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Climate change impacts model parameter sensitivity - What does this mean for calibration?

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Abstract. Hydrological models are useful tools to explore the hydrological impact of climate change. Many of these models require calibration. A frequently employed strategy is to calibrate the five parameters that were found to be most relevant as identified in a sensitivity analysis. However, parameter sensitivity varies over climate, and therefore climate change could influence parameter sensitivity. In this study we explore the change in parameter sensitivity within a plausible climate change rate, and investigate if changes in sensitivity propagate into the calibration strategy. We employed three frequently used hydrological models (SAC, VIC, and HBV), and explored parameter sensitivity changes across 605 catchments in the United States by comparing a GCM-forced historical and future period. Consistent among all models is that the sensitivity of snow parameters decreases in the future. Which parameters increase in sensitivity is less consistent among the models. In 43% to 49% of the catchments, dependent on the model, at least one parameter changes in the future in the top-5 most sensitive parameters. The maximum number of changes in the parameter top-5 is two, in 2-4% of the investigated catchments. The value of the parameters that enter the top-5 cannot easily be identified based on historical data, because the model is not yet sensitive to these parameters. This requires an adapted calibration strategy for long-term projections, for which we provide several suggestions. The disagreement among the models on processes becoming relevant in future projections also calls for a strict evaluation of the adequacy of the model structure and the model parameters implemented therein.

1 Introduction

Earth and environmental computer models are indispensable tools to explore an uncertain future. In the field of hydrology and water resources, hydrological models are frequently used for long term projections on river discharge (e.g. Driessen et al., 2010; Addor et al., 2014; Melsen et al., 2018; Thober et al., 2018; Givati et al., 2019). The simulations provide guidance on decision making, for instance related to assigning inundation regions and dike heightening. The models are thus related to costly and impactful decisions (McMillan et al., 2017; Metin et al., 2018).

Many hydrological models that are used for long term projections, such as the models employed in the previously mentioned references, have parameters that require calibration to identify their values for the catchment under study. Calibration can be

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necessary for several reasons, for instance because a parameter has no directly observable physical meaning, or because the scale of application of the parameter is different from the scale of observation of the parameter (Beven, 2012). Hydrological model parameters are generally calibrated on discharge time series.

Discharge is a lumped catchment response, and therefore only provides limited catchment information (Jakeman and Hornberger, 1993). A rule of thumb suggested by Beven (1989) and employed by many modelers is that, given the limited information available in a discharge time series, three to five parameters can be calibrated based on these data (and this might already be a high number, following the famous quote of von Neumann[1]). Global Sensitivity Analysis (GSA) can be employed to identify the parameters that have most influence on the model output (Demaria et al., 2007; van Werkhoven et al., 2009; Pianosi et al., 2016; Borgonovo et al., 2017). Subsequently, the three to five parameters that show most sensitivity are selected for calibration.

Parameter sensitivity differs over models, target variables, and sensitivity analysis methods (Razavi and Gupta, 2015; Guse et al., 2016; Haghnegahdar et al., 2017; Mai and Tolson, 2019). However, parameter sensitivity also differs over climate (Melsen and Guse, 2019): In a cold catchment with a large fraction of the precipitation falling as snow, snow parameters are supposed to be sensitive, while in a tropical catchment without snowfall, snow parameters are not supposed to show any sensitivity. As such, it is common understanding that parameter sensitivity depends on climate. But reconsidering this fact, this would also imply that parameter sensitivity could change in a changing climate. And that could interfere with the frequently used calibration procedure for hydrological models, where calibration parameters are identified using GSA. Therefore, the question is whether, within a plausible rate of climate change, hydrological parameter sensitivity changes and if this propagates into the parameter prioritization for calibration.

In this study we investigate how parameter sensitivity changes as a consequence of climate change, and if and how this has consequences for parameter prioritization for calibration. We apply a hybrid local-global sensitivity analysis method (Rakovec et al., 2014) to three frequently used hydrological models in 605 basins across the US, and link changes in sensitivity to changes in climate. Finally, we evaluate the impact on the top-5 most sensitive parameters in each basin, and investigate the transmission of sensitivity from one parameter to the other. We end with a recommendation on how to account for changes in sensitivity when calibrating models for long-term projections.

2 Methods

To investigate changes in parameter sensitivity, and the consequences for model calibration, we employed three frequently used hydrological models. The models were run for a historical and future period over 605 catchments, forced with a bias corrected and statistically downscaled global circulation model. A hybrid local-global sensitivity analysis method was applied to the simulations of both periods. Then, the differences in parameter sensitivity between the historical and future period were

[1] *"With four parameters I can fit an elephant, with five I can make him wiggle his trunk"*, John von Neumann (1903-1957)

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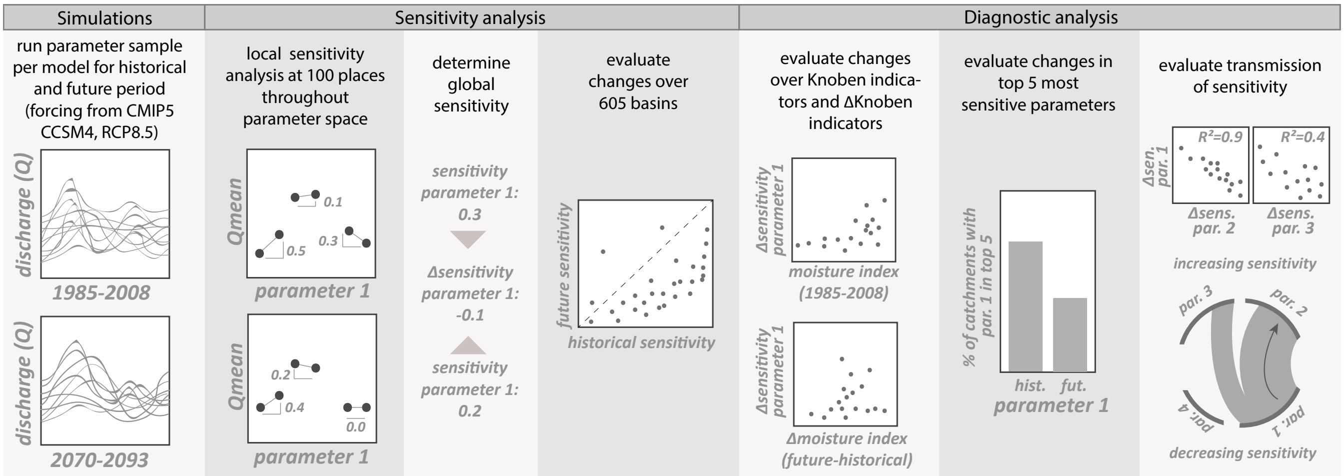

Figure 1. Summary of the methodological approach, to be read from left to right. The first three steps are the calculations, the other four steps are the actual analyses.

explored in several ways. First, per parameter to investigate which parameters change, and over different climate indicators to investigate how climate and climate change explain changes in sensitivity. Then, we assessed how the top-5 most sensitive parameters would change in the future period, thereby impacting the calibration strategy. Finally, we investigated the transmission of sensitivity from one parameter to the other. An overview of the procedure is shown in Figure 1.

2.1 Models

We investigated for three models whether parameter sensitivity changes within a plausible climate change range: the TUW-model following the structure of HBV (Parajka et al., 2007, hereafter referred to as HBV), SAC-SMA combined with SNOW-17 (Newman et al., 2015), and VIC 4.1.2h (Liang et al., 1994). All three models have been used for long-term climate impact projections: e.g. Teutschbein et al. (2011); Wetterhall et al. (2011) for HBV; Koutroulis et al. (2013); Peleg et al. (2015) for SAC-SMA; and Christensen et al. (2004); Wu et al. (2012) for VIC, and are therefore relevant models to consider. The same suit of models was explored in another context in Melsen et al. (2018) and Melsen and Guse (2019).

A simplified representation of the model structures, including a description of the parameters that were accounted for in the sensitivity analysis, are displayed in Figure 2. A more elaborate description of each model can be found in Melsen et al. (2018), and in the respective references of each models: Bergström (1976, 1992) for HBV, Burnash et al. (1973); National Weather Service (2002) for SAC-SMA, and Liang et al. (1994, 1996) for VIC.

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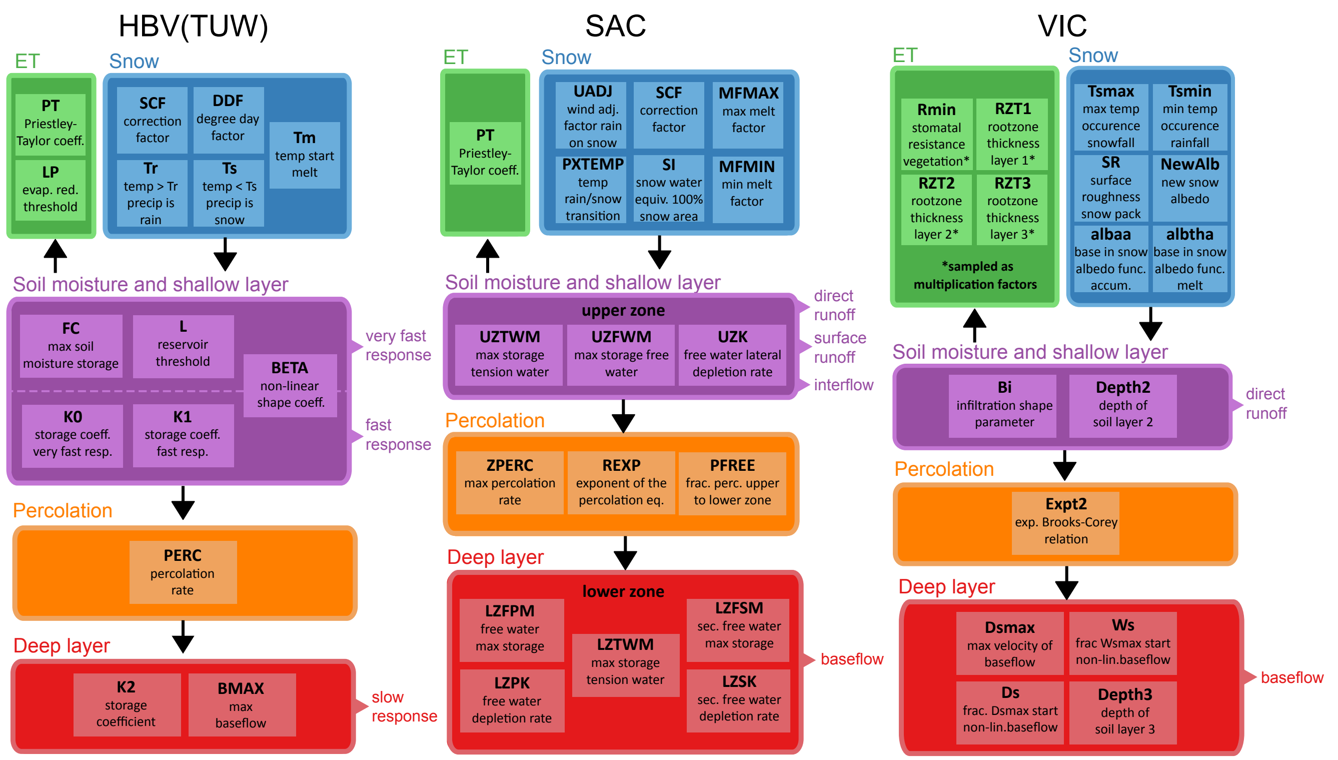

Figure 2. Simplified representation of the model structure of the three models employed in this study. All the parameters that are displayed are included in the sensitivity analysis. Parameters are colored according to the flux or state they influence (evapotranspiration (ET), snow, soil moisture and shallow layer, percolation, deep layer). The colors are used consistently throughout all the figures in this study. Parameter boundaries can be found in Appendix Tables A1, A2, and A3.

2.2 Catchments and Forcing

All three models were run for a historical and future period of 28 years, of which the first five years were omitted from both periods for spin up. As such, the historical period that is analyzed covers 1985-2008, and the future period 2070-2093, 23 years each. The forcing for both periods was obtained from statistically downscaled and bias corrected output from the Community Climate System Model 4.0, from Climate Model Intercomparison CMIP5, using Representative Concentration Pathway 8.5 (RCP8.5). Bias correction was done according to Wood et al. (2004), based on the Maurer et al. (2002) forcing data. Subsequently, the GCM forcing was lumped over the CAMELS basins. The CAMELS data set contains forcing, observations, and catchment characteristics for 671 catchments throughout the contiguous United States with limited human impact (Newman et al., 2014, 2015; Addor et al., 2017). We employed a subset of 605 catchment-averaged forcings.

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Since the models were not calibrated, we employ global sensitivity analysis across the full parameter range, the 605 catchments should be perceived as 605 different climate instances with an individual level of climate change, rather than as catchment representative models. The models are, however, able to achieve acceptable model performance in these basins when forced with observations and confronted with discharge observations (Melsen et al., 2018), providing credibility to the models to be used in this context.

The goal of this study is to investigate how climate might impact parameter sensitivity within a plausible climate change range. As such, it is of second order importance whether the climate model gives highly accurate predictions or whether the hydrological model can exactly capture catchment behavior. It is, however, important to note that we employed the highest emission scenario (RCP8.5), thereby investigating the effect of the higher ranges of plausible climate change. It can be expected that the impact of climate change on parameter sensitivity will be lower for lower emission scenarios. However, RCP 8.5 is often used to provide an upper boundary for long-term projections, thereby demonstrating the relevance of choosing this scenario.

2.3 Sensitivity analysis

In the selection of the sensitivity analysis method, a few points were considered. First, it had to be a global method, because global sensitivity analysis methods are used to identify the most sensitive parameters for calibration (whereas local methods are generally applied after calibration). Secondly, we had to account for a high number of runs (605 basins, two periods, three models). Therefore, we selected the hybrid local-global method DELSA (Rakovec et al., 2014), which is computationally cheaper than traditional global sensitivity analysis methods.

DELSA evaluates local sensitivity at several places throughout parameter space, as such mimicking global sensitivity analysis. First, 100 parameter samples called base-runs were created based on a space filling sampling strategy. The models were run for all 100 samples. Secondly, the parameters are one by one slightly perturbed compared to each of the base-runs. The effect of this perturbation on the model output, compared to the corresponding base-run, represents the parameter sensitivity. We used the average sensitivity from the 100 samples per parameter per basin as a measure of parameter sensitivity. Each parameter that is displayed in Figure 2 was accounted for in the sensitivity analysis. The applied parameter boundaries for sampling are provided in Appendix Tables A1, A2 and A3 (see also Melsen and Guse, 2019).

Besides the selection of a sensitivity analysis method (which will influence the final results, Razavi and Gupta, 2015; Pianosi et al., 2016), we also had to identify a target variable - the variable that is compared between the base-run and the perturbed run. Whereas performance metrics are quite popular as target variable (Van Werkhoven et al., 2008; Herman et al., 2013), they are not well suited for global sensitivity analysis (Razavi and Gupta, 2015; Guse et al., 2016), and besides, it is not possible to obtain model performance for the future. Therefore, this study focuses on mean simulated discharge as target variable. Many other streamflow signatures could have been of interest to evaluate, for instance related to high and low flows, but given the

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goal of this study, an exploration on the effect of climate change on parameter sensitivity, mean discharge seems the most neutral choice.

2.4 Analysis of sensitivity

The sensitivity analysis was conducted for both the historical and future period, for all 605 basins. The first analysis of the calculations was a simple exploration of which parameters increase and which parameters decrease in sensitivity in the future over all 605 basins. The 605 climate instances from the 605 basins are, however, not a representative sample since certain climates might be over- or underrepresented. Therefore, the difference in sensitivity was also related to climate indicators. Given their relevance for discharge, we used the Knoben climate indicators (Knoben et al., 2018) to classify the changes in parameter sensitivity. The Knoben indicators consist of three indicators: aridity index, seasonality, and fraction precipitation falling as snow.

To determine the aridity index, first Thorntwaite's Moisture Index (MI, Knoben et al., 2018; Willmott and Fedema, 1992) is obtained based on mean monthly observations of precipitation, $P(t)$, and evapotranspiration $E_p(t)$. Subsequently, average aridity I_m can be obtained.

$$MI(t) = \begin{cases} 1 - \frac{E_p(t)}{P(t)}, & \text{if} P(t) > E_p(t) \\ 0, & \text{if } P(t) = E_p(t) \\ \frac{P(t)}{E_p(t)} - 1, & \text{if } P(t) < E_p(t) \end{cases} \tag{1}$$

$$I_m = \frac{1}{12} \sum_{t=1}^{t=12} MI(t) \tag{2}$$

Aridity index I_m varies between -1, representing highly arid conditions, and 1, representing humid conditions. The seasonality in the aridity index, $I_{m,r}$, is determined based on the maximum difference in MI over the year:

$$I_{m,r} = \max(MI(1,2,...12)) - \min(MI(1,2,...12)) \tag{3}$$

The seasonality varies between 0 and 2, with 0 indicating no intra-annual variation, and 2 indicating that climate varies from fully arid to fully humid over the year. The last Knoben index is the fraction precipitation falling as snow, f_s.

$$f_s = \frac{\sum P(T(t) \leq T_0)}{\sum_{t=1}^{t=12} P(t)} \tag{4}$$

In this equation, $T(t)$ is the mean monthly temperature, and T_0 the threshold temperature below which precipitation is assumed to occur as snow. The threshold temperature was set to 0°C, in line with Knoben et al. (2018). f_s can have a value between 0, no snow, and 1, all precipitation falling as snow. All three indicators were evaluated based on the climate in the historical period, and based on the change in climate between the future and the historical period (future - historical), this latter one being

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indicated as Δindicator.

Subsequently, to evaluate the impact of change in parameter sensitivity on calibration strategy, we assessed how many parameters in the top-5 most sensitive parameters per basin changed as a consequence of changes in sensitivity. This was again related to the climate indicators, to investigate if in certain climates or climate change rates more changes can be expected in the calibration parameters.

Based on the results of the calibration assessment, we identified the main parameters that leave or enter the top-5. For each of these parameters, we evaluated whether any negative correlations exist between the decreasing and increasing parameters. Strong negative correlations can be an indication that sensitivity is transmitted from one parameter to the other, so we define transmission as a clear negative correlation in change in sensitivity between two parameters. However, since we evaluate correlation, transmission does not refer to absolute sensitivity values. The goal of this analysis is to investigate to what extent sensitivity is transmitted directly from the decreasing parameter to the increasing parameter. When there is no direct relation, it can indicate that sensitivity changes at several places within the model structure.

3 Results

3.1 Changes in sensitivity between historical and future period

Fig. 3 shows the distribution of change in sensitivity between the historical (1985-2008) and future period (2070-2093) over all 605 basins for the three employed models. Consistent over all three models is a decrease in the sensitivity of snow parameters in the future. The parameters that show increasing sensitivity cannot consistently be associated to one specific process. Whereas a strong decrease in sensitivity requires a high sensitivity in the historical period, this is not required for a strong increase in sensitivity. It can be observed, however, that parameters that display an increase in sensitivity were also already sensitive in the historical period.

In the HBV model especially the snow correction factor (SCF) displays a large decrease. This is also the parameter with the highest sensitivity in the historical period, therefore having the highest potential to decrease. The other three snow parameters in HBV displayed lower sensitivity in the historical period, and also show a less consistent decrease in the future. Also in the SAC and VIC models, the snow parameter that displayed the highest sensitivity in the historical period (SCF in SAC and Snowrough in VIC, respectively) show the strongest decrease, although less consistent than SCF in HBV.

Among the three models, different parameters related to different processes display an increase in sensitivity in the future. In HBV, evapotranspiration and soil parameters increase in sensitivity in the future with the largest increase in the evapotranspiration parameter PT, while there is hardly any observable change in sensitivity in percolation and deep layer parameters. In the SAC and VIC model, there are parameters associated to all four processes besides snow that tend to increase in sensitivity

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in the future. Like for HBV, also in SAC the evapotranspiration parameter PT has the highest increase. In the VIC model, the depth of the second soil layer (Depth2) shows the largest positive change in sensitivity.

3.2 Relationship between climatic variables and sensitivity changes

Since the 605 basins employed in the previous section are not a representative, balanced sample over climates and climate changes, the results are split out over climate indicators. Fig. 4 depicts how parameter sensitivity changes between historical and future period, related to the three Knoben climate indicators. From the figure, it can be seen that the patterns relating parameter sensitivity to climate and climate change indicators are weak. The aridity index seems to have most explanatory value, followed by seasonality and fraction precipitation falling as snow, respectively. The change in sensitivity of snow and evapotranspiration parameters can be related to current mean temperature and precipitation, and projected changes in mean temperature, but the patterns vary per model.

In most cases, the patterns that can be identified relate to the projected change in climate. For instance in both SAC and HBV, the sensitivity of snow parameter SCF decreases especially in regions with a strong decrease in aridity index and in regions that were humid (positive aridity index in our definition) in the historical period. Soil moisture/shallow layer parameter Depth2 (VIC) and percolation parameter Expt2 (VIC) demonstrate a more pronounced increase in regions with decreasing aridity index. Sometimes also the historical climate, combined with the projected change, can show some organization. For example, the sensitivity of the evapotranspiration parameter PT in both SAC and HBV is particularly increasing in regions with high historical aridity index, and changes are more pronounced with larger projected changes, either an increase or a decrease, in aridity index.

Given that no clear patterns were revealed based on the Knoben indicators, we also explored patterns related directly to climate: the mean temperature and mean precipitation and their projected changes. These results can be found in Figure A1 in the Appendix. The snow parameters mainly decrease in sensitivity in basins with a historically mean temperature between 5 and 15°C, dependent on the model. In these basins, the fraction of snow will decrease in a warmer climate, whereas in basins with a lower mean temperature, snow will remain a relevant process in the future (Fontrodona Bach et al., 2018).

In HBV, the decrease in sensitivity in SCF is highest in catchments with a mean historical temperature between 5 and 10°C. An increase in the sensitivity of evapotranspiration parameter PT occurs in basins with projected changes in precipitation (both positive and negative). Also here, the largest increase is found in basins with a mean historical temperature between 5 and 10°C. An increase in the sensitivity of shallow layer parameter FC is related to no change or a decrease in precipitation in the future.

In SAC, snow parameter SCF decreases in sensitivity in basins with a mean historical temperature of about 10°C. In these basins, the sensitivity of evapotranspiration parameter PT and lower zone parameter UZTWM increases. Similar to HBV,

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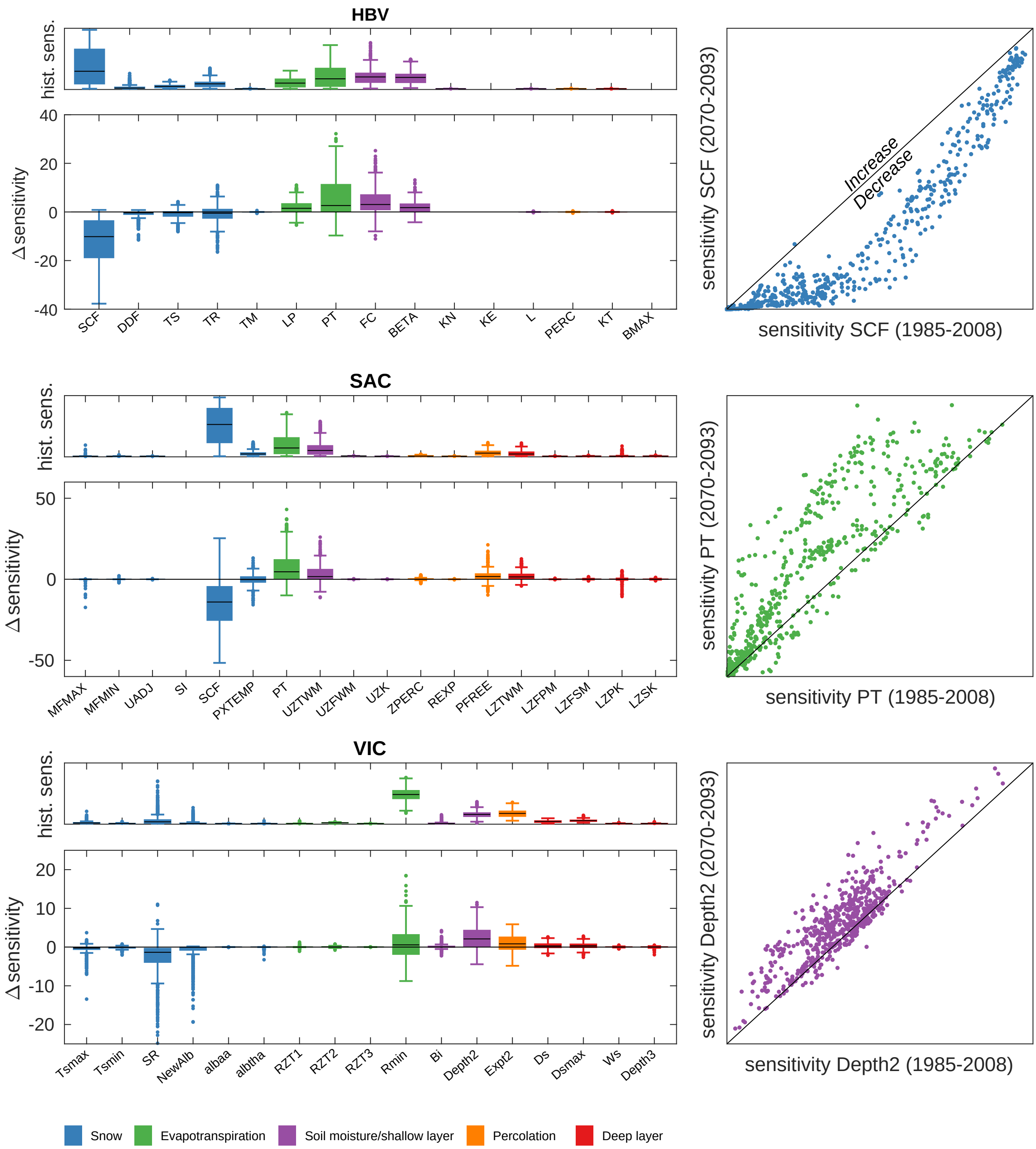

Figure 3. The distribution of change in parameter sensitivity (Δsensitivity) over 605 basins for the period 2070-2093 compared to 1985-2008, displayed per parameter per model. Above each Δsensitivity panel, historical sensitivity is displayed. The panels on the right show the data for a selected case per model.

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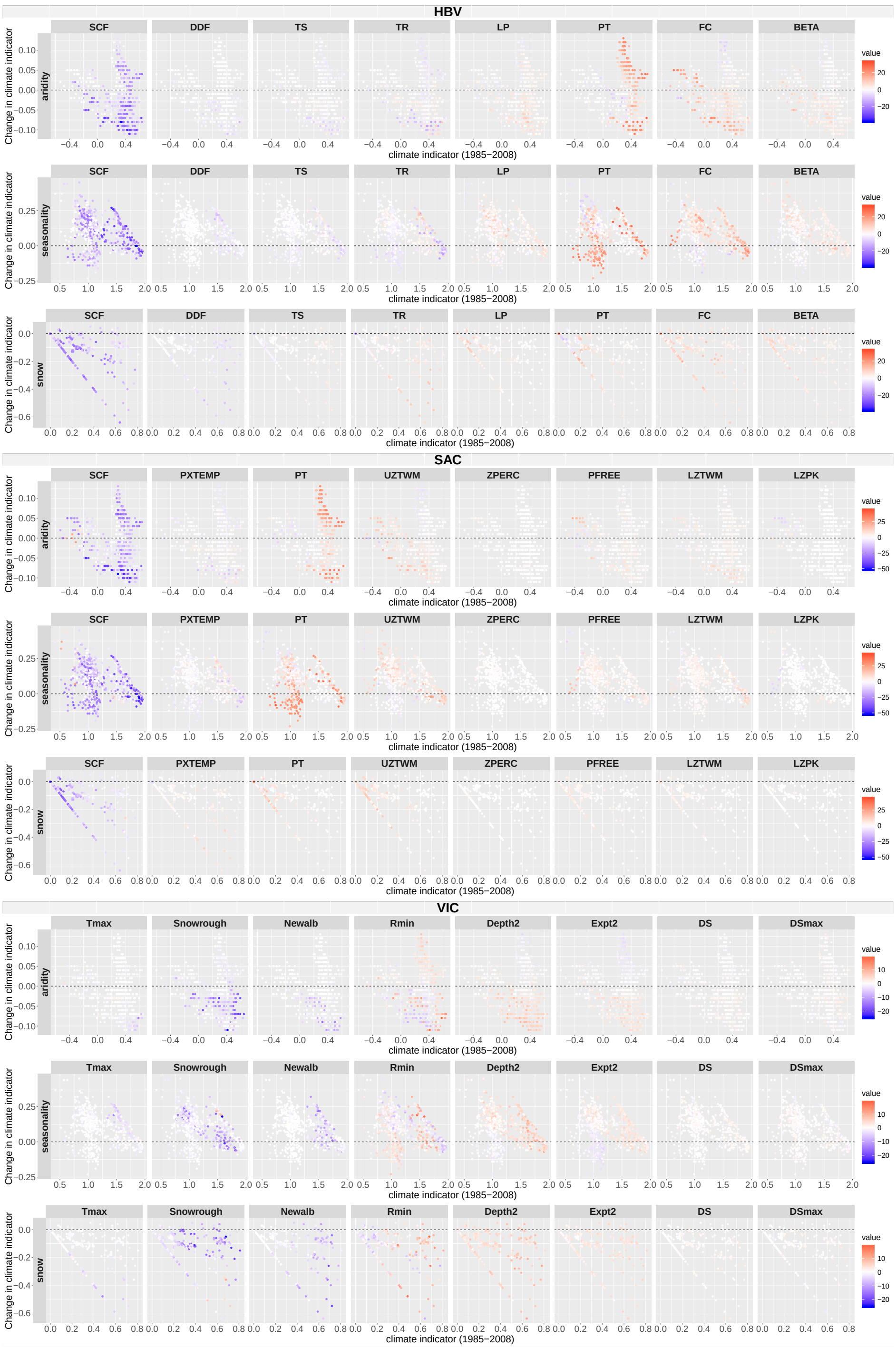

Figure 4. Change in parameter sensitivity versus historical climate indicators and change in climate indicators for 605 basins. The climate indicators are aridity index (-1 highly arid, +1 highly humid), seasonality, and fraction of precipitation falling as snow, as defined by Knoben et al. (2018). Parameter sensitivity for the historical period is expressed in dot size, change in parameter sensitivity in colour: red indicates an increase in sensitivity, blue a decrease.

evapotranspiration parameter PT changes in sensitivity in basins with both positive and negative changes in precipitation in the future.

In VIC, the patterns are weakest. Here, we see a decrease of snow parameters in basins with mean temperatures lower than 5°C, and even around zero combined with no change in precipitation. Evapotranspiration parameter Rmin increases in sensitivity in basins with increase in precipitation and vice-versa. Shallow layer parameter Depth2 and to a lower extent percolation parameter Expt2 decreases in sensitivity in basins with mean temperatures between 0 and 10°C and with decreasing precipitation.

3.3 Impact of sensitivity changes on model calibration

In this section we explore to what extent the changes in parameter sensitivity that were observed in the previous sections propagate into the calibration procedure. Fig. 5 depicts the percentage of catchments in which parameters appeared in the top-5, both historically and in the future. Snow parameters drop out of the top-5 in some cases, while the relevance of parameters with already many top-5 notations further increases. This indicates that the variation among catchments in top-5 parameters decreases in the future. Although changes in top-5 parameters are observed, the overall top-5 of the parameters is in most cases maintained (51 to 57% of the catchments, dependent on the model). In 41 to 45% of the catchments, one parameter changes in the top-5. The maximum number of changes in the parameter top-5 per catchment is two, which occurs only in 2 to 4% of the investigated basins.

For HBV, snow parameter SCF historically has a top-5 notation in 76% of the basins, in the future this drops to 57% - a relative drop of 24%. The largest increase in top-5 notations for HBV is found for evapotranspiration parameter LP (a relative increase of 22%). In SAC, snow parameter SCF loses its top-5 notation in 11% of the basins where it used to be relevant. Lower zone parameter LZTWM shows the strongest increase in top-5 notations (a relative increase of 24%). In VIC, mainly the snow parameter Snowrough loses top-5 notations (a relative decrease of 53%). Deep layer parameters gain most notations, especially DS (a relative increase of 49%).

The results of the left three panels in Fig. 5 cannot directly be generalized because the 605 explored basins are not a well-balanced sample in terms of climate and climate change. Therefore, the change in top-5 parameters is also again displayed against the Knoben indicators (right panels in Fig. 5). It can be observed that one change in parameter top-5 can occur over all climates and climate changes. Only VIC is showing fewer changes in basins in between constant and seasonal, and with decreasing seasonality. Also two changes in parameter top-5 seems to occur across all climates and climate changes. Only for HBV, this seems to be constrained to wet catchments that become drier (lower aridity index) in the future.

In conclusion, the impact of changes in parameter sensitivity on calibration strategy remains limited to a maximum of two parameter changes in the parameter top-5, at least for the explored climates and climate changes. The changes in top-5 positions are model dependent and do not demonstrate a clear relation to climate or climate change.

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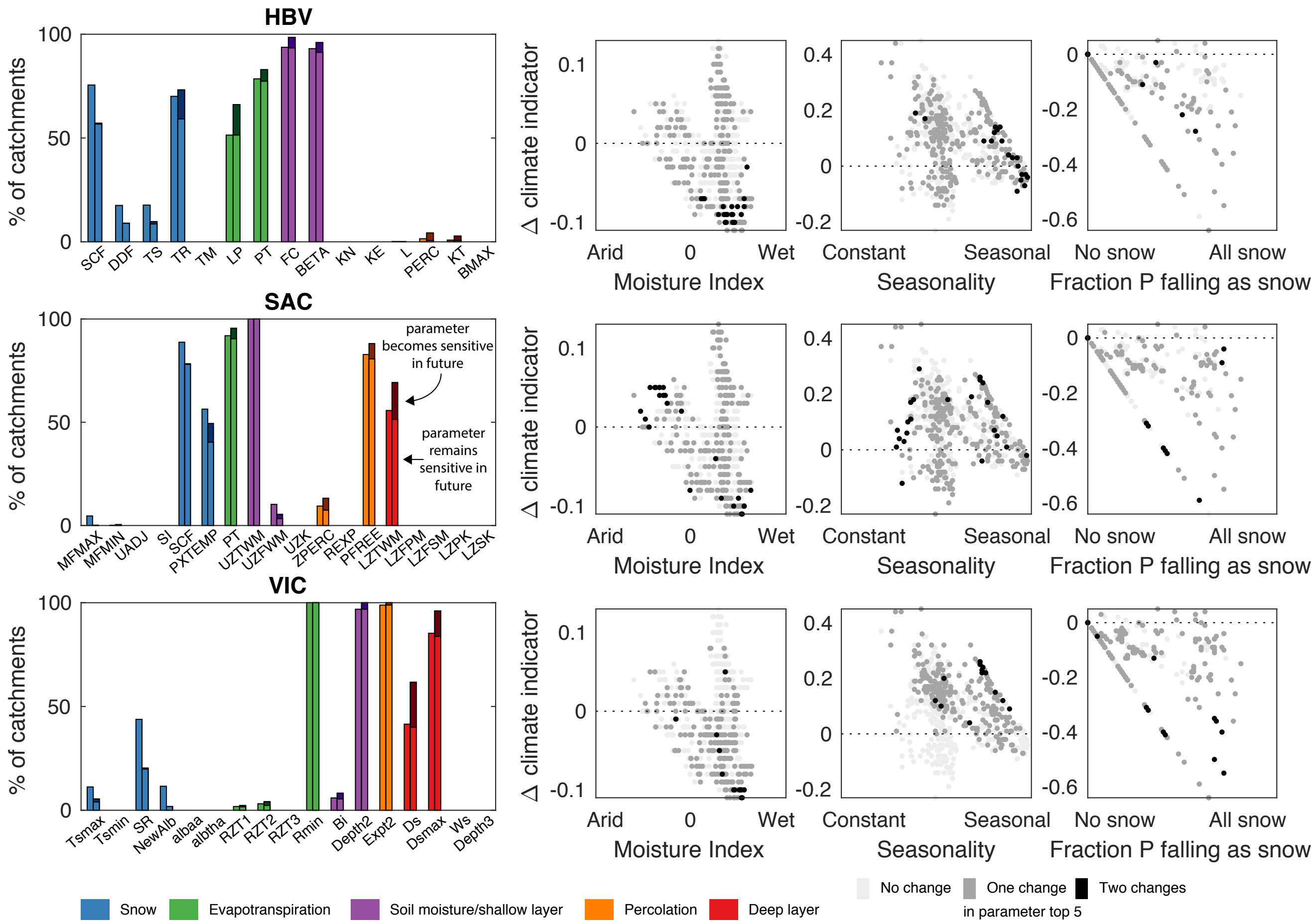

Figure 5. Impact of change in parameter sensitivity on top-5 position, where top-5 refers to the five most sensitive parameters per basin - generally the parameters that are calibrated. The left panels show how often a parameter appears in the top-5 both historically and in the future. The right panels relates the number of changes in the parameter top-5 to climate and climate change indicators.

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3.4 Transmission of sensitivity

The transmission of sensitivity is explored by means of the negative correlation between change in sensitivity among two parameters. An example is the left panel of Fig. 6, depicting a negative correlation between the change in sensitivity of snow parameter SCF and the change in sensitivity of evapotranspiration parameter LP for HBV, which can indicate a transmission of sensitivity from SCF to LP. The chord diagrams in Fig. 6 show the correlations between the parameters with decreasing and increasing sensitivities. All three models display a decrease in sensitivity of the snow parameters, but this sensitivity is transmitted to different process parameters in the three models. In HBV, mainly to evapotranspiration and shallow layer parameters, in SAC evapotranspiration, percolation, and deep layer parameters, and in VIC to shallow layer and deep layer parameters. Weak transmissions indicate that parameter sensitivity changes at several places in the model structure, leading to a complete reconfiguration of sensitivities in the model.

Besides the clear transmission from snow parameter SCF to evapotranspiration parameter LP in HBV, it is also visible in Fig. 6 that snow parameter TS mainly transmits to evapotranspiration parameter PT: different snow parameters transmit to different evapotranspiration parameters. What is also visible in the chord diagram is that snow parameter DDF is mainly transmitting to snow parameter TR, explaining the increase in sensitivity in some regions for this snow parameter. Not displayed in the chord diagram for clarity, is that snow parameter TR then again transmits to evapotranspiration parameters LP, PT, and shallow layer parameter FC.

For SAC, the snow parameter SCF demonstrates a clear negative relation with many parameters that increase in sensitivity. High correlations were found with percolation parameter PFREE (-0.63), deep layer parameter LZTWM (-0.72), and evapotranspiration parameter PT (-0.72). The correlations between snow parameter PXTEMP and the parameters with increasing sensitivity are less pronounced. Two other parameters in SAC experienced a slight decrease in parameter sensitivity; snow parameter MFMAX and shallow layer parameter UZFWM, especially visible in their loss of top-5 positions in Fig. 5. These two parameters, however, did not display any negative correlation with any of the parameters that experience a clear increase in top-5 positions.

For VIC, the negative correlations are generally weaker than what was found for the other two models, but still some insights can be obtained from the chord diagram. For instance that snow parameter Newalb mainly transmits to shallow layer parameter Depth2 (-0.59), while snow parameter Snowrough is the only one that shows a correlation with deep layer parameter DSmax (-0.32). Shallow layer parameter Infilt increases in number of top-5 positions (Fig. 5) but did not display any clear relation with the parameters that decrease in sensitivity.

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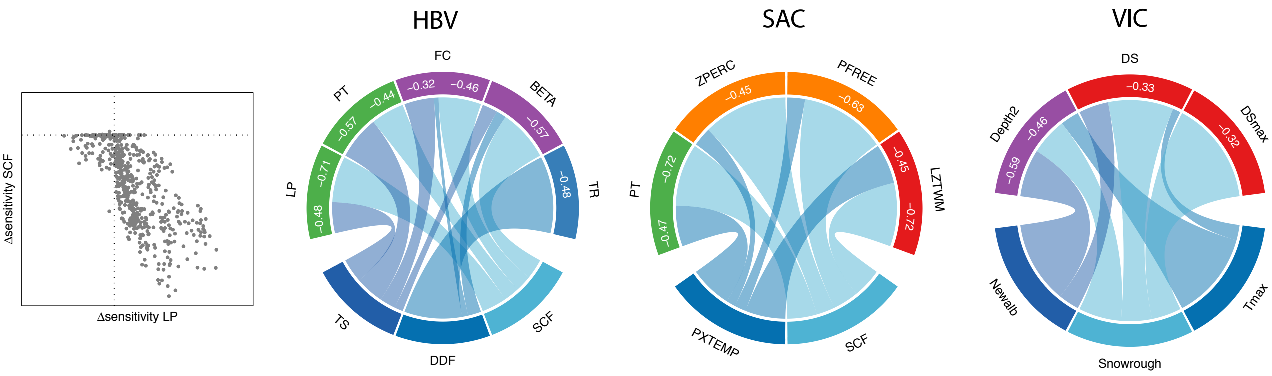

Figure 6. Indication of parameter sensitivity transmission. The panel on the left shows an example for HBV: the decrease in sensitivity of parameter SCF shows a strong correlation with an increase in the sensitivity of parameter LP, which can indicate that SCF transmits sensitivity to LP. In the chord (circle) diagram of HBV, this relation is indicated with the a band from SCF to LP. The white number indicates the strength of the correlation; -0.71 between SCF and LP. In all three chord diagrams, the lower part shows the parameters that decrease in sensitivity, and the upper part the parameters that increase in sensitivity, with the white number indicating the strength of the correlation (for clarity, correlations lower than 0.32 are not displayed). Colors are according to the process they represent (with different shades of blue used for snow parameters for clarity). The chord diagrams are focused around the most relevant parameters based on Fig. 5.

4 Discussion

In this study, we investigated how parameter sensitivity changes as a consequence of climate change. Hereby, we focused on the use of sensitivity analysis to provide the most relevant parameters (factor prioritisation) for an effective model calibration (Saltelli et al., 2006; Reusser et al., 2011). Within this context, we have shown how changes in parameter sensitivity propagate into the selection of relevant parameters for model calibration. We assumed a general calibration strategy where the modeller selects the five most sensitive parameters for calibration. Certainly many other calibration strategies exist. For example, one could select all the parameters that exceed a certain sensitivity-threshold as suggested by van Werkhoven et al. (2009), resulting in a higher or lower number of parameters for the calibration, or simply include all the parameters in the model if the model is highly parsimonious (Melsen et al., 2014). Our results are, however, still relevant in the context of other calibration strategies, as the changes in sensitivity will still influence the calibration results. That is, it is difficult to calibrate a parameter if the model is hardly or not sensitive to changes in its values in current-day climate.

It is well-known that parameter sensitivity changes over time or between different periods (for instance wet versus dry periods, winter versus summer, e.g. Reusser et al., 2011; Guse et al., 2014), because dominant processes vary over time and between seasons. In this study, we focused on changes in parameter sensitivity over longer periods (two times 23 years of daily data), thereby evaluating the signal of long term changes in dominant processes. As such, changes in parameter sensitivity as a con-

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sequence of climate change were expected and foreseen. Because the hydrological system will respond to a change in climate, the decrease of sensitivity of snow parameters in a warming climate fits the line of expectation. On the other hand, the parameters that increase in sensitivity can not directly be determined based on expert judgement. From a hydrological point of view, it is not clear whether the relatively higher amount of rain in the future (due to a decrease in snow) is directly evaporated or infiltrates into the soil. In both cases, different parameters would have an increasing sensitivity. As our results have shown, the parameters with increasing sensitivity vary both among climates and among the three models.

The implication of our result is that, the more the parameter sensitivity changes, the more parameter identifiability decreases for long-term projections. Accordingly, we can expect that in particular the parameters that will enter the top-5 in the future are probably not well identified in the historical period. Therefore, we provide suggestions to account for changing sensitivities in the calibration of hydrological models for long-term projections. A first strategy, related to methods that have been suggested for changing parameters over time (Merz et al., 2011; Vaze et al., 2010), is to conduct sensitivity analysis over different parts of the observation-period, and calibrate the model on the period that best resembles the parameter sensitivity of the future scenario. A risk, however, is that the calibration period becomes too short to determine stable parameter values (Yapo et al., 1996). A second strategy is to sample the parameters that will become sensitive in the future. Provided that, in the current climate, the model is not sensitive to changes in parameter θ_i, the value of θ_i cannot be inverted through calibration. However, in the future the value of θ_i does become relevant. In order to correctly capture spread in long-term projections that results from uncertainty in this parameter-value, the value of θ_i should be sampled. Hereby, we have to emphasise that in this context, parameter uncertainty is specifically related to expected changes in the relevance of the associated processes in future. A third option could be to increase the effort in finding data to be able to calibrate a parameter directly to the associated process. Sensitivity analyses on different processes demonstrate that the sensitivity signal increases using the associated process as target variable (Guse et al., 2016). In this way, it can be expected that parameters are better identifiable and more robust for future simulations.

Assuming that a sensitivity analysis conducted over 23 years of daily data is robust and thus that the observed changes in sensitivity can be attributed to a changing climate rather than to noise, our results demonstrate that parameter sensitivity is nonstationary (Koutsoyiannis and Montanari, 2015). Nonstationarity of parameter sensitivity fits in the growing body of literature identifying nonstationarity when simulating the hydrological system on the long term (e.g. Milly et al., 2008; Thirel et al., 2015; Fowler et al., 2016, 2018). Nonstationarity is not only disclosed through a change in sensitivity, but also through a change in parameter values over time (Vaze et al., 2010; Merz et al., 2011). The identification of nonstationarity in parameter values is the result of the simplified model representations, not capturing dynamics and/or processes that are relevant in the real world. Fowler et al. (2018) provides a framework to evaluate model improvement under nonstationary conditions; Grigg and Hughes (2018) and Westra et al. (2014) adapted model structure to account for nonstationarity, leading to improved model results. This study reinforces this direction of research; even though the decrease in sensitivity among all three models can consistently be found for the snow parameters, the increase in sensitivity can be attributed to completely different processes in the three

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models, which might indicate that a relevant process is missing in any of the models, stressing the need to carefully assess whether these models are appropriate for long-term projections. The differences in which processes and associated parameters becomes more relevant among the models shows that there is no consensus how the hydrological system will change in future.

This study provides suggestions to further validate the calibration procedure of models employed for long-term projections, thereby following the currently dominant paradigm in hydrological modelling. It seems a valid question, however, whether our models are fit for this purpose at all. The results of the sensitivity analysis indicate a change in relevant processes in the future which is captured differently among the three investigated models. This emphasizes the need to improve model structure for long term projections, as suggested by Fowler et al. (2018); Grigg and Hughes (2018); Westra et al. (2014). On the long run, we should perhaps aim for dynamic model structures that are more based on process sensitivity, i.e. in relation to the dominant process, than on the sensitivity of certain parameters that are strongly dependent on the prevailing model structure.

5 Conclusions

The sensitivity of the parameters in three investigated hydrological models changes within a plausible changing climate. In the three models, especially the snow parameters decline in sensitivity. Which parameters increase in sensitivity is less consistent among the models; sometimes mainly ET parameters, sometimes mainly percolation and/or deep layer parameters.

The change in parameter sensitivity propagates into the calibration strategy. Typically, a global sensitivity analysis is conducted to determine the most sensitive parameters, and based on that, the top-5 most sensitive parameters are selected for calibration. Dependent on the model, 43% to 49% of the 605 investigated catchments has at least one parameter changing in the top-5 in the future. The maximum number of changes in the top-5 parameters is two, in 2-4% of the catchments. Since these results were obtained for the highest emission scenario (RCP8.5), fewer changes might be expected for lower emission scenario's.

We were not able to identify a clear pattern in which kind of climates and expected climate changes most changes in parameter sensitivity take place. A higher change in aridity index in the future seems to be an indicator for some models, and also a high seasonality seems to be a predictor, but changes in top-5 positions occur across all explored climates and climate changes.

Some parameters become sensitive in the future, but are currently not sensitive. Therefore, their value cannot be obtained through calibration based on current data. One way to account for changes in sensitivity is to identify a historical period that mimicks the future projected sensitivity. Another approach is to sample the parameter that becomes sensitive in the future, to account for predictive uncertainty as a consequence of the uncertainty in this parameter value. A third approach is to invert the value of this parameter based on observations specifically related to the process that the parameter is related to.

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The results of this study call for a more comprehensive calibration procedure when using models for long-term projections. However, the results also demonstrate that the three employed models consider different processes as relevant, stressing the need to carefully assess their model structure and their validity for long-term projections. In the end, we should perhaps aim for models with dynamic structures based on varying relevant processes over time.

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Data availability. The model output will be made available on the 4TU website

Author contributions. LM and BG designed the study together. LM conducted the calculations and wrote the first draft of the paper. LM and BG processed the data together and finalized the manuscript together.

Competing interests. There are no competing interests

Appendix A: Parameter ranges

Table A1. Selected parameters, their classification, and their boundaries for the HBV model. The parameters and their boundaries are based on Parajka et al. (2007); Uhlenbrook et al. (1999); Abebe et al. (2010). The Priestley-Taylor parameter is based on Lhomme (1997).

	Name	Unit	Lower boundary	Upper boundary	Description
1	Tm	°C	-3.0	3.0	Temperature where melt starts
2	Ts	°C	Tr-0.01	Tr-3	Temp. below which precipitation is snow
3	Tr	°C	0.0	3.0	Temp. above which precipitation is rain
4	DDF	mm $°C^{-1}$ d^{-1}	0.04	12	Degree day factor
5	SCF	-	0.1	5.0	Snow correction factor
6	LP	-	0.0	1.0	Evaporation reduction threshold
7	PT	-	1.0	1.74	Priestley-Taylor coefficient
8	FC	mm	0.0	2000	Max soil moisture storage
9	BETA	-	0.0	20	Non-linear shape coefficient
10	K0	day	0.0	2.0	Storage coefficient of very fast response
11	K1	day	2.0	30	Storage coefficient of fast response
12	L	mm	0.0	100	Reservoir threshold
13	PERC	mm d^{-1}	0.0	100	Percolation rate
14	K2	day	30	250	Storage coefficient of slow response
15	BMAX	day	0.0	30	Max baseflow of low flows

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Table A2. Selected parameters and their boundaries for the SAC model. The parameter boundaries are based on Newman et al. (2015), the Priestley-Taylor parameter has been adapted based on Lhomme (1997).

	Name	Unit	Lower boundary	Upper boundary	Description
1	MFMAX	mm $°C^{-1}$ $6h^{-1}$	0.8	3.0	Max melt factor
2	MFMIN	mm $°C^{-1}$ $6h^{-1}$	0.01	0.79	Min melt factor
3	UADJ	km $6h^{-1}$	0.01	0.40	Wind adjustment factor for rain on snow
4	SI	mm	1.0	3500	snow water equivalent for 100% snow area
5	SCF	-	0.1	5.0	Snow undercatch correction factor
6	PXTEMP	°C	-3.0	3.0	Temperature for rain/snow transition
7	PT	-	1.0	1.74	Priestley-Taylor coefficient
8	UZTWM	mm	1.0	800	Upper zone max storage of tension water
9	UZFWM	mm	1.0	800	Upper zone max storage of free water
10	UZK	day^{-1}	0.1	0.7	Upper zone free water lateral depletion rate
11	ZPERC	-	1.0	250	Max percolation rate
12	REXP	-	0.0	6.0	Exponent of the percolation equation
13	PFREE	-	0.0	1.0	Frac. percolating from upper to lower zone
14	LZTWM	mm	1.0	800	Lower zone max storage of tension water
15	LZFPM	mm	1.0	800	Lower zone max storage of free water
16	LZFSM	mm	1.0	1000	Lower zone max storage of sec. free water
17	LZPK	day^{-1}	1^{-5}	0.025	Lower zone prim. free water depletion rate
18	LZSK	day^{-1}	1^{-3}	0.25	Lower zone sec. free water depletion rate

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Table A3. Selected parameters and their boundaries for the VIC model based on Demaria et al. (2007); Chaney et al. (2015); Melsen et al. (2016); Mendoza et al. (2015).

	Name	Unit	LB	UB	Description
1	Tsmax	°C	0.0	3.0	Max temp. where snowfall can occur
2	Tsmin	°C	Tsmax-0.01	Tsmax-3.0	Min temp. where rainfall can occur
3	SR	-	$5 \cdot 10^{-5}$	0.5	Surface roughness of the snow pack
4	NewAlb	-	0.7	0.99	New snow albedo
5	albaa	-	0.88	0.99	Base in snow albedo function for accum.
6	albtha	-	0.66	0.98	Base in snow albedo function for melt
7	RZT1	-	0.5	2	Multipl. factor rootzone thickness layer 1
8	RZT2	-	0.5	2	Multipl. factor rootzone thickness layer 2
9	RZT3	-	0.5	2	Multipl. factor rootzone thickness layer 3
10	Rmin	-	0.1	10	Multipl. factor min. stom. res. vegetation
11	Bi	-	10^{-5}	0.4	Infiltration shape parameter
12	Depth2	m	0.1	3.0	Depth of soil layer 2
13	Expt2	-	4.0	30	Exponent of the Brooks-Corey relation
14	Ds	-	10^{-4}	1.0	Frac. Dsmax non-linear baseflow starts
15	Dsmax	mm d^{-1}	0.1	50	Max velocity of the baseflow
16	Ws	-	0.2	1.0	Frac. Wsmax non-linear baseflow starts
17	Depth3	m	0.1	3.0	Depth of soil layer 3

Appendix B: Change in sensitivity versus temperature and precipitation

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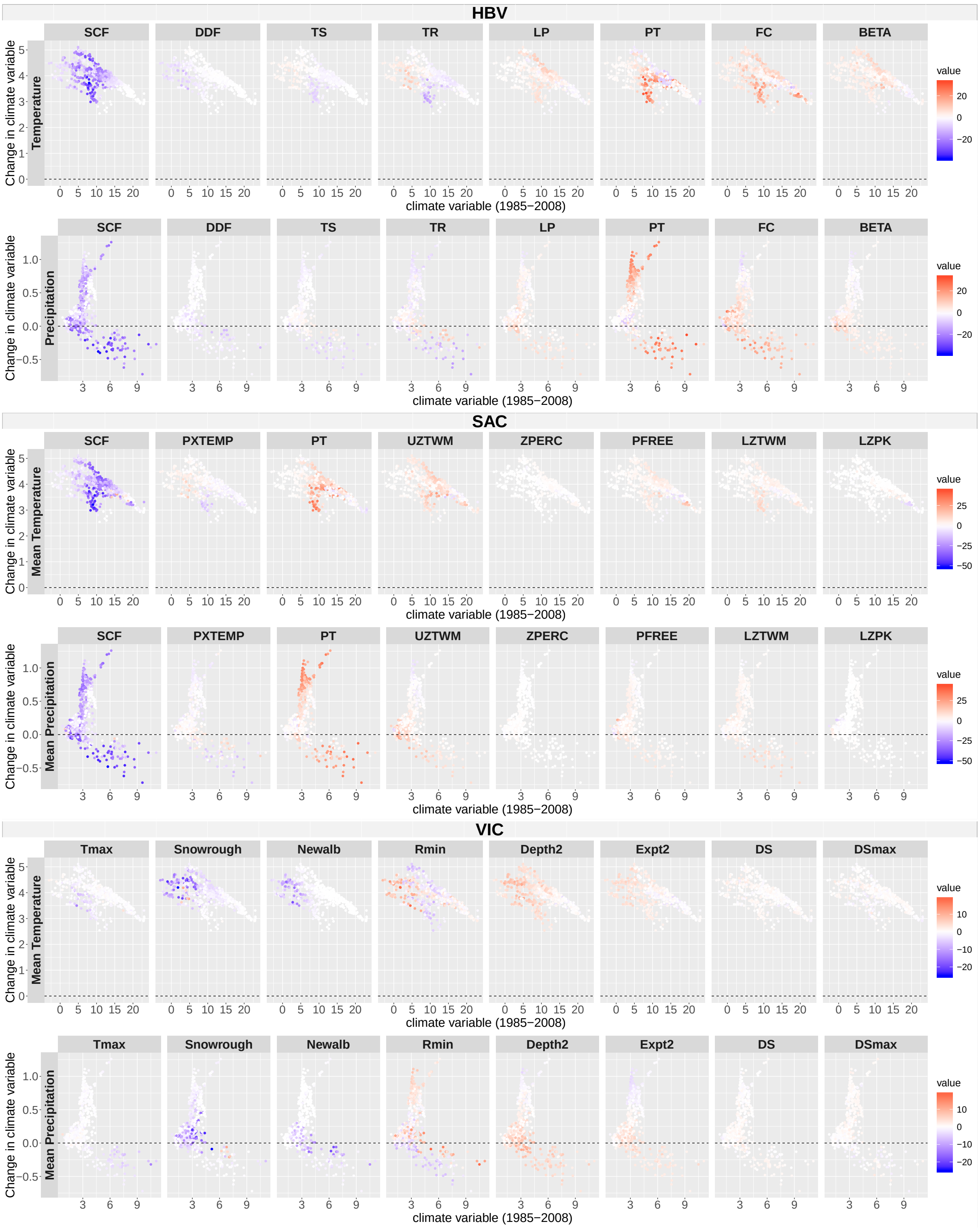

Figure A1. Change versus historical values in mean temperature and mean precipitation over 605 basins, with change in parameter sensitivity indicated. Parameter sensitivity for the historical period is expressed as dot size. Change in parameter sensitivity in colour. Red colours indicate an increase in sensitivity, blue a decrease.

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