Detecting Land Cover Change over a 20 Year Time Period in the Niagara Escarpment Plan Using Satellite Remote Sensing

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

The Niagara Escarpment is one of Southern Ontario's most important landscapes. Due to the nature of the landform and its location, the Escarpment is subject to various development pressures including urban expansion, mineral resource extraction, agricultural practices and recreation. In 1985, Canada's first large scale environmentally based land use plan was put in place to ensure that only development that is compatible with the Escarpment occurred within the Niagara Escarpment Plan (NEP). The southern extent of the NEP is of particular interest in this study, since a portion of the Plan is located within the rapidly expanding Greater Toronto Area (GTA). The Plan area located in the Regional Municipalities of Hamilton and Halton represent both urban and rural geographical areas respectively, and are both experiencing development pressures and subsequent changes in land cover.

Monitoring initiatives on the NEP have been established, but have done little to identify consistent techniques for monitoring land cover on the Niagara Escarpment. Land cover information is an important part of planning and environmental monitoring initiatives. Remote sensing has the potential to provide frequent and accurate land cover information over various spatial scales. The goal of this research was to examine land cover change in the Regional Municipalities of Hamilton and Halton portions of the NEP. This was achieved through the creation of land cover maps for each region using Landsat 5 Thematic Mapper (TM) remotely sensed data. These maps aided in determining the qualitative and quantitative changes that had occurred in the Plan area over a 20 year time period from 1986 to 2006. Change was also examined based on the NEP's land use designations, to determine if the Plan policy has been effective in protecting the Escarpment.

To obtain land cover maps, five different supervised classification methods were explored: Minimum Distance, Mahalanobis Distance, Maximum Likelihood, Object-oriented and Support Vector Machine. Seven land cover classes were mapped (forest, water, recreation, bare agricultural fields, vegetated agricultural fields, urban and mineral resource extraction areas) at a regional scale. SVM proved most successful at mapping land cover on the

Escarpment, providing classification maps with an average accuracy of 86.7%. Land cover change analysis showed promising results with an increase in the forested class and only slight increases to the urban and mineral resource extraction classes. Negatively, there was a decrease in agricultural land overall. An examination of land cover change based on the NEP land use designations showed little change, other than change that is regulated under Plan policies, proving the success of the NEP for protecting vital Escarpment lands insofar as this can be revealed through remote sensing.

Land cover should be monitored in the NEP consistently over time to ensure changes in the Plan area are compatible with the Niagara Escarpment. Remote sensing is a tool that can provide this information to the Niagara Escarpment Commission (NEC) in a timely, comprehensive and cost-effective way. The information gained from remotely sensed data can aid in environmental monitoring and policy planning into the future.

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Abbreviations

AVHRR	Advanced Very High Resolution Radiometer
CEM	Cumulative Effects Monitoring
DEM	Digital Elevation Model
DC	Development Control
DN	Digital Number
ENA	Escarpment Natural Area
EPA	Escarpment Protection Area
ERA	Escarpment Rural Area
GGH	Greater Golden Horseshoe
GRCA	Grand River Conservation Authority
GTA	Greater Toronto Area
IFOV	Instantaneous-field-of-view
MD	Minimum Distance
MDC	Mahalanobis Distance Classification
MLC	Maximum Likelihood Classification
MNR	Ministry of Natural Resources
MREA	Mineral Resource Extraction Area
MSS	Multispectral Scanner
MUC	Minor Urban Centre
NAD	North American Datum
NDVI	Normalized Difference Vegetation Index

NEBR	Niagara Escarpment Biosphere Reserve
NEC	Niagara Escarpment Commission
NEP	Niagara Escarpment Plan
NEPDA	Niagara Escarpment Planning and Development Act
NOAA	National Oceanic and Atmospheric Administration
ONE	Ontario Niagara Escarpment
NTDB	National Topographic Database
RBF	Radial Basis Function
SVM	Support Vector Machine
TM	Thematic Mapper

Chapter 1
Introduction

1.1 Overview

The Niagara Escarpment has been called by many one of the Province's most important natural landscapes (Gertler, 1968; Borodczak, 1995; Ramsay, 1996; Jankovic, 1999; Barnett *et al.*, 2004; Then Niagara Escarpment Plan, 2005). The creation of the Niagara Escarpment Plan (NEP), Canada's first large-scale environmentally based land use plan was created to maintain balance between the natural landscape and the development pressures that threaten it (Barnett et al., 2004). Millions of people live within 100 kilometers of the Escarpment and due to its proximity to the most populous regions in Southern Ontario, urban development and demand for new residential areas, mineral resource extraction for growing infrastructure and the subsequent degradation of natural areas along the Escarpment are all key planning challenges that face the Niagara Escarpment Commission (NEC) (Niagara Escarpment Commission, 2008a). The area of the Escarpment that is cause for the greatest concern is the southern portion since it contains the rapidly growing urban centres of Hamilton and Burlington. These cities are located in the Greater Golden Horseshoe (GGH) region that extends along the western end of Lake Ontario. The GGH is both the most populous and the most heavily urbanized region in Canada (Martel and Caron-Malenfant, 2007). It is home to 8.1 million people, and its population grew by 630,631 between 2001 and 2006 (Martel and Caron-Malenfant, 2007). Overall, the GGH area accounted for 84% of Ontario's population growth during this time period (Martel and Caron-Malenfant, 2007). New areas for concern within proximity to the Escarpment are Milton and Halton Hills (Georgetown), as these two towns saw rapid population growth since 2001 at +71.4% and +14.7% respectively (Martel and Caron-Malenfant, 2007). As development pressure on the Escarpment increases, the need for monitoring land cover changes in the Plan has come to the forefront of monitoring initiatives.

The NEC is responsible for the protection of the landform through the NEP and as the responsible body, must establish consistent ways to monitor and protect the Escarpment. Monitoring the changes that are experienced in this area can be a challenge, since it encompasses such a large geographic area. It stretches from Tobermory to Niagara Falls and beyond, and transcends eight regional municipal boundaries and falls under a variety of governing bodies including respective upper and lower tier municipalities and conservation authorities. The NEC has a monitoring program currently in place called the Ontario Niagara Escarpment (ONE) Monitoring Program that is designed to assess whether the policies of the NEP are effective in protecting the escarpment and examines the linkages between land use change and ecosystem status (Cadman *et al.*, 1997). Through the program, a Cumulative Effects Monitoring (CEM) framework was developed consisting of monitoring objectives, questions, components, indicators, techniques, targets and an information management system (Cadman *et al.*, 1997). Studies on the changing landscape of the Niagara Escarpment were conducted in the past, and in the mid 1990's remote sensing had been used to monitor the changing landscapes of the escarpment. Previous studies have yet to provide the NEC with an effective methodology that can be used to monitor the Escarpment consistently and accurately over time. Remote sensing is a technique used to analyze features on the Earth from a distance, and since it is often difficult to reach many parts of the Escarpment for detailed field studies; the use of remote sensing imagery to perform change detection is an asset to an organization like the NEC to monitor changes in their jurisdiction.

1.2 Objectives

The goal of this research was to examine land cover change in the Regional Municipalities of Hamilton and Halton portions of the NEP. This was achieved through the use of Landsat 5 TM remote sensing data and a supervised classification algorithm over a 20 year time period from 1986 to 2006. The main objectives of the study were to:

1. Create land cover classification maps (as accurately as possible) at a regional scale in the Regional Municipalities of Hamilton and Halton portions of the NEP using remotely sensed data;
2. Identify what land cover changes have occurred in the Regional Municipalities of Hamilton and Halton over a 20 year time period from 1986 to 2006 (qualitative assessment);
3. Determine how much the land cover has changed in the Regional Municipalities of Hamilton and Halton over a 20 year time period (quantitative assessment);
4. Examine both qualitative and quantitative changes that have occurred in the NEP land use designations over a 20 year time period in the Regional Municipalities of Hamilton and Halton;
5. Detect (if any) potential land cover changes that are not compatible with the NEP land use designations and NEP policies.

1.3 Research Significance

Due to human impacts on the Niagara Escarpment landscape, there is a need to establish baseline datasets against which changes in land cover can be assessed (Lunetta and Elvidge, 1998 from Jensen, 2005). Previous studies have worked to provide land cover change information on the Escarpment through the use of air photo analysis and the classification of remotely sensed images for different areas of the NEP. Ramsay (1996) and Jankovic (1999) used air photo images to produce land cover maps in the Regional Municipality of Halton and Grey County respectively. These land cover maps were then used to determine changes in the NEP over time. Through ONE monitoring initiatives two baseline remote sensing studies were also conducted in conjunction with one another to examine the change that had occurred across the entire NEP area. Each study examined different portions of the Plan, one in the northern section and one in the southern section. Land cover change over a 20 year time period from 1976 to 1995 was identified by using unsupervised classification of Landsat imagery (Cowell, 1997; Lusted *et al.*, 1997). There is much room for improvement from these previous studies. No formal accuracy assessment was performed on any of the final classifications causing the results to be unreliable. Also the choice to use an unsupervised classification method neglects to incorporate valuable a priori land cover knowledge that an analyst can bring to a study. In the case of the previous remote sensing studies, little knowledge of the NEP area existed which justified the unsupervised classification approach. In the current study, prior knowledge of Escarpment land cover allowed for a supervised classification approach to be used. Remote sensing has the ability to provide the NEC with accurate and timely land cover information for the NEP area. In a geographic location where minimal remote sensing projects have been conducted, there is a need to identify appropriate land cover classification methods that can produce accurate Niagara Escarpment land cover maps.

With current imagery and an updated approach, land cover information in the Plan area can be updated in a more accurate way. By using Landsat 5 TM imagery from 1986, 1996 and 2006, land cover information was extracted and land cover change was examined over a 20 year time period over almost the entire lifespan of the NEP. Lusted *et al.* (1997) stated that more detailed work at the regional scale should be undertaken to describe the spatial dynamics of the change that is occurring in the Plan area. To achieve this, the study area for the current research was reduced to an urban and rural example, focusing on Hamilton and Halton Regions. Looking at only two regions within the Plan allows for detailed methodological analysis that upon success may be applied to the remainder of the Plan area in future works. Finally, to examine change in the Plan area from a new perspective, land cover change will be examined on an individual NEP land use designation basis to determine the type and magnitude of changes occurring in each designation.

1.4 Thesis Outline

In Chapter 2, literature pertaining to planning on the Niagara Escarpment and the use of remote sensing for planning applications will be discussed. The history of the NEP and its policies will be summarized as well as monitoring initiatives that have already taken place in the NEP area. Remote sensing methods will be assessed for use in the NEP. Chapter 3 sets the geographic context of the study and introduces the data sets to be used for the research. Chapter 4 outlines the detailed methodological approach employed for land cover classification on the Niagara Escarpment and for conducting change detection over a 20 year time period. Chapter 5 reveals the results of the land cover classification and change detection and provides critical analysis of change in the study area. Chapter 6 concludes the research with a brief discussion of the study, ideas for future research and final conclusions drawn from the work.

Chapter 2
Literature Review

2.1 Planning on the Niagara Escarpment

The Niagara Escarpment is situated within Southern Ontario; a geographical area experiencing rapid land cover change. With sections of its length located within the most heavily populated regions in Southern Ontario, exploitation of this valuable resource has become a concern for both the public and the Provincial Government. The Southern Ontario portion of the Niagara Escarpment is approximately 725 km in length and runs from Tobermory, Ontario on the Bruce Peninsula to Queenston, Ontario on the Niagara Peninsula (Niagara Escarpment Commission, 2008b). By the late 1700's the Escarpment was recognized as a valuable resource and forests were cleared for farmland and used for lumber (Reid, 1977). The limestone from the Escarpment was used as building materials and the water power harnessed by the falls on the Escarpment gave rise to the first industrial areas in Southern Ontario, focused around mill villages and towns (Reid, 1977). The population increased as Southern Ontario began to develop and farm land continued to grow. To date, the NEP covers approximately 480,233.3 acres in Southern Ontario with a wide range of land uses occurring in proximity to the landform such as urban areas, rural settlements, agricultural practices, mineral resource extraction, recreation, transportation and utility corridors, forested areas and rural non-farm developments (Ramsay, 1996; Niagara Escarpment Commission, 2007a).

Protection of the Niagara Escarpment is associated with a number of planning challenges that exist for the NEC. Mineral resource extraction, lot creation for residential developments and urban sprawl are just examples of the kinds of land use practices that are cause for concern for the NEC (Niagara Escarpment Commission, 2008a). Today, the population surrounding the Niagara Escarpment continues to grow, and the battle remains, as it always has been, between those who wish to profit from the Niagara Escarpment lands and those who wish to preserve this landscape for future generations (Reid, 1977). Development that occurs on the

Escarpment must be compatible with the landform and sustainable over time all while continuing to support local municipalities through a balance of natural resource management and sustainable economic and urban growth. This balance of protection and appropriate use of escarpment lands presents the greatest challenge to the NEC for monitoring and protecting the Escarpment through NEP policies. Creating policies and preserving natural areas that transcend political boundaries can be a challenge in itself (Fall, 1999). The NEP is Canada's first large scale environmental land use plan and is located in portions of 21 local municipalities, four cities and eight Regional Municipalities (Preston, 2003).

As described by Dovers (2005), policies are positions taken and communicated by governments that identify problems and how to correct them (Dovers, 2005). Policy framework involves problem framing, policy framing, implementation and monitoring (Dovers, 2005). The central purpose of the NEP is to maintain the Escarpment as a continuous landform and to promote compatible development (The Niagara Escarpment Plan, 2005). This purpose is reminiscent of the idea of sustainable development, described by the World Commission on Environment and Development in Dovers (2005) as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs (WCED 1987: 43)". Resource depletion and degradation is one of four constituent issues of sustainability outlined by Dovers (2005), and was the key issue that led to the formation of the NEP for protection of the Escarpment into the future. This work will focus on the final piece of the policy framework outlined by Dovers (2005) and will discuss methods for monitoring land cover changes on the Niagara Escarpment.

There is a need to establish persistent monitoring with a consistent methodology for identifying change over time in the Plan area to ensure that Plan implementation has been effective in regulating land use on the Niagara Escarpment. The study area examined in this work is part of a highly developed region and resource consumption is a highly visible practice occurring on the Escarpment today through agricultural use, urban development and mineral resource extraction. The use of both qualitative and quantitative data are necessary, both of which may be acquired through the use of remote sensing technology.

2.1.1 History of the Niagara Escarpment Planning Policy

Due to an increase in public concern on the state of the Niagara Escarpment, in 1967 an announcement was made that a wide ranging study would be conducted to promote appropriate use of the landform (Schenk and Robinson, 1975). This study preceded the enactment of bill 129 in June 1973 that created the NEC (Schenk and Robinson, 1975). The Commission was put in place immediately to represent the municipalities and the public at large as well as to introduce Development Control (DC) measures while the Plan area was being established and while the Plan was being written (Schenk and Robinson, 1975). The DC area was established to allow for the continuation of all developments that were already in progress, and to protect sensitive areas of the Escarpment from future developments prior to the inception of the Plan (Niagara Escarpment Commission, 1979). The current area under protection can be seen in Figure 2.1 below outlining the Niagara Escarpment Planning Area, the DC area and the current NEP boundaries displaying the land use designations for a portion of the Regional Municipality of Halton. Professor Leonard A. Gertler of the University of Waterloo directed the initial study on the Escarpment, and was assisted by a professional group of planners and geographers and was officially titled "The Niagara Escarpment Study; Conservation and Recreation Report", but was generally referred to as "The Gertler Report". Highlights of the final report, published in 1968, include important recommendations on how to achieve control over the Niagara Escarpment Lands (Schenk and Robinson, 1975).

To begin the study, Gertler outlined ten terms of reference including some geared specifically towards appropriate land use on the Escarpment (Gertler *et al.*, 1968). Gertler and his team aimed to delineate the area of the Niagara Escarpment based on land they felt should be

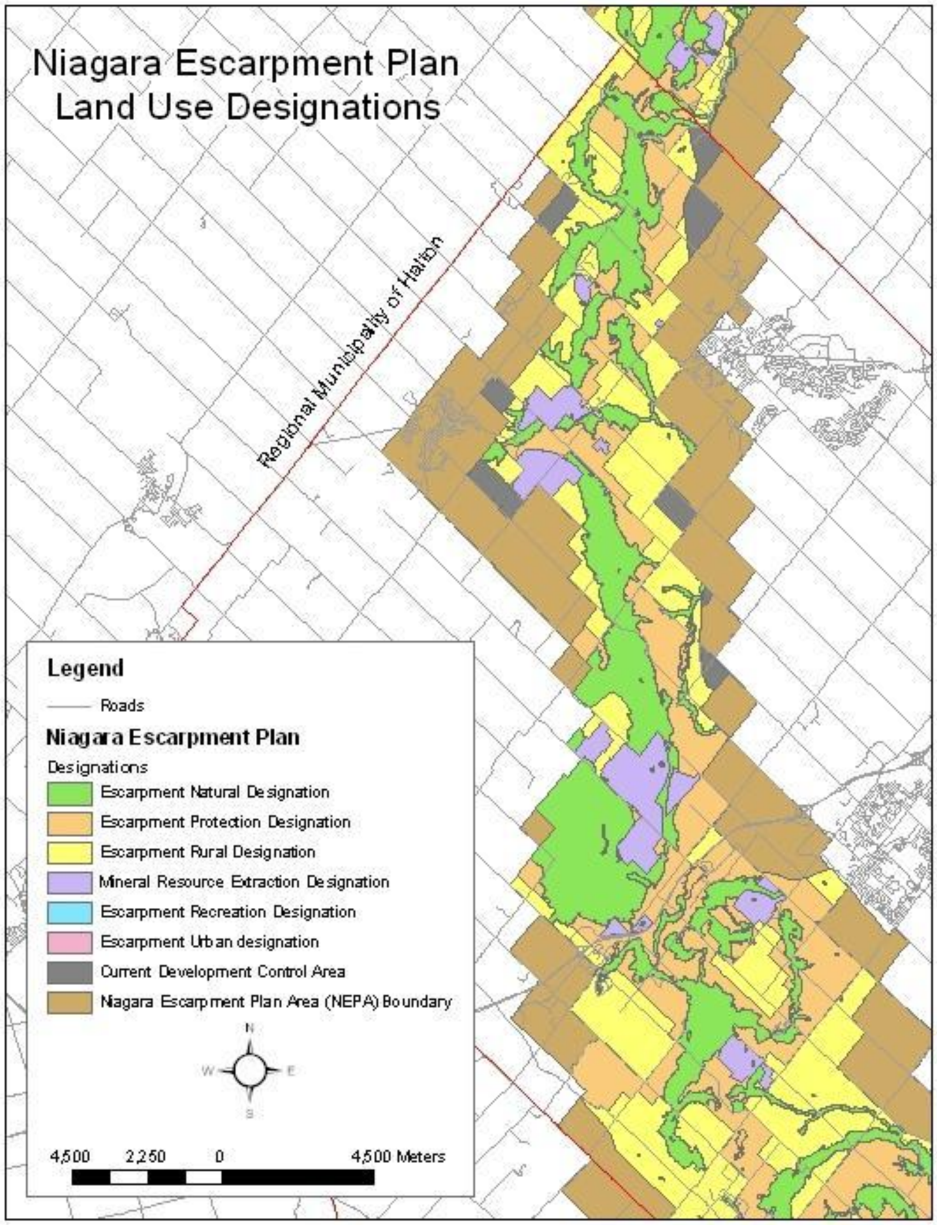


Figure 2.1 Example of Current Niagara Escarpment Plan (NEP) Designations, Development Control and the Niagara Escarpment Planning Area

preserved as a permanent part of the Ontario landscape (Gertler *et al.*, 1968). They focused attention on preserving the Escarpment for recreational purposes based on demand from the public at the time (Gertler *et al.*, 1968). In 1968, the pressure to develop on escarpment land had increased due to high rates of urbanization in Southern Ontario and this necessitated coordination in planning for the future (Gertler *et al.*, 1968). The authors achieved this by identifying activities that were incompatible with preservation, such as quarrying, and by developing a plan to acquire land and regulate its use through legislative and administrative control devices (Gertler *et al*., 1968). Overall the primary objectives of the report were:

1. The delineation of lands to be preserved for their recreational and environmental value
2. The determination of the means of preservation
3. The establishment of priorities for preservation action

(Gertler *et al.*, 1968:2)

To meet the first objective, methods of control over Escarpment lands were developed. Three levels of control were proposed that were early renditions of the plan designations that exist today. The methods of control can be seen below in Table 2.1.

Table 2.1 Gertler Report's Recommended Methods of Control for the Niagara Escarpment

Control	Description
Complete Control	Outright acquisition of lands
Selective Control	Acquisition of defined rights to the land through easements or leases
Regulatory Environmental Control	Through land use regulations (e.g. preserving agricultural or forested lands)

(Gertler *et al.*, 1968)

The second objective was to be met through acquisition of lands and through land use regulations (Schenk and Robinson, 1975). Gertler recommended that two miles on either side of the highest contour (representing the Escarpment edge) should be the study and administration area (Gertler *et al.*, 1968). This broad study area allowed for the inclusion of river headwaters and other areas of environmental significance (Gertler *et al.*, 1968). Gertler also recommended that 7% of the administration area be under complete control and 25% be under land use regulations with the remainder eligible for acquisition (Schenk and Robinson, 1975). The report also outlined major sections on a proposed parkland system, regulations on the extractive industry and an outline of the administration structure for the Niagara Escarpment (Schenk and Robinson, 1975). The completion of the Gertler Report produced almost immediate results in the area of land acquisitions, recognition of the Niagara Escarpment into official plans and minimizing the impact of the extractive industry on the Escarpment (Schenk and Robinson, 1975). In 1970 the Niagara Escarpment Protection Act was born and a year later the Pits and Quarries Control Act of 1971 was put in place (Schenk and Robinson, 1975). The Pits and Quarries Control Act imposed immediate changes in the industry which made it necessary for all pit and quarry operators to operate under a license and with an approved site and rehabilitation plan (Schenk and Robinson, 1975). Random inspections would occur and no new quarrying could occur within 300 feet of the natural edge of the Escarpment (Schenk and Robinson, 1975). Two interim special policy areas were identified by Gertler by 1974. These included areas that were undeveloped as well as a few land use control areas such as Pelham and St. Catharines (Schenk and Robinson, 1975). Government grants were also increased to provide for the purchase of Niagara Escarpment lands (Schenk and Robinson, 1975). The Gertler Report was a significant first step in recognizing the importance of the Escarpment and the need for its protection in a changing landscape.

In 1972, the Niagara Escarpment Task Force was established to develop priorities in the early stages of Escarpment monitoring and protection (Schenk and Robinson, 1975). The Task Force consisted of nine members and was responsible for establishing priorities for the acquisition of land by the Province and creating development standards to ensure the appropriate use of Escarpment lands (Schenk and Robinson, 1975). They achieved this by advising on all proposals that would result in major changes in existing land use patterns (Schenk and Robinson, 1975). Until this point a lot of work had been done at the Provincial level to begin monitoring the use and land cover of the Escarpment, but the Task Force went beyond what had already been accomplished and decided to conduct public meetings in several communities along the Escarpment to understand how the public-at-large felt about the progress being made for its protection (Schenk and Robinson, 1975). Public meetings were held in St. Catharines, Hamilton, Milton, Orangeville, Collingwood, Owen Sound and Lion's Head (Schenk & Robinson, 1975). In the southern locations, the public felt that the Ontario Government had done little until that point to protect the Escarpment (The Niagara Escarpment Task Force, 1972). In the public meeting in Hamilton, concerns were raised about subdivisions and of the divide between rural and urban land (The Niagara Escarpment Task Force, 1972). The public stressed that certain buffer regulations needed to be put in place as well as selective urban and rural development controls to preserve the natural crest and toe of the Escarpment and beyond including adjacent natural areas (The Niagara Escarpment Task Force, 1972). The concerns expressed in Hamilton were echoed in Milton, where major concerns included land protection from further development and from the extractive industry (The Niagara Escarpment Task Force, 1972). The Task Force outlined a specific goal "[T]to maintain the Niagara Escarpment as a continuous natural environment while seeking to accommodate demands compatible with that environment (The Niagara Escarpment Task Force, 1972: 2)." This goal along with several objectives outlined by the Task Force are closely related to the goal and objectives of the final Plan, proving the Task Force was moving in the right direction at the time. A lot of the work undertaken by the Task Force included the following: building provincial and local planning relationships, examining financial impact of land use regulations and compensation, establishing the priority and funding arrangements for land acquisition, taking control of the extractive industry and designing legislation and interim measures of development control until the legislative requirements had been met (Schenk and Robinson, 1975). With all the work done by the Task Force, the creation of the Niagara Escarpment Planning and Development Act (NEPDA) and the formation of the NEC became the next logical step in the fight to protect the Escarpment.

2.1.2 The Current Niagara Escarpment Plan (NEP)

Niagara Escarpment Planning and Development Act (NEPDA)

The NEPDA was passed by the Ontario Government in 1973. The new legislation called for the establishment of the NEC and the subsequent preparation of the NEP by the Commission (Jankovic, 1999). "The purpose of the act is to provide for the maintenance of the Niagara Escarpment and land in its vicinity substantially as a continuous natural environment, and to ensure only such development occurs as is compatible with that environment (R.S.O. 1990, chp. N.2, sec. 2) (Niagara Escarpment Commission, 2007c: 1)." Several characteristics of this legislation made it unique from the Planning Act (Borodczak, 1995). The NEPDA focused on environmental planning as opposed to being oriented toward development like the Planning Act (Borodczak, 1995). Through the NEPDA, the goal was to create a provincial land use plan focused on the protection of the escarpment at the provincial level, with jurisdiction across municipal boarders (Borodczak, 1995). This also varied from the Planning act, since it called for each municipality to plan within its own boundaries (Borodczak, 1995).

The Niagara Escarpment Commission (NEC)

The NEC was created in 1973 and has 17 members made up of municipal representatives and members of the public at large (Schenk and Robinson, 1975). The Commission's first task was to create the NEP. The preliminary proposals for the Plan were released by the Provincial Government in 1978 (Borodczak, 1995). Negative reactions to the Plan from private land owners and municipalities resulted in a 63% reduction in Plan area from the time the NEP area was proposed to the inception of the final Plan and the creation of the final Plan Area (Borodczak, 1995). After public hearings and Provincial recommendations, Cabinet approved the NEP in June 1985 (Borodczak, 1995).

The Niagara Escarpment Plan (NEP)

The NEP is the main piece of legislation that outlines how the province will protect the Niagara Escarpment into the future. The purpose of the NEP was adopted directly from the NEPDA. The Plan outlines seven main objectives, as follows:

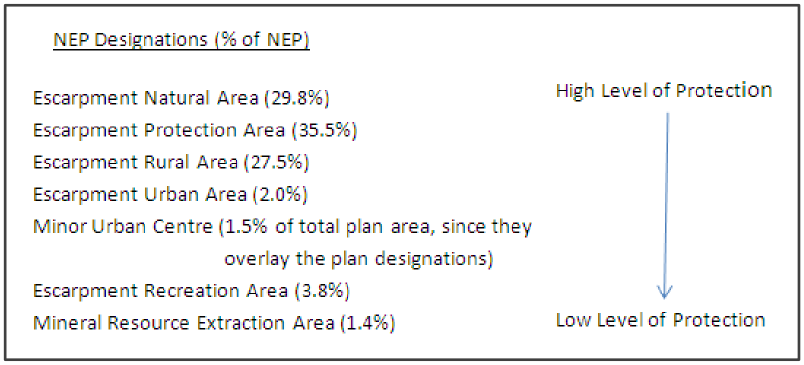
1. To Protect unique ecological and historic areas;
2. To maintain and enhance the quality and character of natural streams and water supplies;
3. To Provide adequate opportunities for outdoor recreation;
4. To maintain and enhance the open landscape character of the Niagara Escarpment in so far as possible, by such means as compatible farming or forestry and by preserving natural scenery;
5. To ensure that all new development is compatible with the purpose of the plan;
6. To provide for adequate public access to the Niagara Escarpment; and
7. To support municipalities within the NEP area in their exercise of the planning functions conferred upon them by the Planning Act.

(The Niagara Escarpment Plan, 2005: 3)

To place regulations on developments that occur in the Plan area, 7 land use designations were outlined in the plan with varying levels of protection (Niagara Escarpment Commission, 2007b). Each land use designation has a specific set of objectives and land use policies attached to it to determine what types of development are permitted in each distinct designation (Borodczak, 1995). As can be seen below in Figure 2.2, the Escarpment Natural Area (ENA) designation has the most restrictive land use policies and the Escarpment Rural Area (ERA) designation has the least (Borodczak, 1995). A summary of each land use designation can be seen in Table 2.2. The policies that the NEP has in place for certain areas within the Plan should translate to the types of land cover that occur in each designation and remote sensing can be used as a cost efficient tool to monitor changes in land cover in the Plan Area.

The Niagara Escarpment as a United Nations Educational, Scientific and Cultural Organization (UNESCO) World Biosphere Reserve

In 1990, UNESCO named the Niagara Escarpment a World Biosphere Reserve under its Man and Biosphere (MAB) program, and is one of only 15 World Biosphere Reserves in Canada (UNESCO – MAB Secretariat, 2008). The MAB program was created in 1971 with the aim



(Niagara Escarpment Commission, 2007a)

Figure 2.2 Designation Percentages in the Niagara Escarpment Plan (NEP)

Table 2.2 NEP Land Use Designation Summary

Plan Designation	Description
Escarpment Natural Area (ENA)	Escarpment areas that are in a natural state and that contain important plant and animal habitats, geological features, cultural heritages sites and scenic areas. These areas will only be used for conservation, education and compatible recreation and the protection of natural flora, fauna and the landform itself.
Escarpment Protection Area (EPA)	The protection area acts as a buffer to the prominent Escarpment features named above in the ENA designation. Its job is to enhance the open landscape character of the Escarpment, to maintain natural areas and to encourage agriculture, forestry and recreation. These designated areas often have more visual prominence than ENAs.
Escarpment Rural Area (ERA)	Areas with minor escarpment slopes and landforms and is a designation used as a buffer to more ecologically sensitive areas of the Escarpment. These are lands near the Escarpment necessary to provide open landscape character, to encourage conservation, agriculture, and forestry and to provide for compatible rural land uses. Despite this, the Plan's final objective is to also provide for the designation of new mineral resource extraction areas (MREAs) which can be accommodated by an amendment to the NEP.
Minor Urban Centre (MUC)	Rural settlements, villages and hamlets in the Plan area.
Urban Area	Urban areas that have encroached upon or are in close proximity to the Escarpment. The purpose of this designation is to minimize future impacts.
Escarpment Recreation Area	Areas of existing or potential recreational development.
Mineral Resource Extraction Area (MREA)	Pits and quarries licensed under the Aggregate Resources Act and where future expansion may be permitted under the Plan.

(The Niagara Escarpment Plan, 2005)

of promoting research, training, communications and the rational use of natural resources (UNESCO – MAB Secretariat, 2008). Biosphere Reserves are protected areas of representative environments internationally recognized for their value for conservation, scientific information, environmental monitoring and local participation to support sustainable development (Ramsay, 1996). More recently, efforts have been made by the MAB program to recognize urban environments that exemplify the Biosphere Reserve Model and could contribute the ideas behind the Biosphere Reserve to improving urban planning and management (Matysek *et al.*, 2006). Parts of the Niagara Escarpment, such as the Hamilton Region portion of the Plan, benefit from the Biosphere Reserve designation and are protected under similar protection strategies. Biosphere Reserves are based on a hierarchy of environmental protection and compatible land use zones ranging from core protected areas (e.g., ENA designation) that conserve significant ecological areas and functions, buffer zones (e.g., EPA and ERA designations) in which research, environmental education and training can take place in a manner which does not impact the core areas, and transition zones (e.g., Urban areas and Minor Urban Centres (MUCs), ERA and MREA designations) where the

Table 2.3 Comparison between the Niagara Escarpment Plan (NEP) Designations and the Biosphere Reserve Designations

Biosphere Reserve Designations	Acres in Biosphere Reserve	Hectares in Biosphere Reserve	Land Use Designations
Total Biosphere	487,946.0	100.0%	Total Area
Core Area*	164,763.3	33.8%	ENA**
Buffer Area	288,513.9	59.1%	EPA and ERA
Zone of Cooperation (Transition Area)	34,668.7	7.1%	Urban Area, ERA and MREA
			Overlay Designation* **
	7,038.5	1.4%	MUC

*The entire Bruce Peninsula National Park is considered core area under the Biosphere Reserve designation

** The ENA includes the Fathom Five National Marine Park and the Bruce Peninsula National Park

***The MUC designation is contained within the NEPA, and overlay the land use designations, therefore they are calculated separately.

(Niagara Escarpment Commission, 2007a)

aim is to develop cooperation between human activities and the natural environment and to promote sustainable development (Ramsay, 1996). The levels of environmental protection within the Biosphere Reserve designation coincide with the designations outlined in the NEP (Niagara Escarpment Commission, 2007a). In both the Biosphere Reserve and NEP, there are portions of heavily protected areas along the cliff face with decreasing levels of protection moving away from the cliff face in both scenarios (Niagara Escarpment Commission, 2007a).

2.1.3 Monitoring on the Niagara Escarpment

Monitoring on the Niagara Escarpment is currently undertaken by the ONE monitoring program. This program was launched to determine if the Plan, with its unique set of environmental land use policies, achieves its goals and objectives (Cadman *et al.*, 1997). The program itself is unique because it focuses on the Niagara Escarpment as a living and interconnected landscape, and as such, the ONE Monitoring Program is designed to assess the linkages between land use change and ecosystem values (Cadman *et al.*, 1997). Initial focus was placed on several key initiatives including land use change, forest cover health and vegetation status, forest fragmentation and corridor linkages, and disturbances from human activities (Cadman *et al.*, 1997). Several key studies were already undertaken and reported on through NEC projects, theses and reports and a select few will be outlined in the following sections. The ONE Monitoring Program uses a CEM framework which consists of a set of monitoring objectives, questions, components, indicators, techniques, targets and information management systems (Cadman *et al.*, 1997). "The CEM is the long term assessment or measurement of changes in the environment within a defined area (Cadman *et al.*, 1997)." This is accomplished through the consideration of two concepts: cumulative environmental effects and monitoring (Cadman *et al.*, 1997).

A study conducted by Ramsay (1996) has provided the Commission with one of its most comprehensive land use change studies to date through the use of the CEM framework. Land cover metrics were calculated through aerial photograph inspection for map creation. All maps were then digitized to be displayed in a GIS. For a time period between 1974 and 1994, Ramsay used a CEM strategy under the guidance of the NEC and the ONE monitoring program, to assess both negative and positive cumulative affects at the landscape-level in a northern portion of the Regional Municipality of Halton (Ramsay, 1996). Cumulative effects are defined as "[T]the combination and interaction of environmental effects due to multiple human activities (past, present and reasonably foreseeable future) occurring in a defined area, over time (Ramsay, 1996)." In a similar work, Jankovic (1999) reports a case study was conducted in Artemesia Township in Grey County where air photo interpretation was used to examine changes in forest cover and forest boundary relationships with the core and buffer zones of the biosphere reserve designation. Instead of using the CEM framework, this examined change on the basis of boundaries. Cross boundary issues exist especially when boundaries are being applied to a continuous natural area such as the Niagara Escarpment. It can be argued that natural areas know no bounds and therefore should not be monitored with boundaries in mind (Jankovic, 1999). Boundary issues present a challenge in the NEP, as all the land in the Plan area is split between private, municipal, provincial and federal ownership.

The purpose of Jankovic's work was to determine the extent of the changes in forested area in the ENA designation of the NEP, an area that corresponds to the core area designation under the Niagara Escarpment Biosphere Reserve (NEBR) designation (Jankovic, 1999). The NEBR buffer zones were also examined to detect forest changes over a 20 year time period from 1974 to 1995 (Jankovic, 1999). Any relationships between the change in forested areas and the boundaries placed around these areas were examined to determine the importance of boundaries and cross-boundary issues in the landscape (Jankovic, 1999). In the CEM study, Ramsay (1996) employed the ABC (abiotic, biotic and cultural) research method. The abiotic portion was used to map physical escarpment features, such as the escarpment brow. The biotic portion focused on forest metrics to predict the amount, percentage and linkages that are suitable for selected bird indicator species, and the cultural portion examined both historical and current land uses divided into six classes: inactive and active agricultural land, rural settlements, mineral resource extraction sites, recreational areas and rural non-farm development (Ramsay, 1996). Jankovic (1999) used aerial photography from three years (1974, 1991 and 1995) to map boundaries of deciduous, coniferous and mixed forest drawn onto 1:10,000 base maps. After the mapping was completed, the maps were overlapped and compared visually (Jankovic, 1999).

Both studies concluded that there was no loss of forested area in either North Halton Region or in Artemesia Township (Jankovic, 1999; Ramsay, 1996). Due to minimal changes being present from 1991 to 1995 conclusions were drawn by using the 1974 to 1995 air photos (Jankovic, 1999). In that time period no forest loss was detected and younger trees began to take over uncultivated land that was adjacent to mature forests (Jankovic, 1999). In 1974 adjacent lands were intensively used for farming and this prevented forest succession (Jankovic, 1999). Another major discovery was that forests showed more connectivity, especially forests outside of the 300m buffer mark from the brow that delineates the ENA (The Niagara Escarpment Plan, 2005: 9). In fact, the period from 1974 to 1995 showed no loss of forested area, and most succession occurred in adjacent abandoned agricultural fields that are no longer cultivated (Jankovic, 1999). Ramsay (1996) recognized in the North section of Halton Region that the most significant land use changes were a decrease in active agricultural land (from 86.3% in 1974 to 75.8% in 1994), an increase in mineral resource extraction sites (from 9.0% in 1974 to 14.8% in 1994) and an increase in recreational development (from 0.1% in 1974 to 4.1% in 1994). The increase that occurred in the mineral resource extraction sites above the escarpment brow have had the most impact on the pattern and area of core habitat in this location, and were present prior to the creation of the NEP (Ramsay, 1996). Continued efforts on MREA rehabilitation were recommended (Ramsay, 1996). Below the escarpment it was concluded that active agricultural lands have the most influence on forest change below the escarpment (Ramsay, 1996).

Similar limitations were expressed in both studies, due to the use of aerial photographs in the analysis. Jankovic (1999) states that a major limitation to the Artemisia Township study was that all three photographs used were at different spatial scales. In addition, the older black and white photos were hard copy photographs while the newer image used was a digital infrared photograph (Jankovic, 1999). Another limitation to this study was the timing for the collection of ground reference data. In situ measurements were collected in November 1999, late in the growing season and four years after the most recent photograph used for analysis (Jankovic, 1999). Typically it is best to collect ground reference information as close to the time of analysis as possible (Jensen, 2005). Qualitative measurements and subjective judgment was of great concern to Ramsay (1996). Individual landscape measures were ranked in a subjective way through the examination of information such as “forest naturalness”, significance of physical features and “landscape change significance” (Ramsay, 1996). These landscape measures were ranked on a scale from “high” to “low” based on guidelines outlined by Ramsay and were very subjective to the author’s opinion and background knowledge (Ramsay, 1996). Furthermore, forest size was based on a range representing small to large forest patches (Ramsay, 1996). Ramsay challenges the NEP and believes that the current state of the ENA designation does not accurately portray the natural area of the Escarpment, and therefore could be improved (Ramsay, 1996). Both works point towards the need to support maintenance of the Escarpment’s continuous natural environment through more intensive monitoring, and creating policies that deal with the Escarpment as a region as opposed to curbing development only at a site specific scale (Jankovic, 1999; Ramsay, 1996). Improved remote sensing technologies can provide effective quantitative monitoring at this scale, and previous studies on the Escarpment using remote sensing have led the way towards a future of monitoring using remotely sensed data at various scales for the Niagara Escarpment.

2.2 The Role of Remote Sensing in Protected Areas Planning

Traditionally, land cover change in an area of interest would be examined through field investigations and/or by using aerial photography (Wilkie and Finn, 1996). This has proven successful in the past, but at the rate and magnitude land cover changes are occurring today, information must be gathered at larger spatial and temporal scales (Wilkie and Finn, 1996). Remote sensing can provide the data necessary for consistent monitoring studies and is an important component of urban and regional planning (Treitz and Rogan, 2004; Wilkie and Finn, 1996). It is a valuable tool that can aid decision makers in the creation of policies for environmental conservation (Treitz and Rogan, 2004). The following section outlines the role of remote sensing in planning and will highlight monitoring initiatives that have already taken place in the NEP area through the use of satellite remote sensing. Remote sensing for land cover change and change detection will be discussed with final recommendations for a remote sensing change detection strategy for the Niagara Escarpment.

2.2.1 Remote Sensing for Planning

Land cover information is an important aspect of the planning process (Treitz, 2004). The rate of consumption of natural resources today is highly visible on our landscape (Wilkie and Finn, 1996). Planning agencies at varying municipal scales have come to recognize the importance of monitoring change patterns and trends into the future (Rogan and Chen, 2004). Remote sensing is a tool that can aid land use planners in making management decisions in a more time and cost efficient way. Planning is a very broad term, and many different sectors that make up the broad discipline of planning can benefit from the use of remote sensing data for land management such as agriculture, forestry, urban planning and environmental monitoring (Prenzel, 2004). Although the information gathered from remote sensing may depend on knowledge of the analyst and cost of the data, and often requires additional field work, it is apparent that remote sensing and other information technology such as GIS is becoming a driving force in planning and protected areas research (Quinn and Alexander, 2008).

Remote sensing has been recognized as a useful environmental planning tool and as technologies improve, remote sensing has played a more important role in improving monitoring programs (Stafford, 1993). As opposed to using aerial photographs for visual assessments, spectral data can be used to provide new information that cannot be obtained from pure visual assessment (Wilkie and Finn, 1996). For example, environmental professionals could determine the type and health of crops in an agricultural field. As new sensors are introduced with higher spatial resolutions, there has been an increase in the number of planning applications that remote sensing can be used for (Treitz and Rogan, 2004). Urban planning, for example, benefits from the use of high spatial resolution data. Broader land cover studies across a landscape still benefit from the use of medium resolution imagery, so a greater understanding of land cover change at a regional scale may be obtained (Vogelmann *et al.*, 1998). Another advantage of remote sensing for natural resources monitoring is that it captures data on earth features without coming into contact with those features. This is particularly useful for monitoring on the Niagara Escarpment where some sections are inaccessible. Finally, information provided through remote sensing analysis can be converted and used within a GIS for mapping and analysis.

Prenzel (2004) states that the analysis of remote sensing data for change analysis involves data input, analysis using a quantitative modeling approach, information output and research and decision making. The accuracy of the information gained from a remote sensing study is very important for decision making, and starts at data acquisition (Quinn and Alexander, 2008). If actions are taken at every step of a project and everything is done to ensure the highest accuracy of the results possible, only then can confident decisions be made at the planning level (Quinn and Alexander, 2008). Of course the classification of land cover using remotely sensed data is only a representation of what is on the ground, and so planners and policy makers should expect some degree of error and uncertainty in the final results whether it be quantitative values or qualitative information displayed on a map (Quinn and Alexander, 2008). All that can be done is to ensure these errors are identified, acknowledged and clearly quantified (Quinn and Alexander, 2008). The benefit of up-to-date information that can be acquired through remotely sensed data far outweigh potential limitations when managing development and planning for change (Treitz and Rogan, 2004). Remote sensing is a key tool for the collection of long-term monitoring data so planning policies and protected areas management may be properly assessed and improved upon for the protection of our natural resources (Quinn and Alexander, 2008).

2.3 Detecting Land Cover Change Using Remote Sensing

Prior to conducting analysis, it is important to identify whether to focus on land cover or land use. Barnsley *et al.* (2001) refer to land cover as the physical materials on the surface of the earth, such as grass, concrete and water. Land use is the human activity that takes place on the land or makes use of it and is described as, for example, commercial, industrial or residential areas. It is important to note that remote sensing does not directly measure land use which is a function of social, cultural, economic and political factors (Treitz and Rogan, 2004). Remote sensing records the spectral properties of surface materials on the earth without actually coming into contact with these features, and for this reason, remote sensing technology is more suitable for collecting land cover information (Treitz and Rogan, 2004). Various classification algorithms are then employed to extract land cover information and can be used to monitor land cover change (Aplin, 2004).

2.3.1 Overview of Land Cover Mapping Methods

Remotely sensed data collected of the earth's surface can be turned into information to monitor land cover changes (Jensen, 2005). Images such as photos and maps of the earth's surface can provide information in much the same way, but multispectral imagery with data collected from multiple bands of the electromagnetic spectrum can aid in providing real-time information on change (Jensen, 2005). Multispectral classification of remote sensing imagery can be done in a variety of ways. A summary of the methods used are summarized in Table 2.4 below.

No one method is necessarily better than the next. Jensen (2005: 338) states that "the biophysical characteristics of the study area, the distribution of the remotely sensed data (e.g. Gaussian distribution), and a priori knowledge determines which classification algorithm will yield useful results." Concern over the accuracy of classification maps produced through remote sensing techniques has prompted further research into improved supervised classification methods (Foody and Mathur, 2004). Early basic algorithms, such as the Minimum Distance (MD) classifier have led to the development of more sophisticated statistical classifiers such as the Maximum Likelihood Classification (MLC), and even more recently, to non-parametric classifiers such as Neural Networks and Support Vector Machines (SVM) (Foody and Mathur, 2004).

For this study much a priori knowledge exists about the types of land cover in the study area from previous field visits and also through interpretation of high resolution orthoimagery. For this reason, supervised classifications were chosen for land cover classification in Halton and Hamilton Region. For a supervised classification four pieces of information must be identified before a classification is performed. The geographic area of interest must be identified as this dictates the resolution of data to be used in the study (Jensen, 2005). The classes of interest must be selected in a way so that they do not overlap and reflect all the land cover types that occur in the study region (Jensen, 2005). Classes should also be hierarchical, so similar classes may be combined to improve land cover accuracy (Jensen, 2005). Classification type must also be identified, choosing between a hard or soft (fuzzy) classification type and a per-pixel or object-oriented classification (Jensen, 2005). The next step is to obtain appropriate remote sensing and ancillary data to conduct the analysis. GIS data, elevation data and orthoimagery are just a small example of ancillary datasets that may aid in the classification process. Data must be chosen based on remote sensing system spatial, spectral/radiometric and temporal resolutions and also environmental considerations must be taken into account (Jensen, 2005). Pre-processing is then performed where both atmospheric (radiometric) and geometric corrections take place. Classification methods are then used for the extraction of thematic information based on training sites created by the

Table 2.4 Summary of Remote Sensing Classification Techniques

Methods	Examples	Definition
Parametric	Maximum Likelihood Classification (MLC) and Unsupervised Classification etc.	Assumptions: Data are normally distributed A priori knowledge of class density functions
Non-parametric	Nearest-neighbour Classifiers, Fuzzy Classifiers, Neural Networks and Support Vector Machines (SVM) etc.	No prior assumptions are made
Non-metric	Rule-based Decision Tree Classifiers	Can operate on both real-valued data (i.e. reflectance values) and nominal scaled data (i.e. class 1 = forest)
Supervised	Maximum Likelihood Classification (MLC), Minimum Distance (MD), Mahalanobis Distance Classification (MDC) Parallelepiped etc.	Analyst identifies Training sites to represent m classes and each pixel is classified based on statistical analysis
Unsupervised	ISODATA, K-means etc.	-A priori ground information not known - Pixels with similar spectral characteristics are grouped according to specified statistical criteria
Hard (parametric)	Supervised and Unsupervised Classification	Classification using discrete categories
Soft (non-parametric)	Fuzzy Set Classification Logic	-Considers heterogeneous nature of real world - Each pixel is assigned a proportion of the m land cover types found within the pixel (e.g. 10% soil, 10% shrub etc.)
Per-pixel		Classification of the image pixel by pixel
Object Oriented		-Image segmented into homogeneous objects -Classification performed on each object vs. each pixel
Hybrid Approaches		Includes expert systems (e.g. decision tree) and artificial intelligence (e.g. neural network)

(Jensen, 2005: 337-338)

analyst (Jensen, 2005). Accuracy assessment is the last and most important step conducted in any classification. It demonstrates that the analyst has identified the possible sources of error, minimized error as much as possible throughout the study and states the level of confidence the analyst has in the classification (Jensen, 2005). After thematic maps are created with the highest level of accuracy, change detection can occur.

2.3.2 Review of Supervised Land Cover Mapping Methods

The literature on using remote sensing techniques for land cover mapping is broad, with research efforts in this field spanning more than two decades (Aplin, 2004; King, 2002). Constant research efforts for improving remote sensing land cover classification techniques aim to improve the accuracy of the land cover information produced from remotely sensed data (Aplin, 2004). Subsequently, there has been much research into the use of different data sources as remote sensing technologies improve and the spatial resolution of remotely sensed images becomes finer. Still today there is much need for larger scale regional studies for which medium resolution imagery is still ideal (Franklin and Wulder, 2002). Medium resolution imagery such as Landsat imagery is beneficial for broader regional land cover studies to support regional landscape planning and resource management (Aplin, 2004). Along with a multitude of work using more traditional classification techniques, newer methods are emerging and showing promise for land cover classification at regional scales.

Very little recent research has focused on the more traditional classification methods such as parallelepiped, MD and Mahalanobis Distance Classifiers (MDC) except to compare them to more current methods being developed. These traditional methodologies were described by Atkinson and Lewis (2000) before a newer approach on using the variogram for texture classification and as a smoothing function was explored (Atkinson & Lewis, 2000). MLC is also discussed as a traditional supervised classification approach, and it is rare in the literature to find methods based purely on conventional methods such as MD or MDC alone. MLC is the most widely used algorithm in the land cover classification literature (Yan *et al.*, 2006), but it is rarely used on its own today and is often used as a baseline study to see how newer techniques can improve classification accuracy.

It was established that typically more traditional supervised and unsupervised classification methods were used for large scale land cover projects (Fuller and Parsell, 1990; Foody and Hill, 1996; Cowell *et al.*, 1997; Lusted *et al.*, 1997; Price *et al.*, 1997; Vogelmann *et al.*, 1998; Guerschman *et al.*, 2003). A study conducted by Price *et al.* (1997) used a MLC and 9 Landsat TM images from 1987, 1989 and 1992 (three for each year) to map land use/land cover in the High Plains Agro-ecosystem in Kansas. Pixels were first classified into 100 different spectral classes that were identified using an unsupervised ISODATA classification technique to extract spatial statistics (Price *et al.*, 1997). The 100 classes were then grouped into one of two classes, cropland or grassland. MLC was then used to classify all cropland pixels into one of five crop land cover types: winter wheat, grain, corn, alfalfa and fallowed lands (Price *et al.*, 1997). Final accuracy results proved to be more than 20% higher on average than original single date classifications that only achieved an accuracy of 70% (Price *et al.*, 1997). The author contributed the increase in accuracy to the use of multi-seasonal images for each year (Price *et al.*, 1997).

An earlier study conducted in lowland Britain used the MLC to map land use in Cambridgeshire, England in 1984. The classes that Fuller and Parsell (1990) identified for the classification were largely vegetation classes ranging from grass, coniferous/deciduous forests, arable land and bare soil. Since vegetation types were the focus of the classification, only bands 3, 4 and 5 (red and infrared bands) from the Landsat TM data were used, as these bands are dominated by reflectance of healthy vegetation (Townshend, 1988; Fuller and Parsell, 1990). Although only 74% accuracy was achieved, some individual classes performed at a higher accuracy than the overall value (Fuller and Parsell, 1990). It was also noted that a MD classifier was attempted, but yielded lower results and was discarded (Fuller and Parsell, 1990). Accuracy assessment was performed by comparing the MLC classified image with an existing map created through air photo interpretation in 1986 (Fuller and Parsell, 1990). The maps were overlain and difference maps were created showing areas that had changed (Fuller and Parsell, 1990). Limitations to this study exist because of the difference in dates of the imagery, as things may have changed over the 2 year time period. Also, having a qualitative accuracy assessment performed could introduce human error, especially since there was no indication of the accuracy of the map that was used for the accuracy assessment.

Many other medium resolution land cover classification programs exist all over the world (Franklin and Wulder, 2002). Some examples of important Canadian classification systems are Baseline Thematic (BTM) from British Columbia using Landsat TM data, the Ontario Land Cover Data Base (OLCDB) produced by the Ministry of Natural Resources (MNR) for the Province of Ontario also using Landsat TM data and finally, a national classification called the Land Cover of Canada, produced using Advanced Very High Resolution Radiometer (AVHRR) data (Franklin and Wulder, 2002). These data are slightly coarser than the TM classifications at an approximate 250m resolution (Franklin and Wulder, 2002). In the United States, it is a classification system, and not any one particular classification that is used for land cover analysis (Navulur, 2007). The United States intelligence community created a standardized classification system known as the National Imagery Interpretability Rating Scale (NIIRS) that may be adjusted depending on the level of spatial scale of the data used in the study (Navulur, 2007). Ten levels exist ranging from 0 to 9, 0 being for very low resolution data and 9 being for very high resolution data. Another classification used is called the Anderson classification that consists of 4 hierarchical classification sections and is used by the United States Geological Survey (USGS) (Blaschke, 2004). The scale of the data being used in any classification is an important consideration so an appropriate classification scheme can be chosen to represent land cover of interest at a particular scale.

Variations in traditional classification methods have been attempted to increase overall accuracy of the classification maps produced. Many variations exist and some techniques have proved more successful than others. Guerschman *et al.* (2003) combined a normalized difference vegetation index (NDVI) with bands 3, 4 and 5 from a Landsat TM scene to create land cover classifications of the Argentine Pampas. The authors also attempted to use multiple Landsat TM scenes for one year to aid in improving the classification (Guerschman *et al.*, 2003). Ancillary data sets were also incorporated to enhance traditional classification methods. The use of a digital elevation model (DEM), GIS data sets and aerial photographs can enhance overall classification accuracies. Fahsi *et al.* (2000) found that using a DEM with Landsat TM data improved classification accuracy by reducing the effect topography had in a mountainous study area. Xiao *et al.* (2006) combined GIS with a MLC to examine urban change in a province of China. GIS was used to digitize historical land use maps to study the urbanization trends in Shijiazhuang City (Xiao *et al.*, 2006). Along with variation of traditional approaches, many new approaches have also emerged such as neural networks, decision tree classifiers, object oriented classifications and SVMs.

Whereas most traditional classification methods are per-pixel classifiers, most features on the earth that analysts are trying to extract are composed of groups of pixels (Navulur, 2007). Image segmentation techniques divide remotely sensed images into a series of objects and use the attributes (such as spectral, shape, texture and morphology) of that object to perform the classification (Navulur, 2007). Described by Wehrmann *et al.* (2004) as imitating human pattern recognition, this is a relatively new approach with many advantages to the user community, one being that the information derived from the object oriented approach can be used directly in a GIS (Geneletti and Gorte, 2003). One great limitation to this method is the spatial scale of the image being used (Geneletti and Gorte, 2003).

Comparisons between traditional per-pixel classifiers and the object oriented approach were examined by Yan *et al.* (2006). They compared land cover classification results from the MLC pixel-based approach and the object oriented approach using ASTER data at a 15m spatial resolution. Accuracy assessments were performed on each method through the creation and comparison of confusion matrices. The object oriented method achieved an accuracy of 83.25%, which was much higher than the accuracy of the MLC at 46.84%. Since the object oriented approach can use a classification algorithm to classify objects after image segmentation has been performed, there are studies that also examine the incorporation of more conventional parametric and non-parametric classifiers to classify the "objects" (Navulur, 2007). Wehrmann *et al.* 2004 began testing the combination of the object oriented approach with SVM using Landsat 5 TM data, a methodology that is explored later in this work. Hill (1999) used MLC to classify both the original Landsat TM data on a per-pixel basis, and on the objects derived from image segmentation being applied to the images. This method was used to classify forest types in humid tropical forests. Heavily forested areas exhibit a homogeneous land cover scenario and previous studies indicate that the object oriented approach may work better for more heterogeneous landscapes, so objects may be adequately segregated (Naumann and Siegmund, 2004). Even though initial accuracy results were low, a combination of the classification of image objects and post classification merging of some of the forest types yielded respectable results that were over 90% accurate (Hill, 1999).

One advantage to the object oriented approach is that objects can be created at various spatial scales, depending on the size of objects the analyst wished to extract from the imagery (Navulur, 2007). The object oriented approach is well suited for high resolution data (Blaschke, 2004), but there are many studies that test the use of the object oriented approach on medium resolution Landsat data (Hill, 1999; Schneider and Steinwendner, 1999; Stuckens *et al.*, 2000; Geneletti and Gorte, 2003; Naumann and Siegmund, 2004; Blaschke, 2005). Stuckens *et al.* (2000) used Landsat TM data to create land cover classification maps for a metropolitan area of Minnesota. They focused on a generalized 10 class classification (a modified Anderson classification level II) scheme and found that the spatial resolution of the imagery was ideal with an overall accuracy of 91.4%. Also because of its ability to integrate remote sensing object oriented methodologies with GIS (Smith and Fuller, 2001; Walter, 2004; Blaschke, 2005), the number of applications for the planning and environmental monitoring communities have increased (Blaschke, 2005).

SVMs have only recently been applied to classification of remotely sensed imagery (Keuchel *et al.*, 2003). A classification based on statistical learning theory (Vapnik, 1995), it had traditionally been used for face recognition in photos, and for handwriting and object recognition before it was recognized for remote sensing use (Hermes *et al.*, 1999; Pal and Mather, 2003). Widely used for hyperspectral remote sensing data (Camps-Valls *et al.*, 2004; Melgani and Bruzzone, 2004; Fauvel *et al.*, 2006), SVMs provide automatic classification of images by projecting data into a higher dimensional space through the use of kernels for increased separability between classes, and use an optimal hyperplane to separate the data (Fauvel *et al.*, 2006). Most studies conducted using SVM in comparison with other traditional parametric and more recently developed non-parametric classification methods have shown promising results, often with SVM producing classification images with higher accuracy (Hermes *et al.*, 1999; Hsu and Lin, 2002; Huang *et al.*, 2002; Keuchel *et al.*, 2003; Pal and Mather, 2003; Foody and Mathur, 2004; Pal and Mather, 2005). Although traditionally used in binary classification scenarios, the SVMs ability to discriminate based on geographical boundaries in feature space has proved successful for multi-class studies. With this success for applications using hyperspectral data, SVM is being tested on various types of data including Landsat multispectral data.

Pal and Mather (2005) conducted a study comparing SVM to the maximum likelihood and neural network classifiers. Landsat 7 ETM+ data and hyperspectral data from the DAIS 7915 airborne imaging spectrometer from June 2000 were used (Pal and Mather, 2005). The goal was to identify seven different agricultural land cover types from the ETM+ data and eight land cover types from the hyperspectral data including water, vegetation, bare soil, pasture lands and built up areas (Pal and Mather, 2005). Both neural network and SVM classifiers depend on user defined parameters to function. In the literature there is a lack of information on how these parameters are derived, so for most applications and in this study, the selection of the SVM parameters were chosen based on trial and error. For this study, the values chosen were γ=2 and C=5000 (Pal and Mather, 2005). The C parameter represents the penalty parameter for an SVM. The penalty parameter controls the magnitude of the penalty for a training pixel on the wrong side of the decision boundary (Foody and Mathur, 2004). The gamma parameter controls the width of the Gaussian kernel used to project the data into a higher dimension (Foody and Mathur, 2004). Results for the classifications showed SVM resulted in the highest overall accuracy for both data types (Pal and Mather, 2005). In a similar study, Hermes *et al.* (1999) found that for Landsat TM data, SVM outperformed the MLC stating that visually the results of the SVM appeared less "noisy".

In a study by Huang *et al.* (2002), SVM was compared to the maximum likelihood, neural network and decision tree classifiers using a high-dimensional data set. TM imagery from eastern Maryland in 1985 was used and was degraded to a spatial scale of 256.5m from the original 28.5m resolution. The objective of the study was to see the effect that training sample size and selection of appropriate input variables would have on the results. A "one against the rest" approach was used to perform a multi-class SVM. Since SVMs are traditionally a binary classification (2 classes) approach, two strategies have been developed to apply SVM's to a multi-class scenario (Pal and Mather, 2005). The "one against the rest" strategy compares one class to all the other classes combined to create the optimal hyperplane (Pal and Mather, 2005). The "one against one" strategy performs comparison of classes in pairs and evaluating all two class classifiers with the winning class getting a "vote" (Pal and Mather, 2005). They concluded that the "one against the rest" strategy adopted by Huang *et al.* (2002) is less than ideal for a multi-class scenario since it may produce areas of unclassified data and therefore lower classification accuracies. Despite this accusation, a familiar conclusion emerged: SVM outperform the other classifiers (Pal and Mather, 2005). Subsequently, Hsu and Lin (2002) found the "one against one" better for operational use in a comparison of the newer "all together" method versus the traditional "one against all", "one against one" and DAGSVM. In all cases SVM proved successful for multi-class classification approaches.

Another advantage to SVMs is that they require few training data (Foody and Mathur, 2004), but are not limited to a small training set. This is merely an advantage to an analyst that has very few training data or very few resources for the collection of a training set. In two studies conducted by Foody and Mathur (2004, 2008) they explore the affect that training set size has on the accuracy of SVMs. In the 2004 study, Foody and Mathur used 5m airborne

TM data of an agricultural area in England in July 1986. A variety of agricultural land uses were examined and six classes were identified in the study (Foody and Mathur, 2004). To ensure optimal classification, individual field boundary pixels were masked out so training sites and ground reference points would be taken from homogeneous land cover types (Foody and Mathur, 2004). The SVM was tested against other classifiers to determine the highest overall accuracy. Discriminant analysis (similar to the MLC), decision tree and neural networks were also used to classify the image using three of the eleven available spectral bands (Foody and Mathur, 2004). The SVM was run with a C value equal to 1 and the γ parameter was identified through trial and error, testing values between 0.005 and 1 (Foody and Mathur, 2004). It was determined that the γ value had an impact on classification accuracy, with accuracy decreasing as the value increased. The SVM classification achieved the highest overall accuracy at 93.8%, and even though the SVM can function with little training data, there was a positive relationship between training set size and overall accuracy. An increased number of training sets produced a higher accuracy result, proving that an increased number and variation of training pixels can aid in identifying appropriate support vectors (Foody and Mathur, 2004). In the second study conducted in 2008, Foody and Mathur explored the use of a small, intelligently selected training set versus a traditionally collected larger training set. Even though the smaller training set yielded a lower accuracy, it was only lower by 1.34% but reduced the costs of training data acquisition (Mathur and Foody, 2008). This shows promise for the use of smaller training sets although this method may require more expert knowledge (Mathur and Foody, 2008).

Unsupervised classifications can be ideal for large scale land cover change studies so time need not be invested in selecting training sites for the classification algorithm, a job that can be both time and labour intensive. Although more time is typically required to train the classifiers, supervised techniques incorporate knowledge of known land cover types on the ground and have the ability to enhance the classification with added knowledge of the study area (Jensen, 2005). Land cover information that is accurate and up to date is ideal for land resource planning, studies of environmental change and conservation efforts (Foody and

Mathur, 2004). Foody and Mathur (2004), state that the only feasible source of information on land cover over large areas is remote sensing since it allows data to be acquired in a repeatable manner.

2.3.3 Land Cover Mapping on the Niagara Escarpment using Remote Sensing

Remote sensing for land cover management on the Niagara Escarpment is a relatively new concept. Two prior studies have been conducted in cooperation with one another to provide land cover change information across the entire Plan area. Each study examined different portions of the Plan area, one in the northern section and one in the southern section. The analysis of the southern portion of the escarpment was undertaken by Geomatics International Inc. The supplemental northern study was conducted by a group of students from Sir Sandford Fleming College. Fourteen classes were established and land cover was identified in the Plan area by using unsupervised classification of the images (Cowell, 1997; Lusted *et al.*, 1997). Both studies compared a 1975/1976 Landsat Multispectral Scanner (MSS) image with a 1995/1996 Landsat Thematic Mapper (TM) image to determine the change over a 20 year time period in the Plan area (Cowell, 1997; Lusted *et al.*, 1997). Unsupervised classification was used in this study to distinguish between a proposed 14 different land cover types in the study regions (Cowell, 1997; Lusted *et al.*, 1997). Unsupervised classification is considered a basic form of classification in the field of remote sensing, as it requires no prior knowledge of the study area on the part of the analyst. Pixels are grouped based on spectral characteristics according to a predetermined statistical criteria (Jensen, 2005). This can be problematic since some classes are spectrally very similar such as agricultural classes and the deciduous forest class as was found in the Northern study (Lusted *et al.*, 1997). Also the change in sensors from the 1975/1976 MSS images and the 1995/1996 TM images can introduce error into the classification as well, since MSS imagery is available at an 80 m resolution and TM data are available at a 30 m resolution. The discrepancy in resolution caused some classes (such as transportation) to be undetectable, especially in the older images and the change in resolution also forced the authors to acknowledge a probable reduction in the overall accuracy of the land cover change statistics stated in the final reports (Cowell *et al.*, 1997). To try and alleviate these potential problems, ancillary GIS data were used to identify known land cover types, such as roads, quarries and recreational areas, in the final classified images. A major drawback to these studies was that no quantitative accuracy assessment was performed on the final classified images. An error matrix should have been produced for each study with overall, user and producer accuracies stated, so the end user will know the accuracy of the information being presented.

2.3.4 Change Detection

Digital change detection using satellite remote sensing data is an effective way to monitor some environmental changes (Howarth and Wickware, 1981). Where land cover changes occur over large geographic areas, monitoring landscape changes over the long term can be made easy through the use of remotely sensed data for change detection (Howarth and Wickware, 1981). Change detection is one of the most popular applications of remote sensing data (Singh, 1989), and there are many ways to perform change detection on remotely sensed data or on classification maps produced by remote sensing data (Naumann and Siegmund, 2004).

There are many different change detection techniques outlined in various works (Singh, 1989; Mas, 1999; Civco *et al.*, 2002; Coppin *et al.*, 2004; Lu *et al.*, 2004; Jensen, 2005). Naumann and Siegmund (2004) place change detection techniques into two categories: One based on unclassified remotely sensed data and one based on classified multi-date images. Change detection that is based on more than one classified image is called post-classification comparison. There are several advantages to this approach: it has been widely used, it minimizes atmospheric, sensor and environmental differences when using multiple images and it provides a complete matrix of land cover change (Lu *et al.*, 2004; Naumann and Siegmund, 2004). However, change detection results derived from this method are only as accurate as the individual classification maps themselves (Civco *et al.*, 2002).

Since there are many change detection techniques, comparative analysis is undertaken by many in an attempt to identify the best change detection method for a particular dataset. In Civco *et al.* (2002), six different change detection techniques were tested using Landsat TM and Landsat ETM data. Their objective was to compare the results of each change detection method both qualitatively and quantitatively (Civco *et al.*, 2002). For the execution of the traditional post-classification method, an unsupervised ISODATA classification was performed on the imagery from March and September 1989 (Civco *et al.*, 2002). A process known as "cluster busting" was used to generate seventy-five different clusters and separate them into nine land cover classes or an unknown class if the clusters could not be identified (Civco *et al.*, 2002). This is an iterative approach to classification that was run for three iterations on the remaining unknown clusters from each step until all were classified (Civco *et al.*, 2002). They concluded that no one approach was better than the other. Alternatively, in a similar study conducted by Mas (1999), the conclusion was reached that post-classification comparison technique was the most accurate procedure when compared to five other change detection techniques. Two Landsat MSS scenes were used and classified into ten land cover classes using the MLC. The author attributed the high change detection accuracy to the high accuracy of each individual classification, which improved when spectrally similar classes were grouped together. Howarth and Wickware (1981) state that although post classification comparison is simple in nature, it is an intricate task that must take into account limitations and accuracy values in every step of the change process.

Chapter 3
Geographical Context and Data

3.1 Study Area

The Niagara Escarpment in southern Ontario is a thin ridge of gently sloping sedimentary rock that runs from Tobermory in the north to Niagara Falls in the south (Niagara Escarpment Commission, 2008b). To conduct this research a study area was chosen so the various types of land cover along the Escarpment would be represented. The study area selected was the NEP portion of the Regional Municipality of Hamilton and the Regional Municipality of Halton. A cartographic representation of the study area can be seen in Figure 3.1. The study area encompasses a portion of the southern extent of the Plan area and is 1,840.9 km^2 in size. It begins in the Regional Municipality of Halton, at the intersection of Winston Churchill boulevard and the 32^{nd} side road in the north (near Terra Cotta, Ontario) and ends in the Regional Municipality of Hamilton at the City of Hamilton and Regional Municipality of Niagara municipal boundary (near Winona, Ontario). This area was selected so the study would be conducted at a regional scale. An attempt was made to select two areas on the Escarpment representative of a "rural" region and of an "urban" region within the NEP boundaries. In each region, there are many different pressures being placed on the Escarpment.

The portion of the Plan in Halton Region is characterized as a largely rural landscape, consisting of mostly agricultural and forested land. This area contains 51.12% of the NEP's Mineral Resource Extraction areas (MREAs) (Niagara Escarpment Commission, 2007a). South of the Halton Region portion of the NEP is the Hamilton portion of the Plan. This area is characterized as heavily urbanized as it contains the largest percentage of the urban land use designation in the NEP at 66.06% (Niagara Escarpment Commission, 2007a). Aside from the urban land cover, a large forested corridor has been maintained along the Escarpment length with some continuous natural areas located inside the urban area designation boundaries. Even with the lowest percentage of rural land use designation, agricultural practices exist west of the city centre and also east of the city along the south shore of Lake Ontario heading toward the Regional Municipality of Niagara. In an urban context most land cover issues begin with a growth in population, as new demands are placed

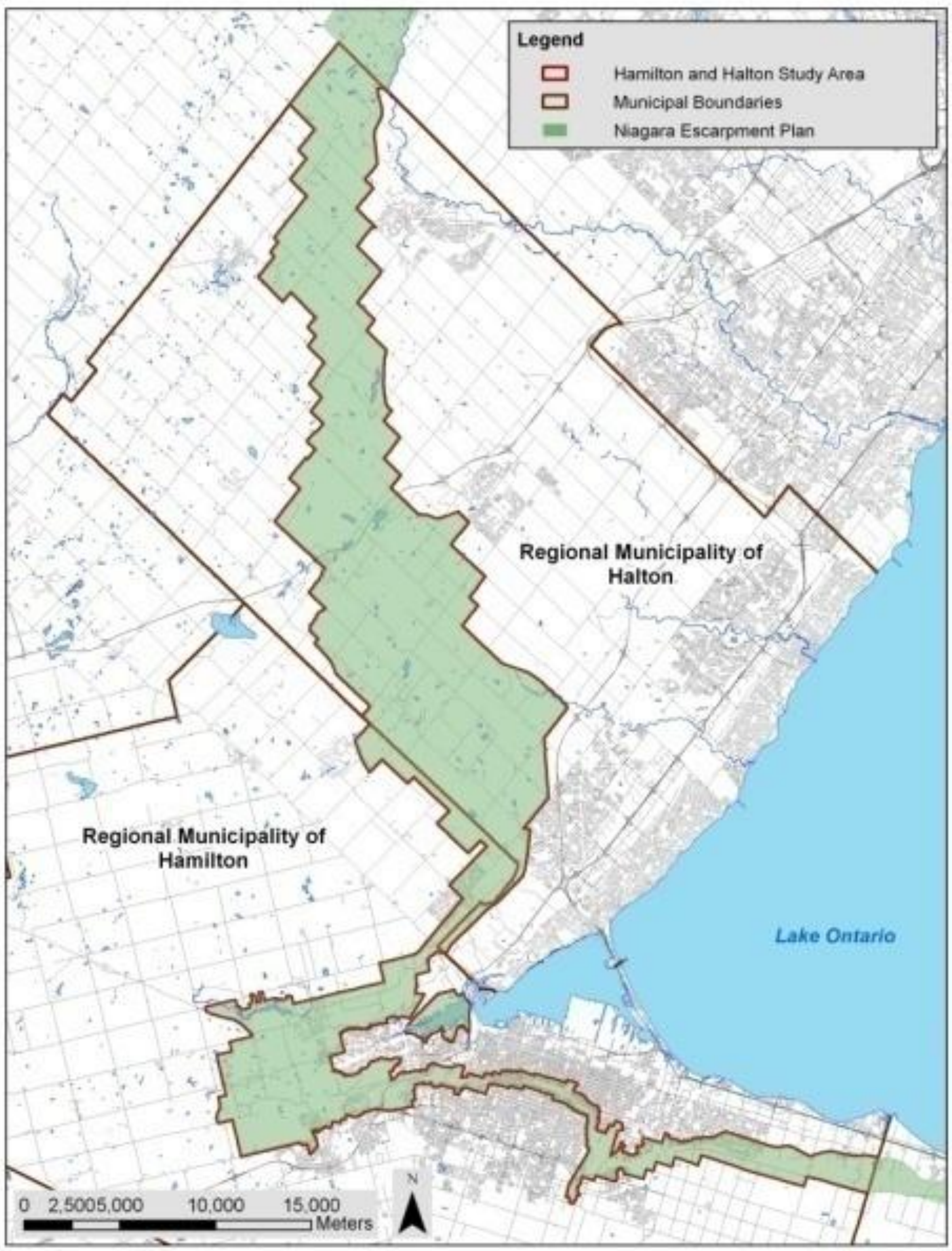


Figure 3.1 Niagara Escarpment Study Area (Regional Municipalities of Hamilton and Halton)

on the landscape. It was estimated by Borodczak (1995) that more than 7 million people live within 100 kilometers of the Escarpment. Today this number has increased and in many ways the preservation of the Escarpment has made it attractive for development (Barnett *et al.*, 2004). The Escarpment environment draws new homeowners to the area, with its scenic views, rural draw and recreation potential as well as organizations wishing to exploit the Escarpment for its natural resources. The southern portion of the Escarpment is cause for concern with its rapidly expanding urban areas. This area contains the rapidly growing urban centres of St. Catherines, Hamilton and Burlington. These three cities are all located in the GGH that extends along the western end of Lake Ontario (Martel and Caron-Malenfant, 2007). New areas for concern within proximity to the Escarpment study area are Milton and Halton Hills, as these two towns have experienced rapid population growth since 2001 (Martel and Caron-Malenfant, 2007). An increase in urban lands in close proximity/within NEP boundaries has given rise to increases in demand for lot creation in the countryside as well as for more mineral resource extraction to supply the demand for aggregate resources, as the demand for building supplies increases with southern Ontario's ever-growing infrastructure (Borodczak, 1995). The increase in urban and rural developments in the NEP area can be cause for a decrease in agricultural land and forested areas outside of the immediate urban centre. There is a need to examine these land cover changes consistently over space and time, so adequate protection measures can be continued into the future.

3.2 Data Resolution Considerations

An important step in any land cover change analysis is the selection of the appropriate scale of the study area, and with this, the selection of appropriate data to conduct the study at an adequate resolution. For a remote sensing based land cover change study, this includes consideration of various scales such as spatial, spectral/radiometric and temporal resolutions of the data (Jensen, 2005).

3.2.1 Spatial Resolution

The spatial resolution of data used in land cover classification is an important consideration, as it dictates the size of features that can be detected in the image (Jensen, 2000). Subsequently, the spatial resolution of the data is also an important consideration for change detection since comparisons are best between sensors with the same instantaneous-field-of-view (IFOV) and georeferenced to ≤ 0.5 of a pixel (Jensen, 2005). In remote sensing terms, spatial resolution refers to the IFOV or the area in metres that is captured by the sensor (Jensen, 2000). For example, Landsat 5 TM multispectral images are created as scan lines move across the landscape in a “whiskbroom” (across-track) fashion, using oscillating mirrors to measure energy below the aircraft in an arc ranging from 90º to 120º (Lillesand, *et al.*, 2004). At a particular moment in time the IFOV’s “ground resolution cell” is a view of one section of the ground, and relays the energy emitted from the ground back to the sensor (Lillesand *et al.*, 2004). This represents the spectral signature from that particular “pixel” in the image. Typically for medium resolution sensors one pixel can contain a combination of land cover classes and is known as a mixed pixel (Lillesand *et al.*, 2004). Spatial resolution of an image can be calculated by using Equation 3.1 and is often represented in metres.

$$IFOV = \frac{HD}{f} \tag{3.1}$$

Where:

D = Detector size

H = Flying height above the earth

f = Focal length of the scanner

(Townshend *et al.*, 1988)

Landsat 5 TM imagery has a 30m×30m resolution for bands 1-5 and band 7 (visible to mid-infrared) and a 120m×120m resolution for band 6 (thermal band) (Richards and Jia, 2006). Landsat imagery is referred to as medium resolution due to its spatial resolution in comparison to other types of sensors. Very high spatial resolution imagery such as IKONOS has a spatial resolution of 4m×4m multispectral (1m×1m panchromatic), whereas very low spatial resolution imagery such as NOAA (National Oceanic and Atmospheric Administration) AVHRR has a spatial resolution of 1.1km (Richards and Jia, 2006). The selection of medium resolution imagery for land cover change analysis on the Niagara Escarpment is ideal since the NEP is a regional land use plan; one of the first large scale land use plans in Canada (Niagara Escarpment Commission, 2008b). At a regional scale, the land cover classes that would be detectable with medium resolution Landsat 5 TM data coincide with land cover types one would expect to find in each land use designation outlined in the NEP.

3.2.2 Temporal Resolution

Temporal resolution of the sensor and the temporal scale of the study are important considerations for land cover change detection (Jensen, 2000). Temporal resolution refers to the frequency that a sensor captures an image on the earth's surface at a particular geographic location. This can have much to do with what sensor an analyst would choose to conduct research. Taking the example of the sensor chosen for this research (Landsat 5 TM), an image is captured at approximately the same time every 16 days (Townshend *et al.*, 1988). Knowing the temporal resolution of the sensor being used in the research can provide much information to the analyst. For example, when examining agricultural crops, variations in growing seasons for different crops occur in different geographic locations (Jensen, 2000). Having knowledge of the growing season for a particular crop can aid the researcher in choosing the appropriate image dates for analysis (Jensen, 2000).

For the temporal scale of the study, the researcher must identify specific anniversary dates that would adequately capture the changes on the ground for a specific case. For the case of the Niagara Escarpment, the Ontario Cabinet approved the final NEP in 1985 (Borodczak, 1995). Prior to the inception of the plan, development control measures were in place, but for the purposes of this research, only changes within the current Plan boundaries/Plan designations were examined. The images used in this study cover a 20 year time period beginning in 1986 and ending in 2006, so as to cover the majority of the lifespan of the NEP. A 1996 image was also used so change over two ten year periods could be examined. The images selected for the study were acquired in the summer months, as close to the same time period each year as possible. Each of the three images was captured between 3:00 and 4:00 GMT, which eliminates diurnal sun angle effects (Jensen, 2005).

3.2.3 Spectral/Radiometric Resolution

The spectral resolution of a sensor refers to the sensitivity of an instrument to capture image objects on the earth's surface (Jensen, 2000). This can mean two things: it defines the number of distinct signal levels, and it describes the number of bands and the total energy each band captures (Schowengerdt, 2007). Landsat 5 TM data records data in 8-bits, which means in each image we can view digital numbers (DNs) from 0-255 (Jensen, 2000). This is an improved radiometric resolution from the old MSS carried aboard the Landsat 1-5 missions, which recorded data in 6-bits (images contained DN values from 0-63) (Richards and Jia, 2006). Landsat 5 TM imagery is multispectral, which means it collects reflected, emitted or back-scattered energy form an area of interest on the ground in multiple bands of the electromagnetic spectrum (Jensen, 2000). A description of the Landsat 5 TM sensor characteristics is discussed in the following section.

3.3 Data

Remote Sensing Imagery

Townshend (1984) states that the accuracy of land cover maps produced with multispectral imagery are dependent upon the resolution of that imagery. Medium spatial resolution imagery is ideal for conducting land cover analysis over a regional scale (Vogelmann *et al.*, 1998). Using higher resolution imagery would be useful for detecting small scale land cover types such as urban areas, but purchasing this imagery would be costly and data processing would take more time, since multiple images would be required. The spectral resolutions should suit the analysis and adequately distinguish the types of land cover to be mapped. Spectral bands sensed by the TM sensor are matched closely to the spectral responses of vegetation and other surface materials (Townshend *et al.*, 1988). This is outlined in Table 3.1. The TM sensor provides a consistent temporal resolution, which is ideal for examining land cover changes over time.

The Landsat 5 TM sensor captures images at medium resolution and provides information in 7 multispectral bands (Ustin and Costick, 2000). Landsat 5 TM data were chosen for this regional land cover study, since the spectral, spatial and temporal resolutions of the TM sensor were ideal for conducting land cover change across Hamilton and Halton Regions.

Table 3.1 Characteristics of the Landsat 5 Thematic Mapper (TM)

Spectral Bands	Wavelength (μm)	IFOV	Dynamic Range (bits)	Applications
1	0.45-0.52 (blue)	30m×30m	8	Separates deciduous/coniferous forests
2	0.52-0.60 (green)	30m×30m	8	Aids in detection of green healthy vegetation through chlorophyll reflection
3	0.63-0.69 (red)	30m×30m	8	Aids in detection of green healthy vegetation through chlorophyll absorption
4	0.79-0.90 (near IR)	30m×30m	8	Identification of vegetation through reflection from the mesophyll layer; also detects water bodies
5	1.55-1.75 (mid IR)	30m×30m	8	Detects soil moisture
6	10.4-12.5 (thermal)	120m×120m	8	Senses heat/longwave radiation from the earth
7	2.08-2.35 (mid IR)	30m×30m	8	Similar to band 5; detects moisture and useful for geological mapping as it discriminates between rock type

(Townshend *et al.*, 1988; Richards and Jia, 2006)

The data used in this study were acquired by the Landsat 5 mission that was launched March 1st, 1984 and continues today (Richards and Jia, 2006). Landsat 5 has two imaging instruments on board, the MSS and the TM, although the TM sensor is much improved in terms of its resolution (spatial, temporal and spectral) in comparison to the MSS (Townshend *et al.*, 1988; Richards and Jia, 2006). Landsat 5 TM has a near polar, sun synchronous orbit, and moves along the sky in a similar path as the sun (Richards and Jia, 2006). It has a 9:30 a.m. local equatorial crossing daily, and captures information from the same place on the earth's surface at approximately the same time each day (Richards and Jia, 2006). It moves around the earth at an altitude of 705km and completes 14.56 orbits per day over a 16 day period which means it takes 16 full days to gain "full" earth coverage (Richards and Jia, 2006). As mentioned previously, the Landsat 5 TM has a "whiskbroom" scanner that moves across the earth in a forward motion and contains a scan mirror that moves back and forth across the landscape along scan lines, collecting radiation from the earth's surface and generates an electrical signal which represents the amount of radiation reflected or emitted from the particular IFOV at a particular time (Townshend *et al.*, 1988). The multispectral characteristics of the TM sensor can be seen in Table 3.1. The Landsat imagery was provided to the University of Waterloo's Mapping and Design office by the Grand River Conservation Authority (GRCA). To conduct this analysis, three Landsat scenes, from 1986, 1996 and 2006 were selected and are described in Table 3.2.

Table 3.2 Landsat 5 Thematic Mapper (TM) Scenes Used for Land Cover Change Analysis

	Satellite	**Instrument**	**Pixel Size or IFOV (m)**	**Date**	**Path**	**Row**
1986 image	Landsat 5	TM	30x30 (re-sampled to 25m)	June 03, 1986	18	30
1996 image	Landsat 5	TM	30x30 (re-sampled to 25m)	May 29, 1996	18	30
2006 image	Landsat 5	TM	30x30 (re-sampled to 25m)	August 13, 2006	18	30

(USGS, 2008)

Supplementary Data Sets

Orthoimages

High resolution orthoimagery of the study area was obtained from the University of Waterloo Map Library to aid in the training of the supervised classification. Greater Toronto Area (GTA) orthoimagery from 2005 and Hamilton orthoimagery from 1995 were used as supplementary data in the creation of training sites for the 2006 and 1996 Landsat image respectively. The high resolution of the orthoimages provided adequate "ground truth" information and thus, field verification of the classification maps was considered unnecessary. The resolution of the 2005 GTA orthoimagery is 20cm and the images are full-colour and cover the entire study area (Morgan, 2007). The images were flown in April 2005 and provided by First Base Solutions (Morgan, 2007). They were projected in UTM coordinates, North American Datum (NAD) 1983 and are in MrSID data format with accompanying SDW world files (Morgan, 2007). The resolution of the 1995 GTA orthoimagery is 1m and these images are also full colour (Morgan, 2006). They cover all of the Hamilton study area and a portion of the Halton study region. The images were provided by the Triathlon Mapping Corporation in Burnaby, British Columbia (Morgan, 2006). They were provided in UTM coordinates, NAD 1927 (and re-projected into NAD 1983) and were compressed from .TIFF files to be made available as MrSID image files (Morgan, 2006). Since there was no available orthoimagery to act as reference information for the 1986 imagery, another Landsat image from 1985 was used as reference information when needed. This image was captured on August 3, 1985 and has the same parameters as the three images used in the study as stated above in Tables 3.1 and 3.2.

GIS Dataset

Shapefiles representing the NEP area were obtained from the NEC. The outer boundary of the Plan and Plan designation boundaries were used to create classification masks to exclude areas outside of the Plan from the analysis. All shapefiles provided by the NEC were created at a 1:50,000 scale, and therefore all subsequent maps created with these shapefiles should only be analyzed at this scale and at smaller scales than 1:50,000. NEP boundaries are approximate and subject to change through plan amendments and site level boundary interpretations, but for the purpose of this research current NEP boundaries were used. These data sets along with datasets obtained by the National Topographic Database (NTDB) and the MNR were also used for mapping purposes and were obtained from the University Map Library free of cost. The NTDB data, which represents the entire set of information one would see on a topographic map in shapefile format, were downloaded from the Geogratis website (www.geogratis.ca). National Topographic Series (NTS) tiles obtained from the site were 30M04, 30M05, 30M12, 40P01, 40P08 and 40P09, and covered the entire study area. MNR datasets were used for reference only and included information such as old land cover map data as well as forestry data.

Chapter 4
Methodology

4.1 Data Pre-processing

Before analysis of the data can take place, each image must be pre-processed individually to reduce any geometric or atmospheric (radiometric) errors that may affect the classification. Pre-processing is an important step in change detection. If corrections are not performed, subtle differences in spatial or spectral reflectance could decrease the accuracy of the classification, especially when examining change in a multi-temporal data set (Jensen, 2005). For each of the three images, geometric correction was performed by the GRCA prior to delivery of the data to the University of Waterloo. Since the images were provided by the GRCA it is assumed that the images were operational within the organization and were corrected to the highest accuracy possible. Atmospheric correction was not performed at the GRCA, so it was performed on each of the images using PCI Geomatica's ATCOR2 module upon acquisition for this study.

Atmospheric correction is performed to remove absorption and scattering of electromagnetic radiation (which can cause haze) in the earth's atmosphere to reveal pure surface reflectance values (PCI Geomatics, 2005). To perform atmospheric correction, PCI Geomatica's ATCOR2 module was used. This module is typically used for flat terrain whereas the ATCOR3 module is used for correcting imagery over rugged terrain. This module allows the user to incorporate a DEM so the terrain of the area may be represented in the atmospheric correction. Based on the study area location over the Niagara Escarpment, the ATCOR3 module would be the preferred module to perform the correction, but since the University of Waterloo does not have access to this module, the ATCOR2 model was used with an assumed average height of 269.01 m above sea level (asl) over the Hamilton and Halton portions of the Plan. This value was calculated by determining the average value of contours in the study area.

When performing atmospheric correction, there are several parameters which must be entered according to the image location and atmospheric conditions. For each of the three subset images the average height was entered as 269.01 m. The sensor type, Landsat 5 TM must be entered and the band setup performed. As mentioned in the previous chapter, the TM sensor has seven spectral bands: six 30 m reflective bands and one 120 m thermal band. The thermal band (band 6) was excluded from the correction and subsequent classification of each image since it consists of a larger resolution than the other 6 TM bands. The images provided to the University by the GRCA were re-sampled to a resolution of 25m and this value is input along with the date each image was captured. Next, a calibration file was selected. For this correction, a revised Landsat 5 TM radiometric calibration file from Chander *et al.* (2007) was used. The radiance unit of each band in the calibration file is in $mW\ cm^{-2}\ sr^{-1}\ \mu m^{-1}$.

Table 4.1 Gain and Bias Values for the Selected Calibration File

Date of Imagery	**June 3, 1986 & May 29, 1996**		**August 13, 2006**	
Band	Gain	Bias	Gain	Bias
1	0.602431	-1.52	0.762824	-1.52
2	1.175100	-2.84	1.442510	-2.84
3	0.805765	-1.17	1.039880	-1.17
4	0.814549	-1.51	0.872588	-1.51
5	0.108078	-0.37	0.119882	-0.37
7	0.056980	-0.15	0.065294	-0.15

(Chander *et al.*, 2007)

One set of gain and bias re-scale values is used for the two older images (1986/1996) and one set of gain and bias re-scale values is used for the new 2006 image. To convert DNs in an image to radiance (Lλ) rescaled gain and bias values are calculated using Equation 4.1.

$$Gain = \frac{(LMAX_\lambda - LMIN_\lambda)}{255} \quad (4.1)$$

$$Bias = LMIN_\lambda$$

Where:

$LMAX_\lambda$ = Spectral radiance (scaled to the minimum DN value in the image between 0 and 255) [W/ (cm2.sr.μm)]

$LMIN_\lambda$ = Spectral radiance (scaled to the maximum DN value in the image between 0 and 255) [W/ (cm2.sr.μm)]

(Chander *et al.*, 2007))

The result of the atmospheric correction is scaled surface reflectance with DN values ranging from 0 to 255 (PCI Geomatics, 2005). These final scaled surface reflectance values are calculated using the following equation:

$$L_\lambda = Gain_{rescale} \times DN + \; Bias_{rescale} \quad (4.2)$$

Where:

L_λ = Spectral radiance collected at the sensor (for this research is rescaled to DN values)

$Gain_{rescale}$ = Detector Gain rescaled

$Bias_{rescale}$ = Detector bias or background response rescaled

(Chander *et al.*, 2007))

As a sensor ages the gain and bias values change slightly and therefore the calibration file must be updated to reflect these changes (Chander *et al.*, 2007). A number of required atmospheric parameters for the geographic area of interest are added into the ATCOR2 module to assist in the correction. Table 4.2 summarizes the various parameters entered into the ATCOR2 module for all three images. All three images had 0% cloud cover and therefore no mask was created to exclude cloud or haze. The ATCOR module was run with constant conditions. Once radiometric (atmospheric) and geometric corrections were completed, classifications took place.

Table 4.2 Parameters Entered for Atmospheric (Radiometric) Correction

	Images			
Parameters	**June 3, 1986**	**May 29, 1996**	**August 13, 2006**	**Explanation**
Sensor Type	Landsat 5 Thematic Mapper (TM)	Landsat 5 Thematic Mapper (TM)	Landsat 5 Thematic Mapper (TM)	
Pixel Size	25 metres	25 metres	25 metres	Re-sampled resolution
Atmospheric Definition Area	Urban	Urban	Urban	Proximity to large urban centres (Hamilton and Burlington)
Condition	Mid-Latitude Summer	Mid-Latitude Summer	Mid-Latitude Summer	Atmosphere that has a total water vapour content of 2.92 (g cm-2)
Thermal Atmospheric Definition	Mid-Latitude Summer	Mid-Latitude Summer	Mid-Latitude Summer	Same as above
Solar zenith	31.06	33.21	34.49	Calculated using the local date and time of image capture as well as the central latitude and longitude value of the study region
Solar azimuth	123.92	120.87	139.96	Same as above
Visibility	23.4 km	22.7 km	24.1 km	Acquired from historical weather data
Adjacency	5 km	5 km	5 km	Calculated to maximum effect (200 pixels×0.025 km)
Offset to surface temperature	0.0 degrees Kelvin	0.0 degrees Kelvin	0.0 degrees Kelvin	Default value

4.2 Classification Algorithm Descriptions

To conduct meaningful change analysis, a key objective of the research was to create the most accurate land cover maps as possible for each time period. The selection of appropriate classification algorithms is an important consideration for land cover mapping using satellite remote sensing (Jensen, 2005). Classification algorithms range in logic, from supervised to unsupervised; parametric to non-parametric to non-metric (Keuchel *et al.*, 2003; Jensen, 2005). Throughout the literature, various methods have been chosen for a wide range of studies over time, and for this research, a decision was made to test a set consisting of supervised parametric and non-parametric algorithms common throughout land cover mapping applications to examine which would yield the best results for the Niagara Escarpment scenario.

Chosen for this study was a set of classifiers that would represent the wide range of classification algorithms used throughout the literature from traditional per-pixel classifiers, to more current methods. All the classification algorithms selected were supervised classifications, so prior knowledge about the study area could be used for accurately selecting optimal training sites for each class. Parametric and non-parametric examples were chosen for the study. MLC, MD classifier and MDC were all tested. All three are traditional per-pixel methods and are parametric classifiers (Jensen, 2005). Parametric classifiers make assumptions about the underlying probability density functions and under normal (Gaussian) distributions, calculate statistics needed to complete the classification such as mean and variance values (for mean vector and covariance matrix computation) (Keuchel *et al.*, 2003; Jensen, 2005). More recently developed classification methods such as object oriented classifications (parametric), and SVM (non-parametric), were also examined for the study. Object oriented classification is a special case of parametric classifier, as it uses image objects to calculate classification parameters and not individual pixels (Jensen, 2005). This classifier, when paired with a supervised classification technique, considers not only the spectral information of the image, but the spatial as well (Jensen, 2005). SVM's are considered non-parametric classifiers since they divide training data into classes by identifying optimal boundaries between classes, thus disregarding any statistical distribution the training data may have (Keuchel *et al.*, 2003). All classifications were conducted using ENVI 4.5, as this program provides various supervised traditional per-pixel classification tools. All the algorithms described above were used to identify which would yield the greatest classification results for all three images. Each algorithm is statistically unique and can offer very different results.

4.2.1 Traditional Per-pixel Supervised Classifications

All three traditional per-pixel classifiers (MLC, MD and MDC) used are distance classifiers that vary in their implementation. The following section describes each of the three classifiers tested for the creation of the final classification maps and discusses the differences between them.

Minimum Distance (MD) Classifier

The MD classifier calculates the MD of each unknown pixel to the nearest mean vector from the training data (Jensen, 2005). In this algorithm, the mean DN values for each training set and for each class are calculated. It then takes each pixel in the image and classifies it based on its distance to the nearest class mean vector. The algorithm provided in ENVI 4.5 uses a Euclidean distance measurement from each unclassified pixel to the mean vector of each class, and then, the unknown pixel is assigned to the class whose mean vector is the shortest Euclidean distance from the unknown pixel (ITT Visual Information Solutions, 2008c). The Euclidean distance is calculated based on the Pythagorean Theorem and is calculated using Equation 4.3 and is demonstrated in Figure 4.1.

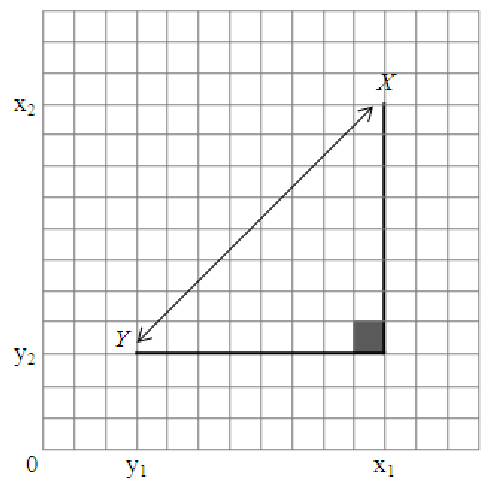
$$D_{XY} = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \tag{4.3}$$

Where:

k = the number of bands used in the classification

x and y = two unknown pixels used in calculating distance from the unknowns to the mean vector.

(Jensen, 2005)

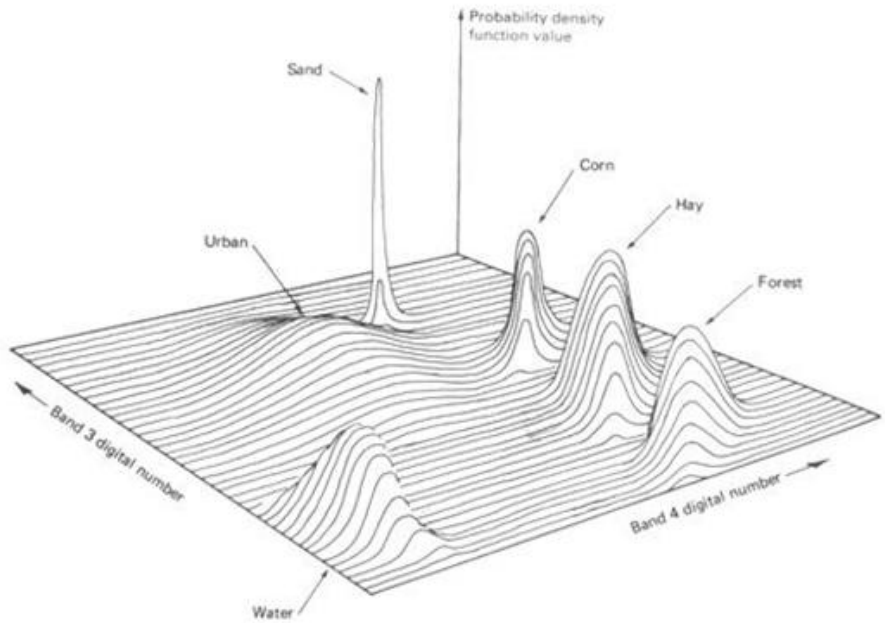


(Adapted from Jensen, 2005: 373)

Figure 4.1 Graphic Representation of Euclidean Distance Parameters for the Minimum Distance (MD) Classifier

Maximum Likelihood Classification (MLC)

The MLC is the most widely used classification algorithm (Jensen, 2005). The MLC is based on probability, and classifies an image based on the probability of an unclassified pixel in the image belonging to one of *n* classes identified by the analyst (through the selection of training classes) and then each unclassified pixel in the image is assigned to the class for which the probability value is highest (Jensen, 2005). The MLC algorithm assumes that the training data collected by the analyst are normally distributed. This means that if a frequency distribution representing each class in each band was created the results would resemble a normal (Gaussian) distribution. Instead of creating frequency distribution graphs for each class in each band, the MLC algorithm assumes normality for all the training classes and approximates the normal curve for all cases. This reduces processing time and the amount of stored data. This approximation of the normal curve for each class in each band allows for the calculation of mean and variance values. The mean and variance values are used to calculate the probability density functions for each class. An example of probability density functions can be seen in the Figure 4.2 below taken from Lillesand *et al.* (2005).



(Lillesand *et al.*, 2004: 560)

Figure 4.2 Probability Density Functions

In this particular example the vertical axis represent the probability density function values for each class. The diagram is also a bivariate example since the x and y axes are represented by the DN values of bands 3 and 4 respectively. In this study, 6 bands are used so the computations required for this research would exemplify a multinomial case and so that the full spectral range of the sensor could be used for a variety of land cover classes. Also in this study, MLC is performed without any prior probability knowledge of the classes for the Landsat 5 TM scene. In some cases, an analyst may know what proportion of land cover classes make up the image prior to classification. If no a priori information is available, an assumption is made that each class has an equal probability of occurring in the landscape. Under this assumption, the probability density function is calculated by the following:

An unclassified pixel is in class *i* if, and only if $p_i \geq p_j$ for all *i* and *j* out of 1,2, …*n* possible classes.

In the case of this research 7 classes are identified to create the land cover maps. The probability density function for each class is calculated using Equation 4.4.

$$p_i = -\frac{1}{2}\log_e|V_i| - \left[\frac{1}{2}(X - M_i)^T V_i^{-1}(X - M_i)\right] \quad (4.4)$$

Where:
M_i = the mean for class *i*
V_i = the covariance matrix of class *i* for all 1,2,…k bands
(Jensen, 2005)

Therefore, to assign an unclassified pixel to a particular class, the MLC decision rule computes the p_i for each class and then assigns the unknown pixel to the class for which the probability value is the highest (Jensen, 2005). Computationally, each unclassified pixel has a measurement vector X computed for it. To create this measurement vector the mean vector (value) (M_i) and covariance matrix (V_i) are calculated for each combination of classes in each band being used in the analysis. An example of the measurement vector between two classes for each band being used from the Landsat 5 TM scene can be seen below:

$$X = \begin{bmatrix} BV_{i,j,1} \\ BV_{i,j,2} \\ BV_{i,j,3} \\ BV_{i,j,4} \\ BV_{i,j,5} \\ BV_{i,j,7} \end{bmatrix} \quad (4.5)$$

Where:
BV = brightness value of the unclassified pixel
i and *j* = two different classes
1,2,…,*k* = image bands from Landsat 5 TM
(Jensen, 2005)

This matrix, calculated for all possible class combinations for each band, calculates the probability of an unclassified pixel belonging to each class and then assigns the pixel to the class with the highest probability value. In the event that the probability density functions of two or more training classes overlap in feature space (which often occurs), the unclassified pixel is assigned to the class with the highest probability density value (Jensen, 2005).

Mahalanobis Distance Classifier (MDC)

The MDC is similar in nature to the MLC with a few assumptions (Richards & Jia, 2006). In fact, the calculation of mahalanobis distance is used in determining maximum likelihood. The major assumption made when calculating MDC is that all class covariance's are equal (i.e. $\Sigma_i = \Sigma$) (Richards & Jia, 2006). This means that there is an average variance (σ) assumed for each class across all *n* bands (in the case of this research, 6 bands), as opposed to the MLC, which examines the variance of all classes across all bands individually. Therefore, the MDC still retains a degree of direction sensitivity, only it is based on the assumption that all the covariance matrices are equal (Richards & Jia, 2006). The following equation defines the squared mahalanobis distance:

$$d(x, m_i)^2 = (x - m_i)^t \, \Sigma^{-1} \, (x - m_i) \qquad (4.6)$$

Where:
Σ^{-1}= the sample variance-covariance matrix
x = the sample value (pixel vector)
m_i= the sample mean value (mean vector)
(Richards and Jia, 2006)

The superscript *t* indicates the transpose of the vector. The equation above represents the squared mahalanobis distance; the true mahalanobis distance is the square root of the above equation (Richards and Jia, 2006). The MDC is a simple measure of distance from an unknown pixel to the mean of each class divided by the variance of that class. The unknown pixel is assigned to the class that yields the shortest distance. Since all three algorithms used in this study are distance measures, each classification algorithm is related to one another. The MDC helps make up the MLC and the MDC can also be reduced to form the MD classifier.

4.2.2 Recent Supervised Classification Methods

Support Vector Machine (SVM)

SVM is a non-parametric classifier that separates image data by identifying boundaries in feature space (Keuchel *et al.*, 2003). Classes are not differentiated by statistical means as in the distance classifiers described above, but by geometric criteria (Fauvel *et al.*, 2006). Developed by Vapnik and colleagues in the 1990's, it was used in a remote sensing context early on by Gualtieri and Cromp in 1998 (Pal and Mather, 2003). For a simple example, an assumption is made that two classes are spectrally separable in feature space (Brown *et al.*, 1999). If a line were to be drawn in feature space to separate these two classes, it should maximize the space between two classes identifying a central hyperplane (Pal and Mather, 2005). The identification of the hyperplane is achieved by measuring the central distance between the closest points of each of the two classes. These points are known as support vectors (Pal and Mather, 2005). A SVM in its simplest form (a binary example in a two dimensional feature space) can be seen below in Figure 4.3.

An assumption is made that N training samples exist in the feature space with corresponding labels $y_i = +1$ or $y_j = -1$ respectively (Fauvel *et al.*, 2006). To define the optimal hyperplane, w represents the vector normal to the hyperplane and b represents the bias so the hyperplane is defined as:

$$w \cdot x + b = 0 \tag{4.7}$$

Where:

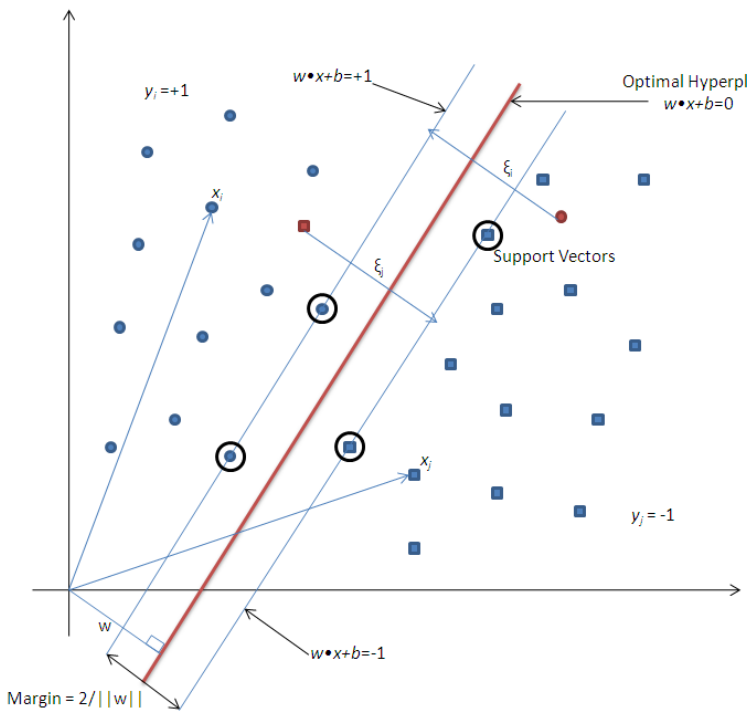
x = a point lying on the hyperplane

w = is normal to the hyperplane

b = bias

$\frac{(|b|)}{(\|w\|)}$ = the perpendicular distance from the hyperplane to the origin with $\|w\|$ the Euclidean norm of w.

(Foody and Mathur, 2004)



(Adapted from Fauvel *et al.*, 2006)

Figure 4.3 Example of a Non-Linearly Separable Case by SVM

For any training pixel x, the distance from the hyperplane can be calculated by:

$$f(x) = w \cdot x + b \tag{4.8}$$

For a training pixel x to be classified to either class, it must satisfy one of the two following conditions:

$$y_i\,(w \cdot x_i + b) \geq +1 \text{ or}$$

$$y_j\big(w \cdot x_j + b\big) \leq -1$$

Linearly separable data are ideal but rarely occur in a real world data set. For data that are non-linearly separable, slack variables ξ are introduced so misclassified pixels may be moved in feature space back to their original class (Fauvel *et al.*, 2006). Therefore the conditions above become:

$$y_i(w \cdot x_i + b) > 1 - \zeta_i, \zeta_i \geq 0 \text{ or}$$

$$y_j\big(w \cdot x_j + b\big) < -1 - \zeta_j, \zeta_j \geq 0$$

Final optimization of the margin is defined as:

$$min\left[\frac{\|w\|^2}{2} + C\sum_{i=1}^{N}\zeta_i\right] \tag{4.9}$$

Where the C represents the penalty parameter (Fauvel *et al.*, 2006).

This penalty parameter is one entered by the analyst in ENVI 4.5, and it allows for some misclassifications to be permitted (ITT Visual Information Solutions, 2008b). The larger the C value assigned, the higher the penalty for pixels that are misclassified (Pal and Mather, 2003). Previously a simple binary class was described, but for examining change in the NEP area a multiclass approach is needed and methods have been developed for dealing with multiclass situations for remote sensing.

ENVI 4.5 runs what Pal and Mather (2005) call a "one against one" strategy for a multiclass classification scenario. SVM was a binary classification in its initial form, but a multiclass classification problem can be broken down so that a combination of several binary classifications are examined, or essentially, each pair of classes are evaluated separately (Pal and Mather, 2005; ITT Visual Information Solutions, 2008b). Pal and Mather (2005) among others determined that this particular strategy provided the best results when dealing with a multiclass scenario (Melgani and Bruzzone, 2004; Pal and Mather, 2005). In fact Melgani and Bruzzone (2004) state that SVMs provide higher accuracies than traditional methods such as the MLC; a theory that was tested in this study for Niagara Escarpment land cover classification mapping (Melgani and Bruzzone, 2004) .

Also in a remote sensing scenario, it is rare to create linearly separable sets of training classes, but through the use of kernels, non linear SVMs can be created (Fauvel *et al.*, 2006). Kernel methods are a way to generalize remote sensing data by sorting and projecting data into a higher dimension (Fauvel *et al.*, 2006). There are different kernels to choose from and ENVI 4.5 provides 4 different types: linear, polynomial, sigmoid and radial basis function (RBF) (ITT Visual Solutions, 2008b). For this study, RBF provided the best results and was the kernel chosen most often throughout the literature (Hermes *et al.*, 1999; Pal and Mather, 2003; Foody and Mathur, 2004; Fauvel *et al.*, 2006). The RBF kernel is defined by the following equation:

$$(x_i, x_j) = exp\left[-\gamma \left\| x_i - x_j \right\|^2\right] \tag{4.10}$$

In which the gamma γ parameter is entered by the analyst and controls the width of the kernel (Foody and Mathur, 2004). To use the RBF kernel in ENVI, the gamma γ and C parameters must be chosen wisely so the SVM does not over fit the training data, commonly caused by using high values for the two parameters (Foody and Mathur, 2004). Little information exists in the literature on how to identify these parameters; therefore a process of trial and error is best for choosing optimal values for γ and C (Pal and Mather, 2005). For the Niagara Escarpment land cover change scenario, a series of kernel types were tested and the RBF kernel was chosen. Through a process of trial and error the values chosen for γ and C were 0.167 and 1000 respectively. Through the trial and error process it was determined that the fluctuations of these values made little difference to the accuracy of the final results, but the RBF kernel outperformed the other kernel types when using the same parameters.

Object Oriented Approach with Supervised Classification: Support Vector Machines (SVMs)

An object oriented approach is one taken to examine a remotely sensed image based on individual objects, as opposed to classifying an image on a pixel by pixel basis in the algorithms described above. Navulur (2007) defines an object in a remote sensing context as a group of pixels that possess similar spectral and spatial properties. The object oriented approach is similar to the more traditional air photo interpretation methods since the human eye and brain identify objects naturally as opposed to pixels. The object oriented approach has the ability to benefit from basic air photo interpretation methods while still taking advantage of more advanced remote sensing classification techniques. ENVI Zoom 4.5 offers a feature extraction tool with supervised classification to conduct object oriented analysis. The feature extraction tool can alternatively be used to extract features from multispectral imagery based on spatial, spectral and texture characteristics (ITT Visual Solutions, 2008a).

The feature extraction tool with supervised classification extracts features of interest and then performs a supervised classification based on the object and not the individual pixel. When analyzing Landsat 5 TM imagery at a 30m resolution mixed pixels can cause problems when trying to identify certain types of land cover. An object oriented approach can be beneficial where spectral variations from pixel to pixel can cause error in classifying certain land cover types such as urban areas or individual agricultural fields. For example, due to moisture variation in a field or health of the crop, an individual field can be misclassified into two separate agriculture classes. This methodology will be examined to see if it can help improve upon the accuracy of each classification map for each time period.

To conduct image segmentation in ENVI 4.5 there are four main steps that lead to the final classification of the image: segmentation, merging segments, colour space and band ratio settings and classification (ITT Visual Information Solutions, 2008a). In the segmentation step, the image is divided into objects using the statistical values from the image (Blaschke, 2004). It is assumed that pixels with similar DN values are likely to represent the same image object (ITT Visual Information Solutions, 2008a). ENVI 4.5 employs an edge-based methodology in which the gradients between the grey scale values of the pixels delineate the boundaries between objects (ITT Visual Information Solutions, 2008a). The object oriented approach worked well with the agricultural classes since they are parcel based in nature (Dean and Smith, 2003). Segmentation was achieved by using a sliding scale (0 to 100) to represent segmentation where a low scale value causes more segmentation to occur and a large scale value causes less segmentation to occur, proportional to the resolution of the imagery (ITT Visual Information Solutions, 2008a). For this case, a segmentation value of 90 was selected for the Landsat 5 TM data.

During the merging step, over-segmentation can be corrected by once again using a sliding scale to define the merge value. If over-segmentation is unavoidable in the segmentation step, merging works to aggregate smaller segments within larger homogeneous areas (ITT Visual Information Solutions, 2008a). Over-segmentation can occur, because the smallest homogeneous areas (such as highways and urban areas) must be represented, and to accomplish this, other areas may become over-segmented. The merging step can correct for this. The optimal merge value in this case was 70. Following the merge step the analyst can perform an optional thresholding of the object means that groups similar objects based on their region DN values, but this option was not used for the Hamilton and Halton regions since it was determined that visually, the segmentation and merging adequately delineated the land cover features of interest (ITT Visual Information Solutions, 2008a).

In the colour space and band ratio step, settings must be set according to the spectral information the analyst wishes to use in the classification. Colour space is set by selecting three spectral bands to be entered into the red, green and blue colour guns, and subsequently used in the classification. Band ratio settings allow the analyst to calculate a normalized band ratio by choosing two bands to be entered into the following equation:

$$\frac{(B2 - B1)}{(B2 + B1 + eps)} \tag{4.11}$$

The *eps* represents a small number to avoid division by zero. By selecting band 3 and tagging it as “band 1” and selecting band 4 and tagging it as “band 2” in the band ratio equation, an NDVI calculation was added to the classification, which aided in distinguishing healthy vegetation from other land cover types, and was employed in this research.

In the final classification step a suitable classification algorithm is selected to create the classification map. This is a detailed step in which the analyst must select training objects and indentify other contextual information that can be gained from the imagery to be used to aid in the classification process. Defining training data post segmentation is an easier and less time consuming process than training individual pixels for pixel-based classification. Homogeneous regions were selected to represent certain land cover types. After all the classes are represented adequately (typically, the more training areas the better) a selection of other contextual information (called attributes by ENVI 4.5) are selected to aid in the classification. Attributes contribute spatial, spectral and textural information to the classification to enhance results. These attributes must be chosen wisely as unnecessary attributes can introduce noise into the classification and possibly reduce accuracy (ITT

Visual Information Solutions, 2008a). Spatial information can introduce size of objects into the classification (such as length and width of features), spectral information can examine min and max DN values among other values and texture offers a unique look at smoothness or roughness of a feature based on spatial variation of tones within the image (Blaschke, 2004; ITT Visual Information Solutions, 2008a). ENVI 4.5 offers a tool which automatically selects the optimal attributes to perform the classification. After automatically selecting the attributes, a classification algorithm must be chosen. ENVI 4.5 offers two: K-nearest neighbour and SVM. For the purposes of this research, SVM was chosen so comparisons may be made between the traditional SVM classifier described above and the use of SVM with object oriented classification. For the classification of the image object by SVM the RBF was selected. Since again, the values of the γ and C parameters changed the results very little the default values of γ=0.02 and C=100 were used.

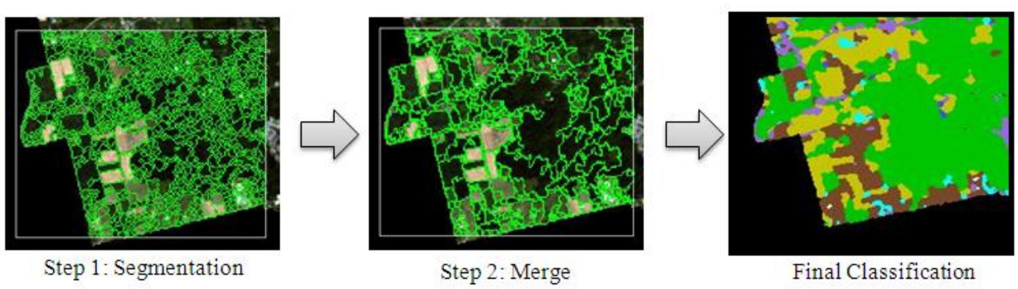


Figure 4.4 Object Oriented Mapping Procedure

4.2.3 Comparison Procedures

After all 5 classifications were performed, comparisons of the accuracy assessments were conducted to select the classification maps with the highest overall accuracy to be used in the change detection. Overall accuracy percentages were used as the final deciding factor as to which maps would be used in the change detection, but Kappa statistics, accuracy values for individual classes and user and producer accuracies were also considered in the selection. Jensen (2005) states that classification maps with high overall accuracy are essential for accurate change detection evaluation. Any classification errors present in the final classification maps would contribute to, and increase error in the final change detection analysis. The consideration of these errors is especially important for land use planning applications, as accurate land cover maps and change detection can contribute much to the planning process.

4.2.4 Training the Algorithms

To create meaningful classification maps for decision making, one must consider several factors when deciding upon the adequate number and type of land cover classes. Land cover classes refer to the types of material present on the ground at a specific place in time (Jensen, 2005). This is in contrast to land use classes which take into account human uses of those materials present on the ground. Remote sensing methodologies are best suited for the former since examining changes in land use over time involves a multi-disciplinary approach, often including examination of socio-economic factors as a reason for the changes detected. As an example, a land cover classification would identify agricultural areas on the landscape where a land use classification would identify various crops and rationalize the type of agriculture at work.

The classification scheme must be selected to represent each type of land cover that occurs in the study region. The classification scheme should be created so that the classes on the final map will be exhaustive of the land cover in the study area. For this research, land cover classes were identified by determining what types of land cover one would expect to find within the NEP area based on each land use designation outlined in the plan. An example of the thought process can be seen below in Table 4.3. Through the analysis of each NEP land use designation, an original group of 12 classes were identified for the classification [coniferous forest, deciduous forest, agriculture 1 (dry, bare soil), agriculture 2 (vegetated agricultural fields), agriculture 3 (wet, bare soil) agriculture 4 (wet, vegetated agricultural fields), water, shallow water, recreation, other vegetation, MREA and urban].

Table 4.3 Identification of Niagara Escarpment Plan (NEP) Land Cover Classes (Based on NEP Land Use Designations)

Plan Designation	Description	Classes
Escarpment Natural Area (ENA)	-Escarpment features which are in a relatively natural state -Associated with relatively undisturbed stream valleys wetlands and forested areas -This designation contains the most significant scenic and natural areas along the escarpment	Forests, Wetlands, Bedrock and Water features
Escarpment Protection Area (EPA)	-Protection areas are important for their scenic value and their environmental significance -This designation acts as a buffer to the ENA designation, as it often includes any development that has significantly altered the natural environment, such as agriculture or residential developments	Agricultural land, Residential/urban developments, Forests, Recreation Areas, Bedrock, Wetlands, Water features
Escarpment Rural Area (ERA)	-The ERA designates areas with minor escarpment slopes and landforms, and is used as a buffer to more ecologically sensitive areas of the escarpment -These lands near the escarpment are necessary to provide for compatible rural land uses	Agricultural land, Residential/urban developments, Forests, Recreation Areas, Bedrock, Wetlands, Water features, Roads
Minor Urban Centre (MUC)	-This designation consists of rural settlements in the Plan (villages or hamlets)	Residential/urban development and Roads
Urban Area	-Urban areas within city boundaries	Residential/urban development and Roads
Escarpment Recreation Area	-Parks, ski resorts, golf courses and areas of manicured grass etc.	Golf courses, Ski resorts, Parks, Manicured grass areas
Mineral Resource Extraction Area (MREA)	-Existing Quarries (operational and non-operational)	Quarries

Niagara Escarpment Plan (2005). The designations are colour coded based on NEP map designation colours

Initial classifications were run with all 12 classes but as the results emerged, decisions were made to merge some of the classes for results with higher accuracies. Due to spatial and spectral limitations, some of the classes initially identified in early experimentations had to be excluded from the final classification. For example, small scale features such as wetlands and minor roads were poorly identified during classification due to the spatial resolution of the data. The “other vegetation” class was one that was spectrally similar to other classes such as deciduous forests, agricultural fields containing crops and recreation areas. After examination of the separability reports of the training sites and the accuracy assessments performed on the classified images, it was determined that this class was doing more harm than good and was eliminated. With the inclusion of this class, the classes with similar spectral characteristics would have been underestimated significantly.

There was consistent separability issues present in the results of each of the training data separability reports as well as the accuracy assessment of each of the final land cover maps. The four types of agriculture were spectrally similar, especially agriculture 1 and 3 (bare agriculture fields) and agriculture 2 and 4 (agriculture fields with crops). In an effort to improve the classification accuracy, the four agriculture classes were merged into 2 – agriculture 1 (representing bare agricultural fields) and agriculture 2 (representing agricultural fields with crops present). Forested areas were spectrally similar as well so the decision was made to combine the coniferous and deciduous forest classes into one forest class. These classes were combined using a post classification merging technique which combines classes that are spectrally similar into one classification. This can often improve classification accuracy. The original 12 classes were merged into the final 7 classes for land cover classification in the Hamilton and Halton portions of the plan. These 7 land cover classes are depicted on a map in Figure 4.5. Figure 4.6 shows the original 12 classes selected for classification and the final 7 used in the study. The final 7 classes were identified by collecting user defined training sites. The advantage to the collection of training data for supervised classification is the user can contribute their own knowledge and create the necessary classes to the highest degree of accuracy. Typically 10 times the number of bands used dictates the number of training pixels that should be collected to represent each class, but the more training pixels collected the higher the accuracy will be (Jensen, 2005). The final classification scheme defined for the study area can be seen in Table 4.4.

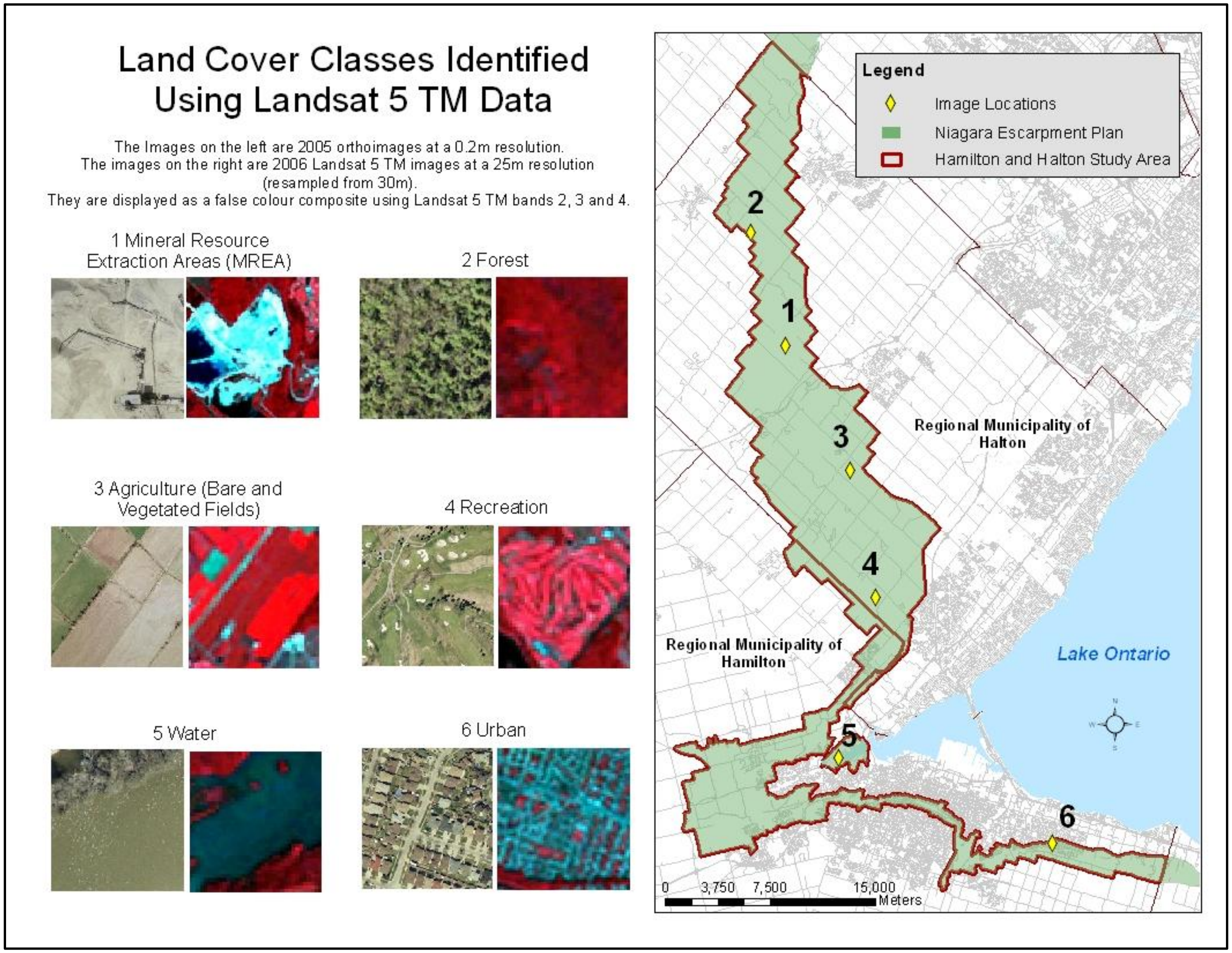


Figure 4.5 Land Cover Class Map

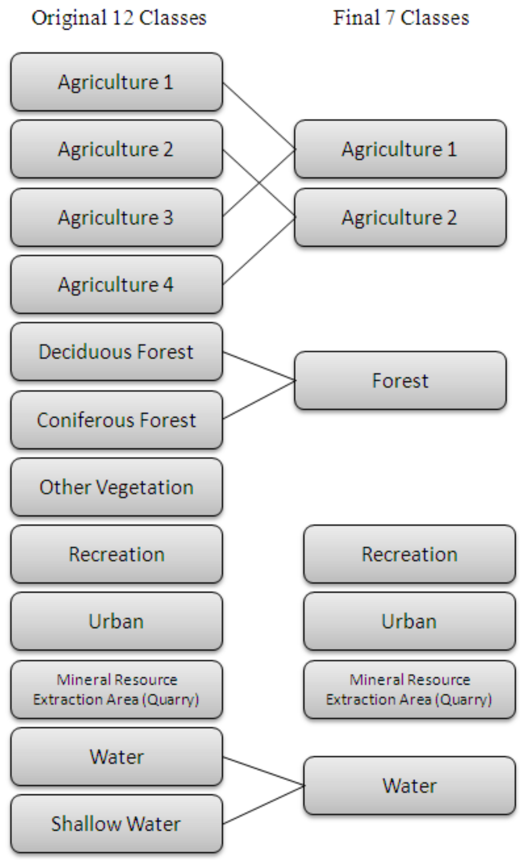


Figure 4.6 Merging of Original 12 Classes into the Final 7 Classes

4.3 Accuracy Assessment

Error may be introduced into a study at any step in the analysis. Errors made in the initial stages of data acquisition and can carry through the subsequent processes such as pre-processing, classification, data conversion for analysis, and even the error assessment itself (Jensen, 2005). For this study an accuracy assessment was performed on the final classification maps using a confusion matrix created by comparing the final classified map with an independent set of ground reference points.

Table 4.4 Description of Final 7 Land Cover Classes for Niagara Escarpment Study

Class	Description
Forest	This class represents all forested areas and is a merge between the original deciduous and coniferous forest classes
Agriculture 1 (Bare agricultural fields)	This class encompasses all bare agricultural fields and was created by merging the original agriculture 1 and agriculture 3 classes This type of agricultural field had a bright tone when viewed as a false colour composite (with bands 3,4 and 5), possibly indicating it was dryer soil with little vegetation in comparison to Agriculture 1
Agriculture 2 (Vegetated field)	This agricultural field represents a merge between agriculture classes 2 and 4. This class represents all agricultural fields with growing vegetation, whether operational or not. This type of agricultural had red fields when viewed as a false colour composite (see above) indicating healthy vegetation, with darker toned fields appearing a deeper red colour exhibiting a higher moisture content
Recreation	The recreation class consists of golf courses, parks, ski hills etc. Typically areas with manicured grass land
Urban	This class was any urban surface, including roadways, dwellings (rooftops), commercial and industrial areas etc. Anything "man-made"
Mineral Resource Extraction Areas or Quarries (MREAs)	Existing quarry operations on the Niagara Escarpment
Water	Water includes deep waters showing lakes, rivers, open water swamps etc. and is a merge of the original water and shallow water classes.

4.3.1 The Confusion Matrix

The confusion matrix (also called a contingency table or error matrix) provides information on classification error (Jensen, 2005). An example of a confusion matrix can be seen below in Table 4.5

Table 4.5 Example of the Confusion Matrix

Ground Reference Point Information						
Classified Image Information	Class	1	2	3	K	Row Total
	1	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,k}$	x_{1+}
	2	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,k}$	x_{2+}
	3	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,k}$	x_{3+}
	K	$x_{k,1}$	$x_{k,2}$	$x_{k,3}$	$x_{k,k}$	x_{k+}
	Column Total	x_{+1}	x_{+2}	x_{+3}	x_{+k}	N

(Adapted from Jensen , 2005)

The confusion matrix states the classification accuracy of k classes used in the analysis. The columns represent the ground reference points and the rows represent the final classification of the image under assessment (Jensen, 2005). Summarized in the intersection of each row and column are either the pixel counts or percentage values assigned to each class in the final classification image as compared to actual ground reference data derived by the analyst (Jensen, 2005). The total number of ground reference pixels collected by the analyst is represented by N.

4.3.2 The Collection of Ground Reference Points

Justification of Sample Size

A set of ground reference points independent from the training data was used for accuracy assessment. The collection of a separate set of ground reference points (pixels) is essential for an appropriate classification accuracy assessment. If the training data are used to perform accuracy assessment, this could result in higher overall accuracies that are overestimated (Jensen, 2005). The collection of training data is biased by the analyst's prior knowledge of the study area (Jensen, 2005). A separate set of ground reference points act as unbiased reference information for which to run the accuracy assessment. For this study a stratified random sample was created and trained to be used as the ground reference information.

Decisions must be made prior to creating the ground reference points such as the sample size and the sampling design.

To calculate the sample size the worst-case multinomial distribution algorithm as outlined in Jensen (2005) was used. This algorithm was selected since no prior information about the proportion that each class makes up of the image was known. An assumption is made that one class occupies 50% of the image (Congalton and Green, 1999). Equation 4.12 represents the worst-case multinomial distribution algorithm.

$$N = \frac{B}{4b^2} \tag{4.12}$$

Where:

N = the sample size required for the ground reference points

B = the upper (α/k) × 100th percentile of the X^2 (chi-squared) distribution (with 1 degree of freedom) where k represents the number of classes used in the analysis

b = the desired precision for the class

(Jensen, 2005)

Therefore, to determine the number of ground reference points per class using a confidence interval of 85% and a precision of 5%, the following calculations were used:

$$B = 1 - \frac{\alpha}{k} = 1 - \frac{0.05}{7} = 0.99286$$

$$\therefore X^2_{(1,0.99286)} = 7.2366$$

$$N = \frac{7.2366}{4(0.05^2)} = 724\ pixels$$

To calculate the number of samples required per class:

$$\frac{724\ pixels}{7\ pixels} = 103\ pixels\ per\ class$$

For this study, approximately 100 ground reference points or pixels per class were collected for use within the confusion matrix. Collecting these ground reference points was a time consuming process since each individual pixel had to be trained (confirmed) individually. In some instances it was not possible to collect 100 ground reference points per class but in all cases, at least 50 ground reference points were collected as deemed suitable by Congalton and Green (1999).

Sampling Design

Once the appropriate number of ground reference points was determined, a sampling design was chosen to determine the geographic location of each point within the study area (Jensen, 2005). For this study, the stratified random sampling method was chosen. The advantage to a stratified random sample is that a minimum number of ground reference points can be collected for each land cover class in the classification (Jensen, 2005). The generation of the ground reference points occurs after the final classification map has been created. In ENVI 4.5, the analyst must choose between a proportionate or disproportionate sample. Ideally a proportionate sample would be selected so that no matter what the size of a class a proportionate number of ground reference points will be allocated to that class. This would reduce bias in the final confusion matrix. However, when dealing with a proportionate sample, the analyst simply chooses the minimum sample size and the number of ground reference points are automatically filled in by ENVI. It was discovered that when using the proportionate sample size, some of the samples for the larger classes (such as the forest class) were very large and would take too much time to train. Therefore, it was decided to create a disproportionate sample size and assign each class 100 ground reference points for a maximum sample of 700 ground reference points per image.

The next step was to label each ground reference point individually. Since these ground reference points were created based on the final classification map, the assumption was made that the map was 100% accurate when in fact this is almost never the case. The analyst must make sure each ground reference point for each class represents that class accurately. Each ground reference point was individually checked and only the cells that contained 50% or more of that particular land cover type were assigned their respective class. This is another example of where error can be introduced. This is also why some sample sizes were either greater than or less than the 100 ground reference point sample size.

Table 4.6 Number of Ground Reference Points per Class

Number of Ground Reference Points per Class				
		1986	**1996**	**2006**
Classes	Forest	273	282	313
	Agriculture 1	284	276	321
	Agriculture 2	264	266	383
	Recreation	85	68	111
	Urban	95	135	163
	Mineral Resource Extraction Area (MREA)	122	109	123
	Water	111	152	250

The final step in the research was to take the classification maps with the highest accuracy and perform change detection over a 20 year time period. As opposed to overall change that was explored in the previous studies, an attempt was made to examine the spatial dynamics of change occurring in the Plan area by examining the change in each NEP land use designation specifically to see how much and what kinds of change are occurring in each designation within the study area.

4.4 Change Detection

To perform change detection over a 20 year time period, the post-classification comparison change detection technique was chosen. This technique is widely used and requires final classification maps with the highest accuracy possible to be compared pixel-by-pixel. If accuracy is not high enough for the classified images, errors may be carried through to the change detection stage, falsifying the true change occurring on the ground. It is essential that classification maps in the Hamilton and Halton Regions of the NEP are created to the highest accuracy possible. In ENVI 4.5, change statistics and change masks for each class in each image are produced. One of the great advantages of the post classification technique is that it allows the analyst to identify the nature of the changes occurring in the study region (Mas, 1999). Change masks are created and show what each class in the initial state image changed to in the final state image. This method is easy to understand and heavily used. Results can also be converted into a vector format and used in a GIS for future analysis.

Chapter 5
Results and Analysis

5.1 Examination of Accuracy Assessment: 1986, 1996 and 2006

To create classification maps with the highest accuracy for each image, several classification methods were tested. MD classification, MDC, MLC, SVM and object oriented classification with SVM were all tested for the production of classification maps in the Hamilton and Halton portions of the Plan. Prior to the final accuracy assessment being performed a majority filter post classification technique was used. In this case a 3×3 window was used to convert outlying pixels to a particular class if the majority of its neighbours belonged to that class. This technique serves to smooth the classes in the map, making it more suitable for analysis and increasing overall accuracy. Below is a summary of overall accuracies and Kappa values for each method tested and for each image.

Table 5.1 Overall Accuracy and Kappa Coefficients for Each Classifier

	Landsat 5 TM 1986 Image		Landsat 5 TM 1996 Image		Landsat 5 TM 2006 Image	
	Overall Accuracy (%)	Kappa Coefficient	Overall Accuracy (%)	Kappa Coefficient	Overall Accuracy (%)	Kappa Coefficient
MDC	63.53%	0.57	72.34%	0.67	79.15%	0.75
MD Classification	67.40%	0.61	75.45%	0.71	77.40%	0.73
MLC	80.31%	0.76	83.37%	0.80	88.03%	0.86
SVM	**82.58%**	**0.79**	**88.04%**	**0.85**	**89.60%**	**0.87**
Object Oriented Classification	73.48%	0.68	77.37%	0.73	82.96%	0.80

After conducting all the classifications for each image, it was determined that SVM provided the highest results. Out of the traditional per-pixel supervised classifications, MLC outperformed the more basic MDC and MD classifications, which was consistent with the literature. The object oriented approach showed promising results when used to classify

Landsat data in previous studies, but that was not true for the Niagara Escarpment scenario. In this case, MLC outperformed the object oriented approach. With alterations to the object oriented methodology, this technique could show great promise for detecting land cover change in the NEP, and will be discussed as recommendations for future work.

The standard for overall accuracy for land-cover maps created using remotely sensed data is between 85% and 90% (Anderson *et al.*, 1976; Lins *et al.*, 1996 as stated in Treitz and Rogan, 2004). Treitz and Rogan (2004) states that according to Rogan *et al.* (2003) a slightly lower overall accuracy value of 80% to 85% appears to be reasonable for studies involving land cover change detection. An example of the final SVM accuracy assessment for the 1986 image can be seen below in Table 5.3, and a map showing the final classifications of the study area can be seen in Figures 5.1, 5.2 and 5.3. SVM achieved the highest overall accuracy and the highest Kappa coefficient for each image, while the MDC had the lowest overall accuracy and Kappa coefficient with the exception of the 2006 image. The MD classification resulted in a lower accuracy than the MDC but only by approximately 2%. Based on the assumption that the ground reference points collected are "ground truth" information, the overall accuracy simply represents the percentage of correctly classified pixels out of the total number of pixels. The Kappa coefficient is an unbiased value for accuracy assessment representing the amount of agreement between the final classification map and the ground reference information collected by the analyst (Jensen, 2005). This value is slightly lower than the overall accuracy for each image since the Kappa statistic also takes into account the row and column totals representing the chance agreement for each class's reference data with respect to the final classification map (Jensen, 2005). The classification of the 1986 image resulted in the lowest accuracy results for all classification algorithms explored in the study. Although overall accuracy was first considered when examining the confusion matrix, it is the errors or the values that occur off the diagonal that can offer more interesting results (Congalton and Green, 1999). These off diagonal values offer clues to possible errors in the classification process such as errors in collecting the ground reference information, human interpretation errors, spatial scale of sensor for the land

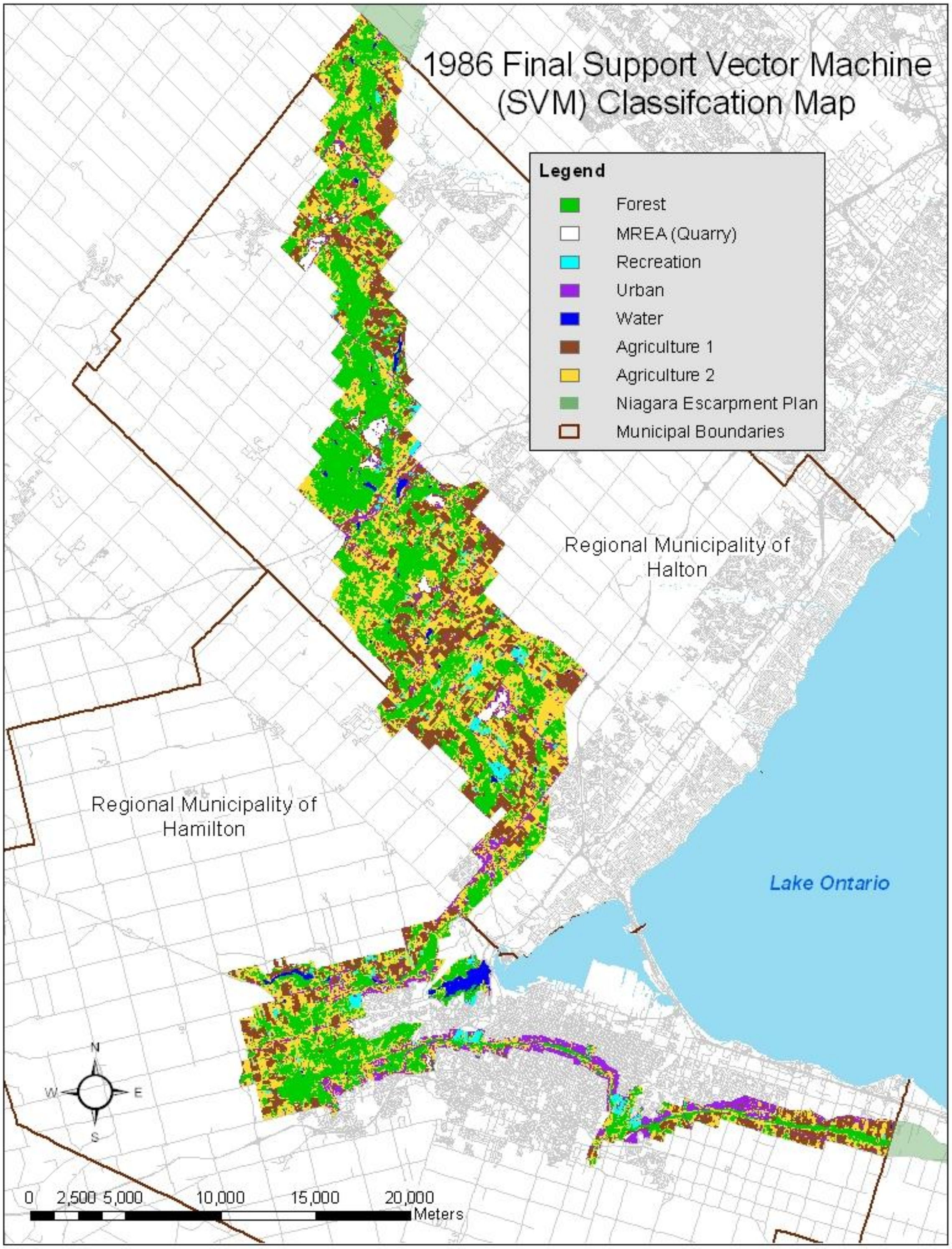


Figure 5.1 1986 Support Vector Machine (SVM) Classification Map

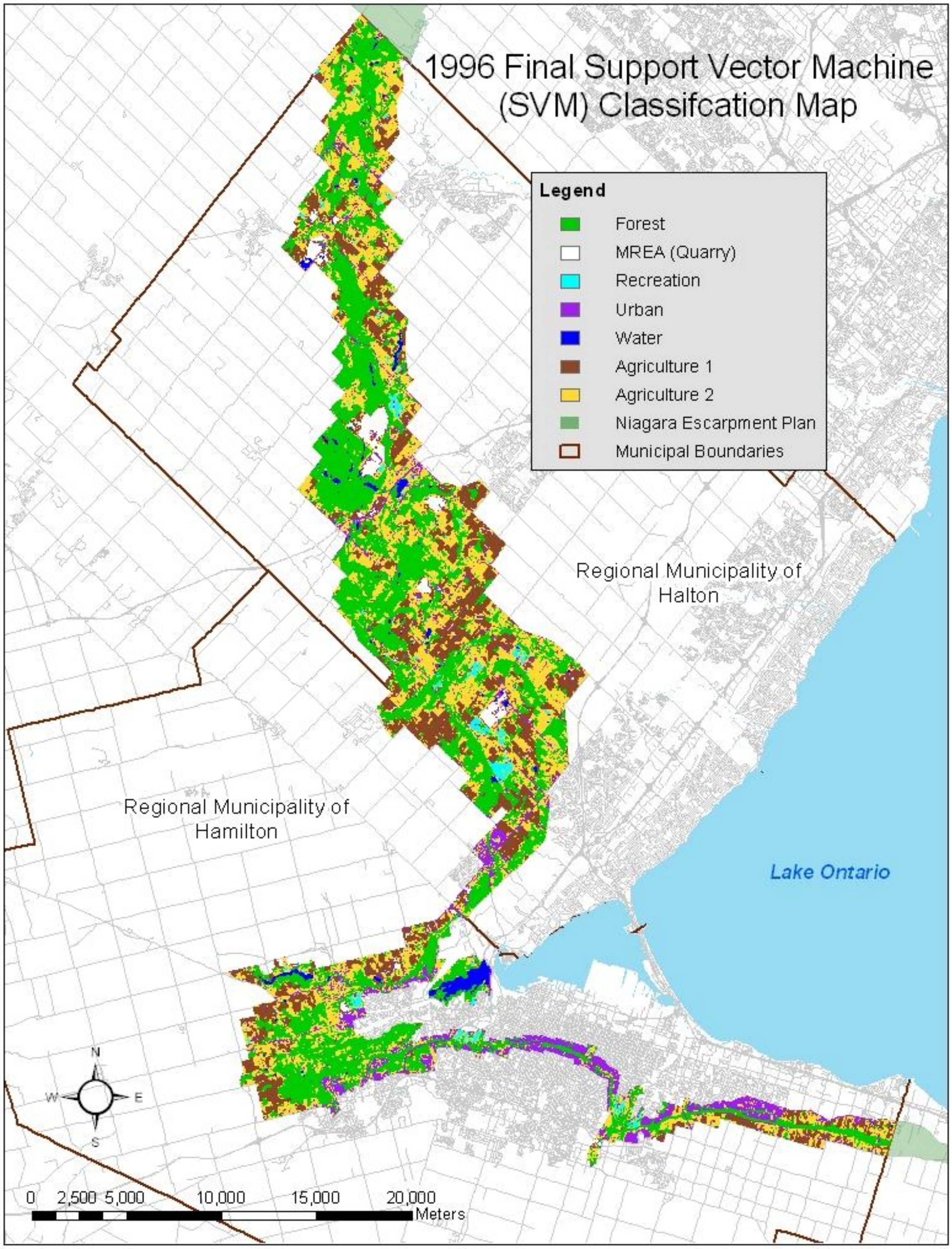


Figure 5.2 1996 Support Vector Machine (SVM) Classification Map

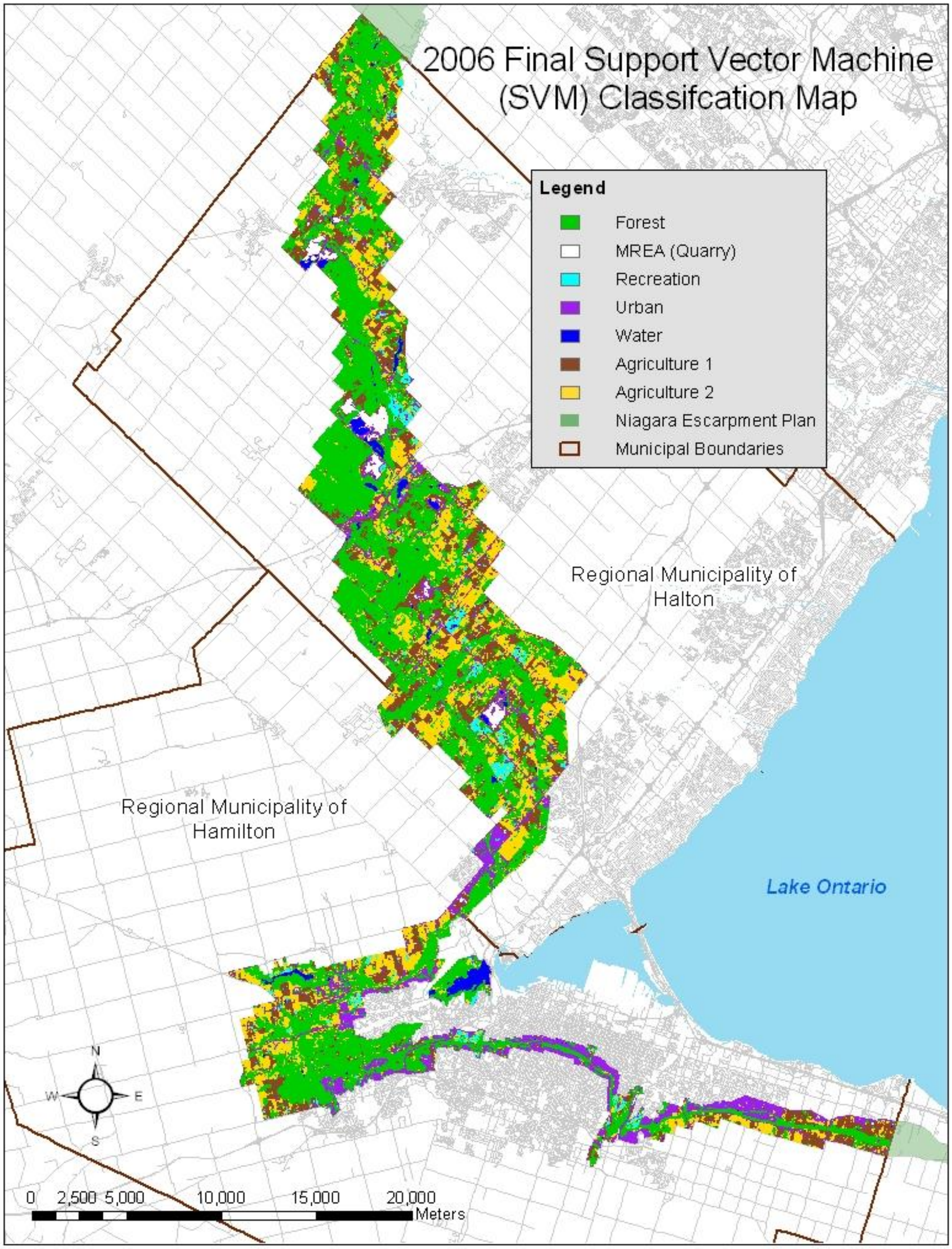


Figure 5.3 2006 Support Vector Machine (SVM) Classification Map

cover classes identified and mapping error (Congalton and Green, 1999). In the case of the 1986 imagery, the reduction in accuracy across all the classification algorithms may have been due to the lack of ancillary data available for the study site during that time period. For the 1996 and 2006 images, high resolution orthoimagery was obtained to aid in the classification of the ground reference points. These supplementary images acted as "ground truth" information. In order to classify each individual ground reference point for this time period, pure spectral response of the image and knowledge of the study area were relied on. The full confusion matrices for the 1996 and 2006 images can be found in Appendix A.

Individually, classes were examined for their accuracy to determine which classes performed well enough to be further studied for change detection. For this study if a class's overall accuracy percentage value was lower than that of the overall accuracy value for that classified image, the class was deemed not accurate enough to predict the changes that occurred in the study area. For each image three out of seven classes fell below that overall accuracy threshold limit and the urban and MREA classes consistently underperformed across the entire time period. These nine classes are highlighted in Table 5.2. The lower accuracy of these classes is primarily due to the use of medium spatial resolution imagery. Typically higher resolution imagery is favoured for urban change detection since urban features are often smaller than the 25m re-sampled resolution of the individual image pixel. Also contributing to the low accuracy of the urban and MREA classes was their spectral similarities.

Table 5.3 shows the confusion matrix for the 1986 image. The highlighted values along the diagonal of the table represent the pixels that were classified correctly during the manual assigning of the ground reference pixels to their correct class. For example, the forest class was created with 84.3% (230/273) accuracy, a value that is high enough to allow for further analysis. Classes that were spectrally similar to the forest class in the 1986 image are also identified by analyzing the off diagonal values. In the 1986 image, the forest class and the

Table 5.2 Summary of Class Accuracies

Class	1986 image (82.6% overall accuracy)	1996 image (88.0% overall accuracy)	2006 image (89.6% overall accuracy)
Forest	84.3%	89.4%	96.49%
Agriculture 1	96.5%	96.4%	96.9%
Agriculture 2	**71.6%**	95.5%	92.7%
Recreation	96.5%	**76.5%**	91.9%
Urban	**48.4%**	**63.7%**	**65.6%**
MREA (Quarry)	**79.5%**	**80.7%**	**78.1%**
Water	91%	89.5%	**87.2%**

agriculture 2 class had low spectral separability, since 37 of the forest ground reference pixels were actually agriculture 2 on the ground. Focusing on other more poorly performing classes in the final 1986 image, such as urban, agriculture and to a lesser degree MREA, it is clear that spectral separability between these classes and some of the other seven classes cause errors. For example, the urban class appears to be most spectrally similar to agriculture 1 which represents bare agricultural soils. It is also spectrally similar to MREA and agriculture 2 classes. The spectral similarity between urban surfaces and MREA can be explained for the same reasons why bare agricultural soils are also spectrally similar. An area of bare soil and rock appear spectrally similar to urban areas since they consist of materials such as gravel and concrete, and have little vegetation cover. Interestingly, there was a similarity between the agriculture 2 class (which represents a vegetated agricultural field) and urban areas. Although vegetation cover in urban areas is restricted to areas such as lawns, trees and parks, these areas do still exist within an urban environment and can account for the similarity. At a spatial resolution of 25m a pixel of urban area can contain some vegetation and will affect the signal received at the sensor. The above reasons also explain why the other two lowest performing classes in the 1986 image were MREA and agriculture 2.

Table 5.3 1986 Image Confusion Matrix

Overall Accuracy (1019/1234) 82.58%

Kappa Coefficient 0.788

	Ground Truth (Pixels)								
		Forest	**MREA (Quarry)**	**Recreation**	**Water**	**Agriculture 1**	**Agriculture 2**	**Urban**	**Total**
Class	**Forest**	**230**	0	0	6	0	34	1	271
	MREA (Quarry)	0	**97**	0	0	1	0	14	112
	Recreation	4	0	**82**	0	0	35	0	121
	Water	0	0	0	**101**	0	0	0	101
	Agriculture 1	2	18	0	0	**274**	6	21	321
	Agriculture 2	37	0	3	1	4	**189**	13	347
	Urban	0	7	0	3	5	0	**46**	61
	Total	273	122	85	111	284	264	95	**1234**

The same can be examined for the 1996 and 2006 images. The low accuracy results of the urban class were consistent for all three images and were previously discussed. Also consistent for all three images was the poor performance of the MREA class, due to its spectral similarity to the urban and agriculture 1 classes. For the 1996 image only 76.5% of the ground reference pixels assigned to the recreation class were actually placed on recreational areas. Recreation showed spectral similarities to agriculture 2, which represents a vegetated agricultural field. This type of land cover can often become confused with other healthy vegetation, such as grass, which explains the spectral similarity with recreational areas, since most recreation areas identified were golf courses or parks. For the 2006 image, other than the urban and MREA classes, water had the lowest overall accuracy at 87.2%. Smith and Fuller (2001) suggest that confusion between water and forests, especially when the water is located in a forested region such as the Escarpment, can occur due to canopy texture and shading effects from vegetation and/or terrain. This is likely why confusion between these two classes exists. Smith and Fuller (2001) also discuss mis-classifications that can occur with mixed boundary pixels. Throughout the analysis it was discovered that many water pixels had a percentage of vegetation cover in the same pixel. For the purposes of this research only the pixels with 50% or more water were classified as water. This mixed pixel problem also occurred with other classes and occurred more often with boundary pixels between one land cover class and the neighbouring class.

Through accuracy analysis, there are alternative accuracy measures that can help the user determine the accuracy of information obtained from the final map. User and producer accuracies are also calculated and can be seen in Appendix B. The producer accuracy is calculated by dividing the number of pixels that were correctly classified for each class by the total number of ground reference pixels for that class (Fung, 1990). Fung (1990) states that producer accuracy determines if change detection can adequately predict land cover changes in a study area, since this accuracy indicates the probability that a ground reference point would be correctly classified, and thus, each class being correctly identified (Jensen, 2005). User accuracy describes to the user of the final produced map the probability that a pixel classified as a certain land cover type on the map actually represents that same land cover type on the ground (Story and Congalton, 1986 as cited by Jensen, 2005). Since the purpose of creating these land cover maps is for land cover change detection over time, user accuracy is a very important statistic to note.

Table 5.4 User and Producer Accuracies

	1986 prod.	1986 user	1996 prod.	1996 user	2006 prod.	2006 user
Forest	84.25	84.87	89.36	91.64	96.49	85.55
Agriculture 1	96.48	85.36	96.38	88.08	96.88	85.67
Agriculture 2	71.59	76.52	95.49	83.28	92.69	95.17
Recreation	96.47	67.77	76.47	89.66	91.89	86.44
Urban	48.42	75.41	63.7	87.76	65.64	82.31
MREA	79.51	86.61	80.73	84.62	78.05	88.89
Water	90.99	100	89.47	93.15	87.2	99.54

The producer accuracy percentage for each class indicates to the producer of the map the probability that the SVM classified the image pixel correctly. In terms of map production the urban classification underperformed consistently, indicating that some pixels classified as urban by the SVM were not actually urban pixels. For the 1986 image, the producer accuracy for the urban class was less than 50%, which will make comparison of urban extent across the entire time period difficult. The degree of confidence in the statistical change results will be lower for this class. Another low producer accuracy result occurred for the agriculture 2 class for the 1986 image. To a lesser degree the MREA class also underperformed in the 1986 and 2006 classification. Qualitative analysis of the change occurring in the classes with the lower accuracies will be important for drawing conclusions about land cover change in the NEP at a regional scale.

The user accuracy states the probability that a classified pixel on the map actually represents that land cover class on the ground. This statistic is of particular importance to the people who will eventually use the map to make decisions. The user values for the 1996 and 2006 images are high enough to indicate that a user may be confident that what is depicted on the map actually exists on the ground for that time period. Again, error lies within the 1986 image where the recreation, urban and agriculture 2 classes underperformed.

5.2 Overall Study Area Change Analysis Overview

This section examines overall trends in the change statistics across the entire study area for the entire time period. Section 5.2.1 is a summary of qualitative changes visibly noticeable across the study area as a whole, covering both Hamilton and Halton Regions. Following this, section 5.2.2 summarizes the overall quantitative change in the entire study area. The previous two sections act as an introduction to sections 5.3 and 5.4 where classes and change statistics of interest are indentified for further study at the individual regional scale discussing changes in Hamilton and Halton Regions separately. Changes in both regions are examined from a qualitative and quantitative perspective followed by an examination of change within the various NEP land use designations in section 5.5.

5.2.1 Qualitative Change Analysis of the Study Area

Initial results of the overall change in the study area from 1986 to 2006 differ from class to class. Qualitative examination across both Halton and Hamilton Regions combined was conducted on a class by class basis prior to more in depth analysis to. Observations were made from classification masked images created while computing change detection statistics from ENVI 4.5 that show what each class (land cover type) in the initial state image (1986) changed to in the final state image (2006).

Table 5.5 Description of Overall Land Cover Changes

		Description of Land Cover Changes
Land Cover Classes	Forest	• Conversions to quarry and urban • Conversion to small agricultural areas • Conversion to a few noticeable areas of recreation in Halton • Conversion to large water bodies within MREA
	Agriculture 1	• (Both agriculture classes showed the majority of changes in the study area with an overall loss) • Majority of conversion to agriculture 2 and urban
	Agriculture 2	• Majority of conversion to forest with some smaller areas converted to agriculture 1 and urban
	Recreation	• Conversion to multiple small areas of agriculture 1 and 2 , forest and urban
	Urban	• Minor conversions to areas of forest or agriculture
	Quarry (MREA)	• Conversion to urban, water and some small areas of agriculture
	Water	• Minor conversions mostly to forest

After initial observation of the results of the change detection, a few interesting observations were made. A multitude of changes occurred in forested areas from 1986 to 2006 which will be examined in more detail in later sections, but a noticeable conversion is from forest in 1986 to large areas of water within MREA boundaries. These are likely created after the previously forested areas were converted to MREA's between 1986 and 2006, exploited to their full potential and converted to ponds, small lakes or wetlands for future rehabilitation efforts.

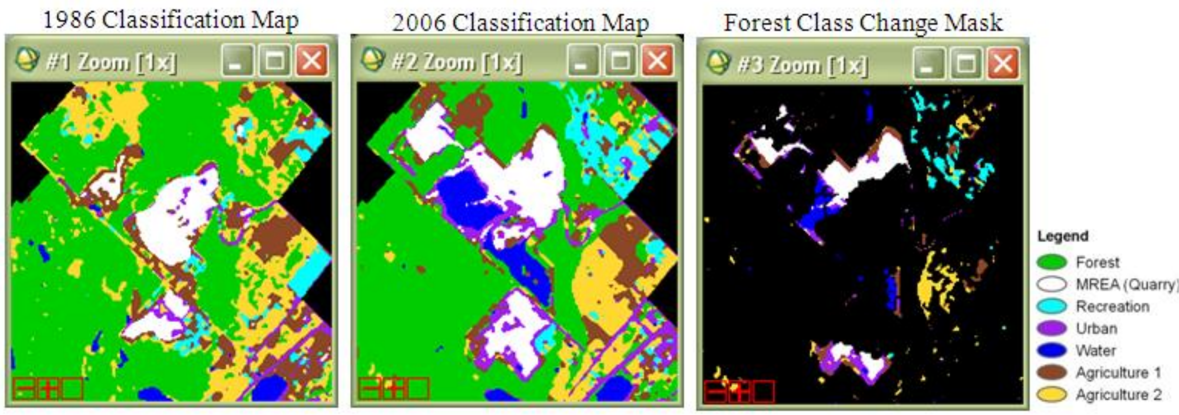


Figure 5.4 Example of Change in Forested Area from 1986 to 2006

(Location: 43°32'9.31"N 79°57'57.32"W in Halton Region)This image shows the change from forest in 1986 to MREA and water within the MREA boundaries in 2006. The forest class change mask represents what forested areas in 1986 changed into in the final 2006 classification map. This exemplifies expansion of an existing quarry in the NEP area as well as conversion of a portion of the MREA to water.

Another change that is highly visible through qualitative analysis is the conversion of the forest and agricultural classes to the urban class, with a few highly visible areas of urban expansion in the Hamilton region. There were also small changes to forest and agriculture from the recreation class. Grasses and other vegetation that occur in many recreational areas are very spectrally similar to the forest and agriculture 2 classes and so in some recreational areas, such as golf courses, this is really just a form of other vegetation. Unfortunately the "other vegetation" class had to be removed early in the classification process due to low accuracy results because of its spectral similarity to the forest and agriculture 2 classes.

Although unlikely that urban areas in 1986 would be converted to alternative land cover types in 2006 some changes were seen, but most changes appear to follow minor roadways and are therefore likely to be errors or roads that have been widened or expanded and therefore are detected more easily by the sensor . Also large areas of urban class surround the MREAs, which is a known error due to the low spectral separability of these two classes. The urban areas surrounding the MREA's are depicted as such due to mixed pixels of bare soil/rock and some vegetation around the boundaries of the MREA. These urban areas are actually part of the MREA class and therefore will negatively affect change statistics in the MREA and urban classes.

The majority of the changes seen in the agriculture 1 class were changes to agriculture 2, which is likely considering the seasonal variation of the imagery. The 1986 imagery was captured in early June and the 2006 image was captured in mid-August. There would be more bare agricultural fields (agriculture 1) early in the growing season when the 1986 image was captured than later in the growing season when the 2006 image was captured showing a "change" to agriculture 2 (vegetated fields). In reality, the 2006 image would have been captured at the height of the growing season for most crops, so more agricultural areas would appear vegetated. Changes from one agricultural type to the next will not be focused on due to seasonal differences in the imagery; rather the conversion of agricultural land to other land cover types will be examined. For the agriculture 1 class there were many conversions to the urban class which will be examined more in depth, but could be attributed to conversion of agricultural land to urban land. These changes may also be erroneous due to the spectral similarity of these two classes. Change to the urban classification was also exemplified in the agriculture 2 class although the majority of the changes in the agriculture 2 class were to forest. Some errors exist in this land cover conversion due the spectral similarity between the agriculture 2 and forest classes.

Final conclusions to be drawn from changes from one class to another will depend on the accuracy of the classification map in each year. Prior to both qualitative and quantitative analysis it must be noted that the urban and MREA land cover classifications will be examined visually (qualitatively) for the most part, as the accuracy values for these two classes fell below the overall accuracy values in all three images. For the Agriculture 2 class, the overall accuracy of 71.6% as quoted in Table 5.2 achieved for the 1986 image means meaningful analysis of the changes that occurred in this class may only be examined for a ten year period from 1996 to 2006. Similarly, the recreation class achieved a low overall accuracy of 76.5% in the 1996 image so change analysis should only be conducted over the entire 20 year time period. These accuracy statistics will be discussed in greater detail in the following sections.

5.2.2 Quantitative Change Analysis of the Study Area

Change statistics across the entire study area can be seen in Table 5.6 below. The table shows which classes increased and which decreased from the initial state 1986 image to the final state 2006 image across the entire study region. There were reductions in agricultural land, recreational land and MREA from 1986 to 2006, while all other classes showed an increase. Forested area showed a 34% growth over the 20 year period with the forest class increasing by 43.8 km^2 in Hamilton and Halton Regions. An increase in forested area was also concluded from previous studies (Ramsay, 1996; Cowell *et al.*, 1997; Lusted *et al.*, 1997; Jankovic, 1999). This increase is due to 45.4 km^2 of agriculture 2 land cover being converted to forested area. Urban land cover showed an almost 60% increase with an added 12.9 km^2 across the study area. This increase is perhaps an overestimation due to the low overall accuracy of the urban class. A 30% increase in water across the study area may also explain the slight decline of MREA. MREAs decreased by a little over 2% and a portion of this decrease can be explained by the increase in ponds created in the MREA's from 1986 to 2006. A decrease in agricultural land from 1986 to 2006 was observed across the entire study area, with a larger percentage of decline occurring in agricultural land with crops. The examination of these agricultural changes must be undertaken carefully, since vegetated fields in one image may not be vegetated in the next due to seasonal differences in the imagery, therefore results of the change from one agriculture class to another may merely be reflecting these seasonal crop rotations.

The overall quantitative changes across the study area for the problem classes identified in Table 5.2 will be examined on an individual basis. The urban and MREA classes had lower overall accuracy results across all three images and therefore conclusions must be drawn carefully for these classes. The other two classes with lower accuracy levels can be examined in specific time periods to increase the validity of the conclusions drawn from the change statistics. Agriculture 2 is best examined in the later 10 year period while the recreation class is best examined across the entire 20 year time period only. These specific cases will be discussed in further detail in the following individual regional sections.

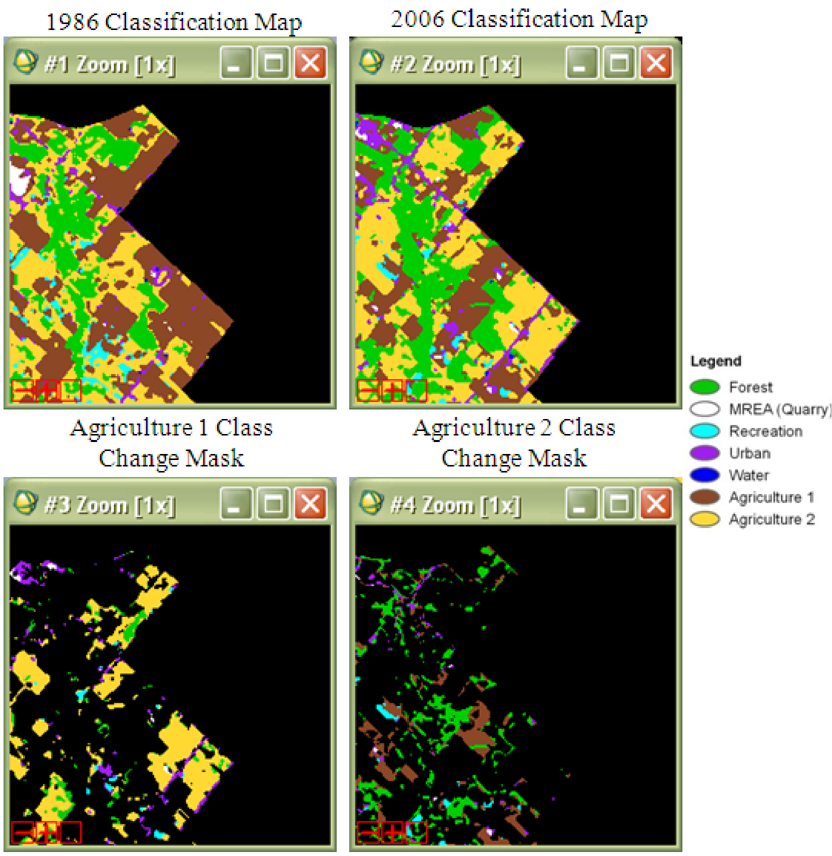


Figure 5.5 Example of Change in Both Agriculture Classes from 1986 to 2006

(Location: 43°29'33.68"N 79°57'32.83"W in Halton Region) This image exemplifies the major changes in both agricultural classes over the 20 year study period. The agriculture 1 change mask shows the conversion of agriculture 1 or bare agricultural soil being converted to agriculture 2 or vegetated fields. This is likely a result of the dates the imagery was captured and conversion of one type of agriculture to another will not be focused on. Instead interesting changes occurring in the agriculture 2 class change mask show a conversion of some cropland to forested areas which was evident throughout the study area.

Table 5.6 Overall Study Area Change Statistics

Final State 2006	**Initial State 1986** [Pixel (area in km^2, **percentage**)]							
	Forest	**MREA**	**Recreation**	**Urban**	**Water**	**Agriculture 1 (bare soil)**	**Agriculture 2 (crop)**	**Row Total/Class Total**
Water	956(0.6,**0.5**)	1117(0.7, **13.5**)	103(0.1,**0.6**)	321(0.2,**0.9**)	5999(3.8, **78.2**)	745(0.5,**0.6**)	722(0.5,**0.4**)	9963(6.2,**100.0**)
Urban	2766(1.7,**1.4**)	2418(1.5, **29.2**)	734(0.5,**4.3**)	25941(16.2, **74.5**)	89(0.1, **1.2**)	10739(6.7, **9.1**)	12695(7.9,**7.0**)	55382(34.6,**100.0**)
MREA	1731(1.1,**0.9**)	3095(1.9, **37.4**)	192(0.1,**1.1**)	589(0.4,**1.7**)	10(0.0, **0.1**)	1153(0.7,**1.0**)	1342(0.8,**0.7**)	8112(5.1,**100.0**)
Forest	180638(112.9, **89.9**)	160(0.1,**1.9**)	2119(1.3, **12.4**)	2386(1.5, **6.9**)	1173(0.7, **15.3**)	11930(7.5, **10.2**)	72588(45.4, **39.7**)	270994(169.4, **100.0**)
Agriculture 2 (crop)	7708(4.8,**3.8**)	215(0.1,**2.6**)	5791(3.6, **33.9**)	1816(1.1, **5.2**)	165(0.1, **2.2**)	44599(27.9, **38.0**)	50917(31.8, **27.9**)	111211(69.5,**100.0**)
Recreation	941(0.6,**0.5**)	25(0.0,**0.3**)	5141(3.2, **30.1**)	109(0.1,**0.3**)	8(0.0,**0.1**)	3849(2.4,**3.3**)	4424(2.8,**2.4**)	14497(9.1,**100.0**)
Agriculture 1 (bare soil)	6166(3.9,**3.1**)	1249(0.8, **15.1**)	3014(1.9, **17.6**)	3646(2.3, **10.5**)	225(0.1, **2.9**)	44435(27.8, **37.8**)	40096(25.1, **21.9**)	98831(61.8,**100.0**)
Class Total	200906(125.6, **100.0**)	8279(5.2, **100.0**)	17094(10.7, **100.0**)	34808(21.8, **100.0**)	7669(4.8, **100.0**)	117450(73.4, **100.0**)	182784(114.2, **100.0**)	
Class Changes	20268(12.7, **10.1**)	5184(3.2, **62.6**)	11953(7.5, **69.9**)	8867(5.5, **25.5**)	1670(1.0, **21.8**)	73015(45.6, **62.2**)	131867(82.4, **72.1**)	
Image Difference	70088(43.8, **34.9**)	-167(-0.1, **-2.0**)	-2597(-1.6, **-15.2**)	20574(12.9, **59.1**)	2294(1.4, **29.9**)	-18619(-11.6, **-15.9**)	-71573(-44.7, **-39.2**)	

5.3 Change in the Regional Municipality of Halton

The Regional Municipality of Halton represents a more rural region in the NEP in comparison to Hamilton region. The results of the change detection show a similar trend to the overall study area results. The forest, urban, MREA and water classes all showed an increase over the 20 year time period while the other four classes showed a decrease. The only difference in terms of image difference from the overall study area analysis was that overall MREA slightly decreased overall but in Halton Region, there was a slight increase of 0.2 km^2.

The forest class in the Regional Municipality of Halton saw a large increase of 29.9 km^2 from 1986 to 2006. Most (90%) of the original 1986 forested area did not change, and increases to the forest area mostly came from conversions of the agriculture 2 class to forest. This is shown in detail in Figure 5.7. Of the original agriculture 2 class, 39.7% changed to forest by 2006. Although the conversion of large amounts of agriculture 2 land into forested area is highly likely, there are spectral similarities between vegetated agricultural fields and forested areas that could cause confusion, so it is possible that this result of a 29.9 km^2 increase is larger than the actual change that occurred on the ground. In terms of loss of forested area from 1986 to 2006, MREA's had the most visual impact. As exemplified in Figure 5.3, large MREA's were added by 2006 but in other areas of Halton there was evidence of rehabilitation as can be seen in Figure 5.6.

In Halton Region the change detection results showed an overall decrease in agricultural land within the plan area over the 20 year study period. Agriculture 1 (bare agricultural soils) showed an 11.3% decrease and agriculture 2 (vegetated agricultural fields) showed a 39.8% decrease in Halton Region. The statistics revealed that large portions of the respective 1986 agriculture classes were converted to the other type of agriculture by 2006. Of the bare agricultural fields in 1986, 38% had changed to vegetated fields by 2006. This accounts for a total of 75.8% or 55.7 km^2 total of the original bare agricultural field class remaining a type of agriculture. Due to annual crop rotations or the different seasons the two images were

Figure 5.6 Evidence of Quarry Rehabilitation in Halton Region

(Location: 43°30'7.19"N 79°55'28.00"W) This figure shows the rehabilitation of the Milton Limestone Quarry in Halton Region (Conservation Halton, 2004)

captured, the agricultural types may have switched from one year to the next. The 1986 imagery was captured on June 03, 1986. This would have been early in the growing season resulting in less vegetated fields being classified by the SVM. The 2006 imagery was captured on August 13, 2006. This is at the height of the growing season therefore the SVM would have classified more vegetated agricultural fields (agriculture 2). This along with seasonal crop rotations would have made it appear as though agriculture was changing from one type to another but this is not the case. For this reason, changes from one agricultural class to another are not significant in this study. This exemplifies why in agricultural land use studies involving remote sensing, the seasonal characteristics of agriculture must be taken into account when conducting a more thorough investigation of changing agriculture over time. There were two other notable changes to the bare agricultural field class (agriculture 1). Portions of what was originally classified as agriculture 1 in 1986 changed to forested areas and urban areas in 2006. 5.6 km^2 changed into forested land and since these two classes have very different spectral signatures, this is likely an accurate portrayal of the conversion of agricultural land to forested areas. Further, 3.4 km^2 of bare agricultural fields in 1986 were converted to urban areas by 2006.

The agriculture 2 class representing vegetated agricultural fields showed the largest decrease of any other class in Halton Region. In total, 31.1 km^2 or 39.8 % of the original agricultural 2 class was converted to other land cover types between 1986 and 2006. In total, 49.8% of the original agriculture 2 class stayed a type of agriculture (either agriculture 1 or 2) but a large portion (39.7%) of the original class changed to forested area by 2006. These values may not be entirely accurate due to the poor performance of this class in the 1986 classified image, therefore more accurate conclusions can be drawn for this class by looking only at the later 10 year study period from 1996 to 2006. The statistical results for this class can be seen in Table 5.7 below.

Table 5.7 Agriculture 2 Change Statistics from 1996 to 2006 in Halton Region

Agriculture 2			
	Pixel	Percent	Area (km^2)
Forest	33766	28.9	21.1
Ag_1	34801	29.8	21.8
Ag_2	38061	32.6	23.8
Recreation	3942	3.4	2.5
Urban	5375	4.6	3.4
MREA	783	0.7	0.5
Water	191	0.2	0.1
Class Total	116919	100.0	73.1
Class Changes	78858	67.4	49.3
Image Difference	-41608	-35.6	-26.0

From 1996 to 2006, 32.6 % of the agriculture 2 class had not changed. This is only a slightly higher percentage than what was noted from 1986 to 2006. Another 29.8% was converted to bare agricultural fields, so a total of 62.4% of the 1996 agriculture 2 class remained a form of agriculture in 2006. The most noticeable change in the agriculture 2 class was the conversion of 21.1 km^2 of vegetated agricultural fields to forested area from 1996 to 2006. A 28.9% change from agriculture 2 to forest is a large change although not as large as was previously stated in the results over the entire 20 year time period. These results showed a much higher

39.7% of the 1986 agriculture 2 class being changed into forest, although there is a lower confidence for the 20 year change statistics. As Table 5.2 shows, the agriculture 2 class achieved better accuracy results in the 1996 and 2006 images with accuracies of 95.5% and 92.7% respectively. Due to the high spectral similarity of the agriculture 2 and forest classes, conclusions can be drawn more confidently through the analysis of the later 10 year period only. This result shows that the conversion of vegetated agricultural fields contributed much to the increase of forested area in Halton region over the 20 year study period although at a loss to agricultural land.

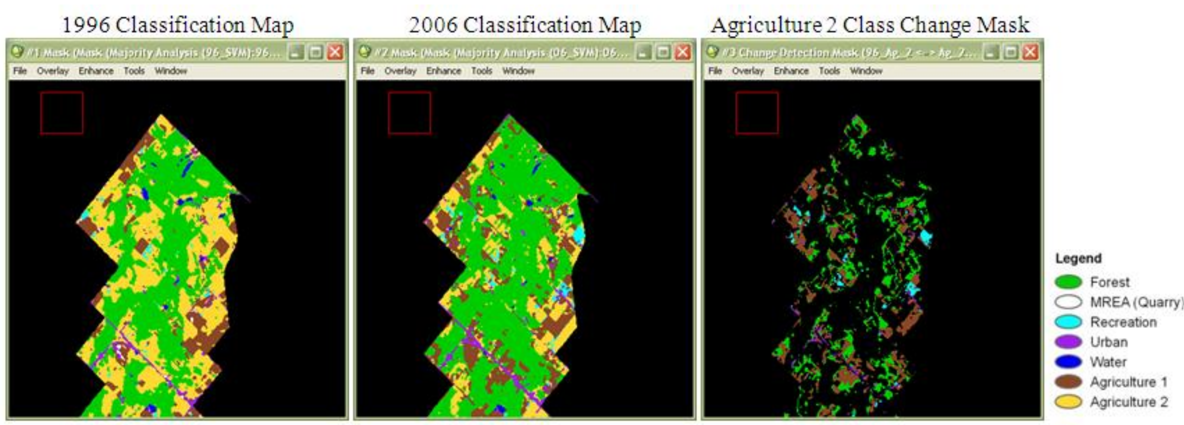


Figure 5.7 Conversion of Agriculture 2 to Forest from 1996 to 2006
(Location: 43°41'35.79"N 79°58'1.00"W in Halton Region)

Other small scale land cover classes also saw changes over the 20 year time period. MREA's showed an overall 4% increase in Halton Region. Changes to this class included conversions to urban areas, bare agricultural fields and water. The change of 1 km^2 of MREA in 1986 to urban area in 2006 is likely to be an error considering the spectral similarity of the two classes. As can be seen in Figure 5.6 and in other images of the study area, white MREA's are for the most part surrounded by purple which represents the urban classification. This is an error that must be taken into consideration for future projects and one of the reasons why the overall accuracy of the urban and MREA classes were lower than the other classes. Since MREAs and urban areas are smaller scale land cover types, it is hard to classify them accurately using Landsat 5 TM imagery. An area of 0.7 km^2 changed to bare agricultural fields. This could be an indication of quarry rehabilitation in the study area as old extraction sites are re-vegetated. Another 0.7 km^2 converted to water is due to the addition of ponds within existing MREA boundaries.

Recreational areas had a slight decrease throughout the region overall, but upon qualitative analysis it appears that there were a few new recreational areas added to the region over the 20 year time period. In Figure 5.8, a new golf course can be seen in Halton region that was developed sometime between 1986 and 2006. Due to the spectral similarity of the recreation class with the two agricultural classes, it was clear that several large agricultural areas were misclassified as recreation in the 1986 image which could explain the slight decrease even though visually there appears to be a slight increase.

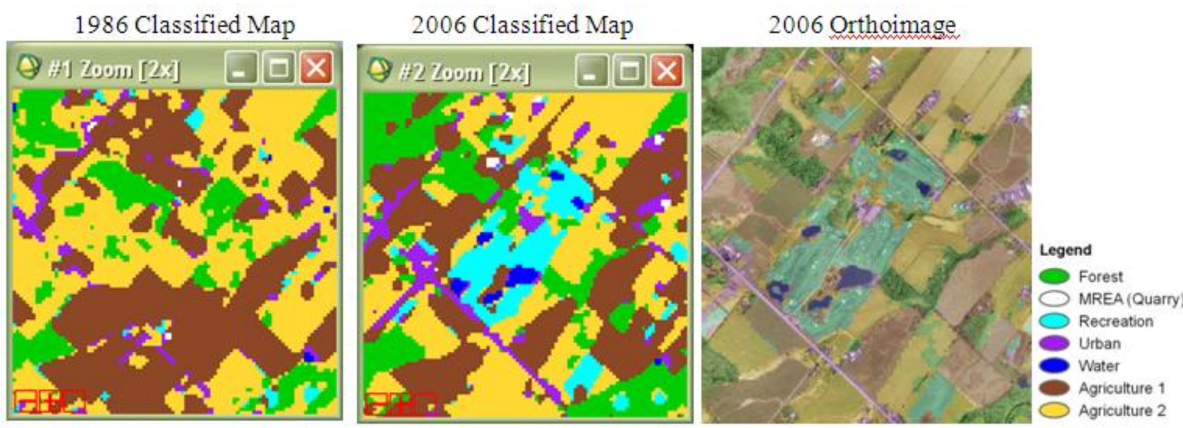


Figure 5.8 Addition of a Golf Course in Halton Region

(Location: 43°26'48.25"N 79°54'45.92"W) This figure shows the addition of a golf course in Halton Region sometime between 1986 and 2006. The 2006 orthoimage tile shows the new golf course overlaid by the transparent 2006 classification map.

The urban class showed a 70.9% increase over the 20 year period and represented an urban expansion of 5.1 km^2 into the countryside. This was visually confirmed by confirming urban expansion into both agricultural land and forested land and by identifying actual areas of urban expansion such as housing developments (addition of a subdivision) and most noticeably the creation of a roadway south of highway 401. The increase in urban area within the NEP will be examined in greater depth in the following detailed Hamilton change section.

5.4 Change in the Regional Municipality of Hamilton

The Regional Municipality of Hamilton is the most heavily urbanized region in the plan area. Similar to those for Halton Region, the results of the independent Hamilton change detection mimic the trends of the overall study area. The forest and urban classes increased while all other classes showed a decrease over the 20 year time period. There was a slight decrease in the MREA, with this class only showing an increase in Halton Region. The water class showed a slight decrease in Hamilton differing from the overall statistics as well as the Halton statistics, but both the MREA and water class losses are very small in comparison to the changes in the other classes.

The forest class in the Regional Municipality of Hamilton increased 13.9 km^2 from 1986 to 2006. This equals a 36.2 % increase from the original forest class size, although this was a much smaller increase than in the forest class in Halton Region. Similar to the changes in Halton region, the majority of the increases to the forest class came from conversions of the agriculture 2 land cover to forest with 14.3 km^2 of agriculture 2 land being converted to Forest by 2006. Decreases to the forest area came in the form of conversions to agricultural land and urban land. The urban changes are important to note since Hamilton is a largely urbanized region. Conversions of rural land to urban land are perhaps the most visually prominent in the forest change mask and examples of expanding urban developments such as subdivision and road construction can be seen in Figure 5.9. Several examples of forested areas being converted to agricultural land can be visually identified from the forest change mask, but most of these changes are errors due to the spectral similarity between the forest and agriculture 2 classes, which will be discussed in detail later in the section.

Table 5.8 Regional Municipality of Halton Change Statistics

		Initial State 1986 [Pixel (area in km^2, percentage)]							
		Forest	**MREA**	**Recreation**	**Urban**	**Water**	**Agriculture 1 (bare soil)**	**Agriculture 2 (crop)**	**Row Total/Class Total**
Final State 2006	**Water**	817(0.5,**0.6**)	1117(0.7, **15.3**)	94(0.1,**0.9**)	273(0.2,**2.4**)	2144(1.3, **69.8**)	702(0.4,**0.9**)	612(0.4,**0.5**)	5759(3.6,**100.0**)
	Urban	1196(0.8, **0.9**)	1656(1.0, **22.7**)	402(0.3,**3.8**)	6036(3.8, **52.2**)	59(0.0,**1.9**)	5434(3.4,**7.0**)	4989(3.1,**4.0**)	19772(12.4, **100.0**)
	MREA	1660(1.0, **1.2**)	3067(1.9, **42.0**)	187(0.1,**1.8**)	554(0.4,**4.8**)	10(0.0,**0.3**)	970(0.6,**1.3**)	1146(0.7,**0.9**)	7594(4.8,**100.0**)
	Forest	125481(78.4, **90.0**)	155(0.1,**2.1**)	1264(0.8, **11.8**)	1161(0.7, **10.0**)	609(0.4, **19.8**)	8923(5.6,**11.5**)	49691(31.1,**39.7**)	187284(117.05, **100.0**)
	Agriculture 2 (crop)	4824(3.0,**3.5**)	181(0.1,**2.5**)	3627(2.3, **34.0**)	1163(0.7, **10.1**)	119(0.1, **3.9**)	29614(18.5, **38.1**)	35783(22.4,**28.6**)	75311(47.1, **100.0**)
	Recreation	811(0.5,**0.6**)	25(0.0,**0.3**)	3077(1.9, **28.8**)	84(0.1,**0.7**)	4(0.0,**0.1**)	2768(1.7,**3.6**)	3459(2.2,**2.8**)	10228(6.4,**100.0**)
	Agriculture 1 (bare soil)	4648(2.9,**3.3**)	1101(0.7, **15.1**)	2027(1.3, **19.0**)	2299(1.4, **19.9**)	126(0.1, **4.1**)	29318(18.3, **37.7**)	29434(18.4,**23.5**)	68953(43.1, **100.0**)
	Class Total	139437(87.2, **100.0**)	7302(4.6, **100.0**)	10678(6.7, **100.0**)	11570(7.2, **100.0**)	3071(1.9, **100.0**)	77729(48.6, **100.0**)	125114(78.2, **100.0**)	
	Class Changes	13956(8.7, **10.0**)	4235(2.7, **58.0**)	7601(4.8, **71.2**)	5534(3.5, **47.8**)	927(0.6, **30.2**)	48411(30.3, **62.3**)	89331(55.8,**71.4**)	
	Image Difference	47847(29.9, **34.3**)	292(0.2,**4.0**)	-450(-0.3, **-4.2**)	8202(5.1, **70.9**)	2688(1.7, **87.5**)	-8776(-5.5, **-11.3**)	-49803(-31.1, **-39.8**)	

Table 5.9 Regional Municipality of Hamilton Change Statistics

		Initial State 1986 [Pixel (area in km^2, **percentage**)]							
		Forest	**MREA**	**Recreation**	**Urban**	**Water**	**Agriculture 1 (bare soil)**	**Agriculture 2 (crop)**	**Row Total/Class Total**
Final State 2006	**Water**	139(0.1,**0.2**)	0(0.0,**0.0**)	9(0.0,**0.1**)	48(0.0,**0.2**)	3855(2.4, **83.8**)	43(0.0,**0.1**)	110(0.1,**0.2**)	4204(2.6,**100.0**)
	Urban	1570(1.0,**2.6**)	762(0.5, **78.0**)	332(0.2,**5.2**)	19929(12.5, **85.6**)	30(0.0,**0.7**)	5308(3.3,**13.4**)	7711(4.8,**13.4**)	35642(22.3, **100.0**)
	MREA	71(0.0,**0.1**)	28(0.0,**2.9**)	5(0.0,**0.1**)	36(0.0,**0.2**)	0(0.0,**0.0**)	183(0.1,**0.5**)	196(0.1,**0.3**)	519(0.3,**100.0**)
	Forest	55198(34.5,**89.7**)	5(0.0,**0.5**)	856(0.5, **13.3**)	1226(0.8, **5.3**)	564(0.4, **12.3**)	3008(1.9,**7.6**)	22934(14.3,**39.7**)	83791(52.4, **100.0**)
	Agriculture 2 (crop)	2884(1.8,**4.7**)	34(0.0,**3.5**)	2164(1.4, **33.7**)	653(0.4, **2.8**)	46(0.0,**1.0**)	14995(9.4,**37.7**)	15144(9.5,**26.2**)	35920(22.5, **100.0**)
	Recreation	130(0.1,**0.2**)	0(0.0,**0.0**)	2064(1.3, **32.2**)	25(0.0,**0.1**)	4(0.0,**0.1**)	1081(0.7,**2.7**)	965(0.6,**1.7**)	4269(2.7,**100.0**)
	Agriculture 1 (bare soil)	1518(0.9,**2.5**)	148(0.1, **15.1**)	987(0.6, **15.4**)	1353(0.8, **5.8**)	99(0.1,**2.2**)	15128(9.5,**38.1**)	10666(6.7,**18.5**)	29899(18.7, **100.0**)
	Class Total	61510(38.4, **100.0**)	977(0.6, **100.0**)	6417(4.0, **100.0**)	23270(14.5, **100.0**)	4598(2.9, **100.0**)	39746(24.8, **100.0**)	57726(36.1,**100.0**)	
	Class Changes	6312(3.9, **10.3**)	949(0.6, **97.1**)	4353(2.7, **67.8**)	3341(2.1, **14.4**)	743(0.5, **16.2**)	24618(15.4, **61.9**)	42582(26.6,**73.8**)	
	Image Difference	22281(13.9, **36.2**)	-458(-0.3, **-46.9**)	-2148(-1.3, **-33.5**)	12372(7.7, **53.2**)	-394(-0.2, **-8.6**)	-9847(-6.2, **-24.8**)	-21806(-13.6, **-37.8**)	

Elsewhere in Hamilton Region urban expansion into the two agriculture classes is visually prominent. Both agricultural classes saw large decreases in area in Hamilton over the 20 year time scale. Of the 1986 agriculture 1 class, 75% maintained its agricultural land cover status in 2006, but only 44.7% of the 1986 agriculture 2 class was still classified as agriculture in 2006. Based on conclusions drawn in previous sections, statistical conclusions for the agriculture 2 class will only be drawn using the later 10 year time period statistics from 1996 to 2006. Using these statistics, as outlined in Table 5.10, 58.2% of the original 1996 agriculture 2 class stayed an agricultural class as either agriculture 1 or 2.

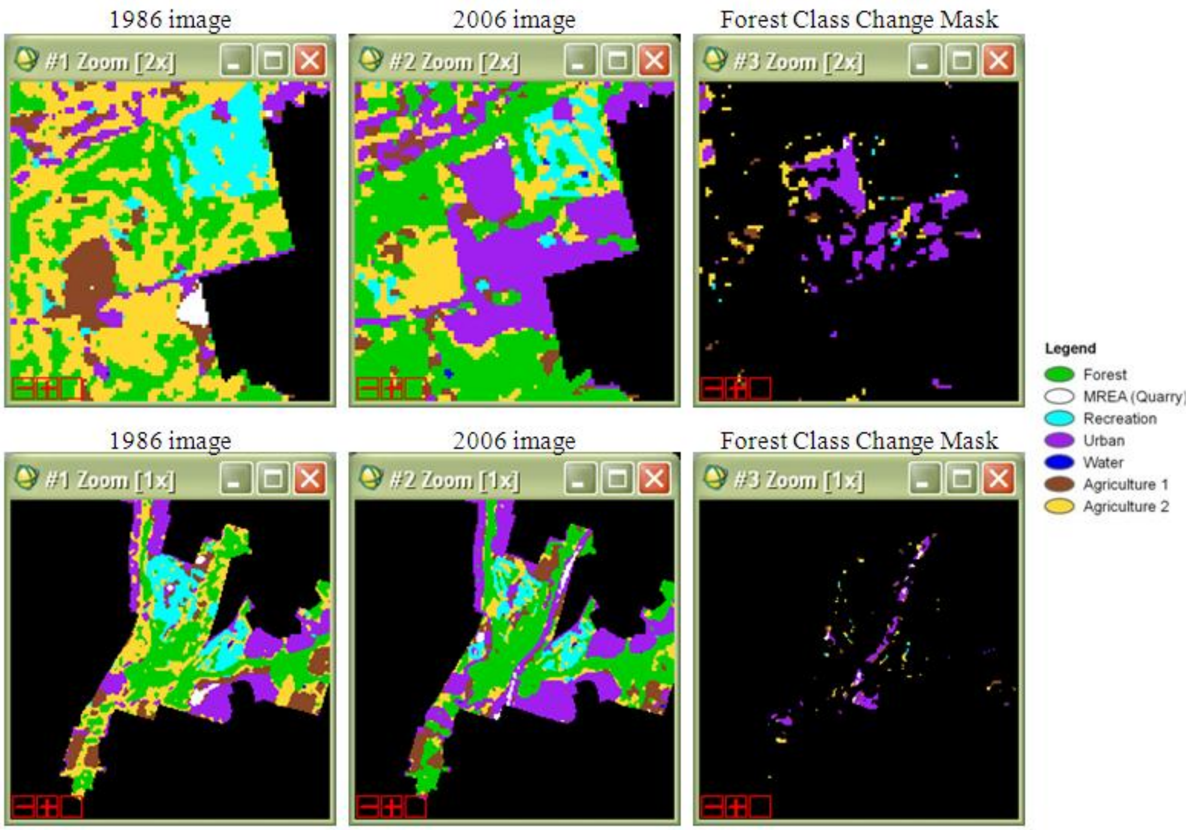


Figure 5.9 Examples of the Forest Class Changing to the Urban Class

Expansion of urban land cover into previously forested land cover can be seen above. The first example (Location: 43°15'33.18"N 79°59'9.66"W) shows the development of a new subdivision in the rural-urban fringe around Hamilton. The second example (Location: 43°12'26.24"N 79°48'25.75"W)shows the development of the Red Hill Valley Parkway that runs through the NEP area.

Conversions from agriculture 1 to both urban and forest land cover occurred in Hamilton. An area of 3.3 km^2 was converted to urban land cover while 1.9 km^2 changed into forest land cover. After qualitative analysis of the agriculture 1 change mask, changes to the urban class were highly visible. Many small areas converted to forest area are likely to be true representations of the changes from agriculture 1 into forested areas, since the spectral signatures of these two classes are very different. The same changes occurred in the agriculture 2 class with 26.5% of agriculture 2 in 1996 changing to the forest class in 2006. An area of 3.5 km^2 (11.4%) was changed to urban area over the ten year time period. Again, in this heavily urbanized area, changes to the urban class were very visually recognizable when examining the agriculture change masks. Examples of the urban expansions that have occurred in the Hamilton study area can be seen in both Figure 5.9 (conversion of forest to urban) and Figure 5.10 (conversion of agriculture to urban).

Table 5.10 Agriculture 2 Change Statistics from 1996 to 2006 in Hamilton Region

Agriculture 2			
	Pixel	Percent	Area (km^2)
Forest	12936	26.5	8.1
Ag_1	13208	27.0	8.3
Ag_2	15215	31.2	9.5
Recreation	1729	3.5	1.1
Urban	5547	11.4	3.5
MREA	170	0.3	0.1
Water	26	0.1	0.0
Class Total	48831	100.0	30.5
Class Changes	33616	68.8	21.0
Image Difference	-12911	-26.4	-8.1

Other small scale land cover changes also took place with the remainder of the land cover classes. There are very few MREAs in Hamilton region, but the class experienced a slight decline over the time period. Only 0.3km^2 was lost from 1986 until 2006 and the most noticeable change was a 0.5 km^2 conversion to urban. Although small, this change raises

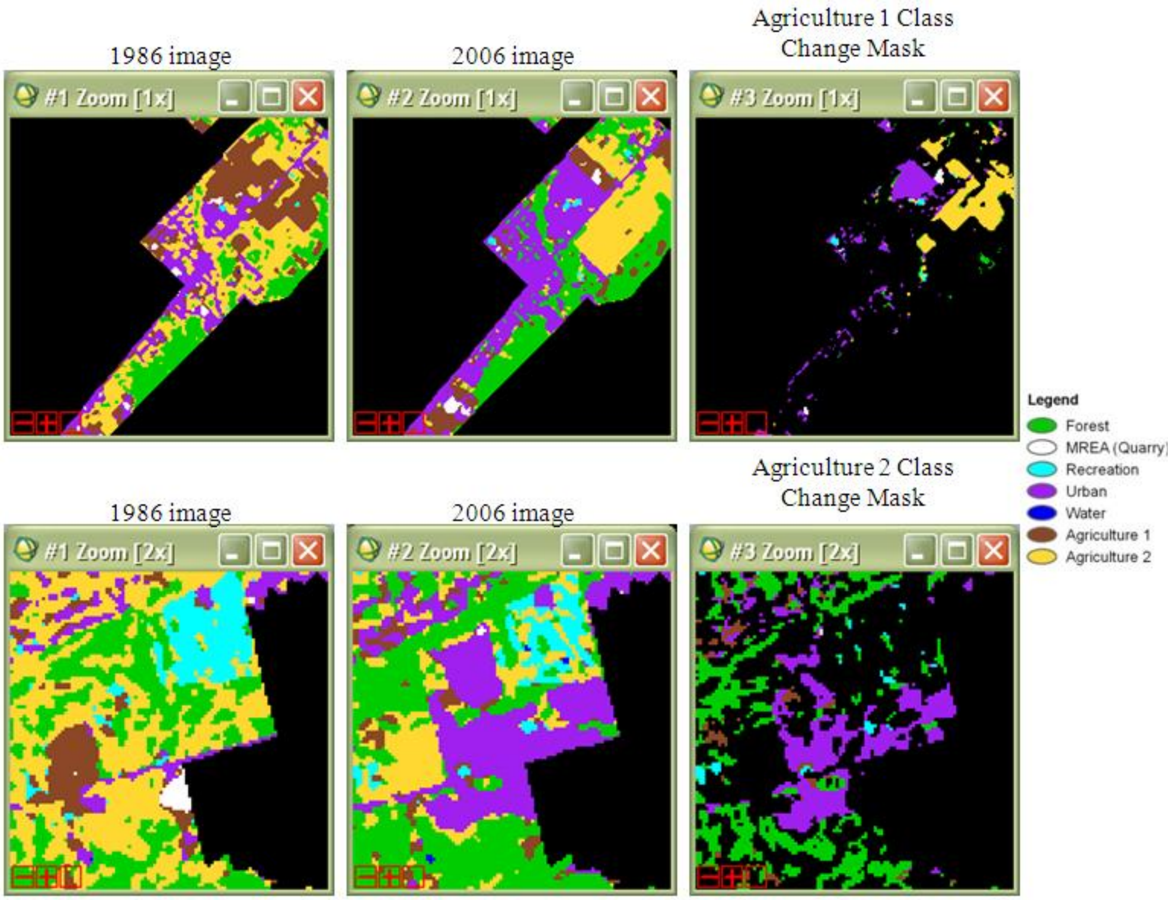


Figure 5.10 Conversions of Agriculture Land Cover to Urban Land Cover

Expansion of urban land cover into previously agricultural land cover can be seen in this figure. The top images (Location: 43°20'7.35"N 79°53'47.58"W) exemplify residential expansion, while the bottom images (Location: 43°15'32.36"N 79°59'8.57"W) show an example of a new subdivision development in the Regional Municipality of Hamilton.

some interesting topics for discussion. The spectral similarities between the urban and MREA classes creates class confusion when performing the classification and resulted in low overall accuracy values. Positive information that can be taken away from the change analysis is that often new development sites are mistaken for MREA due to the excavation in preparation for the development. Excavation unearths rock and bare stone which can be mistaken for an MREA and is a good indication, upon visual inspection where new developments may take place in the future. An example of this can be seen in Figure 5.11 below.

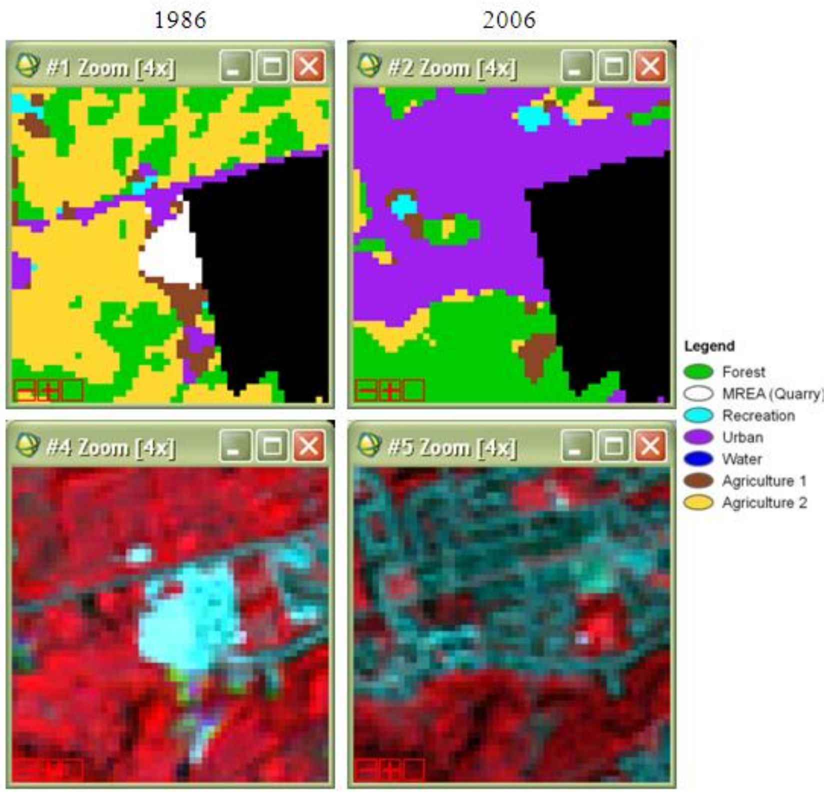


Figure 5.11 Identification of Urban Development Sites

This figure shows how a mistaken MREA area can provide clues to future urban expansion. This example of urban expansion in Hamilton (Location: 43° 15'19.31"N 79°58'59.92"W) was classified as MREA in 1986 and change to an urban class in 2006. False colour imagery reveals that an area of bare rock/soil was converted to a subdivision and was likely the start of a residential development.

The urban class had a 53.2% increase with 86.6% of what was classified as urban in 1986 staying urban in 2006. There were small changes from the urban class to the forest and agricultural classes, which could indicate an increase in green space or parks within urban boundaries. Finally, the recreation and water classes both saw only very slight decreases in Hamilton Region.

Change analysis has been undertaken at the regional level before (Ramsay, 1996; Cowell *et al.*, 1997; Lusted *et al.*, 1997; Jankovic, 1999), but since the NEP consists of its own set of boundaries known as land use designations, further worthwhile analysis would be to examine change based on each individual land use designation. The Plan is monitored based on designation criteria, and land cover change in the Plan area is governed by sets of rules for each designation that range in protection levels. The following section will provide a new angle on change analysis within the NEP.

5.5 Change within the Niagara Escarpment Plan (NEP) Land Use Designations

To go beyond previous studies, change at the designation level was examined. The NEP has seven different land use designations that divide up the Plan area. They are:

- Escarpment Natural Area (ENA)
- Escarpment Protection Area (EPA)
- Escarpment Rural Area (ERA)
- Minor Urban Centre (MUC)
- Urban Area
- Escarpment Recreation Area
- Mineral Resource Extraction Area (MREA)

A designation map for the study area can be seen in Figure 5.12. For this study, change will be examined across five of the seven land use designations: the ENA, EPA, ERA, urban area and the MREA designations. MUC is a designation that identifies the various rural settlements, villages and hamlets that are distributed throughout the Plan area (The Niagara Escarpment Plan, 2005). The boundaries of this designation outlining a rural settlement are superimposed onto the existing land use designations, therefore a MUC may also be, for example, in an area of ERA. Because of the nature of this designation, its changes will not be examined specifically, but changes in MUCs may be reflected in changes within the urban class in each classification map.

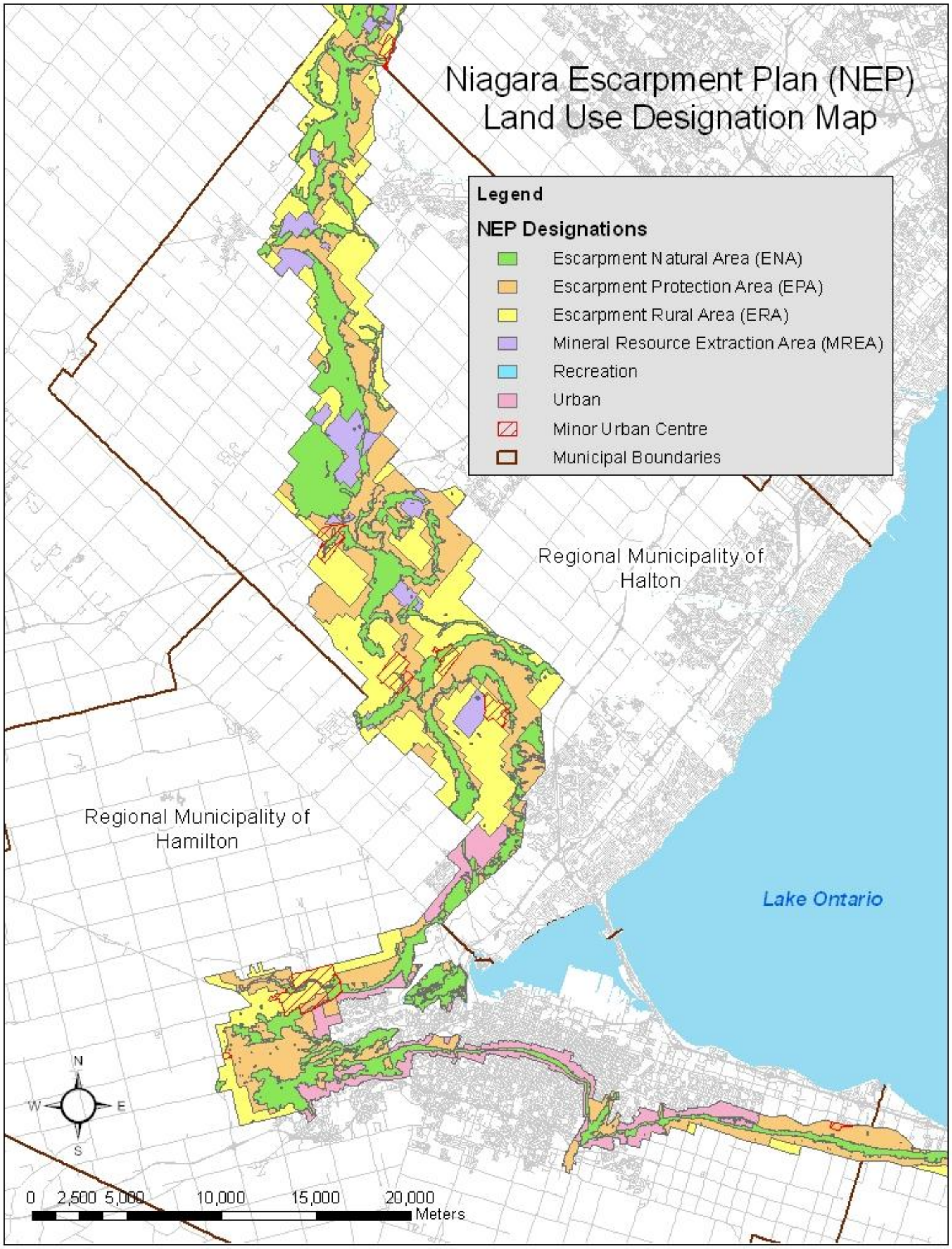


Figure 5.12 Hamilton and Halton Region Land Use Designation Map

The second designation exempt from the final change analysis is the Escarpment Recreation Area designation. Even though recreational areas as defined in this study do exist, there are no areas of actual Escarpment Recreation Area designation in Hamilton and Halton and therefore will not be included in the analysis. For example under the NEP, golf courses are not designated as Escarpment Recreation Areas. However as defined in this study, golf courses along with parks and other small scale recreational areas were defined under the recreation class and had to be included so the classes would be exhaustive. The criterion for Escarpment Recreational Area designation under the Plan is that an area of recreation must be an established, identified or approved larger scale recreational development such as ski facilities and resorts (The Niagara Escarpment Plan, 2005).

Even though the Escarpment land use designations are based on land use (as opposed to land cover), these development criteria outlined in the Plan helped establish the types of land cover an analyst would expect to find in the NEP area for land cover classification using remote sensing. For the designation change analysis, change will only be examined over the entire time scale from 1986 to 2006. Not every class will be examined for every designation as they were for the previous sections on Halton and Hamilton Regions. Instead the analysis will focus on the key classes that changed the most for each designation. Full statistics can be seen in Appendix C. This section begins with the designation that has the highest protection in the Plan area.

5.5.1 Escarpment Natural Area (ENA)

The ENA protects the most natural components of the escarpment. This designation, with the highest level of protection is placed on important natural features within the NEP such as wetlands, streams and forested areas and works to preserve important plant and animal species (The Niagara Escarpment Plan, 2005). Although this policy provides the highest level of protection within the plan, it also allows necessary small scale developments such as single dwellings, non-intensive recreation such as footpaths and essential transportation and utility facilities (The Niagara Escarpment Plan, 2005). The change mask for this designation can be seen in Figure 5.13.

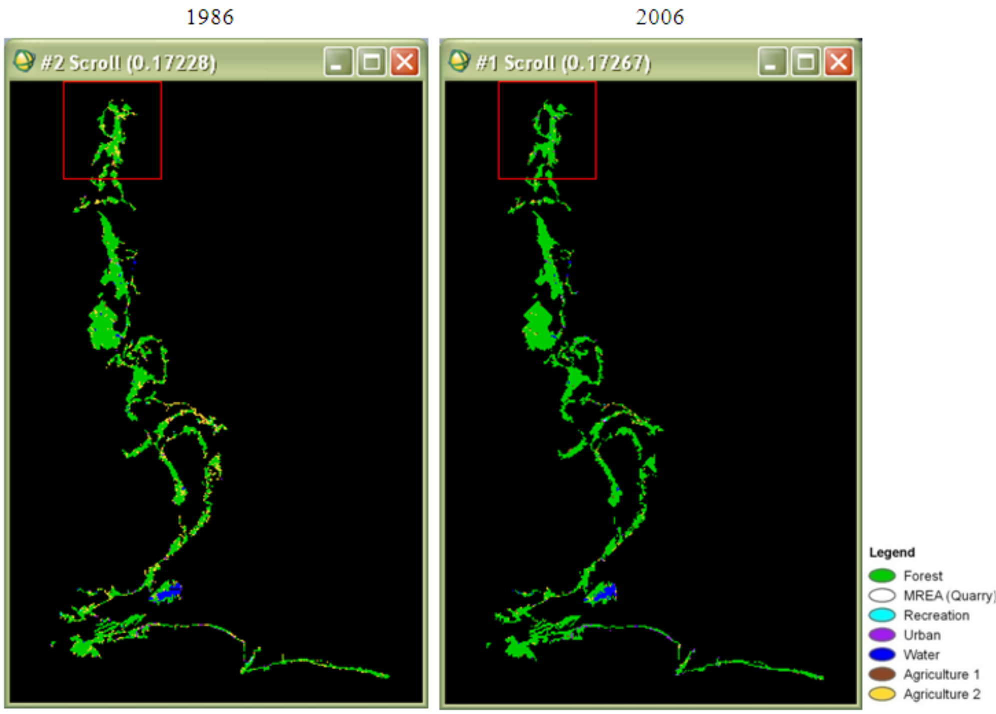


Figure 5.13 Changes in Escarpment Natural Area (ENA) from 1986 to 2006

Overall the changes in the ENA were few. This was the anticipated result for this designation since this area of the escarpment is under the highest level of protection. However, some changes were seen and the changes that did occur over the 20 year time period followed the restrictions as outlined in the Plan. The only significant changes were in the forest and agriculture 2 classes. Forested area increased in the ENA by 12.9 km^2 while areas of vegetated agricultural fields (agriculture 2) decreased by 13.4km^2. Most (98%) of the forested area in 1986 stayed forest in 2006, although there were some minor changes to other classes such as urban, water, agriculture 1 and agriculture 2. Agriculture 2 was the class that contributed most to the growth of the forest class in the ENA. An area of 12.5km^2 (77.9%) of agriculture 2 land cover in 1986 was converted to forest in 2006. Due to the spectral similarities, this statistic may be somewhat overestimated; however changes in the agriculture 1 class also took place. An area of 0.8 km^2 or 44.1% of the 1986 agriculture 1 changed to forested area in 2006 indicating a conversion of agricultural land to forested area for an overall increase in this class. Also interesting to note was a slight increase in the agriculture 1 class but with the 13.4km^2 decrease in the agriculture 2 class, this would indicate an overall loss of agricultural land.

The change statistics results showed little to no change in the remaining classes. The MREA class experienced the smallest change of all with almost no gain in area. This is a positive change result as it means the Plan has succeeded in protecting the most delicate ecological sections of the escarpment from mineral resource extraction operations. A slight increase of 72 pixels was seen in this class, but was determined upon visual inspection to be merely a designation boundary issue, as these boundaries are only accurate to a 1:50,000 scale and are not intended for site specific analysis as outlined in the Plan (The Niagara Escarpment Plan, 2005). There was a slight decline in recreational area by 0.4km^2. Not much recreational area was classified in this designation as most would consist of footpaths such as the Bruce Trail, which would be nearly impossible to detect at the 25m spatial resolution, especially with the full leaf on conditions of the canopy. This designation has succeeded in preventing large scale recreational areas, such as golf courses, as can be seen in other designations throughout the Plan. There was a very small increase (0.5km^2) to the urban area within the ENA with some small pieces of agricultural land and forested areas changing to the urban class.

5.5.2 Escarpment Protection Area (EPA)

Protected for their environmental significance much like the ENA, these areas often represent some of the most visually prominent features of the Niagara Escarpment (The Niagara Escarpment Plan, 2005). Not only do these areas have the most scenic views along the Escarpment, but they also have been significantly modified by land use activities such as residential developments and agricultural practices (The Niagara Escarpment Plan, 2005). EPAs act as a buffer to the highly protected ENAs and aid in preserving what natural slopes still exist on the Escarpment today (The Niagara Escarpment Plan, 2005). Permitted land uses within this designation are agricultural operations, single dwellings, recreational areas requiring minimal impact on the landscape and small scale commercial uses (The Niagara Escarpment Plan, 2005).

Similar changes were experienced in the EPA designation as were seen in the ENA. The major changes in this designation were seen in the forest and agriculture 2 classes. The forest class saw a 16.5 km^2 increase while the agriculture 2 class experienced a 15.4km^2 decrease in area. The majority (81.8%) of forested area in 1986 stayed forest in 2006, which means the forest class in the EPA designation saw a greater percentage of change than the forest class in the ENA designation. The forest class saw small changes to agricultural land, recreational areas and urban areas. Decreases in area occurred for both agricultural classes with the agriculture 2 class seeing the largest decrease. Although there was a slight decrease in the agriculture 1 land cover class, 78.9% of the original class in 1986 remained bare agricultural soils in 2006. The largest changes in this class saw a conversion to forest (2.8 km^2), urban area (2.2 km^2) and recreational areas (0.9 km^2). More than half (55.8%) of 1986 agriculture 2 remained as one of the two agriculture classes in 2006. The largest change to this class, which has been a consistent change throughout the analysis, was the change to forested areas. Smaller agriculture 2 areas also changed to urban and recreational areas. An interesting discovery seen in the change masks of the forest and agriculture 1 and 2 classes was the expansion of a golf course in Halton Region, which is typically prohibited under the policy of the EPA designation. This can be seen in Figure 5.14. Even though the recreation class showed a slight decrease statistically, it was this addition to the class that stood out from the qualitative analysis.

Another increase seen in this designation was the urban land cover class. This class increased by 2.9km^2 and was converted largely from the two agricultural classes and small portions of forested land, which can be seen on the change masks. The conversions to urban from agriculture are largely composed of expansion of previous housing developments and the creation of roadways throughout this designation. Once again, very little change was experienced in the MREA land cover class, with a loss of 4 pixels across the entire designation.

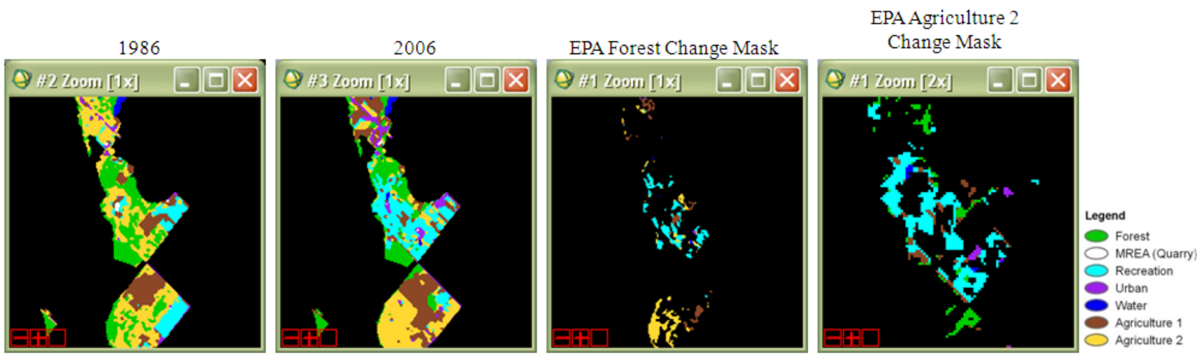


Figure 5.14 Expansion of a Golf Course in the Escarpment Protection Area (EPA) Designation

(Location: 43°32'45.96"N 79°56'48.73"W) Figure 5.10 shows the expansion of a golf course in EPA. Typically, under section 1.4 of the NEP, golf courses are not permitted uses. This expansion would have possibly required an amendment to the NEP.

5.5.3 Escarpment Rural Area (ERA)

The ERA designation provides the buffer for the more ecologically sensitive areas of the escarpment that is protected by the two previous designations discussed (The Niagara Escarpment Plan, 2005). Although this designation allows for the most development, other than the specific urban and MREA designations, it is important in protecting lands in the vicinity of the Escarpment (The Niagara Escarpment Plan, 2005). Permitted uses in this designation range from agricultural operations to small commercial and industrial developments to service rural communities (The Niagara Escarpment Plan, 2005). Changes similar in magnitude and type to the EPA were seen in the change results for the ERA. Since the policies on these two designations are more lenient, a greater magnitude of changes were experienced in the EPA and ERA designations as opposed to the small amounts of change seen in the highly restrictive ENA designation. All classes experienced an increase in area except for the agricultural classes. Once again forest area saw an increase of 13.9 km^2 while the decrease experienced by the agriculture 2 class was a much lower percentage than in previous designations. Only 9.5 km^2 of agricultural 2 land were lost in the ERA designation. The urban class saw the third highest change with the highest percentage of change so far with an increase of 2.5 km^2. The description of this designation and its land use restrictions help to explain the resulting changes.

The forest class lost its lowest percentage of land out of all three designations analyzed so far. The majority (80.3%) of 1986 forested area remained forested in 2006. Minor conversions to agricultural land, recreational land and urban areas were seen, but mostly it was the conversion of agricultural land to forested area that contributed to the overall increase of this class. Agriculture 2 had 13.7 km^2 of land change to forested areas while 60.4% remained agricultural (either agriculture 1 or 2 class). An area of 3.3 km^2 of agriculture 1 land was converted to forest, while 80.7% of agriculture 1 land remained one of the two types of agriculture. Both agriculture classes experienced changes to the urban designation as well. Agriculture 1 had 2.1 km^2 and agriculture 2 had 1.8 km^2 converted to urban lands in the ERA. Overall, both agricultural classes saw a decrease in area with the agriculture 1 class experiencing an 8 km^2 decrease and the agriculture 2 class experiencing a 9.5 km^2 decrease. Although overall agricultural land in the Plan area is decreasing, this designation saw less of a decrease than the previous two designations, possibly suggesting some success of agricultural preservation in this area.

All other classes experienced increases in area in the ERA designation. As stated above, urban area increased in the ERA by 2.5 km^2 mostly from the conversion of agricultural land and forested areas which could be seen when examining the change masks for each of these classes. The recreation, MREA and water classes all saw minor increases in this designation. Small expansions and additions to golf courses were acknowledged as the reason for increase in the recreational class. A very slight increase occurred in the MREA class. Few changes have been seen in this class since changes to MREA classes are restricted to the MREA designation to be discussed in section 5.5.5.

5.5.4 Urban Area

Existing urban areas within NEP boundaries have policies in place to prevent further encroachment on escarpment lands and minimize impacts from new developments (The Niagara Escarpment Plan, 2005). Within the urban designation there are some areas that remain largely undeveloped while in other areas urban growth is encroaching on escarpment slopes and adjacent natural areas (The Niagara Escarpment Plan, 2005). The underlying policy of the urban designation aims to minimize impacts where urban areas already exist while preventing the expansion of urban areas into the remaining natural areas and beyond (The Niagara Escarpment Plan, 2005). To accomplish this, the NEP outlines permitted uses and development guidelines and works to ensure only development compatible with the Escarpment landscape is permitted (The Niagara Escarpment Plan, 2005).

The changes that occurred in the urban classification were much different from the experiences previously discussed in the other designation types. Since the urban designation is specifically used to designate urban areas in the vicinity of the Niagara Escarpment the changes that occurred most were increases in urban area. Since there is no urban designation within the Halton Region portion of the plan, the analysis in this section only took place in Hamilton Region. Urban area increased by 5.4km^2 and forested area increased by 2.3km^2. The recreation and water classes saw almost no change, with both classes' image differences being less than 100 pixels each. The MREA class and both agricultural classes experienced losses of area less than 5.1 km^2.

The majority of the changes seen in the forest class were changes to urban areas. An area of 0.7km^2 or 27% was converted to urban, but 57% or 1.5 km^2 stayed forested over the 20 year time period. The class that contributed the most to the increase in area of the forest class was the agriculture 2 class which had 2.6 km^2 converted to forested area. For the agriculture 2 class, 26.9% remained a type of agriculture; either agriculture 1 or agriculture 2. Of the agriculture 2 class, 38.9% changed to urban area which could be easily seen when analyzing the change mask for the class. An interesting observation that was made from the qualitative analysis of the agriculture 2 class was that some of the conversions to forested areas were occurring within urban subdivisions. A possible explanation for this change is that the vegetation that existed within these urban areas in 1986 may not have completely matured and would therefore be misclassified as a type of agriculture. Since an "other vegetation" type was not included in the analysis, this classification error was experienced in some areas throughout the study. By 2006 this urban forest cover or urban vegetation would have increased, thus showing an increase in forested areas within urban boundaries. An example of this can be seen in Figure 5.15.

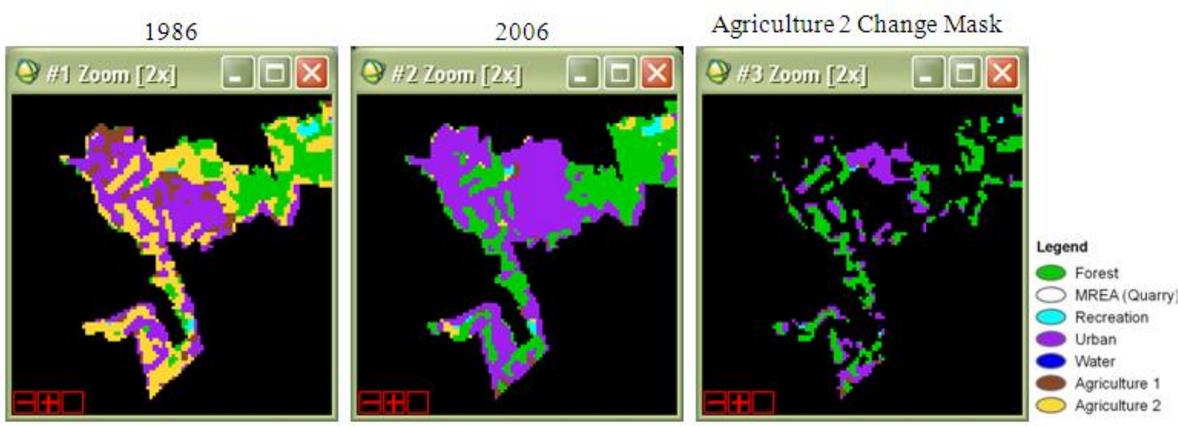


Figure 5.15 Example of Growth in Urban Natural Areas

(Location: 43°13'31.94"N 79°59'46.03"W) This figure shows an example of the maturation of an urban forest as a possible explanation for the increase experienced in the forest class in the urban designation in Hamilton Region.

The original 1986 agriculture 1 class showed 48% of the class staying as one of the two types of agriculture by 2006. Of the agriculture 1 class, 40.8% changed to urban area and a small 8% was converted to forested area. Finally, the MREA class experienced a slight decrease in this designation due to an error discussed previously. Visual inspection of the changes revealed most areas were excavated land for development, spectrally similar to a quarry, that were fully developed by the 2006 imagery date.

5.5.5 Mineral Resource Extraction Area (MREA)

This designation was included in the Plan to place boundaries around existing mineral resource extraction sites to prevent further expansion into the NEP area. This designation includes only pits and quarries that are licensed under the Aggregate Resources Act and allows for areas of minimal expansion to existing MREAs (The Niagara Escarpment Plan, 2005). It is also important to note that new MREAs producing less than 20,000 tonnes annually are permitted in the ERA designation without amendment to the Plan and anything larger would require an amendment (The Niagara Escarpment Plan, 2005).

Interesting changes occurred in the MREA class overall. The actual MREA class was the only class that did not change. This class experienced only a very small increase in area; the equivalent of 35 pixels. No increase in MREA may seem erroneous, since one would expect quarry operations to have expanded over the study time period. Initially this result sounds promising but upon further analysis, there would appear to have been a slightly higher increase in this class than the results suggest. This will be discussed later in the section, but overall an unchanged MREA statistic would indicate the Plan's success in preventing further extraction operations on the escarpment. In fact, qualitative analysis of the MREA change mask shows clearly where rehabilitation efforts are underway as in the Milton Limestone Quarry adjacent to the Kelso Conservation Area in Halton Region (Conservation Halton, 2004). This rehabilitation site can be seen in Figure 5.6.

The forest area in the MREA designation decreased by 0.9 km^2. Some forest area remained but the majority of the changes were conversions to MREAs. There were also smaller changes to the urban, agriculture 1 and water classes that led to some interesting conclusions about limitations with the MREA and urban classes. These two classes had the lowest class accuracies for all three images. Due to their spectral similarities boundary areas between the MREA and the surrounding buffer vegetation get misclassified as the urban class. This was especially evident when examining the change mask for the urban class for this designation.

Visual inspection of the class mask images allow the analyst to see where the changes quoted in the statistical change detection report are occurring in the class geographically. Figure 5.16 shows this boundary pixel effect between the urban and MREA classes. There were many conversions to water mostly from the MREA and Forest classes and were added as lakes or ponds on previous extraction sites. There was minimal agricultural area within the MREA, with the exception of the areas designated for future expansion. Agriculture 1 showed a slight increase while agriculture 2 decreased and had most of its area converted to MREA. In fact, both agriculture classes showed the most change to the MREA class. Of the agriculture 1 class, 45.3% stayed as either agriculture 1 or 2 in 2006, while 14.4% changed to MREA and 17.1% changed to urban. Since the urban classification in this designation actually represents MREA the two values can be totaled for a 31.5% change from agriculture 1 to MREA. The same can be done for the agriculture 2 class where 33.3% of the class stayed agriculture in 2006 and 35.1% changed to MREA. To a lesser degree, there were also changes to the forest and water classes.

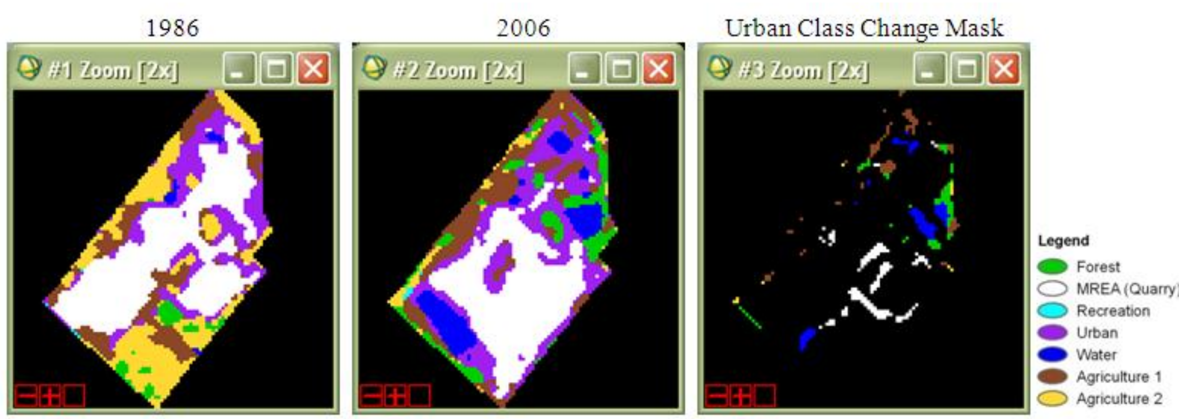


Figure 5.16 Example of Urban Boundary Pixels around the Mineral Resource Extraction Area (MREA) Class

(Location: 43°24'6.07"N 79°53'11.02"W)

Chapter 6
Conclusion

6.1 Discussion

The goal of this research was to examine land cover change in the Regional Municipalities of Hamilton and Halton portions of the NEP. This was achieved through the use of Landsat 5 TM remotely sensed data and an SVM supervised classification algorithm over a 20 year time period from 1986 to 2006. The main objectives of this study were to:

1. Create land cover classification maps (as accurately as possible) at a regional scale in the Regional Municipalities of Hamilton and Halton portions of the NEP using remotely sensed data;
2. Identify what land cover changes have occurred in the Regional Municipalities of Hamilton and Halton over a 20 year time period from 1986 to 2006 (qualitative assessment);
3. Determine how much the land cover has changed in the Regional Municipalities of Hamilton and Halton over the 20 year time period (quantitative assessment);
4. Examine both qualitative and quantitative changes that have occurred in the NEP land use designations over the 20 year time period in the Regional Municipality of Hamilton and Halton;
5. Detect (if any) potential land cover changes that are not compatible with the NEP land use designations and NEP policies

Land cover maps of the Regional Municipalities of Hamilton and Halton Region were created for each image at an average accuracy of 86.7% with an average Kappa coefficient of 0.84. Based on standards quoted by Treitz and Rogan (2004), land cover map accuracy should range between 85% and 90%, or between 80% and 85% for change detection. The accuracy levels achieved with the SVM classification were ideal for the study of land cover change at a regional scale in the NEP area. With high accuracy results, land cover change was detected for the study area. Change was examined across all seven land cover classes: forest, water, agriculture 1 and agriculture 2, recreation, urban and MREAs. The main overall change trend was the increase in forested area within both Regional Municipalities. From 1986 to 2006 forest area increased by 43.8 km^2, which represents an approximate increase of 35% forest cover from the original 1986 forest cover. This was the most important finding as it is evidence of the success of Niagara Escarpment protection by the NEC and the NEP.

There was a decrease in agricultural land overall in Hamilton and Halton Regions. The examination of this class was unique since dates of the images used in the study covered different time periods in the growing season. There was much change from one agriculture type to another (agriculture 1 changing to agriculture 2 or vice versa). The post classification change statistics and change masks produced using ENVI 4.5 were ideal to examine changes in agriculture to other types of land cover and to disregard the changes between the two agricultural classes. For the agricultural classes, the purpose of this work was to examine agricultural land change (whether it increased or decreased) and not focus on change of agriculture type. Upon inspection of the change results, it was determined that the bulk of the decrease in agricultural land was due to a conversion to forest and urban land cover classes. Due to the low accuracy results of the 1986 agriculture 2 class, this class was examined in Hamilton and Halton individually using the 1996 and 2006 images, since this class had a much higher accuracy value for the later 10 year time period. The trends remained the same showing agricultural land being converted to forest and urban land cover but at a reduced percentage value, since forested area would have previously increased from 1986 to 1996.

Despite the fact that the urban class had poor accuracy results, changes in this designation are very important to note. Due to the spectral similarities of the urban class with other classes, such as the MREA and agriculture 1 (bare agricultural field) classes, quantitative change results were not completely accurate. Qualitative analysis was necessary to reveal where true urban expansion took place in the Plan area. Overall and in each Regional Municipality, the change statistics showed an increase in urban area. The results of the urban analysis are best examined in each region individually as opposed to overall change. In Halton Region the increase in urban land would be exaggerated, since spectrally similar boundary pixels of the MREA areas are erroneously classified as urban. The change values in the urban class of the Hamilton Region would be more accurate since very minimal MREA class exists in this region. The examination of urban change in the Hamilton Region alone eliminated this major limitation of this class, therefore yielding more accurate results. The Regional Municipality of Hamilton experienced a 7.7 km^2 increase in urban land cover.

Similarly, there were areas of urban developments that were mistakenly classified as MREA in the Plan area. It was determined that areas of early development, usually with exposed soil or bedrock, were classified MREA in 1986 or 1996 and appeared as urban developments in the final 2006 image. This is due to the spectral similarity of the land cover materials. Overall there was much change in the MREA class but no increase. This is a positive result, as one of the primary reasons the Plan was created was to monitor and control mineral resource extraction operations on the Escarpment. However, this result may be deceiving. Large areas of mineral resource extraction turned into water by 2006. Usually the creation of some of these water bodies came with slight expansions to the quarrying operations, so with the change of MREA to water there were also changes of forest and agricultural area to MREAs. The expansions that did occur remained within the MREA designation and are permitted under the NEP.

Examining change based on each land use designation was a new approach proposed to examine change in the Plan area and also provided the ability to mask out some problem classes such as the MREA and the urban class to examine change based on Plan policies.

Five of the NEP land use designations were examined, and change statistics were calculated individually for each designation. The ENA is the core protection area of the NEP. Largely forested, this area saw minimal land cover change. There was a 12.9 km^2 increase in forested area that was mostly added through the conversion of agriculture 2 land. The EPA and ERA designations represent the buffer areas of the NEP. Put in place to protect the core of the Escarpment, a wider range of land cover changes was seen in these designations. In the EPA the familiar trend of an increase in forested area and a decrease in agricultural land was seen, with the agriculture land being converted to forest area. Although an overall increase was observed, the forest class did change to some areas of recreation and urban. This change of forest to recreation exemplified one of the few negative changes seen in the Plan. A golf course was added in the EPA between 1986 and 2006, but is restricted under Plan policies. There was also a notable increase in urban area that is a more accurate representation of the urban changes in the plan since no MREA areas of similar spectral properties were included. In the ERA, all classes showed some increase except for the agricultural classes, which both decreased in area. If large changes continue to occur in these “buffer” designations, it could reduce the buffer around the most heavily protected section of the Escarpment, making these sensitive areas more vulnerable.

Since two of the land cover classes studied in this work had their own NEP land use designations, studying these designations individually offered much insight into the changes occuring in these classes. The urban designation encompasses most of the heavier urbanized areas within the NEP. As expected the urban class increased, but so too did the forest class. This result could suggest that natural areas even within urban boundaries are increasing. This could be seen visually as the forest class increased within residential developments, for example. The MREA designation made it possible to look at changes in individual quarry operations. It was easy to see expansions and the start of rehabilitation efforts. Forest and agriculture 2 areas decreased as some of these areas were converted to the MREA class, which increased slightly. There was a large increase in urban area, but this was identified earlier as a mis-classification. The urban class surrounding the boundaries of most MREA areas was actually considered MREA, and so there was some increase to the class. There was a large increase in water as ponds were added within MREA boundaries for future rehabilitation efforts. For the most part, all MREA operations stayed within the boundaries of the designation.

6.2 Limitations

Limitations to this study exist and should be identified so correct information may be drawn from the conclusions. Limitations exist at every step of a remote sensing study, from data acquisition, to the decisions that are made with the final information. It is the job of the analyst to do everything possible to minimize these errors at every step of the remote sensing classification process, and it is the job of the final user to acknowledge these potential limitations when making decisions based on the information.

Error may be introduced at any step of the project and can be built upon throughout the work (Jensen, 2005). Error can begin at the point of data acquisition, although the analyst has no control over this error. The analyst starts to have control over the quality of the data and information once pre-processing begins. In the example of this study, the images were acquired from the GRCA. Geometric corrections were performed at the GRCA and upon visual inspection were deemed adequate for the purposes of this study. Once the data was received, atmospheric correction was performed. Even though this correction was performed with as much data input as possible, some assumptions were made which could result in some degree of error.

There are limitations associated with the selection of the Landsat 5 TM data for this study. Issues of spatial and temporal resolutions must be considered for an accurate classification. The 30 m spatial resolution of the Landsat 5 TM data (or in the case of this study, 25 m re-sampled) was chosen, since this scale was ideal for a regional study of the Niagara

Escarpment. Some land cover classes however, had objects on the ground smaller than the resolution of the imagery which reduced the classification accuracy of these classes and introduced a mixed pixel affect. The urban, MREA and recreation classes were affected by this limitation. The major drawback this caused was with the creation of boundary pixels around individual land cover objects. As an example, the edges of agricultural fields were often misclassified due to the other vegetation types surrounding the fields. This was present in other classes as well. The edges of water bodies were often mixed with vegetation, which made these two classes spectrally similar. Also the edges of the MREAs mixed with vegetation and created an erroneous urban classification. Since the object oriented approach obtained an average spectral value from each object, mixed boundary pixels could have an effect on how each object was classified (Dean and Smith, 2003).

There were limitations with the change detection due to the dates of imagery. Even though images were chosen to cover as much of the lifespan of the Plan as possible, each of the three images were captured at different times during the year. An attempt was made to use images from approximately the same time of year, but the dates ranged from May 29, 1996 to June 03, 1986 to August 13, 2006. As a result, slight differences in vegetation phenology, especially with the agricultural classes, introduced error. The 2006 image was fairly late in the growing season and the 1986 image was fairly early in the growing season, and so this difference needs to be acknowledged when examining the change statistics.

Although every precaution was taken to perform an accurate classification, human error may sometimes be introduced. A high degree of knowledge of the study site was incorporated into the creation of the training data and of the classification of the ground reference points used for accuracy assessment. To accomplish this, high resolution orthoimagery from 2005 and 1995 were used for the 2006 and 1996 images respectively. This process would only be as accurate as the skill of the analyst for air photo interpretation. Alternatively field visits could have been conducted for the collection of “ground truth” information. The collection of in situ data was excluded from the analysis since field work would have taken place in 2008 and the high resolution orthoimagery was closer to the Landsat image dates. Unfortunately there was no imagery available for the 1986 image and so the training and ground reference point data sets had to be classified based on the Landsat 5 TM image and user knowledge. This could account for the 1986 image having the lowest overall classification accuracy. For some classification algorithms (such as the SVM and object oriented classifications), the analyst must enter parameter data. The optimal parameters were chosen on a trial and error basis to determine which parameters would yield the best results.

The amount and type of land cover classes were chosen wisely, so the entire image would be classified. Areas of “no data” cannot be included for land cover change detection. Considering the 25m spatial resolution of the images, classes had to be selected based on what land cover feature could be detected at this scale. The original set of 12 classes had to be reduced, once initial classification trials showed potential separability issues between some of the classes. Early on in the study it was determined that one of the original classes under consideration, wetlands, would not be included in the classification. Wetland areas were difficult to classify at the 25m resolution of the Landsat 5 TM data, since different types of wetlands range in size and the amount of water and vegetation present. This class was spectrally similar to the forest, water and agriculture 2 and agriculture 4 classes and was almost impossible to separate. As the study progressed similar classes were merged to obtain the highest accuracy possible. The water/shallow water, coniferous/deciduous forest, agriculture 1/3 and agriculture 2/4 classes were all merged, while the “other vegetation” class was deleted from the classification altogether. Although these changes increased the classification accuracy some remaining classes still presented separability issues. The forest and agriculture 2 classes were the most similar along with the recreation class since typically all these classes contained healthy vegetation. To a lesser degree, spectral similarity between the MREA, Urban and agriculture 1 classes also existed.

Finally, and most importantly to note, any errors accrued throughout the classification process will be carried forward to the change detection results. Since classification of remote sensing data is merely a representation of the information captured at the sensor (which can have errors as well), it is nearly impossible to achieve 100% classification map accuracy, so some degree of error will always exist. Sing (1989) states that if two classified images are used for change detection their combined accuracy is only as good as the product of their accuracies. In this case overall change was calculated using the 1986 and 2006 images that had overall accuracies of 82.6% and 89.6% respectively. This means that they may only have a joined 74% overall accuracy ($0.826 \times 0.896 \times 100 = 74\%$). Due to the above limitations, qualitative visual analysis was necessary to identify problem classes and justify the final change detection statistics. It is important to acknowledge these errors when using the information provided in the final results. One positive aspect of having limitations to any study means that directions and improvements for continued or future work may be identified. It is also important to note where this work falls short in providing land cover change information to the NEC. At a regional scale and with these particular image dates, it was not possible to determine specific changes in agricultural crop types. It was also not possible to determine various types and stages of forest growth. Smaller scale land cover features such as urban, MREA and recreational areas were classified with lower accuracy values, resulting in lower confidence in the statistical change analysis for these classes. Again, due to these limitations, qualitative analysis of the changes occurring in the Hamilton and Halton portions of the NEP were a valuable part of the analysis.

6.3 Summary of Conclusions

Landsat 5 TM remotely sensed data is ideal for a regional land cover study in the NEP area. A SVM supervised classification provided the highest overall accuracy for the creation of land cover maps versus other traditional per-pixel and object oriented supervised classifications. The overall average accuracy of 86.7% was ideal for further land cover change studies through a post-classification qualitative and quantitative analysis.

The results of this study can provide much knowledge on the changing landscape of the Escarpment to the NEC. An advantage to using remote sensing data to monitor land cover changes is that studies can be conducted over regular time intervals, so land cover information can be updated frequently. Cowell *et al.* (1997) stated that changes in land cover in the NEP should be conducted every 5 years. Implementation of a regular land cover monitoring schedule would be useful for the NEC since Plan reviews are required every 5 years so the NEP can be updated. This study shows how remote sensing can help monitor the Escarpment, detect the changes occurring on the landscape and provide useful information to the NEC for monitoring and updating Plan policies.

This study acts as a baseline study to provide a regional look at land cover change in a portion of the NEP. The SVM method provided accurate land cover maps at a regional scale and provided the NEC with an overview of which key land cover types where changing in the NEP area. Through the analysis of the SVM classification results it could be determined which classes were increasing, which were decreasing and where geographically these changes were occurring. Overall, the major changes that occurred in the Plan area were an increase in forested area, a decrease in agricultural land, relatively little increase in MREA and slight urban expansions. Agricultural land is on the decline in the Plan area, mirroring a similar trend to the rest of the Province. The slight expansions of MREA were contained within their designation. There were also some positive changes in the MREA designation, showing some areas of rehabilitation. Urban expansion occurred mostly in the form of residential development and roadways. These urban expansions were also largely contained within the urban designation. An examination of the change in each NEP land use designation indicated that the majority of the changes experienced in the NEP over the 20 year time period coincide with the policies outlined in the Plan. General knowledge of where land cover changes are occurring can direct the NEC to future land cover change research in the NEP area.

To improve upon the work examined in this study, the next step will be to examine where major changes are occurring in greater detail through the use of higher resolution imagery. Higher resolution imagery such as Ikonos will provide multispectral remote sensing imagery at a 4m resolution (Jensen, 2005). It also has a 1m panchromatic band that can be incorporated into the classification and used to increase accuracy (Jensen, 2005). Higher resolution imagery would be better suited for the classification of smaller scale land use classes such as urban areas, MREAs and recreational areas. Although high resolution imagery can enhance the SVM classification, alternative classification methods may also work to improve classification accuracy. Object oriented classification is well suited for high resolution data and could aid the NEC in conducting more in-depth land cover analysis. Since this methodology focuses on image objects as opposed to pixels, this method could help enhance the change analysis of agriculture in the NEP as well as more detailed forest fragmentation studies. The results of object oriented classification mapping can also be easily incorporated with existing NEC GIS data sets. For the incorporation of ancillary data and expert knowledge to enhance classification, an expert systems approach may be useful for the NEC. Expert knowledge is used for a multi-stage classification to make a series of decisions and mimics human decision making with multiple data sets (Richards and Jia, 2006). This technique could be valuable to the NEC since more data and background knowledge could provide extra information for image classification enhancement. Land cover change in the NEP must continue to be monitored into the future to ensure that certain land cover types (such as MREA and urban) remain within their designated boundaries so the more highly protected areas of the Escarpment (such as the ENA and EPA) remain protected for future generations to enjoy. Continued research into new remote sensing data sets and methods is needed to continue monitoring land cover change in the NEP.

6.4 Future Research

With land cover mapping and change analysis completed for portions of the NEP that has been fully assessed for accuracy, further research into the use of remote sensing data for monitoring land cover changes in the NEP can progress. Although the SVM classifier performed well for the study area, there are still many new techniques, such as the object oriented classification and the expert systems approach that should be explored in greater depth to increase mapping accuracy in the Plan area. The object oriented approach may be better suited for more local scale studies along the escarpment with higher spatial resolution data. The final classification maps produced from the object oriented approach are also compatible with GIS, since classification is based on polygons or "objects". An expert systems approach could increase classification map accuracy through the inclusion of expert knowledge and a wealth of ancillary data. Although more work could always be done in terms of choosing the appropriate classification algorithms at the regional scale, more local scale studies should be conducted for problem areas that may be detected at the regional scale specifically. Local scale studies with higher resolution data (such as Ikonos) could be useful for urban area and MREA analysis in the NEP. A whole other body of literature exists on the advances being made in urban area remote sensing (Forster, 1985; Ward *et al.*, 2000; Masser, 2001; Miller and Small, 2003; Maktav *et al.*, 2005).

The use of ancillary data to enhance the classification should also be explored. DEMs could be incorporated into the classification since the topographic effects of the Niagara Escarpment can introduce errors. Similar land cover change studies have been conducted using GIS (Walker and Solecki, 1999; Schultz, 2002). In situ measurements for use in a GIS can be useful for land cover change, but only remote sensing can provide detailed, quantitative land cover information at large spatial scales and at frequent temporal intervals (Prenzel, 2004). GIS could be used to enhance the classification accuracy results. Some areas of known land cover type could be masked out so as to not introduce error. This was attempted for the MREA class but yielded poor results. The resulting classification maps could be converted into vector format and edited in a GIS to improve accuracy and have operational maps for GIS purposes.

Land cover change studies should be continued along the length of the NEP using Landsat 5TM data. Landsat data has ideal spectral temporal and spatial scales for regional land cover analysis and is ideal for a regional land use plan such as the NEP. A move towards a standardized method for mapping land cover change on the Escarpment at regular time intervals should be made for the ONE monitoring initiative, and remote sensing data and methodologies can help to achieve this. More in-depth studies should also be undertaken for each designation. Since each designation has its own land use policies, it is important to monitor these areas to ensure that all developments or changes on the landscape are compatible with the Niagara Escarpment and its Plan.

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Appendix A

Confusion Matrices for 1996 and 2006 Images

1996 Overall Accuracy (1134/1288) 88.04%

Kappa Coefficient 0.8548

Class	Ground Truth (Pixels/Percentages)								
		Forest	**MREA (Quarry)**	**Recreation**	**Water**	**Agriculture 1**	**Agriculture 2**	**Urban**	**Total**
	Forest	**252**	0	3	13	0	3	4	275
	MREA (Quarry)	0	**88**	0	0	4	0	12	104
	Recreation	0	0	**52**	0	0	5	1	58
	Water	7	1	0	**136**	0	2	0	146
	Agriculture 1	1	12	0	3	**266**	1	19	302
	Agriculture 2	21	0	13	0	4	**254**	13	305
	Urban	1	8	0	0	2	1	**86**	98
	Total	282	109	68	152	276	266	135	**1288**

2006 Overall Accuracy (1491/1664) 89.60%

Kappa Coefficient 0.8747

Class	Ground Truth (Pixels/Percentages)								
		Forest	**MREA (Quarry)**	**Recreation**	**Water**	**Agriculture 1**	**Agriculture 2**	**Urban**	**Total**
	Forest	**302**	1	2	23	1	13	11	353
	MREA (Quarry)	0	**96**	0	0	2	0	10	108
	Recreation	0	0	**102**	0	2	12	2	118
	Water	0	0	0	**218**	0	0	1	219
	Agriculture 1	3	9	0	7	**311**	3	30	363
	Agriculture 2	6	0	7	0	3	**355**	2	373
	Urban	2	17	0	2	2	0	**107**	130
	Total	313	123	111	250	321	383	163	**1664**

Appendix B

User/Producer Accuracy and Commission/Omission Values

1986 Commission/Omission Values and User and Producer Accuracies

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Forest	15.13	15.75	41/271	43/273
Agriculture 1	14.64	3.52	47/321	10/284
Agriculture2	23.48	28.41	58/247	75/264
Recreation	32.23	3.53	39/121	3/85
Urban	24.59	51.58	15/61	49/95
MREA	13.39	20.49	15/112	25/122
Water	0	9.01	0/101	10/111

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Forest	84.25	84.87	230/273	230/271
Agriculture 1	96.48	85.36	274/284	274/321
Agriculture 2	71.59	76.52	189/264	189/247
Recreation	96.47	67.77	82/85	82/121
Urban	48.42	75.41	46/95	46/61
MREA	79.51	86.61	97/122	97/112
Water	90.99	100	101/111	101/101

1996 Commission/Omission Values and User and Producer Accuracies

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Forest	8.36	10.64	23/275	30/282
Agriculture 1	11.92	3.62	36/302	10/276
Agriculture 2	16.72	4.51	51/305	12/266
Recreation	10.34	23.53	6/58	16/68
Urban	12.24	36.3	12/98	49/135
MREA	15.38	19.27	16/104	21/109
Water	6.85	10.53	10/146	16/152

Class	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
	(Percent)	(Percent)	(Pixels)	(Pixels)
Forest	89.36	91.64	252/282	252/275
Agriculture 1	96.38	88.08	266/276	266/302
Agriculture 2	95.49	83.28	254/266	254/305
Recreation	76.47	89.66	52/68	52/58
Urban	63.7	87.76	86/135	86/98
MREA	80.73	84.62	88/109	88/104
Water	89.47	93.15	136/152	136/146

2006 Commission/Omission Values and User and Producer Accuracies

Class	Commission	Omission	Commission	Omission
	(Percent)	(Percent)	(Pixels)	(Pixels)
Forest	14.45	3.51	51/353	11/313
Agriculture 1	14.33	3.12	52/363	10/321
Agriculture 2	4.83	7.31	18/373	28/383
Recreation	13.56	8.11	16/118	9/111
Urban	17.69	34.36	23/130	56/163
MREA (Quarry)	11.11	21.95	12/108	27/123
Water	0.46	12.8	1/219	32/250

Class	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
	(Percent)	(Percent)	(Pixels)	(Pixels)
Forest	96.49	85.55	302/313	302/353
Agriculture 1	96.88	85.67	311/321	311/363
Agriculture 2	92.69	95.17	355/383	355/373
Recreation	91.89	86.44	102/111	102/118
Urban	65.64	82.31	107/163	107/130
MREA (Quarry)	78.05	88.89	96/123	96/108
Water	87.2	99.54	218/250	218/219

Appendix C

NEP Designation Change Detection Statistics

Escarpment Natural Area (ENA)

Final State 2006		**Initial State 1986** [Pixel (area in km2, **percentage**)]							
		Forest	MREA	Recreation	Urban	Water	Agriculture 1 (bare soil)	Agriculture 2 (crop)	Row Total/Class Total
	Water	253(0.2,**0.2**)	0(0.0,**0.0**)	1(0.0,**0.1**)	18(0.0,**0.8**)	3598(2.2, **79.5**)	10(0.0,**0.3**)	67(0.0,**0.3**)	3947(2.5,**100.0**)
	Urban	357(0.2,**0.3**)	5(0.0,**27.8**)	19(0.0,**2.3**)	1284(0.8, **59.6**)	24(0.0,**0.5**)	252(0.2,**8.3**)	1021(0.6,**4.0**)	2962(1.9,**100.0**)
	MREA	58(0.0,**0.0**)	12(0.0,**66.7**)	0(0.0,**0.0**)	6(0.0,**0.3**)	0(0.0,**0.0**)	7(0.0,**0.2**)	7(0.0,**0.0**)	90(0.1,**100**)
	Forest	124230(77.6, **98.1**)	0(0.0,**0.0**)	392(0.2,**47.4**)	577(0.4,**26.8**)	749(0.5,**16.6**)	1342(0.8,**44.1**)	20054(12.5, **77.9**)	147344(92.1, **100.0**)
	Agriculture 2 (crop)	910(0.6,**0.7**)	0(0.0,**0.0**)	253(0.2,**30.6**)	113(0.1, **5.2**)	92(0.1,**2.0**)	521(0.3,**17.1**)	2482(1.6,**9.6**)	4371(2.7,**100.0**)
	Recreation	24(0.0,**0.0**)	0(0.0,**0.0**)	78(0.0,**9.4**)	2(0.0,**0.1**)	0(0.0,**0.0**)	32(0.0,**1.1**)	109(0.1,**0.4**)	245(0.2,**100.0**)
	Agriculture 1 (bare soil)	826(0.5,**0.7**)	1(0.0,**5.6**)	84(0.1,**10.2**)	154(0.1,**7.1**)	62(0.0,**1.4**)	876(0.5,**28.8**)	2010(1.3,**7.8**)	4013(2.5,**100.0**)
	Class Total	126658(79.2, **100.0**)	18(0.0,**100.0**)	827(0.5, **100.0**)	2154(1.3, **100.0**)	4525(2.8, **100.0**)	3040(1.9, **100.0**)	25750(16.1, **100.0**)	
	Class Changes	2428(1.5,**1.9**)	6(0.0,**33.3**)	749(0.5,**90.6**)	870(0.5,**40.4**)	927(0.6,**20.5**)	2164(1.4,**71.2**)	23268(14.5, **90.4**)	
	Image Difference	20686(12.9, **16.3**)	72(0.0,**400.0**)	-582(-0.4, **-70.4**)	808(0.5,**37.5**)	-578(-0.4, **-12.8**)	973(0.6,**32.0**)	-21379(-13.4, **-83.0**)	

Escarpment Protection Area (EPA)

		Initial State 1986 [Pixel (area in km2, **percentage**)]							
		Forest	MREA	Recreation	Urban	Water	Agriculture 1 (bare soil)	Agriculture 2 (crop)	Row Total/Class Total
Final State 2006	Water	90(0.1,**0.2**)	1(0.0,**0.2**)	23(0.0,**0.2**)	37(0.0,**0.5**)	1959(1.2, **78.0**)	60(0.0,**0.1**)	150(0.1,**0.2**)	2320(1.5,**100.0**)
	Urban	319(0.2,**0.9**)	177(0.1,**29.0**)	366(0.2,**3.7**)	5135(3.2, **62.9**)	26(0.0,**1.0**)	3540(2.2,**7.8**)	3219(2.0,**4.5**)	12782(8.0,**100.0**)
	MREA	13(0.0,**0.0**)	268(0.2,**43.9**)	8(0.0,**0.1**)	65(0.0,**0.8**)	0(0.0,**0.0**)	171(0.1,**0.4**)	81(0.1,**0.1**)	606(0.4,**100.0**)
	Forest	29666(18.5, **81.8**)	21(0.0,**3.4**)	1019(0.6, **10.4**)	561(0.4,**6.9**)	357(0.2,**14.2**)	4434(2.8,**9.7**)	26545(16.6, **36.9**)	62603(39.1,**100.0**)
	Agriculture 2 (crop)	3449(2.2,**9.5**)	44(0.0,**7.2**)	3498(2.2, **35.5**)	773(0.5,**9.5**)	48(0.0,**1.9**)	16550(10.3, **36.3**)	22900(14.3, **31.8**)	47262(29.5,**100.0**)
	Recreation	560(0.4,**1.5**)	5(0.0,**0.8**)	3435(2.1, **34.9**)	32(0.0,**0.4**)	7(0.0,**0.3**)	1389(0.9,**3.0**)	1776(1.1,**2.5**)	7204(4.5,**100.0**)
	Agriculture 1 (bare soil)	2179(1.4,**6.0**)	94(0.1,**15.4**)	1495(0.9, **15.2**)	1561(1.0, **19.1**)	115(0.1,**4.6**)	19432(12.1, **42.6**)	17247(10.8, **24.0**)	42123(26.,**100.0**3)
	Class Total	36276(22.7, **100.0**)	610(0.4, **100.0**)	9844(6.2, **100.0**)	8164(5.1, **100.0**)	2512(1.6, **100.0**)	45576(28.5, **100.0**)	71918(44.9, **100.0**)	
	Class Changes	6610(4.1,**18.2**)	342(0.2,**56.1**)	6409(4.0, **65.1**)	3029(1.9, **37.1**)	553(0.3,**22.0**)	26144(16.3, **57.4**)	49018(30.6, **68.2**)	
	Image Difference	26327(16.5,**72.6**)	-4(0.0,**-0.7**)	-2640(-1.7, **-26.8**)	4618(2.9, **56.6**)	-192(-0.1, **-7.6**)	-3453(-2.2, **-7.6**)	-24656(-15.4, **-34.3**)	

Escarpment Rural Area (ERA)

	Initial State 1986 [Pixel (area in km2, **percentage**)]							
Final State 2006	Forest	MREA	Recreation	Urban	Water	Agriculture 1 (bare soil)	Agriculture 2 (crop)	Row Total/Class Total
Water	46(0.0,**0.2**)	4(0.0,**1.8**)	20(0.0,**0.4**)	19(0.0,**0.3**)	162(0.1,**58.9**)	64(0.0,**0.1**)	154(0.1,**0.2**)	469(0.3,**100.0**)
Urban	284(0.2,**0.9**)	96(0.1,**43.8**)	143(0.1,**2.7**)	3207(2.0, **54.7**)	13(0.0,**4.7**)	3343(2.1,**5.8**)	2838(1.8,**4.1**)	9924(6.2,**100.0**)
MREA	35(0.0,**0.1**)	39(0.0,**17.8**)	8(0.0,**0.2**)	67(0.0,**1.1**)	0(0.0,**0.0**)	154(0.1,**0.3**)	97(0.1,**0.1**)	400(0.3,**100.0**)
Forest	24241(15.2, **80.3**)	2(0.0,**0.9**)	604(0.4,**11.4**)	468(0.3,**8.0**)	43(0.0,**15.6**)	5228(3.3,**9.1**)	21906(13.7, **31.6**)	52492(32.8,**100.0**)
Agriculture 2 (crop)	2829(1.8,**9.4**)	11(0.0,**5.0**)	1897(1.2, **35.7**)	700(0.4,**11.9**)	19(0.0,**6.9**)	25310(15.8, **44.0**)	23370(14.6, **33.7**)	54136(33.8,**100.0**)
Recreation	334(0.2,**1.1**)	4(0.0,**1.8**)	1345(0.8, **25.3**)	62(0.0,**1.1**)	1(0.0,**0.4**)	2287(1.4,**4.0**)	2396(1.5,**3.5**)	6429(4.0,**100.0**)
Agriculture 1 (bare soil)	2411(1.5,**8.0**)	63(0.0,**28.8**)	1302(0.8, **24.5**)	1341(0.8, **22.9**)	37(0.0,**13.5**)	21104(13.2, **36.7**)	18505(11.6, **26.7**)	44763(28.0,**100.0**)
Class Total	30180(18.9, **100.0**)	219(0.1, **100.0**)	5319(3.3, **100.0**)	5864(3.7, **100.0**)	275(0.2, **100.0**)	57490(35.9, **100.0**)	69266(43.3, **100.0**)	
Class Changes	5939(3.7,**19.7**)	180(0.1,**82.2**)	3974(2.5, **74.7**)	2657(1.7, **45.3**)	113(0.1,**41.1**)	36386(22.7, **63.3**)	45896(28.7, **66.3**)	
Image Difference	22312(13.9, **73.9**)	181(0.1,**82.6**)	1110(0.7, **20.9**)	4060(2.5, **69.2**)	194(0.1,**70.5**)	-12727(-8.0, **-22.1**)	-15130(-9.5, **-21.8**)	

Mineral Resource Extraction Area (MREA)

	Initial State 1986 [Pixel (area in km2, **percentage**)]							
Final State 2006	Forest	MREA	Recreation	Urban	Water	Agriculture 1 (bare soil)	Agriculture 2 (crop)	Row Total/Class Total
Water	565(0.4,**10.6**)	1112(0.7, **16.5**)	59(0.0,**11.3**)	224(0.1,**10.8**)	43(0.0,**37.7**)	604(0.4,**11.8**)	346(0.2,**7.0**)	2953(1.8,**100.0**)
Urban	704(0.4,**13.3**)	1476(0.9, **21.9**)	99(0.1,**19.0**)	809(0.5,**38.9**)	26(0.0,**22.8**)	877(0.5,**17.1**)	677(0.4,**13.8**)	4668(2.9,**100.0**)
MREA	1590(1.0,**30.0**)	2771(1.7, **41.1**)	174(0.1,**33.4**)	443(0.3,**21.3**)	10(0.0,**8.8**)	741(0.5,**14.4**)	1049(0.7,**21.3**)	6778(4.2,**100.0**)
Forest	1653(1.0,**31.1**)	135(0.1,**2.0**)	98(0.1,**18.8**)	191(0.1,**9.2**)	24(0.0,**21.1**)	576(0.4,**11.2**)	1208(0.8,**24.6**)	3885(2.4,**100.0**)
Agriculture 2 (crop)	91(0.1,**1.7**)	156(0.1,**2.3**)	37(0.0,**7.1**)	74(0.0,**3.6**)	2(0.0,**1.8**)	275(0.2,**5.4**)	390(0.2,**7.9**)	1025(0.6,**100.0**)
Recreation	0(0.0,**0.0**)	16(0.0,**0.2**)	5(0.0,**1.0**)	0(0.0,**0.0**)	0(0.0,**0.0**)	11(0.0,**0.2**)	1(0.0,**0.0**)	33(0.0,**100.0**)
Agriculture 1 (bare soil)	705(0.4,**13.3**)	1077(0.7, **16.0**)	49(0.0,**9.4**)	340(0.2,**16.3**)	9(0.0,**7.9**)	2045(1.3,**39.9**)	1247(0.8,**25.4**)	5472(3.4,**100.0**)
Class Total	5308(3.3, **100.0**)	6743(4.2, **100.0**)	521(0.3, **100.0**)	2081(1.3, **100.0**)	114(0.1, **100.0**)	5129(3.2, **100.0**)	4918(3.1, **100.0**)	
Class Changes	3655(2.3,**68.9**)	3972(2.5, **58.9**)	516(0.3,**99.0**)	1272(0.8, **61.1**)	71(0.0,**62.3**)	3084(1.9,**60.1**)	4528(2.8,**92.1**)	
Image Difference	-1423(-0.9, **26.8**)	35(0.0,**0.5**)	-488(-0.3, **-93.7**)	2587(1.6, **124.3**)	2839(1.8, **2490.4**)	343(0.2,**6.7**)	-3893(-2.4, **-79.2**)	

Urban Area

Final State 2006	Initial State 1986 [Pixel (area in km2, **percentage**)]							
	Forest	MREA	Recreation	Urban	Water	Agriculture 1 (bare soil)	Agriculture 2 (crop)	Row Total/Class Total
Water	4(0.0, **0.1**)	0(0.0,**0.0**)	0(0.0,**0.0**)	23(0.0,**0.1**)	5(0.0,**45.5**)	7(0.0,**0.1**)	7(0.0,**0.1**)	46(0.0,**100.0**)
Urban	1135(0.7,**27.1**)	666(0.4,**95.4**)	115(0.1,**16.4**)	15775(9.9, **93.1**)	0(0.0,**0.0**)	2848(1.8,**40.8**)	5103(3.2,**38.9**)	25642(16.0,**100.0**)
MREA	37(0.0,**0.9**)	6(0.0,**0.9**)	2(0.0,**0.3**)	9(0.0,**0.1**)	0(0.0,**0.0**)	85(0.1,**1.2**)	109(0.1,**0.8**)	248(0.2,**100.0**)
Forest	2387(1.5,**57.0**)	2(0.0,**0.3**)	47(0.0,**6.7**)	645(0.4,**3.8**)	2(0.0,**18.2**)	558(0.3,**8.0**)	4237(2.6,**32.3**)	7878(4.9,**100.0**)
Agriculture 2 (crop)	484(0.3,**11.5**)	4(0.0,**0.6**)	134(0.1,**19.1**)	180(0.1,**1.1**)	0(0.0,**0.0**)	2116(1.3,**30.3**)	2111(1.3,**16.1**)	5029(3.1,**100.0**)
Recreation	27(0.0,**0.6**)	0(0.0,**0.0**)	307(0.2,**43.7**)	13(0.0,**0.1**)	0(0.0,**0.0**)	136(0.1,**1.9**)	147(0.1,**1.1**)	630(0.4,**100.0**)
Agriculture 1 (bare soil)	117(0.1,**2.8**)	20(0.0,**2.9**)	97(0.1,**13.8**)	304(0.2,**1.8**)	4(0.0,**36.4**)	1235(0.8,**17.7**)	1415(0.9,**10.8**)	3192(2.0,**100.0**)
Class Total	4191(2.6, **100.0**)	698(0.4, **100.0**)	702(0.4, **100.0**)	16949(10.6, **100.0**)	11(0.0,**100.0**)	6985(4.4, **100.0**)	13129(8.2, **100.0**)	
Class Changes	1804(1.1,**43.0**)	692(0.4,**99.1**)	395(0.2,**56.3**)	1174(0.7,**6.9**)	6(0.0,**54.5**)	5750(3.6,**82.3**)	11018(6.9, **83.9**)	
Image Difference	3687(2.3,**88.0**)	-450(-0.3, **-64.5**)	-72(0.0,**-10.3**)	8693(5.4, **51.3**)	35(0.0,**318.2**)	-3793(-2.4, **-54.3**)	-8100(-5.1, **-61.7**)	