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Vulnerability assessment of drought prone areas in Bangladesh through extreme temperature modeling

Nasrin Sultana

Dept. of Statistics, Bangabandhu Sheikh Mujibur Rahman Agricultural University (BSMRAU), Salna, Gazipur-1706, Bangladesh

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Corresponding author:
nasrinisrtdu@yahoo.com

ABSTRACT

Bangladesh is commonly known as a disaster prone country and drought is one of the frequent natural phenomenon. A series of daily maximum temperature data from drought prone areas such as Bogra, Dinajpur, Ishsurdi, Faridpur and Rangpur districts over the period 1964-2013 years are analyzed in this study. For modelling purposes annual maximum temperature data fitted to generalize extreme value (GEV) distributions and block maxima approach are applied. The trend in GEV model also considers due to the existence of temporal trend in daily temperature data. Likelihood ratio statistics are used as a tool to compare models with trend and without trend. Drought risk is computed through the quantile of the best fitted GEV model which is popularly known as return levels.

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I. Introduction

Drought is one of the sustained and substantial consequences of global warming and Bangladesh has remarkable impact due to this occurrence. There is a risk of increasing hotter day, heat waves and longer dry spells than the past 50 years due to climate change. The Global Circulation Model (GCM) predicts that being a vulnerable country due to climate change, Bangladesh have chance of increase average temperature 1^oC by year 2030 and 14^oC by year 2050 (Habiba et al., 2013). Drought prone regions have lower amount of rainfall during dry seasons along very high temperature. The lower amount of rainfall during the dry season is one of the reasons for this natural calamity (ADB, 2015). Bangladesh faced one of the severe drought in the year 1994 and there were around 24 droughts occurred between the years 1949 and 1991 (DMB, 2015). The North West part of Bangladesh is the

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known as most drought-prone area; however, it is very common in some parts of the country (Shahid et al., 2008). Almost over 5.46 million ha in the districts of Chapai Nawabganj, Naogaon, Rajshahi, Natore, Rangpur, Dinajpur, Joypurjhat, and Bogra is affected by drought. Geophysical features, water resources mismanagement, rainfall variability, temperature increase, absent or insufficient irrigation systems are identified as a reason of drought (Habiba, 2012). Study areas are Bogra, Dinajpur, Faridpur, Ishurdi and Rangpur districts and among them maximum temperature was $44^{o}C$ recorded in 1989 and 1970 at Bogra and Ishurdi respectively (Table 01).

In Bangladesh, around 80% of the population lives in rural areas, relying on agriculture either directly or indirectly. Drought has a major economic impact on agriculture, especially the regions which are more vulnerable to natural calamities. Food production is extremely affected, according to the statistics around 47% of the country and at the same time about 53% of the population suffered (WARPO, 2005). According to World Bank, drought has a more awful effect than flood during 1969-1970 and 1983-1984 (World Bank, 2000). Furthermore, due to long spells of dry weather around 33% of total land acreage is not suitable for agriculture during moderate-to-severe droughts (Habiba et al., 2011). However, the impact of drought now a day's extends disproportionately amongst different regions of Bangladesh, which that makes results in drought risk for both, drought-prone and non-drought-prone areas (Murshid et al., 1987; Paul et al., 1995). Hence, intensive research on risk assessments of extreme climatic variables like rainfall, sea-level rises, humidity should be conduct to precaution for future natural phenomenon to avoid extensive environmental and economic loss.

In weather and climate study, extreme events or rare events are of special interest. The aim of extreme value theory is to provide suitable stochastic models to describe the behavior of extreme observations. This branch of probability and statistics has been widely used during the last decades. The theory and application of extreme value can be found from recent books such as Coles (2001), Embrechts et al.(1998), Kotz and Nadarajah (2000), Beirlant et al. (2005) and a good collection of current journals (Rootzén et al., 2006).

Having temporal trend or non-stationary is very common phenomenon in climate variable. In this paper, a series of temperature data are modelled as a generalized extreme value distribution (GEV). At first, trend in daily maximum temperature data is examined through Mann-Kendall test and Poisson distribution. After that GEV model is applied on annual maximum temperature data considering with and without trend and compare models using likelihood ratio test. Future return level of temperature is estimated from statistically significant generalized extreme value model.

II. Methodology

Statistical model for extreme rainfall

Generalized Extreme Value Distribution

Suppose, $X_1, X_2, X_3 \ldots\ldots\ldots\ldots\ldots. X_n$ is a sequence of independent and identically distributed random variables, having a same continuous distribution function F, M_n is the maximum value of the over $n \in N$ time units of observation, written as below.

$$M_n = \max(X_1, X_2, X_3 \ldots\ldots\ldots\ldots\ldots. X_n).$$

For some normalizing constant a_n>0 and b_n∈R, the limiting distribution of M_n according to extremal theorem is below.

$$\lim_{n\to\infty} \Pr(\frac{M_n - b_n}{a_n} \le x) = \lim_{n\to\infty} F^n(a_n x + b_n) = G(x)$$

Here, *G(x)* is non-degenerate distribution function and *G(x)* follows one of the three types of distributions. These three types of distributions can be combined to a one single family of model by

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changing location and scale according to the re-parametrization technique introduced by von Mises. This single distribution well-known as generalized extreme value (GEV) distribution which can be expressed by the following form below.

$$G(x;\gamma,\mu,\sigma) = exp\left\{-\left(1+\gamma\left(\frac{x-\mu}{\sigma}\right)\right)_{+}^{-\frac{1}{\gamma}}\right\}$$

The center of the GEV distribution provides by the Location (μ) parameter, scale (σ) determines the size of deviations of μ and shape (γ) counts how promptly the upper tail decays. The positive γ implies a heavy tail, negativeγrefers bounded tail, and the limit of $\gamma \rightarrow 0$ suggests an exponential tail. These cases correspond to **type I** (*Fréchet distribution*) and **type II** (*Weibull distribution*) distributions respectively. For γ = 0 interpreted as the limit which leads to the double exponential or **type III** *(Gumbel).*The end point of distributions is $x > \mu - \frac{\sigma}{\gamma}$ for $\gamma > 0$and $x < \mu - \frac{\sigma}{\gamma}$ for $\gamma < 0$.

In reality, there exists trend in the temperature data which follows that the sequences are non-stationary processes. Thus, model this non-stationary data GEV distribution with trend is considered and represented as follows:

$$\mu(t) = \beta_0 + \beta_1 t,$$
$$\sigma(t) = \sigma_0 + \sigma_1 t$$
$$\gamma(t) = \gamma$$

Here, t is the standardized time (year).

So, the models that considered in this study are below.

Model 1: μ , σ *and* γ are constant
Model 2: trend in location (μ) parameter, σ *and* γ are constant
Model 3: trend in scale (σ) parameter μ *and* γ are constant.

Likelihood ratio statistics is used to compare between GEV models with and without trends. Extreme value distribution considered modeling the maximum for each block where the blocks are dividing in to non-overlapping periods of equal sizes (say n). Suppose, a series of independent and identically distributed random variables are partitioned into m blocks of size n, and then $M_{n,1}, \ldots\ldots\ldots.., M_{n,m}$ are the maximum values from each block. The approximate distributions of these maximum observations asymptotically follow GEV and small block size provides a good asymptotic approximation (Coles et al., 2001). In this paper, GEV model is fitted considering without trend, also trend in location parameter and scale parameter is fitted. Finally, compare the models using the likelihood ratio test (Coles et al., 2001).

Return level

The quantiles of extreme value distribution are known as return levels. For a given value of probability p the estimates of extreme return levels associated with 1/p return period is satisfied the following relation $G(z_p) = 1 - p$. Inverting the GEV distribution, extreme quantiles can be estimated as follows:

$$z_p = \begin{cases} \mu - \frac{\sigma}{\gamma}[1-(-\log(1-p))^{\gamma}], & for\ \gamma \neq 0 \\ \mu - \sigma log[-log(1-p)], & for\ \gamma = 0 \end{cases}$$

Therefore, any particular block maima exceeds the value z_p with probability p and the level z_p is expected to be exceded on average once in every 1/p years (Coles et al., 2001).

Measures of stationarity

Geometric distribution is used to model the cluster length of low minimum daily temperatures (Smith et al., 1997). The probability mass function of Geometric distribution is defined as below.

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$$f(t,\theta) = \theta(1-\theta)^{t-1}, \qquad t = 1,2, \ldots.$$

Here, θ is known as extremal index and the reciprocal of the parameter θ is mean and used to measure the tendency of clusters of extreme events under stationary process. In this paper, we model the time lag between two extreme rainfalls over threshold u as a geometric distribution to checks stationarity of the rainfall series. More details are found from several books (Coles et al., 2001).

Trend checking

The Mann-Kendall test is traditionally used as a non-parametric trend analysis technique. This test is flexible as there is no requirement of normality assumptions and also less sensitive to outliers (Onoz et al., 2012). This Mann-Kendall test is basically based on S statistics. The null hypothesis H_0 stated like this there is no trend in the dataset or the data are randomly ordered in time. The alternative hypothesis H_1 is there is an increasing or decreasing monotonic trend exists in the data. Therefore, small p-value confirms the rejection of the null hypothesis and conclude that there is trend exist. For a time series data $X_1, X_2, \ldots \ldots \ldots . X_n$ the test statistics is written as the following form below.

$$\mathrm{S}{=}\sum_{k=1}^{n-1}\sum_{j=k+1}^{n} sgn(y_j - y_k)$$

Where, S is approximately normally distributed for large n with E[T]=0 and

$$\mathrm{V[T]} = \frac{n(n-1)(2n+5)}{18}$$ (Drapela et al., 2011)

The Poisson probability distribution is used to estimate the probability of a number of independent events occurring in a fixed time interval. Poisson distribution also used as a trend checking approach. If the total number of exceedances per year over a fixed threshold modeled as a Poisson distribution, then the series is trend free. The density function of Poisson distribution can be expressed as follows:

$$P(y,\lambda) = \frac{e^{-\lambda}\lambda^{y}}{y!}, y = 1,2,3, \ldots \ldots ..$$

Data

The daily maximum temperature over 1964 to 2013 recorded at five drought risk stations selected from the Bangladesh Meteorological Department (BMD). Missing data are omitted before analysis.

Table 01. Summary statistics of temperature data

Stations	Range	Year of maximum temperature
Bogra	(36.2 ,44)	1989
Dinajpur	(35.4 ,43.3)	1970
Ishurdi	(33.9, 41.2)	2009
Faridpur	(33.9 44)	1970
Rangpur	(35.7 42.8)	1966

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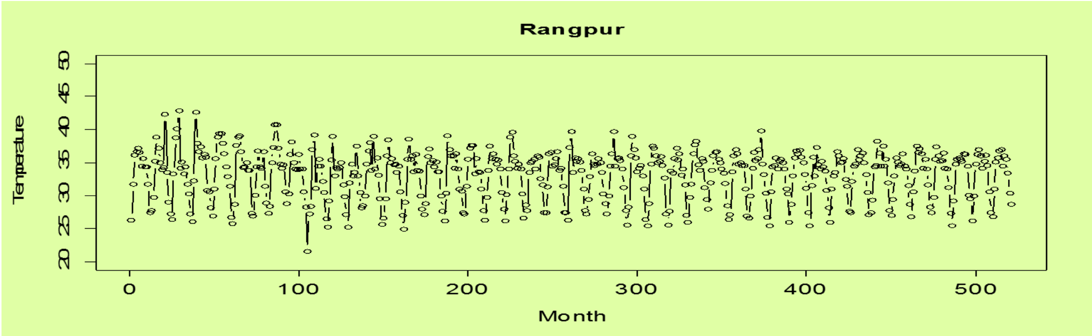

Figure 01. Monthly maximum temperature at Rangpur over 1964-2013.

Figure 01 represents the monthly maximum temperature of Rangpur over the period 1964-2013 and the temperature from Bogra, Dinajpur, Ishurdi, Faridpur are presented in appendix (Figure 02).The figure shows how the monthly maximum temperatures varies over time. There is trend and also non-stationarity observed during the considered period. At Rangpur, the extreme temperatures have decreasing pattern.

Statistical packages: Assessments were implemented by R with packages *Fitdistrplus and in2extRemes*.

III. Results and Discussion

There is a significant trend found by fitting Poisson distribution using daily temperature data. Therefore, the number of extreme temperature over a fixed threshold does not follow Poisson distribution. Mandall-Kendall test apply to the daily maximum temperature data and represents a significant trend at 10% level of significance for all stations.

The annual maximum temperature data of each can be modeled as GEV separately in block maxima approach. Several model checking tool such as density plots, qq-plots are concerned to check suitability of series of data as a model. For simplicity, we only present density plot here (Appendix Figure 03). Maximum likelihood estimation (MLE) method is used to estimate parameters of GEV distribution are presented in the following Table 02.

At station Bogra, fitted GEV with trend in scale is better compared to no trend as well as trend in locatio n parameter. In likelihood ratio test, p-value of the test for $\beta_1 = 0$ is 0.343 implies that the null hypothes is is not strongly rejected. While the null hypothesis for$\sigma_0 = 0$, p-value is 0.01551, indicate significant tr end in scale. AIC and BIC are also small compared to other two model. The shape parameters of model with trend in scale is negative, i.e., γ<0 which refers to type II, Weibull classes with bounded upper bou nd and 95% CI for scale is (-0.44, 0.216). Since 95% CI extends above zero, the strength of evidence fro m the data for a bounded distribution is not strong. Also, density plots (Appendix, Figure 03) with trend in scale shows good approximation with empirical density.

Table 02. Summary of GEV fit at Bogra

	Location ($\hat{\mu}$)	Scale ($\hat{\sigma}$)	Shape($\hat{\gamma}$)	p-value	AIC	BIC
Model 1	38.42	1.61	0.043	-	214.71	220.45
Model 2	39.07 - 0.02t	1.69	-0.054	0.343	215.81	223.46
Model 3	38.32	2.69 -0.03t	-0.12	0.01551	**210.85**	**218.5**

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Summary of GEV models at Dinajpur is presented in the Table 03 .P-value of the test for $\beta_1 = 0$ and $\sigma_0 = 0$ are less than 0.05 which indicate the null hypothesis are rejected. So there is trend in the locatio n and scale parameters. But the AIC and BIC obtained from trend in scale parameter are small and densi ty plot (Appendix Figure 03)shows good approximation with empirical density, so this model can be sel ected for further study. The negative shape parameters refers to type II, Weibull classes with bounded u pper bound as 95% CI for scale is (-0.78 , -0.322).

Table 03. Summary of GEV fit at Dinajpur

	Location ($\hat{\mu}$)	Scale ($\hat{\sigma}$)	Shape($\hat{\gamma}$)	p-value	AIC	BIC
Model 1	38.56	1.88	-0.32		175.90	181.11
Model 2	40.57-0.057t	2.08	-0.60	**0.02819**	173.08	180.03
Model 3	38.68	3.10 -0.04t	-0.55	**0.00282**	168.98	175.94

Summary of fitted GEV models for these stations (Faridpur, Ishurdi and Rangpur) are presented in Table 04 and can be interpreted similar way above. Therefore, that there is significant trend in scale at stations Faridpur, Ishurdi and Rangpur. Also density plots (Appendix Figure 03) are agree with that findings.

Table 04. Summary of GEV fit

Models	Location ($\hat{\mu}$)	Scale ($\hat{\sigma}$)	Shape($\hat{\gamma}$)	p-value	AIC	BIC
Faridpur						
Model 1	37.76	1.46	-0.35		181.10	186.84
Model 2	36.39+0.051t	1.28	-0.371	**0.0001**	168.78	176.43
Model 3	37.20	0.069+ 0.093t	-0.62	**0**	138.56	146.21
Ishurdi						
Model 1	40.3	2.25	-0.59		210.85	216.59
Model 2	41.55 -0.04t	2.39	-0.87	**0.0016**	202.89	210.54
Model 3	40.52	3.08 -0.03t	-0.81	**0.0005**	200.71	208.36
Rangpur						
Model 1	37.34	1.15	0.13		163.88	169.23
Model 2	38.78 -0.05t	1.17	-0.08	**0.003**	156.79	163.93
Model 3	37	2.72-0.05t	-0.23	**0.001**	155.16	162.30

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Return levels

Estimated return values for 10, 20, 50 and 100 years are obtained by the quantile function of the GEV distribution and presented in the following Table 05. The quantile of corresponding model with a specified probability or return period for the non-stationary is estimated. The effective return levels are time varying or depending on the year, so that only 25%, 50% and 75% quantile of return levels are presented in Table 05.

Table 05. Estimated return levels with confidence interval

Station	Quantile	10 year	20 year	50 year	100 year
Bogra	25%	40.92	41.62	42.45	43.01
	50%	41.74	42.67	43.75	44.50
	75%	42.57	43.71	45.06	45.98
	max	**43.39**	**44.76**	**46.37**	**47.46**
Dinajpur	25%	40.70	40.97	41.20	41.30
	50%	41.18	41.51	41.79	41.92
	75%	41.66	42.05	42.38	42.54
	max	**42.51**	**43.02**	**43.44**	**43.64**
Faridpur	25%	38.58	38.74	38.87	38.92
	50%	39.96	40.28	40.54	40.65
	75%	41.33	41.82	42.20	42.37
	max	**42.71**	**43.36**	**43.87**	**44.10**
Ishurdi	25%	42.50	42.67	42.78	42.82
	50%	42.88	43.08	43.22	43.27
	75%	43.26	43.50	43.65	43.71
	max	**43.68**	**43.94**	**44.12**	**44.19**
Rangpur	25%	38.55	38.90	39.28	39.51
	50%	39.45	40.05	40.65	41.03
	75%	40.42	41.20	42.03	42.55
	max	**41.88**	**42.98**	**44.17**	**44.91**

The maximum 10 years return levels of temperature is approximately 43.39 degree centigrade at Bogra. It is true for 25%, 50 % and 75 % quantiles of return values. So the temperature is 43.39 degree centigrade is expected to be exceeded on average once every 10 years with probability 1/10. The minimum temperature for 10 and 20 years return levels obtained at Rangpur. Rangpur have low possibility of having extreme temperature in compared to other studied stations. But next 50 year Rangpur have high risk of extreme temperature and it also true for stations Bogra. Besides, this station Bogra needs more attention for next 100 years due to extreme temperature.

IV. Conclusion

The estimation of environmental risk is a decisive attention nowadays. Generalized extreme value distributions (GEV) have a justifiable contribution in several risk assessments. Significant trend is explored in the daily maximum temperature data series applying Mann-Kendall test. Also, poisson distribution used for trend detection. Time varying location and scale parameters are considered here in fitting GEV. Standardized year is applied as a time covariate. There is a considerable trend in location and scale parameters identified for all stations. The Likelihood ratio test is applied to find the appropriate model. The result shows that almost all stations the models which consider trends in scale parameters are well fitted. Therefore, the return level is estimated from the significant trend in scale model. The effective return levels of trend model are varied over time. So in estimating return level 25%, 50% and 75 % quantiles are presented in this paper. Based on this, station Bogra has maximum risk of having drought. Other stations Dinajpur, Faridpur, Ishurdi and Rangpur also have a very high temperature that may cause a severe drought in the next 20 to 100 years. Hence, these extreme value distributions may applied to other drought prone regions and help to estimate the expected return levels that might assist to predict future environmental and economic loss.

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Appendix

The following plots are the monthly maximum temperature over the years 1964-2013.

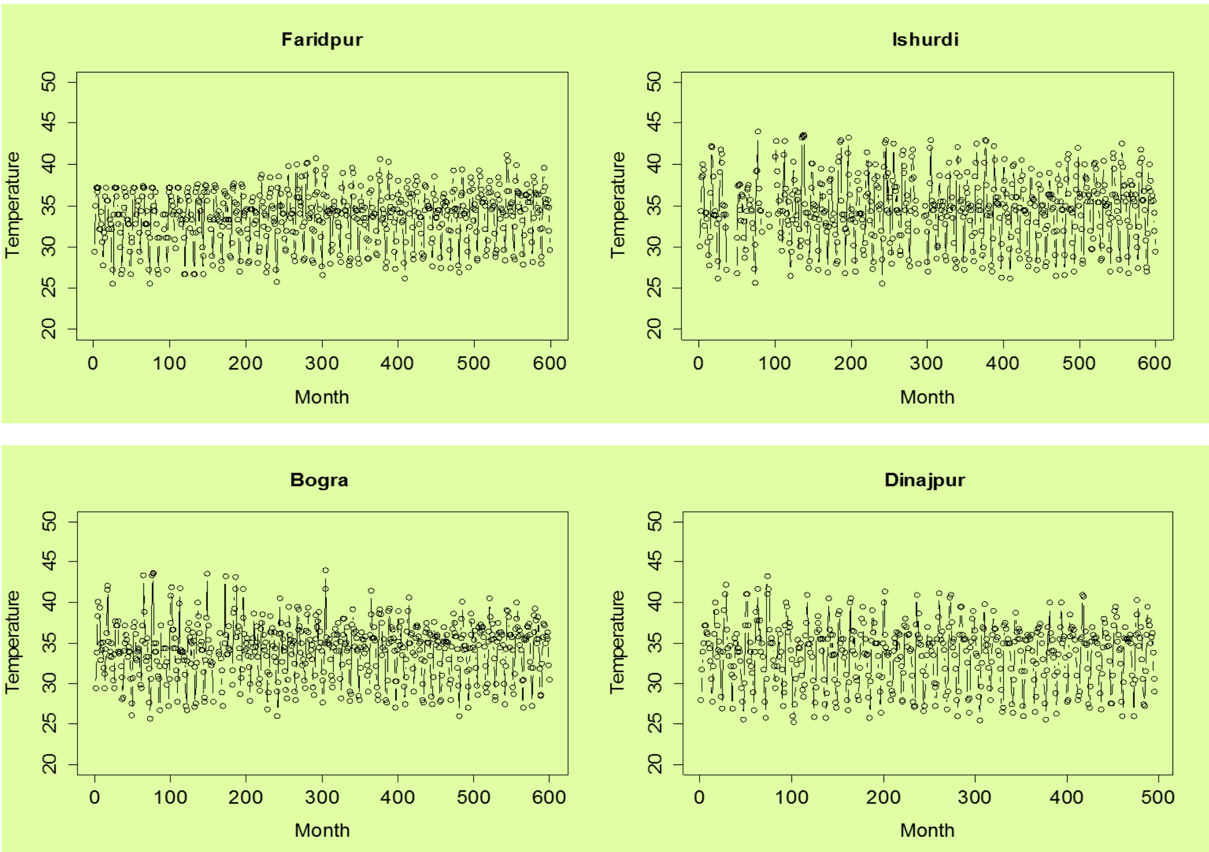

Figure 02. Monthly maximum temperature over the years 1964-2013.

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The following are the model diagnostics density plots of fitted GEV obtained from studied stations.

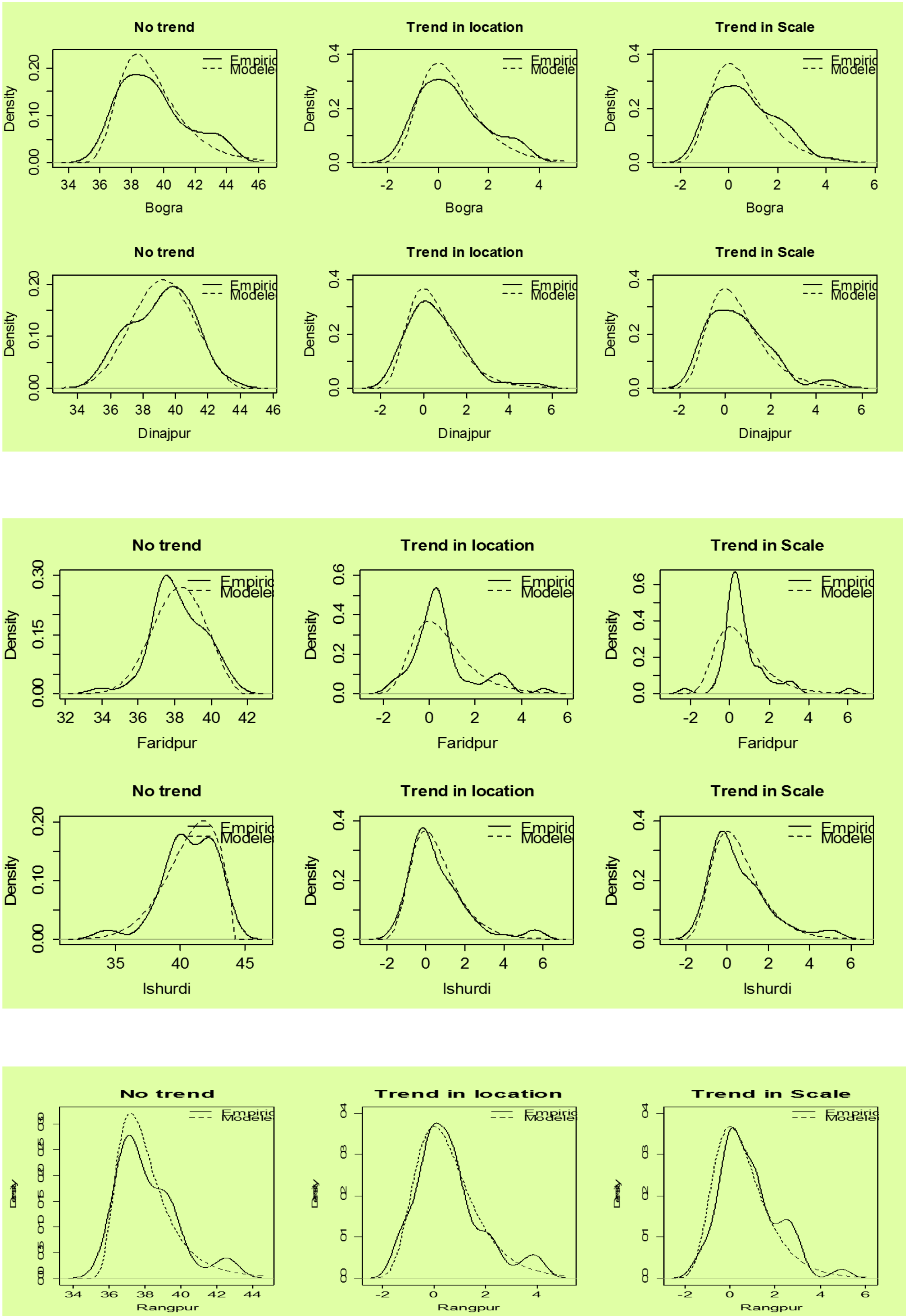

Figure 03. Density plots from fitted models.

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Glossary

Extreme value distribution: The distribution of extremely maximum or minimum random observations.
Poisson distribution: a discrete frequency distribution which gives the probability of a number of independent events occurring in a fixed time.
Time lag: Time difference between two extreme temperatures.
Density plot: The estimated density plot obtained by fitting temperature data.
Quantile: Data divided into four equal sized groups.
QQ-plot: Graphical procedure to compare two distribution using quantiles.
Return levels: Upper quantile of fitted model.
Likelihood ratio: A statistical test usually used to compare the goodness of two fitted models.
AIC & BIC: Akaike information criterion (AIC) and Bayesian information criterion (BIC) measures of quality of a good model and small AIC and BIC refers good model.
Time covariate: Time used as a covariate in model.
Fitdistrplus: An R statistical package for fitting distributions (i.e., Help to fit of a parametric distribution to non-censored or censored data).
in2extRemes: Statistical package in R (i.e., this package provides point-and-click windows for performing extreme value analysis).

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