Dear Editor and Reviewers,

Thank you very much for the constructive comments that helped to considerably improve and clarify the manuscript. The reviewers, put enormous effort into proof-reading our paper line by line and trying to clarify all the less-than-satisfactory statements and mistakes. We believe that the input will improve the manuscript significantly. All comments have been addressed point-by-point. Following the reviewers' feedback we will make the corresponding changes in the manuscript.

Anonymous Referee #1

RC1. General comments

This paper is about the uncertainty of extreme flows with climate change. For that purpose, the authors use seven combinations of global climate models (GCMs) and regional climate models (RCMs) with one greenhouse gas concentration scenario to represent uncertainty in climate change. Furthermore, they use the GLUE method to represent hydrological parameter uncertainty and uncertainty in extreme value distribution parameters to represent the uncertainty in the statistical extreme value distribution. These three sources of uncertainty are investigated using the HBV hydrological model applied to a medium-sized Polish catchment. Although the topic is interesting and relevant for this journal, the paper is moderately written, lacks clarity in parts of the methodology and only briefly discusses results and insufficiently puts outcomes into perspective. For instance, the seemingly arbitrary choice to consider the three uncertainty sources is not justified. Are these three sources the most important ones or the easiest ones to quantify? Furthermore, the uncertainty due to the use of a particular extreme value distribution is not clearly and completely incorporated. A final example is the presentation and analysis of results, such as the analysis of annual maximum precipitation and temperature in relation with annual maximum flows and in particular annual minimum flows. In this case and several other cases it is not always clear which results are shown, why they are shown and what can be concluded from the results. Many other specific (and important) comments can be found below. Furthermore, the English writing style and grammar is moderate (including several typos); some examples can be found in the section 'technical corrections'.

AC1. General answer

Following the reviewer's general and specific comments, the clarity of the methodology will be improved and the outcomes will be described in a wider perspective.

The choice of three particular sources of uncertainty, namely, a set of climate model ensembles, hydrological model parameter uncertainty and uncertainty in fitting extreme value distribution, was dictated by one of the aims of the research – i.e. an assessment of influence of hydrological model uncertainty on projections of low- and high-flow extremes and the relative contribution of that "predictive" uncertainty in the spread of extreme indices related to the climatic model spread and the distribution fitting error.

This choice followed from a discussion on all the sources of uncertainties and a review of research done so far on the assessment of uncertainty of projections of hydrological extremes. The "predictive" model uncertainty is the only one which can be decreased when conditioned on the observations. The other sources of uncertainty have an "epistemic" nature and cannot be decreased. Bearing in mind the aims of the study, we restricted the sources of epistemic uncertainty to those which have the largest impact – i.e. climate model spread, omitting the uncertainty related to bias correction or geography. The error related to the distribution fit was included as an essential part of the extreme index evaluation, which requires extrapolation of annual maximum or minimum flow distributions to higher order quantiles (e.g. 1-in-100 year, or 1-in-200 year). In this paper, the error related to the evaluation of maximum and minimum annual flow statistic was treated as epistemic, that means, not conditioned on real observations.

In addition, Osuch et al. (2016) presented the influence of emission scenario, climate model, bias correction method and geography on flow indices in a case study that included the same catchment, Biala Tarnowska. Therefore we wanted to avoid the repetition. In this regard, our paper is an extension of the former paper, focusing on the influence of hydrologic model uncertainty on annual maximum and minimum flow projections. In our opinion, including the other sources of uncertainty would obscure our aim.

The choice of extreme value distribution followed the validation of suitability of this distribution to describe the projected annual maximum and minimum flows using the probability plots. The MATLAB- based GEV distribution fitting algorithm was applied to all the climate models and the a posteriori hydrological model parameter set. This algorithm provides the estimates of 0.95 confidence bands for the distribution parameters. These parameters were subsequently used to obtain upper and lower confidence bands of the distribution through the inverse GEV model. In order to simplify the procedure, instead of sampling from the GEV parameters within the parameter space common to all hydrologic and climate model simulations, we sampled from each set of parameters assuming a normal distribution with the variance specified by the parameter upper and lower 0.95 confidence value, and in addition, assuming the independence of the GEV model parameters. The obtained 0.95 GEV distribution confidence values were used to estimate the spread of results related to the distribution fit.

Bearing in mind the large number of simulations, it was not possible to choose the best distribution for each projected time series. Furthermore, the aim of this study is to assess the ranges of uncertainty of extreme indices rather than their exact values.

RC2. A final example is the presentation and analysis of results, such as the analysis of annual maximum precipitation and temperature in relation with annual maximum flows and in particular annual minimum flows. In this case and several other cases it is not always clear which results are shown, why they are shown and what can be concluded from the results.

AC2. We agree with the reviewer that the presentation should be much improved and clarified. The following explanation will be added.

In the following section, we present an analysis of the variability of maximum precipitation and temperature series on an annual basis to see the correlation between the projected hydrological extremes and the input climate extremes. In Fig. 2, raw annual maximum daily precipitation and temperature time series for the Biala Tarnowska catchment 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 upper panel of Fig. 2 presents annual minimum precipitation based on corrected precipitation projections (the upper panel), annual maximum precipitation based on raw projections (middle panel) and temperature mean projections for corrected data are presented in the lower panel of Fig. 2.

The results show a visible increase of the annual maximum temperature and an increase of temporal variability with time, in particular for the maximum precipitation values from 2016 onward.

The English and grammar was, and will be, checked by a native English speaker.

Specific comments

RC1. P1, L7-9: *It is not clear what is meant with a 'multi-model approach' and which steps are followed.*

AC1. The 'multi-model approach' is an approach which considers multiple climate models and multiple hydrological parameter sets. To avoid possible confusion this wording will be changed: "The approach followed is based on …."

RC2. P2, L9-11: *The first question probably is related to the magnitude of the uncertainty, since this is still largely unknown and not systematically investigated.*

AC2. The sentence will be changed to:
The question arises as to how large the uncertainty is and if it is acceptable to the end-user in adaptations to climate change and flood and drought risk assessments.

RC 3. P2, L15-16: "*….can never be accurately evaluated ….*" *is a very strong statement, please rephrase.*

AC3. The sentence will be rephrased to: "However, complex hydrological and climate models are difficult to be accurately evaluated, because of uncertainty in observations, parameters and model structure simplifications."

RC 4. P2, L24-P3, L2: *The authors mainly consider hydrological model and parameter uncertainty in their review. It might be worthwhile to firstly give an overview of all uncertainties involved in this type of studies including a classification. One such classification could be input, (hydrological) model system and output, and the literature can be reviewed accordingly. Now, uncertainties in the input (scenarios, GCMs, RCMs, downscaling, initial conditions etc.) are* *hardly reviewed. A complete overview of the uncertainties will also enable a better justification of the uncertainty sources considered in this study (see also page 3, lines 4-5).*

AC 4. As already discussed, the influence of other sources of uncertainty, including the choice of emission scenario, climate models (GCM/RCMs), downscaling and catchment type was performed by Osuch et al (2016) using a case study that included the catchment used in this paper. This paper was focused on predictive hydrological uncertainty to show that different objective functions should be applied when high and low flow extremes are considered. Apart from hydrological model parameters, seven climate models were also used and the spread relating to extreme index distribution was taken into account. However, the reviewer made the important point that our aims were not clearly enough presented and that the review of different sources of uncertainty would help to improve the presentation of that aim considerably. This part of the paper will be changed to justify better the choice of those three sources of uncertainty.

RC 5. P3, L14-15: *The question is whether you can determine the uncertainty due to the choice of the extreme value distribution ('distribution fit') using time series of different lengths. When assessing effects of time series with different lengths on the results you might get an estimate of the influence of data quantity on the uncertainty in the results, but not of the influence of the goodness-of-fit of the distribution on the uncertainty. Furthermore, it seems only part of the statistical uncertainty is assessed in this way, since for instance the influence of different extreme value distributions and extrapolation uncertainty is not taken into account.*

AC 5. Thanks to the reviewer, it is good point. However, we did not use different lengths of time series in order to determine the uncertainty due to the choice of the extreme value distribution. The sentence was misunderstood. In order to make our presentation more clear the sentence should read as follows:

The uncertainty related to the distribution fit is analysed in two stages, using, separately, two different lengths of flow record to derive the quantiles of maximum and minimum annual flows, the 30-year long and 130-year long time series of future flow projections. 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. It is well known that an extrapolation of a distribution function based on 30-year long time series towards 1-in-100 year quantiles involves very large errors (Strupczewski et al. 2011). Even the estimates of 1-in-30 year quantiles based on the 30-year long data are biased with large errors. We compare these errors with those involved on 1-in-100 year estimates obtained using the 130 year long time series. 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.

RC 6. P3, L29-30: *How many precipitation stations have been used to assess the catchment average precipitation (assuming lumped hydrological modelling has been carried out)? Has any elevation (or other) correction been incorporated?*

AC 7. We used five gauging stations to derive aerial precipitation in the catchment using Thiessen polygons. We did not use any elevation correction in this paper. However it was applied to the same catchment by Benninga et al (2016) and showed that the increase in precipitation due to the elevation is about 3%.

RC 7. P4, L11: *An important uncertainty source in climate impact studies is the uncertainty due to greenhouse gas emission scenarios. Hence, a limitation of this study is the use of only one emission scenario (RCP4.5) while one would expect the use of at least two scenarios (which are available in EURO-CORDEX). At least the authors should explain the implications of this limitation for their results.*

AC 7. The RCP 4.5 was applied because it is a stabilization scenario and thus assumes the imposition of emissions mitigation policies. The RCP 4.5 is derived from its own "reference", or "no-climate-policy", scenario. This reference scenario is unique to RCP 4.5 and differs from RCP 8.5, RCP 6.0 and RCP 2.6 (Smith and Wigley 2006; Clarke et al. 2007; Wise et al. 2009). The influence of the emission scenario on flood indices was studied by Osuch et al. (2016) whilst the low flows were analysed by Osuch et al (2017). Both those studies indicated that emission scenario choice has a relatively small influence on the results. The implication of the choice of only one emission scenario will be explained in the revision.

RC 8. P5, L9: *Why is QM applied in this study? The reasoning behind this choice is not completely clear from the preceding sentences.*

AC 8. Many popular existing bias correction methods have been reviewed and compared and quantile mapping (QM) was found to outperform other methods (Gudmundsson et al., 2012; Teutschbein and Seibert, 2013; Chen et al., 2013; Osuch et al., 2016). More recently, the standard non-parametric QM method has been adapted to more explicitly preserve the raw modelled climate change signals (Willems and Vrac, 2011; Sunyer et al., 2014; Cannon et al., 2015). This means, in the QM method, that a raw modelled value is always corrected by the same value of bias or error that is determined by its respective quantile in the reference period.

RC 9. P5, L18-19: *Did Osuch et al. (2015) model the same catchment as in this study and therefore, can it be assumed that the same five parameters are sensitive? And are the same five parameters sensitive for low flows and for high flows? That would be remarkable.*

AC9. The HBV model was applied in different hydro-climatic condition in Poland by different researchers and they found the five most sensitive parameters for both high flow and low flow characteristics. The set of five parameters chosen in this study was dictated by the most common catchment conditions. Therefore it is not surprising that the same parameters are sensitive in both high and low flow conditions. However, in this study we used two objective functions to encapsulate the high and low flow characteristics instead of selected best parameters only belonging to low flow and high flow.

RC10. P6, L15-16: *How many Monte Carlo simulations have been executed and is this number sufficient (compare with literature)?*

AC 10. 20000 MC simulations were executed. Many research papers recommend above 10, 000 MC (e.g. Xiaoli Jin et al., 2010; Romanowicz et al., 2013; Houska T. et al., 2014).

RC 11. P6, L22: *Is it common practice to determine the thresholds in an iterative way? The determination of the threshold based on the requirement that 95% of the observations should be in the 95% confidence interval seems to be reasonable. However, please refer to other studies employing the same approach.*

AC 11. To our knowledge, it is a common practice. The thresholds determine the variance of the predictions. Too high a threshold results in too narrow confidence bands. By iteration we meant the "trial and error approach" which does not involve any algorithm. We would be surprised if the iterative determination of threshold values has not yet been introduced, but we are not aware of any studies that have followed this approach. We will change the wording to avoid confusion.

RC 12. P7, L4-5: *In general it is doubtful whether distributions with a 'large' number of parameters will model data in a more accurate way than distributions with a small number. This partly depends on the data quantity and quality and similarly as in hydrological modelling there will be a balance between the complexity of the distribution (i.e. number of parameters) and the amount of data (and quality).*

AC 12. We agree with the reviewer that there must be a balance achieved between the complexity of the distribution (i.e. the number of parameters) and the quality of data. We admit that this sentence can be deleted as it is a too large generalization.

RC 13. P7, L7-8: *What does an 'overall good performance' mean? Compared to which other distributions?*

AC 13. A number of distributions was tested including a three-parameter lognormal and an inverse Gaussian. GEV was the only distribution that performed well both for the high and low flow extremes. Although it was not necessary to use the same distribution for both extremes, it made our discussion more transparent.

RC 14. P7, L25-27: It is not completely clear why the analyses are performed for a period of 130 years. Since the manuscript is about impacts of climate change on hydrological extremes, you would expect a comparison between historic and future climate conditions. Furthermore, climate change automatically implies the existence of nonstationarity and as such, by considering a period of 130 years assuming stationarity by using the same extreme value distribution will result in serious flaws.

AC 14. We do not think that the impact of climate change on hydrological extremes should be based on a comparison between historic and future climate conditions. What we propose here is to study the trend of projected indices instead of the "change". The Biala Tarnowska catchment does not show any non-stationarity in the extreme flow events (Meresa et al. 2017, submitted for publication). Therefore it is a suitable catchment to compare both approaches. We are aware that non-stationary flood frequency analysis has to be applied for non-stationary extreme events. We want to show here that taking 30-year long time-series to compare between reference and future periods involves large uncertainty even for 30-year return flows. The uncertainty ranges of 30-

year return period flows obtained using 130-year long time series can be nearly four times smaller.

RC 15. P8, L7-12: *The idea behind this section is not clear. Why is the trend in daily annual maximum precipitation and temperature analysed while the interest is in uncertainty in hydrological indices with climate change? Moreover, why is the daily annual maximum precipitation of interest and not for instance the two-day or three day precipitation (which might be stronger correlated to annual maximum discharge values)? Which temporal resolutions of precipitation are relevant for annual minimum flows? And what is the supposed role of daily annual maximum*

AC 15. The idea behind presenting the precipitation and temperature patterns was to show the variability of driving forces behind the changes in flow extreme index. However, the idea was not properly explained and followed. For a catchment of that size, daily maximum and mean sums of precipitation are well correlated with the flow patterns. The temperature patterns, on the other hand, present the changes in the evaporation losses and possibly, indicate the changes in flood regime.

RC 16. P8, L14-20*: How have the different criteria for high and low flows been applied in continuous hydrological modelling for periods of 30 years (or more)? When is the 'high flow' parameter set being used and when the 'low flow' one? What is the threshold for low flows and high flows; a specific discharge value or exceedance frequency?*

AC 16. As explained in section 3.3, we applied a stochastic formulation to the estimation of the HBV model parameters. That means that 20000 simulations of the HBV model were run for the 30-year long calibration period with parameters sampled randomly within the assumed parameter ranges. The calibration is performed using the observed precipitation, temperature and flow records. We applied logNSE criterion for low flow and NSE criterion for high flow index to all the simulated flow series. Then we evaluated thresholds for the criteria, called likelihood thresholds, based on the requirement of 95% of the observations should be in the 95% confidence interval separately for high and low flows (Table 3). In other words, we do not have one "high" or "low" parameter set but we have two multiple sets (each including thousands of parameter sets) representing "high" and "low" flow models.

RC 17. P9, L5: Which best parameter sets are meant here? When is the best low flow parameter set used and when the best high flow parameter set?

AC 17. 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 models under the RCP4.5 scenario for the best parameter sets from the MC parameter samples, giving the highest weights derived from the NSE for the high flows and logNSE for the low flows, respectively. The raw hydro-meteorological projections were applied to study the high flow index whilst bias corrected precipitation and temperature data were used for the low-flow index studies.

RC 18. P9, L7-8: 'twice as large'; where do we see that?

AC 18. Sentence will be corrected to: Obtained flow projections shown in Fig. 4, follow the rainfall projections shown in Fig. 2, with annual maximum flow values even four times larger than historical events occurring after 2016 for some GCM/RCM model projections.

RC 19. P9, L12-22: *This evaluation is not clear to me. Why do the authors evaluate results at a monthly scale? How can you assess annual maximum flows for each month? What do the authors mean with 'range' of annual maximum flows?*

AC 19. Thank you, it is corrected in the main manuscript, "annual" was replaced by "monthly". Analysis of variability of monthly flows was presented to illustrate seasonal changes of extreme flows in the near future period and the uncertainty related exclusively to hydrological model uncertainty for each climate model projection. Some changes of seasonality are visible for high flows, but low flows do not show any distinctive differences between reference period and near future.
We agree with the reviewer that this section is not adding much to the paper scope and we will delete it, together with Fig. 5.

RC 20. P10, L9-10: *The decrease in the spread of Q30 in the far future compared to the near future is strange. The authors should reflect on this. Is it related to the fact that only one RCP scenario is taken into account?*

AC 20. This smaller spread of the far-future projected changes was also observed in the other climate impact studies on the same catchment (Osuch et al., 2017) for both the RCP4.5 and RCP8.5 emission scenarios using the HBV model for hydrological simulations. Research is on-going to explain that phenomenon.

RC 21. P10, L20-22: *Also this observation needs discussion. Why the spread is more evenly distributed for minimum flows compared to maximum flows?*

AC 21. This is related to the influence of the climate model spread on the simulations (Osuch et al., 2017). It is much bigger for high flows and not very big for the low flows. We also have to remember that low flow simulations used bias-corrected meteorological drivers whilst the high-flow simulations were driven by the raw data. Bias correction decreases the variability of climate models.

RC 22. P11, L13-14: *Are the relative differences for annual minimum flows also smaller?*

AC 22. Yes. The sentence should read: The relative 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.

RC 23. P12, L7-9: *This is an interesting topic, but has not been investigated in this study since only one catchment has been considered.*

AC 24. We agree with the reviewer, this sentence is out of context and should be deleted.

RC 24. P12, L11-14: *This is an interesting result assuming that all methodological steps are logical and correctly carried out. What is the reason for the importance of uncertainty due to climate models for high flow and the important of hydrological model parameter uncertainty for low flows? This is very important and interesting to discuss.*

AC 24. The important role of hydrological model uncertainty in low flow predictions was already noticed in forecasting (Beninga et al., 2017). That effect can be explained by the ratio of the prediction noise (in this case described by the hydrological model uncertainty) to the input signal which is much higher for low flows.

RC 25. P12, L23-24: *What do the authors mean with 'this allows the problem of nonstationarity of model parameters to be avoided'?*

AC 25. The sentence should read: (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; this does not solve the problem of non-stationarity of model parameters but allows for focusing on parameter sets adequate for low or high flow regimes.

RC 26. P12, L29-31*: This statement seems to be obvious; the larger the ratio of return period vs. data length the higher the uncertainty. However, this extrapolation uncertainty is not explicitly assessed in this manuscript.*

AC 26. Thank you for the comment. This statement should read "analysis of the influence of length of time series records on the uncertainty bands of the high flow quantile estimates and their changes suggests that the ranges of quantiles of return periods Q30 are up to four times smaller when the long-term flow projections are used (Table 4). The low flow Q30 quantiles are less influenced by the length of the record.

RC 27. P23, Table 2*: The ranges defined by the lower and upper bounds frequently do not match with the optimal values (e.g. for ALFA, PERC, CLFUX). Can you explain this? Furthermore, some lower and upper bounds are exactly the same. Does this indicate that these parameters are deterministic? What about CFMAX (not mentioned as sensitive in section 3.3)? Finally, an upper bound of 2 for LP is impossible and an optimum value of 1 is remarkable at least (it would mean only potential evapotranspiration under fully saturated conditions).*

AC 27. We thank the reviewer for this comment. There was a mistake in Table 2. The HBV model was calibrated using GLUE and optimal parameter sets were derived in the form of multiple parameter sets, different for the high and low flows. When applying this method there is no unique parameter set chosen, but instead, a multiple set of parameters, each with a weight corresponding to the model performance criterion, represents the solution of a calibration problem. Therefore, there is no 'optimal" single solution to the calibration problem, even though a solution with the best goodness of fit criterion can be specified. Therefore this table should not include the "optimal" parameter values. The corrected Table 2 is at the end of the responses.

Technical corrections

RC 1. P1, L11: What is the distribution fit?

AC 1. ‘distribution fit’ will be changed into “theoretical distribution fit error”

RC 2. P1, L13: What kind of weighting do the authors mean?

AC 2. “with a separate criterion for high and low flow extremes”

RC 3. P1, L16: What is the difference between climate model variability and climate projection ensemble spread? Please use a consistent terminology.

AC 3. The meaning of “variability” is not the same as “spread”. Here we meant “variability”.

RC 4. P2, L3: What is inverse modelling in this respect? Is this term commonly used for calibration and validation purposes based on observed (historic) data?

AC 4. “Conditioning” can be used here instead of “inverse modelling”, if it is clearer. Inverse modelling refers to model parameter calibration based on historical data.

RC 5. P2, L6: “weighting” instead of “weighing”.

AC5. Corrected: “weighting” instead of “weighing”.

RC 6. P3, L8: What is the ‘relevant variability’ of extreme index estimates?

AC 6. Changed into “a direct assessment of variability of extreme index estimates”

RC 7. P3, L19: The case study has already been mentioned.

AC 7. Thank you, the sentence will be deleted.

RC 8. P3, L30: The maximum daily precipitation? During which period?

AC 8. Thank you, corrected. ‘Maximum precipitation was 68.3 mm d-1 and annual mean streamflow is 0.4 m^3s^{-1} over the observation period.’ Changed to ‘The annual maximum precipitation, annual minimum streamflow and annual mean streamflow of the catchment were 68.3 mm, 0.4 m^3s^{-1} and 5.43 m^3s^{-1} respectively over the observation period (1971-2000)’.

RC 9. P3, L30-31: Which period for the streamflow) Isn’t 0.4 m3/s a very low value for catchment area of about 1000 km2?

AC 9. Thank you. It is the same as with the previous comment. It is a minimum streamflow.

RC 10. P4, L12-14: Why do the authors use these complex abbreviations for the GCM/RCM combinations? It is not clear what the meaning of all the numbers is. Try to be consistent with the descriptions in Table 1.

AC 10. Corrected as in the Table 1 included at the end of these responses.

RC 11. P5, L12: Do you have a reference for the Matlab version of HBV?

AC 11. The MATLAB version of HBV used in this study was based on Lindstrom et al (1997). The original MATLAB code from Twente University NL, was further developed and adjusted for the purpose of climate impact studies in the Institute of Geophysics PAS.

RC 12. P5, L15-17: Only 12 out of 14 HBV parameters are mentioned. In which routines can we find CFLUX and PERC (see line 19)?

AC 12. Thank you. It is changed to 'These routines are governed mainly by fourteen HBV parameters, of which, six (TT, TTI, CFMAX, DTTM, CFR, WHC), three (FC, LP, BETA, CFLUX), two (KF, ALPHA) and one (KS, PERC) parameters are representing each routine respectively.'

RC 13. P5, L17: 'routines' instead of 'routing stage'?

AC 13. Thank you; corrected: 'routines' instead of 'routing stage'?

RC 14. P6, L24-P7, L3: *This general description of the GEV distribution is not necessary here and can be found in many text books.*

AC 14. It will be deleted

RC 15. P7, L16-17: What do the authors mean with ": : : aggregated speared of flow quantile change : : :"?

AC 15. "…aggregated speared of flow quantile change …" meant "integrated spread …

RC 16. P7, L19: 'squared' instead of 'squere'.

AC 16. Thank you, it is corrected in the main manuscript.

RC 17. P7, L22: The title suggests that the results of this study will be described. Please rephrase the title.

AC 17. "Description of the results" would be better?

RC 18. P7, L23: Different temporal resolutions? Shouldn't it be different lengths of data periods?

AC 18. Agree: 'different temporal resolutions' will be changed to 'different lengths of data periods'

RC 19. P7, L18: *The meaning of all variables should be explained in the text.*

AC 19. All the variables will be explained: where: Where: T_{SSijk} is total sum square error for the specific hydrological extreme indicator (e.g. relative change in Q30) for the ith parameter sets range, jth climate model and kth distribution parameter range and μ is the overall mean and ε_{ijk}denotes the white Gaussian error.

RC 20. P8, L6: "Results and discussion"?

AC 20 Thank you, it is corrected in the main manuscript. As "Discussion of the results"

RC 21. P9, L2: 'the 10-year moving average from the ensemble mean'?

AC 21. Thank you, it is corrected in the main manuscript. Corrected as 'the 10-year moving average from the ensemble mean' changed to 'mean from the ensemble of seven climate models'

RC 22. P9, L15-16: Fig. 5a is mentioned twice.

AC 22. Fig. 5 will be deleted

RC 23. P9, L29-30: *Decreases in minimum flows and increases in maximum flows? Shouldn't it be the other way around (according to the caption of Fig. 6)?*

AC 23. Thank you, it is corrected in the main manuscript: '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; green line denotes the mean value from all the GCM/RCM model realizations, red line denotes the averaged results obtained for the reference period.'

RC 24. P10, L6-7: *Here, the annual minimum flows increase (see previous comment).*

AC 24. Thank you. It is corrected as previous comment

RC 25. P10, L9: *What is Q30? Commonly, that is a discharge with a non-exceedance frequency of 30%. However, here it seems to be an annual maximum flow with a return period of 30 years?*

AC 25. Yes, it is annual maximum flow with a return period of 30 years. For annual maximum flow those two definitions have the same meaning. However, now to avoid confusions, we used as Qt30 in the main manuscript.

RC 26. P11, L7: 'Table 4' instead of 'Table 3'.

AC 26. Thank you, it is corrected in the main manuscript. ‘Table 4’ instead of ‘Table 3’.

RC 27. P11, L26-P12, L2: The first part of the conclusions can be omitted (can be part of introduction section).

AC 27. Thank you, it is corrected in the main manuscript. Deleted

RC 28. P12, L9: ‘hydrological parameter uncertainties’ instead of ‘hydrological model uncertainties’?

AC 28. Thank you, it is corrected in the main manuscript. Corrected to ‘hydrological parameter uncertainties’ instead of ‘hydrological model uncertainties’

RC 29. P12, L24-27: This is a repetition of lines 11-14.

AC 29. Thank you, it is corrected in the main manuscript. Deleted

RC 30. P13, L3: A paper in preparation should not be included in the reference list.

AC 30. This paper has already been submitted (see references included).

RC 31. P13-17: The reference list and referencing contain many errors, typos and inconsistencies. This should be carefully and thoroughly double-checked.

AC 31. The reference list will be corrected.

RC 32. P18, Fig. 1: What is the unit of the DEM map?

AC 32. The unit is meter. Thank you, it is corrected in the main manuscript.

RC 33. P18, Fig. 2: The interquantile range of what? Of the seven GCM-RCM combinations? In that case it would be better to show the individual model results, i.e. one annual maximum for each combination so 7 points per year.

AC 33. We appreciate the reviewer’s point but we decided to use the box-plots instead of seven points for each year, as it gives better overview of the spread of the projected values, including median and outliers in the form of red crosses.

RC 34. P19, Fig. 3: In particular the scale of the upper panel looks strange. Flows in cubic mm? How accurate is your model? Please use the same (realistic) x-axis ranges.

AC 34. We guess that the reviewer means Fig. 4. The y-axis units should be in cubic meters per second. The figure y-axis will be corrected.

RC 35. P19, Fig. 4: This figure (and also Fig. 2) is too small. What do we see here?

AC 35. Fig. 4 presents projected annual maximum and minimum flow. The figures 2 and 4 will be enlarged.

RC 36. P20: The differences between historic and future periods cannot be clearly seen in these figures.

AC 36. Following the reviewer's comments we decided to delete Fig.5 together with the subsection 4.4.

RC 37. P21, Fig. 6: What are the different lines in these figures? And is baseline and reference period the same?

AC 37. Thank you, it is corrected in the main manuscript. Changed to 'Figure 6. Empirical flow quantiles of annual maximum flow (upper panels) and annual minimum flow (lower panels) for the reference period and future climates (near and far future); the climate model spread is presented as a shaded area; green line denotes the mean value from all the GCM/RCM model realizations in each period (near and far future period), red line denotes the averaged results obtained for the reference period. Each black line represents individual climate models'

RC 38. P21, Fig. 7: In the caption 'right hand panel' is mentioned twice.

AC 38. The figure caption will be changed to: Total uncertainty ranges of theoretical GEV-based annual maximum (left hand panels) and minimum (right hand panels) flow quantiles over 30 year periods for the Biala Tarnowska at Koszyce; upper panels - the reference period 1971-2000; middle panels - near future 2021-2050; lower panels - far future 2071-2100.

RC 39. P22, Fig. 8: Idem, annual minimum flow is mentioned twice.

AC 39. Changed to 'annual maximum flow as a function of return level (left panel panel)'

RC 40. P23, Table 1: Which meteorological institute is connected to RACMO?

AC 40. The Table 1 was changed and all the abbreviations are now explained.

RC 41. P23, Table 2: The caption is not clear.

AC 41. Changed by 'Table 2. HBV parameter ranges: upper band (UB), lower band (LB), unit; fixed parameters have lower and upper bands equal.'

RC 42. P24, Table 4: What do the authors mean with 'change in width of …'? What compared to what?

AC 42. Table 4 caption is changed into: Table 4. Change in width of 0.95 confidence intervals for QT30 for annual maximum and minimum flow estimated using time periods of a different length (30-years and 130 years long).

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Anonymous Referee #2

Overview

RC. The authors assess the effect of different uncertainty sources on climate change projections. The presentation of the results is easy to follow and interpret. Especially Figure 9 is very informative. However, there is room for improvement using specific comments and checklist below. I recommend major revision as the model calibration part is not clear.

AC. We thank the reviewer for concise and valuable comments.

Specific Comments:

RC1. *Table 2: Optimal values of some parameters are out of lowerand upper limits e.g. CFMAX which cannot be reached by an algorithm e.g. SCEUA, CMAES etc. How was this achieved by a calibration algorithm? Did you follow a manual calibration scheme?*

AC1.The table 2 is now corrected. We do not use deterministic calibration, instead the GLUE -based stochastic calibration is applied. When applying this method there is no unique parameter set chosen, but instead, a multiple set of parameters, each with a weight corresponding to the model performance criterion, represents the solution of a calibration problem. Therefore, there is no 'optimal" single solution to the calibration problem, even though a solution with the best goodness of fit criterion can be specified.

RC2. Demirel et al (2013a) is in the reference list but not in the text.

AC2. Thank you, it has been corrected.

RC3. Please explain the abbreviations used at legend in figure caption. The legend of Fig8 is confusing: "distn"?

AC3. Thank you, it has been corrected. "distn" replaced by "distribution"

RC4. Did you compare uncertainty in HBV model parameters with other studies (Addor et al., 2014; Demirel et al., 2013b; Osuch et al., 2015) using HBV model for forecasting hydrological extremes? How would the results overlap for 10 day forecast (Demirel et al., 2013b) and long term climate predictions in EUROCORDEX (dataset used in this study)?

AC4. The uncertainty in the HBV model parameters was compared with the other studies, including Osuch (2015) and Demirel et al (2013b). Demirel et al. (2013b) explored the influence of uncertainty in input, hydrological model parameters and initial conditions on a 10-day ensemble flow forecasts. The results showed that parameter uncertainty had the largest effect on the medium range low flow forecasts, which is consistent with the present paper findings. Addor et al. (2014) concentrated on the influence of different hydrological model structure, involving three hydrological models, emission scenarios, climate models, post-processing and catchments. Their results indicate that influence of model structure varies with the catchment. However the authors did not take into account hydrological model parameter uncertainty, which is the main focus of the present paper. Osuch (2015) compared three sensitivity analysis techniques to describe the HBV model parameter interactions. We used the output of that paper to eliminated less sensitive HBV model parameters in order to minimize computational cost.

RC5. Fig5: Parameter uncertainty should be presented differently to assess the contribution of each parameter uncertainty to total uncertainty. From this figure the reader can't see the most uncertain parameter. A figure similar to Figure 4 in Demirel et al (2013b) or Fig9 in the current manuscript can be very useful for modelers. This can be easily done as the GLUE results would allow such ranking.

AC5. Thank you for the comment. We decided to delete this figure and subsection 4.4 following the first reviewer comments.

RC6. Conclusion 2 (ii): Please explain the drizzle effect? Not clear.

AC6. Simulated climate variables (precipitation and temperature) by individual GCMs/RCMs often do not reach agreement with observed climate time series. This is due to the effect of systematic and random model errors of GCMs/RCM simulations. Such systematic errors lead to simulate many drizzle days (i.e., too many days with very low precipitation intensity and too few dry days). The drizzle effect is related to the performance of climate models. It presents itself in the form of frequent rainfall of a very small intensity. The physics behind precipitation generation is very complex and involves processes operating on a wide range of scales. The frequent 'drizzle' is produced mainly by convective parameterization. It appears in many climate models and invokes errors in the intensity and frequency of precipitation (Terai et al. 2016). The correction can be performed using the number of wet days in a month (Osuch et al. 2016). Because of this bias in precipitation, using direct climate model output as inputs to hydrological modelling for low flow analysis often leads to unrealistic results and therefore bias correction is required in the case of low flow projections.

RC7. Section 3.6 and Conclusion 5 (v): Is ANOVA method a global or local sensitivity analysis method? Can interactions (parameter etc.) be assessed using this method? Why ANOVA is used instead of other elementary and global methods e.g. Morris, SOBOL, PEST, FAST etc. These aspects of the ANOVA method should be described in section 3.6 and conclusions should follow these details.

AC7. Nowadays, many global sensitivity methods have been proposed and used, such as Fourier amplitude sensitivity test (FAST), Regional Sensitivity Analysis (RSA), Analysis of Variance

(ANOVA), Parameter Estimation Software (PEST), Morris, and Sobol method. Among these global sensitivity analysis methods, ANOVA is proved to be one of the most robust and effective tools to analyze both continuous and discrete factors (Montgomery, 1997), and it is widely applied in hydrology (Bosshard et al., 2013; Zhan, et al., 2013; Lagerwalla, et al., 2014; Addor et al.,2014; Giuntoli et al., 2015; Osuch, 2015). We used ANOVA approach due to its numerical facility (MATLAB) and ability to evaluate the main and interactive effects between factors considered.

RC8. Conclusion bullets are confusing. Two times "iv" exists and sentences are not clear. There are typos too. For example Conclusion vi should start with capital. Please rephrase them with short and clear conclusions. And relate them to the results section. Bullet conclusions in Demirel et al (2013b) can be an example. For each result section one paragraph is given in conclusion.

AC8. Thank you, it is corrected in the main manuscript.

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The critical role of uncertainty in projections of hydrological ~~Extremes~~extremes

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Abstract. This paper aims to quantify the uncertainty in ~~the~~ projections of future hydrological extremes in the Biala Tarnowska River ~~basin~~at Koszyce gauging station, south Poland. ~~We follow a multi-model~~The approach followed is based on several climate projections obtained from the EURO-CORDEX initiative, raw and ~~downscaled~~ bias-corrected realizations of catchment precipitation, ~~and temperature,~~ and flow simulations derived using ~~the~~multiple hydrological ~~HBV~~ model parameter sets. The projections cover the 21st century. Three sources of uncertainty ~~were~~ are considered: one related to climate projection ensemble spread,~~the uncertainty in hydrological model parameters uncertainty,~~ the second related to the uncertainty in hydrological model parameters ~~climate projection ensemble spread~~ and the third related to the error in the theoretical distribution ~~fitting parameter sets~~fit~~ error~~. 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 (GLUE) approach, with separate ~~weighting~~criteri~~on~~a for high and low flow extremes. ~~Flood~~ Extreme (low and high) flow quantiles were estimated using the Generalized Extreme Value (GEV) distribution at different return periods and were based on two different lengths of the flow time series. ~~The~~ A sensitivity analysis based on the Analysis of Variance (ANOVA) shows that the uncertainty introduced by the ~~HBV~~ hydrological model parameters can be larger than the climate model variability and the 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.

1 Introduction

Hydrological models are useful in water resources planning and management, flood and drought prediction, assessments of catchment-scale impacts of climate change, and the 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 flows (Lawrence and Hisdal, 2011; Meresa et al., 2016~~; Lawrence and Hisdal, 2011~~). Research on the impact of climate changes on future hydrological extremes is usually performed by an application of hydrological models to 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 ~~G~~g~~lobal~~eneral ~~Climate~~circulation ~~M~~model (GCM) driven by an assumed CO_2 scenario, through downscaling of climatic forcing to a catchment scale, e.g., using the regional climate model (RCM), 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. We cannot directly assess the impact of the first three 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). Therefore these first three sources of uncertainty have an “epistemic” nature and cannot be decreased (Beven, 2016). On the other hand, the introduction of conditioning based on available past observations of climatic and hydrological variables allows a decrease of the “predictive” hydrological model uncertainty to be achieved. The calibrated hydrological models are forced with climate projections derived from climate models. However, hydrological models that produce acceptable results for an observed baseline period may respond differently when forced with the climate change scenario (Gosling and Arnell, 2011; Thompson et al., 2013; Lespinas et al., 2014~~; Gosling and Arnell, 2011~~). For several decades interest in hydrological structural and parameter uncertainty has been increasing and has become an important part of modelling (Ouyang et al., 2014; Sellami 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; P~~u~~aoulin et al., 2011). In addition to the parameter and structural uncertainty (P~~u~~aoulin et al., 2011), the hydrological model is also exposed to uncertainty which arises from various sources not directly mentioned above, including interdependency among the climate models (Wilby and Harris, 2006; ~~Tian et al., 2016;~~ Ghosh ~~et al.~~and Katkar, 20~~09~~12; Tian et al., 2016~~; Wilby and Harris, 2009~~).

The issues of uncertainty in hydrological modelling and hydrological projections 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, Abbaspour et al., 2015). However, few of the case studies at a catchment level were trying to assess the influence of uncertain future and hydrological parameter uncertainty (P~~u~~aoulin et al., 2011; Bennett et. al., 2012~~; Vormoor et.al., 2015;~~ Stenschneider et al., 2012, 2015; Vormoor et.al., 2015). ~~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, 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~~conditioning~~, based on available past observations of climatic and hydrological variables, allows a decrease of some types of uncertainty to be achieved. The "predictive" model uncertainty is the only one which can be decreased when conditioned on the observations. The other sources of uncertainty have an "epistemic" nature and cannot be decreased (REF, XXX).~~

Bias correction methods are usually applied to decrease the errors related to global simulation models and downscaling techniques (Sunyer et al., 2015; Vormoor et al., 2015). The hydrological model structural and parametric errors are dealt with using a multi-model approach and ~~weighting~~ introducing weights for hydrological model ~~parameters~~ parameter sets following assumed goodness of fit criteria, ~~(~~e.g. in the form of a likelihood function (Wilby and Harris, 2006, Steinschneider et al., 2012). Addor et al. (2014) concentrated on the influence of different hydrological model structure, involving three hydrological models, emission scenarios, climate models, post-processing and catchments. Their results indicate that influence of model structure varies with the catchment. However the authors did not take into account hydrological model parameter uncertainty, which is the main focus of the present paper. ~~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~~Following the results presented by ~~(~~Demirel et al.~~,~~ (2013a) the choice of the GCM/RCM has larger influence than the choice of the emission scenario on the projections of low flow indices. Similar findings for the high-flow indices were presented by~~, Alfieri et al., 2015).~~ Osuch et al. (2016). There is ~~a~~ general agreement that we cannot avoid uncertainty in climate models (Knutti and Sedlacek, 2012). The question arises as to how large ~~an~~the uncertainty is and if it 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 flows (Meresa et al., 2016; Lawrence and Hisdal, 2011). However, complex hydrological and climate models can never~~are diificult to ~~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 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 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 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).~~

~~The uncertainty in the HBV model parameters was compared with the other studies, including Osuch (2015) and Demirel et al (2013b). Demirel et al. (2013b) explored the influence of uncertainty in input, hydrological model parameters and initial conditions on a 10-day ensemble flow forecasts. The results showed that parameter uncertainty had the largest effect on the medium range low flow forecasts, which is consistent with the present paper findings. Addor et al. (2014) concentrated on the influence of different hydrological model structure, involving three hydrological models, emission scenarios, climate models, post-processing and catchments. Their results indicate that influence of model structure varies with the catchment. However the authors did not take into account hydrological model parameter uncertainty, which is the main focus of the present paper. Osuch (2015) compared three sensitivity analysis techniques to describe the HBV model parameter interactions. We used the output of that paper to eliminated less sensitive HBV model parameters in order to minimize computational cost.~~

In this study, we assess the critical role of ~~the~~ uncertainty in the projection of future hydrological extremes in the ~~BialaTarnowska~~ Biala Tarnowska mountainous catchment in Poland in the 21st century. We consider three sources of uncertainty. These are climate projection uncertainty, hydrological model parameter uncertainty~~,~~ ~~meteorological~~~~climate projection uncertainty~~ and distribution fit parameter uncertainty. ~~Bearing in mind the aims of the study, we restricted the sources of epistemic uncertainty to those which have the largest impact – i.e. climate model spread, omitting the uncertainty related to bias correction or geography.~~ The choice of these three particular sources of uncertainty was dictated by one aim of the research – i.e. an assessment of the influence of hydrological model uncertainty on projections of low- and high-flow extremes and the relative contribution of that "predictive" uncertainty in the spread of extreme indices related to the spread of seven climate models and the distribution fitting error. We restricted the sources of epistemic uncertainty to those which have the largest impact – i.e. climate model spread, omitting the uncertainty related to bias correction or geo~~graphy~~morphology of the catchment. The error related to the distribution fit was included as an essential part of the extreme index evaluation, which requires extrapolation of annual maximum or minimum flow distributions to higher order quantiles (e.g. 1-in-100 year, or 1-in-200 year). Osuch et al. (2016) presented the influence of emission scenario, climate model, bias correction method and ~~geography~~catchment on flow indices in a case study that included the same catchment, Biala Tarnowska. In this respect, our paper is an extension of that paper, focusing on the influence of hydrological model uncertainty on annual maximum and minimum flow projections.

We apply ~~the~~ a 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, 2016). The other sources of uncertainty are dealt with by means of ~~an~~a direct assessment of ~~the~~ variability in ~~relative change of~~ extreme index estimates. Seven ~~Meteorological~~~~C~~climate projections applied are derived from the high-resolution regional climate change ensemble within the World Climate Research 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 in two stages, using, separately, the 30-year long and 130-year long time series of future flow projections 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. It is well known that an extrapolation of a distribution function based on a 30-year long time series towards 1-in-100 year quantiles involves very large errors (Strupczewski et al., 2011). Even the estimates of 1-in-30 year quantiles based on the 30-year long data are biased with large errors. We compare these errors with those involved on 1-in-~~100~~30 year quantile estimates obtained using the 130 year long time series. 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 uncertainty related to the distribution fit is analysed using different lengths of 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 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

The ~~BialaTarnowska~~Biala Tarnowska 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 967~~6.9~~ 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. Observations from five gauging stations were used to derive aerial precipitation in the catchment by means of Thiessen polygons. No elevation correction was applied in this study. However it was applied to the same catchment by Benninga et al (2016) and showed that the increase in precipitation due to the elevation is about 3%.~~The Thiessen polygon method was applied to have the most representative precipitation data.~~ The annual maximum precipitation, annual minimum streamflow and annual mean streamflow of the catchment ~~was~~ were 68.3 mm, 0.4 m^{3}s^{-1} and 5.43 m^{3}s^{-1} respectively over the observation period ~~(~~1971-2000~~)~~.

Biala Tarnowska 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~~Bergström, 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 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 (http://www.eurocordex.net/) ~~that~~ which 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~~2014). This ensemble contains four different RCMs driven by three different GCMs. The names and model affiliations are given in Table 1. ~~(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 MPI-ESMLR-~~

~~RCA4.~~ The RCP 4.5 was applied because it is a stabilization scenario and thus assumes the imposition of emissions mitigation policies. The RCP 4.5 is derived from its own “reference”, or “no-climate-policy”, scenario. This reference scenario is unique to RCP 4.5 and differs from RCP 8.5, RCP 6.0 and RCP 2.6 (Smith and Wigley 2006; Clarke et al. 2007; Wise et al. 2009). The influence of the emission scenario on flood indices was studied by Osuch et al. (2016) whilst the low flows were analysed by Demirel et al. (2013a) and Osuch et al. (2017). ~~Both t~~Those studies indicated that the choice of emission scenario ~~choice~~ has a relatively small influence on the results.

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~~2006) 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 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~~two different lengths of time series (30 and 130 years) 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 (Wilby and Harris, 2006; Steinschneider et al., 2012~~Tian et al., 2016~~).

3.2 Climate projections: 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~~2015). Most of those studies were focused on mean output values. Osuch et al.~~,~~ (2016) compared five different distribution-based Quantile Mapping (QM) ~~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 characteristics most accurately of all the techniques studied. However, ~~a~~ the ~~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 (Ehret et al., 2012; Teng et al., ~~2014~~2015~~; 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)~~. The drizzle effect (i.e., too many days with very low precipitation intensity and too few dry days) is related to the performance of climate models. It presents itself in the form of frequent rainfall of a very small intensity. The physics behind precipitation generation is very complex and involves processes operating on a wide range of scales. The frequent ’drizzle’ is produced mainly by convective parameterization. It appears in many climate models and invokes errors in the intensity and frequency of precipitation (Terai et al., 2016). A correction can be performed using the number of wet days in a month (Osuch et al., 2016). Because of this bias in precipitation, using direct climate model output as inputs to hydrological modelling for low flow analysis often leads to unrealistic results and therefore bias correction is required in the case of low flow projections. Therefore, in this study, we apply ~~both~~ the QM corrected precipitation projections for the estimation of low-flow extremes and raw precipitation projections ~~RCM/GCMs projections~~ for ~~future runoff simulations~~high-flow extremes. Bias-corrected temperature projections using the empirical QM approach were applied for both high and low flows.

3.3 Hydrological modelling

The HBV hydrological model version applied is based on Lindstrom et al.~~,~~ (1997) and ~~it~~ is written in Matlab®. ~~HBV~~ It is a lumped conceptual multi-reservoir-type model for daily runoff simulation from daily inputs (Lindstrom et al., 1997). The original MATLAB code from the Twente University, NL, was further developed and adjusted for the purpose of climate impact studies in the Institute of Geophysics PAS. The model uses ~~rainfall~~precipitation, air temperature and potential evaporation data as inputs. The HBV model has four main routines: (i) 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~~ three (*KF*, *ALPHA*, *CFLUX*) and ~~one~~ two (*KS*, *PERC*) parameters are representing each routine respectively. Not all HBV model parameters have significant impact on the simulated flows. The HBV model was applied in different hydro-climatic conditions by many researchers (e.g., Seibert and McDonnel, 2010~~)~~, Demirel et al., 2013b). Romanowicz et al.~~,~~ (2013) discussed the most sensitive parameters of the HBV model for both high flow and low flow characteristics. Other studies of the HBV model parameter sensitivity were presented by Osuch (2015) and Osuch et al. (2015). The set of ~~five~~six most sensitive parameters for the extreme high and low flow conditions was chosen following those studies. These are *FC, BETA, LP, KS*, *CFMAX* and *PERC*. ~~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~~A full description of the HBV hydrological model which we used can be found in Osuch et al. (2015). Osuch et al. (2015) also compared three sensitivity analysis techniques to describe the HBV model parameter interactions. We used the output of that paper to eliminated less sensitive HBV model parameters in order to minimize computational cost. ~~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-Sutcliffe criterion (*NSE*) (Nash and Sutcliffe, 1970) belongs to those most widely used. When based on the whole calibration 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 w~~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 high flow values. Therefore, in this study we use two objective functions to encapsulate the high and low flow characteristics. 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 (*logNSE*). The criteria are defined as follows:

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

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

(2)

Where $Q_{t,sim}$ denotes simulated flow in time *t (here days)*~~*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.

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~~ a 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

The GLUE approach is one of the non-formal statistical methods that involve direct Monte Carlo MC simulations. ~~Following that approach, t~~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 t~~The idea of an optimal system representation is rejected and the equifinality concept is accepted for the behavioural parameter sets.

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 set weighting. The number of samples depends on the number of model parameters but also on the model computing times and it may vary from hundreds to hundreds of thousands (Beven and Binley, 2014). Many research papers recommend over 10000 MC simulations (~~Xiaoli~~ Jin et al., 2010, Romanowicz et al., 2013, Houska et al., 2014). ~~The HBV model is not very computer-time demanding and 20 000 simulations were applied. That number was dictated by the practical requirement of dealing with not too large data files.~~ 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~~2006). The behavioural thresholds for both criteria are selected following the model performance in the ~~validation~~ calibration period. The choice of high threshold values results in narrow confidence limits of the predictions and (usually) a small behavioural parameter 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.~~by the “trial and error approach”. The choice of two different criteria, one for high and one for low flow extremes, yields two different behavioural parameter sets describing model performance in two different (low- and high- flow) hydro-meteorological conditions.

3.5 Uncertainty related to fitting the Generalized Extreme Value Distribution GEV ~~distribution (Generalized Extreme Value Distribution)~~ to extreme flow projections

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

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

~~(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 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 distribution fitting to be assessed.~~

The choice of the Generalized Extreme Value Distribution GEV (Coles, 2001) followed the validation of suitability of this distribution to describe the projected annual maximum and minimum flows using probability plots for the ~~BialaTarnowska~~Biala Tarnowska. The ~~MATLAB - based~~ GEV distribution ~~fitting algorithm~~model was applied to all the climate models and the a posteriori hydrological model parameter sets. Thi~~se~~s MATLAB-based GEV-fitting algorithm provides estimates of the median and the 0.95 confidence bands for the parameters of GEV distribution. These parameters were subsequently used to obtain lower and upper confidence bands of quantiles of extreme index distribution through the inverse GEV model (Coles, 2001, eq. 3.4). In order to simplify the procedure, instead of sampling from the GEV parameters within the parameter space common to all hydrologic and climate model simulations, we sampled from each set of parameters assuming a normal distribution with the variance specified by the GEV parameter lower and upper 0.95 confidence values, and in addition, assuming the independence of the GEV model parameters. The obtained 0.95 GEV distribution confidence values were used to estimate the spread of results related to the distribution fit. Bearing in mind that the aim of this study was to assess the ranges of uncertainty of extreme indices rather than their exact values, and the large number of simulations, it was not possible to choose among different distribution functions the best distribution for each projected time series.

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 called ANOVA (ANalysis Of VAriance).~~~~Nowadays, m~~Many global sensitivity methods have been proposed and used, such as Fourier ~~a~~Amplitude ~~s~~Sensitivity ~~t~~Test (FAST), Regional Sensitivity Analysis (RSA), Analysis of Variance (ANOVA), Parameter Estimation Software (PEST), Morris, and Sobol method (Saltelli et al., 2006). Among these ~~global sensitivity analysis~~ methods, ANOVA ~~i~~has proved to be one of the most robust and effective tools to analyze both continuous and discrete factors (Montgomery, 1997), and ~~it~~ is widely applied in hydrology (Bosshard et al., 2013; Zhan~~,~~ et al., 2013; Lagerwalla~~,~~ et al., 2014; Addor et al., 2014; Giuntoli et al., 2015; Osuch, 2015). We used the ANOVA ~~(ANalysis Of VAriance)~~ approach due to its numerical facility (MATLAB) and ability to evaluate the main and interactive effects between the factors considered. To identify the relative contribution of each source of uncertainty, ~~(~~corresponding to the parameter sets (~~P_{AR}~~PAR), climate models (~~C_M~~CM) and parameter distribution sets (~~D_{IS}~~DIS), ~~)~~ from the ~~aggregated~~ spr~~e~~ea~~re~~d of flow quantile change in the near and far future, we use the following ANOVA model:

$$TSS_{\cancel{SS}ijk} = \mu + PAR_{\cancel{AR}i} + CM_{\cancel{M}j} + DIS_{\cancel{IS}k} + (PAR\cancel{P_{AR}} + CM\cancel{C_{M}})_{ij} + (PAR\cancel{P_{AR}} + DIS\cancel{D_{IS}})_{ik} + (CM\cancel{C_{M}} + DIS\cancel{D_{IS}})_{jk} + \varepsilon_{ijk} \quad (\cancel{4}3)$$

Where: $TSS_{\cancel{SS}\,ijk}$ is a total sum ~~squared~~squared error for the specific hydrological extreme indicator (e.g. relative change in ~~Q30~~QT30) for the 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 Design of ~~Results and discussion~~numerical experiments

We present here an assessment of the uncertainty in projected hydrological extremes for two different lengths of data periods. Firstly, the annual maximum and minimum flow quantiles are derived for 30-year periods, the so-called near future (2021-2050), 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. Since the Biala Tarnowska flow projections do not show any non-stationarity in extreme flow events (Meresa et al., 2017), it is possible to compare the uncertainty of estimates of extreme indices obtained from the 30-year long and 130-year long time series. It can be expected that the uncertainty of extreme flow quantiles will be larger for short time series, but we do not know how much larger it can be and therefore that comparison is not obvious. The comparison can help in answering our research question on how reliable is the approach commonly used in climate impact studies consisting of a comparison of 30-year based estimates of extreme flow indices between reference and future periods.

20000 uniform samples of HBV model parameters were obtained with parameter ranges presented in Table 2. That number was dictated by the practical requirement of dealing with not too large data files. The parameter ranges were chosen following the results of deterministic optimisation performed earlier and reported by 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 extreme index distribution fitting uncertainty. The latter was evaluated using 10000 MC normal samples of the GEV model parameter space. ~~In~~ As a result we obtained 20000 daily flow simulations 130 years long for raw and bi~~-~~as corrected climate model projections for an ensemble of seven GCM/RCMs listed in Table 1. This gives all together 280000 flow time-series used to derive extreme flow quantiles.~~.~~

4 Results and ~~Discussion~~ discussion

4.1 Variability of projected precipitation and temperature series

In the following section, we present an analysis ~~an analysis~~ of the variability of maximum precipitation and temperature series on annual basis~~.~~ to see the correlation between the projected hydrological extremes and the input climate extremes. The idea behind presenting the precipitation and temperature patterns was to show the variability of driving forces behind the changes in the flow extreme indices. For a catchment of that size, ~~daily~~annual maximum and mean sums of precipitation are well correlated with the flow patterns when the rainfall-driven flood regime prevails. The temperature patterns, on the other hand, present the changes in the evaporation losses and possibly, indicate changes in the flood regime. In Fig. 2, ~~raw annual maximum daily~~ precipitation and temperature time series for the Biala Tarnowska catchment 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 upper panel of Fig. 2 presents annual sum precipitation based on corrected precipitation projections~~ (the upper panel)~~, the annual maximum precipitation based on raw projections ~~(~~is shown in the middle panel,~~)~~ and temperature mean projections for bias-corrected data are presented in the lower panel. The annual sum precipitation illustrates the low-flow patterns whilst the annual maximum precipitation corresponds to possible flow maxima. The results show a visible increase of the annual ~~maximum~~ mean 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

As explained in the section 3.3, a stochastic formulation is applied to the estimation of the HBV model parameters. That means, 20000 simulations of the HBV model were run for the 30-year long calibration period (1971-2000) with parameters sampled randomly within the assumed parameter ranges (Table 2). The calibration was performed using the observed precipitation~~,~~ and temperature from the Biala Tarnowska catchment and flow records from the Koszyce gauging station for the period 1971-2000 for the calibration and 2001-2010 for the validation stage. We applied the *NSE* criterion (eq. 1) for the high flow and the ~~logNSE~~*logNSE* criterion (eq. 2) for the low flow to all the simulated flow series. The thresholds for the criteria, called likelihood thresholds were evaluated (Beven and Binley, 2014) by the "trial and error approach". As a result, two multiple sets (each including thousands of parameter sets) representing "high" and "low" flow modes of the HBV model performance have been derived. ~~Following the discussion presented in section 3.3, we applied different criteria for high and low flow indices.~~ The threshold 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 (*logNSE*) with the threshold set at 0.3 and the ~~obtained~~ sample size obtained is 1625~~ (Table 3)~~. ~~This part of the analysis is was performed using the observations of precipitation and temperature from the BialaTarnowskaBiala Tarnowska 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 model parameters. The upper panel presents the cdf of model predictions conditioned on the *NSE*, while the lower panel presents the cdf of predictions conditioned on the ~~logNSE~~*logNSE* criterion. Also shown are the 0.95 confidence bands in the form of dashed lines. These confidence bands are much narrower for the ~~NSElogNSE~~*logNSE* 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* criterion.

~~4.3 Temporal variability of projected hydrological extremes~~

In Fig. 4, ~~bias corrected~~ the 'best' annual extreme time series of projected flow~~ (mean from the ensemble of seven climate models)~~, corresponding to the deterministic 'optimal' parameter sets ~~of projected flow (mean from the ensemble of seven climate models)~~ for the River ~~BialaTarnowska~~Biala Tarnowska at Koszyce are shown. The upper panel of Fig. 4 presents annual maximum flows, and the annual minimum flows are presented in the lower panel. These results were obtained from the HBV model simulations fed by the precipitation and temperature projections obtained from the seven GCM/RCM models under the RCP4.5 scenario for the parameter sets from the MC parameter samples giving the highest weights derived from the *NSE* for the high flows, and ~~logNSE~~*logNSE* for the low flows, respectively. The raw precipitation projections were applied to study the high flow index whilst bias corrected precipitation data were used for the low-flow index studies. ~~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 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 shown in Fig. 4, follow the ~~rainfall~~precipitation projections shown in Fig. 2, with annual maximum flow values even four times larger than historical events occurring after 2016 for some GCM/RCM model projections~~.Obtained flow projections follow the rainfall patterns shown in Fig. 2, with extremeannual maximum flow values twice as large aseven four times than historical extremes,events occurring after 2016 for some of the GCM/RCM model projections~~. ~~The upper panel of Fig. 4 presents annual maximum flows, while and the annual minimum flows are presented in the lower panel.~~ These time series cover the whole length of the reference and projected years simulated (1971-2100) in an attempt to identify ~~general~~ temporal variabilities in the high and low ~~flows~~flow indices.

~~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 median together with 0.95 confidence limits for each month and each GCM/RCMs realization are shown in Fig. 5a for monthly maximum flows and in Fig. 5b for monthly 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 monthly maximum flows have a wider range for the first three climate models in April, May, June months 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.~~

4.3 ~~4.5~~4.4 Changes in extreme flow quantiles (30-year periods) due to the climate model spread

The empirical quantiles of the future annual maximum and minimum flow projections for the 30-year periods, including the reference period 1971-2000, the near-future period 2021-2050 and the far-future period 2071-2100 are shown in Fig. ~~6~~5. These results present the empirical frequency curves obtained for the best performing hydrological model parameter set for seven climate models listed in Table 1, neglecting the hydrological model parameter uncertainty. ~~The~~ A comparison of the ~~mean~~ median return periods obtained for the near- and far-future with the ~~mean~~ median in the reference period illustrates the predicted changes in quantiles. Substantial decreases in annual minimum flow and increases in ~~extremely high~~annual maximum flow~~s~~ for both near- and far-future periods ~~(2021-2050 and 2071-2100)~~ can be observed. In the case of maximum annual flow (Fig. 5, ~~upper panels~~left column), the reference quantile curves (dashed red lines) are always lower than those from the climate model ensemble medians (dashed green lines), implying increases in both frequency and magnitude of annual maximum flows. Following a similar reasoning it can be deducted that~~,~~ the magnitudes ~~and frequency~~ of annual minimum flows decrease in the future (Fig. 5, ~~lower panels~~right column). However, the differences are not as visible as in the case of high flow extremes due to small flow values.~~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~~~~Following a similar reasoning it can be deducted that , the magnitude and frequency of annual minimum flows decrease in the future (Fig. 5, lower panels).~~ ~~For example,~~In that case, ~~the occurrence of minimum flow ones in every year (1-in-1 year return~~

~~period) s is changing from 1.19 m^{3}s^{-1} to 1.29 m^{3}s^{-1} in the near- and far- future period. while the occurrence of low flow 1-in-15 years changes little, from 2.7 m^3/s to 2.6 m^3/s in the near-future and from 2.7 m^3/s to 2.5 m^3/s in the far-future.~~

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 decrease of annual minimum flows ~~increase~~ ~~decrease~~ in the future~~, which~~ is also consistent with the results published by Meresa et al.~~,~~ (2016).

From Fig. 5, left column, upper ~~left~~ panel, ~~We~~ we note that the uncertainty of the ~~projected median~~empirical high-flow quantile at 30-year return period (QT30) ~~values~~ related to the climate model spread exceeds 100% (600 m^{3}s^{-1}) ~~of the projected values for the QT30~~ in the ~~near~~ near-future. In the contrary, t~~T~~he spread of ~~return period projections of~~ QT30 of annual maximum flows in the far-future decreases ~~in the far-future~~ to 500 m^{3}s^{-1} (Fig. 5, ~~upper~~left column, ~~right~~lower panel).~~.~~ ~~Thise smaller spread of the far-future projected changes was also observed in the other climate impact studies on the same catchment (Osuch et al., 20176) for both the RCP4.5 and RCP8.5 emission scenarios using the HBV model. Research is on-going to explain that phenomenon.~~ Similarly, also the low flow QT30 shows smaller spread for the far future period (Fig. 5, ~~lower panels~~right column). The fact that the spread is more evenly distributed for minimum flows compared to maximum flows is related to the influence of the climate model spread on the simulations. It shows ~~T~~that climate change extremes have larger influence ~~is much bigger for high flows and not very big for the low flows~~on flood frequency than on low flow frequency. The smaller spread of the far-future projected changes was also observed in the other climate impact studies on the same catchment (Osuch et al., 2016) for both the RCP4.5 and RCP8.5 emission scenarios using the HBV model. Research is on-going to explain that phenomenon. ~~In addition, low flow simulations used bias-corrected meteorological drivers whilst the high flow simulations were driven by the raw data and bias correction decreases the variability of climate models.~~

4.~~65~~4 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 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 6 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~~6. The light green and light ~~red~~ pink areas in Fig ~~7~~ 6 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~~ 6 left ~~panel~~column) and the minimum annual flow (~~Fig. .7~~ 6 right ~~panel~~column). 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. Comparison of empirical and theoretical distribution-based flood frequency curves indicates that "outliers" (single very high flow events) have smaller influence on the distribution-based than on empirical flood frequency analyses (Figs. 5 and 6, left columns).

The uncertainties originating in the climate models and the hydrological model parameters were calculated ~~using~~ based on a range of the differences between the 0.95 upper confidence bands and 0.05 lower confidence bands as a measure of the uncertainty in the ensemble projections that were made using multiple GCM/RCMs, hydrological model behavioral parameter sets ~~distribution parameter sets (FFA)~~ and ~~hydrological model behavioral parameter sets~~distribution parameter sets (FFA). When comparing the total uncertainties, it becomes clear that uncertainties from climate projections, hydrological 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~~ 7 presents frequency analysis results of annual maximum flow (left panel) and annual minimum flow~~s~~ (right panel), based 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, the blue corresponds to climate model spread and the 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~~high flow quantiles. On the other hand, for the ~~annual minimum~~low flow quantiles, hydrological model parameter uncertainty contributes more than the other two sources to the uncertainty of the minimum flow frequency ~~and occurrences (Fig. 87)~~.

The uncertainties of the 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~~6) and 130 year (Fig.~~8~~7) periods show significant differences. Table ~~4~~ 3 gives a summary of confidence interval ranges obtained for the QT30 based on different time periods. In general, the QT30 estimated using the 30 year period is characterized by a much larger confidence intervals compared to the QT30 estimated using the 130 year long period. The differences in the width of confidence intervals vary from about 200 m^{3}s^{-1} for the reference period to 1500 m^{3}s^{-1} for the near future period (2021-2050) compared to the 130 year period QT30 estimates. Due to the extrapolation errors, that difference will increase substantially for the QT100 index, thus questioning the usefulness of those estimates.

~~The differences obtained for the annual minimum flow QT30 estimates are smaller, suggesting that low flow quantiles are less susceptible to the errors related to the length of the evaluation period.~~ The relative differences obtained for the annual minimum flow QT30 estimates are smaller, suggesting that low flow quantiles are less susceptible to the errors related to the length of the evaluation period.

The results of the study show that 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. In contrast, for low flows the uncertainty related to hydrological model parameters has a larger impact than the other uncertainty sources studied. The important role of hydrological model uncertainty in low flow predictions has already been noticed in forecasting (Beninga et al., 2017). That effect can be explained by the ratio of the prediction noise (in this case described by the hydrological model uncertainty) to the input signal which is much higher for low flows. Demirel et al. (2013b) explored the influence of uncertainty in input, hydrological model parameters and initial conditions on a 10-day ensemble flow forecasts. The results showed that parameter uncertainty had the largest effect on the medium range low flow forecasts, which is consistent with the present paper findings. 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. In this study we applied the non-formal statistical approach for projections of daily annual extreme low and high flow indices. ~~The last point of conclusions (v) 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).~~

4.~~7~~~~6~~5 Variance decomposition of quantile QT30 values

Fig. ~~9~~ 8 shows the results of an application of the ANOVA variance decomposition technique to the percentage change of QT30 quantiles derived for the near-future period 2012-2050 relative to the reference period 1971-2000 for high flows (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~~*logNSE* weights for low flow quantiles. The symbols correspond to those used in Eq. ~~4~~3. The correlation between parameters is marked wit a star.

The sensitivity analysis presented in Fig. ~~9~~ 8 confirms our earlier results on the major influence of the climate model spread on the total QT30 variability for high flows and supreme influence of hydrological model parameters on the variability of low flow QT30. There is also ~~seen~~ a difference in the influence of distribution fit uncertainty, which is much larger for low flow QT30 variability than for high flow. The sensitivity analysis also confirms the inter-dependence of different sources of uncertainty, visible mainly for high-flow extremes.

~~The results of the study show that 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. In contrast, for low flows the uncertainty related to hydrological model parameters has a larger impact than the other uncertainty sources studied. The important role of hydrological model uncertainty in~~

~~low flow predictions has already been noticed in forecasting (Beninga et al., 2017). That effect can be explained by the ratio of the prediction noise (in this case described by the hydrological model uncertainty) to the input signal which is much higher for low flows. Demirel et al. (2013b) explored the influence of uncertainty in input, hydrological model parameters and initial conditions on a 10-day ensemble flow forecasts. The results showed that parameter uncertainty had the largest effect on the medium range low flow forecasts, which is consistent with the present paper findings. 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. In this study we applied the non-formal statistical approach for projections of daily annual extreme low and high flow indices. The last point of conclusions (v) 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).~~

5. Conclusions

The results of the research on the assessment of the uncertainty of extreme hydrological indices can be summarized in the following points:

~~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 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 BialaTarnowskaBiala Tarnowska 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 the 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 modelparameter 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 handIn contrast, for low flows, the uncertainty related to hydrological model parameters has a larger impact than the other uncertainty sources studied. The important role of hydrological model uncertainty in low flow predictions has already been noticed in forecasting (Beninga et al., 2017). That effect can be explained by the ratio of the prediction noise (in this case described by the hydrological model uncertainty) to the input signal which is much higher for low flows. Demirel et al. (2013b) explored the influence of uncertainty in input, hydrological model parameters and initial conditions on a 10-day ensemble flow forecasts. The results showed that parameter uncertainty had the largest effect on the medium range low flow forecasts, which is consistent with the present paper findings. 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 anIn this study we application applied of much simpler,the 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) tThe bias correction using distribution-based approach has a large influence on projected peak flows (Osuch et al., 2016); therefore~~ In order to eliminate influence of bias correction on flow maxima, the analysis of changes in the ~~high~~ quantiles of maximum annual flow projections was based on the raw ~~data~~ projections of precipitation.~~-~~ However,

(i) ~~T~~t~~(ii) on the other hand, t~~he analysis of low flow projections was based on the bias-corrected data to avoid the drizzle effect which affects the low flow characteristics.~~.~~

(ii) ~~(iii) c~~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 t~~This ~~allows~~ does not solve the problem of ~~nonstationarity~~the non-stationarity of model parameters ~~to be avoided~~but ~~allows for~~permits a focus~~ing~~ on parameter sets adequate for low and high flow regimes.

~~(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 parameter uncertainties, whilst the uncertainty due to~~

~~the distribution fit is the smallest. (v) Sensitivity analysis using ANOVA performed on the relative uncertainty for high and low QT30 quantiles confirms the conclusions obtained from point (iviii) on the larger influence of hydrological model uncertainty on extremes for low flow than for high flow.~~

(iii) A~~(vi) a~~nalysis of the influence of the length of time series records on the uncertainty bands of the low and high flow quantile estimates and their changes suggests that the range of quantiles of return periods ~~longer than~~QT30 are up to four times smaller when the long-term flow projections are used. The low flow QT30 quantiles are less influenced by the length of ~~records used for their derivation are very uncertain~~the record.

(iv) Taking into account the three uncertainty sources considered, the uncertainty of the estimate of 1-in-100 year return maximum flow exceeds 200% of its median value with the largest influence of the climate model uncertainty; whilst the uncertainty of the 1-in-100 year return minimum flow is of the same order (i.e. exceeds 200%), but it is mainly influenced by the hydrological model parameter uncertainty.

(v) A ~~S~~sensitivity analysis using ANOVA performed on the relative total uncertainty for ~~high and low~~ QT30 quantiles shows the largest ~~larger~~ influence of climate model and interactions between climate model and distribution fit uncertainty for high flows, whilst uncertainty of hydrological model parameters ~~uncertainty~~ and distribution fit have the largest influence on the uncertainty of ~~extremes for~~ low flow ~~than for high flow~~quantiles.

(vi) The analyses were performed for a catchment with stationary future extreme flow projections; in the case of nonstationary extreme flows, nonstationary frequency analysis would have to be applied with even larger uncertainty of extreme estimates than those presented here.

(vii) The study has pointed to the need to explore different approaches to projections of climate change.

~~The results of the study show that 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. In contrast, for low flows the uncertainty related to hydrological model parameters has a larger impact than the other uncertainty sources studied. The important role of hydrological model uncertainty in low flow predictions has already been noticed in forecasting (Beninga et al., 2017). That effect can be explained by the ratio of the prediction noise (in this case described by the hydrological model uncertainty) to the input signal which is much higher for low flows. Demirel et al. (2013b) explored the influence of uncertainty in input, hydrological model parameters and initial conditions on a 10-day ensemble flow forecasts. The results showed that parameter uncertainty had the largest effect on the medium range low flow forecasts, which is consistent with the present paper findings. 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. In this study we applied the non-formal statistical approach for projections of daily annual extreme low and high flow indices. The last point of conclusions (v) 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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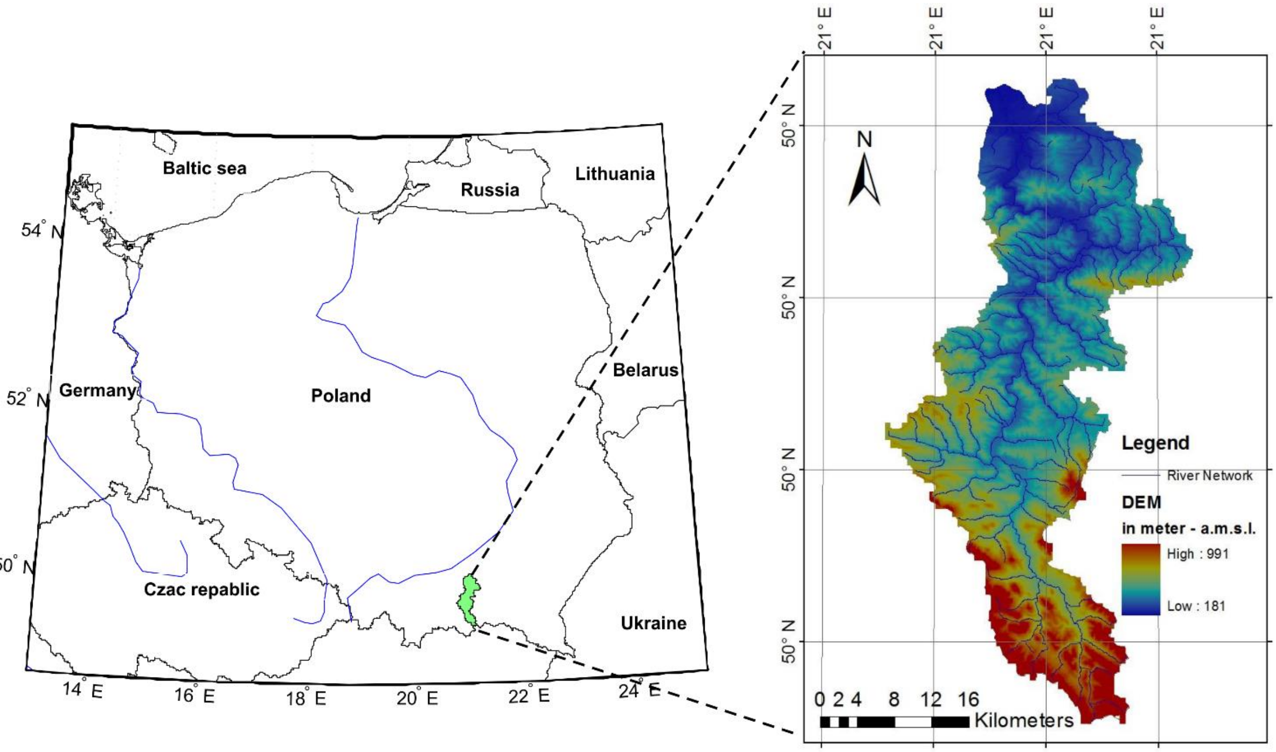
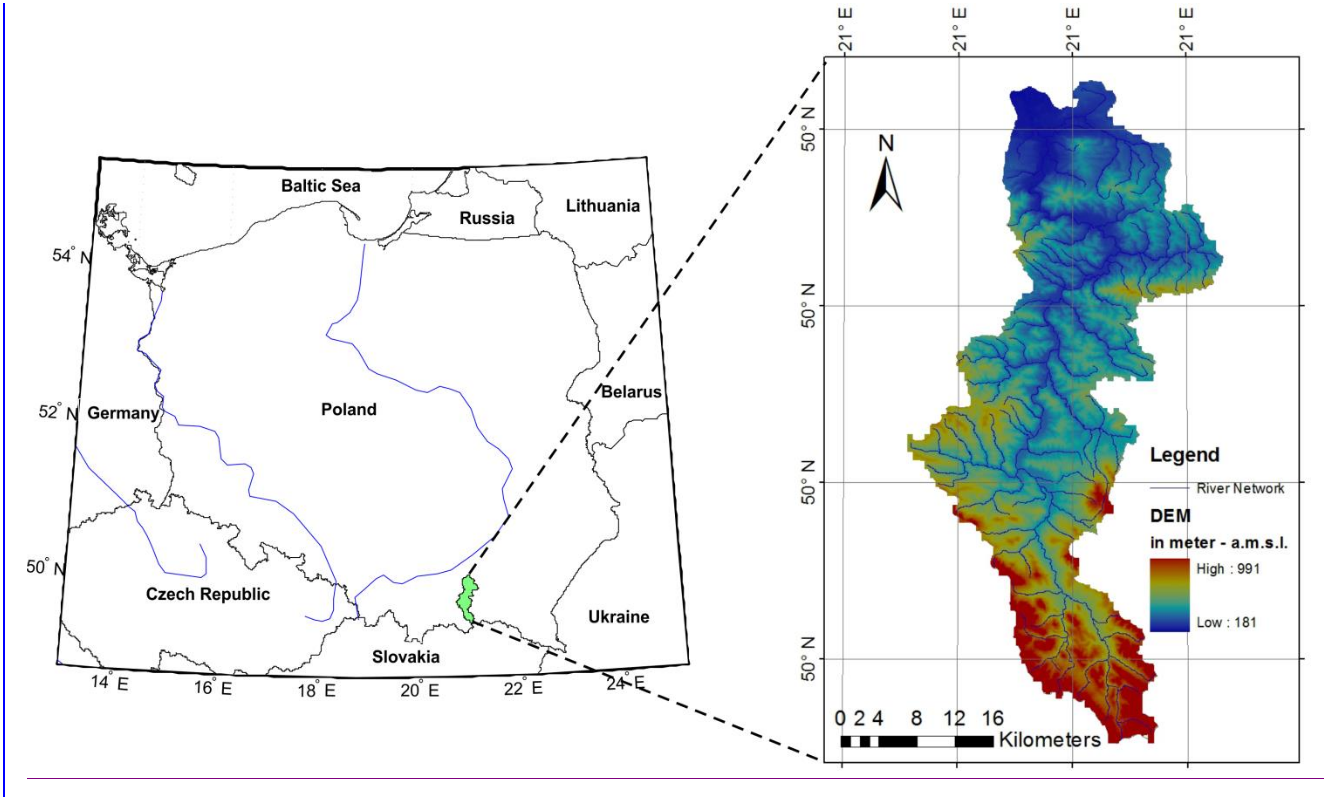
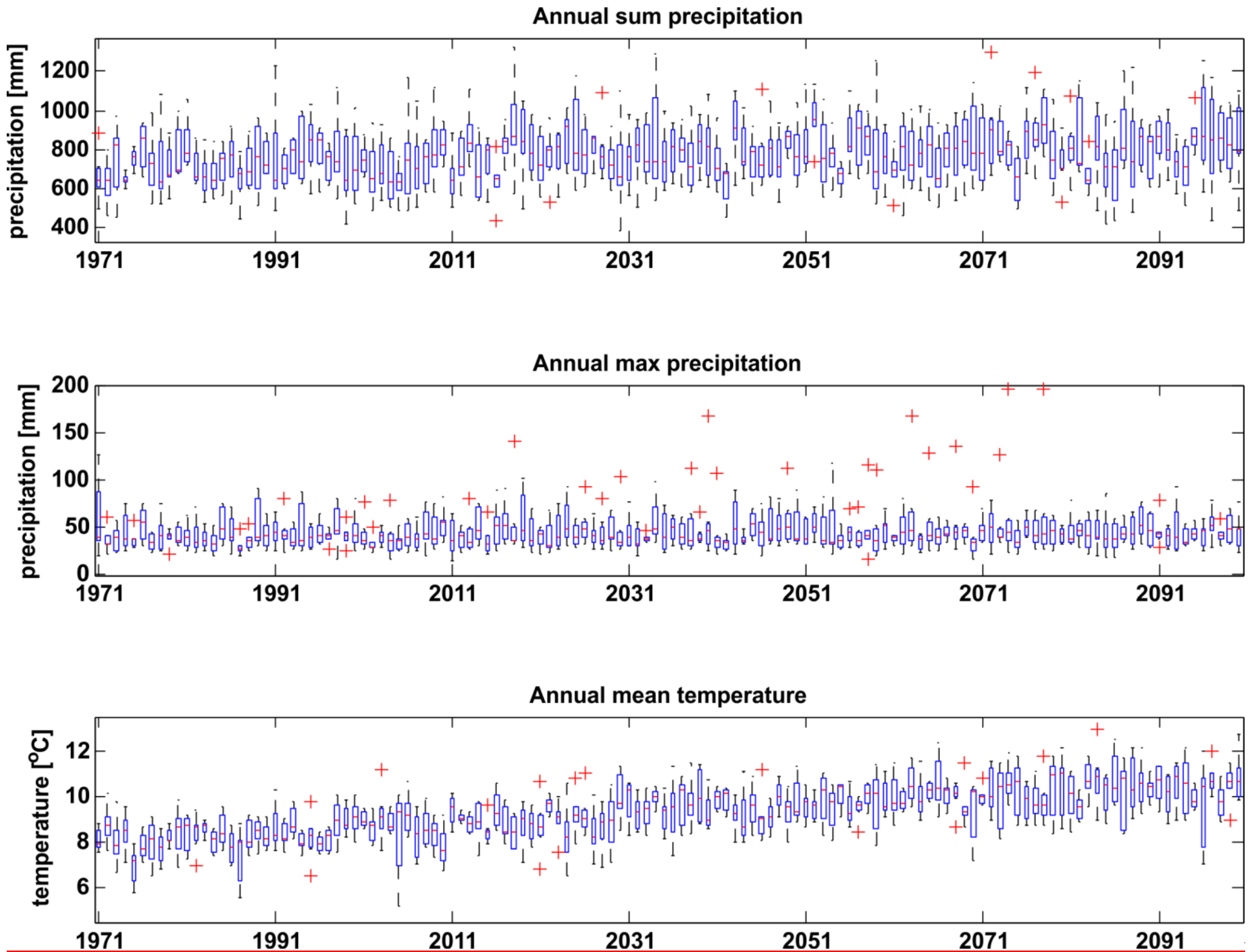


Baltic sea
Russia
Lithuania
Belarus
Germany
Poland
Czac repablic
Ukraine
54° N
52° N
50° N
14° E
16° E
18° E
20° E
22° E
24° E
21° E
21° E
21° E
21° E
50° N
50° N
50° N
50° N
N
Legend
River Network
DEM
in meter - a.m.s.l.
High : 991
Low : 181
0 2 4 8 12 16
Kilometers



5 **Figure 1.** The location of the study catchment.


Annual sum precipitation
precipitation [mm]
1200
1000
800
600
400
1971
1991
2011
2031
2051
2071
2091
Annual max precipitation
precipitation [mm]
200
150
100
50
0
1971
1991
2011
2031
2051
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temperature [ºC]
12
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2031
2051
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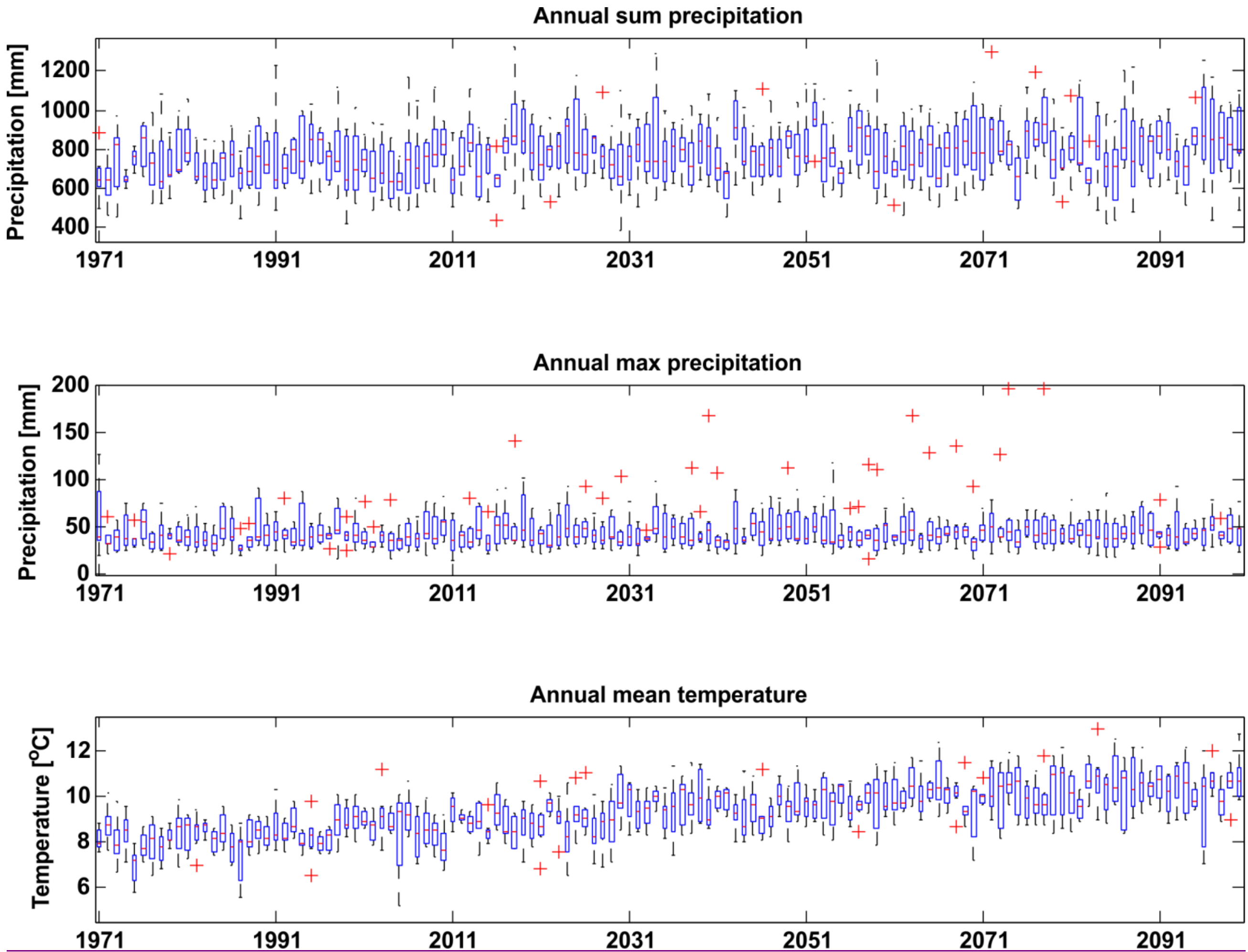
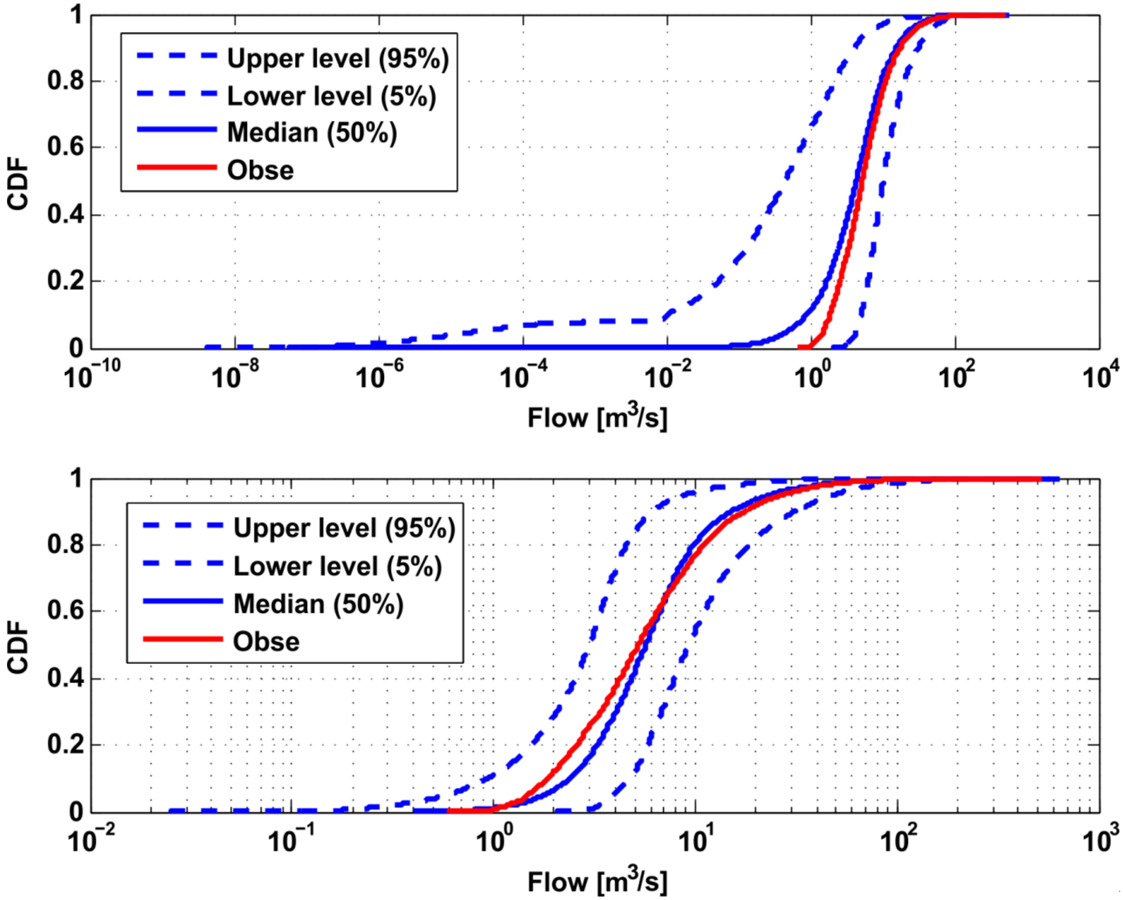


Figure 2. Climate model projections for the Biala Tarnowska catchment in the 1971-2100 period based on seven climate models from the GCMs/RCMs ensemble; ~~Upper~~ upper panel: projected bias-corrected ~~raw~~ annual ~~maximum~~ sum ~~daily~~ precipitation; middle panel: projected ~~corrected~~ raw annual maximum daily precipitation; lower panel: projected ~~raw~~ bias-corrected annual maximum daily temperature~~ for the Biala Tarnowska 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.


Upper level (95%)
Lower level (5%)
Median (50%)
Obse
CDF
Flow [m³/s]
Upper level (95%)
Lower level (5%)
Median (50%)
Obse
CDF
Flow [m³/s]

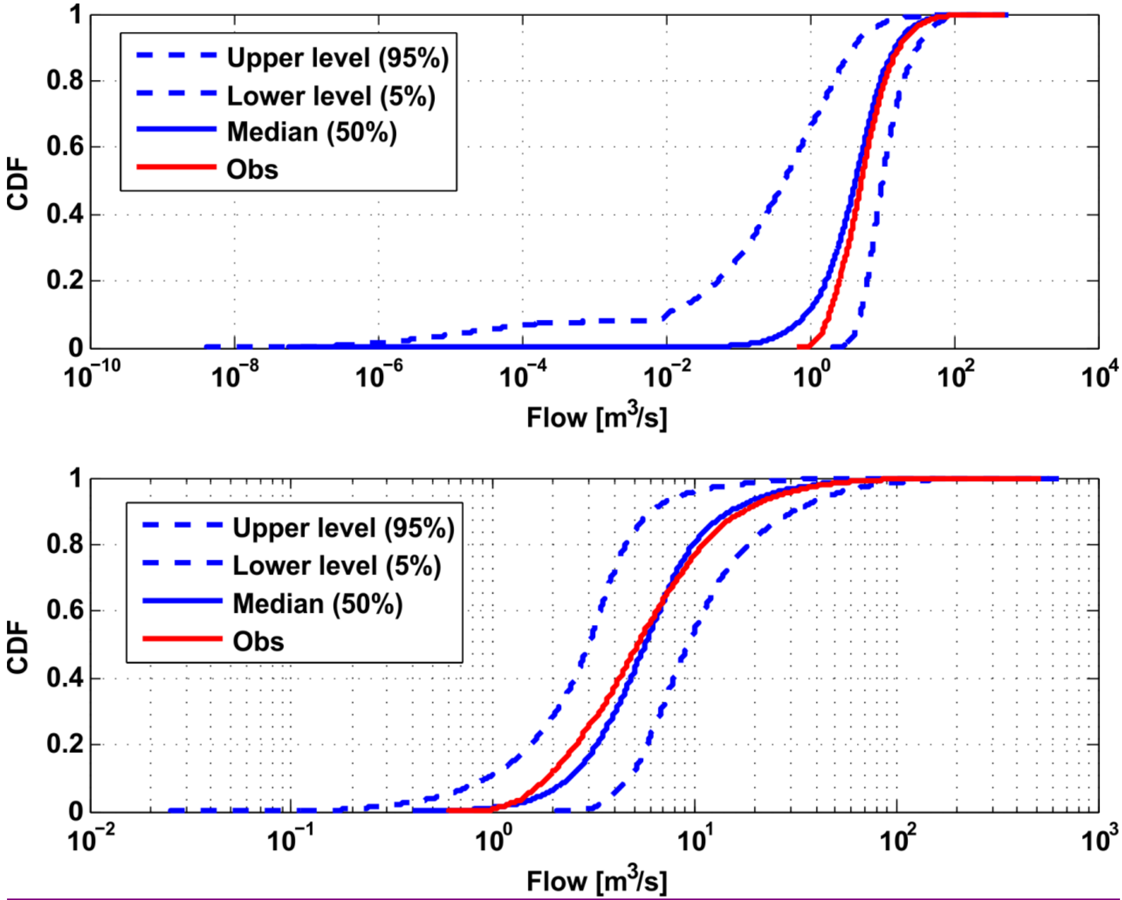


Figure 3. The cdf of flow for the calibration period for the HBV model; the upper panel presents model predictions conditioned on the *NSE*, while the lower panel presents the predictions conditioned on the ~~logNSE~~*logNSE* criterion~~. ~~; ~~The ~~the cdf of observations (red line) ~~is ~~are shown against the cdf of the HBV predictions (blue line) and the associated 95% confidence bounds (dashed line).

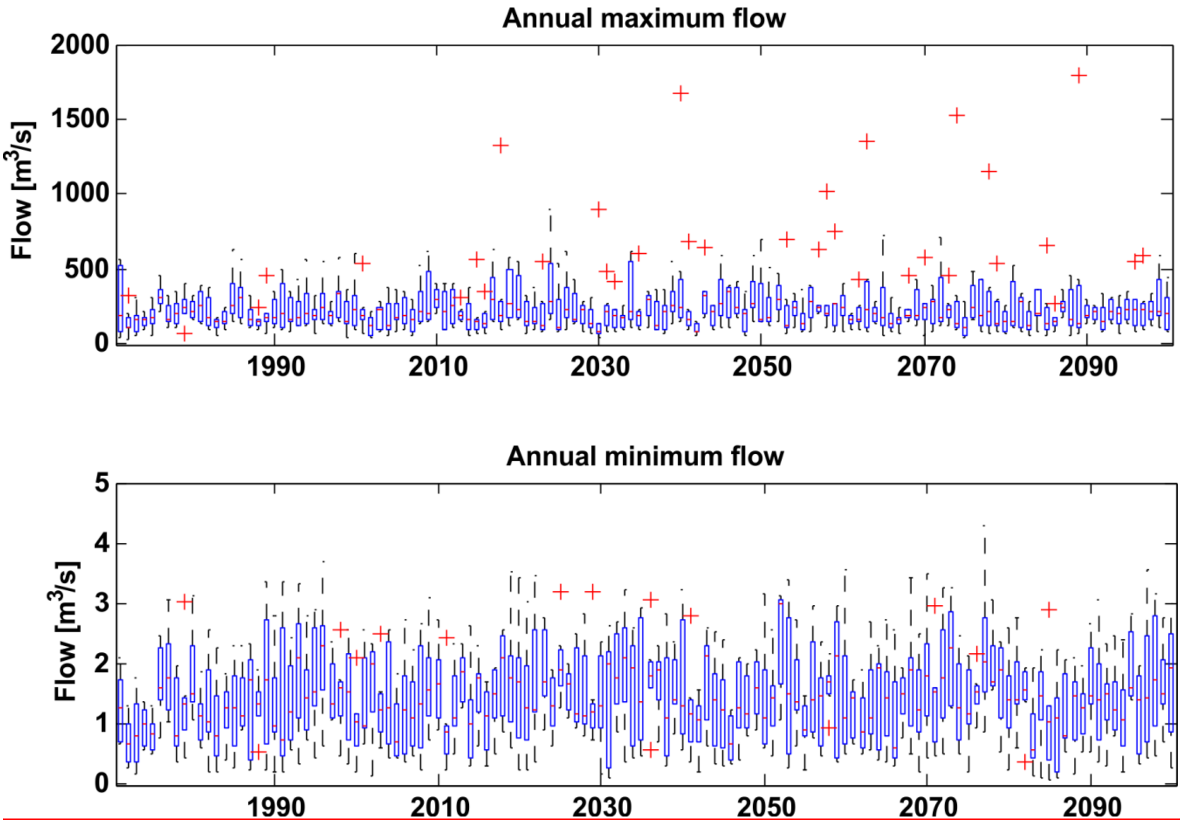


Figure 4. The HBV model extreme projections for the best HBV model parameter sets for the Biala Tarnowska at Koszyce in 1971-2100 based on seven climate models from the GCMs/RCMs ensemble; ~~Upper~~ upper panel: projected~~,~~ annual maximum daily flow for the HBV parameter set corresponding to the best *NSE* value; lower panel: projected annual minimum daily flow for the HBV parameter set corresponding to the best *logNSE* value~~:~~ ; ~~projected annual minimum daily flow for the HBV parameter set corresponding to the best logNSE value for the BialaTarnowska catchment at Koszyce in 1971-2100 based on seven climate models (CMs) from the GCMs/RCMs ensemble;~~ red dashed line shows an ensemble mean for the 1971-2100 period.

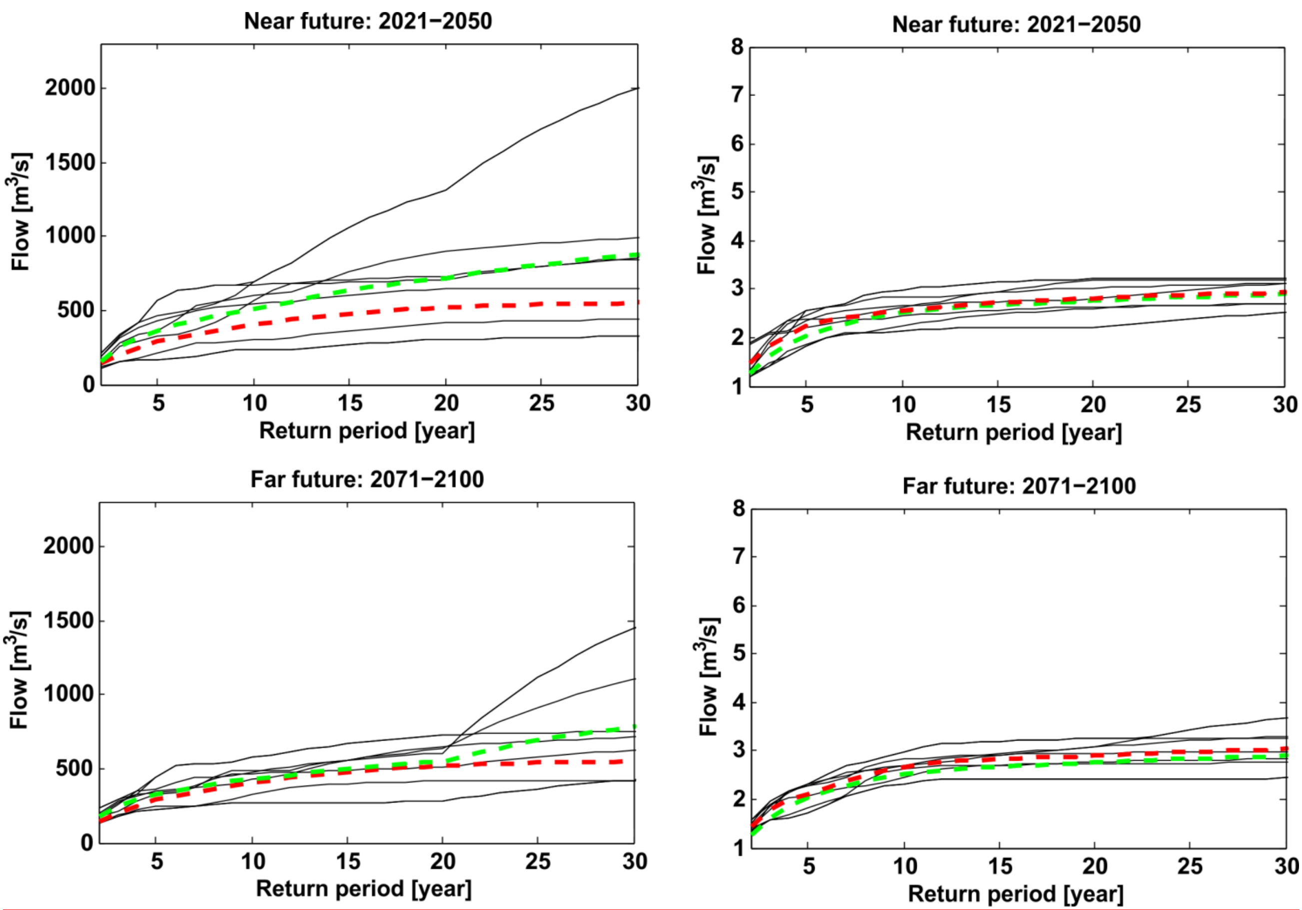


Figure 5. Empirical flow quantiles of annual maximum flow (~~upper panels~~left column) and annual minimum flow (~~lower panels~~right column) ~~under baseline~~ and future climates (near and far future~~ periods~~) for the best sets of the HBV model parameters and seven GCM/RCM model realizations; ~~the climate model spread is presented as a shaded area;~~ green dashed line denotes the mean value from all the GCM/RCM model realizations in each period (near and far future period), red dashed line denotes the averaged results obtained for the reference period~~.~~; ~~Each~~ each black line~~s~~ represents individual climate model~~s~~.

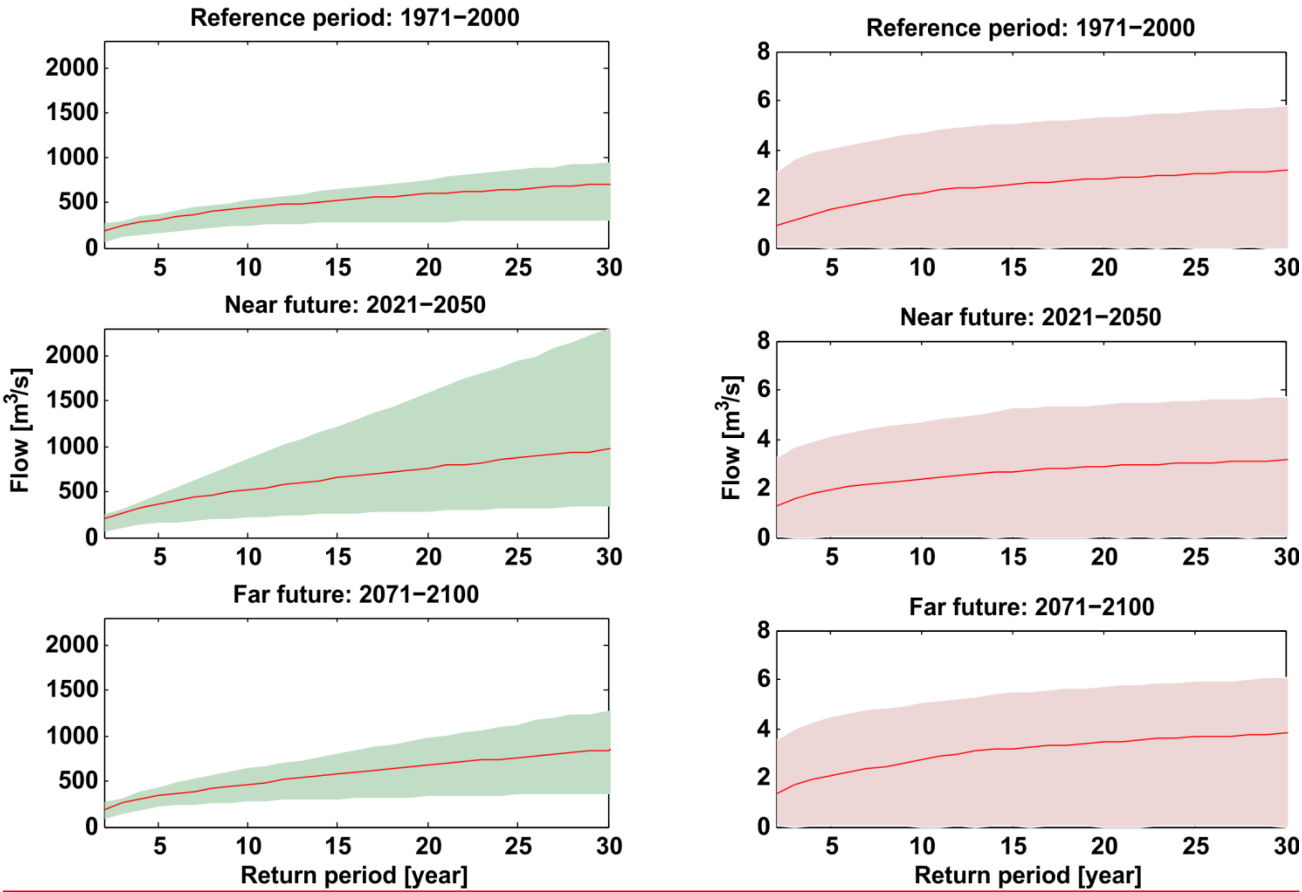


Figure 6. Total uncertainty ranges of ~~theoretical GEV-based~~ annual extreme flow quantiles based on the GEV distribution for projections over ~~30~~ 30-year periods ~~of~~ for the ~~BialaTarnowska~~Biala Tarnowska at Koszyce; the left column presents the annual maximum flow, the right column shows annual minimum flow; upper panels - ~~for~~ the reference period (1971-2000); middle panels - near future (2021-2050); lower panels - far future (2071-2100) periods~~; the right red hand column shows minimum annual flow, the left column presents the annual minimum flow frequency analysis results~~.

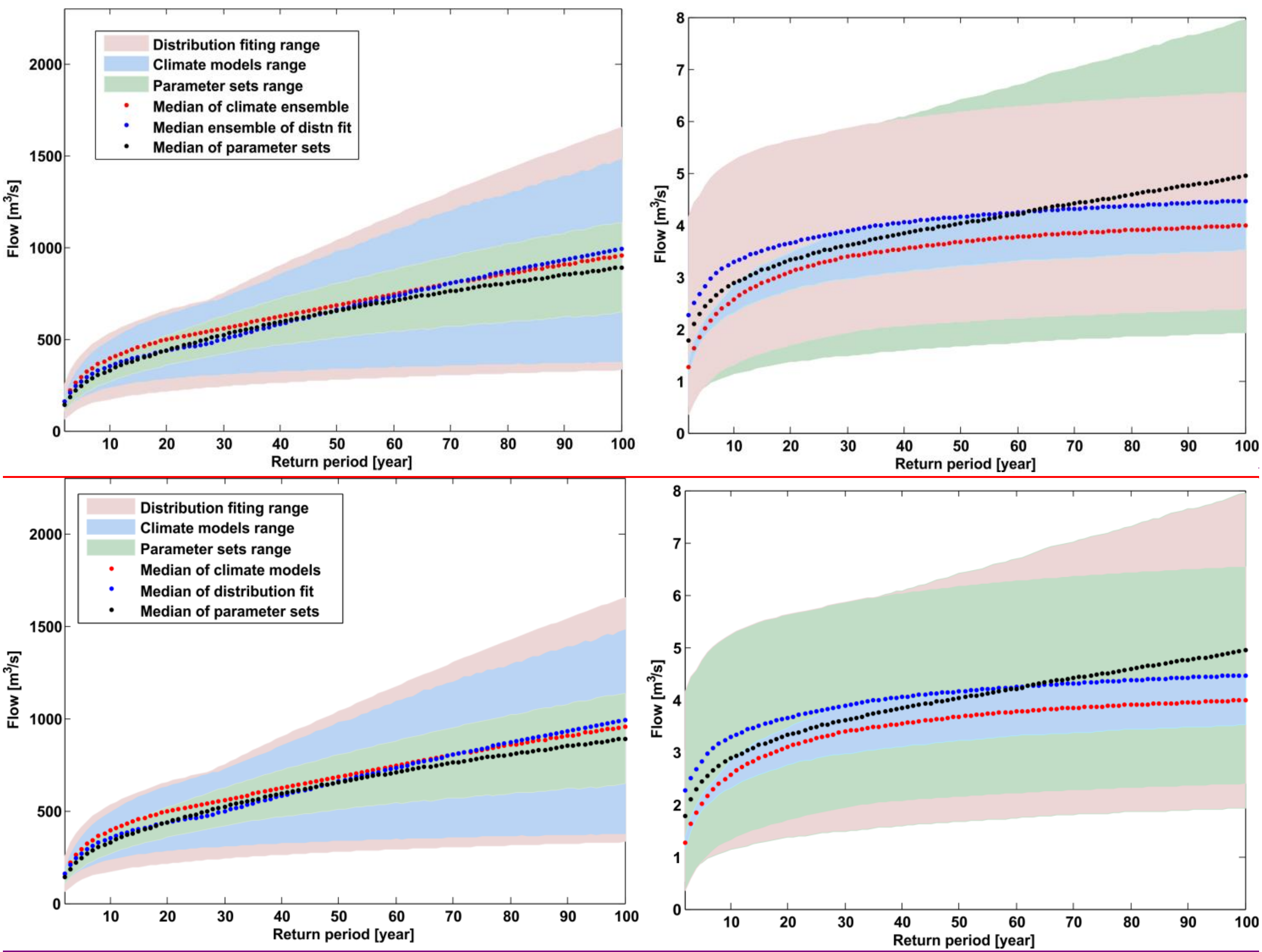


Figure 7. Total uncertainty ranges of flow quantiles for the River ~~BialaTarnowska~~Biala Tarnowska at Koszyce based on the ~~theoretical~~ GEV distribution ~~fit over~~ for projections over ~~130~~ 130-year~~s~~ period (1971-2100~~),~~); the ~~annual minimum flow as a function of return level period (right panel)~~ left panel presents~~and~~ annual maximum flow ~~as a function of a return level period (left panel~~

~~panel~~and the right panel presents annual minimum flow; the blue shaded area denotes the climate model uncertainty, the green shaded area denotes the hydrological model uncertainty and the pink shaded area denotes the distribution fit uncertainty; red dotted lines denote the median of climate ensembles,~~)~~ ~~.~~black dotted lines denote the median of hydrological model parameter sets and blue dotted lines denote the median of the distribution fit.~~ of simulated for the River BialaTarnowska at Koszyce, based on a GEV distribution fit to the projected annual flow (1971-2100).~~

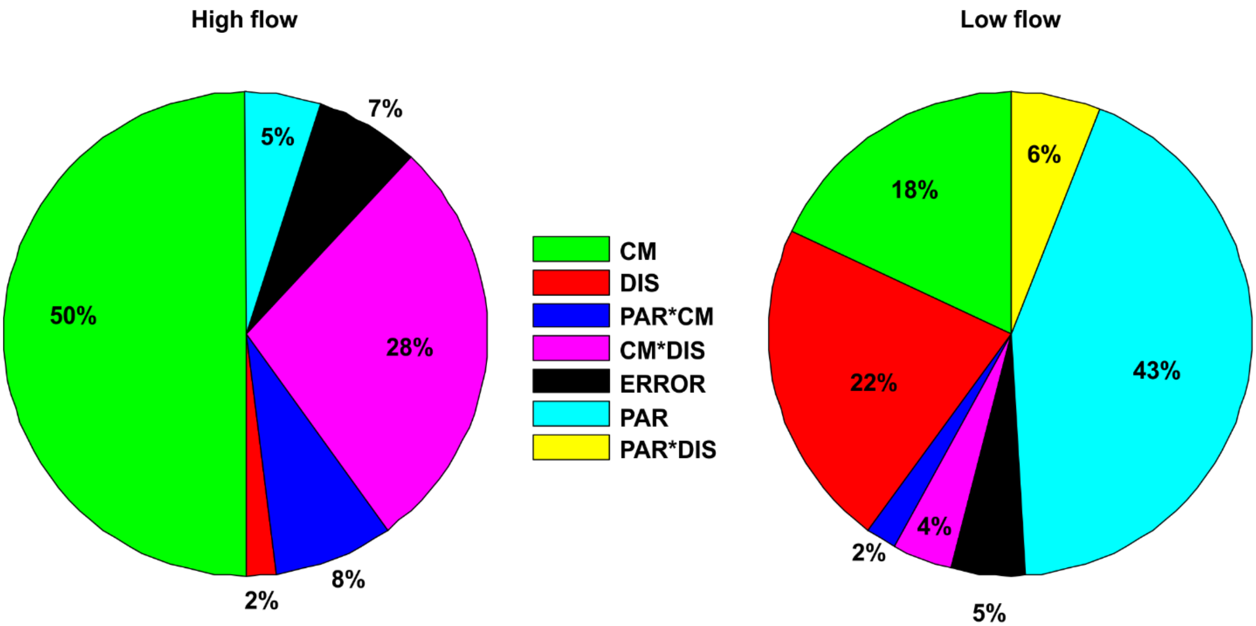


Figure 8. Total variance in estimates for the percentage change in QT30 in 2021-2050 relative to the 1971-2000 reference period. Each color represents the relative contribution of uncertainty in percent; *CM* denotes climate model; *DIS* – distribution fit; *PAR* – hydrological model parameters; *ERROR* denotes the Gaussian error (Eq. ~~4~~3); a “star” denotes the correlation between the factors (*CM*, *DIS* and *PAR*).~~.~~

GCM	RCM	expansion name	Institute
EC-EARTH	RCA4	Rossby Center regional	Swedish Meteorological and Hydrological Institute
EC-EARTH	HIRHAM5	Atmospheric model	Danish Meteorological Institute
EC-EARTH	CCLM-4-8-17	Community land model	NCAR UCAR
EC-EARTH	RACMO22E	Regional atmospheric climate model	Meteorological institute
MPI-ESM-LR	CCLM4-8-17	Community land model	Max Planck Institute for Meteorology
MPI-ESM-LR	RCA4	Regional-scale model	Max Planck Institute for Meteorology
CNRM-CM5	CCLM4-8-17	Community land model	CERFACS, France

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

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

~~GCM~~	~~RCM~~	~~Institute~~
~~EC-EARTH~~	~~RCA4~~	~~Swedish Meteorological and Hydrological Institute~~
~~EC-EARTH~~	~~HIRHAM5~~	~~Danish Meteorological Institute~~
~~EC-EARTH~~	~~CCLM-4-8-17~~	~~NCAR UCAR~~
~~EC-EARTH~~	~~RACMO22E~~	~~Meteorological institute, Netherlands~~
~~MPI-ESM-LR~~	~~CCLM4-8-17~~	~~Max Planck Institute for Meteorology~~
~~MPI-ESM-LR~~	~~RCA4~~	~~Max Planck Institute for Meteorology~~
~~CNRM-CM5~~	~~CCLM4-8-17~~	~~CERFACS, France~~

Table 2. HBV parameter ranges: upper band (UB), lower band (LB), unit ~~value~~ ; fixed parameters have lower and upper bands equal.

~~Parameter~~	~~description~~	~~LB~~	~~UB~~	~~Unit~~
~~FC~~	~~maximum soil storage~~	~~0.1~~	~~250~~	~~mm~~
~~BETA~~	~~Shape coefficient~~	~~0.01~~	~~7~~	~~-~~
~~LP~~	~~SM threshold for reduction of evaporation~~	~~0.1~~	~~1~~	~~-~~
~~ALFA~~	~~measure for non-linearity of flow in quick runoff~~	~~0.2255~~	~~0.2255~~	~~-~~
~~KF~~	~~recession coefficient for runoff from quick runoff~~	~~0.2826~~	~~0.2826~~	~~d^{-1}~~
~~KS~~	~~recession coefficient for runoff from base flow~~	~~0.0005~~	~~0.3~~	~~d^{-1}~~

~~PERC~~	~~percolation rate occurring when water is available~~	~~0.01~~	~~100~~	~~mm d^{-1}~~
~~CFLUX~~	~~Rate of capillary rise~~	~~1.0003~~	~~1.003~~	~~mm d^{-1}~~
~~TT~~	~~Threshold temperature for snowfall~~	~~1.0145~~	~~1.0145~~	~~^{0}C~~
~~TTI~~	~~Threshold temperature interval length~~	~~7~~	~~7~~	~~^{0}C~~
~~CFMAX~~	~~Degree day factor, rate of snowmelt~~	~~0~~	~~20~~	~~mm ^{0}C^{-1} d^{-1}~~
~~FOCFMAX~~	~~Degree day factor, rate of snowmelt~~	~~0.1484~~	~~0.1484~~	~~mm ^{0}C^{-1} d^{-1}~~
~~CFR~~	~~Refreezing factor~~	~~0.2779~~	~~0.2779~~	~~-~~
~~WHC~~	~~Water holding capacity of snow~~	~~0.001~~	~~0.001~~	~~mm mm^{-1}~~

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

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

~~Number of experiment~~	~~1~~	~~2~~	~~3~~	~~4~~	~~5~~	~~6~~	~~7~~	~~8~~	~~9~~
~~Threshold *NSE*~~	~~0.5~~	~~0.53~~	~~**0.55**~~	~~0.57~~	~~0.6~~	~~0.63~~	~~0.65~~	~~0.67~~	~~0.7~~
~~out of bound *NSE* [%]~~	~~10~~	~~9.9~~	~~9.6~~	~~9.8~~	~~9.9~~	~~10~~	~~10~~	~~10.5~~	~~11~~
~~Threshold logNSE*logNSE*~~	~~0.4~~	~~0.37~~	~~0.34~~	~~0.31~~	~~**0.3**~~	~~0.29~~	~~0.26~~	~~0.23~~	~~0.2~~
~~out of bound logNSE*logNSE*~~	~~15~~	~~12.3~~	~~12~~	~~13.5~~	~~11.4~~	~~17.4~~	~~17.8~~	~~18~~	~~20~~

~~[%]~~

Table ~~4~~3. Change in width of 0.95 confidence intervals for QT30 for annual maximum and minimum flow estimated using time periods of a different length (30-~~years~~ year and ~~130~~ 130-~~years~~ year- long).

Evaluation period	1971-2000	2021-2050	2071-2100	1971-2100
Max flow(ΔQT30) [m^3/s]	640.5	1942.6	898.9	459.4
Min flow(ΔQT30) [m^3/s]	4.7	5.0	5.2	4.4