OBJECT-BASED CLASSIFICATION VS. PIXEL-BASED CLASSIFICATION: COMPARITIVE IMPORTANCE OF MULTI-RESOLUTION IMAGERY

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ABSTRACT:

Land Use/Land Cover (LULC) classifications have proven to be valuable assets for resource managers interested in landscape characteristics and the changes that occur over time. This study made a comparison of an object-based classification with supervised and unsupervised pixel-based classification. Two multi-temporal (leaf-on and leaf-off), medium-spatial resolution SPOT-5 satellite images and a high-spatial resolution color infrared digital orthophoto were used in the analysis. Combinations of these three images were merged to evaluate the relative importance of multi-temporal and multi-spatial imagery to classification accuracy. The object-based classification using all three-image datasets produced the highest overall accuracy (82.0%), while the object-based classification using the high-spatial resolution image merged with the SPOT-5 leaf-off image had the second highest overall accuracy (78.2%). While not significantly different from each other, these two object-based classifications were statistically significantly different from the other classifications. The presence of the high-spatial resolution imagery had a greater impact on improving overall accuracy than the multi-temporal dataset, especially with the object-based classifications.

1. INTRODUCTION

Remotely sensed imagery, in the form of satellite and aerial photography, has become an indispensable tool in resource management and in numerous areas of scientific research. A study by McRoberts and Tomppo (2007) of national forest inventories in Europe, reported that remotely sensed data not only increased the speed, cost efficiency, precision, and timeliness of forest inventories, but also contributed to the development of maps of forest attributes with spatial resolutions and accuracies not 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 mapping of urbanization and urban sprawl (Xian and Crane, 2005).

In the past, most LULC classifications have been created using a pixel-based analysis of remotely sensed imagery. They used either a supervised classification, unsupervised classification or some combination (Enderle and Weih, 2005). These pixel-based procedures analyze the spectral properties of every pixel within the area of interest, without taking into account the spatial or contextual information related to the pixel of interest. With the growing availability of higher resolution imagery, this spatial information could be used to produce more accurate LULC classifications (De Jong et al., 2001; Dwivedi et al., 2004).

Researchers have generally found that when pixel-based methods are applied to high-resolution images a "salt and pepper" effect was produced that contributed to the inaccuracy of the classification (Campagnolo and Cerdeira, 2007; De Jong et al., 2001; Gao and Mas, 2008; Van de Voorde et al., 2004). 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 (Blaschke et al., 2000; Csatho et al., 1999; Marpa et al., 2006). Computer software packages such as eCognition® and Feature Analyst® 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 that promises to be more accurate than traditional pixel-based methods (Blundell and Opitz, 2006; Grenzdörffer, 2005; Hay and Castilla, 2006).

The first objective of this study was to compare the three methodologies (object-based, supervised and unsupervised pixel-based classifications). This objective will determine if an object-based analysis of remotely sensed imagery will produce a LULC classification that is statistically more accurate than a pixel-based analysis when applied to the same imagery. The second objective was to determine the relative importance of multi-resolution image datasets to classification accuracy for the above methods.

2. METHODS

2.1 Study Area

The study area was located in and around the city of Hot Springs, Garland County, Arkansas (Figure 1), and included Hot Springs National Park. Hot Springs National Park is approximately 2,250 hectares, while the study area was approximately 16,850 hectares. The study area includes features such as the city reservoir, the city landfill, golf courses, county parks, and several rock quarries. While having some urban areas, the study area was predominantly rural, consisting of fields and pastures, pine plantations, shortleaf (*Pinus echinata*) and loblolly (*P. taeda*), deciduous, oaks (*Quercus* spp.) and hickories (*Carya* spp.), mixed forests and some urban areas. Hot Springs is at the foothills of the Ouachita Mountains, with elevations in the study area ranging from 107 to 433 meters.
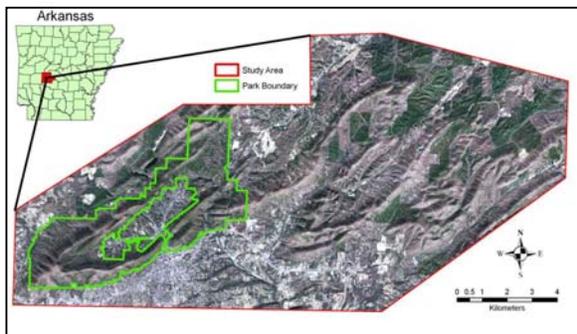
Figure 1. Location of study area in Garland County, Arkansas, including Hot Springs National Park.

2.2 Imagery

Two SPOT-5 images were used to provide multi-temporal data (winter and spring), each with different foliage characteristics (leaf-off and leaf-on). The SPOT-5 leaf-off image (LeafOff) was acquired on 3 February 2007 with an incident angle of 3.384°. The SPOT-5 leaf-on image (LeafOn) was acquired on 27 April 2007 with an incident angle of 10.2366°. Both images were processed as Level 1B imagery.

A true color (RGB) digital aerial image at 1-foot resolution and a 1-meter color infrared (CIR) digital orthophoto quadrangle (DOQ) were captured using the Leica ADS40 camera system. The CIR image was acquired during leaf-off conditions. Color infrared digital aerial imagery of the study area at 1-foot resolution was also acquired during leaf-off conditions and used for photo interpretation of urban areas to supplement the field data and for the development of the training datasets used in the classifications.

The SPOT 5 satellite imagery was orthorectified using a 5-meter digital elevation model. The two SPOT-5 images were resampled to 1-meter when rectified to be coincident with the CIR DOQ pixel resolution. Since we were interested in the comparative value of additional image datasets to classification accuracy, three different combinations of imagery were created. The CIR DOQ, SPOT-5 Leaf-on, and SPOT-5 Leaf-Off image datasets were merged into an 11-band image (CIROnOff, 1-meter). Likewise, the CIR DOQ and SPOT-5 Leaf-off images were merged into a 7-band image (CIROff, 1-meter) and the SPOT-5 Leaf-on and SPOT-5 Leaf-off images were merged into an 8-band image (OnOff, 10-meter). An object-based classification was also produced from the SPOT-5 Leaf-on image (LeafOn, 10-meter).

Because some of the bands of the merged images were correlated, Principal Component Analysis (PCA) versions of each of the merged images were created. The first four PCA bands were used in the study. The first four bands of the subset PCA CIROnOff image accounted for 92.8% of the variance in the data. The first four bands of the subset PCA CIROff image accounted for 97.1% of the variance in the data. The first four bands of the subset PCA OnOff image accounted for 94.8% of the variance in the data. These subset PCA images, as well as the unmerged LeafOn image, were used in the classifications.

2.3 Datasets

Field data, or ground-truth, was used in the study area to create a "test set" to access classification accuracy. Two-person

teams, using Trimble GeoXH handheld GPS units, located the positions of randomly selected points within the study area. This GPS data was later differentially corrected, with an error of less than 1-meter. Along with the GPS coordinates, the following data were collected at each location: 1) tree basal area (BA); 2) major and minor tree/plant species based on BA; 3) description of soil/ground cover conditions; and 4) the LULC classification code. Photo interpretation of random points in urban areas, utilizing 1-foot digital aerial imagery, was used to supplement the field data. Four-hundred and seventy-two ground control points were collected for the accuracy assessment.

The LULC classification codes were determined in conjunction with National Park Service ecologists to produce a medium-level classification of the study area as shown in Table 1. The LULC classification codes are similar to an Anderson Level 2 classification system (Anderson et al., 1976).

A training dataset was created by digitizing polygons for each LULC feature class (Table 1). It was necessary to sample pixels representing variation in forest types as a result of variations of light and shadow due to changes of topography (all images were cloud-free). Similarly, deciduous and evergreen trees required a training set for urban settings. These subset feature classes would later be merged into a single LULC type dataset. This training dataset would be used in the object-based and supervised classifications.

Land Use/Land Cover	LULC Code	Number of Training Polygons
Urban	100	352
Grass	350	267
Deciduous Forest	410	149
Deciduous -Shadow	410	64
Deciduous-Urban	410	81
Evergreen Forest	420	121
Evergreen-Shadow	420	39
Evergreen-Urban	420	78
Clearcut-New	421	28
Clearcut-Old	421	52
Mixed Forest	430	87
Water	530	244
Barren Land	700	148

Table 1. Land Use/Land Cover Training Dataset: LULC code and number of polygons for each Feature Class

2.4 Classification Procedures

An object-based classification was produced from the three-subset PCA images: CIROnOff, CIROff, and OnOff, as well as the LeafOn image using Feature Analyst®. This software utilizes inductive learning algorithms to analyze the spatial context and spectral signatures of pixel clusters or neighborhoods (Blundell and Opitz, 2006). While pixel-based classifiers use only the spectral signature of a single pixel, object-based classifiers also make use of the spatial context

around a pixel to aid in its classification (Visual Learning System Inc., 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. A minimum mapping unit (MMU) of 352 pixels or approximately 0.04 hectares (0.1 acres) was used for all feature classes. Utilizing the training set, each individual feature class was classified. Then a "wall-to-wall" classification was created using all the individual feature classes.

The road, railroad, and stream features were not classified using the imagery, but were later developed from GIS layers. Roads, railroads, and streams were acquired as individual polyline shapefiles. Buffers were created in ArcMap® to represent the approximate width of these features. The buffer for streams was 2 meters. The buffer for railroads was 10 meters. The buffer for roads had two values: 12 meters for highways and 8 meters for all other roads. These buffers were then merged with the other LULC types to produce the final classifications. Since no field data points were collected for the stream feature, it was not used in the accuracy assessment.

Pixel-based methodologies were performed using ERDAS Imagine® 9.3 and included both supervised and unsupervised classifications. Supervised classifications were created from the PCA subsets (CIROnOff, CIROff, and OnOff images) utilizing the previously developed training datasets. The resulting classifications all exhibited the "salt and pepper" appearance commonly associated with pixel-based classifications (Campagnolo and Cerdeira, 2007; De Jong et al., 2001; Gao and Mas, 2008; Van de Voorde et al., 2004). To reduce this effect and aggregate feature classes into patches approximating the minimum mapping unit (0.04 hectares), the "Clump" and "Eliminate" tools in ERDAS Imagine® were used. Unsupervised classifications of the same three subsets PCA images were done using ERDAS Imagine® software.

2.5 Accuracy Assessment

An accuracy assessment using an error matrix (Congalton and Green, 1999) was performed on each of the object-based and pixel-based classifications to determine which produced the most accurate identification of LULC. The error matrix measures an overall accuracy for the classification, as well as a producer and user's accuracy for each feature class.

To determine if two classifications were significantly different (α = 0.05), a Kappa analysis and pair-wise Z-test were calculated (Congalton and Green, 1999; Dwivedi et al., 2004; Zar, 2007):

$$\hat{K} = \frac{p_o - p_c}{1 - p_c} \qquad (1)$$

$$Z = \frac{\left|\hat{K}_1 - \hat{K}_2\right|}{\sqrt{\text{v}\hat{a}\text{r}\left(\hat{K}_1\right) + \text{v}\hat{a}\text{r}\left(\hat{K}_2\right)}} \qquad (2)$$

Where p_0 represents actual agreement, p_c represents "chance agreement", and $\hat{K}_1$, $\hat{K}_2$ represents the Kappa coefficients for the two classifications, respectively. The Kappa coefficient is a measure of the agreement between observed and predicted values and whether that agreement is by chance (Congalton and Green, 1999). Kappa values range from 0 to 1, with values closer to zero indicating higher chance agreement. Pair-wise Z-

scores and probabilities (p-values) were calculated for every combination of two classifications. Using a two-tailed Z-test (α = 0.05 and $Z_{\alpha/2}$ = 1.96), if the p-value $\geq$ 0.025, then the classifications were not considered statistically significantly different (Zar, 2007).

3. RESULTS AND DISCUSSION

In comparing the overall accuracies (Table 2) of the object-based classifications of the four image datasets (CIROnOff = 82.0%, CIROFF = 78.2%, OnOff = 66.1%, and LeafOn = 58.9%), the multi-spatial/multi-temporal image dataset (CIROnOff) produced the best results. However, a comparison of the Z-scores and p-values (Table 3) for the object-based classifications indicates that there was no statistically significant difference between CIROnOff and the CIROff image datasets (Z-score = 1.426 and p-value = 0.0769). This indicates that the addition of the multi-temporal data does not significantly improve the classification accuracy. Similarly, a comparison of the Z-score and p-value of the OnOff and LeafOn image datasets (Z-score = 1.854 and p-value = 0.0319) shows that these two are also not statistically significantly different. However, the CIROnOff and CIROff image datasets were both statistically different from the OnOff and LeafOn image datasets (all p-values < 0.0001) (Table 3). This emphasizes the importance of the 1-meter spatial resolution data when using the object-based method. Of the object-based classifications, the LeafOn image dataset produced the poorest overall accuracy (58.9%) (Table 2). This was expected considering this dataset had the least amount of spectral

Method	Image	Overall Accuracy	Kappa	Kappa Variance
Object-based	CIROnOff	82.0%	0.7842*	0.0004475
	CIROff	78.2%	0.7399*	0.0005164
	OnOff	66.1%	0.5922	0.0007013
	LeafOn	58.9%	0.5219	0.0007358
Supervised	CIROnOff	66.9%	0.6105*	0.0006426
	CIROff	71.8%	0.6619*	0.0005911
	OnOff	64.4%	0.5841	0.0006796
Unsupervised	CIROnOff	64.4%	0.5736	0.0006888
	CIROff	41.5%	0.2955	0.0007769
	OnOff	60.1%	0.5218	0.0007886

* Substantial agreement, based on Landis and Koch (1977) benchmarks

Table 2. Overall Accuracy for each Classification Method and Combination of Imagery

		Classification Method and Image Combinations									
		Object-based				Supervised			Unsupervised		
		CIROnOff	CIROff	OnOff	LeafOn	CIROnOff	CIROff	OnOff	CIROnOff	CIROff	OnOff
Object-based	CIROnOff		**0.0769***	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
	CIROff	**1.4262***		< 0.0001	< 0.0001	< 0.0001	0.0096	< 0.0001	< 0.0001	< 0.0001	< 0.0001
	OnOff	5.6643	4.2328		**0.0319***	**0.3082***	**0.0262***	**0.4143***	**0.3095***	< 0.0001	**0.0342***
	LeafOn	7.6244	6.1604	**1.8539***		0.0085	< 0.0001	**0.0490***	**0.0852***	< 0.0001	**0.4992***
Supervised	CIROnOff	5.2587	3.7994	**0.5008***	2.3875		**0.0718***	**0.2339***	**0.1559***	< 0.0001	0.0095
	CIROff	3.7940	2.3435	**1.9394***	3.8435	**1.4622***		0.0146	0.0068	< 0.0001	< 0.0001
	OnOff	5.9582	4.5037	**0.2165***	**1.6543***	**0.7262***	2.1815		**0.3883***	< 0.0001	**0.0520***
Unsupervised	CIROnOff	6.2455	4.7889	**0.4973***	**1.3708***	**1.0113***	2.4671	**0.2838***		< 0.0001	**0.0888***
	CIROff	13.9664	12.3580	7.7173	5.8220	8.3626	9.9074	7.5639	7.2660		< 0.0001
	OnOff	7.4619	6.0365	**1.8227***	**0.0020***	2.3451	3.7712	**1.6262***	**1.3481***	5.7210	

* Not statistically significant

Table 3. Comparisons of Kappa Coefficients of Classification Methods as applied to different Image Combinations using pair-wise Z-test and probabilities ($Z_{\alpha/2}$ = 1.96; α = 0.05): Z-scores on lower left and p-values on upper right

information (unmerged image with only 4 bands) and a spatial resolution of 10-meters. The addition of the Spot-5 leaf-off data to the LeafOn image substantially improved the user's accuracy for the Deciduous feature class (LeafOn = 59.2% vs. OnOff = 70.5%) (Table 2). This supports the utility of multi-temporal datasets when attempting to distinguish between Evergreen and Deciduous feature classes.

A comparison of the supervised classification accuracies indicates that the CIROff image had the highest overall accuracy (71.8%) (Table 2). While it was significantly greater than the OnOff image (p-value = 0.0145) (Table 3), the addition of the leaf-on data (CIROnOff) did not statistically significantly improve the classification (p-value = 0.718). This indicates that the supervised classification method can be improved with the addition of higher resolution imagery, but that it does not benefit from the inclusion of the multi-temporal (leaf-on and leaf-off) data. This was an unexpected result, as the presence of multi-temporal data should improve classification accuracy, especially in distinguishing between forest feature classes such as Deciduous and Evergreen, as well as between Grassland and Barren areas.

The overall accuracies of the unsupervised classifications show the CIROnOff image had the highest overall accuracy (66.9%) (Table 2) and was statistically significantly greater than the CIROff image (p-value < 0.0001) (Table 3), but not significantly greater than the OnOff image (p-value = 0.0888). This indicates that for the unsupervised classification, the presence of the multi-temporal data was more effective at improving accuracy than the addition of the high-resolution CIR dataset. This may be because

the CIROff image dataset consists of images that are both leaf-off. While spatial resolution improved, this image dataset lacks the spectral information necessary to distinguish between pixels that are spectrally similar, such as barren land and grassy areas during winter months. The OnOff user's accuracy for grass was 92.0%, while the CIROff user's accuracy was 11.1%. For barren land, the OnOff user's accuracy was 52.9% compared to 23.1% for the CIROff user's accuracy.

A comparison of the three classification methods when applied to the CIROnOff image dataset indicates that the overall accuracy of the object-based method was significantly better than the two pixel-based methods (both p-values < 0.0001) (Table 3). There was, however, no statistically significant difference between the overall classification accuracy of the supervised and unsupervised methods (p-value = 0.1559) (Table 3) for this image dataset. In looking at the user's accuracy for the individual feature classes (Table 2), the object-based method generally produced superior results. The object-based method had higher user's accuracy with the following six feature classes: Urban, Deciduous, Evergreen, Clearcut, Mixed, and Barren.

For the CIROff image, the object-based classification had the highest overall accuracy (78.2%), followed by the supervised classification (71.8%) and the unsupervised classification (41.5%) (Table 2). The object-based method was again significantly more accurate than the supervised (p-value = 0.0096) and the unsupervised (p-value < 0.0001) pixel-based methods (Table 3). There was also a significant difference between the overall accuracies of the supervised and unsupervised classifications for

the CIROff image (p-value < 0.0001). When comparing the user's accuracies for the individual feature classes, the object-based classification of the CIROff image generally outperformed the two pixel-based methods. It had higher or equal percentages for every feature class with the exception of Urban (supervised = 86.2% vs. object-based = 79.5%), Mixed Forest (supervised = 33.3% vs. object-based = 28.4%) and Clearcut (unsupervised = 100% vs. object-based = 73.7%).

For the OnOff image dataset, there was no statistically significant difference (p-value = 0.4143) (Table 3) between the overall accuracy of the object-based method (66.1%) and the supervised method (64.4%). Likewise, there was no statistically significant difference (p-value = 0.0520) (Table 3) between the overall accuracy of the supervised (64.4%) and the unsupervised method (60.1%) (Table 2). Nor was there a statistically significant difference (p-value = 0.0342) between the object-based and unsupervised classifications of the OnOff image dataset. This indicates that when only medium-spatial resolution (10-meter pixels), multi-temporal (leaf-on and leaf-off) imagery were used in an analysis, there was no advantage to using an object-based classification over a supervised or unsupervised pixel-based classification.

There are many factors that can affect classification accuracy including: image data quality, the reliability of training data and reference/field data, and the accuracy assessment method used, just to name a few (Gao and Mas, 2008). While the use of randomly selected field data points and error matrices has generally been accepted as a reliable means of conducting an accuracy assessment, this may not hold true with object-based classifications (Gao and Mas, 2008). Object-based classifications, that have clearly reduced or removed the "salt-and-pepper" effect present in pixel-based classifications, may appear more visually appealing to the analyst, yet be under-evaluated by the single point/pixel and kappa index (Carleer and Wolff, 2006; Gao and Mas, 2008). Radoux et al. (2008) have suggested the use of a sampling probability that is weighted or proportional to object area, since the overall accuracy can be impacted to a greater degree by the misclassification of a large area than by misclassifying a small area.

5. CONCLUSION

This research has shown that when merging CIR high-spatial resolution aerial imagery with medium-spatial resolution satellite imagery, an object-based classification will outperform both supervised and unsupervised pixel-based methods. This supports the findings of similar research that has been conducted in the last few years. In general, the addition of the leaf-on data to the image dataset improved overall classification accuracy and it tended to improve the user's accuracy for feature classes such as deciduous and grassland.

While the range of values for user's accuracy for the urban cover across all classification methods was relatively small. The object-based method produced an urban feature class that was much more homogeneous, while both supervised and unsupervised pixel-based methods produced a very fragmented urban feature class. This is important when the classification is used to develop landscape metrics that are sensitive to fragmentation.

From a visual examination of the object-based CIROnOff image classification, it seemed more accurate than the 82.0% stated by the accuracy assessment. This contradiction between the improved visual interpretation and the lack of improvement in the accuracy assessment supports issues related to the use of standard error matrix analysis as applied to object-based classifications (Carleer and Wolff, 2006; Gao and Mas, 2008; Radoux et al., 2008). This is an area for further research that is beyond the scope of this paper.

Technological advances and the growing availability of high-spatial resolution imagery has focused attention on the limitations of traditional pixel-based classification methodologies and precipitated the need for more advanced methods. Object-based classification methodologies, that take advantage of both the spectral and contextual information in remotely sensed imagery, may hold the answer.

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