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# Bayesian Modelling of Extreme Rainfall Data of Some Selected Locations in Nigeria

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***Author's contribution***

*The sole author designed, analysed, interpreted and prepared the manuscript.*

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## ABSTRACT

Climate change occurs when there is rise in average surface temperature on earth, which is mostly due to the burning of fossil fuels usually by human activities. It has been known to contribute greatly to the occurrence of extreme storms and rainfall, this trend continues as the effect of climate change becomes more pronounced. Therefore, this study modelled the extreme rainfall data of three locations (Calabar, Ikeja, Edo) in Nigeria. The block maxima method was used to pick out the maximum rainfall data in each year to form annual maxima data set. The parameters [location, scale, shape] were estimated using both the Classical and Bayesian methods. The result shows that the Bayesian Informative approach is a very good procedure in modelling the Nigerian Extreme Rainfall data.

*Keywords: Climate change; Generalized Extreme Value (GEV); prior elicitation; block maxima; Maximum Likelihood Estimation (MLE).*

## 1. INTRODUCTION

In recent years, there has been a heightened concern about unmitigated alteration of our climate system which has exacerbated extreme weather events, accelerated sea level rise, desertification, coastal erosion, droughts, and unprecedented rise in ambient temperature,

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flooding causing property damage and population displacement and socio economic burdens [1].

The world has been getting drenched as a result of climate change. Heavy downpours in some part of Nigeria have become more frequent over the last 3 to 5 decades, and global warming is thought to have increased rainfall in some part of the world's driest regions. Because of the high impact these extreme precipitation events have on society, it is important to understand the atmospheric condition that set the stage for these incidents.

Climate is influenced by a multitude of factors that operate at timescales ranging from hours to hundreds of millions of years. Many of the causes of climate change are external to the earth system. Others are part of the earth system but external to the atmosphere. Still others involve interactions between the atmosphere and other components of the earth system and are collectively described as feedbacks within the earth system. Feedbacks are among the mostly recently discovered and challenging causal factors to study. Nevertheless, these factors are increasingly recognized as playing fundamental roles in climate variation. Thus, this research aimed to apply Bayesian approach to model the extreme precipitation due to climate change problem and often lead to flooding in three locations (Calabar, Ikeja and Edo) in Nigeria in order to determine the likelihood distribution for the data, to elicit the prior for the parameters in the distribution and to model the extreme rainfall event distribution.

Application of extreme value theory to evaluate some of the most important statistical methods that are used for occurrence anaysis of the extreme precipitation (rainfall) event has been discussed in the work of [2,3,4,5]. Extreme value theory is applied on ten station data located in the Mediterranean region using two main fundamental approaches, block-maxima and Peak over threshold and three commonly used methods for the calculation of the extreme distributions parameters(Maximum Likelihood, L Moment and Bayesian) are analysed and compared. The results showed that the Generalized Pareto Distribution provides better theoretical justification to predict extreme precipitation compared to Generalised Extreme Value Distribution while in the majority of stations the most accurate parameters for the highest precipitation levels are estimated with the Bayesian method.

Modelling the mean annual rainfall for data recorded in Zimbabwe from 1901 to 2009 using extreme value theory to estimate the probabilities of meteorological droughts (beyond and below normal rainfall) was carried out by [6,7]. They exploited the duality between distribution of minimal and maxima and used to fit the generalised extreme value distribution using the maximum likelihood estimation and Bayesian approach to estimate the parameters. His research shows that minimum annual rainfall follows Weibull class of distribution and the augmented Dickey (ADF) test showed that the minimum annual rainfall data were stationary and has no trend. The work is central on using generalised extreme value distribution to model extreme minimum rainfall and concluded after estimating the parameter using Bayesian approach that the parameter estimated were closed to the maximum likelihood estimate with smaller standard deviations using non-informative prior. Similarly, an annual rainfall data of Alor setar rainguage station modelling using generalised extreme value (GEV) distribution and a Bayesian Markov Chain Monte Carlo (MCMC) simulation was established in their work, [8]. The outcome of the informative prior and non-informative prior were compared and concluded on the basis of the outcome that there is a reduction in estimated values which is due to information prior.

## 2. METHODOLOGY

**Block Maxima:** The Block Maxima (BM) method also known as Annual maxima is a fundamental approach in extreme value theory consist of dividing the periodic observation period into non-overlapping periods of equal size restricts attention to maximum observation in each period. Let $Y_1, Y_2, \ldots$ be independently and identically distributed random variable with distribution function F. Define for $n = 1,2, \ldots$ and $i = 1,2, \ldots k$,

The BM$=\max_{(i-1)n<j<in} Y_i$ (1)

Thus, the $n\, x\, k$ observations are divided into k blocks of size n, i.e $m = n\, x\, k$, total number of observations, [9].

The generalized extreme value distribution can be fitted to the series of block maxima $Y_1, Y_2, \ldots, Y_n$ . In most cases, environmental application to the length of the block is usually one year and then we use the data as annual maximum $Y_i$.

**The Generalized Extreme Value Distribution:** The three types of limiting arising distribution function introduced in the theorem 1 can be combined into one family of distribution known as Generalized Extreme Value (GEV) distribution function of the form.

$$J(y:\mu\,,\sigma,\xi) = \exp\left\{-\left[\,1+\xi\left(\frac{y-\mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}\right\} \qquad (2)$$

Equation (2) was defined when $\left\{y:1\,+\xi\,\frac{y-\mu}{\sigma}>0,\right.$ $-\infty<\mu<\infty,$ $\sigma>0$ and $-\infty<\mu<\infty$. where, $\mu,$ $\sigma,$ $\xi$ is the location, scale and shape parameters respectively, Von Mises (1954) and Jenkinson (1955).

## 2.1 Methods of Estimation

**Method of maximum likelihood estimation:** This method was established by R.A. Fisher, which has become the most popular methods of estimation, due to its good theoretical properties (unbiased, consistency, normally distributed and efficient) greatly for large sample. Let a sample of n random variables $X_1, X_2, \ldots, X_n$ where each random variable is distributed according to a probability giving a density function $f(x,\theta)$ with $\theta, \epsilon, \omega$, where $\backslash omega$ is the parameter space. The joint density function for iid $X_1, X_2, \ldots, X_n$ is

$$f(\,x_1, x_2, \ldots, x_n \mid \theta\,) = f(x_1\,;\theta).f(x_2;\theta), \ldots, f(x_n;\theta) \quad (3)$$

Suppose $x_1, x_2, \ldots, x_n$ are fixed where $\theta$ is the function's variable and is allow to vary, then the likelihood function will be:

$$L(\theta; x_1, x_2, \ldots, x_n) = f(x_1, x_2, \ldots, x_n \mid \theta) = \prod\nolimits_{\_(i=1)}^{n} f(x_i;\theta) \quad (4)$$

**Bayesian estimation:** Suppose the data $y = (y_1, \ldots, y_n)$ are random variable with a density from a parametric family $H = \{\,f(y;\theta): \theta\,\epsilon\,\Theta\,\}$.Also let the prior beliefs about $\theta$ be formulated and defined by the probability density function $g(\theta)$ with no reference to the data. Then the likelihood for $\theta$ is

$$\begin{aligned} L(\theta/y) &= f(y/\theta) \\ &= \prod\nolimits_{\_(i=1)}^{n} f(y_i;\theta) \end{aligned}$$

Then the prior information and the likelihood can be combined using bayes's theorem to give a posterior distribution for $\theta$ as follows;

$$\begin{aligned} f(\theta\,/\,x) &= \frac{g(\theta)L(\theta\backslash y)}{(f(y)} \\ &= \frac{g(\theta)L(\theta/y)}{\int_\theta g(\theta)L(\theta/y)} \end{aligned} \qquad (5)$$

i.e $f(\theta/y) \propto g(\theta) \times L(\theta/y) =$ i.e $posterior \propto prior \times likelihood$

**GEV maximum likelihood:** Fitting the GEV distribution to a given data historical dataset there is need to estimate the parameters of the model$(\mu,\sigma,\xi)$. To estimate parameter, one of the common way is maximum likelihood estimation. Supposed that $Y = \{Y_i, \ldots, Y_n\}$ are independent variables having the GEV distribution $\xi \neq 0$.

$$J(y:\mu\,,\sigma,\xi) = \exp\left\{-\left[\,1+\xi\left(\frac{y-\mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}\right\} \qquad (6)$$

and consequently the probability density function (pdf) is

$$\frac{1}{\sigma}\left[\,1+\xi\left(\frac{y-\mu}{\sigma}\right)\right]^{-(\frac{1}{\xi}+1)} \qquad (7)$$

defined when $\{\,y: 1\,+\xi\frac{y-\mu}{\sigma}\,>\,0\,\}$, $-\infty\,<\mu<\infty, \sigma\,>\,0.$

The likelihood is then defined as $L(\mu,\sigma,\xi\,) = j(y:\mu\,,\sigma,\xi)$

$$L(\mu,\sigma,\xi\,) = \frac{1}{\sigma^n}\prod\nolimits_{i=1}^{n}\left[1+\xi\left(\frac{y_i-\mu}{\sigma}\right)\right]^{(\frac{1}{\xi}+1)}\exp\left\{\left[1+\right.\right.$$

$\xi\, yi\text{–}\mu\sigma 1\xi$ (8)

The maximum likelihood Estimators (MLE) $(\hat{\mu},\hat{\sigma},\hat{\xi})$ which maximise $L(\mu,\sigma,\xi\,)$ also maximise $\ell(\mu,\sigma,\xi\,)$ the log-likelihood function:

$$\ell(\mu,\sigma,\xi) = -nlog\sigma - \left(1+\frac{1}{\xi}\right)\sum\nolimits_{i=1}^{n}\log\left[1+\right.$$

$\xi\, yi\text{–}\mu\sigma\text{–}i\text{=}1n1\text{+}\xi\, y\text{–}i\text{–}\mu\sigma\text{–}1\xi$ (9)

when $\xi = 0$ , the Gumbel limit of the GEV distribution in equation (9) is used, similarly to obtain

$$\ell(\mu,\sigma) = -nlog\sigma - \sum\nolimits_{i=1}^{n}\left(\frac{y_i-\mu}{\sigma}\right) - \sum\nolimits_{i=1}^{n}\exp\left\{-\left(\frac{y_i-\mu}{\sigma}\right)\right\} \qquad (10)$$

The MLEs $(\hat{\mu},\hat{\sigma},\hat{\xi})$ are obtained by maximizing equations (9) and (10) with respect to the vector $(\mu,\sigma,\xi\,)$ under the constraints $1+\xi(y_i-\mu)/\sigma > 0\;\; for\; i = 1,2,\ldots,n$ using numerical techniques.

**Prior Elicitation:** The aim of eliciting process is to minimize the impact of biases inherent in surfacing and capturing subjective expert judgment.

$$\tilde{q}_{p_i} \sim\; gamma\;(\alpha_i,\beta_i)\;\alpha_i,\beta_i\;>0 \qquad i = 1,2,3 \quad (11)$$

The gamma parameters are obtained by measures of location variability in prior belief. Let $\bar{q}_{pi}$ and $v_{\bar{q}_{pi}}$ be the mean and variance respectively of a random variable $\tilde{q}_{p_i}$ where $\tilde{q}_{p_i} \sim gamma(\alpha_i, \beta_i)$ It is easily shown that $\alpha_i = (\bar{q}_{pi})^2/(v_{\bar{q}_{pi}})$ and $\beta_i = \frac{v_{\bar{q}_{pi}}}{(\bar{q}_{pi})}\ for\ i = 1,2,3.$

From (10) and (11), the joint prior for the $q_{pi}$ is found to be

$$\pi(q_{p1}, q_{p2}, q_{p3}) \propto q_{p1}^{\alpha_1 - 1} q exp(-\beta_1 q_{p1}) \prod_{i=2}^{3}(q_{pi} - qpi-1\alpha i-1 \exp - \beta i qpi - qpi-1, \quad (12)$$

The Jacobian of the transformation $q_{p1}$, $q_{p2}$, $q_{p3}$ $(0 \leq q_{p1} \leq q_{p2} \leq q_{p3}) \rightarrow (\mu, \sigma, \xi)$ leads directly to the prior in terms of the GEV parameters. The Jacobian is given by

$$J \rightarrow (\mu, \sigma, \xi) = -\frac{\sigma}{\xi^2}\{[\,log(1 - p_2) log(1 - p_3)]^{-\xi}[\,log(-log(1 - p_2)) - log-log1-p3 + log1-p1log1-p3-\xi \log-\log 1-p3-\log-\log 1-p1+ log1-p1log1-p2-\xi[\quad log-log1-p1-log-log1-p2]\}$$
(13)

The construction leads to the prior density:

$$\rho(\mu, \sigma, \xi) \propto J \prod_{i=1}^{3} \tilde{q}_{pi}^{\alpha_i - 1} \exp\left\{\frac{\tilde{q}}{\beta_i}\right\}, \quad (14)$$

provided that $q_{p1} < q_{p2} < q_{p3}$ and $J$ is the Jacobian transformation from $q_{p1}$, $q_{p2}, q_{p3} \rightarrow (\mu, \sigma, \xi)$, $J(\mu, \sigma, \xi)$ which can be further simplified as:

$$\rho(\mu, \sigma, \xi) \propto q_{p1}{}^{\frac{\alpha_1}{3} - 1} exp\left(-\frac{\beta_1}{3}\right) \times \prod_{i=2}^{3}(q_{p1} - qpi-1\alpha 13-1 \exp -\alpha 13 qpi - qqi-1 \times J(\mu,\sigma,\xi) \quad (15)$$

then the posterior is $\pi(\mu, \sigma, \xi / y) \propto \rho(\mu, \sigma, \xi)\, L(\mu, \sigma, \xi / y)$

## 3. ANALYSIS AND DISCUSSION OF RESULTS

### 3.1 Exploratory Data Analysis

Table 1 shows the summary of the rainfall data in Calabar, Ikeja, and Edo, it can be deduced that the highest rainfall was recorded in Calabar with 881.4 mm while the lowest rainfall was recorded in Ikeja with 619.5 mm. The standard deviation is also high in Calabar which indicating a high level of fluctuations of the rainfall data. There is also evidence of positive skewness in all the three locations, which means that the right tail is particularly extreme, an indication that the flooding data has non-symmetric pattern.

Fig. 1 shows the monthly rainfall in Calabar over the period of January 1971- December 2016 and we see some extreme rainfall $(> 600mm)$ over the period which can also be used as a suspect to an outlier. It can be deduced that the data is skewed to right and more of the data are between 200 and 400. It also displays the box-plot of rainfall data in Calabar, it can also be seen that there are presence of outliers in the data with some data fall above the 3rd quartile value of the data.

Fig. 2 shows the time plot for rainfall data in Ikeja. It can be deduced that the data is skewed to right and more of the data are between 150 and 250. It can also be deduced that there are presence of outliers in the data with some data fall above the 3rd quartile value of the data.

Fig. 3 displays the time, density and box plots for Edo rainfall data. It can be deduced that the data is skewed to right and more of the data are between 150 and 300 in Edo. It can be concluded that there are presence of outliers in the data with some data fall above the $3^{rd}$ quartile value of the data.

### 3.2 Estimation Parameter

**Prior Elicitation:** Table 2 shows the elicited prior median and 90% quantiles for the three locations, Calabar, Ikeja and Edo states. The elicitation of prior using quantile approach has a solid hypothetical understanding and practical use to real life data, therefore, the model developed in this study can now serve as a tool to Nigerian meteorological agency to monitor extreme rainfall in Calabar, Ikeja and Edo due to climate change.

**Estimation of Parameters for Calabar:** Table 3 shows the summary of results for the parameter estimations, standard errors and 95% C.I using Maximum Likelihood Estimation (MLE) and Bayesian methods for Calabar rainfall data. For the MLE, the estimates for the parameters $were$ ; $535.7939,\ 107.2431,\ -0.14194$ with the standard errors; 17.5216, 12.1665, 0.09668, and their 95% confidence intervals; $[501.4521,\ 570.1357]$ for $\mu$, $[83.3972,\ 131.0891]$ for $\sigma$ and $[-0.33143,\ 0.04755]$ for $\xi$ respectively. For the Bayesian non informative approach, the parameter estimates were; $538.9323, 100.8245, 0.7860$ with the standard errors, $5.4191,\ 1.02819,$

0.78606 and their 95% confidence intervals were; [531.3111, 552.5534], [100.8093, 104.8390] & [0.77066, 0.8015] for $\hat{\mu}$, $\hat{\sigma}$, and $\hat{\xi}$ respectively. While for the Bayesian informative approach, the estimates were: 540.3314, 102.25397, 0.8204 with the standard errors 5.02332, 1.02254, 0.00820 and the 95% confidence intervals for these parameters $\hat{\mu}$, $\hat{\sigma}$, & $\hat{\xi}$ were; [540.0795, 551.6485], [96.24278, 110.3076 ], and [0.29078, 0.8407] respectively.

**Table 1. Summary of the data**

| Location | MIN | 1st Qu. | Median | Mean | 3rd Qu. | Max | Std. Dev | Skew | Kur. |
|---|---|---|---|---|---|---|---|---|---|
| **Edo** | 0.00 | 51.88 | 157.20 | 180.67 | 283.80 | 722.5 | 145.447 | 0.6797 | -0.1583 |
| **Calabar** | 0.00 | 84.55 | 228.55 | 246.33 | 370.38 | 881.4 | 185.794 | 0.5876 | -0.1698 |
| **Ikeja** | 0.00 | 33.75 | 95.15 | 122.42 | 187.07 | 619.5 | 110.807 | 1.2342 | 1.6567 |

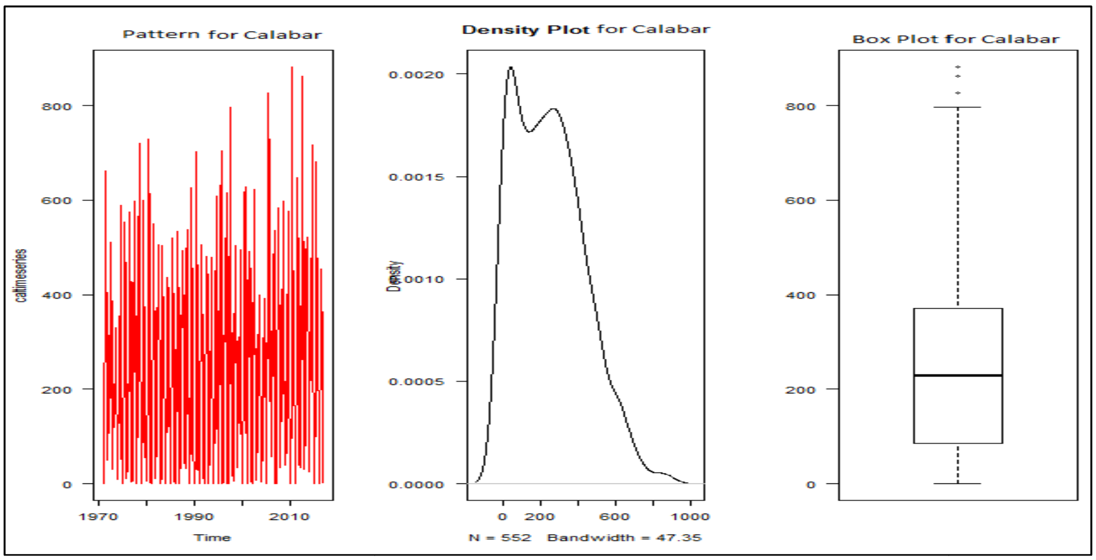


**Fig. 1. Pattern, density and box plots for Calabar rainfall data**

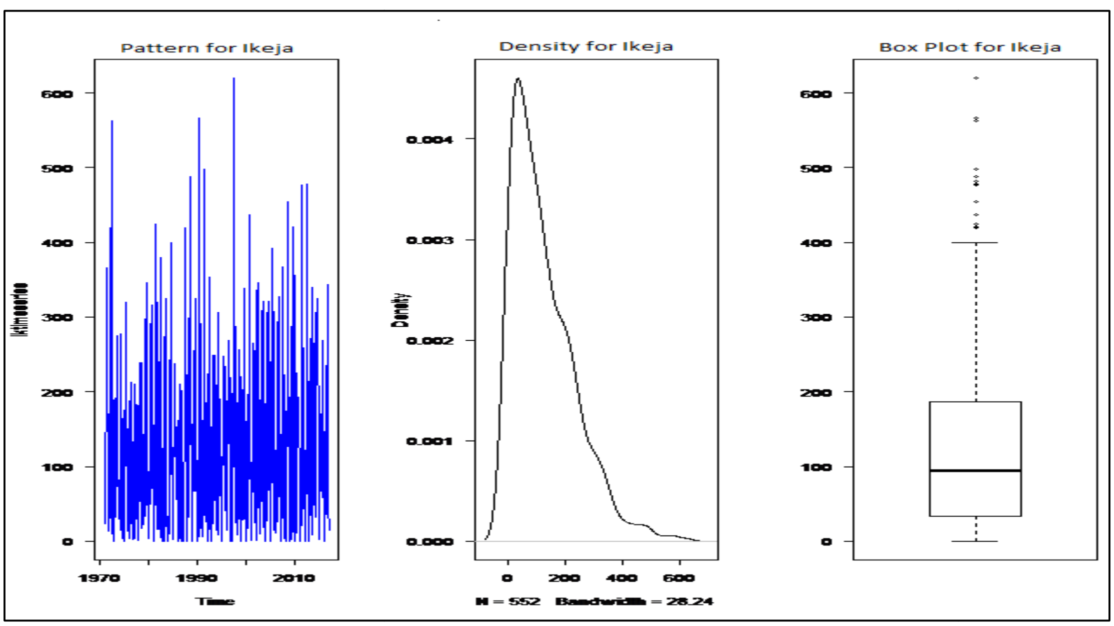


**Fig. 2. Pattern, density and box plots for Ikeja rainfall data**

Fig. 4 shows the model fits, densities, return levels and convergence of the simulations for Calabar using the MLE and Bayesian methods. In both, the Bayesian out performed the MLE approach.

**Estimation of Parameters for Ikeja:** Table 4 shows the summary of results for the parameter estimations, standard errors and 95% C.I using MLE and Bayesian methods for Ikeja rainfall data. For the MLE, the estimates for the parameters $were$; 306.1460, 77.9708, 0.00269 with the standard errors; 13.4032, 10.0203, 0.1365, and their 95% confidence intervals; $[276.8762, 332.4159]$ for $\mu$, $[58.3313, 97.6102]$ for $\sigma$ and $[-0.26484, 0.27000]$ for $\xi$ respectively. For the Bayesian non informative approach, the estimates $were$; 328.3944, 151.0381, 1.69384 with standard errors; 3.283779, 1.510306, 0.01692956, and their 95% confidence intervals were; $[321.9583, 334.8304]$, $[148.0780, 153.9983]$ and $[-1.4498, 4.4705]$ for $\hat{\mu}$, $\hat{\sigma}$, and $\hat{\xi}$ respectively. Also, for the Bayesian informative approach, the parameter estimations were: 335.0072, 156.3385, 1.832606 with standard errors 3.250072, 1.503385, 0.01232606 and the 95% confidence intervals these parameters $\hat{\mu}$, $\hat{\sigma}$, & $\hat{\xi}$ were; $[321.8801, 351.9327]$, $[92.23266, 178.24580]$ & $[0.2703156, 2.1691884]$ respectively.

Fig. 5 shows the model fits, densities, return levels and convergence of the simulations for Ikeja using the MLE and Bayesian methods. In both, the Bayesian out performed the MLE approach.

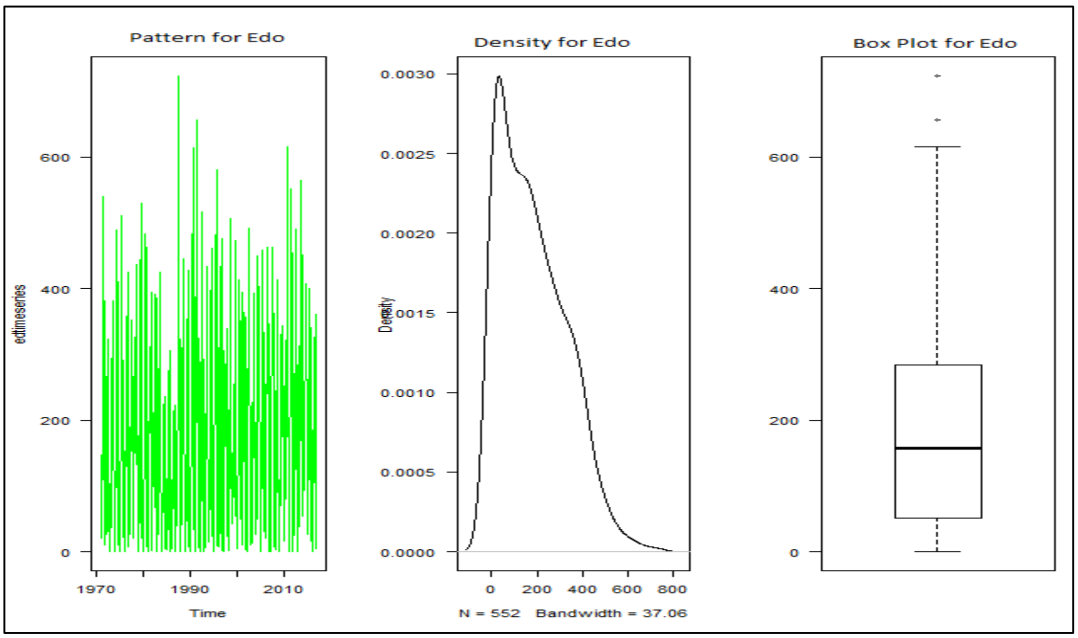


**Fig. 3. Pattern, density and box plots for Edo rainfall data**

**Table 2. Elicited prior median and 90% quantiles**

| Location | Quantile | Median | 90% | $\beta$ | $\alpha$ |
|---|---|---|---|---|---|
| **Calabar** | $q_1$ | 131.13 | 153.66 | 24.5932 | 0.04206 |
| | $q_2$ | 92.209 | 130.34 | 11.8631 | 0.1933 |
| | $q_3$ | 152.25 | 152.25 | 25.3267 | 0.07012 |
| **Ikeja** | $q_1$ | 87.43 | 105.33 | 13.5089 | 0.03847 |
| | $q_2$ | 54.45 | 93.45 | 10.3096 | 0.02690 |
| | $q_3$ | 134.54 | 169.34 | 17.5300 | 0.04329 |
| **Edo** | $q_1$ | 123.43 | 142.88 | 19.980 | 0.04426 |
| | $q_2$ | 98.211 | 128.76 | 8.1047 | 0.01692 |
| | $q_3$ | 140.456 | 185.41 | 23.5435 | 0.06545 |

**Table 3. Summary of results for the different methods of estimation in analysis Calabar**

| Method | | MLE | Bayesian (Non informative) | Bayesian (Quantile Approach) |
|---|---|---|---|---|
| **Estimates** | **Location** | 535.7939 | 538.9323 | 540.3314 |
| | **Scale** | 107.2431 | 100.8245 | 102.25397 |
| | **Shape** | -0.14194 | 0.7860 | 0.8204 |
| **95% Confidence Interval** | **Location** | [501.4521, 570.1357] | [531.3111, 552.5534] | [540.0795, 551.6485] |
| | **Scale** | [83.3972, 131.0891] | [100.8093,104.8390] | [96.24278, 110.3076] |
| | **Shape** | [-0.33143, 0.04755] | [0.77066, 0.8015] | [0.29078, 0.8407] |
| **Standard Error** | **Location** | 17.5216 | 5.4191 | 5.02332 |
| | **Scale** | 12.1665 | 1.02819 | 1.02254 |
| | **Shape** | 0.09668 | 0.78606 | 0.00820 |

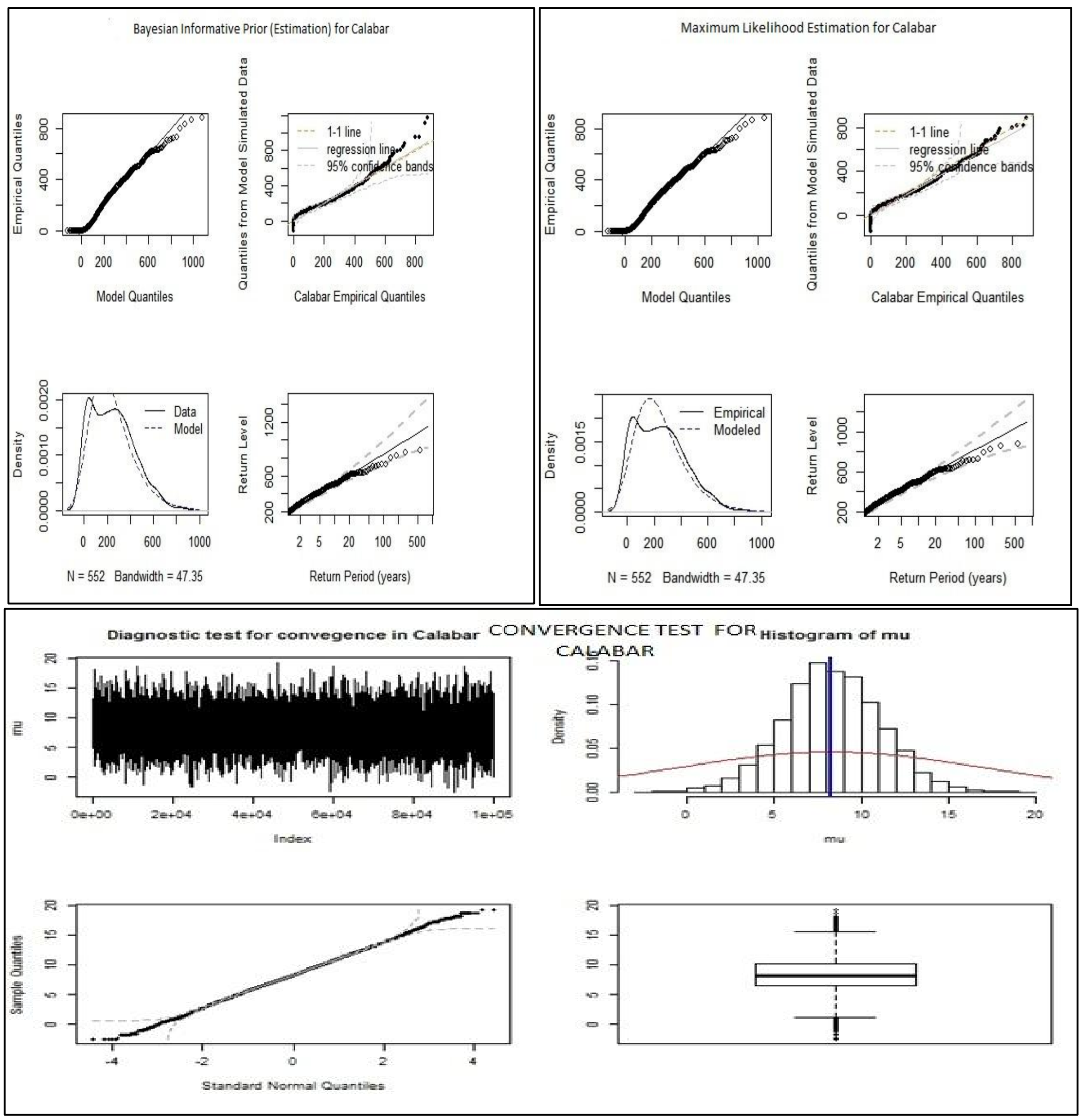


**Fig. 4. Bayesian, MLE and convergence test for Calabar rainfall data**

**Estimation of Parameters for Edo:** Table 5 shows the summary of results for the parameter estimations, standard errors and the 95% C.I using MLE and Bayesian methods for the Edo rainfall data. For the MLE, the estimates for the parameters $were$; $413.3447$, $96.1272$, $-0.2135$ with the standard errors; 15.4349, 10.4103, 0.0765 and their 95% confidence intervals were; $[383.0928, 443.5965]$ for $\mu$, $[75.7234, 116.5410]$ for $\sigma$ and $[-0.36351, -0.06349]$ for $\xi$ respectively. For the Bayesian non informative, the estimates $were$; $397.4792$, $199.825$, $1.624367$ with the standard errors, $3.974567, 1.99815$, $0.016243$ and their 95% confidence intervals for these parameters were; $[389.6891,\ 405.2692]$, $[195.9087,\ 203.7413]$ & $[1.592532, 1.656202]$ for $\hat{\mu}$, $\hat{\sigma}$, & $\hat{\xi}$ respectively. Similarly, for the Bayesian informative, the estimates were: $393.3801$, $212.94210$, $1.77703$ with the standard errors $3.93380$, $1.9471$, $0.01277$ and. their 95% confidence intervals for these parameters $\hat{\mu}$, $\hat{\sigma}$, & $\hat{\xi}$ were; [386.1716,430.8676], [90.73176,251.27909] & [0.261694,2.233644] respectively.

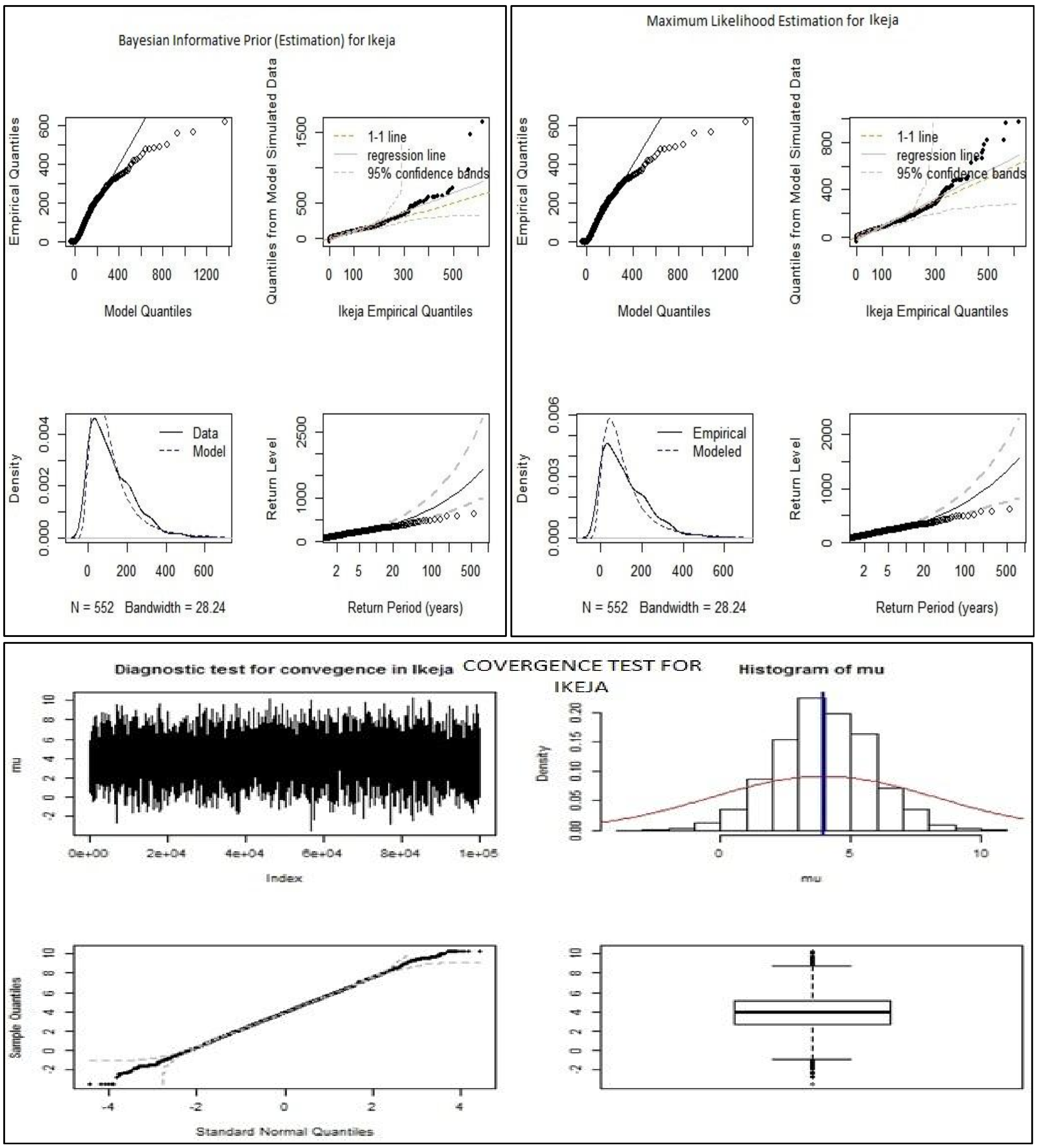


**Fig. 5. Bayesian, MLE and convergence test for Ikeja rainfall data**

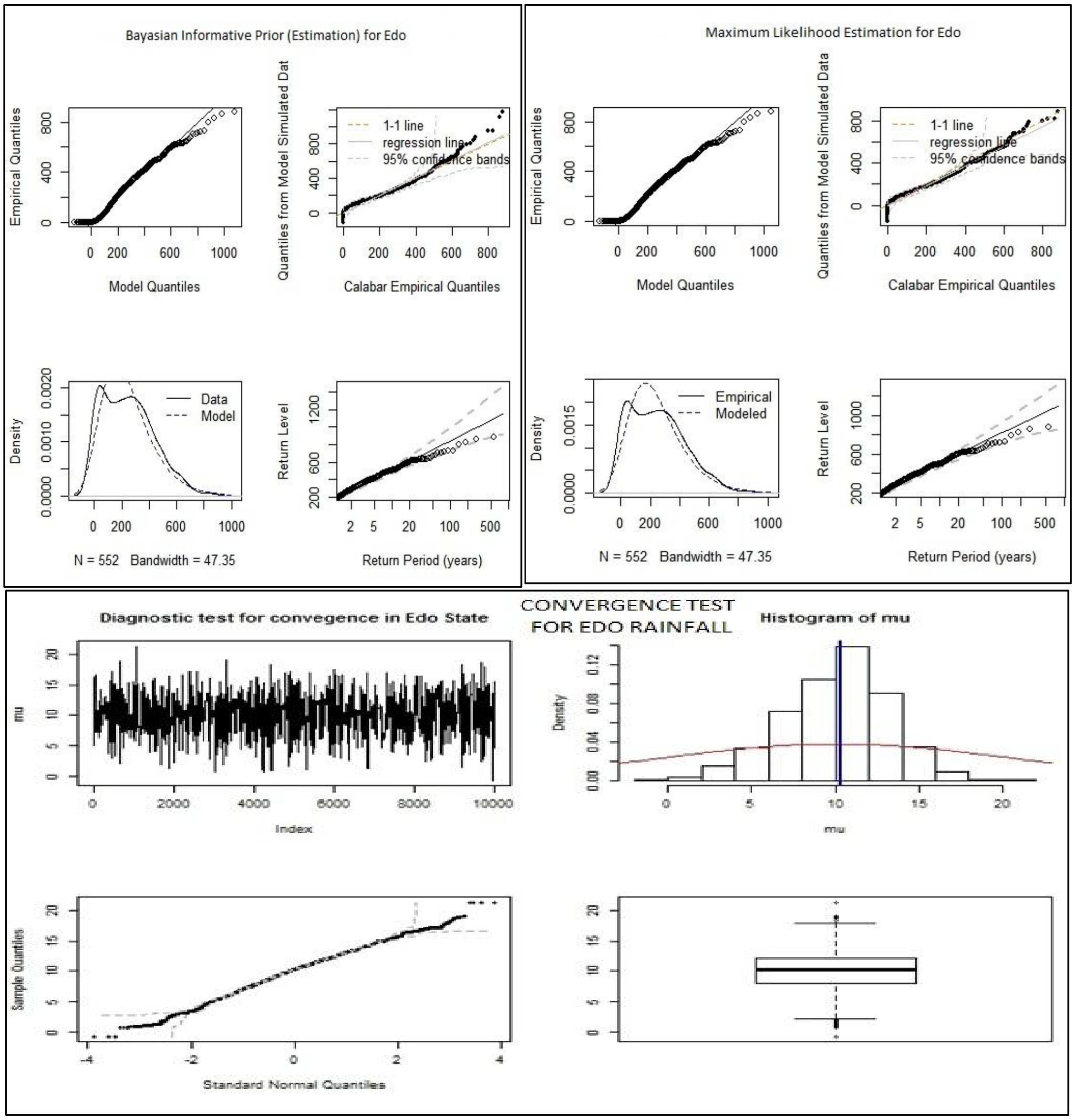


**Fig. 6. Bayesian, MLE and convergence test for Edo rainfall data**

**Table 4. A summary of results for the different methods of estimation in analysis Ikeja**

| Method | | MLE | Bayesian (Non informative) | Bayesian (Quantile Approach) |
|---|---|---|---|---|
| **Estimates** | **Location** | 306.1460 | 328.3944 | 335.0072 |
| | **Scale** | 77.9708 | 151.0381 | 156.0072 |
| | **Shape** | 0.00269 | 1.69364 | 1.83261 |
| **95% Confidence Interval** | **Location** | [279.8762, 332.416] | [321.9583, 334.8304] | [321.8801, 351. 9327] |
| | **Scale** | [58.3313, 97.6102] | [148.0780, 153.9983] | [92.23266, 178.24580] |
| | **Shape** | [-0.26484, 0.27000] | [-1.44984, 4.470451] | [0.2703156, 2.1691884] |
| **Standard Error** | **Location** | 13.4032 | 3.283779 | 3.250072 |
| | **Scale** | 10.0203 | 1.510306 | 1.503385 |
| | **Shape** | 0.13645 | 0.0169296 | 0.0123261 |

**Table 5. A summary of results for the different methods of estimation in analysis Edo**

| Method | | MLE | Bayesian(GEV) | Bayesian (Quantiles Approach) |
|---|---|---|---|---|
| **Estimates** | **Location** | 413.3447 | 397.4792 | 393.3801 |
| | **Scale** | 96.1272 | 199.825 | 212.94210 |
| | **Shape** | -0.2135 | 1.62437 | 1.77703 |
| **95% Confidence Interval** | **Location** | [383.0928,443.5965] | [389.6891, 405.2692] | [386.1716, 430.8676] |
| | **Scale** | [75.7234, 116.5410] | [195.9087, 203.7413] | [90.73176, 251.27909] |
| | **Shape** | [-0.36351, -0.06349] | [1.59253, 1.656202] | [0.26169, 2.23264] |
| **Standard Error** | **Location** | 15.4349 | 3.97459 | 3.93380 |
| | **Scale** | 10.4103 | 1.99815 | 1.9471 |
| | **Shape** | 0.07654 | 0.016243 | 0.012770 |

Fig. 6 shows the model fits, densities, return levels and convergence of the simulations for Edo using the MLE and Bayesian methods. In both, the Bayesian out performed the MLE approach.

## 4. SUMMARY AND CONCLUSION

In this research, the Nigerian Extreme Rainfall data in the three locations follow a Generalized Extreme Value (GEV) Distribution. The parameter estimations for Bayesian informative approach was the highest in most locations with the minimum standard errors in all the locations, followed by the Bayesian non informative and the least was the Maximum Likelihood Estimation with the highest standard errors in all the three locations. The parameter estimates for the three methods fall within the 95% confidence with the closest range of the Bayesian informative approach. Also, the prior elicitation for informative approach has a solid hypothetical underpinning and practical use to real life data. Therefore, the Bayesian informative approach is the best of the three techniques for modelling Nigerian extreme rainfall data in these locations. Also, the rainfall data for all the three locations were positively skewed which implies the right tail is particularly extreme; an indication for the flooding data witiout a symmetric pattern and therefore has much negative effects on the agricultural produce.

## COMPETING INTERESTS

Author has declared that no competing interests exist.

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