ANALYSIS OF THE VARIABILITY IN SOME CLIMATIC PARAMETERS IN OYO, NIGERIA

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Abstract: This study aims at analyzing the variability in some climatic parameters in Oyo Nigeria, with the implication of selecting the right descriptive statistics. 34 years' data (1977-2010) on daily Rainfall amount, maximum and minimum Relative-Humidity, Sunshine hour, Solar irradiance, Evaporation, maximum and minimum Air temperature, and Wind speed were sourced from the International Institute of Tropical Agriculture (IITA) and used in the analysis. The descriptive statistics employed are: Mean, Standard Deviation and Coefficient of Variation. The One-way Analysis of Variance (ANOVA) was employed in checking whether the variability in the climatic parameters is affected by season. The cluster analysis main goal is to divide the climatic parameters into consistent and distinct groups. The study revealed that the mean is a good approximation of the data set of minimum and maximum Air temperature and maximum Relative humidity because the coefficient of variation is small (<20%). Higher values of coefficient of variation (>20%) as observed in rainfall, evaporation, wind speed and sunshine hours indicate higher uncertainty in the use of the mean as an approximation of the center of the data set. The study recommends that measures of dispersion (range, standard deviation and/or variance) be used in addition to the mean in describing the data. The study further revealed that the variability in solar irradiance affects the variability in Evaporation and Sunshine hours, while the variability in rainfall amounts affects the variability in the minimum and maximum Relative humidity and minimum Air temperature. Lastly the variability in maximum Air temperature affects that of Wind speed. The monthly mean of each of the climatic parameters in the month of May and November are very far apart (no similarity) as revealed by the cluster analysis, because it has the highest squared Euclidean distance of 715.612, and 3.997 between the month of June and October which is the shortest distance. This means that the monthly mean of each of the climatic parameters in the month of June and October are so close (little or no difference). Consequently, the researchers opined that it is reasonable to compute monthly descriptive statistics instead of yearly because, computing yearly descriptive statistics collapse seasonal effects as revealed in the result of the One-way Analysis of variance (ANOVA). The study concluded that the use of the value of the coefficient of variation (<20% or >20%) should inform the selection of the mean as a measure of central tendency and that seasonal effects on the measurements should be checked to avoid the collapse of season when there is indeed significant difference in the monthly mean of the climatic parameter.

Keywords: Cadmium, caffeine, *Cola nitida*, contaminants, farmers, pollutants

Introduction

Multivariate analysis consists of a collection of methods that can be used when several measurements are made on each individual or object in one or more samples. Multivariate analysis is concerned generally with two areas, descriptive and inferential statistics. Descriptive statistics provide numerical and graphical ways of summarizing large collection of data into simpler and understandable form. The three major characteristics of a single variable are distribution, central tendency and dispersion. The variation of the data from the mean is called dispersion. Some measures of dispersion include range, standard deviation, mean deviation, quartile deviation and coefficient of variation. The central tendency of a distribution is the center (mean, median and mode) of that distribution. Several studies that center on the analysis of climatic parameters have been done using descriptive statistics. Some of such works include; (Adetayo, 2015; Hassan and Ajibola, 2015; Chegaar *et al*., 1988; Amadi *et al.*, 2015; Zakaria, 2014) to mention but a few.

Understanding and applying the right statistics (in the simple sense of it; descriptive statistics) in analyzing climate change and climate variability helps a lot in the correct interpretation of results. The challenge of most researchers has been the selection of the right descriptive statistics; thus they end up with the wrong selection and application of their statistics. This is an issue this work seeks to address among others. Using just the mean and standard deviation alone may not reflect the variability among climatic parameters (Md Ruhul *et al*., 2015). The low reliability on the use of the mean was also established (Oscar *et al*., 2015). In this paper, descriptive statistics such as mean, standard deviation and the coefficient of variation were computed to ascertain the variability in some climatic parameters. Higher values of coefficient of variation (>20%) indicate higher uncertainty in the use of the mean as an approximation of the centrality of the data but it is an appropriate measure when the coefficient of variation is small (<20%) (Taha, 2007).

The climatic parameters considered include rainfall (mm), wind speed (km/hr), maximum and minimum air temperature (^{0}C), sunshine hours (hr), maximum and minimum relative humidity (%), evaporation (mm) and solar radiation (MJ/m^2/day). The One way Analysis of variance (ANOVA) is used to detect the presence of seasonal effect on each climatic parameter. This is done to inform the researchers of not collapsing the effect of season when it does exist. Further in this work, the cluster analysis is also implemented to search for patterns in the above data set by grouping the (multivariate) observations into clusters. So many literature on cluster analysis has been done (Everitt, 1993; Khattree and Naik, 1999; Kaufman and Rousseeuw, 1990; Seber, 1984). Clusters can also be searched graphically by plotting the observations. Advance plotting by projection pursuit, which seeks two-dimensional projections that reveal clusters, has been introduced (Friedman and Tukey, 1974; Yenyukov, 1988; Jones and Sibson, 1987; Huber, 1985; Sibson, 1984; Posse, 1990).

Materials and Methods

Source of data and method of analysis

The daily Rainfall, maximum and minimum Relative-Humidity, sunshine hour, solar radiation, evaporation, maximum and minimum air temperature, and wind speed data used in this work was obtained from the International Institutes of Tropical Agriculture (IITA**)** Ibadan, Nigeria for the period of 34 years (1977-2010). The monthly mean, standard deviation and coefficient of variation for all the climatic parameter were computed as shown in table one below.

Coefficient of variation

The coefficient of variation eliminates the unit of measurement of the standard deviation of a series of numbers by dividing it by the mean of these numbers. It can be used to compare distribution obtained with different units, such as the variability of wind speed in meter per second with air temperature in degrees. In general, higher values of coefficient of variation (>20%) indicate higher uncertainty in the use of mean as an approximation of data, but the mean can be used as an approximation of the data if the coefficient of variation is small (< 20%)(Taha, 2007).

$$C.V. = \frac{\sigma}{\dot{x}} X100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where: $C.V.$ = Coefficient of Variation, σ= Standard deviation, ẋ= Mean

This is a ratio and therefore has no units.

One-way analysis of variance (ANOVA)

ANOVA is a parametric statistic which provides the opportunity to undertake a multi-group comparison of data set. The comparisons being made using ANOVA are 2-dimensional. The sources of variation as the basis for comparison recognize that difference exists between and within groups being compared. The second dimension has to do with the fact that the direction of difference establishes the homogeneity (closeness) of variance between and within groups. The F-values obtained is usually compared with the F-critical ratio as a base for establishing the acceptance or rejection of the hypothesis stated. ANOVA involves the estimation of within group and between group variations in means of research groups being compared (Emalkwu, 2010).

One-way Analysis of Variance (ANOVA) was employed in checking whether the variability in the climatic parameters is affected by season. This is to avoid the collapse of season when there is indeed a significant difference in the monthly mean of the climatic parameter. The One-way Analysis of Variance (ANOVA) was implemented using the Statistical Package for Social Science (SPSS) version 21.

Cluster analysis

In cluster analysis, patterns in a data set are searched by grouping the (multivariate) observations into clusters. The main goal is to divide the observations into consistent and distinct groups. In cluster analysis, neither the number of groups nor the groups themselves are known in advance, unlike in classification analysis, where each observation is known to belong to one of a number of groups. The various methods of Clustering include: Partitioning methods, Hierarchical methods, Density-based methods, Grid-based methods and Model-based methods (Rencher, 2002). In this study, we hope to find the natural groupings in the data, groupings that make sense using the Hierarchical methods.

Hierarchical agglomerative methods

The hierarchical agglomerative clustering methods are usually used in most analysis. ‘Hierarchical’ because all clusters formed by these methods consist of mergers of previously observations and end with a single cluster containing all observations. The assembly of a hierarchical agglomerative classification can be achieved by the following general algorithm. (Rencher, 2002):

- Find the 2 closest observations and combine them into a cluster
- Find and combine the next two closest points, where a point is either an individual Observations or a cluster of Observations.

A convenient measure of proximity is the distance between two observations. Since a distance increases as two Observations become further apart, distance is actually a measure of dissimilarity. A common distance function is the Euclidean distance between two vectors
x = (x_1, x_2, . . . , x_p) and **y** = (y_1, y_2, . . . , y_p) is defined as (Rencher, 2002):

$$d(x,y) = \sqrt{(x-y)'(x-y)} = \sqrt{\sum_{j=1}^{p}(x_j - y_j)^2} \ldots\ldots\ldots (2)$$

For large data set, it is not generally feasible to examine all possible clustering possibilities for the data set. The number of ways of partitioning a set of n items into g clusters is given by (Duran, & Odell, 1974):

$$N(n,g) = \frac{1}{g!}\sum_{k=1}^{g}\binom{g}{k}(-1)^{g-k}k^n \ldots\ldots\ldots\ldots\ldots (3)$$

Hence, hierarchical aagglomerative methods permit us to search for a reasonable solution without having to look at all possible arrangements. The nearest neighbour (single linkage), furthest neighbour (complete linkage) and average linkage methods are examples of hierarchical agglomerative clustering methods. A compromise method is the average linkage, under which the distance between two clusters is the average of the distances of all pairs of observations (Robert, 1992). The Statistical Package for Social Science (SPSS) version 18 is used to compute the smallest average distance between all group pairs and combines the two groups that are closest, and it is also used to implement the hierarchical aagglomerative methods of the cluster analysis. The groupings and the distance are shown in a tree diagram (dendrogram).

Result and Discussion

The coefficient of variation of the climatic parameters

The coefficient of variation indicates how small or large the standard deviation is with respect to the mean. The analysis presented in Tables 1-3 reveal that the coefficient of variation of minimum and maximum air temperature and maximum relative humidity is small (<20%) while the coefficient of variation of rainfall, evaporation, wind speed and sunshine hour is large (>20%). The coefficient of variation of solar radiation and minimum relative humidity is small in the month of November to March and April to October and large in the month of April to October and November to March, respectively.

The mean is a good approximation of the data set of minimum and maximum air temperature and maximum relative humidity because the coefficient of variation is small (<20%). Higher values of coefficient of variation (>20%) such as in rainfall, evaporation, wind speed and sunshine hours indicate higher uncertainty in the use of mean as an approximation of the data (Taha, 2007). Descriptive statistics such as the standard deviation, variance and range should be used alongside with the mean for the climatic parameters whose coefficient of variation is high (>20%).

Table 1: Monthly descriptive statistics for rainfall, maximum air temperature and relative humidity

Month	Rainfall (mm)			Max.air Temp.(˚C)			Max. Rel. Hum.(%)		
	Mean	St. dev.	C.V (%)	Mean	St. dev.	C.V (%)	Mean	St. dev.	C.V (%)
Jan.	0.186700	1.876873	1004.940	32.88217	1.521810	4.628071	89.43332	15.40706	17.22743
Feb.	0.744630	4.109316	551.8603	34.74925	1.472010	4.236091	92.29361	10.40790	11.27696
Mar.	2.220588	7.786187	350.6363	34.26355	1.956684	5.710687	94.84900	6.367742	6.713557
Apr.	4.139194	11.21779	271.0137	32.76786	2.065827	6.304432	96.30494	2.967285	3.081135
May	5.085028	11.17402	219.7435	31.32126	1.829016	5.839534	96.71347	3.220833	3.330284
June	6.159234	13.86173	225.0561	29.86895	1.718048	5.751953	96.41542	3.715889	3.854041
July	6.179127	13.57757	219.7328	28.12134	1.669215	5.935758	96.20533	3.534099	3.673496
Aug.	4.154981	10.36194	249.3860	27.66260	1.527674	5.522524	96.41103	3.467540	3.596622
Sept.	7.447255	14.60104	196.0594	28.84143	1.585323	5.496685	96.58446	2.930439	3.034069
Oct.	5.531262	11.64704	210.5675	30.07895	1.514714	5.035793	96.88093	2.366706	2.442902
Nov.	0.872745	4.388156	502.7993	31.81417	1.356951	4.265241	96.32392	3.243361	3.367139
Dec.	0.261338	2.998996	1147.556	32.23293	1.382248	4.288311	94.42051	7.988066	8.460096

Max.air Temp.=Maximum air Temperature; Max. Rel. Hum.=Maximum Relative Humidity

Table 2: Monthly descriptive statistics for evaporation, wind speed and sunshine hour

Month	Evaporation (mm)			Wind Speed (km/hr)			Sunshine Hour(hr)		
	Mean	St. dev.	C.V (%)	Mean	St. dev.	C.V (%)	Mean	St. dev.	C.V (%)
Jan.	4.401773	1.541382	35.01730	3.305608	1.528603	46.24272	6.700128	2.213074	33.03033
Feb.	5.343708	1.386125	25.93939	4.075554	1.383140	33.93747	7.003736	.210809	31.56613
Mar.	5.214888	1.466103	28.11379	4.530760	1.449818	31.99945	6.965093	2.250190	32.30667
Apr.	4.685958	1.567140	33.44333	4.222748	1.546745	36.62886	6.707260	2.694341	40.17052
May	4.188863	1.472022	35.14132	3.775573	1.433422	37.96569	6.642151	2.914687	43.88167
June	3.664037	1.357825	37.05817	3.595098	1.350984	37.57850	5.760210	2.882543	50.04231
July	2.888317	1.239975	42.93070	3.627423	1.432742	39.49751	3.693650	2.664913	72.14851
Aug.	2.568372	1.119097	43.57223	3.469657	1.407368	40.56218	2.815652	2.256509	80.14161
Sept.	3.174105	1.225423	38.60688	3.124398	1.339839	42.88309	4.007069	2.601986	64.93490
Oct.	3.599735	1.323393	36.76364	2.770496	1.217337	43.93932	5.734555	2.603644	45.40272
Nov.	4.003708	1.134874	28.34557	2.654283	1.126057	42.42416	7.363409	1.926040	26.15690
Dec.	3.923584	1.237411	31.53778	2.762937	1.150057	41.62444	7.314703	2.043363	27.93501

Table 3: Monthly descriptive statistics for solar radiation, minimum air temperature and relative humidity

Month	Sol.Rad.(MJ/m2/day)			Min. air Temp.(˚C)			Min Rel. Hum.(%)		
	Mean	St. dev.	C.V (%)	Mean	St. dev.	C.V (%)	Mean	St. dev.	C.V (%)
Jan.	14.57392	2.813116	19.30239	20.72795	2.902618	14.00340	34.89446	13.30331	38.12443
Feb.	16.71936	3.042361	18.19663	22.45641	2.266882	10.09459	31.96124	11.90049	37.23412
Mar.	17.54678	3.638620	20.73668	23.32321	1.582698	6.785937	41.36935	12.57444	30.39555
Apr.	17.50272	4.169726	23.82330	23.21336	1.583516	6.821572	53.29641	9.642843	18.09286
May	17.09923	4.078242	23.85044	22.65168	1.374266	6.066948	59.79697	8.033274	13.43425
June	15.82643	4.027860	25.45021	22.17402	1.230995	5.551522	63.91288	8.132903	12.72498
July	13.10725	4.146194	31.63282	21.85161	0.984684	4.506232	69.36262	8.327983	12.00644
Aug.	12.06647	3.937696	32.63338	21.69326	0.853039	3.932276	70.98850	8.675492	12.22098
Sept.	14.20129	3.901165	27.47050	21.81252	1.021558	4.683358	66.69214	7.779605	11.66495
Oct.	15.55939	4.009460	25.76874	22.11670	1.151248	5.205331	62.30583	7.607508	12.20995
Nov.	16.08432	3.150709	19.58870	22.41847	1.762669	7.862573	48.63922	10.52830	21.64569
Dec.	14.45927	2.873310	19.87175	21.13755	2.765319	13.08249	38.97443	12.06556	30.95762

Sol. Rad. =Solar Radiation; Min. air Temp. =Minimum air Temperature; Min. Rel. hum. =Minimum Relative Humidity

The coefficient of variation eliminates the unit of measurement and helps to compare variability across climatic parameters. The variability of Solar radiation, Evaporation, and Sunshine hours have the same pattern as presented in Fig. 1, while rainfall, minimum and maximum relative humidity and minimum air temperature have the same pattern as shown in Fig. 2, lastly maximum air temperature and wind speed follow the same trend, as revealed in Fig. 3.

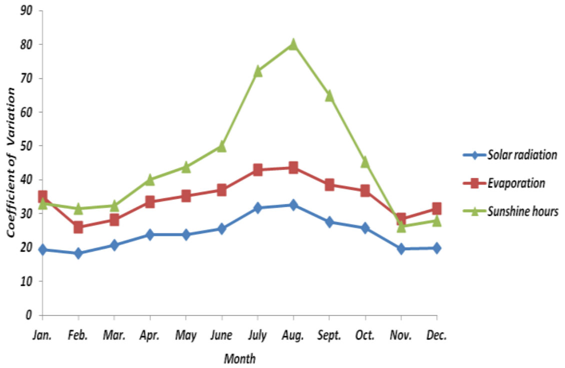

Fig. 1: Monthly coefficient of variation of Solar Radiation, Evaporation and Sunshine hours in Oyo, Nigeria

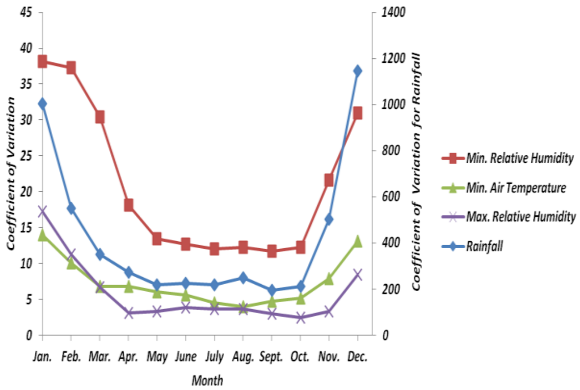

Fig. 2: Monthly coefficient of variation of Rainfall, Max. and Min. Relative Humidity, and Min. Air Temperature in Oyo, Nigeria.

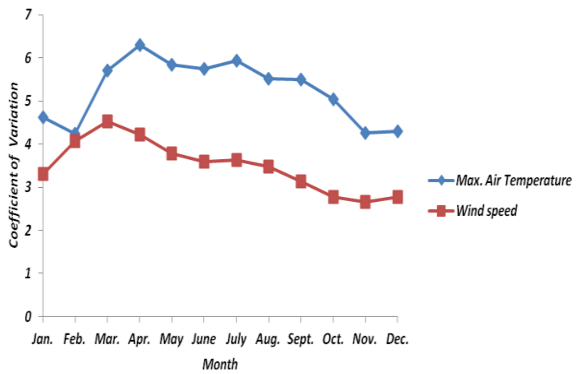

Fig. 3: Monthly coefficient of variation of Max. Air Temperature and Wind Speed in Oyo, Nigeria

This similarity in pattern is an indication that the variability in one climatic variable affects the variability in another related variable. Increased climate variability (high coefficient of variation) points out higher year to year fluctuations and makes prediction very difficult. It is more reasonable and better to compute descriptive statistics monthly instead of yearly. This is because; computing yearly descriptive statistics collapse seasonal effects. In figures 1-3, the variability of the climatic parameters in the raining season (April to November) differs from that of the dry season (December to March). The following discussion on the variability of the monthly means of each climatic parameter across the years of study further buttress this fact.

Comparism of monthly mean of the climatic parameters

The result of the One-way Analysis of Variance (ANOVA) displayed in Table 4 reveals a significant difference in the monthly means for each parameter across the years of study considered.

This explains the existence of a monthly variability in each climatic parameter confirming the influence of seasonal effect. This also indicates the existence of significant climate variability in Oyo metropolis. The collapse of season while computing statistics will therefore amount to committing an error. This explanation strengthens the above discussion on the coefficient of variation of the climatic parameters.

Table 4: Summary of one-way analysis of variance (ANOVA) comparing the monthly mean of the climatic parameters

Climatic parameter	F_value	P_value	Remark
Rainfall	0086.845	0.000	Significant
Evaporation	0409.089	0.000	Significant
Wind Speed	0196.691	0.000	Significant
Solar Radiation	0244.251	0.000	Significant
Min. Air Temperature	0223.977	0.000	Significant
Max. Air Temperature	2156.675	0.000	Significant
Min. Relative Humidity	2141.757	0.000	Significant
Max. Relative Humidity	0138.178	0.000	Significant
Sunshine hour	0056.432	0.000	Significant

$\alpha=0.05$

Cluster analysis of the climatic parameters

The agglomeration schedule in Table 5 is a numerical summary of the cluster solution. At the first stage in Table 5, cases 6 (June) and 10 (October) are combined because they have the smallest squared Euclidean distance of 3.997. This means that the monthly mean of each of the climatic parameters in the month of June and October are very close (little or no difference).

Table 5: The agglomeration schedule of the cluster solution

Stage	Agglomeration Schedule					
	Cluster Combined			Stage Cluster First Appears		
	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	Next Stage
1	6	10	3.997	0	0	3
2	7	8	9	0	0	4
3	5	6	18.065	0	1	9
4	7	9	24.114	2	0	9
5	1	2	29.745	0	0	8
6	3	12	33.106	0	0	8
7	4	11	39.269	0	0	10
8	1	3	77.052	5	6	10
9	5	7	81.874	3	4	11
10	1	4	252.674	8	7	11
11	1	5	715.162	10	9	0

The cluster created by their joining next appears in stage 3. Neither variable (case 6 and case 10) has been previously clustered (the two zeros under Cluster 1 and Cluster 2). At stage 3, Case 6 (June) joins case 5 (May). At Stage 8, the clusters containing Cases 1 (January) and 3 (March) are joined, Case 1 has been previously clustered with Case 2 (February), and Case 3 had been previously clustered with Cases 12 (December), thus forming a cluster of 4 cases (Cases 1, 2, 3, 12). The squared Euclidean distance between the two joined clusters is 77.052 at stage 8. The month of May and November has the highest Euclidean distance of 715.162, that is, the monthly mean of each of the climatic parameters in the month of May and November are far apart (no similarity).
The dendrogram in Fig. 4 is a graphical summary of the cluster solution. The horizontal axis shows the distance between clusters when they are joined. The largest gaps in the coefficients column occur between stages 10 and 11, indicating a 2-cluster solution as shown in the dendrogram. The branching-type nature of the dendrogram allows one to draw backward or forward to any individual case or cluster at any level. It also gives an idea of how great the distance was between cases or groups that are clustered in a particular step.

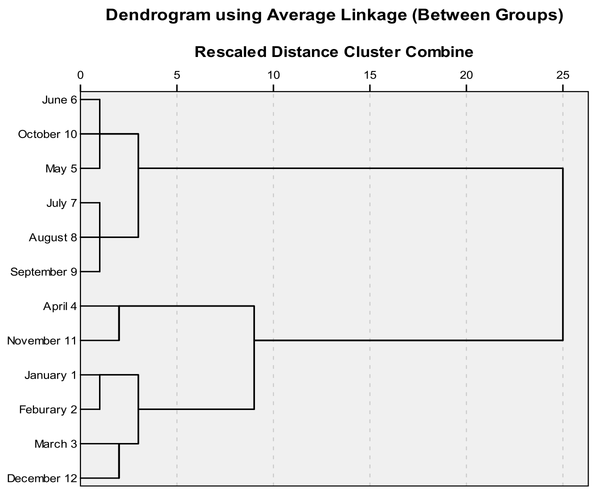

Fig. 4: Dendrogram of average linkage clustering of the climatic data

To interpret the distance in the early clustering phases (the extreme left of the graph) could be difficult, as one moves to the right, relative distance becomes more apparent. The bigger the distances before two clusters are joined, the bigger the differences in these clusters. From figure 4, it is also obvious that there are two major clusters formed, the first cluster is made up of the months of May, June, July, August, September and October while the second cluster comprises of the months of November, December, January, February, March and April. There is a distinct wet and dry season of relatively equal durations in Oyo as revealed by the study.

Conclusion and Recommendation

Conclusion

The following conclusions were drawn from the study;

(i) The variability in one climatic parameter affects the variability in another related parameter.

(ii) The mean is a good approximation of the data set of minimum and maximum Air temperature and maximum Relative humidity because the coefficient of variation is small (< 20%).

(iii) Higher values of coefficient of variation (>20%) as observed in rainfall, evaporation, wind speed and sunshine hours indicate higher uncertainty in the use of the mean as an approximation of the center of data set.

(iv) The coefficient of variation of solar radiation and minimum relative humidity is small (< 20%) in the months of November to March and April to October and large (>20%) in the months of April to October and November to March.

(v) There exists significant climate variability in Oyo metropolis and its persistence over time is a strong indicator of climate change.

(vi) The squared Euclidean distance between the month of June and October is 3.997 which is the smallest distance as revealed by the study. This means that the monthly mean of each of the climatic parameters in the month of June and October are very closer (little or no difference).

(vii) The months of May and November have the highest Euclidean distance of 715.162, that is, the monthly mean of each of the climatic parameters in the month of May and November are far apart (no similarity).

Recommendation

(i) Since mean does not capture variability, the standard deviation, range and variances should be used alongside when the coefficient of variation is large (>20%).

(ii) The Government of Oyo State, Nigeria should watch out and take proactive steps against climate change in the near future.

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