MONITORING LAND COVER CHANGE IN ONTARIO'S GREENBELT REGION FROM 1985 TO 2005

by

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Author's Declaration

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Abstract

Ontario's Greenbelt surrounds the Golden Horseshoe Area (GHA) in Southern Ontario, Canada. The purpose of the Greenbelt is to protect key environmentally sensitive land and farmland from urban development and sprawl. The importance of this land was officially recognized in the Bill 135 (*Greenbelt Act*) and Bill 136 (*Places to Grow Act*) passed on February 2005 by the Ontario provincial government. The GHA is the fourth fastest growing urban region in North America and accounts for over 20 per cent of Canada's Gross Domestic Product (GDP). With rapid population increase in the GHA, there is tremendous pressure on municipalities to expand development into the Greenbelt. This research is focused on the detection of land cover change within the Greenbelt with the use of remote sensing and Geographic Information System (GIS). The image time series data selected for this project consists of Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+); spanning a twenty year period from 1985 to 2005. Various image differencing techniques, Texture Analysis (TA), the Tasselled Cap Transformation (TCT), Principal Component Analysis (PCA) and the Normalized Difference Vegetation Index (NDVI) were used in unsupervised image classification with an overall classification accuracy of 89.33 percent in 1999 and 90.67 percent in 2005. Change detection results indicated an increase of urban land area from 1985 to 2005 and a steady decrease in agricultural land use area from 1985 to 2005.

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List of Acronyms

CMA- Census Metropolitan Area

ETM+ – Enhanced Thematic Mapper plus

GDP – Gross Domestic Product

GHA – Golden Horseshoe Area

GIS – Geographic Information System

L1 T/G – Level 1 systematic and terrain corrected data product

MIR – Mid-infrared

NDVI – Normalized Difference Vegetation Index

NDMI - Normalized Difference Moisture Index

NIR – Near Infrared

ORM – Oak Ridges Moraine

PCA – Principle Component Analysis

PCIDSK – PCI Geomatics Database File

TA – Texture Analysis

TCT – Tasselled Cap Transformation

TEX – Texture Analysis

TM – Thematic Mapper

UTM – Universal Transverse Mercator

USGS – U.S. Geological Survey

CHAPTER 1: INTRODUCTION

1.1: Ontario's Greenbelt

Ontario's Greenbelt is an area of permanently protected green space, farm lands, forest, wetlands and watersheds. It surrounds a significant portion of Canada's most populated and fastest-growing urban region, known as the Golden Horseshoe Area (GHA). A total of 728,434 hectares of countryside in southern Ontario have been designated as the Ontario's Greenbelt (Greenbelt, 2012). The Greenbelt extends 325 kilometres from the Bruce Peninsula to the Niagara Escarpment, which includes the Oak Ridges Moraine (ORM) to the east. The purpose of the Greenbelt is to protect key land cover such as agricultural systems (specialty crop and prime agricultural lands), natural systems (fish habitats, wetlands, woodlands and wildlife habitats) and settlements (towns, villages, and hamlets) from urban development and sprawl. In February 2005, the provincial government recognized the importance of Ontario's Greenbelt in the passing of Bill 135 (*Greenbelt Act)* and Bill 136 (*Places to Grow Act)* (Fung and Conway, 2007). One of the key provisions of the *Greenbelt Act* is to protect, preserve and ensure economic viability for farming communities in the Southern Ontario region due to the fertile soil conditions which are prime for agriculture. Southern Ontario has more than 50 per cent of the province's first-class agricultural lands and procures about 25 percent of the total farm revenues in Canada (Ali, 2008). The *Greenbelt Act* imposes a freeze on privately owned agricultural lands that prevent development of agricultural land for non-agricultural uses. The Bill also restricts urban municipalities located outside of the Greenbelt Boundaries from expanding urban development within the Greenbelt.

Despite these restrictions, the *Greenbelt Act* allows settlement expansion in prime agricultural land and rural areas if the land does not include specialty crops or there are no other lands available in existing settlement to accommodate growth (Northey, 2005). Coinciding with the release of this act, the *Places to Grow Act* helps the provincial government to coordinate growth by providing guidance on land development, management of resources and investment of public money. The *Places to Grow Act* also gives the provincial government authority to appoint any geographic region of the province as a growth plan area, in consultation with local officials, stakeholders and members of the public (Ministry of Infrastructure, 2012). This legislation will promote growth to the communities involved in a way that incorporates a balance of both economic and environmental growth.

1.2: Urban Development and Sprawl

The Province of Ontario accommodates more than one-third of the Canadian population. In 2011, Ontario had a total population of 12.8 million, increase of 5.7 per cent since 2006. Ontario remains the most populous province in Canada, as it is home to 38.4 per cent of all Canadians inhabitants. About 68 per cent of Ontario's population lives in the GHA which includes the four following Census Metropolitan Areas (CMA); Toronto, Hamilton, St. Catharines-Niagara and Oshawa. The GHA is the fourth fastest growing urban region in North America and accounts for over 20 per cent of Canada's GDP (Statistics Canada, 2012). According to the 2011 Census, the fastest growing community in Canada is Milton, Ontario which saw a 56.5 per cent increase in residents from 53,889 in 2006 to 84,362 in 2011 (Statistic Canada, 2012). The town of

Whitchurch-Stouffville was the third fastest growing community, with a 54.3 per cent increase in its population from 24,390 in 2006 to 37,625 in 2011 (Statistics Canada, 2012). Milton being located near Ontario's Greenbelt has enough space to accommodate 350,000 people. The growth of Whitchurch-Stouffville's however, will be contained to around 60,000 because of its location within the Greenbelt area (Whitchurch-Stouffville, 2011). Similarly, the municipalities within the GHA experienced double-digit growth, as seen in Table 1-1.

Table 1-1: Population Growth from 1986 to 2011 (Statistic Canada, 2012)

	Population Growth from 1986 to 1991	Population Growth from 1991 to 1996	Population Growth from 1996 to 2001	Population Growth from 2001 to 2006	Population Growth from 2006 to 2011
Peel	23.7%	16.3%	16%	17.2%	11.8%
Halton	15.4%	8.5%	10.4%	17.1%	14.2%
York	44.0%	17.3%	23.1%	22.4%	8%

With this rapid increase of population in the GHA there is tremendous pressure on the municipalities to expand their city limits into the countryside thus threatening Ontario's first-class agricultural lands. With increasing urban expansion, urban sprawl in Ontario will destroy and pave over wildlife habitat, forest, wetlands and farmlands. Paving over farmlands and natural areas will disrupt the delicate water balance during heavy rain or snow fall. One key feature of the Ontario's Greenbelt is to contain and control urbanization and sprawl in the GHA. Thus, by implementing the *Greenbelt Act* and *Places to Grow Act*, these will help balance the economic development across the GHA while reducing the pressure on the Greenbelt.

1.3: Remote Sensing – Land cover change

With rapid changes in land cover occurring over large areas, the use of remotely sensed data is an essential tool in monitoring and mapping the change. In addition, remote sensing has been globally recognized as an accurate and cost effective method for researchers to monitor land cover changes at the regional scale (Fung, 1990; Lunetta et al., 2004; Vogelmann et al., 1998; Wilson and Sader, 2002). Many studies make use of remote sensing to monitor and evaluate the impact of urban growth on agricultural land (Stefanov et al., 2001; Yeh and Li, 1997). The use of Landsat imagery has been shown in the literature to be an effective dataset for detecting land cover change due to urbanization with high overall accuracy classification result (Forsythe and Waters, 2006; Fung, 1990; Keles et al., 2008; Stefanov et al., 2001). Yeh and Li's study (1997) used remote sensing techniques to detect land cover change. Multi-temporal remote sensing techniques were used to collect data in the Pearl River Delta in Dongguan, China. Close to one-quarter of Dongguan's area experienced rapid change from agricultural land to urban land between 1988 and 1993**.** Fung (1990) used Landsat Thematic Mapper (TM) images to identify land cover change from rural to urban land conversion in the Kitchener-Waterloo area in Ontario, Canada, with an overall accuracy of 85 per cent. A previous study by Cheng and Lee (2008) used pure spectral signatures from Landsat imagery to determine the land cover types within Ontario's Greenbelt. They concluded that the Oak Ridges Moraine had the most land cover change and that the Municipality of York had undergone the greatest amount of land cover change within the Greenbelt. However, their research did not provide an accuracy assessment on their classification. Such information collected through remote sensing can provide a crucial data link to other techniques in order to understand urban development and sprawl on the Greenbelt, within the GHA region.

1.4: Problem Statement and Research Objectives

The purpose of the Greenbelt is to protect key environmentally sensitive land and farmland from urban development and sprawl. Since there was no baseline for monitoring land cover change before and after the Greenbelt Act was introduced, this study may be beneficial when the government reviews the act in 2015. Remote sensing can be used in a change analysis methodology to determine the extent and location of major land cover conversions over the period from 1985 to 2005.

Remote sensing and GIS will be utilized in this study to meet the following objectives:

1) Identify, map and analyze land cover change within the Greenbelt,
2) Establish a baseline for the ongoing monitoring of future changes,
3) Use different imaging techniques to improve classification accuracy results.

1.5: Study Area

The study area is Ontario’s Greenbelt, which is located in Southern Ontario, Canada. The Greenbelt encompasses 728,000 hectares around the GHA which includes many environmentally sensitive areas such as the Bruce Peninsula, Niagara Escarpment, the Holland Marsh and the ORM. This study will focus on the Greenbelt surrounding the GHA as it is the fourth fastest growing urban region in North America and includes some urban centres bordering it. The topography of the study area varies from fertile and productive first-class agricultural lands to the flat and rolling hills of the ORM and to the Niagara Escarpment.

The ORM is an ecologically important geological landform in southern Ontario that covers 190,000 hectares between Caledon and Peterborough (Ministry of Municipal Affairs and Housing, 2007). The ORM was formed by glacial deposits in the late Wisconsonian glacial period about 12,000 years ago. In addition, this area is an important geological landform because it contains the largest concentration of headwater streams and acts as a recharge area for groundwater in the Greater Toronto Area (Barnett et al., 1998). Lastly, the ORM provides an ecologically diverse environment for a variety of flora and fauna communities to develop and thrive in (ORMLT. 2010).

The Holland Marsh is part of the Greenbelt from the western edge of the ORM and extends to Cook's Bay, Lake Simcoe. It comprises of approximately 8,000 hectares of prime agricultural land, also commonly referred to as Ontario's Vegetable Patch, because of the large variety and abundant amount of fresh produce that the area yields (Holland Marsh, 2008). Holland Marsh was incorporated into the Greenbelt to protect the prime fertile soil for farming from urban development and sprawl in the GHA.

The Niagara Escarpment is a largely forested ridge of dolostone, extending 725 km in length from St. Catherines to Tobermory. The highest elevation of the escarpment is over 510 metres above sea level. The Niagara Escarpment area encompasses a rich mixture of forest, farms, wetlands, rolling hills, waterfalls and wildlife habitats. The Niagara Escarpment was globally recognized as one of the World Network of Biosphere Reserves in Europe and North America in 1990 (Ontario's Niagara Escarpment, 2012).

Figure 1-1: Study Area.

CHAPTER 2: LITERATURE REVIEW AND METHODS

2.1: Data

The primary raster data source for this study is the USGS Earth Explorer Landsat data archive, freely accessible at http://earthexplorer.usgs.gov/. Landsat 5 TM and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) level 1 systematic and terrain corrected (L1T/G) images were acquired in Path 18, Row 29 and Path 18, Row 30. Both TM and ETM+ images contain the visible and infrared image bands 1 to 5 and 7 and the sensor has a compatible spatial resolution of 30m. Each image pixel covers a surface area of 900m^2. In the initial stage, over twenty-five images were acquired between 1984 and 2010, to find the most accurate sets of images that had similar growing season conditions (August to September) and that were cloud free over the study area. Another condition was to find three sets of images that would depict the land cover in: the 1980s when the *Greenbelt Act* was introduced, in the 1990s after the act was introduced to restrict urban development in the region, and the land cover close to present. The final sets of images that were selected for analyses are presented in Table 2-1.

Table 2-1: Landsat Images

Image Set	Image Date	Sensor
Path 18/ Row 29	September 20, 1985	Landsat 5 TM
Path 18/ Row 30	September 20, 1985	Landsat 5 TM
Path 18/ Row29	September 3, 1999	Landsat 7 ETM+
Path 18/ Row 30	September 3, 1999	Landsat 7 ETM+
Path 18/ Row29	August 26, 2005	Landsat 5 TM
Path 18/ Row 30	August 26, 2005	Landsat 5 TM

2.2: Image Pre-processing

The selected Landsat L1T/G visible and infrared image bands 1 – 5 and 7 were compiled into PCIDSK database files with a pixel resolution of 30 metres and georeferenced in NAD 1983, UTM Zone 17 North. An initial visual inspection was conducted to ensure they contained all the bands and were correctly aligned before mosaicking the images together. Mosaicking is a process that joins several overlapping images to form a uniform image. To achieve a seamless mosaic, it is best to use images acquired on the same date because the atmospheric conditions are similar and there would be minimal differences in reflectance between the images. Images from Path 18, Row 29 and Path 18, Row 30 were mosaicked into single images for the three chosen dates. The full Landsat mosaicked scene includes the Greenbelt surrounding the GHA and was subset to the Greenbelt's boundary to perform image band differencing techniques.

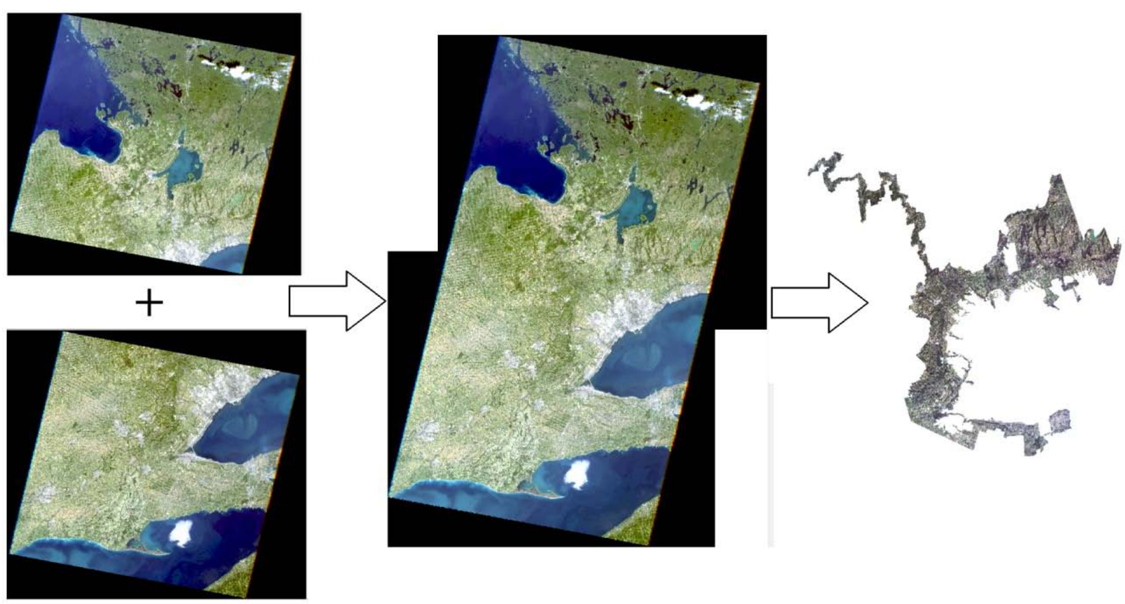

Figure 2-1: Steps use for image pre-processing.

2.3: Texture Analysis

Ontario's Greenbelt is mainly comprised of urbanized, agricultural lands and forested lands. These different types of land uses have distinct spatial edge texture that can be used as input into an unsupervised classification process (Gong and Howarth, 1990; Haralick et al., 1973; Iron and Petersen, 1981; Stuckens et al., 2000). Previous studies (Berberoglu et al., 2000; Forsythe, 2004; Gluch, 2002; Stefanov et al., 2001) have found texture measures to be valuable for detecting urban changes. Urban areas typically have significant texture resulting from buildings and street girds. In comparison, homogeneous areas such as agricultural lands have little to no texture (Lu and Weng, 2005; Stefanov et al., 2001). Various parameters (mean, dissimilarity, contrast and homogeneity) and window sizes (3x3, 5x5, 7x7) were generated using band 2 of the Landsat images. Band 2 was selected because it represents the visible green spectral bands. These parameters and windows sizes were chosen based on previous land cover change detection research (Forsythe and Waters, 2006; Lu and Weng, 2005; Stefanov et al., 2001). The mean texture measure, one of the best for urban applications, outlines the boundary of different agricultural fields and forested land (Zhang et al. 2003). As well, mean texture measures distinguish urban features from forested land (Figure 2-2). Dissimilarity texture measures delineate newly excavated areas and quarries in detail (Forsythe and Waters, 2006). Results from 3x3 window sizes were clearly superior to 5x5 or 11x11 window sizes in term of the amount of details distinguish from the image. In Figure 2-3, the 3x3 window size clearly illustrates the boundary of urban areas while 5x5 and 11x11 window sizes are too blurry to see the outlines of different boundaries. Previous research (Forsythe and Waters, 2006; Zhang et al. 2003) found that smaller window sizes allow greater variability, as seen in urban areas with higher spatial resolution images.

Figure 2-2: Mean Texture near Markham and Whitchurch-Stouffville, Ontario. Forest land is represented in darker shade while agricultural land is represented in lighter shades.

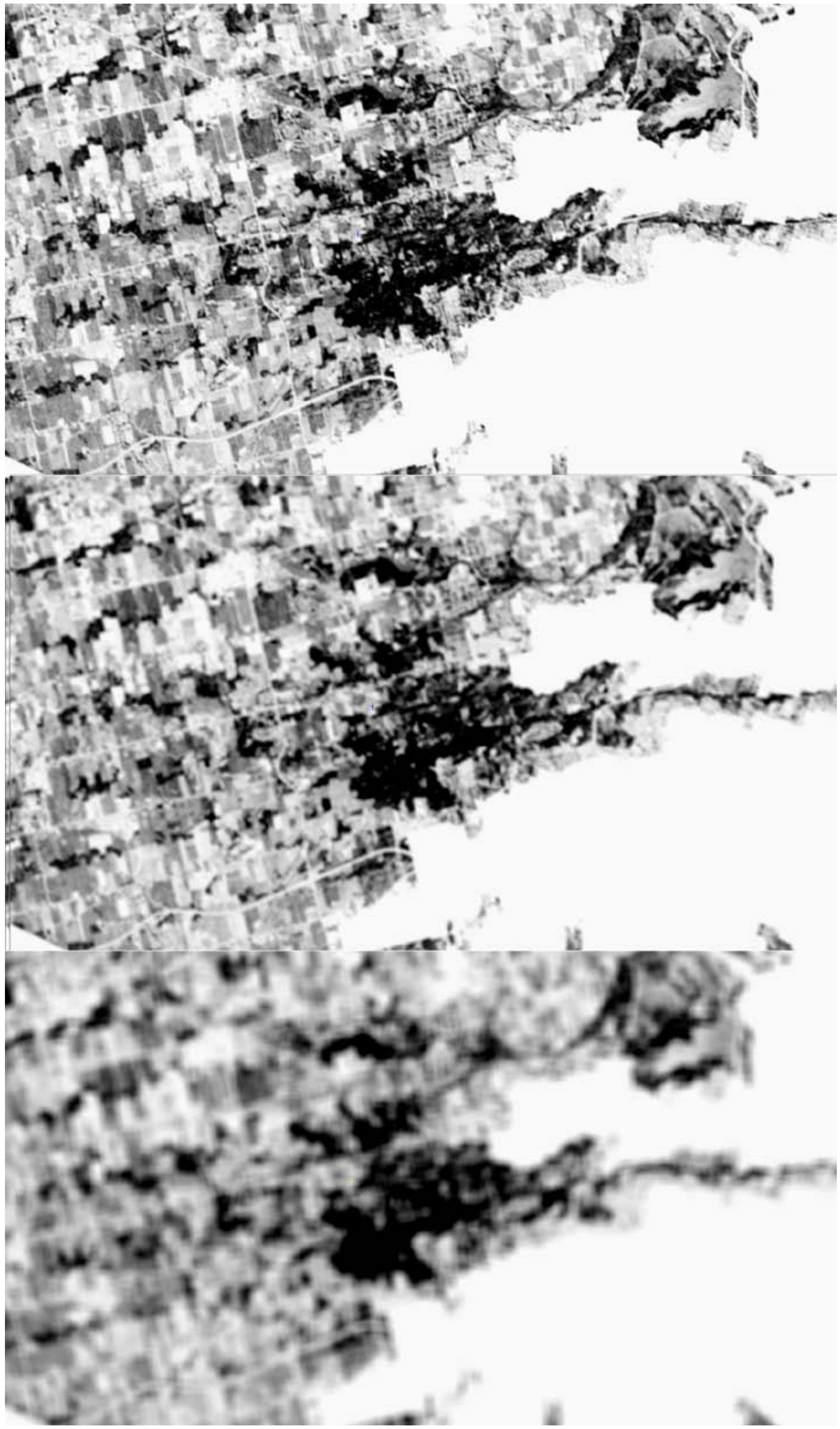

Figure 2-3: Mean texture window sizes 3x3, 5x5, 11x11 near Hamilton, Ontario (from top to bottom). Urban features are represented in white colour while darker shades represent forested land.

2.4: Tasselled Cap Transformation

The Tasselled Cap Transformation (TCT) condenses the original six Landsat reflectance bands and converts these into three known characteristics: brightness, greenness and wetness (Crist and Cicone, 1984; Kauth and Thomas, 1976). Brightness is a weighted sum of all the bands and it measures the soil brightness or total reflectance. Greenness is a contrast between the NIR band and visible bands. High greenness values are created due to high densities of green vegetation and flatter reflectance of soil; forested area has high greenness values while urban areas have a low density of green vegetation (expressed in low greenness values). Lastly, wetness is a contrast of the sum of the visible and NIR bands with the sum of longer-infrared bands (Crist and Cicone, 1984; Kauth and Thomas, 1976). This feature will highlight moisture related scene characteristics such as recently irrigated agricultural fields. TCT indices have been widely studied and successfully used in studies of agriculture, forest, ecology and landscape (Fung, 1990; Han et al., 2007; Healey et al., 2005). For instance, the wetness measure was used to characterize the dynamics of irrigated crops (Serra and Pons, 2008); while other TCT indices were used to assess land-cover change detection in Kitchener-Waterloo, Ontario, Canada (Fung, 1990); and to estimate the age of forest in British Columbia (Wulder et al., 2004). The brightness and wetness indices have also proven to produce more accurate forest disturbance maps in Russia (Healey et al., 2005). TCT was applied to all three sets of images and the brightness index distinctively outlines rivers, ponds and lakes in black shades due to the low reflectance property of water (Figure2-4).

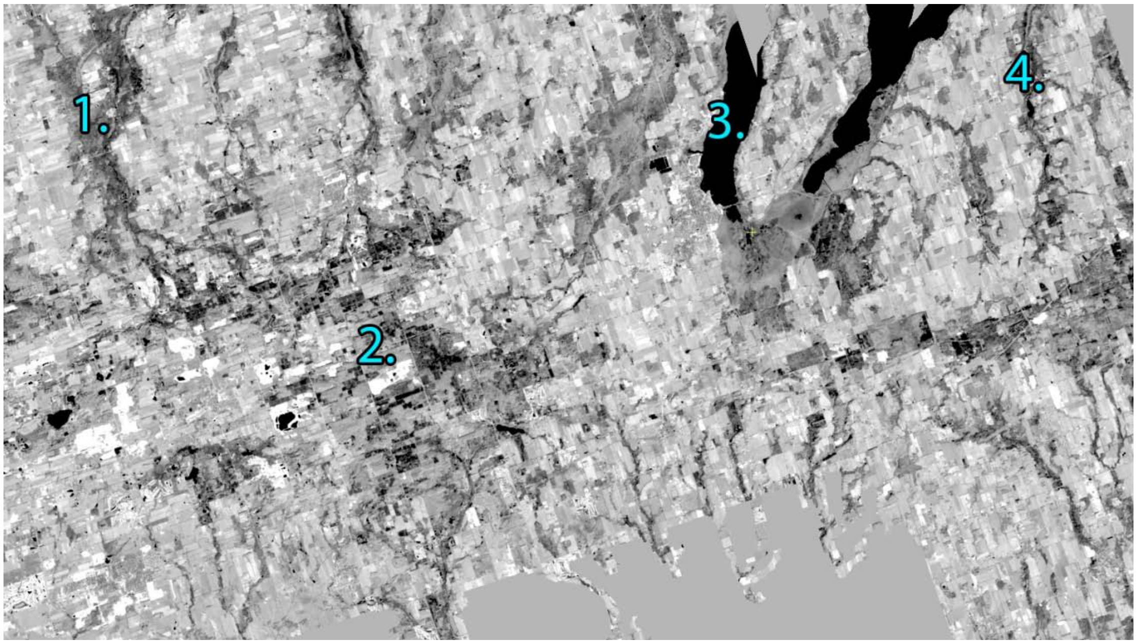

Figure 2-4: TCT Brightness near Uxbridge and Scugog, Ontario: 1. Forested Land, 2. Quarry, 3. Lake and 4. River.

2.5: Principal Component Analysis

Principal Component Analysis (PCA) reduces image dimensionality by compressing data into fewer bands (Byrne et al., 1980; Fung and LeDrew, 1988). PCA transformation produces new principal components (PC 1, PC 2, PC 3…etc.), which are uncorrelated with one another and ordered in terms of the amount of variance they explain from the original band set (Fung and LeDrew, 1988; Maldonada et al., 2002). The first three components typically account for more than 95 per cent of total variance in the original data (Byrne et al., 1980; Singh, 1989; Tsai et al., 2007). PCA has been used in change detection for many years and has become one of the most popular techniques because of its simplicity and capability of enhancing the information on change (Ingebritsen and Lyon, 1985; Lu and Weng, 2005; Maldonada et al., 2002). For instance, Yeh and Li (1997) successfully detected land cover change for nine towns in the Pearl River Delta, China, that had over 63.8 per cent of agricultural land converted into urban development. Prior work in urban classification has experienced overall accuracy improvement with the use of PCA (Maldonada et al., 2002; Lu and Weng, 2005).

The PCA transformation was performed separately on three data sets (1985, 1999, 2005) using three eigenchannels and output raster of 32R. PCA delineated the boundary between different features very clearly (Figure 2-5).

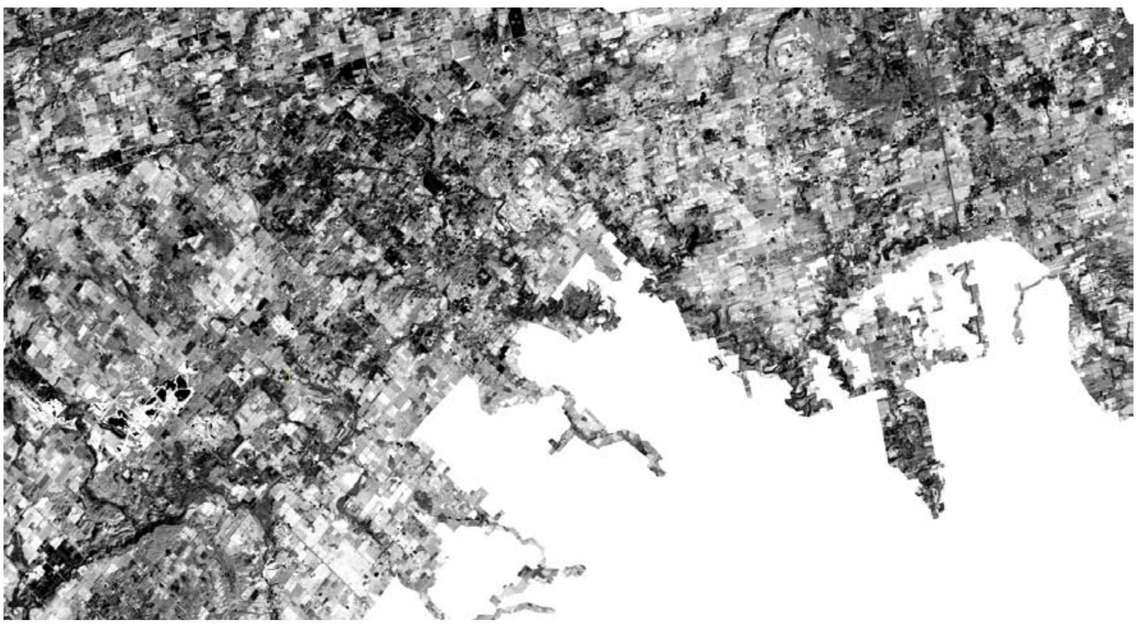

Figure 2-5: PC 1 of 1999 image near Caledon and Brampton, Ontario. Water bodies can be seen in black shade while agricultural lands are in lighter shade.

2.6: Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is used to identify vegetation health by measuring the infrared reflectance to that of the visible red bands (Fung and LeDrew, 1987). Sellers (1985) found that the difference of brightness values from the near infrared and visible red bands has been found to be highly correlated with crown closure, leaf area index and other vegetation parameters. The NDVI is calculated in the following manner:

$$NDVI = (NIR - R) / (NIR + R) \quad (1)$$

where NIR = Near Infrared

and R = Red Band

NDVI provides information about the spatial and temporal distribution of vegetation communities and vegetation biomass. The success of the NDVI in detecting vegetation and simplicity of calculating and interpreting from satellite data has made it a popular spectral vegetation index (Gao, 1996; Wilson et al., 2002). Furthermore, NDVI has been successfully applied to change detection analysis (Lunetta et al., 2005; Petterelli et al., 2005; Wilson and Sader, 2002). Diallo et al. (2009) successfully detected land cover change in the mountainous region of Puer and Simao in Yunnan Province, China using NDVI and DEM data with an overall accuracy of 90.50 per cent and kappa value of 0.87. Similarly, Hayes and Sader (2001) compared PCA and NDVI in change detection and it had an overall accuracy over 85 per cent in detecting vegetation re-growth in Guatemala. Prior research used NDVI to improve predictions and impact assessment of environmental disturbances (Petterelli et al., 2005). The NDVI index will transform urban infrastructure and quarries in a darker shade while vegetation related indices will appear in a lighter shade due to the vegetation reflectance (Figure 2.6).

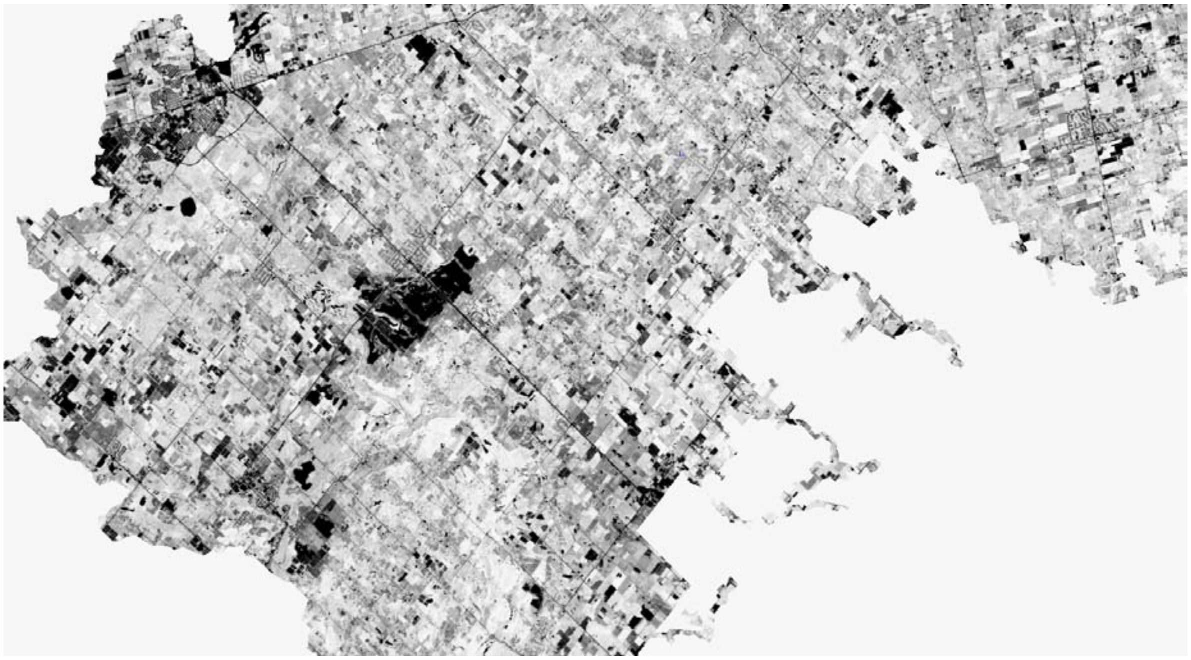

Figure 2-6: NDVI image of 2005 over Caledon, Ontario. Darker shades represent quarries and urban features and lighter shades represent vegetation.

2.7: Unsupervised Classification

Before implementing image classification, the selection of a suitable classification scheme is important (Lu and Weng, 2005). By visually analyzing the TM images in colour composite and comparing the three sets of images (1985, 1999 and 2005), six classes were selected based on the U.S. Geological Survey land use classification system (Anderson et al., 1976). The six classification classes are: forest land, agricultural land, urban land, undergoing development, water and other. Forest land represents all forested areas such as: wood lots and evergreen, coniferous and deciduous trees. Agricultural land represents all types of land used primarily for the production of crops. This includes the distinctive geometric fields and crop patterns on the landscape. Urban land is comprised of areas of intensive land covered by structures such as cities, towns, villages, roads and highways. Undergoing development represents land cover that is being prepared for development which can be identified by the high brightness from gravel or bare soil from a clear field. This class includes open pits and quarries. The water class represents all the different types of bodies of water such as, rivers, ponds, kettle ponds and lakes. Lastly, the other class is a miscellaneous class for landscape features that do not fall under any other classification classes. This class includes, exposed rock, wetlands and bare agricultural land.

Unsupervised classification was carried out on the 1999 and 2005 images using k-means algorithm with 100 spectral classes and 100 iterations. These 100 output spectral classes were then aggregated into six information classes. Since different image differencing techniques (TA, TCT, PCA and NDV) were able to delineate different land cover classes; they were used to categorize the spectral classes in the unsupervised classification. Unsupervised classification was not performed on 1985 image because it was used as a reference image to compare land cover change and it was not used in change detection processing. Hayes and Sader (2001) and Lu and Weng (2005) incorporated various transformed data and indices in the classification process which resulted in an overall classification accuracy increase.

2.8: Accuracy Assessment

Accuracy assessment is considered an important step in the evaluation of different image processing techniques used in image classification (Congalton, 1991; Foody, 2002). Failure to assess the accuracy of the different techniques will severely limit the ability to effectively interpret and use remotely sensed data (Congalton, 1991). There are five common accuracy assessment techniques recommended and described extensively in the literature (Congalton, 1991; Congalton and Green, 1999; Foody, 2002; Janssen and van der Wel, 1994) which include: error matrix, overall accuracy, producer's accuracy, user's accuracy and the kappa coefficient. Error matrix is used to assess the result of each classification by the number of clusters assigned to a particular classification class relative to the actual classification as verified on the ground (Congalton, 1991). The Kappa coefficient represents the proportion of agreement that could be obtained after removing the proportion of agreement that could be expected to occur by chance (Foody, 1992). The importance and power of the Kappa analysis is that it is possible to test if a land use and land cover map is significantly better than if the map had been generated by randomly assigning labels to areas (Congalton, 1996). A high kappa value implies that there is a positive agreement between the established true land cover classification and the classifications used in the study (Congalton, 1991; Lillesand et al., 2007).

An aggregate classification for each image was used to evaluate and determine the accuracy. A reference Landsat TM image for each image date was viewed in the true colour composite of bands 3, 2 and 1 was used visually to interpret and compare the classification result. A random sample of 300 points was generated within the study area as a vector layer and was later imported into the accuracy assessment as reference points. This vector layer was applied to the accuracy assessment of the 1999 and 2005 images in order to maintain the consistency when comparing land cover change from the three sets of images.

2.9: GIS Analysis

After completing the image classification process, the 1999 and 2005 data were imported into the ArcGIS environment for further analysis. First, a reclassified function was processed in the difference change image. Then the reclassified band difference change image was combined with the land cover classifications result by an arithmetic operation in the raster calculator to subtract areas that did not change in the study area. This process will create the change detection map which shows the areas where there were no land cover changes during the study period.

CHAPTER 3: RESULTS AND DISCUSSION

3.1: Image Differencing Results

Each of the four image analysis techniques was able to distinguish the six land cover classes. Using a combination of the image analysis techniques, the results were aggregated into six information classes. ArcGIS was utilized to analyze the difference images that were produced for 1985 to 1999 and 1999 to 2005.

3.1.1: Texture Analysis Results

TA was calculated by the mean texture measure and generated with a 3x3 window size from Band 2 for all the three sets of images. Figure 3-1 illustrates the fuzzy and darker shade is the forested lands boundary. In comparison, agricultural lands have little to no texture because of the overall homogeneity of the area. Another classification class that texture analysis was able to identify was quarries. Similarly, the mean texture detects change from bare agricultural lands to quarries as quarries appear white due to the reflectance characteristic (Figure 3-2). Dissimilarity texture details excavated areas in black areas (Figure 3-3).

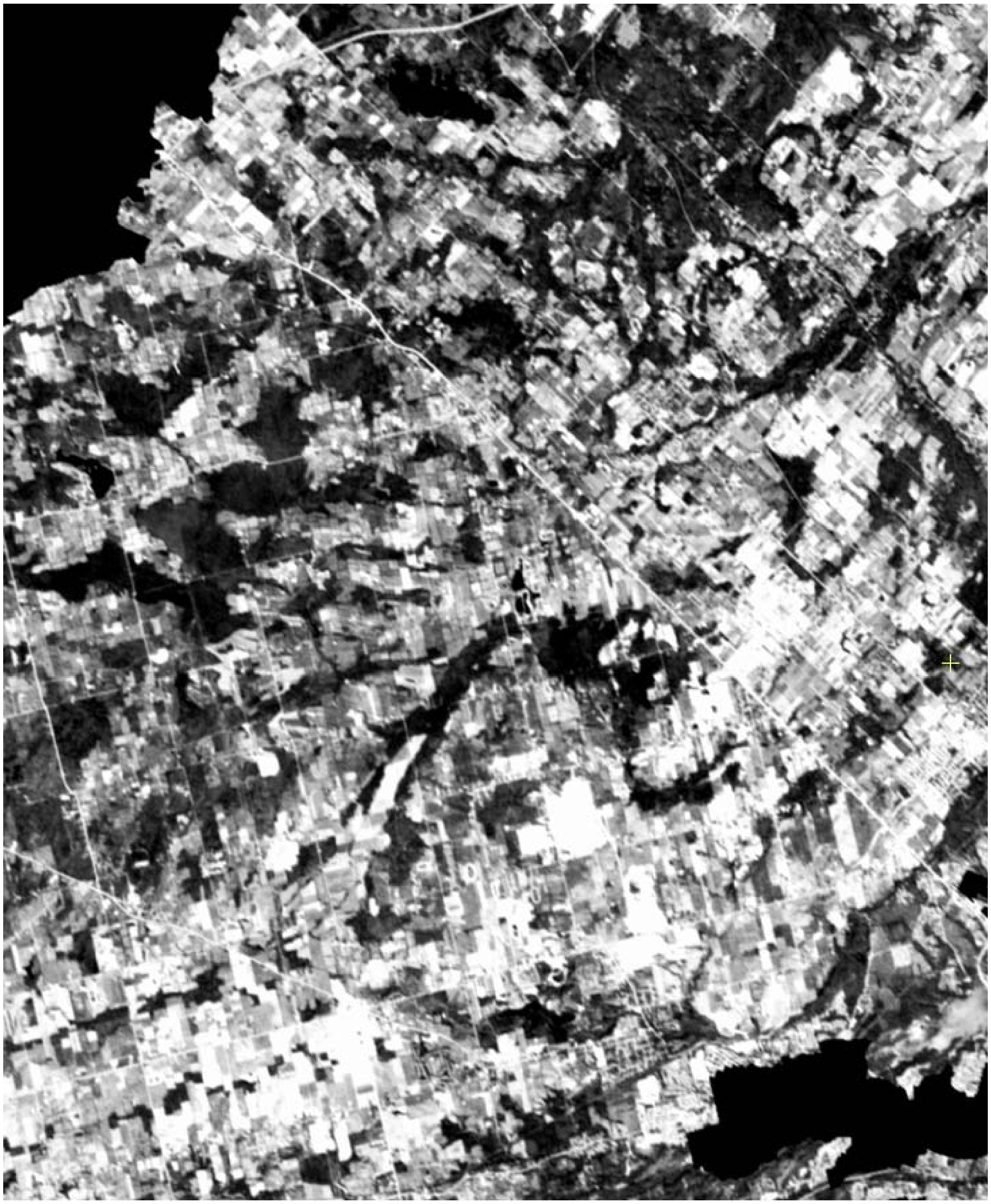

Figure 3-1: Outline of forested land boundary in black shade and road networks in straight white lines near Hamilton, Ontario.

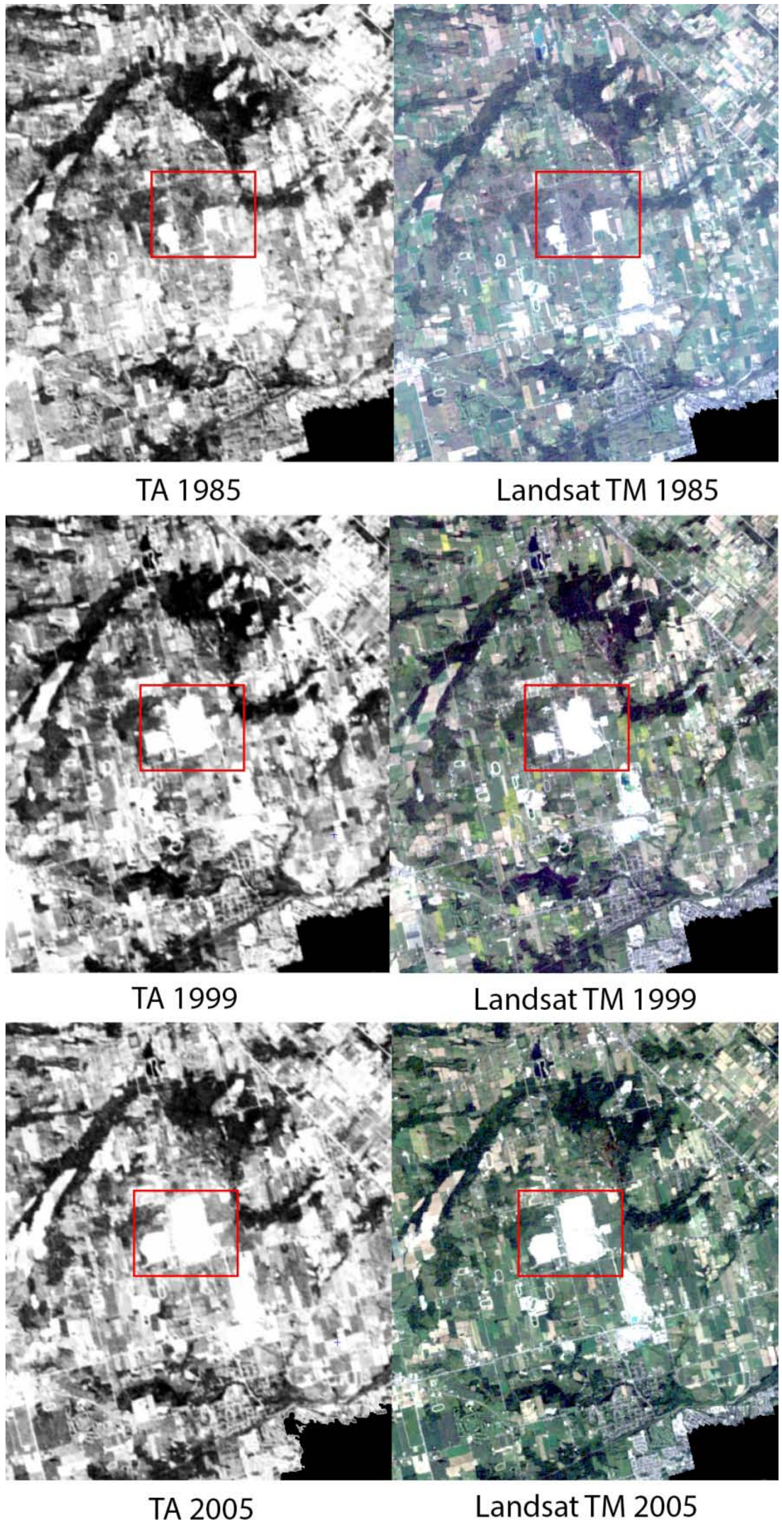

Figure 3-2: TA quarries development result in Hamilton, Ontario. The red box illustrates the development of quarries from 1985 to 2005.

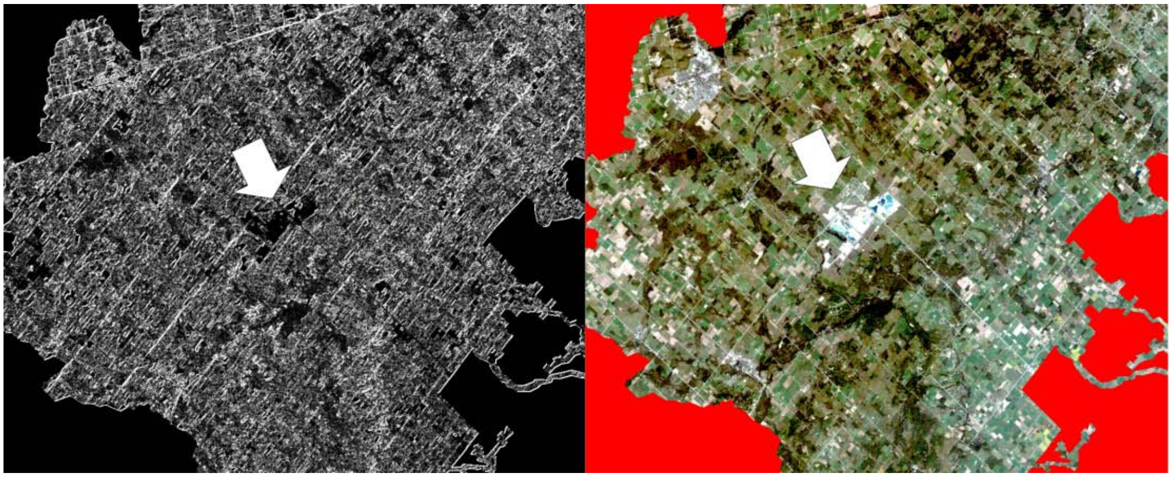

Figure 3-3: Dissimilarity Texture shows black areas as excavated land or quarry in Caledon, Ontario.

3.1.2: Tasselled Cap Transformation Results

TCT compressed the original six Landsat reflectance bands and converted them into three indices: brightness, greenness and wetness. The brightness measure was able to outline the forested land boundary from agricultural land due to the difference in brightness value (Figure 3-4). Water bodies appear black in the brightness index because of the low reflectance property of water bodies. Brighter shades are areas with higher brightness value, such as quarries or harvested farmland. TCT results were used to define forested area and water in the unsupervised classification.

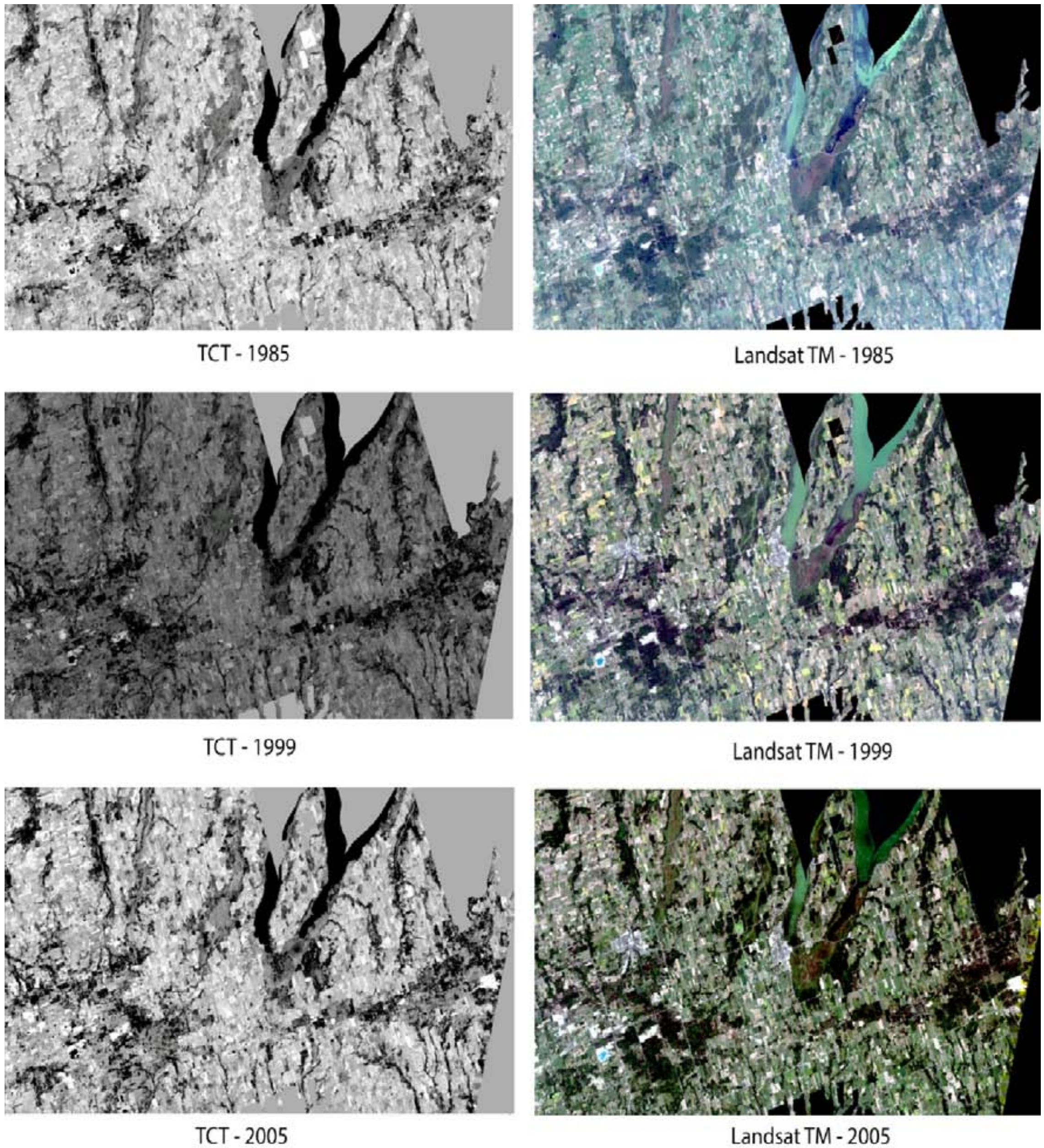

Figure 3-4: TCT Brightness – Forested Land near Scugog, Ontario.

3.1.3: Principal Components Analysis Results

PCA reduces image dimensionality by compressing data into fewer bands. Three eigenchannels were used to reduce the three sets of images. PC 1 for all three sets of image had variance over 98 per cent (Table3-1). However, PC 2 detailed the urban area in remarkable detail (Figure 3-5).

Table 3-1: PCA Reports for 1985, 1999, 2005

	Eigenchannel	*Eigenvalue*	*Deviation*	*%Variance*
1985	1	2.31E+04	1.52E+02	99.61
	2	4.15E+01	6.44E+00	0.18
	3	3.20E-01	5.66E+00	0.14
	4	8.79E+00	2.97E+00	0.04
	5	8.34E+00	2.89E+00	0.04
	6	2.56E-01	5.06E-01	0.00
1999	1	1.80E+04	1.34E+02	98.75
	2	1.29E+02	1.14E+01	0.71
	3	6.35E+01	7.97E+00	0.35
	4	2.35E+01	4.85E-01	0.13
	5	1.02E+01	3.20E+00	0.06
	6	8.27E-01	9.09E-01	0.00
2005	1	1.98E+04	1.41E-01	99.07
	2	1.11E+02	1.05E+01	0.56
	3	6.37E+01	7.98E+00	0.32
	4	7.56E+00	2.75E+00	0.04
	5	2.89E+00	1.70E+00	0.01
	6	1.15E+00	1.07E+00	0.01

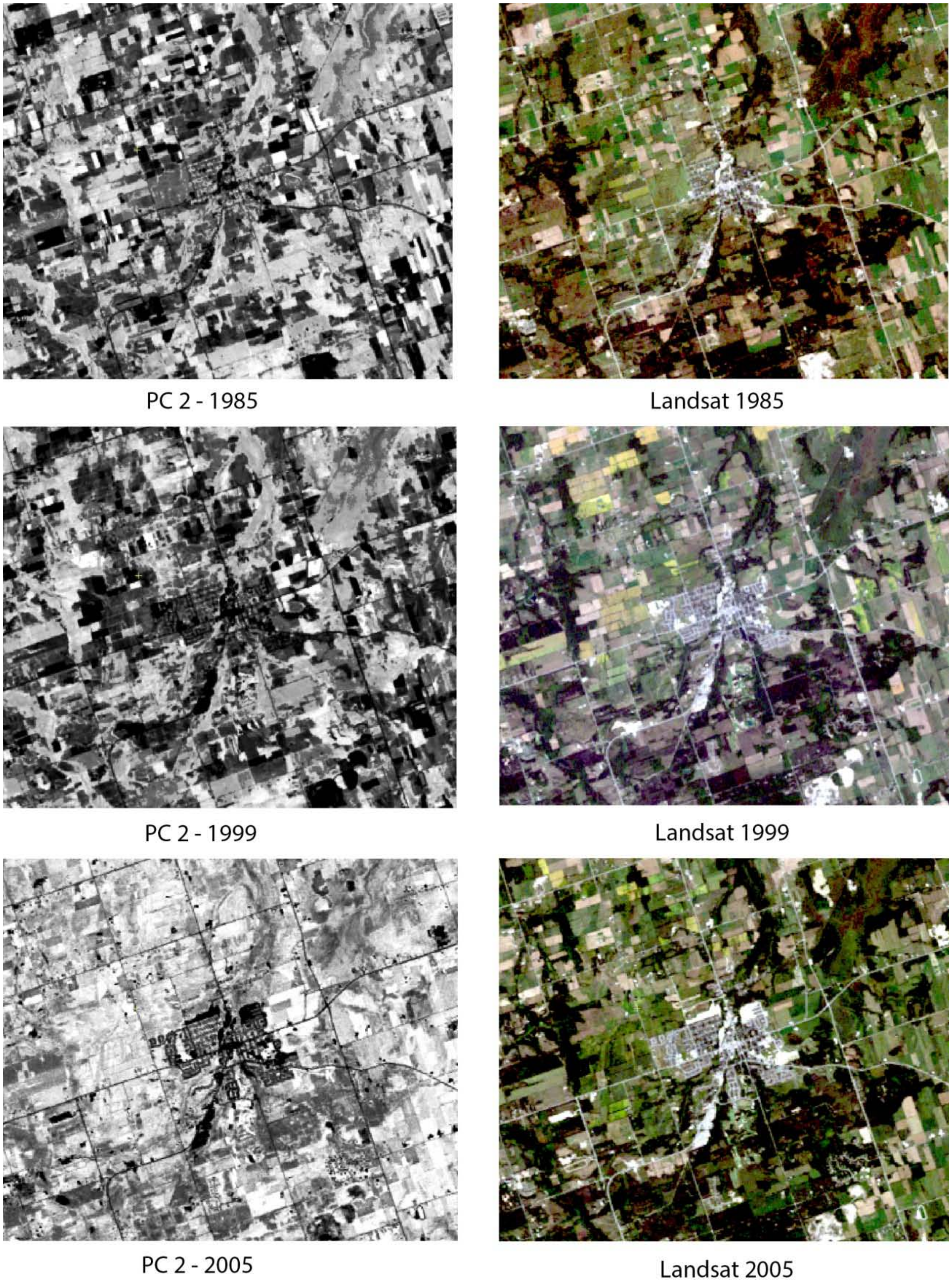

Figure 3-5: Expansion of an urban area Uxbridge, Ontario.

3.1.4: Normalized Difference Vegetation Index Analysis Results

NDVI provides information about the spatial and temporal distribution of vegetation communities and vegetation biomass. The NDVI shows darker shades for areas with urban infrastructure due to a lack of vegetation. Vegetation will appear in lighter shades due to the vegetation reflectance. As a result, development of golf courses within the Greenbelt can be detected using NDVI. Figure 3-6 illustrates the development of golf courses. Developers will purchase an open field in the initial stage which appears in light gray due to vegetation growth in the NDVI image. Next, they will clear the field to the exposed bare soil which will appear in a darker shade in the NDVI image due to lack of vegetation. Lastly, developers will put in the golf course turf which will appear in a lighter shade in the NDVI image.

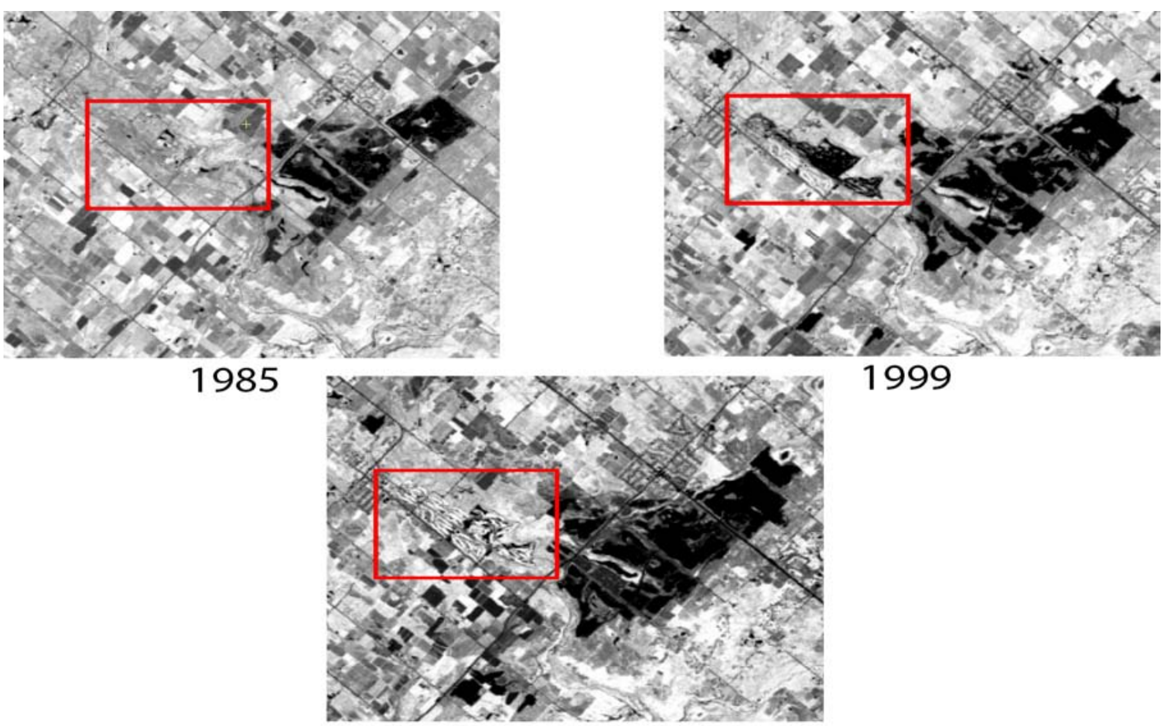

Figure 3-6: NDVI detected golf course development in Caledon, Ontario shown in the red square.

3.2: Image Classification and Accuracy Assessment

The six classification classes are: forest land, agricultural land, urban land, undergoing development, water and other. TA results were used to delineate quarries and undergoing development in the unsupervised classification. TCT results were used to define forested area and water in the unsupervised classification. PCA results were used to outline urban development in the unsupervised classification. NDVI results were used to classify agricultural land, urban development and other classes in the unsupervised classification.

The overall accuracy of the 1999 image classification in Figure 3-7 was 90.00 per cent with a confidence interval of 86.42 per cent to 93.56 per cent. The overall Kappa statistic was 0.86 per cent with an overall variance of 0.001 per cent (Table 3-2). The class that received the lowest Producer's Accuracy was the other classification with a percentage of 78.26. The low Producer's Accuracy was due to the misclassification of eight sample points as agricultural land classes instead of their correct classification in the other classes classification (Table 3-3). The class that received the lowest User's Accuracy was urban land class. Only eight out of the total eleven sample points were classified correctly as urban land. The poor classification accuracy in urban regions is due to the high degree of heterogeneity and subpixel mixing of surficial materials at the scale of a Landsat TM image pixel (Lu and Weng, 2005).

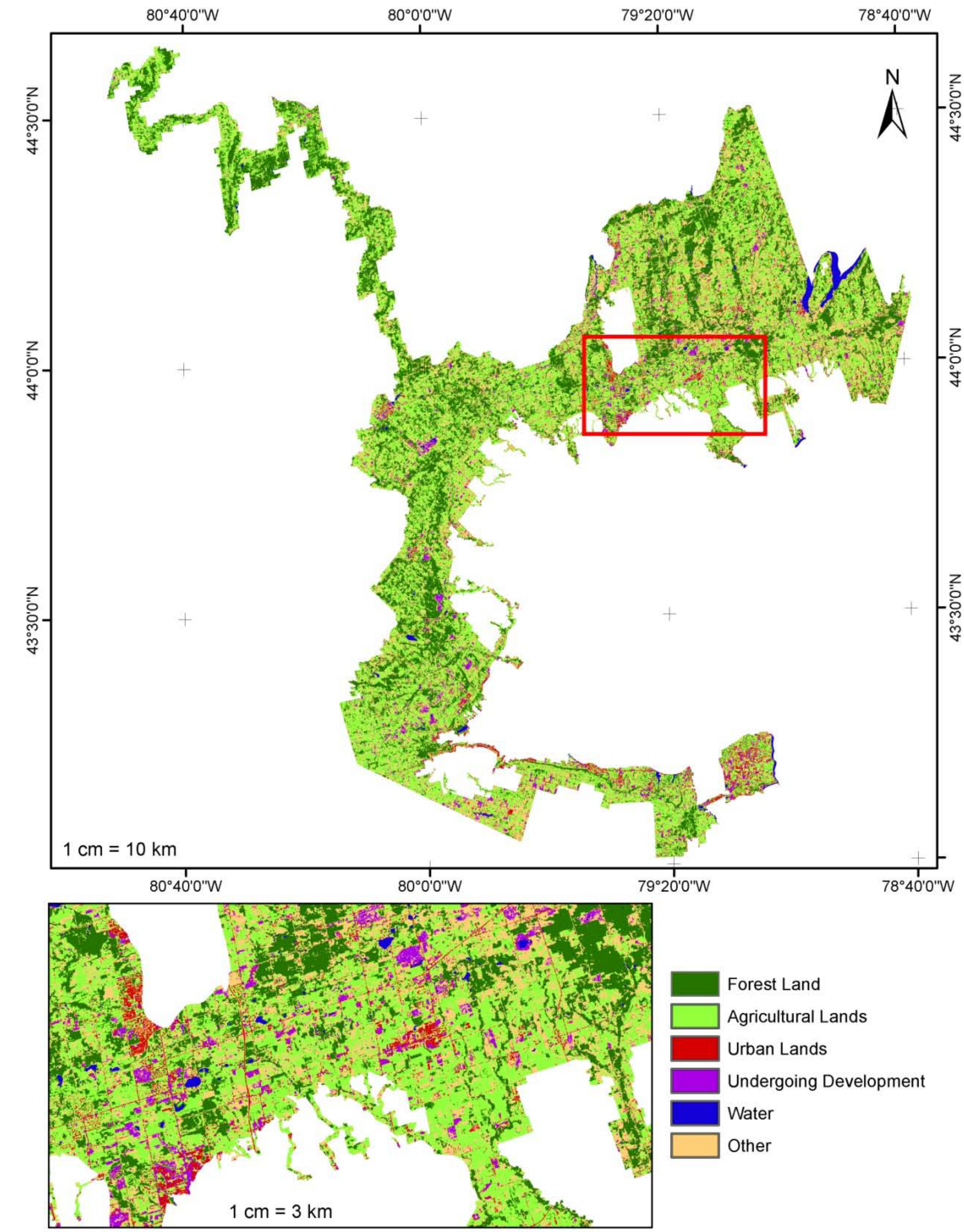

Figure 3-7: Landsat TM 1999 Classification Map.

Table 3-2: Landsat TM 1999 Accuracy Statistics

Overall Accuracy: 90.000% 95% Confidence Interval (86.439% 93.561%)
Overall Kappa Statistic: 0.857% Overall Kappa Variance : 0.001%

Class Name	*Producer's Accuracy*	*95% Confidence Interval*	*User's Accuracy*	*95% Confidence Interval*	*Kappa Statistic*
Forest Land	92.86%	(86.754% 98.960%)	93.98%	(88.255% 99.697%)	0.9163
Agricultural Land	94.36%	(89.889% 98.820%)	92.13%	(87.048% 97.204%)	0.8658
Urban Lands	80.00%	(50.208% 109.792%)	72.73%	(41.863% 103.592%)	0.7179
Undergoing Development	100.00%	(92.857% 107.143%)	77.78%	(45.061% 110.495%)	0.7725
Water	100.00%	(91.667% 108.333%)	85.71%	(52.648% 118.780%)	0.8542
Other	78.26%	(67.804% 88.718%)	85.71%	(76.280% 95.149%)	0.8145

Table 3-3: Landsat TM 1999 Confusion Matrix

Classified Data	**Forest Land**	**Agricultural Land**	**Urban Land**	**Undergoing Development**	**Water**	**Other**	**Totals**
Forest Land	**78**	2	0	0	0	3	83
Agricultural Land	1	**117**	1	0	0	8	127
Urban Land	0	1	**8**	0	0	2	11
Undergoing Development	0	0	1	**7**	0	1	9
Water	0	0	0	0	**6**	1	7
Other	5	4	0	0	0	**54**	63
Totals	84	124	10	7	6	69	300

The overall accuracy of the 2005 image classification in Figure 3-8 was 89.333 per cent with a confidence interval of 85.674 per cent to 92.993 per cent. The overall Kappa statistic was 0.848 per cent with an overall variance of 0.001 per cent (Table 3-4). The class that received the lowest Producer’s Accuracy was undergoing development class (Table 3-5). This low accuracy was because of three of the sample points were classified as other class. It is a possibility that some sample points were misclassified as other class due to expose rock and quarries share similar spectral signatures.

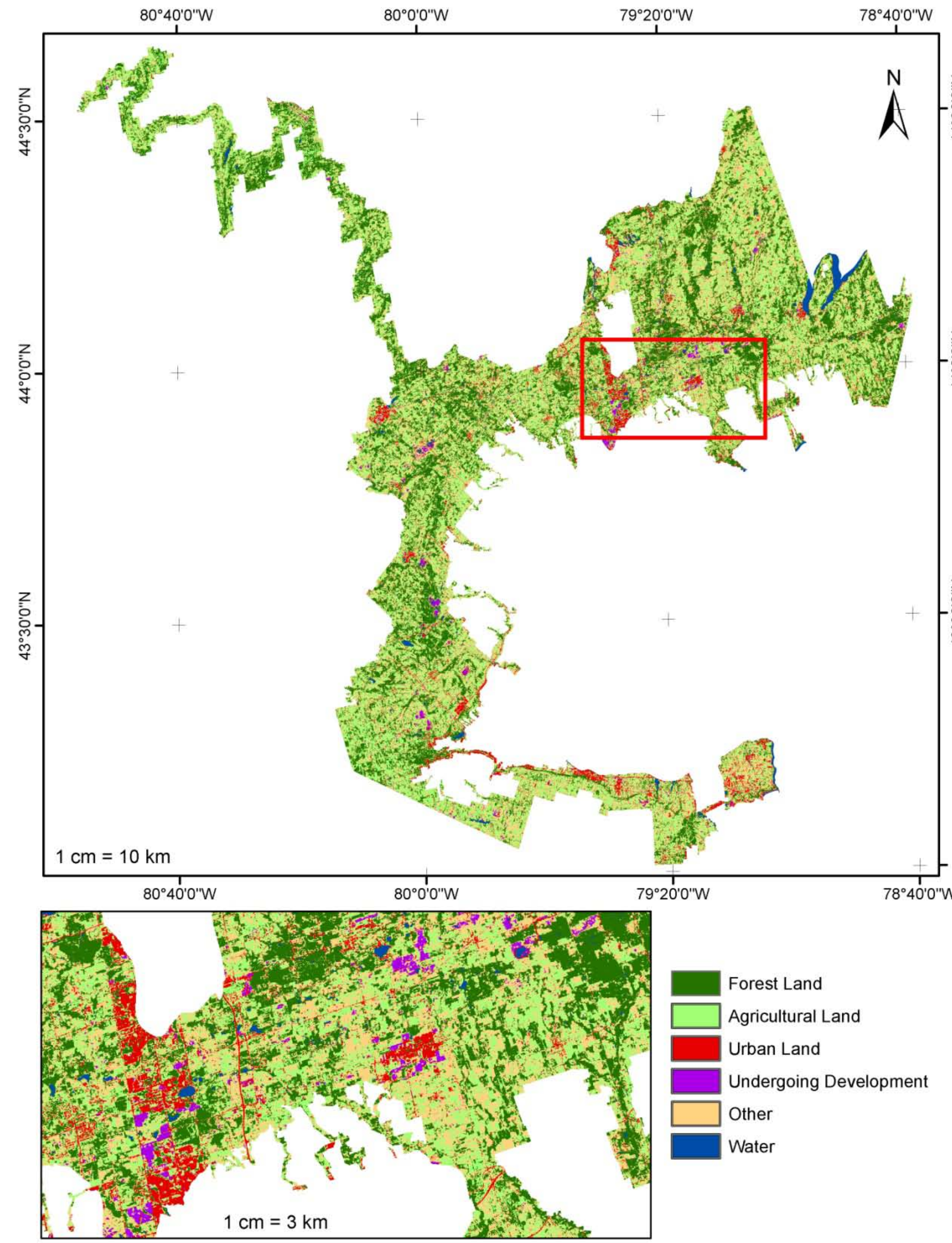

Figure 3-8: Landsat TM 2005 Classification Map.

Table 3-4: Landsat TM 2005 Accuracy Statistics

Overall Accuracy: 89.333% 95% Confidence Interval (85.674% 92.993%)
Overall Kappa Statistic: 0.848% Overall Kappa Variance: 0.001%

Class Name	***Producer's Accuracy***	***95% Confidence Interval***	***User's Accuracy***	***95% Confidence Interval***	***Kappa Statistic***
Forest Land	90.74%	(84.811% 96.671%)	97.03%	(93.224% 100.836%)	0.9536
Agricultural Land	88.24%	(81.492% 94.978%)	90.91%	(84.741% 97.077%)	0.8623
Urban Lands	88.89%	(62.801% 114.977%)	72.73%	(41.863% 103.592%)	0.7188
Undergoing Development	40.00%	(-12.941% 92.941%)	100.00%	(75.000% 125.000%)	1
Water	100.00%	(91.667% 108.333%)	85.71%	(52.648% 118.780%)	0.8542
Other	91.43%	(84.156% 98.701%)	80.00%	(70.610% 89.390%)	0.7391

Table 3-5: Landsat TM 2005 Confusion Matrix

Classified Data	**Forest Land**	**Agricultural Land**	**Urban Land**	**Undergoing Development**	**Water**	**Other**	**Totals**
Forest Land	**98**	2	0	0	0	1	101
Agricultural Land	4	**90**	1	0	0	4	99
Urban Land	0	2	**8**	0	0	1	11
Undergoing Development	0	0	0	**2**	0	0	2
Water	1	0	0	0	**6**	0	7
Other	5	8	0	3	0	**64**	80
Totals	108	102	9	5	6	70	300

3.3: Change Detection Map

Change detection maps use an arithmetic operation in the raster calculator in ArcGIS program to subtract areas that were not changed in the Greenbelt and illustrate areas where land cover change occurred. Two change detection maps were created between 1985 to 1999 and 1999 to 2005. Six classification classes from the classification map were used to identify the land cover within the Greenbelt.

1985-1999

During the 14 year period from 1985 to 1999, shown in Figure 3-9, the Greenbelt experienced an extensive land cover changes. Changes include agricultural land that converted to bare agricultural land when crops were harvested. Agricultural land near suburban towns and cities has been experiencing undergoing developmental change due to urban expansion. The inset maps of Figure 3-9 o Figure 3-13, illustrate the urban expansion in the Greenbelt near the towns of Whitchurch-Stouffville, Newmarket, and Richmond Hill in the Regional Municipality of York, as well as the Town of Orangeville in the Dufferin County and the Town of Collingwood in Simcoe County. A total of 2.07 square kilometres changed into the undergoing development class and 2.22 square kilometres of the Greenbelt changed into urban land (Table 3-6). Urban development land covers (urban land and undergoing development) only 10.32 per cent of the Greenbelt. The majority of the land cover changes were the agricultural land class and other classes. The reason for this being that the agricultural classes included changes in crop type and/or tillage on the land. In addition, forest land grew 2.15 square kilometres in the Greenbelt. The Greenbelt was able to preserve existing forest land and promote growth of the forest. Overall, the majority of 'green' land covers (forest land, agricultural land and other) still covers 89.66 per cent of the overall area within the Greenbelt.

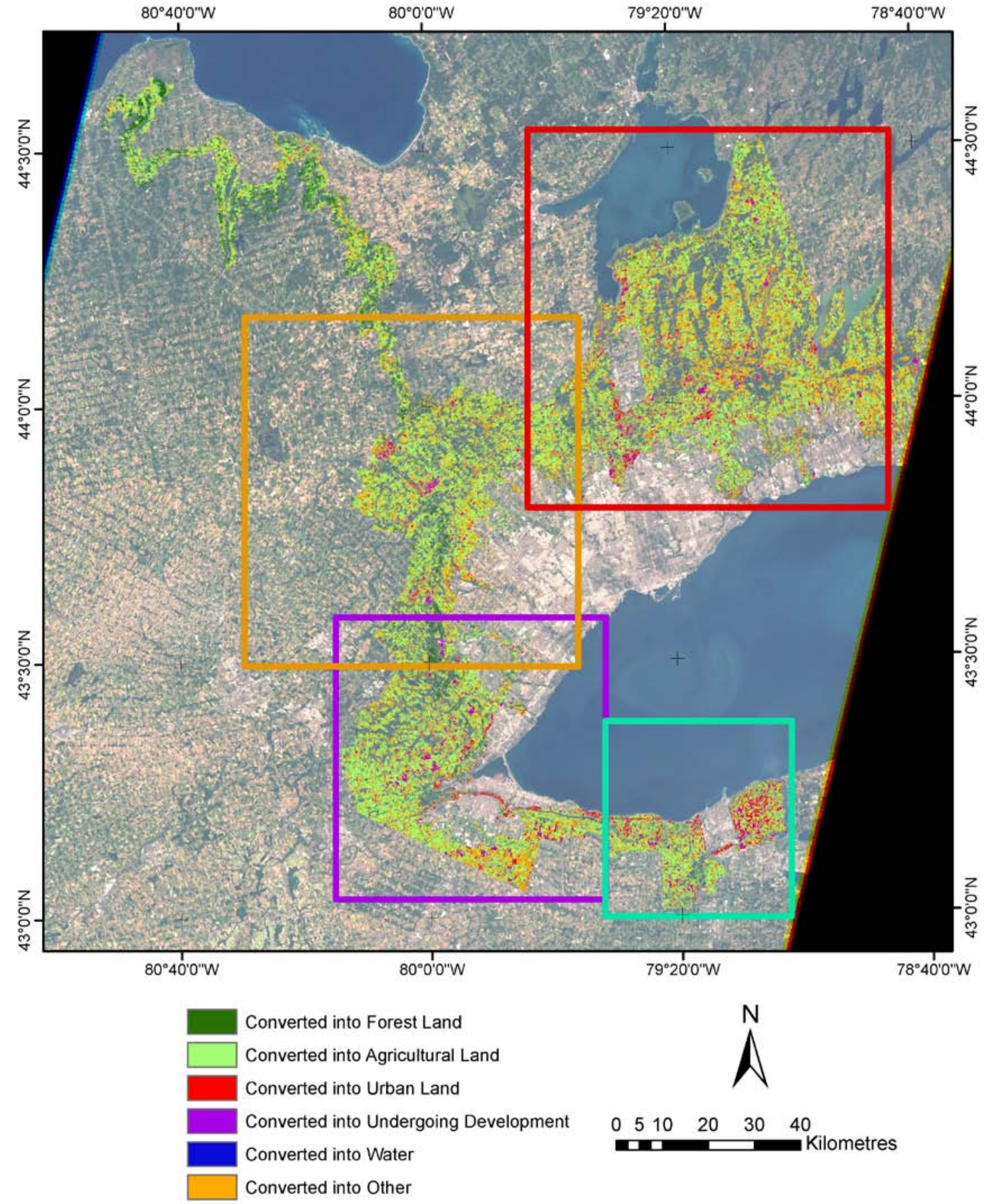

Figure 3-9: Change Detection Map from 1985 to 1999. The different colour frames represent inset maps which are shown in Figure 3-10 to Figure 3-13.

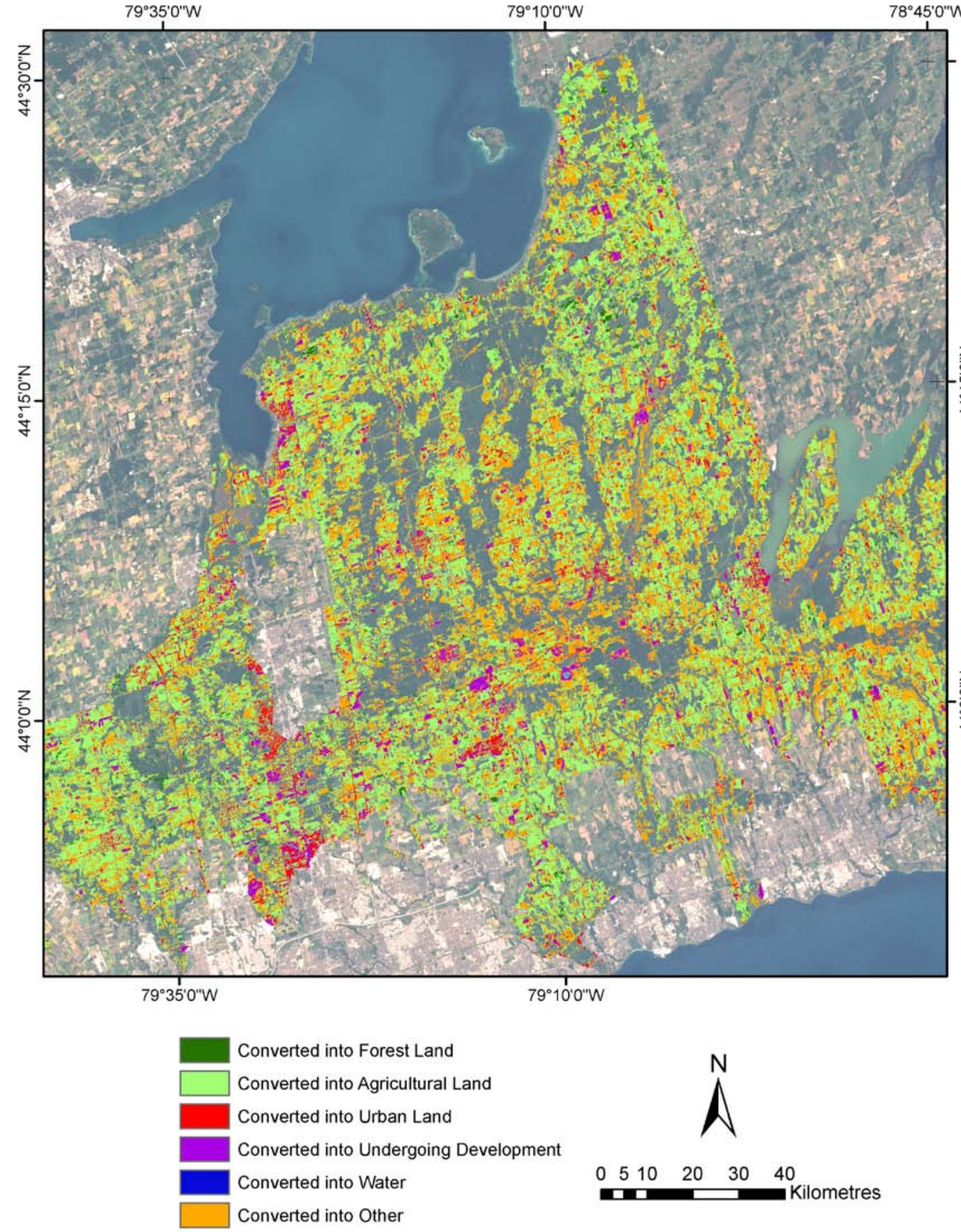

Figure 3-10: Inset map from red frame in Figure 3-9

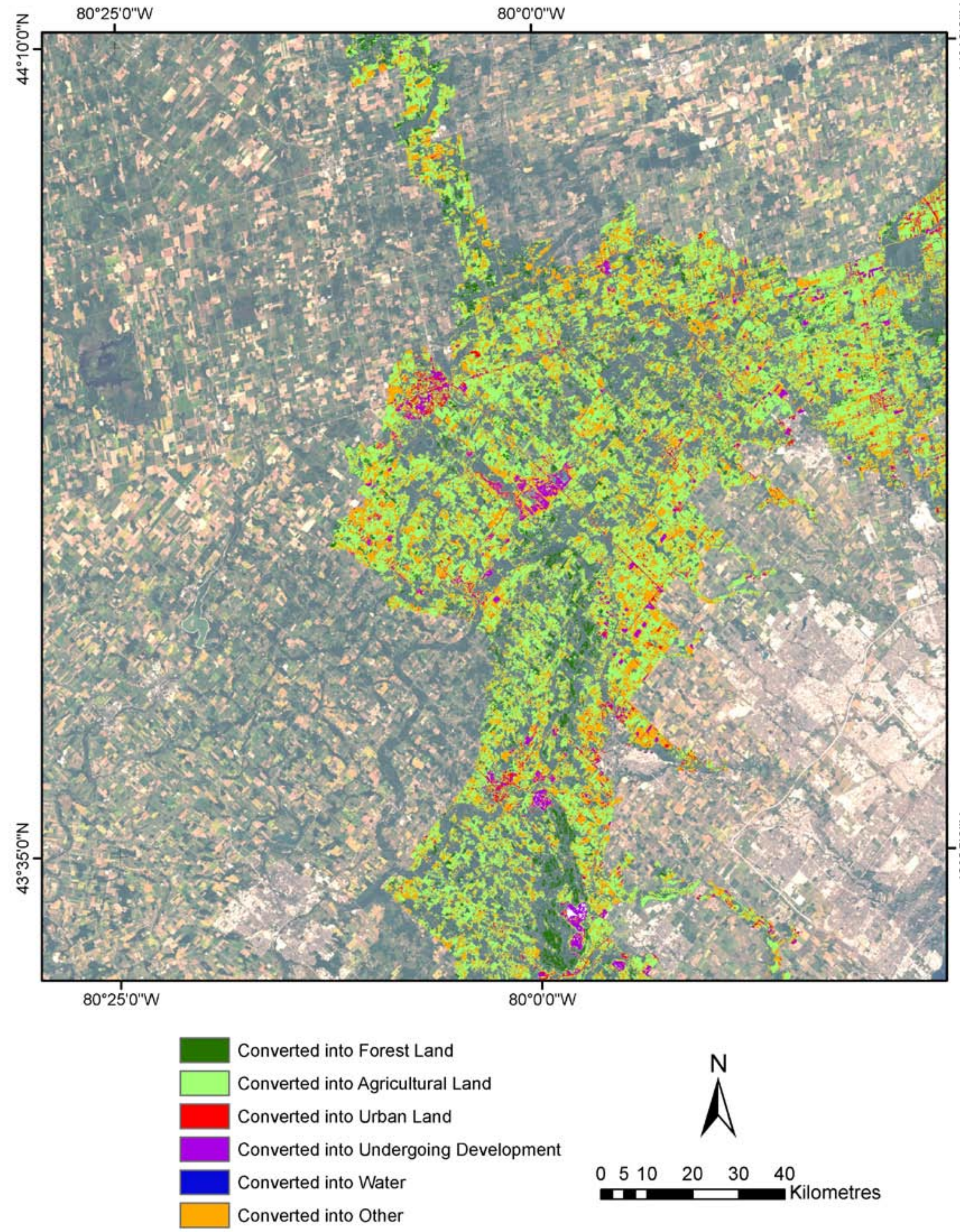

Figure 3-11: Inset map from orange frame in Figure 3-9

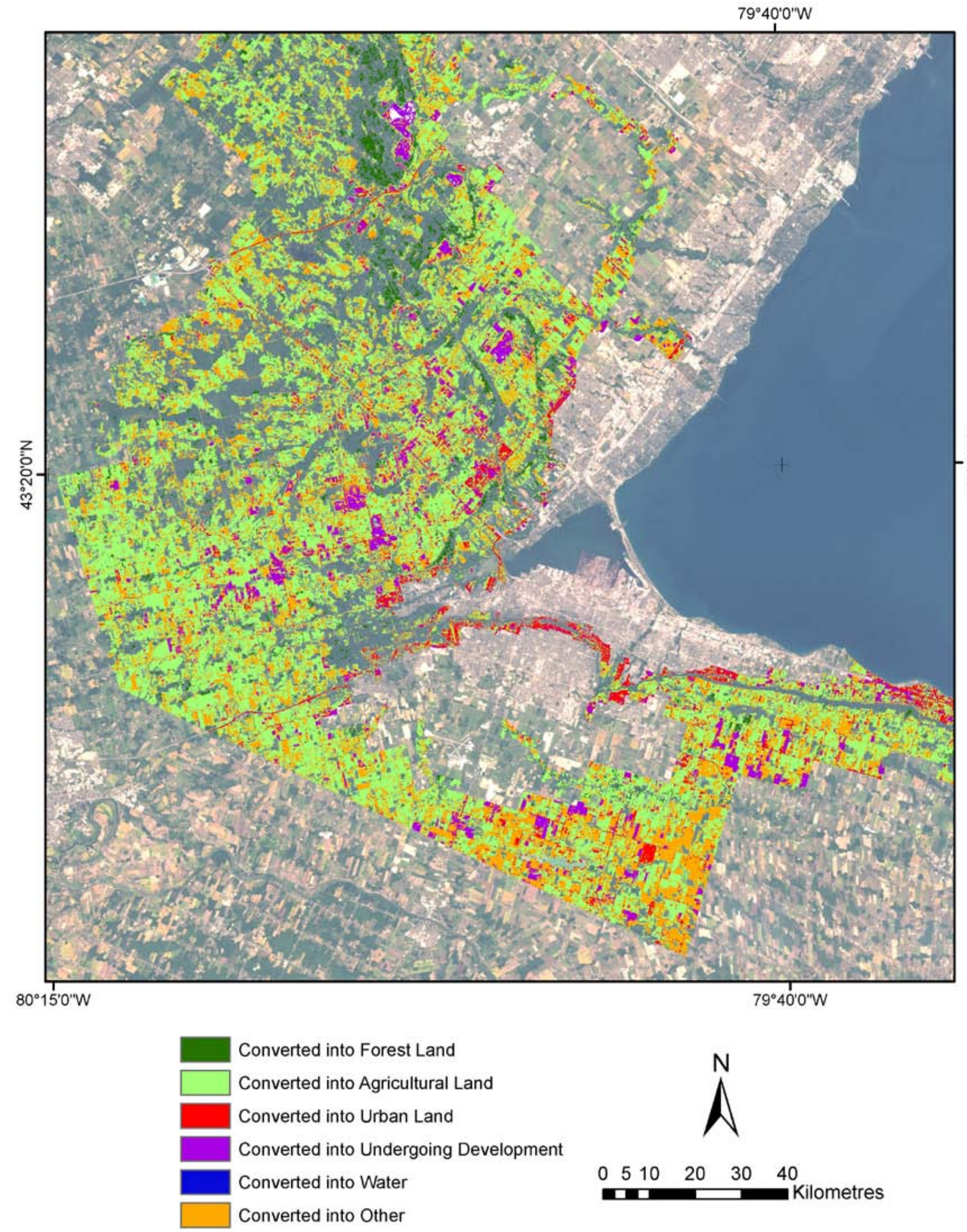

Figure 3-12: Inset map from purple frame in Figure 3-9

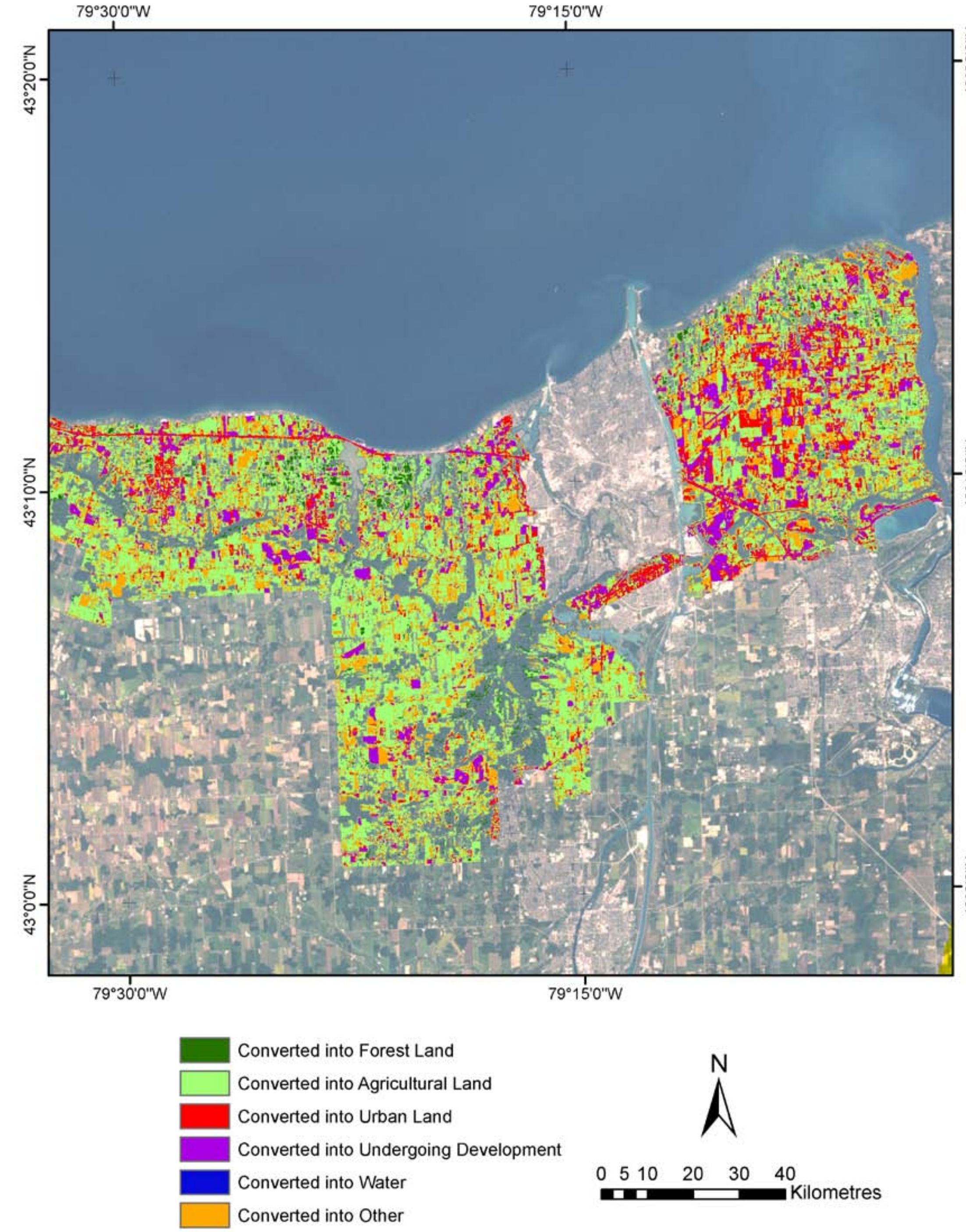

Figure 3-13: Inset map from teal frame in Figure 3-9

Table 3-6: Total are change for each class from 1985 to 1999

Class Name	Area (km^2)	Percentage area cover (%)
Forest Land	2.15343	5.181869
Agricultural	22.62132	54.43442
Urban Lands	2.222685	5.34852
Undergoing Development	2.071251	4.984119
Water	0.000072	0.000173
Other	12.48826	30.0509

1999-2005

As illustrated in Figure 3-14 indicates that, the Greenbelt experienced a similar amount of change in the 6 years period from 1999 to 2005 and 1985 to 1999. Figure 3-14 to Figure 3-18 show in greater details of the land cover changed during this 6 years period. Existing urban expansion in the different municipalities mentioned above, continue to grow into the Greenbelt. There has been an increase of urban land cover of 2.02 square kilometres since 1999 (Table 3-7). Urban development land covers (urban land and undergoing development) increased to 9.86 per cent of the total area in the Greenbelt. One noticeable land cover conversion was that of the agricultural land that was converted into a golf course. An example of this is the King's Riding Golf Club in King City, King Township that was built between 1999 and 2005. There has been very little loss of forest within the Greenbelt. It appears that the forest area increased 3.05 square kilometres within this time period. In general, the majority of 'green' land covers (forest land, agricultural land and other) still covers 90.09 per cent of the overall area within the Greenbelt.

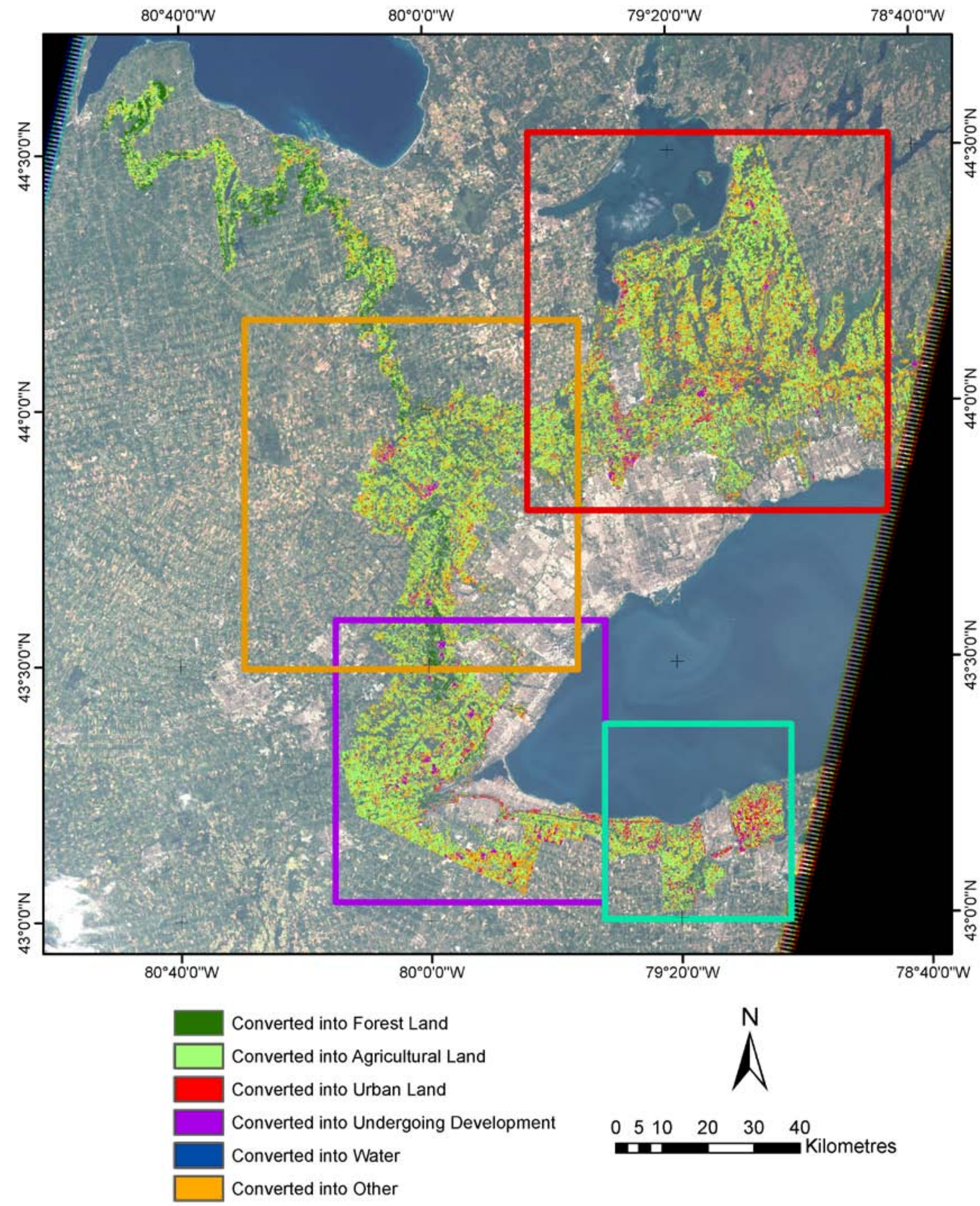

Figure 3-14: Change Detection Map from 1999 to 2005. The different colour frames represent inset maps which are shown in Figure 3-15 to Figure 3-18.

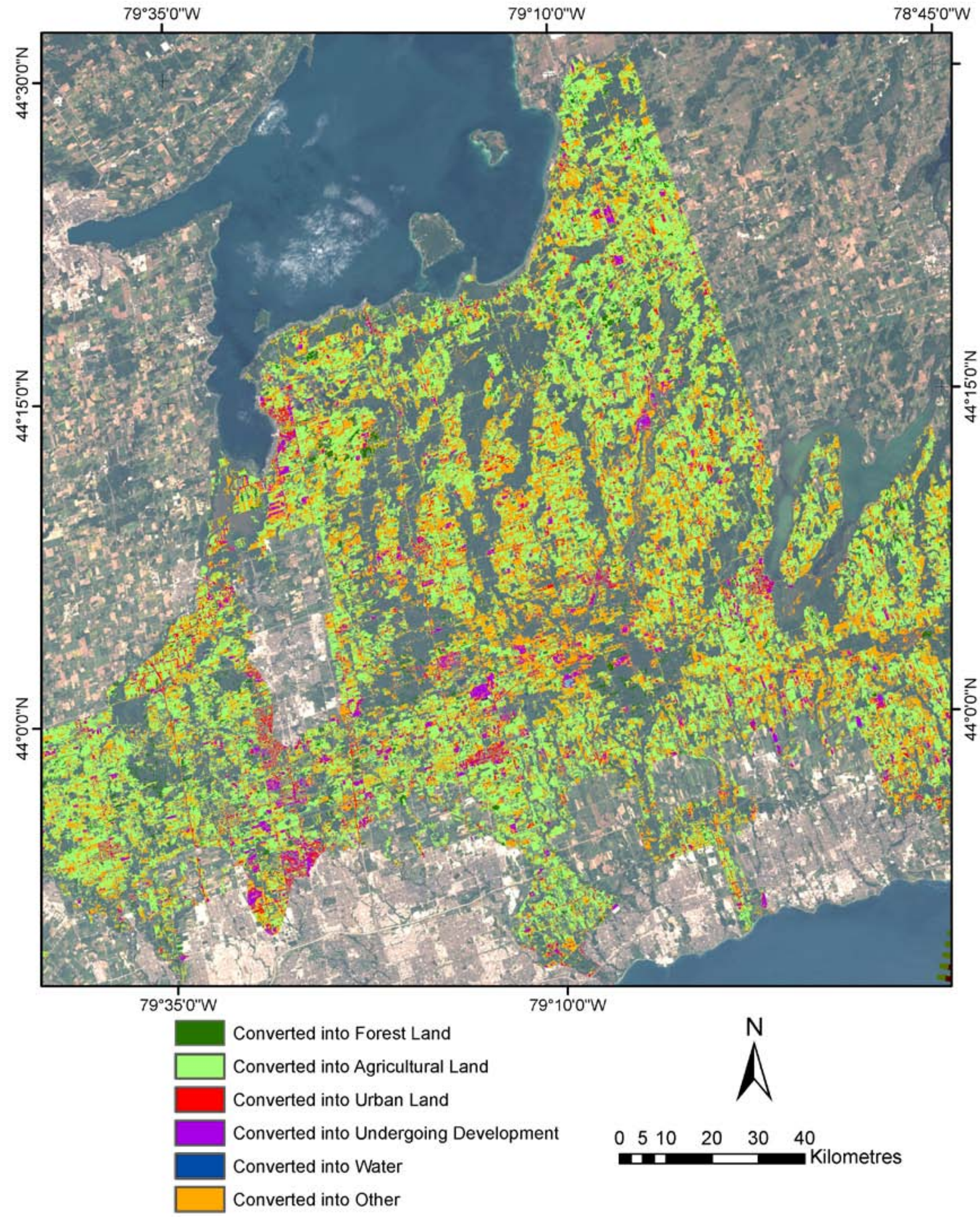

Figure 3-15: Inset map from red frame in Figure 3-14

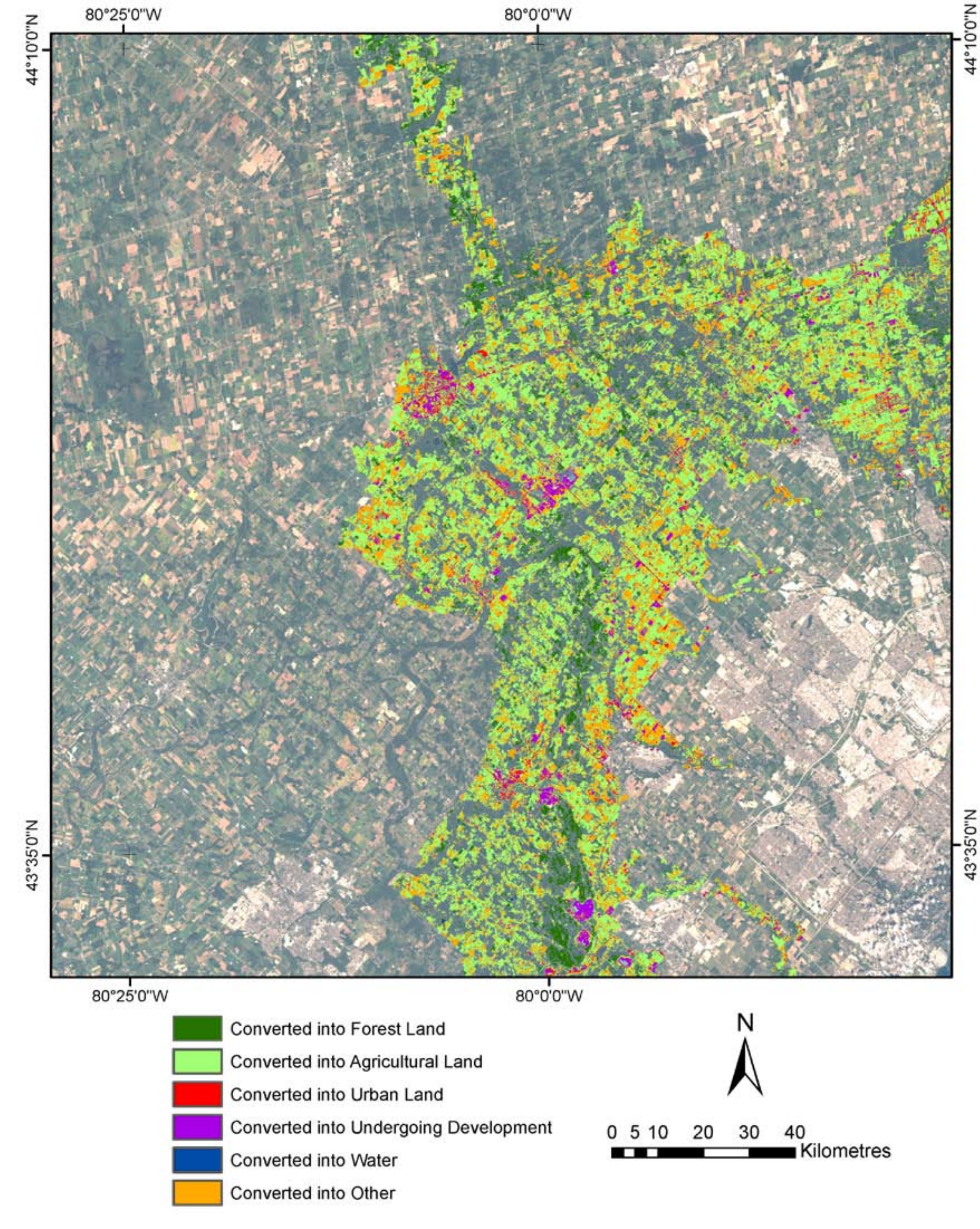

Figure 3-16: Inset map from orange frame in Figure 3-14

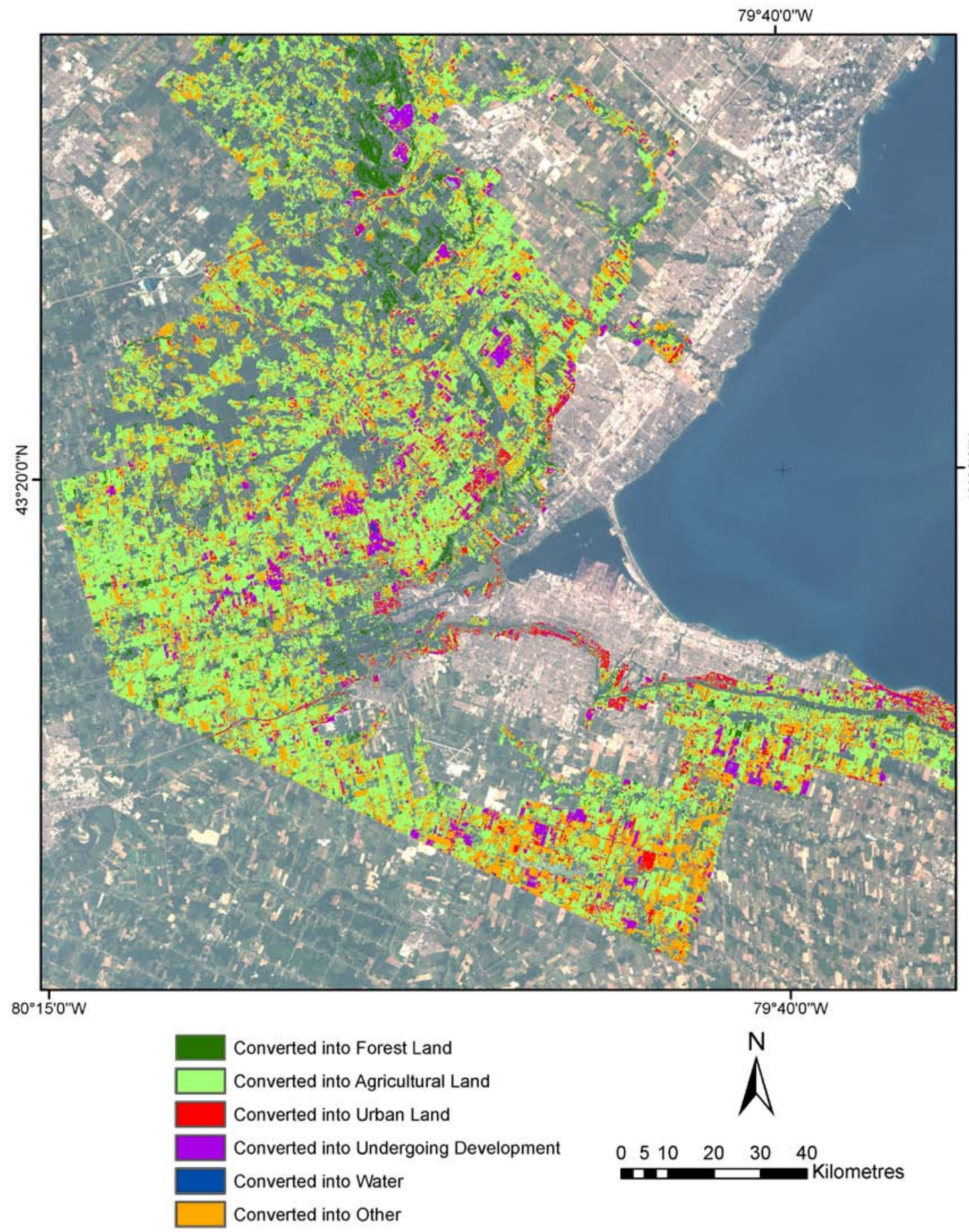

Figure 3-17: Inset map from purple frame in Figure 3-14

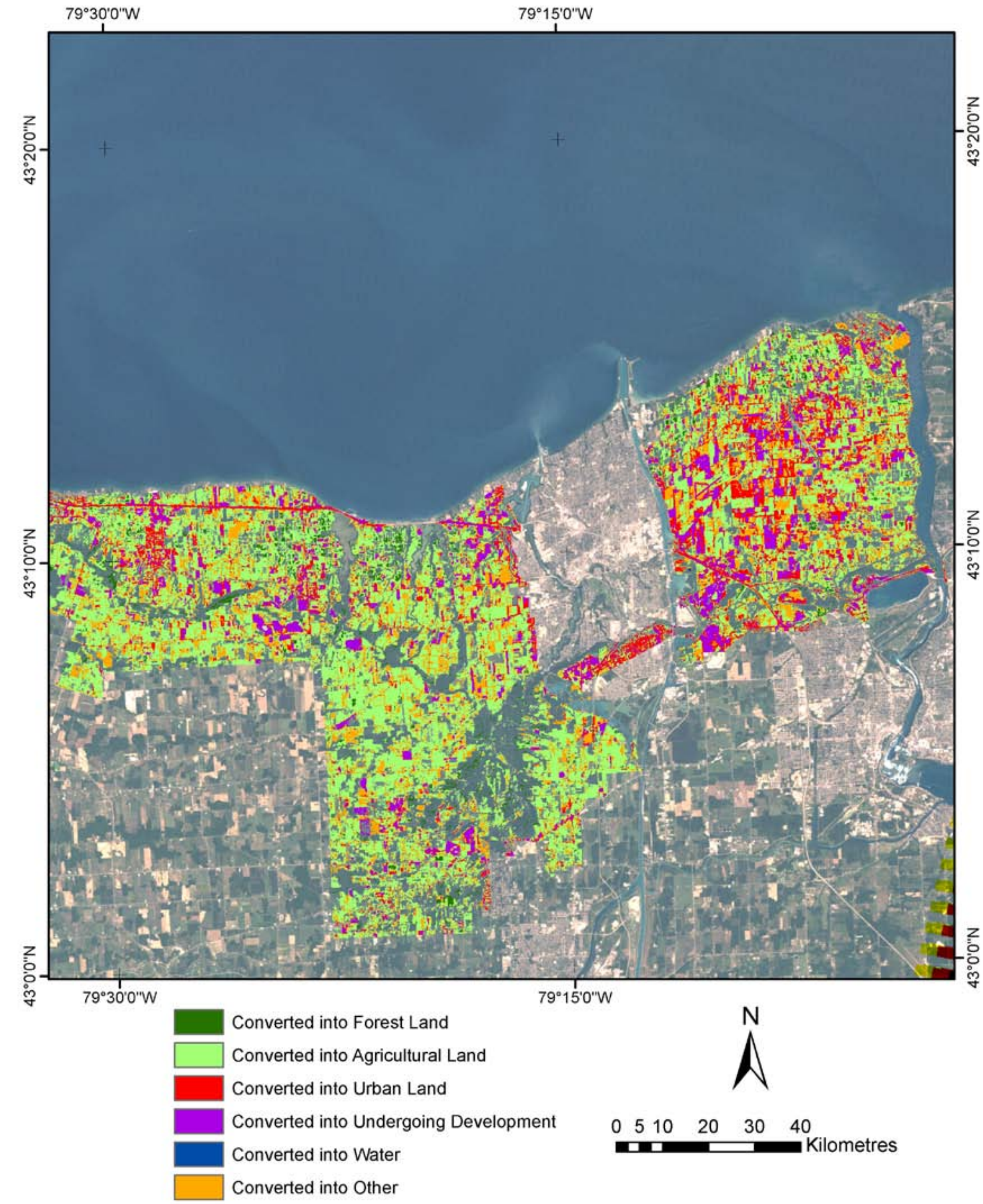

Figure 3-18: Inset map from teal frame in Figure 3-15.

Table 3-7: Total are change for each class from 1999 to 2005

Class Name	Area (km^2)	Percentage area cover (%)
Forest Land	3.054393	7.548839
Agricultural	22.33921	55.21066
Urban Lands	2.015973	4.982416
Undergoing Development	1.973403	4.877205
Water	0.019008	0.046978
Other	11.05978	27.3339

3.4: Discussion

The objective of this study was to accurately and effectively identify land cover change information using remote sensing for the Greenbelt. Since there are no other reliable historical reference data available for the Greenbelt, the image differencing techniques were crucial in determining the appropriate land cover changes within the time period of the images collected. Furthermore as Landsat TM imagery only has a spatial resolution of 30 metres, the image differencing techniques definitely helped with land cover that was hard to identify by simply looking at the image itself. The supporting accuracy assessment produced measures the quality of the classification method. In this study, the use of image differencing techniques with unsupervised classification methods were found to have a high overall accuracy ranging from 89.33 per cent to 90.67 per cent, which meets the level of 85 per cent that the USGS has recommended for acceptability of classification result (Anderson et al., 1976).

There is a visible increase in forest land, urban land and water classes which is shown in Figure 3-19. Firstly, the *Greenbelt Act* was able to promote forest growth within the Greenbelt. Overall, the forest grew 8.173 per cent from 1985 to 2005. Secondly, urban land area quadruples in percentage from 1.256% in 1985 to 4.838% in 2005 (Table 3-8). Lastly, the increase of water area in the Greenbelt is due to tailing or drainage ponds created in quarries. Overall, there has been a steady decrease in agricultural land use from 1985 to 2005.

Some of the common land cover changes were other land classes were converted into undergoing development can be seen in Figure 3-19. The other class experienced a decrease of 11.822 per cent in area from 1985 to 1999; while undergoing developing class increased almost 1 per cent from 1985 to 1999. This meant that bare agricultural land was being converted into the land undergoing development class for future urban development. Another common land cover conversion was agricultural land and undergoing development to urban lands. From the Figure 3-19, both agricultural land and undergoing development experienced a decrease of 7.112 per cent and respectfully, 2.074 per cent from 1999 to 2005. At the same time, urban land had an increase close to 2 per cent from 1999 to 2005.

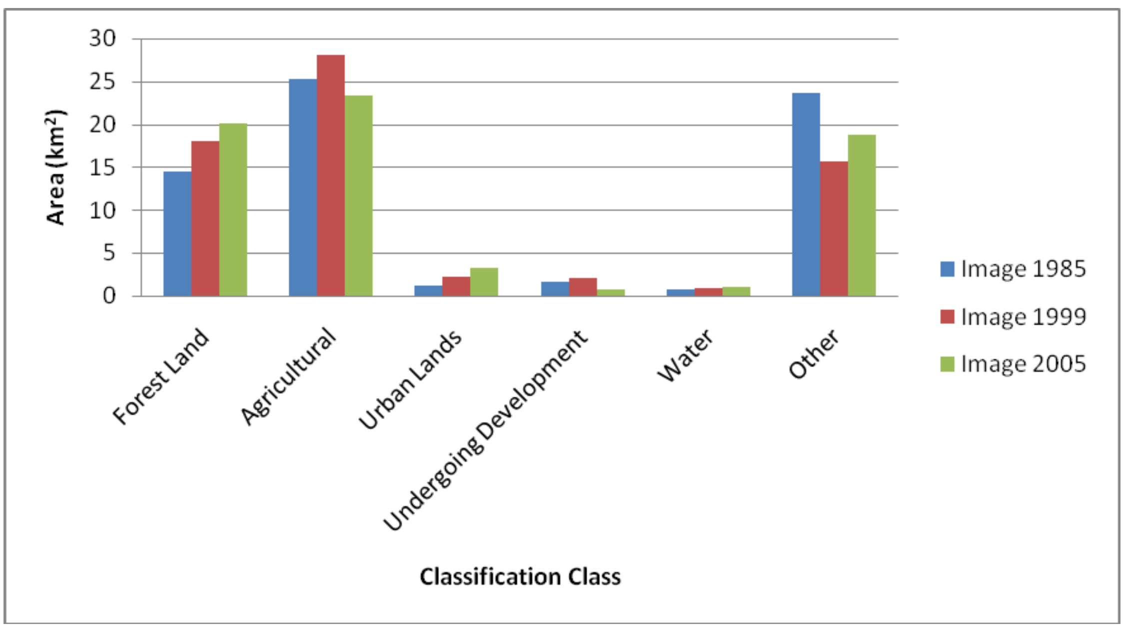

Figure 3-19: Comparing classification class area in 1985, 1999 & 2005 images.

Table 3-8: Total area of each classification class

Classification	Image 1985	Percentage Changes	Image 1999	Percentage Changes	Image 2005	Percentage Changes
Forest Land	14.515	21.658%	18.005	26.871%	20.039	29.831%
Agricultural	25.272	37.708%	28.085	41.915%	23.379	34.803%
Urban Lands	1.256	1.873%	2.267	3.383%	3.250	4.838%
Undergoing Development	1.675	2.499%	2.086	3.113%	0.698	1.039%
Water	0.710	1.059%	0.896	1.337%	1.073	1.598%
Other	23.593	35.203%	15.666	23.381%	18.735	27.890%

From the 2006 Census, Whitchurch-Stouffville was the third fastest growing community in Canada with a population increase of 10.8 per cent from 2001 to 2006. Whitchurch-Stouffville is located within the Greenbelt boundary on the ORM. From the Canadian Census, it is noted that the population has been increasing at a steady rate from 1991 to 2006 (Statistics Canada, 2012). In 2006, the population increased by 10.8 per cent (Table 3-9). Due to the increasing population, the town had to expand the urban region from 1.7955 hectares in 1985 to 3.4263 hectares in 2005 (Table 3-10). The NDVI image showed the transition of agricultural lands in Whitchurch-Stouffville converted into undergoing development which in turn were converted into urban land (Figure 3-20)

Table 3-9: Whitchurch-Stouffville Population

	Whitchurch-Stouffville
Population in 1991	18357
Population in 1996	19835
Population change (%)	**8.1**
Population in 1996	19835
Population in 2001	22008
Population change (%)	**11**
Population in 2001	22008
Population in 2006	24390
Population change (%)	**10.8**

Table 3-10: Classification Class Area in Whitchurch-Stouffville

Whitchurch-Stouffville	**1985 Area (ha)**	**1999 Area (ha)**	**2005 Area (ha)**
Forest Land	1.5786	1.6983	2.5119
Agricultural	4.0266	3.8484	6.7320
Urban Lands	1.7955	3.0294	3.4263
Undergoing Development	0.8712	1.0512	0.3924
Water	0.1053	0.3024	0.4302
Other	4.7637	7.4889	10.2006

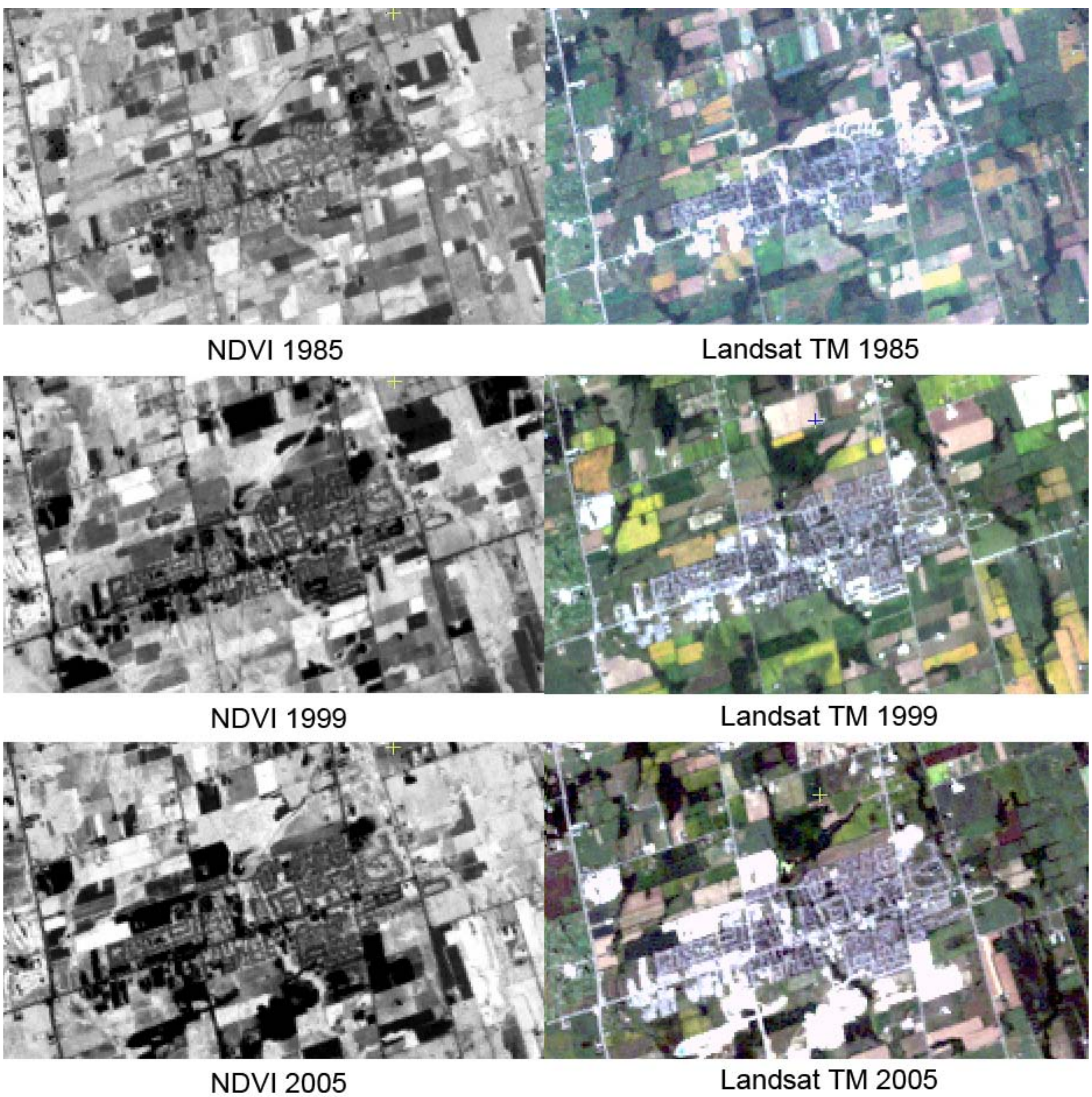

Figure 3-20: Growth of Whitchurch-Stouffville

In a study by Cheng and Lee (2008) on land cover classification in the Greenbelt, they concluded that urban areas are the most significant land use conversion of 68 per cent of all conversion. The rest of the significant land use conversions included golf courses (15 per cent), quarries (13 per cent) and total area converted of 4 per cent. There was very little to no conversion on forest land. Comparing their research to this research, the results were similar; however, Cheng and Lee (2008) did not use accuracy assessment for the land cover classifications. Accuracy assessment is considered an important step in the evaluation of different image processing techniques used in image classification (Congalton, 1991; Foody, 2002). Failure to assess the accuracy of the different techniques will severely limit the ability to effectively interpret and use remotely sensed data (Congalton, 1991). Thus, by incorporating image differencing techniques in the classification process, it provides a better classification accuracy result in comparison to the research conducted by Cheng and Lee (2008).

CHAPTER 4: CONCLUSION

4.1 Summary

This research was completed to accurately and effectively identify land cover change within the Greenbelt from 1985 to 2005. Since there were no other reliable historical reference data available for the Greenbelt, image differencing techniques were crucial in determining the appropriate land cover changes within the time period of the study. The land cover classification maps were mapped using various image differencing techniques (TA, TCT, PCA, and NDVI) to identify the different land cover within the Greenbelt. Two difference images (1985-1999 and 1999-2005) were then used to analyze where land cover change occurred in the Greenbelt.

Extensive land cover change occurred within the Greenbelt from 1985 to 2005. Changes include agricultural land that converted to bare agricultural land when crops were harvested. Agricultural land near suburban towns and cities has experienced developmental change due to urban expansion. The majority of the agricultural land cover modifications included changes in crop type and tillage. Forest land within the Greenbelt experienced growth of 8.173 per cent from 1985 to 2005. As well, the results indicated an increase of urban land area from 1985 to 2005 and a steady decrease in agricultural land use area from 1985 to 2005. Based on the results of the study, it can be concluded that the *Greenbelt Act* was able to preserve 90.09 per cent of ‘green’ land cover (forest land, agricultural land and other) from urban development and sprawl.

4.2: Limitations

Landsat TM imagery was chosen for this study because they have been widely used in land cover change detection and many previous studies had great success with it. As well, these images were provided by the USGS and are freely accessible online. However, there are some limitations to the Landsat TM imagery. First, the spatial resolution of 30 metres was not sufficient to precisely delineate the different land covers. Land cover such as the boundary of agricultural land and bare agricultural land was hard to distinguish. Furthermore, the different acquisition dates and conditions of the imagery will result in different land cover of the same features due to different growing seasons. Even though the acquisition date of each year for this study ranged from August 26 to September 20, there were already noticeable differences in the agricultural land in the three sets of images. As well, farmers tend to grow crops that are in high demand during that time period which will lead to inconsistent growing seasons of the crops, thus the agricultural land will thus appear different in between the set of images.

4.3: Further Research

To further the research, it will be beneficial to perform similar methods but with higher spatial resolution imagery, such as SPOT with spatial resolution of 2.5 metres to 10 metres or IKONOS with spatial resolution of 4 metres. To understand the pressure caused by urban development and sprawl, a distance of 10 kilometres from the Greenbelt boundary should be included in research in order to evaluate the land cover change patterns outside of the Greenbelt caused by embedded urban cities such as Milton. From the recently released 2011 Census, Milton was the fastest growing community in Canada with a 56.5 per cent population increase from 2006 and follow by Whitchurch-Stouffville which was the third fastest growing community in Canada with a population increase of 54.3 per cent from 2006 to 2011 (Statistics Canada, 2012). Large population increases in these municipalities are a concern as they are located near or on the Greenbelt. For further research, change detection should be undertaken with newer Landsat images if they become available to monitor the urban development in these areas particularly closely.

Future studies should explore the use of other image differencing techniques that will increase overall classification accuracy. Previous research (Healey et al, 2005) successfully combined TCT and Disturbance Index to produce a higher accuracy than would be obtained by only using TCT in forest disturbance detection. Another image differencing technique that should be incorporated is the Normalized Difference Moisture Index (NDMI). This index contrasts the NIR with the mid-infrared (MIR) Band 5 which measures the amount of moisture in the vegetation; it would increase the overall classification accuracy and highlights areas of healthy green vegetation with high moisture content such as agricultural land from bare agricultural land. Wilson and Sader (2002) compared NDVI and NDMI in forest harvest detection using Landsat TM imagery. They concluded that NDMI outperformed NDVI with a higher overall accuracy.

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