Object Based Image Classification for Mapping Urban Land Cover Pattern; A case study of Enugu Urban, Enugu State, Nigeria.

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SUMMARY

In this age of rapidly growing global population coupled with growing technological capacity and development, we experience a rapid wide-spread land cover change particularly in urban areas. It now for calls for robust, up-to-date and accurate land cover pattern mapping of our urban areas. This paper focuses on harnessing the potentials of the object based image classification technology in mapping urban land cover pattern in Enugu Urban using a remotely sensed satellite image and an image classification software/tool. A QuickBird image was used as primary data while Erdas Imagine 9.2 was used for the supervised object based image classification. By carrying out training of sample sites on the segmented image, an improved knowledge base was achieved for the supervised classification which was based on some user-defined constraints. The percentages of land use of patterns such as greenery, buildings, paved areas, etc as well as their areas were realized. The classification result gave the land cover pattern map of Enugu city as well as the statistical analyses of the different land cover types in the city with an accuracy of 91.86%. This study can serve as a pilot study for assessing land cover pattern and managing development patterns for cities in the future.

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1 BACKGROUND

Mapping is the accurate representation of part of the earth surface which is spherical on a plane surface to a conventional scale at a particular epoch; maps are finished using cartographic abstractions and generalizations based on the purpose for which the map is made. In recent times mapping is done using remotely sensed imageries. To derive land-cover information from high resolution imagery, however, can be a difficult task depending on the complexity of the landscape and the spatial and spectral resolution of the imagery being used. This study focuses on using the object based classification method to classify map Trans-Ekulu Enugu, Enugu state Nigeria as a means of examining the urban land cover pattern in the area.

In order to achieve object-based image classification, image segmentation is carried out. Image segmentation is carried out on the image using user defined constraints which controls the segmentation of different image objects into independent objects. Segmentation is the division of an image into spatially continuous, disjoint and homogeneous regions. For most previous studies, the aim of image segmentation is to find a single good segmentation result (Carleer et al., 2005; Plaza and Tilton, 2005). On the other hand, since high resolution image usually has limited spectral resolution, the accuracy of the classification using spectral information alone is very limited. Thus, incorporation of spatial information in urban land cover classification would lead to higher classification accuracy (Bruzzones et al., 2006; Carleer and Wolff, 2006; Zhang et al., 2006). In this study, we therefore explore the capabilities of the object-based method in identifying and classifying accurately the different image objects in the urban area according to the chosen themes.

2 STUDY AREA

The study area is located at the north east part of Enugu urban, Enugu state Nigeria, between 330,891.846E and 334,798.096E on the east and 714,523.934N, and 716,716.593N on the north, covering an area of 570.83 hectares.

The study area is an urban area characterized by built up areas with different kind of surfaces and different reflectance abilities (values), water bodies and so many other features which make the high resolution image so complicated.
Due to the heterogeneity of the land cover of the urban area, there is the need for us to use the object based image classification technique to intelligently differentiate this.

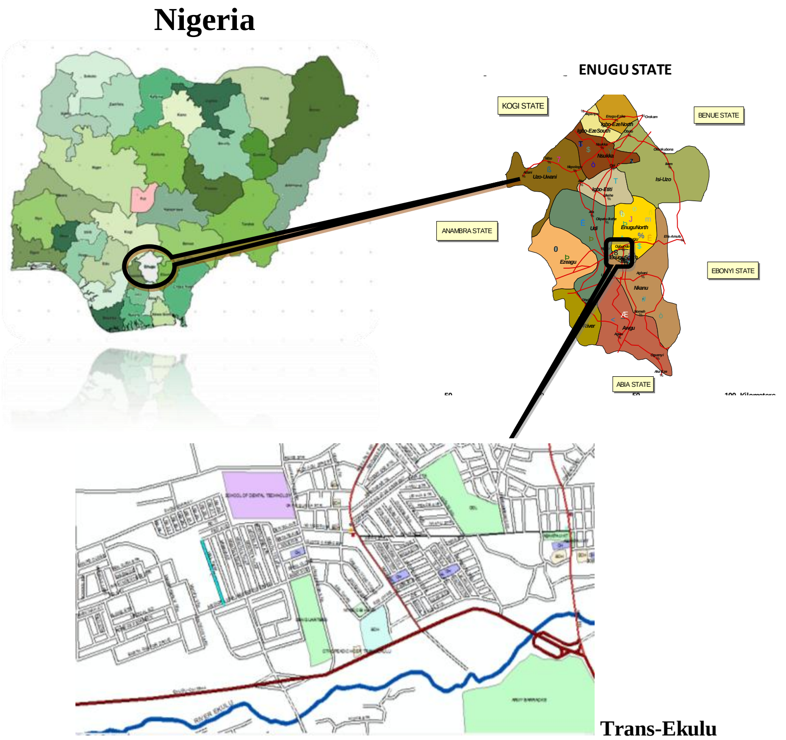

Figure 1: Study Area

3 DATA

The primary data used for this study is the QuickBird imagery of the study area which was captured in 2010. This high resolution data was selected because it shows the urban land cover details. See figure 2 below.

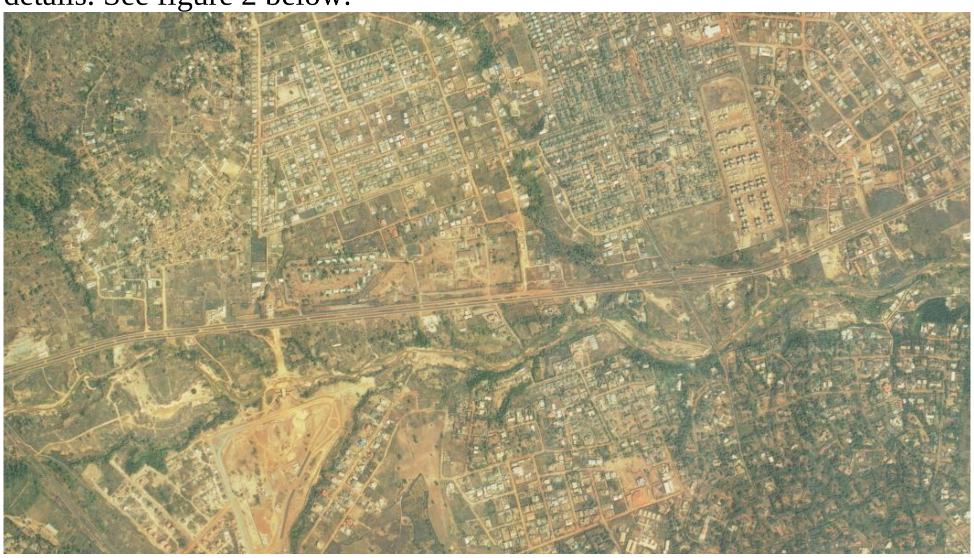
Figure 2. QuickBird imagery of the study area

4 METHODOLOGY

4.1 Overview of Procedure

This study followed the following steps to achieve the object based image classification;

1. Ground Truthing
2. Projection and Georeferencing of the image of the study area
3. Choice of Classes to be classified
4. Choice of segmentation parameter values
5. Segmentation
6. Training of sample sites
7. Classification
8. Class Mapping
9. Class Area Computation
10. Accuracy assessment

4.2 Procedures

The preliminary procedures involved carrying out ground truthing at the study area. This data obtained during ground truthing now form the knowledge base which is applied at the training stage. The image was then re-projected to UTM zone 32N and georeferenced using coordinates gotten during ground truthing.

4.3 Image Segmentation

At the segmentation level we were faced with the challenge of the choice of Similarity threshold and Area (Pixel) threshold that will give us the best classification result as it is on ground. At this point, we tried three different ranges of values which gave us different results.

4.4 Segmentation with Similarity: 10 & Area (Pixel): 25

Here we experienced over segmentation as image objects were split into many part as different objects instead of one.

4.5 Segmentation with Similarity: 30 and Area (Pixel): 50

Here we experienced under-segmentation, there was so much generalization, grouping different image objects as one instead of differentiating them.

4.6 Segmentation with Similarity: 18 and Area (Pixel): 35 (Best Segmentation)

In this threshold range, we got a classification result that is very close to reality. We hereby chose this segmentation as the most appropriate for the purpose of our work. In segmenting this image, the spatial and spectral characteristics of the image pixels were considered.
Using the Similarity:18 and Area (Pixel): 35, the image was segmented.

4.7 Training Sets

Detail site training was carried out on the image covering the study area using the ground truth data, thereby making meaningful the image segments (grouped pixels) which were grouped into the following image themes:

a) River
b) Buildings
c) Vegetation
d) Road
e) Shadow
f) Paved_Area

4.8 Signature Editor

Here the pixel signature and the spatial signature of the classes were defined by picking sample sites uniformly spread on the image.

4.9 Classification

The classification stage was done using the segmented image in association with the training data (class signatures) to achieve a good classification of the land cover pattern of the study area.

4.10 Class Mapping

After classification, class mapping was carried out in order to associate the classes of the image with the themes which were created for further analysis. Classes were assigned to their corresponding themes as can be seen in figure 3.0 below.

5 RESULTS

The results of this study are in the forms of;

a) A classified raster image of the study area.
b) Statistical analyses.

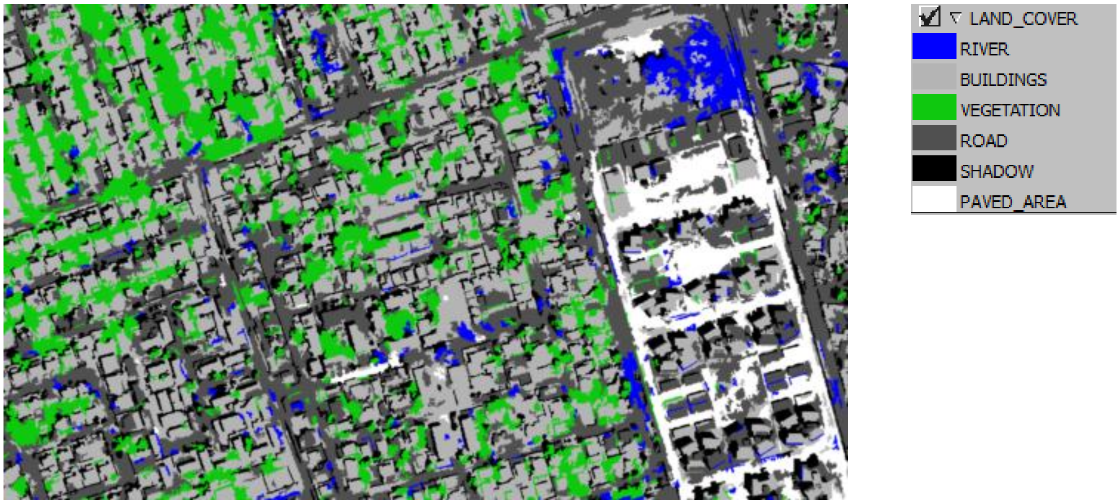

Figure 3: Classified Raster image of the study area (Part of).

5.1 Accuracy Assessment

To assess the accuracy of the classified map, we imported the ground truthing data, that is, the coordinates of the corresponding reference points with their *Reference ID*. With this we were able to assess the accuracy of the classification. The classification accuracy is achieved by comparing the ground truth data points of the six (6) themes with the classified image. The degree of agreement of the classified image position and the ground truth data points now gives us the classification accuracy of the image classification process. See figure 4.0 below
The result of the classification showed that the Object-based classification had up to 91.86% accuracy. The accuracy assessment statistics are shown in tables 1 and 2 below.

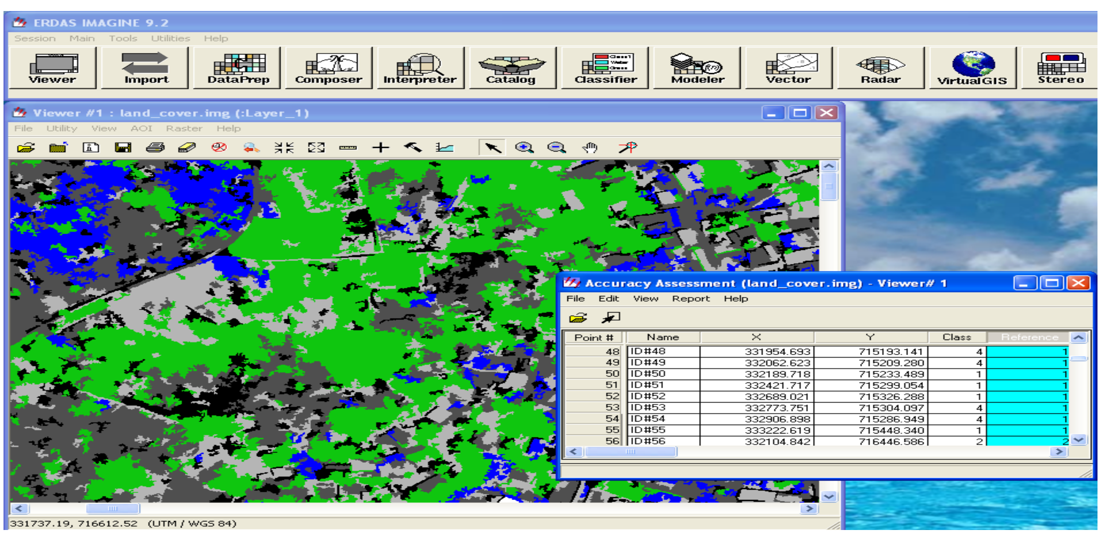

Figure 4.0: Accuracy assessment window

5.2 Error Matrices of Land-use classes as Classified

The error matrices of the land use classes were assessed as classified. The assessment report windows are shown in figures 5.0 and 6.0 below.

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CLASSIFICATION ACCURACY ASSESSMENT REPORT

Image File : e:/paper 2/land_cover.img
User Name : user
Date : Thu Nov 15 08:11:28 2012

ERROR MATRIX

Reference Data

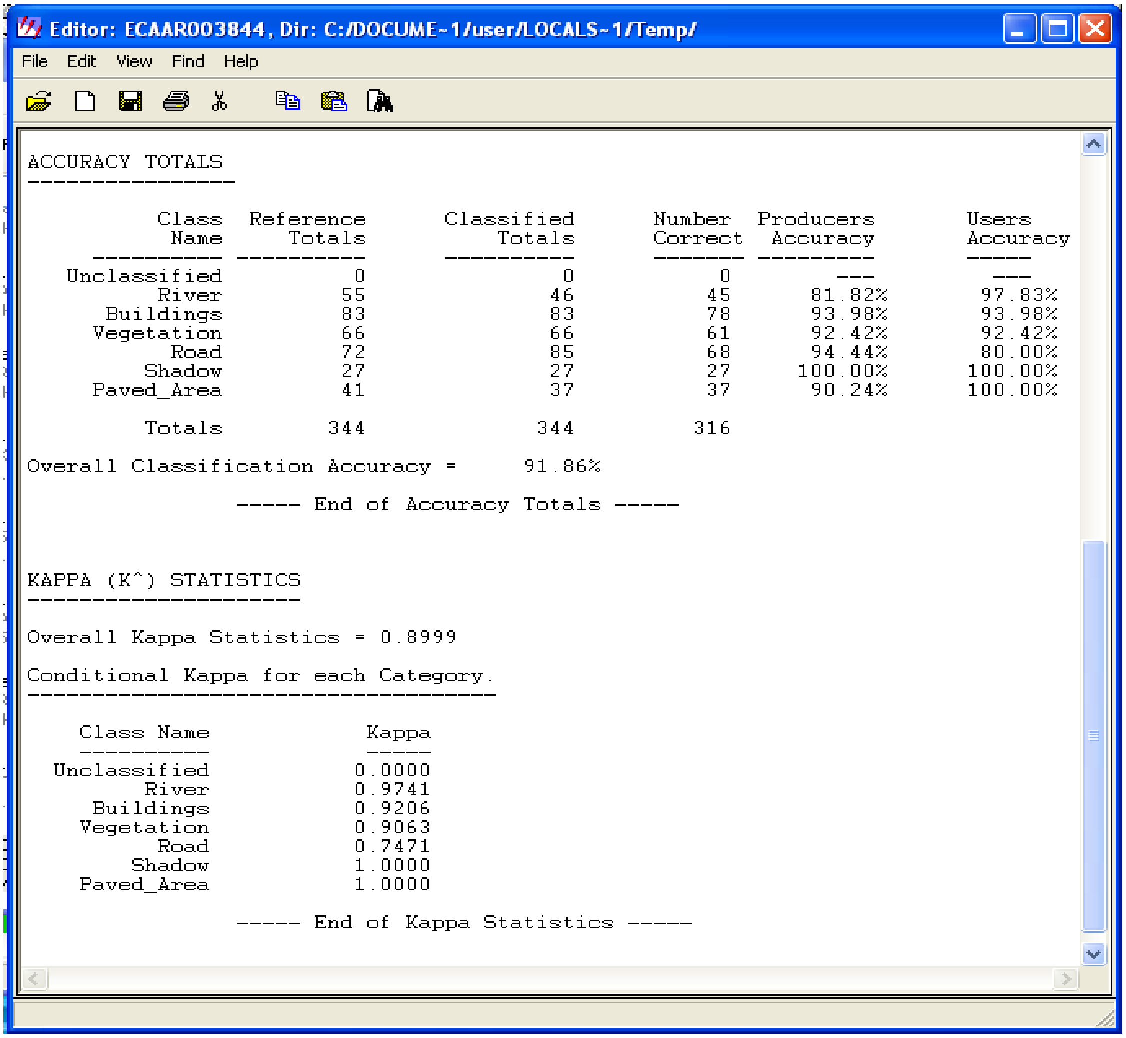
Classified Data	Unclassifi	River	Buildings	Vegetation
Unclassified	0	0	0	0
River	0	45	0	0
Buildings	0	1	78	1
Vegetation	0	3	2	61
Road	0	6	3	4
Shadow	0	0	0	0
Paved_Area	0	0	0	0
Column Total	0	55	83	66

Reference Data

Classified Data	Road	Shadow	Paved_Area	Row Total
Unclassified	0	0	0	0
River	1	0	0	46
Buildings	3	0	0	83
Vegetation	0	0	0	66
Road	68	0	4	85
Shadow	0	27	0	27
Paved_Area	0	0	37	37
Column Total	72	27	41	344

----- End of Error Matrix -----

Figure 5.0: Classification assessment report (Error Matrices of land-use classes)



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ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
River	55	46	45	81.82%	97.83%
Buildings	83	83	78	93.98%	93.98%
Vegetation	66	66	61	92.42%	92.42%
Road	72	85	68	94.44%	80.00%
Shadow	27	27	27	100.00%	100.00%
Paved_Area	41	37	37	90.24%	100.00%
Totals	344	344	316		

Overall Classification Accuracy = 91.86%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8999

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
River	0.9741
Buildings	0.9206
Vegetation	0.9063
Road	0.7471
Shadow	1.0000
Paved_Area	1.0000

----- End of Kappa Statistics -----

Figure .6.0: Classification assessment report (Accuracy Total and kappa statistics)

5.3 ACCURACY TOTALS

Table 1.0: Accuracy Assessment Table

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	KAPPA (K^) STATISTICS
Unclassified	0	0	0			0.0000
River	55	46	45	81.82%	97.83%	0.9741
Buildings	83	83	78	93.98%	93.98%	0.9206
Vegetation	66	66	61	92.42%	92.42%	0.9063
Road	72	85	68	94.44%	80.00%	0.7471
Shadow	27	27	27	100.00%	100.00%	1.0000
Paved_Area	41	37	37	90.24%	100.00%	1.0000
Totals	344	344	316			
Overall Classification Accuracy				91.86%		0.8999

Table 2.0: Land Use Table

Class Name	Area Classified (Hectares)	Total Area	Percentage Land Use
Unclassified	0	83.298954	0
River	2.943912	83.298954	3.53%
Buildings	37.975993	83.298954	45.59%
Vegetation	1.789721	83.298954	2.15%
Road	35.685095	83.298954	42.84%
Shadow	0.780999	83.298954	0.94%
Paved_Area	4.120728	83.298954	4.95%
Totals	**83.298954**	**83.298954**	100%

From the table one can quickly see that the study area is heavily built up covering an area of 37.975993 hectares which is 45.59% of the study area, followed by road which covers about 35.685095 hectares (42.84% of the study area). The other land uses are in smaller percentage.

6. CONCLUSION

As we can see from this study, the classification results has been greatly improved by the object oriented, besides, the whole procedure proves feasible and efficient, and the reasons are as follows:

i. Segmentation has its special way of eliminating the noise problem.
ii. The object concept enables the usage of various features, making full use of high resolution images information. Beyond purely spectral information, image objects contain a lot of additional attributes, which can be used for classification.
iii. With different segmentation parameters (user-defined), it provides the possibility to easily adjust image object resolution (size) to specific requirements, data and tasks depending on application.
iv. There is flexibility in editing which enables one to amend or delete the wrongly classified objects.
v. The object-based method is more suitable for classifying high resolution images especially in urban areas, and will be the trend for the high resolution remotely sensed data.

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