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Discussions

The critical role of uncertainty in projections of hydrological Extremes

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Abstract. This paper aims to quantify the uncertainty in the projections of future hydrological extremes in the BialaTarnowska River basin, south Poland. We follow a multi-model approach based on several climate projections obtained from the EUROCORDEX initiative, raw and downscaled realizations of catchment precipitation and temperature, and flow simulations derived using the hydrological HBV model. The projections cover the 21st century. Three sources of

10   uncertainty were considered: one related to the hydrological model parameters uncertainty, the second related to climate projection ensemble spread and the third related to the distribution fit. The uncertainty of projected extreme indices related to hydrological model parameters was conditioned on flow observations from the reference period using the Generalised Likelihood Uncertainty Estimation approach, with separate weighting for high and low flow extremes. Flood quantiles were estimated using Generalize Extreme Value (GEV) distribution at different return periods and were based on two

15   different lengths of the flow time series. The sensitivity analysis based on ANOVA shows that the uncertainty introduced by the HBV model parameters can be larger than the climate model variability and distribution fit uncertainty for the low-flow extremes whilst for the high-flow extremes higher uncertainty is observed from climate models than from hydrological parameter and distribution fit uncertainties. This implies that ignoring one of the three uncertainty sources may cause great risk to future hydrological extreme adaptations and water resource planning and management.

20   **1 Introduction**

Research on the impact of climate changes on future hydrological extremes is usually performed by an application of hydrological models for the projected meteorological inputs under assumed future climate scenarios (Wilby and Harris, 2006; Honti et al., 2014; Ye et al., 2016). The standard procedure consists of a chain of consecutive actions, starting from the choice of a GCM driven by an assumed CO_2 scenario, through downscaling of climatic forcing to a catchment scale,

25   hydrological modelling and estimation of hydrological extreme indices using statistical tools. Each of the serially linked processes involves uncertainties that propagate through the computational pathway. Among many possible sources of uncertainty, the main sources are the uncertainties related to future climate scenarios, climate models, downscaling techniques and hydrological modelling. Unfortunately, we cannot directly assess the impact of these different sources of

uncertainties on predictions of hydrological extremes in future due to a lack of observations of future climate realizations. This is one of the reasons why the term projections is used instead of predictions (Honti et al., 2014). The introduction of inverse modelling, based on available past observations of climatic and hydrological variables, allows a decrease of some types of uncertainty to be achieved. Bias correction methods are usually applied to decrease the errors related to global

5 simulation models and downscaling techniques. The hydrological model structural and parametric errors are dealt with using a multi-model approach and weighing hydrological model parameters following assumed goodness of fit criteria (e.g. in the form of a likelihood function). An assessment of the spread of future realizations of extreme indices, their consistency, and the relative tendency of changes are used to evaluate the projections (Alfieri et al., 2015). There is a general agreement that we cannot avoid uncertainty in climate models (Knutti and Sedlacek, 2012). The question arises as

10 to how large an uncertainty is acceptable to the end-user in adaptations to climate change and flood and drought risk assessments.

Hydrological models are useful in water resources planning and management, flood and drought prediction, catchment scale climate change impact assessment, and understanding of system dynamics. In particular, coupling of hydrological models and climate models is important in understanding the influence of climate changes on low and high

15 flows (Meresa et al., 2016; Lawrence and Hisdal, 2011). However, complex hydrological and climate models can never be accurately evaluated, because of uncertainty in observations, parameters and model structure simplifications (Lespinas et al., 2014; Abbaspour et al., 2015). Therefore developing a proper strategy to assess and quantify the uncertainty sources in projected hydrological extremes, which result from climate projections and hydrological modelling will enable decision makers, engineers and managers to move forward more effectively with climate change adaptation planning and assure

20 future water resource sustainability for the next generation (Honti et. al., 2014). The issues of uncertainty in hydrological modelling and hydrological projection due to climate change are not new, there is much research published on this subject in global and regional studies (Todd et al., 2011; Addor et al., 2014), however, few of the case studies at a catchment level were trying to assess the influence of uncertain future and hydrological parameter uncertainty (Pualin et al., 2011; Bennett et. al., 2012; Vormoor et.al., 2015; Stenschneider et al., 2012, 2015). For several decades' interest in hydrological structural

25 and parameter uncertainty has been increasing and has become an important part of modelling (Ouyang et al., 2014; Osuch et al., 2015; Sellami et al., 2014). It has been widely verified and acknowledged that different model structures and parameterizations can lead to similar responses and, thus, there are no unique structure and parameter sets for acceptable or behavioural hydrological model responses for reproducing the observation data (Beven, 2006; Pualin et al., 2011). The calibrated hydrological models are forced with climate projections derived from climate models. However, hydrological

30 models that produce acceptable results for an observed baseline period may respond differently when forced with the climate change scenario (Thompson et al., 2013; Lespinas et al., 2014; Gosling and Arnell, 2011). In addition to the parameter and structural uncertainty (Pualin et al., 2011), the hydrological model is also exposed to uncertainty which

arises from various sources, including greenhouse gas emission scenarios and inter-dependency among the climate models (Tian et al., 2016; Ghosh et al., 2009; Wilby and Harris, 2009).

In this study, we assess the critical role of the uncertainty in the projection of future hydrological extremes in BialaTarnowska mountainous catchment in Poland in the 21st century. We consider three sources of uncertainty. These

5 are hydrological model parameter uncertainty, meteorological projection uncertainty and distribution fit uncertainty. We apply the non-formal approach to estimate the uncertainty related to hydrological model parameters, namely, the Generalized Likelihood Uncertainty Estimation (GLUE) method of Beven and Binley (1992). The other sources of uncertainty are dealt with by means of an assessment of the relevant variability of extreme index estimates. Meteorological projections are derived from the high-resolution regional climate change ensemble within the World Climate Research

10 Program Coordinated Regional Downscaling Experiment (EURO-CORDEX) initiative (Jacob et al., 2014).

Two separate goodness-of-fit criteria are chosen to constrain the hydrological parameter uncertainty of high and low flow estimates. In this way, different parameter sets are chosen for the description of high and low flow catchment regimes. This approach does not eliminate the problem of parameter non-stationarity but helps to choose the model behaviour adequate to the flow regime. The uncertainty related to the distribution fit is analysed using different lengths of

15 flow record to derive the quantiles of maximum and minimum annual flows. The popular method of a comparison of changes in flow quantiles between the reference period and future periods is based on relatively short (e.g. 30-year) periods. The question we pose is whether the estimates of future trends of extreme indices and their relative changes can be useful at all in view of the uncertainties involved. The critical role of the uncertainties of future extreme hydrological projections is being assessed using the River BialaTarnowska as a case study.

20 The paper is organized into five sections. The second and third sections describe, respectively, the case study and the methodology applied. The fourth section presents the results and discussions of the uncertainty analysis and derived changes in future low and high flow extremes; the fifth section presents the conclusions.

2 Study areas and Hydro-climate data

2.1 Study areas and observed data characteristics

25 The BialaTarnowska catchment, located in the mountainous part of Poland, was chosen as a case study. This catchment is one of the representative Polish catchments chosen following an extensive analysis of available hydro-meteorological and geomorphological data (Romanowicz et al. 2016). The catchment area is about 966.9 km^2, with forests covering much of the upper elevations and the river characterized by nearly-natural conditions. The location of the catchment is given in Fig. 1. Precipitation varies in intensity and duration over the catchment area. The Thiessen polygon method was applied to have

30 the most representative precipitation data. Maximum precipitation was 68.3 mm d^{-1} and annual mean streamflow is 0.4 m^{3}s^{-1} over the observation period.

BialaTarnowska has a mixed (rainfall and snow-melt originated) flood regime. In this study, daily hydro-meteorological observations and estimated potential evapotranspiration were used as an input to the hydrological model HBV (Bergstrm, 1995). Observed historical hydrological and climate daily time series of precipitation, temperature and flow for 39 years from November 1970 to October 2010 were obtained from the National Water Resource and Meteorology

5   Office (IMGW) in Poland. Daily potential evapotranspiration was calculated using the temperature based Hamon approach (Hamon, 1961). The daily flow data from the Koszyce Wielkie hydrological station for a period of 39 years (1971-2010) were used in the calibration (1971-2000) and validation (2001-2010) stages.

2.2 Future climate data

Daily temperature and precipitation projections were obtained from the EURO-CORDEX initiative project
10   (http://www.eurocordex.net/) that provides regional climate projections at a spatial resolution of 12.5 km (EUR-11) for median (RCP45) emission scenario and covering the time period 1971-2100 (Kotlarski et al., 2014). This ensemble contains four different RCMs driven by three different GCMs (see Table 1 for the name and model details): CNRM-CM5-CCLM4-8-17, EC-EARTHCCLM4-8-17, EC-EARTH-HIRHAM5, EC-EARTHRACMO22E, EC-EARTH-RCA4, MPI-ESM-LR-CCLM4-8-17, and MPIESMLR-RCA4.

15   ## 3 Methodology

3.1 Research approach

The approach applied here to the derivation of future projections of flow extremes follows the forward modelling chain (Wilby and Harris, 2009) and consists of the following steps: (i) choice of climate projections simulated using the ensemble of GCM/RCMs under the assumed carbon emission scenario (here RCP4.5) and dynamically downscaled to the catchment
20   scale; (ii) bias correction of projected meteorological time series of temperature and precipitation; (iii) hydrological simulations of flow extremes using raw and bias-corrected meteorological projections for a set of hydrological model parameters; (iv) derivation of extreme flow indices using empirical and distribution-based frequency analysis tools and different temporal resolution of the analysed flow extremes. The assessment of projection uncertainty is performed by running multiple simulations and evaluating the impact of each of the chain modules on the total uncertainty of the results
25   (Tian et al., 2016).

3.2 Climate projection: bias correction

The downscaling of the GCM output using either statistical or dynamic (RCM) approaches does not take into account any feedback mechanisms existing within land-surface processes and therefore the meteorological projections can be biased (Falloon et al., 2014). Several studies have identified the need to check and correct bias, in the GCM/RCMs output, before

its use in impact studies (Gudmundsson et al., 2012; Gutjahr and Heinemann, 2013; Teutschbein and Seibert, 2013; Teng et al., 2014). Most of those studies were focused on mean output values. Osuch et al., (2016) compared five different distribution mapping techniques applied in the derivation of extreme flow indices (flow quantiles and mean annual maximum flow). Their results showed the single gamma distribution mapping to be the one which produced the observed

5 characteristics most accurately of all the techniques studied. However, a distribution-based Quantile Mapping (QM) technique applied to an observed and simulated precipitation series in the reference period (1971-2000) may result in an alteration of the modelled maximum runoff (Teng et al., 2014; Ehret et al., 2012). On the other hand, the low extreme values require bias-corrected precipitation input due to the persistent and unrealistic drizzle present in raw precipitation data (Dimirel et al., 2013). Therefore, in this study, we apply both QM corrected and raw RCM/GCMs projections for

10 future runoff simulations.

3.3 Hydrological modelling

The HBV hydrological model version applied is based on Lindstrom et al., 1997 and it is written in Matlab®. HBV is a lumped conceptual multi-reservoir-type model for daily runoff simulation from daily inputs (Lindstrom et al., 1997). The model uses rainfall, air temperature and potential evaporation data as inputs. The HBV model has four main routines: (i)

15 snow; (ii) soil moisture; (iii) fast response; and (iv) slow response routing. These routines are governed mainly by fourteen HBV parameters, of which, six (TT, TTI, CFMAX, DTTM, CFR, WHC), three (FC, LP, BETA), two (KF, ALPHA) and one (KS) parameters are representing each routing stage respectively. Not all HBV model parameters have significant impact on the simulated flows. Therefore, following the study of Osuch et al., (2015) five sensitive parameters for the model output have been selected. These are FC, BETA, LP, KS and PERC. Further information and a full description of

20 the HBV hydrological model which we used can be found in Romanowicz et al., (2016).

Hydrological models are usually calibrated using the available observations under the assumption of stationarity of their parameters. Depending on the purpose of the modelling different criteria may be used (Romanowicz et al., 2013). Usually, the research is aimed at finding the compromise of a model performance between high and low flow simulations. The Nash-Sutcliff criterion (Nash Sutcliff, 1970) belongs to those most widely used. When based on the whole calibration

25 observation series, it provides parameter sets that favour medium-to-high flows (Gupta et al., 2009). Deckers et al., (2010) applied different time periods of observations related to high and low flows. The authors used multi-objective criteria that combined different aspects of model performance. However, we do not always need to look for a compromise in model performance when choosing the parameter sets of a model. In the case where hydrological extremes are concerned, the average model performance is not of interest. Rather, we want to obtain robust model performance for very low or very

30 high flow values. The NSE criterion is used here to calibrate the high-flow-oriented HBV model. The low-flow HBV model is calibrated using the NSE for the logarithm of flow. The criteria are defined as follows:

5

$$N_{SE} = 1 - \frac{\sum_{t=1}^{T}(Q_{t,sim}-Q_{t,obs})^2}{\sum_{t=1}^{T}(Q_{t,obs}-\overline{Q_{obs}})^2} \, , \tag{1}$$

$$N_{SE(\log)} = 1 - \frac{\sum_{t=1}^{T}(\log(Q_{t,sim})-\log(Q_{t,obs}))^2}{\sum_{t=1}^{T}(\log(Q_{t,obs})-\overline{\log(Q_{obs})})^2} \, , \tag{2}$$

Where $Q_{t,sim}$ denotes simulated flow in time t, t=1,…,T, $Q_{t,obs}$ denotes observed flow in time t, $\overline{Q_{t,obs}}$ denotes mean observed flow and $\overline{\log(Q_{t,obs})}$ denotes mean of logarithm of flows.

5   Depending on the formulation of the problem, either deterministic or stochastic methods can be used to derive a set of the best model parameters (Romanowicz and Macdonald, 2005). In this study we use the stochastic formulation and we apply the Generalized Likelihood Uncertainty Estimation GLUE approach of Beven and Binley (1992) to calibrate the HBV model and provide an estimation of the model parameter uncertainty.

3.4 Hydrological model parameter uncertainty

10   The GLUE approach is one of the non-formal statistical methods that involve direct Monte Carlo simulations. Following that approach, the entire parameter space is explored by running the model simulations for a large number of parameter combinations and evaluating the model response using some chosen goodness of fit criterion (Beven, 2007). In this method the idea of an optimal system representation is rejected and the equifinality concept is accepted for the behavioural parameter sets.

15   Following that approach, the parameter space is sampled over the whole feasible range and the errors between simulated model results and observations are used to derive the parameter weighting. In this study we apply the version of GLUE that uses the behavioural parameter sets, defined by a threshold value of the selected criterion (Beven, 2009). The behavioural thresholds for both criteria are selected following the model performance in the validation period. The choice of high threshold values results in narrow confidence limits of the predictions and (usually) a small behavioural parameter

20   set. However, when the chosen threshold is too high, the 0.95 confidence limits do not include 95% of the observations. On the other hand, too low a threshold value will result in too wide confidence limits. Therefore it is important to choose the right threshold value. In this work the threshold values are chosen in an iterative way.

3.5 GEV distribution (Generalized Extreme Value Distribution)

The GEV distribution is a family of continuous probability distributions that combines theWeibull, Gumbel (EV1) and

25   Frechet distributions (Cunnane, 1989). GEV makes use of three parameters: scale, location and shape. The scale parameter describes how spread out the distribution is, and defines where the mass of the distribution lies. The distribution will become more spread out as the scale parameter increases. The location parameter describes the swing of a distribution in a given direction on the horizontal axis. The third parameter in the GEV family is the shape parameter, which strictly affects the shape of the distribution, and governs the tail of a distribution. The GEV density function has the form:

$$G(x) = \exp\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}\} \tag{3}$$

Where: σ, μ and ξ are called the scale, location and shape parameters, respectively. The shape parameter is derived from skewness, as it represents where the majority of the data lies, which creates the tail of a distribution.

A distribution with a large number of flexible parameters, such as GEV, will be able to model the input data more

5 accurately than a distribution with a small number of parameters.

In this study we use GEV distribution to perform frequency analyses for both annual maximum flow and annual minimum flow projections. The choice of this distribution was dictated by its overall good performance during the frequency analysis of the observed annual maximum and minimum flows for the BialaTarnowska. In addition, GEV parameters can be estimated together with the 0.95 confidence interval which allows the uncertainty that comes from the

10 distribution fitting to be assessed.

3.6 Sensitivity analysis using ANOVA: variance decomposition

A sensitivity analysis can be performed using regression- or variance- based techniques. Regression based techniques use a regression model of the output on the input vector and variance based techniques decompose the variance of the output as an aggregation of contributions of each input variable/components. The most popular variance based techniques are

15 called ANOVA (ANalysis Of VAriance). To identify the relative contribution of each source of uncertainty (corresponding to the parameter sets (P_{AR}), climate models (C_M) and parameter distribution sets (D_{IS})) from the aggregated speared of flow quantile change in the near and far future we use the following ANOVA model:

$$T_{SSijk} = \mu + P_{ARi} + C_{Mj} + D_{ISk} + (P_{AR} + C_M)_{ij} + (P_{AR} + D_{IS})_{ik} + (C_M + D_{IS})_{jk} + \varepsilon_{ijk} \tag{4}$$

Where: T_{SSijk} is total sum squere error for the specific hydrological extreme indicator (e.g. relative change in Q30) for the

20 i^{th} parameter sets range, j^{th} climate model and k^{th} distribution parameter range and μ is the overall mean and ε_{ijk} denotes the white Gaussian error.

3.7 Results

We present here an assessment of the uncertainty in projected hydrological extremes for two different temporal resolutions. Firstly, the annual maximum and minimum flow quantiles are derived for 30-year periods, the so-called near future (2021-

25 2050), and far-future (2071-2100) and are compared with the reference period (1971-2000). Secondly, a frequency analysis of annual maximum and minimum flows is performed based on the whole 130 years of seven GCM/RCM projections for the period 1971-2100.

20000 uniform samples of HBV model parameters were obtained with parameter ranges presented in Table 2. The parameter ranges were chosen following the results of deterministic optimisation performed earlier and reported by

30 Romanowicz et al. (2016) and they include the derived optimal values. The range of parameter variability was chosen

following the HBV model sensitivity studies reported by Osuch (2015). As discussed earlier, we focus on three sources of uncertainty, the first related to the HBV model input, in the form of ensemble projections of temperature and precipitation, the second, related to hydrological model parameter uncertainty and the third related to the distribution fitting uncertainty. In a result we obtained 20000 daily flow simulations 130 years long for raw and bi-as corrected climate model projections

5   for an ensemble of seven GCM/RCMs listed in Table 1. This gives all together 280000 flow time-series.

4 Discussion

4.1 Variability of projected precipitation and temperature series

In the following section we present an analysis of variability of maximum precipitation and temperature series on annual basis. In Fig. 2, raw annual maximum daily precipitation and temperature time series for the BialaTarnowska catchment

10   obtained from the seven GCM/RCM models under the RCP4.5 scenario are shown. The periods cover the whole length of historical and projected years (1971-2100). The results show a visible increase of the annual maximum temperature trend and an increase of temporal variability with time, in particular for the maximum precipitation values from 2016 onward.

4.2 Calibration and validation of hydrological model: GLUE analysis

Following the discussion presented in section 3.3, we applied different criteria for high and low flow indices. The threshold

15   value of a goodness of fit criterion determining the GLUE-based behavioural model parameter set for high flow indices was selected at 0.55 of the NSE (Table 3). The threshold value was selected to assure that 95% of observations lay within the 0.95 confidence bands. The sample size of this behavioural set is 8616. The maximum Nash-Sutcliffe efficiency (NSE) values over the calibration and validation periods are 0.79 and 0.75, respectively. The low-flow model parameter set was selected using the NSE of log-transformed flow values with the threshold set at 0.3 and the obtained sample size is 1625

20   (Table 3). This part of the analysis is performed using the observations of precipitation and temperature from the BialaTarnowska catchment and observed flows from the Koszyce gauging station for the period 1971-2000 for the calibration and 2001-2010 for the validation stage.

   Fig. 3 shows the cumulative density functions (cdf) of observed daily hydrographs for the calibration and validation periods,as well as the cdf of flow estimates generated from the posterior distribution of the HBV parameters. The upper

25   panel presents cdf of model predictions conditioned on the NSE, while the lower panel presents the cdf of predictions conditioned on the logNSE criterion. Also shown are the 0.95 confidence bands in the form of dashed lines. These confidence bands are much narrower for the NSElog weights than for the NSE conditioning. This indicates the strong influence of low flow predictions on the HBV model performance. Moreover, the shape of the cdfs suggests that the logarithmic transformation of flows gives a superior match of simulations to the observations in comparison with the NSE

30   criterion.

4.3 Temporal variability of projected hydrological extremes

In Fig. 4, bias corrected annual extreme time series of projected flow (the annual maximum and the 10-year moving average from the ensemble mean) for the River BialaTarnowska at Koszyce are shown. Results shown in Fig. 4 were obtained from the HBV model simulations fed by the precipitation and temperature projections obtained from the seven GCM/RCM

5   models under the RCP4.5 scenario for the best parameter sets from the MC samples. Bias corrected temperature and precipitation series were used for low flow projections while the maximum flow projections were obtained from raw input data. Obtained flow projections follow the rainfall patterns shown in Fig. 2, with extreme flow values twice as large as historical extremes, occurring after 2016 for some of the GCM/RCM model projections. The upper panel of Fig. 4 presents annual maximum flows, while the annual minimum flows are presented in the lower panel. These time series cover the

10 whole length of the reference and projected years simulated (1971-2100) in an attempt to identify general variabilities in the high and low flows.

4.4 Evaluation of uncertainty in seasonal flow

We analysed monthly maximum and minimum daily flows for the raw and bias corrected climate projections in the far-future (2071-2100) and estimated their uncertainty related to hydrological model parameters. The results of the estimated

15 median together with 0.95 confidence limits for each month and each GCM/RCMs realization are shown in Fig. 5a for maximum flows and in Fig. 5a for minimum flows. The comparison with the spread of minimum and maximum monthly flows in the reference period presented in Fig. 5 shows differences between the GCM/RCMs models in their depiction of future changes.

The annual maximum flows have a wider range for the first three climate models in April, May, June months

20 whilst for the remaining four climate models the range looks similar for all months. Particularly, in all climate models small range were observed in December, January and February months, similarly as in the reference period. However in five out of seven GCM/RCM model realizations May seems to have the highest flows in the year.

4.5 Changes in extreme flow quantiles (30-year periods) due to the climate model spread

The quantiles of the future annual maximum and minimum flow projections for the 30-year periods, including the reference

25 period 1971-2000, the near-future period 2021-2050 and the far-future period 2071-2100 are shown in Fig. 6. These results present the empirical frequency curves obtained for the best performing hydrological model parameter set for seven climate models listed in Table1, neglecting the hydrological model parameter uncertainty. The comparison of the mean return periods obtained for the near- and far-future with the mean in the reference period illustrates the predicted changes in quantiles. Substantial decreases in minimum flow and increases in extremely high flows for both future periods (2021-

30 2050 and 2071-2100) can be observed. In the case of maximum annual flow, the reference quantile curves are always lower than those from the climate model ensemble medians, implying increases in both frequency and magnitude of annual

maximum flows. If we treat the median as a deterministic value, the maximum river flow occurring once every 15 years is projected to increase from 462.87 to 615.06 m^3s^{-1} (in the near future) and 462.87 to 582.7 m^3s^{-1} (in the far-future). In a similar manner, the magnitude and frequency of annual minimum flows decrease in the future. For example, the occurrence of minimum flow ones in every years is changing from 1.19 m^3s^{-1} to 1.29 m^3s^{-1} in the near future period.

5   The results for high flow extremes are consistent with those published by Osuch et al., (2016), which is not surprising when we note that the same GCM/RCM projections were used for the study catchment. The annual minimum flows increase in the future, which is also consistent with the results published by Meresa et al., (2016).We note that the uncertainty of the projected median values related to the climate model spread exceeds 100% (600 m^3s^{-1}) of the projected values for the Q30 in the near future. The spread of return period projections of Q30 of annual maximum flows decreases

10   in the far-future to 500 m^3s^{-1}. Similarly, also the low flow Q30 show smaller spread for the far future period.

4.6 Evaluation of combined uncertainty in extreme flow quantiles for 30 and 130 year periods

The empirical frequency curves do not allow the extrapolation of a return period beyond the available number of simulation years to be performed and instead theoretical distributions fitted to the data are applied. In addition, quantiles are nonlinearly dependent on flow extremes and the averaging the best hydrological projections is not equivalent to averaging

15   over the whole set of realizations resulting from the behavioural parameter sets. The results of fitting the GEV distribution to annual maximum and minimum flow (Fig.7 right panel) for 30 year periods, including the reference period (1971-2000), the near-future period (2021-2050) and the far-future period (2071-2100) are presented in Fig. 7. The light green and light red areas in Fig 7 present the uncertainty arising from the combined effect of the hydrological model parameter uncertainty, ensemble spread and uncertainty related to the GEV fitting, respectively for the maximum annual flow (Fig.7 left panel)

20   and the minimum annual flow (Fig.7 right panel). The quantiles of annual maximum flow show significant spread among the fitted GEV distributions, which is more pronounced for higher recurrence intervals whilst the quantiles of minimum annual flow are spread evenly.

     The uncertainties originating in the climate models and the hydrological model parameters were calculated using a range of the differences between the 0.95 upper confidence bands and 0.05 lower confidence bands as a measure of the

25   uncertainty in the ensemble projections that were made using multiple GCM/RCMs, distribution parameter sets (FFA) and hydrological model behavioral parameter sets. When comparing the total uncertainties, it becomes clear that uncertainties from climate projections, hydrologic model parameter and distribution parameter sets cannot be independently assessed to generate reliable predictive bounds for the estimates of hydrologic extremes and their characteristics.

     Figure 8 presents frequency analysis results of annual maximum (left panel) and minimum flows (right panel), based

30   on the 130 years (1971-2100) of simulations of the HBV model. Each colour of shading represents the contribution of a different uncertainty source. The green colour denotes the hydrological model uncertainty, blue corresponds to climate model spread and pink colour describes the GEV distribution fit error. This kind of analysis does not illustrate the

interactions between different sources of uncertainty. Generally, the uncertainty from climate models is larger than the other two for the annual maximum flow. On the other hand, for the annual minimum flow hydrological model parameter uncertainty contributes more than the other two sources to the uncertainty of the minimum flow frequency and occurrences (Fig. 8).

5   The uncertainties of quantiles of annual maximum flow due to total uncertainty accounted for (climate models, parameter sets, distribution fitting parameter sets) for the 30 year (Fig. 7) and 130 year (Fig.8) periods show significant differences. Table 3 gives a summary of confidence interval ranges obtained for the Q30 based on different time periods. In general, the Q30 estimated using the 30 year period is characterized by a much larger confidence interval compared to the Q30 estimated using the 130 year long period. The differences in the width of confidence intervals vary from about

10   200 m^3s^{-1} for the reference period to 1500 m^3s^{-1} for the near future period (2021-2050) compared to the 130 year period Q30 estimates. Due to the extrapolation errors, that difference will increase substantially for the Q100 index, thus questioning the usefulness of those estimates.

     The differences obtained for the annual minimum flow Q30 estimates are smaller, suggesting that low flow quantiles are less susceptible to the errors related to the length of the evaluation period.

15   **4.7 Variance decomposition of quantile Q30 values**

Fig. 9 shows results of an application of ANOVA variance decomposition technique to the percentage change of Q30 quantiles derived for the near-future period 2012-2050 relative to the reference period 1971-2000 for high (left panel) and low flows (right panel). The analysis was performed on the flow simulation sets including all three sources of uncertainty and conditioned by the NSE weights for high flow quantiles and logNSE weights for low quantiles.

20   The sensitivity analysis presented in Fig. 9 confirms our earlier results on the major influence of the climate model spread on the total Q30 variability for high flows and supreme influence of hydrological model parameters on the variability of low flow Q30. There is also seen a difference in the influence of distribution fit uncertainty, which is much larger for low flow Q30 variability than for high flow. The sensitivity analysis also confirms the inter-dependence of different sources of uncertainty, visible mainly for high-flow extremes.

25   **5. Conclusions**

The impact of climate change on hydrological extremes has been widely studied, particularly after the publication of the IPCC AR4 report in 2007. The methodology applied to derive hydrological extremes under climate change adopted by most scientists consists of running a cascade of models, starting from assumed emission scenarios applied to a global circulation model (GCM) and ending at hydrological model simulations. Therefore, the projected hydro-meteorological

30   extremes are highly uncertain due to uncertainties inherent in all the links of the modelling chain. In addition, due to the

complexity of hydrological models that use a large number of parameters to characterize hydrologic processes, many challenges arise with respect to quantification of uncertainty.

An assessment of the uncertainty of extreme hydrological indices was the main aim of this study. We evaluated three different sources of uncertainty in the projections of both high and low flow extremes for the 21st century. These included climate model, hydrological parameter sets and distribution-fit uncertainty. The River BialaTarnowska at Koszyce gauging station was used as a case study. This case study supports our ultimate goal of estimating uncertainty in projections of hydrological extremes originating from three sources mentioned above. Different catchment characteristics can result in different relative proportions of different sources of uncertainty in total variance of the output (Osuch et al., 2016). The hydrological model uncertainties were estimated using the GLUE technique. The other sources of uncertainty were quantified by their spread, as conditioning on observations was not possible for the future flow projections. The uncertainties in extreme maximum and extreme minimum indices behave differently. In extreme high flow, larger uncertainty is observed from the climate model (ensemble) spread than from the other sources. On the other hand, for low flows, the uncertainty related to hydrological model parameters has a larger impact than the other uncertainty sources studied. This implies that ignoring one of the three uncertainty sources may cause great risk to future hydrological extreme adaptations and water resource planning and management. Steinschneider et al. (2012) used the formal statistical approach to quantify uncertainty quantiles of monthly flow projections including climate, hydrological model parameter and distribution fit uncertainties. We show that an application of much simpler, non-formal statistical approach leads to consistent with the latter work conclusions also for projections of daily annual extreme low and high flow indices.

The results of the research can be summarized in the following points: (i) the bias correction using distribution-based approach has a large influence on projected peak flows (Osuch et al., 2016); therefore the analysis of changes in high quantiles of maximum annual flow projections was based on the raw data. (ii) on the other hand, the analysis of low flow projections was based on the bias-corrected data to avoid the drizzle. (iii) conditioning of the hydrological model was performed using different criteria for low and high flows in order to ensure the best model fit for the extremes; in addition this allows the problem of nonstationarity of model parameters to be avoided. (iv) the uncertainty related to hydrological model parameters is larger than the spread of projections related to the different GCM/RCM models and to the uncertainty of distribution fit for low flows; for high flows the climate model spread is larger than hydrological model uncertainty, whilst the uncertainty due to the distribution fit is the smallest. (v) Sensitivity using ANOVA performed on the relative uncertainty for high and low Q30 quantiles confirms the conclusions obtained from point (iv) on the larger influence of hydrological model uncertainty on extremes for low flow than for high flow. (vi) analysis of the influence of length of records on the uncertainty bands of the low and high flow quantile estimates and their changes suggests that quantiles of return periods longer than the length of records used for their derivation are very uncertain.

The last point draws an attention to the problem of stationarity of future climate projections and the resulting projections of annual flow extremes. This issue will be addressed in a further paper on trend analysis of projections of extreme flow indices (Meresa et al., 2017).

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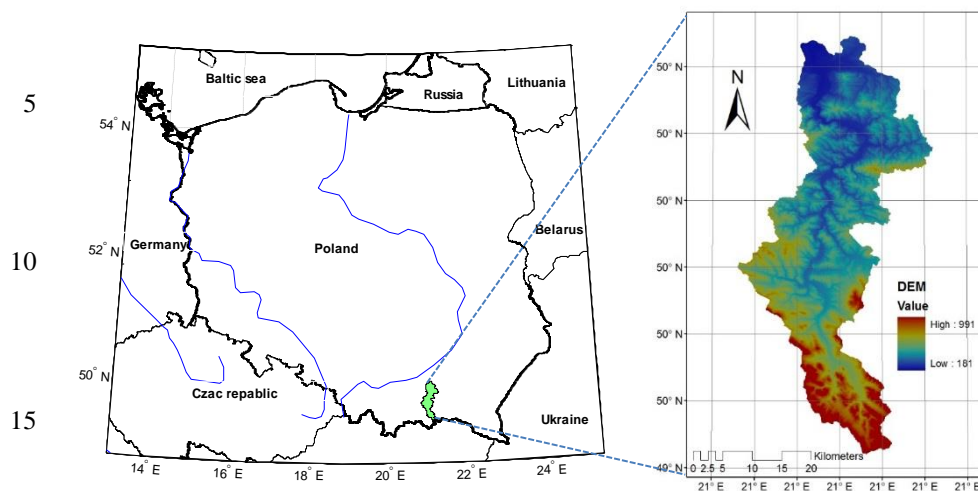
**Figure 1.** The location of the study catchment.
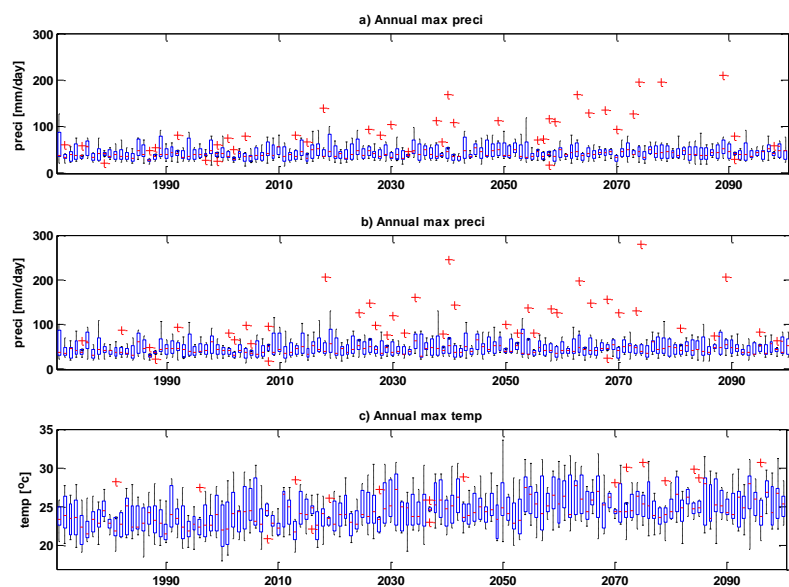
20 **Figure 2.** Upper panel: projected raw annual maximum daily precipitation; middle panel: projected corrected annual maximum daily precipitation; lower panel: projected raw annual maximum daily temperature for the BialaTarnowska catchment in the 1971-2100 period based on seven climate models (CMs) from the GCMs/RCMs ensemble; boxes show interquartile range; whiskers show 5th and 95th percentiles.
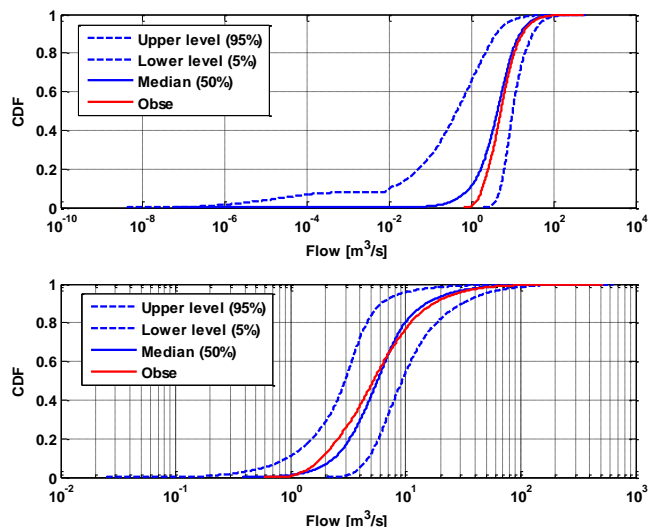
Figure 3. cdf of flow for the calibration period for the HBV model; the upper panel presents model predictions conditioned on the NSE, while the lower panel presents the predictions conditioned on the logNSE criterion. The cdf of observations (red line) is shown against the cdf of the HBV prediction (blue line) and the associated 95% confidence bounds (dashed line).
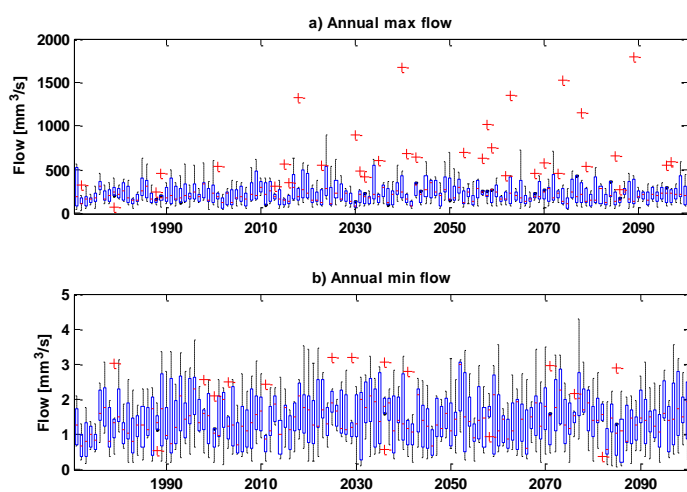
Figure 4. Upper panel: projected, annual maximum daily flow; lower panel: projected annual minimum daily flow for the BialaTarnowska catchment in 1971-2100 based on seven climate models (CMs) from the GCMs/RCMs ensemble; red line shows an ensemble mean for the 1971-2100 period.
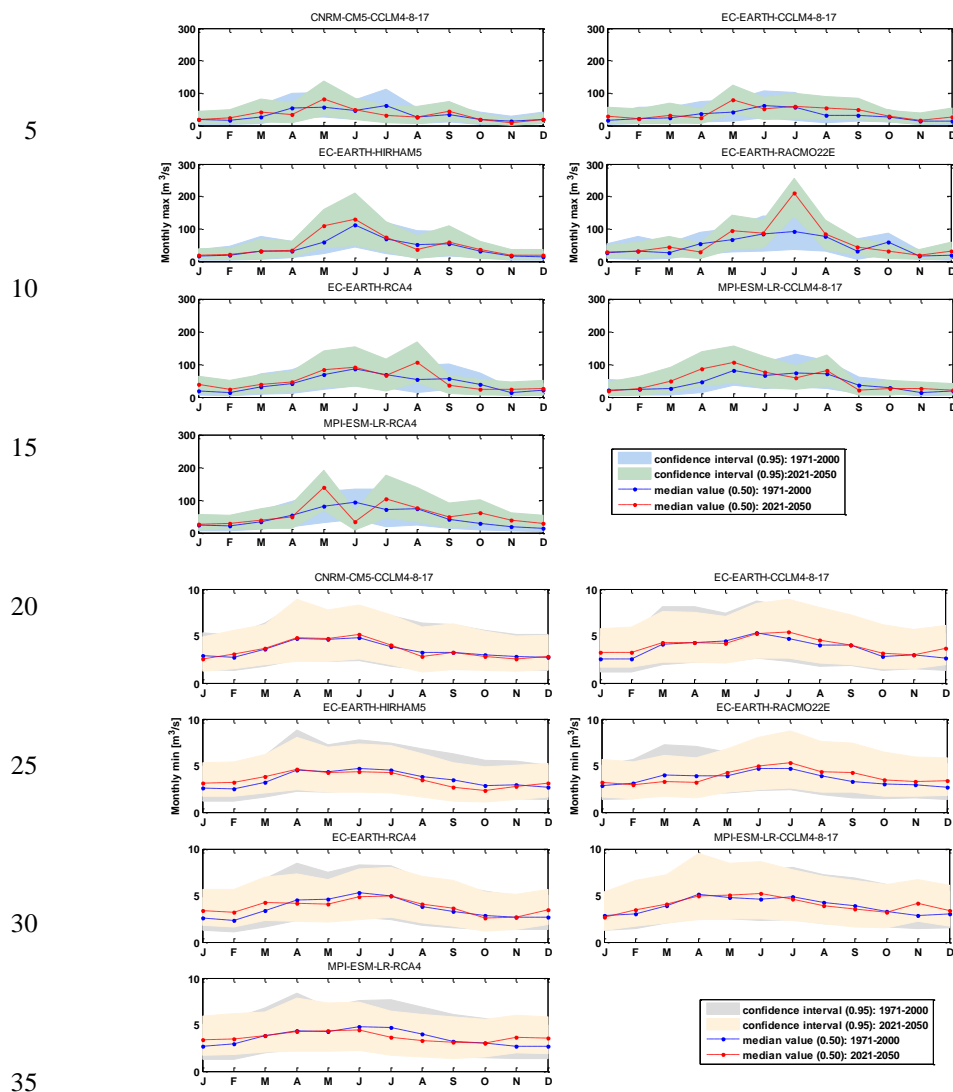
Figure 5. (a) Parameter uncertainty intervals for monthly maximum flow for seven climate models for the period 2071-2100 (the blue and green shaded figure- upper seven panel figs.); (b) parameter uncertainty intervals for monthly minimum flow for seven climate models for the period 2071-2100(the gray and reddish shaded figure- lower seven panel figs.); Koszyce gauging station, the River BialaTarnowska.
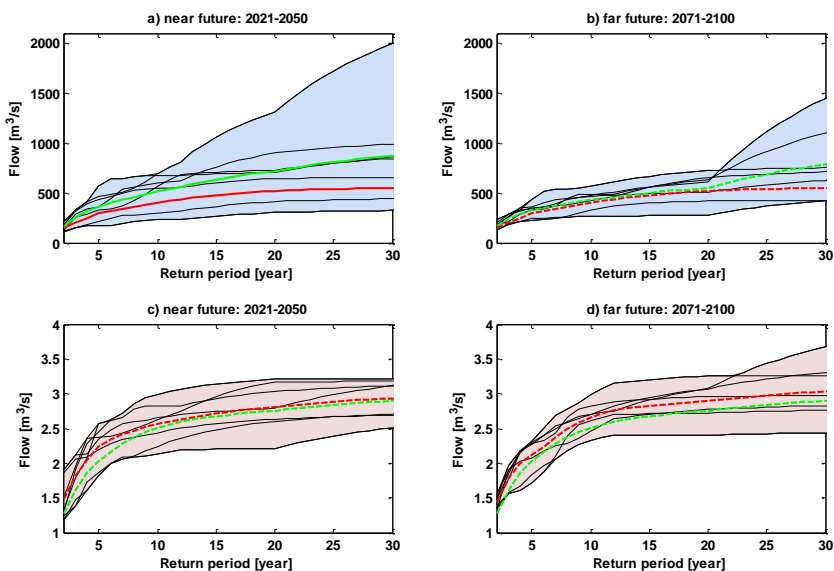
Figure 6. Empirical flow quantiles of annual maximum flow (upper panels) and annual minimum flow (lower panels) under baseline and future climates (near and far future periods); the climate model spread is presented as a shaded area; red line denotes the mean value from all the GCM/RCM model realizations, green line denotes the averaged results obtained for the reference period.

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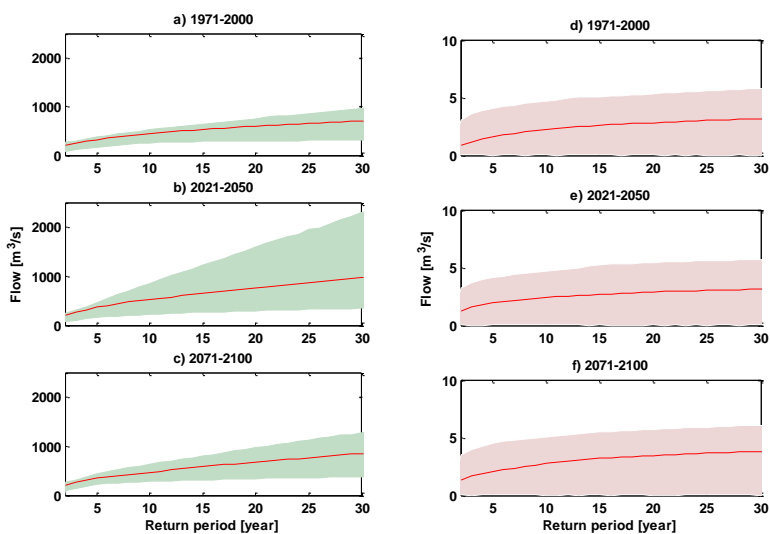
Figure 7. Total uncertainty ranges of flow quantiles over 30 year periods of the BialaTarnowska at Koszyce; upper panels - for the reference period (1971-2000); middle panels - near future (2021-2050); lower panels - far future (2071-2100) periods; right hand panels
10   show maximum annual flow, right hand panels present the annual minimum flow frequency analysis results.
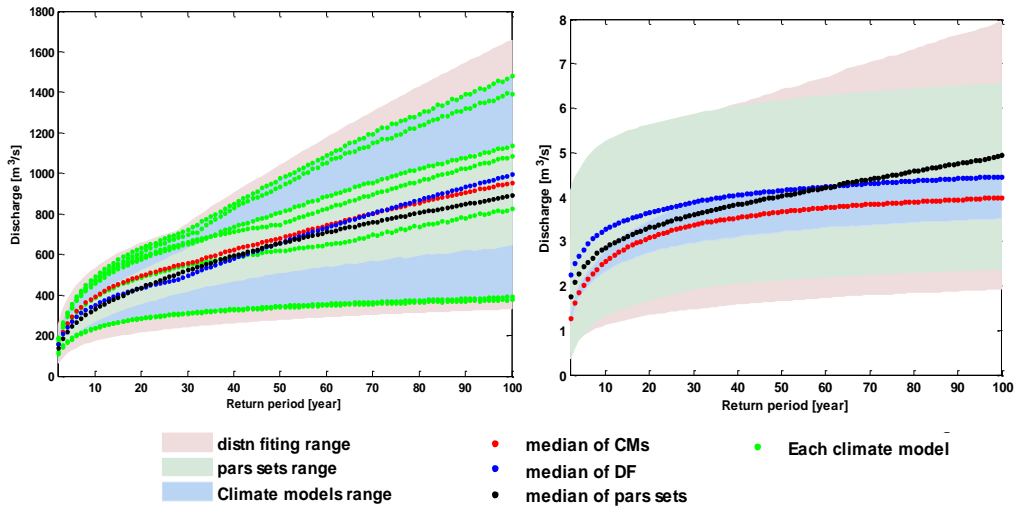
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Figure 8. Total uncertainty ranges of flow quantiles over 130 years period, annual minimum flow as a function of return level (right panel) and annual minimum flow as a function of return level (left panel panel) of simulated for the River BialaTarnowska at Koszyce, based on a GEV distribution fit to the projected annual flow (1971-2100).

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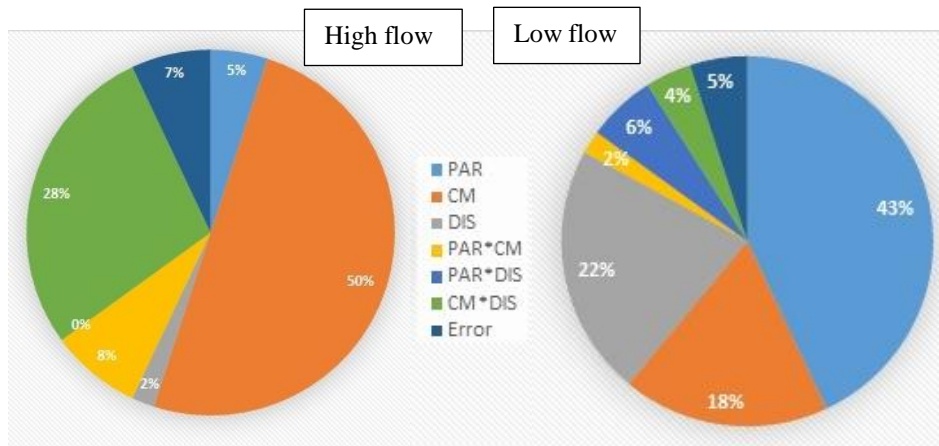
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Figure 9. Total variance in estimates for the percentage change in Q30 in 2021-2050 relative to the 1971-2000 reference period. Each color represents the relative contribution of uncertainty in percent.

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Discussions

Table 1. List of RCM/GCMs used in this study

GCM	RCM	expansion name	Institute
EC-EARTH	RCA	Rossby Center regional	Swedish Meteorological and Hydrological Institute
EC-EARTH	HIRHAM	Atmospheric model	Danish Meteorological Institute
EC-EARTH	CCLM	Community land model	NCAR UCAR
EC-EARTH	RACMO	Regional atmospheric climate model	Meteorological institute
MPI	CCLM	Community land model	Max Planck Institute for Meteorology
MPI	REMO	Regional-scale model	Max Planck Institute for Meteorology
CNRM	CCLM	Community land model	CERFACS, France

5

10   Table 2. HBV parameter ranges Parameter description LB UB Optimal Unit

Parameter	description	LB	UB	Optimal	Unit
FC	maximum soil storage	0.1	250	100	mm
BETA	Shape coefficient	0.01	6	7	-
LP	SM threshold for reduction of evaporation	0.1	2	1	-
ALFA	measure for non-linearity of flow in quick runoff	0.2255	0.2255	3	-
KF	recession coefficient for runoff from quick runoff	0.2826	0.2826	0.3	$1/ d^{-1}$
KS	recession coefficient for runoff from base flow	0.0005	0.3	0.3	$1/ d^{-1}$
PERC	constant percolation rate occurring when water is available	0.01	4	100	$mm\ d^{-1}$
CFLUX	Rate of capillary rise	1.0003	1.003	100	$mm\ d^{-1}$
TT	Threshold temperature for snowfall	1.0145	1.0145	3	^0C
TTI	Threshold temperature interval length	7	7	7	^0C
CFMAX	Degree day factor, rate of snowmelt	0	3	20	$mm\ ^0C^{-1}\ d^{-1}$
FOCFMAX		0.1484	0.1484	1	
CFR	Refreezing factor	0.2779	0.2779	1	-
WHC	Water holding capacity of snow	0.001	0.001	0.8	$mm\ mm^{-1}$

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Table 3. Choice of the likelihood threshold for the NSE and the logNSE criterion

Number of experiment	1	2	3	4	5	6	7	8	9
Threshold NSE	0.50	0.53	0.55	0.57	0.60	0.63	0.65	0.67	0.70
% out of bound NSE	10.0	9.90	9.60	9.80	9.90	10.0	10.0	10.5	11.0
Threshold logNSE	0.40	0.37	0.34	0.31	0.30	0.29	0.26	0.23	0.20
% out of bound logNSE	15.0	12.3	12.0	13.5	11.4	17.4	17.8	18.0	20.0

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Table 4. Change in width of 0.95 confidence intervals for Q30 based on annual maxima from different time periods.

Flow [m3/s]	1971-2000	2021-2050	2071-2100	1971-2100
Max flow(ΔQ30)	640.45	1942.56	898.93	459.35
Min flow(ΔQ30)	4.70	5.00	5.20	4.40