DEVELOPMENT PATTERNS IN CANADA'S LARGEST URBAN AGGLOMERATION: FOUR DECADES OF EVOLUTION

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ABSTRACT

The city of Toronto, Ontario and its surrounding regions constitute the largest urban agglomeration in Canada and the fifth largest in North America. Urban development within this area is an important planning and environmental issue. Landsat images from 1972 to 2004 (a total of 10 scenes covering a period of 32 years) were used in this research that cover the majority of the contiguous urban area. A series of change detection experiments were performed that compared methodologies and techniques. The results greatly improved classification accuracy, particularly for Landsat Multispectral Scanner (MSS) data.

The distribution of urban growth becomes apparent when divided by municipality. The City of Toronto is the largest municipality, and it accounted for 16.07% of total urban change. Mississauga was the largest contributor, accounting for 21.29%, although its municipal area is only about half that of Toronto. Development prior to 1972 within the Toronto municipal boundaries helps in providing an explanation for this finding. The next largest contributors were Brampton (14.91%), Vaughan (13.62%), and Markham (10.02%). Ajax and Pickering accounted for the smallest proportion of the total change, at 3.37% and 3.93% respectively although this may have been influenced by missing data (due to WRS-2 scene divisions) in the northeast corner of some of the Landsat5 and Landsat7 Path 18 Row 30 scenes. Overall, a yearly average of 14.1 km^2 of new development was observed.

INTRODUCTION

The underlying assumption for change detection using remotely sensed data is that there will be a difference in the spectral response of a pixel on two dates if land cover changes from one type to another (i,ii). Ideally, data used for change detection should have constant spatial, spectral, and radiometric resolutions (i). It is difficult to have such ideal situations and therefore, a thoughtful understanding of the nature of remotely sensed data and environmental characteristics is essential. Failure to understand the impact from the various data and environmental conditions on change detection applications can lead to inaccurate results (iii,iv).

Geographically, urban change refers a difference in which rural areas are converted to urban areas from one time to another. The Greater Toronto Area (GTA) is experiencing rapid urban expansion. From 1991 to 2001 the population increased 20%, to 5.1 million people (44.5% of the total Ontario population, and 16.9% of the total Canadian population) (v). It is North America's fifth largest and second-fastest growing urban area region (vi). The latest estimates show that Toronto will continue to be Canada's biggest urban-population magnet, growing by as many as 100000 people a year and more than two million people will be added to the GTA in the next 30 years. Rapid urbanization has led to the consumption of agricultural land, urban sprawl and pollution issues. Twice as much land in the Toronto area could be developed in the next 20 years as was covered during the past two centuries (vii). Increased population, traffic, and infrastructure needs burden the urban environment and seriously affect the overall quality of life. Thus, monitoring urban change in terms of the amount and spatial pattern in the GTA area is significant for urban planning, land-use planning, and the sustainable management of land resources. Urban change detection research in this area has been successfully conducted by Forsythe (viii, ix) and Zhao (x). However, this study examines urban change detection from 1972 to 2004 with a greater number of images and a smaller image acquisition interval. The objectives are to: explore efficient methods to quantify urban growth over large agglomeration areas using a time series of multi-sensor Landsat data; assess the accuracy of land cover classification and detected urban changes; and to calculate and delineate the amount of urban change and the spatial patterns associated with it.

METHODS

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

Since change detection techniques have different conditions in data and purposes, it is difficult to compare the vast array of change detection methods (i, xii , xiii , ii). No one single technique/algorithm is optimal. For instance, image differencing, image regression, and Principal Component Analysis (PCA) are thought to perform better than postclassification techniques (ii). However, Mas (xii) reported that postclassification performed better than image differencing and PCA. This is because urban change detection techniques are closely related to data quality, resolutions, study area, and accuracy requirements (i). Overall, preclassification or enhancement techniques such as image differencing (xi, xiii, ii, xiv, xv, iv), image regression (xiii), PCA differencing including standardized and selective PCA (xvi, xvii, xviii, xii, ii), and Normalized Difference Vegetation Index (NDVI) differencing (xix,xx,xxi) greatly improve the classification results and accuracy of detected urban change (xxii). The postclassification technique has from-to patterns (xviii), but its accuracy is not as good as results from preclassification change detection techniques (xxiii, xiv, xv). Fung and LeDrew (xxiv) reported the threshold values tightly associated with accuracies for different algorithms and noted that they are sensitive to different natures of change. Jensen (xxiii) pointed out that differencing or ratioing of spectral data is practical but may be too simple. Therefore, a combination of methods (such as multi-date classification, preclassification with postclassification, and preprocessing operations) may produce better results in terms of decreasing the chance of error, and in improving the accuracy of detecting the nature and amount of change (xxv, xviii, xii).

The methodology used in this research focuses on determining urban extent and the change that occurs between dates of image acquisition. However, due to the differences between Landsat sensor data, a single method is not sufficient. The development of the methodology mainly depended on experiments, by which the optimal methods were selected and some new combined methods were created. These include classification with and without enhancement (enhancement here refers to including items that are derived from the original satellite bands such as principal components - PCs, texture, and NDVI), radiometric ratioing (between image dates), image differencing, and Geographic Information System (GIS) post-classification processing.

Accuracy assessment was also an essential step. With the advent of more advanced digital satellite remote sensing techniques, the necessity of performing an accuracy assessment received renewed interest (xxvi). The accuracy of remote sensing-derived thematic information is the foundation for further data analysis and decision-making (xxvii, xxviii). The finalized methodology (based on the experiments) is shown in Figure 1.

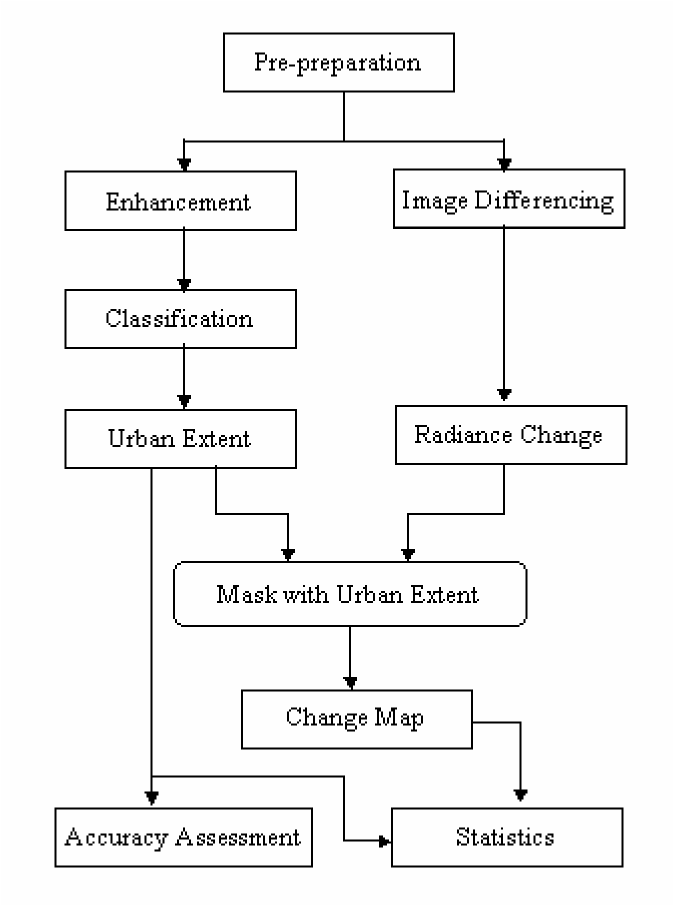

Figure 1: Data processing Procedures

RESULTS

For radiometric ratioing using Multi-Spectral Scanner (MSS) and Thematic Mapper (TM) imagery, the unchanged urban area between two dates has a ratio value of 1.0, showing a common tone in the resampled image, which is different from urban growth areas, which have values either higher or lower than 1 with either brighter or darker tones. More important is that the resampled 30m spatial resolution results in the unchanged urban area having a more detailed urban texture, which greatly helps in distinguishing urban, rural, and change areas. The results for the classification of enhanced MSS data showed that including PCs, texture, and NDVI is insufficient for distinguishing urban from rural areas. When ratio derived elements are included, the results are significantly better in terms of visual and statistical results.

The classification of urban growth was the primary goal of this research and the results indicate that flexible methods must be used in order to achieve the best results. The generation of enhancements to include in classification procedures provides additional information that is useful in obtaining higher classification accuracies. Ratios between MSS and TM data were especially helpful in distinguishing urban growth. Image differencing when combined with urban extent masks allowed for agricultural changes to be readily identified and separated from urban area modifications.

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

The greater spectral and spatial resolution of the TM and the Enhanced Thematic Mapper plus (ETM+) data allowed for improved performance in capturing urban features when compared to MSS data. However, the gap between MSS data and TM/ETM+ data was reduced by enhancements, in which the MSS data were resampled.

Figure 2 represents the total urban change from 1972 to 2004.

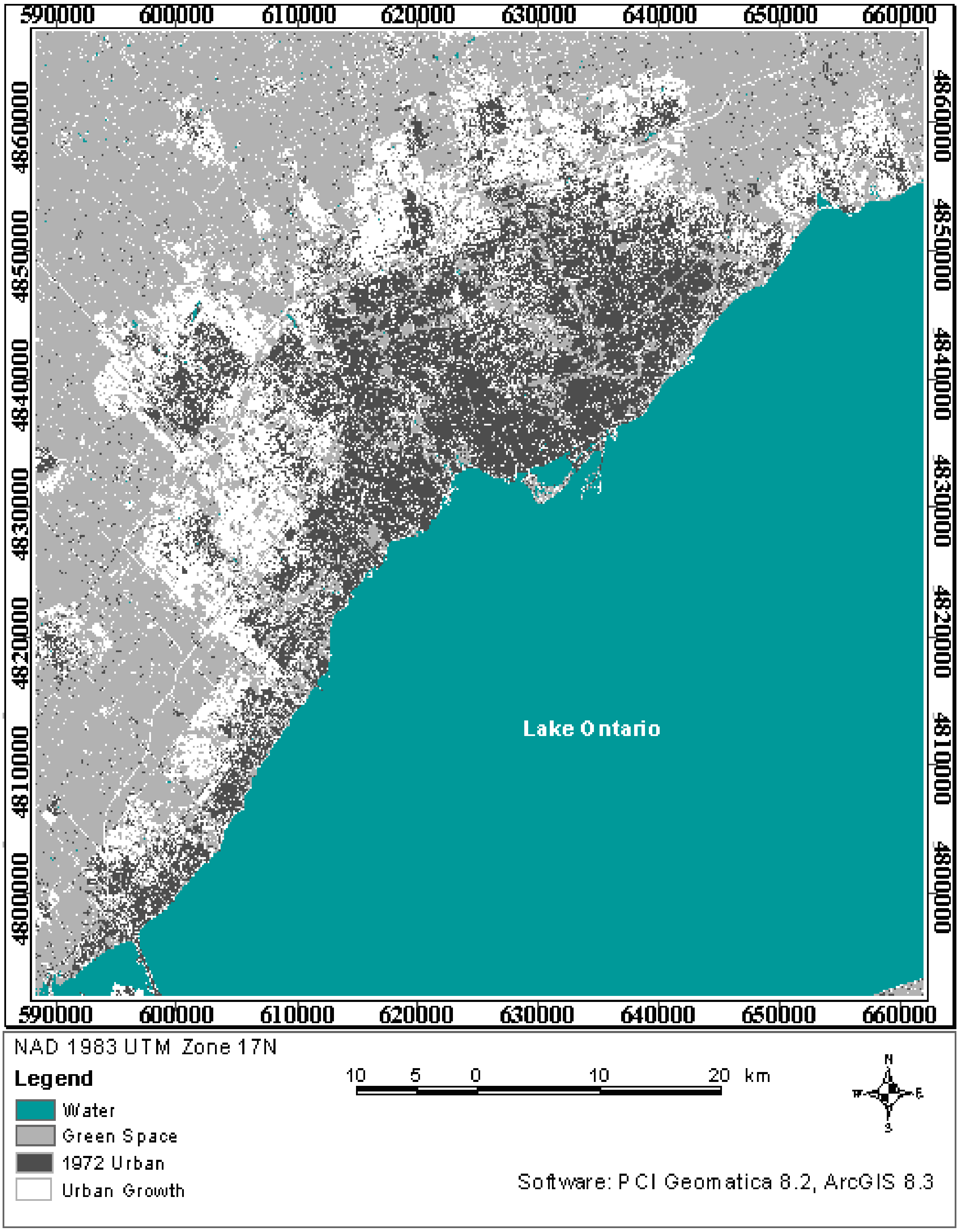

Figure 2: Total urban change from 1972 to 2004.

By visual comparison, it is clear that since 1972 the urban area has expanded in three directions, W, NW, and NE while it was limited by Lake Ontario on the south side. The amount of urban growth from 1972 to 2004 is remarkable. The urban area in 1972 was 663.1 km^2 whereas it was

1327.6 km^2 by 2004. The total urban growth between these two dates is 664.5 km^2, which is double the urban area in 1972. Urban growth has varied over this 32-year period of time. In addition, urban extent includes three different components – developed area, new excavated area, and new developed area. Developed area is the unchanged part between two compared dates.

New excavated area is converted from green space, but not built-up yet. Therefore, the new developed area converted from the excavated area to the built-up area is of more concern. Table 1 summarizes the growth data for comparison purposes. The annual growth is produced from the new developed area by dividing with the length of an interval.

Table 1: Annual growth statistics for all available dates.

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

Places of Growth

Using raster manipulation in ArcGIS, the amount of urban growth from 1972 to 2004 was calculated for each municipality. The difference in municipal urban extents between 1972 and 2004 is strongly illustrated in Figure 3. There is an uneven distribution of urban changes. Mississauga was the largest contributor to the urban change between 1972 and 2004, accounting for 21.29% of the total although its municipal area is only about half of the City of Toronto. Toronto accounted for 16.07% of the total. Notice that Toronto is the largest municipality within the contiguous urban area. The next largest contributors were Brampton (14.91%), Vaughan (13.62%), and Markham (10.02%). Ajax and Pickering accounted for the smallest proportion of total urban change in the study area, at 3.37% and 3.93% respectively although this may have been influenced by the missing data (due to WRS-2 scene divisions) in the northeast corner of some of the Landsat5 and Landsat7 Path 18 Row 30 scenes.

The results from Table 1 show the growth rates throughout the different historical periods from 1972 to 2004. The first peak of urban growth occurred between 1972 and 1977, with an annual growth rate of 17.82 km^2 between 1972 and 1974, and 16.05 km^2 between 1974 and 1977. The second peak of new urban development occurred at the end of 1980's, i.e., between 1987 and 1990, in which yearly urban growth was 16.9 km^2. From 1977 to 1985, the speed of new urban development slowed down, in which the yearly new developed area went from 16.05 km^2 in 1977 to 12.11 km^2 in 1985. The second slow period for new urban development occurred from 1990 to 1994 (16.99 km^2 in 1990 to 12.10 km^2 in 1994). After 1994, i.e. during the last 10 years, the pace of new urban development was the lowest among compared dates. The yearly growth was 12.1 km^2 between 1994 and 1999, 11.6 km^2 between 1999 and 2001, and 11.9 km^2 between 2001 and 2004. The slow period in new urban development between 1990 and 1994 can in part be explained by the impact of an economic recession that occurred in this period of time. The reason for slow growth between 1977 and 1985 is not completely clear because of the longer time period (8 years), although an early 1980's recession certainly played a role.

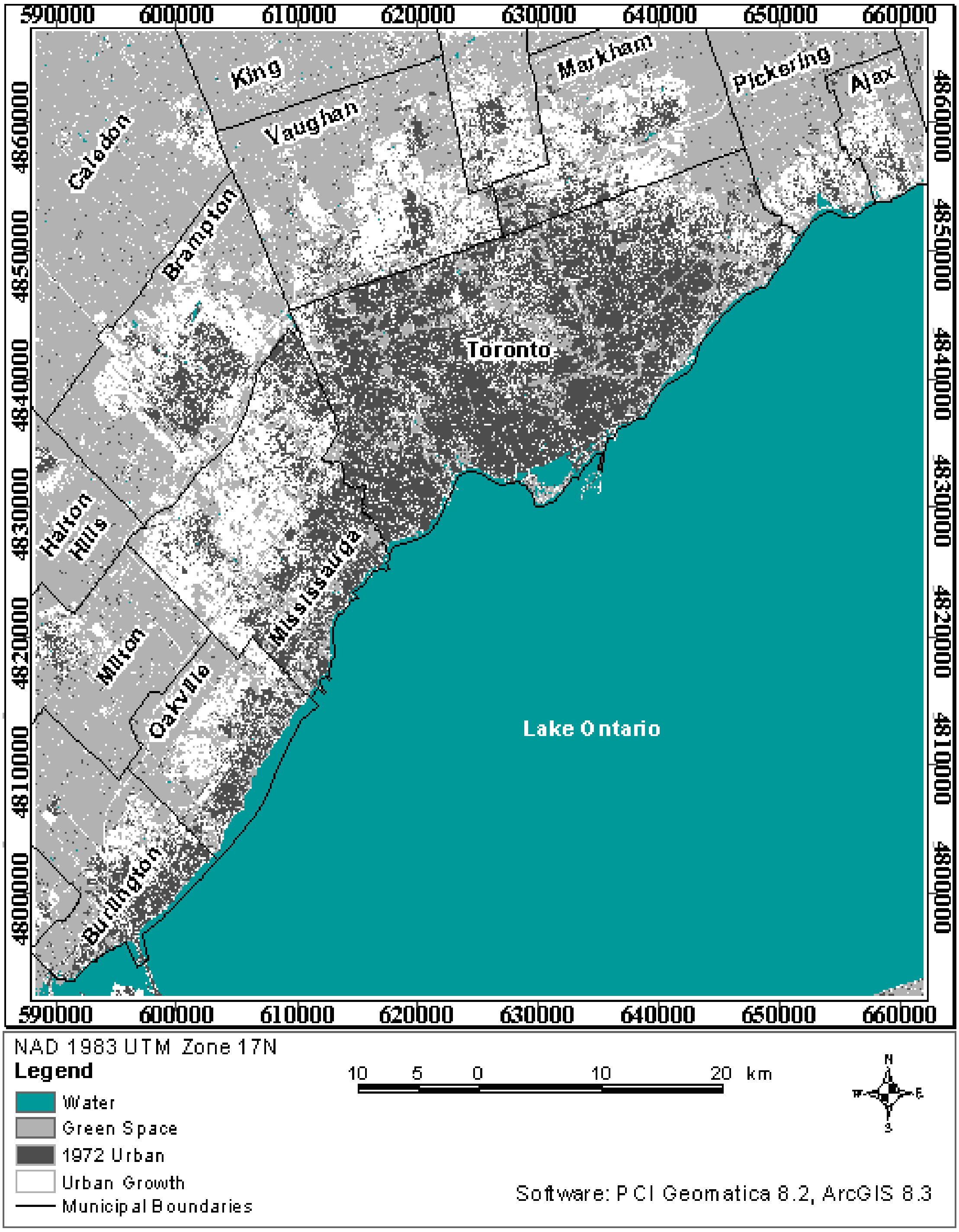

Figure 3: Urban growth in different municipal areas.

CONCLUSIONS

A series of new urban development periods with varied growth rates have occurred over the 32 year period. Two peak new development periods occurred between 1972 and 1977 and between 1987 and 1990. Two periods with lower new urban development rates occurred from 1977 to 1985 and from 1990 to 1994. Over the last 10 years, a relatively stable rate in new urban development has occurred.

Peak yearly new urban development periods seemed to be synchronized with times of urban development backfill whereas the slower growth periods seem synchronized with times of outward urban expansion and sprawl.

The images did not cover the full GTA area and were not completely consistent in coverage for the northeast corner of the study area. This research would have been improved if image data for 1980 or 1981 were available.

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

REFERENCES

i Jensen, J.R., 2004, Introductory Digital Image Processing: A Remote Sensing Perspective, Prentice Hall: Upper Saddle River, N.J. 526 pp.

ii Singh, A., 1989, Digital Change Detection Techniques Using Remotely-sensed Data, International Journal of Remote Sensing, 10(6): 989-1003.

iii Dobson, J.E., Ferguson, R.L., Feld, D.W., Wood, L.L., Haddad, K.D., Iredale, H., Jensen, J. R., Klemas V.V., Orth, R.J., and Thomas, J.P., 1995. NOAA Coastal Change Analysis Project (CCAP): Guidance for Regional Implementation, Washington: NOAA, NMFS 123, 92 pp.

iv Yuan, D. and Elvidge, C., 1998. NALC Land Cover Change Detection Pilot Study: Washington D.C. Area Experiments, Remote Sensing of Environment, 66: 166-178.

v Statistics Canada, 2001, 2001 Census GTA Population Comparison, http://www.region.peel.on.ca/planning/stats/2001/2001_pop_gta.htm

vi The Office for the Greater Toronto Area, Ministry of Municipal Affairs and Housing, Ontario, 2001. Benchmarking the Intelligent Community - A comparison study of regional communities by the Intelligent Community Forum of World Teleport Association, Province of Ontario, Canada, http://www.intelligentcommunity.org/art/pdf/Benchmarking_the_IC.PDF

vii Immen, W., 2000, Sprawling city at crossroads, In: The Globe and Mail, http://www.theglobeandmail.com/series/sprawl/0925.html (Accessed January 20, 2006).

viii Forsythe, K.W. 2002. Stadtentwicklung in Calgary, Toronto, und Vancouver: Interpretation mit Landsatdaten. In: Proceedings of the 14th Symposium for Applied Geographic Information Processing (Angewandte Geographische Informationsverarbeitung XIV), AGIT 2002. July 3-5, 2002. Salzburg, AUSTRIA. Herbert Wichmann Verlag, Hüthig GmbH & Co. KG, Heidelberg, Germany. pp. 105-110. ISBN 3-87907-372-4

ix Forsythe, K.W., 2004, Pansharpened Landsat 7 Imagery for Improved Urban Area Classification, Geomatica, 58(1): 23-31.

x Zhao, H., 2004. Urban Change Detection and Population Prediction Modeling Using Remote Sensed Images, Geomatics and Virtual Environment Lab, Department of Civil Engineering, Ryerson University, Toronto, Ontario.

xi Jensen, J.R. and Toll, D.L., 1982. Detecting Residential Land-Use Development at the Urban Fringe, Photogrammetric Engineering & Remote Sensing, 48(4): 629-643

xii Mas, J.F., 1999, "Monitoring land-cover changes: a comparison of change detection techniques, International Journal of Remote Sensing, 20(1): 139-152.

xiii Ridd, M.K. and Liu, J., 1998. A Comparison of Four Algorithms for Change Detection in an Urban Environment, Remote Sensing of Environment, 63: 95-100.

xiv Toll, D.L., Royal, J.A., and Davis, J.B., 1980. Urban Area Update Procedures Using Landsat Data," In: Proceedings, American Society of Photogrammetry, 12 pp.

xv Weismiller, R.A., Kristof, S.J., Scholz, D.K., Anuta, P.E., Momin, S.A., 1977. Change Detection in Coastal Zone Environments, Photogrammetric Engineering & Remote Sensing, 43(12): 1533-1539.

xvi Chavez, P.S. and Kwarteng, A.Y., 1989. Extracting Spectral Contrast in Landsat Thematic Mapper Image Data Using Selective Principal Component Analysis, Photogrammetric Engineering & Remote Sensing, 55: 339-348.

xvii Fung, T. and LeDrew, E., 1987. Application of Principal Components Analysis to Change Detection, Photogrammetric Engineering & Remote Sensing, 53(12): 1649-1658.

xviii Macleod, R.D. and Congalton, R.G., 1998. A Quantitative Comparison of Change-Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data, Photogrammetric Engineering & Remote Sensing, 64(3): 207-216.

xix Howarth, P.J. and Boasson, E, 1983. Landsat Digital Enhancement for Change Detection in Urban Environment, Remote Sensing of Environment, 13: 149-160.

xx Lyon, J.G., Yuan, D., Lunetta, R.S., and Elvidge, C.D., 1998. A Change Detection Experiment Using Vegetation Indices, Photogrammetric Engineering & Remote Sensing, 64(2): 143-150.

xxi Masek, J.G., Lindsay, F.E., and Goward, S.N., 2000. Dynamics of Urban Growth in the Washington DC Metropolitan Area, 1937-1996, from Landsat Observations, International Journal of Remote Sensing, 21(18): 3473-3486.

xxii Dai, X.L. and Khorram, S., 1999. Remotely Sensed Change Detection Based on Artificial Neural Networks, Photogrammetric Engineering & Remote Sensing, 65: 1187-1194.

xxiii Jensen, J.R., 1986. Introductory Digital Image Processing: A Remote Sensing Perspective, Prentice Hall: Englewood Cliffs, N.J. 379 pp.

xxiv Fung, T. and LeDrew, E., 1988. The Determination of Optimal Threshold Level for Change Detection Using Various Accuracy Indices, Photogrammetric Engineering & Remote Sensing, 54(10): 1449-1454.

xxv Jensen, J.R., 1981. Urban Change Detection Mapping Using Landsat Digital Data, The American Cartographer, 8: 127-147.

xxvi Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data, Remote Sensing of Environment, 37: 35-46.

xxvii Muchoney, D.M., and Strahler, A.H., 2002."Pixel- and Site-based Calibration and Validation methods for Evaluating Supervised Classification of Remotely Sensed Data, Remote Sensing of Environment, 81: 290-299.

xxviii Kyriakidis, P.C., Liu, X., and Goodchild, M.F., 2004. Geostatistical Mapping of Thematic Classification Uncertainty, In: Lunetta, R.S., and Lyons J.G. (Eds.), Geospatial Data Accuracy Assessment, Las Vegas: U.S. Environmental Protection Agency, Report No. EPA/600/R-03/064, 335 pp.