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Accuracy Assessment of Pixel-Based Image Classification Of Kwali Council Area, Abuja, Nigeria

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Abstract
In this study, Kwali Council Area located on the western part of the Federal Capital Territory, Abuja was selected as a study area covering approximately 1,206 km ^{2} for comparing the two major pixel-based image classification algorithms (Supervised and Unsupervised classification). For this purpose, land use and land cover classification of the study area was conducted by supervised classification particularly maximum likelihood classification (MLC) and Iso-cluster unsupervised classification procedures and the results were compared with one another using 2011 Landsat-7 ETM+ satellite. However, the result of classification accuracy illustrates that light vegetation shrubs records dominance value of 27.54%, savannah grasses 23.04%, cultivated areas 20.12%, wetland flood plain 13.78%, sand open surfaces 11.01% and water body 4.52%. Overall, supervised pixel-based classification methods are found to be more reliable, accurate and outperformed unsupervised pixel-based classification methods in this study. The higher accuracy was attributed to the fact that supervised classification took advantage of spectral information of land cover, based on the spectral signature defined in the training set and digital image classification software that determines each class on what it resembles most in the training set in the remotely sensed imagery. This study is a good example of some of the limitations of unsupervised pixel-based image classification techniques, whereby the unsupervised image classification technique is commonly used when no sample sites exist. These improvements are likely to have significant benefits for land-cover mapping and change detection applications. It is recommended that, the two approach can be used together to provide a standard, accurate and finest result for specific applications by users in different parts of the world.
Keywords: Accuracy, assessment, pixel-based image classification algorithms, iso-cluster unsupervised, MLC

1.0 Introduction

Pixel-based image classification techniques are distinguished in two main ways as supervised and unsupervised classifications (Fabio et al. 1997; Avery and Berlin, 1985; Blaschke, 2010). Additionally, supervised classification has different classification methods which are named as parallelepiped, maximum likelihood, minimum distances and Fisher classifier methods (Jayme, 2000). There are different image processing and GIS software of which a lot of them have similar properties and capabilities for remote sensing purposes (Draeger et al. 1997). Pixel-based Image classification algorithms analyze the numerical properties of image features and objects, and then classify data into categories. More importantly, the classification algorithms typically employ the process of training *and* testing *(*Cracknel, 1999). First and foremost, according to Sabins (1997) the description of training classes is an extremely important component of the classification process. In supervised classification, statistical processes (Chervaney et al. 1977) or distribution-free processes can be used to extract class descriptors, while unsupervised classification relies on clustering algorithms to automatically segment the training data into prototype classes (Liu, et al. 2002; Lo and Watson, 1998). The functions of remote sensing data (Draeger, 1997) are to classify the myriad of features in a scene usually presented as an image into meaningful categories or classes. The image then becomes a theme that is selectable this is done by creating an unsupervised classification when features are separated solely on their spectral properties and a supervised classification when we use some prior or acquired knowledge of the classes in a scene in setting up training sites to estimate and identify the spectral characteristics of each class as used in this study.

1.1 Background of the Study Area

The Federal Capital Territory lies within latitudes 9^0 20’ N and 9^0 25’ N of the equator and within longitudes 5^0 45’ E and 7^0 39’ E (Figure 1.1). The study area Kwali is an area council of the Federal Capital Territory is bordered to the north by Gwagwalada area council, to the east by Kuje area council, to the south by Kuje area council and to the west by Abaji Area Council. Kwali area council has an area of 1,206 km ^{2} and a population of 85,837 at the 2006 census.

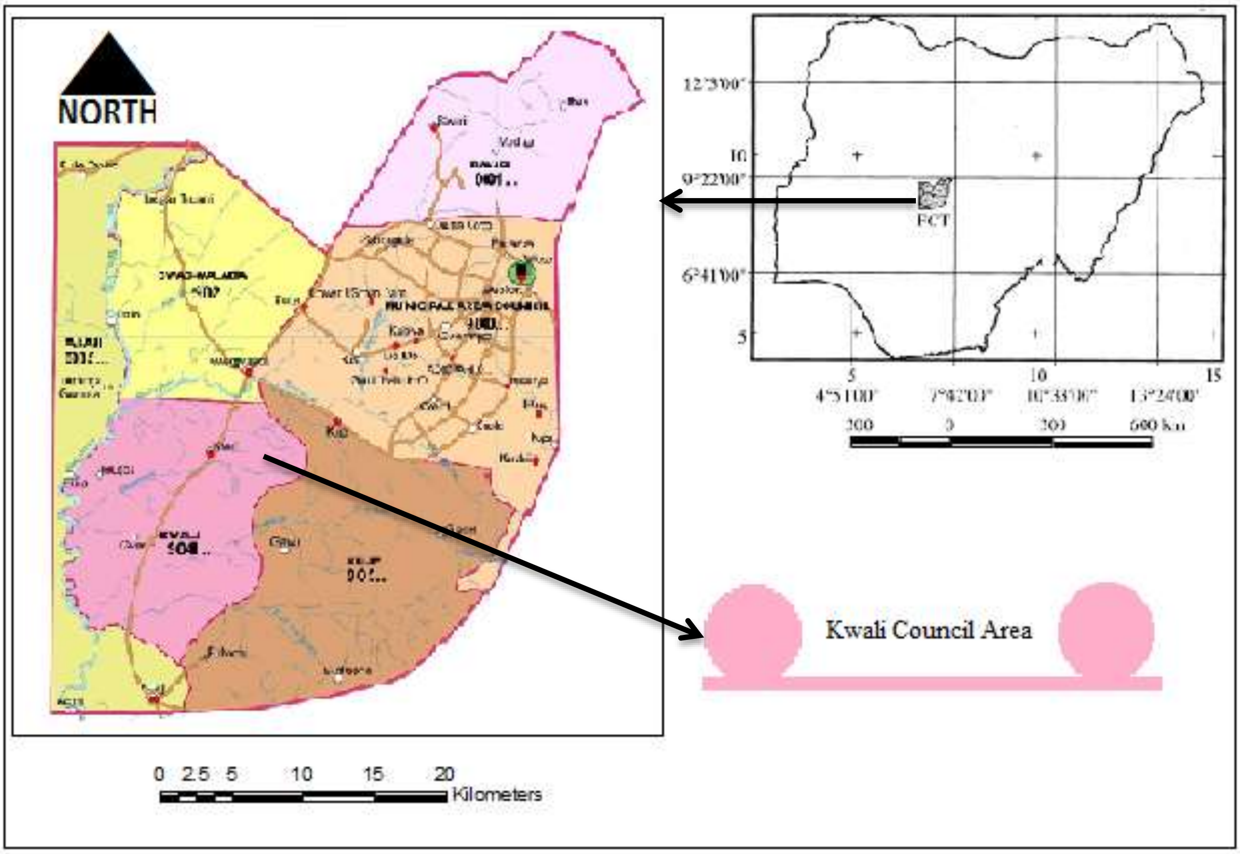

Figure 1. The study Area

1.2 Statement of Research Problem

There are different methods of assessing the capability and ability of pixel-based image classification algorithms (supervised and unsupervised). Many found it difficult to separate there spectral differences and appreciate their variant results, which is capable of misleading users. As a result of this, an experimental study area is conceptualized to compare the two major approach for the same data set from 2011 landsat-7 ETM+ remote sensing satellite and Geographic information system which is also necessary to provide a standard guideline and interpretability model for specific applications.

1.3 Aim and Objectives

The aim of the study is to assess the Accuracy assessment of using pixel-based image classification approach at Kwali Council Area, Abuja, Nigeria. To achieve the above aim of the study, the specific objectives were as follows:

a. To carry out detailed fieldwork and ground trothing exercise of the study area for the development of the training sites.
b. To put into use the two major pixel-based image classification algorithms (supervised and unsupervised) classifiers for the land-use and land-cover types.
c. To carry out a comparative spatial variation analysis of supervised classification and iso-cluster unsupervised classification algorithms and display their findings
d. To determine the accuracy of the classifications

2.0 Image classification studies

According to Chen and Stow (2002), Chen and Stow (2003) and Rogan & Chen (2004) adequate training samples and their representativeness are important for image classifications especially when using ArcMap 10.0

polygon collection method, training samples were collected from areas that appear relatively alike on the Landsat-7 ETM+ and Landsat-1 MSS images. Richards (1995) states that ground truth data, previous knowledge of the study area and the result of the unsupervised classification aid the training set samples. Richards further illustrates that one of the objectives of classification process is to categorize all pixels in a digital image into one of several land cover classes of which categorized data may then be used to produce land cover present in an image (Gibson and Power, (2000). In the word of Lillesand and Kiefer (1994), multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel used as the numerical basis for categorization. Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most (Eastman, 1999). Hill and Megier (1986) perfectly performed a multi-class digital classification of some areas using Landsat-5 TM data as a part of a region wide resources inventory being conducted by the Government of French. In the same vein Pettinger (1982) also carried out a comprehensive digital classification of vegetation and land cover producing several maps of different levels of detail for natural resources management purposes. Furthermore, Adeniyi (1985) analysis the Multitemporal Landsat data for Land use and Land cover classification in a semi-arid area of Nigeria. Adeniyi examined the possibilities and constraints of digital classification of land use and land cover. The classify procedure includes the sub-area creation, image to grid and image to image registration, various enhancement techniques and the use of supervised classification technique. In support of the ability of Landsat series LeBash et al. (1989) conducted a digital image analysis of Landsat-TM data in eastern Connecticut for regional land use and land cover classification. Civco (1989) emphasized that knowledge-based image analysis for classifying Landsat Thematic Mapper region-based spectral data, ancillary digital spatial information in deriving land use and land cover information for natural resources management, and developed a Relational Image-based GIS (RIGIS) for interfacing GIS and remotely sensed data for land resources studies. Lyle and Frederick (1989) described systematic methods using GIS and remote sensing for rural land planning which formed the basis for land use planning for the areas of southern California. Image classification algorithms has become a household for LULC determination of which Teotia et al (1988) have made a comprehensive study for land use planning in semi-arid regions of northeastern Brazil, using SPOT HRV data. Kennard et al (1988) further used a GIS technique for land use planning and management of semi-arid regions of northeastern Brazil, using digital image on Landsat-TM and SPOT data respectively. On a general note the work of Sirindhorn (1990) using unsupervised and supervised classifications of Landsat-TM data found that Landsat sensor with its high resolution provide reliable results in mapping land use/land cover. Sirindhom's work was supported by Ripple (1987) that provides specific examples involving water, soil and vegetation resources management applications based on the integrated use of GIS (Eastman, 1999) and Image Processing Technologies. Agbu and Nizeyiman (1991) adopted pixel-based image classification to examine the textural features of detailed land cover and land use planning programs.

3.0 Methods

3.1 Data Collection Mode and Source

The data collected for the study includes, 2011 Landsat-7 ETM 345 image of the study area obtained and the rectangular grid coordinates (Easting (x) and Northing (y)) of topographical locations and features in the study area. 2011 Landsat-7 ETM+ Entity ID: L72189056_05620110121, Acquisition Date: 21st January, 2011, Path: 189 Row: 56, Band Combination: 123456.16.278.

3.2 Image Classification Procedure

The training site for six land use and cover types was created based on the fieldwork and ground truthing exercise of the study areas. The land use and cover types in the image that includes, wetland flood plain, water body, light vegetation shrubs, cultivated areas, savannah grass and sand open surfaces were assigned unit integer identifier class 1,2,3,4,5 and 6, digitized to produce the training site. The spectral signature files which contain the statistical information about the reflectance values of the pixels within the training site for each of the six land use and cover classes has to be developed. Having created the signature file, each pixel in the study area now have a land use and land cover value in each of the three (3) bands of the Landsat-7 ETM+ Imagery, hence the data is ready for supervised classification using Maximum Likelihood (MLC) on the 2011 Landsat-7 ETM+ from the Image Classification/Hard Classifier module of Arcmap-10.1. Pixels are grouped based on the reflectance properties of pixels. The number of clusters is identified to generate the bands to use. With this information, the image classification software generates clusters and manually identifies each cluster with land cover classes.

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4.0 Results

4.1 Unsupervised Classification

Figure 2 shows that the study areas contains seven major colour based on classes of colour identified on the Landsat-7 ETM+ image using iso-cluster unsupervised classification approach. The Figure 2 also identified that the colour of layer-5 (cultivated areas) of the classified colour legend highly dominates the scene of the imagery, particularly toward the North, North central, North West and South of the image, while others colour layer (1,3,4,6 and 7, which are light vegetation, water body, wetland flood plain, savannah grass and sand open surface respectively) are partially distributed of which colour of layer-2 (isolated dense vegetation) shows the lowest occurrences.

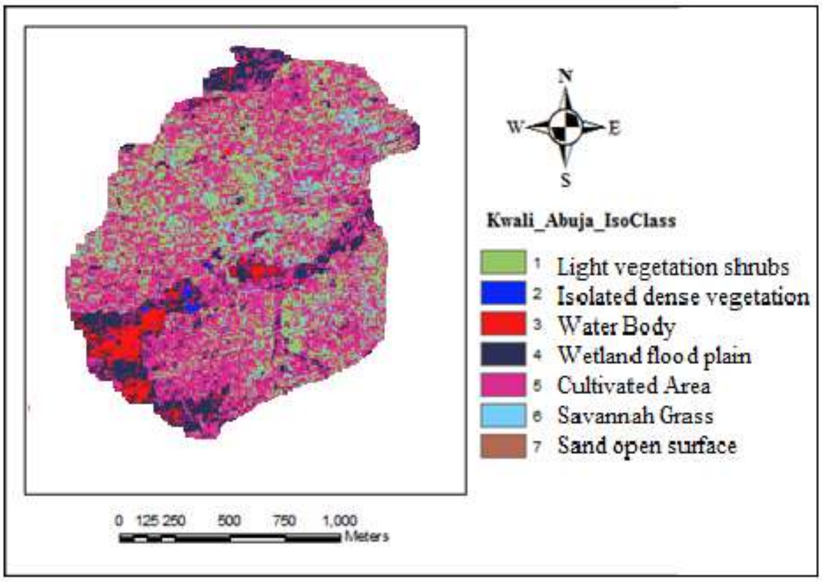

Figure 2. Iso-unsupervised Classification of the study area

4.2 Training sites classification

Figure 3 shows training samples collected for the supervised classification with number of training samples cells and histogram of training samples (Ozesmi and Bauer, 2002). The Figure 3 went further to caption the different properties of the training sites that includes Identity (ID), Class name, Value, Color and Counts. Therefore, the Figure 3 properly illustrates and gives the estimate of the property of training sites of which the water body has the highest count of 5383, other are sand open surface 2150 counts, savannah grass 959 counts, light vegetation shrubs 699, wetland flood plain 414 counts and cultivated areas 389 based on the classified histogram result.

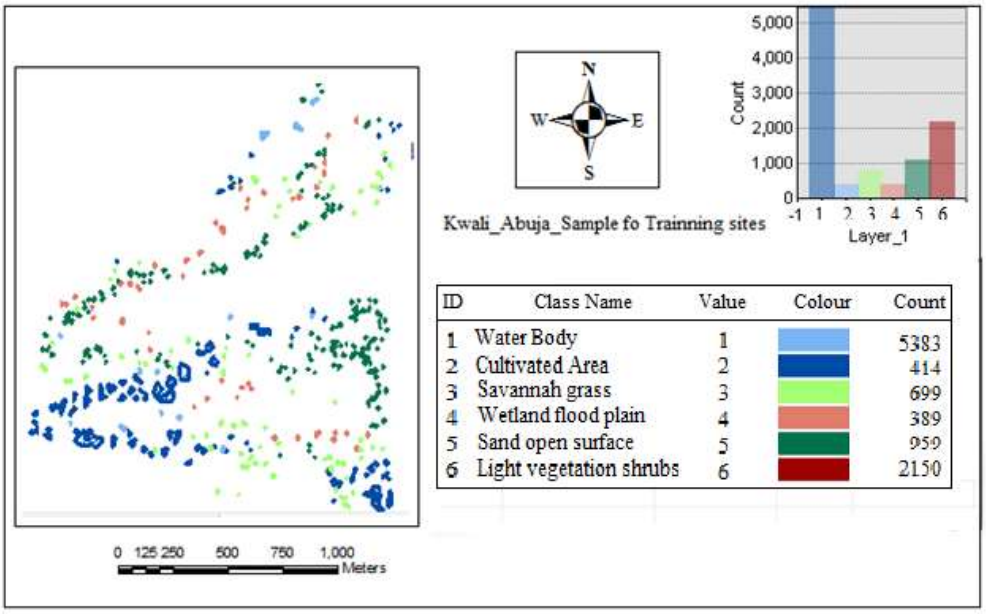

Figure 3. Training sites, samples cells and histogram of training ready for the Supervised Classification

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4.3 Supervised Classification

Figure 4 indicates the presence of six layers of colours on 2011 Landsat-7 ETM+ images using supervised classification particularly maximum likelihood classification approach. This work buttresses those of Jayme (2000), Teotia, et al. (1990), Teotia, et al. (1991), Dean and Smith (2003), that adopted MLC as one of the best methods for land cover classifications. The Figure 4 identified the land-use and land-cover type namely; cultivated area (35.2%), light vegetation shrubs (32.4%), sand open surface (16.5%), savannah grass (14.2%), water body (12.0%) and wetland flood plain (9.1%) of which cultivated areas and light vegetation shrubs shows sign of dominance.

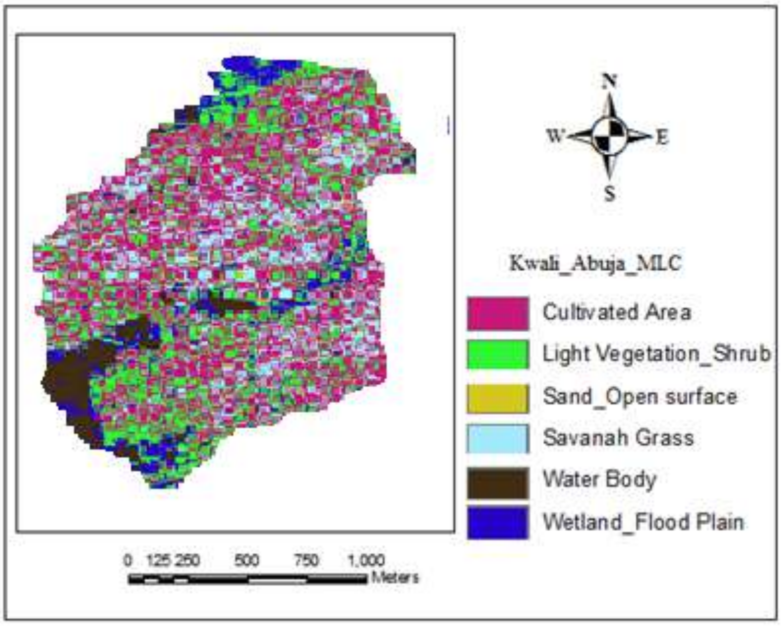

Figure 4. Supervised Classification of the study area

4.4 Filtered Image classification

Figures 5 and 6 shows the capability of using the generalized toolset of ArcMap 10.1 Spatial Analyst tool (Blaschke, 2010), the classified output was filtered as shown in Figure 5 to remove the noise; this was done using eight nearest neighbours kernel majority filter. The Figure 5 further shows that cultivated area (35.2%), light vegetation shrubs (32.4%), sand open surface (16.5%), savannah grass (14.2%), water body (12.0%) and wetland flood plain (9.1%), and that cultivated areas shows higher sign of dominance.

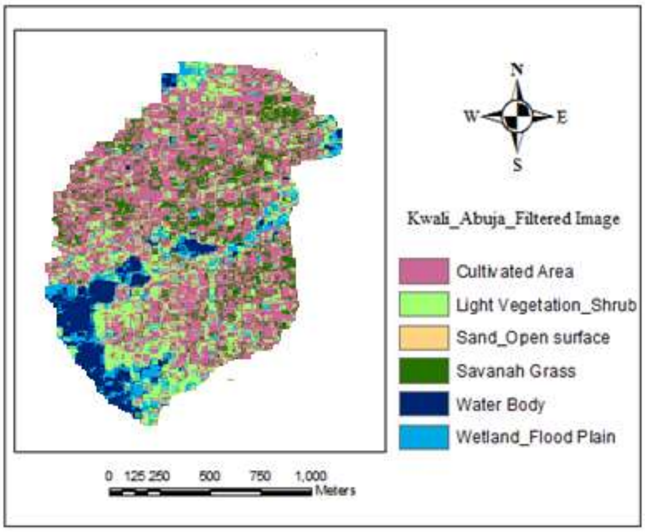

Figure 6. The Filtered and generalized classified image of the study area

4.5 Smoothen Image classifications

Figure 6 also shows that, the ragged boundaries of the classified output were smooth as well as clumping the classes together using boundary clean toolset (Dean and Smith, 2003). The Figure 6 further illustrates that the smooth images shows that cultivated area (35.2%), light vegetation shrubs (32.4%), sand open surface (16.5%), savannah grass (14.2%), water body (12.0%) and wetland flood plain (9.1%). However, cultivated areas dominate a larger part of the study areas.

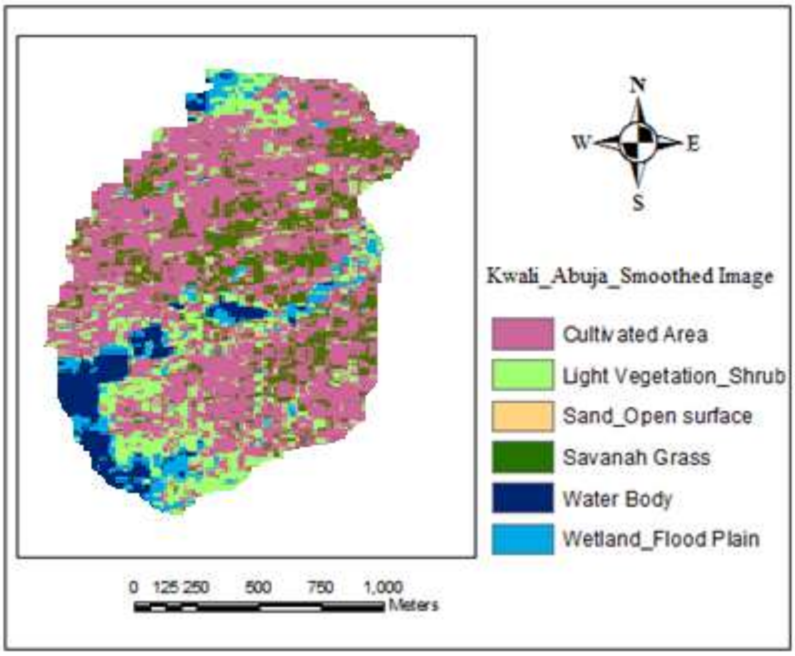

Figure 6. The smooth and generalized classified image of the study area

4.6 Discussion and Analysis of Results

The result has shown that the classified satellite images (Figures 2 -6) put Pixel-based supervised classification (Figure 4) as the most approximate ahead of pixel-based unsupervised classification methods. In comparison, the supervised classification (MLC) and iso-cluster unsupervised classification (ICUC) algorithms postulates a classification accuracy differences of 48.47% & 51.53% of cultivated areas, 50.68% & 46.32% light vegetation shrubs, 53.70% & 46.30% sand open surface, 46.76% & 53.24% savannah grass, 70.39% & 29.61% water body and 40.56% & 59.44% wetland flood plain respectively (Table 1). Total classification accuracies of 20.12%, 27.54%, 11.01%, 23.04%, 4.52% and 13.78% were recorded for cultivated areas, light vegetation shrubs, sand open surface, savannah grasses, water body and wetland flood plain respectively (Table 1). The Filtering's method (Figure 5) produced 83% of cultivated areas, 12% light vegetation shrub, 23% sand open surface, 43% savannah grasses, 11% water body and 79 % wetland flood plain agreement with the supervised classification method particularly maximum likelihood classification (MLC), while the smoothen method (Figure 7) indicates 83% of cultivated areas, 12% light vegetation shrub, 23% sand open surface, 43% savannah grasses, 11% water body and 79 % wetland flood plain also in agreement with MLC. In the final analysis this result shows that tangible agreement of 88% exist when using supervised classification as against 77% agreement with iso-cluster unsupervised classification methods. The filtering and smoothening result implies that the two methods further buttress the capability of using pixel-based supervised classification approach (MLC) ahead of pixel-based iso-cluster unsupervised classification to identify and evaluate object accurately.

Table 1. Areas (Hectares) of LU/LC of Kwali Area Council, Abuja from Classification Algorithms

Class	LU/LC Types	Unsupervised classifications of LULC (hectares)	Supervised classifications (MLC) of LULC (hectares)	Classification accuracy		
				MLC (%)	Unsupervised (%)	Total Accuracy results
1	Cultivated Areas	2305.2	2450.5	48.47	51.53	20.12%
2	Light vegetation shrubs	3494.4	3014.8	50.68	46.32	27.54%
3	Sand open surfaces	1397.4	1204.9	53.70	46.30	11.01%
4	Savannah grass	2546.7	2900.2	46.76	53.24	23.04%
5	Water body	751.8	316.3	70.39	29.61	4.52%
6	Wetland flood plain	1321.1	1936.4	40.56	59.44	13.78%
Total		11816.6	11823.1	310.56	286.24	100.00%

Conclusions

In the final analysis, the study has shown evidence of similarity and agreement between pixel-based supervised classification and pixel based Iso-cluster unsupervised classification algorithms toward verification of the LU/LC types of the study area. However, the two methods produces significant contribution in assessing the best result for LU/LC classification of Kwali area council, Abuja Nigeria using 2011 Landsat-7 ETM+ data. However, the supervised classification results shows that the distribution of the LULC classes identified were established by the investigator who knew their nature, and found their location of each class at one or more training sites. This study has shown that supervised classification algorithms produces best result ahead of unsupervised for examining LU/LC classification of the study areas using 2011 Landsat-7 ETM+ data.

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