International Journal of Engineering Science Invention (IJESI)
ISSN (Online): 2319-6734, ISSN (Print): 2319-6726
www.ijesi.org ||Volume 10 Issue 4 Series II || April 2021 || PP 01-13

Comparative Analysis of Urban Mapping Techniques In Owerri Urban Using High Resolution Satellite Imagery

Njoku, R.E[1] Baywood, C.C[1], Igbokwe, E.C[2] and Udo, E.[1]
[1] Department of Surveying and Geoinformatics
Federal University of Science and Technology Owerri, Imo State, Nigeria
[2]Department of Surveying and Geoinformatics
Nnamdi Azikiwe University Awka, Anambra State, Nigeria.

Abstract
There is an increasing need to be able to precisely describe and classify urban areas in order to define sustainable urban systems. The driving force for most urban changes is population growth, although there are several other interacting factors involved and description and modelling of urban areas are highly dependent on the availability and quality data. The aim of this study was to perform a comparative analysis of urban mapping techniques using high resolution satellite imagery. It's objectives were to identify and extract regions of interest (ROI) from the study area subset of the high-resolution imagery, to perform image classification using Maximum Likelihood Classifier, Support Vector Machine, rule-based, example-based and index-based classifiers and to evaluate the performances of Maximum Likelihood Classifier, Support Vector Machine, rule-based, example-based and index-based classifiers using error matrix, kappa, correlation coefficient, standard deviation, standard error, mean square error and root mean square error. The methodology covered data acquisition of high-resolution satellite image data, data preprocessing for the acquired image data, image classification and image classification assessment with error matrix, kappa, correlation coefficient, standard deviation, standard error, mean square error and root mean square error. The classification results obtained from maximum likelihood, support vector machine, rule-based, example-based and index-based classification indicated that maximum likelihood and support vector machine classifiers achieved higher classification values for agricultural area and commercial area, while achieving lower values for the classification of open space and residential areas. Rule-based, example-based and index-based classifies, all had the values for agricultural, commercial areas, open space, industrial and residential areas in similar range. In the classification of waterbody, all classifiers had all their values in the same range. Using the final ranking of the results from error matrix, kappa, correlation coefficient, standard deviation, standard error, mean square error and root mean square error, example-based classification ranked as the best in the group, rule-based classification ranked second best, support vector machine classification and index-based classification ranked third best, while maximum likelihood classification ranked fourth. The study recommends the example based object-oriented classification approach as it is a robust and efficient tool for mapping different features within the settings of an urban landscape.

Keywords: ***Accuracy Assessment, LULC, Support Vector Machine, Object-based Classification***

Date of Submission: 29-03-2021 Date of Acceptance: 12-04-2021

I. INTRODUCTION

Information on urban dynamics is the basis on which the past, present developments and the impacts of such interactions with the natural resources and the environment can be understood. Such knowledge is also required for rational and sustainable allocation of land resources for future development. In Nigeria, all urban development projects have evolved without an appreciation of the value of landuse and landcover information (Adamatzky,1994).

Economic development and population growth have triggered rapid changes to earth's landcover over the last two centuries; and there is every indication that the pace of these changes will accelerate in the future. Urban change can affect ability of the land to sustain human activities through the provision of multiple ecosystem services and the resultant economic activities can affect climate and other facets of global change (Ayodeji,2006). Accordingly, systematic assessments of earth landcover must be repeated, at a frequency that permits monitoring of both long-term trends as well as inter annual variability and at a level of spatial detail to allow the study of human-induced change (Hathout,2002).

In order to use land optimally, it is not only necessary to have the information on existing urban state, but also the capability to monitor and map accurately the dynamics of urban growth resulting from both changing demands of increasing population and natural forces that act to alter and shape the landscape (Lambin *et al*, 2003). An improved and accurate understanding of urban patterns provides a means to evaluate complex causes and responses in order to better project future trends of human activities on land. Thus, the need to study urban dynamics has become a central component in current strategies in managing natural resources and monitoring environmental changes.

In mapping urban dynamics, it is most important that a suitable mapping technique is used, remote sensing and GIS technology is slowly becoming cost effective, easy to use, and a viable technology that can produce fast, reliable, and low-cost alternative for urban development studies. Therefore, its use especially in highly developing countries is the need of the present time (Enedah *et al*., 2015). Remote sensing on its own provides information relating to LC/LU metrics and it needs to be processed and combined with population and other data in a GIS environment (Yagoub, 2006). Little wonder Igbokwe (2012) maintains that "Geographic Information System when combined with Remote Sensing is a powerful tool for solving problems".

However, using remotely-sensed data does not guarantee more accurate feature extraction. The image classification techniques used are a very much an important factor for better accuracy (Blaschke, 2010). Hence this study comparatively analyzed urban mapping techniques using high resolution satellite imagery in order to quantitatively decide which urban mapping technique can be used for better and efficient results.

Owerri in Imo State, Nigeria, has seen remarkable change in the level of physical development. This is due to the introduction of a large number of socio-economic infrastructures and developmental institutions through the activities of both the public and private sectors. These, which are indeed innovations, consequently induced a modern development of its urban environment.

Mapping LULC using remote sensing has been widely used in the fields of geography, wetland ecology, forestry, natural resources, geology, agriculture, and urban planning (Lillesand and Kiefer 2003). Schowengerdt (1997) observed that Satellite remote sensing has become instrumental in understanding global and regional Landcover processes in the past 30 years.

Landuse change over time in Owerri is an inevitable phenomenon occurring globally due to both temporary and/or permanent interest of the inhabitants. The phenomenon could be revealed either in a small or large scale but the most interesting and fundamental observation is that change occurs over time in any particular place.

There has been an increasing need to be able to precisely describe and classify urban areas in Owerri in order to define sustainable urban systems. The driving force for most urban changes is population growth, although there are several other interacting factors involved (Ramankutty, *et al,* 2002). Description and modelling of urban areas are highly dependent on the availability and quality data (Tayyebi *et al.*, 2010).

Although remote sensing techniques have been used for mapping urban areas in Imo State by (Njoku et al, 2010 & Okeke, 2015) at various levels for some time now, there has been no attempt to assess or evaluate the accuracy of different urban mapping techniques and which is the best fit for urban studies. These studies all used maximum likelihood supervised classification for classifying urban area. In recent times classification algorithms such as support vector machine, artificial neural networks, random trees classifier, principal component analysis and object-based classification have been introduced to improve classification accuracy in urban studies and there have been limited studies to analyze the accuracies of these algorithms in Owerri, Imo State.

Therefore, this presents an opportunity and an exigent need for such study to be conducted, in order to ascertain the best suited technique for urban studies in Owerri, Imo State. This will enhance the quality of urban maps produced and also provide accurate and efficient data for urban planning and management in the study area.

II. MATERIAL AND METHODS

2.1 Study Area

Owerri is the capital of Imo State in Nigeria. It is also the state's largest city, followed by Orlu and Okigwe as second and third respectively. Owerri consists of three Local Government Areas, this include Owerri Municipal, Owerri North and Owerri West. It has an estimated population of about 1,401,873 as of 2016 (Okeke, 2015), and is approximately 100 square kilometers (40 sq mi) in area. Owerri is bordered by the Otamiri River to the east and the Nworie River to the south. It is located between latitudes 5° 20'N and 5° 30'N and longitudes 6° 55'E and 7° 5'N see fig 1.0.

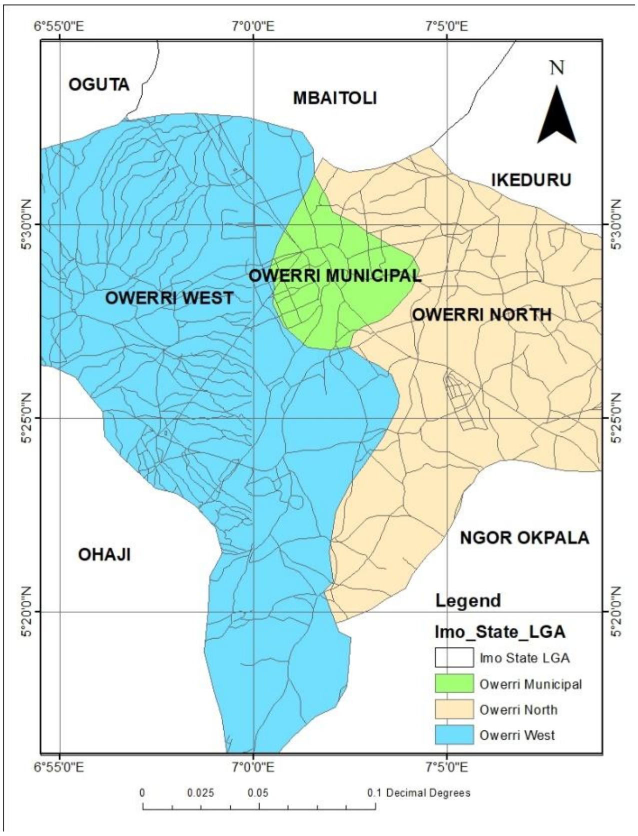


Figure 1.0: Map of Owerri, Imo State, Nigeria (Study Area)

2.2 Material and Methods

The methodology that was incorporated in this study involved acquisition of high-resolution imagery of the study area, image processing, image classification, image classification assessment. The methods used in achieving the set objectives are discussed.

2.2.1 Image Processing

Image processing was done in this study to correct the imagery for atmospheric errors, the correction filter used was the autonomous atmospheric correction in Erdas imagine. Autonomous atmospheric correction is a sophisticated tool for correcting imagery to material reflectance. The tool was used to correct imagery for atmospheric conditions, sensor viewing angle, and sensor effects, all of which can impact the interpretability of remotely sensed imagery. These contributions, together with illumination differences, distort the recorded material radiance spectra and limit the ability of most spectral processing algorithms to properly and consistently identify materials of interest.

2.2.2 Image Subset

This process was carried out in order to cut out the area of interest from the image using the shape file of the study area This was achieved using the ArcGIS 10.7 software

2.2.3 Identification and extraction of region of interest on the image

This was done to identify and define various class features on the scene before following a familiarization visit to the site. Regions of Interest (ROIs) are selected samples of a raster, such as areas of water, residential, commercial etc. that are identified to extract statistics for classification.

Thus, the following ROI in Owerri were identified and defined according to level three classification scheme, this scheme was adopted because of the resolution of the image sets and to ensure that the features are discriminated adequately following the field visits to the study area.

1. Agricultural
2. Commercial
3. Industrial

4. Open Space
5. Recreational
6. Residential
7. Waterbody

2.2.4 Ground Truthing

Ground truth was carried out to assess the accuracy of the image classification by collecting sample data for accuracy assessment. For this purpose, the coordinates of 600 selected ground feature points were collected and used to assess the accuracy of classification of images. Random sampling technique was used to determine the location of the points. Handheld GPS Garmin 76 was used to collect the field data.

2.2.5 Image Classification and Assessment

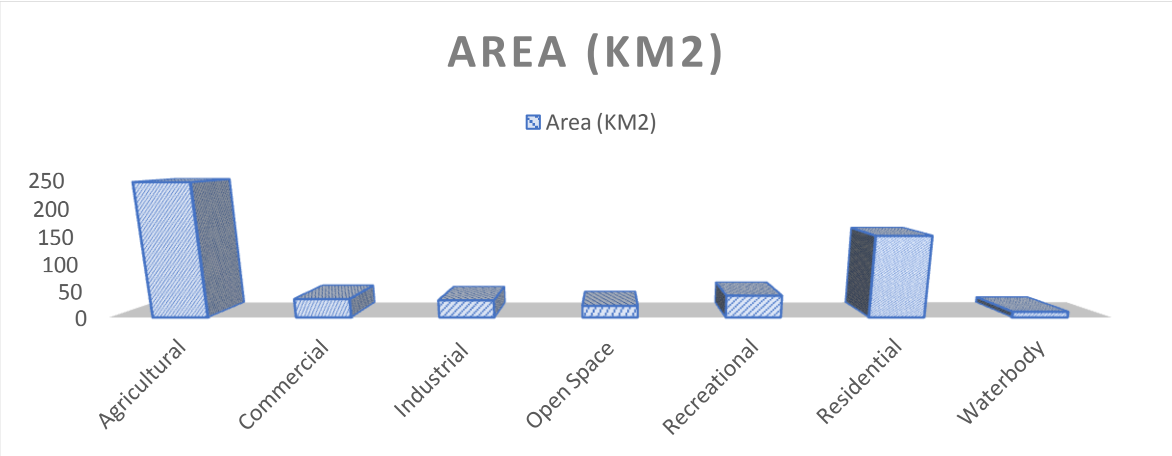
Image classification to extract the landuse classes using from maximum likelihood, support vector machine, rule-based, example-based and index-based classification indicated that maximum likelihood and support vector machine classifiers and image classification assessment was carried out to assess the quality of the classification using error matrix, kappa, correlation coefficient, standard deviation, standard error, mean square error and root mean square error.

III. RESULTS

3.1 Pixel-Based Urban mapping

3.1.1 Maximum Likelihood Classifier

The results obtained using maximum likelihood classifier as shown in figure 3.1 indicated that agricultural area accounted for the largest land cover/use of about 45.83% and an area of about 224.92 km^2, commercial area had 6.44% and a coverage area of 34.44 km^2, industrial area had 5.97% and a coverage area of 31.89 km^2, open space had 4.06% with an area of 21.68 km^2, recreational area had 7.63% and a coverage area of 40.78km^2, residential area had 28.10% and a coverage area of 150.15km^2 , and waterbody had 1.97% and an area coverage of 10.53km^2.

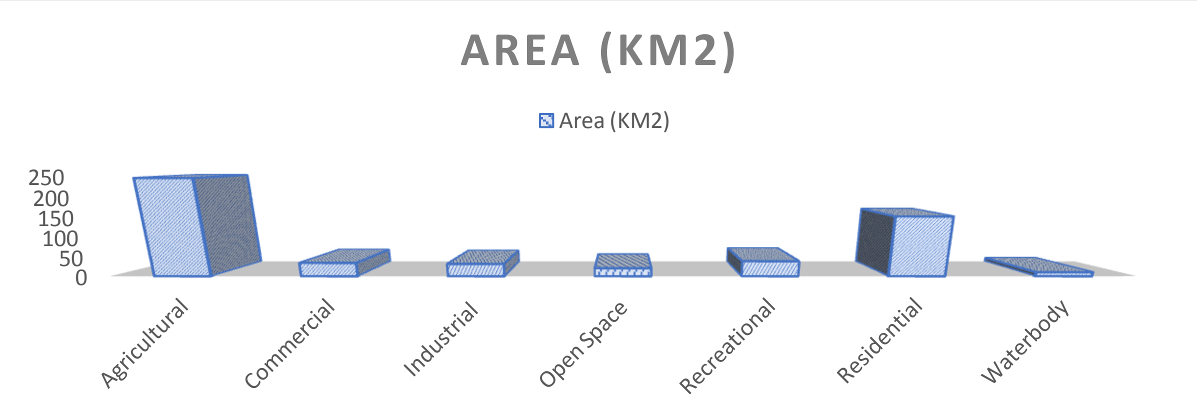


	Agricultural	Commercial	Industrial	Open Space	Recreational	Residential	Waterbody
Area (KM2)	244.92	34.44	31.89	21.68	40.78	150.15	10.53

Figure 3.1: Landcover/landuse distribution from MLC classifier

3.1.2 Support Vector Machine Classifier

The results obtained using support vector machine classifier indicate that agricultural area had land cover/use coverage of 46.02% and an area of 245.92 km^2, commercial area had 6.44 % and a coverage area of 34.44 km^2, industrial area had 5.97% and a coverage area of 31.89 km^2, open space had 3.87% with an area of 20.68 km^2, recreational area had 7.26% and a coverage area of 38.78 km^2, residential area had 28.47 % and a coverage area of 152.15km^2 , and waterbody had 1.97% and an area coverage of 10.53km^2, this is shown in figure 3.2.



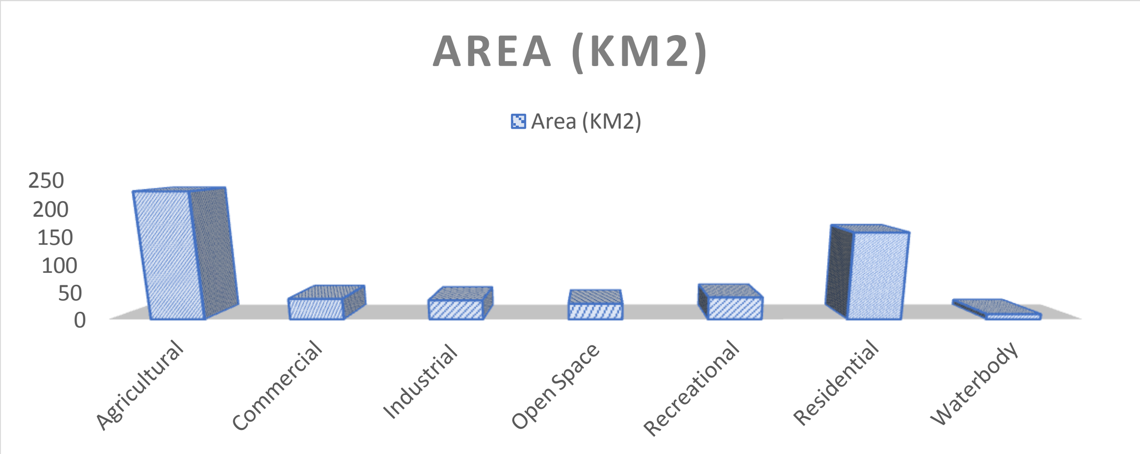
	Agricultural	Commercial	Industrial	Open Space	Recreational	Residential	Waterbody
Area (KM2)	245.92	34.44	31.89	20.68	38.78	152.15	10.53

Figure 3.2: Landcover/landuse distribution from SVM classifier

3.2. Object-Based Urban Mapping

3.2.1 Rule-based object classifier

The results obtained using rule-based classifier indicated that agricultural area had a land cover/use coverage of 42.59% and an area of 227.57km^2, commercial area had 7.02% and a coverage area of 37.49km^2, industrial area had 6.48% and a coverage area of 34.63 km^2, open space had 5.37% with an area of 28.69km^2, recreational area had 7.53% and a coverage area of 40.24km^2, residential area had 29.26% and a coverage area of 156.38km^2 and waterbody had 1.76% and an area coverage of 9.38km^2, this is shown in figure 3.3



	Agricultural	Commercial	Industrial	Open Space	Recreational	Residential	Waterbody
Area (KM2)	227.57	37.49	34.63	28.69	40.24	156.38	9.38

Figure 3.3: Landcover/landuse distribution from rule-based object classifier

3.2.2 Example-based object classifier

The results obtained using example-based classifier indicate that agricultural area accounted had land cover/use coverage of 42.34% and an area of 226.27km^2, commercial area had 7.23% and a coverage area of 38.62km^2, industrial area had 7.23% and a coverage area of 32.99km^2, open space had 5.58% with an area of 29.82km^2, recreational area had 7.25% and a coverage area of 38.72km^2, residential area had 29.43% and a coverage area of 157.27km^2 and waterbody had 2.00% and an area coverage of 10.69km^2, this is shown in table 3.4.

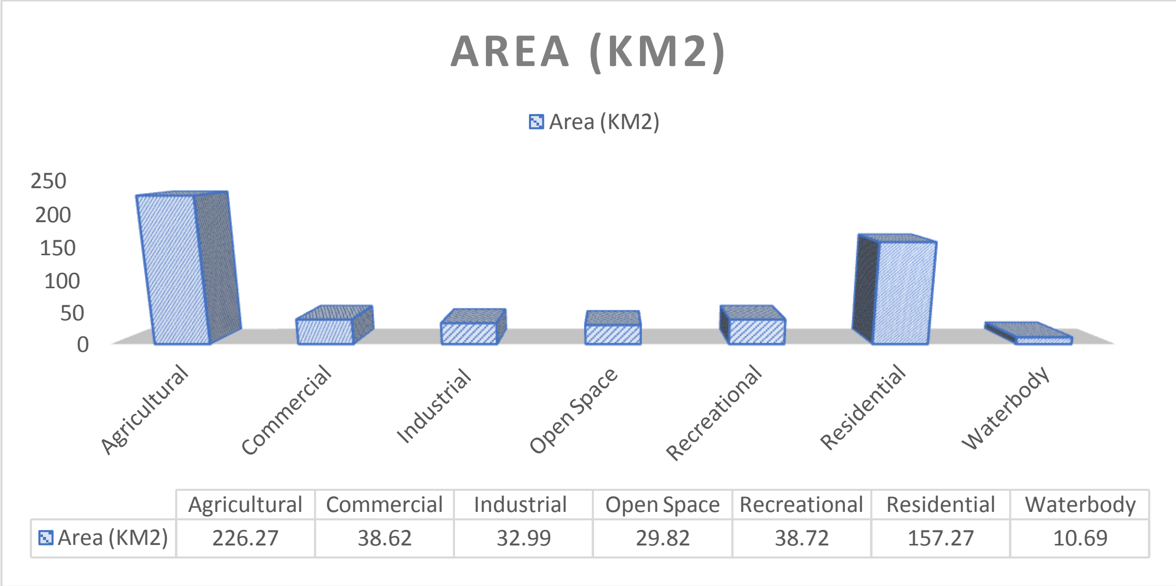


Figure 3.4: Landcover/landuse distribution from example-based object classifier

3.3. Index-based Urban Mapping

The results obtained using index-based classifier indicate that agricultural area accounted had land cover/use coverage of 42.92% and an area of 219.33 km^2, commercial area had 6.93 % and a coverage area of 37.02km^2, industrial area had 6.29% and a coverage area of 33.59km^2, open space had 5.17% with an area of 27.64km^2, recreational area had 7.38% and a coverage area of 39.44km^2, residential area had 29.45% and a coverage area of 157.37km^2 and waterbody had 1.87% and an area coverage of 9.99km^2, this is shown in table 3.5.

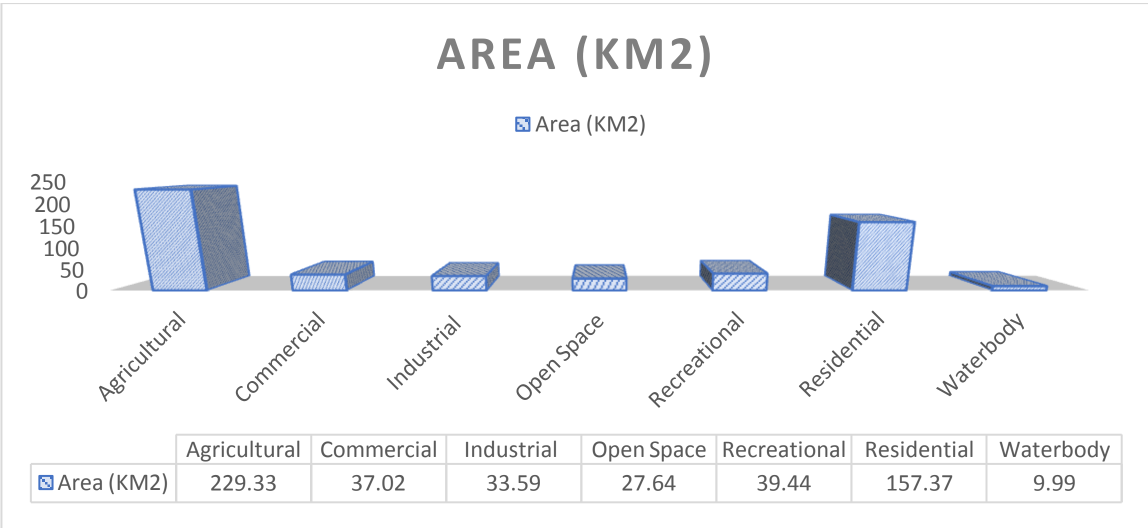


Figure 3.5: Landcover/landuse distribution from index-based classifier

3.4 Assessment of Classification Accuracy

The evaluation parameters used in this study were error matrix, kappa, correlation coefficient, standard deviation, Standard error, mean square error, root mean square error and final ranking.

3.4.1 Error Matrix and Kappa Statistics

A confusion matrix was calculated to determine the accuracy of the landcover/landuse classification from the different classifiers, the confusion matrix is an indication of major problems in situation where spectral responses of scene features overlap, where categories shares identical spectral signatures (Ndukwe, 1997).

The precision of the classified images was ascertained and accuracy assessment was carried out by comparing the classified image with ground reference points, see figure 3.6

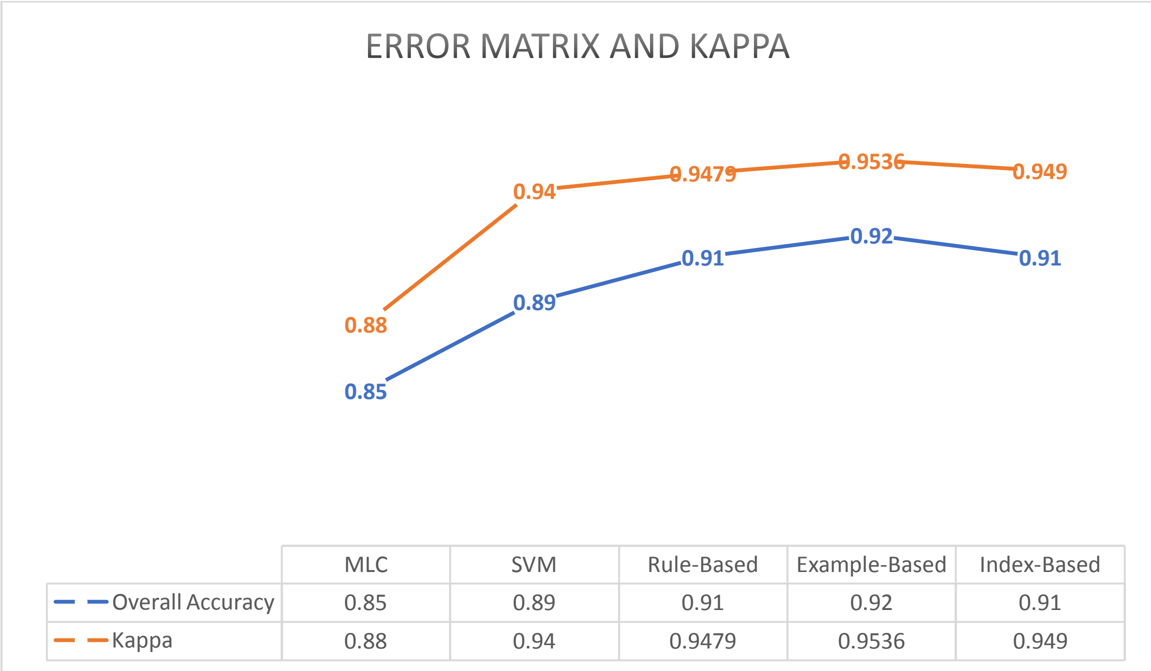


Figure 3.6: Overall Accuracy and Kappa

3.4.2 Pearson's Correlation Coefficient

Pearson's correlation coefficient measures the statistical relationship, or association, between two continuous variables. It is known as the best method of measuring the association between variables of interest because it is based on the method of covariance. It gives information about the magnitude of the association, or correlation, as well as the direction of the relationship. In this instance, a correlation value of 1 indicates a strong positive relationship while a value of -1 indicates a strong negative relationship. The resulting scatter plots are shown in figure 3.7 – 3.11 and subsequently discussed.

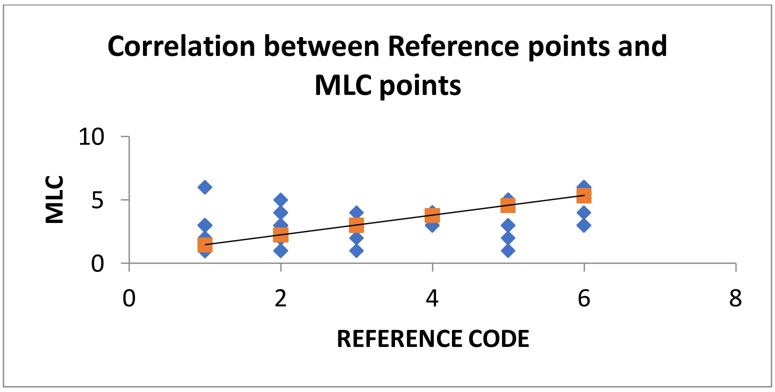


Figure 3.7: Reference against MLC fit graph

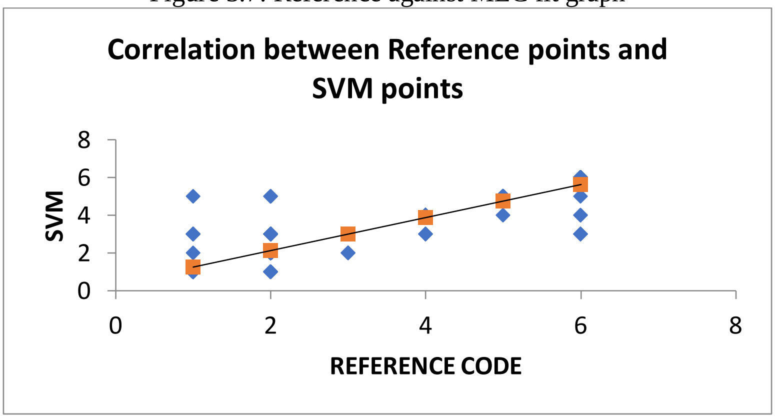


Figure 3.8: Reference against SVM fit graph

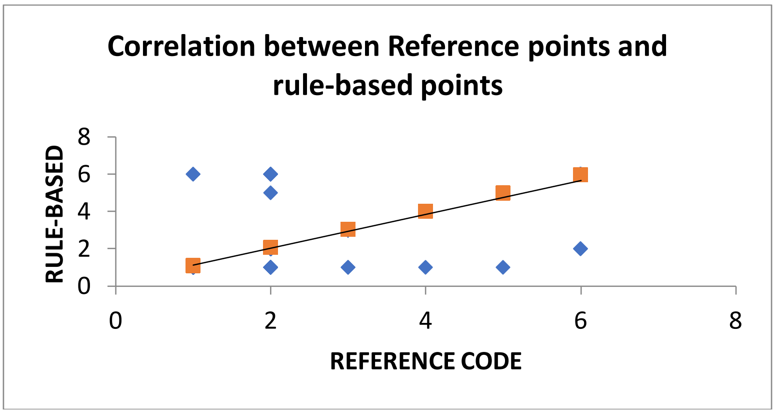


Figure 3.9: Reference against Rule-based fit graph

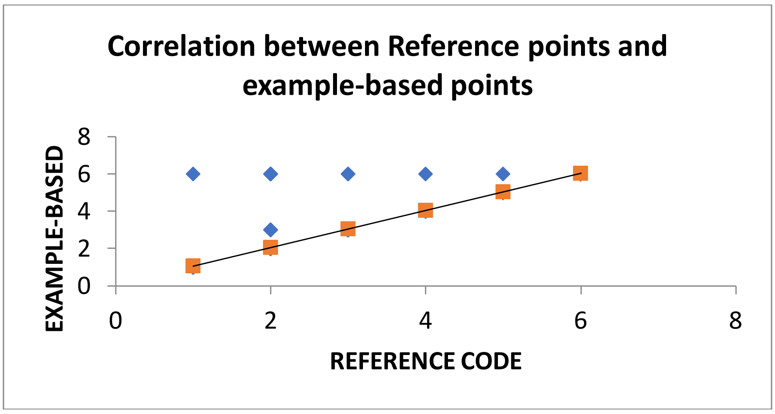


Figure 3.10: Reference against example-based fit graph

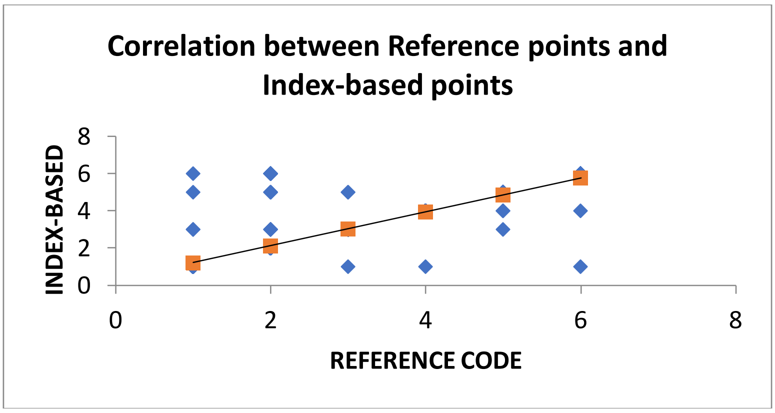


Figure 3.11: Reference against index-based-based fit graph

From the results shown in figure 3.7 – 3.11, when compared to the ground reference points, maximum likelihood gave a coefficient of 0.8059, support vector machine gave a coefficient of 0.8832, rule-based gave a coefficient of 0.9231, example-based gave a coefficient of 0.9381 while index-based gave a coefficient of 0.8534. the coefficients showed that all the classifiers obtained a relatively good relationship with the ground reference points, with example-based coming on top, followed by rule-based, support vector machine, index-based and maximum likelihood coming last.

3.4.3 Standard Deviation

Standard deviation was used in this study to measure of the amount of variation the image classification results and the reference ground data. A low standard deviation indicates that the values tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the values are spread out over a wider range. the result is shown in figure 3.12.

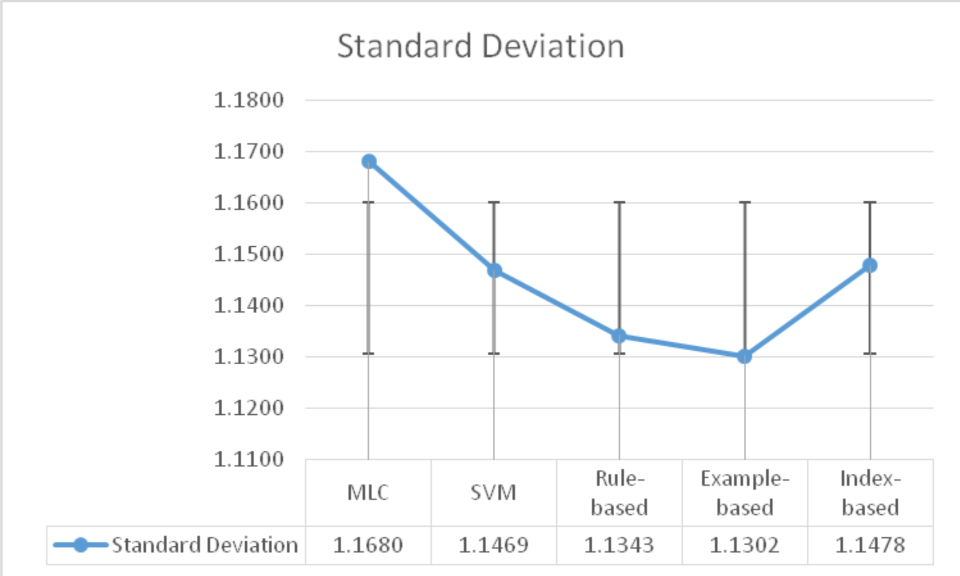


Figure 3.12: Standard deviation for the different classifiers

From the results shown in figure 3.12, when compared to the ground reference points, maximum likelihood gave a standard deviation of 1.167, support vector machine gave a deviation of 1.146, rule-based gave a standard deviation of 1.134, example-based gave a standard deviation of 1.130 while index-based gave a standard deviation of 1.147. the deviations showed that example-based had the least dispersion from the reference, followed by rule-based, support vector machine, index-based and maximum likelihood having the highest dispersion.

3.4.4 Standard Error

The standard error is a statistic measure that tells you how accurate the mean of any given sample from that population is likely to be compared to the true population mean. When the standard error increases, i.e. the means are more spread out, it becomes more likely that any given mean is an inaccurate representation of the true population mean. This metric was also used to assess the close fit of the results of the classifiers to the reference data. The result is shown in figure 3.13.

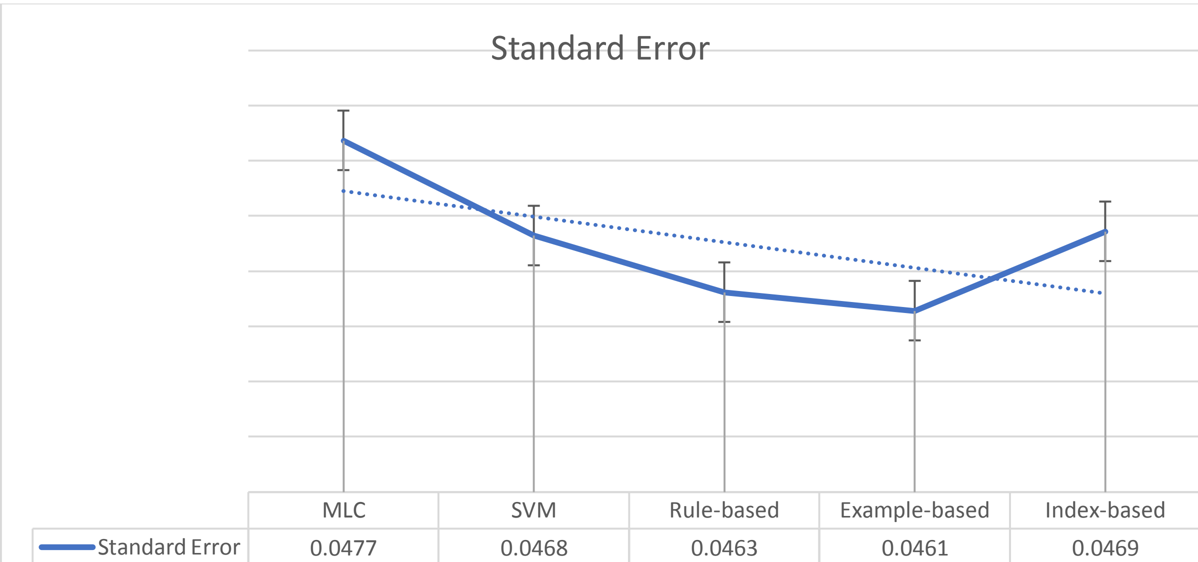


Figure 3.13: Standard Error for the classifiers

The results showed that maximum likelihood gave a standard error of 0.0477, support vector machine had a standard error of 0.0468, rule-based had a standard error of 0.0463, example-based had a standard error of 0.0461 while index-based had a standard error of 0.0469. the standard errors showed that example-based had the least error from the reference, followed by rule-based, support vector machine and index-based with maximum likelihood classification having the biggest error margin.

3.4.5 Mean Square Error

Mean squared error (MSE) measures the average of the squares of the errors that is, the average squared difference between the estimated values and the actual value (Lehmann and George, 1998). MSE is a measure of the quality of an estimator, it is always non-negative, and values closer to zero are better. The MSE was used to assess the quality of the results obtained from the classifiers and the results is shown in figure 3.15.

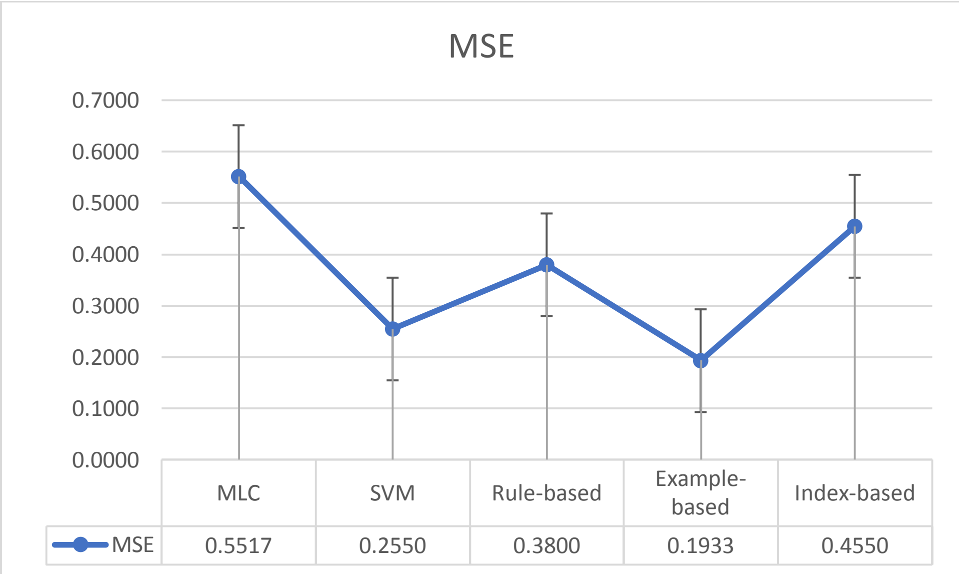


Figure 3.15: Mean square error of the classifiers

The results in figure 3.15 showed that maximum likelihood classification had an MSE value of 0.5515, support vector machine classification had an MSE value of 0.2550, rule-based classification had an MSE value of 0.3800, example-based classification had an MSE value of 0.1933 while index-based classification had an MSE value of 0.4550. the mean square errors showed that example-based classification had the least error when compared to the reference points, followed by SVM classification, rule-based classification and index-based classification. With maximum likelihood classification having the biggest error margin.

3.4.6 Root Mean Square Error

The RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data how close the observed data points are to the model's predicted values.

The RMSE was also used to assess the quality of the results obtained from the classifiers and the results is shown in figure 3.16.

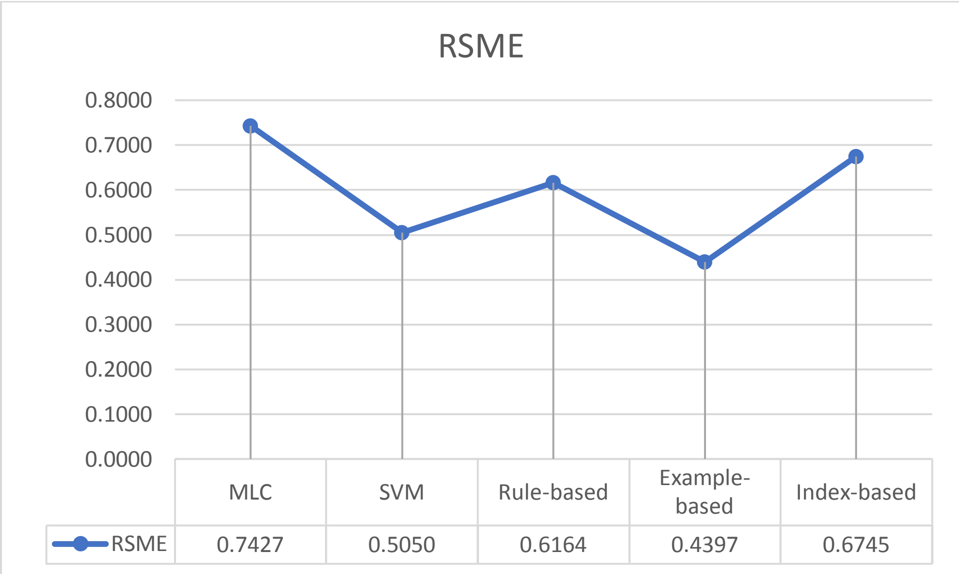


Figure 3.16: Mean square error of the classifiers

As also seen in MSE, the results in figure 3.16 showed that maximum likelihood classification had an RMSE value of 0.7427, support vector machine classification had an RMSE value of 0.5050, rule-based classification had an RMSE value of 0.6164, example-based classification had an RMSE value of 0.4397 while index-based classification had an RMSE value of 0.6745. the root mean square errors like the mean square errors also showed that example-based classification had the least error when compared to the reference points, followed by SVM classification, rule-based classification and index-based classification. With maximum likelihood classification having the biggest error margin.

4.6.8 Summary of Accuracy Assessment and Ranking

When the results were assessed with kappa, example-based classification, rule-based and index-based ranked all ranked first, support vector machine ranked second while maximum likelihood classification ranked third. When assessed with correlation coefficient, example-based classification ranked first, rule-based ranked second, support vector machine ranked third, index-based ranked fourth while maximum likelihood classification ranked fifth.

Assessing the accuracy with standard deviation, example-based classification and rule-based classification ranked first, support vector machine and index-based classification ranked second while maximum likelihood classification ranked third. Also, assessed with standard error, example-based classification ranked first, rule-based ranked second, support vector machine ranked third, index-based ranked fourth while maximum likelihood classification ranked fifth.

When assessed with mean square error, example-based classification ranked first, rule-based ranked second, support vector machine ranked third, index-based ranked fourth while maximum likelihood classification ranked fifth and lastly, when assessed with root mean square error, example-based classification ranked first, rule-based classification ranked second, support vector machine classification and index-based classification ranked third, while maximum likelihood classification ranked fourth.

Overall, using the final ranking of all the assessment metrics, example-based classification ranked as the best in the group, rule-based classification ranked second best, support vector machine classification and index-based classification ranked third best, while maximum likelihood classification ranked fourth

The summary is illustrated in table 3.1.

Table 3.1: Summary of Accuracy Assessment Metrics

Metric															
Class	EM	RK	K^	RK	CoR	RK	SD	RK	SE	RK	MSE	RK	RSME	RK	Final Rank
MLC	0.85	4	0.88	3	0.80	5	1.16	3	0.0477	5	0.55	5	0.74	5	4
SVM	0.89	3	0.94	2	0.88	3	1.14	2	0.0468	3	0.25	2	0.50	2	3

Rule-Based	0.91	2	0.95	1	0.92	2	1.13	1	0.0463	2	0.38	3	0.61	3	2
Example-Based	0.92	1	0.95	1	0.94	1	1.13	1	0.0461	1	0.19	1	0.44	1	1
Index-Based	0.91	2	0.95	1	0.85	4	1.14	2	0.0469	4	0.45	4	0.67	4	3

Where 1 = Best in the group
2 = Better than average
3 = Average
4 = Below Average

IV. SUMMARY AND CONCLUSION

Image classification methods have been in use for years now; it is not new to image analysts in today's market. However, focus is on analyzing and ascertaining the best fit classifier that can be used for urban classifications while providing as close information as possible to what we have on ground. Therefore, based from the analysis and results of this study, most research on image classification basically make use of error matrix and kappa statistics as a metric for assessing image classification accuracy. However, this study went further to analyze the image classification accuracy using correlation coefficient, standard deviation, standard error, mean square error and root mean square error in addition to error matrix and kappa statistics. These metrics can be adopted because they have proved to be useful when comparing the close fit of an observed data to an expected data, in this case, the classification results and ground reference data.

From the results obtained, the study was able to ascertain example-based image classification as the best tool for mapping different features within the settings of an urban landscape due to its robustness in classification efficiency

Also, from the results, it is not that the pixel-based, rule-based or index-based classification methods are purely bad classifiers but most of these classifiers are sophisticated in their own way and their peculiarities have to be catered to in order to achieve a meaningful result, pixel-based can only be used for images where the feature classes are spectrally homogenous as well as using majority filters to remove pixel fragmentation, rule-based and index-based classifications need in addition accurate ancillary data describing the characteristics of the feature class of interest.

The study has successfully compared and analyzed different urban mapping techniques using high resolution satellite imagery, based on the experience and results obtained, the following recommendations are hereby proffered:

1. Example based object-oriented classification method is recommended as it is a robust and efficient tool for mapping different features within the settings of an urban landscape.
2. It is recommended that caution should be applied when using pixel-based classification method for classifying high resolution imageries as it leads to misclassifications when two or more classes have the similar spectral characteristics.
3. Rule based object-oriented classification method is also an effective to for extracting and mapping urban features but caution should be applied as its accuracy is dependent on the segmentation parameter's robustness.

REFERENCES

[1]. Adamatzky, A. (1994). *Identification of cellular automata.* Taylor and Francis, London
[2]. Ayodeji, O.Z. (2006). Change detection in landuse and landcover using Remote sensing data and GIS: A case study of Ilorin and its environs in Kwara state. Unpublished M.A. Thesis, Department of Geography, University of Ibadan 44.
[3]. Blaschke T. (2010). Object Based Image Analysis for Remote Sensing. *ISPRS Journal of Photogrammetry and Remote Sensing* vol. 65 pp. 2 – 16
[4]. Enedah I. C., J. I. Igbokwe, J. C. Ojiako, and E. C. Igbokwe (2015) Spatio-Temporal Analysis and Mapping of Urban Development Trends in The Federal Capital City (FCC) Abuja, Nigeria From 1990 To 2014. *International Journal of Scientific Research and Engineering Studies (IJSRES) pp36-39 Volume 2 Issue 9,* September 2015. Available online www.ijsres.com/2015/vol-2issue-9/paper7.pdf Accessed February, 2017.
[5]. Igbokwe, J. I. (2012). *Advanced Remote Sensing Techniques*, Nnamdi Azikiwe University, Unpublished Lecture Notes.
[6]. Hathout, S. (2002). The use of GIS for monitoring and predicting urban growth in East and West St. Paul. Winnipeg, Canada. *Journal of Environmental Management 66* (1), 229 – 238.
[7]. Lambin, E. F., H . Geist, and E. Lepers (2003). Dynamics of LU and LC Changes in Tropical Regions. *Annual Review of Environment Resources*, 28: 205 – 41 (online) available http://www.globalrestorationnetwork.org/uploads/files/LiteratureAttachments/93_dynamics-of-land- use-and-land-cover-change-in-tropical-regions.pdf Accessed February, 2017.
[8]. Lillesand T. M. and R. W. Kiefer (2003). *Remote Sensing and Image Interpretation*, 4th Edition, p. 724, John Wiley & Sons, Inc
[9]. Njoku, J.D., Ebe, T.E. & Edith, P. (2010). Detection and mapping of landuse and landcover classes of a Developing city in South eastern Region of Nigeria using Multi-band Digital Remotely – Sensed Data. *Journal of Environmental science 2*(2), 100-150

[10]. Okeke, D.C. (2010). Environmental and Urban Renewal Strategies: Theoretical and Analytical Frameworks. Institute for development studies UNN Enugu 258 P.

[11]. Yagoub M. M. (2006). Application of Remote Sensing and Geographic Information systems (GIS) to Population Studies in the Gulf: A Case of Al Ain City (UAE). *Journal of the Indian Society of Remote Sensing*, Vol. 34, No. 1.9

[12]. Ramankutty, N., Foley, J.A and Olejniczak, N.J., (2002) People on the Land: Changes in Population and Global Croplands during the 20th Century, Ambio, 31 (3), 251-257.

[13]. Schowengerdt R. A. (1997). *Remote Sensing: Models and Methods for Image Processing*, Second Edition, pp. 522, Academic Press, San Diego, California

[14]. Tayyebi, A., Delavar, M., Yazdanpanah, M., Pijanowski, B., Saeedi, S., and Tayyebi, A. (2010). A Spatial Logistic Regression Model for Simulating LU Patterns: A Case Study of the Shiraz Metropolitan Area of Iran. In E. Chuvieco, J. Li and X. Yang (Eds.), *Advances in Earth Observation of Global Change* (pp. 27-42): Springer Netherlands.

Njoku, R.E, et. al. "Comparative Analysis of Urban Mapping Techniques In Owerri Urban Using High Resolution Satellite Imagery." *International Journal of Engineering Science Invention (IJESI)*, Vol. 10(04), 2021, PP 01-13. Journal DOI- 10.35629/6734