

# 1 **Uncertainty contributions to low-flow projections in Austria**

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## 15 **Abstract**

16 The main objective of the paper is to understand the contributions to the uncertainty in  
17 low-flow projections resulting from hydrological model uncertainty and climate projection  
18 uncertainty. Model uncertainty is quantified by different parameterizations of a conceptual  
19 semi-distributed hydrologic model (TUWmodel) using 11 objective functions in three  
20 different decades (1976-86, 1987-97, 1998-08), which allows disentangling the effect of the  
21 objective function-related uncertainty and temporal stability of model parameters. Climate  
22 projection uncertainty is quantified by four future climate scenarios (ECHAM5-A1B, A2, B1  
23 and HADCM3-A1B) using a delta change approach. The approach is tested for 262 basins in  
24 Austria.

25 The results indicate that the seasonality of the low-flow regime is an important factor  
26 affecting the performance of model calibration in the reference period and the uncertainty of  
27  $Q_{95}$  low-flow projections in the future period. In Austria, the range of simulated  $Q_{95}$  in the  
28 reference period is larger in basins with summer low-flow regime than in basins with winter

1 low-flow regime. Using different calibration periods may result in a range of up to 60% in  
2 simulated  $Q_{95}$  low flows.

3 The low-flow projections of  $Q_{95}$  show an increase of low flows in the Alps, typically in the  
4 range of 10-30% and a decrease in the south-eastern part of Austria mostly in the range -5 to -  
5 20% for the climate change projected for future period 2021-50 relative the reference period  
6 1978-2007. The change in seasonality varies between scenarios, but there is a tendency for  
7 earlier low flows in the Northern Alps and later low flows in Eastern Austria. The total  
8 uncertainty of  $Q_{95}$  projections is the largest in basins with winter low-flow regime and, in  
9 some basins it exceeds 60%. In basins with summer low flows, the total uncertainty is mostly  
10 less than 20%. The ANOVA assessment of the relative contribution of the three main  
11 variance components (i.e. climate scenario, decade used for model calibration and calibration  
12 variant representing different objective function) to the low-flow projection uncertainty shows  
13 that in basins with summer low-flows the climate scenarios contribute more than 75% to the  
14 total projection uncertainty. In basins with winter regime, the median contribution of climate  
15 scenario, decade and objective function is 29%, 13% and 13%. While the objective function-  
16 related uncertainty dominates over climate projection uncertainty in terms of low-flow  
17 magnitudes, the opposite is the case for low-flow seasonality. The implications of the  
18 uncertainties identified in this paper for water resources management are discussed.

19

## 20 **1 Introduction**

21 Understanding climate impacts on hydrologic water balance in general and extreme flows in  
22 particular is one of the main scientific interests in hydrology. Stream flow estimation during  
23 low-flow conditions is important also for a wide range of practical applications, including  
24 estimation of environmental flows, effluent water quality, hydropower operations, water  
25 supply or navigation. Projections of low flows in future climate conditions are thus essential  
26 for planning and development of adaptation strategies in water resources management.  
27 However it is rarely clear how the uncertainties in assumptions used in the projections  
28 translate into uncertainty of estimated future low flows.

29 There are numerous regional and national studies that have analyzed the effects of climate  
30 change on the stream flow regime, including low flows (e.g. Feyen and Dankers, 2009,  
31 Prudhomme and Davies, 2009, Chauveau et al., 2013 among others). Most of them apply  
32 outputs from different global or regional climate circulation models, which are based on

1 different emission scenarios. The projections of low flows are then typically simulated by  
2 hydrologic models of various complexity. There is an increasing number of studies evaluating  
3 different sources of uncertainty in river flow projections resulting from different GCMs,  
4 downscaling methods or hydrologic model parametrization (e.g. Dobler et al., 2012, Finger et  
5 al., 2012, Coron et al., 2012, Addor et al., 2014, Chiew et al., 2015). Only few studies,  
6 however, evaluate the uncertainty of low-flow projections and the relative contribution of its  
7 different sources (i.e. climate projection, hydrologic model structure and/or model  
8 parameterizations). Such studies include assessment of the impact of different climate  
9 projections on low flows evaluated e.g. in Huang et al. (2013) and Forzieri et al. (2014).  
10 While Huang et al. (2013) assesses the low-flow changes and uncertainty in the five largest  
11 river basins in Germany, Forzieri et al. (2014) evaluates the uncertainty of an ensemble of 12  
12 bias corrected climate projections in the whole of Europe. Both studies quantify uncertainty in  
13 terms of the number of low-flow projections that suggest the same change direction. Their  
14 results indicate a consistent pattern of low-flow changes across different regions in Europe. A  
15 common feature of such ensemble climate scenarios is an increase in the agreement between  
16 ensemble members with increasing future time horizon of climate projections. The impact of  
17 hydrologic model structure and climate projections was evaluated in Dams et al. (2015). They  
18 applied four hydrologic models calibrated with four objective functions to simulate the impact  
19 of three climate projections on low flows for a basin in Belgium. They found that besides the  
20 uncertainty introduced by climate change scenarios, hydrologic model selection introduces an  
21 additional considerable source of uncertainty in low-flow projections. The model structure  
22 uncertainty was particularly important under more extreme climate change scenarios. A  
23 similar study was performed by Najafi et al. (2011) who investigated the uncertainty  
24 stemming from four hydrologic models calibrated by three objective functions and applied on  
25 eight Global Climate Model (GCM) simulations in a basin in Oregon. Their results show that  
26 although in general the uncertainties from the hydrologic models are smaller than from GCM,  
27 in the summer low-flow season, is the impact of hydrologic model parametrization on overall  
28 uncertainty considerably larger than of the GCM.

29 The quantification of the relative contribution of different sources to the overall uncertainty of  
30 stream flow projections is recently evaluated by using analyses of variance (ANOVA) (Storch  
31 and Zwiers, 1999). Bosshard et al. (2013) synthesized previous studies that investigate  
32 hydrological climate-impact projections and their sensitivity to different uncertainty sources.  
33 They propose an ANOVA framework to separate the uncertainty from climate models,

1 statistical post-processing (bias correction and delta change approach) and hydrological  
2 models. Addor et al. (2014) use the ANOVA framework to quantify the uncertainty of stream  
3 flow projections resulting from the combination of emission scenarios, regional climate  
4 models, post-processing methods, and hydrological models of different complexity. They  
5 report that the main source of uncertainty stems from the climate models and natural climate  
6 variability, and the impact of emission scenario increases with increasing future time horizon  
7 of climate projections. Hingray and Said (2014) propose a quasi-ergodic two-way ANOVA  
8 framework for the partitioning of the total uncertainty of climate projections. This framework  
9 is recently tested for the estimation of climate and hydrological uncertainties of transient low  
10 flow projections in two basins in the southern French Alps (Vidal et al., 2015). The results  
11 show that a large part of the total uncertainty arises from the hydrological modelling and it  
12 can be even larger than the contribution from the GCMs.

13 The objective of this paper is to understand the relative contribution of the impact of  
14 hydrologic model calibration and ensemble climate scenarios to the overall uncertainty of  
15 low-flow projections in Austria. Here, the uncertainty and variability of low-flow projections  
16 is assessed for four climate scenarios, 11 variants of objective functions and three decades  
17 used for model calibration. Austria is chosen as a case study since it is an ideal test bed for  
18 such analysis, as it allows to disentangle the uncertainties separately in regions with summer  
19 and winter low-flow regimes. The assessment of uncertainties for winter and summer regimes  
20 allows to make generalisation for a similar spectrum of physiographic conditions around the  
21 world.

22

## 23 **2 Methodology**

### 24 **2.1 Low-flow projections**

25 In this study, low-flow projections of future climate scenarios are analysed by comparing  
26 future to past flows by using model forcing from a delta change approach. This concept  
27 allows to remove biases resulted from simulations when regional climate model (RCM)  
28 outputs are used as an input in hydrologic modelling. Instead of using RCM simulations of  
29 daily air temperature and precipitation for hydrologic model calibration, the model is first  
30 calibrated by using observed climate characteristics in the reference period. In a next step,  
31 RCM outputs are used to estimate monthly differences between simulations in the reference

1 (control) and future periods. These differences (delta changes) are then added to the observed  
 2 model inputs and used for simulating future hydrologic changes. The daily precipitation is  
 3 scaled by the relative monthly delta changes, with no change in the frequency of rainy days.  
 4 The daily air temperature is changed by the absolute value of monthly delta changes. The  
 5 differences between daily simulations of a hydrologic model in the reference and future  
 6 periods are then used to interpret potential impacts of changing climate on future river flows.

7 The future low-flow changes are quantified by the  $Q_{95}$  low-flow quantile and seasonality  
 8 index  $SI$ . The  $Q_{95}$  represents river flow that is exceeded on 95% of the days of the entire  
 9 reference or future period. This characteristic is one of the low-flow reference characteristic  
 10 which is widely used in Europe (Laaha and Blöschl, 2006). Seasonality index  $SI$  represents  
 11 the average timing of low flows within a year (Laaha and Blöschl, 2006, 2007). It is estimated  
 12 from the Julian dates  $D_j$  of all days when river flows are equal or below  $Q_{95}$  in the reference  
 13 or future periods.  $D_j$  represents a cyclic variable. Its directional angle, in radians, is given by:

$$14 \quad \theta_j = \frac{D_j \cdot 2\pi}{365} \quad (1)$$

15 The arithmetic mean of Cartesian coordinates  $x_\theta$  and  $y_\theta$  of a total of  $n$  single days  $j$  is defined  
 16 as:

$$17 \quad x_\theta = \frac{1}{n} \sum_j \cos(\theta_j) \quad (2)$$

$$18 \quad y_\theta = \frac{1}{n} \sum_j \sin(\theta_j)$$

19 From this, the directional angle of the mean vector may be calculated by:

$$20 \quad \theta = \arctan\left(\frac{y_\theta}{x_\theta}\right) \quad 1^{\text{st}} \text{ and } 4^{\text{th}} \text{ quadrant: } x > 0 \quad (3)$$

$$21 \quad \theta = \arctan\left(\frac{y_\theta}{x_\theta}\right) + \pi \quad 2^{\text{nd}} \text{ and } 3^{\text{rd}} \text{ quadrant: } x < 0 \quad (4)$$

22 Finally, the mean day of occurrence is obtained from re-transformation to Julian Date:

$$23 \quad SI = \theta \cdot \frac{365}{2\pi} \quad (5)$$

1 and the variability of the date of occurrence about the mean date (i.e. seasonality strength) is  
2 characterized by the length parameter  $r$ . The parameter  $r$  is estimated as (Burn, 1997):

$$3 \quad r = \sqrt{\bar{x}^2 + \bar{y}^2} / n \quad (6)$$

4 and ranges from  $r=0$  (low strength, uniform distribution around the year) to  $r=1$  (maximum  
5 strength, all extreme events of floods occur on the same day).

6 The SI index is estimated for observed and simulated low flows. The differences between  
7 model simulations (i.e.  $Q_{95}$  and  $SI$  estimates) in the reference and future periods are then used  
8 to quantify potential impacts of climate change on low flows. Both  $Q_{95}$  and  $SI$  measures are  
9 estimated independently for the reference and future periods by the `lfstat` package in R  
10 software (Kofler and Laaha, 2014).

11

## 12 **2.2 Hydrologic model**

13 Low-flow projections are estimated by a conceptual semi-distributed rainfall-runoff model  
14 (TUWmodel, Viglione and Parajka, 2014). The model simulates water balance components  
15 on a daily time step by using precipitation, air temperature and potential evapotranspiration  
16 data as an input. The model consists of three modules which allow simulating changes in  
17 snow, soil storages and groundwater storages. The calibrated model parameters are presented  
18 in Table 1. More details about the model structure and examples of application in the past are  
19 given e.g. in Parajka et al. (2007, 2008), Viglione et al. (2013) and Ceola et al. (2015).

20 In this study, the TUWmodel is calibrated by using the SCE-UA automatic calibration  
21 procedure (Duan et al., 1992). The objective function ( $Z_Q$ ) used in calibration is selected on  
22 the basis of prior analyses performed in different calibration studies in the study region (see  
23 e.g. Parajka and Blöschl, 2008, Merz et al., 2011). It consists of weighted average of two  
24 variants of Nash–Sutcliffe model efficiency,  $M_E$  and  $M_E^{log}$ . While the  $M_E$  efficiency  
25 emphasize the high flows, the  $M_E^{log}$  efficiency accentuates more the low flows. The  
26 maximized objective function  $Z_Q$  is defined then as

$$27 \quad Z_Q = w_Q \cdot M_E + (1 - w_Q) \cdot M_E^{log} \quad (7)$$

28 where  $w_Q$  represents the weight on high or low flows. If  $w_Q$  equals 1 then the model is  
29 calibrated to high flows, if it equals to 0 then to low flows only.  $M_E$  and  $M_E^{log}$  are estimated as

$$1 \quad M_E = 1 - \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^n (Q_{obs,i} - \overline{Q_{obs}})^2} \quad (8)$$

$$2 \quad M_E^{\log} = 1 - \frac{\sum_{i=1}^n (\log(Q_{obs,i}) - \log(Q_{sim,i}))^2}{\sum_{i=1}^n (\log(Q_{obs,i}) - \overline{\log(Q_{obs})})^2} \quad (9)$$

3 where  $Q_{sim,i}$  is the simulated discharge on day  $i$ ,  $Q_{obs,i}$  is the observed discharge,  $\overline{Q_{obs}}$  is the  
4 average of the observed discharge over the calibration (or verification) period of  $n$  days.

5

### 6 **2.3 Uncertainty estimation**

7 The uncertainty, defined as the range of simulated low-flow indices, is evaluated for two  
8 contributions. The first analyses the uncertainty (i.e. the range of  $Q_{95}$  and  $SI$ ) estimated for  
9 different variants of hydrologic model calibration. Here, two cases are evaluated. In order to  
10 assess the impact of time stability of model parameters (Merz et al., 2011), TUWmodel is  
11 calibrated separately for three different decades (1976-1986, 1987-1997, 1998-2008). The  
12 effect of objective functions used for the TUWmodel calibration is evaluated by comparing  
13 11 variants of weights ( $w_Q$ ) used in  $Z_Q$ . Following  $w_Q$  are tested: 0.0, 0.1, 0.2, 0.3, 0.4, 0.5,  
14 0.6, 0.7, 0.8, 0.9 and 1.0. The hydrologic model is calibrated for all 11 variants in each  
15 selected decade. Calibrated models are then used for flow simulations and hence  $Q_{95}$  and  $SI$   
16 estimation in the reference and future periods.

17 The second contribution evaluates the uncertainty of  $Q_{95}$  and  $SI$  changes simulated for  
18 different climate scenarios. The effect of calibration uncertainty (case 1) is compared for four  
19 selected climate scenarios (more details are given in Data section). The delta change approach  
20 is used to derive model forcing for selected future period and simulated future river flows are  
21 compared to model simulations in the reference period 1976-2008. The relative changes of  
22  $Q_{95}$  and  $SI$  values between reference and future periods are estimated for four selected climate  
23 scenarios, 11 variants of model calibration and three selected decades. The relative  
24 contribution of the impact of model calibration (i.e. time stability and objective function  
25 selection) and climate scenario is evaluated seasonally at the regional scale.

1 The uncertainty of low flow projections is then compared to the range of low-flow indices  
2 obtained by different calibration variants in the reference period. In addition, the total  
3 uncertainty of future low flow projections is decomposed to individual components by means  
4 of analysis of variance (ANOVA; e.g. Hingray and Said, 2014; Lafaysse et al., 2014; Vidal et  
5 al, 2015; and von Storch and Zwiers, 1999, chap. 9 for a general introduction to ANOVA).  
6 The 3-way ANOVA approach is employed to decompose total uncertainty of the projected  
7 low-flow changes into three main variance components. These variance components represent  
8 uncertainty contributions of 3 main effects: climate scenario (factor A with  $I = 4$  levels),  
9 decade used for model calibration (factor B with  $J = 3$  , levels) and calibration variant  
10 representing different objective functions (factor C with  $K = 11$  levels). The ANOVA model  
11 is defined as follows:

$$12 \quad \Delta Q95_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + \epsilon_{ijk} \quad (10)$$

13  
14 In this linear equation (Eq.10),  $\Delta Q95_{ijk}$  denotes the ensemble projected changes in  $Q_{95}$  for the  
15 future horizon at a gauge. It is modelled by a global mean  $\mu$  and the mean effects (deviations  
16 of factor-means from the global mean) of climate scenario ( $\alpha_i ; i = 1, \dots, I$ ), decade  
17 ( $\beta_j ; j = 1, \dots, J$ ), and calibration variant ( $\gamma_k ; k = 1, \dots, K$ ), and  $\epsilon_{ijk}$  are the residual errors of  
18 the model. In an ANOVA framework, the total variability of  $\Delta Q95_{ijk}$  is characterised by the  
19 total sum of squares  $SS_T$ , and is decomposed into additive variance components of individual  
20 effects:

$$21 \quad S_T = SS_A + SS_B + SS_C + SS_E \quad (11)$$

22 The variance components of the main effects A, B, C are computed as follows:



$$SS_A = JK \sum_{i=1}^I (\bar{y}_{i..} - \bar{y}_{...})^2 \quad (12)$$

$$SS_B = IK \sum_{j=1}^J (\bar{y}_{.j.} - \bar{y}_{...})^2 \quad (13)$$

$$SS_C = IJ \sum_{k=1}^K (\bar{y}_{..k} - \bar{y}_{...})^2 \quad (14)$$

The variance component of the residuals representing the unexplained variance is:

$$SS_e = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K (y_{ijk} - \bar{y}_{i..} - \bar{y}_{.j.} - \bar{y}_{..k} + \bar{y}_{...})^2 \quad (15)$$

Based on the  $SS_e$ , an estimate of the variance contributions of each effect A,B,C is computed as:

$$\eta_A^2 = \frac{SS_A}{SS_T} ; \eta_B^2 = \frac{SS_B}{SS_T} ; \eta_C^2 = \frac{SS_C}{SS_T} ; \eta_e^2 = \frac{SS_e}{SS_T} \quad (16)$$

The measure eta-square is also termed the coefficient of determination  $R^2$  (Von Storch and Zwiers, 1999). Eta-square tends to overestimate the variance explained by one factor and is therefore a biased estimate of the effect size. A less biased estimator is given by the measure  $\omega^2$ :

$$\omega_A^2 = \frac{SS_A - df_A * MS_e}{SS_T + MS_e} \quad (17)$$

1 where  $df_A$  denotes the degrees of freedom of a factor (e.g. for factor A with I levels,  
2  $df_A = I - 1$ ), and  $MS_e = SS_E/df_e$  is the residual mean square error. The quantity  $MS_e$   
3 denotes the mean residual sum of squares. It is computed by

$$4 \quad MS_e = SS_e/df_e \quad (18)$$

5  
6 The measure omega-square is also termed the adjusted  $R^2$ , in analogy to the adjusted  
7 coefficient of determination of multiple regression. Note that the degrees of freedom of the  
8 error term  $df_e$  depend on the total number of effects in the ANOVA design. For 3-way  
9 ANOVA without interactions  $df_e$  is obtained by:

$$10 \quad df_e = df_T - df_A - df_B - df_C = IJK - I - J - K + 2 \quad (19)$$

11  
12 Clearly, the adjustment of effect size increases if the residual degrees of freedom are small,  
13 what is the case when overall sample size is small. Hence the difference between both  
14 measures of effect size will be negligible for designs with large  $df_e$ , as it is the case for our  
15 study. In our assessment, we will therefore only present  $\omega^2$  which is the more general  
16 measure of effect size at each catchment. A spatial synthesis of uncertainty contributions for  
17 summer and winter dominated basins is finally obtained from the distribution of variance  
18 components across basins falling into each low-flow regime group.

### 20 **3 Data**

21 Study region is Austria (Fig.1). Austria represents diverse climate and physiographic  
22 conditions of Central Europe, which are reflected in different hydrologic regimes (Gaál et al.,  
23 2012). The topography varies from 115 m a.s.l. in the lowlands to more than 3700 m a.s.l. in  
24 the Alps. Austria is located in a temperate climate zone influenced by the Atlantic, meridional  
25 south circulation and the continental weather systems of Europe. Mean annual air temperature

1 varies between  $-8^{\circ}\text{C}$  to  $10^{\circ}\text{C}$ . The mean annual precipitation ranges from 550mm/year in the  
2 Danube lowlands, to more than 3000mm/year on the windward slopes of the Alps.

3 The analysis is based on daily river flow measurements at 262 gauges (Fig. 1). This dataset  
4 represents a subset of data used in Laaha and Blöschl (2006), which consists of gauges for  
5 which hydrographs are not seriously affected by abstractions and karst effects during the low-  
6 flow periods. Fig.1 shows two main low-flow regimes in Austria. While orange and red  
7 colours indicate 130 stations with dominant summer (June-November) low-flow occurrence,  
8 blue colour indicates 132 gauges with winter (December-May) flow minima. These two  
9 groups represent basins with distinct low-flow seasons, which are controlled by different  
10 hydrologic processes. While the winter flow minima in the mountains are controlled by  
11 freezing processes and snow storage, summer low flows occur during long-term persistent dry  
12 periods when evapotranspiration exceeds precipitation. The different low-flow generating  
13 processes, together with the hydro-climatic variety of the study area, gives rise to an  
14 enormous spatial complexity of low flows in Austria. The largest values occur in the Alps,  
15 with typical values ranging from 6 to  $20\text{ l s}^{-1}\text{ km}^{-2}$ . The lowest values occur in the east ranging  
16 from  $0.02$  to  $8\text{ l s}^{-1}\text{ km}^{-2}$ , although the spatial pattern is much more intricate.

17 Climate data used in hydrologic modeling consists of mean daily precipitation and air  
18 temperature measurements at 1091 and 212 climate stations in the period 1976-2008,  
19 respectively. Model inputs have been prepared by spatial interpolation and zonal averaging  
20 described in detail in previous modeling studies (please see e.g. Merz et al., 2011 or Parajka et  
21 al, 2007). These data serve as a basis for hydrologic model calibration and as a reference for  
22 future change simulations. Fig. 2 shows basin averages of mean annual air temperature,  
23 precipitation and runoff in the period 1976-2008. The two groups of basins (winter vs.  
24 summer low flow regimes) clearly differ in the climate regime. Basins with summer low  
25 flows are characterized by higher air temperatures, less precipitation and less runoff. The  
26 comparison of three different decades indicates that mean annual air temperatures have  
27 increased by  $1^{\circ}\text{C}$  in the period 1976-2008. This increase is similar for both groups of basins.  
28 Interestingly, the mean annual precipitation has increased over the last three decades, which is  
29 likely compensated by increased evapotranspiration, as the mean annual runoff remains rather  
30 constant.

31 The regional climate model (RCM) scenarios used in this study are based on the results of the  
32 reclip.century project (Loibl et al., 2011). The ensemble climate projections are represented

1 by COSMO-CLM RCM runs forced by the ECHAM5 and HADCM3 global circulation  
2 models for three different IPCC emission scenarios (A1B, B1 and A2, Nakicenovic et al.,  
3 2000). These represent a large spread of different emission pathways from a “business as  
4 usual” scenario with prolonged greenhouse gas emissions (A2), a scenario with moderate  
5 decline of emissions after 2050 (A1B) and a scenario indicating considerably reduced  
6 emissions from now on (B1).

7

8 Table 2 summarizes the annual and seasonal differences (delta changes) of mean basin  
9 precipitation and air temperature between the future (2021-2050) and reference (1978-2007)  
10 periods. Table 2 indicates that the largest warming is obtained by simulations driven by  
11 HADCM3. The median of air temperature increase in summer exceeds 2°C. In numerous  
12 basins, a small decrease in air temperature in winter is simulated by ECHAM5 A2 and B1  
13 simulations. The changes in mean annual precipitation are within the range  $\pm 9\%$  in all  
14 selected basins. The increase tends to be larger in winter than in the summer period.

15

## 16 **4 Results**

### 17 **4.1 Low-flow simulations and uncertainty in the reference period**

18 The runoff model efficiency ( $Z_Q$ ) in the three calibration periods obtained for different  
19 variants of the objective function is presented in Fig. 3. The results show that  $Z_Q$  is larger and  
20 thus runoff simulations are more accurate in basins with winter (blue colour) than summer  
21 low-flow minimum (red colour). Most of the basins with winter low-flow regime are situated  
22 in the alpine western and central part of Austria, where the runoff regime is snow dominated.  
23 Such a regime has stronger runoff seasonality (see e.g. Fig. 5 in Laaha et al, this issue) and  
24 less difference in rainfall regime, which allows to model rainfall–runoff process easier than in  
25 basins with rainfall-dominated runoff regime..  $Z_Q$  increases with decreasing weight  $w_Q$ , which  
26 indicates that the runoff model performance likely tends to be better for low than high flows.  
27 The comparison of  $Z_Q$  in the three calibration periods indicates that the difference in model  
28 performance between basins with winter and summer low-flow regime is the largest in the  
29 period 1976-1986. While the  $Z_Q$  for basins with winter low regime is very similar in all three  
30 calibration periods, the  $Z_Q$  has an increasing tendency in basins with summer regime. For  
31 example, the median of  $Z_Q$  for  $w_Q=1.0$  increases from 0.64 in the period 1976-1986 to 0.71 in

1 the period 1998-2008. This increase is likely related to increasing number of climate stations  
2 and data quality (Merz et al., 2009).

3 How the different calibration variants and periods translate into low-flow 95%- quantile  $Q_{95}$   
4 and seasonality  $SI$  is examined in Fig. 4. The model calibrated for 11 year period is used to  
5 simulate daily flows in the entire reference period 1976-2008. The results show that the model  
6 calibrated in the period 1976-1986 significantly overestimates  $Q_{95}$  of the reference period  
7 particularly in basins with summer low-flow regime. The period 1976–1986 is characterized  
8 by lower air temperatures with less evapotranspiration and relatively higher runoff generation  
9 rates which translates into different soil moisture storage (FC model parameter) and runoff  
10 generation (BETA) model parameters. Such effects are consistent with findings of Merz et al.,  
11 (2011). The hydrologic model applied to the entire reference period hence produces larger  
12 runoff contribution which tends to overestimate  $Q_{95}$  particularly in the warmer and drier parts  
13 of the reference period and drier and warmer parts of Austria. The overestimation is consistent  
14 for large range of  $w_Q$  ( $w_Q$  in the range 0.0-0.9) and the median of  $Q_{95}$  difference exceeds 20%.  
15 Also the scatter around the median is rather large, where 25% of the basins with the summer  
16 low-flow regime have  $Q_{95}$  differences larger than 35%. The simulated  $Q_{95}$  in basins with  
17 winter low flows fit closer to the observed estimates. The median is less than 10% for variants  
18  $w_Q < 1$ . Interestingly, the model simulations based on calibration periods 1987-1997 and 1998-  
19 2008 are much closer to the observed values. The results for both groups of basins are very  
20 similar and essentially unbiased in terms of 95% low-flow quantile. The exception is the  
21 calibration variant  $w_Q = 1$  that tends to underestimate  $Q_{95}$ . There are any significant differences  
22 between calibration to low-flow only ( $w_Q = 0.0$ ) and other weights, with exception of  $w_Q = 1$ ,  
23 which represents a typical calibration of using classical Nash-Sutcliffe coefficient.

24 The results of the seasonality estimation are presented in the bottom panels of Fig. 4. It is  
25 clear that this hydrologic model tends to estimate the low-flow period later. This shift is larger  
26 in basins with summer low-flow regimes. While the median of  $SI$  difference in basins with  
27 winter regime is around 10-12 days in the period 1976-1986 and increases to 12-19 days in  
28 the period 1998-2008, the median of  $SI$  difference in basins with summer low flows is in the  
29 range of 18-32 days. The scatter is, however, much larger for basins with summer regime.  
30 Here the model simulates the season of low-flow occurrence with more than 2 months shift  
31 (earlier or later) in almost 50% of the basins. A typical example of such shift is provided in  
32 Fig. 5. The periods with flows below 95% quantile are often very short and the timing of

1 simulated low flows does not fit well with these periods. In some cases there is also a  
2 difference in the length of observed and simulated low-flow periods. Some small rainfall-  
3 runoff events in the summer or autumn cause an interruption of the observed low-flow  
4 periods, but the model simulates a complete absorption of the precipitation event by the soil  
5 storage and hence a longer low-flow period.

6 The spatial pattern of the variability of  $Q_{95}$  estimation in the reference period 1976-2008 is  
7 presented in Fig. 6. Fig. 6 shows the range of differences between simulated and observed  $Q_{95}$   
8 for the different calibration variants. Left panels show the range for model calibrations  
9 performed by the same objective function (i.e. top left panel -  $w_Q=0.5$  and bottom left panel -  
10  $w_Q=0.0$ ) used for calibration in the three different calibration periods (1976-86, 1987-97,  
11 1998-08). Contrary, right panels show the range of differences for one calibration period but  
12 between 11 variants of the objective function ( $w_Q$ ) (i.e. top right panel -1976-1986, bottom  
13 right panel -1998-2008). The results indicate that the  $Q_{95}$  differences vary more between the  
14 different objective functions (right panels), however in many basins the range exceeds 60%  
15 even if the model is calibrated by one objective function but in the different calibration  
16 periods. As already indicated in Fig.4, the differences are larger in basins with summer low  
17 flows, particularly for variants calibrated in the period 1976-1986. For particular basins, the  
18 differences are not strongly related to the weight  $w_Q$  used in the calibration, with an exception  
19 of  $w_Q=1$ , which tends to have the largest difference to observed  $Q_{95}$ . Some examples of the  
20 model performance for individual basins are given in companion paper of Laaha et al. (this  
21 issue).

22 Spatial variability of the model variability in terms of low-flow seasonality is presented in  
23 Fig. 7. The results clearly indicate that basins with winter low-flow regime (i.e. situated in the  
24 Alps) vary significantly less for different calibration settings than the basins with summer  
25 low-flow regime. The range of differences is typically less than 14 days in the mountains,  
26 compared to more than 90 days in many basins with the summer regime.

27 The comparison of  $SI$  and  $Q_{95}$  ranges indicates that large  $SI$  variability does not systematically  
28 mean large variability in terms of  $Q_{95}$ . For example, a cluster of basins situated in the south-  
29 eastern part of Austria (Styria) has a large  $SI$  range of difference (i.e. more than 90 days) for  
30 11 calibration variants in the period 1976-1986, but the variability in  $Q_{95}$  is less than 20% for  
31 this case. The same applies for the opposite case of small  $SI$  and large  $Q_{95}$  variability in the  
32 alpine basins.

1

## 2 **4.2 Low-flow projections and uncertainty in the future period**

3 Low-flow projections for selected climate scenarios and different calibration weights  $w_Q$  are  
4 presented in Fig. 8. Rather than to evaluate in detail the projections in terms of absolute  
5 values of low-flow changes, the main focus is to assess the range of possible changes caused  
6 by different scenarios and objective function used for model calibration. The results show  
7 projections based on model calibration in 1998-2008, but the results are almost identical with  
8 results for the other two calibration periods (i.e. the average difference is around 1%). Fig. 8  
9 clearly shows the difference in projections for basins with summer and winter low-flow  
10 regime, particularly for  $Q_{95}$  changes. It is hence important to evaluate the projections and their  
11 variability separately for different regimes. The comparison of different scenarios indicates  
12 that they are similar in terms of projecting an increase of winter low flows and a tendency for  
13 no change or decreasing low flows in the summer period. The increase of winter  $Q_{95}$  slightly  
14 varies between climate scenarios and tends to increase for calibration variants with larger  $w_Q$ .  
15 The difference in median between  $w_Q < 0.4$  and  $w_Q > 0.8$  is approximately 9%. The projections  
16 of  $Q_{95}$  changes in basins with summer low flows have significantly smaller variability and do  
17 not depend on  $w_Q$ . The change in low-flow seasonality (Fig. 8, bottom panels) is less  
18 pronounced. The median of projections is around 5 and 10 days earlier than in the reference  
19 period for basins with summer and winter regime, respectively. Interestingly, the variability  
20 between basins and  $w_Q$  is significantly smaller than obtained for different calibration variants  
21 in the reference period (Fig. 4).

22 Examples of spatial patterns of low-flow projections are presented in Fig. 9 and 10. The  
23 projections of  $Q_{95}$  changes (Fig. 9) indicate an increase of low flows in the Alps, typically in  
24 the range of 10-30%. A decrease is simulated in south-eastern part of Austria (Styria) mostly  
25 in the range of -5 - -20%. The most spatially different projection is provided by the HADCM3  
26 A1B climate scenario which simulates the strongest gradient between an increase of  $Q_{95}$  in the  
27 Alps in winter and a decrease in south-eastern part in summer. The change in the seasonality  
28 varies between the scenarios, but there is a tendency for earlier low flows in the Northern  
29 Alps and a shift to later occurrence of low flows in the Eastern Austria (Fig. 10). As already  
30 indicated in Fig. 8, the shift in seasonality is larger than one month only in a few basins.

1 Figure 9 and 10 show projections of lows flows for four climate scenarios, but only one  
2 variant of hydrologic model parameters. The evaluation of the impacts of different calibration  
3 variants on the variability of low-flow projections is presented in Fig. 11 and 12. These  
4 figures indicate the range of  $Q_{95}$  (Fig. 11) and the seasonality occurrence (Fig. 12) changes  
5 obtained by 11 calibration variants and three calibration periods. The range of  $Q_{95}$  changes is  
6 interestingly the largest in basins with the winter low-flow regime. In the Alps, the increase of  
7  $Q_{95}$  is often in the range of 15% to more than 60%. On the other hand, the future  $Q_{95}$   
8 estimates vary only slightly between the calibration variants in basins with the summer low  
9 flows. The change is less than 20% in most of the basins. The impact of the selection of  
10 objective function is, however, much larger for the estimation of the seasonality changes.  
11 Depending on the calibration variant, the change in seasonality can vary within more than 3  
12 months, e.g. in the south-eastern part of Austria.

13 The total uncertainty of low-flow projections of  $Q_{95}$  and  $SI$  is presented in Fig. 13. While the  
14 top panels show the range of low-flow characteristics for all climate scenarios, calibration  
15 variants and periods, the bottom panels show the ratio between the uncertainty of future  
16 low-flow projections to the range of low-flow indices simulated in the reference period. The  
17 results show that the  $Q_{95}$  range is less than 25% in approximately one third of analyzed  
18 basins. On the other hand, 20% of basins have a range larger than 50%. These are the basins  
19 with the winter low-flow regime. The variability in the date of low-flow occurrence is less  
20 than three months in 40% of the basins. In almost 20% of the basins, however, it is larger than  
21 five months. The ratio between the range of projections to the range of calibration differences  
22 (bottom panels in Fig. 13 and Fig. 14) indicates that only in 15% of the cases the climate  
23 projection uncertainty of  $Q_{95}$  is larger than the range obtained in the calibration period. Most  
24 of these basins are situated in the mountains (mean basin elevation above 1000m a.s.l.) and  
25 have winter low-flow regime. The range of calibrated  $Q_{95}$  is larger in almost all basins with  
26 the summer low-flow regime, which are characterized by lower mean basin elevation and  
27 larger aridity. On the other hand, the climate projection uncertainty dominates for the low-  
28 flow seasonality and is more than three times larger in 50% of basins, particularly in the Alps.  
29 The  $SI$  projection uncertainty is only in 15% of the basins lower than the  $SI$  range obtained in  
30 the calibration period. The  $SI$  uncertainty ratio tends to be lower with increasing mean basin  
31 elevation and the basin area, but there is no apparent relationship with the aridity of the  
32 basins.



1 The relative contribution of the three main variance components (i.e. climate scenario, decade  
2 used for model calibration and calibration variant representing different objective function) to  
3 the overall uncertainty of future low-flow projections is evaluated in Fig. 15. Left and right  
4 panels show the distribution of ANOVA variance components for basins with winter (left  
5 panel) and summer (right panel) low-flow regime, respectively. The results indicate that the  
6 variability from climate scenarios has a dominant contribution to the overall projection  
7 uncertainty in basins with summer low-flow regime. While in basins with winter low-flows  
8 the median contribution of the three variance components is 29% (climate scenario), 13%  
9 (calibration decade) and 13% (objective function), in basins with summer low-flow regime is  
10 the median contribution from climate scenario larger than 76%.

11

## 12 **5 Discussion and conclusions**

13 The objective of the study is to explore the relative role of hydrologic model calibration and  
14 climate scenarios in the uncertainty of low-flow projections. While many previous studies  
15 simulate only the change in hydrologic regime or extreme characteristics due to changes in  
16 climate, in this study we focus on the quantification of the range of low-flow projections (i.e.  
17 uncertainty) due to differences in the objective function used in model calibration, temporal  
18 stability of model parameters and an ensemble of climate projections.

19 There are a number of studies that compare the uncertainty of projected runoff changes due to  
20 different model structure, objective function or GCM and emission scenarios. These studies  
21 found that the hydrologic model uncertainty tends to be considerably smaller than that from  
22 GCM or emission scenarios (Najafi et al., 2011, Prudhomme and Davies, 2009). Such results,  
23 however, refer to the seasonal or monthly runoff and are based on only a limited number of  
24 basins. The quantification of the uncertainty in low flows is still rather rare. Some studies  
25 (e.g. Huang et al., 2013 and Forzieri et al., 2014) evaluate the low-flow uncertainty in terms  
26 of the number of projections with the same change direction. They showed that the  
27 uncertainty is controlled mainly by the differences in emission scenarios and it decreases with  
28 increasing projection horizon. Our results indicate that, although the uncertainty from  
29 different climate scenarios is larger than 40% in many basins, the range of low-flow indices  
30 from model calibration can exceed 60%. This result particularly relates to the assessment of  
31 low-flow quantile changes.

1 Some recent low-flow studies suggest to more explicitly distinguish between the processes  
2 leading to low-flow situations (see e.g. Fleig et al., 2006, Laaha et al., 2006, Van Loon et al.,  
3 2015, Forzieri et al., 2014). Following this recommendation, we analyzed the effects of model  
4 calibration and climate scenarios separately for basins with dominant winter and summer  
5 low-flow regimes. Our results indicate that the calibration runoff efficiency in basins with  
6 winter low-flow regime is larger (more accurate), and varies between basins less than in  
7 basins with summer low-flow regime. The calibration uncertainty in basins with summer  
8 regime exceeds in many basins 60% even if the model is calibrated by the same objective  
9 function but in different calibration periods. This finding confirms and quantifies the potential  
10 impact of time stability of model parameters reported by Merz et al. (2011). The model  
11 parameters calibrated in colder periods with relatively larger runoff generation rates tend to  
12 overestimate low flows, particularly in basins with summer low-flow regime and in warmer  
13 and drier parts of the simulation period. The results indicate that the time stability of model  
14 parameters is not sensitive to the weighting of normal ( $M_E$ ) and logarithmic transformed  
15 ( $M_E^{log}$ ) Nash-Sutcliffe efficiency in the objective function used for calibration. The exception  
16 is the case of using only  $M_E$  with no weight on  $M_E^{log}$ , which does not allow accurate low-flow  
17 simulations. This finding partly supports the studies that propose logarithmically transformed  
18 discharge values for calibrating hydrologic models with a focus on low flows (please see  
19 review in Pushpalatha et al., 2012). Our results show that the impact of the objective function  
20 is larger for  $SI$  estimation in basins with summer regime in the reference period and for future  
21 projections of  $Q_{95}$  in basins with winter regime. Depending on the calibration variant, the  
22 change in seasonality can vary within more than three months, which clearly indicates a shift  
23 in the main hydrologic processes causing the low flows.

24 The climate change signals captured in selected scenarios are well within the range of the  
25 projections of the ENSEMBLES regional climate simulations for Europe (van der Linden and  
26 Mitchell, 2009; Heinrich and Gobiet, 2011). Jacob et al. (2015) showed that the most recent  
27 regional climate simulations over Europe, accomplished by the EURO-CORDEX initiative  
28 (RCPs, Moss et al., 2010), are rather similar to the older ENSEMBLES simulations with  
29 respect to the climate change signal and the spatial patterns of change. Although this  
30 ensemble of four scenario runs seems rather small, the selection accomplished by the  
31 reclip:century consortium was not arbitrary, but based quantitative metrics. Prein et al. (2011)  
32 investigated the performance of all GCMs in CMIP3 for Central Europe based on a  
33 performance index including various parameters. They found that for the given domain the

1 ECHAM5 and the HADCM3 showed highest scores, which justified the selection of these  
2 GCMs for driving the RCM. In addition, these two models show different climate sensitivity,  
3 where the warming over the course of the 21st century is lower in ECHAM5 and higher in  
4 HADCM3. This feature in combination with the utilization of three different scenarios for  
5 ECHAM5 provides broad ensemble bounds, although the climate change signal of the  
6 different scenarios for the given investigation period (2021-2050) is rather similar,  
7 particularly for temperature (cf. Table 1). The projected future decrease of  $Q_{95}$  is most  
8 pronounced in the AIT\_HADCM3\_A1B run, particularly in basins with summer low-flow  
9 regime in the low lands. As indicated in Heinrich and Gobiet (2011), the climate sensitivity of  
10 HADCM3 is higher than that of ECHAM5, which translates into a higher warming rate of 2.1  
11 °C in summer (c.f. Table 1) compared to 1.2 °C in the ECHAM5 driven run. The higher  
12 evaporative demand due to the increased air temperature signal translates into the strongest  
13 change of the summer low-flow signal.

14 The comparison of the ranges of low-flow indices projected for different climate scenarios  
15 and simulated by different calibration settings (i.e. objective function and calibration decade)  
16 in the reference period indicates that the variability of low-flow magnitudes is larger for  
17 simulations in the reference period, while the range of seasonality is larger for future  
18 projections. Even if the variability and uncertainty of GCM and emission scenarios can be  
19 large, the results clearly indicate the importance of selecting objective functions in hydrologic  
20 model calibration for simulating low-flow projections.

21 In our study, we use a 3-way ANOVA approach to decompose the contribution of climate  
22 scenarios and hydrologic model settings to the total uncertainty of low-flow projections.  
23 While previous studies (e.g. Hingray and Said 2014; Lafaysse et al., 2014, Vidal et al, 2015)  
24 assessed the variance components of a temporal change from the multi-member ensemble  
25 runs in individual basins, in our study, we lumped the temporal change to one time slice  
26 (future horizon) and assessed the variance components in a spatial context of 262 basins. The  
27 spatial synthesis of the uncertainty contribution is evaluated for two groups of basins,  
28 representing to main (summer and winter) low-flow regimes in Austria. We found that the  
29 relative contribution of three variance components - climate scenarios, calibration decade and  
30 calibration objective function differs for basins with different low-flow regimes. The  
31 uncertainty from climate scenarios dominates in basins with summer low flows, however in  
32 basins with winter low flows is the relative contribution from hydrological modelling

1 significantly larger. This is consistent with previous studies that show a substantial  
2 uncertainty contribution of hydrological models in basins dominated by snow and ice melt  
3 (Addor et al.,2014, Vidal et al., 2015).

4 The assessment in Austria enabled us to account for one conceptual hydrologic model and  
5 two different low-flow regimes. In the future we plan to extend such comparative assessment  
6 to more types of low flows (e.g. as classified in Van Loon and Van Lanen, 2012), their  
7 combinations linked with changes in land use and management at the wider, European scale,  
8 as well as to account for hydrologic models of different complexity, wider range of climate  
9 scenarios and different downscaling techniques. This will allow us to shed more light on the  
10 factors controlling the possible scenarios of low-flow and water resources changes in the  
11 future.

12 From the practical point of view, the projections of  $Q_{95}$  changes and related uncertainties are  
13 an essential input to water quality modelling. The exceedance of environmental quality  
14 standards (BGBI II Nr. 99/2010; Zessner, 2008) in case of emissions from point sources (e.g.  
15 waste water treatment plants) increases the vulnerability of water resources, particularly  
16 during low-flow conditions. We therefore also plan to evaluate the impact of climate  
17 projection and hydrologic model uncertainties on the assessment of water quality and its  
18 changes.

19

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25

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Table 1. TUWmodel parameters. Calibration range is given for parameters calibrated by an automatic routine. Parameters with fixed value are not calibrated.

Model parameter	Definition	Model component	Calibration range
SCF	Snow correction factor (dimensionless)	Snow	1.0-1.5
DDF	Degree-day factor (mm/°C day)	Snow	0.0-5.0
T <sub>R</sub>	Threshold temperature for rain (°C)	Snow	2.0
T <sub>S</sub>	Threshold temperature for snow (°C)	Snow	0.0
T <sub>M</sub>	Melt temperature (°C)	Snow	-1.0-3.0
LP/FC	Ratio of limit for potential evapotranspiration and FC (dimensionless)	Soil	0.0-1.0
FC	Maximum soil moisture storage (mm)	Soil	0.0-600.0
BETA	Nonlinearity parameter of runoff generation (dimensionless)	Soil	0.0-20.0
K <sub>0</sub>	Storage coefficient of additional outlet (days)	Runoff	0.0-2.0
K <sub>1</sub>	Fast storage coefficient (days)	Runoff	2.0-30.0
K <sub>2</sub>	Slow storage coefficient (days)	Runoff	30.0-250.
C <sub>P</sub>	Percolation rate (mm/d)	Runoff	0.0-8.0
C <sub>R</sub>	Free routing coefficient (days <sup>2</sup> /mm)	Runoff	25.0
LS <sub>UZ</sub>	Storage capacity threshold (mm)	Runoff	1.0-100.0
B <sub>max</sub>	Routing parameter (days)	Runoff	10.0

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Table 2. Summary of seasonal and annual changes in the mean basin precipitation and air temperature as simulated by four selected RCM runs. The first value and values in the brackets are the median and range (min/max) of differences between the future (2021-2050) and reference (1978-2007) periods in 262 basins. Winter and summer seasons are defined as December-May and June-November, respectively.

Delta change	WEGC* ECHAM5 A1B	ZAMG** ECHAM5 A2	AIT*** HADCM3 A1B	ZAMG ECHAM5 B1
Air temperature				
winter (°C)	+1.5 (0.9/1.7)	+0.7 (-1.1/2.1)	+1.3 (0.8/1.5)	+1.0 (-0.8/2.5)
Air temperature				
summer (°C)	+1.2 (0.8/1.7)	+0.9 (-0.1/2.2)	+2.1 (1.4/2.4)	+1.3 (0.4/2.5)
Air temperature				
year (°C)	+1.3 (0.9/1.5)	+0.8 (-0.4/2.2)	+1.7 (1.2/1.9)	+1.2 (0.0/2.5)
Precipitation				
winter (%)	+8.2 (-0.7/16.2)	-1.5 (-5.8/6.4)	+1.3 (-9.6/6.8)	0.0 (-8.5/3.3)
Precipitation				
summer (%)	-6.2 (-9.9/3.7)	+0.2 (-8.9/5.7)	-5.0 (-13.5/0.2)	-2.3 (-6.3/2.5)
Precipitation				
year (%)	+0.9 (-4.6/8.7)	-0.9 (-4.1/3.4)	-2.0 (-9.3/1.8)	-1.2 (-5.5/2.8)

\*WEGC= Wegener Center for Climate and Global Change  
 \*\*ZAMG= Zentralanstalt für Meteorologie und Geodynamik  
 \*\*\*AIT= Austrian Institute of Technology

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2 Figure captions:

3 Figure 1. Topography of Austria and location of 262 river flow gauges. Colour and symbol  
4 size of the gauges represent seasonality of low flows  $SI$  and its strength ( $r$ ) in the period 1976-  
5 2008, respectively. The  $SI$  and its strength are estimated by R lfstat package (Koffler and  
6 Laaha, 2014).

7 Figure 2. Mean annual air temperature (MAT, top), precipitation (MAP, middle) and runoff  
8 (MAR, bottom) for basins with summer (yellow/red) and winter (blue) low-flow minima  
9 (Fig.1). Thin lines represent the median of mean annual values of MAT, MAP and MAR.  
10 Thick lines indicate the average for each of the three periods: 1976-86, 1987-97 and 1998-08.  
11 Scatter (i.e. 75% and 25%- percentiles) indicates the variability between the basins.

12 Figure 3. Runoff model efficiency ( $Z_Q$ ) for different calibration weights  $w_Q$  in three different  
13 calibration periods. Lines represent the medians, scatter (i.e. 75%-25% percentiles) shows the  
14  $Z_Q$  variability over basins with dominant winter (blue) and summer (orange) low-flow regime.

15 Figure 4. Difference between simulated and observed low-flow characteristics (top panels  
16 low-flow quantile  $Q_{95}$ , bottom panels seasonality index  $SI$ ) for different calibration variants  
17 ( $w_Q$ ) and calibration periods. Lines represent the median, scatter (i.e. 75%-25% percentiles)  
18 show the variability over basins with dominant winter (blue) and summer (orange) low flow  
19 regime. The differences are estimated between model simulations and observations in the  
20 entire reference period 1976-2008.

21 Figure 5. Comparison of observed (blue) and simulated (red) flow for  
22 Hoheneich/Braunaubach, 291.5 km<sup>2</sup>). Thick lines show flows below low-flow quantile  $Q_{95}$ .  
23 Model simulations are based on calibration variant  $w_Q=0.5$  in the period 1998-2008. The  
24 relative difference between  $Q_{95}$  estimated from simulated and observed flows is 8%.

25 Figure 6. Uncertainty of  $Q_{95}$  model simulations estimated from 11 calibration variants  
26 calibrated in the same calibration period (right panels, top - calibration period 1976-1986,  
27 bottom - calibration period 1998-2008) and from three calibration periods calibrated by the  
28 same calibration variant (left panels, top  $w_Q=0.5$ , bottom  $w_Q=0.0$ ). The uncertainty is  
29 expressed as the range of relative differences (%) between simulated and observed  $Q_{95}$   
30 obtained by particular calibration variants in the period 1976-2008. Colour patterns in the  
31 background show the interpolated ranges by using top-kriging method (Skoien et al., 2014).

1 Figure 7. Uncertainty of simulations of low-flow seasonality ( $SI$ ) estimated from 11  
2 calibration variants calibrated in the same calibration period (right panels, top - calibration  
3 period 1976-1986, bottom - calibration period 1998-2008) and from three calibration periods  
4 calibrated by the same calibration variant (left panels, top  $w_Q=0.5$ , bottom  $w_Q=0.0$ ). The  
5 uncertainty is expressed as the range of differences (days) between simulated and observed  $SI$   
6 in the period 1976-2008. Colour patterns in the background show the interpolated ranges by  
7 using top-kriging.

8 Figure 8. Projections of low flows for selected climate scenarios and calibration variants. Line  
9 represents the medians, scatter (i.e. 75%-25% percentiles) shows the variability over 262  
10 basins. Top and bottom panels show projected changes of low-flow quantiles  $Q_{95}$  and  
11 seasonality index  $SI$  in basins with winter (blue) and summer (orange) low-flow regimes,  
12 respectively. Projections indicate future changes with respect to the reference period 1976-  
13 2008. Calibration variants are calibrated in the period 1998-2008.

14 Figure 9. Projections of low-flow quantiles  $Q_{95}$  changes for four climate scenarios in 262  
15 Austrian basins. Model simulations are based on variant  $w_Q=0.5$  calibrated in the period 1998-  
16 2008. Colour patterns in the background show the interpolated projections by using top-  
17 kriging.

18 Figure 10. Projections of changes in low-flow seasonality ( $SI$ ) for four climate scenarios in  
19 262 Austrian basins. Model simulations are based on variant  $w_Q=0.5$  calibrated in the period  
20 1998-2008. Colour patterns in the background show the interpolated projections by using top-  
21 kriging.

22 Figure 11. Uncertainty of  $Q_{95}$  model projections of low flows for four different climate  
23 scenarios. The uncertainty is expressed as the range of relative differences (%) between  $Q_{95}$   
24 simulated in the future and reference period obtained for 11 calibration variants calibrated in  
25 three calibration periods. Colour patterns in the background show the interpolated ranges by  
26 using top-kriging.

27 Figure 12. Uncertainty of model projections of low-flow seasonality for four different climate  
28 scenarios. The uncertainty is expressed as the range of relative differences (%) between  
29 seasonality occurrence ( $SI$ ) simulated in the future and reference period obtained for 11  
30 calibration variants calibrated in three calibration periods. Colour patterns in the background  
31 show the interpolated ranges by using top-kriging.

1 Figure 13. Total uncertainty of model projections of low flows for four different climate  
2 scenarios, 11 calibration variants and three calibration periods. The uncertainty is expressed  
3 as the range of  $Q_{95}$  (left panel) and seasonality (right panel) of differences between model  
4 simulations in the future and reference periods. Bottom panels show the ratio between the  
5 range of climate projections to the range of differences in the reference period. Colour  
6 patterns in the background show the interpolated ranges by using top-kriging.

7 Figure 14. Relationship between the uncertainty ratio between calibration and projection  
8 uncertainty and basin area (left panels), mean basin elevation (middle panels) and aridity  
9 index (right panels). Top and bottom panels show the uncertainty ratio for the low-flow  
10 quantile ( $Q_{95}$ ) and seasonality index ( $SI$ ), respectively. Basins with winter low-flow  
11 seasonality are plotted in blue, basins with summer low-flow seasonality are in yellow.

12 Figure 15. Relative contribution of the three variance components (i.e. climate scenario,  
13 calibration decade and objective function) to the overall uncertainty of future low flow  
14 projection in basins with winter (left panel) and summer (right panel) low-flow regime. The  
15 boxes and whiskers show 25%- and 75%- percentiles and 5%- and 95%- percentiles of the  
16 uncertainty contributions in 130 (summer low-flow regime) and 132 (winter low-flow regime)  
17 basins, respectively.

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1 Figures:

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