

Impervious Surface Mapping Using High-Resolution, Multi-Spectral, Digital Imagery

**A Comparison of Object-Based and
Pixel-Based Classification Methods**

July 2008

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Publication no. 32-08-045

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ACKNOWLEDGMENTS

This report was prepared for the Metropolitan Council by Steve Kloiber (651-602-1056) of the Metropolitan Council's Environmental Services (MCES) Division. Questions about the content of this report can be referred directly to him.

The digital imagery used in this analysis were collected by Markhurd, Inc. The collection of this imagery was funded by the Metropolitan Council, the Metropolitan Mosquito Control District, and the U.S. Fish and Wildlife Service.

Thanks go to Dr. Marvin Bauer for sharing his insight on this project and for providing access to the computing facilities of the Remote Sensing Laboratory of the University of Minnesota. Thanks also go to Dr. Fei Yuan for her technical assistance with eCognition. Their participation does not constitute an endorsement of the findings or conclusions of this report.

EXECUTIVE SUMMARY

Many management and policy decisions of local, county, and regional agencies require timely, accurate land information. The decreasing costs and increasing availability of digital imagery can help lead to more effective land monitoring programs. One important new application of this technology is the use of digital imagery to map changes in urban development and imperviousness. In this application, we evaluate the potential to use automated image processing techniques, including a new object-based classifier, to map the extent of urban land and imperviousness using high-resolution (0.6 meter), multi-spectral digital aerial photography acquired for the Twin Cities Metropolitan Area in late-Spring 2004. The spectral bands from a color-infrared image and a standard color image were combined to create a 4-band multi-spectral image that was used for a comparison of two automated classification procedures. Training areas were developed from the image objects delineated using the object-based classifier so that the same training areas could be applied in both methods. The automated classification procedures were applied to the imagery to stratify the data into generalized land cover classes, which were then reclassified into impervious/pervious cover data sets. The coefficient of determination (r^2) for the automated and manually delineated imperviousness were essentially equal for the two methods ($r^2 \sim 0.9$) and the slopes between the predicted and observed values for the two methods were also comparable. The pixel-based classification showed some considerable speckling of impervious areas throughout the study area. Whereas, the object-based classification map showed less noise, but processing time was longer for this method, but not long enough to make a significant cost difference.

INTRODUCTION

Among the Metropolitan Council's key functions is the coordination of the orderly and economic development of the seven-county Twin Cities Metropolitan Area (TCMA) as well as providing technical assistance to communities as they plan for anticipated growth. As part of this function, the Council has had a long history of providing land use and land cover information for the region.

Many management and policy decisions of local, county, and regional agencies require timely, accurate data on urban land growth. For example, urban land information is critical for planning for adequate capacity of urban infrastructure such as roads, water, and sewers. Other policy decisions relating to public services also rely on land information, such as siting new schools, retail development, public parks, and landfills. In addition, urban growth information is needed to identify natural resource areas in need of protection. One important aspect of urban land information is the extent of impervious surfaces such as roads, parking lots, and rooftops which lead to decreased infiltration of rainfall and increased stormwater runoff.

To address land use information needs, many cities, counties, and other governmental units routinely acquire high-resolution digital imagery. However, processing this information has historically been labor-intensive and costly. A number of recent efforts have been directed at reducing the effort and cost of classifying digital imagery by using automated and semi-automated classification methods for monitoring and mapping urban land cover and imperviousness.

Research using Landsat TM data shows there is a strong relationship ($r^2 \sim 0.9$) between the Landsat spectral-radiometric response and percent impervious surface area (Bauer et al., 2004). A similar study conducted using high-resolution IKONOS imagery showed a very strong relationship ($r^2 = 0.98$) between the NDVI and percent imperviousness (Sawaya et al. 2003). This classification, as with most other efforts to date, used pixel-based classification methods. An alternative object-based classification system has been developed, which purports to offer significant advantages over the pixel-based classifiers (Benz et al. 2003).

For the most part, pixel-based classifiers classify each pixel independently and without regard to its neighboring pixels. In doing so, these classifiers ignore spatial autocorrelation, which is the tendency of an observation at one location to be related to other nearby observations. By contrast, object-based classifiers group similar pixels into image objects. Doing this not only addresses the issue of spatial autocorrelation, but it also allows for numerous object-based metrics to be calculated for the image

objects such as the mean and standard deviation of the brightness, area, length, as well as various other shape, texture, and topological metrics. These objects-based metrics can be included with the spectral-radiometric information to potentially enhance the accuracy of the classification.

In this application, we evaluate the potential to use image processing techniques, including an object-based classifier (eCognition) and a pixel-based classifier (ERDAS Imagine) to automate the process of classifying the image into a simple land cover map to facilitate the assessment urban land and imperviousness.

METHODS

Sample imagery was acquired by Markhurd for a portion of the eastern Twin Cities metropolitan area using a digital mapping camera (DMC) in late Spring 2004. The DMC collects high-resolution imagery with a panchromatic band and four bands covering the blue, green, red, and infrared portion of the spectrum. The imagery was delivered from the contractor as high-resolution (0.6 meter), color and color-infrared digital photographs. The spectral bands from these images were recombined to create a 4-band, multi-spectral image that was used for classification. The sample image used for this study was 8.55 km wide (east-west) by 4.80 km tall (north-south) and was centered primarily on White Bear Township located in northeastern Ramsey County (Figure 1).

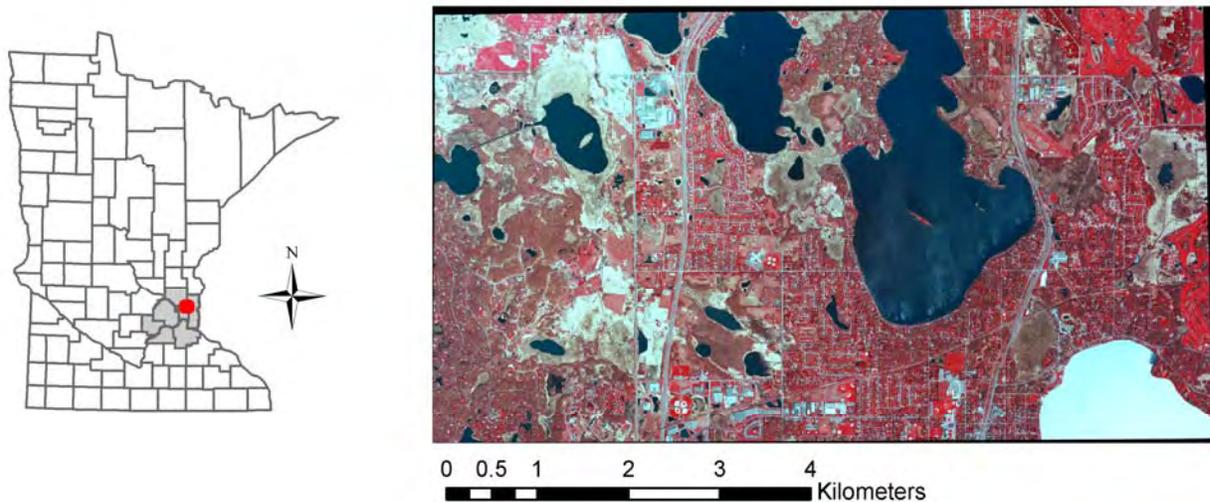


Figure 1: The digital image used for this study was centered on White Bear Township, Minnesota.

Two software packages were used to classify the imagery. eCognition is an object-based classifier and ERDAS Imagine is a pixel-based classifier. An initial comparison was made just using the brightness levels of the four spectral bands. The object-based method used a nearest-neighbor classification and the pixel-based method used a maximum-likelihood classification. The nearest-neighbor classification creates land cover groups based on the Euclidean distance the average brightness values of a training dataset, whereas the maximum-likelihood method considers the statistical variance within training dataset. Both software packages support other classification techniques as well, but fully testing all of these is beyond the scope of this study. eCognition also supports the use of many object-based metrics including measures of texture, length, and shape as well as measures of spatial relationships to other objects (super-objects, sub-objects, and neighboring objects). These object-based metrics are supposed to provide one of the key advantages over pixel-based classifiers. Therefore, a second classification was performed using several of these metrics selected using the tools provided in eCognition to determine if the use of the metrics would improve the classification (Table 1). A second classification was also performed with ERDAS Imagine using a second set of manually delineated training data and following the guided clustering technique described by Bauer et al. (1994). This technique uses a combination of supervised and unsupervised classification methods.

A classification scheme was developed to represent the main land cover classes of interest: pervious areas (primarily vegetated), impervious areas, and water. In addition, to address the observed spectral detail of the image a class for shadows was added. To ensure good spectral representation of the pervious class, this class was subdivided into four spectral subclasses: woody vegetation (trees and shrubs), maintained/planted herbaceous vegetation, unmaintained/natural herbaceous vegetation, and dry vegetation. Impervious areas were divided into three spectral subclasses: light-colored imperviousness (mainly bright rooftops), medium-colored imperviousness, and dark-colored imperviousness. After the initial classification, the spectral subclasses were re-coded into the four main classes. For the purposes of assessment, water and shadows were treated as pervious. Correctly distinguishing between shadows occurring on an impervious surface versus a pervious surface was considered beyond the scope of this effort, but the error associated assumption is believed to be fairly small. Visual inspection of the classified image shows that most of the observed shadows were tree shadows occurring in pervious areas, but this may not be the case for other imagery.

For the object-oriented analysis, the image pixels are grouped into “objects” depending upon several image characteristics, including size, shape, compactness and smoothness of an area in the image. This process is called image segmentation and, in theory, it should improve the speed and quality of the

classification. The image was segmented into image objects using eCognition with a scale factor of 100, shape factor of 0.3, compactness of 0.5, and smoothness of 0.5. Classification training areas were selected from these image objects for each of the classes and sub-classes. Approximately ten samples were selected for each class. To make the comparison between the software packages, these same training areas were also used in the ERDAS classification. A second ERDAS classification was performed using the area-of-interest (AOI) tool in ERDAS to manually delineate training areas. ArcGIS was used to manually delineate the percent imperviousness for twenty-four small test areas (30 meters by 30 meters) randomly distributed across the study area. Manually delineated imperviousness was then compared to imperviousness derived from the automated classification procedures.

Table 1
Classification Methods and Variables

Software	Classification Method	Variables
1 ERDAS Imagine	Maximum Likelihood	Brightness Blue, Green, Red, and Infrared
2 ERDAS Imagine	ISODATA and Maximum Likelihood	Brightness Blue, Green, Red, and Infrared
3 eCognition	Nearest Neighbor	Brightness Blue, Green, Red, and Infrared
4 eCognition	Nearest Neighbor	Mean Brightness Blue, Red, and Infrared Standard Deviation Blue, Green, and Red Ratio to Total Brightness Infrared Mean Difference to Neighbors Blue

RESULTS

Classification with Brightness Only

The general trend between manually delineated impervious cover and automatically delineated impervious cover was good for both the pixel-based and object-based classifications. The coefficient of determination (r^2) was 0.89 for ERDAS Imagine and 0.90 for eCognition (Figure 2). The standard error for the estimate was 11% and 12% for the ERDAS Imagine and eCognition classifications using brightness data; however, some individual test areas exhibited significant differences.

Pervious areas classification was better with eCognition than with ERDAS Imagine. Of the eight pervious test sites, eCognition correctly classified seven of them as 0% impervious. The only error of commission for eCognition occurred in an entirely pervious area that was incorrectly classified as 17% impervious (Figure 3). At the scale of the test samples, eCognition's classification errors can be large because it is classifying entire objects rather than pixels. In this case, an object in the test area was incorrectly identified as impervious rather than as a shadow. Whereas ERDAS Imagine estimated the imperviousness for this test area as 3%, which is much closer to the expected value.

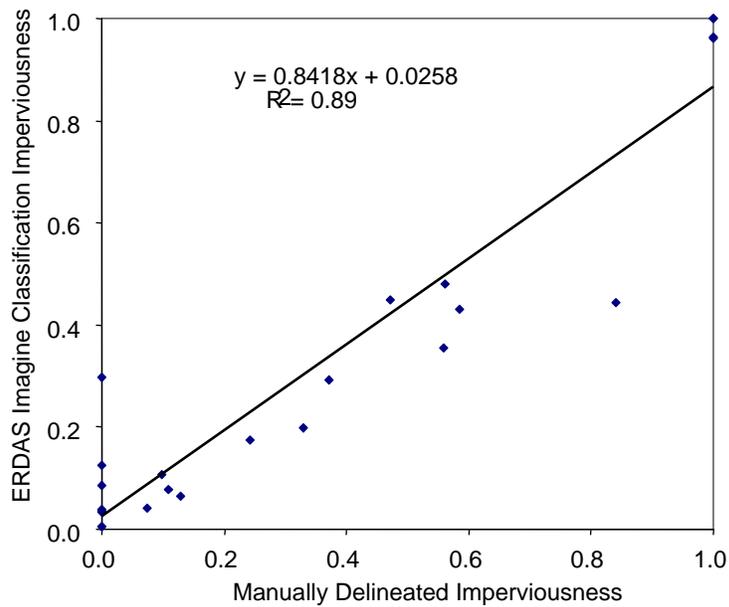
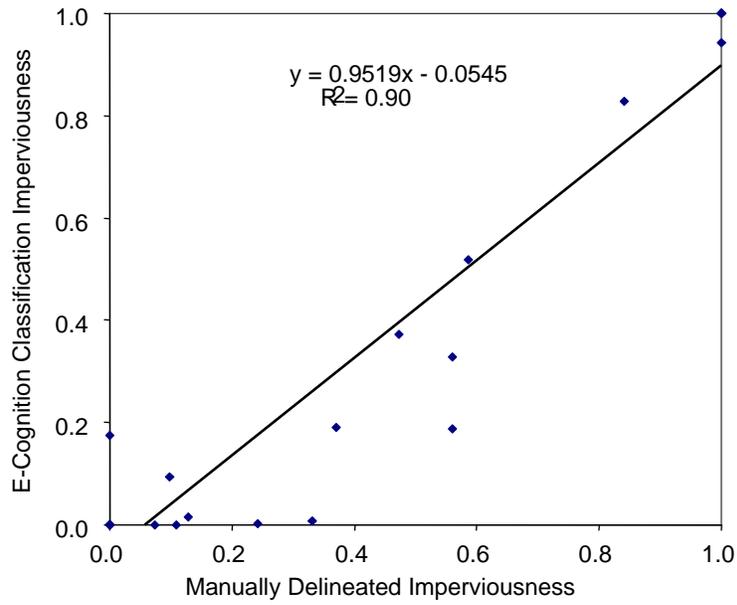


Figure 2: Comparison of manual and automated delineation of imperviousness for E-Cognition and ERDAS Imagine using 4-band brightness data

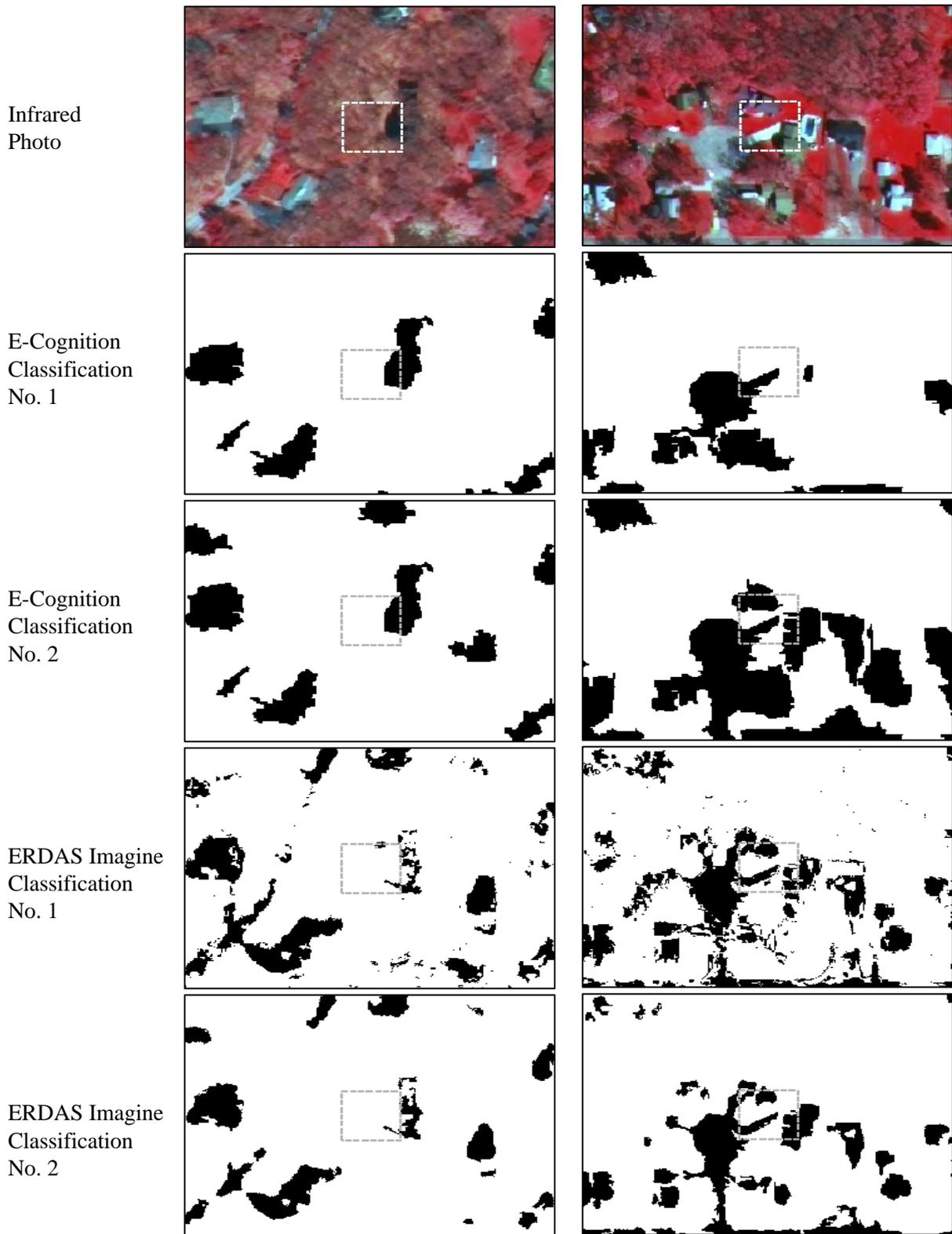


Figure 3: Comparison of impervious surface classification for a test area with 0% imperviousness and a test area with 56% imperviousness.

At intermediate values of imperviousness ($100\% > \text{imperviousness} > 0\%$), ERDAS Imagine appears to have classified the test areas slightly better than eCognition did. However, both classifiers have some problems correctly classifying the mixed test sites. Nearly all of the errors for intermediate values of imperviousness were errors of omission, where impervious areas were incorrectly classified as pervious. The median error for ERDAS Imagine was 7%, whereas the median error for eCognition was 11%. In addition, 75% of the errors for ERDAS Imagine were less than 14%, whereas 75% of the errors for eCognition were within 23%. One of the larger errors was for a test site with a manually estimated imperviousness of 56% (Figure 3). The estimate from the ERDAS Imagine classification was 36% and the estimate from eCognition was 19%.

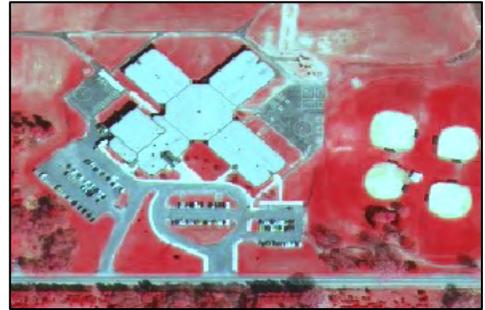
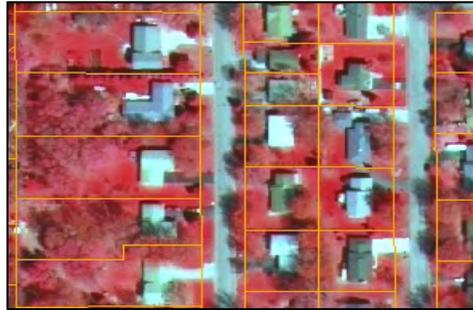
Both classifiers performed well at high levels of imperviousness. Of the four test areas with 100% impervious cover, ERDAS Imagine estimates of imperviousness were within 4% and eCognition estimates were within 6%.

A visual inspection of the classification results shows that both ERDAS Imagine and eCognition delineate large impervious features, such as schools and parking lots, fairly accurately (Figure 4). Smaller impervious features, such as houses, seem to be captured better by ERDAS Imagine. This is because eCognition occasionally erroneously classifies a house-object, thus the object will be missing entirely from the pervious class (Figure 4). ERDAS Imagine typically classifies at least part of the house correctly as an impervious surface, but the building shape is may not be very accurately represented for small buildings. The ERDAS Imagine classification showed considerable speckling of impervious areas throughout the pervious areas of the image, although this did not seem to have much of an effect on the accuracy. Both classifiers seemed to frequently misclassify small areas of impervious surfaces such as residential driveways as pervious areas (Figure 4).

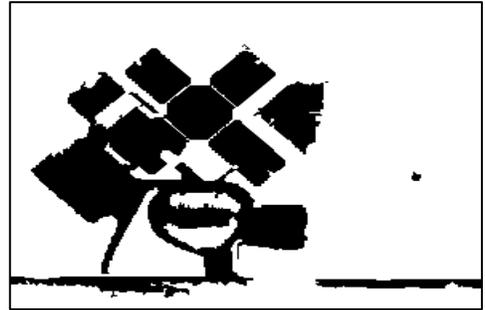
eCognition Classification with Object-Based Metrics

Several object-based metrics were considered for use in classifying the image with eCognition. These included the mean brightness, the standard deviation of brightness, the ratio to total brightness, and the mean difference to neighboring objects. Of these, the eight most significant factors were included based on the output from eCognition's feature space optimizer (Table 1). These factors were applied to a nearest neighbor classification for all classes. This approach resulted in a less accurate classification. The r^2 value was reduced to 0.61 and larger errors were introduced at all imperviousness levels (Figure 5).

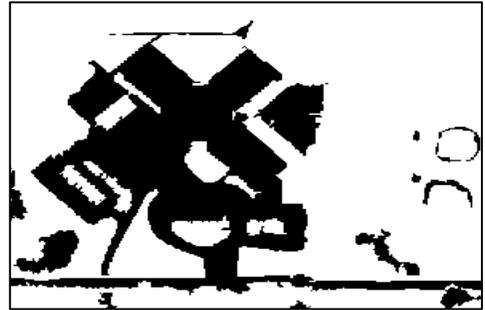
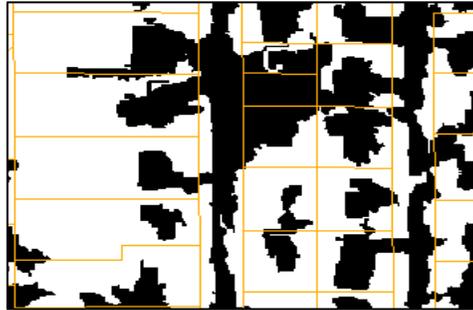
Infrared
Photo



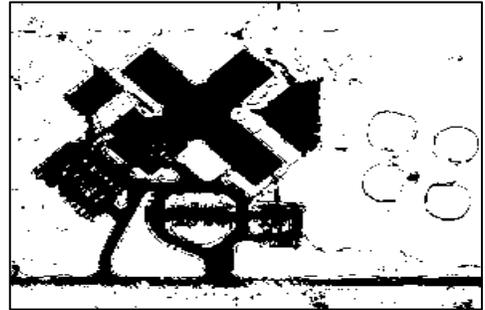
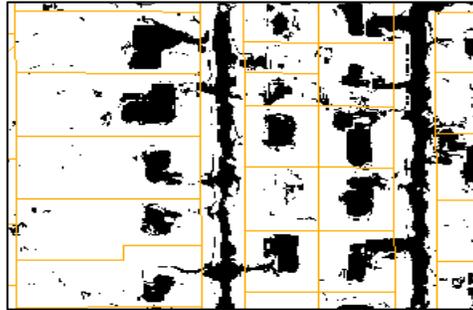
E-Cognition
Classification
No. 1



E-Cognition
Classification
No. 2



ERDAS Imagine
Classification
No. 1



ERDAS Imagine
Classification
No. 2

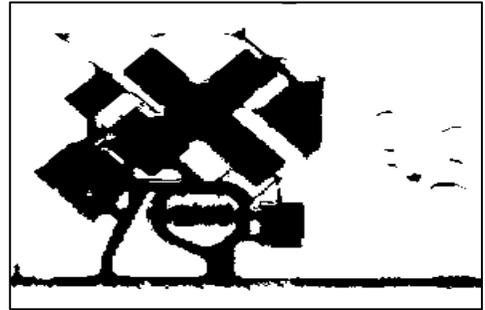
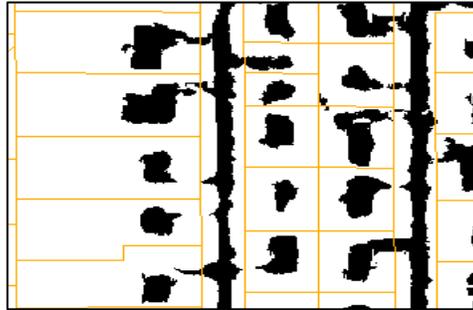


Figure 4: Comparison of impervious surface classification for an area with several smaller residential buildings and an area with a large public school building.

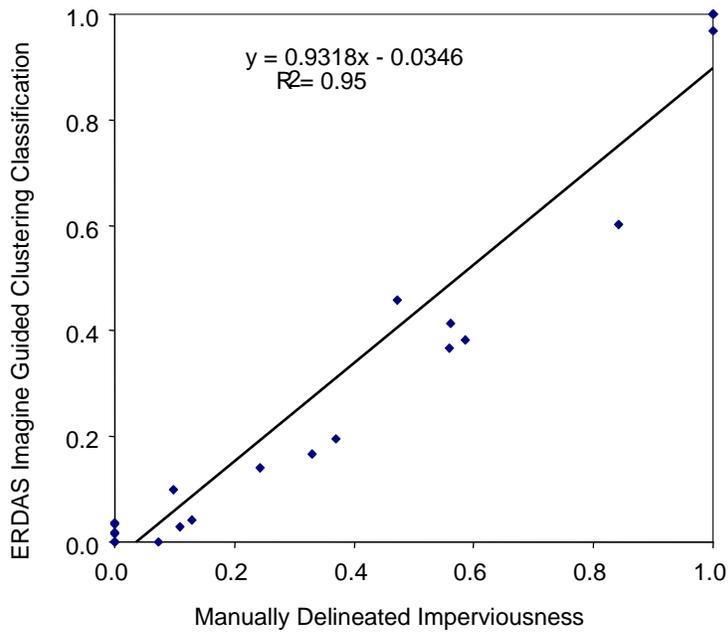
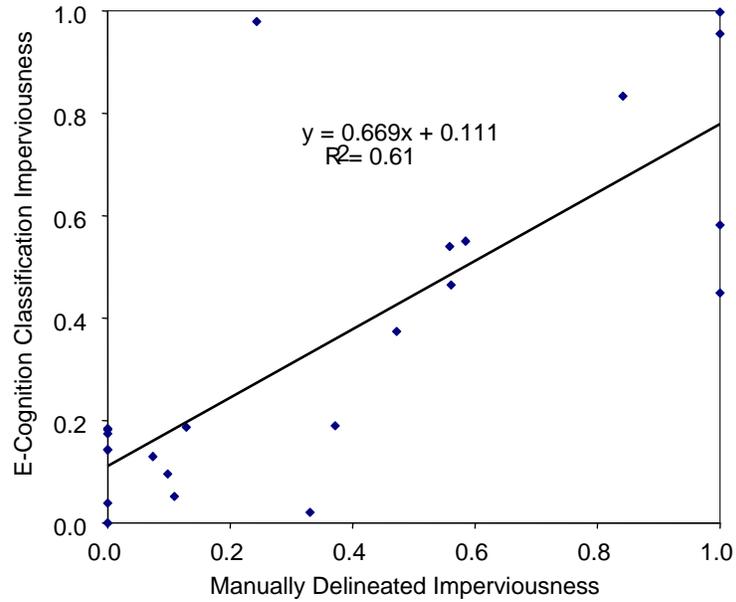


Figure 5: Comparison of manual and automated delineation of imperviousness for E-Cognition using object-based variables and ERDAS Imagine guided-clustering.

ERDAS Imagine Guided Clustering Classification

The manually delineated training areas were not confined to the segmentation scale defined in eCognition. These training areas were generally larger than those defined using the segmented image. In addition, some additional spectral subclasses were identified through the unsupervised classification and were added to the training data set for this classification. This approach also incorporated a post-classification processing step to eliminate some of the salt-and-pepper effects that result from the pixel-based classification. Using the guided clustering method improved the classification. A comparison between the manually delineated impervious test areas and this classification resulted in an improved r^2 value of 0.95 and the standard error was reduced to 8.3% (Figure 5).

DISCUSSION

Classification Accuracy

Both ERDAS and eCognition provided reasonable, although somewhat different, results using just the 4-band brightness data. The r^2 and standard error values are comparable to previous studies using Landsat (Bauer et al. 2004) as well as higher resolution IKONOS data (Sawaya et al. 2003). As noted earlier, there was some class confusion between bright pavement areas and dry, light-colored vegetation. Incorporating additional object-based metrics did not improve the separability of the land cover classes. While this study did not exhaustively test all possible combinations of the object-based metrics, the fact that the classifications based solely on brightness were fairly good suggests that spectral-radiometric information is still the major factor for effectively separating land cover classes. Using the guided clustering method described by Bauer et al. (1994), which incorporates both supervised and unsupervised classification techniques, did improve the classification somewhat.

Another potentially effective strategy for improving the classification would be to include imagery from later in the growing season. The additional vegetation development should provide better spectral separation between the pervious and impervious areas; however, the additional leaf cover in the late summer would also obscure some impervious surfaces.

Classification Problems

One issue in dealing with high-resolution imagery is the increased spectral-radiometric variability. The most obvious effect of this is the increased presence of shadows in the image. Not only do shadows

obscure features of interest, but the shadow class is also somewhat confused with the open water class. Another more subtle effect is the variation in brightness for different sides of objects such as residential rooftops and tree crowns depending upon the angle of illumination. Using coarser resolution imagery, these differences tend to be minimized due to the spatial averaging that occurs. With high-resolution imagery, some of these effects can be handled by ensuring that these different spectral classes are included in the training samples. This is a relatively simple task; however, the spectral class for shadows still needs to be divided into either the pervious or impervious land cover class. For this study, all the shadows were reclassified to the pervious land cover class.

Another obvious problem with the classification of the test image used for this study is the occurrence of specular reflectance. While open water was generally well separated from other classes for water with low brightness values, very smooth surfaces, such as calm lakes, exhibited specular reflectance where almost all of the incoming radiation is reflected at an angle equal to the angle of incidence. This results in very bright areas that are spectrally similar to bright impervious surfaces and thus incorrectly classified.

Use of the Classification Results

The results of this effort do suggest that the data are sufficiently accurate for estimating the percent impervious cover on a parcel basis, but none of the classification methods used here led to a cartographically accurate representation of buildings and roads. This likely has as much to do with the resolution of the data as with the classification process. Even manually delineating edges for small buildings and roads is difficult with 0.6-meter resolution data because these edges are not always clearly discernable. Recently, many local units of government have moved to even higher resolution imagery. Most of the TCMA counties, for example, have acquired 6-inch resolution color imagery. This higher resolution imagery might be combined with the 4-band multi-spectral data to better delineate building and road edges.

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