CLASSIFICATION OF RED PINE STANDS USING REMOTE SENSING TECHNIQUES

By

Hannah Rideout

Source: University of Minnesota (n.d.)

FACULTY OF NATURAL RESOURCES MANAGEMENT
LAKEHEAD UNIVERSITY
THUNDER BAY, ONTARIO

APRIL 2019

Classification of red pine Stands Using Remote Sensing Techniques

By

Hannah Rideout

An Undergraduate Thesis Submitted in
Partial Fulfillment of the Requirements for the
Degree of Honours Bachelor of Science in Forestry

Faculty of Natural Resources Management
Lakehead University
April 2019

Major Advisor

Second Reader

LIBRARY RIGHTS STATEMENT

Signature:__________________.
Date:_04/23/19_____________.

A CAUTION TO THE READER

This HBScF thesis has been through a semi-formal process of review and comment by at least two faculty members. It is made available for loan by the Faculty of Natural Resources Management for the purpose of advancing the practice and science of professional forestry.

The reader should be aware that opinions and conclusions expressed in this document are those of the student and do not necessarily reflect the opinions of the thesis supervisor, the faculty, or Lakehead University.

ABSTRACT

Red pine is a historically important species for forestry in the boreal forest. Its large diameter and straight and knot free form has made it ideal for many purposes, including construction. With the new sudden turn towards renewing the forests in their historical state, understanding the current management requirements of red pine in their limited distribution is becoming more and more necessary. The use of remote sensing techniques and applications enable it so that these scattered stands can be inventoried and mapped accurately for management purposes.

ACKNOWLEDGEMENTS

I would like to first thank both of my advisers / readers, Dr. Ulf Runesson and Mr. Alex Bilyk, for their help and guidance throughout the duration of this project. This thesis would not have been able to be thoroughly completed without their extensive knowledge of remote sensing. I would also like to thank Gerry Racey, retired from the MNRF, for providing me with custom maps of the 25th Side Road tree farm to use for image analysis.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1.0 INTRODUCTION

1.1 Introduction

Red pine (*pinus resinosa*) is a historically important species for forestry in Canada. It is native conifer species, with a range from Newfoundland to Manitoba It used to be one of the most abundance species throughout the country and was very valuable for construction due to its large size and straight bole. The red pine has distinct features that make it easily identifiable (Figure 1). The needles grow in groups of two, and are longer than the needles of other pines, and the form is rather bushy in the crown when viewed from a distance.

There has been a shift in recent years towards maintaining a historical forest composition, which would involve planting the species that would have been present before any form of management began in that area. For some areas, that would include the managing for both red and white pine (*pinus strobus)* again, and possibly trying to plant these species to bring back the former composition.

Figure 1: Red pine Form (Ontario, 2014)

Managing for red pine still needs more research, especially with the possibility of the range changing due to climate change. The current range may not be suitable in the future, and if trying to return this species to the landscape is a management goal, this species will require more in-depth analysis.

1.2 Objectives

The use of remote sensing software and tools will be helpful in finding new ways to manage for red pine in the future. There are many factors that are involved with managing any one species, especially for one that has decreased in population since first use. The species will be examined in depth, as well as how to manage a tree species using remote sensing software, and possible ways to help identify and map the species more accurately. It is also hopeful that this thesis can shed new light on red pine management in Canada. The use of spectral signatures and remote sensing techniques and software will effectively separate red pine stands from jack pine stands in their transition areas.

1.3 Literature Review

RED PINE MANAGEMENT

Red pine is a historically important species for Canada. Over-exploitation has left it limited in its range in Ontario. As a species, it is very remarkable in size and form, although it is fairly shade intolerant, and prefers drier sites. Management units are starting to incorporate management of this species into their plans, coming up with ways to increase the numbers. Different management techniques can result in different amounts of stand growth and yield for red pine, depending on what the result product is. Despite higher stand-level growth with dominant thinning than with thinning from below, the economic value of dominant thinned stands for some products, such as cabin logs, poles, and saw timber, may be lower than that of stands thinned from below because of reduced mean diameters (Bradford, 2009). One of the issues when trying to maintain this species on the landscape is the fact that there is high variability in crop years. Although it is possible to grow red pine in either even-aged or uneven-aged stands, an even-aged silvicultural system will give better results because red pine grows best in full sunlight. Red pine seed crops are too variable to depend on for natural regeneration, so seed must be collected during good seed years for direct seeding, growing container seedlings or growing bare root stock (Benzie, 1976).

Maintaining red pine on the landscape can be beneficial for more than the forest industry. Red pine can be helpful in maintaining wildlife populations, especially those that may require old growth for their habitat. Forest dominated by red and white pines are important habitats for wildlife in central Ontario. … OMNR is just beginning to address concerns about the supply of pine forests (as habitat for wildlife) by planning for landscape diversity within the context of timber management plans (Naylor, 1994). The large straight form makes it a good wildlife trees for species that are cavity nesters, such as woodpecker.

REMOTE SENSING TECHNIQUES

Remote sensing is a field that has been around for a century, growing as technology advances and ease of access to the data also advances. It is generally acknowledged that digital remote sensing can provide information that is not currently part of an existing forest inventory (Franklin *et al*. 2000). This is a relatively fast way of collecting a lot of information about a certain forested area, as larger areas can be covered by different aerial sources in one swath. As the technology improves, the access time for this data is improving and the manager can access the data within a few hours of it being updated and can begin the data analysis. Assessment of forests within an ecosystem management framework implies both geographic and economic advantages in applying remote-sensing methods to generate data on forest extent and location (Wulder, 1998). The implementation of remote sensing techniques can help with giving a broader look at the whole forest that is being managed or studied.

Remote sensing uses methods of sensing the electromagnetic energy given off by the object to obtain the image that will be used. This energy forms a spectral range, which can have wavelengths ranging from 400μm to a microwave (1meter). Since objects (including vegetation) have their unique spectral features (reflectance or emission regions), they can be identified from remote sensing imagery according to their unique spectral characteristics. A good case in vegetation mapping using remote sensing technology is the spectral radiances in the red and near-infrared regions (Xie *et al*, 2008). The different sensors can achieve different results, based on what the desired outcome is. They can each show different aspects of the forest, including the health of the standing crown, and can give a rough estimate of the percentage of deciduous compared to conifer within the stand. Remote-sensing studies of vegetation normally use specific wavelengths selected to provide information about the vegetation present in the area from which the radiance data emanated. … . Without a strong spectral contrast, vegetation-canopy information is degraded or confused with non-vegetation information (Tucker and Sellers, 1986). The sensors can vary in their resolution, providing different amount of details depending on what he image will be used for. While high spatial resolution remote sensing provides more information than coarse resolution imagery for detailed observation on vegetation, increasingly smaller spatial resolution does not necessarily benefit classification performance and accuracy (Yu *et al.* 2006). There is the payoff between increased resolution and classification. The smaller pixel size may

make it more difficult when trying to classify the area based off aerial photography. In these cases where the remote sensing data will be used for classification, the amount of resolution chosen should be the one that results in a higher accuracy for classification. Although using remote sensing data may facilitate classifying a stand, it is not a perfect system. It can not fully replace the accuracy of physical data collection and classification, and so the two should be used together to ensure the best possible results.

AERIAL PHOTOGRAPHY

Aerial photography is one of the outputs from remote sensing satellites and data collection. One of the more attractive benefits of using aerial photography for management is the ease and practicality of the data source. Forest management inventories in Canada rely extensively on information derived from aerial photos. Aerial photos are an attractive and cost-effective source of tree species information for individual forest stands and for large tracts of forest land (Magnussen, 1997). Photographs become more useful when classifying the different stand types in a forest. Aerial photography can also identify other aspects within the forest, including the health as well as the total volume. For example, satellite imagery (*e.g.* Landsat TM or SPOT XS with spatial resolutions of 30 and 20 m, respectively) has been widely used as auxiliary data in forest inventories to produce information on forest resources for large areas (municipal, regional or national level) (Tuominen and Pekkarinen, 2004). The different resolution can give a different level of detail, depending on the use and the number of features to be classified from the image. The aerial classification of forests is more often accompanied by a ground assessment. However, it is not possible for all forest stands, as there are too many stands and not enough man power in order to check the accuracy for each stand. Although uniform single species stands can probably be assessed at medium (1-10 meters/pixel) or even low (10-100 meters/pixel) spatial resolutions, we believe that in order to convey adequately the species composition levels needed in today's typical forest management inventories of natural stands, high spatial resolution aerial imagery (30-70 cm/pixel) and individual tree-based species recognition capabilities are required (Gougeon, 1995). This would require a high level of skill by the individual classifying the images, as some species may have similar crown shapes. A skilled analyst would give more accurate results than someone who may not have many hours spent looking at aerial photography.

Texture information represents the spatial variation in image tone (*i.e.* digital grey values) that is the result of the arrangement of forest vegetation and other objects in a digital image. The variability in stand structure results in unique variations of image tones that can be used to stratify stands, and to possibly increase the accuracy of forest classification and mapping of biophysical attributes (Franklin *et al.* 2000). The different attributes and shapes, as well as colours present in the images can be very useful for the classification.

FOREST CLASSIFICATION

Forest classification allows for different forest stands to be identified, so that the proper species composition of the forest can be known. Within the last decade, several instruments with higher spatial and spectral resolution have been developed. These instruments may provide the spectral resolution necessary to improve upon existing classification method (Martin *et al*. 1998). This forest classification makes it so that the forest composition can be identified. There are many uses for forest classification, for example it can determine the vitality of the tree or the forest. The condition of a tree is evaluated by interpreting the color of its crown in a color infrared aerial photograph. Since, compared to damaged vegetation, healthy vegetation tends to reflect more light in the infrared band and less in the red one, healthy trees look red in a color infrared photograph, while unhealthy trees will have less red and more green color, thus appearing pale. But the color of a tree will depend on both the tree's vitality and the tree species. For example, a healthy pine will show a similar colour to the one of a damaged spruce (Pinz, 1991). This knowledge can facilitate the identification for forest management purposes. One main classification issue is the separation of red pine from other conifer species, especially jack pine. It has been concluded through much research that this species is difficult for a variety of reasons. Without red pine crowns, the overall accuracies with most of these classification schemes could be of the order of 75-80% for four coniferous species (black spruce, white spruce, white pine and jack pine). It is hoped that the addition of textural (structural) parameters will alleviate the red pine crown identification problem (Gougeon, 1994). As this is a historically important species, as well as one whose presence on the landscape is in management plans to be increased, facilitating the accurate classification is becoming more important.

2.0 MATERIALS AND METHODS

2.1 Materials

The data used for analysis is from the 2017 North Western Ontario Orthophotography Project (NWOOP), as well as forest resource inventory (FRI) from the Ontario Ministry of Natural Resources Forestry (OMNRF). The areas used in the NWOOP project (Figure 2) were flown using an ADS100 Leica digital camera system. It is 20 cm stereo and ortho imagery that is color and color infrared. The current species composition from the Hogarth plantation, the MNR 25rd side road, as well as areas around Fort Frances was used for the imagery analysis.

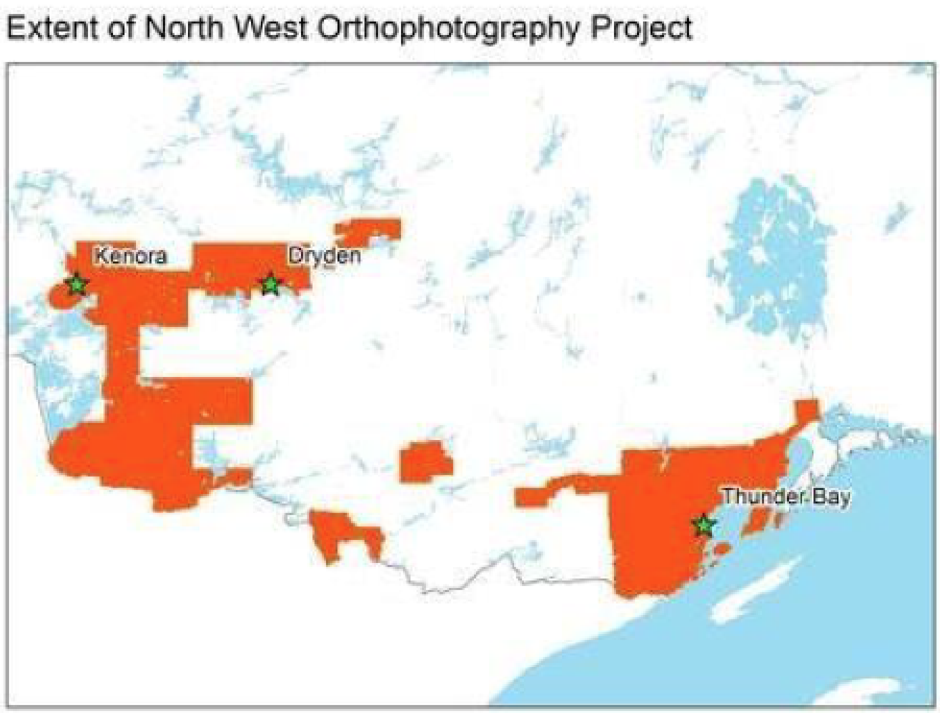

Figure 2: Map of NWOOP Area

Most of the areas in the Thunder Bay area used were around the MNR 25th Side Road office (Figure 3). The NWOOP data set cut off through the tree farm, resulting in some compartments missing, as well as no NWOOP imagery for the Hogarth plantation.

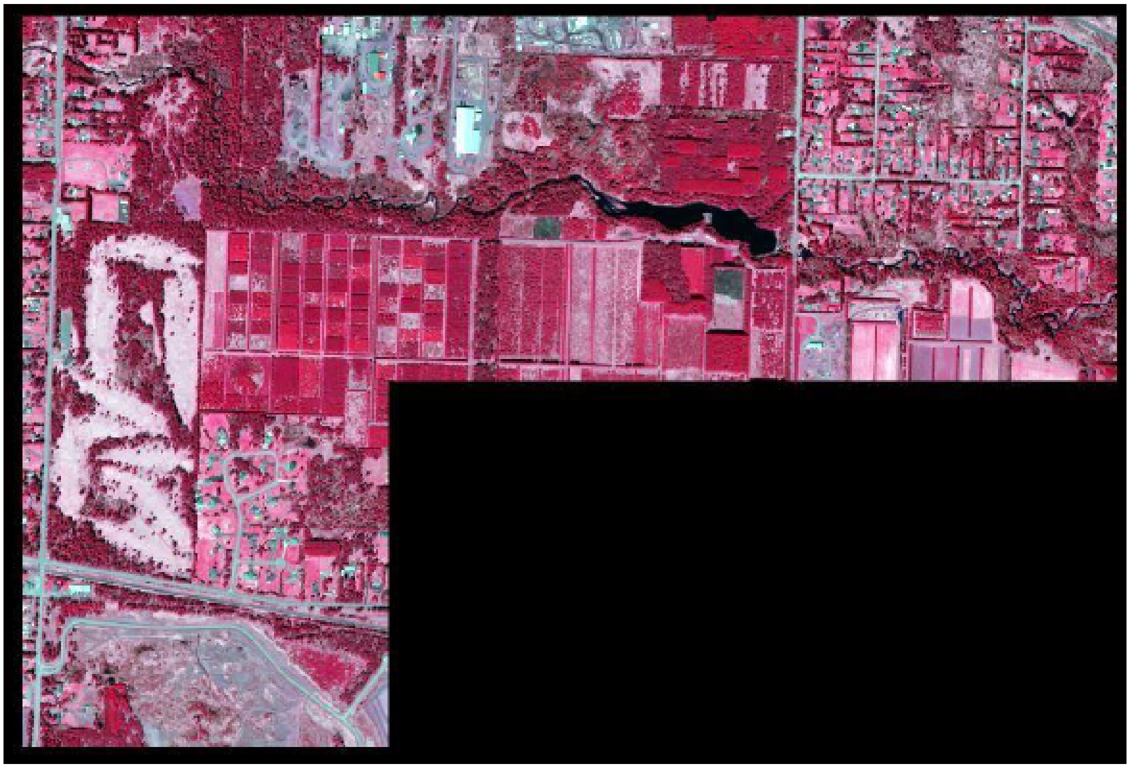

Figure 3: Thunder Bay Imagery

The areas chosen for application in Fort Frances were west of the town (Figure 4). The pine transition areas are known to be west of the town in the forested areas. The exact locations were unknown before implementing the methods on these images.

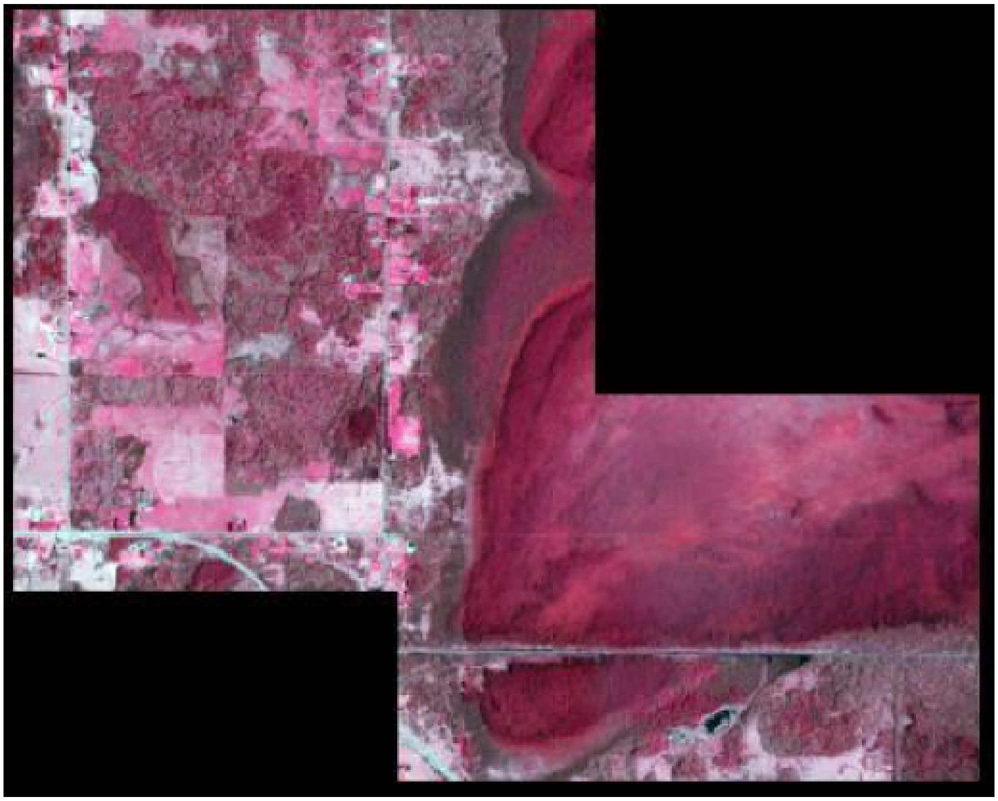

Figure 4: Fort Frances Area

The knowledge of the layout of the 25th side road tree farm was also essential for this image analysis, as it gave the location of the compartments that contain red pine and jack pine (Appendix 1). This helped focus the classification methods only on those areas and finding ways to remove the unnecessary species from the analysis. Another compartment map was provided (Appendix 2), which included areas of mixed plantations. Some of these compartments included mixes of jack pine and red pine, which was used as part of the test areas for the classification.

2.2 Methods

The images will be analysed using remote sensing software, including ERDAS Imagine looking at the metadata of the images. The different programs will be used depending on what data is required from each image. Current charts with information about vegetative reflectivity (Figure 2) will also be used to compare the values found to the theoretical ones.

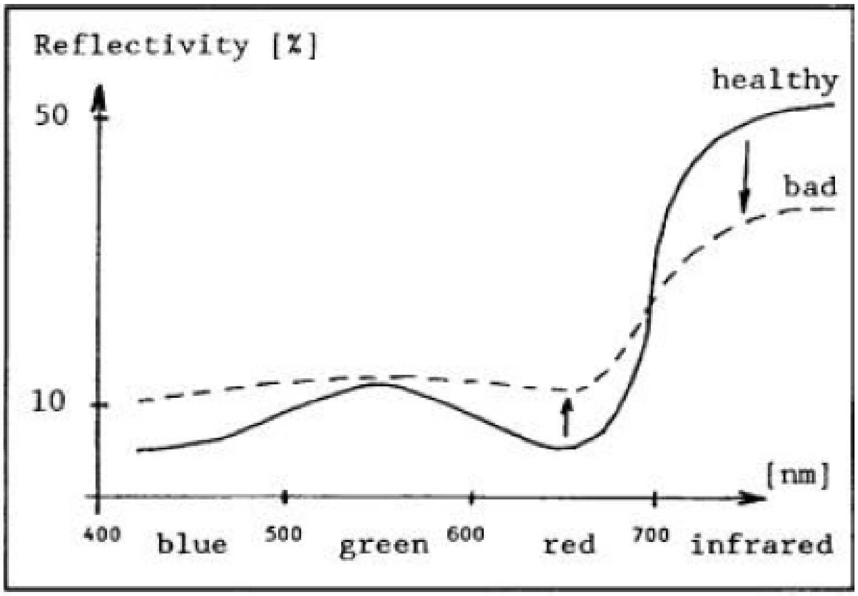

Figure 5: Reflectivity of Vegetation (Pintz, 1991)

The known spectral signatures and found histogram values of red pine and jack pine will be used as a baseline to test the values in order to determine which value will work to classify red pine.

2.2.1 Thunder Bay Imagery

The tiles from the NWOOP image set were compiled into one image using the mosaic function on ERDAS, and then subset and chip was performed to isolate the area of the 25th side road.

First, classification was run on the image of 25th Side Road. Using the maps, samples were taken from each species to build into the signature editor. This gave different classes for each species to use during supervised classification. The same analysis was performed on the areas marked as red pine on the compartment maps. Some of the compartments that were marked containing species were relatively empty on the aerial image, and so these were not added so that the chances of error would be reduced. The compartment map indicated white birch (Bw) in some compartments, however on the NWOOP aerial image, these compartments had no trees, so these areas were excluded.

Multiple classification attempts were made until the procedure was fine tuned enough to provide the most accurate results. Supervised and unsupervised classification was run on the tree farm, spacing trial, and the area to try and reduce errors within ERDAS processing.

2.2.2 Fort Frances Imagery

The tiles were processed into a mosaic using the same methods as the Thunder Bay imagery.

A spectral transformation is the name for the list of processes used for this image analysis and classification. A spectral transformation aids with the analysis and processing of images, and begins a principal component analysis (PCA), as it creates components that are derived in decreasing order of importance. These new components are linear combinations of the original image bands and are derived in decreasing order of importance so that, for example, the first principal component accounts for as much as possible of the variation in the original data (Landmap, 2005). In most cases, the first component will account for varying changes within the albedo, *ie* reflectivity of the aspects of the image. PCA was run in ERDAS, and is found under the spectral menu for the raster tab.

The next process required for the spectral transformation is the tasseled cap. A tasseled cap, or tasseled cap transformation, is run in ERDAS, and is also found on the spectral menu for the raster tab. The Tasseled Cap Transformation in remote sensing is the conversion of the readings in a set of channels into composite values. … One of these other composite values represents the degree of greenness of the pixels and another might represent the degree of yellowness of vegetation or perhaps the wetness of the soil (Watkins, 2005). The different colors of the resulting output correspond with the different composite values and their pixel values related to the intended purpose of performing a tasseled cap transformation.

The third process is a spatial filtering. Spatial filtering is named “Convolution” on ERDAS, under the spatial menu for the raster tab. Convolution refers to moving the chosen filter (or kernel as it is referred to on ERDAS) over the image and rotating it 180°, and then finding the sum of the products of the pixels that fall within the filter. The kernel used in this process was the low pass. A low-pass filter, also called a "blurring" or "smoothing" filter, averages out rapid changes in intensity. The simplest low-pass filter just calculates the average of a pixel and all of its eight immediate neighbors. The result replaces the original value of the pixel. The process is repeated for every pixel in the image (Diffraction Limited, n.d.) The kernel can be different sizes, depending on the desired use of the spatial filtering. This low-pass kernel had a value of 3x3, meaning when it was applied, it was placed as 3 pixels down and across, for a total of 9 pixels.

The final step for a spectral transformation is RGB to IHS. This converts the RGB (redgreen-blue) layer from the low pass spatial filtering to an IHS (Intensity-Hue-Saturation) layer. This tool is found under the spectral menu of the raster tab. Transforming the layer to an IHS layer allows for the pixel value to be seen for each individual layer present on the image. The concept behind transforming the layer to an IHS is to make the colors more comparable to that visible to the human eye. Intensity is the overall brightness of the scene (like PC-1) and varies from 0 (black) to 1 (white). Saturation represents the purity of color and also varies linearly from 0 to 1. Hue is representative of the color or dominant wavelength of the pixel. It varies from 0 at the red midpoint through green and blue back to the red midpoint at 360. It is a circular dimension. In the following figure, 0 to 255 is the selected range; it could be defined as any data range. However, hue must vary from 0 to 360 to define the entire sphere (Buchanan, 1979).

After the spectral transformation is completed, unsupervised classification will be run on the images the same way as it was for Thunder Bay Imagery. The spectral transformation has made it so that the areas of vegetation are more prominent on the image, which would eliminate any unnecessary noise that may occur from the surrounding structures and roads. The images are compared next to the image of the 25th side road, so that when classification is performed, the 25th side road can aide in photo interpretation for finding the areas of red pine. A recode was set up on the resulting unsupervised classification images, to make the classes easier to read and grouped together.

3.0 RESULTS

3.1 Thunder Bay Imagery

The initial signature editor had distinct colouring for each of the species found in the tree farm (Table 1). The initial classification results showed distinct areas of red pine and jack pine, especially when the in large areas (Figure 6). Other areas showed mixes of species; the classification did not result in pure areas of color for the corresponding species like how the original imagery was. This could be due to actual mixes within the compartments, or different colorings due to shadows / age of the compartments.

Table 1: 25th Side Road Signature Editor

Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1		Jack Pine		0.357	0.341	0.344	17	17	327480	1.000	✔	✔	✔	✔	
2		Black Spruce		0.414	0.363	0.373	5	22	41432	1.000	✔	✔	✔	✔	
3		Tamarack		0.388	0.481	0.471	6	36	24470	1.000	✔	✔	✔	✔	
4		White Spruce		0.482	0.337	0.355	14	47	174524	1.000	✔	✔	✔	✔	
5		White Pine		0.658	0.384	0.410	12	56	167833	1.000	✔	✔	✔	✔	
6		Red Pine		0.627	0.328	0.360	3	59	87684	1.000	✔	✔	✔	✔	
7	▶	Empty Space		0.567	0.868	0.786	9	65	44396	1.000	✔	✔	✔	✔	

The areas of the darker green are jack pine, and the areas of a redder color are red pine. The colors from the initial attribute table were changed to make it easier to discern each class from the next. Unsupervised classification was performed to achieve better results (Figure 7). Without changing the colors from the classification, the compartments were more evenly colored, with the same distinctions from the original image.

These two classifications provided baselines for how to proceed with more accurate methods. Since the colors were very similar on the original image, a lot were classified under the same class when in fact they were different. This became more evident when trying to group the classes to species under the unsupervised classification (Figure 7).

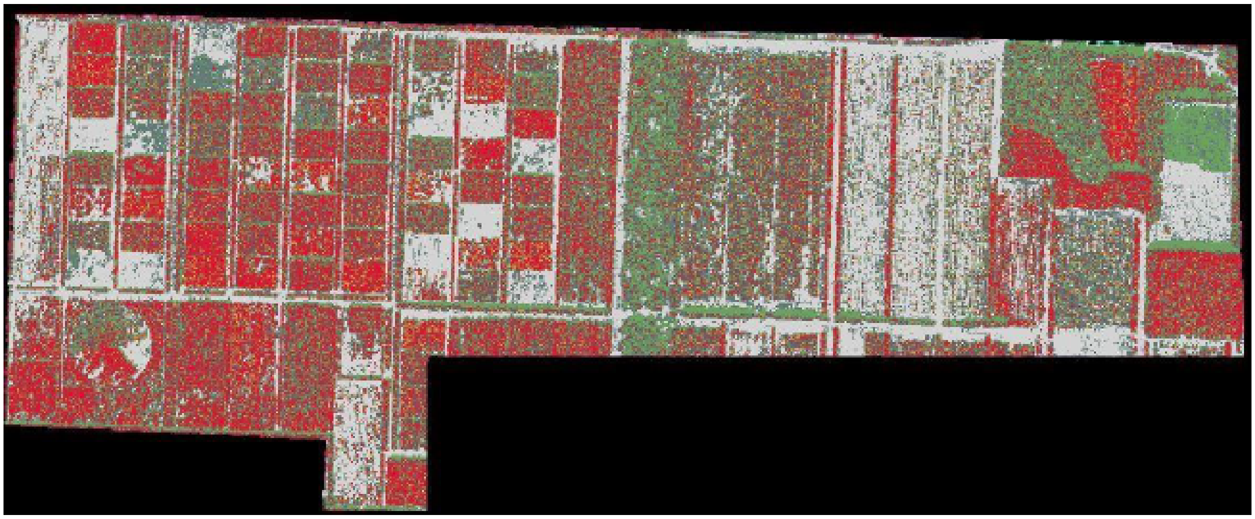

Figure 6: Initial Supervised Classification

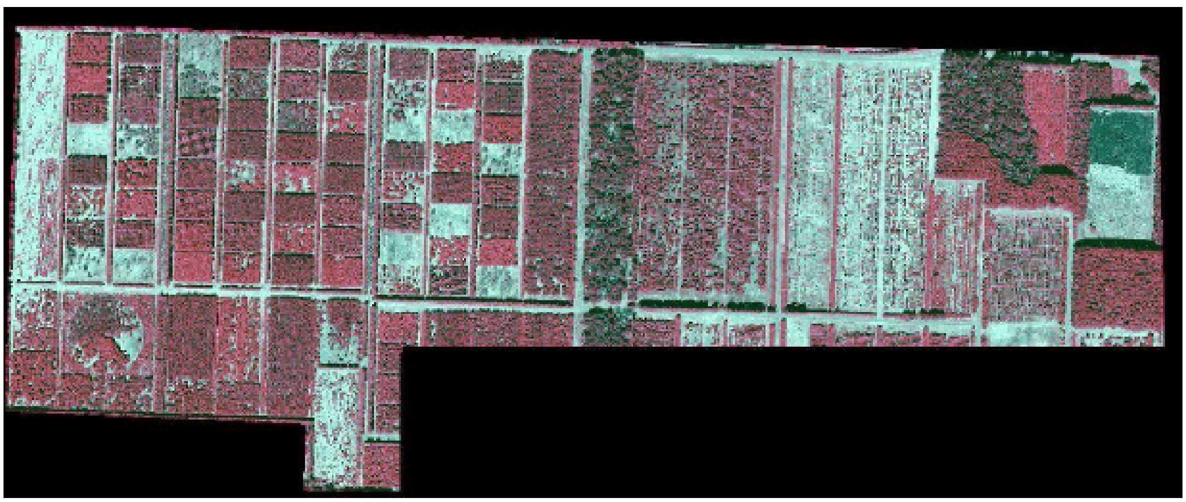

Figure 7: Unsupervised Classification

Trying to combine the classes in unsupervised classification resulted in a messy image that did not keep the original separation in compartments from the original images. It became solid blocks of color, especially in areas were the compartments were closer together or similar in color. For this reason, the unsupervised classification was not grouped by classes to make analysis easier and were left with the original number of classes not grouped together from the original output.

The same issues were encountered when running supervised and unsupervised classification on the spacing trial imagery. While the unsupervised classification

(Figure 8) provided promising results on the initial output, once the grouping of classes was attempted, the image became very unclear with large groups of general color in areas that did not belong to the class.

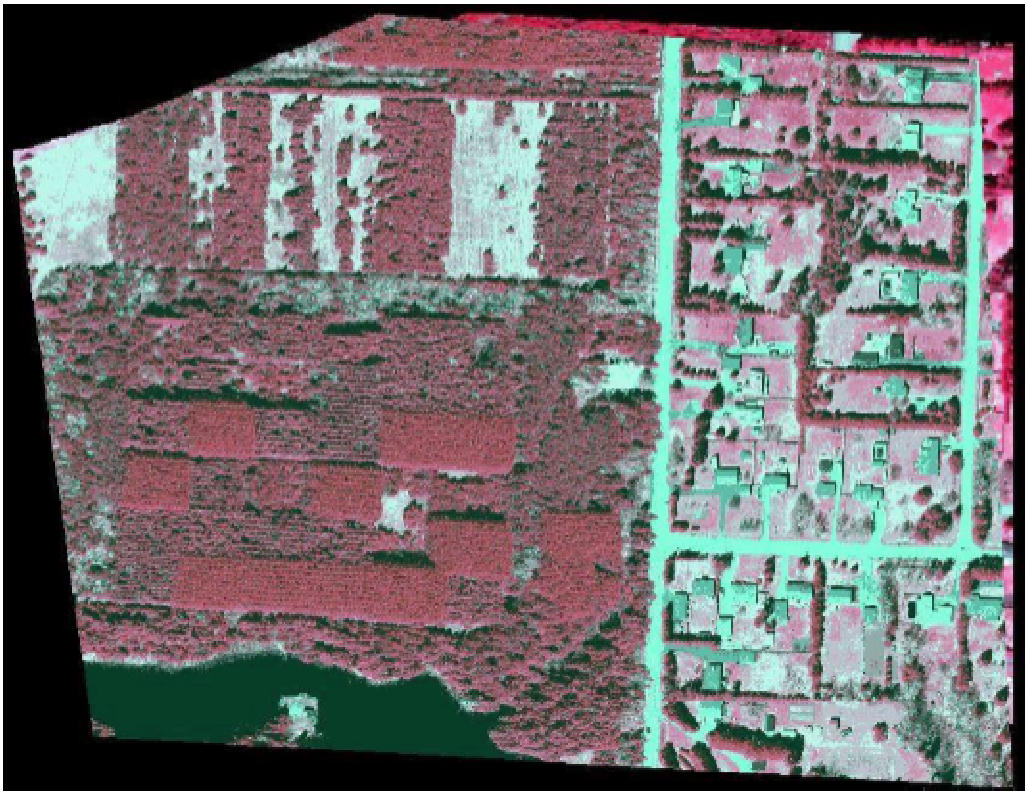

Figure 8: Red Pine Spacing Trial Unsupervised Classification

The supervised classification (Figure 9) of the spacing trial did not have the same distinct areas as the original, however it was able to maintain almost pure areas of red pine, which are colored in yellow to make them more visible and distinguishable.

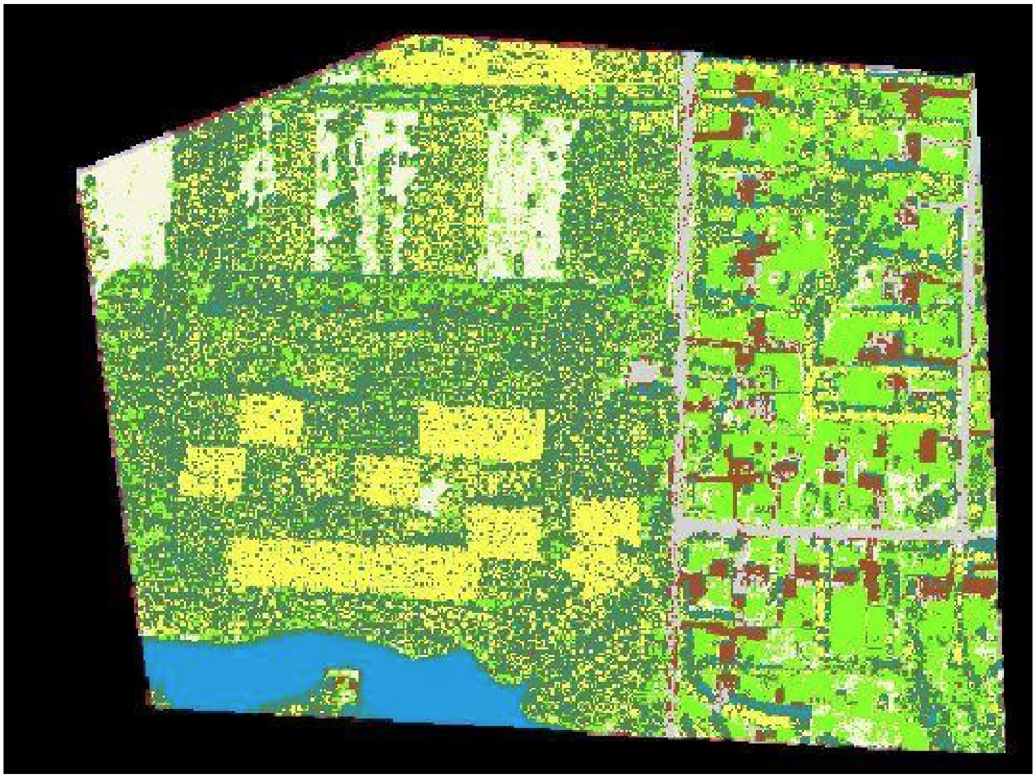

Figure 9: Red Pine Spacing Trial Supervised Classification

The classification methods have so far been able to partially separate the species, especially red pine from jack pine in the initial outputs. This ability to separate the species was aided using the layout maps. The number of classes and samples taken were changed for each run, to determine what amount gave the optimal results of species classification.

Classification on the area was the next course of action, as the larger area could help improve upon the results. This would improve by taking in more classification samples, as there is more area and features for ERDAS to analyze. Classification on the entire area would hopefully remove any error caused by the lawns and other urban features surrounding the area.

Unsupervised classification (Figure 10) yielded similar results to that from the isolated images. The classes and features appeared to be fairly separated, until the classes began to be edited and changed to belong to the features, then the image became muddy and didn't keep the species as separate as the supervised classification (Figure 11).

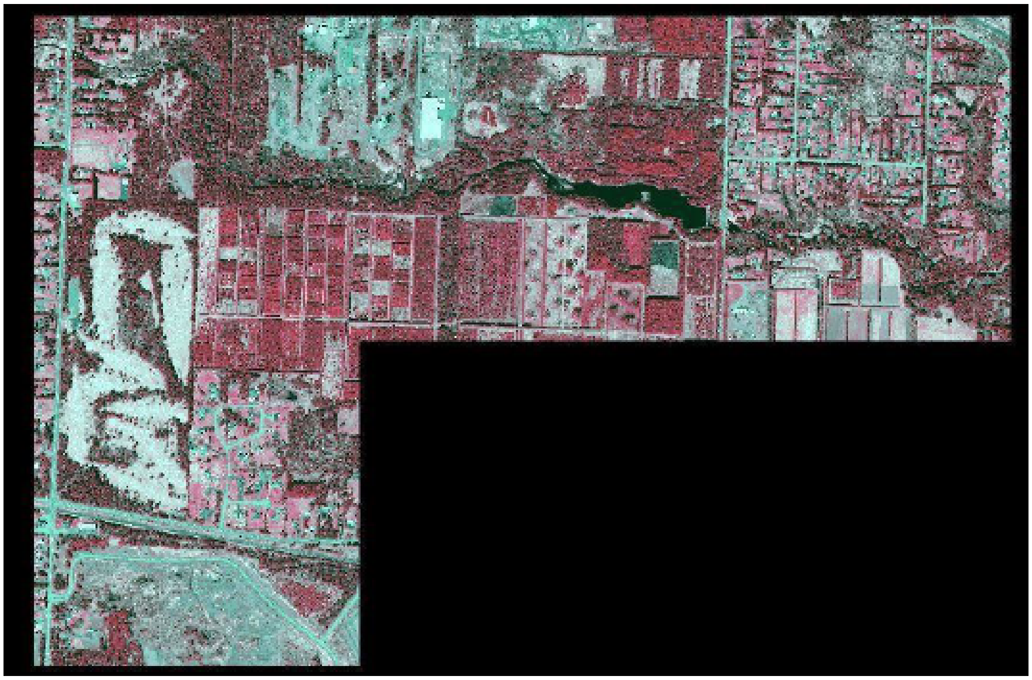

Figure 10: Thunder Bay Area Unsupervised Classification

Figure 11: Thunder Bay Area Supervised Classification

While using layout maps, with the known location of red pine, it was possible to separate it from jack pine with both supervised and unsupervised classification on ERDAS. However, the supervised classification gave the best results, as it was easier to pick the areas that will be red pine on the output image, forcing the classification to separate the species.

3.2 Fort Frances Imagery

The Fort Frances Imagery was broken into the two sections for the methods application. The first area (Figure 12) contains more urban features and some fields, and the other area (Figure 18) contains more forested area than urban features. They were done separately to test the methods on Area 1 before implementing on a more forested area. This was to determine how well the spectral transformation will help with species classification.

Figure 12: Fort Frances Area 1

The principal component analysis (PCA) of the first area resulted in areas of blue and purple for vegetation (Figure 13).

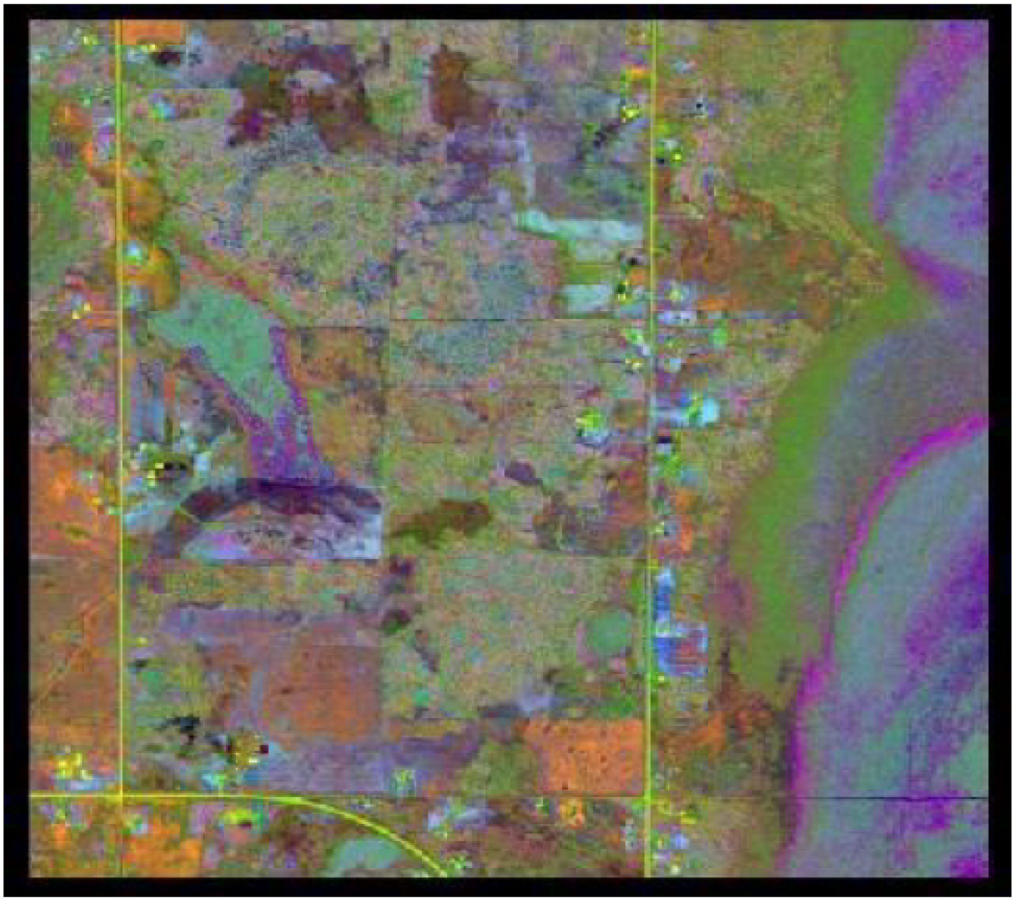

Figure 13: Principal Component Analysis Area 1

The first component that is generated through a PCA can account for changes in albedo, resulting in blues and purples and some greens for the areas that have a higher albedo factor.

The next transformation which was a tasseled cap transformation (Figure 14) has vegetation colored lighter than the non-vegetation features. This step resulted in an image with more prominent vegetation areas, darkening the other features.

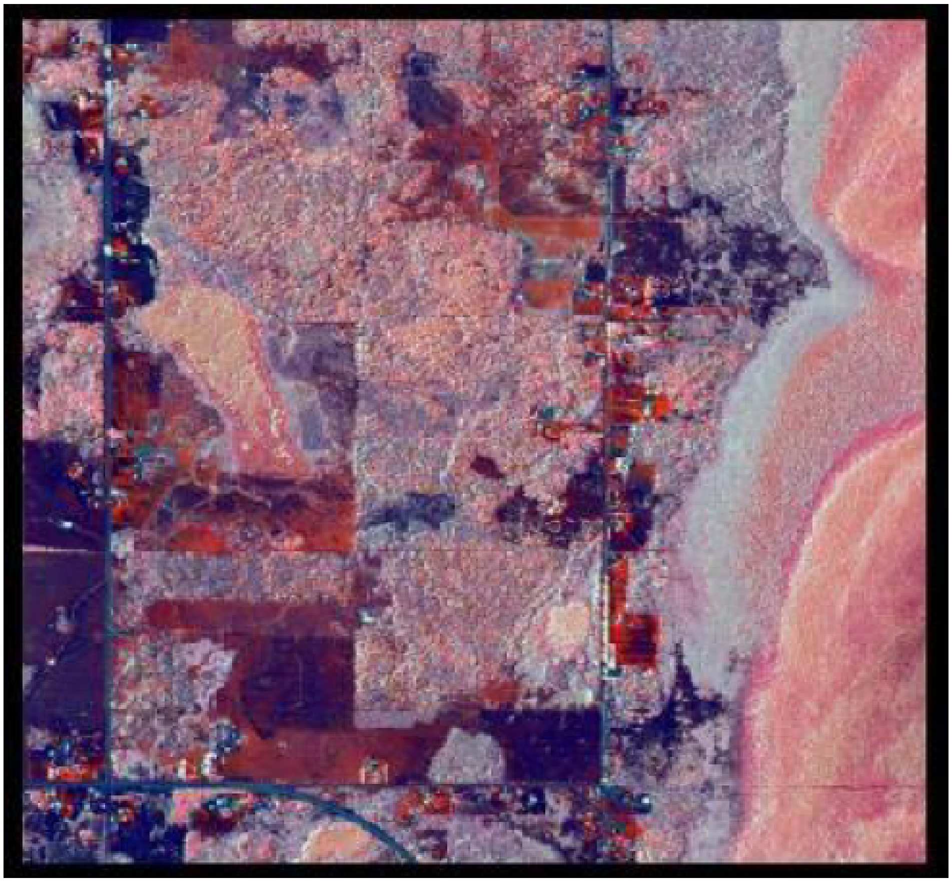

Figure 14: Tasseled Cap Transformation Area 1

The 3x3 low pass spatial filtering (Figure 15) is not that different from the tasseled cap transformation, however there are some slight differences. The colors are slightly brighter, and the pixels are less distinct when zoomed in on the image in ERDAS. The image appears slightly blurry as a result of the low pass, which was the intended output from this process.

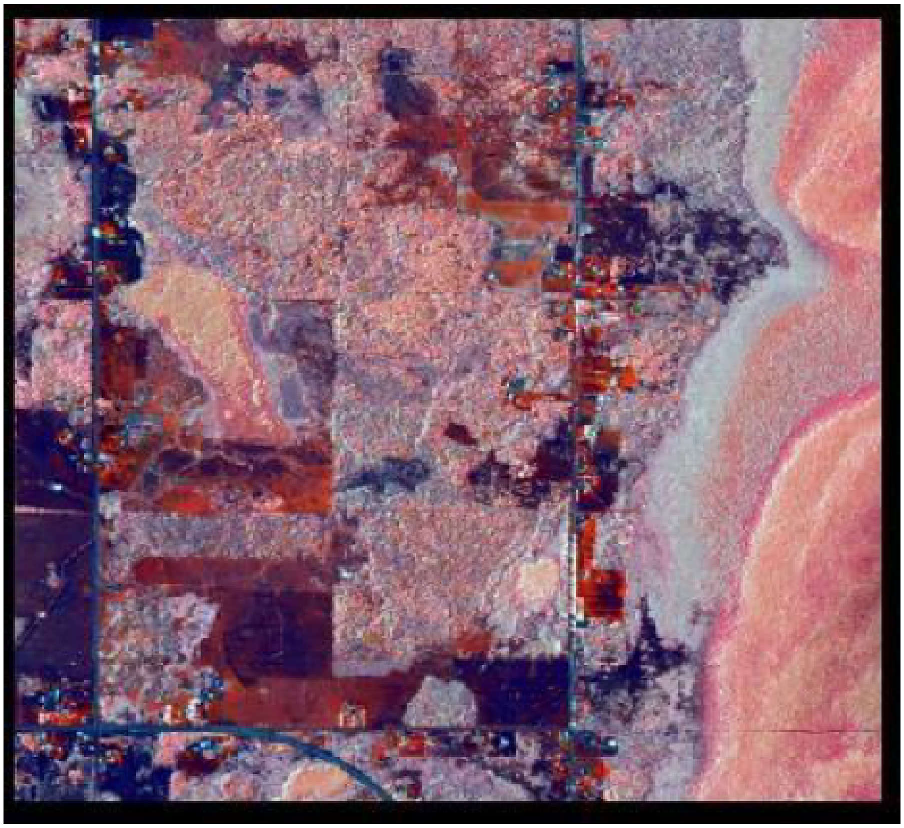

Figure 15: 3x3 Low Pass Area 1

The transformation from RGB to IHS (Figure 16) resulted in different colorings throughout the forested area of the image, and the urban features to be darker on the image.

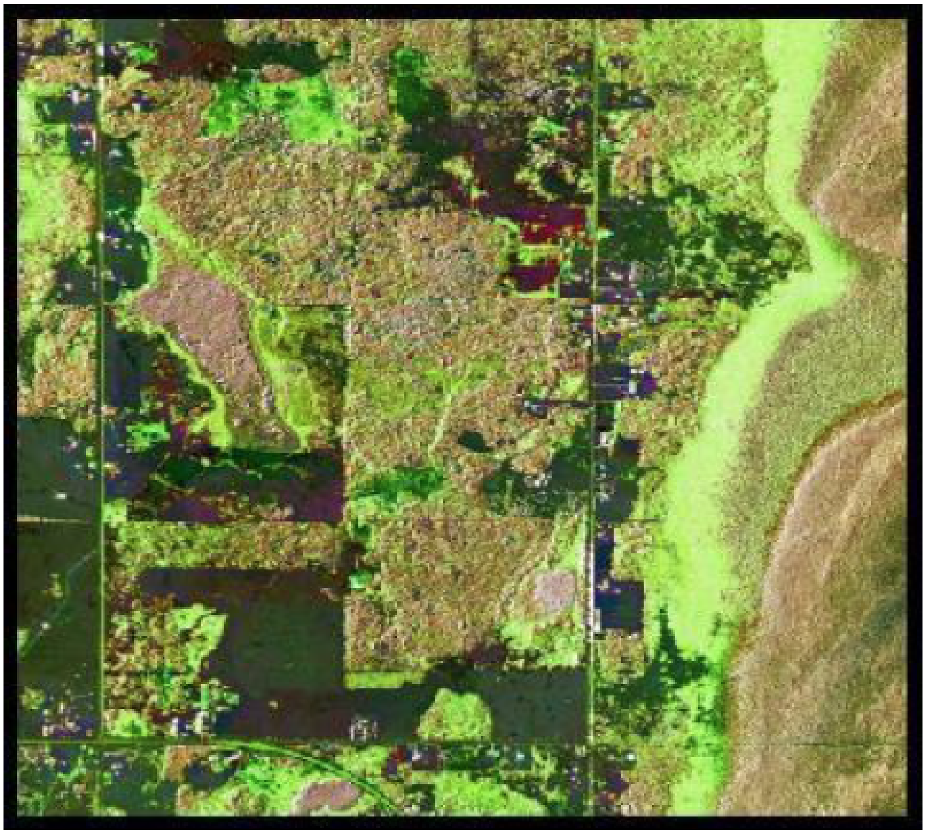

Figure 16: RGB to IHS Area 1

It can be assumed that the different colors in the IHS image could reflect the different species composition within the forested area. This difference is more visible in the output from unsupervised classification (Figure 17), which was run on the IHS image. There are different areas of color within the forested area.

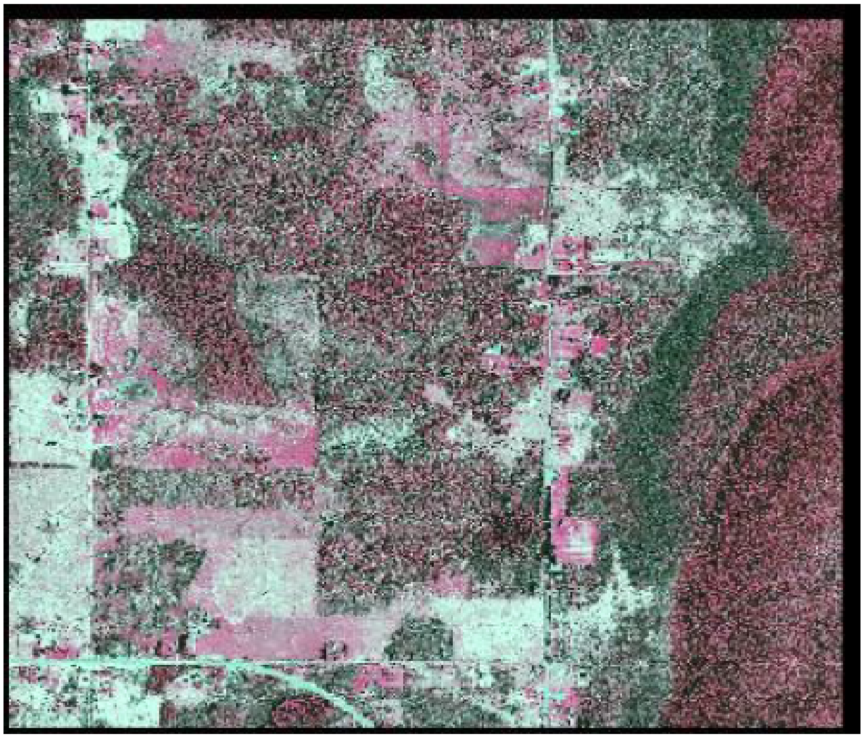

Figure 17: Unsupervised Classification Area 1

There were some areas based on photo interpretation that matched the aerial crown shape of red pine. However, after changing the classes to try and isolate these areas, more than what appeared to be pine was classified under this same color group. For this reason, it has been classified as 'pine' (Table 2). A high presence of shadow made the resulting features to be not as distinct as the original.

Table 2: Unsupervised Classification Attribute Table Area 1

Row	Histogram	Color	Red	Green	Blue	Opacity	
0	0		0	0	0	0	Unclassified
1	33841339		0.647	0.165	0.165	1	Shadow
2	30951574		0.271	0.592	0.208	1	Pine
3	43232326		0	0.392	0	1	Conifer
4	3947295		0.823529	0.705882	0.54902	1	Vegetation
5	21295145		0.961	0.961	0.863	1	Road
6	91732321		0.827	0.827	0.827	1	Field

The urban areas are less discernable on the output; however, the vegetation was more successfully classified (Figure 18). The lighter green areas are the ones assumed to be red pine, however the amount of shadow and other non-tree vegetation resulted in an image with lower quality classification than was the intent.

Figure 18: Recode Unsupervised Classification Area 1.

The next area for Fort Frances had higher forested area (Figure 19). This was chosen in the hopes of decreasing the noise that occurred from the urban features in the first area that was chosen. This larger forested area also has a higher chance of containing the red pine to jack pine transition areas that are being classified and separated.

Figure 19: Fort Frances Area 2

The principal component analysis of this area (Figure 20) also resulted in the vegetation areas being various shades of blue and purple, with some green. The other features are not as bright as the vegetation in this output. The section of vegetation that has lost its foliage, most likely due to the time of year, is similar in color to the road and bare areas.

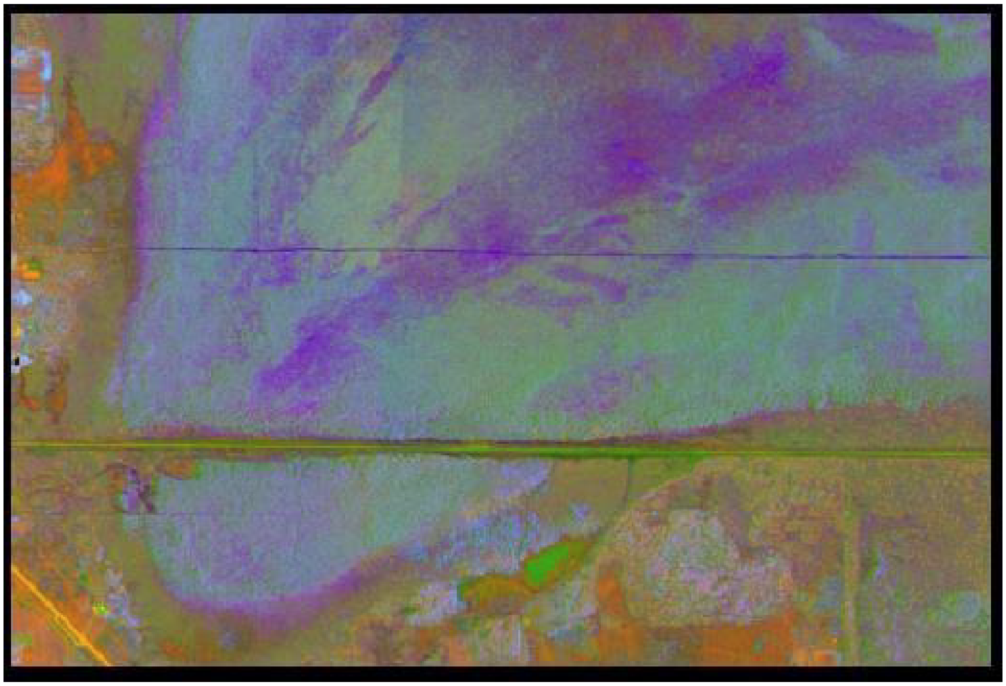

Figure 20: Principal Component Analysis Area 2

After the tasseled cap transformation (Figure 21), the changes in vegetation are more noticeable. There are differing levels of orange/red within the live vegetation, and the other areas of vegetation that may be bare or without foliage, are the same bluish color and are different from the urban features, such as the road.

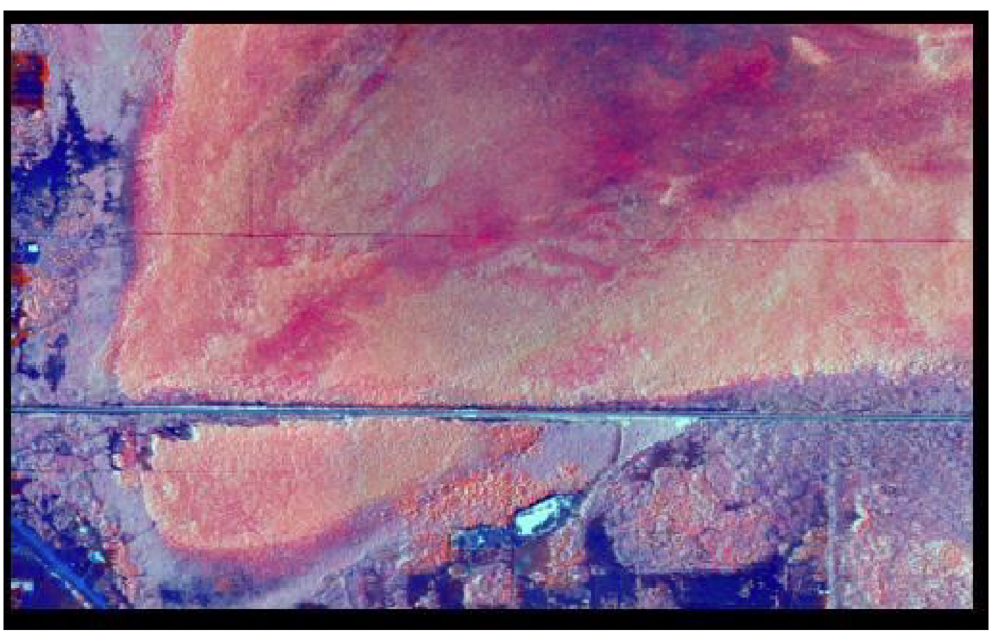

Figure 21: Tasseled Cap Transformation Area 2

The 3x3 low pass spatial filtering also didn't have much of a change on the output image (Figure 22) as compared to the input tasseled cap transformation. In some areas, the colors of the vegetation are a little brighter, and also blurrier of an image than the input.

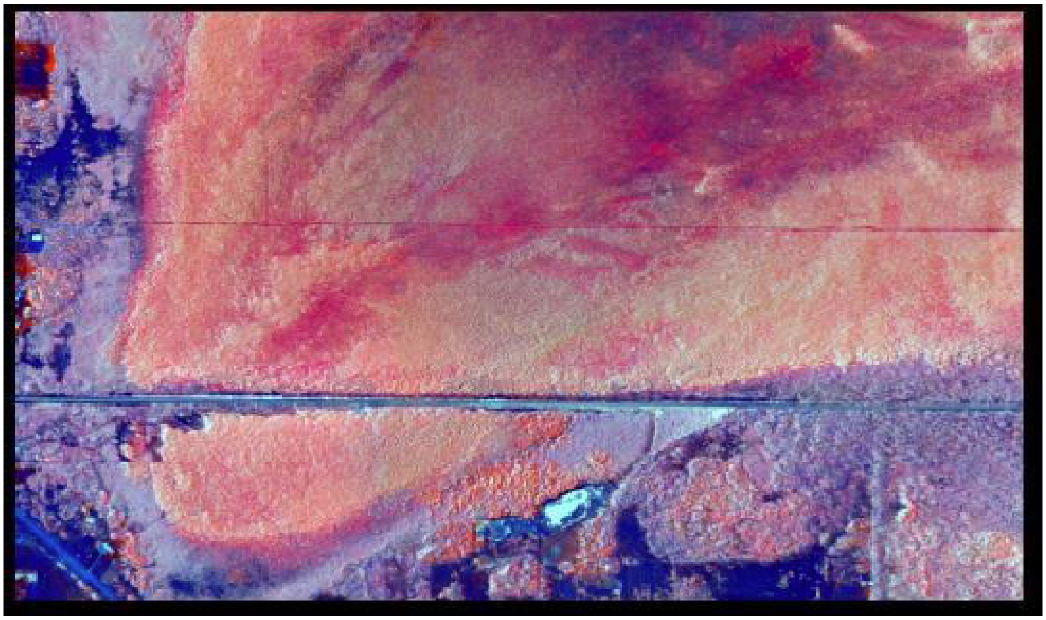

Figure 22: 3x3 Low Pass Area 2

The RGB to IHS output (Figure 23) accounts for more of the variation in the vegetation in the image. The areas where it is a different species, or a different age are different colors than the rest of the vegetation present.

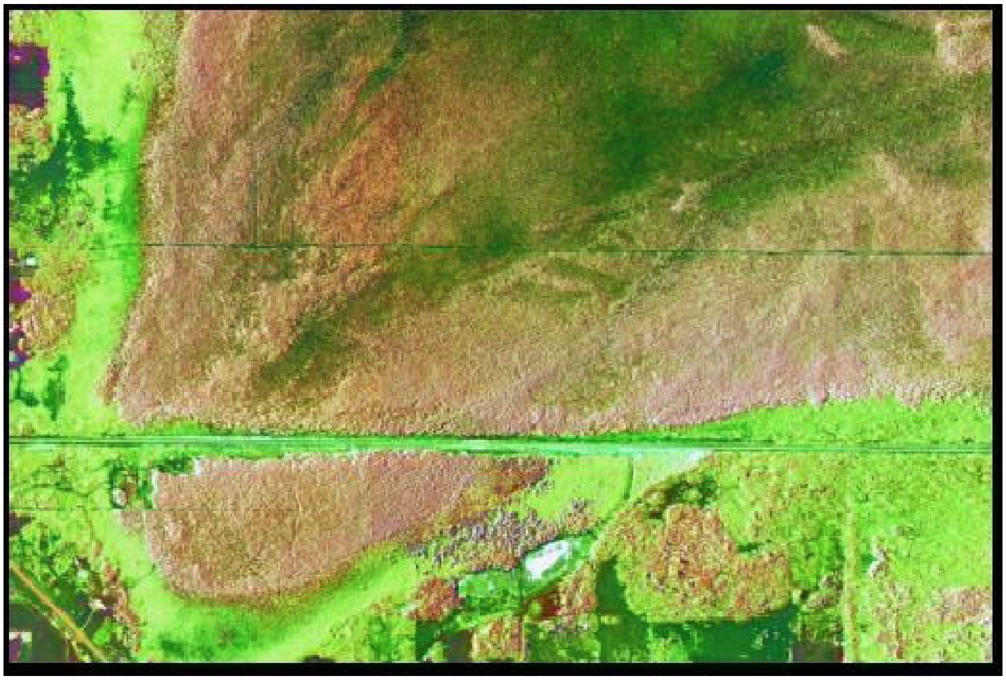

Figure 23: RGB to IHS Area 2

This will help in the classification as there is more variation to account for, and hopefully it will be used in the process to help differentiate the species found in the forested area. The output from the unsupervised classification for area 2 (Figure 24) had different colorings within the forested area, making it appear to be different species colored appropriately. Once the classes from the attribute table were started to be colored the same for the different features, it became obvious that a lot of the image was classified for shadows present, as well as the areas inside that had been harvested and have smaller trees, as well as areas where the trees are lacking foliage due to the time of the year.

Figure 24: Unsupervised Classification Area 2

A high amount of the image ended up being colored for shadow, resulting in an image that was difficult to classify (Figure 25). Based on photo interpretation, there are areas of pine within the forested area of area 2; however, the angle and time of year resulted in shadow. Figure 24 had better results for the classification and separation than the attempt to recode the attributes (Table 3) and simplify the number of classes.

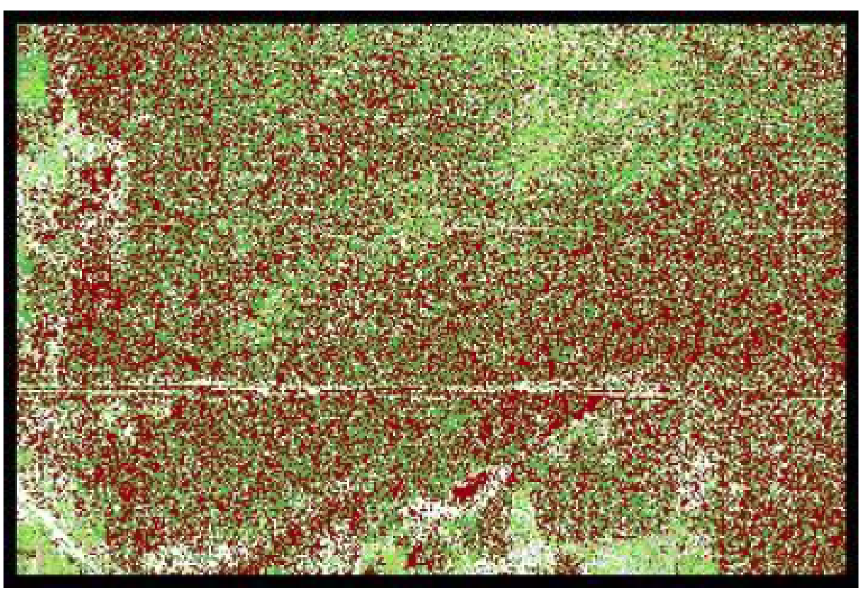

Figure 25: Recode Unsupervised Classification Area 2

The image was classes for pine and conifer, as some of the area had smaller trees that were hard to distinguish based on the crown shape. There are some features that were hard to pull apart from the shadow, as they were other parts of the image that were darker due to the nature of the feature.

Table 3: Unsupervised Classification Attribute Table

Row	Histogram	Color	Red	Green	Blue	Opacity	
0	0		0	0	0	0	Unclassified
1	4186199		0.824	0.706	0.549	1	Bare
2	5472901		0.498	1	0	1	Conifer
3	58767351		0.275	0.714	0.165	1	Pine
4	29552162		1	1	1	1	Ice/Snow
5	52021387		0.647	0	0	1	Shadow

Overall, the attempt to separate red pine from jack pine was not fully conclusive. There was some progress with promising results that appeared successful after many attempts. Separating red pine from jack pine was successful when the species composition and location was known. This ensured the success of both supervised and unsupervised classification on these areas. The ability to separate pine from other coniferous species was successful, but when applying the methods to an area of unknown species composition, separating the two pines was not successful.

4.0 DISCUSSION

The timing of year for the NWOOP imagery caused some issues within the classification. Since it was captured in the fall, the hardwood trees would have lost their leaves, and larch would have been in the process of losing their needles. The larch in the tree farm cause some issues when classifying the compartments, as ERDAS read it the same as the empty compartments of grass. Although it was not a species of interest, attempts were made to fix it as it provided opportunities to fine tune the classification and make it as accurate as possible for other species distinctions. The same issue was encountered with the image of the spacing trial. The high amount of lawn present caused some issues in the jack pine areas, as well as the residential area in proximity to the trial. All the red pine was labelled in the map, whereas the other species were not labelled, aside from a few areas of jack pine. This made for the areas surrounding the red pine to be classified as jack pine, lawn and red pine in the output. This factor was also evident in the imagery from Fort Frances. In the image for the first area, there is a fair amount of areas that have trees without foliage. There is also some shadow present, especially in the areas closest to urban features. This caused some muddling of the image when trying to group the classification results. Areas of grass also caused some issues with results. If they were the same shade roughly on the original image, classification became messy as grass became grouped with the trees, resulting in unclear results.

One key factor that may ensure further success with this type of project would be the added step of ground truthing. This can ensure that the trees in the image are in fact the trees on the ground. Depending on the time frame between when the imagery was taken and when the analysis happens, there may be changes or disturbances that were not captured in the imagery. In the case of the tree farm, the layout may not have been updated recently, and could show compartments of trees that are a different age or no longer present in the area.

Another essential benefit of ground truthing would be to find the exact areas of red pine in the Fort Frances area. While it may not be possible to survey the entire forested area surrounding Fort Frances searching for the red pine, knowing a rough idea of the areas would be beneficial. The red pine and jack pine transition areas are to the west of the town, but the exact frame of reference is relatively unknown, especially if they had been mislabelled in the most recent enhanced forest resources inventory (eFRI) database.

The lack of results after applying the methods could be due to many factors. The first could be the areas chosen around Fort Frances for the application could have been the areas in which no red pine was present. This would give results in that the methods were not successful, however the error of not knowing a rough location could yield false results. Another possibility would be the methods applied. A more precise method may be the best way to approach this problem.

It has been found in many studies that classification attempts from aerial imagery have lower accuracy results when compared to sample plots. Using spectral classes in the analysis helps to improve the accuracy results. A more reasonable perspective is to assume that error exists in both field and remote sensing surveys, and that both datasets can lead to a reasonable generalization of the forest inventory (Franklin *et al*, 2000). This can arise from user or surveyor error, as some aspects of the composition can be easily missed. While many different classification runs were performed to try and get the most accurate results in the test areas, there remains possibility for error, whether within the user or the program itself not being able to handle the commands at such a resolution.

The study could be improved with implementing different imagery analysis techniques. A way to assess the accuracy would also be beneficial. As mentioned above, there is a high amount of error that could be present within the data set, either from ground survey error or user classification error. Congalton (1991) outlines two different techniques for accuracy assessment that goes beyond referencing photointerpretation for the assessment. An obvious assumption made here is that the photointerpretation is 100% correct. This assumption is rarely valid and can lead to a rather poor and unfair assessment of the digital classification (Biging and Congalton, 1989). Interpretation was used to estimate where the Fort Frances red pine areas where, based on similarities in crown appearance to the Thunder Bay areas. An accuracy assessment technique would have improved upon this, as it would have ensured the areas were the proper areas to be implementing the methods.

There is a need for more recent information on the use of remote sensing in forest classification. A lot of the studies and papers are dated and could use more information as the technologies and the quality of the information improves. More high-resolution methods are becoming more commonly used for forest classification, and the information on how to use the data is not as common. Especially in forest classification, it is all dated techniques that could be improved or revisited to try and make more modern and keep up with the new technology.

5.0 CONCLUSION

Remote sensing can be a useful tool for many aspects of natural resources management. Being able to properly identify and classify tree species is becoming an essential part in forest resource inventories, as well as for smaller forest inventories. There are still challenges to be faced with species separation and classification. The issue of separating red pine from jack pine is still prevalent in aerial imagery classification and remote sensing analysis of images.

LITERATURE CITED

Benzie, J,W. (April 27, 1976) Manager's Handbook for Red Pine in the North Central States. General Technical Report NC-33.

Biging, G. and Congalton, R. (September 1989) Advances in Forest Inventory Using Advanced Digital Imagery. Proceedings of Global Natural Research Monitoring and Assessments: Preparing for the 21st Century. 3, 1241-1249

Bradford, J,B. and Palik, B,J. (2009) A Comparison of Thinning Methods in red pine: Consequences for Stand-Level Growth and Tree Diameter. Can. J. For. Res. 39, 489496

Buchanan, M,D. (November 2, 1979) Effective Utilization of Color in Multidimensional Data Presentations. The International Society for Optical Engineering. 199, 9-19.

Congalton, R.G (April 14, 1991) A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. Remote Sens. Environ. 37, 35-46

Diffraction Limited (n.d.) Low-Pass Filtering (Blurring). Spatial Filtering, Imaging with MaxIm DL. Accessed from https://diffractionlimited.com/help/maximdl/MaxImDL.htm#Low-Pass_Filtering.htm

Franklin, S.E. Hall, R.J. Moskal, L.M. Maudie, A.J, Lavigne, M.B. (2000) Incorporating Texture into Classification of Forest Species Composition from Airborne Multispectral Images. International Journal of Remote Sensing 21 (1) 61-79

Gougeon, F.A. (1995) A Crown-Following Approach to the Automatic Delineation of Individual Tree Crowns in High Spatial Resolution Aerial Images. Canadian Journal of Remote Sensing 1995, 274-284

Gougeon, F,A. (November, 1994) Comparison of Possible Multispectral Classification Schemes for Tree Crowns Individually Delineated on High Spatial Resolution MEIS Images. Canadian Journal of Remote Sensing 1994, Accessed from http://www.cfs.nrcan.gc.ca/pubwarehouse/pdfs/4452.pdf

Government of Ontario (July 18, 2014) Red Pine. Tree Atlas, Accessed from https://www.ontario.ca/page/red-pine

Landmap (2005) 10.2 Principal Components Analysis. ENVI Image Processing Course. Accessed from http://learningzone.rspsoc.org.uk/index.php/LearningMaterials/Image-Processing-for-ENVI/10.2.-Principal-Components-Analysis

Martin, M.E. Newman, S.D, Aber, J.D, Congalton, R.G, (April 10, 1998) Determining Forest Species Composition Using High Spectral Resolution Remote Sensing Data. Remote. Sens. Environ 65 249-254

Magnussen, S. (July/August 1997) A Method for Enhancing Tree Species Proportions from Aerial Photos. The Forestry Chronicle 73(4) 479-487

Naylor, B,J. (July/August 1994) Managing Wildlife Habitat in red pine and white pine Forests of Central Ontario. The Forestry Chronicle 70(4) 411-419

Pinz, A,J. (1991) A Computer Vision System for the Recognition of Trees in Aerial Photographs. Accessed from https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19910006312.pdf

Tucker, C,J. and Sellers, P.J. (1986) Satellite Remote Sensing of Primary Production. Int. J. Remote Sensing. 7(11) 1395-1416

Tuominen, S. Pekkarinen, A. (October 23, 2004) Performance of Different Spectral and Textural Aerial Photograph Features in Multi-source Forest Inventory. Remote Sensing of Environment 95 (2005) 256-268

Watkins, T (2005) The Tasseled Cap Transformation in Remote Sensing. San José State University Economics Department

Wulder, M (1998) Optical Remote-sensing Techniques for the Assessment of Forest Inventory and Biophysical Parameters. Progress in Physical Geography 22(4) 449476

Xie, Y. Sha, Z. Yu, M. (March 2008) Remote Sensing Imagery in Vegetation Mapping: A Review. Journal of Plant Ecology. 1(1) 9-23

Yu, Q. Gong, P. Clinton, N. Biging, G. Kelly, M. Schirokauer, D. (July 2006). Objectbased Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery. Photogrammetric Engineering & Remote Sensing. 72(7) 799-811

APPENDIX 1

Custom 25th Side Road Compartment Map

Gerry Racey, 2019

APPENDIX 2

NRC 25th Side Road Compartment Layout

Ministry of Natural Resources, 2012