Modelling the relationship between climatic variables and land use/land cover classes in Yewa South Local Government Area of Ogun State, Nigeria

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Abstract. Climate change and land use/land cover (LULC) change are among the global environmental issues that have recently dominated international debates in order to monitor earth resources. The burning of fossil fuels, clearing of land and burning of bush has given rise to the highest levels of greenhouse pollution in the atmosphere. It is on this note that this study was carried out to determine the effect of climate change on land use/land cover change of Yewa South Local Government Area of Ogun State in Nigeria. The supervised parallelepiped classification scheme was used to classify land use land cover into five classes namely agriculture land, built-up, vegetation, wetland and water body. A multivariate linear regression model was developed and program in MATLAB to model the relationship between climatic variables namely, rainfall (mm), average temperature (°C), evaporation (mm), relative humidity (%), average soil temperature (°C) and some particular land use/land cover variables. After statistical analysis between climatic variables and land use/land cover classification, results indicated a significant relationship between climatic variables and land use/land cover change. The statistical analysis between the variables shows that the climatic parameters has an accuracy of 84.12% prediction model for land use/land cover classification.

Keywords: Land Use/Land Cover, Climate Change, Pollution Abatement, Environmental Sustainability, Multivariate regression model.

1. Introduction
Climate change and land use/land cover are two environmental concerns. The two are global problems that require monitoring of earth resources. The adverse effect of climate change such as: unequal weather pattern, temperature rise, increased atmospheric menaces and rise in sea level are likely to increase the event and strength of exciting event that threaten human health and welfare [1]. The effects of the climate change vary greatly on land use and land cover changes. For example, deforestation may lead to temperature increase in the tropic zone, while it may course regional temperature decrease in the Frigid Zone [2].

Drivers of climate change include natural processes (Biogeographical) and human activities (Anthropogenic). [3,4]. The natural processes are the astronomical and the extraterrestrial factors which change the eccentricity of the earth’s orbit and solar radiation quantity. The anthropogenic driver of the
climate change are the activities of human beings which produce large amount of greenhouse gases into the atmosphere [3,4]. In other words, the land-cover changes rapidly and abruptly due to anthropogenic activities. Increase in population and activities of human being also increases the pressure on the limited land and soil resources for human needs [5]. Due to increasing population, agricultural land is being converted to build up areas and forest areas which are converted to agricultural land and vice versa. Change in land use and land cover, and the associated habitat loss and fragmentation are major causes of biodiversity loss [6].

Introduction of Remote Sensing (RS) and Geographical Information Systems (GIS) performances, mapping of land use/Land cover are designed to classify an area to be of use for agricultural, residential and for urban and/or industrial areas [7]. The availability of Landsat (Satellite) images data served as an important tool in the classification of land use and land cover, and the application of remote sensing made it possible to study the changes in land use and land cover in a short time with greater accuracy for future planning of the study area. GIS technique offers appropriate platform for data analysis, update and retrieval [8,9]. Predicting future climate trends relies on a large network of meteorological stations and modelling outputs from satellite data [10,11]. In fact, throughout history, the prosperity of nations has always been known to correlate very closely with the well-being of future generations depending largely on its wise management. Multivariate regression model techniques were used to understand the spatial relationship between climatic variables and land use/land cover [12].

To improve social economics activities of a study area without further disintegrating the environment, it is necessary to obtain qualitative data to model the relationship between climate change and land use/land cover change for effective future planning of land use/land cover. To understand this relationship, information about how the changes occurred, the rate and the extent at which it occurs is needed [13]. This information would be in the form of map and statistical data that is very vital for spatial planning, controlling and exploitation of land. As a result, mapping LULC and its change detection as well as updating it overtime has been recognized by various researchers; for example, mapping of land use and land detection analysis in Yewa South Local Government by [14] and monitoring of land cover dynamic by [15].

To achieve the relationship, a program in MATLAB was developed to take a set of input data (Climatic variables) namely, rainfall (mm), average temperature (°C), evaporation (mm), relative humidity (%) and average soil temperature (°C) to model for particular land use class namely water body, wetland, vegetation, built up area and agricultural land. Therefore, the study is an attempt to apply the use of GIS technology, remote sensing and multivariate regression model to assess and model the temporal changes in land use and land cover as a result of environmental dynamic induced by climate change in the past and relate it to the future planning of land use/land cover of the study area.

2. Methodology

2.1. The Study Area
Yewa South Local Government cover with a total land area of 629.38 square kilometers, with population of 150,850 (NPC, 2006) in Ogun State. It is one of the regional Local Government in Ogun State of Nigeria. It is located between 2°47′24″E and 3°6′48″E and 6°37′46″N and 6°55′42″N of the Equator. The area is surrounded in the East by Ifo and Ado – Odo/ Ota Local Government and in the West by Ipokia Local Government, north by Yewa North and in the South by the ocean. The Local government area is populated primarily by the Yoruba people of Nigeria [15]. Figure 1 shows the map of Yewa South LGA of Ogun State. The Local Government is divided into ten (10) wards (Ilaro I, Ilaro II, Ilaro III, Iwoye, Idogo, Owode I, Owode II, Ilobi/Erinja, Oke – Odan and Ajilete). Furthermore, the faming
system in this area is mixed crop farming and livestock. The area is characterized to be moisture sufficient, even with some flooding events in some part of the town [16].

![Figure 1. Yewa South Local Government, Ogun State.](image)

Figures 2 and 3 show the flow diagram to illustrate the framework of the methodology process used in modelling the effect of climate variables on land use/land cover change of the study area, and also provide understanding of the method used in data processing. The first part of the work was on image processing, image classification, LULC change detection and preparation of thematic map. This section employed the techniques of satellite Remote Sensing with Geographic Information Systems in the generation and analysis of geospatial data on LULC dynamics. The second part was the use of multivariate linear regression model for the relationship between climatic parameters (independent variables) and patterns of land use land cover change (dependent variables) to predict for the future, with reasonable accuracy.

![Figure 2. Flow chart of change Detection from imageries](image)
2.2. Data Source
The following data of the study area were obtained from various departments of relevant organizations. These are:
(a) Acquisition of Satellite Images downloaded from the USGS website [www.earthexplorer.usgs.gov](https://www.earthexplorer.usgs.gov) (Table 1)
(b) Climatic data such as rainfall, temperature, and relative humidity were collected from Ogun – Osun River Basin Development Authority (Table 2)
(c) The Nigerian Administrative map downloaded in form of shape file from DIVA-GIS. The shape file is a geospatial vector format and exported into the ArcGIS environment.

2.2.1. Acquisition of Satellite Images for LULC Analysis
The properties of the Landsat images are presented in Table 1. These images have similar spatial and spectral resolution of 8 and 11 bands with 30m x 30m resolution.

| Sensor           | Date       | Acquisition source | Data format | Spatial Resolution | No. of Bands | Datum       |
|------------------|------------|--------------------|-------------|--------------------|--------------|-------------|
| LANDSAT 7ETM+    | 06/02/2000 | USGS               | GeoTIFF     | MS: 30m Pan: 15m   | 8            | WGS1984     |
| LANDSAT 7ETM+    | 28/12/2002 | USGS               | GeoTIFF     | MS: 30m Pan: 15m   | 8            | WGS1984     |
| LANDSAT 7ETM+    | 07/12/2006 | USGS               | GeoTIFF     | MS: 30m Pan: 15m   | 8            | WGS1984     |
| LANDSAT 7ETM+    | 16/01/2011 | USGS               | GeoTIFF     | MS: 30m Pan: 15m   | 8            | WGS1984     |
| LANDSAT 8 OLI/TIRS| 23/12/2013| USGS               | GeoTIFF     | MS: 30m Pan: 15m   | 11           | WGS1984     |
| LANDSAT 8 OLI/TIRS| 26/12/2015| USGS               | GeoTIFF     | MS: 30m Pan: 15m   | 11           | WGS1984     |
| LANDSAT 8 OLI/TIRS| 22/01/2019| USGS               | GeoTIFF     | MS: 30m Pan: 15m   | 11           | WGS1984     |

2.2.2. Climatic Data
The climatic data (rainfall, temperature, evaporation, and relative humidity and soil temperature) was obtained from weather stations across the study area (Yewa local government) between 2000 and 2019 from Ogun - Osun River Basin Development Authority and presented in Table 2.
Table 2: Average agro meteorological observational data

| Year | Rainfall (mm) | Temperature (°C) | Evaporation (ml) | Relative Humidity (%) | Average soil temperature (°C) |
|------|--------------|-----------------|------------------|----------------------|-------------------------------|
| 2000 | 79.03        | 24.90           | 6.90             | 87.30                | 32.48                         |
| 2001 | 79.21        | 24.10           | 5.99             | 74.90                | 32.12                         |
| 2002 | 144.71       | 21.60           | 5.89             | 77.8                 | 31.75                         |
| 2003 | 100.56       | 23.50           | 6.27             | 78.20                | 32.13                         |
| 2004 | 92.73        | 23.20           | 4.06             | 81.40                | 32.51                         |
| 2005 | 91.14        | 29.78           | 4.875            | 71.30                | 32.89                         |
| 2006 | 112.6        | 25.78           | 5.69             | 72.05                | 33.27                         |
| 2007 | 162.16       | 27.4            | 5.02             | 72.8                 | 32.49                         |
| 2008 | 106.11       | 26.31           | 5.45             | 66.66                | 31.71                         |
| 2009 | 118.98       | 26.70           | 5.01             | 68.78                | 30.94                         |
| 2010 | 102.83       | 34.35           | 6.20             | 90.26                | 30.16                         |
| 2011 | 251.69       | 30.80           | 3.96             | 87.91                | 29.38                         |
| 2012 | 270.25       | 32.00           | 4.92             | 87.01                | 29.39                         |
| 2013 | 77.44        | 28.52           | 4.21             | 97.71                | 29.40                         |
| 2014 | 103.45       | 32.33           | 4.09             | 78.57                | 29.36                         |
| 2015 | 97.35        | 33.68           | 4.20             | 78.22                | 29.32                         |
| 2016 | 91.59        | 33.74           | 4.10             | 79.52                | 29.38                         |
| 2017 | 85.83        | 33.80           | 4.08             | 80.02                | 29.40                         |
| 2018 | 90.11        | 33.40           | 4.15             | 79.98                | 29.50                         |
| 2019 | 74.31        | 33.93           | 4.30             | 83.42                | 29.55                         |

2.3. Image Enhancement and land use/land cover Classification

The supervised Parallelepiped classification scheme was used to develop the classified land use land cover classification. The satellite images were converted into digital format and enhanced image. To improve the classification accuracy, the spatial resolution of the multispectral images (layer-stacked images) of all the epochs of the study area was improved from 30 meters to 15 meters by executing a panchromatic sharpening process. The Panchromatic sharpening algorithm used in the ENVI environment was the Gram-Schmidt Spectral sharpening which employs the insertion of the low-resolution image (Multispectral image) and the high-resolution image (Panchromatic band). The image enhancement in the form of pan-sharpening was done for all the epochs. The subset of the multispectral images of the study area for this research was overlaid on the image scenes of the Landsat products (Landsat 7ETM+ and Landsat 8 OLI/TIRS) and the subset of the study area was created, The Nigeria administrative map as downloaded in form of shapefile from DIVA-GIS was brought into the ArcMap 10.3.1 environment where the clipping tool was used to extract the study area (Yewa-South LGA). The resulting raster from image classification was used to create thematic maps as showing in Figures 9 (a-g). Training sites were created to identify homogeneous groups of pixels, which represent various land cover classes of interest in the study area. The combine process of visual image interpretation of tones/colours, patterns, shape, size, and texture of the imageries and digital image processing was used for the identification [17]. The supervised Parallelepiped classification scheme was used to develop the classified land use land cover classification. The classes are vegetation, wetland, waterbody, built-up and agricultural land as described in Table 3.

After classification, the feature classes were transferred to ArcGIS 10.3.1 for editing of classes and removal misclassified sections due to the imperfection of the classification algorithms, elimination of spurious clusters and refinement of the output. Having done the necessary editing and ground-truthing, specific colours were used for the classes as selected from the ramp of colours in ArcGIS. The colours...
include Quetzel green for wetland, Tzavorite green for agricultural land, Fir green for vegetation, Cretan blue for waterbody and Mars red for built-up as shown in Figure 4.

The classification shape files for the five classes for all the epochs were presented in ArcGIS and the computation of the area for each class using the “calculate geometry” was obtained. The classification accuracies for all the epochs were computed on ArcGIS 10.3.1 using the Frequency tool and the Pivot table tool. The Classification data was successfully classified with overall accuracy of the classification’s ranges from 70% overall accuracy to 86% accuracy on average.

| S/N | Class           | Description                                               |
|-----|-----------------|-----------------------------------------------------------|
| 1   | Vegetation      | Cropland and pasture fields, grassland, greenhouses, and fallow land |
| 2   | Wetland         | Marsh or swamp                                            |
| 3   | Waterbody       | Sea, rivers, ponds and a small lake                       |
| 4   | Built-up        | Residential, commercial and industrial areas,             |
| 5   | Agricultural land | Farmlands                                                 |

Table 3. Land use/Land cover classification scheme

2.4. Land use/Land Cover Change Detection Analysis
The classification shape files for the five classes of all the epochs were presented in ArcGIS and an area field for the computation of the area was added to each class. The area was calculated using the “calculate geometry” function to populate the field with area values. The statistics showing the sum of the area was obtained. The area values for all the classes were obtained and displayed in Microsoft excel worksheet as showing in Table 4 for the calculation of the changes that have occurred over the years.

2.4.1 Linear Interpolation
This study embarked on linear interpolation to compensate for the missing data in the land use land cover classification. According to [18] linear interpolation is the process of using points with known values to estimate values at (unknown points). The formula is applied in Equation 1. Two data points \((x_0, y_0)\) and \((x_1, y_1)\) are known and value of \(y\) is to be estimated for given value of \(x\) somewhat in-
between these two data points. Figure 5 shows the interpolated value of x, which is shown in blue color, within the range of known data points, which are shown in red color. To determine unknown value of y, first the function \( (x) \) that passes through these known points are to be calculated with the known techniques and once it is known, the function value for any value of x can be determined \[19\].

\[
Y = \frac{(X-X_0)(Y_1-Y_0)}{(X_1-X_0)} + Y_0 \tag{1}
\]

Figure 5: Interpolation.

where \(X_0\) and \(Y_0\) define the points to perform the interpolation. But Y is unknown and the interpolated value. X, \(X_1\), \(X_0\), \(Y_0\), and \(Y_1\) are other points of known value. From the linear interpolation, the missing data in Table 4 was developed for the land use classification per km\(^2\) in different land use/land cover change in the Yewa South LGA between years 2000 and 2019.

| Point | Years | Water body (km\(^2\)) | Wetland (km\(^2\)) | Vegetation (km\(^2\)) | Build up Area (km\(^2\)) | Agric land (km\(^2\)) |
|-------|-------|-----------------------|--------------------|------------------------|---------------------------|-----------------------|
| 1     | 2000  | 0.32                  | 147.10             | 262.01                 | 25.28                     | 222.17                |
| 2     | 2001  | 0.38                  | 121.05             | 224.41                 | 25.50                     | 285.41                |
| 3     | 2002  | 0.44                  | 95.00              | 186.81                 | 25.72                     | 348.65                |
| 4     | 2003  | 0.47                  | 90.76              | 175.45                 | 26.39                     | 363.60                |
| 5     | 2004  | 0.48                  | 86.52              | 164.03                 | 27.05                     | 378.55                |
| 6     | 2005  | 0.49                  | 82.28              | 152.69                 | 27.72                     | 393.50                |
| 7     | 2006  | 0.50                  | 78.04              | 141.35                 | 28.38                     | 408.45                |
| 8     | 2007  | 0.50                  | 76.26              | 136.53                 | 29.23                     | 414.13                |
| 9     | 2008  | 0.50                  | 74.48              | 131.72                 | 30.08                     | 419.81                |
| 10    | 2009  | 0.50                  | 72.70              | 126.90                 | 30.93                     | 425.49                |
| 11    | 2010  | 0.50                  | 70.93              | 122.09                 | 31.79                     | 431.17                |
| 12    | 2011  | 0.50                  | 69.15              | 117.27                 | 32.64                     | 436.84                |
| 13    | 2012  | 0.65                  | 68.26              | 141.46                 | 37.53                     | 408.62                |
| 14    | 2013  | 0.79                  | 67.36              | 165.65                 | 42.41                     | 380.39                |
| 15    | 2014  | 0.80                  | 80.50              | 202.85                 | 44.58                     | 327.98                |
| 16    | 2015  | 0.80                  | 93.64              | 240.04                 | 46.74                     | 275.57                |
| 17    | 2016  | 0.75                  | 90.36              | 211.52                 | 52.01                     | 302.12                |
| 18    | 2017  | 0.69                  | 87.08              | 183.00                 | 57.28                     | 328.67                |
| 19    | 2018  | 0.64                  | 83.81              | 154.49                 | 62.56                     | 355.22                |
| 20    | 2019  | 0.58                  | 80.53              | 125.97                 | 67.83                     | 381.76                |
Multivariate Linear Regression

In order to determine the effect of climate change on land use/land cover (LULC) change and to create a regression model to predict for land use/land cover change, a multivariate linear regression model was developed. This is based on the statistical principle of multivariate statistics, which involves observation and analysis of more than one statistical outcome variable at a time. Consider the following in multivariate linear regression:

\[
y = \begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_n \\
\end{bmatrix} = f(x_1, x_2 \ldots x_n)
\]

where \( f(x_1, x_2 \ldots x_n) \) are the causal variables or Independent variables or inputs and \( y_1 \) = the response variable or dependent variable or output. Note: \( y \) has been changed to a column vector which contains all output variables.

Key points from Equation 2 is that:

i. There is a many to many relationships between the vector \( y \) and function \( (x_1, x_2 \ldots x_n) \)

ii. Dimensionality should agree in this case.

The general form for the multivariate linear regression is given as:

\[
Y_1 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon
\]

where \( \beta_0, \beta_1, \beta_2, \beta_k \), and \( \varepsilon \) are unknown and are to be estimated from the data. These parameters are usually called regression coefficients.

\( \beta_0 \) is the constant term or intercept in the model and term Least square estimate and \( \varepsilon \) is the random error or error estimate and are normally distributed. The error component \( \varepsilon \) represents the difference between the true (predicted data) and observed data of \( y \).

2.5. Working Variables

To design the graph theory for the process of modelling, Table 5 which is the working variables for the model equation was used.

| VARIABLES          | SYMBOL | TYPE            |
|--------------------|--------|-----------------|
| Rainfall           | \( x_1 \) |                 |
| Temperature        | \( x_2 \) | INPUT DATA      |
| Evaporation        | \( x_3 \) |                 |
| Relative Humidity  | \( x_4 \) |                 |
| Average Soil Temp  | \( x_5 \) |                 |
| Waterbody          | \( y_1 \) | OUTPUT DATA     |
| Wetland            | \( y_2 \) |                 |
| Vegetation         | \( y_3 \) |                 |
| Built-up           | \( y_4 \) |                 |
| Agric Land         | \( y_5 \) |                 |

2.6. Concept of Graph Theory

At the beginning of the modelling process, the concepts of graph theory was employed as shown in Figure 6.
From 6, the following relationships are deduced

\[ y_1 = \beta_{10} + \beta_{11}x_1 + \beta_{12}x_2 + \beta_{13}x_3 + \beta_{14}x_4 + \beta_{15}x_5 + \epsilon_1 \]
\[ y_2 = \beta_{20} + \beta_{21}x_1 + \beta_{22}x_2 + \beta_{23}x_3 + \beta_{24}x_4 + \beta_{25}x_5 + \epsilon_2 \]
\[ y_3 = \beta_{30} + \beta_{31}x_1 + \beta_{32}x_2 + \beta_{33}x_3 + \beta_{34}x_4 + \beta_{35}x_5 + \epsilon_3 \]
\[ y_4 = \beta_{40} + \beta_{41}x_1 + \beta_{42}x_2 + \beta_{43}x_3 + \beta_{44}x_4 + \beta_{45}x_5 + \epsilon_4 + \epsilon_5 \]
\[ y_5 = \beta_{50} + \beta_{51}x_1 + \beta_{52}x_2 + \beta_{53}x_3 + \beta_{54}x_4 + \beta_{55}x_5 + \epsilon_5 \]

where \( y = y_1, \ldots, y_5 \),

\( y_1 \) = Prediction for each dependent variable.

\( X_1 \) = Independent variable or design matrix

\( \beta \) = Least Square Estimate

\( \epsilon \) = Error Estimate. It is also an additive constant to the model

From 6, the following relationships are deduced

The Least square Estimates (\( \beta \)) and Error of Estimation (Residual) (\( \hat{\epsilon} \)) can now be computed using the following least squared residual approach

\[ \hat{\beta} = (X'X)^{-1}X'Y \]  \hspace{1cm} (5)
\[ \hat{\epsilon} = Y - \hat{Y} \]  \hspace{1cm} (6)

2.7. Model development

2.7.1 Assumptions in Multivariate linear regression Analysis

Before continuing with the Multivariate Linear Regression, the data should be satisfied with the following assumptions:

i. The errors \( \epsilon_{n \times q} \) are multivariate normal. This assumption indicated that the expected value of the error term should be zero, that is, \( \epsilon = 0 \).

ii. Error variances are equal (homogenous) across observation.

Errors have common covariance structures across observation.

Using multivariate linear regression to examine the effect of climatic variables on land use /land cover change and to create a regression model to predict for land use/land cover change from climatic parameters, a program in MATLAB was develop and a set of input data were taken (causal variables namely, rainfall (mm), temperature (°C), evaporation (mm), relative humidity (%) and average soil temperature (°C) to model for particular land use class namely water body, wetland, vegetation, built up
area and agricultural. We may sometimes find it more reasonable to refer climatic variables as independent variables or “predictors”, and land use land cover as dependent variables or “response (outcome) or Sample output A least square Estimate $\beta$ and Error Estimate $\epsilon$ as well as the predicted model to determine the effect of climatic variables on land use/land cover change as stated in Equation 7, 8 and 9

$$
\begin{align*}
\beta &= \\
&= \begin{bmatrix}
0.006014 & -0.06665 & -0.000745 & -0.001364 & -0.05505 \\
-1.288 & 9.685 & -0.09898 & 0.38 & -0.07351 \\
-2.843 & 9.729 & -0.3835 & 0.4064 & -11.78 \\
0.4234 & -2.143 & -0.03448 & -0.07503 & -3.237 \\
3.703 & -17.19 & 0.5166 & -0.7102 & 15.16
\end{bmatrix} \\
\epsilon &= \begin{bmatrix}
2.596 \\
75.8 \\
588.7 \\
143.2 \\
-120.5
\end{bmatrix}
\end{align*}
$$

$$
Wb = 0.006014Te - 0.06665Ev - 0.000745Ra - 0.001364Rh - 0.05505A + 2.596
$$

$$
Wl = -1.288Te + 9.685Ev - 0.09898Ra + 0.38Rh - 0.07351As + 75.8
$$

$$
Vg = -2.843Te + 9.729Ev - 0.3835Ra + 0.4064Rh - 11.78As + 588.7
$$

$$
Bu = 0.4234Te - 2.143Ev - 0.03448Ra - 0.07503Rh - 3.237As + 143.2
$$

$$
Al = 3.703Te - 17.19Ev + 0.5166Ra - 0.7102Rh + 15.16As - 120.5
$$

where:

$Wb$ = Water body, (ii) $Wl$ = Wetland, (iii) $Vg$ = Vegetation, (iv) $Bu$= Built-up and (v) $Al$ = Agriculture land while $Te$= Temperature, $Ev$ = Evaporation, $a$= Rainfall, $Rh$= Relative humidity, and $As$ = average soil temperature

2.8. Model Verification
Model Verification is the process of determining whether the model meets its specification. When using regression to create a predictive model. Several criteria are used to evaluate model performance and the difference between simulated and observed data is determined. The criteria used for evaluating model performance are: model validation, correlation analysis, the root means squared error (RMSE) and error estimate called residual.

2.8.1. Model Validation
This is the process of representing the model specification. The degree of agreement between the result of the model and real life data was established. Table 6 shows the data usage.

| Item                  | Year    | Duration | Percentage |
|-----------------------|---------|----------|------------|
| Model Development     | 2000 – 2015 | 15 years | 80%        |
| Testing and Validation| 2016 – 2019 | 4 years  | 20%        |
To ascertain the degree of accuracy of each parameter in the developed model, the set of equation in 10 was used to judge the accuracy of the regression prediction model:

\[
\delta_i = \frac{|O_i - P_i|}{O_i} \times 100\% \\
\bar{\delta} = \frac{\sum_{i=1}^{n} \delta_i}{n} \\
\text{Accuracy} = (100 - \bar{\delta})\% 
\]

where \(\delta_i\) = percentage deviation of single sample data, \(O_i\) = the observed data, \(P_i\) = the predicted data, \(n\) = sample size and \(\bar{\delta}\) = total deviation.

3. Results and Discussion

3.1. Result for Model validation

The model performance was assessed by comparing the (sample output) observed data of 2016 – 2019 to the predicted output data 2016 – 2019 using the validated module in MATLAB. The result of the validation is presented in Tables 7a and 7b, and the residual is presented in Table 7c indicating the extent to which the observed data and the predicted data agreed.

| Years | Wb (km²) | Wl (km²) | Vg (km²) | Bu (km²) | Al (km²) |
|-------|----------|----------|----------|----------|----------|
| 2016  | 0.49270  | 71.6610  | 220.668  | 49.6971  | 330.341  |
| 2017  | 0.57941  | 127.466  | 233.601  | 55.932   | 379.881  |
| 2018  | 0.72512  | 94.6925  | 186.951  | 61.586   | 399.051  |
| 2019  | 0.66075  | 82.5436  | 175.594  | 65.3955  | 285.915  |

| Years | Wb (\(y_1\)) | Wl (\(y_2\)) | Vg (\(y_3\)) | Bu (\(y_4\)) | Al (\(y_5\)) |
|-------|--------------|--------------|--------------|--------------|--------------|
| 2016  | 0.75         | 90.36        | 211.52       | 52.01        | 302.12       |
| 2017  | 0.69         | 87.08        | 183.00       | 57.28        | 328.67       |
| 2018  | 0.64         | 83.81        | 154.49       | 62.56        | 355.22       |
| 2019  | 0.58         | 80.53        | 125.97       | 67.83        | 381.76       |

| Year  | Water body | Wetland | Vegetation | Built-up area | Agric Land |
|-------|------------|---------|------------|---------------|------------|
| 2016  | 0.257299   | 18.69897| 9.147965   | 2.312948      | 28.22118   |
| 2017  | 0.110585   | 40.38626| 50.60144   | 1.347786      | 51.21059   |
| 2018  | 0.085122   | 10.88253| 32.46133   | 0.973632      | 43.83146   |
| 2019  | 0.080748   | 2.013666| 49.62433   | 2.434509      | 95.84509   |
The model validation performance values ranging from 74% to 95% accuracy

3.2. Result of Correlation Analysis
This aspect was used to study the strength of a relationship between two successive land use classes. The Pearson’s product-moment correlation coefficient was used to determine the correlation coefficients between the model-predicted and observed for each climatic variable in the region.

\[
\rho_{pq} = \frac{cov(P, O)}{\sigma_P \cdot \sigma_O}
\]  

where \( \rho_{pq} \) is the Correlation Coefficient, \( cov(P, O) \) is the covariance between P (Predicted) and O (Observed) and \( \sigma_P \cdot \sigma_O \) are the standard deviations of P and O respectively. The Correlation Coefficient is a dimensionless quantity which satisfies the inequality \( -1 \leq \rho_{pq} \leq 1 \) and standardizes the measure of interdependence between two variables and, consequently, tells you how closely the two variables move. The result of the Correlation Analysis is in Table 8 and Figure 7.

|                  | Waterbody | Wetland | Vegetation | Built-up | Agric. Land |
|------------------|-----------|---------|------------|----------|-------------|
| Waterbody        | 1.00      | -0.66   | 0.09       | 0.98     | 0.08        |
| Wetland          | -0.66     | 1.00    | 0.68       | -0.66    | -0.80       |
| Vegetation       | 0.09      | 0.68    | 1.00       | 0.05     | -0.98       |
| Built-Up         | 0.98      | -0.66   | 0.05       | 1.00     | 0.11        |
| Agric. Land      | 0.08      | -0.80   | -0.98      | 0.11     | 1.00        |

3.3. Result of Root Mean Square Error (RMSE)
This was used to determine the magnitude of the error in the model output as the correlation technique is however limited when it comes to this. The Root Mean Square Error represents the square root of the

From the Table 7 and Figure 7, there is a negative correlation between waterbody and wetland and a positive correlation between Waterbody and Vegetation, Waterbody and Built-up and Waterbody and Agriculture Land. It should be noted that this analysis is limited to the data used in the study area.
differences between predicted values and observed values which are termed as residuals. It was used to determinite the magnitude of the error in the model. Equation 12 was used to compute the RMSE:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2 }
\]

where \( P_i \) = predicted, \( O_i \) = Observed, \( n \) = size of the data.

3.4. The Root Mean Square Error (RMSE)
The Root Mean Square Error (RMSE) was used to determinite the magnitude of the error in the the model output as the correlation technique is however limited when it comes to this. It measures the difference between fitted and observed values and this was used to evaluate the systematic bias of the model [20]. The result of the Root Mean Square Error (RMSE) is in Figure 8. It represents the differences between the square root of the predicted values and observed values that are termed as residuals.

![Figure 8: The Root Mean Square Error.](image)

Table 9 shows that agriculture land has the highest root mean square error of 50.7741 followed by vegetation (37.6253). This is due to the random nature of the data constituting agriculture land whereas Waterbody has the least (0.0801).

3.5. Classification of Land Use Land Cover
Land use/land cover was classified successfully with overal accuracy ranging from 70% to 86% accuracy. Five different classes of land use/land cover types and land cover map were developed. The land cover maps are shown in Figures 9a to 9g. The magnitude of change at different land use/land cover classes in the study area between years 2000 – 2019 is showing in Tables 9a and 9b. The resulting land cover types were Water body/watershed, built-up, Vegetation, wetland, and agricultural land in the study area.
Table 9a: The area of the different land use/land cover categories in the study area between years 2000 – 2019

| Year | Land cover | Area (km²) |
|------|------------|------------|
| 2000 | Waterbody  | 0.32       |
| 2002 | Wetland    | 147.10     |
| 2006 | Vegetation | 262.01     |
| 2011 | Built-up   | 25.28      |
| 2013 | Agric land | 222.17     |
| 2015 | Total      | 656.88     |
| 2019 |            | 656.80     |

Table 9b: The percentage of the different land use/land cover categories in the study area between years 2000 – 2019.

| Year | Land cover | % |
|------|------------|---|
| 2000 | Waterbody  | 0.05|
| 2002 | Wetland    | 22.39|
| 2006 | Vegetation | 39.89|
| 2011 | Built-up   | 3.85|
| 2013 | Agric land | 33.82|
| 2015 | Total      | 100.00|
| 2019 |            | 100.00|
The result from the model indicated the relationship between the predicted land use/land cover change and the classified land use/land cover change (Observed) is displayed in Table 10a &10b

Table 10a: Relationship between Predicted value (output) and Observed (sample) Data

| Years | Wb (km²) | Wl (km²) | Vg (km²) | Bu (km²) | Al (km²) | Wb (km²) | Wl (km²) | Vg (km²) | Bu (km²) | Al (km²) |
|-------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 2000  | 0.31793  | 134.577  | 206.146  | 24.5314  | 324.414  | 0.32     | 147.10   | 262.01   | 25.28    | 222.17   |
| 2001  | 0.41094  | 121.834  | 202.065  | 28.2496  | 340.501  | 0.38     | 121.05   | 224.41   | 25.50    | 285.41   |
| 2002  | 0.36401  | 118.633  | 186.757  | 26.1091  | 359.247  | 0.44     | 95.00    | 186.81   | 25.72    | 348.65   |
| 2003  | 0.49880  | 104.739  | 177.982  | 26.3626  | 342.383  | 0.47     | 90.76    | 175.45   | 25.50    | 363.60   |
| 2004  | 0.36401  | 118.633  | 186.757  | 26.1091  | 359.247  | 0.44     | 95.00    | 186.81   | 25.72    | 348.65   |
| 2005  | 0.35180  | 112.033  | 165.094  | 24.9325  | 388.658  | 0.50     | 78.04    | 141.35   | 28.38    | 393.50   |
| 2006  | 0.40451  | 98.7136  | 144.934  | 27.8060  | 419.484  | 0.50     | 76.26    | 136.53   | 29.23    | 414.13   |
| 2007  | 0.46781  | 107.842  | 183.599  | 31.3327  | 371.672  | 0.50     | 74.48    | 131.72   | 30.08    | 419.81   |
| 2008  | 0.46781  | 107.842  | 183.599  | 31.3327  | 371.672  | 0.50     | 74.48    | 131.72   | 30.08    | 419.81   |
| 2009  | 0.52867  | 102.603  | 184.183  | 34.3538  | 374.044  | 0.50     | 72.70    | 126.90   | 30.93    | 425.49   |
| 2010  | 0.51729  | 114.642  | 195.919  | 36.5017  | 346.454  | 0.50     | 70.93    | 122.09   | 31.79    | 431.17   |
| 2011  | 0.56821  | 81.1017  | 134.502  | 37.3595  | 438.696  | 0.50     | 69.15    | 117.27   | 32.64    | 436.84   |
| 2012  | 0.80807  | 85.8947  | 127.913  | 34.8568  | 428.762  | 0.65     | 68.26    | 141.46   | 37.53    | 408.62   |
| 2013  | 0.66545  | 105.783  | 211.431  | 40.9621  | 341.966  | 0.79     | 67.36    | 165.65   | 42.41    | 380.39   |
| 2014  | 0.70838  | 92.1225  | 171.003  | 43.5664  | 287.572  | 0.80     | 80.50    | 202.85   | 44.58    | 327.98   |
| 2015  | 0.61524  | 91.2993  | 199.135  | 45.3885  | 366.027  | 0.80     | 93.64    | 240.04   | 46.74    | 275.57   |

Note that; For predicted value, Wb= Waterbody, Wl= Wetland, Vg= Vegetable, Bu= Built-up Al = Agric land, and for sample value, Wb= Waterbody, Wl= Wetland, Vg= Vegetable, Bu= Built-up and Al= Agric land

Table 10b: Residual (Error Estimates)

| years | wb     | wl     | Vg     | Bu     | Al     |
|-------|--------|--------|--------|--------|--------|
| 2000  | 0.0021 | 12.5228| 55.86451| 0.749633| 102.239903|
| 2001  | 0.031941| 0.7840| 22.3447 | 2.749594| 55.091261|
| 2002  | 0.075986| 23.63267| 0.053289| 0.38850| 10.596381|
| 2003  | 0.10486| 33.74789| 22.60497| 0.027369| 21.226664|
3.6. Land use/land cover variations
The study clarified five periods of land use land cover based on the supervised classification known as Parallelepiped classification method. Table 4.1a showed the temporal changes in waterbodies, wetland, vegetation, built up land and agricultural land. These were obtained from seven periods Landsat images. The Land cover pattern has shown much and steady increase for some classes. The Classification data was successfully classified with overall accuracy of the classification’s ranges from 70% overall accuracy to 86% accuracy on average.

3.7. Statistical Analysis of climate and land use/land cover change
The assessment of LULC classification in the study area was supplemented by the multivariate regression analysis to determine the effect of climate change on land use land cover classification. The land use and land cover classification and the climatic variables were subjected to statistical analysis and tested for, among others to ensure that the data meets the necessary accuracy and utility standards. The following criteria were used to evaluate model performance and the difference between simulated and observed data was determined [20]. Such criteria are model validation, correlation analysis, the root means squared error (RMSE) and error estimate called residual. After addressing and satisfied that the assumptions for multivariate regression model were met, Multivariate Linear Regression model was utilized.

From the model performance, the climatic data has the following accuracy for the land use land cover prediction model:

i. Parameter Rainfall has accuracy of 87.35% Prediction Model for water body
ii. Parameter Temperature has accuracy of 71.83% Prediction Model for Wetland
iii. Parameter Evaporation has accuracy of 80.66% Prediction Model for Vegetation
iv. Parameter Relative humidity has accuracy of 92.91% Prediction Model for Built up area
v. Parameter Average soil temperature has accuracy of 87.84% Prediction Model for Agric land

The above analysis confirmed the relationship between Climatic variables and land use/land cover change. With this we can say that climate changes are closely related to changes in land use/land cover.
In particular, it is widely acknowledged that the climatic variables are the significant factors that influencing the land use/land cover change in any region.

4. Conclusion
The research work analyzed the impact of climate change on land use/land cover using LANDSAT 7ETM+ & LANDSAT 8 OLI/TIRS images and climatic variables and further demonstrated a relationship between them. The supervised Parallelepiped classification helped in this research to determine the changes in LULC cover for a period of 19 years from 2000 to 2019 during which significant environmental, vegetation and human changes have taken place in the study area. A multivariate model was developed to determine the relationship between climatic variables and land use/land cover classification. It is known that there is a relationship between land use land cover (LULC) with climatic variables as an input data. After statistical analysis of the relationship between climatic variables and land use /land cover classification, it was found that 97.9359% of the original uncertainty has been explained by the model. The result supports the conclusion that the multivariate model represents an excellent fit as indicated in the graphs. The multivariate model was successfully tested with the help of MATLAB 2017 on the Windows 10 operating system supports the conclusion that the model represents “an excellent” fit as indicated in the assumption and the graphs. The findings in this research shows that there is a relationship between climatic variables with land use land cover (LULC). From the analysis, the climatic parameter has an average accuracy of 84.12% prediction for land use/land cover. The result supports the conclusion that the multivariate model was successfully tested and represents an excellent fit as indicated in the graphs. This study also proves that integration of GIS and remote sensing technologies is effective tool for urban planning and management. The quantification of LU/LC changes of the study area is very useful for environmental management groups, policy makers and for public to better understand the surrounding.

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