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recommendations: There is need for the relevant agencies of government and stakeholders in the water sector to create greater social awareness about the right and responsibilities in the use of public water and put in place management practices in the utilisation of this available resource. Users will be willing to pay more if they understand the benefit they will derive. A re-introduction of open public taps for collection by households will assist the State in its aspiration to meet the Sustainable Development Goal 6 of ensuring availability and sustainable management of water and sanitation for all.

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A Comparative Evaluation of Different Techniques of Supervised Classification in Landuse/Landcover Mapping of Awka South L.G.A, Anambra State, Nigeria.

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Abstract:

The aim of this study is to compare the different techniques of supervised classification using Awka South LGA, of Anambra State as a case study. The techniques considered include: Maximum Likelihood (MLC), Minimum Distance, Mahalanobis Distance, Spectral Angle Mapper and Parallelepiped. Landsat 7 ETM+ (2000 and 2007) and Landsat 8 OLI/TIRS (2015) were acquired. The images were pre-processed. The scan-line effect present in the Landsat 7 image was corrected using the analysis tool of Quantum GIS (QGIS) 2.18 software. To compensate for atmospheric effects, Fast Line-of-site Atmospheric Analysis of Hypercube (FLAASH) Atmospheric Module of ENVI software was used. Image enhancement was carried out on the images. The images were classified using the different techniques and the results compared. Change detection was also carried out to determine the rate of changes between 2000 and 2015. Error matrices of the various techniques were calculated to determine the accuracy level of the algorithms and to judge which is the better choice. It can be deduced from the results that Maximum Likelihood (99.63%) produced the best result, followed closely by Mahalanobis Distance (98.54%), Spectral Angle (89.28%), Minimum Distance (84.42%) and Parallelepiped (85.00%). The study recommends Maximum Likelihood Classification algorithm for supervised classification.

Key words: Classification, Maximum Likelihood, Algorithm, Land cover land use

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1. Introduction

Classification of Satellite Images is a key component for various Object Recognition Systems and Automatic Thematic Map Generation Systems. Image classification is the most important part of image analysis, remote sensing and pattern recognition applications. In remote sensing, it is used to generate various thematic maps such as land use maps, landform maps etc. In some cases, image classification may serve as the ultimate product while in other cases it can serve only as an intermediate step. Therefore, image classification is a significant tool for digital images analysis and object recognition. The major steps involved in image classification are determination of suitable classification system, selection of training and testing samples and the classification technique. Moreover, the selection of the appropriate classification technique to employ can have considerable upshot on the results of whether the classification is used as an ultimate product or as one of numerous analytical procedures applied for deriving information from an image for additional analyses (Gabrya, and Petrakieva 2004; Kalra et al. 2013).

Proper classification of LULC is a very essential requirement for all modelling tasks in environmental problems (Rashid and Romshoo 2014). Therefore, utilizing automatic remote sensing techniques will provide a reasonable answer to this problem. Nevertheless, knowing the best classification method to perform this task is a very important aspect in order to utilize the right approach for classification. Thus, this paper evaluates five remote sensing classification methods for automatically obtaining LCLU from Landsat images.

This study therefore compares the performances of a range of supervised classification techniques; Maximum Likelihood classifier, Minimum Distance, Spectral Angle, Parallelepiped and Mahalanobis, using as a reference, LULC obtained from object based classification of Awka South LGA of Anambra State thereby detecting the land consumption rate and the changes that has taken place during the last two decades.

2 The Study Area

Awka South LGA is one of the 21 local governments in Anambra State. It was created in 1989 from Awka local government area. It is one of the local governments that make up the capital city. Its geographical coordinate is

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6° 10' 0" North, 7° 4' 0" East; bounded on the north by Awka North local government area, on the east by Oji-River local government area of Enugu State, on the south by Anaocha local government area and on the west by Njikoka local government area. It has a land area of 180 square kilometers and it is made up of nine towns namely: Awka (HQ), Amawbia, Ezinato, Nibo, Nise, Umuawulu, Isiagu, Okpuno, and Mbaukwu. There are three major streets that span this area, which are the Zik Avenue, Works Road and Arthur Eze Avenue. In the past, the people of Awka South LGA were well known for blacksmithing. Today they are respected among the Igbo people of Nigeria for their technical and business skills.

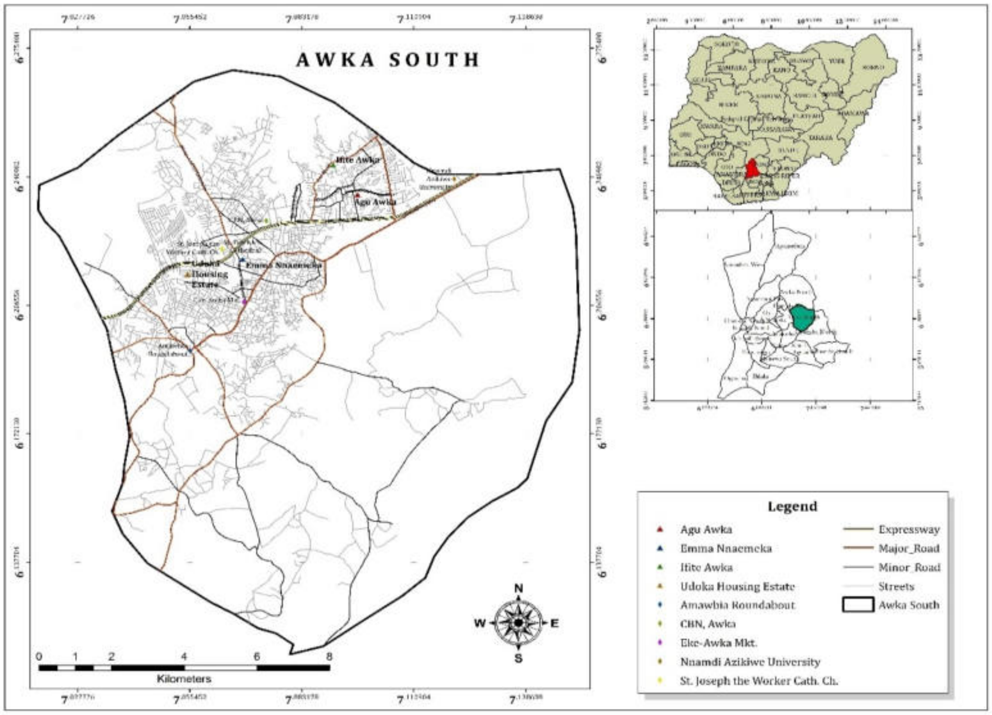

Figure 1: Study Area

3 Methodology

3.1 Data Used

The data used for this research include remotely sensed data: Landsat 8 OLI/TIRS imagery of 2015; Landsat 7 ETM imagery of 2007; and Landsat 7 ETM of 2000, all acquired from the archives of the United States Geological Services (Earth Explorer). Aerial image of the study area was acquired for object based classification which was used as a reference for the comparison.

3.2 Data Processing

3.2.1 Scan-Line Correction Gap Filling

On May 31, 2003, the Scan Line Corrector (SLC), which compensates for the forward motion of Landsat 7, failed. Subsequent efforts to recover the SLC were not successful, and the failure appears to be permanent. Without an operating SLC, the Enhanced Thematic Mapper Plus (ETM+) line of sight now traces a zig-zag pattern along the satellite ground track. There are various methods established to fill the gaps and many software capable of filling the gaps, all with varying results. The software used for this project is Quantum GIS (QGIS) 2.18, the software used the Gap Mask images provided in the zipped file of the Landsat 7 image.

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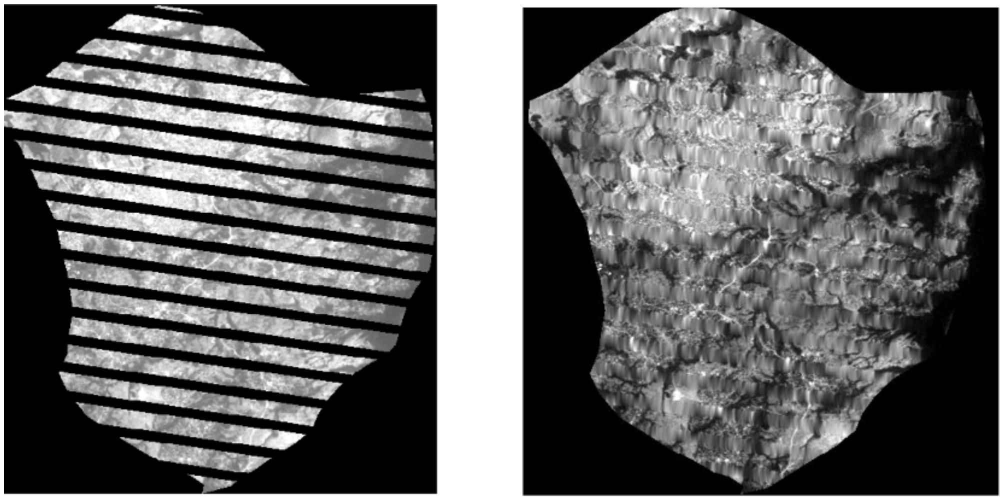

Figure 2: Original SLC-OFF Image of the study Area and the Gap filled Image

3.2.2 Atmospheric Correction

The nature of remote sensing requires that solar radiation pass through the atmosphere before it is collected by the instrument. Because of this, remotely sensed images include information about the atmosphere and the earth's surface. To compensate for atmospheric effects, properties such as the amount of water vapor, distribution of aerosols, and scene visibility must be known.

FLAASH Atmospheric Module on ENVI is a first-principles atmospheric correction tool that corrects wavelengths in the visible through near-infrared and shortwave infrared regions, up to 3 µm. FLAASH work with most hyper-spectral and multispectral sensors. Water vapor and aerosol retrieval are only possible when the image contains bands in appropriate wavelength positions. FLAASH can correct images collected in either vertical (nadir) or slant-viewing geometries. The FLAASH Module was used for this project.

3.2.3 Image Classification

The purpose of Image classification is to categorize all pixels in a digital image into different land use / land cover classes. Depending on the interaction between computer and interpreter during classification process, there are two types of classification. These two main categories used to achieve classified output are called Supervised and Unsupervised Classification techniques. Out of the two major methods of image classification, supervised classification is generally chosen when analyst have good knowledge of the area. In supervised classification, analyst select representative samples for each land cover class. The software then uses these "training sites" and applies them to the entire image. Supervised classification uses the spectral signature defined in the training set. The multispectral or hyperspectral data from the pixels in the sample area or spectral signatures from spectral library will be used to train a classification algorithm (Kamaruzaman *et al.,* 2009). Once trained, the algorithm will then be applied to the entire image and a final classification image is obtained. The algorithms explored in this project include; Maximum Likelihood, Minimum Distance, Mahalanobis Distance, Spectral Angle Mapper and Parallelepiped. The classifications were done using ENVI Classic.

3.2.3.1 Maximum Likelihood:

the maximum likelihood algorithm is the most common and widely used in supervised image classification. It assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability, that is the maximum likelihood. If the highest probability is smaller than a specified threshold, the pixel remains unclassified.

3.2.3.2 Minimum Distance:

The minimum distance technique uses the mean vectors of each endmember and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria.

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3.2.3.3 Mahalanobis Distance:

This classification technique is a direction-sensitive distance classifier that uses statistics for each class. It is similar to Maximum Likelihood classification but assumes all class covariance are equal and therefore is a faster method. All pixels are classified to the closest class unless a distance threshold is specified, in which case some pixels may be unclassified if they do not meet the threshold.

3.2.3.4 Spectral Angle Mapper:

SAM is a physically-based spectral classification that uses an n-D angle to match pixels to reference spectra. The algorithm determines the spectral similarity between two spectra by calculating the angle between the spectra and treating them as vectors in a space with dimensionality equal to the number of bands. Endmember spectra used by SAM can come from ASCII files or spectral library or can be extracted from an image. SAM compares the angle between the endmember spectrum vector and each pixel vector in n-D space. Smaller angles represent closer matches to the reference spectrum, pixels further away than the specified maximum angle threshold in radians are not classified.

3.2.3.5 Parallelepiped:

Parallelepiped classification uses a simple decision rule to classify multispectral data. The decision boundaries form an n-dimensional parallelepiped classification in the image data space. The dimensions of the parallelepiped classification are defined based on a standard deviation threshold from the mean of the selected class. If a pixel value lies above the low threshold and below the high threshold for all n bands being classified, the pixel is assigned to the first class matched. Areas that do not fall within any of the parallelepiped classes are designated as unclassified.

4 Results

In supervised classification, false color composite of the image is created for the classification is, bands 7, 4, 2 for Landsat 7 images and 7, 5, 3 for Landsat 8 images. Training pixels/samples are collected to aid the software in the classification process. The ROI tools on ENVI were used to collect training samples from the different images and separability between the ROIs were evaluated. After the collection of training samples, the images are classified based on the algorithm specified. The Anderson 1976 Level 1 classification scheme was used, and identified on the image are four land use land cover classes: Built-up Area, Bare Ground, Vegetation and Water Body. Figure 4.1a-4.1e shows the landuse/landcover map obtained from the different techniques for the year 2000. Similarly, figure 4.2a-4.2e and 4.3a-4.3e shows the results obtained for 2007 and 2015 respectively.

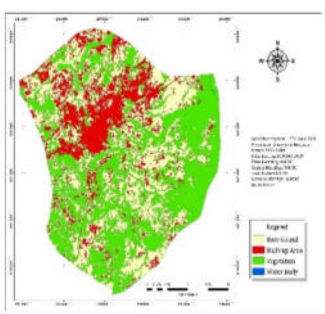

Fig. 4.1a: Maximum Likelihood

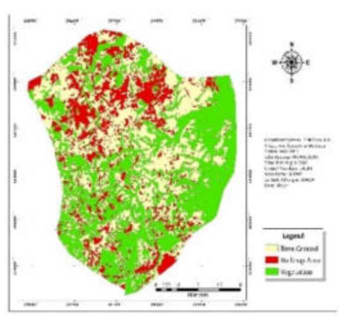

Fig. 4.1b: Minimum Distance

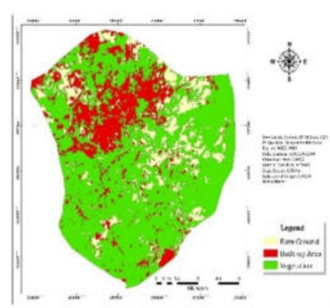

Fig. 4.1c: Mahalanobis Distance

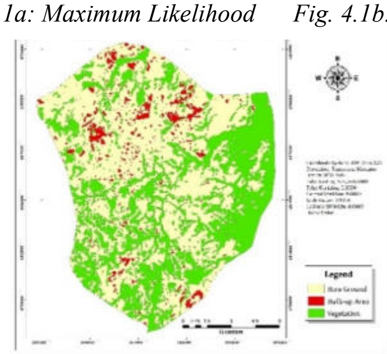

Fig. 4.1d: Spectral Angle Mapper

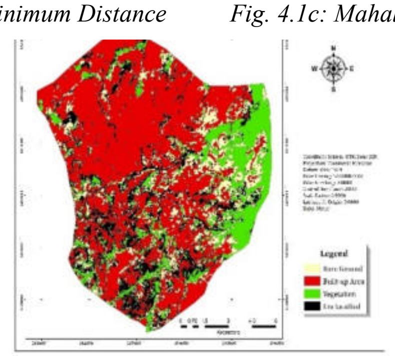

Fig. 4.1e: Parallelepiped

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Figures 4.1a, 4.1b, 4.1c, 4.1d and 4.1e shows the result obtained from the Maximum likelihood, Minimum Distance, Mahalanobis Distance, Spectral Angle Mapper and Parallelepiped supervised classification algorithms of the year 2002 respectively.

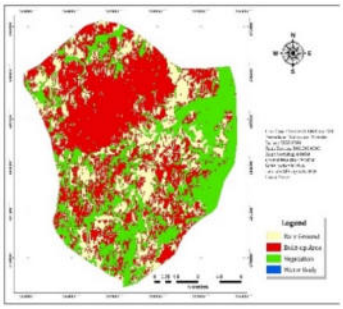

Fig. 4.2a: Maximum Likelihood

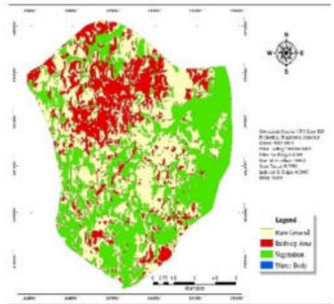

Fig. 4.2b: Minimum Distance

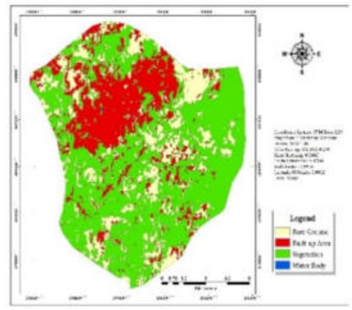

Fig. 4.2c: Mahalanobis Distance

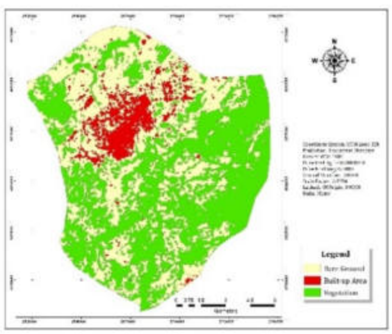

Fig. 4.2d: Spectral Angle Mapper

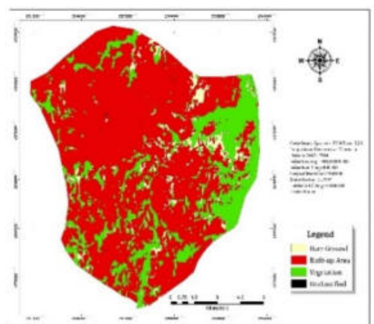

Fig. 4.2e: Parallelepiped

Figures 4.2a, 4.2b, 4.2c, 4.2d and 4.2e shows the result obtained from the Maximum likelihood, Minimum Distance, Mahalanobis Distance, Spectral Angle Mapper and Parallelepiped supervised classification algorithms of the year 2007 respectively. Due to the scan line error of Landsat 7, the scar from the missing lines are quite noticable.

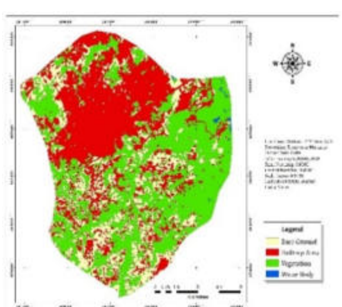

Fig. 4.3a: Maximum Likelihood

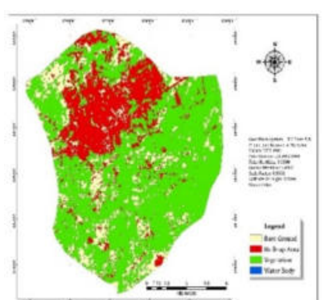

Fig. 4.3b: Minimum Distance

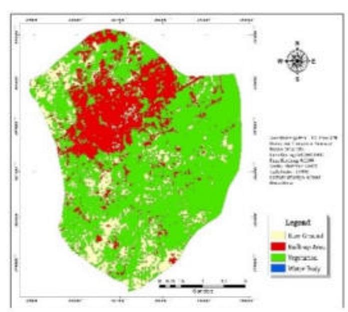

Fig. 4.3c: Mahalanobis Distance

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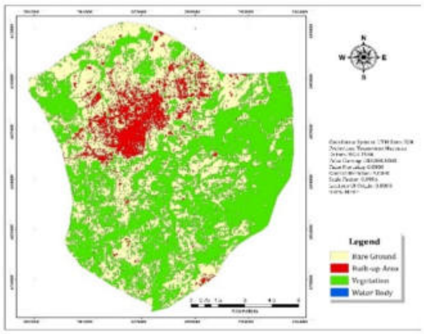

Fig. 4.3d: Spectral Angle Mapper

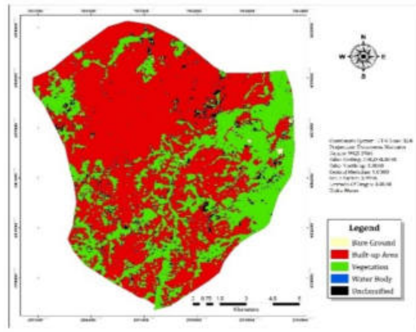

Fig. 4.3e: Parallelepiped

Figures 4.3a, 4.3b, 4.3c, 4.3d and 4.3e shows the result obtained from the Maximum likelihood, Minimum Distance, Mahalanobis Distance, Spectral Angle Mapper and Parallelepiped supervised classification algorithms of the year 2015 respectively.

4.1 Accuracy Assessment

Classification of remotely sensed images are not complete without assessing the accuracy of the classification result. One of the important ways of representing accuracy assessment information is in the form of an error matrix, or contingency table (Congalton, 1991). Error matrices provide assessment on how much the reference data and the classified data agree at specific locations. Below are accuracy assessment tables of the different algorithms of the different years of interest, the table shows the Producer accuracy (error of commission) and User accuracy (error of omission), along with the Overall Classification accuracy and Kappa coefficients of agreement.

4.1.1 Error Matrices for the different Algorithms used for each years of Interest

Table 4.1-4.5 shows the accuracy assessment results obtained from the different techniques for the year 2000. Similarly, table 4.6-5.0 and 5.1-5.5 shows the results obtained for 2007 and 2015 respectively

Table 4.1: Accuracy Assessment of MLC for the year 2000

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**35**	0	0	0	35	100%
Bare Ground	0	**17**	0	0	17	100%
Vegetation	0	0	**84**	0	84	100%
Water Body	0	0	0	**4**	4	100%
Total	**35**	**17**	**84**	**4**	**140**	
Producer Accuracy	100%	100%	100%	100%		
Overall Accuracy					100%	
Overall Kappa Index					1.0000	

Table 4.2: Accuracy Assessment of Min. Distance for the year 2000

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**20**	0	0	0	20	100%
Bare Ground	15	**17**	0	0	32	53.13%
Vegetation	0	0	**84**	4	88	95.45%
Water Body	0	0	0	**0**	0	0%
Total	**35**	**17**	**84**	**4**	**140**	
Producer Accuracy	57.14%	100%	100%	0%		
Overall Accuracy					86.4286%	
Overall Kappa Index					0.7574	

Table 4.3: Accuracy Assessment of Mahalanobis Distance for the year 2000

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	35	0	0	0	35	100%
Bare Ground	0	17	0	0	17	100%
Vegetation	0	0	84	4	88	95.45%
Water Body	0	0	0	0	0	0%
Total	35	17	84	4	140	
Producer Accuracy	100%	100%	100%	0%		
Overall Accuracy					97.1429%	
Overall Kappa Index					0.9476	

Table 4.4: Accuracy Assessment of Parallelepiped for the year 2000

CLASS	Unclassified	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Unclassified	**5**	0	0	0	0	5	
Built-up Area	0	**35**	3	0	0	38	92.11%
Bare Ground	0	0	**14**	0	1	15	93.33%
Vegetation	0	0	0	**84**	3	87	96.55%
Water Body	0	0	0	0	**0**	0	0%
Total	5	35	17	84	4	**145**	
Producer Accuracy	100%	100%	82.35%	100%	0%		
Overall Accuracy						85.0000%	
Overall Kappa Index						0.8085	

Table 4.5: Accuracy Assessment of the Spectral Angle Algorithm for the year 2000

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**25**	1	0	0	26	96.15%
Bare Ground	10	**16**	0	0	26	61.54%
Vegetation	0	0	**84**	4	88	95.45%
Water Body	0	0	0	**0**	0	0%
Total	35	17	84	4	**823**	
Producer Accuracy	71.43%	94.12 %	100%	0%		
Overall Accuracy					89.2857%	
Overall Kappa Index					0.8066	

Table 4.6: Accuracy Assessment of MLC for the year 2007

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**90**	0	s0	2	92	97.83%
Bare Ground	0	**85**	0	0	85	100%
Vegetation	0	0	**523**	2	525	99.62%
Water Body	0	0	0	**32**	32	100%
Total	90	85	523	36	**734**	
Producer Accuracy	100%	100%	100%	88.89%		
Overall Accuracy					99.4550%	
Overall Kappa Index					0.9881	

Table 4.7: Accuracy Assessment of Minimum Distance for the year 2007

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**71**	0	0	0	71	100%
Bare Ground	19	**85**	0	0	104	81.73%
Vegetation	0	0	**523**	4	527	99.24%
Water Body	0	0	0	**32**	32	100%
Total	90	85	523	36	**734**	
Producer Accuracy	78.89%	100%	100%	88.89%		
Overall Accuracy					96.8665%	
Overall Kappa Index					0.9316	

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Table 4.8: Accuracy Assessment of Mahalanobis Distance for the year 2007

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	90	0	0	0	90	100%
Bare Ground	0	85	0	0	85	100%
Vegetation	0	0	523	4	527	99.24%
Water Body	0	0	0	32	32	100%
Total	90	85	523	36	734	
Producer Accuracy	100%	100%	100%	88.89%		
Overall Accuracy					99.4550%	
Overall Kappa Index					0.9881	

Table 4.9: Accuracy Assessment of Parallelepiped Algorithm for the year 2007

CLASS	Unclassified	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Unclassified	**0**	0	0	0	0	0	
Built-up Area	0	**90**	6	0	0	96	93.73%
Bare Ground	0	0	**79**	0	35	114	69.30%
Vegetation	0	0	0	**523**	1	524	99.81%
Water Body	0	0	0	0	**0**	0	0%
Total	0	90	85	523	36	**734**	
Producer Accuracy	0%	100%	92.94 %	100%	0%		
Overall Accuracy						94.2779%	
Overall Kappa Index						0.8749	

Table 5.0: Accuracy Assessment of Spectral Angle Mapper for the year 2007

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**78**	0	0	0	78	100%
Bare Ground	12	**85**	0	0	97	87.63%
Vegetation	0	0	**523**	4	527	99.24%
Water Body	0	0	0	**32**	32	100%
Total	90	85	523	36	**734**	
Producer Accuracy	86.67%	100 %	100%	88.89%		
Overall Accuracy					97.8202%	
Overall Kappa Index					0.9524	

Table 5.1: Accuracy Assessment of MLC for the year 2015

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**77**	0	0	0	77	100%
Bare Ground	0	**69**	0	0	69	100%
Vegetation	0	0	**667**	3	670	99.55%
Water Body	0	0	0	**7**	7	100%
Total	77	69	667	10	**823**	
Producer Accuracy	100%	100%	100%	70%		
Overall Accuracy					99.6355%	
Overall Kappa Index					0.9888	

Table 5.2: Accuracy Assessment of Minimum Distance for the year 2015

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**73**	0	0	0	73	100%
Bare Ground	4	**69**	0	0	73	94.52%
Vegetation	0	0	**667**	10	677	98.52%
Water Body	0	0	0	**0**	0	0%
Total	77	69	667	36	**823**	
Producer Accuracy	94.81%	100%	100%	0%		
Overall Accuracy					98.2989%	
Overall Kappa Index					0.9464	

Table 5.3: Accuracy Assessment of Mahalanobis for the year 2015

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**75**	0	0	0	75	100%
Bare Ground	2	**69**	0	0	71	97.18%
Vegetation	0	0	**667**	10	677	98.52%
Water Body	0	0	0	**0**	0	0%
Total	77	69	667	10	**823**	
Producer Accuracy	97.40%	100%	100%	0%		
Overall Accuracy					98.5419%	
Overall Kappa Index					0.9541	

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Table 5.4: Accuracy Assessment of Parallelepiped Algorithm for the year 2015

CLASS	Unclassified	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Unclassified	**0**	0	0	1	0	1	
Built-up Area	0	**77**	67	1	0	145	53.10%
Bare Ground	0	0	**2**	0	0	2	100%
Vegetation	0	0	0	**665**	10	675	98.52%
Water Body	0	0	0	0	**0**	0	0%
Total	0	77	69	667	10	**823**	
Producer Accuracy	0%	100%	2.90 %	99.70%	0%		
Overall Accuracy						90.4010%	
Overall Kappa Index						0.6987	

Table 5.5: Accuracy Assessment of Spectral Angle Mapper for the year 2015

CLASS	Built-up Area	Bare Ground	Vegetation	Water Body	Total	User Accuracy
Built-up Area	**77**	16	0	0	93	82.80%
Bare Ground	0	**53**	0	10	63	84.13%
Vegetation	0	0	**667**	0	667	100%
Water Body	0	0	0	**0**	0	0%
Total	77	69	667	10	**823**	
Producer Accuracy	100%	76.18 %	100%	0%		
Overall Accuracy					96.8408%	
Overall Kappa Index					0.9031	

4.2 Quantitative Values of the LULC Classes of the different Algorithms

Table 5.6-6.0 shows the quantitative values of landuse / landcover classes obtained from the different classification algorithm for the different epoch.

Table 5.6: MLC Quantitative Values of Classes

LULC Classes	**2000**		**2007**		**2015**	
	AREA (ha)	**%**	**AREA (ha)**	**%**	**AREA (ha)**	**%**
Built-up Area	3047.42	17.899	7425.84	43.616	6313.04	37.080
Bare Ground	6258.39	36.759	4372.71	25.683	3670.88	21.560
Vegetation	7714.87	45.313	5226.45	30.69	7001.78	41.124
Water Body	4.95	0.029	0.63	0.004	39.9402	0.236

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Table 5.7: Min. Distance Quantitative Values of Classes

LULC Classes	2000		2007		2015	
	AREA (ha)	**%**	**AREA (ha)**	**%**	**AREA (ha)**	**%**
Built-up Area	3064.74	18.00	3440.1	20.209	3604.12	21.17
Bare Ground	6684.84	39.26	6980.68	41.00	2979.73	17.50
Vegetation	7276.06	42.74	6604.67	38.79	10441.4	61.328
Water Body	-	-	0.18	0.001	0.36	0.002

Table 5.8: Mahalanobis Distance Quantitative Values of Classes

LULC Classes	2000		2007		2015	
	AREA (ha)	**%**	**AREA (ha)**	**%**	**AREA (ha)**	**%**
Built-up Area	3179.07	18.672	3726.51	21.888	3581.18	21.034
Bare Ground	2503.06	14.702	3498.31	20.547	2901.64	17.043
Vegetation	11343.5	66.626	9798.47	57.551	10542.1	61.919
Water Body	-	-	2.34	0.014	0.72	0.004

Table 5.9: Parallelepiped Quantitative Values of Classes

LULC Classes	2000		2007		2015	
	AREA (ha)	**%**	**AREA (ha)**	**%**	**AREA (ha)**	**%**
Built-up Area	9231.49	54.221	12327.9	72.408	10629.6	62.433
Bare Ground	2331.04	13.691	870.085	5.110	39.3882	0.231
Vegetation	2642.15	15.519	3812.03	22.390	5467.55	32.114
Water Body	-	-	-	-	0.364165	0.002
Unclassified	2820.96	16.569	15.5959	0.092	888.7	5.220

Table 6.0: Spectral Angle Mapper Quantitative Values of Classes

LULC Classes	2000		2007		2015	
	AREA (ha)	**%**	**AREA (ha)**	**%**	**AREA (ha)**	**%**
Built-up Area	736.299	4.325	1320.49	7.756	1444.36	8.483
Bare Ground	9774.76	57.412	7104.67	41.729	7009	41.167
Vegetation	6514.57	38.263	8600.48	50.515	8571.82	50.347
Water Body	-	-	-	-	0.45	0.003

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The graphical summary of the quantitative values obtained from the different supervised classification types is presented in figure 4.4-4.8.

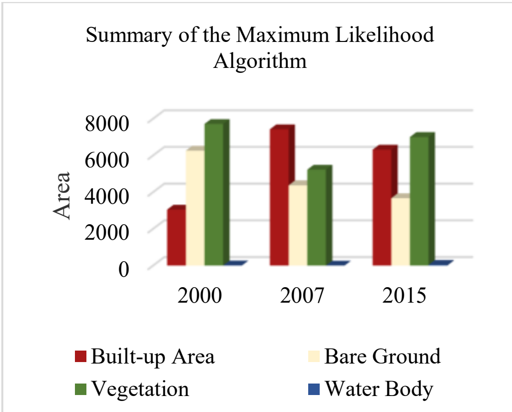

Fig. 4.4: Maximum Likelihood

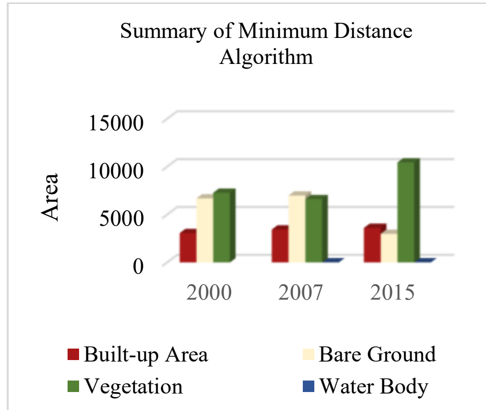

Fig. 4.5: Minimum Distance

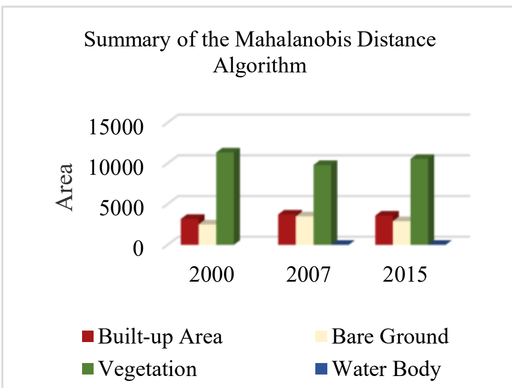

Fig. 4.6: Mahalanobis Distance

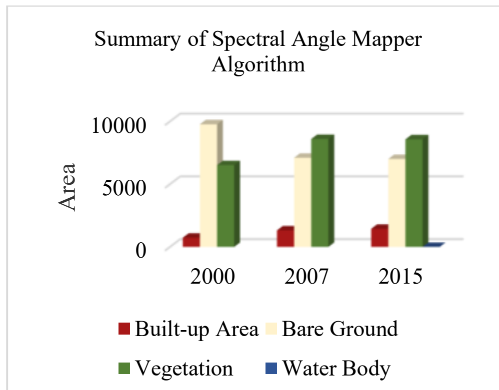

Fig. 4.7: Spectral Angle Mapper

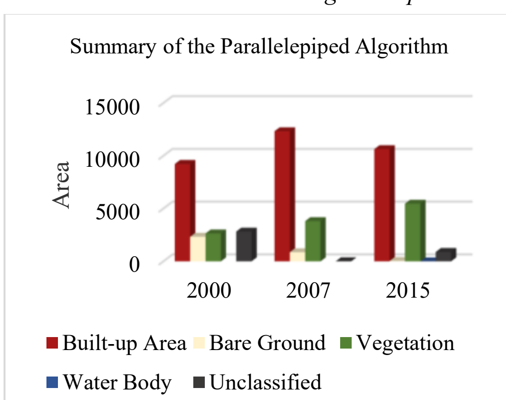

Fig. 4.8: Parallelepiped

4.3 Comparison of the techniques

Maximum likelihood classification is commonly agreed to be the best supervised classification method. In this study, the MLC had the highest accuracy, ranging from 99.06 to 100 percent, and it produced the best result. The Mahalanobis distance classification, similar to Maximum Likelihood classification, had a high accuracy (98.54 to 99.45%), but it did not detect water body in the classified image of 2000, as shown in table 5.8. The result of the minimum distance classification, compared to the maximum likelihood is not very accurate. In the

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classification of the image of the year 2000, the Min. Distance algorithm failed to detect Water body as shown in table 5.7, owing to the fact that water body covered a very small area. The overall accuracy of the image was 86.428%. Compared to MLC, the SAM algorithm falls short, with an accuracy of 89.24%, and it can be deduced from the graph that the SAM overestimated bare ground and under estimated built-up area, while failing to detect water body in the years 2000 and 2007. Unlike the other algorithms, the parallelepiped classification falls short with an accuracy of 85%, and with the image showing a whole lot of unclassified pixels.

Further comparisons were made using the LCLU image obtained from object based classification of an aerial imagery of the study area for the year 2015. The object based classification was performed on the eCognition software and had an overall accuracy of 99.91%. Figure 4.9 shows the result of the object based classification of the study area, which was used as reference data in comparing the different techniques for the year 2015. Table 6.1 shows the accuracy assessment result for the object based classification.

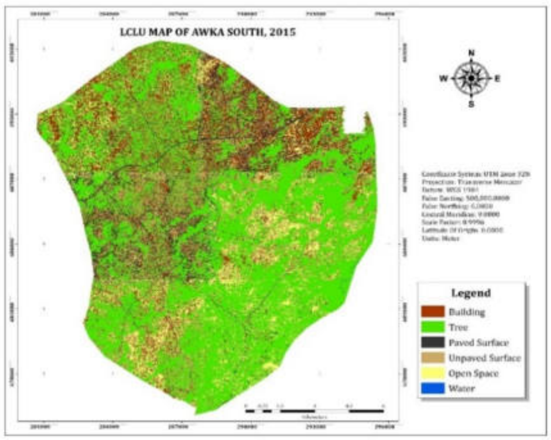

Figure 4.9: Result of Object Based Classification

Table 6.1: Error Matrix of Object Based Classification

CLASS	Building	Tree	Paved Surface	Unpaved Surface	Open Space	Water	Total	User Accuracy
Building	**4905**	0	1	1	0	0	4907	99.97%
Tree	0	**10458**	0	0	0	0	10458	100%
Paved Surface	0	0	**872**	3	0	0	875	99.83%
Unpaved Surface	0	0	0	**3192**	0	0	3192	100%
Open Space	0	0	0	1	**944**	0	945	99.94%
Water	0	0	0	0	0	**27**	27	100%
Total	4905	10458	873	3197	944	27	**20398**	
Producer Accuracy	100%	100%	99.94%	99.84%	100%	100%		
Overall Accuracy							99.91%	
Overall Kappa Index							0.998	

With an overall accuracy of 99.63%, the MLC came the closest to the object based classification result of 99.91%, performing well with 98.29% and 98.54% are the Minimum Distance and Mahalanobis Distance algorithms respectively, the SAM algorithm, while having a poor result visually, outperformed the parallelepiped algorithm with accuracies 96.84% and 90.40% respectively. Overall, the maximum likelihood algorithm produced the best result visually and in its accuracy.

4.3 Change Detection

In LULC mapping, the post comparison technique is the only method that resulted in a change matrix that provided "from – to" information. The change detection statistics was developed on ENVI, an "Initial state" (2000) and "final state" (2015) images were specified and the land cover classes were matched to generate the statistics of change between them. The land cover changes were computed between 2000 and 2015, tables 6.2 and 6.3 depicts per-pixel and percentage changes respectively.

Table 6.2: Per-Pixel Change between 2000 and 2015

CLASS		Initial State					Row Total	Class Total
		Unclassified	Built-up Area	Bare Ground	Vegetation	Water Body		
Final State	Unclassified	0	0	0	0	0	0	0
	Built-up Area	0	70492	24254	6819	45	101610	101610
	Bare Ground	0	35678	25541	4143	24	65386	65386
	Vegetation	0	36084	9534	70573	291	116482	116482
	Water Body	0	175	13	568	804	1560	1560
Class Total		0	142429	59342	82103	1164		
Class Changes		0	71937	33801	11530	360		
Image Difference		0	-40819	6044	34379	396		

Table 6.3: Percentage Change between 2000 and 2015

CLASS		Initial State					Row Total	Class Total
		Unclassified	Built-up Area	Bare Ground	Vegetation	Water Body		
Final State	Unclassified	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Built-up Area	0.0	49.493	40.872	8.305	3.866	100	100
	Bare Ground	0.0	25.050	43.040	5.046	2.062	100	100
	Vegetation	0.0	25.335	16.066	85.957	25.00	100	100
	Water Body	0.0	0.123	0.022	0.692	69.072	100	100
Class Total		0.0	100	100	100	100		
Class Changes		0.0	50.507	56.960	14.043	30.928		
Image Difference		0.0	-28.659	10.185	41.873	34.021		

Tables 6.2 and 6.3 shows the change detection statistics between 2000 and 2015. There were changes experienced in the various classes, built-up area experienced the most change with 49% increase from 2000 to 2015 as should be due to developments occurring in the study area. Bare ground with 40% change decreased between 2000 and 2015, development is a major factor in the changes experienced between the years of interest, bare ground 40% and vegetation 8% went through changes as they gave way to built-up areas. Water body in the study area showed an increase of 3.8 %

5 Conclusion and Discussion

The crux of this study was to compare the different supervised classification algorithms which include; Maximum Likelihood Classification, Minimum Distance, Mahalanobis Distance, Parallelepiped and Spectral Angle Mapper. This was achieved first, by processing the acquired images and classifying them while specifying the various algorithms.

The choice of the best results in this work was based on the results of the Kappa index and visual analysis of the results generated, thereby it was concluded that the use of the Maximum Likelihood classification method was more efficient than other tested methods. However, the definition of the parameters and their training were long, requiring tests with modified parameters, in order to reach an acceptable result.

Comparison was made also to object based classification image of the study area; it was used to judge the visual result obtained from ground truthing and accuracy of the different algorithms. The MLC result was accurate both visually and by its Kappa index. The Mahalanobis distance algorithm working on a similar principle as the MLC also had a high Kappa index with a visual result that was acceptable. The algorithm with the least accuracy was the Parallelepiped method, with an accuracy of 85% it was also inaccurate visually. The Minimum Distance and SAM algorithms had fairly accurate results. Visually, the minimum distance had a fairly good result while the SAM algorithm showed major misclassification of classes.

Between 2000 and 2015 major changes took place in the study area, built-up areas experienced the most change with 49.5%, followed by bare ground with 40%, vegetation with 8%, and water body with 3.8% change. A lot of these changes can be attributed to the development that took place in the study area.

The success of an image classification depends on many factors. The availability of high-quality remotely sensed imagery and ancillary data, the design of a proper classification procedure, and the analyst's skills and experiences are the most important ones. For a particular study, it is often difficult to identify the best classifier due to the lack of a guideline for selection and the availability of suitable classification algorithms to hand. Comparative studies of different classifiers are thus frequently conducted. (Benediktsson and Kanellopoulos 1999, Steele 2000, Lunetta et al. 2003).

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