

The influence of non-stationarity in extreme hydrological events on flood frequency estimation

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Abstract: Substantial evidence shows that the frequency of hydrological extremes has been changing and is likely to continue to change in the near future. Non-stationary models for flood frequency analyses are one method of accounting for these changes in estimating design values. The objective of the present study is to compare four models in terms of goodness of fit, their uncertainties, the parameter estimation methods and the implications for estimating flood quantiles. Stationary and non-stationary models using the GEV distribution were considered, with parameters dependent on time and on annual precipitation. Furthermore, in order to study the influence of the parameter estimation approach on the results, the maximum likelihood (MLE) and Bayesian Monte Carlo Markov chain (MCMC) methods were compared. The methods were tested for two gauging stations in Slovenia that exhibit significantly increasing trends in annual maximum (AM) discharge series. The comparison of the models suggests that the stationary model tends to underestimate flood quantiles relative to the non-stationary models in recent years. The model with annual precipitation as a covariate exhibits the best goodness-of-fit performance. For a 10% increase in annual precipitation, the 10-year flood increases by 8%. Use of the model for design purposes requires scenarios of future annual precipitation. It is argued that these may be obtained more reliably than scenarios of extreme event precipitation which makes the proposed model more practically useful than alternative models.

Keywords: Nonstationarity; Trends; Flood frequency analysis; Return period; Design discharge; Climate variability.

INTRODUCTION

Air temperatures around the world have increased significantly in the past decades (Jones et al., 1999; Pachauri et al., 2014), which may be reflected by a more intense processes of the water cycle and an increase in the frequency and magnitude of extreme precipitation (Groisman et al., 2005; Wobus et al., 2014). However, the magnitudes of the surface air temperature changes differ between regions. For example, Blöschl and Montanari (2010) reported that recent anomalies of the temperature in the European Alps have been about twice those of the global mean over the world. Similarly, researchers found significant changes in precipitation that differ between regions. Mean annual precipitation has increased in the North of Europe, but decreased in the South of Europe (Pachauri et al., 2014).

However, increasing or decreasing precipitation trends are not necessarily associated with the corresponding upward or downward trends of high flows, as discharges do not only depend on climatic conditions but also on other variables, such as antecedent soil moisture. Consequently, no uniform patterns of streamflow changes have been found around the globe (Bezak et al., 2015b; Cunderlik and Ouarda, 2009; Douglas et al., 2000; Kundzewicz et al., 2005; Robson et al., 1998; Stahl et al., 2010; Zhang et al., 2001). Significant positive discharge trends were detected in some continents (South and North America, Asia), whereas a negative trend was identified for others (e.g. Africa) (Labat et al., 2004). Although no significant (increasing or decreasing) discharge trends were identified for Europe (Bormann et al., 2011; Labat et al., 2004; Mediero et al., 2015; Robson et al., 1998), Stahl et al. (2010) found some regional patterns indicating decreasing annual discharge trends in southern and eastern regions of Europe and generally positive trends

elsewhere; furthermore, upward trends were identified in the winter months in most of the considered catchments in Europe. Likewise, based on a literature review Hall et al. (2014) noted that, over the past decades, there were generally decreasing trends of floods in the western part of the Mediterranean and the Northern and Eastern Europe, and increasing trends elsewhere.

Flood frequency analysis or risk analysis for flood hazards is an important part of the engineering practice whose aim is to obtain relationships between design variables corresponding to a chosen hydrologic risk (Khaliq et al., 2006; Salas and Obeysekera, 2014). Statistical methods employed in traditional flood frequency analysis are based on the assumption of independence and stationarity of extreme events. As numerous studies have identified significant trends in annual floods, the assumption of stationarity may be questioned (Blöschl et al., 2015; Douglas et al., 2000; Milly et al., 2008; Montanari and Koutsoyiannis, 2014; Robson et al., 1998; Strupczewski et al., 2001; Vogel et al., 2011; Zhang et al., 2001).

Therefore, alternative approaches incorporating the effects of non-independence and non-stationarity have been explored (Khaliq et al., 2006). Non-stationarity may be attributed to climate variability or different human influences (e.g. urbanisation, regulation of rivers, construction of dikes, deforestation, etc.) (Coles, 2001; Lopez and Frances, 2013; Merz et al., 2012; Prosdocimi et al., 2015; Salas and Obeysekera, 2014; Strupczewski et al., 2001; Villarini et al., 2009; Vogel et al., 2011). Recently, more attention has been paid to non-stationary frequency estimation of flood extremes. A relatively large number of studies have already performed non-stationary flood frequency analyses. However, the way of incorporating changing climate and anthropogenic influences in hydrologic practice has

still not been exactly defined (Singh et al., 2013) and this is clearly an area which should be considered with much more effort in the future (Kjeldsen et al., 2014).

Most of the non-stationary flood frequency analysis methods proposed in the literature involve parameters of a chosen distribution that are dependent on time (see Khaliq et al. (2006) for a review). Strupczewski et al. (2001) implemented time trend components into the first two statistical parameters of the Gamma and lognormal probability distribution functions. Delgado et al. (2010) tested the GEV model, with the location and scale parameter varying with time, for the Mekong River. They found that the increase in the probability of extreme floods was driven by an increase in the scale parameter. Vogel et al. (2011) derived a decadal flood magnification factor which only depends on the slope of the log-linear trend of the annual maximum streamflow series and the time interval using the non-stationary lognormal distribution. They computed recurrence reduction factors for streamflow data across the US and reported that today's 100-year flood may become more frequent in the future in many watersheds. Singh et al. (2013) applied non-stationary flood frequency analysis based on generalized extreme value (GEV) and lognormal distributions and reported significant variation in return periods, and Gül et al. (2014) conducted an analysis with a GEV-CDN (GEV conditional density estimation network) where the GEV parameters were allowed to vary with time.

The problem with time varying distribution parameters is that it is difficult to justify why they would continue to change in the future exactly in the same way they did in the past. As an alternative, models have therefore been developed that correlate the distribution parameters to hydrological variables such as land use or climatological variables, for example El Niño Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO) and other circulation indices (e.g. Wilby and Quinn, 2013). Delgado et al. (2014) modelled the scale parameter of a log-normal distribution as a function of the non-stationary standard deviation of an atmospheric circulation index representing Western Pacific monsoon activity. By evaluating a deviance statistic based on the log-likelihood of the parameter fit they found the non-stationary model to be a significant improvement over the stationary model for their case of the lower Mekong flood series. Some authors allowed the distribution parameters to vary both with hydrological variables and with time. Villarini et al. (2009) conducted a covariate analysis using time, population density and daily maximum rainfall for a flood frequency analysis based on the Generalized Additive Models for Location, Scale and Shape parameters (GAMLSS) for a number of basins in the US, suggesting that the return period for a given flood discharge has varied substantially during the time of record. Similarly, Prodocimi et al. (2014) allowed the location parameter of a lognormal distribution to vary with time and with the 99th percentile of daily rainfall, indicating different patterns of changes in peak flow series across the UK. Gilroy and McCuen (2012) adjusted flood frequencies based on maximum annual 24 hour precipitation estimated from GCM scenarios, and on urbanisation estimates.

As an increase in the number of extreme flood events has been observed over recent decades in Slovenia (Kobold et al., 2012), the accuracy of existing flood estimation methods has likely diminished. Therefore the need for a non-stationary approach of flood frequency analyses has arisen. The main objective of this paper is to compare stationary and non-stationary flood frequency methods for selected gauging stations in Slovenia that exhibit clear non-stationarity in the flood data series. The methods use GEV distribution considering non-stationarity for one or two parameters in different combinations. This paper extends the work of previous authors by testing the GEV distribution with two parameter estimation techniques, the maximum likelihood method (MLE) and a Bayesian method through Markov chain Monte Carlo (MCMC) simulations. The parameters depend either on time or on annual precipitation to ascertain whether the change in annual precipitation is connected with the change of extreme flood events, which could be used for non-stationary flood frequency estimation in a meaningful way.

DATA AND METHODS

Previous studies have shown that some gauging stations in Slovenia exhibit statistically significant trends in annual maximum (AM) flood series (Bezák et al., 2015a, b; Kobold et al., 2012; Menih et al., 2015). Two gauging stations with statistically significant upward trends in AM series were selected for analysis in this study. Discharge data were measured by the Slovenian Environment Agency (ARSO, 2015a). Some basic characteristics of the analysed stations are presented in Table 1. Both catchments are natural and mostly undisturbed by anthropogenic influences. Three typical climates prevail in Slovenia, namely the sub-Mediterranean, temperate continental and mountain climates. The annual precipitation in Slovenia amounts from less than 900 mm/yr in the eastern part to as much as 3200 mm/yr in the western part of the country. The average elevation of the country is 557 m. With the exception of the coast, snow cover is a regular phenomenon (Frantar et al., 2008). The selected gauging stations are located in different parts of the country and have therefore different water regimes. Skocjan at the Radulja River has a Dinaric pluvial-nival regime which is characteristic of the Dinaric area rivers with two fairly similar peaks in spring and autumn; Kobarid at the Soca River has an Alpine nival-pluvial regime which is the characteristic of the rivers with catchments that extend to the high mountains where the effect of snow melt is pronounced (Frantar and Hrvatin, 2005). The first peak in this regime typically occurs in late spring when the snow starts to melt and the second one in autumn due to a precipitation maximum.

Time trend analysis should be a major consideration prior to dealing with non-stationary flood frequency analysis (Singh et al., 2013; Strupczewski et al., 2001). Detection of trend is a critical issue as it has a considerable effect on the non-stationary analysis results (Douglas et al., 2000; Strupczewski et al., 2001). The existence and statistical significance of

Table 1. Basic characteristics of the considered gauging stations and AM series.

No. of the station	Gauging station - stream	Drainage area [km ²]	Elevation [m a.s.l.]	Mean annual precipitation [mm/yr]	Considered period	AM series length [years]
7380	Skocjan - Radulja	108	160	1144	1961–2013	53
8080	Kobarid - Soca	437	195	2452	1949–2013	65

the time trend in hydro-meteorological variables can be detected by parametric and nonparametric tests. Parametric tests usually require normality, linearity and independency of the time series (Bates et al., 2010) but these assumptions are often not fulfilled by hydrological and meteorological time series. Among nonparametric tests, the Mann-Kendall (MK) test (Kendall, 1975) is one of the most widely accepted as it does not require normality and is more robust against tied and missing values (Douglas et al., 2000; Singh et al., 2013). The null hypothesis H_0 of the MK test is that there is no (monotonic) trend in the series. The resultant Mann-Kendall test statistic (τ) indicates how strong the trend is and whether it is increasing or decreasing. In this study, MK test using a significance level of 0.05 was applied in order to evaluate the possible presence of a time trend in the AM flood series. The test was performed using the R-package *Kendall* (McLeod, 2011). However, at the same time the presence of serial correlation in data series should be considered as it may lead to a higher probability of incorrectly rejecting the null hypothesis of no trend in the time series (Douglas et al., 2000; Yue et al., 2002). In fact, a trend in the variance or in the autocorrelation function is rarely analysed, therefore numerous studies incorrectly reported significant trends of the mean in time series (Vogel et al., 2011). The autocorrelation function (ACF) plot and the Ljung–Box test (Ljung and Box, 1978) were used to examine the presence of serial correlation, i.e. the null hypothesis of independence in a given time series. Again, a significance level of 0.05 was applied. The significance of the linear correlation between AM flood series and annual precipitation was tested using a t-test. The significance indicator of the t-test is the p-value with the chosen significance level of 0.05.

The non-stationary GEV model is a commonly accepted model to describe non-stationarity in flood data series due to the skewed character of annual maximum flows and the flexibility of the distribution in terms of the inclusion of covariates in the parameters (Delgado et al., 2010; Gül et al., 2014; Katz et al., 2002; Prosdocimi et al., 2015; Salas and Obeysekera, 2014; Singh et al., 2013). The cumulative distribution function of the GEV distribution is defined as:

$$F(x; \mu, \alpha, \kappa) = \exp \left\{ - \left[1 - \kappa \frac{(x-\mu)^{\frac{1}{\kappa}}}{\alpha} \right]^{\kappa} \right\}, \quad \kappa \neq 0, \quad (1)$$

and GEV quantile function associated with a given return period as:

$$x(T) = \mu + \frac{\alpha}{\kappa} \left[1 - \left(\ln \frac{T}{T-1} \right)^{\kappa} \right], \quad (2)$$

where μ, α and κ are location, scale and shape parameters, respectively. The three types of distribution in the extremal types theorem are determined by the sign of the shape parameter, i.e. when $\kappa \rightarrow 0$, the equation (1) approaches a Gumbel distribution and when $\kappa < 0$ or $\kappa > 0$, the model becomes a heavy tailed Fréchet or the upper bounded Weibull distribution, respectively (Gilleland and Katz, 2011).

The methods for estimating the parameters of the distribution vary between studies. The parameter estimation is usually performed using the maximum likelihood method (MLE) (Katz et al., 2002; Obeysekera and Salas, 2014; Prosdocimi et al., 2015) or the generalized maximum likelihood method (GMLE) (El Adlouni et al., 2007; Gül et al., 2014) and sometimes the Bayesian method through the Markov chain Monte Carlo (MCMC) approach (Cheng et al., 2014). However, the study of

Cheng et al. (2014) was dedicated to the annual temperature frequencies rather than floods. The MLE and Bayesian (MCMC) methods were applied and compared in this study. A detailed description of both methods is provided in Coles (2001).

Also, the non-stationarity models for the distribution parameters vary between studies as discussed above. Most of the studies considered non-stationarity for only one parameter (location parameter), whereas studies considering non-stationarity for more parameters in different combinations are more limited. In this study, four cases were considered:

- 1) A stationary case, where all model parameters were assumed to be constant.
- 2) A non-stationary case where the location parameter (μ) was assumed to be a function of time: $\mu(t) = \mu_0 + \mu_1 t$.
- 3) A non-stationary case where the location (μ) and scale (α) parameters were assumed to be a function of time: $\mu(t) = \mu_0 + \mu_1 t$, $\ln \alpha(t) = \phi_0 + \phi_1 t$.
- 4) A non-stationary case where the location parameter (μ) was assumed to be a function of annual precipitation: $\mu(P) = \mu_0 + \mu_1 P$.

Time (t) was counted from the beginning of the record for all models. To ensure the positive value of the scale parameter (α), a log link function was used in the third model which is often applied (El Adlouni et al., 2007; Salas and Obeysekera, 2014). The shape parameter (κ) is usually assumed to be constant as its value is difficult to estimate reliably (Coles, 2001; Salas and Obeysekera, 2014), so we also made this assumption in the study.

Various goodness-of-fit indicators (diagnostic plots) were inspected to check the overall performance of the fitted models, e.g. a quantile–quantile plot, a probability plot, etc. In order to determine the best fitting model, the Akaike Information Criterion (AIC) (Akaike, 1974) was performed which is commonly used for model selection among various nested models in the case that model parameters are estimated using the MLE method (Gül et al., 2014; Salas and Obeysekera, 2014). The model associated with the smallest AIC value indicates the best model performance. Additionally, the likelihood-ratio test was performed to test whether the inclusion of the covariates into the model is significant (Coles, 2001; Gilleland and Katz, 2011). The test is applicable only for comparing nested models and it becomes clumsy when more than two models are compared. In the case of the Bayesian parameter estimation method, the deviance information criterion (DIC), representing a Bayesian version of the AIC was calculated to compare the models (Gilleland and Katz, 2011). DIC is based on the deviance function $D(\vartheta)$ which is defined as minus twice the log-likelihood evaluated at the parameter values given by ϑ , i.e.:

$$DIC = D(\bar{\vartheta}) + 2(\bar{D}(\vartheta) - D(\bar{\vartheta})) \quad (3)$$

The means are taken over the posterior MCMC sample. Again, the model associated with the smallest DIC value indicates the best model performance.

In order to calculate confidence intervals and quantifying the uncertainty of non-stationary models for parameters estimated by the MLE method, a normal approximation was used. For the flood quantiles the delta method introduced by Obeysekera and Salas (2014), based on the large sample properties of maximum likelihood estimators using the parameter covariance matrix was applied (Gilleland and Katz, 2011). For the Bayesian esti-

mation credible intervals were estimated using the percentile method ($\alpha/2$ and $1-\alpha/2$ percentiles) of the resulting MCMC sample (after removing the first burn-in values) (Gilleland and Katz, 2011; Viglione et al., 2013).

Stationary and non-stationary flood frequency analyses based on the annual maximum (AM) flood series method including statistical tests were performed using the freely available R software (R Core Team, 2013) and R-package *extRemes* (Gilleland and Katz, 2011).

RESULTS AND DISCUSSION

The analyses were carried out for the two selected gauging stations in Slovenia. As a first step the results of the change detection of the annual maximum (AM) flood series are presented. Table 2 shows the test statistics of the MK test to evaluate the presence of a trend, and the Ljung-Box test to evaluate the presence of serial correlations. Figure 1 plots the time trends of the AM flood series and regressions with annual precipitation.

The MK test shows a statistically significant upward trend ($p < 0.01$) of the AM flood time series for both stations which indicates the presence of non-stationarity. The Ljung-Box test suggests that there is no evidence of serial autocorrelation in the AM samples ($p > 0.05$) (Table 2). As peak flows are normally

closely connected to high precipitation we also investigated whether there is a statistically significant linear correlation between the AM flood series and annual precipitation (Figure 1) using a t-test. A strongly significant positive correlation was found for both stations with p -values $\ll 0.01$.

Detailed examination of the flood peaks and annual precipitation relationship demonstrated an obvious connection of high annual precipitation and high flow peaks for Skocjan at the Radulja River (Figure 1). For example, the highest annual precipitation (1438 mm/yr) is associated with the second highest observed discharge (50.3 m³/s) occurring in 2005, which was estimated as a 100-year flood. In just two days there were 137 mm of rain which corresponds to a 100-year return period (Kobold et al., 2005). Similarly, the highest observed discharge (59.1 m³/s) is associated with very high annual precipitation (1359 mm/yr) in 2010. The event was the consequence of heavy rainfall in September all over Slovenia. In fact, the 48-hours precipitation in the catchment amounted to as much as 163 mm, which corresponds to more than a 100-year return period (ARSO, 2015b). However, there is an anomalous event associated with high discharge (47.8 m³/s) and average annual precipitation (985 mm/yr) in May 2006 (Figure 1). The unusually high waters of the Radulja River during that time of the year were associated with relatively high 48-hours precipitation (120 mm) and high antecedent soil moisture (Polajnar, 2007).

Table 2. Results of the MK test for trend and the Ljung-Box test for serial correlation for the considered gauging stations.

No. of the station	Gauging station - stream	MK test		Ljung-Box test	
		tau	p-value	test-statistic	p-value
7380	Skocjan - Radulja	0.353	$2.04 \cdot 10^{-4}$	23.18	0.208
8080	Kobarid - Soca	0.259	$2.32 \cdot 10^{-3}$	19.03	0.520

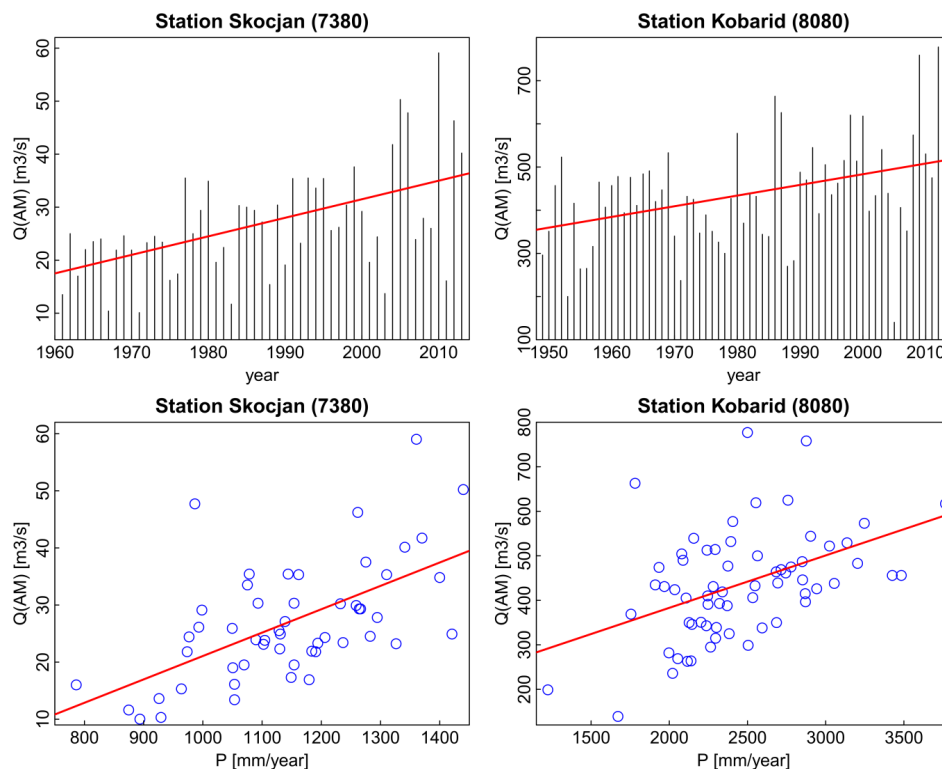


Fig. 1. AM flood series with corresponding time trends and linear regression plots between AM series and annual precipitation P for Skocjan and Kobarid.

Similarly, also in the case of Kobarid at the Soca River increasing high precipitation is obviously associated with high flows, however, there are three anomalous events associated with the three highest observed discharges in years with more or less average precipitation (Figure 1). The highest observed discharge (778 m³/s) is associated with an average annual precipitation (2493 mm/yr) in 2012. That discharge was a result of a high precipitation on the 5th of November and very high antecedent soil moisture at the same time as a consequence of heavy rainfall one week before which also caused floods with a return period of 50 years (ARSO, 2012). However, in the same year there was a severe drought lasting from the end of 2011 till autumn 2012 and the net result was an average annual precipitation for that year. Likewise, also the extreme discharge (664 m³/s) in 1986 was associated with very high rainfall intensities and antecedent soil moisture. In just 48 hours as much as 300 mm of rain occurred (ARSO, 2015b) and the soil moisture was very high due to the 165 mm of rain one week before. The second highest discharge (759 m³/s) associated with the above average annual rainfall (2869 mm/yr) in 2010 was the result of prolonged 5-days rainfall of moderate intensity at the end of December and sudden warming that came with the rain, quickly melted the snow (15 cm in the lowlands) and significantly contributed to the increased flow of the Soca River and its tributaries (ARSO, 2010). As we already emphasized, discharges are not only dependent on climatic conditions but also on other variables, such as antecedent soil moisture and snow melting.

In the next step of the study, stationary and non-stationary flood frequency analyses using the GEV distribution were performed. Parameters were estimated by the MLE and Bayesian (MCMC) approaches. Case (1) was stationary, cases (2) and (3) non-stationary with the location parameter (μ), and the location (μ) and scale (α) parameters incorporated as linear time trend, respectively. A statistically significant linear correlation between AM flood series and annual precipitation was identified, so annual precipitation was incorporated as a covariate in the location parameter (μ) in case (4). The results of the fitted model parameters estimated by the MLE method and the Bayesian method through the MCMC approach along with the confidence and credible limits are presented in Table 3 and Table 4, respectively. In order to assess the MCMC convergence, trace plots were used which illustrate model iterations against the corresponding parameter values showing the mixing of the chain and allowing to estimate a reliable burn-in period, i.e. the time the model needs to converge to the optimum parameter values. Chains of the size 50000 and a burn-in period of 3000 runs, and chains of size 100000 with a burn-in period of 30000 runs were used for station Skocjan and station Kobarid, respectively. The estimated parameter values presented in Table 4 are the means of the posterior distributions. Comparison of the parameter values estimated by the two methods indicates consistency. However, both techniques have their advantages and disadvantages. The results in Tables 3 and 4 indicate that the MCMC approach has significantly narrowed the credible intervals, i.e. reduces the potential range of estimated parameter values. Also Finch and French (2012) showed that MCMC approach for smaller samples provides more accurate parameter estimates, i.e. narrower confidence intervals than MLE approach. Furthermore, Katz et al. (2002) noted that the MLE method can be unstable and give unrealistic estimates of the shape parameter and therewith the extreme flood quantiles of the GEV distribution in the case of small samples ($N < 50$). However, comparing the complexity of the methods, the MLE method is much simpler and easier to implement since the

MCMC approach requires many decisions prior to the application such as the prior distribution function and their parameters and is therefore much more time consuming.

For each model, the significance of the inclusion of each covariate was evaluated by adding one covariate in a parameter at a time and using the AIC or DIC criterion to assess whether inclusion of a covariate into a specific parameter resulted in a better model fit. Additionally, in the case of the MLE parameter estimation method, also a likelihood-ratio test was performed to test whether the inclusion of the covariates into the model is significant. The models were ranked according to the tests and calculated criterion values (Tables 3 and 4). Furthermore, various diagnostic plots were inspected to check the overall performance of the fitted models by evidence of independence and normality of the residuals. Visual inspection did not highlight significant problems associated with the performance of the fitted models. The results presented in Tables 3 and 4 demonstrate that each step of our procedure resulted in a better model fit. In fact, all non-stationary models exhibit better fitting than the stationary ones for both considered gauging stations. Inclusion of the time trend into the location parameter results in a significant (at the 5% level) improvement over the stationary model. Furthermore, incorporation of the time trend into the scale parameter, in addition to the location parameter, yields a significant improvement over the non-stationary model with time trend only in the location parameter, which demonstrates that the variability of floods for both stations increased especially during the 21st century. These findings are in accordance with the results from previous studies since most of the studies reported significant improvement of time dependant non-stationary models over stationary ones, however, not all of them recognized the further improvement of non-stationary models after the inclusion of the time trend also in the scale parameter (El Adlouni et al., 2007; Delgado et al., 2010; Gül et al., 2014; Salas and Obeysekera, 2014). Finally, inclusion of annual precipitation as a covariate into the location parameter demonstrates a significant improvement over the fit with the time covariate. Thus, it appears that the model with annual precipitation dependence of the location parameter most adequately represents the AM flood series variability of both stations.

Once the parameters of the models have been estimated, the flood quantiles for specific return periods (T) can be simulated. Estimated flood quantiles versus time are presented in Figures 2 and 3 for gauging stations Skocjan and Kobarid, respectively. Note that flood quantiles associated with 2-year return period correspond to the median of the model. The results for both stations demonstrate that the stationary model in almost all cases underestimates flood quantiles of the non-stationary models in recent years (Table 5 and Figures 2 and 3). Traditionally estimated flood quantiles associated with a specific return period match the non-stationary flood quantiles from many years or even decades ago. The same finding was reported by Gül et al. (2014). Relative to the non-stationary model with time trend in both parameters (NS_{t2}), the stationary model started to underestimate flood quantiles associated with a 2-year return period already after the first 23 years (in 1983) and with a 100-year return period after 48 years (in 2008) (Figure 2). Relative to the non-stationary model with annual precipitation as a covariate (NSP), the stationary model underestimates the flood quantiles in wet years. For example, for Skocjan the 100-year flood is underestimated by the stationary in years with annual precipitation larger than 1150 mm/yr, which is very close to the average annual precipitation (1144 mm/yr). The non-stationarity is even more apparent for the station Kobarid (Figure 3).

Table 3. Parameters of the stationary (S) and non-stationary (NS) models estimated by the MLE method.

Model	Parameter estimates with 95% conf. intervals in brackets					AIC	rank
	μ_0	μ_1	α_0	α_1	κ		
Station Skocjan (7380)							
S	22.51 [19.99; 25.02]	–	8.36 [6.56; 10.15]	–	–0.049 [–0.236; 0.138]	395.3	4
NS: $\mu(t)$	15.64 [10.03; 21.26]	0.293 [0.084; 0.502]	8.27 [6.44; 10.11]	–	–0.192 [–0.397; 0.012]	386.7	3
NS: $\mu(t), a(t)$	16.71 [13.40; 20.01]	0.287 [0.139; 0.434]	1.48 [1.16; 1.81]	0.022 [0.012; 0.032]	–0.390 [–0.574; –0.206]	374.6	2
NS: $\mu(P)$	–15.36 [–27.64; –3.07]	0.034 [0.023; 0.045]	5.81 [4.33; 7.30]	–	0.097 [–0.184; 0.378]	368.0	1
Station Kobarid (8080)							
S	389.99 [359.54; 420.43]	–	115.01 [94.43; 135.60]	–	–0.192 [–0.318; –0.066]	812.3	4
NS: $\mu(t)$	309.76 [247.09; 372.43]	2.734 [0.903; 4.564]	114.64 [93.252; 136.02]	–	–0.315 [–0.486; –0.144]	804.7	3
NS: $\mu(t), a(t)$	335.81 [288.66; 382.97]	1.994 [0.538; 3.451]	4.36 [4.06; 4.66]	0.010 [0.003; 0.017]	–0.357 [–0.529; –0.185]	799.9	2
NS: $\mu(P)$	90.95 [–37.24; 219.15]	0.124 [0.074; 0.173]	86.64 [67.88; 105.40]	–	–0.023 [–0.222; 0.177]	789.3	1

Table 4. Parameters of the stationary (S) and non-stationary (NS) models estimated by the Bayesian method (MCMC).

Model	Parameter estimates with 95% cred. intervals in brackets					DIC	rank
	μ_0	μ_1	α_0	α_1	κ		
Station Skocjan (7380)							
S	22.46 [21.33; 23.61]	–	8.81 [6.94; 11.38]	–	–0.018 [–0.212; –0.231]	1174.4	4
NS: $\mu(t)$	15.63 [14.94; 16.34]	0.284 [0.181; 0.388]	8.59 [6.65; 11.10]	–	–0.144 [–0.345; 0.107]	1145.1	3
NS: $\mu(t), a(t)$	16.72 [15.57; 17.76]	0.280 [0.172; 0.382]	1.51 [1.18; .85]	0.022 [0.012; 0.032]	–0.337 [–0.534; –0.107]	1104.6	2
NS: $\mu(P)$	–15.35 [–16.04; –14.67]	0.033 [0.031; 0.036]	6.13 [4.54; 8.19]	–	0.131 [–0.124; 0.455]	1088.6	1
Station Kobarid (8080)							
S	390.64 [388.33; 393.20]	–	118.50 [97.49; 45.27]	–	–0.180 [–0.294; –0.057]	2423.6	4
NS: $\mu(t)$	305.68 [304.94; 306.41]	2.84 [2.61; 3.07]	119.57 [96.14; 50.51]	–	–0.303 [–0.456; –0.149]	2396.6	3
NS: $\mu(t), a(t)$	335.83 [333.42; 338.34]	1.95 [1.11; 2.76]	4.40 [4.09; 4.73]	0.010 [0.002; 0.018]	–0.320 [–0.502; –0.132]	2379.9	2
NS: $\mu(P)$	90.81 [88.95; 92.87]	0.123 [0.113; 0.133]	87.71 [71.95; 08.14]	–	–0.023 [–0.044; –0.002]	2348.5	1

Table 5. Estimated flood quantiles for specific return periods (T) for the year 2013 along with confidence/credible intervals for the MLE and MCMC method.

Model	Quantile estimates with 95% confidence limits [m ³ /s] for MLE method		Quantile estimates with 95% credible limits [m ³ /s] for MCMC method	
	T = 10	T = 100	T = 10	T = 100
Station 7380				
S	40.3 [35.3; 45.3]	56.9 [43.4; 70.4]	42.2 [37.0; 51.3]	63.6 [49.0; 101.1]
NS: $\mu(t)$	46.3 [40.1; 52.5]	56.4 [50.0; 62.9]	47.3 [41.4; 54.1]	60.3 [52.1; 79.0]
NS: $\mu(t), s(t)$	53.3 [47.3; 59.4]	62.5 [54.5; 70.5]	54.9 [47.7; 64.3]	66.6 [57.7; 84.2]
Station 8080				
S	600.1 [557.0; 643.2]	741.3 [661.9; 820.6]	610.2 [573.0; 662.3]	762.9 [691.4; 885.4]
NS: $\mu(t)$	672.2 [610.6; 733.8]	765.8 [713.4; 818.2]	682.5 [628.6; 742.4]	780.3 [728.0; 855.8]
NS: $\mu(t), s(t)$	701.1 [637.2; 765.0]	809.6 [718.9; 900.3]	718.6 [645.1; 819.5]	851.7 [751.5; 1043]

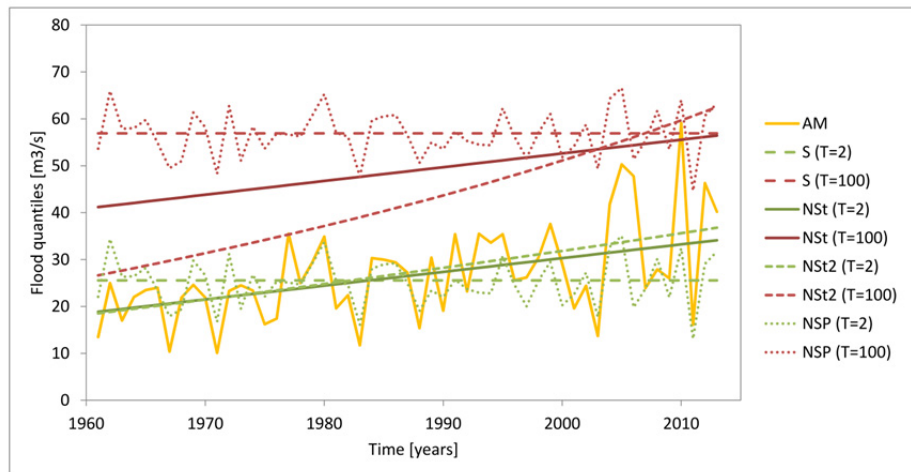


Fig. 2. Comparison of estimated flood quantiles for stationary (S) and non-stationary (NS) models for the gauging station Skocjan (7380) fitted with the MLE method. The non-stationary model with the time covariate incorporated only into the location parameter is denoted as NSt, the non-stationary model with time trend in both parameters as NSt2 and the non-stationary model with annual precipitation as a covariate as NSP. The NSP model estimates the flood quantile for each year depending on the corresponding annual precipitation.

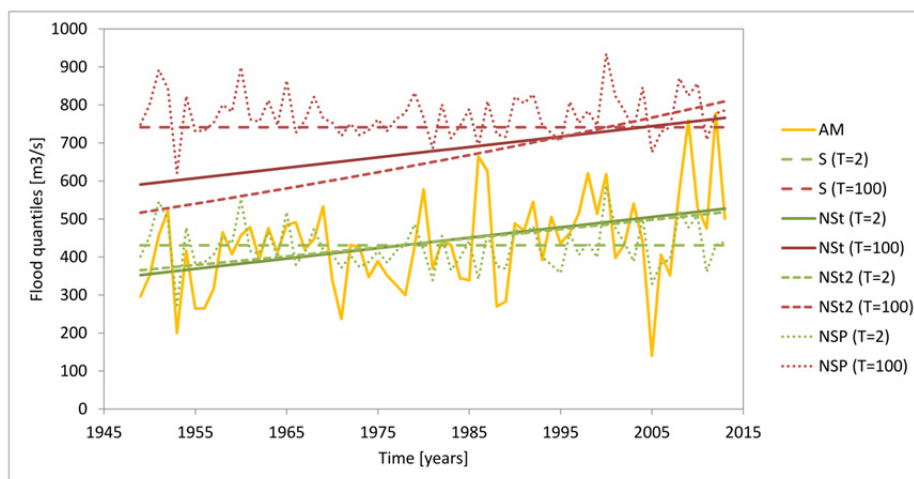


Fig. 3. Same as Figure 2 but for the station Kobarid (8080).

Interestingly, the results of the non-stationary model with annual precipitation as a covariate show no trend in the quantiles since there was no significant time trend identified in the annual precipitation data series. However, a statistically significant linear correlation between the AM flood series and annual precipitation was identified. High floods in both catchments are mainly associated with high autumn precipitation which tends to have an increasing trend all over Slovenia (Kobold et al., 2012). Furthermore, the results presented in Table 5 indicate that the Bayesian (MCMC) approach offers slightly higher flood estimates than the MLE approach for all considered models and return periods. The MCMC approach has significantly wider credible intervals.

Consistent with the goodness-of-fit results, a visual inspection of Figures 4 and 5 show that the last two non-stationary models NSt2 and NSP exhibit a better fit than the stationary (S) and the non-stationary (NSt) models for both gauging stations. Both non-stationary models (NSt2 and NSP) demonstrate better fits to the flood peaks in recent years. For example, in the case of Skocjan models S and NSt significantly underestimate the highest flood that occurred in 2010 (Figure 4). The 2010 flood peak was even higher than the prediction of the 100-year flood for the NSt model for 2023. In the case of Kobarid, models S

and NSt again underestimate the floods of 2009 and 2012 (Figure 5).

Figure 4 illustrates that, in the case of station Skocjan, a 100-year flood under stationary conditions (S) ($57 \text{ m}^3/\text{s}$) corresponds to a 20-year flood under non-stationary conditions (NSt2) in the year 2013. In other words, an exceedance probability of 0.01 increased to 0.05. Similarly, to ensure a return period of 100-years under non-stationary conditions in the year 2013, a return period of more than 230 years should be used considering stationary conditions. Provided the model can be extrapolated into the future, a return period of 100-years in the year 2023 under non-stationary conditions would require a return period of more than 1200 years considering stationary conditions. These changes in the flood quantiles are similar to those found by Salas and Obeysekera (2014).

With annual precipitation as a covariate (NSP), the 100-year flood under stationary conditions corresponds to a flood associated with an annual rainfall of $1143 \text{ mm}/\text{yr}$ which is the average of the observation period (Figure 4). The same flood discharge will occur with an exceedance probability of 0.03 ($T = 33$ years) if annual rainfall equals the maximum observed rainfall ($1438 \text{ mm}/\text{yr}$). For each additional $100 \text{ mm}/\text{yr}$ of precipitation, the 100-year flood increases by almost $3.5 \text{ m}^3/\text{s}$.

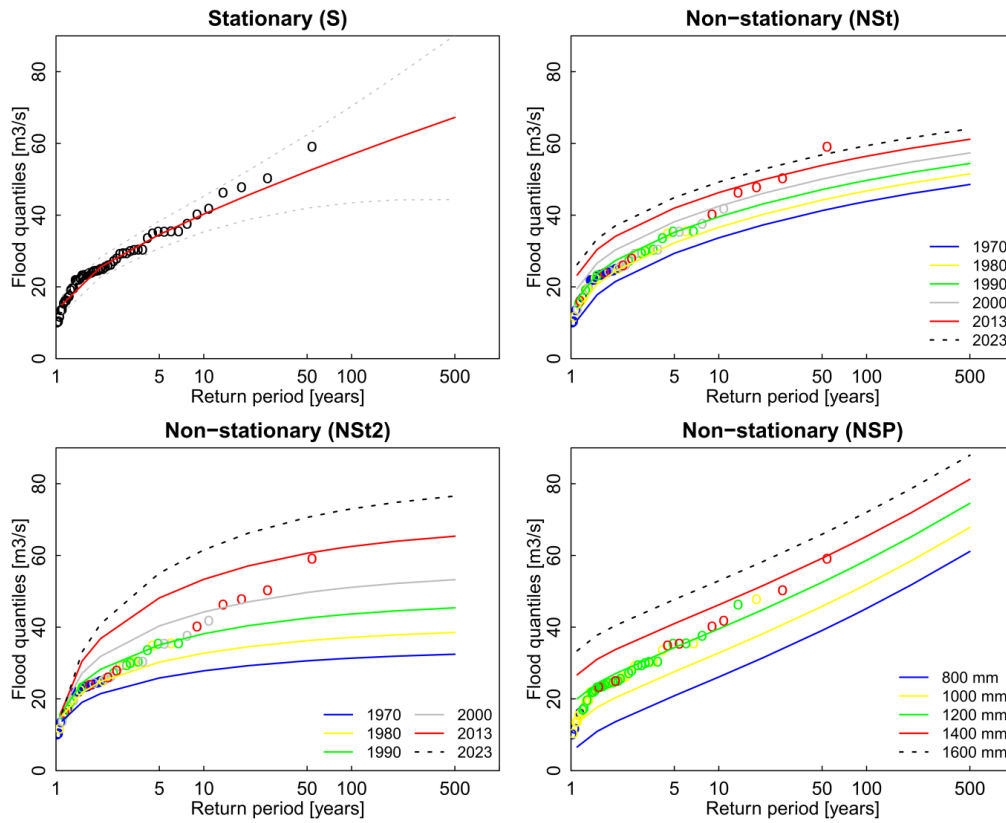


Fig. 4. Estimated flood quantiles for all considered models for gauging station Skocjan (7380) fitted with the MLE method.

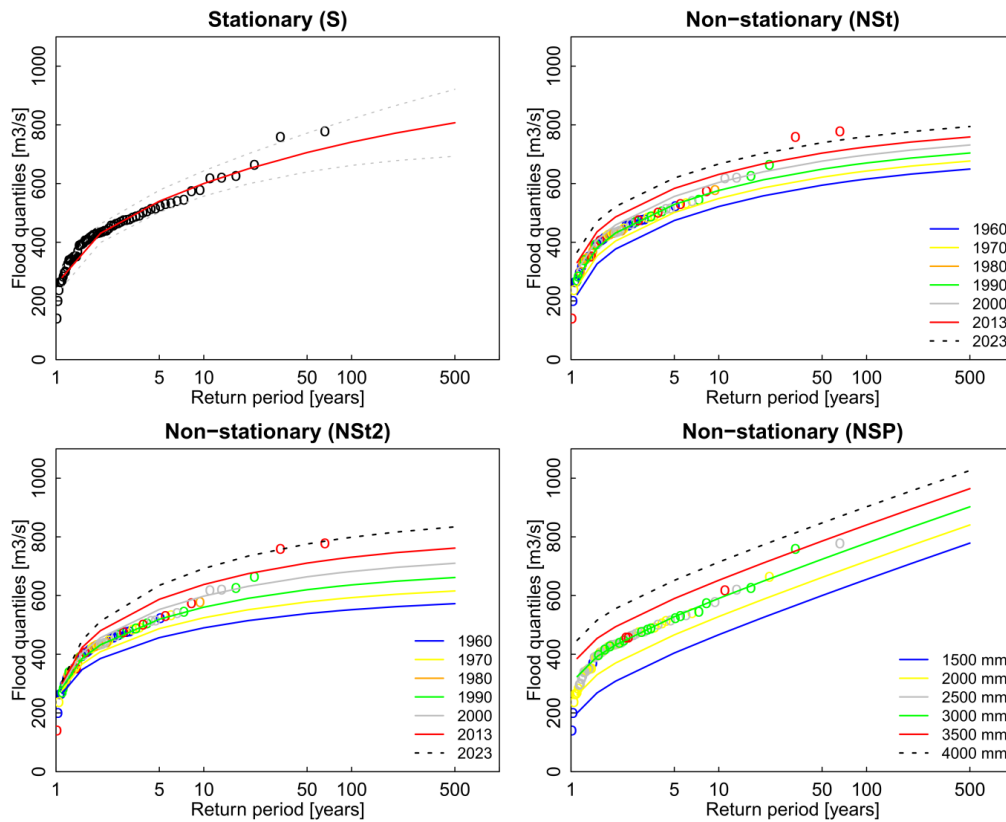


Fig. 5. Estimated flood quantiles for all considered models for gauging station Kobarid (8080) fitted with the MLE method.

Likewise, in the case of Kobarid (Figure 5) the return period associated with a given peak discharge decreases as one moves from the past into the future. With annual precipitation as a

covariate (NSP) a 67-year flood associated with the average annual rainfall of 2452 mm/yr becomes a 9-year flood for the rainfall equal to the maximum observed one (3758 mm/yr).

This discharge corresponds to a 100-year flood if stationary conditions are assumed. For each additional 100 mm/yr of precipitation, the 100-year flood increases by more than $12 \text{ m}^3/\text{s}$.

The main difference between the four models is the temporal variability (Figures 4 and 5). As the stationary model (S) remains constant all the time, both time dependant non-stationary models (NSt, NSt2) reveal an increasing trend of estimated quantiles with time. The increasing trend of NSt2 is even more pronounced since it also accounts for the time variability of the scale parameter of the GEV distribution. On the other hand, the estimated quantiles of the NSP model increase with increasing annual precipitation. The skewness of the NSP model is higher than those of the other models which may be a consequence of the large range of flood peaks associated with the same annual precipitation.

Predicting the design flood for the life span of structure in the future using time dependant non-stationary models needs to be considered with care. It is possible that changes in the future will not be exactly the same as those in the past, especially for periods longer than 10 years into the future. The advantage of the non-stationary model with annual precipitation as a covariate is that it avoids this direct temporal extrapolation, as it builds on a relationship between the floods and annual precipitation. To use this model for design purposes, reliable scenarios of future annual precipitation are needed. It is suggested that the usage of annual precipitation is of benefit here. As compared to the alternative of estimating floods by the design storm method (see, e.g., Viglione and Blöschl, 2009; Viglione et al., 2009) there is no need of obtaining projections of extreme event precipitation, which tend to be less reliable than projections of

annual precipitation (Blöschl and Montanari, 2010). This makes the proposed model more practically useful than alternative methods.

Figure 6 shows the parameter estimation uncertainty of the models associated with a 100-year flood obtained by the MCMC method for the Skocjan station. The uncertainty is the highest for the non-stationary model with the time covariate incorporated into the first two parameters (NSt2). This finding would be expected since five parameters had to be fitted for the NSt2 model, and the uncertainty tends to increase with the number of parameters. Also, the degree to which the uncertainty changes in time is larger for the NSt2 model, as it changes from relatively modest uncertainty in 1970 to significantly larger uncertainty in 2013, which is the consequence of the time increasing variance of the NSt2 model. For the recent years the uncertainty is comparable with the uncertainty of the stationary model (S). Comparing all models, the smallest uncertainty is obtained for the model with the time covariate incorporated only into the location parameter (NSt). In non-stationary models, part of the variance of the data is explained by the trend; therefore the deviations around them are smaller than for the stationary model (Table 4). Finally, inclusion of annual precipitation as a covariate into the location parameter (NSP) demonstrates a constant uncertainty that is independent of the value of the covariate. It is larger than the uncertainty of the NSt model and smaller than that of the NSt2 model. Although the NSt and NSP models have the same number of parameters to be fitted, there is a difference between the uncertainties of the two models which may be attributed to the variability of the flood peaks associated with the same rainfall class.

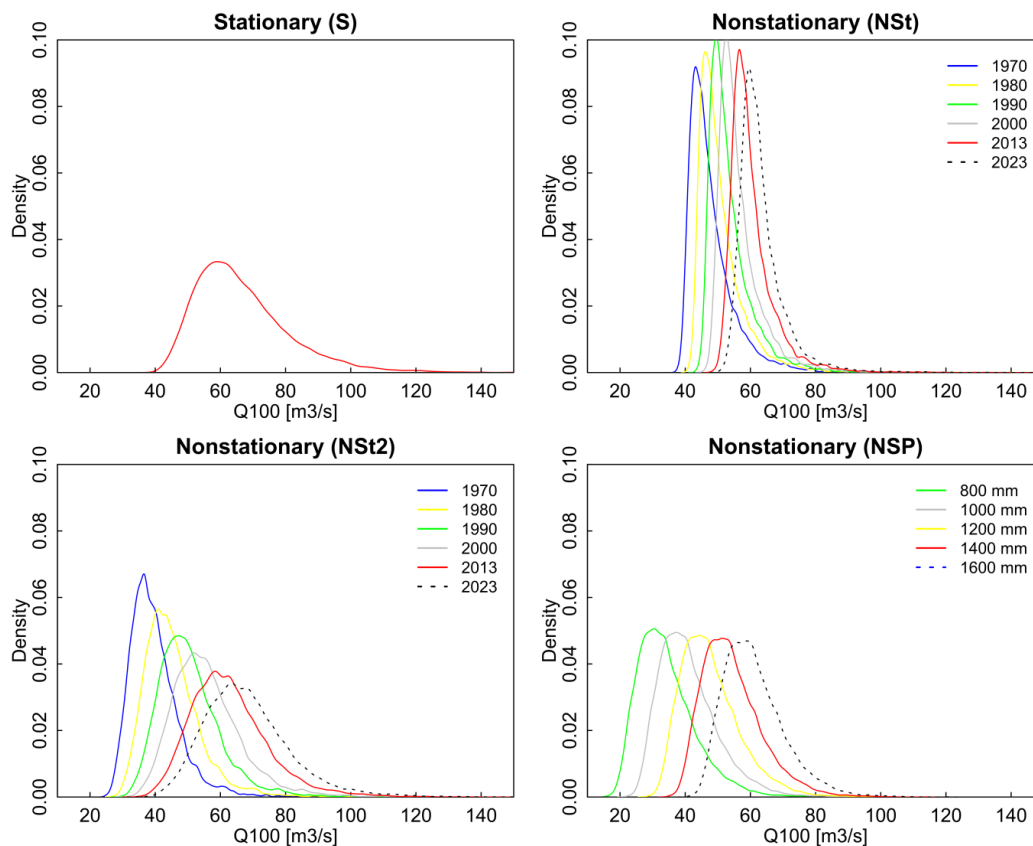


Fig. 6. Density plots for the 100-year flood for all considered models using the MCMC parameters estimation approach for gauging station Skocjan (7380).

CONCLUSIONS

This paper analyses the influence of non-stationarity on flood frequency estimates. One stationary and three non-stationary models are considered, with parameters dependent on time and on annual precipitation. All non-stationary models examined exhibit a better fit to the maximum annual flood data of two stations than the stationary model. Inclusion of a linear time trend into the location parameter results in a significant improvement over the stationary model. Additional incorporation of a time trend into the scale parameter yields further improvements. This may be attributed to the increasing variability of the flood discharges of the two stations in the last decade. Various goodness-of-fit tests demonstrate that the model with annual precipitation as a covariate provides the best fit to the flood data of both stations.

Annual precipitation is not usually used as a covariate in the literature. Climate indices (e.g. Delgado et al., 2014; Salas and Obeysekera, 2014) and extreme precipitation (e.g. Prosdocimi et al., 2014; Villarini et al., 2009) are more common. We believe that annual precipitation is a better indicator of non-stationary river floods than short-term extreme event precipitation. First, event precipitation and annual precipitation are usually highly correlated, in particular for synoptic storms that may make up a considerable part of the annual precipitation. Second, annual precipitation will affect the antecedent catchment soil moisture of individual events, which will directly affect the flood magnitudes (Gaál et al., 2012). Third, annual precipitation, typically, also has long-term effects on the evolution of catchment characteristics with high precipitation being associated with more efficient runoff generation and routing through soil erosion and land form evolution (Perdigão and Blöschl, 2014; Sivapalan and Blöschl, 2015). In a spatial context, these processes usually lead to mean annual precipitation being a better predictor of flood frequencies in ungauged basins than shorter term extreme precipitation (Rosbjerg et al., 2013). Similarly, one would expect annual precipitation to be a better predictor of decadal flood frequency changes. Perdigão and Blöschl (2014) highlight the role of annual precipitation in the long-term flood peak evolution.

Comparison of the parameters estimated by the maximum likelihood (MLE) and the Bayesian (MCMC) methods indicates consistency. However, even relatively small differences in the parameter estimates result in slightly higher estimates of the design discharges estimated by the Bayesian (MCMC) approach in the case of all considered models and return periods. As reported by Katz et al. (2002), in the case of small samples, the MLE method can give unrealistic estimates of extreme flood quantiles which could be a reason for preferring the Bayesian approach over MLE.

The Bayesian (MCMC) approach demonstrates that the model with the highest number of parameters (i.e. the model with both location and scale parameters depending on time, NST2, which has 5 parameters) gives the highest uncertainty. This model also exhibits the highest variation of uncertainty depending on the period of interest. On the other hand, the smallest uncertainty is found for the model with the location parameter depending on time (NSt). This is because the trend of non-stationary models already explains part of the variance of the data, so the deviations around them are smaller than those of the stationary model. The model with annual precipitation as a covariate (NSP) gives a higher uncertainty than the NSt model due to flood peak variability for the same rainfall class. It should be noted that all the uncertainties in the flood quantiles evaluated by the MCMC method only relate to the uncer-

tainty associated with parameter estimation due to a limited record length, assuming that the model (GEV distribution and trend models) is perfect. This explains the largest uncertainty for the case with the largest number of parameters which makes the least assumptions about the model. From a practical design perspective one would additionally have to take the model uncertainty into account which, for this case, is smaller than in the other cases.

The information criteria used in the paper (AIC and DIC) for the model choice account for record length and variance. They involve a penalty factor for more complex (non-stationary) models, which are chosen only if the data support the additional complication. Measurement uncertainty is not explicitly accounted for. Random measurement uncertainty can be considered to be part of the sampling uncertainty as the latter is estimated from the observed data. Systematic measurement errors due to changes in the rating curve would, however, affect the results (Kuczera, 1996). Based on the information available for the stream gauges used here, there is no indication of systematic changes, suggesting that the relative performance of the methods would probably not change if measurement uncertainty is accounted for explicitly.

The results also demonstrate that there are significant differences in the quantile estimates between stationary and non-stationary models. The stationary model in almost all cases underestimates the flood quantiles in recent years relative to the non-stationary models. For example, the flood quantile associated with a 100-year return period under stationary conditions corresponds to a return period of about 20-years under non-stationary conditions (NST2) for both stations. If we want to ensure today's level of protection associated with a return period of 10 years to be the same under non-stationary conditions (NST2) after 10 years, the design discharge should be increased by 15 and 6 % for stations Skocjan and Kobarid, respectively. Relative to the estimation uncertainty due to sampling effects, the difference between stationary and non-stationary models is rather drastic for a return period of 10 years, as most non-stationary quantile estimates lie outside the stationary confidence or credibility limits. In contrast, for a return period of 100 years the opposite is the case, and all non-stationary quantile estimates lie outside the stationary confidence or credibility limits. This is a reflection of the increasing sampling uncertainty with increasing return period. Variability associated with long time scales relative to the record length would be reflected as a trend in the estimation; while variability associated with short time scales (within the flood record) would be considered sampling variability. As such, the method separates the long-time scales from the short-time scales.

Using the model with annual precipitation as a covariate, a 10% increase in annual precipitation translates into an 8% increase of the 10-year flood for the station Skocjan. One of the main advantages of this model is that it allows estimation of the design discharge for a specific value of annual precipitation that is likely to occur over the life span of the structure. However, reliable precipitation scenarios for the future are needed.

Overall, the results of the study indicate that an unjustified assumption of stationarity could lead to an underestimation of extreme floods. Therefore, non-stationary models are certainly one of the options to explore when estimating design discharges.

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