COMPARING HYPERSPECTRAL AND MULTISPECTRAL IMAGERY FOR LAND CLASSIFICATION OF THE LOWER DON RIVER, TORONTO

by

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Abstract

Urban greenspace is important for the health of cities. Up-to-date databases and information are vital to maintain and record growth in cities. Despite detailed mapping of urban land cover through high resolution imagery, medium resolution data should not be ignored. During the last decade, advances in spaceborne hyperspectral sensors have proven to be beneficial over multispectral sensors for land cover monitoring due to their increased spectral resolution. The objective of this research was to compare Earth Observing-1 (EO-1) Hyperion hyperspectral data to Landsat 5 Thematic Mapper (TM) and Satellite Probatoire d'Observation de la Terre (SPOT) 5 multispectral data for land cover classification in a dense urban landscape. For comparative analysis, aerial orthorectified imagery provided by the Toronto and Region Conservation Authority (TRCA) was used as a ground truth method for accuracy assessment. This study utilized conventional and segmented principal components (CPCA and SPCA) for data compression on the Hyperion imagery, and used principal components analysis (PCA) as a visual enhancement technique for multispectral imagery. Image processing including the generation of the normalized difference vegetation index (NDVI), and mean texture was also performed for both Landsat and SPOT sensors. An unsupervised ISODATA classification was generated on all images to produce a land cover classification map for a portion of the Lower Don River in Toronto, Ontario, Canada. Experiments conducted in this research demonstrated that hyperspectral imagery produced a higher overall accuracy (5-6% better) than multispectral data with the same resolution for defining vegetation cover. However, SPOT generated greater accuracy results than Landsat and Hyperion for vegetation classes.

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List of Acronyms

CPCA – Conventional PCA/Hyperion

EMS – Electromagnetic Spectrum

GIS – Geographic Information System

HSI – Hyperspectral Imaging

ISODATA - Iterative self-organizing data analysis

NDVI – Normalized Difference Vegetation Index

NIR – Near Infrared

PCIDSK – PCI Geomatica Database file

PCA – Principal Components Analysis

SPCA – Segmented PCA/Hyperion

SPOT – Satellite Probatoire d’Observation de la Terre

SWIR – Short wave infrared

TM – Thematic Mapper

TRCA – Toronto and Region Conservation Authority

USGS – United States Geologic Survey

UTM – Universal Transverse Mercator

VIS – Vegetation, Impervious areas, soil

VNIR – Visible and the Near Infrared

CHAPTER 1: Introduction

Urban greenspace has been most valued for its positive effect on air and water quality, the urban heat island effect and ecosystem health. It also allows for rainfall to soak into the ground leading to a decrease in flood events (Arnold and Gibbons, 1996; Banzhaf and Hofer, 2008; Heiden et al., 2012). The spatial distribution of greenspace within dense cities is important for urban planning, sustainable development, as well as an increase in the quality of urban life for surrounding residents. This is important because urban greenspace including individual street trees, public parks, edges of roads, public or private gardens and green infrastructure helps to sustain the quality of urban life and reduces street noise (Ahem, 2007; Davies et al., 2008; Zhou and Rana, 2012). Therefore, the value of greenspace is not necessarily expressed in a monetary term, but a concern for establishing urban social-environmental worth (Cairns, 2006; Paquot, 2005; Zhou and Rana, 2012). Therefore, working towards conservation within densely populated areas is essential. Identifying where these areas are located is important, prior to any efforts being made to protect them.

Since urban green is significant to the health of cities, databases and information are used to keep and record land cover and land use in cities. The Toronto and Region Conservation Authority (TRCA) is a large organization that supports sustainable development in the city. The TRCA manages all nine watersheds and various conservation areas in the Greater Toronto Area (GTA). An important component of their contribution includes land use classification. The TRCA's involvement in conservation is important because the use of satellite imagery allows for the update and storage of historical information on land types. Therefore, prior to analysing patterns and trends such as vegetation change and urban development, it is important to first identify earth surface features from land classification analyses. In this study, by examining land classification accuracies of hyperspectral and multispectral imagery, organizations such as the TRCA can benefit from using new sensor technology for preparation of thematic maps. In summary, spaceborne sensors with high spectral resolutions are ideal for land cover extraction in dense urban areas (Heidens et al., 2012; Jung et al., 2005). This study specifically, is important because it tests multispectral and hyperspectral sensors for classifying land cover.

1.1 Image resolution

There are four types of resolutions in remote sensing including radiometric, temporal, spatial and spectral. Radiometric resolution is the sensors ability to distinguish the differences of intensity in an image, while temporal resolution is the repeat time for a sensor to pass over a geographic region. The most significant components of remotely sensed images are the spectral and spatial resolutions. These resolutions represent the geometric makeup of each pixel and relationship to surrounding neighbourhood pixels in a scene or image. Ultimately, the spatial and spectral resolutions are what set hyperspectral and multispectral imagery apart. Spatial resolution refers to the sharpness level of spatial detail shown in an image (Jensen, 2007; Purkis and Klemas, 2011). It is the measure of the smallest object on the ground set by the sensor representing a single picture element (pixel) in the image. As a result, distance is associated with pixel size describing the side length of a pixel. Thus, the finer spatial resolution is associated with a smaller distance (i.e. 30m by 30m) making it easier for one to define features in a scene.

Spectral resolution represents a particular range in wavelength of the electromagnetic spectrum (EMS) including the number and width of spectral bands measured by the sensor (Purkis and Klemas, 2011). If the sensor captures a small number of wide bands, it has a low spectral resolution. In contrast, if the sensor captures a large amount of narrow bands, the greater the spectral resolution. The advantage of a higher spectral resolution is for interpreters to distinguish between features in an image. The greater/finer detail in a scene, the more likely unique characteristics are to be defined (Jensen, 2007). Based on spectral responses, hyperspectral imagery captures more narrow bands than multispectral in the same portion of the EMS.

1.2 Spectral reflectance of land features

Energy from the sun that reaches the earth's atmosphere and surface is reflected, transmitted or absorbed. The suns position in the sky, time of year, and the terrain on the ground are equally important to the characteristics of features and interaction between these phenomena. Earth surface materials have unique interactions with the atmosphere; hence, the spectral reflectance curve of each feature is affected differently (Jensen, 2007). For example, the spectral reflectance of vegetation varies over different portions of the EMS (Purkis and Klemas, 2011). First, in the visible spectrum, vegetation reflectance and transmittance are small due to a plants ability to greatly absorb chlorophyll (Jensen, 2007). Second, vegetation in the high near infrared (NIR) portion is a strong reflectance that enables great detection of healthy foliage. Third, in the short wave region, moisture in vegetation can be detected because the absorption is strong for water.

1.3 Land cover and land use classification

Land classification is important because it aims to identify and label each pixel in an image to define land cover types. This is followed by pixels being accurately classified, inaccurately classified or unclassified (Purkis and Klemas, 2011). There are two main classification types: supervised and unsupervised. Supervised classification excerpts quantitative information of known training sites by the user in an image while unsupervised classification does not require known areas in an image (Jensen, 2007). Each method results in determining the number and spatial distribution of spectral classes through cluster analysis.

Accurate land cover classification and mapping is important for planning, influencing management and decision making for policy. The ability of satellite imagery is significant for the identification of urban forest and health of vegetation at large scales. Ultimately, to predict the global environment using increased spectral resolution and environmental conditions detected from sensor technology, land cover detection can be analyzed and associated with the parameters of human impacts on Earth (Arnold and Gibbons, 1996; Banzhaf and Hofer, 2008). For data integration and analysis, modelling and map production, spaceborne technology enhances the ability to find ideal solutions to environmental problems. Flood events in a city are an example of an environmental problem; a realistic solution is to plant trees that will reduce the impact of excessive rainfall. Urban landscapes are composed of various materials which make them spectrally complex in satellite imagery. A variety of ground features close together make land identification challenging, and therefore new sensor technology with a higher number of spectral bands such as hyperspectral satellites is crucial for greater analyses.

1.4 Multispectral vs. hyperspectral

Monitoring land cover using satellite sensors such as Landsat and SPOT has been predominant in ecological applications since the 1970s (Pignatti et al., 2009). Considerable advances in remote sensing technology are driven by environmental issues rapidly arising at regional scales. There is lack of literature on the subject of spaceborne hyperspectral imagery comparison and the assessment of land cover information, specifically in urban areas. By comparing hyperspectral and multispectral imagery, accurate vegetation mapping is possible, especially at dense urban scales (Liew et al., 2002). The spectral resolution is the main factor that distinguishes hyperspectral imagery from multispectral imagery (Barry et al., 2001). Hyperspectral sensors contain bands with narrow wavelengths while multispectral sensors contain bands with broad wavelengths. The advantage of using hyperspectral data over multispectral data is the ability to define surface features with a higher spectral resolution. A complete list of spaceborne hyperspectral satellites currently in orbit and set to launch is found in Buckingham and Staenz (2008).

1.5 Research objectives

The objective of this research is to compare hyperspectral imagery to multispectral imagery for classifying urban greenspace surrounding Toronto's Lower Don River. The goal of this study is to make use of Earth Observing-1 (EO-1) Hyperion, Landsat 5 Thematic Mapper (TM), and Satellite Probatoire d'Observation de la Terre (SPOT) 5 for comparing land cover and land use information as well as to examine which sensor is best for defining vegetation. To achieve these objectives, data analyses will be performed by:

- deriving the normalized difference vegetation index (NDVI) and mean texture from original sensor bands for image classification. NDVI and mean texture as well as principal component analysis (PCA) will also be used for visual interpretation;
- producing a conventional and segmented principal component analysis (CPCA and SPCA) on the hyperspectral image as a data compression method; and
- utilizing aerial orthorectified imagery as a ground reference method for accuracy assessment while comparing all three sensors.

1.6 Study area

The study area is the Lower Don River and Toronto's waterfront (Figure 1-1). The Don River is the most urbanized watershed in Canada (TRCA, 2012). Loss of natural areas threatens the Don's watershed health. Significant wetlands are disappearing, and only 7.2% of forested land remains in the Don River watershed (TRCA, 2012). It is affected by its industrial past which makes it a significant area for studying the health of vegetation cover. Today, the Don River watershed consists of 360 square kilometres of land throughout Toronto. A large portion of this area is urbanized development (with over 800,000 residents) which puts stress on the land (TRCA, 2012). The Don River watershed has nine sub-basins. This research will contribute significantly to the assessment of land cover classification and through its use of hyperspectral imagery. In a previous study, Forsythe (2003) used multispectral data fusion techniques to examine residential development over time for the City of Toronto. Ultimately, by using imagery from SPOT 5, Landsat 5 TM and EO-1 Hyperion, this study addresses the gap in literature by incorporating hyperspectral data for assessing land classification in a dense urban watershed.

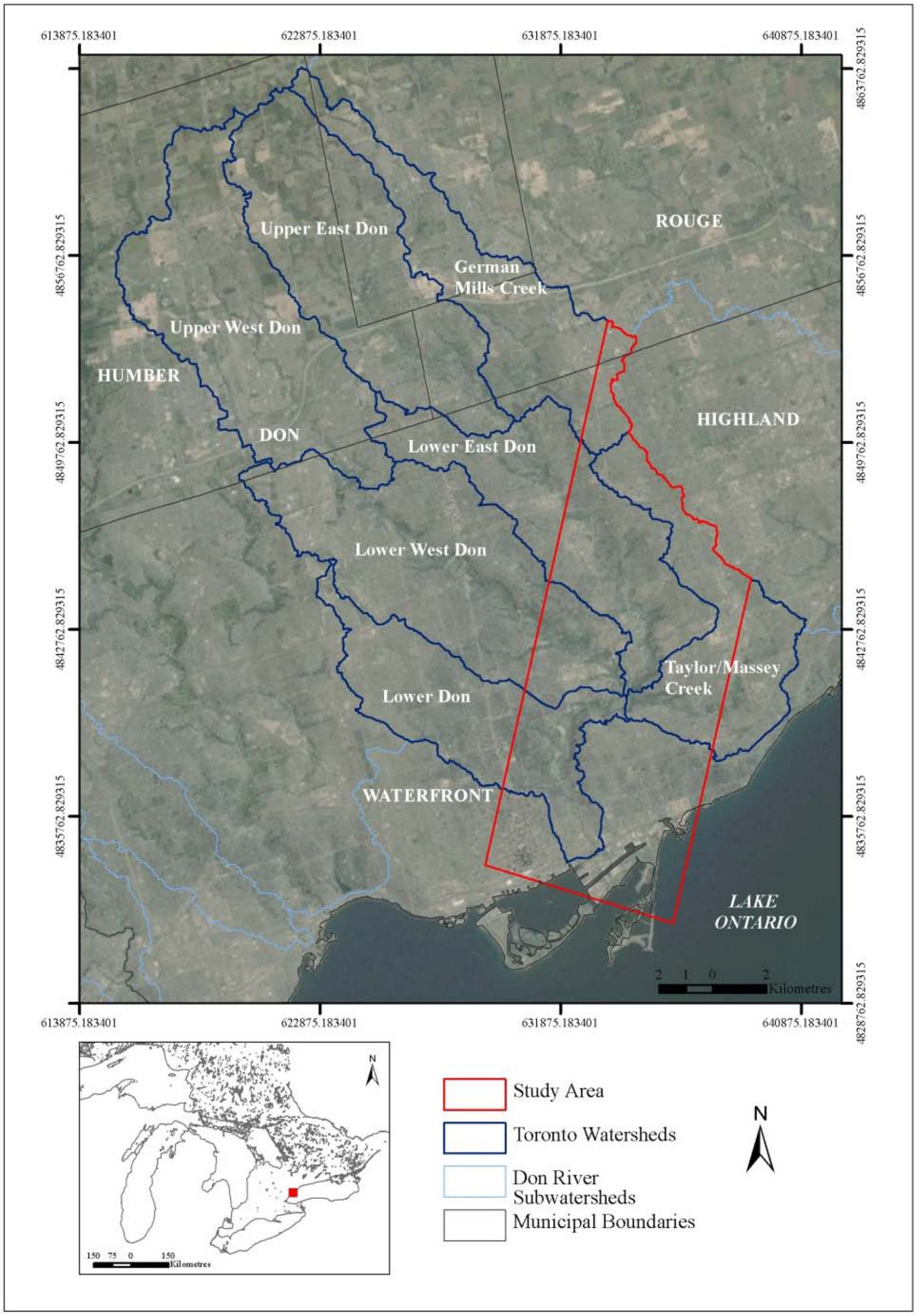

Figure 3-1: Lower Don River Study Area

CHAPTER 2: Literature Review

2.1 Remote sensing and land classification

Remotely sensed data are regularly used for monitoring and assessing land features across large spatial scales and replacing traditional data collection methods, which involve time and cost-intensive ground surveys (Heiden et al., 2012; Pignatti et al., 2009). Classification and mapping of land cover is necessary for sustainable management in growing urban cities, and land cover information extracted using digital and visual image processing is an important approach used to make decisions for such planning endeavours. There are two types of sensors used in this study and discussed throughout this chapter, including optical-mechanical systems, such as the Landsat 5 TM multispectral sensor; and the linear area array system, such as the SPOT 5 multispectral sensor; and the EO-1 Hyperion hyperspectral sensor, also referred to as an imaging spectrometer (Jensen, 2007).

2.2 Differences between hyperspectral and multispectral data

Multispectral satellite remote sensing technologies have been commonly used for remotely sensed classification of vegetation since the early 1960s (Govender et al., 2008; Jensen, 2007). In a single observation, multispectral sensors generate three to six spectral bands of data that range from the visible to NIR of the EMS (Jensen, 2007). This small window of spectral bands is a primary disadvantage to multispectral sensors. During the last decade, advances in imaging spectrometers have begun to fill the gap in multispectral sensor limitations providing better performance in object detection, classification, and identification of earth features (Heiden et al., 2012; Pignatti et al., 2009; Purkis and Kemis, 2011). Hyperspectral sensors commonly collect more than 200 spectral bands that range from the visible to short wave infrared (SWIR) section of the EMS; they provide extensive analyses of earth surface features that would be limited with coarser bandwidths collected by multispectral data. Hyperspectral sensors not only produce detailed spectral data consisting of hundreds of bands in a single collection, linear area arrays are also used, which improves image geometry and radiometry allowing longer instaneous field of view (IFOV) detection and resulting in a more precise reading of an objects radiant flux as it passes over a given landscape (Jensen, 2007). Thus, these advantages have led to recent scholarly and governmental explorations of classification and mapping for land cover and vegetation with the application of hyperspectral imagery (HSI) (Heiden et al., 2012; Jung et al., 2005).

Ultimately, hyperspectral images have advantages over multispectral images. Peijun et al. (2010) demonstrated the benefits of EO-1 Hyperion compared to Landsat TM imagery, and suggest that image spectrometry is more effective when examining urban impervious surfaces. In relation to the advantages of HSI, the unmixing method using linear spectral mixture analysis (LSMA) with hard classification (identifying land classes as impervious surfaces) methods provides greater accuracy (Peijun et al., 2010). When both HSI and multispectral imagery (MSI) are used in classification, such as including different data analysis techniques, accuracy assessment is made easier due to the integration of a higher number of spectral bands and techniques to define earth features. Figure 2-1 shows the differences of multispectral and hyperspectral data in three dimensional space.

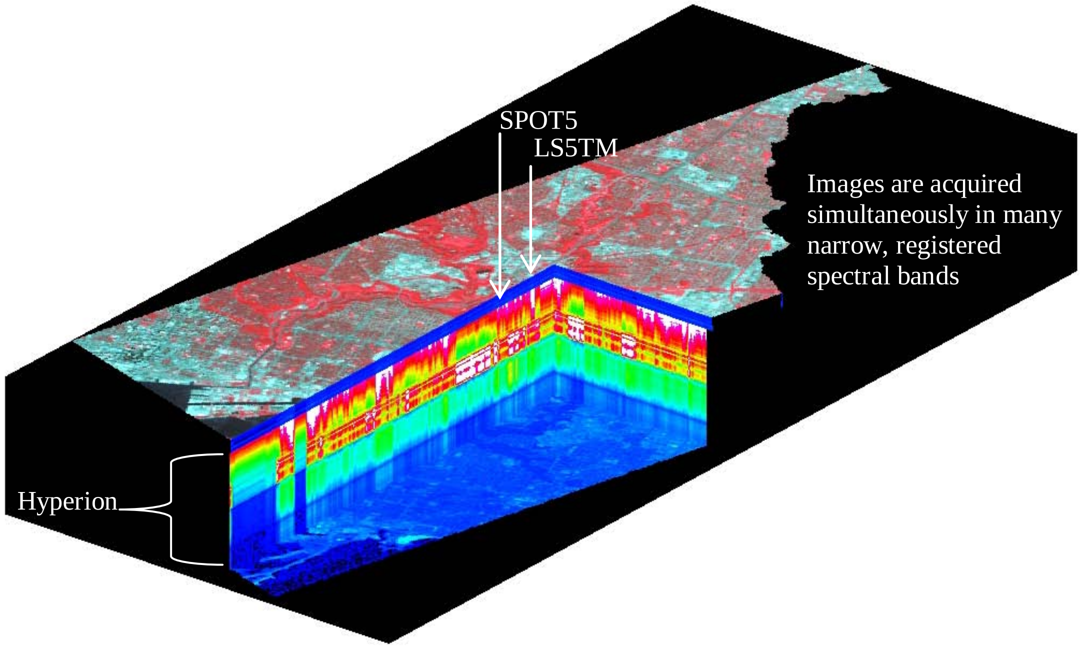

Figure 4-1: 3D data cube

2.3 Data analysis with multiple sensors

Data analysis in remote sensing sometimes involves the integration of information from two or more sensors in order to examine a common theme. In their study, Kruse et al. (2003) compared the performance of the spaceborne Hyperion sensor and the airborne visible/infrared imaging spectrometer (AVIRIS) sensor for mineralogy mapping. By integrating medium spatial resolution multispectral and hyperspectral data with aerial orthorectified imagery, land feature identification is improved due to the higher spectral and spatial resolution combined (Kruse et al., 2003; Smith 2003). This way, more than six spectral bands are used for better definition of earth surface features.

According to recent literature, accurate land cover mapping is best when high spatial resolution data are used (Petropoulos et al., 2012; Pignatti et al., 2008; Smith, 2003; Yang et al., 2010). However, there is a gap in literature that compares high spatial resolution to high spectral resolution when discriminating land types. Govender et al.

(2008) used the Hyperion hyperspectral sensor and the multispectral Proba CHRIS (Compact High Resolution Imaging Spectrometer) sensor and found an overall accuracy of 98%. The authors compared different classification techniques to determine the best accuracy results by verifying the spatial distribution of vegetation classification to true colour images. Various studies have investigated the ability of integrating Hyperion data with other image data (Pu and Gong, 2004; Thenkabaul, 2004; Galvao et al., 2005; Giardino et al., 2007). Ultimately, by analyzing different data processing technology, information in an image can be extracted more accurately.

2.4 Applications of multispectral and/or hyperspectral remote sensing in land resources

Multispectral satellite sensors have been commercially available since the first Landsat satellite was sent into orbit in 1972 (Jensen, 2007). Since the launch of Landsat 1, several sensors have been sent into space with varying spatial and spectral resolutions including the French SPOT 1 satellite that was sent into space in 1986 (European Space Agency, 2012). It was not until 1984 that the Landsat 5 sensor was launched, and in 2002 the SPOT 5 sensor was sent into space (Jensen, 2007). Since the launch of these sensors, various applications and analyses of earth have been undertaken.

In recent studies, SPOT 5 has proven suitable for crop identification, area estimation (Yang et al., 2011) and regional studies of tree canopy-cover patterns (Boggs, 2010). Yang et al. (2011) evaluated the overall accuracy results (91%) of the SPOT 5 sensor alone with a maximum likelihood classification technique; however, their study does not analyze different sensor data, which may influence accuracy results for identifying crop types. In contrast, studies that include image enhancement techniques along with other sensors, have proven to be effective (Boggs, 2010; Peijun et al., 2010;

Pignatti et al., 2009). Boggs (2010) analyzed the ability of the NDVI technique for mapping tree canopy clusters while integrating Quickbird and SPOT 5 imagery and found that by combining these two sensors, regional studies of tree canopy patterns increase accuracy results by ten per cent (85-95%). The two studies previously mentioned are related due to both studies investigating detailed classification of crops and tree canopy while using SPOT 5 imagery.

A major theme in published literature is the use of high spatial resolution data used as reference information to test the performance of hyperspectral and multispectral medium spatial resolution sensor data for accuracy mapping of various land classifications (Peijun et al., 2010; Yang and Everitt, 2010; Winjanarto and Amhar, 2010). Yang and Everitt (2010) suggest that by combining aerial photography with hyperspectral and multispectral data, monitoring and mapping infestations of broom snakeweed in the western United States increases overall accuracy results for classification maps of 95%. Similarly, Peijun et al. (2010) found that using high resolution Quickbird imagery as a ground reference produced an overall accuracy of approaching 87% in their study.

Within the last decade, hyperspectral remote sensing has gained awareness in research and analysis. Currently, with spaceborne sensors such as the EO-1 Hyperion, hyperspectral data collection is rapidly expanding to applied satellite sensor research studies. Applications including water management, agriculture and ecological monitoring have advanced with the aid of hyperspectral imagery (Govender et al., 2007; Pignatti et al., 2009). The importance of using imaging spectrometry lies in the spectral resolution rather than spatial resolution compared to multispectral imagery.

Hyperspectral data can be used for analyzing various terrestrial applications. Griffin et al. (2005) provide three examples for analyzing EO-1 Hyperion data in different applications including cloud-cover analysis, coastal water feature extraction, and terrestrial analysis applications. Classification of different terrain types, including soil moisture, vegetation chlorophyll, and plant liquid water, was observed to define several agricultural fields. Through this research, they suggest that hyperspectral data offer value when using selected or full spectral bands (Griffin et al, 2005). Ultimately, HSI is versatile when extracting data such as band thresholds, ratios, and differences of earth features for object definition.

Applications in vegetation studies have been conducted by integrating multiple sensors. Recent applications for integrating both multispectral and hyperspectral sensor types involve vegetation classification at larger scales. Van de Voorde et al. (2008) compared the unmixing mapping potential at the pixel level of Hyperion with that of Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and stressed that to classify urban vegetation at a spatially detailed level, linear spectral unmixing attains sufficient accuracy in Brussels, Belgium. In contrast, Wijanarto and Amhar (2010) used the combination of Hyperion and the Moderate Resolution Imaging Spectroradiometer (MODIS) to conduct tropical biodiversity mapping in Bogor Botanical Gardens in Indonesia to address the need of a tropical spectra library, while at the same time suggesting that band selection is most significant for defining features. Souza et al. (2010) conducted a more detailed study using 18 narrowband Hyperion data for canopy cover in the Brazilian Savannah. The authors found that physical parameters of different vegetation species, including grassland and savannah to tall semi-deciduous forest, largely correlated with Hyperion vegetation indices such as the NDVI, therefore comparing Hyperion spectral bands and biophysical parameters together. In similar research conducted by Pu et al (2008) in California, USA, three different sensors including Hyperion, Advanced Land Imager (ALI) and Landsat 7 ETM were used to map forest crown closure and the leaf area index (LAI) for comparative analyses. The study found that Hyperion outperforms all sensors due to its high spectral resolution.

An emerging application in urban environmental studies is to compare the ability of Hyperion sensor data to other satellite sensors, mainly ones that are multispectral including airborne sensors (Goodenough et al., 2003; Walsh et al., 2008). Hyperspectral remote sensing has become common in urban environments to monitor the urban influence on impervious surfaces (Van der Linden et al., 2009; Weng et al., 2008; Lu and Weng, 2006). At a regional level, Peijun et al. (2010) analyzed Hyperion and Landsat 5 TM data for urban impervious surface extraction and compared it to Quickbird images as referencing earth features for assessing the accuracy for each sensor in Xuzhou City, China. In their study, Heiden et al. (2011) describe an urban structure type (UST) application to assess ecological state in urban planning for Munich, Germany. The findings demonstrate the hyperspectral sensors ability to derive urban land cover for complex analyses of large dense areas and updating surface material databases for use in urban development. Chang et al. (2011) present a challenging analysis where they develop techniques to perform an unsupervised linear spectral mixing analysis (ULSMA) to determine the number of signatures in an image. This study located spectral signatures used to unmix data; this is complex compared to supervised linear spectral mixing analysis (SLSMA) because the target signatures are unknown rather than a priori. Jung et al. (2005) examined hyperspectral imagery and its detection of vegetation in an urban landscape and found that when discriminating different types of vegetation, the SWIR bands are most reliable. They attempted to detect the effect of vegetation on micro-scale environmental problems among build-up conditions.

Successful applications for defining vegetation at medium spatial resolution by incorporating spectral unmixing techniques are seen in various studies (Liew et al., 2002; Peijun et al., 2010; Petrou and Foschi, 1999; Pignatti et al., 2009; Ridd, 1995; Settle and Drake, 1993; Van de Voorde et al., 2008). These studies have shown that ULSMA is an effective way to map land surface and vegetation where it uses fractions of land cover to define in each pixel. By characterizing urban environments through LSMA, the Vegetation-Impervious-Soil (VIS) model is widely used in urban landscapes (Van de Voorde et al., 2008). The VIS model is useful because it represents three physical components of urban environment including vegetation, impervious areas and soil (VIS). If these three components could be clearly signified as endmembers in space, fractions extracted from unmixing a dense area would enable pixels to be placed in the VIS model. Van de Voorde et al. (2008) found that unmixing pixels using LSMA provides greater accuracy then hard classification methods while using linear modelling portions of impervious surfaces for each sensor compared. They suggest that the use of the VIS model is important when extracting impervious areas from dense cities. The potential analysis of urban form and features on the ground for medium resolution satellite imagery can therefore be analyzed with the VIS model.

2.5 Data Compression using Principal Components (PC)

Use of hyperspectral imaging (HSI) potentially gives researchers (Datt et al., 2003; Khurshid et al., 2006; Tsai et al., 2007) the advantage to accomplish complex analyses that are often difficult with multispectral imaging. One advantage of HSI is maintaining a greater amount of spectral bands to define land cover in dense urban regions. Nevertheless, hyperspectral sensors compared to multispectral sensors may cause new difficulties in data processing and analysis that could hinder the success of certain research endeavours. One of the difficulties of handling hyperspectral datasets is the size of data that requires more attention due to its high data dimensionality and redundancy (Khurshid et al., 2006; Tsai et al., 2007). These concerns alone may result in low accuracies when classifying land features. Ultimately, hyperspectral analysis involves crucial attention to data compression. By not compressing hyperspectral data and only selecting a few bands for analysis, the continuity of spectral data and the sensors full capacity would not be considered.

Reducing dimensionality in a large dataset while maintaining the data and their complexity is the best tactic. An example of a developed algorithm for such data handling includes maximum noise fraction (MNF) proposed by Green et al. (1988). Ultimately, this data compression approach specifically considers the large amount of data in HSI while maintaining useful information to redevelop a dataset with as few bands as possible which ideally represent most of the important data and, as a result, reduce dimensionality of data (Small, 2001).

Another approach to reduce data dimensionality for large datasets is PCA. Studies often use PCA for visualization interpretation purposes such as feature extraction for reducing data dimensionality and defining classes when performing classification (Kaarna et al., 2006; Liew et al., 2002; Myint et al., 2011; Sanchez-Hernandex et al., 2007). However, greater research and usability of PCA for data compression is not as common in literature. Nevertheless, Cheriyadat and Bruce (2003) used airborne hyperspectral data and found that data compression is effective, but ineffective for supervised classification where areas of known features are defined. They argued that PCA does not necessarily retain the important feature characteristics in higher order principal components where crucial information may be present in a lower order component and can therefore be eliminated for analysis. In this study, each PC was closely examined to include the best results for classification.

For more effective extraction of vegetation over complex study areas, segmented principal components analysis (SPCA) has been applied to enhance conventional principal components analysis (CPCA) methods (Datt et al., 2003; Kaarna et al., 2006). Since vegetation contains diverse structure types, the characteristics, including absorption and reflectance across different portions of wavelengths, also differ (Bell and Baranoskie, 2004). If PCA were to be generated for each range of the spectrum (VNIR, SW1 and 2) the significant information is better maintained for each separate portion rather than CPCA which is generated across an entire spectrum (Tsai et al., 2007). Ideally, a SPCA should produce greater accuracy results for classification purposes.

In summary, recent research has shown that greater accuracy results are produced when analyzing hyperspectral data in combination with multispectral data for identifying various land cover in complex landscapes (Barry et al., 2001; Koch et al., 2005; Liew et al., 2002; Peijun et al., 2010; Pignatti et al., 2008; Wijanarto and Amhar, 2010). This research will compare the three sensors for mapping and classification of vegetation health in urban areas using hyperspectral and multispectral data.

CHAPTER 3: Data and Methodology

3.1 Data collection

Hyperion is a hyperspectral satellite aboard the EO-1 spaceborne platform covering the spectral range of 450-2600 nanometres (nm) consisting of 220 bands at a spatial resolution of 30 metres (Jarecke and Yokoyama, 2000; USGS, 2011). This push-broom imaging spectrometer satellite was launched in November, 2000 by NASA for the purpose of studying terrestrial vegetation (Griffin et al., 2005) and to establish the viability and performance of advanced sensors for the Landsat series (USGS, 2011). In contrast, multispectral sensors contain broad spectral bands ranging from the blue, green, red, NIR, mid-infrared (MIR) and far-infrared (FIR) of the EMS for Landsat 5 TM and green to the MIR and the SWIR for SPOT 5. The imagery used for this study were obtained from the US Geological Survey's Earth Explorer (http://earthexplorer.usgs.gov/) server and the GeoBase Canada (http://www.geobase.ca/) server, which were preprocessed at level one radiance, systematic and terrain corrected (See Table 3-1). All three images were subset to conform to the Hyperion dataset and within the boundaries of the Lower Don River watershed as well as the Toronto waterfront.

Ultimately, this study utilizes three different satellite images including Landsat 5 TM, EO-1 Hyperion and SPOT 5 from July 17th in 2008, August 1st, August 11th in 2007 respectively. Table 3-2 shows a complete list of the data and will be further explained. The multispectral data from both sensors were subset based on data available from Hyperion. Aerial orthorectified imagery provided by the TRCA was used as a ground reference for accuracy assessment of the study area. This research attempts to perform a land cover classification using hyperspectral and multispectral data over the Lower Don River at Toronto's harbour front.

Table 3-1: Hyperspectral and multispectral data characteristics

Parameters	Multispectral	Multispectral	Hyperspectral
WRS - 2 Projection	**SPOT 4**	**LS5TM**	**EO-1 Hyperion**
Spectral Range	500-1750 nm	400-2400 nm	400-2600 nm (10 nm ea.)
Spatial Resolution	20 nm	30 m	30 m
Swath Width	60 km	185 km	7.5 km
Acquisition Date	August 1st, 2007	July 17th, 2008	August 11th, 2007
Number of Bands	4	6 & Thermal	220
Bands used	1-4	1-5, 7	14-55, 135-163, & 191-212

The NDVI, PCA and mean texture image processing techniques were performed on each image scene to evaluate certain spectral characteristics for vegetation health in a complex urban landscape as well as to achieve dimensionality reduction. An unsupervised classification and iterative self-organizing data analysis (ISODATA) classification were performed to examine the difference in spectral classes for land cover. Classification was only performed on those bands in common with Landsat and SPOT; the effect of the SWIR band on classification results was examined. The data collected for this study included the three sensors that were based on their medium resolution and no cost availability.

3.2 Image acquisition

The image time of acquisition presented in Table 3-1 shows different dates for each sensor. It is inevitable that freely available data from three separate sensors are acquired at a different date and time, and with minimal cloud coverage. The EO-1 Hyperion image acquired on August 11th, 2007 is the only image available for this sensor, thus, the Landsat 5 TM and SPOT 5 images had to be as closely matched as possible in acquisition dates. Various multispectral images were examined, and the two considered in this study have the less than 10% cloud coverage. Although the SPOT sensor is within days (August 1st, 2007) of the Hyperion sensor, the closest available data for Landsat 5 TM is unfortunately acquired almost an entire year after (July 17th, 2008). Although not much change can occur in a large city within a span of a year, this time difference may affect results of this particular study. For example, underdeveloped land for commercial purposes may be developed within a year.

3.3 Hyperion data pre-processing

Data preparation for hyperspectral imagery was necessary. Image rectification, also known as geometric correction was conducted on Hyperion by using PCI Geomatica OrthoEngine's generic satellite model by collecting eighteen ground control points (GCPs) in reference to the Landsat 5 TM imagery. An overall root mean square (RMS) error of 0.59 was achieved as less than one is a necessity. Prior to analysis, all three images were projected to the North American Datum 1983 universal transverse Mercator (UTM) Zone 17 North projection and visually inspected for alignment. For the reason that multispectral sensors have few and wide band widths, the Hyperion band selection involved carefully choosing spectral responses that resemble those of Landsat and SPOT in the VNIR and SWIR regions.

3.4 Good Band Selection for the EO-1 Hyperion Dataset

This section briefly describes the pre-processing methods applied for good band selection of Hyperion imagery. Level one terrain corrected data was converted into PCI Geomatica format files (.pix). 'Bad' band selection was performed first, non-calibrated bands according to Petropulos et al. (2012), Pu et al. (2008), Wijanarto and Amhar

(2010), Carter et al. (2009) and Jarecke et al. (2001) were removed including bands 1-7, 58-78, 225-242; these bands were also visually reviewed. According to the USGS (2011) 198 calibrated bands cover 426 to 2395 nm of the EMS. Second, water absorption bands including 120-132, 165-182, 185-187, 221-224 were eliminated to reduce the influence of atmospheric scatter, and water vapour absorption that are caused by mixed gasses (Petropoulos et al., 2012). Third, bands visually identified as vertical stripes were eliminated including 8-13, 56-57, 79-83, 97-102, 119, 133-134, 152-153, 164, 183-184, 188-190, 213-220. Images containing vertical stripes are a result of faults with push-broom based sensors and usually removed after visual inspection (Petropoulos et al., 2012; Pu et al., 2008; Wijanarto and Amhar, 2010). Atmospheric correction was not conducted because the images are already terrain corrected and according to Petropoulos et al. (2012) it is not necessary in a single observation. The Hyperion wavelength (nm) ranges were then compared to Landsat 5 TM and SPOT 5 and reduced from 122 to 93 Hyperion bands (correlated between each of the sensors wavelength portions) and used for analysis. The Hyperion bands selected to correlate with the two multispectral sensors were chosen based on Carter's et al. (2009) study and are shown in Table 3-2.

Table 3-2: Sensor image data

<table>
<tr><th>EMS</th><th>LS5TM</th><th>WL(nm)</th><th>SPOT5</th><th>WL (nm)</th><th>Hyperion</th><th>WL (nm)</th><th>Correlated nm)</th></tr>
<tr><td>Visible</td><td>1</td><td>450-520</td><td>n/a</td><td>n/a</td><td>14</td><td rowspan="4">488-926</td><td>488-520</td></tr>
<tr><td>Visible</td><td>2</td><td>520-600</td><td>1</td><td>500-590</td><td>21</td><td>520-590</td></tr>
<tr><td>Visible</td><td>3</td><td>630-690</td><td>2</td><td>610-680</td><td>31</td><td>630-680</td></tr>
<tr><td>NIR</td><td>4</td><td>760-900</td><td>3</td><td>780-890</td><td>48</td><td>780-890</td></tr>
<tr><td>SWIR 1</td><td>5</td><td>1550-1750</td><td>4</td><td>1580-1750</td><td>150</td><td>1488-1790</td><td>1580-1750</td></tr>
<tr><td>SWIR 2</td><td>7</td><td>2080-2350</td><td>n/a</td><td>n/a</td><td>206</td><td>1972-2365</td><td>2080-2350</td></tr>
</table>

3.5 Methodology

Principal component analysis, as previously mentioned, is a transformation that extracts useful features from the image correction matrix (Sanchez-Hernandex et al., 2007; Tsai et al., 2007). It can be used in analysis as an additional parameter to classify data together with original RGB imagery and also is used as the basis for classification methods. In this paper, PCA is used in both ways, to compress Hyperion data, and to use in visual interpretation of multispectral data. A complete methodology work flow for this paper is shown in Figure 3-1.

By using PCA to compress data, Liew et al (2002) produced a land cover classification map using unsupervised ISODATA from a PCA (on dominant components) for two tropical regions in Southeast Asia. They compared the results of classification to land cover maps during the same time period. The authors state that hyperspectral data contains redundant spectral bands and this issue can be removed using PCA (Liew et al., 2002). This could be the reason why hyperspectral data are unable to classify properly due to the coefficient variables for each detailed spectral channel, which is too small to produce an error matrix (Kaarna et al., 2006). Therefore, by using PCA, all original 93 bands (good bands) are able to be processed for analysis.

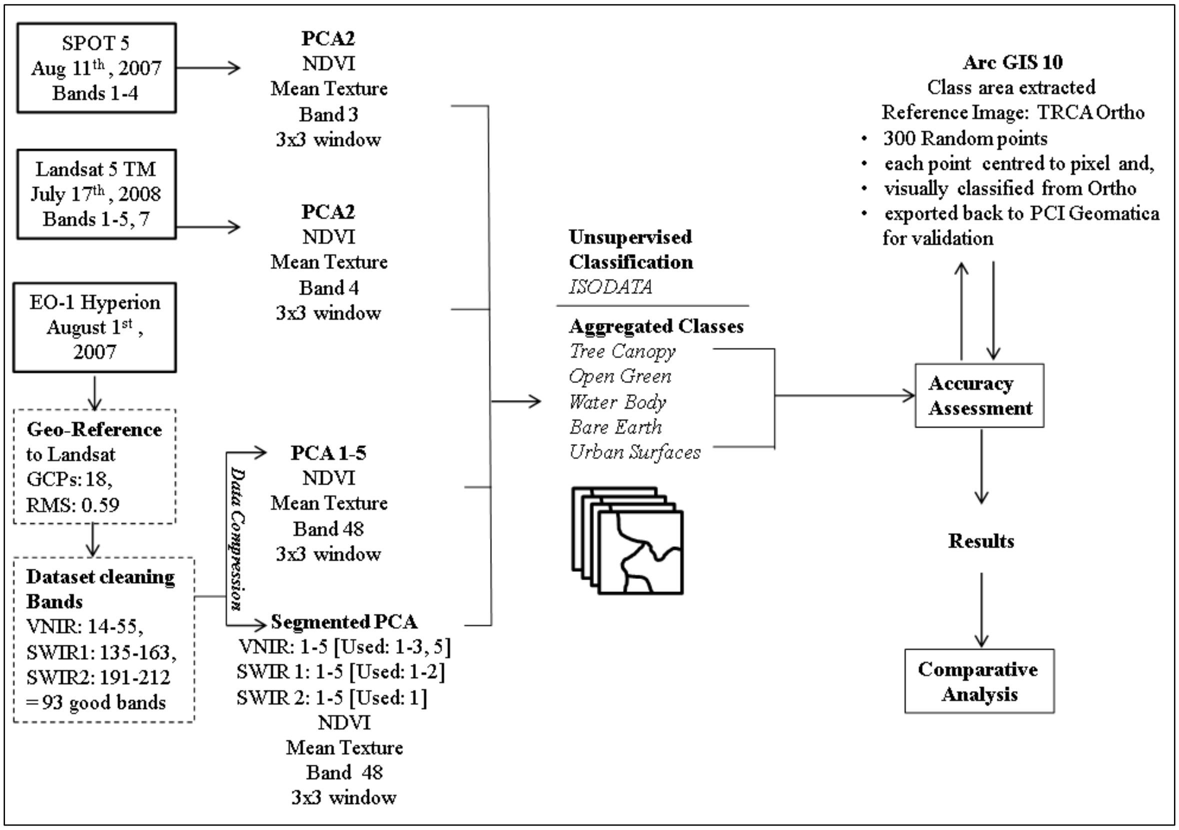

Figure 5-1: Methodology workflow

Figure 3-2 shows the PCs generated from conventional Hyperion. There are five PCs generated because of the large amount of spectral bands to be compressed. According to Tsai et al. (2007), even though the first three PCs contain the most information with fewer bands, there may be a PC in lower order that contains important information when using hyperspectral imagery. In addition to the CPC data compression method, a PCA segmentation was performed which separated the VNIR (PCs 1-3 and 5) and SW1 (PCs 1-2) and SW2 (PC 1) for defining land cover from land use (See Figure 3-3 and Figure 3-4). Based on the eigenvalues and the PCs that visually looked unaffected by stripes, these PCs were combined to generate an additional classification for Hyperion. In contrast, the PCA 2 was chosen by visual inspection of the images that contained the least image distortion for the multispectral images.

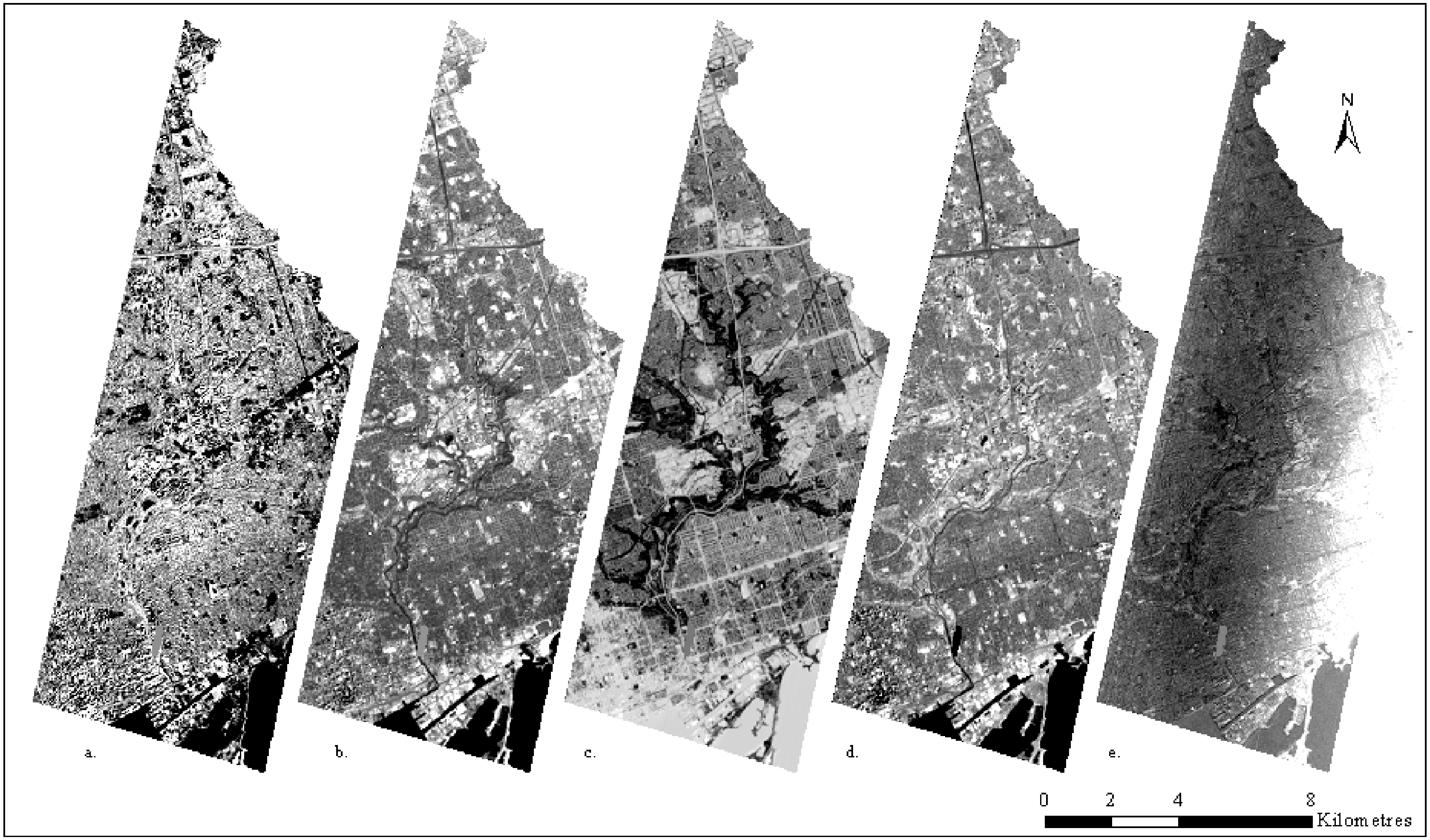

Figure 3-2: PCs 1-5 (a–e) for conventional Hyperion.

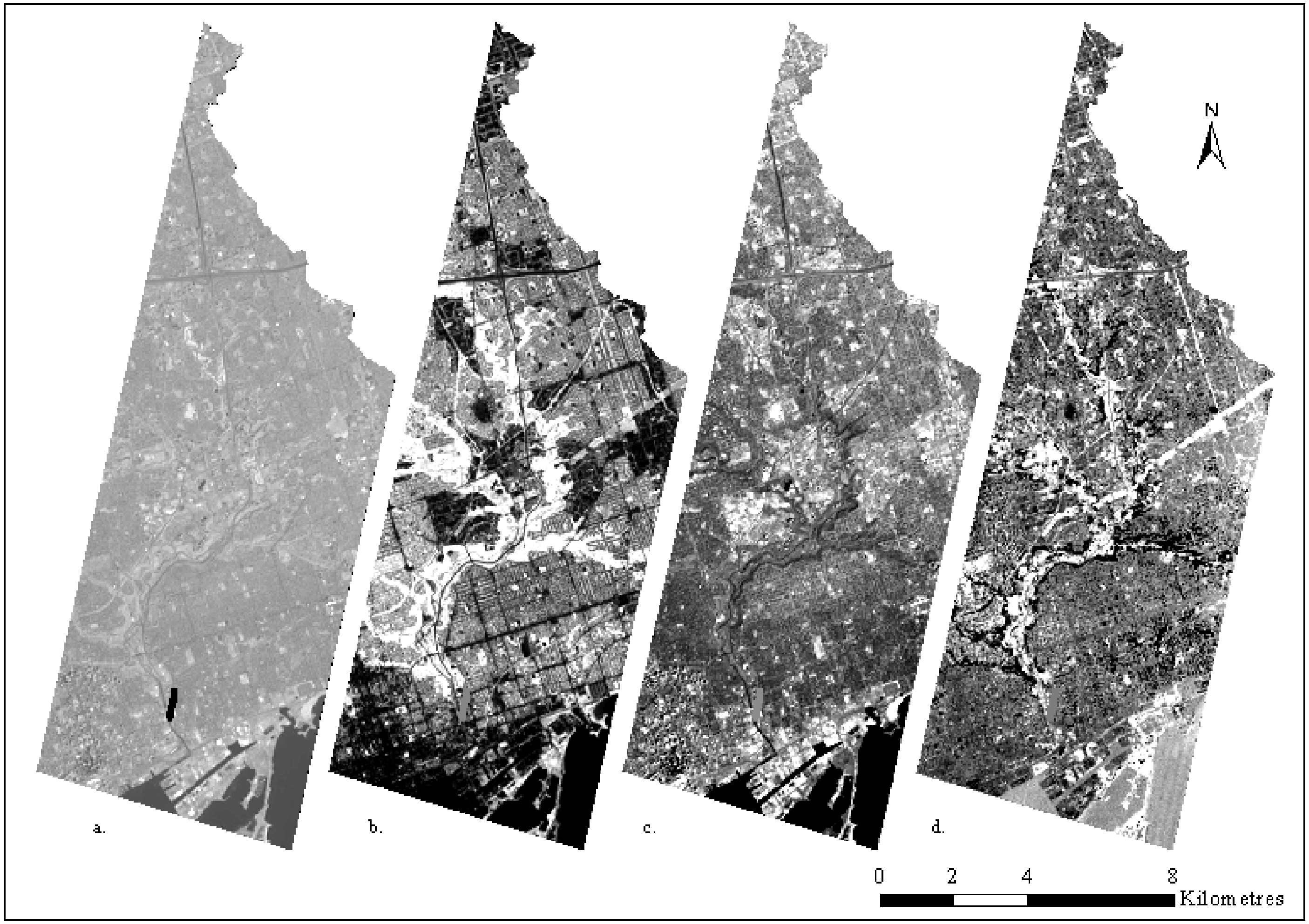

Figure 3-3: Principal components for segmented Hyperion, VNIR (a–d).

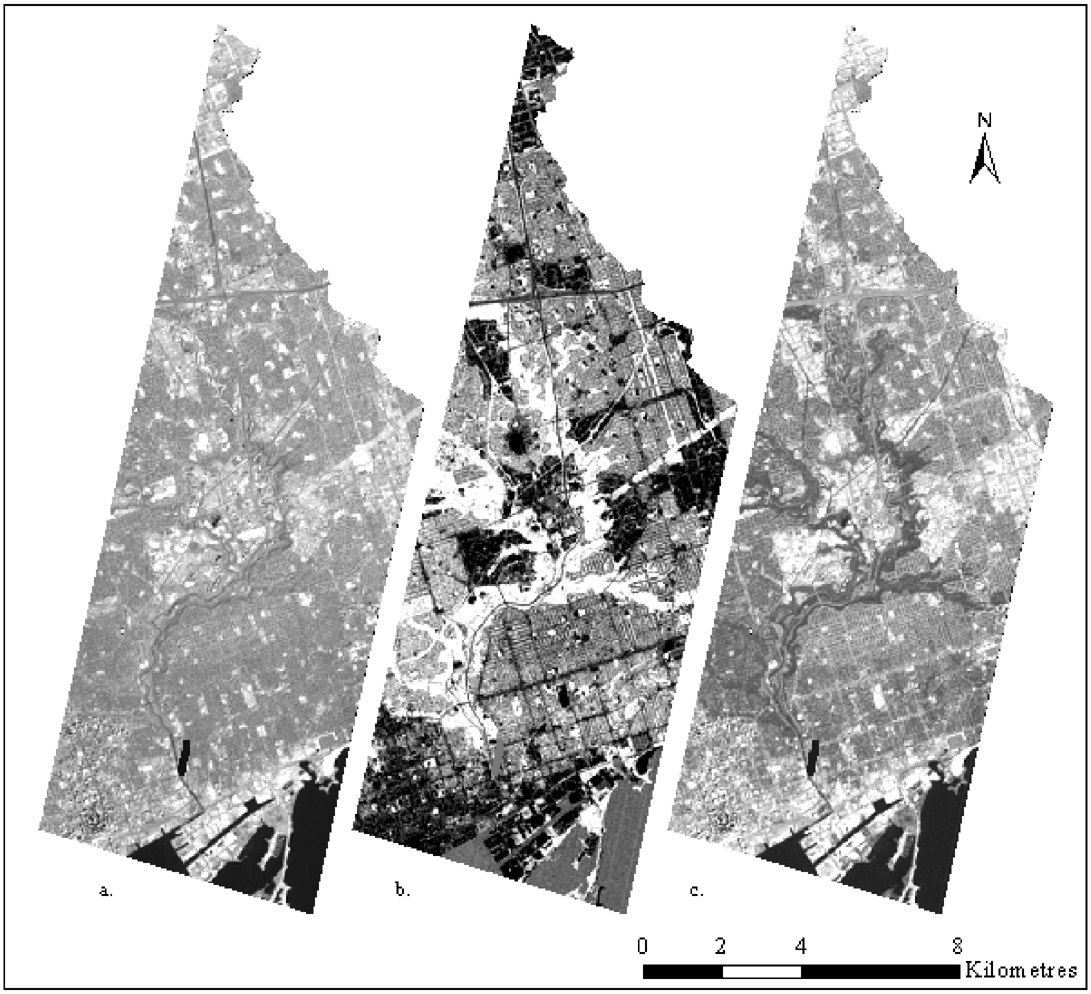

Figure 3-4: Principal components for segmented Hyperion, SW1 (PCs a-b), SW2 (PC c)

The aim of this analysis was to distinguish vegetation from non-vegetation in complex urban environments. To achieve this objective, the algorithm for PCA used as a feature extraction and data compression method (in order to compare both multispectral and hyperspectral data) must be able to define vegetation characteristics and effective variations among trees and open green space for classification.

3.6 Image Enhancement Techniques for Analysis

3.6.1 The Normalized Difference Vegetation Index

There are various image analysis processes that can be applied to data for greater feature analysis and extraction. The NDVI is a widely used image ratio for monitoring vegetation conditions that is based upon the fact that healthy plants and biomass that absorb visible light and reflect NIR (Jensen, 2007; Purkis and Klemas, 2011). Therefore, NDVI measures the amount of biomass in an image and is represented by diverging shades of black and white in PCI Geomatica that signify a higher level of vegetation. In this study, the NDVI should provide a more accurate definition between vegetation and built areas in the Don River Valley (Figure 3-5). Forsythe (2003) distinguished classes by incorporating the NDVI analyses for urban change detection. Thus, one method for processing data includes integrating NDVI.

3.6.2 Principal Component Analysis

PCA is often used in remote sensing to reduce the dimensionality of spatial features in an image. As previously mentioned, there are two valuable reasons why this method is used, first, to compress data, and second, to extract features for classification (Jensen, 2007). Cheriyadat and Bruce (2003) argue that PCA should not be used for supervised classification on hyperspectral data due to poor feature extraction and dimensionality reduction. In contrast, Tsai et al. (2006) suggest that spectrally SPCA is the best method for defining specific plant species with Hyperion hyperspectral imagery centred on spectral appearances of vegetation over different wavelength regions that resulted in an overall accuracy of 86% as opposed to CPCA of 66%.

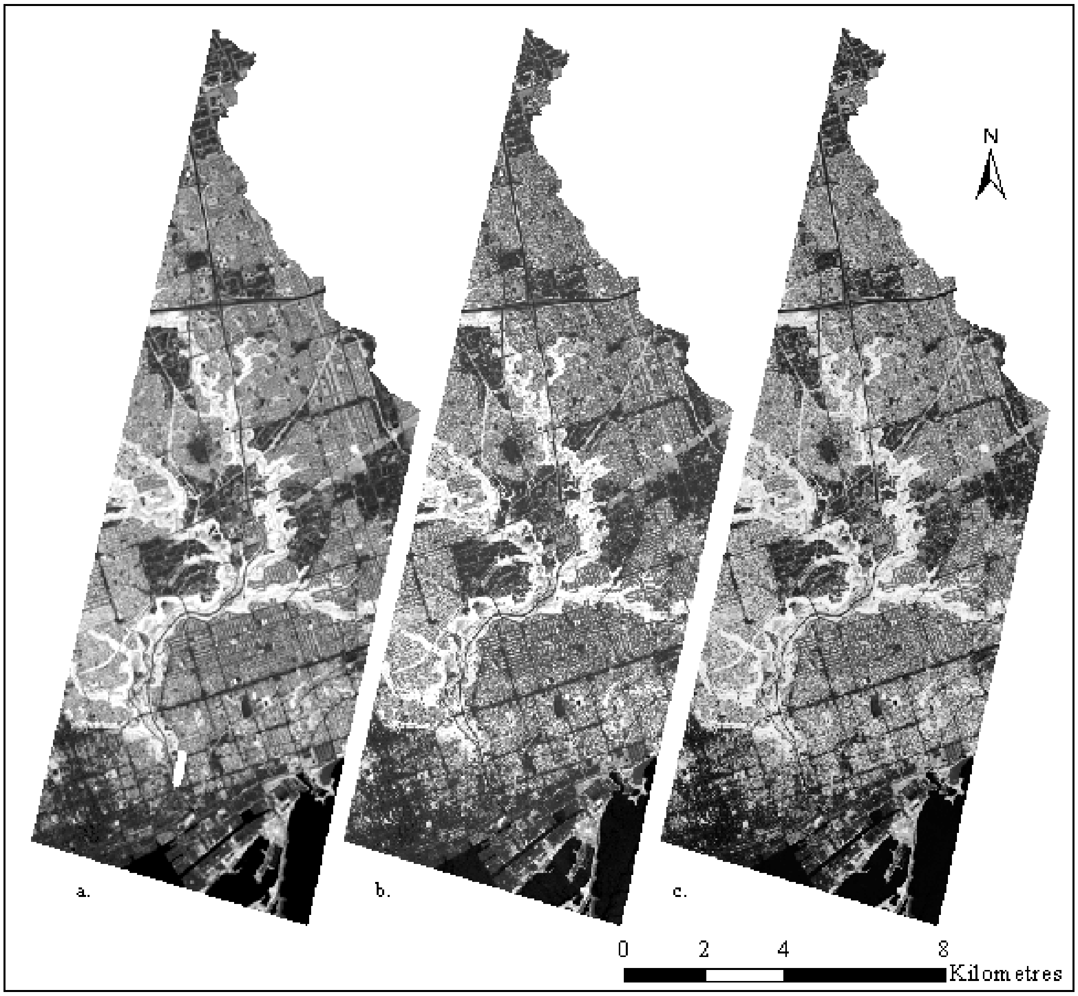

Figure 3-5: The normalized difference vegetation index for Hyperion (a) Landsat 5 TM (b) and SPOT 5 (c).

Liew et al. (2002) performed a land cover classification of tropical region and forest cover surrounding urban areas in Singapore using an unsupervised ISODATA classification and PCA with VNIR bands. Both Liew et al. (2002) and Wijanarto and Amhar (2010) found that the spectra data of VNIR bands far exceeded the performance ability of the SWIR for forest cover. However, Jung et al. (2005) suggests that SWIR are the most efficient bands to examine the differences in vegetation. Liew et al. (2002) suggest that further improvement of classifying data would be to incorporate the SWIR bands instead of just the VNIR bands used in their study. As previously mentioned, PCA is used in this study as a data compression method for Hyperion data only, while PCA 2 is used as a visual interpretive method for defining features in Landsat 5 TM and SPOT 5 imagery (Figure 3-6).

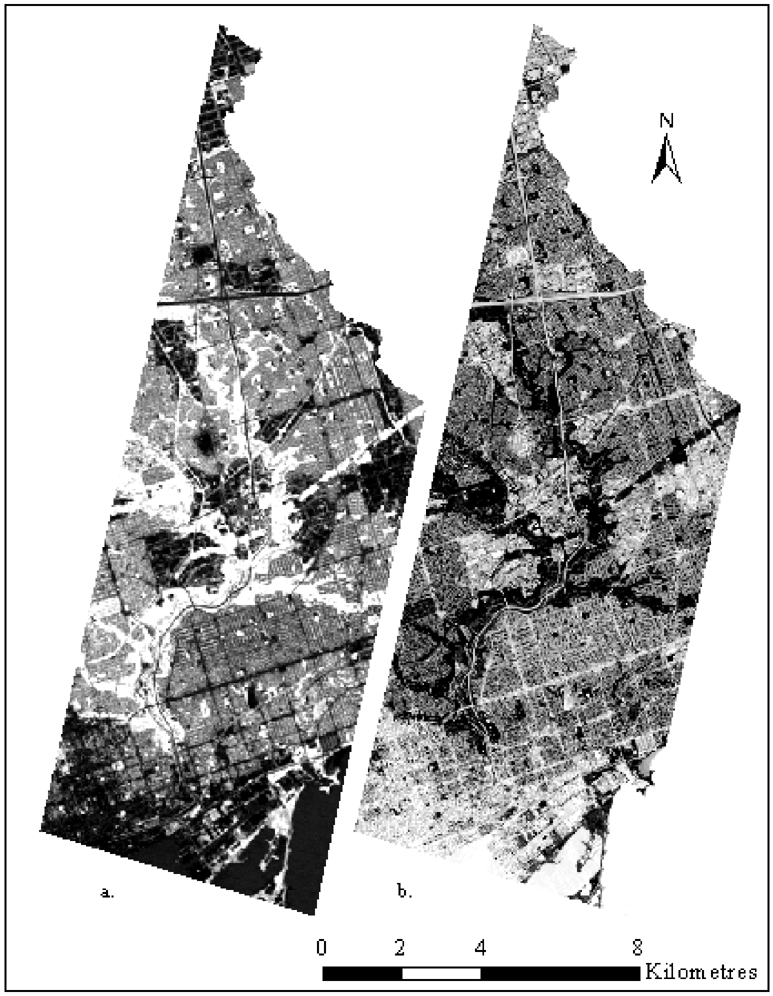

Figure 3-6: Principal component 2 for Landsat 5 TM (a) and SPOT 5 (b).

3.6.3 *Texture and False Colour Composites*

Texture is a measure of the amount of graininess in an image searching for areas that have the same roughness characteristic (Jensen, 2007; Purkis and Klemas, 2011). An example for using texture includes distinguishing between barren ground and open green areas. Texture is important in defining areas to improve classification accuracy. Furthermore, texture is a simple related measure that is extracted from a certain sized window set by the user, and then added to the original image dataset prior to classification (Jensen, 2007; Forsythe and Waters, 2006; Purkis and Klemas, 2011).

There are different texture measures including homogeneity, contrast, dissimilarity and mean texture (Forsythe and Waters, 2006; Purkis and Klemas, 2011). Mean image texture is used in this research and is a simple texture description of the grey levels in the texture window used for each image pixel (Jensen, 2007). Forsythe and Waters (2006) examine different texture measures for the expanding City of Calgary, Alberta. They found that by implementing a 3x3 window, it produced greater results than a 7x7 window due to the finer detail that was highlighted within densely urban areas. Therefore, in this study, mean texture (Figure 3-7) with a 3x3 window size is used.

Another image enhancement technique for determining spectral clusters involved the false colour composites. These composites were challenging at first to analyze visually as opposed to referring to a true colour composite. As previously mentioned, false colour composites are beneficial for understanding vegetated areas of interest in the NIR and red regions of the spectrum. (See Figure 3-8).

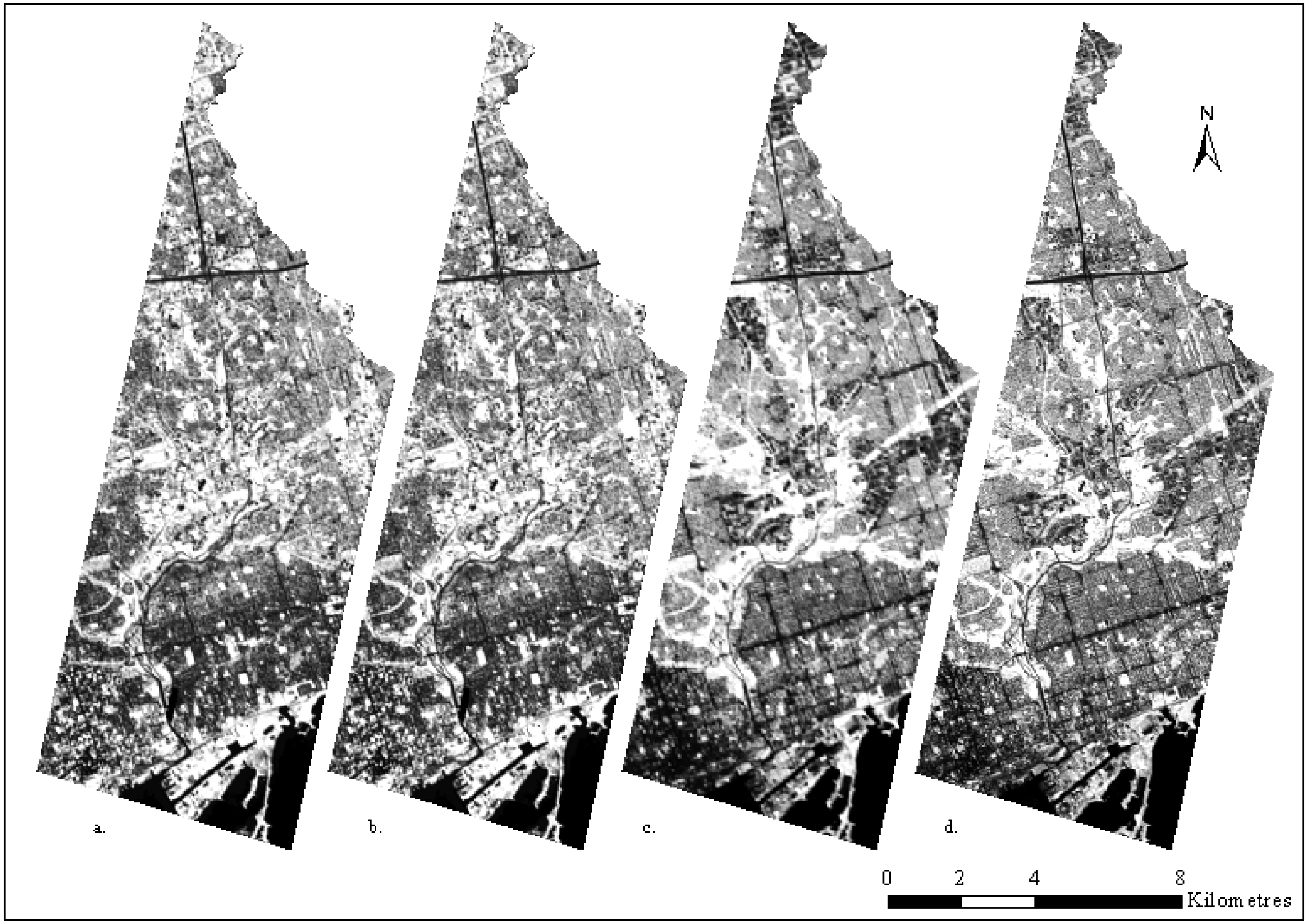

Figure 3-7: Mean texture measure for conventional Hyperion (a) segmented Hyperion (b) Landsat 5 TM (c) and SPOT 5 (d).

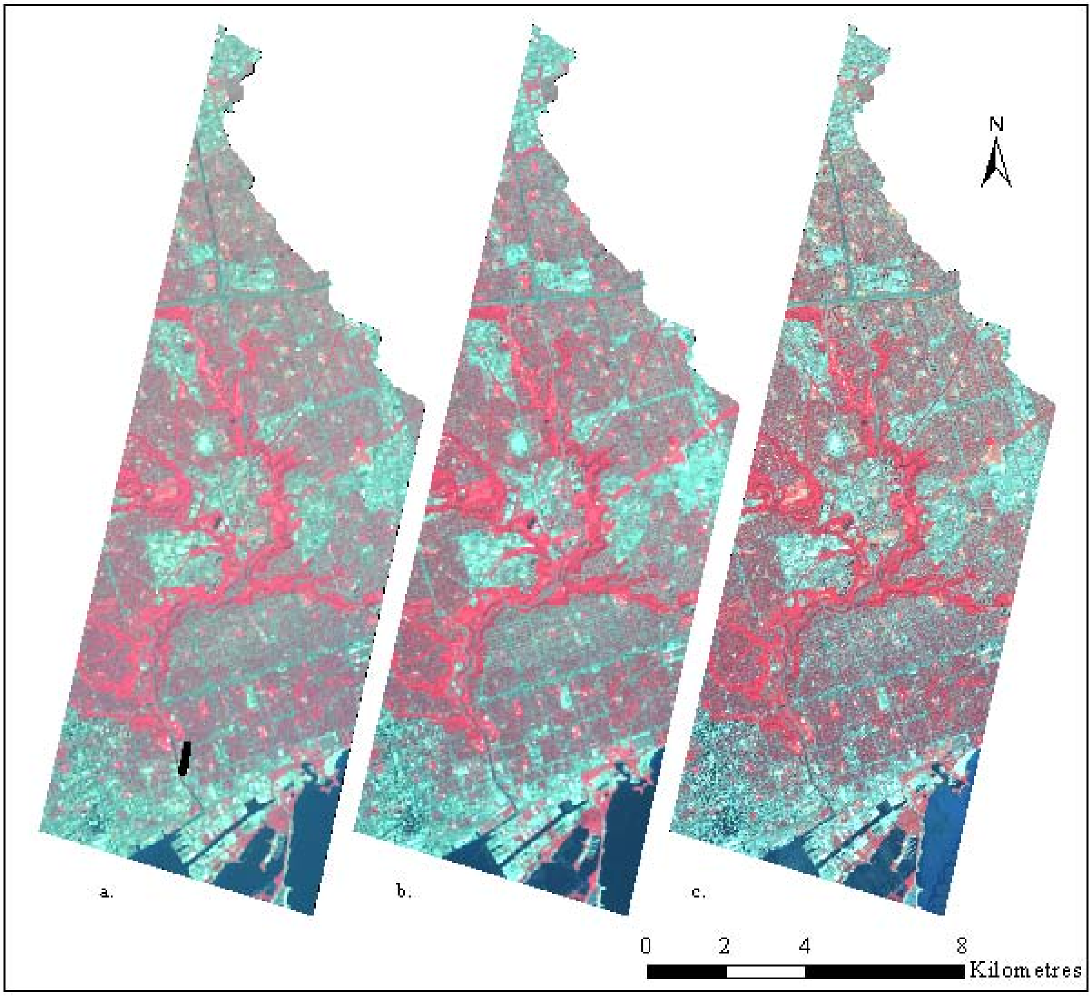

Figure 3-8: False colour composites (NIR, Red, Green) for Hyperion (a) segmented Hyperion (b) Landsat 5 TM (c) and SPOT 5 (d).

3.7 Classification Mapping: Aggregated Classes

In this research, classification labelling was considered. The classes used are derived from the Level I classification system from Anderson et al. (1976). Due to this paper's study area and the spatial resolutions of 20 to 30 metres, five classes were used including *tree canopy, open green, barren ground, water body, and urban surfaces*. Due to the objective of this research for examining urban green, the urban surfaces include white tops of industrial buildings, parking lots, roads and rows of houses and roof tops of commercial buildings. The open green class includes parks, golf courses, and fields. In addition, Peijun et al (2010) used the VIS model proposed by Ridd (1995) where vegetation, impervious surfaces and soil are to be examined in areas of increased densities. This idea was also considered when creating the classes for this study, however, the vegetation class was further divided and a water body class was added due to the study area containing large amounts of open spaces, water bodies, and trees along the Don River. In addition, there are significant areas of barren ground that needed to be classified separately.

3.8 Unsupervised classification

Many studies have used hyper/multispectral imagery for extracting land cover information using an unsupervised classification (Cheng et al., 2011; Liew et al., 2002; Yuan and Niu, 2007). An unsupervised classification is used for all images and the produced imaging techniques. When using the unsupervised classification approach, the entire image is analyzed with unknown training data (Jensen, 2007). Clusters of data can then be identified in association to pixel values. The interative self-organizing data analysis (ISODATA) algorithm was used to categorize the spectral clusters from the three images. This algorithm has been used in vegetation studies for comparing Hyperion hyperspectral data to Landsat 7 ETM+ data over Yunnan province in China for land classification (Yuan and Niu, 2007). In this study, 100 output spectral clusters (with 20 iterations) were generated. The algorithm identified between 60 and 64 output clusters. The generated clusters were assigned to one of the five land cover classes.

Thus, the ISODATA method is used consisting of the user specifying the number of clusters that may be within the image (Yang, 2007). The computer then assigns coordinates to each cluster within the section and every pixel is allocated to its suitable clusters (Rees, 2001). In other words, the ISODATA algorithm group's pixels with similar intensity values within all of the different layers in a classification to ultimately match spectral classes with the information classes of interest.

By using both hyperspectral and multispectral satellite remote sensing data, Govender et al. (2008) compared the classification of distinct vegetation classes using different classifying techniques. They found that by using a supervised classification process, maximum likelihood and Mahalanobis distance provided the best accuracy results. The authors found that the classification and mapping of different tree species depends on hyperspectral and multispectral to produce different degrees of accuracy and are strongly affected by seasonal changes in vegetation from winter to summer. The study also found that multispectral images detected genus level classification compared to hyperspectral that provided greater detail of genus and species level classification therefore suggesting that finer spectral resolution using a unique set of spectral bands can substantially improve vegetation classification and hyperspectral data should be used together with multispectral data for defining different vegetation classes accurately (Govender et al, 2008). Related studies involving forestry and agriculture have incorporated supervised classification methods (Pignatti et al., 2009; Wijanarto and Amhar, 2010). It is apparent in the previously mentioned literature that the supervised method for classifying objects is more suitable for rural studies where landscapes are less complex.

3.9 Accuracy assessment

Classification accuracy is a necessary component in land cover/use classification because it analyzes the difference between the classified data in a study compared to the original reference data (Foody, 2002; Jensen, 2007; Thenkabail et al., 2004). It is expected to accomplish an accuracy that reflects true land cover. This study assessed the accuracy of classification for each of the three images which created an error matrix and calculated user's accuracy (percentage of pixels classified correctly on the ground), and producer's accuracy (percentage of given class that is correctly identified on an image), and overall accuracy (Smith et al., 2003; Thenkabail et al., 2004). The kappa coefficient of agreement for each classification was generated from the error matrix.

In this study, the post classification accuracy assessment demonstrates an overall percentage of the aggregated classes (*tree canopy, open green, barren ground, water body, and urban areas*) in association to the aerial orthorectified imagery (See Figure 3-9). First however, in order to proceed with accuracy assessment, Geographic Information Systems (GIS) was used to generate three hundred random sample points to be compared to across the three classified images and the aerial orthorectified image. The random point's shapefile was generated and the pixels from Hyperion were extracted; the *Raster to Point* tool was used to limit the amount of mixed pixels in the imagery. This procedure was done to eliminate the potential of bias results for mixels (mixed pixels). The random sample points were created in ArcGIS so that consistency was upheld for comparing the three images together and against the aerial orthorectified image. Therefore, the accuracy points will fall within the centroid of the pixel, rather than a stratified point potentially skewing the aggregation by falling on the edge of a pixel with, for example, 10% water and 90% vegetation. Although these points may be slightly off-centre with SPOT 5 data due to the finer spatial resolution, the accuracy should not alter drastically.

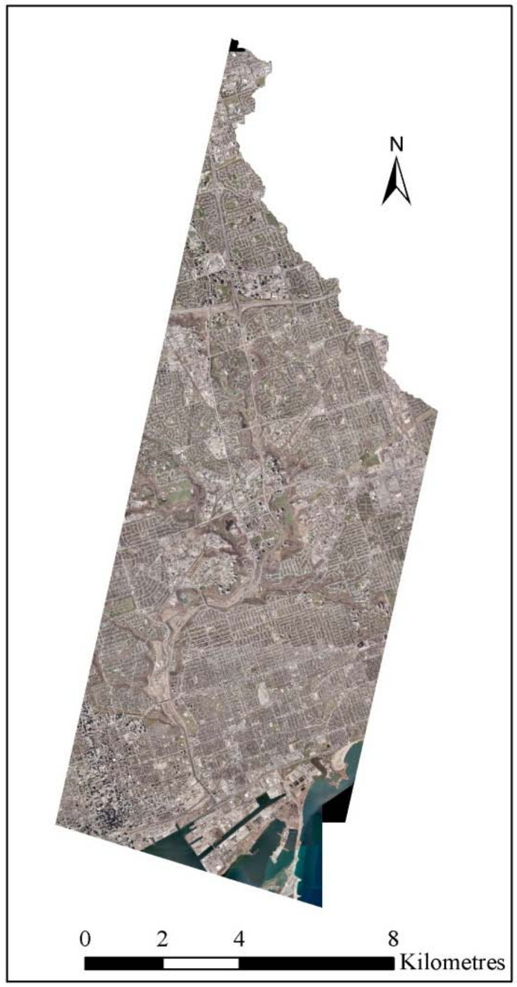

Figure 3-9: Aerial orthorectified imagery for ground reference for accuracy measure.
Source: Orthophoto: Fall 2007, First Base Solutions Inc. provided by the TRCA.

CHAPTER 4: Results & Discussion

The overall classification accuracy for the five classes in each image ranged from 64% to 69%. The Hyperion unsupervised classification with CPCA had an overall accuracy of 65.33% and a Kappa value of 0.48, which indicated that agreement in the error matrix was largely greater than chance. Hyperion’s SPCA resulted in a 64.00% overall accuracy. The Landsat 5 TM and the SPOT 5 unsupervised classification had an overall accuracy of 65.00% and 68.67% respectively. By comparing the three classification accuracies, the hyperspectral classification with CPCA slightly outperformed the SPCA and Landsat 5 TM multispectral classification, however, SPOT 5 produced the best classification for this study. A complete table of accuracy statistics is presented in Table 4-1.

The overall accuracy suggested by Foody and Mathur (2006) is greater than 80% as a threshold to superior classification. However, an overall accuracy threshold was not the significance of this research for comparative analysis between each sensor for indicating vegetation. Tsai et al. (2007) found in their study that CPCA produced an overall accuracy of 66%. Accuracy assessments were used to determine which sensor generated the best classification results by incorporating the same random sample points across the images in comparison with the aerial orthorectified image as a ground reference, and included the NDVI and mean texture. In other words, the classification of the land cover and land use classes with the same coordinates of accuracy were verified by visually interpreting the land cover and land use in the aerial orthorectified image. The different dates of the satellite imagery and the aerial orthorectified image were taken into consideration.

Table 4-1: Confusion matrices of classification results from each sensor

Conventional Hyperion		Reference Data: *Tree Canopy*	*Open Green*	*Water Body*	*B. Ground*	*Urban Areas*	Totals	**UA**
Classification data	*Tree Canopy*	**46**	15	0	1	19	81	0.57
	Open Green	15	**24**	0	0	16	55	0.44
	Water Body	1	1	**18**	0	0	20	0.9
	B. Ground	0	0	0	**2**	3	5	0.4
	Urban Areas	16	13	0	4	**106**	139	0.76
	Totals	78	53	18	7	144	**300**	
	PA	0.59	0.45	1	0.29	0.74		
Overall accuracy = 0.65					**Kappa = 0.48**			

Segmented Hyperion		Reference Data: *Tree Canopy*	*Open Green*	*Water Body*	*B. Ground*	*Urban Areas*	Totals	**UA**
Classification data	*Tree Canopy*	**48**	16	0	0	16	80	0.6
	Open Green	12	**24**	0	1	19	56	0.43
	Water Body	1	1	**18**	0	0	20	0.9
	B. Ground	4	3	0	**2**	9	18	0.11
	Urban Areas	13	9	0	4	**100**	126	0.79
	Totals	78	53	18	7	144	**300**	
	PA	0.62	0.45	1	0.29	0.69		
Overall accuracy = 0.64					**Kappa = 0.48**			

Landsat 5 TM		Reference Data: *Tree Canopy*	*Open Green*	*Water Body*	*B. Ground*	*Urban Areas*	Totals	**UA**
Classification data	*Tree Canopy*	**44**	13	0	0	16	73	0.6
	Open Green	13	**20**	0	0	6	39	0.51
	Water Body	0	0	**18**	0	0	18	1
	B.Ground	0	2	0	**2**	11	15	0.13
	Urban Areas	21	18	0	5	**111**	155	0.72
	Totals	78	53	18	7	144	**300**	
	PA	0.56	0.38	1	0.29	0.77		
Overall accuracy = 0.65					**Kappa = 0.48**			

SPOT 5		Reference Data: *Tree Canopy*	*Open Green*	*Water Body*	*B. Ground*	*Urban Areas*	Totals	**UA**
Classification data	*Tree Canopy*	**58**	15	0	0	25	98	0.59
	Open Green	8	**26**	0	0	12	46	0.57
	Water Body	1	0	**18**	0	0	19	0.95
	B.Ground	0	4	0	**2**	5	11	0.18
	Urban Areas	11	8	0	5	**102**	126	0.81
	Totals	78	53	18	7	144	**300**	
	PA	0.74	0.49	1	0.29	0.71		
Overall accuracy = 0.68					**Kappa = 0.54**			

Results show that among the three sensors, *tree canopy* was highly misclassified as *urban areas.* The segmented Hyperion additionally misclassified *tree canopy* for *open green*. These results may be produced from neighbourhoods that are mostly made up of urban surfaces and contain tree cover, the spectral reflectance's may be mixed when wavelengths penetrate through the tree crown and hit the surface of a road or house that reflects back for that particular area. This can also be explained for the classification of *open green* which was mixed with *urban areas* and mostly *tree canopy*. In addition, *urban areas* were predominantly mixed with *tree canopy* and with segmented Hyperion; *urban areas* were mixed with *open green* areas. *Barren ground* is mostly misclassified as *urban areas;* this could be from buildings containing white roof tops which have similar reflectance to bare soils. *Water bodies* were correctly classified, with one or two mixed pixels for *tree canopy* and *open areas* possibly due to high moisture content in the peak summer months for Hyperion.

The SPCA (four PCs in the VNIR, two in the SW1, and one in the SW2) maintained the best results compared to CPCA. Figure 4-1 displays the two classified images for SPCA and CPCA as well as the multispectral sensors. Moreover, there were more pixels classified as *urban areas* instead of *water bodies* and a greater number of *tree canopy* pixels classified as *urban areas* with the SPCA methodology. This could be explained by the shadows having similar reflectance characteristics as water in the downtown. By examining CPCA, the highest amount of pixels misclassified were *urban areas* mixed with *tree canopy*. Older residential areas (*urban areas*), as previously mentioned, being misinterpreted as residential tree cover may cause these two classes to be mixed.

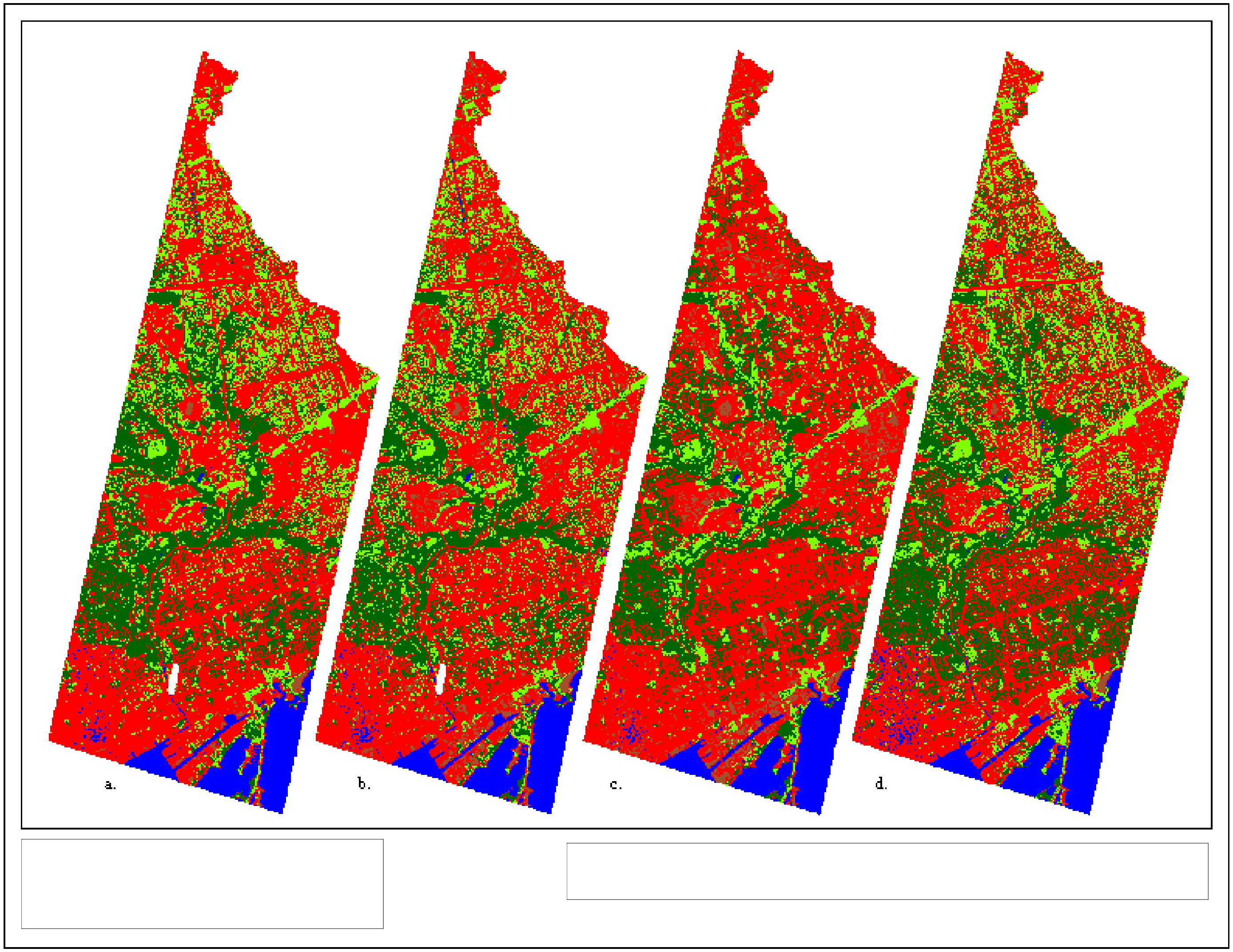

Figure 4-1: Aggregated results for conventional Hyperion (a) segmented Hyperion (b) Landsat 5 TM (c) and SPOT 5 (d).

4.1.1 Aggregated Results and Discussion

Further experiments should be conducted to assess the accuracy with greater PCA segments for each range of the EMS. Tsai et al. (2007) suggest that the greater number of SPCAs does not increase accuracy, instead, greater segments in each portion of the spectrum increase accuracy. In this study, the reason for low accuracy may be caused by the atmospheric affects not being properly corrected. As shown in Figure 3-2 (e), the fifth PC is a result of conventional Hyperion's data spectral 'smile' effect which does not represent reflectance anomalies of features (Datt et al., 2003). Tsai et al. (2007) argue that data in the short wave range with longer wavelengths may be noisy and cause poor data results. Taking this into account, the noisy PC bands were eliminated for classification when performing the spectrally SPCA to generate higher overall accuracy; however, in this study, this method resulted in a moderate overall accuracy amongst the three satellites. A table of accuracy results organized by classes for each sensor is shown in Table 4-2.

Although literature suggests that SPCA should produce greater accuracy results over CPCA (Bell and Baranoskie, 2004; Tsai et al., 2007), this study found the opposite. It was found that SPCA did not have the expected results for classification as a whole, however, it is essential to note that conventional Hyperion and segmented Hyperion methods did outperform the Landsat 5 TM sensor for vegetation differences (for *tree canopy* and *open green* spaces). The resulting higher accuracy obtained using Hyperion data proves that spectral analysis is a significant component for applying classification to an urban setting (between 5-6% better). Although SPOT 5 mostly outperformed the other two sensors, this can be explained by the difference in spatial resolution, as SPOT 5 image pixels have higher spatial resolution. By examining *urban areas*, Hyperion did outperform SPOT 5 for *barren ground* with a user's accuracy of 40% and a Kappa of 0.39 and also produced a greater Kappa of 0.46 for *tree canopy*.

Table 4-2: Accuracy results for comparison organized by classes and the highest values (highlighted boxes indicate the highest values).

Class Sensor	**Producer's Accuracy**	**User's Accuracy**	**Kappa Statistic**
Tree Canopy			
Hyperion	58.97%	56.79%	0.42
Segmented	61.54%	60.00%	0.46
LS5TM	56.41%	60.27%	0.46
SPOT5	74.36%	59.18%	0.45
Open Green			
Hyperion	45.28%	43.64%	0.32
Segmented	45.28%	42.86%	0.31
LS5TM	37.74%	51.28%	0.41
SPOT5	49.06%	56.52%	0.47
Water Body			
Hyperion	100.00%	90.00%	0.89
Segmented	100.00%	90.00%	0.89
LS5TM	100.00%	100.00%	1.00
SPOT5	100.00%	94.74%	0.94
B.Ground			
Hyperion	28.57%	40.00%	0.39
Segmented	28.57%	11.11%	0.09
LS5TM	28.57%	13.33%	0.11
SPOT5	28.57%	18.18%	0.16
Urban Areas			
Hyperion	73.61%	76.26%	0.54
Segmented	69.44%	79.37%	0.60
LS5TM	77.08%	71.61%	0.45
SPOT5	70.83%	80.95%	0.63

Image classification is a successful method used to define land cover in complex landscapes (Govender et al., 2008; Peijun et al., 2010; Yang and Everitt, 2010). The aggregated classification results for Landsat and SPOT were derived using NDVI, PCA 2, and mean texture (See Figures 3-5, 3-6, and 3-7). Hyperion aggregated classes were also derived from these parameters with exception that the original five principal components were used to perform classification as a form of data compression for assessing CPCA and selected principal components for SPCA.

By applying image enhancement techniques such as the NDVI, principal components and texture, there is a greater possibility for class separability. Amongst the three sensors, mean texture clearly defined *urban areas* along the Harbourfront from barren groundsurfaces that may have similar spectral reflectance. Although texture did not effectively differentiate between *urban areas* and *open green*, mean texture was useful for defining *tree canopy* from *water bodies*, for example in the Don River Valley. PCA 2 became useful for effectively outlining *open green* spaces including fields, parks and golf courses. The NDVI effectively defined *open green* spaces from *urban areas* and vegetation from *water bodies*. This enhancement was also useful for greater separability between vegetation and roads around the Don Valley Parkway. Vegetation is in a lighter and brighter tone therefore, it has the ability to distinguish between urban surfaces with higher reflectance from white roofs (which are displayed dark). Full accuracy statistics are presented in Table 4-1.

In the aggregated images (Figure 4-1), it is visually apparent that some of the land classes are misclassified in Downtown Toronto (southwest corner of image). Since there is low reflectance of light caused by building shadow, these pixels are severely mixed with the *water body* class (most evidently with the Spot and Hyperion sensors). In the conventional and segmented Hyperion *tree canopy* and *open green* are misrepresented by *water bodies*, however, the accuracy results may not include the mixed pixels in the downtown area possibly because an accuracy point does not fall on these pixels. Furthermore, on the Don Valley Parkway towards highway 404, *urban areas* are mixed with *water bodies*. Landsat imagery was able to outline the spectral reflectance in the downtown as *urban areas* better than the other sensors. Ultimately, the results of the aggregated classes of the Hyperion and Spot sensors embody clear definition of vegetation/urban green space compared to the Landsat sensor of approximately 6-14 % greater foliage.

The aerial orthorectified imagery was used to assess how well the classification system worked for hyperspectral and multispectral data. Peijun et al. (2010) used Quickbird images as a ground reference in Xuzhou City, China and found that the EO-1 Hyperion hyperspectral image is more efficient than Landsat 5 TM multispectral imagery for extracting vegetated areas. Thus, by comparing medium spatial resolution data to finer spatial resolution aerial orthorectified imagery provided by the TRCA, land classification can be accurately measured (see Figure 3-9 for aerial orthorectified image).

Figure 4-2 shows the resulting class differences between the four images. It is found that both CPCA and SPCA Hyperion outline vegetation, specifically *tree canopies*, greater than Landsat and are almost as detailed as SPOT classification. This is especially evident for areas around Sunnybrook Park and surrounding the Withrow Park residential area. It is evident that there are areas of mixed pixels with the Landsat and Hyperion imagery for the vegetated classes. In addition, in Figure 4-2 a, it is evident that Landsat detected *barren ground* and *water bodies* greater than the other sensors. However, this does not necessarily represent true land cover and could contain mixed pixels. In Figure 4-2 b, conventional and segmented Hyperion, and SPOT detect *water body* pixels in the Don River, where Landsat is unable to determine this area as having water. Figure 4-3 shows the differences between conventional PCA and the three remaining images (SPCA, Landsat 5 TM, and SPOT 5). These results define the change and no change of all classes (*tree canopy, open green, barren ground, water bodies and urban surfaces)* between the hyperspectral and multispectral images.

Further comparative analysis was conducted in ArcGIS by extracting the area of classes in each image. It was found that conventional Hyperion contained the largest area of *tree canopy* with approximately 41 square kilometres compared to segmented Hyperion (roughly 39 km^2), SPOT (roughly 35 km^2) and Landsat holding the lowest amount of *tree canopy* coverage at around 25 square kilometres. These area measures are similar to *open green* coverage and can be seen Table 4-3.

The percentages of each class were calculated in ArcGIS for comparison. It is interesting that although segmented Hyperion is known to produce better results than conventional Hyperion (Tsai, et al., 2007), the coverage in Table 4-3 does not show this for the classes (with exception of *barren ground* displaying 4% greater coverage). Table 4-3 also shows that the SPOT sensor identified 30% of the image as *tree canopy*, compared to Landsat with the lowest percentage of *tree canopy* (22%). Additionally, conventional Hyperion (25%) and segmented Hyperion (23%) detected *tree canopy* cover greater than Landsat. For *open green* spaces, Hyperion and SPOT satellites maintained approximately the same amount between 16-17% coverage while Landsat identified only 11% of *open green* space. In relation to these figures, Landsat identified 4-12% more *urban* coverage than Hyperion and SPOT satellites. These figures therefore confirm that higher spectral and spatial resolution sensors can outperform sensors with less spectral resolution and coarser spatial resolution.

Table 4-3: Area of aggregated classes

	Tree Canopy	*Open Green*	*Water Body*	*B. Ground*	*Urban Areas*	*Total*
C. Hyperion						
Pixel Count	45821	30989	10915	2020	96266	186011
Area km^2	41.24	27.89	9.82	1.82	86.64	167.41
Percentage	**24.63**	**16.66**	**5.87**	**1.09**	**51.75**	**100.00**
S. Hyperion						
Pixel Count	42954	29225	11053	9594	93185	186011
Area km^2	38.66	26.30	9.45	8.63	83.87	167.41
Percentage	**23.09**	**15.71**	**5.94**	**5.16**	**50.10**	**100.00**
Landsat 5						
Pixel Count	28500	14577	7688	6388	73776	130929
Area km^2	25.65	13.12	6.92	5.75	66.40	117.84
Percentage	**21.77**	**11.13**	**5.87**	**4.88**	**56.35**	**100.00**
SPOT 5						
Pixel Count	87925	49949	18983	7483	130260	294600
Area km^2	35.17	19.98	7.59	2.99	52.10	117.84
Percentage	**29.85**	**16.95**	**6.44**	**2.54**	**44.22**	**100.00**

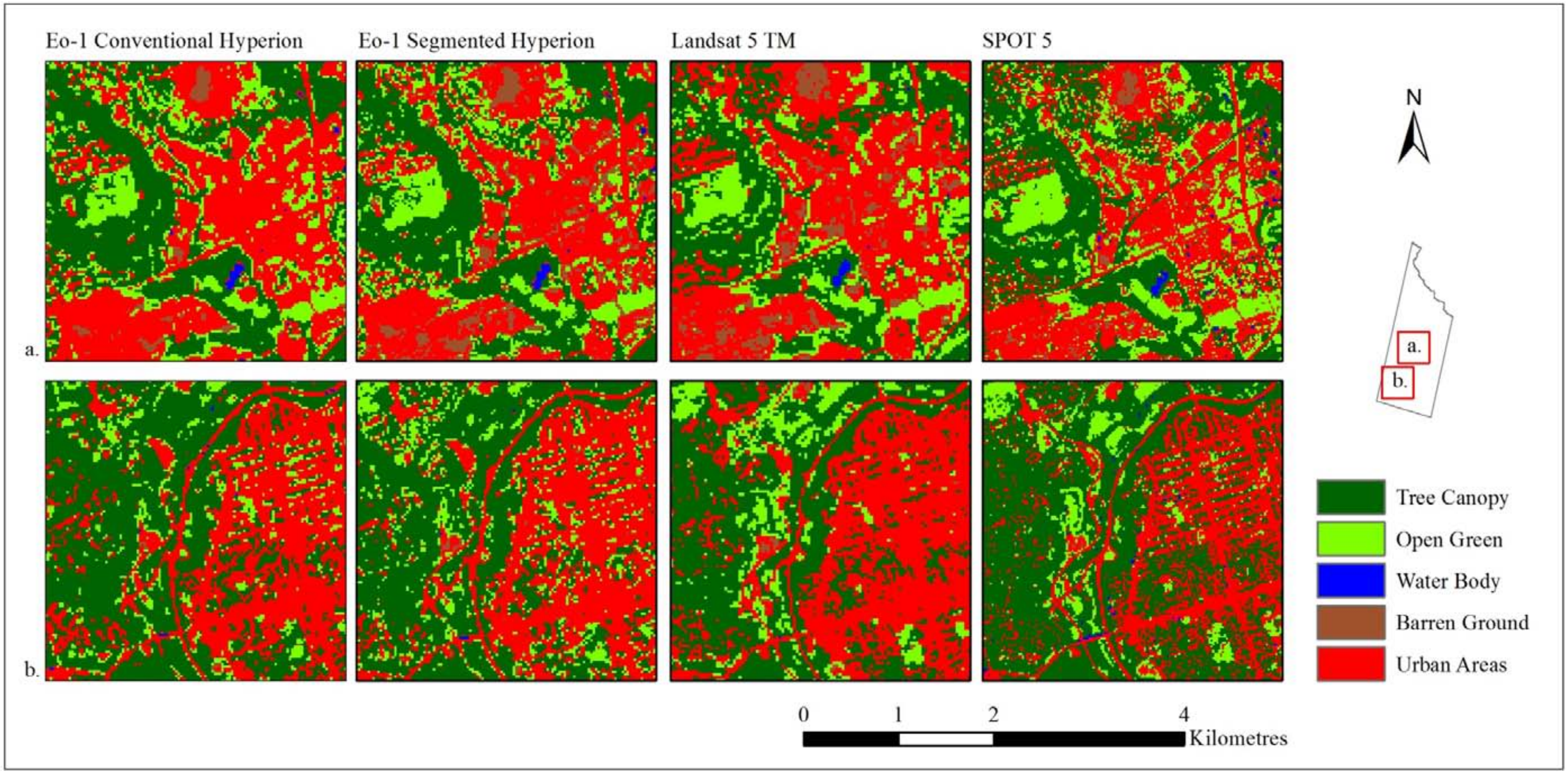

Figure 4-2: Aggregated results for the Don River and Sunnybrook Park area (a) and Evergreen Brickworks area, Rosedale and Withrow Park (b).

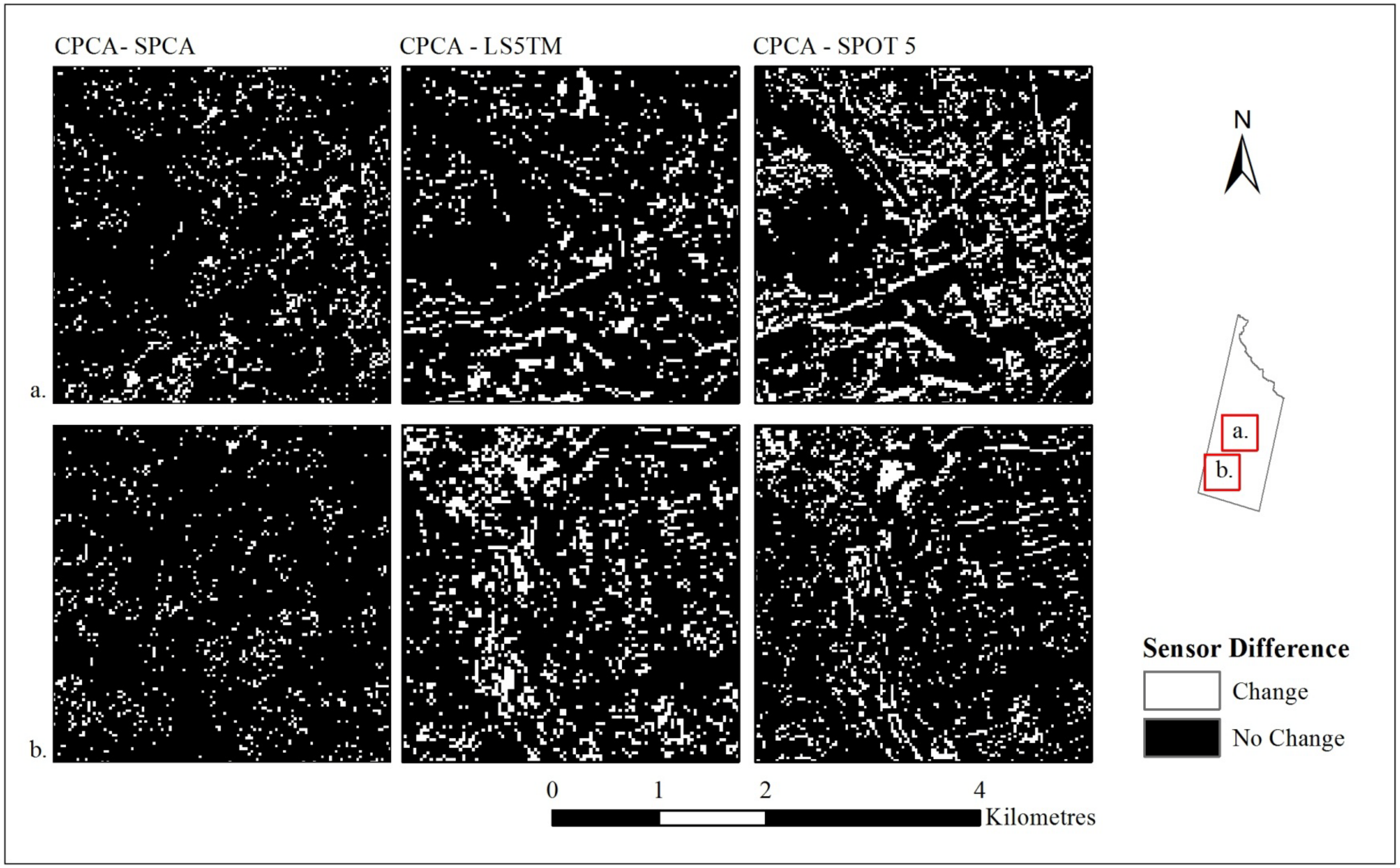

Figure 4-3: Differences between each sensor from CPCA and all five classes. Results for the Don River and Sunnybrook Park area (a) and Evergreen Brickworks area, Rosedale and Withrow Park (b).

CHAPTER 5: Conclusion

Hyperspectral remote sensing technology exhibits the capacity for vegetation definition. This major research paper presents a comparative analysis between hyperspectral and multispectral imagery for mapping land cover in the City of Toronto, Ontario, Canada that surrounds the Lower Don River. This study performed spectrally SPCA and CPCA on Hyperion imagery in order to compare classification of vegetation with Landsat 5 TM and SPOT 5 data. In addition, aerial orthorectified imagery as a ground reference was used for accuracy measure. After comparing the results from Hyperion, TM and SPOT data, it was found that HSI is slightly more effective than multispectral imaging with the same spatial resolution for *tree canopy* and open *green* space extraction. Nevertheless, SPOT had the highest overall accuracy among all sensors in this study. For two of the vegetation classes (*tree canopy* and *open green*), it is significant to note that Hyperion, both conventional and segmented, outperformed Landsat 5 TM by approximately 5-6% overall accuracy. Nevertheless, SPOT generated greater accuracy results among Landsat and Hyperion for the vegetated classes.

Ultimately, unsupervised land cover classification with ISODATA was performed using data from three separate sensors. Moreover, band ratios or spectral indices are commonly derived from imagery to enhance certain features to differentiate between various vegetation types mixed in with other land uses (Govender et al., 2007). Particular data enhancement methods include NDVI to define healthy vegetation and PCA to determine non vegetated and vegetated areas. These indices and methods are used as a separability technique to classify vegetation across large land areas. Image classification is a successful method used to define land cover in complex landscapes (Peijun et al., 2010). This research found that, data analysis of hyperspectral imagery has the potential for improving classification accuracies of land cover and land use over multispectral imagery with the same resolution. Classification error occurred mostly in classes such as *bare earth*, *water bodies* and *urban areas,* with low separability values.

5.1 Limitations

This research was limited by data constraints. Data for the EO-1 Hyperion is restricted to one date (August 1st, 2007), and limited to a portion of the Lower Don River. Due to this data constraint of one available image and narrow extent, sub-watershed change detection could not be analyzed. In addition, because only one Hyperion image was available, the Landsat and SPOT imagery had to be matched to the temporal resolution of Hyperion. However, imagery was not available for the specific date. The closest date to Hyperion and SPOT for Landsat was one year later in 2008. Also, there are missing data at the mouth of the Don River where the Keating channel is located in the Hyperion imagery. Moreover, SPOT 5 spatial resolution of 20 metres was not resampled to match the 30 metre spatial resolution of Hyperion and Landsat which could have affected accuracy results.

Data compression of hyperspectral imagery was a challenge because PCI Geomatica and ENVI are unable to process data for classification due to the software's threshold of processing no more than sixteen channels at one time. This affects the data because the purpose is to measure accuracy across a large data set with detailed spectral bands. Although parameters for output data can be set to 32 bit-real file storage, hyperspectral data cannot be processed. This is why the literature (Datt et al., 2003; Small, 2001; Tsai et al., 2007) suggests certain data compression algorithms that allow a large dataset to be condensed, thus redirected the scope of the study. Tsai et al. (2007) argue that poor results for vegetation classification can be explained by the inconsistency among vegetation and non-vegetation pixels if PCA is performed on an entire hyperspectral dataset. To avoid this from occurring, the authors suggest that non-vegetated pixels be masked out from the PCA process. By masking vegetated areas, better results could be generated for defining tree species because the PC's consider the variance across entire classes and focus on useful data for separating vegetation. Therefore, discrimination among plant species only, will produce better overall accuracy instead of comparing what is vegetation and what is not. This is useful for detailed studies where targeting different plant species is the purpose (Tsai et al., 2007).

The predefined features by the user formulated during classification affect the user's ability to identify validation points. This was avoided by using aerial orthorectified imagery from the same year to determine the classes for each accuracy point. However, depending on the satellite imagery, this could still be affected. The fixed accuracy points were used to reduce bias, but there is still bias because each sensor captured the image on a different date. In addition, interpretative error at initial classification is possible and could be the reason for classification errors once validation points were developed. Nevertheless, low accuracy is expected because the three images are compared to an aerial orthorectified image, which is higher resolution. The aerial orthorectified image acts as ground truth, the only difficulty is that it is on a later date in the fall than the three sensors in the summer. If images were acquired the same day and time, then accuracies would be even more comparable.

Since urban green is significant for the quality of urban life, databases and information are even more important to keep and record in cities. Further work is to explore other more effective data compression and classification methods to increase classification accuracy. Although comparing hyperspectral and multispectral data for land cover classification with various data analyses was beneficial for measuring spectral separability at medium resolution, further research could be conducted on detailed analysis of Hyperion spectral bands such as spectral unmixing. By unmixing the pixels in an image, a more detailed study for mapping health of tree species along the Don River Valley can be examined.

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