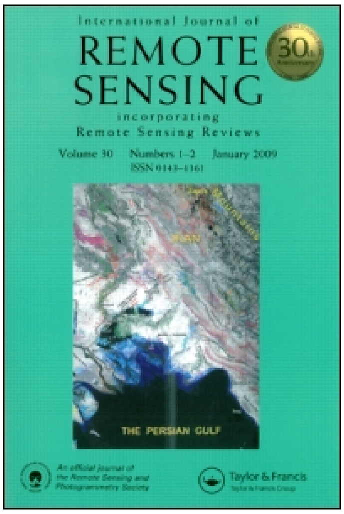

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Comparison of pixel- and object-based classification in land cover change mapping

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Land use/land cover (LULC) change occurs when humans alter the landscape, and this leads to increasing loss, fragmentation and spatial simplification of habitat. Many fields of study require monitoring of LULC change at a variety of scales. LULC change assessment is dependent upon high-quality input data, most often from remote sensing-derived products such as thematic maps. This research compares pixel- and object-based classifications of Landsat Thematic Mapper (TM) data for mapping and analysis of LULC change in the mixed land use region of eastern Ontario for the period 1995–2005. For single date thematic maps of 10 LULC classes, quantitative and visual analyses showed no significant accuracy difference between the two methods. The object-based method produced thematic maps with more uniform and meaningful LULC objects, but it suffered from absorption of small rare classes into larger objects and the incapability of spatial parameters (e.g. object shape) to contribute to class discrimination. Despite the similar map accuracies produced by the two methods, temporal change maps produced using post-classification comparison (PCC) and analysed using intensive visual analysis of errors of omission and commission revealed that the object-based maps depicted change more accurately than maximum likelihood classification (MLC)-derived change maps.

1. Introduction

By 2100 land use/land cover LULC change is predicted to have the greatest effect on global ecological systems, including a more significant effect than climate change and invasive species threats (Chapin *et al.* 2000). With increasing conversion of natural lands to human-use landscapes and intensification of altered lands, there is associated loss of habitat for many species as well as increasing fragmentation and modification of the spatial configuration of habitat. LULC change affects all vegetated systems including terrestrial, aquatic and wetland ecosystems (Chapin *et al*. 2000, Tilman *et al*. 2001) and urban areas (Lo *et al.* 1997). Eastern Ontario, Canada (figure 1) has experienced significant LULC change (Statistics Canada 2001, Guindon *et al.* 2004, Zhang and Guindon 2005, Mitsch and Gosselink 2007). Approximately 20% of all of Canada's wetlands are located in Ontario (National Wetlands Working Group 1988), and destruction of these has been extensive, with estimated losses of 66% of pre-European settlement wetlands (Mitsch and Gosselink 2007). In eastern Ontario, wetland losses mapped by township vary from negligible to over 80% (Snell 1987).

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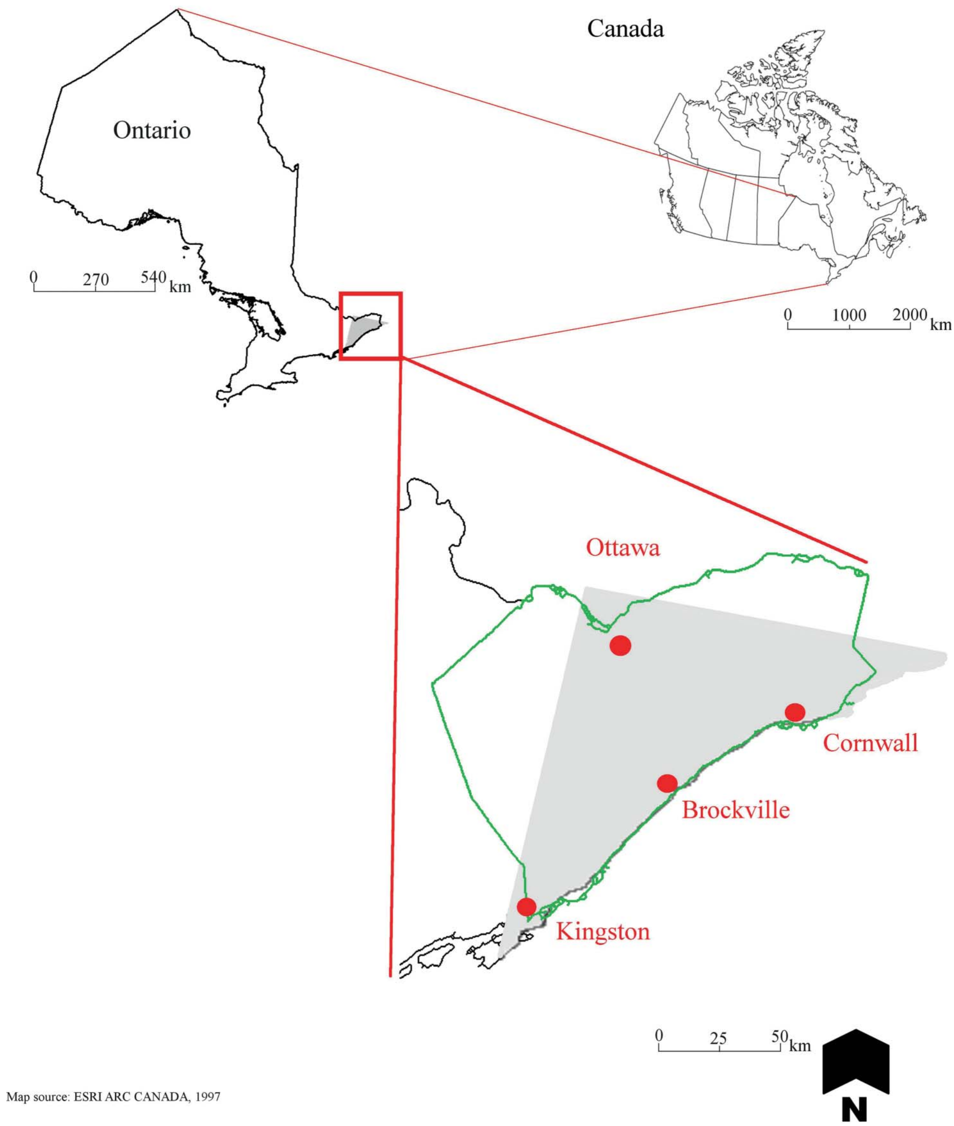

Figure 1. Study region of eastern Ontario, Canada. Grey outline represents the coverage of the Landsat image. Green boundary outlines eastern Ontario as defined by the Eastern Ontario Model Forest (EOMF) organization. Software: Environmental Research Institute Canada (1997).

Total farm area in Ontario increased 9.7% between 1996 and 2001 (Statistics Canada 2001), with almost all of this land being converted from forest or wetland. The Eastern Ontario Model Forest (EOMF) programme has found that in the past 150 years, forests of the region have been in an ongoing state of decline (EOMF 2006b).

Land use policies must consider the importance of LULC change to human welfare (e.g. increased food production) while minimizing environmental effects (Foley *et al*. 2005). It is therefore important to map and monitor LULC change through time using accurate land cover maps of regional extent produced for multiple dates. Remote sensing land cover classification methods have been shown to provide accurate land cover maps over large regions (Foody 2002, Cingolani *et al*. 2004) and comparison of thematic maps for two dates has been shown to provide accurate from–to change information (Collins and Woodcock 1996, Abuelgasim *et al.* 1999, Mas 1999, Lu *et al*. 2005, Janzen *et al*. 2006, Virk and King 2007). The quality of the input maps is of primary importance when using thematic maps for LULC change analysis. Object segmentation and classification has recently been shown to have significant promise to improve map quality over traditional pixel-based maximum likelihood classification (MLC) (e.g. Flanders *et al.* 2003, Gao *et al.* 2006, Yu *et al*. 2006, Seidelmann and Merry 2007). The premise behind object-based methods is that by first defining and then classifying objects, more useful thematic maps can be produced that show landscape entities as humans perceive them.

In single date analysis, Flanders *et al.* (2003) found the accuracy of object-based classification of forestry-related classes in Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image data to be 3–36% (class-dependent) better than a pixel-based MLC. Gao *et al*. (2006) mapped 12 land cover classes in China using ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) data with overall accuracies of 46.48% (MLC) and 83.25% (object-based). Yu *et al*. (2006) used four-band airborne digital camera image data, including intensity, hue and saturation transformations, as well as elevation, slope, aspect, and distance to waterways to map 48 classes with an overall accuracy of 56.3%, and 13 classes of vegetation at over 60% accuracy. In LULC change mapping, Seidelmann and Merry (2007) used census data and object-based classification of Landsat image data to assess change in the urban/rural fringe area of Cleveland, Ohio, USA. Seven of eight land cover classes in the maps for both dates met suitable user's and producer's accuracies ranging from 68 to 100%, but they did not compare these results to other classifiers (e.g. MLC) because initial results showed confusion between important classes (e.g. urban and forest). Im *et al.* (2008) assessed change using a new method of object/neighbourhood correlation image analysis and image segmentation, and Desclée *et al.* (2006) assessed change using image segmentation, image differencing and statistical analysis of reflectance. This research builds on this existing knowledge regarding potential increases in single date LULC mapping accuracy using object-based classification and evaluating its usefulness in LULC change mapping. The objectives of this research were to compare the accuracy of traditional pixel-based maximum likelihood classification to object-based segmentation/classification at a regional scale, and to evaluate the effects of each type of classification on LULC change mapping using post classification comparison.

2. Methodology

2.1 *Site selection*

This study is part of a larger body of research in the Carleton University Geomatics and Landscape Ecology Research Laboratory (GLEL) that has been initiated to study the effects of LULC configuration and change on biodiversity in eastern Ontario. Few published studies have been specifically concerned with LULC change in eastern Ontario, and those that exist have focused on urban areas (Guindon *et al*. 2004, Zhang and Guindon 2005).

Eastern Ontario (figure 1) is a region of approximately 15,500 km^2 that comprises a mix of agricultural, forest, and urban lands, and includes the City of Ottawa on the northern edge. Agriculture is dominant near the St. Lawrence and Ottawa Rivers, and in the flat landscapes from Ottawa east towards the Québec border. To the northwest, the Canadian Shield, an expansive area with very thin soil on top of igneous and metamorphic bedrock, limits agriculture. Forest covers about 38% of the region, and varies from about 60% in the northwest, to less than 30% in the east. Most forests are deciduous or mixed deciduous–coniferous and are dominated by sugar maple (*Acer saccharum*), with lesser amounts of other temperate species (e.g. American beech (*Fagus grandifolia*), red oak (*Quercus rubra*), red pine (*Pinus resinosa*); low-lying wetter areas are often dominated by white cedar (*Thuja occidentalis*)). Wetlands are distributed throughout the region and are predominantly swamps and marshes with fewer bogs and fens (as defined in the Canadian Wetland Classification System (National Wetlands Working Group 1997)).

2.2 *Satellite data and fieldwork*

Landsat Thematic Mapper 5 (TM) scenes from 1 August 1995 and 13 September 2005 (figures 2(*a*),(*b*)) were selected as the best available cloud-free scenes covering the spatial and temporal resolution of interest for the leaf-on period of late spring through summer. Forest leaf colour change does not occur until very late September–mid October, thus the 13 September imagery did not include significant changes in forest reflectance. Fieldwork for training and validation sampling was conducted in late July 2006 using the Landsat image data, air photos, and topographic maps as guides. A total of 334 reference sites were assessed and information regarding each site was noted throughout the study area in an effort to find all possible land cover types and represent their natural variance in the region. A set of 30 initial classes (table 1) was

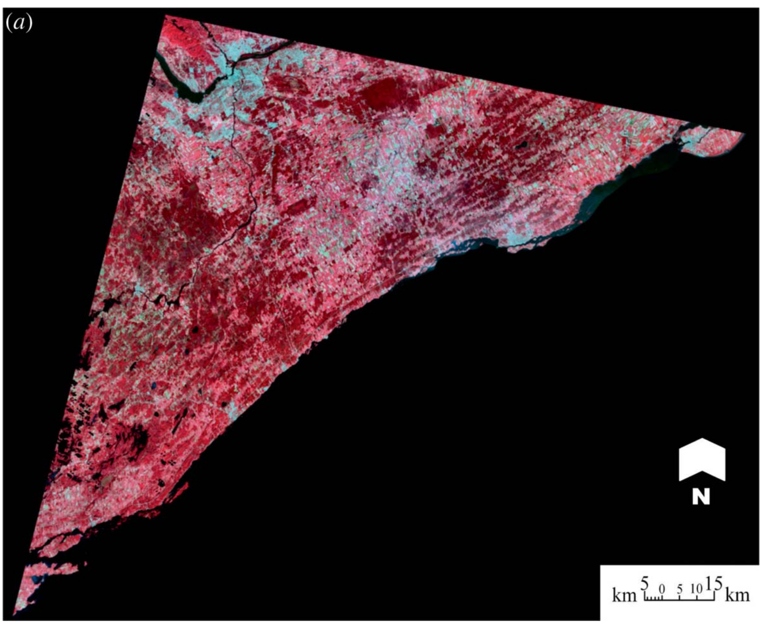

Figure 2. (*a*) 13 September 2005 Landsat TM CIR composite of eastern Ontario; (*b*) 1 August 1995 Landsat TM CIR composite of eastern Ontario.

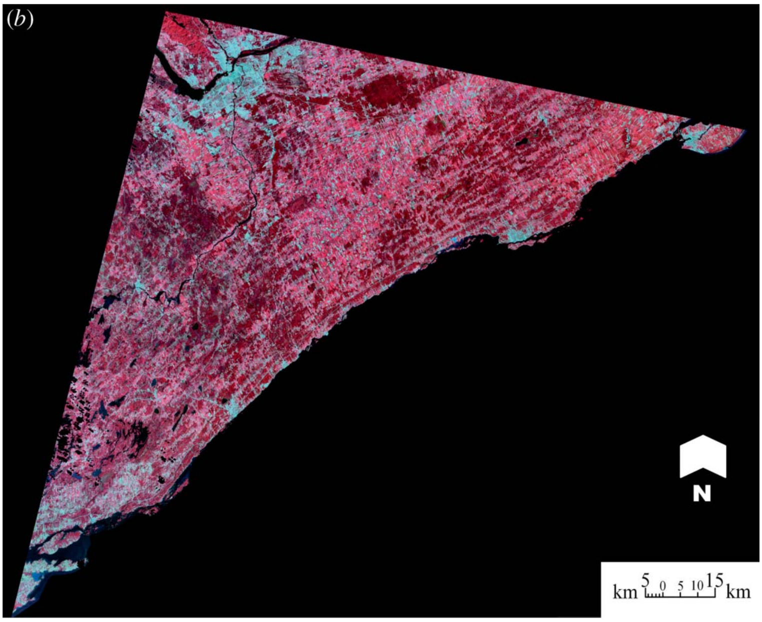

Figure 2. *Continued.*

visually interpreted and identified, with the intention of merging them later to a smaller set that could be well mapped. An attempt was made to accumulate at least 15 sites for each class, but this was not possible for some rare classes. Class sample sites were constrained by public road access and land cover homogeneity over a spatial extent of at least 3×3 pixels (90×90 m). The region has public roads throughout at less than 2 km spacing, and for all classes (excluding forest classes) visibility was generally several hundred metres; i.e. all classes were well represented in the viewshed from these roads. Each site was geo-referenced using a Trimble Geo XT real-time differential Global Positioning System (GPS) with Wide Area Augmentation System (WAAS) corrections (FAA 2005) that provided sub-metre accuracy (Trimble Navigation Ltd. 2004). The eight-month difference between the 2005 image data and the fieldwork dates, and the two-month difference within the growing season between the 1995 and 2005 scenes were not expected to impact the results at the coarser classification level following merging of the initial classes. Care was taken to note possible dynamic land cover types, such as agricultural classes that could have changed between image and field data acquisition dates.

The GPS coordinates of the sites and other control points collected at landmarks such as road intersections were used. A first-order polynomial transformation and nearest neighbour re-sampling were used resulting in a Root Mean Square Error in x (RMSE_x) = 0.06 and RMSE_y = 0.13 pixels. Eastern Ontario is relatively flat with less than 200 m change in elevation across the entire area; therefore additional Ground Control Points (GCPs), a higher-order polynomial or ortho-rectification were not required. The same process was used to subsequently align the 1995 scene to the 2005 georeferenced scene ($\mathrm{RMSE}_x = 0.08$ and $\mathrm{RMSE}_y < 0.01$ pixel).

Table 1. Class lists showing how the initial 30 classes identified in the field were merged first to 20 classes and then to 10 distinct classes.

	30 Observed land covers	20 aggregated classes	10 aggregated classes
1	Urban Commercial, Urban Commercial (dense), Urban Suburb (not treed), Urban Parking Lot	High-density Urban (dominated by impervious surfaces)	High-density Urban
2	Urban Rural, Urban Suburb (treed), Urban Schools, Urban Residential (dense and treed)	Low-density Urban (equal or less than ½ impervious - more vegetation).	Low-density Urban
3	Pine Plantation (open), Pine Plantation (closed)	Coniferous (open), Coniferous (closed)	Coniferous Forest
4	Deciduous (open); Deciduous (closed); Mixed (open); Mixed (closed)	Deciduous (open), Deciduous (closed), Mixed (open), Mixed (closed)*(merged because of extremely low Bhattacharrya Distances between all four classes)	Deciduous/ Mixed Forest
5	Exposed Sand or Rock	Exposed Sand or Rock	Bare Rock and Sand
6	Dirt areas/piles, Harvested Field (soil mixed with dead vegetation), Bare Field/soil	Harvested Field, Bare Field	Bare Field
7	Rivers, Lakes, Ponds	Water (deep), Water (shallow)	Water
8	Wetlands (no dead/dying trees), Wetlands (bog), Wetlands (with dead/dying trees)	Wetlands (swamp), Wetlands (marsh)	Wetlands
9	Pasture, Soccer Field, Golf Course, Mowed Grass, Shrubby Field; Tall Green Crops (e.g. corn)	Vegetated Field 1, Vegetated Field 2	Agriculture 1 (green)
10	Yellow Crops (e.g. hay, cereals), Fallow/wild Fields.	Vegetated Field 3, (which was subsequently split into Cultivated Field (mowed Grass), Wild Field)	Agriculture 2 (yellow)

2.3 *Separability analysis, atmospheric correction and maximum likelihood classification*

A minimum of 15 sites (Jensen 2005) was not obtained for some of the 30 field classes, and so merging was conducted to produce a set of 20 classes (table 1) with as large a sample size as possible for each class. Using random sampling, one-third of all field sites for each of the 20 classes were selected to be used as training sites. The GPS location of each training site was found in the image data and, with the aid of the field notes and photographs, training polygons were delineated. Separability of the training data for all class pairs was assessed using the Bhattacharrya Distance (Jensen 2005). The histograms of the 20 training classes were also evaluated to determine if any were bi-modal or overlapping. Based on the separability results, classes were further merged until 10 distinct and separate classes were produced (table 1). These 10 classes were subsequently used for both the pixel- and object-based classifications.

In temporal analysis, minimization of atmospheric effects is critical if image information from one date is used to derive image information another date (Pax-Lenney *et al.* 2001, Song *et al.* 2001). In this research, because 1995 reference data were unavailable across the whole scene, training signatures derived from the 2005 scene were used to classify the 1995 data. This process, known as signature extension, is an alternative to using selected reference sites from historical image data when field sites have not been assessed in the past. It can result in less user-influence and misinterpretation of historical reference data (Pax-Lenney *et al.* 2001). Atmospheric correction of the 1995 and 2005 image data was required before conducting such signature extension, especially as there was a large hazy area in the south-east of the 2005 image. Several atmospheric correction methods were tested including two absolute methods, the Atmospheric Correction (ATCOR) program (Richter 1991, 1996), which is based on Moderate Resolution Atmospheric Transmission (MODTRAN 4 (Berk *et al.* 1998)), and dark-object subtraction (DOS) (Chavez 1989), selected over 'modified' DOS algorithms based on findings of Pax-Lenney *et al.* (2001) showing the original DOS algorithm to perform just as well. These two methods were applied to both the 2005 and 1995 image data in classification tests. One relative method was tested to match the 1995 data to the 2005 data using linear relations for pseudo-invariant feature (PIF) data between the two dates (Song *et al.* 2001). Combinations of these methods were also tested for the 1995 data to see if results would improve. The methods were compared through assessment of the overall accuracy of maximum likelihood classifications using the 334 field sites randomly split into 1/3 training, 2/3 validation. Table 2 lists the atmospheric correction methods and the resulting overall MLC accuracies and kappa coefficient values for the 10 aggregated classes of table 1. To compare these overall classification accuracies, McNemar's test (McNemar 1947) was used as recommended by de Leeuw *et al.* (2006) because the same validation samples were used. It was deemed not appropriate to use Cohen's Z-test, as it assumes the samples are independent (Cohen 1960). McNemar's test is non-parametric and is based on the classifiers' error matrices, determining if column and row frequencies are equal (null hypothesis) (de Leeuw *et al.* 2006, Gao *et al.* 2006). The statistic is applied to a 2×2 contingency table which presents a cross-tabulation of the correct and incorrect class distributions for each individual classifier as derived from the error matrices and is calculated as (Gao *et al.* 2006):

$$Z = \frac{f_{12} - f_{21}}{\sqrt{f_{12} + f_{21}}} \tag{1}$$

Table 2. Overall accuracy (%) and κ values assessed for the atmospherically corrected 2005 and 1995 scenes. The last three columns represent, respectively: 1995 uncorrected scene matched to 2005 uncorrected scene using PIF relative method; 1995 DOS corrected scene matched to 2005 DOS corrected scene using PIF relative method; 1995 ATCOR corrected scene matched to 2005 ATCOR corrected scene using PIF relative method.

Scene and correction type	2005	2005 DOS	2005 ATCOR	1995 DOS	1995ATCOR	1995 to 2005	1995 DOS to 2005 DOS	1995 ATCOR to 2005 ATCOR
Overall accuracy (%)	73.9	78.4	74.8	79.2	75.1	77.2	77.2	77.7
κ	0.68	0.73	0.69	0.73	0.67	0.71	0.71	0.71

where f_{ij} is the frequency of the validation data at row i, column j; f_{12} and f_{21} are the number of pixels that one method correctly classified as compared to the number of pixels the other method incorrectly classified (Gao *et al.* 2006). McNemar's test uses a population ratio of $\psi = f_{12}/ f_{21}$ and the null hypothesis is represented by $\psi = 1$ (de Leeuw *et al.* 2006). The test bases its evaluation on the chi-squared distribution where the square of Z follows a chi-squared distribution with one degree of freedom (de Leeuw *et al.* 2006) and is:

$$\chi 2 = \frac{(f_{12} - f_{21})^2}{f_{12} + f_{21}} \tag{2}$$

De Leeuw *et al.* (2006) suggests that the tests work well when $(f_{12}+f_{21})/2>10$, which was the case for this research. Using McNemar's test, the differences between the varying classifications for the atmospheric correction tests were found not to be significantly different. With further assessment of the individual class accuracies, the 2005 DOS corrected scene was found to have higher accuracies and kappa coefficient values in general. For 1995, the highest accuracies were obtained for DOS correction without the relative correction (PIF) to the 2005 DOS scene (table 2). Based on these assessments, it was decided to use the 2005 and the 1995 DOS corrected scenes (without a PIF correction between the two scenes) for the two classification methods and the temporal analysis.

2.4 *Object-based segmentation and classification*

All processing of the object-based segmentation/classification was completed using Definiens Professional 5.0 (formerly eCognition) software (Definiens AG, Munich, Germany). The 2005 scene was processed first. This processing used multi-resolution segmentation. The key parameter in multi-resolution segmentation is a unitless variable of scale that is related to the image's pixel size and to the parameters of colour (spectral information) and shape (smoothness and compactness), all of which can be weighted by the user (Laliberte *et al.* 2004). Larger scale values result in larger delineated objects. Objects are grown simultaneously across the scene based on spectral similarity of pixels and the contrast of an object with neighbouring objects. The output is a set of delineated objects representing one level in a segmentation hierarchy. Scale parameters of 5, 10 and 20 were tested. Since many land cover entities are best seen at differing scale levels, it becomes difficult to determine the 'best' scale parameter using only one level of segmentation for classification. In most studies to date, parameter selection for this type of segmentation has been done mostly by trial and error. In time, through such tests, optimal parameter values can emerge for given landscape/scale types. Examples of studies that have tested a variety of scale parameters through this 'trial and error' process include Flanders *et al.* (2003), Gao *et al.* (2006), Yu *et al.* (2006), Seidelmann and Merry (2007), Tian and Chen (2007), and Im *et al.* (2008). Colour values from 0.1 to 0.9 were tested, with shape values as {1-colour}. Shape can be further developed with the parameters smoothness and compactness. Following the trial and error nature of these tests, these parameters were kept at 0.5 in an attempt to understand how the segmentation changed while altering only the shape/colour relationship. Object outputs were visually analysed with regard to classes of interest (e.g. agriculture field, urban areas, etc.) to assess which parameter settings best captured the objects of interest. The optimal parameters found from these tests were: scale = 10; colour = 0.6; shape = 0.4. An in-depth visual analysis of zoomed in results allowed for a discernment of how well urban, forest, water and agricultural objects were represented by the segmented objects in terms of holes, edges, shape, and representation of whole entities such as fields, etc. These optimal parameters were also applied in the segmentation of the 1995 image as the distribution of image brightness, texture and object shapes and sizes in the 1995 image were very similar to those in the 2005 image.

In classification of the delineated objects, at the same field sites as for the MLC, training data were generated using the mean spectral values of objects found at these sites. Object shape can also be an input variable in the object classification phase so tests were conducted of the following shape parameters: shape index (the border length of the object divided by four times the square root of its area), area (area covered by one pixel times the number of pixels forming the object), compactness (product of the length and width of the object divided by the number of inner pixels), and rectangular fit (ratio of the area inside a minimum bounding rectangle for the object divided by the area of the object outside the rectangle) (for more details, see www.definiens.com). These parameters were selected because of their relation to the shape of segmented objects and the potential for certain classes to be discriminated based upon specific shape parameters (e.g. rectangular fit for agriculture, compactness for urban, etc.). Tests of a variety of values for each parameter and for combinations of parameters were conducted to evaluate their impacts on classification accuracy. In all cases, the shape parameters did not improve overall classification accuracy. In some cases, applying given parameter values to all classes improved certain individual class accuracies, but when these parameters were applied only to those specific classes, the improvement did not occur. Consequently, it was felt that these shape parameters were too variable in each class and they were therefore not integrated into the training data. Classification was conducted using only the spectral information for each object. A nearest-neighbour classifier (Jensen 2005) was then applied using this classification hierarchy for both the 2005 and 1995 segmented scenes.

2.5 *Classification accuracy assessment*

As was the case for the accuracy assessment of thematic maps produced from the various atmospherically corrected scenes, for the 2005 MLC and object-based classifications the remaining two-thirds of the field sites not used in training were used for validation. Accuracy for both classifications was assessed in detail using error matrices, and their associated statistics, namely: overall accuracy, class Producer's Accuracy (PA), class User's Accuracy (UA), the average UA and PA, and the kappa (κ) coefficient of agreement (Lillesand *et al.* 2004, Jensen 2005).

For the 1995 accuracy assessments, validation data (such as air photos) were not available for the whole study area, nor were field reference data. Interpretation directly from the Landsat image data was deemed to be too susceptible to error and user influence (Foody 2002). The only available field data were the 2006 data. Therefore to use these data for 1995 additional processing had to occur in order to not include sites that had changed. Image differencing is one of the most widely used image-based change detection algorithms and it is considered one of the most accurate (Nelson 1983, Mas 1999, Lu *et al.* 2005). Unchanged pixels are usually clustered about the mean of a difference histogram distribution, while changed pixels are found within the tails. For this research, the atmospherically corrected 2005 and 1995 scenes were differenced using ±1 standard deviation as a threshold (Yuan and Elvidge 1998, Mas 1999). All 2005 validation sites were assessed in comparison to this change image and those sites that fell on or near (±1) pixels that were greater than ± one standard deviation from the mean were discarded. The remaining sites were assumed to have not changed over the 10-year period and were used as validation data for both the MLC and object-based 1995 classifications.

In addition to quantitative evaluation of map accuracy, maps produced for both dates were intensively searched to compare locations of significant visible errors of omission and commission and the classes that were subject to such errors.

2.6 *Temporal analyses of land cover change*

Post classification comparison (PCC) analysis has been found to provide accurate representations of change in the landscape and is commonly ranked highly amongst various alternatives such as image differencing, principal components analysis and multi-date classification (e.g. Collins and Woodcock 1996, Abuelgasim *et al.* 1999, Mas 1999, Lu *et al*. 2005, Janzen *et al*. 2006, Prenzel and Treitz 2006, Virk and King 2007). In addition, PCC allows direct evaluation of the success in representation of from–to class changes. The 2005 and 1995 thematic maps were cross-tabulated on a pixel-by-pixel basis (i.e. for both the MLC and object-based maps) to create overall change maps as well as change matrices. These were analysed to evaluate the nature and magnitude (area) of LULC change that occurred in eastern Ontario during the 10-year period. In addition, as for the single date classifications, intensive searching and visual assessment were conducted to identify errors of omission and commission in LULC change and to compare the change maps produced from the two types of classification.

3. Results and discussion

3.1 *Pixel- vs. object-based single date classification accuracy*

Table 3 presents a summary of the accuracy statistics from MLC and object-based classifications for both dates. Using McNemar's test as described previously, no significant differences were found between the ten-class MLC and object-based maps for either date. Results from the 2005 MLC and object-based classifications

Table 3. Summarized accuracy statistics of the four classifications ((10 classes) OB – object-based; MLC, maximum likelihood classification).

	2005 MLC (10 Class)	2005 OB (10 Class)	1995 MLC (10 Class)	1995 OB (10 Class)
Overall accuracy (%)	75.7	75.6	79.2	75.6
κ	0.70	0.70	0.73	0.70
Average PA (%)	71.8	65.2	70.7	69.2
Average UA (%)	73.9	66.6	73.5	64.3
Average PA without Bare Rock and Sand (%)	72.0	72.4	70.5	71.6
Average UA without Bare Rock and Sand (%)	73.5	74.0	74.8	79.2

are presented in detail below with associated tables and figures while the results of the 1995 classifications are summarized only.

3.1.1 Ten-class maximum likelihood classifications. Figure 3 presents the 2005 MLC ten class map. The area circled in red shows Deciduous/Mixed Forest with patches of Coniferous Forest, irregularly shaped Agriculture (both types) and Wetlands. The area to the north of Cornwall circled in blue is classified mostly as Agriculture 1 interspersed with Bare Fields and Agriculture 2. There are also some forested (Deciduous/Mixed and Coniferous) regions. Areas classified as High-density and Low-density Urban are situated in each of the major urban centres that are labelled on the map. These three general classifications are correct because the western portion of the study area is on the Canadian Shield where there is little farming and more forest, the central and eastern portions are extensively farmed but have interspersed woodlands and wetlands, and the cities and towns are well separated and distinct.

Table 4 presents the accuracy statistics and error matrix for this classification. There was a wide variation in the numbers of samples for each class, resulting in greater weight for classes with more samples contributing to the calculation of the overall accuracy values. The Wetlands class had the lowest accuracy while Water had the highest accuracy; however, the low PA reflects extensive confusion with Wetlands.

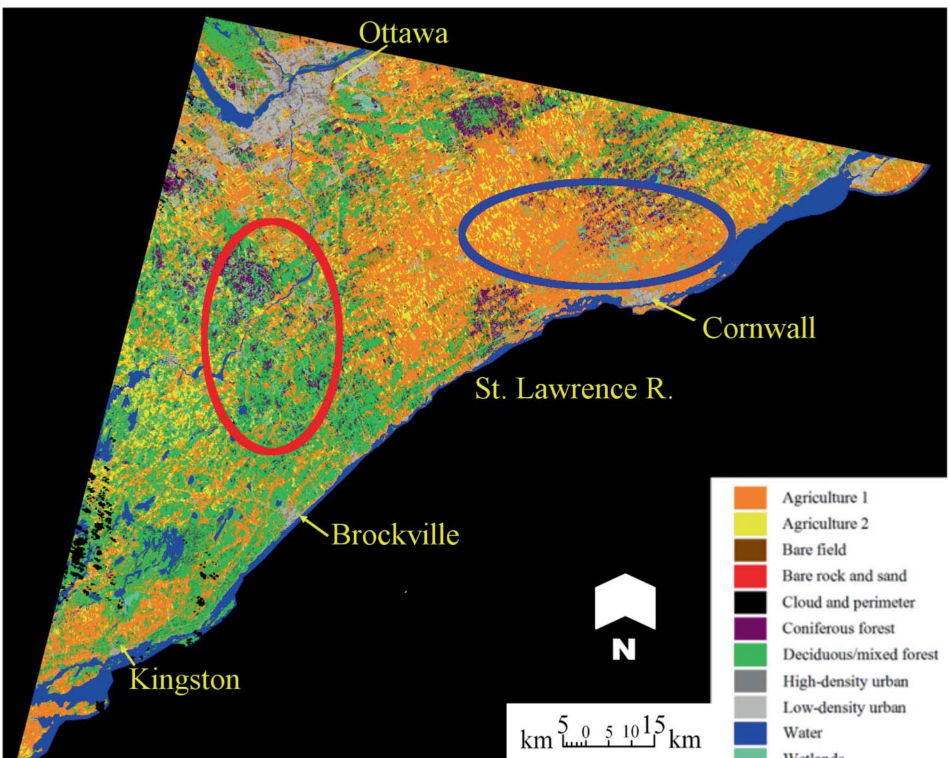

Figure 3. Thematic map of eastern Ontario developed from 2005 scene using MLC and 10 classes.

Table 4. Accuracy statistics and error matrix for the 2005 maximum likelihood classification (10 classes). Columns represent reference cover types. Rows represent classified cover types.

	Agriculture 1	Agriculture 2	Bare Field	Bare Rock and Sand	Coniferous Forest	Deciduous/ Mixed Forest	High-density Urban	Low-density Urban	Water	Wetlands	Total	UA (%)
Agriculture 1	69	0	0	0	0	5	0	1	0	1	76	90.8
Agriculture 2	1	19	0	0	0	1	0	1	0	1	23	82.6
Bare Field	0	1	4	0	0	0	0	0	0	0	5	80.0
Bare Rock and Sand	0	0	1	2	0	0	0	0	0	0	3	66.7
Coniferous Forest	0	0	0	0	8	3	0	0	0	1	12	66.7
Deciduous/ Mixed Forest	4	0	0	0	1	18	0	0	0	0	23	78.3
High-density Urban	0	4	0	1	0	0	16	1	1	0	23	69.6
Low-density Urban	3	5	0	0	1	2	5	20	1	0	37	54.1
Water	0	0	0	0	0	0	0	0	5	0	5	100.0
Wetlands	3	0	0	0	0	0	0	0	4	7	14	50.0
Unknown	1	0	0	0	0	0	0	0	0	0	1	
Total	81	29	5	3	10	29	21	23	11	10	222	
PA (%)	85.2	65.5	80.0	66.7	80.0	62.1	76.2	87.0	45.0	70.0	Overall accuracy = 75.7%	
κ	0.86	0.80	0.80	0.66	0.65	0.75	0.66	0.49	1.00	0.48		

Table 5. Summary of different levels of confusion between classes for the 2005 MLC and 2005 object-based classification.

Image classification	Type of accuracy	Level of confusion	Classes confused
2005 MLC	PA	Extensive	Water with Wetlands,
		Moderate	High-density Urban and Low-density Urban; Deciduous/Mixed Forest and Coniferous Forest; Agriculture 2 with Low and High-density Urban; and Agricultural 1 with Deciduous/Mixed Forest, Low-density Urban and Wetlands
	UA	Extensive	None
		Moderate	Agriculture 1 and Deciduous/Mixed Forest; Coniferous Forest and Deciduous/Mixed Forest; Deciduous/ Mixed Forest and Agriculture 1; High-density Urban and Agriculture 2; Low Density Urban with Agriculture 1, Agriculture 2, and High-density Urban; and Wetlands with Agriculture 1 and Water
2005 Object-based	PA	Extensive	Coniferous Forest with Deciduous/Mixed Forest, Low-density Urban with Agriculture 2, and Bare Rock and Sand with High-density Urban (although the sample size was low for the rare Bare Rock/Sand class)
		Moderate	Agriculture 1 with Agriculture 2; and Deciduous/Mixed Forest with Low-density Urban and Wetlands
	UA	Extensive	Deciduous/Mixed Forest with Coniferous Forest
		Moderate	Low-density Urban with Deciduous/Mixed Forest and High-density Urban

Table 5 provides a summary of the different levels of confusion among classes for this classification, and the 2005 object-based classification. Among the land use classes, the class with the highest accuracy was Agriculture 1. Agriculture 1 and Bare Field had PAs and UAs over 70% with High-density Urban, Bare Rock and Sand, Coniferous Forest, and Agriculture 2 just below 70%. The average PA and UA values were above 70%.

The MLC thematic map derived from the 1995 scene was visually similar to figure 3, but areas classified as Deciduous/Mixed Forest were more apparent in the south and southeast. The overall accuracy (table 3) was slightly better than that for 2005. The Wetlands class was again the poorest and Water had the highest accuracy, with its PA being greater than that for the 2005 classification. Similar classes as described in table 5 for the 2005 classification were moderately confused but overall, the accuracy was slightly better. Five classes, Bare Rock and Sand, Agriculture 1, Water, Deciduous/ Mixed Forest and High-density Urban had UAs and PAs over 70%.

3.1.2 Ten-class object-based classifications. Figure 4 presents the 2005 object-based thematic map derived using the optimal parameters identified in testing as described above. Overall, all object-based maps produced in this study were smoother than the pixel-based MLC maps, with larger, continuous classified areas, few abrupt changes between discretely classified areas, and no single pixels classified differently from surrounding pixels resulting in a salt-and-pepper texture as in the MLC maps. The red circled area (same as in figure 3) is classified to the same classes as the MLC

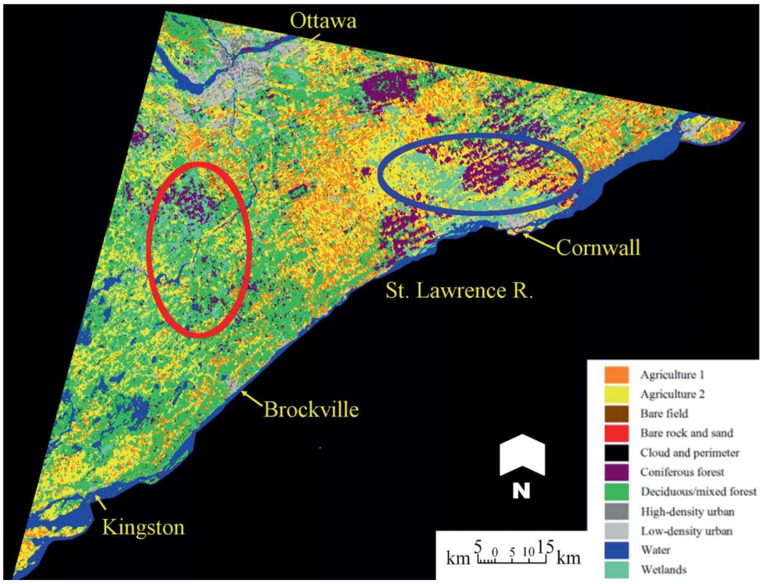

Figure 4. Thematic map of eastern Ontario developed from 2005 scene using object-based classification and 10 classes.

although, Agriculture and Wetland objects are more apparent. The blue circled area (same as in figure 3) has much less area classified as Agriculture than in the MLC map, because a large portion in the centre is classified as Wetlands and Coniferous Forest.

Table 6 presents the accuracy statistics and error matrix for the 2005 object-based classification. In comparison with the PA of the 2005 pixel-based classification, more (and different) classes were extensively confused (table 5). Bare Rock and Sand was the poorest class. (This class was maintained in the class list to have an equivalent number of classes for each method.) The Coniferous Forest class was the second poorest class with lower UA than the 2005 pixel-based classification. Bare Field had the highest accuracy while Water had the second highest accuracy with improved PA over the MLC. Five classes Agriculture 1, Agriculture 2, High-density Urban, Deciduous/Mixed Forest, and Bare Field had UA and PA values higher than 70%. This is three more classes than for the MLC. Overall, more classes developed from the object-based method had higher UAs and PAs. Unlike the 2005 MLC, however, the average PA and UA values (including the Bare Rock and Sand class) were below 70%.

The object-based thematic map derived for the 1995 scene was visually similar to figure 4; however, Agriculture 2 classified areas were not as apparent in the southwest and there were less Wetland classified areas. The region in the central part of the blue ellipse in figure 4 that was classified mostly as Wetlands and Coniferous Forest in the 2005 image data was classified mostly as Deciduous/Mixed Forest in the 1995 map. The most accurate land cover class was Deciduous/Mixed Forest. For land use classes, the most accurate class was Low-density Urban. Four classes: Deciduous/Mixed Forest, Low-density Urban, High-density Urban, and Agriculture 2 had UAs and PAs over 70%.

Table 6. Accuracy statistics and error matrix for the 2005 object-based classification (10 classes). Columns represent reference cover types. Rows represent classified cover types.

	Agriculture 1	Agriculture 2	Bare Field	Bare Rock and Sand	Coniferous Forest	Deciduous/ Mixed Forest	High-density Urban	Low-density Urban	Water	Wetlands	Total	UA (%)
Agriculture 1	19	2	0	0	0	1	0	0	0	0	22	86.4
Agriculture 2	4	69	0	1	1	0	1	5	0	2	83	83.0
Bare Field		1	5	0	0	0	0	0	0	0	6	83.3
Bare Rock and Sand	0	0	0	0	0	0	0	0	0	0	0	0.0
Coniferous Forest	0	0	0	0	3	0	0	0	3	1	7	42.9
Deciduous/ Mixed Forest	0	0	0	0	6	25	0	1	0	0	32	78.1
High-density Urban	1	0	0	4	0	0	16	0	0	0	21	76.2
Low-density Urban	0	7	0	1	0	2	4	16	0	1	31	76.2
Water	0	0	0	0	0	0	0	0	6	0	6	60.0
Wetlands	1	0	0	0	0	2	0	1	1	9	14	69.2
Unknown	0	0	0	0	0	0	0	0	0	0	0	
Total	25	79	5	6	10	30	21	23	10	13	222	
PA (%)	76.0	87.2	100.0	0.0	30.0	83.3	69.6	51.6	100.0	64.3	Overall accuracy = 75.6%	
κ	0.70	0.77	0.83	0.00	0.40	0.75	0.74	0.46	1.00	0.62		

Additional data allowed for further comparison of the 2005 MLC and object-based maps from external data sources that exist for eastern Ontario. This comparison was conducted for forest, agriculture, and wetlands. For forest (Coniferous and Deciduous/Mixed classes combined), the total coverage in eastern Ontario was 353,300 ha (MLC) and 422,297 ha (object-based). These represent 31% and 37% of the study area, respectively. The EOMF states that in 2004 there were 550,000 ha of forest in a slightly larger area (figure 1, green outline) corresponding to approximately 34% of total land cover (EOMF 2006b). Thus, both 2005 classifications come similarly close to estimating the total per cent of forest cover. For agriculture (Agriculture 1, Agriculture 2, and Bare Field combined), the total coverage in eastern Ontario was approximately 516,000 (MLC) and 462,000 ha (object-based). According to the agriculture census in 2001, there were 526,000 ha of croplands in eastern Ontario (the exact boundaries are unknown so the per cent cover could not be calculated) (Statistics Canada 2001). This shows that both classifications estimate agriculture area across the region well with the pixel based MLC being a better estimate, possibly because of its better representation of small fields that were only a few pixels in size. For wetlands, the EOMF (2006a) states that there are approximately 100,000 ha of wetlands in the eastern Ontario region. The 2005 object-based classification was closer to this estimate with 93,872 ha as Wetlands as opposed to 77,044 ha for the MLC.

3.2 *Temporal change analysis: overall LULC change*

Table 7a is a summary of the areas of change per class (hectares) derived from PCC of the MLC pixel-based classifications. Based on these data, 44.4% of the area changed from 1995 to 2005. Table 7b is the summary for the object-based classification showing 49.2% of the area as having changed over the same 10-year period. The class that changed the least for both classifications was Water (–0.02%, 1.4%, respectively) and the classes with large changes of close to, or greater than, 100% were Bare Field (+147.0%, +107.8%, respectively), Agriculture 2 (+122.0% MLC), Coniferous Forest (199.9% object-based), Wetlands (+136.0%, +98.4%, respectively), and Bare Rock and Soil (–94.0% object-based).

Table 7(*a*). Summary of change statistics derived from the pixel-based post-classification comparison for 10 classes. All absolute cell values are in hectares.

	Total	Unchanged	Changed	Area changed (%)
Total	1,140,444	633,870	506,574	44.4
	Total 1995	Total 2005	Change	Change (%)
Agriculture 1	436,521	430,419	–6,101	–1.4
Agriculture 2	36,820	81,751	44,931	122.0
Bare Field	1,533	3,786	2,254	147.0
Bare Rock and Sand	1,739	1,717	–22	–1.2
Coniferous Forest	76,275	93,091	16,817	22.1
Deciduous/Mixed Forest	350,529	260,208	–90,321	–25.8
High-density Urban	24,215	32,798	8,583	35.4
Low-density Urban	111,623	91,208	–20,414	–18.3
Water	68,541	68,417	–124	–0.02
Wetlands	32,647	77,044	44,397	136.0

Table 7(*b*). Summary of change statistics derived from the object-based PCC for 10 classes. All absolute cell values are in hectares.

	Total	Unchanged	Change	Area changed (%)
Total	1,136,146	577,215	558,931	49.2
	Total 1995	Total 2005	Change	Change (%)
Agriculture 1	226,838	122,008	–104,831	–46.2
Agriculture 2	224,484	324,619	100,135	44.6
Bare Field	7,449	15,481	8,032	107.8
Bare Rock and Sand	1,023	61	–962	–94.0
Coniferous Forest	28,790	86,329	57,540	199.9
Deciduous/Mixed Forest	433,537	335,968	–97,569	–22.5
High-density Urban	15,562	14,222	–1,340	–8.6
Low-density Urban	77,908	66,345	–11,563	–14.8
Water	69,542	70,534	992	1.4
Wetlands	47,305	93,872	46,566	98.4

Bare Field and Agriculture 2 probably increased due to the timing of harvest of many crops in the region, which is often towards the end of August or in early September, i.e. the 2005 Landsat image was acquired after harvest of most crops. This could be combined with changes in agricultural practices during the 10 years and changes due to the 2 years being mismatched with crop rotation cycles. The increase in Coniferous Forest detected by the object-based classifer would not be expected to be accurate as this class is comprised almost entirely of plantations in the study area, and it was unlikely that their total area doubled in the 10-year period.

The MLC result for wetlands (+136%) is an obvious error as they are known to have declined in the region during this period (National Wetlands Working Group 1997, Mitsch and Gosselink 2007). This increase was not due to differences in overall wetness in the two years as total precipitation in the months prior to image acquisition was very similar. These incorrect changes in Coniferous Forest and Wetland areas are probably due to their relatively poor classification accuracies (tables 4 and 6), resulting in errors being propagated through the PCC process. Total urban area was found to have decreased from 1995 to 2005 by both analyses (–11,831 ha MLC; –12,903 ha object-based). This may be due to vegetation growth in city centres, in newly developed areas on the peripheries of urban centres, and in previously barren areas such as quarries. However, Zhang and Guindon (2005) assessed an increase of 75 km^2 in urban cover around the region from 1966 to 2001 and an extensive portion of this was expected to have occurred between 1995 and 2005. Thus, classification and temporal mapping of urban areas requires more precise attention to determine where vegetation cover is overtopping and obscuring urban land cover from the sensor's view.

Overall, based on visual assessment and relating the changes to the other data sources, the object-based method assessed the change in the area more precisely (especially agriculture and forest change). The following analyses of specific locations highlight some of these changes and illustrate the types of errors that were apparent.

3.3 *Analysis of classifications and temporal change for selected sites*

Intensive searching of the change maps produced from both types of classification was conducted to identify and compare errors in the 1995 and/or the 2005 thematic maps

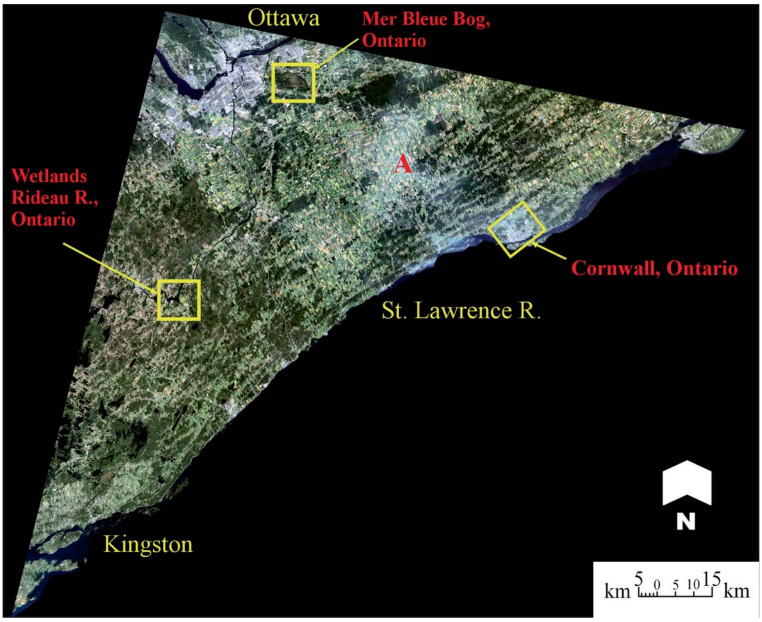

Figure 5. Location of sub-sites of interest located on the true colour 2005 scene. ‘A’ shows location of haze.

and the associated LULC changes derived from PCC. From analysis of many sites, three were selected for detailed presentation and discussion (figure 5) that represent the types of differences found and provide a basis for definitive evaluation of which of the two classifiers performed better in LULC change mapping. The sites are: (1) a well-known and commonly studied ‘natural’ area, the Mer Bleue Bog; (2) an area near Cornwall, Ontario where temporal change appeared to be dominant; and (3) a riparian wetland area that was the subject of an intensive field campaign for another GLEL project (Dillabaugh and King 2008).

In figure 6, both MLC maps show many pixels classified as Low-density Urban within the Mer Bleue Bog, a nationally significant RAMSAR wetland (white outline) while the object-based class is Wetlands for both dates. The overall classification of the area by the MLC method is incorrect and the PCC temporal change analysis is also incorrect.

The object-based classifications suffer from errors as shown in the middle bottom of figure 6 (blue ellipses), where some roads have been erroneously classified as Wetlands on both the 2005 and 1995 object-based subsets. These types of small objects were often misclassified in the object-based maps and would not be reliable in mapping of LULC change; here they indicate ‘no change’, but of the wrong class. In the upper left corners of the object-based maps, blue circles show an additional area where roads were not detected.

At ‘1’ in figure 6, in the 1995 Colour Infrared (CIR) composite the area is vegetated agriculture fields (light red tones) and in the 2005 CIR composite one of the large fields is bare (bright cyan tones). Both 1995 classifications show the area as Agriculture (types 1 and 2), but the 2005 MLC has the Bare Field classified as Bare Rock and Sand, Agriculture 2 and a small portion of Bare Field. Thus, the MLC has

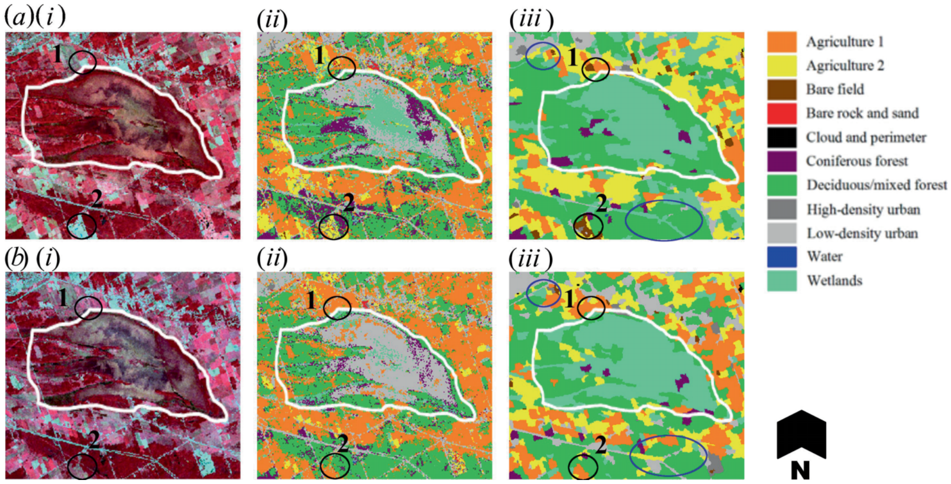

Figure 6. Classification and change analysis of the Mer Bleue Bog, Ontario, between methods and between years. White outlines the bog. Blue circles highlight erroneously classified pixels. Black circles (1 and 2) outline areas of real change. (*a*) is 2005, (*b*) is 1995 (i, CIR composite; ii, MLC 10-class; iii, Object-based 10-class).

incorrectly distributed the change amongst several classes, whereas the object-based map has correctly distributed the change to one class, Bare Field.

A visual comparison of the classifications in figure 7 of the Cornwall region shows detected LULC change that is incorrect for both methods (at '1'). In reviewing the overall area to the north of Cornwall, both 1995 classifications show mostly Deciduous/ Mixed Forest. However, the 2005 object-based classification shows predominantly Coniferous Forest and the 2005 MLC shows predominantly Agriculture 1. Both methods for 2005 erroneously classifed the area due to the haze that was present

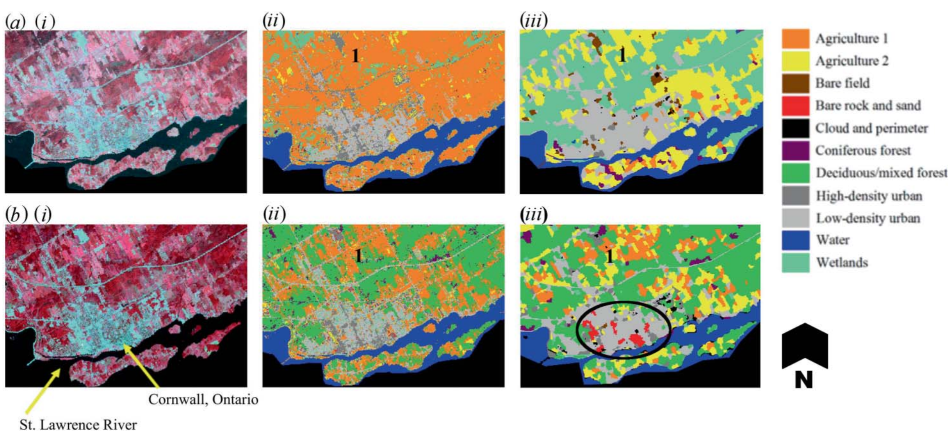

Figure 7. Classification and change analysis of Cornwall, Ontario: between methods and between years. Black circle highlights erroneously classified bare rock and sand. '1' is the location of false change. (*a*) is 2005, (*b*) is 1995 (i, CIR composite; ii, MLC 10-class; iii, Object-based 10-class).

in the image but the object-based classification is closer in classifiying it as Forest as opposed to Agriculture. Over the whole study area, both temporal change analyses show a reduction in Deciduous/Mixed Forest (–25.8% MLC; −22.5% object-based). For the object-based analysis this is coupled with a large increase in Coniferous Forest of 199.9% that may be partly attributed to the haze in this portion of the 2005 scene. In addition, both methods showed a significant increase in Wetlands, which could also be attributed to misclassification of forest in hazy areas. Based on the above analysis, significant LULC change may be falsely detected if image data is affected by haze. Overall, the object-based classifier was less affected than the MLC as forest in hazy areas was classified as forest, even though the forest type (Deciduous/Mixed or Coniferous) was wrong.

Three marsh wetlands (see Dillabaugh and King (2008)) shown at ‘1’ in the 1995 CIR composite in figure 8 have been mostly classified as Low-density Urban in the 2005 and 1995 MLC maps, whereas they are correctly classified as Wetlands in both object-based maps (except in the blue circle of the 1995 object-based map). Both change maps correctly show no change overall in these wetlands, but for the MLC this is for the wrong class.

Classified pixels of High-density Urban and Low-density Urban appear in the centre of the river at ‘2’ in the 1995 MLC map. These areas are classified as Wetlands and Water in the 1995 object-based map. In 2005, these areas were classified as Water by both classifiers. The 1995 features could be waves or floating vegetation.

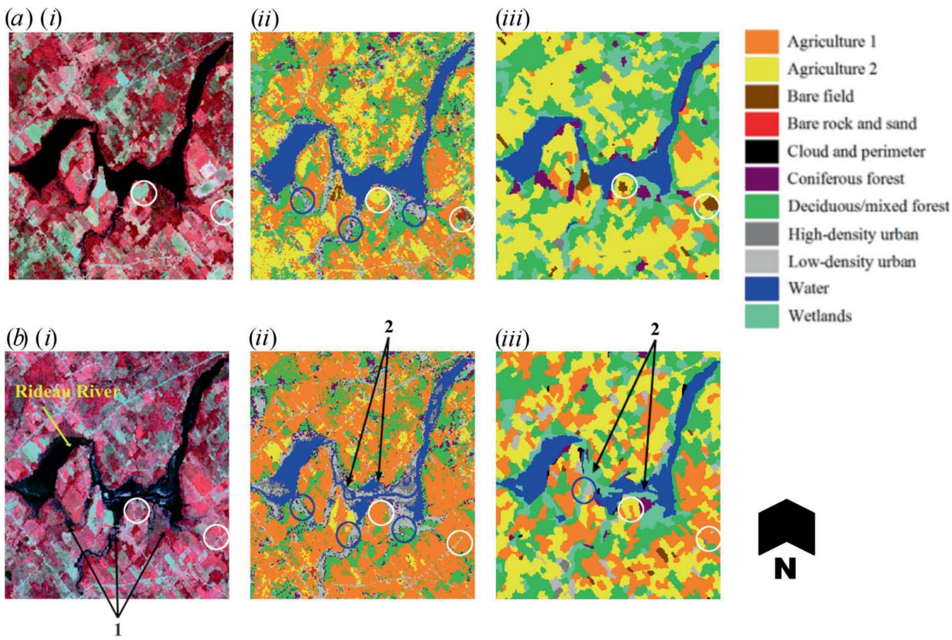

Figure 8. Classification and change analysis of Rideau River, Ontario: between methods and between years. White circles outline areas of real change of Agriculture to Bare Field. Blue circles highlight erroneously classified Wetland. ‘1’ is the location of three wetlands. ‘2’ is the location of floating vegetation. (*a*) is 2005, (*b*) is 1995 (i, CIR composite; ii, MLC 10-class; iii, Object-based 10-class).

Despite a change correctly being detected by both classifiers, the MLC from–to change is incorrect, while the object-based change is very likely correct (vegetation (aquatic) to water). The 1995 image was recorded 1 August when there are typically large mats of floating vegetation, and the 2005 image was recorded on 13 September when such vegetation has usually senesced and disappeared.

The two white circles depict areas where real change is visually obvious in the CIR composites. Vegetated fields (Agriculture 1) have changed to Bare Field. The object-based maps show this change for both examples. The MLC, however, only detected the change in the circles on the right side, having erroneously mapped the 2005 field in the left circle as Agriculture 2.

Other areas of change are highlighted (circled) on figures 6–8 and are representative of the types of changes or errors assessed on the many sites of interest spanning the whole research area. Overall, it was assessed that despite similar map accuracies, the object-based temporal analysis detected from–to change correctly more often than did the MLC analysis. Additionally, the object-based classifier produced more uniform objects for easier interpretation in the structured urban environment, while the MLC maps had a salt and pepper appearance and were harder to interpret for LULC change.

4. Conclusions

Using Landsat TM image data and object-based segmentation/classification, 5 of 10 classes (2005) and 4 of 10 classes (1995) had PAs and UAs over 70%. Using a pixel-based maximum likelihood classifier, 2 of 10 (2005) and 5 of 10 classes (1995) had accuracies greater than 70%. Statistically, based on McNemar's test, the overall accuracies of the two classifiers were not significantly different for either the 1995 or 2005 data. Accuracies were lower for the object-based classifications for small and rare classes. This could be related to the segmentation process and the scale factor selected for segmentation and warrants further investigation. Although optimal weights in the object segmentation phase for spectral (colour) information versus shape information could be found through testing for this region and scale of imagery, shape parameters were not found to improve accuracy during the object classification phase. Preliminary results of merging impervious classes (Bare Rock and Sand, and High-density Urban) showed that accuracy improved in both object-based classifications for a single scale classification. Further work is warranted to assess these segmentation weights for other regions and for other scales of imagery. Additional work is also needed to incorporate shape parameters during the object classification phase.

Intensive visual assessment of sub-areas of the thematic maps and the change maps revealed that overall the object-based method had fewer significant errors in large entities with distinct edges such as forest stands, wetlands, fields, and urban areas. As a result, many examples could be found where LULC change was more accurately detected than for the MLC pixel-based classifications. This may have been partially due to the salt-and-pepper appearance of the MLC maps, which rendered them difficult to interpret and search for locations where they were correct in detecting change while the object-based maps were incorrect. Both classifiers suffered from haze in part of the 2005 image data. This resulted in misclassification, although the object-based classifier produced classes that were thematically closer to the actual classes than did the MLC.

As an alternative to the post-classification change analysis method using the two object-based classified images, some preliminary tests of segmentation were completed using both dates of imagery as input. It was found that the segmented objects were similar to those obtained by segmenting either date alone. With the two dates of data within each object, from–to classes as well as stable classes would need to be defined, resulting in a multitude of possibilities for classification. Continuation of this experimentation was considered out of the scope of this research and is now being considered for future work.

This research adds to existing knowledge regarding object-based classification by providing an in-depth comparison with a standard maximum likelihood pixel-based classification in single date imagery and in LULC change analysis. The results show that, although classification accuracy of images from individual dates may not be significantly different, object-based classification detected more realistic LULC changes with fewer illogical errors than did the MLC. However, as the object segmentation and classification method is much more complex than MLC, there are several aspects that need to be addressed in further work. Use of a single global scale factor in segmentation resulted in the absorption of rare class areas of small spatial extent. A single scale factor was used in this study to maintain direct comparability with the MLC, which was implemented at a single scale. Future work will include multiple scales and segmentation layers for small and rare objects versus larger more common objects, as this is a potentially very advantageous aspect of hierarchical object-based methods. In both segmentation and classification, shape parameters can be used. In segmentation, the weighting of shape versus spectral information is set by the user. Here, and in many studies cited earlier, these weights were determined empirically using visual analysis. At this point, this is a limitation of the specific software and method; only through repeated testing on different data sets can optimal parameter weightings be gradually ascertained. In classification, it was found rather unexpectedly that shape parameters did not improve accuracy, even though many class objects appeared to be of regular geometry. The use of such parameters is a real advantage over MLC and also warrants further research.

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