IMPROVING CLASSIFICATION ACCURACY OF SPECTRALLY SIMILAR URBAN CLASSES BY USING OBJECT-ORIENTED CLASSIFICATION TECHNIQUES: A CASE STUDY OF NEW YORK CITY

Dr. Sunil Bhaskaran, Prof. in GIS & Remote Sensing
Department of Environmental, Geographic and Geological Sciences
Lehman College, City University of New York (CUNY)
250 Bedford Park Boulevard West Bronx, New York, NY 10468-1589
Tel:718-960-1120, Fax:718-960-8684
Sunil.Bhaskaran@lehman.cuny.edu

ABSTRACT

Paper describes a methodology to improve classification of urban features by using object oriented classification techniques. Mapping urban features from satellite data is challenging due to several reasons. Urban objects are spectrally similar and they have different shapes, sizes, patterns, all of which contribute to their low accuracy. For example, features such as roofs, roads, and other spectrally similar objects like open space (concrete) appear spectrally similar leading to their low accuracy in classification. Very high resolution satellite data (Ikonos) was classified using both supervised and object oriented classification techniques. A combination of spectral, spatial attributes and membership functions were employed for mapping urban features. Accuracy assessment was carried out using ground truth data acquired from field surveys and from other reliable secondary data sources. Whilst the per-pixel supervised classification approach produced reasonable overall accuracy, specific classes such as white roof and vegetation registered low user's accuracy (79.82% and 70.07%) respectively. These classes were mapped using an object oriented classification approach. Spectral thresholds and membership functions were employed after the image was segmented. Results show the potential benefits of using object oriented classification techniques for mapping urban features using VHR satellite data. The methodology and results have useful implications for improving urban mapping accuracy particularly for those data that have high spatial resolution but low spectral resolution. GIS layers may be extracted after image analysis that can assist in the production of high quality digital maps for planning, emergency applications, risk assessment, integration with census data, analysis and modeling.

INTRODUCTION

Urban environments are also dynamic and undergo rapid physical and socioeconomic changes. From a development and management perspective acquiring current information about land use development, policy formulation, and in general for managing resources is critical in these rapidly changing environments (Sanchez 2004; Aysan et al., 1997; Wright 1996; Clark and Jantz, 1995). By using satellite data urban planners can map the current land use and acquire information about specific urban features. Urban planning therefore must involve the analysis of current geographic data to study various interrelated aspects of urban environment such as land use, zoning, recreation, transportation, air pollution and environmental impact assessment. It is therefore vital to use technologies that enable rapid and cost effective acquisition of current spatial data. Although there are several means of collecting and analyzing geospatial data remote sensing has been used successfully over the years to understand and manage urban environments across the globe. Remote sensing is an important technology for acquiring spatial data. The availability of new satellite data from a suite of space programs initiated by different countries present exciting opportunities for extracting urban features. Classification of VHR data by using spectral, spatial and textural methods individually or in combination has also increased their application for urban feature extraction and mapping. VHR multispectral imagery in particular have many potential benefits to government organizations, non-profit agencies, and a wide array of mapping and commercial companies (Dial, 2003; Sawaya et al., 2003; Tanaka and Toshiro, 2001). Remotely sensed data are therefore potentially useful sources of extracting land cover and land use information. Remote sensing along with GIS tools are therefore used to gather, store, retrieve, analyze, display, and output data related to the urban and suburban environment and can provide planners with certain data sets that help in managing the urban and suburban areas (Donnay et al., 2001; Bahr 2001). The majority of remote sensing work have been focused on natural environments over the past decades. Applying remote sensing technology to urban areas is relatively new.

The primary objective of this study was to classify urban features from an Ikonos image by using both per-pixel parametric supervised classification (MLC algorithm), and object oriented classification methods. An Ikonos image was acquired over the study site covering sections of Queens and Brooklyn boroughs in New York City. The study site that best represents the heterogeneity of urban landscape was chosen after a detailed visual examination of the image. A classification scheme was developed based on the range of urban objects in the study site.

STUDY SITE

Study site consists of Queens and Brooklyn boroughs in New York City (see Fig1). The land use varies from dense built up to low-density built up, recreational sites, open spaces, trees, water bodies including the East river that virtually bisects the study area into two sections. The northern boundary of the image comprises of dense residential apartments with some trees along side of the roads. Some recreational areas (parks) are also found in the northern parts of the study area. The northern and western parts of the image consist of large industrial buildings, open spaces with scattered vegetation, trees and some residential houses. Several industrial areas and small residential houses are located in the southern and the eastern parts of the study site.

A cloud-free and orthorectified Ikonos satellite image was used for the analysis. The image was acquired in geotiff format and has a single (1m by 1m) panchromatic and four multispectral bands (4m by 4m). The images have a radiometric resolution of 11 bits per pixel and were projected to the Universe Transverse Mercator (UTM), zone 18, WGS84 datum. The data specifications and resolution characteristics of Ikonos are shown in table 1. Ground truth data is important to understand the features in the real world and to map a mental picture of the type of land cover and land use. A hand held Trimble Geo-XT Global Positioning System (GPS) and a digital camera was used to collect sampling points from the study site. The sampling strategy involved walking to the study site with a digital camera for sampling specific class locations. X and Y coordinates were recorded using GPS data dictionary and the map features (polygons) were uploaded using the pathfinder software. A data table with different types of samples (classes) was created from the study site. Apart from this primary data we also used secondary data from existing internet portals such as the Open Accessible Space Information System Cooperative (OASIS) that is created and hosted by the Center for Urban research, City University of New York (CUNY). OASIS is a partnership of more than 30 federal, state, and local agencies, private companies, academic institutions, and nonprofit organizations to create a one-stop, interactive mapping and data analysis application via the Internet to enhance the stewardship of open space for the benefit of New York City (NYC) residents. OASIS website accesses GIS maps and planning data sets from different agencies (URL: http://www.oasisnyc.net/pages/about_OASIS.html). We used both raster and vector data (aerial photo images, street and road networks, buildings) from the OASIS website to visually compare the results from both supervised and object oriented classifications.

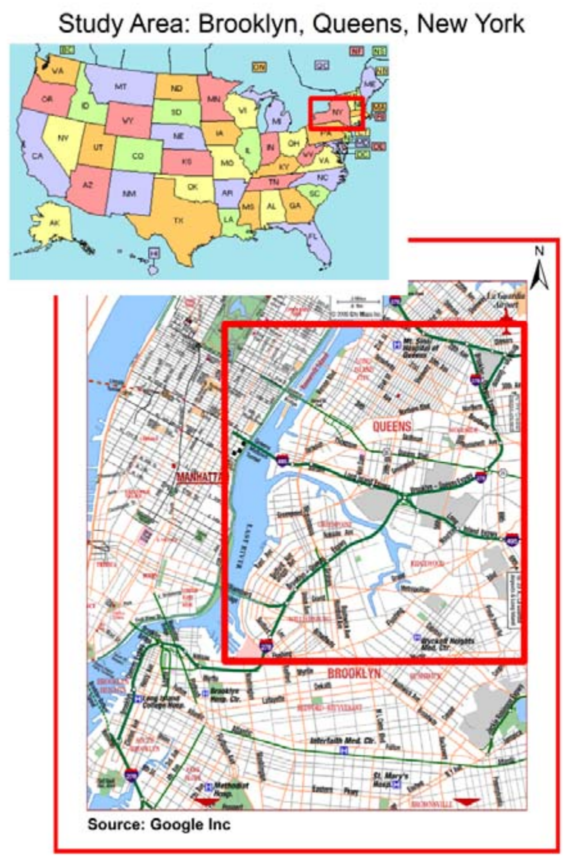


Figure 1. Ikonos characteristics and ground truth data.

METHODOLOGY

A cloud-free Ikonos image was acquired by way of an award from the GeoEye foundation in Colorado, USA. The training data samples were identified from the image after a detailed visual examination. The classification scheme was based on the criteria as laid out by Anderson (1971). We made minor modifications to the classification scheme in order to focus more on specific urban features. Seven (7) classes were determined after a detailed visual examination and analysis of class separability between different pairs of classes. The classification was carried out initially by using the supervised method (maximum likelihood classification) or MLC algorithm. The accuracy assessment was carried out using both primary and secondary ground truth data. Overall accuracy for the supervised classification was good. However, user's accuracies for 2 classes 'vegetation' and 'white roof' were low. We employed an object oriented classification approach to improve the class accuracies for both vegetation and white roof classes. The first step in the analysis was to segment the image into different homogenous objects. The estimation of optimal segments for both classes was therefore necessary to improve thematic accuracy. The optimal segments were derived from the results of an ongoing research. In this research the optimal segments were estimated from a series of Ikonos satellite data by employing both empirical and statistical methods. Scale parameters such as shape, compactness, color, layer values, band weightings were used in the analysis of 6 images and 40 classes (Bhaskaran et al., Unpublished). In this study we used a multi-resolution segmentation to generate new image objects. The image was then classified by using spectral and spatial attributes with different membership functions. The methodology is shown by figure 2. The classification methods, accuracy assessments and results are discussed in more detail in the following paragraphs. The process of sorting pixels into individual classes, or categories of data based on their data file values is called classification. Under classification pixels that satisfies a certain set of criteria, are assigned to the class that corresponds to that criteria. However, for this process to be successful, the computer system must be trained to recognize patterns in the data. Training is the process of defining the criteria by which these patterns are recognized. We selected training classes prior to performing supervised classification. The image was enhanced with the histogram equalization and visually examined before different ROIs were selected for 7 classes. The class separability between the ROIs was determined by using the 'Jeffries-Matusita and Transformed Divergence separability' measures and a separability index (SI) was computed between each pair of training classes (J.A. Richards, 1999). ROIs for all 7 classes had a high SI index and therefore were selected for classification. A total number of 40,369 pixels were used to train the classification and 6,117 were used to validate the results.

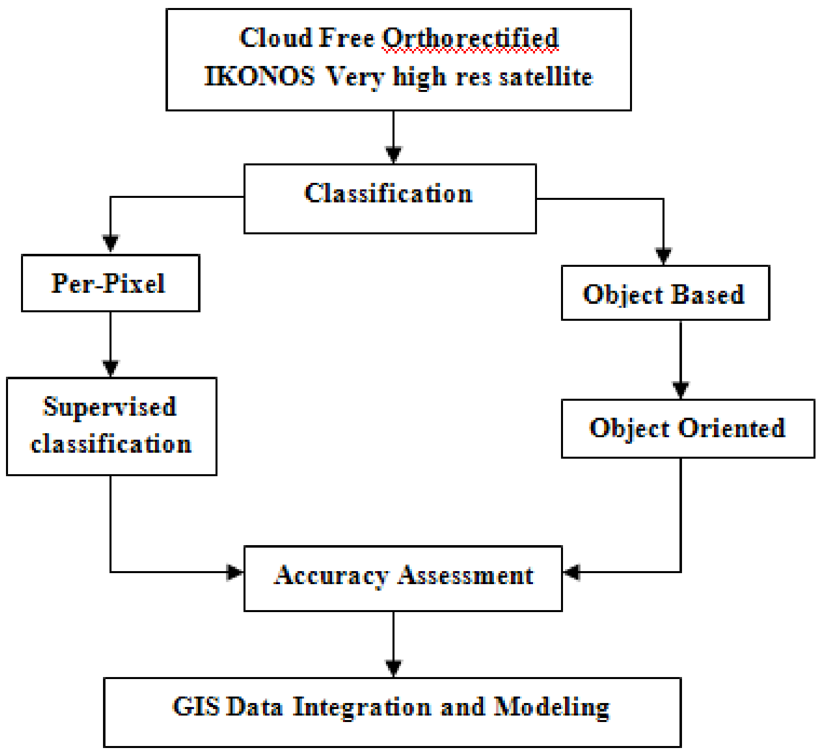
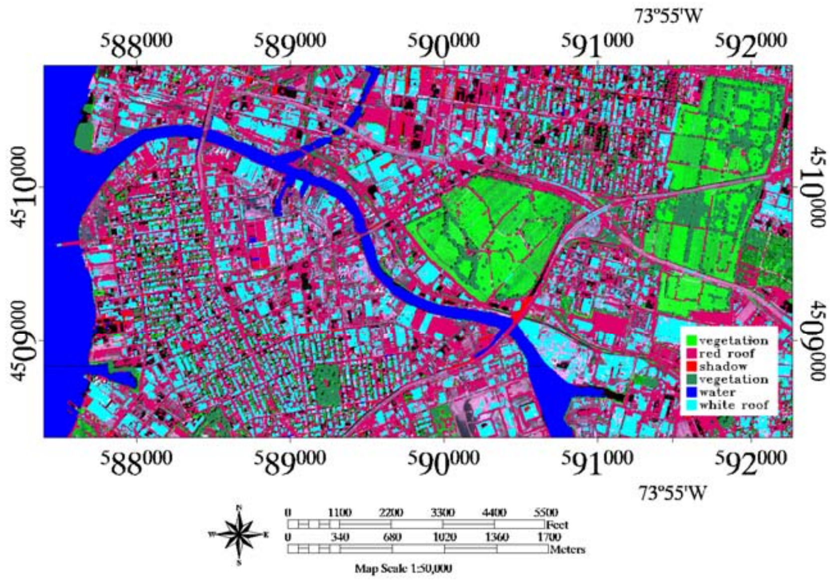


Figure 2. Methodology.

ACCURACY ASSESSMENT – OF SUPERVISED AND OBJECT BASED CLASSIFICATION

The classification accuracy was measured by using a standard error matrix. The matrix was compared by using a pair-wise z-score significance test (Congalton & Green, 1999). We compared the classification results with ground truth image data to assess the overall accuracy. An error matrix was computed to obtain the user's and producer's accuracy. The producer's accuracy represents the measure of omission errors that correspond to those pixels belonging to a class of interest that the classifier has failed to recognize. The user's accuracy, on the other hand, refers to the measure of commission errors that correspond to those pixels from other classes that the classifier has labeled as belonging to the class of interest (Richards & Jia, 1999). The overall accuracy and Kappa coefficient for the supervised classification was 85.2163% and 0.8088 respectively. The results of the classification are described separately in the 'results' section. The user's accuracy for classes 'white roof' and 'vegetation' was low in comparison to the overall accuracy. It is well documented that spatial attributes may significantly improve the accuracy of different class features. Various studies conducted by (Zhou and Robson, (2001); Blaschke and Strobl, 2001; Dean and Smith, 2003; Pizzolato and Haertel, 2003) have demonstrated that the spectral attributes the shape, size, color, pattern, may also improve the thematic mapping accuracy of certain classes Therefore an object oriented approach was employed to improve the accuracies of these classes.

Object-oriented classification starts with the crucial initial step of grouping or segmenting neighboring pixels into meaningful areas. The segmentation routine in Definiens is based on a multiresolution segmentation strategy, which utilizes a type of region growing approach, and is generally implemented in an interactive, trial-and-error fashion (Baatz & Schape, 2000; Yu et al., 2006). Resultant segmentations are controlled by both scale and shape parameters. Segmentation categorizes the image into homogeneous and non-intersecting regions. It combines spectral and non-spectral information present in images which leads to better detection of image features and superior accuracy (Yan et. al., 2006). The accuracy of the classification depends directly on the segments and an erroneous segmentation will result in inaccurate classification. Segmentation is followed by classification. The image classification in Defeniens is based on user defined fuzzy class descriptions based on spectral and spatial features. The classification process can include variety of different information, ranging from spectral mean values for each object, to measures of texture, context and shape. For this study specific image objects related to the different classes were created iteratively in Definiens eCognition software by using the multi-resolution segmentation process. A study by Kim M, and Madden M, (2009) highlighted the importance of estimating optimal segments since the accuracy of the segments directly influences the accuracy of classification. Kim and Madden used an empirical and statistical approach to derive the optimal segments for forested regions. In another ongoing research (Bhaskaran, et al, Unpublished results), on deriving optimal segments, a time-series of 6 Ikonos multispectral images were segmented to extract 8-14 urban classes independently by using a combination of varying scale parameters. Different shape, compactness, and scale parameters for each of the 4 multispectral bands were used for extracting a range of urban classes. Layer weights were assigned to specific multispectral bands based on their spectral and spatial information content and different combinations of layer mixes (band combinations) were used to derive the optimal segments. The accuracy of these segments was tested with ground truth samples derived from a combination of primary and secondary ground truth data/images. User's and producer's accuracies were calculated for optimal segments. The accuracy assessment yielded good results. In addition, spatial autocorrelation (Moran's I curve) was also examined to assess the relationship between spectral values and different segmentation scale parameters. This empirical and statistical approach has value particularly for mapping urban features and is being discussed in detail in another paper (Bhaskaran, et al, Unpublished results). We used the following multi-resolution segmentation parameters for this study: Scale Factor=3, Color (or Spectra): Shape=8: 2, Compactness: Smoothness=2:8 for extracting different urban classes. Multi-resolution segmentation of the image was followed by classification of image objects. We used different membership functions for each class through a set of rules. The function slope (ascending, curved etc.) describes how the membership value for the specific expression is calculated for a certain feature value of an image object. Membership functions offer a transparent relationship between feature values and the degree of membership to a class. It is defined by its 'Left' and 'Right' border values in combination with the function slope. In Definiens 'contained' and 'inherited' expressions in the class description produce membership values for each object. Each object is then classified according to the highest membership value. For example, if the membership value of an image object is lower than the pre-defined minimum membership value, the image object remains unclassified. If two or more class descriptions share the highest membership value, the assignment of an object to one of these classes is random (Definiens, 2004). We used a combination of spectral threshold values and assigned membership functions to generate classes. The classification image derived from object oriented method is shown by Fig 3. We generated accuracy assessment matrix by using ground truth samples.



Source - Geoeye

Figure 3. Object oriented classification.

Accuracy Assessment – Object Based Classification

Samples (vector) for white roofs and vegetation were exported from Definiens and overlain on the Ikonos image. A ground truth class image (raster format) was created by using the vector samples collected from the field and by converting them to a raster format. Care was taken to locate and collect samples of different sizes of roofs for use in the accuracy assessment. For secondary data we used a superior resolution (1m by 1m) panchromatic as well as another (1m by 1m) multispectral merged hybrid image. An error matrix was prepared for each resulting thematic map. The matrix provided the correspondence between the predicted and the actual classes of membership for an independent testing dataset. This made it possible to derive a range of quantitative measures of classification accuracy. Producer's, user's, and overall accuracy were computed to evaluate the accuracies of the thematic maps.

RESULTS OF SUPERVISED CLASSIFICATION – SPATIAL DISTRIBUTION OF CLASSES

Water

The feature class water consisted of East River located in the north-western part of the study site. This class produced the highest user's (90.77%) and producer's accuracy (97.25). The producer's accuracy gives a measure of commission errors that correspond to those pixels belonging to the class of interest that the classifier has failed to detect. User's accuracy gives a measure of commission errors that corresponds to those pixels from other classes that the classifier has assigned to a class of interest. The high spectral absorption feature of water in the VIS-NIR bands clearly distinguishes it from all other urban features resulting in low omission errors. However, due to spectral similarity of water to dark roofs led to commission errors. Of the total pixels assigned to water 4.9% of were misclassified as dark roofs and 3.9% as shadows.

Vegetation

The feature class vegetation (lawns, parks) was found in the northern and eastern parts of the study site. The lawns and parks (recreational) are mostly confined to residential areas. The user accuracy for vegetation (79%) was on the low side due to mixed pixels and the heterogeneous representation of land surface features in residential and park areas. The heterogeneity in surface features contributed to high commission errors. From total of 398,915 pixels, 11% was classified as trees and 8.8% as gray roof tops. However, producer's accuracy for vegetation 87.86% was relatively high due to low omission errors. The classification was improved by using combination of spectral and spatial attributes in object oriented domain that is discussed in this paper.

Trees

Trees are dispersed throughout the image. They are found in clusters in parks, rows along the roads and independently otherwise. Supervised classification approach showed high user's and producer's accuracy 83.02%, 93.88% respectively for the feature class trees. User's accuracy comparatively to the producer's accuracy was low since some pixels of vegetation were labeled as trees (commission error). Trees and vegetation (grass) are spectrally similar and thus challenging to delineate without spatial rules.

White Roof

White roof vary in sizes throughout the image area. Small white roofs (residential) and large white roofs (Industrial) are located throughout the study site. However, there is a distinct correlation between the area of all the roofs and the patterns displayed by the features around these roofs. For example, the smaller residential roofs (approximate area - 816 m^2) are located in close proximity to vegetation and trees, while large industrial roofs (approximate area - 7,152 m^2) exists near urban built-up. The producer's and user's accuracy for white roofs were both low - 72.32% and 70.07% respectively. The lower producer's accuracy is due to spectral variations among white roofs as the composition of the material used in residential white roofs is different to that of industrial roofs. Therefore, the classifier failed to detect some pixels of residential white roofs accurately (high omission errors). On the other hand, low user's accuracy (high commission errors) were reported for white roofs which is due to spectral mixing caused by adjacent features such as gray roofs (20%), vegetation (7.8%) and trees (1%). We used a combination of spatial and spectral attributes in an object oriented domain to improve this classification (discussed in this paper under the section – Object oriented classification).

Dark and Grey Roof

Dark roof tops are found in a dispersed pattern in the southern parts of the study site and have a wide range of sizes (small residential and large industrial). User's and producer's accuracies (88.44%, 87.81%) for dark roofs were high since they were spectrally separable from other urban features. The classification of the gray roofs produced acceptable user's and producer's accuracy. Similar to dark roofs, gray roofs were also spectrally distinguishable from other urban features. The user's accuracy for gray roofs was 89.01%. The producer's accuracy was 85.63% which may be further improved by using additional ground truth samples.

Shadow

Since the image was exposed in the afternoon shadows were found evenly distributed throughout. However, classifying shadows were extremely challenging since shadows varies spectrally based on the feature that is casting it. For example, shadows cast by trees, buildings, bridges have different textures and shapes. This class registered lowest user's accuracy of 59.53% for any feature due to a high number of commission errors. From the total number of pixels classified as shadow, 5.6% was misclassified as water, 30.7% as dark roof and 3.9% as gray roof. One major reason is that spectral characteristics of shadows can be either similar to other surface materials such as water (Sawaya et al., 2003) and other land cover types e.g. roof/road, built-up (Zhan et al., 2002; Goetz et al., 2003. Furthermore, the problem of shadow is particularly significant in high spatial resolution imagery of urban environments, where elevation varies dramatically across short distances (Dare, 2005; Yuan, 2008). With the dominance of elevated objects such as buildings, bridges, towers and trees in the landscape, the proportion of the imagery that is affected by shadowing could be significant (Yuan & Bauer, 2006). However the producer's accuracy for shadows was on the higher side (85.920%) since all pixels assigned to shadows were detected accurately. However, pixels assigned to class shadow were misclassified as dark roofs and gray roofs contributing to high errors of commission.

RESULTS FROM OBJECT ORIENTED CLASSIFICATION

White Roof

We classified a total of 5,027/5,631 pixels as white roofs and 604 pixels were unclassified producing an overall accuracy of 89.27%. The study area is dominated by white roofs which were found in different shapes and sizes. Most of the smaller roofs were found to the south west and east of the image with some small roofs (residential areas) found to the north east of the classified image. Scattered large roofs (commercial) were found to the Northern and North eastern parts of the image. We calculated 'User's', 'Hellden' and 'Short' accuracies which were 1, .94 and .89 respectively. The mean accuracy (MA) index developed by Hellden (1980) "denotes the probability that a randomly chosen point of a specific class on the map has a correspondence of the same class in the same position in the field and that a randomly chosen point in the field of the same class has a correspondence of the same class in the same position on the map. A similar index is the mapping accuracy MA index given by Short (1982).

Vegetation

The overall accuracy for vegetation was 97.73% which was higher than the accuracy achieved by the supervised classification. Tree cover and independent trees were accurately detected by using the 'Ratio to Scene' and 'Ratio' spectral operators. Apart from the large park there are 2-3 significant clusters of trees and many scattered trees that may be found in conjunction to residential houses. Out of a total of 8,990 pixels only 8,786 pixels were classified as vegetation. 204 were unclassified. The 'Hellden', 'Short' and 'user's' accuracies were .98, .97 and 1 respectively which indicated a high accuracy.

CONCLUSION

We have demonstrated a method using both spectral and spatial attributes for extracting land use, vegetation, water bodies, and a range of different roof types. An Ikonos orthorectified image was acquired over sections of Brooklyn and Queens Boroughs in New York City. The image was classified using per-pixel supervised MLC algorithm. The classification accuracy was good but for 2 specific classes – 'white roof' and 'vegetation', it was marginally lower than the remaining classes. The classes 'white roof' and 'vegetation' has the lowest accuracy for supervised classification 70.07 % and 79.82 % respectively. Pixels of white roof tops were misclassified as gray roof tops by a larger percent when compared to the other classes due to the spectral similarity of these two classes. Therefore, we improved the classification of both of these classes using an object oriented classification approach. In a different ongoing research (Bhaskaran et al., Unpublished) detailed analysis was carried out on a range of classes for 6 multispectral Ikonos images to estimate the optimal segmentation scale, shape and compactness parameters. Optimal segments for extracting different urban features were derived by assessment that used an empirical (visualization based) approach. User's, producer's and overall accuracies were assessed for each segment against ground truth data. Optimal segments to extract urban features were estimated and a multi-resolution segmentation was carried out to create image objects from the Ikonos data. Segmentation of image into meaningful objects is fundamental to the accurate classification of urban scenes. Different spatial attributes and membership functions were used in addition to the spectral attributes for mapping urban classes. Accuracy assessment was carried out using samples collected from the field survey and other reliable data sources.

Object oriented approach increased the overall accuracy including the accuracies for the two classes significantly. GIS layers may be created by the above methodology that may be analyzed further for modeling different applications covering a range of urban and environmental issues. For example emissivity index may be developed by using respective locations of all white roofs versus dark roofs in New York City. This information may then be cross analyzed with census databases for estimating number of people and their demographic characteristics at different scales who may be living in houses with white or light colored roofs. The cost-effectiveness of this methodology is a significant feature of this methodology that can be used in developing plans and policies for urban agencies which may require high spatial and temporal information in near real time.

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