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N. D. Riggan Jr.  
*University of Arkansas at Monticello*

Robert C. Weih Jr.  
*University of Arkansas at Monticello, [weih@uamont.edu](mailto:weih@uamont.edu)*

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## A Comparison of Pixel-based versus Object-based Land Use/Land Cover Classification Methodologies

N.D. Riggan, Jr.<sup>1</sup> and R.C. Weih, Jr.<sup>1,2</sup>

<sup>1</sup>Arkansas Forest Resources Center, University of Arkansas at Monticello, School of Forest Resources, Spatial Analysis Laboratory, 110 University Court, Monticello, Arkansas 71656

<sup>2</sup>Correspondence: weih@uamont.edu

### Abstract

Land Use/Land Cover (LULC) classification data have proven to be valuable assets for various governmental agencies, park managers, and natural resource managers. Traditional pixel-based classification methods have difficulty with high-resolution imagery, resulting in a “salt and pepper” appearance. Newer object-based methods may prove to be more accurate. This study compared an object-based classification procedure utilizing Feature Analyst<sup>®</sup> software with a traditional pixel-based methodology (supervised classification) when applied to medium-spatial resolution satellite imagery merged with high-spatial resolution aerial imagery. This study utilized two multi-spectral SPOT-5 satellite images, leaf-on and leaf-off, merged with a color infrared aerial image. Because of correlation between some of the bands of the merged image, Principal Component Analysis (PCA) was used to reduce redundancy in the data. Field data was collected in the study area to serve as a reference for the accuracy assessment. A training set was produced by selecting and identifying specific LULC class-types using 1-foot high-spatial resolution aerial imagery. This training set was used by both of the classification methods (supervised and object-based) to identify the various cover types within the study area. An accuracy assessment was performed on each image utilizing error matrices, the Kappa coefficient, and a two-tailed Z-test. Results indicate that the overall accuracy of the object-based classification was 82.0%, while the pixel-based classification was 66.9%. A Kappa analysis and a two-tailed Z test were calculated. These values indicated a significant difference in the overall accuracies of the classifications.

### Introduction

Remotely sensed imagery, in the form of satellite and aerial photography, has become an indispensable

tool in scientific research, with applications in numerous fields of study. In a study by McRoberts and Tomppo (2007) of national forest inventories in Europe, they reported that remotely sensed data had not only increased the speed, cost efficiency, precision, and timeliness of forest inventories, but it had also contributed to the development of maps of forest attributes with spatial resolutions and accuracies that had not been previously possible. Methods have been developed for the mapping of large-scale forest cover change (Fraser et al. 2005) and estimating the extent of burned areas (Gitas et al. 2004). Likewise, new analytical techniques have been developed for the mapping of urbanization and urban sprawl (Xian and Crane 2005). In the field of geology, maps have been constructed to illustrate glaciated landscapes, eolian and fluvial landscapes, mass wasting, and soil types (Paine and Kiser 2003). Remote sensing also has been applied to bathymetric mapping in oceanography (Mishra et al. 2004) and to the locating of archaeological sites in the rainforests of Central America (Sever and Irwin 2003). Remote sensing can be used to monitor the condition of park resources, to assess the effectiveness of management practices and restoration efforts, and to indicate areas most likely to be threatened by encroachment. LULC monitoring can provide a baseline reference to help delineate the current limits of land cover types, can become standards with which to compare future land cover changes, can provide a basis for judging what constitutes ecological threats or impairments, and can help identify the need for corrective management actions (DeBacker et al. 2005).

In the past, LULC maps have primarily been created using a pixel-based analysis of remotely sensed imagery. This procedure analyzes the spectral properties of every pixel or picture element within the area of interest. Originally designed for use with coarse resolution imagery, numerous studies have pointed out problems with the use of pixel-based procedures when applied to high resolution imagery (Chen et al. 2005, Whiteside and Ahmad 2005, Yang

and Lo 2002). The pixel-based methodologies cannot set a minimum mapping unit, resulting in an over-classification of individual pixels. This lack of aggregation of pixels results in a “salt and pepper” appearance and data sets that can be difficult to process and analyze.

For decades GIS specialists have theorized about the possibility of developing a fully-automated classification procedure that would be an improvement over pixel-based procedures. With the advent of satellites providing images with higher and higher resolutions, the need for an improved procedure has become a necessity. Within recent years, computer software packages such as eCognition<sup>®</sup> and Feature Analyst<sup>®</sup> have been developed utilizing object-based classification procedures. These packages analyze both the spectral and spatial/contextual properties of pixels and use a segmentation process and iterative learning algorithm to achieve a semi-automatic classification procedure, which promises to be more effective and more accurate than traditional pixel-based methods.

Feature Analyst, which has been designed for use with software such as ArcGIS, and ERDAS Imagine<sup>®</sup>, may prove to be an outstanding tool in LULC mapping (Visual Learning Systems, 2004). Developed by Visual Learning Systems, Inc. in Missoula, Montana, with funding from NASA and the Department of Defense, Feature Analyst uses a machine-learning algorithm to achieve automated feature extraction (Visual Learning Systems, 2004). Once the software is given user-specified examples, it utilizes “software agent technology” which learns to identify features and identifies its classification (Visual Learning Systems, 2004).

In a comparison with hand digitizing methods used at the National Imagery and Mapping Agency (NIMA), Feature Analyst reduced production time and achieved more accurate and consistent results, while scoring high marks with technicians as easy to learn and use (O’Brien, 2003). In a study for the USDA Forest Service Northern Regional Office, three methods of change-detection analysis were performed on Landsat Thematic Mapper (TM) imagery taken before and after the western wildfires that occurred in the summer of 2000 (Redmond and Winne 2001). The three methods employed were 1) temporal image differencing, 2) principal component analysis, and 3) the hierarchical learning technology of the Feature Analyst<sup>®</sup>. The Feature Analyst distinguished between burn and non-burn 100% of the time, while the other two methods were only correct 89% of the time (Redmond and

Winne 2001). In all areas of the test, Feature Analyst performed better than the other two methods and was the easiest technique to use (Redmond and Winne 2001).

While relatively few studies using Feature Analyst have been published, a parallel software package that has been used in numerous research studies is eCognition<sup>®</sup>. Developed by Definiens Imaging GmbH of Germany, eCognition is object-based image processing software that was released in 2000 (Flanders et al. 2003).

In a comparison of “traditional” pixel-based procedures with the newer object-based methodology, Whiteside and Ahmad (2005) found that the eCognition object-oriented classification provided better overall accuracy. Their study involved creating a land cover map of a region of Litchfield National Park, in the northwest of the Northern Territory of Australia. They found that although pixel-based classification was successful in classifying land cover of a homogeneous nature, such as a closed forest, object-oriented classification did a better job of accurately identifying areas that were spectrally heterogeneous (Whiteside and Ahmad 2005).

While Whiteside and Ahmad’s study dealt with a natural landscape, another study conducted in Australia focused on the object-based classification of an urban landscape. Syed et al. (2005) compared pixel-based methods with object-based methods in the classification of land cover features in the town of Mathoura in southern New South Wales. The study area consisted of office buildings, storage sheds, silos, vegetated areas, and open space (Syed et al. 2005). Their results indicated that the object-based method was more flexible and produced more accurate land cover maps than were attainable using a pixel-based classification (Syed et al. 2005).

The purpose of this project is to compare these methodologies and determine if an object-based analysis of merged medium-resolution, multi-temporal satellite imagery and high-resolution digital aerial imagery will produce a LULC map that is more accurate than a supervised pixel-based analysis.

## Materials and Methods

The area of interest for the project is located in and around Hot Springs, in Garland County, Arkansas (Figure 1). The study area includes Hot Springs National Park, part of the city of Hot Springs, and areas north and east of the city. Hot Springs National Park is approximately 2,250 hectares, while the study

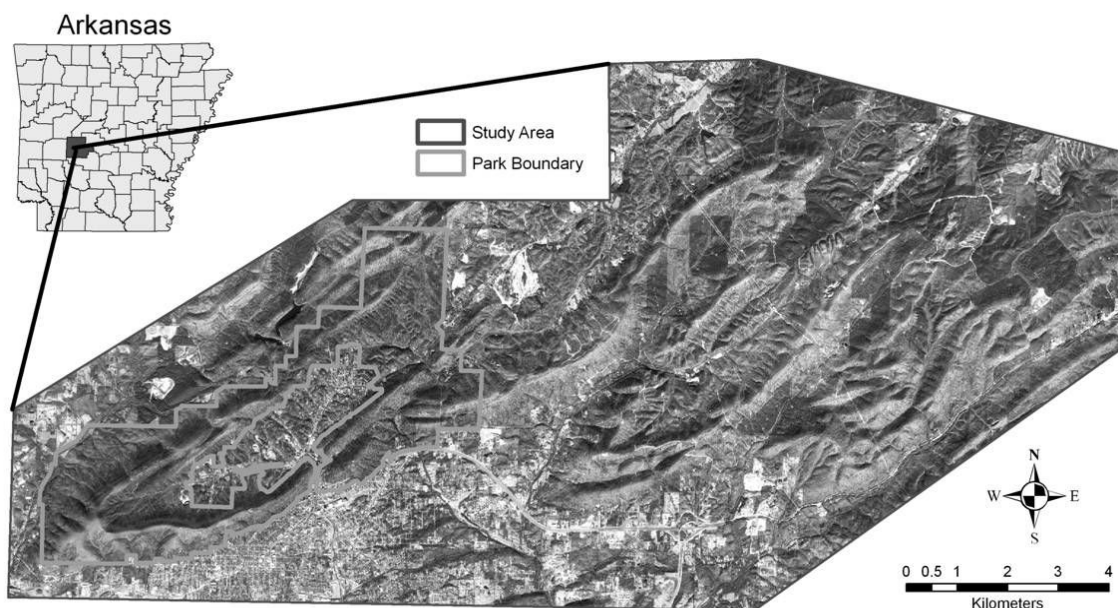
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Figure 1. Location of study area in Garland County, Arkansas, including Hot Springs National Park.

area is approximately 16,850 hectares. The National Park lies on the northern edge of the city, adjacent to streets and homes. The study area includes features such as the city reservoir, the city landfill, golf courses, county parks, and several rock quarries. The study area is thought to include the recharge watershed for the thermal springs (personal correspondence with Steve Rudd, Hot Springs National Park geologist, 2008). While having some urban areas, the study area is predominantly rural, consisting of fields and pastures, pine plantations, and deciduous and mixed forests. The pines are shortleaf (*Pinus echinata*) and loblolly (*Pinus taeda*). The deciduous trees are oaks (*Quercus* spp.) and hickories (*Carya* spp.). Hot Springs is at the foothills of the Ouachita Mountains, with elevations in the study area ranging from a minimum of 107 meters to 433 meters above sea level.

The SPOT-5 imagery used in this project was acquired from SPOT Image Corporation. Two SPOT-5 images were used representing two seasonal periods (winter and spring), each with different foliage characteristics (leaf-on and leaf-off). The SPOT-5 leaf-off image was taken on 3 February 2007 with an incident angle of 3.384°. The SPOT-5 leaf-on image was taken on 27 April 2007 with an incident angle of 10.2366°. Both images contain four bandwidths of spectral information: visible green (0.50-0.59  $\mu\text{m}$ ), visible red (0.61-0.68  $\mu\text{m}$ ), near-infrared (0.79-0.89  $\mu\text{m}$ ), and mid-infrared (1.58-1.75  $\mu\text{m}$ ). Both images

were at 10-meter resolutions, with the mid-infrared (MIR) band being resampled from 20-meters, and were processed as Level 1B imagery (not orthorectified). A true color (RGB) aerial image at 1-foot resolution and a 1-meter color infrared (CIR) digital orthophoto quadrangle (DOQ) (leaf-off) was acquired from the State of Arkansas.

Color infrared aerial imagery of the study area at 1-foot resolution was acquired from Kingwood Forestry Services. This imagery was captured 15 June 2007. The camera system used for the acquisition of these photos was the Applanix DSS™ Model-301 System. In a study by Weih and Rowton (2007), this camera system was shown to have a spatial accuracy of less than 2 pixels. The 1-foot CIR aerial imagery, along with the 1-foot RGB imagery flown by the State of Arkansas, was used for photo interpretation of urban areas to supplement the field data and for development of the training data set used in both classification procedures.

The SPOT-5 satellite imagery and the 1-meter CIR DOQ aerial imagery were imported into ERDAS Imagine and ground control points were located on each image and used to orthorectify the image. The two SPOT-5 images were resampled to 1-meter when rectified to match the DOQ pixel resolution. Then the 3 image data sets were merged into an 11-band image. The merging of these 3 image data sets was part of a larger study that would evaluate the relative

importance of each data set in conjunction with various combinations of these images. While the merging of SPOT-5 leaf-on and SPOT-5 leaf-off could improve the identification of some classes, it might potentially increase within-class variability to the point of having a detrimental effect on the classification of other classes.

Because some of the data in the bands of the merged image were correlated, we used a Principal Component Analysis (PCA) procedure in ERDAS Imagine 9.1 to create a PCA image. PCA is a mathematical procedure designed to reduce the size of data sets by transforming data that may be correlated or redundant. It transforms the data set based on the characteristics that contribute most to the variance of the data. The procedure places the greatest variance in the first principal component and as much of the remaining variance as possible is placed in each succeeding component. The first 4 bands of the PCA image accounted for 92.8% of the variance in the data and were used in the classification procedures.

Field data, or ground-truthing, was conducted in the study area in order to create a "test set" to be used in the accuracy assessment of the two classifications. This was done primarily in the rural and forested areas of the study site. A 2-person team, using Trimble GeoXH handheld GPS units, located the positions of randomly selected points within the area of interest. The following data was collected at each plot-point location: 1) digital photos in the four cardinal directions; 2) calculations of slope using a clinometer; 3) aspect (the direction of maximum slope) determined with a compass; 4) calculation of tree basal area (BA) with a 10x prism wedge; 5) identification of major and minor tree/plant species based on BA; 6) a general description of soil/ground cover conditions; and 7) a LULC classification developed for this study similar to an Anderson Level 2 classification system (Anderson et al. 1976). The LULC classification codes for this study were determined in conjunction with National Park Service ecologists and remote sensing specialists to produce a medium-level classification of the study area. Photo interpretation of random points in urban areas utilizing 1-foot aerial imagery was used to supplement the field data.

A training data set was created by digitizing polygons, which selected pixels representing each LULC type in the area of interest. It was important to sample pixels throughout the study area, as well as pixels representing variation in cover types, such as water bodies that were light and dark, deciduous and conifers in rural and urban settings, etc. This training

data set would later be used by both classification methods.

The object-based classification was accomplished using Feature Analyst. This software uses inductive learning algorithms to analyze the spatial context and spectral signatures of pixel clusters or neighborhoods. Some key concepts of Feature Analyst are: 1) it is an intelligent software agent that uses a training set provided by the technician to "learn" feature extraction concepts; 2) the better the spatial and spectral distribution of the training set, the better the recognition of class features throughout the area of interest; and 3) the technician can make adjustments for clutter (false positives) and/or missed features (false negatives) on-the-fly, leading to an iterative learning process by which these errors are identified and corrected (Visual Learning Systems 2004).

While pixel-based classifiers use only the spectral signature of a pixel, Feature Analyst also makes use of the spatial context around a pixel to aid in its classification (Visual Learning System 2004). Feature Analyst has numerous options for the selection of window shape and size. For this classification, a Manhattan (diamond) shape with a 13 pixel-width was selected (Figure 2). This provided a window with a total of 85 cells per band. This particular input representation was selected because it had proven effective in previous research (Weih and White 2008). Feature Analyst also allows the user to set a minimum mapping unit (MMU) before the classification is run so that only areas having this specified aggregated area, as well as certain spectral characteristics, will be classified as a particular cover type. With a resampling value of 4 and a minimum aggregate area of 22 pixels, a MMU of 352 pixels or approximately 0.04 hectares (0.1 acres) was established for all cover types. The MMU was determined by the Heartland Monitoring Program, a division of the National Park Service, as an acceptable LULC scale.

Utilizing the training set, each cover type was classified individually. The user can then select areas identified as a particular cover type (water, urban, conifer, etc.) as either correct or incorrect and then rerun the classification process. The user repeats this process until satisfied with the classification of that cover type. Once the user is confident about the classification of a cover type, Feature analyst can use these areas as "masks" during subsequent identification of other cover types. This can aid in reducing confusion by excluding these areas from being reclassified. After all the individual cover types were identified, the Combine Features tool was used to

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produce a wall-to-wall classification. The road, railroad, and stream features were not classified using the imagery, but were later developed from GIS layers.

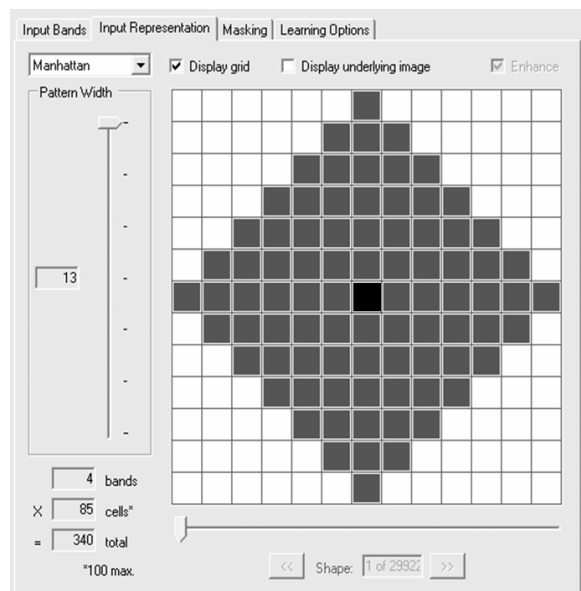


Figure 2. Input Representation (spatial pattern) of the object-based classifier used to classify a single pixel (black square).

Pixel-based methodologies include both unsupervised and supervised classifications. For this comparison a supervised classification was used. The supervised classification was created from the subset PCA image utilizing the training data set produced in ArcMap. Using ERDAS Imagine, signature files were created and used to perform the supervised classification of the Hot Springs study area. A Maximum Likelihood Parametric Rule was selected for the classification. The resulting classification exhibited the “salt and pepper” appearance commonly associated with pixel-based classifications. To reduce this effect and aggregate cover types into patches approximating the minimum mapping unit, the “Clump” and “Eliminate” tools were used. As the name implies, the “Clump” tool aggregates contiguous groups of pixels into a single thematic class. After the “Clump” tool is applied, the “Eliminate” tool was used to identify any patches smaller than the minimum mapping unit of 0.04 hectares (0.1 acres) and remove these smaller areas by replacing their pixel value with the value of nearby larger clumps.

An accuracy assessment was performed on each classification to determine which produced the most accurate identification of LULC. This was accomplished utilizing the error matrix method (Congalton and Green 1999, Enderle and Weih 2005).

The error matrix measures an overall accuracy for the classification, as well as a producer’s and user’s accuracy for each cover type. Producer’s accuracy provides a measure of how well the analyst did when classifying the reference data and its agreement with the classification map. If the data is arranged such that the reference/field data is in the columns and the classification/map data is in the rows, then for each row in the matrix, the proportion of correctly classified pixels to the total number of pixels in the row, provides a measure of the producer’s accuracy for the land cover category represented by that row. User’s accuracy provides a measure for the map user of the probability that the pixels on the classification map are the same as the reference data. This measure of accuracy can be calculated for each column by comparing the proportion of correctly classified pixels in the column with the total number of pixels in the column and expressed as a percentage. Overall Accuracy is equal to the probability that any randomly selected pixel or point is correctly classified by the map. This value is determined by summing the major diagonal (from left to right) of the error matrix, which represents the correctly identified pixels of each cover type and dividing it by the total number of pixels identified in the data set.

### Results and Discussion

The overall accuracy of the pixel-based classification was 66.9%, while the overall accuracy of the object-based classification was 82.0% (Table 1). This object-based classification accuracy is similar to the 87.8% overall accuracy that Weih and White (2008) achieved for the Buffalo River Sub-Basin. The Producer’s and User’s accuracies varied with LULC type. The Producer’s accuracy for the pixel-based classification varied from 29.7% to 94.7%, while the Producer’s accuracy for the object-based classification ranged from 50.0% to 91.2%. The User’s accuracy for the pixel-based classification varied from 22.2% to 100.0%, while the User’s accuracy for the object-based classification ranged from 50.0% to 100.0%.

Neither of the classification methods could distinguish the Mixed Forest class very well. The low User’s and Producer’s accuracies for this feature class were due to confusion with the Deciduous and Conifer Forest classes. This is not too surprising as the Mixed Forest class is a combination of the other two tree types. The intention was to determine if in fact the object-based method could reliably identify this feature type separately. It should be mentioned that the

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removal of the Mixed Forest class would have probably improved the accuracies of both the Deciduous and Conifer classes.

Table 1. Producer’s and user’s accuracy by LULC.

LULC	Object-based Classification		Pixel-based Classification	
	Producer’s Accuracy	User’s Accuracy	Producer’s Accuracy	User’s Accuracy
Urban	85.9%	85.9%	29.7%	70.4%
Roads	86.8%	94.3%	86.8%	94.3%
Railroads	83.3%	100.0%	83.3%	100.0%
Grassland	91.2%	83.8%	94.1%	86.5%
Deciduous	78.4%	87.2%	66.2%	76.6%
Conifer	90.7%	85.7%	73.3%	79.7%
Clearcut	82.4%	50.0%	82.4%	22.2%
Mixed	66.7%	55.8%	44.4%	36.4%
Water	89.5%	100.0%	94.7%	100.0%
Barren	50.0%	64.3%	72.2%	41.9%
Overall Accuracy	82.0%		66.9%	

The low User’s and Producer’s accuracies for the Barren class, as well as the low User’s accuracy for the Clearcut class, for both object-based and pixel-based methods was probably due to two contributing factors. Due to the small area they represented in the overall study area, both Barren and Clearcut had a relatively small number of field data points to use for the accuracy assessment (18 and 17, respectively). Subsequently, any misclassification of these data points would have a substantial impact on the accuracies of these features. The second factor was classification confusion with features having similar spectral values. With the object-based method, the Barren class was misclassified as either Urban or Grassland, while Clearcut was confused with Deciduous and Barren. For the pixel-based method, the Barren class was most often misclassified as Urban,

while the Clearcut class was confused with Urban and Deciduous. This problem clearly points out that more field data points were needed for the Barren and Clearcut feature classes.

To determine if the values for the overall accuracies were statistically significant, Kappa coefficients were calculated for both methodologies and a pair-wise Z test was calculated (Congalton and Green 1999):

$$\hat{K} = \frac{p_o - p_c}{1 - p_c} \tag{1}$$

$$Z = \frac{|\hat{K}_1 - \hat{K}_2|}{\sqrt{\text{var}(\hat{K}_1) + \text{var}(\hat{K}_2)}} \tag{2}$$

Where  $p_o$  represents actual agreement,  $p_c$  represents “chance agreement”, and  $\hat{K}_1, \hat{K}_2$  represents the Kappa coefficients for the object-based classification, and pixel-based classifications, respectively. The Kappa coefficient is a measure of the agreement between observed and predicted values and whether that agreement is by chance. A Kappa value generally ranges from 0 to 1, with values closer to zero indicating higher chance agreement. The Kappa coefficients for the pixel-based and object-based classifications were 0.61 and 0.78 respectively. Using the Kappa values and their variances, a pair-wise Z test was calculated. The Z-score (5.259) and p-value (< 0.0001) indicates a statistically significant difference between the classification methods.

Table 2 illustrates the difference in the number of features and percentage of the total area for each

Table 2. Number of features and area by LULC.

LULC	Object-based Classification				Pixel-based Classification			
	Number of Features	Acres	Hectares	Percentage of Area	Number of Features	Acres	Hectares	Percentage of Area
Urban	5999	2850.7	1153.0	6.8%	12660	1146.6	461.6	2.7%
Road	35	1312.9	531.3	3.2%	35	1312.9	531.3	3.2%
Railroad	2	41.7	16.9	0.1%	2	41.7	16.9	0.1%
Grassland	3242	2323.8	940.3	5.6%	4340	2248.7	910.0	5.4%
Deciduous	5338	17750.5	7183.0	42.6%	15762	16536.0	6690.0	39.7%
Conifer	5344	9805.4	3967.6	23.5%	10215	7676.9	3105.8	18.4%
Clearcut	853	1810.9	732.9	4.4%	12328	6328.5	2559.5	15.2%
Mixed	5420	4825.6	1952.6	11.6%	11537	5213.7	2108.9	12.5%
Stream	322	85.5	34.5	0.2%	382	85.6	34.5	0.2%
Water	156	181.6	73.4	0.4%	767	231.4	93.5	0.6%
Barren	3211	667.2	269.8	1.6%	3529	831.8	335.9	2.0%
Total	29922	41655.8	16855.3	100.0%	71557	41653.8	16847.9	100.0%

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LULC resulting from the two classification methods. Because Feature Analyst allows the operator to set a minimum mapping unit during the classification, the object-based method produced a LULC with a total of 29,922 features. The supervised classification, however, originally produced a LULC with a total of 1,270,060 features. After utilizing the Clump and Eliminate filtering tools, the number of features was reduced to 71,557. While this represents 2.4x as many features as the object-based LULC, this was a considerable improvement over the original 1.27 million features.

Even after filtering with the Clump and Eliminate tools, the pixel-based classification suffered from an “over-classification” of several of the cover types. The clearcut cover type was clearly over-represented by the pixel-based classification, with 15.19% of the total area identified as this cover type compared to only 4.35% identified as clearcut by the object-based classification and this is reflected in the User’s accuracy. The deciduous cover type also illustrates differences between the two classification methods. While the difference in percent of total area for the two classifications is small (object = 42.62% vs. pixel = 39.71%), the object-based method only identified 5338 features as deciduous compared to the pixel-based method, which identified 15,762 features as deciduous. This represents 2.95x as many features.

This study indicates that an object-based methodology utilizing Feature Analyst software can produce an accurate LULC classification when applied to medium-spatial, multi-spectral satellite imagery merged with high-spatial resolution aerial imagery. When compared with the overall accuracy of a pixel-based (supervised) classification of the same imagery, the object-based method was significantly more accurate.

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