# URBAN CHANGE DETECTION AND ANALYSIS IN THE GREATER TORONTO AREA FROM 1972 TO 2004 USING REMOTE SENSING AND GIS

**by**

**Paul (Baorong) Du**

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## AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this Research Paper.

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Paul (Baorong) Du

## ABSTRACT

Urban change is an important urban planning and environmental issue. Previous urban change detection studies in the Greater Toronto Area (GTA) usually involved limited dates and/or study areas. Landsat imagery from 1972 to 2004 were used in this research that cover the majority of the contiguous urban area in the GTA. A series of urban change detection experiments were performed that compared methodologies and techniques. The results greatly improved classification accuracy, particularly for Landsat Multispectral Scanner (MSS) data. A yearly average of 14.1 $km^2$ of new development was observed, which corresponds well with results from previous studies in this area. The patterns and rates of urban change varied among municipalities inside the GTA.

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**ASM -** Angular Second Moment
**CLUMP -** Canada Land Use Monitoring Program
**NAD83** - North American Datum of 1983
**DVI** – Difference Vegetation Index
**ERTS** - Earth Resources Technology Satellite
**ETM+ -** Enhanced Thematic Mapper plus
**GIS** - Geographic Information System
**GRS** - Geodetic Reference System
**GTA -** Greater Toronto Area
**ISODATA -** Interactive Self-Organizing Data Analysis
**LULC –** Land Use and Land Cover
**MSS** - Multi-spectral Scanner
**NDVI -** Normalized Difference Vegetation Index
**PCA** – Principal Component Analysis
**PVI** - Perpendicular Vegetation Index
**RMS** - Root Mean Square
**RVI -** Ratio Vegetation Index
**SARVI** - Soil Adjusted Ratio Vegetation Index
**SAVI -** Soil Adjusted Vegetation Index
**SPCs** – Selected Principal Components
**TM** - Thematic Mapper
**TSAVI -** Transformed Soil Adjusted Vegetation Index
**UTM** – Universal Transverse Mercator
**V-I-S** - Vegetation-Impervious-Surface soil

# CHAPTER 1: INTRODUCTION

## 1.1 Background

Urbanization refers to a process in which an increasing proportion of an entire population lives in cities and the suburbs of cities, by which rural areas become transformed into urban areas (Eldridge, 1956). In 1950, 30 percent of the world population lived in urban areas, by 2000 the proportion of urban dwellers had risen to 47 per cent, and by 2030 it is expected to reach 60 per cent. In the meanwhile, the number of mega-cities, which is defined by a city size of more than 10 million population, increased from 1 (New York) in 1950, to 5 (Tokyo, New York, Shanghai, Mexico City and São Paulo) in 1972, and to 19 in 2000. In 2015 current projections put this number at 23 (United Nations, 2000).

The process of urbanization brings about a significant and long-term change in population, social, economic, ecological, environmental, and political structures. For instance, people originally depending on agriculture move to urban areas where people no longer depend on natural based occupations. The city needs new land for additional settlements and work places for the newly emerging population. However, this causes conflicts with agriculture, ecology, environment, and energy (University of Michigan, 2005). Therefore, to monitor with up-to-date information about urban change becomes an important issue for both government and private sectors (Sheppard, 1964).

Geographically, urban change refers a difference in which rural areas are converted urban areas from one time to another. Change detection is the process of identifying differences in the state of an object, a surface, or a process by observing it at different times (Singh, 1989). Current urban change detection mainly relies on traditional land information investigation combined with aerial photography interpretation. However, such interpretation is slow, tiring to interpreters, and subject to considerable errors of omission. Moreover, the availability of aerial photographs for a specific area and time depends on the flight conditions, which are not always favourable (Sheppard, 1964; Jackson, et al, 1980; Lillesand, et al, 2005).

Since the launch of Landsat 1, originally named ERTS-1, in 1972, Landsat satellite imagery has become an important data set in identifying the change on the surface of Earth (Jensen, 1986). The spatial resolution of four broad Landsat Multi-spectral Scanner (MSS) bands – (79x79 metres) is relatively coarse and is not sufficient to differentiate signatures between agriculture and residential land use (Jensen, 1981). Since the launch of Landsat 4 in 1982, and Landsat 7 in 1999 (with improved spatial and spectral resolutions), Landsat satellite imagery has been widely applied in urban change detection (Jensen, 1986; Forsythe, 2004).

## 1.2 Problem definition

Canada is the second largest country by area in the world. It has a 79.3% urbanized population, i.e., 23.9 million out of 30 million total population. Four major urban regions account for a large and growing proportion of the nation's population. They are Ontario's extended Golden Horseshoe, Montréal and adjacent regions, British Columbia's Lower Mainland and southern Vancouver Island, and the Calgary-Edmonton corridor (Bennett, 2005).

The Greater Toronto Area (GTA) (Figure 1.1), the major part of Ontario’s extended

Golden Horseshoe, is experiencing rapid urban expansion.

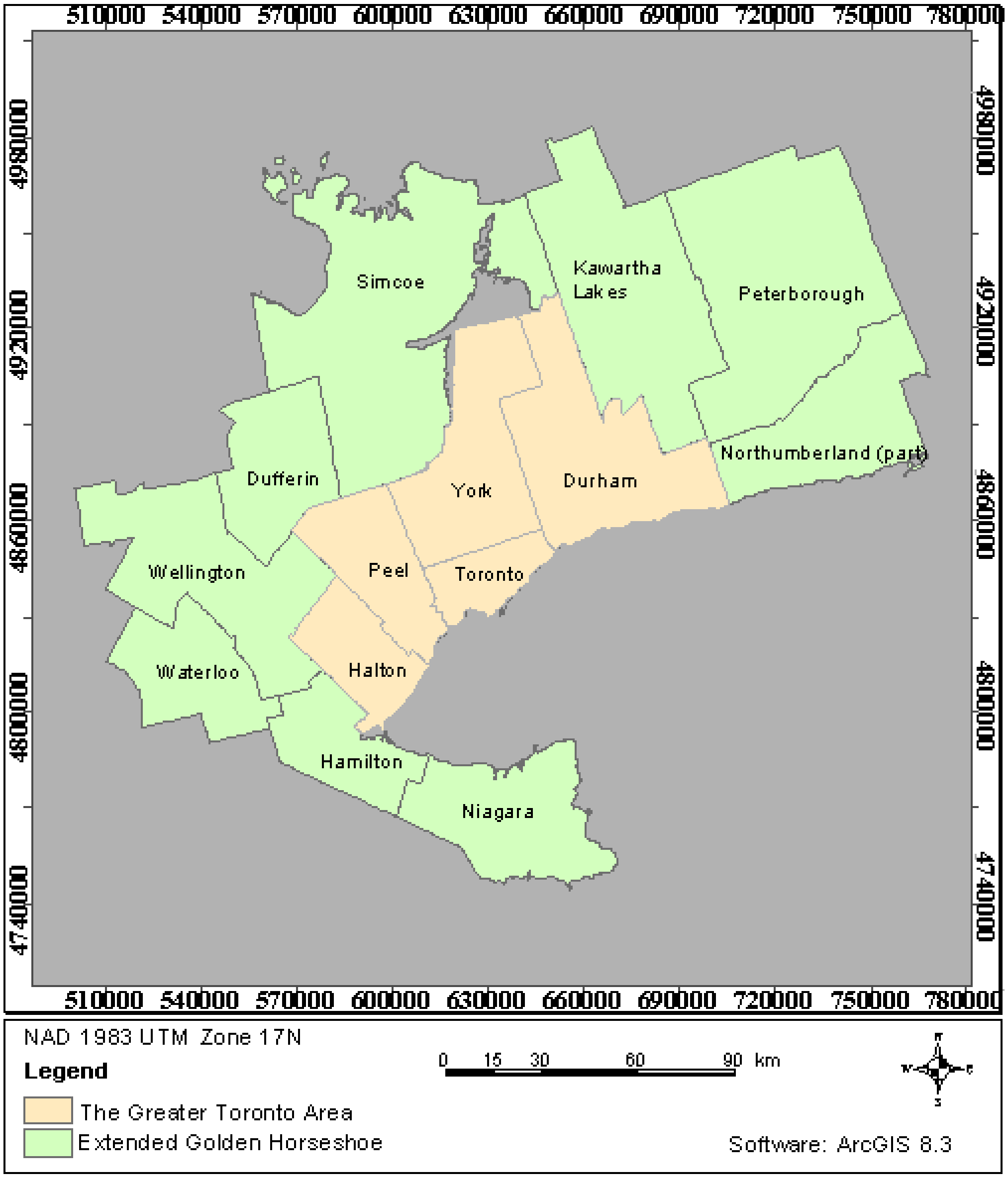



Figure 1.1 GTA in Ontario's extended Golden Horseshoe

From 1991 to 2001 the population increased 20%, to 5.1 million people (44.5% of the total Ontario population, and 16.9% of the total Canadian population) (Statistics Canada, 2001). It is North America's fifth largest and second-fastest growing urban area region (The Office for the Greater Toronto Area, Ministry of Municipal Affairs and Housing, Ontario, 2001). The latest estimates show that Toronto will continue to be Canada's biggest urban-population magnet, growing by as many as 100000 people a year and more than two million people will be added to the Greater Toronto Area in the next 30 years (Immen, 2001). Rapid urbanization has led to the consumption of agricultural land, urban sprawl and pollution issues. Twice as much land in the Toronto area could be developed in the next 20 years as was covered during the past two centuries (Immen, 2001). Increased population, traffic, and infrastructure needs burden the urban environment and seriously affect the overall quality of life. Thus, monitoring urban change in terms of the amount and spatial pattern in the GTA area is significant for urban planning, land-use planning, and the sustainable management of land resources.

## 1.3 Study area

The GTA consists of five upper level regions - Peel, Durham, Halton, Toronto, and York with a total area of over 7000 square kilometres (The Greater Toronto Marketing Alliance, 2003). The study area starts from Halton in the west to Durham in the east, Lake Ontario in the south to York in the north. Figure 1.2 shows the extent of study area in the GTA. It corresponds to the majority of urban areas, particularly the contiguous urban areas in the GTA. The municipalities are Toronto, Burlington, Oakville, Mississauga, Brampton, Vaughan, Richmond Hill, Markham, Pickering, and Ajax (Figure 1.3).

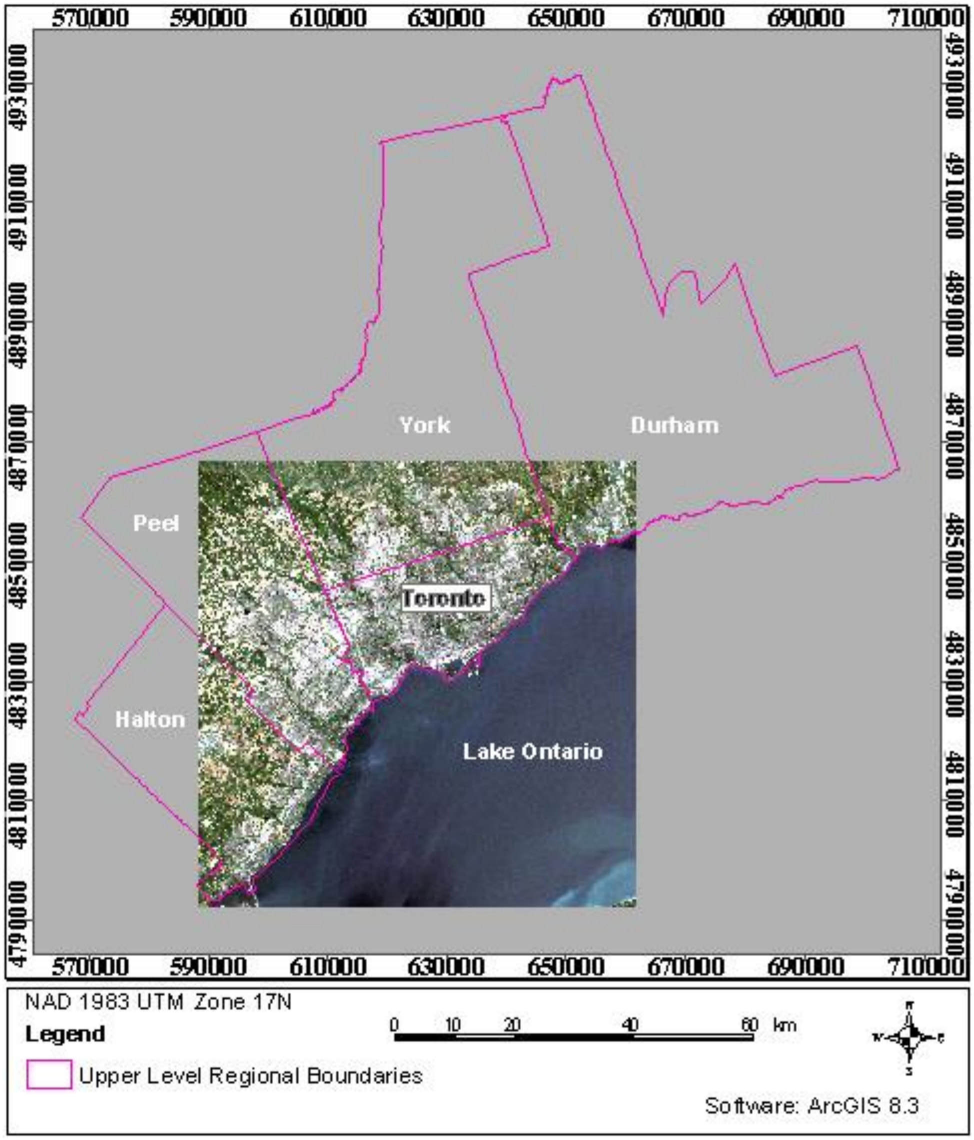



Figure1.2 Study area represented by image in the GTA

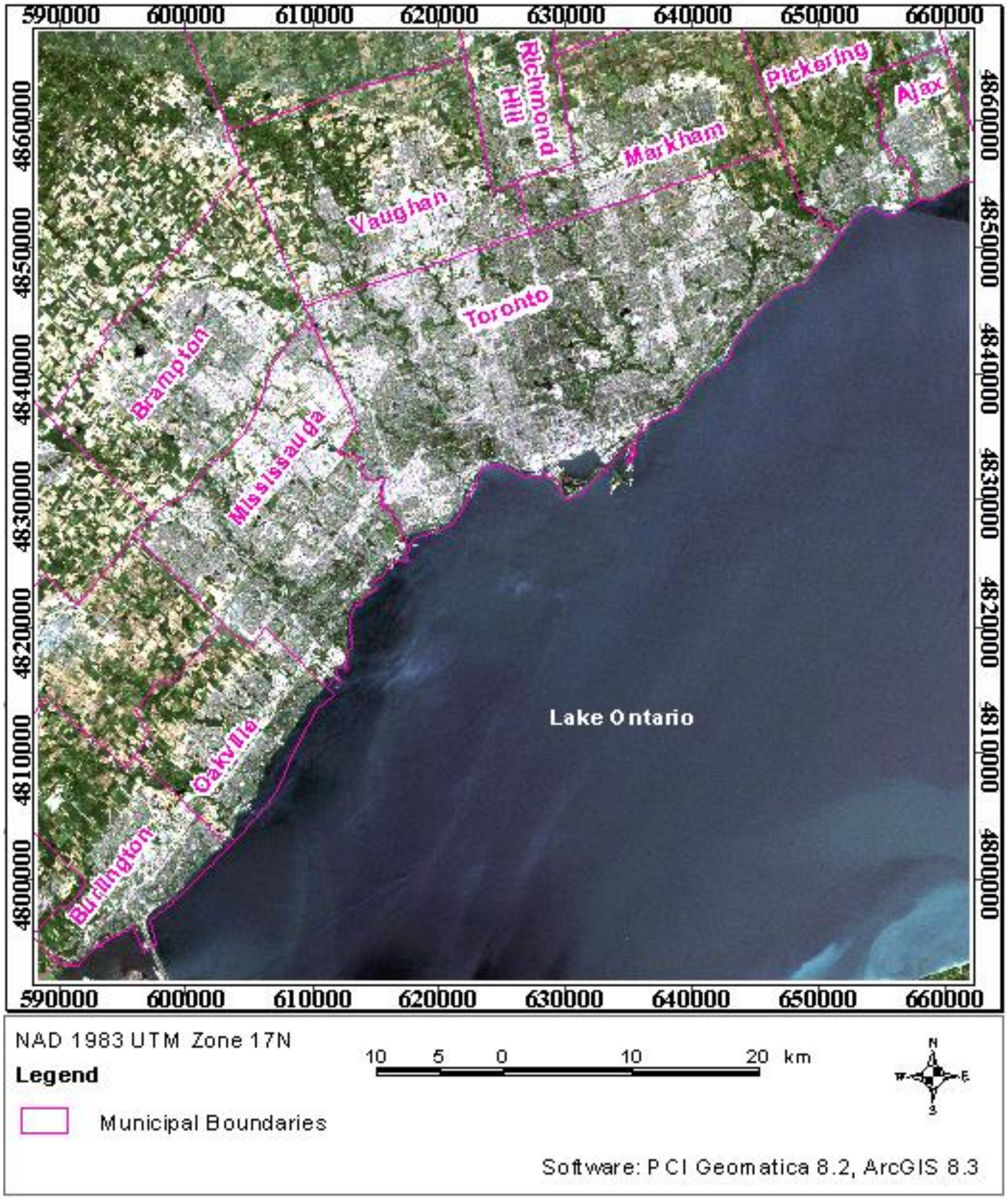



Figure 1.3 Municipal boundaries in study area

## 1.4 Data

### 1.4.1 Data Availability

The data are grouped into two categories: primary data and ancillary data. Primary data include 10 different years of Landsat MSS, Thematic Mapper (TM), and Enhanced

Thematic Mapper plus (ETM+) data from 1972 to 2004. The ancillary data consist of census data from Statistics Canada and supporting data for validation from other data sources. Table 1.1 shows the data characteristics.

Table 1.1 Data availability

| **Landsat Data** | **Census Data** | **Other Supporting Data** |
|---|---|---|
| MSS – 1972 (1972-08-21), 1974 (1974-07-06), 1977 (1777-06-11)<br>TM – 1985 (1985-09-20), 1987 (1987-05-05), 1990 (1990-09-02), 1994 (1994-07-11), 2001 (2001-08-15)<br>ETM+ - 1999 (1999-09-03)<br>Registered and mosaiced (K. W. Forsythe, Ryerson University)<br><br>TM – 2004 (2004-07-05) (NEPTIS) | 1971, 1976, 1981, 1986, 1991, 1996, 2001, 2004 | Aerial Photography1995, 1999, 2002 (Map Library, University of Toronto)<br><br>Canada Land Use Monitoring Program (CLUMP) 1971, 1976, 1986 (Natural Resources Canada) |

### 1.4.2 Coverage of Data in Study Area

Some years of the data do not fully cover the study area. Some images are missing data in the northeast corner, which affects the north part of Ajax, and the northeast corner of Markham. The study area is fully covered by data from years – 1972, 1974, 1977, 1985, and 2004. The missing data in the northeast corner include years from 1987 to 2001, i.e., 1987, 1990, 1994, 1999, and 2001. Figures 1.4 to 1.8 show the coverage for these years.

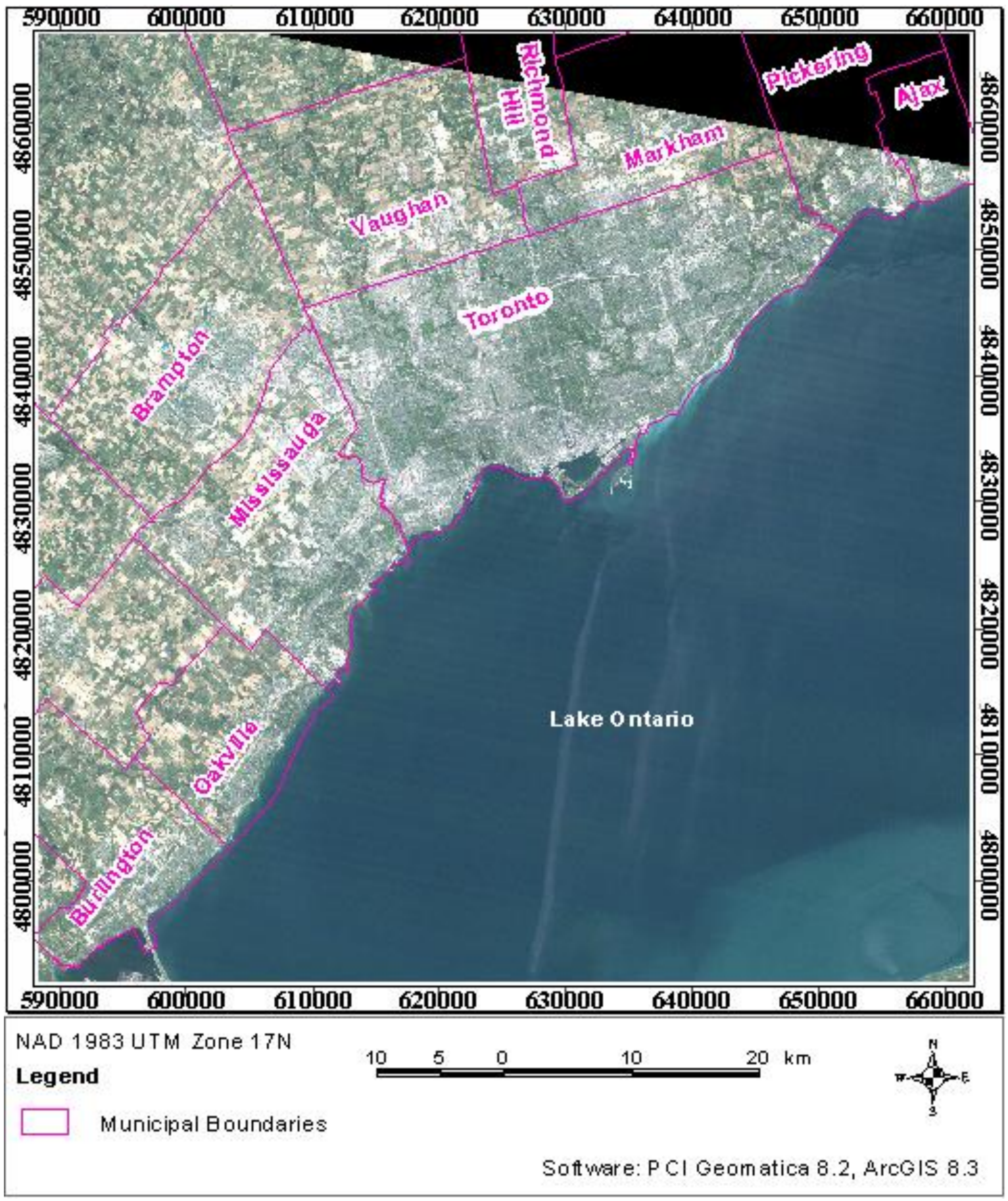



Figure 1.4 1987 data coverage

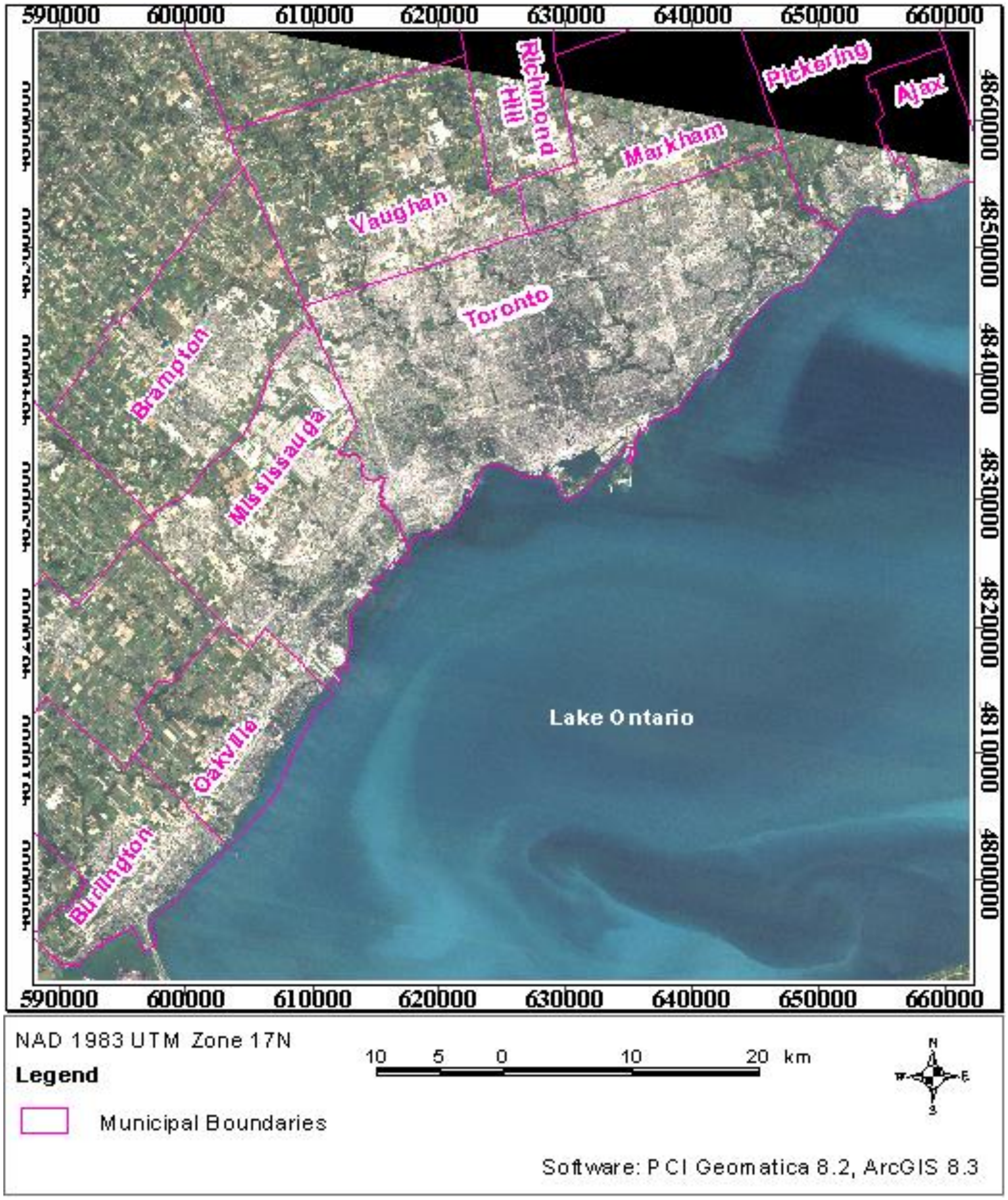



Figure 1.5 1990 data coverage

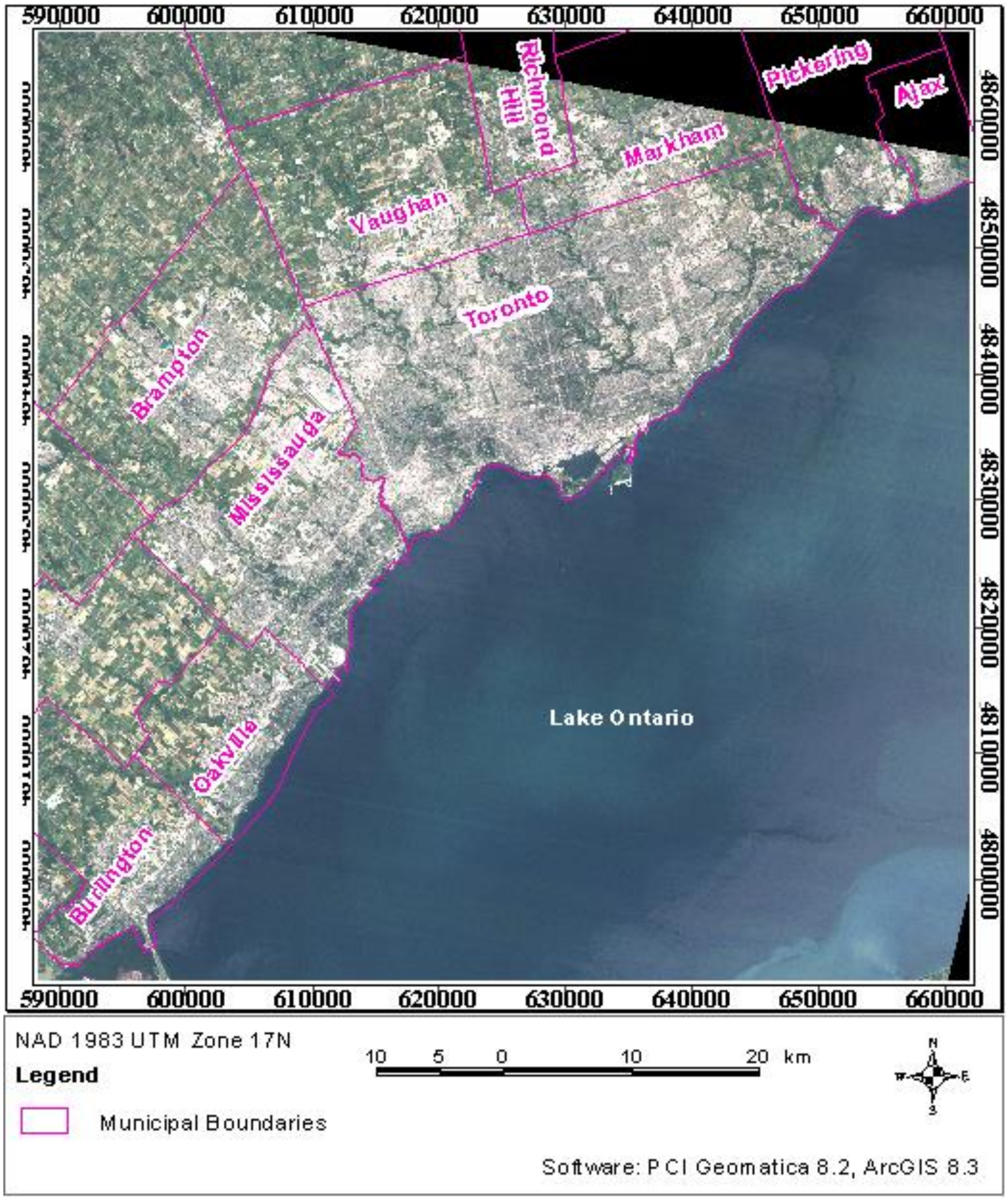



Figure 1.6 1994 data coverage

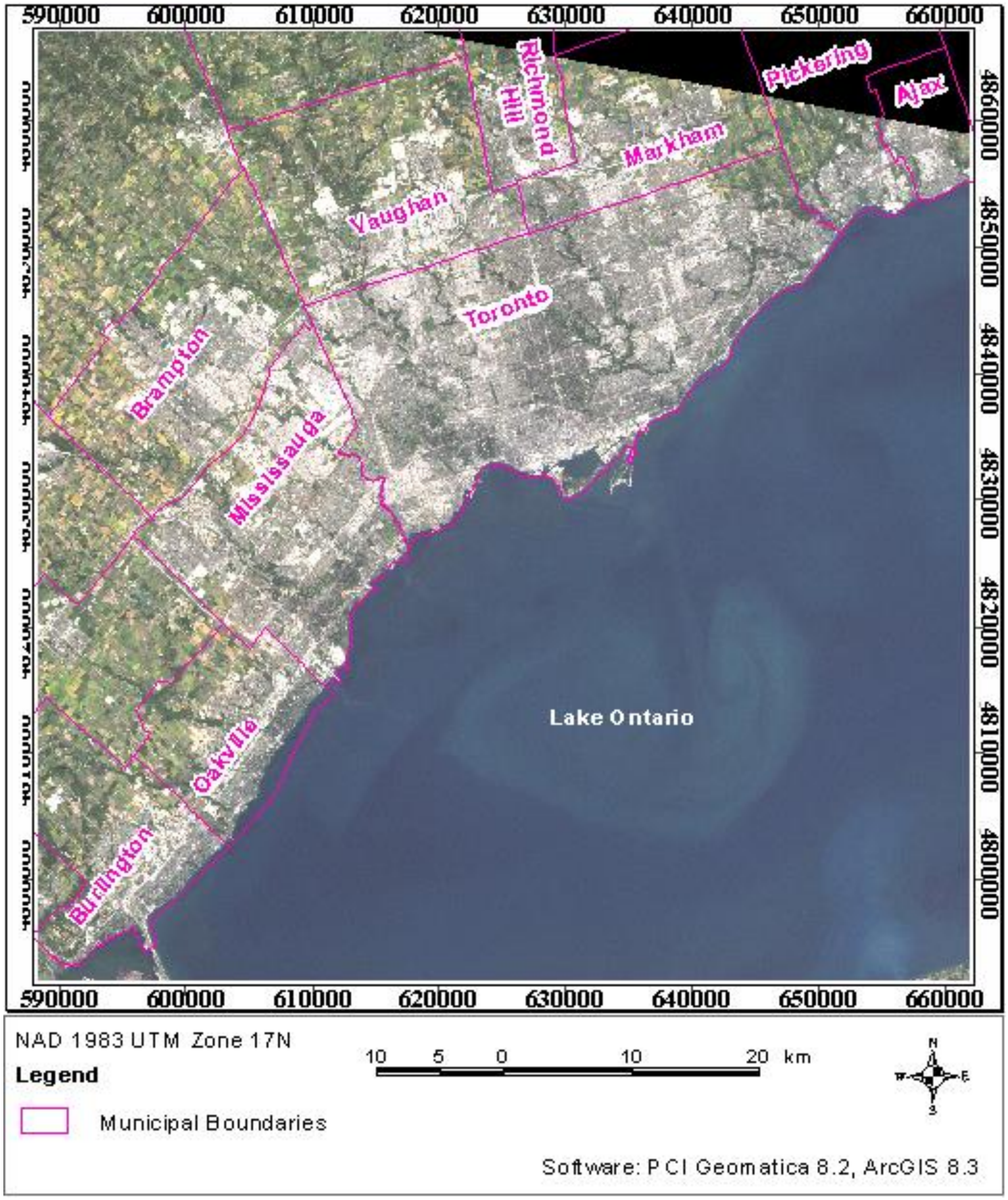



Figure 1.7 1999 data coverage

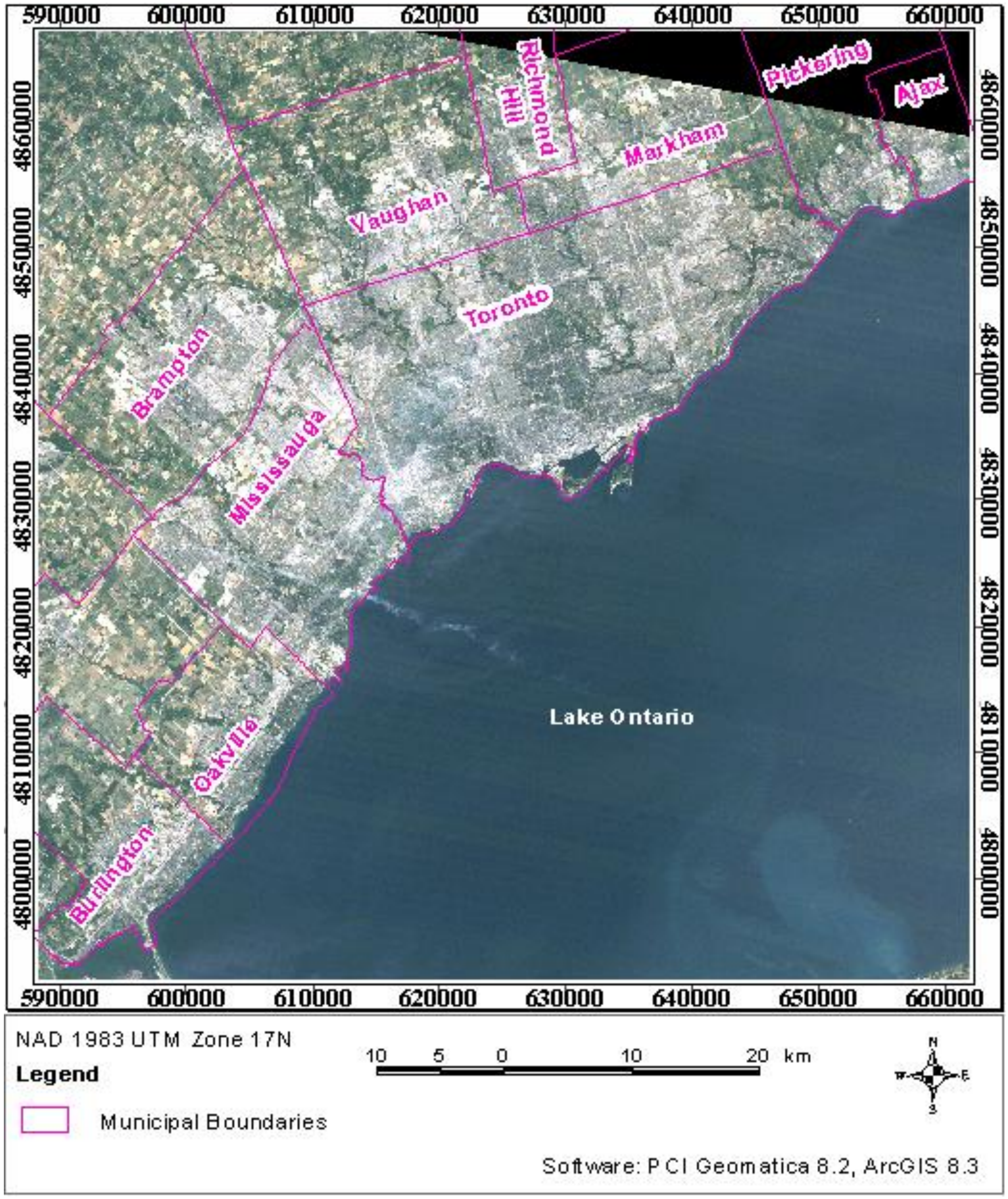



Figure 1.8 2001 data coverage

## 1.5 Research objectives

As mentioned in section 1.2, the GTA is the biggest population magnet in Canada and experiencing the most dynamic growth. Therefore, time-series urban change detection in the GTA is significant for government agencies and industrial firms in such fields as urban development, highway planning, land use, new construction, and agricultural studies (Sheppard, 1964). Urban change detection research in this area has been successfully conducted by Forsythe (2002 and 2004) and Zhao (2004). However, this study examines urban change detection in the GTA from 1972 to 2004 with a greater number of images and a smaller image acquisition interval.

### 1.5.1 Objectives

The objectives include:

- Explore efficient methods to quantify the urban growth over large agglomeration areas with remote sensing and GIS technologies;
- Explore urban change detection methods involving multi-date and different qualities of data;
- Assess accuracy of land cover classification and detected urban changes with ground truth referenced data;
- Calculate the amount of detected urban change and delineate the spatial patterns of urban change at the upper regional level and the lower municipal level;
- Analyze relationship between urban change and population over the GTA;
- Recommend the potential extension in further study.

## 1.6 Structure of final research paper

Chapter 1: Introduction – Introduces the background, problems, available data, and research objectives.

Chapter 2: Literature Review – Reviews previous methodologies in urban change detection with remote sensing and GIS.

Chapter 3: Methodology – Explores methodologies that are most appropriate to the research objectives and applied data.

Chapter 4: Results and Discussion – Shows all dates of satellite-derived results, including urban extent maps, urban change maps, area statistics, and accuracy assessments. Based on derived results, spatial analysis of urban change and its association with census population data are also analyzed.

Chapter 5: Conclusion – Summarizes the values of the methods and results in terms of accuracy achieved. Findings of the detected urban change, limitations of this research, and recommendations for further study are also given.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Introduction

Changes occurring on the Earth's surface are uneven in time and space. Some features are fairly static while others are dynamic, changing rapidly (Jensen, 2004). Land-use/land-cover change is deemed as a major component of global change with an impact perhaps greater than that of climate change (Skole, 1994; Foody, 2001). Keeping information up-to-date is crucial not only to more fully understand the physical and human processes at work, but also for government agencies, environmental groups, and industrial firms to monitor and regulate such changes (Sheppard, 1964; Anderson, 1977; Howarth and Boasson, 1983; Jensen, 1986; Pilon et al., 1988; Lunetta and Elvidge, 2000; Zhan et al., 2002). Without up-to-date information, effective urban planning is hardly possible (Zhang, 2001).

The underlying assumption for change detection using remotely sensed data is that there will be a difference in the spectral response of a pixel on two dates if the land cover changes from one type to another (Jensen, 1986; Singh, 1989). Ideally, data used for change detection should have constant spatial, spectral, and radiometric resolutions under constant environmental conditions - atmospheric conditions, soil moisture, phonological cycle, and so on when they are acquired from remote sensing systems (Jensen, 2004). However, it is difficult to have such ideal situations because those conditions vary. Therefore, a thoughtful understanding of the nature of remotely sensed data and environmental characteristics is essential. Failure to understand the impact from the various data and environmental conditions on the change detection applications can lead to inaccurate results (Dobson et al., 1995; Yuan and Elvidge, 1998).

The following sections review urban change detection techniques from previous research. Ground truth validation and the integration of GIS are also introduced.

## 2.2 Change Detection Techniques

There have been many new urban change detection techniques developed during the past two decades. The techniques have focused on: (1) changes that occurred; (2) the nature of the change; (3) the amount of the change; and (4) the spatial patterns of the change (Macleod and Congalton, 1998).

More often the techniques of change detection are grouped into one of two categories: the postclassification comparison method and the enhancement methods (Nelson, 1983; Pilon et al., 1988; Singh, 1989; Yuan and Elvidge, 1998). The techniques below are based on these categories.

### 2.2.1 Postclassification Comparison

In postclassification change detection, two images from different dates are independently classified. The areas of change are then extracted through direct subtraction of the classification results (Wickware and Howarth, 1981; Jensen, 1986). This method creates a new classification with "from" and "to" identifiers, thus directly capturing the nature and direction of change (Macleod and Congalton, 1998; Dai and Khorram, 1999). The disadvantages of this method include greater computational and labelling work, severe difficulty in obtaining individual classification accuracy, and difficulty to keep consistent between independent classifications (Stow et al. 1980; Howarth and Boasson, 1983; Jensen, 1981; Yuan and Elvidge, 1998; Mas, 1999).

### 2.2.2 Enhancement Methods

**Image Differencing:**

Image differencing involves subtracting the imagery of one date from that of another. The subtraction results in positive and negative values in areas of radiance change and zero values in areas of no change (Jensen, 1983, and 1986). In this method, pixels of no radiance change are distributed around the mean, while pixels of radiance change are located at both tails of the histograms of these transformed data (Singh, 1986). To acquire quantitative information about the areas of land-cover change, thresholding is applied to the transformed data to separate the pixels of change from those of no-change (Fung and LeDrew, 1988). The threshold levels can be determined as a standard deviation from the mean or chosen interactively with various thresholds until optimal ones are identified (Jensen, 1986). The selection of an optimal threshold should also be based on the accuracy of classifying the pixels as change or non-change (Nelson, 1983; Singh, 1986; Fung and LeDrew, 1988). In this method, Jensen and Toll (1982) reported the accuracy of detecting residential land-use development at the urban fringe was improved from 77% to 81% when Band 5 (MSS) spectral image differencing was used in conjunction with texture differencing based on the use of grey tone spatial dependency matrices. Ridd and Liu (1998) found that Band 2 (TM) in image differencing was superior for most of urban change applications.

**Image Ratioing:**

The image ratioing method is useful when changes in viewing conditions degrade the ability of a classifier to identify materials correctly because the ratioing algorithm can reduce the effect of environment and system multiplicative factors present (Jensen, 1981; Jensen, 1986). The area of non-change will yield a ratio value 1.0 while areas of change in multiple date imagery will have values either higher or lower than 1.0. As with the image differencing method, the changes are also located at both tails of the histogram. The selection of thresholds is based on empirical judgment (Friedman, 1978). Howarth and Boasson (1983) applied image ratioing and found that Band 5 data were sensitive to cultural change. However, compared with other methods such as image overlay, it only emphasized major changes.

**Principal Component Analysis (PCA):**

Principal Component Analysis (PCA) defines a new set of variables, which are uncorrelated or mutually orthogonal (Toll et al., 1980). One major use of PCA is to reduce the number of variables that are needed for analysis (Jensen, 1986). The reduction in dimensionality is often desired when large volumes of data and computational tasks are involved (Chavez and Kwarteng, 1989). Research also shows that different principal components account for different information related to specific land cover features. Higher-order principal components (PCs) - (e.g., PC3 and PC4) were able to account for land-cover changes (Byrne et al., 1980; Richard, 1984). Fung and LeDrew (1987) found that standard principal components (SPCs) are more accurate than the non-standardized components because of their better alignment along land-cover changes in the multitemporal data structure. Chavez and Kwarteng (1989) reported that selective PCA results are easier to visually interpret than those from SPCs.

**Texture Analysis:**

The basic theory of texture analysis is that a discrete tonal feature is a connected set of pixels that all have the same or almost the same grey shade (brightness value) and each pixel of the texture image has a brightness value that represents the texture at that location (Jensen, 2004). If a small area of the image has little variation of discrete tonal features, the dominant property of that area is a grey shade. Conversely, if a small area has a wide variation of discrete tonal features, the dominant property of that area is texture. Texture analysis approaches are based on first and second order grey-level statistics and on the Fourier power spectrum and measures based on fractals. The first-order statistics of local areas such as means, variance, standard deviation, and entropy in pixel windows typically ranging from 3x3 to 5x5 to 7x7 are used (Hsu, 1978; Gong et al., 1992). However, they were not as effective as the brightness value spatial-dependent co-occurrence matrix measures (Haralick et al., 1973; Schowengerdt, 1997). Jensen and Toll (1982) reported on the use of Haralick's angular second moment (ASM) for use as an additional feature in the supervised classification of remotely sensed data obtained at the urban fringe and in urban change detection mapping. They found it improved the classification when used as an additional feature in the multispectral classification.

**Vegetation Indices:**

Vegetation indices are based on the differential absorption, transmittance, and reflectance of energy by the vegetation in the red and near-infrared portions of the electromagnetic spectrum (Derring and Haas, 1980; Lyon et al., 1998; Jensen, 1996). In Landsat MSS data the ratio of near-infrared - band 4 and red - band 2 is significantly correlated with the amount of the green leaf biomass (Tucker, 1979). For Landsat TM, the ratio of near-infrared - band 4 and red - band 3 is adopted (Jensen, 1986; Masek et al., 2000). Vegetation indices have many subdivisions, including the Difference Vegetation Index (DVI), Normalized Difference Vegetation Index (NDVI), Perpendicular Vegetation Index (PVI), Ratio Vegetation Index (RVI), Soil Adjusted Ratio Vegetation Index (SARVI), Soil Adjusted Vegetation Index (SAVI), and the Transformed Soil Adjusted Vegetation Index (TSAVI) (Richardson and Everitt, 1992). Lyon et al. (1998) reported that NDVI was the best vegetation index for change detection as judged by laboratory and field results.

## 2.3 Land-use/land-cover Classification

Land-use/land-cover classification (LULC) based on statistical pattern recognition techniques applied to multispectral remote sensor data is one of the most often used methods of information extraction (Narumalani et al., 2002). In terms of emphasis on different pattern recognition, spectrally oriented classification procedures for land cover currently form the backbone of most multispectral classification activities (Lillesand et al., 2004). They include supervised classification and unsupervised classification.

### 2.3.1 Supervised Classification

In a supervised classification, the identity and location of some land-cover types are known a priori through a combination of fieldwork, interpretation of aerial photography, map analysis, and personal experience (Hodgson et al., 2003). The analyst attempts to locate specific sites in the remotely sensed data that represent homogenous examples of these known land-cover types. These sites are referred to as training sites. Multivariate statistical parameters (mean, standard deviation, covariance matrices, and correlation matrices) are calculated for each training site. Every pixel is then evaluated and assigned to the specific class based on these evaluation criteria (Jensen, 2004). Methods used to evaluate the pixels include minimum distance, parallelepiped, and maximum likelihood. Minimum distance is mathematically simple and computationally efficient, but it is insensitive to different degrees of variance in the spectral response data. Parallelepiped is insensitive to covariance, resulting in confusion for a parallelepiped classifier. The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns (Lillesand et al., 2004).

### 2.3.2 Unsupervised Classification

Unsupervised classification does not utilize training data as the basis for classification. Rather, it involves algorithms that examine the unknown pixels in an image and aggregate them into a number of classes based on the natural groupings or clusters present in the image values. The basic premise is that values within a given land cover type should be close together in the measurement space, whereas data in different classes should be comparatively well separated (Lillesand et al., 2004). Algorithms include

K-means clustering (also called sequential clustering), Interactive Self-Organizing Data Analysis (ISODATA), fuzzy classification, and classification based on object-oriented image segmentation (Jensen, 2004). K-means and ISODATA clustering approaches are widely used (Lillesand et al., 2004). K-means clustering accepts the number of clusters to be located in the data first, and then assigns pixels in sequence to different classes according to the spectral distance of each pixel from the mean of each class. After all pixels have been classified in this manner, revised mean vectors for each of the clusters are computed. The revised means are then used as the basis to reclassify the image data. The procedure repeats until there is no significant change in the location of class mean vectors between successive iterations of the algorithm. ISODATA is an opposite method to the K-mean clustering. It starts with all pixels as a class and gradually splits it to a desired number of classes with standard deviation (Tou and Gonzalez, 1974).

## 2.4 Combined Applications

### 2.4.1 Differencing and Ratioing Methods for Other Enhancement

Image differencing and ratio methods are not only limited to band-by-band subtraction and ratioing. They are also used as an important means to enhance results. Jensen and Toll (1982) used the differenced results from two different dates of texture analysis to improve change detection. Singh (1989) believed that NDVI differencing was one of the few, most accurate change detection techniques. Yuan and Elvidge (1998) adopted differencing and ratioing methods for PCAs to compare and evaluate accuracies of land-cover change detection. Forsythe (2004) applied differencing methods to pansharpened images.

### 2.4.2 Direct Multi-date Classification

Direct multi-date classification is based on the single analysis of a combined dataset of the two dates in order to identify areas of change (Singh, 1986). Classes where changes occurred are expected to present statistics significantly different from where change did not take place and thus can be identified. Unsupervised classification is carried out by using the ISODATA method, in which the spectral distance is used and the pixels are iteratively classified until all pixels in the data are emerged into appropriate classes (Jensen, 1981; Mas, 1999; Weismiller, Scholz, and Momin, 1977). Fung and LeDrew (1987) and Macleod and Congalton (1998) applied PCs from merged multi-date data for change detection.

### 2.4.3 Combination Image Enhancement/Post-classification Analysis

Image enhancement is often combined with post-classification analysis. The change produced by an enhancement procedure is recoded into a binary mask, consisting of the change and non-change between the two dates. The binary mask is then overlaid with data from the second date. A traditional post-classification is conducted to yield from-to change information. This method may reduce change detection errors and provides detailed from-to change patterns (Pilon et al. 1988; Jensen 1996; Mas, 1999; Macleod and Congalton, 1998).

### 2.4.4 Preprocessing Operations

In addition to enhancement algorithms that are directly applied in change detection, geometrical registration, atmospheric correction, image normalization, and any other preprocessing operations, such as low and high pass filtering may also be important to improve accuracy of change detection (Jensen, 1981; Hall et al., 1991; Yuan and Elvidge, 1998; Song, et al., 2001; Yang and Lo, 2002).

### 2.4.5 Other Methods

Other methods in urban change detection include image regression, change vector analysis, tasselled cap transformation, Chi-square transformation, artificial neural networks, fuzzy fusion, Vegetation-Impervious Surface-soil (V-I-S), and knowledge-based vision systems (Singh, 1989; Ridd and Liu, 1998; Jensen, 2004; Ridd, 1992; Wang, 1993; Dai and Khorram, 1999; Abuelgasim et al., 1999; Foody, 2001; Zhang, 2001; Forsythe, 2004).

## 2.5 Comparison of Change Detection Techniques

Since change detection techniques have different conditions in data and purposes, it is difficult to compare the vast array of change detection methods (Jensen, 1986, 1996; Singh, 1989; Ridd and Liu, 1998; Mas 1999). From this point, no one single technique/algorithm is optimal. For instance, image differencing, image regression, and PCA are thought to perform better than the postclassification technique (Singh, 1989). However, Mas (1999) reported that the result of postclassification performed better than image differencing and PCA. This is because urban change detection techniques are closely related to data quality, resolutions, study area, and accuracy requirements (Jensen, 1986). Overall, preclassification or enhancement techniques such as image differencing (Singh, 1989; Weismiller et al., 1977; Toll, 1980; Jensen and Toll, 1982; Ridd and Liu, 1998; Yuan and Elvidge, 1998), image regression (Ridd and Liu, 1998), PCA differencing (including standardized and selective PCA) (Singh, 1989; Mas, 1999; Chavez and Kwarteng, 1989; Fung and LeDrew 1987; Macleod and Congalton, 1998); NDVI differencing (Howarth and Boasson, 1983; Masek et al., 2000; Lyon et al., 1998) greatly improve the classification results and accuracy of detected urban change (Dai and Khorram, 1999). The postclassification technique has from-to patterns (Macleod and Congalton, 1998), but its accuracy is not as good as results from preclassification change detection techniques (Weismiller, 1977; Toll, 1980; Jensen, 1986). Fung and LeDrew (1988) reported the threshold values tightly associated with accuracies for different algorithms and noted that they are sensitive to different natures of change. Jensen (1986) pointed out that differencing or ratioing of spectral data is practical but may be too simple. Therefore, combination of methods (such as multi-date classification, preclassification with postclassification, and preprocessing operations) may produce better results in terms of decreasing the chance of error, and in improving the accuracy of detecting the nature and amount of change (Jensen, 1982; Macleod and Congalton, 1998; Mas, 1999).

## 2.6 Accuracy Assessment

With the advent of more advanced digital satellite remote sensing techniques, the necessity of performing an accuracy assessment received renewed interest (Congalton, 1991). The accuracy of remote sensing-derived thematic information is the foundation for further data analysis and decision-making (Muchoney and Strahler, 2002; Kyriakidis et al., 2004).

Errors in remote sensing-derived products may come from a variety of sources including system errors from detectors in satellite sensors, severe atmospheric conditions, and human errors when processing the data. Randomly unwanted atmospheric conditions, such as haze, smog, or fog will dramatically affect the quality and accuracy of the information that is extracted. It is likely that human errors will be introduced throughout the image processing, information extraction, data conversion, error assessment, and even decision-making stages (Jensen, 2004).

### 2.6.1 Methods of Accuracy Assessment

Jensen (2004) gives a general procedure of accuracy assessment:

- State accuracy assessment objectives and problems
- Select methods of accuracy assessment
- Compute total observations required in the sample
- Select sampling design
- Obtain ground reference data at observation locations using a response design
- Error matrix creation and analysis
- Accept or reject previously stated hypothesis
- Distribute results if accuracy is acceptable

**Reference Data:** In order to adequately assess the accuracy of the remotely sensed classification, accurate ground or reference data must be collected (Congalton, 1991). Ideally, the ground reference test data are obtained by visiting the site on the ground and making very careful observations that can be compared with the remote sensing-derived information for the exact location. Unfortunately, it is difficult to actually visit all the sites identified in the random sample (Jensen, 2004). Therefore, people may select other available reference data, such as land-use or aerial photography as a surrogate for ground reference test information (Congalton, 1991; Morisette et al., 2004). The general rule of thumb is that the resolution of aerial photography should be substantially higher in spatial or spectral resolution than the imagery used to derive the classification (Jensen, 2004; Congalton, 2004).

**Sample Size:** The actual number of ground reference test samples to be used to assess the accuracy of individual categories in a remote sensing classification map is very important.

Due to the expense to collect sample points, sample size must be kept to a minimum, yet it is critical to maintain a large enough sample size so that any analysis performed is statistically valid (Congalton, 2004). Generally, an appropriate sized sample may be estimated using conventional statistics (Foody, 2002). However, the majority of researchers have used an equation based on the binominal distribution or the normal approximation to the binomial distribution to compute the required sample size (Congalton, 2004).

**Sampling Design:** Sampling design is an important part of any accuracy assessment (Congalton, 2004). Sampling design (or sampling scheme) includes simple random sampling, stratified random sampling, systematic sampling, unaligned sampling, and cluster sampling (Jensen, 2004). Congalton (1988) performed simple random sampling and got desirable statistical properties, however, he pointed out this sampling scheme is not always very practical to apply. Simple random sampling tends to undersample small but possibly very important areas unless the sample size is significantly increased. The random samples may also be located in inhospitable or access-denied locations (Jensen, 2004). Therefore, stratified random sampling is recommended where a minimum number of samples are selected from each stratum. Even stratified random sampling can be somewhat impractical because of having to collect information for accuracy assessment at random locations on the ground (Congalton, 2004).

**Descriptive Evaluation** – The most common descriptive statistic is overall accuracy, which is computed by dividing the total correct (i.e., the sum of the major diagonal) by the total number of sample units in the error matrix. Producer's accuracy (related to omission error) is a measure to indicate how correct a reference sample unit can be classified. User's accuracy (related to commission error) indicates how well a sample on map represents category on the ground (Story and Congalton, 1986).

**Discrete Multivariate Analysis** – Since 1983, discrete multivariate techniques have been used for performing statistical tests on the classification accuracy of digital remotely sensed data (Congalton and Mead, 1983; Hudson and Ramm, 1987; Lillesand and Kiefer, 1994; Foody, 2002). One analytical step to perform once the error matrix has been built is to "normalize" or standardize the matrix using a technique known as "MARGFIT" (Congalton et al., 1983). The second discrete multivariate technique of use in accuracy assessment is called Kappa (Cohen, 1960). Kappa can be used as another measure of agreement or accuracy. Improvement has been made by Landis and Koch (1977) by lumping the possible range (from –1 to +1) into three groups: a value greater than 0.8 representing a strong agreement; a value between 0.4 and 0.8 representing moderate agreement, and a value below 0.4 representing poor agreement.

The power of kappa analysis is that it provides two statistical tests of significance. It is possible to test whether an individual land-cover map generated from remotely sensed data is significantly better than a map generated by randomly assigning labels to areas. The second test allows for the comparison of any two matrices to see whether they are statistically, significantly different. In this way, it is possible to determine that one method/algorithm/analyst is different from another one and, based on a chosen accuracy measure (e.g., overall accuracy), to conclude which is better (Congalton, 2004).

## 2.7 Integration with GIS

A Geographic Information System (GIS) is a computer-based systems that can store and retrieve, edit and create, analyse and calculate, display and map spatial data (Aronoff, 1991; Maguire et al., 1991). More important is that most of traditional vector datasets, including many ancillary data for remote sensing, are stored on GIS (Jensen, 2004). GIS is not only good at manipulating vector data, but also good for analyzing raster data. Besides, the seamless integration between spatial and aspatial attributes make it powerful in spatial analysis associated with census data, demographic data, and statistic methods (ESRI, 2005). Therefore, it is important to integrate GIS into urban change detection so that the results produced from image processing are further analysed and developed by introducing census data and other socio-economic data.

## 2.8 Summary

The vast array of change detection techniques show that each technique has its own characteristics, which are probably only suitable for specific situations closely associated with data conditions and study purposes (See Section 2.5). Therefore, no one technique is absolutely optimal to apply in all cases. Deeply understanding the original data, suitability of related techniques, accuracy requirements and exploring appropriate algorithms (including the combined methods) would be helpful to more fully utilize the potential of Landsat data (Jensen, 1986; Singh, 1989).

# CHAPTER 3: METHODOLOGY

The methodology is based on the availability and quality of Landsat data for this research, therefore a data analysis was first conducted.

## 3.1 Data Analysis and Preparation

### 3.1.1 Years

The interval between the available Landsat images ranged from 2 to 8 years, i.e., 2 year interval from 1999 to 2001 and 8 years between 1977 and 1985. However, most intervals between adjacent dates ranged between 2 and 5 years. The length of interval between compared dates does affect the method that is used to detect the change. The reason is that urban growth generally follows a forward rotation from green space to excavated, and from excavated to built-up (Forsythe, 2002; Forsythe, 2004). A long interval between compared years will skip some changes in this forward rotation because the majority of urban change has already completed more than one forward rotation. A short interval, however, will detect each change within this forward rotation. Therefore, appropriate techniques to deal with these two situations must be considered. Another consideration is the connection with census data. The closest census data specifically associated with the Landsat data are 1971, 1976, 1981, 1986, 1991, 1996 and 2001.

### 3.1.2 Registration

To make all selected data comparable, geometric registration is required. The data from 1972 to 2001 were previously registered with Root Mean Square (RMS) errors of 0.25 pixels or less in both the X and Y directions. The 2004 image was registered to these years of data.

## 3.2 Method Development

The methodology focused on two parts: the urban extent and the change between dates of image acquisition. However, due to the differences between Landsat MSS data and Landsat TM/ETM+, a single method may be not sufficient. Moreover, urban change detection techniques as outlined in Chapter 2 may not be completely suitable for the data available for this research. Therefore, the development of the methodology mainly depended on experiments, by which the optimal methods were selected and some new combined methods were created.

### 3.2.1 Experiment # 1 – Enhancement vs. Without Enhancement

Although enhancement techniques help improve classification, their effects may be different for different types of Landsat data. The comparison between classifications with enhancement and without enhancement will examine effects on MSS, TM, and ETM+ data. Three years (1977, 1999, and 2001) were selected to conduct the comparison between enhancement and without enhancement. The Town of Bolton (Figure 3.1) is located in the northwest corner in the study area in Peel region. Bolton is isolated from the contiguous urban areas, and surrounded by the farm fields. This is an ideal place to examine the different results from enhancement and without enhancement in terms of how well the urban land cover is separated from green space or fields.

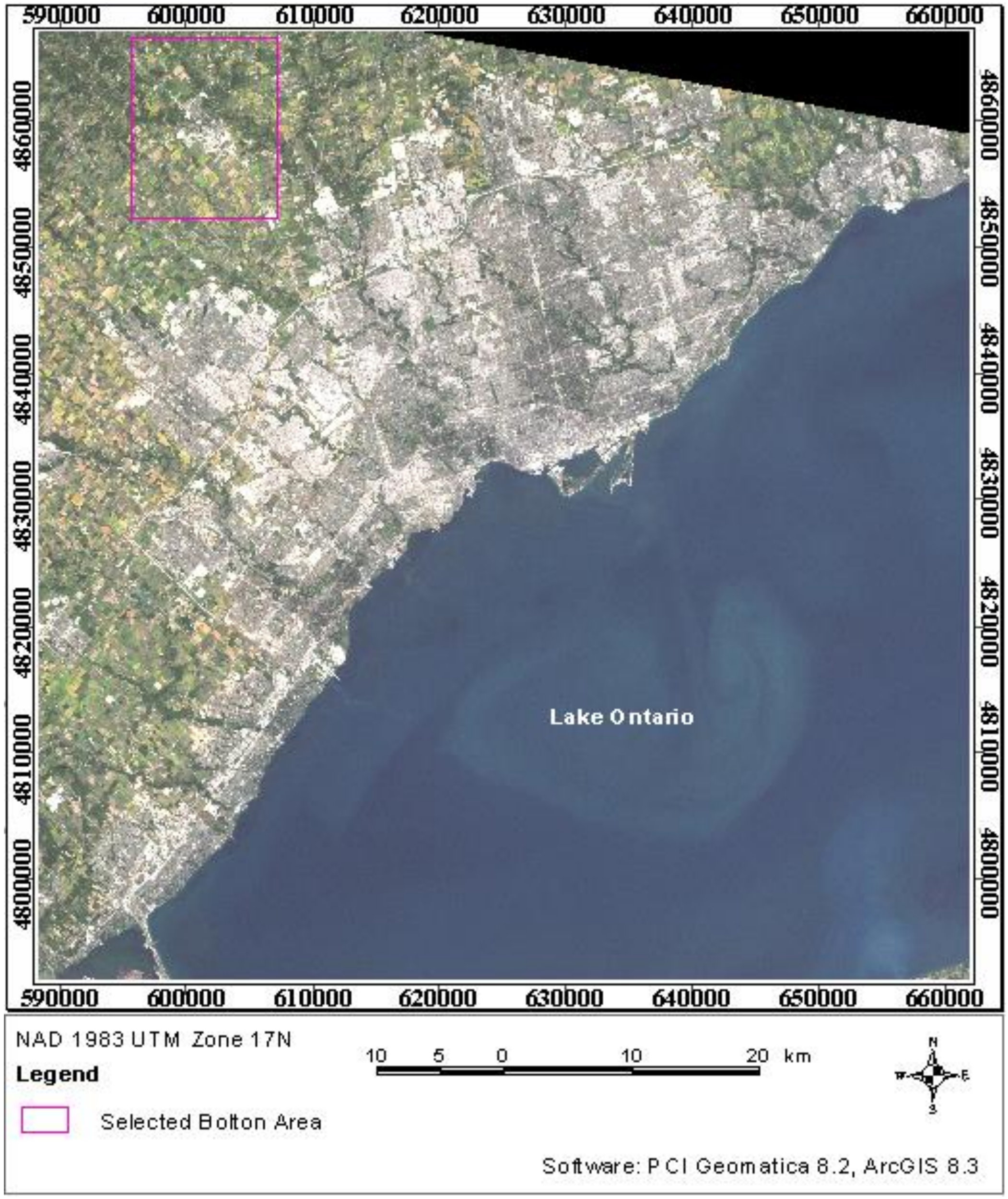



Figure 3.1 Bolton area in 1999 ETM+ imagery

The comparison between enhancement and without enhancement was conducted by supervised classification. Classification without enhancement only included original bands as input whereas classification with enhancement included additional enhanced results as input. The selected enhancements were NDVI, texture analysis, and principal components because they were deemed as the most common enhancement methods

(Jensen, 1986; Howarth, 1989; Masek et al, 2000; Forsythe, 2004). The training sites between two classifications were kept the same.

The greatest change between enhancement and without enhancement occurred with the TM data. Figure 3.2 shows that before enhancement, Bolton's urban area is not completely separated from farm fields and rivers on its north side. However, enhancement helps separate urban from rural areas. Landsat MSS data also benefit from enhancement. Figure 3.3 shows that before enhancement, Bolton's urban area is totally indiscernible from its surrounding rural areas. Enhancement removes a lot of noise in rural areas. However, it is not completely removed. From Figure 3.4, the enhancement for ETM+ data is also obvious. However, the change between enhancement and without enhancement is not as great as TM or MSS data. Bolton's urban area is separated very well even before the enhancement.

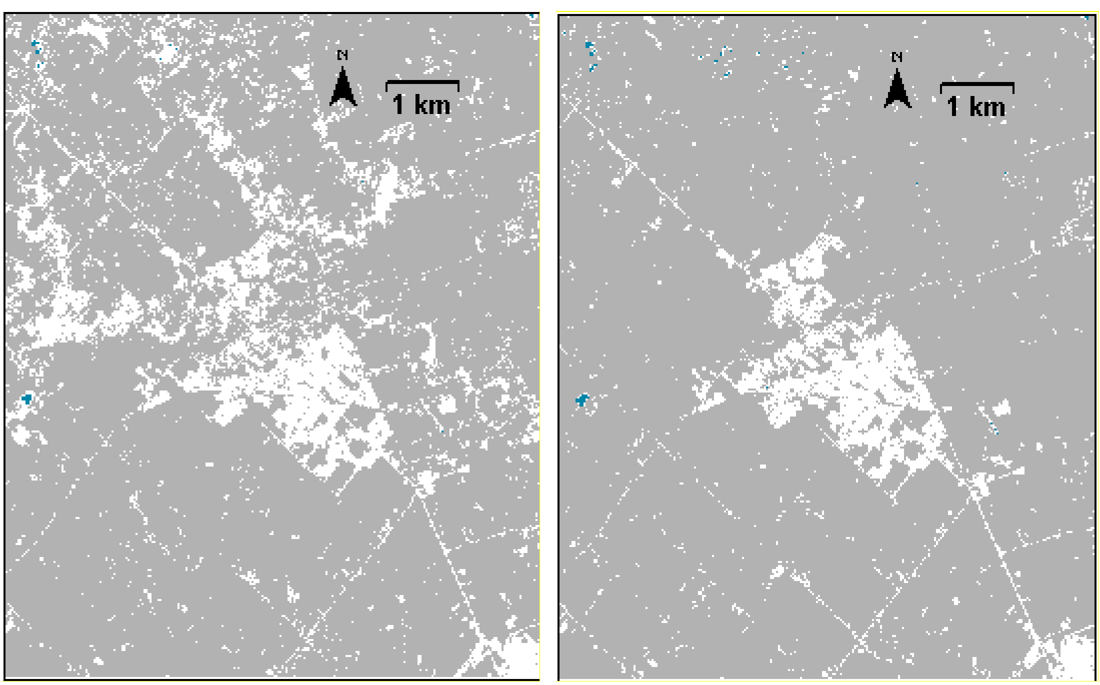



Figure 3.2 Classification with enhancement and without enhancement (2001 TM).
Left: without enhancement; Right: enhancement

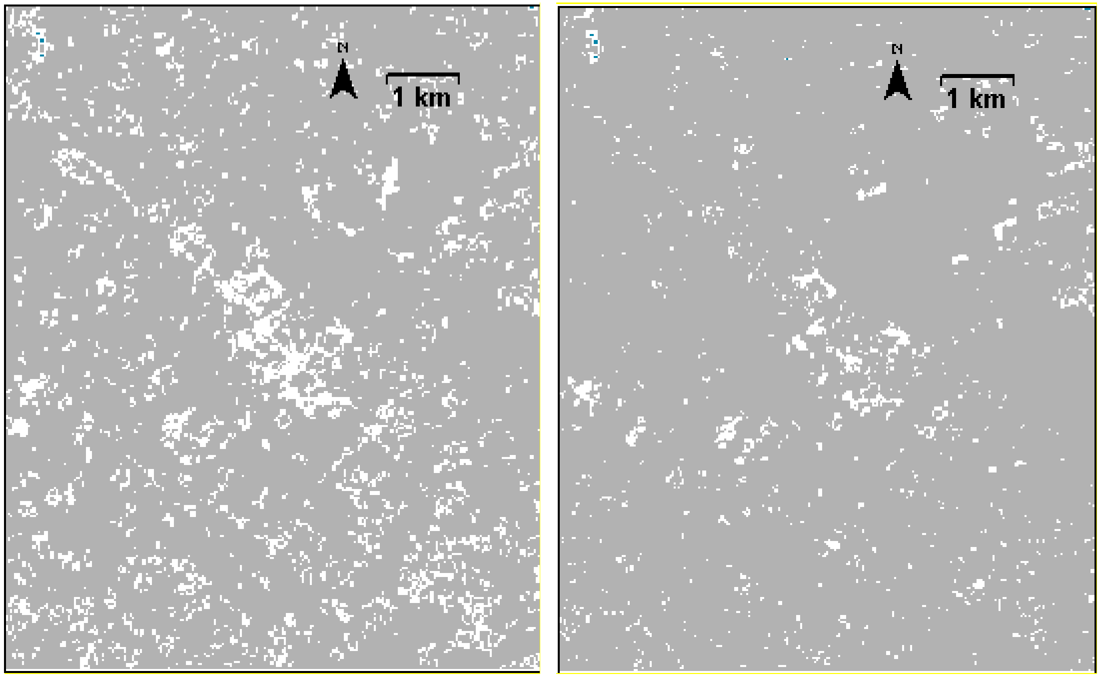



Figure 3.3 Classification with enhancement and without enhancement (1977 MSS).
Left: without enhancement; Right: enhancement

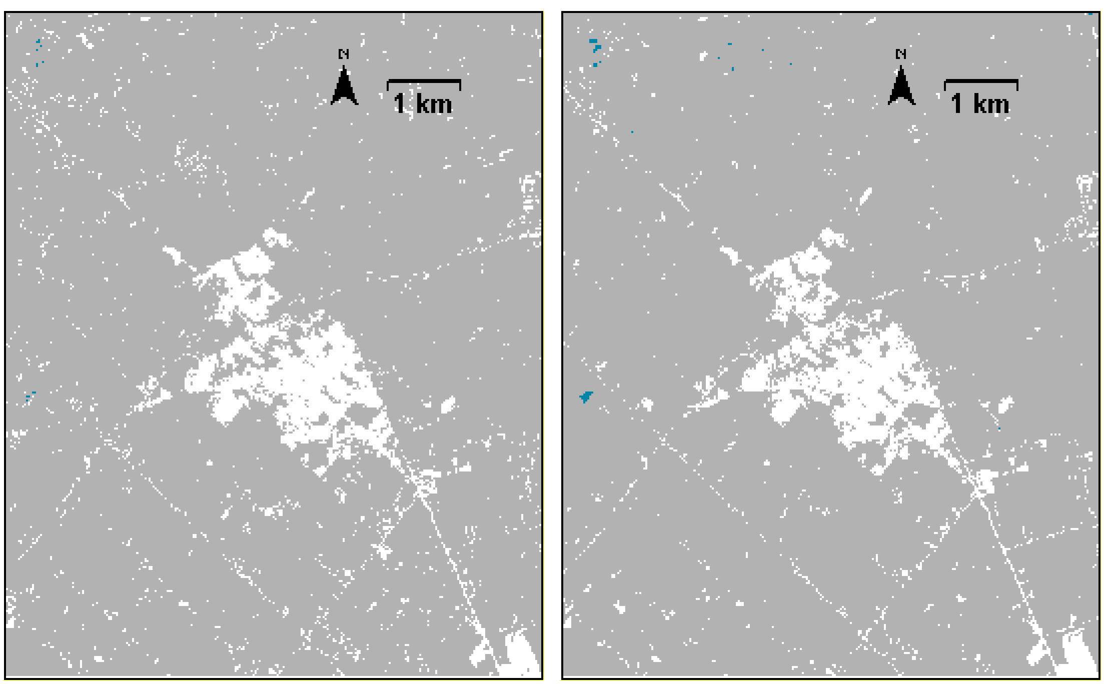



Figure 3.4 Classification with enhancement and without enhancement (1999 ETM+).
Left: without enhancement; Right: enhancement

### 3.2.2 Experiment # 2 – Different Types of Enhancement

The results from Experiment #1 show that these selected enhancements are still insufficient to distinguish urban from rural areas with MSS data and their effects on the three types of Landsat data are quite different. It is necessary to explore the enhancements further and discover some other combination of enhancements so that the urban can be maximally separated from the rural areas.

**NDVI**

NDVI helps to differentiate vegetation and non-vegetation in two aspects: healthy status and water content. As stated in Experiment # 1, Bolton is surrounded by the farm fields. It is also a good place to verify the NDVI results due to its ability to separate the urban areas from rural. In order to see the images more clearly, the selected area is zoomed in compared with the previous selected area. MSS NDVI uses Band 2 and Band 4 as input (Jensen, 1986; Howarth, 1989) whereas TM and ETM+ data use Band 3 and Band 4 as input (Masek et al., 2000).

Figure 3.5 shows the NDVI results for the 1977 MSS, 2001 TM, and 1999 ETM+ data. Dark tones in images are non-vegetated land cover that represent urban and bare soil. The light tones in the images are vegetated crop fields and forests. The TM and ETM+ data were better than MSS data in separating non-vegetation from the vegetation land cover through NDVI. This is because the spatial resolution of input channels – 30m in TM and ETM+ is much higher than the 79m MSS data.

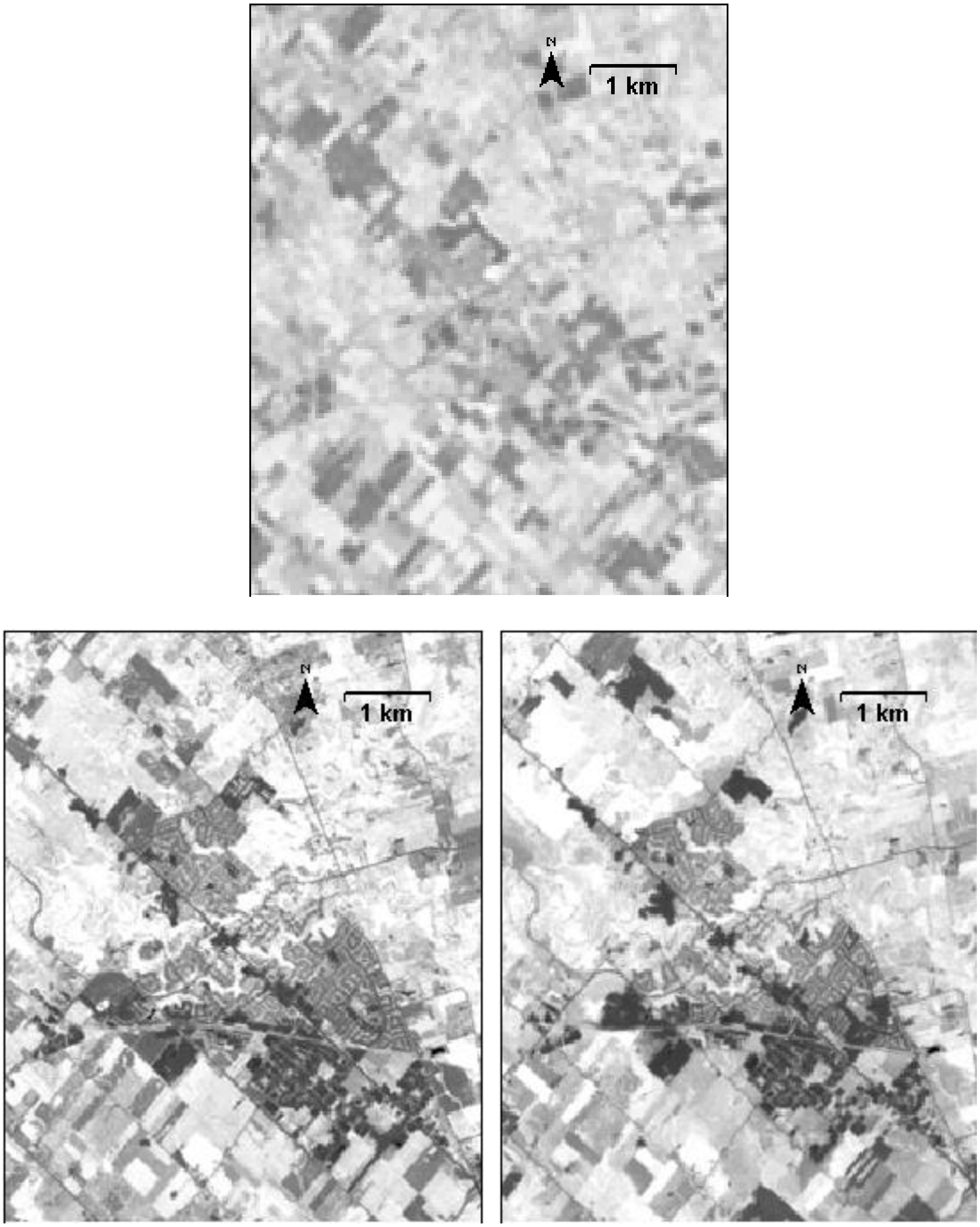



Figure 3.5 NDVI between MSS, TM, and ETM+
Upper: 1977 MSS; Lower left: 2001 TM data; Lower right: 1999 ETM+

### Texture Enhancement

Texture enhancement is widely used to differentiate urban features from rural areas. Band 2 in TM data is deemed the best data for texture analysis (Masek et al., 2000; Forsythe, 2004). The experiment used band 2 from the 1999 ETM+ as input. ETM+ band 2 has the same spectral resolution as TM band 2 and is close to MSS band 1. The selected area is Vaughan (Figure 3.6). This area includes a typical urban area adjacent to a rural area. The experiment indicated that texture analysis using a mean measure was the best. Window size is also associated with the texture enhancement and the results showed that a 3x3 window was the best. Figure 3.7 shows the result from the homogeneity measure with a 3x3 window. It is totally unable to differentiate the urban features. Figure 3.8 shows the results from the mean measure with different window sizes. Obviously, the 3x3 size is able to capture the texture in more detail than the 7x7 size.

### PCA

PCA simplifies information into fewer components, which are very useful in enhancing classification procedures. The 1999 ETM+ data was selected with input bands/channels 1, 2, 3, 4, 5, and 7. The selected area is the same as the texture analysis because this area not only includes built-up areas and rural area, but also includes excavated areas.

Figure 3.9 shows the PCA results – PC1, PC2, and PC3. PC1 captures the excavated area, rural area, and all built-up areas. PC2 is only sensitive to the built-up urban feature, which shows as dark in picture, but insensitive to the excavated. PC3 is sensitive to both the excavated and the built-up areas. Main components accounting for different land cover features will greatly improve the classification.

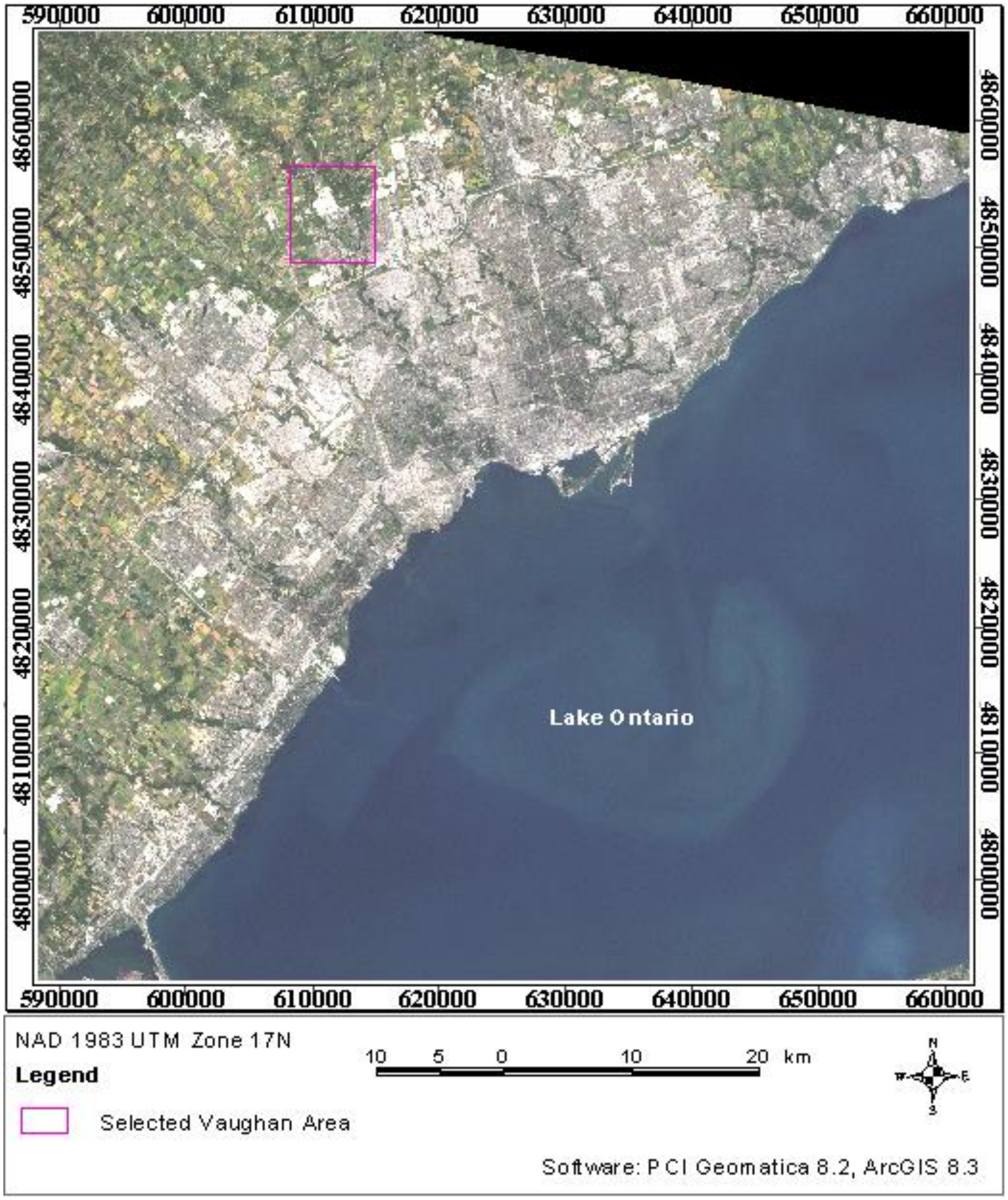



Figure 3.6 Vaughan area in 1999 ETM+ imagery

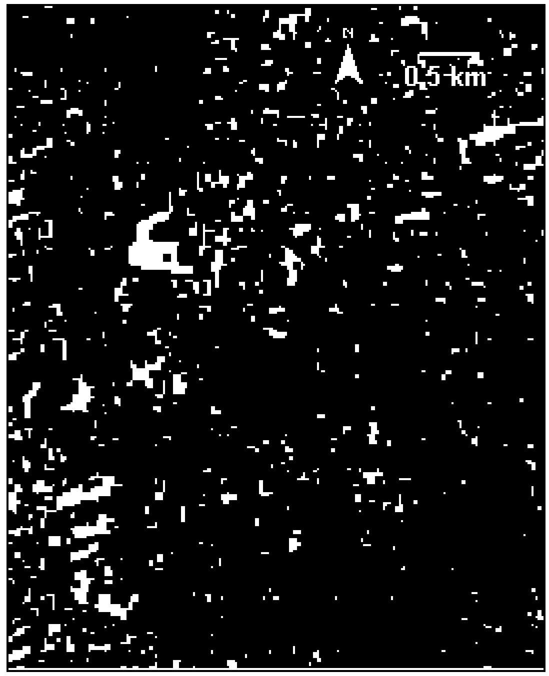



Figure 3.7 Texture analysis – Homogeneity (3x3 FLSZ).

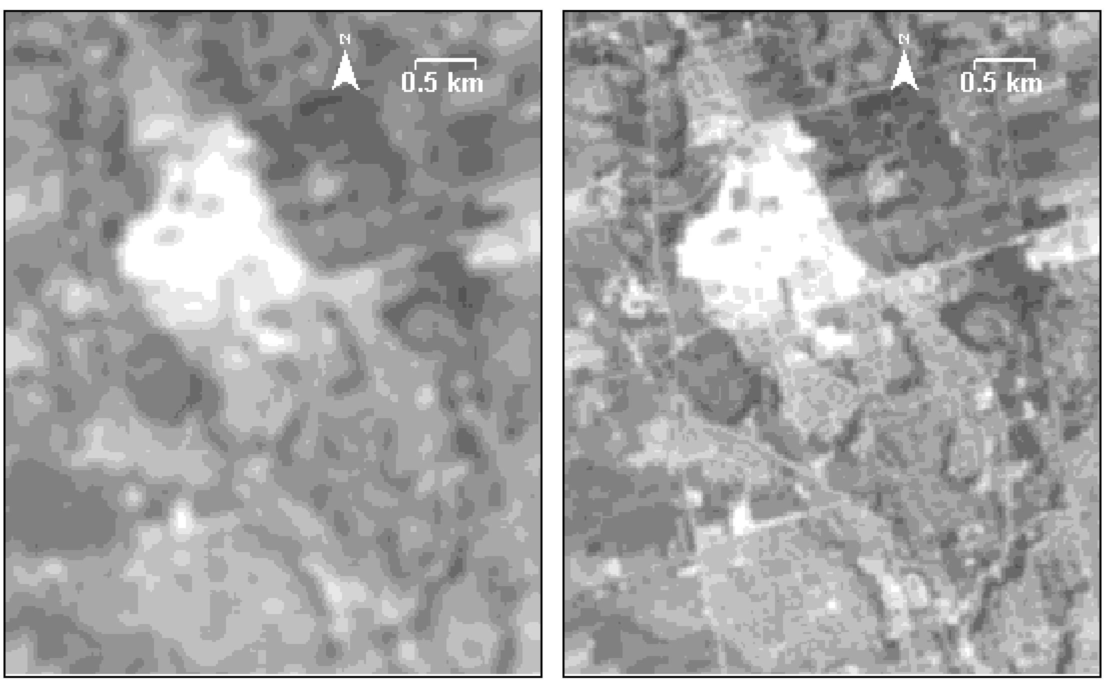



Figure 3.8 Texture analysis – Mean with different window sizes.
Left: 7x7 FLSZ; Right: 3x3 FLSZ; Both with mean measure

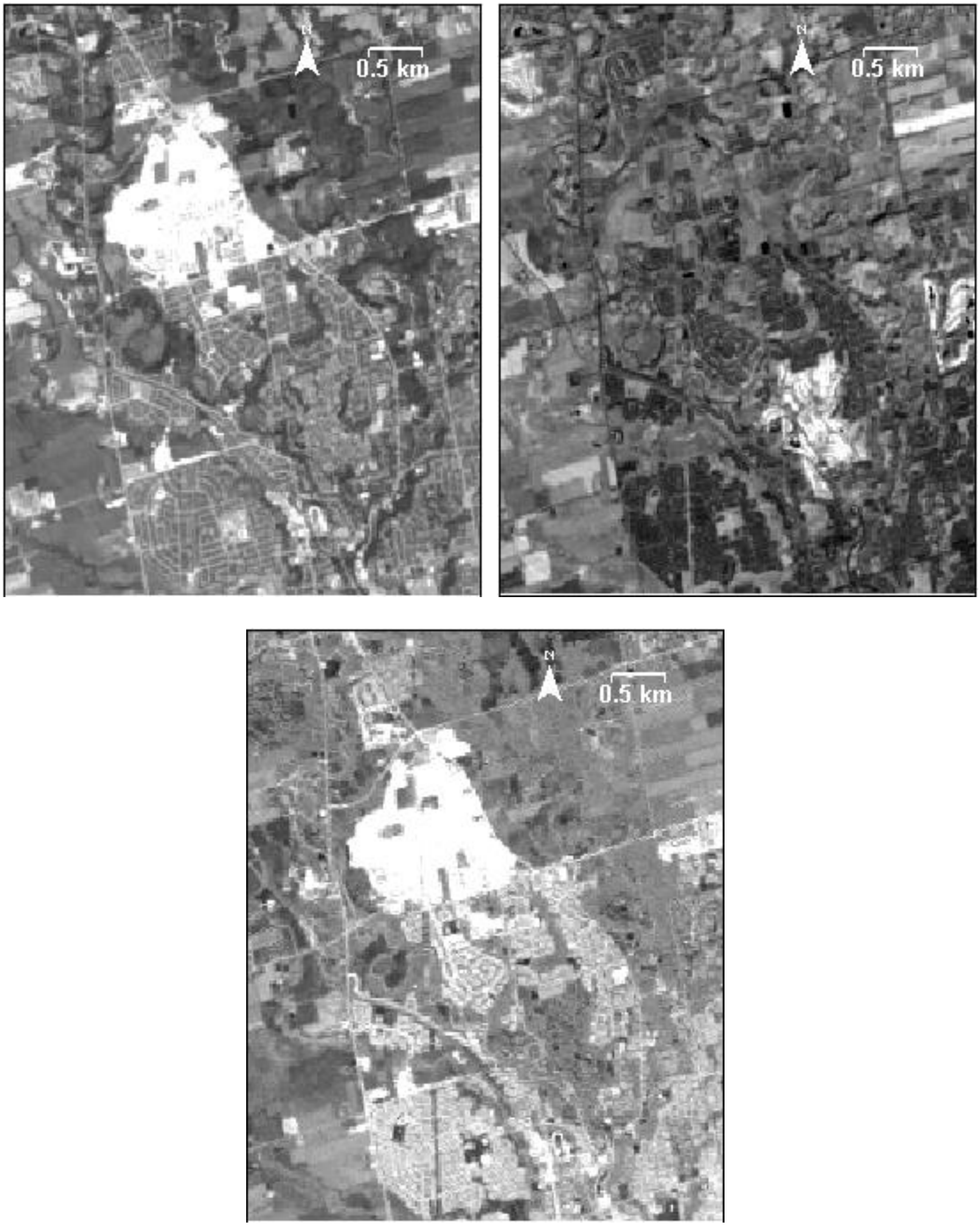



Figure 3.9 PCA results from 1999 ETM+ data
Upper row is PC1 and PC2 from left to right. Bottom is PC3

**Radiometric ratioing**

Due to the coarser resolution, it is often more difficult to differentiate urban from rural areas in MSS than TM data. If image ratioing (Howarth and Boasson, 1983) is used, the MSS data will be resampled to 30m resolution in unchanged areas between two dates. To verify this idea, the Brampton area was selected (Figure 3.10). Between 1977 and 1985 representing MSS and TM respectively, Brampton expanded greatly. This area consists of not only residential built-up area, but also industrial areas, which are surrounded by the rural areas. It is a good place to verify ratioing results between different types of Landsat data.

Image ratioing is a resampling process. The image ratio between TM 2 and MSS 1 is the division of values between one pixel in the1977 MSS image and four corresponding pixels in 1985 TM image. Each MSS pixel is split into four pixels and resampled to a 30m spatial resolution. Figure 3.11 shows this resampling process.

The unchanged urban area between two dates has a ratio value 1.0, showing a common tone in the resampled image, which is different from growth urban areas, which have values either higher or lower than 1 with either brighter or darker tones in the resampled image. More important is that the resampled 30m spatial resolution results in the unchanged urban area having a more detailed urban texture, which greatly helps in distinguishing unchanged urban areas from urban growth and rural areas.

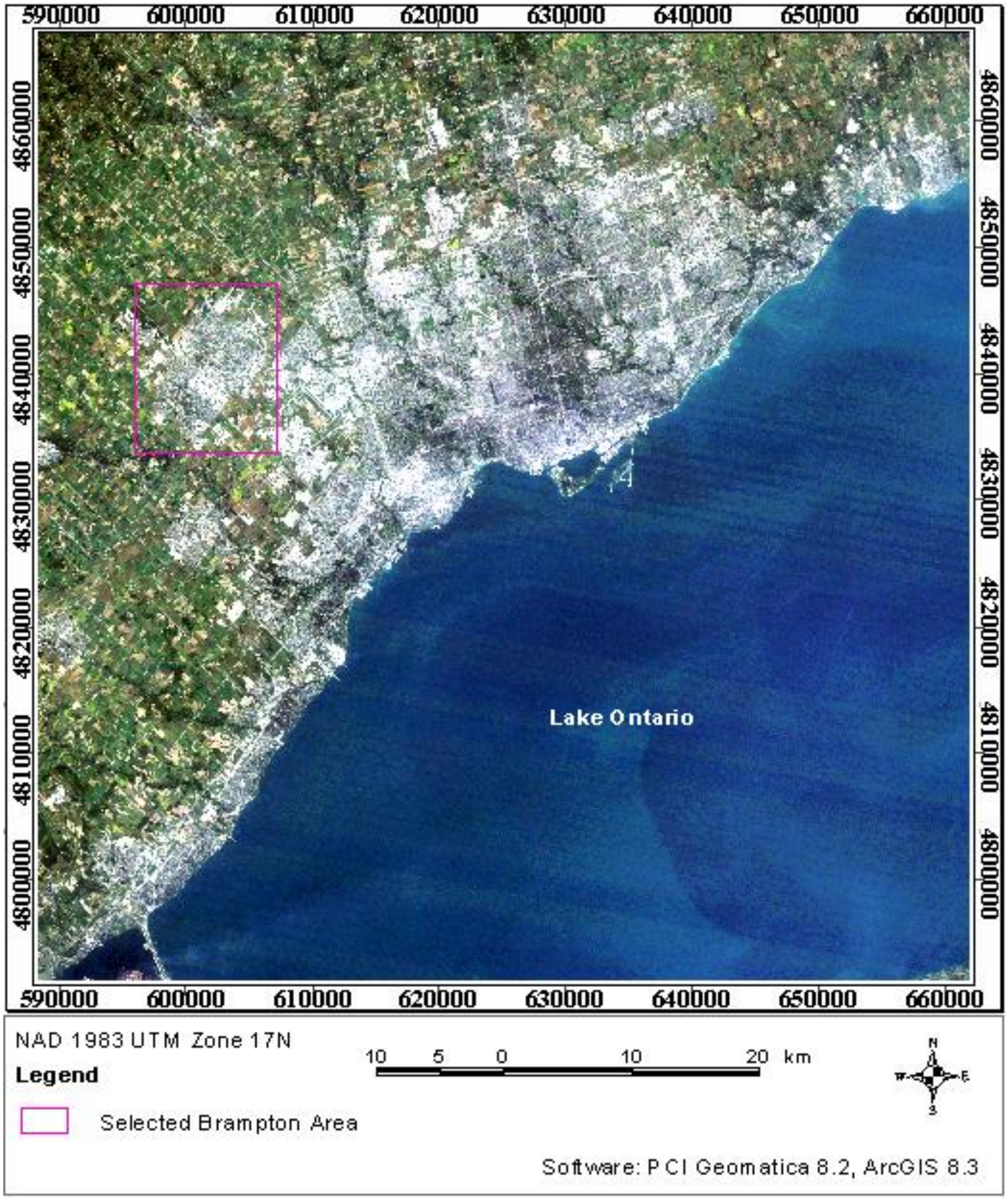



Figure 3.10 Brampton area in 1985 TM imagery

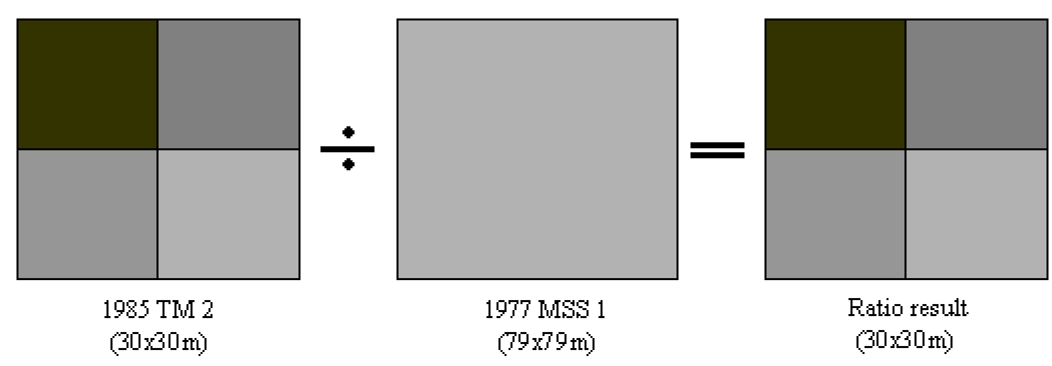



Figure 3.11 Resampling MSS data into 30m spatial resolution with TM data

Figure 3.12 shows the difference of between original 1977 MSS 1 and 1985 TM 2 in terms of separating urban from the rural areas, where urban boundaries are marked with pink in left picture and yellow in right picture. Figure 3.13 is the result of radiometric ratioing between 1977 MSS 1 and 1985 TM 2. Zone I is the unchanged urban where the resolution becomes 30m after image ratioing. Zone II is the growth urban area since 1977, in which the new excavated showed brighter tone and new developed darker tone. Zone III is rural area for both years.

The result in Figure 3.13 indicates that unchanged urban area in Zone I are easier to identify than urban areas marked with pink in Figure 3.12 (before resampling), in which the improvement in urban texture is obvious. It indicates that when this method is applied to other MSS bands – 2, 3, 4, and the enhanced results from NDVI, texture analysis, and PCA, information will be enhanced. Table 3.1 is contrast table of bands between MSS and TM used in image ratioing.

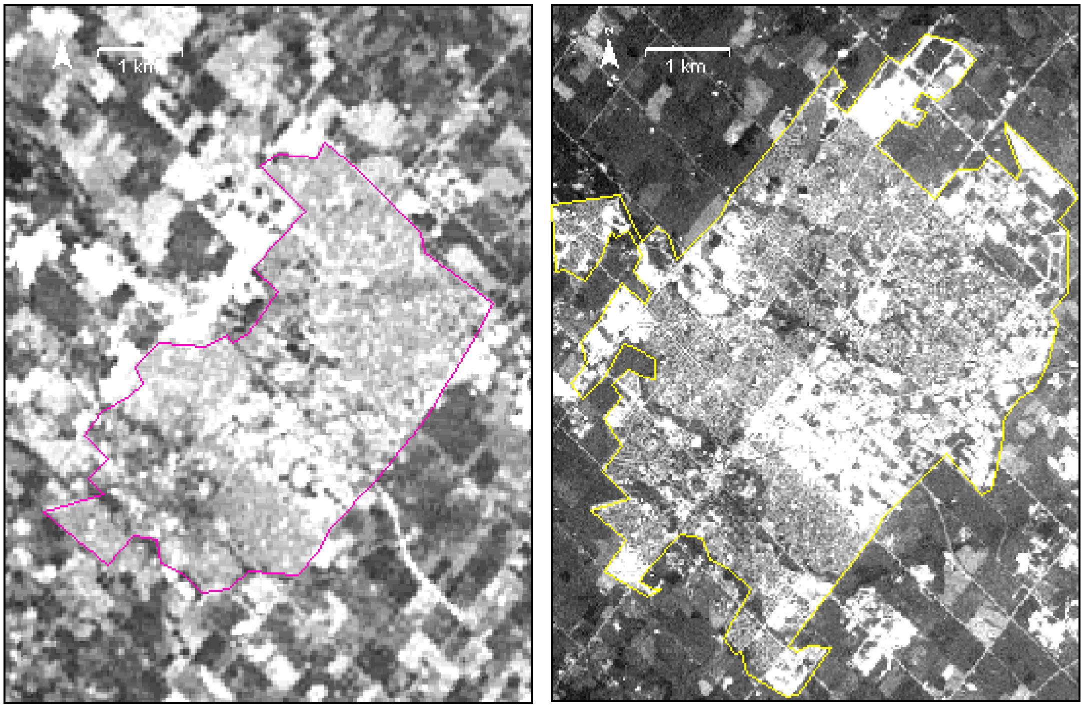



Figure 3.12 Comparison between 1977 MSS and 1985 TM
Left: 1977 MSS 1 with pink urban boundary;
Right: 1985 TM 2 with yellow urban boundary

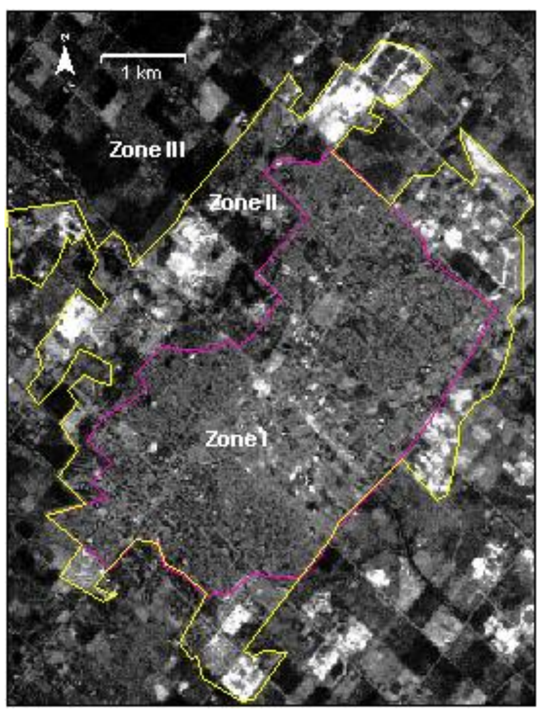



Figure 3.13 Ratioing result between 1977 MSS 1 and 1985 TM 2

Table 3.1 Image ratioing between 1977 MSS and 1985 TM

| Ratio | 1977 | 1985 | Ratioing |
|---|---|---|---|
| R1 | MSS 1 | TM 2 | TM 2 / MSS 1 |
| R2 | MSS 2 | TM 3 | TM 3 / MSS 2 |
| R3 | MSS 3 | TM 4 | TM 4 / MSS 3 |
| R4 | MSS 4 | TM 5 | TM 5 / MSS 4 |
| R5 | NDVI | NDVI | 1985 NDVI/ 1977 NDVI |
| R6 | Texture | Texture | 1985 Tex/ 1977 Tex |
| R7 | PC1 | PC1 | 1985 PC1/ 1977 PC1 |
| R8 | PC2 | PC2 | 1985 PC2/ 1977 PC2 |

Figures 3.14 – 3.17 below show the different classification results with the addition of enhancements in 1977 MSS data. Figure 3.14 is the classification without any enhancements, i.e., using original 4 bands as input. The main problem is the noise in rural areas that makes it difficult to isolate the urban features from the rural. Figure 3.15 uses additional enhancements - NDVI, texture, and PC1, PC2. The result removed both noise in the rural areas and pixels inside the contiguous urban. The remarkable improvement occurred after using image ratioing with 1985 TM data, which have a 30m spatial resolution. Figure 3.16 shows the classification result from the addition of 4-band ratioing enhancements with 1985 TM data from R1 to R4.  Figure 3.17 uses all enhancements – 4 original bands, NDVI, texture, PC1, PC2, and 8 ratioing enhancements from R1 to R8 (See Table 3.1). Ratios from NDVI, texture analysis, PC1, and PC2 improve the delineation of contiguous urban areas, particularly in the central part of Toronto.

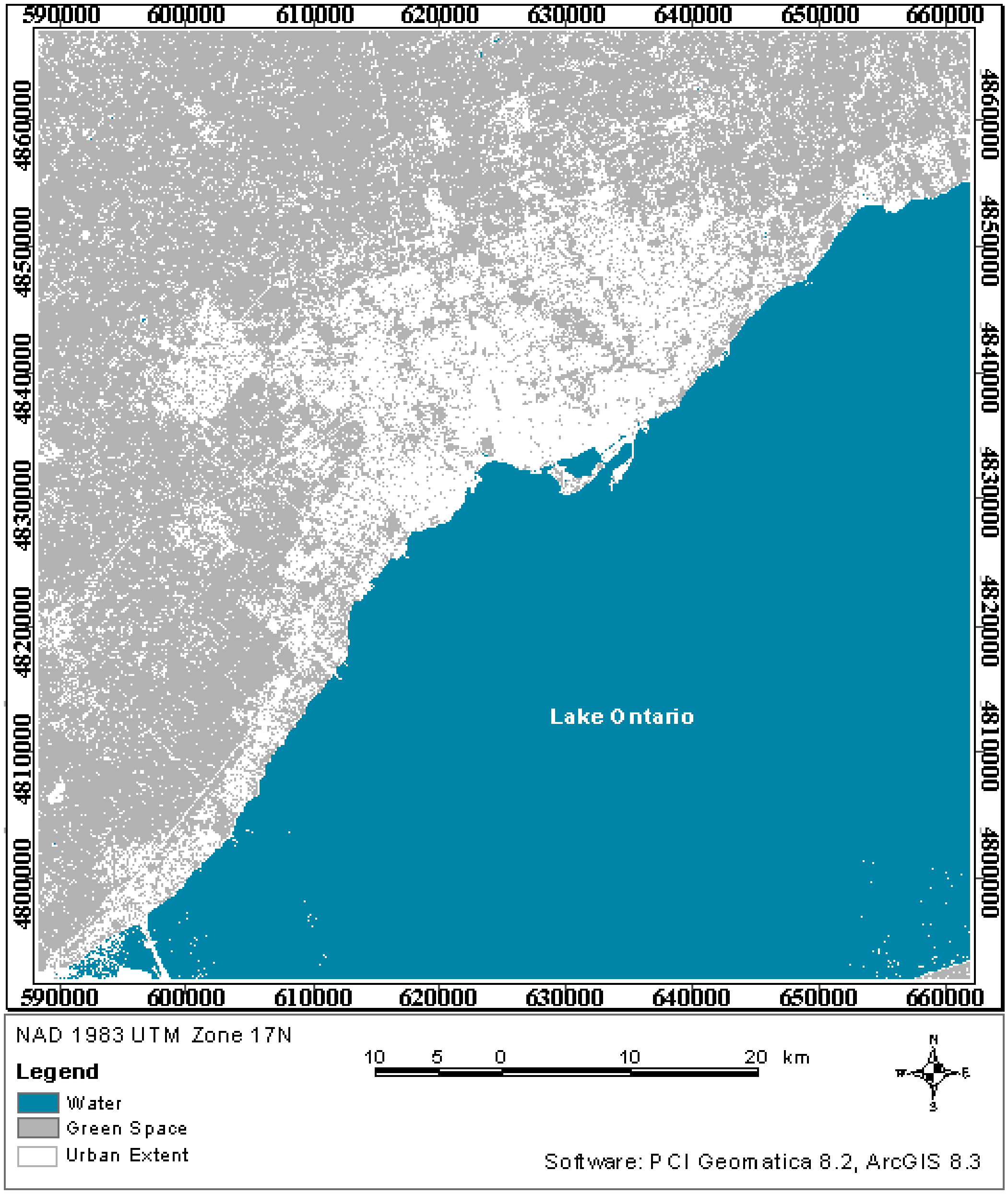



Figure 3.14 Classification without any enhancement from 1977 MSS
Input: 1, 2, 3, 4

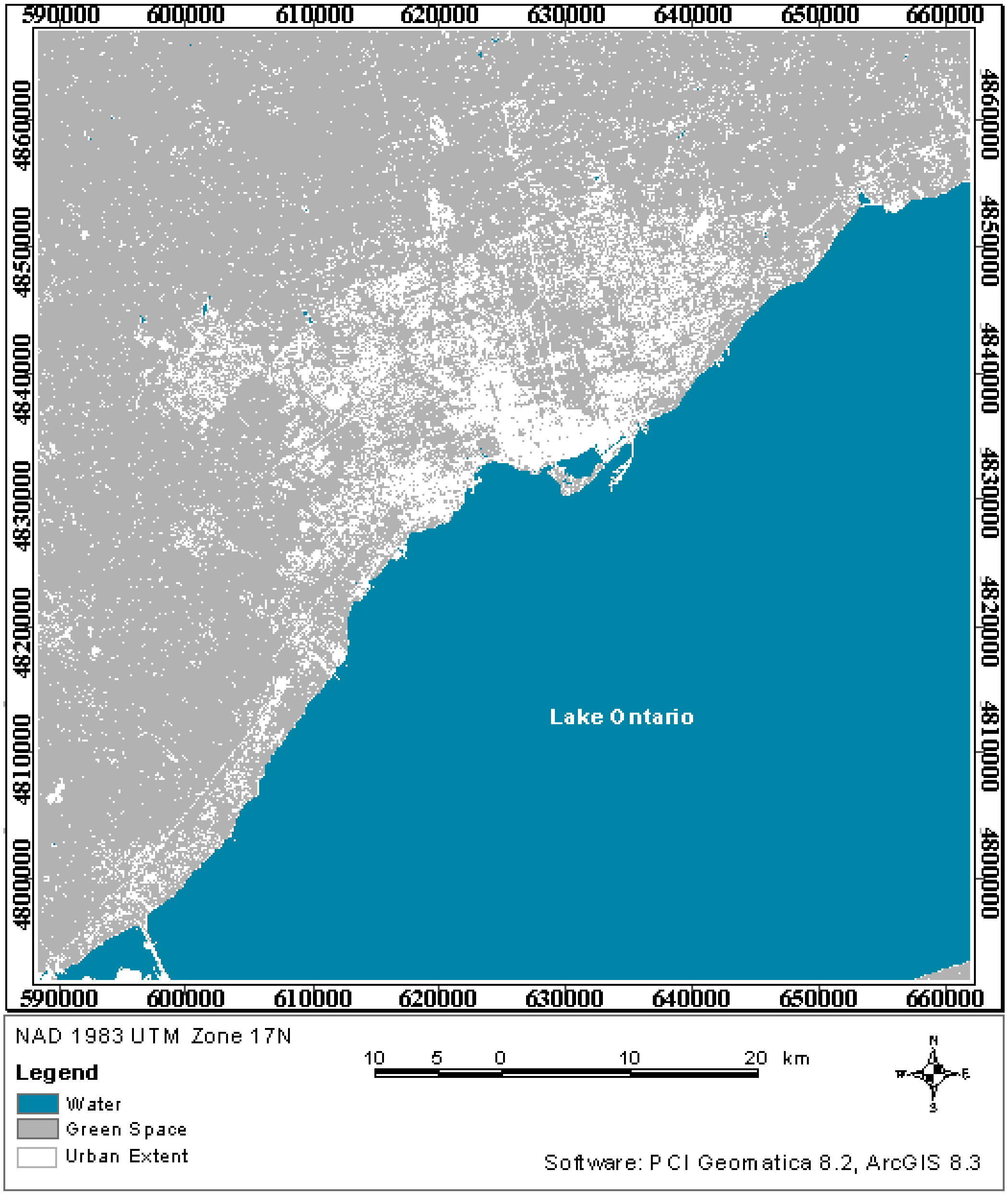



Figure 3.15 Classification with enhancement – I from 1977 MSS
Input: 1, 2, 3, 4, NDVI, Texture, PC1, PC2

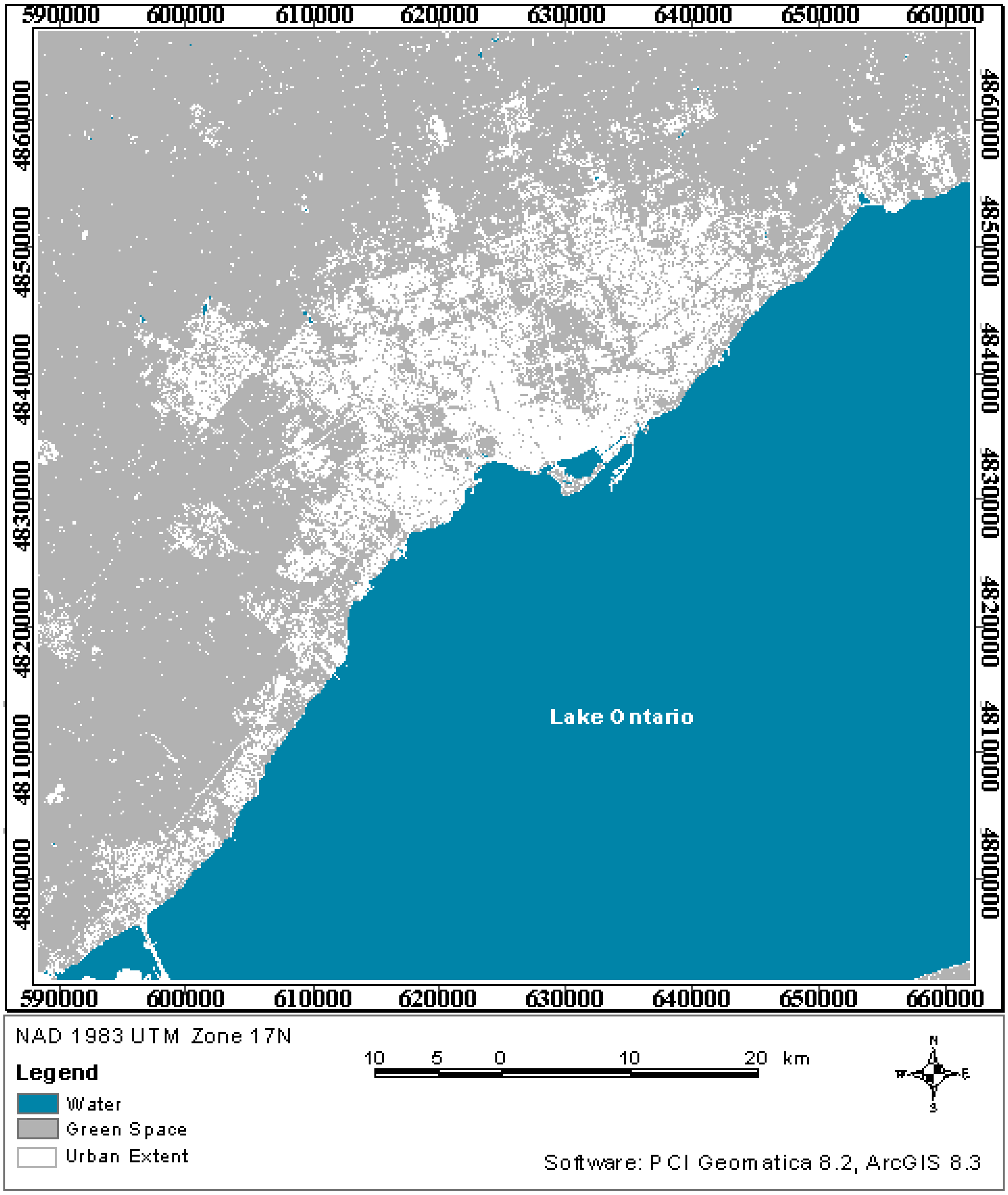



Figure 3.16 Classification with enhancement – II from 1977 MSS
Input: 1, 2, 3, 4, NDVI, Texture, PC1, PC2,
+ R1, R2, R3, and R4

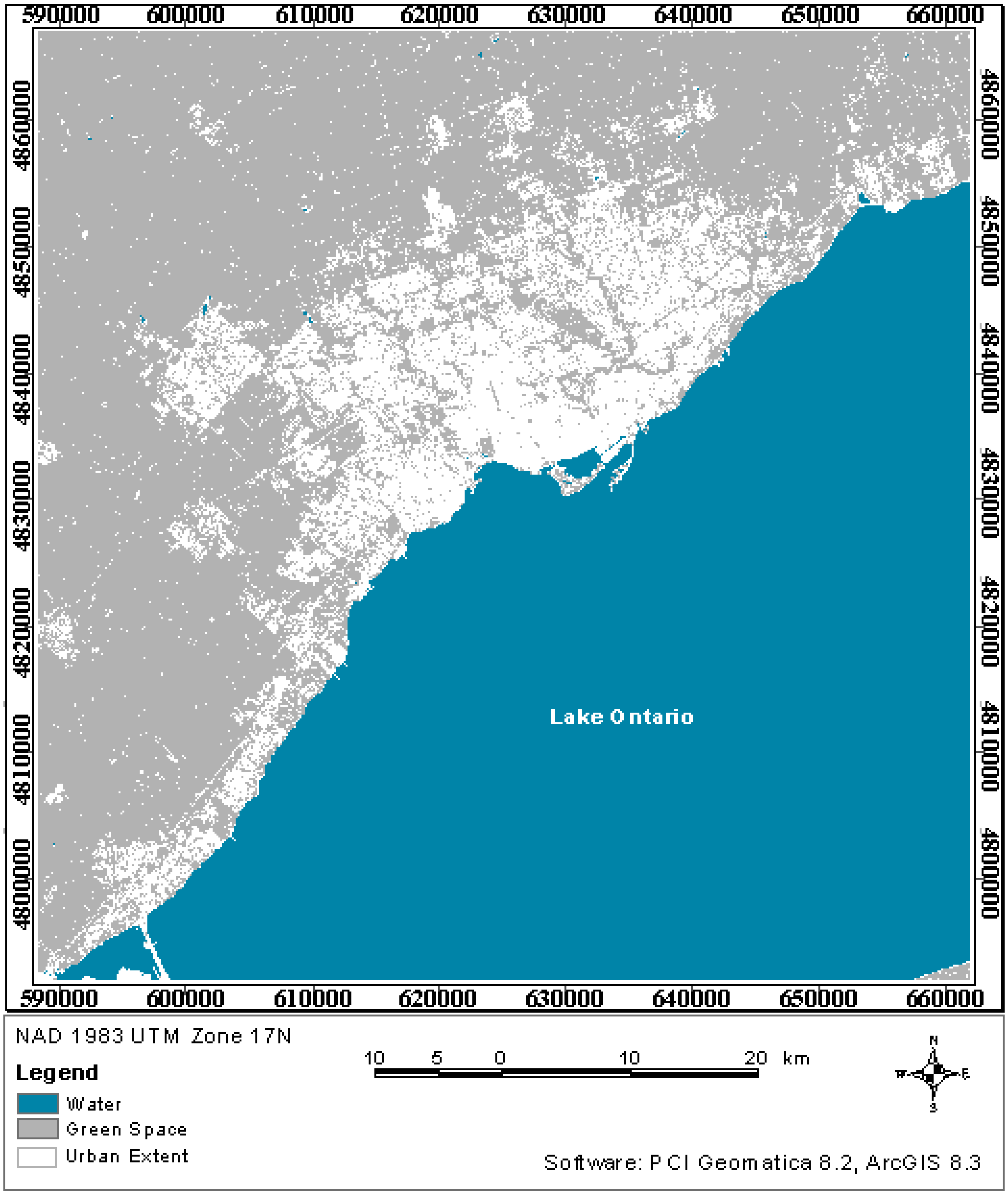



Figure 3.17 Classification with enhancement – III from 1977 MSS
Input: 1, 2, 3, 4, NDVI, Texture, PC1, PC2,
R1, R2, R3, R4
+ R5, R6, R7, and R8

**Image differencing**

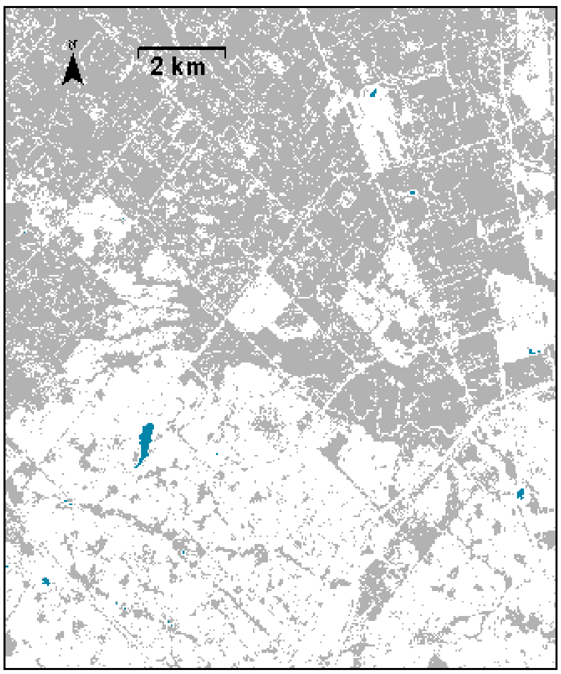
All TM data are of high quality imagery except for 2004, which includes a small number of clouds. Compared with other years of TM data, it is also found that 2004 produces more noise in rural areas under the same enhancements with other TM data. It is possible to have different quality TM imagery between different dates due to the different seasons and atmospheric conditions. To solve this problem, the image differencing method is considered.

Image differencing is an enhancement usually used to detect the change between two different dates (Jensen, 1986; Singh, 1989). However, image differencing is not limited to this, it is widely used in other enhancements as the combined enhancement (Toll, 1982; Singh, 1989; Masek et al., 2000).

Different bands in TM data are designed for different purposes. The first three bands (blue-green, green, red) are all sensitive to cultural/urban features band 5 and 7 (two mid-infrared bands are sensitive to moisture and water content (Jensen, 1983; Campbell, 1996). Ideally, the subtraction between visible bands and short wave infrared bands will enhance the separation of urban features from the rural background.

Image differencing was conducted using the 2004 TM data in the north part of Brampton area. This is because this area consists of urban features, excavated areas (to the north of Brampton), and a complicated rural background – farm fields, vegetation along with rivers, and bare-soils.

Figure 3.18 shows the classification without enhancement and with enhancements. The enhancements used in right image were NDVI, texture analysis, PC1, PC2, and PC3. With these enhancements, urban feature pixels inside the contiguous urban area are removed when noise pixels in rural areas are eliminated.



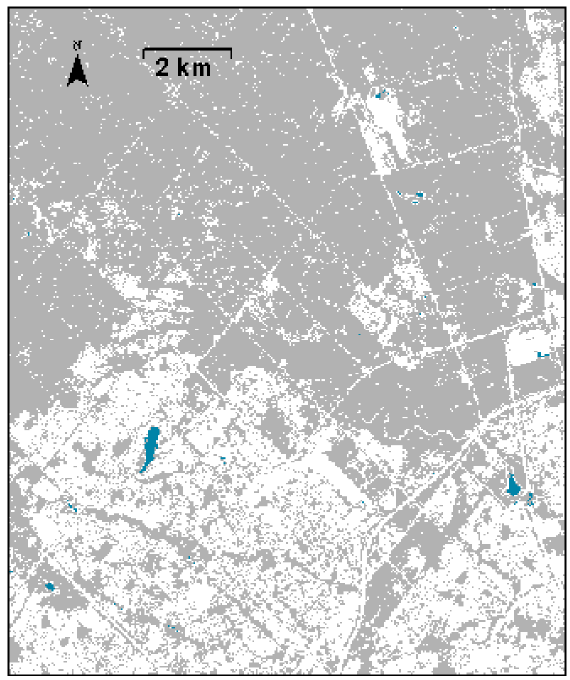



Figure 3.18 Classification with enhancement and without enhancement in 2004
Left: without enhancement. Input: 1, 2, 3, 4, 5, 7;
Right: enhancement. Input: 1,2 , 3, 4, 5, 7, NDVI, Texture, PC1, PC2, and PC3
Colouring: white - urban extent; grey – green space; blue – water

Figures 3.19 and 3.20 show original enhancements created from the 2004 TM data. Figure 3.19 has a NDVI and texture enhancement. Dark tones representing non-vegetated areas are well isolated from vegetation features – i.e. crop fields and forests. However, non-vegetated bare soils make it difficult to separate urban features. The texture enhancement produced from the 2004 TM data has a similar problem. Figure 3.20 shows the PCA enhancements. Only PC2 and PC3 separated urban from green space to some extent. PC2 captures the majority of urban features, but is not sensitive to the excavated areas. PC3 is sensitive to the excavated areas, thus performs well in isolating excavated from other land cover features. However, it is not sensitive to the difference between urban and rural features. In the PC3 image, the tone of rural areas is very close to the tone of urban areas. This explains why urban feature pixels are also eliminated along with the removal of noise pixels in rural areas.


Figure 3.19 NDVI and texture analysis from 2004 TM

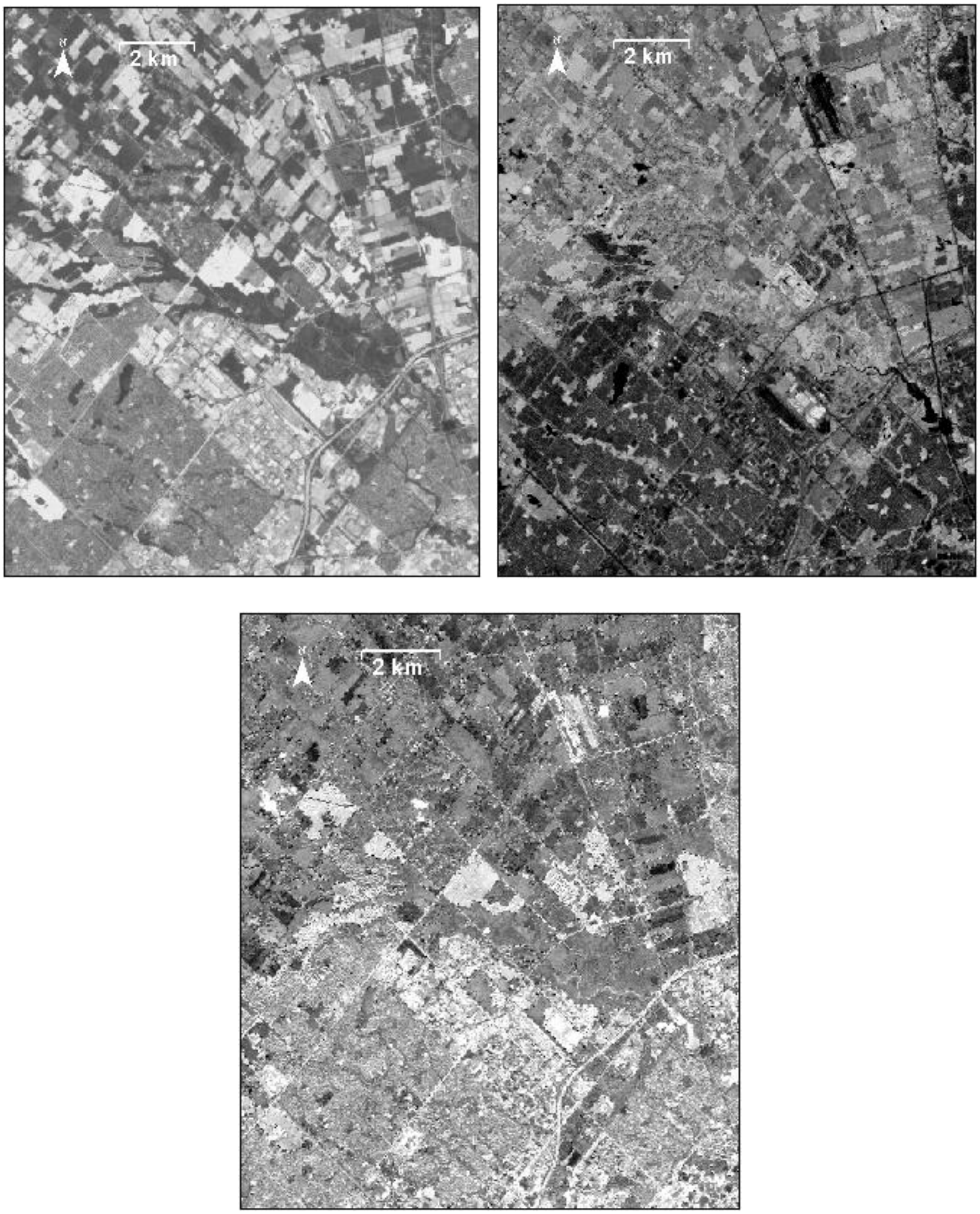



Figure 3.20 PCA from 2004 TM
Upper row is PC1 and PC2 from left to right. The bottom is PC3

Therefore, the new combination of bands was explored. Four subtractions (Figure 3.21 and 3.22) were created, including subtraction between bands 5 and 1, subtraction between bands 5 and 2, subtraction between 7 and 1, and subtraction between 7 and 3. These four subtractions performed better than any other combination. In order to make the value of subtractions positive, a 60 value is added to these subtractions because mean values in band 1, 2, 3, 5, and 7 range from 74 to 91. The results in Figure 3.21 indicate that the subtraction between band 5 and 1 is almost the same as the subtraction between band 5 and 2, particularly for urban features. This is because band 5 is sensitive to the moisture in vegetation and soil, the subtle change between left and right images in Figure 3.21 only occurred on the rural areas. The differencing results from band 5 with band 1 and 2 perform very well in separating urban from rural areas. Subtraction between band 7 and 1 and subtraction between band 7 and 3 (Figure 3.22) also enhance the separation of urban features from rural areas. However, the subtraction between band 7 and 1 is better than the subtraction between band 7 and 3. The result between band 7 and 3 cannot distinguish the excavated from the rural areas. This is because band 3 is not sensitive to soil features.

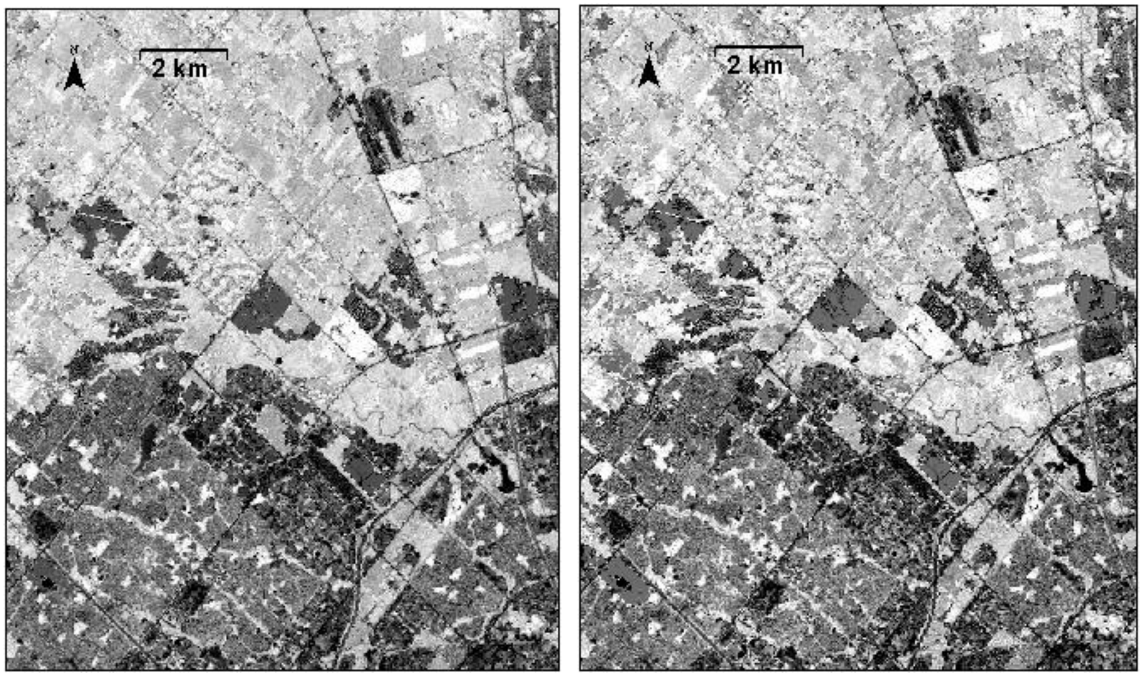



Figure 3.21 Image differencing between bands in 2004 TM – I
Left - 1/5: ΔB1 = B5 - B1 + 60; Right – 2/5: ΔB2 = B5 - B2 + 60

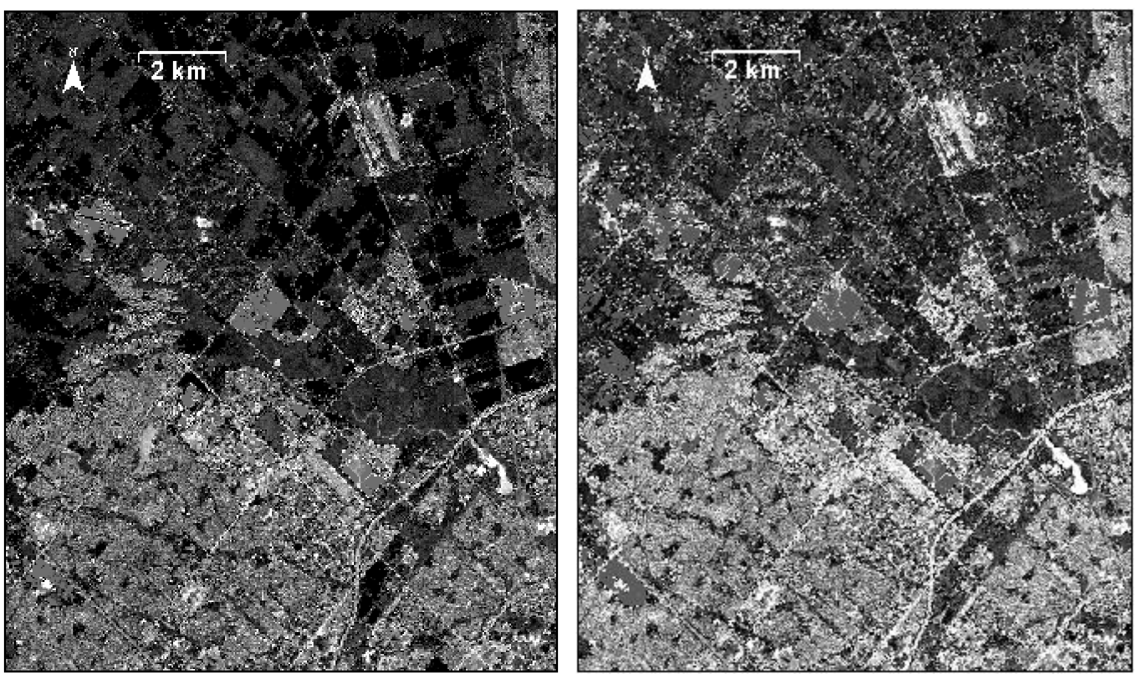



Figure 3.22 Image differencing between bands in 2004 TM – II
Left - 1/7: ΔB3 = B1 - B7 + 60; Right – 3/7: ΔB4 = B3 – B7 + 60

The classification was conducted by inputting the original bands (1, 2, 3, 4, 5, and 7), enhancements from NDVI, texture, PC1, PC2, PC3, and new image differencing enhancements – B5/1, B5/2, B7/1, and B7/3. The result is showed in Figure 3.23. The result indicates that the new image differencing enhancements helped in identifying the excavated areas, keeping urban feature pixels in contiguous urban area are excluded by the previous enhancements – NDVI, texture, and PCs, when removing the noise in the rural areas.

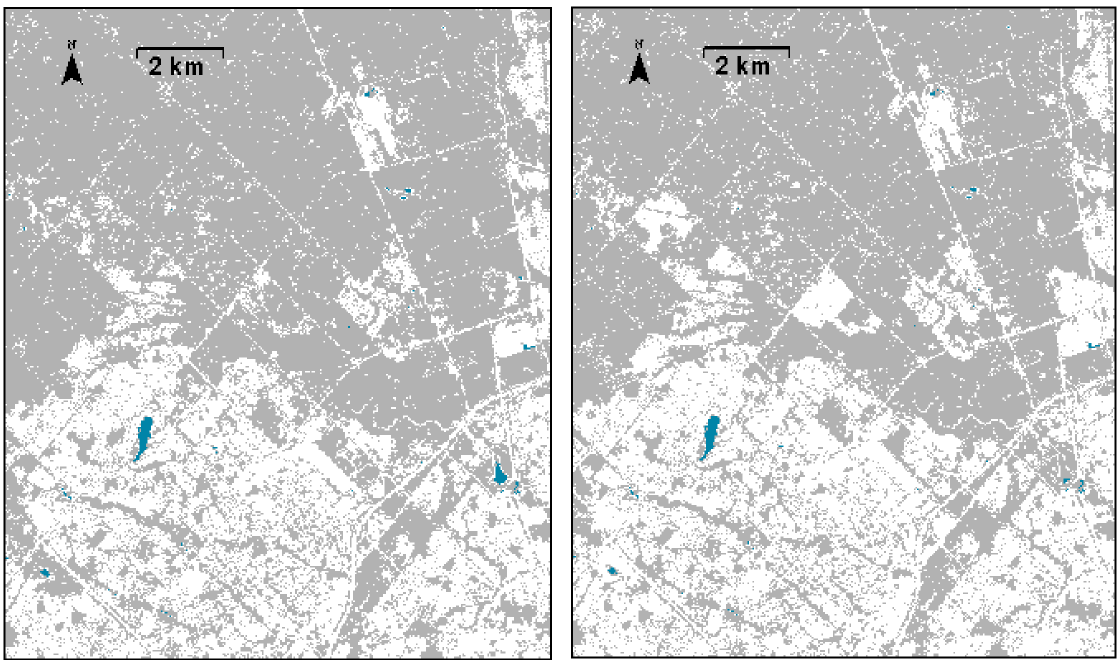



Figure 3.23 2004 Classifications between different enhancements
Left: 5 enhancements – NDVI, Texture, PC1, PC2, and PC3
Right: 5 enhancement – NDVI, Texture, PC1, PC2, and PC3 +
4 differencing enhancements – ΔB1, ΔB2, ΔB3, ΔB4.
Colouring: white - urban area; grey – rural area; blue - water

### 3.2.3 Experiment # 3 – Supervised vs. Unsupervised Methods

The determination of methods of classification is also important. For this urban extent classification, only three types of land cover - urban, green space, and water were involved. For instance, urban features consist of residential buildings, industrial buildings, playgrounds, roads, and airports. They are straightforward to identify and train. The potential problem with this method in this research is the consistency of site training work between different dates. Unsupervised methods are superior to supervised method in terms of being consistent between different dates of imagery because it mainly depends the radiance value itself. Unsupervised classification is however likely to introduce the human errors when merging or transferring unknown types of land covers into known classes. No matter which method was used, the resulting classifications were verified for accuracy.

To find out the best classification method, three pairs of comparisons between supervised classification and unsupervised classification are performed. The 1977 MSS, 2001 TM, and 1999 ETM+ data were used. The unsupervised classification used the K-means clustering method with 255 classes, which are eventually merged into three classes – urban, green space (rural area), and water. The supervised classification used the Maximum Likelihood method, using training sites for each of the classes – urban, green space, and water. The input channels between the unsupervised classification and supervised classification were the same. To verify the results, accuracy statistics are also given in each result, in which 300 random sampling points were generated in PCI. The Brampton area was selected for comparison.

Figure 3.24 and Table 3.2 show the results for unsupervised and supervised classifications using the 1977 MSS data. Figure 3.25 and Table 3.3 show the results for the 2001 TM, while Figure 3.26 and Table 3.4 show the results for the 1999 ETM+ data.

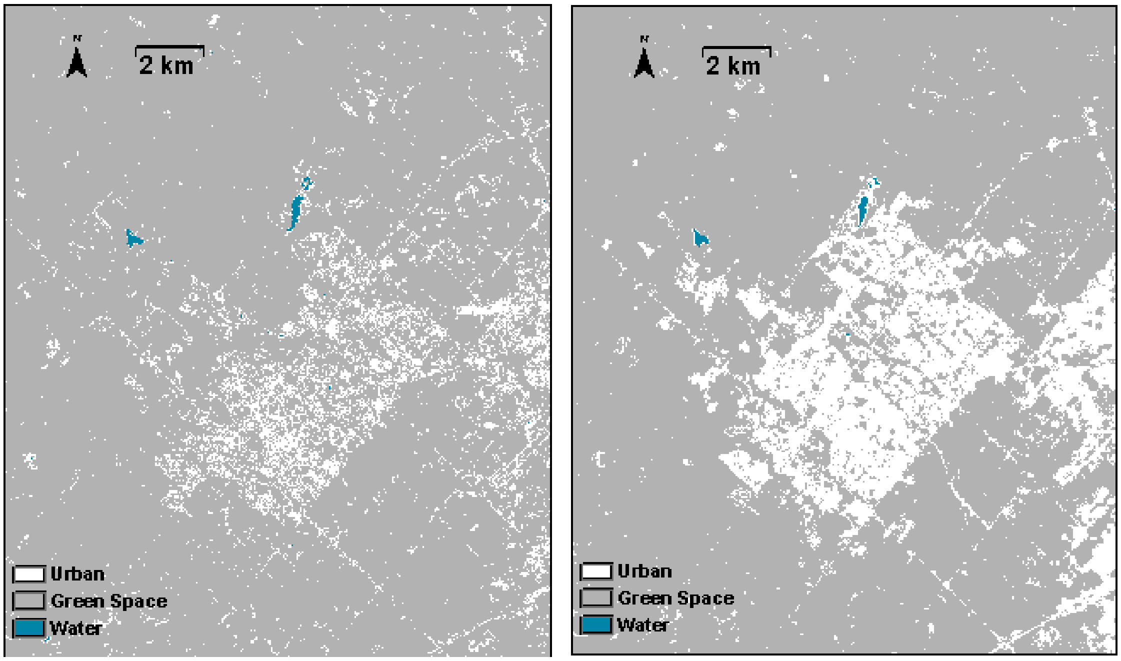



Figure 3.24 Unsupervised and supervised classifications in 1977 MSS
Left: unsupervised; Right: supervised.
Input: 1,2, 3, 4, NDVI, texture, PC1, PC2, R1 to R8

Table 3.2 Accuracy statistics for two classifications (1977MSS)

| Statistics | Unsupervised (left) | Supervised (right) |
|---|---|---|
| Overall Accuracy | 86.333% | 97.667% |
| Overall Kappa | 0.777% | 0.963% |
| Producer's Accuracy | 36.364% | 91.837% |
| User's Accuracy (urban) | 76.923% | 93.750% |
| Kappa Statistic (urban) | 0.7174 | 0.9253 |

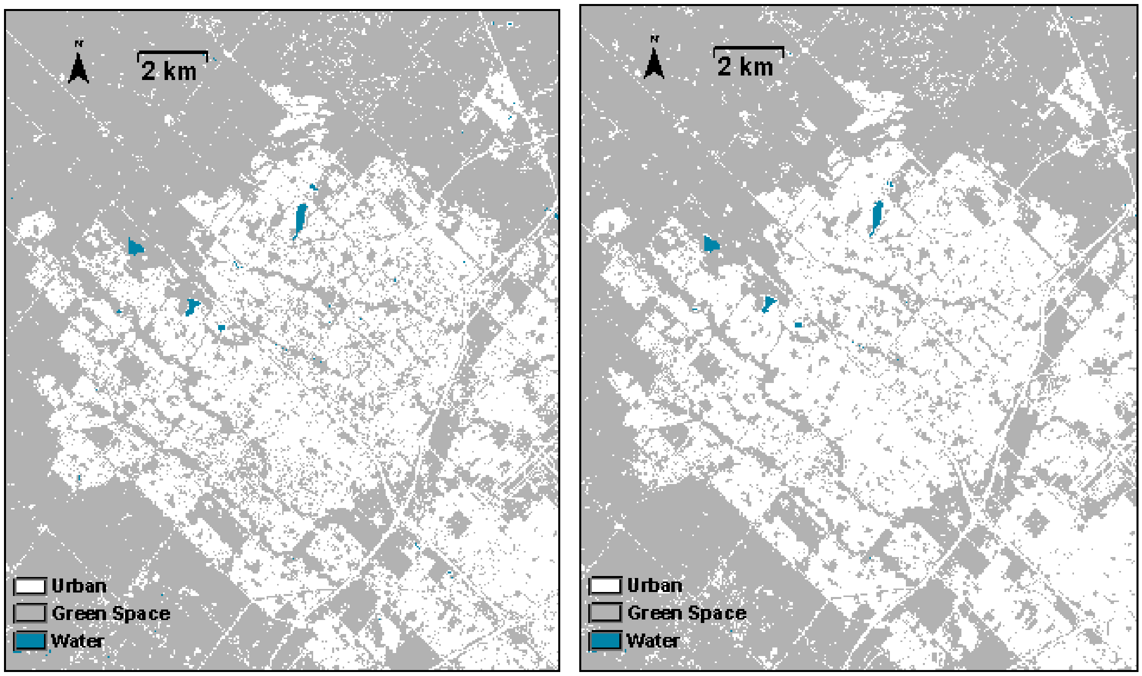
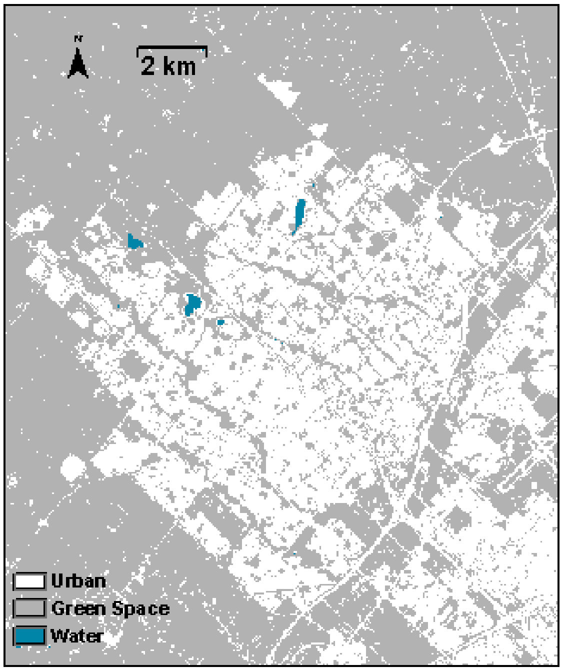



Figure 3.25 Unsupervised and supervised classifications in 2001 TM
Left: unsupervised; Right: supervised.
Input: 1,2, 3, 4, 5, 7, NDVI, texture, PC1, PC2, PC3

Table 3.3 Accuracy statistics for two classifications (2001 TM)

| Statistics | Unsupervised (left) | Supervised (right) |
|---|---|---|
| Overall Accuracy | 97.000% | 97.000% |
| Overall Kappa | 0.955% | 0.954% |
| Producer's Accuracy | 92.000% | 91.139% |
| User's Accuracy (urban) | 95.833% | 97.297% |
| Kappa Statistic (urban) | 0.9444 | 0.9633 |



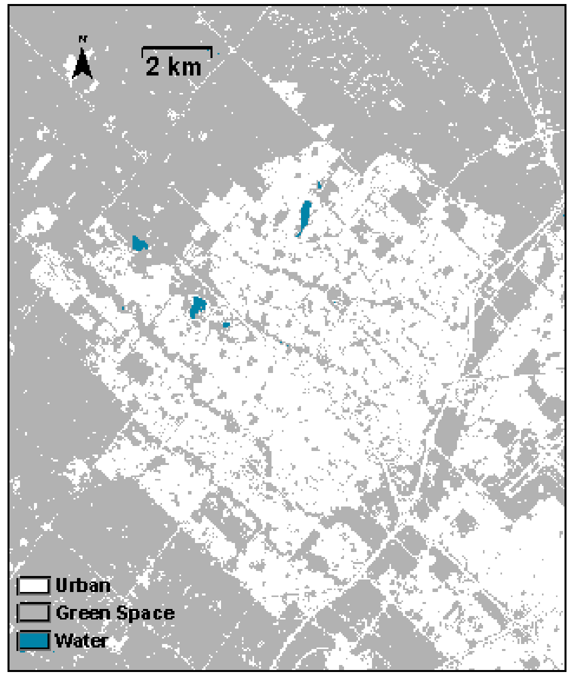




Figure 3.26 Unsupervised and supervised classifications in 1999 ETM+
Left: unsupervised; Right: supervised.
Input: 1,2, 3, 4, 5, 7, NDVI, texture, PC1, PC2, PC3

Table 3.4 Accuracy statistics for two classifications (1999 ETM+)

| Statistics | Unsupervised (left) | Supervised (right) |
|---|---|---|
| Overall Accuracy | 97.667% | 97.667% |
| Overall Kappa | 0.980% | 0.964% |
| Producer's Accuracy | 93.243% | 95.833% |
| User's Accuracy (urban) | 97.183% | 94.521% |
| Kappa Statistic (urban) | 0.9626 | 0.9279 |

From the three comparisons, the 1977 MSS data showed a great difference between unsupervised classification and supervised classification whereas the TM and ETM+ data did not show remarkable differences between these two methods. Table 3.2 showed the accuracy statistics for two classifications in 1977 MSS. The overall accuracy of 1977 MSS is 86.333% from the unsupervised classified map while it is 97.667% from the supervised map. The producer's accuracy from the unsupervised classified map result is 36.364% while it is 91.837%. The user's accuracy from the unsupervised map result is 76.923% while it is 93.75%. This indicates that the urban feature is not well categorized; only about one third of the urban features are captured. Nearly one quarter of the categorised urban features in the result map is not truly representing the ground truth urban feature in the unsupervised classification result. Conversely, above 90% urban features are categorised into urban class and above 90% categorised urban class truly represented the ground truth urban feature. Kappa for urban feature from unsupervised classification is 0.7174 while that from supervised classification is 0.9253. The overall Kappa is 0.777% for the unsupervised result, and 0.963% for the supervised result. It also indicates that supervised classification is superior to the unsupervised classification in terms of inclusively and correctly capturing urban feature from 1977 MSS data.

The results from TM and ETM+ data (Figure 3.25 and 3.26 respectively) did not show distinct differences between unsupervised classification and supervised classification. Table 3.3 showed the accuracy statistics for the two classification methods in 2001 TM. The overall accuracy in 2001 TM is 97% for both unsupervised and supervised classification. The producer's accuracy for the 2001 unsupervised classification 92% is very close to that for the supervised classification (91.139%). The user's accuracy is 95.8% for unsupervised classification and 97.3% for supervised classification. The overall kappa (0.955% for unsupervised and 0.954 for supervised) and kappa for urban feature (0.9444 for unsupervised and 0.9633 for supervised) keep consistent with the accuracy statistics above. It indicates that supervised classification is a little bit superior to unsupervised classification in 2001 TM data.

Table 3.4 showed the accuracy statistics for two classifications in 1999 ETM+. The overall accuracy of two classifications is the same, 97.667%. The producer's accuracy of the unsupervised method 93.243% is little bit lower than the supervised method 95.833%, indicating supervised classification in 1999 ETM+ is more inclusive in categorizing urban feature than unsupervised classification. However, the user's accuracy of the unsupervised method is higher than the supervised method, indicating that unsupervised classification is more accurate in categorizing the urban feature. The overall kappa 0.98% for unsupervised, 0.964% for supervised, and kappa for urban 0.9626 for unsupervised, 0.9279 for supervised show that unsupervised classification is a little bit superior to supervised classification in overall.

In order to further justify which method is more appropriate for TM and ETM+ data, additional TM data were analyzed. The 1985 TM data (Figure 3.27) demonstrated a distinct difference between unsupervised classification and supervised classification. Table 3.5 shows the accuracy statistics. The overall accuracy for unsupervised classification is 88.667% while it is 97% for supervised classification. Producer's accuracy for unsupervised classification is only 53.125% while it is 91.525% for supervised classification. User's accuracy for unsupervised classification is 94.444%, which is very close to 93.103 for supervised classification. Accuracy statistics above indicate that the main difference between these two classification is the inclusion performance, in which supervised classification is much superior to the unsupervised classification. Nearly only half urban features are categorised into urban class. The overall kappa is consistent with conclusion above.

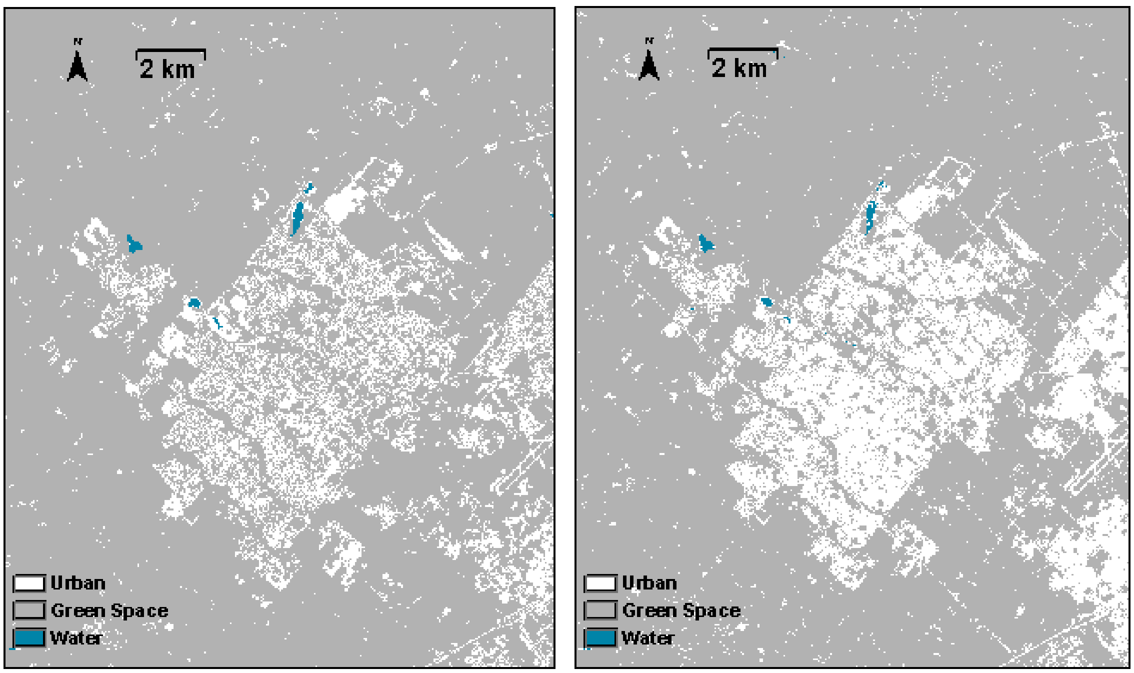



Figure 3.27 Unsupervised and supervised classifications in 1985 TM
Left: unsupervised; Right: supervised.
Input: 1,2, 3, 4, 5, 7, NDVI, texture, PC1, PC2, PC3

Table 3.5 Accuracy statistics for two classifications (1985TM)

| Statistics | Unsupervised (left) | Supervised (right) |
|---|---|---|
| Overall Accuracy | 88.667% | 97.000% |
| Overall Kappa | 0.820% | 0.953% |
| Producer's Accuracy | 53.125% | 91.525% |
| User's Accuracy (urban) | 94.444% | 93.103% |
| Kappa Statistic (urban) | 0.9294 | 0.9142 |

The 1990 TM data (Figure 3.28) also showed a significant difference between the two classifications. Table 3.6 shows the overall accuracy is 93.667% for unsupervised classification whereas it is 98.333% for supervised classification. The supervised classification performed better than the unsupervised classification in overall land cover classification. The producer's accuracy is 72.581% for unsupervised classification whereas it is 94.03% for supervised classification. Nearly one third of urban features were missed in the unsupervised urban classification whereas urban features in the supervised classification were well categorised. The user's accuracy 95.745% for the unsupervised classification and 98.438% for supervised classification are very close, but the supervised classification is still a little bit better than unsupervised classification in terms of truly representing urban features. The overall kappa of 0.906% for the unsupervised classification and 0.974% for the supervised classification show that the supervised is more accurate in overall land cover classification. The kappa for urban extent of 0.9464 for unsupervised and 0.9799 for supervised demonstrated that supervised classification is superior to unsupervised classification in urban classification.

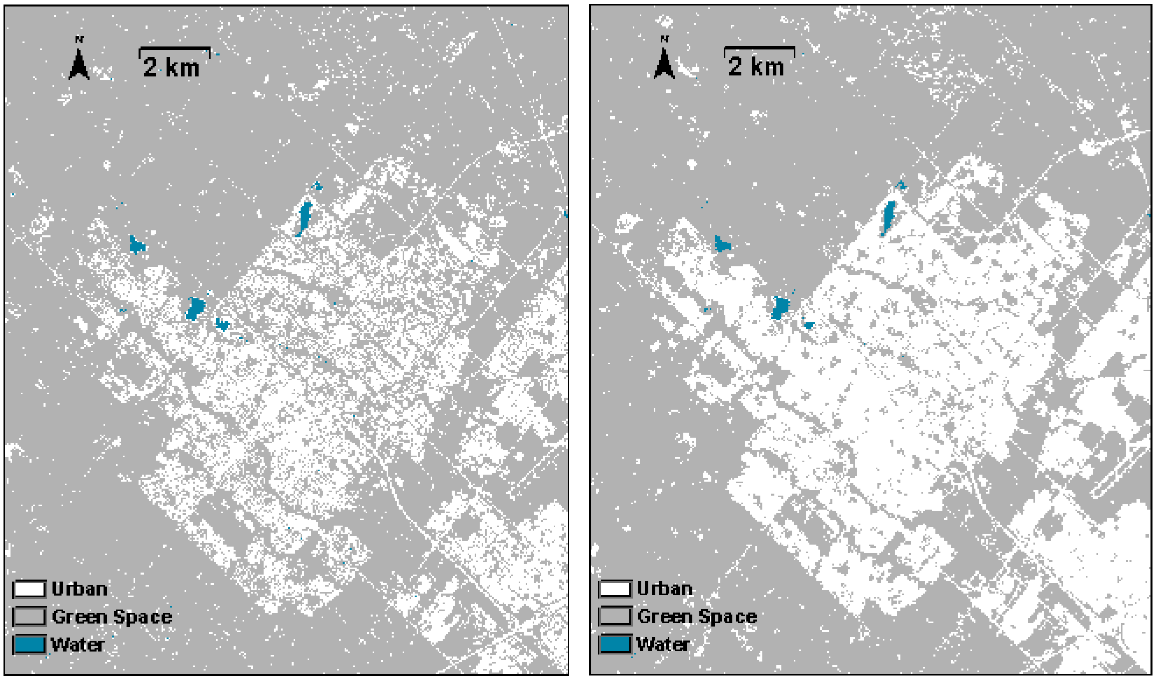



Figure 3.28 Unsupervised and supervised classifications in 1990 TM
Left: unsupervised; Right: supervised.
Input: 1,2, 3, 4, 5, 7, NDVI, texture, PC1, PC2, PC3

Table 3.6 Accuracy statistics for two classifications (1990TM)

| Statistics | Unsupervised (left) | Supervised (right) |
|---|---|---|
| Overall Accuracy | 93.667% | 98.333% |
| Overall Kappa | 0.906% | 0.974% |
| Producer's Accuracy | 72.581% | 94.030% |
| User's Accuracy (urban) | 95.745% | 98.438% |
| Kappa Statistic (urban) | 0.9464 | 0.9799 |

Based on the these 5 years of comparisons between unsupervised classification and supervised classification, it can be concluded that using supervised classification for MSS and TM data is superior to the unsupervised classification. It also can be used to 1999 ETM+ data because the performance between supervised and unsupervised classification is very close. To make the classification consistent, the supervised classification was selected for all data.

### 3.2.4 Experiment # 4 – Change Detection

Using band 2 for image differencing is superior for most of urban change applications (Ridd and Liu, 1998). Therefore, urban change detection is performed by subtracting the radiance values from two different years. Because pixels of the change are distributed in two tails in histogram whereas pixels of unchanged features stay in the middle part close to the mean value, it is necessary to add a value to the change result so that both tails can be captured (Jensen, 1983).

The process uses the following equation for change between two different dates, in which a 127 value as a median of 255 is added.

$$\Delta V = V_2 - V_1 + 127 \qquad (1)$$

Where

$\Delta V$ is radiance difference between two different years

$V_2$ is radiance value in present year

$V_1$ is radiance value in previous year

The Figures 3.29 and 3.30 show the samples of image differencing between 1994 and 1999. The two tails in yellow in Figure 3.29 are the parts where land cover changed whereas the middle part around the mean value (here is 149) is the unchanged part between the two dates. To capture the two tails of changes between 1994 and 1999, a script is used:

```
if ( %20 >= 166) then
%30=%20+50
elseif (%20 < 142.75) then
%30=%20 -50
else
%30 = 149
endif
```
(2)

Where

%20 is information channel from equation (1)

%30 is information to store new result

The result is showed in Figure 3.30.

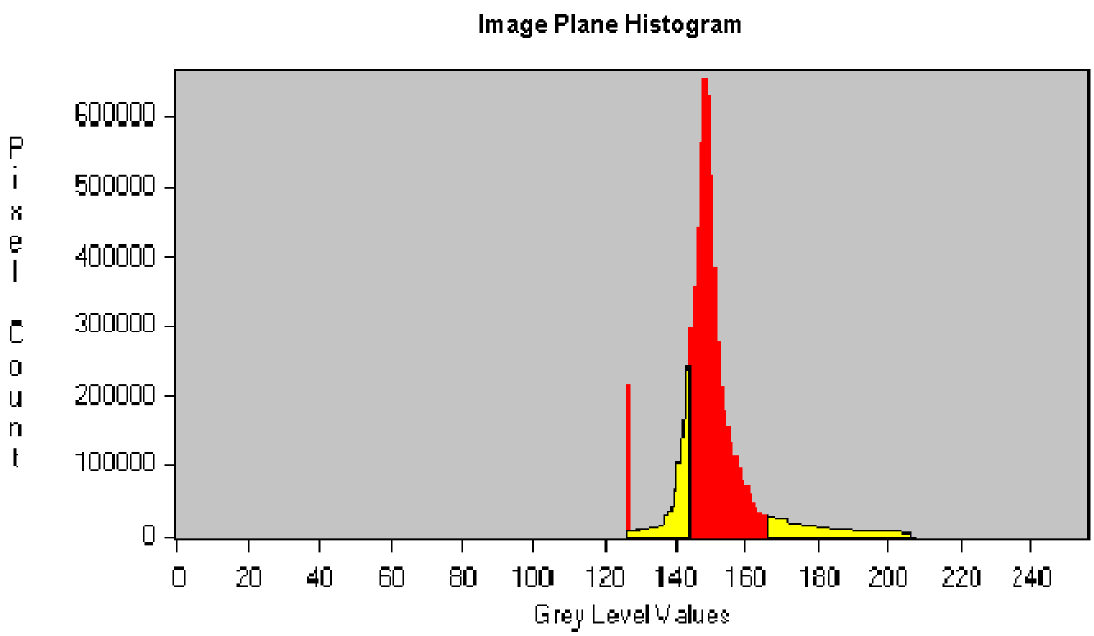



Figure 3.29 Change distribution in image differencing histogram

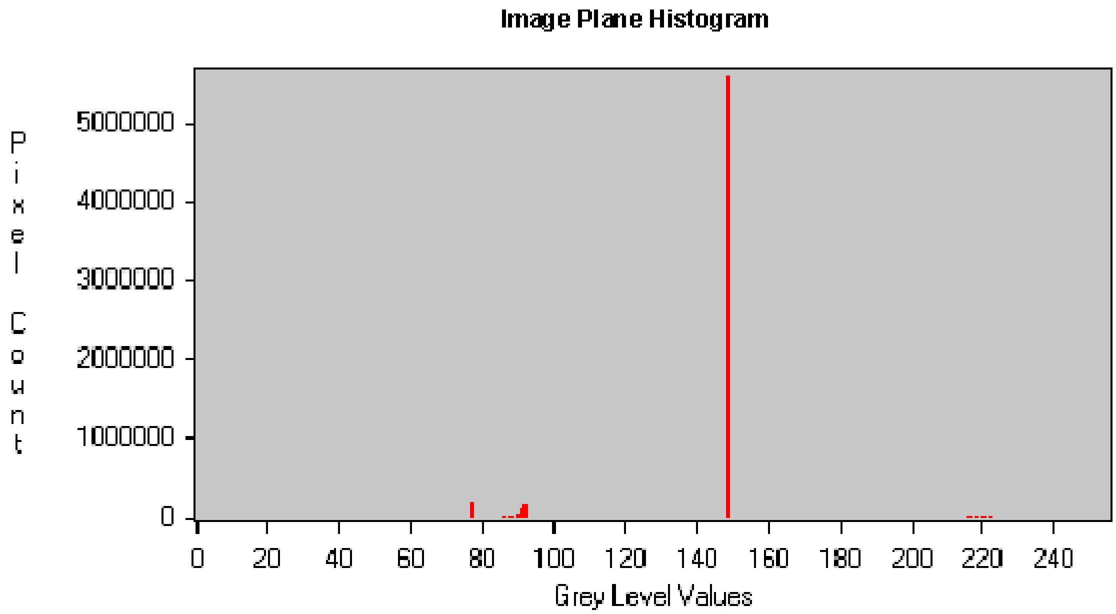



Figure 3.30 Captured change in two tails

The script from equation (2) reclassifies the distribution of pixels. All unchanged pixels are given a value 149 (original mean value) whereas the values of the two tails remain what they were originally. Optimal thresholds to cut off the two tails were adjusted on the basis of experiment by checking against imagery and aerial photography between the two dates. Two captured tails represent different types of changes (Jensen, 1986; Forsythe, 2002; Forsythe, 2004). The left tail in imagery showing dark tones is the change from the excavated to built-up areas or from the ploughed back to the crop fields, which will be categorised into the change class – new developed. The right tail showing brighter imagery is the change from green space to excavated, which will be categorised into the change class - new excavated. However, the right tail is more complicated than the left tail. The right tail may also include change directly from green space to built-up, which will also be categorised into change class – new developed. The first change in right tail from green space to excavated has brighter tones than the second change directly from green space to built-up. Pixels in the second change are distributed adjacent to pixels in the middle (unchanged) part. Noise is the main problem when the lower threshold boundary is close to the mean value representing the unchanged pixels.

To solve this problem, an unsupervised classification with ISODATA was conducted, in which 20 classes were used in change classification. The original classes were merged into unchanged, change from green space to excavated, change from green space to built-up, and change from excavated to built-up. Compared with changes distributed in the two ends of the histogram, the second change directly from green space to built-up was not separated well from the unchanged part distributed in the middle of the histogram. When the threshold was selected to fully capture the second change, the pixels in the unchanged were also introduced. It indicated that the values of pixels between the second change and the unchanged part in band 2 could not be completely separated. The resolution is inadequate to allow doing so. Appropriate additional enhancements are necessary.

Whether or not the second change is involved in urban change depends on the length of interval for the two dates of imagery. The length of intervals between available dates is listed in Table 3.7, from which it can be determined how many dates involve the second change and what method is appropriate for urban change detection.

Table 3.7 Lengths of interval between compared dates

| **Intervals** | **Length (Years)** |
|---|---|
| 1972 - 1974 | 2 |
| 1974 - 1977 | 3 |
| 1977 - 1985 | 8 |
| 1985 - 1987 | 2 |
| 1987 - 1990 | 3 |
| 1990 - 1994 | 4 |
| 1994 - 1999 | 5 |
| 1999 - 2001 | 2 |
| 2001 - 2004 | 3 |

Urban development follows a rotation from green space to excavated and from excavated to built-up. If the period of one rotation is longer than the length of intervals, the changes from green space to excavated and from excavated to built-up will represent all the changes. If the period of one rotation is shorter than the length of intervals, changes will include not only the change from green space to excavated and from excavated to built-up, but also include the change directly from green space to built-up because more than one rotation may have been completed during this interval. For the first case (two-end tail changes), two tails in the histogram fully represent all types of urban changes. For the second case, the right tail also needs to include the second change from green space to built-up. Therefore, two intervals – 3 and 5 years were selected.

The first interval is the 3-year interval from 2001 to 2004. The second one is the 5-year interval from 1994 to 1999. The test area is assigned to Vaughan where urban areas grew rapidly in the past decade. Figure 3.31 shows that urban changes in the 3-year interval are fully captured. The new developed class represents the change from excavated to built-up, which is the left tail in the histogram. The new excavated areas represent the change from green space to excavated, which is the right tail in the histogram (Forsythe, 2002; Forsythe, 2004). These two types of changes include all changes that occurred between the two compared dates.

Urban changes in the 5-year interval are not fully captured as shown in Figure 3.32. In addition to the new developed and new excavated, there are changes directly from the green space to the built-up (purple colour). This part of changes is the second change in the right tail of the histogram and needs to be categorised into new developed class. Therefore, the detected new developed is underestimated in this interval.

Theoretically, it is possible to capture the second part of the changes. However, only two compared intervals are equal or longer than 5 years, i.e., interval from 1977 to 1985 and interval from 1994 to 1999. It is feasible to apply the two-end tail urban change detection for all intervals within 5 years whereas the other method is applied for intervals longer than 5 years.

For intervals within 5 years, the two-end tail urban change detection can fully capture the two types of urban changes – the new developed and the new excavated except for the interval between 1990 and 1994 and theinterval between 1994 and 1999, in which the new developed change areas are underestimated. For intervals longer than 5 years from 1977 to 1985, the new developed area is detected by using the post-classification method, i.e., subtracting two classified maps from two dates.

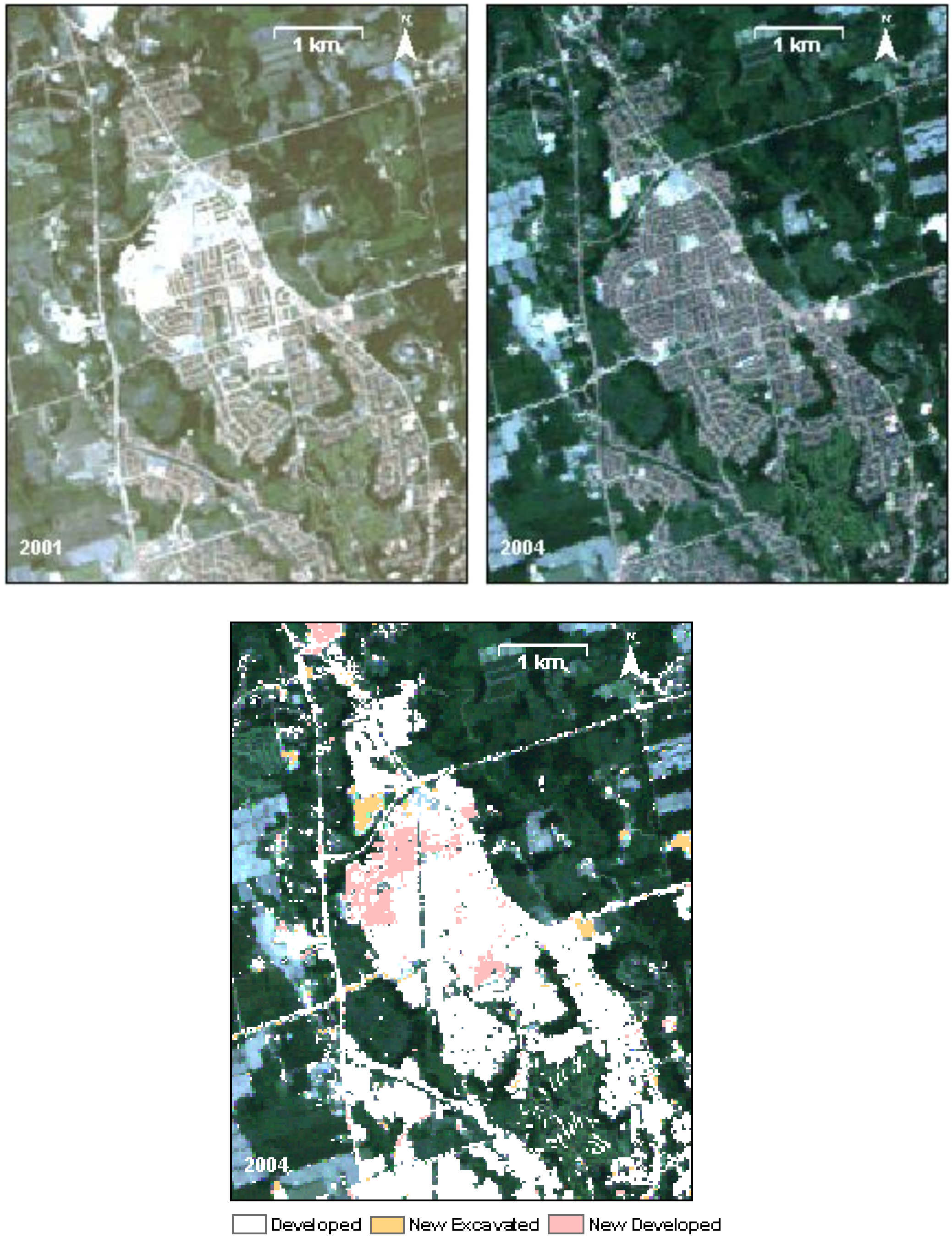



Figure 3.31 Fully captured urban change in 3-year interval from 2001 to 2004
Image in upper left: 2001 imagery; Image in upper right: 2004 imagery;
Image at bottom: captured changes: from green space to excavated (new excavated) and from the excavated to built-up area (new developed)

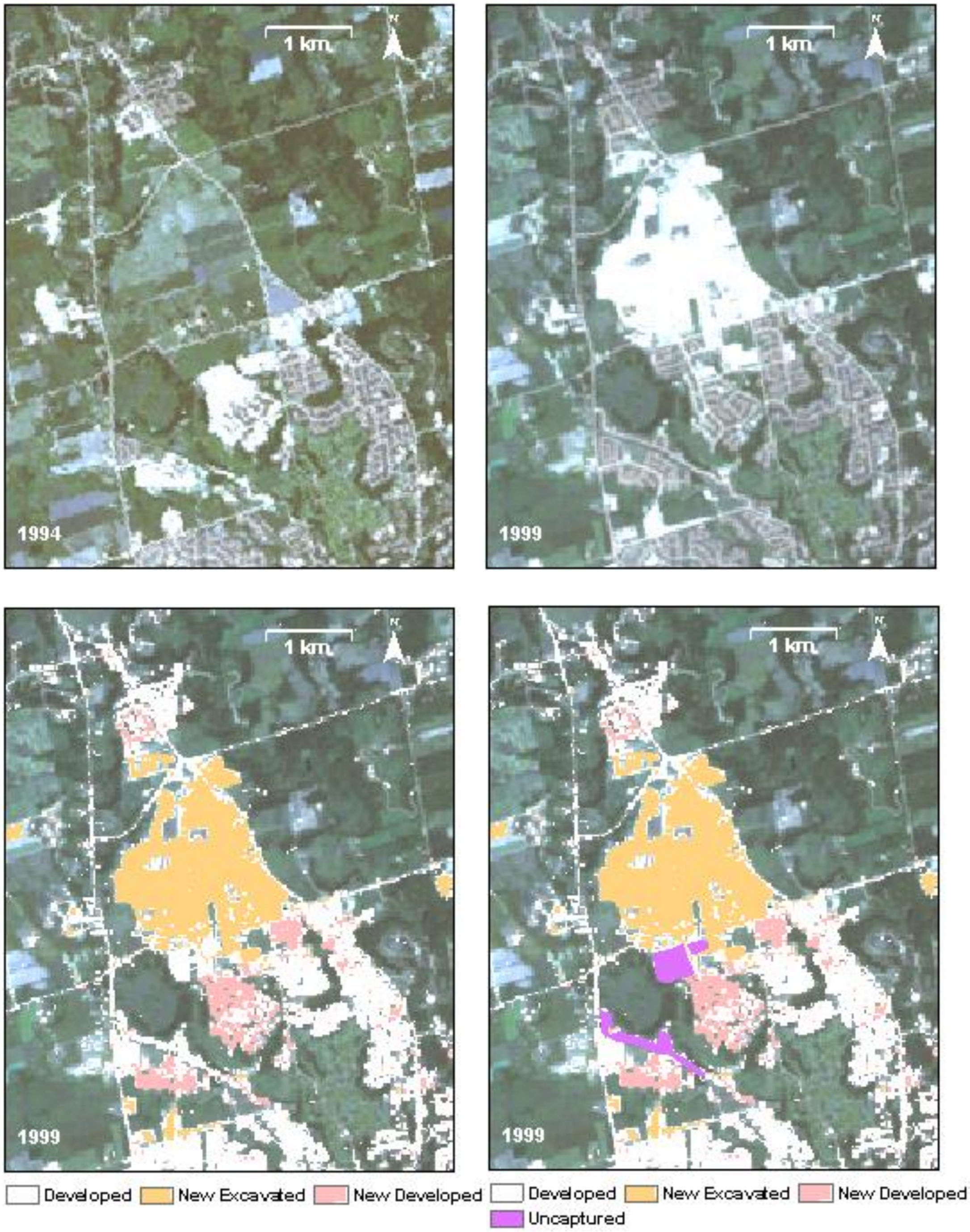



Figure 3.32 Partially captured urban change in 5-year interval from 1994 to 1999
Images on the top are two years of original imagery; Images at bottom are
Captured changes: new excavated and new developed. Area not captured: uncaptured.

### 3.2.5 Image Processing in ArcGIS

In the northeast corner of the study area, the no data area is inconsistent between image dates. ArcGIS was used to process the images so that the calculations were consistent for all acquisition dates.

## 3.3 Data Processing

The finalized methodology (based on the experiments above) is shown in Figure 3.33

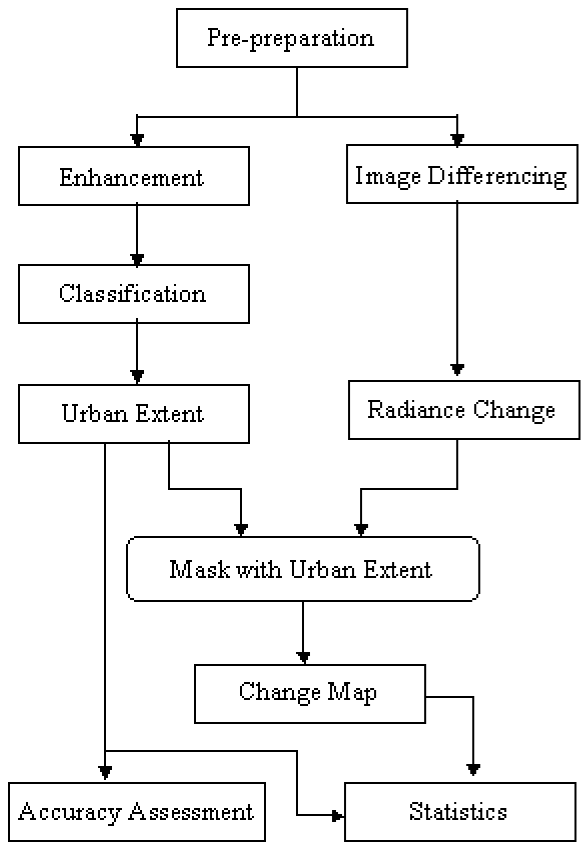



Figure 3.33 Procedure of data processing

### 3.3.1 Enhancement

Due to the varying resolutions and image characteristics, different enhancement strategies were implemented. They were:

- **Data 1985, 1987, 1990, 1994, 1999, and 2001**

    - NDVI – Input: 3, 4;
    - Texture- Input: 2; Method: mean; FLSZ: 3x3
    - PCA- Input: 1, 2, 3, 4, 5, 6, 7; Output: PC1, PC2, and PC3

- **Data 1972, 1974, and 1977**

    - NDVI- Input: 2, 4;
    - Texture- Input: 1; Method: mean; FLSZ: 3x3
    - PCA- Input: 1, 2, 3, 4; Output: PC1, PC2
    - Ratioing between MSS with TM
        - R1: TM 2 / MSS 1
        - R2: TM 3 / MSS 2
        - R3: TM 4 / MSS 3
        - R4: TM 5 / MSS 4
        - R5: TM NDVI / MSS NDVI
        - R6: TM texture / MSS texture
        - R7: TM PC1 / MSS PC1
        - R8: TM PC2 / MSS PC2

- **Data 2004**

    - #NDVI – Input: 3, 4
    - #Texture- Input: 2; Method: mean; Size of window: 3x3
    - #PCA- Input: 1, 2, 3, 4, 5, 6, 7, (8 for 1999 image); Output: PC1, PC2, and PC3
    - B1/5: $\Delta B1 = B5 - B1 + 60$
    - B2/5: $\Delta B2 = B5 - B2 + 60$
    - B1/7: $\Delta B3 = B1 – B7 + 60$
    - B3/7: $\Delta B4 = B3 – B7 + 60$

### 3.3.2 Classification

Supervised classification with maximum likelihood method was used. Input channels included both the original bands and enhanced results.

- **Input channels**

  - Data 1985, 1987, 1990, 1994, 1999, and 2001

    - Original: 1, 2, 3, 4, 5, 6, 7
    - Enhancement: NDVI, texture, PC1, PC2, PC3

  - Data 1972, 1974, and 1977

    - Original: 1, 2, 3, 4
    - Enhancement: NDVI, texture, PC1, PC2, R1, R2, R3, R4, R5, R6, R7, R8

  - Data 2004

    - Original: 1, 2, 3, 4, 5, 6, 7
    - Enhancement: NDVI, texture, PC1, PC2, PC3, ΔB1, ΔB2, ΔB3, ΔB4

- **Training sites**

  Three types of land covers - urban, green, and water were trained. A visual control in a specific known area (such as river valley areas in the centre of Toronto) was necessary for consistency. This made the images more comparable.

### 3.3.3 Image Differencing

Figure 3.34 shows image differencing procedures. Band 2 was used to conduct the image differencing. By adding a 127 value to original differenced imagery, the pixel distribution is more easily identified. The initial selection of threshold values depends on the mean value as well as other distribution features in the histogram. Based on visual comparison between two dates of imagery, the threshold values for two tails were adjusted until all types of changes were captured with satisfactory results.

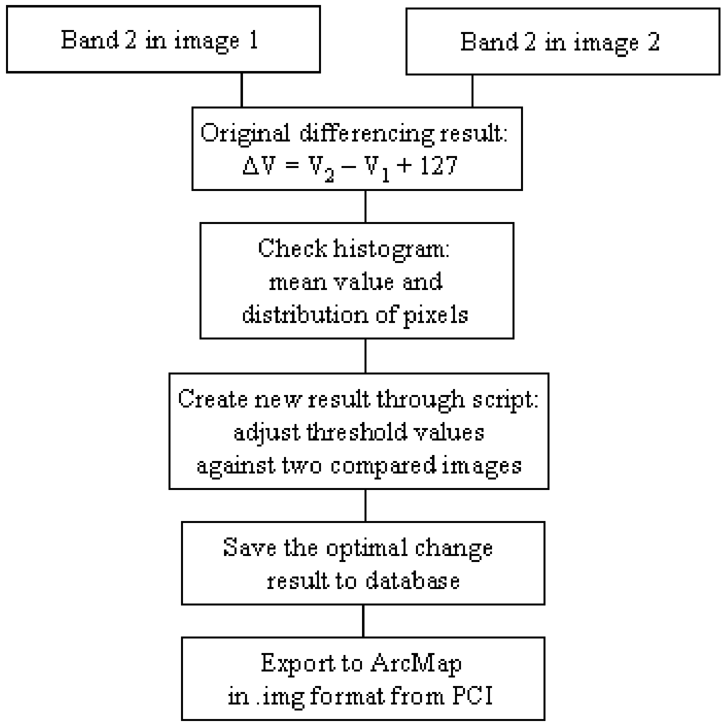



Figure 3.34 Image differencing

The manipulation of the threshold was performed using a script in the PCI EASI Modelling module. To simplify and enhance the changes, a 50 value was added to right tail while a 50 value was given to left tail (Equation 3).

$$
\begin{array}{l}
\text{if ( \%D >= } T_{upper}\text{) then} \\
\text{\%N = \%D + 50} \\
\text{elseif (\%D < } T_{low}\text{) then} \\
\text{\%N = \%D - 50} \\
\text{else} \\
\text{\%D = } T_{mean} \\
\text{endif}
\end{array}
\qquad (3)
$$

Where:

$T_{upper}$ – threshold value for right tail, the change from green space to excavated
$T_{low}$ – threshold value for left tail, the change from excavated to built-up
$T_{mean}$ – threshold value for middle part, the unchanged part
%D – channel of original band 2 differencing by adding 127
%N – new channel to store adjustment of change

Table 3.8 lists all the values of thresholds for each year of data

Table 3.8 Thresholds for image differencing in band 2

| **Time** | **$T_{mean}$** | **$T_{low}$** | **$T_{upper}$** |
|---|---|---|---|
| 1972_1974 | 128 | 110 | 150 |
| 1974_1977 | 126 | 115 | 149 |
| 1977_1985 | 128 | 110 | 154 |
| 1985_1987 | 141 | 120 | 167 |
| 1987_1990 | 135 | 123 | 155 |
| 1990_1994 | 127 | 123 | 146 |
| 1994_1999 | 149 | 143 | 166 |
| 1999_2001 | 103 | 70 | 115 |
| 2001_2004 | 159 | 80 | 250 |

### 3.3.4 Masking with Urban Extent

To detect the change that occurred within the urban extent, radiance change maps from image differencing procedures were masked with the urban extent map in ArcGIS. Before creating the urban change map, the urban extent map was produced by reclassifying satellite derived urban extent images with the classes – water, green space, and urban extent. The satellite derived radiance change maps were also reclassified into new developed, unchanged, and new excavated.

The reclassified values for both maps are given below:

- **<u>Urban extent map</u>**
  - 50 – water
  - 180 – green space
  - 250 – urban extent

- **<u>Reclassified radiance change map</u>**
  - 10 – new developed
  - 1 - unchanged
  - 30 – new excavated

Urban change maps were produced using the raster calculator by adding the urban extent maps and the reclassified radiance change maps, which were subsequently reclassified map. The intermediate calculation and reclassification results are shown below:

- **<u>Intermediate results and reclassifications</u>**
  - 51 – unchanged water → water
  - 60 – darker water → water
  - 80 – brighter water → water
  - 181- unchanged green space → green space
  - 190 – ploughed to crop → green space
  - 210 - green to ploughed → green space
  - 251 – unchanged urban → developed urban
  - 260 – excavated to built-up → new developed
  - 280 – green space to excavated → new excavated

- **Final urban change map:**
  - 50 – water
  - 180 – green space
  - 100 – new developed
  - 200 – new excavated
  - 250 – developed urban

### 3.3.5 Accuracy Assessment

To validate the urban change results derived from remote sensing, accuracy assessment was necessary. The urban change detection involved 10 different images from 1972 to 2004 over a 32-year span. It was impossible to conduct the validation with field work. Therefore, the validation relied on Landsat imagery that was used to detect urban change, and supporting data, including historical land use and aerial photos. The dates of the supporting data are close to the Landsat imagery dates.

Another consideration is the classification to be assessed. The results include urban extent maps, which are further combined with image differencing to differentiate new developed area, new excavated area, and unchanged developed area inside the urban. The new developed and new excavated are merged together with the developed for the accuracy assessment. This is because it is difficult to ensure enough random sampling sites inside these small areas and validate their accuracy independently.

# CHAPTER 4: RESULTS AND DISCUSSION

## 4.1 Results

The results include urban extent maps, urban change maps, statistics, and accuracy assessments for all dates from 1972 to 2004.

### 4.1.1 Urban Extent

#### 1972

Landsat MSS data in 1972 has a full coverage of the study area (Figure 4.1). Table 4.1 shows the area statistics. Urban features cover 663.1 km$^2$ accounting for 12.4% of the study area.

The producer's and user's accuracy for water features for all dates was 100%, indicating that water area is fully and correctly classified. Therefore, urban and green space features were selected to assess the accuracy of derived urban extent maps with statistics - producer's accuracy, user's accuracy, and overall accuracy. These three statistics are adequate to assess how well the classification for each date performed.

The results of accuracy assessment in Table 4.2 are very good. The overall accuracy is 95.333%. It indicates that overall performance of classification for the urban extent maps from 1972 is very good. The producer's accuracy for green space is 95.35% where it is 81.82% for urban feature, indicating urban feature is not as fully captured as the green space feature, but it still achieved a very good accuracy level. The user's accuracy for green space is 93.89% whereas it is 85.71% for the urban feature. It indicates that urban feature is not as accurately captured as the green space feature in the classification.

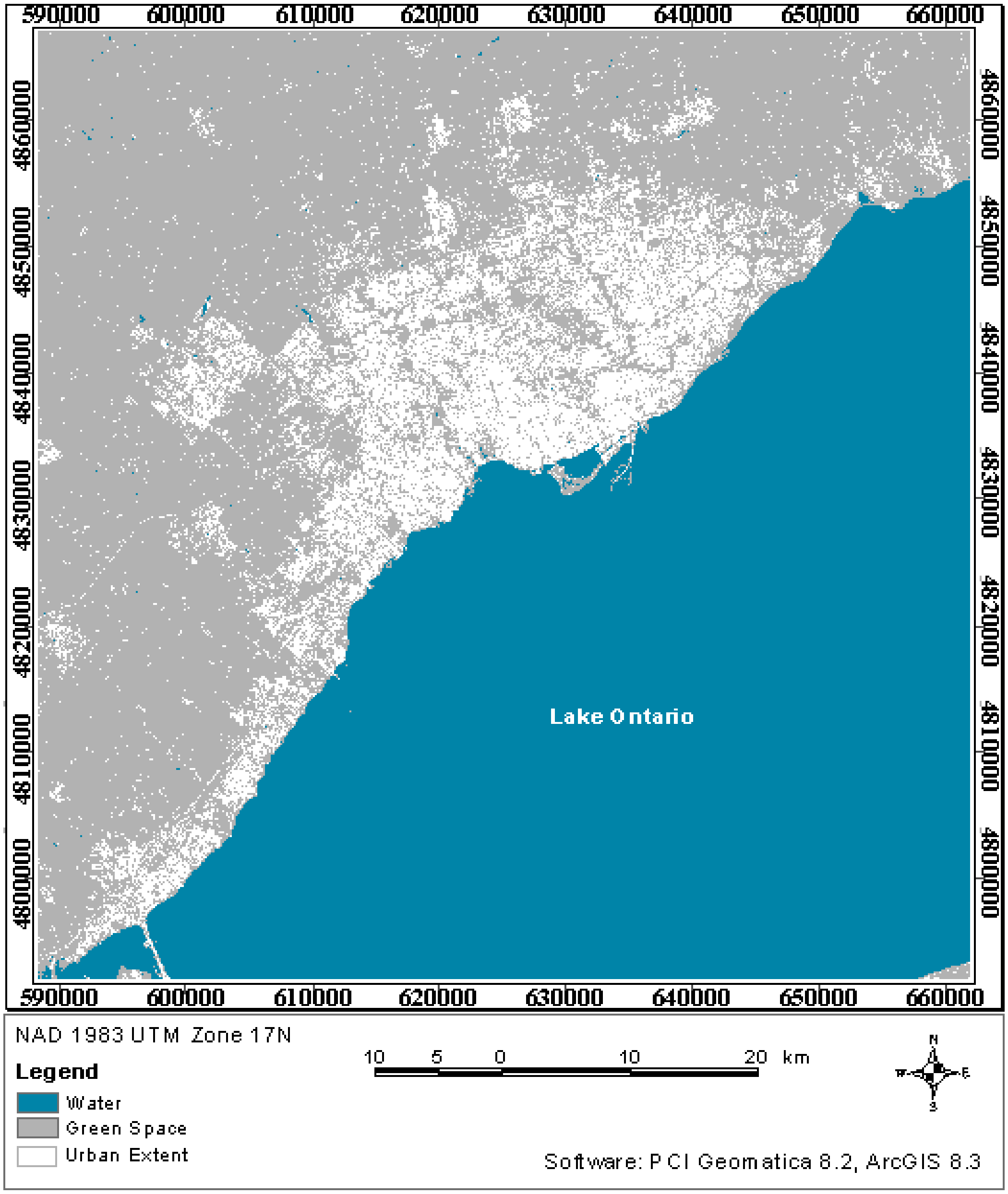



Figure 4.1 Derived urban extent map from 1972 Landsat MSS data

Table 4.1 Area statistics for urban extent map from 1972

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 663.1485165 |
| Green Space | 2259.595838 |
| Water | 2521.273547 |
| Unclassified | 2.0842335 |

Table 4.2 Accuracy statistics for urban extent map from 1972

| Overall Accuracy: 95.333% - 95% Confidence Interval (92.780% 97.887%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.924% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 81.82% | (69.285% 94.351%) | 85.71% | (73.941% 97.488%) | 0.8326 |
| Green Space | 95.35% | (91.327% 99.371%) | 93.89% | (89.411% 98.375%) | 0.8929 |
| Water | 100.00% | (99.606% 100.394%) | 100.00% | (99.606% 100.394%) | 1.0000 |

**1974**

Landsat MSS data in 1974 fully covered the study area (Figure 4.2). Table 4.3 shows that the unclassified area in 1974 is the same as in 1972. The water area remains almost the same. The areas that changed were green space and urban extent, the urban extent increased whereas the green space decreased.

The results of accuracy assessment in Table 4.4 are better than results from 1972. The overall accuracy is 97.667%. It indicates that overall performance of classification for urban extent maps from 1974 is excellent. The producer's accuracy for green space is 99.19% whereas it is 88% for the urban feature. It shows that the green space is more fully captured than the urban feature, in which the green space is almost fully captured.

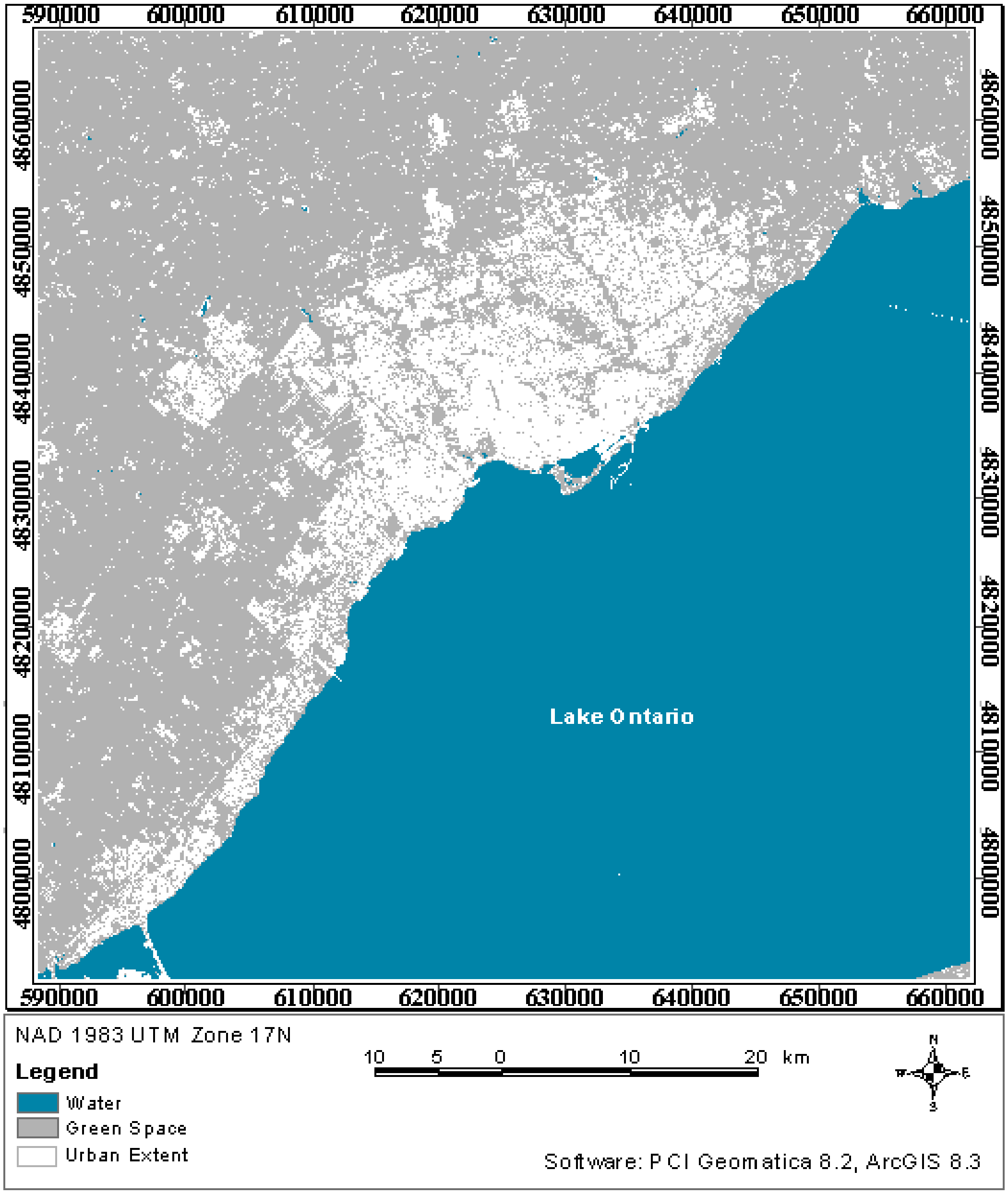



Figure 4.2 Derived urban extent map from 1974 Landsat MSS data

However, the producer's accuracy for urban feature is very close to 90%, indicating that identifying urban features was performed well. The user's accuracy for green space is 95.31% whereas it is 97.78% for the urban feature. It indicates that both green space and urban features achieved a great accuracy in categorizing features into correct classes.

However, the urban feature is more accurately captured than green space feature in the classification.

Table 4.3 Area statistics for urban extent map from 1974

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 725.6828318 |
| Green Space | 2196.196477 |
| Water | 2522.138594 |
| Unclassified | 2.0842335 |

Table 4.4 Accuracy statistics for urban extent map from 1974

| Overall Accuracy: 97.667% - 95% Confidence Interval (95.792% 99.542%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.962% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 88.00% | (77.993% 98.007%) | 97.78% | (92.360% 103.196%) | 0.9733 |
| Green Space | 99.19% | (97.193% 101.181%) | 95.31% | (91.260% 99.365%) | 0.9206 |
| Water | 100.00% | (99.606% 100.394%) | 100.00% | (99.606% 100.394%) | 1.0000 |

**1977**

Landsat MSS data for 1977 fully covered the study area (Figure 4.3). Table 4.5 shows that the unclassified area and water area remain almost the same as 1972 and 1974. The urban extent continues to expand and green space to shrink.

The results of accuracy assessment in Table 4.6 are very good. The overall accuracy is 97.667%. It indicates that the overall performance of the classification is excellent. The producer's accuracy for green space is 97.6% whereas it is 91.84% for the urban feature.

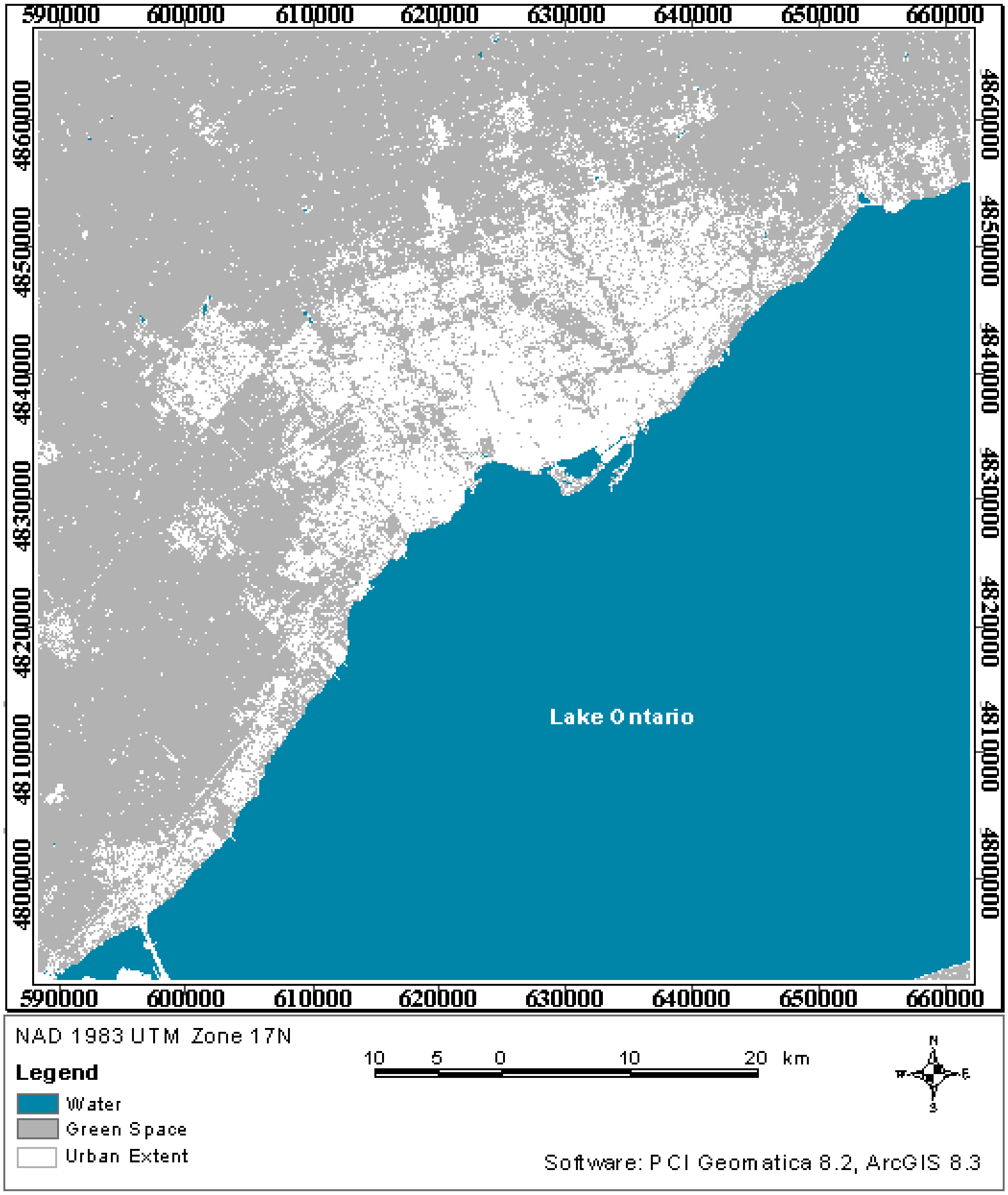



Figure 4.3 Derived urban extent map from 1977 Landsat MSS data

It shows that the green space is more fully captured than the urban feature. However, notice that the producer's accuracy for the urban feature is over 90%. It indicates that identifying the urban feature in the classification for urban extent achieved a high accuracy level. The user's accuracy for green space is 97.6% whereas it is 93.75% for the urban feature, indicating that both green space and urban features achieved a great accuracy in categorizing features into correct classes. Relatively, the green space feature is more accurately captured than urban feature in classification for urban extent map from 1977.

Table 4.5 Area statistics for urban extent map from 1977

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 752.0484668 |
| Green Space | 2177.008695 |
| Water | 2514.96074 |
| Unclassified | 2.0842335 |

Table 4.6 Accuracy statistics for urban extent map from 1977

| Overall Accuracy: 97.667% - 95% Confidence Interval (95.792% 99.542%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.963% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 91.84% | (83.150% 100.524%) | 93.75% | (85.860% 101.640%) | 0.9253 |
| Green Space | 97.60% | (94.517% 100.683%) | 97.60% | (94.517% 100.683%) | 0.9589 |
| Water | 100.00% | (99.603% 100.397%) | 99.21% | (97.282% 101.144%) | 0.9864 |

**1985**

The 1985 TM data fully covered the study area (Figure 4.4). Table 4.7 shows that the urban extent continues to expand and green space to shrink.

The results of accuracy assessment in Table 4.8 are very good. The overall accuracy is

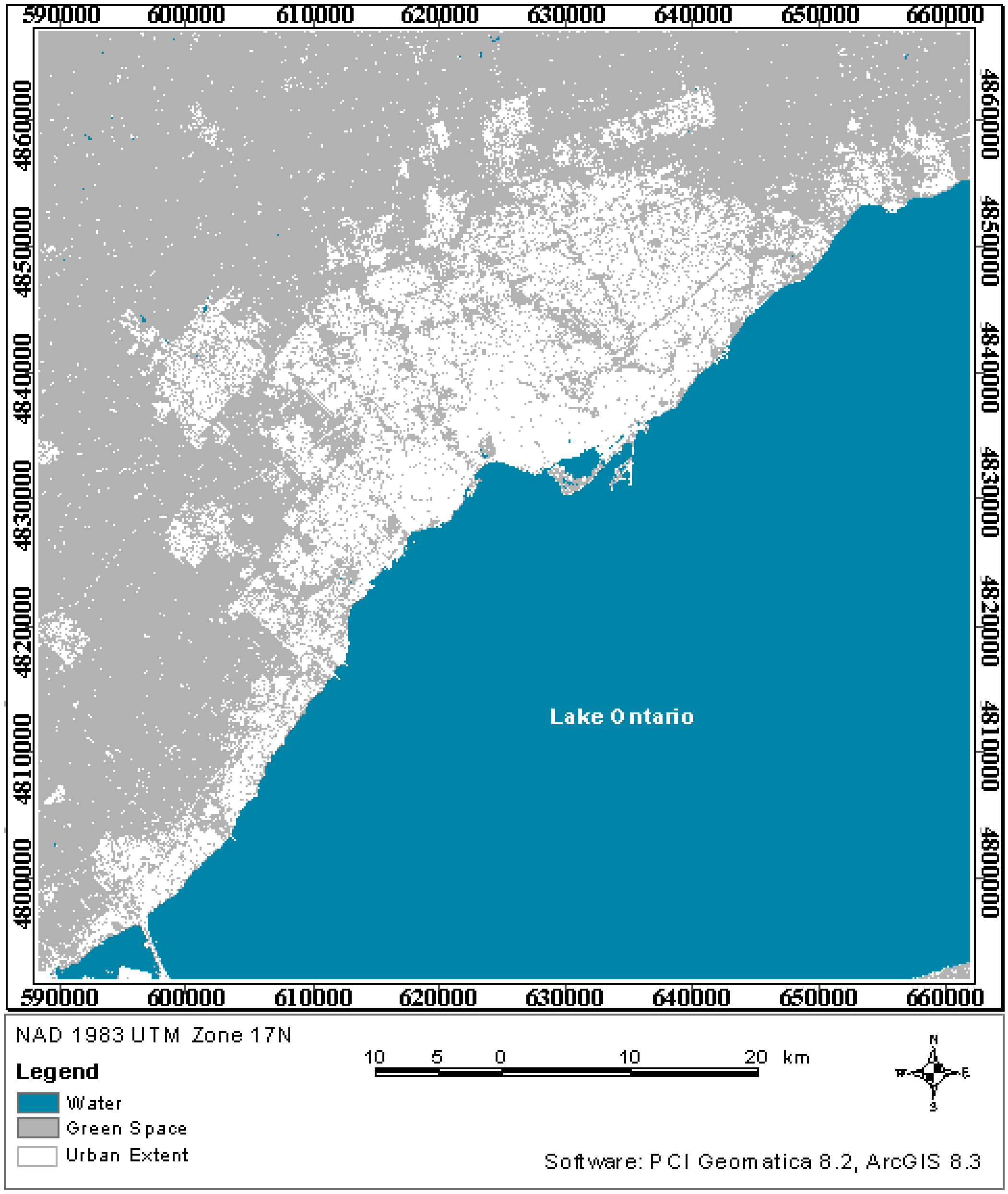



Figure 4.4 Derived urban extent map from 1985 Landsat TM data

97%. It indicates that the overall performance of the classification is very good. The producer's accuracy for green space is 96.46% whereas it is 91.53% for urban features. This shows that green space is more fully captured than the urban feature. However, the producer's accuracy for the urban feature is over 90%. The user's accuracy for green space is 95.61% whereas it is 93.1% for urban features, indicating that both green space and urban features achieved a great accuracy in class categorization. Relatively, the green space feature is more accurately captured than urban features.

Table 4.7 Area statistics for urban extent map from 1985

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 861.9881288 |
| Green Space | 2066.571936 |
| Water | 2515.457837 |
| Unclassified | 2.0842335 |

Table 4.8 Accuracy statistics for urban extent map from 1985

| Overall Accuracy: 97.000% - 95% Confidence Interval (94.903% 99.097%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.953% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 91.53% | (83.571% 99.479%) | 93.10% | (85.720% 100.487%) | 0.9142 |
| Green Space | 96.46% | (92.611% 100.310%) | 95.61% | (91.416% 99.812%) | 0.9296 |
| Water | 100.00% | (99.609% 100.391%) | 100.00% | (99.609% 100.391%) | 1.0000 |

**<u>1987</u>**

The 1987 TM data did not fully cover the study area (Figure 4.5). There is not very much urban development in NE corner of the image where there are no data. Therefore to make the mapping representation consistent between full coverage images (1972, 1974, 1977, 1985, 2004) and partial coverage images (1987, 1990, 1994, 1999, 2001), this area was filled with green space in ArcGIS. This means that green space inside the study area is a

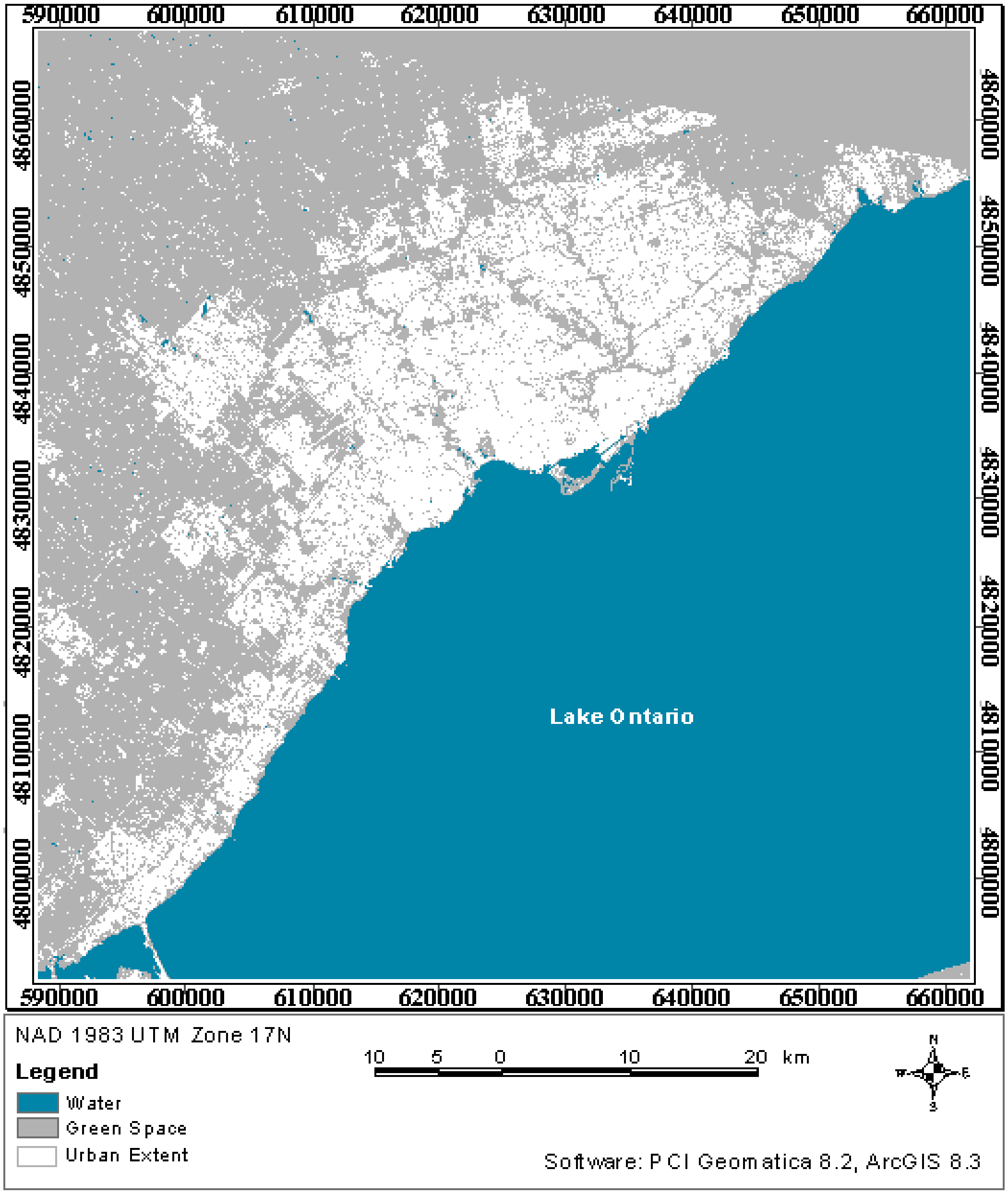



Figure 4.5 Derived urban extent map from 1987 Landsat TM data

little overestimated whereas the urban extent is a little bit underestimated. The areas of green space and urban extent in dates with the NE no data corner in tables are represented by *. Table 4.9 shows the area statistics for urban extent map from 1987. In the accuracy assessment, the NE corner is just green space.

The results of accuracy assessment in Table 4.10 are very good. The overall accuracy is 97.667%, indicating overall performance of classification for urban extent maps from 1987 is excellent. The producer's accuracy for green space is 96.33% whereas it is 95.31% for urban features. It shows that both green space and urban features are near to be fully captured. The producer's accuracy for urban features is over 95%, which is a great accuracy level. The user's accuracy for green space is 97.22% whereas it is 93.85% for urban features, indicating that both green space and urban features achieved a great accuracy in categorizing features into correct classes. Relatively, the green space feature is more accurately captured than urban features.

Table 4.9 Area statistics for urban extent map from 1987

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 987.5879708* |
| Green Space | 1934.209301* |
| Water | 2522.220631 |
| Unclassified | 2.0842335 |

Table 4.10 Accuracy statistics for urban extent map from 1987

| Overall Accuracy: 97.667% - 95% Confidence Interval (95.792% 99.542%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.964% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 95.31% | (89.353% 101.272%) | 93.85% | (87.235% 100.458%) | 0.9218 |
| Green Space | 96.33% | (92.342% 100.319%) | 97.22% | (93.660% 100.785%) | 0.9564 |
| Water | 100.00% | (99.606% 100.394%) | 100.00% | (99.606% 100.394%) | 1.0000 |

**1990**

The 1990 TM data did not fully cover the study area (Figure 4.6). The area of no data in the NE corner is consistent with the 1987 TM data. Table 4.11 shows the area statistics.

The results of accuracy assessment in Table 4.12 are very good. The overall accuracy of 98.333% indicates the overall performance of the classification is excellent. The producer's accuracy for green space is 99.06% whereas it is 94.03% for urban features, indicating that green space is almost fully captured and urban features are also very well captured. The producer's accuracy for urban features is near to 95%. The user's accuracy for green space is 96.33% whereas it is 98.44% for urban features, indicating that both green space and urban feature achieved great accuracy. Urban features are more accurately captured than green space features.

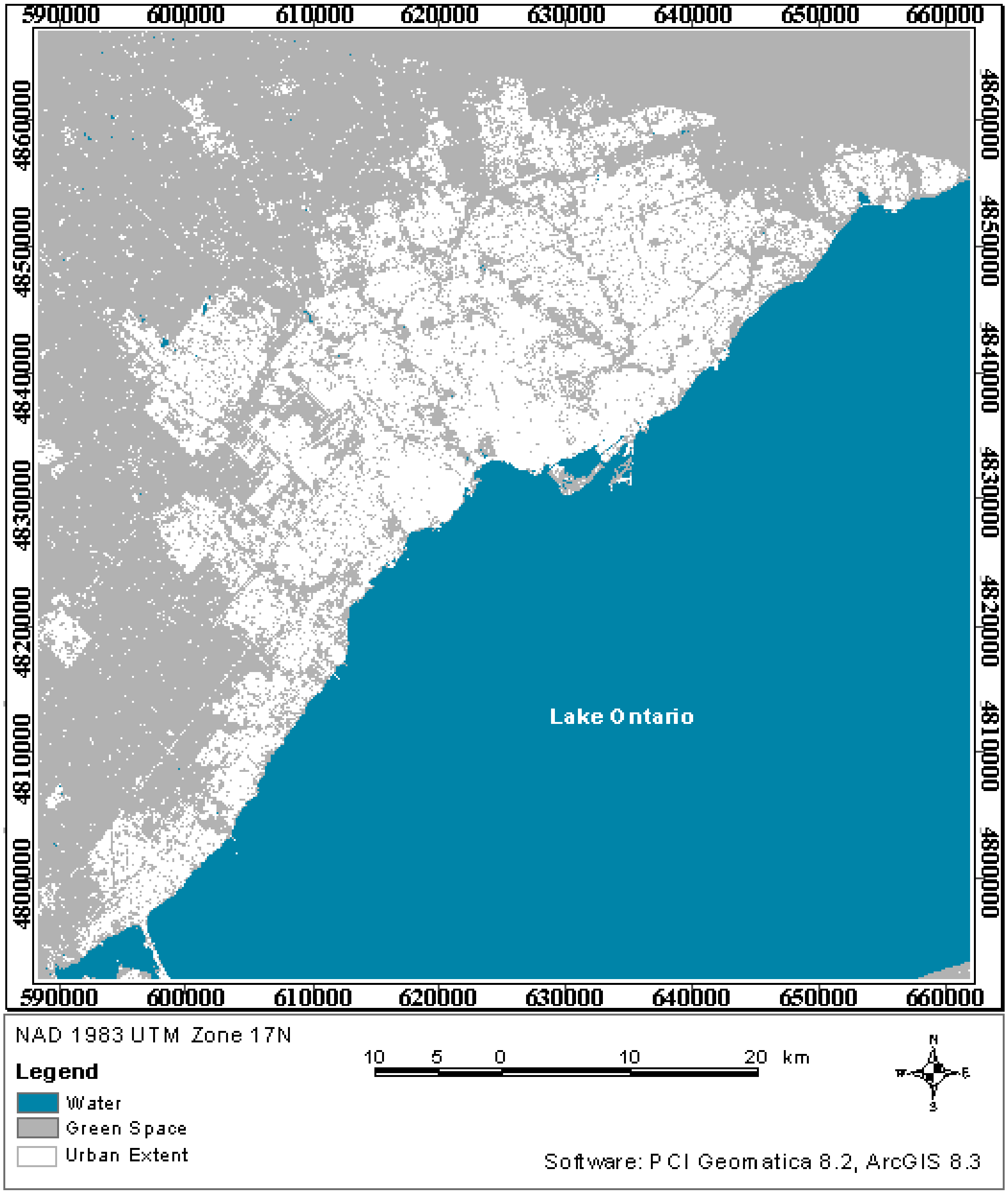



Figure 4.6 Derived urban extent map from 1990 Landsat TM data

Table 4.11 Area statistics for urban extent map from 1990

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 1045.738573* |
| Green Space | 1882.823929* |
| Water | 2515.455401 |
| Unclassified | 2.0842335 |

Table 4.12 Accuracy statistics for urban extent map from 1990

| Overall Accuracy: 98.333% - 95% Confidence Interval (96.718% 99.949%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.974% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 94.03% | (87.610% 100.450%) | 98.44% | (94.618% 102.257%) | 0.9799 |
| Green Space | 99.06% | (96.745% 101.369%) | 96.33% | (92.342% 100.319%) | 0.9433 |
| Water | 100.00% | (99.606% 100.394%) | 100.00% | (99.606% 100.394%) | 1.0000 |

**1994**

The 1994 TM data did not fully cover the study area (Figure 4.7). The area of no data in the NE corner is smaller than that in 1987 and 1990. Table 4.13 shows the area statistics.

The results of accuracy assessment in Table 4.14 are very good. The overall accuracy of 97.667% indicates an excellent overall performance. The producer's accuracy for green space is 98.1% whereas it is 92.54% for urban features, indicating that green space is almost fully captured and urban features are very well captured. The user's accuracy for green space is 95.37% whereas it is 96.88% for urban features, indicating that both green space and urban feature achieved great accuracy.

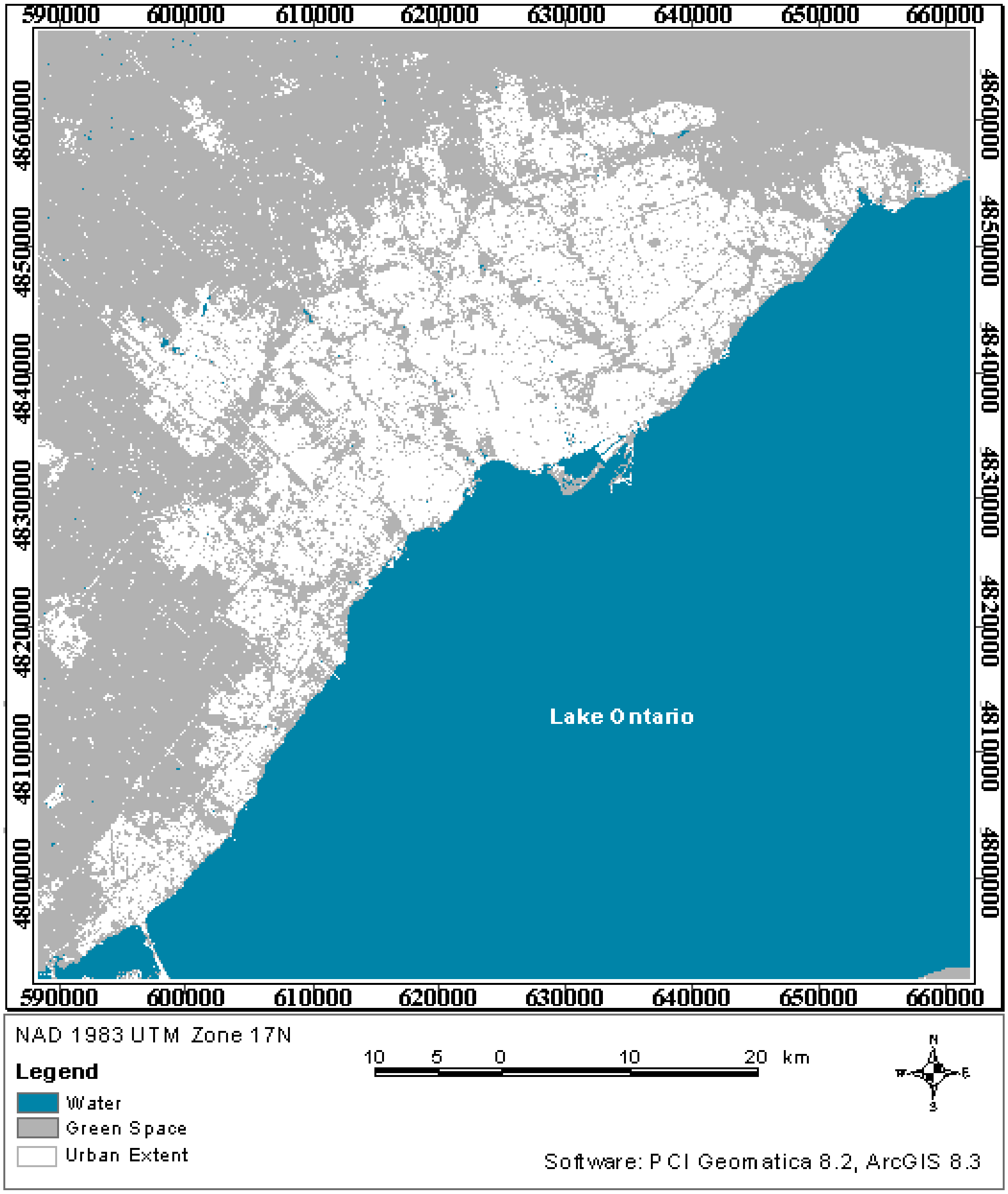



Figure 4.7 Derived urban extent map from 1994 Landsat TM data

Table 4.13 Area statistics for urban extent map from 1994

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 1072.757257* |
| Green Space | 1847.656753* |
| Water | 2523.603893 |
| Unclassified | 2.0842335 |

Table 4.14 Accuracy statistics for urban extent map from 1994

| Overall Accuracy: 97.667% - 95% Confidence Interval (95.792% 99.542%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.964% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 92.54% | (85.499% 99.576%) | 96.88% | (91.831% 101.919%) | 0.9598 |
| Green Space | 98.10% | (95.004% 101.186%) | 95.37% | (90.944% 99.796%) | 0.9288 |
| Water | 100.00% | (99.609% 100.391%) | 100.00% | (99.609% 100.391%) | 1.0000 |

**1999**

The 1999 ETM+ data did not fully cover the study area (Figure 4.8). The area of no data in NE corner is smaller than that in 1987 and 1990 but larger than that in 1994. Table 4.15 shows the area statistics.

The results of the accuracy assessment in Table 4.16 are excellent. The overall accuracy of 97.667% indicates an excellent overall performance. The producer's accuracy for green space is 96% whereas it is 95.83% for urban features, indicating that both green space and urban features achieved a high accuracy level in terms of being fully captured. The user's accuracy for green space is 96.97% whereas it is 94.52% for urban features, also showing that both green space and urban features achieved great accuracy.

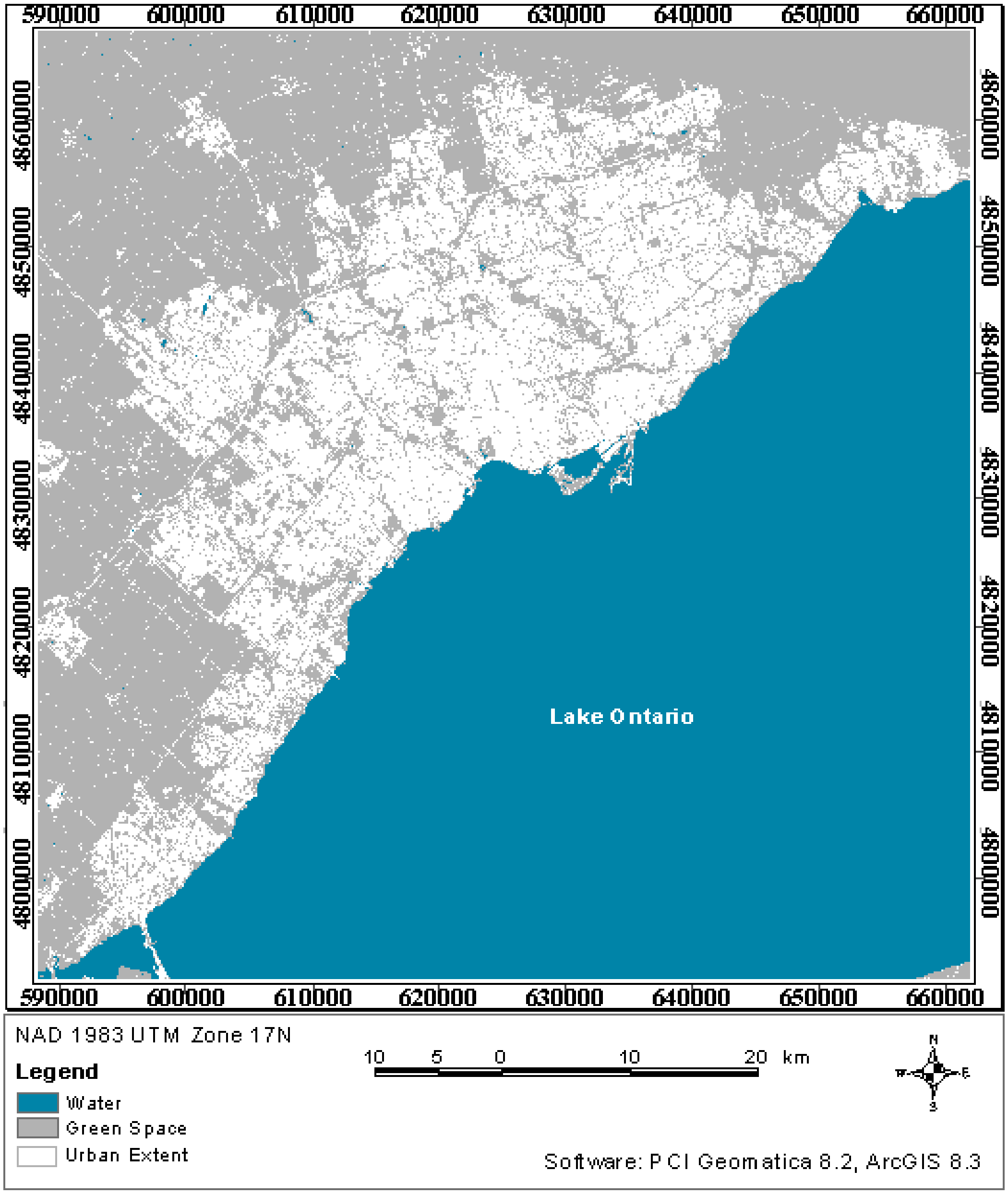



Figure 4.8 Derived urban extent map from 1999 Landsat ETM+ data

Table 4.15 Area statistics for urban extent map from 1999

| Classes | Area (km$^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 1177.7625* |
| Green Space | 1749.519896* |
| Water | 2516.735507 |
| Unclassified | 2.0842335 |

Table 4.16 Accuracy statistics for urban extent map from 1999

| Overall Accuracy: 97.667% - 95% Confidence Interval (95.792% 99.542%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.964% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban Extent | 95.83% | (90.523% 101.144%) | 94.52% | (88.615% 100.426%) | 0.9279 |
| Green Space | 96.00% | (91.659% 100.341%) | 96.97% | (93.088% 100.852%) | 0.9545 |
| Water | 100.00% | (99.609% 100.391%) | 100.00% | (99.609% 100.391%) | 1.0000 |

**2001**

The 2001 TM data did not fully cover the study area (Figure 4.9). The urban extent and green space in 2001 remained almost the same as those in 1999. This is because the area of no data in NE corner is larger than that in 1999 and the urban extent is a little bit underestimated. Table 4.17 shows the area statistics.

The results of the accuracy assessment in Table 4.18 are very good. The overall accuracy of 97% indicates a very good overall performance. The producer's accuracy for green space is 97.87% whereas it is 91.14% for urban features, indicating that green space is more fully captured than urban features. The producer's accuracy for urban features in classification is over 90%. The user's accuracy for green space is 92.93% whereas it is 97.3% for urban features, indicating that urban features are not as fully captured as green space features.

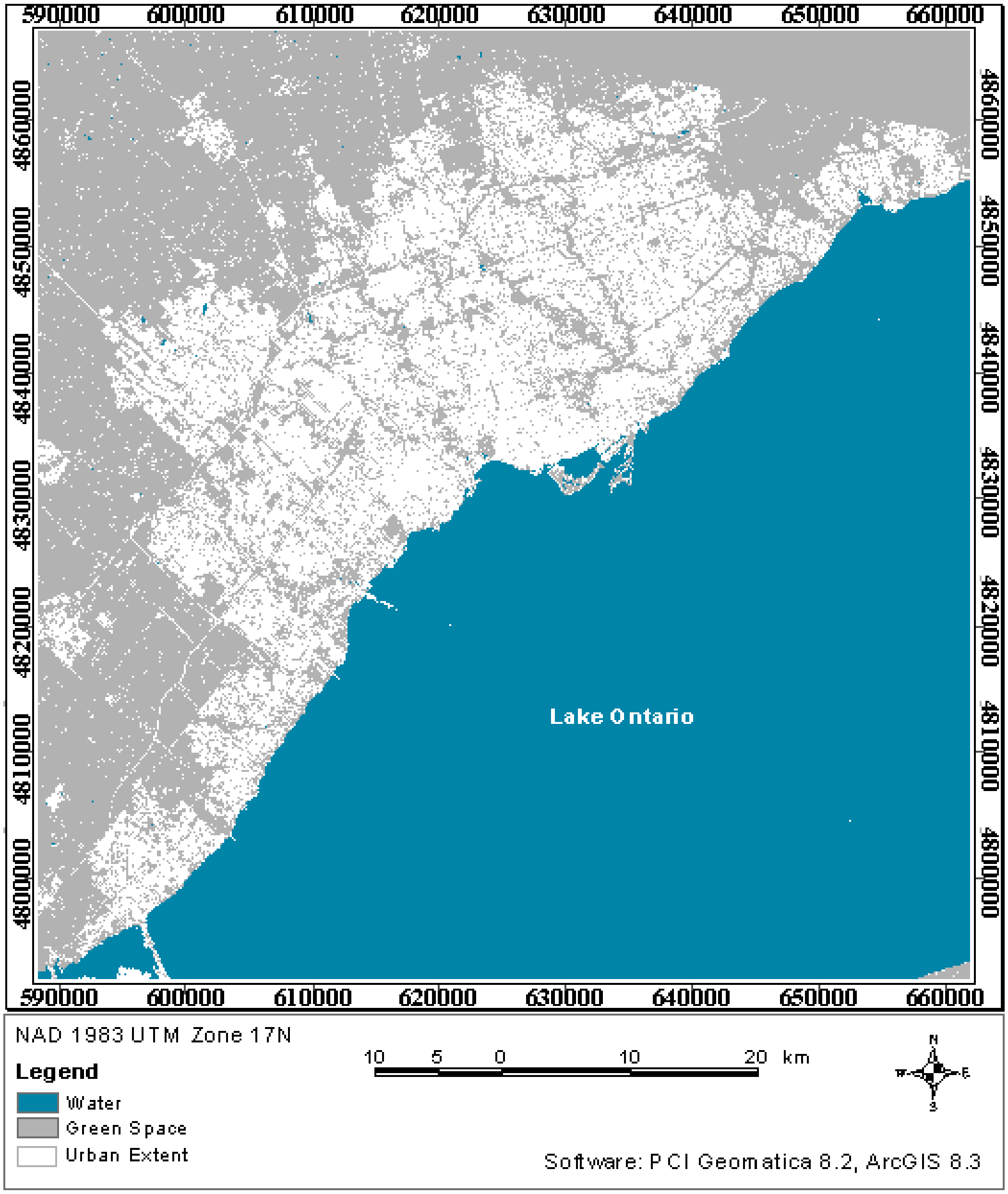



Figure 4.9 Derived urban extent map from 2001 Landsat TM data

Table 4.17 Area statistics for urban extent map from 2001

| Classes | Area (km$^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 1178.468345* |
| Green Space | 1749.445981* |
| Water | 2516.103576 |
| Unclassified | 2.0842335 |

Table 4.18 Accuracy statistics for urban extent map from 2001

| Overall Accuracy: 97.000% - 95% Confidence Interval (94.903% 99.097%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.954% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban | 91.14% | (84.240% 98.039%) | 97.30% | (92.927% 101.668%) | 0.9633 |
| Green Space | 97.87% | (94.423% 101.322%) | 92.93% | (87.375% 98.484%) | 0.8970 |
| Water | 100.00% | (99.606% 100.394%) | 100.00% | (99.606% 100.394%) | 1.0000 |

**2004**

The 2004 TM data fully covered the study area (Figure 4.10). Table 4.19 shows that area changes occurred in urban extent and green space. The green space shrank from 2259.6 km$^2$, (accounting for 41.5% of the total study area in 1972) to 1603.8 km$^2$ (accounting for 29.5% in 2004). The urban extent expanded from 663.1 km$^2$, (accounting for 12.4% of total study area in 1972) to 1327.6 km$^2$ (accounting for 24.4% of total study area in 2004).

The results of the accuracy assessment in Table 4.20 are very good. The overall accuracy of 97.333% indicates a very good overall performance. The producer's accuracy for green space is 98.88% whereas it is 91.55% for urban features, indicating that green space is more fully captured than urban features. The producer's accuracy for urban features is over 91%. The user's accuracy for green space is 92.63% whereas it is 98.49% for urban features, indicating that although urban features are not as fully captured as green space features, they are more accurately captured. The user's accuracy for urban features is the highest among all dates of urban extent maps.

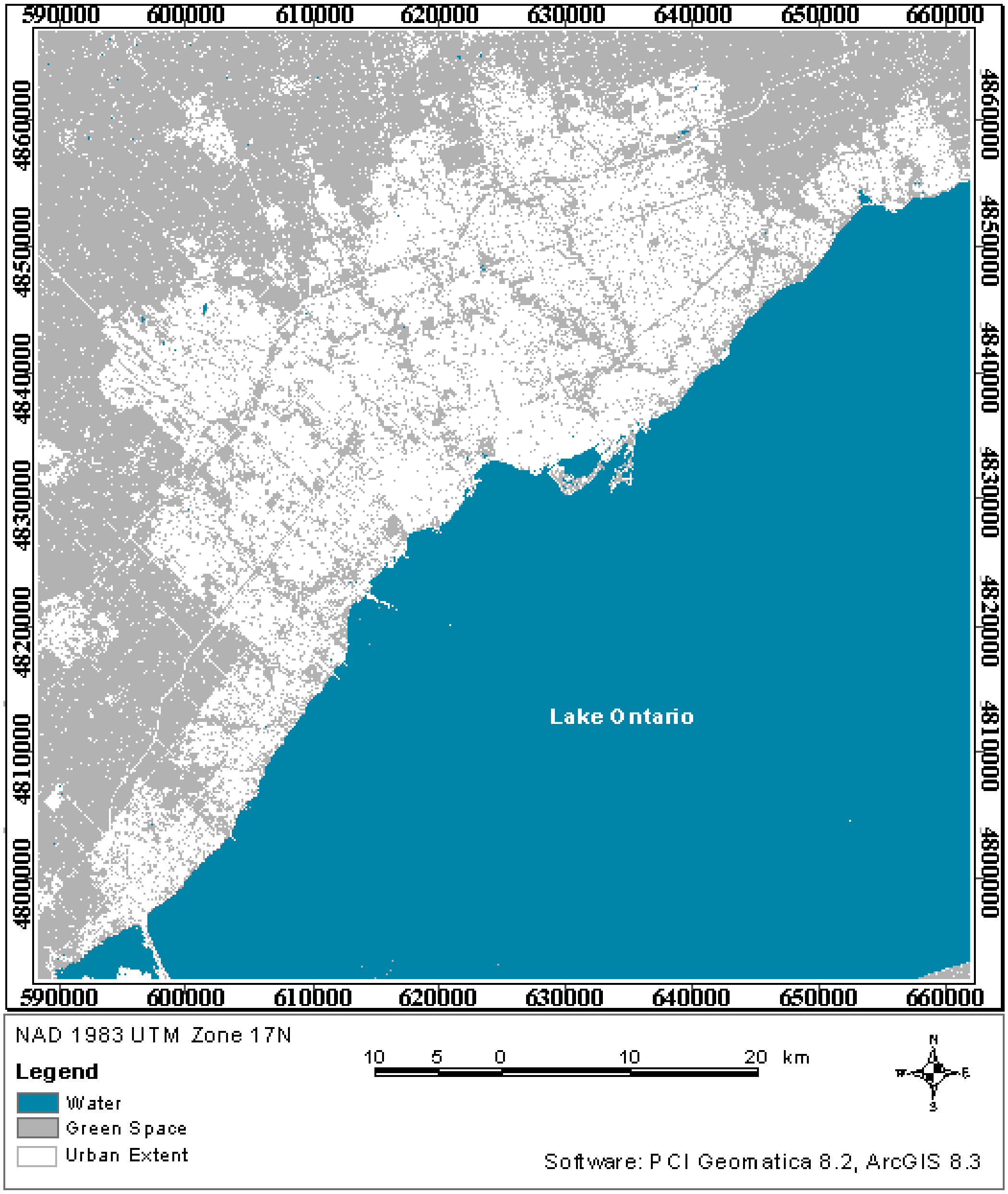



Figure 4.10 Derived urban extent map from 2004 Landsat TM data

Table 4.19 Area statistics for urban extent map from 2004

| Classes | Area ($km^2$) |
|---|---|
| Study Area | 5444.017902 |
| Urban Extent | 1327.635056 |
| Green Space | 1603.764581 |
| Water | 2512.618265 |
| Unclassified | 2.0842335 |

Table 4.20 Accuracy statistics for urban extent map from 2004

| Overall Accuracy: 97.333% - 95% Confidence Interval( 95.344% 99.323%) | | | | | |
|---|---|---|---|---|---|
| Overall Kappa Statistic: 0.958% - Overall Kappa Variance: 0.000% | | | | | |
| Class Name | Producer's Accuracy | 95% Confidence | User's Accuracy | 95% Confidence | Kappa Statistics |
| Urban | 91.55% | (84.375% 101.038%) | 98.49% | (94.780% 100.360%) | 0.9802 |
| Green Space | 98.88% | (96.125% 101.628%) | 92.63% | (86.852% 98.412%) | 0.8952 |
| Water | 99. 29% | (97.534% 101.038%) | 100.00% | (99.640% 100.360%) | 1.0000 |

Table 4.21 is a collection of accuracy statistics for comparison purpose between dates from 1972 to 2004, in which producer's accuracy, user's accuracy, and overall accuracy are provided.

Table 4.21 Accuracy comparison for all dates

| Year | Producer's Accuracy | | User's Accuracy | | Overall Accuracy |
|---|---|---|---|---|---|
| | Urban (%) | Green (%) | Urban (%) | Green (%) | (%) |
| 1972 | 81.82 | 95.35 | 85.71 | 93.89 | 95.33 |
| 1974 | 88.00 | 99.19 | 97.78 | 95.31 | 97.67 |
| 1977 | 91.84 | 97.60 | 93.75 | 97.60 | 97.67 |
| 1985 | 91.53 | 96.46 | 93.10 | 95.61 | 97.00 |
| 1987 | 95.31 | 96.33 | 93.85 | 97.22 | 97.67 |
| 1990 | 94.03 | 99.06 | 98.44 | 96.33 | 98.33 |
| 1994 | 92.54 | 98.10 | 96.88 | 95.37 | 97.67 |
| 1999 | 95.83 | 96.00 | 94.52 | 96.97 | 97.67 |
| 2001 | 91.14 | 97.87 | 97.30 | 92.93 | 97.00 |
| 2004 | 91.55 | 98.88 | 98.49 | 92.63 | 97.33 |

From the accuracy levels for all dates, the following observations can be made:

1) The overall accuracy of the urban extent maps is 97% or better for all dates but 1972, which is also above 95%. This indicates that the overall performance from all dates is

very good.

2) The producer's accuracy for green space is better than that for urban features for all dates. It shows that urban features are not as fully captured as green space features.

3) The producer's accuracy for urban features for all dates is above 91% except for two dates of MSS data – 1972 and 1974, which are 81.82% and 88.00% respectively. The results indicate that identifying urban features performed very well, particularly for the classification of MSS data, in which the producer's accuracy of the 1974 classification – 88.00% is very close to the average TM level. The producer's accuracy for the 1977 MSS data – 91.84% is even a little bit higher than some dates of TM data.

4) The user's accuracy represents how accurate urban and green space features are captured. Different from producer's accuracy, it did not show the unanimous difference between green space and urban features. The lowest user's accuracy for urban is 85.71%, which is from the 1972 MSS data. But all other dates are above 93%. This indicates the categorised urban class for all dates well represents the ground truth urban feature.

5) The greater spectral and spatial resolution of the ETM+ and TM data allowed for improved performance in capturing urban features when compared to MSS data. However, the gap between MSS data and TM/ETM+ data is reduced by enhancements, in which MSS was resampled into the same spatial resolution with TM.

### 4.1.2 Urban Change

#### 1972-1974

Urban change from 1972 to 1974 (Figure 4.11) is produced from the subtraction of band 2 between these two dates, then masked by the 1974 urban extent map. These two dates of imagery fully covered the study area, therefore, the changes between these two dates inside the study area are fully detected.

Table 4.22 shows the area statistics. The developed class in the urban change map is the unchanged urban from 1972 to 1974. The new excavated class is the area changed from green space in 1972 to excavated in 1974. The new developed class is the area changed from excavated in 1972 to built-up in 1974. Annual growth is the result calculated from the new developed divided by the length of interval between two dates. The urban change is fully detected because the length of interval is shorter than 3 years.

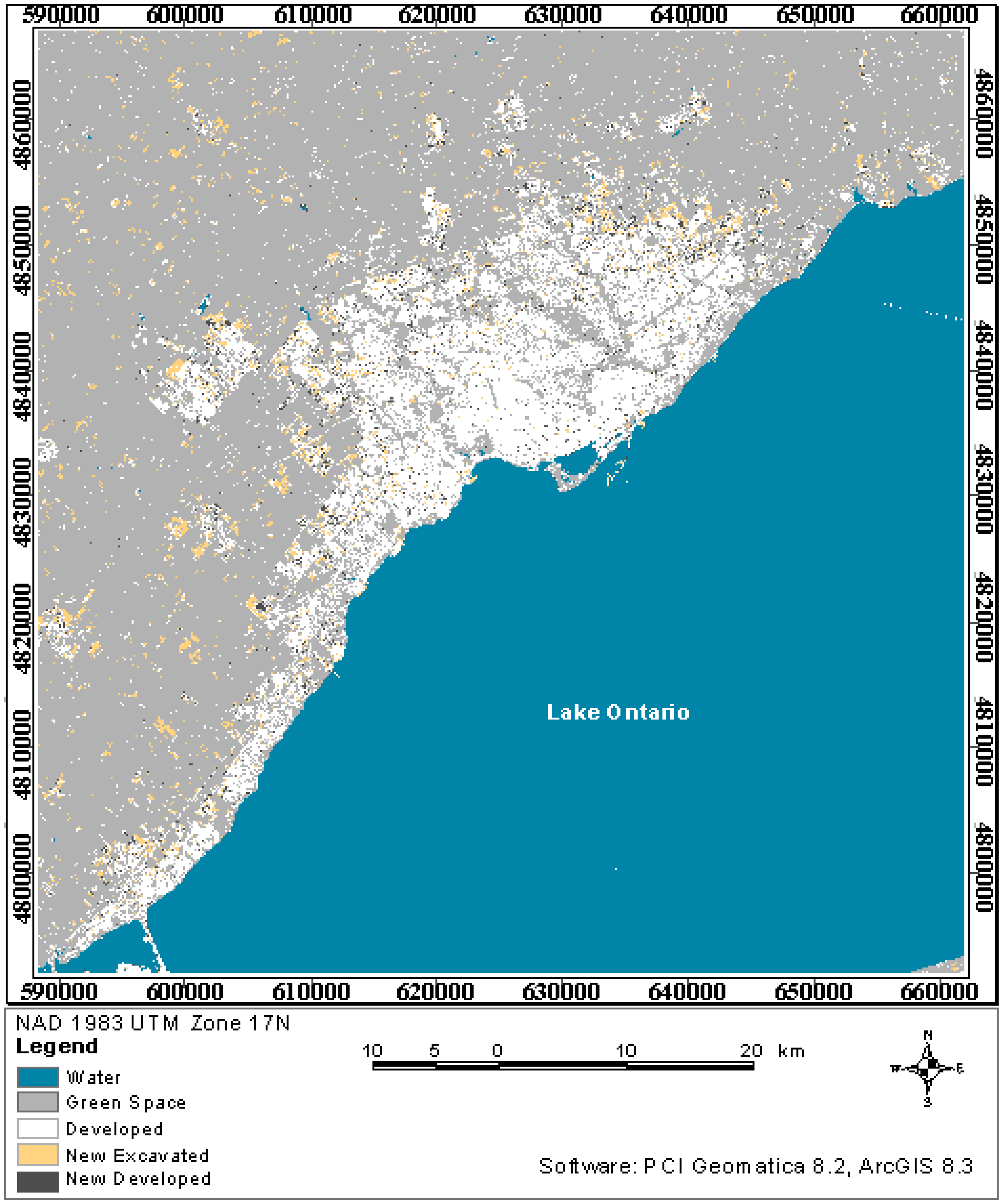



Figure 4.11 Detected urban change map from 1972 to 1974

Table 4.22 Area statistics for urban change (1972-1974)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2522.138594 |
| Greenspace | 2196.196477 |
| Developed | 603.0322695 |
| New Excavated | 87.00415875 |
| New Developed | 35.6464035 |
| Annual Growth | 17.82320175 |

**<u>1974-1977</u>**

Urban change from 1974 to 1977 (Figure 4.12) is produced from the subtraction of band 2 between these two dates, then masked by the 1977 urban extent map. These two dates of imagery fully cover the study area, therefore, the changes between these two dates inside the study area are fully detected.

Table 4.23 shows the area statistics. Classes and annual growth calculation in urban change map from 1974 to 1977 are the same as the previous urban change map from 1972 to 1974. The urban change is fully detected because the length of interval is 3 years.

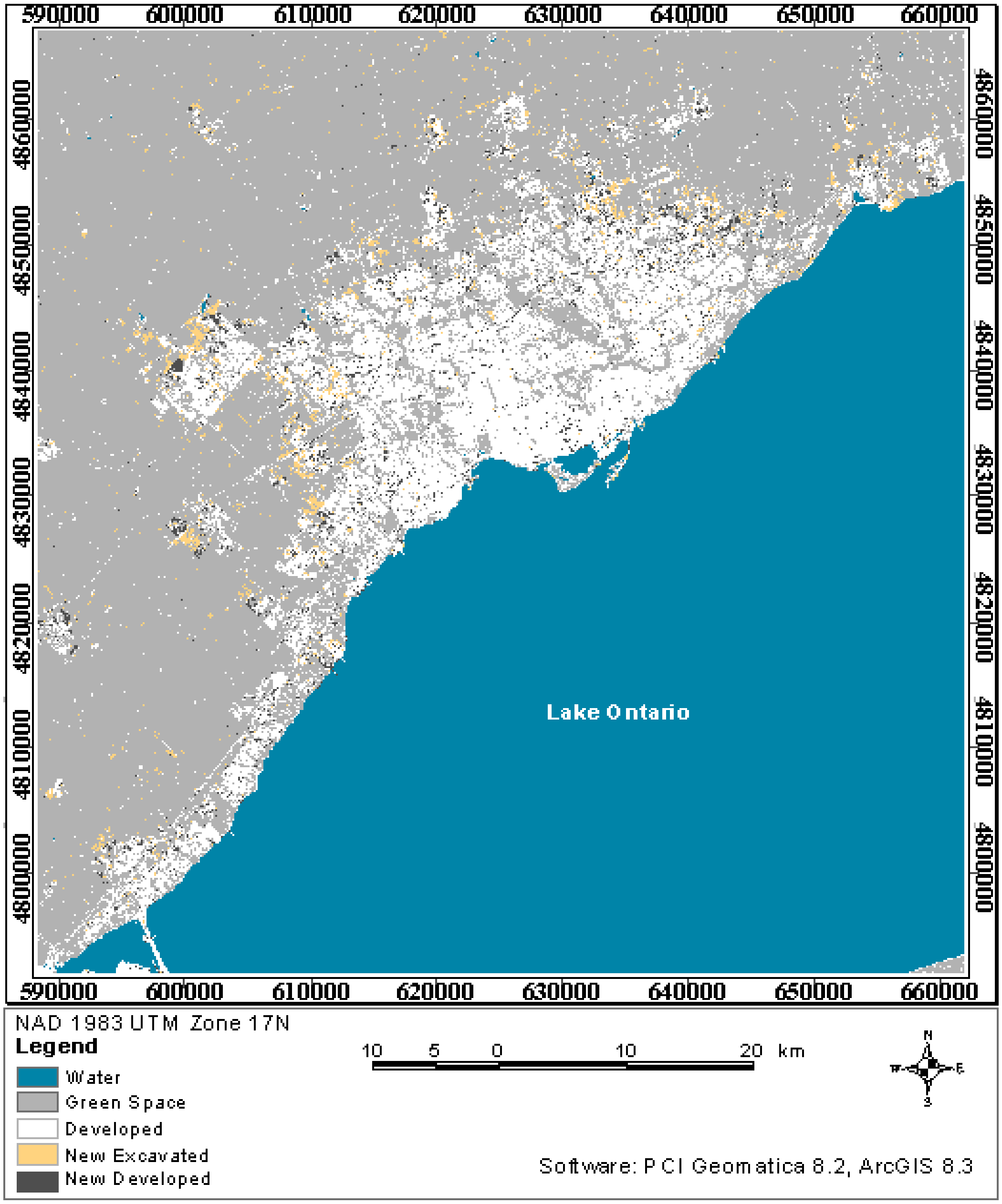



Figure 4.12 Detected urban change map from 1974 to 1977

Table 4.23 Area statistics for urban change (1974-1977)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2514.96074 |
| Greenspace | 2177.008695 |
| Developed | 652.402449 |
| New Excavated | 51.483654 |
| New Developed | 48.16236375 |
| Annual Growth | 16.05412125 |

**1977-1985**

Urban change from 1977 to 1985 (Figure 4.13) is produced from the subtraction of band 2 between these two dates, then masked by the 1985 urban extent map. These two dates of imagery fully covered the study area, therefore, the changes between these two dates inside the study area are fully detected.

Table 4.24 shows the area statistics. Classes in urban change map from 1977 to 1985 are the same as the previous urban change maps. However, the calculation of annual growth from 1977 to 1985 is different from previous calculations due to the long interval between two dates. Annual growth is not directly derived from the new developed, instead from subtraction of developed urban areas between two dates.

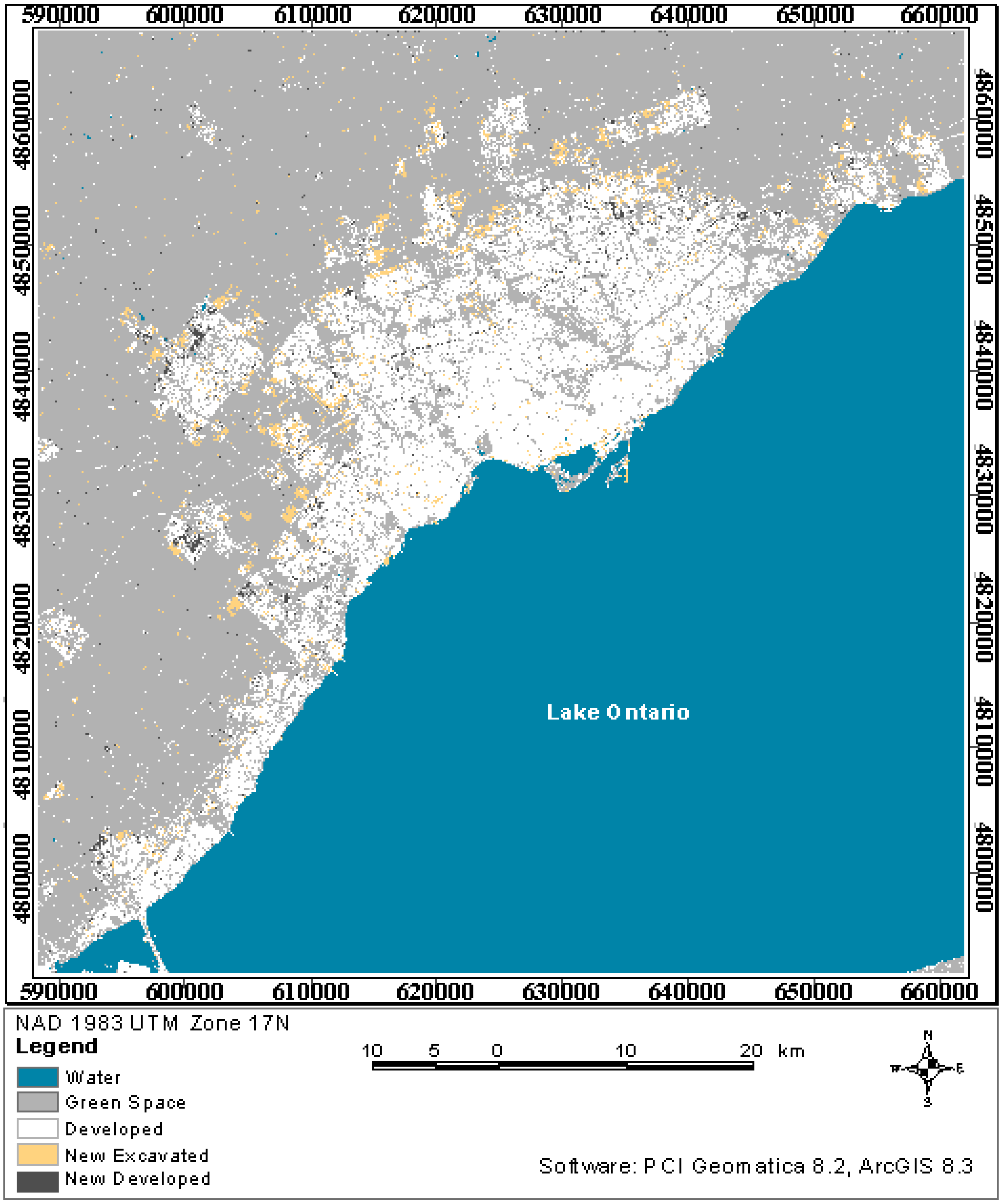



Figure 4.13 Detected urban change map from 1977 to 1985

Table 4.24 Area statistics for urban change (1977-1985)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2515.457837 |
| Greenspace | 2066.571936 |
| Developed | 774.7719728 |
| New Excavated | 64.5560055 |
| New Developed | 22.6601505 |
| Annual Growth | 12.10841381* |

The calculation is as follows:

$$\Delta G = (N_2 + D_2 - N_1 - D_1) / 8 \qquad (4)$$

Where

$\Delta G$ - annual growth in $km^2$
$N_1$ – new developed area in 1977
$N_2$ – new developed area in 1985
$D_1$ – developed area in 1977
$D_2$ – developed area in 1985

The reason is the long interval included more than one urban development rotation. The detected new developed can only partially account for the urban change between these two dates. The subtraction between two dates of developed and new developed can more accurately account for the urban change over a long interval of time.

**1985-1987**

Urban change from 1985 to 1987 (Figure 4.14) is produced from the subtraction of band 2 between these two dates, then masked by the 1987 urban extent map. The 1987 imagery contains no data in the NE corner, in which some urban missed. Thus, urban change that occurred in the NE corner is not detected.

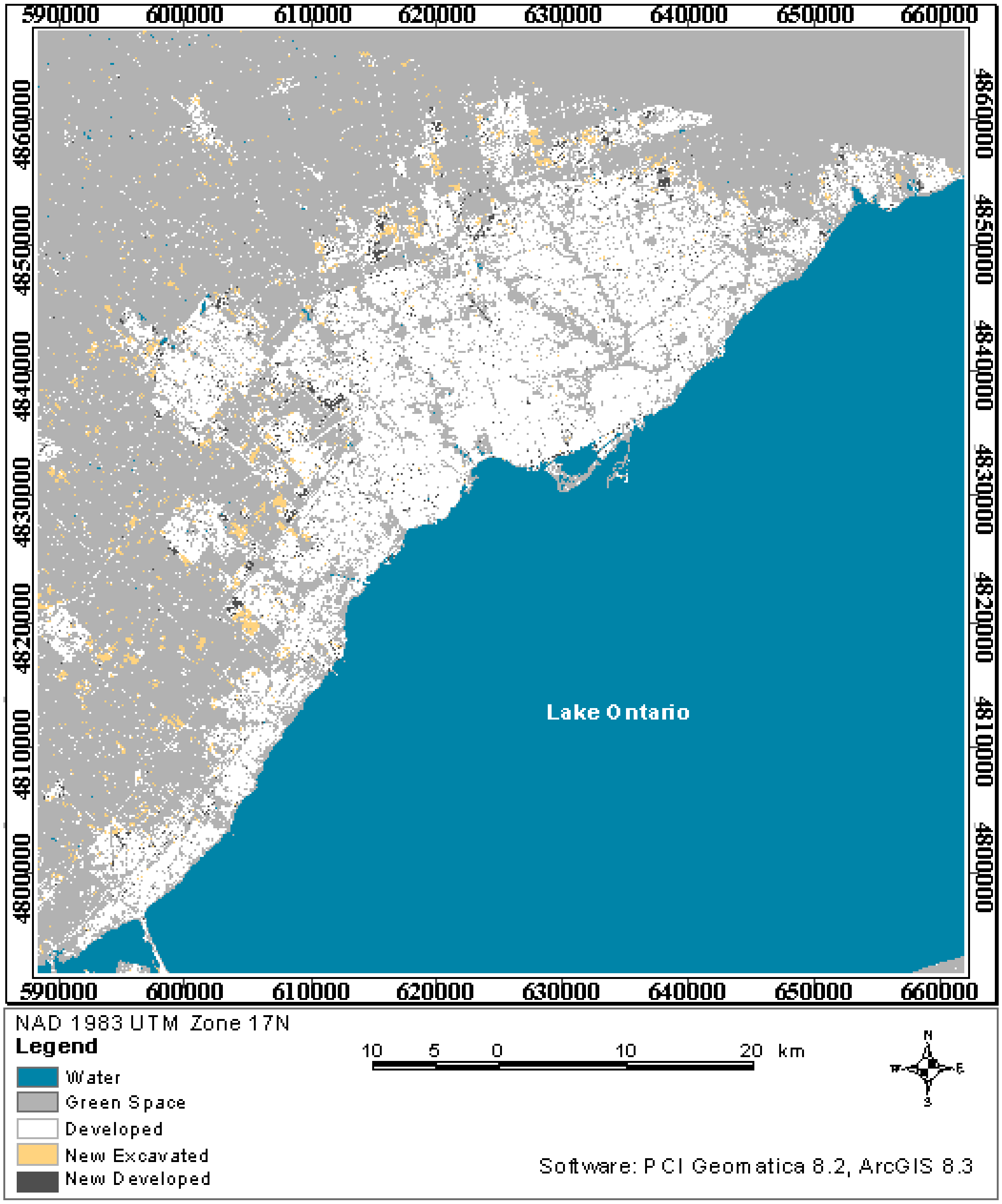



Figure 4.14 Detected urban change map from 1985 to 1987

Table 4.25 shows the area statistics. Classes and annual growth calculation from 1985 to 1987 are the same as the previous urban change maps from 1972 to 1974. The urban change is fully detected because the length of interval is shorter than 3 years.

Table 4.25 Area statistics for urban change (1985-1987)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2522.220631 |
| Greenspace | 1934.213362 |
| Developed | 905.8910535 |
| New Excavated | 54.6952905 |
| New Developed | 26.9975655 |
| Annual Growth | 13.49878275 |

<u>**1987-1990**</u>

Urban change from 1987 to 1990 (Figure 4.15) is produced from the subtraction of band 2 between these two dates, then masked by the 1990 urban extent map. Both 1987 and 1990 imagery have no data in the NE corner, thus urban change that occurred in the NE corner between the two dates is not detected.

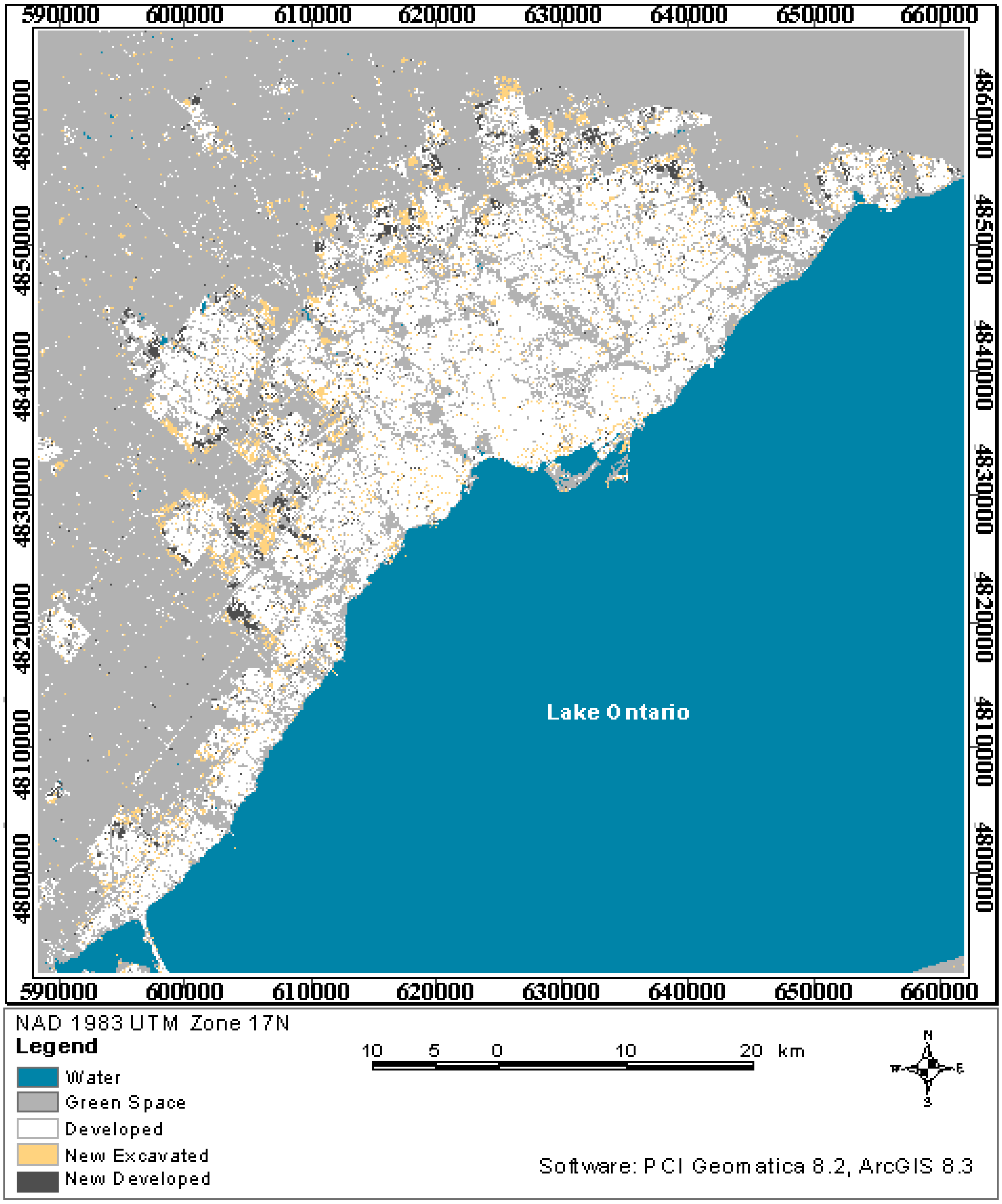



Figure 4.15 Detected urban change map from 1987 to 1990

Table 4.26 shows the area statistics. Classes and annual growth calculations are the same as the previous urban change maps. The detected new excavated from 1987 to 1990 is overestimated and some unchanged urban areas are also included. For this reason the developed urban area 888.9 $km^2$ is smaller than 905.9 $km^2$ from the previous date. However, the new developed is appropriately detected. The urban change is fully detected because the length of interval is 3 years.

Table 4.26 Area statistics for urban change (1987-1990)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2515.455401 |
| Greenspace | 1882.823929 |
| Developed | 888.8890365 |
| New Excavated | 105.8865345 |
| New Developed | 50.96300175 |
| Annual Growth | 16.98766725 |

**1990-1994**

Urban change from 1990 to 1994 (Figure 4.16) is produced from the subtraction of band 2 between these two dates, then masked by the 1994 urban extent map. Both 1990 and 1994 imagery have no data in the NE corner, thus urban change that occurred in the NE corner between the two dates is not detected.

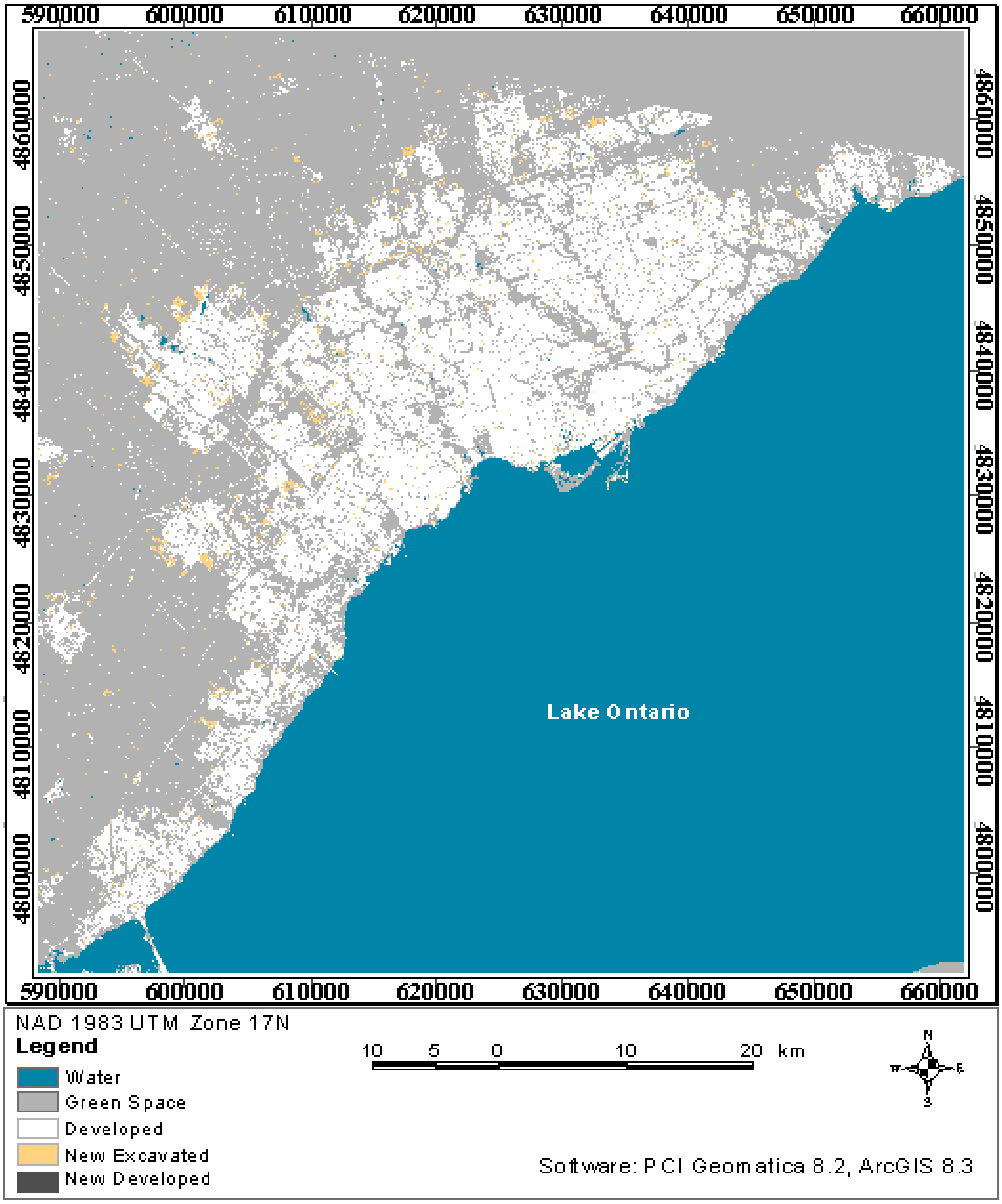



Figure 4.16 Detected urban change map from 1990 to 1994

Table 4.27 shows the area statistics. Classes and annual growth calculations are the same as the previous urban change maps. New developed area and derived annual growth are probably underestimated because the interval (4 years) is longer than 3 years.

Table 4.27 Area statistics for urban change (1990-1994)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2523.603893 |
| Greenspace | 1853.25478 |
| Developed | 970.4105078 |
| New Excavated | 38.786562 |
| New Developed | 57.96216* |
| Annual Growth | 14.49054 |

**1994-1999**

Urban change from 1994 to 1999 (Figure 4.17) is produced from the subtraction of band 2 between these two dates, then masked by the 1999 urban extent map. Both 1994 and 1999 imagery have no data in the NE corner, thus urban change that occurred in the NE corner between the two dates is not detected.

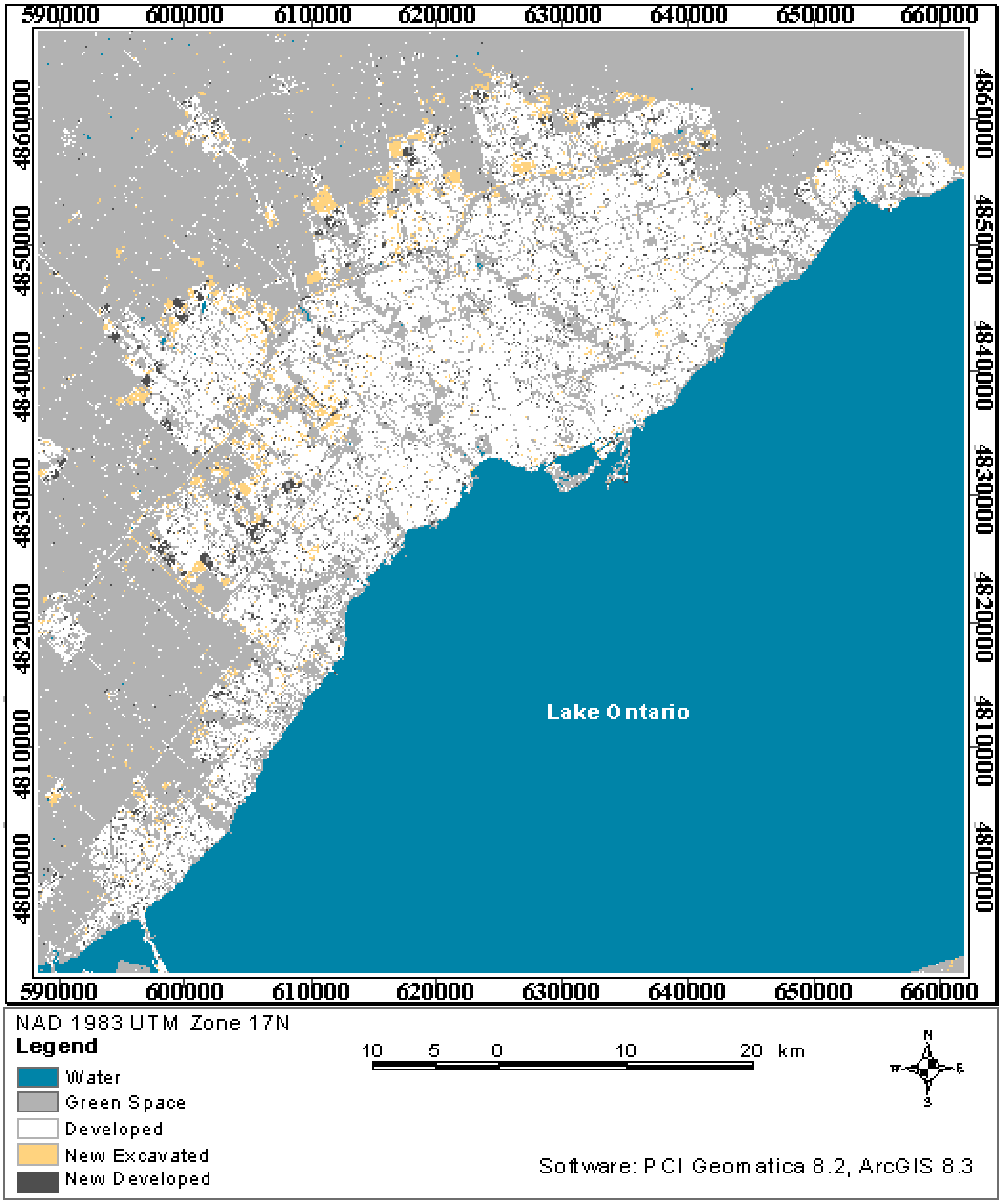



Figure 4.17 Detected urban change map from 1994 to 1999

Table 4.28 shows the area statistics. Classes and annual growth calculations are the same as the previous urban change maps. New developed area and derived annual growth are underestimated because the interval (5 years) is longer than 3 years.

Table 4.28 Area statistics for urban change (1994-1999)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2516.735507 |
| Greenspace | 1766.300981 |
| Developed | 1029.459458 |
| New Excavated | 71.04019725 |
| New Developed | 60.4817595* |
| Annual Growth | 12.0963519 |

**1999-2001**

Urban change from 1999 to 2001 (Figure 4.18) is produced from the subtraction of band 2 between these two dates, then masked by the 2001 urban extent map. Both 1999 and 2001 imagery have no data in the NE corner, thus urban change that occurred in the NE corner between the two dates is not detected.

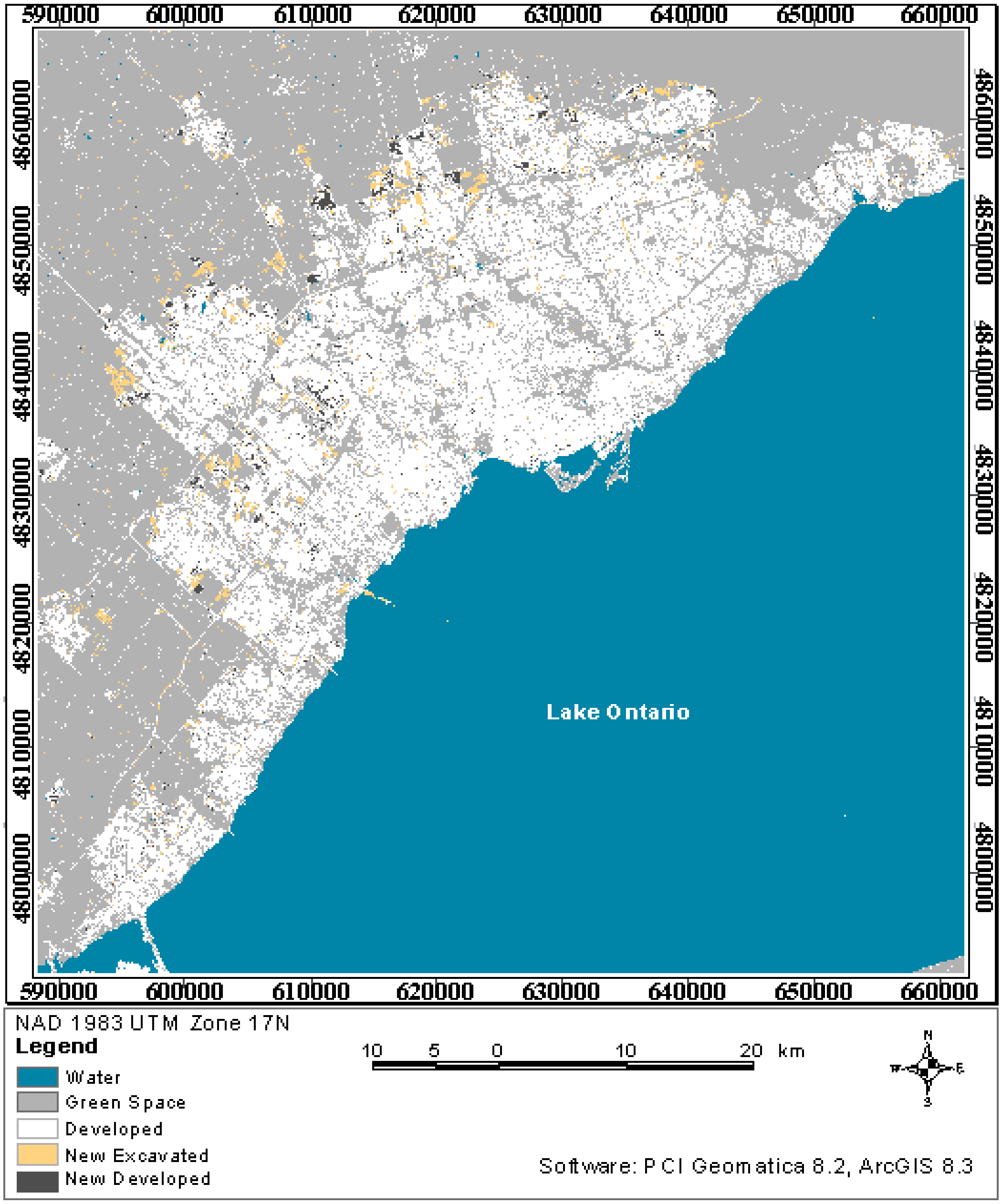



Figure 4.18 Detected urban change map from 1999 to 2001

Table 4.29 shows the area statistics. Classes and annual growth calculations are the same as the previous urban change maps. The urban change is fully detected because the length of interval is shorter than 3 years.

Table 4.29 Area statistics for urban change (1999-2001)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2516.103576 |
| Greenspace | 1749.471161 |
| Developed | 1109.538374 |
| New Excavated | 45.76135275 |
| New Developed | 23.14343925 |
| Annual Growth | 11.57171963 |

**2001-2004**

Urban change from 2001 to 2004 (Figure 4.19) is produced from the subtraction of band 2 between these two dates, then masked by the 2004 urban extent map. The 2001 image has no data in the NE corner, thus urban change that occurred in the NE corner between the two dates is not detected.

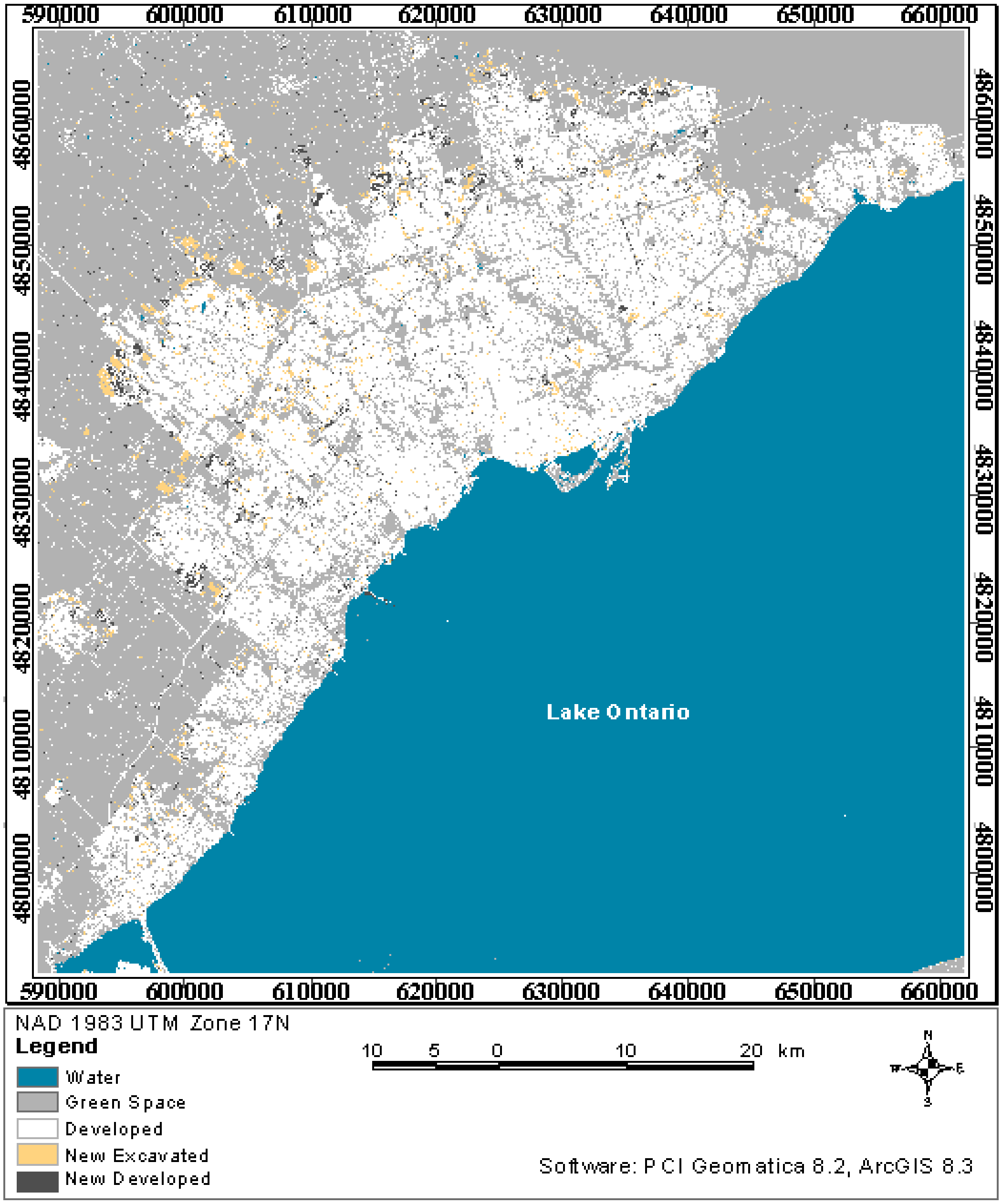



Figure 4.19 Detected urban change map from 2001 to 2004

Table 4.30 shows the area statistics. Classes and annual growth calculation in urban change map from 2001 to 2004 are the same as the previous urban change map from 1972 to 1974. The urban change is fully detected because the length of interval is 3 years.

Table 4.30 Area statistics for urban change (2001- 2004)

| Class Names | Area ($km^2$) |
|---|---|
| Water | 2512.618265 |
| Greenspace | 1622.650843 |
| Developed | 1225.019635 |
| New Excavated | 47.79064424 |
| New Developed | 35.938514 |
| Annual Growth | 11.97950467 |

## 4.2 Discussion

### 4.2.1 Growth

In order to analyse the total urban change from 1972 to 2004, two satellite derived urban extent maps from 1972 and 2004 are selected. The imagery of these two dates has a full coverage with the study area, thus the urban feature in the maps is fully captured without any no data areas. Figure 4.20 is the map representing the total urban change over the GTA from 1972 to 2004. Urban extent in 1972 is represented in black colour. The total urban growth from 1972 to 2004 is represented in white.

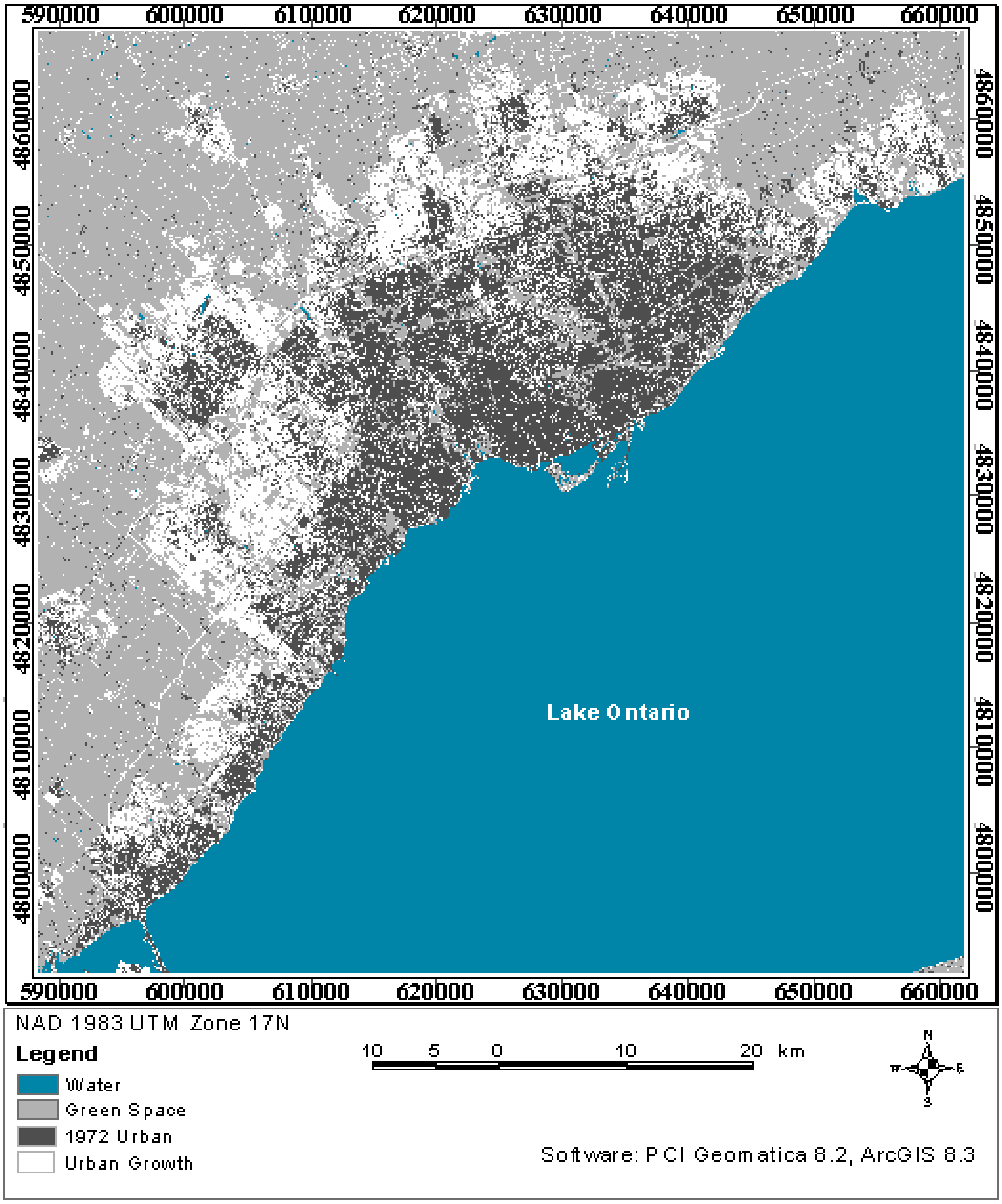



Figure 4.20 Total urban change from 1972 to 2004 over the GTA

By visual comparison, it is clear that the urban area has expanded along with its edge in three directions – west, northwest, and northeast while it was limited by Lake Ontario on the south side. The amount of urban growth over the GTA from 1972 to 2004 is remarkable. The urban area over the GTA in the study area in 1972 was 663.1 $km^2$ (Table 4.1) whereas it was 1327.6 $km^2$ by 2004 (Table 4.19). The total urban growth between these two dates is 664.5 $km^2$, which is nearly the urban area in 1972. Annual urban growth between these two dates is 20.8 $km^2$ (i.e., 664.5/32).

However, the urban growth has not evenly occurred over this 32-year period of time. It is necessary to check the difference between different historical times. Besides, urban extent in urban extent maps includes three different components – developed area, new excavated area, and new developed area. Developed area is the unchanged part between two compared dates.

New excavated area is converted from green space, but not built-up yet. Therefore, the new developed area converted from the excavated area to the built-up area is of more concern. Table 4.31 summarizes information from Table 4.22 to Table 4.30 for comparison purposes. The annual growth is produced from the new developed area by dividing with the length of an interval. In order to make the result more straightforward, a bar graph was also produced (Figure 4.21).

Table 4.31 Annual growth statistics for all available dates

| Intervals | Developed ($km^2$) | New Developed ($km^2$) | New Excavated ($km^2$) | Annual Growth ($km^2$) |
|---|---|---|---|---|
| 1972-1974 | 603.0323 | 35.6464035 | 87.00415875 | 17.8 |
| 1974-1977 | 652.4024 | 48.16236375 | 51.483654 | 16.1 |
| 1977-1985 | 774.772 | 22.6601505 | 64.5560055 | 12.1 |
| 1985-1987 | 905.8911 | 26.9975655 | 54.6952905 | 13.5 |
| 1987-1990 | 888.889 | 50.96300175 | 105.8865345 | 16.9 |
| 1990-1994 | 970.4105 | 57.96216 | 38.786562 | 14.5 |
| 1994-1999 | 1029.459 | 60.4817595 | 71.04019725 | 12.1 |
| 1999-2001 | 1109.538 | 23.14343925 | 45.76135275 | 11.6 |
| 2001-2004 | 1225.02 | 35.938514 | 47.79064424 | 11.9 |

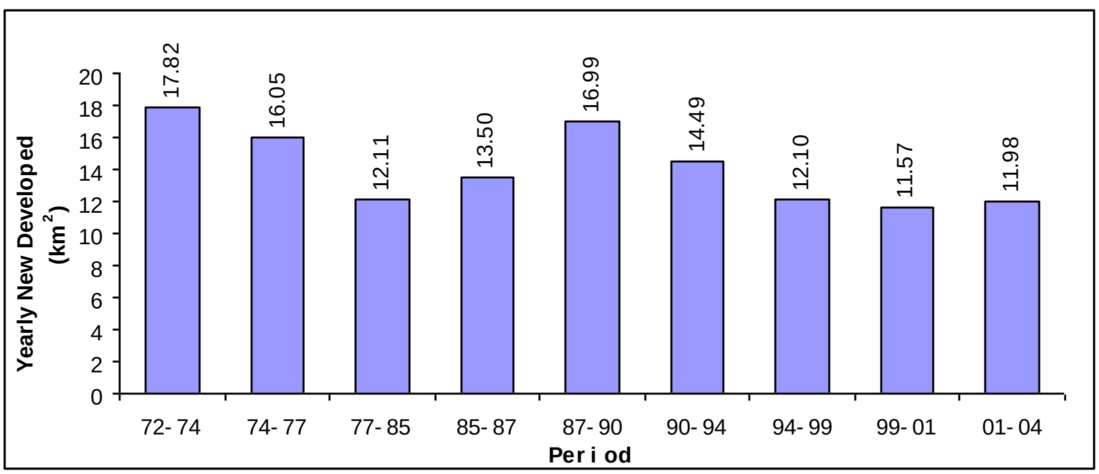



Figure 4.21 Yearly new developed change over different historical periods

The results from Table 4.31 and Figure 4.21 show the growth rates throughout the different historical periods from 1972 to 2004. The first peak of urban growth occurred between 1972 and 1977, in which annual growth rate is 17.82 $km^2$ between 1972 and

1974, 16.05 km$^2$ between 1974 and 1977. The second peak of new urban development occurred in the end of 1980's, i.e., between 1987 and 1990, in which yearly urban growth is 16.9 km$^2$. From 1977 to 1985, the speed of new urban development slowed down, in which the yearly new developed amount went from 16.05 km$^2$ in 1977 to 12.11 km$^2$ in 1985. The second slow period for new urban development occurred from 1990 to 1994 (16.99 km$^2$ in 1990 to 12.10 km$^2$ in 1994). After 1994, i.e. during the last 10 years, the pace of new urban development was the lowest among compared dates. The yearly growth was 12.1 km$^2$ between 1994 and 1999, 11.6 km$^2$ between 1999 and 2001, and 11.9 km$^2$ between 2001 and 2004. The slow period in new urban development between 1990 and 1994 can in part be explained by the impact of a economic recession that occurred in this period of time. The reason slow growth between 1977 and 1985 is not clear because of the longer time period (8 years).

The overall yearly new development was 14.1 km$^2$. The new developed growth rate from 1999 to 2004 – 11.6 km2 and 11.9 km$^2$ are very close to the result captured by Forsythe (2004) with pansharpening enhancement from 1999 to 2002 – 10.6 km$^2$ however the study areas do not have the same coverage.

### 4.2.2 Places of Growth

Urban growth over the GTA is uneven. If it is divided into municipalities, the distribution of the urban growth becomes clear. Figure 4.22 shows the same area as Figure 4.20, but adds the municipal boundaries. By raster manipulation in ArcGIS, the amount of growth from 1972 to 2004 is calculated for each municipality. Table 4.32 shows the uneven contribution of municipalities to urban growth in the study area. In Table 4.32, ten municipalities related to the majority of contiguous urban areas are selected. They are Toronto, Burlington, Oakville, Mississauga, Brampton, Vaughan, Richmond Hill, Markham, Pickering, and Ajax. Urban areas for Milton, Halton Hills, Caledon, and King in study area are not calculated.

The difference of municipal urban extents between 1972 and 2004, is strongly illustrated in Figure 4.22. There is an uneven distribution of urban changes in the study area.

Mississauga was the largest contributor to the urban change between 1972 and 2004, accounting for 21.29% of total urban change although its municipal area is only about half of the City of Toronto. Toronto accounted for 16.07% of total urban change. Notice that the Toronto is the largest municipality among all municipalities with the contiguous urban area. The next largest contributors were Brampton (accounting for 14.91%), Vaughan (13.62%), and Markham (10.02%). Ajax and Pickering accounted for the smallest proportion of total urban change in the study area, at 3.37% and 3.93% respectively although this may have been influenced by the missing data in the NE corner of the study area.

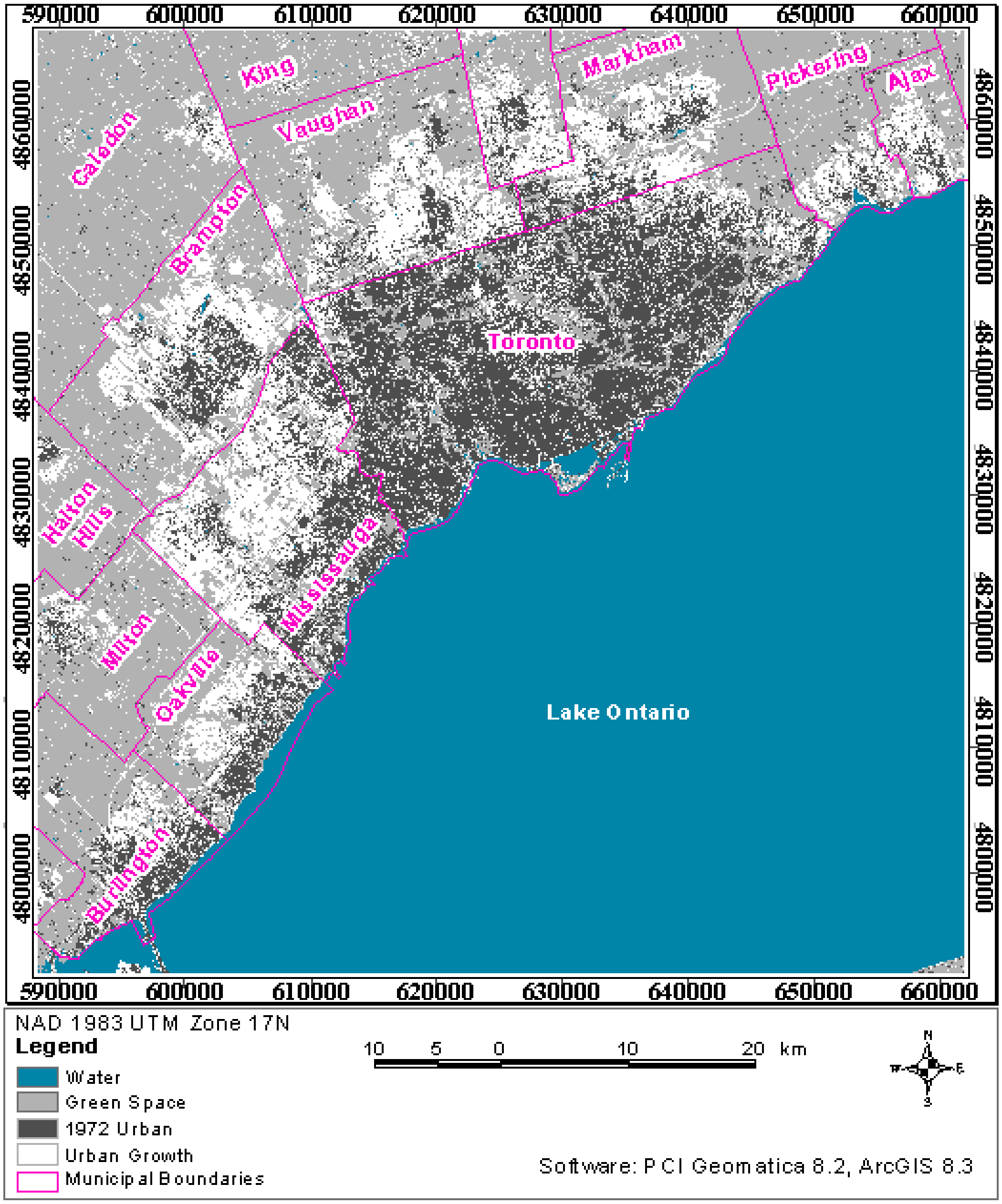



Figure 4.22 Urban growth in different municipal areas

Table 4.32 Urban change in municipalities over the GTA from 1972 to 2004

| **Municipalities** | **Municipal Area ($km^2$)** | **1972** | | **2004** | | **Urban Growth ($km^2$)** | **Percentage of Total Change (%)** | **Annual Growth ($km^2$)** |
|---|---|---|---|---|---|---|---|---|
| | | **Urban** | **Urbanized %** | **Urban** | **Urbanized %** | | | |
| Toronto | 647.40 | 382.50 | 59.08 | 479.58 | 74.08 | 97.08 | 16.07 | 3.0 |
| Mississauga | 291.60 | 86.60 | 29.70 | 215.17 | 73.79 | 128.56 | 21.29 | 4.0 |
| Brampton | 268.80 | 34.39 | 12.79 | 124.46 | 46.30 | 90.07 | 14.91 | 2.8 |
| Vaughan | 275.00 | 27.37 | 9.95 | 109.63 | 39.86 | 82.26 | 13.62 | 2.5 |
| Richmond Hill | 101.70 | 9.45 | 9.29 | 43.27 | 42.55 | 33.82 | 5.60 | 1.1 |
| Markham | 213.70 | 25.64 | 12.00 | 86.16 | 40.32 | 60.52 | 10.02 | 1.9 |
| Burlington | 191.70 | 34.28 | 17.88 | 63.07 | 32.90 | 28.79 | 4.77 | 0.9 |
| Oakville | 153.10 | 26.39 | 17.24 | 65.15 | 42.56 | 38.76 | 6.42 | 1.2 |
| Pickering | 234.50 | 9.22 | 3.93 | 32.95 | 14.05 | 23.73 | 3.93 | 0.7 |
| Ajax | 67.28 | 6.00 | 8.93 | 26.36 | 39.18 | 20.36 | 3.37 | 0.6 |
| Total | - | 641.85 | - | 1245.80 | - | 603.95 | 100.00 | - |

If municipalities are categorized into upper level regions, Peel region accounted for the highest proportion of total urban change (36.20%) even though Newmarket has not been included in this study. York is the second accounting for 29.24% of total urban change. Toronto only accounts for 16% of total urban change. Halton region is the least. Table 4.33 shows urban change distributions in different upper level regions. Urban change data in Table 4.33 did not include Milton, Halton Hills, Caledon, and King in the study area.

Table 4.33 Urban change distributions in upper level regions

| **Region** | **Urban Change ($km^2$)** | **Percentage of Total Change (%)** | **Annual Growth ($km^2$)** |
|---|---|---|---|
| Toronto | 97.08 | 16.07 | 3.0 |
| Peel | 218.63 | 36.20 | 6.8 |
| York | 176.6 | 29.24 | 5.5 |
| Halton | 67.55 | 11.18 | 2.1 |
| Durham | 44.09 | 7.30 | 1.4 |
| Total | 603.95 | 100.00 | - |

### 4.2.3 Spatial Patterns of Growth

Apart from the uneven pace of growth, the spatial pattern of urban development also shows an interesting evolution from 1972 to 2004. Figure 4.23 below shows the spatial evolution of urban growth from 1972 to 2004. It was created from the satellite derived urban extent maps for 1972 to 2004. The black colour in map represents the urban extent in 1972. Dark brown represents urban growth from 1972 to 1985. Pink represents urban growth from 1985 to 1994. Yellow represents urban growth from 1994 to 2004. The most active municipalities (Mississauga and Brampton) were selected to show the course of urban development.

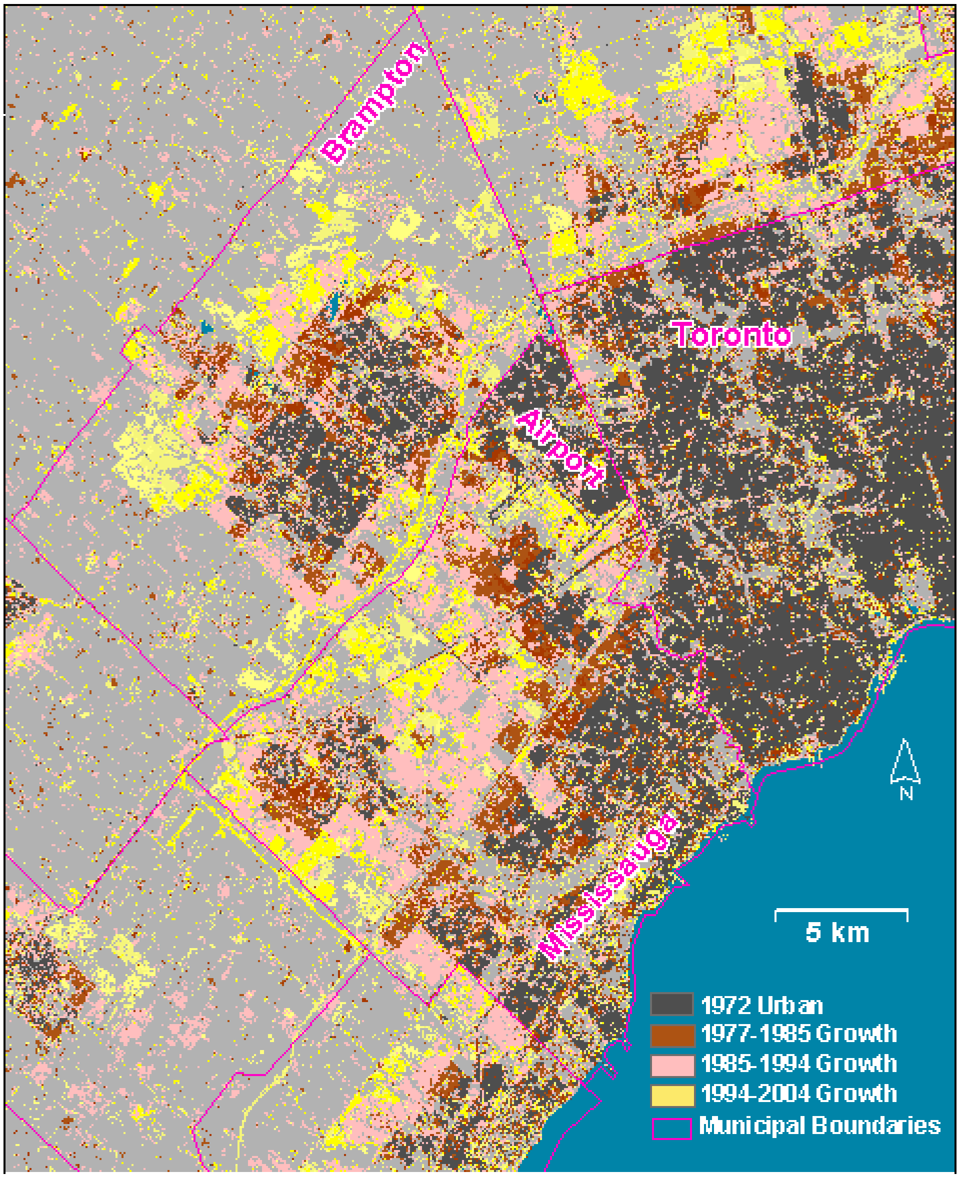



Figure 4.23 Spatial pattern evolution of urban from 1972 to 2004

In 1972, Mississauga consisted of areas in the old Mississauga town along with the lakeshore, Streetville in the west corner, and area to the southwest of Lester B. Pearson International Airport. Prior to the 1985, the urban area mainly expanded outward. This type of development can also be seen in Brampton. It developed along with its four urban edges, particularly to the northwest and northeast. The urban edge adjacent to the airport and Mississauga was more stable. From 1985 to 1994, urban expansion mainly tended to backfill the non-developed area between developed urban areas. After 1994, urban expansion tended to the outward type of expansion again – urban sprawl along the urban edge. This tendency occurred not only in Mississauga, but also in Brampton. The outward expansion in Brampton in the last 10 years is more remarkable than that in Mississauga. The types of urban expansion indicate two directions – outward sprawl and backfilling. More interesting is that two urban expansions seemed to occur in different periods of times. The middle period from 1985 to 1994 with much backfill has a higher rate of new urban development. The periods before 1985 and after 1994 (with tendency of outward urban expansion) coincide with periods with lower rates of new urban development. If this is not by chance, it can be concluded that when urban areas tend to outward sprawl, the real new urban development – from excavated area to built-up area is slowed down. In other words, the higher rates of new urban development usually coincided with large amounts of backfilling. However, this conclusion cannot be validated. A truly spatial pattern of urban growth requires further study.

### 4.2.4 Urban Growth and Population

To explore the associated drivers for urban growth, population data were selected because population is a very active factor in urban development. Population data in census years close to the available Landsat data acquisition dates were obtained from Statistics Canada. Census population is showed in Table 4.33. Seven years of population data were analyzed from 1971 to 2001 (Statistic Canada, 2001) and the 2004 GTA population was estimated based on the 2003 GTA population (Statistics Canada, 2001 and Ontario Ministry of Finance, 2004). The percentage of population change between two adjacent census dates was calculated by subtracting population in adjacent census dates divided by the population of earlier census date.

Table 4.34 Population change from 1971 to 2004 over the GTA

| **Year** | **Population** | **Intervals between Two Dates** | Population Change (%) |
|---|---|---|---|
| 1971 | 2,900,000 | | |
| 1976 | 3,217,401 | 1971 - 1976 | 10.94 |
| 1981 | 3,417,701 | 1976 – 1981 | 6.23 |
| 1986 | 3,733,085 | 1981 – 1986 | 9.23 |
| 1991 | 4,235,755 | 1986 – 1991 | 13.47 |
| 1996 | 4,628,883 | 1991 – 1996 | 9.28 |
| 2001 | 5,081,826 | 1996 – 2001 | 9.79 |
| 2004 | 5,547,068* | 2001- 2004 | 9.16 |

The census dates do not completely coincide with the Landsat imagery dates. In order to associate urban change with census population change, the amount yearly new development was selected to correspond with the nearest percentage of population change. During the census interval from 1971 to 1976, the closest urban changes are change from 1972 to 1974 and change from 1974 to 1977. The yearly new developed (annual growth) is calculated from total amount of new developed from these two intervals divided by the period from 1972 to 1977. From 1976 to 1986, the urban change interval from 1977 to 1985 is closest to the census dates. Yearly new development from 1977 to 1985 was associated with both the census interval from 1976 to 1981 and the census interval from 1981 to 1986. The association between population change and yearly new developed is shown in Table 4.35.

Table 4.35 Population changes vs. yearly new developed

| Population Interval | Yearly Population Change | Urban Change Interval | Yearly New Developed (km$^2$) |
|---|---|---|---|
| 1971 – 1976 | 10.94 | 1972 – 1977 | 16.76 |
| 1976 - 1981 | 6.23 | 1977 - 1985 | 12.11 |
| 1981 – 1986 | 9.23 | 1977 – 1985 | 12.11 |
| 1986 – 1991 | 13.47 | 1985 – 1990 | 15.59 |
| 1991 – 1996 | 9.28 | 1990 – 1994 | 14.49 |
| 1996 – 2001 | 9.79 | 1994 – 2001 | 11.95 |
| 2001- 2004 | 9.16 | 2001 - 2004 | 11.98 |

A bar graph based on Table 4.35 was also created (Figure 4.24), in which the blue bar represents the yearly new developed and the brown bar the percentage of population change over different historical times.

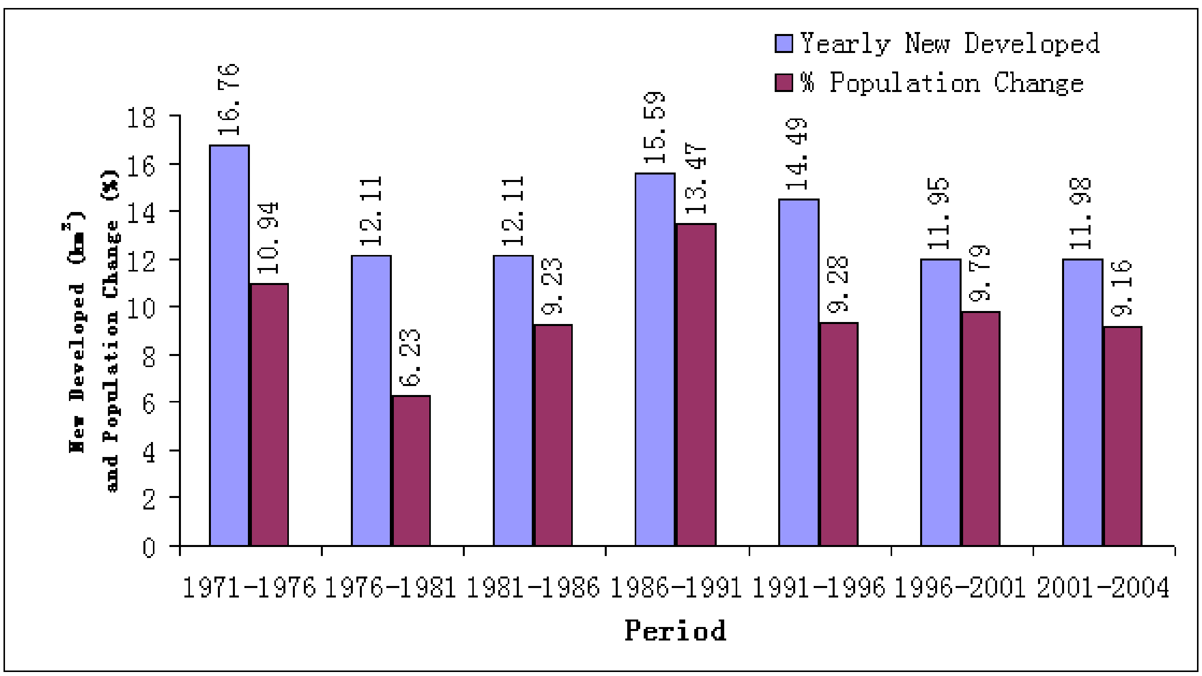



Figure 4.24 Urban change growth rate and the population change

The bar graph in Figure 4.24 shows the yearly new developed in different census intervals corresponds with the percentage of population change very well. The highest peak in population growth in the GTA occurred in the census interval from 1986 to 1991 with a growth rate of 13.47%. A secondary peak occurred in census interval from 1971 to 1976. These two population growth peaks are consistent with the peaks of yearly new development that occurred in interval from 1971 to 1976 and interval from 1986 to 1991. The slowest population growth in the GTA occurred in census interval from 1976 to 1981 with a rate of 6.23%, which is coincident with the low new development rate that occurred during this interval. Since 1991, the population change is consistent with the low rates of yearly new development over this time period. This indicates that population is an important driver for new urban development.

# CHAPTER 5: CONCLUSION

## 5.1 Findings

The results of this research can be categorized as follows:

1) The GTA experienced a series of new urban development periods with varied growth rates. Two peak new development periods occurred between 1972 and 1977 and between 1987 and 1990. Two periods with lower new urban development rates occurred from 1977 to 1985 and from 1990 to 1994. Over the last 10 years, a relatively low and stable rate in new urban development has occurred.
2) Peak yearly new urban development periods seemed to be synchronized with the time of urban development backfill whereas the slower growth periods seem synchronized with times of outward urban expansion and sprawl. The period of outward new urban development and expansion appeared to be the period of urban sprawl
3) Urban development demonstrated a distinctly uneven spatial distribution in the study area. Peel and York regions account for most of the urban growth in the study area (65.44%), in which Mississauga, Brampton, and Vaughan are the most active and fastest growing areas.
4) Changes in population over different historical periods are associated with the speed of new urban development quite well. This indicates that population is an important driving force in urban development.

## 5.2 Limitations

The images did not cover the full GTA area and were not completely consistent in coverage for the northeast corner of the study area. Another shortcoming was the absence of data for around 1980 or 1981. The second limitation was time. It would be possible to explore more involved methods for urban change detection if time were available. Two parts of this research are left to improve in possible further study. The first is to quantify different lengths of interval associated with urban development rotations and find ways to fully capture the urban change. The second is to quantify the spatial evolution patterns in two urban development ways – sprawl and backfill.

## 5.3 Recommendations

The study area should be extended to the entire GTA. Another direction is to further differentiate land use inside urban areas (i.e. residential, commercial, and industrial areas), which can be a great value for both government and private sectors. The third is to continue to explore Landsat data. Its potential is far from being fully utilized, particularly when combined with other higher resolution data.

## 5.4 Summary

Urban change detection by using a variety of remote sensing techniques allows for the identification of urban features and the capturing of urban changes over time. In combination with GIS, the total urban area and its change can be easily assessed. The accuracy of derived the urban map results is very good. The overall accuracy for all years of classification was above 97% with the exception of 1972, which was 95%. The producer and user's accuracies for all TM data were above 91% and 93%, respectively, for the urban class. By using enhancements, the producer and user's accuracies for MSS data were greatly improved, and above 81% and 85% respectively for urban areas.

As an efficient technique in terms of time and cost, change detection is valuable for urban planners or other users to track the urban development. However, no single technique is the best. Further exploration to fully utilize the potential of Landsat imagery is necessary. The customization of techniques should be based on different study purposes, data conditions, and other situations that arise.

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## Appendix

### Results of urban change detection in original image formats

1972 maskmap.pix/img

1974 maskmap.pix/img

1977 maskmap.pix/img

1985 maskmap.pix/img

1987 maskmap.pix/img

1990 maskmap.pix/img

1994 maskmap.pix/img

1999 maskmap.pix/img

2001 maskmap.pix/img

2004 maskmap.pix/img

72_74 urbanchange.pix/img

74_77 urbanchange.pix/img

77_85 urbanchange.pix/img

85_87 urbanchange.pix/img

87_90 urbanchange.pix/img

90_94 urbanchange.pix/img

94_99 urbanchange.pix/img

99_01 urbanchange.pix/img

01_04 urbanchange.pix/img

**Database in PIXDSK format in data processing**

1972MSS.pix

1974MSS.pix

1977MSS.pix

1985TM.pix

1987TM.pix

1990TM.pix

1994TM.pix

1999TM.pix

2001TM.pix

2004TM.pix

**Original imagery**

Paul.pix