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# Statistical Investigation of the Interrelations among Weather Parameters in Nigeria

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**ABSTRACT**

This study investigates the interrelations among weather parameters in Nigeria using the Principal component method. Principal Component Analysis (PCA) is a multivariate technique that reduces the dimensionality of a data set consisting of a large number of interrelated variables, while retaining the characteristics present in the data set. Daily weather data on air temperature, solar radiation, relative humidity, precipitation and wind speed was obtained from National Aeronautic and Space Administration (NASA) for the period of 37 years (1984-2020). The first Principal Component is positively correlated with wind speed, solar radiation and air temperature, and negatively correlated with precipitation and relative humidity. The second Principal Component is positively correlated with precipitation, relative humidity, solar radiation and air temperature and negatively correlated with wind speed. The first two (three) Principal Components account for 81% (93%) of the total variance of the observed weather parameters. The variation among all of the weather parameters for Yobe, Kastina, Borno, Sokoto, Kebbi, Yola, Kano, Kogi and Ekiti can be explained by a single principal component (PC1) made up of Precipitation and Relative humidity.

**Keywords:**
Weather,
Precipitation,
Principal Component,
Solar radiation,
Wind speed.

## INTRODUCTION

Weather is the state of the atmosphere at any given place and time, while climate is the long-term mean of the weather in a given place. Most of the weather that affects agriculture, people and ecosystems occurs in the lower layer of the atmosphere (troposphere). Common daily weather phenomenon includes air temperature, clouds, precipitation, relative humidity, sunshine hour, solar radiation and wind. Weather and climate are two different concepts. Whereas weather can change in minutes or hours, the change in climate is something that develops over longer periods (decades to centuries). When energy from the sun reaches the Earth, the planet absorbs some of this energy and radiates the rest back to space as heat. A variety of physical and chemical factors (some natural and some influenced by humans) can shift the balance between incoming and outgoing energy, which forces changes in the Earth's climate. These changes are measured by the amount of warming or cooling they can produce, which is called "radiative forcing."

Changes that have a warming effect are called "positive" forcing, while those that have a cooling effect are called "negative" forcing. When positive and negative forces are out of balance, the result is a change in the Earth's average surface temperature. Warmer temperatures are one of the most direct signs that the climate is changing. In response, average temperatures at the Earth's surface are increasing and are expected to continue rising. Because climate change can shift the wind patterns and ocean currents that drive the world's climate system, some areas become warmer and others cooler (U.S. Environmental Protection Agency. 2016). Extreme variations in weather and climate pose a threat to society. Prevailing wind is also a factor in temperature controls. In an area where prevailing winds are from large water bodies, temperature changes are rather small. On the other hand, temperature changes are more pronounced where prevailing wind is from dry, barren regions. The weather parameters considered in this study are daily precipitation, air temperature, relative humidity, wind speed and solar radiation data from 1984-2020 over Nigeria.

A condition OF 100% relative humidity indicates that the air is saturated with moisture, and that any further increase in moisture content will result in precipitation. Precipitation occurs when hydrometeors are large and heavy enough to fall to the Earth's surface. Hydrometeors are liquid and ice particles that form in the atmosphere and it ranges from small cloud droplets and ice crystals to large hailstones. The microphysics of precipitation-particle formation is affected by super-saturation, diffusion, nucleation, and collision (Stull, 2017). Super-saturation specifies the amount of excess water vapor available to form rain and snow. Diffusion is the random movement of water-vapor molecules through the air toward existing hydrometeors. The formation of new liquid or solid hydrometeors as water vapor attaches to tiny dust particles carried in the air is known as nucleation. These particles are called cloud condensation nuclei or ice nuclei. Collision between two hydrometeors allows them to combine into larger particles. These processes affect liquid water and ice differently (Stull, 2017). Changes in precipitation can upset a wide range of natural processes, mostly if these changes occur more quickly than animal and plant species can adapt. Some areas will experience increased or decreased precipitation (U.S. Environmental Protection Agency. 2016).

Many studies have been carried out on weather and climate change in Nigeria using different meteorological parameters and a spectrum of techniques over various time scales. Falayi (2013) examined the impact of cloud cover, relative humidity, rainfall on solar radiation over eight locations in Nigeria, using different proposed empirical models over a period of 16 years (1995-2010). It was observed that the new model can be used for estimating daily values of global solar radiation with a higher accuracy and has good adaptability to highly variable weather conditions. Akinsanola and Ogunjobi (2014) investigates rainfall and temperature variability's in Nigeria using observations of air temperature ($^oC$) and rainfall (mm) from 25 synoptic stations from 1971-2000 (30years). Statistical approach was deployed to determine the confidence levels, coefficients of kurtosis, skewness and coefficient of variations. The result reveals significant increases in precipitation and air temperature in Nigeria. Amadi *et al.* (2014) analyzed monthly mean maximum and minimum temperature over Nigeria for the period 1950-2012. Statistical techniques such as time-series plots, correlation analysis, descriptive statistics and Mann-Kendall's test were used for the analysis. The findings show that minimum temperatures have higher trend coefficients than the maximum temperatures for almost all the stations. The Mann-Kendall's test results show a general warming trend across the stations.

Nnabuenyi *et al.* (2017) developed empirical correlation equations for the estimation of global solar radiation using monthly mean daily values of sunshine duration, maximum temperature, minimum temperature and average temperature of Oko, Nigeria. The result of the statistical analysis shows that, the sunshine and temperature based models proposed for Oko town correlate well with the measured value of the global solar radiation from NASA. Several researchers have used one or more metrological parameters in the study of weather and climate change in Nigeria (Awachie and Okeke 1990; Augustine and Nnabuchi, 2009; Ogolo and Adeyemi, 2009; Olofintoye and Sule 2010; Abiodun *et al*, (2011); Odjugo, 2011; Ewona and Udo 2011, Ezekoye *et al.*, 2011; Falayi *et al.*, 2011; Akinsanola and Ogunjobi 2017). Meteorologists and researches place a huge deal of effort into observing, understanding and predicting the daily, monthly and yearly evolution of weather systems. Usually the meteorological parameters are measured simultaneously on each sampling unit and are correlated; which researchers hardly take note of the association among these weather parameters. Thus, the goal of this study is to untangle the overlapping information provided by correlated multivariate variables and reduce the set of dimensions based on Principal Component analysis technique.

## MATERIALS AND METHODS

### Study Area, Data and Methods

Nigeria lies between latitudes $4^0$ and $14^0$N and longitudes $4^0$ to $14^0$E. The country is bounded on the north, east and west by the Republic of Niger, Cameroon and Benin Republic respectively, while the southern boundary is the Gulf of Guinea, an arm of the Atlantic Ocean. Nigeria is composed of various ecotypes and climatic zones. The Nigerian climate is characterized mainly by the dry north-easterly and the moist south-westerly winds. The main ecological zones are the tropical rainforest along the coast, savannah in the middle belt and semi-arid zones in the northern fringes. The daily air temperature, solar radiation, relative humidity, precipitation and wind speed data was obtained from National Aeronautic and Space Administration (NASA) (Modern Era Retrospective Analysis Version 2 (MERRA-2)) for the period of 37 years (1984-2020).


Figure 1: Map of Nigeria

**Principal Component Analysis**

Principal component analysis is a multivariate technique for transforming a set of correlated variables into a set of uncorrelated variables that account for decreasing proportions of the variation of the original observations. The rationale behind this method is an attempt to reduce the complexity of the data by decreasing the number of variables that need to be considered. The principal component variables $y_1$, $y_2$, …, $y_q$ are defined to be linear combinations of the original variables $x_1$, $x_2$, …, $x_q$ that are uncorrelated and account for maximal proportions of the variation in the original data, i.e., $y_1$ accounts for the maximum amount of the variance among all possible linear combinations of $x_1$, …, $x_q$, $y_2$ accounts for the maximum variance subject to being uncorrelated with $y_1$ and so on. Explicitly, the principal component variables are obtained from $x_1$, .. …, $x_q$ as follows (Landau and Everitt, 2014):

$$y_1 = a_{11}x_1 + a_{12}x_2 + \dots\dots.. + a_{1q}x_q$$
$$y_2 = a_{21}x_1 + a_{22}x_2 + \dots\dots.. + a_{2q}x_q$$
.
.
.
$$y_q = a_{q1}x_1 + a_{q2}x_2 + \dots\dots.. + a_{qq}x_q \qquad (1)$$

where the coefficients $a_{ij}$ ($i = 1, …, q$, $j = 1, …, q$) are chosen so that the required maximal variance and uncorrelated conditions hold.

Since the variances of the principal components variables could be increased without limit, simply by increasing the coefficients that define them, a restriction must be placed on these coefficients. The constraint usually applied is that the sum of squares of the coefficients is one so that the total variance of all the components is equal to the total variance of all the observed variables. It is often convenient to rescale the coefficients so that their sums of squares are equal to the variance of that component they define. In the case of components derived from the correlation matrix of the data, these rescaled coefficients give the correlations between the components and the original variables. It is these values that are often presented as the result of a principal components analysis. The coefficients defining the principal components are given by what is known as *eigenvector* of the sample covariance matrix, **S**, or the correlation matrix, **R**. Components derived from **S** may differ considerably from those derived from **R**, and there is not necessarily any simple relationship between them. In most practical applications of principal components, the analysis is based on the correlation matrix, i.e., on the standardized variables, since the original variables are likely to be on very different scales so that linear combinations of them will make little sense.

Principal component scores for an individual $i$ with vector of variable values $x_1^T$ can be obtained by simply applying the derived coefficients to the observed variables, generally after subtracting the mean of the variable, i.e., from the equations:

$y_1 = a_1^T(x_i - \bar{x})$

.

.

$y_{iq} = a_q^T(x_i - \bar{x})$ (2)

where $a_i^T = [a_{i1}, a_{i2}, \ldots, a_{iq}]$, and $\bar{x}$ is the mean vector of the observations.

If the first few of the derived variables (the *principal components*) among them account for a large proportion of the total variance of the observed variables, they can be used both to provide a convenient summary of the data and to simplify subsequent analyses. In every application, a decision must be made on how many principal components should be retained in order to effectively summarize the data. The following guidelines have been proposed:

i. Retain sufficient components to account for a specified percentage of the total variance, say, 80%.
ii. Retain the components whose eigenvalues are greater than the average of the eigenvalues, $\sum_{i=1}^{p} \lambda_i / p$. For a correlation matrix, this average is 1.
iii. Use the *scree graph*, a plot of $\lambda i$ versus $i$ , and look for a natural break between the “large” eigenvalues and the “small” eigenvalues.
iv. Test the significance of the “larger” components, that is, the components corresponding to the larger eigenvalues.

The coefficients defining the principal components are found by solving a series of equations involving the elements of the observed covariance matrix, although when the original variables are on very different scales, it is wiser to extract them from the observed correlation matrix instead. The first two principal component scores for each sample member can be plotted to produce a scatter plot of the data. If more than two components are thought necessary to adequately represent the data, other component scores can be used in three-dimensional plots or in scatter plot matrices (Landau and Everitt, 2014). The SPSS (Software Package for the Social Sciences) statistical software was employed in running the Principal Component Analysis.

## RESULTS AND DISCUSSION

Scatter plots of average yearly air temperature, relative humidity, wind speed, precipitation and solar radiation respectively are presented in Figures 1-5. The highest air temperature, relative humidity, wind speed, precipitation and solar radiation occurred around Borno, Bayelsa, Lagos, Cross river and Kano respectively. Plateau, Yobe, Delta, Yobe and Delta recorded the lowest value of air temperature, relative humidity, wind speed, precipitation and solar radiation respectively. The descriptive analysis reveals that the average yearly mean and standard deviation of the weather parameters are: air temperature 25.83 $\pm$ 1.00 $^o$ C; relative humidity 67.87 $\pm$ 17.93 %; wind speed 1.82 $\pm$ 0.55 m/s; precipitation 3.863 $\pm$ 1.65 mm/day; solar radiation 20.645 $\pm$ 7.713 MJ m$^{-2}$ day$^{-1}$. Precipitation, wind speed, relative humidity and air temperature is above normal in Lagos and Cross River.

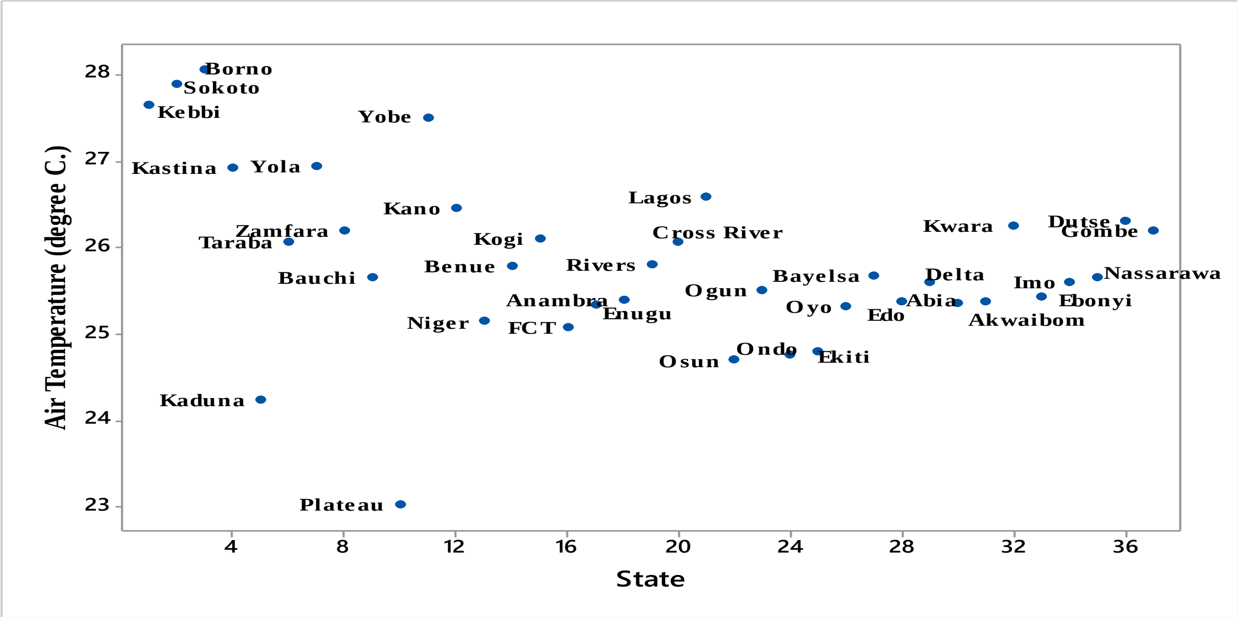


Figure 1: Yearly Average Air Temperature across states in Nigeria.

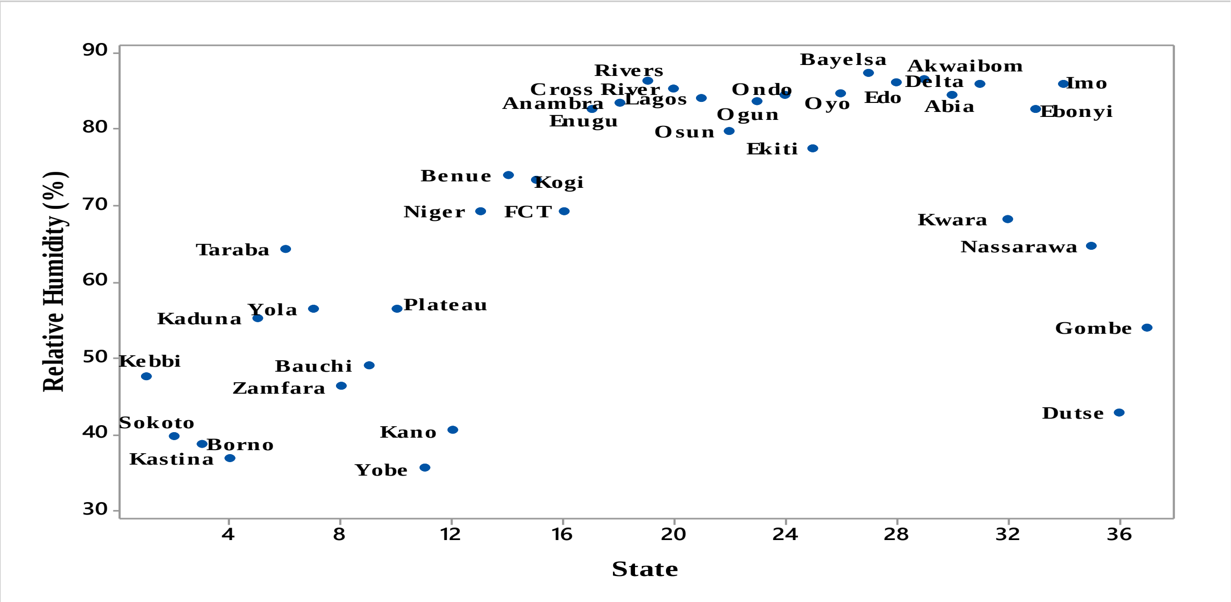


Figure 2: Yearly Average Relative Humidity across states in Nigeria.

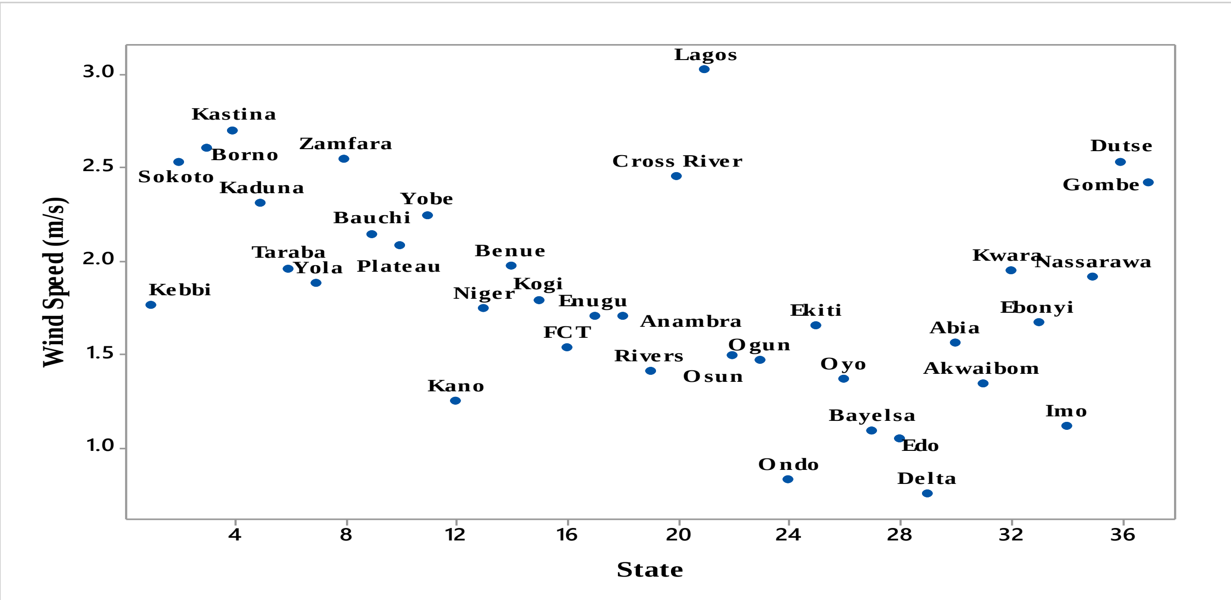


Figure 3: Yearly Average Wind Speed across states in Nigeria.

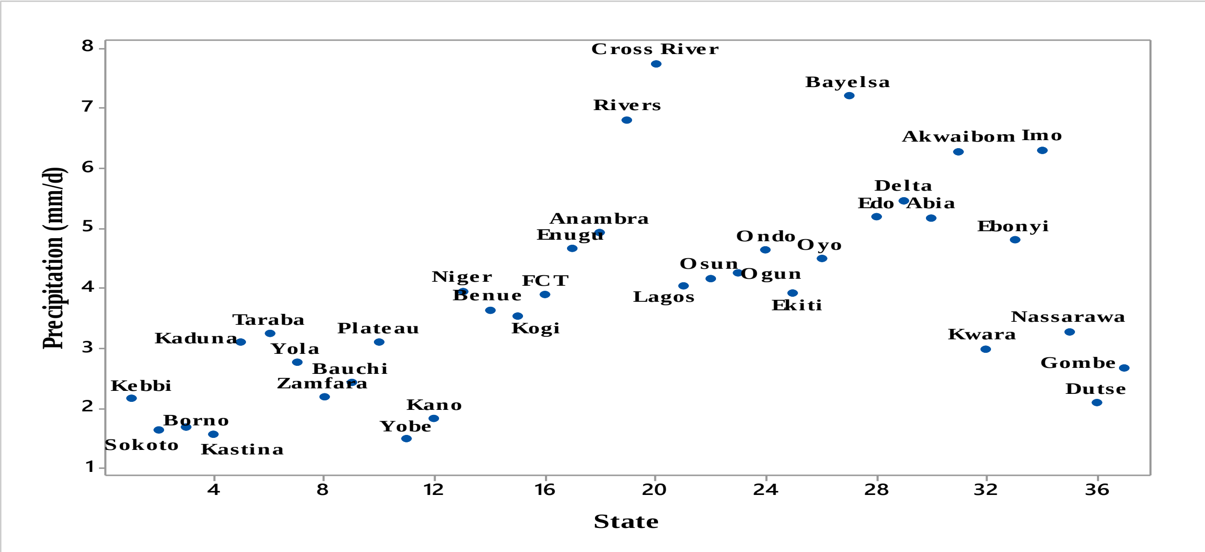


Figure 4: Yearly Average Precipitation across states in Nigeria.

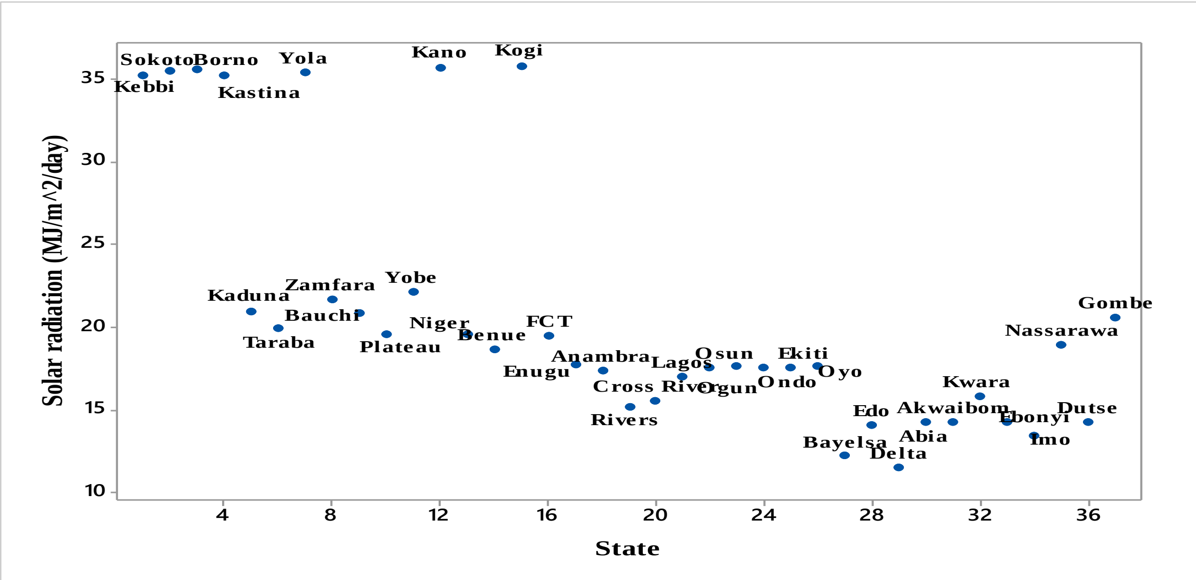


Figure 5: Yearly Average Solar radiation across states in Nigeria.

The descriptive statistics summarize the univariate distributions of the rates for each of the climatic parameters in Nigeria (Table 1). The variances of rates for different types of climatic parameter differ considerably (wind speed rate is relatively low and show small variability, while relative humidity rate is relatively high and variable, see Table 1).

**Table 1: Descriptive statistics of the climatic parameters from 1984-2020 in Nigeria**

| Parameters | Minimum | Maximum | Mean | Std. Deviation | Variance |
|---|---|---|---|---|---|
| Precipitation (mm/day) | 1.46 | 7.74 | 3.8638 | 1.652 | 2.731 |
| Wind Speed (m/s) | 0.75 | 3.02 | 1.8239 | 0.551 | 0.304 |
| Relative Humidity (%) | 35.47 | 87.41 | 67.8727 | 17.933 | 321.599 |
| Solar radiation (MJ $m^{-2}$ $day^{-1}$) | 11.48 | 35.77 | 20.6426 | 7.7137 | 59.501 |
| Air Temperature ($^0$C) | 23.02 | 28.05 | 25.8267 | 1.004 | 1.009 |

A correlation matrix of the data (Table 2) shows that the correlations between climatic parameters are significant suggesting that some simplification of the data using a principal component analysis is possible. Working with the correlation matrix amounts to using the climatic parameters rates after standardizing each to have unit standard deviation, seems sensible since without standardization the derived components are likely to be dominated by single variables with large variances.

**Table 2: Correlation Matrix for the various climatic parameters.**

| | Correlation Matrix | | | | |
|---|---|---|---|---|---|
| | **Precipitation** | **Wind Speed** | **Relative Humidity** | **Solar radiation** | **Air Temperature** |
| Precipitation | 1.000 | -0.558 | 0.893 | -0.683 | -0.439 |
| Wind Speed | -0.558 | 1.000 | -0.611 | 0.368 | 0.426 |
| Relative Humidity | 0.893 | -0.611 | 1.000 | -0.699 | -0.528 |
| Solar radiation | -0.504 | 0.207 | -0.512 | 1.000 | 0.540 |
| Air Temperature | -0.439 | 0.426 | -0.528 | 0.598 | 1.000 |

The principal Component Matrix and Communalities for each climatic parameter is presented in Table 3. The coefficients in Table 3 specify the linear function of the observed variables that define each component. The coefficients listed under PC1 show how to calculate the principal component scores:

PC1 = -0.893P + 0.710 W/S – 0.928 R/H + 0.827 S/R + 0.713 A/T

Where P is Precipitation, W/S is Wind Speed, R is Relative Humidity, S/R is Solar Radiation and A/T is Air temperature. The “Communalities” in Table 3 simply contains all ones since all five components were requested and these will explain the total variance of the observed variables.

**Table 3: Component Matrix and Communalities for each climatic parameter.**

| **Parameters** | **Component** | | | | | **Communalities** |
|---|---|---|---|---|---|---|
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **Initial** |
| Precipitation | -0.893 | 0.183 | 0.313 | 0.164 | -0.210 | 1.000 |
| Wind Speed | 0.710 | -0.506 | 0.452 | 0.186 | 0.015 | 1.000 |
| Relative Humidity | -0.928 | 0.142 | 0.189 | 0.169 | 0.232 | 1.000 |
| Solar radiation | 0.827 | 0.361 | -0.230 | 0.365 | -0.005 | 1.000 |
| Air Temperature | 0.713 | 0.500 | 0.456 | -0.183 | 0.030 | 1.000 |

Extraction Method: Principal Component Analysis.

It should be noted that the interpretation of the principal components is subjective; however, noticeable patterns emerge quite often. From Table 3, the first principal component is positively correlated with wind speed, solar radiation and air temperature and negatively correlated with precipitation and relative humidity. The second principal component is positively correlated with precipitation, relative humidity, solar radiation and air temperature and negatively correlated with wind speed. The higher the component loadings, the more important that variable is to the component. Hence, the first components (PC1) variables are Precipitation and relative humidity; second components (PC2) variables are wind speed and air temperature with the highest component loadings (Table3).

**Table 4: Total Variance Explained for each component**

| **Component** | **Initial Eigenvalues** | | | **Extraction Sums of Squared Loadings** | | |
|---|---|---|---|---|---|---|
| | **Total** | **% of Variance** | **Cumulative %** | **Total** | **% of Variance** | **Cumulative %** |
| 1 | 3.355 | 67.094 | 67.094 | 3.355 | 67.094 | 67.094 |
| 2 | 0.690 | 13.802 | 80.896 | 0.690 | 13.802 | 80.896 |
| 3 | 0.599 | 11.981 | 92.877 | 0.599 | 11.981 | 92.877 |
| 4 | 0.257 | 5.140 | 98.017 | 0.257 | 5.140 | 98.017 |
| 5 | 0.099 | 1.983 | 100.000 | 0.099 | 1.983 | 100.000 |

Extraction Method: Principal Component Analysis.

Total Variance Explained in Table 4 shows how much of the total variance of the observed variables is explained by each of the principal components. The first principal component (scaled eigenvector), by definition the one that explains the largest part of the total variance, has a variance (eigenvalue) of 3.355; this amounts to 67.094% of the total variance. The second principal component has a variance of 0.690 and accounts for a further 13.802% of the variance and so on. The "Cumulative %" column in Table 4 explains how much of the total variance can be accounted for by the first *k* components together. Thus, the first two (three) principal components account for 81% (93%) of the total variance of the observed weather parameters.

The Scree plot (Figure 6) displays this distribution of variance among the components graphically. For each principal component, the corresponding eigenvalue is plotted on the *y*-axis. The variance of each principal component is less than the preceding one, and the shape of the plot is decreasing.

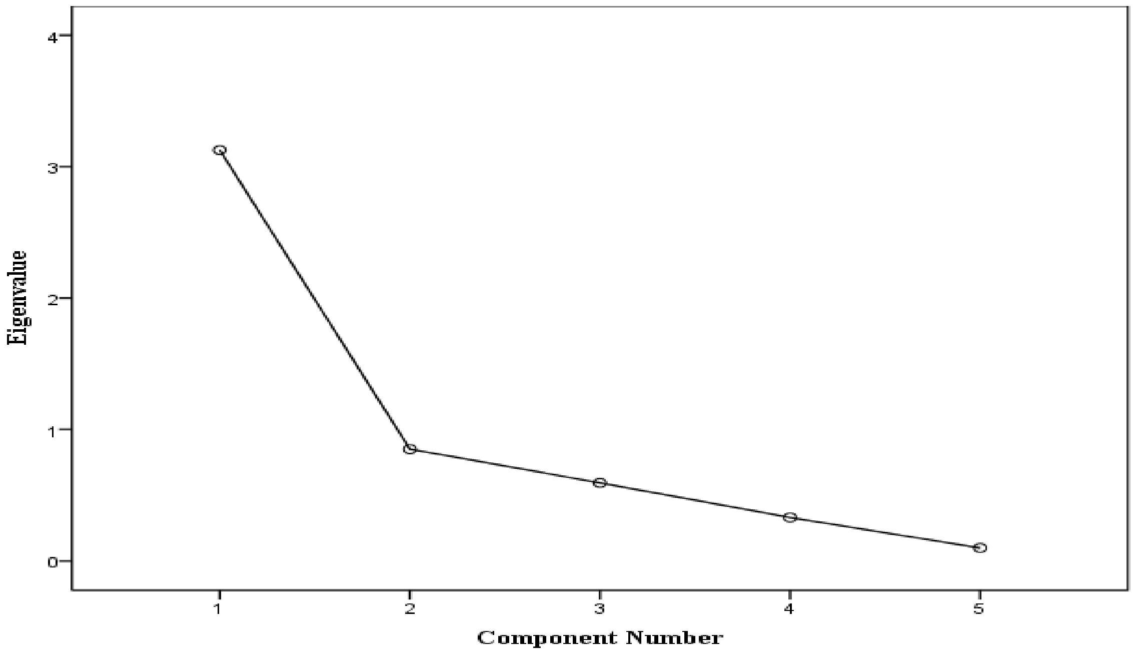


Figure 6: Scree plot for the climatic parameters.

There appears to be a marked decrease in downward slope after the second or third principal component implying that the five weather parameters can be summarize by the first two or three principal components. Thus, most of the data structure can be captured in two or three underlying dimensions. The remaining principal components account for a very small proportion of the variability and are probably unimportant. According to Landau and Everitt (2014), the first two-component solution is assumed to be adequate.

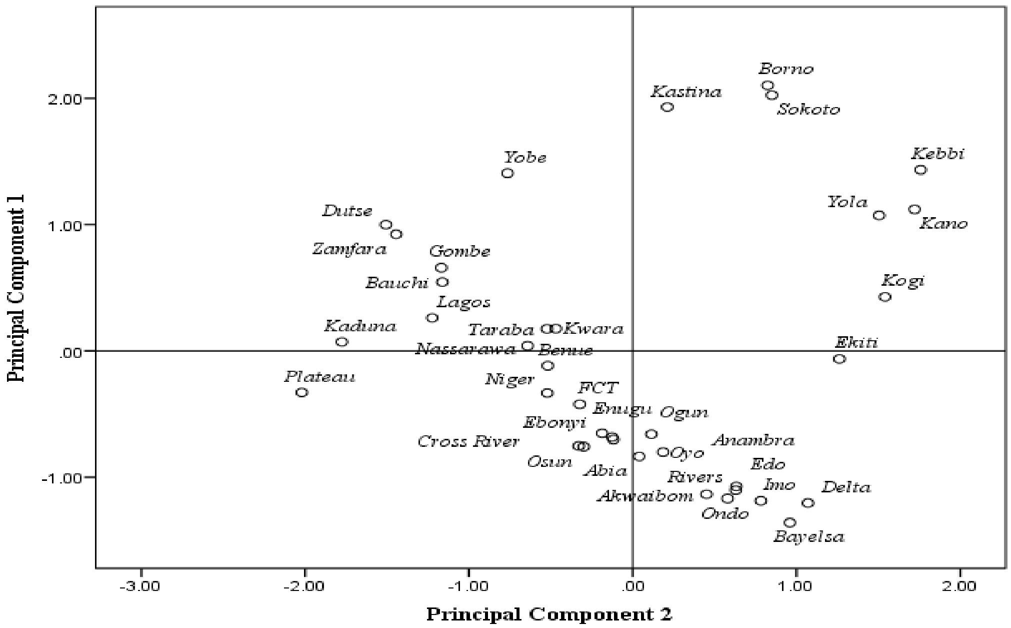


Figure 7: Scatter plot of the first two principal components.

The scatter plot of the first two principal components given in Figure 7 helps to visualize the climate patterns of the thirty-six states in Nigeria. Scores on the *y*-axis indicate the overall level of climate change patterns, while scores on the *x*-axis indicate the differential between insignificant and significant climate change pattern in Nigeria. Kastina, Borno and Sokoto clearly stand out from the other states in Nigeria with the highest overall climate change pattern and a large differential between insignificant and significant climate change pattern in favor of significant climate change (highest rates of precipitation, relative humidity, solar radiation and air temperature). Nassarawa, Benue, Kaduna, Taraba and Kwara states are very close to average (insignificant climate change pattern), while the remaining states are above or below average of overall climate parameter rate with a large differential in rates between climate parameter in favor of significant climate change. Yobe, kastina, Borno, Sokoto, kebbi, Yola, Kano, Kogi and Ekiti are the only states that load highly on a single component (Figure 7). Scoring highly on a single component simply means that the original weather parameters values for these states are overwhelmingly explained by a single component. This means that the variation among all of the weather parameters for Yobe, Kastina, Borno, Sokoto, Kebbi, Yola, Kano, Kogi and Ekiti are completely explained by a single component (PC1) made up of Precipitation and Relative humidity.

## CONCLUSION

This paper presents a multivariate technique (Principal component analysis) for transforming a set of related variables into a set of unrelated variables that account for decreasing proportions of the variation of the original observations. The results show that the first two (three) principal components account for 81% (93%) of the total variance of the observed weather parameters. Further result reveals that the higher the component loadings, the more important that variable is to the component. Hence, the first principal components (PC1) variables are Precipitation and relative humidity, while the second principal components (PC2) and third principal components (PC3) variables are wind speed and air temperature. The main benefit of this method is to reduce the complexity of data by decreasing the number of variables that need to be considered. This study shows that wind speed and air temperature parameter explains the weather condition in Nigeria better.

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