International Journal of Basic and Applied Sciences, 15 (2) (2026) 7-14

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/0c9qv646
Research paper

Modelling of Extreme Rainfall Patterns in Accra

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Received: December 27, 2025, Accepted: February 5, 2026, Published: February 13, 2026

Abstract

Concerns about climate change and its possible impacts on human activities have increased the awareness that climatic conditions are dynamic. West Africa, of which Ghana is part is one of the areas in the world that had experienced major climatic anomalies in the past century. The purpose of this research is to model rainfall data using block maxima approach of extreme value theorem. Monthly rainfall data covering the period 1960 – 2022 were obtained from the Ghana Meteorological Agency, Accra Airport substation. Statistical properties of the data indicated data was stationary, however it was not normally distributed. Time series analysis of the data indicated consistent increase in rainfall values with both downward and upward spikes indicating fluctuations in the rainfall values. The Generalized Extreme value distribution was used to fit the model of rainfall values. The rainfall values were fitted using the Generalized Extreme value distribution. The Fréchet distribution was found to be the most appropriate model for the monthly rainfall data. Additionally, it was discovered that the amplitude of the extreme values grows with return periods, with higher return levels predicted to become more uncommon but severe over time.

Keywords: *Block maxima; Climate change; Extreme rainfall; Fréchet Distribution; Return levels.*

1. Introduction

Concerns about climate change and its possible impacts on human activities have increased the awareness that climatic conditions are dynamic. Examinations of past climates showed fluctuations and variations on a variety of time and space scales, although almost all analyses assumed a static baseline. Dai (2013) reports that between 1950 and 2008, the percentage of dry areas worldwide increased by roughly 1.74% every ten years. Drought episodes are occurring more frequently and with greater intensity as a result of global climate change's effects on temperature, precipitation, and the hydrological system as a whole (Njoka, 2019; Yang and Ying, 2022). Climate is the synthesis of the weather in a particular region while weather refers to what is happening now or at any instance in time in the atmosphere, for example, whether rainy, dry, sunny, cold or windy. (Ekwezuo, 2016).

West Africa, of which Ghana is part is one of the areas in the world that had experienced major climatic anomalies in the past century. According to (Roehrig et.al.,2013; Redelsperger et.al. 2006), the sub-region underwent climatic shifts, transitioning from rainy conditions in the 1950s to drier conditions during the 1970s and 1980s. Thus, the sub-region experienced the most severe and longest drought at a continental scale in the world during the 20th century, (IPCC, 2007).

Climatic conditions within the region are characterized by significant variability in both temporal and spatial distribution of rainfall across the basin, resulting in correspondingly high fluctuations in streamflow.

The 2019 report on climate by the intergovernmental panel on climate change (IPCC) indicated that there were universally dry conditions globally with southern Africa and other parts of the world receiving abnormally low amounts of precipitation. According to the report, the longest period of consecutive wet days (CWD) in 2019 was longer than average in tropical western Africa while the longest period of consecutive dry days (CDD) was also longer than normal in western Africa. (IPCC, 2021; IPCC, 2023). Concerning heavy rainfall and floods, there was widespread flooding globally. However, some countries in West Africa experienced some floods although the overall Sahel seasonal rainfall was mostly fairly close to average. (World climate guide, 2019)). Thus, climate conditions continue to be varied with precipitation becoming increasingly unpredictable.

Many countries have taken the issues of flooding seriously and have go on to develop both deterministic and stochastic methods or models in order to predict the occurrence of flood or put intensity frequency models, Markov chain, depth duration models, run off coefficient analysis, extreme value theory, etc. There is a relationship between rainfall intensity, duration, and the return period summarized by the intensity-duration -frequency curves. From early studies on Bartlett –Lewis and Neyman Scott rainfall equations, many models have been developed to study rainfall patterns. (Twenefour et.al, 2018) used Autoregressive Moving Average (ARMA) to model rainfall distribution in the western region of Ghana while Aziz et.al (2013) used Seasonal Autoregressive Integrated Moving Average (SARIMA) to model

rainfall distributions in Ghana using Ashanti region as a case study. (Twenefour, et.al, 2018; Aziz et.al). (Oti et.al, 2019) used Gumbel, Log Normal and Log Pearson distributions to study the rainstorm Intensity duration frequencies for watersheds at Tarkwa.
Several methods have been developed to combat or manage flood some of which use extreme value theorem and intensity duration frequency curves. Others use geographical information systems which use satellites to look at the physical process of rainfall leading to flooding. The extreme value theorem has also gained widespread applications in modelling climate issues especially flooding. Under the extreme value theorem, the Block Maxima and the Peak-Over Threshold have been used extensively to model extreme rainfall. (Niyotwizera and Safari, 2024; Moghaddasi, et.al, 2022; Hassan, 2021) used the block maxima approach to study extreme rainfall in Kigali. The researchers determined that the Generalized Extreme Value Theorem offered superior theoretical basis for assessing extreme precipitation and the Gumbel was found to be the optimal model for the GEVD. It also indicated an increase in return periods over the years. (Onwuegbuche, 2019; Ngailo et.al, 2016). Some studies on modelling extreme rainfall in some part of the Upper East and some part of coastal and Northern regions of Ghana, showed the yearly maximum rainfall follow the Gumbel distribution. It also indicated that retuned levels have been increasing over the years. While GEVD was the best fit for extremes in the northern part of Ghana, GPD was the best fit for extremes along the coastal station. (Angbing et.al, 2020; Ankrah, et.al, 2024)
There is a need to note that most of the research in Ghana is about the rainfall distribution patterns or trends in some selected regions. This research intends to model extreme rainfall in the Greater Accra Region using Extreme Value Theory model. This research is timely as Accra has been experiencing flooding quite often in recent times. The whole climatic conditions have also change as the traditionally known months which happens to be dry are all experiencing rains. Thus, this research will add to knowledge in terms of flooding in Accra and will help policy makers in flood risk assessment and management.

2. Method

2.1. Study area

This study covers Greater Accra region. Greater Accra is situated on the southern coast of Ghana. It is bounded to the north by the Eastern region, to the east by the Volta region, to the south by the Gulf of Guinea, and to the west by the Central region. (Asiedu, 2024; Doku, 2013; GSS, 2010). It is the least extensive region in Ghana by total area. Accra serves as both the regional capital and the capital city of Ghana. Accra is also the largest city in Ghana. A hot semi-arid climate borders Accra's marginal tropical wet and dry climate. Rainfall averages around 730 mm per year. There is a brief rainy season in October after the major rainy season, which starts in April and ends in mid-July. Accra was selected as in the recent past; the capital city has experienced most of the flooding incidents in Ghana. Following two hours of intense rain, areas of Accra and its streets were completely flooded, demonstrating the city's susceptibility to flooding while a month later on the 22nd of June, 2010, the nation endured its most severe flood catastrophe, with thirty-five bodies recovered from floodwaters nationwide by volunteers and rescue personnel who characterized the devastation following the rains as the worst flood event in Ghana’s recent history. (Abiri, 2022; Kuffour, 2024)

2.2. Data

In this research, daily rainfall data were collected from the Ghana Meteorological Agency, Airport substation. Daily precipitation is documented at 08:30 hours each day nationwide. The daily rainfall recorded at an observatory represents the cumulative precipitation over the prior 24 hours, concluding at 08:30 hours on the measurement date. (GMA website, 2024). The monthly precipitation is the aggregate of all daily rainfall documented throughout that month.

2.3. Extreme value theory

According to (Ayitey et.al, 2022, Bako et.al ,2020), the theory behind the extreme value theory was developed from the study of Block maxima when sample of variables $Y_1, Y_2, \cdots, Y_n$ are given. The variables $Y_1, Y_2, \cdots, Y_n$ must be independent and have identical distribution with a typical distribution H. Extreme value theory functions as a tool for modeling the distribution of maxima within sequences and sample sizes, grounded in established theorems. To characterize extreme rainfall behavior, it is essential to find the distribution(s) that most accurately represent the data. (Alaswed, 2024; Onwuegbuche, 2019).

2.4. Generalized extreme value distribution (G.E.V)

The Generalized Extreme Value (G.E.V) distribution is a combination of three extreme value distributions: the Gumbel, the Fréchet, and the Weibull. (Abdulali et.al, 2022; Alaswed, 2024, Gyasi and Cooray, 2024). This model was chosen because of its ability to handle maximum observations of each block or period when the maximum observations are drawn from a pre-defined and fixed length which are identically and independently distributed. (Ngailo, et.al, 2016; Onwuegche et.al, 2019; and Bako et.al, 2020). The G.E.V was also chosen because of its ability to model and predict tail behaviour of distributions.
Let $Y_1, Y_2, Y_3, \cdots, Y_n$ be a sequence of independent and identically distributed (iid) random variables. (Bako, et.al. and Rydman, 2018)). The cumulative distribution function of the Gumbel, Fréchet and Weibull distributions can be summarized by the Generalized Extreme Value distribution given by

$$\mathrm{GEV}(y, \beta, \sigma, \mu) = \begin{cases} \exp - \left[1 + \beta\left(\frac{y-\mu}{\sigma}\right)\right]^{-\frac{1}{\beta}} & \beta \neq 0 \\ \exp\left[-\exp\left(-\frac{y-\mu}{\sigma}\right)\right] & \beta = 0 \end{cases} \tag{1}$$

Where y_s are the extreme values from the blocks, μ, is a location parameter, σ is a scale parameter and β a shape parameter. We have Fréchet distribution if $\beta > 0$, the Gumbel distribution if $\beta = 0$ and the Weibull if $\beta < 0$. To estimate the unknown parameters of G.E.V, we have to obtain the maximum likelihood of the parameter vectors (μ, σ, β). This is given by

$$l(\mu, \sigma, \beta) = -n\log\sigma - \left(1 + \frac{1}{\beta}\right)\sum_{i=1}^{n}\left[1 + \beta\left(\frac{y_i - \mu}{\sigma}\right)\right] - \sum_{i=1}^{n}\left[1 + \beta\left(\frac{y_i - \mu}{\sigma}\right)^{-\frac{1}{\beta}}\right] - \tag{2}$$

Provided $\left[1 + \beta\left(\frac{y_i - \mu}{\sigma}\right)\right] > 0$ for $i = 1, 2, \cdots, n$. (Abdulali et.al, 2022; Gyasi and Cooray, 2024)

2.5. Quantiles and return period

The quantiles of the Generalized Extreme Value or Generalized Pareto distribution function are significant due to their interpretation as return levels. (Safari, 2022; Iyamuremye et.al, 2019).
If the likelihood of witnessing an extreme event of a certain intensity is P, then the mean return period T_p is defined by the equation $T_p = \frac{1}{p}$. The mean return period denotes the average number of years anticipated before witnessing another extreme event of equivalent or greater severity. (Safari, 2022). For the G.E.V distribution, the return period T_p for any given block maximum of data is given as

$$G(y_p) = P\{X \le y_p\} = 1 - \frac{1}{T_p} \tag{3}$$

$$y_p = G^{-1}\left(1 - \frac{1}{T_p}\right) \tag{4}$$

Where y_p is the value expected to be equaled or exceeded on average once every T_p years, and $1 - \frac{1}{T_p}$ is the specific probability associated with the quantiles.
If we let $y_p = \frac{-1}{\ln(1 - T_p)}$ then its corresponding return level y_p is:

$$\begin{cases} Y_p = & \mu + \frac{\sigma}{\beta}\left(q_p^{\beta} - 1,\right)\ \beta \neq 0 \\ & \mu + \sigma \ln q_p, \beta = 0 \end{cases} \tag{5}$$

2.6. Block maxima method

The block maximum method is employed to evaluate data sets in hydrology and climatology. The block maximum model's main drawback is how to calculate block sizes. One of the methods employed in Extreme Value analysis is the block maxima method. The process involves dividing the data into equal-sized, non-overlapping segments and concentrating solely on the largest observations inside each segment. (Niyotwizera and Safari, 2024). Observations can be grouped using the block maxima approach on a monthly, quarterly, semi-annual, or annual basis. This article examines extreme rainfall events using the block maximum method. The block maxima method was chosen because of its simplicity, straightforwardness and robustness.

2.7. Parameter estimation of G.E.V

2.7.1. Probability weighted moments (PWM) (L- moments estimation method)

The probability weighted moments (PWM) is also known L- moments estimation method. Probability Weighted Moments were chosen as they are more reliable and robust to outliers, the PWM were selected as the parameter. (Bezak et.al, 2014). Additionally, when the sample size is limited, they provide more accurate parameter estimations. The probability weighted moments' L-moments are linear functions. A random variable Y's probability-weighted moments with a distribution function $F(Y) = P(Y \le y)$ is

$$M_{p,r,s} = E[\, Y^p \{F(Y)\}^r \{1 - F(Y)\}^s\,] \tag{7}$$

Where the numbers p, r and s are real.
The most efficient method for assessing these moments occurs when the inverse distribution function $y(F)$ can be expressed in a closed form:

$$M_{p,r,s} = \int_0^1 \{y.(F)\}^p F^r (1 - F)^s dF \tag{8}$$

The probability-weighted moments are combined linearly to get the M-moments. Consequently, the first M-moments are described by

$$\begin{aligned} m_1 &= \propto_0 \\ m_2 &= 2 \propto_1 - \propto_0 \\ m_3 &= 6 \propto_2 - 6 \propto_1 + \propto_0 \\ m_4 &= 20 \propto_3 - 30 \propto_2 + 12 \propto_1 - \propto_0 \end{aligned} \tag{9}$$

The location parameter or mean is the first M-moment. The scale parameter is represented by the second M-moment, which is a product of difference in average of Gini statistics. To derive the ratio of each of the moments, the higher order moments are divided by scale parameter.

$m_r = \frac{m_r}{m_2}$ where $r = 1, 2\ 3 \ldots$

The cumulative distribution function $F(y)$ of the probability weighted moments is described as

$$\beta_r = \int y\{F(y)\}^r dF(y)\text{ , where } r = 0, 1, 2, \cdots \tag{10}$$

2.8. Augmented dickey fuller test (A.D.F.)

You can use the Dickey Fuller test to see if time series data is stationary. It is a test of a unit. The unit root is a property of time series that shows whether there is a random tendency in the series that pulls it away from its mean value. (Santa, et.al. 2023; Mastaq, 2011). The A.D.F. test is an extension of the Dickey-Fuller test that works with more complicated models than AR(1). One can distinguish between difference stationery and trend stationary processes using the unit root test. (Paparoditis and Politis, 2016, Ghaffar, et.al. 2021, Mashtaq, 2011, Dickey & Fuller, 2012). An AR(p) type time series model is assumed by the Augmented Dickey Fuller test, which is expressed mathematically as

$$y_t = \mu + \sum_{i=1}^{p} \varphi_i\, y_{t-1} + \varepsilon_t$$

The test statistic $t_{\hat{\beta}} = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}$

The ADF test is based on the following assumption:
H_0: there exist a unit root in time series, indicating non-stationarity
H_1: there is no unit root in time series and it is stationary
The null hypothesis, H_0 is rejected if $P < 0.05$

2.9. Shapiro-wilk test

We conducted the Shapiro-Wilk test to see if the data was normal. The null hypothesis states the data is normally distributed. The null hypothesis is rejected if the P-value is less than the significance level and we fail to reject the null hypothesis if P-value is greater than the significance level. (Gonzalez – Estrada, et.al, 2022; Shapiro & Wilk, 1965). Thus, if P-value is smaller than the significance level, it implies the data is not normal.

3. Results and Discussions

Table 1: Summary Statistics

Count	Mean	Stand Dev. (std)	Minimum	Skewness Value	Kurtosis	Maximum
768	188.72	4.72	2	0.55	-0.598	399

From table 1, we can see that there are 768 observations. The mean of the distribution is 188.72 with a standard deviation of 4.72. This indicates that the degree of dispersion relative to the mean is narrow thus data dispersion is moderate. Table 1 also indicates that the maximum and minimum values of the data set are 399 and 2 giving a range of 397. This wide range indicates there might be unusually large or small (extreme) values in the data set. Thus, there might be outliers in the data set. These outliers or extreme values may require extra care when modelling for extreme occurrences. Concerning the symmetry of the distribution, we can see that the skewness value is 0.55 indicating a moderately positively skewed distribution. The distribution being skewed to the right implies the right tail of the distribution is longer than the left, with more values concentrated on the lower end fewer extreme values on the upper end. It can also be seen from table 1 that the distribution is platykurtic with a kurtosis value of -0.598 implying the data has lighter tails and flatter peak in comparison with a normal distribution. This also means that extreme occurrences happen less often irrespective of whether they are very high or very low.
In summary, the data has a moderate degree of dispersion, having extreme values at both ends of the distribution. Compared to a normal distribution, this one has a lower peak, skewed to right, and contains fewer extreme outliers. These are important features to consider when selecting appropriate statistical models for the data.

3.1. Conditional test of the model

Table 2: Stationarity and Normality Test of Data

Stationary Test ($\alpha = 0.05$)		
ADF-test		
	H_0: Data is Stationary	P-value = 0.0012 Test Statistic =-26.30
Normality Test ($\alpha = 0.05$)		
Shapiro-Wilk Test		
	H_0: Data is Normally Distributed	P-Value= 1.56×10^{-16} Test Statistic=0.943

Table 2 is on conditional tests covering both stationarity and normality which are important conditions in understanding the data's suitability for statistical modelling and forecasting.
To test for stationarity of the data, Augmented Dickey-Fuller (ADF) test was employed. The ADF test is used to test a null hypothesis which states that there is a unit root in time series making it non- stationary. From table 2, the P-value of 0.0012 is far less than the significance level of 0.05. Thus, the null hypothesis is rejected and we conclude that the data is stationary. This finding satisfies the prerequisite for time series analysis and modeling, which is that the statistical properties of the data do not change over time.
Concerning the normality test, the Shapiro- Wilk test was used to determine the assumption of normality of the data. The null hypothesis of the Shapiro-Wilk test states that the distribution is normal. From table 2, the P-value for the normality test is 1.56 x 10^{-16}, which is far less than the significance level of 0.05, so the null hypothesis is rejected. This implies that the data is not normally distributed and exhibits skewness. As such, specialized techniques, such as transformations or non-parametric methods, may be needed to account for the non-normality when modeling the data.

Thus, the stationarity test suggest that the data is suitable for time series analysis due to its stationarity. However, the findings from the normality test indicate that the distribution is not normal, this could influence choice of modeling techniques. These results will guide the subsequent steps in data analysis and model selection

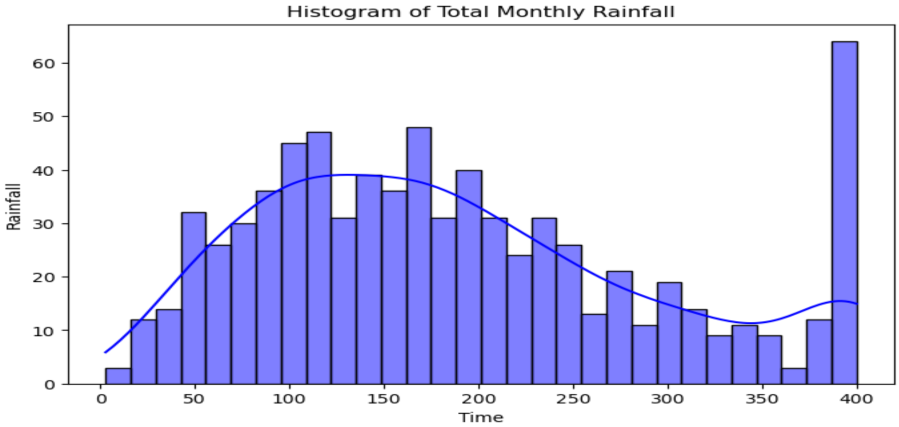

Fig. 1: Histogram of Monthly Totals.

3.2. Trend analysis of rainfall

Table 3: Summary Statistics Rainfall Growth Rate

	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
Rainfall Growth rate	0.0627%	3.3815	-9.9872%	9.3323%	0.0234	-0.0529

From the time series plot in figure 2, it shows a mild upward trend of the rainfall values over the years. One can see a consistent gradual increase in the levels of rainfall indicating a steady growth in rainfall over the sixty-two (62) year period. The summary statistics of rainfall growth rates in table 3 provide further insights into the behaviour of the data. From table 3, the mean growth rate is 0.0627% which signifies a modest, consistent increase in rainfall values confirming the gradual upward trend seen in the times series plot. This mild upward trend is supported by standard deviation of 3.3815 which captures the spread in the data, highlighting fluctuations in monthly rainfall levels around the trend line. These fluctuations are noticeable, especially during periods where there are significant changes in rainfall figures. We can also see from Table 3 the maximum and minimum growth rates of 9.3323% and -9.9872% respectively. The minimum growth of -9.9872% depicts months with significant downward spikes in rainfall indicating the more extreme decreases in rainfall values that disrupt otherwise steady trend while maximum growth of 9.3323% reflects sharp upward peaks in the data representing months which had significant rainfall that stood from the overall pattern. In addition, the 0.0234 value for skewness the rainfall growth is almost symmetrical with mild tendency towards positive values supporting the overall upward trend observed in the time series while -0.0529 value of kurtosis implies extreme rainfall events are rare relatively, reinforcing the idea of mostly steady trend with infrequent extreme rainfall occurrences. Combining the time series plot and the statistical summary give a clearer picture of rainfall patterns from 1960 to 2022. The mild upward trend in rainfall values is confirmed by the rainfall growth rates while the extreme events, trend and variability in overall distribution help to explain dynamics of rainfall fluctuations over time.

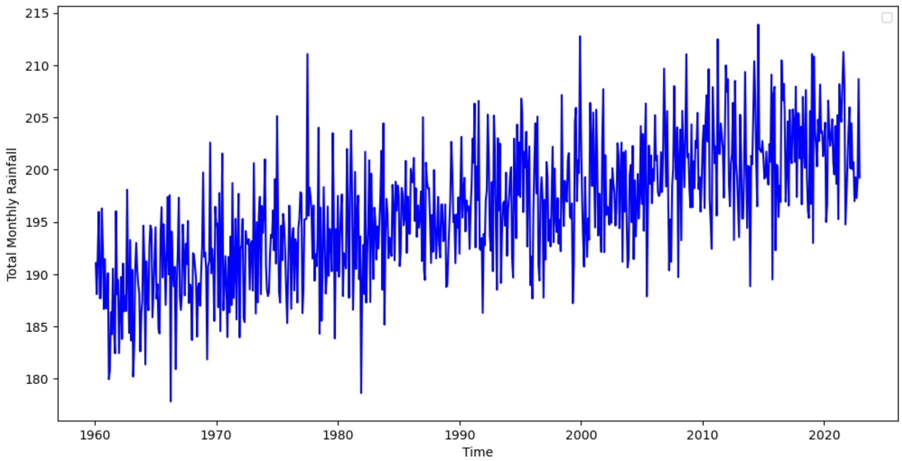

Fig. 2: Times Series Plot of Total Monthly Rainfall.

3.2.1. Model

Table 4: Maximum Likelihood Estimates of GEV

Parameter	Estimated Value	Confidence Interval (95%)	p-value	Significance
Shape (c)	0.218	(0.198, 0.238)	<0.001	Significant
Location (loc)	140.748	(138.188, 143.308)	<0.001	Significant
Scale (σ)	89.386	(88.886, 89.886)	<0.001	Significant
AIC	896.42	–	–	–
BIC	902.33	–	–	–

Table 4 presents the maximum likelihood estimate of the Generalized Extreme Values model. From the table, it can be seen that the shape parameter (ε) is 0.218 with a 95% confidence interval of (0.192, 0.238) indicating that the data follows a Fréchet distribution. This positive shape parameter indicates a higher probability of extreme values having the tail of the distribution extending indefinitely. The confidence interval is narrow highlighting the precision of this estimate and further indicating the data's positively skew nature where larger values are more probable.

We also see a location parameter (μ) of 140.748 having a 95% confidence interval of (138.188, 143.308). This location parameter represents the threshold for which extreme values are likely to occur. The narrow confidence interval indicates that the location of extreme values is well estimated, providing a good estimate for this threshold. Extreme events are expected to occur around or above the value of 140.748, with confidence interval (138.188, 143.308) which offers a good range for this threshold.

Also, it can be seen from table 4 that the scale parameter (σ) is 89.386 having a 95% confidence interval of (88.8886, 89.886). The scale parameter deals with the spreads around the location parameter. The confidence interval around the location parameter is small signifying a high degree of precision in its estimation making the spread of extreme values stable around the scale parameter. This in turn implies the magnitude of the extreme values is controlled tightly with a consistent spread around the location parameter.

Now, the data following Fréchet distribution contrast research done by Angbing, et.al. In their studies on extreme analysis of maximum rainfall in Upper East Region; case study of Navrongo, they found that extreme cases of rainfall can be modelled using Gumbel distribution. (Angbing, et.al, 2020). This contrast may be due to the fact that climate conditions in Ghana's Upper East is different from that of the coastal area.

This study also contrasts studies done in the East Africa by Ngailo et.al and Onwuegbuche et.al which all confirm Gumbel distribution as the best fit for the GEVD model. The contrast with East African research may also be due to the fact that the raining season in Ghana may be different from that of Kenya and Tanzania.

The GEV equation is given: $G\,(y) = \exp\left[-1 + 0.218\left(\frac{y-140.748}{89.386}\right)\right]^{-1/0.218}$

3.3. Model adequacy

The adequacy of the model was assessed through the use of maximum likelihood estimation. From table 4, the P-values for all the three estimated parameters; shape, location and scale were all less than the significance level of 0.05. That is, 0.001 less than 0.05, making all the three estimated parameters very statistically significant in the GEV model. This demonstrates that the estimated parameters captured meaningful characteristics of the Fréchet distribution implying that extreme events of bigger magnitude were plausible in the data. The AIC of 896.42 signify the model is good for prediction while BIC of 902.33 indicates the model's parsimony and can easily be applied. Thus, the AIC and BIC values further demonstrates model's ability to predict extreme rainfall.

3.4. Model diagnostic analysis

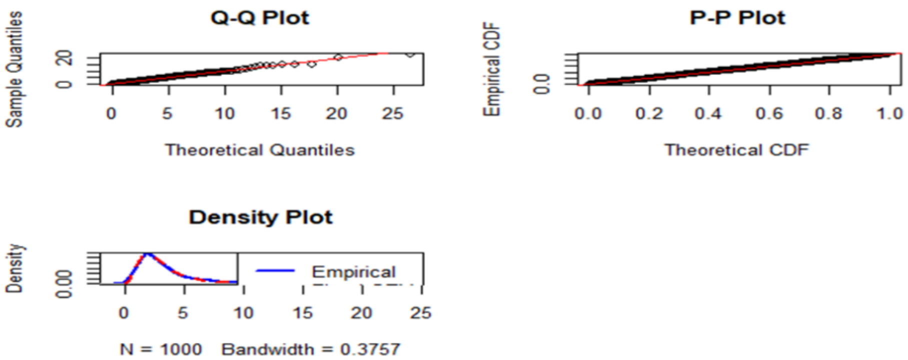

Fig. 3: Model Diagnostic Plots.

The Generalized Extreme Value (GEV) distribution model was also evaluated using visual presentations. Quantile-quantile (Q-Q), Probability -Probability and density plots were used to assess the consistency between the theoretical model and the observed data. From figure 3, it can be seen that the Q-Q plot mostly aligns with the 45-degree reference line, which in this case signify that there is consistency between the empirical and theoretical quantiles however, minor difference appears to exist in the distribution tails, indicating the model may not represent extreme values at both ends adequately. Similarly, the P-P plot points also closely match the diagonal reference line implying that the model captures the overall distribution accurately while the density plot captures consistency between the empirical density and the fitted GEV density. Using blue curve to represent empirical density and red to represent fitted GEV, we can see that the two curves align well across most regions of the data demonstrating that the GEV model captures the important features of the distribution. Nevertheless, the fitted GEV density diverges slightly from the empirical density in the upper and lower tails. This difference may indicate the model's limited ability to fully capture extreme values. However, when all the three (3) plots are combined, they confirm that the model fits satisfactorily, howbeit the minor deviations may call for further investigations or refinement of the model.

Thus, further works with GPD will be carried out for further investigations.

Table 5: Return Level Estimates

Return Period (Years)	Return Level
3	160.0
5	170.9
10	226.21
15	429.68
20	532.28

Table 5 presents estimates for different return periods and their corresponding return levels. From table 5, taking the 3-year return level, Accra is expected to experience a rainfall value of 160.0mm once a every 3 years. For 10- year return period, Accra is expected to experience a rainfall amount of 226.21 once in every 10 years while for 20-year return levels, Accra is expected to experience a rainfall amount of about 532.28 years. These values clearly demonstrates that as the length of return period increases, the amount of rainfall will also increase. The increase in return levels confirms the research by Angbing et.al (2020) and Ngailo et.al (2016) studies in the Upper East of Ghana and Tanzania. This means that extreme rainfall will continue to occur in shorter interval period. This calls for pragmatic effort on the part of city authorities to put in place risk assessment and management measures in handling issues associated with extreme events. Climate change is here with us and changes in the weather and for that matter rainfall patterns means, proper flood risk measures are to be put in place to help manage the impacts of floods if it occurs. It is important Accra metropolitan assembly and that matter policy makers come together for proper flood risk assessment to be made to ensure safety of human lives and properties during the rainy season. We need all hands-on deck in tackling the flooding problem in Ghana. That is city planners, hydrologists, policy makers and citizenry must all come together to find a lasting solution to Accra's perineal flooding problem. Town and country planners under the metropolitan assembly must ensure builders comply with the rule and regulations. Builders must avoid building in flood prone areas.

The researchers would like to state that, peak -over-threshold (POT) method will be considered in future to model rainfall in Accra to enable comparison between the two methods. We will also include more stations for spatial and temporal analysis of the rainfall in the country.

4. Conclusion

- From the analysis, the Fréchet distribution was found to be the most suitable distribution for modeling total monthly rainfall in Accra.
- It was found that estimated return levels increase with increases in return periods. Thus, rainfall values become rare as return period lengthens.
- We expect rainfall to increase over time as the return periods also increases. This implies more rainfall which may lead to more floods in subsequent years. It's important for authorities in Accra to put in place proper risk management assessment that will help manage flooding in Accra.

5. Recommendations

- It recommended that future research should look at hydrological and inundation flood models.
- Policy makers, hydrologists, researchers and urban planners come together to design and plan flood risk assessment based on scientific data for our cities.

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