Urban Development Detection within the Upper Thames River Conservation Authority for the Period 1991 – 1999 using Landsat TM and ETM+ data

by

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Author's Declaration

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

I authorize Ryerson University to lend this Research Paper to other institutions or individuals for purposes of scholarly research.

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Abstract

The use of remotely sensed satellite image data for the generation of information concerning large areas is relatively inexpensive when compared to other methods. Urban development within the Upper Thames River Conservation Authority was determined using an image differencing approach for the period 1991 to 1999.

Six urban regions within the UTRCA were examined, ranging in population from over 400000 to less than 4000. Band 2 differencing was found to be the most adept technique for determining development, in combination with a three class *Minimum distance* supervised classification of the region. Accuracies of initial remotely sensed classification were improved following orthophoto post classification editing, producing an overall accuracy of 90% with *user's* and *producer's* accuracies ranging between 84% - 98%. Results show the UTRCA experienced 17.36km^2 of urban development over the study period. Smaller urban regions had the highest percentage rates of development, while slightly lower growth levels were found in two 'middle' sized cities.

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List of Acronyms

BLQ	Beachville Lime and Quarry
BV	Brightness Value
CA	Census Agglomeration
CCRS	Canadian Centre for Remote Sensing
CMA	Census Metropolitan Area
CSD	Census Sub Division
DDV	Dense Dark Vegetation Approach
DOS	Dark Object Subtraction
ESRI	Environmental Systems Research Institute
ETM+	Enhanced Thematic Mapper Plus
GCP	Ground Control Point
GIS	Geographic Information Systems
GPS	Global Positioning System
Isodata	Iterative Self-Organizing Data Analysis
MSS	Multi-Spectral Scanner
NDVI	Normalized Difference Vegetation Index
OCA	Ontario Conservation Authority/Authorities
PARA	Path Radiance Approach
PC	Principal Component
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
RS	Remote Sensing
SLC	Scan Line Corrector
SPOT	Systeme Pour l'observation de la Terre
TM	Thematic Mapper
USFWS	United States Fish and Wildlife Services
USGS	United States Geological Survey
UTRCA	Upper Thames River Conservation Authority

Chapter 1: Introduction

The Upper Thames River Conservation Authority (UTRCA) is situated in southwestern Ontario, and includes 28 sub-watersheds associated with the Thames River with a total area of 3447 km^2 (Figure 1.1). The mandate of the authority is to protect the watershed's rivers, streams, and lakes while conserving the region's natural habitats through various programs (UTRCA, 2003). Threats to the region's environment include urban encroachment, deforestation, and pollution causing loss of water and natural resource quality (UTRCA Report Cards, 2001).

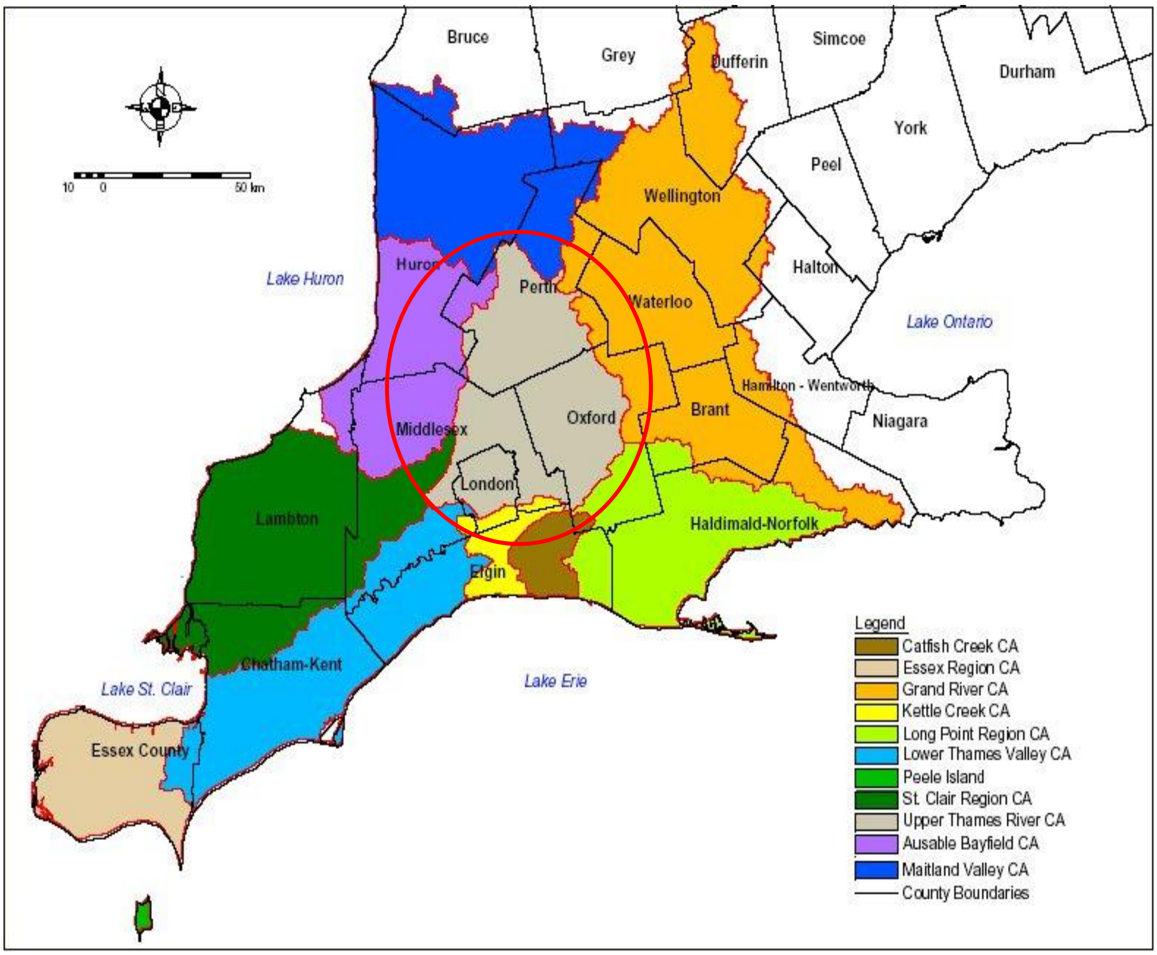


Figure 1.1: Southwestern Ontario Conservation Authorities and County Boundaries
(Source: modified from UTRCA, 2003)

Satellite Remote Sensing (RS) provides tools for researchers that allow for the determination of land use and land use change in large areas (Lillesand and Kiefer, 2000). The conservation authority has little knowledge of how land use has changed over time and is interested in determining where urban development has occurred.

1.1 Study Area

Southwestern Ontario is a triangular area bordered by Lake Erie to the south and Lake Huron and Georgian Bay to the north, with the UTRCA directly in the middle of the region. London Ontario (pop. 432451) is the largest urban centre in the conservation authority, and ranks as the tenth largest urban area in Canada. Other main UTRCA urban centres are: Woodstock (pop. 33061), Stratford (pop. 29676), Ingersoll (pop. 10977), St. Marys (pop. 6293) and Mitchell (pop. 4022) – population data are from 2001 (Statistics Canada, 2003) (Figure 1.2).

Ontario conservation authorities (OCA) were set up in 1946 under the *Conservation Authorities Act* based on fears of environmental deterioration and provision of employment opportunities for soldiers returning from WWII (Shrubsole, 1996; Ivey et al., 2002). There are currently 38 OCA in the province, most of whose boundaries are based on watersheds – the UTRCA boundary is based on the northern portion of the Thames River watershed. The region is predominantly rural in nature, with 66% of land cover considered agriculture with an estimated 5500 farming operations (UTRCA, 2003).

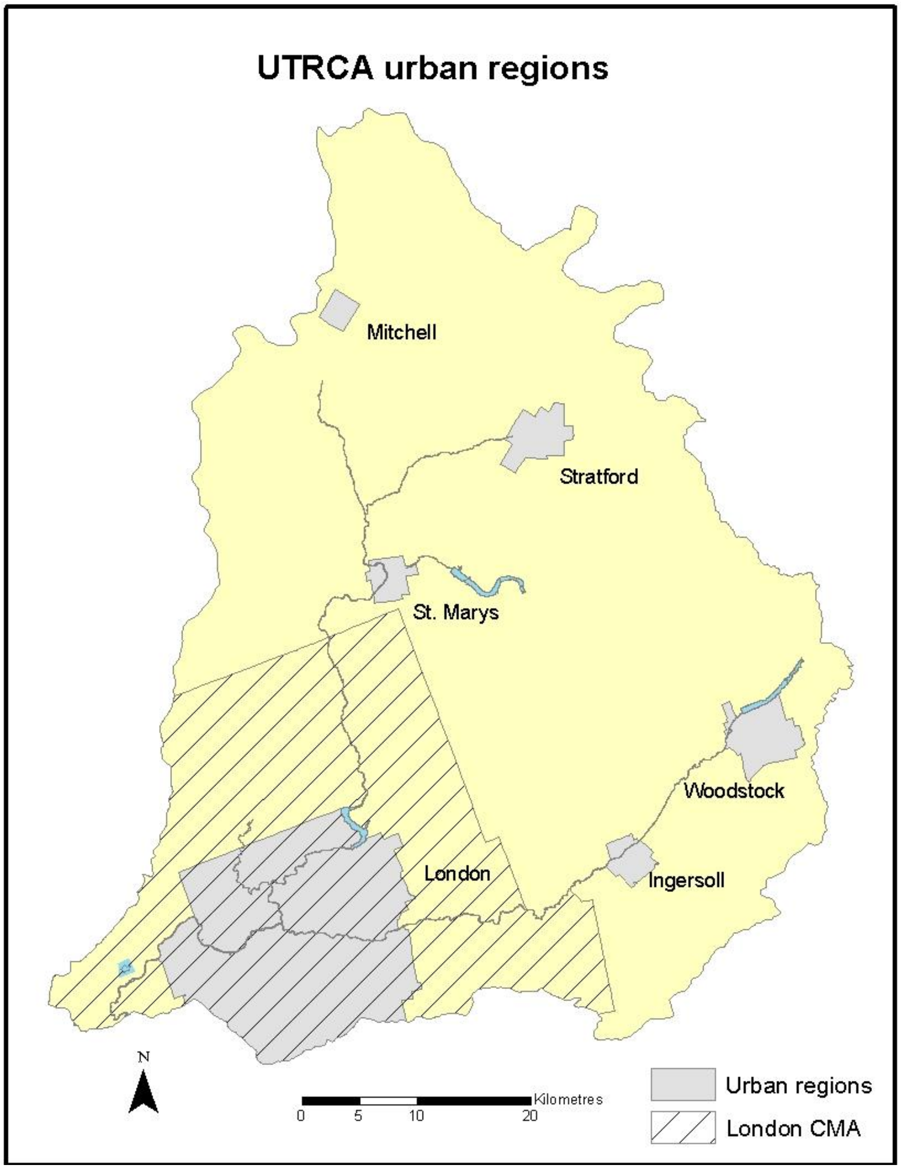


Figure 1.2: UTRCA urban regions

1.1.1 Water Monitoring

The UTRCA and other OCA were initially concerned with surface water and natural resource management, with an emphasis on flood management and reforestation (Shrubsole, 1996; Ivey et al., 2002). Efforts in flood control are still a major focus of OCA efforts; flood and erosion control was listed as one of four major initiatives that OCA should undertake by a 1987 Ontario Ministry of Natural Resources (OME) committee (OME, 1987 as found in Shurbsole, 1996). Land use and land use change information are required to ensure development is not occurring in regions which may be prone to flooding, thereby placing lives and resources at risk.

Recently efforts have shifted from solely surface water management to groundwater management (Ivey et al., 2002) especially in light of the 2000 Walkerton, Ontario disaster where seven people died as a result of consumption of E. Coli contaminated water (OME, 2003). E. Coli is one of many organisms that can be found in fresh water that can threaten human health. Others include: Vibrio cholera, Shigella, Campylobacter jejuni, Salmonella, Yersinia enterocolitica, Giardia lamblia, Cryptosporidium parvum, Entamoeba histolytica, Toxoplasma gondii, Balantidium coli, Norwalk virus, Rotavirus, and Hepatitis A and E. (Davies and Mazumder, 2003). The potential for these compounds to be found in drinking water requires OCA to monitor and manage the quality of water within their regions through maintaining up-to-date information on water quality, planning for water protection, and remediation of water use (Ivey et al., 2002).

Land use and land use change information are very important in terms of water management, as different types of land use processes can contaminate both surface water and groundwater. Davies and Mazumder (2003) state that the impacts of industrialization, agriculture, and urbanization are closely linked to drinking water supplies. Major agricultural contributors to the deterioration of water quality include the use of fertilizers and pesticides as well as waste produced from livestock farming (Maticic, 1999).

Sources of urban pollutants that may affect water quality are innumerable, ranging from waste caused by transportation to everyday litter.

1.1.2 Natural resources other than water

As well as having a mandate to protect the region's water supply, the UTRCA is also charged with maintaining the health of its other natural resources. These include wooded areas, natural areas, and parks. The UTRCA has many projects underway intended to facilitate the conservation of these areas including tree planting services, management of bogs/wetlands, and the provision of natural areas for the public to enjoy (UTRCA, 2003). Determination of land use and land use change is important for the UTRCA in the above areas for reasons of resource allocation and determining if current and past efforts are successful.

1.1.3 Challenges to the UTRCA

Increasing demand for analysis undertaken by OCA has been met with decreases in funding from governments due to cutbacks. On average total revenues for the 38 OCA dropped 11% from 1993 to 1998, with some OCA reporting losses of almost 50%. UTRCA provincial funding, which was 31% of UTRCA revenues in 1992, fell 68% by 1998 (Ivey et al., 2002).

In order to maintain its mandate the UTRCA requires accurate information for decision-making processes, which includes land use information (Shrubsole, 1996). The UTRCA has little knowledge of satellite remote sensing and associated applications; to date there have been no studies conducted by the authority using these techniques. Analysis of satellite images, which are available free of charge through the Canadian Ministry of Natural Resources and similar organizations, can be used in conjunction with other information sources to provide geospatial data analysis at relatively low costs.

1.2 Landsat Satellite Program

Satellite imagery has been available for civilian land use classification and analysis since 1972 with the launch of Landsat 1. Since the launch of Landsat 1 there have been five subsequent Landsat satellites put into orbit (Table 1.1).

Table 1.1: Landsat Satellite History and Status

Satellite	Launched	Status
Landsat 1	July, 1972	decommissioned 1978
Landsat 2	January, 1975	decommissioned 1982
Landsat 3	March, 1978	decommissioned 1983
Landsat 4	July, 1982	standby mode
Landsat 5	March, 1984	still operational
Landsat 6	October, 1993	failed to achieve orbit
Landsat 7	April, 1999	still operational – experiencing Scan Line Corrector (SLC) problems since May 31, 2003

(Source: modified after Lauer et al., 1997)

The instruments on board have included the Return Beam Vidicon (RBV) on Landsats 1-3, the Multispectral Scanner (MSS) on Landsats 1-5, as well as an instrument introduced for the Landsat 4 and 5 missions called the Thematic Mapper (TM). An Enhanced Thematic Mapper (ETM+) was launched on the most recent Landsat 7 satellite. Landsat imagery is archived, meaning time-series data are available for analysis (Lauer et al., 1997). Landsat 7 data acquired since May 31, 2003 are not considered useable for analysis due to a malfunction with the Scan Line Corrector (SLC), which compensates image distortion caused by the forward motion of the satellite (USGS, 2003). This study is not affected by this malfunction, as Landsat 7 images are taken prior to the date of the SLC malfunction. It is however hoped that this problem can be corrected in the near future.

1.3 Data

One satellite image was acquired free of charge through the *Global Land Cover Facility* at the University of Maryland, and two were acquired free of charge from *Natural Resources Canada*, via the GeoGratis website (Table 1.2) (GLCF, 2003; GeoGratis, 2003).

Table 1.2: Acquired Landsat images

Satellite	Landsat 5 TM	Landsat 7 ETM+	Landsat 7 ETM+
Image date	11-Aug-91	3-Sep-99	30-Oct-00
Path/Row	Path 19, Row 030	Path 18, Row 030	Path 19, Row 030
Pixel Resolution	28.5m	30m	30m
Source	GLCF	GeoGratis	GeoGratis

The 1999 image was used as the latter image in this study, even though the 2000 image is more recent. The time of acquisition of the 2000 image meant spectral confusion between urban and agriculture features was felt potentially too great for an accurate classification. This is a result of fallow and tilled fields having similar spectral characteristics to urban features (Griffiths, 1988 as found in Masek et al., 2001). The 2000 image was acquired in late October, when most fields have been harvested and are being prepared for the winter season. The 1999 image was acquired in early September, when presumably more agricultural fields are ‘green’.

Other data used in the analysis include:

- A network of black and white aerial photographs of the UTRCA at 35cm resolution, taken April 18 – 21, 2000. While these are valuable to the authority, and were used in this research, obtaining these photos is expensive and therefore impractical for constant analysis purposes due to the large size of the conservation authority.

- UTRCA data consisting of ESRI shapefiles of geographic features (watershed boundaries, watercourses, road networks etc…).

1.4 Objectives

A combined radiometric band differencing and supervised classification method was used for change detection analysis with the 1991 and 1999 Landsat images. Specifically, urban encroachment on surrounding environments was examined. This affects the entire watershed, especially with the increasing size of the City of London (UTRCA Report Cards, 2001). Urban development has been detected using radiometric differencing in many studies (Ridd and Liu, 1998; Masek et al., 2000; Ji et al., 2001; Forsythe, 2002a). Through completion of this analysis, the UTRCA will further understand urban development within its region and potentially use this information to maintain water quality and natural resource conservation mandates.

Chapter 2: Literature Review

2.1 Remote sensing for land use classification and change detection

Data acquired by satellite sensors can be transformed into information by the user through image classification and change detection. Jensen (1996) states there are many parameters that must be considered to ensure the most accurate results possible. These include: determination of appropriate classification scheme, image correction, consideration of classification type, selection of bands to use in classification, error assessment, and final map production.

Urban development detection methods must include the above considerations as well as temporal and spatial resolution consistency issues. Examination of the above parameters helps in establishing which method of identifying change is most appropriate for the data and classification methods employed (Jensen, 1996).

2.2 Classification Scheme

There are several standard recognized classification systems, which can be altered to fit the needs of the analyst. The United States Geological Survey (USGS) land cover classification system for use with remotely sensed data focuses on nine major land cover types with as many as seven subheadings for each. A total of 38 different land cover types are represented (USGS, 1992). This differs from the US Fish and Wildlife Service

(USFWS) Wetland Classification System, which is focused on wetland and marine environments. This system contains 55 different classes based on five major aquatic systems and ten subsystems (Cowardin et al., 1979). A Canadian equivalent to the USFWS system is the Canadian Wetlands classification system developed by the National Wetlands Working Group. This system is based on classification of five major types of wetland: bog, fen, swamp, marsh and open shallow water with further division into wetland types (CCRS, 2003).

Very rarely do end classifications exactly resemble a standard classification system. Some can be relatively simple; Tole (2002) used a 3-category classification of 'water/cloud/shadow', 'forest' and 'land not forest' for an MSS forest classification and change detection study in Jamaica. These systems are used in order to reduce spectral variation and obtain a more accurate classification (Tuomisto et al., 1994). Other classification systems can be quite complex when the mapping of unique land cover types is wanted. Shaban and Dikshit (2001) using SPOT images of India had 19 classes with some as unique as 'water station' and 'cremation ground'. The chosen classification system will be a compromise between level of detail wanted and accuracy required.

2.3 Corrections to RS data

Remotely sensed data when initially acquired can be prone to error (Vogelmann et al., 2001). The correction process, be it geometric or radiometric, is designed to reduce or eliminate error in an image (Song et al., 2001; Vogelmann et al., 2001).

2.3.1 Geometric Correction

Geometric error in satellite data can result from a wide range of factors including sensor misalignment, spacecraft velocity, and the curvature of the earth. This results in geometric distortions in the data, meaning the image does not line up perfectly with the area of the earth with which it is concerned. Corrections for these errors are usually performed at ground processing stations and will not be discussed further (Jensen, 1996; Vogelmann et al., 2001).

2.3.2 Geometric Rectification

For purposes of change detection it is essential images are aligned perfectly (Yang and Lo, 2002). This requires a re-sampling of the image to a known source that is appropriately projected. Many change detection studies (Masek et al., 2000; Forsythe, 2002a; Prol-Ledesma et al., 2002) use a system of ground control points (GCP) for disk-to-disk registration in order to ensure images are aligned with each other. Transformation of one image to fit another image is accomplished via polynomial equations that are fit to the GCP data. The equations for a first order six-parameter transformation are:

$$x' = a_0 + a_1x + a_2y \qquad (1)$$

$$y' = b_0 + b_1y + b_2y \qquad (2)$$

where x and y are reference positions, x' and y' are positions on the original image and a_0, a_1, a_2, b_0, b_1 and b_2 are parameters representing features such as scale changes in x and y, image skew and satellite rotation (Novak, 1992). The more GCP used in analysis, the higher the polynomial that can be used for aligning the uncorrected image. Error, measured by Root Mean Square Error (RMSE) should be as low as possible (Ton and Jain, 1989);

$$RMSE = ((x' - x)^2 + (y' - y)^2)^{0.5} \qquad (3)$$

where x and y are original co-ordinates of the GCP image and x' and y' are calculated co-ordinates from the original image. However, it is not always possible to eliminate error due to image discrepancies. Masek et al. (2000) reported satisfactory errors of less than 0.6 pixels in examining urban change in Washington D.C. Seto et al. (2002) reported pixel errors of 0.3 in a Chinese land use study. A usual rule is to reduce errors in the vicinity of 0.5 pixels or less (Jensen, 1996).

2.3.3 Radiometric Correction

Radiometric error ('noise') can be a result of errors with the sensor itself (Teillet, 1986) or the composition of the atmosphere between the target and the sensor (Tso and Mather, 2001). These effects distort data to be analysed by the researcher.

Sensor error causing data 'striping' (total loss or distortion of data) is corrected through processes designed to calculate the value of an affected pixel through the examination of surrounding pixels. Crippen (1989) describes these techniques in greater detail.

Reducing 'noise' caused by atmospheric effects requires the atmospheric transmittance to be known:

$$\textit{Transmittance} = 1 - \begin{array}{c}\textit{Total \% radiation}\\ \textit{from the sun}\end{array} - \begin{array}{l}\textit{(\% radiation lost through Rayleigh}\\ \textit{scattering, Mie scattering, and}\\ \textit{atmospheric absorption)}\end{array} \qquad (4)$$

where *Rayleigh scattering* is caused by molecules with diameter smaller than the size of the band wavelength, *Mie scattering* is caused by molecules with diameter approximately the same size as the diameter of the wavelength and where *atmospheric absorption* is caused by larger molecules which absorb the sun's energy (Tso and Mather, 2001). Song et al., (2001) list several methods for atmospheric correction including Dark Object Subtraction (DOS), the Dense Dark Vegetation approach (DDV), the Path Radiance approach (PARA) and relative atmospheric correction.

Many studies, both involving individual classifications and land use change detection, have employed radiometric normalization in order to improve classification accuracy (Mas, 1999; Prol-Ledesma et al., 2002; Seto et al., 2002). However radiometric errors in images are often considered very small (Vogelmann et al., 2001) and some feel radiometric normalization is not necessary if images have been properly ground processed or their dates of acquisition are similar (Yang and Lo, 2002). Many studies therefore do not include radiometric normalization (Hill, 1999; Ji et al., 2001). Song et al. (2001) state that change detection studies using image differencing do not always require atmospheric correction. They suggest that if stable change classes (with zero means) are required by the researcher, atmospheric correction procedures should be applied.

2.4 Classification type

Two basic approaches for pixel classification are the unsupervised and supervised methods:

2.4.1 Unsupervised classification

This type of classification is employed when knowledge about the ground cover being examined is not known (Lillesand and Kiefer, 2000). The computer will classify each pixel into a pre-defined number of clusters with similar reflectance values. When the operation is complete it is then up to the analyst to determine which land cover is represented within each cluster.

2.4.2 Unsupervised classification algorithms

The *Chain method* performs clustering based on two examinations of RS data. The first analysis examines each pixel in a chain, starting at line 1 pixel 1 and ending at the bottom right corner of the image, and creates clusters based on dominant spectral statistics. The second examination selects all those pixels not categorized in the first pass and assigns pixels to a cluster based on the minimum distance method outlined in the previous section (Jensen, 1996). Bouvet et al., (2003) used a modified *Chain method* algorithm for analysis of benthic ecosystems in New Caledonia. While they found results that were satisfactory for visually discriminating different reef types, it was felt a supervised classification was needed to distinguish spectral characteristics for further analysis.

The Iterative Self-Organizing Data (Isodata) analysis technique algorithm examines data through many passes. It organizes data into a pre-defined number of clusters based on parameters set by the researcher. Aniello et al., (1995) used this method successfully for mapping of heat islands in Texas based on band 6 (thermal) Landsat TM data. Yang and Lo (2002) used an Isodata unsupervised classification algorithm for urban change detection in Chinese cities, and produced within class accuracies of 77% - 94% for six classes.

2.4.3 Supervised Classification

Supervised classification is a form of pixel classification based on some *a priori* knowledge of the land being classified (Lillesand and Kiefer, 2000). This knowledge can come from personal experience, existing maps, or aerial photographs. The classification procedure is based on the selection of training sites by the researcher. Training sites are evaluated visually and statistically to determine the amount of separability between classes. Examination of correlation matrices and scatter plots provides analysts with information detailing which classes are overlapping and which are unique, based on training site collection (Table 2.1, Figure 2.1)

Table 2.1: Correlation matrix; Charleston SC 1982 Landsat TM data

Correlation matrix for 'Residential'						
	Band 1	**Band 2**	**Band 3**	**Band 4**	**Band 5**	**Band 7**
1	1.00					
2	0.91	1.00				
3	0.92	0.91	1.00			
4	0.40	0.46	0.47	1.00		
5	0.47	0.56	0.64	0.46	1.00	
7	0.66	0.70	0.82	0.43	0.84	1.00

Source: modified after Jensen, 1996

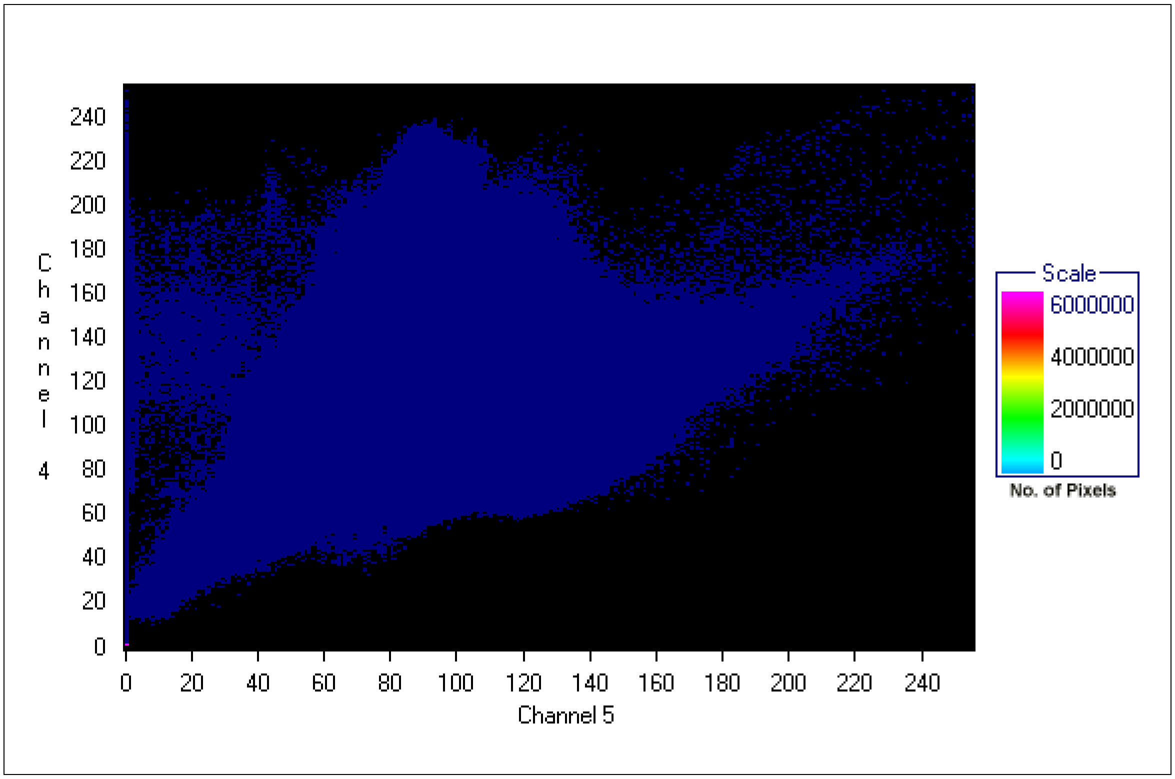


Figure 2.1: Scatterplot 1999 UTRCA ETM+ data, channel (Band) 4 vs. channel (Band) 5.

This allows the analyst to examine data and edit training sites so that minimal overlap between classes occurs (Jensen, 1996). Stefanov et al. (2001) acquired multiple training sites for each class type with a minimum of 70 pixels per class in an urban change study in Arizona. This allowed for meaningful statistical comparisons. It is desirable to have a unique normally distributed range of pixels in each training class to ensure minimal class confusion (Jensen, 1996).

Hill (1999) performed supervised classifications on Landsat 5 TM images of tropical forest types in Peru with accuracies between 100% for general forest cover and over 90% for six classes following post classification procedures. Bianchin and Bravin (2003) employed several supervised classification algorithms in an urban land classification using Ikonos data, reporting accuracies in the range of 95-97%. Torres-Vera et al. (2003) performed supervised classifications in an eight class urban study of Mexico City.

2.4.4 Supervised Classification algorithms

Pixels are assigned to a class based on an algorithm applied to training site data. Algorithms commonly used in supervised image classification include *Maximum Likelihood, Parallelepiped,* and *Minimum Distance*.

The *Maximum Likelihood* method is more computationally intensive than other methods and requires detailed analysis of generated training site statistics, based on the equation:

$$Pc = \{-0.5 \log_e[\det (V_c)]\} - [0.5 (X-M_c)^T V_c^{-1}] \tag{5}$$

where Pc represents the probability of pixel X being assigned to class c, det (V_c) is the determinant of the covariance matrix V_c, and M_c is mean vector for each class. Many studies can be found where *Maximum likelihood* supervised classifications have been undertaken. Masahiro et al. (2001) utilized a supervised classification with a *Maximum Likelihood* algorithm on a Landsat 5 TM image to map eight vegetation types in northeastern Syria with an average accuracy of 85%. Stefanov et al. (2001) used *Maximum Likelihood* supervised classifications on Landsat 5 TM images to monitor urban change in the state of Arizona with overall accuracies of 85%, using 12 classes.

Parallelepiped classifications apply a threshold value to classes based on training site data. A pixel will be assigned to class n if its brightness value (BV) falls within the range of

$$L_{ck} < BV_{ijk} < H_{ck} \tag{6}$$

where $c = 1, 2, 3\ldots m$ classes, $k = 1, 2, 3\ldots n$ bands, BV_{ijk} represent an unknown pixel's value in one band and L and H are upper and lower decision boundaries for assignment of a pixel with BV to created classes.

Studies sighting the use of this classification on remotely sensed satellite data are not common in the literature. This may be a result of its relative simplicity and the ability of faster computers to handle more complex algorithms. However, Meyer et al. (1996)

found this classification algorithm was more successful than the *Maximum Likelihood* method at determining tree species based on digitization of colour photographs.

Minimum Distance algorithms place pixels into created classes based on the minimum distance from an unknown pixel's *BV* to the mean of training class vectors (*ck)*, based on either Euclidian distance or 'round the block' calculations:

$$\text{Dist} = ((BV_{ijk} - \mu_{ck})^{2} + (BV_{ijl} - \mu_{cl})^{2})^{0.5} \qquad (7)$$

where BV_{ijk} and BV_{ijl} represent unknown pixel values in two bands (*k, l*) and μ_{ck} and μ_{cl} represent the mean of vector class *n* for two bands *(k, l)*. Whichever class mean is closest, the unknown pixel is assigned to that class (Jensen, 1996). This algorithm is the simplest common classification algorithm, as it does not take additional information such as standard deviation and correlation matrices statistics into account when calculating to which class each pixel should be assigned. It is only concerned with the mean of each sample vector (CCRS, 2003). Studies sighting the use of *Minimum Distance* classification are not common in the literature, perhaps due to its simplicity when compared to the *Maximum Likelihood* classification. Franey (1995) compared several classification algorithms, including the *Minimum Distance* algorithm, in Botswana for geological studies.

2.5 Selection of bands for use in classification (Feature selection)

Band information from satellite sensors may be redundant. This is a function of the type of ground cover represented in the image. *Feature selection* is the process by which individual bands are analysed in order to determine which combination of bands should be used to be able to best classify the image (Swain and King, 1973). This can be done visually through examination of band *n* vs. band *n* scatter plots and histograms to determine the amount of band separability. Statistical applications such as the *Jeffreys – Matusita* or *Bhattacharyya* distance measures provide values between 0 and 2000 based on each band's separability within each training class, where 0 = complete redundancy and 2000 = complete separability (Mausel, 1990). Combining visual and statistical methods of band separability ensures that relevant data for the classification scheme are included in the analysis.

2.5.1 Generation of additional image information

As well as original sensor data, it is possible to perform mathematical operations on bands to extract additional information. Several of these operations will be discussed here including: Principal Component Analysis (PCA), the Normalized Difference Vegetation Index (NDVI), and image texture analysis. These processes provide the analyst with more information to perform classifications.

2.5.2 Principal Component Analysis

Principal Component Analysis (PCA) reduces the amount of information available by discarding data that are highly correlated, creating new unrelated variables. The user determines the number of principal components to be created through the operation. The basic concept is to re-align the X and Y axes so they no longer represent real data, but represent variance in the original data. By doing this, it is possible to determine where the major principal components (or eigenvectors) lie (Figure 2.2) (Ricotta et al., 1999).

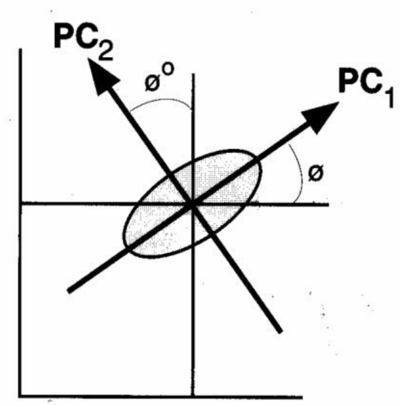


Figure 2.2: Principal components transformation.
Source: Jensen, 1996

Generally the first eigenvector (PC_1) represents around 90% of the variance in any satellite data set, with the first three components representing up to 98%. One or more of the principal components may represent certain ground cover features and therefore can help in image classification. Using PCA also reduces the amount of data to be analysed, and therefore can reduce a study's time and memory requirements (Jensen, 1996).

Bouvet et al. (2003) used PCA in their study of New Caledonia in order to reduce data processing requirements. They found the first three components accounted for 98% of data variance, with PC_1 accounting for 90%.

2.5.3 Normalized Difference Vegetation Index (NDVI)

The NDVI is designed to measure the amount of biomass within a scene. It is a normalized ratio between the near infrared and green visible components of an image, based on the amount of photosynthetic (green) material in each image pixel. In TM and ETM+ datasets it is generated using the following equation;

$$NDVI = (Band\ 4 - Band\ 3) / (Band\ 4 + Band\ 3) \qquad (8)$$

High values of NDVI indicate high levels of biomass, whereas areas low NDVI levels are associated with low levels of green material (Masek et al., 2000). Being able to distinguish areas of high NDVI with those of low NDVI can help with image classification. Stefanov et al. (2001) used an index similar to the NDVI – the Soil Adjusted Vegetation Index (SAVI) - as the base for selection of training sites in a supervised classification of regions of Arizona using Landsat TM data. By using the vegetation index they were able to separate types of vegetation without having *a priori* knowledge.

NDVI differencing is also a very useful technique for change detection studies. Being able to determine where areas of high NDVI have converted to areas of low NDVI is a means of highlighting urban change as green spaces are replaced with urban areas. Forsythe (2002a) used NDVI differencing in order to determine urban change in major Canadian cities. Torres – Vera et al. (2003) used two NDVI differencing approaches for determining urban change in Mexico City.

2.5.4 Texture analysis

Texture analysis attempts to add definition or a distinct boundary to pixels with similar features that might be part of the same land cover category. There are various algorithms available to compute texture features, but the basic principles apply to all. A window, of size defined by the user, is passed over the image. The centre pixel value is compared to the surrounding pixels and the average is computed. In this way similar regions can be highlighted and image classifications can be made easier (Jensen, 1996).

Shaban and Dikshit (2001) compared various texture algorithms of differing window size in an urban classification study in India. They found a SPOT band3 homogeneity algorithm, with a 7 x 7 window, worked best for isolating urban features in the Indian city of Lucknow. Improvements were much higher for homogeneous classes than for heterogeneous classes. Heterogeneous land features (wetlands for example) are much harder to define as there are many types of ground cover found within these features (Harvey and Hill, 2001). Homogenous regions, such as defined agricultural fields or urban areas, are easier to isolate as spectral characteristics are relatively uniform within these features.

2.6 Change detection

Change detection studies require the above-mentioned areas to be considered as well as several other considerations, to ensure the later band differenced image is as accurately classified as possible. Image resolutions must be identical for real change to be detected (Jensen, 1996). This may require re-sampling of an image in order to alter pixel sizes – i.e. reducing from 30.0m pixels to 28.5m pixels. Re-sampling can be done through software applications such as 're-project' or through the previously mentioned GCP procedure (Masek et al., 2000).

Temporal resolutions must also be around the same time of year and same time of day in order for change detection to be valid. Comparing a summer and winter image does little to show change in agriculture, as spectral characteristics will be different and ground cover type will not be uniform – i.e. leafy vegetation (summer) vs. bare vegetation (winter). Comparing an image taken at 7am vs. an image taken at 3pm will be problematic due to effects such as shadow and radiation differences (Jensen, 1996).

Masek et al. (2000) compared images over a 25-year period, with all acquired in the April to October range. Yang and Lo (2002) also compared images over a 25-year time period, using images from between April and July. They point out it is often difficult to obtain cloud free images which represent the desired scene, possibly hindering change detection studies. There are many different techniques available to the researcher for determining change (Table 2.2).

Table 2.2: Change detection methods

Change detection methods
Write function memory insertion
Multi-date composite image change detection
Image algebra change detection (Band differencing or Band ratioing
Post-Classification comparison change detection
Multi-date change detection using a binary mask
Multi-date change detection using ancillary data source as date 1
Manual, on screen digitization of change
Spectral change vector analysis
Knowledge-based vision systems for detecting change

Source: modified after Jensen, 1996

Post classification analysis requires the user to classify an image into a desired land use scheme, and then subtract the older image from the newer image(s). It is the most common change detection technique, but is prone to errors. Any error associated with the original classifications is compounded, requiring very precise initial classifications. Ridd and Liu (1998), Yang and Lo (2002), and Torres-Vera et al. (2003) did not use post classification change detection techniques because of the possibility of compounding errors from their original classifications. However the major advantage of this technique is being able to determine 'to-from' change, which is not possible with many other change detection methods (Jensen, 1996).

Band differencing involves subtraction of the latter year's band *n* from the newer year's same band (i.e. band2 1999 - band2 1991, etc…). Examination of *BV* will determine if change has occurred (Jensen, 1996). This type of change detection is not useful for determining 'to-from' change, but can produce very accurate change maps. Ridd and Liu (1998) in a comparison of four change detection algorithms (band differencing, image regression, tasseled cap change, and a chi-square method) found band2 differencing produced the highest accuracies in a change detection project in Salt Lake City.

2.7 Accuracy assessment

Whether performing image classification or a change detection study, it is critical that the accuracy of the results be determined. By placing a random number of points on a classified image and comparing them to reference data, it is possible to see which pixels have been misclassified and produce statistics that reveal any misclassification. A general rule is to have at least 50 points per class and for larger datasets at least 100 points (Congalton, 1991). Generation of these statistics is arrived at through the creation of an error matrix with the classified image pixels represented on one axis and a reference dataset represented on the other (Table 2.3).

Table 2.3: Example confusion matrix

		Reference Data			
		Forest	Not Forest	No Data	**Total**
Classified Data	Forest	154	1	0	**155**
	Not Forest	47	297	0	**344**
	No Data	0	1	0	**1**
	Total	**201**	**299**	**0**	**500**

The reference dataset could be the initial image, a set of GPS points of known ground cover, or an accurately created map. Four statistics are generally available for determining classification accuracy. Overall accuracy represents the total number of pixels correctly classified vs. incorrectly classified. Jensen (1996) feels this measure alone is not enough to determine whether a study is accurate as individual class accuracies can vary. The results can be better interpreted by looking at the *producer's* (omission) and *user's* (commission) accuracies in the error matrix. *Producer's* accuracies show when a pixel has been assigned to the incorrect class while *user's* accuracies show when a pixel has not been assigned to the correct class, based on the reference data. For example; if pixel *X* is classified as 'Forest' when it is in fact 'Not Forest' (according to the reference data) two errors have occurred: a) the class 'Forest' is gaining pixel *X* (which it should not), and b) class 'Not Forest' does not obtain pixel *X* (when it should). A fourth measure of accuracy is known as the Kappa statistic. Like overall accuracy this compares total numbers of pixels accurately and inaccurately classified, but also takes into account off-diagonal values in the error matrix. Therefore Kappa statistics are often lower than overall accuracy statistics. Congalton (1991) feels all statistics should be analysed to determine accuracy of classification. If the accuracies produced are not satisfactory data must be re-examined and more accurately classified.

Yang and Lo (2002) sight both Kappa and overall statistics to determine accuracy of their study. Harvey and Hill (1999) use overall accuracy, producer and user statistics to validate their study on wetland vegetation classification in Australia. Ridd and Liu

(1998) compare Kappa and overall statistics in a comparison of land use change detection algorithm accuracies.

The newer image in band differenced urban change detection studies should be classified as accurately as possible (Yang and Lo, 2002) to be able to discern where ‘real’ urban change has occurred as opposed to change in agriculture from green to fallow or tilled field (Griffiths, 1988 as found in Masek et al., 2001). Few published urban change detection studies cite final overall accuracies lower than 80% and few cite within-class *user* and *producer* statistics less than 80%. Stefanov et al. (2001) had overall accuracies of 85% with within-class *user's* accuracies of 49% to 99% in an Arizona urban change detection study. Lower accuracies were considered unsatisfactory and are thought to be a result of spectral confusion. Seto et al. (2002) in a Pearl River Delta study reported overall accuracies of over 93%. Within class *user's* accuracies of 51% - 100% were reported in nine classes. Again, the lower accuracies were considered unsatisfactory.

Chapter 3: Methodology

Several steps were necessary in order to create an urban development file including data preparation, image classification, and change detection.

3.1 Data preparation

3.1.1 Image sub-setting

Initial images covered areas much larger than the UTRCA. Images had to be subset to fit the perimeter of the conservation authority, using the ‘subset’ tool in PCI v 9.0 (PCI, 2003). The 1999 image does not cover the entire western portion of the UTRCA, however this was not considered problematic as all major urban centers are within this image (Figure 3.1).

3.1.2 Radiometric correction

No radiometric procedures were applied to any images. Following Song et al. (2001) it was felt radiometric errors were minimal and did not require any correction for this urban change detection study. Radiometric normalization of an image creates a file much larger than its initial size, which can impede computing efficiency.

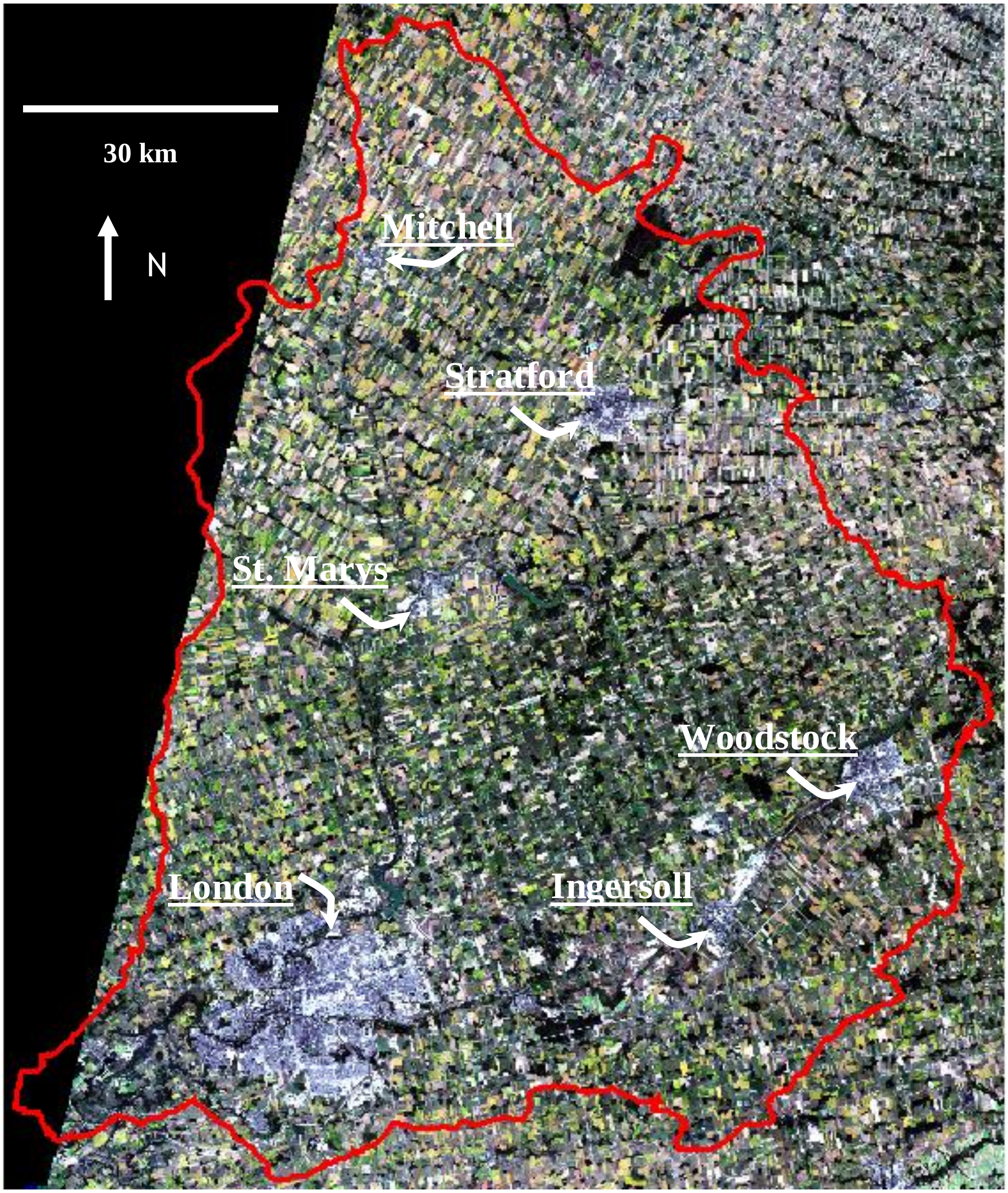


Figure 3.1: 1999 UTRCA Image. Bands 3, 2 and 1.

3.1.3 Geometric rectification

The 2000 image was previously orthorectified to the UTM Zone 17, (NAD83 GRS1980) coordinate system by Natural Resources Canada and then ‘Pansharpened’ (PCI, 2003) to a 15-metre spatial resolution with PCI Geomatica v. 9.0 software. The resulting image was then used as the reference image for placement of Ground Control Points (GCP) for disk-to-disk registration. Each of the 1991 and 1999 images were rectified to the 2000 image using 25 GCP with total RMSE of less than 0.25 pixels. This procedure re-sampled the 1991 and 1999 data to 15m pixels.

3.2 Image classification

Various parameters were considered in order to classify the 1999 image. These included classification scheme, feature selection, classification type and accuracy assessment.

3.2.1 Classification scheme

Four classes were chosen for this study:

Urban – represents all pixels considered 'human-made', including city buildings, residential areas, commercial areas, farm houses, roads and construction (excavated) areas.

Greenspace – represents all pixels deemed to be ground cover that is not 'developed' including all fields, forests and wetlands.

Water - represents all pixels associated with water, including lakes, ponds, rivers, and streams.

No data – represents all pixels with no data values. These were not present in the 1991 image, but were found in the 1999.

More classes may have been desirable, but as the study is only concerned with urban development (no matter what type) in the UTRCA, this simple classification strategy was employed. Within this classification scheme are land cover types which can be considered both urban and greenspace, such as golf courses. While golf courses are 'green', they are of certain importance to OCA as they consume large amounts of water and introduce pollutants into the water table. Golf courses being built in 1999 were included in the urban class within the UTRCA due to reflectance values for excavated lands being considered ‘developing’. However, golf courses in existence were classified as greenspace. This does not affect this study severely, as golf courses being built are considered a ‘human – induced’ change on the surrounding environment, and therefore fall within the definition of the ‘urban’ class as found above.

3.2.2 Feature selection

Certain features were calculated for each image in order to help distinguish urban developed land cover from other land cover types. These included Principal Component Analysis (PCA), a Normalized Difference Vegetation Index (NDVI) and a Texture feature.

Principal Component Analysis:

The first three Principal Components (PC) were calculated for the 1999 image. These amounted to approximately 99% of the total variability in the data for both images (Table 3.1). Upon visual inspection, it was determined that PC_3 coincided best with urban features found in the UTRCA (Figure 3.2). Therefore this feature was included in subsequent classifications of the 1999 data.

Table 3.1: PCA analysis for 1999

PCA 1 Variance	81.50%
PCA 2 Variance	13.93%
PCA 3 Variance	3.42%
Total Variance	98.85%

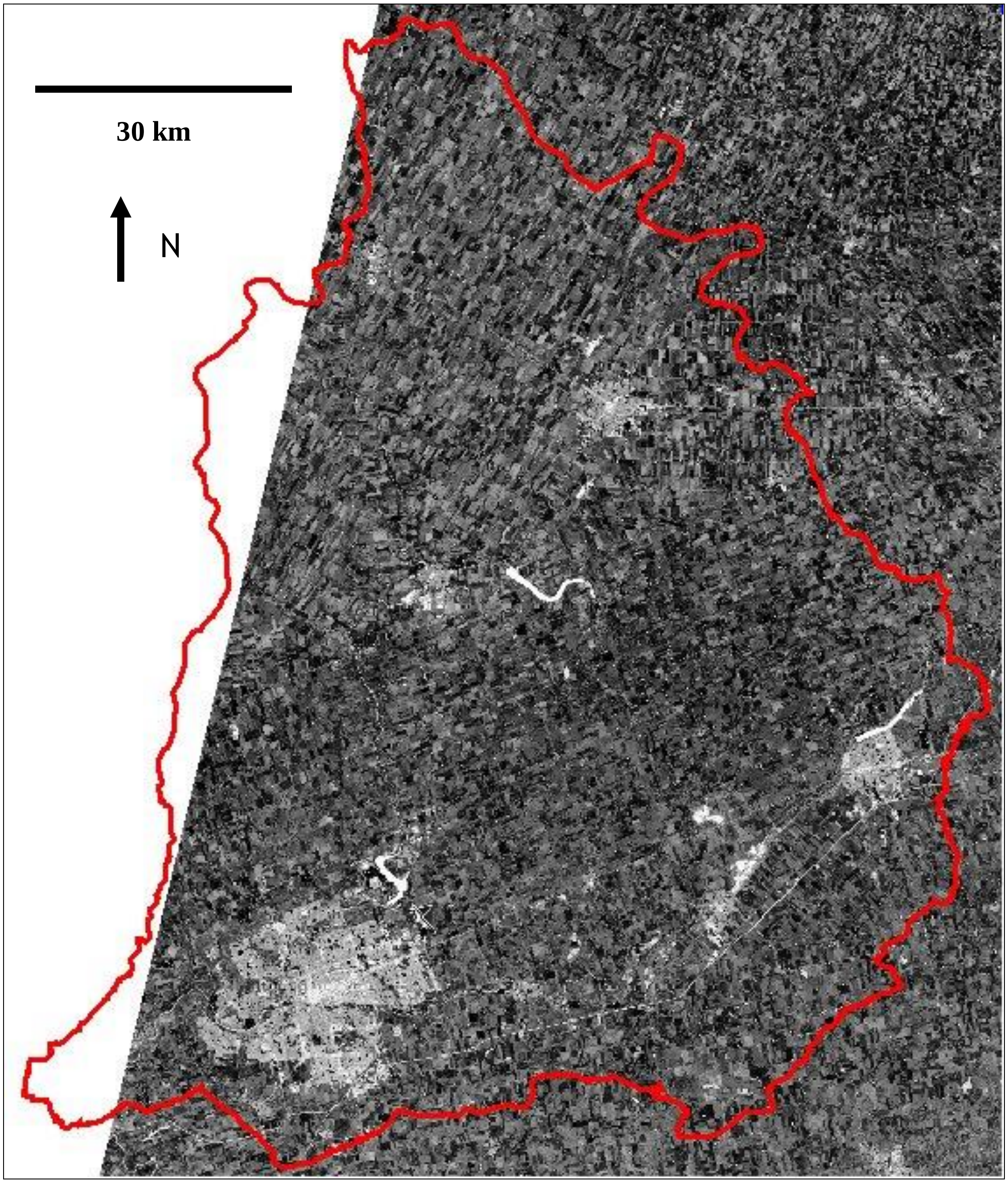


Figure 3.2: PCA 3 1999 UTRCA Image

Normalized Difference Vegetation Index:

The NDVI calculates a ratio of the amount of biomass present in an image and is used in urban change detection studies to help separate ‘green’ (light) from ‘not green’ (dark) as in figure 3.3. NDVI was included in classification of the 1999 image as it was felt it helped distinguish urban and greenspace ground cover.

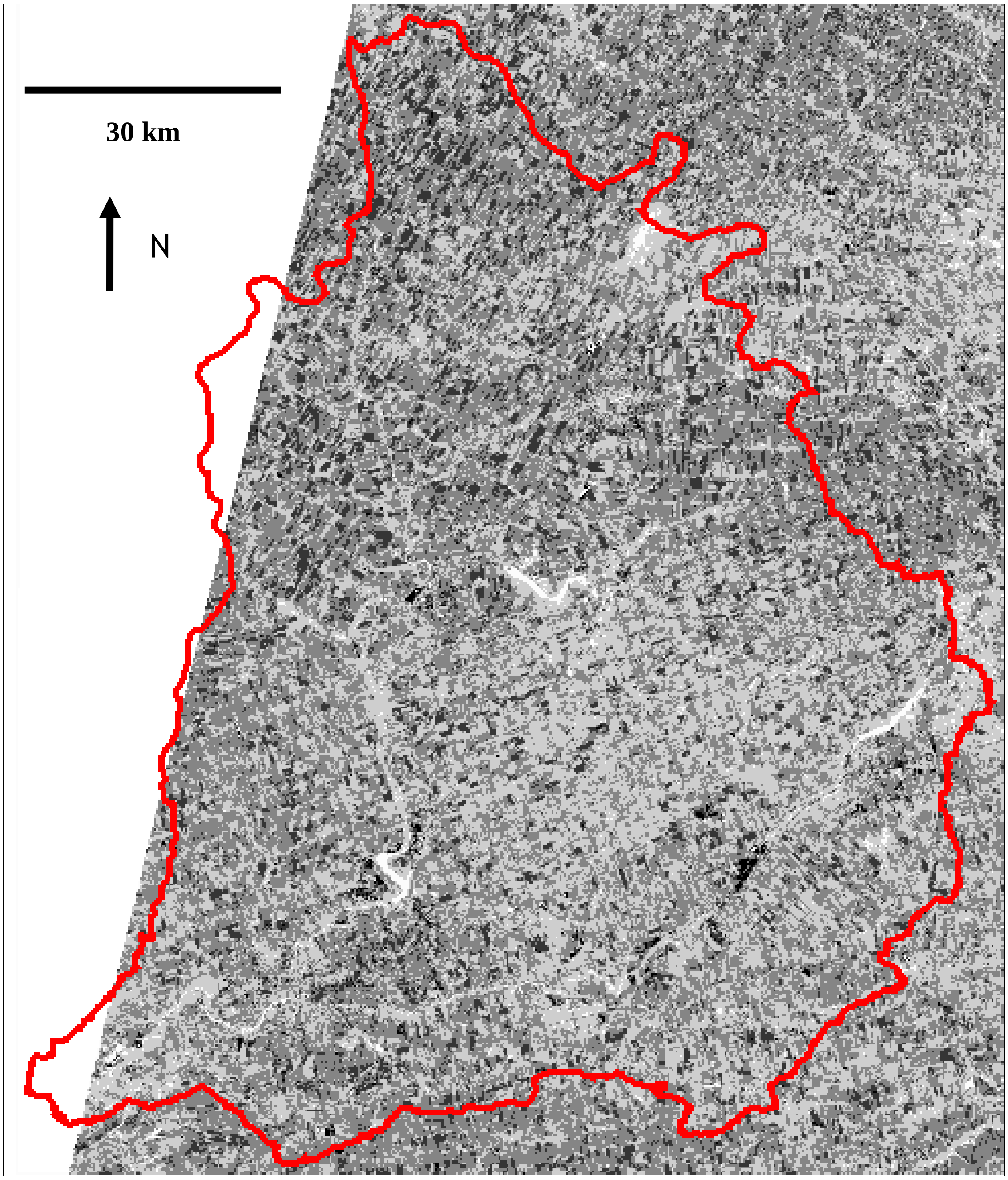


Figure 3.3: NDVI 1999 UTRCA Image

Texture:

Determining 'boundaries' to help isolate urban features was aided using a texture measure. There are many texture algorithms available to the analyst - based on the input of one band or feature from the dataset (Table 3.2).

The same algorithm and window parameters were applied to the 1999 Landsat image as in the Shaban and Dikshit (2001) study, with unsatisfactory results. This is not surprising considering different satellite platforms were used. Various combinations of band input, window size and algorithm were applied until a PCA 3 homogeneity algorithm with a 5 x 5 window was applied. It was felt this texture measure best separated urban and non-urban features in the UTRCA (Figure 3.4).

Table 3.2: Texture algorithms
GLDV = grey level difference vector

Texture Measure Algorithms PCI v. 9.0

Homogeneity	Correlation
Contrast	GLDV Angular Second Moment
Dissimilarity	GLDV Entropy
Mean	GLDV Mean
Variance	GLDV Contrast
Entropy	Inverse Difference
Angular Second Moment	

3.2.3 Unsupervised classification

A total of 255 classes were created using the *Kmeans* algorithm in PCI v. 9.0. Created classes were then aggregated into the desired classification scheme (Figure 3.5).

The combination of bands and features that produced the highest urban accuracy was of ETM+ Bands 1-5 and 7, plus PCA 3, NDVI, and the 5 x 5 homogeneity texture measure.

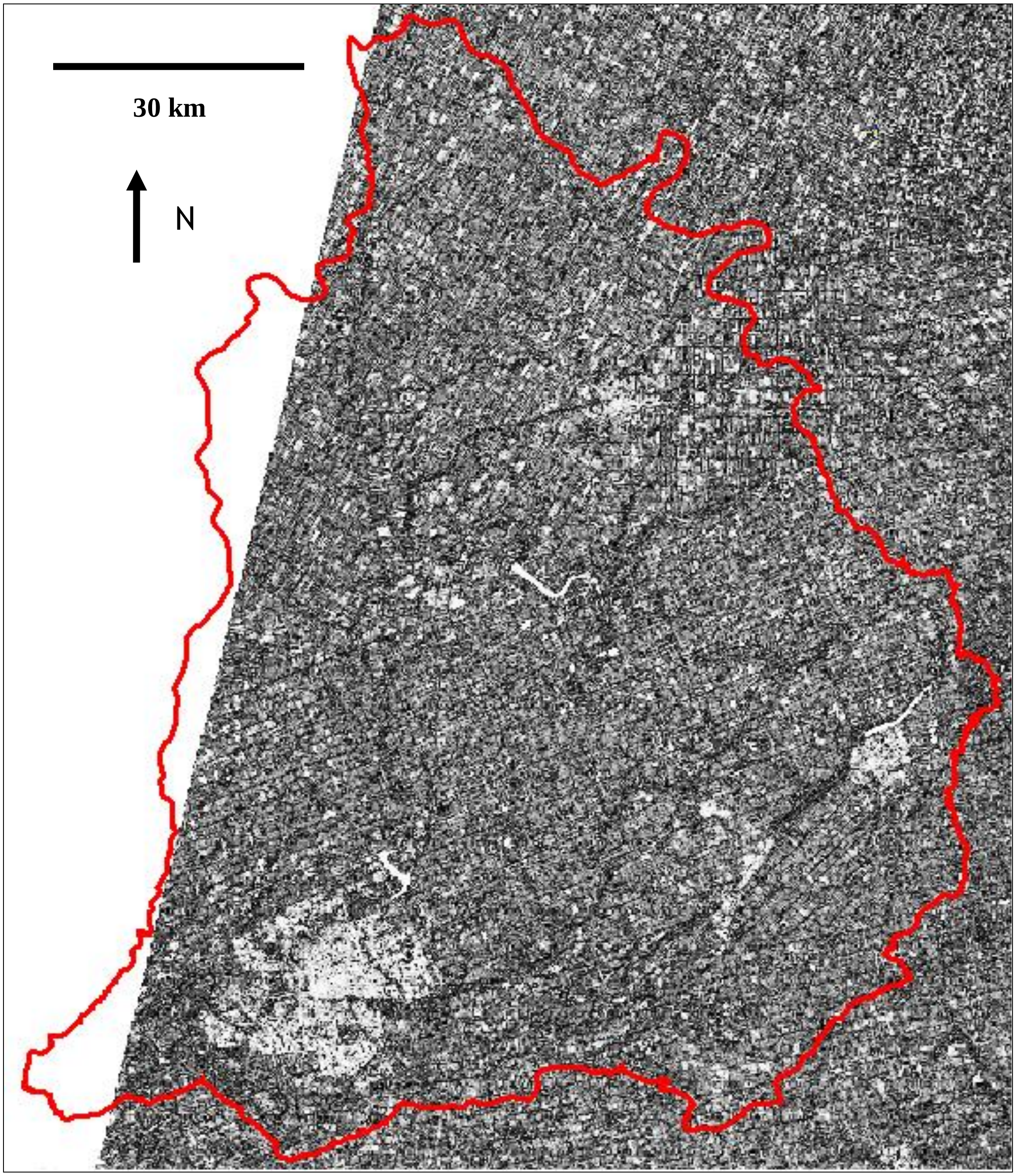


Figure 3.4: Texture analysis for 1999 UTRCA Image;
Homogeneity (PCA 3) - 5 x 5 window.

Major error resulted due to misclassification between urban and agriculture land cover, included in the greenspace class. Entire fields and single pixels were incorrectly classified as urban (Figure 3.6).

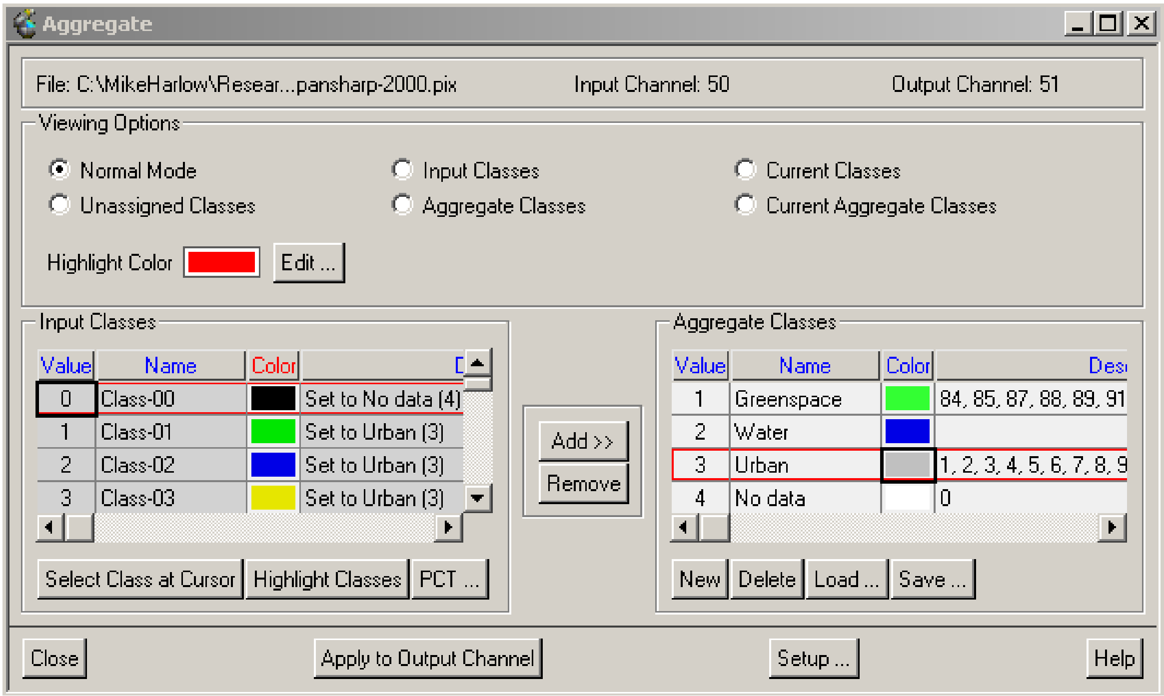


Figure 3.5: Kmeans class aggregation for unsupervised classifications
1999 UTRCA dataset

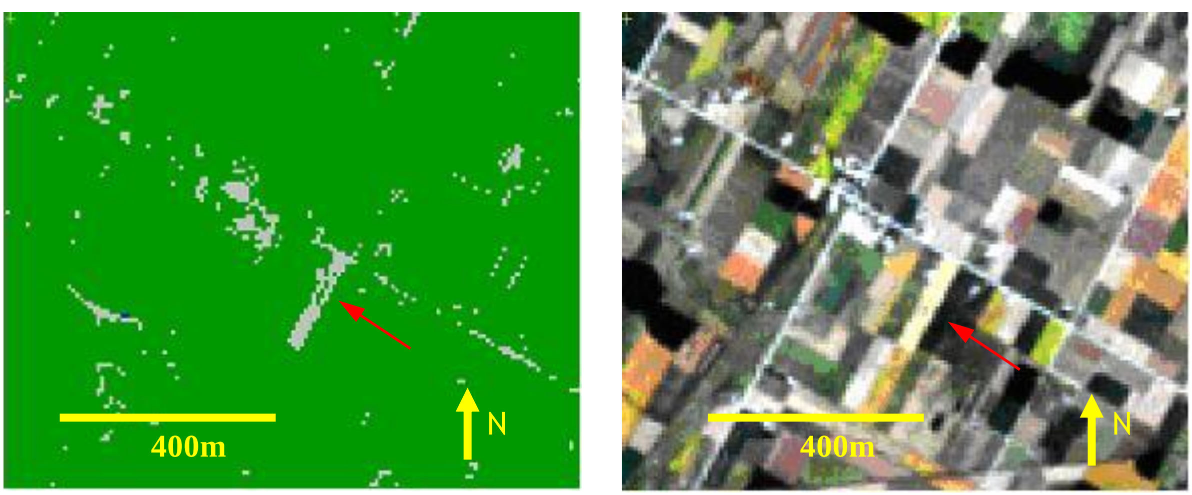


Figure 3.6: Urban confusion with greenspace. Unsupervised classification ETM+ Bands 1-5, 7, + PCA 3 + NDVI + 5 x 5 Texture measure of 1999 UTRCA dataset. Red arrows indicate an agricultural field classified as urban.

This is further seen through comparison of *producer* and *user* statistics (Table 3.3) and examination of the confusion matrix for the ETM+ Bands 1-5 and 7, plus PCA 3, NDVI, and the 5 x 5 homogeneity texture measure unsupervised classification (Table 3.4).

Table 3.3: Accuracies for ETM+ Bands 1-5 and 7, PCA 3, NDVI, and 5 x 5 Texture measure unsupervised classification of the 1999 UTRCA dataset

Overall Accuracy	77.2%	
Overall Kappa	0.631	
	Producer's	*User's*
Greenspace	92.2%	70.3%
Water	66.3%	93.8%
Urban	65.3%	86.7%
No Data	0%	0%

Table 3.4: Confusion matrix for ETM+ Bands 1-5 and 7, PCA 3, NDVI, and 5 x 5 Texture measure unsupervised classification of the 1999 UTRCA dataset

	Reference	Greenspace	Water	Urban	No Data	**Total**
Classified	Greenspace	201	22	64	0	**287**
	Water	2	61	2	0	**65**
	Urban	15	4	124	0	**143**
	No Data	0	5	0	0	**5**
	Total	**218**	**92**	**190**	**0**	**500**

High numbers of ‘greenspace’ pixels classified as ‘urban’ equate to low urban *producer’s* accuracies as classified urban pixels are not are being assigned to this class, based on the reference data. *Producer’s* accuracies for the greenspace class are very high as few pixels that are not ‘green’ are being classed as green. These errors were consistent throughout all unsupervised classifications; therefore it was decided to abandon this method of classification.

3.2.4 Supervised classification

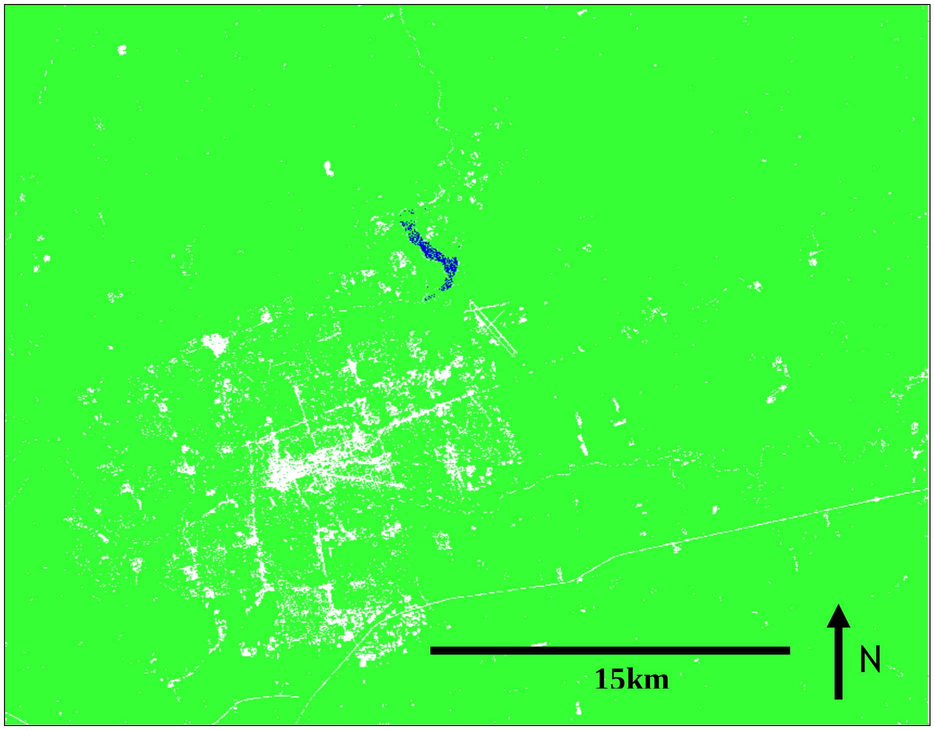
Supervised classifications were successful at producing an acceptably classified image, as similar studies have shown (Stefanov et al., 2001; Prol-Ledmesma et al., 2001; Bianchin and Bravin, 2003; Torres-Vera et al., 2003). Three parameters were examined in order to achieve a desired classification: selection of bands used for classification, choice of algorithm, and training site evaluation.

It was decided the combination of ETM+ bands 1-5 and 7, plus PCA 3, NDVI, and the 5 x 5 homogeneity texture measure would be utilized as they provided the best results for the unsupervised classifications. Initially only four classes were included for classification with many small training sites for each class (Table 3.5).

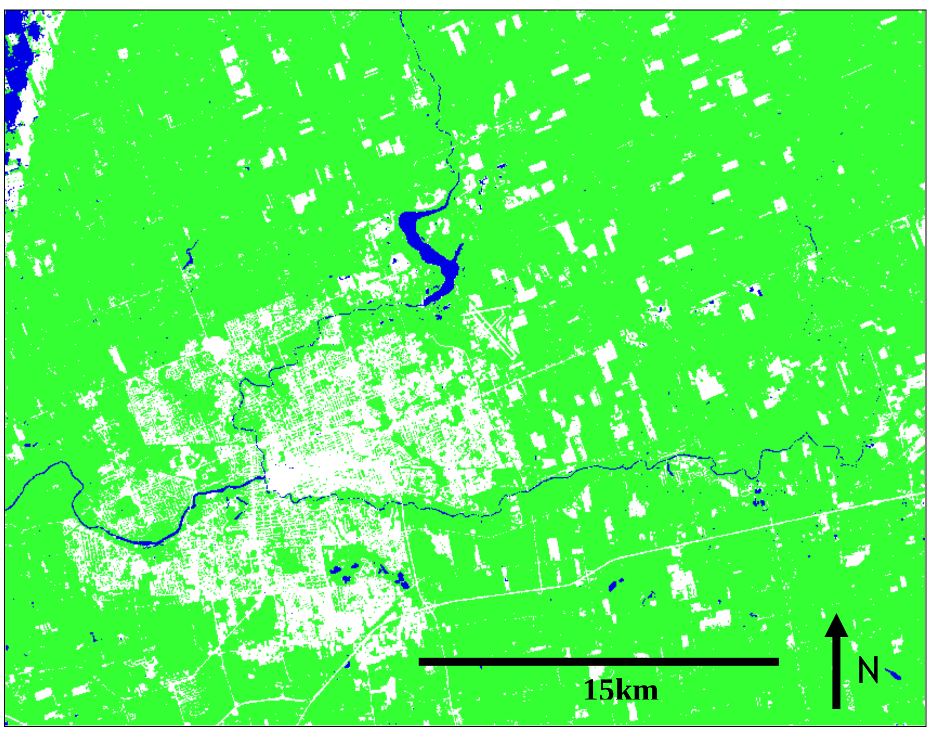
Table 3.5: Initial training site criteria

Class	**Training Sites**
Greenspace	25
Water	15
Urban	20
No Data	1

Training sites were selected based on visual interpretation of ETM+ bands 3, 2, and 1 for pixels representing forest, urban, and water, and with the NDVI for identifying all types of agricultural fields (‘green’ vs. ‘fallow’). After several iterations using the popular *Maximum Likelihood* algorithm with poor visual results, it was decided to switch to the *Minimum Distance* algorithm, which immediately improved results (Figure 3.7). It is possible to preview supervised classifications in PCI before classifying the image,



Maximum Likelihood supervised classification



Minimum Distance supervised classification, training sites as in table 3.6

Figure 3.7: Initial supervised classification, UTRCA 1999 dataset.
Green = greenspace, white = urban and blue = water

allowing for visual comparison between different classifications. Therefore only accuracy statistics for the final supervised classification are presented.

Although results were better with the *Minimum Distance* classification, they were not acceptable. Figure 3.8 shows the high degree of overlap in spectral response between 'greenspace' and 'urban' classes, which resulted in many urban regions being classified as 'greenspace', and vice versa.

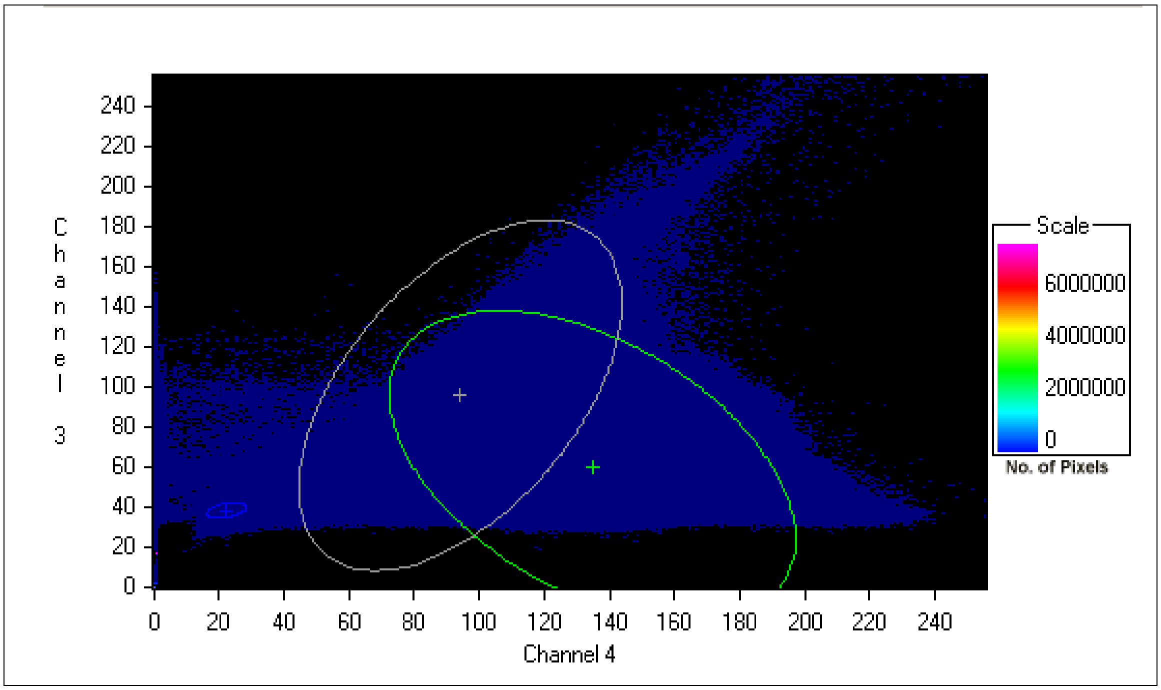


Figure 3.8: Scatterplot ETM+ Channel (Band) 3 vs. Channel (Band) 4 UTRCA 1999 dataset.

One reason for changing to a *Minimum distance* algorithm was it was found easier than the *Maximum likelihood* method to edit training sites for pixels with very similar reflectance values that represent different land cover classes i.e. 'urban' vs. 'green'. Editing was attempted for the above classification through addition of training sites directly where class confusion had occurred. The cumulative addition of 50 new training sites per class made for a classification that confused urban and agricultural features. To attempt to solve these problems two new classes were created to help distinguish areas of urban and greenspace confusion. By placing training sites directly on regions known to be urban but classified as agriculture (and vice versa) it was hoped spectral confusion would be reduced. This helped increase the accuracy of the classification, but was still not acceptable. The new classes' spectral response fell between the original classes of 'urban' and 'greenspace', continuing with the pattern of spectral confusion between the two main classes (Figure 3.9).

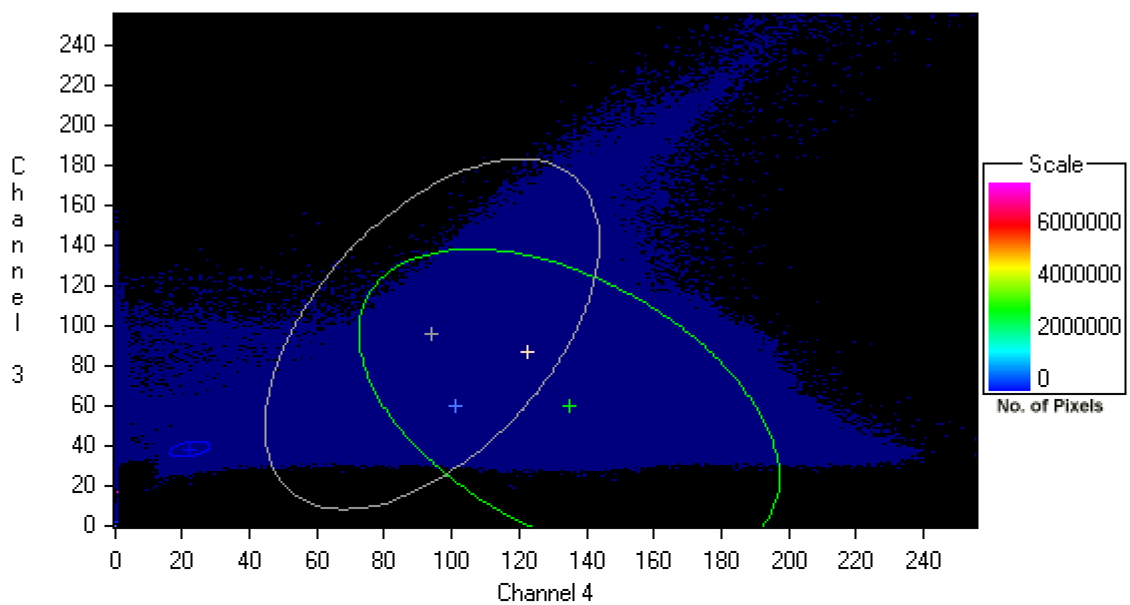


Figure 3.9: Scatterplot ETM+ Channel (Band) 3 vs. Channel (Band) 4 UTRCA 1999 dataset. As in figure 3.8 with the addition of two 'confusion' classes; pink = greenspaces that are not urban and light blue (no ellipse) = urban lands that are not greenspace

Confusion between urban and greenspace classes was a result of each individual class being too large, resulting in spectral overlap. To correct this it was decided to attempt a *Minimum Distance* classification using 17 classes with three small training sites for each, which would isolate different land cover types. Again, ETM+ Bands 3, 2, l and the NDVI were used to discriminate between various land cover types. 'Dark', 'Middle' and 'Light' NDVI agricultural fields were found in the northern, central, and southern sections of the UTRCA and were each considered a separate class, for a total of nine agricultural classes. Training sites for forested areas were chosen based on forested locations in northern and southern regions, and a known wetland in the northeastern portion of the UTRCA. Urban regions were chosen based on the location of pixels representing what was thought to be 'City Centre', 'Residential' and 'City Outskirt' regions (Table 3.6).

Table 3.6: Revised Training site strategy

Class	Training Sites	Class	Training Sites
Dark Field North	3	Wetland	3
Dark Field Middle	3	Forest North	3
Dark Field South	3	Forest South	3
Middle Field North	3	City Outskirts	3
Middle Field Middle	3	Residential	3
Middle Field South	3	City Centre	3
Light Field North	3	Water	3
Light Field Middle	3	No Data	1
Light Field South	3		

This greatly improved results, as it was much easier to distinguish urban and non-urban features (Figure 3.10). To help improve mapping characteristics, all areas of the image that were not part of the study area were removed. This required the use of a bitmap mask created in PCI Geomatica Focus to highlight all those areas that are outside the boundaries of the UTRCA and discard them from classification. Fields being

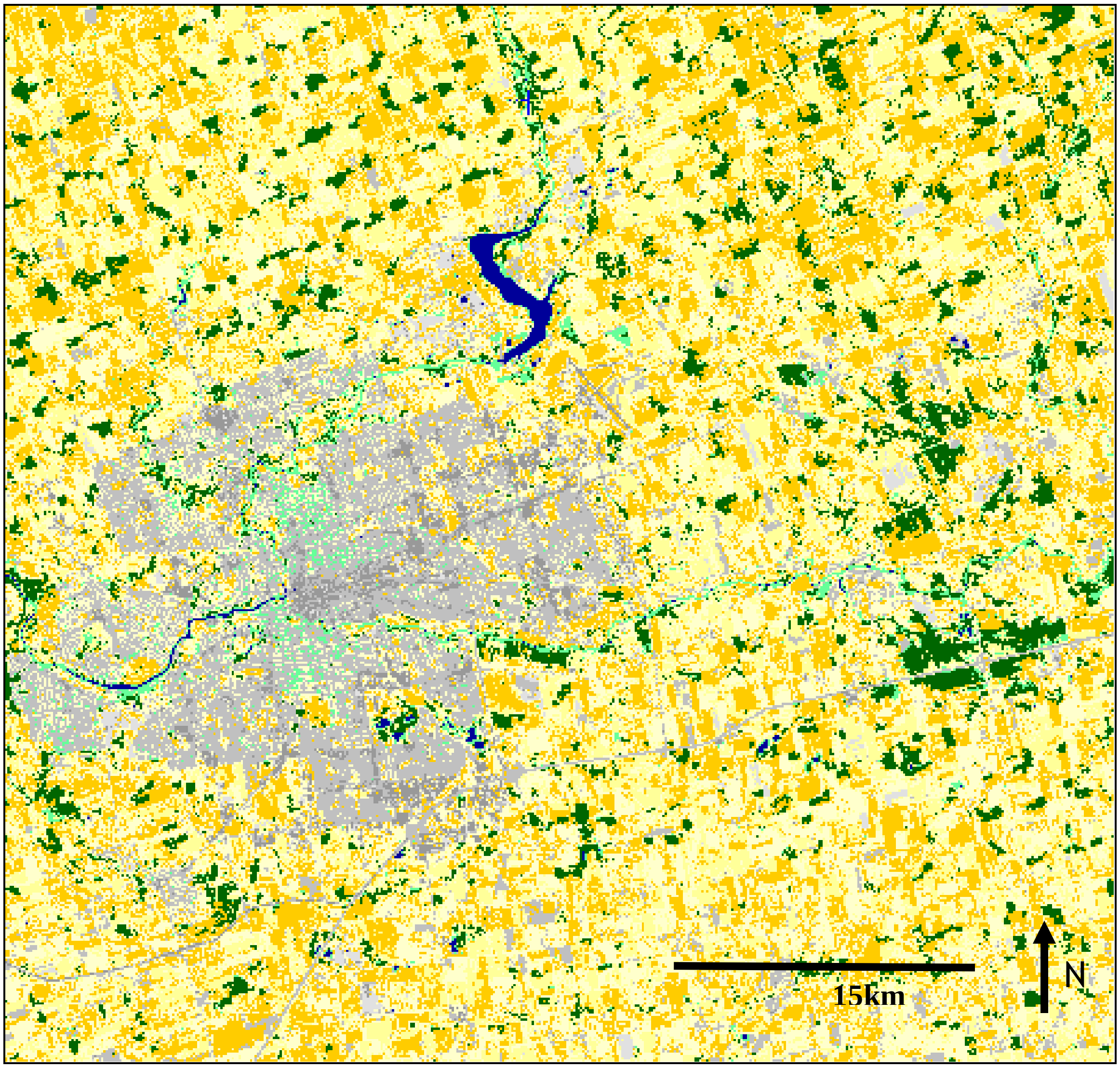


Figure 3.10: Modified *Minimum Distance* supervised classification from Table 3.6. Yellow colours = agricultural fields, green colours = forested land and grey colours = urban land.

confused with urban features was still a problem, as not all pixels were accurately classified (Figure 3.11).

3.2.5 Accuracy assessment

Accuracy assessment proved initially difficult for this study as an adequate number of points was required for each class represented (Jensen, 1996). Placing a random sample of 500 points over the region indefinitely meant a higher number of points were being

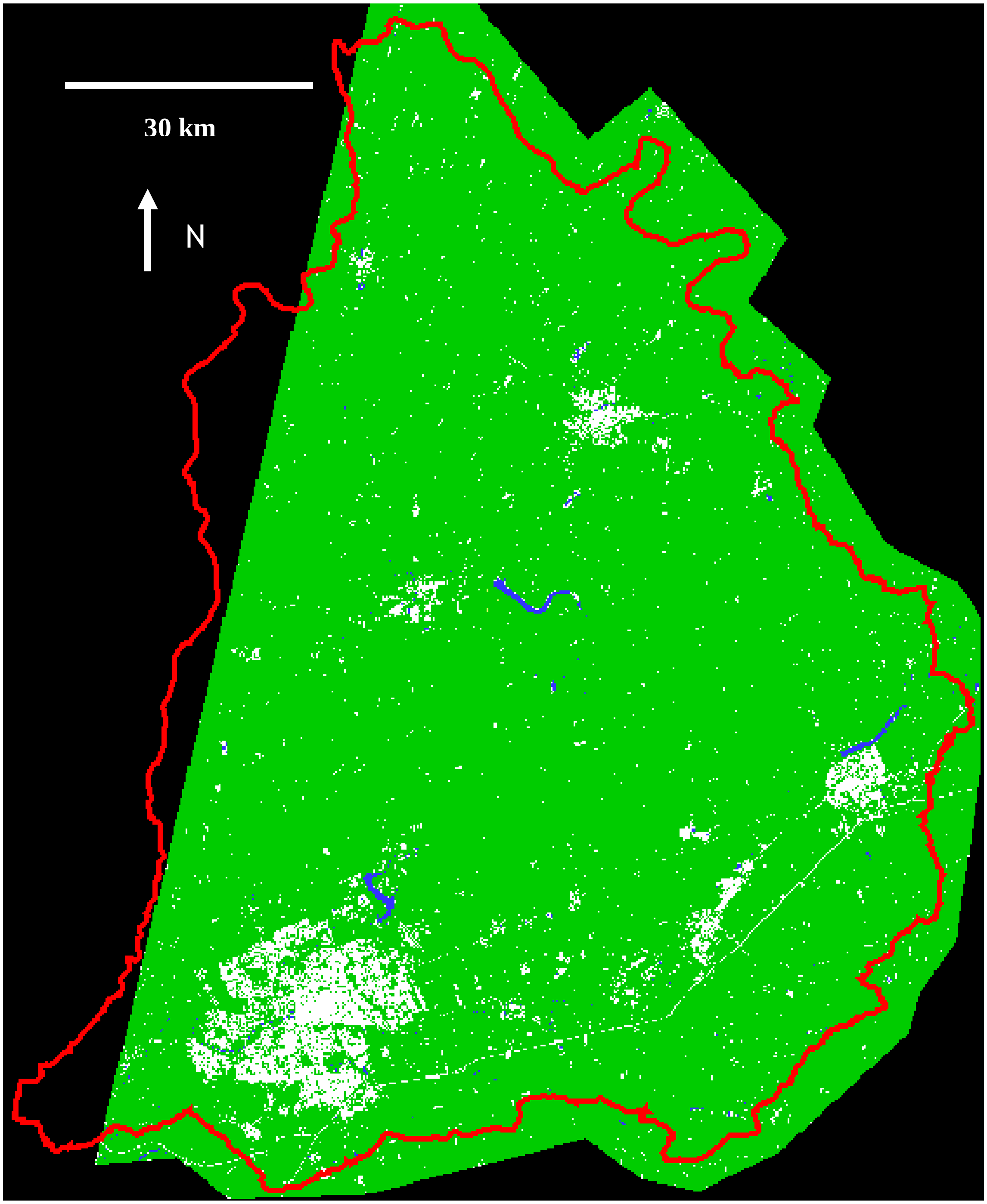


Figure 3.11: Final classification preview – bitmap mask applied. UTRCA 1999 dataset

assigned to the greenspace class which dominates the image as compared to an insufficient number of points assigned to the urban and water classes, which each represent a small portion of the UTRCA. Therefore the following sampling strategy was decided on: 200 points ‘greenspace’, 200 points ‘urban’ and 100 points ‘water’. This was accomplished using the EASI Modeling function in PCI Geomatica Focus where individual classes can be converted to individual image channels. It was then possible to stratify a point sample over all pixels of a particular classification. Each sample was then merged together to form one 500 point sample for the entire image, guaranteeing the desired number of sample points were present in each class. The sampling strategy was somewhat modified for the final classification after the bitmap had been applied. The classes were then more equally represented (Figure 3.12). Tables 3.7 and 3.8 show an overall classification accuracy of 87% with no within-class *producer* or *user* accuracy statistics below 80%.

3.3 Change detection

3.3.1 Band differencing

Following Ridd and Liu (1998) band2 differencing was chosen as the optimum method for determining urban development in the UTRCA. This was done through subtraction of 1991 band2 values from 1999 band2 values, using the Image Arithmetic Algorithm in PCI Xpace.

The resulting development image had brightness values (*BV*) in the range of 44 – 136. It was determined through visual analysis the range of 44 – 89 was synonymous with urban development (green in 1991 to urban in 1999). These values also coincided with many agricultural fields, which were green in 1991 and tilled or fallow in 1999 (Figure 3.13).

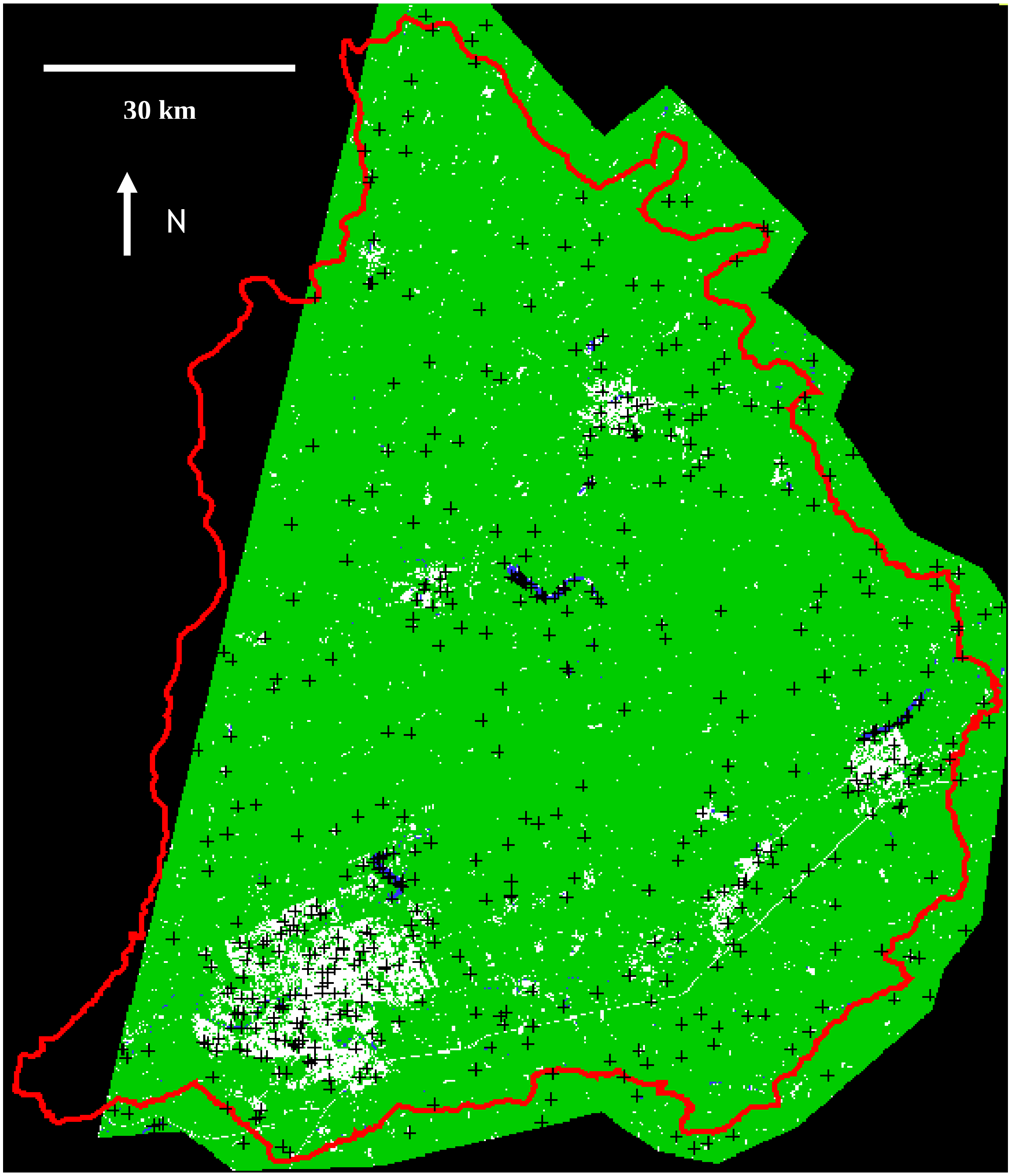


Figure 3.12: Example stratified sample for each individual class merged into one 500 point sample

Table 3.7: *Minimum distance* final classification accuracies
UTRCA 1999 dataset

Overall Accuracy	87.20%	
Overall Kappa	0.797	
	Producer's Accuracy	*User's Accuracy*
Greenspace	94.7	80.5
Water	80.1	91.3
Urban	82.3	98.8

Table 3.8: *Minimum distance* final classification confusion matrix UTRCA 1999 dataset

	Reference	Greenspace	Water	Urban	No Data	**Total**
	Greenspace	198	14	34	0	**246**
Classified	Water	1	80	0	0	**81**
	Urban	10	5	158	0	**173**
	No Data	0	0	0	0	**0**
	Total	**209**	**99**	**192**	**0**	**500**

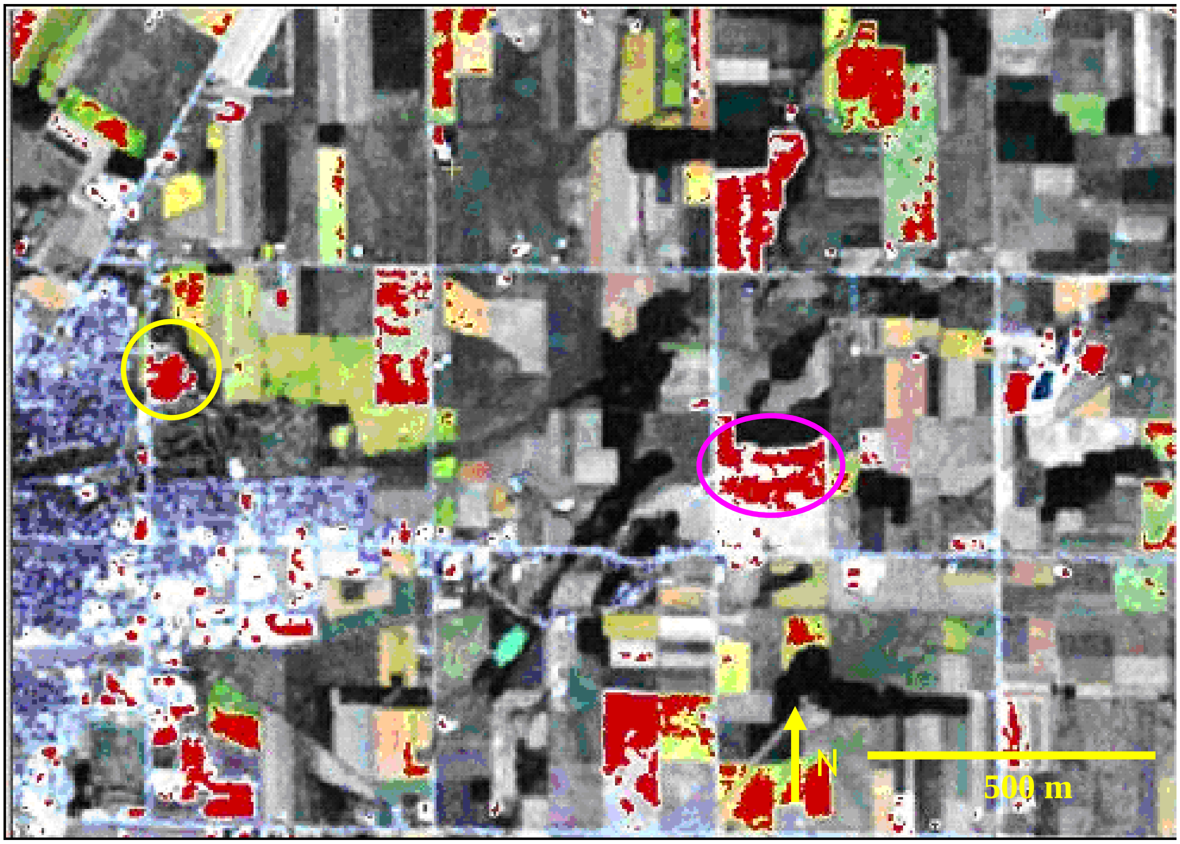


Figure 3.13: Urban and agricultural change, Band2 differencing UTRCA 1999 – 1991. The yellow circle = actual urban development and the purple circle = green areas deemed as 'developed'.

Currently methods for assessing urban change are considered fairly well developed. However, the detection of different types of change – for example greenspace to excavated or excavated to fully developed – are not very common in the literature. Research in this area is ongoing and as a result, no attempts were made to classify the development data in this way.

3.3.2 Geographic Information System (GIS) Analysis

Classified and development images created in PCI were exported into ArcGIS 8.3 for GIS analysis. Each class in the classified image was separated into individual 'urban, 'greenspace' and 'water' shapefiles. In order to separate agricultural fields deemed as 'developed' from real urban development an overlay function was applied between the 'urban' and 'developed' shapefiles. This is where accurate classification of urban regions is crucial, as any 'change' pixels which fall on an incorrectly classified agricultural field (i.e. a field which has been classified as urban) will be shown as 'urban development' following the overlay process. This process eliminated a number of 'developed' agricultural fields, but many were still present due to error in urban classification from the previous supervised classification process.

Post classification editing was performed through comparison of the remotely sensed urban development data with 35cm resolution aerial photographs of the UTRCA acquired from April 18 - 21, 2000. The development shapefile was overlaid onto the photographs and any 'development' pixels found in a 'greenspace' region were deleted. It was felt that any classified urban areas located away from major centres could not have reverted from urban to greenspace in the 8-month time period between the acquisition of the 1999 Landsat image and the air photos. Development accuracies were recalculated following post classification editing. Classification accuracies improved in all three classes as found in tables 3.9 and 3.10.

Table 3.9: *Minimum distance* final classification accuracies with ortho-photo editing UTRCA 1999 dataset

Overall Accuracy	90.8	
Overall Kappa	0.856	
	Producer's	*User's*
Greenspace	97.5%	84.2%
Water	88.0%	98.9%
Urban	85.7%	95.6%

Table 3.10: *Minimum distance* final classification confusion matrix with ortho-photo editing UTRCA 1999 dataset

	Reference	Greenspace	Water	Urban	No Data	**Total**
	Greenspace	192	8	28	0	**228**
Classified	Water	0	88	1	0	**89**
	Urban	5	3	175	0	**183**
	Total	**197**	**99**	**204**	**0**	**500**

Chapter 4: Result and Discussion

4.1 UTRCA Urban development, 1991 – 1999

Over the period 1991 to 1999, 17.36 km^2 of urban land was developed or added in the UTRCA. No distinction has been made between the type of development (i.e. 'new urban', 'industrial' etc…). Summary population and development statistics for each urban region are presented in Tables 4.1 and 4.2. The majority of development activity occurred in or around urban centres within the UTRCA (Figure 4.1).

Table 4.1: UTRCA urban region population statistics

	Population				*Percentage Change*			
Region Name	*1991*	*1996*	*1999**	*2001*	*91-96*	*96-01*	*91-99#*	*91-99 / year*
London CMA	381522	416546	426089	432451	4.50	3.80	10.46	1.31
London CSD	303165	325669	332191	336539	6.91	3.23	8.74	1.09
Woodstock	30075	32253	32738	33061	6.70	2.50	8.13	1.02
Stratford	27666	29007	29408	29676	4.80	2.30	5.92	0.74
Ingersoll	9378	9849	10526	10977	5.00	4.50	10.90	1.36
St Marys	5496	5952	6157	6293	8.30	5.70	10.73	1.34
Mitchell	3382	3670	3881	4022	8.50	9.60	12.86	1.61

* based on the formula: ((2001pop -1996pop/5)*3) +1996pop
#from 1999 population, formula: ((1999pop -1991pop)/1999pop)*100
Source: Statistics Canada, 2003

Table 4.2: UTRCA development statistics

Region Name	*Size, 2003 (km^2)*	*Development 1991 - 1999 (km^2)*	*Development/year (km^2)*	*Change (%)*	*Change/year (%)*
London CMA	1042.95	10.39	1.30	1.00	0.12
London CSD	424.56	7.59	0.95	1.79	0.22
Woodstock	30.60	0.55	0.07	1.80	0.23
Stratford	22.09	0.66	0.08	2.97	0.37
Mitchell	13.22	0.43	0.05	3.23	0.40
Ingersoll	12.99	0.29	0.04	2.23	0.28
St Marys	12.61	0.65	0.08	5.14	0.64
BLQ	49.01	2.49	0.31	5.07	0.63

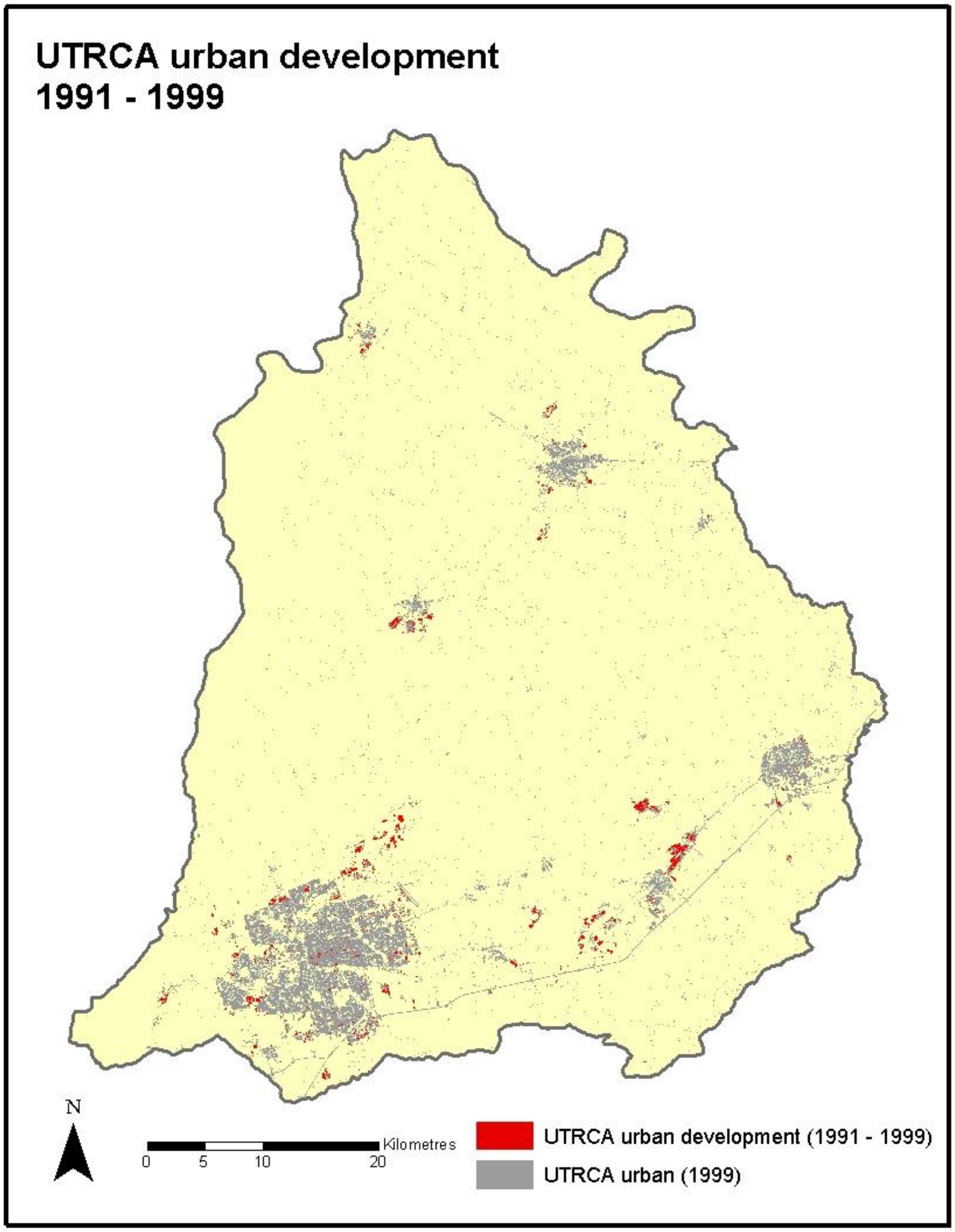


Figure 4.1: UTRCA urban developments, 1991 – 1999

Urban region development is almost entirely found within the urban boundaries as defined by Statistics Canada whereas what is thought to be construction/industrial development, based on visual analysis of the 35cm orthophotos and the development file, is predominantly found outside urban polygons, with the exception of the London Census Metropolitan Area (CMA) and the St. Marys Census Sub Division (CSD).

4.1.1 London (Census Metropolitan Area and Census Sub Division)

CMAs are defined as having an urban core population of over 100000 with adjacent municipalities having a large degree of integration with the urban core (Statistics Canada, 2003). Not all of the London CMA is inside the UTRCA, but the urban core is found within the conservation authority. During the study period, the calculated London CMA population growth was 10.5%, or 1.31%/year. London's CMA urban development totalled 1% (10.39 km^2) or yearly growth of 0.12% (1.30 km^2/year) of the developed urbanized area as a percentage of the urban polygon found within the UTRCA during the study period (Figure 4.2).

The majority of London's CMA development is found in the periphery of the city's urban core, especially in northeastern areas surrounding the Fanshawe Conservation Area. London's development accounts for over half of UTRCA development during the study period. London's urban development was concentrated in the London CSD. CSDs are defined as a municipality by Statistics Canada (Statistics Canada, 2003). Total urban CSD growth over the study period was 1.79% (7.59 km^2), or 0.22%/year (0.95 km^2/year). London CSD population growth for the same period was calculated at 8.74% or 1.1 % yearly.

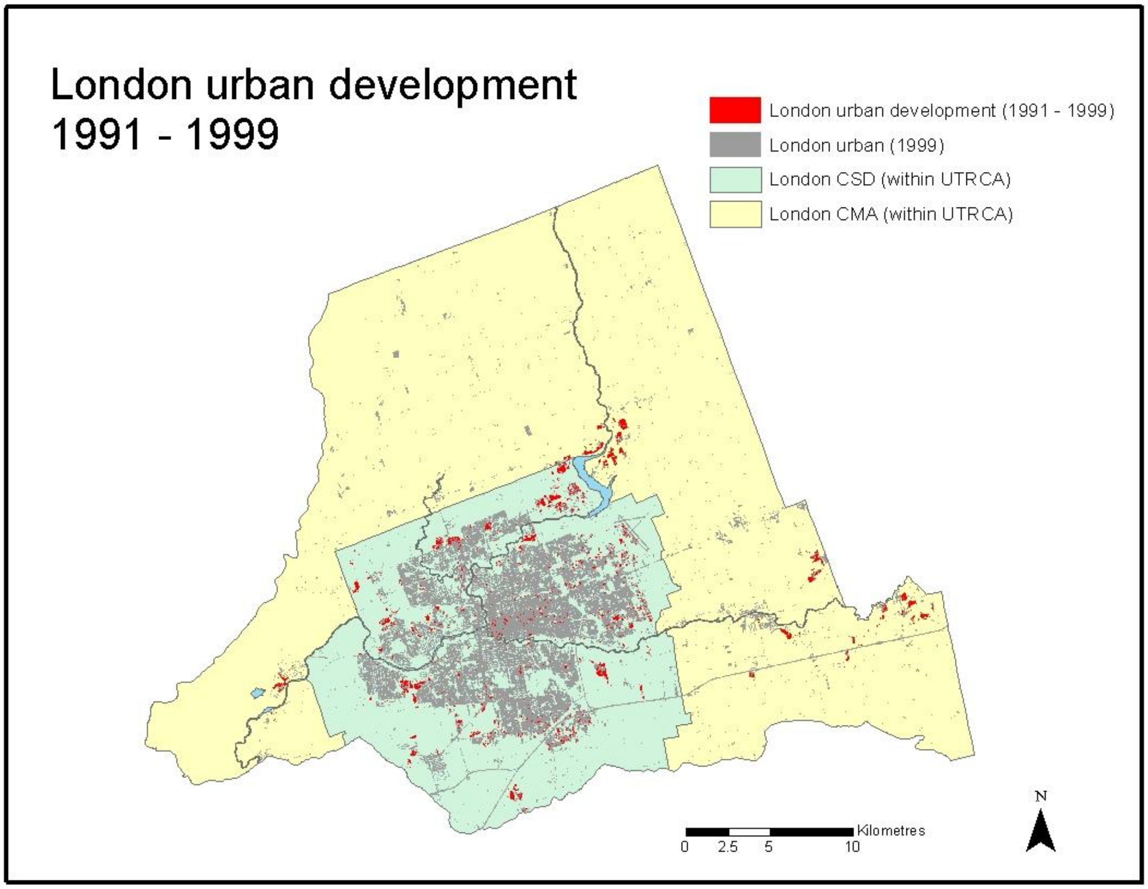


Figure 4.2: London urban development, 1991 – 1999

4.1.1 Woodstock (Census Agglomeration)

Woodstock is the second largest urban area in the UTRCA. It is considered a Census Agglomeration (CA) by Statistics Canada – an urban area with a core population of at least 10000 and surrounding municipalities that interact with this core (Statistics Canada, 2003). Woodstock's population grew by 8% over the study period at a yearly rate of 1.02%, while urban development was found to be 1.8% (0.55 km^2) of the urban region (Figure 4.3). This equates to yearly development at a rate of 0.23% (0.07 km^2/year). Development primarily occurred along the western and southern portions of the CA. Southern development might be due to the proximity of Highway 401, which connects Montreal to Windsor, via Toronto. Fully one half of Ontario's population lives along this corridor (ASG, 2002). Eastern development may be a result of proximity to Toronto, Canada's largest city.

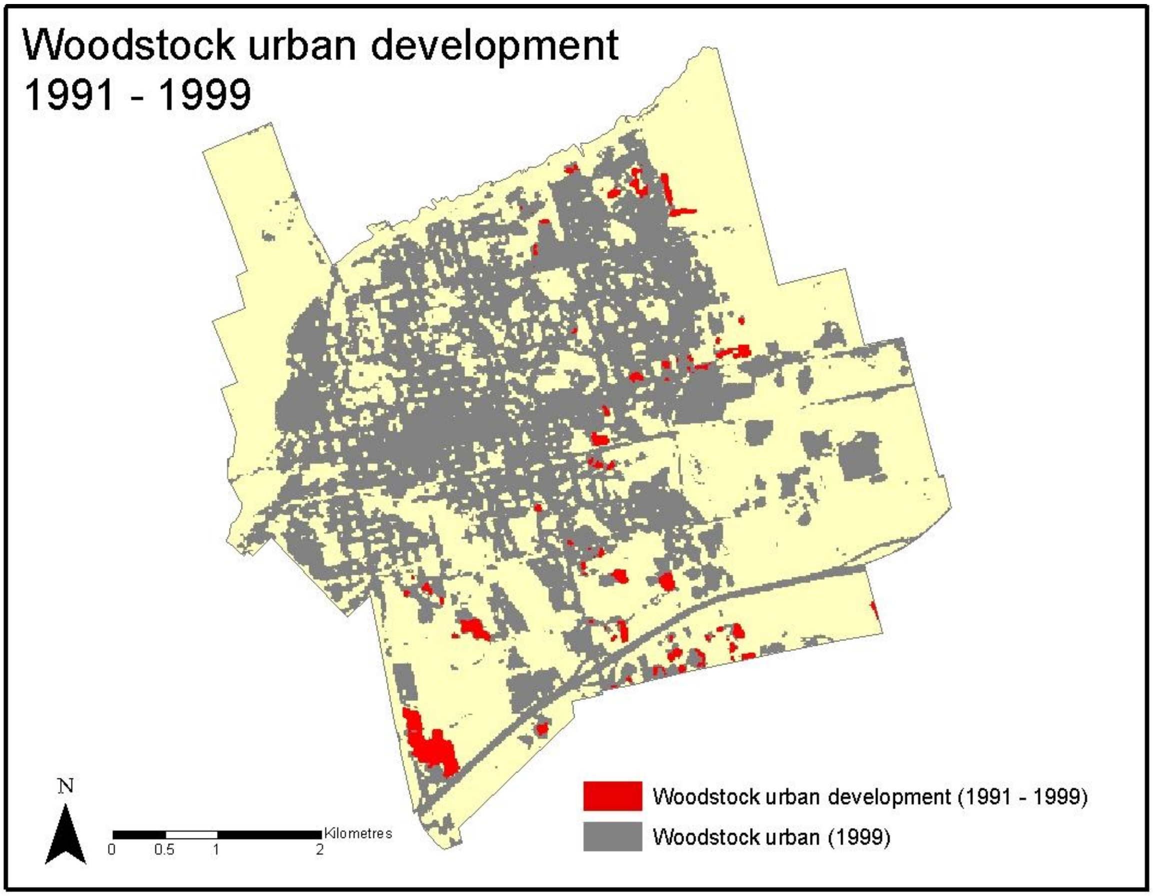


Figure 4.3: Woodstock CA urban development, 1991 - 1999

4.1.2 Stratford (Census Agglomeration)

Stratford experienced the lowest population growth of any UTRCA urban region over the study period at 5.92% or 0.74%/year. However this did not affect urban development as a total increase of 2.97% (0.66 km^2) or 0.37%/year (0.08 km^2/year) was observed (Figure 4.4). These figures are much higher than London and Woodstock, as a percentage of the urban area. Expansion was predominantly found on the periphery of the CA, especially in the southern areas. This may be due to the close proximity to London, Ontario, and Highway 401.

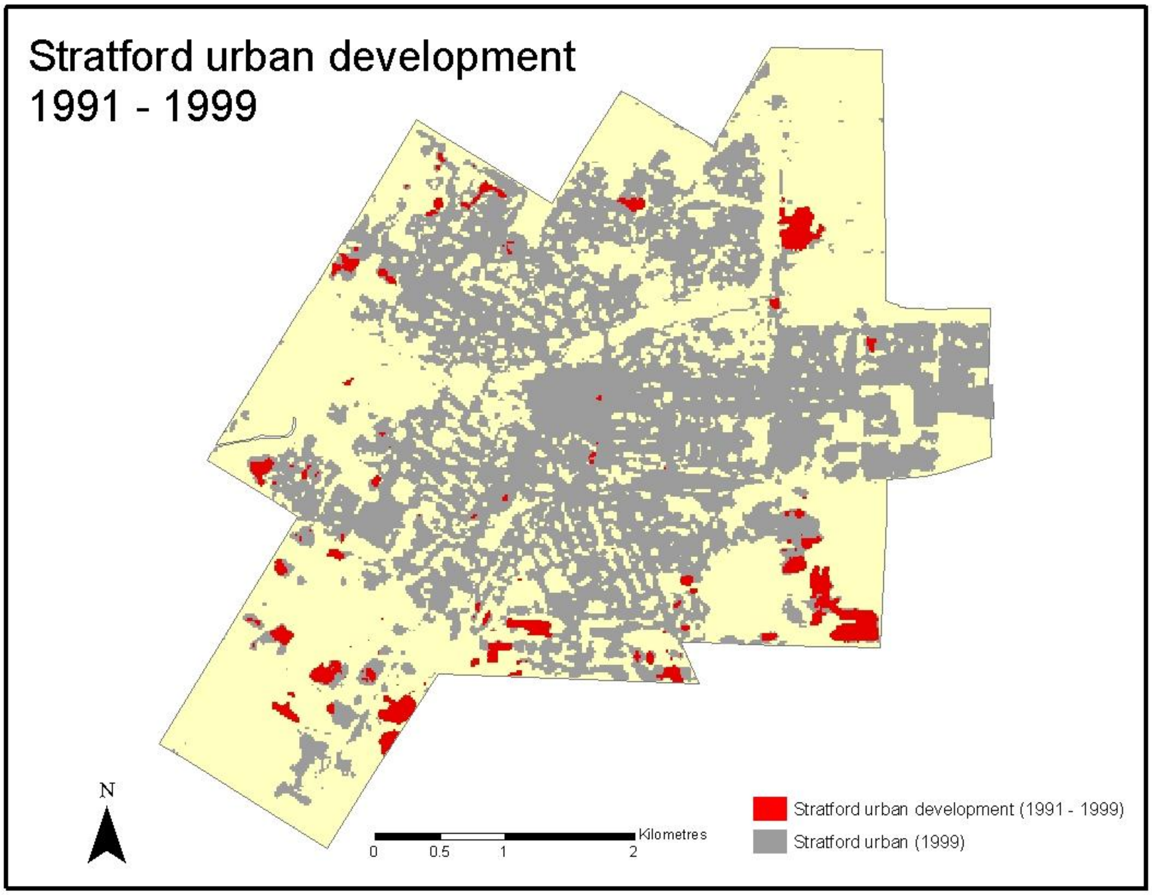


Figure 4.4: Stratford CA urban development, 1991 - 1999

4.1.3 Ingersoll (Census Sub Division)

Ingersoll's population is too small to be considered a CA, so it is considered a Census Sub Division (CSD). Ingersoll's population grew by 1.36%/year over the study period for a total increase of 10.9%. Total urban development was calculated as 2.23% (0.29 km^2) or 0.28%/year (0.04 km^2/year). The majority of development occurred in the southwestern sections of the municipality, which are closer to London (Figure 4.5).

Growth in northeastern portions may be related to the Beachville Lime and Quarry industrial site (BLQ), which is found directly to the northeast of Ingersoll.

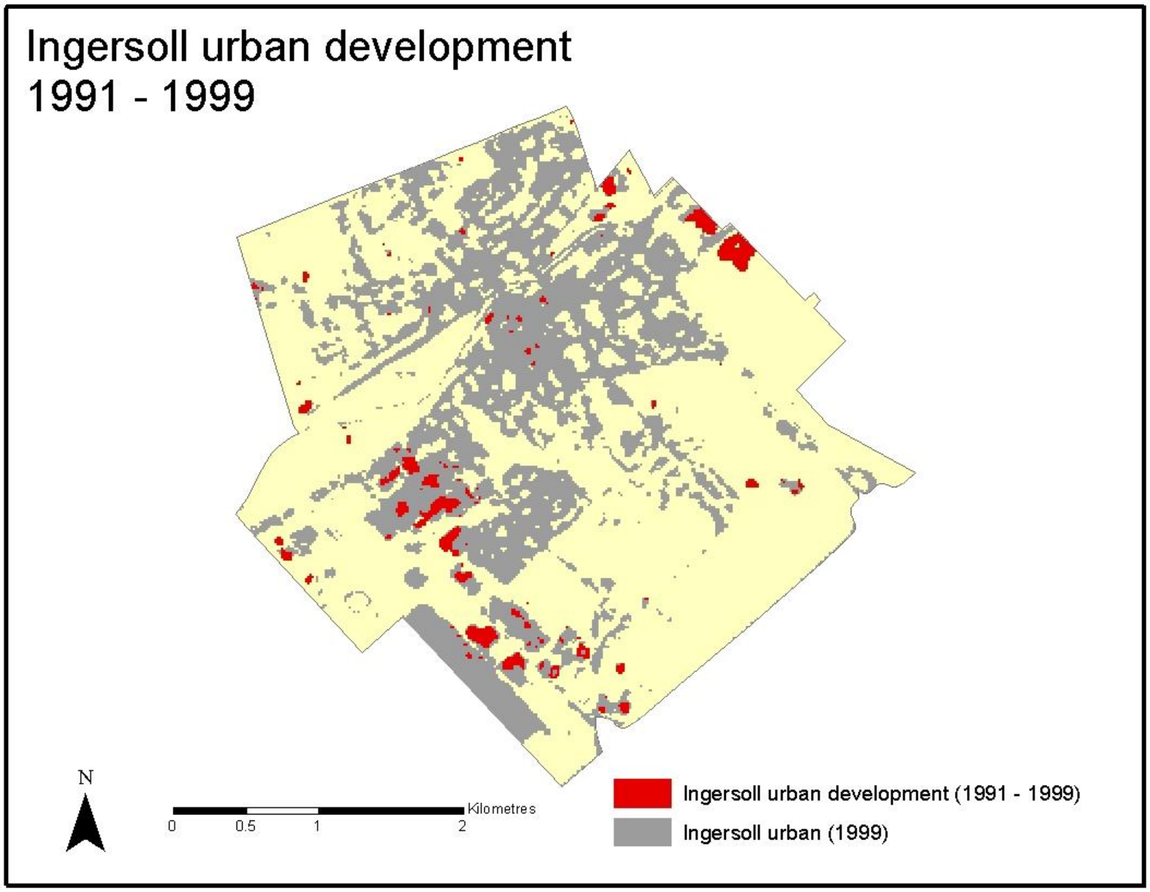


Figure 4.5: Ingersoll CSD urban development, 1991 – 1999

4.1.5 St. Marys (Census Sub Division)

St. Marys is considered a CSD by Statistics Canada. St. Marys population grew by 10.73% over the study period (1.34%/year), and its urbanized region grew by 5.14% (0.65 km^2) - the highest of any UTRCA urban region – at a rate of 0.64%/year (0.08 km^2/year). Development took place predominantly in the southern regions of the CSD (Figure 4.6). Some of this growth may be attributed to the presence of a large pre-existing industrial area in the southwestern regions of the CSD. Significant urban development in the southeastern region of the CSD was not present in 1991 and was present in 1999.

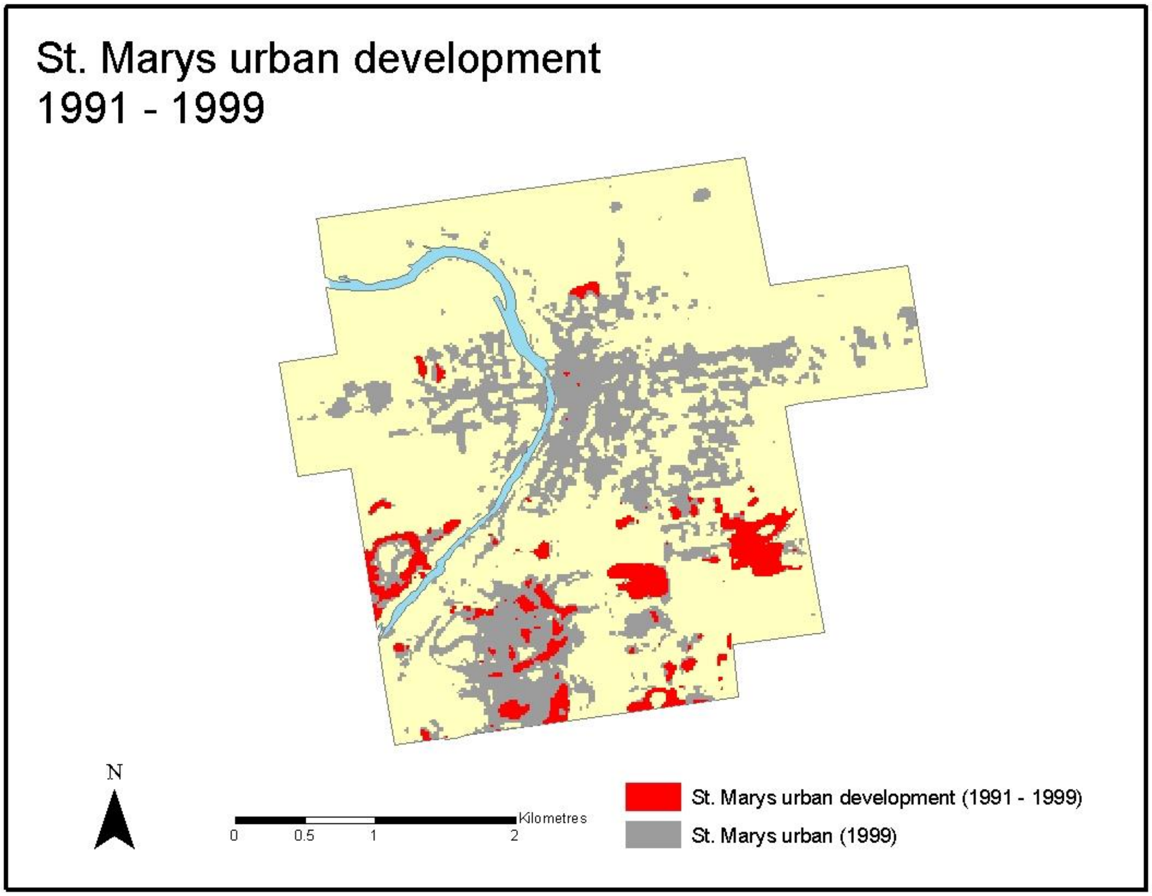


Figure 4.6: St. Marys CSD urban development, 1991 – 1999

4.1.6 Mitchell

Mitchell is the smallest of the six urban regions studied and does not qualify as a municipality or a region. Therefore a polygon was created which encompassed what was thought of as the 'Town of Mitchell' prior to analyzing where urban development occurred. When 'development' was overlaid, it was found to be completely within the created polygon. Mitchell's population grew faster than any urban region in the UTRCA at 12.86% over the study period or 1.61%/year. Urban development was calculated at

3.23% (0.43 km^2) of the study area, which average 0.24%/year (0.05 km^2/year) (Figure 4.7). Major development occurred to the southeast of the urban core, with other significant development in the northwest of the area.

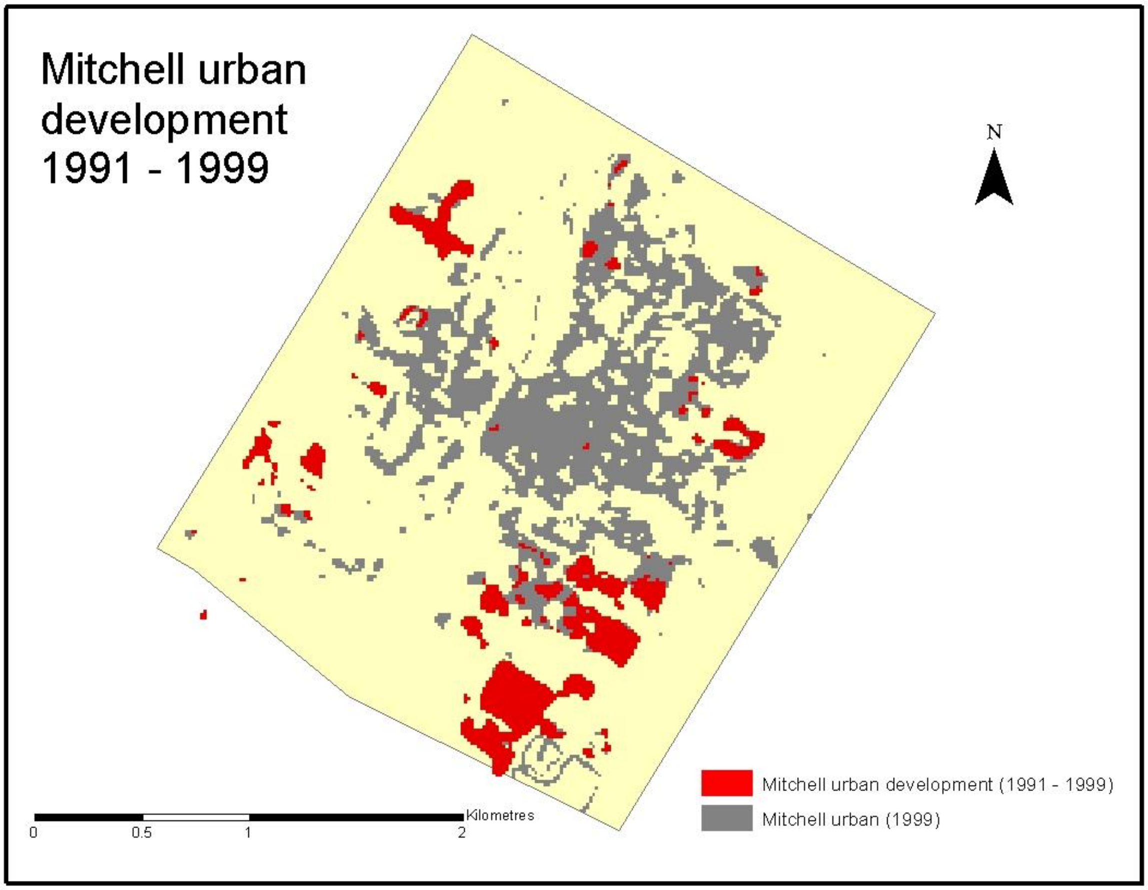


Figure 4.7: Mitchell urban development, 1991 – 1999

4.1.7 Pre-existing construction sites not found within urban polygons

Some UTRCA development occurred at sites away from urban centres, thought to be construction and industrial sites, and has been counted as urban development within the UTRCA. BLQ is a large industrial development found to the northeast of Ingersoll and west of Woodstock and represents a large portion of UTRCA development (Table

4.2). Regions such as BLQ represent a mix of urban development encroaching on green areas and continuing existing development from 1991.

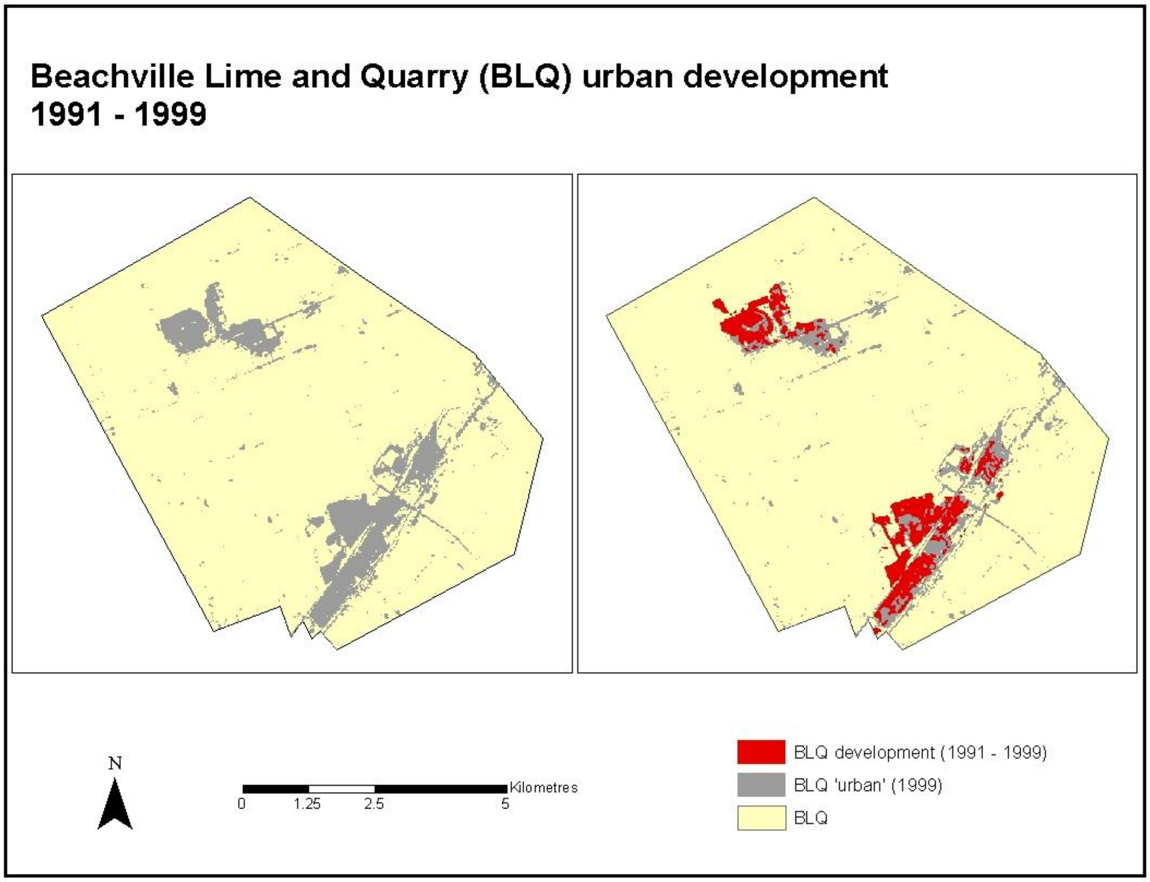


Figure 4.8: BLQ development: actual development and change in BV intensity

4.2 General Development Patterns

London's growth of 1.30km^2/year is in line with other studies concerning Ontario urban development over the same time period. Forsythe (2002b), using a band2 differencing approach, found the Toronto CMA grew by 9.45km^2/year for the period 1990-2000. Toronto is approximately ten times the size of London (Statistics Canada, 2003), which makes the London figure reasonable.

The UTRCA's smaller urban centres are generally growing faster than the region's larger urban areas. Mitchell had the highest population growth at over 12% during the study period, and also recorded the second highest development growth. St. Marys experienced the highest development growth of any urban region within the UTRCA and had population increases of over 10% during the study period, third highest among the six regions studied. These two regions (with the lowest populations) are developing lands at a yearly rate of over 13m^2/capita, well above any other urban areas within the UTRCA; yearly per capita development was highest at 13.85m^2/year in Mitchell (Table 4.3).

Table 4.3: Development statistics per Capita

Urban Region	*Development/Capita in m^2*	*(Development/Capita) /year in m^2*
London CMA	24.38	3.05
London CSD	22.85	2.86
Woodstock	16.80	2.10
Stratford	22.44	2.81
Mitchell	110.79	13.85
Ingersoll	27.55	3.44
St Marys	105.58	13.20

The three largest urban areas within the UTRCA experienced the region's lowest growth and development. Stratford and Woodstock experienced the lowest population increases, at 5.92% and 8.13% respectively. The London CMA had a population growth rate of 10.46% during the study period, while the London CSD, which contains the city's urban core, only grew by 8.74%. Development figures in the three urban areas of London, Woodstock, and Stratford were the lowest in the UTRCA. London CMA yearly development was 3.05 m^2/capita, and was the highest of the three largest urban areas: 2.1m^2/capita in Woodstock and 2.81m^2/capita in Stratford.

4.3 Examples of Landuse Development

There are many types of growth that can be seen within the UTRCA. While no attempt was made here to classify them separately, some examples of the success of the classification procedure can be examined. Figures 4.9 and 4.10 outline different types of development in and around Mitchell. Figure 4.9 represents a change from greenspace into an urban feature (an industrial warehouse and storage area). Figure 4.10 demonstrates urban change in the form of a residential development on the northwestern edge of Mitchell.

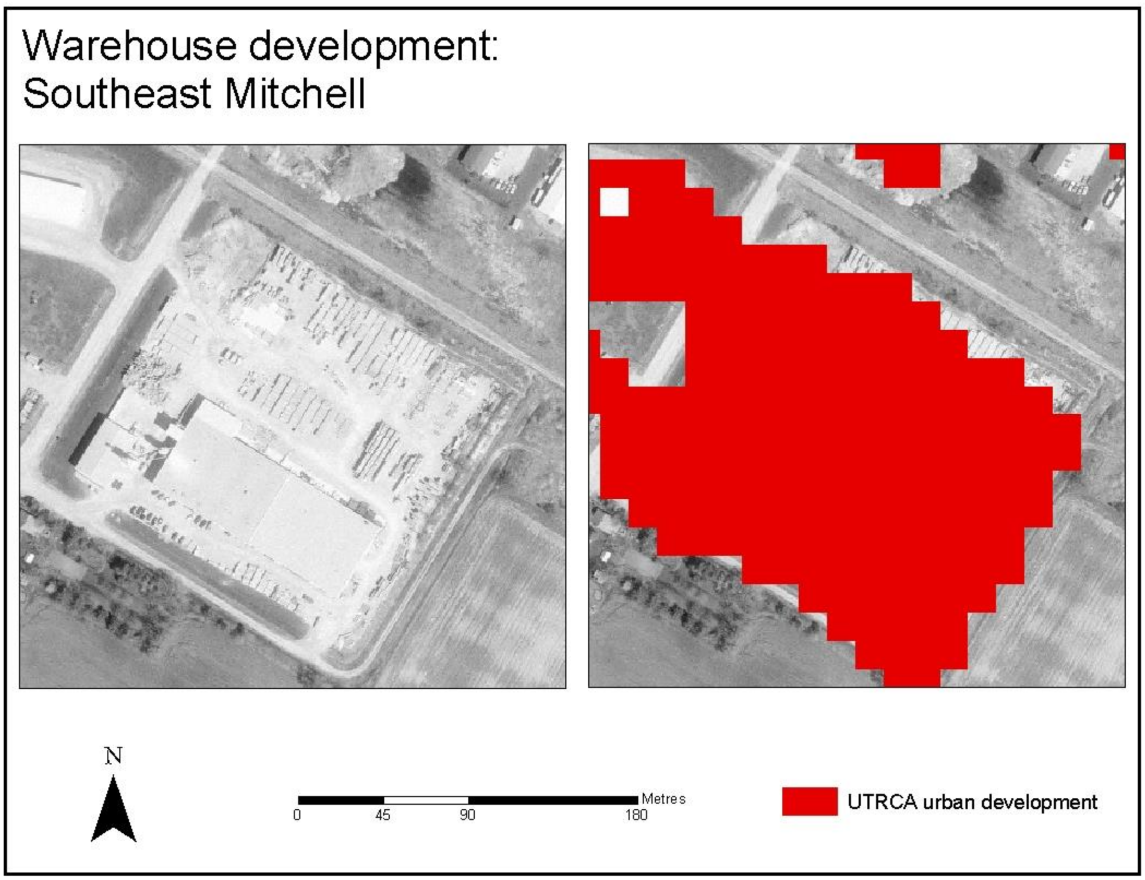


Figure 4.9: Warehouse and storage development, 1991 – 1999; Southeast Mitchell.

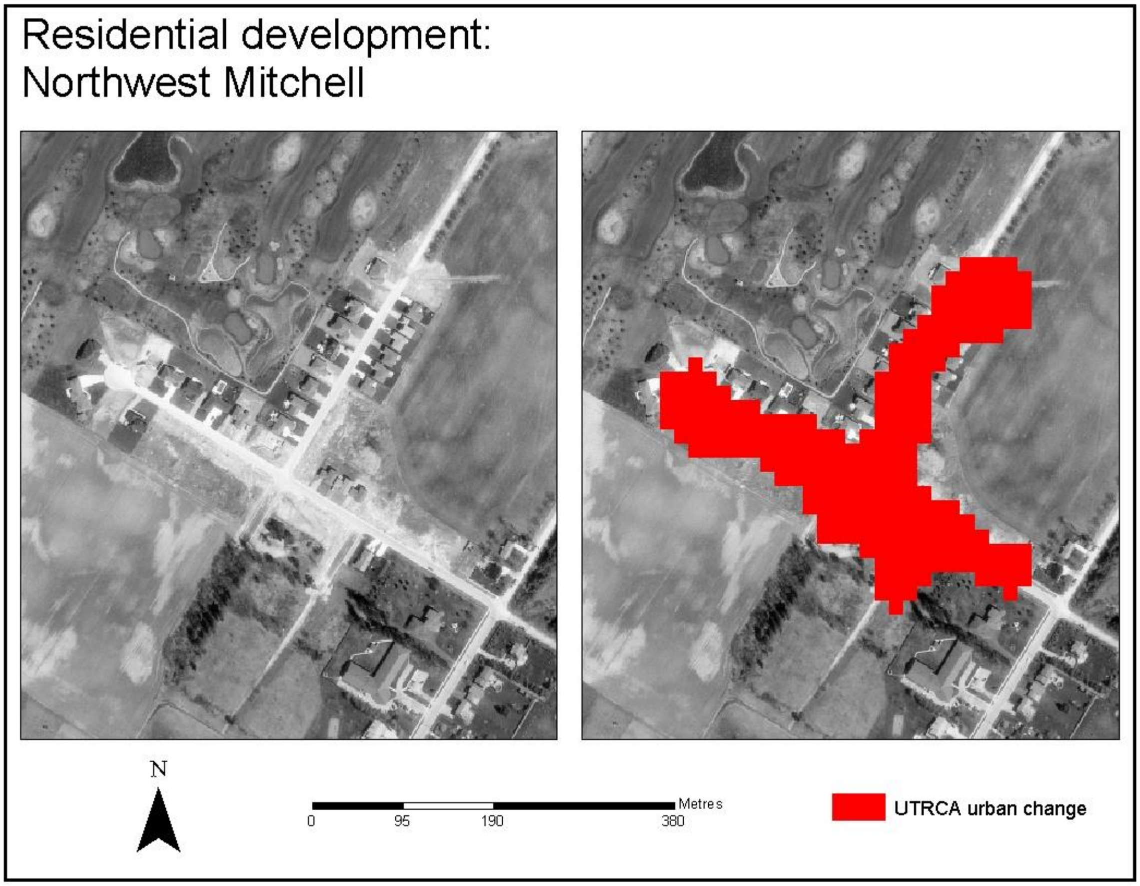


Figure 4.10: Residential development, 1991 – 1999; Northwest Mitchell

Chapter 5: Conclusion

Urban development within the UTRCA was determined from analysis of Landsat TM and ETM+ images. Using a combined band2 differencing and supervised image classification method, urban development was determined to be 17.36 km^2 from 1991 to 1999. The majority of development was concentrated in six UTRCA urban centres. Overall classification accuracy was 90% with no within class *producer's* or *user's accuracy* statistic below 84%.

Development during the study period generally occurred in the southern portions of most of the UTRCA urban centres, with the exception of London CMA which experienced most of its growth in its northeastern sections. Growth in percentage terms was highest in the smaller centres of St. Marys and Mitchell and smallest in the larger regions of London and Woodstock. This could be a result of baby-boomer retirees moving out of larger urban places into smaller communities or larger urban centres focusing on denser housing and development compared to smaller urban areas which do not have the same service provision problems (i.e. public transit) as a city the size of London.

One area where future work could improve upon this analysis is in determining what type of development has occurred in different regions. This research has only focused on 'development', determined through change in brightness values in satellite imagery, and has made no attempt at highlighting different types of urban growth.

If the UTRCA wishes to use this type of analysis to its fullest capabilities it will require that regular development detection study be performed, which should one day include development type analysis when the techniques have been made available. Benefits of this type of research to OCA might occur in many areas including monitoring development in and around floodplains and water quality hazard analysis. While Conservation Authorities such as the UTRCA have a voice in determining where development should occur based on flood risk, their recommendations are not always considered by developers and city planners. Conservation Authorities can use urban development detection analysis to establish whether development is occurring in regions that might be prone to flooding during high rainfall events. If development detection research is conducted on a regular basis it will be possible to monitor development trends and perhaps use this information to divert urban growth from possible areas of flooding.

The UTRCA and other conservation authorities in Ontario can benefit from RS in many ways, such as land use mapping, vegetation analysis, and change detection studies. Limitations of RS studies using optical data revolve around spatial resolution and clear-sky image acquisition issues. Currently it is possible to acquire certain Landsat ETM+ 30m datasets free of charge, which can be further 'Pansharpened' to 15m resolution. These resolutions allow for examination of large areas, but are not suitable for precise smaller study area analysis due to lack of sufficient detail to isolate individual features such as trees or automobiles. This study was confined to using free images available via the World Wide Web, and therefore the study period was determined by the availability of no-cost cloud free images. However, archived Landsat images are available at a cost of $600(US) per image if specific date analysis is required. Finer resolution images, such as IKONOS (1m) and SPOT (2.5m) can be acquired for analysis, but at a higher cost.

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