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Modeling the Effects of Climate Change and Socio-Ecomonic Variables on Agricultural Production

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Abstract

Climate change has serious effects on human life and existence in various forms. This study used Principal Component Analysis (PCA) and Mutiple Regression model (MRM) to determine the effects of meteorological factors and socio-economic factors on agricultural production. PCA showed 95.6% aggregated variation within the variables and the correlation matrix of the principal components was used to reduce the variables to six. MRM was employed for determining linear association within agricultural productions and the reduced factors showed that climate change and socio-economic factors influenced Nigerian agriculture production. The model obtained was validated with respect to coefficient of determination, adjusted coefficient of determination and Durbin Watson statistics values. Overall, this study indicated that climate change and socio-economic factors influenced the level of agriculture productions in Nigeria.

Keywords: *Climate change, Meteorological factors, Socio-economic factors, Agricultural production*

Abstrak

Perubahan iklim berdampak serius pada kehidupan dan keberadaan manusia dalam berbagai bentuk. Penelitian ini menggunakan Analisis Komponen Utama (PCA) dan model Regresi Mutiple (MRM) untuk mengetahui pengaruh faktor meteorologi dan faktor sosial ekonomi terhadap produksi pertanian. PCA menunjukkan variasi agregat 95.6% dalam variabel dan matriks korelasi komponen utama digunakan untuk mengurangi variabel menjadi enam. MRM digunakan untuk menentukan hubungan linier dalam produksi pertanian dan pengurangan faktor menunjukkan bahwa perubahan iklim dan faktor sosial ekonomi mempengaruhi produksi pertanian Nigeria. Model yang diperoleh divalidasi terhadap koefisien determinasi, koefisien determinasi yang disesuaikan dan nilai statistik Durbin Watson. Secara keseluruhan, penelitian ini menunjukkan bahwa perubahan iklim dan faktor sosial ekonomi mempengaruhi tingkat produksi pertanian di Nigeria.

Kata Kunci: *Perubahan iklim, Faktor meteorologi, Faktor sosial ekonomi, Produksi pertanian.*

1. Introduction

Climate change can be defined as an acclimatization of the statistical classification if it goes on over a lengthy time. It is a significant phenomenon that has an impact on human survivorship [1,2]. This too is a characteristic and anthropogenic exercises viewed as one of the serious natural issues on the planet [3]. The global threat posed by climate change to crop productivity necessitates the immediate development of novel strategies for adapting crops to these environmental changes. Climate change-induced high temperatures have an effect on the physiological and developmental processes of plants, which in turn have an effect on crop yield and quality. The uptake of water and nutrients by plant roots is controlled by changes in soil temperature, which slows plant development. For an anticipated varying weather figure, the improvement of an effective root foundation better adjusted in soil turnaround and ecological circumstances will be essential for upgrading plant efficiency [4]. According to [5], it is a universal phenomenon that leaves no part of the world untouched. It has had an effect on gaseous and particulate waste from combustion and other activities for thousands of years. It has also been discovered to be very self-cleaning. The majority of air pollutants vanish within a few days of being released into the atmosphere through deposition to the ground, particularly through precipitation washout. Many volatile organic compounds (VOCs), for example, undergo oxidation in the atmosphere to become water, carbon dioxide, and water-soluble compounds, which are quickly eliminated. It should be noted that once the pollutants leave the atmosphere, they can have significant environmental effects on terrestrial and aquatic ecosystems [6]. [5] reported that global surface water temperatures are rising and oceanic acidification is turning up acidic based on climate change. This change threatens the livelihoods of coastal and small-scale fishing communities and has a negative impact on fish stocks. The effects of environmental change on farming and other key financial areas in the food creation and store network, like ranger service and energy in such that it threatens food security across sub-Saharan Africa [7]. In general, it is believed that climate change's potential to have negative and unrecoverable consequences on modern facilities, foodstuff production, water distribution and conflicts over precipitation and natural resources, makes it a significant challenge for countries anticipating feasible development must respond and proffer way-outs for the future [8].

Meteorological transpose has so far become reality in Africa based on available occurrences in the continent [9]. Different regions have witnessed different hazardous events. These incorporate events like drawn-out and strengthened dry spells in eastern Africa; floods unlike any other in western Africa; consumption of tropical jungles in central Africa; and rise in ocean's acidity near Africa southern coast. Africa's capacity for growth and development is harmed by drastically altered weather patterns and climate extremes, which also threaten human wellbeing, power production, water and agricultural production along with food and health security. Disasters related to the climate or the environment that put human security at risk can lead to forced migration and competition between communities and nations for water and basic necessities. All of these have the potential to have adverse effects on political stability and the resolution of conflicts [9]. Despite the fact that it could have negative economic effects, such as a decrease in eco-tourism, biodiversity loss is unfortunately viewed as a minor issue on the African climate change agenda. Climate change adaptation, essential energy infrastructure and supply of environmentally friendly power sources like sunlight-based, wind, hydro, and geothermal power must be important considerations for policy.

Some precise human activities have been perceived as the fundamental drivers of progressing natural change. One of these is frequently alluded to as a dangerous atmospheric deviation. Changes in ecosystems, animal, plant species and natural resources have been observed and documented by humans around the globe. Almost certainly, there will be an ever increasing number of effects from here on out. Adaptation to climate change and its effects presents difficulties for developed and developing nations alike. Forest dynamics and ecosystem dynamics are likely to be altered by temperature changes. The effects of rising hotness on trees and crops is expected to change yearly due to the fact that warming can lessen plant stress in colder months and increase it in hotter ones. Environmental change will probably build the gamble of dry spells in certain regions and the gamble of outrageous precipitation and flooding in others.

Due to the fact that dry trees and shrubs provide fire fuel, drought increases wildfire risk. Additionally, drought reduces trees' capacity to produce sap, which shields them from harmful insects like pine beetles. As far as different variables like water and nutrients is not limited, higher atmospheric CO2 levels because plant and tree growth rates to increase and water use efficiency to improve. As a result of climate warming, it is anticipated that the distribution of forest plants and trees will move northward or to higher altitudes. The variety of habitats that are suitable for many plant species will also change as temperature rises and precipitation changes. Environmental change is supposed to influence the vulnerability of woods to aggravations and furthermore influence the recurrence, force, span and timing of such aggravation. Aggravation, for example, fire, dry spells, avalanches, flavors attacks, bug and sickness flare-ups and tempests, for example, typhoons, windstorms and ice storms impact the synthesis, design and capability of woodland to unsettling influences and influence the recurrence, power, span, and timing of such unsettling influences. The structure, composition, and function of the forest are affected by disturbances like fire, dry season, avalanches, species attacks, bug and sickness flare-ups, and storms like typhoons, windstorms and ice storms. Meteorological transpose is a situation that is affecting all countries in the different forms. It is a general issues and several decisions has been made by world bodies, regional organisations, nations and individuals to control and combat it effects. Since this has been shown to affect, agricultural production, sea level, glacial level, ecosystem and many more. Despite several researches which was done for discussing the effect about meteorological transpose affecting human existence. Much work has not been done on the determination of the effects of climatic variables and some other related factors that can affect agricultural production in Nigerian situation. Therefore, in this research, the intention is to discuss how meteorological transpose in addition to some other related factors is affecting agricultural products. This will be done by using Principal component analysis and regression analysis model.

2. Material and Method

2.1. Regression Analysis

A regression model is a bunch of measurable cycles for assessing the connections among factors. At the point when the emphasis is on the connection between a reliant variable and at least one free factor, it incorporates various displaying and dissecting procedures. Specifically, relapse investigation empowers one to appreciate how the typical worth of the reliant variable when any of the autonomous factors is changed while the other free factors stay steady.

If regression equation is given as:

$$Y = \alpha + \beta X \tag{1}$$

it is deterministic and probabilistic when given in the form

$$Y = \alpha + \beta X + \varepsilon \tag{2}$$

in which Y is response factor, X is predictor factors, α is constant, β is parameter and ε is residual.

2.2. Multiple Regression Model

Various multivariate regression method is utilized to decide the relationship between numerous autonomous factors and the reliant variable. The emphasis is on finding a condition of the free factor that limits sum of squares of error in foreseeing the upsides of the reliant variable (Y).

Generally speaking, the point isn't just about expectation but to find which factors are connected with the reaction variable. The numerous linear regression models are communicated as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + e_t \tag{3}$$

where the intercept is β_0, the coefficient are $\beta_1, \beta_2, \ldots, \beta_p$, and the random error is assumed to be normally distributed with a mean of 0 and a variance of σ^2.

A similar technique utilized in the straightforward direct relapse is relevant to different straight relapses with the exception of that there are more boundaries to be assessed.

As a matrices

$$Y = X\beta + \varepsilon \tag{4}$$

This implies

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ . \\ . \\ . \\ Y_n \end{bmatrix}, \qquad X = \begin{bmatrix} 1x_{1\,1} & x_{1\,2} & \cdots & x_{1\,n} \\ 1x_{2\,1} & x_{2\,2} & \cdots & x_{2n} \\ \vdots \cdots & \cdots & \cdots & \vdots \\ 1 & x_{k\,1}x_{k2} & & x_{kn} \end{bmatrix}, \qquad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_1 \\ \varepsilon_1 \\ . \\ . \\ . \\ \varepsilon_n \end{bmatrix} \tag{5}$$

2.3. Estimation of Parameter

2.3.1. Least Square Estimation method

Given that

$$Y = \alpha + \beta X + \varepsilon \tag{6}$$

Therefore

$$\varepsilon = Y - \alpha - \beta X$$
$$\sum\varepsilon^2 = \sum(Y - \alpha - \beta X)^2$$
$$S = \sum(Y - \alpha - \beta X)^2$$
$$\frac{\partial s}{\partial \alpha} = 2\sum(Y - \alpha - \beta X)(-1) = 0$$
$$\sum Y = n\alpha + \beta\sum X \tag{7}$$
$$\frac{\partial s}{\partial \beta} = 2\sum(Y - \alpha - \beta X)(-X) = 0$$
$$\sum XY = \alpha\sum X + \beta\sum X^2 \tag{8}$$
$$\sum Y = n\alpha + \beta\sum X$$
$$\sum XY = \alpha\sum X + \beta\sum X^2$$

By solving (7) and (8) simultaneously to obtain

$$\beta = \frac{n\sum XY - \sum X\sum Y}{n\sum X^2 - \sum(X)^2} \tag{9}$$

and

$$\alpha = \bar{Y} - \beta\bar{X} \tag{10}$$

where $\bar{y} = \frac{\sum Y}{n}$ and $\bar{X} = \frac{\sum X}{n}$

2.3.2. Ordinary Least Square Method

By using equation (6) and making the error term the subject, then this gives

$$\varepsilon = Y - X\beta \tag{11}$$

By squaring both side to obtain

$$S = \varepsilon'\varepsilon = (Y - X\beta)'(Y - X\beta) \tag{12}$$
$$= y'y - y'X\beta - \beta'X'y + \beta'X'X\beta$$
$$= y'y - 2\beta X'y + \beta'X'X\beta$$
$$\frac{\partial S}{\partial \beta} = -2X'y + 2\beta x'x = 0$$
$$X'y = \beta X'X$$
$$\beta = (X'X)^{-1}X'y \tag{13}$$

The β obtained are the coefficient of the multiple regression model.

2.4. Principal Component Analysis

With respect to less count of unassociated variables, principal components analysis assists in presenting and elucidating the covariance associations between P metrical related variables [10] by more sparingly combining linearly the standardized observables over the specified samples [11]. This is generally helpful when there is will for decreasing somewhat huge factor counts to fewer factors that actually catch similar data, as it is a lot simpler to decipher a few uncorrelated factors than twenty or thirty that have a convoluted example of interrelationships.

2.4.1 The Outline of PCA

A set of correlated variables (x's) is transformed by principal components analysis to portion of unassociated elements (y's). The important parts include straight blends of X's composed as

$$\begin{cases} y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{p1}x_p \\ y_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{p2}x_p \\ \vdots \\ y_p = a_{p1}x_1 + a_{p2}x_2 + \cdots + a_{pp}x_p \end{cases} \tag{14}$$

The $a_{ij}'s$ are the coefficients for the variables i and j, and every element is a weighted sum of X's.

$$\sum_{i=1}^{p} a_{ij}^2 = 1, \qquad j = 1,2,\cdots,p \tag{15}$$

$$\sum_{i=1}^{p} a_{ij}a_{ik} = 0, \qquad j \neq k;\; j = 1,2,\dots,p;\; k = 1,2,\dots,p \tag{13}$$

Consequently, total variance of y's is the same as variance of X's, then

$$\sum_{i=1}^{p} var(y_i) = \sum_{i=1}^{p} var(x_i) \tag{17}$$

This implies total variance is stable, rather variance is reconstructed in a manner which crucial element y, possess the greatest variance as a result accounts for total variance greatest amount.

The goal for selecting count of elements is for keeping possible few while still having a significant number that accurately represents the authentic data.

The eigenvalue $\lambda_1, \lambda_2, \dots \lambda_p$is the variance of component j because the components are derived in variance order. Assuming the x's are normalized with the goal that the relationship grid is dissected, the amount of the fluctuations of the x's will be equivalent to p. In this manner eigenvalues sum and y's total variance is equivalent to p.

Total variance proportion that component j elucidate is

$$\frac{\lambda_1}{\lambda_1 + \lambda_2 + \cdots + \lambda_p} \tag{18}$$

Together, the proportion that the first k component explains is

$$\frac{\lambda_1 + \lambda_2 + \cdots + \lambda_k}{\lambda_1 + \lambda_2 + \cdots + \lambda_p} \tag{19}$$

2.4.2 Variance of the components

The formula for variance used in the study is

$$S^2 = \frac{\sum_{i=1}^{n}(X_I - \bar{X})^2}{n-1} \tag{20}$$

2.4.3 Covariance of the components

Covariance is constantly estimated within 2 dimensions. The variance can be obtained by calculating the covariance between one dimension and itself. Subsequently, estimating the covariance between the x and y aspects, and y and z aspects in the event that has an informational collection with three aspects (x, y, and z). The covariance formula is

$$Cov(X,Y) = \frac{\sum_{i=1}^{n}(X - \bar{X})(Y - \bar{Y})}{n-1} \tag{21}$$

2.5. The covariance Matrix

Always keep in mind that covariance is measured between two dimensions. It is possible to calculate more than one covariance measurement in a data set with more than two dimensions. We are able to calculate, for instance, $cov(x,y)$, $cov(x,z)$ and $cov(y,z)$from a three-dimensional data set (x, y, z). Truth be told, for n-layered informational collection, you can workout $\frac{n!}{(n-2)*2}$ different covariance values as

$$C^{n\times n} = \left(c_{i,j}c_{i,j} = cov\left(Dim_i, Dim_j\right)\right) \tag{22}$$

in which $C^{n\times n}$ is a grid with n lines and n segments and Dim_x is the x^{th} aspect.

Using the standard x, y, and z dimensions for a data set with three dimensions. Then, at that point, the covariance grid has three lines and segments each and the qualities are

$$C = \begin{pmatrix} cov(x,x) & cov(x,y) & cov(x,z) \\ cov(y,x) & cov(y,y) & cov(y,z) \\ cov(z,x) & cov(z,y) & cov(z,z) \end{pmatrix} \tag{23}$$

5.1 Computing the Principal Components

The principal components can be determined computationally by calculating the data covariance matrix's eigenvectors and eigenvalues. Looking for system axis where diagonal of covariance matrix is equivalent to this procedure. The direction with the greatest variation is represented by the eigenvector in place of eigenvalue highest, followed by direction that has the next highest variation. The eigenvectors and eigenvalues can be gotten by

Let A be $n \times n$ grid. The roots are used to define A's eigenvalues:

$$Determinant(A - \lambda I) = |A - \lambda I| \tag{24}$$

where the identity matrix for n is I. This condition is known as characteristic equation and has n roots. Let λ be an eigenvalue of A. Then there exists a vector x, for example:

$$Ax = \lambda x \tag{25}$$

The vector x is called an eigenvector of A related with the eigenvalue λ. Notice that there is no special answer for x in the above condition. It is a course vector in particular and can be scaled to any greatness. To find a mathematical answer for x we really want to set one of its components to an erratic worth, say 1, which provides us with a bunch of concurrent conditions to tackle for different components. Assuming there is no arrangement, the interaction rehash with another component. Conventionally by standardize the last qualities so $xx^T = 1$. Assume we have a 3 × 3 grid A with eigenvectors $x_{1,}x_2, x_3$ and eigenvalues $\lambda_1, \lambda_2, \lambda_3$ so:

$$Ax_1 = \lambda_1 x_1, \qquad Ax_2 = \lambda_2 x_2, \qquad Ax_3 = \lambda_3 x_3$$

Inserting the eigenvectors as the segments of a framework gives:

$$A(x_{1,}x_2, x_3) = [x_{1,}x_2, x_3]\begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_1 & 0 \\ 0 & 0 & \lambda_1 \end{bmatrix} \tag{26}$$

writing

$$\Phi = [x_{1,}x_2, x_3]\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_1 & 0 \\ 0 & 0 & \lambda_1 \end{bmatrix} \tag{27}$$

and this gives (28) in matrix form

$$A\Phi = \Phi\Lambda \tag{28}$$

Therefore by getting the eigenvectors to unit greatness and they are symmetrical, so:

$$\Phi\Phi^T = \Phi^T\Phi = 1 \tag{29}$$

which can be written as

$$A = \Phi\Lambda\Phi^T \tag{30}$$

Let's now take a look at how this relates to the PCA process's covariance matrix. Assume that S is a n-by-n covariance matrix. There is a symmetrical n x n grid F whose segments are eigenvectors of S and an inclining network L whose corner to corner components are the eigenvalues of S, with the end goal that

$$\Phi^T\Sigma\Phi = \Lambda \tag{31}$$

Data points in the [X, Y] axis system are transformed by the matrix of eigenvectors F into the [U,V] axis system using a linear transformation. In the general case the straight change given by F changes the data of interest into an informational collection where the factors are uncorrelated. The relationship framework of the information in the new direction framework is L which has zeros in every one of the off askew components.

3.6. Factor Analysis

The definition of the factor analysis model is

$$X = \mu + LF + e \quad (32)$$

where X is the p x 1 vector of estimations, m is the p x 1 vector of means, L is a p x m network of loadings, F is a m x 1 vector of normal variables and e is a p x 1 vector of residuals. In this case, the number of measurements on a subject or item is represented by p, and the number of common factors is represented by m. It is assumed that F and e are distinct entities, as well as that each of the Fs is distinct from the others. The identity matrix Cov(F)=I and the diagonal matrix Cov(e)= define the mean of F and e as 02 respectively. This is an orthogonal factor model because the F's are assumed to be independent.

Under the factor analysis model, the p x p covariance matrix of the data X is:z

$$Cov(X) = LL' + \Psi \quad (33)$$

where L is the p x m grid of loadings, and Y is a p x p framework of fluctuations of residuals. The ith commonality is the sum of the squared loadings and the ith diagonal element of LL. The proportion of variability that can be explained by common factors can be used to evaluate the values of communality. The uniqueness of the ith diagonal element of Y is known as the ith specific variance. The portion of variability that cannot be explained by the common factors is called the specific variance. The goodness of fit can be evaluated using the sizes of the communalities or specific variances.

3. Results and Discussion

This section of the study will be used to implement the methods used in the research. The data that will be analysed are Agricultural production, climatic variable (rainfall, temperature, humidity and evaporation). Other factors considered are Agricultural land, Fertilizer usage, Labour force, Interest rate, pollution, rural population and Bank loan. The data were collected from Nigerian meteorological Agency (NIMET) and Central Bank of Nigeria from 1992 to 2022.

4.1 Principal Component Analysis result

Principal component analysis based on correlation matrix that has the capacity of standardizing the variables under consideration because they did not have the same measurement was used for assessing the background pattern for 11 units of climatic and socio-economic factors of Agricultural production. All principal components will have an average of zero due to standardization.

With a variance (eigenvalue) of 5.2834, the first principal component in Table 4.1 accounted for 48% of the total variance. The second principal component made up 18.3 percent, the third principal component made up 10.8 percent, and the fourth principal component made up 7.2 percent.

The first to the seventh principal components accounted for cumulative total variability of 96.5%. According to Table 4.1, the first three and the first seven principal components account for 77.1% and 96.5 percent, respectively, of the total variability. As a result, the majority of the data structure was represented by three to seven underlying dimensions. The remaining principal components probably have little impact and only make up a very small portion of the variability since the interpretation of the principal components is subjective. This is as well confirmed using the Scree plot give figure 4.1.

Table 1. Eigen analysis of the Correlation Matrix

Eigenvalue	5.28	2.009	1.193	0.7952	0.511	0.453	0.373	0.234	0.12	0.026	0.007
Proportion	0.48	0.183	0.108	0.072	0.046	0.041	0.034	0.021	0.01	0.002	0.001
Cumulative	0.48	0.663	0.771	0.844	0.89	0.931	0.965	0.987	0.997	0.999	1.000

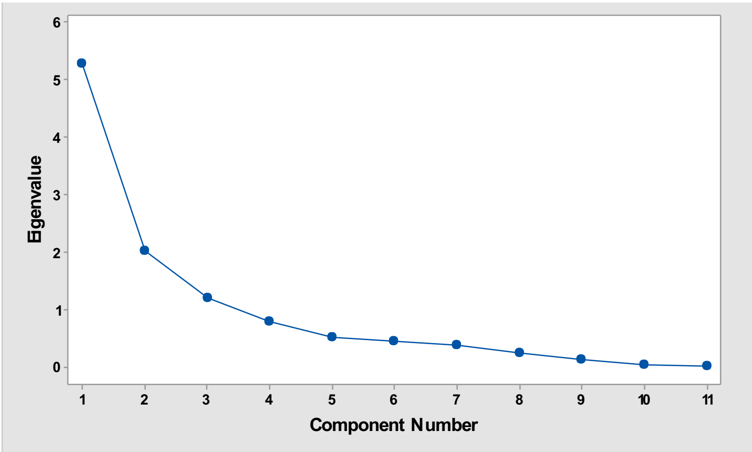
Table 2 displayed a comprehensive analysis of the principal component results revealing that there is no correlation between the components. Finding the variables that are most strongly correlated with each component is the foundation for interpreting the principal components; a large correlation is considered to be the number that is the farthest from zero in either direction. Subsequently, a relationship above 0.3 is considered significant. These bigger relationships are in boldface in Table 4.2 for effective identification. We treat the principal component results in Table 4.2 according to the value we consider significant.

Six of the initial variables are strongly correlated with the first principal component. The first primary component rises in proportion to rainfall, evaporation, Agricultural land, bank loan, and labour force while it decreases with rural population. This recommends that the initial five models change together. On the off chance that one expands, the excess ones will generally increment also. The effects can be measured by the components (rainfall, temperature, evaporation, Agricultural land, bank loan, and labour force). But decrease in rural population will have a negative effect. A critical look at the other principal components based on the correlation matrix, the following variability of the following variable will have either positive of negative effects on Agricultural production. The important variables according to the principal component analysis result in Table 4.2 are rainfall, temperature, evaporation, agricultural land, rural population and labour force. The principal component analysis results was checked for outlier and based on figure 4.2, all points fall below the y-axis reference line. This appears that there is no any outliers in the data.

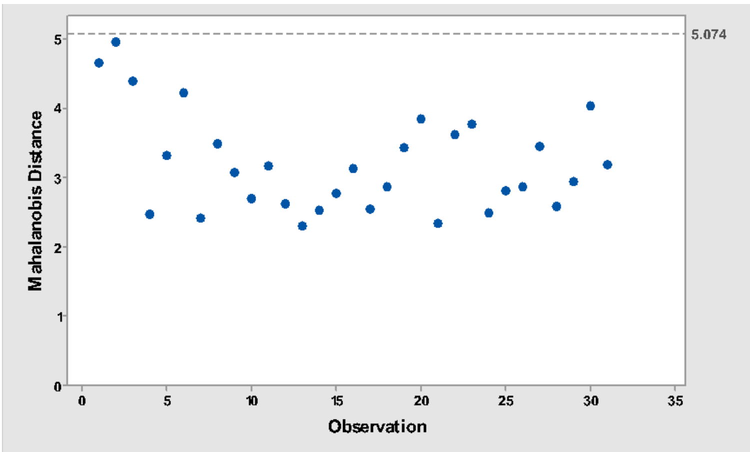
Table 2. Principal Component results

Variable	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**	**PC9**	**PC10**	**PC11**
Rainfall	**0.39**	0.02	-0.08	0.05	0.22	-0.04	0.02	**-0.68**	**0.56**	0.10	-0.04
Temperature	0.15	**0.57**	0.12	0.25	-0.26	**-0.35**	**-0.31**	**-0.32**	**-0.44**	0.06	0.06
Evaporation	**0.32**	0.26	0.09	0.15	**-0.38**	**0.58**	**-0.32**	**0.32**	**0.32**	0.09	-0.07
Humidity	0.07	0.02	**-0.86**	-0.04	-0.26	0.25	0.18	-0.16	-0.25	0.02	0.02
Agric. land	**0.38**	-0.12	0.02	**-0.45**	0.24	0.01	-0.18	0.10	-0.30	**0.65**	-0.16

Fertilizer	0.03	**0.62**	0.10	-0.02	0.22	0.10	**0.70**	0.16	0.03	0.17	-0.03
Labour force	**0.42**	0.00	0.02	-0.16	0.18	0.05	-0.01	0.12	-0.10	-0.29	**0.81**
Interest rate	0.20	**-0.42**	**0.36**	**0.44**	-0.14	**0.34**	**0.36**	-0.24	**-0.36**	0.12	0.03
Pollution	-0.28	0.11	0.30	**-0.65**	-0.28	**0.34**	0.03	**-0.42**	-0.07	-0.13	0.07
Rural population	**-0.42**	-0.03	-0.04	0.14	-0.17	-0.04	-0.02	-0.04	0.22	**0.64**	**0.56**
Bank loan	**0.32**	-0.16	0.07	-0.23	**-0.64**	**-0.49**	**0.34**	0.15	0.19	0.03	-0.02



Gambar 1. Screen plot of the Variables



Gambar 2. Outlier plot of the variable

4.3 Regression Analysis results

The principal component analysis was used for reducing variables that influenced agricultural production in Nigeria from 11 variables to 6 most important variables. Determining the linear relationship between the variables using the results of the regression analysis. that is rainfall, temperature, evaporation, agricultural land, rural population, labour force and agricultural production from 1988 to 2018 is given as

$$\begin{aligned}\text{Crop prod.} = {} & 176.9 + 0.000008 \text{ Rainfall} - 0.0341 \text{ Temp} + 0.2868 \text{ Evap} \\ & + 0.000347\text{Agric land} + 000001 \text{ Labour} - 0.573 \text{ Rural pop.}\end{aligned} \quad (33)$$

with $R^2 = 97.36\%$, $\bar{R}^2 = 97.30\%$ and Durbin Watson statistics = 2.3240

The regression equation in equation 4.1 implies that a unit increase in rainfall, Evaporation, agricultural land and Labour force will increase Nigerian agricultural production. While a unit decrease in temperature and rural population will decrease agricultural production in Nigeria.

This results implies that climatic variables used for determining climate change level and some social economic factor has influence on Nigerian agriculture production.

The model coefficient of determination revealed that predictor variables account for 97.4% of the variation in the response variable. Adjusted coefficient of determination (97.3%) indicated the model has a strong fit and high predictive power. The residual of the model as well is stable based on the value of Durbin Watson statistics = 2.3240.

4. Conclusion

The purpose of this study is to discuss how agricultural production in Nigeria is affected by social and economic variables as well as climate change. The data used spanned from 1992 to 2022. The variables used are Agricultural production, climatic variable (rainfall, temperature, humidity and evaporation), Agricultural land, Fertilizer usage, Labour force, Interest rate, pollution, rural population and Bank loan. The data were collected from Nigerian meteorological Agency (NIMET) and Central Bank of Nigeria. Out of the 11 variables that were taken into consideration, the important variables were narrowed down using the principal component analysis. The results of the principal component analysis indicated 95.6% of total variability within principal component were explained by the first seven principal components. This was validated using the screen plot. The correlation matrix was used to reduce the variables to six has these variables are the most important since they have high correlation value in the principal component. The reduced variables are rainfall, temperature, evaporation, Agricultural land, labour force and rural population.

The linear relationship between agricultural production, climatic variables and some social economic factors were determined using multiple regression analysis. From the result obtained, a unit increase in rainfall, Evaporation, agricultural land and Labour force will increase Nigerian agricultural production. While a unit decrease in temperature and rural population will decrease agricultural production in Nigeria. This implies that climatic variables used for knowing climate change level in addition to some social economic factor has influence on Nigerian agriculture production.

The model acquired was verified in light of the coefficient of determination from the model and this showed 97.4% of the variation in the response factor was explained through predictor factors. Adjusted coefficient of determination (97.3%) demonstrated that the model throws a tantrum and has high prescient power. The model residual was stable based on the value of Durbin Watson statistics = 2.3240.

This study has been used to discuss the effect of climate change and some socio-economic variables on Nigerian agricultural production. The results obtained indicated that climate change in terms of rainfall, temperature, evaporation has been influencing Nigerian agricultural production over the years. While other factors like agricultural land, labour force and rural population as well as militated against agricultural production in Nigeria. The results obtained from the analysis based on principal component and regression analysis make this study to conclude that climate change and some socio-economic factors influenced the level of agriculture production in Nigeria.

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