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STATISTICAL ANALYSIS OF RELATIVE HUMIDITY PATTERNS OF LOKOJA, NIGERIA

***[1]Akinyemi, Oluwadare, [2]Imoni, Sunday O., [3]Kupolusi J. Ayodele and [1]Okutu, Felix**

[1]Department of Statistics, Ekiti State University, Ado Ekiti,Ekiti,
[2]Department of Mathematics, Federal University Lokoja
[3]Department of Statistics, the Federal University of Technology, Akure

*Corresponding authors' email: oluwadare.akinyemi@eksu.edu.ng

ABSTRACT

This study focuses on the management of moisture and the monitoring of relative humidity (RH) patterns in order to maintain optimal conditions for finished products and human comfort. High humidity levels in homes can lead to issues such as the growth of dust mites, causing various irritations and allergies. The research emphasizes the importance of considering relative humidity values in the planning of tropical humid cities to create healthy and comfortable urban environments. Statistical measures and methods are employed to analyze the trend and project future relative humidity measurements. The study presents summary statistics of monthly relative humidity patterns, highlighting the variations across different months. Cumulative summaries indicate the overall range of relative humidity recorded over the years. Stationarity and normality tests are conducted to ensure the suitability of the data for modeling. Autocorrelation and partial autocorrelation analyses are used to identify potential ARIMA models for future humidity prediction. The information criteria aid in selecting the best-fitting ARIMA model, and the estimated coefficients are presented. Finally, predictions of relative humidity are provided for future dates. The study concludes that the ARIMA (9,1,1) model is suitable for predicting future relative humidity, and it highlights the importance of monitoring and managing relative humidity for maintaining optimal conditions.

Keywords: ARIMA model, Lokoja, Prediction, Relative Humidity, Trend

INTRODUCTION

Humidity which is one of the prominent climatic variables depicts the quantity of moisture in the air. Humidity greatly affects living organisms, plants and production processes. Relative humidity measures the amount of water vapour in the air. Water vapour is the key agent in both weather and climate (Korotcenkov, 2020), hence its study is very crucial to assess weather and climate. Yahaya et al. (2024) monitored the rate of change of the relevant climate extreme indices in the three climate zones of Nigeria and observed that the entire country is getting drier.

Relative humidity affects man and the environment either singly or when associated with other climatic variables; for example, Ayinde et al. (2013) reported that a 1% increase in humidity reduced rice production by 17% while Lawal and Omotona (2014) posited that physiological processes for pod production in cocoa improved with increase in both relative humidity and temperature. The distribution, occurrence and abundance of pests and the severity of the pest risk have been evaluated using atmospheric and climatic factors such as temperature, carbon dioxide and ozone and changing humidity patterns (Juroszek and von Tiedemann, 2015; Godefroid et al.; 2020). In general, all important life-cycle stages of insect pests, pathogens and weeds are influenced by temperature, relative humidity wind, light quantity and quality (IPPC, 2021)

In humans, the occurrence and prevalence of infectious diseases are strongly associated with relative humidity. The occurrence and prevalence of climate-sensitive infectious diseases are significantly associated with ambient humidity (Xu et al. 2018); relative humidity contributes to respiratory damage (Jericho and Magwood 1977). Chan et al. (2011) and Wu et al. (2020) identified that incidence and mortality due to coronavirus is significantly dependent on temperature and relative humidity. In animal health, relative humidity is also associated with incidence of infectious diseases and other abnormalities (Philbey et al. 1991; Weaver and Meijerhof, 1991; Lin et al. 2005; Berman 2006; Cox et al., 2008).

MATERIALS AND METHODS

Lokoja is located between latitude $7^0 45'$ and $7^0 52'$ North, and between longitude $6^0 41'$ and $6^0 45'$East of the Meridian. Lokoja belongs to the tropical climate with a rainy season that typically runs from May to October with average annual rainfall of 1000 mm and average relative humidity of about 30% during the dry season and 70% during the raining season. The research used secondary data collected from the Nigerian Meteorological Agency (NiMet), Lokoja, Kogi State. The data covered a period of ten years (2011-2020). The aim of this paper is to examine both monthly and annual patterns of relative humidity in Lokoja and to make forecast for future relative humidity values.

Model Specification

This study used the Augmented Dickey-Fuller unit root tests for stationarity. Variables are tested for stationarity because most economic and time series data are non-stationary and frequently lead to spurious estimation. The Dickey-Fuller test like any other unit root test, has its own weaknesses of low power and inability to detect a false null hypothesis which means that they tend to accept the null of unit root more frequently than is warranted. The major weakness of the Dickey-Fuller test is that it does not take account of possible autocorrelation in error process ε_t, thus the reason for the preference of Augmented Dickey-Fuller (ADF) test to the Dickey-Fuller test. The ADF test here consists of estimating the following regression:

$$y_t = c + \beta_t + ay_{t-1} + \sum_{k=1}^{p} \varphi_k \nabla y_{t-k} + \varepsilon_t \quad (1)$$

Where ε_t is pure white noise error term and $\nabla y_t = y_t - y_{t-1}$

Autoregressive (AR) model

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \ldots .. \emptyset_p + \emptyset_t Y_{t-p} + \varepsilon_1 \quad (2)$$

Where Y_t = dependent variable at time t
$Y_{t-1}, ... Y_{t-2}, ... Y_{t-p}$ = responses in previous time periods play the role of independent variables.

Moving Average (MA) model

$$X_t = \mu + e_t + \sum_{i=1}^{q} \theta_i e_{t-i} \quad (3)$$

Where the $\theta_1, \ldots \theta_q$ are the parameters of the model, μ is the expectation of X_t (often assumed to equal 0), and the $e_t, e_{t-1}, \ldots$ are again identically and independently distributed white noise errors terms that are commonly normal random variables.

Autoregressive Integrated Moving Average (ARIMA) model

The ARIMA models combine AR and MA models to obtain:

$$X_t = \mu + \varnothing_1 X_{t-1} + \varnothing_2 X_{t-2} + \cdots + \varnothing_p X_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_2 e_{t-q} + \varepsilon_t \quad (4)$$

Autocorrelation function (ACF)

$$\rho_k = \frac{\sum_{t=k+1}^{T}(r_i - r)(r_{t-k} - r)}{\sum_{t=1}^{T}(r_i - r)^2} \quad (5)$$

Partial Autocorrelation function (PACF)

$$\hat{p}_k = \frac{\hat{X}_k}{\hat{X}_0} = \frac{Covariance\ at\ lag\ K}{Variance} = \frac{\sum (X_t - \bar{X})(X_{t+k} - \bar{X})}{\sum (X_t - \bar{X})^2}, \quad k = 0,1,2,\ldots \quad (6)$$

RESULTS AND DISCUSSION

Table 1: Summary Statistics of Annual Relative Humidity

Year	Minimum	Maximum	Sum	Mean	Std. Deviation	Kurtosis	Skewness
2011	69	95	997	83.08	9.366	-1.404	-.335
2012	66	97	1015	84.58	9.539	-.484	-.576
2013	61	98	1034	86.17	14.090	-.608	-.967
2014	66	82	907	75.58	4.379	.853	-.723
2015	51	84	869	72.42	9.346	1.265	-1.200
2016	50	92	838	69.83	11.543	.687	-.185
2017	53	81	822	68.50	9.530	-1.521	-.282
2018	51	92	827	68.92	11.634	.055	.294
2019	52	79	833	69.42	9.671	-.916	-.623
2020	46	80	816	68.00	11.029	-.399	-.798

Table 1 presents summary statistics of annual relative humidity from 2011 to 2020. It displays that minimum measure of the weather condition was between 46 to 69, while, maximum measure was between 79 to 98. The negative skewness for almost all the years indicate that there is gradual increase in humidity within months of each year under consideration except for 2018. This is in agreement with a study conducted in neighboring Kwara State by Adeniyi (2020) that showed an upward trend in relative humidity

Table 2: Summary Statistics of Monthly Relative Humidity

Month	Minimum	Maximum	Sum	Mean	Std. Dev.	Skewness	Kurtosis
January	72	98	794	79.40	9.371	1.202	-.006
February	65	96	756	75.60	11.017	1.155	.020
March	72	96	847	84.70	8.895	.189	-1.742
April	50	80	600	60.00	10.822	.894	-.606
May	73	97	846	84.60	8.462	.350	-1.629
June	76	96	823	82.30	7.119	1.125	-.156
July	73	98	803	80.30	7.288	1.878	3.691
August	46	77	615	61.50	10.927	.314	-1.227
September	54	84	676	67.60	9.477	.392	-.659
October	60	84	722	72.20	8.297	.071	-1.082
November	68	96	803	80.30	9.310	.704	-.851
December	59	80	673	67.30	6.550	1.057	.501

Table 2 presents summary statistics of monthly relative humidity from January to December. The least humidity condition was 50 in April while the maximum was 98 in January. As calculated and presented, the month of August was the month least amount of humidity with the sum of 615, while, the month of March was the most with the sum of 847. This is slightly different from a study conducted in Akwa Ibom State by Umoh et al. (2013) with least humidity in January and Highest in July.

Table 3: Cumulative Summary of Relative Humidity

Variable	Minimum	Maximum	Sum	Mean	Std. Dev.	Skewness	Std. Err.	Kurtosis	Std. Err.
Reading	46	98	8958	74.65	12.067	-.076	.221	-.319	.438

Table 3 presents cumulative summary of relative humidity recorded through the years. It contains that while the minimum and maximum amount of the weather condition were 46 and 98 respectively, the total amount was 8958 where there was 74.65 record of it on the average.

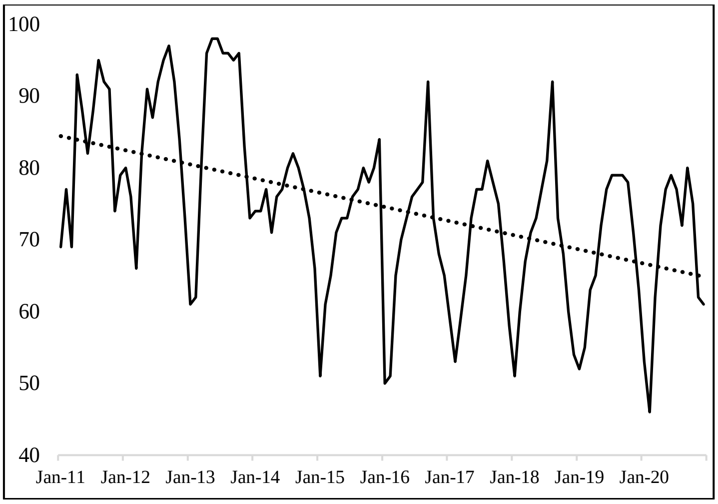

Figure 1: Trend of Relative Humidity in Kogi State

Table 4: Test for Stationarity

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	P-Value
-14.653	-3.504	-2.889	-2.579	0.000

Having carried out stationarity test, with the use of Augmented Dickey-Fuller (ADF) test, on the first difference of data about relative humidity, it is observed that p-value is 0.000 which is less than 0.05, we reject null hypothesis, and conclude that it is stationary. It is then concluded that the data is fit for the application of autoregressive integrated moving average in its first difference.

Table 5: Test for Normality

Variable	Observations	W	V	z	P > z
Relative Humidity	119	0.98828	1.12	0.253	0.40014

The results drawn from Shapiro-Wilk's test for normality are presented in the table above. Hypothetically, p-value is 0.4001 which is greater than 0.05. Therefore, we accept null hypothesis, and conclude that the data in its first difference is normally distributed.

Autocorrelation and Partial Autocorrelation

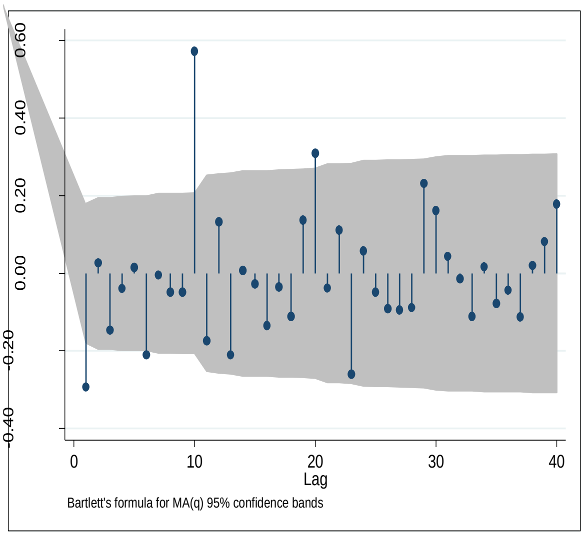

Figure 2: Correlogram for Autocorrelation on Relative Humidity

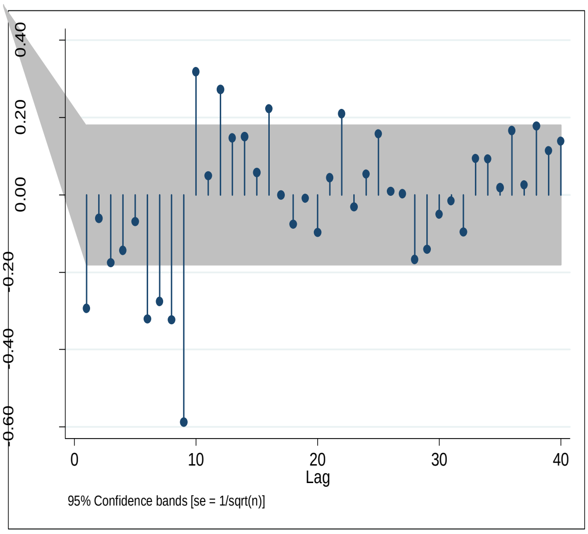

Figure 3: Correlogram for Partial Autocorrelation on Relative Humidity

Table 6: Information Criteria

PDQ	AIC	BIC
1,1,1	868.7314	879.8479
6,1,1	853.8908	878.903
7,1,1	851.0365	878.8277
8,1,1	843.5923	874.1626
9,1,1	788.1404*	827.49*
10,1,1	791.3614	834.1373
12,1,1	790.8548	832.5417
16,1,1	795.3475	848.1508
1,1,10	839.4868	872.8362
6,1,10	803.659	845.3459
7,1,10	798.087	845.3321
8,1,10	798.3952	851.1985
9,1,10	790.2091	843.7229
10,1,10	800.7878	851.3498

Autocorrelation and partial autocorrelation correlograms were plotted above. It is used to indicate possible ARIMA models (p,d,q) that can be used to estimate future occurrence of relative humidity. The partial correlation function plotted tells that there were 13 significant lags, while, the autocorrelation function plotted tells that there were two significant lags outside the plot region. These significant lags serve as the basis of the ARIMA models to be tested.

As for the information criteria, Akaike and Baye's methods were used. After testing possible models, it was observed that the least AIC and BIC was in the ninth PACF and first ACF. This implies that the best ARIMA model was (9,1,1).

Table 7: Autoregressive Integrated Moving Average Estimates

Parameter	Coefficient	Std. Error	Z	P > |z|	95% Confidence Interval	
Constant	0.055565	0.108042	0.51	0.607	-0.15619	0.267324
AR L1	-1.05428	0.108464	-9.72	0.000	-1.26687	-0.84169
AR L2	-0.84431	0.124611	-6.78	0.000	-1.08854	-0.60007
AR L3	-0.89261	0.121055	-7.37	0.000	-1.12988	-0.65535
AR L4	-0.81123	0.125253	-6.48	0.000	-1.05672	-0.56574
AR L5	-0.79077	0.113131	-6.99	0.000	-1.0125	-0.56904
AR L6	-0.91268	0.105364	-8.66	0.000	-1.11919	-0.70617
AR L7	-0.84654	0.109168	-7.75	0.000	-1.06051	-0.63258
AR L8	-0.80296	0.11774	-6.82	0.000	-1.03372	-0.57219
AR L9	-0.71037	0.075402	-9.42	0.000	-0.85816	-0.56259
MA L1	0.481646	0.133096	3.62	0.000	0.220783	0.742509
Sigma	6.117286	0.435107	14.06	0.000	5.264491	6.97008

Table 7 presents results obtained from ARIMA estimates. It consists of their respective coefficient, standard error, Z-value, p-value and confidence interval at 95%. Estimates on ARIMA (9,1,1) carried out are written as $0.0556 - 1.05428X_{t-1} - 0.84431\ X_{t-2} - 0.89261\ X_{t-3} - 0.81123\ X_{t-4} - 0.79077\ X_{t-5} - 0.91268\ X_{t-6} - 0.84654\ X_{t-7} - 0.80296\ X_{t-8} - 0.71037\ X_{t-9} + 0.481646\ \mu_{t-1} + \delta_t$. The p-value is significant for all the estimates at 5%, therefore, the model is best fit for predicting future records of relative humidity.

Table 8: Predictions on Relative Humidity

Date	Predictions	Lower Boundary	Upper Boundary
Jan-21	110.8478	110.7398	110.9559
Feb-21	95.09554	94.9875	95.20358
Mar-21	101.3358	101.2277	101.4438
Apr-21	92.5003	92.39226	92.60834
May-21	109.5046	109.3966	109.6127
Jun-21	82.60573	82.49769	82.71377
Jul-21	95.07971	94.97167	95.18775
Aug-21	93.09948	92.99144	93.20752
Sep-21	105.3896	105.2815	105.4976
Oct-21	96.22691	96.11887	96.33495
Nov-21	106.5688	106.4608	106.6769
Dec-21	96.99056	96.88252	97.0986
Jan-22	102.1405	102.0325	102.2486
Feb-22	94.04791	93.93987	94.15595
Mar-22	105.1888	105.0807	105.2968

Date	Predictions	Lower Boundary	Upper Boundary
Apr-22	85.95842	85.85038	86.06646
May-22	97.30225	97.19421	97.41029
Jun-22	92.74077	92.63273	92.84881
Jul-22	104.1119	104.0039	104.22
Aug-22	96.01025	95.90221	96.11829
Sep-22	104.3785	104.2704	104.4865
Oct-22	97.93594	97.8279	98.04398
Nov-22	102.0061	101.898	102.1141
Dec-22	95.35241	95.24437	95.46045
Jan-23	102.3348	102.2268	102.4429
Feb-23	88.93956	88.83152	89.0476
Mar-23	98.22919	98.12115	98.33723
Apr-23	92.91502	92.80698	93.02306
May-23	103.0033	102.8953	103.1114
Jun-23	95.76303	95.65499	95.87107
Jul-23	103.2471	103.139	103.3551
Aug-23	98.19593	98.08789	98.30397
Sep-23	101.6647	101.5567	101.7728
Oct-23	96.26982	96.16178	96.37786
Nov-23	100.5394	100.4313	100.6474
Dec-23	91.41209	91.30405	91.52013
Jan-24	98.39909	98.29105	98.50713
Feb-24	93.48322	93.37518	93.59126
Mar-24	101.9605	101.8524	102.0685
Apr-24	95.69174	95.5837	95.79978
May-24	102.554	102.4459	102.662
Jun-24	98.09157	97.98353	98.19961
Jul-24	101.3621	101.254	101.4701
Aug-24	96.80589	96.69785	96.91393
Sep-24	99.51949	99.41145	99.62753
Oct-24	93.30858	93.20054	93.41662
Nov-24	98.23696	98.12892	98.345
Dec-24	94.24779	94.13975	94.35583
Jan-25	100.9736	100.8656	101.0817
Feb-25	95.84241	95.73438	95.95045
Mar-25	101.9718	101.8638	102.0799
Apr-25	97.88393	97.77589	97.99197
May-25	101.1145	101.0065	101.2226
Jun-25	97.06102	96.95298	97.16906
Jul-25	99.03432	98.92628	99.14236
Aug-25	94.65353	94.54549	94.76157
Sep-25	98.01891	97.91087	98.12695
Oct-25	95.02631	94.91827	95.13435
Nov-25	100.0904	99.98234	100.1984
Dec-25	96.16049	96.05245	96.26853

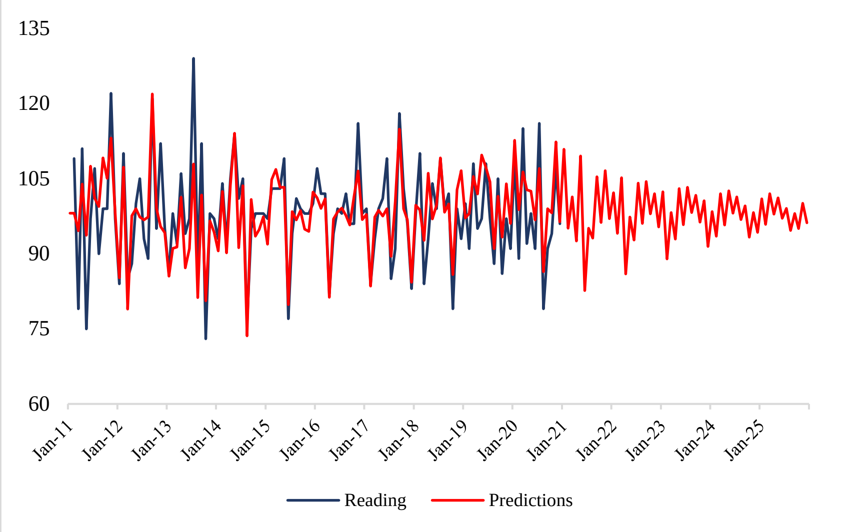

Figure 4: Predicted Pattern of Relative Humidity from January, 2021 to December, 2025

The table above contains predictions, lower and upper bounds for anticipated relative humidity records from January 2021 to December 2025. The subsequent line graph illustrates the hypotheses and preliminary findings.

CONCLUSION

The paper analyzed the relative humidity of Lokoja from 2011 to 2020, examining both annual and monthly patterns. The summary statistics revealed that the minimum humidity levels ranged from 46 to 69, while the maximum levels ranged from 79 to 98. The lowest recorded humidity was in 2020, with a total of 816, while the highest was in 2012, with a total of 1034. The monthly analysis indicated that April had the lowest humidity (50), while January had the highest (98). Furthermore, the study confirmed that the data exhibited stationarity and followed a normal distribution after taking the first difference. Autocorrelation and partial autocorrelation plots were used to determine the best ARIMA model, and it was found that ARIMA (9, 1, 1) provided the best fit. The estimates for this model indicated that the data had a negative autoregressive effect on the relative humidity, with coefficients ranging from -1.05428 to -0.71037. The predictions for future relative humidity values were also provided. Overall, the findings suggest that the ARIMA (9, 1, 1) model can be utilized to predict future occurrences of relative humidity accurately.

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