International Journal of
Science and Engineering Investigations vol. 7, issue 72, January 2018

ISSN: 2251-8843

Unsupervised Classification in Land Cover Types Using Remote Sensing and GIS Techniques

Martins A. Oyekola[1], Gbola K. Adewuyi[2]
[1,2]Department of Surveying and Geoinformatics, The Polytechnic Ibadan, Oyo State, Nigeria
([1]kolamartins@yahoo.com, [2]adewuyismart@yahoo.com)

Abstract- Satellite images and the thematic maps extracted will provide higher-level of information in recognizing, monitoring and management of natural resources. It is very difficult to identify land cover classification manually from a satellite image. Therefore the need of remotely-sensed satellite images as sources of information for various investigations is required since they provide spatial and temporal information about the nature of the surface of the earth and feature therein. This paper examines image identification and classification using an unsupervised method with the use of Remote Sensing and GIS techniques. The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground. Three classes identify in this study are the Soil, Vegetation and Water. Landsat 7 ETM+ Satellite imagery was used in identifying each class. This study also used parallelepiped method to determine the land cover through software ENVI 5 and ArcGIS 10.2. From the results, it showed that the three classes of land cover were properly demarcated and distinguished.

Keywords- *Thematic Maps, Land Cover, Classification, Objects, Parallelepiped Method*

I. INTRODUCTION

The image classification process involves conversion of multi-band raster imagery into a single-band raster with a number of categorical classes that relate to different types of land cover. Generally, land-cover mapping is a complicated process with numerous factors influencing the quality of the final product [1]. Image classification cannot be overemphasized in object detection and image analysis. Various image classification techniques have been proposed till date. Series of studies have been conducted in order to conclude about the best satellite image classification technique. It is hard to decide any one technique as the best technique among all, because the results and its accuracy depend on a number of factors [2]. Application of remote sensing in image classification deals with clustering of the pixels of an image to a set of classes in such a way that pixel in the same class having similar properties. In Unsupervised classification, grouping of pixels is based on unlabeled data. Image classification is defined as the pixel assigning process of raster data specified in classes [3]. Thus, land cover classification involves the discrimination of land cover types through different classification methods which were developed in the field of remote sensing [4, 5]. Improvements in computer software and hardware have contributed significantly to the development of image interpretation methods through the development of pattern recognition techniques [6]. Multispectral Scanner (MSS) by Landsat 1, 2 and 3; Thematic Mappers (TM) by Landsat 4 and 5, which also provided MSS images; Enhanced Thematic Mappers (ETM+) by Landsat 7; and Observation Land Images (OLI) provided by Landsat 8 [7]. Landsat MSS, TM, ETM+ and OLI have all been used in land cover classification using different methods of land cover classification [5, 8].

In order to maintain continuity in the provision of Landsat data, Landsat 9 will be launched in 2023 with improved qualities [9]. Research on land cover classification methods based on Landsat images has been an important topic over the past four decades, especially with the current effects of climate change [10, 11]. While many review articles covered topics related to Landsat and land cover classification [5, 12, 13, 8]. Early land cover classification with Landsat images involved delineating land cover classes in a systematic way by marking boundaries of land cover types by using transparent surfaces. In the final stage of classification, the land cover types were marked with specific symbols to differentiate land cover types [14, 15]. As a living being, we are intimately familiar with remote sensing in such a way that we rely on visual perception to provide us with much of the information about our surroundings. As sensors, however, our eyes are greatly limited by; sensitivity to only the visible range of electromagnetic energy, viewing perspectives dictated by the location of our bodies; and inability to form a lasting record of what we view. As a result of these limitations, humans have continuously find a way to develop the technological means in order to increase our ability to see and record the physical properties of our environment. To date, a number of different classification methods have been developed, especially with the increasing knowledge in the fields of computer science and GIS [16]. The first methods of Landsat land cover classification were developed at pixel level and hence they are called pixel-based classification [17, 18].

Parallel piped technique method of image classification can be used by determining the parallel piped-shaped boxes for each pre-defined class [19]. The parallel piped boundaries for the classes will be determined by the minimum and maximum of pixels in a particular class. These boundaries help in assigning a pixel to a given class. In an unsupervised classification, pixels are grouped into clusters based on their properties. Therefore, in order to create “clusters, analysts use image clustering algorithms such as ISODATA or K-mean. In using an unsupervised classification method, the software finds the spectral classes or clusters in the multi-band image without the analyst’s intervention. Once the clusters are determined, then identification of what the cluster will represents is next e.g. water, soil, vegetation etc. The merit of image classification is to provide earth's surface information like land cover and time-series changes.

Unsupervised classification methods do not require prior knowledge of land cover types before classification and the interpreter is responsible for assigning a class to each cluster of pixels [16]. Unsupervised classification was developed first through different clustering methods such as K-means and Interactive Self-Organization Data analysis (ISODATA) [20, 21, 22]. Therefore, this study aimed at using unsupervised classification method to classify image into land cover types with the use of Landsat satellite image and GIS application software.

II. MATERIALS AND METHODS

- Materials
- Equipment Used
- Software Used
  - ❖ Landsat Image
  - ❖ Envi 5 classic
  - ❖ ArcGIS 10.2 (Arc Map)
- Hardware Used
  - ❖ Laptop Computer
  - ❖ 16 gigabyte memory card
  - ❖ Hp Laserjet 2014 Printer (Print for proof reading)

A. Method

The supplied image is first extracted from its compressed format of around 513 x 513 for the bands 5, 4, 3, and 2 of NIR, Red, Green and Blue around 513 x 513 pixels of the image is the clipped out and saved. A composite of Bands 4,3,2 (true color) was performed and gave an output dimension of 513 x 513 x 3 and saved as TIFF/GEOTIFF. Then the Parallelepiped classification of extracted image to identify Soil, Vegetation, and water classes was done based on the spectral reflectance soil, vegetationa nd water. Signature files were built from the raw data set to give the software an idea of the type of pixel value it must try to match to that class. First, an unsupervised classification was performed on the Image using the ISODATA clustering method to classify the image into the desired classes of which three (3) different classes were effectively identified. A thematic raster layer was generated using the ISODATA algorithm while running ENVI. Three (3) classes were derived in the classification with: maximum number of iterations set to 12, convergence threshold set to 0.95. The pixels were identified for each of the categories and they were grouped into land cover categories with Green as soil, blue as vegetation and Red as deep-shallow water.

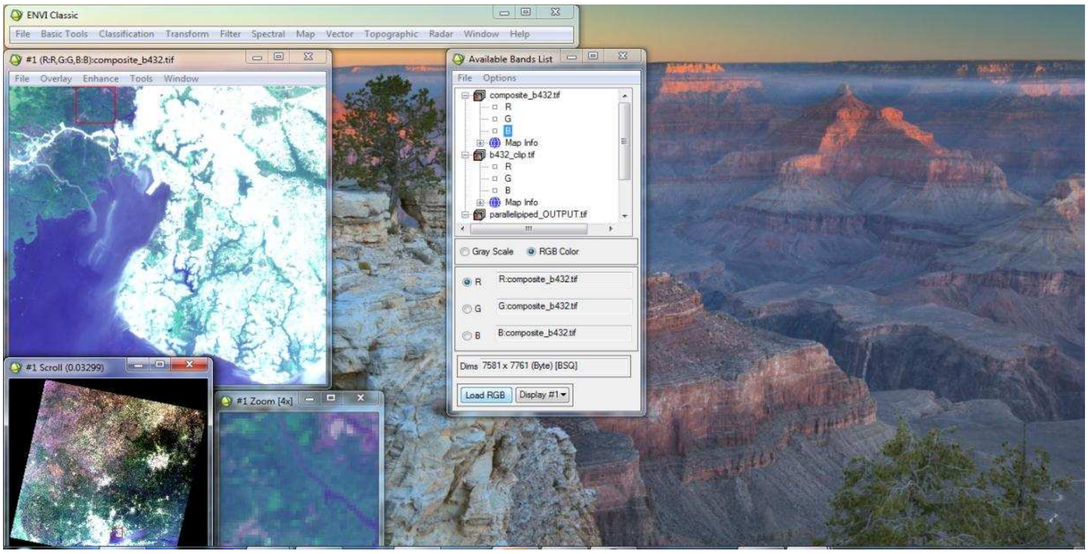


Figure 1. Generation of true colour composite using bands 4(Red), 3(Green) and 2(Blue) with full scene.

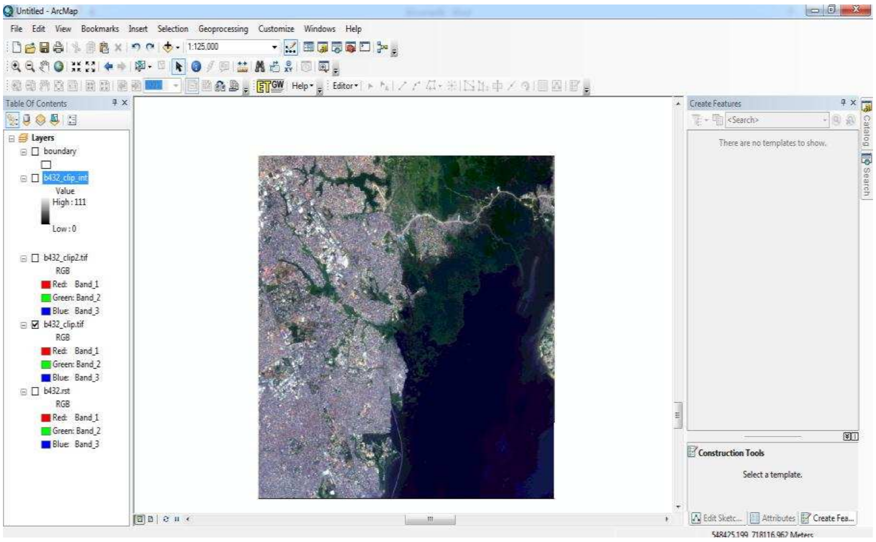


Figure 2. Clip of around 513 x 513 pixels from the main image containing soil, vegetation and water

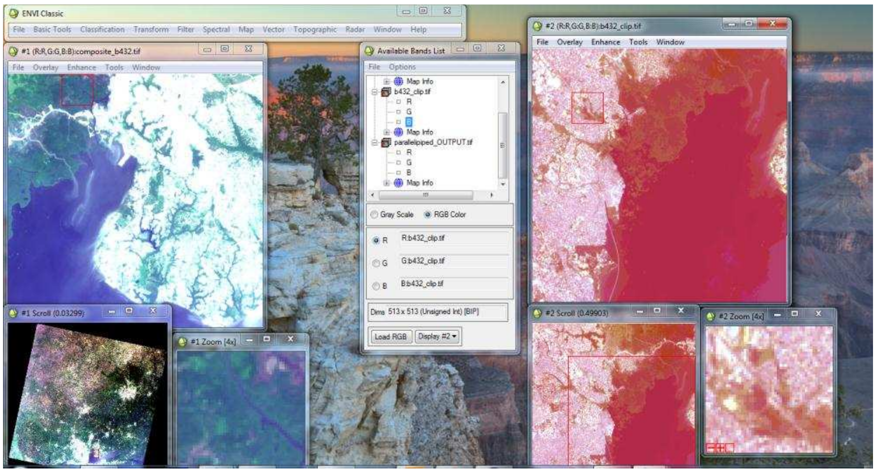


Figure 3. Loading of clipped image into the ENVI 5.0 classic environment (on the right hand side)

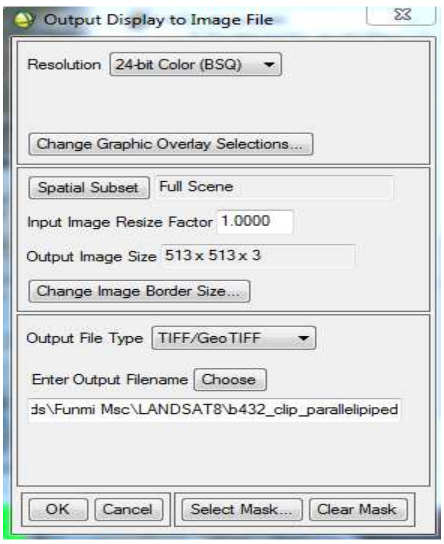


Figure 4. Output image size seen as 513 x 513 x 3

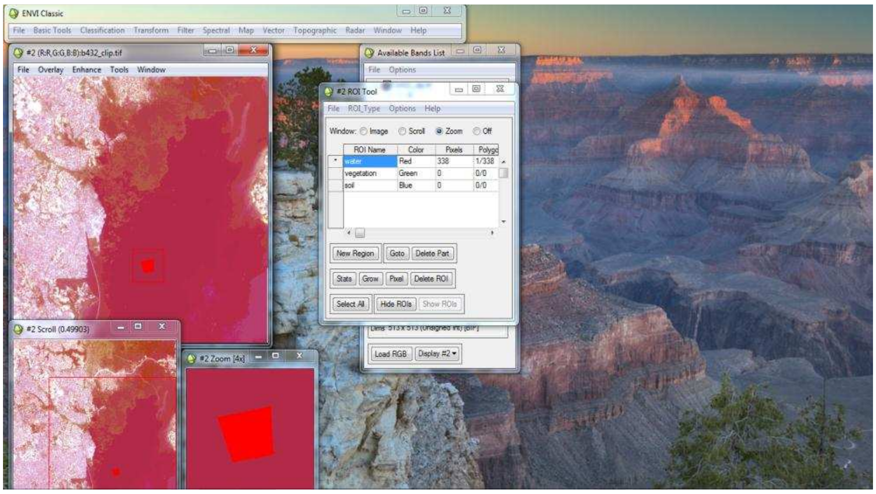


Figure 5. Training of spectral signature classes (soil, vegetation and water)

III. RESULTS AND DISCUSSION

Histogram of Number of pixels vs. Brightness value for each of the Blue, Green, Red and NIR bands extracted were drawn. Relationship between atmospheric effect and signal wavelength for an assumption of some pixels at or close to zero values were done.

Derivation of atmospheric effect corrections to each band and application of corrections.

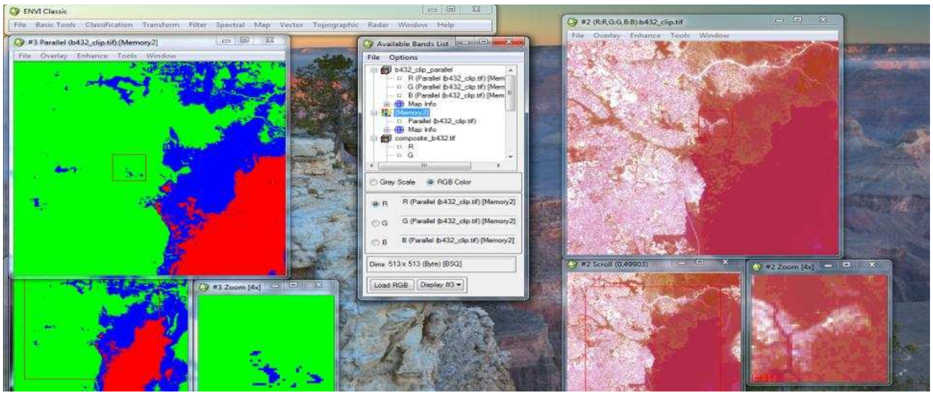


Figure 6. Parallelepiped classification of clipped region with green as soil, blue as vegetation and red as water. Threshold values of 28, 8 and 20 were used respectively for water, vegetation and soil respectively.

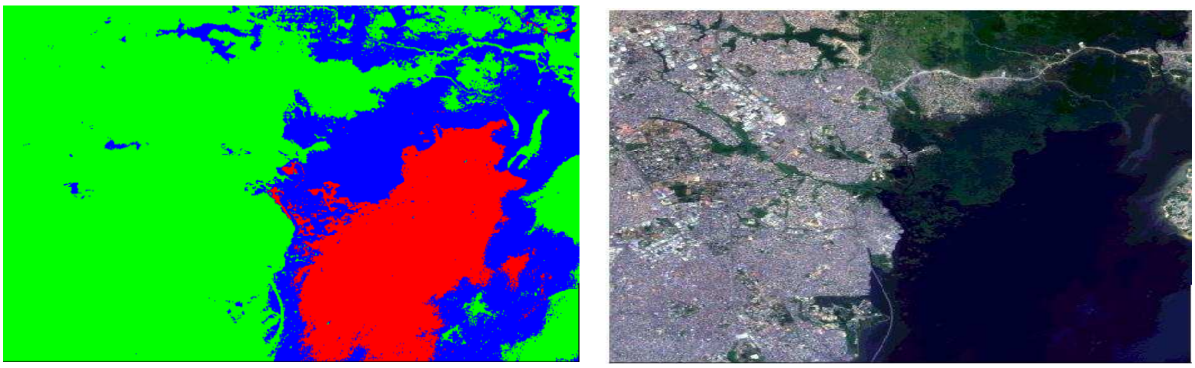


Figure 7. Side-by-side comparison/identification of spectral signature with Green as soil, blue as vegetation and Red as deep-shallow water

- Conversion of bands 5, 4, 3, 2 raster bands to integer
- Extraction of attribute data values showing ID, counts and values (DN).
- Plotting of Number of pixels Vs. Brightness values for each of the bands extracted.

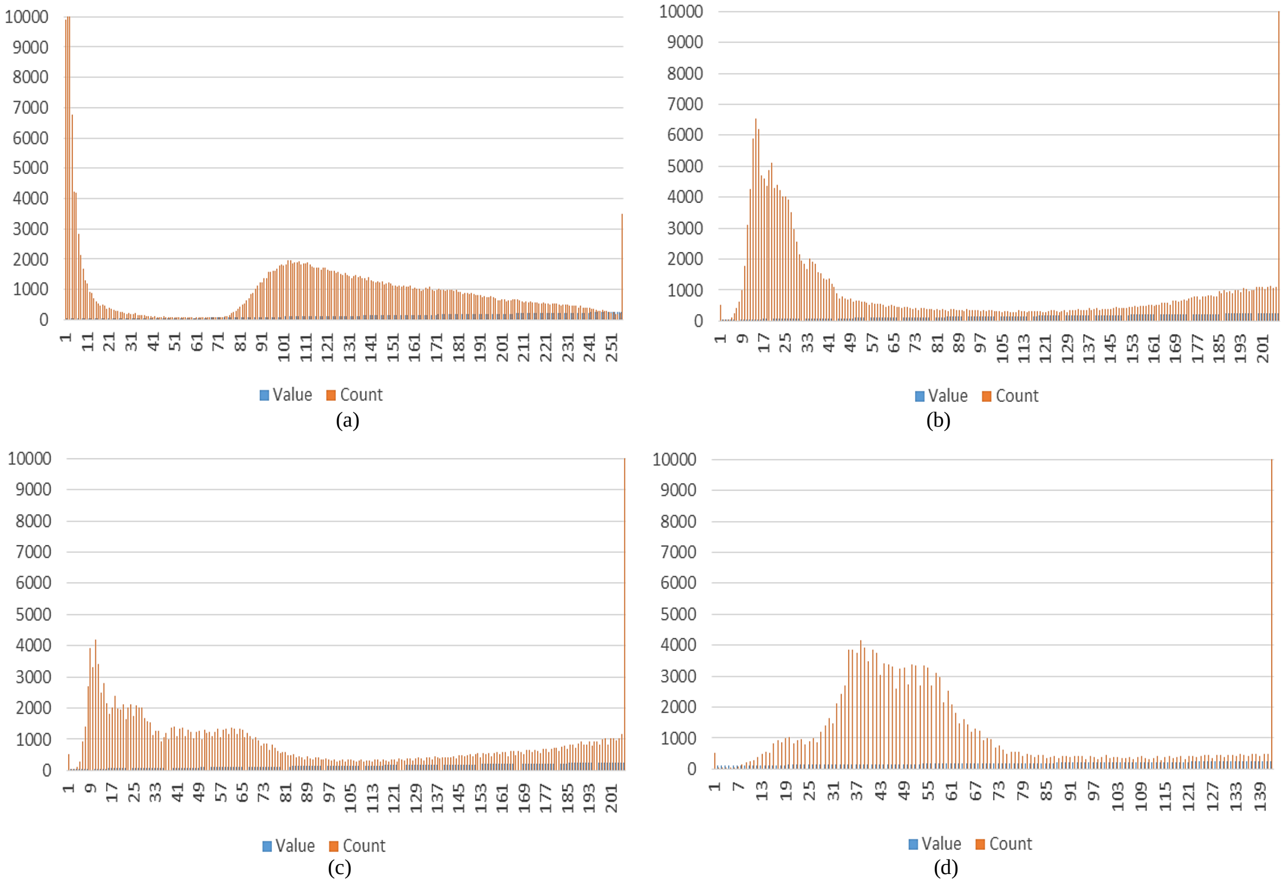


Figure 8. Description of the relationship between atmospheric effect and signal wavelength for the bands. a) Number of Pixels Vs. Brightness Value (Band 5). b) Number of Pixels Vs. Brightness Value (Band 4). c) Number of Pixels Vs. Brightness Value (Band 3). d) Number of Pixels Vs. Brightness Value (Band 2)

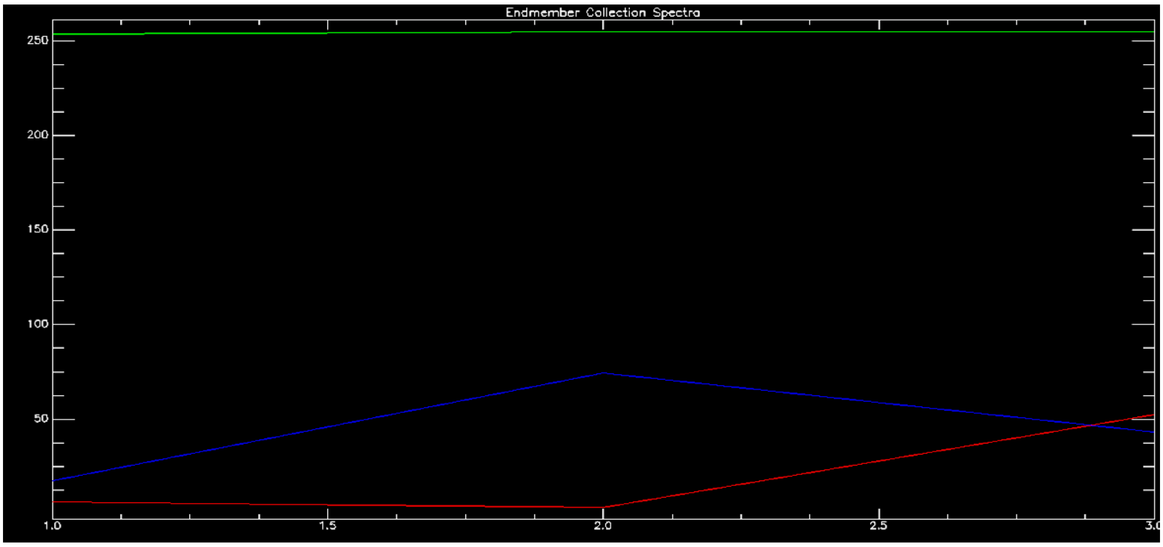


Figure 9. Relationship between atmospheric effect and the wavelength

For the bands of the area already extracted and with focus on the three features of soil, vegetation and water, the effects relative to the wavelengths in Micrometer units was plotted in a graphical form as shown above with the assumption that some pixels contain values of brightness at or close to zero. The red shows that for the water class, green for soil and blue for vegetation.

Correction for atmospheric effect was applied to each band and its application was done using the formula below; the spectral radiance (L_l) is calculated using the equation below:

$$L = L_{\min} + \frac{L_{\max} - L_{\min}}{QCAL_{\max} - QCAL_{\min}} QCAL - QCAL_{\min} \qquad (1)$$

Where:

QCAL is the calibrated and quantized scaled radiance in units of digital numbers (DNs)

$LMIN_l$ is the spectral radiance at QCAL = 0

$LMAX_l$ is the spectral radiance at QCAL = QCALMAX.

The resulting radiance (L_1) is in units of watts per square meter per steradian per micrometer (W/(m^2*sr*um)). The exoatmospheric reflectance (r_o) was calculated using the following equation:

$$p = \frac{Ld^2}{ESUN \cos_s} \qquad (2)$$

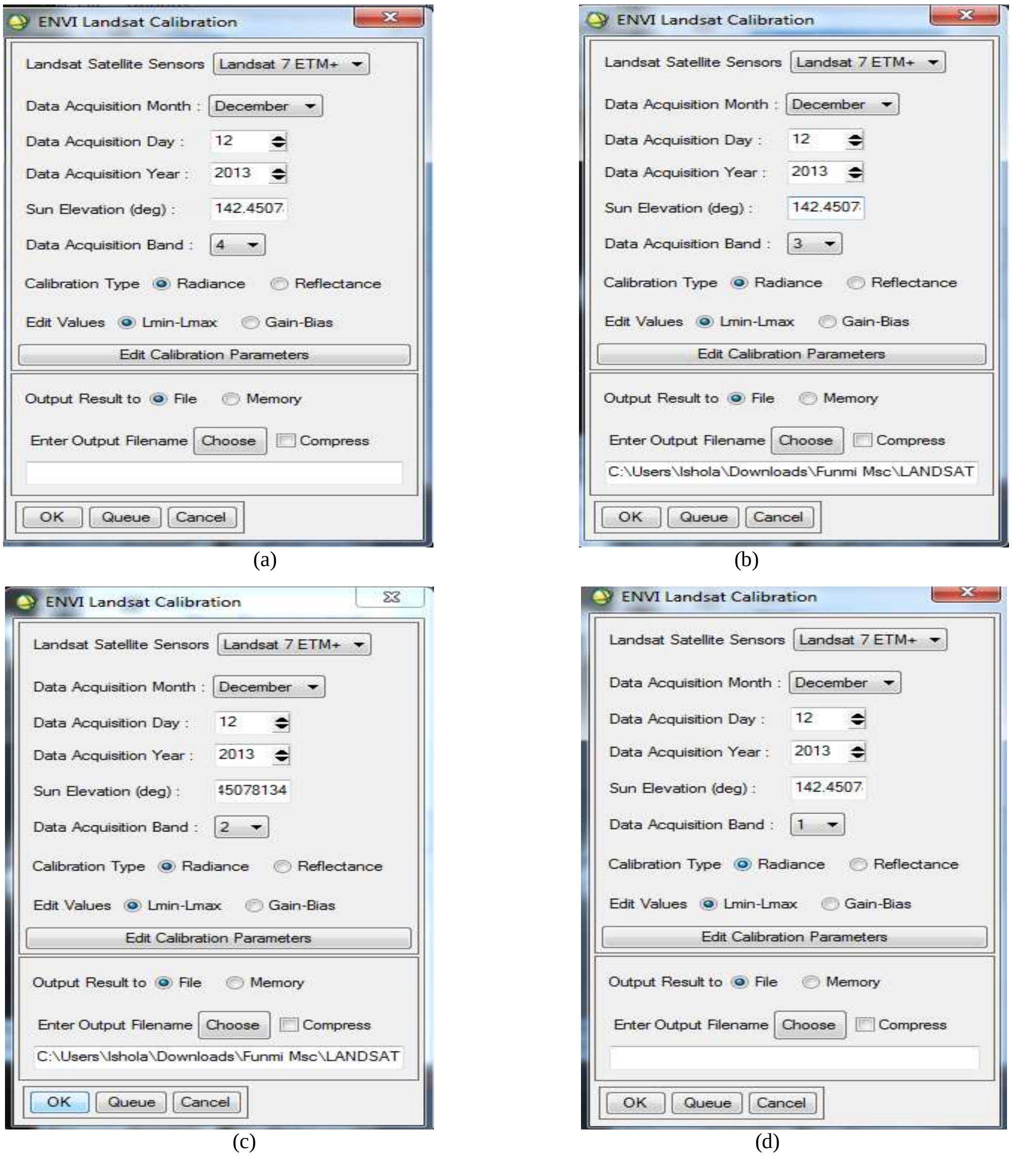
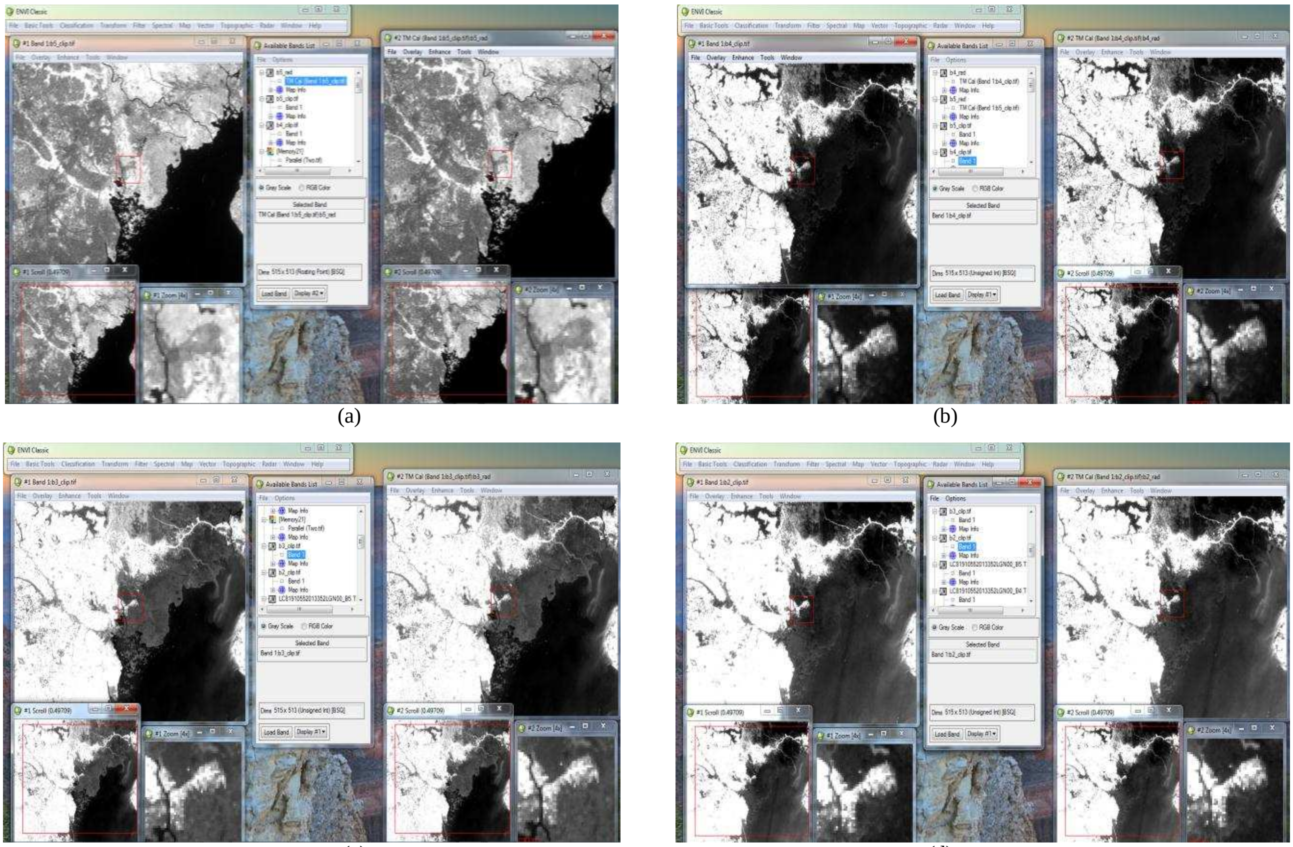


Figure 10. a) Correction for band 5 (NIR) of extracted region using the Lmin/Lmax values, insertion of Sensor type, day/month/year of acquisition as well as sun elevation angle. b) Correction for band 4 (Red) of extracted region using the Lmin/Lmax values, insertion of Sensor type, day/month/year of acquisition as well as sun elevation angle. c) Correction for band 3 (Green) of extracted region using the Lmin/Lmax values, insertion of Sensor type, day/month/year of acquisition as well as sun elevation angle. d) Correction for band 2 (Blue) of extracted region using the Lmin/Lmax values, insertion of Sensor type, day/month/year of acquisition as well as sun elevation angle.



(a) (b) (c) (d)

Figure 11. Mask of the mixed class on visual observations on the classes of soil, vegetation, and water. a) Original corrected from band 5 (NIR) corrections above; it is observed that the water class is more enhanced being the brightest in visual appearance but the soil feature is well distinguished. b) Original corrected from band 4 (Red) corrections above; it is observed that the vegetation class is well distinguished. c) Original corrected from band 3 (Red) corrections above; it is observed that the soil class is well distinguished and demarcated. d) Original corrected from band 2 (Blue) corrections above; it is observed that the water and vegetation classes are well distinguished.

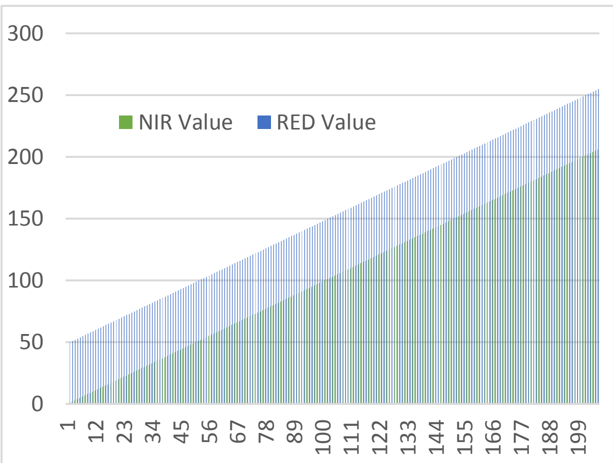


Figure 12. Brightness values of Infrared vs. Red Bands

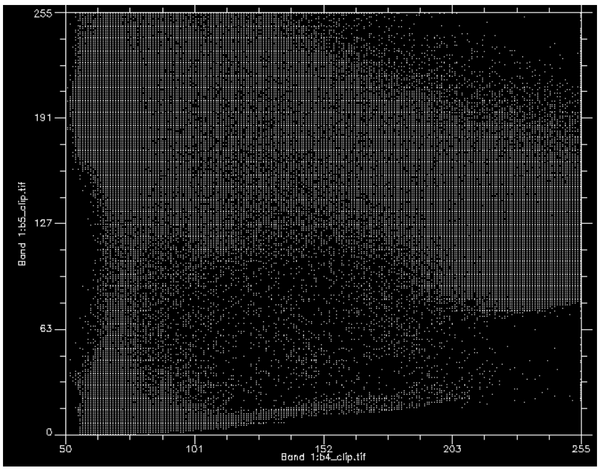


Figure 13. Scattered plot of brightness values of Infrared vs. Red Band.

After plotting, the groupings were such that at the end more of the infrared bands were with higher pixel values compared to the grouping done in 1.

IV. DISCUSSION OF RESULTS

The Parallelepiped classification (figure 6) showed from the clipped region the three features idenfied. The pixels were identified for each of the categories and they were grouped into land cover categories. These land cover classes included; Soil, Vegetation and water. From the identification of spectral signature (figure 7) of the side by side of the three unsupervised classes and the mask of the mixed class showed Green as soil from the middle to the left side of the image and the green area looks to be an urban area due to little vegetations around the area, blue as vegetation from the middle to the right side of the image in which such area looks like an undeveloped area and the area might be used for agricultural purpose and Red as deep-shallow water probably used for drinking and irrigation purposes for the citizen living around and the result showed that the three classes were properly demarcated and distinguished one from the other. From the mask of the mixed value observation on the three classes; soil, vegetation and water from band 5 NIR (figure 11a), it was observed that water is more enhanced being the brightest in appearance while soil was well distinguished. And from band 4 (figure 11b), it was observed that vegetation was well distinguished. From band 3 (figure 11c), it was observed that soil was well distinguished and demarcated within the three classes. From band 2 (figure 11d), it was observed that water and vegetation were well distinguished

V. CONCLUSION

The effectiveness use of Landsat imagery in identifying and classifying images into land cover and application of Envi 5 classic and ArcGIS 10.2 software package for acquiring and classifying Satellite images into land cover classes cannot be over-emphasized. Classification was properly done based on unsupervised method (Computer Guided). From the result of classification, it showed that soil, vegetation and water were properly demarcated and distinguished. It can be concluded that the use of satellite imagery will help in identifying features on the ground and land cover types in an environment.

REFERENCES

[1] R. Khatami, G. Mountrakis, and S.V. Stehman, "A meta-analysis of remote sensing research on supervised pixel-based land-cover image classification processes: general guidelines for practitioners and future research". Remote Sens. Environ., 2016, 177, 89–100.

[2] Kalra K., Goswami A.K., Gupta R., "A Comparative Study of Supervised Image Classification Algorithms for Satellite Images", International Journal of Electrical, Electronics and Data Communication, ISSN: 2320-2084, Volume-1, Issue-10, Dec-2013

[3] Y. H. Araya and C. Hertagen, "A Comparison of Pixel and Object-based Land Cover Classification : A Case Study of The Asmara Region, Eritrea". WIT Transaction on Built Environment, 2008, Vol. 100, ISSN 1743-3509 (Geo-Environment Landscape Evolution III)

[4] W. Ahmad, L.B. Jupp, and M. Nunez, "Land cover mapping in a rugged terrain area using Landsat MSS data". Int. J. Remote Sens. 1992, 13, 673–683. [CrossRef]

[5] D. Lu, and Q. Weng, "A survey of image classification methods and techniques for improving classification performance. Int. J. Remote Sens. 2007, 28, 823–870. [CrossRef]

[6] D. Steiner, "Automation in photo interpretation". Geoforum 1970, 1, 75–88. [CrossRef]

[7] Z. Zhu, Y. Fu, C.E. Woodcock, P. Olofsson, J.E. Vogelmann, C. Holden, M. Wang, S. Dai, and Y. Yu, Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014). Remote Sens. Environ. 2016, 185, 243–257. [CrossRef]

[8] M. Li, S.Y. Zang, B. Zhang, S.S. Li, and C.S. A Wu, "Review of remote sensing image classification techniques: The role of spatio-contextual information. Eur. J. Remote Sens. 2014, 47, 389–411. [CrossRef]

[9] M.A. Wulder, J.C. White, T.R. Loveland, C.E. Woodcock, A.S. Belward, W.B. Cohen, E.A. Fosnight, J. Shaw, J.G. Masek, and D.P. Roy, "The global Landsat archive: Status, consolidation, and direction". Remote Sens. Environ. 2016, 185, 271–283. [CrossRef]

[10] V. De Sy, M. Herold, F. Achard, G.P. Asner, A. Held, J. Kellndorfer, and J. Verbesselt, "Synergies of multiple remote sensing data sources for REDD+ monitoring". Curr. Opin. Environ. Sustain. 2012, 4, 696–706. [CrossRef]

[11] J.Q. Chambers, G.P. Asner, D.C. Morton, L.O. Anderson, S.S. Saatchi, F.D. Espírito-Santo, M. Palace, and C. Souza, "Regional ecosystem structure and function: Ecological insights from remote sensing of tropical forests". Trends Ecol. Evol. 2007, 22, 414–423. [CrossRef] [PubMed]

[12] W. Turner, C. Rondinini, N. Pettorelli, B. Mora, A.K. Leidner, Z. Szantoi, G. Buchanan, S. Dech, J. Dwyer, and M. Herold, "Free and open-access satellite data are key to biodiversity conservation". Biol. Conserv. 2015, 182, 173–176. [CrossRef]

[13] T. Hansen, "A review of large area monitoring of land cover change using Landsat data". Remote Sens. Environ., 2012, 122, 66–74. [CrossRef]

[14] A. Reinhold, and G. Wolff, "Methods of representing the results of photo interpretation". Photogrammetria 1970, 25, 201–207. [CrossRef]

[15] L. Venkataratnam, "Use of remotely sensed data for soil mapping". J. Ind Soc. Photo-Interpret. Remote Sens. 1980, 8, 19–25.

[16] M.M. Thompson, and E.M. Mikhail, "Automation in photogrammetry: Recent developments and applications" (1972–1976). Photogrammetria 1976, 32, 111–145. [CrossRef]

[17] S. Shlien, and A. Smith, "A rapid method to generate spectral theme classification of Landsat imagery". Remote Sens. Environ. 1975, 4, 67–77. [CrossRef]

[18] Fisher, and S. Pathirana, "The evaluation of fuzzy membership of land cover classes in the suburban zone". Remote Sens. Environ. 1990, 34, 121–132. [CrossRef]

[19] Sunitha Abburu and Suresh Babu Golla, "Satellite Image Classification Methods and Techniques: A Review", International Journal of Computer Applications (0975 – 8887) Volume 119 – No.8, June 2015 [19] P.F.

[20] J.B. Campbell, and R.H. Wynne, "Introduction to Remote Sensing". Guilford Press: New York, NY, USA, 2011; Vol. 5.

[21] R.O. Duda, P.E. Hart, and D.G. Stork, "Pattern Classification and Scene Analysis Part 1: Pattern Classification"; Wiley: Chichester, UK, 2000.

[22] K. Fukue, H. Shimoda, Y. Matumae, R. Yamaguchi, and T. Sakata, "Evaluations of unsupervised methods for land-cover/use classifications of Landsat TM data". Geocarto Int. 1988, 3, 37–44. [CrossRef]

Martins Adewale Oyekola was born in Ibadan, Oyo State Nigeria on 15th October, 1978. He received the Professional Master's degree in Geoinformation Production and Management (Professional) in 2014 from Regional Centre for Training In Aerospace Survey (RECTAS), OAU, Ile-Ife.

Gbola Kehinde Adewuyi was born in Oyo town, Oyo State Nigeria on 11th September, 1983. He is awaiting his Master's Degree result in Surveying and Geoinformatics from the University of Lagos Akoka, Nigeria.