AN ASSESSMENT OF METHODS FOR CLEARCUT DETECTION USING LANDSAT SATELLITE IMAGES OF NOVA SCOTIA

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ABSTRACT

An Assessment of Methods for Clearcut Detection Using Landsat Satellite Images of Nova Scotia

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In an attempt to replicate Global Forest Watch Canada (2009) and Weeks, et al. (2013), this research project evaluated five core methods to determine which one should be used for clearcut detection. The five methods assessed were: Band 5 Differencing, Band 7 Differencing, Normalized Difference Vegetation Index Differencing, Enhanced Wetness Difference Index Differencing, and Unsupervised Classification. The project used three phases to determine which method was the most accurate, whether or not a supervised classification increased method accuracy, and whether an increase in the interval between images dates had an impact on method accuracy. It was hypothesized that Normalized Difference Vegetation Index Differencing would be the most accurate method, a supervised classification would increase accuracy, and an increase in time interval between image dates would decrease method accuracy. A set of study areas in Nova Scotia were selected for the project. Trout Lake Training Area was used to learn how clearcut pixels appeared on Landsat images by using a high resolution IKONOS satellite image as a reference. The five aforementioned methods, were then applied to the Long Lake Evaluation Area. A supervised classification was conducted prior to method implementation for Governors Lake Evaluation Area, in an attempt to determine if the methods' accuracy would increase. Once the first two phases were completed, the methods were assessed for accuracy. The most accurate method was applied to Kelly Lake Application Area, Guysborough County, to determine if the accuracy would decrease with an increased time interval between image dates. Band 7 Differencing post-supervised classification was determined to be the most accurate method, contrary to the hypothesis. The supervised classification did increase accuracy of clearcut detection. When Band 7 Differencing with prior supervised classification was applied to images with an increased time interval, the accuracy decreased.

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RÉSUMÉ

An Assessment of Methods for Clearcut Detection Using Landsat Satellite Images of Nova Scotia

By: Marc A. Therrien

Dans une tentative de reproduire Global Forest Watch Canada (2009) et Weeks, et al. (2013), ce projet de recherche a évalué cinq méthodes de base pour déterminer quelles méthodes devraient être utilisées pour la détection de la coupe à blanc. Les cinq méthodes évaluées étaient : Band 5 Differencing, Band 7 Differencing, Normalized Difference Vegetation Index Differencing, Enhanced Wetness Index Difference Differencing et Unsupervised Classification. Le projet a utilisé trois phases pour déterminer quelle était la méthode la plus précise, si une classification supervisée augmente la précision de la méthode, et si un allongement de l'intervalle d'image a eu un impact sur la précision de la méthode. Les trois hypothèses sont : la Normalized Difference Vegetation Index Difference serait la méthode la plus précise, une classification supervisée augmenterait la précision de la méthode, et une augmentation de l'intervalle de temps entre les dates d'image diminuerait la précision de la méthode. Pour compléter le projet quatre régions situées en Nouvelle Écosse ont été utilisé. La première region a été utilisée pour apprendre l’apparence d’un pixel du coup à blanc sur une image Landsat en utilisant une image satellite de haute résolution IKONOS come vérification. Les cinq méthodes, mentionnées ci-dessus, ont ensuite été appliquées à la zone d'évaluation Long Lake situé dans la Vallée d'Annapolis. Une classification supervisée a été réalisée avant l’application des méthodes d'évaluation pour la zone du Lac Gouverneurs dans une tentative de déterminer si la précision des méthodes augmenterait. Une fois les deux premières étapes ont été réalisées, les méthodes ont été évaluées pour la précision. La méthode la plus précise a été appliquée à Kelly Lake situé dans le Comté de Guysborough, afin de déterminer si la précision diminuerait avec l’augmentation de l’intervalle de temps entre les dates d'image. Band 7 Differencing après la classification supervisée était la méthode la plus précise, contrairement à l'hypothèse. La classification supervisée a augmenté la précision de la méthode. Lorsque l’intervalle de temps avait augmenté entre les dates des images, la précision du Band 7 Differencing avait diminué.

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CHAPTER 1

Introduction and Project Overview

1.1 Introduction

Clearcutting is defined as the process of cutting every tree in a single area (Bowyer et al., 2009). The province of Nova Scotia has experienced change in vegetation cover due to clearcutting (Nova Scotia Public Lands Coalition, 2012). The removal of large quantities of trees, allows for the distinction between forest and clearcut areas via satellite imagery using remote sensing. Remote sensing is the process of gathering information about the planet's surface using satellite or plane mounted platforms. These platforms sense and record the energy that is emitted and reflected by the planet. These recordings can then be processed, analyzed, and manipulated to conduct studies and increase the knowledge of the mechanisms which take place on or around the Earth (Natural Resources Canada, 2014). Satellite images are used for the creation; and development of clearcut detection and monitoring projects which has been ongoing for the last 30 years. Using knowledge acquired from previous studies, as well as new developments in the field of clearcut detection methods, a project was developed to assess the accuracy of clearcut detection methods.

1.2 Study Overview

Using satellite images, the project evaluated the application of remotely sensed images for the task of clearcut detection using a multi-phase project. A learning area was used to learn how clearcut pixels appear on satellite imagery. The clearcut detection methods were then tested on two evaluation areas and an application area located in Nova Scotia. The learning area is located in the Annapolis County and was used to learn how clearcut areas appear on a remotely sensed images. The first phase of the project used the first evaluation area located in the Annapolis County. The second phase used an evaluation area located in the Halifax Regional Municipality and one in Guysborough County. These two evaluation areas were compared to determine which clearcut detection method is the most accurate.

Five processing methods were selected for use on the two evaluation areas:

- Band 5 Differencing (B5D),
- Band 7 Differencing (B7D),
- Normalized Difference Vegetation Index Differencing (NDVID),
- Enhance Wetness Difference Index Differencing (EWDID), and
- Unsupervised classification (UC)

A supervised classification was conducted prior to method implementation for the second evaluation area. The supervised classification was used to determine whether or not the overall accuracy of the methods would increase. Once the supervised classification was conducted and the methods implemented, the accuracy was assessed and ranked. Using the data collected during the first two phases of the project, the most accurate method was applied to an application area located in the Halifax Regional Municipality. The application area, third phase, was used to determine the effects of increasing the time interval between image dates and to determine if this would impact the method's accuracy.

1.3 Literature Review

Several different techniques can be used for land cover change detection. Some methods are combined with others to produce accurate results. Some of the most common methods used for clearcut detection are the Normalized Difference Vegetation Index (NDVI), band differencing and computerized classifications. The use of satellite imagery and specialized methods can accurately detect clearcut areas. All of these methods produce different results with different accuracies. Using previous studies, remotely sensed images and the five selected methods (i.e., unsupervised classification, NDVID, EWDID, band differencing and supervised classification), the accuracies will be assessed using a three-phase project.

The aforementioned methods have been used in several comprehensive land cover change-detection and clearcut-detection projects. Accuracies and suitability for the projects were developed by analyzing these methods and their previous uses. A prior study conducted by Weeks et al. (2013) compared image differencing, NDVI differencing post-classification (conducting the NDVI differencing once the classification has been completed), and visual interpretation to determine which method produced the highest accuracy for vegetation cover change detection. The researchers determined that the visual interpretation had the highest accuracy at 98%, whereas the Normalized Difference Vegetation Index Differencing (NDVID) and post-classification methods had accuracies which ranged from 47% to 56%. High accuracy methods must be used for land cover change detection to ensure reliable results. It is important for methods to be tested and evaluated based on their accuracies in an attempt to determine which method or methods produced the most accurate results.

1.3.1 Band Differencing

Image differencing is considered one of the most common methods of change detection that uses satellite based images. It consists of a cell by cell subtraction of digital numbers of one image to another image, thus, the resulting image demonstrates areas of change and no change. This process can then be used for all image bands present in the image file. Depending on the goal of the researchers, specific bands can be used to emphasize features for further analyses.

In 2009, Global Forest Watch Canada (GFWC) released a report that outlined the rate at which Nova Scotia was losing forest cover due to clearcutting activities. The organization used band 5 differencing to determine the amount of change between two images for a specified time period (GFWC, 2009). This research conducted accuracy assessments and verification through site visitations, which determined whether or not the land was clearcut or forested. For locations that were inaccessible, the researchers used air photo images to confirm clearcut and forested areas (GFWC, 2009). Although the researchers were able to determine the percentage of forest lost per region, the overall accuracy of the band differencing was not presented. In another study, Weeks et al. (2013) used band 2 differencing to determine vegetation change in semi-arid areas. The results produced with the band 2 differencing were used to create a change and no change map through thresholding. The overall accuracy of the differencing technique was 54%. In a separate study, Guild et al. (2003) used several change detection methods to conduct a deforestation and land conversion study in Rondonia, Brazil. Tasseled cap image differencing was used to detect areas which were clearcut. Areas subject to water fluctuation, such as a river or lake, were masked to increase the accuracy of the methods.

The overall accuracy for the tasseled cap image differencing was 71.4%, the second highest accuracy compared to the other results.

Overall, the accuracies of band differencing vary greatly. For example, an accuracy difference of 20% is present between the two aforementioned studies. If the GFWC had presented their overall accuracy, this could have helped to determine whether or not most band differencing is higher than 50% in accuracy. The number of studies using band differencing as a primary method is limited. Fortunately, band differencing can be combined with other methods to increase the overall accuracy of the research project. Variations of band differencing, such as NDVI differencing, can also be used for clearcut detection.

1.3.2 Normalized Difference Vegetation Index

The NDVI separates green vegetation from other types of surface cover by using chlorophyll. When green vegetation absorbs red light for photosynthesis, it reflects the near-infrared light. This light is then captured by the Landsat sensor allowing for the calculation if the NDVI, which uses a mathematical formula to detect land-cover changes (Sader, et al., 2001). The high values in an image, such as bright areas, represent large amounts of biomass, whereas darker areas represent less vegetation. Image differencing can also be used for the NDVI, which is used to calculate land cover change in a pair of images by way of image ratios that can divide one wave band by another (Sader et al., 2001). Lyon et al. (1998) determined that NDVI differencing was the most successful change detection method. Their findings indicated that NDVID results should be higher in terms of accuracy than simple band differencing. NDVID is also capable of detecting forest canopy disturbances as well as clearcut areas in a scene (Wilson and Sader, 2002; Jin and Sader, 2005), which increases the range sensitivity of NDVID and can lead to higher accuracies.

Two NDVI images from different dates can be compared to delineate areas that have changed from forested to deforested areas, or vice versa. For example, Morawitz et al. (2006) and Pu et al. (2008) used the NDVI method to assess vegetative land cover change in Puget Sound. The researchers used cloud free Landsat 5 and 7 data from 1986 to 1999 and were able to assess the amount of vegetation lost in the image. Areas next to bodies of water were omitted from the NDVI analysis, as the fluctuation in water levels can give false readings. To produce accurate results, the NDVI from one year can be subtracted from a previous or later year (thus conducting NDVID). Using a threshold technique, areas of no change, or change, can be distinguished. Within a five year period of time, the study area was subject to a 19.0-21.1% change. This indicated a high amount of human development in the area. One key aspect that was not mentioned by the researchers was the overall accuracy of the study. The authors presented their findings but they did not indicate whether these findings were highly accurate. The NDVI can also be combined with other methods, such as supervised and unsupervised classifications, to produce accurate results. Sader et al. (2001) and Cassidy et al. (2013) both used a NDVI in conjunction with a computerized ISODATA (Iterative Self-Organizing Data Analysis Technique) classification. This is a technique that highlights areas that have changed from forested to deforested and reports accuracies greater than 80%. These two methods are common for land cover change detection.

Cassidy et al. (2013) also used a similar approach to determine land cover changes in the Mekong River area (Thailand, Cambodia, Laos). Cassidy and colleagues used Landsat TM data that was collected from 1989 to 2005 during the dry season. This allowed for greater spectral separability from other types of vegetation and features. To ensure proper land cover detection, the images were radiometrically calibrated. The images were then classified using a hybrid supervised-unsupervised approach as well as the ISODATA technique with an NDVI for the continuous surfaces. The researchers were thus able to calculate the amount of forest in the area as well as the transition from forest to rice fields using both methods.

Bakr et al. (2010) also used a hybrid classification with a NDVI to detect land cover change in Egypt. A hierarchical land cover classification system was used to determine three different land types in the images used. The maximum likelihood decision rule (a type of supervised classification) was used for land cover detection. Once completed an unsupervised classification ISODATA method (clustering) was used. Both supervision techniques were altered to ensure the results produced the same number of classes. The final step of the project was to conduct the NDVI. The researchers did not use a NDVID, but rather a NDVI for each image was calculated and created. This allowed for a comparison between the classification and the NDVI produced, and an error matrix was used to determine the accuracy of the results. In this study, the overall accuracy for the 4 NDVIs was reported. NDVI accuracy ranged from 94% to 100% and the accuracy for the hybrid classification ranged from 94.5% to 100%. This particular study found that the hybrid classification method produced more accurate and reliable results in comparison to the NDVI. However, during one of the years, the NDVI failed to produce results (Bakr et al., 2010). The conclusions provided by Bakr et al (2010) do not support the research aforementioned. The previous studies found that the NDVI produced more accurate results compared to computerized classification.

Pu et al (2008) used NDVI differencing and supervised classification to monitor areas of sparse vegetation in Nevada for the monitoring of saltcedars, which is an invasive species in many American states. Using the NDVI technique, the researchers were able to identify areas which had higher amounts of saltcedar than others. Using the NDVI differencing technique to determine the range and impact of saltcedar spread in an area can give a good indication as to whether or not this method is accurate. Since the NDVI can distinguish between tree types, it can be used for general land cover change detection but more specifically, the detection of forested to deforested areas. This allows for thresholding where pixels can be defined based on whether or not they have changed. Pu et al. (2008) also found the accuracy produced by NDVI differencing (93.04%) was greater than the results produced by the classification method (91.56%). The methods used by Pu and colleagues have both pros and cons. The classification method can produce a complete matrix of change whereas the NDVI cannot. The final conclusions by the researchers indicated the NDVI differencing method is more of a change detection method compared to the classification method. This indicates that NDVI differencing will outperform computerized classifications in terms of land cover change detection and possibly band differencing, which has demonstrated low accuracy results.

Kiage et al. (2007) employed three different methods to monitor land cover use and change in the Lake Baringo catchment of Kenya. Their goal was to detect land degradation. Post-classification image differencing (unsupervised-ISODATA), tasseled cap transformation and NDVI differencing were all used throughout the study. In this study, Kiage and colleagues demonstrated the versatility of the NDVI and how it can be used with other methods to produce accurate results. These three methods used in conjunction helped identify hotspots of change in the catchment area. The overall accuracy of the unsupervised classification was between 87.3% and 88% and the NDVI results were able to distinguish the areas which were subjected to deforestation. The researchers did not provide an accuracy assessment for the NDVI; therefore, this study does not indicate whether or not the NDVI outperformed the unsupervised classification for land cover change detection. The researchers did conclude that NDVI differencing and post-classification comparison was successful in identifying the hotspots for deforestation and land cover change.

Weeks et al. (2013) also tested four different methodologies for their accuracies in New Zealand. NDVI differencing was used to produce a change map and thresholding was applied to the resulting image to properly identify areas of change and no change. The overall accuracy of the NDVID was 56%, which was the second highest overall accuracy for NDVID. The highest overall accuracy was the visual interpretation at 96%.

Previous research has demonstrated that NDVI differencing can outperform band differencing. During the testing of this particular method in the research project, one can expect it to outperform several other methods. Since the NDVI was created for the purpose of vegetation cover detection, it would naturally be useful for clearcut detection. It comes as no surprise that the NDVID can detect areas of vegetation versus areas of no vegetation.

A problem, which is also true for band differencing, is the lack of data on accuracy from previous studies. With overall accuracy ranging between 50% and 90% one cannot determine whether or not this method should outperform other methods due to the lack of data for the overall accuracy of the method.

1.3.3 Enhanced Wetness Difference Index

A similar method to the NDVI is the Enhanced Wetness Difference Index (EWDI). The EWDI calculates the amount of wetness present in vegetation by discriminating between variations in land cover based on the wetness of an area. The EWDI is based on the reflectance capabilities of the Thematic Mapper (TM) and Enhanced Thematic Mapper+ (ETM+) data for Landsat satellites (Pape, 2006). It was used in a project which conducted forest cover change in New Brunswick, Canada. Research has demonstrated that the EWDI is superior in comparison to straight ratio-based indices (Pape, 2006). An index offers better advantages in comparison to single band radiometric responses since spectral values are across the entire scene rather than single band detection. The spectral detection properties of the EWDI should be perfect for generating maps of change or no change.

Another way to obtain wetness indices is by tasseled cap transformation (Skakun et al., 2003). Once completed, Skakun and colleagues used a pixel-by-pixel subtraction to achieve an enhancement and thresholding of wetness-index difference. The resulting EWDI can then be used to interpret spectral patterns that allow for land cover change detection. In this study, the EWDI was accurate enough to determine the extent of damage caused by mountain pine beetle infestation in the Prince George Forest Region of British

Columbia. The accuracy for the study ranged between 67% and 78%. Using thresholding, ten classes were identified and then transformed into six classes: old cut blocks, healthy, healthy to red-attack, red-attack, red-attack to foliage loss, and new cut blocks. This method allowed for the comparison and detection of land cover change. The EWDI may be effective for detecting deforestation due to the decrease in moisture for areas that have been clearcut; however, the accuracy of the method may not provide the results needed to be viable for continuous land cover change detection projects.

Due to limited data on the EWDI, it is difficult to determine whether or not this method was ultimately useful. This method is relatively new and has not been tested extensively. Preliminary results demonstrate the method does not produce highly accurate results, but it has the potential to outperform NDVI differencing and band differencing. It is important that this method is tested in future studies to determine its accuracy.

1.3.4 Unsupervised Classification

As discussed in the aforementioned research, unsupervised classifications can be used separately or in conjunction with other methods, thus increasing their versatility, for pre or post processing purposes. These methods are used in several research projects and have proven to be accurate for land cover change detection. The results from these methods are expected to be high as well as outperforming some of the methods already presented in this paper.

Ibrahim et al. (2005) used three different types of classification. The Maximum likelihood classifier, fuzzy c-means and possibilistic c-means were all used for the classification of an image for land cover mapping in a region located in India. To determine accuracy of the classifications on the panchromatic image, a fuzzy error matrix was used. The maximum likelihood classifier had the lowest accuracy at 66.8% whereas the possibilistic c-means classifier had the highest accuracy at 70%. The fuzzy c-means classification had an accuracy of 69.2%. These results are surprising. A supervised classification is supposed to be more accurate compared to an unsupervised classification; however, these results demonstrated that a supervised classification and an unsupervised classification can produce similar results in terms of accuracy.

For the purpose of the research project, the most accurate method must be used. Ibrahim et al. (2005) indicated that mixed pixels severely declined the accuracy of the classification. However, these mixed pixels were a point of contention when the time came to implement computerized classifications. It is important to reduce the amount of mixed pixels (forested and non-forested areas) to produce accurate results. This was difficult as none of the research had demonstrated how to work with or reduce the number of mixed pixels in a classification. The researchers concluded that mixed pixels must be incorporated in all stages of the classification process for accurate and meaningful results (Ibrahim et al., 2005). Yan et Al. (2006) also found that the maximum likelihood classifier did not outperform other classification methods. After conducting an error matrix for their classification, the accuracy of the maximum likelihood was of 46.83% compared to an object based classification that had 83.25% accuracy. These results appear to be in agreement with other studies that have demonstrated low accuracy rates in supervised classification.

Rozenstein and Karnieli (2010) used a combination of supervised and unsupervised technique to compare methods for land-use classification. The ISODATA unsupervised classification was used, which produced 80 classes. The maximum likelihood supervised classification produced 120 different signatures and spectrally similar classes were then united until six classes were produced. A confusion matrix was also produced for both the supervised and unsupervised classification. The overall accuracy of the unsupervised classification was 70.67% whereas the overall accuracy of the supervised classification was 60.83%, which was approximately a 10% drop in accuracy. These findings are surprising as previous studies have shown that the supervised classification is generally more accurate than the unsupervised classification.

Rozenstein and Karnieli (2010) did demonstrate how the accuracies for the supervised classification are equal to, or better than, those of the unsupervised classification on a class by class basis. It is the low (27%) user accuracy in the first class (urban land) for the supervised classification which differs greatly in comparison to the same class (urban, user accuracy of 61%) in the unsupervised classification. The researchers concluded it was perhaps their lack of intimate knowledge of the study area which may have influenced their training sites. The knowledge a researcher has about a study area can significantly affect the results of a supervised classification. Therefore, it is imperative that researchers gather as much information as possible on the area to ensure accurate training sites to produce accurate results.

In a study conducted by Rahman et al. (2013), a supervised classification using the maximum likelihood decision rule and band-ratio supervised classification was used for mangrove mapping on the border of Bangladesh and India. When training areas were properly selected, the results became more accurate than the unsupervised classification. The training classes were selected using the Landsat image and Google Earth. The researchers used a minimum of three training sites per class as well as ensured distribution throughout the Landsat image. The accuracy of the supervised classification was determined using an error matrix and the overall accuracy of the supervised classification was 89%. The researchers also employed an unsupervised classification using the *k*-means clustering algorithm, which produced 50 user defined classifications and a maximum iteration number of 10. The results were then compared to field data and merged to ensure a mangrove class as well as five other classes: natural forest, crop land, water, urban, and sandy land. An overall accuracy of 86% for the unsupervised classification was determined using an error matrix. The unsupervised classification is lower than the supervised classification by 3%. This was expected as the supervised classification used training pixels to properly classify the image, which resulted in higher accuracies.

Overall, each method discussed in the aforementioned studies appeared to produce both high and low results in terms of accuracy. It will be important to test each method carefully in future research to ensure a reduction in human error. Based on previous research, it can be concluded that a unanimous decision cannot be reached as to what method should be used for clearcut detection. For this reason more testing is needed to determine which method should be used based on accuracy.

1.4 Overall Purpose

The main purpose of the present research project is to evaluate five methods which can be used for clearcut detection projects. Using a three-phase strategy, five different methods (B5D, B7D, NDVID, EWDID and UC) were tested. Images with a one year time gap were used to determine which clearcut detection method is the most accurate. Once a method was selected, it was then applied to set of images with multiyear time gaps.

1.5 Objectives

This project will answer three main questions using a three phase system. The first phase will answer: W*hich of the five methods presented above will produce the most accurate method for detecting clearcut areas for a one-year interval?* The second phase will answer: *Does conducting a supervised classification prior to method implementation increase the accuracy of the results for a one-year interval?* After having answered the first two questions, the third and final question is: *How is the accuracy of the selected method impacted by intervals greater than one year?*

Using the previously discussed research, three hypotheses have been derived for each phase. The three hypotheses are:

- Hypothesis One: One of the band differencing techniques, NDVID, will be more accurate than the other four methods evaluated.
- Hypothesis Two: Conducting a supervised classification prior to method implementation will increase the accuracy of the methods implemented.

- Hypothesis Three: The most accurate method will produce results for a one year time interval that will diminish in accuracy as time intervals between image dates increased. The hypothesized reduction in accuracy is attributed to the length of time between image dates thus reducing distinctiveness of clearcut areas in the image.

1.6 Preview

The GFWC (2009) and Weeks et al (2013) projects were used as a foundation for a three-phase comparison. This comparison will test five methods (B5D, B7D, NDVID, EWDID and UC) and assess them based on the accuracy each method can produce through identifying areas that have transitioned from forested to clearcut. These five methods will be tested on two evaluation areas and an application area. The five methods will first be implemented on an evaluation area where no prior manipulation has been conducted. The second phase will implement a supervised classification prior to method implementation. The final step is the application of the most accurate method, as determined by the first two phases. This will occur on an application area and will determine if the accuracy of the method fluctuates over a multi-year time interval.

CHAPTER 2
Data and Study Areas

2.1 Data Acquisition

The data used for this project was acquired from various sources and diverse platforms. Images from Landsat and IKONOS sensors were used to detect clearcut areas. The Landsat images have lower pixel resolution whereas the IKONOS images have a higher pixel resolution. The IKONOS images were used for evaluating how clearcut areas appeared on a Landsat image, as well as for accuracy assessment during the third phase of the project.

2.2 Landsat

The Landsat images were downloaded at no charge from the United States Geological Survey's Earth Explorer website (*earthexplorer.usgs.gov*). These images were captured by the Landsat 5 sensor, which was launched on March 1st 1984 and decommissioned on June 5th 2013 (USGS, 2014). The Landsat images have a pixel resolution of 30 meters and the Thematic Mapper (TM) sensor on the Landsat 5 satellite has seven spectral bands covering different ranges of the electromagnetic spectrum. There are three visible bands (0.45 – 0.52 µm; 0.52 – 0.60 µm; 0.63 – 0.69 µm), one near-infrared band (0.76 – 0.90 µm) two mid infrared bands (1.55 – 1.75 µm; 2.08 – 2.35 µm) and one longwave infrared (thermal) band (10.40 – 12.50 µm) (USGS, 2014).

2.3 IKONOS

The IKONOS images were purchased for two areas located in Nova Scotia, Canada. The first area is located in the Annapolis Valley region and the second area is located in Guysborough County. The IKONOS platform was launched in 1999 and has a resolution of four meters in multispectral mode or one meter in panchromatic mode. There are four bands in which the sensor can capture data: panchromatic, blue, green, red and near infrared bands (GeoEye, 2006).

2.4 Image Pre-Processing

Prior to image processing, certain steps were taken to ensure images captured at different times could be compared. The images were first cropped to a specific area to reduce image size. The digital numbers were then converted to their original radiance values. The first pre-processing step was required to reduce image size from hundreds of square kilometers to a smaller selected area only tens of square kilometers in area.

The second pre-processing step was the conversion of digital numbers to the original radiance values. The conversion of digital numbers to original radiance values is possible due to the linear relation between digital numbers (DNs) and radiance values. Digital numbers have brightness values which range from 0-255 for each individual image. This indicates that each pixel is relative for a specific image. Since DNs are relative for images, the comparison of images which were captured at different times is therefore not possible (Campbell, 2007). Since the relation between radiance values and digital numbers is linear, a mathematical formula can be used to convert the digital numbers to radiance values. Gain and bias values, which can be found online for the specific date, Landsat sensor, and a mathematical formula ($Q = G * L + B$; where Q is the at sensor spectral radiance; G is the instrument gain; and B is the bias was used). This formula was applied to each of the bands, using the PCI Geomatica raster calculator, and the results produced were then saved. Once completed the images were manipulated and compared.

2.5 Location of Study Areas

Four study areas located within the province of Nova Scotia, Canada, were used throughout this project (see Figure 2.1). The first study area was used for learning purposes. The second study area was used for phase one, the third area for phase two, and the final study area was used for phase three. Two sites were located in the Annapolis Valley, one site in the HRM and the last site in Guysborough County. Each test site consisted of lakes, forest, clearcut areas and logging roads. The sites were selected due to their similarities and availability of Landsat 5 data for two consecutive years.

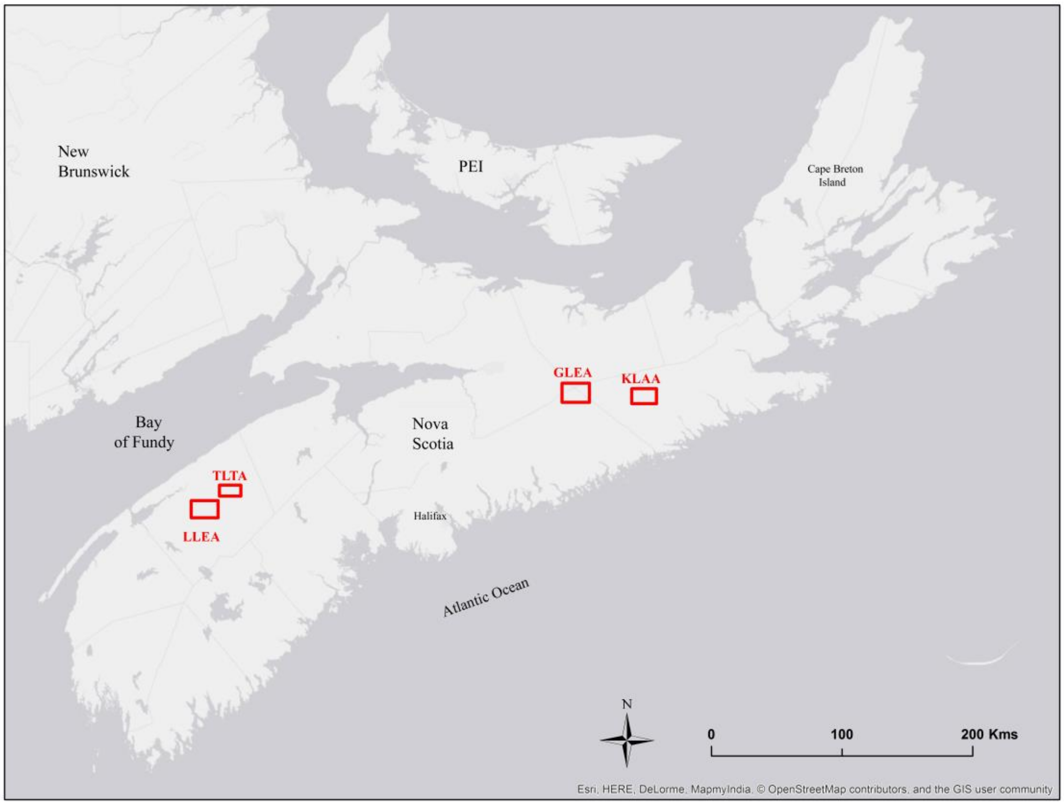


Figure 2.1: Locations of all four test sites (red) within the province of Nova Scotia.

2.5.1 Phase 1 Test Site and Use

The first location used for the project is located in the Annapolis Valley near Trout Lake. This site was used for learning purposes. The first location was thus named the Trout Lake Training Area (TLTA; see Figure 2.2) where Landsat 5 and IKONOS images were available for similar dates (July 29 2006 and July 29 2006). The Landsat 5 data was manipulated to highlight clearcut areas (bitmap). The IKONOS image for the area was overlaid the Landsat image to learn how clearcut areas appear on Landsat imagery. Areas which appeared as clearcut on the IKONOS image was bitmapped as well as areas border cut areas. This helped the researcher learn how clearcut areas appeared and was thus capable of using this information to conduct a visual inspection of thresholding for methods which required the process and for the accuracy assessment.

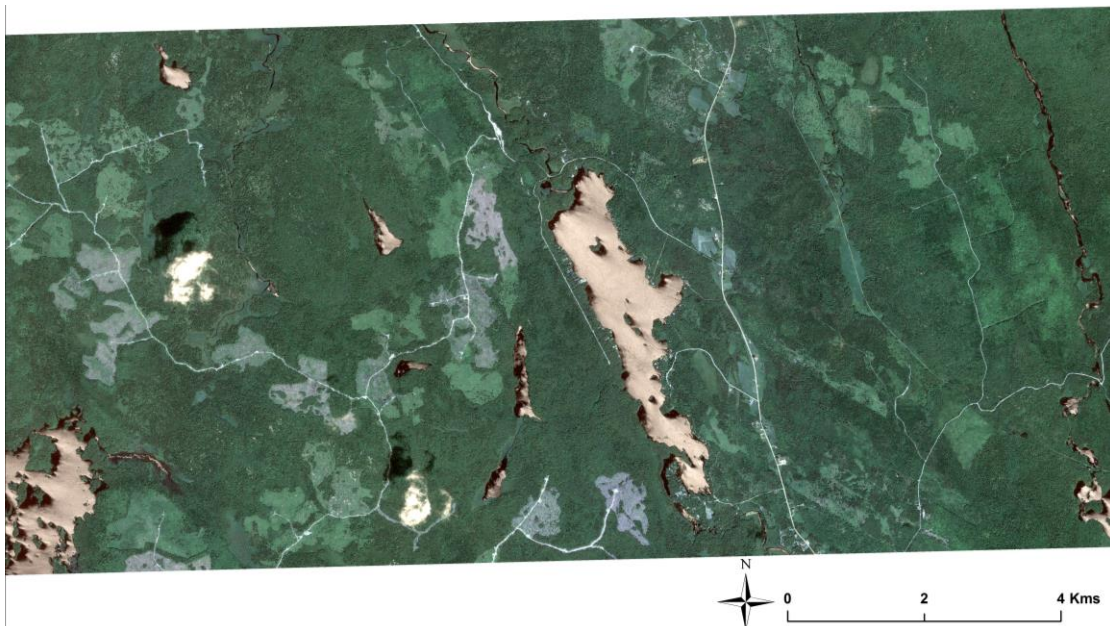


Figure 2.2: IKONOS image used for training purposes. The IKONOS image helped identify clearcut, no change and border cut pixels on a Landsat 5 Image.

2.5.2 LLEA

The first evaluation area was located in the Annapolis Valley near Long Lake. The evaluation area was thus named the Long Lake Evaluation Area (LLEA; see Figure 2.3a, Figure 2.3b). The five selected methods (Band 5 Differencing, Band 7 Differencing, Enhanced Wetness Difference Index, Normalized Vegetation Difference Index and Unsupervised Classification) were applied to the image to determine which method produced the most accurate clearcut detection results. Once the image manipulation was completed, a thresholding technique was applied to highlight areas which were deforested. The creation of the bitmap will also allow for the accuracy assessment to be completed.

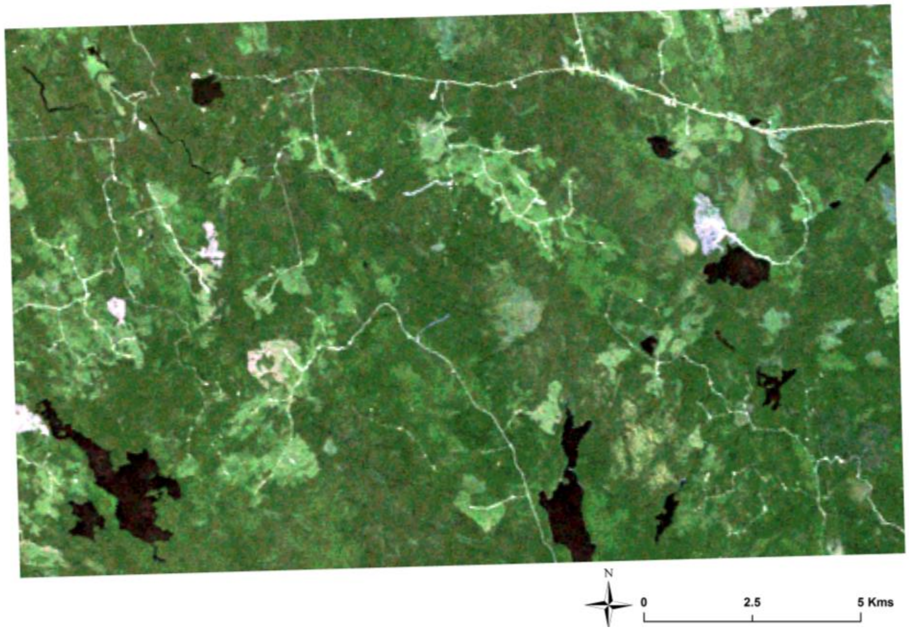


Figure 2.3a: Landsat 5 image acquired for Phase 1 which was used for method implementation. The image was captured on August 24 2004.

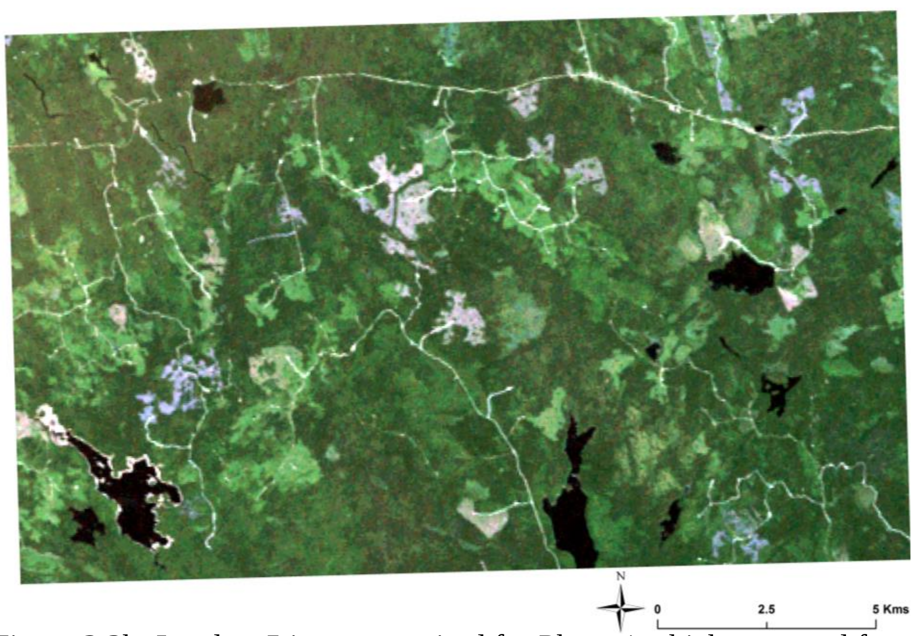


Figure 2.3b: Landsat 5 image acquired for Phase 1 which was used for method implementation for a one year interval. The image was captured on August 27 2005.

2.5.3 GLEA

The second evaluation area was located in the Halifax Regional Municipality in proximity to Governors Lake; therefore, the study area was named the Governors Lake Evaluation Area (GLEA; see Figure 2.4a and 2.4b). The GLEA was subjected to a supervised classification that highlighted the areas which were forested. Once completed, the resulting bitmap was transferred to all other images used during this process. This allowed for better clearcut detection, thus, increasing the accuracy of the results. The five selected methods were applied and a thresholding technique was used to determine which areas were clearcut. The thresholding technique also allowed for an accuracy assessment.

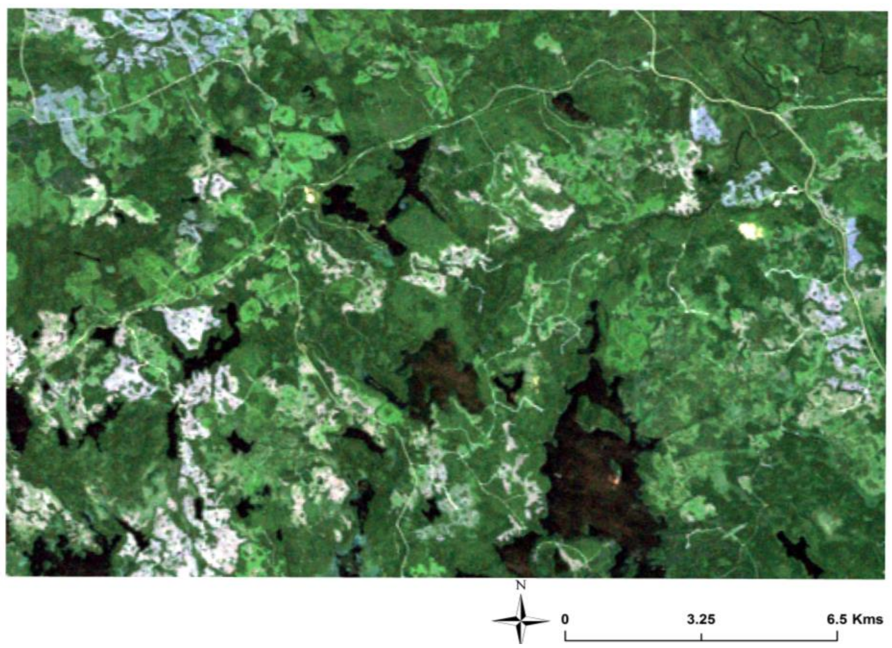


Figure 2.4a: Landsat 5 images used for the second phase of the project for method implementation on a one year interval after having conducted a supervised classification. The image was captured on August 21 2008.

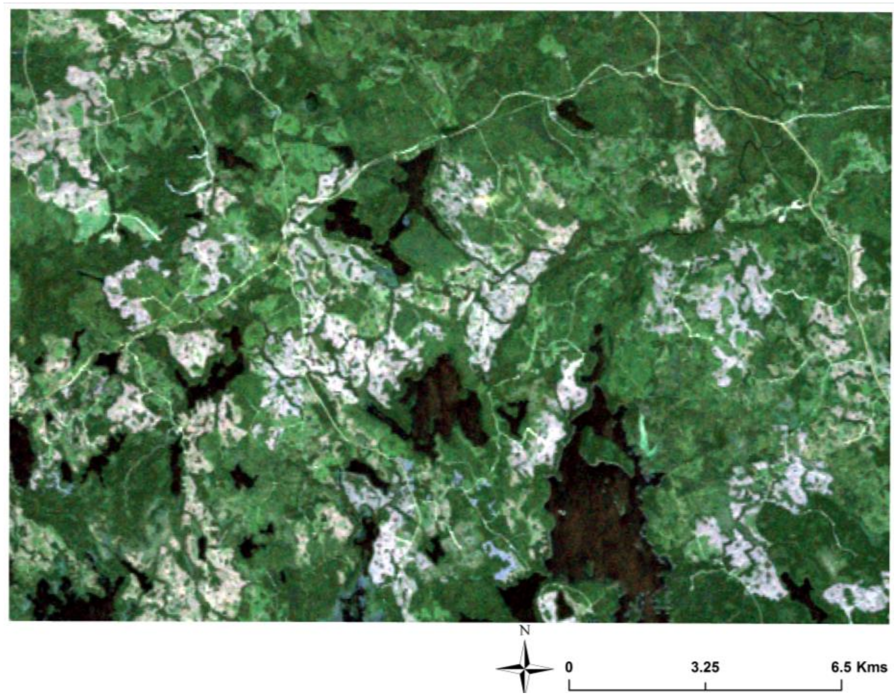


Figure 2.4b: Landsat 5 images used for the second phase of the project for method implementation on a one year interval after having conducted a supervised classification. The image was captured on September 9 2009.

2.5.4 KLAA

The application area was in the vicinity of Kelly Lake in the Halifax Regional Municipality and thus named the Kelly Lake Application Area (KLAA, see Figure 2.5a and 2.5b; 2.5c and 2.5d). This final area was used for applying the most accurate method on a multi-year basis, as determined by the first two phases. The resulting method was applied on a one-, three-, and nine-year time interval to determine the effects of an increased time gap on image accuracy. An IKONOS image with high resolution imagery, (see Figure 2.6) was also purchased for this location. This allowed for a more accurate accuracy assessment when using high resolution satellite image to determine which areas had been clearcut. Thresholding was also applied to the resulting images and an accuracy assessment was conducted.

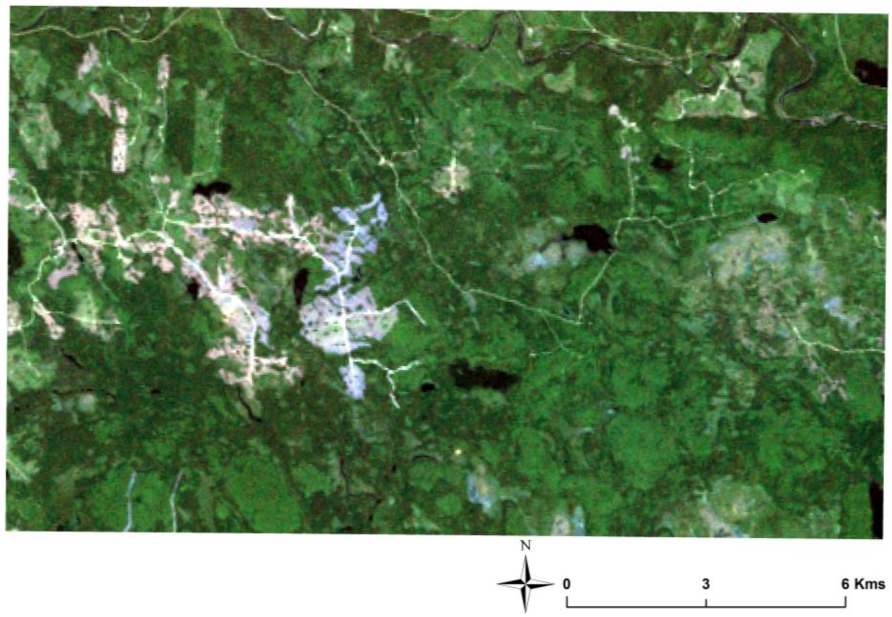


Figure 2.5a: Landsat 5 images used for the third phase of the project to determine the effects of an increased time interval on methods accuracy. The image was captured on August 10 1998.

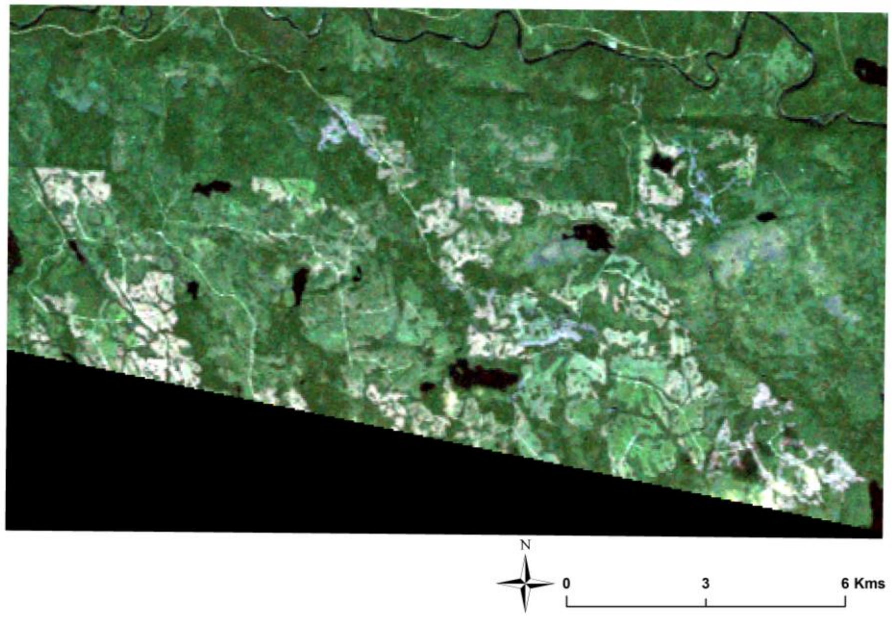


Figure 2.5b: Landsat 5 images used for the third phase of the project to determine the effects of an increased time interval on methods accuracy. The image was captured on September 27 2004.

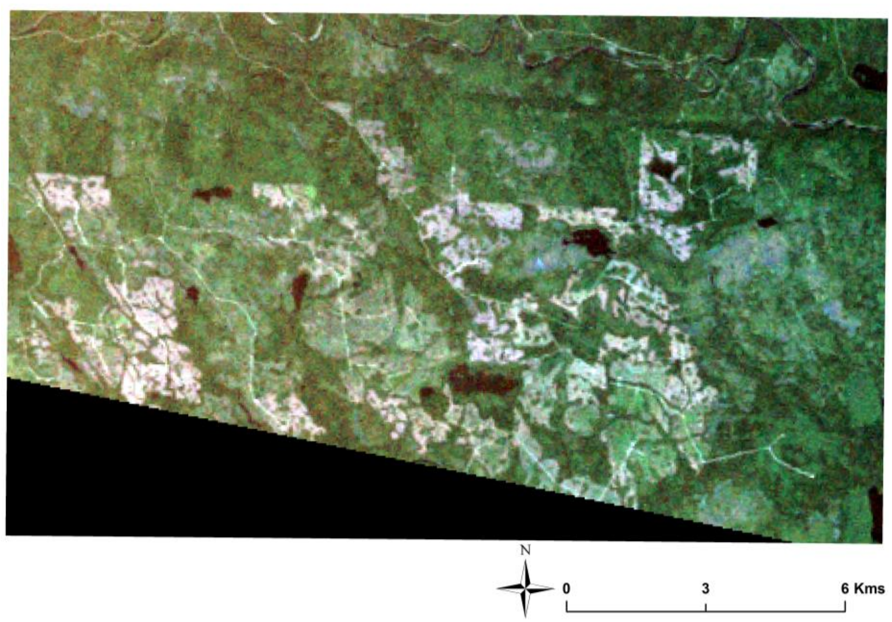


Figure 2.5c: Landsat 5 images used for the third phase of the project to determine the effects of an increased time interval on methods accuracy. The image was captured on September 17 2006.

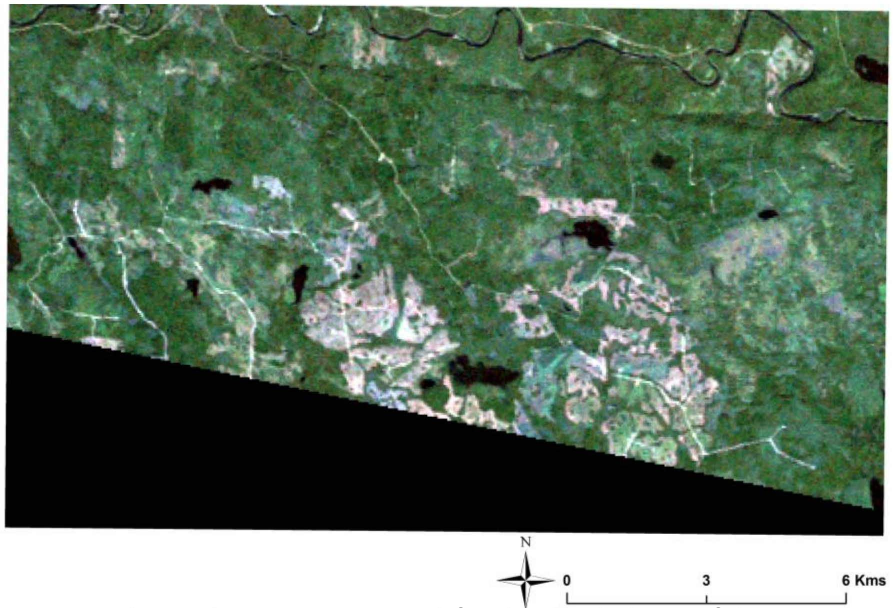


Figure 2.5d: Landsat 5 images used for the third phase of the project to determine the effects of an increased time interval on methods accuracy. The image was captured on September 20 2007.

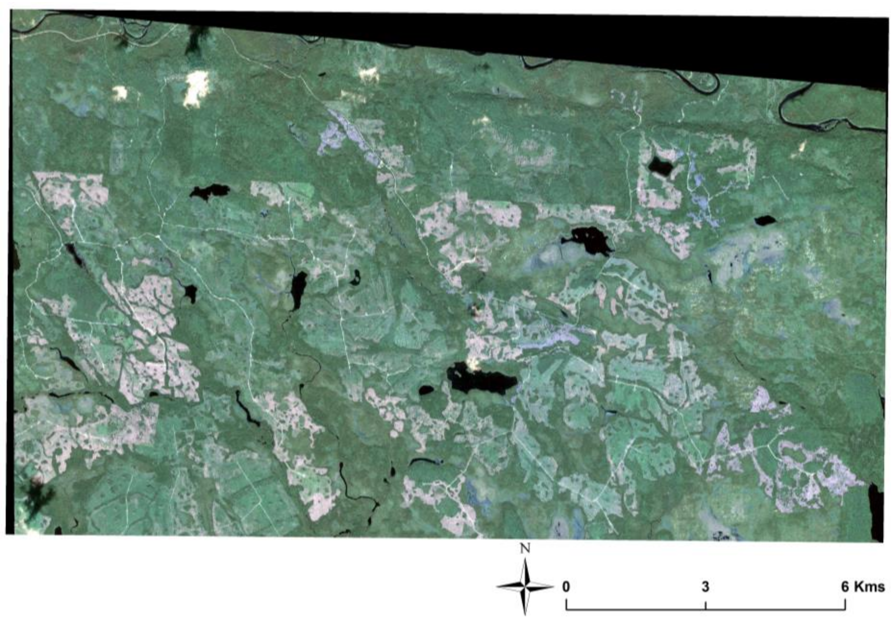


Figure 2.6: The 2007 IKONOS image used as confirmation for clearcut, no change and border cut areas during the third phase of the project. The image was capture on September 13 2007

CHAPTER 3

Methodology

3.1 Image Pre-processing

Prior to method implementation, each image underwent a pre-processing procedure. The images were converted from their digital numbers (DN) to original radiance values. DN values typically range between 0 and 255 based on the intensity of the pixel (Vincent, 1997). DN values are derived from original radiance values which are converted to produce a DN value for each specific image (Campbell, 2007). This produces a linear relationship between DN values and original radiance values. Using the following mathematical formula: $L_\lambda = \text{Grescale} \times DN_\lambda + \text{Brescale}$, the DN values are reconverted to the original radiance values. The Grescale is the band specific rescaling gain factor, the DN is the pixel value for each band, and the Brescale is the band specific rescaling bias factor (see Table 1). The value for both of these rescaling factors can be found online, or in the image records from where the image was acquired (Finn, Reed and Yamamoto, 2014).

Table 3.1: Values for Gain and Bias factors used for DN to radiance conversion.

	Images between March 1st 1984 to May 4 2003		Images between May 5 2003 to April 1 2007		Images between April 2 2007 to present	
	Gain	Bias	Gain	Bias	Gain	Bias
Band 1	0.6240964	-1.52	0.762824	-1.52	0.762824	-1.52
Band 2	1.17647059	-2.84	1.44251	-2.84	1.44251	-2.84
Band 3	0.80645161	-1.17	1.03988	-1.17	1.03988	-1.17
Band 4	0.81300813	-1.51	0.872588	-1.51	0.872588	-1.51
Band 5	0.10810811	-0.37	0.119882	0.37	0.119882	0.37
Band 7	0.05698006	0.15	0.065294	0.15	0.065294	0.15

3.2 Thresholding

After implementing the clearcut detection methods, a threshold was applied to highlight clearcut areas. The thresholding algorithm is found within the PCI Geomatica software that was used for this project. The thresholding algorithm contains two tabs: the first tab allows for the selection of the algorithm input and output, and the second tab, titled Input Params 1, is where the researcher can specify the maximum, minimum, and compliment for the thresholding technique. The minimum for each image, as well as the maximum, can be found by analyzing pixel values. When completed, the algorithm produced a bitmap which covered the areas that were specified by inputting minimum and maximum values. The resulting bitmap also aided in conducting the accuracy assessment.

3.3 Accuracy Assessment

An error matrix was produced for each image, which allowed for the accuracy assessment and accuracy comparison of methods. Random pixels were selected using a random number generator which produced a set of coordinates leading to individual pixels. The randomly selected pixels were assessed for one of three classes: clearcut (CC), no change (NC) and border cut (BC) (see Section 3.3.1). Each pixel was visually assessed and was deemed to belong to a specific class by use of the bitmap that was produced during the thresholding step. The pixels were either correctly or incorrectly identified depending on the visual classification of the researcher and the resulting bitmap. The pixels were then added to the proper category in the error matrix. Using a total of 100 pixels per category

(CC, NC, BC), the accuracy assessment was completed and the methods could be compared and ranked.

3.3.1 Clearcut (CC), No Change (NC) and Border Cut (BC) pixels

A CC pixel is defined as a pixel that indicated a forested area in previous years; however, in recent years is showing as clearcut (see Figure3.1). This indicated that the spectral signature of the pixel between the two image dates had changed drastically.

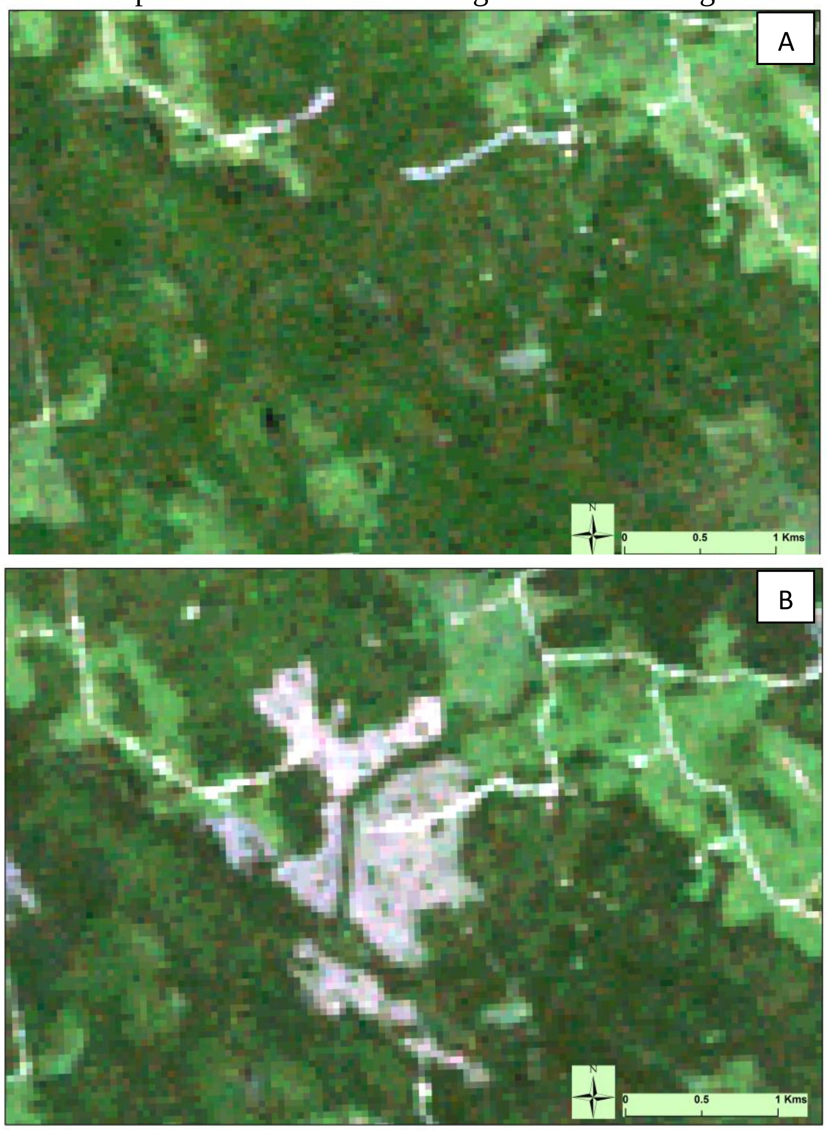


Figure 3.1: Landsat 5 images representing the transition of forested to clearcut areas. Image A represents a forested in 2004 and image B represents the same area which was clearcut in 2005.

A NC pixel is a pixel that shows forested in previous years and remained forested in the second year (see Figure 3.2). This indicated limited variation in spectral signatures between the two images.

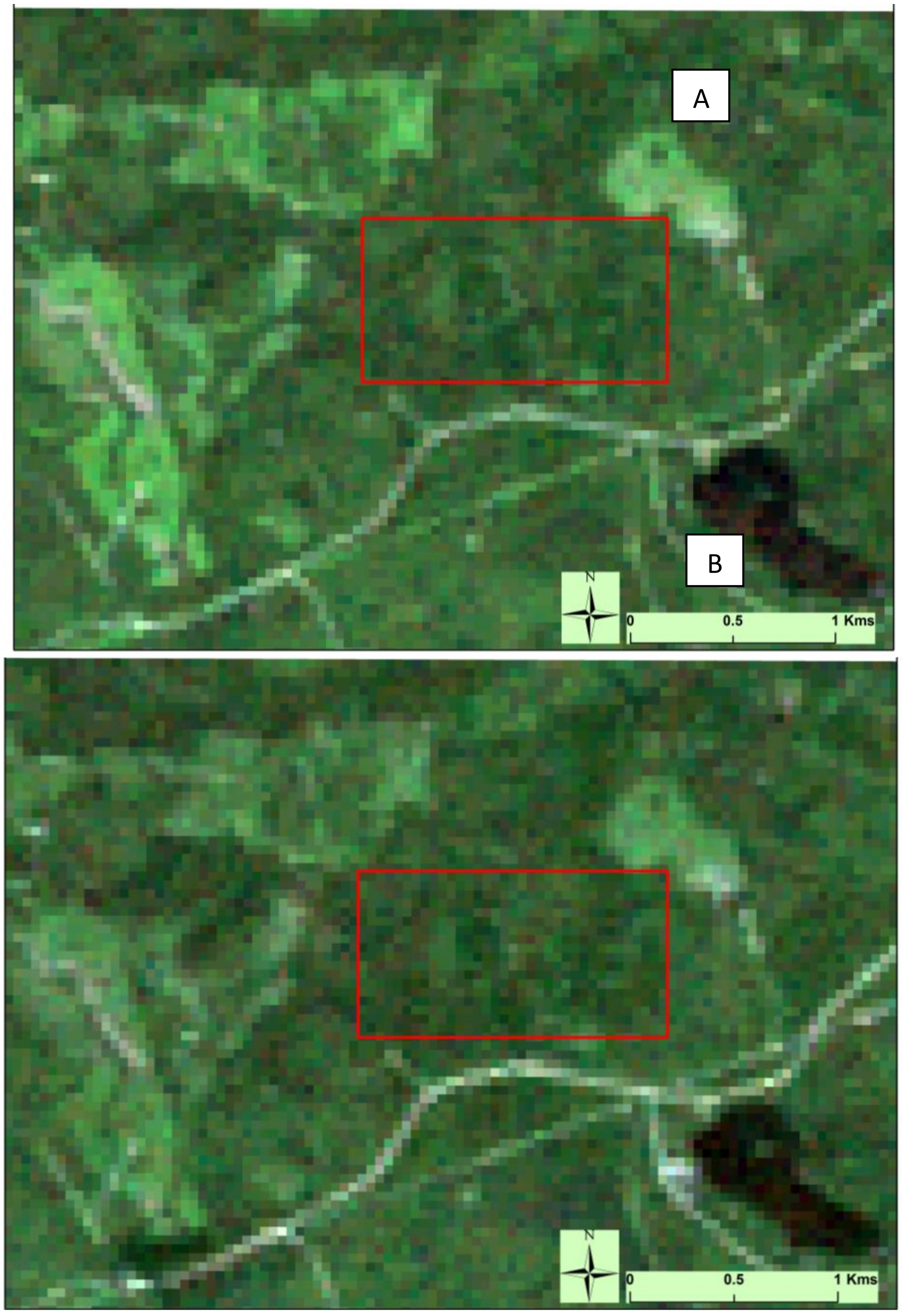


Figure 3.2: Landsat 5 images representing forested areas. Image A represents an area (in red) which was forested in 2008 and image B represents the same area (in red) in 2009 which was still forested.

A BC pixel is described as a pixel that is located on the edge of a forested and clearcut area (see Figure 3.3). These types of pixels were subjected to clearcut practices and are considered as CC for accuracy assessment purposes. The spectral signatures of BC resemble those of NC and CC pixels, and therefore, BC pixels will most likely be the deciding factor in choosing the most accurate method.

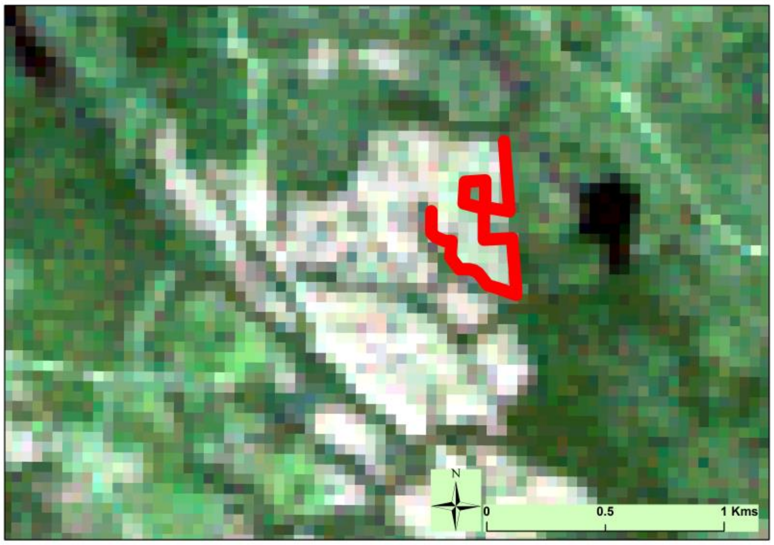


Figure 3.3: The image represents an area (red) which is considered as BC. These areas are found in all clearcut areas and will play an important role in method accuracy.

3.4 Description of Project Phases

Phase 1 and Phase 2 were used for the evaluation of the five selected methods (see Figure 3.4). These methods were then assessed based on their accuracies. Phase 2 however, implemented a supervised classification prior to method implementation with the goal of increasing the accuracy of the methods. Phase 3 was used to apply the most accurate method as determined by Phase 1 and Phase 2 (see Figure 3.4). Phase 3 also used a multi-year time interval between image dates to assess how the accuracy of the chosen method varied with an increased time interval between image dates (see Figure 3.4).

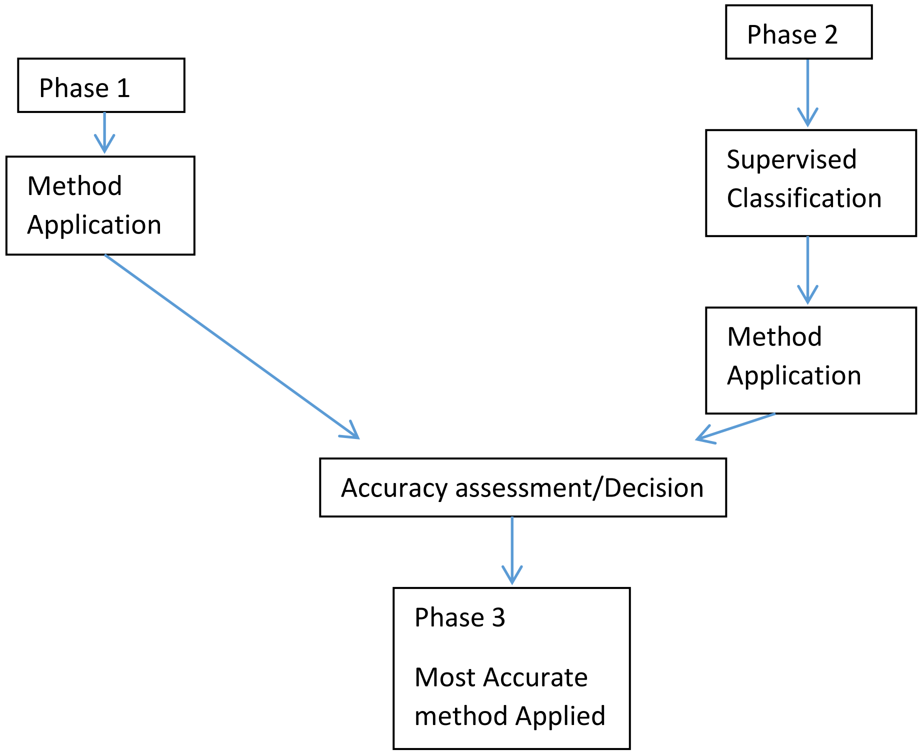


Figure 3.4: Flowchart depicting the main sequences of the multi-phase project.

3.5 Phase 1

Five methods were implemented and assessed for their accuracy during the first phase of the project. These five methods (see section 3.5.1- 3.5.5) were implemented using strict guidelines to produce the best results possible (see Figure 3.5). These methods were selected due to their prior used in clearcut and land cover change detection studies.

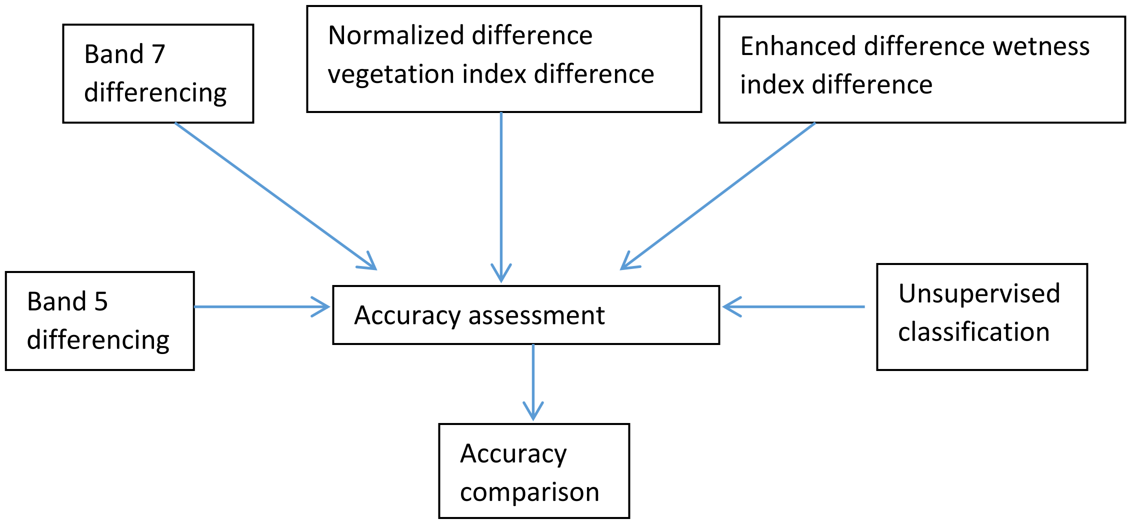


Figure 3.5: Flow chart depicting Phase 1 of the research project.

3.5.1 Band 5 Differencing (B5D)

Band 5 is a mid-infrared band that has the capacity to distinguish between water, forest lands and croplands (Quinn, 2001). Water bodies are represented in dark tones with croplands and grasslands in lighter tones. If Band 5 for one year is subtracted from band 5 from the second year, areas which were clearcut should appear on the resulting B5D image. To complete B5D, the 2004-2005 Landsat images were combined into one image. Band 5 from the 2004 image was subtracted from the 2005 band 5. The thresholding technique was applied with the minimum value used being 0.35 and no maximum value was specified.

3.5.2 Band 7 Differencing (B7D)

Band 7, a mid-infrared band, is capable of distinguishing between water and land. It can accurately detect regions with strong water abortion, rocky areas or soil regions (Quinn, 2001). This indicated that regions that have changed from forested to deforested are visible. Deforested regions have less capacity to hold moisture, whereas bare soil and rock have limited amounts of biomass in the image. For the purposes of this project, the 2004 and 2005 images were combined into a single file to conduct B7D. The 2004 image was subtracted from the 2005 image, which allowed for a result to be produced. The thresholding technique was applied with a minimum of 0.065 to the resulting image. No maximum value was specified and the accuracy assessment was conducted.

3.5.3 Normalized Difference Vegetation Index Differencing (NDVID)

The Normalized Differential Vegetation Index is a band ratio which uses band 3 (red wavelengths) and band 4 (near infrared wavelengths), to highlight the amount of vegetation in an image (Quinn, 2001). Areas of higher values have more biomass and areas of lower values have less biomass. If the NDVI for one year is calculated and the NDVI for a second year is also calculated, NDVI differencing can be conducted to highlight areas which have lost biomass. The algorithm used to calculate the NDVI was: (Band 4 – Band 3) / (Band 4 + Band 3). The NDVID was completed by combing the 2004 and 2005 images into the one image file; however, the NDVI for 2004 and 2005 were calculated separately. Once completed, the 2004 NDVI was subtracted from the 2005 NDVI producing the NDVID. The thresholding technique with a minimum value of -0.18 was applied and no maximum value was specified. The accuracy assessment was then conducted.

3.5.4 Enhanced Wetness Difference Index Differencing (EWDID)

The Enhanced Wetness Difference Index is a vegetation index that calculates the amount of moisture in a remotely sensed image (Yalte, 2007). The EWDI can also detect the amount of moisture change within an image. If the change in moisture is detected, values are positive, whereas no moisture change yields negative values. This indicated that areas that had changed from forested to clearcut had a positive change value due to the lack of vegetation that is needed to capture moisture. Bands 1, 2, 3, 4, 5, and 7 were used to calculate the amount of wetness change within an image along with a specialized mathematical formula. The formula to calculate the EWDI is: (0.1446*TM1) – (0.1761*TM2) – (0.3322*TM3) – (0.3396*TM4) – (0.621*TM5) – (0.4186*TM7) where TM1= Band 1, TM2= Band 2, etc. (Yalte, 2007). To complete EWDID, the Landsat images were combined into one image file. The first step was to calculate the EWDI for the 2004 and 2005 image using the aforementioned mathematical formula. When completed, the 2004 EWDI was subtracted from the 2005 EWDI, which creating the EWDID. The thresholding technique was applied with a minimum value of 5.22, as determined by visually analyzing the EWDID image, and no maximum value specified. The accuracy assessment was then conducted.

3.5.5 Unsupervised Classification (UC)

The unsupervised classification is a tool within PCI Geomatica that groups similar features with similar spectral signatures in the same classes. Using the built-in computer program, the iterations, the number of desired classes, and the type of classification to be run were specified. The Landsat images that were used were combined into one image file. The image bands 2, 3, 4, 5, 7 from both images dates were included in the unsupervised classification, and the ISODATA was the selected method. Several unsupervised classifications with different band combinations, itineration, classes, and classification types were conducted to determine which classification produced the highest visual accuracies. For this project, 32 classes were used, with an itineration value of 40. The classes which represented clearcut areas were combined to allow for the creation of a bitmap using the thresholding algorithm. The minimum value used for the thresholding algorithm was the corresponding class number, and once completed, the accuracy assessment was conducted.

3.6 Phase 2

The methods used in Phase 2 had the same parameters as those used in Phase 1 to confirm that the methods were applied consistently. The difference between Phase 1 and Phase 2 was the use of supervised classification prior to method implementation, and the values used to complete the thresholding (see figure 3.6).

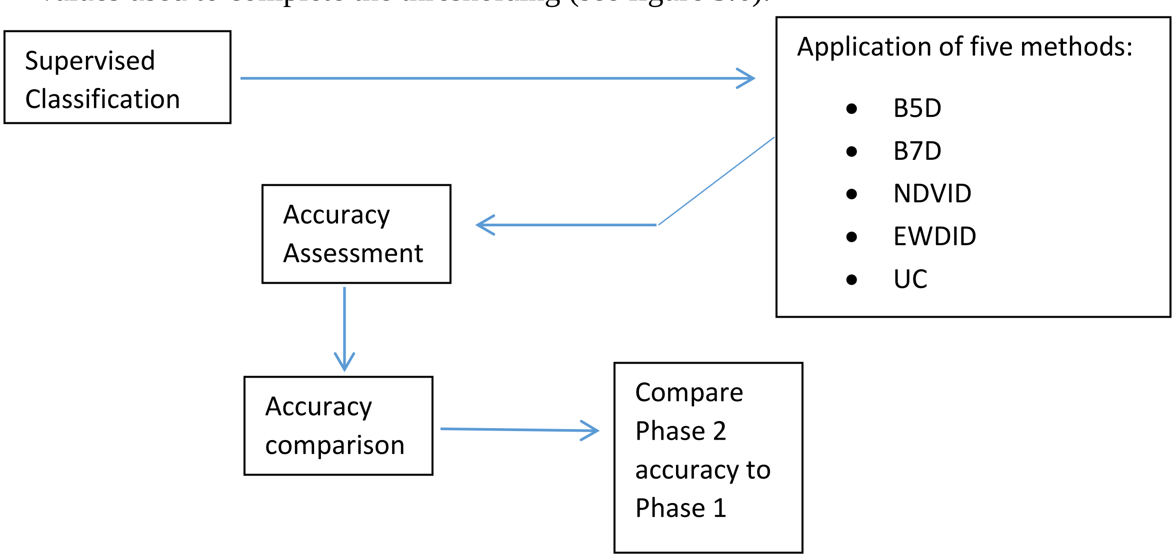


Figure 3.6: Flow chart depicting the main procedures in Phase 2.

3.6.1 Supervised Classification (SC)

The SC was completed on the 2008 image with the results being exported to the images files to be used during the second phase. The supervised classification used bands 2, 3, 4, 5, and 7 along with the creation of two classes. The two classes used for the SC were a deciduous forest class and a coniferous forest class with 600 training pixels for each class. The maximum likelihood classification with Null classes was selected as the preferred method. An accuracy assessment was conducted to ensure the SC produced accuracy no less than 85%. If the accuracy was below 85%, the supervised classification was altered by changing the selected training pixels, or the threshold values were altered. Once the classification reached the minimum of 85%, a bitmap was produced and exported to the second phase image files. Two bitmaps were required to properly cover the deciduous and coniferous forest classes. The purpose of the forest mask was to highlight areas that changed from forested to deforested, as well as eliminate areas that were bare, previously clearcut, or had water features.

3.6.2 Band 5 Differencing (B5D)

To complete B5D, the 2008 and 2009 images were combined into the same file along with the bitmap created during the SC. The band 5 from 2008 was subtracted from band 5 of the 2009 image with the supervised classification forest mask on. Using the B5D result image, a threshold was applied to the image to highlight clearcut areas. The minimum threshold value used was 3.0 with no maximum value indicated. An accuracy assessment was then conducted.

3.6.3 Band 7 Differencing (B7D)

B7D was completed by combining the 2008 and 2009 images in the same file along with the forest mask created prior to method implementation. The 2008 band 7 was subtracted from the 2009 band 7 using raster calculator with the supervised classification mask on. The thresholding technique was applied with a minimum value of 0.55 with no maximum value was used. An accuracy assessment was then conducted.

3.6.4 Normalized Difference Vegetation Index Differencing (NDVID)

The NDVID was completed by combining the 2008 and 2009 images into one file. The NDVI for each year was conducted using the mathematical formula: (%4 - %3)/(%4 + %3) where %4 represents bands 4 and %3 represents band 3. The NDVI was calculated for both images separately and when completed, the 2008 NDVI was subtracted from the 2009 NDVI with the forest mask on. Using a minimum value of -0.3 the thresholding technique was and an accuracy assessment was conducted.

3.6.5 Enhanced Wetness Difference Index Differencing (EWDID)

The EWDID was completed by combining the two images into one file. The EWDI for each image was calculated using the EWDI mathematical formula: (0.1446*%1) + (0.1761*%2) + (0.3322*%3) + (0.3396*%4) + (-0.621*%5) + (-0.4186*%7), where %1= band 1, %2= band 2, etc. Once the EWDI for each image date was calculated, the 2008 EWDI was subtracted from the 2009 EWDI with the forested mask on. The thresholding technique was applied to the image. To successfully highlight clearcut areas, two bitmaps were produced using the thresholding algorithm. The first bitmap had a value of 0.000001 whereas the second bitmap had a value of -0.90. The two bitmaps were combined using the BLO algorithm with the AND function activated. An accuracy assessment was then conducted.

3.6.6 Unsupervised Classification (UC)

The UC was completed by combining the 2008 and 2009 Landsat images into one image file. Bands 2, 3, 4, 5 and 7 from the 2008 and 2009 images were used as input channels. The ISODATA classification method was selected and the forested mask was turned on. Thirty-two classes were used and had an itineration value of 40. Once the classification was run and the resulting UC classification was analyzed. Three bitmaps were created to properly highlight the clearcut areas. The first bitmap had a minimum value of 4, the second had a minimum value of 7 and the final bitmap had a value of 10. Once completed the accuracy assessment was conducted.

3.7 Phase 3 Methods

The third and final phase of the project implemented the most accurate method as assessed by the first two phases. The images used for Phase 3 were captured in 1998, 2004, 2006 and 2007 (see Figure 3.7). All images were compared to the 2007 image since an IKONOS image was available for this date. This created a range of time gaps for the method to be tested, thus it assessed how the accuracy of the method varies over time. The method that was applied to the third phase used the same procedures as described above. For the thresholding technique, the one-year, three-year and nine-year time gaps had the same 0.5 minimum value for thresholding.

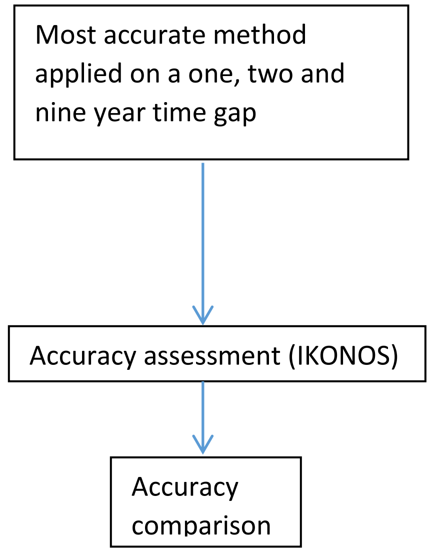


Figure 3.7: Flow chart depicting Phase 3.

CHAPTER 4

Results

Once the methods were implemented, each method underwent an accuracy assessment. The accuracy assessment would determine which method was the most accurate for clearcut detection in a remotely sensed image. An error matrix was developed for each method by using the bitmap created, along with the Landsat 5 image. One hundred pixels were used for each category. Once this was completed, the error matrices were analyzed and the most accurate method was selected for Phase 3.

4.1 Phase 1

4.1.1 Band 5 Differencing (B5D)

For Band 5 Differencing, 300 pixels were analyzed to determine the accuracy of the clearcut detection method (see Table 4.1). 100% of the CC pixels were classified as clearcut, and 100% of the NC pixels were correctly identified. 59% of the BC pixels were classified as CC and 41% of the BC pixels were classified as NC (see Figure 4.1).

Table 4.1*:* Error matrix demonstrating the 300 pixels which was classified during the accuracy assessment during B5D.

		Known	
		CC	NC
Classified as	CC	100	0
	NC	0	100
	BC	59	41

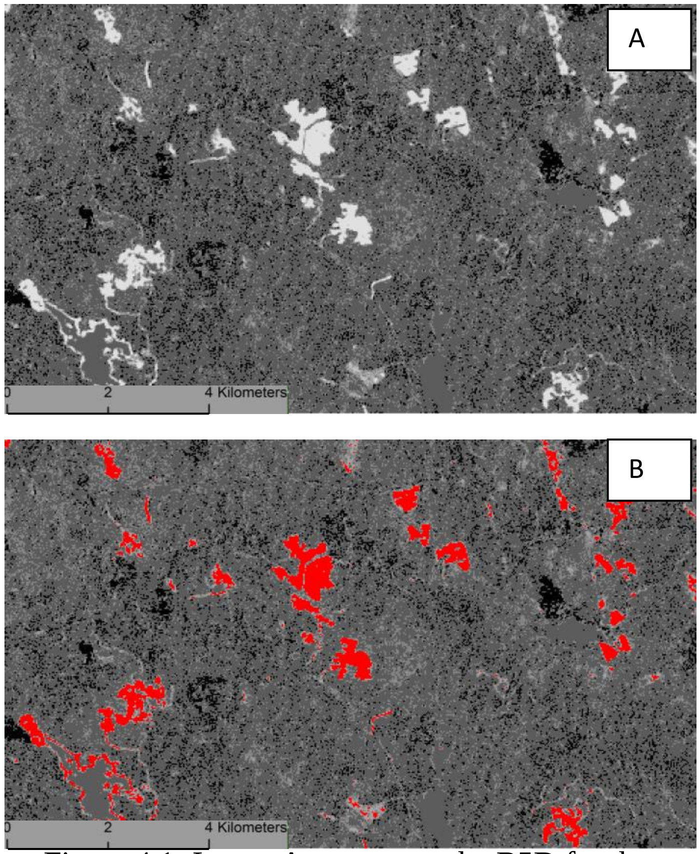


Figure 4.1: Image A represents the B5D for the 2004-2005 period. Image B demonstrates the coverage of the thresholding which was used to highlight clearcut areas.

4.1.2 Band 7 Differencing (B7D)

For Band 7 Differencing, 300 hundred pixels were also analyzed to determine the accuracy of the method (see Table 4.2). 100% of the CC pixels were classified as clearcut and 95% of the NC pixels were classified as NC. Five percent of the NC pixels were incorrectly identified as CC. 65% of the BC pixels were classified as CC and 35% of the BC pixels were classified as NC (see Figure 4.2).

Table 4.2*:* Error matrix demonstrating the 300 pixels which was classified during the accuracy assessment during B7D.

		Known	
		CC	NC
Classified as	CC	100	0
	NC	5	95
	BC	65	35

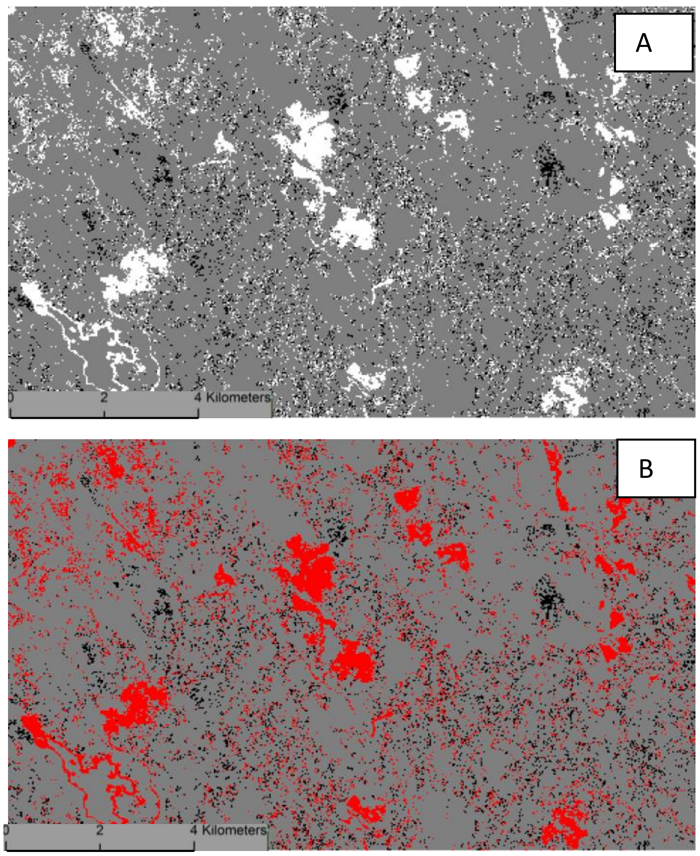


Figure 4.2 Image A representing the B7D for the 2004-2005 period. Image B demonstrates the coverage of the thresholding which was used to highlight clearcut areas.

4.1.3 Normalized Difference Vegetation Index Differencing

For the Normalized Difference Vegetation Index Differencing (NDVID), 90% of the CC pixels were identified as CC, with the remaining 10% being classified as NC (see

Table 4.3). As for the NC category, 99% of the pixels were correctly identified indicating that 1% of NC pixels were incorrectly identified as CC. The BC pixels are also classified in two groups. 36% of the BC pixels were correctly identified as CC and 64% were identified as NC (see Figure 4.3).

Table 4.3*:* Error matrix demonstrating the classification of the 300 pixels used for the accuracy assessment.

		Known	
		CC	NC
Classified as	CC	90	10
	NC	1	99
	BC	36	64

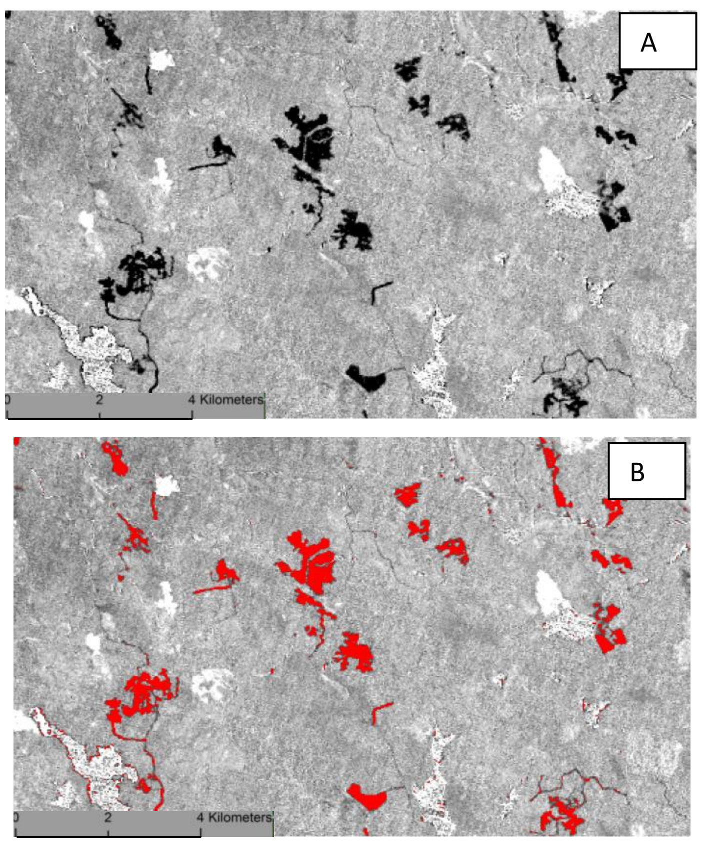


Figure 4.3: Image A is the NDVID results whereas image B is the coverage of the threshold which was used to highlight clearcut areas from 2004-2005.

4.1.4 Enhanced Wetness Difference Index Differencing (EWDID)

For the Enhanced Wetness Difference Index Difference, 96% of the CC pixels were correctly identified with the remaining 4% of the pixels identified as NC. The NC pixel category had an accuracy of 99% with 1% of the pixels identified as CC. 56% of the BC pixels were classified as NC and 44% identified as CC (see Table 4.4; Figure 4.4). .

Table 4.4: Accuracy assessment for the EWDID based on 300 pixels.

Classified as	Known CC	Known NC
CC	96	4
NC	1	99
BC	44	56

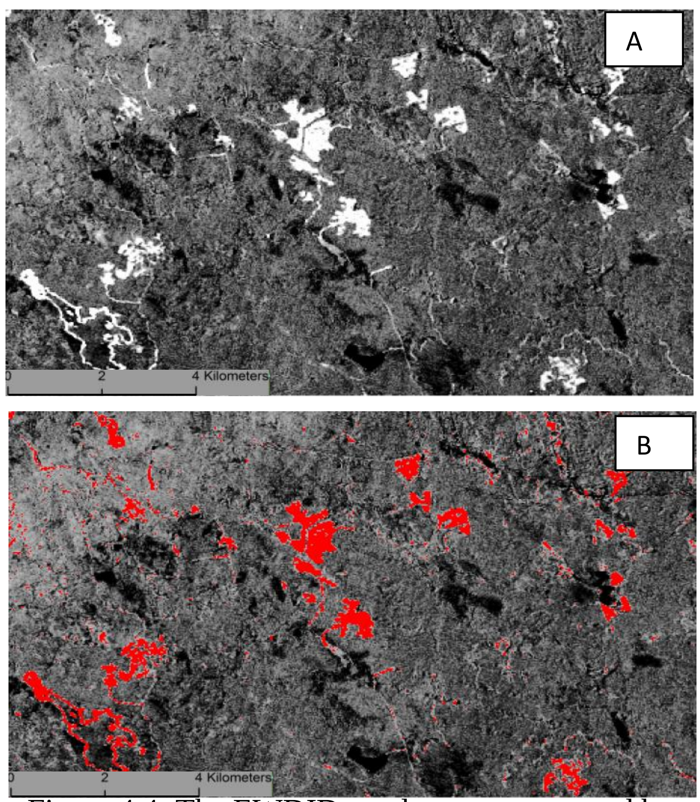


Figure 4.4: The EWDID results are represented by image A. Image B represents the results of the thresholding algorithm for the 2004-2005 periods.

4.1.5 Unsupervised Classification (UC)

For the unsupervised classification, 91% of the CC pixels were correctly identified and 100% of the NC pixels correctly identified. 9% of the CC pixels were identified as NC pixels (see table 4.5; Figure 4.5). As for the BC pixels, 88% were identified as NC and 12% as CC.

Table 4.5: Error matrix presenting the results for the unsupervised classification accuracy assessment.

		Known	
		CC	NC
Classified as	CC	91	9
	NC	0	100
	BC	12	88

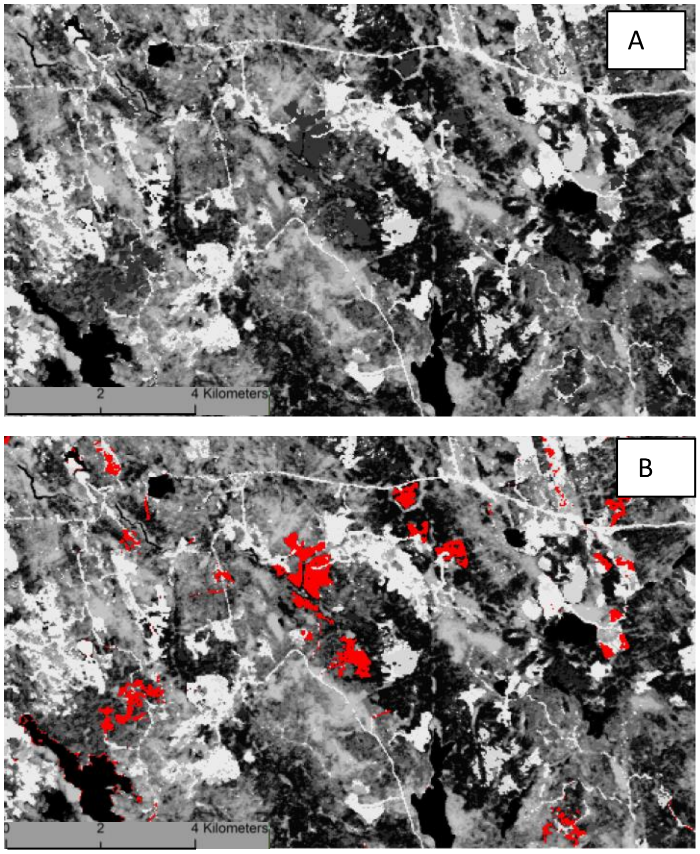


Figure 4.5: Image A represents the UC for the 2004-2005 period. Image B depicts the coverage of the thresholding conducted to highlight clearcut areas.

4.1.6 Determining Method with the Highest Accuracy

Having reviewed the data, the B5D method was determined to be the most accurate method for the first phase of the project. B5D had 100% accuracies for correctly identifying CC pixels (see Figure 4.6). The EWDID had and accuracy of 96% and the NDVID had an accuracy of 90%. The UC classification had an accuracy of 91% (see Figure 4.6). This indicates that the B5D and the B7D had the best accuracies for CC pixel detection at 100%.

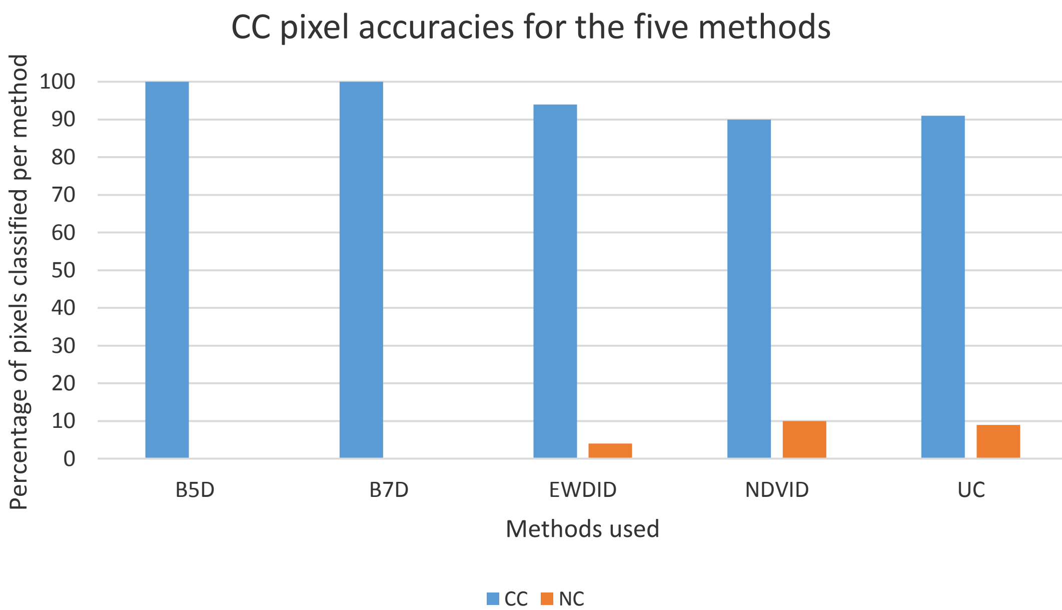


Figure 4.6: Graphical representation of CC pixels which was correctly identified versus incorrectly identified NC pixels for the five methods tested.

For the NC pixel category, B5D and UC both had accuracies of 100% whereas the NDVID and EWDID had accuracies of 99% (see figure 4.7). B7D had the lowest accuracy at 95%. This shows that B5D is still ranked the highest in comparison to the other four methods.

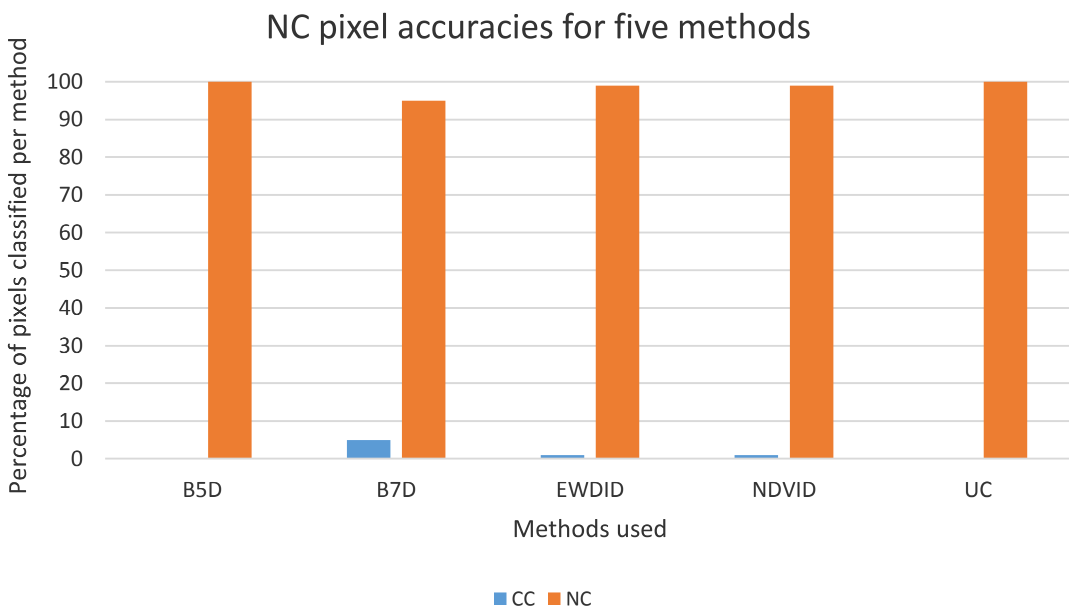


Figure 4.7: Graphical representation of NC pixels which was correctly identified versus incorrectly identified CC pixels for the five methods tested.

For BC pixel category, 59% of the BC pixels were correctly identified using the B5D method (see Figure 4.8). B7D had an accuracy of 65% therefore outperforming the B5D for in correctly identifying BC pixels. The EWDID method had an accuracy of 44% and the NDVID accuracy lower than 36%. The UC method had the lowest accuracy for correctly identifying BC pixels at 12%. After having reviewed all the data, B5D is ranked the highest method for Phase 1.

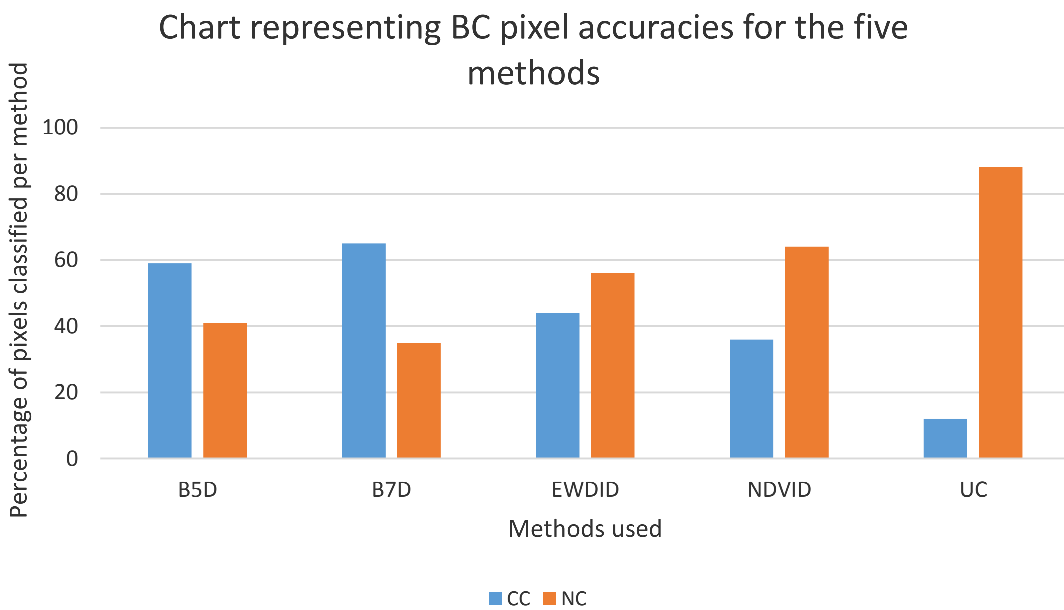


Figure 4.8: Graphical representation of BC pixels which was correctly identified versus incorrectly identified NC pixels for the five methods tested.

4.2 Phase 2

4.2.1 Supervised Classification

Prior to implementing the five methods in Phase 2, a supervised classification was conducted. The goal of the supervised classification is to increase the accuracy of the five methods. During the supervised classification, only forest regions were of interest; therefore, two forest classes were used: coniferous (F1) and deciduous (F2). By conducting the supervised classification in this manner, only regions that changed from forested to deforested were included. One hundred pixels for each category, totaling 200 pixels, were used to create the error matrix. For the F1 classification, 98% of the pixels were properly identified as F1. 93% of the F2 pixels were properly identified (see Table 4.6). The error matrix also demonstrated that 100% of the pixels that were not supposed to be classified were included in the Null class. With accuracies greater than 85%, the supervised classification was completed and the methods could be implemented.

Table 4.6*:* The error matrix for the supervised classification prior to method implementation

Classified as \ Known	F1	F2	Null
F1	98	1	1
F2	7	93	0
Null	0	0	100

4.2.2 Band 5 Differencing

After implementing B5D with the supervised classification, it was found that 100% of the pixels were correctly identified as CC (see Table 4.7). The same statistic holds true for the NC pixel category. 59% of the BC pixels were correctly identified as CC and 41% were incorrectly identified as NC (see Figure 4.9).

Table 4.7*:* Error matrix showing the distribution of pixels for B5D post supervised classification.

Classified as \ Known	CC	NC
CC	100	0
NC	0	100
BC	59	41

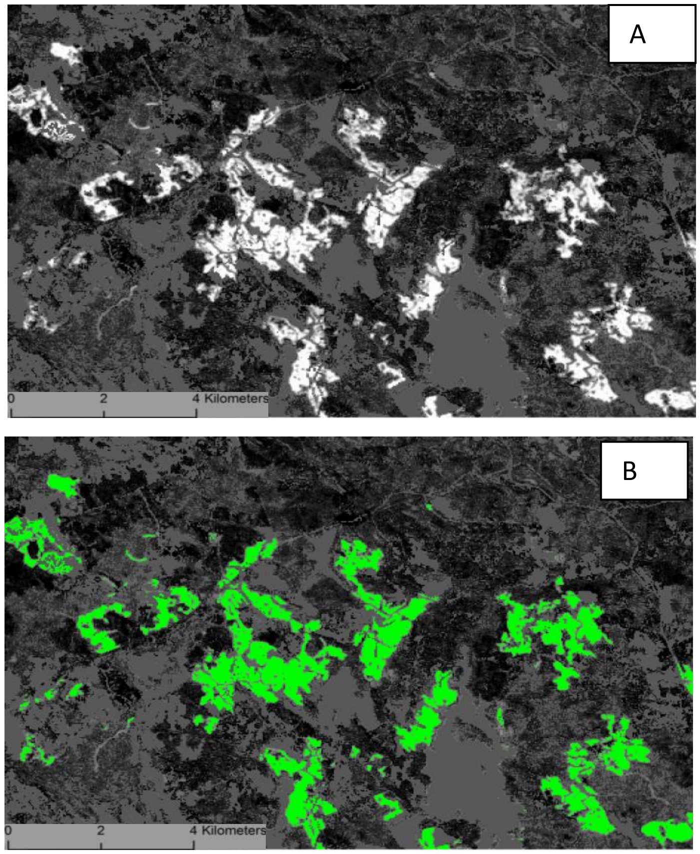


Figure 4.9: Image A depicts the results for the B5D post-classification for the 2008-2009 period. Image B is the coverage of the thresholding algorithm.

4.2.3 Band 7 Differencing

For B7D, 100% of the CC pixels were correctly identified as CC however, 99% of the NC pixels were correctly identified as NC (see Table 4.8). In terms of BC pixels, B7D post supervised classification had the highest accuracy at 95% of the pixels being correctly identified as CC. 5% of the BC pixels were incorrectly identified as NC pixels (see Figure 4.10).

Table 4.8*:* Error matrix for B7D as implemented in Phase 2.

		Known	
		CC	NC
Classified as	CC	100	0
	NC	1	99
	BC	95	5

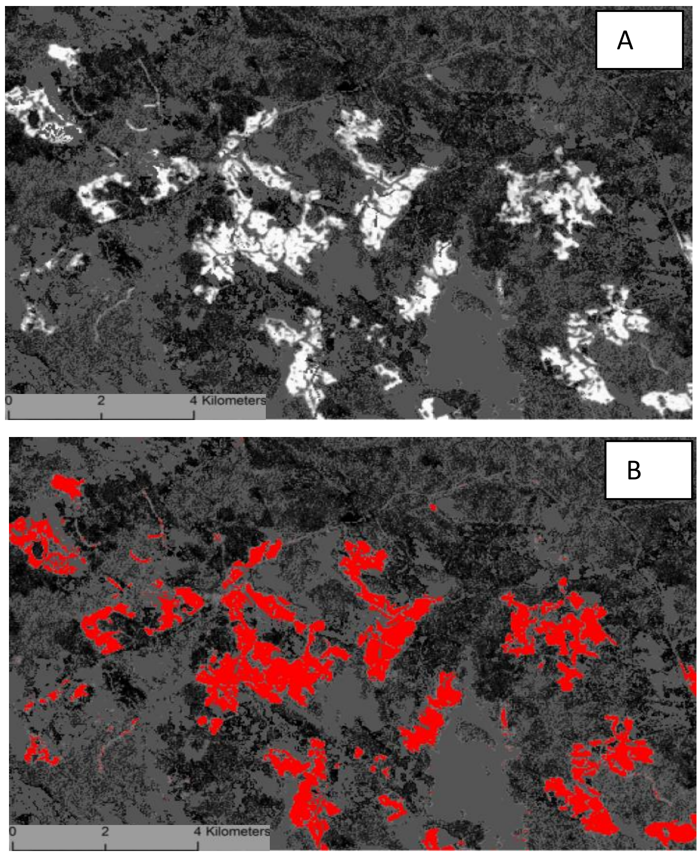


Figure 4.10: Image A represents the results for B7D for the 2008-2009 period. Image B represents the highlighted clearcut areas as detected by the thresholding technique.

4.2.4 Normalized Difference Vegetation Index Differencing

The NDVID for the second phase correctly identified 95% of the CC pixels and incorrectly identified 5% of CC pixels as NC (see Table 4.9). For the NC pixels category, 100% of the pixels were correctly identified as NC. 70% of the BC pixels were identified as NC and 30% of the pixels were correctly identified as CC (see Figure 4.11).

Table 4.9: Error matrix demonstrating the number of pixels classified per category for NDVID.

Classified as	Known CC	Known NC
CC	95	5
NC	0	100
BC	30	70

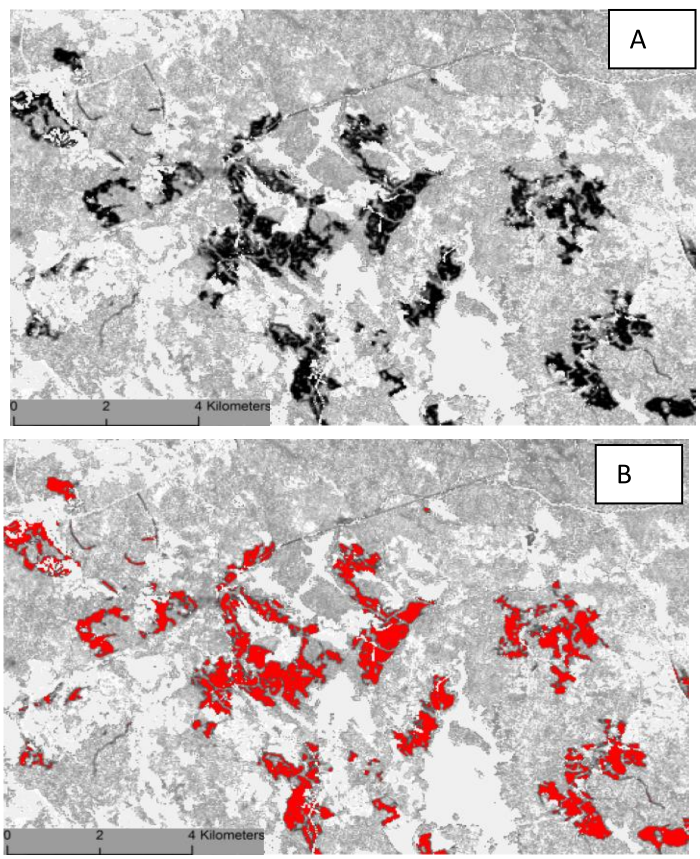


Figure 4.11: Image A represents the NDVID results for the 2008-2009 period while image B represents the applied thresholding used to highlight clearcut areas.

4.2.5 Enhanced Wetness Difference Index Differencing

The EWDID had 51% of the CC pixels correctly identified with 49% being incorrectly identified as NC (see Table 4.10). For the NC pixels, 91% of the NC pixels were correctly identified as NC and 9% were misidentified as CC. 22% of the BC pixels were appropriately identified as CC and 78% of the pixels were identified as CC (see Figure 4.12).

Table 4.10: Error matrix for the EWDID during the second phase.

		Known	
		CC	NC
Classified as	CC	51	49
	NC	9	91
	BC	22	78

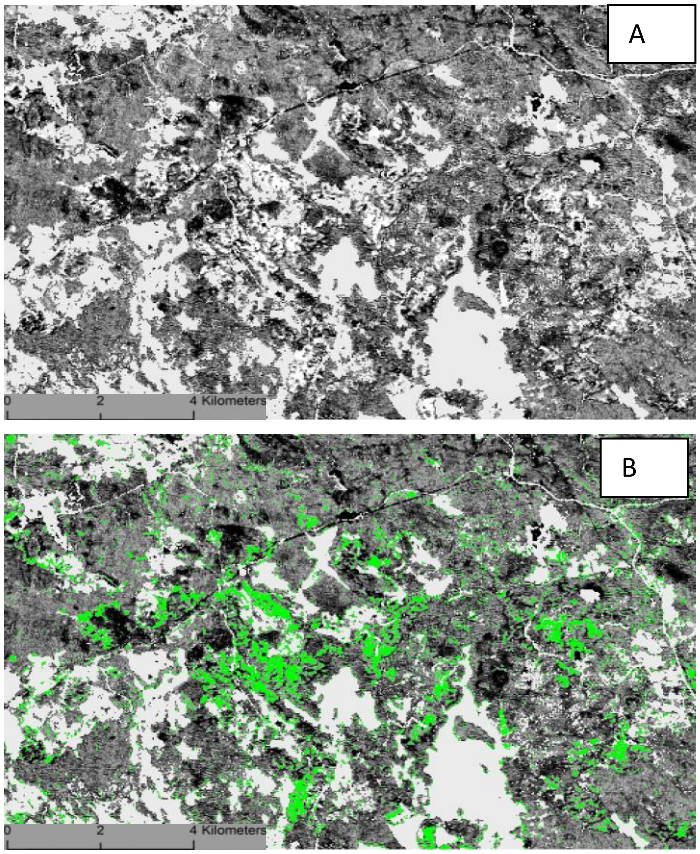


Figure 4.12: Image A is the EWDID results for the 2008-2009 period while image B represents the threshold used to highlight clearcut areas.

4.2.6 Unsupervised Classification

The UC for the second phase had 100% of the CC pixels correctly identified. These results are similar for the NC category, which had 100% of the pixels correctly identified (see Table 4.11). 54% of the BC pixels were identified as CC and 46% was identified as NC (see Figure 4.13).

Table 4.11: The UC error matrix for Phase 2.

Classified as		Known CC	Known NC
	CC	100	0
	NC	0	100
	BC	54	46

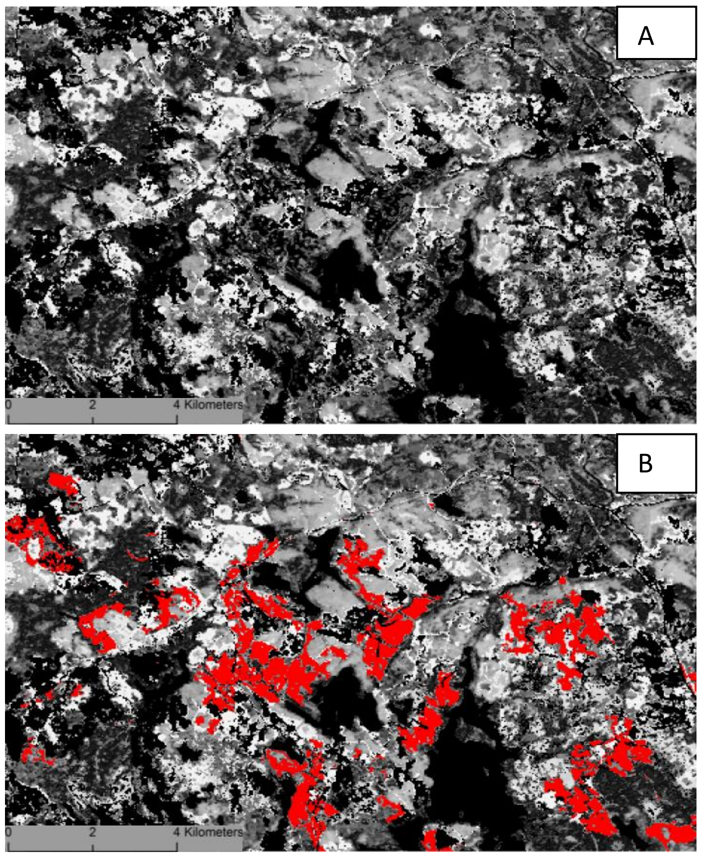


Figure 4.13: Image A is the UC results displayed in black and white for the 2008-2009 period. Image B represents the coverage of the thresholding algorithm used to highlight clearcut areas.

4.2.7 Determining Method with the Highest Accuracy

B5D, B7D and the UC all had accuracies of 100% for correctly identifying CC pixels. The EWDID had the lowest accuracy, and correctly identified 51% of the pixels (see Figure 4.13). Since the EWDID was not accurate in Phase 1 and Phase 2, it cannot be used in Phase 3.

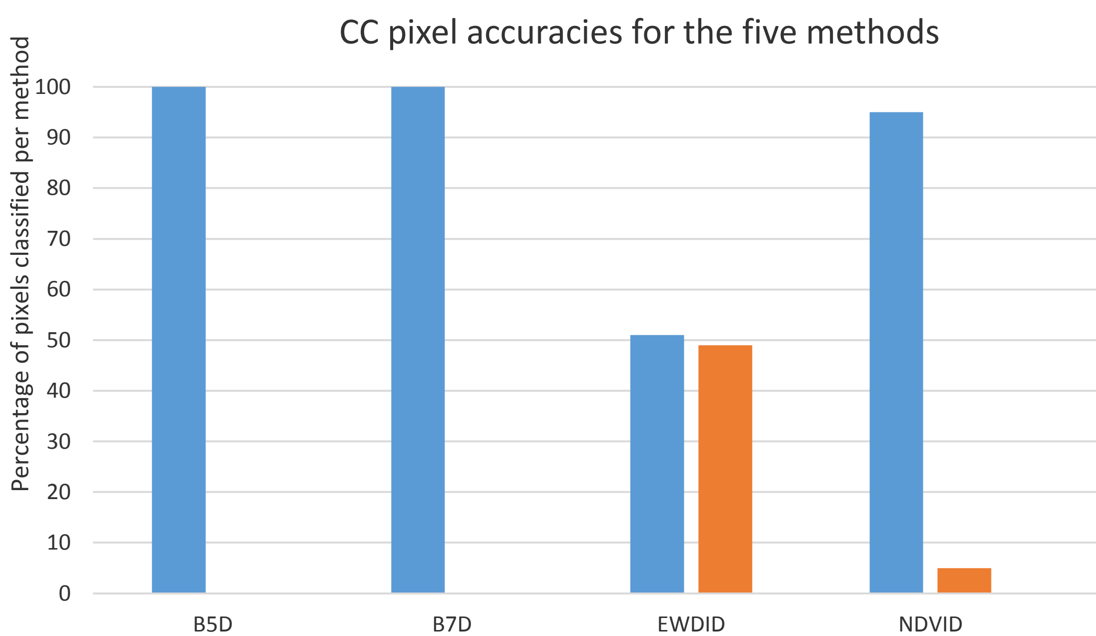


Figure 4.14: Graphical representation of CC pixels which was correctly identified versus incorrectly identified NC pixels for the five methods tested.

B5D, NDVID and the UC had accuracies of 100% and correctly identified NC pixels. B7D had an accuracy of 99%, whereas the EWDID had and accuracy of 91% (see Figure 4.15). The low result for identifying NC pixels for the EWDID confirms the removal of the method for Phase 3.

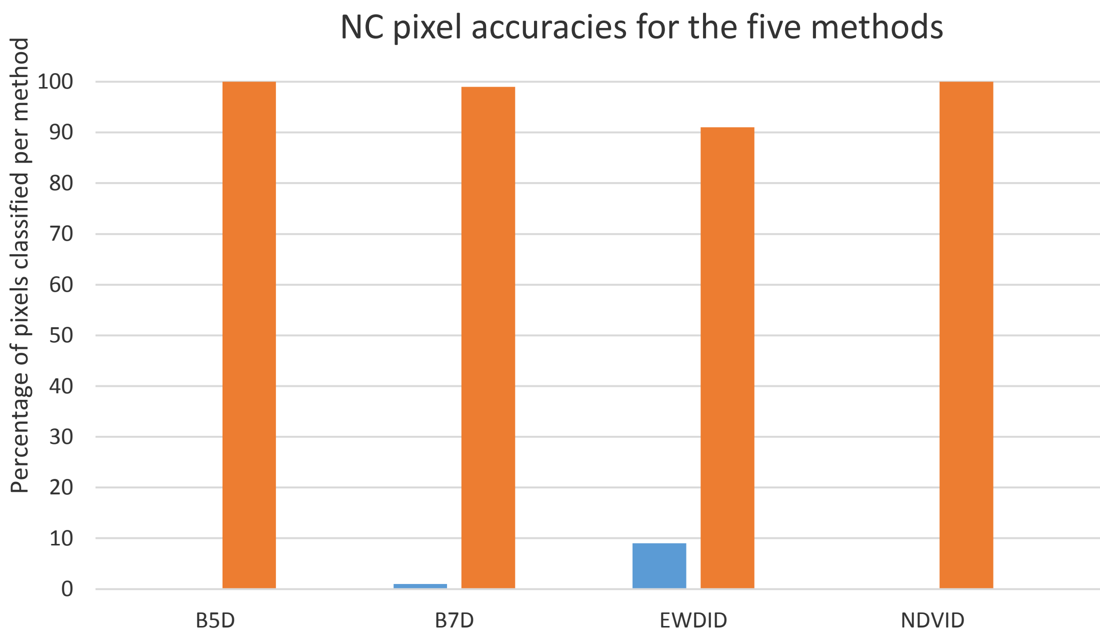


Figure 4.15: Graphical representation of CC pixels which was correctly identified versus incorrectly identified pixels for the five methods tested.

B5D had an accuracy of 59% for correctly identifying BC pixels (see Figure 4.16). B7D had the highest accuracy at 95% and the EWDID had the lowest accuracy at 22%. The NDVID had an accuracy of 30% for correctly identifying BC pixels. The UC had the third highest accuracy for BC pixel detection at 54%.

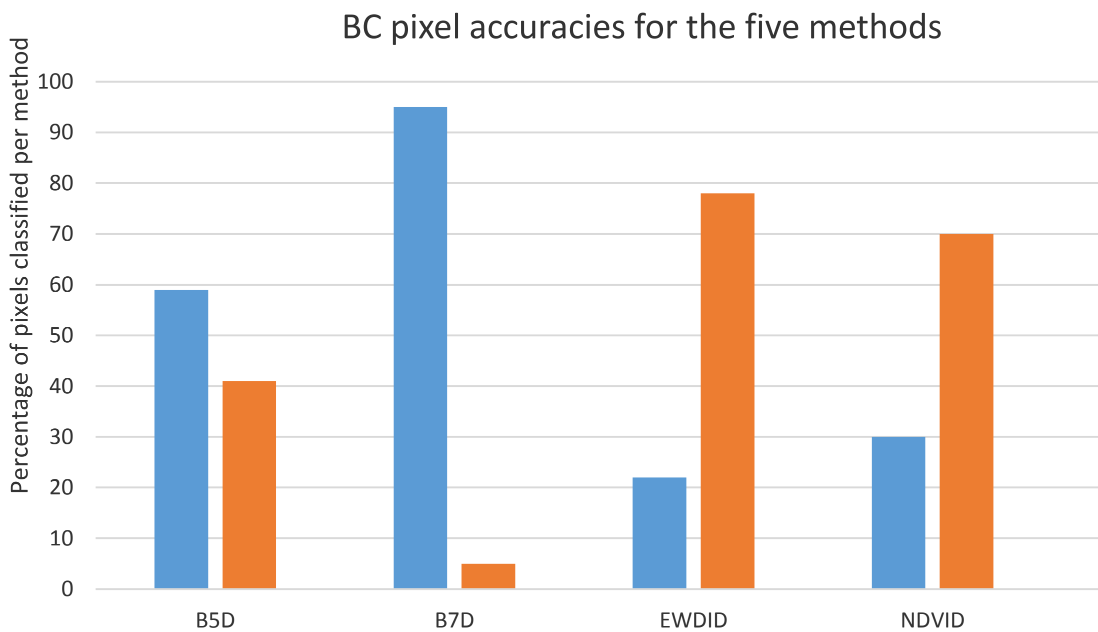


Figure 4.16: Graphical representation of BC pixels which was correctly identified versus incorrectly identified pixels for the five methods tested.

After analyzing all methods from Phase 1 and Phase 2, it was determined that B7D, with prior supervised classification, was the most accurate method. This method does have a misclassified pixel; however, it also had the highest accuracy for BC pixels. Due to the significant different between B7D post-classification, and the second highest ranking method for BC pixels accuracy, B7D post-classification was selected to be used during the third phase of the project.

4.3 Phase 3

4.3.1 Supervised Classification

Due to B7D post-classification being selected as the highest ranking clearcut detection method, a supervised classification was conducted for the multi-year phase of the project. A supervised classification was conducted for the one-, three-, and nine year interval. During the supervised classification, only forest regions were of interest; therefore, two forest classes were used during the supervised classification: coniferous (F1) and deciduous (F2).. By conducting the supervised classification in this manner, only regions which were subjected to clearcut would be highlighted during method implementation.

4.3.2 One-Year Time Interval

The one-year time interval supervised classification had accuracies of 97% for F1 and 98% for F2 forest categories (see Table 4.12). This indicates that 3% of the F1 class was misclassified as F2 pixels. 2% of the F2 pixels were classified in the F1 category. These accuracies produced by the supervised classification were accurate enough to implement B7D post-classification on the one-year time interval image.

Table 4.12: Error matrix for the one-year supervised classification.

Classified as	Known F1	Known F2
F1	97	3
F2	2	98

4.3.3 Three-Year Time Interval

The three-year time interval supervised classification had accuracies of 94% for the F1 class and 99% for F2 forest category (see Table 4.13). This indicates that 6% of the F1 forest pixels were classified as F2 and 1% of the F2 pixels were classified as F1. The 94%

accuracy was high enough to proceed to method implementation for the B7D post-classification on a three year interval image.

Table 4.13: Error matrix for the three-year supervised classification

Classified as	Known F1	Known F2
F1	94	6
F2	1	99

4.3.4 Nine-Year Time Interval

The nine-year supervised classification had accuracies of 94% for F1 class and 95% for F2 forest class (see Table 4.14). 6% of the F1 forest pixels were classified as F2 and 5% of the F2 pixels were classified as F1. These accuracies were greater than the 85% required, indicating the B7D post-classification method could be implemented.

Table 4.14: Error matrix for the nine-year supervised classification

Classified as	Known F1	Known F2
F1	94	6
F2	5	95

4.4 Band 7 Differencing with IKONOS Verification

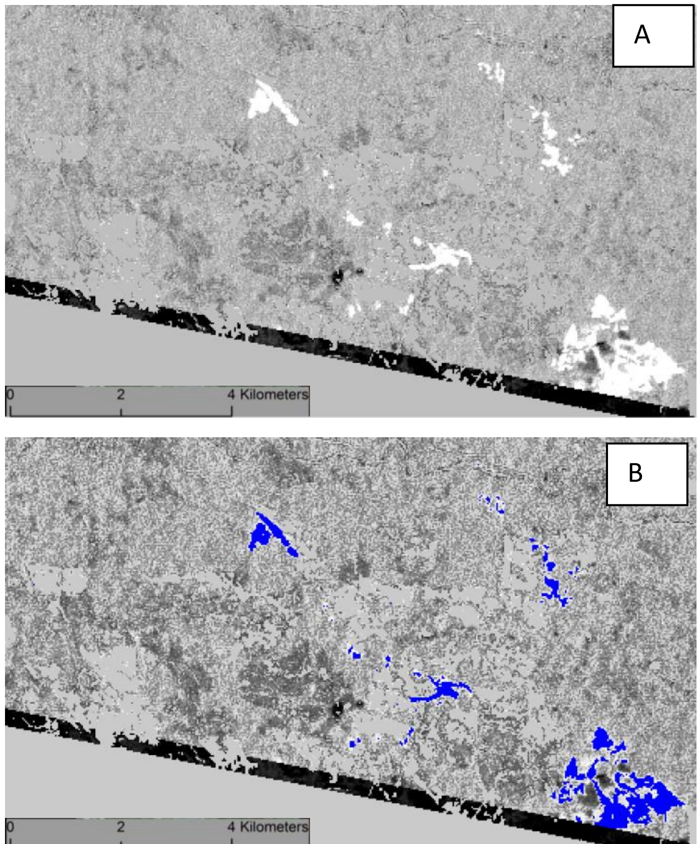
Once the supervised classification was completed for each image interval, B7D post-classification could be implemented. For the accuracy assessment, an IKONOS image was used to determine if the clearcut detection method properly identified CC, NC and BC pixels.

4.4.1 B7D One-Year Time Interval

For the B7D on a one year interval, 95% of CC pixels were correctly identified and 100% of the NC pixels were also correctly identified (see Table 4.15). 5% of the CC pixels were misidentified as NC pixels. As for BC pixels, 87% of the pixels were correctly identified as CC indicating that 13% of these pixels were misidentified as NC pixels (see Figure 4.17).

Table 4.15: The error matrix for a one-year interval after having conducted B7D post supervised classification.

		Known	
		CC	NC
Classified as	CC	95	5
	NC	0	100
	BC	87	13



classification results for the 2006-2007 period. Image B demonstrates coverage of the thresholding which was used to highlight clearcut areas.

4.4.2 B7D Three-Year Time Interval

B7D applied to images with a three year interval produced accuracies of 100% for the CC category. As for the NC class, 99% of the pixels were correctly identified (see Table 4.16). 1% of the NC pixels were identified as CC. The BC category had an accuracy of 83% indicating that 17% of the pixels were misidentified as NC pixels (see Figure 4.18).

Table 4.16: Error matrix for the B7D post-classification for a three year interval.

Classified as		Known CC	Known NC
	CC	100	0
	NC	1	99
	BC	83	17

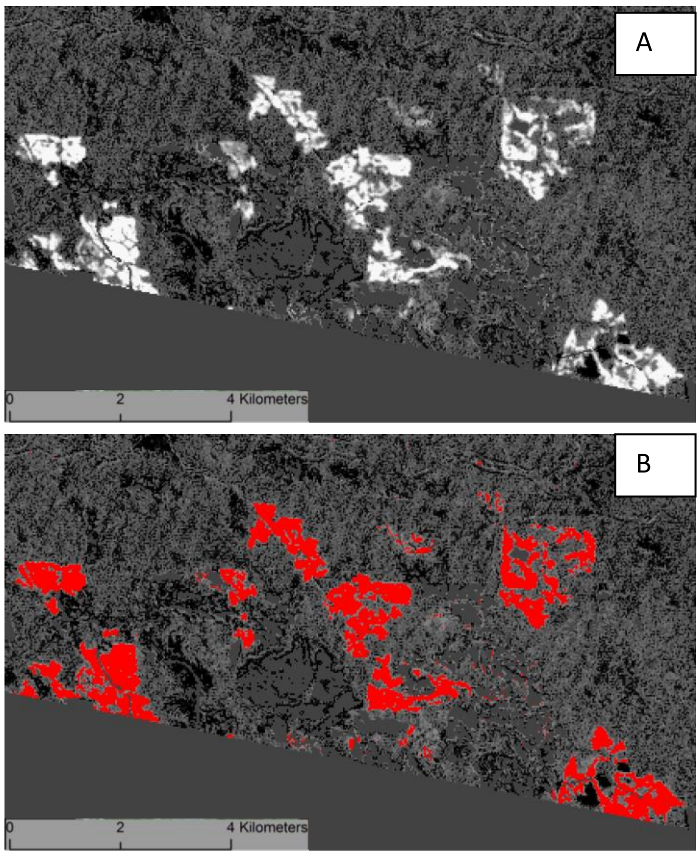


Figure 4.18: Image A represents the B7D post-classification results for the 2004-2007 period. Image B depicts the coverage of the thresholding which was used to highlight clearcut areas.

4.4.3 B7D Nine-Year Time Interval

The application of B7D on a nine-year interval produced accuracies of 95% for the CC category and 99% for the NC category (see Table 4.17). 1% of the NC pixels were identified as CC and 5% of the CC pixels were identified as NC. 80% of the BC pixels were correctly identified indicating that 20% of these pixels were misidentified as NC pixels (see Figure 4.19).

Table 4.17*:* Error matrix for the B7D post-classification for a nine-year interval.

		Known	
		CC	NC
Classified as	CC	95	5
	NC	1	99
	BC	80	20

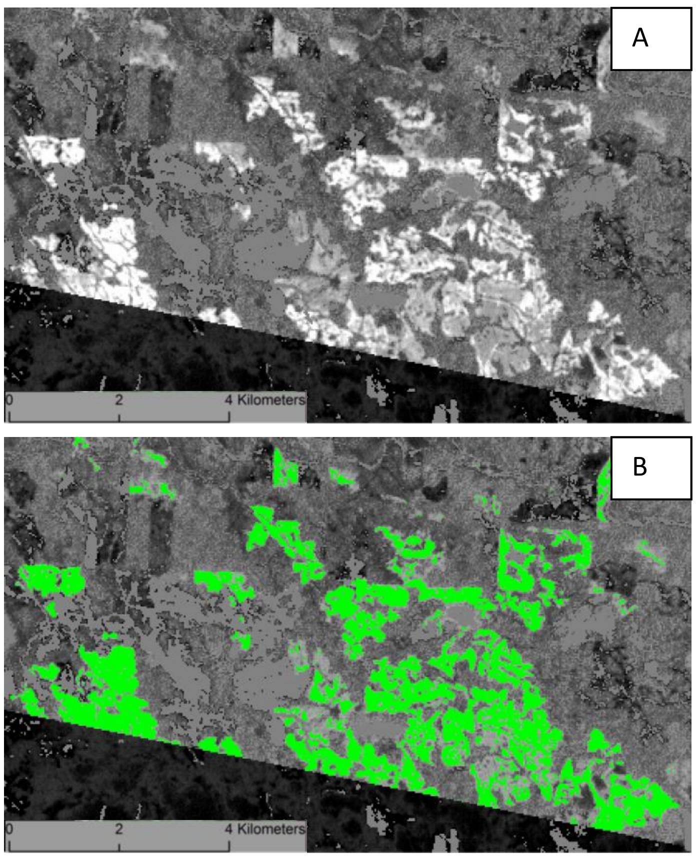


Figure 4.19: Image A depicts the B7D post-classification for the 1998-2007 period. Image B demonstrates the coverage of thresholding used to highlight clearcut areas.

CHAPTER 5
Discussion

5.1 Analysis of Phase 1

B5D was a successful method for clearcut detection with the majority of the CC and NC pixels being correctly classified; however, the BC pixel accuracy was lower than 60%. Since border pixels were subjected to clearcutting, the pixels should have been identified when the thresholding technique was applied. This would show that the BC pixels, which were analyzed during the B5D during the first phase, were not influenced by clearcutting to alter the pixel value for it to be identified as CC.

Similar statistics hold true for B7D, as 100% of the CC and 95% of the NC pixels were correctly identified. The 5% misclassified NC pixels may have been caused by different reasons. Band 7 can detect strong water absorption and soil/rock reflectance (Quinn, 2001); therefore, 5% of the misclassified pixels may have varied in moisture (water). This could indicate the presence of rain prior to the image being captured in 2004, or the 2005 image could have been captured during a dry spell in the province. A dry spell would indicate the presence of less vegetation in the pixel in comparison to the previous year. Since the pixels are 30 meters by 30 meters, it is possible that clearcutting did take place, however the quantity was not significant enough to change the visual appearance of the pixel. Sixty-five percent of the BC pixels were correctly identified as CC; however, 35% of the pixels were misidentified.

The NDVID produced 90% accuracy for the CC pixel category. This indicated that 10% of the pixels were identified as NC pixels. The misidentification of the CC pixels could derive from the mathematical formula which is used to calculate the NDVI. The pigment (absorbs) and the structure of the leaves (reflect) can have an effect on the amount of electromagnetic radiation which is absorbed or reflected by vegetation (Sader, Bertrand and Wilson, 2000). Using the NDVI mathematical formula produces values that range from (-1) to (+1). These values determine whether or not an area has vegetation or no vegetation. Since the NDVI functions on leaf structure and leaf pigment, it is possible that the temperature at the time the images were captured may have varied. Leaf colour and moisture content causing a discoloration or distortion in the leaves. These changes can affect the vegetation in the image; however, it should not have affected 10% of the misclassified pixels. The NDVID correctly identified 36% of the BC pixels as CC and 64% of them were incorrectly classified as NC. This could indicated that the pigment and structure of the leaves resemble those of a fully vegetated pixel.

The EWDID was also highly accurate in terms of correctly identifying CC and NC with accuracies of 96% and 99%. The misclassified 4% of CC pixels could be caused due to a decrease in moisture for those pixels. Overall, CC pixels may have a limited amount of moisture caused by the lack of vegetation and are therefore easy to identify. The CC pixels which were classified as NC could be caused by these pixels having less than average wetness. This lack of moisture may be produced by a dry spell in the region or, as in the previous method, the pixel could have been subject to deforestation; however, the quantity of trees removed would have been minimal and thus not influenced the pixel signature. The EWDID misclassified 56% of the BC pixels as NC pixels. This could indicate that these pixels have the same wetness values as a forested pixel meaning precipitation could have occurred prior to the image being captured. This would lead to clearcut areas showing higher amounts of moisture present, and therefore, false wetness readings were provided. Due to BC pixels being on the fringe of NC and CC areas, the pixels can easily be misidentified by the clearcut detection method.

The final method tested for Phase 1 was the UC. This method correctly identified 91% of CC pixels and 100% of NC pixels. Nine percent of the CC pixels were misclassified. These misclassified pixels could have been a result of similar spectral values between CC pixels and NC pixels. The UC had the lowest BC accuracy with 12%. This means 88% of the pixels were misclassified. These border pixels would have been misclassified since the determined that their spectral signatures were similar to NC pixels. Since multiple bitmaps were used to highlight CC areas, it is possible that BC pixels may have been omitted from the clearcut classification resulting in the low accuracy.

5.2 Analysis of Phase 2

During the second phase, all five methods were re-applied to the second evaluation area post supervised classification. The goal of the supervised classification was to increase the accuracy of each method. Therefore a supervised classification was conducted on the forested areas to increase the overall accuracy of the implemented methods.

In the case of B5D post-classification, the CC and NC pixel accuracies were 100% indicating that B5D post-classification produces highly accurate results. The BC pixels were correctly identified 59% of the time. These results were the same as in Phase 1. This would indicate that B5D is a reliable method for CC and NC pixels. As for BC pixels, B5D is not a reliable method as it incorrectly identified 41% of the BC pixels. These pixels could have been misidentified for the same reasons as indicated in Phase 1. For example, the BC pixels may not have suffered enough clearcutting to significantly alter the spectral signature when differencing was conducted. This means BC pixels would have a closer spectral signature to NC pixels causing the misidentification.

As for the B7D, 100% of the CC pixels were correctly identified and 99% of the NC pixels were properly identified. The 1% of NC pixels that were misidentified could have been caused by the spectral similarity between the pixel and the CC pixels. The BC pixels were correctly identified 95% of the time. This was the highest BC accuracy amongst all the results. For this reason B7D post-classification was used during Phase 3. The 5% incorrectly identified pixels for B7D could have been caused by the similar spectral values between those pixels and NC pixels. These BC pixels could have suffered less from clearcutting therefore having similar spectral values to forested pixels. The B7D post-classification has higher accuracy in terms of properly identified NC pixels and a higher number of properly identified BC pixels in comparison to the same methods implemented in Phase 1.

The third method tested during Phase 2 was the NDVID. This method produced accuracies of 95% for CC pixels and 100% for NC pixels. In comparison to the NDVID results in Phase 1, the CC accuracy increased by 5% and the NC accuracy increased by 1%. The BC was less accurate for CC at 30%. The BC pixels that were identified as CC decreased by 6% and the NC pixels increased by 6%. The NDVI ratio functions on the amount of vegetation in a pixel. If a pixel was clearcut in the first year and grass or small shrubs began to grow, this pixel would be identified as NC, something which is usually observed in BC pixels and this could explain why BC pixels were identified as NC pixels 70% of the time. Five percent of the CC pixels could have also been identified as no change due to spectral similarity.

For the EWDID, 51% of CC pixels were correctly identified. Since the EWDI calculates the amount of moisture in a remotely sensed image, this may indicate a higher amount of dryness in one of the images compared to the other. Conversely there also could have been significant rainfall prior to one of the images being captured. If it did rain, the moisture in the vegetation and the ground would misidentify pixels as NC due to the increased amount of moisture in the pixel. The EWDID can be used for clearcut detection, but the amount of moisture in each image would have an impact on the results. This highlighted the importance of using two images that have similar quantities of moisture to produce the best possible results. As for BC pixels, 22% of the pixels were correctly identified as CC. The amount of moisture in these BC pixels could have been similar to the amount of moisture in NC pixels and would therefore explain the misidentification. In comparison to the EWDID results in Phase 1, the CC accuracy decreased significantly, by 45% and the NC accuracy decreased by 8%. The BC pixels identification decreased by 22%.

The UC had accuracies of 100% for CC and NC pixels. This indicated that the algorithm was capable of properly separating the spectral values of CC pixels from NC pixels. In terms of BC pixels, only 54% of the pixels were correctly identified as CC pixels. This indicates the algorithm is not reliable to distinguish between pixels which are on the fringe of CC and NC areas. These forests within the pixels may not have be fully clearcut therefore the algorithm automatically placed them in the NC category. In comparison to the UC results in Phase 1, the CC accuracy increased by 9% and the NC accuracy remained the same. There was an increase of 34% in BC pixel accuracy.

5.3 Analysis of Phase 3

B7D differencing was determined to be the most accurate method; therefore, it was applied in Phase 3 to three images with varying intervals between image dates. These time intervals were selected to demonstrate whether or not the applied method would be subjected to an increase or decrease in accuracy. An IKONOS image was used to confirm whether or not the pixels were correctly identified as field visits were not possible.

For the one-year interval, B7D post-classification was able to correctly identify 95% of CC pixels and 87% of BC pixels. This method also correctly identified 100% of NC pixels. The misidentified pixels could be caused by the similar spectral values between CC to NC pixels. Due to Landsat and IKONOS images having different pixel size (30 meters versus 4 meters), border pixels highlighted as CC with the bitmap may have appeared as forested when using the IKONOS image (see Figure 5.1). The spectral similarities between BC and NC pixels could also explain the misidentification.

On the three-year time interval, the accuracies are similar to those of a one year interval for B7D post-classification. The CC pixel identification increased by 5% indicating that CC pixels were correctly identified 100% of the time. NC pixels were correctly identified 99% of the time. The increase of CC pixel identification could derive from greater spectral variability between CC and NC pixels (see Figure 5.1). The 1% of misidentified NC pixels could be caused by the quality of Landsat versus IKONOS images. The pixel could have been identified as NC in Landsat, however, when verified using the IKONOS image, the pixel was CC. This would mean the pixel had some vegetation (shrubs) in it, but it was in a CC area. The BC pixel identification produced the same statistics as in the one year interval, indicating the reasons for misidentification would be similar to those in Phase 1.

The nine-year time interval produced accuracies of 95% for CC pixels and 99% for NC pixels. The BC pixels had the lowest accuracy at 80%. As the time gap increased, the spectral signatures between CC and NC pixels increased as well. However, CC pixels also had the time to be subjected to vegetation regrowth (see Figure 5.1). This regrowth could explain why the CC pixels, and 20% of BC pixels, were misidentified. As the image interval increased so did the chance for potential pixel misidentification. Five percent of misidentified CC pixels may be the result of spectral similarity to NC pixels. The bitmap used to identify CC areas would have highlighted all clearcut areas above a certain value (specified by the researcher); therefore, when analyzing the pixels they would have appeared as clearcut, but when confirming this information using the IKONOS image, the pixels were actually NC pixels. This would indicate that NC pixels had similar spectral signatures as CC pixels. As for the BC pixels, there is a 7% decrease in accuracy between the nine-year interval and three-year interval. This indicates the spectral signatures of BC pixels closely resemble NC pixels as the amount of time increases between image dates. This means that there is a certain amount of clearcutting a BC area must have in order to be properly identified as a CC pixel.

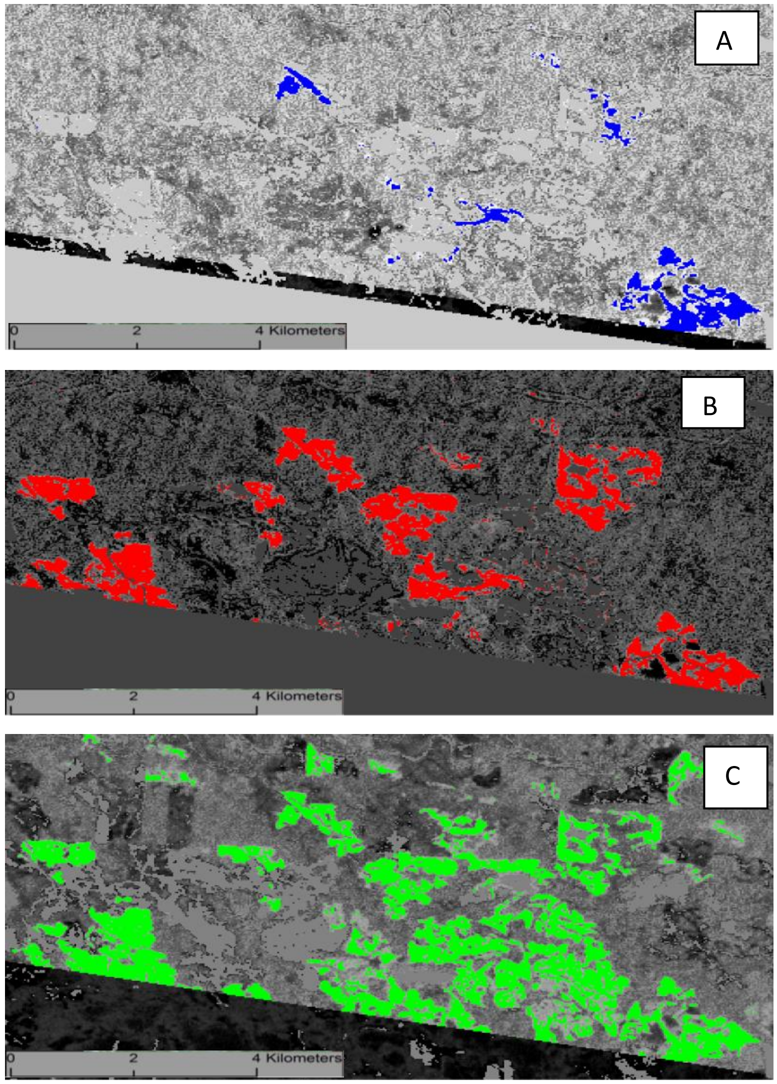


Figure 5.1: This figure demonstrates the variation between clearcut detection between the one year (A), three year (B) and nine year (C). As can be seen, the amount of clearcutting has increased and the reduction of correctly identified pixels.

Overall, each of the methods had relatively high CC and NC accuracies meaning each method can correctly identify CC pixels from NC pixels. The BC accuracies varied greatly from one method to another. Certain method had accuracies above 80% whereas other methods had accuracies less than 40%. The most accurate method was determined to be B7D post supervised classification. After having tested the method from a one year, three year and nine year time interval the overall accuracy of the method remains relatively stable with accuracies greater than 80% for BC pixels and above 95% for CC and NC pixels. As the time gap increase the method does become less accurate. However, the nine year time gap does produce accuracies greater than other methods tested through Phase 1 and Phase 2.

These results and comparison between the methods tested answers the three main questions asked at the start of the project. With the completion of Phase 1 and Phase 2 B7D post supervised classification was determined to be the best method as it produced high accuracies for CC pixel detection, NC pixel detection and BC pixel detection. For four of the five methods, a supervised classification produced similar or better accuracies in terms of CC, NC and BC pixel detection. The EWDID implementation post-classification declined in terms of accuracy, thus indicating that a supervised classification does increase method implementation accuracy. As B7D was determined to be the highest ranking method, it was used for a multiyear study. After having implemented the clearcut detection method on a one-, three- and nine year time interval between image dates the third and final question can be answered. Overall the accuracies for the method remained consistent; there was a decline in the BC pixel detection accuracy. This accuracy declined from 87% to 80%. The CC and NC pixel detection accuracies remained greater than or equal to 95 percent. The declining accuracies for the BC pixels were expected as these types of pixels would become more difficult to distinguish from NC pixels. This indicates that errors of omission or commission increased therefore reducing the accuracies. The amount of BC pixels included in the NC pixels increased. This increase of incorrectly identified BC pixels would be caused by the similar spectral values of the BC regions and

NC pixels. This also indicates that there need to be a greater spectral value difference between areas of NC and CC areas. The gap between NC and CC increases but yet the spectral gap between NC and BC reduces.

CHAPTER 6
Conclusion

The goal of the project was to determine which clearcut detection method was the most accurate at detecting clearcut areas in a remotely sensed image. Five methods were tested in two phases and a third phase to determine if the most accurate method is still accurate over multiple years. The five methods tested in Phase 1 were:

- Band 5 Differencing (B5D),
- Band 7 Differencing (B7D),
- Normalized Difference Vegetation Index Differencing (NDVID),
- Enhance Wetness Difference Index Differencing (EWDID)
- Unsupervised classification (UC)

The objective of the project was to answer three main questions. The first question to be answered throughout the first phase of the project was: *Which method would produce the highest accuracy for a one-year interval between image dates?* The second phase attempted to answer the second question: *Would conducting a supervised classification prior to method implementation increase the accuracy of the results for a one-year interval?* Once these two questions were answered, the third phase attempted to answer: *Would time intervals of greater than one year between image dates impact the accuracy of the selected method?* From these questions three hypotheses were created.

- Hypothesis One: The NDVID method would be the most accurate results since the NDVI was created for vegetation detection.

- Hypothesis Two: Conducting a supervised classification prior to method implementation would increase the overall accuracy of the methods.
- Hypothesis Three: The accuracy of the most accurate method would remain accurate over a one year time gap but have limited success over an increased period of time.

To accept or reject these hypotheses, three phases were created to test methods and implement the methods for each hypothesis. The first phase of the project was to implement the five methods on the first evaluation area, LLEA, with a one year time interval between image dates. The second phase of the project was to implement the same five methods on the second evaluation area, GLEA, post-supervised classification. The third phase was to use the most accurate method, as determined by the first two phases, on the KLAA. Once Phase 1 and Phase 2 were completed, B7D post-classification was determined to be the most accurate method. This third phase saw the application of the most accurate method on a one-, three-, and nine-year time interval between image dates.

After having conducted implemented the five methods during the first phase of the project, B5D was determined to be the most accurate method with accuracies for CC and NC pixels of 100% and BC pixels at 59%. For the second phase of the project, a supervised classification was conducted prior to method implementation. Once completed the methods were ranked and B7D post supervised classification had the highest overall accuracy with CC pixel accuracy at 100%, NC pixel accuracy at 99% and BC pixel accuracy at 95%. The B7D was determined to be the method overall when Phase 1 and

Phase 2 methods were compared. It was also determined that on average, except for one case, conducting a supervised classification prior to method implementation would increase the accuracies of the chosen methods. The third phase of the project took the most accurate method, B7D post-classification, and applied it on a multiyear basis. The method was applied on a one-, three-, and nine-year interval. The overall accuracies of the method over these time intervals remained relatively constant with a fluctuation of five percent for CC pixels, one percent for NC pixels and seven percent for BC pixels.

Some of the findings from the current project support results found by previous researchers; however, other findings contradict previous findings. For example, the GRWC used B5D as their method of choice for band differencing. While this method is excellent for detecting CC and NC pixels, it has limited success on accurately detecting BC pixels. This indicates that the results found in this project support the decision of GFWC. As for Weeks et al. (2013), the researchers used Band 2 differencing (B2D). This method was not used through the course of this project, therefore it is difficult to confirm or reject the author's decision to use this method.

Several authors used the NDVI method in conjunction with a computerized classification or as a differencing technique. Lyon et al. (1998) found that the NDVI was the best method to use for clearcut detection. Assuming the researchers are correct with this statement, an NDVID should also provide highly accurate results. Sader et al. (2001) and Cassidy et al. (2013) also found that the NDVI technique was an appropriate method to use for clearcut detection. Bakr et al. (2010) used an NDVI with an ISODATA classification prior to method implementation as a good method for clearcut detection.

These researchers used an appropriate method; however, after having tested the five methods, the NDVID was not the best method to use. Conducting a classification prior to method implementation increased the overall accuracy of the method but not enough to validate its use in future clearcut detection projects.

The EWDI is a relatively new method used for clearcut detection and is based on the amount of wetness or moisture found in the captured image. Skakun et al. (2003) used the EWDI as their main method for detecting vegetation variations in remotely sensed images. The researchers found that the method accuracy varied between 67 and 78&. Using wetness in an image is a good way to detect the amount of vegetation in an image in theory. After having tested the method with limited success and provided low accuracies. This would therefore indicate the method should not be used as a clearcut detection method.

Using a supervised or unsupervised classification provides accurate results according to several previous researchers. Rahman et al. (2013) used a supervised classification with accuracies greater than 85% whereas Rozenstein and Kanieli (2010) found that a supervised classification had accuracies of 60%. The supervised classification was not tested as an individual method through the project; however, it is an option for future research. It would be important for future research to test this method as it could have the potential to reduce errors of omission or commission. Rozenstein and Kanieli (2010) found that an unsupervised ISODATA classification produced accuracies of 70%. The accuracy produced in previous was not replicated throughout the study. The accuracies produced in the study are greater than 70% thus indicating the unsupervised classification as an appropriate method for clearcut detection.

Having completed the project, these three objectives of the project can be evaluated. B7D post-classification was the most accurate method as determined by Phase 1 and Phase 2. Overall, a supervised classification prior to method implementation increased the accuracy of B7D, B7D, NDVID, and UC. The EWDID method was the only method which accuracy declined after having conducted a supervised classification prior to method implementation. As for the third and final objective, the accuracy of the most accurate method as determined by the first two phases did not vary significantly from a one, three and nine year time gap. For the one year time gap, the accuracies for CC, NC and BC pixels were greater than 87% associated with BC pixels. For the three year time interval the lowest accuracy was 83% for the BC pixels. For the nine year time interval BC pixels had the lowest accuracy at 80%. This would therefore indicate that the B7D post-classification is impacted by a time interval greater than one year with declining BC accuracies.

There is also a large potential for future research in the field of clearcut detection method accuracy assessments. Weeks et al. (2013) used B2D which would be a method to investigate in future research. As previously mentioned, a supervised classification is another method which should be investigated for future research. These two methods could provide better accuracy than B7D post-classification and should be tested.

LIST OF REFERENCES

Bakr, N., Weindorf, D.C., Bahnassy, M.H., Marei, S.M., and El-Badawi, M.M. (2010). Monitoring land cover changes in a newly reclaimed area of Egypt using multi-temporal Landsat data. *Applied Geography*, 30, 592-605.

Bowyer, J., Fernholz, K., Lindburg, A., Howe, J., and Bratkovich, A. (2009*). The power of silviculture: employing thinning, partial cutting systems and other intermediate treatments to increase productivity, forest health and public support for forestry*. Retrieved from: http://www.dovetailinc.org/report_pdfs/2009/dovetailsilvics0509.pdf. Accessed on January 3rd 2015.

Cassidy, L., Southworth, J., Gibbes, C., and Binford, M. (2013). Beyond classification: combining continuous and discrete approaches to better understand land-cover change within the lower Mekong River region. *Applied Geography*, 39, 26-45.

Campbell, J.B. (2007). *Introduction to remote sensing* (4th ed). New York, NY: the Guildford Press.

El-Kawy, A., Rod, J.K., Ismail, H.A., and Suliman, A.S. (2011). Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data. *Applied Geography*, 31, 483-494.

Finn, M.P., Reed, M.D., and Yamamoto, K.H. (2012). A straight forward guide for processing radiance and reflectance for EO-1 Ali, Landsat 5 TH, Landsat 7 ETM+, and ASTER. *Unpublished Report from USGS/Center of Excellence for Geospatial Information Science.*

GeoEye. (2006). *IKONOS imagery product guide*. Retrieved from: http://glcf.umd.edu/library/guide/IKONOS_Product_Guide_jan06.pdf. Accessed on January 3rd 2015

Global Forest Watch Canada (GFWC). (2009). *Recent (1990-2007) anthropogenic change within the forest landscapes of Nova Scotia.* Edmonton: AL: Global Forest Watch Canada.

Guild, L.S., Cohen, W.B., and Kauffman, J.B. (2003). Detection of deforestation and land coversion in Rondonia, Brazil using change detection techniques. *International Journal of Remote Sensing*, 25, 731-750.

Ibrahim, M. A., Arora, M. K., and Ghosh, S. K. (2005). Estimating and accommodating uncertainty through the soft classification of remote sensing data. *International Journal of Remote Sensing*, 26, 2995-3007.

Jin, S.M., and Sader, S.A. (2005). Comparison of time series tasseled cap wetness and the normalized difference moisture index in detecting forest disturbances. *Remote Sensing of Environment*, 94, 364-372.

Kiage, L. M., Liu, K-B., Walker, N. D., Lam, N., and Huh, O. K. (2007). Recent land-cover/use change associated with land degradation in the Lake Baringo catchment, Kenya, East Africa: evidence from Landsat TM and ETM+. *International Journal of Remote Sensing*, 28, 4285-4309.

Kim, M.K., and Daigle, J.J. (2011). Detecting vegetation cover change on the summit of Cadillac Mountain using multi-temporal remote sensing datasets: 1979, 2001 and 2007. *Environmental Monitoring and Assessment*, 180, 63-75.

Lillesand, T.M., Kiefer, R.W., and Chipman, J.W. (2008). *Remote sensing and image interpretation* (6th ed). Hoboken, NJ: John Wiley & Sons Inc.

Liu, H., and Zhou, Q. (2004). Accuracy analysis of remote sensing change detection by rule based rationality evaluation with post-classification comparison. *International Journal of Remote Sensing*, 25, 1037-1050.

Lyon, J., Yuan, D., Lunetta, R. and Elvidge, C. (1998). A change detection experiment using vegetation indices. *Photogrammetric Engineering and Remote Sensing*, 64, 143-150.

Masek, J.G., and Sun, G. (2004). A spectral-angle methodology for mapping net forest cover change in northeastern China. *International Journal of Remote Sensing*, 25, 5629-5636.

Miller, A.B., Bryant, E.S., and Birnie, R.W. (1998). An analysis of land cover changes in the Northern forest of New England using multitemporal Landsat MSS data. *International Journal of Remote Sensing*, 19, (2), 245-265.

Morawitz, D. F., Blewett, T. M., Cohen, A., and Alberti, M. (2006). Using NDVI to assess vegetative land cover change in central Puget Sound. *Environmental Monitoring and Assessment*, 114, 85-106.

Natural Resources Canada (2014). *Fundamentals of remote sensing*. Retrieved from: http://www.ldeo.columbia.edu/res/fac/rsvlab/fundamentals_e.pdf. Accessed on January 15th 2015.

Nova Scotia Public Lands Coalition. (2012). *Clearcutting*. Retrieved from: http://www.publicland.ca/issues/clearcutting.html. Accessed on August 6th 2014.

Pape, A. (2006). Multiple spatial resolution image change detection for environmental management applications (Unpublished Master's thesis). University of Saskatchewan, Saskatoon, Saskatchewan.

Pu, R., Gong, P., Tian, Y., Miao, X., Carruthers, R., and Anderson, G. L. (2008). Using classification and NDVI differencing methods for monitoring sparse vegetation coverage: a case study of saltcedar in Nevada, USA. *International Journal of Remote Sensing*, 29, 14, 3987-4011.

Quinn, J. W. (2001). *Band Combinations*. Retrieved from: http://web.pdx.edu/~emch/ip1/bandcombinations.html. Accessed on January 16th 2015.

Rahman, M. M., Ullah, M. R., Lan, M., Sumantyo, J. T. S., Kuze, H., and Tateishi, R. (2013). Comparison of Landsat image classification methods for detecting mangrove forests in Sundarbans. *International Journal of Remote Sensing*, 34, 1041-1056.

Rozenstein, O., and Karnieli, A. (2011). Comparison of methods for land-use classification incorporating remote sensing and GIS inputs. *Applied Geography*, 31, 533-544.

Sader, S.A., Bertrand, S., and Wilson, E. H. (2000). Satellite change detection of forest harvest patterns on an industrial forest landscape. *Forest Science*, 49, 341-353.

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

Skole, D., and Tucker, C. (1993). Tropical deforestation and habitat fragmentation in the Amazon: satellite data from 1978-1988. *Science*, 260, 1905-1910.

Schmook, B., Dickenson, R. P., Sangermano, F., Vadjunec, J. M., Eastman, J. R., and Rogan, J. (2011). A step-wise land-cover classification of the tropical forests of the Southern Yucatan, Mexico. *International Journal of Remote Sensing*, 32, 1139-1164.

Tole, L. (2002). An estimate of forest cover extent and change in Jamaica using Landsat MSS data. *International Journal of Remote Sensing*, 25, 91-106.

USGS. (2014). *frequently asked questions about the Landsat Missions.* Retrieved from: http://landsat.usgs.gov/band_designations_landsat_satellites.php . Accessed on December 17 2014.

Weeks, E. S., Ausseil, A-G. E., Shepherd, J.D., and Dymond, J.R. (2013). Remote sensing methods to detect land-use/cover changes in New Zealand's 'indigeneous' grasslands. *New Zealand Geographer*, 69, 1-13.

Wilson, E.H., and Sader, S.A. (2002). Detection of forest harvest type using multiple variables for predicting soil loss by geostatistical methods with TM images and a slope map. *Photogrammetric Engineering and Remote Sensing*, 96, 889-898.

Yalte, K. (2007). *Relative Change Detection: An Overlooked Advantage* (Unpublished Masters Thesis). University of Calgary, Calgary, Alberta.

Yan, G., Mas, J. F., Maathuis, B. H. P., Xiangmin, Z., and van Dijk, P. M. (2006). Comparison of pixel-based and object-orientated image classification approaches- a case study in a coal fire area, Wuda, Inner Mongolia, China. *International Journal of Remote Sensing*, 27, 4039-4055.