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Analyzing and forecasting rainfall patterns in the Manga-Bawku area, northeastern Ghana: Possible implication of climate change

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ABSTRACT

Understanding rainfall processes is crucial in addressing several hydrological challenges that have both positive and negative impacts on agriculture, climate change, and natural hazards including floods and droughts. Statistical modeling is a key instrument for studying these processes. This study presents the trends and forecasted rainfall patterns from 2017 to 2035 in the Manga-Bawku area, northeastern Ghana using rainfall data spanning from 1976 to 2016. The simple seasonal exponential smoothing and ARIMA (0,1,1) models were employed in this study while the R software and the Statistical Package for the Social Sciences were the modeling tools used in this study. The results obtained from the test of the efficiency of the forecast model showed a Stationary R-squared value of 0.698 and 0.669, Root-Mean-Square Deviation (RMSE) of 48.775 and 50.717, and normalized Bayesian Information Criteria (BIC) of 7.800 and 7.904 for the exponential smoothing and ARIMA (0,1,1) models respectively. This indicated that the models are a good fit for the time-series analysis. However, a line plot of the two models and observed data showed that the simple seasonal exponential smoothing model was a better fit. The Autocorrelation Function (ACF) plot showed that coefficient values were recorded in equal time lags. The peak recorded at lag 1 was similar to lags 12 and 24 which suggest that the seasonal component in the time series occurred within twelve months. The study further showed that the seasonal component was uniform on an annual basis which signifies that it was an additive impact instead of multiplicative effect. The rainfall forecast predicts a decline in rainfall levels over the next 19 years. This suggests the need for proper water resources planning, and the formulation of policies to curtail the factors that are likely to have debilitating impacts on the local hydrological system.

1. Introduction

The distribution and variability of rainfall are signals to predicting the occurrence and impacts of climate change since its variation has debilitating implications on food security, freshwater resources and economic growth and development (Cruz et al., 2007; Ekwe et al., 2014; Ampadu et al., 2019). Studies by Bedeke et al. (2020), Chase et al. (2020), and Sidibe et al. (2020) have respectively shown dramatic climatic changes in East Africa, South Africa, and West and Central Africa. Corroborative to these studies, Adiku and Stone (1995), Dietz et al. (2020), Yaro (2013), Kumasi et al. (2019), and Yomo et al. (2020) indicated a decline in Ghana's annual rainfall which results in extreme weather and climatic conditions including the occurrence and prolonged drought and flood which affect social, economic, health and agricultural systems. Sraku-Lartey et al. (2020) discussed an increase in temperature in Ghana from 1960 to 2000. The study further predicts an increase of 0.6 °C, 2.0 °C, and 3.9 °C by 2020, 2050, and 2080 respectively.

In Ghana, most farmers rely on weather patterns and natural phenomena to predict rainfall, forecast cropping season, and possible weather condition (Adiku et al., 2007). However, Roncoli et al. (2001) and Twenefour et al. (2018) showed that the changes and variations in climatic conditions in recent times have increased, making local observations and predictions less accurate and unreliable for agricultural planning and decision-making. Therefore, adopting the use of hydrological models to understand the prevailing changes and making projections has become essential in supporting man's livelihood.

Also, climate change has become a threat to the livelihoods of most Ghanaians. The occurrence of droughts and flooding in certain parts of the country are becoming worrisome they affect fishing, and farming

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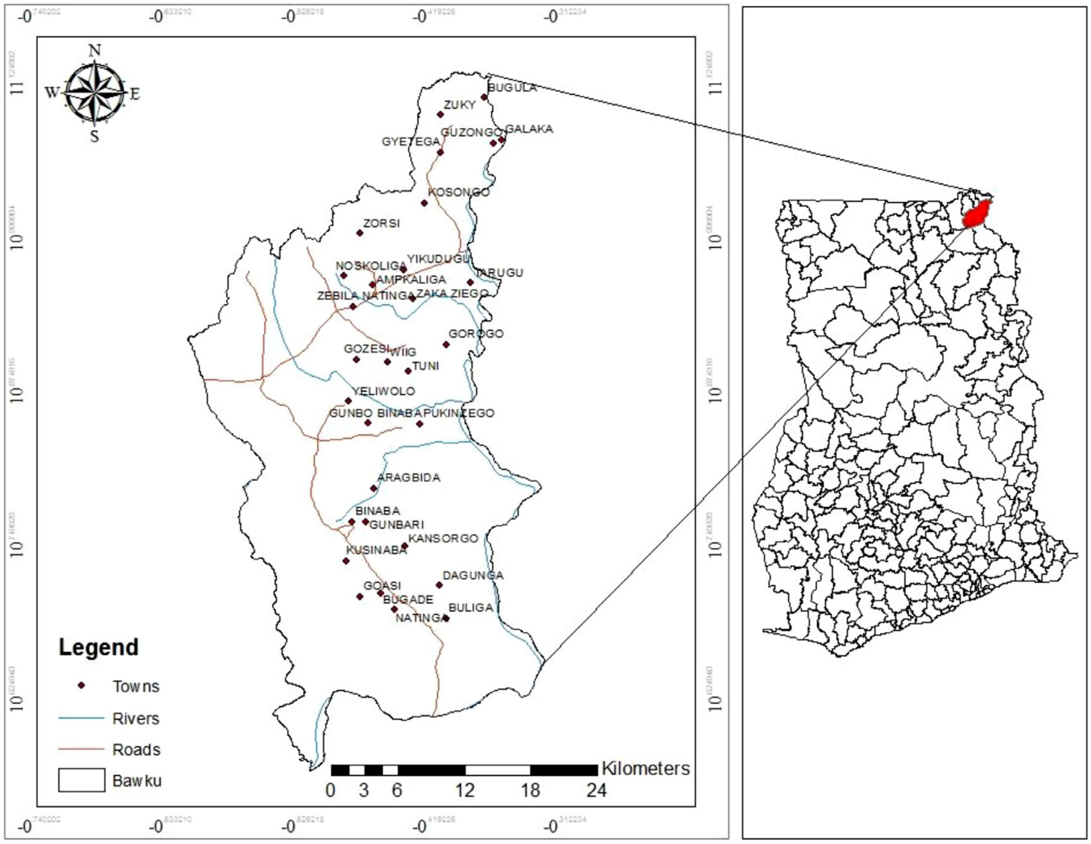

Fig. 1. Map of the study area.

in the coastal, middle and northern zones of Ghana, even in areas that were considered drought and flood-resistant. These factors have debilitating impacts on both local and national economies. In a communiqué by Daily Graphic (2015), the country's capital (Accra) has been hit by flooding dating to 1968. In 2010, 161,000 people were displaced nationwide and in 2011, flooding displaced 43,000 and 14 deaths. In the same period, 105 farms were destroyed with 5 deaths in Atiwa. Similarly, the Upper East and West, and Northern Regions were extirpated by flooding in 1999 and 2007. Based on this, Abdul-Aziz et al. (2013) mentioned that the Government of Ghana urges researchers to tackle climate change and its associated impacts.

Rainfall in Ghana has become variable compared to the early 1970s–1980s (Ampadu et al., 2019). This makes it difficult to determine long-term trends in rainfall. This has made efficient planning and management of water resources to meet food production targets by farmers and urban planning essential. Manga-Bawku falls within sub-Saharan Africa which has experienced more frequent and more intense climate extremes over the past decades, and the ramifications of the world's warming by more than 1.5 °C would be profound. The area is characterized by a dry sub-humid climate. Therefore, developing a model for predicting changing rainfall patterns or utilizing available forecasted information has become prudent to forecast trends in the rainfall understanding the spatiotemporality and shifting rainfall patterns in the area for agricultural and livelihood planning, forecasting the occurrence of climate-related disasters such as floods and droughts, promoting public health, and providing stakeholders with empirical information for policy formulation and decision-making. Studies by Delleur and Kavvas (1978), Singh and Borah (2013), Dastorani et al. (2016), and Singh (2018a), (2018b), (2021) have shown the effectiveness of time series in forecasting rainfall. Based on these, this study employs time series analysis to understand past and current trends of rainfall in a systematic approach and also helps in fitting models for forecasting rainfall patterns to manage future occurrences that may pose debilitating impacts.

2. Materials and methods

2.1. Study area description

Manga-Bawku is located in the Bawku Municipality in the northeastern part of Ghana. The area falls within latitudes 10° and 11° north and longitudes 0° and 1° west with a land cover of about 8842 km^2. The Municipality borders Burkina Faso, Garu-Tempane District, Binduri District, and Bawku West District, and Pusiga District to the north, south, east, and west respectively (Fig. 1). It has a population of 98,538 with a majority of its inhabitants engaged in agriculture. The area falls within the semi-arid zone of Ghana and is characterized by a mono-modal rainfall spanning from May to September with a mean rainfall ranging between 800 and 1100 mm. The study site lies within the interior continental climatic zone which is characterized by profound long-term dryness and a short-wet season. It is underlain by various granitic suites of rocks belonging to the Paleoproterozoic Birimian Domain of Ghana (Ghana Statistical Service, 2014; Kazapoe et al., 2019).

2.2. Data collection and analysis

To understand the rainfall variability in the Bawku catchment, average daily rainfall and temperature data from January to December were aggregated as monthly rainfall data from 1976 to 2016 (41 years) obtained from the Ghana Meteorological Agency, Upper East Region was used. This study considered a model-based approach using obtained real-time data. Missing data were estimated using linear interpolation of the data of the same months of the adjacent year. The observed data was used to forecast rainfall for the next 19 years which are from the year

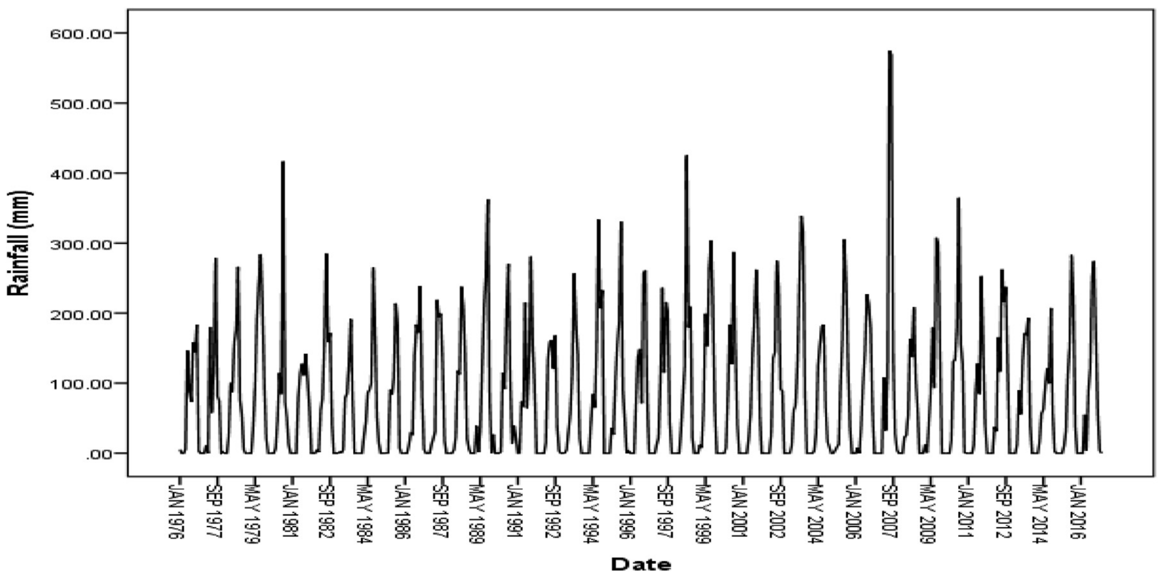

Fig. 2. Time plot of rainfall data.

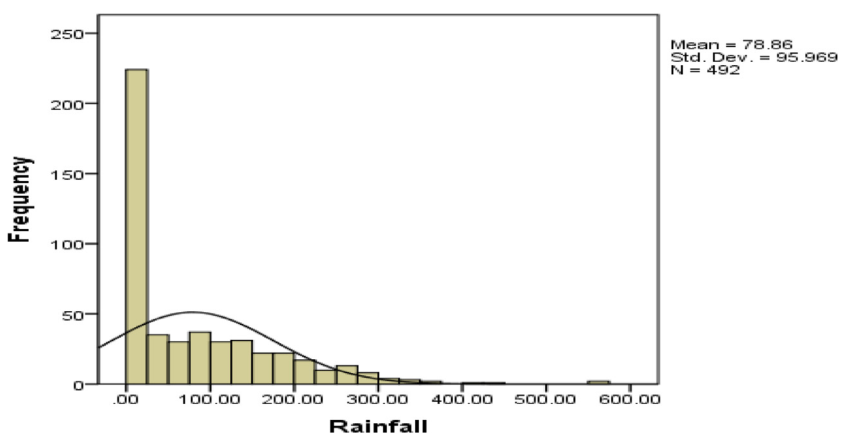

Fig. 3. Histogram with a normal curve.

2017 to 2035. The *R* software (version 4.1.0) and the Statistical Package for the Social Sciences (SPSS version 20) were used for the analyses of the data.

2.3. Rainfall time-series analysis

The time plot of the rainfall data depicts that rainfall was nearly evenly distributed (Fig. 2). The occurrence of rainfall within the study area has been erratic over the past four decades of the data collection for this study. The distribution reveals repeated peaks in June and July indicating non-stationarity in the rainfall distribution. The normal curve plotted using the time series data presented in Fig. 3 showed that the data distribution was skewed. The normal Q-Q plot of the rainfall data further showed that the data was not normally distributed (Fig. 4). The test of normality analysis (Supplementary Table 1) also showcased both the Kolmogorov-Smirnov test and the Shapiro-Wilk test with a significance value of .000 which suggest an erratic distribution of rainfall within the study area and thus we reject the null hypothesis that the data is normally distributed. Due to the abnormal distribution of the rainfall data and the duration of the data distribution, the most appropriate model for the time series would be an exponential smoothing model. The non-stationarity observed in the time plot could be due to trend, seasonality, or cyclical variations.

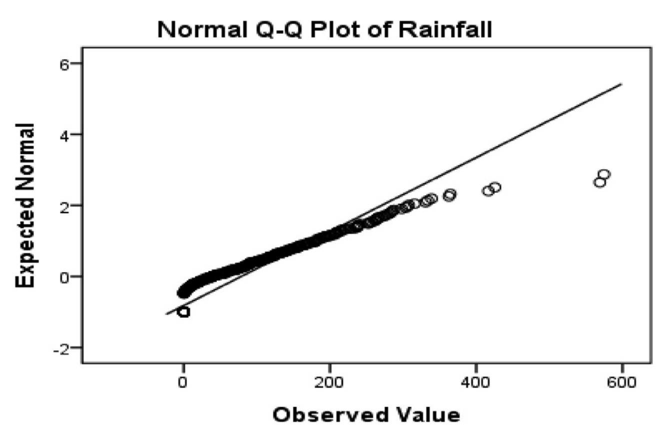

Fig. 4. Normal Q-Q plot of the time series.

2.4. Trend and seasonal analyses of time series data

To ascertain if the non-stationarity of the time series was due to trend behavior, the Mann-Kendall trend test which is a non-parametric hypothesis test (Generally distribution-free test) was applied. The test detects trends in time series data but does not quantify the size of the

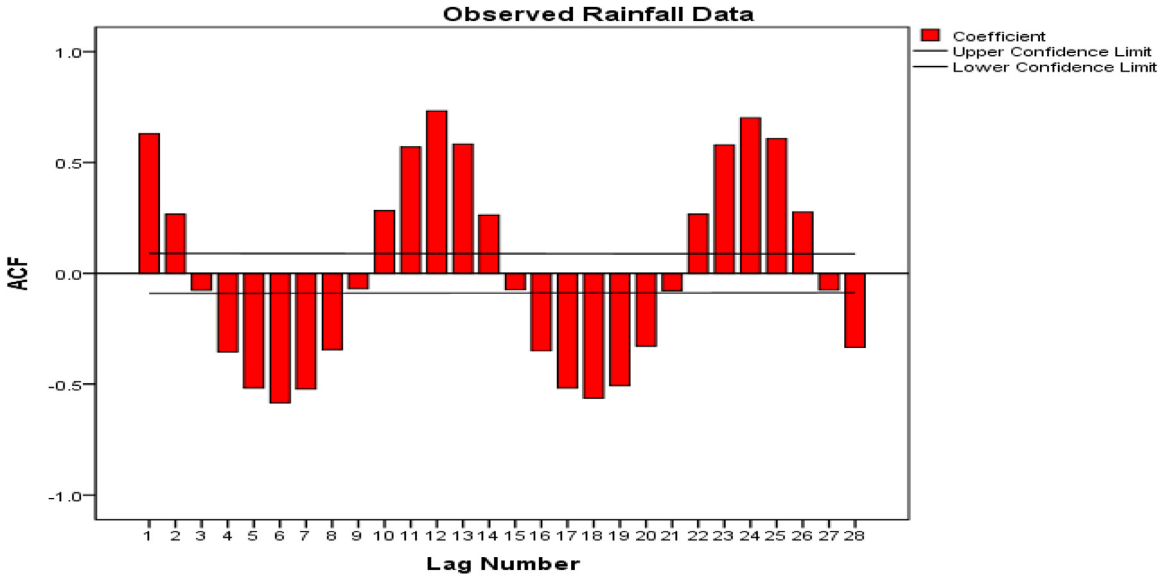

Fig. 5. Autocorrelation function plot of rainfall data.

Table 1
Mann-Kendall trend test/Two-tailed test (Rainfall).

Test	Output
Kendall's tau	0.017
S	1933.000
Var(S)	12863282.333
p-value (Two-tailed)	0.590
Alpha	0.050

trend. The null hypothesis (H_o) of the test is that 'there is no trend in the data' whereas the alternate hypothesis (H_1) asserts that 'there is a trend in the data'. As shown in Table 1, the computed *p*-value (0.590) is greater than the significance level, alpha (0.050). Hence, we fail to reject the null hypothesis and conclude that there is no trend behavior in the time series data.

The Autocorrelation Function (ACF) plot is used to detect the association and strength between a variable's existing values and its previous values. The patterns detected is useful in determining the characteristics of any time series such as its seasonal component and properties. The strength of the association is detected using the coefficient values. A coefficient of positive 1 indicates a perfect positive correlation whereas a coefficient of negative 1 also indicates a perfect negative correlation. From the ACF plot (Fig. 5), it can be observed that similar coefficients have been recorded in equal time lags. The peak recorded at lag 1 is similar to that of lags 12 and 24 (Fig. 5). Since the time series has 12 months, it can be inferred that there is a seasonal component in the time series which occurred within twelve months. As the seasonal component repeats on an annual basis, it is asserted to be an additive impact instead of multiplicative.

2.5. Model selection and fitting

2.5.1. Simple seasonal model

Due to the nature of the time series data and its characteristics such as the absence of trend and the presence of additive seasonal components, the simple seasonal exponential smoothing model was selected as the optimal model to fit the data after comparing its output and efficiency to other models such as the ARIMA (0,1,1) which according to Gardner (1985) is optimal for the simple seasonal model. Both models have been proven to share similar characters in terms of output and thus both have been applied in the current study. In the current study, the expert modeller utility package in the IBM Statistical Package for the Social Sciences (SPSS) v. 20 was used to carry out the time series analysis of the data. The result of the analysis revealed simple seasonal as the best-fitted exponential smoothing model compared to the ARIMA (0,1,1) model for the analysis. The forecast equation of the simple seasonal model presented in Eq. (1) is given as:

$$y'_{t+h|t} = l_t + h + s_{t+h-m(k+1)} \tag{1}$$

Where m = the length of the seasonality (which is equal to 12 because the data is monthly data for 12 months in each year), l_t = the level of the series, S_t = the seasonal component, $\acute{y}_t$+h|t = is the forecast for h periods ahead and k= the integer part of (h-1)/m which guarantees that the estimates of the seasonal indices used for the forecast are derived from the last year of the data sample. The equations of each of the components of the simple seasonal model are given below as:

$$The\,level\,equation\,is\,:\; l_t = \alpha\left(y_t{-}S_{t-m}\right) + (1-\alpha)l_{t--1} \tag{2}$$

$$The\,seasonal\,equation\,is\,:\; S_t = \gamma\left(y_t - l_{t-1}\right) + (1-\gamma)S_{t--m} \tag{3}$$

In Eqs. (2) and (3), α and γ are the smoothing parameters of the model. The initial step to choosing an appropriate exponential smoothing model for any time series data is to determine the values of the smoothing parameters α and γ (Winters, 1960). Gardner (1985) proposed selecting a value in the range of 0–1 for the smoothing parameter α. However, Jacobs et al. (2010) also suggest an α value between 0.1 and 0.3.

To determine the appropriate values for the smoothing constants of our time series, the IBM SPSS statistical package was employed which yielded an exponential smoothing model with both level and seasonal parameters. The estimated values for the parameters are:

Level (α): 0.99, and Seasonal (γ): 1.054E-006.

Fitting the values of these parameters into the forecast equation of the model becomes;

$$'y_{t+h|t} = 0.99 + h + 1.054E - 0.006_{+h-12(k+1)} \tag{4}$$

2.5.2. ARIMA (0,1,1) model

The ARIMA (Auto-regressive Integrated Moving Average) model in time series is defined by three components (*p, d, q*). These components are *p*, the auto-regressive term, *d*, is the differencing term whereas *q*, is the moving average term. To determine the optimal values of each term, a methodology developed by Box and Jenkins (1970) is used. This approach involves three main steps:

Table 2
Model efficiency statistics (Time series models).

	Mean	
Fit Statistic	ARIMA (0,1,1) Model	Exponential smoothing model
Stationary R-squared	.669	.698
R-squared	.726	.742
RMSE	50.717	48.775
MAPE	126.763	125.572
MaxAPE	5778.445	4601.663
MAE	30.135	30.468
MaxAE	378.553	386.999
Normalized BIC	7.904	7.800

- Model identification: Identify trends, seasonality, and autoregression elements using plots and summary statistics.
- Model parameters estimation: Apply a fitting procedure to determine the coefficients of the regression model.
- Model diagnostics: Decide the amount and type of temporal structure not captured by the model using plots and statistical tests of the residual errors.

The current study employed the expert modeller utility package in SPSS v20 to run an ARIMA model with components (0,1,1). The ARIMA (0,1,1) model was subjectively chosen because according to Gardner (1985) is the best compliment the ARIMA model to the simple seasonal exponential smoothing model. The ARIMA (0,1,1) model has 0 orders of auto-regression, 1 order of difference, and one order of moving average. The output and efficiency of both the simple seasonal model and ARIMA (0,1,1) models are explained in Table 2.

3. Results and discussion

3.1. Model output for simple seasonal and ARIMA (0,1,1) models

The model output for both simple seasonal and ARIMA (0,1,1) models are presented in Table 2. The models fit statistics for the two models showed a Stationary R-squared value of 0.698 for the simple seasonal model and 0.669 for the ARIMA (0,1,1) model. Both models yielded R-squared values of 0.742 and .726, RMSE values of 48.775 and 50.717, and normalized BIC value of 7.800 and 7.904 for the simple seasonal and ARIMA (0,1,1) models respectively. These are indications that both models are good fits for the time-series data. Also, the Ljung-Box *Q* test (Supplementary Table 2) showed a statistic of 21.843 and 14.748, and significance levels of 0.148 and 0.543 for the simple seasonal model and the ARIMA (0,1,1) models respectively. Hence, we fail to reject the null hypothesis that both models are a good fit for the data (Supplementary Table 2).

Furthermore, the plots of the residual Autocorrelation Functions and Partial Autocorrelation Functions for both models presented in Fig. 6 corroborate with the above findings and assert that the residuals of the analysis are not serially correlated. Therefore, both models are a good fit for the time series. However, A line graph (Fig. 7) comparing the predicted values for both the simple seasonal and ARIMA models against the observed data revealed that the simple seasonal model is a better fit for the time series data than the ARIMA (0,1,1) model. The simple seasonal model better modelled the pattern of the observed rainfall data compared to the ARIMA model. Hence further discussion on the forecast of future rainfall pattern and characteristics are based majorly on the simple seasonal model.

3.2. Rainfall forecast for the next 19 years

The fitted exponential smoothing model was used to forecast the rainfall pattern for the next 19 years using a confidence interval level of 95%. The range of the forecast data is from January 2017 to December 2035. The series chart of the rainfall data including the forecast data is displayed in Fig. 8. The forecast showed that the amount of rainfall to be received at the weather station is expected to significantly reduce over the next 19 years (Fig. 8). These findings were dissimilar to Twenefour et al. (2018) and Abdul-Aziz et al. (2013) that forecasted a rise in rainfall in southwestern and south-central Ghana respectively. This dissimilarity could be related to the differences in the ecological zones where these stations are located. As presented in Fig. 8, peaks were observed within June, July, August, September, and October where rainfall records exceeded 102 mm which is described as the minimum limit for a season to be classified as "wet" (Acheampong, 1988). Also, in these months, the average rainfall of 101.4 mm for Ghana was exceeded. Meanwhile, lower amounts of rainfall were recorded in December, January, February, and March. Fig. 7 further showed highly variable rainfall compared to the forecasted rainfall levels.

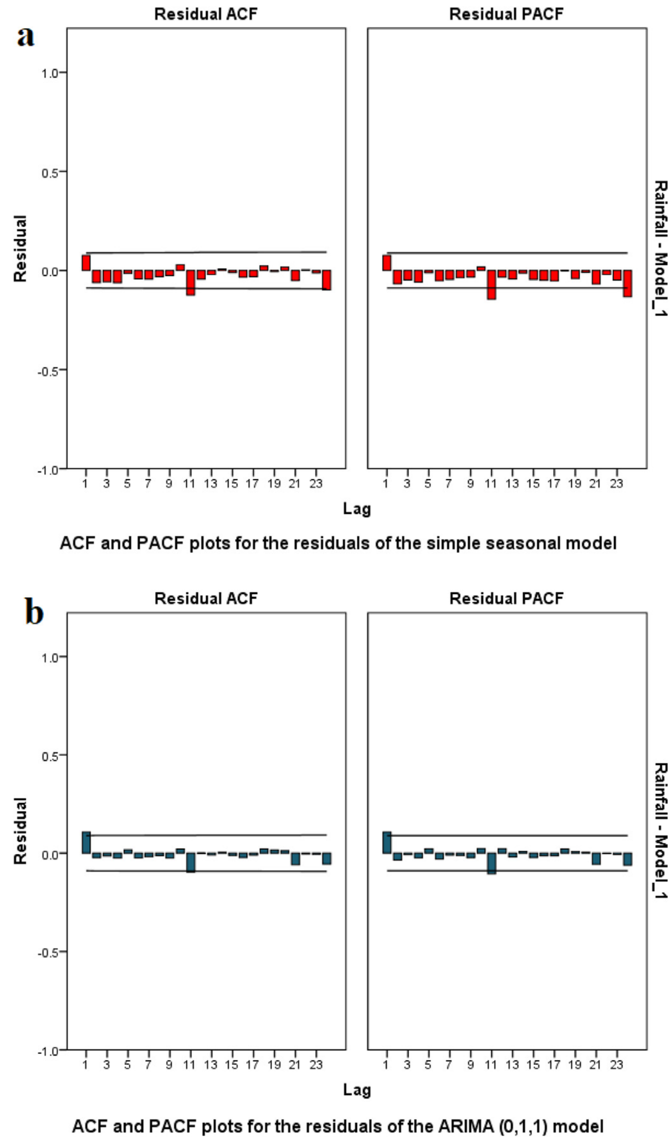

Fig. 6. ACF and PACF plots of the residuals for (a) simple seasonal and (b) ARIMA (0,1,1) models.

3.3. Rainfall pattern for the next 19 years

To ascertain the significant difference between the amount of rainfall in the observed and forecasted data, and to make an inference on the pattern of future rainfall in the study area, an Analysis of Variance (ANOVA) was conducted. The data was divided into inter-decadal pe-

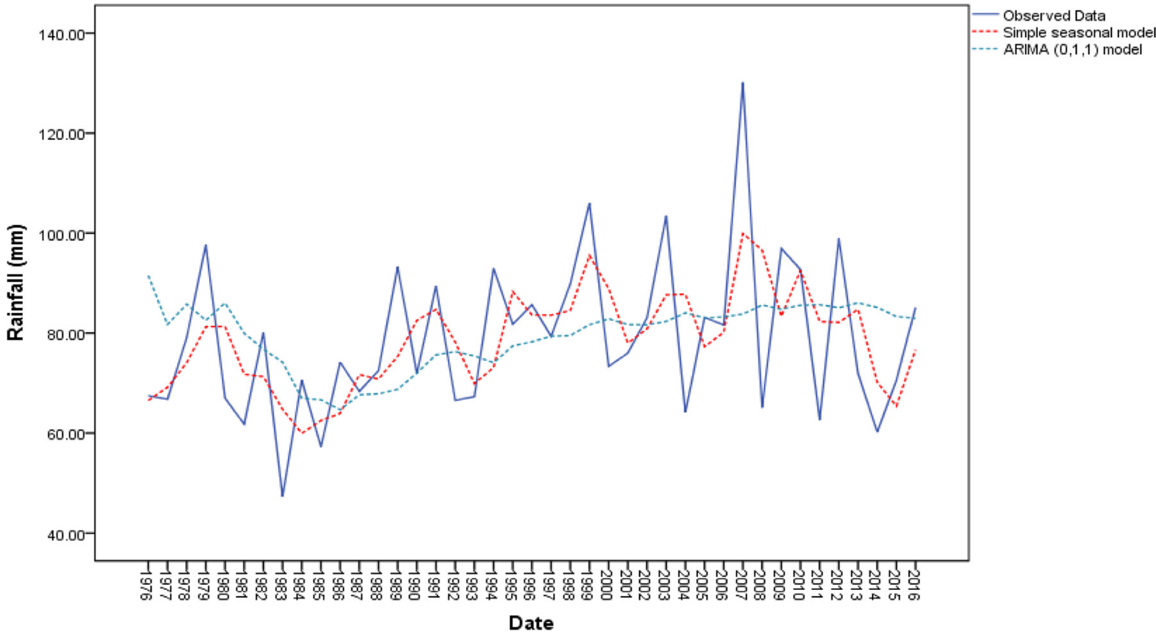

Fig. 7. Comparative line graph of predicted values for simple seasonal and ARIMA models.

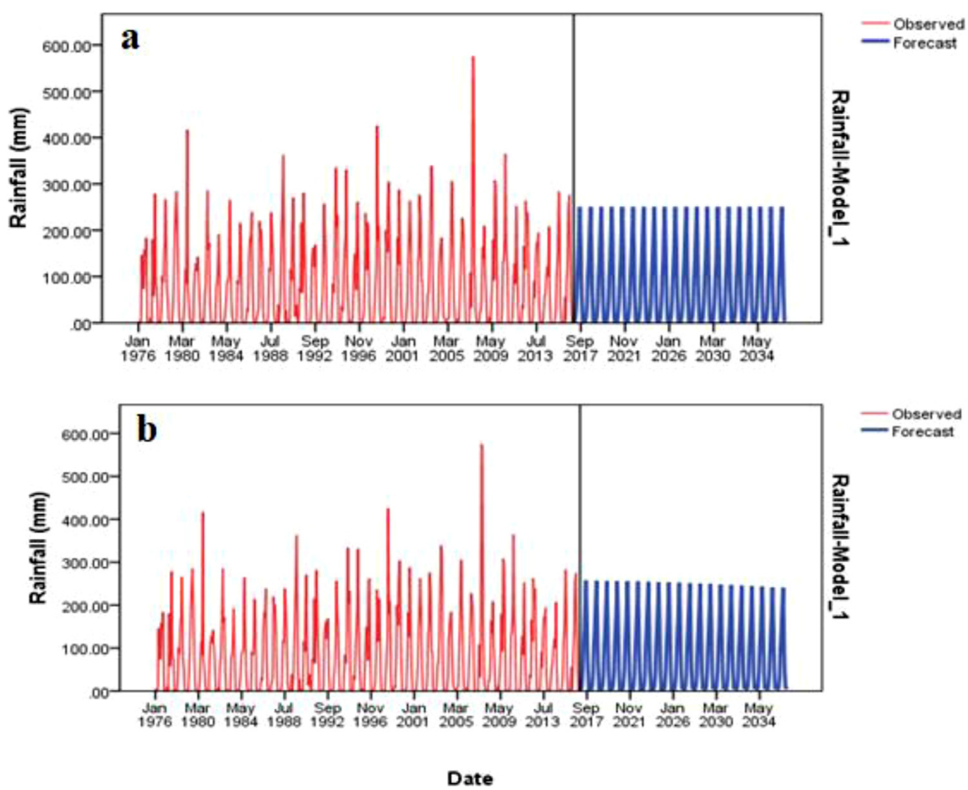

Fig. 8. Time series forecast chart for (a) simple seasonal model and (b) ARIMA model.

riods. Hence, six (6) decades (1976–2034) period was achieved. This division includes four decades for the observed data and two decades for the forecasted data. The results of the analysis (Table 3) showed that there was no statistically significant difference in the means of rainfall across the decades. However, since the data was characterized into decadal periods, spikes in the observed and forecasted data may have been overlooked. In conducting the ANOVA analysis, the null hypothesis was that there is no statistically significant difference in the means of the rainfall data across the decades. This was at a 5% level of significance. The ANOVA analysis (Table 3) showed that the difference in the means of the rainfall data across the six decades was not statistically significant. Hence, the study fails to reject the null hypothesis.

Fig. 8 depicts a decline in rainfall levels within the two forecasted decade periods. However, significantly high rainfall averages were received in 1995–2004 and 2005–2014 which could be attributed to the formulation of several policies to combat climate change including the 1994 National Forest and Wildlife Policy (NFWP), the National Climate Change Adaptation Strategy in 2012, and National Climate Change Pol-

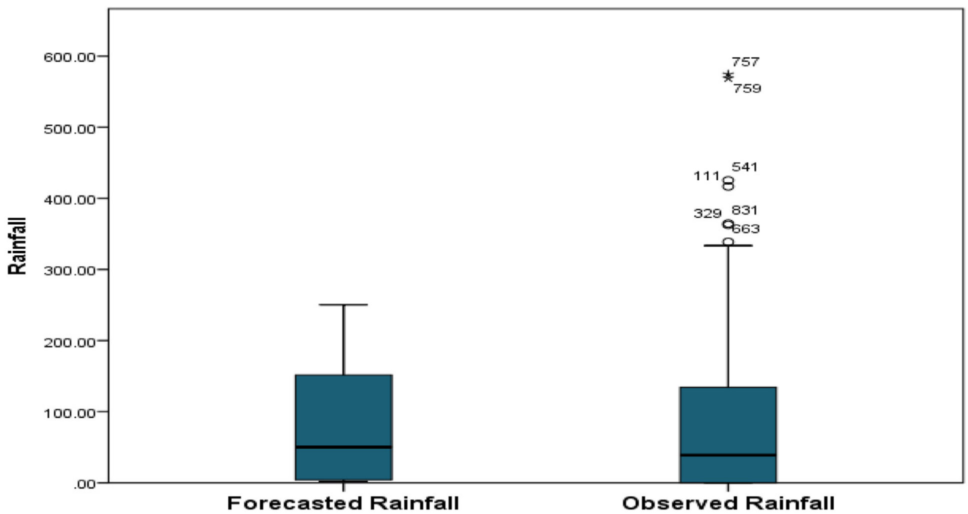

Fig. 9. Box and whiskers plot of observed rainfall against forecasted rainfall.

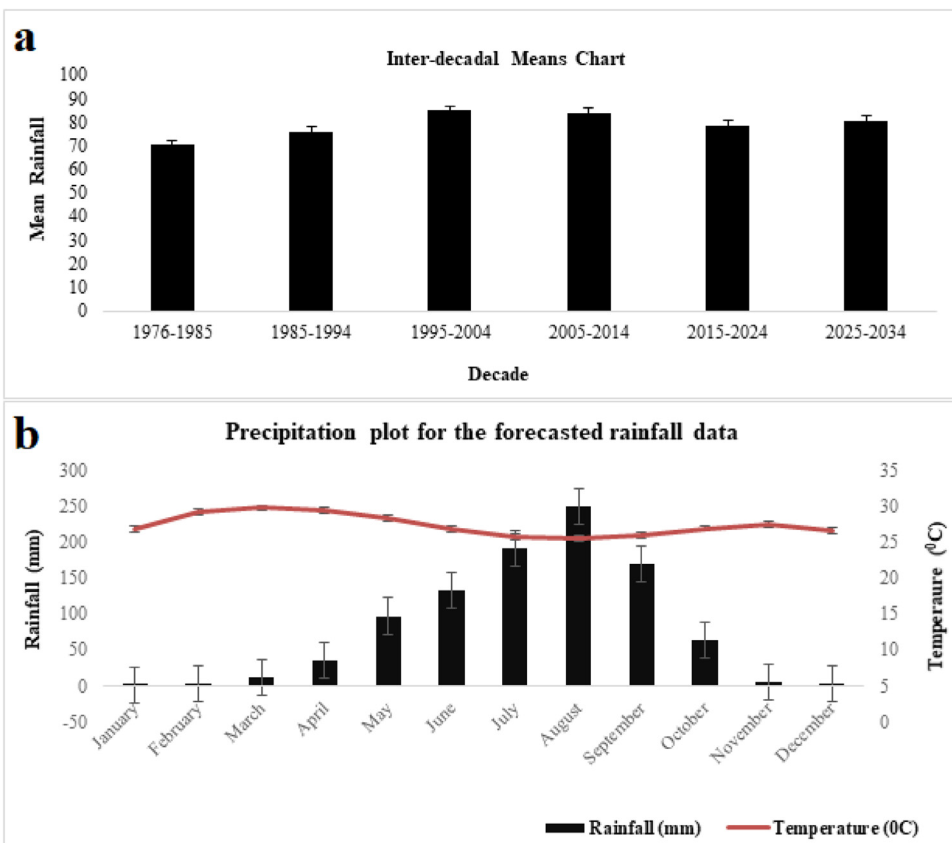

Fig. 10. (a) Bar chart of the means of the data across the decades (b) Precipitation plot for forecasted rainfall data.

Table 3
ANOVA Test of Rainfall amount.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	17330.209	5	3466.042	.492	.782
Within Groups	5030955.220	714	7046.156		
Total	5048285.430	719			

icy (NCCP) 2014. Though other climate change-related policies and agreements have been formulated in recent times, there has been a reduction in rainfall amounts from 2015. This is projected to decline to 2034 if the underlying factors including deforestation, bush burning, and poor agricultural practices that contribute to the decline in rainfall remain unaddressed. Some other factors include institutional constraints for effective implementation of environmental policies, poor community participation and compliance, poor coordination amongst regulatory bodies, deforestation, poor focus and continuity of environmental policies by successive governments, poor communication of information and awareness of policies (Ayee, 1998; Eshun and Okyere, 2017; Tuokuu et al., 2018). For instance, the International Union for Conservation of Nature (IUCN) indicated that deforestation in Ghana is widespread and the country loses about 2% of its forest resources yearly (International Union for Conservation of Nature IUCN, 2016).

Similarly, the box and whiskers plot (Fig. 9) of the observed data against the forecasted data revealed a decline in rainfall amounts in

Table 4
Multiple comparisons of rainfall levels.

Decade (I)	Decade (J)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1976–1985	1985-1994	-5.59	10.84	1.00	-36.55	25.38
	1995-2004	-14.49	10.84	0.76	-45.46	16.48
	2005-2014	-13.45	10.84	0.82	-44.42	17.51
	2015-2024	-8.47	10.84	0.97	-39.43	22.50
	2025-2034	-10.39	10.84	0.93	-41.36	20.57
1985–1994	1976-1985	5.59	10.84	1.00	-25.38	36.55
	1995-2004	-8.90	10.84	0.96	-39.87	22.06
	2005-2014	-7.87	10.84	0.98	-38.83	23.10
	2015-2024	-2.88	10.84	1.00	-33.85	28.08
	2025-2034	-4.81	10.84	1.00	-35.77	26.16
1995–2004	1976-1985	14.49	10.84	0.76	-16.48	45.46
	1985-1994	8.90	10.84	0.96	-22.06	39.87
	2005-2014	1.04	10.84	1.00	-29.93	32.00
	2015-2024	6.02	10.84	0.99	-24.94	36.99
	2025-2034	4.10	10.84	1.00	-26.87	35.06
2005–2014	1976-1985	13.45	10.84	0.82	-17.51	44.42
	1985-1994	7.87	10.84	0.98	-23.10	38.83
	1995-2004	-1.04	10.84	1.00	-32.00	29.93
	2015-2024	4.98	10.84	1.00	-25.98	35.95
	2025-2034	3.06	10.84	1.00	-27.91	34.03
2015–2024	1976-1985	8.47	10.84	0.97	-22.50	39.43
	1985-1994	2.88	10.84	1.00	-28.08	33.85
	1995-2004	-6.02	10.84	0.99	-36.99	24.94
	2005-2014	-4.98	10.84	1.00	-35.95	25.98
	2025-2034	-1.92	10.84	1.00	-32.89	29.04
2025–2034	1976-1985	10.39	10.84	0.93	-20.57	41.36
	1985-1994	4.81	10.84	1.00	-26.16	35.77
	1995-2004	-4.10	10.84	1.00	-35.06	26.87
	2005-2014	-3.06	10.84	1.00	-34.03	27.91
	2015-2024	1.92	10.84	1.00	-29.04	32.89

the forecasted years. These are commensurate with the findings of Issahaku et al. (2016) and Asamoah and Ansah-Mensah (2020) which indicated a decline in rainfall amounts at a rate of 4.4% per decade in the region. Table 4 is the multiple comparisons of decadal rainfall means obtained from the ANOVA analysis. The analysis shows an erratic rainfall pattern within the area. Fig. 10a also presents a slight decline in rainfall from 2015 to 2034. However, this will be higher than the measured rainfall from 1976 to 1994. The decline in rainfall also relates to the Climate Change 2014 Synthesis Report by the Intergovernmental Panel on Climate Change (IPCC) which forecasted a decline in rainfall amounts in many mid-latitude and subtropical dry regions including Ghana (Intergovernmental Panel on Climate Change IPCC, 2014).

The precipitations plot (Fig. 10b) of the forecasted data depicts the months and the respective monthly average rainfall amounts in the forecasted period and their mean temperatures. The chart shows that July, August, and September will receive the highest amounts of rainfall in the forecast period. On the other hand, November, December, January, and February are expected to receive the least amounts of rainfall and hence can be anticipated to be dry in the upcoming years.

4. Conclusion

This research employs a holistic and rigorous approach towards analyzing and forecasting rainfall for 19 years in the Manga-Bawku area in northeastern Ghana. A simple seasonal model was applied to level out seasonal fluctuations in the time series data and to also generate a forecast model for the series. The study has provided empirical evidence and predicted a decline in rainfall within the study area. The causes of the forecasted decline in the rainfall quantity for the study area may not be predominantly emanating *in situ* as a global warning, the sole causative agent for the world's changing climate is a global issue and needs to be considered on a global scale. However, some human-induced activities within the study area such as deforestation, environmentally-unfriendly agriculture activities, and urbanization are potential agents that alter the micro-climate of the study area, therefore, exacerbating the impact of global warming at the local scale within the area. Considering the study area which has an agricultural-dependent population, a decline in rainfall amount will adversely affect households. A side effect of this will lead to a shortage in freshwater, water availability and poor sanitary practices which could also result in an increase in water-related diseases such as malaria, cholera, meningitis, and shigella. Also, agricultural productivity is expected to decline because rainwater is the main recharge medium for the source of water for agriculture in the study area. A decline in rainwater may contribute to a decline in groundwater recharge and as a result increase groundwater salinity. Agricultural production and public health will also be at risk. This may hamper Ghana's ability to achieve the Sustainable Development Goals 3, 6, and 13 which focus on "good health and well-being", "clean water and sanitation" and "climate action" respectively. It is recommended that (1) government agencies and policymakers consider options for improving the local inhabitants' resilience to climate change through advocacy for the use of alternative sources of fuel and sustainable livelihood practices that could reduce the levels of greenhouse gases that are emitted into the atmosphere, and (2) improving the availability and accessibility of other sources of water for domestic and agricultural activities, and advocacy to combat deforestation in the area.

Consent for publication

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Declaration of Competing Interest

The authors declare that they have no competing interests.

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Supplementary materials

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