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Blackett, M, Chima, C & Trodd, N

Original citation & hyperlink:
Blackett, M, Chima, C & Trodd, N 2017, 'Assessment of Nigeriasat-1 satellite data for urban land use / land cover analysis using Object Based Image Analysis in Abuja, Nigeria' *Journal Geocarto International*, vol (in press), pp. (in press)
http://dx.doi.org/10.1080/10106049.2017.1316778

DOI 10.1080/10106049.2017.1316778
ISSN 1010-6049
ESSN 1752-0762

Publisher: Taylor and Francis

This is an Accepted Manuscript of an article published by Taylor & Francis in Geocarto International on 3rd May 2017, available online: http://www.tandfonline.com/10.1080/10106049.2017.1316778

Publisher: Taylor & Francis
Journal: *Geocarto International*
DOI: http://dx.doi.org/10.1080/10106049.2017.1316778

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Acknowledgements- The author wishes to thank Nigerian Space Research Development Agency, SPOT OASIS Project, Global Land Cover Facility and Abuja Geographic Information Systems for making the data available for this research.

Assessment of Nigeriasat-1 satellite data for urban land use / land cover analysis using Object Based Image Analysis in Abuja, Nigeria

Abstract

This study assesses the usefulness of Nigeriasat-1 satellite data for urban land cover analysis by comparing it with Landsat and SPOT data. The datasets for Abuja were classified with pixel and object based methods. While the pixel based method was classified with the spectral properties of the images, the object based approach included an extra layer of land use cadastre data. The classification accuracy results for OBIA show that Landsat 7 ETM, Nigeriasat-1 SLIM, and SPOT 5 HRG had overall accuracies of 92%, 89% and 96% respectively, while the classification accuracy for pixel based classification were 88% for Landsat 7 ETM, 63% for Nigeriasat-1 SLIM and 89% for SPOT 5 HRG. The results indicate that given the right classification tools, the analysis of Nigeriasat-1 data can compare with Landsat and SPOT data which are widely used for urban land use and land cover analysis.

Keywords: Nigeriasat-1, Object Based Image Analysis, Land use/Land cover, Abuja

1. Introduction

Urban areas contain half of the world population (UNFPA 2011) and more than a third of world urban population live in large cities (United Nations 2011). This makes cities places of primary concern to administrators because they generate a larger proportion of national economic activity and provide greater employment opportunities and services due to their diversified economic base. The favourable economic environment ensures continued growth of cities which in turn may lead to some diseconomy as the large concentrations of people produce huge demands for available resources (Oyesiku 2010). This drives up rents and cost of land in the core of the city leading to development of sub-urban settlements or sprawl as people seek cheaper land in the outskirts. This may also result in increased transportation costs as distance and travel time to work increase (Frank *et al.* 2000, O'Meara 1999, Oyesiku 2010). Other undesirable effects of increased urban population may, include congestion, pollution, poor welfare and health, increased social disorganisation, unemployment, economic stratification, and overcrowding (Pacione 2009). Additionally, cities in developing countries may experience the following - primacy of growth, rural-urban migration, inadequacy and over utilisation of housing/basic services, infrastructure and informal settlements (Ayeni 1981). According to UNFPA (2015,p.106)

> "rapid urban development has concentrated populations and taxed environmental resources, making cities epicentres of risk. Disaster preparedness planning needs to better reflect the likelihood that the face of crisis will be increasingly urban. As part of managing risks, city and national planners need the capacities, resources to orchestrate growth well".

Some of these resources are the large archives of satellite data which can be used to map and take quick inventory of urban areas.

Satellite data can be classified with pixel or object based techniques. However, classification of satellite data in urban areas with pixel based approaches presents its own challenges. Pitfalls of pixel based classification like the mixed pixel problem (Mather 1999, Welch 1982) makes it difficult to accurately classify satellite data and produce classification accuracies above 80% (Mather 1999). The integration of remote sensing and ancillary data like socio-economic data and geocoded cadastral information helps to characterise land use and give proper interpretation. Barnsley and Barr (2000) noted that identification of complex urban features is one of the human photo-interpretation techniques that have developed with time. They also postulated that if this process can be formalised into a means of digitally measuring features and patterns in remote sensing, then it may be possible to evolve an automated or semi-automated system for urban land use mapping. With the advent of geocoded cadastral data, high resolution satellite sensors and several other satellites owned by countries such as the USA, Russia, Brazil and Nigeria among others, urban monitoring approaches can now be undertaken at a higher thematic and geometric level (Maktav, Erbek and Jurgens 2005, Taubenbock, Esch and Roth 2006). However, with pixel sizes becoming smaller than the imaged objects, object-oriented classification methodologies came into focus (Benz *et al.* 2004, Blaschke and Strobl 2001, Blaschke *et al.* 2000, Blaschke 2010).

This paper considers object based image analysis (OBIA) of Nigeriansat-1 satellite data for urban land use and land cover mapping. Nigeriasat-1 is one of nine satellites that form the Disaster Monitoring Constellation (DMC) (Surrey Satellite Technology Ltd 2016) and was launched in 2003. All the DMC satellites carry a Surrey Linear Imager sensor (SLIM) and captures data in the green, red and near infrared (NIR) bands at 32m ground resolution. Initial land cover studies with Nigeriasat-1 data were carried out by researchers at the behest of the Nigerian Space Research and Development Agency (NASRDA) to ascertain the potentials of the imagery from the satellite. Omojola (2004) evaluated the potentials of the datasets for rural and urban land cover mapping in Ekiti state, southwest Nigeria. The study noted that mapping of observable urban areas in the state from Nigeriasat-1 was limited to mere outline or extent detection as the internal structure of the towns were virtually unobservable. Furthermore in the case of the rural landscape, Omojola (2004) observed that the coarse resolution of the data tended to average together separate components of the landscape thereby making it difficult to map specific classes in a complex mosaic of the rural landscape. In a separate study conducted by Olaleye, Sangodina and Hamid-Mosaku (2004), also in southwestern Nigeria, the potentials of Nigerisat-1 for mapping transportation networks was tested. The results show that errors of between 0.4 - 2% were present in the route location maps compiled from Nigeriasat-1. This was blamed on the low tonal variation, which leads to low contrast of the image features, noting that image enhancement methods are of limited success when image quality is poor. A study to evaluate the potentials of Nigeriasat-1 data to assess water resources was also carried out by Ibrahim (2004)and the result showed that water bodies could be easily identified, but it was difficult to identify settlements due to spectral confusion with other features like hills and irrigated farmlands, but these ambiguities were cleared during field visits. In the identification of potential tourism sites, the limitations of Nigeriasat-1 data included low spatial resolution and poor visibility due to cloud cover within the study area. In addition, it was noted that ancillary data was required to identify features because spectral signatures for some land cover types, were similar in several bands (Ayeni, Uluocha and Saka 2004). For the purposes of broad land cover mapping the Nigeriasat-1 imagery was able to compare with Landsat TM. A combination of both datasets have been used to study natural phenomena like decreasing water bodies in Lake chad basin (Babamaaji and Lee 2014) and the regional development in parts of Ekiti state in Nigeria (Ojo and Adesina 2010) with some success. However, some artefacts in the Nigeriasat-1 imagery like alternating striping and smooth surfaces across the imagery meant that linear features like minor roads and minor waterways could not be identified (Oyinloye, Agbo and Aliyu 2004). One common thread in all the reviewed studies that used the Nigeriansat-1 data was that they applied pixel based approaches to the study of the Nigeriasat-1 data. Pixel based procedures analyse 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 (Weih and Riggan 2010). Often spectral properties of the datasets are not enough to extract useful information from satellite imageries and this maybe the case with studies that observed the limitations of Nigeriasat-1 data. The emergence of OBIA presents new opportunities to use Nigeriasat-1 for the study of urban areas. In OBIA contextual information is taken into account and it is also possible to combine satellite data and ancillary data using data fusion techniques (Pohl and van Genderen 1998). This paper compares the classification accuracy of urban maps derived from Nigeriasat-1 data with Landsat and SPOT which Blaschke (2010) referred to as the 'workhorses' of satellite remote sensing and GIS studies. This investigation is part of a larger study to assess the use of multi-date/multi-sensor satellite remote sensing to monitor and model urban growth in African cities. Given the long term objective of combining information from multiple Earth observation satellites, this paper presents a better understanding of the compatibility of Nigeriansat-1 data and other data like SPOT and Landsat data. Hence the specific objectives of this research are to:

1) Design an object based classification method to extract urban land cover and land use,

2) Validate a method to extract Land use/Land Cover in developing countries from multiple sources of remotely sensed data, and

3) Apply the method developed in objective 2 to extract LULC data of Abuja for 1991 to 2006

2. Methods

2.1 Study area

Insert Fig.1 here

In order to achieve the objectives of this study satellite image of Abuja and vicinity was used as a case study. Abuja is one of the relatively new and emergent cites with modern urban plans which can serve as ancillary data for analysis. The city is located between latitude 8° 52' and 9° 07' North and longitude 7° 22' and 7° 32' East in the geographical centre of the country (Figure 1). Planned in 1976, the area covered by the urban plan occupies approximately 800 square kilometres. According to the Nigerian census Abuja grew from a population of 107,067 in 1991 when it officially became the seat of government in 1991to 590,400 in 2006. It is estimated to be 3,300,000 in 2020 (UN-Habitat 2014).

2.2 Data sets

Three cloud-free images were acquired. The scenes were captured by Landsat ETM+, Nigeriasat-1 SLIM and SPOT-5 HRG (Table 1). They were all acquired during the dry season to reduce the effects of seasonal variations in vegetal cover and solar illumination.

Insert Table 1 here.

2.3 Image Classification using pixel and object based image analysis.

A four category land cover classification scheme, adapted from Anderson et al. (1976), was developed from field survey in 2011. Four land cover types were classified namely: built up, vegetation, water body and bare (soil) surface

The satellite imageries were classified using three different approaches. These were designed to test the classification methods and assess how they performed with each imagery. Subsequently accuracy assessment was performed on all the classified images with the error matrix.

a) First, the satellite images were classified with Maximum Likelihood Classification, a pixel based method.
b) Secondly, they were classified with OBIA using only the spectral properties of the images.
c) Finally they were classified with OBIA using a combination of the cadastre data and spectral properties.

2.3.1 Selection of sampling sites

In order to enable direct comparison between the three classification approaches or experiments, similar sampling sites were prepared and imported as X and Y coordinates into the pixel based and object based classifiers. The X and Y coordinates were prepared using stratified random sampling to select training sites in such a way that they were spread throughout the study area. The trade-off faced in the development of the training data is that of having sufficient sample size to ensure the accurate determination of the statistical parameters used by the classifier and to represent the total spectral variability in a scene

(Congalton and Green 1999, Congalton 2001) without going past the point of diminishing returns (Lillesand, Kiefer and Chipman 2008). Due to the nature of stratified random sampling design, some land cover types may be under-represented in the selection of samples. To ensure that all land cover classes were represented sampling was allocated with respect to variability within each land cover category (Congalton and Green 1999, Lillesand, Kiefer and Chipman 2008).

Using ArcMap (within the ArcGIS 9.1 environment) grid areas measuring 1km^2 were generated over the images of the datasets. In four separate iterations, the grid areas covering each land cover area were selected and populated with 150 random points using the Hawth's tools extension for ArcGIS 9.1. Then based on the variability of the land cover type samples were selected. For example out of the 150 points generated for the built up areas the first 50 points were selected. The rest of the training locations were selected as follows; first 50 out of 150 for vegetation,first 30 out 150 for water bodies and first 20 out of 150 for bare (soil) surface. A total of 150 training locations were selected for all the land cover classes.

2.3.2 Per pixel classification

Clusters of pixels that fall directly or near the imported X and Y coordinates were delineated and saved as signature files. Emphasis was made to zoom in to ensure that areas delineated contained homogenous pixels representing a single land cover category. Subsequently the signature files were used for supervised Maximum Likelihood Classification.

2.3.3 Object based classification

In respect of the OBIA (within Definiens 5.0 software environment), before the classifications could proceed the first task was to segment the image into object primitives. The second and third experiments used OBIA methods; the difference was to determine if there is a significant difference between the segmentation performed with the thematic layer and the segmentation performed without it. The second experiment was segmented without the thematic layer using only the spectral properties of the images, while the third experiment was segmented with the thematic layer switched on. Three image object levels were created. The actual classification was on image object level 2. Image object level 3 consisted of image objects that were identical to the polygons of the thematic layer and image object level 1 formed sub-object to level 2. Areas outside the coverage of the thematic layer were segmented based only on local homogeneity criteria without the spatial constraint of parcel boundaries shapefile. The segmentation parameters remained the same in both iterations. The image segmentation parameters are shown in Table 2. Portions of the segmented images before the images were classified are shown in Fig. 2 below.

Insert Table 2 here

Insert Figure 2 here

2.3.4 Use of prepared training sites for OBIA classification: After the segmentation procedure, the X and Y coordinates were imported and used to create Training Areas (TA) masks (Fig. 3) that were later used to classify the images. The image objects that corresponded with the imported coordinates were selected as training samples as shown in Figs. 4 (a) and (b)

Insert Figure 3 here

3.4.5 Classification accuracy

The error matrix was used to calculate the accuracy of the classification (Foody 2002). The error matrix can be used to calculate several measures of map accuracy like Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), Kappa Index of Agreement (KIA) and Conditional Kappa (CK). Kappa Index of Agreement expressed as k (*KHAT*) is a measure of how well the remotely sensed classification from the automated classifier agrees with the reference data (Congalton 2001, Landis and Koch 1977). k = is defined as

Insert Equation 1 here

Conditional Kappa is measure of how well individual land categories are classified in the error matrix. Kappa values are measured on a scale of 0-1, such that 0.80 (i.e. 80%) represents strong agreement, 0.40 and 0.80 (i.e. 40–80%) represents moderate agreement and a value below 0.40 (i.e. 40%) represents poor agreement.

The sampling sites for the accuracy assessment were selected from random sampling using different sets of coordinates from the training sample locations. Stratified random sampling, similar but slightly different from the procedure used earlier for the selection of training parcels was used. The difference this time was that the selection of the accuracy assessment locations was different for each of the land cover classifications. This was deemed necessary because the area extent of the land cover development varied in each of the classification outputs. The sampling sites had to spread across entire classified area for each image to ensure that all land cover developments were considered in the accuracy assessment. For OBIA, the X and Y coordinates were imported into the classifier and used to create a training area mask used for the accuracy assessment.

Insert classified images near here (Figures 4 to 12)

4 Results and Discussion

4.1 Assessing the classification accuracy assessment.

Accuracy assessment is a key component of any project employing spatial data, which helps to ensure that the resulting information has enough quality to be used for decision making processes (Congalton 2001). Anderson *et al.* (1976) recommended that minimum level of classification accuracy, in the identification of land use and land cover categories from remotely sensed data, should be at least 85%. This suggestion is particularly relevant in the identification of broad land cover classes, such as those in Anderson's Level 1 land cover mapping (Foody 2008), which has been used for the identification of land cover classes from sensors like Landsat 7 ETM (28.5m), Nigeriasat-1 SLIM (32m) and SPOT 5 HRG (10m) in this study.

The individual classification accuracy for the 3 datasets showed that Overall Accuracy (OA) for the land cover maps produced from Maximum Likelihood Classification (Table 3) were 88% for Landsat 7 ETM, 63% for Nigeriasat-1 SLIM and 89% for SPOT 5 HRG. These figures showed that in terms of Overall OA the Nigeriasat-1 data had the lowest percentage. The Kappa Index of Agreement (KIA) also showed that the land cover map from Nigeriasat-1 recorded a moderate agreement (0.50) with the reference data. While the maps produced from Landsat 7 and SPOT -5 recorded a strong agreement at 0.83 and 0.85 respectively. The reasons for these low accuracy results in the land cover map produced from the Nigeriasat-1 data were evident when the Conditional kappa for each of the classified categories was examined. As shown in Table 3, two of the land cover categories, water body (0.00) and bare surface (0.17), had very low agreement with the reference data. These two categories contributed to the low OA of the Nigeriasat-1 classification. The bare surface category was confused with vacant lands in built up areas and the waterbodies were full of impurities and algal blooms which resulted in confusion with the vegetation category. There has been an increase in developments around the lake edges as residential/commercial land use and roads continue to expand. Natural activities like run off from rainwater carry silt into water bodies leading to eutrophication (silting and algal bloom) within the receiving water bodies.

Insert Table 3 here.

The result of the Maximum Likelihood Classification shows that the classification of the Nigeriasat-1 data did not have a satisfactory classification accuracy that would permit its usage for land use or land cover analysis. According to Foody (2002), accuracy assessment helps to determine if maps produced from land use/ land cover classification have sufficient or "insufficient quality for operational applications". On the other hand the overall accuracy in the error matrix results achieved with OBIA was higher than those achieved from the Maximum Likelihood Classification in respect of the Nigeriasat-1 and SPOT 5 classifications. As earlier shown in Table 3 (Maximum Likelihood Classification) the OA for Nigeriast-1 was 63%, Landsat was 88% and SPOT 5 was 89%. With OBIA, the datasets returned the values of 87%, 88% and 94% respectively. The kappa index of agreement from the OBIA analysis also showed strong agreement between the datasets and reference datasets.

Insert Table 4 here

Insert Figure 13 here

From Table 4 and Fig. 13, the Conditional kappa for each category also showed strong agreement for water body and vegetation in the three land cover maps. In the built up category the Conditional Kappa showed moderate agreement for the three maps. However, the bare surface category showed low agreement for the maps from Landsat 7 and Nigeriasat-1 while showing strong agreement for the SPOT 5 map. The moderate to low agreement between the land cover maps and the reference data suggests that land cover maps produced from Landsat 7 and Nigerisat-1 classifications do not meet the criteria for inclusion in a mapping project because it had insufficient quality.

It has been noted that sometimes spectral information is not enough for image analysis (Definiens 2006). Therefore to improve the results an extra layer of ancillary data was integrated into the OBIA process to improve the classification. This extra information came in the form of the Abuja land use cadastre. The results of the error matrix of the OBIA with the cadastre presented in Table 5 show that OA for three land cover maps are Landsat7 - 92%, Nigeriasat-1 89% and SPOT- 96%. In addition, the KIA shows strong agreement with the reference data as follows Landsat 7 - 0.82, Nigeriasat-1- 0.81 and SPOT 5 -0.83. The conditional kappa (Fig. 14) per category also shows that the three land cover maps have moderate to high agreement. Maps from Nigeriasat-1 and Landsat7 have 0.46 and 0.51 respectively for the bare surface category while the SPOT-5 has 0.89 for the bare surface category. A marked departure from the values recorded in the pixel based classification especially for the water body category which had a conditional kappa value of 0 (refer to Table 3) in the land cover map produced from Nigeriasat-1 SLIM data.

Insert Table 5 here.

Insert Figure 14 near here.

5 Conclusion

This research has demonstrated that conventional classification approaches based on the spectral properties of individual pixels of Nigeriasat-1 SLIM data are less likely to make a substantial contribution to urban land cover analysis than SPOT-5 HRG and Landsat7 ETM+ data. Data fusion techniques that provide a framework to process data at the object level open up the prospect of using Nigeriasat-1 data as part of a multi-date/multi-sensor study of land cover. Where land parcel boundary data are widely available, as found for several of the 'new' capital cities of African nations, Nigeriasat-1 data could be used to support an OBIA approach to urban monitoring and modelling. Further research in this direction is encouraged given the growing archive of data from the DMC mission. This research also shows that given the right analysis tools and supporting data Nigeriasat-1 data can compare with Landsat and SPOT data in terms of classification accuracy and therefore useful for mapping purposes.

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$$k = \frac{observed\ accuracy - chance\ agreement}{I - chance\ agreement} \qquad \text{Equation 1}$$

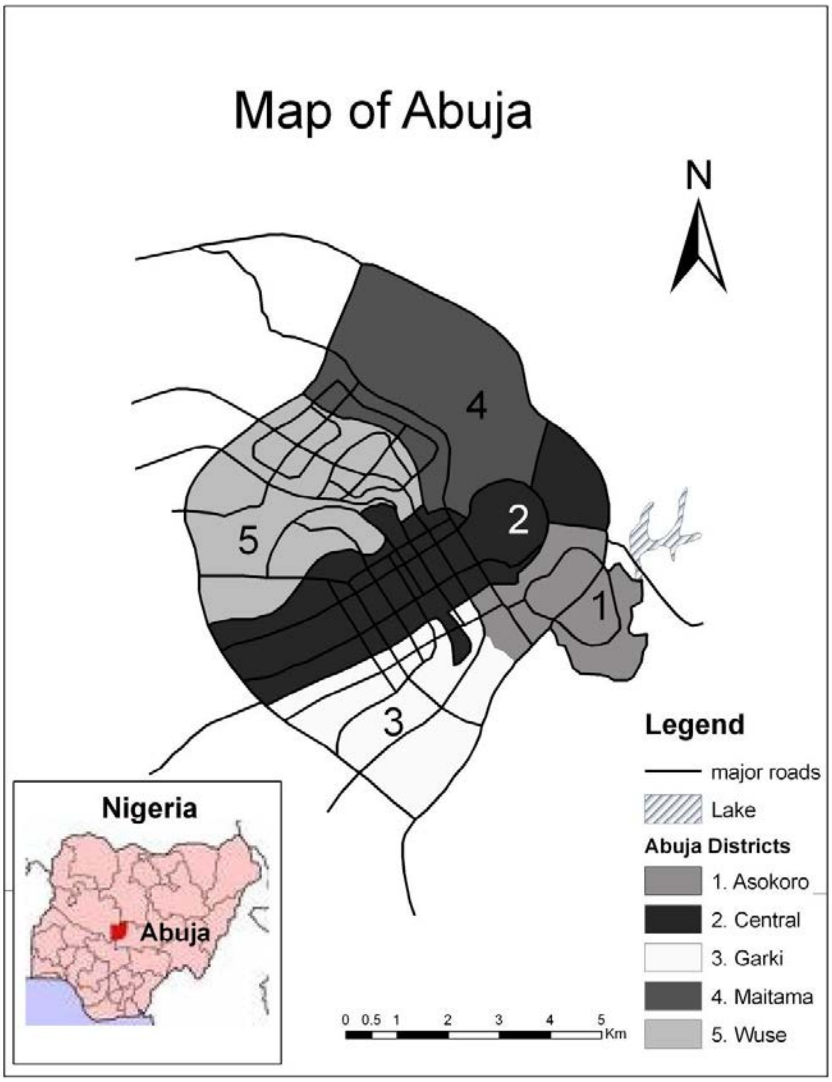
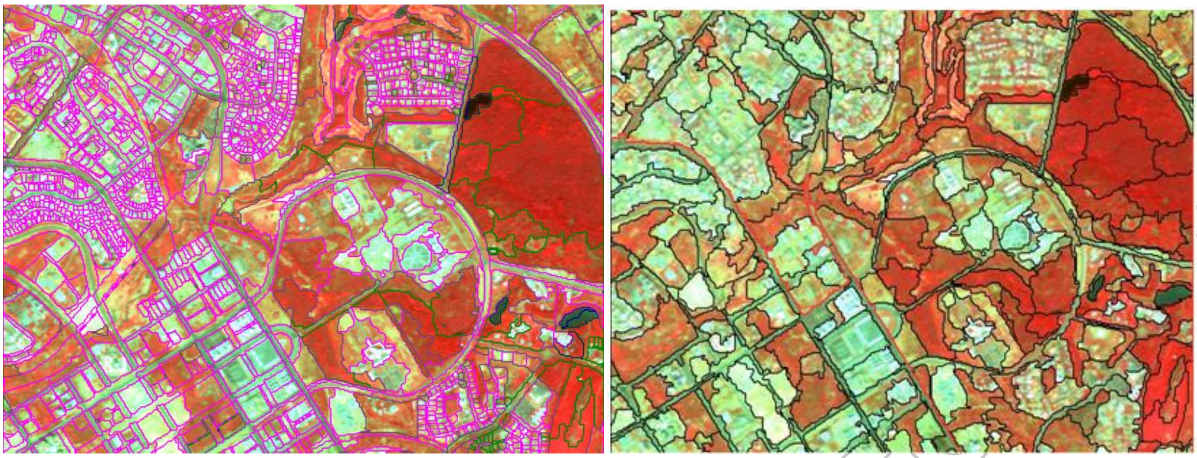
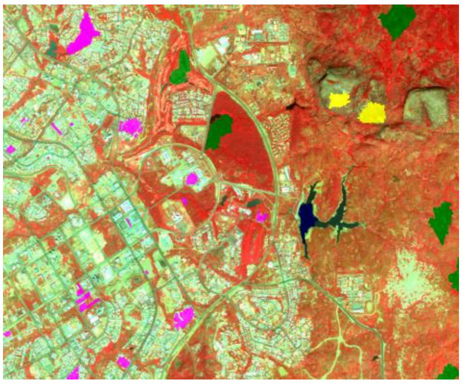


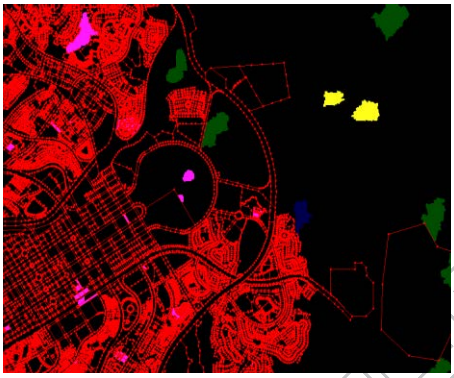
Fig. 1. Map of Abuja



Figs. 2a & 2b Screen shots of Abuja image segmented with land use cadastre (left 2a) and spectral properties (right 2b)

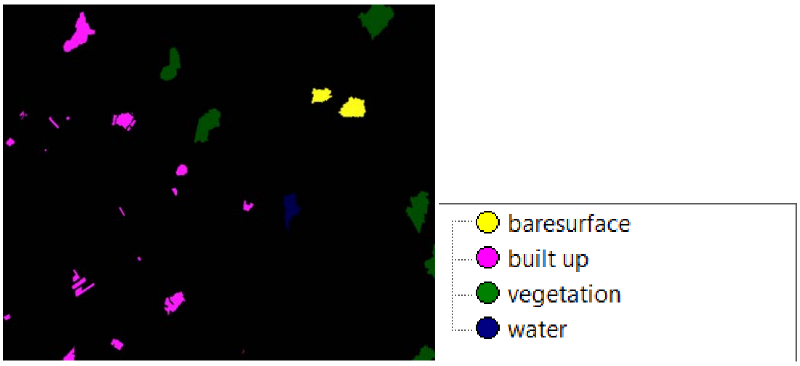


(a) Sample objects selected on satellite image



(b) Sample objects selected on fusion of satellite image and cadastral data

(c)



(d) Training Area mask used for classification

Fig. 3 Training Area mask used to classify the Images in OBIA. Sample objects are selected based on x and y coordinates of the imported training sites. The Training Area mask ensures that the same sample locations are used as training sites for the classification of all the images.

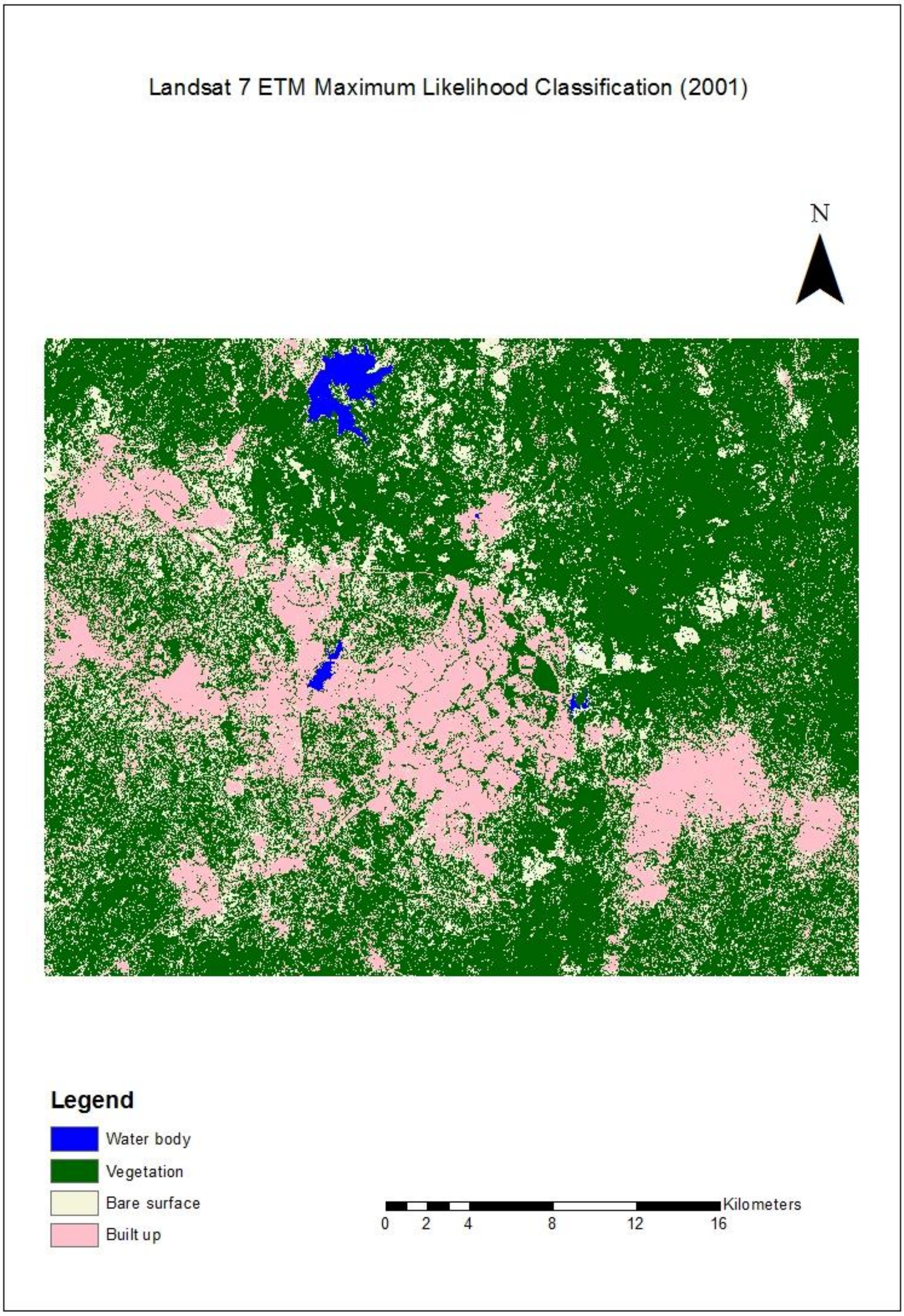


Fig.4: 2001 Land cover map produced by Maximum Likelihood Classification

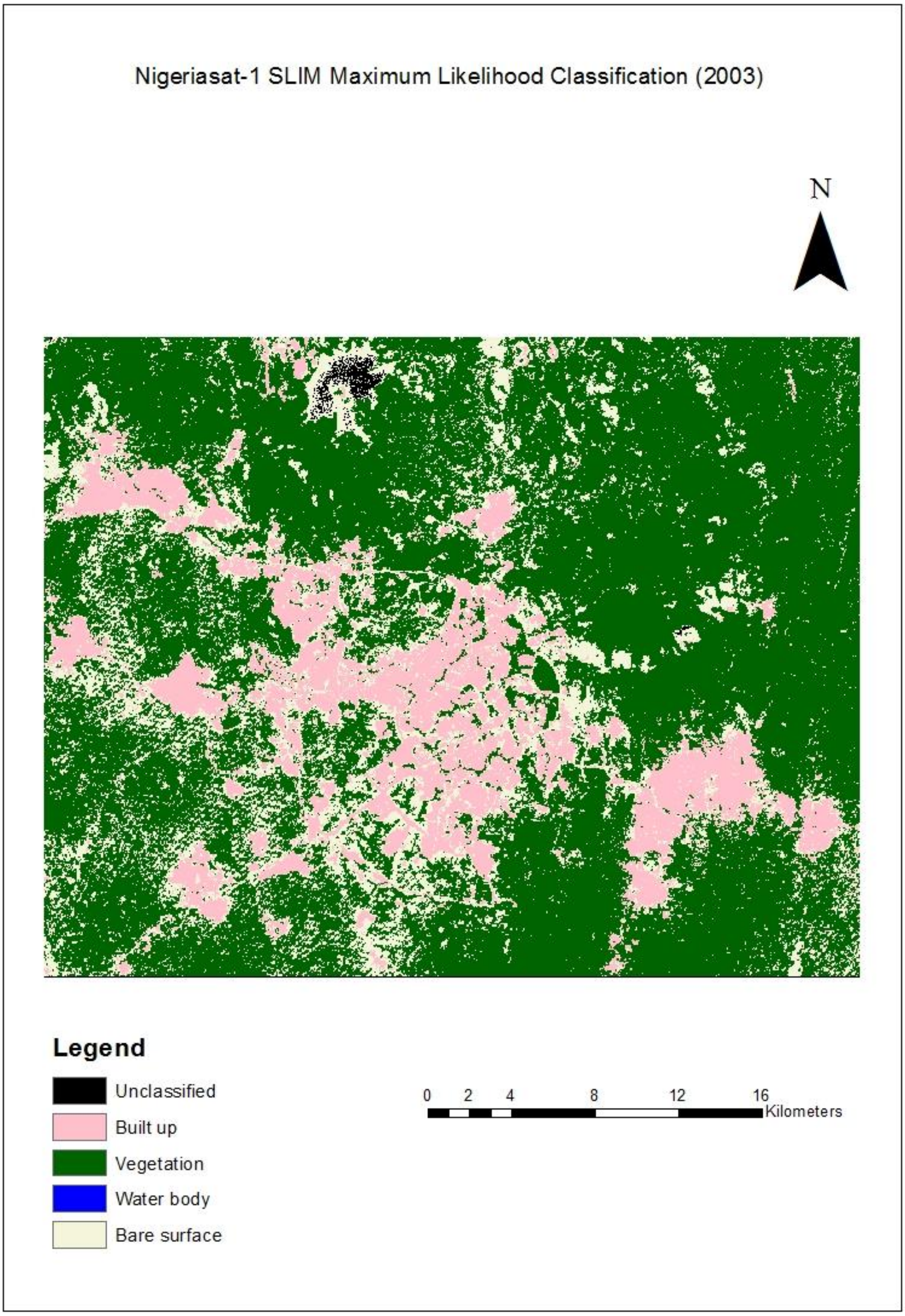


Fig. 5: 2003 Land cover map produced by Maximum Likelihood Classification

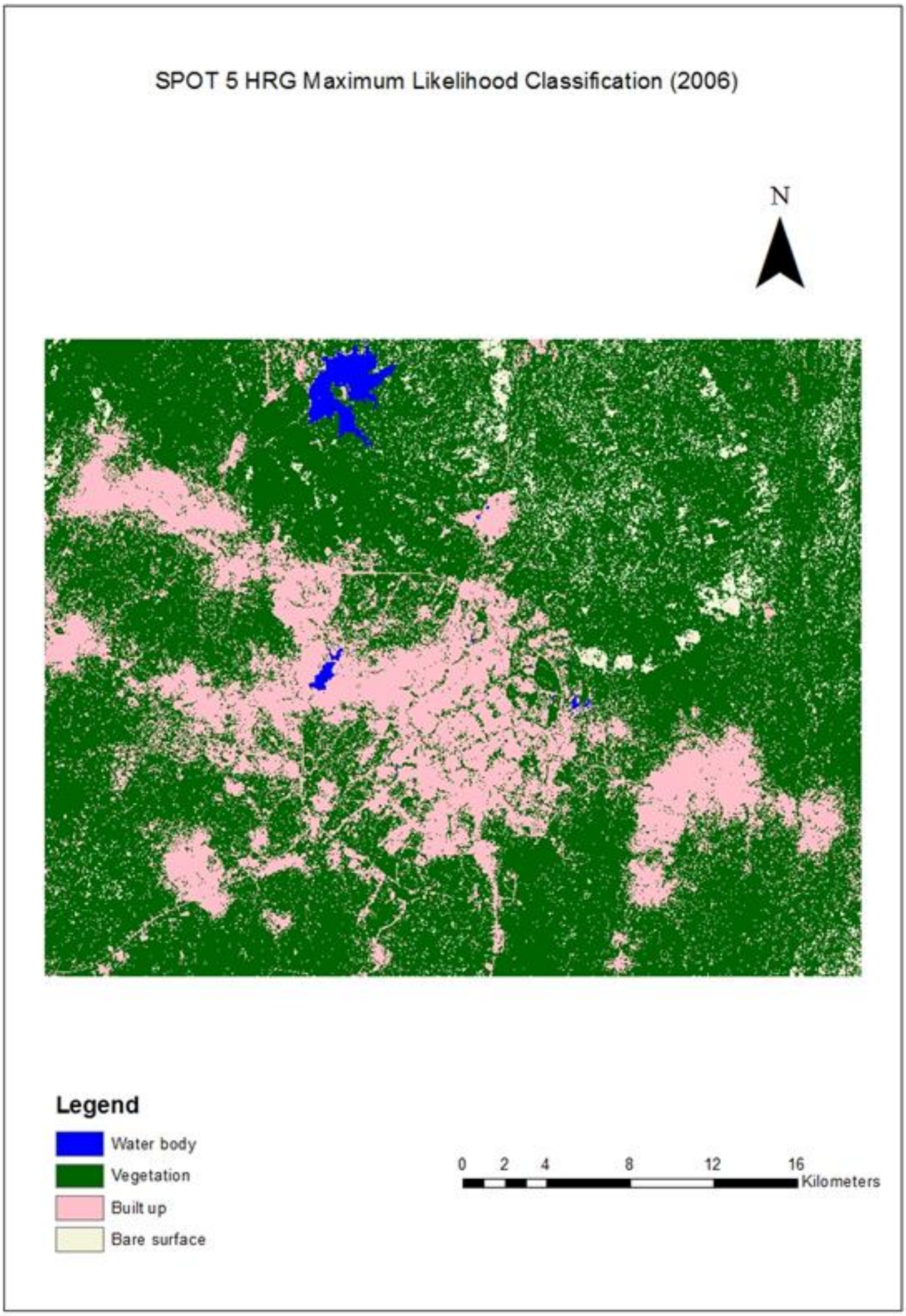


Fig. 6: 2006 Land cover map produced by Maximum Likelihood Classification

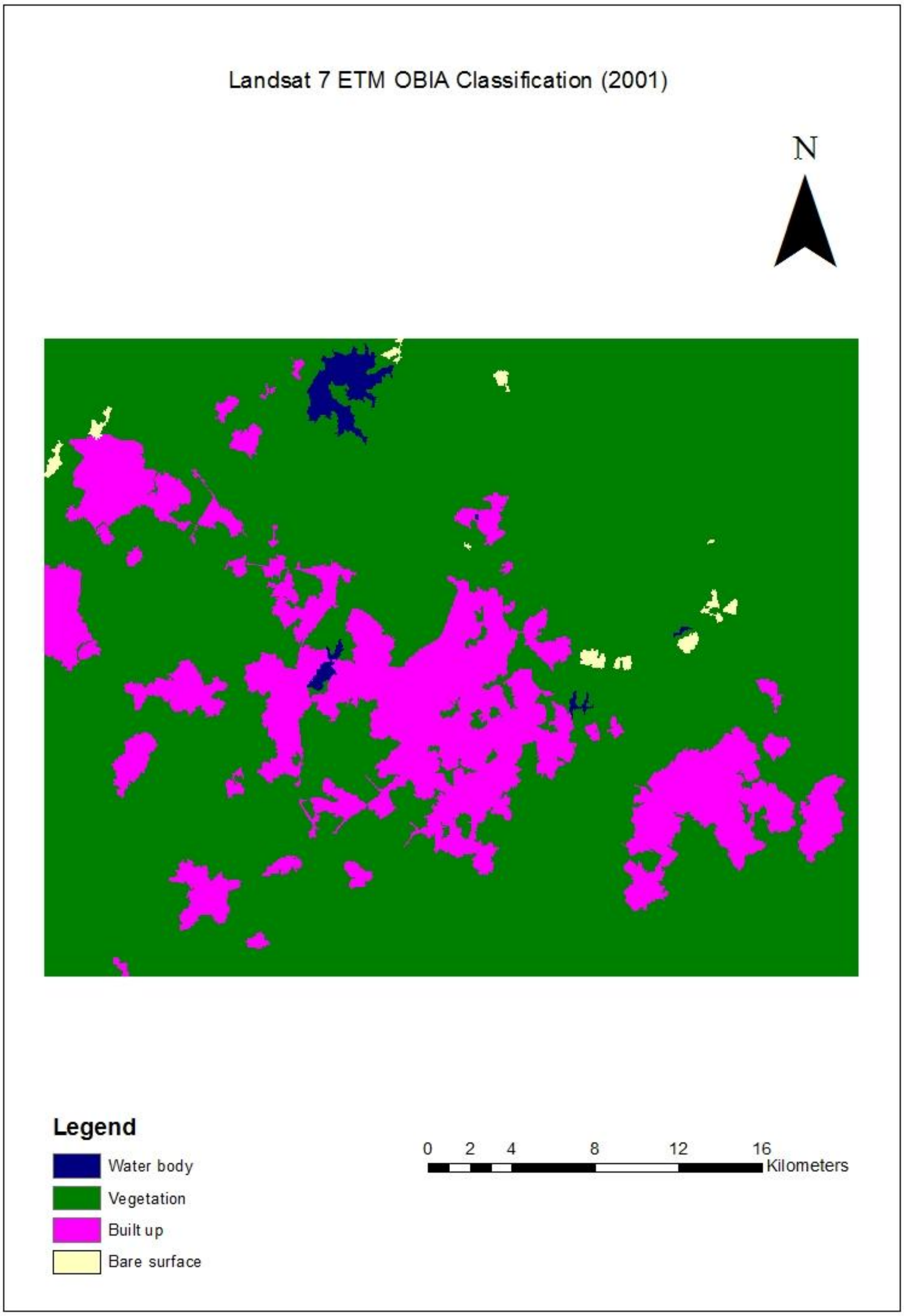


Fig. 7: 2001 Object Based Image Analysis (OBIA) with spectral properties

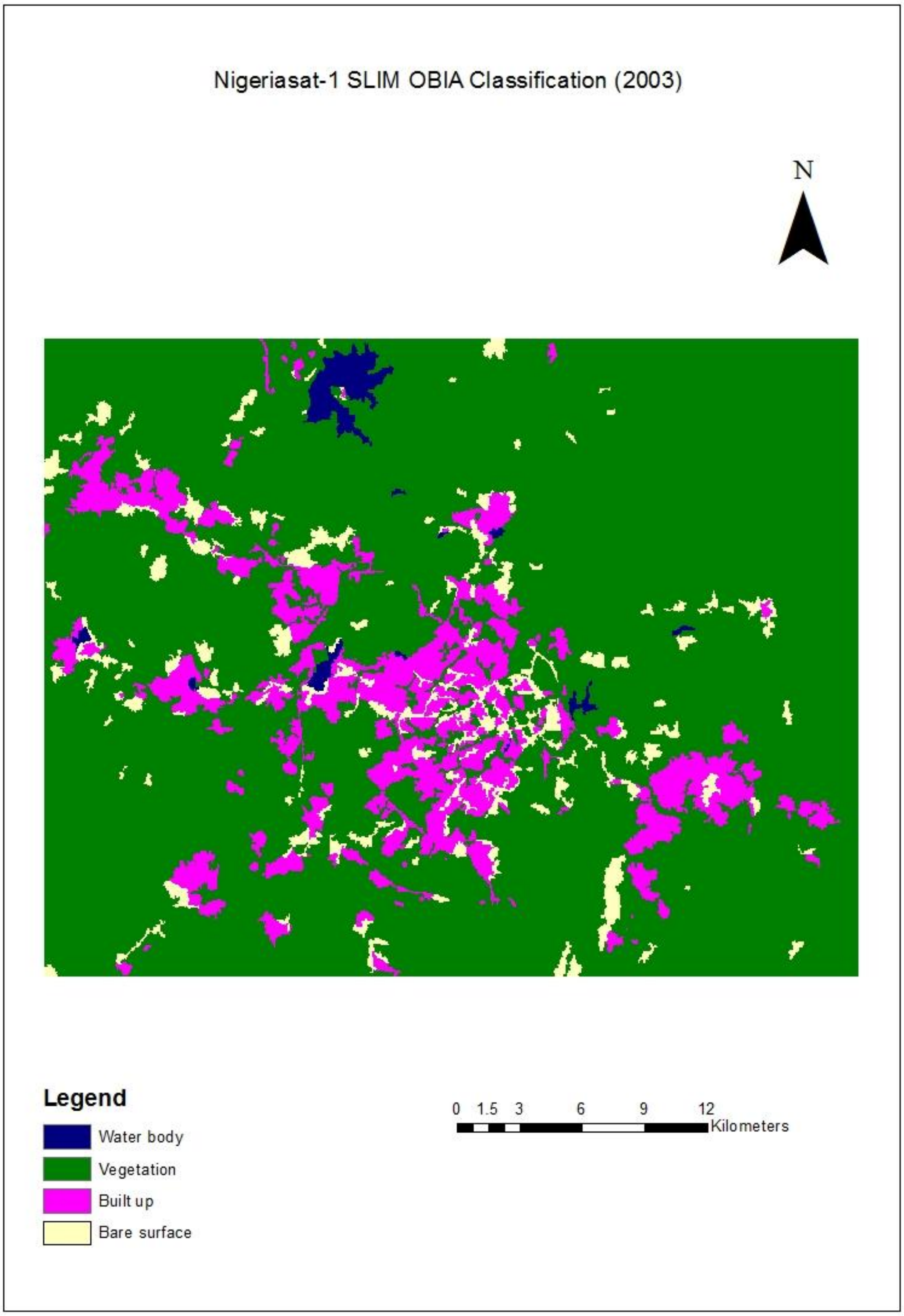


Fig. 8: 2003 Object Based Image Analysis (OBIA) with spectral properties

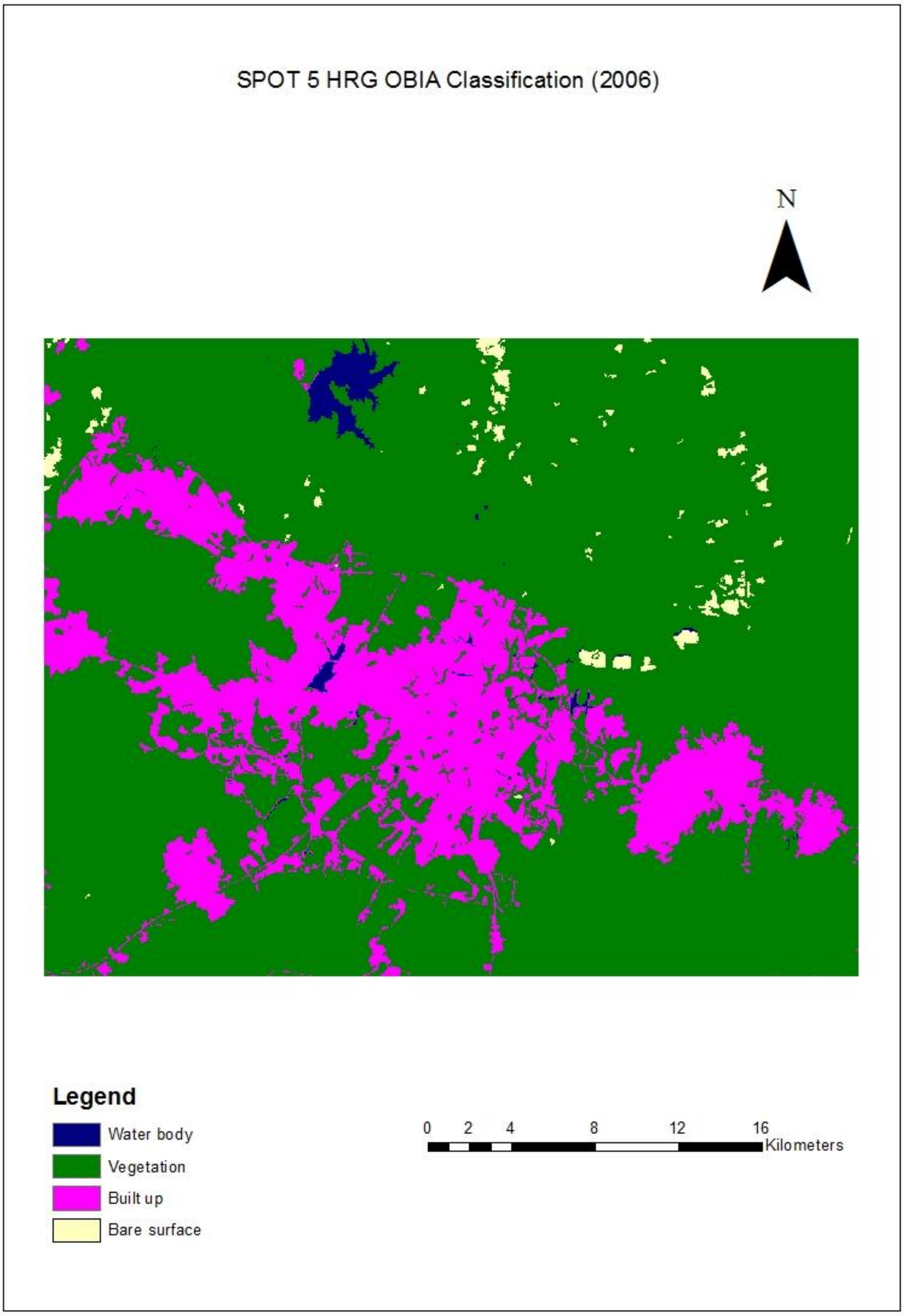


Fig. 9: 2006 Object Based Image Analysis (OBIA) with spectral properties

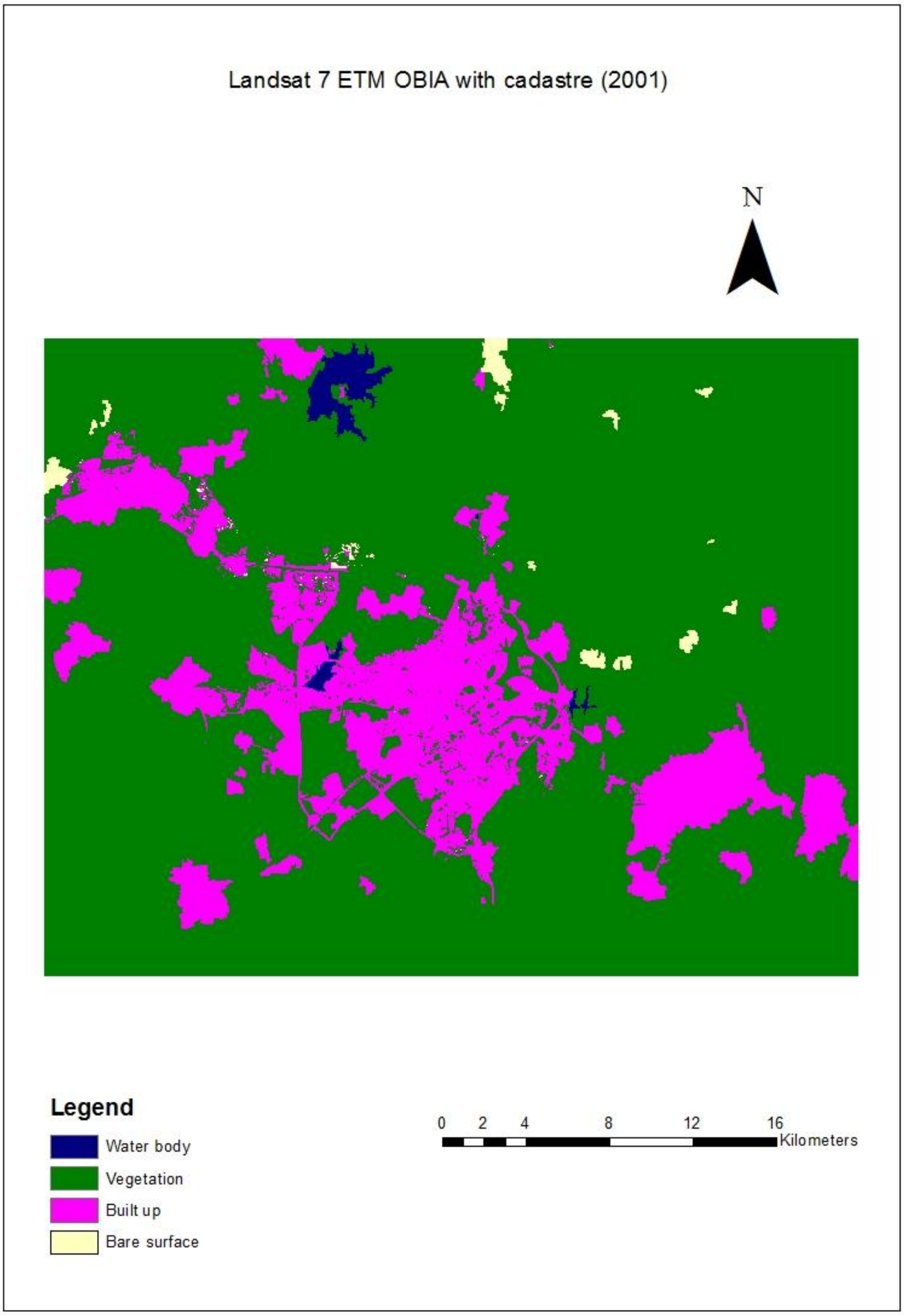


Fig. 10. Landsat 7 ETM 2001 OBIA with Cadastre data

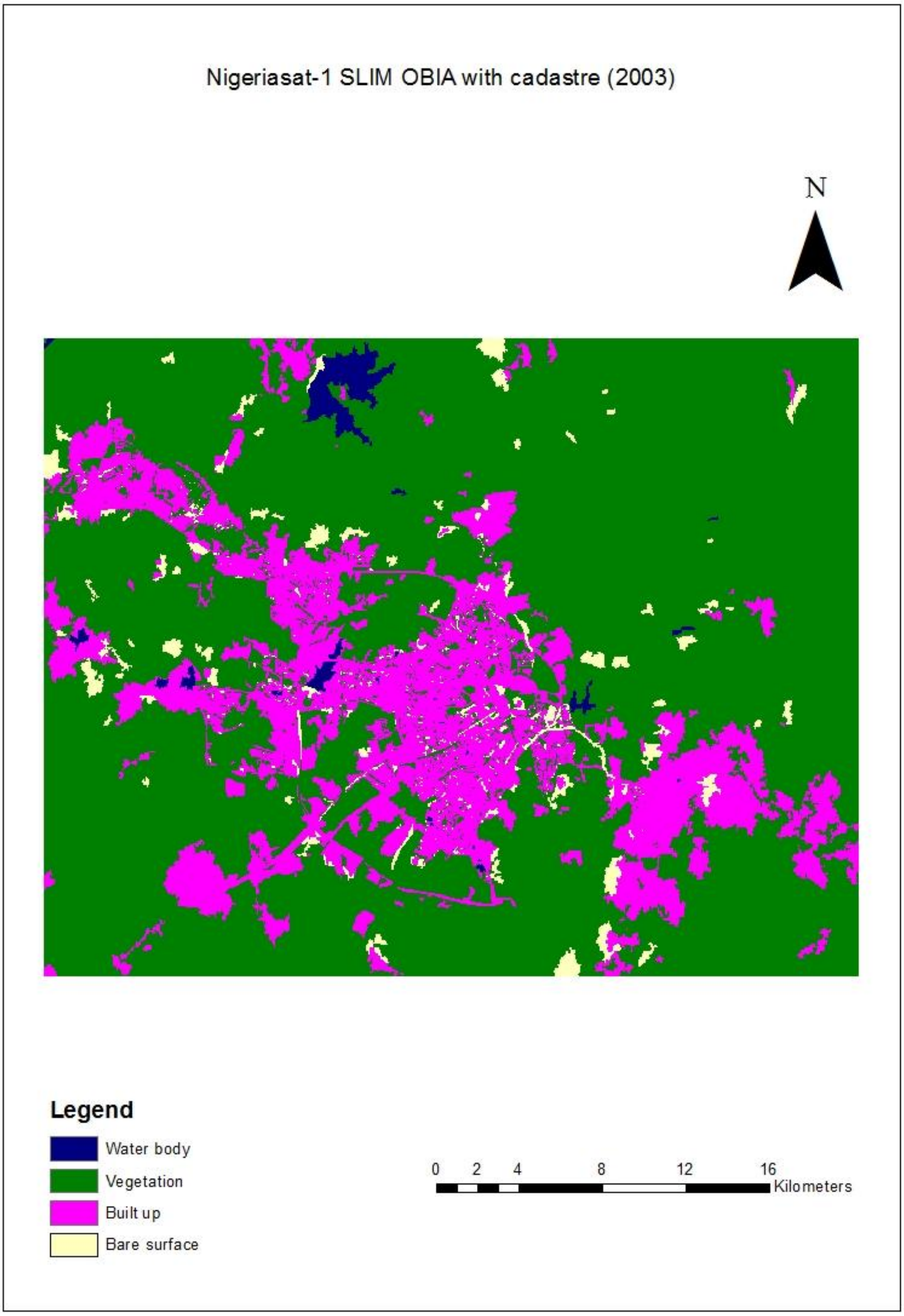


Fig. 11: Nigerisat-1 SLIM 2003 OBIA with Cadastre data

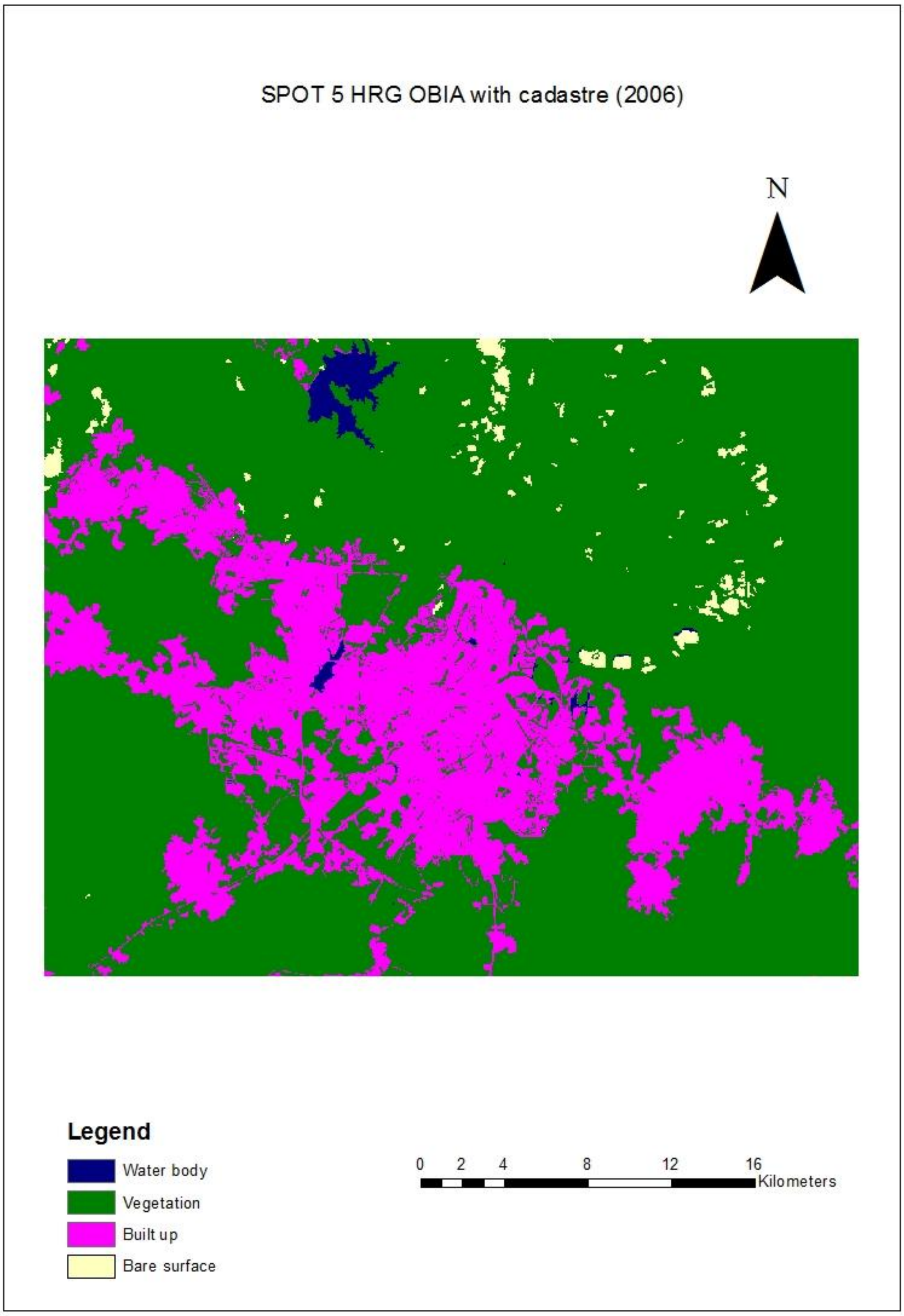
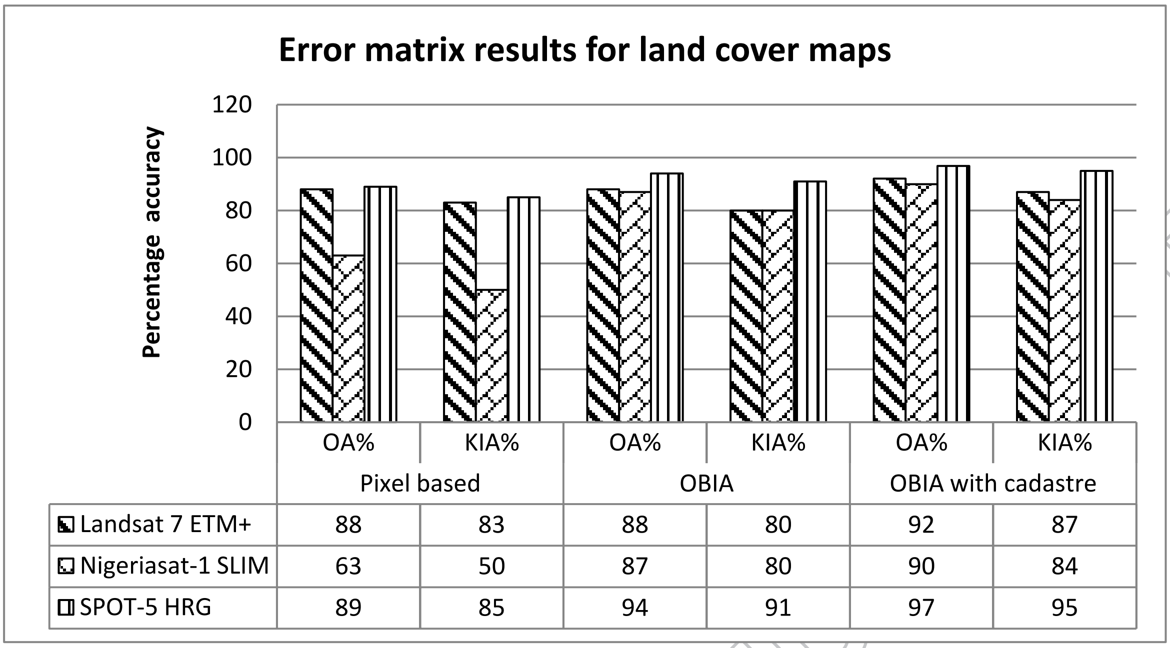
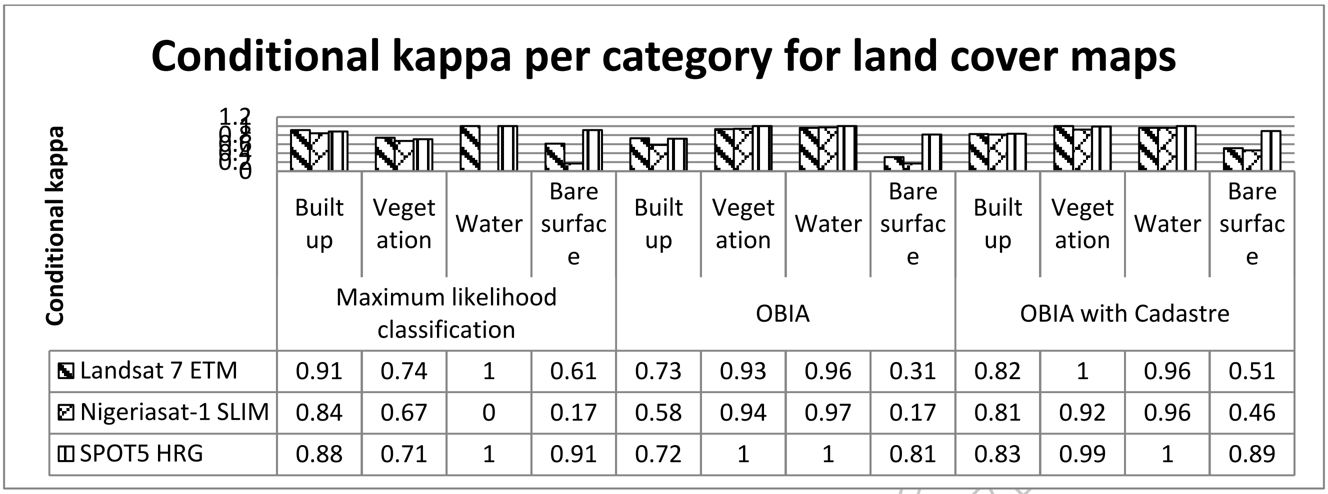


Fig. 12: SPOT 5 HRG 2006 OBIA with Cadastre data



	Pixel based OA%	Pixel based KIA%	OBIA OA%	OBIA KIA%	OBIA with cadastre OA%	OBIA with cadastre KIA%
Landsat 7 ETM+	88	83	88	80	92	87
Nigeriasat-1 SLIM	63	50	87	80	90	84
SPOT-5 HRG	89	85	94	91	97	95

Fig. 13 A comparison of the error matrix results from the land cover maps for 2001 (Landsat 7 ETM), 2003 (Nigeriasat-1 SLIM) and 2006 (SPOT 5 HRG). The statistics are provided as percentages for the OA and KIA



	Maximum likelihood classification				OBIA				OBIA with Cadastre			
	Built up	Vegetation	Water	Bare surface	Built up	Vegetation	Water	Bare surface	Built up	Vegetation	Water	Bare surface
Landsat 7 ETM	0.91	0.74	1	0.61	0.73	0.93	0.96	0.31	0.82	1	0.96	0.51
Nigeriasat-1 SLIM	0.84	0.67	0	0.17	0.58	0.94	0.97	0.17	0.81	0.92	0.96	0.46
SPOT5 HRG	0.88	0.71	1	0.91	0.72	1	1	0.81	0.83	0.99	1	0.89

Fig. 14 Conditional Kappa for the three land cover maps from Landsat 7 ETM, Nigeriasat-1 SLIM and SPOT 5 HRG showing the improvements in classification for the land cover categories. The improvement is particularly noticeable for water body in Nigeriasat-1 SLIM with 0 kappa in Maximum Likelihood Classification compared to 0.96 in OBIA with cadastre.

Table 1 Data sets used and sources of data

Data	Date of acquisition	Image bands used	Image resolution	Scene identification	Local time of overpass
Landsat 7 ETM+	27 Dec 2001	Bands 1-5, 7	28.5m	LE71890542001361EDC01	09:39:04am
SPOT 5 HRG	26 Nov 2006	Bands 1-4	10m	KJ 74-332	10:06:54am
Nigeriasat-1 SLIM	4 Dec 2003	Bands 1-3	32m	Abuja and environs	09:24:49am

Table 2 Image Segmentation Parameters*

Image/ Segmentation Level	Scale Parameter	Colour	Shape		Segmentation mode	Classification Method
			Smoothness	compactness		
Level 1	1000	0.8	0.3	0.7	Thematic layer /Spectral properties	
Level 2	35	0.7	0.3	0.7	Thematic layer /Spectral properties	Nearest neighbour
Level 3	15	0.8	0.3	0.7	Thematic layer /Spectral properties	

* The Scale Parameter (SP) is an abstract term, which determines the maximum allowed homogeneity (or heterogeneity) for the resulting image objects. Homogeneity criterion is a combination of *colour* (spectral values) and *shape* properties (*shape* splits up in *smoothness* and *compactness*).The higher the SP the larger the segmentation and vice-versa.

Table 3: Results from Maximum Likelihood Classification

Sensor/ Data	Overall Accuracy%	Kappa Index of Agreement	Conditional kappa per category			
			Built up	Vegetation	Water body	Bare surface
Landsat7 ETM	88%	0.83	0.91	0.74	1.00	0.61
Nigeriasat-1 SLIM	63%	0.50	0.84	0.67	0.00	0.17
SPOT 5 HRG	89%	0.85	0.88	0.71	1.00	0.91

Table 4: Results of OBIA with spectral properties of the datasets

Sensor/ Data	Overall Accuracy%	Kappa Index of Agreement	Conditional kappa per category			
			Built up	Vegetation	Water body	Bare surface
Landsat7 ETM	88%	0.80	0.73	0.93	0.96	0.31
Nigeriasat-1 SLIM	87%	0.80	0.58	0.94	0.97	0.17
SPOT 5 HRG	94%	0.91	0.72	1.00	1.00	0.81

Table 5: Results of OBIA with cadastre data

Sensor/ Data	Overall Accuracy%	Kappa Index of Agreement	Conditional kappa per category			
			Built up	Vegetation	Water body	Bare surface
Landsat7 ETM	92%	0.87	0.82	1.00	0.96	0.51
Nigeriasat-1 SLIM	89%	0.84	0.81	0.92	0.96	0.46
SPOT 5 HRG	96%	0.95	0.83	0.99	1.00	0.89