

SPATIAL ANALYSIS OF LAND COVER CHANGES IN THE GRAND LAKE MEADOWS, NEW BRUNSWICK

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January 2016



**TECHNICAL REPORT
NO. 301**

**SPATIAL ANALYSIS OF LAND COVER
CHANGES IN THE GRAND LAKE
MEADOWS, NEW BRUNSWICK**

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January 2016

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PREFACE

This technical report is a reproduction of a thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Engineering in the Department of Geodesy and Geomatics Engineering, January 2016. The research was supervised by Dr. Raid Al-Tahir and Dr. Yun Zhang and funding was provided by the Grand Lake Meadows Endowment Fund.

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Shodimu, Oluwatimilehin Okikiolu (2016). *Spatial Analysis of Land Cover Changes in the Grand Lake Meadows, New Brunswick*. M.Sc.E. thesis, Department of Geodesy and Geomatics Engineering Technical Report No. 301, University of New Brunswick, Fredericton, New Brunswick, Canada, 89 pp.

ABSTRACT

The ever growing human activities and economic development will eventually change the relationships between human and the environment. A matter of grave concern is the unsustainable patterns of land use that are considered a major cause for the deterioration of the environment. The Grand Lake Meadows is an important part of the Saint John River wetlands that form the largest freshwater wetland habitat in the Maritimes (east Canada).

In this paper, remotely sensed images were used for mapping the use of land use and cover in the Grand Lake Meadow over a period of 20 years. The goal was to undertake a detailed spatially explicit inventory of local trends in land use and land cover changes through classifying the historical images. Other available data like the road network to mention a few were combined with this information to create a database that was used to investigate consequences of land use/cover change.

The results demonstrates the flexibility and effectiveness of this technology in establishing the necessary baseline and support information for sustaining eco-services of a wetland thereby depicting the rate of change undergone in the GLM area over time. The study identified a 38% decrease in the wetland from the 1990 to 2001, while there was 4.32% overall increase in the wetland area since then. The result will help the managers to comprehend the dynamics of the changes, prompting a better management and implementation of LULC administration in the GLM area.

DEDICATION

This work is dedicated to my lovely parents for their support during this study without their great help and sacrifices during my upbringing I would not have gone to school.

ACKNOWLEDGEMENTS

I am heartily thankful to my supervisors, Dr. Raid Al-Tahir and Dr. Yun Zhang whose encouragement, guidance and support from the initial to the final level enabled me to develop an understanding of the subject. Additionally, Ms. D. Paradis-Lacey at Department of Natural Resources, Public Services for her assistance acquiring forestry maps and aerial photographs of the project area.

I'd like to thank my family for their support, especially my parents for their useful comments and always pushing me to completion of this work, to the Akandes am utmost grateful for all the support and words of encouragement. Special thanks also goes to Mohammad Rezaee and Amir Abouhamzeh for the advice and efforts in making this study come fruition.

Lastly, I am grateful for the funding support of this research which was provided by the Grand Lake Meadows Project Management Committee through the Grand Lake Meadows Endowment Fund in New Brunswick, Canada.

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Chapter 1

INTRODUCTION

Extensive loss of wetlands has occurred in many countries throughout the world [Mitsch and Gosselink, 1993]. About 80% of the world's wetlands are either degrading or disappearing, thus more attention is being paid to conservation of wetlands as the value of wetlands cannot be overemphasized. Landscape fragmentation divides wetlands into isolated islands which thereby hinder the energy flow and nutrient cycling within the wetland. Changes in the land cover and land use significantly affect key aspects of ecosystem functioning and services. They directly impact the biotic diversity; contribute to local and regional climate change and soil degradation by altering the ecosystem and affect the ability of biological systems to support human needs.

Grand Lake Meadows (GLM) is the largest fresh water wetland in New Brunswick. The area is classified as a Protected Natural Area due to its historical and ecological significance to the province of New Brunswick. The area is home to a number of species of diverse and significant plant communities and can be counted as one of the unique treasures of Canada's Heritage. GLM provides several ecosystem services that a wetland would typically provide, such as carbon storage, timber production, water-quality improvement and sediment retention. It also provides several economic services that include recreation (bird watching, boating, cross country skiing, duck hunting, and snowmobiling), beef cattle operation, growing crops (cabbage, pumpkins, corn, tomatoes, and potatoes) and harvesting (firewood, fiddleheads, and muskrats) [Washburn and Gills,1996].

Historical maps of the region and data from Canadian census depict changes in the demographic aspects and trends in the GLM area. The maps show also changes in the land cover and use of the area. There are considerable amounts of highway and settlements that can be seen in the topographic maps of the area. Land cultivation decreased significantly from 1901 - 2001 primarily due to the construction in Gagetown and people's movement from a rural area to an urban area as noted by the acreage of Hay, Buck wheat and Oats [Paponnet-Cantat and Black, 2003].

There has been very little work done to depict the biodiversity of the GLM and as a result there is a lack of public awareness and appreciation of the GLM area [Papoulias, Chaplin, and Bishop, 2006; McGrath and Stefanakis, 2013]. The decision-makers need to identify the driving forces responsible for these changes and hence, to develop management strategies to protect the GLM wetland effectively.

1.2 THE STUDY AREA

Washburn and Gillis [1996] were responsible for a preliminary environmental impact assessment of the proposed rerouting of the Trans-Canada highway in the 1990s and defined the area of GLM as being bounded: on the east by the Jemseg River to the north by various bodies of water including Grand Lake, Back Lake, Maquapit Lake, French Lake, and two extensive thoroughfares - the Main Thoroughfare and the Lower Thoroughfare: the southern extent of the GLM area is bound by the Saint John River: the western limit as being a road that connects McGowans Corner to Lakeville Corner [Washburn & Gillis, 1996; Paponnet-Cantat and Black, 2003]. Figure 1.1 illustrates the location of the Grand

Lake Meadow area in a map of New Brunswick, Canada and that of New Brunswick in a map of Canada.

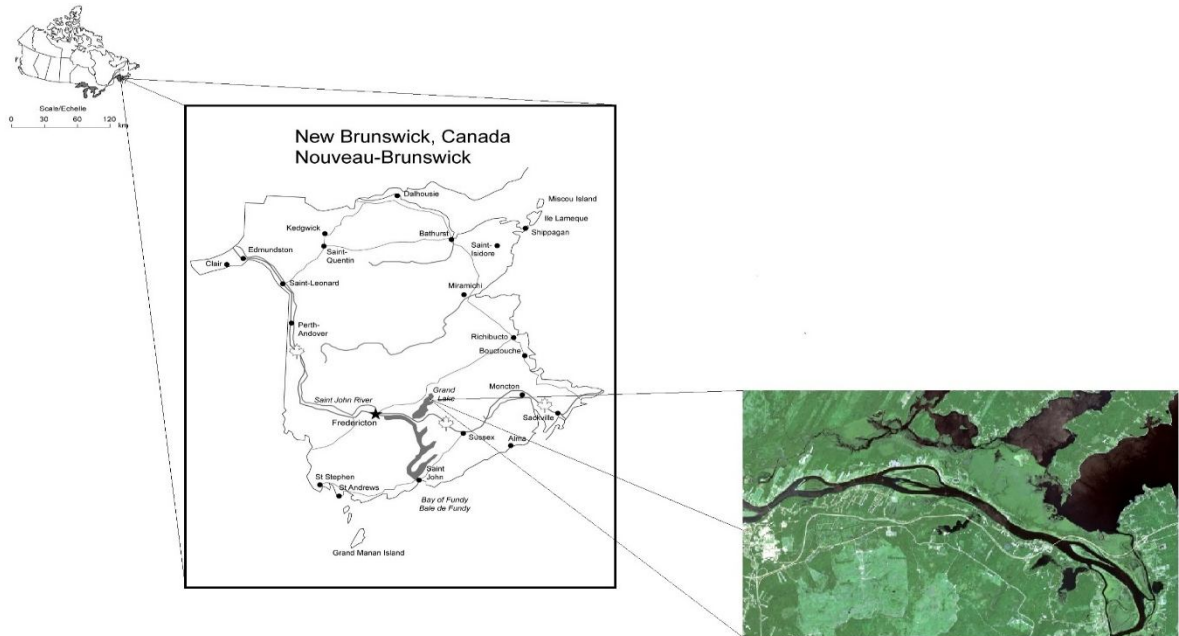


Figure 1.1: Location of the Grand Lake Meadows in New Brunswick, Canada.

1.3 BRIEF HISTORY OF DEVELOPMENT IN GLM

The Maliseet (Wolastoqiyik) and Mi'kmaq people existed in the GLM as early as the 1600's [Zelazny, 2007]. From the 1700's and 1800's inhabitants including the English, French, and Loyalists in this area vied for its rich mineral resources [Queens County Heritage, 2013]. In the 1800s' land conflicts dissipated, coal and wood commercial ventures developed and got to be extremely prosperous, enticing more immigrants [Wright, 1966]. As the population of people increased, the resources of the GLM diminished at an increasing pace.

A depletion of mineral resources was envisaged in the 1880s. Towards the start of the Cold War in 1947 the Canadian government was searching for an area to secure a suitable military base for the Canadian Army [Bruce, 2013]. The territory under consideration was the plateau west of the St. John River between St. John and Fredericton. In the early 1950s the seizure of lands started as the development of facilities began for the Canadian Forces Base (CFB) in Gagetown, Oromocto [Govcda, 2013]. This seizure of lands is regarded by a few as the "end of cultivation" in the area as pioneers were relocated from their property and migrated to a different area in the province. This base and seizure of lands, while being outside to the GLM area, affected those living in GLM.

Transportation routes in the province were enhanced to encourage movement to and from the base. The developments included railway connections made possible by the Canadian National and the Canadian Pacific Railway, another alternative to the Trans-Canada Highway (Route 2) in the early 1960s, and the development of another bridge over the St. John River at the town of Burton.

In the late 1990s an alternate re-alignment of the Trans-Canada Highway started. This extended the Trans-Canada Highway to a 4-lanefreeway with a specific goal of meeting the area's developing transportation needs and this was completed in 2001 [GNB, 2013]. This interstate spanned six kilometers of GLM and included building two new extensions: one over the St. John River and the other spanning over Jemseg River and influenced an expected 55 ha of GLM wetlands [Blair and Perley, 2004]. In 1990, the government of New Brunswick proclaimed GLM a "Class 2 Protected Natural area" [McGrath and

Stefenakis, 2013] which in-turn limits the utilization of the territory to low-impact recreational activities and conventional sustenance gathering activities, while limiting industrial, business and horticultural improvements [Zelazny, 2013].

The Province of NB collaborated with the five other easternmost enterprises that included the Canadian Wildlife Service, Ducks Unlimited Canada and Wildlife Habitat Canada (to mention a few) to structure the Eastern Habitat Joint Venture [PCNWA/GLM Mgmt. Plan, 2000]. The commissioning of this joint venture of about 3,050ha of land in the GLM has been secured [PCNWA/GLM Mgmt. Plan, 2000]. Also, the GLM Project Management Committee was commissioned to raise the awareness of the GLM area and its unique ecology. This prompted a history of developments and the bounty of improvement prompted concerns over a risk to its ecology which has risen to secure the region and raise awareness of its importance in the province.

1.3 CHARACTERISTICS AND IMPORTANCE OF THE GLM

1.3.1 Agricultural Use

The two soil types predominantly found in the GLM area are clay-loam and loam soil. Therefore the well-drained slopes in the region are quite fertile and are used for the cultivation of crops such as vegetable and fruits while the rest of the well-drained regions are less fertile due to the lack of relief and the generally fine texture of the soils often impedes drainage, which decreases the growth rate of vegetation [Paponnet-Cantatand Black, 2003].

1.3.2 Forestry Use

The Grand Lake Meadow is one of the richest wetlands in Eastern Canada. Most of the lands around the region are around the Trans-Canada Highway. The GLM acts as a heat sink to the province of New Brunswick thereby aiding in temperature moderation of the province. There are some vegetation species that are exclusive to the region for example the eskers with the red oak dominant forests [Paponnet-Cantatand Black, 2003].

The Grand Lake Meadows provides a complex setting for migrating waterfowl, aquatic and terrestrial plants, animals and unique communities of hardwood swamp vegetation which are abundant south of the GLM [Paponnet-Cantatand Black, 2003]. This occurs basically on the broad, fertile and alluvial flood plains. Some of these plant species grow predominantly in certain parts of the GLM for example the coarse, alluvial deposits support trees such as white pine. Fertile alluvial soil support trees such as bur oak and silver maple [Paponnet-Cantatand Black, 2003]. Disturbances associated with settlement, particularly agriculture and forestry, have altered the original forest considerably, resulting in numerous stands of red maple, gray birch, white birch and trembling aspen, with scattered spruce and fir [Paponnet-Cantatand Black, 2003].

1.3.3 Transportation and Communication Routes

A review of accessible maps acquired for the zone creates the impression that the essential land transportation courses have been located along the well-drained levee to the south of the GLM. The earliest maps created by the Geological Survey of Canada in 1880 and 1884, show that a bit of what is currently the Trans-Canada Roadway was available, reaching out

to more or less the region as of now known as The Intervale. At this point Highway 690, from McGowans Corner to Lakeville Corner, is likewise indicated to have been in presence, crossing at Fulton Island as it does today. At low water, the remaining parts of the bridge pilings are still obvious at the western tip of the island, promptly east of the current bridge [Paponnet-Cantatand Black, 2003].

Map data for the study region was hard to get for the initial years of the twentieth Century. This map data shows that by the early parts of the twentieth Century, the route that finished at The Intervale was stretched-out eastward to a point where it crossed the waterway at Jemseg. Highway 690 had already been constructed at this time, found in basically the same area as it is today [Paponnet-Cantatand Black, 2003].

By 1958, the main road through the Grand Lake Meadows had gotten to be a piece of the Trans-Canada Highway. Likewise, a ship connection was added connecting The Intervale to Upper Gagetown, on the southern shore of the Holy person John Waterway. This ship association stayed in administration until the end of the twentieth Century, when an extension was developed over the Saint John River roughly 3 km downstream from the ship crossing.

All through the twentieth Century, the essential land transportation courses stayed unaltered; in any case, towards the end of the twentieth Century, another course was proposed through the Grand Lake Meadows for the development of the new Trans-Canada Highway [Paponnet-Cantatand Black, 2003].

1.3.4 Demography

Grand Lake Meadows is located within Queens and Sunbury areas. Notwithstanding, just two of the ten Queens District wards, Cambridge and Canning, and one Sunbury parish, Sheffield, are inside the Grand Lake Meadows. Canadian Census information was acquired by Paponnet-Cantat and Black in 2003 for eight registration years comprising of 1901, 1911, 1921, 1931, 1941, 1961, 2001 and 2011. On the other hand, just a segment of the information has been discharged for the 2001 statistics year.

Thereafter, census information were used between 1901, 1911, 1921, 1931, 1941, 1961, 2001 and 2011 thereby trying to isolate the information acquired from Queens and Sunbury districts. The seven areas found inside Sunbury region incorporates: Blissville, Burton, Gladstone, Lincoln, Maugerville, Northfield and Sheffield. Inside Queens's district, data from ten areas is incorporated in the statistics information, including: Brunswick Cambridge and Canning, Chipman, Gagetown, Hampstead, Johnston, Petersville, Waterborough, and Wickham [Paponnet-Cantatand Black, 2003].

The demographic data referred to in the contents of the report addresses total population, total migration, provincial and urban economy, estimation of timberland production, farming land patterns relating to significant field harvests, for example field crops such ashay, oats and buckwheat. The same questions were not generally asked in each year; in this manner, it was not generally achievable to compare information from year to year. A few inquiries reflect patterns relating to the registration year [Paponnet-Cantatand Black, 2003]. As seen in (Figure 1.2), the GLM area and its surrounding region has undergone a

steady increase in its total population from the year 1901 till 2011 which is also noted in this study with increase in roads from 1992 till 2013 thereby resulting in urbanisation of the GLM area.

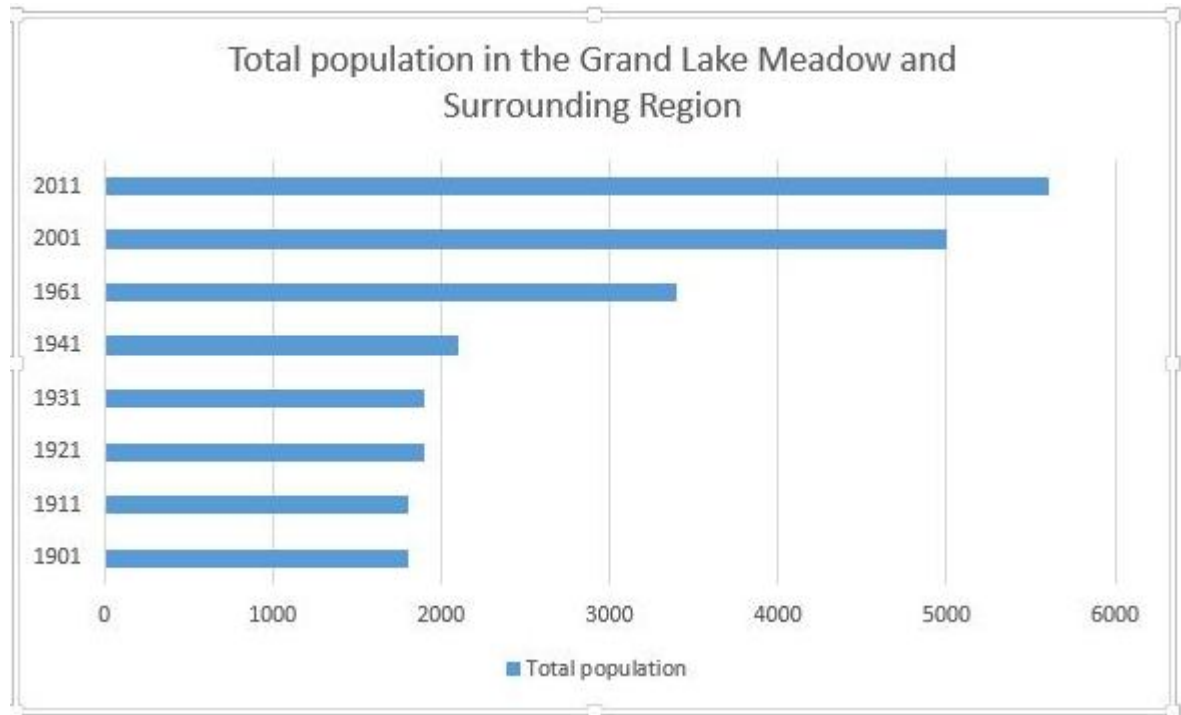


Figure 1.2: Total population in the GLM as of 2011.

1.4 RESEARCH QUESTIONS

The previous review of the biophysical and historical changes in the Grand Lake Meadows area leads to few research questions;

1. How has the landscape of GLM changed over the years?
2. Is there a relationship between the landscape changes with other physical or policy changes?
3. Can satellite remote sensing images help in answering these questions? How?

4. How this study can influence the planning and strategies for a sustainable management of the GLM area and its resources?

1.5 RESEARCH OBJECTIVES

The main goal for this study is to assess the state of the GLM landscape through identifying the land use land cover patterns over the years using satellite images. To achieve this main goal, this study must address the following objectives:

1. Identification of the best methods used to extract relevant/useful information from satellite imagery. To answer this question after completing an inventory of the available set of geo-images, the study will:
 - Establish a methodology for selecting ground control points that ensure consistent referencing between the images and with other data sets.
 - Select spatial ecological parameters and indicators relevant to the study that can be extracted from all images.
 - Identify the appropriate methods and their parameters to extract the information from the multispectral satellite images.
2. Determination of the spatial scale that is appropriate for conducting this study and producing meaningful results. Answering this question requires also defining the spatial frame of reference that will be applied to all extracted information as well as to the secondary data.
3. The selection of an appropriate approach for analysing changes in the use and cover of GLM.

1.6 THESIS ORGANISATION

The subsequent part of the thesis is outlined as follows. Chapter 2 is a general overview of the classification methods and classification schemes employed for the analysis of the satellite imageries and forestry maps. It also provides a review of literature and case studies on the use of satellite images in wetland mapping and monitoring. Chapter 3 provide details on data used in the study, the pre-processing stage (georeferencing and clipping) followed by multi-resolution segmentation, spectral indices used for classification in section 3.4 and subsequently an insight into the following Class selection for classification, GLM Image classification using Feature Space Optimization and lastly Accuracy Assessment. The analysis of results obtained from change detection i.e. change matrix is addressed in Chapter 4 subdividing the results into two subsections from 2013 till 2001 and 2001 till 1992, another table showing changes with respect to area in hectares and difference and finally the results in individual pie-charts. Finally, Chapter 5 discusses briefly the change detection results, sheds more light into the most appropriate spatial and suggest future work that can be done on this study.

Chapter 2

MAPPING AND CHANGE DETECTION OF LAND USE AND LAND COVER

There are few landscapes remaining on the Earth's surface that have not been significantly altered or are not being altered by humans in some manner [Yang and Lo, 2002]. Maps of urban land use and land cover (LULC) are very important sources for many applications such as socio-economic studies, urban management, planning and urban environmental evaluation. Land uses are primarily the result of human actions and decisions on land. In fact human activities arising from a multiplicity of social objectives are the immediate source of land cover change. To understand these social objectives one needs to analyze the underlying driving forces that motivate or constrain the associated human activities. Biophysical driving forces (such as global and local climate change/ variability, geomorphic processes) are also responsible for changes in land cover and ultimately land use [Suzanchi and Kaur, 2011].

Environments in sub-urban territories are emphatically affected by anthropogenic activities; furthermore more consideration is at present being regulated towards monitoring changes in land use land cover changes [Chen and Stow, 2002]. Studies on change detection are particularly important because the spatial characteristics of LULC are useful for understanding the various impacts of human activity on the overall ecological condition of the urban environment [Li and Yeh, 1999]. The objective of change detection is to compare spatial representation of two points in time by controlling all variances caused by

differences in variables that are not of interest and to measure changes caused by differences in the variables of interest [Green et al., 1994].

Modern technologies such as Remote Sensing (RS) and Geographic Information System (GIS), provide some of the most accurate means of measuring the extent and pattern of changes in landscape conditions over a period of time [Miller et al., 1998]. Satellite data have become a major application in change detection because of the repetitive coverage of the satellites at short intervals [Mas, 1999].

GIS is a widely used technique in wetland analysis. Modern GIS gives users the capacity to do visual and quantitative investigation using various sorts of digital spatial information, including remotely sensed imagery. In many studies, Landsat data post-classification are combined with GIS data for further wetland examination. Using GIS different component layers can be overlaid to investigate relationships between individual wetland components. Classified images can be combined with additional shape files, such as permanent water bodies, rivers, soils types and population changes [Ummal et al., 2011]. The image overlaying and binary masking techniques are useful in revealing quantitatively the change dynamics in each category. GIS permits the use of aerial photographic data of current and past land use data with other map data while its disadvantage is due to the fact that different data might have geometric accuracy and classification systems might reduce the accuracy of results [Lu et al., 2004].

This chapter reviews the main techniques of extracting information from satellite images and it also reviews how remote sensing and GIS are used in similar studies of wetlands.

2.1 MULTI-RESOLUTION SEGMENTATION

Segmentation is simply the sub-division of an image into separated regions of similar spectral reflectance. A reason why segmentation is very important to image processing is because of the high number of degrees of freedom which the image must be reduced to or the few segments which satisfy the given requirements. Another reason is that in many cases regions of interest (ROI) are heterogeneous; ambiguities arise and the necessary discerning information is not directly available. Requirements concerning quality, performance, size of data set and processing time and reproducibility can be fulfilled at the same time only by very few approaches [Karakış et al., 2004].

In object-oriented classification approaches, segmentation is not an aim in itself. The image objects resulting from a segmentation procedure are intended to be rather image object primitives, serving as information carriers and building blocks for further classification or other segmentation processes [Karakış et al., 2004]. In this sense, the best segmentation result is the one that provides optimal information for further processing [Hofmann et al., 1998].

Image segmentation uses two basic approaches to segment images; these are top-down methods and bottom-up methods. The basic difference between both approaches is: top-down methods usually lead to local results because they just mark pixels or regions that

meet the model description, whereas bottom-up methods such as multi-resolution segmentation perform a segmentation of the complete image. They group pixels to spatial clusters which meet certain criteria of homogeneity and heterogeneity [eCognition, 2004]. Figure 2.1 depicts how homogenous objects result in larger objects and heterogeneous objects result in smaller ones in the right image and the RGB layer in the left image.

Multiresolution segmentation is a bottom up region-merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects are merged into larger ones. How homogeneous/heterogeneous the objects are allowed to get is operated by the ‘scale parameter’.

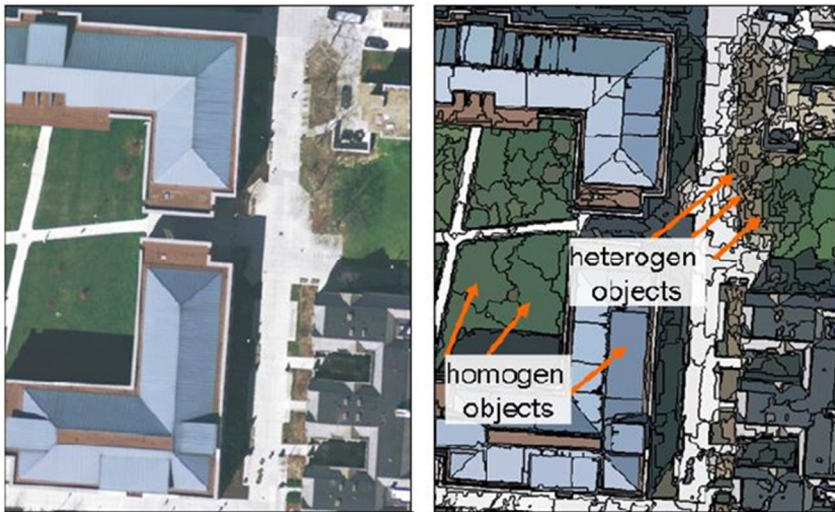


Figure 2.1: Differences between homogenous-objects and heterogenic-objects [eCognition, 2004].

2.2 SATELLITE IMAGE CLASSIFICATION

Image classification is perhaps the most important part of digital image analysis. Classification is used in remote sensing analysis by which pixels with similar spectral reflective characteristics are grouped together to form a distinct cluster. More innovative approaches do not treat pixels in isolation but consider neighborhoods. Texture metrics are used to quantify the distribution of spectral reflectance in a pixel's immediate vicinity. Contextual classifiers look at the land types within a pixel's neighborhood to detect and fix illogical class assignments. Object-oriented approaches categorize polygons rather than individual pixels [Jensen et al., 2009].

There are two main categories for classification methods which are the supervised classification method and the unsupervised classification method. Supervised classification requires labelled training data to establish the statistics to identify spectral classes (or clusters) in a multiband image. On the other hand, unsupervised classification is a method which examines unknown pixels and divides the pixels into classes based on natural groupings present in the image values. Unsupervised classification doesn't require labelled training data, and, as such, it does not require the analyst's intervention.

The main principle of unsupervised classification is that features which have the same range of values have the same cover type and should be classified in the same category and vice versa. The two unsupervised classifications most commonly used in remote sensing are the ISODATA and K-mean algorithm. They are both iterative procedures in which the cluster properties are gradually defined from the pixels belonging to that cluster and all

pixels are assigned to the closest cluster [Yale Center for Earth Observation, 2009]. The advantage of using the unsupervised classification approach is possibility to discover classes that were not known before classification.

For the supervised classification all classes have to be derived usually through a training stage with the use of training examples. The selection of appropriate variables is a critical step for successfully implementing an image classification and land cover classification. But it is noted that the usage of large number of variables would result in a reduction in classification accuracy. It is important to select only the variables that are most useful for separating land-cover or vegetation classes, especially when hyper spectral or multisource data are employed. Different combinations of variables will be evaluated to successfully get a consistent set of land cover information through the time period of this study.

Pixel based classification plays a very vital role in LULC classification. Lu and Weng (2006) in their study discussed that because of the nature of the urban environment and the large number of mixed pixels associated with moderate resolution images, it is often difficult to classify land use/land cover based on spectral signatures. They are of the opinion that using medium data whose sensors mainly reveal land details is more appropriate for land cover classification rather than land use classification. The following are types of classification techniques. For further research on image classification, the reference (Jensen et al., 2009) will be a good source of information. The classification techniques that will be discussed are:

- Nearest neighbour classification

- Maximum likelihood classification
- Fuzzy classification
- Parallelepiped classification
- Minimum distance
- Support Vector Machine (SVM)
- Object-oriented classification
- Decision tree classification

2.2.1. Nearest Neighbor Classification

Nearest-neighbor classification is a simple and commonly used method for supervised classification. The basic principle is to classify a query point as being a member of a certain class of the k-nearest neighbors of the query point, more of them belong to this class than to any other class [Sutton, 2012].

The nearest neighbour method classifies images with of 256 possible class signature segments as identified by signature parameter on a database file. Each has its special signature, for example, it stores signature data related to a particular class [Zhang, 2014], and only the mean vector in the individual class signature segment is used. Other data, such as standard deviations and covariance matrices are not used but it must be noted that the maximum likelihood classifier also uses this concept. Classification with membership functions is based on user-defined functions of object features, whereas Nearest Neighbor classification uses a set of samples of different classes to assign membership values. The procedure consists of two major steps these are

- Training the system by giving it certain image objects as samples
- Classifying image objects in the image object domain based on their nearest sample neighbors

The Nearest Neighbor classifier returns a membership value of between zero and one, based on the image object's feature space distance to its nearest neighbor [eCognition, 2004]. The membership value has a value of one if the image object is identical to a sample. On the off chance that the image object varies from the example, the feature space distance has a fuzzy dependency on the feature space distance to the nearest example of a class. The user has the option to choose the elements to be considered for the feature space. Figure 2.2 demonstrates the nearest neighbour classification and shows the membership value with respect to feature space distance.

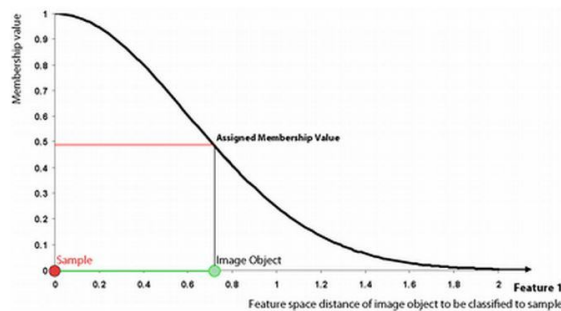


Figure 2.2: Membership function created by Nearest Neighbor classifier [e-Cognition, 2004].

For an image object to be classified, only the nearest sample is used to evaluate its membership value. The effective membership function at each point in the feature space is a combination of fuzzy function over all the samples of that class. When the membership

function is described as one-dimensional, this means it is related to one feature; in higher dimensions, depending on the number of features considered. Figure 2.3 shows how difficult it is to depict the membership functions with two features and two classes only [eCognition, 2004].

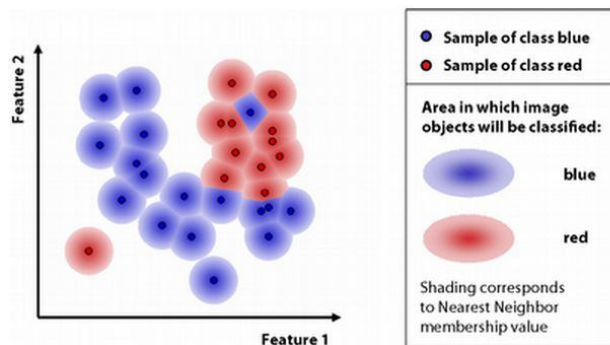


Figure 2.3: Membership function showing class assignment in two dimensions. [eCognition, 2004].

In the figure, the samples are represented by little circles. Membership values are in red and blue classes compare to shading in the particular color, whereby dissimilar areas will be classified red, the blue membership value is disregarded, and vice-versa. Note that in areas where all membership values are below a defined threshold (0, 1 by default), image objects get no classification; those areas are depicted white in Figure 2.3 [eCognition, 2004].

2.2.2 Maximum Likelihood Classification

Maximum likelihood classification is a pixel-based statistical classification method which helps in the classification of overlapping signatures; pixels are assigned to the class of

highest probability. When conducting a maximum likelihood classification, one must know quite a bit about the land-cover present in the study area [Jensen et al., 2009].

The maximum likelihood classifier produces most accurate results than any other method of classification however it takes a longer time to generate results due to extra computations. The reason it is more accurate is due to the fact that it assumes that classes in the input data have a Gaussian distribution and that signatures were well selected but this is not always the case. This method is prone to misclassification of results which is dependent on the class threshold selection.

Figure 2.4 shows an example of maximum likelihood classification with point 1 belonging to the blue class as it is the most probable and point 2 would generally be unclassified as the probability for fitting one of the classes would be below the threshold.

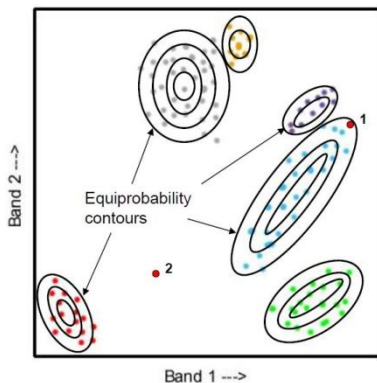


Figure 2.4: Maximum likelihood diagram [Zhang, 2014].

2.2.3 Fuzzy Classification

Fuzzy classification can be regarded as a procedure for sorting data that permits characteristics to apply objects by membership values, therefore an object can be considered as a whole or partial member of that class where 1 is regarded as full

membership of the class and zero as no membership of the class therefore objects are permitted to lie in between zero and one. In GIS, fuzzy classification can be used in the examination of vegetation and phenomena that slightly change in physical composition. Figure 2.5 shows a simple illustration of a fuzzy set depicting the membership function in a crisp set named A.

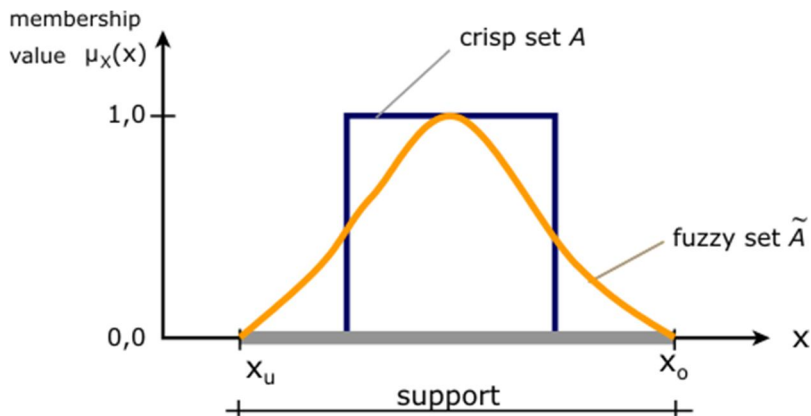


Figure 2.5: An illustration of fuzzy sets.

2.2.4 Parallelepiped Classification

The parallelepiped classifier uses the class limit and class signature to determine what class a pixel falls into. The class limit gives the standard deviation of each side of a parallelepiped surrounding the mean of the class in feature space [Zhang, 2014]. If the pixel falls inside the parallelepiped, it is allotted to the class. However, if the pixel falls within more than one class, it is allotted to the overlap class. If the pixel does not fall inside any class, it is assigned to the null class.

The parallelepiped classifier is a time efficient method. The disadvantage is in most cases is low accuracy and a large number of pixels are classified as misclassified [Zhang, 2014].

Figure 2.6 shows an illustration of the parallelepiped classification method with six classes.

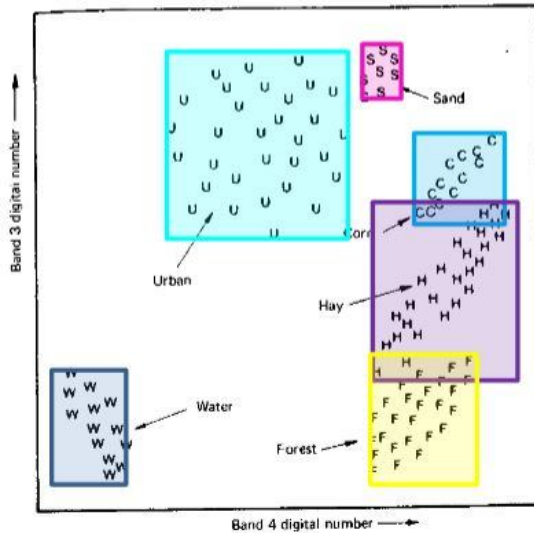


Figure 2.6: Pixel observations from selected training sites plotted on a scatter diagram [Zhang, 2014].

2.2.5 Support Vector Machine (SVM)

A support vector machine (SVM) is a concept in computer science for a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis [eCognition, 2004]. The standard SVM takes a group of input data and predicts, for every given input, which of two possible classes the input could be a member of. For example a set of training examples, each regarded as belonging to one of two classes, a SVM training algorithm assembles a model that assigns out new examples into one spectral class or the other.

A SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. Support Vector Machines are based on the concept of decision planes defining decision boundaries. A decision plane separates between a set of objects having different class memberships [eCognition, 2004].

2.2.6 Object-Oriented Classification (OOC)

The availability of high-spatial resolution multispectral imagery from satellite sensors requires new approaches to classify remote sensing data. Traditional classification algorithms based on per-pixel analysis may not be ideal to extract the information desired from the high spatial resolution remote sensing data [Visual Learning Systems, 2002].

Object-oriented analysis typically incorporates both spectral and spatial information in the image segmentation phase by subdividing the image into meaningful homogeneous regions based on shape, texture, size, and other features as well as spectral characteristics, and organizing them hierarchically as image objects (commonly referred to as image segments) [Blaschke 2005].

Once homogeneous image objects are created, any classification algorithm such as nearest neighbor, maximum likelihood, decision trees and neural networks can be used to classify the objects [Civco et al., 2002]. However, only a few algorithms integrate both spectral and spatial characteristics to produce image objects. One of the algorithms widely used in

remote sensing digital image classification was developed by Baatz et al. (2001) which incorporates both color criterion and shape criterion. Figure 2.7 shows an example of how object oriented classification can be used to classify roof-tops using eCognition the red vectors are rooftops at a site.

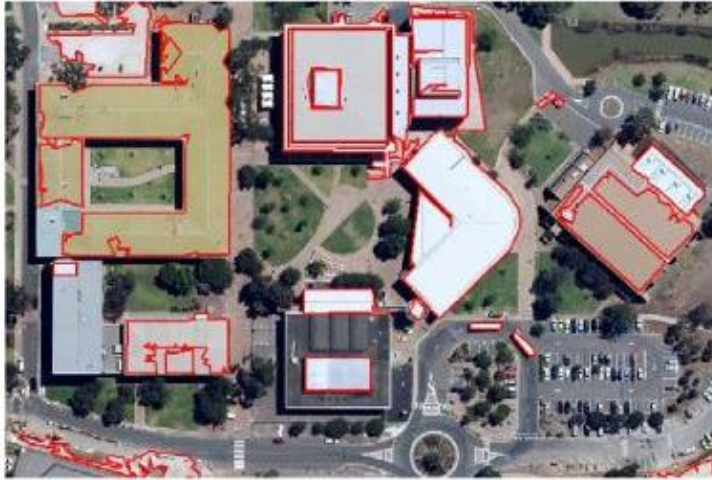


Figure 2.7 Object oriented classification of roof tops [Bruce, 2008].

2.2.7 Decision Tree Classification

Decision trees have tree-like structures where leaves in the tree represent classes and branches represent conjunctions of features that lead to the classes [Jensen, 2005]. A decision tree takes a set of attributes as input, which can be discrete or continuous, and returns an output (i.e., decision) through a sequence of tests [Russell and Norvig, 2003]. Decision trees can be converted into a series of “if-then” rules, which are easier to understand in the decision-making process. It is often difficult to understand and interpret the weights and biases formed during the creation of an Artificial Neural Network [Jensen et al., 2009].

The output value can be discrete or continuous. For example in image classification, analysts are interested in extracting discrete class information (e.g., forest, agriculture). However, many applications require the extraction of biophysical information about a pixel. Such classification is based on the use of continuous functions and is called regression learning [Lawrence and Wright, 2001].

2.3 CLASSIFICATION SCHEMES

Two widely used classification schemes are usually used to classify land use and land cover types. The classification schemes are:

- Anderson Classification System.
- IGDP Classification System.

2.3.1 Anderson Classification System (ACS)

The ACS, essentially developed by Anderson et al. (1976), was designed for national use in the United States, aimed at categorizing remote-sensing information (Table 2.1). The classification system itself offers four levels of increasing detail from level I to level IV, being adaptable to user demands by defining categories that are more detailed and simultaneously compatible for generalizations up to the smaller scales at the national level [Herold et al., 2009]. Level II was intended for statewide and inter-state regional land-use/land-cover compilation and mapping. The level II class, in this work, has been translated into LCCS [Anderson et al., 1976].

Table 2.1 Anderson Classification System [Anderson et al., 1976].

	LEVEL 1		LEVEL 2
1	Urban or built-up	11	Residential
		12	Commercial and services
		13	Industrial
		14	Transportation, communication and utilities
		15	Industrial and commercial complexes
		16	Mixed urban and built-up land
		17	Other urban or built-up land
2	Agricultural land	21	Cropland and pasture
		22	Orchards, groves, vineyards, nurseries, and ornamental horticultural areas
		23	Confined feeding operations
		24	Other agricultural land
3	Rangeland	31	Herbaceous rangeland
		32	Shrub and brush rangeland
		33	Mixed rangeland
4	Forestland	41	Deciduous forestland
		42	Evergreen forestland
		43	Mixed forestland
5	Water	51	Streams and canals
		52	Lakes
		53	Reservoirs
		54	Bays and estuaries
6	Wetland	61	Forested wetland
		62	Non-forested wetland
7	Barren Land	71	71 Dry salt flats
		72	Beaches
		73	Sandy areas other than beaches
		74	Bare exposed rock

		75	Strip mines, quarries, and gravel pits
		76	Transitional areas
		77	Mixed barren land
8	Tundra	81	Shrub and brush tundra
		82	Herbaceous tundra
		83	Bare ground tundra
		84	Wet tundra
		85	Mixed tundra
9	Perennial snow or ice	91	Perennial snow fields
		92	Glaciers

2.3.2 International Geosphere Biosphere Program Data and Information System (IGBP-DIS)

The Land cover working group of IGBP-DIS data was created with guidance of the U.S Geological Service in order to meet the demands of the various IGBP initiatives for global land cover data since data sets proved unsuitable for upcoming IGBP core projects (IGBP 1990). Its legend comprises classes designed to provide a consistent and exhaustive characterisation of global land cover as shown in Table 2.2. More detailed specifications can be found in Belward (1996).

Table 2.2: IGBP Nomenclature [IGBP, 1990]

CLASSIFICATION CODE	IGBP CLASS
1	Evergreen Needle-leaf Forests

2	Evergreen Broad-leaf Forests
3	Deciduous Needle-leaf Forests
4	Deciduous Broad-leaf Forests
5	Mixed Forests
6	Closed Shrub lands
7	Open Shrub lands
8	Woody Savannas
9	Savannas
10	Grasslands
11	Permanent Wetlands
12	Cropland
13	Urban and Built-up
14	Cropland/ Natural Vegetation Mosaics
15	Snow and Ice
16	Barren or Sparsely vegetated
17	Water Bodies

2.4 THE USE OF REMOTE SENSING IN WETLAND MONITORING

Wetland classification is the fundamental step to generating a wetland inventory. In recent times, computer-based classification of wetland from satellite image data has been widely used because these methods are less time consuming and the source data provide high temporal resolution and high accuracy in geo-referencing procedures [Jensen, 1996]. Various datasets have been effectively utilized as a part of wetland classification, for example, aerial photos, Landsat images, and Système Pour l'Observation de la Terre (SPOT) image.

Landsat-based image classification of wetland is regarded as having the best accuracy [Bolstad and Lillesan, 1992] which is primarily due to the sensitivity of the bands of

Landsat sensors (Thematic Mapper - TM, and Enhanced Thematic Mapper Plus - ETM+). TM band 1 can detect water depth mapping along coastal zones and is helpful for soil-vegetation separation and for recognizing forest types. TM band 2 can recognize green reflectance from viable vegetation, and band 3 is intended for recognizing chlorophyll absorption in vegetation. TM band 4 is perfect for near infrared reflectance peaks in healthy green vegetation and for identifying wetlands. The two mid-infrared groups on TM are helpful for vegetation and soil water studies, and distinguishing between mineral types. The thermal infrared band on TM is intended to support in thermal mapping, and for soil dampness and vegetation studies.

Unsupervised and supervised classification techniques are most common approaches in wetlands analysis [Ozesmi and Bauer, 2002]. The major disadvantage of using supervised method for classification is the problem of misclassification; therefore any mislabelling in the training examples will affect the accuracy of the final result. For example with supervised maximum likelihood classification method, Ndzeidze (2008) utilized the Region of Interest tool (ROI) to generate training set of pixels. Each chosen pixel, both within and outside the training site was assessed and assigned to the class where it had the highest probability of being a member.

The study by Jiang et al. (2014) used pixel by pixel classification, GIS and redundancy analysis (RA) were used to classify wetlands in the Heihe region of China. The main aim of this project was to characterise wetland fragmentation in this region. Wetlands in this region were classified into four different classes which were core, edge, perforated and

patch. This study shows that there was a decrease in the mean patch size of the wetland between the years 1975-2010. In summary there was a 42.54% decrease of core wetland from 1975 – 2010 and correspondingly a decrease in pixel size from 49.17% - 36.83% over the stated period [Jiang et al., 2014].

Frohn et al. (2009) used object oriented analysis and ancillary GIS data to classify a Landsat 7 image to determine the utility of Landsat 7 image to accurately detect and classify isolated wetlands in St Johns River area in Florida. GIS data layers of buffered hydrology and lakes were also used in the classification process. These were used to mask data where potential wetlands intersected stream, river, and lake buffers, to prevent these data from being classified as isolated wetlands. The segmentation/object-oriented classification was also compared to a potential isolated wetland of Landsat 7 imagery from January 2000 till October 2000. At this point, the study discovered that there were about 4388 isolated wetland spanning about 27.7 sqkm. Accuracy for individual isolated wetlands was determined based on the intersection of reference and remotely sensed polygons. The January data yielded producer and user accuracies of 88% and 89%, respectively, for isolated wetlands larger than 0.5 acres (0.20 ha). The producer and user accuracies increased to 97% and 95%, respectively, for isolated wetlands larger than 2 acres (0.81 ha). Remote sensing was also used to classify wetlands in and around the Tibetan Plateau, where rule-based classification was used to classify these images [Zhao et al., 2015]. The Tibetan plateau has about 131900 km of wetland which is of special significance to China. In the past 40 years the research objective of the Tibetan Plateau has gone through dynamic changes in wetland monitoring, landscape patterns and the eco-environment based on

remote sensing technology. More attention has been attached to constructing models with an ecological system perspective and analyzing patterns and change in trends within the Tibetan Plateau wetlands. The result derived on the Tibetan plateau using remote sensing were as follows somewhere around 1970 and 2006, the Tibetan Plateau wetland area diminished at a rate of 0.23%/a while the landscape diversity declined at a rate of 0.17%/a. In other words somewhere around 1976 and 2009, the lake area of the inland river basin in the Tibetan Plateau increased at a rate of 0.83% per year [Zhao et al., 2015].

Supervised method of classification was used to classify Landsat images (TM and ETM+) in Mar Mengor Lagoon between the year 1984-2000 [Carreño et al., 2008]. Change patterns in the vegetal communities were studied due to hydrological and biological changes. Each classification was carried out with two images and Normalised Difference Vegetation Index (NDVI) was used to increase classification accuracy of vegetation cover. It was noticed that the overall accuracies were higher than those found in other studies due to the inclusion of NDVI the accuracy increased to about 84.17% and 91.06% [Carreño et al., 2008].

Powers et al. (2012) made use of a multi-scale segmentation and multi-scale geographic object based image analysis (GEOBIA) to classify 15 different wetland types in Canada. This method took into consideration the object based texture measure (geotex) and a decision tree classifier to assess 5 common spatial resolutions which were 5m, 10m, 15m, 20m, 25m, 30m. Two themes were used which were Ducks Unlimited (DU: 15 classes) and Canadian Water Inventory (CWI: 5 classes). Results reveal that the highest overall

accuracies (67.9% and 82.2%) were achieved at the 10 m spatial resolution for both the DU and CWI classification schemes respectively. It was also found that the DU wetland types experienced greater area differences through scale with the largest differences for both classification schemes occurring in classes with a large treed component.

2.5 CHANGE DETECTION

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times [Singh, 1989]. Change detection is a critical process in monitoring and overseeing natural resources and urban advancement on the grounds that it gives quantitative examination of the spatial distribution of the feature of interest.

The rate of change can either be dramatic or abrupt (such as changes caused by logging, hurricanes, and fire) or subtle and gradual events (such as regeneration of forests or damage caused by insects) [Verbesselt et al., 2010]. A major objective of land use land cover change detection is to better understand the relationships and interactions between humans and its environment in order to manage and use resources in a better way for sustainable development [Lu et al., 2004].

In recent times the availability of Landsat satellites since 1972 and its use has made available a lot more information such as large volumes of multi-temporal data which can be used for land use land cover investigation. Various digital change detection techniques have been developed over the last two decades. Several review papers and book have

summarized and compared these techniques. A good source would be [Lu et al., 2004] and [Coppin and Bauer, 1996] to mention a few. Some common change detection algorithms are listed below:

- Post classification comparisons.
- Composite analysis.
- Image differencing.
- Multi-temporal linear data transformation.
- Change vector analysis.
- Image regression.
- Multi-temporal biomass index
- Image ratio

The following section provide details on a few common techniques of change detection:

2.5.1 Spectral Mixture Analysis (SMA)

In SMA, the signal recorded for a pixel is assumed to be a mixture of the radiances of the component end-members contained within that pixel [Giri, 2012]. Knowing or deriving spectrally pure end-members of all the components within a pixel, using linear or non-linear mixture approaches [Chen et al., 2004]. Some previous land cover change techniques have aimed at detecting changes that are smaller at individual pixels. The SMA techniques can be used to quantify cover fractions of the interested vegetation [Lu et al., 2004].

SMA is practically appropriate and practical for detecting image-element changes over time coarse-resolution images especially subtle changes such as vegetation regeneration to mention a few [Giri, 2012]. For further research on this method Remote Sensing of Land Use Land Cover by Giri, 2012 would be a good resource.

2.5.2 Bi-Temporal Analysis

Bi-temporal change detection enables comparison of land cover of the same area, based on a two-point scale [Giri, 2012]. The basic principle of bi-temporal change detection is to find the difference of two images. This can be done either using the original image information (e.g. radiance or reflectance data) or derived imagery for example spectral indices [Giri, 2012]. Therefore both images will need to be geo-registered or radiometrically corrected [Coppin et al., 2004].

A major disadvantage of this method is that it only uses two dates of imagery in the process thus there is no way to really distinguish between older changes/disturbances from the more recent ones [Giri, 2012].

The method requires a careful selection of dates because the detected changes may reveal differences in phenology and not in the features of interest [Weber, 2001]. For bi-temporal change detection images from the summer peak greenness period work best because they minimize reflectance difference from the same cover type caused by seasonal vegetation phenology such as leaf-off conditions, autumn coloration and sun angle difference [Coppin et al., 2004].

2.5.3 Multi-Temporal Change Detection

This strategy is a snappy and productive method for showing changes between comparative images of varying dates. It utilizes a basic unsupervised classification on two combined images. The regions that have changed will bring about varying classification statistics or color than the regions that no change has occurred. The system is not utilized for quantitative purposes, it gives little data on 'from-to' class changes and can be hard to name the changed classes. In any case, this strategy is especially helpful as an exploratory system for recognizing regions that have changed.

2.5.4 Principal Component Analysis (PCA)

Another method for accomplishing this change detection is the Principal Components Analysis. This system is a multivariate statistical strategy that is utilized with the end goal of data reduction. The two images must be put inside of the same planimetric base map and same database. PCA is used to minimize the amount of spectral components by recognizing the uncorrelated primary components that expatiate on the most variance.

These principal components are illustrative of the new dataset of which a few are typically straightforwardly identified with change. This method does not give from-to change class information and may be hard to label the changed classes. In any case, this technique is generally utilized and advantageous as only classification is necessary.

2.5.5 Post-classification Change Detection

This method avoids problems encountered at the pixel level (such as shadows and reflections) and requires both images to be individually rectified and classified before they can be compared pixel by pixel (Jensen 1996). This comparison is accomplished using a change detection matrix (see Table 4.1 and Table 4.2 in Chapter 4). Care must be taken to guarantee that all the image classifications are as accurate as can be because any lapses/errors that happen in the classification will be extended into the change detection.

This method provides good from-to information and results in a base map that can be used for the next year. It identifies where the change has occurred and how much change has occurred. Be that as it may, creating a change map taking into consideration that the classification of two images can be a little tasking and the final change detection is just as precise as the result of reproducing the accuracies of every individual classification.

Post-classification comparison characterizes images from different time frames independently and afterwards analyzes class values on pixel by pixel basis between dates. High sensitivity to the individual characterization accuracy is a real downside of this classification method. Error is multiplicative as misclassification from base maps affect the accuracy of this procedure. In any case, post-classification can be carried out without the need for radiometric calibration and make do with the training examples set by the user.

Post-classification change detection was used in this study due to the fact that eliminates effects of shadow and due to the availability of several Landsat data available in the GLM

area and the relatively high classification accuracy archived which would further result in relatively high change detection analysis.

2.6 CHANGE DETECTION TECHNIQUES IN WETLAND STUDIES.

Satellite information have turned into a significant application in change identification due to the repetitive coverage of the satellites at short intervals. The study by Li and Yeh (1998) found out that the principal component analysis of multi- temporal images combined with supervised maximum likelihood classification can effectively monitor urban land use change in the Pearl River Delta.

Yang and Lo (2002) used an unsupervised classification approach, GIS-based image spatial reclassification with GIS to map the spatial dynamics of urban land-use/land cover change in the Atlanta, Georgia metropolitan area. GIS approaches have shown many advantages over traditional change detection methods in multi-source data analysis [Yang and Lo, 2002].

Adia and others investigated the spatio-temporal change detection of vegetation cover of Jos (Nigeria) and its surrounding areas. The study used Landsat images (TM and ETM+) of November, 1986 and Nov, 2001. For recognition of vegetation reflectance, layer stacking of bands 4, 3 and 2 (false color composite) for TM and ETM+ were performed to generate change maps of the vegetation cover for the respective dates and find out the pattern of change[Adia et al, 2008].

Miwei (2009) observed transient vegetation in Poyang Lake utilizing Moderate-Resolution Imaging Spectrometer (MODIS) satellite image. The study delved into the change over time in Area of Ephemeral Vegetation (AEV) by investigating time change of satellite imagery and explored how this change is identified with changes in hydrological conditions [Miwei, 2009].

Dewan and Yamaguchi (2009) used the GIS method where past and present maps of land use with topographic and geological data. Image overlaying and binary masking are useful in showing quantitatively change dynamics. This method allows incorporation of aerial and photographic data of current and past land use data with other map data but different GIS data with varying geometric accuracy and classification system reduces the quality of results [Lu et al, 2004]. Likewise, Damizadeh et al. (2000) utilized satellite images, as a compelling procedure to study how changes in vegetation spread is developing.

Thereafter, Suzanchi and Kaur (2011) used data derived from Landsat imageries, survey if India-topo sheets to map the spatial temporal attributes of the national capital region of India. This study aims at quantifying the spatial temporal pattern of the land use land cover change thereby identifying the major bio-physical factors governing LULC. This study shows that the study area experienced a steep increase of 67.4% in its cropland during 1989-1998 and a relatively smaller increase between the years 1998-2006 of about 5.7%.

Post classification comparison was used by Abd El-Kawy and others (2011) to classify multi-temporal images into thematic maps. Thereby a pixels by pixel comparison is

implemented which would minimize the impact of atmospheric sensor and environmental differences between multi-temporal images this could be time wasting and requires a great deal of expertise to produce classification results.

In other words, unsupervised change detection was used by Yang and Lo (2002) in which similarly spectral groups of pixels are selected and clusters from the first image into primary clusters and then labels spectrally similar groups into the second image into primary clusters in the second image and finally identifies changes and outputs results. This method makes use of the unsupervised nature and automation of change analysis process but there is a difficulty in identifying and labelling change trajectories [Lu et al, 2004].

Another method that can be used is the change vector analysis (CVA) by Baker et al. (2007) and land cover change mapper (LCM) by Castilla et al. (2009) which are based on spectral change between acquisition dates [Du et al., 2013]. The CVA technique identifies changes in pixel values by considering the pixel locations for the two dates in the multi-dimensional spectral space. It recognizes the change magnitude threshold which is utilized to distinguish between real land cover changes from unobtrusive/subtle changes [Hame et al., 1998]. Moreover, like other methods that use the radiometric change, CVA has an absence of programmed or semi-automatic strategies to viably determine the change magnitude threshold between change and no-change pixels. LCM works better with small regions and is extremely successful likewise in recognizing areas with sizeable changes. The major

disadvantage of this method is that the type of change in the region of interest must be identified by the analyst.

Im et al. (2008) performed object-based change detection using correlation image analysis and image segmentation using bi-temporal QuickBird datasets. They created object/neighborhood correlation images to extract change information from the composite imagery based on the single set of objects showing bi-temporal topology using two different classification methods (i.e., machine learning decision trees and nearest neighbor classifiers).

Chapter 3

METHODS

The goals for the study will be achieved by undertaking a detailed and spatially explicit inventory of patterns in land use and land cover changes thereby analyzing the state of degradation in the GLM. This study tends to depict the state of ecological management in the GLM across a range of spatial and temporal scales. Figure 3.1 shows the GLM area in an ArcGIS environment showing the study area as polygon on GIS.

The methodology's main thrust is the use of a series of archival satellite images covering a period from the years 1986 till as recent as 2013. Comprehensive land cover maps for the Grand Lake Meadows area will be extracted from these images and then analyzed to depict the changes in land cover. A specific set of indicators (for example land use and vegetation cover) will be selected based on being easily extracted and updated, directly or indirectly, using geo-imaging techniques. This would give answer to the issues of ecological administration in the GLM over a scope of spatial and temporal scales. Of special interest is assessing the ecological impacts of the Trans-Canada Highway on the GLM area.

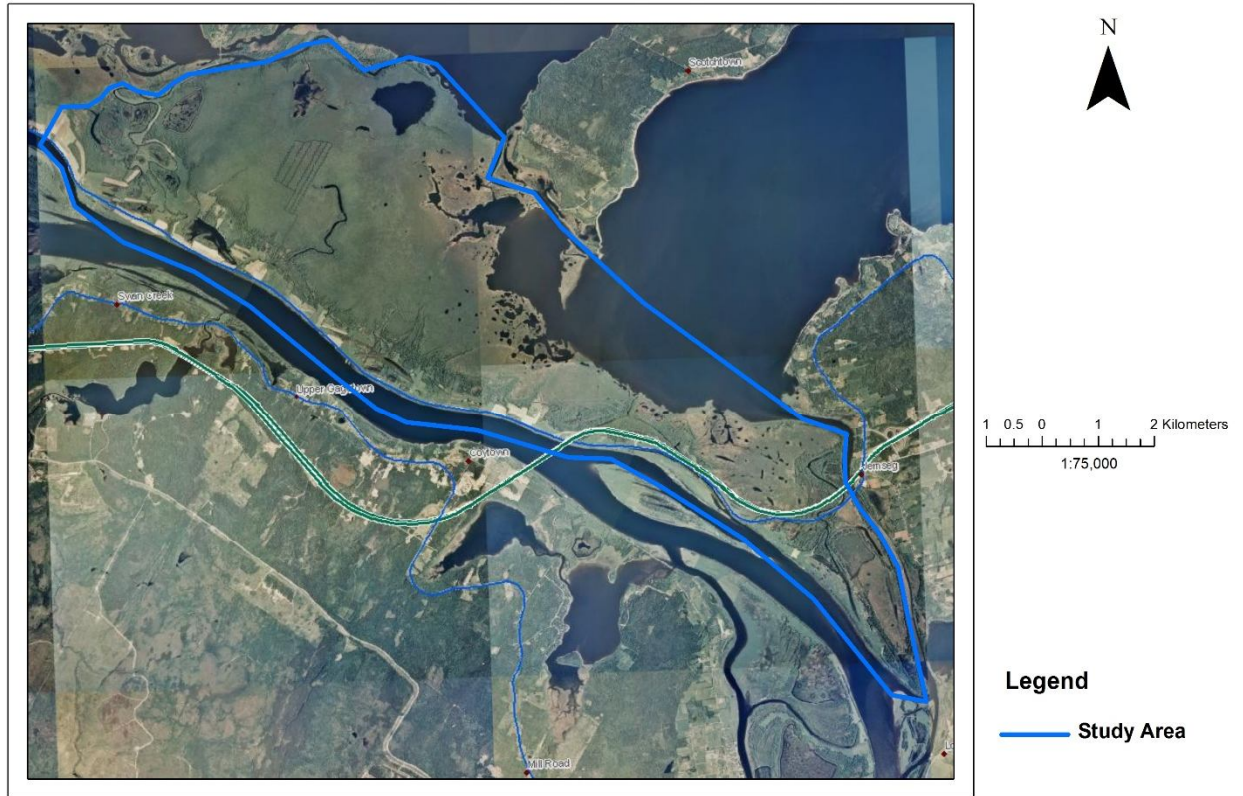


Figure 3.1: The Grand Lake Meadow (Google Maps) and the study area.

GIS is used in this study to enable the integration and the presentation of the spatial and temporal information. Additionally, it allows for conducting a series of spatial and geo-statistical analysis to quantify the rate of changes and the association between different parameters.

Figure 3.2 is a flow chart depicting the process to achieve the aim of analyzing the state of degradation in the GLM region. It can be used as a summary of the project depicting each stage of the project from data acquisition through image classification and to the presentation of the final report. The following paragraphs detail the procedure to achieve the intended goals of the study.

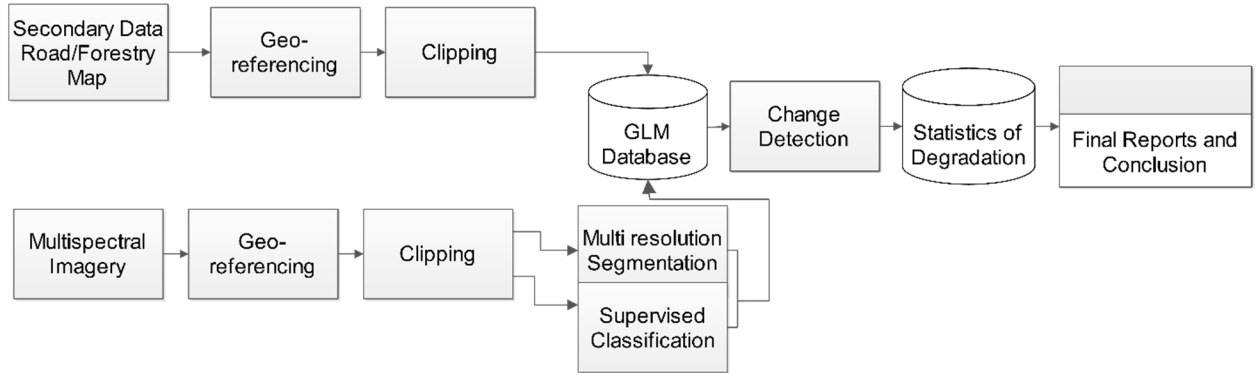


Figure 3.2: Data and processes flow.

The following sections provide details on data used in the study (Section 3.1) and the pre-processing stage (georeferencing and clipping) followed by multi-resolution segmentation in section 3.3, spectral indices used for classification in section 3.4 and subsequently an insight into the following class selection for classification, GLM Image classification using Feature Space Optimization and lastly Accuracy Assessment.

3.1 DATASETS

The images used for this study were all Landsat imagery with world reference system 10/28 from <http://earthexplorer.usgs.gov/> covering the study area dating as the 27th of July, 1986 till the 28th of August, 2013. All the images used in this study are of the same time-frame which is between the months of May and July to negate vegetative effects on the image, cloud cover or snow. It must be noted that the Landsat guide [Landsat 8 User Guide, 2015] was used to make sure the right combination of bands was used and for the proper utilisation of various spectral indices for classification of the images.

The Landsat TM and ETM+ have similar 7 bands (Table 3.1), while ETM+ band 6 has a higher resolution of 60 meters. The Landsat 7 satellite also has newly added panchromatic band 8 with resolution of 15 meters [Shi, 2013].

Table 3.1: Landsat 7 and ETM+ bands and wavelength range [Landsat 8 User Guide, 2015]

Band	Region	Wavelength (μm)	Resolution (meters)
1	Blue-green	0.441 – 0.514	30
2	Green	0.519 – 0.601	30
3	Red	0.631 – 0.692	30
4	Near IR	0.772 – 0.898	30
5	SWIR - 1	1.547 – 1.749	30
6	Thermal IR	10.31 – 12.36	60
7	SWIR - 2	2.064 – 2.345	30
8	Pan	0.515 – 0.896	15

Table 3.2 shows the spectral bands of the Landsat 8 OLI and TIRS with the band 1 Coastal/Aerosol basically used for ocean color observations and Cirrus which is useful in detection of thin clouds [Landsat 8 User Guide, 2015].

Table 3.2 Landsat 8 OLI and TIRS Spectral bands [Landsat 8 User Guide, 2015]

Band	Region	Wavelength (μm)	Resolution (meters)
1	Coastal/Aerosol	0.435 – 0.451	30
2	Blue	0.452 – 0.512	30
3	Green	0.519 – 0.601	30
4	Red	0.636 – 0.673	30
5	NIR	0.851 – 0.879	30
6	SWIR - 1	1.566 – 1.651	30
7	SWIR -2	2.107 – 2.294	30
8	Pan	0.503 – 0.676	15
9	Cirrus	1.363 – 1.384	30
10	TIR - 1	10.60 – 11.19	100
11	TIR - 2	11.50 – 12.51	100

Table 3.3 shows an inventory table of imageries used during the course of this study. All satellite data included, at least, images from four spectral bands (Band 1: Blue, Band 2: Green, Band 3: Red, Band 4: Near-infrared) with a resolution of 30m. All images used in this study had a cloud threshold value of less than 10% to minimize the effects of cloud cover in this study.

The 1986 image could not be used for classification due to the fact that the Landsat imagery available has 3 bands because a criteria was set to negate effects of cloud cover to less than

10%. Secondly, the absence of the 4th band makes it difficult for classification to be done as there was a lot of inconsistency with classification.

Table 3.3: Satellite images used in the study

Date	File name	Satellite	Spectral Bands	Spatial Resolution
1986/05/01	MTN-19-45_LOC	Landsat 5	3: B, G, R,	All bands: 30m
1992/08/07	ETP009R28_5T19920807	Landsat 5	4: B, G, R, IR	All bands: 30m
2001/06/28	ELP010R028_7T2001628	Landsat 7	7: B, G, R, NIR, SWIR 1, TIR, SWIR 2, Panchromatic	VIR: 30m, TIR: 60m
2013/08/24	LC80100282013236LGN00	Landsat 8	11: B, G, R, NIR, SWIR-1, TIR, SWIR-2, Panchromatic, TIRS, Cirrus	VIR: 30m, Pan: 15m, Cirrus: 30m, TIRS: 100m

Two other datasets were used for this study; forestry maps and the road network. Forestry maps were acquired from the Department of Natural Resources (DNR) to provide training sample selection to classify the satellite images. These maps are of 1:12,500 scale and bear the numbers 4852, 4952 and 5053 and represent the area in 2014. Figures 3.3, 3.4 and 3.5 show the forestry map used to select samples for classification. The road network dataset for 2013 was downloaded from <http://www.snb.ca/geonb1/e/DC/catalogue-E.asp>, the file name for the road network shapefile is called New Brunswick Road Network (NBRN) and it has a scale of about 1:15000.

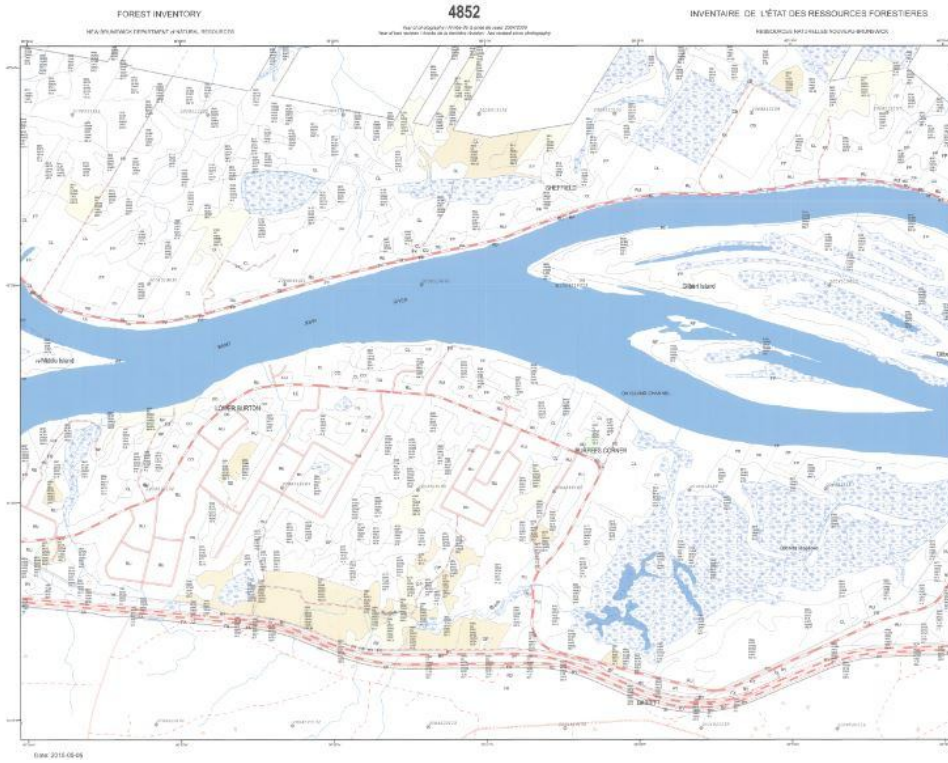


Figure 3.3: Forestry map (4852) for the west part of the study area.

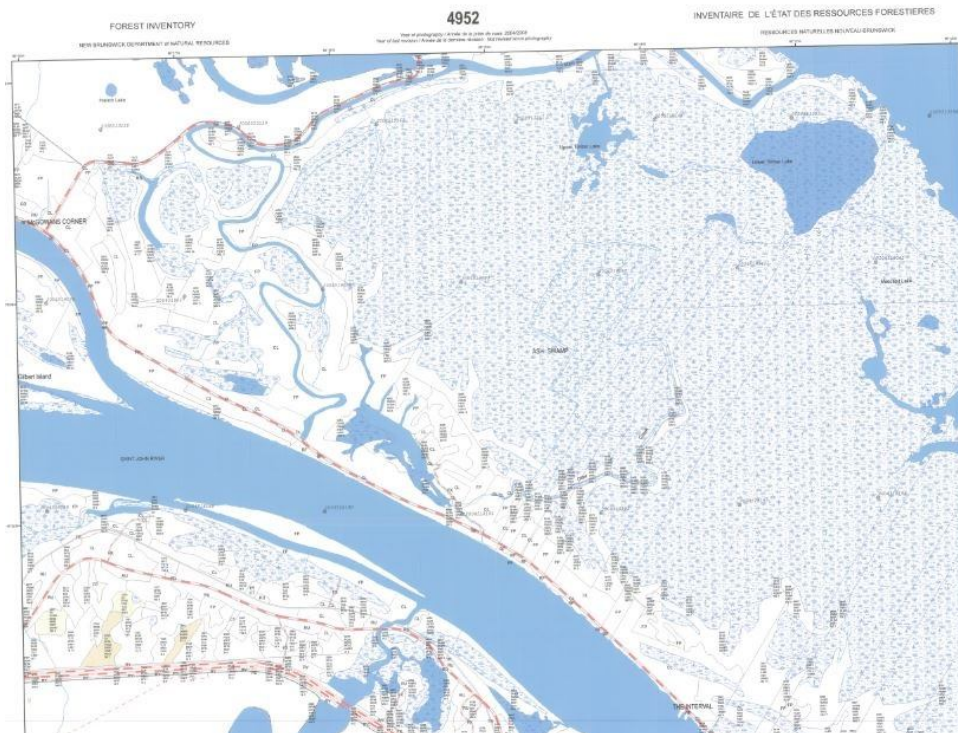


Figure 3.4: Forestry map (4952) representing the central part of the study area.

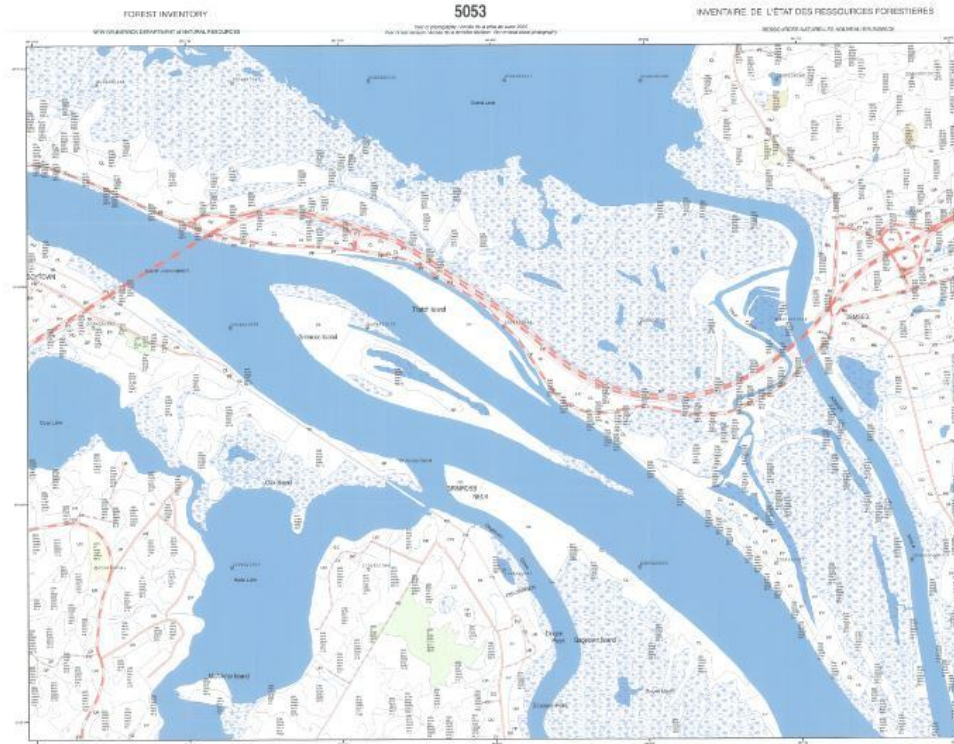


Figure 3.5: Forestry map (5053) representing the eastern part of the study area.

3.2 DATA PRE-PROCESSING

The satellite imagery was georeferenced to the New Brunswick's coordinate reference system and map projection (NAD83 CSRS 19N, New Brunswick Stereographic Double projection). An Ortho-image for the area downloaded from GeoNB was used for Ground Control Point (GCP) selection; PCI Geomatica was used for georeferencing the images for the fact that it has an automated GCP finder which reduced processing time significantly.

To ensure consistent referencing between the images, the same ground control points (GCP) are to be used on all the imagery classified. This task is challenged by the fact that there have been changes between the different years. As such, some of the points chosen for georeferencing an image may not be the same for another image. However, there was

a good set of the same points available on all imageries that ensured correct co-referencing among the images. An average of 18 ground control points was used for geo-referencing the image, two check points were also used to further verify the accuracy of results.

The RMSE for the georeferenced imageries was less than 0.25 of a pixel (about 8m) based on selected representative ground control points. Atmospheric calibration is compulsory when a multi sensor data is used for image classification. However, it was not implemented in this study considering that all images were of Landsat. Figure 3.6 is a natural colour composite for 2000 Landsat image (used as the base image) showing its GCP points. Figure 3.7 shows the output of georeferencing including the RMSE result of the 2000 image which is about 0.25 of a pixel (8m) based on selected representative GCP's.

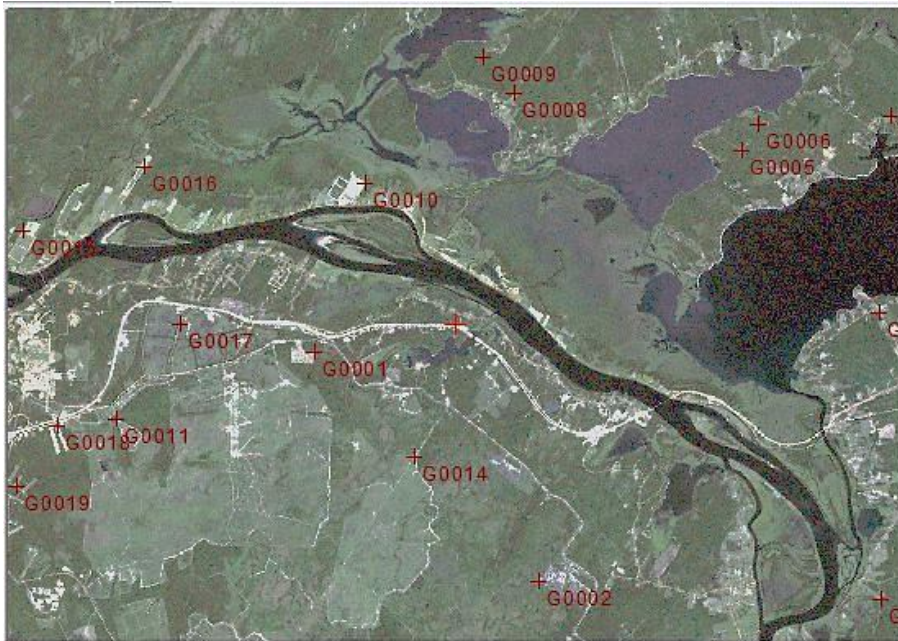


Figure 3.6: Geo-referenced Landsat 2000 image showing GCP points.

```

Residual Error Report

Residual Units: Image pixels

Residual Summary for 1 Images
  GCPs: 17 X RMS  0.32 Y RMS  0.25
Check points:   0 X RMS      Y RMS

Listing: GCPs only All images

```

Point ID	Res	Res X	Res Y	Type	Image ID	Image X	Image Y	Comp X	Comp Y
G0018	0.73	0.71	-0.16	GCP	LN7_2000	58.9	499.8	59.6	499.7
G0001	0.66	0.50	-0.44	GCP	LN7_2000	366.9	413.0	367.4	412.6
G0009	0.61	0.51	-0.34	GCP	LN7_2000	569.2	59.2	569.8	58.9
G0008	0.57	-0.51	0.24	GCP	LN7_2000	605.7	103.3	605.1	103.5
G0010	0.55	-0.12	0.54	GCP	LN7_2000	427.2	210.1	427.1	210.7
G0017	0.47	-0.38	0.28	GCP	LN7_2000	206.0	379.0	205.6	379.3
G0019	0.43	-0.41	0.15	GCP	LN7_2000	9.9	573.0	9.5	573.1
G0016	0.32	-0.09	-0.31	GCP	LN7_2000	163.7	191.9	163.7	191.6
G0014	0.23	-0.23	0.00	GCP	LN7_2000	487.1	536.6	486.8	536.6
G0006	0.20	-0.02	0.20	GCP	LN7_2000	897.9	139.8	897.9	140.0
G0013	0.18	-0.01	-0.18	GCP	LN7_2000	1042.9	365.9	1042.9	365.7
G0012	0.17	0.02	0.17	GCP	LN7_2000	1043.9	708.6	1043.9	708.8
G0002	0.16	0.01	-0.16	GCP	LN7_2000	634.5	686.6	634.6	686.4
G0005	0.13	0.13	0.02	GCP	LN7_2000	878.2	171.8	878.3	171.8
G0007	0.11	-0.04	-0.11	GCP	LN7_2000	1056.1	130.6	1056.1	130.5
G0011	0.11	-0.04	0.10	GCP	LN7_2000	130.8	491.7	130.8	491.8
G0015	0.01	-0.01	0.01	GCP	LN7_2000	19.4	266.5	19.4	266.6

```

Residual Summary for LN7_2000
  GCPs: 17 X RMS  0.32 Y RMS  0.25

```

Figure 3.7: RMSE result of geo-referencing 2000 image.

The roads of 2013 was then modified (backdated) using the satellite images to represent the road network at the different time frames as shown in (Figure 3.8), and later superimposed with other relevant environmental data which would depict the rate of change of the road network in the GLM.

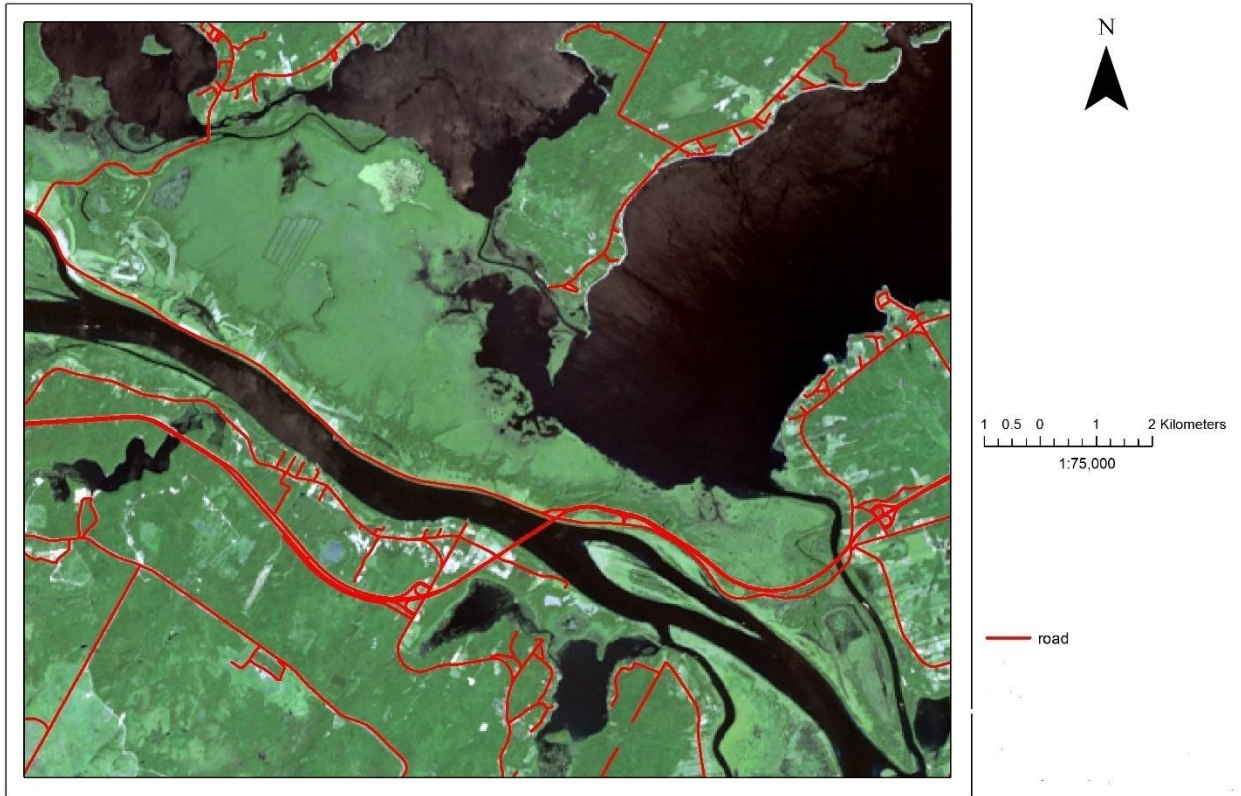


Figure 3.8: 2013 road network (in red) superimposed on the Landsat 8 (2013) image.

3.3 MULTI-RESOLUTION SEGMENTATION

To get the best segmentation results in eCognition the value scale parameter was set as 185. The scale parameter is an abstract term which simply restricts objects from being too heterogeneous. By modifying the value in the scale parameter one can vary the size of image objects [eCognition, 2004]. This process basically done by trial and error method because there is no rule in using a certain scale parameter this is a pretty iterative process and should be repeated with varying scale parameter till the required result/goal is achieved.

The downside of having a low scale parameter and using multi-resolution segmentation is the very huge processing time, sometimes it took as much as 12 hours to segment an image which is also due to huge size of the Landsat satellite imagery used in this study. Figures 3.9 and 3.10 show the image for the study area been segmented at different zoom levels. As can be seen, Figure 3.9 has more heterogenous feature due to the fact that it has a higher scale parameter, while Figure 3.10 has more homogenous features for the same reason.

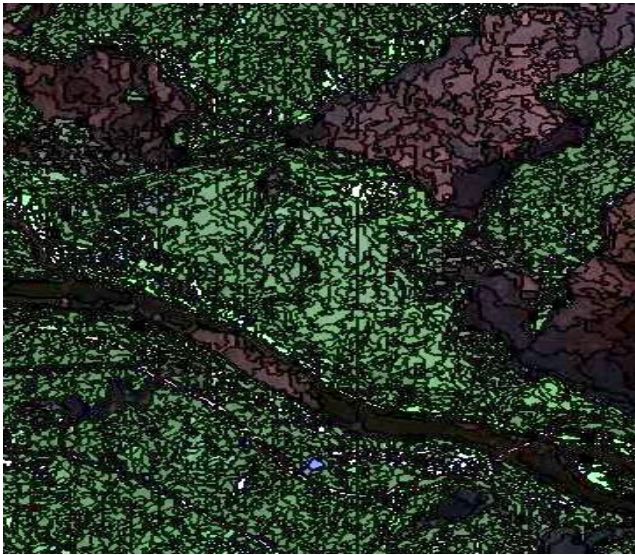


Figure 3.9: Segmentation of the image (5000 scale parameter).

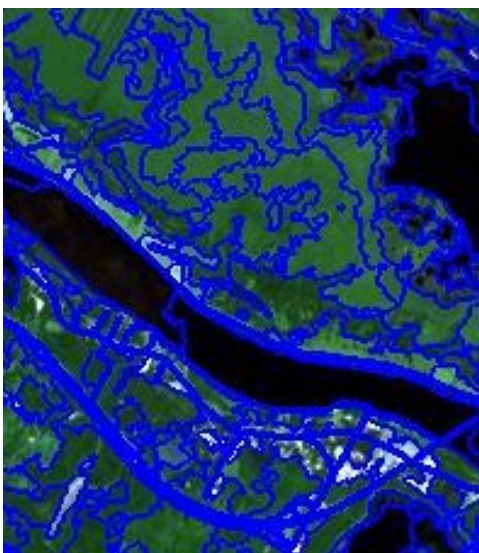


Figure 3.10: Segmentation of the image (185 scale parameter).

3.4 SPECTRAL INDICES FOR GLM AREA

Spectral indices are composed of surface reflectance at two or more wavelengths that demonstrate relative abundance of components of interest. Vegetation indices are the most prominent type, however different other indices are available for burned regions, man-made (built-up) features, water, and geologic elements. They can reduce the data volume for processing and analysis thereby providing information that is more strongly related to the changes in the scene than any single band [Coppin et al., 2004]. Due to the fact that the spectral bands in Landsat 7 ETM+ is quite different from the Landsat 8 OLI and TIRS spectral bands more attention to detail was taken in band selection so as not to confuse the 4th band which is red in Landsat 8 with the 4th which is near infra-red band in Landsat 7.

The main reason for using spectral indices is to properly distinguish between vegetation classes. For example, NDVI can be very useful in distinguishing between forest and non-forest land. Spectral indices can also be used to quantify cover fractions of the interested ground components such as forest canopy, pasture, second growth, impervious surface and damaged vegetation [Lu et al., 2004].

3.4.1 Normalized Difference Vegetation Index (NDVI)

NDVI is a widely used vegetation index, which can reduce the atmospheric and illumination effects by using the difference of the mean and the ratio of red and near-infrared band bands [Giri, 2012]. NDVI values strongly correlate with green vegetation and changes in NDVI indicate changes in forest activities [Verbesselt et al., 2010]. NDVI decreases significantly after green biomass is removed so it's used significantly for

mapping and monitoring fire disturbance, land cover changes, urbanization and so on [Verbesselt et al., 2010].

Due to the Normalized Difference Vegetation Index's (NDVI) inability to accurately distinguish between the classes used in this study, it was disregarded as a parameter used to distinguish between the classes solely due to the fact that the Feature Space Optimization in eCognition technique didn't regard the NDVI as a viable method in distinguishing between these classes i.e. it shows a weak separation distance between the samples. Figure 3.11 show the result for NDVI in the 2013 image (Landsat 8 image).



Figure 3.11 NDVI result for 2013 image (Landsat 8 image).

3.4.2 Near-Infrared Ratio

A simple division of the near- infrared with the red band (i.e. NIR/R) was used instead of NDVI. It can be said that the classes were a lot more separable using this method especially forest and non- forest. Figure 3.12 shows the result of NIR ratio on the 2013 image.



Figure 3.12 NIR ratio result for 2013 image (Landsat 8 image).

3.5 CLASS SELECTION FOR CLASSIFICATION

The classes used for classification in this study was derived from the forestry maps obtained from the Department of Natural Resources (DNR) and followed roughly Anderson Classification system. The legend for forestry maps has an extensive list of LULC maps has an extensive list of LULC classes as shown in Figure 3.13. Classes in this study are somewhat modified to meet the requirement of this study. Accordingly, the adopted classification scheme comprises of the following classes:

- Water: covers streams, river, lakes and other water bodies.
- Wetland
- Submerged Wetland: wetland that is seasonally flooded with water.
- Non-forest: combines the classes of non-forest land, partial cuts, burns and cutovers.
- Forest: Includes all the different categories and forest types.
- Roads: Includes all the different types and categories of roads.

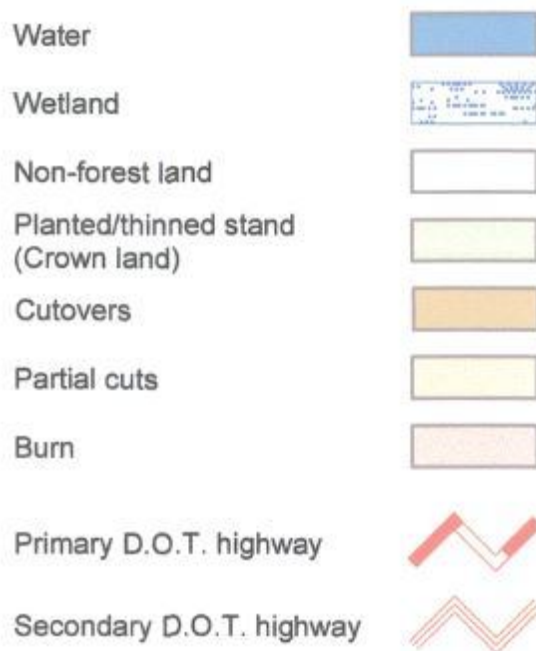


Figure 3.13: Forestry map Legend.

3.6 GLM IMAGE CLASSIFICATION USING FEATURE SPACE OPTIMISATION (FSO)

Feature Space Optimization is a tool that helps to find the combination of features most suitable for separating classes, in conjunction with a nearest neighbor classifier [eCognition, 2004]. It compares the features of selected classes to find the combination of features that produces the largest average minimum distance between the samples of the

different classes. The Feature Space Optimization function offers a method to mathematically calculate the best combination of features in the feature space.

The results without the use of feature space optimization was very unrealistic as it couldn't properly distinguish between the water class, forest and non-forest. Therefore the feature space optimization was deemed important to properly distinguish between the classes used for classification.

Figure 3.14 shows the feature space optimisation dialog box showing the best separation distance, classification classes and dimension and Figure 3.15 is the advanced feature space optimisation dialog box depicting the feature that best separate the individual classes in this study. Bands used in this study for a better separation of the classes are Brightness, Mean layers 4, 5, 6, Standard deviation 1, 3, 4, 5, 6 and the near infrared ratio.

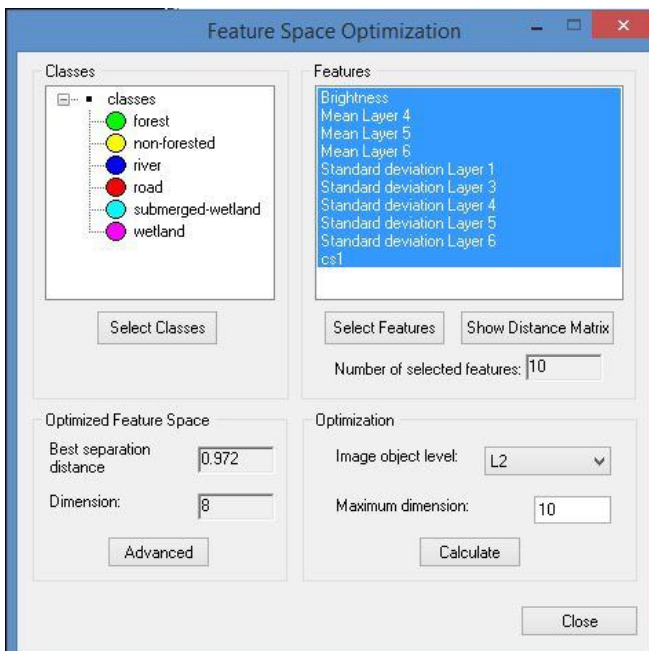


Figure 3.14: The Feature Space Optimization dialog box.

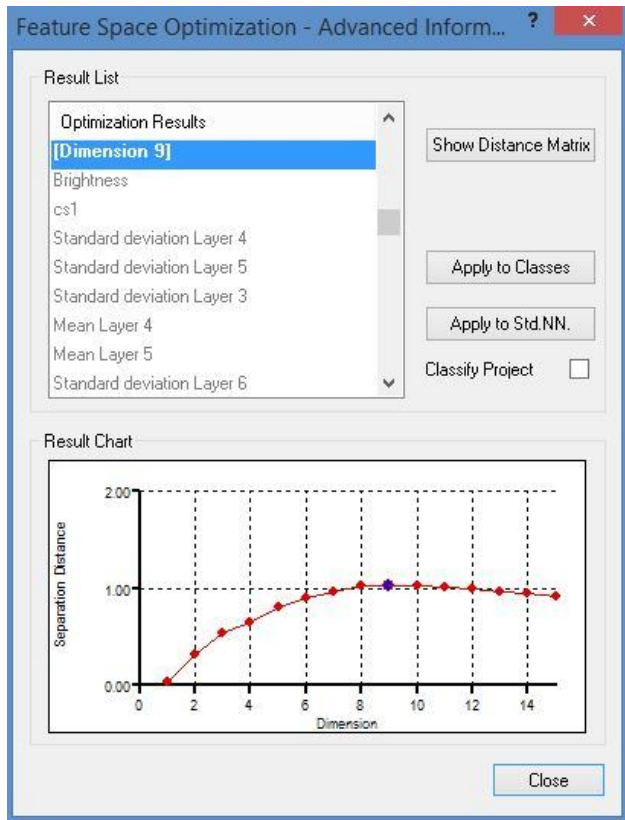


Figure 3.15: Feature Space Optimization – Advanced Information dialog box.

In this research, satellite images of the Landsat 7 ETM+ and Landsat 8 OLI and TIRS downloaded from the USGS website between the years 1986 and 2013 were used in the classification for land-cover. Six land cover and land use classes were applied namely: forest, non-forest, wetland, submerged-wetland, water class and roads.

Definiens eCognition software was used to perform object oriented classification since it is an object oriented program designed by Definiens Imaging GmbH. The method used in the classification for this study is the standard Support Vector Machine (SVM) because of the ability of the SVM algorithm to take a group of input data and predict, for every given input, which of two possible classes the input could be a member.

Sample areas required for supervised classification (Figure 3.16) were extracted from forestry maps of the GLM and were imported into the project scene by means of Training and Test Area (TTA) mask [eCognition, 2004]. Spectral signatures were obtained from different locations on the image which were then grouped according to the classes.

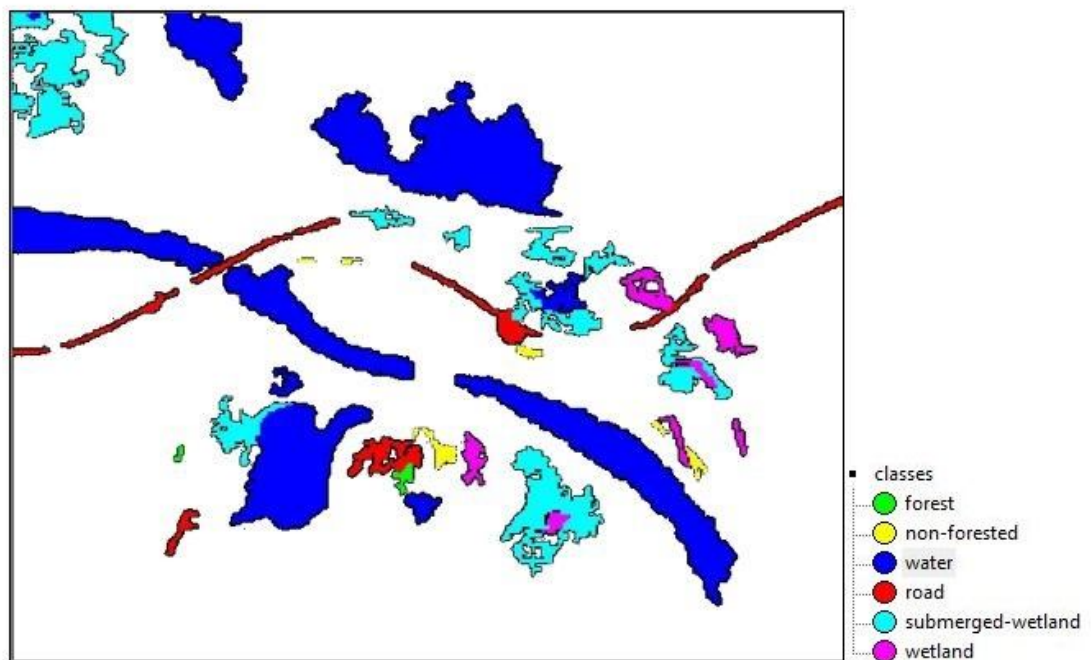


Figure 3.16: Training samples.

There appears to be some confusion between the road network, non-forest land and forest which is due to the spectral resemblance between the two classes. The main reason for this misclassification between the road, forest and non-forested land is primarily due to the fact that some of the secondary roads are not tarred and thereby give a similar spectral

reflectance to the non-forested land. Another reason is that some of the roads are covered by trees so in that scenario it also emit similar spectral reflectance close to the forest.

Figure 3.17 shows the classification result of 2013 image using the eCognition software; Figure 3.18 shows the classification result of 2001 image and Figure 3.19 shows the classification result of 1992.

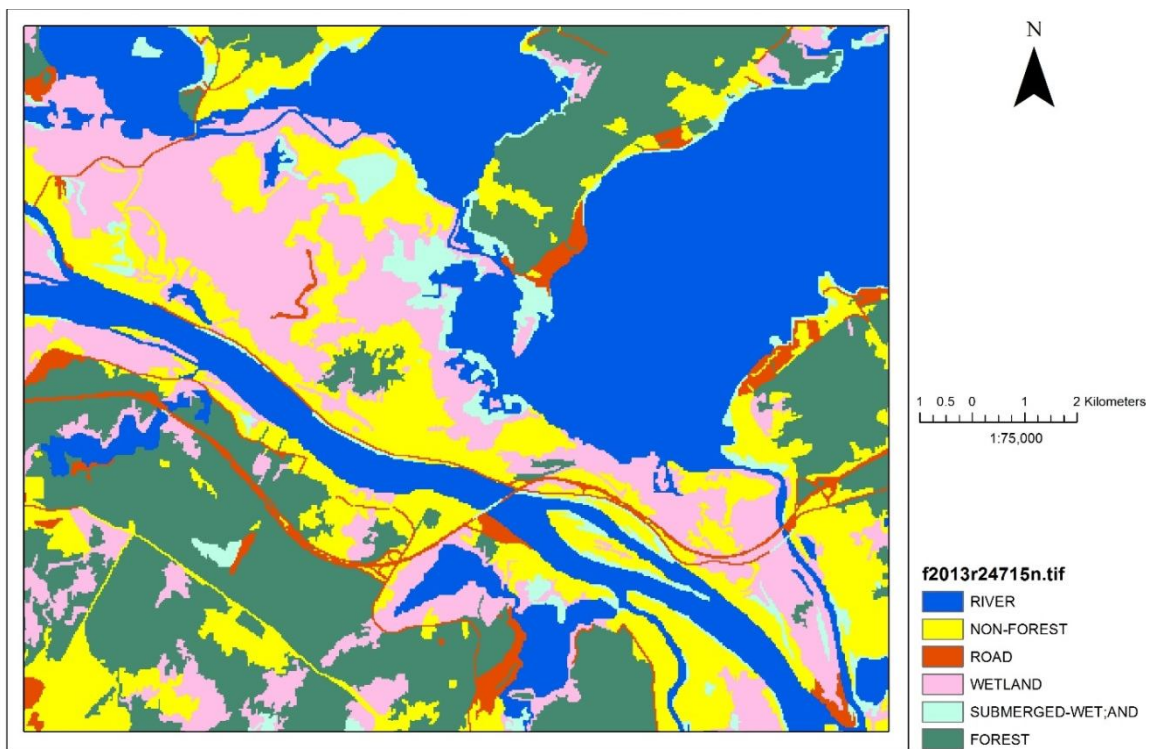


Figure 3.17: LULC classification results for 2013.

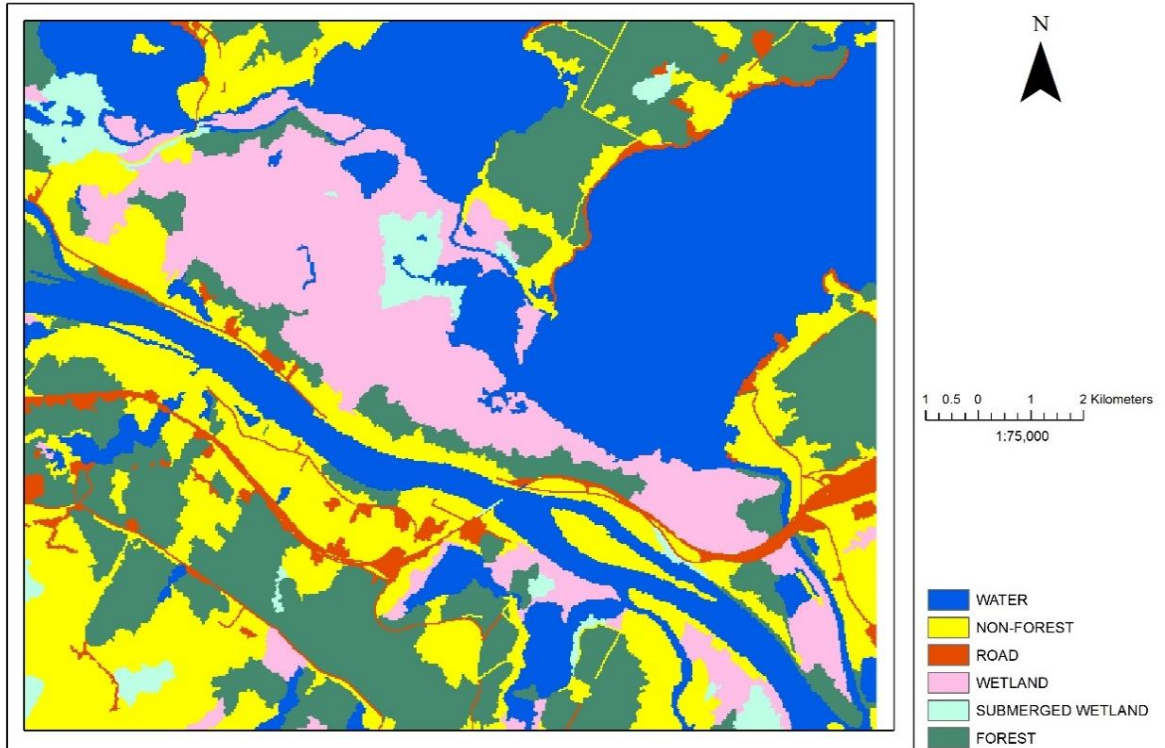


Figure 3.18: LULC classification results for 2001.

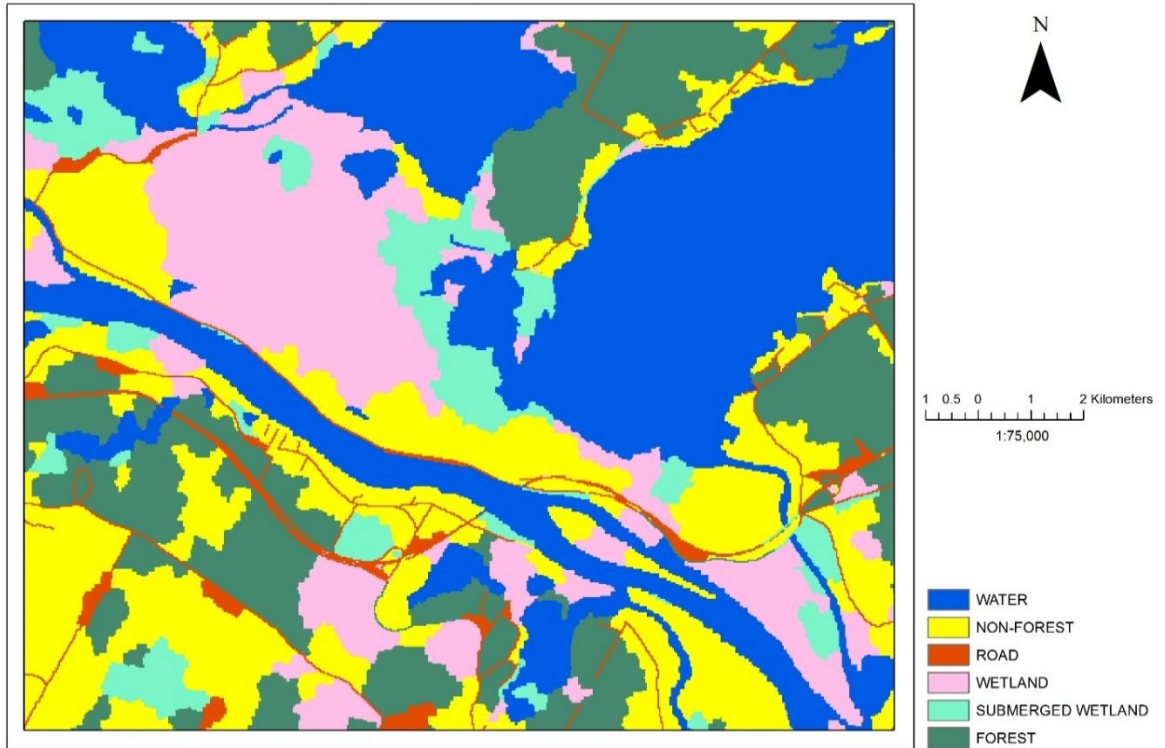


Figure 3.19: LULC classification results for 1992.

3.7 ACCURACY ASSESSMENT OF LULC MAPS

To evaluate the accuracy of an image classification, it is a regular practice to create a confusion matrix. In a confusion matrix, the classification results are contrasted with additional reference (Google maps) data. The quality of a confusion matrix is that it distinguishes the nature of the classification errors, and also their quantities. Frequently, surrogates to ground truths are obtained from existing land cover data (e.g., forestry map) which are perceived as suitable reference and which obviously are independent of the sample selection data.

The classification accuracy was evaluated using reference data (forestry maps), Figure 3.19 shows the test area samples used for the accuracy assessment; the set of sample used for the TTA mask differs from that of the training samples. The same test area samples were used in all the images to get the classification accuracy of each image to maintain consistency.

The corresponding classes were linked to form the confusion matrix. Several measurements such as Producer's, User's, Overall accuracy and Kappa index of agreement were derived for each class. Figure 3.20 shows the confusion matrix of the classification result for the 2013 image. It shows an overall accuracy of about 84%. Figure 3.21 and Figure 3.22 show the accuracy assessment for 2001 and 1992 respectively where the accuracy is about 85% for 2001 and about 82% for 1992.

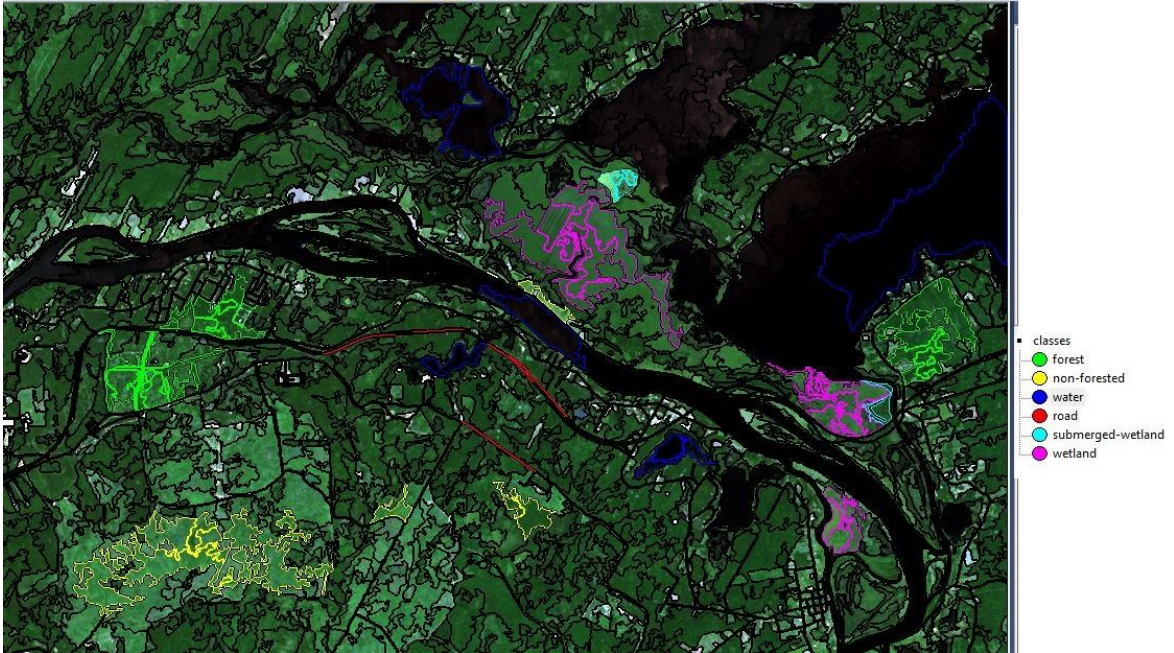


Figure 3.19: Test area samples.

3.7.1 Producer Accuracy

It is the fraction of correctly classified pixels with regard to all pixels of that ground truth class. For each class of ground truth pixels (row), the number of correctly classified pixels is divided by the total number of ground truth or test pixels of that class [Akbari, 2006]. For example the producer accuracy for wetland in the Figure 3.20 is $9383/13917 = 67\%$ (Producer, User and Overall accuracy are usually in percentile).

3.7.2 User Accuracy

The figures in the User column represent the reliability of classes in the classified image: it is the fraction of correctly classified pixels with regard to all pixels classified as this class in the classified image. For each class in the classified image (column), the number of correctly classified pixels is divided by the total number of pixels which were classified as

this class [Zhang, 2014]. For example the user accuracy for wetland in Figure 3.20 is $9383/11682 = 80\%$.

3.7.3 Overall Accuracy

The percentage of all correctly classified pixels (from all the classes) against the total number of pixels being checked [Zhang, 2014]. For example the overall accuracy in Figure 3.20 is $51,185/60974 = 84\%$

3.7.4 Kappa Coefficient

Cohen's Kappa (often simply called Kappa) coefficient is a measure of agreement between two sets of datasets. Kappa coefficient measures the percentage of data values in the main diagonal of the table and then adjusts these values for the amount of agreement that could be expected due to chance alone.

User \ Reference Class	water	non-forested	road	wetland	submerged-wetland	forest	Sum
Confusion Matrix							
water	23936	0	0	269	0	0	24205
non-forested	0	10231	119	4224	0	1720	16294
road	0	0	333	0	0	0	333
wetland	0	0	0	9383	523	1776	11682
submerged-wetland	0	0	0	41	722	0	763
forest	0	1115	2	0	0	6580	7697
unclassified	0	0	0	0	0	0	0
Sum	23936	11346	454	13917	1245	10076	
Accuracy							
Producer	1	0.9017275	0.7334802	0.6742114	0.58	0.653	
User	0.9888866	0.6278998	1	0.8032015	0.9462647	0.8548785	
Hit	0.9944122	0.7403039	0.8462516	0.733	0.7191235	0.7404490	
Short	0.9888866	0.5876845	0.7334802	0.5786260	0.5614308	0.5878674	
KIA Per Class	1	0.8658892	0.732	0.597	0.5745964	0.603	
Totals							
Overall Accuracy	0.8394562						
KIA	0.78						

Figure 3.20: Accuracy assessment for Land cover classification for 2013.

User \ Reference Class	water	non-forested	road	wetland	submerged-wetland	forest	Sum
Confusion Matrix							
water	23717	0	0	0	1274	0	24991
non-forested	0	13103	0	0	0	5041	18144
road	0	0	1075	0	0	17	1092
wetland	0	0	0	11629	1067	0	12696
submerged-wetland	0	0	0	0	24	0	24
forest	0	0	0	841	690	2436	3967
unclassified	0	0	0	0	0	0	0
Sum	23717	13103	1075	12470	3055	7494	
Accuracy							
Producer	1	1	1	0.9325581	0.007855973813	0.325	
User	0.949	0.7221671	0.9844322	0.916	1	0.614	
Hellden	0.9738441	0.8386725	0.9921551	0.9241834	0.0155894771	0.425	
Short	0.949	0.7221671	0.9844322	0.859	0.007855973813	0.27	
KIA Per Class	1	1	1	0.9148004	0.007464916881	0.278	
Totals							
Overall Accuracy	0.8533999						
KIA	0.7978414						

Figure 3.21: Accuracy assessment for Land cover classification for 2001.

User \ Reference Class	water	non-forested	road	wetland	submerged-wetland	forest	Sum
Confusion Matrix							
water	21761	59	0	0	1385	0	23205
non-forested	0	17903	0	1480	1140	4803	25326
road	0	0	1366	0	0	336	1702
wetland	0	1380	0	7795	0	0	9175
submerged-wetland	39	741	0	414	0	0	1194
forest	0	0	154	0	155	7412	7721
unclassified	0	0	0	0	0	0	0
Sum	21800	20083	1520	9689	2680	12551	
Accuracy							
Producer	0.9982110	0.8914505	0.8986842	0.8045206	0	0.5905506	
User	0.9377720	0.707	0.8025852	0.8495913	0	0.96	
Hellden	0.967	0.7885221	0.848	0.8264419	0	0.7312549	
Short	0.9361986	0.6508762	0.736	0.7042190	0	0.5763608	
KIA Per Class	0.9972909	0.8275129	0.896	0.7741979	-0.01778664959	0.5383846	
Totals							
Overall Accuracy	0.8231050						
KIA	0.7614779						

Figure 3.22: Accuracy assessment for Land cover classification for 1992.

The overall accuracies (which are 84% for 2013, 85% for 2001 and 82% for 1992) obtained from the classification are quite similar to each other and of high standard with 82% as the least classification accuracy obtained in this study. Table 3.4 shows the producer accuracy for the combined case of wetland and submerged wetland in the 3 different images.

Table 3.4: Producer accuracy of the three images

YEAR	(WETLAND + SUBMERGED)%
2013	67
2001	75
1992	63

The wetland and submerged wetland accuracy in the three images can be said to be very different due to the fact that the wetland and submerged wetland depend on the weather conditions, especially rainfall in the period prior to the imaging. Consequently, so they differ in their natural state greatly for instance an area in 2013 that is classified as a partly a submerged wetland and wetland is classified as water in both 2001 and 1992 this might be due to the decrease in water level during the time of capture of the satellite imagery.

CHAPTER 4

CHANGE DETECTION ANALYSIS

4.1 CHANGE DETECTION RESULTS FROM THE YEAR 1992 TILL 2001.

Figure 4.1 shows wetland changes from the year 1992 to the year 2001 with its change matrix both in pixel and percentage (Tables 4.1 and 4.2). This shows a 38% decrease from the year 1992 to 2001. To get this change we assume that wetland to wetland there is no change and that change exists between wetland and the several different classes. The total number of pixels in this change matrix is 526580.

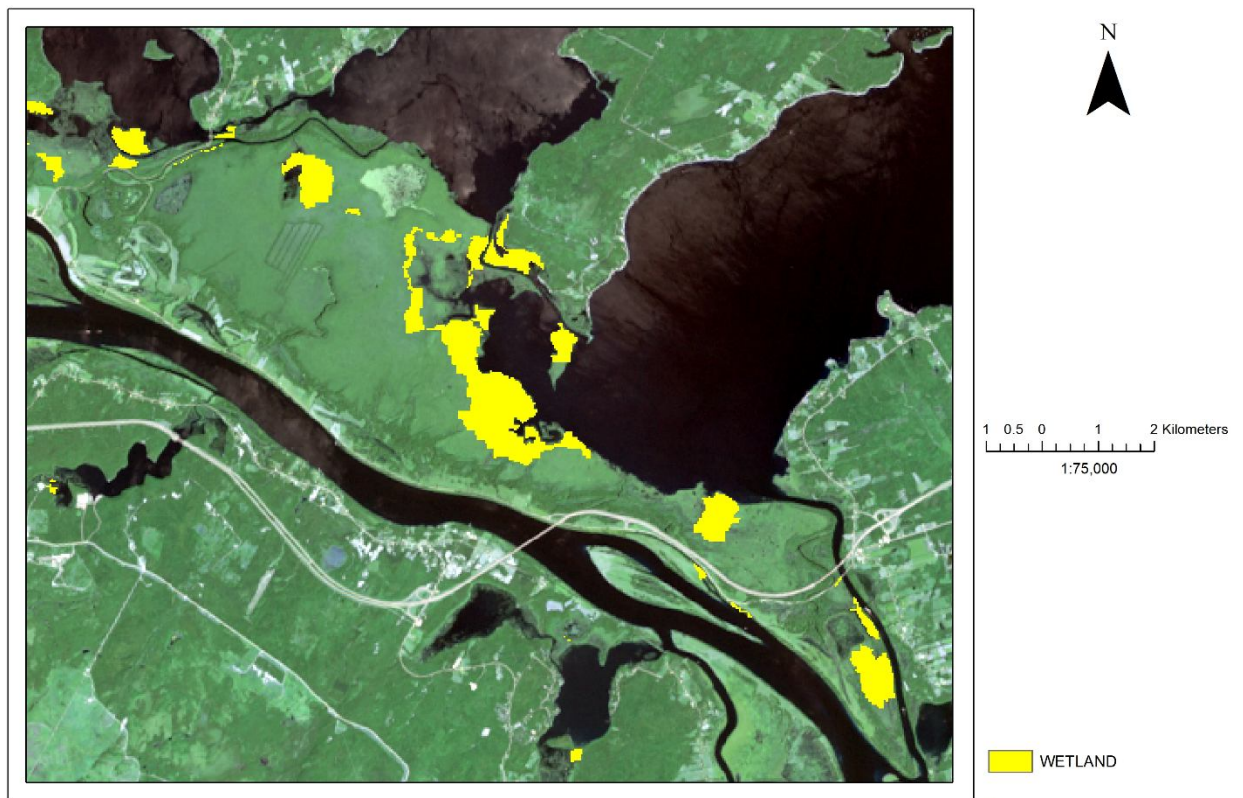


Figure 4.1: wetland changes from the year 1992 to the year 2001

Table 4.1: Change matrix 2001 x-axis and 1992 y-axis (in pixels).

		1992						
CLASSES		Water	Wetland	Non-Forest	Forest	Road	Submerged-Wetland	SUM
2001	Water	94794	2709	2267	2743	59	2095	104667
	Wetland	1829	34296	12865	2815	274	9081	61160
	Non-Forest	3095	12750	107853	21363	7842	14267	167170
	Forest	849	30047	31702	90349	2992	1640	157579
	Road	674	1844	8831	5655	6418	978	24400
	Submerged-Wetland	1007	1889	2289	997	159	5263	11604
SUM		102248	83535	165807	123922	17744	33324	526580

Table 4.2: Change matrix 2001 x-axis and 1992 y-axis (in percentage).

		1992					
CLASSES		Water	Wetland	Non-Forest	Forest	Road	Submerged-Wetland
2001	Water	92	4	1.3	2	0.3	6
	Wetland	2	41	8	2	2	27

	Non-forest	3	15	65	17	44	43
	Forest	1.3	36	19	73	17	5
	Road	0.7	2	5.3	5	36	3
	Submerged wetland	1	2	1.4	1	1	16

4.2 CHANGE DETECTION RESULTS FROM THE YEAR 2001 TILL 2013 IN THE GLM

Figure 4.2 shows wetland changes from the year 2001 to the year 2013 with its change matrix both in pixel and percentage (Tables 4.3 and 4.4). This shows a 68% increase from the year 2001 to 2013. To get this change we assume that wetland to wetland there is no change and that change exists between wetland and the several different classes.

N.B Percentile is derived from the total number of pixels in a class divided by the number of pixels in the image.

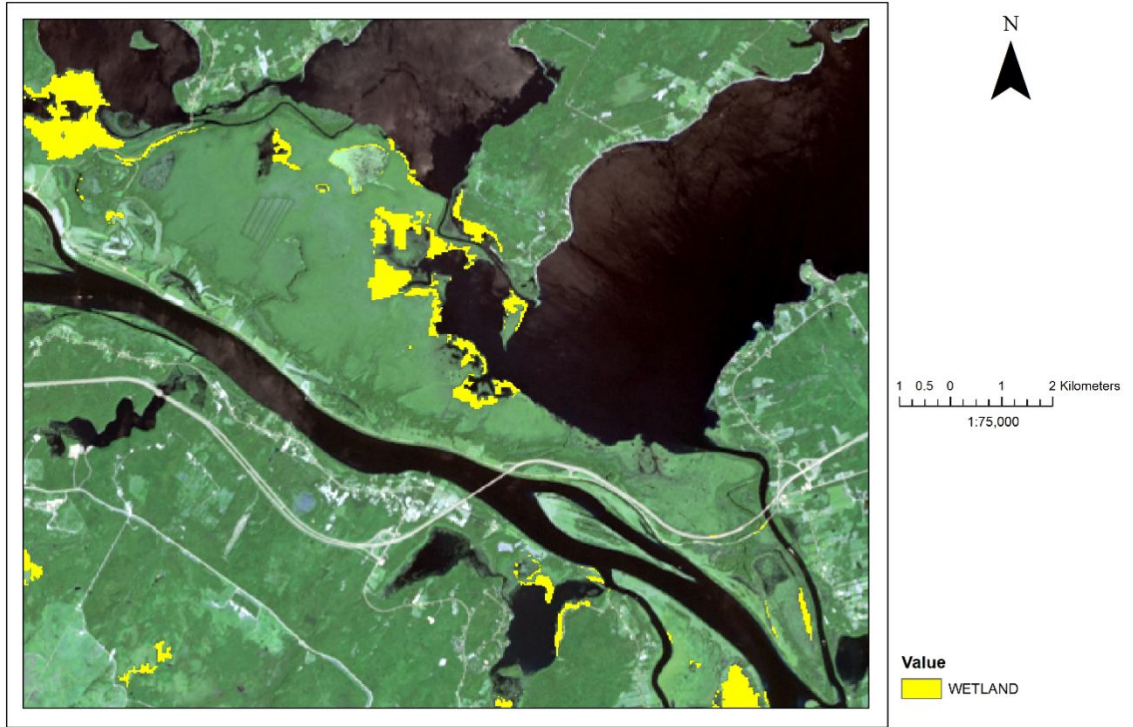


Figure 4.2: wetland changes from the year 2001 to the year 2013

Table 4.3: Change matrix 2001 x-axis and 2013 y-axis (in pixels)

		2001						
		Water	Wetland	Non-Forest	Forest	Road	Submerged -Wetland	SUM
2013	Water	94389	3888	2775	1173	794	677	103696
	Wetland	2919	27681	23211	38469	1608	6161	100049
	Non-Forest	962	16328	82875	15132	9036	951	125284

	Forest	566	6486	41784	90490	4437	1338	14510
	Road	315	2509	11784	8280	7217	492	30597
	Submerged -Wetland	5516	4268	4741	4035	1308	1985	21853
	SUM	10466	61160	16717	15757	2440	11604	52658
		7		0	9	0		0

Table 4.4: Change matrix 2013 x-axis and 2001 y-axis (in percentage).

		2001					
CLASSES		Water	Wetland	Non-Forest	Forest	Road	Submerged-Wetland
2013	Water	91	6	2	1	3	6
	Wetland	2	45	14	24	7	53
	Non-forest	1	27	50	10	37	8
	Forest	0.5	11	25	57	18	12
	Road	0.3	4	7	5	30	4
	S/W	5.2	7	2	3	5	17

4.3 TABLE OF SHOWING CHANGE IN HECTARES

Table 4.5 shows four classes instead of the regular six because in this table forest and non-forest land was grouped as one class just because non-forest doesn't mean bare land as

there is vegetation such as shrubs, orchids to mention a few and wetland and submerged wetland are also grouped as one class just because submerged wetland is also a kind of wetland that the water level increases or decreases seasonally or due to rainfall.

Table 4.5: Change matrix showing land cover types with respect to area and percentage

Land Cover Type	1992		2001			2013		
	AREA (ha)	%	AREA (ha)	%	CHANGE (2001-1992)	AREA (ha)	%	CHANGE (2013-2001)
Roads	1597	3.36	2196	4.63	599	2754	5.81	558
Water	9202	19.41	9420	19.88	218	9333	19.69	-87.
Forest + Non-forest	26076	55.03	29227	61.67	3151	24334	51.35	-4893
Wetland + Submerged wetland	10517	22.2	6549	13.82	-3968	10971	23.15	4422
Sum	47392	100	47392	100	0	47392	100	0

Figure 4.3 shows a bar-chart depicting the different Land cover types and with respect to the area each land cover type covers in hectares.

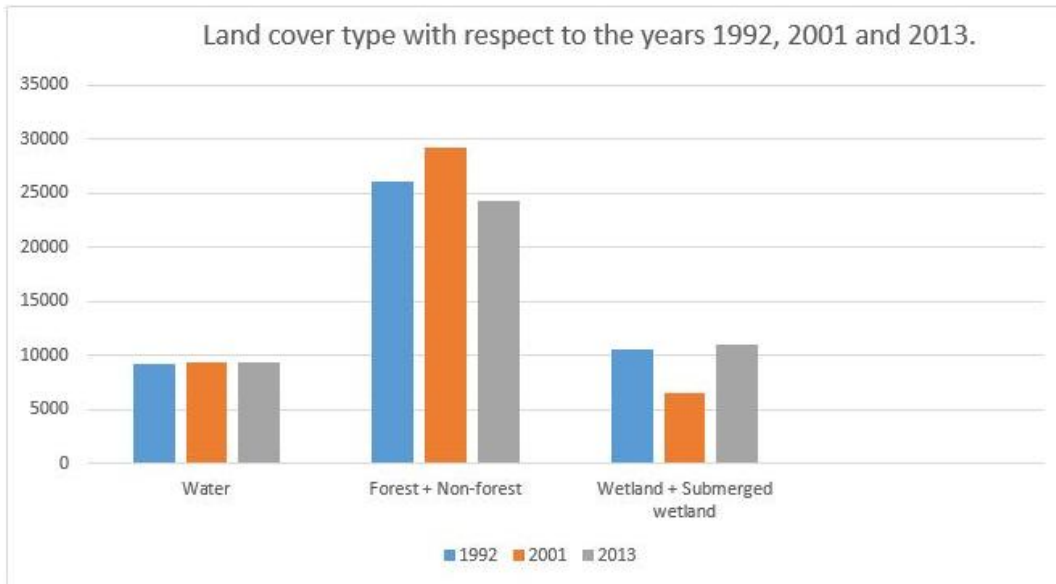


Figure 4.3: Land cover type with respect to area in the years 1992, 2001 and 2013.

Water body area increased by 2.36% from 1992 till 2001 but there was steady decline of about 1.42% from 2001 – 2013 due to the fact that more submerged wetland was regarded as water.

There was increase by 12% in the forest and non-forest from 1992 – 2001 which is called afforestation (planting of trees), this might be solely because of the classification of the GLM area in the 1990's as a "Class 2 Protected Natural area" which in-turn limits the utilization of the territory to low-impact recreational activities and conventional sustenance gathering activities, while limiting industrial, business and horticultural improvements. In the year 2001 – 2013 there has been a steady depletion (deforestation) of about 7%, this could result in the fact that urbanisation has resulted significantly in the area over time. This might also be the reason why from the year 2007 – 2012, a crown land management plan was enacted. The Annual allowable cut (AAC) of the hardwood

was reduced from 1.77 million cubic metres to 1.41 million cubic metres. This reduction will ensure a sustainable hardwood supply in the future.

Lastly, the result of this study show a decrease in the wetland resources which also includes the submerged wetland class from 1992 – 2001 of about 38% decrease and an increase of 68% from 2001 – 2013 and a 4.32% overall increase in the wetland in the GLM area. As noticed there was a decrease in the wetland as the water class increased which could be due to rainfall as the land is partially or fully submerged in water.

CHAPTER 5

CONCLUSION

After reviewing the characteristic of the GLM area, this study was concerned with three main questions:

1. How has the landscape of GLM changed over the years?
2. Is there a relationship between the landscape changes with other physical or policy changes?
3. Can satellite remote sensing images help in answering these questions? How?

With these questions in mind, an extensive literature review was executed. The findings supported the thesis's proposal, and the main goal, for using geo-images for mapping the land cover status of GLM area and assessing the changes at different times.

5.1 ACHIEVED OBJECTIVES

This study was successful in developing a methodology to monitor and evaluate the land use and land cover changes of the study area using remote sensing. Thereby highlighting the wetland changes in the GLM undergone over a period of about 20 years with the aid of other secondary data such as road network downloaded from the Service New Brunswick (SNB) and Forestry Maps obtained from the Department of Natural Resources (DNR).

With respect to establishing a methodology to extract relevant information from satellite imagery, this study succeeded in:

1. Establishing a methodology for selecting ground control points. To ensure consistent referencing between the images and other datasets, the study used mostly the same set of control points to georeference all satellite images. The coordinates for these points were extracted from an ortho-photo map downloaded from Service New Brunswick.
2. Selecting the land cover types and their areas as the spatial ecological indicators relevant to the study. The study also developed the land cover classification scheme that incorporated the used land cover scheme by the forestry maps, and follow the Anderson Classification System. The chosen parameters can be extracted consistently and easily from all images used in this study.
3. As with respect to the best method used to extract relevant information from satellite imagery, this study found that the support vector machine classifier was appropriate for the task. This study established a set of training samples of land cover types to aid in the classification, as well as testing samples to assess the accuracy of the land cover maps. Both datasets were used consistently in processing the Landsat satellite images of 1992, 2001, 2013.

The study also answered the question on the spatial scale that is appropriate for conducting this study and producing meaningful results. Theoretically there should be a multiple of spatial and categorical scales to accommodate the internal variations of different landscape patches. However, the scale used in this study was constrained by the resolution of Landsat

data used in this study. Landsat images have a resolution of 30m, therefore the spatial scale for this study was equivalent to around 1/100,000, or at the best condition, 1/50,000.

This study adopted the post classification change detection approach for analysing changes in the use and cover of GLM after mapping the land cover type for each of the study years 1992, 2001, 2013.

Pertaining to the research questions, the outcome of this study was an information base that reflected and aided in visualizing how the landscape of GLM has changed over several years. This information base was also essential to understand the relationship and interaction between human and natural phenomena. The aim is to better manage and use the resources in the Grand Lake Meadows. By having information from the past and up to date, change detection is a relevant tool for ecological studies, assessing the accuracy of results derived from change detection critical step for the use of remote sensed information to biological administration framework as a relevant tool for decision making.

It is found in this study that there have been a 68% increase of the GLM from 2001 till date and a 38% decrease from the previous decade. There is a potential to predict shifts in trend (change detection) of land use which would in turn recommend to the managers of the GLM the best way to maintain this Protected Area. The developed methodology provides for continuous environmental monitoring of the GLM wetland. This is important for evaluating the effectiveness of the implemented management strategies.

5.2 FUTURE WORK

There are still few issues one can address in the future work. One set of issues will rise when dealing with archival aerial images for the periods before the launching of imaging satellites being of one band (panchromatic), they cannot be classified in the same approach as multi-spectral images. The next phase should address issues associated with linking other environmental, demographic, and economical data with the land cover information to create a GIS database. Another issue is identifying the appropriate spatial analysis tools to provide an understanding of the driving forces responsible for the socio-economic and environmental changes in the GLM area. In conclusion, satellite imagery can be collected for both the winter period of the GLM area and the summer period to determine the effects of moisture on the wetland.

Spatial analysis of such database will provide a better understanding of the interaction between human and the environment in the GLM area.

In conclusion, satellite imagery can be collected for both the winter period of the GLM area and the summer period to determine the effects of moisture on the wetland.

5.3 PROBLEMS ENCOUNTERED

The use of different geospatial software in this project brought about its own set of problems. One of such is that ArcGIS counts its pixels from the center and most other remote sensing software select theirs from the left corner of the pixels.

5.4 CONTRIBUTION TO RESEARCH

- Little research has been carried out with the use of satellite imageries with remote sensing as a tool for the spatial analysis of the GLM area, therefore this was done successfully in this research.
- Even though object oriented classification has been done in different parts of the world not much has been done in the GLM area in which this study carried out.

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HIGHLIGHTS OF QUALIFICATIONS

- Over a year's accumulated experience in performing various engineering assistant activities such as land surveying and plot numbering.
- Over a year's experience as a research assistant using different geospatial software to analyze the GLM area.
- Ability to work independently or collaboratively on projects to achieve the desired objectives.
- Highly adaptable to any new environment; I am a self-motivated individual with good communication skills.

EDUCATION

- Master of Engineering, Geodesy & Geomatics Engineering
- GLM Endowment Fund Award
- The University of New Brunswick, Canada, Sept. 2013 – January, 2016.

- Bachelor of Science, Surveying & Geo-informatics (Second-class Upper Division)
The University of Lagos, Nigeria, Nov. 2006 – Aug. 2011.

RELEVANT COURSES / PROJECT WORK

- Advanced Technologies in remote sensing: An introduction to the concept and basic theory of Artificial Neural Network (ANN), Wavelet Transformation (WT) and Fuzzy Logic (FL); literature review of remote sensing applications.
- Advanced Topics in Environmental Impact Assessment – EIA theoretical foundation and methodology, procedures in conducting EIA.
- Principles of Geographic Information Systems (GIS) I & II – Definition of basic concepts and components of GIS, spatial data models, database structure, applications.
- Digital Mapping I – Digital representation of graphic objects and cartographic symbols, raster and vector graphics, coordinate transformation and mapping analysis.

TECHNICAL SKILLS

Proficiency in the use of:

- ESRI ArcGIS.
- E-cognition.
- Google Earth.
- MS Office – Word, Excel, PowerPoint & Access.
- MS Project.
- ENVI
- PCI Geomatica

RELEVANT EXPERIENCE

Graduate Research Assistant

University of New Brunswick

1st March, 2015 – till present.

- Spatial analysis of the land cover changes in the Grand Lake Meadows, New Brunswick (was funded)

Junior Surveyor (January 2013 – September 2013)

SURVEYOR GENERALS OFFICE (Lagos State Government)

- Land surveying
- Plot numbering
- Land registration
- Subdivision

Community Engagement Representative

CHEVRON Nigeria Limited, 2 Chevron Drive, Lekki-Lagos.

- Served as an intermediary between Chevron and the Oil producing states.
- Served in the Agbami scholarship scheme.

Surveyor [Intern]

INTERSPATIAL Technologies Lagos, Nigeria, May – Oct. 2009.

- DGPS base station/rover personnel as part of field team that carried out GPS observations for the coordination of newly established control beacons.
- Field personnel responsible for data collection and entry for the digital mapping project of Lagos State.
- The use of mapping software (AutoCAD, ArcGIS) and data entry software (Microsoft Excel, ArcPad), also used the Juno which was used to capture features of places of interest for the Lagos State Digital Mapping Project.

VOLUNTEERING WORK

University of Lagos Alumni Association Meeting (Lagos, Nigeria) – Responsible for collection and dispersal of conference presentations (digital copies).

INTERESTS & HOBBIES

- Watching soccer and playing table tennis.