At regional and local scales, numerous factors play a role, including topography, soils, tree species, ecoclimate, biotic influences, human impacts, and site history (Holtmeier & Broll, 2005). Butler et al. (2007) agree that scale is critical when analyzing treeline controls, but they insist that treelines in the American West are strongly controlled by geological history, geologic structure, lithology, geomorphic processes, and landforms. Within a local treeline ecotone, Stueve et al. (2011) discovered a spatial transition in treeline controls where biotic factors largely control tree establishment at lower elevations, while abiotic factors (including climate) play a more significant role at upper elevations. The broad definition of treeline and remote sensing approach employed here allows the above-mentioned discrepancies to be more thoroughly investigated, ultimately improving context for past and future

work by filling in knowledge gaps of the spatial and temporal structures of treeline (Holtmeier & Broll, 2007).

3.2. REGIONAL TREELINE CHANGE STUDIES

Over the past several decades numerous treeline studies have taken place in mountain environments throughout the world. The studies mentioned earlier by Brink (1959) and Franklin et al. (1971) took place in the Pacific Northwest and document a past (early 1900s) period of warming. Brink observed trees establishing in meadows in British Columbia and attributed it to loss of snow pack. Franklin et al. surveyed and dated trees invading meadows at Mount Rainier National Park and a few other areas in the North Cascades region and found that there was a distinct 20-30 year period in which seedlings became established in meadows in the first half of the 20th Century. They examined possible causes of the invasion, and were able to rule out all of them except for climate change. A climatic flux occurring during the same time period as the invasion occurred, along with good seed crops, could largely explain the invasion, they speculated. Cooper (1986) also speculates that the warming trend documented in Alaska may be responsible for treeline shifts.

More recent studies in the U.S. have shown snow pack or soil moisture levels to be key factors in treeline change. In the Sierra Nevada of Sequoia National Park, Lloyd and Graumlich (1997) found that rates of treeline change in response to rapid climate change are likely to be slow, lagging decades to even centuries (see also Noble, 1993). They also caution against the simple assertion that warmer temperatures will cause advancing treelines; warming is unlikely to cause an expansion if precipitation is reduced at the same time. Hessl and Baker (1997) examined tree invasions in patch forest openings in Rocky Mountain National Park and found that seedlings established during warmer temperatures that occurred after the Little Ice Age ended, and speculated that temperatures may have become too high to support further establishment after 1980. Their research showed, however, that high snow depth is a likely additional requirement for the establishment of seedlings. Likewise, Bunn et al. (2005) highlight the importance of examining soil moisture, a factor influenced by snow pack, in addition to temperature as an influence on alpine treelines. Their study in the Sierra Nevada of Sequoia National Park found that in drier alpine areas, lack of precipitation may mediate the impacts of an advancing treeline resulting from increased temperatures.

Although some researchers have found significant lag times between changing climate conditions and tree responses (see Lloyd & Graumlich, 1997), Peterson and Peterson (2001) found that tree growth varied at both annual and decadal time scales, and this was largely attributed to climatic variability. Klasner and Fagre (2002) found that patch areas of trees, including krummholz, patch-forest, and continuous canopy forest, increased over a period of 46 years in Glacier National Park. In Denali National Park, Stueve et al. (2011) found that the upper tree limit on south-facing slopes advanced 150 m in elevation and extensive infilling occurred between 1953 and 2005. Although elevation and winter sun exposure were found to be important predictors of tree establishment at the upper tree limit, the authors warn that the proximity to trees may still prevent making a direct link between treeline advance and climate.

In the Swiss Alps, Grabherr et al. (1994) observed the migration of alpine plant species upward in elevation along with increases in species richness. Subsequent to the Grabherr et al. study, a review of the potential impacts of climate change to vegetation in the European Alps was published by Theurillat and Guisan (2001). Findings include the colonization of the subalpine-alpine ecocline by Arolla pine (*Pinus cembra*) and Norway spruce (*Picea abies*) and the prediction that an increase of 3.3 K in mean air temperature could reduce the area of the alpine vegetation belt by 63%. Similarly, a later study by Camarero and Gutierrez (2004) found an increase in treeline establishment and densities in the Spanish Pyrenees.

In the southern hemisphere, few alpine treeline studies have taken place. In Patagonia, Daniels and Veblen (2003) found that disturbance plays a large role in alpine treeline locations in Chile and Argentina, and by controlling for disturbance researchers were able to distinguish climatic effects on treeline characteristics at different scales. In New Zealand Cullen, et al. (2001) found no recent upslope treeline movement, suspecting that a lack of natural disturbance has prevented tree recruitment.

Predicting how treelines may react to a changing climate is another research focus. For example, Malanson et al. (2007) outlined some potential responses to climate change under two scenarios. First, under a warmer, wetter scenario in the Pacific Northwest, an increase in snowpack is possible, which would inhibit the establishment and growth of trees. Second, under a warmer, drier scenario in the Pacific Northwest, tree species and establishment shouldn't be affected by less moisture, and expansion of the treeline and infilling of meadows could occur. A site-specific study by Rochefort and Peterson (1996) at Mount Rainier National Park substantiated these results: on the west side of the park (a cooler, wetter area) seedling generation increased during relatively warmer and drier summers, whereas on the east side of the park (warmer, drier) seedling generation increased during cooler, wetter summers.

3.3. IMPLICATIONS OF TREELINE CHANGE

What are the implications of a rising alpine treeline? Franklin et al. (1971) discussed management implications in areas such as Paradise at Mount Rainier National Park, where meadows are a large visitor attraction and managers may feel pressure to conduct "vista clearing" in order to facilitate the viewing of subalpine meadows. A tree removal program was undertaken at the park in the 1970s to address these concerns; however the program ended in 1979 (Rochefort & Peterson, 1996).

Since the 1970s more serious ecological implications of rising treelines have been identified. Based on the latest warming predictions, climate change may be the largest single threat to biodiversity, especially in high mountain regions (Pauli et al., 2007). Mountain zones are so biodiverse because climate zones are compressed, slopes cause exposure to vary, gravity-induced erosion fragments land area, summits are 'islands in the sky, ' and topography-climate interactions create a multitude of microhabitats, each with its specific sets of organisms (Korner, 2004). We are likely to see the loss of alpine species as their ranges expand upward in elevation and potentially disappear off the tops of mountains (Grabherr et al., 1994). For example, isolated orophytes (coldresistant high-elevation plants) that are now living in such refugia as the peaks of low mountains in the Alps will likely be threatened because it would be almost impossible for them to migrate higher, either because they cannot move rapidly enough or the habitat has disappeared (Theurillat & Guisan, 2001). It is also likely that greater numbers of invasive, non-native species will be able to invade alpine areas due to warming temperatures (Pickering et al., 2008), further threatening the survival of endemics and other rare plant species.

Significant threats exist to the survival of animal species that are unable to track shifting climates, or for those whose suitable habitat disappears (Walther et al., 2002). In a study in Yosemite National Park that resampled an elevational transect surveyed by Joseph Grinnel from 1914 to 1920 (Moritz et al., 2008), it was found that high elevation small mammal species experienced range contractions and low-elevation species expanded their ranges upward. Highelevation species found to have contracted ranges included the alpine chipmunk, Belding's ground squirrel, water shrew, and American pika. In Washington and Oregon, one third of all vertebrate fauna use high elevation habitat during some portion of their life history (Martin, 2001), underscoring the importance of monitoring mountain ecosystems.

Perhaps most importantly, shifting treeline positions can change feedbacks within the climate system (Bonan, 2008). For example, forest expansion into formerly treeless areas creates a positive feedback by reducing albedo. At the same time, forest expansion can create a negative feedback by sequestering carbon and thus reducing net CO² emissions (Betts, 2000). The full impact of these and many other climate feedbacks is currently not well understood (Bonan, 2008). Additional studies and fine-tuning of climate models are required to best predict how climate will respond to advancing treelines.

3.4. REMOTE SENSING OF TREELINE

Remote sensing has become a key tool to map and monitor treeline areas (Danby, 2011) due to the growing availability of remotely sensed data and interest in using treeline as an indicator of climate change. In rugged areas, remote sensing can provide a systematic means to understand current spatial structures and to monitor change in otherwise inaccessible terrain. Furthermore, it can be used to monitor very large areas (Rees et al., 2002). However, automation of remote sensing approaches to mapping treeline remains in its infancy because the identification of individual trees is a complex pattern recognition task (Rees et al., 2002). For example, because of complications associated with shadows in rugged terrain and variable image quality, researchers have had to use manual classifications and/or visual interpretations of change (Stueve et al., 2011; Allen & Walsh, 1996).

SCALE AND SPATIAL RESOLUTION

Scale is an important factor to consider in remote sensing applications (Culvenor, 2003). Since patterns of individual treeline elements can be scale-dependent (Resler et al., 2004), it is essential that the resolution of remotely sensed data is appropriate for detecting individual components. For example, to characterize vegetation such as individual trees at the local scale, high spatial resolution imagery will be most useful (Wulder et al., 2004). For the purpose of this study, high spatial resolution imagery has a maximum pixel resolution of 1 m x 1 m. In contrast to lower resolution imagery, where a pixel represents the average reflectance of numerous trees, the pixels of high resolution imagery can be equal to or smaller than an individual tree. Important variations in patterns could be overlooked by using images with resolutions that are too low (e.g., 30 m x 30 m Landsat imagery) to recognize individual landscape elements. Although some studies have used Landsat satellite imagery to map treeline (Brown, 1994; Allen & Walsh, 1996), most have used higher-resolution (\leq 5 m) satellite imagery or aerial photography (Baker et al., 1995; Kral, 2009; Stueve et al., 2009), recognizing that there are limitations to vegetation classification at lower spatial resolutions (Baker & Weisberg, 1994; Brown, 1994; Butler et al., 2003).

A recent study examining scale-dependency is a pertinent example. At Glacier National Park, Resler et al. (2004) used different window sizes and texture parameters to classify aerial imagery and found that the scale at which different landscape patterns operate varies by ecotone component. A 2 m pixel resolution panchromatic digital orthophoto was used to derive texture parameters (standard deviation, variance, skewness, kurtosis, and distance). Each parameter was calculated for several window sizes starting at 5 x 5 and moving upwards by a factor of 2 to 15 x 15, resulting in a total of 30 new images (one for each texture parameter at each window size). A maximum likelihood classification was performed on each image using the following four classes: tundra/bare, alpine meadow, open forest/krummholz, and closed canopy forest. Results were compared to a reference map generated from a helicopter photo survey and photos taken from the ground. An accuracy assessment revealed that all of the overall classification results were significantly different from each other, but no one texture measure was significantly better than any other. However, individual class accuracies for the texture images were shown to be higher than that of a control image, and it was found that texture made a difference in a scale-dependent manner. Most importantly, it was found that in order to obtain higher accuracies in the open forest/krummholz class (i.e., treeline as defined in this paper), higher resolution data is needed because of the high complexity of the landscape in this class.

RECENT TREELINE MAPPING EFFORTS

There is great variety in the types of remotely sensed data and methods that have been used to map treeline. Some studies have used aerial photography and manual interpretation, others have used digital multispectral imagery or satellite imagery with more automated techniques, and yet others have used a combination of inputs and techniques. Some studies have only mapped cover types, while others only delimited ecotone limit lines, and a few have done both. The following is a review of treeline mapping efforts that have taken place over the last several decades. Provided in Table 1 is a summary of published works on treeline mapping.

Table 1. Treeline Mapping Efforts.

Location	Resolution & Data Type	Mapping Techniques	Author(s), Date					
MANUAL TECHNIQUES AND/OR CORRECTIONS								
Rocky Mountain National Park, Colorado, USA	m color-infrared air photos Limit lines drawn onto mylar overlays of stereo photos while cross- checking in the field, then digitized in GRASS		Baker, W. L., et al. 1995					
Presidential Range, New Hampshire & Mount Katahdin, Maine, USA	1:5,000 color air photos and 1:3,000 color-infrared air photos	Visual photo interpretation in the field using mylar overlays on photos, then digitized as vectors and converted to raster; treeline delimited by hand	Kimball, K. & Weihrauch, D. M. 2000					
Central Alps, Italy	1:40,000 black & white air photos, 1:33,000 color air photos	Manual classification of vegetation types, automated delineation of treeline ecotone elements (forest line, treeline, tundra line)	Diaz-Varela, R. A., et al. 2010					
Denali National Park and Preserve, Alaska, USA	1.5 m panchromatic air photos, 1 m pan-sharpened IKONOS	Manual classification of sample points	Stueve, K. M., et al. 2011					
Glacier National Park, Montana, USA	25 m Landsat TM	Unsupervised classification to identify major covertypes, then maximum likelihood decision rule, then manual corrections	Allen, T. R. & Walsh, S. J. 1996					
AUTOMATED TECHNIQUES (see also Allen & Walsh 1996, above)								
Mount Rainier National Park, Washington, USA	1.9 m panchromatic satellite imagery, 1 m color DOQQ	Supervised classification of tree/treeless areas; manual adjustments where trees obscured by snow; forest lines identified using GIS	Stueve, K. M., et al. 2009					
Hrubý Jeseník Mountains, Czech Republic	0.9 m color-infrared orthophotos	Maximum likelihood classifier, followed by texture analysis, knowledge-based classification, image filtering & thresholding	Kral, K. 2009					
Finnmark County, Norway (arctic treeline)	3 m multispectral imagery, 2 m LiDAR-derived tree height surface	ISODATA clustering, image filtering using tree heights	Rees, W. G. 2007					
Glacier National Park, Montana, USA	30 m Landsat TM	ISODATA to identify spectral clusters, maximum likelihood, reassignment to 1 of 4 cover classes	Brown, D. G. 1994					
Hohe Tauern Mountains National Park, Austria	SPOT 5 HRG (4 bands at 10 m, 1 panchromatic band at 2.5 m)	Soft classification using probability mapping, alpha-cuts to map seven hard vegetation classes, and a probability ratio image to visualize the transitional landscape	Hill, R. A. et al. 2007					
OBJECT-BASED TECHNIQUES								
Lommoltunturi Fell, Lapland, Finland	0.5 m panchromatic & false color air photos	Image segmentation using automated attribute selection; support vector machines in supervised classification	Middleton, M., et al. 2008					

Table 1 (continued)

Location	Resolution & Data Type	Mapping Techniques	Author(s), Date					
Circumpolar taiga-tundra	500 m MODIS Vegetation	Image segmentation using percent tree cover; threshold values to	Ranson, K. J., et					
ecotone	Continuous Fields tree cover data	classify the treeline ecotone	al. 2011					
LIDAR TECHNIQUES								
Hedmark County, Norway	25 m Landsat (resampled), LiDAR with 2.7 m ⁻² pulse density	Used strip samples of LiDAR to delineate portions of the subalpine zone, then binomial logistic regression to extrapolate the LiDAR classes to the entire county with Landsat data	Ørka, H. O., et al. 2012					
Rollag, Norway	LiDAR with 7.7 m ⁻² pulse density	Compared field-measured trees and terrain objects to LiDAR measurements	Næsset, E. & Nelson, R. 2007					
North-south transect through Norway	LiDAR with 6.8 & 8.5 m ⁻² pulse density	Compared field-measured trees to LiDAR measurements	Thieme, N. et al. 2011					

Manual Techniques

A number of studies have used manual (i.e., visual) interpretation of remotely sensed data (typically aerial photographs) to map vegetation cover and/or to delimit treeline. One of the most significant limitations of manual interpretation is subjectivity. Even well-trained interpreters can produce different maps even if they use the same rules to identify classes. For example, in Rocky Mountain National Park, Baker et al. (1995) used color-infrared aerial photographs scanned at 5 m resolution to map treeline. Limit lines (i.e., closed forest limit, krummholz limit, etc.) were drawn onto mylar overlays of stereo photographs while in the field and then digitized using the GRASS GIS. Mapping rules were adopted to maintain consistency in drawing the limit lines; however, a difference in light conditions between different photos was identified as a major limiting factor in using scanned aerial photographs for change research. The authors were able to digitize the limit lines, but they admitted that the resultant lines contained more human subjectivity than would those derived from ecotone identification algorithms. A similar problem was encountered in New England, where Kimball and Weihrauch (2000) mapped treeline in the field by drawing dominant vegetation polygons onto mylar-covered air photos, and then digitizing the polygons. The lower limit of the subalpine forest was defined as areas where trees were less than 2.5 m high, and the upper limit was defined as the uppermost limit of birch-alder and krummholz community types. They encountered problems in delineating the lower limit line because of difficulty in identifying the boundary where trees were less than 2.5 m high in the field. As a result, lines were interpolated between identifiable reference points that intersected easy access points such as trails. The authors described the placement of this lower limit as an arbitrary and subjective decision.

Interestingly, the objective of a recent study by Diaz-Varela et al. (2010) was to develop an automated and repeatable process for the delineation of ecotone elements (forest lines, treelines,

and tundra lines), but they used manual techniques to classify vegetation types. They visually interpreted 1:40,000 and 1:33,000 scale stereoscopic aerial photographs. Then they created an algorithm to detect the uppermost pixels, or outposts, of vegetation classes on slopes. Outpost maps for each ecotone element were created for 1954 and 2003 and were then used to measure change between the two maps.

Other authors have resorted to manual techniques because of issues with image quality and/or shadows that resulted in poor accuracies when automated techniques were used. In one recent study designed to examine how local site conditions control tree establishment patterns in Denali National Park, Stueve et al. (2011) initially used an automated classification to derive land cover type, but shadows in the imagery and patchy image quality resulted in low classification accuracy. Therefore, they chose to visually interpret land cover type (i.e., tree or no tree) for sample points.

In another example, Allen and Walsh (1996) used automated techniques with Landsat TM imagery to map treeline and quantify patterns in Glacier National Park; however, due to shadows that occurred on steep, north-facing slopes, manual corrections were performed to correctly classify barren cliffs, which were frequently misclassified as either forested scree or water. More recently, Kral (2009) resorted to manual digitization of some cover classes after a maximum likelihood classification resulted in mixed classes (i.e., multiple cover types in each class) and the addition of a texture analysis was unable to improve the results.

Automated Techniques

Many of the treeline mapping studies that we found in the literature used automated, pixelbased approaches with relatively high resolution ($\leq 5 \text{ m x } 5 \text{ m}$) imagery. For example, a treeline disturbed by fire at Mount Rainier National Park was mapped by Stueve et al. (2009) using 1.9 m panchromatic satellite imagery from 1970 and a 1 m color DOQQ from 2003. A minimum distance supervised classification was performed on each of the datasets to produce binary outputs of tree and non-tree. Filters were used to assign areas in shadow to either of the two classes, and manual adjustments were made to the classification where snow obscured trees. GIS was used to delineate the forest line by identifying the highest tree pixels that were contiguously connected to the closed forest. Then a change detection calculation was performed between the two images.

Arctic treelines were mapped by Rees (2007) using high resolution (resampled to 5 m) multispectral data. An unsupervised classification was performed using the ISODATA clustering algorithm. Results were of mixed quality, with some cover classes such as bare ground and water being clearly delineated, however, the tundra-forest transition was less clear. Due to sensor noise and variations in viewing geometry between image strips, several classes were unrealistic. No accuracy assessment was conducted. Other arctic treeline mapping efforts have also taken place that use imagery of coarser resolution (Ranson et al., 2004; Heiskanen & Kivinen, 2007), which is more useful for mapping the expansive tundra-taiga ecotone boundary of the sub-arctic.

Two examples of the use of lower resolution (Landsat) imagery to map treeline exist from the 1990s. Landsat TM imagery was used in Glacier National Park to map vegetation types at treeline (Brown, 1994). The ISODATA unsupervised classification technique was first used to identify 50 spectral clusters. Inputs included visible, near-infrared, and middle-infrared bands, as well as a band ratio that was used to reduce illumination issues related to topography. Canopy composition data collected during field-based sampling and canopy closure estimated using color-infrared air photos was used in combination with the spectral signatures of the clusters and spatial autocorrelation to iteratively join similar classes and to assign them to one of five cover classes. Overall accuracy was 84%. In Glacier National Park, Allen and Walsh (1996) used Landsat TM imagery to map treeline and quantify patterns. The multidate images were classified using a hierarchical approach, which included an unsupervised classification, a supervised classification, and manual corrections. The unsupervised classification was used first to divide the image data into major cover types. Then training sites were used in a maximum likelihood supervised classification, followed by manual corrections to address misclassifications.

Probability mapping was used by Hill et al. (2007) to create a soft classification of treeline in Austria using SPOT 5 satellite data. Posterior probabilities of class memberships were calculated from the results of a maximum likelihood classification. Validation data were mainly derived from high spatial resolution data. Two approaches were used to produce a thematic map of the ecotone. First, alpha-cuts were applied to the posterior probability of the forest membership class, which resulted in seven classes that ranged from closed forest up to alpine grass/meadow. For comparison, ratios were calculated between the posterior probabilities of the forest and the nonforest class, resulting in a thematic map that contained gradations of color to represent transitions between vegetation types. In contrast to the map produced using the alpha-cuts, which contained imposed boundaries between classes, the ratio map displays the ecotone transition without artificial boundaries.

Other researchers have used object-based image analysis to map treeline. In Finnish Lapland, Middleton et al. (2008) used object-based image analysis to map an alpine treeline near the arctic treeline. After image segmentation was performed, support vector machines (i.e., a model that analyzes inputs and predicts which of two classes forms the output) were applied in a supervised classification. The upper limit of treeline was defined as trees higher than 1.3 m (based on field data). No accuracy assessment was conducted to validate the classification results. In another example involving arctic treeline mapping, Ranson et al. (2011) used 500 m MODIS Vegetation Continuous Fields (VCF) tree cover data to map the circumpolar treeline using an image segmentation approach. The segmentation process created image objects that represented varying tree cover densities. The objects were then classified according to VCF threshold values. Objects with mean VCF values ranging from 5% through 20% or with mean VCF less than 5% and standard deviation greater than 5% were considered part of the treeline ecotone class, with the former group representing the core of the ecotone and the latter group representing colonization areas or dieback areas. Accuracies were calculated using LiDAR for reference data, with 67.7% overall accuracy.

LiDAR Techniques

LiDAR data has been shown to be a suitable tool for mapping treeline areas. For example, in the same arctic treeline study mentioned earlier, Rees (2007) used LiDAR data to produce a tree height dataset by subtracting a last-return DEM from a first-return DEM. He used the tree height dataset to construct a binary forest cover map, where forest was defined as pixels at least 2 m tall and no more than 10 m from one another. This output was used to investigate scale dependence of the forest structure by averaging pixel values of increasing window sizes. Results demonstrated that for pixel sizes up to 10 m, pure forest pixels were still found, and at coarser resolutions all pixels are mixed (i.e., some forest and some non-forest).

A combination of high resolution LiDAR strip samples and lower resolution Landsat imagery were used to delineate the subalpine zone in Norway (Ørka et al., 2012). The subalpine zone was defined as the area where the crown coverage of trees higher than 5 m is between 5 and 10%, or where the crown coverage of both trees and shrubs higher than 0.5 m is greater than 10%. A rulebased classification was used to identify cover types using the LiDAR point cloud data. Then the entire area was mapped using the full coverage data. A binomial logistic regression model was used to predict a probability surface using the following candidate variables: NDVI, brightness, wetness, greenness, elevation, slope, solar radiation, curvature, latitude, and longitude. Alpha-cuts were used to separate the probability surface into hard classes (forest, subalpine, alpine). Although overall classification accuracy was 68.8%, for the subalpine class the producer's accuracy was 56.6% and the user's accuracy was 32.5.% due to a high degree of mixing with the other classes. The authors note that this can be partially explained by the fact that reference data, in the form of forest lines and tree lines, was delineated in the field using GPS, which resulted in some subjectivity of the delineation of the reference data.

LiDAR data with high pulse frequencies has also proven to be highly accurate in the detection of small pioneer trees. For example, Næsset and Nelson (2007) used LiDAR data to detect small trees at treeline in Norway. Three different terrain models (created from the last returns, with varying iteration angles and therefore varying levels of smoothness) were tested and it was found that 91% of all trees greater than 1 m were detected regardless of the model. For trees shorter than 1 m, fewer were detected (between 5 and 73% depending on the model used). Additionally they found that tree heights were systematically underestimated from actual tree heights measured in the field by 0.40 to 1.01 m. Errors of commission were due to terrain objects such as rocks with positive height values being identified as trees. Without additional spectral classification to separate trees from terrain objects, these errors would remain in the dataset.

Thieme et al. (2011) also used LiDAR data to detect small trees at treeline in Norway. They had similar success rates as Næsset and Nelson (2007), with 90% of trees taller than 1 m being detected, and 49% of trees shorter than 1 m being detected. Once conifers reach 1.4 m high or 1.1 m² in crown area, almost all of them can be detected when laser pulse densities are greater than 7

m². They also found that conifer trees had a higher likelihood of being detected than did deciduous (birch) trees, which was due to a lower foliage density of the birch trees. Underestimations of tree heights ranged between 0.2 and 1.08 m, with the largest underestimations of conifer trees being for those between 1 and 2 m tall.

3.5. The Need for Further Research

According to National Park Service Director Jon Jarvis, climate change is the greatest threat to the integrity of our national parks (NPS, 2010). It is suspected that forest expansion may be occurring within the climatically-controlled treeline areas of North Cascades National Park; however, no published treeline change studies have been conducted to date within park boundaries. As public land management agencies develop adaptation strategies for climate change, awareness of treeline trends will help to make well-informed decisions. Although this study did not involve measurement of treeline change over time, it has established a reliable baseline for the current altitudinal position of treeline, from which future change can be measured. Finding improved and more automated ways for mapping and monitoring of treeline is the first step in supporting future treeline studies.

4. Study Area

North Cascades National Park Complex is located in northwest Washington State in the heart of the North Cascades ecosystem (Figure 1). Ninety-four percent of the park complex is designated as the Stephen Mather Wilderness, which is part of over two million acres of federally designated wilderness. Spanning the Cascade Crest, it encompasses a varied landscape with an impressive 3,000 m of vertical relief. The Goodell Creek drainage within the park complex was chosen for this study because it has recent (2009) airborne LiDAR data coverage. About 10,390 hectares in size, the Goodell Creek watershed drains one of the most rugged mountain ranges in the conterminous U.S., the Picket Range. The valley has a north-south orientation and drains into the Skagit River from the north. The mouth of the valley falls within Ross Lake National Recreation Area (a unit of the park complex), while the remaining area falls within North Cascades National Park proper. Additionally, the valley is almost entirely within the Stephen Mather Wilderness. In a recent Wild and Scenic River Suitability and Eligibility Study, the creek was found eligible and suitable for wild and scenic river designation. Treeline species in this drainage include subalpine fir (*Abies lasiocarpa*), mountain hemlock (*Tsuga mertensiana*), and whitebark pine (*Pinus albicaulis*) (Franklin & Dyrness, 1988). All three species have similar growth behavior, with erect trees near forest line (the upper limit of contiguous forest) and reducing to shrubby krummholz forms at high elevations, but with whitebark pine forming krummholz at higher elevations than the other species (Franklin & Dyrness, 1988). Orographic treelines, where features such as steep rock walls, debris aprons, talus slopes, and avalanche chutes limit forest establishment, are common in the North Cascades.

In the northern latitudes low sun angles can affect the accuracy of image classification. When in shadow, objects reflect very little light and are therefore difficult to discern. Shadows cast from mountains and ridgelines as well as from trees can also be a considerable problem within the North Cascades. We used eCognition software to estimate the amount of shadow in the orthoimagery, and it was found that 21% of the pixels within the study area were not directly illuminated by the sun. This high proportion of shaded pixels is due to the fact that the Goodell drainage contains extremely steep terrain that casts deep shadows on north-facing slopes. With this information it became evident that shadows would indeed be a problem and that additional steps would need to be taken in order to achieve an acceptable level of accuracy.



Figure 1. Study area.

5. MATERIALS AND METHODS

Chapter 5 contains a description of the datasets that we used, the preprocessing steps that were implemented, and the classification routines that were performed. An explanation of the methods we used in the accuracy assessment is provided, followed by a description of the canopy cover calculations. Figure 2 is a project workflow diagram.



Figure 2. Workflow.

5.1. DATA AND PREPROCESSING

The National Park Service (NPS) provided the data for this study. Two types of high spatial resolution data were used: digital orthoimagery and airborne LiDAR data, described in more detail below.

DIGITAL ORTHOIMAGERY

Multispectral aerial imagery was acquired by the National Agriculture Imagery Program (NAIP) on August 26, 2011. The program collects imagery for the conterminous United States with a focus on agricultural areas; however, cost share partnerships between federal agencies allow the program to acquire complete state coverage. The imagery (hereafter, NAIP imagery) has a 1 m pixel resolution and a four-band spectral resolution. The bands include blue (0.4 - 0.5 μ m), green (0.5 - 0.6 μ m), red (0.6 - 0.7 μ m), and near-infrared (0.7 – 1.3 μ m). The vendor performed radiometric and geometric corrections, and the data was rectified using USGS 10 m Digital Elevation Models (DEMs). The result was a 16-bit, radiometrically calibrated ortho-image strip that represents the footprint

collected by the sensor for one flight line. This final product, consisting of six image tiles, was delivered to the NPS in the GeoTIFF format.

Because of the pre-processing that was performed by the vendor, very little further manipulation of the NAIP imagery was necessary. However, because of the large amount of shadow within the study area due to high topographic relief, we chose to use a band ratio to minimize the topographic effect. Band ratios are a simple, yet effective method that can be used to adjust for differences in illumination conditions (Hale & Rock, 2003). In this case we calculated the Normalized Difference Vegetation Index (NDVI, Rouse, Jr. et al., 1973). The NDVI is a difference formula that is used to measure relative amounts of vegetation. It is calculated using visible and near-infrared bands that are absorbed and reflected by vegetation. Healthy vegetation absorbs most visible light and reflects most near-infrared energy, while unhealthy or sparse vegetation reflects more visible light and less near-infrared energy. Because it uses a ratio, the NDVI helps to compensate for changing illumination conditions that if not corrected can cause identical land cover types to reflect differently and consequently lower the accuracy of land cover classifications. Conceptually, NDVI values for identical land cover classes should be consistent across a range of sun sensor configurations because the ratios between the bands in each area should be similar. NDVI values for areas in complete shade, however, will be more different from their sunlit counterpart values because considerably less light is reflected when in shade. The NDVI equation is:

$$NDVI = rac{NIR - RED}{NIR + RED}$$

In addition to the NAIP imagery, the NPS also provided digital orthoimagery of the study area that was acquired in July 2009 by US Customs and Border Protection. It has 0.3 m pixel resolution and three-band (blue, green, and red) spectral resolution. The vendor performed all preprocessing, which included the following: image strips were rectified with a recent DEM of the area (resolution unknown). The 12-bit image data was color balanced by performing tonal enhancements prior to being radiometrically adjusted for output as eight bit data. The eight bit images were further adjusted to provide seamless imagery. They were mosaicked and then project-specific tiles were extracted from the mosaic. The accepted measure of positional accuracy of a dataset is the mean square root of squared differences between the map and reference points, or the root-mean-square error (RMSE, Congalton & Green, 2009). An RMSE score of 0 means that the reference samples were identical to the map samples and the map is considered perfectly accurate. In this case, photo-identifiable ground control points were used to determine horizontal accuracy, which was estimated to be less than 6.0 m RMSE. The orthorectified imagery (hereafter 0.3 m imagery) served as reference data for this study because of the extreme ruggedness of the area and inability to access random sample points distributed throughout the area.

LIDAR

LiDAR data was acquired within the study area by Watershed Sciences, Inc. during September 2009. Real-time kinematic (RTK) ground surveys using GPS were conducted over monuments with known coordinates within the study area to confirm antenna height measurements and reported positional accuracy. The reported RMSE for the dataset was 0.04 m. Data resolution averaged 10.42 m⁻² for total pulse density and 1.42 m⁻² for ground pulse density. The ground pulse density is much lower than the total because many of the pulses were intercepted by vegetation before they hit the ground. Consequently, the bare ground model, or DEM, created from these points is based on only between 1 and 2 sample points per square meter.

In addition to point data the vendor provided a bare ground model and an above ground model with 1 m resolution. We used the Raster Calculator feature in ArcGIS to subtract the bare

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ground model from the above ground model, which resulted in a tree height dataset (i.e., similar to Rees W. G., 2007)). The resultant dataset contained both negative values (up to -53 m) and positive values that were well above realistic values for tree heights (up to 250 m). These outliers, representing about 0.5 percent of pixels in the dataset, were reclassified to zero.

Another problem with the tree height dataset occurred along ridges, steep slopes, and snow, where values were expected to be zero (i.e., no vegetation present), but in some areas values ranged between 20 and 90 m (Figure 3). These errors were likely the result of the orientation of extremely steep slopes to incoming LiDAR pulses as well as from penetration into snow. Attempts to address the errors included applying a filter as well as masking the non-vegetated areas. First, Focal Statistics were used in ArcMap to apply a 3 x 3 and a 5 x 5 median filter to the highest hit dataset in order to smooth out the extreme values. The resulting outputs were rejected because errors with higher values were still maintained (though they were slightly lower, they were still prominent), while shorter trees at treeline were smoothed and some became indiscernible. Secondly, a mask of non-vegetation was created by using threshold values from the NDVI image. We hoped that the mask would remove most of the errors since they occurred in extremely steep areas or in snow, both having little to no vegetation. However, this technique resulted in too many vegetated areas being masked out since the non-vegetation mask still included some vegetation. Instead, we used the tree height dataset as-is in both the pixel-based classification and in the objectbased classification. We reasoned that since it would be used with the other spectral data as part of the classification, the spectral information could be used to classify those areas as non-tree instead of tree.


Figure 3. Errors in the tree height dataset, running northwest to southeast, are long and narrow, often following steep ridgelines or snow.

MOSAICKING AND IMAGE REGISTRATION

The NAIP image tiles were mosaicked together using ENVI. Feathering was used to blend the seams between image tiles, and color balancing was used to minimize the contrast between the images. Then the tree height dataset was registered to the NAIP imagery. Eleven ground control points were selected, with even distribution throughout the study area. The final registered image had an RMSE of 0.84 m.

5.2. CLASSIFICATION

Two types of classifications were performed on various combinations of the datasets. First, using ENVI software, pixel-based classification was performed on the NAIP imagery and on various combinations of the NAIP imagery and ancillary data. Next, the tree height dataset was added to the inputs that achieved the two highest percent accuracies for the pixel-based results and the same classifications were performed again. Then, using eCognition software, the same inputs were used in object-based classifications. The eight final outputs consisted of binary images containing "tree" and "non-tree" classes. The minimum mapping unit for all outputs was 1 m². Figure 4 depicts the general classification process.



Figure 4. Classification process.

PIXEL-BASED CLASSIFICATION

We used both supervised and unsupervised classification logic to classify the NAIP imagery. The difference between these classification algorithms is whether or not land cover types are known a priori (Jensen, 2005). In supervised classification, at least some of the land cover types are known ahead of time through field work and/or interpreting imagery or maps, for example. Training sites are selected that represent the known cover types and are used to train the classification algorithm that will be applied to the entire image. In unsupervised classification, cover types are not known ahead of time. Unsupervised classification algorithms group pixels with similar spectral characteristics into clusters that are then relabeled into classes by the analyst.

We first performed a maximum likelihood supervised classification of the NAIP imagery. This algorithm calculates the probability of a pixel belonging to each of a predefined set of classes and then assigns it to the class for which the probability is the greatest (Strahler, 1980). Training areas are used to identify the predefined classes, and statistics are compiled that describe the spectral response pattern of each class. We visually selected the training areas and digitized them as polygons from the 0.3 m imagery. The Region of Interest Tool in ENVI was used to define the training areas, which included trees, shrubs, sparse vegetation, rock, snow, and water. Training areas were refined after viewing a separability report, which quantifies the statistical separation of the spectral response pattern between all pairs of classes (Lillesand et al., 2004). Using the refined training areas, the maximum likelihood classification routine was performed on the NAIP imagery. The resultant classes were grouped to create a binary image, where pixels classified as trees remained as "trees," and all other pixels that were classified as shrubs, sparse vegetation, rock, snow, and water were re-classed to "non-trees." Visual inspection of the results revealed that most shadows were unclassified in this process, and a preliminary accuracy assessment confirmed low accuracy levels. Although the subsequent creation of a separate shadow training area was found to be effective at selecting shadows in the image, identification of land cover type within the shadow class was not possible with the maximum likelihood classification method. Figure 5 is an example of a large area in shadow within the dataset.



In an attempt to improve the pixel-based classification of the NAIP imagery, the ISODATA (Iterative Self-Organizing Data Analysis Technique, Tou & Gonzales, 1974)) unsupervised classification algorithm was performed. ISODATA is a clustering technique that iteratively classifies pixels by recalculating statistics and redefining each class (ERDAS, 2005). We used the ISODATA classification on the NAIP imagery and the NDVI image. Twenty classes were identified as spectral clusters in each of the outputs. The classes were

Figure 5. Large shaded area, NAIP imagery.

grouped to create a binary image that contained the classes "tree" and "non-tree." Visual inspection of the results indicated that the shadows in the NAIP imagery were too extensive to create meaningful classes, however, a preliminary accuracy assessment of the classified NDVI image results showed promise in identifying land cover types in shadow.

In another attempt to identify land cover types in areas of shadow, we used layer stacking. Layer stacking creates a multi-layer image by combining two or more separate images into a single dataset. Since the results of the ISODATA classification on the NDVI image showed promise, we decided to examine the results of the same classification on a layer stacked image that contained the four bands of the NAIP imagery and the NDVI band. Prior to layer stacking, the NDVI image was stretched to have a similar data range as the NAIP imagery. The stretched NDVI image was then stacked with the NAIP imagery. The ISODATA clustering algorithm was run on the stacked images. A maximum of 20 clusters were formed as a result, which were then re-classed to a binary image containing the classes "tree" and "non-tree."

In order to adequately compare the results between pixel-based and object-based classification outputs, we decided to select the two pixel-based outputs that achieved the highest percent of overall accuracy. These inputs included the NDVI and the NAIP and NDVI layer stack; both were classified using the ISODATA classification algorithm. To determine whether the tree height dataset might improve classification results, it was stacked with each of these inputs, i.e., NDVI and tree heights and NAIP, NDVI, and tree heights. The ISODATA clustering algorithm was run on each of the stacked images after stretching the tree height data range to match the range of the other input bands. Twenty clusters were formed as a result of each classification, and binary images containing the classes "tree" and "non-tree" were created by re-classing the clusters.

OBJECT-BASED CLASSIFICATION

We also used object-based classification logic to classify the NAIP imagery using eCognition software. The first step in object-based image analysis is to segment the image pixels into objects using one of several segmentation algorithms. A more sophisticated algorithm, multiresolution segmentation is a bottom-up strategy that merges pixels or existing image objects based on relative homogeneity criteria (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). The algorithm is based on a pairwise region merging technique, whereby one-pixel objects are merged into small objects that are subsequently merged into bigger objects. We used multiresolution segmentation in this study because it is successful in extracting features using both color and shape homogeneity (Trimble, 2012). After the image is segmented it can be classified, or additional segmentations can be applied to further subdivide, merge, or reshape existing objects. We assigned objects to classes by selecting different object features and adjusting threshold values by trial and error. We used the Feature View window to test algorithms and change their parameters for each object feature.

It should be noted that the parameter settings of the multiresolution segmentation and the assignment of classes based on object feature threshold values were both subjective processes. In the parameter settings of the multiresolution segmentation process, we assigned image layer weights based on what we had learned from the pixel-based classifications. This includes the finding that the NDVI improved the detection of cover types in shadow, and that tree height data could further improve the detection of cover types in very deep shadow where NDVI was not as useful. Thus, an image layer weight of "1" was given to the band or bands perceived to provide the least amount of information. For example, image layer weights of "1" were assigned to each of the four bands of the NAIP imagery in order to minimize the influence that shadows had on the segmentation. When NDVI and tree heights were used in addition to the NAIP imagery, the NDVI was assigned a layer weight of "2" in order to outweigh the NAIP imagery values, and tree heights were assigned a layer weight of "4" in order to outweigh both of the other datasets.

The other parameter settings of the multiresolution segmentation included a scale parameter, which determines the resulting image object size, and the composition of homogeneity criterion, which is another weighting tool that allows the analyst to determine the relative importance of color vs. shape and compactness vs. smoothness. Each of these settings is userdefined and final settings were determined through trial and error.

The object features that we used to assign classes were chosen based on our best judgment and knowledge about the kind of information that each feature contained. This was an iterative process that involved testing different algorithms, adjusting their threshold values, and visually evaluating their results on the screen. We chose this method to assign classes because it allowed for more fine-tuning than an established classification approach. For example, a threshold value for mean NDVI was an object feature that we used frequently to assign objects to either a tree or a nontree class. Using different threshold values for mean NDVI allowed us to assign the more straightforward objects to the appropriate class (i.e., all objects with mean NDVI > 0.3 are trees), while leaving the more difficult objects, such as those in shade with low NDVI values that still contained trees, for further fine tuning (i.e., using maximum NDVI pixel values).

eCognition processes are arranged in a rule set, which is used to organize and modify algorithms. Appendix B contains the rule sets that we used in eCognition for each of the objectbased classifications in this study.

NDVI

The NDVI image was first segmented using multiresolution segmentation. Since it was the only image layer used in the segmentation, we assigned it a layer weight of "1." Following segmentation, we used object features to assign objects to classes. We first used mean NDVI to find obvious non-trees, where objects with very low NDVI values (≤ 0) would not likely be trees. Then we used similar logic to find obvious trees, i.e., objects with very high NDVI values (> 0.3) would most likely be trees. The remaining unclassified objects had mean NDVI values between 0.0001 and 0.3 and contained a mix of non-trees and trees. In an attempt to separate the objects with trees from those that did not contain trees, we selected objects that had slightly higher mean NDVI values (≥ 0.1) and high maximum NDVI pixel values (≥ 0.3). All remaining unclassified objects were assigned to the non-tree class. The object features and threshold values are described below.

- NDVI (*Mean NDVI ≤ 0*) was used to identify non-trees. Low NDVI values indicate non-vegetated surfaces.
- NDVI (Mean NDVI > 0.3) was used to identify trees. Higher NDVI values correspond to denser vegetation (i.e., trees).

- NDVI (Mean NDVI ≥ 0.1 and Maximum pixel value NDVI ≥0.3) was used to identify less obvious trees within objects that had low average NDVI values but higher maximum NDVI values, indicating the presence of trees that are likely in shadow.
- The remaining unclassified objects were assigned to the non-tree class.

NAIP Imagery and NDVI

The image was first segmented using multiresolution segmentation. The image layers used in this first step included the four bands (blue, green, red, and near-infrared), which were given layer weights of "1," and an NDVI band, which was given a layer weight of "3." The NDVI band was given a higher weight because of the increased ability it has to distinguish between land cover types in shadow (Hale & Rock, 2003). Sunlit and shaded areas were classified separately due to the tendency for darker subalpine vegetation in sun to be confused with trees in shade. Shaded areas that are not directly illuminated by sunlight are lit by diffuse skylight, which has a greater proportion of light in the blue wavelengths. Therefore, we used a threshold value for the blue light ratio (Ratio blue ≥ 0.269) to isolate the resulting segmented objects that occurred in shade. The threshold value was effective in separating shaded objects from objects in full sun, with shaded objects assigned to a shade class and all other objects left unclassified. The following additional object features were used to identify land cover types within the shade class: mean brightness, mean and standard deviation (sd) of NDVI, and maximum pixel value of NDVI. NDVI was selected most often because of its value in discriminating vegetation from non-vegetation. The object features and threshold values are described below.

- Brightness (Mean Brightness ≥ 320) was used to identify snow. Brightness values correspond to digital number (DN) values assigned to each pixel in each band. Mean Brightness is the average pixel value of the four bands, with higher values approaching white.
- NDVI (Mean NDVI ≥ 0.15 and Standard Deviation NDVI ≥ 0.06) was used to identify trees. Higher NDVI values, although they were not high compared to solar-illuminated trees, correspond to denser vegetation (i.e., trees). Higher sd values reflect a greater variance in NDVI values belonging to the pixels that compose each object (i.e., a mix of brighter trees

represented by higher NDVI values and the spaces between the trees with lower NDVI values).

- **NDVI** (*Mean NDVI < 0*) was used to identify rock mixed with tall, dark trees. Trees in extremely deep shadow had NDVI values below zero, and were mixed with rock.
- NDVI (*Maximum pixel value NDVI* ≥ 0.15) was used to identify the trees mixed in the above rock/tree class. If an object had maximum pixel values above this threshold, it likely contained trees, even though the object's mean NDVI value was below zero.
- The remaining objects in the shade class were assigned to the non-tree class.

Since image objects in sunlit areas were considerably smaller in size than those in shade, a

second multiresolution segmentation was applied to the remaining unclassified (sunlit) objects. This

created more meaningful objects that could then be classified using object features. The following

object features and threshold values were used to classify the sunlit objects:

- Brightness (Mean Brightness > 2120) was used to identify snow.
- **NDVI** (*Mean NDVI < 0.37*) was used to identify rock. Extremely low NDVI values represent non-vegetated surfaces.
- **Green** (Mean green ≥ 790) was used to identify shrubs. This feature was found to separate bright green shrubs from darker trees.
- **Red** (*Mean red* ≥ 550) was used to identify sparse subalpine vegetation. This feature was found to separate sparse vegetation found in the subalpine from darker trees.
- The remaining unclassified objects were assigned to the tree class.

The merge region algorithm was used to merge objects in each of the classes created from the

shade group and the sunlit group, and a final output image of "tree"/"non-tree" was created.

NDVI and Tree Height Dataset

In this trial, the tree height dataset was added as an image layer to the NDVI image. Image

segmentation was performed using layer weights of "1" for the NDVI band and "3" for the tree

height dataset. This allowed for meaningful objects to be created that represented trees. Following

segmentation, a simple threshold value was used to assign all objects with mean tree heights less

than or equal to 1.0 m to a non-tree class (Mean tree height \leq 1.0), since LiDAR has been shown to

accurately detect trees higher than 1 m (Næsset & Nelson, 2007). Had there been an absence of

errors in the dataset, the remaining objects would have been assigned to the tree class and the final

image output would have been quickly created. However, numerous tree height errors existed that first needed to be addressed. First, all objects with higher mean NDVI values (Mean NDVI > 0.37) were assigned to the tree class. Then the remaining unclassified objects with higher mean tree heights (Mean tree height > 1.5) and higher maximum NDVI pixel values (Maximum pixel value NDVI \geq 0.37) were also assigned to the tree class. The remaining unclassified objects that had mean tree heights less than 1.5 m were assigned to the non-tree class. The few remaining unclassified objects were assigned to the tree class if they had maximum NDVI pixel values \geq 0.1, which helped to capture trees in dark shade, and all remaining unclassified objects were assigned to the non-tree class. The object features and threshold values used to assign classes are described below.

- **Tree Height** (*Mean tree height* ≤ 1) was used to assign object s with low tree height values to the non-tree class.
- NDVI (Mean NDVI > 0.37) was used to assign objects with very high NDVI values to the tree class.
- Tree Height (Mean tree height > 1.5) and NDVI (Maximum pixel value NDVI ≥ 0.37) were used to assign additional objects to the tree class.
- **Tree Height** (*Mean tree height* \leq 1.5) was used to assign objects to the non-tree class.
- **NDVI** (*Maximum pixel value NDVI* \geq 0.1) was used to assign objects to the tree class.
- The remaining unclassified objects were assigned to the non-tree class

NAIP Imagery, NDVI, and Tree Height Dataset

In the last trial, the tree height dataset was included as an image layer along with the NAIP imagery and NDVI image. First, image segmentation was performed using layer weights of "1" for the four bands (blue, green, red, and near-infrared), "2" for the NDVI band, and "4" for the tree height dataset. This allowed for meaningful objects to be created that represented trees, as well as the clear isolation of the errors in the dataset. NDVI was still important (thus its layer weight of "2"), however, tree heights were assigned the highest weight. Following segmentation, a simple threshold value was used to assign all objects with mean tree heights less than or equal to 1.0 m to a non-tree class (Mean tree height \leq 1.0). Similar to the previous classification of the NAIP imagery and NDVI image, it was more effective to separate shaded from sunlit areas and then to remove tree

height errors separately in each of these areas. This was accomplished by using the same threshold

value for the blue ratio (Ratio blue ≥ 0.269), creating a shade class, which allowed sunlit and shaded

areas to be classified separately. The object features and threshold values used to classify the

shaded objects included the following:

- **NDVI** (*Mean NDVI* \geq 0.1) was used to assign objects with high NDVI values to the tree class.
- Brightness (Mean Brightness ≥ 325) was used to identify snow.
- Tree height (Mean tree height ≤ 2) and NDVI (Mean NDVI ≤ 0) were used to assign objects with low tree height values and low NDVI values to the non-tree class. These thresholds helped to remove some of the tree height errors from the dataset that were under 2 m.
- Slope (Mean slope ≥ 55) and NDVI (mean NDVI ≤ 0.1) were used to assign objects on steep slopes with low NDVI values to the non-tree class. Because many of the tree height errors occurred in steep areas, a threshold value for slope was used, and to minimize the amount of trees growing on steep slopes that would be classified as non-tree under this scenario, the NDVI threshold value was used in combination with the slope threshold.
- NDVI (*Mean NDVI ≤ -0.16*) was used to assign remaining objects with low NDVI values to the non-tree class.
- The remaining objects in the shade class were assigned to the tree class.

The object features and threshold values that were used to classify the remaining

unclassified (sunlit) objects included the following:

- NDVI (*Mean NDVI ≤ 0.2*) was used to classify objects with low NDVI values as non-tree, effectively moving objects that would have been classified as trees due to their erroneous tree height value to the non-tree class because low NDVI values confirmed that those objects were not vegetation.
- NDVI (Mean NDVI ≤0.37) and Tree Heights (Mean tree height ≤ 2.5) were used to classify objects with low NDVI and low tree heights to the non-tree class, since tree height errors still existed in areas with somewhat higher (up to 0.37) NDVI values.
- Slope (Mean Slope ≥ 55) and NDVI (Mean NDVI ≥ 0.45) were used to assign objects with high NDVI and steep slopes to the tree class.
- Slope (Mean Slope ≥ 55) and NDVI (Mean NDVI ≤0.45) were used to assign remaining objects with steep slopes and with lower NDVI values to the non-tree class.
- The remaining unclassified objects were assigned to the tree class.

The merge region algorithm was used to merge objects in each of the classes created from the

shade group and the sunlit group, and a final output image of "tree"/"non-tree" was created.

5.3. ACCURACY ASSESSMENT

We assessed thematic map accuracy for each of the eight outputs. The three basic components of an accuracy assessment are 1) the sampling design used to select the reference sample; 2) the response design used to obtain the reference land cover classification for each sampling unit; and 3) the estimation and analysis procedures (Stehman & Czaplewski, 1998).

SAMPLING DESIGN

We employed a stratified random sampling design in which each land cover class (i.e., tree and non-tree) was stratified to ensure that an adequate sample size was obtained in each mapped class. This sampling scheme has been found to be the best at estimating the population mean, especially when sample size is 100 or more (Congalton R. G., 1988). Following Congalton and Green (2009), we created a polygon shapefile using the final image segmentation output of the NAIP imagery, NDVI, and tree height dataset. We chose to collect 75 samples for each map class based on Congalton's (1988) finding that at least 50 samples per class was a good "rule of thumb." We used ArcInfo to generate 150 random sample points (Figure 6) throughout the study area, stratified by tree and non-tree. This was accomplished by using a mask of the non-tree class to generate 75 random points located throughout the tree class, then using a mask of the tree class to generate another 75 random points located throughout the non-tree class. Polygons were sampled by selecting those polygons in which randomly chosen point locations fell. One polygon was removed from the selection because it was located on the study area boundary line, leaving 149 sample polygons. The existing attributes in the polygon shapefile containing the classification information (i.e., tree or non-tree) was deleted from the attribute table to avoid any bias in assigning each polygon to its reference class. Since the polygons were of varying sizes, larger polygons had a higher probability of being hit by a random point, thus their inclusion probabilities were higher.



Figure 6. Random point locations used to select reference sample polygons.

REFERENCE DATA COLLECTION

Due to extreme ruggedness and inaccessibility of the study area (see Appendix A for photos), we used the 0.3 m imagery for reference data. Field work involved collecting a subset of data on the ground using GPS and visual comparisons with USGS 7.5 minute quadrangle maps to verify reliability of the reference labels interpreted from the imagery. We chose to use the higher resolution imagery for reference data due to the inability to safely acquire random samples within the study area; this technique is acceptable when simple classification schemes with few classes are used and field work confirms the reliability of reference labels (Congalton & Green, 2009).

We visually interpreted the reference imagery at each sample polygon location according to the classification scheme (i.e., "tree" and "non-tree"), and each polygon was labeled as one of the land cover classes based on its primary cover. The final reference dataset contained 66 polygons identified as tree and 83 identified as non-tree.

ESTIMATION AND ANALYSIS PROTOCOL

An error matrix was generated for each of the eight classified outputs. The error matrix summarizes agreement and disagreement between the classified output and the reference data (Stehman & Czaplewski, 1998). The columns of the error matrix represent the reference data, and the rows represent the classified data. Overall accuracy was calculated by summing the correctly classified polygons, located along the major diagonal, and dividing by the total number of sample polygons. In addition to overall accuracy, producer's and user's accuracies were calculated; these measures represent the accuracy of each class (Congalton & Green, 2009). Producer's accuracy is calculated by dividing the number of correct polygons in a class by the total number of polygons in that class according to the reference data, resulting in a measure of omission error. User's accuracy

is calculated by dividing the number of correct polygons in a class by the number of sample polygons classified as that class, resulting in a measure of commission error (Stehman & Czaplewski, 1998).

Following generation of the error matrix, Kappa analysis, or the coefficient of agreement, was calculated. Kappa analysis is a discrete multivariate technique used to measure agreement between the classified map and the reference data (Congalton & Oderwald, 1983). It adjusts overall accuracy to account for chance agreement, and can be used to statistically test for agreement between two matrices (Foody, 2002). Kappa analysis results in a KHAT statistic, which was computed for each error matrix. KHAT values range from 0 to 1, with higher positive values representing stronger agreement (Congalton & Green, 2009).

5.4. CANOPY COVER AND TREELINE DELINEATION

We used the binary image with the highest overall percent accuracy to derive a canopy cover image. Similar to Kral (2009), we used a moving window approach applied to the binary image (where tree = 1 and non-tree = 0) to calculate canopy cover. This approach calculates a summary statistic (e.g., minimum, mean, maximum) for all of the cells within the window, and assigns the value to the center pixel before systematically shifting to the next pixel neighborhood (Lillesand et al., 2004). Using ArcGIS, we chose to use the arithmetic mean of pixel values within a 32 x 32 window size, corresponding to 1,024 m². We selected the window size through trial and error, and similar to Kral (2009) and Gehrig-Fasel et al. (2007), we found that a window size of approximately 1,000 m² best represented local canopy cover in the surrounding area. The resulting image consisted of a surface with pixel values ranging between 0.0 and 1.0. Multiplying each pixel in the image by 100 resulted in pixel values that represented percent canopy cover within a 1,024 m² surrounding area.

We used percent canopy cover thresholds based on the definition established in Section 3.1 to identify the closed canopy forest (canopy cover > 30%), treeline (canopy cover \leq 30% and > 0%), and alpine (canopy cover = 0%). We reassigned pixels to one of these three classes using the threshold values and a minimum mapping unit of 1 m². We calculated descriptive characteristics, including average, minimum, and maximum elevations of treeline, as well as the range of treeline elevations.

6. RESULTS

Eight final image outputs were assessed for accuracy, including four pixel-based outputs and four object-based outputs. Error matrices calculated for each output are provided in Table 2, with correctly classified percentages in bold along the diagonal. Overall accuracy, producer's accuracy, and user's accuracy are provided in Table 3, along with errors of omission and commission, and the KHAT statistic. Table 2. Error Matrices.

Input	Classified Data	Reference Data			
		Non-tree (%)	Tree (%)	Total (%)	
	PIXEL-BASED CL	ASSIFICATIONS	1		
NDVI	Non-tree	81.23	11.25	35.99	
	Tree	18.77	88.75	64.01	
	Total	100.00	100.00	100.00	
NAIP & NDVI	Non-tree	85.49	14.75	35.06	
	Tree	14.51	85.25	64.94	
	Total	100.00	100.00	100.00	
NDVI & Tree Heights	Non-tree	86.53	11.72	33.21	
	Tree	13.47	88.28	66.79	
	Total	100.00	100.00	100.00	
NAIP, NDVI & Tree Heights	Non-tree	85.44	10.46	31.99	
	Tree	14.56	89.54	68.01	
	Total	100.00	100.00	100.00	
	OBJECT-BASED C	LASSIFICATIONS	·		
NDVI	Non-tree	41.48	2.07	13.39	
	Tree	58.52	97.93	86.61	
	Total	100.00	100.00	100.00	
NAIP & NDVI	Non-tree	72.19	10.20	28.00	
	Tree	27.81	89.80	72.00	
	Total	100.00	100.00	100.00	
NDVI & Tree Heights	Non-tree	42.98	3.05	14.52	
	Tree	57.02	96.95	85.48	
	Total	100.00	100.00	100.00	
NAIP, NDVI & Tree Heights	Non-tree	80.62	2.20	24.72	
	Tree	19.38	97.80	75.28	
	Total	100.00	100.00	100.00	

Table 3. Accuracy Summary.

Input	Class	Producer's Accuracy (%)	Omission Error (%)	User's Accuracy (%)	Commission Error (%)	Overall Accuracy (%)	КНАТ
	PIXEL-	BASED CLA	SSIFICATIO	ONS			
NDVI	Non-tree	81.23	18.77	79.79	20.21	0.5.4	0.70
	Tree	88.75	11.25	89.63	10.37	86.1	
NAIP & NDVI	Non-tree	85.49	14.51	70.02	29.98	9E 2	0.66
	Tree	85.25	14.75	93.58	6.42	65.5	
NDVI & Tree Heights	Non-tree	86.53	13.47	74.84	25.16	87.8	0.71
	Tree	88.28	11.72	94.21	5.79		
NAIP, NDVI & Tree Heights	Non-tree	85.44	14.56	76.70	23.30	00 /	0.73
	Tree	89.54	10.46	93.85	6.15	88.4	
OBJECT-BASED CLASSIFICATIONS							
NDVI	Non-tree	41.58	58.52	88.99	11.01	81 7	0.47
	Tree	97.93	2.07	80.60	19.40	81.7	
NAIP & NDVI	Non-tree	72.19	27.81	74.04	25.96	847	0.62
	Tree	89.80	10.20	88.91	11.09	04.7	
NDVI & Tree Heights	Non-tree	42.98	57.02	85.03	14.97	91 E	0.47
	Tree	96.95	3.05	80.84	19.16	01.0	
NAIP, NDVI & Tree Heights	Non-tree	80.62	19.38	93.66	6.34	02.0	0.82
	Tree	97.80	2.20	92.61	7.39	92.9	

6.1. PIXEL-BASED CLASSIFICATION

Both of the pixel-based classifications that were conducted without the tree height dataset resulted in acceptable overall accuracies that were within 1 percentage point of each other, with the NDVI input resulting in 86.1% accuracy and the NAIP and NDVI input resulting in 85.3% accuracy.

KHAT statistics were 0.70 for the NDVI input and 0.66 for the NAIP and NDVI input, indicating moderate agreement between the classification and the ground reference data. The NDVI input resulted in both the lowest producer's accuracy for the non-tree class (81.23%) and the highest producer's accuracy (88.75%) for the tree class (i.e., the percentage of pixels in the reference data that were correctly classified). The user's accuracy was lowest for the non-tree class of the NAIP and NDVI input, with 70.02% of the pixels classified as non-tree in the image were non-tree in the reference data.

When tree heights were stacked with the two input combinations (i.e., 1) NDVI and tree heights and 2) NAIP, NDVI, and tree heights), overall accuracies improved to 87.8% and 88.4%, respectively. KHAT statistics continued to indicate moderate agreement between the classification and the ground reference data, with 0.71 for NDVI and tree heights and 0.73 for NAIP, NDVI, and tree heights. Producer's accuracies ranged from 85.44% for the non-tree class of the NAIP, NDVI, and tree height combination, to 89.54% for the tree class of the same input combination. User's accuracies ranged from 74.84% for the non-tree class of the NDVI and tree height combination (indicating that a large percentage of trees (25.16% error of commission) were included in the nontree class) to 94.21% for the tree class of the same input combination, which was the highest user's accuracy of all of the classifications.

6.2. OBJECT-BASED CLASSIFICATION

The object-based image classifications that were conducted without the tree height dataset resulted in a slight decrease in overall accuracy compared to the pixel-based classifications that used the same inputs. The NDVI input had an overall accuracy of 81.7% and the NAIP and NDVI input had an overall accuracy of 84.7%. The NDVI input had the lowest KHAT statistic (0.47), indicating that agreement between the classification results and the reference data occurred less than half the

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time, while the NAIP and NDVI input had a KHAT statistic of 0.62. Producer's accuracies for both sets of inputs were high for the tree class, with 97.93% for the NDVI input, the highest of all classifications, and 89.80% for the NAIP and NDVI input, while producer's accuracies for the nontree class were considerably worse, with 41.58% for the NDVI input, the lowest of all classifications, and 72.19% for the NAIP and NDVI input. User's accuracies improved for the non-tree class with this method, with 88.99% for the NDVI input and 74.04% for the NAIP and NDVI input, while they decreased for the tree class, with 80.60% for the NDVI input and 88.91% for the NAIP and NDVI input.

The addition of the tree height dataset to the object-based classifications produced mixed results. When the tree height dataset was added to the NDVI input, overall accuracy remained the essentially same as it was without the dataset (81.5%), with the same low KHAT statistic (0.47). It still resulted in a low producer's accuracy of 42.98% for the non-tree class, and a high producer's accuracy of 96.95% for the tree class. User's accuracies remained similar to those produced by the NDVI input alone, with 85.03% for the non-tree class and 80.84% for the tree class. Conversely, when the tree height dataset was added to the NAIP and NDVI input, overall accuracy was the highest of all classifications at 92.9%, along with the KHAT statistic of 0.82. Producer's accuracy of the tree class was second highest at 97.8%, and for the non-tree class it was 80.6%. User's accuracies were very high at 93.6% for the non-tree class and 92.6% for the tree class.

IMAGE OUTPUTS

Figure 7 shows a subsetted section of the study area, followed by subsets of each of the eight classification outputs. Appendix C contains figures that display the full scene results for each output.



Figure 7. Results of each classification method using a subset of the study area. Original NAIP image (a). Pixelbased NDVI (b). Pixel-based NAIP & NDVI (c). Pixel-based NDVI and tree height (d). Pixel-based NAIP, NDVI & tree height (e). Object-based NDVI (f). Object-based NAIP and NDVI (g), Object-based NDVI and tree height (h), Object-based NAIP, NDVI and tree height (i).

6.3. TREELINE DELINEATION

The object-based classification output that used the NAIP imagery, NDVI, and tree height dataset, since it had the highest percent accuracy, was used to delineate elements of the treeline ecotone (Figure 8). To define the lower boundary of the treeline ecotone we used the upper limit of the closed canopy forest cover class and to define the upper boundary we used the upper limit of the treeline cover class. Results (Table 4) show that the ecotone extends from an average of 1,586 meters above sea level (masl) on the lower end to 1,734 masl on the upper end, resulting in a range of 148 m. The minimum lower elevation of ecotone is 1,033 masl, and the maximum upper elevation of the ecotone is 2,121 masl. Total area of the closed canopy forest within the study area is 7,477 hectares, and total area of the treeline ecotone is 1,220 hectares.

Cover Class	Minimum Elevation (m)	Maximum Elevation (m)	Average Elevation (m)	Range of Elevations (m)	Area (ha)
Closed Canopy Forest (upper limit)	1,033	2,047	1,586	1,014	7,477
Treeline (upper limit)	1,266	2,121	1,734	855	1,220

Fable 4. Descriptive	Characteristics of th	e Treeline Ecotone.
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Figure 8. Treeline delineation results.

7. DISCUSSION

7.1. THE SHADOW PROBLEM AND NDVI SOLUTION

In the North Cascades and other mountainous regions, shadows from trees and topography make land cover classification of multispectral images difficult. Manual interpretations have been necessary to address shadow problems, such as those conducted by Stueve et al. (2011), Allen and Walsh (1996), and Kral (2009). This study has demonstrated that spectral indices (NDVI) can greatly reduce the issues that shadows present in automated image classification. For example, trial classifications using just the NAIP imagery resulted in low overall accuracies (under 65%), which is largely explained by the inability to identify cover types that were in shadow. Figures 9 and 10 visually demonstrate the difference between using a true color image to distinguish cover type versus using the NDVI, respectively. In Figure 9, large portions of the image appear black due to deep shadows; only snow is discernible in some of the shaded areas. In Figure 10 the same areas that appear to be black in the RGB image show clear differences in cover type. The value of the near infrared band for discerning cover types in shadow becomes evident upon visual examination of the two image examples.

This concept was applied in subsequent pixel-based classifications that used the ISODATA classifier to classify various layer combinations that included the NDVI image. All of the classification outputs resulted in overall accuracies greater than 85%. The largest source of error in these classifications remained in the shadowed areas. Class confusion occurred between shaded areas in trees and sunlit areas in the subalpine (which had similar NDVI values). More trees were misclassified as non-trees due to lingering unresolved issues with shadow, because NDVI was not as effective in the areas of deep shadow.



Figure 9. Example of shadows below north-facing slopes, NAIP imagery.

Figure 10. NDVI allows cover type to be discerned in deep shadow.

The object-oriented classification result that used both the 4-bands of the NAIP imagery and the NDVI image, with a higher weight given to the NDVI image, produced a similar level of accuracy (84.7%) to the pixel-based approaches. Again, the use of NDVI proved to be invaluable in distinguishing cover types in shade. The use of the other four bands likely helped to achieve a higher level of accuracy, and the use of image segmentation prior to classification undoubtedly improved the results. For example, in Figure 11 below, object A consists of tall trees and object B consists of rock, both of which are in deep shadow. Mean NDVI for each of these objects is -0.14, so if mean NDVI is used alone to assign classes, these objects would be classified under the same cover type (i.e., non-tree because of its low mean NDVI). In this case, the maximum NDVI per object (using pixel values within the object) was used to separate trees from non-trees. The maximum pixel value for object A is 0.18 and the maximum pixel value for object B is 0.14, a small yet important distinction used to help separate the two classes more accurately.

Although the use of object features and threshold values, such as maximum pixel values, helped to improve the results, the object-oriented technique still resulted in higher than desired errors of omission (27.8%) and commission (26.0%) for the non-tree class. This was due to our inability to identify object features and threshold values that would accurately separate some sparsely vegetated objects from other objects consisting of trees when they were both in deep shadow.



Figure 11. Mean NDVI values are identical for object A and object B, but maximum pixel values differ, allowing trees to be separated from rock.

7.1. USING TREE HEIGHTS AS ANCILLARY DATA (DATA FUSION)

At treeline, where tree migration is a key monitoring objective, the use of LiDAR data to detect trees is a valuable tool. LiDAR has been used to detect trees taller than 1 m with an accuracy of 91% (Næsset & Nelson, 2007). Although the use of NDVI has proven to be quite effective in determining land cover types in shadow, there were still areas in which, for example, mean, maximum, or standard deviation of NDVI values were similar for different objects and thus they could not be separated. The tree height dataset allowed for a more straightforward separation of objects with differing heights. The dataset was used to complement the spectral information contained in the NDVI image, thereby improving both the pixel-based and one of the object-based classification results. Although the object-based method that used only the NAIP imagery and the NDVI had 84.7% accuracy, when the tree height dataset was added, the accuracy jumped to 92.9%, the highest overall accuracy of all the outputs. The object-oriented classification that included the NAIP imagery, NDVI, and tree height dataset effectively addressed some of the issues encountered with separating trees from non-trees in the previous classification attempts.

The high omission errors (19.4% for NAIP, NDVI, and tree heights and 57.02% for NDVI and tree heights) for the non-tree class can be attributed to the remaining errors in the tree height dataset that could not be eliminated, which includes objects that were called trees when they should have been non-trees because their tree heights were erroneous. The errors in the tree height dataset were more prevalent in the NDVI and tree height combination because no other ancillary data was used to further reduce the errors. In the NAIP, NDVI, and tree height combination, slope was used as ancillary data to further remove tree height errors that occurred on steep slopes. The high omission errors for the non-tree class illustrates that the dataset, because of the errors, could not be used alone. However, if it weren't for the errors in the dataset, tree heights could be used very efficiently on their own to identify trees and delineate the treeline ecotone. Unfortunately, in mountainous areas that have very steep ridgelines the errors will likely be prevalent, thus requiring the use of multiple datasets to achieve acceptable accuracies. When tree height data was used in conjunction with spectral data and ancillary data, the accuracies above 90% help to justify the acquisition and use of LiDAR. Since LiDAR acquisition costs can be high, it may not be cost-effective to obtain it for large areas, but it could be used to sample the more remote areas (e.g., see Ørka et al., 2012). Combining high resolution samples with lower resolution full coverage data can help to

keep costs down by reducing the amount of high resolution data needed while allowing mapping and monitoring of large areas.

7.2. PIXEL-BASED OR OBJECT-BASED CLASSIFICATION

All of the classifications produced results with overall accuracies over 80%, with the objectbased approach producing the highest overall percent accuracy when ancillary data was used to correct for tree height errors. However, all of the pixel-based approaches produced results with accuracies over 85%, which were higher than three of the object-based results. That said, image segmentation results can be more visually appealing and realistic, not requiring the filtering to remove salt and pepper effects that pixel-based methods possess (Blaschke et al., 2000). The objectbased results show more contiguous groupings of trees, which is more realistic and typical of the object-based method. The pixel-based approach is weakest in user's accuracies of non-trees, meaning that a low percentage of pixels called non-trees are actually non-trees, and that many trees are erroneously classified as non-trees. The object-based approach is weakest in producer's accuracies of non-trees, meaning that a low percentage of non-tree pixels are actually classified as non-trees.

Both of the classification approaches involved some degree of human decision-making, which introduced subjectivity into the results. The unsupervised pixel-based approach required the analyst to assign spectral clusters to classes. This decision was completely subjective; it was based on visual comparisons of which class presented a better fit for each cluster. The object-based approach required the analyst to select which object features and corresponding threshold values were to be used to assign classes. This was also completely subjective; the Feature View window was used to test algorithms and change their parameters, and to visualize different threshold values on the screen. The value in this method is that parameters can be adjusted and tested, allowing for fine-tuning of algorithms to attain the highest degree of accuracy; however, the fine-tuning used in the processing of one dataset may not be an appropriate application for processing another dataset. Therefore, the object-based method is less replicable than the pixel-based method.

Although the object-based approach produced the highest overall accuracy (92.9%), the pixel-based approach produces a more consistent, high (>85%) accuracy. These results are all extremely close, and without further statistical testing, such as the computation of confidence intervals, it is difficult to determine if one method is significantly better than another simply based on overall accuracy. However, because the pixel-based approach was more straightforward and more easily repeatable, we conclude that it is the better option for most analysts.

7.3. APPLICATION FOR TREELINE MAPPING AND MONITORING

Although a substantial body of research exists on treeline ecology and change (Holtmeier F.-K. , 2009), considerably less research has been conducted on the spatially explicit mapping of treeline ecotones. For ecologists whose focus may be on explaining the factors that control treeline, or on predicting if or how treelines might respond to climate change, for example, reliable maps of treeline can help to provide context to their work. Moreover, reliable maps are essential for accurately quantifying treeline change. The spatially explicit delineation of treeline is therefore critical for many types of treeline-related research (Diaz-Varela et al., 2010; Ørka et al., 2012; Holtmeier & Broll, 2007).

This research demonstrates that treeline can be successfully mapped in North Cascades National Park using automated techniques. A key finding of the project was that manual interpretations and corrections to adjust for inaccuracies caused by shadows were not necessary if a near-infrared band exists to produce a vegetation index. Also, tree height data is a valuable addition to classification routines, regardless of which method (pixel-based or object-based) is used. Furthermore, an object-based approach produces a more realistic-looking final map. Results underscore the value that high resolution (< 1 x 1 m) data has in mapping treeline areas, where the detection of single trees is an important consideration (Resler et al., 2004). Also demonstrated is the ability of remote sensing data to systematically and objectively map treeline across large areas and in rugged, mountainous areas where access is limited. As interest grows in measuring treelines, the ability to do so accurately and objectively will be of primary concern, and of great use to future treeline change studies.

8. CONCLUSION

This study successfully mapped treeline in a major drainage of North Cascades National Park using automated techniques. The research resulted in three primary findings. First, the use of a vegetation index, such as NDVI, to adjust for illumination conditions proved to be an invaluable tool in overcoming the issue of shadows in steep, mountainous terrain. These results highlight the importance of the availability of 4-band imagery (containing a near-infrared band) in land cover studies that take place in mountainous areas.

Second, LiDAR-derived tree heights contributed to higher overall accuracies. The spectral information contained in the NAIP imagery and the NDVI image, combined with the tree height data brought a new dimension to the analysis that could not have been derived from other sources. The unfortunate issue of errors in the dataset is likely to be common in other steep mountainous and/or snowy areas. Consequently, tree height cannot be used alone in such classifications. It is still, however, a substantial contribution to the accuracy of this classification, and proves that in treeline areas, where it is difficult to split spectral reflectances of trees, shrubs, and areas in shadow, tree height data can yield enhanced contrast between classes.

Finally, although object-based classification improved the accuracy of the identification of trees with ancillary data, overall accuracies of both approaches are nearly identical when four-band data is used in conjunction with an NDVI image. Though the use of object-based approaches to process these datasets is likely to grow as the software becomes more available and affordable, we recommend the pixel-based approach because it is more straightforward and more easily repeatable compared to the object-based approach.

With the growing availability of high resolution datasets, such NAIP and LiDAR, researchers are presented with the challenge of how to derive the most meaningful and accurate results from image analysis. Since ecotones are often the first areas to experience visible change, accurate mapping of these areas is vital. It is likely that treeline areas will continue to be the focus of monitoring efforts related to climate change, necessitating the automation of land cover detection over large areas and making manual interpretations impractical. In mountainous areas where reflectance values can be uneven due to trees and topography, the use of NDVI as well as tree height data to help determine land cover in areas of shadow is a promising approach. The techniques presented in this study provide a reliable means to map and aid in the monitoring of the alpine treeline ecotone. Results will be important to the National Park Service as it develops adaptation strategies for addressing climate change and by the greater research community as a tool to assist with the monitoring of landscape change.

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APPENDIX A. PHOTOGRAPHS OF STUDY AREA



Figure 12. Photograph looking northwest toward Mount Triumph. Access is extremely limited in this area. Photograph by Cathi Winings, October 2011.



Figure 13. Photograph of subalpine area below Trappers Peak. Tree patch includes subalpine fir (*Abies lasiocarpa*) and mountain hemlock (*Tsuga mertensiana*). Photograph by Cathi Winings, October 2011.

APPENDIX B. ECOGNITION RULE SETS

This appendix contains the rule sets used in eCognition for each of the object-based

classifications used in this study. A rule set is an arrangement of processes that are performed in a

defined order. Each process executes an algorithm on an image object domain (Trimble, 2012).

Figure 14 is the rule set developed for the first object-based classification, which used the NDVI as

the input layer, or band.



Figure 14. Rule set for NDVI input band.

Figure 15 is the rule set developed for the second object-based classification, which used

the 4-band NAIP imagery and NDVI for input bands.



Figure 15. Rule set for NAIP and NDVI input bands.

Figure 16 is the rule set developed for the third object-based classification, which used the

NDVI and tree height dataset for input bands.



Figure 16. Rule set for NDVI and tree height input bands.

Figure 17 is the rule set developed for the fourth object-based classification, which used the

4-band NAIP imagery, NDVI, and tree height dataset for input bands.



Figure 17. Rule set for NAIP, NDVI, and tree height dataset bands.

APPENDIX C. FULL SCENE RESULTS



Figure 18. NAIP image, displayed in true color for comparison to classification results.



Figure 19. Pixel-based classification results of NDVI input band.



Figure 20. Pixel-based classification results of NAIP and NDVI input bands.



Figure 21. Pixel-based classification results of NDVI and tree height input bands.



Figure 22. Pixel-based classification results of NAIP, NDVI, and tree height input bands.



Figure 23. Object-based classification results of NDVI input band.



Figure 24. Object-based classification results of NAIP and NDVI input bands.



Figure 25. Object-based classification results of NDVI and tree height bands.



Figure 26. Object-based NAIP, NDVI, & tree height dataset classification results.