Extreme value analysis of precipitation and temperature over western Indian Himalayan State, Uttarakhand

CHHAVI P PANDEY[1,*], VINEET AHUJA[2], LOKESH K JOSHI[2] and HEMWATI NANDAN[2,3,4]

[1]*Wadia Institute of Himalayan Geology, 33 GMS Road, Dehradun, Uttarakhand 248 001, India.*
[2]*Gurukula Kangri (Deemed-to-be University), Haridwar, Uttarakhand 249 404, India.*
[3]*Department of Physics, Hemvati Nandan Bahuguna Garhwal University, Srinagar Garhwal, Uttarakhand 246 174, India.*
[4]*Centre for Space Research, North-West University, Mafikeng 2745, South Africa.*
Corresponding author. e-mail: chhavi@wihg.res.in

Precipitation and temperature are the most important meteorological parameters and their quantitative measurement at various return periods is one of the key inputs in the design of various hydraulic structures in diverse contexts. The present research focuses on statistical modelling of monthly maximum precipitation and temperature in the western Indian Himalayan state, Uttarakhand, over the last century (1901–2002), applying extreme value theory (EVT). EVT is an excellent statistical tool to interpret the records to estimate the future probability of the occurrence of extremities. In addition, return levels are used to forecast the likelihood of extremes of the stated meteorological parameters occurring once every 50, 100, 200, 300, and 500 years. The primary goal of this research is to provide statistical information on the behaviour of extreme temperatures and precipitation that will be useful to disaster management organisations and government policymakers in determining appropriate risk mitigation measures for the natural disaster-prone Indian Himalayan state of Uttarakhand.

Keywords. Extreme value analysis; statistical modelling; meteorology; Himalaya; Uttarakhand.

1. Introduction

Precipitation and temperature extremes are the most important meteorological, hydrological, and climatological parameters and have been extensively analysed in the past few decades (Seneviratne *et al.* 2012). Some of the most significant impacts of climate change on mountain systems include rapid melting of glaciers, changes in vegetation cover, species migration and loss, erratic weather patterns, loss of snow cover, water scarcity, and an increase in the frequency and magnitude of natural disasters. Localised rainfall and temperature extremes can have a profound impact on human activities. Specifically, for water resource management, it is essential to know the probability of exceedance of rainfall from the known amount. Heavy rainfall is one of the most frequent and widespread severe weather hazards which affects Uttarakhand. From past studies, it has been observed that high temperatures with no atmospheric moisture are one of the main reasons for forest fires in Uttarakhand, which cause significant loss to the forest ecosystem, flora, and fauna as well as economic wealth (Negi and Kumar 2016). The main reason behind using statistical modelling

techniques for weather extremes is its ability to cope with the weather conditions that may occur in the future. For any civil engineering work, the knowledge of extreme weather conditions at the site of interest is essentially required to design engineering structures such as dams that can withstand extreme weather stresses. For this purpose, a risk model is developed by selecting the best-fit probability distribution method. Statistical models for extreme value analysis are based on extreme value theory (EVT). Extreme value theory is an advanced statistical analysis tool to evaluate and simulate the extremes of an independent identical distribution (Reiss and Thomas 2001). Extreme value theory deals with the stochasticity of natural variability by describing extreme events with respect to their probability of occurrence at large or small levels (Hasan *et al.* 2012). This statistical modelling method has already been successfully applied in various climatological time series to model the extremities by various researchers worldwide, viz., Uppsala, Sweden (Rydén 2011); Botswana (Wilson Moseki Thupeng 2019); Zimbabwe (Chikobvu and Chifurira 2015); middle Ebro Valley, Spain (Beguería and Vicente-Serrano 2006); Penang, Malaysia (Hasan *et al.* 2012); Nigeria (Sunday *et al.* 2020); Mbonge, Cameroon (Arreyndip and Joseph 2015); Ghana (Sampson and Kwadwo 2018); western Black Sea subregion, Turkey (Yozgatlıgil and Türkeş 2018); southwest western Australia (Li *et al.* 2005); Debuncha, Cameroon (Ayuketang *et al.* 2016); Maharashtra (Gandhre 2020); Tiruchirappalli, India (Sasireka *et al.* 2019); etc. Extreme rainfall records from different field stations in Uttarakhand during the last century (1900–2013) were analysed (Nandargi *et al.* 2016). The decreasing trend in extreme rainfall is nearly 42% of recording stations, especially after 1970. Kumar *et al.* (2017) analysed the statistical distribution of rainfall over all the districts in the state of Uttarakhand. It was observed that in the earlier statistical investigations of meteorological time series in this region, there had been no significant attempt towards understanding the characteristics of statistical (probabilistic) methods for forecasting extreme events in the Himalayan region. Climate affects humans directly through the weather experienced (physically and psychologically) on a day-to-day basis and the impacts of weather on daily living conditions, and indirectly through its impacts on economic, social, and natural environments. Extreme rainfall may result in landslides,

flash floods, and crop damage that might have a major impact on society, the economy, and the environment as a whole. In recent years, a greater percentage of precipitation in Uttarakhand has occurred as extreme one day episodes. In June 2013, a cloudburst centred on the north Indian state of Uttarakhand caused devastating floods and landslides and was reported as the worst natural disaster in our country since the Tsunami (the year 2004). The rainfall was observed to be 200% above the average at many sites, including Rudraprayag, Uttarkashi, Chamoli, Pauri, Tehri, and neighbouring districts. When the event actually occurred, the Weather Research and Forecasting System (WRF) model predicted rainfall to fall between 320 and 400 mm above Kedarnath, which is in a fair amount of agreement with the actual amount of rainfall (325 mm) measured by the Wadia Institute of Himalayan Geology (Shekhar *et al.* 2015).

Because of the topography of Uttarakhand, it would be fair to say that small changes in temperature melt glaciers and turn ice and snow into water. Where extreme slopes lead to rapid changes in climatic zones over small distances, these will show marked impacts in terms of biodiversity, water availability, agriculture and hazards, and this will have an impact on general human well-being. On February 07, 2021, a landslide at the glacier's terminus at an altitude of 5600 m triggered a snow avalanche, covering approximately 14 km^2 area and caused a flash flood downstream of Rishi Ganga (Chamoli), where at least 70 people at Raini are believed to have been buried or washed away in the sludge that the floods carried, and around 35 were reported stuck in a tunnel that was choked by the sludge (Rana *et al.* 2021; Sati 2022). Although the prediction of such extreme weather events is still fraught with uncertainties, a proper assessment of likely future trends would help in setting up infrastructure for disaster preparedness.

The current study focuses on determining the effects of excessive precipitation and temperature, employing a regional approach. In this study, we looked at a century-long time-series dataset (1901–2002) for all 13 districts of Uttarakhand, which is part of the Indian western Himalayas. The monthly precipitation and temperature data were analysed at a seasonal level with the primary goal of maximising the information in the data series and providing a more accurate estimation of the distribution parameters. The physiographic and climatological features of the region are described in section 2. The mathematical basis for the EVT

approach is presented next, followed by results and discussions. Concluding thoughts on the statistical modelling of meteorological factors are presented in the final section.

2. Physiographic and climatologic description of the region

In the northern region of India, Uttarakhand is found between 28°43′–31°27′N latitudes and 77°34′–81°02′E longitudes (figure 1). This Indian state is located on the southern slope of the majestic Himalayas, with Tibet to the north and Nepal to the east. Himachal Pradesh is located northwest of Uttarakhand and Uttar Pradesh is located south of it. Uttarakhand is primarily a hilly state, with mountains covering 86% of the land and forests covering the remaining 65%. Ice and bare rock cover the high Himalayan highlands, which are glaciated. However, at lower elevations, there is a lush tropical forest. In general, the altitude of the state varies between 180 and 7800 m amsl (meters above mean sea level). The glaciers in this state are the source of the rivers Ganga and Yamuna. The western half of Uttarakhand is known as the Garhwal region, while the eastern half is known as the Kumaun region. The topography and ecology of this state are diverse, and it is rich in natural resources, particularly water and forest.

The tropical monsoon in the summer and western disturbances in the winter affect the state's climate, which is defined by variable seasonal temperatures. According to the India Meteorological Department (IMD), seasons of the state are characterised as winter (December–February), pre-monsoon (March–May), monsoon (June–September), and post-monsoon (October–November). The monsoon season receives about 90% of the annual rainfall. Heavy rainfall events in Uttarakhand were statistically analysed in detail (Nandargi *et al.* 2016). Uttarakhand is eco-sensitive and extremely vulnerable to natural disasters (viz., cloud bursts, floods, landslides, earthquakes, etc.). Table 1 illustrates the characteristics of Uttarakhand state where population and density of the state are taken from census data available at https://www.census2011.co.in/census/state/districtlist/uttarakhand.html. Elevation (metres) represents average elevation of each district from mean sea level; the area of the districts is represented in km square, while JJAS mean rainfall (mm/month) for each district is calculated from a monthly century-long dataset (1901–2002) which we have considered for the study.

3. Material and methods

3.1 *Data source*

The present research examines monthly maximum precipitation and temperature time series data for all 13 districts of Uttarakhand during a 102-year span. The dataset used in the present analysis is obtained from the Climate Research Unit (CRU) TS2.02, Tyndall Centre for Climate Change Research, School of Environmental Sciences, and the University of East Anglia in Norwich, UK (Mitchell and Jones 2005) (https://crudata.uea.ac.uk/cru/data/hrg/timm/grid/CRU_TS_2_0_text.html). The empirical analysis is performed using the 'extRemes' (Gilleland and Katz 2016) and 'evd' (Stephenson 2018) packages within the R-open source software (R Core Team 2020).

3.2 *Extreme value theory (EVT)*

EVT is a theoretical framework for modelling the extremities and provides a robust statistical tool for the probabilistic prediction of extreme and rear
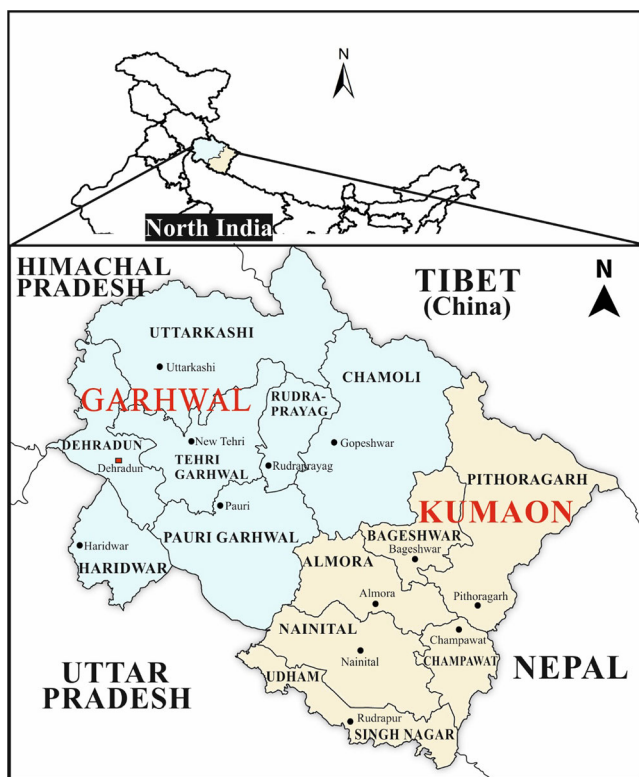

Figure 1. Map of the study site indicating all 13 districts residing in Kumaon and Garhwal regions of the states of Uttarakhand in NW Himalaya India.

Table 1. *Characteristics of Uttarakhand state.*

District name	Area (km^2)	Density (per km)	Population	Elevation (m)	JJAS mean rainfall (mm/month)
Kumaun Region					
Almora	3,090	198	622,506	1,604	240.45
Bageshwar	2,310	116	259,898	934	248.13
Champawat	1,781	147	259,648	1,615	267.14
Nainital	3,853	225	954,605	2,084	232.58
Pithoragarh	7,110	68	483,439	1,627	240.41
USN	2,912	649	1,648,902	550	219.01
Garhwal Region					
Chamoli	7,692	49	391,605	1,550	221.54
Dehradun	3,088	549	1,696,694	600	188.08
Haridwar	2,360	801	1,890,422	314	175.68
Pauri Garhwal	5,438	129	687,271	1,765	212.16
Rudraprayag	1,896	122	242,285	895	218.98
Tehri Garhwal	4,085	170	618,931	1,750	212.55
Uttrakashi	7,951	41	330,086	1,165	198.29

Source: https://www.census2011.co.in/census/state/districtlist/uttarakhand.html.
USN: Udham Singh Nagar.

events. The generalized extreme value (GEV) distribution forms a family of continuous probability distributions which are developed between extreme value theory (EVT). EVT is a branch of statistics dealing with extreme deviations from the median of a probability distribution. Let $X_1, ..., X_n$ be a series of independently identical distributions (iid) of random variables with an unknown distribution. EVT deals with the stochastic behaviour of the maximum and minimum of identically independent random variables. The essential concept of extreme data is about the limiting behaviour of the series as $n \to \infty$.

The peaks over threshold (POT) method (Leadbetter 1991) and the Block Maxima (BM) method (Huang *et al.* 2016) are two principal models that exist for extreme values.

In the present analysis, the BM method is applied. The BM method is widely suitable for applying to the GEV distribution, which is a single three-parametric model with the cumulative distribution function as follows:

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

where μ is a location parameter that represents the centre of the GEV distribution, σ is a scale parameter that determines the size of deviations from μ, and finally, the maximum distribution's tail behaviour (i.e., how quickly the upper tail decays) is represented by ξ, which is the shape parameter.

The GEV distribution incorporates three limiting extreme value distributions depending on the value contained by the shape parameter ξ. The shape parameter ξ is also referred to as the extreme value index, and ξ^{-1} here represents the rate of tail decay.

$$\text{GEV}(x, \xi, \sigma, \mu) = \exp\left\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\},$$
$$\xi \neq 0, \quad (2)$$

$$\text{GEV}(x, \xi, \sigma, \mu) = \exp\left\{-\exp\left[-\left(\frac{x-\mu}{\sigma}\right)\right]\right\}, \xi = 0. \quad (3)$$

The Gumbel, Frechet, and Weibull distributions are the three members of the GEV distribution family. These three cases are referred to be bounded, light-tailed, and heavy-tailed and can be used to model maxima statistically. When $\xi = 0$, the GEV takes on a lightly-tailed Gumbel distribution. For $\xi > 0$, the GEV takes on a heavy-tailed Frechet distribution, whereas, for $\xi < 0$, the GEV takes on a bounded Weibull distribution. GEV is a more generic or convenient technique for modelling block maxima since it can represent all three types of tail behaviour.

3.3 *Stationary/non-stationary test*

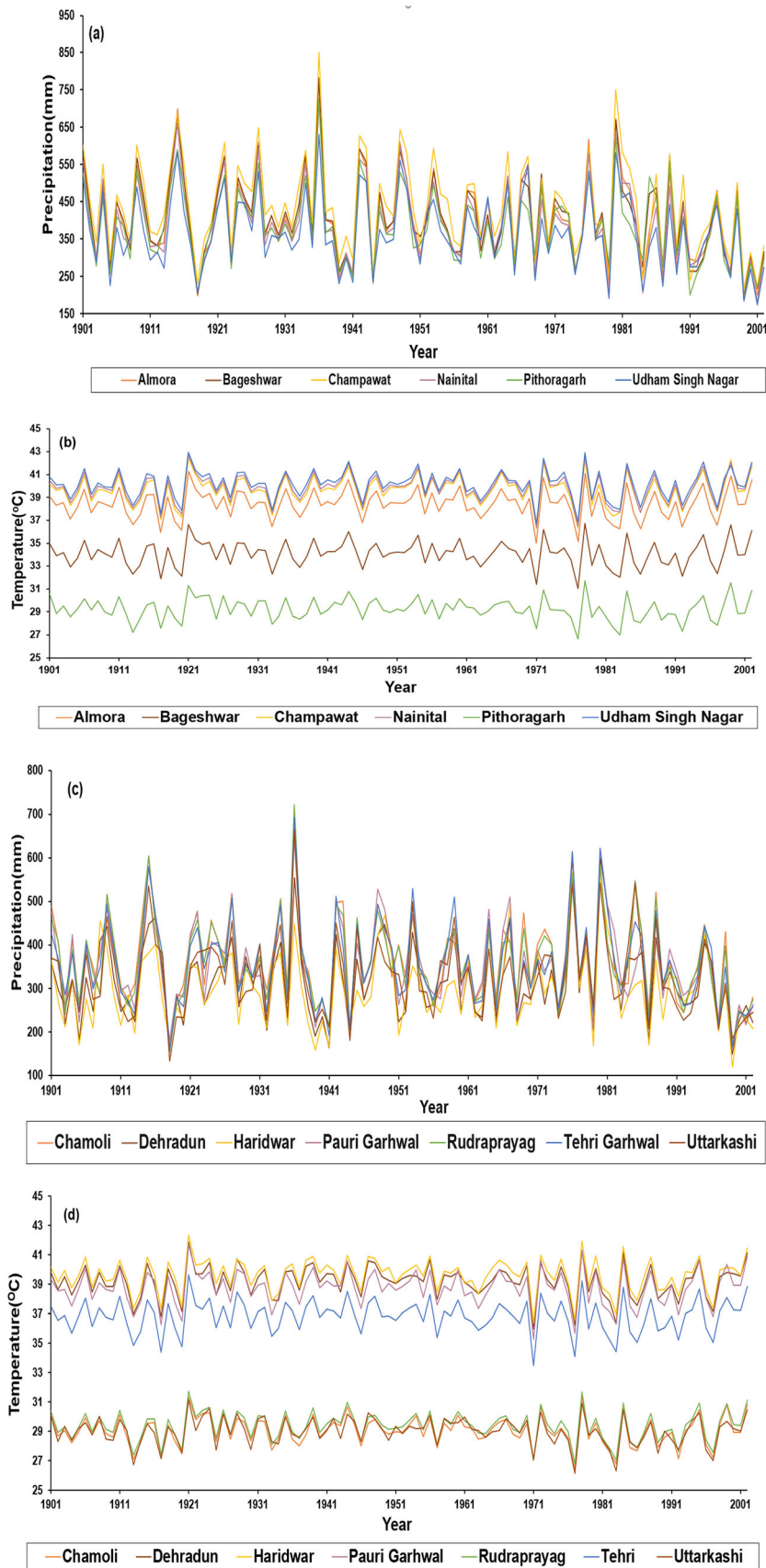If a time series has no trend, constant variance, and a consistent autocorrelation structure over time, it

Figure 2. Annual maximum precipitation and temperature trends in Uttarakhand from 1901 to 2002. (**a** and **b**) representing the Kumaun region and (**c** and **d**) representing the Garhwal region, respectively.

is considered to be 'stationary'. The ADF test (Augmented Dickey-Fuller test) is a typical statistical technique for determining if a time series is stationary. When it comes to analysing the stationary of a series, it is one of the most widely employed statistical tests. The null and alternative hypotheses are as follows:

- **H_0:** The time series is non-stationary. In other words, it has a time-dependent structure and does not have constant variance over time.
- **H_A:** The time series is stationary.

If the tested *p*-value is less than a certain level of significance (=0.05), we can reject the null hypothesis and conclude that the time series is stationary.

3.4 *Parameter estimation*

The generalised extreme value distribution was used to investigate the extreme behaviour of precipitation and temperature. Maximum likelihood estimation (MLE) (Naveau *et al.* 2005), Generalised maximum likelihood estimation (GMLE), L-moments, and Bayesian approaches are used to estimate the three model parameters (location, scale, and shape). The MLE fitting method is the most common way to fit data, even though it can
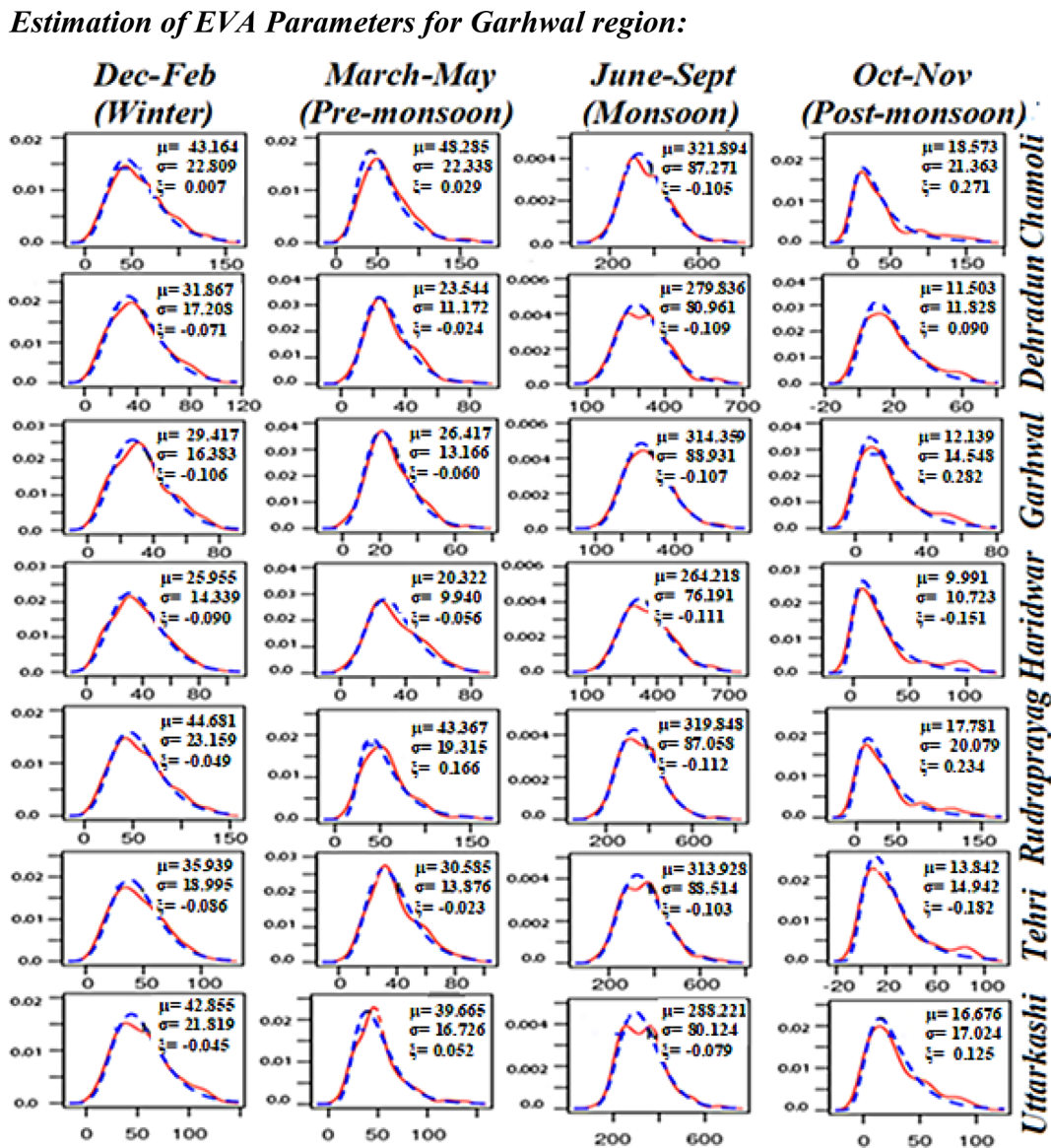

Figure 3. Probability density for seven districts in the Garhwal region. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon, is presented in four different columns, respectively, and seven rows indicate seven districts. The blue colour indicates empirical and the red colour depicts the best model fit using either MLE, GMLE, L-moments, or Bayesian methods. Corresponding location scale and shape parameters are embedded in each plot.

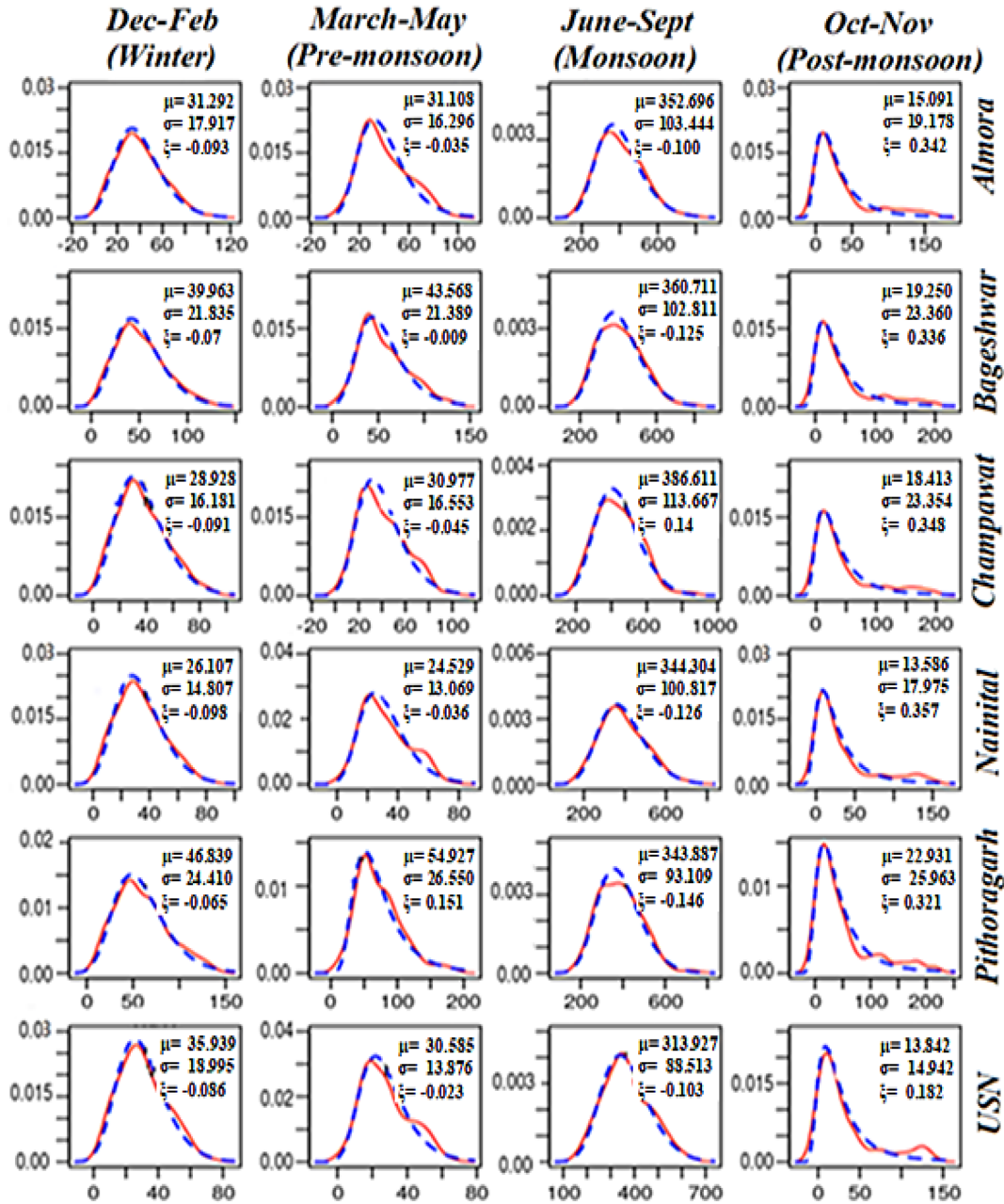### *Estimation of EVA Parameters for Kumaun region:*

Figure 4. Probability density for six districts in the Kumaun region. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon, is presented in four different columns, respectively, and six rows indicate six districts. The blue colour indicates empirical and the red colour depicts the best model fit using MLE, GMLE, L-moments, and Bayesian methods. Corresponding location scale and shape parameters are embedded in each plot.

overestimate the parameters for small samples. GMLE, L-moments, or a Bayesian technique may be used to partially solve this problem. Eventually, for parameter estimate and return value estimation, the best-fitted model was chosen. The return level is defined as a value that is expected to be equalled or exceeded on average once every interval of time (T) (with a probability of $1/T$). Therefore, we obtain the equation: CDF of the GEV distribution $(X_T) = 1–1/T$ (where X_T is the level exceeded on an average only once in T years).

4. Results and discussion

This present study utilised precipitation and temperature records from 13 districts in the Indian state of Uttarakhand for statistical modelling and

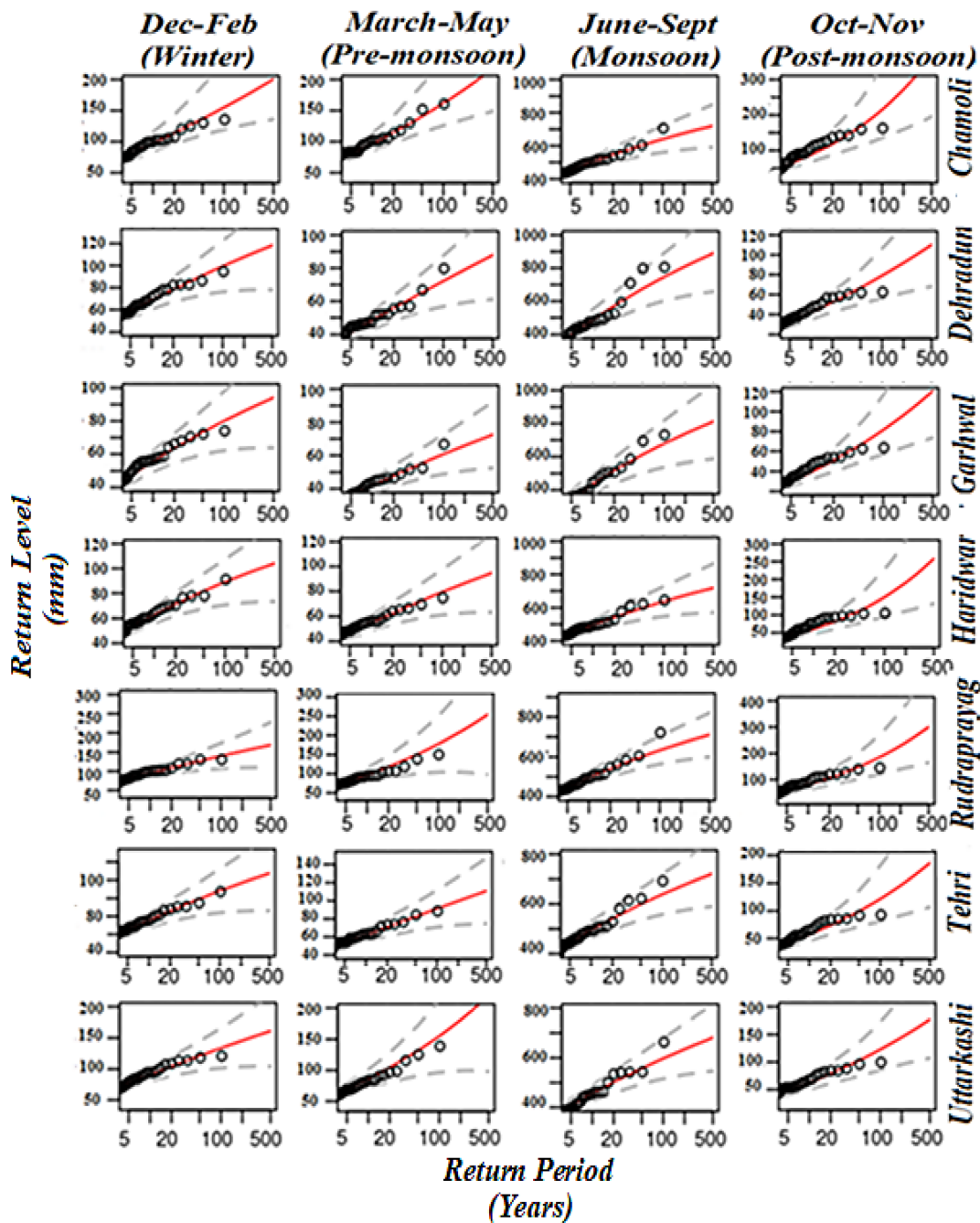**Return value estimation for Garhwal region:**

Figure 5. Estimated return values for seven districts in the Garhwal region where x-axis represents return period and y-axis represents the return level. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon is presented in four different columns, respectively, and seven rows indicate seven districts (indicated right side of each row).

forecasting. All datasets are subjected to the ADF test, which yields a p-value of <0.05. As a consequence, the null hypothesis must be rejected. This indicates that the time series is stationary. In other words, it has a structure that seems to be time-independent and has constant variance over time. The analysis is based on seasonal maxima of monthly mean precipitation and temperature. The precipitation and temperature time series are depicted in figure 2(a–d).

4.1 Precipitation

The rainfall in the state varies from place to place due to its rugged topography. The region of study is strongly influenced by the monsoon,
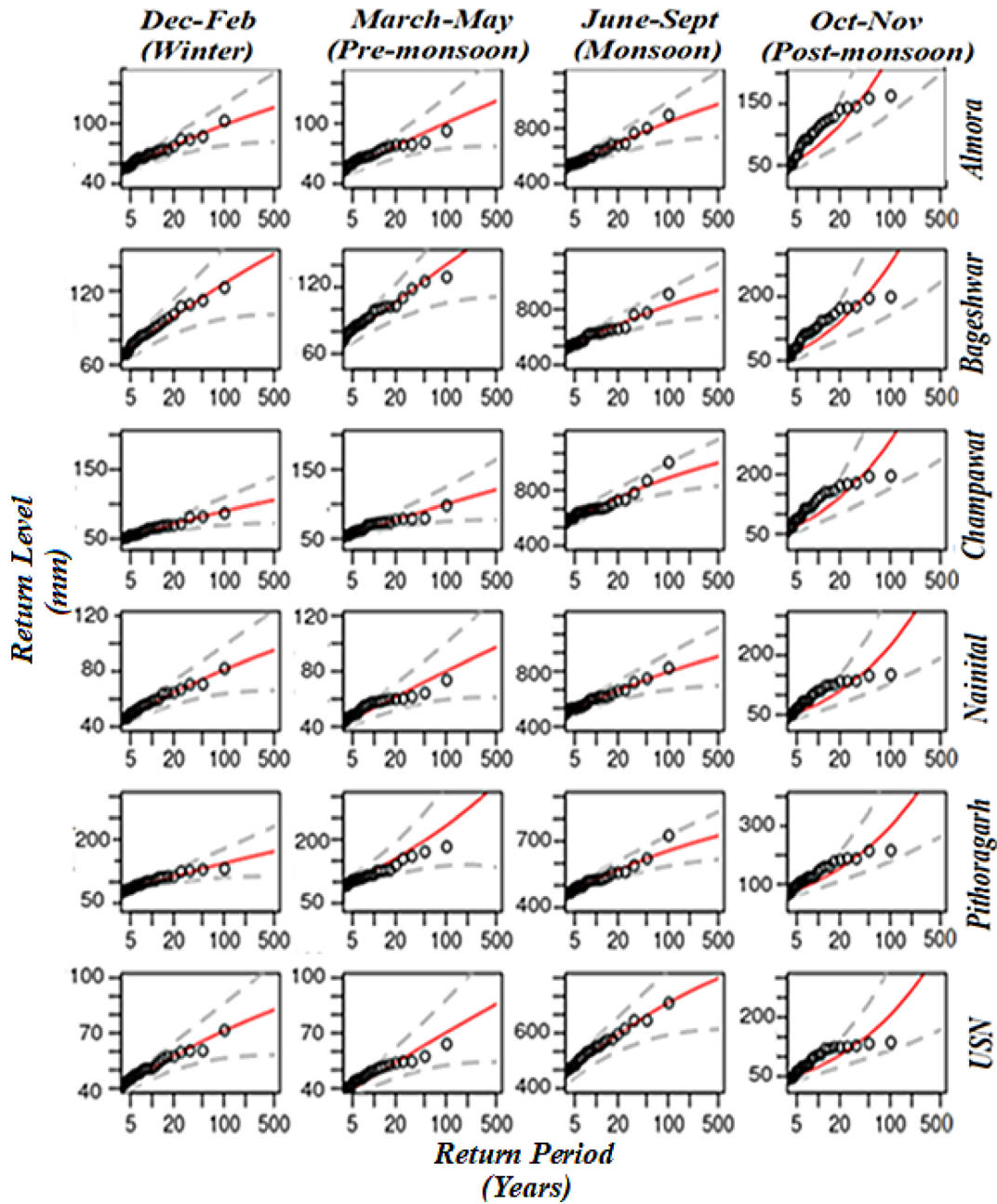
Return value estimation for Kumaun region:

Figure 6. Return value estimation for six districts in the Kumaun region where x-axis represents the return period and y-axis represents the return level. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon is presented in four different columns, respectively, and six rows indicate six districts (indicated on the right side of each row).

which results in a significant contribution of annual precipitation during June–September. Extreme precipitation and flooding are most common in Uttarakhand during the monsoon season. Because of this, the predictability of seasonal precipitation characteristics, particularly extremes, is important. Because of this fact, there is an interest in the predictability of seasonal precipitation characteristics, including extremes. Understanding how heavy precipitation works enables us to forecast the likelihood of a flood, as well as plan for water supplies and do hydrological modelling.

Figures 3 and 4 provide probability density graphs for the GEV fit for precipitation in Garhwal and Kumaun regions, respectively. Return period values for 50, 100, 200, 300, and 500 years were investigated further and are shown in figures 5 and 6 accordingly.
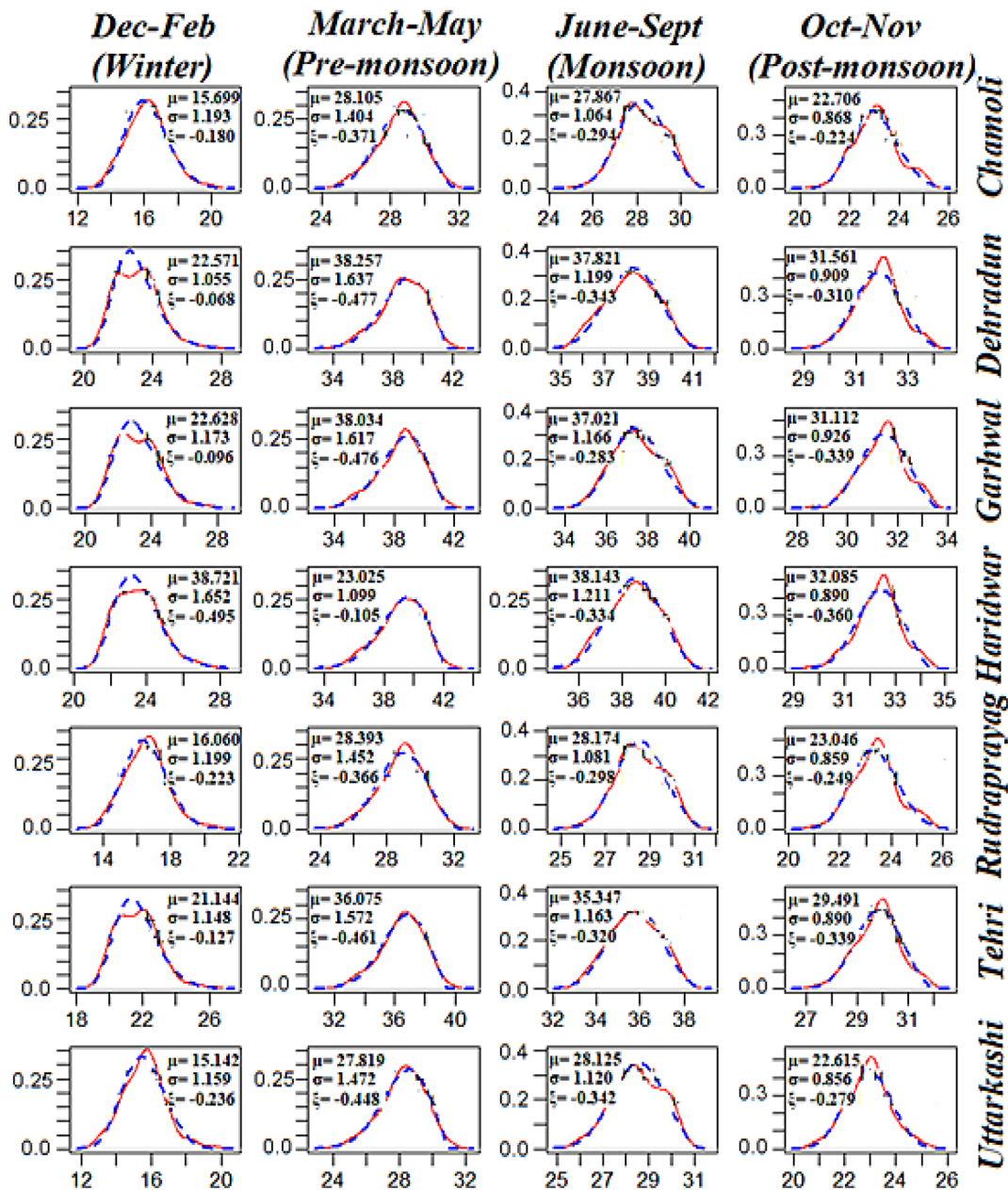
Parameters estimation for Garhwal region:

Figure 7. Probability density for seven Garhwal districts. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon, is presented in four different columns, respectively, and seven rows indicate seven districts. The blue colour indicates empirical and the red color depicts the best model fit using either MLE, GMLE, L-moments, or Bayesian methods. Corresponding location scale and shape parameters are embedded in each plot.

The return periods indicate how long a specific amount of precipitation is predicted to be exceeded once for a given period.

4.2 *Temperature*

The state is hilly, except for a few plain areas near its southern border. As a result, temperatures in the state vary widely based on elevation, location, slope, and geography.

Figures 7 and 8 provide probability density graphs for the GEV fit for maximum temperatures in the Garhwal and Kumaun regions, respectively. Return period values for 50, 100, 200, 300, and 500 years were investigated further and are shown in figures 9 and 10 accordingly. The return periods indicate how long a specific temperature is predicted to be exceeded once for a given period.

From figures 3–10, the model diagnostic plot looks reasonable for precipitation and temperature
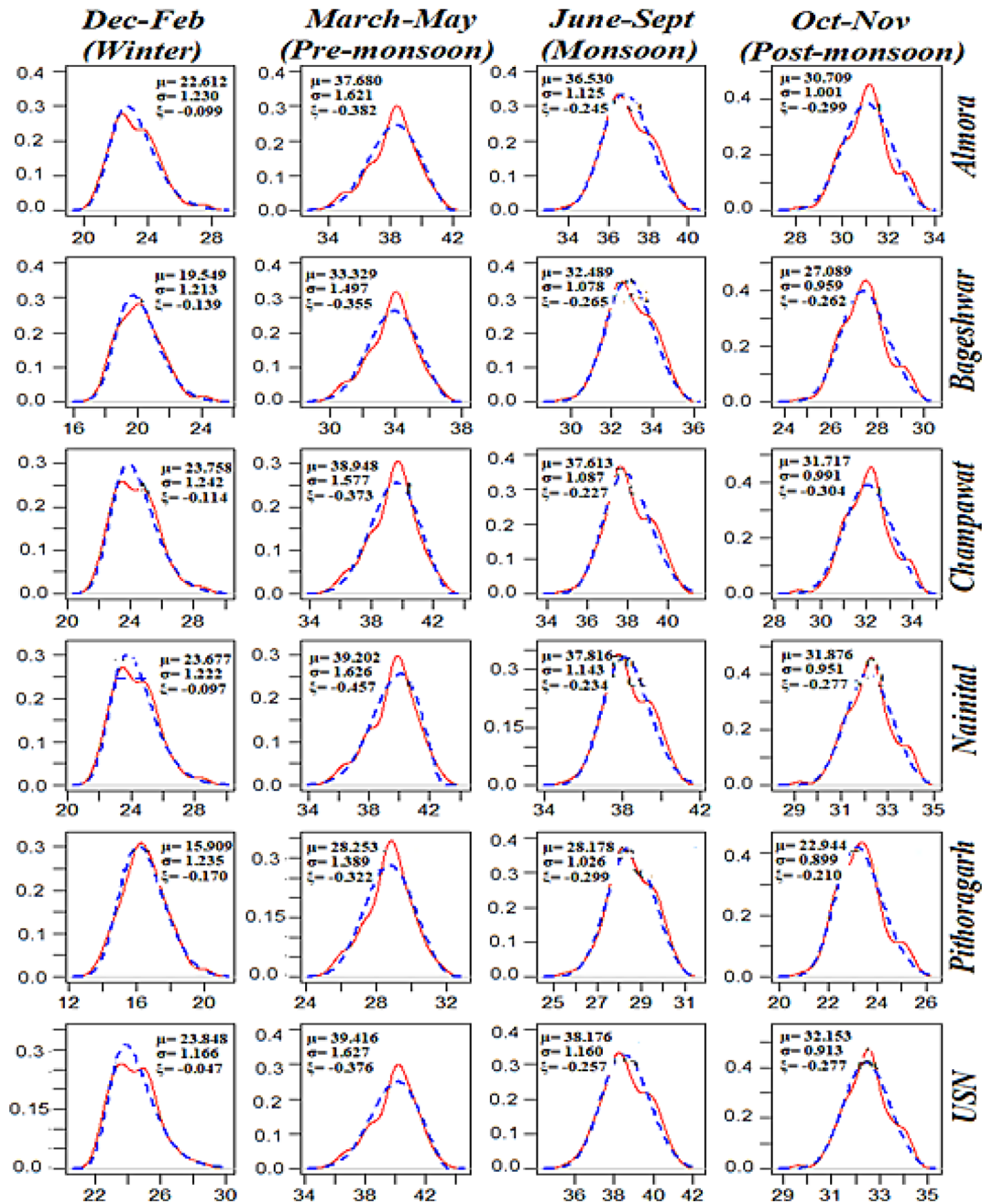
Parameters estimation for Kumaun region:

Figure 8. Probability density for six districts in the Kumaun region. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon, is presented in four different columns, respectively, and six rows indicate six districts. The blue colour indicates empirical and the red colour depicts the best model fit using either MLE, GMLE, L-moments, or Bayesian methods. Corresponding location scale and shape parameters are embedded in each plot.

data for GEV distribution. All of the diagnostic plots for all the districts provide evidence that GEV is a good fit for the block maxima. Each density plot is embedded with location, scale, and shape parameters, where location (μ) denotes the position of the GEV mean, scale (σ) is a multiplier that scales function, and shape (ξ) is the parameter that describes the relative distribution of probabilities.

The density plots indicate that the normality of the residual is obtained. The normality of the residual is an assumption made when running a linear model. Therefore, if our residuals are normal, it means our assumption is valid, and model inference should also be valid (confidence intervals, model predictions).

Next, we fitted a GEV to the monthly maximum precipitation and temperature by applying the
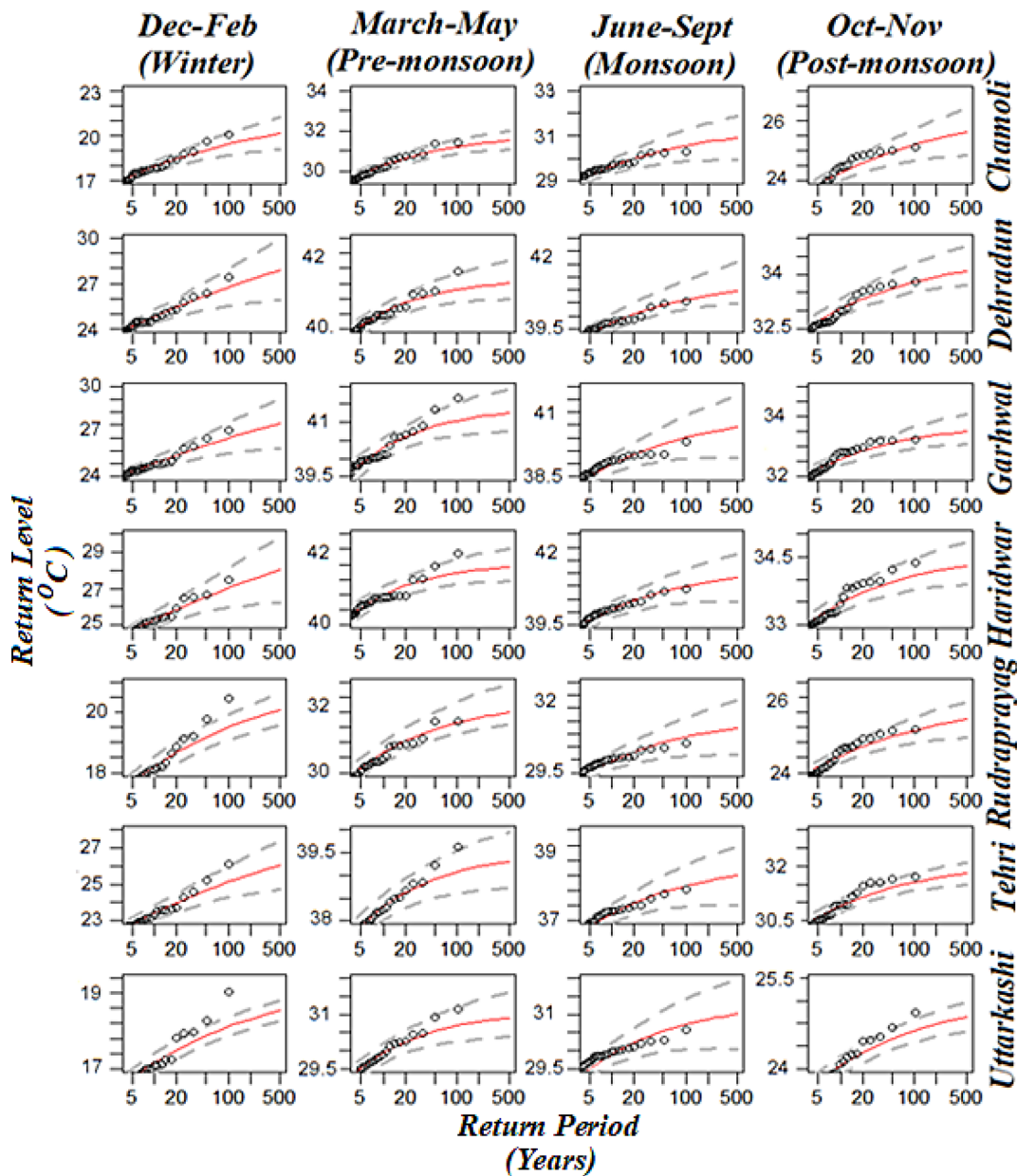
Return value estimation:

Figure 9. Return value estimation for seven districts in the Garhwal region where x-axis represents the return period and y-axis represents the return level. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon, is presented in four different columns, respectively, and seven rows indicate seven districts (indicated right side of each row).

maximum likelihood estimation, generalised maximum likelihood estimation, Baysian, and L-moments methods to seasonwise data for all the districts of Uttarakhand and considered the best method for each seasonal dataset in order to estimate the return values and their return level. The parameter estimates and their corresponding 'standard errors' at a 95% confidence interval for the maximum precipitation and temperature for the Garhwal and Kumaun regions are represented in tables 2 and 3, respectively.

To study the impact of climate change on a global scale, many studies have come forth showing an increasing trend of extreme events in the Uttarakhand region. If the occurrence of such extreme events can be forecasted based on return periods and their corresponding return levels, then the loss of precious lives and property can be minimised. So far, many studies have been carried out to determine extreme events based on large datasets by using both techniques, namely the generalised extreme value distribution method
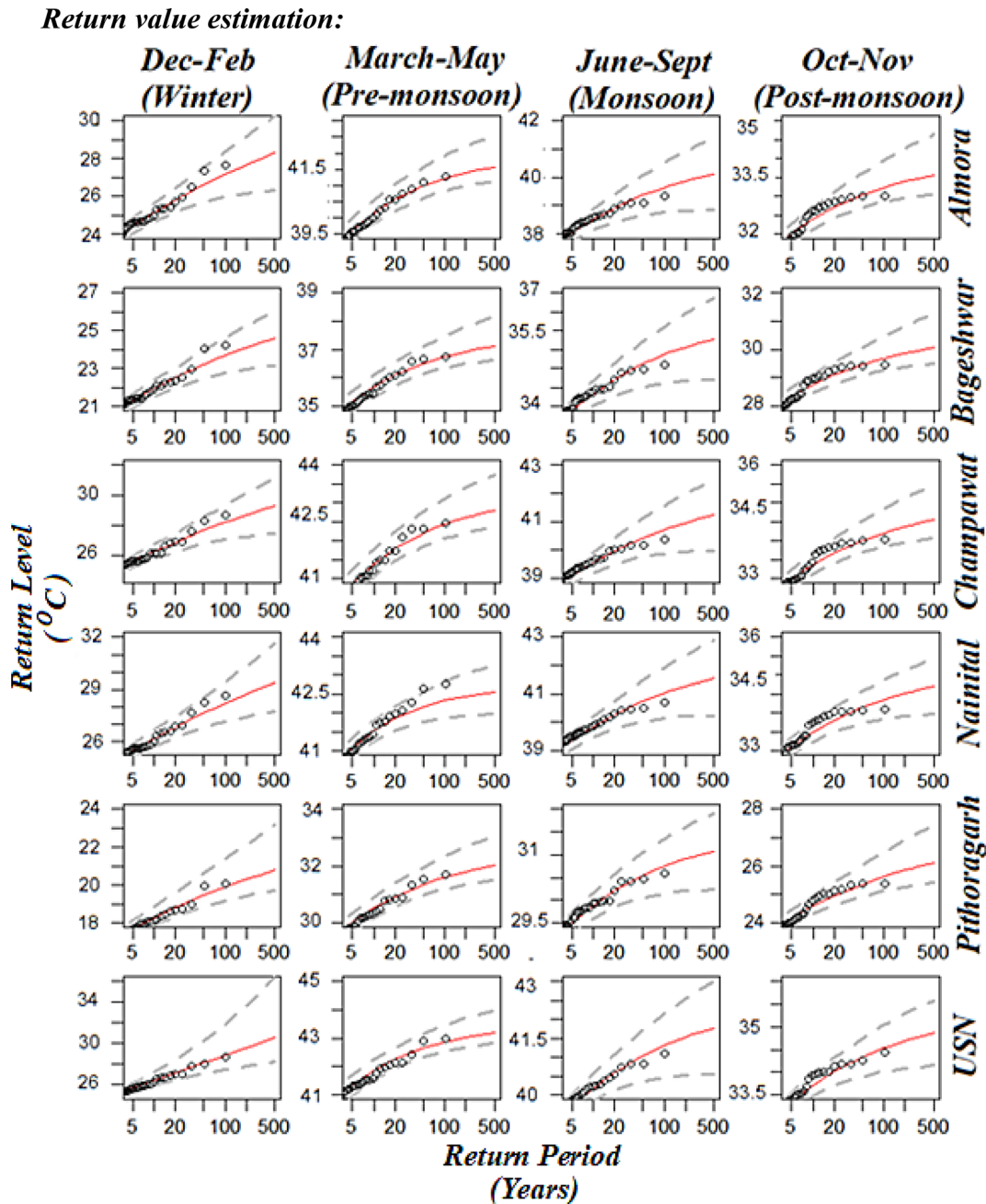
Return value estimation:

Figure 10. Return value estimation for six districts in the Kumaun region where x-axis represents the return period and y-axis represents the return level. Seasonal analysis, viz., winter, pre-monsoon, monsoon, and post-monsoon, is presented in four different columns, respectively, and six rows indicate six different districts (indicated on the right side of each row).

and the generalised Pareto distribution method. The GEV technique is based on the block maxima and minima approach, while the GP technique is based on the peaks over threshold approach. The present study is dedicated to the statistical modelling of monthly maximum precipitation and temperature for all the 13 districts of Uttarakhand during the last century (1901–2002). The generalised extreme value (GEV) analysis approach is utilised for the probabilistic forecasting of the extremities, as our motive is to

determine the occurrence of all the extreme events that may occur in the future. Yearly as well as seasonal analysis is performed for a detailed understanding of these parameters.

The analysis based on the extreme value theory has been carried out for various return levels and return periods and is summarised as follows:

(i) Since the dataset is too large, we have divided it into two time periods, i.e., 1901–1950 and 1951–2002, to observe any changes in the last

Table 2. *Precipitation and temperature (EVA and return value estimation) for Garhwal region.*

	Return level	Precipitation return values					Temperature return values				
		50 year	100 year	200 year	300 year	500 year	50 year	100 year	200 year	300 year	500 year
Chamoli	Winter	135.50 (111.88, 181.97)	151.96 (120.69, 216.49)	168.68 (127.91, 257.32)	178.63 (131.73, 284.67)	191.39 (136.24, 322.46)	19.04 (18.45, 19.63)	19.43 (18.71, 20.15)	19.77 (18.90, 20.64)	19.95 (18.99, 20.91)	20.16 (19.09, 21.23)
	Pre-monsoon	141.37 (116.06, 188.75)	160.66 (126.51, 228.46)	180.94 (136.18, 274.75)	193.33 (141.14, 305.34)	209.58 (147.28, 348.43)	30.99 (30.68, 31.32)	31.20 (30.84, 31.56)	31.36 (30.95, 31.76)	31.43 (31.00, 31.86)	31.51 (31.05, 31.97)
	Monsoon	600.97 (538.63, 663.32)	639.87 (560.01, 719.74)	675.88 (576.31, 775.45)	695.72 (583.79, 807.64)	719.51 (591.30, 847.72)	30.34 (29.77, 30.90)	30.55 (29.86, 31.24)	30.72 (29.90, 31.54)	30.81 (29.91, 31.70)	30.90 (29.92, 31.88)
	Post-monsoon	166.92 (118.23, 231.10)	214.33 (142.24, 321.36)	271.42 (166.19, 452.78)	310.10 (180.71, 553.20)	365.28 (200.47, 698.27)	24.97 (24.54, 25.39)	25.20 (24.67, 25.73)	25.40 (24.77, 26.03)	25.50 (24.81, 26.20)	25.62 (24.85, 26.39)
Dehradun	Winter	89.99 (73.65, 106.32)	98.53 (76.77, 120.28)	106.53 (78.67, 134.40)	110.99 (79.27, 142.72)	116.39 (79.56, 153.22)	26.18 (25.28, 27.09)	26.74 (25.54, 27.93)	27.26 (25.73, 28.79)	27.55 (25.81, 29.30)	27.91 (25.88, 29.95)
	Pre-monsoon	65.09 (53.65, 76.52)	72.11 (56.80, 87.41)	78.98 (59.15, 98.80)	82.94 (60.17, 105.70)	87.86 (61.10, 114.62)	41.15 (40.77, 41.53)	41.31 (40.88, 41.79)	41.41 (40.96, 41.95)	41.46 (40.98, 42.05)	41.51 (41.01, 42.15)
	Monsoon	536.94 (480.95, 592.92)	572.44 (500.67, 644.21)	605.21 (515.58, 694.85)	623.23 (522.37, 724.10)	644.81 (529.11, 760.50)	40.42 (40.09, 41.08)	40.63 (40.26, 41.46)	40.80 (40.38, 41.79)	40.89 (40.43, 41.97)	40.98 (40.48, 42.17)
	Post-monsoon	66.82 (51.23, 87.72)	78.94 (57.98, 109.84)	91.80 (64.36, 136.28)	99.69 (67.86, 155.35)	110.05 (72.33, 183.68)	33.62 (33.36, 34.09)	33.79 (33.51, 34.36)	33.93 (33.62, 34.61)	34.00 (33.66, 34.74)	34.08 (33.72, 34.89)
Pauri Garhwal	Winter	81.81 (67.97, 95.65)	89.12 (70.84, 107.40)	95.88 (72.63, 119.14)	99.61 (73.24, 125.98)	104.08 (73.60, 134.55)	26.45 (25.55, 27.34)	26.99 (25.82, 28.16)	27.50 (26.01, 28.99)	27.78 (26.10, 29.46)	28.12 (26.17, 30.07)
	Pre-monsoon	72.22 (58.69, 85.74)	79.34 (61.21, 97.47)	86.14 (62.74, 109.54)	89.99 (63.23, 116.74)	94.70 (63.45, 125.95)	40.90 (40.51, 41.32)	41.05 (40.60, 41.56)	41.15 (40.65, 41.73)	41.20 (40.67, 41.81)	41.25 (40.69, 41.91)
	Monsoon	598.00 (529.04, 666.96)	637.40 (547.72, 727.08)	673.83 (560.91, 786.74)	693.89 (566.43, 821.34)	717.92 (571.33, 864.51)	39.77 (39.11, 40.44)	40.02 (39.19, 40.85)	40.22 (39.22, 41.21)	40.32 (39.23, 41.40)	40.43 (39.23, 41.63)
	Post-monsoon	115.60 (78.38, 170.06)	149.34 (93.50, 239.86)	190.27 (110.94, 338.68)	218.16 (121.48, 414.58)	258.14 (135.10, 534.70)	33.11 (32.79, 33.45)	33.27 (32.91, 33.71)	33.39 (32.99, 33.93)	33.45 (33.02, 34.03)	33.51 (33.05, 34.17)

Table 2. (Continued.)

	Return level	Precipitation return values					Temperature return values				
		50 year	100 year	200 year	300 year	500 year	50 year	100 year	200 year	300 year	500 year
Haridwar	Winter	73.09 (59.73, 86.44)	79.90 (62.06, 97.74)	86.28 (63.38, 109.17)	89.82 (63.73, 115.90)	94.09 (63.79, 124.39)	26.54 (25.70, 27.37)	27.03 (25.94, 28.12)	27.48 (26.10, 28.86)	27.73 (26.17, 29.29)	28.03 (26.22, 29.83)
	Pre-monsoon	55.15 (46.16, 64.14)	60.62 (48.80, 72.43)	65.85 (50.81, 80.90)	68.82 (51.71, 85.93)	72.46 (52.58, 92.33)	41.57 (41.19, 41.97)	41.72 (41.29, 42.20)	41.82 (41.35, 42.39)	41.86 (41.38, 42.48)	41.90 (41.40, 42.57)
	Monsoon	505.27 (450.86, 559.68)	538.39 (468.49, 608.30)	568.93 (481.62, 656.23)	585.69 (487.51, 683.88)	605.75 (493.25, 718.26)	40.78 (40.25, 41.32)	40.99 (40.33, 41.64)	41.15 (40.38, 41.92)	41.23 (40.39, 42.07)	41.31 (40.40, 42.23)
	Post-monsoon	67.02 (49.22, 90.79)	81.28 (56.45, 118.09)	97.06 (63.19, 150.63)	107.07 (67.12, 172.57)	120.59 (72.27, 205.33)	33.95 (33.65, 34.25)	34.08 (33.74, 34.46)	34.19 (33.80, 34.64)	34.24 (33.83, 34.76)	34.29 (33.86, 34.87)
Rudraprayag	Winter	126.82 (102.29, 151.34)	139.90 (106.64, 173.17)	152.50 (109.11, 195.89)	159.66 (109.75, 209.56)	168.47 (109.78, 227.15)	19.18 (18.80, 19.57)	19.51 (19.08, 19.93)	19.78 (19.31, 20.26)	19.93 (19.41, 20.44)	20.09 (19.53, 20.64)
	Pre-monsoon	149.53 (99.72, 199.34)	176.93 (103.84, 250.01)	207.59 (104.27, 310.90)	227.21 (102.46, 351.95)	253.87 (97.63, 410.12)	31.42 (31.08, 31.97)	31.64 (31.28, 32.31)	31.81 (31.43, 32.59)	31.90 (31.50, 32.75)	31.99 (31.56, 32.92)
	Monsoon	595.23 (539.74, 650.71)	633.05 (563.22, 702.89)	667.92 (581.87, 753.98)	687.07 (590.81, 783.34)	709.98 (600.24, 819.71)	30.67 (30.07, 31.27)	30.88 (30.14, 31.62)	31.05 (30.17, 31.93)	31.14 (30.18, 32.09)	31.23 (30.18, 32.28)
	Post-monsoon	145.95 (102.45, 209.49)	183.99 (122.25, 282.45)	228.61 (142.76, 381.47)	258.25 (154.86, 453.76)	299.81 (170.31, 568.03)	25.19 (24.84, 25.54)	25.40 (24.98, 25.82)	25.57 (25.08, 26.07)	25.66 (25.12, 26.20)	25.76 (25.16, 26.36)
Tehri	Winter	98.90 (80.91, 116.89)	108.10 (84.01, 132.19)	116.73 (85.73, 147.73)	121.54 (86.17, 156.91)	127.36 (86.20, 168.52)	24.67 (23.99, 25.36)	25.14 (24.28, 26.00)	25.56 (24.50, 26.63)	25.80 (24.61, 26.99)	26.07 (24.72, 27.42)
	Pre-monsoon	82.36 (67.23, 97.50)	91.15 (70.72, 111.58)	99.76 (73.14, 126.39)	104.73 (74.08, 135.37)	110.92 (74.80, 147.03)	38.92 (38.55, 39.30)	39.08 (38.66, 39.54)	39.19 (38.72, 39.73)	39.24 (38.75, 39.81)	39.29 (38.78, 39.93)
	Monsoon	598.31 (535.49, 661.14)	638.20 (557.62, 718.79)	675.20 (574.53, 775.86)	695.60 (582.30, 808.91)	720.11 (590.10, 850.12)	37.94 (37.38, 38.50)	38.15 (37.46, 38.84)	38.32 (37.50, 39.13)	38.40 (37.52, 39.28)	38.49 (37.52, 39.45)
	Post-monsoon	98.73 (69.87, 130.74)	121.35 (80.76, 172.12)	146.94 (92.20, 226.27)	163.44 (98.65, 263.14)	186.04 (105.93, 316.18)	31.41 (31.20, 31.63)	31.56 (31.32, 31.80)	31.68 (31.41, 31.95)	31.73 (31.45, 32.02)	31.79 (31.48, 32.10)

Table 2. *(Continued.)*

	Return level	Precipitation return values					Temperature return values				
		50 year	100 year	200 year	300 year	500 year	50 year	100 year	200 year	300 year	500 year
Uttarkashi	Winter	120.98 (97.31, 144.65)	133.58 (101.42, 165.73)	145.74 (103.75, 187.74)	152.68 (104.34, 201.01)	161.23 (104.34, 218.12)	18.10 (17.78, 18.41)	18.39 (18.07, 18.71)	18.64 (18.32, 18.97)	18.77 (18.44, 19.10)	18.92 (18.58, 19.25)
	Pre-monsoon	131.22 (90.99, 171.45)	154.65 (96.37, 212.93)	180.72 (99.20, 262.24)	197.34 (99.43, 295.24)	219.83 (97.96, 341.70)	30.53 (30.15, 30.93)	30.68 (30.26, 31.16)	30.79 (30.31, 31.34)	30.85 (30.35, 31.44)	30.90 (30.40, 31.54)
	Monsoon	557.03 (494.42, 619.63)	596.94 (515.69, 678.18)	634.56 (531.99, 737.12)	655.59 (539.46, 771.71)	681.11 (546.90, 815.32)	30.54 (29.97, 31.11)	30.72 (30.02, 31.42)	30.87 (30.05, 31.68)	30.93 (30.05, 31.82)	31.01 (30.04, 31.97)
	Post-monsoon	102.36 (78.41, 133.95)	122.62 (89.05, 170.01)	144.65 (98.08, 214.43)	158.44 (103.56, 245.73)	176.82 (110.77, 290.66)	24.65 (24.42, 24.88)	24.83 (24.57, 25.09)	24.98 (24.69, 25.27)	25.06 (24.75, 25.37)	25.14 (24.81, 25.48)

50 years as compared to the first 50 years. The analysis shows an average increase in temperature of about 2.44°C during the winter season and an average decrease in temperature of about 0.44°C is observed during the monsoon season.

(ii) For the Garhwal region, with a 50-year return level, the maximum temperatures of 26.54°, 41.57°, 40.78°, and 33.95°C are expected to exist for Haridwar district (altitude ~ 314 m amsl) for winter, pre-monsoon, monsoon, and post-monsoon seasons, respectively. Similarly, the maximum precipitation of 135.50, 600.97, and 166.92 mm is expected to exist for Chamoli district (alt. ~ 1550 m amsl) for winter, monsoon, and post-monsoon seasons, respectively, whereas, for the pre-monsoon season, the maximum precipitation of 149.53 mm is expected to exist for Rudraprayag district (alt. ~ 895 m amsl).

(iii) For the Kumaun region, with a 50-year return level, the maximum temperatures of 28.09°, 42.65°, 41.03°, and 34.33°C are expected to exist for Udham Singh Nagar district (alt. ~ 550 m amsl) for winter, pre-monsoon, monsoon, and post-monsoon seasons, respectively. Similarly, the maximum precipitation of 131.02, 196.17, and 225.22 mm is expected to exist for Pithoragarh district (alt. ~ 1630 m amsl) for winter, pre-monsoon, and post-monsoon seasons, respectively, whereas for the monsoon season, the maximum precipitation of 723.42 mm is expected to exist for Champawat district (alt ~ 1660 m).

(iv) From our investigations, we have observed that the Pithoragarh, Champawat, Rudraprayag, and Chamoli districts being at high elevation zones, are more prone to extreme events due to low temperatures and a consistent increase in cloud cover in association with precipitation, whereas Udham Singh Nagar and Haridwar, being at a lower elevation, have high temperatures, low precipitation, and cloud cover. Therefore, having a lower probability of high precipitation events based on the climatic trends. Undoubtedly, this will impact the physical, social, as well as cultural settings of the state.

(v) The present analysis shows that the temperature in hilly areas of Uttarakhand is rising more prominently than in the plains. This increment will affect wind patterns, cloud formation, and rainfall. Therefore, more cloud bursts are expected to occur in the future

Table 3. *Precipitation and temperature (EVA and return value estimation) for Kumaun region.*

	Return level	Precipitation return values					Temperature return values				
		50 year	100 year	200 year	300 year	500 year	50 year	100 year	200 year	300 year	500 year
Almora	Winter	89.92 (74.48, 105.35)	98.34 (77.94, 118.74)	106.21 (80.19, 132.23)	110.57 (81.01, 140.13)	115.84 (81.60, 150.08)	26.59 (25.66, 27.52)	27.15 (25.95, 28.36)	27.68 (26.16, 29.20)	27.97 (26.25, 29.68)	28.31 (26.33, 30.29)
	Pre-monsoon	90.56 (71.90, 109.21)	100.37 (74.99, 125.74)	109.90 (76.72, 143.08)	115.37 (77.15, 153.59)	122.14 (77.10, 167.18)	40.97 (40.61, 41.58)	41.21 (40.82, 41.92)	41.39 (40.97, 42.22)	41.48 (41.04, 42.39)	41.57 (41.11, 42.56)
	Monsoon	686.90 (604.46, 769.33)	734.12 (626.45, 841.79)	778.00 (641.88, 914.13)	802.26 (648.25, 956.26)	831.42 (653.81, 1009.03)	39.36 (38.66, 40.05)	39.64 (38.76, 40.51)	39.87 (38.82, 40.92)	39.99 (38.83, 41.14)	40.12 (38.84, 41.41)
	Post-monsoon	172.04 (107.45, 246.29)	229.52 (130.92, 359.23)	302.20 (154.74, 526.61)	353.38 (169.45, 655.12)	428.80 (188.49, 861.14)	33.01 (32.69, 33.56)	33.21 (32.84, 33.90)	33.38 (32.95, 34.20)	33.46 (32.99, 34.35)	33.55 (33.04, 34.54)
Bageshwar	Winter	114.50 (93.23, 135.77)	125.81 (97.28, 154.35)	136.55 (99.70, 173.40)	142.58 (100.45, 184.71)	149.94 (100.74, 199.13)	23.20 (22.46, 23.94)	23.67 (22.74, 24.61)	24.10 (22.95, 25.25)	24.33 (23.04, 25.61)	24.60 (23.14, 26.06)
	Pre-monsoon	125.56 (100.43, 150.70)	139.93 (105.72, 174.14)	154.16 (109.25, 199.06)	162.42 (110.53, 214.32)	172.79 (111.33, 234.24)	36.49 (36.11, 37.12)	36.73 (36.32, 37.47)	36.92 (36.48, 37.77)	37.01 (36.54, 37.93)	37.11 (36.61, 38.11)
	Monsoon	677.95 (607.96, 747.95)	720.09 (630.33, 809.84)	758.55 (646.65, 870.46)	779.52 (653.80, 905.23)	804.43 (660.61, 948.25)	35.11 (34.51, 35.72)	35.36 (34.61, 36.10)	35.56 (34.67, 36.45)	35.66 (34.68, 36.64)	35.78 (34.70, 36.85)
	Post-monsoon	207.89 (130.83, 322.06)	276.24 (159.02, 470.51)	362.34 (188.29, 680.77)	422.77 (208.28, 850.34)	511.60 (233.24, 1124.70)	29.45 (29.10, 30.07)	29.68 (29.26, 30.46)	29.88 (29.39, 30.82)	29.98 (29.44, 31.01)	30.09 (29.50, 31.24)
Champawat	Winter	82.05 (67.30, 96.80)	89.72 (70.09, 109.35)	96.89 (71.74, 122.03)	100.87 (72.25, 129.48)	105.68 (72.47, 138.89)	27.67 (26.79, 28.55)	28.20 (27.07, 29.34)	28.70 (27.27, 30.13)	28.97 (27.35, 30.58)	29.29 (27.44, 31.14)
	Pre-monsoon	90.21 (72.07, 108.34)	99.75 (75.14, 124.36)	108.96 (76.86, 141.06)	114.21 (77.29, 151.13)	120.68 (77.26, 164.11)	42.20 (41.83, 42.84)	42.44 (42.04, 43.19)	42.62 (42.19, 43.50)	42.71 (42.25, 43.65)	42.81 (42.32, 43.83)
	Monsoon	723.42 (658.38, 788.45)	765.70 (684.38, 847.03)	803.70 (704.09, 903.30)	824.14 (713.17, 935.12)	848.19 (722.38, 974.01)	40.43 (39.75, 41.10)	40.72 (39.87, 41.56)	40.96 (39.94, 41.99)	41.09 (39.96, 42.21)	41.23 (39.98, 42.49)
	Post-monsoon	212.31 (136.17, 343.20)	284.14 (165.69, 506.69)	375.35 (197.28, 764.75)	439.79 (217.18, 977.40)	535.01 (245.68, 1329.27)	33.99 (33.68, 34.50)	34.19 (33.83, 34.82)	34.35 (33.94, 35.08)	34.43 (33.99, 35.23)	34.52 (34.04, 35.40)

Table 3. *(Continued.)*

	Return level	Precipitation return values					Temperature return values				
		50 year	100 year	200 year	300 year	500 year	50 year	100 year	200 year	300 year	500 year
Nainital	Winter	74.15 (61.15, 87.15)	80.98 (63.75, 98.22)	87.34 (65.34, 109.34)	90.86 (65.86, 115.85)	95.09 (66.14, 124.04)	27.65 (26.74, 28.55)	28.21 (27.09, 29.42)	28.74 (27.39, 30.34)	29.03 (27.53, 30.86)	29.38 (27.70, 31.54)
	Pre-monsoon	72.08 (57.09, 87.06)	79.89 (59.51, 100.28)	87.49 (60.84, 114.14)	91.84 (61.14, 122.54)	97.22 (61.05, 133.39)	42.16 (41.73, 42.60)	42.32 (41.84, 42.87)	42.44 (41.91, 43.07)	42.49 (41.93, 43.19)	42.55 (41.97, 43.30)
	Monsoon	655.06 (579.83, 730.28)	696.27 (598.86, 793.68)	733.88 (611.90, 855.86)	754.37 (617.17, 891.57)	778.71 (621.65, 935.78)	40.74 (40.02, 41.46)	41.03 (40.14, 41.93)	41.28 (40.20, 42.37)	41.41 (40.22, 42.61)	41.56 (40.23, 42.88)
	Post-monsoon	165.85 (103.78, 265.33)	223.15 (126.63, 403.68)	296.34 (152.39, 602.17)	348.29 (168.52, 764.01)	425.35 (188.89, 1030.86)	34.14 (33.72, 34.57)	34.35 (33.83, 34.86)	34.51 (33.90, 35.12)	34.60 (33.93, 35.26)	34.69 (33.96, 35.42)
Pithoragarh	Winter	131.02 (106.12, 155.91)	143.96 (110.34, 177.59)	156.29 (112.66, 199.93)	163.24 (113.22, 213.26)	171.74 (113.16, 230.31)	19.46 (18.84, 20.54)	19.90 (19.16, 21.30)	20.29 (19.42, 22.07)	20.50 (19.55, 22.48)	20.75 (19.69, 23.03)
	Pre-monsoon	196.17 (131.82, 260.53)	231.48 (138.27, 324.70)	270.58 (140.37, 400.78)	295.39 (139.22, 451.57)	328.88 (134.82, 522.94)	31.34 (30.96, 32.00)	31.60 (31.18, 32.39)	31.80 (31.35, 32.73)	31.90 (31.43, 32.90)	32.02 (31.51, 33.10)
	Monsoon	620.88 (566.04, 675.71)	655.85 (587.04, 724.66)	687.32 (602.89, 771.75)	704.28 (610.16, 798.40)	724.25 (617.48, 831.01)	30.54 (30.05, 31.03)	30.74 (30.14, 31.34)	30.91 (30.20, 31.61)	30.99 (30.22, 31.75)	31.08 (30.23, 31.92)
	Post-monsoon	225.22 (150.03, 354.14)	296.42 (180.68, 515.54)	385.17 (213.09, 763.10)	446.95 (233.32, 958.48)	537.13 (258.70, 1275.04)	25.35 (24.94, 26.03)	25.62 (25.13, 26.50)	25.85 (25.26, 26.96)	25.97 (25.33, 27.22)	26.12 (25.40, 27.54)
USN	Winter	65.44 (54.24, 76.65)	71.10 (56.31, 85.89)	76.31 (57.53, 95.08)	79.16 (57.90, 100.42)	82.57 (58.06, 107.09)	28.09 (27.08, 29.99)	28.81 (27.50, 31.54)	29.54 (27.86, 33.30)	29.97 (28.05, 34.38)	30.51 (28.26, 35.88)
	Pre-monsoon	63.18 (50.17, 76.19)	70.14 (52.47, 87.81)	76.92 (53.83, 100.01)	80.81 (54.22, 107.40)	85.64 (54.30, 116.98)	42.65 (42.32, 43.16)	42.87 (42.53, 43.48)	43.04 (42.68, 43.76)	43.12 (42.75, 43.90)	43.21 (42.82, 44.04)
	Monsoon	597.12 (530.13, 664.12)	631.46 (544.84, 718.07)	662.37 (554.34, 770.41)	679.04 (557.88, 800.20)	698.67 (560.55, 836.79)	41.03 (40.36, 41.71)	41.31 (40.46, 42.15)	41.53 (40.52, 42.54)	41.65 (40.54, 42.75)	41.78 (40.55, 43.00)
	Post-monsoon	154.05 (98.21, 238.25)	204.61 (119.04, 352.87)	268.17 (142.50, 517.69)	312.72 (157.38, 647.86)	378.12 (177.37, 857.69)	34.33 (33.91, 34.75)	34.53 (34.02, 35.04)	34.69 (34.09, 35.29)	34.77 (34.12, 35.42)	34.86 (34.14, 35.58)

during the monsoon as well as pre- and post-monsoon seasons. The Uttarakhand Himalaya is enriched with a diversity of forests distributed from subtropical to alpine zones. The seasonwise temperature analysis, however, shows that the state is losing its seasonal contrast as winters are becoming warmer and the rainy season is losing its heat. Therefore, phonological behaviour, such as flowering, fruiting, and germination, will be influenced by the seasonal and climatic change. This analysis indicates that the climate of Uttarakhand is changing notably. Although at this stage, the misery of climate change may not be visible, the scenario that is emerging warns that these changes may alter the regional energy balance and, thus may change the pace of ongoing geomorphologic processes.

The significance of this study rests on the fact that Uttarakhand has varied topography, and the climate and vegetation vary greatly with elevation. Conservation strategies for the important temperate medicinal plants need to be developed. Long-term changes in these parameters can directly or indirectly affect many aspects of society in potentially disruptive ways. Due to changes in temperature and rainfall, there has been an increased migration of lowland species towards higher altitudes. The effective use of remote sensing technology can help to improve the current knowledge of vegetation responses to a changing climate. Also, extreme events such as floods, landslides, and cloudbursts are quite common in most of the districts of Uttarakhand. The estimated extreme values and their return level may help the decision-makers plan appropriate risk mitigation measures to reduce the damage caused by extreme weather phenomena. Furthermore, research will be focused on a non-stationary approach.

Acknowledgements

Author statement

Chhavi P Pandey: Conceptualization, data analysis, interpretation and draft manuscript preparation; Vineet Ahuja: Data collection, analysis, interpretation, visualisation and manuscript preparation; Lokesh K Joshi: Data interpretation, drafting and critical revision of the article; Hemwati Nandan: Draft preparation, critical revision and final approval of the final version.

References

Arreyndip N A and Joseph E 2015 Extreme temperature forecast in Mbonge, Cameroon through return level analysis of the generalised extreme value (GEV) distribution; *Int. J. Math. Phys. Sci.* **9(6)** 347–352.

Ayuketang Arreyndip N and Joseph E 2016 Generalised extreme value distribution models for the assessment of seasonal wind energy potential of Debuncha, Cameroon; *J. Renew. Energ.* **2016** 1–9, https://doi.org/10.1155/2016/9357812.

Beguería S and Vicente-Serrano S M 2006 Mapping the hazard of extreme rainfall by peaks over threshold extreme value analysis and spatial regression techniques; *J. Appl. Meteorol. Climatol.* **45** 108–124, https://doi.org/10.1175/JAM2324.1.

Chikobvu D and Chifurira R 2015 Modelling of extreme minimum rainfall using generalised extreme value distribution for Zimbabwe; *South Afr. J. Sci.* **111** 1–8, https://doi.org/10.17159/sajs.2015/20140271.

Gandhre N 2020 Analysis of precipitation extremes for coastal Districts of Maharashtra; Proceedings of the International Conference on Recent Advances in Computational Techniques (IC-RACT) 2020.

Gilleland E and Katz R W 2016 ExtRemes 2.0: An extreme value analysis package in R; *J. Stat. Softw.* **72**, https://doi.org/10.18637/jss.v072.i08.

Hasan H B, Ahmad Radi N F B and Kassim S B 2012 Modeling of extreme temperature using generalised extreme value (GEV) distribution: A case study of Penang; *Lecture Notes in Eng. Comput. Sci.* **2197** 181–186.

Huang W K, Stein M L, McInerney D J, Sun S and Moyer E J 2016 Estimating changes in temperature extremes from millennial-scale climate simulations using generalised extreme value (GEV) distributions; *Adv. Stat. Climatol. Meteorol. Oceanogr.* **2(1)** 79–103, https://doi.org/10.5194/ascmo-2-79-2016.

Kumar V, Shanu and Jahangeer 2017 Statistical distribution of rainfall in Uttarakhand, India; *Appl. Water Sci.* **7** 4765–4776, https://doi.org/10.1007/s13201-017-0586-5.

Leadbetter M R 1991 On a basis for 'Peaks over Threshold' modeling; *Stat. Probab. Lett.* **12(4)** 357–362, https://doi.org/10.1016/0167-7152(91)90107-3.

Li Y, Cai W and Campbell E P 2005 Statistical modeling of extreme rainfall in southwest Western Australia; *J. Climate* **18** 852–863, https://doi.org/10.1175/JCLI-3296.1.

Mitchell T D and Jones P D 2005 An improved method of constructing a database of monthly climate observations

and associated high-resolution grids; *Int. J. Climatol.* **25** 693–712.

Nandargi S, Gaur A and Mulye S S 2016 Hydrological analysis of extreme rainfall events and severe rainstorms over Uttarakhand, India; *Hydrol. Sci. J.* **61** 2145–2163, https://doi.org/10.1080/02626667.2015.1085990.

Naveau P, Nogaj M, Ammann C, Yiou P, Cooley D and Jomelli V 2005 Méthodes statistiques pour l'analyse des extrêmes climatiques; *Comptes Rendus – Geosci.* **337** 1013–1022, https://doi.org/10.1016/j.crte.2005.04.015.

Negi M S and Kumar A 2016 Assessment of increasing threat of forest fires in Uttarakhand, using remote sensing and GIS techniques; *Glob. J. Adv. Res.* **3(6)** 457–468.

Rana N, Sundriyal Y, Sharma S, Khan F, Kaushik S, Chand P and Juyal N *et al.* 2021 Hydrological characteristics of 7th February 2021 Rishi Ganga Flood: Implication towards understanding flood hazards in higher Himalaya; *J. Geol. Soc. India* **97(8)** 827–835, https://doi.org/10.1007/s12594-021-1781-4.

R Core Team 2020 R*: A language and environment for statistical computing*; R Foundation for Statistical Computing, Vienna, Austria, https://www.R-project.org/.

Reiss R D and Thomas M 2001 Statistical analysis of extreme VALUES with applications to insurance, finance, hydrology and other fields; *Technometrics* **44** 516.

Rydén J 2011 Statistical analysis of temperature extremes in long-time series from Uppsala; *Theoret. Appl. Climatol.* **105** 193–197, https://doi.org/10.1007/s00704-010-0389-1.

Sampson T-A and Kwadwo N A 2018 Statistical modeling of temperature extremes behaviour in Ghana; *J. Math. Stat.* **14** 275–284, https://doi.org/10.3844/jmssp.2018.275.284.

Sasireka K, Suribabu C R and Neelakantan T R 2019 Extreme rainfall return periods using Gumbel and Gamma distribution; *Int. J. Recent Technol. Eng.* **8** 26–29, https://doi.org/10.35940/ijrte.d1007.1284s219.

Sati V P 2022 Glacier bursts-triggered debris flow and flash flood in Rishi and Dhauli Ganga valleys: A study on its causes and consequences; *Nat. Hazards Res.*, https://doi.org/10.1016/j.nhres.2022.01.001.

Seneviratne S I, Nicholls N, Easterling D, Goodess C M, Kanae S, Kossin J and Zwiers F W *et al.* 2012 Changes in climate extremes and their impacts on the natural physical environment. Managing the risks of extreme events and disasters to advance climate change adaptation; Special Report of the Intergovernmental Panel on Climate Change **9781107025066** 109–230, https://doi.org/10.1017/CBO9781139177245.006.

Shekhar M S, Pattanayak S and Mohanty U C 2015 A study on the heavy rainfall event around Kedarnath area (Uttarakhand) on 16 June 2013 **7** 1531–1544.

Stephenson M A 2018 Package 'evd'.

Sunday S B, Agog N S, Magdalene P, Mubarak A and Anyam G K 2020 Modeling extreme rainfall in Kaduna using the generalised extreme value distribution; *Sci. World J.* **15** 73–77.

Wilson Moseki Thupeng 2019 Statistical modelling of annual maximum rainfall for Botswana using extreme value theory; *Int. J. Appl. Math. Stat. Sci. (IJAMSS)* **8** 1–10.

Yozgatlıgil C and Türkeş M 2018 Extreme value analysis and forecasting of maximum precipitation amounts in the western Black Sea subregion of Turkey; *Int. J. Climatol.* **38** 5447–5458, https://doi.org/10.1002/joc.5738.

Corresponding editor: Parthasarathi Mukhopadhyay