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Large scale mapping: an empirical comparison of pixel-based and object-based classifications of remotely sensed data

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Abstract

In the past, large scale mapping was carried using precise ground survey methods. Later, paradigm shift in data collection using medium to low resolution and, recently, high resolution images brought to bear the problem of accurate data analysis and fitness-for-purpose challenges. Using high resolution satellite images such as QuickBird and IKONOS are now preferred alternatives. This paper is aimed at comparing pixel-based (PIXBIA) and Geo-object-based (GEOBIA) classification methods using ENVI 4.8 and eCongnition software respectively, and ArcGIS 10.1 for map layout creation. It uses Aba main city in south-eastern Nigeria as a case study. The paper further evaluates the classification accuracies obtained using error matrix and then test the classifications' agreement to geographic reality using Kappa Coefficient statistical analysis. Analyzing 2012 QuickBird image as a proof of concept, the study shows that the object-based approach had a higher overall accuracy (OA= 98.75%) than the pixel-based approach (OA=79.44%). With a Kappa Coefficient of K=0.97 (very good) for object-based approach and K=0.62 (good) for pixel-based, the object-based method showed a higher class separability between and among examined geographic objects such as water, bare-land and tree canopy as evidenced in the Golf Course under re-construction in Aba city. In addition, the object-based results also show a higher overall producer accuracy (PA=98.42% > PA=85.37) and user accuracy (UA=96.70 > UA=81.04%) respectively. The paper, therefore, recommends that object-based classification method be applied in analyzing high resolution satellite image. The approach is also recommended for mapping urban areas in developing countries such as Nigeria where the paucity of fund required in flying airplane for the production of orthophotos is a major challenge in large scale mapping.

Keywords: Image Classification, Object-based Classification, Pixel-based Classification, Remote Sensing, Urban Planning and Mapping.

1 Introduction

Geospatial elements that vary aerially over earth's surface are almost limitless (Akinbode, 1996). However, the importance of accurate and up to date land cover and land use information is increasing (Verhulp and Niekerk, 2017). Consequently, studies using Remote Sensing data, Cartographic principles and Geographic Information System (GIS) in examining earth's surface spatial elements are specifically aimed at making informed decisions because the spatial outputs, mostly in the form of maps and accompanied statistics, help in resource allocation and landuse management on one hand, and policy impact analysis on the other hand (Goodchild, 1992; Ojigi, 2006; 2012). In addition, informed decisions are useful for planning purposes in areas like topographical mapping (Ikhuoria and Ogedegbe, 1998; Soneye and Akintuyi, 2013), environmental management (Worboys, 2003), land suitability and crop production (Verhulp and Niekerk, 2017; Rilwani, 2014), topographic analysis and visualization (Yokoyama, Shirasawa and Pike, 2002; Fabiyi, Ige-Olumide and Enaruvbe, 2012; Nkeki and Asikhia, 2014), as well as urbanisation, industrialization and regional planning (Omuta, 1984; Fasona and Omojola, 2004). In other words, having reliable and up-to-date spatial data sources such as Satellite Remote Sensing, ground surveying and croudsourced mapping are regarded as fundamental to effective planning and infrastructural development (Ufuah, 2003; Bello and Ojigi, 2013).

Previous studies showed that the dearth of reliable and up-to-date geographic data is a major drawback in making informed decisions as far as good governance and development are concerned in developing countries like Nigeria (Ufuah, 2003; Nkeki and Asikhia, 2014; Rilwani, Bello and Onothoja, 2015). Besides, the high temporal resolution in continuously providing multi-date satellite image data over a given geographic space is germane (Roostaei, Alavi, Nikjoo, and Valizadeh-Kamran, 2012). The Shuttle Radar Topography Mission (SRTM) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) datasets also provide data for timely production of topo-maps (McRoberts and Tomppo, 2007). There is usually the professional need to interpret and classify these datasets into information outputs such as maps. Since maps are beneficial for planning purposes, it is, therefore, very imperative that information contained in a map also reflect record of reality in space over time as accurately as possible (Ufuah, 2003).

Literature, however, shows that governments are less willing to foot the bill for national map making efforts (Goodchild, 2009). This has given room for amateurs' involvement in crowdsource mapping and Volunteered Geographic Information (VGI) (Bello and Ojigi, 2013). VGI is, however, not without fit-for-purpose data quality challenges (kraak and Ormeling, 2010). In literature, map making from aerial photos has been criticized for its time consumption, tedium, high cost and low accuracy (Collier, 2002; Ozah and Kufoniyi, 2008). This is because, prior to the introduction of GIS technology, cartographers relied heavily on data derived from conventional survey which also relied heavily on instruments such as ranging poles, Günter's chain, and tapes (Ikhuoria, 1998) to produce topographical maps that were largely interpolated with contour lines and manually produced hill shaded maps (Nkeki and Asikhia, 2014; Alpha and Winter, 1971; Imhof, 1965). With the advent of aerial photographs, most maps were produced photogrammetrically through mathematical measurements of features in the photos.

Conceptually, a map could be described as a scaled diagrammatical representation, simplification or model of any part of the earth surface on a projected plane or medium in 2D or 3D (Imhof, 2007; Chang, 2012; Osborne, 2013). Whether using ratio, representative fraction or statement scale

(Kraak and Ormeling, 2010), maps may be generally divided into (a) small scale (1:20,000,000 and above - e.g. world map), medium scale (1:600,000 – 1:2,000,000 – e.g. country wide maps) or large scale (1:0 – 1:600,000 – e.g. town plan, cadastral and urban maps). In fact, regardless of the type of projection system used (Snyder, 1993), large scale mapping show small area with more details while small or medium scale mapping show larger areas with less details (Imhof, 2007; Olomo, 2007). Unfortunately, in most developing countries in Africa such as Nigeria, Ufuah (2003) argued that some of the aerial photographs used for the production of the Nigeria's scale 1:50,000 map series were acquired between 1956 and 1972 implying an age range between 31 to 47 years old. Yet, these maps still remains, more or less, the most authentically available base maps being used today in the country without visible updating in tandem with the United Nations Organisation's (UNO) recommended revision period of 10 years for areas of high human activities and 15 years for remote areas. This paucity is common with most African countries like Nigeria, where poverty and inadequacy in technological advancement in the area of geospatial information has resulted in the inability of such countries to regularly produce new topographical maps especially on a wider scale (Ozah and Kufoniyi, 2008). Consequently, there is now a shift from terrestrial survey and air photo to space-based satellite remote sensing for many applications such as urban planning and management (Myint *et al.,* 2011) and topographic mapping (Ufuah, 2003).

Since 1972 when the first Earth Observation Satellite (EOS) was launched for environmental applications, the traditional method of mapping was first through analogue or visual analysis and later through the use of pixel-based method by classifying satellite image into landcover information classes (Ikhuoria, 1998). As a result of available low spatial resolution images characterised by coarseness and the salt-and-pepper-like short-comings, the pixel-based method could better be used for a generalized small scale mapping (large area with lesser details) especially in landcover change detection (Verhulp and Niekerk, 2017) and topographic mapping applications of a region (Matinfar *et al.,* 2007; Roostaei *et al.,* 2012). With the advent of high resolution satellite data such as IKONOS (1m), QuickBird (0.6m) and NigeriSat-2 (2.5m Pan & 5m Multispectral) that are suitable for urban and cadastral large scale mapping, the development of robust Object-Oriented (object-based) classification method now provides a valid alternative to the 'traditional' pixel-based methods (Baatz, 2004; Benz, 2004; Whiteside and Ahmad, 2005). Importantly, maps generated from remotely-sensed data and other ancillary sources cuts across a number of sectorial usages (Olomo *et al.,* 1998).

Due to rigours in the use of Global Positioning System (GPS) receivers in rapid mapping, the advent of remote sensing and orthorectified satellite image classifications has not only reduced drudgery but has also improved mapping accuracies. Conceptually, satellite image classification is the grouping, rendering, conversion or mapping of picture elements (PIXEL) with similar digital numbers representing a spatial feature as information class (Yu *et al.,* 2006; Matinfar *et al.,* 2007). The geographical reliability, relevance, usefulness and accuracies of acquired and analysed remotely sensed data is important for various applications and uses as this is the crux of differentiating and comparing the pixel-based and object-based classification methods.

Previous studies on the above methods of classifications include those of Roostaei *et al.*, (2012); Whiteside and Ahmand (2005); Matinfar *et al.*, (2007); Flores *et al.*, (2009); Myint *et al.* (2011); and Lu and Weng (2007). The trend and relevant studies on passive or active Remote Sensing using either pixel-based, object-based and or direct field survey with ancillary data for landuse/cover mapping, urban studies, environmental management and planning include the works of Erol and Akdenz (1998); Dymond and Shepherd (1999); Syed, Dare and Jones (2005); Matinfar *et al.,* (2007); Rilwani (2014); and Yu, *et al.,* (2006). Their findings indicate that a better approach to geospatial data analysis usually guarantees a reliable use of the derived products for informed decision making and planning.

This paper is, therefore, aimed at comparing object-based and pixel-based classification methods to urban mapping with empirical applications using part of Aba city in south-eastern Nigeria.

Theoretically, the pixel-based image classification (PIXBIA) technique is based on conventional computer-based statistical techniques, such as supervised and unsupervised classifications or both (Verhulp and Niekerk, 2017; Matifar *et al.,* 2007). Supervised classification (semi-automatic) entails selecting training samples (Congalton and Green, 1999); performing classification using algorithms and assessing the accuracy of the classified image through the analysis of a confusion matrix that is generated either from random sampling or using test areas as reference data (Jensen and Gorte, 2001). Conversely, unsupervised classification requires no training data or sample classes. Pixels are assigned spectral classes based on their reflectance properties into "clusters".

According to Matinfar *et al., (*2007), considerable advancements have recently been made in the development of Geo-object-based image analysis (GEOBIA) method of satellite image classification as a result of perceived low accuracy and salt-and-pepper-like anomalies in the traditional pixel-based approach. The theory or principle behind the GEOBIA method is called the *fuzzy theory.* Based on this theory, objects (earth features) are classified into more than one class with different membership values (Benz *et al.,* 2004). Hay *et al.,* (2001) defined the objects in GEOBIA technique as "basic entities located within an image, where each pixel group is composed of similar digital values, and possesses an intrinsic size, shape, and geographic relationship with the real-world scene component it models". In object-based classification method, segmentation (feature grouping) generally uses membership to express an object's assignment to a landcover class. The membership value usually lies between 1.0 and 0.0; where 1.0 expresses a complete assignment to a class, and 0.0 expresses absolutely improbability (Matinfar *et al.,* 2007). In addition, the techniques of image segmentation are grouped into three (Fu and Mui, 1981) viz: *(1) thresholding/clustering, (2) region based, and (3) edge based;* all of which together with classification depends on set parameters such as *scale level, shape factor, smoothness* and *compactness* (Gao and Mas, 2008). Practically, GEOBIA combines spectral, spatial, texture and context information in the process of classification. Operationally, the steps involved in object-based classification are: (i) image segmentation, (ii) rule setting, (ii) training sample, and (iv) classification into information classes.

It is important to examine the context under which regionalization and spatial proximity models are used in satellite image segmentation. This is because; satellite image segmentation may be explained using the *regionalization model* credited to Paul Vidal de la Blache (1845-1918). Based on this model, during image segmentation, images are divided based on certain criteria of homogeneity forming a feature region that requires spatial contingency and geographical proximity of unbroken contiguity (Gao and Mas, 2008). Explaining the application of the concept of *regionalisation* further, Tobler's first law of Geography (or principle of spatial auto-correlation) states that "everything is related to everything, but near things are more related than distant things" (Tobler, 1970). Although two major options of assigning classes in segmented objects are based on (i) membership function classifier, and (ii) nearest neighbour classifier – NNC (Myint *et al.*, 2011), a large number of image segmentation algorithms are based on region growing methods. Following Tobler's first law of Geography, the segmentation approach always provides closed boundary of objects and makes use of relatively large neighbourhoods for decision making (Yu *et al.,* 2006). Since the region growing approac is mostly adopted, it requires consideration of *seed selection*, *growing criteria*, and *processing* order. Some studies have developed hybrid methods in which edge or gradient information has been used in combination with region growing for image segmentation (Gambotto, 1993; Lemoigne and Tilton, 1995 in Yu *et al.,* 2006). The level of membership now depends on the degree to which the objects fulfil the class-describing condition (Matinfar *et al.,* 2007) based on set parameters (Whiteside and Ahmad, 2005).

In view of the above, this research uses an empirical case study of a typical urbanizing environment in comparatively assessing pixel-based (PIXBIA) and object-based (GEOBIA) remote sensing classification methods for large scale rapid mapping with a view to ascertaining the level of reliability in terms of their respective accuracies and fitness-for-use or fitness-for-purpose.

2 Materials and Method

2.1 The Study Area

Aba is a major trading city in the south-eastern part of Nigeria. The study area is geographically located within Latitudes 5^0 3'47''N and 5^0 9' 16''N, and Longitudes 7^0 19' 22''E and 7^0 24' 25'' E respectively as shown in Figure 1. Located on the Aba River, Aba City is made up of many villages with an average elevation of 205 m (673 ft). On the average, the study area has a temperature of 28°C, Wind Speed of 8 km/h, and Humidity of 80%. Though ethnically an Igbo speaking urban space, the geographical influx of people from different parts of the country as a result of socio-economic (mostly trade) and political factors has made Aba a city with different ethnic population.

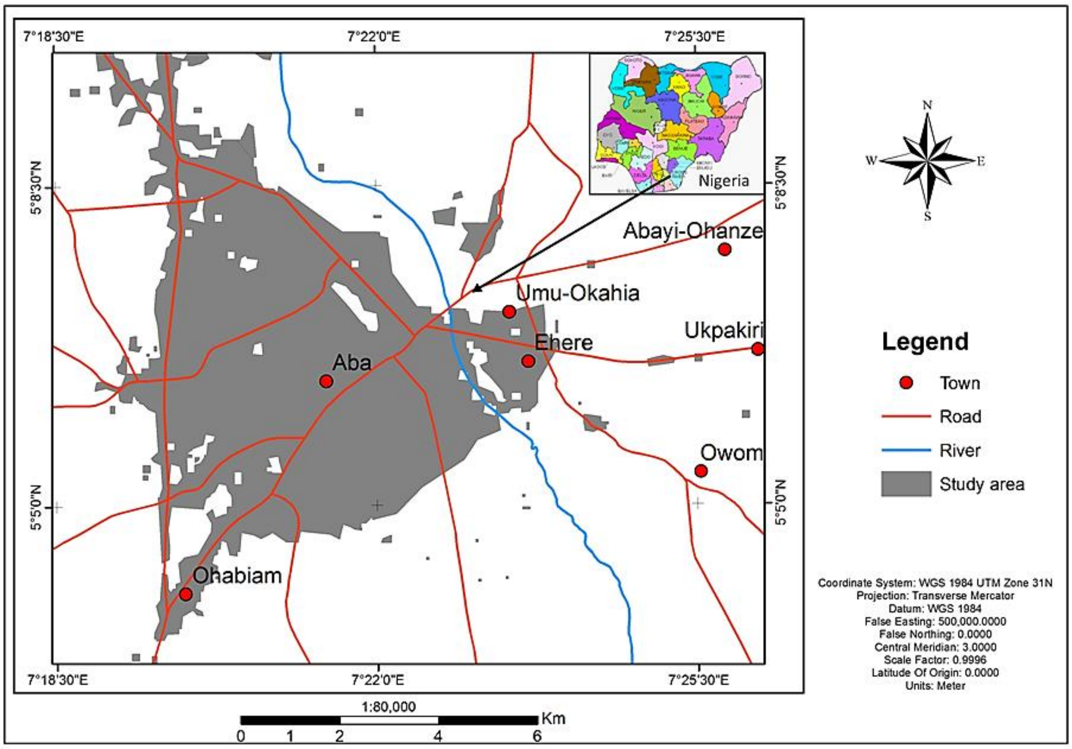

Figure 1. The Study area

The 2014 Population estimate puts Aba at 1,277,300 (Hoiberg, 2010). The study area is surrounded by several oil wells in the neighbouring city of Port-Harcourt, and its major economic contributions are textiles and palm oil (Falola and Heaton, 2008) along with pharmaceuticals, breweries, distilleries, plastics, cement, and cosmetics which made the Ariaria international market to become the largest market in West Africa seconded by the Onitsha main market. In view of the above, Aba city was used in this study as a 'proof of concept' in empirically demonstrating the differences between pixel-based and object-based classification for large scale urban mapping.

2.2 Data collection, analysis and presentation

In this paper, we rely mostly on secondary sources of data which include 2012 QuickBird (0.6m) satellite image covering Aba main town. Other data and information used for the study were sourced from e-libraries of host publishers, books and other ancillary data. The adopted study workflow is shown in figure 2. The methods of data analysis and presentation are explained below.

a) Image analysis

For both methods examined in this study, the landcover classes produced were based on 'Anderson's Landuse and landcover scheme of 1976 (Anderson *et al.*, 1976). Figure 3 shows details of the workflow used in the implementation of the empirical work.

i) The pixel-based image analysis (PIXBIA) method was actualised using the semi-automatic supervised classification approach. The process generally involved a training site selection over region/area of interest (R/AOI) based on inherent knowledge of landuse/cover and ground truth (Verhulp and Niekerk, 2017). The systematic–random sampling technique was used in obtaining the training data (Jensen and Gorte, 2001; Matinfar *et al.*, 2007). The study area was divided into four

(4) quadrants and in every quadrant; at least ten (10) samples each were collected for every landcover class. The randomly collected samples were used to train the computer (semi-automatic) and prescribe the different landuse/cover classes to be classified.

Using ENVI 4.8 software, the maximum likelihood classifier (MLC) which is based on a normalized (gausian) estimate of the probability density function of each class was used because according to Roostaei *et al.* (2012), MLC has a major advantage over other classifiers. Thus, based on the Bayesian probability theory:

"an unknowm pixel X with multispectral values (n bands) is classified into the class (k) that has the maximum likelyhood (max Lk (x))". The likelihood function is given on the assumption that the ground truth data of class *k* will form the gausian (normal) distribution as denoted in equation 1 (Roostaei *et al.,* 2012):

$$L_k(x) = 1/(2\pi)^{n/2} \left| \sum_k \right|^{1/2 exp} \left[-1/2(x-\mu_k)\sum(x-\mu_k) \right] \quad [1]$$

Where μ_k: mean vector of the ground truth data class k$\sum_k$: variance- covariance matrix of k class produced from the ground data and $\left|\sum_k\right|$ is the determinant of $\sum$k.

Though robust and simple, sufficient sample data are required for the MLC algorithm to give best result hence the ten training samples collected from each quadrant in the study area.

ii) The Geo-object-based image analysis (GEOBIA) method was actualized based on image segmentation following rule set (brightness/colour and shape) and scale levels and, finally merging similar objects. Classification into information classes were performed using the fuzzy and Nearest Neighbour Classifier methods (Table 1).

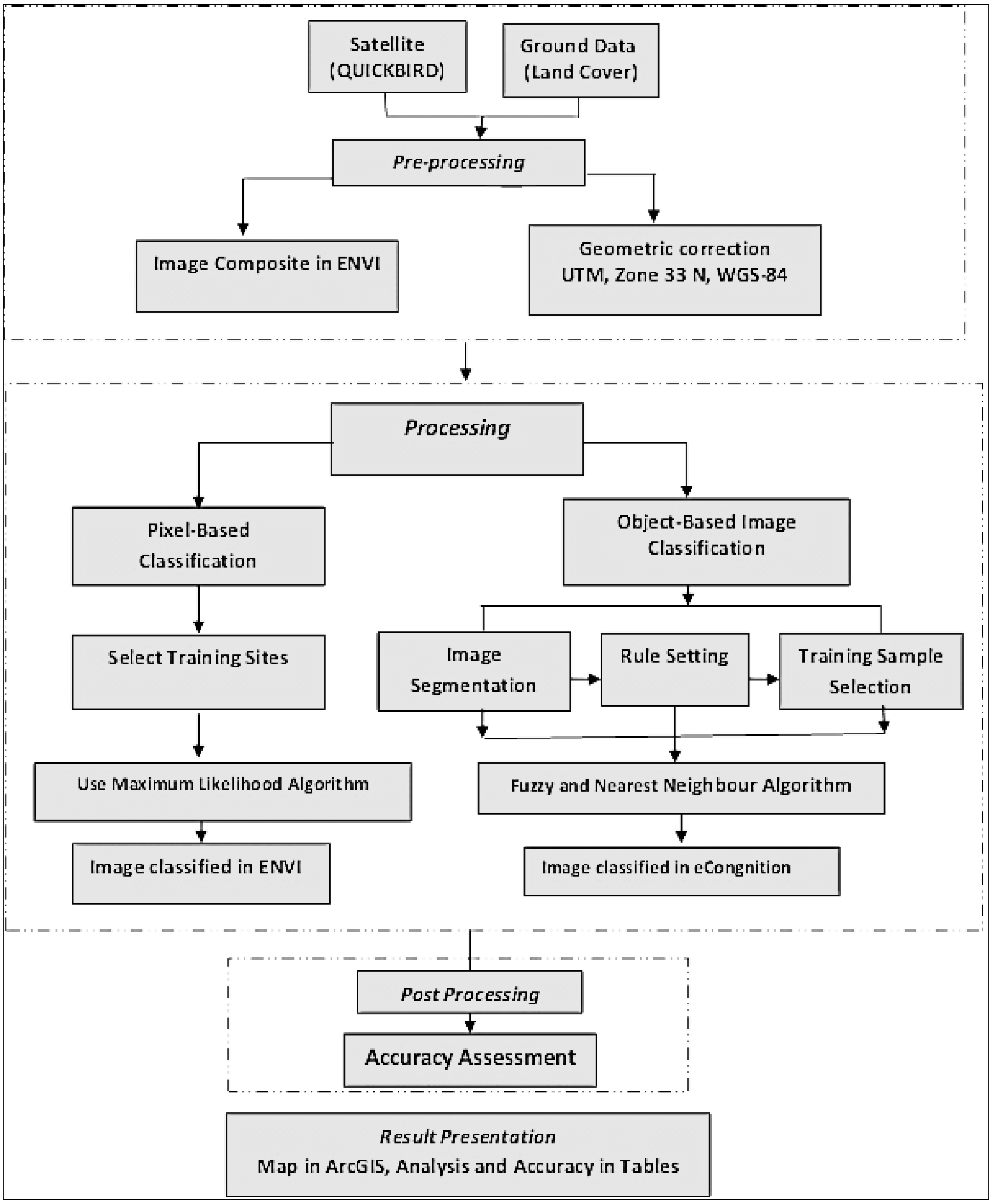

Figure 2. Empirical study workflow

The object-based classification was executed using Definiens (or eCongnition) software after merging and tidying objects into information classes based on set rule for each level of land cover as follows:

Level- 1 set rules is as follows:

- **Builtup:** unclassified with brightness => 120, unclassified with rectangular fit => 0.6 and <=0.8;
- **Bareland:** unclassified with brightness => 120 and <=140;
- **Forest:** unclassified with Red-band=> 70 and <=90;
- **Agriculture:** unclassified with Red-band =>90 and <=100;

Level- 2 set rules is follows:

- **Water**: Nearest Neighbour Classifier

b) Accuracy assessment: Overall Accuracy and Kappa Coefficient Statistical Analysis

Evaluating classification results is an important process in classification procedure ((Lu and Weng, 2007) because classification is incomplete without accessing its accuracy (Matinfar *et al.*, 2007). Confusion Matrix (error matrix) and Kappa Coefficient are both Post Classification (PC) methods for respectively evaluating classification accuracies and comparing classifications agreement to geographic reality (Congalton and Green, 1999; Lu and Weng, 2007; Roostaei *et al.*, 2012). The error matrix (in contingency table) shows the producer (error of omission), user (error of commission) and overall accuracies of classification in percentages (Jensen, 1996). Thus, the higher the accuracy percentage the better. Similarly, the Kappa (K) statistical analysis is 'a discrete multivariate technique used in accuracy assessment' (Congalton and Mead, 1983). Kappa (K) assessment shows the strength of classifications agreement arising from the classification accuracies. The results ranges from 0 – 1; where '0' means no agreement and '1', a perfect agreement (Altman, 1991; Warrens, 2010).

i) The Overall Accuracy (OA) equation (Matinfar *et al.*, 2007) is given as :

$$\mathrm{OA} = \frac{\sum_{i=1}^{c} \mathrm{Eii}}{\mathrm{N}} \qquad [2]$$

Where ***c*** is the number of classes, N is the number of certain classes; **Eii** is the error matrix diagonal cell.

Producer and user accuracies are the mean accuracy value of all classes respectively examined.

ii) Object-based Segmentation Accuracy formula for the segmentation (i.e. the upper bound on classification accuracy), denoted as A(Uλ), is calculated using equation 3 (Liu and Xia, 2010):

$$A(U\lambda) = \sum_{i=1}^{N} \max(mi, j) \,/\, \sum_{i=1}^{N} ni \qquad [3]$$

Where ***U*** denotes the segmentation unit; **λ** denotes the scale parameter at which the segmentation unit is generated; mi,j denotes the number of pixels belonging to the class *j* in the *i*-th image object; and *ni* denotes the number of pixels in the *i*-th image object (Liu and Xia, 2010).

iii) The Kappa (K) statistical analysis equation (Congalton and Green, 1999; Lu and Weng, 2007; Roostaei *et al.*, 2012) is given as:

$$\mathrm{K} = \frac{\mathrm{N}\sum_{i=1}^{k} \mathrm{nii} - \sum_{i=1}^{k} \mathrm{ni{+}n{+}1}}{\mathrm{N}^2 - \sum_{i=1}^{k} \mathrm{ni{+}n{+}1}} \qquad [4]$$

Where **nii** is the number of observations in $\mathbf{i_{th}}$ row and $\mathbf{i_{th}}$ column on the main matrix diagonal, **n+1** is the total number of observations in $\mathbf{i_{th}}$ row and $\mathbf{i_{th}}$ column and N is the total observations.

c) Data presentation and interpretation

The cartographic map embellishments were carried out using ArGIS 10.1 software. Map making was based on conventional cartographic symbols and visual variables such as colour or hue, texture, shape or form, size, pattern, etc. (see Bertin, 1983: Myint *et al.*, 2011). This was aimed at communicating effectively and efficiently to users (Kraak and Ormeling, 2010); most of whom may not be specialist in geoinformation or allied disciplines (see ITC, 2010: 343). With reference to the 1976 Anderson LULC Classification Scheme (Anderson *et al.,* 1976), five landcover classes of (i) Builtup (red), (ii) Bareland (brown), (iii) Thick vegetation or forest (forest green), (iv) Light vegetation or Agric (light green) and (v) Water (blue) were visualized appropriately. The accuracy assessment of both classification methods were presented in Contingency table as percentages (%) while the Kappa Coefficient result ranges between 0 and 1. The closer the Kappa value is to 1, the higher and better the level of classification agreement to reality, and vice versa (Altman, 1991).

3 Results and Discussion

3.1 Pixel-based and object-based classification assessment

Table 1, Figures 3a, b and 4 results show that in the pixel-based classification findings, the Bare-land (including earth roads) and Builtup (including tar-roads) were aggregated as a result of their similarity in reflectance values thus not very effective in separating urban landcover classes when using high resolution images. Conversely, these same features were well distinguished in the object-based approach. The bare-land (especially the Golf Course under preparation when the image was captured by the sensor) is well classified and visualised using **GEOBIA** than in the PIXBIA result (Figure 3). These findings are similar to those of Myint *et al.* (2011).

Table 1: Percentage Composition and Differences in Landcover Classes

	LULC Type	Pixel (No. of pixel)	Object (No. of pixel)	Pixel Distribution (%)	Object Distribution (%)	Differences: Pixel to Object (%)
1.	Builtup	20252935	25099242	54.5	48	-6.5
2.	Forest (Thick Vegetation)	7877365	14622829	21.2	28	+6.8
3.	Bare-land	7350012	3182542	10.0	6.1	-3.9
4.	Water	10388	364686	0.1	0.7	+0.6
5.	Agriculture (Cultivation)	5285276	9057575	14.2	17	+2.8
	TOTAL	***52326874***	***52326874***	***100***	***100***	

In addition, Water, thick and light vegetation covers are also well captured and visualized in the object-based approach as evidenced in the tree canopy shape zoomed at scale 1:500 within the golf course under construction when the image was captured in 2012 (Figure 3b). The high class separability in the object-based approach is because the classification of an object into a given landcover class is based on segmentation (shape/colour) and eventual clustering of end member pixel based on fuzzy theory (0 or 1) and the nearest neighbour principle likened to the regionalisation and proximity concept credited to Vidal de la Blache (1845-1918). Hence, a feature which forms a contiguous shape of interest is classified into one information class based on the established threshold in spectral differences.

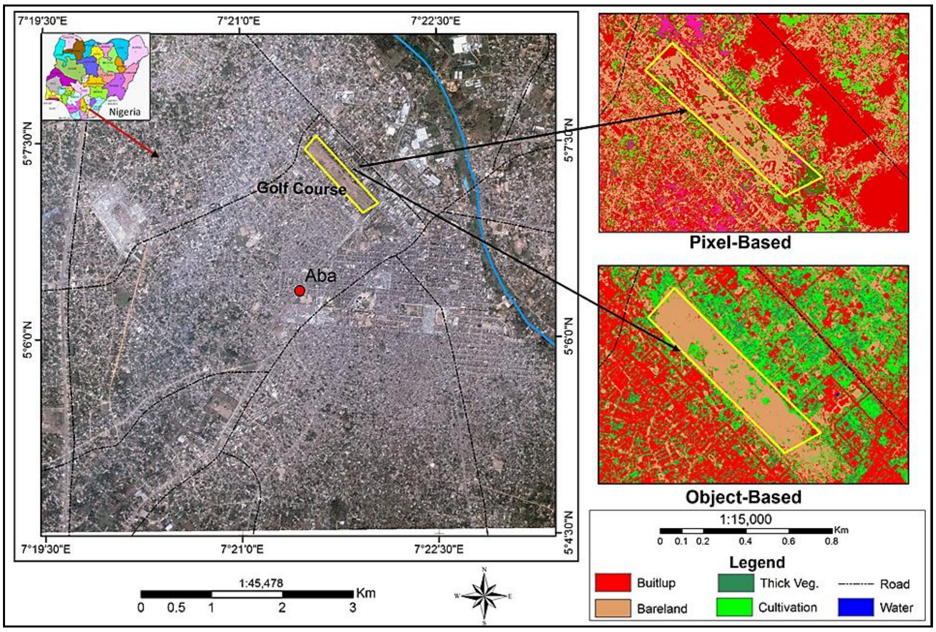

Figure 3a: LULC of Aba: pixel-based method (upper right), object-based method (lower right)

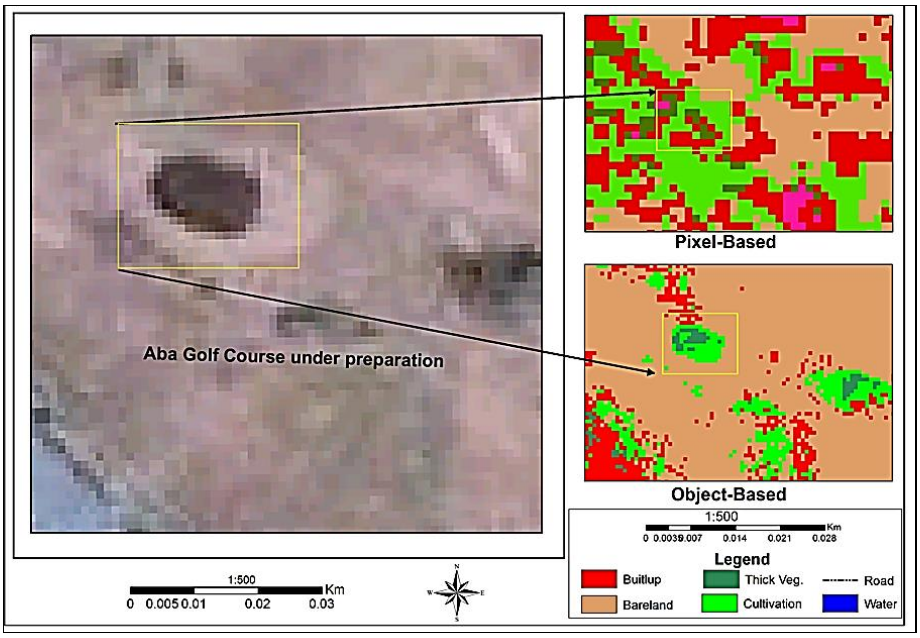

Figure 3b: Scale 1:500 Zoom of pixel-based (upper right) and object-based (lower right) classifications of tree canopy within the cleared golf course within Aba City

Figures 3a and 4 (right) shows that bare-land, water and light vegetation covers were better classified in the object-based approach. The above findings suggest that the object-based analysis had greater potential for extracting landcover classes from high resolution satellite images than the pixel-based as corroborated in a similar study conducted in northern Australia by Whiteside and Ahmad (2005).

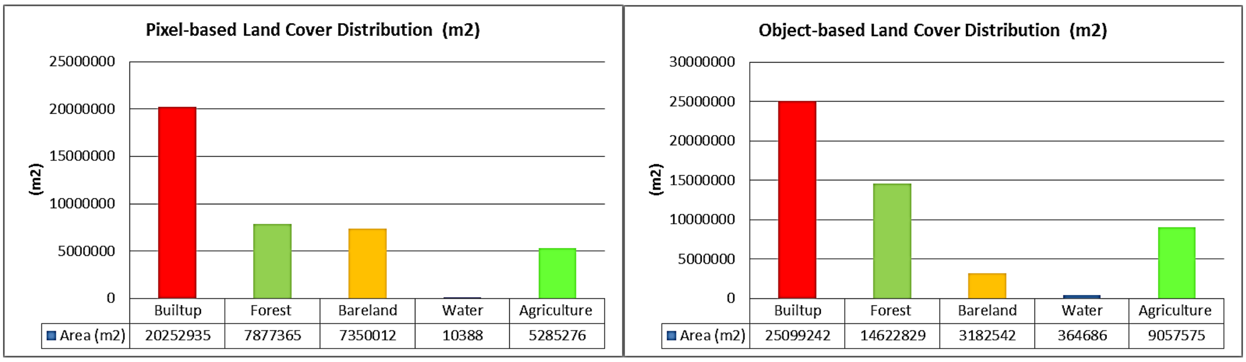

Figure 4: Land cover Composition – (left) pixel-based, (right) object-based

3.2 Accuracy assessment of PIXBIA and GEOBIA classification results

Tables 2 and 3 respectively show that the object-based approach offers the best overall accuracy of 98.75% as against the 79.44% of the pixel-based. Similarly, the object-based approach gave a better reliable producer accuracy (PA = 98.42%) and user accuracy (UA = 96.70%) than the pixel-based of PA = 85.37% and UA = 81.04% respectively.

Table 2: Pixel-based - Confusion matrix showing classification accuracy assessment

Classes	**Builtup**	**Thick Veg.**	**Bareland**	**Water**	**Agric.**	**Total**	**UA**
Builtup	**81440**	883	409	0	416	***83148***	***97.95***
Thick Veg.	7765	**12926**	0	0	642	***21333***	***60.59***
Bareland	11106	1	**8865**	0	18	***19990***	***44.45***
Water	0	0	0	**3739**	0	***3739***	***100***
Agric.	3547	4532	0	0	**6308**	***14387***	***43.8***
Total	**103858**	**18342**	**9274**	**3739**	**7684**	**142597**	***UA = 81.04***
PA	***78.41***	***70.74***	***95.59***	***100***	***82.09***	**PA=85.37**	***OA =79.44***

Kappa Coefficient (K) = 0.62

Table 3: Object-based - Confusion matrix showing classification accuracy assessment

Classes	**Builtup**	**Thick Veg.**	**Bareland**	**Water**	**Agric.**	**Total**	**UA**
Builtup	**103040**	0	0	0	0	***103040***	***100***
Thick Veg.	304	**14601**	0	0	150	***15055***	***96.98***
Bareland	0	0	**10321**	0	0	***10321***	***100***
Water	0	0	0	**3821**	0	***3821***	***100***
Agric.	496	833	0	0	**8534**	***9863***	***86.53***
Total	103840	15434	10321	3821	8684	**142100**	***UA=96.70***
PA	***99.23***	***94.60***	***100***	***100***	***98.27***	***PA=98.42***	***OA=98.75***

Kappa Coefficient (K) = 0.97

In specific, Bare-land (44.45%) and Light Vegetation (43.8%) had very low user accuracies in the pixel-based approach. Result of Kappa Coefficient level of classification agreement to geographic reality shows that the object-based approach had a ‘very good’ agreement of K= 0.97 while the pixel-based had a ‘good’ agreement of K=0.62. The findings above suggest that the object-based approach is better relied on than the pixel-based (Warrens, 2010) especially when dealing with large scale mapping using a high resolution satellite image such as QuickBird. The lower Kappa value of K=0.62 for the pixel-based is partly due to the associated mixed classification (MIXELS) resulting from contiguous area of divergent DN values. The study shows that the Object-based, is therefore, a better ‘soft-landing’ when carrying out rapid urban mapping.

3.3 Implication of findings

The findings in this paper further corroborate previous studies (Whiteside and Ahmad, 2005). It also further reaffirms that the main advantage of GEOBIA classification over the PIXBIA is that the basic processing units are image objects or segments (aggregates of pixels) which represents real world feature. In addition, object-based approach is a good alternative to traditional pixel based method because it is able to overcome the low resolution problem of salt-and-pepper effect which invariably reduces the local spectral variation caused by crown textures, gaps, and shadows (Yu *et al.,* 2006). Furthermore, the objects in object-based approach as observed from figure 3b are spectrally more homogeneous with distinct boundaries (of spatial contiguity), compactness and representative within individual regions than between their neighbours as observed in the pixel-based result. In other words, it has extended mapping capabilities by incorporating, within the traditional spectral mix input, the spatial and textural attributes of homogenous sets of pixel which are spatially auto-correlated from which individual objects are derived (Flores *et al.*, 2009). For in instance, in high spatial resolution imagery, a group of pixels can represent the characteristics of land-cover targets better than single pixel; so, groups of adjacent pixels are organized into objects and each treated as part of a minimum classification unit (Yu *et al.,* 2006).

It is further re-emphasized that the object-based method also has superior performance in classifying vegetation and water areas with a high capability in separating roads and barren (bare-land) from builtup (Roostaei *et al.*, 2012). The ancillary data such as the vector layers utilised within object-based classification is advantageous in improving the classification process (Whiteside and Ahmad, 2005) as shown in Figure 3a true colour band composition of satellite image of part of Aba city. Another advantage of object-based method in large scale mapping is that a thematic output composed of geographical entities labelled with land cover classes can be directly sorted into GIS databases, creating or updating usable geoinformation (Hay and Gastila, 2006). Though best for high resolution data, it is informative to also stress that GEOBIA higher accuracies are also guaranteed when compared to the PIXBIA classification approach.

It is instructive to add here that the object-based method equally has its limitations such as over-segmentation or under-segmentation which invariably affect classification accuracy (Liu and Xia, 2010). This may arise from small gaps between discontinuous edges which allow merging of dissimilar regions (Kermad and Chehdi, 2002). It may also cluster dissimilar contiguous pixel which represents a completely different land cover feature. For instance, the edge-based segmentation in object-based approach has not been very successful because of its poor performance in the detection of textured objects (Kermad and Chehdi, 2002). This study has further shown that appreciable reconnaissance knowledge of the study area through field check is a necessity for improved classification and reliable result.

4 Summary and Conclusion

This study examined the concept of Remote Sensing, pixel-based image analysis (PIXBIA) and Geo-object-based image analysis (GEOBIA) classification methods and large scale mapping. It consequently reviewed the role of Remote Sensing in geospatial data provision in geographic studies. It further highlighted the prevailing conditions of mapping from the conventional approach (i.e., land surveying, photogrammetry, etc.) to satellite Remote Sensing. In particular, the study acknowledged that as a result of the rigour in dataset collection, huge financial cost involved, time taken to process them, and envisaged higher accuracy requirements in analysing and mapping geographic data, there is the need to choose wisely the best approach in timely delivering highly accurate information in a manner that they can be readily used for decision making with less errors. Using 2012 Quickbird satellite image covering Aba city in South-eastern Nigeria for an empirical study, the paper examined the pixel-based and object-based methods of classification. The study further assessed the classification accuracies (error matrix) for both classification methods and also tests the level of accuracy agreement to geographic reality using Kappa Coefficient statistical analysis.

The study shows that the object-based approach provides a higher overall accuracy (OA) of 98.75% than the pixel-based approach (79.44%). In addition, the object-based approach also gave a better producer accuracy (PA=98.42% > PA=85.37) and user accuracy (UA=96.70 > UA=81.04%) respectively. With a Kappa Coefficient of K=0.97 (very good) for object-based approach and K=0.62 (good) for pixel-based, the object-based approach proved to be better for separating tree canopies from bare-land especially when carrying out rapid large scale mapping. This include cadastral or property map as obtains in the lands, urban planning and surveys departments in Nigeria (Ufuah, 2003). The higher accuracy of object-based approach over the pixel-based corroborates similar studies conducted in Northern Australia by Whiteside and Ahmad (2005) and Myinth *et al.* (2011). In view of the above findings, the object-based classification of high resolution images is recommended for rapid large scale mapping especially when funding is limited for flying airplane for the production of orthophotos.

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