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MIXED (REGRESSION – ARIMA) TIME SERIES MODELING OF RELATIVE HUMIDITY OF UMUDIKE

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Abstract

This paper considers the assessment of the trend, seasonality and the Irregular components of Relative humidity of Umudike and its general modeling using a modified mixed Regression-ARIMA model. The data for this work are obtained from the Meteorological Unit of the National Root Crop Research Institute, Umudike of Nigeria. The data consist of the monthly Relative Humidity of Umudike from 2002 to 2018. From the analysis, it is observed that the trend of the relative humidity for the period under consideration is on the decrease, though not statistically significant. Also, it is found that there are influences of the Calendar months in the data and the general model for the prediction of the future values of the relative humidity is also found to be adequate.

Keywords: Relative Humidity, Regression-ARIMA model, seasonality, trend.

1.0 Introduction

In recent times climate change and its effects on human lives, environment, plant lives and other factors has attracted utmost attention from government, researchers, corporate organisation and people from different works of lives. Many researches have conceived that climate changes trends and variability in many parts of the world can be deduced from some climatic factors such as temperature, rainfail, relative humidity wind speed, sunshine duration etc.

Relative humidity is one of the key determinants of weather and climate. According to [1], relative humidity is a measure of the water content of the air at a given temperature. In other words it is the measure of the actual amount of water vapour in the air compared to the actual amount of water vapour that the air can content at its current temperature. Relative humidity is an important climatic factor that can affect human comfort. Humans are very sensitive to humidity because the human body relies on the air to get rid of moisture. The human body sweat in other to keep cool and maintain its current temperature. Therefore when there is low relative humidity people feel much cooler than the actual temperature because their sweat evaporate easily thereby cooling them off; but when the relative humidity is high sweat will not evaporate into the air and as a result people will feel much hotter than the actual temperature.

Recent studies have significantly shown the impact of climatic factors including relative humidity on the yields and performances of some economic crops. Kamba and Ajaji [2] investigated the effects of some weather parameters on maize yield in Ibadan, southwest of Nigeria from 2001 to 2010. The result of the study showed that maize yields, minimum and maximum temperature, relative humidity, number of rain day and amount of rainfall varied significantly from year to year and from season to season. Its always deduced that there was a significant effect of relative humidity, rainfall variability and temperature or maize yield in the study area.

In their recent study of the trends in climatic variables, their impact or rice yields variation in Nigeria from 1980 to 2010, [3] revealed that temperature, relative humidity and rice yield showed decreasing trend. They further showed that relative humidity have a little significant effect on rice yield, while temperature, solar radiation and rainfall were found to have the most significant effect on rice yield.

Relative humidity can also be regarded as an important factor in determining the distribution and occurrence of clouds (see [4]). The current interest in analysing relative humidity for detecting global warming has brought relative humidity to the front burner.

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Ajileye [5] worked on the effect of climate variability on relative humidity anomaly over Nigeria using meteorological data of 1983 to 2005 and 2008 to 2013. There discovered that relative humidity anomaly over Nigeria generally revealed negative trend in most of the stations under investigation. There also added that each selected months had its peculiar characteristics along latitudinal belt. Ogolo and Adeyemi [6] investigate variation and trends of some meteorological parameters at over a tropic humid station, Ibadan, Nigeria. The data collected were daily mean data of each parameter taken from the international institute of tropical Agriculture (ITTA) Ibadan, between 1988 and 1997. The study revealed that the monthly series of the meteorological parameters showed an annual decreasing trend, which was not statistically significant except those of rainfall and relative humidity data series that showed an increasing trend which was statistically significant when Man-KendalL and Spearman rho statistics where applied.

Amadi, Udo and Udoimuk[1] posited that the mean relative humidity values decreased from south to North in Nigeria. They also added that the relative humidity distribution Pattern strongly followed the divides of the ecological zones and climatic regions, though there were some deviations. The trends observed from the study corroborate the fact that surface relative humidity is controlled by a number of processes such as atmospheric circulation, vertical mixing, surface evaporation, wind speed moisture and solar heating. In view of the non-deterministic nature of relative humidity, [7] modelled the annual relative humidity of Ogun basin, Southwest of Nigeria from 1982 to 2009. He found that the relative humidity can be forecasted using Autoregressive moving average (ARMA) model denoted by ARMA (2,2). Also a similar attempt was made by [8] to study the temperate dynamics of trend in relative humidity using SARIMA model, taking 13 stations in Malaysia as a case study. The study concluded that the trend behaviour of relative humidity in the 13 stations was decreasing in nature. It also deduced that relative humidity data was influenced by seasonal behaviour and the appropriate models for forecasting the future observations of relative humidity in the 13 stations were seasonal Auto-Regressive Integrated Moving Average (SARIMA) models. Most of the researches conducted in relative humidity have been on its variations, trends and sometimes behaviours, using Mann-Kendall coefficients and test statistic, and the common least squares trend analysis; but not much have been done on the evaluation, modeling and prediction of this important climatic factor - relative humidity, using some modified and more robust statistical models. Moreover, in view of the importance and usefulness of relative humidity to humans and plants' lives, global warming and weather prediction and climate changes, there is need for its proper understanding and prediction for proper planning and policy implementation towards national and economic development. This study therefore seeks to construct a modified time series model that can be used to forecast monthly relative humidity of Umudike in Abia State, Nigeria.

2.0 Materials and Methods

The data for this research work are obtained from the Meteorological Unit of the National Root Crops Research Institute, Umudike, Abia State of Nigeria. The data consist of the monthly Relative Humidity of Umudike from 2002 to 2018.

The method used is the mixed(Regression-ARIMA) Time Series Analysis. According to [9], Multiple Regression Techniques are versatile in modeling a variety of relationships. In this work, we illustrate their use in decomposing a time series using dummy(dichotomous) variables on the monthly data of the relative humidity. The dummy variables created are used to measure the seasonal components of the data. Before this, the set of data is first detrended using any method of modeling the trend of a time series.

For the Additive model, the relationship is given as:

$$X_t = T_t + S_t + I_t \tag{1}$$

where $T_t,\ S_t,\ I_t$ represent the Trend, Seasonal and Irregular Components respectively and

$$T_t = a + bt \tag{2}$$

$$S_t = \sum_{i=1}^{12} d_i M_i \tag{3}$$

$$I_t = u_t \tag{4}$$

where,

a, b, t are trend constant, coefficient and the time variable respectively.

d_i, M_i represent the ith coefficient of the ith month and the ith month respectively.

u_t is the random error component.

Therefore, the general Additive model here is given by:

$$X_t = a + bt + \sum_{i=1}^{12} d_i M_i + u_t \tag{5}$$

It is worthy here to note that in our modified model, if u_t is not a purely random process, it can now be estimated using any of the ARIMA models. Thus, the estimated model can be expressed as:

$$\hat{X}_t = \hat{a} + \hat{b}t + \sum_{i=1}^{12} \hat{d}_i M_i + \hat{u}_t \tag{6}$$

For the Multiplicative equivalent, the model can be considered as the modeling of percentage growth, which is usually done by taking the natural logarithm of the series. Thus:

$$lnX_t = a' + b't + \sum_{i=1}^{12} d_i' M_i + u_t' \qquad (7)$$

To obtain the original series after estimation, the antilog of equation seven is taken as:

$$X_t = e^{a'+b't+\sum_{i=1}^{12} d_i' M_i + u_t'} \qquad (8)$$

The advantage of this method over the ARIMA and SARIMA models is that series can be investigated and its properties studied on the basis of the trend, seasonal and irregular influences, in addition to prediction; whereas ARIMA or SARIMA models do not have these versatile characteristics save prediction or forecasting.

3. Results and Discussion

3.1 Trend Analysis

Looking at figure 1, it can be observed that there is a significant seasonal effect on the Relative Humidity data. Also, because of the characteristic pattern of the original relative humidity data, a multiplicative model is considered.

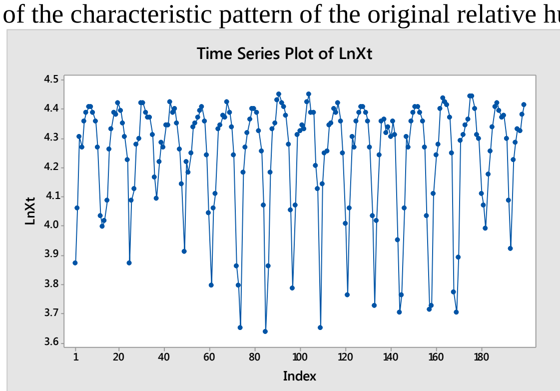

Fig 1: Plot of the Original Series of Relative Humidity

3.2: Estimation of Trend and Seasonal Components

The seasonal component is estimated by means of Multiple Regression Analysis using MINITAB software. The fitted seasonal model is given as:

$$\hat{S}_t = 0.1938\, M_2 + 0.3908M_3 + 0.4597M_4 + 0.5099M_5 + 0.5490\, M_6 + 0.5998M_7 + 0.5764M_8 + 0.5646M_9 + 0.5259M_{10} + 0.4200M_{11} + 0.2026M_{12} \qquad (9)$$

Table 1: Test for the significance of the parameter estimates of the seasonal model

Predictor	Coef	SE Coef	T	P
$Constant$	3.8393	0.0225	170.56	0.000
t	-0.000124	0.00010	-1.21	0.230
M_2	0.1938	0.0285	6.79	0.000
M_3	0.3908	0.0286	13.68	0.000
M_4	0.4597	0.0285	16.10	0.000
M_5	0.5099	0.0286	17.86	0.000
M_6	0.5490	0.0286	19.26	0.000
M_7	0.5998	0.0286	20.30	0.000
M_8	0.5764	0.0290	19.88	0.000
M_9	0.5646	0.0290	19.47	0.000
M_{10}	0.5259	0.0290	18.14	0.000
M_{11}	0.4200	0.0290	14.49	0.000
M_{12}	0.2026	0.0290	6.99	0.000

S = 0.08323 R-Sq = 83.28% R-Sq(adj) = 82.20%

It is also seen from Table 1 that the trend in the data is not statistically significant, as the p-value of the trend coefficient (0.230) is not less than 5% level of significance. The only significant coefficient in the Table is the constant, 3.8393. Hence, there is a constant trend of relative humidity data of Umudike all through the considered months of the years. It can still be observed from the sign of the trend coefficient, in Table 1, that there is an indication of a decreasing trend, though not statistically significant.

We note that M_1 is removed to avoid a dummy variable trap and the interpretation of the seasonal influences would be done relative to the M_1(January component). From Table 1, it is observed that all the variables in the model are all significant except the coefficient of t. This is seen as the p-values of these parameter estimates are all less than 0.05.Figure 2 shows the plot of the seasonal component.

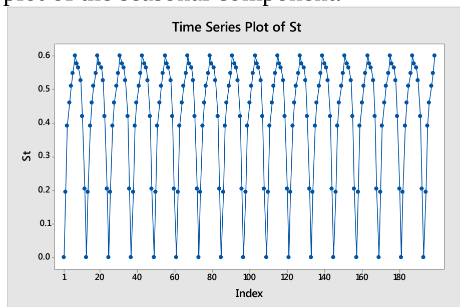

Fig. 2: Plot of the seasonal component

3.3: Assessment and Estimation of the Irregular Component

In assessing the error component of the model, the Autocorrelation(ACF) and Partial Autocorrelation(PACF) functions of the error, u_t in order to identify and suggest the type of ARIMA model to be fitted to the series. Figures 3 and 4 indicate both the ACF and PACF of the error component. From these figures, the ACF shows a sine wave pattern, while there is a cut off at lag one in PACF. From the foregoing, an Autoregressive model of order 1 [AR(1)] is suggested for the estimation of the error component.

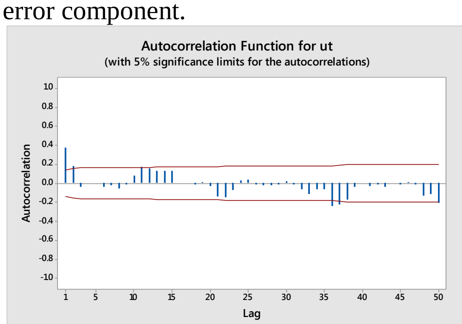

Fig. 3: ACF of the error component

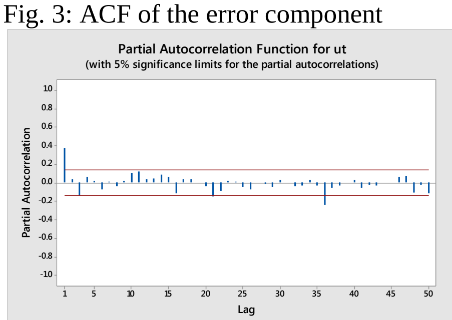

Fig. 4: PACF of the error component

Therefore, the estimates of the suggested model are given below:

Table 2: Final Estimates of Parameters and their test of significance

Type	Coef	SE Coef	T	P
AR 1	0.3798	0.0657	5.78	0.000

Number of observations: 199

Residuals: SS = 1.10271 (backforecasts excluded)

MS = 0.00557 DF = 198

From Table 2, it is observed that the estimate of the parameter of the model is significant in the model at 5% level, as its p-value is less than 0.05. Therefore the estimated model can be expressed as:

$$\hat{u}_t = 0.3798u_{t-1} \qquad (10)$$

3.4: The General Mixed Model for the Relative Humidity Data

Combining the various components produces the general model to be given as:

$$lnX_t = 3.8393 + 0.1938\,M_2 + 0.3908M_3 + 0.4597M_4 + 0.5099M_5 + 0.5490\,M_6 + 0.5998M_7 + 0.5764M_8 + 0.5646M_9 + 0.5259M_{10} + 0.4200M_{11} + 0.2026M_{12} + 0.3798u_{t-1} \quad (11)$$

The estimates of the series can now be obtained by taking the antilog of the right hand side of equation (10). Thus:

$$\hat{X}_t = exp[3.8393 + 0.1938\,M_2 + 0.3908M_3 + 0.4597M_4 + 0.5099M_5 + 0.5490\,M_6 + 0.5998M_7 + 0.5764M_8 + 0.5646M_9 + 0.5259M_{10} + 0.4200M_{11} + 0.2026M_{12} + 0.3798u_{t-1}] \quad (12)$$

Equation (12) can now be used to estimate and forecast the Relative Humidity of Umudike.

We can assess and appraise the influences of these time series components on the original data. For the trend, Table 1 has shown that there exists a little trend effect in the data though the trend seems to be decreasing and statistically insignificant. In addition, the trend percentage growth rate per month is given as:

$$e^{-0.000124} - 1 = -0.000124$$

Table 3: Interpretations of the coefficients of the seasonal component

Months	Coefficients	Index	Interpretation
February	0.1938	1.214	1.214 times that of January
March	0.3908	1.478	1.478 times that of January
April	0.4597	1.584	1.584 times that of January
May	0.5099	1.665	1.665 times that of January
June	0.5490	1.732	1.732 times that of January
July	0.5998	1.822	1.822 times that of January
August	0.5764	1.780	1.780 times that of January
September	0.5646	1.759	1.759 times that of January
October	0.5259	1.692	1.692 times that of January
November	0.4200	1.522	1.522 times that of January
December	0.2026	1.225	1.225 times that of January

This means that there is a 0.0124% decrease in relative humidity each month, which is very insignificant. This goes a long way to confirm our earlier inference.

Also, for the seasonal component, it is also observed that the months have a great significant effect on the series. This is evident in the significance of all the variables in the seasonal model. Further, the coefficients of the various months in those years can be interpreted relative to the January month. Thus, for the month of February, we have its interpretation to be:

$e^{0.1938} = 1.2139$

This means that the February relative humidity data is 1.214 times that of January.

Interpretations for other Calendar months could be explained in a similar way as shown in Table 3.

3.5: Model Adequacy

To assess the adequacy of the model, the residual from the fitted model is investigated using the ACF and the Modified Ljung Box test.

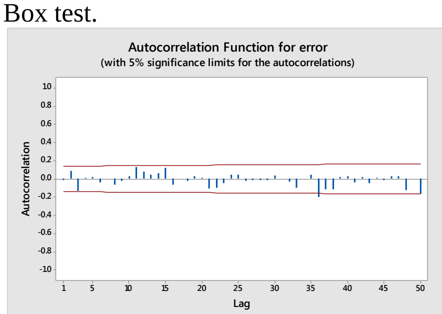

Fig. 5: Plot of ACF of the Residual

Table 4: Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24	36	48
Chi-Square	11.7	23.1	36.9	49.0
DF	11	23	35	47
P-Value	0.390	0.454	0.381	0.393

From figure 5, it is observed that the ACF of the Residual lie within the confidence limits, indicating that the residual is a purely random process. Also, the Modified Box-Pierce (Ljung-Box) test statistic clearly shows that the p-values exceed 5% for all lag orders; implying that there is no significant departure from white noise for the residuals.

4.0: Conclusion

In this paper, the trend, seasonal and Irregular components have been assessed and their properties investigated. The general model for predicting the relative humidity has been constructed. From these analyses, it is observed that there is an increase in the trend, though the trend has been found to be insignificant. The seasonality of the series is found to be 12 months with a great influence in the series. Finally, the model for the estimation and forecasting of the relative humidity has been found to be very adequate.

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