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A Model for the Sequence of Positive and Negative Maximum Air temperature Anomaly in Port Harcourt, Nigeria

AGADA, P.O. [1], AGADA, I.O. [2] and ANNONGU, W.D.[3]

[1, 3] *Department of Mathematics/Statistics/Computer Science, University of Agriculture, Makurdi. Benue State, Nigeria.*
[2] *Department of Physics, University of Agriculture, Makurdi. Benue State, Nigeria.*

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Abstract: This work employ the Markov Chain model in modeling the sequence of positive and negative maximum air temperature anomaly in order to provide information for weather or climate assessment of the city of Port Harcourt, Nigeria. This was achieved by determining; the order of the Markov Chain model that fits the maximum air temperature data, the transition probability matrix for the sequence of positive and negative maximum air temperature anomaly, the steady state probabilities of a positive and negative maximum air temperature anomaly and the mean recurrence time (in days) of a positive and negative maximum air temperature anomaly. These were determined for each month of the year (January – December). The Results from the study showed that the first order Markov Chain model is found suitable for analyzing the positive and negative maximum air temperature anomaly in Port Harcourt, Nigeria for each month of the year, the positive - positive (+ +) and negative - negative (- -) anomaly sequences have equal chance of 0.8, 0.8, 0.7, 0.8, 0.9 and 0.8 in the months of January, February, July, October, November and December respectively, while the positive - negative (+ -) and negative - positive (- +) anomaly sequences also have equal chance of 0.2, 0.2, 0.3, 0.2, 0.1 and 0.2 in the same months. Furthermore, the results revealed that, in the long run, the positive and negative maximum air temperature anomalies have equal chance of 0.5 in the months of January, February, July, October, November and December and equal mean recurrence time of 2.00 days in the same months. The study recommends that the first order Markov Chain model be used in analyzing the sequence of positive and negative maximum air temperature anomaly in Port Harcourt, Nigeria and that the results of the study be made available to stakeholders for use wherever they deem fit.

Keywords: Model, Sequence, Air temperature, Anomaly

1. INTRODUCTION

The city of Port Harcourt is located in the South-South geopolitical zone of Nigeria. It is a coastal city located in the Niger Delta region of Nigeria within latitudes 6º58' –7º60'E and longitudes 4º40' – 4º55'N. Niger Delta is one of the largest wetlands of the world. Its total land area is approximately over 2900 [21], its economy is primarily based on the Oil and Gas industry whose operations usually result to climatic change.

In recent times, temperature in Nigeria is constantly rising and falling as a result of general global warming. According to current scientific understanding, the spatial and temporal fluctuations of Air temperature are generated by natural- and anthropogenic activities [13]. Anthropogenic activity such as population growth, deforestation, unsustainable agriculture, and the widespread use of fossil fuels are contributing to global warming [7]. This global warming is caused by excessive quantities of greenhouse gases emitted into Earth's near-surface atmosphere. However, increasing levels of these gases are the causes of rising surface air temperature, resulting in the most severe ecological crisis that the Niger-Delta region of Nigeria has certified. IPCC [13] discovered that greenhouse gases are responsible for most of the observed temperature increase since the middle of the twentieth century. Ekpoh and Nsa [10] observed that there is sufficient evidence of rising global air temperatures due to increased emission of greenhouse gases into the atmosphere which have the capacity to trigger large scale climatic changes thereby having significant effect on the air temperature. According to O'Hare [23], increase in temperature will cause higher frequency and intensity of extreme weather events such as severe heat and drought, intense rainfall and serious flooding, excessive wind and violent storm. In the light of the above the significance of a study of this nature, which analyzes the maximum air temperature data of Port Harcourt, Nigeria in order to assess the weather or climate of the area cannot be overemphasized.

E-mail address: gadexx@yahoo.com

According to Baldwin *et al.* [4] weather impact is the main factor causing delay and cost overruns on construction project. This impact of weather on construction activities can be in the form of reduced labour productivity and (or) work stoppage. Reduced labour productivity is generally attributed to reduced human performance due to heat or cold stresses resulting from the combined effect of air temperature. This work annuls the effect this impact in the city of Port Harcourt, Nigeria as it models the sequence of positive and negative maximum air temperature anomaly. This is because its results will provide Civil Engineers and Architects with important information that will assist them in construction planning, in such a way that the influence of air temperature on their project works disruption would be minimal.

Furthermore, 40% of the rural inhabitants are committed to agricultural activities in River state. Over the years, a pattern has emerged in the fresh water flood plains of the region; a variety of short season crops including cocoyam, water yam, sweet-potato, groundnut, maize, sugar-cane and assorted vegetables are grown [20]. It must be mentioned that crops respond differently to variations in the climatic condition of an area and temperature is a major component in climate assessment [6]. In addition, high air temperature affects climate change, which in turn exerts multiple stresses on the biophysical as well as the social and institutional environments that underpin agricultural production [13]. Since this work models the sequence of warmer (positive anomaly) and colder (negative anomaly) air temperature days in Port Harcourt, its results are of no doubt of relevance to Agriculture.
Temperature anomaly is the difference between the long-term average temperature (sometimes called a reference value) and the temperature that is actually occurring. In other words, the long-term average temperature is one that would be expected. The anomaly is the difference between what you would expect and what is happening. According to Fan *et al.* [11], temperature anomaly is the variation between a particular temperature for a particular station in a particular month, and the average for that month for a selected baseline period. It also means a departure from a reference value or long-term average.

There are two types of temperature anomaly; a positive anomaly and a negative anomaly. Positive anomaly indicates that the observed temperature was warmer than the reference value, while a negative anomaly indicates that the observed temperature was cooler than the reference value [16]. Widespread cold anomalies may be an indication of a harsh winter with lots of snow on the ground. Small, patchy warm anomalies that appear in forests or other natural ecosystems may indicate deforestation or insect damage. Many urban areas also show up as hot spots because developed areas are often hotter in the daytime than surrounding natural ecosystems or farmland. Warm anomalies that persist over large parts of the globe for many years can be signs of global warming.

Works that apply the Markov Chain in modeling the sequence of positive and negative air temperature anomaly are rare. Most works focused on the computation, interpretation as well as the analysis of its trend over time. Such works include those of [15], [24], [18], [26], [3] and [19] among others. These works do not model the daily sequence of a warmer or colder air temperature an issue this paper is determined to address.

Some works that apply the Markov Chain model in the analysis of rainfall data include that of Gabriel and Neuman [12] were the authors used a first order stationary Markov Chain to describe rainfall occurrence in Tel Aviv. They reported that a first-order model is adequate for describing the situation in Tel Aviv (Israel), that of Jackson [14] which is concerned with modeling the sequence of wet and dry days in Kano and Benin cities of Nigeria. The researchers noted that the optimum order of the Markov Chain model varies with seasons and could be as high as three. The list also includes the work of Ochala and Kerkides [22]. The authors developed a Markov Chain simulation model for predicting wet and dry spell in Kenya, that of Drton *et al*. [9] were the researchers developed a Markov Chain model of tornado activities based on data on tornado counts, the work of Dastidar *et al.* [8] were the authors focused on the determination of the order of the Markov Chain model for simulating the pattern of rainfall during the Monsoon season (June –September) over Gangetic West Bengal (India).

Ajayi and Olufayo [2] is another research work in this regard, it was carried out in Nigeria in the cities of Onne and Ibadan where emphasis was on the implication of the work to agriculture. Raheem *et al.* [25] introduced a three state Markov Chain which was employed to examine the pattern and distribution of rainfall in Uyo metropolis of Nigeria. Chi square and Wilcoxon Signed test statistics were used to test the appropriateness of Markov Chain techniques on the data base on the assumption that the current state of the process (occurrence of rainfall) depends on the immediate preceding state. Agada *et al.* [1] used Bayesian information criterion to examine the proper order of the Markov chain that can be used to model the sequence of wet and dry days in Port Harcourt, Nigeria. They proved that a Markov Chain of order one should be used to model the sequence of wet and dry days in this city.

Since most works that apply the Markov Chain model in analyzing rainfall data chiefly depend on the Markov property and base on the fact that daily air temperature auto correlates due to the cumulative effect [5], then the fact that there exists a Markov property in a set of air temperature data can be assumed and tested. The aforementioned fact made the authors to conceive the idea of applying the Markov Chain model in modeling the sequence of positive and negative maximum air temperature anomaly. The rest of the paper is organized as follows; Methodology, Results and Discussion.

2. METHODOLOGY

2.1 Data description and transformation

The data employed in this work is a 34 year data (1977-2010) of daily maximum air temperature (in Degree Celsius) for the city of Port Harcourt, Nigeria. The data is sourced from the International Institution for Tropical Agriculture (IITA) in Ibadan, Nigeria.

The raw data which gives the daily air temperature over the period was first transformed into sequence of binary events: the positive and negative anomaly as follows. For any K^{th} day, a random variable X_k is defined to represent this event with the realization; 0 if the air temperature (T) is less than the grand average $(\overline{T})$ or with realization 1 if the air temperature (T) is greater than the grand average $(\overline{T})$. This is done for the maximum air temperature data sets for each month of the year. The random variable is therefore defined as;

$$X_k = \begin{cases} 0, if\ T\ < \overline{T}(\text{negative anomaly or colder air temperature}). \\ 1, if\ T > \ \overline{T}(\text{positive anomaly or warmer air temperature}). \end{cases}$$

Where; $k = 1,2,...,(days)$ and air temperature anomaly $= T - \overline{T}$, [17].

The Microsoft Excel Package (2007) was used to implement this for accuracy and computational ease.

2.2 Markov chain modeling of the sequence of positive and negative air temperature anomaly

The 0 and 1 realizations of the random variable X_k in section 2.1 above automatically define a two-state Markov chain for modeling the positive and negative sequence of maximum air temperature anomaly. This means that initially the process may be in any of the two states and thereafter transit to the other state. The probability of this transition is what is known as the transition probability.

We adopt the notations of Dastidar *et al.* (2010) in the modeling process. Let $\{X_t, t \in T\}$ be a Markov chain with index set T and state space S. Particularly for this work, since $S = \{0,1\}$ then $\{X_t, t \in T\}$ is a two-state Markov Chain as earlier mentioned. The most common of this is its first order which is defined as

$$P(X_{n+1} = j \setminus X_0 = i_0, X_1 = i_1..., X_n = i_n) = P(X_{n+1} = j \setminus X_n = i_n) \quad . \quad . \quad . \quad 1$$

for all $i_0, i_1,..., i_n \in S)$

The two-state Markov Chains of the second and third order are modeled respectively as follows;

$$P(X_{n+1} = j \setminus X_0 = i_0, X_1 = i_1..., X_n = i_n) = P(X_{n+1} = j \setminus X_n = i_n, X_{n-1} = i_{n-1}) \quad . \quad . \quad . \quad 2$$

for all $i_0, i_1,..., i_n \in S)$

$$P(X_{n+1} = j \setminus X_0 = i_0, X_1 = i_1..., X_n = i_n) = P(X_{n+1} = j \setminus X_n = i_n, X_{n-1} = i_{n-1}, X_{n-2} = i_{n-2})$$

for all $i_0, i_1,..., i_n \in S)$ . . . 3

It is important to mention that a two-state Markov Chain of any order is completely determined by its initial state and a set of transition probabilities $p_{ij}, p_{ijk}, p_{ijkl}, ...$ for order 1,2,3 and so on. The permutation of the sequence of transitions, ij, ijk and ijkl for i, j, k = 1, 0 completely specify the positive and negative anomaly air temperature day sequence of the Markov Chain of order one, two and three respectively. The probability of transition for each order of the Markov Chain is estimated from data using relative frequencies. These frequencies are transition frequencies of the positive and negative anomaly day sequence for each order of the Markov Chain. They were obtained for each specific month of the year and averaged over the 34 years period for that particular month. Due to the huge amount of data involved in this work, a computer program was written in Pascal programming language version 1.5 for obtaining the transition frequencies which helps in determining the order of the Markov Chain.

2.3 Determining the Suitability of the Markov Chain of Varying Order

The suitability of the Markov chain of order one, two and three in modeling the sequence of positive and negative anomaly days was examined by the Bayesian information criterion (BIC). Dastidar *et al.* (2010), states that qualitatively, BIC gives a mathematical formulation of the principle of parsimony in model building and that quantitatively for eight or more observations, BIC leans towards lower dimension models. They further explained that for large data, BIC selects the optimal model because of certain asymptotic properties which are yet to be proved for other available criteria like the AIC. It is for this reason that it was be adopted in this study.

According to the BIC, an ‘S’ state Markov Chain of order ‘m’ is the most appropriate model if it minimizes the function:

$$BIC(m) = -2L_m + s^m \ln(\text{n}) \quad . \quad . \quad . \qquad 4$$

where,

$$L_0 = \sum_{j=0}^{s-1} n_{ij} \ln(p_j) \quad . \quad . \quad . \qquad 5$$

$$L_1 = \sum_{i=0}^{s-1}\sum_{j=o}^{s-1} n_{ij} \ln(p_{ij}) \quad . \quad . \quad . \qquad 6$$

$$L_2 = \sum_{i=0}^{s-1}\sum_{j=0}^{s-1}\sum_{k=0}^{s-1} n_{ijk} \ln(p_{ijk}) \quad . \quad . \quad . \qquad 7$$

$$L_3 = \sum_{i=0}^{s-1}\sum_{j=0}^{s-1}\sum_{k}^{s-1} n_{ijkl} \ln(p_{ijkl}) \quad . \quad . \quad . \qquad 8$$

$$\text{and } n = \sum_{i=0}^{s-1}\sum_{j=0}^{s-1} n_{ij} \quad . \quad . \quad . \qquad 9$$

In this work, $n_{ij}, n_{ijk}, n_{ijkl}$ denote the average transition frequencies respectively for the Markov chain of order one, two and three respectively. This criterion would be employ in selecting the most appropriate order of the Markov Chain model judging from the one that minimizes the BIC function in equation (4)

Further in this work the steady state probabilities for the first order Markov chain model are determined using the computational formula:

$$\pi_1 = \frac{p_{01}}{1 + p_{01} - p_{11}} \quad . \quad . \quad . \qquad 10$$

$$\pi_0 = 1 - \pi_1 \quad . \quad . \quad . \qquad 11$$

where;

π_0 = Steady state probability of a negative anomaly occurrence

π_1 = Steady state probability of a positive anomaly occurrence.

The mean recurrence time for a negative and positive maximum air temperature anomaly day are computed as the reciprocal of respectively

3. RESULT

This section presents the results of the study for each month of the year (January – December). This include BIC scores for determining; the order of the Markov Chain that fits the maximum air temperature data, the first order transition probability matrix for the sequence of positive and negative maximum air temperature anomaly, the steady state probabilities of a positive and negative maximum air temperature anomaly and the mean recurrence time (in days) of a positive and negative maximum air temperature anomaly.

Table 1: BIC Scores of the Markov Chain Model for Maximum Temperature (January-June)

	Jan.		**Feb.**		**Mar.**		**Apr.**		**May**		**Jun.**	
Order(i)	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i
1	-9.08	**24.97**	-11.57	**29.73**	-17.74	**42.34**	-16.02	**38.78**	-17.73	**42.34**	-17.74	**42.34**
2	-14.35	42.44	-10.02	33.22	-16.64	47.27	-13.40	40.93	-16.22	46.18	-14.08	45.60
3	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil

Table 2: BIC scores of the Markov Chain Model for maximum air temperature (July-December)

	Jul.		**Aug.**		**Sep.**		**Oct.**		**Nov.**		**Dec.**	
Order(i)	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i	L_i	BIC_i
1	-17.48	**41.76**	-17.74	**42.34**	-17.36	**41.53**	-15.23	**37.34**	-11.95	**30.70**	-15.46	**37.85**
2	-16.22	46.18	-16.22	46.18	-16.22	46.18	-13.92	41.69	-9.91	33.42	-15.17	45.60
3	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil

Note : In both tables above, BIC values in bold indicate order one Markov Chain model as the best, Nil indicates p_{ijkl} values are undefined due to zero transition frequencies

Table 3: First Order Markov Chain transition probability values for the sequence of maximum air temperature anomaly

Month	Previous Day	Actual Day	Actual Day
		+	-
January	+	0.80	0.20
	-	0.20	0.80
February	+	0.80	0.20
	-	0.20	0.80
March	+	0.75	0.25
	-	0.30	0.70
April	+	0.70	0.30
	-	0.20	0.80
May	+	0.70	0.30
	-	0.25	0.75
June	+	0.75	0.25
	-	0.30	0.70
July	+	0.70	0.30
	-	0.30	0.70
August	+	0.75	0.25
	-	0.30	0.70
September	+	0.80	0.20
	-	0.30	0.70
October	+	0.80	0.20
	-	0.20	0.80
November	+	0.90	0.10
	-	0.10	0.90
December	+	0.80	0.20
	-	0.20	0.80

Table 4: A monthly distribution of steady state probabilities and mean recurrence times (days) for maximum air temperature anomaly

Month	Steady state probability of a positive (+) anomaly	Steady state probability of a negative(-) anomaly	Mean recurrence time (days) for a positive(+) anomaly	Mean recurrence time (days) for a negative(-) anomaly
January	0.50	0.50	2.00	2.00
February	0.50	0.50	2.00	2.00
March	0.55	0.45	1.82	2.22
April	0.40	0.60	2.50	1.67
May	0.45	0.55	2.22	1.82
June	0.55	0.45	1.82	2.22
July	0.50	0.50	2.00	2.00
August	0.55	0.45	1.82	2.22
September	0.60	0.40	1.67	2.50
October	0.50	0.50	2.00	2.00
November	0.50	0.50	2.00	2.00
December	0.50	0.50	2.00	2.00

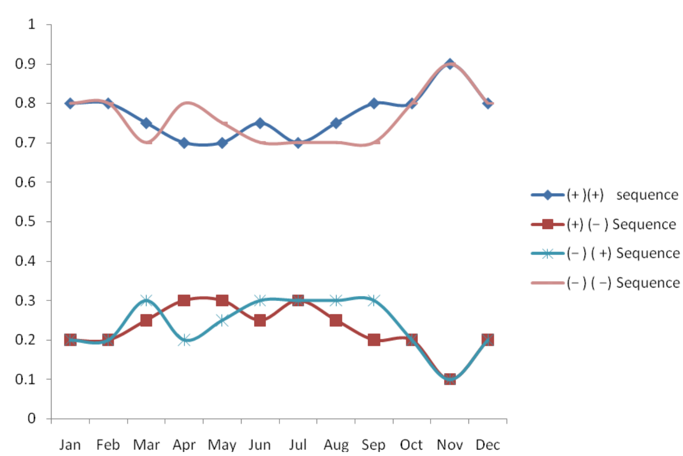

Figure 1: First order transition probability for the sequence of positive and negative maximum air temperature anomaly

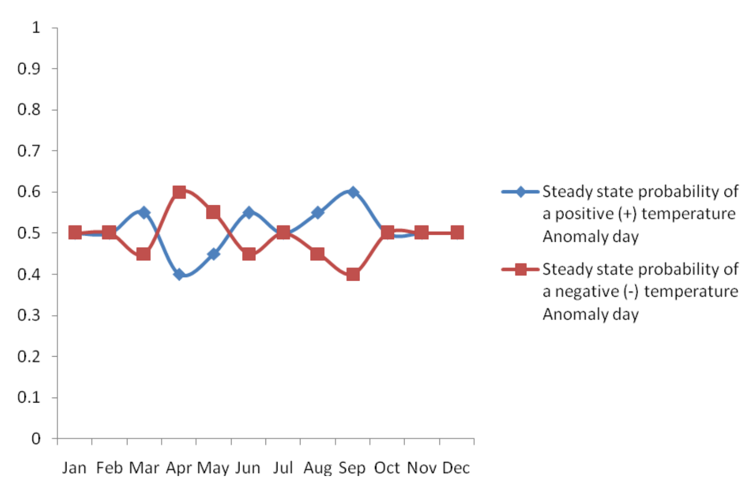

Figure 2: Graph of steady state probability of positive and negative maximum air temperature anomaly

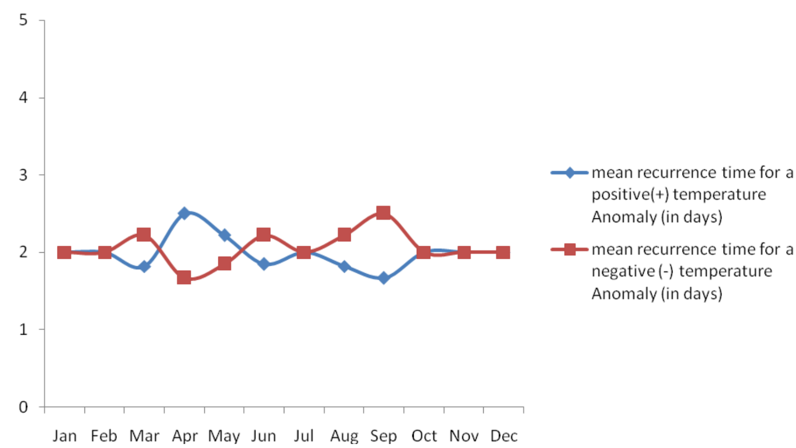

Figure 3: Graph of mean recurrence time of positive and negative maximum air temperature anomaly (in days)

4. DISCUSSION

This section presents the discussion on the results of the study. This include discussions on the BIC scores for determining the order of the Markov Chain that fits the maximum air temperature data, the first order transition probability matrix for the sequence of positive and negative maximum air temperature anomaly, the steady state probabilities of a positive and negative maximum air temperature anomaly and the mean recurrence time (in days) of a positive and negative maximum air temperature anomaly. Finally, a discussion on the study implications is presented.

4.1 Discussion on the BIC scores for determining the order of the Markov Chain model.

In order to determine the order of the Markov Chain model that fits the Maximum air temperature data, the BIC scores for order one, two and three were computed and found minimal for order one in each month of the year. These scores are written in bold in tables 1 and 2, indicating that the Markov Chain of order one best fit the maximum air temperature data for the city of Port Harcourt, Nigeria for each month of the year.

4.2 Discussion on the first order transition probability matrix for the sequence of positive and negative maximum air temperature anomaly

Since the Markov Chain model of order one fits the data as stated in 4.1 above, the researchers therefore focus the research discussion on the results of the analysis of the order one Markov Chain model. The first result in this regard is that of the first order transition probabilities for the sequence of positive and negative maximum air temperature anomaly. This is found in table 3 and graphed - superimposed for the (+ +), (- -) and (+ -), (- +) pairs of sequence. The figure shows that the (+ +), (- -) pair revealed six notable intersection points one each in the months of January, February, July, October, November and December. The (+ -), (- +) pairs also revealed six notable intersection points one each in the same set of months. This shows each pair of sequence has equal chance of occurrence in these months. See table 2 and figure 1 for details.

4.3 Discussion on the steady state probabilities and mean recurrence time for positive and negative maximum air temperature anomaly.

The graphs of steady state probabilities of positive and negative maximum air temperature anomaly over the year depicts that of positive anomaly turning maxima in the months of March, June and September with probabilities 0.55, 0.55 and 0.6 respectively and minima in the months of April and July with probabilities 0.4 and 0.5 respectively. That of negative anomaly turned maxima in the months of April and July with probabilities 0.6 and 0.5 respectively and minima in the months of March, June and September with probabilities 0.45, 0.45 and 0.4 respectively. The superimposed nature of the graphs revealed that six intersection points exist one each in the months of January, February, July, October, November and December. This shows that, in the long run, the positive and negative maximum air temperature anomaly have equal chance of occurrence (probability of 0.5) in the aforementioned months. See table 4 and figure 2 for details.

The graphs of mean recurrence times for positive and negative maximum air temperature anomaly over the year depicts that of positive anomaly turning minima in months of March, June and September with mean recurrence times of 2.00, 2.00 and 1.67 days respectively and maxima in the months of April and July with mean recurrence times of 2.50 and 2.00 days respectively. That of negative anomaly turned minima in the months of April and July with mean recurrence times of 1.67 and 2.00 days and maxima in the months of March, June and September with mean recurrence times of 2.22, 2.22 and 2.50 days respectively. The superimposed nature of the graphs also revealed that six intersection points exist one each in the months of January, February, July, October, November and December. This shows that, in the long run, the positive and negative maximum air temperature anomaly have equal mean recurrence times of 2.00 days in the aforementioned months. See table 4 and figure 3 for details.

4.4 Study implications

The (+ +) anomaly indicates a sequence of two higher than normal (warmer) air temperature days. High chances of this sequence as captured by the matrix of transition probabilities are no doubt the evidence of rising global air temperature due to increased emission of greenhouse gases into the atmosphere causing high frequency and high intensity of extreme weather events such as severe heat and drought, intense rainfall and serious flooding, excessive wind and violent storm besides the outbreak of epidemics like cerebrospinal meningitis. The (- -) anomaly indicates a sequence of two lower than normal (colder) air temperature days. Higher chances of this sequence which is also captured by the matrix of transition probabilities is a warning for extremely cold weather and outbreak of certain disease conditions like cough and Pneumonia. The researchers emphasize that it is not out of place to categorically state that the use of the monthly information of the matrix of transition probabilities for positive and negative sequence of maximum air temperature anomaly, that of the steady state probability of a positive and of a negative anomaly as well as that of the mean recurrence time (days) for a positive and negative anomaly in the periodic (monthly) assessment of the weather or climate of Port Harcourt, has positive implications to stakeholders. This will help stakeholders in taking precautionary or control measures in respect of the aforementioned consequence of rising air temperature. We also envisage that the results of this study would be of benefit to the Engineering Society in planning their work time table, Farmers who at least farm on a subsistence level as well as the Atmospheric Physicists and Meteorologists in the better understanding of the climate of Port Harcourt.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The following conclusions were drawn from the study;

(i) The first order Markov Chain is found suitable for analyzing the monthly maximum air temperature data in Port Harcourt, Nigeria.

(ii) The (+ +) and (- -) sequences have equal chance of 0.8, 0.8, 0.7, 0.8, 0.9 and 0.8 in the months of January, February, July, October, November and December respectively, while the (+ -) and (- +) sequences also have equal chance of 0.2, 0.2, 0.3, 0.2, 0.1 and 0.2 in the same months.

(iii) In the long run, the positive and negative maximum air temperature anomalies have equal chance of 0.5 in the months of January, February, July, October, November and December and equal mean recurrence time of 2.00 days in the same months.

5.2 Recommendation

The study recommends that the first order Markov Chain model be used in analyzing the sequence of positive and negative maximum air temperature anomaly in Port Harcourt, Nigeria and that the results of the study be made available to stakeholders for use wherever they deem it fit.

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