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Comparative Analysis of Trigonometric and Polynomial Models in Meteorological Parameter Prediction for Sub-Saharan West African Stations

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Abstract: Meteorological parameter modeling is imperative for predicting future atmospheric conditions. This study focuses on the Sub-Saharan region of West Africa, a region characterized by its climatic diversity and unique weather patterns, making it an ideal subject for meteorological research. The objective was to model meteorological parameters using trigonometric and polynomial functions, assessing their predictive accuracy in selected West African stations. The parameters considered include air temperature, air pressure, wind speed, rainfall, and relative humidity, with data sourced from the HelioClim satellite archive, spanning 1980 to 2022. The data, recorded in comma-separated value (CSV) format, were analyzed using descriptive statistics, specifically mean and standard deviation. Each meteorological parameter underwent modeling through both polynomial and trigonometric functions. The comparative effectiveness of these models was evaluated using the adjusted coefficient of determination and Root Mean Square Error (RMSE). The preference for the adjusted coefficient of determination over the standard coefficient of determination (R^2) was due to its ability to account for biases arising from variances in the number of parameters in both model types. The results indicated that both trigonometric and polynomial models are robust in their predictive capabilities, demonstrating their utility in accurate parameter estimation and future weather prediction. These findings suggest that such models are valuable tools in climate studies, enhancing understanding and awareness of weather conditions in the Sub-Saharan West African region.

Keywords: Meteorological modeling; Statistical analysis; Polynomial models; Trigonometric models; Climate research

1 Introduction

Energy's role in global development has been increasingly recognized as pivotal, as evidenced by extant research. Its significance extends beyond environmental improvement to encompass worldwide comfort and wellbeing [1]. The environmental performance of systems, particularly in the realms of heating, air conditioning, and ventilating of buildings, is influenced by solar cells and collectors, green power plants, and cooling towers. These systems depend on meteorological parameters such as air temperature, wind speed, wind direction, air pressure, and relative humidity, each contributing variably to the cooling and heating of the environment [2–5].

Research has shown that atmospheric energy consumption calculations, particularly in regions with high wind speeds, can be enhanced by incorporating wind speed parameters into energy generation models [6–11]. Precise planning, optimization, and performance forecasting of solar technology and environmental system control are fundamentally grounded in weather modeling [3, 4, 12–14]. However, the accessibility of meteorological data in Africa is hampered by several challenges. Financial constraints, mismanagement of funds by political office holders, and population migration are notable factors impeding energy production in African nations. The development of meteorological data characteristics for African energy production studies is based on these varied challenges. Additionally, various mathematical and statistical methods have been employed to determine data for forecasting and weather modeling in diverse settings. The creation of weather data modeling utilizes these methods [15–17]. Several studies have highlighted the influence of climatic factors on solar energy and the implications for energy concerns, particularly wind energy, in different global regions.

Calculations of Global Solar Radiation (GSR) have been undertaken by numerous researchers [18–20], yet these estimates often exhibit variations from the results reported by Kasten and Czeplak [21] and Poudyal et al. [22]. Such variations encompass factors like air pressure and air temperature [23], and the positioning of rainfall [24–27]. It has been noted that weather limitations, including relative humidity, air temperature, air pressure, wind speed and direction, as well as environmental elements like sand and haze, show tendencies to fluctuate over the years [28]. Research conducted by various authors [3, 28–32] indicates that climatic disparities in urban areas are significantly influenced by suburban activities due to environmental factors.

In studies focusing on correlation models for global diffuse and slanted irradiation [33], it was found that air temperature notably influences other weather variables, including sunshine hours and relative humidity, as observed in Valencia, Italy. The coefficient of determination for these models was reported to range between 0.75 and 0.85 [34]. Research has also been conducted to establish polynomial relationships between relative sunshine and the clearness index in various environments [35]. Over a span of 15 years, statistical analyses of worldwide insolation data were performed at six locations in Pakistan [36]. Additionally, Aweda et al. [3] have contributed to environmental awareness by modeling weather characteristics in selected African sub-stations. Regression models based on weather data collected in Oman between 1987 and 1992 have been developed for predicting future environmental developments [15, 37, 38].

The impact of climate change on national development has been acknowledged as either positive or negative, presenting a range of challenges. This variability can significantly influence global energy growth and development. Notably, there has been limited research on climatic studies in the African sub-region and Asian countries [17, 39, 40]. Consequently, this study aims to model meteorological parameters in selected Sub-Saharan West African stations through the comparison of trigonometric and polynomial functions. This approach intends to enhance occupant awareness by providing more accurate predictive models for meteorological parameters.

2 Material and Methods

2.1 Data Collection

For the purpose of this study, a range of meteorological variables was sourced from the HelioClim-1 Solar Radiation Data, as delineated in previous research [41]. These variables included air pressure, relative humidity, air temperature, rainfall, wind speed, and wind direction. Data retrieval occurred on March 5, 2023, and encompassed a time frame from January 1980 to December 2022, spanning 42 years. The data, in CSV format, were downloaded following protocols outlined in prior studies [37, 42].

2.2 Study Area

The study was conducted across selected locations within the West African sub-region, as indicated in Figure 1. Six sites were specifically chosen for their distinct geographic and climatic characteristics: Abidjan, Abuja, Bamako, Conakry, Dakar, and Niamey. Data spanning from 1980 to 2022 were utilized for all these stations. Distinctions between hinterland and coastal regions at each station were systematically tabulated (Table 1), providing a clear differentiation of the geographical context of each location.

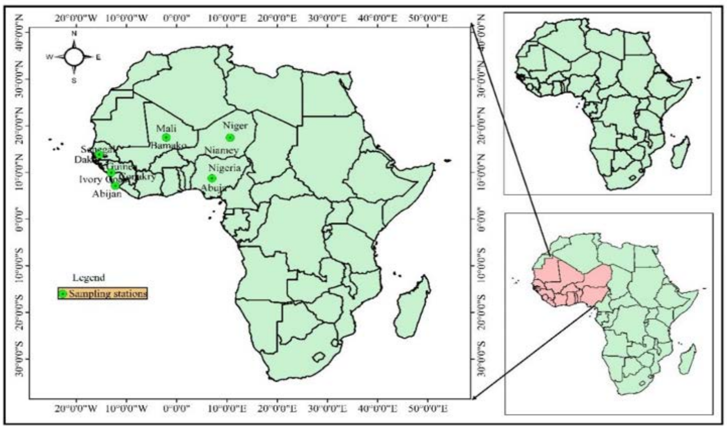

Figure 1. Map of selected West Africa pinpointing stations of the study

Table 1. Separation of the hinterland and coastal regions of the African stations

Location	Geographical Distinction	Nation	Longitude	Latitude	Data Timeframe
Abidjan	Coastal region	Cote d'Ivoire	04.008°W	05.360°N	1980 – 2022
Abuja	Hinterland region	Nigeria	07.399°W	09.077°N	1980 – 2022
Bamako	Hinterland region	Mali	08.003°W	12.639°N	1980 – 2022
Conakry	Coastal region	Guinea	13.578°W	09.641°N	1980 – 2022
Dakar	Coastal region	Senegal	17.366°W	14.765°N	1980 – 2022
Niamey	Hinterland region	Niger	12.125°W	13.512°N	1980 – 2022

2.3 Statistical Analysis

The collected data were subjected to descriptive statistical analysis, specifically employing mean and standard deviation, to evaluate the meteorological parameters. Subsequently, these parameters were modeled using both polynomial and trigonometric functions. To compare the efficacy of these models, the adjusted coefficient of determination and RMSE were utilized. The preference for the adjusted coefficient of determination over the standard coefficient of determination (R^2) was to mitigate biases arising from the differences in the number of parameters in the polynomial and trigonometric models. In instances where a contradiction between the adjusted R^2 and RMSE was observed, the RMSE was given precedence. This was due to its focus on measuring the agreement between actual and predicted values, which is crucial for this study. The parameters of these functions were estimated using the Econometric View (E-view 7.0) software. Statistical significance was determined at a 5% threshold, with a p-value of less than 0.05 deemed to indicate statistical significance. Table 2 provides a comprehensive summary of the functions employed in this study, with 'm' representing the month in all equations.

Table 2. Summary of the models used in the study

S/N	Meteorological Parameters	Trigonometric Function	Polynomial Function
1	Temperature	$T = a + b\sin(m) + c\sin\left(\frac{m}{2} + d\right)$	$T = a + b.m + c.\left(m^2\right) + d.\left(m^3\right) + e.\left(m^4\right)$
2	Relative humidity	$RH = a + b\sin(m) + c\sin\left(\frac{m}{2} + d\right)$	$RH = a + b.m + c.\left(m^2\right) + d.\left(m^3\right) + e.\left(m^4\right)$
3	Pressure	$P = a + b\sin(m) + c\sin\left(\frac{m}{2} + d\right)$	$P = a + b.m + c.\left(m^2\right) + d.\left(m^3\right) + e.\left(m^4\right)$
4	Wind speed	$WS = a + b\sin(m) + c\sin\left(\frac{m}{2} + d\right)$	$WS = a + b \cdot m + c \cdot \left(m^2\right) + d \cdot \left(m^3\right) + e \cdot \left(m^4\right)$
5	Rainfall	$RF = a + b\sin(m) + c\sin\left(\frac{m}{2} + d\right)$	$RF = a + b \cdot m + c \cdot \left(m^2\right) + d \cdot \left(m^3\right) + e.\left(m^4\right)$

3 Results and Discussion

Table 3 delineates the results from the comparative analysis of polynomial and trigonometric functions in modeling meteorological parameters across six African capital cities. It was observed that the trigonometric function exhibited superior performance over the polynomial function in modeling temperature for Abidjan (Adj. R^2 = 0.987627, RMSE = 0.110032), Abuja (Adj. R^2 = 0.569552, RMSE = 0.761431), Bamako (Adj. R^2 = 0.854366, RMSE = 0.940537), Conakry (Adj. R^2 = 0.964589, RMSE = 0.098281), and Niamey (Adj. R^2 = 0.876062, RMSE = 0.999433). However, in Dakar (Adj. R2 = 0.937577, RMSE = 1.0258864), the polynomial function outperformed the trigonometric model (Table 2). In the cases of Abidjan, Abuja, and Bamako, the trigonometric function yielded more accurate predictions for atmospheric pressure compared to the polynomial function, whereas in other locations, the polynomial model provided superior results. Regarding wind speed, the trigonometric function was found to be more effective in Abidjan, Abuja, Bamako, and Niamey, while in Conakry and Dakar, the polynomial function demonstrated better performance (Table 3). Additionally, the trigonometric function consistently resulted in lower RMSE for rainfall across all locations compared to the polynomial function (Table 2).

In subgraph (A) of Figure 2 illustrates the trend in mean monthly temperature, showing a consistent decrease in Abidjan and Abuja, while in Bamako, Conakry, Dakar, and Niamey, a decline was observed between July and August (Figure 2). Mean monthly relative humidity across all locations was found to increase consistently from January to August in subgraph (D) of Figure 2). Air pressure remained relatively constant throughout the year with minor variations month-to-month in subgraph (C) of Figure 2. From January to April, a consistent decrease in monthly mean wind speed was recorded in Bamako, Dakar, and Niamey, whereas in Abidjan, an increase was noted from

February to March, followed by a decrease towards year-end in subgraph (D) of Figure 2. A rise in monthly mean rainfall was observed in all locations from January to mid-year, followed by a consistent decrease towards year-end in subgraph (E) of Figure 2).

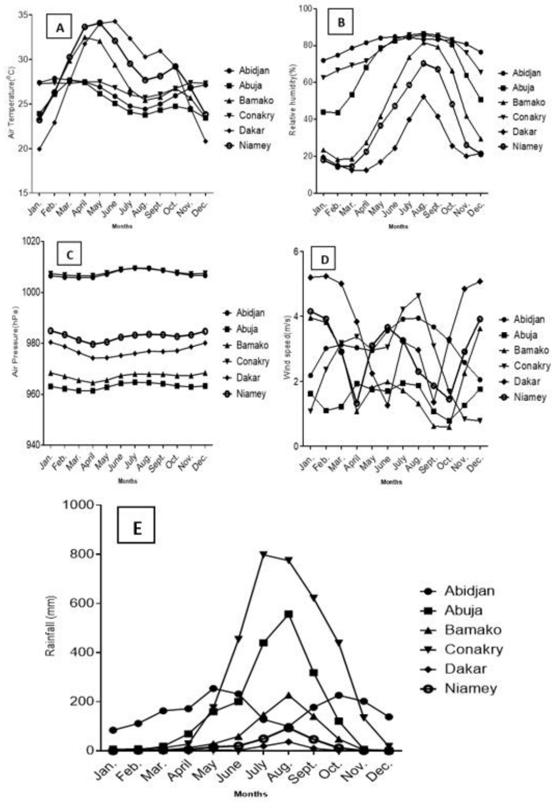

Figure 2. Average monthly Air temperature (A), relative humidity (B), air pressure (C), wind speed (D), and rainfall (E) in the selected African capital cities

The analysis of the monthly variations in meteorological parameters across the studied stations, as depicted in Figure 1, revealed distinct patterns. Air temperature exhibited a sinusoidal trend, peaking around April, May, and June, as shown in subgraph (A) of Figure 2. This period represents the hottest months across all observed stations. Notably, Dakar and Abidjan recorded the highest temperatures, ranging between 34.5℃ and 34.7℃. The cooler months, specifically January and December, were characterized by lower temperatures in Dakar, approximately 20℃. August, typically the wettest month in Africa, marked a significant temperature decline at all stations. It has been observed that Dakar, influenced by the country's distinctive natural characteristics and the implications of human activities, exhibits a notable range in temperature extremes.

Air temperature and relative humidity are interconnected meteorological parameters. The study found that air temperature significantly influences relative humidity, which varied between 15% to 80% across the different study areas, as shown in subgraph (B) of Figure 2. The highest relative humidity levels, around 80%, were recorded in Abidjan, Conakry, and Abuja. Dakar exhibited the lowest relative humidity, indicating a wetter climate possibly influenced by the city's topography. It is established that meteorological factors such as cloud cover, wind speed, and rainfall impact relative humidity. A notable decrease in relative humidity was observed in January at all stations, potentially due to the onset of winter conditions.

It was observed from subgraph (C) of Figure 2 that Conakry and Abidjan registered the highest air pressure readings, each measuring 1005 hPa, predominantly in July. While these peak values were recorded during this month, the average pressure for both locations typically fluctuated around 1000 hPa. The investigation further revealed a gradual increase in atmospheric pressure, culminating in the highest recorded values in July. Conversely, the lowest temperature readings across all the observed stations were recorded in the same month, indicating a significant correlation between air pressure and temperature. Specifically, higher air temperatures were associated with elevated air pressure. Abuja, in contrast, exhibited the lowest air pressure, approximately 960 hPa, noted in March. An increase in air pressure was observed in December, following a consistent decline in November. Notably, November emerged as the month with the second-highest temperatures across all study locations.

Further analysis, as depicted in subgraph (D) of Figure 2, focused on wind speed measurements in selected West

African sites. The highest wind speed was recorded in Dakar, reaching 5.3 m/s, while Bamako reported the lowest at 0.56 m/s. The average minimum wind speed across all stations was identified as 1.5 m/s. These findings suggest that the wind speeds in West African stations are generally low, rendering these locations less suitable for wind energy production.

Rainfall patterns, as shown in subgraph (E) of Figure 2, revealed that rainfall was relatively low during January, February, March, April, October, November, and December. Conakry experienced the highest rainfall in July, indicating favorable climatic conditions for its inhabitants. A gradual increase in rainfall was observed across all locations, peaking in July. This indicates that July is the month of highest rainfall. In contrast, Abuja experienced its heaviest rainfall in August, approximately 500 mm. Other locations like Abidjan, Bamako, and Dakar also recorded significant rainfall values. Notably, the values highlighted in bold represent the highest adjusted R^2 and the lowest RMSE, indicating the most effective model for each parameter and city.

Table 3, Table 4, Table 5 encompass monthly parameter estimates from 1980 to 2022 for air temperature, air pressure, wind speed, rainfall, and relative humidity across the West African stations. These meteorological characteristics were derived from the HelioClim satellite's archive and modeled using specifically developed polynomial and trigonometric models. The models' parameters (a, b, c, d, and e) were determined based on the predictor variable for the 12 calendar months. Figure 3, Figure 4, Figure 5, Figure 6, Figure 7 graphically represent the outcomes of the data under investigation, offering visual insights into the temporal patterns and variations of these meteorological parameters.

Table 3. Summary of the models used in the study

		Polynomial Function		**Trigonometric Function**	
Parameters	Cities	Adj. R^2	RMSE	Adj. R^2	RMSE
Temperature	Abidjan	0.821035	0.418463	**0.987627**	**0.110032**
	Abuja	0.553166	0.775788	**0.569552**	**0.761431**
	Bamako	0.711436	1.323932	**0.8543662**	**0.940537**
	Conakry	0.610523	0.325944	**0.964589**	**0.098281**
	Daka	**0.937577**	**1.0258864**	0.936335	1.036024
	Niamey	0.767679	1.368343	**0.876062**	**0.999433**
Relative humidity	Abidjan	**0.965789**	**0.633172**	0.957141	0.708694
	Abuja	0.956999	2.818256	**0.968617**	**2.407623**
	Bamako	0.937462	4.921210	**0.987659**	**2.186102**
	Conakry	**0.987303**	**0.811618**	0.940283	1.760160
	Daka	0.575555	6.770688	**0.923755**	**2.869646**
	Niamey	0.871642	6.031381	**0.966022**	**3.103150**
Pressure	Abidjan	0.650581	0.353862	**0.910264**	**0.344415**
	Abuja	0.458817	**0.315741**	**0.703239**	0.502397
	Bamako	0.478922	**0.486730**	**0.621890**	0.630402
	Conakry	0.498133	**0.284950**	**0.799790**	0.376006
	Daka	**0.879559**	**0.536230**	0.873317	0.599942
	Niamey	0.559615	**0.639941**	**0.692521**	0.714088
Wind speed	Abidjan	0.799428	**0.218187**	**0.800379**	0.224606
	Abuja	-0.114642	0.184043	**-0.021995**	0.324418
	Bamako	**0.676810**	**0.476439**	0.604958	0.613943
	Conakry	**0.705858**	**0.558136**	0.827614	0.431710
	Daka	0.618720	0.687925	**0.676000**	**0.684713**
	Niamey	**0.062119**	**0.584839**	0.005871	0.791989
Rainfall	Abidjan	0.095654	40.67009	**0.686795**	**25.21385**
	Abuja	0.620787	78.09367	**0.914404**	**45.04271**
	Bamako	0.575719	36.27035	**0.897049**	**19.63651**
	Conakry	0.810411	89.81055	**0.984948**	**31.23856**
	Daka	0.243695	7.316231	**0.640960**	**5.444344**
	Niamey	0.460500	15.84816	**0.798712**	**10.46585**

In Table 4, the comparative analysis of the best models for temperature and relative humidity across various African cities is presented. For Abidjan, the trigonometric model was identified as the most effective for temperature, evidenced by an adjusted R^2 of 0.987627 and RMSE of 0.110032 (Table 3), and a significant p-value of less than 0.01 . In contrast, the polynomial model was found to be superior for relative humidity in Abidjan, as indicated by an adjusted R^2 of 0.965789 and RMSE of 0.633172 (Table 3), with a p-value signifying significance at the 5% level (Table 4).

Table 4. Parameter estimates for the best models for temperature and relative humidity across various African cities

			Temperature				**Relative Humidity**	
Cities	BM	MP	Estimates	P-value	BM	MP	Estimates	P-value
		a	26.49385			a	66.12922	
		b	-0.447818			b	5.799516	
Abidjan	Trig.	c	1.562093	$0.000**$	Poly.	c	-0.579862	0.0000**
		d	0.664873			d	0.024093	
		e	-			e	-0.000817	
		a	25.07733			a	67.34932	
		b	-0.491269			b	-3.049751	
Abuja	Trig.	c	1.483299	0.02045*	Trig	c	-22.46636	0.0000**
		d	-0.275201			d	7.260378	
		e	-			e	-	
		a	27.15154			a	45.65734	
		b	-1.925019			b	5.320054	
Bamako	Trig.	c	3.358603	$0.0002**$	Trig.	c	-31.92620	0.0000**
		d	-0.875937			d	6.917727	
		e	-			e	-	
		a	26.94685			a	62.95621	
		b	-0.452497			b	-1.097139	
Conakry	Trig.	c	0.712343	0.0000**	Poly.	c	1.344814	0.0000**
		d	19.49772			d	-0.106692	
		e	-			e	0.000305	
		a	13.00654			a	24.80436	
		b	6.728311			b	8.130538	
Dakar	Poly.	c	-0.558213	0.0000**	Trig.	c	-14.35138	0.000023**
		d	-0.002020			d	6.800895	
		e	0.000542			e	-	
		a	28.54337			a	36.15838	
		b	-2.142196			b	6.257349	
Niamey	Trig.	c	-4.037011	$0.0002**$	Trig.	c	-26.83707	0.000001**
		d	8.177715			d	7.021166	
		e	-			e	-	

**Significant at 1% (p¡.01), *significant at 5 %(p¡.05), BM- Best model, MP - model parameters

Similarly, in Abuja, Bamako, and Conakry, the trigonometric model showed better performance for temperature, while for Dakar, the polynomial regression model was more effective (adjusted $\mathrm{R}^2 = 0.937577, \mathrm{RMSE} = 1.0258864$) as outlined in Table 3.

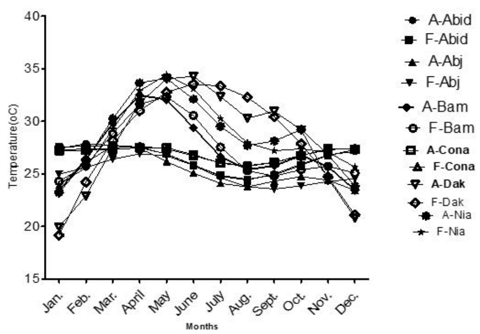

Figure 3. Graph of the actual and predicted temperature for the different African cities. The designations "A" and "F" precede city abbreviations to denote 'actual' and 'predicted' data, respectively.

In the analysis presented in Table 4, trigonometric models were identified as the most effective for relative humidity in Abuja, Bamako, Dakar, and Niamey, as indicated by high adjusted R^2 values and low RMSEs. Conversely, in Abidjan and Conakry, polynomial models demonstrated superior performance (Table 3). Table 4 summarizes the best model estimates for temperature and relative humidity, with all study locations showing significant p-values, ranging

Table 5. Parameter estimates for the best models for pressure and wind speed

		Pressure				**Wind Speed**		
City	BM	MP	Estimates	P-value	BMA	MP	Estimates	P-value
		a	1007.348			a	1.943611	
		b	0.571421			b	0.496931	
Abidjan	Trig.	c	-1.751883	0.0000**	Poly.	c	-0.079811	0.003827 ∗∗
		d	13.36563			d	0.010696	
		e	-			e	-0.000627	
		a	963.1581			a	2.767525	
		b	0.477319			b	-1.750868	
Abuja	Trig.	c	-1.249084	0.02045**	Poly.	c	0.630849	0.024520**
		d	13.07528			d	-0.079500	
		e	-			e	0.003212	
		a	967.1373			a	6.294823	
		b	0.778008			b	-2.563289	
Bamako	Trig.	c	-1.195484	0.0002**	Poly:	c	0.633935	0.00839**
		d	12.09733			d	-0.075196	
		e	-			e	0.003221	
		a	1011.128			a	2.538059	
		b	-4.859096			b	0.609879	
Conakry	Poly	c	1.536227	0.0007 ∗∗	Trig.	c	1.511391	0.000577 ∗∗
		d	-0.167237			d	11.05659	
		e	0.005901			e	-	
		a	985.8604			a	3.707578	
		b	-5.918450			b	0.214354	
Dakar	Poly-	c	1.114903	0.0005**	Trig.	c	-1.773804	0.006833**
		d	-0.086875			d	10.57882	
		e	0.002639			e	-	
		a	991.9065			a	2.921020	
		b	-8.127671			b	0.361979	
Niamey	Poly	c	1.998818	0.0095**	Poly.	c	-0.594285	0.432696**
		d	-0.191172			d	10.17621	
		e	0.006395			e	-	

**Significant at 1% (p¡.01), *significant at 5%(p¡.05), BM- Best model, MP - model parameters

between 0.0000 and 0.02045 for pressure, and between 0.000577 and 0.432696 for wind speed. The regression results were significant at all stations for pressure ($p<.05$), except for wind speed in Niamey, where the regression did not reach significance ($p<.05$) as shown in Table 5.

Regarding wind speed, polynomial functions were determined to be the best model for Abidjan, Abuja, and Bamako, while trigonometric models were more suitable for Conakry, Dakar, and Niamey (Table 3). For rainfall, trigonometric functions consistently outperformed polynomial functions across all considered stations (Table 3), with p-values below 0.05, indicating a well-fitting model (Table 6).

The range of wind speed values across the studied stations was determined to be between 2.538059 and 3.707578 m/s. The p-values for these stations varied from 0.003827 to 0.432696. When these results were compared with those documented in source [5], it was evident that the models used in this study yielded improved performance. This enhancement in predictive accuracy can be ascribed to the specific climatic conditions prevailing at the examined stations. Furthermore, it was ascertained that the polynomial function exhibited superior performance over the trigonometric function in modeling both air pressure and wind speed. As presented in Table 6, the significance of the models was affirmed by p-values less than 0.05 (p¡.05) at all stations, validating the statistical significance of the models in these contexts.

The results were further validated by plotting graphs of the actual versus predicted monthly mean for each meteorological parameter in each of the six African capital cities. These visual representations, as illustrated in Figure 3, Figure 4, Figure 5, Figure 6, Figure 7, revealed a general agreement between actual and predicted values for all meteorological parameters, except for rainfall, where some discrepancies were observed in certain months (Figure 7).

This format is consistent across 3, Figure 4, Figure 5, Figure 6, Figure 7, facilitating easy comparison between actual observations and model predictions for each city.

Table 6. Parameter estimates for the best models for rainfall

City	BM	MP	Estimates	P-value
Abidjan	Trig.	a	163.5817	0.005990 ∗∗
		b	-58.81370	
		c	28.22748	
		d	4.452345	
Abuja	Trig.	a	149.4851	0.000036 ∗∗
		b	101.6396	
		c	225.8660	
		d	4.111632	
Bamako	Trig.	a	53.29268	0.000075 ∗∗
		b	47.27955	
		c	84.67203	
		d	3.948423	
Conakry	Trig.	a	275.6750	0.000000 ∗∗
		b	137.4656	
		c	395.9395	
		d	3.916508	
Daka	Trig.	a	5.894232	0.010172 ∗∗
		b	7.461341	
		c	10.45099	
		d	4.023459	
Niamey	Trig.	a	19.64075	0.001062 ∗∗
		b	18.19402	
		c	30.52752	
		d	4.013247	

**Significant at 1% (p¡.01), *significant at 5 %(p¡.05), BM- Best model, MP - model parameters

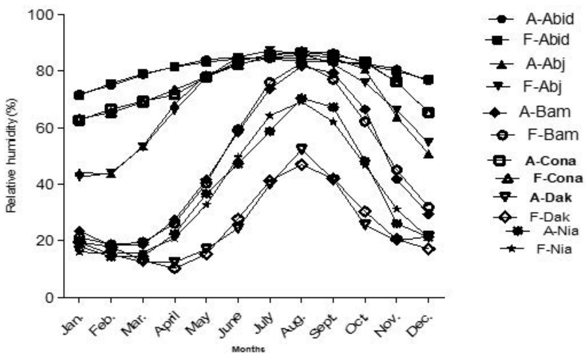

Figure 4. Graph of the actual and predicted relative humidity for the different African cities

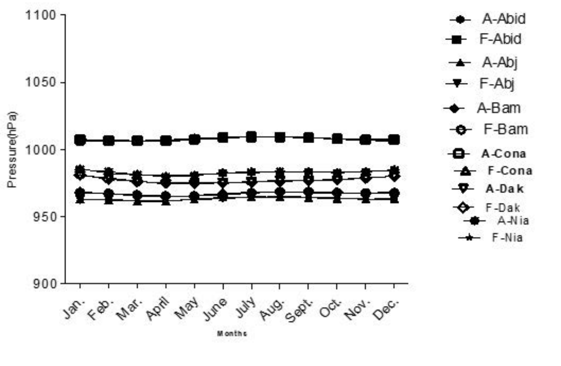

Figure 5. Graph of the actual and predicted pressure for the different African cities

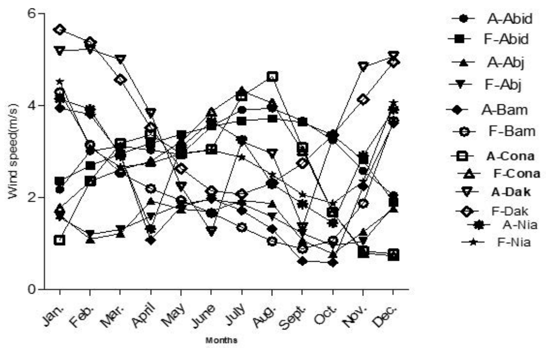

Figure 6. Graph of the actual and predicted wind speed for the different African cities

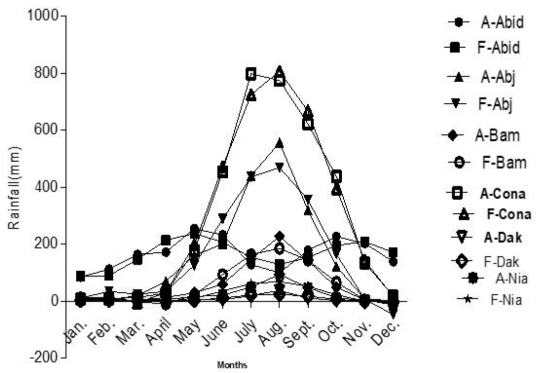

Figure 7. Graph of the actual and predicted rainfall for the different African cities

4 Conclusion

This study, utilizing data from the HelioClim satellite archive, analyzed meteorological variables including air temperature, air pressure, wind speed, relative humidity, and rainfall in selected Sub-Saharan West African stations. The study employed five-parameter models (a, b, c, d, and e) and concluded that trigonometric and polynomial functions were the most suitable for modeling these meteorological parameters. Notably, Dakar was observed to experience both the highest and lowest temperatures, while Abidjan and Dakar recorded the highest and lowest relative humidity, respectively. Conakry exhibited the highest air pressure, with Abuja having the lowest. In terms of wind speed, Dakar reported the highest values, whereas Bamako had the lowest. Furthermore, Conakry experienced the highest rainfall, contrasting with Dakar's minimal precipitation.

The regression analysis of the weather data indicated that air temperature had a higher RMSE than other factors, with the polynomial function generally outperforming the trigonometric function. However, for air pressure predictions, the trigonometric function was more accurate in Abidjan, Abuja, and Bamako, while the polynomial function was preferable in other locations. For wind speed, the trigonometric function surpassed the polynomial model in Abidjan, Abuja, Bamako, and Niamey, whereas the opposite was true for Conakry and Dakar. Moreover, the trigonometric function consistently yielded the lowest RMSE for rainfall across all locations. The study posits that the developed models can serve as effective tools in climatic studies, enhancing understanding of weather conditions in various regions.

Therefore, this study concludes that the trigonometric function generally demonstrates superior performance in modeling meteorological parameters in most West African stations assessed. This work could guide further research and development in Africa's meteorological studies.

5 Recommendation

It is recommended that African governments prioritize the establishment of more research centers dedicated to data collection for research and application. This initiative is crucial for raising awareness about environmental cleanliness and the urgent need to curb deforestation and bush burning across the continent. Such practices contribute to ozone depletion, potentially leading to increased solar radiation and adversely affecting agricultural productivity. Furthermore, it is imperative that African governments formulate and implement policies to mitigate environmental pollution and disruptions, which have significantly contributed to the continent's ecological challenges.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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