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Parametric Distribution Fitting and Extreme Value Inference for Rainfall in Maiduguri

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Flood Risk Assessment,
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ABSTRACT

The paper takes a stringent approach of statistical characterization and existence of extreme values of monthly rainfall in Maiduguri capital city of Borno State, Nigeria and applies a 4-decade dataset (1981-2023). Descriptive statistics show that there is a highly skewed, discontinuous rainfall regimen as indicated by the wide gap between the value of mean (53.86 mm) and the median (1.60 mm). As this aims to determine the best probabilistic model that describes the non-zero monthly rainfall, Gamma, Weibull, and Lognormal distributions were both fit using Maximum Likelihood Estimation (MLE) and compared using Akaike (AIC) and Bayesian (BIC) Information Criteria. The Gamma distribution proved to be the best model to choose since it gave the smallest AIC (3007.99) and BIC (3018.78) values and its estimation value was strong though in the lower and middle quantile ranges. To select the Gumbel distribution (as opposed to the Generalized Extreme Value (GEV) distribution) to model annual maxima, the shape parameter ξ closes to zero ($\xi \approx 0.14$) and the principle of parsimony were used. The estimation of the level at returns describes the large flood events indicating a 469.44 mm and 516.21 mm of the significant floods 50-year and 100-year returns respectively. The results offer crucially designed site values critical to improving the urban drainage-related infrastructure and flood resilience mechanisms of the semi-arid Sudano-Sahelian region.

CITATION

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INTRODUCTION

Rainfall being a quantitative environmental variable follows a complicated stochastic behaviour in the sense that it is never negative, has a right skew, with heavy tails. These characteristics are natural results of the infrequent appearance of precipitation and a great variety of magnitudes that are seen throughout the scope of time. These inherent stochastic features of the rainfall demand accurate statistical modelling of the rainfall data with flexibility of probability distributions. The classical parametric distributions that are normally used to describe the marginal behaviour of rainfall intents are the Gamma, Weibull, and Lognormal because they offer support on the positive real line, and by virtue of the fact that they can model skewed distributions. As well, extreme value theory (EVT) gives a rigorous mathematical interpretation of extreme events in terms of generalized extreme value (GEV) distributions and other models, which are needed to model the behaviour of tails of empirical distributions of rainfall (Montes-Pajuelo et al., 2024).

Distribution fitting and EVT methods have found extensive application in characterizing rainfall data, in different geographical settings in recent statistical applications. As an illustration, rainfall observations at Jos, Nigeria were analyzed with a set of probability distributions and this gave way to identification of optimum model on the basis of goodness of fit test and parameter estimation procedures like the maximum likelihood and Bayesian. Equally, Nwaigwe et al. (2023) used GEV models to model annual maximum rainfall series, showing that EVT can be used flexibly in the frequency side of rainfall. These statistical methods make it straightforward to make probabilistic characterizations of rainfall and its extremes without any reference to physical or climatological processes, and rather concentrating directly on the mathematical aspects of the underlying random processes.

Although there is an increasing body of research in the study of rainfall variability in semi-arid areas, however, a research gap is still critical in terms of site-specific validation of probability distributions of Maiduguri. Although the theoretical use of Generalized Extreme Value (GEV) and Gumbel has been established by the global literature, a significant gap in the literature that empirically develops and validates the two parametric distributions to the specific rainfall regime of Maiduguri is conspicuous. Majority of the local studies that are available have concentrated at broad variability patterns or general flood risks without undertaking the thorough testing of goodness-of-fit that enables the engineering design to be based on the best statistical models. Sealing this gap squarely, this paper does a stringent frequency investigation of 42 years of rainfall record to determine a legitimized as well as localized model of extreme worth inference in Maiduguri.

Literature Review

Rainfall in semi-arid and arid areas is well known to be the zero inflated stochastic process with a high percentage of dry periods interrupted with occasional rainfall events of different magnitudes. Mixed distribution which take the form of a discrete Bernoulli process to produce zero rainfall with a continuous distribution Markovian of positive rainfall such as Gamma or Weibull is shown to give better results, including rainfall regime representation in a semi-arid climate (Serinaldi, 2009). Simultaneously, the findings of the application of the Extreme Value Theory (EVT) to rainfall extremes are based on the enormous premise of being stationary, and recent Hydrology rather focuses on the significance of previously performing stationary or trend testing before extreme value modelling (Nerantzaki and Papalexiou, 2022). The adoption of stationary EVT models in design rainfall estimation, e.g., by the use of the Generalized Extreme Value distribution to annual maximum rainfall in Nigeria by Ilesanmi et al. (2024), is further evidenced by the popularity of stationary EVT models in design rainfall estimation, as well as, implicitly, by the requirement of validating underlying assumptions when there is climatic variability. The systematic under or over-estimation of design rainfall may be caused by the failure to consider the non-stationarity that might arise as a result of the variability of climate at long-term scales or due to the changes in climates over a long period. However, in recent rainfall literature a more hierarchical approach is becoming a general trend, with mixed or hurdle models being used to describe the entire rainfall process, and EVT being further applied in the tail behaviour of the extremes (especially in semi-arid, data sparse conditions) in the form of either stationary or non-stationary models (Serinaldi & Kilsby, 2015).

The probability distribution and extreme value approaches to statistical modelling of rainfall have been of interest to statistical hydrology and environmental statistics over the last few decades. Rainfall is intuitively non-negative, usually skewed to the right, and it can be tail-heavy; in most applications, classical Latin symmetric distributions, such as the Normal distribution, cannot be applied, whereas more flexible families of distribution are constructed, such as Gamma, Lognormal, Weibull, and extreme value ones.

Some of the recent investigations have conducted systematic performance assessments of various parametric distributions to represent rainfall frequency data in any region and at all scales of time. As an illustration, Jain et al. (2025) compared the quality of modelling rainfall data (in the Bundelkhand region of Madhya Pradesh, India) when using Lognormal, Gamma, and Weibull distributions versus the Normal distribution and observed that models based on distributions with desirable skewness and tail behaviour performed much better with all the metrics of Akaike and Bayesian information criteria as well as standard Akaike and Anderson-Darling goodnessoffit tests. Abdullah et al., (2019) analysis of rainfall in making of Makkah and Jeddah cities tested the hypothesis of the mean annual rainfall series by the use of normal, Gamma and Weibull distributions and found out that the non-normal distributions are more apt to describe the skewness of rainfall distributions.

Adjunct methodology research has also highlighted the benefits of using EVT on the precipitation data. Louzaoui et al. (2023) made a comparison between stationary and non-stationary GEV models of extreme rainfall in Souss Massa region of Morocco, and found that the Gumbel model was an adequate model to describe the yearly maximum rainfall series, and determine high quantile values relating to diverse return times. Simultaneously, it has been demonstrated that a Bayesian extreme value modelling provides strong parameter inferences and predictor information about extreme rainfall, as is the case with a recent study of Somali rainfall, which used Bayesian Markov chain Monte Carlo modeling to provide GEV and generalized Pareto parameters and corresponding levels of predictor returns.

Elsewhere in the statistical literature, reviews of the probabilistic methods of hydrologic extremes highlight the variety of their use, including classical likelihood-based methods of estimating extremes, modern non- Stationary variants, and the persistence of distribution fitting and EVT to understand extremes in various hydro-climatic conditions (Nerantzaki& Papalexiou, 2022).

Nevertheless, within the context of this body of research, it is still possible to consider region-specific statistical analysis, which analyzes the overall distributional behaviour of rainfall as well as the tail behaviour of the extremes using rigorous distribution theory, especially in regions with scarce data sources of interest as is the case in Maiduguri, Nigeria. The current research expands on this body of literature by utilizing a systematic collection of distribution fitting model and extreme value model to the long-term monthly rainfall data at Maiduguri whose parameters are estimated by maximum likelihood, parameter selection by information criteria, and assessed by quantile-based plots and goodness of fit plots.

Even though Extreme Value Theory (EVT) is an established method of the global hydrological modelling, the application of this rigorous method to semi-arid environment in Northeastern Nigeria has failed to be attempted comprehensively. Other available studies have been able to implement GEV models in other regions of Nigeria. For example, the Generalized Extreme Value (GEV) distribution has been applied to annual maximum rainfall in Akure, Ondo State (Ilesanmi *et al.*, 2024) and to extreme rainfall in Katsina City using block maxima and return level estimation (Kane *et al.*, 2023). This lack of local model validation is essential since the nature of rainfall in semi-arid areas vary fundamentally as compared to the humid areas that are usually a priority in the mainstream literary sources. This thus creates an urgent need to step beyond the blanket generalizations and statistically demonstrate what parametric distributions, in particular Gamma of monthly totals and Gumbel of annual maximum, best fit Maiduguri. The need to fill this gap is to ensure the minimization of uncertainty in estimating the level of returns and the inclusion of critical infrastructure planning with site-specific statistical analysis.

MATERIALS AND METHODS

The statistical model used in this paper entails three different stages of analysis: a statistical analysis, probabilistic analysis of monthly rainfall, and an extreme value analysis.

First, descriptive statistics were calculated in order to describe the central tendency, variability and shape of the distribution of rainfalls series. Then the nonzero monthly rainfall data was fitted by parametric probability distributions which are commonly used in hydrological studies namely the Gamma, Lognormal and Weibull distributions using the method of Maximum Likelihood Estimation (MLE). Performance of models was carefully measured using information theoretic measures as well as using goodness of fit measures. Lastly, to estimate the risks of floods, extreme value analysis has been performed. This included looking at the maximum monthly series of rainfall per annum and fitting the data to both the Generalized Extreme Value (GEV) and the Gumbel distributions to estimate the levels of returns at different levels of returns after the different return periods are considered.

Dataset Description and EVT Modelling Framework

The data of 42 years of monthly rainfall (mm) was gathered by the Nigerian Meteorological Agency (NiMet) at its ground-based stations covering the period between 1981 and 2023. Being the official meteorology authority in Nigeria, NiMet is the main provider of data on the observational climate data, with the information not being completely stored in the open-access, open-global depositories, yet the data can be retrieved by formal data requests and working partnerships, which both grants the data credibility and traceability. This dataset was chosen due to its extended temporal continuity, consistency and station observability which renders the dataset ideal in terms of climate variability, rainfall dynamics as well as extreme rainfall behaviour analysis in semi-arid areas, particularly Maiduguri, where records are mostly not available on a long-term basis. Time series are especially valuable because long-term variability is highlighted, trends can also be identified as well as the extreme value analysis in settings characterized by unstable climatic conditions. Maximal monthly rainfall in this study is applied rather than the daily rainfall measurements in extreme values analysis because it takes into account the climatic conditions of the area as well as the factual data. Strong intermittency, large percentages of zero rainfall, missing values, and measurement variability often contemplate records of rainfall each day so that in semi-arid areas like Maiduguri, uncertainty in the modelling of extreme values on the daily scale goes up. Monthly maxima aggregation gives a more consistent description of extremes and mitigates noise due to observation error and the remaining information required to describe extreme rainfall events and offers greater statistical strength. Even though the Peaks Over Threshold (POT) technique is popularly applied in Extreme Value Theory (EVT) applications, success here requires a good parameter choice of the threshold and frequency to obtain reasonable parameter estimates, although in data-sparse semi-arid environments with very irregular rainfall distributions threshold definition is highly sensitive and tends to be subjective resulting in unstable model behavior. This is why the study chose a block maxima framework using maximum monthly rainfall and uses both Generalized Extreme Value (GEV) and Gumbel distributions since it is more structured on the basis of existing data and offers a more consistent and transparent approach to the modelling of extreme rainfall in the study area.

Descriptive Statistical Analysis

Let $R_1, R_2, R_3, \ldots, R_n$ denote the observed monthly rainfall amounts, where $R_i > 0$

The following descriptive statistics were computed:

Mean rainfall $\bar{R} = \frac{1}{n-1}\sum_{i=1}^{n} R_i$ (1)

Variance $\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(R_i - \bar{R})^2$ (2)

Coefficient of Variation $CV = \frac{\sigma}{\bar{R}}$ (3)

Skewness $\gamma_1 = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{R_i-\bar{R}}{\sigma^2}\right)^3$ (4)

Kurtosis $\gamma_2 == \frac{1}{n}\sum_{i=1}^{n}\left(\frac{R_i-\bar{R}}{\sigma^2}\right)^4$ (5)

These measures describe the central tendency, dispersion, and distributional shape of monthly rainfall.

Probability Distribution Modelling

Let $f(r/\theta)$ denote the probability density function (PDF) of rainfall r with parameter vector θ.

Gamma Distribution

The Gamma distribution is a two-parameter family widely used for skewed hydrological data. Its PDF is given by:

$$f(r) = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} r^{\alpha-1} e^{-\frac{r}{\beta}}, r > 0 \quad (6)$$

Where $\alpha > 0$ shape Parameter, $\beta > 0$ Scale Parameter and, $\Gamma(\alpha)$ Gamma Function

Lognormal Distribution

The Lognormal distribution assumes that the logarithm of the variable r is normally distributed. Its PDF is defined as:

$$f(r) = \frac{1}{r\sigma\sqrt{2\pi}} exp\left(\frac{-(lnr-\mu)^2}{2\sigma^2}\right), r > 0 \quad (7)$$

where μ and σ are the mean and standard deviation of $ln(R)$

Weibull Distribution

The Weibull distribution is versatile in modelling various types of failure rates and natural phenomena. Its PDF is expressed as:

$$f(r) = \frac{k}{\lambda}\left(\frac{r}{\lambda}\right)^{k-1} exp\left[-\left(\frac{r}{\lambda}\right)^{k}\right], r > 0 \quad (8)$$

Where $k > 0$ Shape Parameter, $\lambda > 0$ Scale Parameter

Parameter Estimation Using Maximum Likelihood Estimation (MLE)

To estimate the parameter θ for each distribution, the method of Maximum Likelihood Estimation (MLE) was employed due to its asymptotic consistency and efficiency. For a sample of independent and identically distributed observations, the likelihood function $L(\theta)$ is:

$$L(\theta) = \prod_{i=1}^{n} f(R_i/\theta) \quad (9)$$

The log-likelihood function, which transforms the product into a sum for computational convenience, is given by:

$$l(\theta) = \sum_{i=1}^{n} lnf(R_i/\theta) \quad (10)$$

The parameter estimates $\hat{\theta}$ are obtained by maximizing this function:

The MLE estimate

$$\hat{\theta}_{MLE} = arg \max_{\theta} l(\theta) \quad (11)$$

Numerical optimization techniques were employed due to the non-linear nature of the likelihood functions.

Model Selection and Goodness-of-Fit

Model parsimony and goodness-of-fit were evaluated using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC):

$$AIC = 2k - 2l(\hat{\theta}) \quad (12)$$

$$BIC = kln(n) - 2l(\hat{\theta}) \quad (13)$$

Where k is the number of estimated parameters, n is the sample size, $\hat{\theta}$ is the maximized value of the likelihood function.

In both criteria, lower values indicate a superior model that balances goodness-of-fit with model complexity.

Extreme Value Analysis

To characterize extreme precipitation behavior, the Block Maxima approach was applied. Annual maximum monthly rainfall values were extracted to form a series:

$$M_j = max\{R_{j1}, R_{j2}, \ldots, R_{j12}\}, j = 1,2,\ldots,N \quad (14)$$

Generalized Extreme Value (GEV) Distribution

The Cumulative Distribution Function (CDF) of the GEV distribution is defined as:

$$F(m) = exp\left\{-\left[1 + \xi\left(\frac{m-\mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}\right\} \quad (15)$$

Where μ location Parameter, $\sigma > 0$ scale parameter, ξ shape parameter

Gumbel Distribution (Type I Extreme Value)

$$F(m) = exp\left[-exp\left(-\frac{m-\mu}{\sigma}\right)\right] \quad (16)$$

This is a special case of the GEV distribution when $\xi = 0$

These estimates quantify the probability of extreme rainfall events, providing the necessary design values for hydraulic infrastructure and flood management planning.

Return Level Estimation

The return level $\boldsymbol{z_T}$ corresponding to a return period $\boldsymbol{T}$ years is defined by:

$$P(m) = \frac{1}{T} \quad (17)$$

For the GEV distribution

$$z_T = \mu - \frac{\sigma}{\xi}\left[\left(-ln\left(1-\frac{1}{T}\right)^{-\xi} - 1\right)\right] \quad (18)$$

For the Gumbel distribution

$$Z_T = \mu - \sigma ln\left[-ln\left(1-\frac{1}{T}\right)\right] \quad (19)$$

These return level quantify the flood risk associated with extreme rainfall events over specified return periods.

RESULTS AND DISCUSSION

Statistical Characterization of Monthly Rainfall

Figure 1 and Table 1 collectively elucidate the statistical characteristics of monthly rainfall in Maiduguri for the period 1981–2023. The histogram reveals a highly asymmetric empirical distribution, characterized by a clustering of observations near zero and a scarcity of months exhibiting moderate to high rainfall. This distributional behavior is quantitatively corroborated by the descriptive statistics in Table 1; while the mean monthly rainfall is 53.86 mm, the median (50th percentile) is merely 1.60 mm, indicating that over half of the recorded months receive negligible precipitation. This substantial divergence between the mean and median underscores the heavy right-skew observable in the histogram.

Although infrequent, extreme rainfall events are evident in the histogram's long tail, which extends beyond 300 mm to a maximum observation of 461.50 mm. The high variability of the rainfall regime is further confirmed by a large standard deviation of 87.52 mm. Furthermore, the comparison between the 75th percentile (77.50 mm) and the lower quartile (0.00 mm) provides strong evidence of zero inflation, indicating a mixture process composed of a structural zero-generating regime and a continuous positive rainfall-generating regime. the majority of precipitation is concentrated within a minor fraction of the year, consistent with the unimodal, spike-like morphology of the histogram. These findings align with established hydrological literature, which characterizes semi-arid rainfall as intermittent, highly skewed, and driven by sporadic, intense convective events. Similar distributional patterns have been documented in Jos (Nwaigwe et al., 2023) and across the West African Sahel, where numerous low-rainfall months are punctuated by infrequent high-impact storms.

Table 1: Descriptive Statistics

Count	515
Mean	53.86
Std	87.52
Min. Rainfall	0.00
25%	0.00
50%	1.60
75%	77.50
Max. Rainfall	461.50

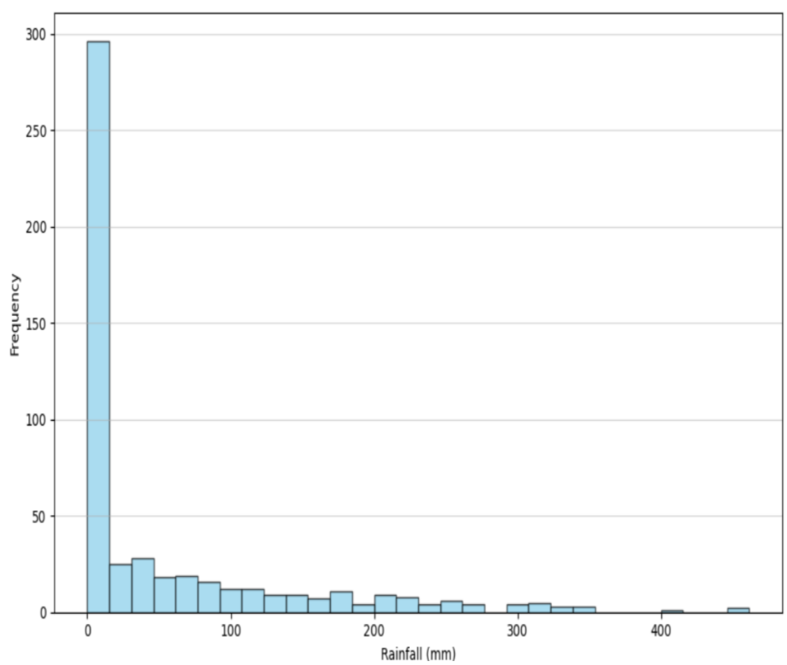

Figure 1: Histogram of Monthly Rainfall (Empirical Distribution)

Probability Distribution Modelling

Accordingly, the fitted CDFs *Figure 2* should be interpreted strictly as conditional distributions of rainfall amounts given non-zero rainfall and not as models of rainfall occurrence probability. When analyzed in conjunction with the parameter estimates and log-likelihood values in *Table 2*, distinct patterns regarding model suitability emerge. Visually, the Gamma distribution (red curve) demonstrates the superior alignment with the empirical CDF across the rainfall spectrum. It tracks the empirical data with high precision in the lower-to-middle quantiles (0–200 mm), where the bulk of observations reside. Deviations in the upper quantiles (>300 mm) remain minimal, suggesting the model's robust capacity to approximate both moderate and extreme values.

The statistical superiority of the Gamma model is substantiated by its log-likelihood value of –1500.9957, the highest (least negative) among the candidate distributions. The estimated shape parameter (0.7797) reflects a highly right-skewed distribution, consistent with the empirical prevalence of low rainfall amounts interspersed with occasional heavy events. This finding mirrors prior hydrological studies in West Africa and other semi-arid regions, where Gamma models frequently outperform symmetric or less flexible distributions. Conversely, the Weibull distribution offers a moderate visual approximation but diverges in the mid-range values. Its lower log-likelihood (–1506.0069) indicates that, while theoretically viable for skewed data, it lacks the flexibility required for optimal fitting in this context. The Lognormal distribution exhibits the poorest fit, particularly in the lower quantiles, with a significantly lower log-likelihood (–1540.4503). This underperformance is consistent with research indicating the Lognormal distribution's limitations in modelling data with extreme right-skewness and heavy tails. Consequently, both graphical and statistical evidence identify the Gamma distribution as the most accurate model for non-zero monthly rainfall in Maiduguri.

Table 2: Parameter Estimates for Fitted Probability Distribution

Distribution	Parameters			Log-Likelihood
	Shape	Location	Scale	
Gamma	0.7797	0.3	126.1747	-1500.9957
Log-Normal	1.1014	-6.9859	67.4264	-1540.4503
Weibull	0.8352	0.3	93.9671	-1506.0069

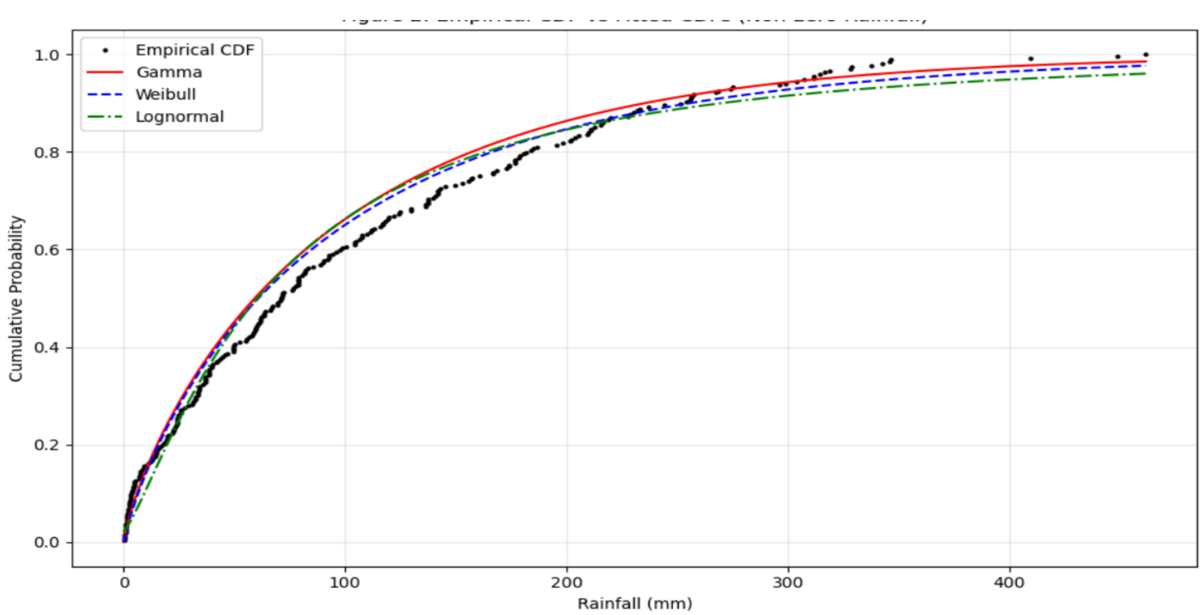

Figure 2: Empirical CDF vs Fitted CDFs (Non-zero Rainfall)

Goodness-of-Fit and Tail Behaviour

Figure 3 displays the Quantile-Quantile (Q–Q) plot for the Gamma distribution, while Table 3 summarizes the information criteria and goodness-of-fit statistics. These results reinforce the selection of the Gamma distribution as the optimal probabilistic model. In the Q–Q plot, the data points follow the 1:1 reference line closely across the lower and middle quantiles (<200 mm), indicating excellent model agreement. A slight upward curvature appears in the 250–300 mm range, reflecting typical tail behaviour associated with variable heavy rainfall events. At the extreme upper quantiles (>400 mm), empirical points deviate slightly above the reference line, suggesting a minor underestimation of the most extreme events.

However, given the volatility and sparsity of data in the upper tail of semi-arid rainfall distributions, these deviations are expected and do not undermine the model's overall validity.

Table 3 quantitatively supports the visual analysis, with the Gamma distribution achieving the lowest Akaike Information Criterion (AIC: 3007.99) and Bayesian Information Criterion (BIC: 3018.78) values, indicating it is the most parsimonious model. Additionally, the Kolmogorov–Smirnov statistic (0.0667) and associated p-value (0.1772) confirm no significant departure from the empirical distribution. These results align with broader hydrological consensus, such as findings by Nwaigwe et al. (2023) and Jain et al. (2023) that the Gamma distribution offers an optimal balance of flexibility and simplicity for monthly rainfall modelling.

Table 3: Model Selection and Goodness-of-Fit Statistics

Distribution	AIC	BIC	KS-Stat	p-value
Gamma	3007.9914	3018.7755	0.0667	0.1772
Weibull	3018.0139	3028.7980	0.0669	0.17724
LogNormal	3086.9007	3097.6848	0.0701	0.1360

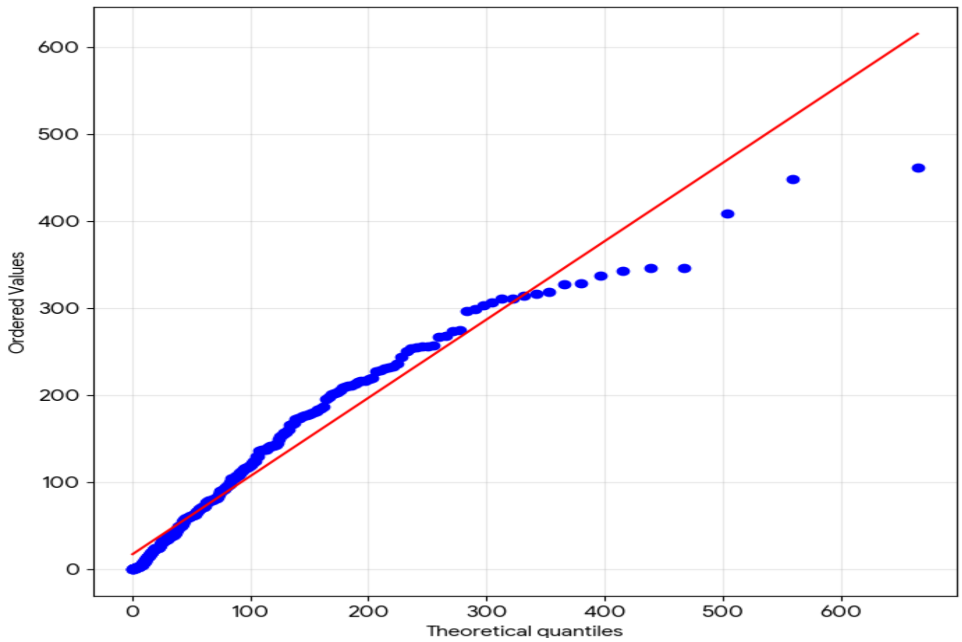

Figure 3: Q-Q Plot for Best-Fitting Distribution (Gamma)

Extreme Value Analysis

Figure 4 presents the diagnostic Q–Q plot for the Gumbel extreme value model fitted to the annual maximum rainfall series. In conjunction with the parameter estimates in *Table 4*, the evidence strongly supports the Gumbel distribution's suitability for modelling rainfall extremes in Maiduguri. The Q–Q plot reveals that theoretical quantiles align closely with observed values along the 1:1 reference line for the majority of the data (150–300 mm). Mild deviations occur only at the extreme upper tail (>350 mm); such behavior is attributable to natural variability and data sparsity inherent to hydrological extremes and does not indicate systematic model failure.

The parameter estimates in *Table 4* further validate the choice of the Gumbel model. The Generalized Extreme Value (GEV) shape parameter (= 0.14) is close to zero, implying convergence toward the Gumbel class of extreme value distributions, which is further supported by minimal difference in log-likelihood between the GEV and Gumbel models. This aligns with extreme value theory, which posits that the GEV simplifies to the Gumbel distribution. Although the GEV model yields a marginally higher log-likelihood (–246.7286) than the Gumbel (–247.4000), the difference is negligible and does not justify the added complexity of the shape parameter, supporting the selection of the simpler model via the principle of parsimony. These findings are consistent with regional studies, including Louzaoui et al. (2023) in Morocco and Kane et al. (2023) in northern Nigeria, which have reported the efficacy of the Gumbel distribution for similar climatic regimes.

Table 4: Parameter Estimates for Extreme Value Models

Model	Parameter		Log-likelihood
	Scale	Shape	
GEV	69.16	0.14	-246.7286
Gumbel	66.99	0.00	-247.4000

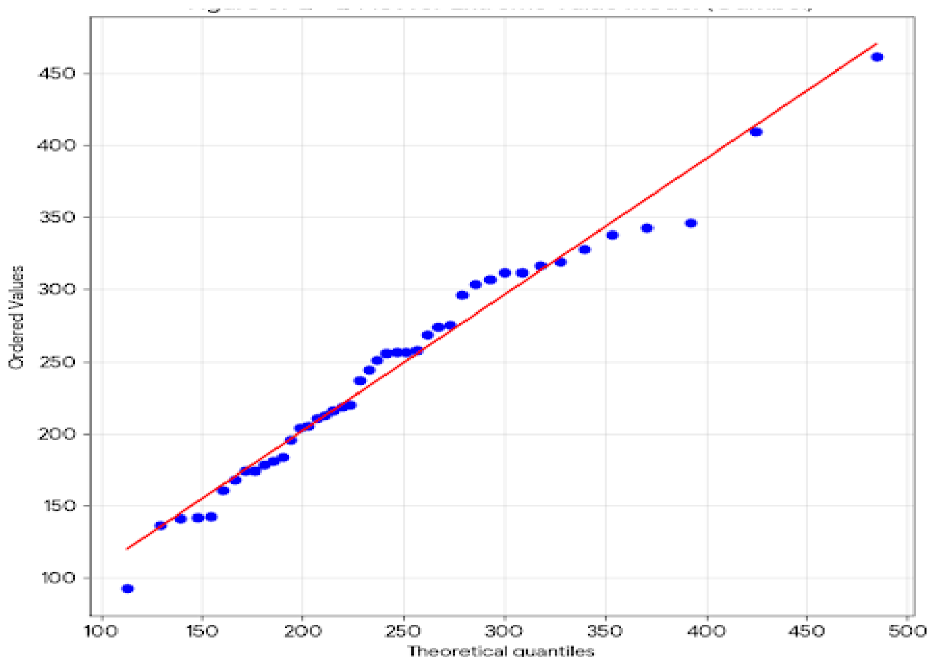

Figure 4*:* Q-Q plot for Extreme Value Model (Gumbel)

Return Level Estimation

Figure 5 shows the return level plot obtained of Gumbel model with numerical estimates in *Table 5*. The plot has a nearly linear relationship between the magnitude of rainfall as a function of the logarithm of the period and this is characteristic of the Gumbel distribution making it to confirm the stability of the model. The fact that the plotted points are heavily consistent with the fitted line will demonstrate that the model is very realistic and there is little uncertainty in the return period.

Table 5: Estimate Return Levels (Gumbel)

Return Period (Years)	Estimate Return Level
2	232.61
5	308.54
10	358.81
20	407.03
50	469.44
100	516.21

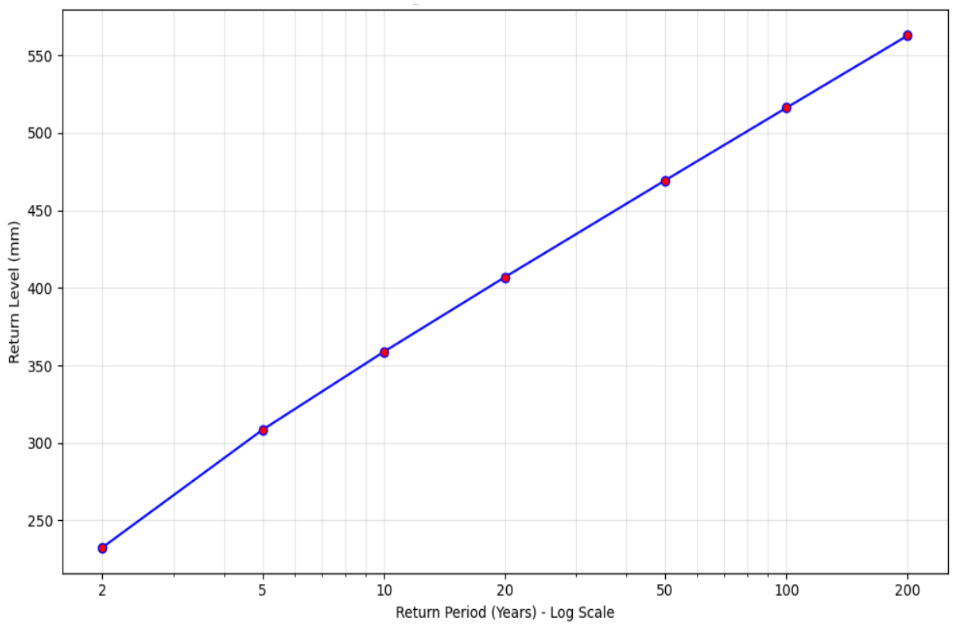

Figure 5: Return Levels plots

CONCLUSION

In this research paper, a stringent statistical profile of rainfall and extreme precipitation every month in Maiduguri, Nigeria was performed by the use of 42-year records (1981-2023). It was found that the rainfall regime of the area is highly skewed and intermittent with most of the rainfall focused within a limited season and with rare but high intense events.

By using the Gamma distribution as the proposal probabilistic distribution of the non-zero monthly rainfall, Gamma distribution was derived using the Maximum Likelihood Estimation and information-theoretic criteria. It always fitted better than the Weibull and Lognormal distributions as it had the highest value of log-likelihood, lowest values of AIC and BIC. In extreme value analysis, Gumbel distribution was the most appropriate model to use in case of annual maxima of rainfall. The choice was guided by an approximation of a shape parameter (GEV) that was close to zero ($\xi \approx 0.14$) and the principle of parsimony that embraced the simpler Gumbel model against the more complex GEV.

The deduced levels of returns are reflective of great flood threats to the area. The approximated rainfall in 50 years and 100 years is 469.44mm and 516.21 mm respectively. By this, critical design values on hydraulic planning and urban drainage remain close to affordability and focus all efforts to ensure that there are stringent flood control measures to have in place given the prospective disastrous storm events within Maiduguri.

Limitations and Future Scope

While this study offers significant insights into the statistical behaviour of rainfall in Maiduguri, certain limitations must be acknowledged to guide future research. Primarily, the extreme value analysis assumes stationarity, a premise that may be challenged by climate change and observed increasing trends; consequently, future research should implement non-stationary Extreme Value models, such as GEV with time-varying parameters, to explicitly account for temporal trends. Additionally, the study's focus is restricted to a univariate analysis of rainfall depth, overlooking critical flood factors like storm duration and intensity, which necessitates the expansion of future work into multivariate analysis using copulas to model joint probabilities. Finally, the reliance on a single-station record limits the broader applicability of the design estimates, suggesting that future studies should employ Regional Frequency Analysis (RFA) to pool data from homogeneous stations, thereby enhancing robustness and reducing uncertainty across the Sudano-Sahelian zone.

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