Effect of (quasi-)optimum model parameter sets and model characteristics on future discharge projection of two basins from Europe and Asia

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Abstract:	Uncertainty is an inherent, unavoidable feature in the modeling of natural processes. This is particularly a sensitive issue when dealing with forecasting, especially in the context of climate change impacts. Apart from the uncertainty introduced by different climate projections, additional sources of uncertainty appear in the analysis of rainfall-runoff and associated prediction of water discharge changes due to climate change models, input information in calibration steps, regionalization, parameter choices, and downscaling techniques, among others. In this study, we focus on the uncertainty introduced by various set of parameters in the 21st century projections of runoff for two large river basins: the Rhine river in Europe, and the Ganges in Asia. To estimate the relative impact of parameter-induced uncertainty, various scenarios are compared with those given by general circulation models (GCM) and climate change emission scenarios (Representative Concentration Pathways, RCP). We apply a robust parameter estimation optimization algorithm ROPE to account for the uncertainty in a quasi-optimum parameter set choice. A total of 1,000 well performed parameter sets are analyzed for this purpose. Also, two hydrological models are used to test the impact of model conception. The analysis of the ensemble of projected discharge suggests that the parameter uncertainty is strongly related to model complexity in both basins considering the best one thousand performing sets. The contribution to uncertainty of parameter sets for the Ganges is rather stable in time and comparatively small for the periods 2006 to 2035, 2036 to 2065 and 2070 to 2099. Major differences are attributable to GCMs ranging from 60% to 80% followed by RCPs in the range 12-30%, whereas parameter differences account for 3-8%. Results for the Rhine are more heterogeneous and change over time, with increasing importance of GCM/RCPs toward the end of the century. The major differences are also observed in the GCM outcomes representing a proportion of 49-77% in contrast to 11-40% of model parametrization (parameter sets).

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Effect of (quasi-)optimum model parameter sets and model characteristics on future discharge projection of two basins from Europe and Asia

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Abstract

Uncertainty is an inherent, unavoidable feature in the modeling of natural processes. This is particularly a sensitive issue when dealing with forecasting, especially in the context of climate change impacts. Apart from the uncertainty introduced by different climate projections, additional sources of uncertainty appear in the analysis of rainfall-runoff and associated prediction of water discharge changes due to climate change models, input information in calibration steps, regionalization, parameter choices, and downscaling techniques, among others. In this study, we focus on the uncertainty introduced by various set of parameters in the 21st century projections of runoff for two large river basins: the Rhine river in Europe, and the Ganges in Asia. To estimate the relative impact of parameter-induced uncertainty, various scenarios are compared with those given by general circulation models (GCM) and climate change emission scenarios (Representative Concentration Pathways, RCP). We apply a robust parameter estimation optimization algorithm ROPE to account for the uncertainty in a quasi-optimum parameter set choice. A total of 1,000 well performed parameter sets are analyzed for this purpose. Also, two hydrological models are used to test the impact of model conception. The analysis of the ensemble of projected discharge suggests that the parameter uncertainty is strongly related to model complexity in both basins considering the best one thousand performing sets. The contribution to uncertainty of parameter sets for the Ganges is rather stable in time and comparatively small for the periods 2006 to 2035, 2036 to 2065 and 2070 to 2099. Major differences are attributable to GCMs ranging from 60% to 80% followed by RCPs in the range 12-30%, whereas parameter differences account for 3-8%. Results for the Rhine are more heterogeneous and change over time, with increasing importance of GCM/RCPs toward the end of the century. The major differences are also observed in the GCM outcomes representing a proportion of 49-77% in contrast to 11-40% of model parametrization (parameter sets).

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1. Introduction

Mathematical representation and state representation at a given time of a natural phenomenon that allow a precise description and detailed picture of the phenomenon is not possible. In the context of hydrological modelling, several sources of errors and uncertainties have been identified. Although there are various classifications, the main sources of predictive uncertainty can be divided according to input uncertainty, state uncertainty, process abstraction-related uncertainty, model structure uncertainty and output uncertainty (Götzinger and Bárdossy, 2008). In spite of their role, addressing their relative contribution to the final predictive uncertainty is far from being trivial. Furthermore, predictive uncertainty is often partially assessed as the best model state, evaluated with defined goodness-of-fit metrics (Singh and Woolhiser, 2002). Isolating source of errors and quantifying their contribution to the overall predictive uncertainty has been matter of various efforts (Kavetski et al., 2003; Schaefli et al., 2007). This can be significant when future statements are pursued, and a certain confidence is expected.
Several researchers have investigated uncertainty for climate change projections. Efforts have been placed in various aspects including input data uncertainties in the process of calibration and validation, downscaling related uncertainties, general circulation models (GCMs) and rainfall-runoff models, among others. The object of analysis can affect the impact on mean discharge values, flood frequency, extreme values or drought characteristics. Teng et al., 2011 for example assessed the relative uncertainties in modeling climate change impact on runoff across

southeast Australia given by GCMs and rainfall-runoff models. Their results showed that uncertainty sourced from the GCMs is much larger than the uncertainty in the rainfall-runoff models. The contribution of various sources of uncertainty have also been investigated by Exbrayat et al., 2014 for a remote and data-sparse catchment in Ecuador. There, the contribution of differences between model structures to the total uncertainty was found to be similar compared to GCM and emission scenarios for discharge simulations. Harding et al., 2012 investigated the impact of future climate conditions using a multi-model ensemble approach from 16 GCMs in the Upper Colorado River Basin. They found that the impact of projected 21th century climate conditions on streamflow ranges from a decrease of approximately 30% to an increase of similar magnitude. Jung and Chang, 2011 studied runoff trends under multiple climate change scenarios consisting of 8 GCMs and 2 emission scenarios, and the effects of elevation and geological characteristics on uncertainty. Some of their results showed that long-term trends of water balance components in the Willamette River Basin can be highly affected by anthropogenic climate change.

The parameter uncertainty has been a topical subject in rainfall-runoff modeling in the last decades (Beven and Binley, 1992), especially in the context of climate change. For example, Wilby, 2005, analyzed the uncertainty related to model parameter for climate change impact assessments in the River Thames, UK. He explored the effect of the non-uniqueness of parameters on projections using hydrological model CATCHMOD. Uncertainty in future river flows was explored using the 100 best performing parameter sets generated by Monte Carlo simulation. Wilby and Harris, 2006, presented a probabilistic approach for combining sources of uncertainties such as emission scenario, GCM, downscaling techniques, parameter model parameters and model structure for the River Thames and low-flow scenarios. Uncertainty due to parameter choice was addressed by using two sets and found that low-flow cumulative distribution functions are most sensitive to uncertainty in the climate change scenarios and downscaling of different GCMs.

Overall, quantification of uncertainty has been a major topic in hydrology, where substantial effort have been placed into their effects in climate change scenarios. The contribution of the different uncertainty sources or the main sources remains as an outstanding open problem, where case-dependent characterization appears be the most appropriate approach. Addressing all potential uncertainty sources is far from the scope of most or possibly all research studies we can find in the literature.

While the major uncertainty sources have been attributed to GCMs in the aforementioned studies, other investigations have arrived to different conclusions. For example, Haddeland et al., 2011 used a multimodel approach for models intercomparison and showed that major source of uncertainty are due to considerable differences in simulated runoff between models. They pointed that studies of climate change impacts should not be based on a single model. Nonetheless, Uncertainty in rainfall-runoff modeling can be caused by both model structure and parameters (Teng et al., 2011).

In this study, we investigate the effect of various sets of parameters on the projected discharge of Rhine at Lobith located in Europe and Ganges at Farakka located in Asia for the periods 2006-2035, 2036-2065, and 2070-2099. We apply a robust parameter optimization algorithm (ROPE) to generate a large number (*n=1,000*) of well performing parameter sets for each instance. We address the influence of model structures/complexity on these projections by using two state-of-the-art hydrological models. First, we calibrate and validate against observed discharge. Then, we use climate projections from five GCMs driven by four Representative Concentration Pathways (RCPs) emission scenarios for the 21st century. GCMs chosen here present ranges of uncertainties in projections of annual temperature and precipitation comparable with all of CMIP5 models (see protocol-report on www.isimip.org).

2. Material and methods

2.1 Study areas and available data

Main features of the Rhine River at Lobith's and the Ganges at Farakka's basins can be found in the introductory paper of the Inter-Sectoral Impact Model Intercomparison Project Phase 2 ISI-MIP2 (Krysanova and Hattermann, 2016). The WATCH forcing dataset is used to calibrate and validate the hydrological models. It is based on the 40-yr ECMWF Re-Analysis (ERA-40) and reordered reanalysis data for 1958-2001 and 1901-1951, respectively. The dataset contain several climatological variables including air temperature, rainfall rate, specific humidity, amongst others, which are regularly distributed grids with 0.5 degree resolution. For details on WATCH and ERA-40 refer to Weedon et al., 2011 and Uppala et al., 2005.

Climate change scenario data are based on five GCMs participating in the Coupled Model Intercomparison Project Phase 5 (Taylor et al., 2012): HadGEM2-ES, IPSL CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M, and NorESM1-M. These models are based on a set of different scenarios accounting for anthropogenic fossil-fuel emissions as well as land use and land cover change. We use 20 combinations consisting of five GCMs and four representative concentration pathways (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) scenarios; last identified by the approximate gain in radiative forcing in year 2100 mostly due to human emissions of greenhouse gases compared to the baseline level in 1750 (IPCC 2013). These climate projections were downscaled and bias corrected following Hempel et al., 2013.

2.2 Hydrological models

Parameter values affect the outcomes of a model. This may induce not negligible variations of the simulated discharges. In order to account for this effect, two conceptual hydrological models, namely HBV and HYMOD are used to evaluate this interdependence. A large number of robust parameter sets (see section 2.3) is search for and the variations in the simulations is compared for each model.

The semi-distributed HVB model is a rainfall-runoff type originally developed by the Swedish Meteorological and Hydrological Institute (SMHI) (Bergström, 1995; Lindström et al., 1997). This conceptually based model comprises routines for calculating snow accumulation and melt, soil moisture, and runoff generation as a function of soil water content and infiltration rates, runoff concentration and discharge flood routing within the river network. Our HBV version uses modified components; for example, the incorporation of a new parameter in the degree-day factor for accounting additional energy available in rainwater at positive temperatures, and a non-linearity of the rainfall-runoff proportion expressed by a power-law relationship. Details can be found in Hundecha and Bárdossy, 2004, and Hundecha Hirpa, 2005.

The HYMOD is a relatively simpler conceptual rainfall-runoff model defined by two components, namely the rainfall excess (two parameters) and two series of linear reservoirs (three parameters) arranged in parallel. The first reservoir represents a quick response and the second one a slow response. The version used here also considers a snow routing routine as in the HBV model. Details can be found in Moore, 1985, Boyle et al., 2001 and Wagener et al., 2001.

2.3 Robust Parameter Estimation

Robust Parameter Estimation (ROPE) optimization procedure is performed to get an estimation of the uncertainty in the expected discharge variation due to parameter choice. The analysis of geometrical properties of parameter sets is key. It has been investigated by Bárdossy, 2007 in a 2D case showing a well-defined structure of the sets.

Later, Bárdossy and Singh, 2008, Singh, 2010, investigated these properties in a hydrological modeling framework in higher dimensions. The parameter search aims to find robust sets that have important features such as good model performance in the selected period, a reasonable representation of the modelled processes, small sensitivity and transferability to other time periods. This was investigated in detail by Bárdossy and Singh, 2008. However, to the best of our knowledge a robust parameter estimation has not been performed to generate an ensemble of well-performing parameter sets in the scope of climate change uncertainty assessment. Hereafter, we briefly describe the ROPE algorithm and the underlying calculations of parameter depth, the key concept in the search of optimum parameter sets.

Depth function

The depth function was first introduced by Tukey, 1975, as a measure of centrality of a data set within a population set in a multi-dimensional space. Let $\boldsymbol{x}$ be a vector from a set $\boldsymbol{S}$ such that $\boldsymbol{x} \in \boldsymbol{S}$, and $\boldsymbol{S} \subseteq R^p$. A depth function is defined as:

$$D: R^p \to R$$

$$\{\boldsymbol{x} \in R^p\} \to y$$

in which to each vector $\boldsymbol{x}$, a number (depth) y is associated so that an ordering of $\boldsymbol{x} \in S$ in the center-outward direction is defined. It can be seen as a quantitative measure of how central a vector is located when compared with a given vector set. Several definitions of depth function have been proposed; for example, Liu, 1990 indicated non-negativeness and a bounded domain as a prerequisite to be fulfilled. Others include Affine invariance, maximality at center, monotonicity relative to deepest point and vanishing at infinite (Zuo and Serfling, 2000). From the listed properties follow that the data lying in the vicinity of the center of the cloud have a high depth value; conversely, those located far from the center have a low depth value. More details can be found in Donoho and Gasko, 1992, Miller et al., 2003. Others depth functions include the L_1 depth ((Hugg et al., 2006), Oja median (Oja, 1983), Convex Hull Peeling (Barnett, 1976; Liu et al., 1999), Likelihood-based depth functions (Fraiman et al., 1997) and a method for constructing individual depth functions (Vardi and Zhang, 2000).

Halfspace depth function

Tukey, 1975, proposed the halfspace depth function as a kind of generalization in the multivariate space of the univariate rank (order statistics). The depth of a point $\boldsymbol{p} = \{p_i\}_{i=1}^{d}$ in dimensional space d with respect to a finite set $\boldsymbol{X}$ is defined as the minimum number of points in $\boldsymbol{X}$ lying on one side of a hyperplane though the point $\boldsymbol{p}$. Considering all possible directions for the hyperplane given by its unit normal vector the minimum is then calculated, and mathematically expressed as:

$$D_x(\boldsymbol{p}) = min_{\boldsymbol{n_h}}(min(|\{\boldsymbol{x} \in \boldsymbol{X}, \langle \boldsymbol{n_h}, \boldsymbol{x} - \boldsymbol{p} \rangle > 0\}|), (|\{\boldsymbol{x} \in \boldsymbol{X}, \langle n_h, \boldsymbol{x} - \boldsymbol{p} \rangle < 0\}|)) \qquad (1)$$

In this equation $\langle \boldsymbol{\alpha}, \boldsymbol{\beta} \rangle$ and $\boldsymbol{n_h}$ represent the scalar product and an arbitrary unit vector of a selected hyperplane so that $\boldsymbol{n_h} \in R^{\boldsymbol{d}}$. The dimension of the space is denoted by d. The scalar product represents the projection of the vector $(\boldsymbol{x} - \boldsymbol{p})$ onto the unit vector $\boldsymbol{n_h}$. It can be shown that this depth function satisfies all properties listed in the previous point (Zuo and Serfling, 2000). In this study, the calculation of the depth is based on that suggested by Rousseeuw and Struyf, 1998, which is an approximate estimation of the location depth, especially appropriate when dealing with large data sets or a high-dimension parameter space (number of parameters).

ROPE algorithm

As suggested by Bárdossy and Singh, 2008, the following optimization procedure is used to find a set of good performing and deep parameter vectors for robustness in the modelling step. Given the dimension of the parameter vector d,

1. Identify the limits for the d selected parameters.
2. Generate n random parameter vectors conforming the set $\boldsymbol{X_n} = \{\boldsymbol{\theta_1}, \ldots, \boldsymbol{\theta_n}\}$, $\boldsymbol{\theta_j} \in \boldsymbol{R^d}$, $j = 1, \ldots n$. The limits are those defined in 1
3. Run the hydrological model For each parameter vector $\boldsymbol{\theta_i} \in \boldsymbol{X}_n$, and calculate the performances of the model $\{g_{\theta_i}\}_{i=1}^{n}$.
4. Define a new set $\boldsymbol{X}_m$ containing the m-parameter vectors with the best performance. The number of the m selected vectors can be for example the 10% of best performing vectors from $\boldsymbol{X_n}$.

5. Generate a set of p new random vectors $\boldsymbol{Y}_p$ such that

   $\boldsymbol{Y}_p = \{\boldsymbol{\theta_1}, \dots, \boldsymbol{\theta_p} / D(\boldsymbol{\theta_i}) \geq L, i = 1, \dots, p\}$

   In this step, the depth $D(\boldsymbol{\theta})$ is calculated with respect to the set $\boldsymbol{X}_m$ defined in the previous step.

6. Relabel the constructed vector set $\boldsymbol{Y}_p$ as $\boldsymbol{X}_n$ and repeat the procedure from point 3

As expected, for increased number of iterations in step 3, the run time involved in each step also increases. Consequently, the algorithm can be stopped when the performance of two consecutive simulation steps does not differ more than expected from the observation errors (Bárdossy and Singh, 2008). Note that it depends on specific factors such as the amount of data (range of the period used for calibration and validation); the entire process may be computationally expensive. Here, the performance of the parameters plays also an important role in the required iterations.

2.4 Experimental setup

Uncertainty in model projections due to good performing robust parameter vectors is based on the $n_{opt} = 1000$ parameters from the last iteration of ROPE showing the best performance. The commonly-used Nash-Sutcliffe function was chosen (Nash and Sutcliffe, 1970) as objective function for model evaluation. The initial number of parameter vectors randomly generated is set to $n_0 = 100{,}000$; each parameter having plausible lower and upper limits previously defined. The number of best performing parameter vectors after running the model is set to $m = 1{,}000$. Finally $n_p = 5{,}000$ number of vectors are generated in each iteration through Monte Carlo Simulations constrained to *depth>1* (eq.1). Parameter related uncertainty is calculated based on the range of projected discharge out of this final set.

As pointed, the effect on this uncertainty due to model structure is analyzed comparing the hydrologic simulation given by the two hydrological models HBV and HYMOD. Effects of GCMs and RCPs on the parameter uncertainty are also included in this analysis. An ensemble of simulations is performed for each basin considering one GCM and one RCP. A set of 20 combinations is compared for HBV and HYMOD, and for the two basins Rhine and Ganges. Finally, we summarize the relative contribution of parameter sets, rainfall-runoff model and GCM choice to the overall uncertainty.

3 Results and discussion

3.1 Optimization results

An iteration traduces in a set of better performing parameter sets. This can be easily observed by comparing the distribution of the set performance step by step. Figure 1 shows the histograms for the two models HBV and HYMOD and for the two basins, Rhine and Ganges. Each histogram is built out of 5,000 parameter sets generated so that *depth*>1 (eq. 1). The subplots include the histograms of three consecutive iterations showing the evolution of the parameter set performance. It is observed that the mean value as well as the spread in each iteration varies significantly. The range for the objective function evaluation corresponding to the last iteration involving selected best $n_{opt} = 1{,}000$ vectors used for simulations varies from $NS = 0.845$ to $NS = 0.867$ for HBV and from $NS = 0.70$ to $NS = 0.79$ for HYMOD. Performances show a larger spread for the Rhine basin from standard deviation $std = 0.012$ to $std = 0.016$ in contrast to Ganges with limits $std = 0.004$ and $std = 0.006$. Statistics as the mean, minimum and maximum values for the best n=1000 performing final sets are summarized in table 1.

3.2 Parameter related uncertainty in future projections

The prime focus of this study is on the quantification parameter uncertainty has in future discharge projections. A large number (*n=1,000*) well performing parameter sets derived from the last iteration of ROPE are used to draw the range/uncertainty out of all possible simulated discharge for each basin and model. We consider the 90% confidence interval of the simulated discharge curves for the three defined time periods.

The analysis reveals differences depending on the model used and region under consideration. When comparing parameter uncertainty contrasting HBV and HYMOD, uncertainty associated to HBV is smaller than that observed by HYMOD in terms of the mean values. This occurs in both the Rhine and the Ganges basins. While HBV shows expected uncertainties of *d = 4.67%* and *d = 1.69%* for Rhine and Ganges respectively, HYMOD present uncertainties of *d = 5.389%* and *d = 6.921%*. Analyzing results given by HBV model, uncertainty might be considered not significant when compared with differences given by other sources such as GCMs. This is clear in the case of Ganges in which parameter associated uncertainty shows a significant smaller mean value in the projection range (about 1/3 of that corresponding to Rhine with a magnitude of 1.69% in the complete period). The simpler model HYMOD shows more uncertainty attributed to parameter choice in both analyzed regions, although the difference between them is not as accentuated as for HBV in terms of mean values. This suggests the effect that model structures have on the expected parameter related uncertainties: A more-complex structure yield to a smaller uncertainty estimation. Same conclusion has been pointed in others studies from other regions. Wilby, 2005, found that uncertainty in projected river flows changes in Thames basin, UK was more significant in simpler model structures (comparable to emission scenarios uncertainties) than those from more-complex model structures. The analysis was based on Monte Carlo simulations by randomly generating parameter values, and considering the best 100 performing sets for analysis. Considering two sets of hydrological models parameters, Wilby and Harris, 2006, analyzed Low-flow scenarios for the River Thames and found the uncertainties less important than those given by GCMs.

The difference in the projected uncertainties has impacts on the contribution to the total uncertainty, as showed in the next section. Inter-period comparisons considering one RCP separately also present differences, but in general (with some exceptions, e.g. RCP8.5 and period 2006-2035) they do not exhibit important differences. Figure 2 shows the associated parameter related uncertainties for both impact models and the two regions in the whole period of analysis (2006-2099). It can be shown that the time periods present similar behavior. Each case consider *n=1,000* well-performing parameter sets found in the optimization step. Each boxplot summarize the calculated uncertainties for each of the five GCMs and four RCPs comprising a set of 20 points. Each point of each boxplot refers to the uncertainty out of 1000 parameter sets for a certain and single GCM and RCP.

3.3 Quantifying the contribution of hydrological models and GCMs to future projection discrepancies

It is acknowledged that GCMs may have a major impact on the projections relative to other sources; for example rainfall-runoff models in different environments. Teng et al., 2011 showed this in a dry condition, while Chen et al., 2011, in a snow-dominated area. Recently, Exbrayat et al., 2014, analyzed the uncertainty given by seven hydrological models in terms of the relative contribution to the total range of projections. In a context with limited historical calibration data, they found that differences in projections given by different hydrological model structures may be comparable to GCMs for two SRES scenarios in the near-future. Also, the climate projections uncertainties grew toward the end of the 21st century. Although we use less (n = 5) GCMs compared to Exbrayat et al. (2014), it is observed that they nevertheless dominate the differences in projections in the context of our study, as shown in Figures 3 and 4.

Here, we analyze the spread of the differences in projections out of GCMs choice and two hydrological models, and calculate the relative contribution of hydrological models and GCMs to the overall range in the projections. Projections are calculated by means of a single optimum parameter set calculated for each GCM and hydrological model, as a part of the Inter-Sectoral Impact Model Intercomparison Project Phase 2 ISI-MIP2 (Krysanova and Hattermann, 2016). We also consider the previously defined five GCMs, the four RCPs as well as the three defined periods independently to disaggregate the effects. Uncertainty given by model parametrization is included in the final results to provide a general view.

As expected, results indicate that the major contribution to differences is given by GCMs independently of the RCP and period under consideration. This has been suggested by several authors in the analysis of different regions. Using a multi-model ensemble consisting of 112 future climate projections from 16 GCMs, Harding et al., 2012 showed that the effect of different scenarios on projected streamflow changes is small relative to the effect of GCMs in the Upper Colorado River Basin. However, our study suggests that this relative contribution is case dependent. The projection divergences for the Rhine river, with exception of the first period of RCP4.5 and RCP8.5, is largely explained by GCMs, with a minimum of round 50%. For the Ganges, the minimum value (contribution) is roughly 70%, which indicates that GCMs explain divergences in large part for both regions. The maximum expected differences do not differ significantly with each other; they are 78.1% and to 83.9% for the Rhine and Ganges. These results are in agreement when considering the expected uncertainty contribution as a function of time (period), which occurs in the mid-century (2036-2065) in both regions. The dependency difference-Region found here has also been acknowledged by other authors. E.g., Based on the analysis on three basins with different elevation and geology characteristics in the Willamette River Basin, USA, Jung and Chang, 2011 found that apart from the more significant contribution of GCMs the uncertainty differences depend on the catchment under study.

The relative contribution of model impacts obtained from the parameter sets is found smaller than those given by GCMs. Projected discharge time series analysis show that HBV estimates slightly higher discharge values compared to HYMOD. Same pattern is shown irrespective of the chosen GCM. HBV present a smaller uncertainty in projections, which is in agreement with the results previously highlighted. As mentioned, this is a general result independent of the time period and model (GCM). To visualize how model impacts may influence the uncertainty given by parameter selection, plots of projected discharge contrasting the two rainfall-runoff models are shown in figure 5 as cumulative runoff. As pointed earlier, other time periods and models show similar patterns and, hence, are not shown here for brevity.

Exploring both regions, differences in the discharge projections for the Ganges are mainly driven by GCMs and models impacts. In contrast, the Rhine shows a different pattern that balances impact models effect and parameter sets uncertainty, which become even more significant in the period 2006-2035 (disregarding GCMs). Figures 3 illustrates the results for each RCP and time period for the basin Ganges at Farakka, whereas figure 4 summarizes the same results for Rhine basin at Lobith. The GCMs induces the major differences in projections; parameter uncertainty contribute to a less extent, but it may become comparable to the RCPs differences.

4 Conclusions

This study focused on the analysis and characterization of model parameterization uncertainty and the effect on this uncertainty given by different GCMs (*n=5*), RCPs (*n=4*) and impact models (*n=2*). For this purpose, ensemble of simulated discharge projections were compared for three future periods. The analysis was carried out in two basins from Europe and Asia. Expected parameter uncertainty was estimated performing the ROPE algorithm which is based on the half-space depth function to produce robust parameter sets. In each step *n=5,000* sets were generated such that $depth \geq 1$ and found *n=1,000* well performing parameter sets. These quasi-optimum sets were then used to run the models under several projected time series.

Results indicate that uncertainty from parameter choice may become important, either in magnitude or variability over time. It was also found a dependency between model structure complexity and parameter uncertainty. Inspection of the discrepancies of projections shows a major contribution due to GCMs in Rhine and Ganges. Interestingly, these results cannot be generalized as other researchers found an equivalent uncertainty introduced by model structure. Overall, we conclude that relative discrepancies of impact rainfall-runoff models and its influence on uncertainty in the parametrization (parameter uncertainty) are not negligible. This pattern was observed in both regions varying in proportion according to period and RCP projection. This uncertainty might be reduced by utilizing more sophisticated models that better capture input signals and able to react more accurately to them; its general influence on global predictive model uncertainty should not be ignored.

In the light of the results, It is advisable to consider different contributions of uncertainty when performing projections. As it is shown in this study, parameter uncertainty may contribute to some extent to differences in projected values.

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References

Bárdossy, A., 2007. Calibration of hydrological model parameters for ungauged catchments. Hydrol. Earth Syst. Sci. Discuss. 11, 703–710.

Bárdossy, A., Singh, S.K., 2008. Robust estimation of hydrological model parameters. Hydrol. Earth Syst. Sci. 12, 1273–1283.

Barnett, V., 1976. The Ordering of Multivariate Data. J. R. Stat. Soc. Ser. Gen. 139, 318–355. doi:10.2307/2344839

Bergström, S., 1995. The HBV model. 443–476.

Boyle, D.P., Gupta, H.V., Sorooshian, S., Koren, V., Zhang, Z., Smith, M., 2001. Toward improved streamflow forecasts: value of semidistributed modeling. Water Resour. Res. 37, 2749–2759. doi:10.1029/2000WR000207

Chen, J., Brissette, F.P., Poulin, A., Leconte, R., 2011. Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed. Water Resour. Res. 47, W12509. doi:10.1029/2011WR010602

Donoho, D.L., Gasko, M., 1992. Breakdown Properties of Location Estimates Based on Halfspace Depth and Projected Outlyingness. Ann. Stat. 20, 1803–1827. doi:10.1214/aos/1176348890

Exbrayat, J.-F., Buytaert, W., Timbe, E., Windhorst, D., Breuer, L., 2014. Addressing sources of uncertainty in runoff projections for a data scarce catchment in the Ecuadorian Andes. Clim. Change 125, 221–235. doi:10.1007/s10584-014-1160-x

Fraiman, R., Liu, R.Y., Meloche, J., 1997. Multivariate Density Estimation by Probing Depth. Lect. Notes-Monogr. Ser. 31, 415–430.

Götzinger, J., Bárdossy, A., 2008. Generic error model for calibration and uncertainty estimation of hydrological models. Water Resour. Res. 44, W00B07. doi:10.1029/2007WR006691

Haddeland, I., Clark, D.B., Franssen, W., Ludwig, F., Voß, F., Arnell, N.W., Bertrand, N., Best, M., Folwell, S., Gerten, D., Gomes, S., Gosling, S.N., Hagemann, S., Hanasaki, N., Harding, R., Heinke, J., Kabat, P., Koirala, S., Oki, T., Polcher, J., Stacke, T., Viterbo, P., Weedon, G.P., Yeh, P., 2011. Multimodel Estimate of the Global Terrestrial Water Balance: Setup and First Results. J. Hydrometeorol. 12, 869–884. doi:10.1175/2011JHM1324.1

Harding, B.L., Wood, A.W., Prairie, J.R., 2012. The implications of climate change scenario selection for future streamflow projection in the Upper Colorado River Basin. Hydrol Earth Syst Sci 16, 3989–4007. doi:10.5194/hess-16-3989-2012

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., Piontek, F., 2013. A trend-preserving bias correction – the ISI-MIP approach. Earth Syst Dynam 4, 219–236. doi:10.5194/esd-4-219-2013

Hugg, J., Rafalin, E., Seyboth, K., Souvaine, D., 2006. An Experimental Study of Old and New Depth Measures, in: 2006 Proceedings of the Eighth Workshop on Algorithm Engineering and Experiments (ALENEX), Proceedings. Society for Industrial and Applied Mathematics, pp. 51–64.

Hundecha Hirpa, Y., 2005. Regionalization of parameters of a conceptual rainfall runoff model.

Hundecha, Y., Bárdossy, A., 2004. Modeling of the effect of land use changes on the runoff generation of a river basin through parameter regionalization of a watershed model. J. Hydrol. 292, 281–295. doi:10.1016/j.jhydrol.2004.01.002

Jung, I.-W., Chang, H., 2011. Assessment of future runoff trends under multiple climate change scenarios in the Willamette River Basin, Oregon, USA. Hydrol. Process. 25, 258–277. doi:10.1002/hyp.7842

Kavetski, D., Franks, S.W., Kuczera, G., 2003. Confronting Input Uncertainty in Environmental Modelling, in: Duan, Q., Gupta, H.V., Sorooshian, S., Rousseau, A.N., Turcotte, R. (Eds.), Calibration of Watershed Models. American Geophysical Union, pp. 49–68.

Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P., 1983. Optimization by Simulated Annealing. Science 220, 671–680. doi:10.1126/science.220.4598.671

Lindström, G., Johansson, B., Persson, M., Gardelin, M., Bergström, S., 1997. Development and test of the distributed HBV-96 hydrological model. J. Hydrol. 201, 272–288. doi:10.1016/S0022-1694(97)00041-3

Liu, R.Y., 1990. On a Notion of Data Depth Based on Random Simplices. Ann. Stat. 18, 405–414. doi:10.1214/aos/1176347507

Liu, R.Y., Parelius, J.M., Singh, K., 1999. Multivariate analysis by data depth: descriptive statistics, graphics and inference, (with discussion and a rejoinder by Liu and Singh). Ann. Stat. 27, 783–858. doi:10.1214/aos/1018031260

Miller, K., Ramaswami, S., Rousseeuw, P., Sellarès, J.A., Souvaine, D., Streinu, I., Struyf, A., 2003. Efficient computation of location depth contours by methods of computational geometry. Stat. Comput. 13, 153–162. doi:10.1023/A:1023208625954

Moore, R., 1985. The probability-distributed principle and runoff production at point and basin scales. Hydrol. Sci. J. 30, 273–297.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I — A discussion of principles. J. Hydrol. 10, 282–290. doi:10.1016/0022-1694(70)90255-6
Oja, H., 1983. Descriptive statistics for multivariate distributions. Stat. Probab. Lett. 1, 327–332. doi:10.1016/0167-7152(83)90054-8
Rousseeuw, P.J., Struyf, A., 1998. Computing location depth and regression depth in higher dimensions. Stat. Comput. 8, 193–203. doi:10.1023/A:1008945009397
Schaefli, B., Talamba, D.B., Musy, A., 2007. Quantifying hydrological modeling errors through a mixture of normal distributions. J. Hydrol. 332, 303–315. doi:10.1016/j.jhydrol.2006.07.005
Singh, S.K., 2010. Robust parameter estimation in gauged and ungauged basins.
Singh, V.P., Woolhiser, D.A., 2002. Mathematical modeling of watershed hydrology. J. Hydrol. Eng. 7, 270–292.
Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. Bull Amer Meteorol Soc 93(4):485–498
Teng, J., Vaze, J., Chiew, F.H.S., Wang, B., Perraud, J.-M., 2011. Estimating the Relative Uncertainties Sourced from GCMs and Hydrological Models in Modeling Climate Change Impact on Runoff. J. Hydrometeorol. 13, 122–139. doi:10.1175/JHM-D-11-058.1
Tukey, J.W., 1975. Mathematics and the picturing of data. Presented at the Proceedings of the international congress of mathematicians, pp. 523–531.
Uppala, S. M., KÅllberg, P. W., Simmons, A. J., Andrae, U., Bechtold, V. D. C., Fiorino, M., Gibson, J. K., Haseler, J., Hernandez, A., Kelly, G. A., Li, X., Onogi, K., Saarinen, S., Sokka, N., Allan, R. P., Andersson, E., Arpe, K., Balmaseda, M. A., Beljaars, A. C. M., Berg, L. V. D., Bidlot, J., Bormann, N., Caires, S., Chevallier, F., Dethof, A., Dragosavac, M., Fisher, M., Fuentes, M., Hagemann, S., Hólm, E., Hoskins, B. J., Isaksen, L., Janssen, P. A. E. M., Jenne, R., Mcnally, A. P., Mahfouf, J.-F., Morcrette, J.-J., Rayner, N. A., Saunders, R. W., Simon, P., Sterl, A., Trenberth, K. E., Untch, A., Vasiljevic, D., Viterbo, P. and Woollen, J. (2005), The ERA-40 re-analysis. Q.J.R. Meteorol. Soc., 131: 2961–3012. doi:10.1256/qj.04.176
Vardi, Y., Zhang, C.-H., 2000. The multivariate L1-median and associated data depth. Proc. Natl. Acad. Sci. 97, 1423–1426. doi:10.1073/pnas.97.4.1423
Wagener, T., Boyle, D.P., Lees, M.J., Wheater, H.S., Gupta, H.V., Sorooshian, S., 2001. A framework for development and application of hydrological models. Hydrol. Earth Syst. Sci. Discuss. 5, 13–26.
Weedon, G.P., Gomes, S., Viterbo, P., Shuttleworth, W.J., Blyth, E., Österle, H., Adam, J.C., Bellouin, N., Boucher, O., Best, M., 2011. Creation of the WATCH Forcing Data and Its Use to Assess Global and Regional Reference Crop Evaporation over Land during the Twentieth Century. J. Hydrometeorol. 12, 823–848. doi:10.1175/2011JHM1369.1
Wilby, R.L., 2005. Uncertainty in water resource model parameters used for climate change impact assessment. Hydrol. Process. 19, 3201–3219. doi:10.1002/hyp.5819
Wilby, R.L., Harris, I., 2006. A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK. Water Resour. Res. 42, W02419. doi:10.1029/2005WR004065
Zuo, Y., Serfling, R., 2000. General Notions of Statistical Depth Function. Ann. Stat. 28, 461–482.

Figure

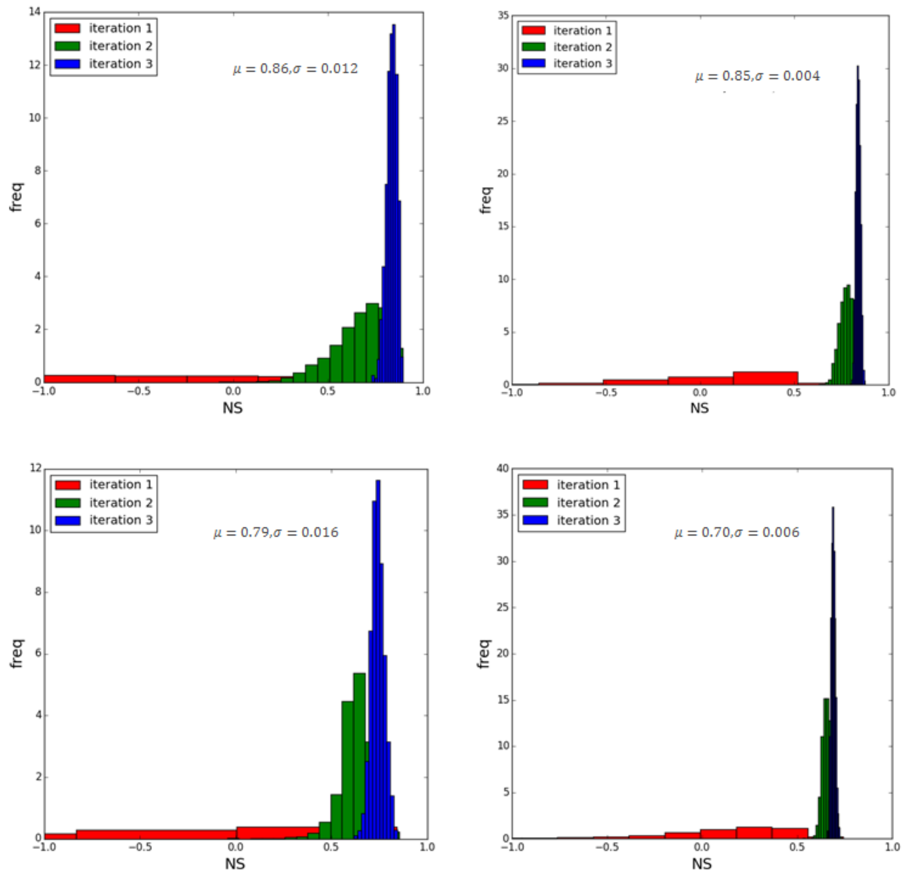

Figure 1: Histograms of the model performances (NSE) for the $m = 5{,}000$ parameter sets showing the different iterations of ROPE for both basins and both models: Model HBV basin Rhine (top left), HBV Ganges (top right), HYMOD Rhine (bottom left) and HYMOD Ganges (bottom right).

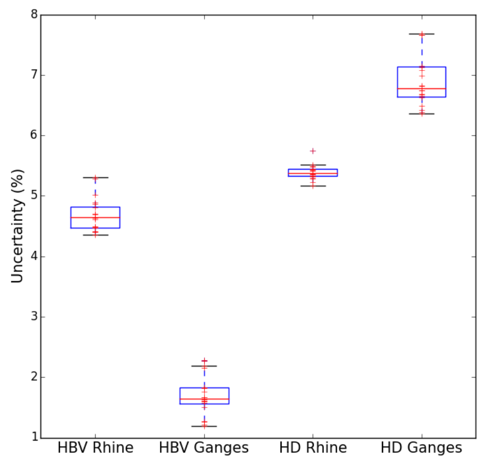

Figure 2: Parameter related uncertainty in discharge projections for the models HBV and HYMOD (HD) for the basins Rhine at Lobith and Ganges at Farakka. Time period considered 2006-2099.

Table 1: Statistics corresponding to the final iteration of ROPE algorithm with the selected 1,000 best performing sets for the two basins Rhine and Ganges and both models HBV and HYMOD

Basin		Min NS	Max NS	Mean	Std
Rhine	HBV	0.836	0.894	0.856	0.012
	HYMOD	0.770	0.845	0.790	0.016
Ganges	HBV	0.848	0.869	0.854	0.004
	HYMOD	0.690	0.723	0.701	0.006

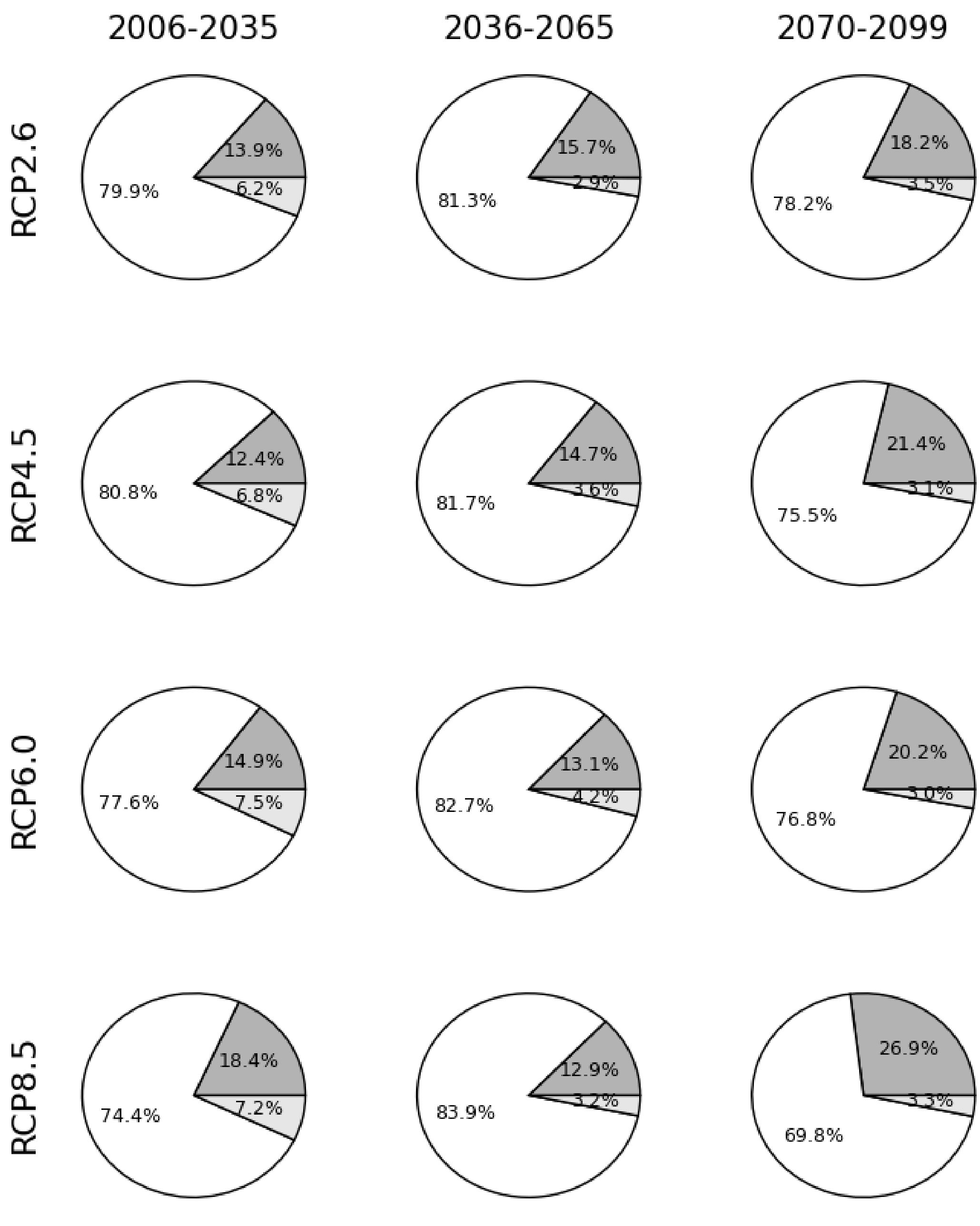

Figure 3: Contribution of GCM (white), rainfall-runoff model (grey) and parameter set (light grey) to the global model uncertainty. Basin Ganges at Farakka.

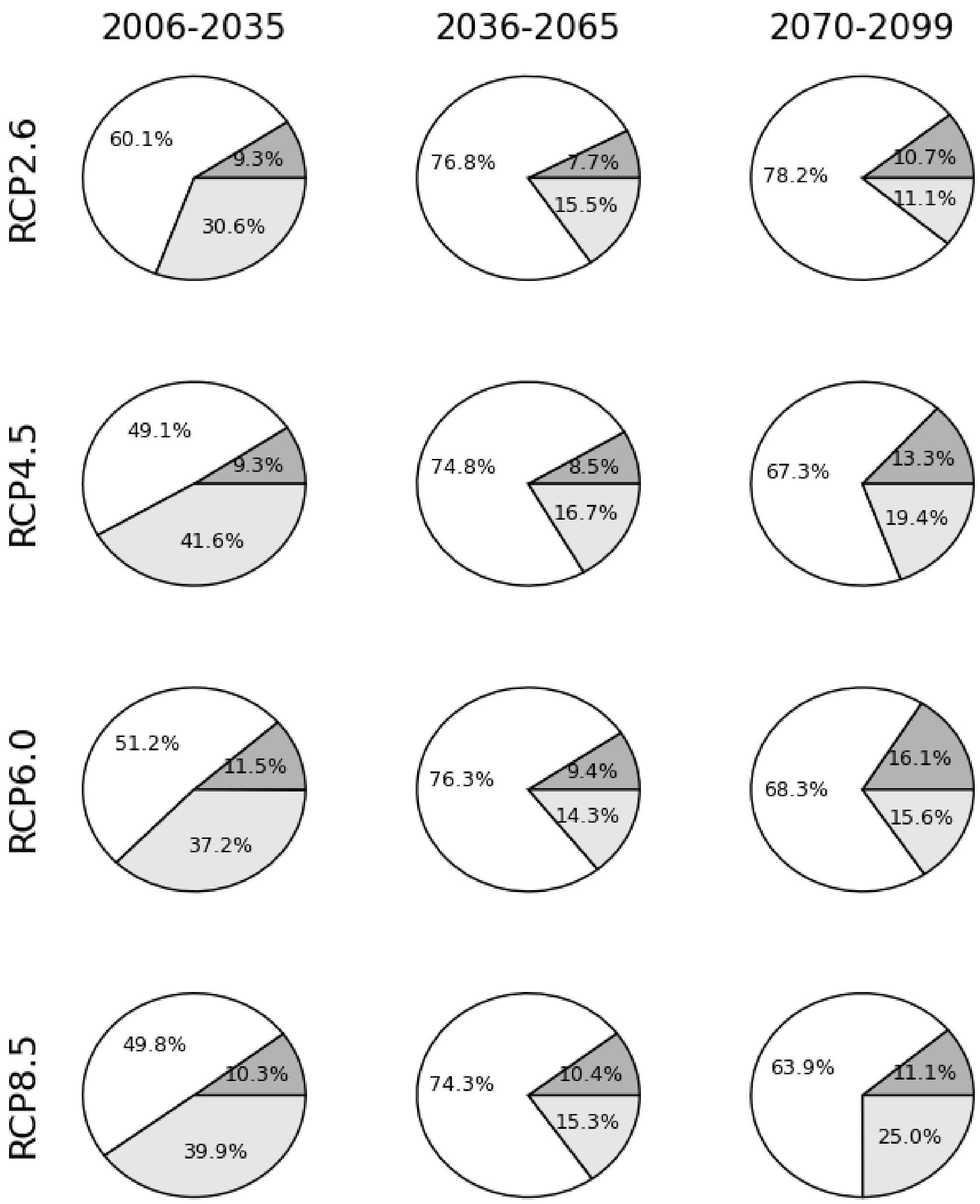

Figure 4: Contribution of GCM (white), rainfall-runoff model (grey) and parameter set (light grey) to the global model uncertainty. Basin Rhine at Lobith.

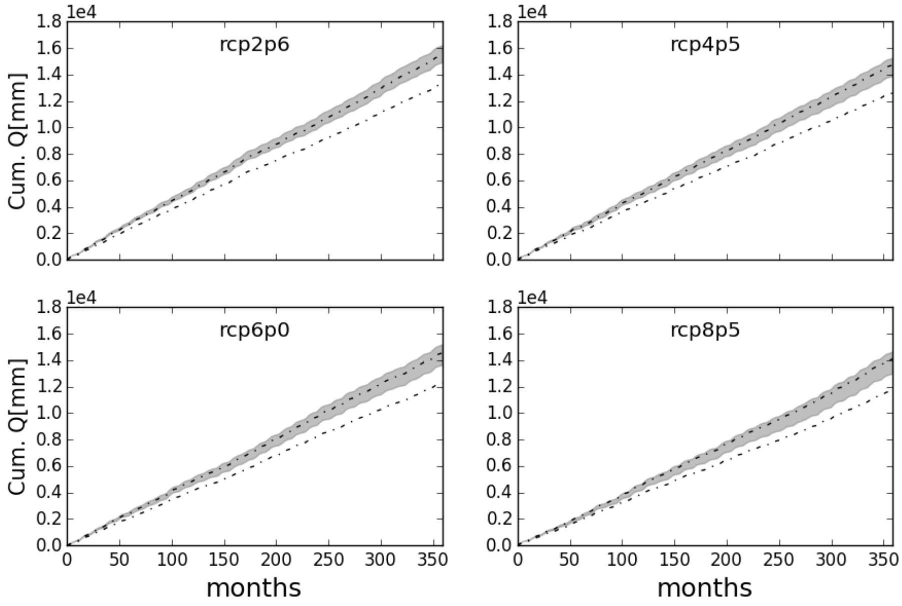

Figure 5: Projected discharge plots from the two impact models runs with data from GFDL-ESM2M and RCP2.6. Basin Rhine.