USE OF LANDSAT IMAGERY FOR EVALUATION OF LAND COVER / LAND USE CHANGES FOR A 30 – YEAR PERIOD FOR THE LAKE ERIE WATERSHED

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ABSTRACT

Current and historical land cover / land use information is an important contribution to many urban and watershed planning activities. This information is invaluable for those investigating the relationship between changes in human activity and changes in water quality. Understanding past activities will assist in the planning of future land development.

The main objective of this study was to use medium resolution (Landsat) satellite imagery to produce an accurate historical land use / land cover map along the Lake Erie coastline, focusing on areas located in the rural / urban fringe. This is traditionally a difficult task due to the heterogeneous nature of developed areas. A test area was chosen in the Cleveland, Ohio area because this was a good representation of the rural / urban fringe. The satellite imagery was geometrically and radiometrically corrected to minimize errors created by seasonal and atmospheric variations between images. When initial attempts using traditional pixel-based classification techniques failed to create satisfactory land use / land cover results, an object – based mapping technique was used. To further improve the quality of the resulting land cover maps, an extra image layer – NDVI difference layers of a leaf - on and leaf -off image – was used in the classification process. Also, standard deviation values of feature objects on Landsat image bands were added to the classification process to increase separation between land cover classes. The final land cover / land use classification map was produced with an 89.8% overall accuracy.

Once land cover maps were created for the study area for each time period, a change detection analysis was performed. It was found that the total area of high density urban, forest, industrial, water, and exurban or rural land cover type stays relatively constant. The low density urban areas increase from 1974 to 1994. The suburban land area decreases between 1994 and 2004. Between 1974 and 1994 the predominant land cover change in the study area was from agriculture to suburban and low density urban, which explains both the increase in area for low density urban and the decrease in area for agriculture. Between 1994 and 2004 a major land cover change from suburban land cover to low density urban was found. This would explain the decrease in total area for suburban land cover for this time period.

INTRODUCTION

The southern shore of Lake Erie has become the focus of an interdisciplinary project focused on biocomplexity. The land cover / land use along the Lake Erie shoreline is being studied for changes throughout time. Part of this investigation focuses on how human interaction with the lake and human development has contributed to changes within the lake itself. Understanding the linkages between changes in the physical systems (climate and hydrology), the biological systems (lower trophic and fish), and the human systems (land and water use) may help predict future water quality issues. Point and non-point sources of pollution within the watersheds that drain into Lake Erie contribute to water quality issues. Contribution from point sources within the area have largely been eliminated through regulation, but non-point sources from urban and agricultural land use are harder to understand and regulate without a better understanding of current land use activities. The influence that human development has on water quality for input to Lake Erie hydrologic models needs to be studied. Accurate land cover information is required to help map the source of non-point source pollution. Land cover is also an important source of information for developing hydrologic models to predict how much water drains into the lake for given storm events. Different land cover types have different surface runoff and infiltration characteristics.

Current sources of land cover information in an urbanized area include census and parcel information. In some areas current or historical information can be inaccurate or incomplete. The Landsat program provides consistent coverage over a 30 year period. The medium resolution of the Landsat imagery allows for complete coverage of the area with manageably sized files. A historical record of consistently classified land cover maps that are snapshots at a specific period of time would be very useful. Current pixel-based classification techniques, both supervised and unsupervised, have been used to map natural land covers, such as vegetation or water, very well. Due to the heterogeneous nature of urban land cover, classification techniques that simply examine the image one pixel at a time do not separate these land cover types very well. To create a more detailed land cover map of the rural / urban fringe an object-oriented classification technique was developed, which takes advantage of spatial patterns in land cover. These patterns were found to be useful in characterizing the urban / rural fringe area of land cover / land use change. The purpose of this study is to use medium resolution satellite images to map the changes in the rural-urban fringe. Historical block group census data are also available for several time periods to assist in this mapping effort.

STUDY AREA

The scope of this project is to prepare a land cover map of the entire Lake Erie shoreline within the state of Ohio. The Landsat coverage for this area is shown in Figure 1. The Landsat 16 to 18 day repeat coverage across the United States over the past 34 years provides for one of the most extensive remote sensing archives available. In this study Landsat-1 through -5 images provided for a complete coverage every ten years over the entire Lake Erie watershed. Landsat-1, -5 and -7 data purchased for this study are terrain corrected images (level 1T products) in the Universal Transverse Mercator (UTM), zone 17 north projection with the WGS 84 ellipsoid. The data were systematically and terrain corrected and resampled using the nearest neighbor algorithm to minimize the modification of pixel values.

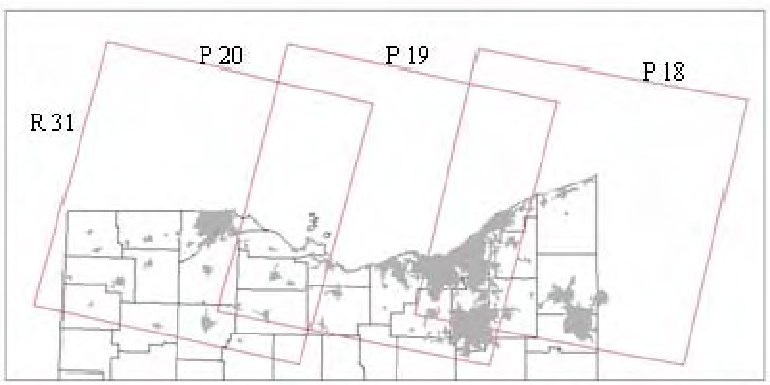

Figure 1. Landsat coverage of southern shore of Lake Erie.

To test and develop the process of creating the land cover map, a demonstration test site was chosen to test the results. The three Landsat scenes were examined to determine an appropriate site. The site chosen for this investigation includes Cuyahoga County and parts of Lorain, Medina, Summit, Portage, Geauga, and Lake Counties (Figure 2). This study area was chosen because of its good representation of the rural / urban fringe and the surrounding agricultural and forest areas. This area was also chosen because of the availability of historical demographic information. Three out of the four time periods that were used in this study had a cloud free Landsat image for both leaf-on and leaf-off periods. However, for 1984 only one cloud-free leaf-on image was available.

Another purpose of this study is to examine changes in population distributions, especially in the interface between the rural and urban areas. Cuyahoga County is an interesting example of changes in population distribution. Over the past 30 years there has been a decrease in the total population of the county. Looking at the change in population distribution, there is a definite outward migration of population towards the less developed parts of the county.

Figure 2. Study Area.

ATMOSPHERIC CORRECTION

The Landsat images were converted to radiance. A bulk atmospheric correction was performed on the images using MODTRAN. This is a multiple step procedure that begins by using data from the metadata file. These parameters include the Julian day of the image, the center longitude and latitude, the altitude of the sensor, height of the center point of the image, season, and the time of acquisition. When this information is input into MODTRAN and the type and range of output is defined, the MODTRAN model uses standard atmospheric models and profiles to calculate the radiance that is added to the scene due to atmospheric scattering. Because of the coarse spectral resolution of the Landsat satellites, this is an intermediate output that was aggregated to average the atmospheric effect over the specific Landsat bands. These MODTRAN output values needed to be averaged over the Landsat band widths to obtain a constant radiance value that is due to the effects of atmospheric scattering. This constant value is then subtracted from the calculated radiance values. The output of the Matlab code is an input into an ERDAS Imagine model that was used to convert digital number (DN) to radiance and then to atmospherically correct the image.

GEOMETRIC CORRECTIONS

Because of the need for precise geometry when detecting change over an extended period of time and the use of several different satellite platforms, an image - to - image registration was performed using ERDAS Imagine. The reference image for this operation was a terrain-corrected Landsat-7 image. This image was chosen because of the quality of the geometric accuracy of the Landsat-7 1T data, which is reported to be less then 30 m (NASA, 2004). Examples of points chosen were road and railroad intersections and point features, such as small buildings. Finding corresponding points in each image becomes more difficult with the older Landsat images. This was particularly true for the Landsat-1 image due to the difference in spatial resolutions (Landsat-1 of 60 m, Landsat-7 of 30 m). Within each image 50 evenly distributed ground control points (GCP's) that were easily identifiable in both images were located (Figure 3). Once all the GCP's are located in both the reference image and the image to be registered, a first or second order polynomial equation was calculated to transform the image so that the GCP's in both images are coincident within an expectable amount of error. Within this study the goal was to have an RMS error of less then half of a pixel, which was achieved.

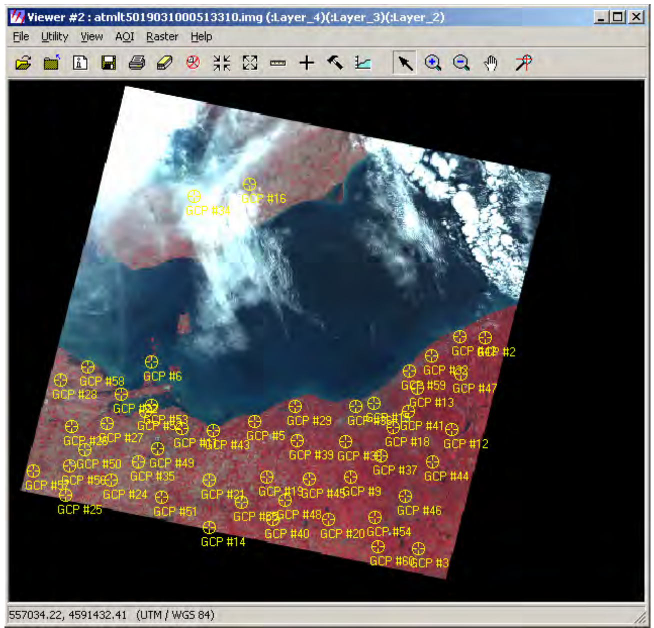

Figure 3. Sample distribution of GCP's for image to image rectification.

CENSUS DATA

Census data that were used in this investigation were obtained from the United States Census Bureau web site (www.census.gov). The data were taken from Summary File 1, which is a 100% representation of the data collected in the 2000 census. Data for the 2000 census were downloaded from the census web site in 39 database files, a geographic header file, and an ESRI shapefile. The 39 database files are linked by the field called LOGRECNO, or logical record number. The LOGRECNO allows a user to obtain all 286 items of population, housing, and demographic information. This information is linked to the boundary file through the use of a geographic header file that contains both the LOGRECNO and a STFID field that is unique to the block level.

Census data can be ordered at the state, county, county subdivision, place, census tract, block group, and block levels. Census block data are the finest resolution of data available. The data are defined by both visible objects, such as streets, streams, and railroad tracks, and invisible borders, such as municipal and county boundaries. There was a desire to use block level data to get the finest resolution of information, but there are some census blocks that are no more then two Landsat pixels wide. This means that it is possible to have a census block that does not contain an entire Landsat pixel, only several partial pixels. This would especially be a problem when examining the older and coarser (80 m) Landsat-1 data. The next level up in the hierarchy is a block group. This division is defined as all the blocks within a census track that have the same first digit of its four digit identifying number (U.S. Census Bureau, 2007). Block groups (outside of tribal lands) never cross state, county or census tract boundaries and generally contain between 600 and 3,000 people. Using data at this level of detail allowed comparison with a historical census data set that was used in Irwin and Reese (2002). The historical data contains information from the 1970, 1980, 1990 and 2000 census population density information aggregated into 1990 block group boundaries.

CLASSIFICATION

The original classification attempt using a pixel-based classification in ERDAS Imagine did not produce expected results. Attempts to group the clusters produced by the ISODATA classifier into coherent land cover classes that represented reasonable demographic groupings were not possible. By visual inspection of clusters, the water, forest and agriculture land cover types outside urban areas were defined very well. However, urban areas with extensive tree cover were confused with the forest category. Since urban area mapping was critical for this study, this land cover classification procedure was abandoned. Since the pixel-based classification did not produce satisfactory results with regards to identifying the various classes of urban land cover, an object-oriented classification scheme was used. The object-oriented software allows for a large amount of flexibility in all of the steps involved in classification. Many of the parameters that were chosen were either the defaults or values recommended in Darwish et al. (2003). The initial classification was tested on the 2004 data set in and around the Cuyahoga County area. This study site was chosen because it is a highly urbanized area that also has a variety of land cover types. Lake Erie provides an open water component in the north, the southwest corner of the study area is an agricultural area, and the remaining area was a mixture of light urban and forest land. Also, the 2004 time period was chosen because of auxiliary census data and aerial photography available for the area. The Landsat image and demographic information were used to develop the image objects for use in the classification process. Aerial imagery taken in 2004 with a 1-m spatial resolution was used to assess the accuracy of the classification.

Another factor considered in the generation of image objects is whether or not to consider the block group boundaries when creating the image objects. If the block group boundaries are not used for the creation of the image objects, the resulting segmentation has objects that span several different demographic classes. This could be a true reflection of the land cover, but it could also create confusion in every step of the classification process from selecting training objects to accessing the accuracy of the classification. If the individual block groups are used to help define the objects, the block group borders are, of course, the primary factor in creating the objects. This would negate some of the benefit gained from using the object-oriented software (Definiens) to help define the objects.

To balance these considerations, a processed demographic layer was used to help define the objects. The layer created is a raster layer that has the four demographic values being studied. Because the demographic layer has been dissolved to only distinguish between demographic classes, the only time the demographic layer will define the image object is at the border between two demographic classes. Otherwise, the satellite image is the primary factor that decides the object border. In this way all objects created for this land cover classification do not cross demographic borders. If a low density urban area object spills over into an area classified as suburban by the census data, a separate object will be mapped and classified as low density urban. By using demographic information, then objects that are created will be contained within the population class. The demographic class information minimizes the confusion between land cover classes in the training and accuracy assessment phases of the classification.

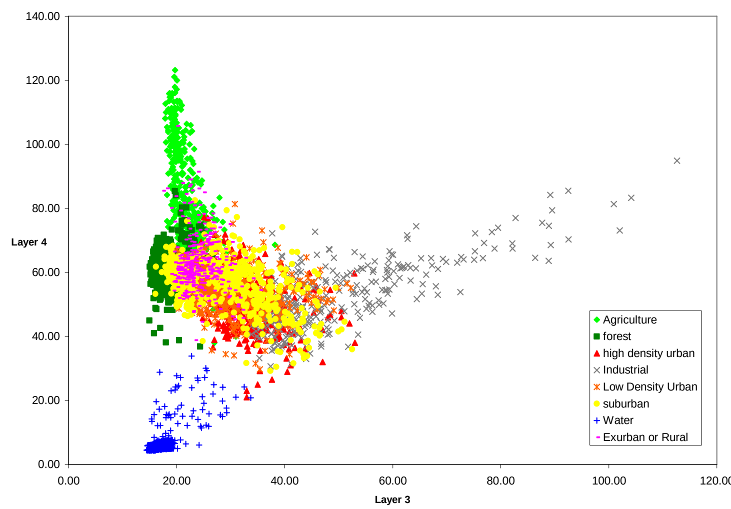

Figure 4. Feature Space image.

The main difficulty that was encountered was in separating the spectrally similar urban classes. This is shown graphically with a feature space plot of object means for layers 3 and 4 (Figure 4). Using just two layers (3 and 4), water, industrial, and agriculture are well separated (lower left, upper right and upper left, respectively), but the urban areas overlap each other in the center region. General trends can be seen within this region of confusion. The exurban or rural land cover class is centered towards the agricultural and forest land cover classes. Suburban overlaps with forest more than with low density urban areas, and high density urban overlaps with the industrial side of the plot.

To find the combination of parameters needed to separate the urban classes, signatures of the average statistics of classified objects were examined. These plots helped to determine how well the classes were defined by the mean and standard deviation of each layer. An example signature is shown in Figure 5, which shows the signatures of all classes involved. Water and industrial land cover classes are separated well by simply using the object means for Landsat-5 bands, but there is still confusion seen within the other urban classes. By looking at plots that involve different combinations of land cover classes, the ways to separate overlapping classes becomes more evident. It is seen that the industrial and high density urban land cover classes are separated well from the other urban classes by the object means of Landsat bands 2, 3 and 4, but low density urban and suburban are nearly identical. The non-urban land cover classes were separated using the mean and standard deviations of Landsat bands 2, 3, 4, and the NDVI difference layer. The addition of the NDVI difference layer and the object standard deviation statistics provide further separation between low density urban and suburban.

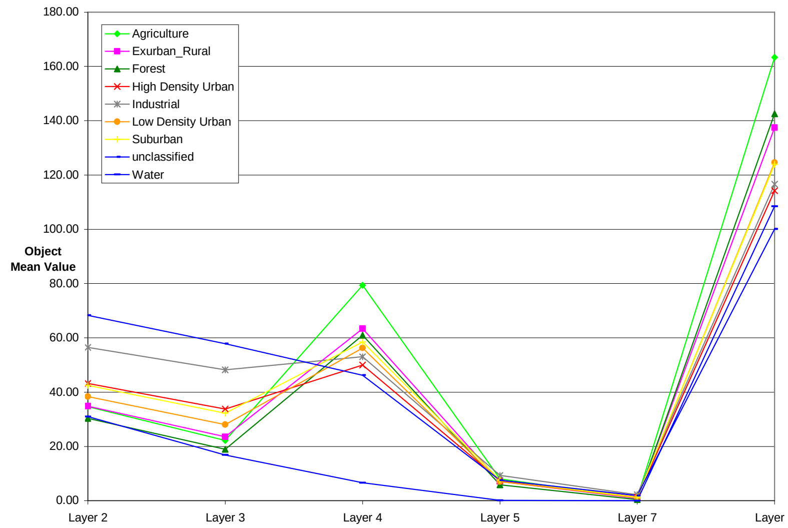

Figure 5. Signature plot of all classes.

The processed imagery and census data were placed into the Definiens software for use in an object-oriented classification. The 8–band image, along with the classified census demographic information, was input into Definiens and formed the basis of the original pixel segmentation. A multi-resolution segmentation was performed using the spectral information from Landsat bands 2-5, 7 and 8 and taking the demographic layer into consideration. The Landsat layer 1 was removed from the classification due to its high amount of atmospheric interference and layer 6 was removed due to its coarse spatial resolution.

The demographic information used in the segmentation shows dissolved blocks of demographic class areas, not individual block groups, so that objects did not cover multiple demographic classes defined by the census data. Once the layers involved in the segmentation were chosen, parameters for the homogeneity criterion were defined. Darwish et al. (2003) found that changes in segmentation criterion had little change in classification accuracy when performing an object-oriented classification using Landsat imagery. The segmentation factors used in this investigation were based on Darwish et al. (2003) to set the homogeneity criterion weight factors. These factors included:

Color: 0.8
Shape: 0.2
Compactness: 0.6
Smoothness: 0.4

Two different scale parameters (25 and 50) were tested. A scale parameter of 25 was used because it incorporated surrounding pixels without creating objects that span several land cover types. Once the image was segmented, the next step was to define sample objects within the image to train the classifier. This can be done within the Definiens software by using the sample editor (Definiens AG, 2006a and 2006b). Within the user interface dialog box, the sample characteristics can be viewed for any object that is selected. This dialog box shows statistics of the currently selected samples. As more classes have sample objects defined, the statistics associated with each land cover class are more precisely defined, and the membership values for each class are provided. These statistics can be taken into account when selecting sample objects that are a good representation of each land cover class. Ten sample objects were chosen that were a good representative of each land cover class. For example, the water class is represented by 10 objects that would include objects in the center of Lake Erie, objects along the shoreline, and objects in smaller inland lakes and on rivers. The distribution of training objects used to create the

1994 land cover map is seen in Figure 6. Once the objects for each class are identified, they are exported as a TTA mask file that is used by the software to define the input parameters of the classification.

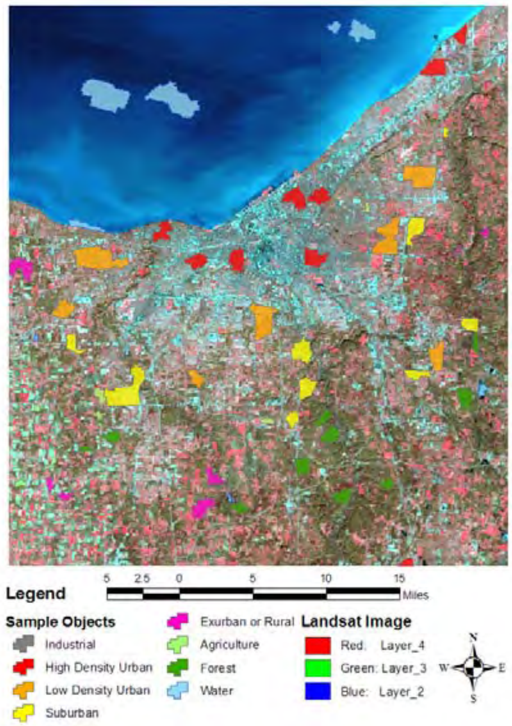

Figure 6. Distribution of sample objects for the 1994 image classification.

The land cover hierarchy classification that was developed for this project included:

- 1 Water – lakes and rivers
- 2 Urban – man-made structures
- 2.1 Industrial – highly developed areas with low population, business districts, shopping plazas
- 2.2 High Density Urban – areas with population density > 5,000 persons / mi^2 (~1931 persons / km^2)
- 2.3 Low Density Urban – areas with population density between 1,000 persons / mi^2 (~386 persons / km^2) and 5,000 persons / mi^2 (~1931 persons / km^2)
- 2.4 Suburban – areas with population density between 325 persons / mi^2 (~125 persons / km^2) and 1,000 persons / mi^2 (~386 persons / km^2)
- 3 Exurban or Rural – areas with population density < 325 persons / mi^2 (~125 persons / km^2).
- 3.1 Forest – areas where the predominant land cover is trees.
- 3.2 Agriculture – areas where the predominant land cover is cultivated vegetation to include crops, grasses, or golf courses.

Parameters that are used to define each land cover type can be customized within the classification process. The parameters that were used with the standard nearest neighbor classification were the mean values of layers 2, 3, 4, 5, 7, the NDVI difference, and the standard deviation of the same layers. All other parameters involved in the classification were left as defaults.

CHANGE DETECTION

Once the classification was performed in Definiens, the results were exported to a shapefile format with the attribute table populated with the “classified as” for each of the eight classes. If an object is classified as water, the “classified as water” = 1 and all other “classified as” values are 0. When the shapefile is opened in ArcGIS, a new field is created called Class_1, which is populated by selecting objects where “agriculture = 1, forest = 1, high density urban = 1. The only unique value is exurban or rural, since this class is all the exurban or rural that is not forest or agriculture. For this class objects must be selected where "exurban or rural = 1, forest = 0 and agriculture = 0. For each class of objects that is selected, the class_1 value needs to be populated with a number. The classification scheme adopted was:

Suburban	= 2
Low Density Urban	= 3
High Density Urban	= 4
Agriculture	= 5
Forest	= 6
Industrial	= 7
Water	= 8
Exurban or Rural	= 9

Using class_1 as the attribute, the shapefile is converted to a raster file (.img format) so that it can be easily processed in ERDAS Imagine. When the raster file is opened within Imagine, the layer type is changed from a continuous layer to a thematic layer. The thematic layer can be used to generate random points (50 for each class) within the classified image. These sample points are used to assess the accuracy of the classification. The generated points have class values attributed to them. The classified image, the satellite image, the classified demographic layer, and an aerial image (if available), can be evaluated to assign the reference value (the actual land cover) for each point. Once all the points have a reference value assigned, an accuracy report can be generated.

The first step in analyzing the change in land cover types over time is to calculate the general changes in land cover area between two time periods. Total area for each land cover type was calculated for each time period, and changes in total area, percent of total area, and percent change was also determined. Percent of total area and percent change were calculated with the following equations:

$$\%Total\_Area = \frac{Area\_Land\_Cover}{Total\_Area} * 100$$

$$\%Change\_Area = \frac{New\_Area - Old\_Area}{Old\_Area} * 100$$

where:

New_Area = Area of land cover type in most recent time period.
Old_Area = Area of land cover type in previous time period.

The overall change was calculated using the classification results. To create a layer that can easily give "to-from" change information, the image values need to be recoded so that post-classification change detection can be performed. The 1974 classification values were kept the same as 2, 3, 4, 5, 6, 7, 8, and 9. The 1984 classification values were changed to 20, 30, 40, 50, 60, 70, 80, and 90. The 1994 classification values were changed to 200, 300, 400, 500, 600, 700, 800, and 900. The 2004 classification values were changed to 1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, and 9000. To determine "to-from" attributes the older classification is subtracted from the most recent classification using the raster calculator function in ArcGIS. The resulting change detection matrix can be used to isolate areas of change. The results of the raster calculation were converted to a vector layer and the boundaries were dissolved to create a layer that represents every possible change scenario.

RESULTS

Various parameters of the classifier were investigated to determine if the land cover accuracy could be improved. One of the parameters that had a large effect on how well the classification matches the demographic land cover is the scale parameter. If the scale parameter was too small, the objects that were classified will match specific land cover types and possibly be no better than a pixel-based classification. If the scale parameter is too large, the different land cover types will be merged into single objects. With all other parameters in the classifier held constant, the 2004 image was classified with three scale parameters – level 1 – 10, level 2 – 25 and level 3 – 50. Level 1 was dismissed after a visual inspection showed that the objects that were created were too small. Both the levels 2 and 3 classification were assessed. Although the level 3 objects more closely matched the size of the block group, the level 2 object classification resulted in a more accurate classification based on an accuracy assessment. This could be due to the balance that was found between incorporating surrounding pixels and overgeneralization of image objects. Level 3 objects may have created objects that span several land cover classes. The error matrices created during the accuracy assessment (Table 1) showed that the larger objects (the level 3 classification) resulted in a confusion of the transitional area between low density urban, suburban, and rural areas.

Table 1. Example Error Matrix From Level 2 classification of 2004 imagery.

Level 2 objects (Scale Factor 25)

Classified Data	Class 2 - Suburban	Class 3 - Low Density Urban	Class 4 -High Density Urban	Class 5 - Agriculture	Class 6 - Forest	Class 7 - Industrial	Class 8 - Water	Class 9 - Exurban or Rural	Row Total
Class 2 - Suburban	37	8	0	1	0	2	0	2	50
Class 3 - Low Density Urban	6	34	0	1	0	1	0	8	50
Class 4 -High Density Urban	0	2	44	2	0	2	0	0	50
Class 5 - Agriculture	0	0	0	50	0	0	0	0	50
Class 6 - Forest	1	0	0	1	48	0	0	0	50
Class 7 - Industrial	0	1	0	0	0	49	0	0	50
Class 8 - Water	0	0	0	0	0	0	50	0	50
Class 9 - Exurban or Rural	0	2	0	1	0	0	0	47	50
Column Total	44	47	44	56	48	54	50	57	400

The initial object-oriented classification for the level 3 image objects met the accuracy requirements set forth in Jensen (1996) with an 86.25% overall accuracy. The overall classification accuracy for level 2 image objects was 89.75% (Table 2). Since the urban transitional area was a critical area to define for this study, the level 2 object classification was selected.

Table 2. Classification accuracy for Level 2 classification of 2004 imagery.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Class 2 - Suburban	44	50	37	84.09%	74.00%
Class 3 - Low Density Urban	47	50	34	72.34%	68.00%
Class 4 -High Density Urban	44	50	44	100.00%	88.00%
Class 5 - Agriculture	56	50	50	89.29%	100.00%
Class 6 - Forest	48	50	48	100.00%	96.00%
Class 7 - Industrial	54	50	49	90.74%	98.00%
Class 8 - Water	50	50	50	100.00%	100.00%
Class 9 - Exurban or Rural	57	50	47	82.46%	94.00%
Totals	400	400	359		

Overall Classification Accuracy = 89.75%

The NDVI difference layer was added to help differentiate between forested areas and urban areas with extensive tree cover. A decrease in accuracy for all classes involving urban features can be seen in all categories. The producer’s accuracy was 69.39% with the NDVI difference layer. Low density urban land cover class had a 75.51% producer’s accuracy with the NDVI difference. The results of the 1994 land cover map had an overall accuracy of 85.25%. Some confusion was seen in the southwest region of the study area between exurban and rural and agriculture. Examination of the image objects showed that objects classified as exurban or rural were centered on small pockets of houses or other man-made features and also contained portions of agricultural land.

For the classification performed for 1984 only, the NDVI layer was created and added in the image processing step rather than using the NDVI difference layer created using two images. The resulting image segmentation using an NDVI layer from one image created a classification that did not represent the land cover in urbanized areas. Upon visual inspection many linear urban features were segmented creating objects that overly separate urban land covers. The objects created using the NDVI layer were too small and the texture information that was found by creating image objects was lost. The 1984 image was classified without the added NDVI information. As expected, the classification accuracy of the 1984 image was lower than that observed for the 1994 and 2004 images. The

75.75% accuracy seen in the 1984 land cover map is comparable to the 78.50% accuracy that was seen in the land cover map created in 2004 without the NDVI difference layer. The 1974 land cover map also saw a decrease in overall accuracy of 73.00%. This can be attributed to the fact that the sensor onboard Landsat-1 had only four spectral bands, the radiometry is only 7-bit, and the spatial resolution is coarser. Much of the confusion was seen between the agriculture (76.47%) and exurban or rural (68.00%), suburban (56.00%), or low density urban (60.00%) categories. An example of a final land cover map is seen in Figure 8. Additional land cover maps can be found in Seidelmann (2006).

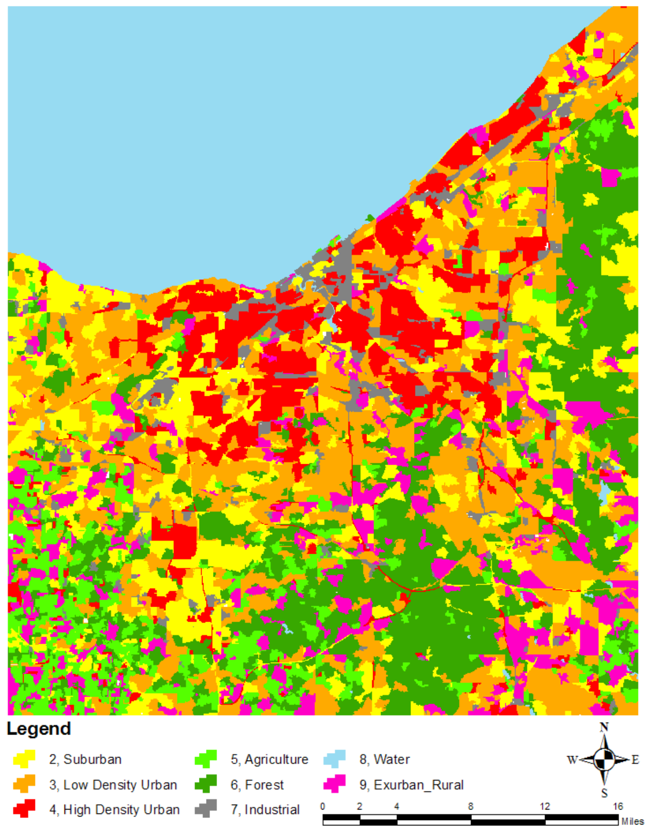

Figure 7. 2004 Classification Results.

CONCLUSIONS

The results of this study show that an object-oriented classification approach can be used to create an accurate land cover map for an urbanized area much better than a traditional pixel-based classification. Classified census data were used in the segmentation phase of the classification process to ensure that image objects do not cross multiple population classes. The developed technique uses classified census population density data to train the classifier. The availability of the census information was critical for this study. The ability of the object-oriented approach to take into consideration surrounding pixels when classifying a certain area allows the heterogeneous nature of urban areas to become a defining attribute. With a pixel-based classification the heterogeneity is a hindrance. The addition of a leaf-on / leaf-off NDVI difference layer allows for better discrimination between urbanized areas and surrounding forested areas. The NDVI layer also helps to discriminate between the suburban and low density urban areas along the rural fringe surrounding a city. A test of object size and other defining parameters also showed an increase in classification accuracy. The final classification hierarchy was defined as:

- Urban
  - High density urban
  - Low density urban
  - Suburban

- Industrial
- Exurban or rural
  - Exurban or rural
  - Agriculture
  - Forest
- Water

The final classification parameters that were used in the object-oriented classifier include:

- Image Layers: mean of Landsat-1 bands 1,2,3,4 and NDVI difference; Landsat-5 bands 2,3,4,5,7 and NDVI difference. Standard deviations of spectral bands for each class were also used.
- Thematic layer is used: a dissolved, classified census population density layer.
- Scale Factor: 25
- Color factor: 0.8
- Shape factor: 0.2
- Compactness: 0.6
- Smoothness: 0.4
- The standard nearest neighbor membership function was used.

The change detection analysis that was performed in the Cleveland metropolitan area showed that the total area of high density urban, forest, industrial, water and exurban or rural land cover type stays relatively constant. The suburban and low density urban areas increase from 1974 to 1994. The suburban land area decreases between 1994 and 2004. Between 1974 and 1994 the predominant land cover change in the study area was from agriculture to suburban and low density urban, which explains both the increase in area for low density urban and suburban and the decrease in area for agriculture. Between 1994 and 2004 a major land cover change was seen from suburban land cover to low density urban. This would explain the decrease in total area for suburban land cover for this time period.

ACKNOWLEDGMENTS

This study was funded by the National Science Foundation under project “Interactions among human, biological, and physical processes within large lake ecosystems”, National Science Foundation, award #DEB-0410336.

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