Hydrol. Earth Syst. Sci. Discuss., 9, 8173–8211, 2012
www.hydrol-earth-syst-sci-discuss.net/9/8173/2012/
doi:10.5194/hessd-9-8173-2012

Hydrology and
Earth System
Sciences
Discussions

Quantifying different sources of uncertainty in hydrological projections at the catchment scale

C. Dobler[1], S. Hagemann[2], R. L. Wilby[3], and J. Stötter[1]

[1]Institute of Geography, Innsbruck, Austria
[2]Max Planck Institute for Meteorology, Hamburg, Germany
[3]Department of Geography, Loughborough, UK

Received: 30 May 2012 – Accepted: 15 June 2012 – Published: 4 July 2012

Correspondence to: C. Dobler (christian.dobler@uibk.ac.at)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Many studies have investigated potential climate change impacts on regional hydrology; less attention has been given to the components of uncertainty that affect these scenarios. This study quantifies uncertainties resulting from (i) General Circulation Models (GCMs), (ii) Regional Climate Models (RCMs), (iii) bias-correction of RCMs, and (iv) hydrological model parameterization using a multi model framework. This consists of three GCMs, three RCMs, three bias-correction techniques, and sets of hydrological model parameters. The study is performed for the Lech watershed ($\sim 1000\,\mathrm{km}^2$), located in the Northern Limestone Alps, Austria. Bias-corrected climate data are used to drive the hydrological model HQsim to simulate runoff under present (1971–2000) and future (2070–2099) climate conditions. Hydrological model parameter uncertainty is assessed by Monte Carlo sampling. The model chain is found to perform well under present climate conditions. However, hydrological projections are associated with large uncertainty, mainly due to the choice of GCM and RCM. Uncertainty due to bias-correction is found to have greatest influence on projections of extreme river flows and the choice of method(s) is an important consideration in snowmelt systems. Overall, hydrological model parameterization is least important. The study also demonstrates how an improved understanding of the physical processes governing future river flows can help focus attention on the scientifically tractable elements of the uncertainty.

1 Introduction

The global climate has changed during recent decades and there is high confidence that this is partly due to human activity (Oreskes, 2004; Solomon et al., 2007; Jones et al., 2008; Rosenzweig et al., 2008). Over coming decades, changes in climate are expected to exceed those observed during the 20th century (Kharin et al., 2007; Solomon et al., 2009; Trenberth, 2011). As a consequence, climate change risk assessment has become an important part of sectoral and national adaptation planning (e.g. Biesbroek et al., 2008; Howden et al., 2007; Milly et al., 2008).

General Circulation Models (GCMs) are the most favoured tools for assessing climate change. These models represent major earth system components including atmosphere, oceans, land-surface and sea-ice. GCMs operate on a global to continental scale and, thus, are unable to resolve regional climate effects. Dynamical and statistical downscaling is therefore used to generate climate information at finer spatial resolutions. Dynamical downscaling includes Regional Climate Models (RCMs) which are nested within the domain of a GCM over a region of interest (Giorgi et al., 1990; Giorgi and Mearns, 1999). RCMs use GCM output as initial and lateral boundary conditions and can now generate climate information at resolutions as fine as 7 km (Pavlik et al., 2012). Statistical downscaling is based on empirical relationships between large-scale atmospheric indices and local meteorological data (Wilby et al., 2004). Comprehensive reviews of downscaling methods are provided elsewhere (e.g. Fowler et al., 2007; Maraun et al., 2010; Wilby et al., 2009).

Projects such as PRUDENCE (Christensen and Christensen, 2007) and ENSEMBLES (van der Linden and Mitchell, 2009) have increased the availability of RCM outputs whereas increasing computational resources have lead to their improved spatial resolution, as well as their appeal for hydrological impact assessment (e.g. van Roosmalen et al., 2011). However, systematic biases are often found in the RCM output, especially in the simulation of precipitation (e.g. Frei et al., 2006; Themeßl et al., 2010; Pavlik et al., 2012). Hence, statistical bias-correction techniques are widely applied to RCM output before using the scenarios in hydrological assessment (e.g. Bóe et al., 2007; Beyene et al., 2010; Dobler et al., 2010; Quintana-Seguí et al., 2010; Hagemann et al., 2011; Stoll et al., 2011).

Although many studies rely on this type of approach, relatively few have assessed the associated uncertainties. Estimating uncertainty in climate change impact studies is still very much in its infancy although early studies suggest that widely divergent scenarios can emerge (e.g. Kay et al., 2009; Quintana-Seguí et al., 2010; Chen et al., 2011a; Stoll et al., 2011; Ledbetter et al., 2012). This uncertainty arises from the emission scenario, GCM structure and parameterization, RCM structure and parameterization, bias correction method, impact model structure and parameterization, as well as natural variability in the impact system. These sources can be grouped into (i) uncertainty originating from the future emission pathways and aerosols, (ii) uncertainty related to the model projections and (iii) uncertainty arising from natural fluctuations (Maurer and Duffy, 2005; Hawkins and Sutton, 2009; Fischer et al., 2011). In the present investigation we focus on uncertainty originating from model projections because we are particularly interested in identifying those components of uncertainty that are potentially reducible through further field work and research (e.g. Hawkins and Sutton, 2009).

Many studies have already explored the significant uncertainty originating from GCMs (e.g. Jasper et al., 2004; Maurer and Duffy, 2005; Chen et al., 2006; Minville et al., 2008; Buytaert et al., 2009). Uncertainty related to the RCM, the statistical downscaling approach, the hydrological model structure and parameterization, has received less attention and studies show mixed results. For example, Quintana-Seguí et al. (2010) found major differences between three downscaling and bias-correction techniques when assessing climate change impacts on the hydrology of Mediterranean basins. Similar findings are reported by Stoll et al. (2011), Teutschbein et al. (2011) and Chen et al. (2011a). Conversely, van Roosmalen et al. (2011) found only small differences when comparing projected groundwater and stream discharge using two different bias-correction methods. Chen et al. (2011b) report that the choice of calibration period for deriving bias correction parameters is found to be of minor importance.

Gosling et al. (2011) investigated impacts of climate change on river runoff using seven GCMs and two distributed hydrological models (a global hydrological model and a catchment-scale hydrological model). GCM structural uncertainty was found to be larger than hydrological model structural uncertainty. Bae et al. (2011) studied the effects of climate change by driving three semi-distributed hydrological models with a number of GCMs. They found that the choice of hydrological model can induce major differences in runoff change under the same climate forcing. This is consistent with Bastola et al. (2011) who report large uncertainty associated with hydrological models in an investigation of four Irish catchments. Poulin et al. (2011) demonstrated that the effect of the hydrological model structure is more important than the effect of parameter uncertainty when studying climate change impacts in a snow-dominated river basin.

The majority of studies focus on a single source of uncertainty; only a few attempt to quantify uncertainty originating from multiple factors. For example, Wilby and Harris (2006) report that uncertainty due to climate change scenarios and downscaling methods is greater than uncertainty related to the hydrological model parameters. Kay et al. (2009), Prudhomme and Davies (2009) and Chen et al. (2011c) confirm that impacts are most sensitive to GCM structures, but Chen et al. (2011c) show that the downscaling method or GCM initial conditions can produce comparable or even larger uncertainty. In general, the importance of each uncertainty source depends on (i) the time interval, (ii) the impact variable, (iii) season, and (iv) the region considered.

The aim of this study is to quantify different sources of uncertainty in hydrological projections for an Alpine river basin. We examine uncertainty originating from (i) GCM structure, (ii) RCM structure, (iii) bias-correction method, and (iv) hydrological model parameterization. We begin with a description of the study area and data involved then explain the calibration and uncertainty analyses at each stage. The four components of uncertainty are diagnosed in terms of changes to annual, mean and high flows. The final section identifies some important caveats and opportunities for further research.

2 Study area and data

The study is performed for the Lech watershed, located in the Northern Limestone Alps of Austria (Fig. 1). The watershed is drained by the river Lech, a tributary of the Danube river. The catchment area upstream of the gauge at Lechaschau, near Reutte, is approximately 1000 km^2. For a detailed description of the study area (see Dobler et al., 2010).

The Lech valley is a typical Alpine valley with major variations in topography, climate, soil and vegetation over short distances. The elevation ranges from approximately 800 m a.s.l. to around 3000 m with 85 % of the area located at an elevation of 1200 m to 2400 m. Annual precipitation varies between ∼1300 mm and ∼1800 mm measured at the stations illustrated in Fig. 1. At an elevation of 1080 m (station Holzgau; see Fig. 1), mean annual air temperature is around 6.1 °C, with maximum monthly mean temperature of 15.2 °C in July and minimum monthly mean temperature of −3.5 °C in January.

Daily data for temperature, precipitation and runoff for the years 1971 to 2005 are obtained from the "Hydrographischer Dienst Österreich", "Zentralanstalt für Meteorologie und Geodynamik (ZAMG)" and "Deutscher Wetterdienst (DWD)". Figure 1 shows the location of the temperature and precipitation stations in or close to the catchment.

Large-scale climate data are derived from the ENSEMBLES project (http://ensemblesrt3.dmi.dk/) for the period from 1971 to 2099. The time slice from 1971 to 2000 is used as present climate while the period 2070 to 2099 served as the future scenario. Surface air temperature and precipitation were extracted from the RCM output.

3 Models and methods

An ensemble of downscaled and bias-corrected climate scenarios is used to drive a hydrological model in order to simulate runoff for present and future time horizons. The projections of future climate are produced by three different GCMs, which are dynamically downscaled by three different RCMs and subsequently bias-corrected in three different ways. Uncertainty originating from (i) GCM, (ii) RCM, (iii) bias-correction, and (iv) hydrological model parameterization is systematically assessed by varying the modelling component under focus, while holding others constant. For example, in order to assess uncertainty related to the GCM, the three GCMs are varied while the remaining model chain consists of a fixed RCM, a fixed bias-correction technique and a fixed hydrological model parameter set. Differences between model outputs provide an estimate of the uncertainty originating from each modelling component. Figure 2 gives an overview of the approach and the combinations of models used to assess each source of uncertainty.

3.1 GCMs

Three GCMs, the Max Planck Institute for Meteorology ECHAM5 model (Roeckner et al., 2006), the Met Office Hadley Centre for Climate Prediction and Research HadCM3 (Johns et al., 2003; Jungclaus et al., 2006) and the Bergen Climate Model BCM (Furevik et al., 2003) are used. All models are forced with the Special Report on Emission (SRES) A1B scenario (Nakicenovic et al., 2000), which can be considered as mid-range scenario in terms of greenhouse gas emissions.

3.2 RCMs

The RCMs used are RCA (Kjellström et al., 2005), REMO (Jacob et al., 2001) and RACMO (Lenderink et al., 2003). The output of these models has a spatial resolution of about 25 km (0.22°). Figure 2 gives an overview of the RCMs under study and their driving GCMs. The RCA model is driven by all of the three different GCMs, while the REMO and RACMO models are only forced with the ECHAM5 model.

3.3 Bias-correction techniques

In order to correct RCM output for systematic biases, three different bias-correction techniques are applied: the delta change method (delta), local scaling (scal), and quantile-quantile (QQ) mapping. All methods depend on establishing an empirical relationship between the RCM control simulation (1971–2000) and observations (1971–2000), for each of the stations shown in Fig. 1. Subsequently, the same relationship is applied when adjusting the scenario simulation (2070–2099). The methods are based on the fundamental assumption that the empirical relationship derived from present climate conditions is also valid for the future scenario (e.g. Wilby et al., 2004).

The grid box overlying the target station is used for the bias-correction of temperature and precipitation. For temperature, the bias-correction is only applied to data of the station at Holzgau, the reference station. In order to differentiate temperature in the catchment vertically, fixed monthly temperature lapse rates derived from observed data are used. The application of observed lapse rates is necessary because mean monthly temperature lapse rates as simulated by the RCMs show large systematic biases. For example, Kotlarski et al. (2012) evaluated temperature lapse rates simulated by the RCM COSMO-CLM over the Alps. Deviations from the observed lapse rate of ∼0.15 °C per 100 m were reported, which would result in large temperature biases at higher elevations.

However, Gardner et al. (2009) and Minder et al. (2010) show that the assumption of a constant surface lapse rate (e.g. −0.65 °C per 100 m) is questionable and recommend the application of temporally variable lapse rates. Thus, we derive monthly varying temperature lapse rates based on observed data by regressing the mean monthly temperature of the station Holzgau (1080 m a.s.l.) and Zugspitze (2960 m a.s.l.) (Fig. 1) against their elevation. The application of monthly constant lapse rates assumes that the lapse rates will not change in future. However, this is a questionable (e.g. Kotlarski et al., 2011) but necessary assumption when studying climate change impacts in a complex Alpine catchment where steep temperature gradients are not properly represented by RCMs.

The monthly lapse rates show strong seasonal variations with a minimum during June at −0.66 °C per 100 m and a maximum in January at −0.34 °C per 100 m, based on the years 1971 to 2000. Similar lapse rates are also reported by Prömmel et al. (2010) for other station pairs in the Alps.

3.3.1 Delta change method

Due to its simplicity, the “delta change” or “change factor” method is one of the most widely applied downscaling techniques in climate change impact assessments (e.g. Prudhomme et al., 2002; Wilby and Harris, 2006; Minville et al., 2008; Dobler et al., 2010). Observed temperature and precipitation series are altered with delta change factors to obtain future climate scenarios. The change factors are derived from RCM data as the mean monthly change between the control and future simulations and are additive for temperature and multiplicative for precipitation. Note that the basic method accounts for shifts in mean and ignores changes in variability (Fowler et al., 2007). The number of days with precipitation does not change between the reference and scenario simulations.

3.3.2 Local scaling

The second method is local scaling, following the approach of Widmann et al. (2003) and others (e.g. Salathé, 2005; Graham et al., 2007; Stoll et al., 2011). Local scaling is a straightforward approach as it preserves the dynamic characteristics of the scenario simulation. Daily RCM precipitation at each grid point is multiplied by a monthly factor, which is derived from the quotient between the precipitation simulated by the RCM for the reference period and the precipitation observed at each site. The same factor is then applied to the RCM scenario data. For temperature, an additive adjustment instead of a multiplicative is used. In this method, it is possible for the future precipitation frequency to differ from the control period.

Bias-correction of the variance of monthly temperature was also undertaken following the method of Chen et al. (2011a). This is necessary as large biases in the variance of monthly temperatures are found in RCM output, which could significantly affect modelled snow accumulation and melt. Thus, the standard deviation of the RCM temperature is corrected by the ratio between the standard deviation of the temperature simulated by the RCM for the reference period and the standard deviation of observed temperature. The same correction factor is then applied to the future scenario data.

3.3.3 Quantile-quantile mapping

The third technique is the quantile-quantile (QQ) mapping approach, as employed in a growing number of studies (e.g. Bóe et al., 2007; Déqué, 2007; Quintanta-Seguí et al., 2010; Hagemann et al., 2011; Themeßl et al., 2012). QQ mapping is based on adjusting quantiles of RCM output to observations in order to eliminate systematic errors in RCM output.

First, cumulative distribution functions (cdfs) of observed and RCM simulated data for the control period are used to calculate transfer functions for each percentile. A moving window of 31 days centered on the day under investigation is used to construct the cdfs. Thus, transfer functions are determined for each day of the year with the two percentiles related by linear interpolation. Note, that after this step, the corrected variables of the control simulations have the same cdf as observations.

Second, simulated variables for the present climate are bias-corrected using the transfer function. Finally, the same transfer function is applied to the future scenario. Values smaller than the observed minimum or greater than the maximum are assumed to be the lowest and highest percentiles, respectively. For temperature, we followed the study of Beyene et al. (2011) and removed the linear warming trend before applying the QQ technique and re-imposed it afterwards. Due to a significant temperature increase in the future scenario, the cdf of future temperature is very different from the cdf of simulated present temperature. This would lead to many temperature corrections outside the calibration range, and may significantly alter the climate change signal. Removing the linear trend before applying the QQ technique helps to reduce the number of extrapolations.

3.4 Hydrological model

In order to simulate hydrological conditions for present and future climate, the semi-distributed hydrological model HQsim (Kleindienst, 1996) is applied. HQsim has been tested extensively for Alpine watersheds (e.g. Dobler et al., 2010; Achleitner et al., 2011) and has already been used to study climate change impacts on the runoff regime of the Lech river (Dobler et al., 2010).

In brief, HQsim is best described as a semi-distributed, conceptual model. HQsim simulates all relevant processes controlling runoff in mountain watersheds: snow accumulation and melt, evapotranspiration, interception and infiltration. For a detailed description of the model see Achleitner et al. (2011) or Dobler and Pappenberger (2012). The watershed is divided into hydrological response units (HRUs), which are defined as areas with similar runoff characteristics (Flügel, 1997). The delineation of HRUs is done on the basis of gridded layers of altitude, soil and land use. Input to the hydrological model includes daily temperatures for 100 m altitudinal belts and daily precipitation for the stations shown in Fig. 1. Temperatures for different altitudinal belts are calculated by applying the lapse rates obtained from the two meteorological stations (see Sect. 3.3). The model is run with a daily time step.

HQsim is specified by a number of global and local parameters, which must be adjusted during the calibration period. Dobler and Pappenberger (2012) identified the most sensitive parameters in the model. They found 17 parameters to be sensitive for the simulation of runoff, which are considered for calibration in this study. These parameters mainly control snow and soil processes and are calibrated by maximizing the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970).

The model is calibrated for the Lech watershed using flows at the gauging station Lechaschau, for the years 1981 to 2000. Subsequently, the model is validated using the periods 1971 to 1980 and 2001 to 2005. Figure 3 gives an example of the performance of HQsim for one year during the validation period (red line). As can be seen, the model performs fairly well in this complex Alpine watershed. For the calibration period, the NSE is 0.85 and for the two validation periods 0.83 (1971–1980) and 0.87 (2001–2005), respectively.

3.5 Hydrological model parameters

Of the 17 parameters selected for calibration, Dobler and Pappenberger (2012) classified five as being highly sensitive (Table 1). Of those five parameters, one relates to snow melting (meltfunc_max) and the remaining four to soil properties. In order to account for uncertainty related to the choice of hydrological model parameters, a Monte Carlo framework is applied. Five thousand parameter sets are generated randomly from the parameter ranges in Table 1, assuming a uniform distribution. The 20 parameter sets with the highest NSE are then selected to evaluate the effects of different parameter sets on projected climate impacts.

As can be seen in Table 1, for the parameters s0_depth, s2_depth and s2_drain, good simulations can be obtained with values varying over wide ranges. This indicates that values of these parameters have little influence. Other parameters such as meltfunc_max and s2_m only produce acceptable simulations when concentrated within certain intervals.

Figure 3 illustrates an example for the range of the simulations obtained from the 20 different model parameter sets. The NSE for these 20 simulations varies between 0.84 and 0.85, based on the years 1971 to 2000. Thus, different sets of model parameters yield the same functional output, consistent with the concept of model equifinality (Beven and Freer, 2001).

In order to evaluate the effects of different hydrological model parameter sets on the hydrological projections, relative changes between the present and future runoff simulations are calculated for each parameter set. As can be seen in Fig. 2, the modelling chain consisting of the ECHAM5 model, the RACMO model and the delta change approach is used as a basis for this assessment.

4 Results

Section 4.1 presents the performance of the bias-corrected control simulations, while Sect. 4.2 shows temperature and precipitation projections obtained from the spectrum of model combinations. Finally, uncertainties in the hydrological projections resulting from different sources are assessed.

4.1 Performance for present climate conditions

Figure 4 shows HQsim simulations driven by observed meteorological data (denoted as the reference simulation) and bias-corrected RCM data for the control period. Note that HQsim simulations forced with bias-corrected data are compared with the reference simulation, instead of observed runoff. This is to separate model biases in the HQsim simulations from those originating from the bias-corrected climate data (e.g. Lenderink et al., 2007; Minville et al., 2008).

The control simulations are bias-corrected by applying the local scaling and the QQ mapping approaches. Figure 4a shows a relatively good agreement between the reference simulation and the six control simulations. The seasonal cycle is captured very well, indicating that the applied model chains perform well in this complex catchment. The clearest differences occur in the winter season when some of the control simulations are slightly lower than the reference simulation (see Fig. 4b). Biases in winter range from −36 % (ECHAM5_REMO_SCAL) to −10 % (HadCM3Q3_RCA_SCAL). Comparatively small biases are found in summer, ranging from −7 % (BCM_RCA_SCAL) to +4 % (ECHAM5_RACMO_QQ) and from −9 % (REMO_RCA_SCAL) to −3 % (ECHAM5_RACMO_QQ) in autumn.

For the 90%-quantile of daily runoff, almost all control simulations slightly underestimate runoff (see Fig. 4c). The largest biases are found during winter, with deviations ranging from −44 % (ECHAM5_REMO_SCAL) to −19 % (HadCM3Q3_RCA_SCAL). During summer, instead, a relatively good agreement between observation and the control simulation is obtained, with biases ranging from −9 % (ECHAM5_RCA_SCAL) to +6 % (ECHAM5_RACMO_QQ).

4.2 Uncertainty related to climate models and downscaling

In the next step, temperature and precipitation scenarios are compared to assess the spread of uncertainty originating from the choice of the (i) GCM, (ii) RCM and (iii) bias-correction approach. Note that for the delta change approach the climate change signal is calculated between the future scenario and the control simulations of the RCM, while for local scaling and QQ mapping it is derived from the bias-corrected RCM control and scenario simulations.

Figure 5 shows temperature and precipitation scenarios for the different model chains. The differences among the projections provide an estimate of the uncertainty involved in the simulations. GCM inter-model variability is found to be very large for both temperature and precipitation projections (Fig. 5a). Most of the simulations show warming between 2.0 °C and 3.5 °C for the period 2070 to 2099, compared to the reference period (1971 to 2000). The largest increase of 4.5 °C originates from the ECHAM5 scenario in July, whereas the lowest increase of +1.3 °C is obtained from BCM scenario in October. Temperature scenarios vary among the different GCMs by 0.3 °C in January and by 2.1 °C in November. No clear temporal pattern in the temperature change is evident, but precipitation shows strong decreases during summer and increases during winter and spring. These results are consistent with findings obtained from other studies in the Alps (e.g. Solomon et al., 2007; Smiatek et al., 2009; Kjellström et al., 2011). The largest decrease is in the ECHAM5 scenario with −28 % in July, and largest increase is simulated by the BCM scenario with +35 % in December. The spread of the precipitation scenarios is similar throughout the year.

Figure 5b shows the range of uncertainty related to the choice of RCM. During winter and spring, the spread of uncertainty in the temperature projections resulting from the RCM structure is similar to that originating from the GCM structure, while it is lower during summer and autumn. The range of uncertainty in the projections of precipitation is slightly smaller for the RCMs than for the GCMs. For mean monthly temperature, the inter-model variability ranges between 0.3 °C in July and 1.8 °C in April. Generally, the RCMs produce more similar temporal patterns for both variables than the GCMs. For precipitation, the largest deviations among the different simulations are found in September, while the lowest differences occur in April.

Uncertainty related to the choice of the bias-correction approach is shown in Fig. 5c. It can be seen that inter-model variability is comparatively small in the projections. However, it must be noted that two out of three bias-correction techniques (local scaling and the delta change approach) are directly calibrated on monthly values. Thus, the climate change signals obtained by these methods are the same when focusing on mean monthly projections. The QQ mapping approach (which has not been calibrated on monthly values) generates climate change signals comparable to the delta change and local scaling technique. But, it can be seen, that the QQ mapping approach modifies the climate change signal. Similar findings are reported by Hagemann et al. (2011) and Themeßl et al. (2012).

The spread of the temperature projections ranges up to 0.3 °C in April and May. The lowest difference between the precipitation projections occurs in November and the highest in May. Overall, Fig. 5c shows that uncertainty related to the bias-correction approach is comparatively small when focusing on mean monthly values.

4.3 Uncertainty in hydrological projections

4.3.1 Mean annual runoff

In the next step, uncertainty in projected mean annual runoff is evaluated. Figure 6 shows the spread of uncertainty originating from (i) GCM, (ii) RCM, (iii) bias-correction, and (iv) hydrological model parameters. All projections indicate a slight downward trend in mean annual runoff.

Projections based on different GCMs show modest variations, ranging from −17 % (HadCM3Q3_RCA_SCAL) to −8 % (BCM_RCA_SCAL). Uncertainty originating from the RCMs is slightly larger, with projected changes ranging between −17 % (HadCM3Q3_RCA_SCAL) and −4 % (ECHAM5_RACMO_SCAL), while uncertainty related to the bias-correction step is smaller than GCM and RCM uncertainty. The hydrological model parameter sets have relatively little effect on the uncertainty.

It is interesting to note that although RCM uncertainty is found to be less than GCM uncertainty for temperature and precipitation (see Sect. 4.2), it is the most important source of uncertainty when focusing on projections of mean annual runoff. This suggests that the relationship between climate forcing and hydrological response is highly non-linear, consistent with the findings of Arnell (2011).

4.3.2 Mean monthly runoff

Figure 7 illustrates uncertainty in the projections of mean monthly runoff originating from different sources. All simulations indicate considerable increases in mean monthly runoff from December to April, and decreases from June to August. In other months no clear tendency towards an increase or decrease are found. Larger uncertainties in the hydrological projections are found during winter compared with summer. However, it has to be noted that the results are presented in relative terms, whereas comparatively small percentage differences during winter translate into relatively large changes in absolute discharges.

On average, the GCM structure has the largest effects on the model output. Relatively large deviations are found between the three different simulations from January to May and in November. This is due to the fact that the BCM driven simulation (Fig. 5a) shows a smaller increase in temperature compared to the other two GCMs in these months. Snowmelt-dominated rivers like the Lech are particularly sensitive to changes in temperature (e.g. Dobler et al., 2010) as this determines whether precipitation falls as snow or rain. Thus, large uncertainty in the temperature projections during these months results in large uncertainty in runoff projections.

Uncertainty originating from the RCM structure is in general slightly smaller than those related to the GCM structure. However, during winter relatively large uncertainty is obtained, due to the spread of uncertainty in the temperature projections in these months (Fig. 5b). Uncertainty resulting from the bias-correction approach is smaller than uncertainty related to GCM and RCM structure, although comparatively large differences among the three simulations are obtained for some months. Note that although only small differences in the forcing projections are found (Fig. 5c), relatively large differences in the hydrological simulations are evident. Again, this indicates that there is a non-linear hydrological response to the climate forcing (Arnell, 2011).

Uncertainty resulting from hydrological model parameters has generally less influence on projected changes in monthly runoff, compared to the other uncertainty sources. The largest uncertainty is found during winter, when the impact range is up to 20 %, while during summer only a small spread of uncertainty is obtained. As can be seen in Fig. 3, model skill during low flow periods in winter is comparatively small, arising from a poorer representation of base flow than surface runoff and inter flow in the model structure. However, it should be pointed out that the uncertainties during winter are comparatively small in absolute terms. Nevertheless, these results demonstrate that the hydrological model parameterization also affects projections under certain conditions.

4.3.3 Mean high flows

Finally, uncertainty in projected high flows is assessed. Figure 8 shows the spread of uncertainty in the mean high flows resulting from different sources. Except for the ECHAM5_RACMO_QQ and ECHAM5_RACMO_SCAL scenarios, all show a decrease in mean high flows by the end of this century. The spread of results range from −27 % (HadCM3Q3_RCA_SCAL) to −9 % (ECHAM5_RACMO_QQ) for flows exceeded 10 % of the time and from −18 % (HadCM3Q3_RCA_SCAL) to +15 % (ECHAM5_RACMO_QQ) for flows exceeded 1 % of the time. In general, there are large variations across the spectrum of the different projections, stressing the importance of using different model combinations when assessing the spread of uncertainty.

Figure 8 indicates that the GCM and RCM structure have significant effects on the projections of high flows. While the magnitude of GCM uncertainty is similar for different exceedance probabilities, uncertainty related to the RCM and the bias-correction approach increases with the rarity of the hydrological event. For example, GCM, RCM and bias-correction uncertainty are the main sources of uncertainty for flows exceeded 10 % of the time, while RCM and bias-correction uncertainty are the most important uncertainty source for flows exceeded 1 % of the time. As can be seen in Fig. 8b and 8c, the spread of uncertainty in the projections of mean high flows originating from the RCM and the bias-correction approach is very large. The projections even suggest different sign changes. This clearly indicates that the RCM and the bias correction approach play a significant role when assessing climate change impacts on hydrological extremes (at least in this catchment).

When comparing the ECHAM5_RACMO_DELTA and ECHAM5_RACMO_SCAL scenarios, comparatively large uncertainty for the highest flows are obtained. Although the methods generate the same monthly temperature and precipitation scenarios (Fig. 5c), the results are very different for high flows. The delta change approach only considers changes in the mean, whereas the local scaling approach also changes the variability. However, as changes in climate variability are at least as important as changes in the mean when focusing on extremes (Katz and Brown, 1992), it is not surprising that both methods differ in the simulation of high flows. This result echoes the findings of Lenderink et al. (2007), who compared runoff in the river Rhine using two different bias-correction techniques. Although similar results were found in mean summer and mean winter runoff, large differences for extreme flows during winter were reported.

In contrast to the delta change and local scaling techniques, the QQ mapping approach explicitly accounts for changes in both precipitation and temperature extremes. Themeßl et al. (2010) showed that the technique performs well for higher quantiles of the precipitation distribution. Thus, the QQ mapping approach appears to be more reliable when focusing on extremes than the delta change and local scaling approaches. Uncertainty related to hydrological model parameters has only a minor influence on projections of high flows, compared to the other sources discussed above. This reflects the fact that the objective function (NSE) used for HQsim calibration favours the reproduction of high flows.

5 Discussion and conclusion

Most climate change impact studies are based on a modelling chain consisting of (i) GCMs, (ii) RCMs, (iii) bias-correction techniques, and (iv) an impact model such as a hydrological model. Although a large number of studies are based on this kind of approach, relatively little attention has been given to assessing uncertainty in the hydrological projections. While some studies focus on one source of uncertainty, such as GCM structure (Maurer and Duffy, 2005) or the downscaling approach (e.g. Quintana-Seguí et al., 2010), fewer attempts have been made to look at multiple sources (e.g. Wilby and Harris, 2006; Kay et al., 2009; Prudhomme et al., 2009; Chen et al., 2011c). This study explores uncertainty resulting from different sources by applying a multi-model ensemble. The highly complex Lech watershed (~1000 km^2), located in the Northern Limestone Alps of Austria, was selected as the study area.

Our results generally show that hydrological projections are subject to considerable uncertainty. The size of the impact range among the spectrum of scenarios spans 90 % in some months (see Fig. 7e). Sometimes the models even show different sign changes. When focusing on flows exceeded 1 % of the time, for instance, some models indicate a decrease of −18 % while others show an increase of +15 %. This demonstrates that the use of multi-model ensembles is a necessary prerequisite for quantifying climate change impacts at regional or local scales. Results from studies based on a single GCM, should thus be interpreted with extreme caution (Chen et al., 2011c; Harding et al., 2012).

Overall, our results confirm that GCM structure is the most important source of uncertainty in climate change impact studies on a regional scale. The wide range of uncertainty in the hydrological projections is mainly the result of large uncertainty in the forcing projections. This finding agrees with earlier work (e.g. Wilby and Harris, 2006; Kay et al., 2009; Chen et al., 2011c). Uncertainty related to the choice of RCMs is found to be of comparable magnitude. The effect of the bias-correction approach is found to increase with the rarity of the hydrological event: there is less influence on the simulation of average hydrological conditions compared with extremes. Hydrological model parameter uncertainty is found to be less important compared to the other factors.

For practical purposes most assessments cannot apply multi model ensembles as herein, so effort is best focused on using different GCMs and RCMs when assessing the main spread of uncertainty in hydrological projections. However, if information is needed on extremes, different bias-correction techniques should also be included. Simple bias-correction techniques such as the delta change method and local scaling are only calibrated on monthly data and do not take into account changes in the extremes. Thus, their applicability should be limited to mean values. The delta change method, even though it has been regularly used in the past, is identified as insufficient to study extremes. Moreover, direct use of the RCM output as in local scaling and the QQ approach is more straightforward (plus changes in variability are also considered unlike in the delta change approach). In contrast, the delta change method is very easy to implement and it provides reliable estimates for mean conditions.

The use of more sophisticated methods may also increase the data requirements for bias correction (e.g. Haerter et al., 2011), even though the uncertainty introduced by the method may be reduced. However, the bias-correction approach selected to simulate extremes should be specially designed to handle extreme events, such as the QQ mapping approach, as it explicitly considers possible changes in extremes. Themeßl et al. (2010) compared several empirical-statistical downscaling and error correction methods for daily precipitation downscaling over the Alpine region. The QQ mapping approach showed the best performance in reducing error characteristics, particularly at high quantiles. Thus, the method seems to be more reliable when focusing on extremes than other bias-correction techniques.

Nevertheless, all of these approaches have one main limitation. In mountain watersheds, the combination of temperature and precipitation is crucial as it determines whether precipitation falls as rain or snow. The bias-correction techniques adjust both variables independently, which may destroy the physical relationship between the two variables (e.g. Boé et al., 2007; Maraun et al., 2010; Hagemann et al., 2011; Themeßl et al., 2012). Further research is needed to determine the extent to which these inter-variable relationships matter when evaluating climate change impacts over annual and multi-decadal time-scales.

The results of this study show that the hydrological model parameterization is generally of low significance. This may be due to the relatively long calibration period (20 yr) which increases the chance of sampling varied hydrological conditions and thereby results in more generalized parameters (Merz et al., 2009). Hence, with these parameter sets, a wider range of hydrological conditions can be simulated well, maybe even conditions which have not been observed during the calibration period (Merz et al., 2009). Similar findings were reported by Vaze et al. (2010).

In addition to the uncertainty sources investigated in this study, other components may also affect the model output. For example, Bae et al. (2011) demonstrated that the hydrological model structure has a significant impact on projected changes. Future studies should also take into consideration this source of uncertainty.

Quantifying the distribution of temperature is particularly important for mountain hydrology. Model errors resulting from the assumed spatio-temporal constant lapse rate are widely unknown, but may be of high significance in mountain regions. Minder et al. (2010), for instance, analysed the consequences of lapse rate characterization for hydrological projections in the Cascade Mountains and found considerable differences in runoff projections when using different lapse rate assumptions. However, the sparse distribution of temperature stations, especially at higher elevation zones, and the influence of local climate effects, makes it very difficult to resolve temperature variability in mountain regions (Minder et al., 2010). Nevertheless, a better understanding of the spatio-temporal dynamics of the temperature lapse rate is essential in marginal situations between snow/ice accumulation, melting, and bare ground. Additionally, field experiments may help to better constrain the parameters of HQsim and to reduce uncertainty due to model parameterization.

Despite the large range of uncertainty in the hydrological projections, some robust findings emerge from this study. Mean runoff during winter, for example, is projected to increase substantially in all simulations. In this case, the climate change signal is by far larger than the uncertainty associated with the projections. These findings suggest some confidence in hydrological projections on a regional local scale, whilst acknowledging the small suite of GCMs used. For mean high flows, instead, no clear signals towards an increase or a decrease were obtained.

The study has several limitations. Due to a relatively small number of models and methods applied, only a limited estimation of the overall uncertainty could be quantified. In order to assess uncertainty originating from hydrological model parameters, only 20 parameter sets were used. Considering more parameters may result in a wider uncertainty range. Also the relatively low number of GCM-RCM combinations as well as the selection of the ECHAM5 and RCA models to be held constant when varying the other components will understate the spread of uncertainty due to GCM and RCM structure. This could lead to misleading impressions of the relative significance of individual uncertainty sources (Kay and Jones, 2012). However, very large ensembles of GCM-RCM combinations are yet not available due to the associated high computational demand (e.g. Kendon et al., 2010).

Finally, it should also be noted, that even if we can characterize all the components of uncertainty in climate change impact assessments, we must not lose sight of the fact that the present generation of GCMs exhibit large errors. Recent work has highlighted considerable deficiencies in the representation of precipitation (Stephens et al., 2010) and the global atmospheric moisture balance (Liepert and Previdi, 2012). Therefore, we should always be circumspect about just how much uncertainty can be characterized given the flawed nature of the inputs to our studies. Future research in Alpine basins should thus focus on the tractable elements of uncertainty: especially those linked to snow accumulation and melt processes.

Acknowledgements. This work is funded by the Austrian Climate and Energy Fund within the program line ACRP (Austrian Climate Research Program). The ENSEMBLES data used in this work was funded by the EU FP6 Integrated Project ENSEMBLES (Contract number 505539) whose support is gratefully acknowledged. This work was supported by the Austrian Ministry of Science BMWF as part of the "UniInfrastrukturprogramm" of the Research Platform Scientific Computing at the University of Innsbruck.

References

Achleitner, S., Schöber, J., Rinderer, M., Leonhardt, G., Schöberl, F., Kirnbauer, R., and Schönlaub, H.: Analyzing the operational performance of the hydrological models in an alpine flood forecasting system, J. Hydrol., 412–413, 90–100, 2011.

Arnell, N. W.: Uncertainty in the relationship between climate forcing and hydrological response in UK catchments, Hydrol. Earth Syst. Sci., 15, 897–912, doi:10.5194/hess-15-897-2011, 2011.

Bae, D. H., Jung, I. W., and Lettenmaier, D. P.: Hydrologic uncertainties in climate change from IPCC AR4 GCM simulations of the Chungju Basin, Korea, J. Hydrol., 401, 90–105, 2011.

Bastola, S., Murphy, C., and Sweeney, J.: The role of hydrological modelling uncertainties in climate change impact assessments of Irish river catchments, Adv. Water Res., 34, 562–576, 2011.

Beven, K. and Freer, J.: Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology, J. Hydrol., 249, 11–29, 2001.

Beyene, T., Lettenmaier, D., and Kabat, P.: Hydrologic impacts of climate change on the Nile River Basin: implications of the 2007 IPCC scenarios, Climatic Change, 100, 433–461, 2010.

Biesbroek, G. R., Swart, R. J., Carter, T. R., Cowan, C., Henrichs, T., Mela, H., Morecroft, M. D., and Rey, D.: Europe adapts to climate change: comparing national adaptation strategies, Global Environ. Change, 20, 440–450, 2010.

Boé, J., Terray, L., Habets, F., and Martin, E.: Statistical and dynamical downscaling of the Seine basin climate for hydro-meteorological studies, Int. J. Climatol., 27, 1643–1655, 2007.

Buytaert, W., Célleri, R., and Timbe, L.: Predicting climate change impacts on water resources in the tropical Andes: effects of GCM uncertainty, Geophys. Res. Lett., 36, L07406, doi:10.1029/2008GL037048, 2009.

Chen, C., Haerter, J. O., Hagemann, S., and Piani, C.: On the contribution of statistical bias correction to the uncertainty in the projected hydrological cycle, Geophys. Res. Lett., 38, L20403, doi:10.1029/2011GL049318, 2011b.

Chen, D., Achberger, C., Räisänen, J., and Hellström, C.: Using statistical downscaling to quantify the GCM-related uncertainty in regional climate change scenarios: a case study of Swedish precipitation, Adv. Atmos. Sci., 23, 54–60, 2006.

Chen, J., Brissette, F. P., and Leconte, R.: Uncertainty of downscaling method in quantifying the impact of climate change on hydrology, J. Hydrol., 401, 190–202, 2011a.

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

Christensen, J. and Christensen, O.: A summary of the PRUDENCE model projections of changes in European climate by the end of this century, Climatic Change, 81, 7–30, 2007.

Déqué, M.: Frequency of precipitation and temperature extremes over France in an anthropogenic scenario: model results and statistical correction according to observed values, Global Planet. Change, 57, 16–26, 2007.

Dobler, C. and Pappenberger, F.: Global sensitivity analyses for a complex hydrological model applied in an Alpine watershed, Hydrol. Process., submitted, 2012.

Dobler, C., Stötter, J., and Schöberl, F.: Assessment of climate change impacts on the hydrology of the Lech Valley in Northern Alps, J. Water Clim. Change, 3, 207–218, 2010.

Fischer, A. M., Weigel, A. P., Buser, C. M., Knutti, R., Künsch, H. R., Liniger, M. A., Schär, C., and Appenzeller, C.: Climate change projections for Switzerland based on a Bayesian multimodel approach, Int. J. Climatol., in press, 2011.

Flügel, W. A.: Combining GIS with regional hydrological modelling using hydrological response units (HRUs): an application from Germany, Math. Comput. Simulat., 43, 297–304, 1997.

Fowler, H. J., Blenkinsop, S., and Tebaldi, C.: Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modeling, Int. J. Climatol., 27, 1547–1578, 2007.

Frei, C., Schöll, R., Fukutome, S., Schmidli, J., and Vidale, P. L.: Future change of precipitation extremes in Europe: intercomparison of scenarios from regional climate models, J. Geophys. Res., 111, D06105, doi:10.1029/2005JD005965, 2006.

Furevik, T., Bentsen, M., Drange, H., Kindem, I. K. T., Kvamstø, N. G., and Sorteberg, A.: Description and evaluation of the Bergen climate model: ARPEGE coupled with MICOM, Clim. Dynam., 21, 27–51, 2003.

Gardner, A. S., Sharp, M. J., Koerner, R. M., Labine, C., Boon, S., Marshall, S. J., Burgess, D. O., and Lewis, D.: Near-surface temperature lapse rates over Arctic glaciers and their implications for temperature downscaling, J. Climate, 22, 4281–4298, 2009.

Giorgi, F.: Simulation of regional climate using a limited area model nested in a general circulation model, J. Climate, 3, 941–963, 1990.

Giorgi, F. and Mearns, L. O.: Introduction to special section: regional climate modeling revisited, J. Geophys. Res., 104, 6335–6352, 1999.

Graham, L., Hagemann, S., Jaun, S., and Beniston, M.: On interpreting hydrological change from regional climate models, Climatic Change, 81, 97–122, 2007.

Gosling, S. N., Taylor, R. G., Arnell, N. W., and Todd, M. C.: A comparative analysis of projected impacts of climate change on river runoff from global and catchment-scale hydrological models, Hydrol. Earth Syst. Sci., 15, 279–294, doi:10.5194/hess-15-279-2011, 2011.

Haerter, J. O., Hagemann, S., Moseley, C., and Piani, C.: Climate model bias correction and the role of timescales, Hydrol. Earth Syst. Sci., 15, 1065–1079, doi:10.5194/hess-15-1065-2011, 2011.

Hagemann, S., Chen, C., Haerter, J. O., Heinke, J., Gerten, D., and Piani, C.: Impact of a statistical bias correction on the projected hydrological changes obtained from three GCMs and two hydrology models, J. Hydrometeorol., 12, 556–578, 2011.

Harding, B. L., Wood, A. W., and Prairie, J. R.: The implications of climate change scenario selection for future streamflow projection in the Upper Colorado River Basin, Hydrol. Earth Syst. Sci. Discuss., 9, 847–894, doi:10.5194/hessd-9-847-2012, 2012.

Hawkins, E. and Sutton, R.: The potential to narrow uncertainty in regional climate predictions, B. Am. Meteorol. Soc., 90, 1095–1107, 2009.

Howden, S. M., Soussana, J. F., Tubiello, F. N., Chhetri, N., Dunlop, M., and Meinke, H.: Adapting agriculture to climate change, P. Natl. Acad. Sci., 104, 19691–19696, 2007.

Jacob, D.: A note to the simulation of the annual and inter-annual variability of the water budget over the Baltic Sea drainage basin, Meteorol. Atmos. Phys., 77, 61–73, 2001.

Jasper, K., Calanca, P., Gyalistras, D., and Fuhrer, J.: Differential impacts of climate change on the hydrology of two alpine river basins, Clim. Res., 26, 113–129, 2004.

Johns, T. C., Gregory, J. M., Ingram, W. J., Johnson, C. E., Jones, A., Lowe, J. A., Mitchell, J. F. B., Roberts, D. L., Sexton, D. M. H., Stevenson, D. S., Tett, S. F. B., and Woodage, M. J.: Anthropogenic climate change for 1860 to 2100 simulated with the HadCM3 model under updated emissions scenarios, Clim. Dynam., 20, 583–612, 2003.

Jones, G. S., Stott, P. A., and Christidis, N.: Human contribution to rapidly increasing frequency of very warm Northern Hemisphere summers, J. Geophys. Res., 113, D02109, doi:10.1029/2007JD008914, 2008.

Jungclaus, J. H., Botzet, M., Haak, H., Keenlyside, N., Luo, J. J., Latif, M., Marotzke, J., Mikolajewicz, U., and Roeckner, E.: Ocean circulation and tropical variability in the coupled model ECHAM5/MPI-OM, J. Climate, 19, 3952–3972, 2006.

Katz, R. W. and Brown, B. G.: Extreme events in a changing climate: variability is more important than averages, Climatic Change, 21, 289–302, 1992.

Kay, A. and Jones, R.: Comparison of the use of alternative UKCP09 products for modelling the impacts of climate change on flood frequency, Climatic Change, in press, 2012.

Kay, A., Davies, H., Bell, V., and Jones, R.: Comparison of uncertainty sources for climate change impacts: flood frequency in England, Climatic Change, 92, 41–63, 2009.

Kendon, E. J., Jones, R. G., Kjellström, E., and Murphy, J. M.: Using and designing GCM-RCM ensemble regional climate projections, J. Climate, 23, 6485–6503, 2010.

Kharin, V. V., Zwiers, F. W., Zhang, X., and Hegerl, G. C.: Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations, J. Climate, 20, 1419–1444, 2007.

Kjellström, E., Bärring, L., Gollvik, S., Hansson, U., Jones, C., Samuelsson, P., Rummukainen, M., Ullerstig, A., Willèn, U., and Wyser, K.: A 140-yr Simulation of European Climate with the New Version of the Rossby Centre Regional Atmospheric Climate Model (RCA3), SMHI Reports Meteorology and Climatology, 108, SMHI, Norrköping, Sweden, 54 pp., 2005.

Kjellström, E., Nikulin, G., Hansson, U. L. F., Strandberg, G., and Ullerstig, A.: 21st century changes in the European climate: uncertainties derived from an ensemble of regional climate model simulations, Tellus A, 63, 24–40, 2011.

Kleindienst, H.: Erweiterung und Erprobung eines anwendungsorientierten hydrologischen Modells zur Gangliniensimulation in kleinen Wildbacheinzugsgebieten, Institut für Geographie, Ludwig Maximilians Universität München, Germany, 1996.

Kotlarski, S., Bosshard, T., Lüthi, D., Pall, P., and Schär, C.: Elevation gradients of European climate change in the regional climate model COSMO-CLM, Climatic Change, 112, 1–27, 2012.

Ledbetter, R., Prudhomme, C., and Arnell, N.: A method for incorporating climate variability in climate change impact assessments: sensitivity of river flows in the Eden catchment to precipitation scenarios, Climatic Change, in press, 2012.

Lenderink, G., van den Hurk, B., van Meijgaard, E., van Ulden, A., and Cujipers, H.: Simulation of present-day climate in RACMO2: first results and model developments, KNMI Technical Report, 252, De Bilt, The Netherlands, 24 pp., 2003.

Lenderink, G., Buishand, A., and van Deursen, W.: Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach, Hydrol. Earth Syst. Sci., 11, 1145–1159, doi:10.5194/hess-11-1145-2007, 2007.

Liepert, B. G. and Previdi, M.: Inter-model variability and biases of the global water cycle in CMIP3 coupled climate models, Environ. Res. Lett., 7, 014006, doi:10.1088/1748-9326/7/1/014006, 2012.

Maraun, D., Wetterhall, F., Ireson, A. M., Chandler, R. E., Kendon, E. J., Widmann, M., Brienen, S., Rust, H. W., Sauter, T., Themeßl, M., Venema, V. K. C., Chun, K. P., Goodess, C. M., Jones, R. G., Onof, C., Vrac, M., and Thiele-Eich, I.: Precipitation downscaling under climate change: recent developments to bridge the gap between dynamical models and the end user, Rev. Geophys., 48, RG3003, doi:10.1029/2009RG000314, 2010.

Maurer, E. P. and Duffy, P. B.: Uncertainty in projections of streamflow changes due to climate change in California, Geophys. Res. Lett., 32, L03704, doi:10.1029/2004GL021462, 2005.

Merz, R., Parajka, J., and Blöschl, G.: Scale effects in conceptual hydrological modeling, Water Resour. Res., 45, W09405, doi:10.1029/2009WR007872, 2009.

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., and Stouffer, R. J.: Stationarity is dead: whither water management?, Science, 319, 573–574, 2008.

Minder, J. R., Mote, P. W., and Lundquist, J. D.: Surface temperature lapse rates over complex terrain: lessons from the Cascade Mountains, J. Geophys. Res., 115, D14122, doi:10.1029/2009JD013493, 2010.

Minville, M., Brissette, F., and Leconte, R.: Uncertainty of the impact of climate change on the hydrology of a nordic watershed, J. Hydrol., 358, 70–83, 2008.

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grübler, A., Jung, T. Y., Kram, T., Rovere, E. L. L., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Raihi, K., Roehl, A., Rogner, H.-H., Sankovski, A., Schlesinger, M., Shukla, P., Smith, S., Swart, R., Rooijen, S. V., Victor, N., and Dadi, Z.: Emission Scenarios, a Special Report of Working Group III of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK, 2000.

Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptional models 1: discussion of principles, J. Hydrol. 10, 282–290, 1970.

Oreskes, N.: The scientific consensus on climate change, Science, 306, 1686, doi:10.1126/science.1103618, 2004.

Pavlik, D., Söhl, D., Pluntke, T., Mykhnovych, A., and Bernhofer, C.: Dynamic downscaling of global climate projections for Eastern Europe with a horizontal resolution of 7 km, Environ. Earth Sci., 65, 1475–1482, 2012.

Poulin, A., Brissette, F., Leconte, R., Arsenault, R., and Malo, J. S.: Uncertainty of hydrological modelling in climate change impact studies in a Canadian, snow-dominated river basin, J. Hydrol., 409, 626–636, 2011.

Prömmel, K., Geyer, B., Jones, J. M., and Widmann, M.: Evaluation of the skill and added value of a reanalysis-driven regional simulation for Alpine temperature, Int. J. Climatol., 30, 760–773, 2010.

Prudhomme, C. and Davies, H.: Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK, part 2: future climate, Climatic Change, 93, 197–222, 2009.

Prudhomme, C., Reynard, N., and Crooks, S.: Downscaling of global climate models for flood frequency analysis: where are we now?, Hydrol. Process., 16, 1137–1150, 2002.

Quintana-Seguí, P., Ribes, A., Martin, E., Habets, F., and Boé, J.: Comparison of three downscaling methods in simulating the impact of climate change on the hydrology of Mediterranean basins, J. Hydrol., 383, 111–124, 2010.

Roeckner, E., Brokopf, R., Esch, M., Giogetta, M., Hagemann, S., Kornblueh, L., Manzini, E., Schleese, U., and Schulzweida, U.: Sensitivity of simulated climate to horizontal and vertical 15 resolution in the ECHAM5 atmosphere model, J. Climate, 19, 3771–3791, 2006.

Rosenzweig, C., Karoly, D., Vicarelli, M., Neofotis, P., Wu, Q., Casassa, G., Menzel, A., Root, T. L., Estrella, N., Seguin, B., Tryjanowski, P., Liu, C., Rawlins, S., and Imeson, A.: Attributing physical and biological impacts to anthropogenic climate change, Nature, 453, 353–357, 2008.

Salathé, E. P.: Downscaling simulations of future global climate with application to hydrologic modeling, Int. J. Climatol., 25, 419–436, 2005.

Smiatek, G., Kunstmann, H., Knoche, R., and Marx, A.: Precipitation and temperature statistics in high-resolution regional climate models: evaluation for the European Alps, J. Geophys. Res., 114, D19107, doi:10.1029/2008JD011353, 2009.

Solomon, S., Qin, D., Manning, M., Alley, R. B., Berntsen, T., Bindoff, N. L., Chen, Z., Chidthaisong, A., Gregory, J. M., Hegerl, G. C., Heimann, M., Hewitson, B., Hoskins, B. J., Joos, F., Jouzel, J., Kattsov, V., Lohmann, U., Matsuno, T., Molina, M., Nicholls, N., Overpeck, J., Raga, G., Ramaswamy, V., Ren, J., Rusticucci, M., Somerville, R., Stocker, T. F., Whetton, P., Wood, R. A., and Wratt, D.: Technical Summary, Climate Change 2007: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., Cambridge University Press, UK, 2007.

Stephens, G. L., L'Ecuyer, T., Forbes, R., Gettlemen, A., Golaz, J. G., Bodas-Salcedo, A., Suzuki, K., Gabriel, P., and Haynes, J.: Dreary state of precipitation in global models, J. Geophys. Res., 115, D24211, doi:10.1029/2010JD014532, 2010.

Stoll, S., Hendricks Franssen, H. J., Butts, M., and Kinzelbach, W.: Analysis of the impact of climate change on groundwater related hydrological fluxes: a multi-model approach including different downscaling methods, Hydrol. Earth Syst. Sci., 15, 21–38, doi:10.5194/hess-15-21-2011, 2011.

Teutschbein, C., Wetterhall, F., and Seibert, J.: Evaluation of different downscaling techniques for hydrological climate-change impact studies at the catchment scale, Clim. Dynam., 37, 2087–2105, 2011.

Themeßl, J. M., Gobiet, A., and Leuprecht, A.: Empirical-statistical downscaling and error correction of daily precipitation from regional climate models, Int. J. Climatol., 31, 1530–1544, 2010.

Themeßl, J. M., Gobiet, A., and Heinrich, G.: Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal, Climatic Change, 112, 449–468, 2012.

Trenberth, K. E.: Changes in precipitation with climate change, Clim. Res., 47, 123–138, 2011.

van der Linden, P. and Mitchell, J. F. B. (Eds.): ENSEMBLES: Climate Change and its Impacts: Summary of Research and Results from the ENSEMBLES Project, Met Office Hadley Centre, Exeter, UK, 2009.

van Roosmalen, L., Sonnenborg, T. O., Jensen, K. H., and Christensen, J. H.: Comparison of hydrological simulations of climate change using perturbation of observations and distribution-based scaling, Vadose Zone J., 10, 136–150, 2011.

Vaze, J., Post, D., Chiew, F., Perraud, J. M., Viney, N., and Teng, J.: Climate non-stationarity – Validity of calibrated rainfall-runoff models for use in climate change studies, J. Hydrol., 394, 447–457, 2010.

Widmann, M., Bretherton, C. S., and Salathé, E. P.: Statistical precipitation downscaling over the Northwestern United States using numerically simulated precipitation as a predictor, J. Climate, 16, 799–816, 2003.

Wilby, R. L. and Harris, I.: A framework for assessing uncertainties in climate change impacts: low-flow scenarios for the River Thames, UK, Water Resour. Res., 42, W02419, doi:10.1029/2005WR004065, 2006.

Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P., and Mearns, L. O.: Guidelines for use of climate scenarios developed from statistical downscaling methods, supporting material of the Intergovernmental Panel on Climate Change, available from the DDC of IPCC TG-CIA, 27, Intergovt. Panel on Clim. Change, Geneva, Switzerland, 2004.

Wilby, R. L., Troni, J., Biot, Y., Tedd, L., Hewitson, B. C., Smith, D. G., and Sutton, R. T.: A review of climate risk information for adaptation and development planning, Int. J. Climatol., 29, 1193–1215, 2009.

Table 1. Parameters and their ranges used for uncertainty analysis. Values in brackets indicate the range of the 20 parameter sets.

parameter	range	unit	Description
meltfunc_max	1.0–6.0 (1.1–1.6)	mm °C^{-1} d^{-1}	maximum degree day factor
s0_depth	500–2500 (575–2477)	mm	depth of unsaturated soil zone of soil type 0 (lithosol)
s2_depth	500–2500 (910–2283)	mm	depth of unsaturated soil zone of soil type 2 (rendzina)
s2_m	0.1–0.9 (0.2–0.4)		Mualem-van Genuchten parameter *m* for soil type 2 (rendzina)
s2_drain	0–0.3 (0.1–0.3)		ratio of the outflow of the unsaturated soil zone, which comes to base flow storage (soil type 2 – rendzina)

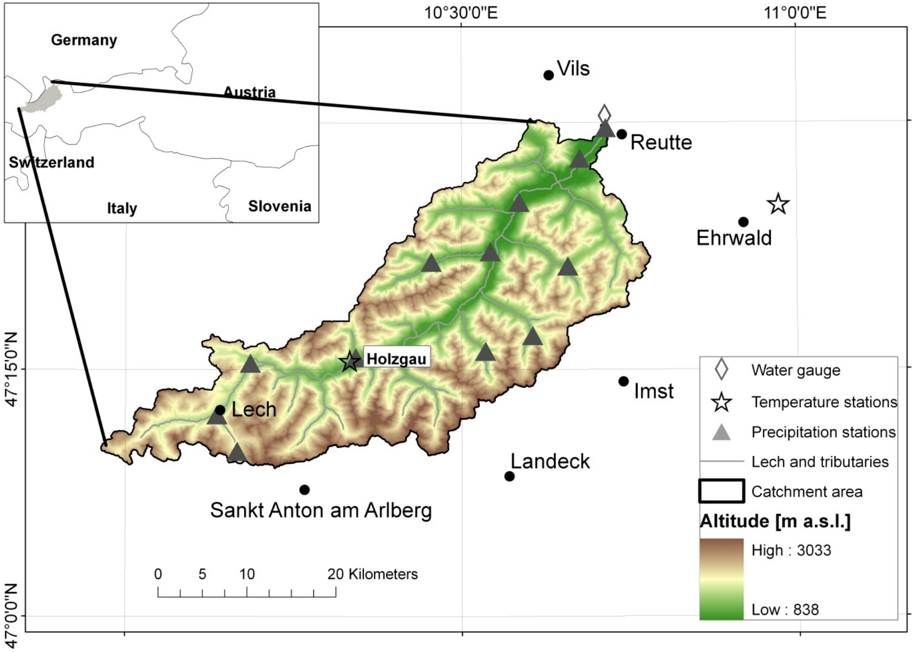

Fig. 1. Study area Lech watershed.

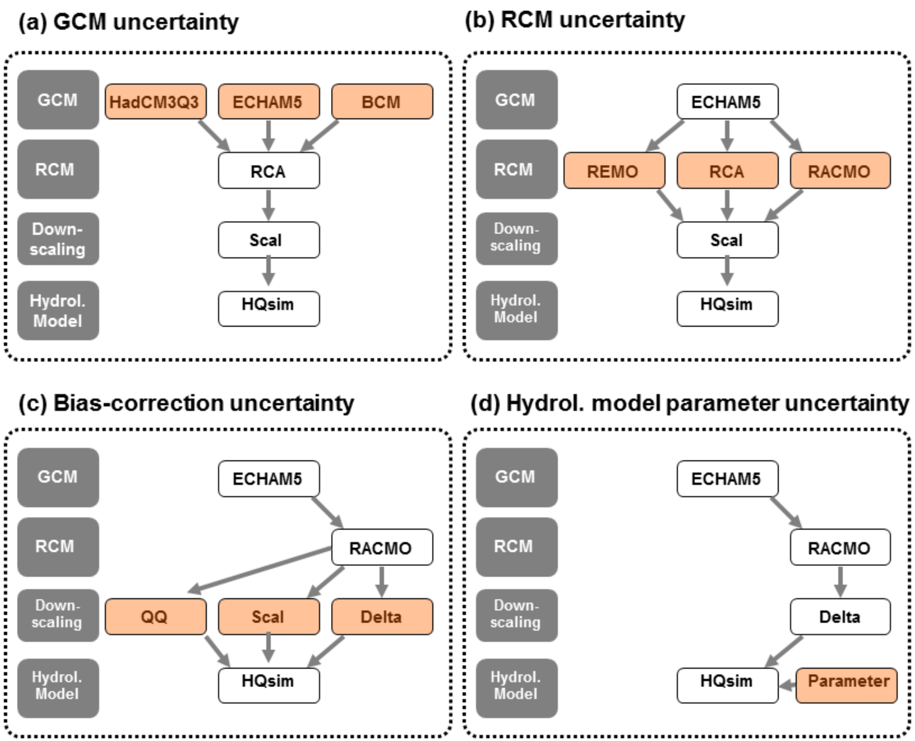

Fig. 2. Modelling chains used to assess **(a)** GCM uncertainty, **(b)** RCM uncertainty, **(c)** bias-correction uncertainty and **(d)** hydrological model parameter uncertainty.

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
|◀
▶|
◀
▶
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

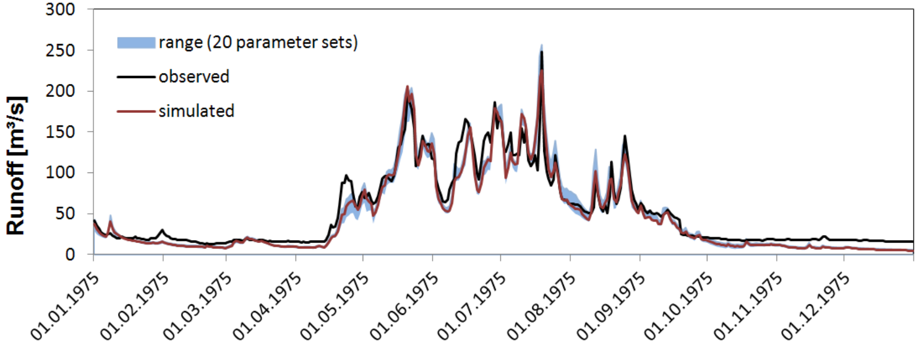

Fig. 3. Observed and HQsim simulated runoff for the year 1975. The blue shading indicates the range obtained when using 20 different parameter sets.

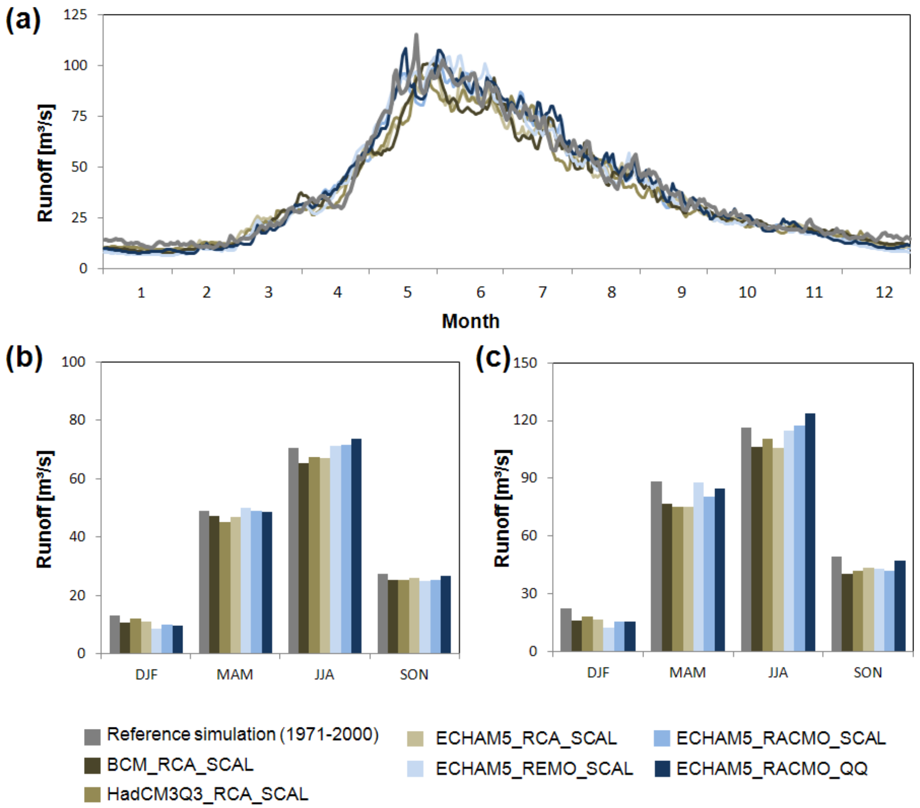

Fig. 4. Runoff from HQsim simulations using observed station data (reference simulation) and the different modelling chains showing **(a)** mean daily runoff, **(b)** mean seasonal runoff and **(c)** the mean seasonal 90%-quantile of daily runoff.

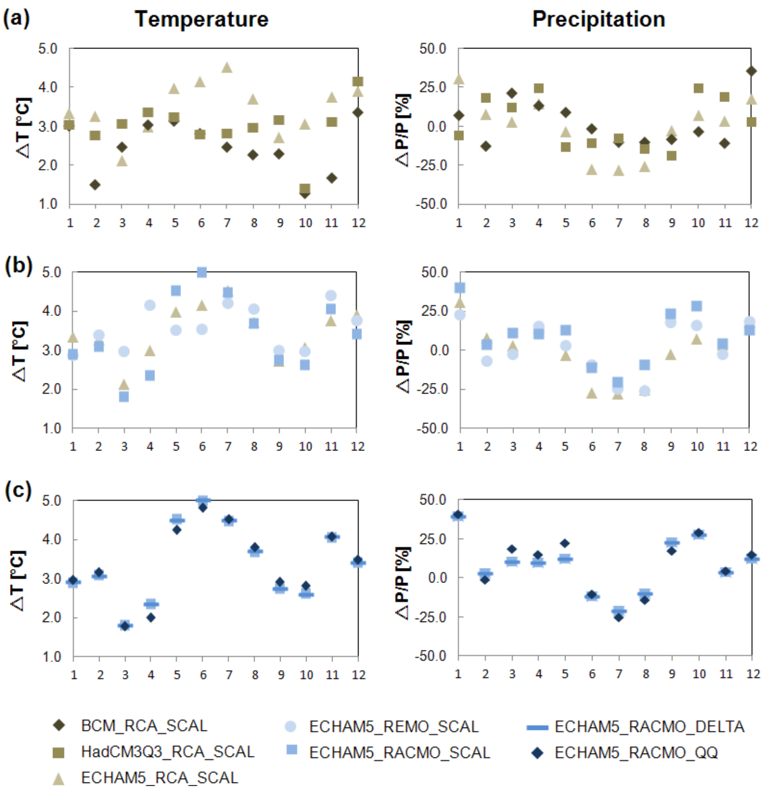

Fig. 5. Mean monthly changes in temperature (T) and precipitation (P) between the reference period (1971–2000) and the future scenario (2070–2099). Uncertainty originating from **(a)** GCM, **(b)** RCM and **(c)** bias-correction is illustrated. Temperature and precipitation data are averaged across the catchment.

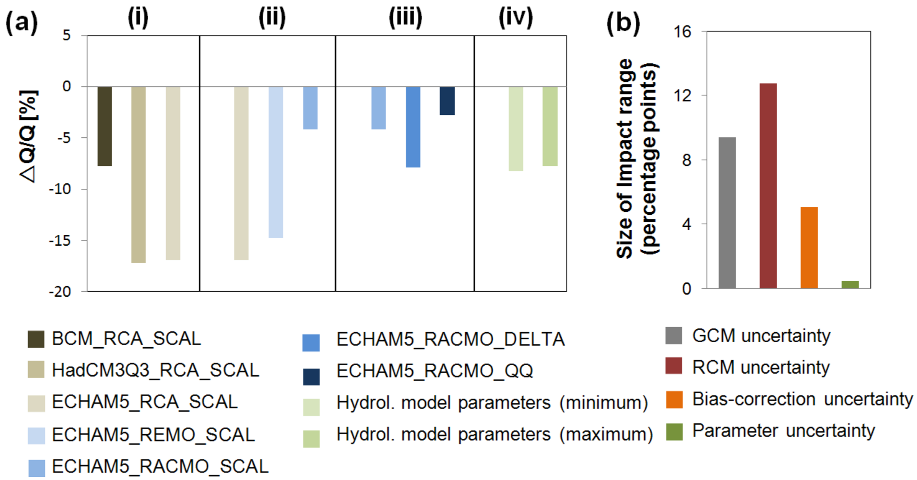

Fig. 6. (a) Uncertainty in the projection of mean annual runoff (Q) resulting from (i) GCM, (ii) RCM, (iii) bias-correction and (iv) hydrological model parameters. **(b)** Size of impact range originating from each uncertainty source.

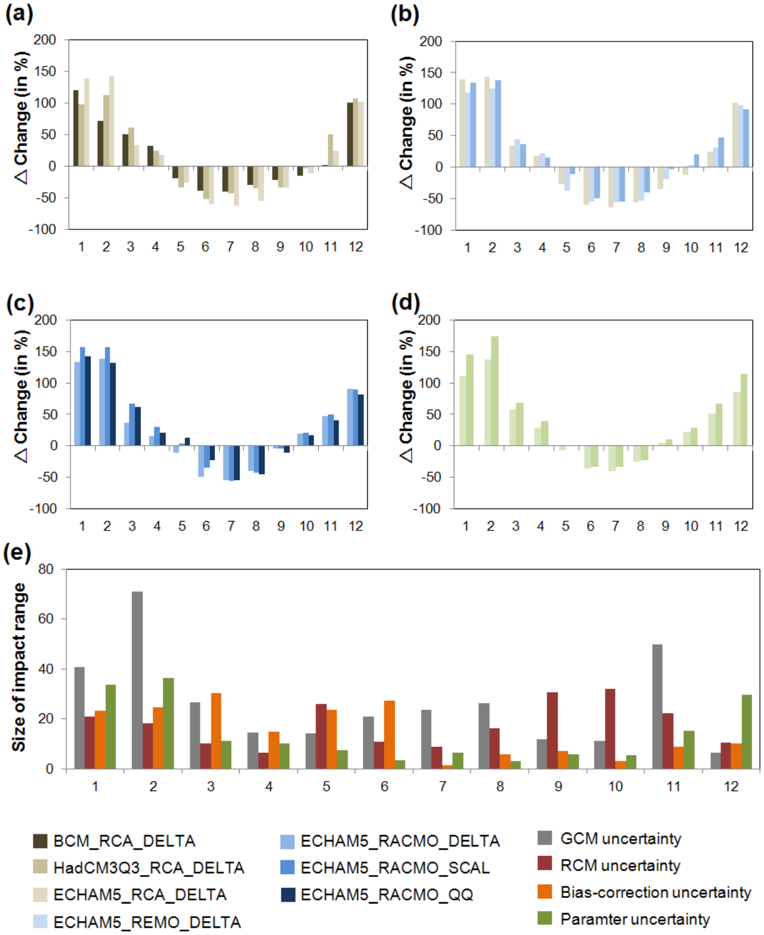

Fig. 7. Uncertainty in the projections of mean monthly runoff (*Q*) resulting from **(a)** GCM, **(b)** RCM, **(c)** bias-correction and **(d)** hydrological model parameters. **(e)** Size of impact range originating from each uncertainty source.

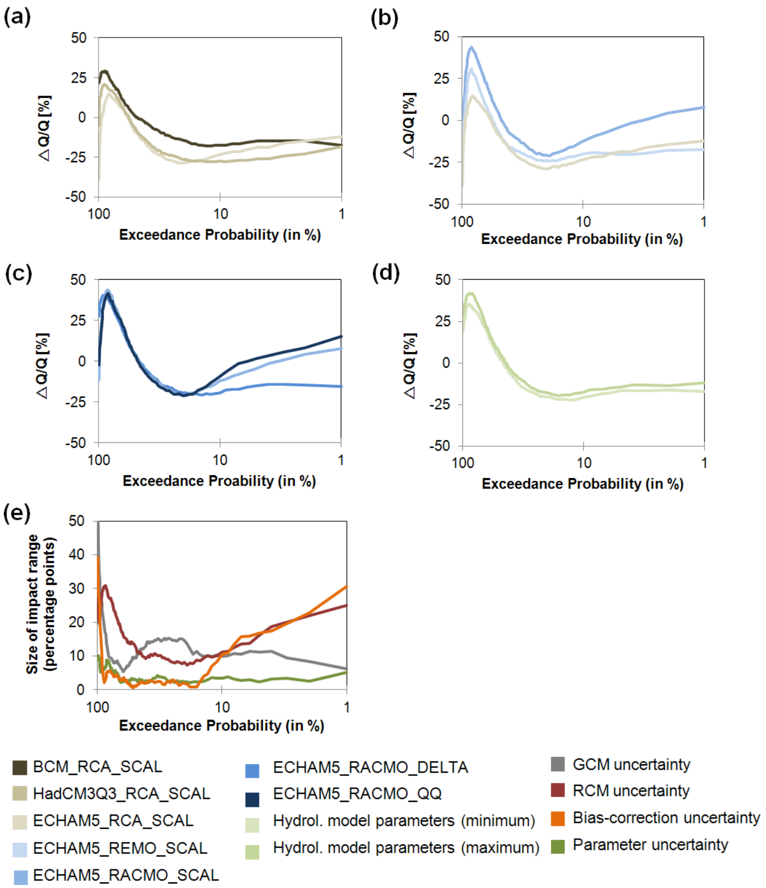

Fig. 8. Uncertainty in the projections of mean high flows (*Q*) resulting from **(a)** GCM, **(b)** RCM, **(c)** bias-correction and **(d)** hydrological model parameters. **(e)** Size of impact range originating from each uncertainty source.

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
◀I
▶I
◀
▶
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion