



# Mixed General Extreme Value Distribution for Estimation of Future Precipitation Quantiles Using a Weighted Ensemble - Case Study of the Lim River Basin (Serbia)

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## Abstract

Considering the recent extreme precipitation in southeast Europe, it has become necessity to investigate the impact of climate change on extreme precipitation. The aim of this study was to determine the change in precipitation quantiles with longer return periods under changing climate conditions. The study was conducted using the daily records gathered at 11 precipitation stations within the Lim River Basin, Serbia. The simulated precipitation datasets were collected from three regional climate models for the baseline period (1971–2000), as well as the future period (2006–2055) under the 2.6, 4.5 and 8.5 representative concentration pathways. The raw precipitation data from the climate models were transformed by employing four bias correction methods. Using the bias-corrected precipitation, an ensemble of annual maximum daily precipitation was developed. A weighted ensemble approach was applied to estimate the weights of each ensemble member favorizing the members whose quantiles were closer to observed measurements. The mixed general extreme value distribution was used to derive the projected quantiles with 100, 50, 25, 10, five and two year return periods based on the estimated quantiles and the normalized weights of all ensemble members. An overall increase of 69% and 56% for the 100 and 50 year return periods, respectively, can be expected within the northern part of the basin. Similarly, an overall increase of 50–57% and 39–42% for the 100 and 50 year return periods, respectively, may be expected for the central and southern parts of the Lim River Basin.

**Keywords** Extreme precipitation · Quantiles · Mixed GEV distribution · Climate change · Lim River basin

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## 1 Introduction

In recent years, a significant increase in flood frequency and magnitude across Europe have been observed, including the devastating flooding in the southeast in 2014 (ICPDR 2015; Stojkovic et al. 2017). This flood event affected the Sava River Basin, due to a low-pressure cyclone, which led to total precipitation being three times higher than the monthly average (ICPDR 2015). Consequently, the annual maximum daily precipitation in 2014 was breaking previous records at a number of sites across Serbia (Tošić et al. 2017). For instance, the observed daily precipitation in Negotin during the flood event was only expected once every 200 years.

For many mid-latitude regions, heavy precipitation events have been increasing over the last decade as compared to the historical values between 1951 and 2003 (Hartmann et al. 2013). If this trend continues, it would have a severe impact on human societies. Research conducted at the European scale implies a prevailing negative trend in the return periods of daily precipitation for the southern regions, indicating increase in precipitation extremes. The relative change in the return periods for the observed events occurring once in five, 10, or 20 years ranges from  $-4.5\%$  to  $-18.4\%$  (Van den Besselaar et al. 2013). In Serbia, statistically significant trends in heavy precipitation have been found during summer and autumn, and the most pronounced trends are in the northern and western parts of the country (Malinovic-Milicevic et al. 2016).

Although the precipitation records provide a visible signal regarding the increase in magnitude and frequency of heavy precipitation, high-resolution climate information from regional climate models (RCMs) should be used to explore changing precipitation under global warming (Aalbers et al. 2018). Generally, the changes in extremes vary substantially by season, considering the different physical processes that trigger precipitation. For instance, precipitation commonly occurs in the winter season within large-scale fronts, while in the summer the occurrence of precipitation is usually caused by localized convective activity (May 2008). Extreme precipitation in Serbia (e.g. the Belgrade station) analyzed from 1888 to 1995 was associated with two dominant factors: (i) cold fronts and thunderstorms in cold air masses and (ii) cyclones above the eastern Mediterranean originating from the southwestern Black Sea (Unkasievic and Radinovic 2000).

The results of the studies conducted for different regions of Europe are summarized in Table 1, where the relative changes in quantiles of extreme precipitation for the future are shown. Projections of precipitation over Europe were analysed using an extensive data set of 86 RCMs under different representative concentration pathways (RCPs), namely RCP2.6, RCP4.5, and RCP8.5 (Rajczak and Schär 2017). The results imply that significant changes in the precipitation patterns can be expected as compared to the present climate, although their character is conditioned by location and season. For example, summer precipitation quantiles with a 50-year return period in central Europe are likely to intensify by 4%–44% under the RCP 8.5 scenario. The results are most obvious for the winter season, where 25% increase in the magnitude of heavy precipitation is suggested. The increase in 50-year return period precipitation was also reported in a study conducted over central Europe with an ensemble of 12 RCMs (Kysely et al. 2011). In northern Europe precipitation quantiles with a 20-year return period corresponded to the estimates of 40 to 100 year return periods with respect to present-day conditions (Frei et al. 2006). In this study, several RCMs indicated a strong increase in the magnitude of the 50-year winter precipitation, exceeding 100% for the period of 2070–2099. The increase in quantiles of summer precipitation was not as clear as in the winter, but the outcomes suggest a heavier upper tail of the precipitation distribution. In the case of southern Europe,

**Table 1** The relative change in extreme precipitation quantiles compared to the baseline period for different regions of Europe

No.	Region:	Annual/ seasonal extreme precipitation:	Return period of extreme precipitation:	Relative change with respect to the baseline period:	Emission scenario:	Publication:
1	Central Europe	Summer season	two- to 100-year periods	+4 to +44%	RCP2.6, RCP4.5, RCP8.5 (IPCC 2014)	Rajczak and Schär (2017)
2	Central Europe	Summer season	five-year return period	-13% to +21%	A2 (IPCC 2007)	Frei et al. (2006)
3	Central Europe	Winter season	100-year return period	23.9%	A1B (IPCC 2007)	Kyselý et al. (2011)
4	Central Europe	Summer season	100-year return period	22.6%	A1B (IPCC 2007)	Kyselý et al. (2011)
5	Europe	Annual	20-year return period	50%	A2 (IPCC 2007)	Semmler and Jacob (2004)
6	North Europe (Baltic Sea)	Annual	20-year return period	more than 100%	A2 (IPCC 2007)	Semmler and Jacob (2004)

intensification of the precipitation extremes was also apparent (Rajczak and Schär 2017). In the Mediterranean region, precipitation events with a 10- and 20-year return period showed substantial increase, by more than 40 mm/day (Semmler and Jacob 2004).

Hydrologists and water resources managers commonly use precipitation quantile method for longer return periods (from 5 to 1000 years) to feed the hydrologic and hydraulic models for evaluation of the future risks (Roy et al. 2001). However, raw precipitation data from the climate models are not in a form that could be directly utilized for such analysis (Markus et al. 2018). Prior to a frequency analysis, bias-correction methods (BCMs) have been used to correct the climate model outputs. BCMs can be classified (Chen et al. 2013) as: (i) change factor methods and (ii) quantile mapping methods. For instance, the constant scaling (CS) approach (Cannon et al. 2015) can be categorized as a change factor approach, while empirical quantile mapping (EQM) (Teutschbeina and Seibert 2012), Gamma quantile mapping (GQM) (Piani et al. 2010), and Gamma-Pareto quantile mapping (GPQM) (Gutjahr and Heinemann 2013) belong to quantile mapping methods. Apart from the previous classification, the latter could be further divided into methods based on either empirical (e.g. EQM) or theoretical distribution functions (e.g. GQM, GPQM).

A frequency analysis of the climate model outputs has been mostly using the block maxima method and/or the peaks-over-threshold (POT) method (Katz et al. 2002). The block maxima approach identifies only one precipitation extreme per year, usually under the assumption that extreme daily precipitation follows the general extreme value (GEV) distribution. On the contrary, the POT method based on the generalized Pareto distribution allows setting a different threshold to consider a broader range of heavy precipitation events (Coles 2001). Many studies have been based on the block maxima approach in frequency analysis of annual precipitation extremes under future climate (e.g. Millington et al. 2011; Kysely et al. 2011; Das et al. 2013; Mallakpour and Villarini 2017). It has been shown that the GEV distribution using the block maxima technique was often preferred over the Log-Pearson Type 3 or Extreme Value Type 1 (Millington et al. 2011; Das et al. 2013). Also, the GEV distribution has been fitted to the annual maximum daily precipitation for 16 stations in Serbia from 1961 to 2014 indicating the validity of the approach (Tošić et al. 2017). The POT approach has been shown to fit better a long-tailed distribution of heavy precipitation due to an increase in the amount of information (Kysely and Beranová 2009). This feature enables the POT approach to reveal the changes in the frequency of heavy precipitation and therefore it has been recommended for its quantification rather than the block maxima approach (Mallakpour and Villarini 2017). Dealing with the uncertainty in the climate outputs requires a robust technique to quantify the change in the magnitude of heavy precipitation. Although the POT approach is capable of capturing a complex behaviour of extreme precipitation, it requires setting a large number of parameters, particularly thresholds for each ensemble member. It has been shown that a mixed GEV distribution alongside the block-maxima method could reduce random variations in the estimates of parameters within individual GEV distributions originating from the climate model outputs (Kysely et al. 2011). Such a feature makes the mixed GEV distribution suitable for frequency analysis of extreme precipitation from an ensemble.

The main objective of the work presented in the paper is examination of climate change impacts on extreme precipitation within the Lim River Basin in Serbia. The main contributions of the presented research are twofold. First, it represents an original integration of existing approaches into a method for the estimation of quantiles of extreme precipitation under a changing climate. This approach combines the following steps to derive precipitation quantiles under the future climate: (1) statistical post-processing of a raw precipitation data from multiple RCMs, (2) fitting of the GEV distribution to each ensemble member, and (3)

weighting of the individual distributions within the ensemble to estimate the mixed GEV distribution. Second, the study is a first time implementation of the integrated approach for identifying climate change impacts on precipitation extremes within the Lim River Basin. Such an approach aims at supporting the decision-making processes within the heavily regulated river basin including four reservoirs as a part of the Lim water system (World Bank 2017). It represents a multipurpose complex system extending over an area of around 3600 km<sup>2</sup>. This water system incorporates four reservoirs, all of them with a primary hydropower purpose with annual energy production of 532 GWh. The existence of large reservoirs within the Lim River Basin makes the propagation of flood waves through the basin less adverse (World Bank 2017). The management of the Lim water system depends on the actual storage of reservoirs, inflows, and energy demand of Serbia and the region needed to support electric power system reliability. The hydropower generation can satisfy most of all needs of the system, particularly regular coverage of the consumption and different forms of reserves in the electric power system (World Bank 2017). By regulating the outflows, reservoirs can act to prevent floods at downstream segments in the broader area (the Lim River Basin, the Drina River Basin). Besides hydropower and flood mitigation, the Lim water system has to realize the environmental flows maintaining downstream river health.

The Potpec reservoir is located on the Lim River, while the Uvac, Kokin Brod, and Radojnja reservoirs are on its biggest tributary, the Uvac River which provides a significant contribution to the total annual volume of the whole system. Releases from the Uvac reservoir (1.2 m<sup>3</sup>/s) and the Potpec reservoir (13.9 m<sup>3</sup>/s) are made to meet environmental flows on the downstream sections. It is important to highlight that the spillway capacity of the Potpec, Uvac, Kokin Brod, and Radojnja reservoirs are equal to 3000 m<sup>3</sup>/s, 1400 m<sup>3</sup>/s, 1050 m<sup>3</sup>/s, and 1050 m<sup>3</sup>/s, respectively (World Bank 2017). Uvac and Kokin Brod reservoirs with the total active storage capacity of  $369 \times 10^6$  m<sup>3</sup> can achieve a positive retention effect on the flood flows (World Bank 2017). The active storage of the Radojnja ( $7.6 \times 10^6$  m<sup>3</sup>) and Potpec reservoirs ( $27.5 \times 10^6$  m<sup>3</sup>) does not play a significant role in flood mitigation. To secure flood control, the flow rates are released by spillways and turbines until reaching the normal levels in the Potpec (435.6 m.a.s.l.), Uvac (988 m.a.s.l.), Kokin Brod (885 m.a.s.l.), Radojnja (812 m.a.s.l.) reservoirs.

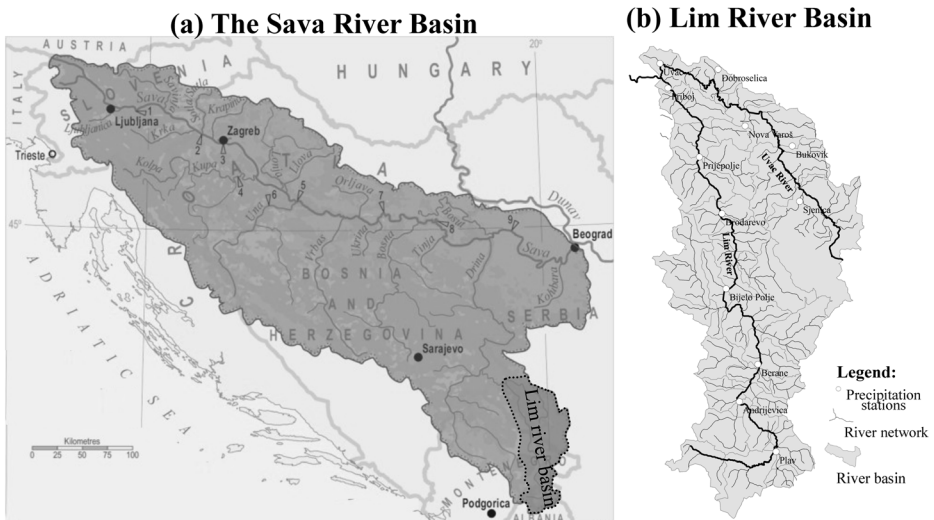
The reservoir system water levels are fluctuating with change of climatic conditions. Also, it is more likely that the changing environment will affect the operational rules of the system, highlighting the needs to examine water management plans for flood mitigation under a more severe climate. Implementation of the proposed approach provides a solid base for water resource management planners to close a gap between the present flood operational rules of the Lim water system and those related to a future change in extreme precipitation.

The rest of the paper is organized as follows. The materials including the study area and data are described in Section 2. Section 3 demonstrates the methodology in terms of processing the climate datasets from the RCMs and deriving quantiles of extreme precipitation affected by climate change. The results are discussed in Section 4, while conclusions are presented in Section 5.

## 2 Materials

### 2.1 Study Area

This study was conducted for the Lim River Basin, which represents an important part of the Sava River Basin (Fig. 1a). The Lim River is in southeast Europe running through Montenegro



**Fig. 1** Location of the Lim River Basin: **(a)** regional scale – Sava River Basin, **(b)** local scale – Lim River Basin **(b)**

and Serbia (Fig. 1b). The analyzed river basin is exposed to the Mediterranean precipitation regime with the highest precipitation observed between November and December, and lowest during the month of August. The precipitation gauging network within the analyzed area consists of the 11 stations listed in Table 2 as depicted in Fig. 1b.

## 2.2 Data Collection

The daily precipitation records from the listed stations (Table 2) were provided by the Hydro-Meteorological Service of the Republic of Serbia and the Republic of Montenegro. Most stations are operated daily, but Sjenica operates at an hourly rate. With regard to the availability of the records, many sites include the observed daily precipitation for several decades. However, there were many gauging stations with discontinuous record. The gaps were filled by means of the non-linear multiple regression method. Taking into account the availability and reliability of daily precipitation, the 30-year time interval from 1971 to 2000 was selected in this study as the baseline/reference period.

Climate change and its uncertainty within the Lim River Basin were assessed under the IPCC recommended RCP emission scenarios (IPCC 2014). RCMs were used because the dynamic downscaling technique, although applied to the limited spatial region, provided a finer spatial resolution than the combination of statistical downscaling with GCMs. The EURO-CORDEX regional climate model simulations covered the analyzed area for two different spatial resolutions, 0.44 degrees (~50 km) and a finer resolution of 0.11 degrees (~12.5 km) (Jacob et al. 2014). For the purpose of this study, three RCMs with the 0.11 degree resolution were selected from the EURO-CORDEX project. The better spatial resolution enables the capture of extreme precipitation behaviour. The availability of simulated precipitation for the future period under the RCP 2.6, RCP 4.5, and RCP 8.5 emission trajectories was used as an additional selection criterion for the RCM simulations from the EURO-CORDEX project. These emission trajectories were selected to cover a wide range of the projected greenhouse gas concentrations and the expected future socio-economic changes. The

**Table 2** Precipitation gauging stations within the Lim River Basin

No.	Station:	Altitude (m a.s.l.):	Country:
1	Berane	670	Montenegro
2	Sjenica	1015	Serbia
3	Andrijeвица	750	Montenegro
4	Bijelo Polje	560	Montenegro
5	Bukovik	1150	Serbia
6	Prijepolje	450	Serbia
7	Priboj	383	Serbia
8	Plav	908	Montenegro
9	Nova Varoš	960	Serbia
10	Brodarevo	500	Serbia
11	Dobroselica	880	Serbia

RCP 2.6 scenario was selected since it is recognized as the most optimistic scenario with limited greenhouse gas emissions. The RCP 4.5 emission trajectory assumes that the emission peak will occur mid-century accompanied by rapidly declining emissions for the next several decades. The RCP 8.5 is the worst case scenario with emissions continuing to rise rapidly throughout the century.

The precipitation data were collected for the gauging stations and the baseline period from 1971 to 2000, as well as for the future time frame from 2006 to 2055 (Fig. 1b, Table 2). The selected RCMs are listed in Table 3 together with the driving global models (i.e. global climate models - GCMs), which were used at the boundary of the RCM domain.

### 3 Methodology

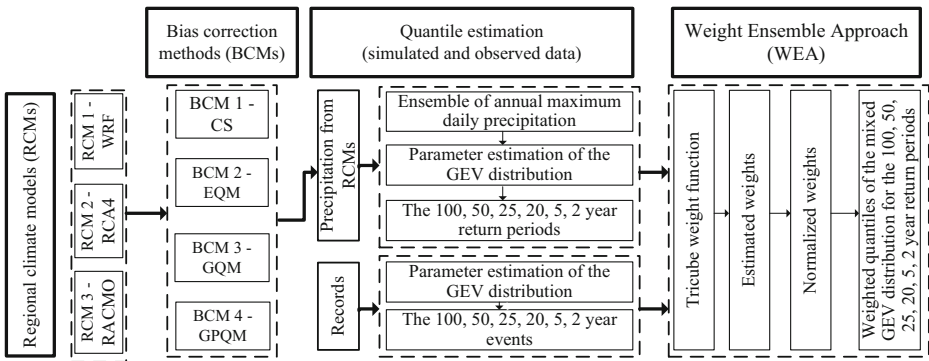
#### 3.1 General Concept

A flowchart in Fig. 2 shows a visual representation of the steps performed to estimate extreme precipitation quantiles under changing climate. There are three main steps in the proposed approach: (i) adjustment of raw precipitation data from RCMs using different bias correction methods (BCMs), (ii) quantile estimation for the ensemble members of maximal annual precipitation, and (iii) the weighting to derive quantiles from the mixed general extreme value (GEV) distribution. Three RCMs and three BCMs were used in the study. Selected BCMs include: constant scaling (Cannon et al. 2015), empirical quantile mapping (EQM) (Teutschbeina and Seibert 2012), Gamma quantile mapping (GQM) (Piani et al. 2010), and Gamma-Pareto quantile mapping (GPQM) (Gutjahr and Heinemann 2013). It should be noted that BSMs were applied a monthly time scale to preserve the intra-annual distribution of the simulated precipitation for the observed and predicted periods. With the BCMs applied to the climate modelling outcomes, maximum annual daily precipitation was calculated for the baseline period of 1971–2000. The weighted ensemble approach (WEA) was then applied to the climate modelling outputs assigning weights in accordance with the hindcast accuracy of RCMs and BCMs (Markus et al. 2018). The quantiles of the observed and simulated extreme precipitation events were estimated for the longer return periods (100, 50, 25, 10, five, and two years) with the assumption of a GEV distribution. The weights were determined by comparing bias-free precipitation from RCMs with those based on the observed data, favorizing the

**Table 3** List of RCMs selected from the EURO-CORDEX project used in the study

No.	RCMs:	GCMs:	Country:	Institution:	Spatial resolution:	Contact information:
1	WRF361H	MPI-M-MPI-ESM-LR	Germany	DWD - Deutscher Wetterdienst	0.11 degrees/12.5 km	Klima.projektionen@dwd.de
2	RCA4	ICHEC-EC-EARTH	Sweden	SMHI - Swedish Meteorological and Hydrological Institute	0.11 degrees/12.5 km	rossby.cordex@smhi.se
3	RACMO0022E	MOHC-HadGEM2-ES	Netherlands	Royal Netherlands Meteorological Institute	0.11 degrees/12.5 km	vanmeijg@knmi.nl





**Fig. 2** Flowchart of the proposed concept for the estimation of future precipitation quantiles founded upon the mixed GEV distribution using a weighted ensemble

estimates that were closer to the observed data. The weights were then normalized to determine the mixed GEV cumulative distribution function, which considered all ensemble members over the baseline period. In the next step, the normalized weights alongside the mixed GEV distribution were applied to the future period of 2006–2055 so as to estimate the predicted quantiles under the RCP 2.6, RCP 4.5, and RCP 8.5 trajectories.

### 3.2 Bias Correction Methods

The CS method (Cannon et al. 2015), also known as the delta approach, involves adjusting the raw precipitation data from the RMC outputs by multiplying the observed daily precipitation with the precipitation ratio. The precipitation ratio is defined as the quotient of the mean monthly precipitation during the baseline period ( $P_{RCM,baseline}^{month}$ ) and the future period ( $P_{RCM,future}^{month}$ ). The adjusted daily precipitation ( $\hat{P}_{RCM,future}^{daily}$ ) for the future time frame was then estimated as follows:

$$\hat{P}_{RCM,future}^{daily} = P_{Obs}^{daily} \times \frac{P_{RCM,baseline}^{month}}{P_{RCM,baseline}^{month}} \tag{1}$$

where  $P_{Obs}^{daily}$  represents the observed daily precipitation.

The EQM method was also applied to the RCM output correcting the shape of the cumulative distribution function of daily precipitation. It transformed the simulated values during the reference period to the observed values using the same value of the cumulative probability function. The obtained transformation function for the baseline period was further interpolated for the future time frame to remove bias in the predicted daily precipitation from the raw dataset. The transformation function for adjusting the predicted daily precipitation ( $\hat{P}_{RCM,future}^{daily}$ ) is shown in the next equation (Teutschbeina and Seibert 2012; Cannon et al. 2015):

$$\hat{P}_{RCM,future}^{daily} = F_{obs}^{-1} \left\{ F_{RCM,baseline}^{daily} \left[ P_{RCM,future}^{daily} \right] \right\} \tag{2}$$

where  $F_{obs}^{-1}$  is the inverse empirical cumulative distribution function of daily precipitation over the observed period, while the empirical cumulative distribution of the simulated precipitation is denoted  $F_{RCM,baseline}^{daily}$ .

The parametric quantile mapping approach is based upon the assumption that the observed and simulated precipitation distributions are well approximated by a certain theoretical distribution. The standardized Gamma distribution was used, since it is generally accepted as an appropriate model for the observed daily precipitation (Piani et al. 2010). A Gamma distribution ( $\Gamma$ ) depends only on two parameters and can be defined as:

$$f(P) = \frac{\left(\frac{x}{\beta}\right)^{\alpha-1} \exp(-P/\beta)}{\beta\Gamma(P)} \tag{3}$$

where the scale and shape parameter are  $\beta$  and  $\alpha$ , respectively ( $\alpha, \beta > 0$ ). The Gamma distribution is not defined for  $P=0$  mm/day, requiring the application of a dual approach to estimate the integrated cumulative distribution function for both dry and wet periods during the year (Piani et al. 2010). The integrated cumulative distribution function was then used to replace the empirical distribution function from Eq. (1) providing the daily precipitation estimates for the future time period.

The extreme daily precipitation is usually represented by a heavy-tailed distribution (Gutjahr and Heinemann 2013). A Pareto distribution was thus applied together with the Gamma distribution to values above the threshold given by the 90th percentile of the cumulative distribution function. For precipitation in this range, the share of 25% and 75% for a Pareto and Gamma distribution was respectively used to define the jointed distribution function (Gamma-Pareto cumulative distribution function). This share was estimated arbitrarily in order to match the observed and theoretical quantiles in the domain of the extreme events. Furthermore, it was assumed that the values smaller than the 90th percentile followed a Gamma distribution (Gutjahr and Heinemann 2013). To adjust raw precipitation data, a GPQM was employed in the following manner:

$$\hat{P}_{RCM,future}^{daily} = \begin{cases} F_{obs,G-P}^{-1} \times \left\{ F_{RCM,G-P}^{daily} \left[ P_{RCM,future}^{daily} \right] \right\} & \text{if } P_{RCM,future}^{daily} \geq 90^{th} \text{ percentile} \\ F_{obs,G}^{-1} \times \left\{ F_{RCM,G}^{daily} \left[ P_{RCM,future}^{daily} \right] \right\} & \text{if } P_{RCM,future}^{daily} < 90^{th} \text{ percentile} \end{cases} \tag{4}$$

where  $F_{obs,G}^{-1}$  and  $F_{obs,G-P}^{-1}$  are the inverse Gamma and Gamma-Pareto cumulative distribution functions for the observed period, respectively, and  $F_{RCM,G-P}^{daily}$  and  $F_{RCM,G}^{daily}$  represent the cumulative distributions of the aforementioned distributions.

### 3.3 Weight Ensemble Approach

Combining the datasets from several RCMs and BCMs is a common practice used to define a selection criterion to choose subsets of more skilful climate models (Knutti et al. 2010). Generally, there are no formal methods to weight the outputs of RCMs. In this study, the weighted ensemble approach (WEA) was selected since it relies on the tricube weight function, which has been suggested as an appropriate tool for weighting the ensemble members in the processing of climate model outputs (Markus et al. 2018).

The weights for the data sets were determined considering the goodness of fit among the observed and simulated theoretical values of annual maximum daily precipitation with the

return periods of two, five, 10, 25, 50, and 100 years. The tricube weight function was then employed to derive the weights for each dataset in the ensemble (Tukey 1977):

$$w_{m,i} = \begin{cases} \left\{ 1 - \left( \frac{\Delta_{m,i}}{h} \right)^3 \right\}^3 & \text{if } |\Delta_{m,i}| \leq h, i = 1, 2, \dots, N_{station}, m = 1, 2, \dots, M \\ 0 & \text{if } |\Delta_{m,i}| > h, i = 1, 2, \dots, N_{station}, m = 1, 2, \dots, M \end{cases} \tag{5}$$

where  $w$  is a weight (the averaged value for all frequencies) of the dataset for the return periods considered, the subscriptor  $i$  indicates the  $i^{th}$  gauging station,  $N_{station}$  is the number of gauging stations, the subscriptor  $m$  represents the  $m^{th}$  member of ensemble,  $M$  is the number of members,  $\Delta$  represents the percent deviation of the simulated and observed quantiles, and  $h$  is the half-window width defined as 25% of the averaged deviation ( $\Delta$ ) for the ensemble.

The deviation between the observed and simulated quantiles was defined for the whole range of return periods ( $N_{event} = 1, 2, \dots, 5, 6$ ; for the return periods of two, five, 10, 25, 50, and 100 years):

$$\Delta_{m,i} = \frac{\sum_{n=1}^{N_{event}} \left[ \frac{q_{sim,mi}(T_n) - q_{obs,i}(T_n)}{q_{obs,mi}(T_n)} \right]}{N_{event}} 100\%, \quad i = 1, 2, \dots, N_{station}, m = 1, 2, \dots, M \tag{6}$$

where  $q_{sim}(T)$  and  $q_{obs}(T)$  correspond, respectively, to the observed and modeled quantiles drawn from the GEV distribution for a return period T.

### 3.4 Mixed GEV Distribution

Making use of the tricube weight function, quantiles of maximal daily precipitation were calculated based on the assumption that annual maximum daily precipitation follows the mixed GEV distribution. A mixed GEV distribution within the block maxima method was formed by combining different GEV distribution functions from the ensemble.

$F_m(P)$  for  $m = 1, 2, \dots, M$  is the cumulative distribution function of the maximum annual daily precipitation, given that  $P$  is from the  $m$ th distribution (Yoon et al. 2013). In addition, the weights  $w_i$  from Eq. (5) were normalized ( $\tilde{w}_m$ ) to a scale of one satisfying the following condition:  $\sum_{m=1}^M \tilde{w}_m = 1$ . The weights can then be considered as the probability of a random variable from  $F_m(P)$ . Hence, the normalized weights were used to define the mixed GEV cumulative distribution in the following manner:

$$F_{Mixed\ GEV,i}(P) = \tilde{w}_{1,i} F_{1,i}(P) + \tilde{w}_{2,i} F_{2,i}(P) + \dots + \tilde{w}_{M-1,i} F_{M,i}(P) \quad i = 1, 2, \dots, N_{station}, \tag{7}$$

considering the distribution functions of the whole ensemble ( $F_1, F_2, \dots, F_M$ ).

The cumulative distribution function  $F_m(P)$  of the GEV is given by (Hosking and Wallis 1997):

$$F_m(P) = \exp \left\{ - \left( 1 + k \frac{P - \alpha}{\beta} \right)^{-\frac{1}{k}} \right\} \tag{8}$$

where  $\alpha$ ,  $\beta$  and  $k$  represent the position, the scale, and the shape parameter, respectively. In the case that  $k = 0$ ,  $k > 0$ , and  $k < 0$  the GEV distribution becomes a Gumbel, Frechet or Weibull distribution, respectively.

To determine the goodness of fit between the empirical distribution and the mixed GEV distribution, a Kolmogorov–Smirnov test was used. The maximum deviation,  $D_{max}$ , between the observed (empirical) distribution and the GEV distribution was calculated by the equation:

$$D_{max} = \text{Max}|F_{obs}(F) - F_{Mixed\ GEV}| \quad (9)$$

where  $F_{obs}(F)$  and  $F_{Mixed\ GEV}$  denote the empirical (observed) and theoretical (mixed GEV) cumulative distribution functions, respectively. The null hypothesis assumes that data follows a specified distribution against the alternative hypothesis. If  $D_{max}$  is larger than the critical value ( $D_n^\alpha$ ) at a significance level of 5%, then the null hypothesis is rejected.

## 4 Results

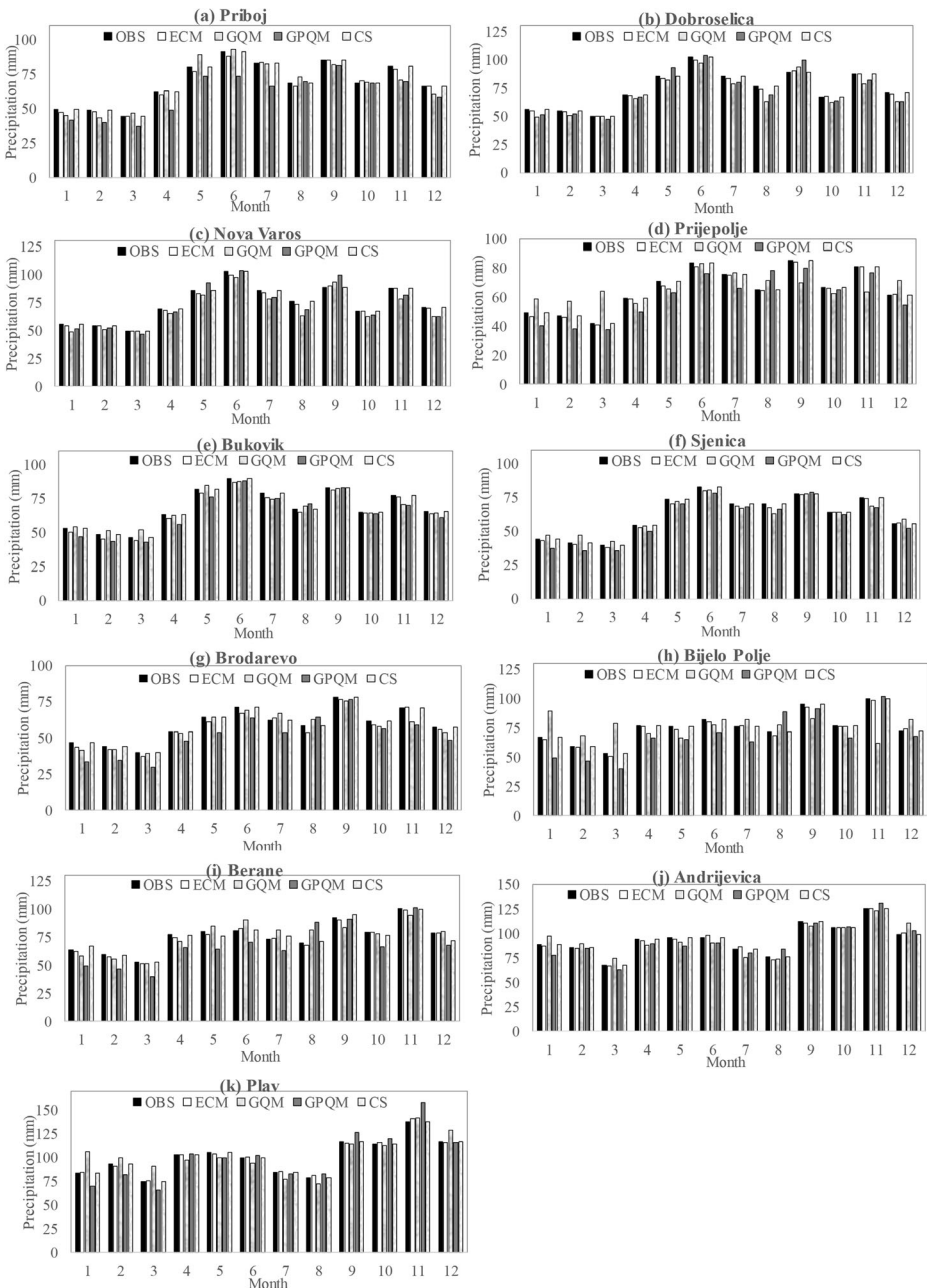
The coupled information of different RCMs provides an insight into uncertainty associated with climate modelling by identifying the influence of incomplete knowledge arising from the inherent physical, chemical processes as well as the parameterization of climate models (Solaiman et al. 2012). However, the outputs of different climate models also expose the variability in extreme precipitation. This increases the difficulty of detecting visible behaviour in the estimates under changing climate (Solaiman et al. 2010). Although the choice of RCMs was reported to be the largest source of uncertainty, the research conducted by Mandal et al. (2016) has highlighted that the selection of the downscaling methods was also one of the significant sources of uncertainty.

Therefore, in this study, special attention was given to the selection and application of BCMs is addressing the uncertainties in precipitation signals. Firstly, the daily precipitation data were gathered from the EURO-CORDEX project from three RCMs (WRF361H, RCA4, and RACMO0022E) for 11 precipitation stations within the Lim River Basin (Fig. 1b, Table 2). Secondly, four BCMs were introduced to capture and transform the derivatives from the RCMs, since the outputs from climate modelling do not preserve the pattern of the observed precipitation. To fit the raw climate modelling outputs onto the river basin scale, four BCMs were employed: CS, EQM, GQM, and GPQM. For each precipitation station, the transformation functions were estimated on the monthly time scale for the baseline period of 1971–2000.

Uncertainties in future precipitation due to the choice of projected greenhouse gas concentration trajectories plays a significant role in the overall uncertainty. Such uncertainty is brought about by insufficient knowledge regarding future social, economic, and technical development (IPCC 2014). Thus, several future scenarios were considered, namely RCP 2.6, RCP 4.5, and RCP 8.5 (IPCC 2014). In accord with these scenarios, the transformation functions assessed for the baseline period of 1971–2000 were extrapolated for a future time frame of 2006–2055 to adjust the raw precipitation. The resulting data set for each station over the baseline period and the future time frame were comprised of 12 and 36 daily precipitation time series, respectively. Details regarding the climate datasets are outlined in Section 2.2, while a comprehensive description of BCMs is provided in Section 3.2.

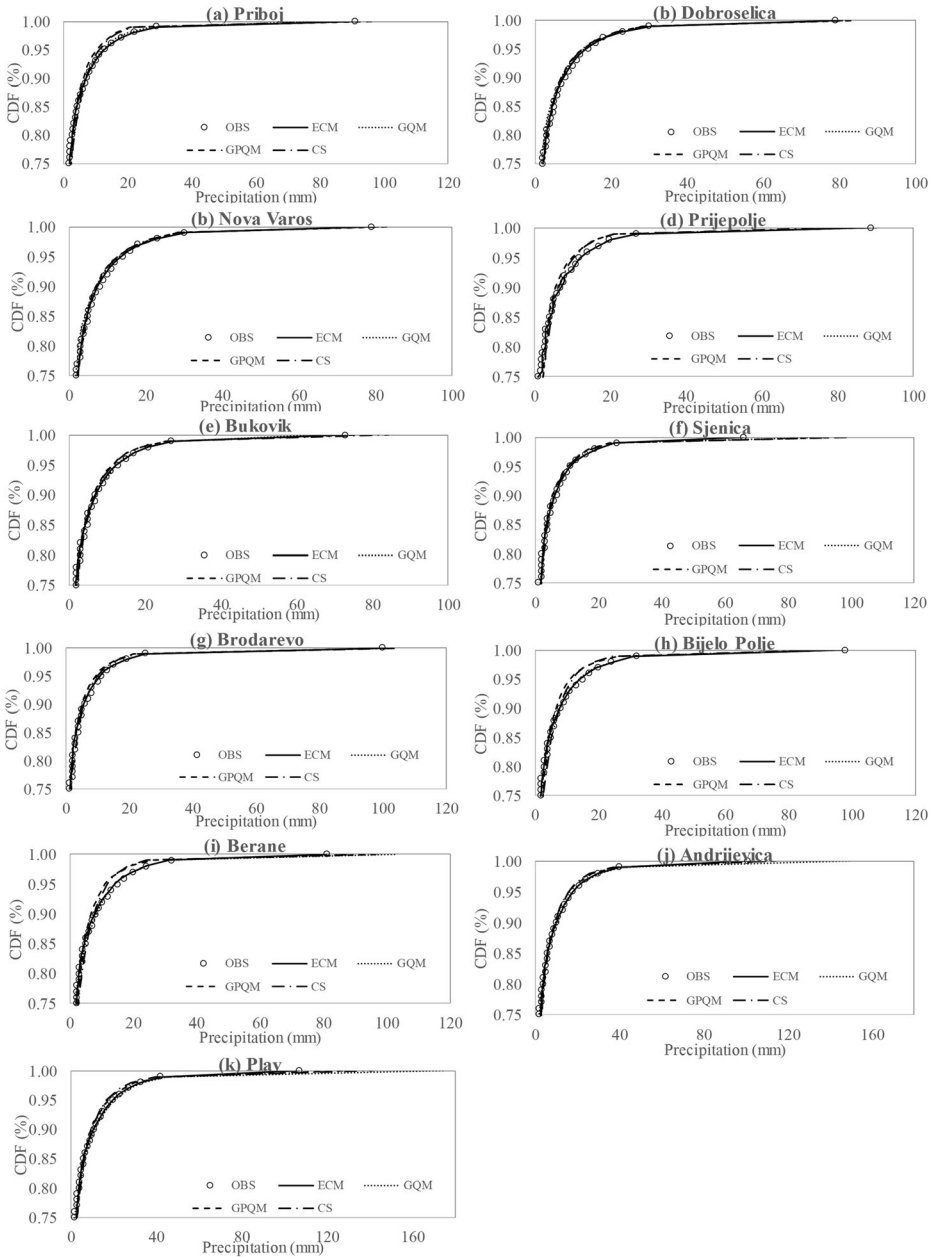
The intra-annual distribution and the cumulative distribution function were used to demonstrate the ability of various BCMs to appropriately transform raw precipitation data. Given that applied BCMs are based on different underlying assumptions, the results suggest that the choice of BCM also have a substantial impact on the derivatives. The illustrations in terms of the

seasonal precipitation characteristics are provided in Fig. 3 for the case of the WRF361H model. The results imply that EQM and CS matched the observed monthly precipitation values better than the other methods. It was also clear that the parametric quantile mapping



**Fig. 3** The observed and modeled intra-annual distribution of precipitation for the WRF361H model during the baseline period of 1971–2000 (OBS represents observed precipitation, EQM, GQM, GPQM, and CS denote the bias-free precipitation)

approaches (i.e. GQM, GPQM) reproduced the seasonal changes of the observed precipitation fairly well, although GPQM tended to overestimate monthly precipitation during the autumn and winter (Fig. 3k, Fig. 3d).



**Fig. 4** Cumulative distribution function (CDF) of daily precipitation for BCMs of the WRF361H model during the baseline period of 1971–2000 (OBS represents observed precipitation, EQM, GQM, GPQM, and CS denote the bias-free precipitation)

An example based on the WRF361H model was used to demonstrate the efficiency of the applied BCMS in properly correcting the daily precipitation values. The cumulative distribution functions of the observed and bias-corrected precipitation are shown in Fig. 4. EQM outperformed other methods, especially in the domain of extreme precipitation. Although the CS approach reproduced the precipitation seasonality well, it overestimated the extreme values of precipitation for several stations (Fig. 4k, j). Figure 4f, j suggest that the GPQM approach displayed complementary behaviour to that of the CS approach. It is also plausible that the results derived from the parametric methods (i.e. GQM, GPQM) slightly differed from the values of the cumulative distribution function greater than 90% (Fig. 4a–i).

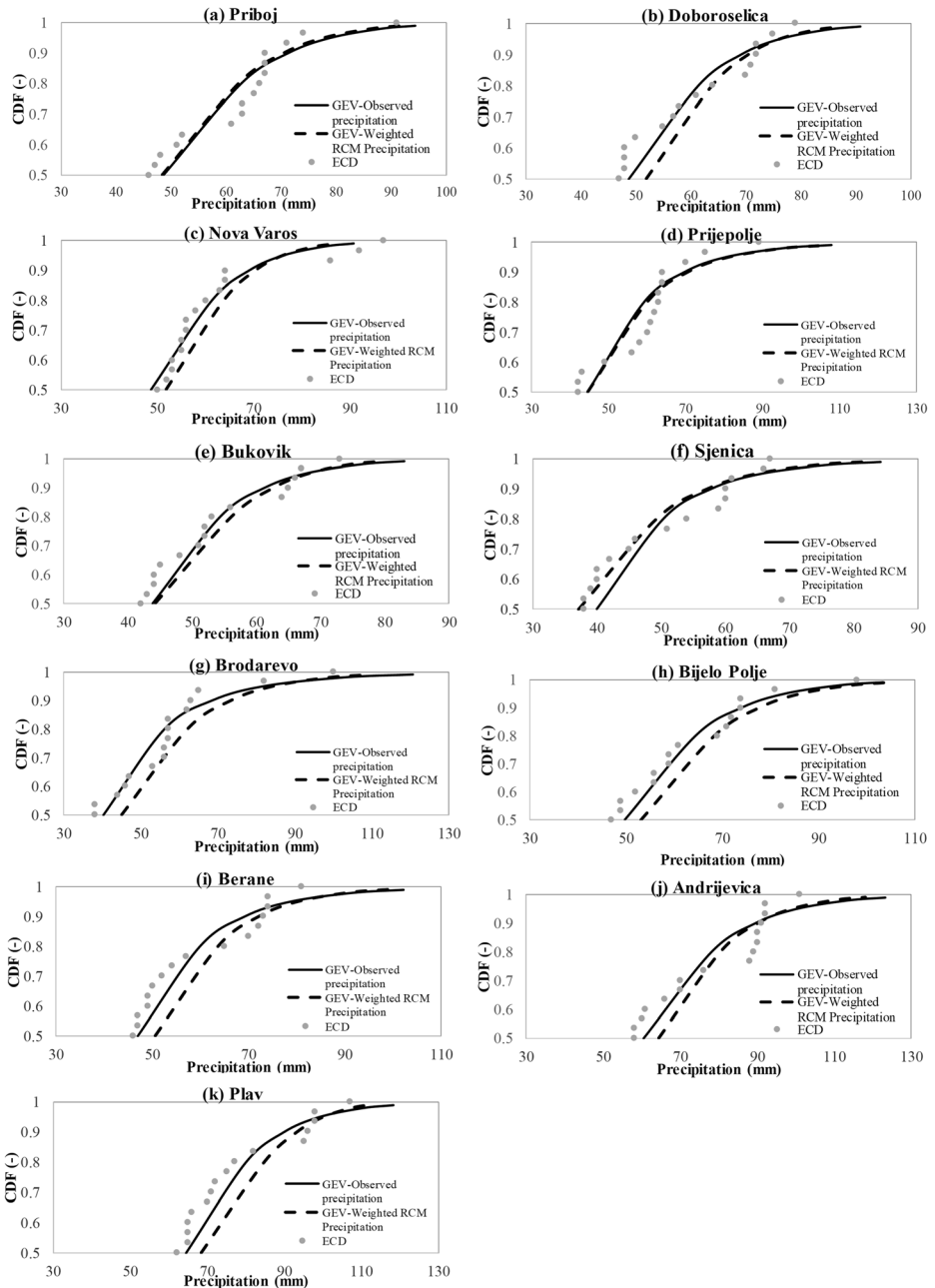
Once the ensemble of the annual maximum daily precipitation for the baseline period of 1971–2000 was formed by combining the results from RCMs and BCMS, the weights for each ensemble member were assigned reflecting the hindcast accuracy of RCMs and BCMS. Specifically, the quantiles for each ensemble member were determined for the return periods of two, five, 10, 25, 50, and 100 years. The values were compared with corresponding observed quantiles for the same return periods in order to derive the weights using Eq. 5. Accordingly, the ensemble members that were closer to those based on the observed data were favorized. Given Eq. 6, the percentile deviations among the quantiles based on the observed and simulated data were determined for each member as an averaged value for the whole frequency range. The GEV cumulative distribution function of the annual maximum daily precipitation was then determined for each ensemble member using the data from the baseline period of 1971–2000. The estimated weights were normalized so as to assess the mixed GEV cumulative distribution function. Detailed theoretical insight regarding this issue is given in Eq. 7 and Section 3.4.

Having determined the mixed GEV function for the precipitation stations, a Kolmogorov–Smirnov test was applied to determine if the annual maximum daily precipitation followed a specified distribution. The results in Table 4 imply that samples belong to the mixed GEV distribution at a significance level of 5%, since the test statistics were lower than the critical value,  $D_{30}^{0.05} = 0.2417$ .

The mixed GEV cumulative distribution functions are illustrated in Fig. 5 (dashed line) alongside the empirical cumulative distribution (grey points). Furthermore, Fig. 5 shows a standard GEV distribution (dashed line) with the parameters deduced from the records. Despite the fact that the parameters of the mixed and standard GEV distribution were estimated using different data sets, several precipitation stations reported comparable behaviour (Fig. 5a–f). However, there was also a noticeable departure between the distributions, especially for lower return periods (e.g. Figure 5b), while the higher frequencies suggested remarkable agreement.

**Table 4** The Kolmogorov–Smirnov test statistics (the critical value at a significance level of 0.05 is equal to  $D_{30}^{0.05} = 0.2417$ )

No.	Precipitation stations:	Test statistics:
1	Berane	0.177
2	Sjenica	0.079
3	Andrijeвица	0.123
4	Bijelo Polje	0.119
5	Bukovik	0.114
6	Prijepolje	0.100
7	Priboj	0.112
8	Plav	0.169
9	Nova Varoš	0.157
10	Brodarevo	0.193
11	Dobroselica	0.146



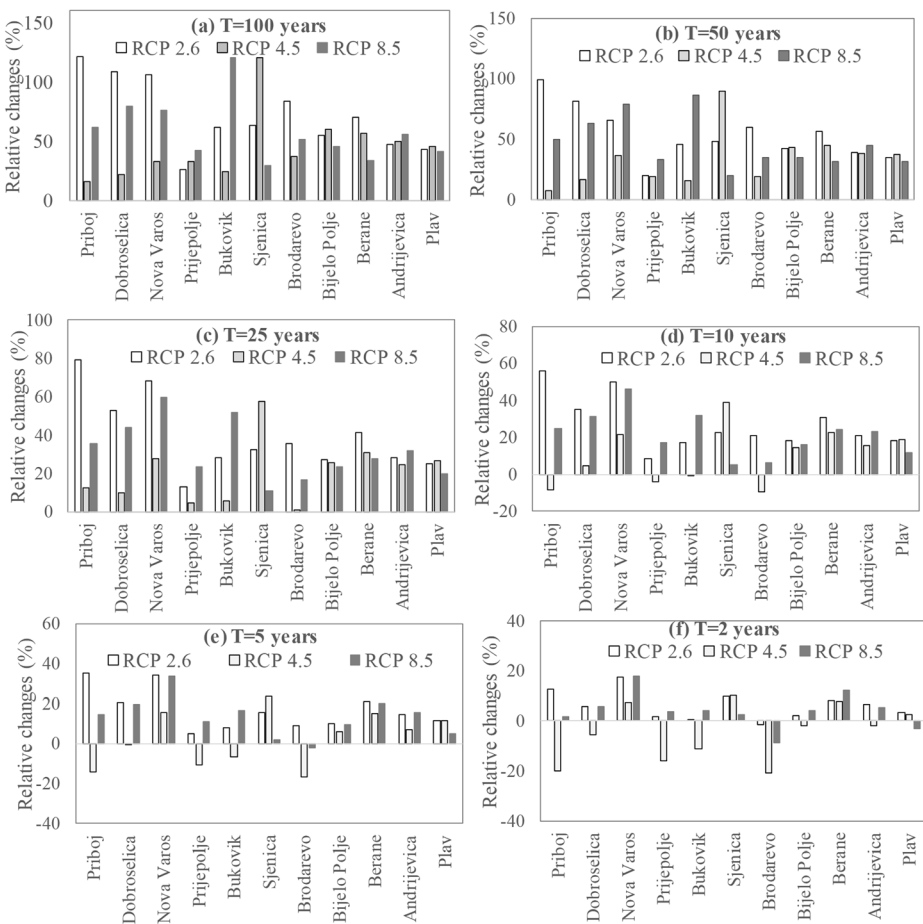
**Fig. 5** The cumulative distribution functions of the maximum daily precipitation for the baseline period of 1971–2000; the mixed GEV distribution based on simulated data (dashed line), a standard GEV distribution based on observed data (solid line), and the empirical cumulative distribution function (grey points)

The inconsistencies in both cumulative distribution functions are attributed to the uncertainties in climate modelling rather than the applied distribution function.



In order to estimate the future changes in quantiles of extreme precipitation, the weights estimated during the baseline period were applied to the projected ensemble under the RCP 2.6, RCP 4.5, and RCP 8.5 scenarios. Similarly to the baseline period, the mixed GEV function for the future time frame of 2006–2005 was determined for the precipitation stations used in the study. The relative percent changes in quantiles over the future time frame of 2005–2055 were related to the baseline period of 1971–2000, as depicted in Fig. 6. This illustration provides the change in precipitation signal for each RCP.

As can be seen from Fig. 6 the changes in quantiles depended on either the location of the precipitation station or the choice of RCP. The most significant changes can be expected for the Prijepolje, Dobroselica, and Nova Varos stations located in the northern part of the Lim River Basin. For these stations and all RCPs, the quantiles are expected to increase by 66–71% and 52–60% for the return periods of 100 and 50 years, respectively (Fig. 6a, b). Note that the most significant increase of quantiles was due to the RCP2.6 and RCP8.5 scenarios, while the results from RCP4.5 showed moderate changes in quantiles for longer return periods (Fig. 6a–



**Fig. 6** The relative changes (%) of the quantiles for the future time frame of 2006–2055 under the RCP2.6, RCP4.5, and RCP8.5 scenarios with respect to the baseline period of 1971–2000 (the following return periods were considered: (a) 100 years, (b) 50 years, (c) 25 years, (d) 10 years, (e) five years, and (f) two years)

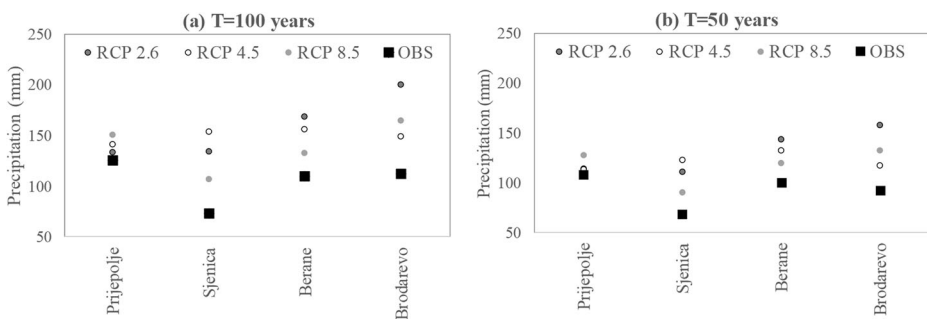
c). The central Lim River Basin contains the Prijepolje, Bukovik, Sjenica, and Brodarevo stations. An overall rise of precipitation quantiles of 57% and 42% for the 100 and 50 year return periods, respectively was predicted for the central region (Fig. 6a, b). In this case, the most obvious changes in quantiles are suggested for the RCP 8.5 and RCP 4.5 scenarios. The stations located in the south Lim River Basin, namely the Brodarevo, Bijelo Polje, Andrijevica, and Plav, displayed lower variation in quantiles amongst different climate scenarios. However, the changes in quantiles were still significant at 43–57% and 34–44% increases for the return periods of 100 and 50 years, respectively (Fig. 6a, b).

The significant changes in quantiles within the return periods of 25 and 10 years were also apparent (Fig. 6c, d). Prominent changes were visible in the northern portion of the river basin at a 30% increase. A moderate increase in the quantiles was expected in the south, with an overall change of 20%.

These results are in the line with a study conducted by Rajczak and Schär (2017), where climate simulations in central Europe showed an increase in quantiles of 4–44% with respect to the baseline period. In this study, an extensive multimodel ensemble of RCMs was used forced by RCP2.6, RCP4.5, and RCP8.5. In addition, Kysely et al. (2011) reported an overall increase in extreme precipitation during wet and dry seasons in central Europe under the A1B scenario (IPCC 2007), where the quantiles for the 100-year return period are expected to rise 24% related to present-day conditions.

Although the projected quantiles with longer return periods proposed significant changes in the intensity of daily precipitation, the relative changes in extreme precipitation for lower return periods (two- and five-year) exposed variable behaviour (Fig. 6c, d). For instance, the change in quantile with the two-year return period indicated a substantial decrease for several precipitation stations. Similar results were suggested in a study by Frei et al. (2006), where the expected changes in extreme precipitation with a five-year return period in Europe were generally consistent between all RCMs. However, there was large variation in the total response ranging from –13% to 21% with respect to the baseline period.

The projected quantiles were compared to corresponding quantiles officially published in the Water Resource Management Plan of Serbia and Montenegro (WRMPS 2010; WRMPM 2000). Despite the fact that the previously published results had nonsynchronous referent periods, the substantial discrepancies among the projected and observed quantiles at the same frequencies were inferred for the considered stations (Fig. 7). The qualities affected by climate change were larger than those based on past observed data in the WRMPS (2010) and



**Fig. 7** The observed (OBS) and predicted quantiles under RCP2.6, RCP4.5, and RCP8.5 scenarios for the following return periods: (a) 100 years, (b) 50 years (the observed quantiles were officially published in WRMPS (2010) and WRMPM (2000))

WRMPM (2001). A notable increase in projected quantiles for the 100 and 50 year return periods was highlighted for the Sjenica station, although the Berane and Brodarevo stations showed a fairly upturn. In the case of the Prijepolje station, a rise of quantiles was not highlighted, which could be attributed to the longer observed period (1947–2004) accounting for more precipitation extreme events.

## 5 Conclusions

In this study, quantiles of heavy precipitation under changing climate for precipitation stations within the Lim River Basin were determined. The study was limited to the uncertainties in extreme precipitation linked to the climate model outputs and bias correction methods; therefore, it did not consider the uncertainties due to parameterization or the structure of the RCMs.

As a reference period, a time slice from 1971 to 2000 was selected, due to the availability and reliability of the recorded daily precipitation. The dynamic downscaling data were gathered for the baseline period of 1971–2000, as well as the future time frame of 2006–2055. The data were collected from the EURO-CORDEX project for three RCMs (WRF361H, RCA4, RACMO0022E) with a spatial resolution of 0.11 degrees.

Three BCMs were used to apply the climate modelling outputs to the sites of the precipitation stations. It should be noted that the BCMs were applied on a monthly time scale to preserve the intra-annual distribution of simulated precipitation. The CS approach was not capable of preserving the intensity of heavy precipitation at low frequencies, though it maintained the intra-annual distribution quite well. EQM, however, may successfully preserve the seasonal precipitation pattern and the characteristics of the extreme events over the baseline period. The drawback of EQM lies in the fact that it cannot extrapolate the extreme event beyond the observed level. For this reason, two parametric approaches (i.e. GQM, GPQM) were used, which have been defined as more powerful tools in the domain of extreme precipitation. Finally, different BCMs were used alongside multiple RCMs to adequately investigate uncertainty related to the choice of bias correction methods.

The hindcast accuracy of the simulated precipitation varied among the different RCMs and BCMs, which had a significant impact on the precipitation quantiles for the gauging stations in the Lim River Basin. Promoting the ensemble members that were closer to the observed measurements, the weights for the whole frequency range were estimated for each precipitation station. Subsequently, the mixed GEV distribution was applied to the simulated precipitation within the ensemble members, accounting for the normalized weights of each of them. The estimates affected by changing climate were more reliable than those directly estimated from the ensemble.

The results presented in this study imply that climate change can have a significant impact on heavy precipitation. The most significant changes in quantiles can be expected in the north region, exceeding the estimates over the reference period by 69% and 56% for the 100 and 50 year return periods, respectively. An overall increase of quantiles by 57% for the 100 year return period and 42% for the 50 year return period was predicted for the central part of the river basin. In the south a lower rise in precipitation quantiles was predicted at 50% and 39% for the return periods of 100 and 50 years, respectively.

Projected quantiles for stations within the Lim River Basin were much greater than the officially published quantiles which have been commonly used in engineering practice to design civil infrastructure systems. The location of precipitation stations and the choice of climate scenario have played a significant role in the assessment of the predicted quantiles,

which is especially highlighted for lower frequencies. Note that an increase in greenhouse gas concentration trajectories did not correspond with an increase in predicted quantiles, since the most severe scenario was RCP2.6 for the stations located in the north. Such behaviour can be ascribed to the following factors. First, predicted quantiles were estimated for the time period of 2006–2055 where the differences in greenhouse gas concentration among the RCP2.6, RCP4.5, and RCP8.5 were relatively moderate (a sharp difference is projected at the end of the twenty-first century). Therefore, the relationship between concentration trajectories and extreme precipitation will not be straightforward. Second, the weights of the ensemble member were calculated under the assumption that the relationship between the observed and simulated precipitation over the reference period was stationary. Such an assumption is practically questionable under climate change (Pichuka and Maity 2018) and could be an additional source of uncertainty in the predicted quantiles.

It is important to emphasize that increased extreme precipitation events are more likely to increase the magnitude of flood hazards in Serbia. For this reason, the projected quantiles should be used by water resource planners in adaptation studies to test the resiliency of the current civil infrastructure systems, particularly the Lim water system. This will allow for the potentially harmful effects of climate change to be considered. In spite of the fact that the study was conducted for the Lim River Basin with a particular climate conditions, the results give visible insight pertaining to the changes in the magnitude of extreme precipitation events. Thus, the proposed method should be widely applied for the Serbian river basins.

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## Compliance with Ethical Standards

**Conflict of Interest** None.

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