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Full Length Research Paper

Comparison of object-based and pixel based infrared airborne image classification methods using DEM thematic layer

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An airborne infrared image was used to produce a map of land cover types in the Eastern shore of Lake Huron, Ontario province of Canada. Maximum likelihood pixel-based and nearest neighbor object-based methods were used in this approach. Land cover classes that obtained traditional pixel-based classification approaches showed a salt-and-pepper effect having the lowest producer accuracy (59.5%). Overall classification results increased up to 80% in object- based approach but still failed to distinguish buildings and creeks. Contours and DEM thematic layers enhanced classification results to a higher level (94%) and increased the producer accuracy for buildings and creek by creating reasonable objects in segmentation process in the object-based approach.

Key words: Infrared image classification, pixel-based, object-based, DEM thematic layer, land cover mapping.

INTRODUCTION

Remote sensing provides a useful source of data to extract accurate land cover information. High spatial resolution remote sensing is becoming increasingly available from airborne sources and this makes it possible to get a detailed land cover map from such data. Classification of remotely sensed data has been a major concern for many users.

Since remote sensing images consist of rows and columns of pixels, conventional land-cover mapping has been pixel-based (Dean and Smith, 2003). Pixel-based classification uses multi-spectral classification techniques that assign a pixel to a class by considering the spectral similarities with the class or with other classes. In pixel-based classification, two kinds of traditional classification methods — unsupervised classification and supervised classification are commonly used methods. Unsupervised classification is used when there is little or no external information about the distribution of land-cover types. The results of unsupervised classification are spectral classes. The analyst associates the spectral class with the land-cover types using reference data. Unsupervised classifiers do not utilize training data as the basis for classification. These classifiers examine the unknown pixels in an image and aggregate them into a number of classes based on the natural groupings or clusters present in the image values. The basic premise is that values within a given cover type should be close together in the measurement space, whereas data in different classes should be comparatively well separated (Lillesand, 2008). There are numerous classification algorithms that can be used to determine the natural spectral groupings present in a data set (Lillesand, 2008). One common form of clustering, called the “K-means” approach, accepts from the analyst the number of clusters to be located in the data. The algorithm then arbitrarily locates that number of cluster centers in the multidimensional feature-space. Each pixel in the image is then assigned to the cluster which arbitrary mean vector is the closest. After all pixels have been classified in this manner, revised mean vectors for each of the clusters are computed. The revised means are then used as the basis to reclassify the image data. The procedure continues until there is no significant change in the location of class mean vectors between successive iterations of the algorithm. Once this point is

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reached, the analyst determines the land cover identity of each spectral class (Lillesand, 2008).

In supervised classification, the image analyst supervises the pixel categorization process by specifying, to the computer algorithm, numerical descriptors of the various land cover types present in an image. Training samples that describe the typical spectral pattern of the land-cover classes are defined. Pixels in the image are compared numerically to the training samples and are labeled to the land-cover class that has similar characterristics.

There are three basic stages involved in the supervised classification method: training stage, classification stage and accuracy assessment stage. In classification stage, the classic classifiers used in pixel based image analysis are hard classifiers, which assign a membership of 1 or 0 to the objects, expressing whether an object belongs to a certain class, or not. Here the classifiers are called "hard classifiers" because they express the objects' membership to a class only in a binary manner (yes or no). The commonly used classifiers are minimum distance to mean classifier, parallelepiped classifier, and maximum likelihood classifier.

The maximum likelihood classifier is most widely used which suppose to create better results. The maximum likelyhood decision rule is based on a normalized (Gaussian) estimate of the probability density function of each class (Pedroni, 2003). The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. An assumption needed in maximum likelihood classifier is the distribution of the cloud of points forming the category training data is Gaussian (normally distributed). Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix. Given these parameters, the statistical probability of a given pixel value being a member of a particular land cover category may be computed. An undefined pixel is classified by computing the probability of the pixel value belonging to each category. After evaluating the probability in each category, the pixel would be assigned to the one with highest probability value or be labeled "unknown" if the probability values are all below a threshold set by the analyst (Lillesand, 2008).

An alternative classification approach was introduced in the 1970s (de Kok et al., 1999). Ketting and Landgrebe (1976) proposed an idea and developed the spectral-spatial classifier called extraction and classification of homogeneous objects. Applications of this method were limited by lack of good software and poor resolution of imageries. By rapid increase in availability of high resolution airborne and space born imageries and development of eCognition software (Definiens Imaging GmbH, 2002) the demand for object-oriented analysis has increased. Nowadays, object-based classification may be a good alternative to the traditional pixel-based methods. To overcome the High-resolution problem and salt-and-pepper effect, it is useful to analyze groups of contiguous pixels as objects instead of using the conventional pixel-based classification unit.

The most evident difference between pixel based image analysis and object-oriented image analysis is that first, in object-oriented image analysis, the basic processing units are image objects or segments, not single pixels. Second, the classifiers in object- oriented image analysis are soft classifiers that are based on fuzzy logic. Soft classifier use membership functions to express an object's assignment to a class. Membership values usually range between 1 and 0, where 1 expresses a complete assignment to a class and 0 expresses absolutely improbability. The degree of membership depends on the degree to which the objects fulfill the class-describing conditions. One advantage of these soft classifiers lies in their ability to express uncertainties about the classes' descriptions. The basic processing units in object oriented image analysis are objects or pixel clusters; with object oriented approach to analyze images — the first step is always to form the processing units by image segmentation.

Software *eCognition* (Definiens Imaging GmbH, 2002) provides a *fuzzy realization* of the nearest neighbor classification. The nearest neighbor is applied to selected objected features and is trained by sample image objects. The fuzzy realization of the nearest neighbor approach, which is used in *eCognition* automatically, generates multidimensional membership functions. They are suitable for covering relations in multi-dimensional feature space. The nearest neighbor classifies image objects in a given feature space and with given samples for the class of concern. The principle for the nearest neighbor is: first, declare a representative set of sample objects for each class, then the algorithm starts to search for the closest object in the feature space for each image object.

In high relief areas, such as undulated glaciated till landscapes, the effect of topography may cause pixels of the same cover type to have different spectral values and pixels of different cover types to have similar spectral values. Consequently, errors may be introduced during image classification which will decrease the classification accuracy. A number of techniques have been developed to restore the information altered by atmospheric and radiometric effects using ancillary data and improved image processing techniques (Chavez, 1988; Kawata et al., 1988). One of the most recent developments in image restoration is the improvement of topographic effect on the images. Topographic effect can produce enormous errors in image classification, particularly in areas of high relief. Fortunately, Digital Elevation Models (DEM) has proven to be efficient in reducing this effect and improving image classification accuracy (Fahsi, 1993).

Attempts have been made to improve the accuracy of image classification based on various approaches, such as use of multi-temporal imagery to individualize information classes (Conese and Maseli, 1991) GIS based methodology with ancillary information like soils, topography, bio-climates (Gastellu-Etchegorry et al., 1993; Dobos et Al., 2000), GIS rules with ancillary data on terrain mapping units, elevation data (Prieto and Gonzalez, 1996) and use of ancillary data such as DEM for improving classification accuracy (Franklin et al., 2002; Amarsaikhan and Douglas, 2004; Lu and Weng, 2007).

The objectives of this study are to compare the maximum likelihood pixel-based classifier with the nearest neighbor object-based classifier firstly with just using near infrared imageries, secondly with using DEM and ancillary data. Therefore, this research examines the role of thematic layers (DEMs and contour line) on the accuracy assessment of object-oriented image classification. A bare ground LiDAR DEM with a contour line thematic layer applied in second stage to improve accuracy assessment. The assumption is that these thematic layers increase differentiation of creek (waterway) and buildings from other land cover as well.

MATERIALS AND METHODS

Study area and data

The study area, Griffin Creek, is located in the Eastern shore of Lake Huron, in Southern Ontario, Canada (Figure 1). The rolling hills and glaciated till topography is characterized by gentle slope. The study site covers approximately 45 ha, a rural area, which is dominated by a small waterway namely Griffin Creek and its surrounding riparian woods. The main agricultural land usages are cropland including corn, soybean and with wheat rotation. Our corresponding images have been taken during wheat growing season. The Airborne infrared images having spatial resolution of 0.25 m was acquired with the LiDAR data containing first and last returns elevation points, from LASEMAP IMAGE PLUS Company (Biosboriand, Quebec, Canada).The classified thematic maps which were provided by Ontario Ministry of Natural Resources and provincial land cover data from Ontario Minister of Agriculture and Food, Canada were used to provide ground truth information for accuracy assessment.

Data preparation

LiDAR elevation points with approximately 1 m point space interpolated using simple kriging algorithm to create both the DTM (Digital Terrain Model) over the top of the buildings and vegetations and the DEM just over bare surfaces using SURFER software (Golden software Inc, 2002). Infrared images were registered using geocoded DEM images, with UTM (Universal Transverse Mercator) projection, Zone 17 and NAD 27 datum. Because each image had insufficient coverage (250 × 250 m), 12 images (with 50 percent overlap) were se-lected to create a mosaic for study area using software PCI Geomatica (PCI Geomatics, 2005). Arc GIS spatial analyst tool (ESRI, 2005) was used to create thematic layers. Consequently, raster DEM and the DTM converted to ESRI shape files. Contour lines (1 m interval) were created from DTM. These ancillary data were used as extra thematic layers to see whether they improve object-based classification or not.

Pixel-based classification

Supervised classification was applied on the infrared image using the maximum likelihood algorithm in PCI Geomatica. The maximum likelihood classifier is considered to give more `accurate' results than parallelepiped classification. However, it is much slower due to extra computations. We use the word `accurate' in quotes because this assumes that classes in the input data have a Gaussian distribution and that signatures were well selected.

A brief description of land cover classes is as following. The land covers are distributed from 4863057 to 4863503 N along the Lake’s shore and from 442000 to 443000 E in UTM projection including the lands which drains by Griffin Creek. Eleven land cover types categorized using maximum likelihood classifier by Image Works module of PCI Geomatica version 10.0.3. The Creek is drained into Lake Huron at Perfect Beach from East to West. Tilled field and Wheat are characterized as the most prominent land covers and distributed over Northern and Southern part of the Creek, respectively. The Creek is surrounded by Wood and Open spaces. The wood, the natural vegetation of study area, is mainly deciduous, the commonly occurring associations being: Sugar maple, this association is common to the well drained soils, except those of heavy texture. Other species included in the association are basswood, white ash, and some oak. Pine occasionally occurs on the light textured outwash soils. Most of the land is now cleared and used for agricultural purposes, but still some barren lands are distributed along main waterway called Open spaces. These Open spaces correspond to barrens soils which locally differ in texture. According to Canadian soil classification system (Soil Classification Working Group, 1998), the soil is categorized as Orthic Grey brown Luvisol as part of the Luvisols Great Soil Group and are specialized as heavy textured limestone till soils. These soils have developed on clayey calcareous till derived largely from Nortfolk limestone (a local limestone formation) and to a lesser extent from shale The Road land cover is characterized as country roads which intersect the study area from East to West. Rural settlements and their farms are the outstanding building units which are surrounded by grass. A small proportion of study area is an unknown unit namely No Data land cover. Image information in this part has missed, in other words there is no any spectral information and it is not possible to assign a specific land cover type to this part.

Object-based classification and image segmentation

Before running object-based classification in eCognition, the infrared image was overlaid on thematic layers and

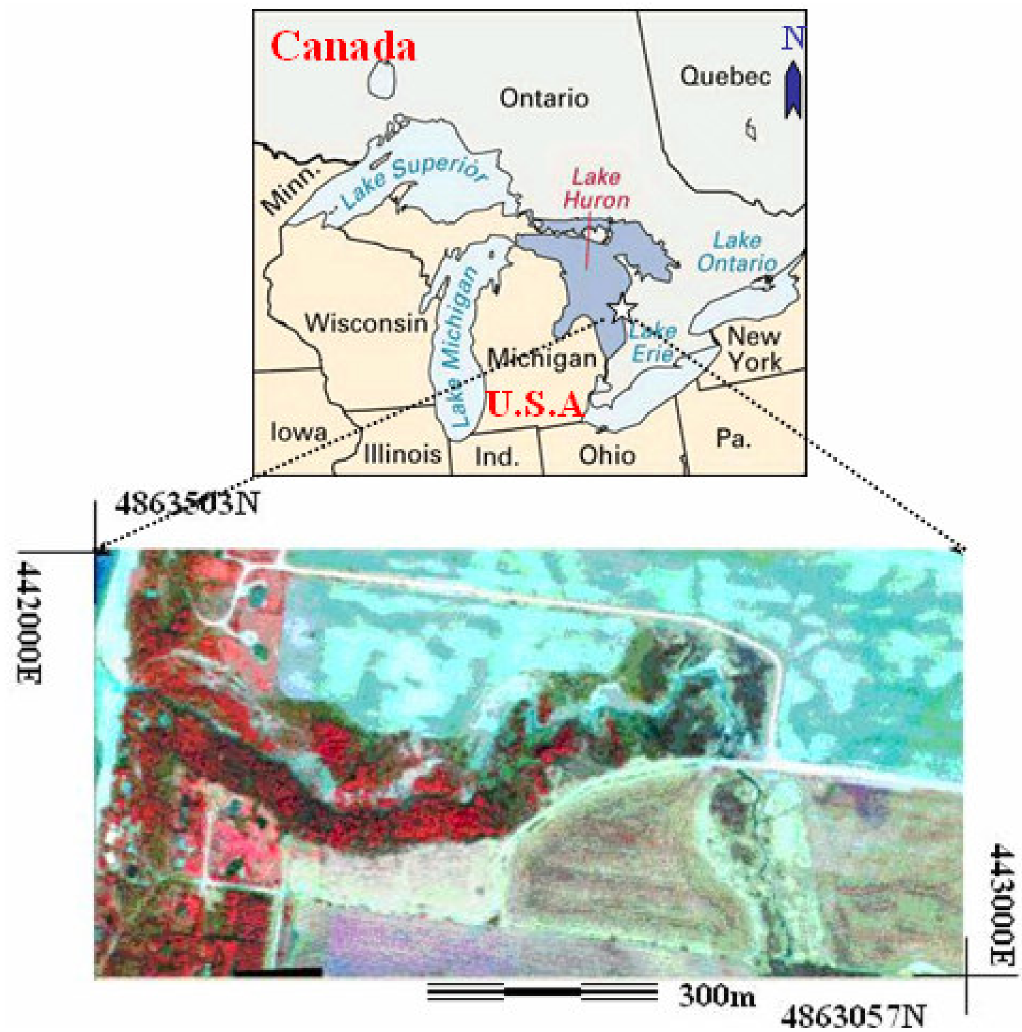

Figure 1. Study area based on infrared image extent in UTM (Universal Transverse Mercator) projection, located along the Eastern shore of Lake Huron, Ontario, Canada.

image was segmented with and without using ancillary data at three levels. The scale parameters at object stage (dividing image into objects) play a critical role in segmentation processes. The higher the scale factor the larger the resultant objects. In order to get meaningful objects the smallest objects must be taken into account within an image. The scale parameter is an abstract term, which determines the maximum allowed heterogeneity for the resulting image objects. In heterogeneous data, the resulting objects for a given scale parameter are smaller than in more homogeneous data. The shapes of objects are also as important as scale factors. This means that the shapes of each object in question (for instance a building as rectangle) which, in our case should represent building area that precisely overlap with corresponding DEM. However, a scale parameters analysis applied to find and adjust the best homogeneity criterion for segmentation stage. Finally, when satisfied with segmentation results the nearest neighbor algorithm of eCognition was used to classify image with and without thematic layers. To enhance creek and building differentiation, image was segmented using bare ground DEM and contour. In other words creek pass through dense vegetation (*wood*) and it is not well recognizable from infrared images. From the lowest elevation at creek mouth and highest elevation value at creek head (source) along creek direction will represent a gradual gray scale pattern in DEM, which will be helpful in segmentation of creek. Therefore, combining ancillary data (DEM) with image will represent a narrow route of the creek, which makes it possible to enhance differentiation of this unit (Figure 2). Consequently, image segmentation with these thematic layers led to distinguishable objects for creek. Also in order to increase producer's accuracy for building, a vector file contour map (with 5 m interval) was created using DTM (non-ground DEM). Combination of infrared image with this layer led to re-enforcement of segmenting the buildings as rectangular and distinctive objects.

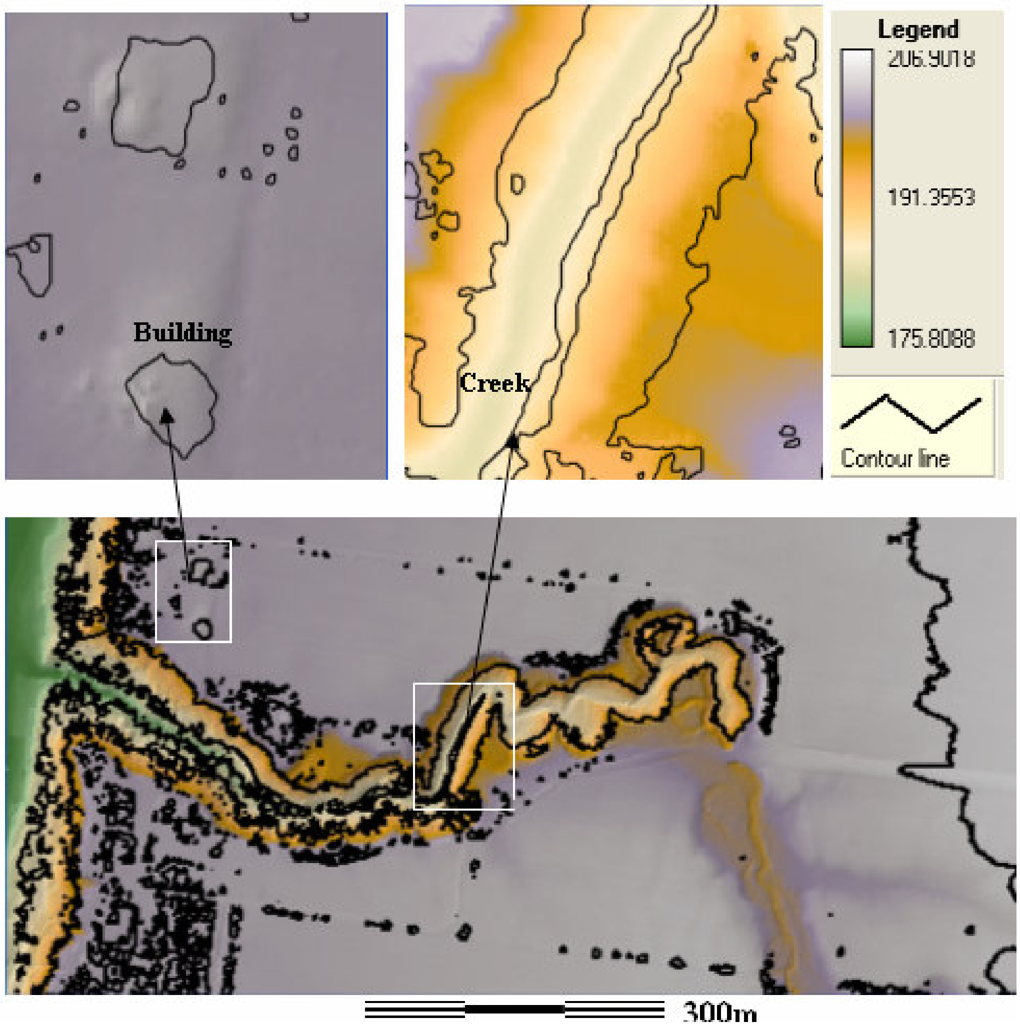

Figure 2. Contour line from non-ground DEM (DTM) as thematic layer overlaid on bare ground DEM, showing buildings and creek as distinct feature, Eastern shore of Lake Huron, Ontario, Canada.

Accuracy assessment

An evaluation classification was carried out based on random sampling. It means that samples were assigned to each class based on software random selection to classified image. Training samples are selected according to the ground truth from previous classified thematic maps provided by Ontario Ministry of Natural Resources and provincial land cover data from Ontario Minister of Agriculture and Food, Canada. Regarding sample size, Congalton (1991) proposed a minimum of 50 samples for each land use to produce an error matrix. In our case accuracy was evaluated using 1200 samples which were assigned to each class based on software random selection to classified image. A stratified sampling method was adopted because land cover sizes differ too much in size so that minimum number of samples were 3 for No Data class and the maximum samples was selected for Tilled field class (326 samples). In other words samples were distributed bases on spatial extent of each land cover. The more the unit size the more samples were assigned to that unit.

In order to determine accuracy of classification results, confusion matrixes were calculated for both pixel-based and object based approaches. Error matrixes were formed with data from the thematic map and classified image. An error matrix is a two-dimensional contingency table; the cell entries in the error matrix present the number of sampled points which category in classified image is the row label, and whose category in thematic map (reference data) is the column label. The diagonal entries represent correct classifications and the off-diagonal entries represent misclassifications. Accuracy indexes such as the overall accuracy, and user's and producer's accuracy were calculated. The overall accuracy is the probability that a pixel is classified correctly by the classified image. Producer's accuracy for a certain land-cover class shows the probability that a pixel classified as this cate-

Table 1. Error matrix produced with supervised classification results.

	Reference data												
Classified data	**Building**	**Wood**	**Grass**	**Wheat**	**Road**	**Beach**	**Open spaces**	**No data**	**Tilled field**	**Creek**	**Lake**	**Total**	**User's accuracy**
Building	0	1	0	0	0	0	1	0	0	0	0	2	0
Wood	10	171	5	6	0	0	24	0	0	2	0	218	73
Grass	1	0	34	5	0	0	3	0	0	0	0	43	37
Wheat	1	2	20	265	7	0	81	0	7	2	0	385	59
Road	0	0	0	0	18	1	2	0	0	0	0	2	81
Beach	0	0	0	1	4	26	11	0	38	0	0	80	18
Open spaces	2	1	0	11	1	0	53	0	1	0	0	69	43
No data	0	0	0	0	0	0	0	2	0	0	0	2	100
Tilled field	1	0	0	8	1	3	51	1	273	0	0	341	80
Creek	1	2	0	4	0	0	6	0	5	8	0	26	13
Lake	0	0	0	0	0	0	3	0	2	5	3	13	36
Total	16	177	59	300	31	30	235	3	326	20	3	1200	
Producer's accuracy	0.00	84	65	70	52	79	17	100	68	67	100		
Overall accuracy= (0+171+34+265+18+26+53+2+273+8+3)/1200=59.52%													

gory in the reference data is classified as this category in the image. User's accuracy shows the conditional probability that a pixel classified as this category in the image is classified as this category in the reference data. User's and producer's accuracy are related to commission and omission error, respectively (Boschetti et al., 2004). Pixels incorrectly excluded from a particular class are defined as error of omission and Pixels incorrectly assigned to a particular class that actually belong in other classes are defined as commission error.

RESULTS AND DISCUSSION

Pixel based classification results

The accuracy results for maximum likelihood supervised classification as error matrix are represented in Table 1. Overall accuracy for pixel-based image classification is 59.5%. No Data and Lake Classes have both higher accuracies (100%) because other parts of the image represent very different spectral information compared to these units. Road and Open spaces represent lower accuracy. The reason why Road produced low accuracy is that some of them (e.g. bottom left hand corner of the image) are characterized as abandoned country roads and these part of roads are no longer in use as much as other part of image. Therefore, this proportion of road's classes show less brightness compared to the other regions and led to decreasing of the road accuracy. Open Space*s* introduce barren soils, and it is expected that different soil type must have different digital number to easily be located in a unique class. Because in the study area; this unit is distributed within or around other land cover types. The maximum likelihood classifier for this specific image was not able to differentiate buildings from other units. There are different roofs and covers for the Buildings all over the study area. Buildings were mainly mixed pixel objects which made it difficult to distinguish with pixel based classification. Thus this class land cover type had 100% omission and commission error. In other words, the most pixels which must be correctly assigned to Building were excluded from the building class, also other land cover such as Open Spaces and Tilled Field incorrectly classified as Building class.

The appearance of unwanted local pixels from other classes in a specific class normally changes textural characteristics of a certain class. This phenomenon which is usually called salt and pepper effect was more prominent in Open Spaces class. In pixel-based classification approach such results may improve by applying filtering method to image. Another approach is class aggregation. For the classes such as Open Spaces which combine from different soil type, each soil type can be dedicated to a specific land unit then in classified image; aggre-gation of soil type classes (which represent very similar textural information) can be implemented to amalgamate these classes together. However, these approaches were not recommended in this research as we proceeded with object oriented approach.

Object-based classification results

Classification results without using DEM thematic layer

In this section at first image segmentation results are represented, then image classification results based on confusion matrix are discussed. The infrared image was

Table 2. Segmentation results of airborne Infrared image with and without using ancillary data (contour line and DEM) in object-based classification approach.

Segmentation method	Level	Homogeneity criterion			Standard deviation of scale parameter analysis	Number of objects
		Scale	*Color*	*Compactness*		
Segmentation	L3	30	0.7	0.1	26.52	4617
without	L2	20	0.7	0.1	17.75	10062
thematic layers	L1	15	0.7	0.1	12.72	17774
Segmentation with	L3	30	0.7	0.1	24.13	4115
thematic layers	L2	20	0.7	0.1	16.18	8646
	L1	15	0.7	0.1	11.17	15021

segmented at 3 levels; each segmentation process had different results (Table 2). Homogeneity criterion was chosen 30 for scale parameter, 0.7 for color and 0.1 for compactness. Different object layers were used for the classification of structures of different scale. Image objects at the largest possible scale was produced which in turn still distinguish different image regions (as large as possible and as fine as necessary). To get ideal results we tried to use as much color criterion as possible and as much shape criterion as necessary to produce image objects of the best boarder smoothness and compactness. The reason for this rule is that the spectral information is ultimately the primary information contained in image data. For instance, classification results in pixel based method showed that maximum likelihood classifier failed to distinguish *buildings*. To come up with this problem, it was found that in homogeneity criterion for image segmentation, the best scale factor has to be chosen 30 at level 3. This factor had a great effect in keeping each *building* as a unique rectangular object. The segmented infrared image did not have meaningful objects for the *building* units in levels 1 and 2.

Referring to Table 3, still *Building* has low user's accuracy (14%), but it has been improved with object based classification. Also *Road* failed to be recognized well in this classification method, but they have better accuracy (86%) compared to pixel based approach. Figure 4 shows object-based classification results without using thematic layer. All classes have better accuracy in object based classification method than pixel based one, except *Creek.* The user accuracy for this unit is still low (25%).The reason why *Creek* is not distinguishable is that this unit has no reasonable objects in image segmentation stage. Because in final step of object–based classification approach the objects are main component of each land cover. Consequently, we decided to run object-based classification again with helping thematic layers, to get more meaningful objects for the *Creek* as well as *Buldings* classes.

Classification results using DEM thematic layer

Overall accuracy increased from 80 to 94% in object based classification method with using DEM thematic layers; while it was 60% in pixel-based classification(Table 4). It means that, producer's accuracy for all land cover classes should have been increased due to the role of DEM and contours in segmentation stage. A membership function of shape was used for *building* differentiation. *Buildings* have distributed along Easting coordination between 442000 and 442200E m. In other words any rectangle shapes which were located within this threshold and holding a rectangular shape (due to contour effect in segmentation process) will be considered as *Buildings* land cover. The gradual changes of elevation in DEM enhanced *Creek* differentiation very clearly compared to last two classification methods. Again, a membership function using threshold values of height were used. This process created a well defined object features for C*reek*, based on elevation feature space of DEM. Scale, color and compactness factors were the same as segmentation without using thematic layers. In segmentation process each layer was given a weight which lies between 0 and 1, therefore we assigned weight 1 to thematic layers, so they were fully concerned in segmentation process. This improved standard deviation of the homogeneity criterion in scale parameter analysis and it was decreased from 26.5 to 24.1 in level 3. The number of objects also decreased from 4617 to 4115 as well as their shape. Because each land cover class will be formed with joining segmented objects the final pattern of each class is a function of object's shapes. For example, *building* should have a rectangular shape and the *Creek* units

Table 3. Error matrix produced with object based classification without using thematic layers.

	Reference data												
Classified data	**Building**	**Wood**	**Grass**	**Wheat**	**Road**	**Beach**	**Open spaces**	**No data**	**Tilled field**	**Creek**	**Lake**	**Total**	**User's accuracy**
Building	8	12	0	0	0	0	8	0	18	10	0	56	14
Wood	2	124	0	8	0	0	1	0	0	2	0	146	85
Grass	0	2	24	0	4	0	4	0	0	2	0	32	75
Wheat	0	20	2	310	0	0	28	0	2	2	0	364	85
Road	2	0	0	0	12	0	0	0	0	0	0	14	86
Beach	0	4	0	0	6	10	0	0	12	0	0	32	31
Open spaces	6	14	0	18	2	0	146	0	4	0	0	190	76
No data	0	0	0	0	0	0	0	4	0	0	0	4	100
Tilled field	4	12	0	2	0	2	6	0	314	6	0	346	91
Creek	0	0	0	2	2	0	2	0	0	2	0	8	25
Lake	0	0	2	0	0	0	0	0	0	2	4	8	50
Total	22	188	59	340	26	12	200	4	360	26	4	1200	
Producer's accuracy	0.00	84	65	70	52	79	17	100	68	67	100		
Overall accuracy= (8+124+24+310+12+10+146+4+314+2+4)/1200=80%													

Table4. Error matrix produced with object-based classification results using thematic layers.

	Reference data												
Classified data	**Building**	**Wood**	**Grass**	**Wheat**	**Road**	**Beach**	**Open spaces**	**No data**	**Tilled field**	**Creek**	**Lake**	**Total**	**User's accuracy**
Building	12	0	0	0	0	0	0	0	0	0	0	12	100
Wood	0	228	0	4	4	0	6	0	2	0	0	248	92
Grass	0	0	16	0	0	0	0	0	0	0	0	16	100
Weed	0	4	8	334	0	0	0	0	0	0	0	342	97
Road	0	0	0	0	18	0	0	0	0	4	0	18	100
Beach	0	0	0	0	0	16	0	0	0	0	0	16	100
Open spaces	0	24	0	2	0	0	116	0	0	0	0	142	81
No data	0	0	0	0	0	0	0	4	0	0	0	4	100

Table 4. Contd.

Tilled field	0	2	0	0	0	0	0	0	360	0	0	362	98
Creek	0	4	0	0	0	0	2	0	0	18	0	24	46
Lake	0	0	0	0	0	0	0	0	0	0	10	10	90
Total	12	262	24	342	22	16	124	4	362	22	10	1200	
Producer's accuracy	0.00	84	65	70	52	79	17	100	68	67	100		
Overall accuracy= (12+228+16+334+18+16+116+4+360+18+10)/1200=94%													

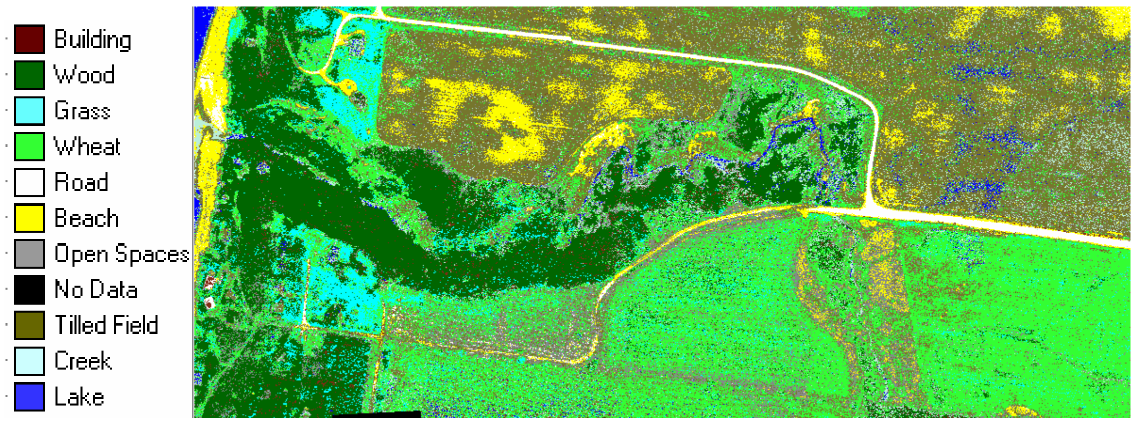

Figure 3. Pixel-based classification results of airborne Infrared image based on Maximum likelihood classifier, Eastern shore of Lake Huron, Ontario, Canada.

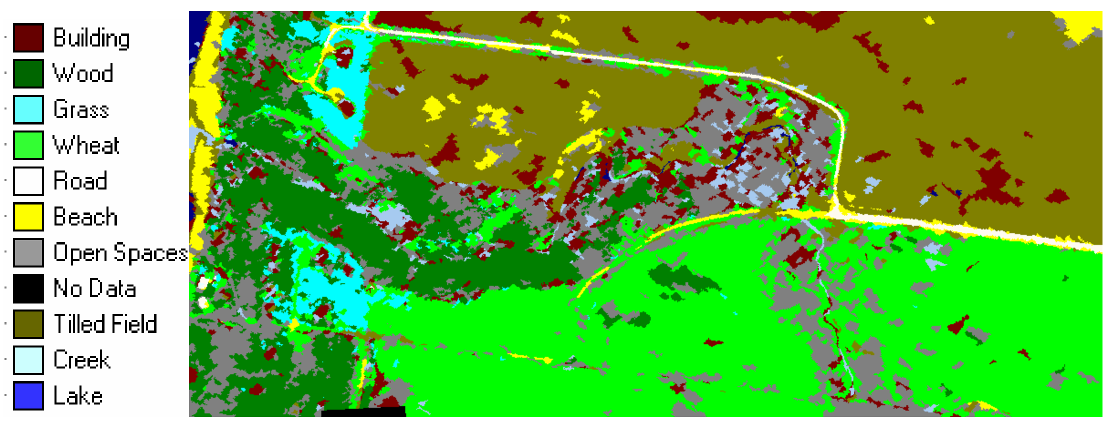

Figure 4. Object-based classification results of airborne Infrared image, without using thematic layers Eastern shore of Lake Huron, Ontario, Canada.

should be representing a narrow and twisted route along its direction. Considering classified images Figures 3 to 4 reveal that neither pixel based nor object based classification (without using thematic layers) produced such pattern for *Creek*. In Figure 5 waterways (*Creek*) is recognizable as a real flow route. This is because DEM thematic layer has had a great impact in segmentation of creek in producing continuous objects forming creek route. The same results have been obtained by others. Fahsi et al. (2000) used Landsat –TM data over a rugged area in the Atlas Mountains, Morocco. This study showed that DEM data considerably improved the classification accuracy by reducing the effect of relief on satellite images. The variation coefficient (standard deviation divided by the mean) for homogeneous cover type areas was substantially reduced for all the spectral bands on the corrected image. Consequently, the overall accuracy was notably improved on the corrected image. The indivi-

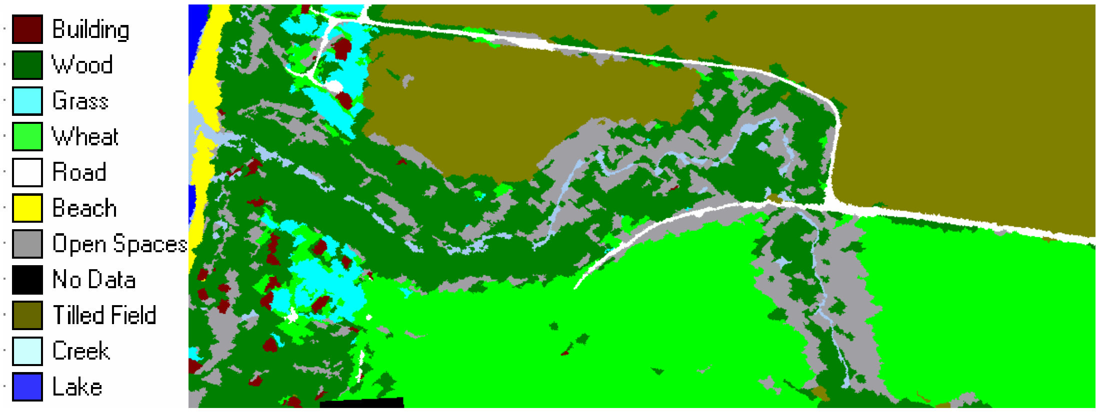

Figure 5. Object-based classification results of airborne Infrared image, with using thematic layer Eastern shore of Lake Huron, Ontario, Canada.

dual accuracies of the different classes also increased by up to 60%.

Effect of DEM thematic layer has also increased accuracy results of vegetation mapping (Bork and Jason, 2007). Subsequent integration of the LIDAR and digital image classification schedules resulted in accuracy improvements of 16 to 20%, resulting in a superior final accuracy of 91 and 80.3%, respectively, for the three and eight classes of vegetation. A final land cover map including 8 classes of vegetation, fresh and saline water, as well as bare ground, was created for the study area with an overall accuracy of 83.9%, highlighting the benefit of integrating LIDAR and multispectral imagery for enhanced vegetation classification in heterogenous rangeland environments.

DEM thematic layers also had a great impact on other land covers in our study area. A large proportion of *Tilled Field* and *Open Spaces* land covers wrongly was classified as *Building* in object based classification method without thematic layers. Contour thematic layer changed the way of building segmentation in form of rectangular shapes which suit with their structures. Each building unit was surrounded by a rectangular contour which finally leads to creating a suitable object in performing image segmentation process. Consequently, the second approach of object based classification (with thematic layers) increased the producer's accuracy for *Building* and *Creek*. Our results have good adjustment and correlation with Shackeford and Davis (2003) in distinguishing *Buildings* Creeks and *Roads.* Using membership function's techniques the object-based classifier is able to identify *Buildings, Roads and Creeks* even in dense area.

Conclusion

Although pixel-based classification approaches have created acceptable results with low spatial resolution imageries but the increase in spatial resolution, single pixels no longer capture the characteristics of classification targets. For the air born infrared images (as high resolution imageries) land cover classes with traditional pixel-based classification approaches, show a salt-and-pepper effect, with individual pixels classified differently from their neighbors. Consequently, classification accuracy and the results are reduced, with pixel-based approaches, due to using only spectral information of images. The accuracy assessment using confusion matrix produced overall accuracy about of 60% in this method. However, this method may no longer be used because it is limited by only utilizing spectral information without considering texture and contextual information.

Pixel-base classification approaches also failed to distinguish some of land covers in high resolution airborne Infrared images. For instance, classification results for *Building* showed that maximum likelihood classifier is not able to differentiate *Buildings, Creek and Open Spaces* land covers. In pixel-based classification approach such results may be improved by applying filtering method to the image. Another approach is class aggregation. However, these approaches were not recommended in this research as we proceeded with object oriented approach. To come up with this problem, we found that object-based classification approach, will improve the classification results if we adjust a well defined homogeneity criterion for image segmentation (e.g. the best scale factor have to be chosen 30 at level 3). This approach increased the Overall classification results up to 80 %.

However, although classification results improved in object-based method, still some classes produced low accuracy. The lowest user's accuracy in object-based classification approach belongs to the *Building* (14%).The reason why it is so, is that this unit have no realistic object in image segmentation stage. Digital elevation models (DEMs) have proved to be an effective aid to improving land cover classification. To increase the producer accuracy for these specific land covers, thematic layers in object-based classification method were used. Contours and bare DEM thematic layers increased classification results in object-based approach, by crating reasonable objects especially for differentiating *Buildings* and *Creeks,* using membership functions. Consequently, the overall accuracy increased from 80 to 94% in object based classification method with DEM thematic layers; while it was 60% in pixel-based classification.

Finally, it was found that in most cases (in terms of class type) object-based approach has priority to pixel-based approach; still object-based method may fail to distinguish some specific land covers (*Creek*). Our approach showed that in such cases classification results will increase by using thematic layers and their effects in segmentation process and membership functions. This study also concludes that DEM as one type of ancillary data integrated in image classification can improve the classification result. Further work is needed on the membership rules for the identification of the *Creek* and *Building* segments to include features and rules to discriminate between different types of buildings, such as residential, commercial, and industrial.

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