Subalpine Tree Species Classification Using Remote Sensing Methods and Techniques

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ABSTRACT

Whitebark pine (*Pinus albicaulis*) can be found throughout western Canada and the United States. The species is listed as endangered federally in Canada due to comprehensive impacts such as white pine blister rust, pine beetle, fire suppression and climate change. Understanding the species' distribution and occurrence will aid in establishing localized recovery strategies to help conserve this keystone species. Remote sensing has streamlined traditional field-based data collection methods, reducing the time and resources needed to map detailed forest information over large spatial extents. The objective of this research was to explore the use of multispectral satellite imagery to distinguish between whitebark pine and two other main subalpine tree species within the Darkwoods Conservation Area in southeast British Columbia, Canada. An Object-Based Image Analysis (OBIA) and the maximum likelihood classification algorithm were used to classify WorldView-2 imagery. The mean spectral signatures of the three tree species had similar values across the eight bands available in the imagery, but Engelmann spruce has slightly lower reflectance values in the Red Edge, NIR 1 & 2 bands. The overall producer's accuracy was 68.8% and the Kappa coefficient was 64.3%. Whitebark pine's individual classification accuracy was low at 21%, compared to that of spruce (68%) and fir (63%). The overall classification accuracies were relatively low compared to other similar studies. This could have been due to several factors including a smaller sample size of geo-referenced trees, the quality of reference data points, the classification algorithm used, or that the available spectral signatures for species were too similar.

Keywords: whitebark pine, WorldView-2, satellite, Object-Based Image Analysis, species identification

INTRODUCTION

Whitebark Pine

Whitebark pine (*Pinus albicaulis*) is a species integral to high-elevation ecosystems in western North America. It is considered a keystone species for the many ecological benefits it provides including snowpack retention, flood mitigation, protection for other species, and its high-quality food source that is relied upon by many wildlife species including the Clark's Nutcracker (*Nucifraga columbiana*) (Keane et al. 2012). In Canada, whitebark pine is federally listed under the Species at Risk Act and continues to rapidly decline due to the comprehensive impacts of white pine blister rust, mountain pine beetle, fire suppression and climate change (Achuff and Wilson 2010). Extensive recovery strategies have been implemented in efforts to mitigate those impacts (Keane et al. 2017; Shepherd et al. 2018). However, being aware of the distribution of whitebark pine across the landscape is the key to understanding and mitigating the impacts this species faces (Landenburger et al. 2008).

The extent and distribution of whitebark pine occurrence on the subalpine landscape is still uncertain due to inadequate mapping and remote occurrences being undiscovered due to complex terrain (Environment and Climate Change Canada 2017). Forest inventories are imperative in understanding ecosystem diversity, forest health and species extent and provides resource managers with the information needed to make effective localized recovery strategies (Wilson and Stuart-Smith 2002; Keane et al. 2012; Environment and Climate Change Canada 2017). Field-based assessments have generally been used to conduct forest inventories but can be time consuming and costly in acquiring up-to-date data over vast areas. The integration of remote sensing in the fields of ecology, biodiversity and conservation has streamlined data collection reducing the time and resources needed for traditional field-assessments (Wang et al. 2010; Fricker et al. 2019; Nezami et al. 2020), as well as provides detailed information over large spatial extents (Immitzer et al. 2012; Maschler et al. 2018).

Remote Sensing

Remote sensing methods and techniques are integral tools utilized by forest and land managers (Fricker et al. 2019). Applications such as tree species mapping and classification have become a popular research topics as they can provide detailed ecosystem information that can be used for many different purposes. These include the monitoring of invasive species (Maschler et al. 2018), assessing biodiversity (Fassnacht et al. 2016), building wildlife habitat models (Immitzer et al. 2012), and observing fire risk as well as forest disturbance (Fricker et al. 2019).

For classifying individual tree species within complex forest environments, high spatial and spectral resolution data are preferred (Immitzer et al. 2012). Unmanned Aerial Vehicles (UAV) can host a wide variety of sensors, including high resolution Red Green and Blue (RGB), hyperspectral, multispectral or Light Detection and Ranging (LiDAR), which makes this method of real-time data acquisition flexible and task specific. Guimarães et al. (2020) reviews recent UAV applications in forestry and includes various studies related to tree species mapping and classification. Despite the many benefits of using UAVs, smaller organizations may not have access to the desired sensors or lack the resources and manpower for operating those systems.

Spaceborne satellite imagery has become more accessible with time, and can be a viable alternative to UAVs, especially in areas inaccessible to airborne platforms (Fricker et al. 2019). Traditionally, spaceborne satellite imagery was costly and could host either high spatial or high spectral sensors. For example, high spatial resolution satellite sensors, such as Quickbird (0.7m), have a limited spectral resolution of only four bands (R, G, B and NIR), while sensors such as Landsat 7 Enhanced Thematic Mapper + (ETM+) and Sentinel-2 have higher spectral resolutions but can only maintain low to medium spatial resolutions (Immitzer et al. 2012). Landenburger (2008) mapped the regional distribution of whitebark pine in the Greater Yellowstone Ecosystem using medium spatial resolution satellite imagery (Landsat Enhanced Thematic Mapper Plus). The study had highly accurate results (74.5-94.4%), which was generally unlikely when using lower spatial resolution Landsat imagery for species level classifications. Additional factors such as using remote sensing specific classification algorithms, focusing on a single tree species, the use of considerable reference data and the availability of high quality aerial imagery were said to contribute to the overall results of this study (Landenburger et al. 2008). A study conducted by Immitzer et al. (2016), reported satisfactory results when classifying two heterogenous forest stands in Germany using Sentinel-2 imagery. That study suggested that the use of multi-temporal Sentinel-2 data may further increase overall accuracies for future studies. However, it was noted that the spatial resolution of Sentinel-2 data may not be adequate for classifying heterogenous forests to an individual tree level but could potentially be more successful at broader scales. Immitzer et al. (2016) compared the results of their study to others focused on tree species mapping and classification and found that those were lower than those using a combination of high spatial and spectral data such as WorldView-2 satellite imagery.

The WorldView-2 satellite-borne sensor was launched in 2009 and hosts a very high spatial resolution panchromatic band (0.5m) and eight high spatial resolution multispectral bands (2.0m) (Satellite Imaging Corp. 2021). The multispectral data includes four basic bands (Red, Green, Blue and Near Infrared) and four distinct bands (Coastal, Yellow, Red Edge and Near Infrared 2) said to be ideal for observing vegetation characteristics (Immitzer et al. 2012). Using WorldView-2 satellite data, Immitzer et al. (2012) was successful in classifying 10 coniferous and deciduous tree species within a mid-European submontane forest with an overall accuracy of 82%. The methodology used outperformed a number of studies that were carried out utilizing remote sensing data from various sensors with different spatial and spectral resolutions conducted from 2002 to 2012, see Immitzer et al. (2012) for a detailed list of studies.

When classifying high resolution data, such as WorldView-2 satellite imagery, an Object-Based Image Analysis (OBIA) is known to outperform a pixel-based approach (Immitzer et al. 2012). An OBIA groups individual pixels into homogenous clusters that have similar spatial and spectral properties, which can be used to consider textural, geometric and neighboring characteristics during classification (Wang et al. 2010). Immitzer et al. (2012) concluded that the object-based approach outperformed the pixel-based method by approximately 10% using WorldView-2 satellite imagery.

Parametric (Maximum Likelihood) and non-parametric (Random Forest & Support Vector Machines) classification algorithms have been widely used for tree species classification (Maschler et al. 2018). Studies have compared different classification algorithms, however, the results depend heavily on the area being studied, the remote sensing and ancillary data used, as well as the experience and abilities of the analyst (Xie et al. 2019). Although non-parametric methods have become a more popular option for tree species classification within the past decade (Fassnacht et al. 2016), traditional parametric methods, such as the Maximum Likelihood, provide a simple and rapid way of classifying an image (Xie et al. 2019).

Objectives

Only a limited number of studies have explored the use of remote sensing for mapping whitebark pine (Landenburger et al. 2008; McDermid and Smith 2008). Additionally, few studies apply high spatial resolution and multispectral data to distinguish whitebark pine from surrounding tree species. Therefore, the objective of this research was to explore the potential of distinguishing whitebark pine from Engelmann spruce (*Picea engellmanii*) and subalpine fir (*Abies lasiocarpa*) using an OBIA approach. To achieve this objective, we completed the following:

1. Collected high-resolution drone imagery to validate reference data and manually delineate individual tree crowns,
2. Identified potential spectral differences among whitebark pine, Engelmann spruce and subalpine fir using spectral information derived from WorldView-2 imagery,
3. Conducted an OBIA and classify the WorldView-2 imagery, and;
4. Provided insight on the limitations and considerations based on current literature and methods utilized as well as recommendations for further research.

METHODS

Study Site

The study was conducted in the Darkwoods Conservation Area (Darkwoods) which spans 63,000 hectares of land located between Nelson and Creston (NCC: Darkwoods) (figure 1). Darkwoods is privately owned and operated by the Nature Conservancy of Canada and represents a large

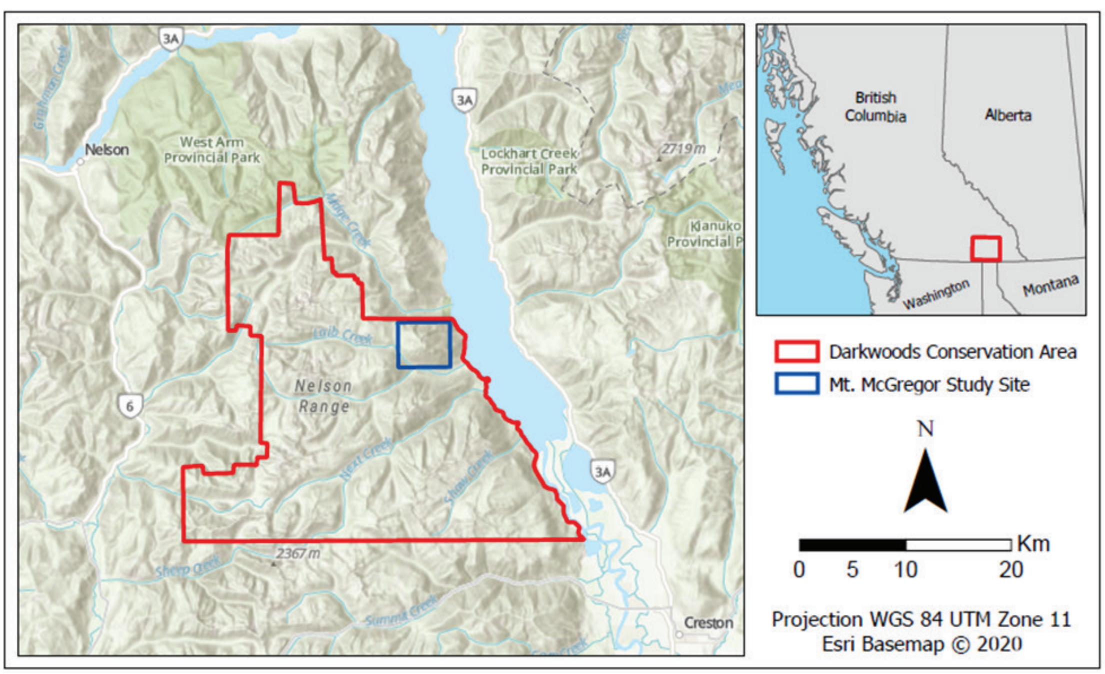

Figure 1. Darkwoods Conservation Area and McGregor site boundary, British Columbia.

tract of land used for the purpose of maintaining ecological and cultural integrity. The area consists of complex and remote terrain that encompasses valleys, mountains, lakes, creeks and diverse forests that provide important habitat to many different plant and animal species including a number of species listed as threatened or endangered by the Species At Risk Act (SARA) (NCC: Darkwoods). Field data was collected at the peak of Mount McGregor, which was identified to have whitebark pine occurrence (figure 2).

The study site lies within the Engelmann Spruce - Subalpine Fir Wet Mild Woodland (ESSFwmw) Biogeoclimatic (BEC) zone which is characterized by cold and wet summers and cold winters with a heavy persistent snowpack. This BEC zone is found in the uppermost forested areas with the elevation ranging from 1920-2150 m on cool aspects and 2000-2200 m on warm aspects (MacKillop and Ehman 2016). The dominant and co-dominant tree species in the ESSFwmw are subalpine fir and Engelmann spruce, respectively. Whitebark pine are common and generally found on drier sites. Alpine larch are also found on drier sites but are known to occupy submesic and mesic sites as well. (MacKillop and Ehman 2016).

Data

Acquisition & preprocessing of high-resolution drone imagery

The high-resolution drone imagery was recorded on August 13, 2020, using a DJI Mavic 2 Pro (figure 3). Flight conditions were clear with cloud cover and winds increasing throughout the day. The DJI Mavic 2 Pro is equipped with an RGB camera with a 1-inch CMOS sensor. The lens focal length is 28mm and has a 77-degree field of view and variable f/2.8-f/11 aperture. The imagery was captured at 20MP resolution (5472 x 3648 pixels). Ground control points were collected using a Trimble Geo7X receiver and were used to process the drone images in Agisoft Metashape and used to build a dense point cloud,

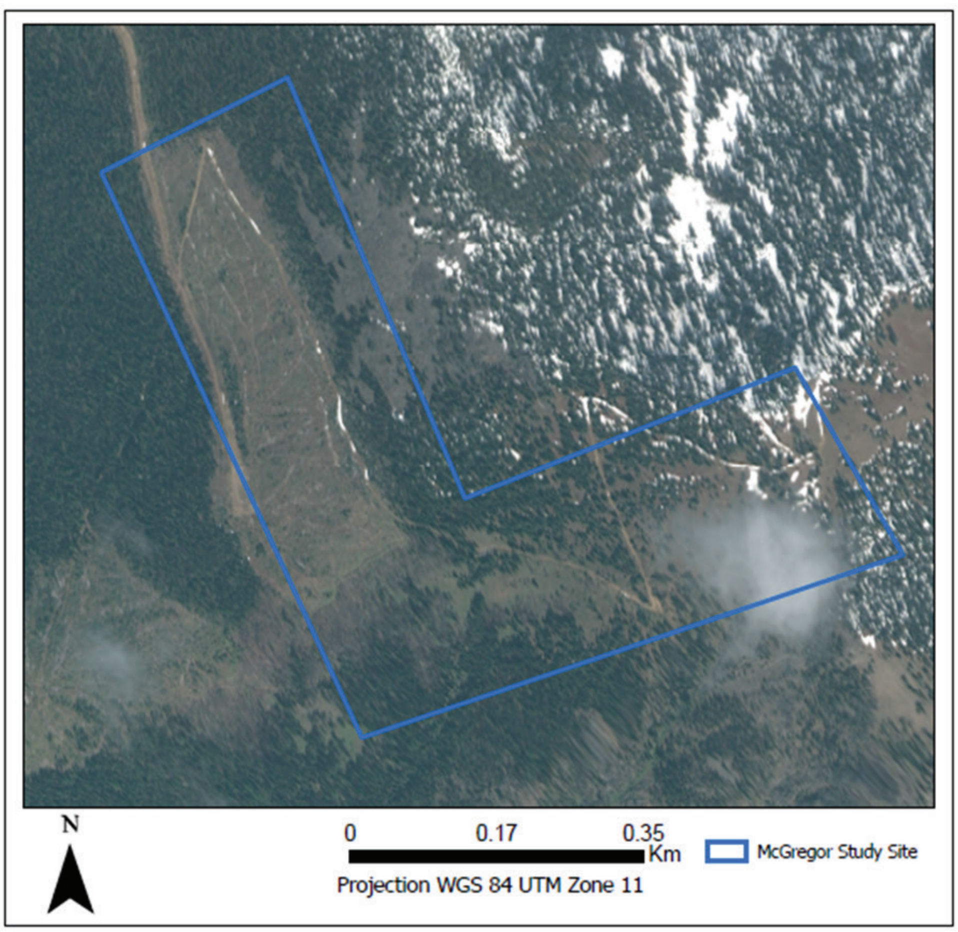

Figure 2. McGregor site located within the Darkwoods Conservation Area, British Columbia.

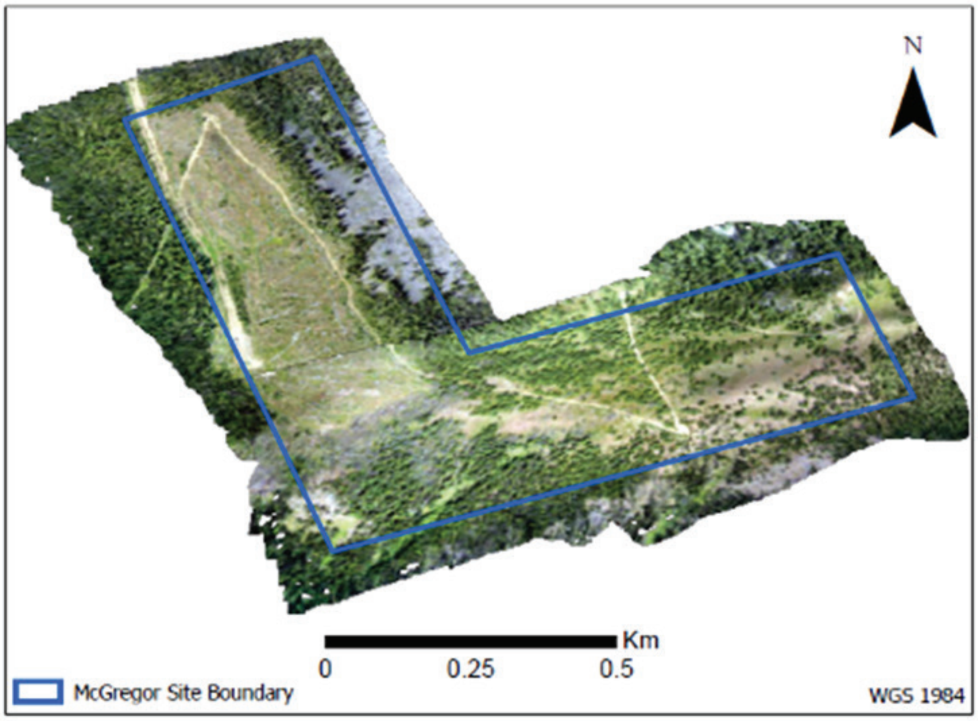

Figure 3. Orthorectified drone imagery of McGregor site, British Columbia.

Digital Elevation Model (DEM) and orthomosaic. To reduce processing time, two separate ortho images were created.

Reference data

Field data was collected over the span of 2 years with acquisition dates as follows: July 3, 2019; July 14, 2020; August 13, 2020 and September 5, 2020. Data collection consisted of geotagging trees with a high-accuracy GNSS Trimble Geo7X receiver. Tree species of interest included subalpine fir, whitebark pine and Engelmann spruce and individual trees were selected based on the intent of visually identifying the selected trees within the imagery in order to delineate the crowns. Therefore, the focus was on collecting large, isolated trees to ensure they could be clearly identified when viewing the imagery. In addition to recording the position of each tree, the species, vigor, diameter at breast heigh (DBH) and canopy area were collected. The Trimble points were post processed using differential GPS (Pathfinder Office) and exported to a shapefile format.

The WorldView-2 imagery was used to visually assign the field data to the respective trees within the imagery. The high-resolution drone imagery was also used as a reference when it proved difficult to determine the correct tree to classify within the WorldView-2 imagery. In addition, five more classes were created by visual interpretation (bare ground, cloud, shadow and vegetation). This was done referencing the WorldView-2 imagery in order to represent the other features within the image and identify any spectral differences between them and the tree classes.

Worldview-2 satellite-borne imagery

WorldView-2 satellite imagery was captured on June 2, 2019, covering the entire study area, and with minimal cloud cover (2.3%) (figure 4). The ground resolution at nadir was 30 cm and 50 cm for the panchromatic bands (0.46-0.80 µm) and 200 cm for the multispectral bands (Immitzer et al. 2012). The multispectral imagery had eight bands that includes Blue (0.45-0.51 µm), Green (0.51-0.58 µm), Red (0.63-0.69 µm), Near Infrared 1 (0.77-0.90 µm), Coastal (0.40-0.45 µm), Yellow (0.59-0.63 µm), Red Edge (0.71-0.75 µm) and Near Infrared 2 (0.86-1.04 µm) (Satellite Imagery Corp. 2021).

Radiometric and Atmospheric Corrections were applied to the multispectral imagery in ENVI 5.6 (64-bit). The Radiometric Calibration module converted the digital numbers to 'at-sensor' radiance (Immitzer, 2012) and the FLAASH module resulted in a top-of-canopy reflectance (FLAASH Settings: Atmospheric Model: Sub-Arctic Summer, Aerosol Model: Rural, Initial Visibility: 60 km), to produce meaningful spectral profiles. The multispectral im-

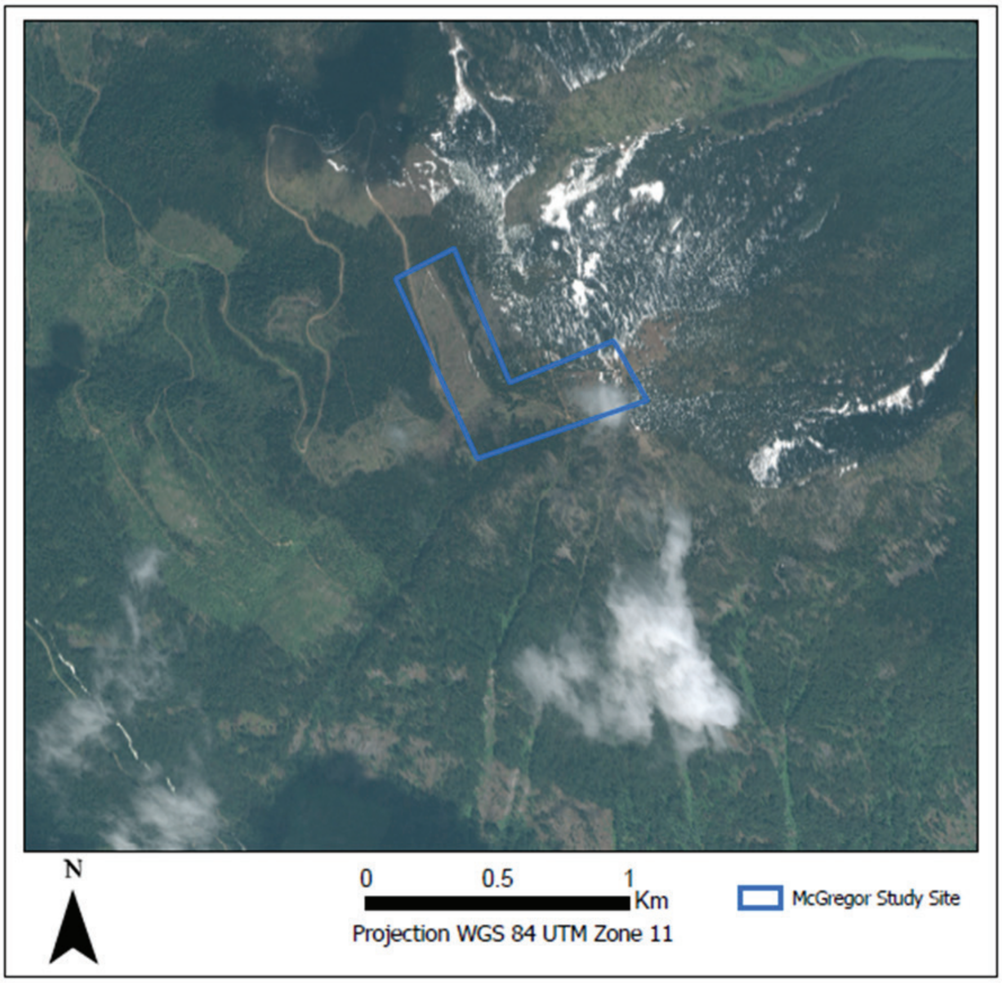

Figure 4. WorldView-2 Satellite Imagery purchased for the McGregor site.

agery was further pansharpened using the 30 cm panchromatic band and orthorectified using the Gram-Schmidt tool as well as a 25 m resolution digital elevation model (DEM)

Classification & validation

The reference data was randomly divided into two datasets, training and validation. The training data was used to conduct an example-based classification, in ENVI, that used the maximum likelihood algorithm. This algorithm assumes that the statistics for each of the classes are normally distributed and assigns the pixels with the highest probability of being within that class (Harris Geospatial Solutions, Inc. 2020). The maximum likelihood algorithm is generally biased to small sample sizes but was ultimately selected due to its ease of use and availability within the ENVI software (Fassnacht et al. 2016).

The validation dataset was used to generate fifty random points within each class. The random points were additionally assigned the classification results and used to conduct the confusion matrix to assess the accuracy of the classification.

RESULTS

Spectral Variability Among Classes

The mean spectral signatures were calculated by averaging the pixel values for all polygons within each class and are found below in figure 5. The reflectance values for snow, cloud and vegetation differ greatly from the three tree species making it easy to distinguish them from the tree species of interest. Bare shows similarities in the Blue and Red Edge bands but differ slightly in the Yellow and Red. Shadow has similarities in the Blue and Red bands but differs in the Red Edge and NIR 1 & 2 bands. Figure 6 summarizes the mean spectral signatures of the three tree species of interest. They have similar values across the bands but Engelmann spruce

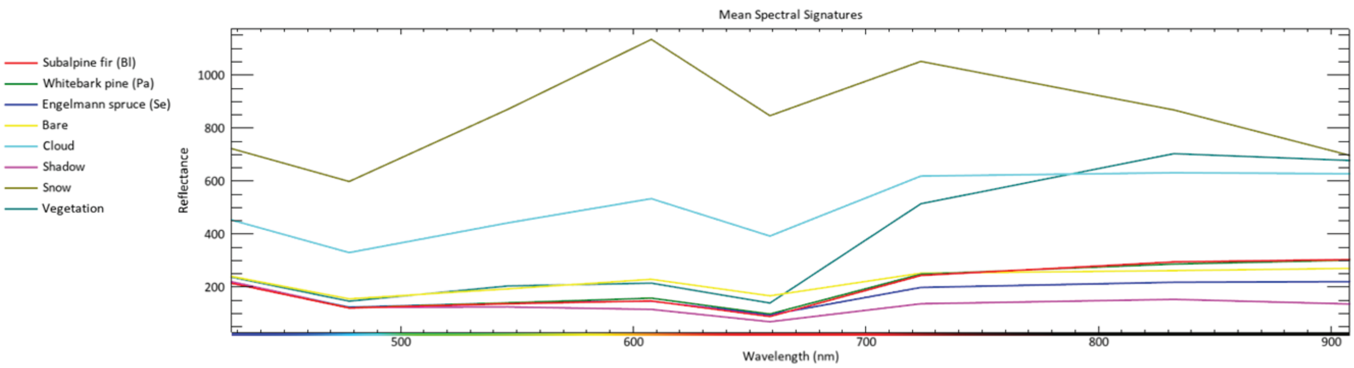

Figure 5. Mean spectral signatures of all classes derived from the 8 WorldView-2 bands using the delineated polygons.

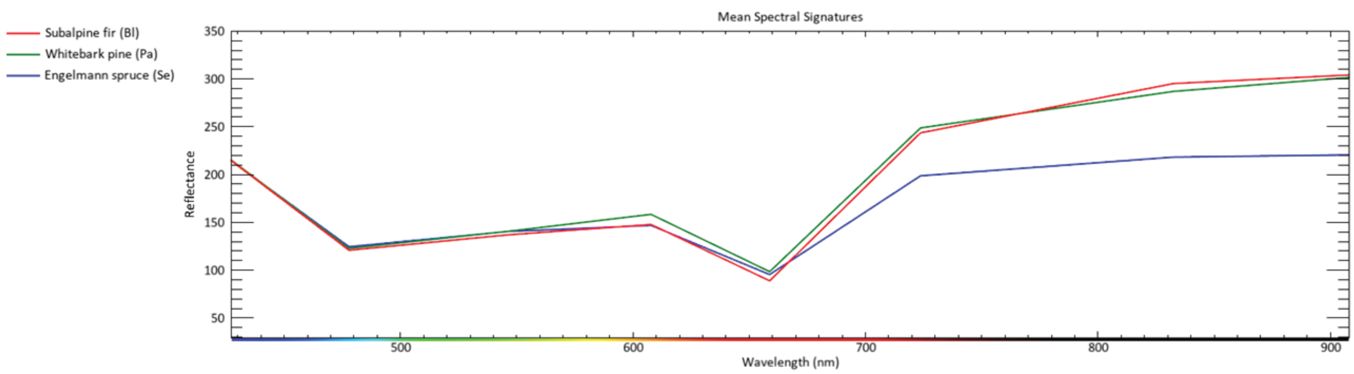

Figure 6. Mean spectral signatures of the 3 tree species of interest derived from the 8 WorldView-2 bands using the delineated polygons.

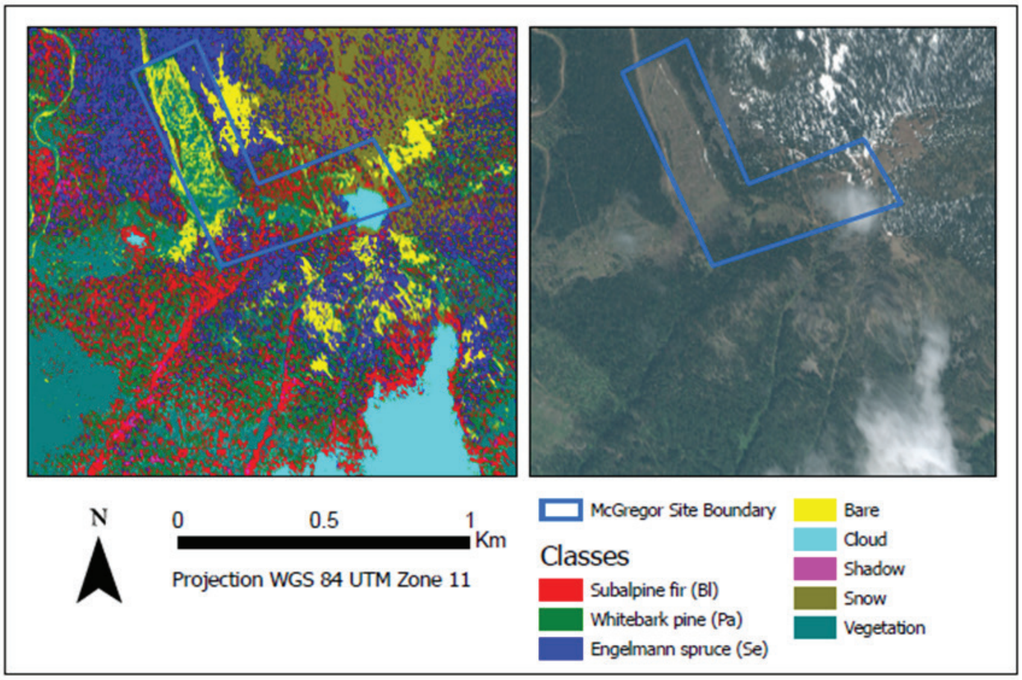

Figure 7. Classified WorldView-2 imagery.

has slightly lower reflectance values in the Red Edge, NIR 1 & 2 bands.

Validation of Classification

The confusion matrix in Table 1 outlines the accuracy results of classifying the WorldView-2 Imagery (figure 7) using all eight bands. The overall accuracy was 68.75% and the Kappa coefficient was 64.29%. The shadow and whitebark pine classes had the highest and lowest producer's and user's accuracies, respectively. Of the tree species, Engelmann spruce had the highest producer's and user's accuracies.

Table 1. Confusion matrix summarizing the classification results of the WorldView-2 Imagery using the Maximum Likelihood algorithm.

Class	Reference Data: Subalpine fir (Bl)	Whitebark pine (Pa)	Engelmann spruce (Se)	Bare	Cloud	Shadow	Snow	Vegetation	Total	User's Accuracy
Subalpine fir (Bl)	17	10	0	0	0	0	0	0	27	0.62963
Whitebark pine (Pa)	12	7	2	2	0	0	5	4	32	0.21875
Engelmann spruce (Se)	4	9	43	1	2	0	4	0	63	0.68254
Bare	5	7	0	37	0	0	12	1	62	0.596774
Cloud	3	0	0	0	48	0	1	0	52	0.923077
Shadow	0	0	0	0	0	50	0	0	50	1
Snow	3	3	5	3	0	0	28	0	42	0.666667
Vegetation	6	14	0	7	0	0	0	45	72	0.625
Total	50	50	50	50	50	50	50	50	400	
Prouducer's Acc.	0.34	0.14	0.86	0.74	0.96	1	0.56	0.9		0.6875
Kappa	0.642857									

DISCUSSION & RECOMMENDATIONS

Small Sample Sizes

Due to the scope of the project, there were limited field days in which data could be collected, resulting in small data sets for each of the tree species of interest. Studies have found that when conducting tree species classifications, the classes with the smallest sample sizes generally result in the lowest accuracies while larger sample sizes and extensive data sets are said to increase the success of the overall classification results for those specific classes (Landenburger et al. 2008; Immitzer et al. 2012; Grabska et al. 2019).

Data was collected for an additional site within the Darkwoods area, however, due to time constraints and difficulty confidently identifying the tree crowns with the satellite imagery, the data was not included in this study. Although the additional site data would not be significant in size, it would increase the sample size slightly and potentially result in a higher classification accuracy or encourage less spectral overlap between the whitebark pine and subalpine fir classes.

Quality of Reference Data

The study was conducted at a site with complex terrain and a highly diverse forest network which could have made it difficult to collect and validate the reference data accurately. There was an element of subjectivity when matching the geotagged points to the tree crowns as it was done based on visual interpretation of the WV-2 imagery. Isolated trees were easiest to reference, however, in heterogenous stands, it was difficult to confidently assign the points to its respective tree.

Initially, the high-resolution drone imagery was used to delineate the tree crowns. However, there were slight visual differences between the drone imagery and WV-2 imagery that caused positional inaccuracies when overlaying the polygons onto the WV-2 imagery. Therefore, the WV-2 imagery was used to visually delineate the polygons and the drone imagery was used to reference tree crowns that were difficult to distinguish. The WV-2 imagery had a lower spatial resolution than the drone imagery making it harder to confidently delineate the tree crowns and could have resulted in spectral overlap between classes reducing the overall classification accuracies for those classes (Immitzer et al. 2012).

In order to reduce the subjectivity of the manual delineation process, it is recommended that this be completed by a number of individuals, compared, and then include only the confidently identified data. This method, however, would be very time consuming and may still have a level of subjectivity imposed by the analysts. Automation tools are also available, such as the mean shift algorithm used in Maschler et al. (2018), that could remove some level of subjectivity within the segmentation step. Overall, object extraction is an essential step in achieving highly accurate results when classifying tree species, however, both manual and automated approaches are time consuming and difficult to implement properly (Michałowska and Rapiński 2021).

LiDAR

Recent studies have suggested that LiDAR has demonstrated great potential for mapping out forest environments (Michałowska and Rapiński 2021). Specifically, the ability of LiDAR technology to extract single tree parameters such as location, height, crown size, DBH and biomass estimates, by way of the three-dimensional point clouds created (Michałowska and Rapiński 2021). LiDAR derived data can be divided into three components: geometric, radiometric and full-waveform metrics that provide their own advantages for remote sensing research that are outlined in the review conducted by Michałowska and Rapiński (2021). Geometric components of generated LiDAR point clouds, for example, can provide information on tree foliage and branching structures (Michałowska and Rapiński 2021), which could be particularly useful for distinguishing between whitebark pine and subalpine fir as they are structured very differently. LiDAR in combination with other remote sensing data, including multispectral or hyperspectral imagery, has become widely used in remote sensing research today and has been found to increase the overall accuracies of tree species classification studies (Zhao et al. 2020).

Classification Algorithm

The maximum likelihood algorithm was used due to the scope of the project as well as it being easily available within ENVI (Fassnacht et al. 2016). However, this algorithm is said to be more suited to larger sample sizes and data this is normally distributed which could have contributed to the low classification results of the study (Fassnacht et al. 2016).

Traditionally, parametric classification algorithms such as supervised maximum likelihood, K-means or ISODATA have been widely used to distinguish between tree species (Fassnacht et al. 2016). However, non-parametric methods have become a great alternative as they do not require input data to be normally distributed and may be less sensitive to input variables (Fassnacht et al. 2016). Random Forest (RF) is a non-parametric method that has become popular within the world of remote sensing and has been used to successfully assess species diversity (Mallinis et al. 2020), conduct forest stand mapping (Grabska et al. 2019) and identify spectral characteristics for individual tree species classification (Immitzer et al. 2012). Immitzer et al. (2012) compared the use of Random Forest (non-parametric) and Linear Discriminant Analysis (LDA) (parametric) classifiers to distinguish between tree species in a diverse mid-European forest in Austria. The results concluded that the RF performed relatively the same as the established LDA classifier, however, RF was found to be more flexible when dealing with small sample sizes (Immitzer et al. 2012).

Should this study be continued, it is recommended that the Random Forest algorithm is used as it has been used in many tree species classification studies with high success rates (Fassnacht et al. 2016) and is ideal for dealing with small sample sizes (Immitzer et al. 2012). Despite the importance of selecting the appropriate classification algorithm for each study, collecting quality reference data may be a more important aspect to focus on to increase the overall classification results (Maschler et al. 2018).

CONCLUSION

This small-scale study evaluated the potential use of WorldView-2 imagery to distinguish whitebark pine from two separate subalpine species, subalpine fir and Engelmann spruce, at a highly diverse forest site in British Columbia. Multispectral WorldView-2 imagery was used to determine spectral differences among the tree species of interest as well as to classify the study site using the maximum likelihood algorithm. The overall classification accuracies were relatively low compared to other studies conducting tree species classification (Immitzer et al. 2012), which could have been due to a number of factors including small sample sizes, the quality of reference data, classification algorithm used, and perhaps the inherent closeness of the species spectral signatures. Should this study be continued, it is recommended to collect additional reference data to build a more extensive dataset, explore the combination of LiDAR and multispectral imagery as well as select a classification algorithm such as RF that is more flexible when working with small data sets (Immitzer et al. 2012). Although, the WorldView-2 Satellite sensor is still relatively new, there have been many recent studies that focus on tree species classification within diverse forests and complex terrain (Immitzer et al. 2012; Fassnacht et al. 2016; Immitzer et al. 2016; Fricker et al. 2019; Xie et al. 2019; Nezami et al. 2020; Michałowska and Rapiński 2021). As remote sensing technologies become more advanced and widely available, further studies should focus on distinguishing endangered species such as whitebark pine. This can streamline the process of identifying species distributions among the landscape so resource managers can implement effective large and small-scale recovery strategies to protect imperative species, such as whitebark pine, and help maintain the ecological integrity of the ecosystems they inhabit.

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