PREDICTING EXTREME RAINFALL IN REGIONAL AREAS OF BANGLADESH: A BAYESIAN APPROACH

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ABSTRACT: Extreme weather events are anticipated to become more common around the world and they impact yield volatility i.e. reduce food production. Given the changing nature of the world's climate, and the disproportionate effect this might have on developing countries such as Bangladesh, this is an important topic to study. Agriculture is the major employment source and a significant economic contributing sector in Bangladesh. Moreover, extreme rainfall has a significant effect on agricultural production, which negatively affects the nation's food security and may make it more difficult to end hunger and achieve United Nations Sustainable Development Goal 2. Therefore, understanding and modelling the extremes of rainfall in Bangladesh is crucial. This study considers extreme rainfall in different regional domains of Bangladesh and estimates predictive return levels using the Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD) in the Bayesian setting. Finally, a comparative study is carried out among return levels at regional areas determined by the distributions considered here. Results depict that in the case of the GEV, once every 100 years, on average, we can expect daily rainfall levels to exceed 400 mm in some locations. However, in the case of the GPD, once every 50 years, on average, we can expect daily rainfall levels to exceed 800 mm in Dinajpur and Mymensingh regions. More rainfall will be observed in Chattogram, Cox's Bazar, Dinajpur, Faridpur, Khulna, and Mymensingh regions compared to other parts of Bangladesh. It is also observed that the 100-year return levels are closer to the lower bound than the upper bound of the credible intervals. This information may also be used to identify regions that are particularly vulnerable to the kind of heavy rain that causes flooding.

KEYWORDS: Bangladesh; Bayesian inference; climate change; extremes rainfall; predictive return levels.

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1. INTRODUCTION

Weather is a significant determinant of yields of agricultural crops, whether in respect of averages or incidents. Extreme weather events are anticipated to become more common around the world (Powell and Reinhard, 2016), thus predicting and calculating their effects on crop yields is a vital topic to address in order to ensure food security and eliminate hunger to meet the United Nations (UN) Sustainable Development Goal 2. Researchers pointed out that extreme events are expected to affect yield volatility and are seen as the principal immediate threat to crop production globally (Min *et al.*, 2011; Urban *et al.*, 2012; Lobell *et al.*, 2013). Moreover, experts predict that extreme weather events will reduce food production (Porter *et al.*, 2014).

Bangladesh is one of the most vulnerable nations to climate threats and natural disasters, and it frequently experiences severe floods, cyclones, droughts, heatwaves, and storm surges (Dastagir, 2015; Hossain *et al.*, 2019; Roy and Haider, 2019). Given the changing nature of the world's climate, and the disproportionate effect this might have on countries such as Bangladesh, and the country's heavy reliance upon agricultural production, understanding and modelling extremes of rainfall, temperature, wind speed, sea levels, and so on in Bangladesh is crucial. Among the climate variables, this study considers extreme rainfall in different regions of Bangladesh because it occasionally results in floods that seriously harm agricultural production. The most destructive floods were those in 1974, 1984, 1987, 1988, and 1991, which resulted in fatalities and significant damage to agricultural production (Agrawala *et al.*, 2003; Hossain *et al.*, 2019). In Bangladesh, the distribution of rainfall is erratic and irregular (Amin *et al.*, 2015). Previous studies also pointed out that rainfall was raised during the monsoon and reduced during other seasons, perhaps lengthening the dry season, therefore, Bangladesh may experience more severe floods and droughts (Amin *et al.*, 2015; Pörtner *et al.*, 2022). Moreover, historical data suggest that the frequency, magnitude, and duration of floods have increased significantly over the past few decades, and climate models predict that by 2030, mean monsoon rainfall will likely increase by 10–15% as a result of climate change (Ahmad *et al.*, 1996; Hossain *et al.*, 2020).

Crop yields may vary and agricultural productivity may decline as a result of reductions in rainfall or heavy rainfall since changes in rainfall have a significant impact on soil fertility and moisture. A previous study reported that different climate variables such as temperature, rainfall, humidity, and sunshine significantly impacted the yield of major food crops in Bangladesh (Amin *et al.*, 2015). Additionally, rainfall patterns have a significant impact on irrigation and water management (Rahman *et al.*, 2018). Therefore, changes in various aspects of nature and intense floods would result in a significant loss of agricultural productivity, human livelihood, and life. In addition, Bangladesh's crop production is expected to decline due to climate change by the mid-2050s (Ruane *et al.*, 2013), and the sustainability of agriculture is crucial for maintaining global food security (Shamsudduha *et al.*, 2022).

However, it is evident from the literature that Bangladesh's nationwide rainfall variability and future predictions have not been well investigated, particularly in light of recent data. Thus, in order to adapt to changes and impacts as well as to come up with an appropriate remedy, a country-level investigation of recent environmental data and information about climatic variability and change—particularly variations in rainfall—is required. Therefore, this study considers extreme rainfall in different regional domains of Bangladesh and aims to estimate predictive return levels using the Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD) in the Bayesian setting. Finally, a comparison of return levels at different regions, obtained by the GEV and GPD distributions, is conducted.

2. METHODS AND MATERIALS

Data Source and Study Area

Extreme rainfall was extracted from daily rainfall records (mm) that were collected from twelve meteorological stations situated in different parts of Bangladesh. The required data were purchased from the Bangladesh Meteorological Department following the proper guidelines (Bangladesh Meteorological Department, 2021). The daily data were collected over the period 1948 to 2020. The selected locations are presented in the following Figure 1.

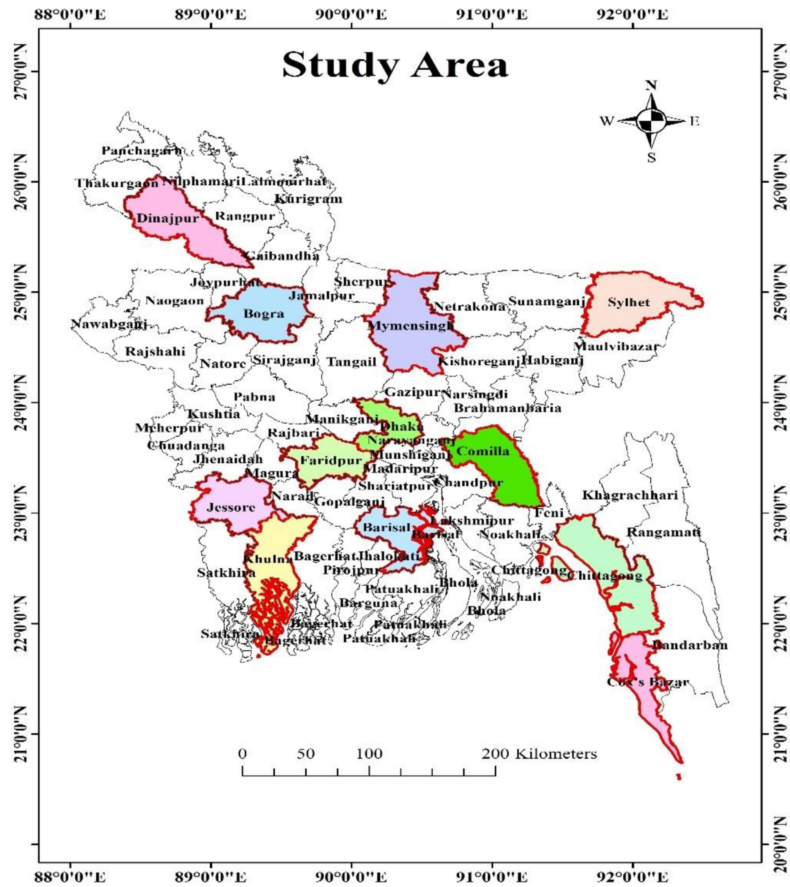

Figure 1. Study Area Map of Selected Twelve Locations in Bangladesh. Source: the Author.

Block Maxima and Generalized Extreme Value Distributions

In the context of extreme value theory, "block maxima" refers to the maximum value of observations in a specific time interval. For the rainfall data considered here, the block refers to calendar years, where only one observation i.e. maximum rainfall from each block is considered for fitting the GEV distribution. Suppose, yearly maxima $X_1, X_2, ..., X_n$ are drawn from independent and identically distributed random variables with common distribution function $F(X)$. Let $M_n = \max(X_1, X_2, ..., X_n)$. If there exist sequences of normalising constants $a_n > 0$ and $b_n \in \mathbb{R}$ such that

$$P\left(\frac{M_n - a_n}{b_n} \le x\right) = P(X \le x) = F^n(a_n x + b_n) \to G(x) \qquad (1)$$

as $n \to \infty$, where G is a non-degenerate distribution function, the distribution F is said to be in the domain of attraction of the extreme value distribution G. Then, G belongs to the family of distributions that can be summarised by the GEV distribution and has the form

$$G_{\mu,\sigma,\xi}(x) = \begin{cases} \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\}, & \xi \ne 0 \\ \exp\left[-\exp\left\{-\left(\frac{x-\mu}{\sigma}\right)\right\}\right], & \xi = 0 \end{cases} \qquad (2)$$

defined on $\{x : 1 + \xi(x-\mu)/\sigma > 0\}$ where both the shape parameter ξ, and location parameter μ take values on $\mathbb{R}$ (Coles, 2001; Kotz and Nadarajah, 2000). The scale parameter σ is strictly positive. The parameter ξ determines the shape of the distribution. Whether the distribution has a light tail or heavy tail depends on the value and sign of this parameter. If the parameter $\xi < 0$, the GEV family gives a Weibull distribution which has a finite support whereas a Fréchet distribution for $\xi > 0$, and a Gumbel in the case of $\xi = 0$. It is important to remember that these distributions are used to model the maximum of the samples, not the entire data set, which is commonly misunderstood (Kotz and Nadarajah, 2000; Dahab, 2011).

Peaks Over Threshold Method and Generalized Pareto Distributions

In terms of statistical practice, the main shortcoming of the GEV is that it has the potential to waste data because it models block maxima. The GPD is another extreme value distribution that addresses some of the GEV's drawbacks. Given a threshold u and for large enough u, the distribution function of $(X-u)$, conditional on $X>u$, is approximately generalised Pareto with distribution function

$$H(y)=\begin{cases}1-\left(1+\frac{\xi y}{\varsigma}\right)^{-\frac{1}{\xi}}; \ \xi\neq 0\\ 1-\exp\left(-\frac{y}{\varsigma}\right); \ \xi=0\,.\end{cases} \tag{3}$$

Here, $y>0$ and $\left(1+\frac{\xi y}{\varsigma}\right)>0$, where $\varsigma=\sigma+\xi(u-\mu)$ and ξ are the scale and shape parameters of the GPD respectively (Coles, 2001).

Return Level Estimation

Estimates of return levels and return periods are often the ultimate goal of any extreme value analysis (Gumbel, 1941; Embrechts *et al.*, 2013). The value that is expected to occur (on average) only once during a particular return period is known as the return level. High quantiles from the fitted extreme value distribution are used as return level estimates. For example, for the GEV we have:

$$Z_r=\begin{cases}\mu-\frac{\sigma}{\xi}\left[1-\{-\log(1-r)\}^{-\xi}\right], \ \xi\neq 0\\ \mu-\sigma\log\{-\log(1-r)\}, \qquad \xi=0\,.\end{cases} \tag{4}$$

To a reasonable degree of estimation, r^{-1} is the return period and Z_r is the associated return level and represents the r -year return level when we use just one observation per year. The return level Z_r is expected to be exceeded on average once every r^{-1} years (Coles, 2001).

In the case of the GPD, the return level Z_r that is exceeded on average once every r observations is the solution of

$$\lambda_u \left[1+\xi\left(\frac{Z_r-u}{\sigma}\right)\right]^{-\frac{1}{\xi}} = \frac{1}{r}. \tag{5}$$

After rearranging, we have, $Z_r = u + \frac{\sigma}{\xi}\left[\left(r\lambda_u\right)^{\xi} - 1\right]$ provided r is sufficiently large to ensure that $Z_r > u$ and $\lambda_u = P(X > u)$ i.e., the proportion of points exceeding u (Coles, 2001). If there are n_y observations per year, this corresponds to the m-observation return level, where $m = r \times n_y$. Hence, the r-year return level can be written as

$$Z_r = \begin{cases} u + \frac{\sigma}{\xi}\left[\left(rn_y\lambda_u\right)^{\xi} - 1\right], \ \xi \neq 0 \\ Z_r = u + \sigma \log\left(rn_y\lambda_u\right), \ \xi = 0. \end{cases} \tag{6}$$

Predictive Distribution

Let θ denote the parameters of interest. For example, in the case of the GEV, we have $\theta = (\mu, \sigma, \xi)'$. Suppose we have prior beliefs about likely values of θ expressed by a probability (density) function $\pi(\theta)$, Bayesian inference proceeds via the posterior density

$$\pi(\theta \mid x) = \frac{\pi(\theta) f(x \mid \theta)}{\int_{\Theta} \pi(\theta) f(x \mid \theta) d\theta}, \tag{7},$$

where x denotes the data (Gelman *et al.*, 2013; McElreath, 2020; Rahman, 2008; Rahman and Upadhyay, 2015).

The numerator of the above expression is straightforward to calculate, since the likelihood $f(x \mid \theta)$ can be written in closed form. However, the denominator involves intractable integrals, resulting in the use of sampling based method such as Markov chain Monte Carlo (MCMC). For a review of MCMC methods, we refer the reader to the existing literature (Gamerman, 1997; Gamerman and Hedibert, 2006).

Bayesian analysis of extremes has an advantage in that it naturally extends to cover prediction via the posterior predictive distribution (Fawcett and Green, 2018). Suppose Y denotes future extremes of our rainfall series. The predictive distribution for extremes that allows both for parameter uncertainty and randomness in future observations and can be written as:

$$P(Y \leq y \mid x) = \int_{\theta} P(Y \leq y \mid \theta)\pi(\theta \mid x)\,d\theta \qquad (8)$$

where x represents past observations, θ is a generic parameter vector and $\pi(\theta \mid x)$ is the posterior density for θ (Coles, 2001).

The predictive r-year return level, i.e., $Z_{r,pred}$ that incorporates uncertainty due to model estimation can be obtained by solving the following for $Z_{r,pred}$

$$P\left(Y \leq Z_{r,pred} \mid x\right) = 1 - r^{-1}. \qquad (9)$$

Despite the fact that equation (8) may seem intractable, it can be approximated easily if realisations from the posterior distribution have already been obtained through simulation, for instance using MCMC. After deletion of the values generated in the burn-in period, we have a sample $\theta_1, \theta_2, \ldots, \theta_s$ that may be regarded as realisations approximately distributed according to $\pi(\theta \mid x)$. Now, we can write

$$P\left(Y \leq Z_{r,pred} \mid x\right) \approx \frac{1}{S}\sum_{i=1}^{S} P\left(Y \leq Z_{r,pred} \mid \theta_i\right) \qquad (10)$$

which can be set equal to $1 - r^{-1}$ and solved for $Z_{r,pred}$ using a numerical solver, where S is the sample size of posterior sample (Coles, 2001; Fawcett and Green, 2018).

3. RESULTS AND DISCUSSION

Findings of GEV

In this study, we adopted independent priors by specifying $\mu \sim N\left(0, 1000^2\right)$, $\sigma \sim N\left(0, 1000^2\right)$, and $\xi \sim N\left(0, 100^2\right)$ for the parameters in the GEV. We used random walk proposal and the Metropolis–Hastings random algorithm for the MCMC output. For computational convenience, we considered $\eta = \log(\sigma)$ and transformed back to the usual scale. Now, we used a random walk proposal with Gaussian innovations with standard deviation $w_\mu = 1$ and $w_\eta = w_\xi = 0.1$

which is consistent with other studies (Ragulina and Reitan, 2017; Ahmad *et al.*, 2022). Though the tuning parameters w_μ, w_η, and w_ξ for our algorithm - did not affect the model, however, they did affect the efficiency of the algorithm and it is observed that our choices yielded good acceptance probabilities. Initializing with $(\mu, \eta, \xi) = (50, 10, 0.5)$, the values generated by 100,000 iterations of the chain are plotted in Figure 2. The settling-in period seems to take around 10,000 iterations; thereafter, the stochastic variations in the chain seem reasonably homogeneous.

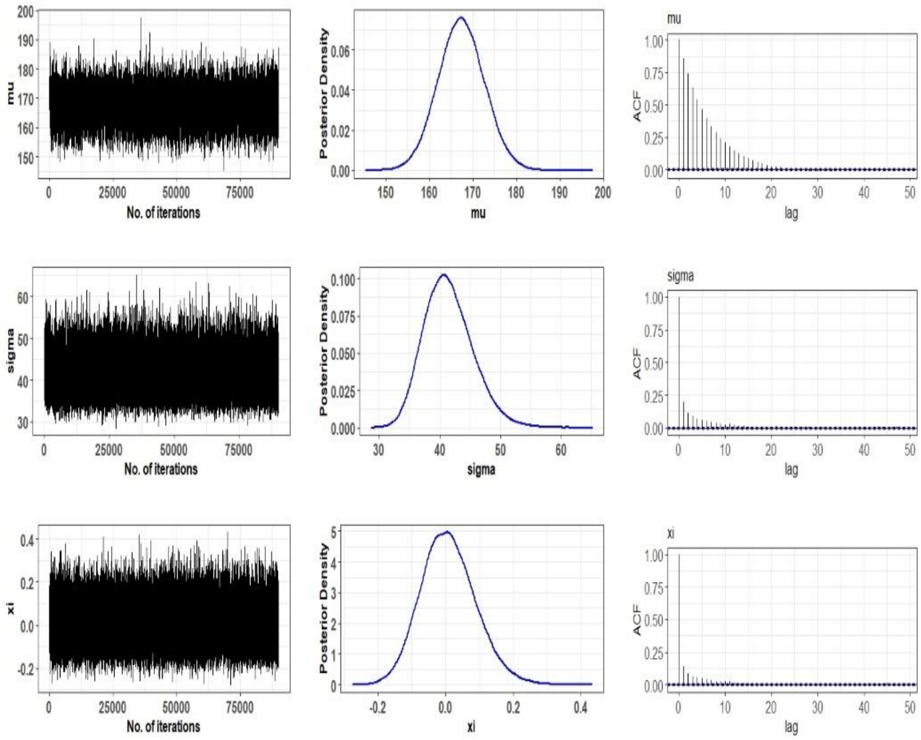

Figure 2. MCMC Realizations of GEV Parameters in a Bayesian Analysis of the Annual Maximum Rainfall in Sylhet. Source: the Author. Notes: Top panel: μ; Middle panel: σ; Bottom panel: ξ.

After deleting the first 10,000 simulations, the remaining 90,000 simulated values can be treated as dependent realizations whose distribution is the target posterior. The posterior mean and standard deviation of each of the marginal components are calculated using the simulated values. The posterior marginal means of the model parameters and their standard deviations (in parentheses) of the selected regions are presented in the following table (Table 1).

Table 1. Posterior Means of the GEV Parameters of the Selected Locations of Bangladesh. Source: the Authors. Notes: Standard deviations are presented in parentheses.

Locations	Estimates		
	μ	σ	ξ
Barishal	118.30 (5.99)	45.27 (4.60)	-0.05 (0.11)
Bogra	104.41 (5.39)	38.96 (4.25)	0.05 (0.12)
Chattogram	177.78 (7.17)	52.63 (5.79)	0.17 (0.11)
Comilla	115.96 (4.35)	32.21 (3.82)	0.32 (0.10)
Cox’s Bazar	183.61 (7.59)	58.15 (5.03)	-0.08 (0.05)
Dhaka	100.79 (4.80)	35.08 (4.15)	0.27 (0.12)
Dinajpur	132.03 (7.34)	57.01 (6.23)	0.14 (0.11)
Faridpur	106.93 (4.85)	36.40 (4.14)	0.27 (0.11)
Jessore	96.09 (4.83)	36.39 (4.07)	0.20 (0.11)
Khulna	102.74 (5.17)	38.27 (4.16)	0.23 (0.09)
Mymensingh	122.85 (6.77)	52.56 (4.88)	0.09 (0.05)
Sylhet	167.06 (5.12)	41.38 (4.00)	0.01 (0.08)

A previous study pointed out that predictive return level estimates may be preferable to standard return level estimates since they give the practitioner a single-point summary that encapsulates uncertainty in parameter estimation (Fawcett and Walshaw, 2016). Therefore, we estimated the return levels and predictive returns of the selected regions for return periods r = 50, 100, 1000, and 10000 years. Plots of the future annual maximum rainfall up to 10,000 years of the considered locations are shown in Figure 3 on the usual return period scale. We used the usual $-\log\left\{-\log\left(1-r^{-1}\right)\right\}$ scale in the x-axis for the case of interpretation - for plotting of both Z_r and $Z_{r,pred}$ over a range of values for r (on the usual logarithmic scale) for these plots to magnify results for long-range return periods; posterior means are shown for Z_r (blue line), along with the 95% credible intervals (purple shaded region), and green lines depict the predictive return ($Z_{r,pred}$).

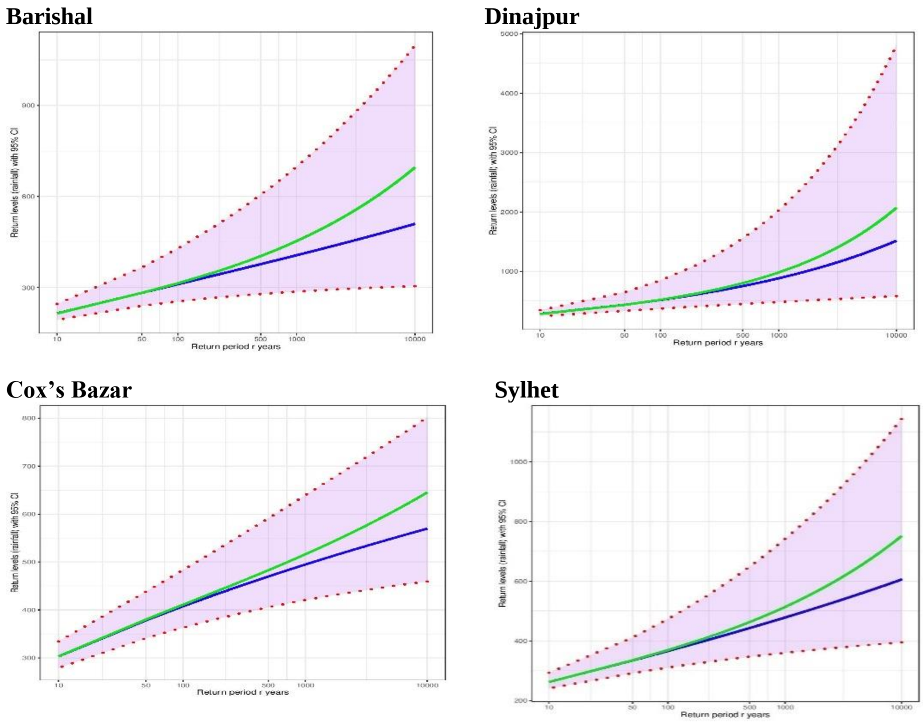

Figure 3. Return Levels Plots of Annual Maxima of Rainfall (mm) of the Selected Locations. Source: the Authors. Notes: Posterior means (blue line); 95% credible intervals (purple shaded region). The corresponding estimates of the predictive return levels $Z_{r,pred}$ (green line).

Findings revealed that the 100-year return levels of rainfall vary across the country. Researchers noted that rainfall variability tends to decrease from Bangladesh's northwest region towards its northeast portion which is consistent with our study findings (Bari *et al.*, 2017; Chowdhury *et al.*, 2019). Moreover, the return levels of rainfall for 50, 100, 1,000 and 10,000 years exhibit differences depending on location. In the case of the 100-year return level, the posterior means are less than 400 mm in some locations, however, in some locations, it is more than 400 mm. It is also observed that the 100-year return levels are closer to the lower bound than the upper bound of the credible intervals. The very positively skewed nature of the return level posterior distribution could lead to inaccuracies in the standard likelihood approach (which uses the $MLE \pm 1.96 \times s.e.$).

Findings of GPD

In the case of the GPD, it is necessary to select an appropriate threshold for rainfall at the twelve locations. We used the mean residual life (MRL) plot for this purpose (Coles, 2001). We again used the Metropolis–Hastings random walk sampling algorithm for sampling from the posterior. In the case of the scale parameter $\sigma > 0$, we considered $\eta = \log(\sigma)$. We also assumed that the prior distribution follows a normal distribution $\sigma \sim N(0, 1000^2)$ and $\xi \sim N(0, 100^2)$. Moreover, we used random walk proposals with Gaussian innovations with standard deviations 0.1. We considered 100,000 iterations for MCMC sampling. Trace plots were used to check whether the Markov chains of two parameters converged or not. The trace plots of the scale parameter σ and shape parameter ξ of the Barishal region are shown in Figure 4.

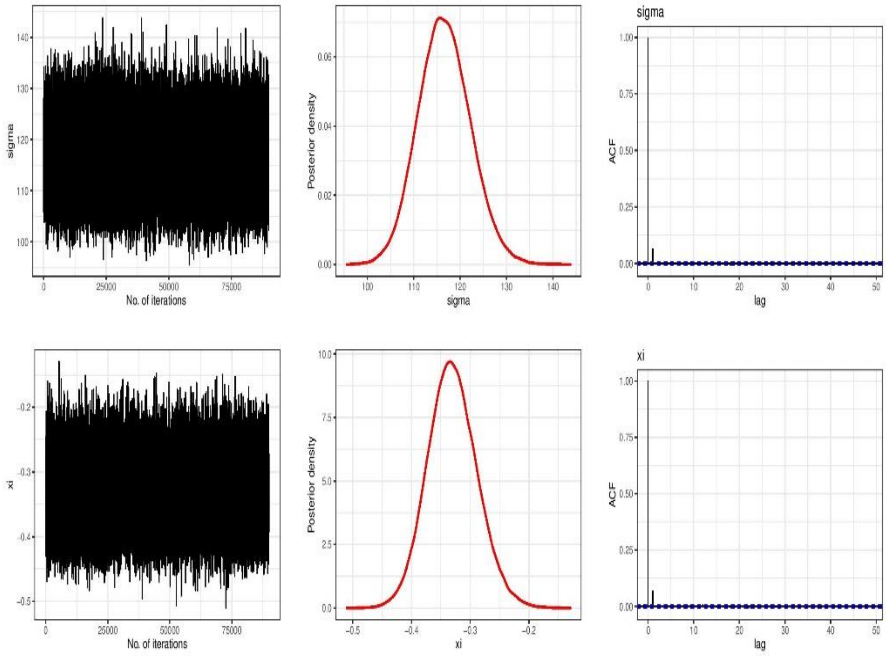

Figure 4. MCMC Realizations of GPD Parameters in a Bayesian Analysis of the Daily Maximum Rainfall in Barishal. Source: the Authors. Top Panel: σ; Bottom Panel: ξ.

Following the burn-in periods, the Markov chains of the two parameters are considered to converge. The posterior mean and standard deviation of each of the parameters are calculated using the simulated values. The posterior mean of the GPD model parameters, and their standard deviations (in parentheses) for twelve locations in Bangladesh were considered in this study and are presented in Table 2.

Table 2. Posterior Means of the GPD Parameters of the Selected Locations of Bangladesh. Source: the Authors. Notes: Standard deviations are presented in parentheses. Thresholds ( ) and proportion of observations over threshold ( ) are also presented.

Locations	**Estimates**			
	Threshold	λ_u	σ	ξ
Barishal	70	0.011	114.35 (5.51)	-0.32 (0.04)
Bogra	65	0.011	105.80 (5.21)	-0.3 (0.04)
Chattogram	120	0.009	183.82 (9.88)	-0.27 (0.04)
Comilla	105	0.005	137.94 (10.67)	-0.14 (0.05)
Cox’s Bazar	145	0.007	191.09 (11.59)	-0.25 (0.05)
Dhaka	105	0.004	133.49 (11.99)	-0.11 (0.05)
Dinajpur	130	0.003	178.88 (18.06)	-0.08 (0.05)
Faridpur	128	0.002	161.24 (19.62)	-0.06 (0.05)
Jessore	105	0.002	136.57 (16.23)	-0.06 (0.05)
Khulna	130	0.001	156.26 (23.32)	-0.03 (0.05)
Mymensingh	150	0.002	156.26 (24.47)	-0.03 (0.05)
Sylhet	90	0.018	151.04 (5.79)	-0.4 (0.02)

The return levels are illustrated in Figure 5 and findings reveal that the return levels of rainfall vary by location in Bangladesh. Once every 50 years, on average, we can expect daily rainfall levels to exceed 800 mm in Dinajpur and Mymensingh regions. The lowest rainfall will be available (375.70 mm) in Barishal region. More rainfall will be observed in Chattogram, Cox’s Bazar, Dinajpur, Faridpur, Khulna, and Mymensingh regions compared to other parts of Bangladesh. Our findings are consistent with a previous study which highlighted that rainfall is rising in the coastal region and northern Bangladesh, but it is declining in the country's central part (Shahid and Khairulmaini, 2009).

Comparison of GEV and GPD

In this study, we obtained the return levels of rainfall by using both the GEV and GPD. The predictive return levels are also calculated for the selected regions and results are presented in Table 3. From the findings

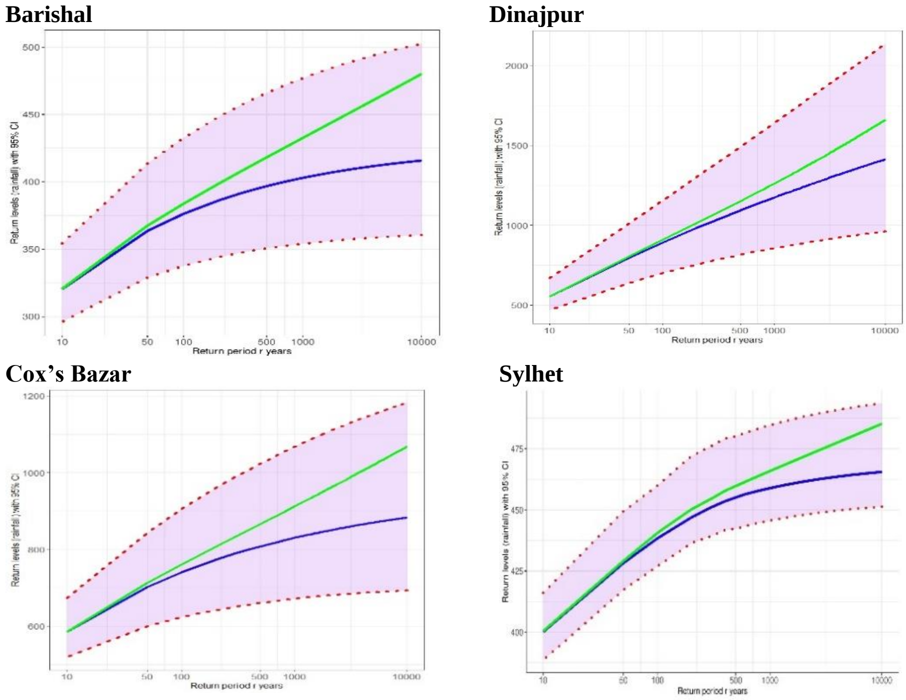

Figure 5. Return Levels Plots of Annual Maxima of Rainfall (mm) of the Selected Locations Used in this Study. Source: the Authors. Notes: Posterior means (blue line); 95% credible intervals (purple shaded region). The corresponding estimates of the predictive return levels (green line).

presented in Table 3, it is observed that in the case of the GEV, after 50-years of the study period i.e. the highest amount of rainfall at Barishal region would be 282.88 mm in 2070, however, the maximum rainfall will be 310.91 mm and 504.42 mm after 100 and 10,000 years, respectively, at Barishal. However, in the case of the GPD, it is observed that more than 800 mm of rainfall will occur in Dinajpur and Mymensingh regions. The lowest rainfall will be observed (375.70 mm) in Barishal region. More rainfall will be observed in Chattogram, Cox's Bazar, Dinajpur, Faridpur, Khulna, and Mymensingh regions compared to other parts of Bangladesh (Table 3). An earlier study noted that the northeast region of the country frequently experiences heavy rainfall (Ahmed *et al.*, 2017). Another study mentioned that rainfall is rising in Bangladesh's northern region and coastal areas (Shahid and Khairulmaini, 2009) which is consistent with our findings. Moreover, the monsoon depressions travel from the Bay of

Bengal into Bangladesh in a south-to-north direction before being diverted by the Meghalaya Plateau to the northwest and west. As these depressions travel farther and farther inland and their moisture content decreases, reduced rainfall is observed toward the northwest and western parts of Bangladesh (Ahmed and Kim, 2003). However, the additional uplifting effect of the Meghalaya plateau raised the rainfall in the northeast of Bangladesh (Shahid and Khairulmaini, 2009).

Table 3. Predictive Return Levels for Several Periods of the Selected Locations of Bangladesh Using GEV and GPD. Source: the Authors.

Locations	Return levels estimate							
	50-year		100-year		1000-year		10000-year	
	GEV	GPD	GEV	GPD	GEV	GPD	GEV	GPD
Barishal	282.99	367.46	314.45	383.75	453.38	432.54	695.89	480.12
Bogra	275.57	350.08	316.14	366.09	519.83	414.03	947.29	461.22
Chattogram	476.79	647.11	564.79	682.44	1051.42	789.33	2219.40	894.14
Comilla	372.98	592.13	472.82	648.78	1134.74	832.82	3142.91	1031.41
Cox's Bazar	380.01	712.78	410.87	760.65	515.87	911.86	645.04	1067.56
Dhaka	347.70	592.91	436.82	659.43	1019.21	880.30	2803.51	1124.12
Dinajpur	435.01	805.50	519.92	909.56	980.67	1261.20	2070.73	1659.93
Faridpur	364.58	741.87	455.79	854.64	1026.11	1243.66	2644.66	1693.48
Jessore	316.01	622.19	385.50	715.48	792.53	1036.37	1856.50	1405.77
Khulna	348.56	724.27	428.71	855.67	889.69	1318.85	2048.74	1865.25
Mymensingh	375.03	855.09	433.85	998.07	683.52	1497.90	1081.76	2084.98
Sylhet	335.15	434.21	369.23	443.63	513.42	465.89	751.36	485.25

In the Cox's Bazar and Mymensingh regions, it has been noted that all return levels computed using the GPD are higher than all return levels obtained using the GEV. For fewer than 100 years, the return levels determined by the GPD are higher in some places than the return levels computed by the GEV. While the return levels estimated using the GEV are higher than the return levels computed using the GPD for the longer return period i.e. 10,000 years.

4. CONCLUSION

In this study, we used Bayesian modelling to perform extreme value analyses on maximum rainfall data from twelve locations in Bangladesh using both the GEV and GPD distributions. Findings suggest that more rainfall will be observed in Chattogram, Cox's Bazar, Dinajpur, Faridpur, Khulna, and Mymensingh regions compared to other parts of Bangladesh.

It has been observed that the width of the 95% credible interval increases with return period, implying that both the variability ranges of return levels and the uncertainty increase with return period lengthening. In general, in light of the study's findings, the authors suggested that the appropriate governing body implement appropriate adaptation strategies to prevent climate change impacts on agriculture in order to achieve sustainable agricultural development and ensure food security for Bangladesh's ever-growing population. This information may also be used to identify regions that are particularly vulnerable to the kind of heavy rain that causes flooding. Future studies will focus on how sites and seasonal effects could be used to improve these analyses.

COMPETING INTEREST: The authors declared no competing interest.

REFERENCES

Agrawala, S., Ota, T., Ahmed, A. U., Smith, J. and Van Aalst, M. (2003). *Development and climate change in Bangladesh: focus on coastal flooding and the Sundarbans*, Organisation for Economic Co-operation and Development (OECD), Paris, pp. 1-49.

Ahmed, M. R., Rahaman, K. R., Kok, A. and Hassan, Q. K. (2017). Remote sensing-based quantification of the impact of flash flooding on the rice production: A case study over Northeastern Bangladesh. *Sensors*, 17(10), pp. 2347.

Ahmed, R. and Kim, I. K. (2003). Patterns of daily rainfall in Bangladesh during the summer monsoon season: case studies at three stations. *Physical Geography*, 24(4), pp. 295-318.

Ahmad, T., Ahmad, I., Arshad, I. A. and Bianco, N. (2022). A comprehensive study on the Bayesian modelling of extreme rainfall: A case study from Pakistan. *International Journal of Climatology*, 42(1), pp. 208-224.

Ahmad, Q. K., Warrick, R. A., Ericksen, N. J. and Mirza, M. Q. (1996). The implications of climate change for Bangladesh: a synthesis. In R. A. Warrick and Q. K. Ahmad (eds.) *The Implications of Climate and Sea–Level Change for Bangladesh*, Springer, Dordrecht, pp. 1-34.

Amin, M. R., Zhang, J. and Yang, M. (2015). Effects of climate change on the yield and cropping area of major food crops: A case of Bangladesh. *Sustainability*, 7(1), pp. 898-915.

Bangladesh Meteorological Department (2021). Climate Data Portal. Dhaka, Bangladesh.

Bari, S. H., Hussain, M. and Husna, N. E. (2017). Rainfall variability and seasonality in northern Bangladesh. *Theoretical and Applied Climatology*, 129(3), pp. 995-1001.

Chowdhury, A. K., Kar, K. K., Shahid, S., Chowdhury, R. and Rashid, M. M. (2019). Evaluation of spatio-temporal rainfall variability and performance of a stochastic rainfall model in Bangladesh. *International Journal of Climatology*, 39(11), pp. 4256-4273.

Coles, S. (2001). *An introduction to statistical modeling of extreme values*, Springer, London.

Dahab, A. (2011). Predicting internet traffic bursts using extreme value theory. PhD thesis, Universiti Teknologi Petronas, Perak, Malaysia.

Dastagir, M. R. (2015). Modeling recent climate change induced extreme events in Bangladesh: A review. *Weather and Climate Extremes*, 7, pp. 49-60.

Embrechts, P., Klüppelberg, C. and Mikosch, T. (2013). *Modelling extremal events: for insurance and finance*, Springer Science & Business Media, Berlin.

Fawcett, L. and Green, A. C. (2018). Bayesian posterior predictive return levels for environmental extremes. *Stochastic Environmental Research and Risk Assessment*, 32(8), pp. 2233-2252.

Fawcett, L. and Walshaw, D. (2016). Sea-surge and wind speed extremes: optimal estimation strategies for planners and engineers. *Stochastic Environmental Research and Risk Assessment*, 30(2), pp. 463-480.

Gamerman, D. (1997). *Markov Chain Monte Carlo: Stochastic Simulation for Bayesian Inference*, Chapman & Hall/CRC, New York.

Gamerman, D. and Hedibert F. L. (2006). *Markov chain Monte Carlo: stochastic simulation for Bayesian inference*, Chapman and Hall/CRC, New York.

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A. and Rubin, D. B. (2013). *Bayesian data analysis*, 3rd edition, Chapman and Hall/CRC, New York.

Gumbel, E. J. (1941). The return period of flood flows. *The Annals of Mathematical Statistics*, 12(2), pp. 163-190.

Hossain, M. S., Qian, L., Arshad, M., Shahid, S., Fahad, S. and Akhter, J. (2019). Climate change and crop farming in Bangladesh: an analysis of economic impacts. *International Journal of Climate Change Strategies and Management*, 11(3), pp. 424-440.

Hossain, B., Sohel, M. S. and Ryakitimbo, C. M. (2020). Climate change induced extreme flood disaster in Bangladesh: Implications on people's livelihoods in the Char Village and their coping mechanisms. *Progress in Disaster Science*, 6, pp. 100079.

Kotz, S. and Nadarajah, S. (2000). *Extreme value distributions: theory and applications*, Imperial College Press, London.

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, 3(5), pp. 497-501.

McElreath, R. (2020). *Statistical Rethinking: A Bayesian Course with Examples in R and STAN*, 2nd edition, Chapman and Hall/CRC, New York.

Min, S. K., Zhang, X., Zwiers, F. W. and Hegerl, G. C. (2011). Human contribution to more-intense precipitation extremes. *Nature*, 470(7334), pp. 378-381.

Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., Lobell, D. B. and Travasso, M. I. (2014). Food security and food production systems. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, L. L. White (eds.) *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects*, Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, pp. 485–533.

Pörtner, H. O., Roberts, D. C., Adams, H., Adler, C., Aldunce, P., Ali, E., Begum, R. A., Betts, R., Kerr, R. B., Biesbroek, R. and Birkmann, J. (2022). Climate change 2022: Impacts, adaptation and vulnerability. IPCC Sixth Assessment Report.

Powell, J. P. and Reinhard, S. (2016). Measuring the effects of extreme weather events on yields. *Weather and Climate Extremes*, 12, pp. 69-79.

Ragulina, G. and Reitan, T. (2017). Generalized extreme value shape parameter and its nature for extreme precipitation using long time series and the Bayesian approach. *Hydrological Sciences Journal*, 62(6), pp. 863-879.

Rahman, A. (2008). *Bayesian Predictive Inference for Some Linear Models under Student-t Errors* (1st ed.), VDM Verlag Dr. Müller, Riga.

Rahman, A. and Upadhyay, S. K. (2015). A Bayesian reweighting technique for small area estimation. In U. Singh, A. Loganathan, S. K. Upadhyay and D. K. Dey (Eds.), *Current trends in Bayesian methodology with applications* (1st ed.), CRC Press, New York, pp. 503-519.

Rahman, M., Lateh, H. and Islam, M. (2018). Climate of Bangladesh: temperature and rainfall changes, and impact on agriculture and groundwater—a GIS-based analysis. In M. Islam and A. van Amstel (eds.), *Bangladesh I: Climate change impacts, mitigation and adaptation in developing countries*, Springer, Cham, pp. 27-65.

Roy, A. and Haider, M. Z. (2019). Stern review on the economics of climate change: Implications for Bangladesh. *International Journal of Climate Change Strategies and Management*, 11(1), pp. 100-117.

Ruane, A. C., Major, D. C., Winston, H. Y., Alam, M., Hussain, S. G., Khan, A. S., Hassan, A., Al Hossain, B. M. T., Goldberg, R., Horton, R. M. and Rosenzweig, C. (2013). Multi-factor impact analysis of agricultural production in Bangladesh with climate change. *Global Environmental Change*, 23(1), pp. 338-350.

Shahid, S. and Khairulmaini, O. S. (2009). Spatio-temporal variability of rainfall over Bangladesh during the time period 1969-2003. *Asia-Pacific Journal of Atmospheric Science*, 45(3), pp. 375-389.

Shamsudduha, M., Taylor, R. G., Haq, M. I., Nowreen, S., Zahid, A. and Ahmed, K. M. U. (2022). The Bengal Water Machine: Quantified freshwater capture in Bangladesh. *Science*, 377(6612), pp. 1315-1319.

Urban, D., Roberts, M. J., Schlenker, W. and Lobell, D. B. (2012). Projected temperature changes indicate significant increase in interannual variability of US maize yields. *Climatic Change*, 112(2), pp. 525-533.