IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Environmental and Earth Sciences Research Journal
Vol. 11, No. 3, September, 2024, pp. 61-71
Journal homepage: http://iieta.org/journals/eesrj

Influence of Temperature Fluctuations on Rainfall Variations Using Statistical and Machine Learning Approaches over Selected Stations in Nigeria

Francis Olatunbosun Aweda[1*], Timothy Kayode Samson[2], Solomon Oluwadara Adeola[3], Olusanya Odunayo Jegede[1], Isaac Adewale Ojedokun[4], Jacob Adebayo Akinpelu[1]

[1] Physics Programme, College of Agriculture, Engineering and Science, Bowen University, Iwo 540004, Nigeria
[2] Statistics Programme, College of Agriculture, Engineering and Science, Bowen University, Iwo 540004, Nigeria
[3] Bangor University International College, Oswalds Building, Bangor North Wales LL57 2EN, UK
[4] Electrical and Electronics Programme, College of Agriculture, Engineering and Science, Bowen University, Iwo 540004, Nigeria

Corresponding Author Email: aweda.francis@bowen.edu.ng

https://doi.org/10.18280/eesrj.110303

Received: 25 July 2024
Revised: 21 August 2024
Accepted: 3 September 2024
Available online: 19 September 2024

Keywords:
atmospheric parameters, meteorology, statistical tools, machine learning algorithms, MERRA-2

ABSTRACT

Rainfall and temperature studies were conducted on selected Nigerian stations using data from the HelioClim website archive. This study investigates the relationship between temperature fluctuations and rainfall variations across selected Nigerian stations from 1980 to 2022 using statistical tools and Machine Learning Algorithms (MLA). The used data were analyzed using the Kolmogorov-Smirnov test, Spearman's rank correlation, and five regression models: linear, logarithmic, inverse, quadratic, and cubic regression models. The models were fitted and their performances were evaluated using R^2, MSE, and RMSE as performance metrics. Moreover, the data were analyzed with E-view 7.0 and the Statistical Package for Social Sciences (SPSS version 20.0). 20% of the data was tested, while the remaining 80% was trained using 24 MLA. The statistical analysis revealed that the maximum rainfall and temperature for the stations ranged from 200 to 240 mm and 25.8 to 26.8℃. In comparison, the minimum rainfall and temperature ranged from 110 to 140 mm and 24.2 to 24.6℃. The Kolmogorov-Smirnov shows that rainfall was not normally distributed in all locations ($p < 0.05$) while temperature followed normal distribution in Ibadan ($p = 0.182$, $p > 0.05$), Akure ($p = 0.200$, $p > 0.05$) and Abeokuta ($p = 0.107$, $p > 0.05$). More so, a negative relationship was more pronounced in Ikeja ($r = -0.408$, $p = 0.000$, $p < 0.01$) and Abeokuta ($r = -0.408$, $p = 0.000$, $p < 0.01$), compared with what was obtained in other locations. The MLA of regression type revealed that temperature has its highest R^2 (1.00) in 15 models while rainfall has its highest in 5 models. As a result, it is demonstrated that temperature affects rainfall. The findings suggest that temperature fluctuations significantly influence rainfall patterns. The research recommended that necessary agencies be required to establish more data collection centres for improved climate monitoring and forecasting.

1. INTRODUCTION

Temperature changes have been identified as a global challenge, with serious consequences for global rainfall distribution over decades, resulting in low water distribution by water distribution companies, most notably in African sub-regions, specifically Nigeria. Temperature and rainfall variability, as reported by Aweda and Samson [1], has become a serious challenge around the world as a result of researcher forecasts and predictions. According to Buishand and Brandsma [2], temperature changes have a significant impact on rainfall variation. According to Intergovernmental Panel on Climate Change (IPCC) [3], diplomatic groups on climate change lead to serious challenges on climate, which pose effects on water reservoirs as well as drought, which mostly affects all areas causing death and serious challenges over various governments at all levels in Africa sub-regions. According to the report, countries such as India have greatly improved the development and management of water resources as important on rainfall over temperature changes in the country, indicating that rainfall is a seasonal occurrence [4]. Aweda et al. [5], on the other hand, report that the government at all levels should create good rules for the utilization of rainfall collected during the period of heavy rainfall for the benefit of farmers and domestic usage during periods of high temperatures, whereby drainage, streams, and rivers may have dried across the country. IPCC [6] stated in the report that there are variations in the rise of temperature in the Indian subcontinent due to changes in the country's weather conditions. This, however, applies to what has been observed in Nigerian stations, where air temperature has a significant effect on the rainfall observed. Rainfall varies in time with a large amount of value experienced on a monthly, annual, and seasonal basis; however, different authors such as

Aweda et al. [1, 7, 8] reported that there is a significant decline in rainfall at various stations due to temperature variation. According to Parthasarathy et al. [9], there is a significant decline trend over some specific areas in India. However, it was discovered in the Nigeria region that some locations experienced a decrease in rainfall as a result of high-temperature variations that occurred during a specific period of the year [1]. It has been observed that there is a decrease in the trend of rainfall across some detachments [10, 11] except as a result of global warming which could increase the dryness in different areas of some locations in the monsoon rainfall which could be less than 2.4% during 1979-2009 as compared to what was observed during 1949-1978 in the India region [4, 12]. However, as reported by Aweda and Samson [1], an alternative is the case in the Nigeria sub-region. However, due to dynamic seasonal wet season flow, recurrent development in rainfall production of meteorological conditions in primary and secondary turbulences shaped the activities of the wet season across some selected areas [1, 4, 5]. According to Ranade et al. [13], there are approximately seventeen junctions established crosswise throughout Asia's Pacific region. This, however, was not found in the African sub-region. Rainfall has been reported to be a major factor influencing water quality, hydrology, and vegetation, which contributes to the development of any region in terms of agricultural production and the quality of an individual's livelihood. However, this could result in a global weather variation. Furthermore, the effect of rainfall on temperature across the African region has been observed to be a significant prerequisite in the preparation and organization of quality water possessions for agricultural use. Furthermore, according to the report, farmers in the northern part of Nigeria primarily practice irrigation farming for the production of their crops during the country's dry season, which helps the country's food production and reduces the importation of some food items. However, research has shown that rainfall and temperature have contributed to the growth of any environment, resulting in agricultural planning and management in various regions, which can lead to drought and food scarcity in any environment [14-17]. Researchers such as Gentilucci et al. [16-20] reported that floods cause economic losses, reducing the importance of food security in society. However, the effect of drought in any environment, as reported by various authors Fuwape et al. [15-20], demonstrates that there is a need in agriculture, irrigation, and energy for the development and implementation of appropriate mechanisms for predicting rainfall and temperature using machine learning algorithms. Water engineering management has been reported as one of the major activities in water management in Nigeria. Oloruntade et al. [21] conducted research on the principle of wet-water storage and dry-water extraction in rivers and, most likely, the ocean. Climate change has been observed to have a significant impact on rainfall and temperature variability, resulting in a long-term effect on some meteorological parameters [22]. Historically, the Nigeria sub-region has been observed to significantly contribute to the production of water for their nearby neighbouring countries [23-25]. This aids the development of those countries and food production for their development. According to the report, farming has played an important role in the development of Nigeria, with an increase in the production of agricultural products [1] as a result of Nigeria's rainfall and temperature variability. This has met the increased demand for food by citizens through improved water quality and temperature variability, resulting in increased food production [26]. Several revisions to rainfall and temperature reported both positive and negative influences across any study region [5, 21, 27-29]. However, reclassification of rainfall and temperature variation revealed that the rising or gathering of rainwater depends on location [30]. As a result, this study focused on temperature fluctuations and their impact on rainfall variations in selected Nigerian stations using statistical tools and machine learning. The data for this study were obtained from the HelioClim satellite archive. Many authors have worked on the variability of rainfall and temperature in African sub-regions, both temporally and spatially [21]. Rainfall trends in Nigeria have been reported by various authors, according to a report [1, 31-33]. However, the objective of this study is: (1) to investigate the relationship between data-driven atmospheric practices and agricultural productivity in arid regions by determining the variation of rainfall and the effect of temperature on it; (2) to analyze the effectiveness of predictive models in forecasting atmospheric and agricultural outcomes by studying the similarities between air temperature and rainfall patterns in the study areas using statistical tools and machine learning algorithms; (3) to evaluate the potential of data science in reducing resource wastage in agriculture by checking the performance of the quadratic regression over all stations considered using the R^2, RMSE, MSE and MAE based on different models.

2. RESEARCH METHODOLOGY

2.1 Study area

For this study, some selected stations in South Western State Nigeria as shown in Figure 1 were considered. The selected locations for this research were: Abeokuta (3.3619°E, 7.1475°N), Ado-Ekiti (5.2371°E, 7.6124°N), Akure (5.2058°E, 7.2571°N), Ibadan (3.9470°E, 7.3775°N), Ikeja (3.3515°E, 6.6018°N), Osogbo (4.5418°E, 7.7827°N). This study used the data from 1980 to 2022 for the selected stations. Table 1 shows the station coordinate, climatic division, period of data collection and stations used for this study.

Table 1. The division of the studied Nigeria-selected stations into their tropical regions

Station	Climatic Division	Longitude	Latitude	Period of Data
Abeokuta	Tropical/Savanna	$3.3619^{\circ}E$	$7.1475^{\circ}N$	1980-2022
Ado-Ekiti	Tropical Humid	$5.2371^{\circ}E$	$7.6124^{\circ}N$	1980-2022
Akure	Tropical Humid	$5.2058^{\circ}E$	$7.2571^{\circ}N$	1980-2022
Ibadan	Tropical Wet/Dry	$3.9470^{\circ}E$	$7.3775^{\circ}N$	1980-2022
Ikeja	Tropical	$3.3515^{\circ}E$	$6.6018^{\circ}N$	1980-2022
Osogbo	Tropical	$4.5418^{\circ}E$	$7.7827^{\circ}N$	1980-2022

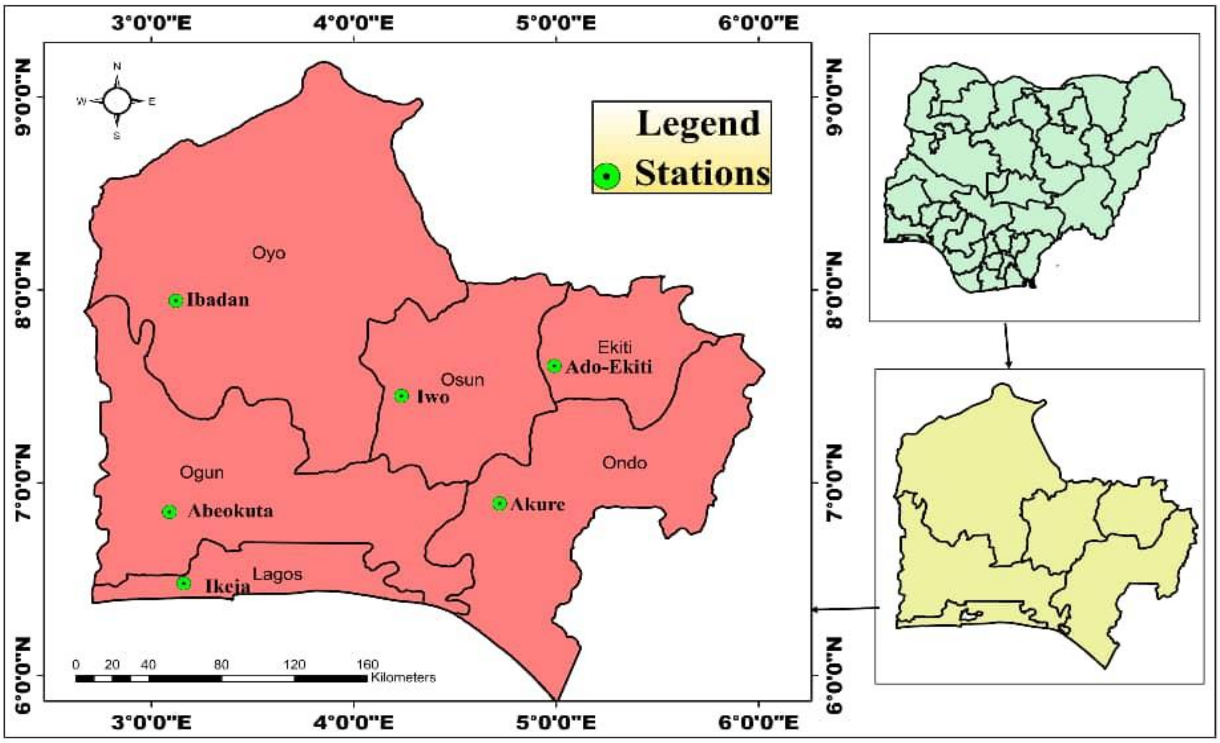

Figure 1. South west states map displaying the data collection stations [1]

2.2 Data collection

The data used for this study was obtained from the site of HelioClime. The data used were obtained in comma-separated value (CSV) data format. The date for the assessment was on 10th February 2023 and the data spread from 1st January 1980 to 31st December 2022. Using the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) technique, monthly air temperature and rainfall for selected stations in Nigeria were obtained from the HelioClim-1 (www.soda-pro.com) website. This followed what was reported by those researchers [1, 34-36].

2.3 Data processing

The data processing was carried out using data downloaded from the MERRA-2 database. The data was extracted from the soda website to produce the air temperature and rainfall for the selected stations. Tools such as Python were used to prepare and filter data for reading and it was converted to Excel data format. The data was subjected to a quality control check to identify any missing values. The missed or zero data were separated from the real data thereafter, statistical tools were used to analyze the data visualization. The data process data were then saved for later analysis.

2.4 Machine Learning Algorithms (MLA) analysis

This study's data was subjected to machine learning algorithms which used train and test. The train data was at 80% accuracy, while the test data was at 20% accuracy. The MAE, MSE, RMSE, and R^2 of the data were computed. Twenty-four (24) machine learning algorithms of the regression type were determined for each of the stations used, that is air temperature and rainfall value. For this study, the twenty-four regression-type machine learning algorithms used were selected to ensure a thorough assessment of the relationship between air temperature and rainfall values at each station. This diverse selection enabled the identification of the most effective algorithm for each station's specific characteristics. The algorithms used included linear and nonlinear models, such as decision trees, random forests, and neural networks. Each algorithm was trained and validated on historical climate data, with hyperparameters tuned to improve performance. This rigorous approach allowed the selection of the best-performing algorithm for each station, resulting in accurate predictions and insights into local climate dynamics.

2.5 Statistical analyses

Mean data was computed for the monthly temperature and rainfall [37-41] while the normality of the data was tested using the Kolmogorov-Smirnov test. The relationship between rainfall and temperature was explored with Spearman's rank correlation and five different regression forms: linear, logarithm, inverse, quadratic and cubic regression models were fitted and their performances were evaluated using R^2, MSE and RMSE as performance metrics. The data used were analysed using E-view 7.0 and the Statistical Package for Social Sciences (SPSS version 20.0).

3. RESULTS AND DISCUSSION

Figure 2 depicts the yearly correlation results of selected Nigerian stations labelled Osogbo, Ikeja, Ibadan, Akure, Ado-Ekiti, and Abeokuta. The Machine Learning Algorithm (MLA) method revealed that the minimum rainfall in Osogbo was recorded in 1984, while the minimum temperature was recorded in 1980, and the maximum rainfall was recorded in 2015, while the maximum temperature was recorded in 2018. This demonstrates that the outcome of machine learning can predict what will happen in the future. The rainfall and temperature findings show that almost every station studied has a nearly identical pattern. This demonstrates that all of the selected Nigerian stations are in the same climatic region. However, the results show that all of the Nigerian stations studied have nearly the same rainfall and temperature pattern. Furthermore, the results show that the rainfall and temperature patterns are nearly identical at each station, indicating that the rainfall and temperature at the chosen station move at a similar rate. Short-term rainfall and temperature predictions are critical when rainfall and temperature output are increasing. According to the results, the maximum rainfall and temperature for the stations ranged from 200 to 240 mm and 25.8 to 26.8℃, while the minimum rainfall and temperature ranged from 110 to 140 mm and 24.2 to 24.6℃. This shows that the rainfall at the reported stations will be beneficial to farmer production.

As shown in Figure 3, the heat map for air temperature and rainfall revealed that both parameters are in correlation with each other. The result shows that the more the air temperature the more the rainfall for the selected stations.

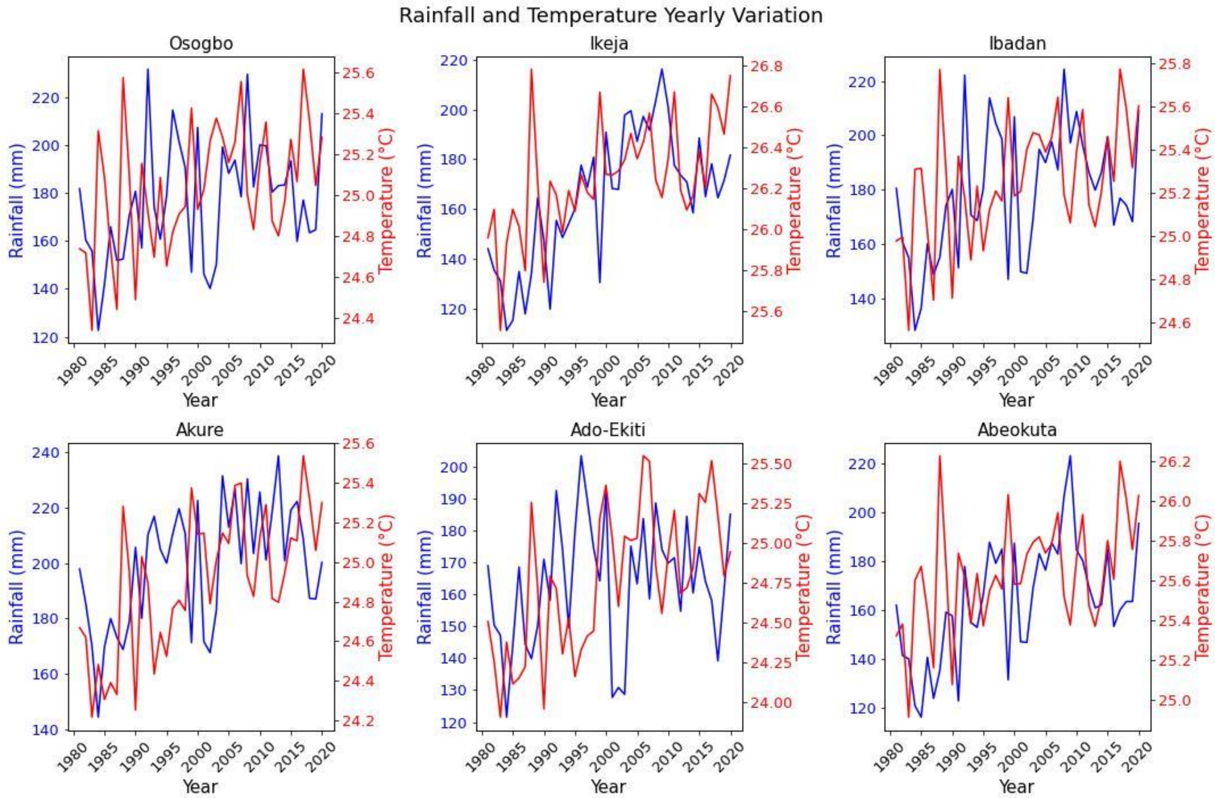

Figure 2. Yearly correlation between rainfall and temperature for the stations considered

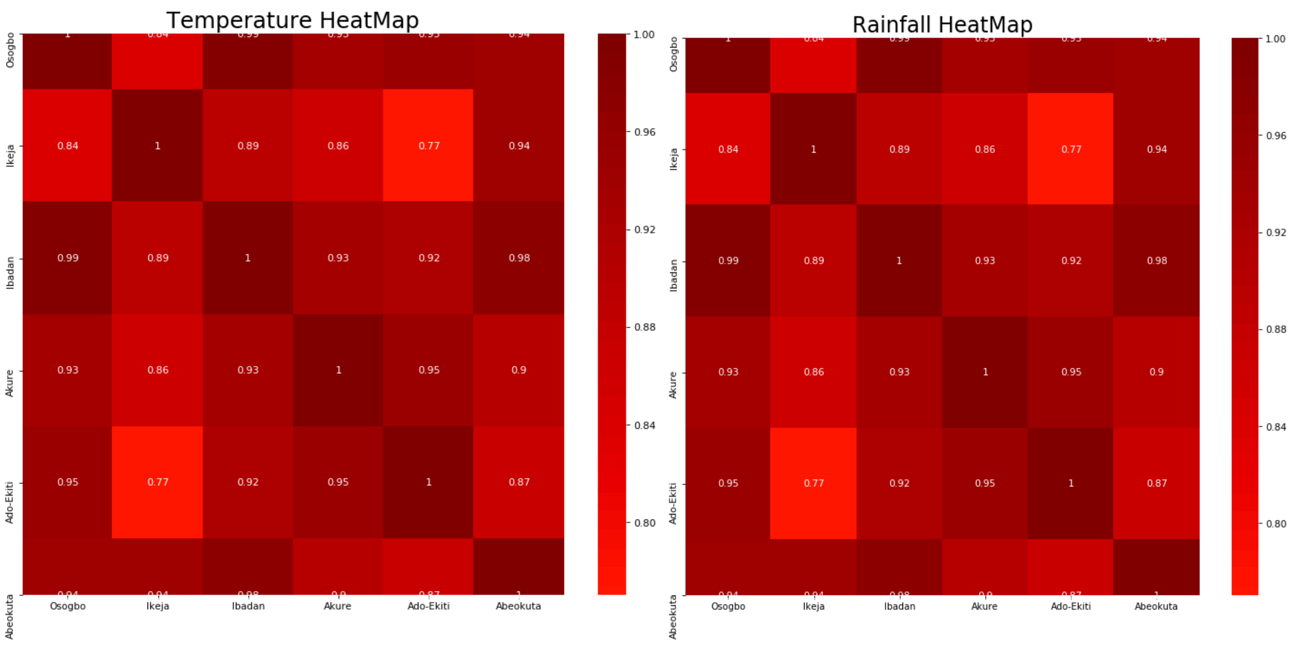

Figure 3. The heat map for rainfall and temperature

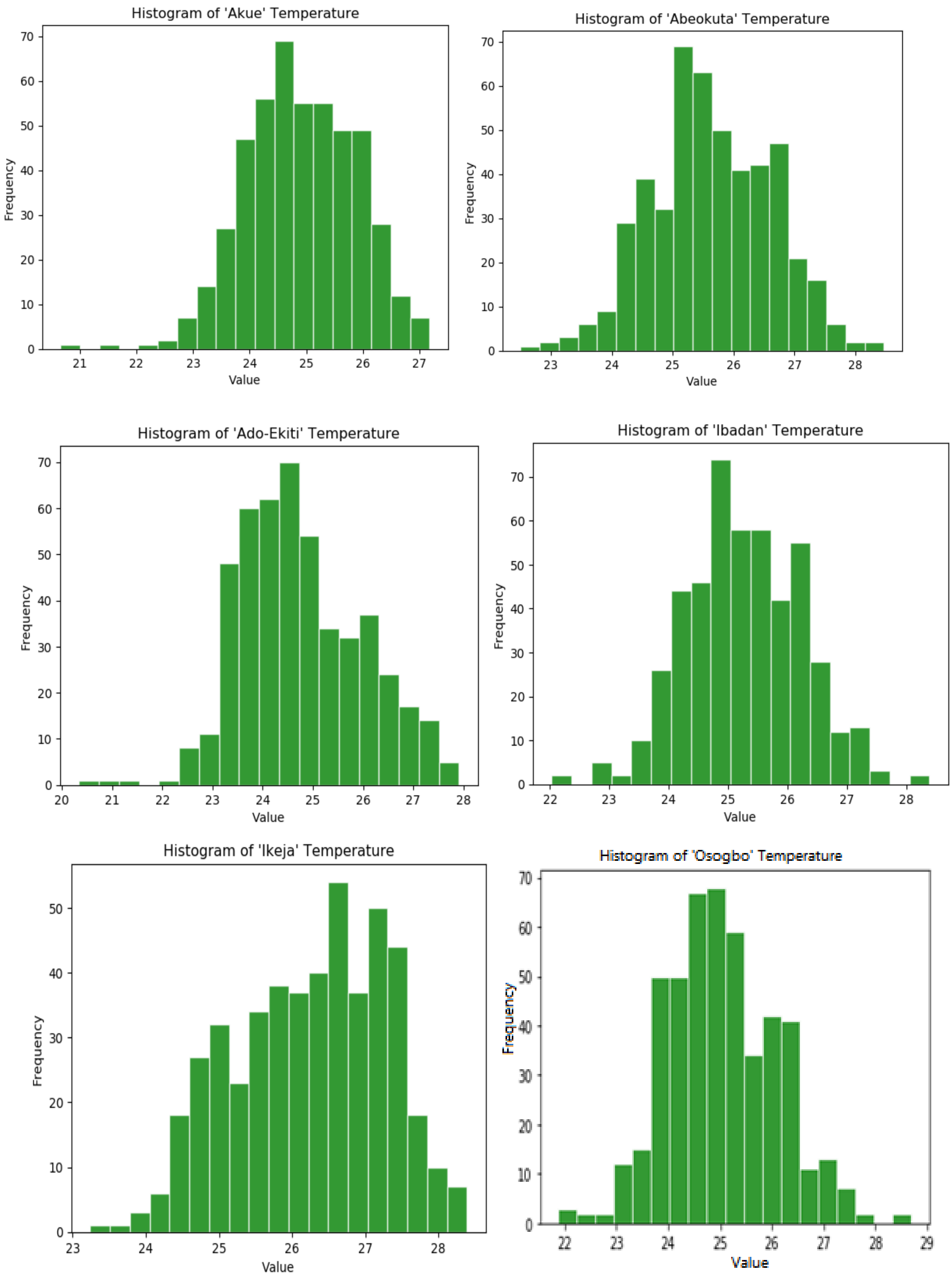

Figure 4. Frequency distribution graph for temperature across the selected stations

The result as shown in Figure 4 and Figure 5 revealed the frequency distribution of rainfall and temperature for all the stations considered. It was observed that the highest frequency observed in all the stations is around 70. This shows that all the stations are located around the same climatic zone. However, the minimum value recorded across the station was observed in Ibadan (Frequency < 0.1) and Ikeja (Frequency < 0.1). This was due to the proximity of the two stations nearer to the ocean which could influence the temperature of the area. More so, the frequency distribution of rainfall in all the stations considered revealed that the highest frequency was observed in Ado-Eiti (Frequency > 110). While the lower frequency distribution observed is found in Abeokuta (Frequency < 1.0).

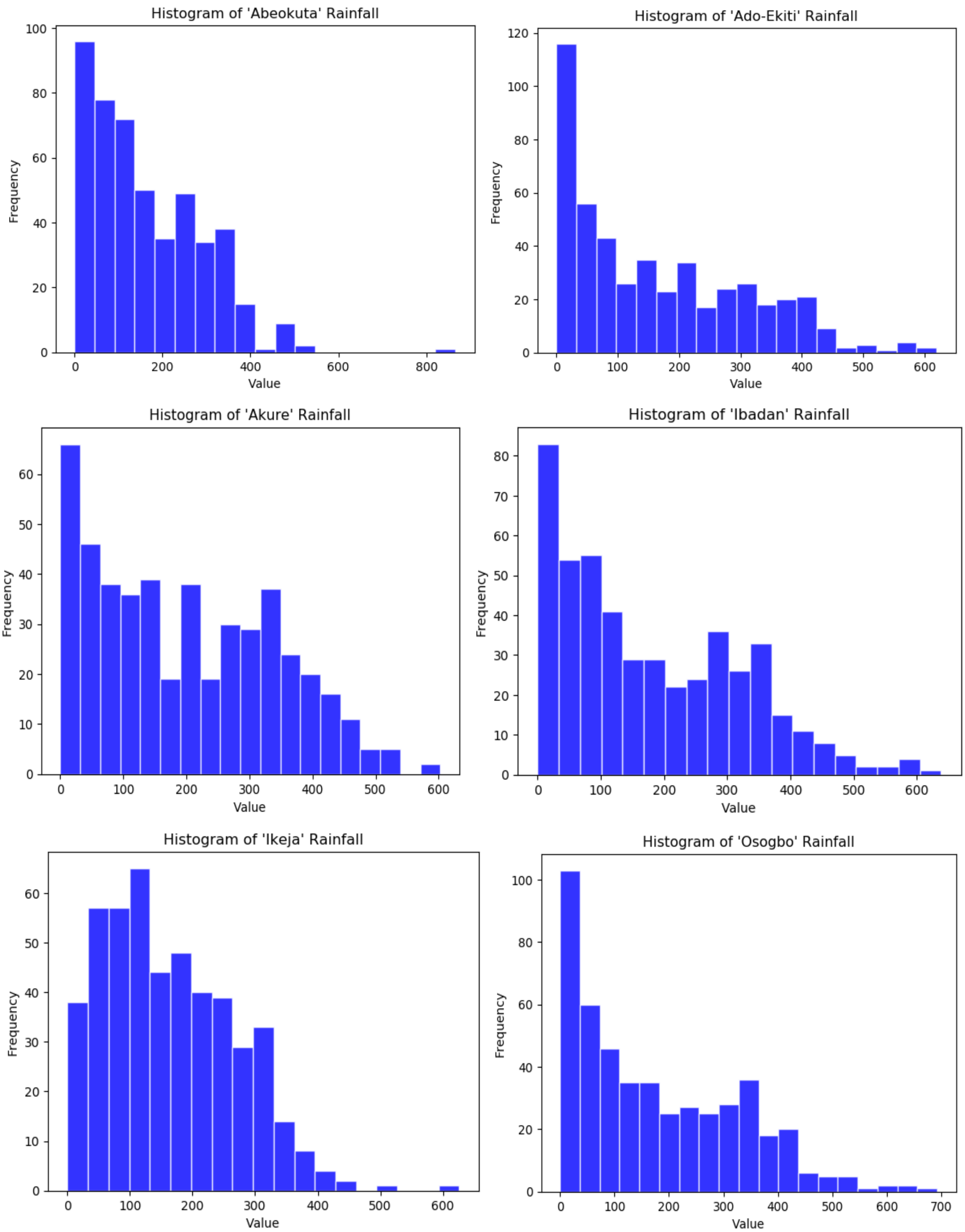

Figure 5. Frequency distribution graph for rainfall across the selected stations

3.1 Temperature and rainfall statistical analysis

The result in Table 2 shows the monthly mean temperature and rainfall in the selected six locations in Nigeria. The result shows that the maximum monthly temperature was reported in March in all locations while rainfall was at its peak in September in all locations. The lowest temperature in all locations was obtained in August while rainfall was at its lowest values in December in five of the locations (Osogbo, Ibadan, Akure, Ado-Ekiti and Abeokuta) while in Ikeja, the least rainfall was obtained in January (Table 2). This result indicates similarities in temperature and rainfall patterns in the study areas.

The Kolmogorov-Smirnov test was used to test the normality of the variables and the result as presented in Table 3 reveals that rainfall was not normally distributed in all locations ($p < 0.05$) while temperature followed normal distribution in only Ibadan ($p = 0.182$, $p > 0.05$), Akure ($p = 0.200$, $p > 0.05$) and Abeokuta ($p = 0.107$, $p > 0.05$) while that obtained in other locations were not normally distributed (p <

0.05). Hence, the relationship between variables was determined using Spearman rank correlation which is non-parametric correlation and the result is as presented in Table 3. Result showed that in all locations, there was a significant negative relationship between temperature and rainfall ($p < 0.05$) indicating that as the temperature increases significantly, there is a significant decrease in rainfall. This negative relationship was more pronounced in Ikeja ($r = -0.408$, $p = 0.000$, $p < 0.01$) and Abeokuta ($r = -0.408$, $p = 0.000$, $p < 0.01$) compared with that obtained in other locations.

Different functional forms of regression models (linear, logarithm, inverse, quadratic and cubic regression) were used to examine the relationship between rainfall as the dependent variable and temperature as the predictor variable and the result obtained is as presented in Table 4. The result shows that in all locations, different regression models were significant ($p < 0.05$) indicating that a regression relationship exists between rainfall as the response variable and temperature as the predictor variable. The result shows that the cubic regression model was found to be outperformed other models in Osogbo ($R^2 = 0.1450$, RMSE = 137.6308), Ikeja ($R^2 = 0.174$, RMSE = 94.07199), Ibadan ($R^2 = 0.152$, RMSE = 130.4768), Akure ($R^2 = 0.125$, RMSE = 133.3977), Ado-Ekiti ($R^2 = 0.144$, RMSE = 133.8516) and Abeokuta ($R^2 = 0.188$, RMSE = 109.9167). The performance of the quadratic regression in Ikeja was better than that of other locations as the R^2 in this location was higher than others while the RMSE was lower than that obtained in other locations. Based on the best model among the competing regression models, the regression equation as shown in Eqs. (1)-(6) was written for each of the locations.

For Osogbo:

$$\hat{R}_i = -6486.285 + 580.639T_i - 12.539T_i^2 \quad (1)$$

Ikeja:

$$\hat{R}_i = -8129.771 + 676.661T_i - 13.720T_i^2 \quad (2)$$

Ibadan:

$$\hat{R}_i = -9624.811 + 829.338T_i - 17.442T_i^2 \quad (3)$$

Akure:

$$\hat{R}_i = -15391.175 + 1296.119T_i - 26.868T_i^2 \quad (4)$$

Ado-Ekiti:

$$\hat{R}_i = -5763.411 + 518.90T_i - 11.263T_i^2 \quad (5)$$

Abeokuta:

$$\hat{R}_i = -6392.832 + 564.808T_i - 12.038T_i^2 \quad (6)$$

Table 2. Monthly mean temperature and rainfall in the selected six locations

	Osogbo		**Ikeja**		**Ibadan**		**Akure**		**Ado-Ekiti**		**Abeokuta**	
Month	Temp.	Rainfall	Temp.	Rainfall	Temp.	Rainfall	Temp.	Rainfall	Temp.	Rainfall	Temp.	Rainfall
Jan.	24.45	18.84	26.21	42.64	24.73	24.55	24.22	28.06	24.14	12.95	25.31	27.65
Feb.	26.09	35.81	27.22	64.99	26.16	43.71	25.63	53.40	25.87	27.98	26.64	46.24
Mar.	26.58	84.01	27.53	115.75	26.60	95.02	26.14	117.46	26.52	71.74	26.99	92.48
Apr.	26.30	118.92	27.36	136.23	26.40	125.45	26.05	157.99	26.27	109.07	26.75	117.25
May	25.71	195.88	26.90	202.75	25.89	197.54	25.56	246.06	25.51	187.86	26.22	178.92
Jun.	24.88	264.70	25.97	268.59	25.10	269.93	24.77	308.63	24.59	237.17	25.38	248.88
Jul.	24.04	350.51	24.98	260.91	24.27	345.65	24.00	363.57	23.71	342.06	24.54	308.25
Aug.	23.80	332.57	24.67	191.75	24.05	304.45	23.84	346.22	23.50	352.91	24.33	257.67
Sept.	24.36	389.72	25.18	282.74	24.60	379.63	24.32	365.42	23.97	353.66	24.85	334.19
Oct.	24.92	262.11	25.88	251.22	25.15	273.01	24.86	285.16	24.49	215.96	25.40	250.61
Nov.	25.07	52.12	26.66	109.59	25.43	65.91	25.15	87.55	24.63	38.41	25.86	71.99
Dec.	24.26	16.33	26.42	47.25	24.69	22.70	24.26	27.45	23.86	11.09	25.31	27.37

Table 3. Summary of the result of normality and rank correlation for the relationship between rainfall and temperature in the selected locations

Location	**Kolmogorov-Smirnov Test for Normality**				**Spearman Rank Correlation**		
	Temp.		Rainfall				
	Statistic	P-value	Statistic	P-value	r-value	P-value	Remarks
Osogbo	0.042	0.041*	0.126	0.000**	-0.293	0.000**	Significant negative relationship
Ikeja	0.061	0.000**	0.081	0.000**	-0.408	0.000**	Significant negative relationship
Ibadan	0.036	0.182	0.112	0.000**	-0.316	0.000**	Significant negative relationship
Akure	0.031	0.200	0.086	0.000**	-0.233	0.000**	Significant negative relationship
Ado-Ekiti	0.073	0.000**	0.130	0.000**	-0.255	0.000**	Significant negative relationship
Abeokuta	0.038	0.107	0.111	0.000**	-0.408	0.0000**	Significant negative relationship

***Significant at 1% (p < 0.01), *significant at 5% (p < 0.05).*

Table 4. Summary of the result of different regression models for the relationship between rainfall and temperature

Location	Statistic	Linear	Logarithm	Inverse	Quadratic	Cubic
Osogbo	$R^2_{adj.}$	0.1280	0.1250	0.1210	**0.1450**	0.1430
	MSE	19311.12	19384.66	19468.32	**18942.23**	18978.11
	RMSE	138.9645	139.2288	139.5289	**137.6308**	137.7611
	P-value	0.000**	0.000**	0.000**	0.000**	0.000**
Ikeja	$R^2_{adj.}$	0.153	0.153	0.147	**0.174**	0.173
	MSE	9073.43	9103.07	9135.86	**8849.54**	8865.22
	RMSE	95.25455	95.41001	95.58169	**94.07199**	94.1553
	P-value	0.000**	0.000**	0.000**	0.000**	0.000**
Ibadan	$R^2_{adj.}$	0.126	0.123	0.119	**0.152**	0.150
	MSE	17537.24	17608.46	17687.38	**17024.19**	17061.76
	RMSE	132.4282	132.6969	132.9939	**130.4768**	130.6207
	P-value	0.000**	0.000**	0.000**	0.000**	0.000**
Akure	$R^2_{adj.}$	0.057	0.053	0.049	0.125	**0.127**
	MSE	19168.09	19248.13	19331.76	**17794.95**	17824.07
	RMSE	138.4489	138.7376	139.0387	**133.3977**	133.5068
	P-value	0.000**	0.000**	0.000**	0.000**	0.000**
Ado-Ekiti	$R^2_{adj.}$	0.121	0.117	0.112	**0.144**	0.142
	MSE	18932.34	18479.66	18580.39	**17916.24**	17953.41
	RMSE	137.5948	135.9399	136.3099	**133.8516**	133.9903
	P-value	0.000**	0.000**	0.000**	0.000**	0.000**
Abeokuta	$R^2_{adj.}$	0.171	0.168	0.164	**0.188**	0.183
	MSE	13019.84	13067.34	13122.25	**12081.69**	12824.20
	RMSE	114.1045	114.3125	114.5524	**109.9167**	113.244
	P-value	0.000**	0.000**	0.000**	0.000**	0.000**

***Significant at 1% ($p < 0.01$), *significant at 5% ($p < 0.05$). Bolded values are the highest adjusted R^2 and least value of MSE and RMSE (MSE- Mean Square Error, RMSE- Root Mean Square Error).*

Table 5. The average results of the Machine Learning Algorithm (MLA) for rainfall and temperature data for the selected stations used

Different Models Used	Temperature				Rainfall			
Machine Learning Algorithm	**R^2**	**RMSE**	**MAE**	**MSE**	**R^2**	**RMSE**	**MAE**	**MSE**
Linear Regression	1.00	0.044261	0.030806	0.001959	0.99	9.9079	5.7428	98.167
Interaction Linear	1.00	0.045521	0.031983	0.0020721	1.00	9.3881	5.7458	88.137
Robust Linear	1.00	0.045759	0.030903	0.0020939	1.00	9.5334	5.7588	90.887
Stepwise Linear	1.00	0.044468	0.03027	0.0019774	0.99	9.9001	5.7862	98.012
Fine Tree	0.98	0.1200	0.075739	0.014418	0.99	13.996	9.3352	195.89
Medium Tree	0.98	0.13293	0.10276	0.01767	0.98	17.419	11.623	303.43
Coarse Tree	0.94	0.22272	0.16692	0.049605	0.96	28.53	20.582	813.95
Linear SVM	1.00	0.056751	0.047472	0.0032207	0.99	10.817	7.5734	117
Quadratic SVM	1.00	0.061868	0.050807	0.0038276	0.99	11.414	8.0184	130.28
Cubic SVM	0.99	0.066006	0.050619	0.0043568	0.99	12.443	8.407	154.82
Fine Gaussian SVM	0.88	0.31336	0.15039	0.098194	0.96	28.761	19.258	827.19
Medium Gaussian SVM	0.99	0.070568	0.051188	0.0049799	0.99	11.39	8.3929	129.73
Coarse Gaussian SVM	0.99	0.081542	0.063015	0.0066491	0.99	14.106	10.141	198.99
Ensemble Boosted Trees	-0.41	1.0637	1.0609	1.1314	0.98	17.913	1.639	320.89
Ensemble Bagged Trees	0.99	0.08464	0.055217	0.0071639	0.99	13.824	8.5047	91.11
Gaussian-Squared Exponential GPR	1.00	0.04617	0.029965	0.0021316	0.99	9.887	5.8942	97.754
Gaussian-Matern 5/2 GPR	1.00	0.045962	0.029041	0.0021125	0.99	11.416	7.4011	130.32
Exponential GPR	1.00	0.044957	0.028875	0.0020211	0.99	9.8516	6.1126	97.053
Rotational Quadratic GPR	1.00	0.04585	0.029886	0.0021022	0.99	10.53	6.8403	110.88
Narrow Neural Network	1.00	0.04369	0.029318	0.0019088	1.00	9.5963	5.8116	92.09
Medium Neural Network	1.00	0.047873	0.033779	0.0022918	1.00	10.324	6.1279	106.58
Wide Neural Network	1.00	0.049215	0.030296	0.0024221	0.99	10.405	6.503	108.27
Bilayered Neural Network	1.00	0.047878	0.03316	0.0022923	0.99	9.8878	5.9984	97.768
Trilayered Neural Network	1.00	0.054511	0.035294	0.0029714	1.00	9.4977	5.9163	90.207

Table 5 shows the average results of the performances of the different 24 Machine Learning Algorithms (MLA) of regression type for the selected stations used. For all the stations, it was observed that temperature has is highest R^2 (1.00) in 15 models as shown in the result. while the lowest temperature value was Ensemble Boosted Trees ($R^2 = -0.41$). This implies that these Machine Learning Algorithms (MLA) models with R^2 (1.00) performed better in terms of fitness as compared with other MLA models. In terms of the forecasting performance of these MLA based on RMSE, the best forecasting Machine Learning model was Ensemble Boosted Trees (RMSE = 1.0637). The result also reveals that Narrow Neural Network gave the least (MAE = 0.029318), while the lowest MSE for the station is (MSE = 0.0019088) meaning that these ML algorithms are less formed as compared with other MLA models. For the rainfall in all the observed stations, the MLA shows that the stations have their highest value in terms of R^2 (1.00) this can be observed in five models namely

Interaction Linear, Robust Linear, Narrow Neural Network, Medium Neural Network, and Trilayered Neural Network. While other models as their value of less than 1.00. However, their values range between 0.98 and 0.99. The highest RMSE (28.761) value observed for the rainfall in all the observed stations is the Fine Gaussian SVM model while the lowest model value was observed in the Interaction Linear model with RMSE (9.3881). Furthermore, it was observed that the highest MLA model in terms of the rainfall for MAE (20.582) was the Coarse Tree model and the lowest value was observed in Ensemble Boosted Trees (1.639). The highest MSE value and the lowest value observed in the stations are as follows Fine Gaussian SVM (827.19) and Trilayered Neural Network (90.207) respectively. This shows that the models used for this study can be categorised as good models for the future forecast and prediction of temperature and rainfall.

The study's findings offer vital insights for improving climate and water resource management in Nigeria. By identifying key climate variables affecting water resources, the research guides policymakers in developing targeted interventions, such as enhancing infrastructure to improve resilience against climate change. The application of machine learning models enables more accurate predictions, supporting better early warning systems and resource allocation. These insights can also optimize water usage in agriculture, promote sustainable practices, and strengthen community-based climate education. Ultimately, integrating these findings into national strategies will bolster Nigeria's efforts to manage climate-related risks and ensure sustainable water resources.

4. CONCLUSIONS

The results of the study of the rainfall and temperature relationship and correlation revealed that the chosen models for temperature and rainfall variability for selected stations were based on various machine learning algorithms and statistical tools. Furthermore, the study's findings explained the standardization of temperature and rainfall data used for the selected stations, owing to high rainfall due to moisture in the air temperature exceeding the long-term average. According to the findings, the average temperature and rainfall decreased, indicating a negative correlation. Furthermore, the statistical evaluations of the expected outcomes demonstrate the analysis' thoroughness. However, this will enhance agricultural production if rainfall and temperature are properly harness.

Future research should expand on this study by conducting multi-site studies to increase generalizability and extend data collection periods for long-term monitoring. Developing machine learning models for predictive analytics can also improve forecasting capabilities. Potential improvements include integrating additional data sources, leveraging machine learning algorithms, and utilizing cloud-based infrastructure for scalability. Implementing real-time data processing and edge computing can enhance efficiency. Expanding to diverse geographical regions and exploring data assimilation techniques can further improve the robustness and accuracy of the proposed methods.

REFERENCES

[1] Aweda, F.O., Samson, T.K. (2022). Relationship between air temperature and rainfall variability of selected stations in Sub-Sahara Africa. Iranica Journal of Energy & Environment, 13(3): 248-257. https://doi.org/10.5829/ijee.2022.13.03.05

[2] Buishand, T.A., Brandsma, T. (1999). Dependence of precipitation on temperature at Florence and Livorno (Italy). Climate Research, 12(1): 53-63. http://doi.org/10.3354/cr012053

[3] Intergovernmental Panel on Climate Change (IPCC). (2007). Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Agenda, 6(7): 333.

[4] Yaduvanshi, A., Ranade, A. (2015). Effect of global temperature changes on rainfall fluctuations over river basins across Eastern Indo-GangeticPlains. Aquatic Procedia, 4: 721-729. http://doi.org/10.1016/j.aqpro.2015.02.093

[5] Aweda, F.O., Adeniji, A.A., Akinpelu, J.A., Abiodun, A.J. (2021). Analysis of rainfall trends and variabilities for three decades in Sub-Sahara Africa. Ruhuna Journal of Science, 12(1): 55-63. http://doi.org/10.4038/rjs.v12i1.100

[6] Intergovernmental Panel on Climate Change (IPCC). (2001). Climate Change 2007: Impacts, Adaptation and Vulnerability. Working group II Contribution to the Intergovernmental Panel on Climate Change Fourth Assessment Report. Genebra, Suíça.

[7] Mooley, D.A., Parthasarathy, B. (1984). Fluctuations in all-India summer monsoon rainfall during 1871-1978. Climatic Change, 6(3): 287-301. https://doi.org/10.1007/BF00142477

[8] Kulkarni, A. (2012). Weakening of Indian summer monsoon rainfall in warming environment. Theoretical and Applied Climatology, 109: 447-459. https://doi.org/10.1007/s00704-012-0591-4

[9] Parthasarathy, B., Rupa Kumar, K., Kothawale, D.R. (1992). Indian summer monsoon rainfall indices: 1871-1990. Meteorological Magazine, 121(1441): 174-186.

[10] Guhathakurta, P., Sreejith, O.P., Menon, P.A. (2011). Impact of climate change on extreme rainfall events and flood risk in India. Journal of Earth System Science, 120: 359-373. https://doi.org/10.1007/s12040-011-0082-5

[11] Rajeevan, M., Bhate, J., Jaswal, A.K. (2008). Analysis of variability and trends of extreme rainfall events over India using 104 years of gridded daily rainfall data. Geophysical Research Letters, 35(18). https://doi.org/10.1029/2008GL035143

[12] Sontakke, N.A., Singh, N. (1996). Longest instrumental regional and all-India summer monsoon rainfall series using optimum observations: Reconstruction and update. The Holocene, 6(3): 315-331. https://doi.org/10.1177/095968369600600306

[13] Ranade, A., Singh, N., Singh, H.N. (2010). Effect of La Niña-El Niño on climatic fluctuations over major hydro-ecozones across India. Journal of Hydrological Research and Development, 25: 13-36. https://www.researchgate.net/publication/258028383.

[14] Ojo, O.S. Ogunjo, S.T. (2022). Machine learning models for prediction of rainfall over Nigeria. Scientific African, 16: e01246. https://doi.org/10.1016/j.sciaf.2022.e01246

[15] Fuwape, I.A., Ogunjo, S.T., Oluyamo, S.S., Rabiu, A.B. (2017). Spatial variation of deterministic chaos in mean daily temperature and rainfall over Nigeria. Theoretical

and Applied Climatology, 130(1-2): 119-132. https://doi.org/10.1007/s00704-016-1867-x

[16] Gentilucci, M., Bisci, C., Burt, P., Fazzini, M., Vaccaro, C. (2018). Interpolation of rainfall through polynomial regression in the Marche region (Central Italy). In: Mansourian, A., Pilesjö, P., Harrie, L., van Lammeren, R. (eds) Geospatial Technologies for All: Selected Papers of the 21st AGILE Conference on Geographic Information Science. Springer, Cham, pp. 55-73. https://doi.org/10.1007/978-3-319-78208-9_3

[17] Zaw, W.T., Naing, T.T. (2009). Modeling of rainfall prediction over Myanmar using polynomial regression. In 2009 International Conference on Computer Engineering and Technology, Singapore, pp. 316-320. https://doi.org/10.1109/ICCET.2009.157

[18] George, J., Janaki, L., Parameswaran Gomathy, J. (2016). Statistical downscaling using local polynomial regression for rainfall predictions – A case study. Water Resources Management, 30: 183-193. https://doi.org/10.1007/s11269-015-1154-0

[19] Chandler, R.E., Wheater, H.S. (2002). Analysis of rainfall variability using generalized linear models: A case study from the west of Ireland. Water Resources Research, 38(10): 10-1-10-11. https://doi.org/10.1029/2001WR000906

[20] Abreu, M.C., de Souza, A., Lyra, G.B., Pobocikova, I., Cecílio, R.A (2021). Analysis of monthly and annual rainfall variability using linear models in the state of Mato Grosso do Sul, Midwest of Brazil. International Journal of Climatology, 41: E2445-E2461. https://doi.org/10.1002/joc.6857

[21] Oloruntade, A.J., Mogaji, K.O., Imoukhuede, O.B. (2018). Rainfall trends and variability over Onitsha, Nigeria. Ruhuna Journal of Science, 9(2): 127-139. http://192.248.48.10/rjs/index.php/rjs/article/view/221.

[22] Nkuna, T.R., Odiyo, J.O. (2016). The relationship between temperature and rainfall variability in the Levubu sub-catchment, South Africa. International Journal of Education and Learning Systems, 1: 66-75. https://www.iaras.org/iaras/filedownloads/ijes/2016/008-0011.pdf.

[23] Aziz, O.I.A., Burn, D.H. (2006). Trends and variability in the hydrological regime of the Mackenzie River Basin. Journal of Hydrology, 319(1-4): 282-294. https://doi.org/10.1016/j.jhydrol.2005.06.039

[24] Ridwan, W.M., Sapitang, M., Aziz, A., Kushiar, K.F., Ahmed, A.N., El-Shafie, A. (2021). Rainfall forecasting model using machine learning methods: Case study Terengganu, Malaysia. Ain Shams Engineering Journal, 12(2): 1651-1663. https://doi.org/10.1016/j.asej.2020.09.011

[25] Oguntunde, P.G., Abiodun, B.J., Lischeid, G. (2011). Rainfall trends in Nigeria, 1901-2000. Journal of Hydrology, 411(3-4): 207-218. https://doi.org/10.1016/j.jhydrol.2011.09.037

[26] Smith, M. (2000). The application of climatic data for planning and management of sustainable rainfed and irrigated crop production. Agricultural and Forest Meteorology, 103(1-2): 99-108. https://doi.org/10.1016/S0168-1923(00)00121-0

[27] Xu, Z., Liu, Z., Fu, G., Chen, Y. (2010). Trends of major hydroclimatic variables in the Tarim River basin during the past 50 years. Journal of Arid Environments, 74(2): 256-267. https://doi.org/10.1016/j.jaridenv.2009.08.014

[28] Wang, D., Hejazi, M., Cai, X., Valocchi, A.J. (2011). Climate change impact on meteorological, agricultural, and hydrological drought in central Illinois. Water Resources Research, 47(9). https://doi.org/10.1029/2010WR009845

[29] Anghileri, D., Pianosi, F., Soncini-Sessa, R. (2014). Trend detection in seasonal data: From hydrology to water resources. Journal of Hydrology, 511: 171-179. https://doi.org/10.1016/j.jhydrol.2014.01.022

[30] Mondal, A., Kundu, S., Mukhopadhyay, A. (2012). Rainfall trend analysis by Mann-Kendall test: A case study of north-eastern part of Cuttack district, Orissa. International Journal of Geology, Earth and Environmental Sciences, 2(1): 70-78. https://www.researchgate.net/publication/268438767.

[31] Adefolalu, D.O. (2007). Climate change and economic sustainability in Nigeria. In International Conference on Climate Change and Economic Sustainablility, Nnamdi Azikiwe University, Enugu, Nigeria, pp. 12-14.

[32] Abaje, I.B., Ishaya, S., Usman, S.U. (2010). An analysis of rainfall trends in Kafanchan, Kaduna State, Nigeria. Research Journal of Environmental and Earth Sciences, 2(2): 89-96. https://www.researchgate.net/publication/49593845.

[33] Akinsanola, A.A., Ogunjobi, K.O. (2014). Analysis of rainfall and temperature variability over Nigeria. Global Journal of Human-Social Science: B Geography, Geo-Sciences, Environmental Disaster Management, 14(3): 1-17. https://globaljournals.org/GJHSS_Volume14/1-Analysis-of-Rainfall-and-Temperature.pdf.

[34] Gelaro, R., McCarty, W., Suárez, M.J., et al. (2017). The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). Journal of Climate, 30(14): 5419-5454. https://doi.org/10.1175/JCLI-D-16-0758.1

[35] Aweda, F.O., Olufemi, S.J., Agbolade, J.O. (2022). Meteorological parameters study and temperature forecasting in selected stations in Sub-Sahara Africa using MERRA-2 data. Nigerian Journal of Technological Development, 19(1): 80-91. http://doi.org/10.4314/njtd.v19i1.9

[36] Aweda, F.O., Akinpelu, J.A., Samson, T.K., Sanni, M., Olatinwo, B.S. (2022). Modeling and forecasting selected meteorological parameters for the environmental awareness in sub-Sahel West Africa stations. Journal of the Nigerian Society of Physical Sciences, 4(3): 820. http://doi.org/10.46481/jnsps.2022.820

[37] Aweda, F.O., Adeola, S.O., Adeniji, A.A., Adebayo, S., Akinpelu, J.A., Jegede, O.O. (2023). Temperature forecasting for Iwo City, Nigeria using statistical models and selected machine learning algorithms. IOP Conference Series: Earth and Environmental Science, 1219(1): 012027. http://doi.org/10.1088/1755-1315/1219/1/012027

[38] Aweda, F.O., Agbolade, J.O., Oyewole, J.A., Sanni, M. (2021). Seasonal variation of some atmospheric parameters in fresh water swamp and Sudan Savanna areas of Nigeria. Nigerian Journal of Technology, 40(4): 740-750. http://doi.org/10.4314/njt.v40i4.21

[39] Samson, T.K., Aweda, F.O. (2024). Forecasting rainfall in selected cities of Southwest Nigeria: A comparative study of random forest and long short-term memory models. Acadlore Transactions on Geosciences, 3(2): 79-

88. https://doi.org/10.56578/atg030202
[40] Samson, T.K., Aweda, F.O. (2024). Seasonal autoregressive integrated moving average modelling and forecasting of monthly rainfall in selected African stations. Mathematical Modelling of Engineering Problems. 11(1): 159-168. https://doi.org/10.18280/mmep.110117
[41] Aweda, F.O., Samson, T.K. (2024). Comparative analysis of trigonometric and polynomial models in meteorological parameter prediction for Sub-Saharan West African stations. Acadlore Transactions on Geosciences, 3(1): 1-12. https://doi.org/10.56578/atg030101