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PERFORMANCE OF MULTIPLE LINEAR REGRESSION AND AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODELS IN PREDICTING ANNUAL TEMPERATURES OF OGUN STATE, NIGERIA

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ABSTRACT

The performance of Autoregressive Moving Average and Multiple Linear Regression Models in predicting minimum and maximum temperatures of Ogun State is herein reported. Maximum and Minimum temperatures data covering a period of 29 years (1982 -2009) obtained from the Nigerian Meteorological Agency (NiMet), Abeokuta office, Nigeria, were used for the analyses. The data were first processed and aggregated into annual time series. Mann-Kendal non-parametric test and spectral analysis were carried out to detect whether there is trend, seasonal pattern, and either short or long memory in the time series. Mann-Kendal Z-values obtained are –0.47 and –2.03 for minimum and maximum temperatures respectively, indicating no trend, though the plot shows a slight change. The Lo's R/S Q(N,q) values for minimum and maximum temperatures are 3.67 and 4.43, which are not within the range 0.809 and 1.862, thus signifying presence of long memory. The data was divided into two and the first 20 years data was used for model development, while the remaining was used for validation. Autoregressive Moving Average (ARMA) model of order (5, 3) and Autoregressive (AR) model of order 2 are found best for predicting minimum and maximum temperatures respectively. Multiple Linear Regression (MLR) model with 4 features (moving average, exponential moving average, rate of change and oscillator) were fitted for both temperatures. The ARMA and AR models were found to perform better with Mean Absolute Percentage Error (MAPE) values of -2.89 and -1.37 for minimum and maximum temperatures, compared with the Multiple Linear Regression Models with MAPE values of 141 and 876 respectively. Results of ARMA model can be relied on in generating forecast of temperature of the study area because of their minimal error values. However, it is recommended other climatic elements that were not captured in this paper due to unavailability of information be considered too in order to see which model is best for them.

Keywords: ARMA model, MLR model, Mann-Kendal test, Minimum and Maximum temperatures.

INTRODUCTION

Temperature is one of the major input variables for land evaluation, characterization systems, hydrological and ecological models. These models use air temperature to drive processes such as evapotranspiration, soil decomposition, and plant productivity (Benavides, *et al.,* 2007). Air temperature is an important site characteristic used in determining site suitability for agricultural and forest crops (Benavides, *et al.,* 2007), and it is used in characterizing the habitat of plant species (Rubio, *et al*., 2002; Sanchez-Palomares *et al.,* 1999) and in determining the patterns of vegetation zonation (Richardson, *et al.,* 2004). Modeling temperature therefore, is an important task for efficient agricultural development and sustainability.

Models are simplifications of reality that reflect our understanding of the process they represent. Just as any other tool, the results given by models are dependent on how they are applied, and the quality of these answers is not better than the quality of our understanding of the system (Robin, 2003). Some models are based solely on empirical equations while others are built on more complex, physically based principles (Butcher, *et al*., 1998).

One of the most popular and frequently used stochastic time series models for temperature analysis is the Autoregressive Integrated Moving Average (*ARMA*) model (Zhang, 2003). The basic assumption made to implement this model is that the considered time series is linear and follows a particular known statistical distribution, such as the normal distribution. *ARMA* model has subclasses of other models, such as the Autoregressive (AR), Moving Average (MA) and Autoregressive Moving Average (ARMA) models (Box *et al.,* 2008). According to Box *et al*., (2008) a quite successful variation of *ARMA* model, viz; the Seasonal ARMA *(SARMA)* for seasonal time series forecasting were proposed. The popularity of the *ARMA* model is mainly due to its flexibility to represent several varieties of time series with simplicity as well as the associated Box-Jenkins methodology (Zhang, 2003) for optimal model building process. But the severe limitation of these models is the pre-assumed linear form of the associated time series which becomes inadequate in many practical situations.

Also, Multiple Linear Regression models are often used for estimating the future events or values using features of a particular time series or other related time series data (Chatfield, 1994). However, they are more of deterministic, which is unlikely of an ideal situation.

The selection of a proper model is extremely important as it reflects the underlying structure of the series and this fitted model in turn is used for future forecasting. A time series model is said to be linear or non-linear depending on whether the current value of the series is a linear or non-linear function of past observations.

Atmospheric temperature is seen as a major determinant of hydrologic processes. That is, change in temperature level at any point in time leads to change in other climatic elements (Benavides, *et al.,* 2007). Despite this importance of temperature, no literature has shown any work on temperature trend in the study area, and perhaps, if possible make an attempt to build a model and validate. This research paper therefore, intended to check for trend in the temperature time series data, develop and validate a MLR and *ARMA* models and as well, compare the performance of each.

MATERIALS AND METHODS

Ogun State is bounded by Oyo state to the north, Osun and Ondo States to the east and Lagos State to the South as shown in (Fig. 1).

It is located in south-western Nigeria, on latitudes 6.26^0 N and 9.10^0 N and longitudes 2.28^0 E and 4.8^0 E. The land area is about 23,000km^2. It is located at an elevation of 77m above sea level. The relief is generally low, with the gradient in the North-South direction (Ewomoje and Ewomooje, 2011).
The two major vegetation zones that can be identified in the area are the high forest vegetation in the north and central parts, and the swamp/mangrove forests that cover the southern coastal and floodplains, next to the lagoon. It has two distinct seasons throughout the year. The monthly rainfall distribution in the study area shows a distinct dry season extending from November through March and a rainy season divided into two periods: April – July and September – October. The mean annual rainfall data for 30 years showed a variation from about 1,150mm in the northern part to around 2,285mm in the southern extremity. The estimates of total annual potential evapotranspiration have been put between 1600 and 1900mm. (Ewemoje and Ewemooje, 2011).

Data Collection and Preprocessing

The minimum and maximum temperature data used for this study were obtained from the Nigerian Meteorological Agency (NiMet), Abeokuta office, Nigeria. The data collected are the time series type, on monthly bases for a period of 29 years (1982-2009), with the aid of Global Position System (GPS) equipment. For the purpose of this study, the data are pre-whitened and mean annual values were first determined before use.

Figure 1: Map of Nigeria showing the study Area

Test for Trend, Long-range Dependency and Serial Correlation

Time series data are generally represented in the form:

$$T(t) = Tr + P(t) + \varepsilon(t) \quad (1)$$

Where, (t) = Time series

Tr = trend component

$P(t)$ = Periodic component

$\varepsilon(t)$ = Stochastic component

In order to check for the stationarity of the data, the following equations were considered:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(X_j - X_k) \quad (2)$$

Where, X_j and X_k are the annual values in years j and k, j > k, respectively, and

$$Sgn(X_j - X_k) = \begin{Bmatrix} 1 & if\ X_j - X_k > 0 \\ 0 & if\ X_j - X_k = 0 \\ -1 & if\ X_j - X_k < 0 \end{Bmatrix} \quad (3)$$

$$Var(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q}(t_p - 1)(2t_p + 5)\right] \quad (4)$$

Where, q is number of tied groups and t_p is number of data values in the p^{th} group. The values of S and $Var(S)$ were used to compute the test statistic Z as follows

$$Z = \begin{cases} (S-1)\big/ Var(S)^{1/z} & S > 0 \\ 0 & S = 0 \\ (S+1)\big/ Var(S)^{1/z} & S < 0 \end{cases} \quad (5)$$

The Mann-Kendall test was carried out in accordance with the works of Otache *et al.*, (2011); Edwin and Otache, (2014) and Chatfield (2004), with the aid of the excel template of 'MAKESEN's version 1. Lo's modified re-scaled (R/S) test was also done to ascertain if the trend persisted in accordance with the works of Robinson, (2003) and Palma, (2007). To check for serial correlation, the Durbin-Watson test was considered in accordance with the works of Christian, (2006); Richard, (2015) and Ramanathan, (2002). The tests were carried out in order to make sure the time series data conforms to the basic criteria for stochastic modeling. There is no clear seasonal nature in the time series, therefore, only the stochastic component was considered and the Box-Jenkins methodology was applied in the model building as described by Figure 2.

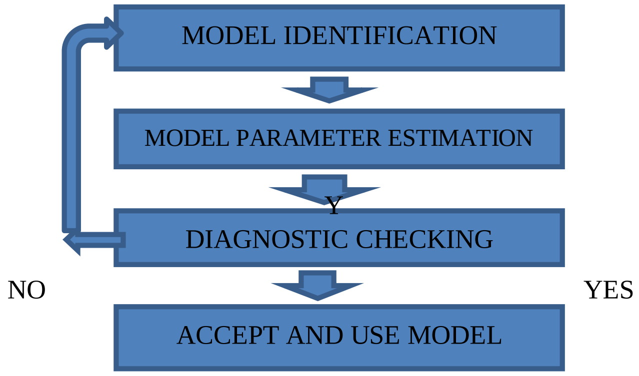

Figure 2: Flow chart of *ARMA* Model Building Procedures

Based on the fact that the ACF and PACF diagrams are sometimes difficult to interpret (Kumar and Vanajakshi, 2015), the iterative techniques was utilized, and best model order determined by the Akaike Information Criterion (AIC) test in accordance with the works of Kumar and Vanajaksh (2015).

Features of Annual Temperature Determined for MLR Models

Moving Average (MA): It was calculated progressively according to the equation:

$$MA = (d_t + d_{t-1} + d_{t-2} + \cdots \ldots d_{t-N})/N \qquad 6$$

Exponential Smoothening (ESM): It was also determined in accordance with (NOHC, 2012). Using the equation:

$$ESM = F_{t+1} = \alpha Y_t + (1-\alpha)F_t \qquad 7$$

Where;

F_{t+1} = forecast of the time series for period t+1

Y_t = actual value of the time series in period t

F_t = forecast of the time series for period t.

α = is called the smoothing constant having value ($0 \leq \alpha \leq 1$).

Oscillator (OSC): Oscillator was calculated using either equations 8 and 9.

$$OSC = MAN_1 - MAN_2 \qquad 8$$

$$OSC = ESMN_1 - ESMN_2 \qquad 9$$

Where, N_1 and N_2 are different periods and $N_1 > N_2$.

Rate of Change (ROC): It was determined by:

$$ROC = \left(1 - \frac{d_t}{d_{t-a}}\right) 100 \qquad 10$$

Where,

d_t = the value of the time series at present time t

d_{t-a} = the value of the time series at time *t – a* back.

Using the features or predictors determined as in Tables 4 and 5, Multiple Linear Regression (MLR) equations were developed using the first part of the features; and the remaining was used for testing the validity. Microsoft Excel 2010 version and Minitab version 16 were used to process the data.

RESULT AND DISCUSSIONS

ARMA Model Building for Maximum and Minmum Temperature

The Mann-Kendal Z-values of -2.03 and -0.47 were observed for maximum and minimum temperatures respectively, which indicated no trend in the time series, although, the time series plot shows slight change. Models of order AR (2) and ARMA (5, 3) for maximum and minimum temprture were developed and considered for validation as shown in Tables 1 and 2. The highlighted (AIC) values in Tables 1 and 2 are the leasts in magnitude when compared with others, this make them the best.

ARMA Model equations developed are shown in Table 3. They were used to generate forecast for each parameter, and the actual values were ploted with the predicted for validation as shown in Figures 3 and 4 in accordance with the works of Tizro, *et al.,* (2014).

MLR Model Built for Maximum and Minmum Temperature

The features obtained are as shown in Tables 4 and 5. The magnitude of the value of actual data is observed to be higher than the predicted values due to the use of 6-year moving average that were considered for both minimum and maximum temperatures. MLR models developed were as shown in Table 6. Temperatures were represented by Y1 and Y2 while, X_1, X_2, X_3 and X_4 are the moving average, exponential smoothening, oscillator and rate of change respectively. The plots of actual and predicted values of Minimum and Maximum temperatures for MLR models developed were as shown in Figures 5 and 6.

Comparing the Performance of the two Models

The comparism was based on Lewi's error scaling, which considers the least value of Mean Absolute Percentage Error (MAPE). Best models for minimum and maximum temperatures are respectively Autoregressive Moving Average (ARMA) model of order (5, 3) with Mean Absolute Percentage Error (MAPE) value of -2.89 and Autoregressive (AR) model of order (2) with Mean Absolute Percentage Error (MAPE) value of -1.37, compared with the MAPE values of 141 and 876 obtained from the Multiple Linear Regression (MLR) models.

Table 1: Model order selection for AR

Model Order (P)	Sum of Sqrs (SS)	AIC - Value	Constant (c)	Mean (µ)
1	410.637	77.19	21.3224	38.230
2	287.573	69.23	6.2514	37.350
3	284.973	70.97	7.5523	37.593
4	284.694	72.94	7.9863	37.672
5	278.559	74.33	5.9148	37.356

Table 2: Model order selection for ARMA

S/No	Model Order (p, q)		Sum of Sqrs (SS)	AIC - Value	Constant (c)	Mean(μ)
1	1	1	759.51	196.35	6.19	19.00
2	1	2	793.23	199.60	2.30	18.35
3	2	1	759.47	198.35	6.38	19.00
4	2	2	597.69	193.40	8.04	20.67
5	1	3	786.76	201.37	2.78	18.26
6	3	1	702.57	198.09	8.96	19.52
7	3	2	489.81	189.63	9.26	20.83
8	2	3	568.44	193.94	2.63	17.42
9	3	3	482.63	191.20	11.23	20.02
10	1	4	541.46	192.53	3.39	18.41
11	4	1	589.67	195.01	11.43	19.89
12	2	4	404.85	186.10	3.48	17.50
13	4	2	479.94	191.04	12.03	19.63
14	3	4	395.56	187.43	4.21	17.45
15	4	3	477.60	192.90	15.16	20.60
16	4	4	386.28	188.74	6.05	17.63
17	1	5	551.62	195.07	3.29	18.49
18	5	1	535.99	194.24	11.37	17.49
19	2	5	427.50	189.68	3.38	17.54
20	5	2	527.53	195.78	13.48	17.51
21	3	5	428.39	191.74	6.15	17.45
22	5	3	333.48	184.48	14.85	17.40

Table 3: Best Model Equations obtained for Maximum and Minimum Temperature

S/No	Model Type	Model Order	Model Equation
1	AR	2	$y_t = 6.25 + 0.1952y_{t-1} + 0.6374y_{t-2} + \varepsilon_t$
3	ARMA	5, 3	$y_t = 14.8530 + 0.3050y_{t-1} + 0.0535y_{t-2} + 0.6600y_{t-3} - 0.2895y_{t-4} - - 0.0551\varepsilon_{t-1} - 0.4487\varepsilon_{t-2} + 0.8142\varepsilon_{t-3} + \varepsilon_t$

Table 4: Observed values of minimum temperature, features and predicted values of minimum temperature

Year	Observed Min. Temp.	3 Years MA	6 Years MA	ESM 0.80	OSC	ROC	Predicted Min. Temp.
1	20.80						
2	17.20			20.80		17.31	
3	29.50			17.92		-71.51	
4	18.20	22.50		27.18		38.31	
5	21.85	21.63		20.00		-20.05	
6	25.50	23.18		21.48		-16.70	
7	17.30	21.85	22.18	24.70	0.33	32.16	18.45
8	13.80	21.55	21.59	18.78	0.04	20.23	12.44
9	17.20	18.87	21.03	14.80	2.16	-24.64	18.47
10	16.25	16.10	18.98	16.72	2.88	5.52	15.87
11	15.30	15.75	18.65	16.34	2.90	5.85	15.38
12	18.40	16.25	17.56	15.51	1.31	-20.26	19.08
13	20.20	16.65	16.38	17.82	-0.28	-9.78	19.29
14	18.20	17.97	16.86	19.72	-1.11	9.90	16.86
15	23.10	18.93	17.59	18.50	-1.34	-26.92	22.82
16	28.00	20.50	18.58	22.18	-1.93	-21.21	26.10
17	10.60	23.10	20.53	26.84	-2.57	62.14	13.20
18	10.30	20.57	19.75	13.85	-0.82	2.83	9.07
19	13.40	16.30	18.40	11.01	2.10	-30.10	15.03
20	10.70	11.43	17.27	12.92	5.83	20.15	10.03
21	8.30	11.47	16.02	11.14	4.55	22.43	6.35
22	10.00	10.80	13.55	8.87	2.75	-20.48	11.99
23	11.70	9.67	10.55	9.77	0.88	-17.00	12.11
24	13.50	10.00	10.73	11.31	0.73	-15.38	13.82
25	26.00	11.73	11.27	13.06	-0.47	-92.59	32.37
26	23.70	17.07	13.37	23.41	-3.70	8.85	21.65
27	24.10	21.07	15.53	23.64	-5.53	-1.69	22.11
28	24.00	24.60	18.17	24.01	-6.43	0.41	20.53
29	25.00	23.93	20.50	24.00	-3.43	-4.17	23.10

Table 5: Observed values of maximum temperature, features and predicted values of maximum temperature

Year	Observed Max. Temp (0C)	3 Years MA	6 Years MA	ESM 0.8	OSC	ROC	Predicted Max. Temp (0C)
1	42.60						
2	37.00			42.60		13.15	
3	35.50			38.12		4.05	
4	35.50	38.37		36.02		0.00	
5	38.05	36.00		35.60		-7.18	
6	40.60	36.35		37.56		-6.70	
7	40.00	38.05	38.21	39.99	0.16	1.48	40.13
8	41.20	39.55	37.78	40.00	-1.78	-3.00	41.19
9	42.60	40.60	38.48	40.96	-2.13	-3.40	42.28
10	42.35	41.27	39.66	42.27	-1.61	0.59	42.29
11	42.10	42.05	40.80	42.33	-1.25	0.59	42.06
12	40.70	42.35	41.48	42.15	-0.88	3.33	40.54
13	40.80	41.72	41.49	40.99	-0.23	-0.25	40.64
14	41.90	41.20	41.63	40.84	0.42	-2.70	41.71
15	42.10	41.13	41.74	41.69	0.61	-0.48	42.08
16	42.30	41.60	41.66	42.02	0.06	-0.48	42.32
17	43.50	42.10	41.65	42.24	-0.45	-2.84	43.37
18	34.50	42.63	41.88	43.25	-0.75	20.69	34.85
19	37.66	40.10	40.85	36.25	0.75	-9.16	38.15
20	36.70	38.55	40.33	37.38	1.77	2.55	35.73
21	36.80	36.29	39.46	36.84	3.17	-0.27	37.20
22	36.30	37.05	38.58	36.81	1.52	1.36	36.03
23	35.80	36.60	37.58	36.40	0.98	1.38	35.60
24	38.80	36.30	36.29	35.92	-0.01	-8.38	39.00
25	25.50	36.97	37.01	38.22	0.04	34.28	24.43
26	35.90	35.80	36.40	35.92	0.60	-40.78	52.68
27	27.70	35.90	34.85	35.90	-1.05	22.84	26.16
28	35.00	31.80	33.33	29.34	1.53	-26.35	38.89
29	38.00	32.87	33.12	33.87	0.25	-8.57	37.62

Table 6: MLR equation and R- square value obtained for Minimum and maximum temperature

Experiment	Regression equation developed	R- square value
Minimum temperature estimation using its features	Y2 = - 2.92 - 0.352 X1 + 1.46 X2 + 0.795 X3 - 0.222 X4	0.92
Maximum temperature estimation using its features	Y1 = - 1.01 - 0.448 X1 + 1.47 X2 + 0.514 X3 - 0.414 X4	0.98

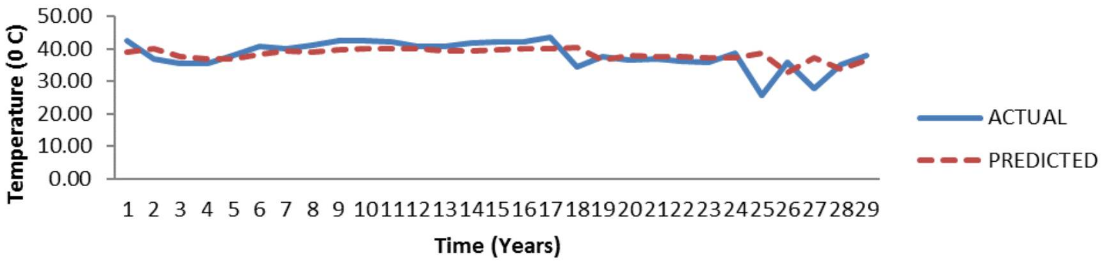

Fig. 3: Actual and Predicted Maximum temperature Plot for AR (2) Model

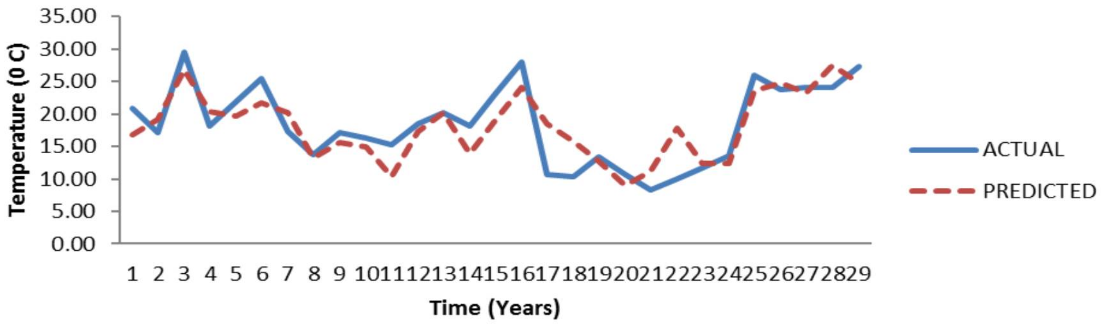

Fig. 4: Actual and Predicted Minimum temperature Plot for ARMA (5, 3) Model

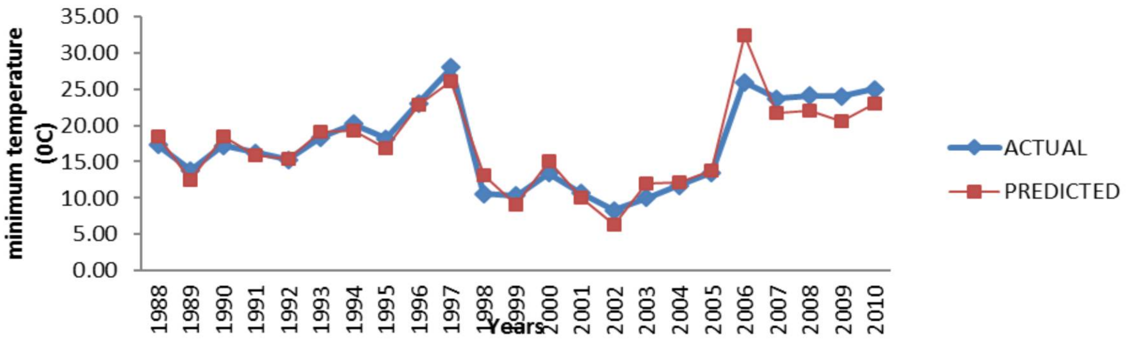

Fig. 5: Actual and Predicted Minimum temperature Plot for MLR Model Developed

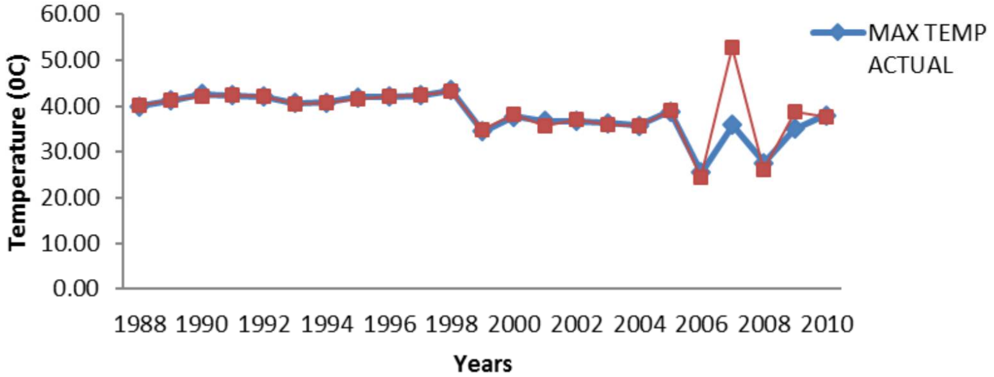

Fig. 6: Actual and Predicted Maximum Temperature Plot for MLR Model Developed

Table 7: Mean Absolute Percentage Error Values used in Comparing the Models

Model Type	Parameter	Mode of Comparing		Remark
AR (2)	Max. Temperature	MAPE	(-1.37)	Preferred
MLR (Y1)	Max. Temperature	" "	(876)	Not Preferred
ARMA (5, 3)	Min. Temperature	" "	(-2.89)	Preferred
MLR (Y2)	Min. Temperature	" "	(141)	Not Preferred

CONCLUSIONS

No trend was established in the temperature time series based on the Mann-Kendal test. The best models for minimum and maximum temperatures are Autoregressive Moving Average (ARMA) model of order (5, 3) with Mean Absolute Percentage Error (MAPE) value of -2.89 and Autoregressive (AR) model of order (2) with Mean Absolute Percentage Error (MAPE) value of -1.37. This best conform to Lewi's error scaling, compared with the MAPE values of 141 and 876 obtained from the Multiple Linear Regression (MLR) models. The overall results of the best models are promising and could be used for predicting temperature in the study area.

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