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Comparison and Analysis of the Pixel-based and Object-Oriented Methods for Land Cover Classification with ETM+ Data

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Abstract: *Automated features extraction techniques have gone a long way to ameliorate pains on image processing and information extraction from remotely sensed image; this has opened many doors for many applications. However, pixel based image classification and feature extraction of Nigerian urban areas are still very difficult due to the spectral similarity of many of the urban features such as roads, bare ground, rock outcrop, built-up areas and many more. This is as a result of the nature of the roads (untarred) and other features like built-up areas with large area coverage of bare ground rather than well landscaped with grass gardens. This makes high classification accuracy of urban feature extraction very difficult to achieve. The performance of urban feature extraction from LANDSAT imagery of Abuja, Nigeria with eCognition is overwhelming. This research compared the result of object oriented image classification (i.e. eCognition) and other traditional (i.e. Erdas Imagine) methods of image classification vis-à-vis urban feature extraction from medium resolution remotely sensed image of Abuja Nigeria which has a very highly similar spectral reflectance value. The result shows overall accuracy of 94.9% as against the overall accuracy of 89% in using the traditional method in Erdas Imagine. While the ever difficult and very confused class differentiation in image classification in Nigerian urban areas between built-up and bare ground was clearly separated with high level of accuracy*

Keyword: *Pixel Based Classification, Object-Oriented Classification, Automatic Feature Extraction, e Cognition.*

I. Introduction

Remote Sensing helps in obtaining data about the earth surface which can be used in urban planning, agriculture yield prediction, environmental modeling, disaster monitoring and many more. The data is obtained in the form of an image through electromagnetic radiation from objects of interest, which needs interpretation into meaningful information. This process is called digital image classification and interpretation. In digital image processing, each pixel is categorized and assigned to a particular class (Matinfar et al., 2007), this is referred to as image classification in remote sensing.

This research analyzes two method of digital image classification techniques namely pixel based (i.e. traditional method) and object-oriented based. The pixel based (PBC) techniques assigned to a particular class of land cover type e.g. vegetation, built-up based on its spectral similarities to that class (Casals-Carrasco et al., 2000). The result of this classification are mostly what Lilesand et al. (2008) referred to 'pepper-and-salt' because the statistical technique used such as maximum likelihood which considers only the spectral characteristic of an image without considering the spatial characteristic (e.g. texture, context) which are important in order to attain high classification accuracy (Flanders et. al, 2003; Blaschke and Strobl, 2001; Blaschke et al., 2000).

In order to achieve high classification accuracy, object oriented based classification (OOC) technique is introduced. In object-oriented classification the image is partition into different contiguous homogeneous objects called segment (Yoon et al., 2005). The process of segmenting the image is called segmentation and each segment is partition based on its spectral and spatial homogeneity and no two adjacent segment are homogeneous (Yan et al., 2006). Segmentation forms the bases for OOC and the result of this segmentation is used for further analysis.

The advances in both computer hardware and software technology brought tremendous improvements; more sensors with very high resolution for data capture in remote sensing are made available. So also are image classification software both in PBC and OOC (Ouyang et al., 2010; Blaschke and Strobl, 2001). For this reason, many studies have been carried out between the relative accuracies of PBC and OOC (Yan et al., 2006; Blaschke and Strobl, 2001).

This study considers the capability of both pixel-based and objects oriented-based image classification techniques for urban feature extraction.

II. Study Area

The study area is the capital city of Nigeria, Abuja. Abuja is on latitude 9° 00' North, longitude 6° 00' East and latitude 14° 08' North, longitude 7° 58' East of Greenwich.

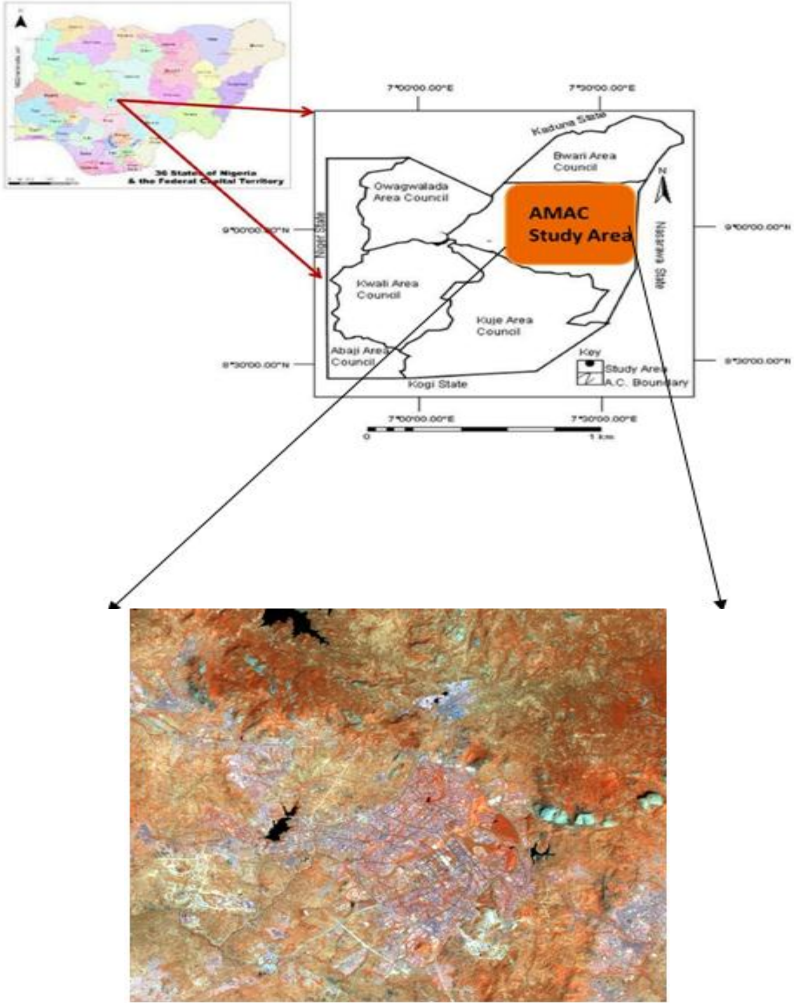


Fig. 1: Study Area

III. Methodology And Datasets

3.1.0

Data-Sets: Landsat data sets are the most widely used satellite data in remote sensing application in view of the fact that their spectral, spatial and temporal resolutions are valuable in mapping and modeling projects (Sadidy et al., 2009). In this studysix bands (i.e. band 1, 2,3,4,5 and 7) of Landsat 7 Enhanced Thematic Mapper plus (ETM+) dataset were utilized. While ground truth datawas obtain from field observation. Table 1 provides spectral and spatial resolution of the sensor:

3.1.1

Band number	Spectral range (micron)	Ground resolution (m)
1	0.45 to 0.515	30
2	0.525 to 0.605	30
3	0.63 to 0.690	30
4	0.75 to 0.90	30
5	1.55 to 1.75	30
6	10.40 to 12.5	60
7	2.09 to 2.35	30
8	0.52 to 0.9	15
Date of acquisition		
Swath width	185 Kilometres	
Repeat coverage interval	16 days (233 orbits)	
Altitude	705 Kilometres	

Table 1: Characteristics of Landsat ETM

3.1.1 Pre-processing: Image enhancement is essential in order to improve the visual difference of features or classes in an image (Lillesand et al., 2008). They include false colour RGB composite, contrast stretching, and spatial filtering among others. In this research, in order to achieve the image enhancement purpose so that there can be apparent distinction between features, contrast stretching was applied and a false colour composite of 4:5:3 was applied and this colour composite was used for visual interpretation using the on screen digitising.However, before the segmentation in e-cognition, the image pre-processing was carried out in an Erdas imagine environment.

3.1.2 Geometric Corrections and Sub-setting: Image-to-image method was used to geometrically project the Landsat ETM to UTM Zone 32 N and WGS-84 in order to avoid distortion and also to be processed using both pixel base and object base classification approaches (Sun et al., 2007). The spatial extent of Landsat ETM+ image scene utilized in this study is larger than the study area, so therefore, a subset of the study area was carried outwith ERDAS imagine so as to obtain an image that is more manageable (fig 1). Shapefiles of roadsextracted in ArcMap was brought to aid segmentation in eCognition; an added advantage that enrich the process.

3.2.0 Image Processing:

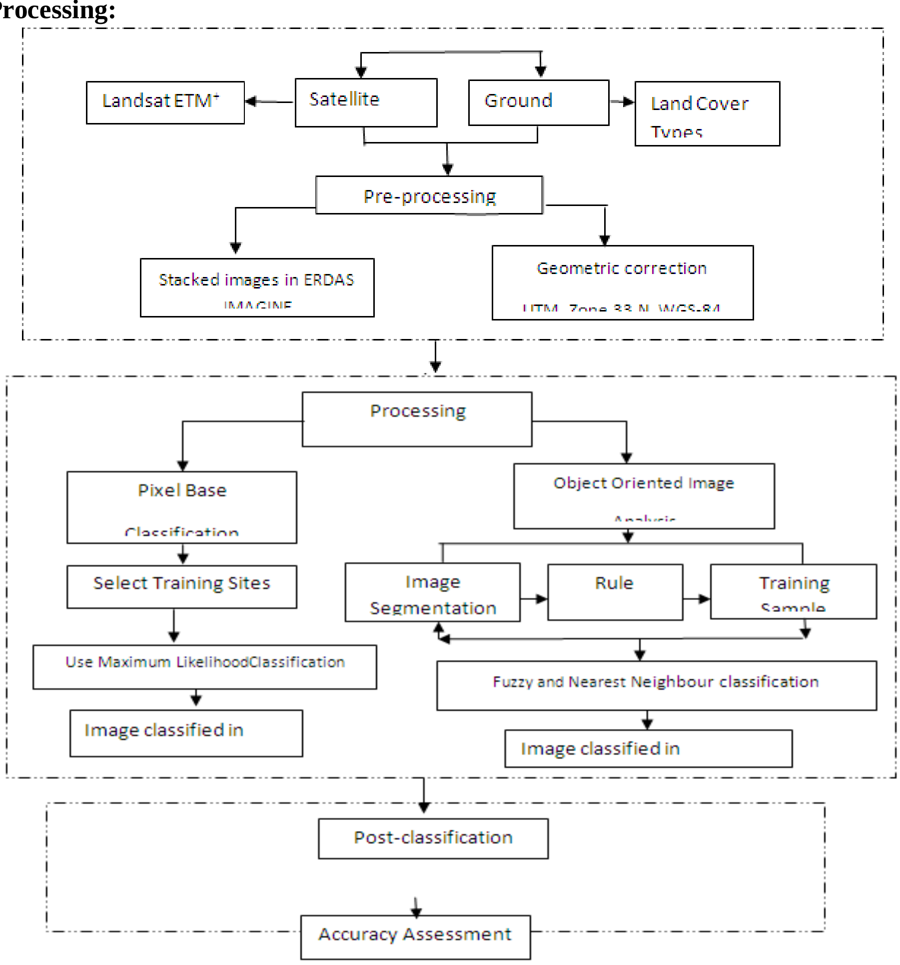


Figure 3: Flow chart of methodology

IV. Results And Discussion

4.1Pixel-based Image Classification

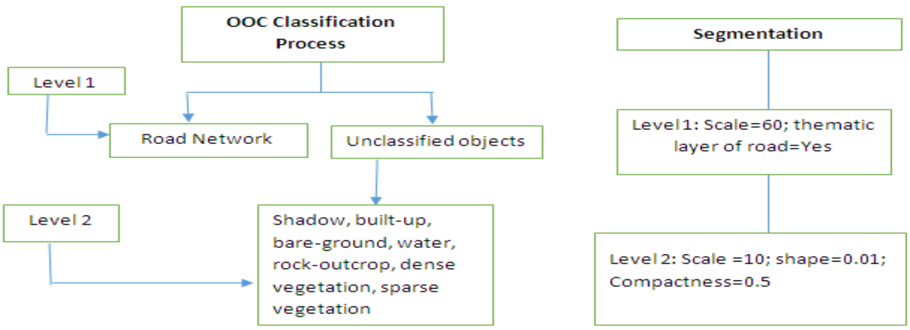
Lu & Weng (2006) in their study discussed that because of the nature of the urban environment and the large number of mixed pixels associated with moderate resolution images, it is often difficult to classify land use/land cover based on spectral signatures. They are of the opinion that using medium data whose sensors mainly reveal land details is more appropriate for land cover classification rather than land use classification. Therefore, in this research, land use is not included but only land cover and eight land cover classifications were applied namely: built-up, water, shadow, road, dense vegetation, sparse vegetation, and bare surface (fig 2). In this study,DefinienseCognition software was used to perform object oriented classification since it is an object oriented program designed by Definiens Imaging GmbH.

In a supervised classification method, conventional per pixels is widely used (Lu &Weng, 2007). In this research, a hard classification of the Landsat ETM+ data acquired in 2006 was applied in the classification of the features. There appears to be some confusion between the road network and built up due to the spectral resemblance between the two classes. Each pixel count is grouped together based on the classes. Spectral signatures are obtained from different locations on the image which are then grouped according to the classes. The images were in false colour RGB combination of 4:5:3 and training sites were created for each class identified. The signature of each of the pixels counts were compared and labelled as those that look similar to the reference data using the Imagine signature editor. Training sites were taken using the digitizing polygon, region growing as well as create polyline tools and multiple training regions were created. Apart from the water and shadow classes, more than 70 sample signatures were taken for each classes in accordance with the 10 n criterion, where n= number of bands used for the classification (Congalton& Green, 1999).

Maximum likelihood parameter rule was applied. Supervised classification thematic image was created and the classes without values were recorded. In order to correct what Lillesand et al. (2008) referred to as 'salt and pepper' which occurs as the result of the use of pixel-by-pixel classification algorithm, a post classification smoothing was applied using majority filtering method.

4.2 Object Based Classification

One of the best features of eCognition is its image segmentation ability since the accuracy of image classification directly depends on the accuracy of image segmentation (Yan et al., 2006). Image segmentation involves dividing the image into smaller object; each object contains pixel(s) of the same homogeneity. The image can be segmented as much as the user needs using different scale (Meinel et al. 2001 &Sun et al. 2007). Segmentation is termed the most important step in object oriented classification because it allows the user to identify objects not just by their spectral similarities but also by their spatial characteristics for example shape/colour, texture and context (Pham et al. 2009 and Walter 2004).The second important step is to set the rule that is suitable for each object (Pham et al., 2009). Based on the terrain setting, both nearest neighbour classifier (NN) and fuzzy logic were used (see flow chat 1&2 and table 2).



Flow-chart 2: steps of object oriented classification used for land-cover mapping of Abuja.

In this process, segmentation was done several times until a quadratic correlation between scale factor and mean item size was established; thenQuadtree segmentation method at a scale of 60 and the aid of a road shapefile was used for level 1. While for the extraction of water bodies, built-up areas, bare-ground, dense and sparse vegetation, shadow and rock-outcrop segmentation in level 2 (see flow-chart 2) was used.Each segmentation procedure corresponding to one level is conducted with specific morphologic features such as scale, ratio compactness/shape appropriate for each type of object as shown in flow-chart 2. For the classification, fuzzy logic (see table 2) was applied in level 1 for road extraction. Nearest neighbor classifier utilizes feature space for object classification by taking samples representing classes of interest (Definiens Imaging GmbH, 2002). Nearest neighbor classifier uses membership function in which an object is assigned to a class base on its value lying between 0.0 to 1.0; where 0.0 represent not belonging to a class and 1.0 represent belonging to a particular class (Yan et al., 2006).Segment creation prevents 'salt-n-pepper' effect found in pixel based classification (Blaschke2000a;Blaschke 2000b).

LEVELS	RULE SET	Features
LEVEL 1	Unclassified with Length/width >= 4 at level 1:Roads Unclassified with Rectangular fit <0.2 at level 1:Road Unclassified with Elliptic fit<=0.1 and Asymmetry >=0.9 at level 1: Road	Road network
LEVEL 2	Nearest Neighbour classifier	Water, built-up, dense vegetation, sparse vegetation, shadow, rock-outcrop

Table 2: Object Oriented Ruleset and classes.

4.3 Comparison of Classification Results and their Implementation

4.3.1Visual Comparison of Classification: Visual comparison of the two images indicates 'salt-and-pepper' effects (i.e. small-element pixel classification pattern) in left image while the right image appears smoother due to segmentation done before classification.

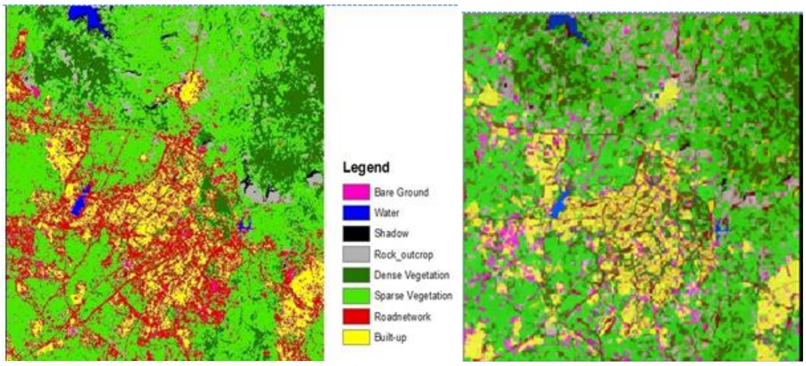


Fig. 2: Classification results (Left: Erdas Imagine and Right: eCognition).

Fig4: Left: Landsat TM+, Center: Erdas Imagine classification result, Right: eCognition classification result.

The top and last row shows how water bodies were classified correctly in eCognition while the same water bodies are missing in Erdas classification. The middle row shows how road network was classified accurately as a line feature in eCognition while the same road was classified as a polygon feature (i.e. because some of the pixels belonging to bare-ground and built-up areas where classified as road) in Erdas imagine. The last row showed how a built-up area (actually a stadium) was classified as bare-ground in Erdas while the same area was classified as built-up in eCognition.

4.4Comparison of Classification Accuracy with Error Matrix

A close look at the results revealed that object oriented classification accurately identified some of the urban features e.g. built-up, water bodies and road network. The accuracy tool in both Erdas imagine and DefinienseCognition where both used to calculate the accuracy in each of the classification respectively. The overall accuracy was found to be 94.9%. This is higher than the overall accuracy of the pixel-based classification, which is 89.0%. The same trend was also observed for each classified land cover class (Producer's and User's Accuracy) except for water and shadow classes.

Class	Erdas Imagine		DefinienseCognition	
	Producers Accuracy (%)	Users Accuracy (%)	Producers Accuracy (%)	Users Accuracy (%)
Water	96	92	86	89
Dense Vegetation	82	92	78	98
Sparse Vegetation	88	92	98	98
Built-Up	74	92	94	97
Rock-Outcrop	95	92	91	97
Shadow	92	88	71	96
Bare-ground	92	84	96	96
Road	100	80	100	100

V. Conclusions

From the above classification and analysis, it has been established that eCognition (object oriented classification) performed better in classifying and identifying different land cover classes. Therefore, as the demand for land use/land cover increases for various purposes, object oriented software will go a long way to meet those demands.

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