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Transferability of regionalization methods under changing climate

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ABSTRACT

Regionalization methods have been extensively discussed as the solution for runoff predictions in ungauged basins (PUB), especially during the PUB decade (2003–2012). At the same time, research topics relevant to climate change appear to be an essential and attractive field for hydrologists in recent decades, because the availability and quality of water resources are strongly affected by climate change. However, it is still unknown whether regionalization methods can be used to predict hydrological impacts of climate change for ungauged catchments or how much uncertainty of future predictions may result from the use of regionalization methods. Therefore, in this study, we investigate the transferability of regionalization methods (i.e. spatial proximity and physical similarity methods, regression method) under changing climate conditions and compare the uncertainty resulting from regionalization methods with that from using climate models. The investigation is based on 108 catchments in Norway, with large variability in climate conditions and geographic characteristics. The study applies a lumped conceptual rainfall-runoff model (WASMOD) with simple structure and six model parameters. Our result shows that (a) the differences in the predictions by the regionalization methods tend to increase in the future, (b) the physical similarity method with parameter option (i.e. the model parameters from the physically-similar donor catchments are first averaged and then used to run the model for the target catchment) shows higher transferability than other methods, (c) the uncertainty contributions from climate models and regionalization methods to future runoff prediction are basin dependent, and (d) the uncertainty of future runoff prediction due to regionalization methods can be higher than that from climate models in low precipitation areas. This study provides insight to the choice of regionalization methods under changing climate conditions and the role of regionalization methods to the uncertainty contributions in future runoff predictions.

1. Introduction

From economic, social and environmental perspectives, runoff predictions have significant influence on the engineering design and sustainable water management. Using hydrological models is the most popular solution to this problem by hydrologists and water managers. For runoff prediction of gauged basins, the models are typically calibrated to get the optimized parameter set by comparing the simulated result with the observed runoff, and then, applying the optimised model parameter set to predict the runoff for the future period. If the catchments lack observed runoff data, i.e. ungauged basins, hydrological models cannot be calibrated anymore and the model parameters are unknown (He et al., 2011; Oudin et al., 2010). Since the majority of basins worldwide are effectively ungauged, predictions in such basins become an interesting but challenging topic for hydrologists (e.g. Merz and Blöschl, 2004; Oudin et al., 2008; Parajka et al., 2007; Sivapalan et al., 2003; Xu, 2003; Young, 2006; Brugan and Aksoy, 2018). Taking these problems into consideration, the International Association of Hydrological Sciences (IAHS) was motivated to establish a “Decade on Predictions in Ungauged Basins (PUB): 2003–2012”, which was aiming to improve hydrological predictions in ungauged basins.

During the PUB Decade, many new methods were developed for runoff predictions in ungauged basins (e.g. Xu, 2003; Merz and Blöschl, 2004; Young, 2006; Parajka et al., 2007; Yang et al., 2018a). According to the review report from IAHS after the PUB decade, the most common method to solve the PUB problem is the use of so-called regionalization methods (Hrachowitz et al., 2013). Researchers applied and compared regionalization methods in different regions using different models. The conclusions about which approach performed best differ between the studies and depend on, among other factors, the study area and model choice (e.g. He et al., 2011; Oudin et al., 2008; Parajka et al., 2005; Razavi and Coulibaly, 2013; Reichl et al., 2009; Salinas et al., 2013; Samuel et al., 2011; Viglione et al., 2013). For example, Parajka et al. (2005) used the semi-distributed HBV (Hydrologiska Byråns

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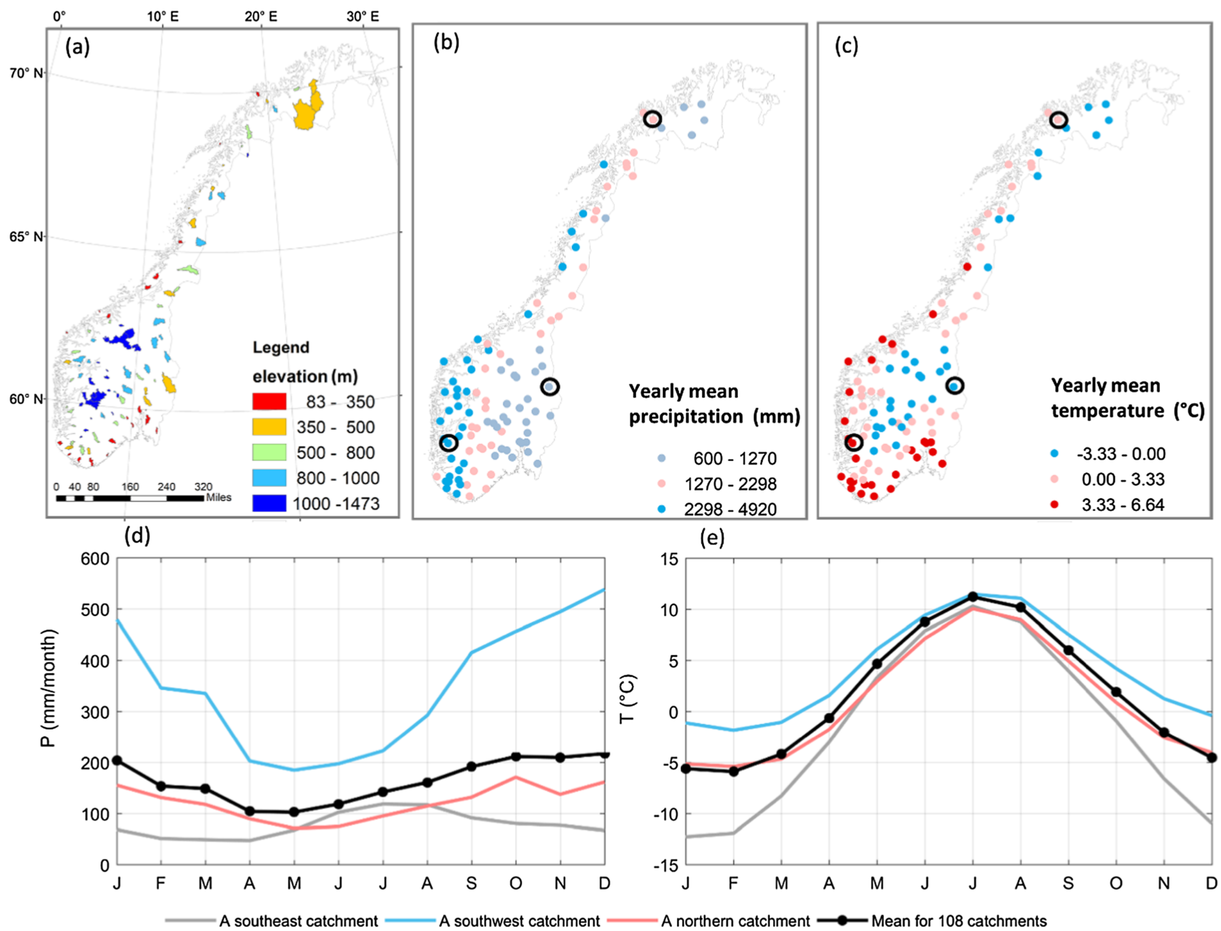

Fig. 1. Overview of the 108 catchments used in this study: (a) average catchment elevation above sea level, (b) yearly average precipitation; (c) yearly average temperature; (d) seasonal variations in precipitation; (e) seasonal variations in temperature. The climate characteristics are computed using data for the period from 1976 to 2005.

Vattenbalansavdelning) model in Austria and showed that the physical similarity method produced better results than regression and spatial proximity methods. Oudin et al. (2008) used 913 catchments in France and concluded that spatial proximity yielded the highest accuracy, followed by physical similarity, and then regression methods. Applying regionalization methods in high latitude regions, Yang et al. (2018a) reported that the physical similarity methods perform best followed by spatial proximity methods and regression methods produce the worst simulations based on more than 100 catchments in Norway. The poorer performance of the regression methods in these studies may relate to the assumption of a linear relationship between catchment descriptors and model parameters, which might not be valid in their cases. However, Young (2006), using 260 catchments from the UK, concluded that the regression method performed better than the proximity method based on a single physiographically nearest donor catchment. All these studies show different outcomes and there is no consistent conclusion about which regionalization method performs best. To address this problem, Parajka et al. (2013) made a second comparison of regionalization methods based on 34 studies reported in the literature involving 3874 catchments. Their statistical result shows that spatial proximity and physical similarity methods overall perform better than the regression method.

Studies evaluating regionalization methods have so far been using data for periods too short to show a pronounced influence by global warming. However, climate conditions are changing or are becoming non-stationary (IPCC, 2014), and under non-stationary climate conditions, the reliability of transferring the conclusions or patterns needs to be investigated (e.g. Broderick et al., 2016; Li et al., 2012). The simulation of hydrological consequences to climate change has received increasing attention from the hydrology communities, which usually consists of three related fields, i.e. (a) use general circulation models (GCMs) to provide future global climate scenarios, (b) use downscaling techniques (both nested regional climate models, and statistical methods) for “downscaling” the GCM output to the scales compatible with hydrological models, and (c) use hydrological models to simulate the effects of climate change on hydrological regimes at various scales. Progress and uncertainty involved in each field has been evaluated and reported extensively in the literature (e.g. Broderick et al., 2016; Chen et al., 2011; Etter et al., 2017; Xu, 1999a; Xu et al., 2005). To the future runoff prediction in ungauged catchments, regionalization methods are almost equally essential as hydrological models, global/regional climate models and statistical downscaling methods. However, the transferability of regionalization methods under climate change has not achieved similar attention. We are unaware of any studies that has evaluated how well different regionalization methods perform under different climate conditions, which motivates our study.

Therefore, the main objectives of this study are to (a) evaluate the transferability of regionalization methods for climate change impact assessments and, (b) compare the uncertainty contribution in the runoff predictions stemming from the choice of regionalization methods and the choice of climate models. To fulfil those study aims, we focus on the following specific research questions: (i) How much will the runoff projections for the future period differ from the past period by regionalization methods? (ii) Will the regionalization method that performed best for the past period also show the best performance for the future period? (iii) How much uncertainty stems from the regionalization methods when projecting runoff for the future period compared to other factors, such as the uncertainty given by the climate models? To answer the research questions stated above, we assessed the transferability of five commonly used regionalization methods using a lumped conceptual hydrological model, forcing by bias-corrected data from five climate models during past period (1976–2005) and future period (2071–2100). For comparing the uncertainty contributions given by the climate models and regionalization methods, the regionalized runoff predictions during 2071–2100 are analysed for 108 evenly distributed catchments throughout Norway.

2. Study area and data

2.1. Study area

This study was conducted using data for 108 independent (i.e. not nested) and evenly distributed catchments in Norway, one of Europe's most mountainous countries located on the Scandinavian Peninsula. Due to the mountainous terrain and large latitudinal extension (Vormoor et al., 2016), the variation in mean elevation of the catchments is large (80–1500 m) (see Fig. 1a) and the hydro-climatological conditions differ much (see Fig. 1b to e). High pressure systems and extratropical cyclones dominate precipitation patterns, along with orographic lifting. Variations in latitude and altitude determine temperature patterns in the study region. The average annual precipitation over the 108 catchments is approximately 1950 mm, with a strong decrease from coastal to interior areas (see Fig. 1b). Three example catchments, which are marked on Fig. 1b and 1c by black circles, are selected to show the typical seasonal climate conditions for their regions. The south-western catchment located close to the coast shows much higher precipitation amounts, in particular from September to May, than the northern and south-eastern basins (see Fig. 1d). For air temperature, the largest difference between the catchments occurs in the period from October to March. In this period, the catchment located in the south-eastern inland region shows the lowest temperature, even lower than the northern basin located close to the coast. In summary, the climate in coastal area is wetter and maritime and changes to drier conditions in the interior regions.

2.2. Data

2.2.1. Observed hydrological and meteorological data

The precipitation and temperature data for each catchment was acquired from grid dataset with a resolution of 1 km retrieved from the SeNorge dataset by the Norwegian Meteorological Institute (Tveito et al., 2005; Mohr, 2009; Jansson et al., 2007). The discharge data are selected from the hydrometric observation network of the Norwegian Water Resources and Energy Directorate (NVE).

Catchment descriptors are applied to quantify the catchment similarity index in physical similarity methods or build the relationship with model parameters for regression methods in this study. The catchment descriptors used in this study are similar as those presented in Yang et al. (2018a). Table 1 shows a selection of indices from terrain characteristics and land use.

Table 1
Catchment descriptors for the 108 watersheds used in this study.

	Mean	Median	Maximum	Minimum
Area (km^2)	301	137	5620	2.84
Terrain characteristics				
Mean slope (°)	10.60	9.00	26.00	2.00
Mean elevation (m)	680	621	1472	83
Land use				
Urban (%)	0.42	0.00	8.01	0.00
Agriculture (%)	3.92	0.90	57.56	0.00
Forest (%)	85.01	88.78	100.00	34.80
Wetland (%)	7.17	2.28	41.58	00
Waterbody (%)	3.48	2.55	15.05	0.00

2.2.2. Climate model data

Typically, bias-corrected climate model data are used for impact studies (Hewitson et al., 2014). The importance of using bias-corrected data for hydrological modelling studies has been described in the special report of the IPCC (Seneviratne et al., 2012). The main reason for using bias-corrected data is that the raw simulation data from climate models often contain large systematic errors, which are much reduced by the bias-correction step (e.g. Teutschbein and Seibert, 2010, 2013).

In this study, the data we used for each catchment is from bias-corrected and downscaled climate model data with a spatial resolution of 1 km available for the periods 1976–2005 and 2071–2100. For the hydrological model simulations, we use monthly precipitation and temperature data. Detailed information about the datasets as well as the downscaling and bias-correction procedures is available in the report “Climate in Norway 2100” (Hanssen-Bauer et al., 2017). In this study, we use data from (a) five global climate models (see Table 2), (b) one regional climate model RCA4 (Kupiainen et al., 2014), and (c) one representative concentration pathway - RCP 8.5.

Fig. 2 shows a comparison between the bias-corrected climate model data and the SeNorge dataset (see Section 2.2.1). For the past period, the bias-corrected climate model results agree well with the observations, and there is almost no difference between the climate models and the observations for both precipitation and temperature due to the bias-correction step. For the future period, on the other hand, the data from climate models differ more between each other. The median increase in air temperature is approximately 5 °C and precipitation increases with approximately 21% from the past to the future period.

As climate affects the basic components of hydrologic cycle such as soil moisture, evaporation and atmospheric water content (Gleick, 1986; Jiang et al., 2007; Yang et al., 2018b), the climate characteristics are often included in regionalization methods (e.g. He et al., 2011; Oudin et al., 2008). The climate indices applied are the same as those presented in Yang et al. (2018a) except that they are calculated from bias-corrected climate model data used in this study. Table 2 summarised the climate indices calculated from 108 catchments for all five climate models for both past and future periods.

3. Methods

3.1. Hydrological model

3.1.1. Model description

Conceptual rainfall-runoff models are commonly used for research on regionalization methods (e.g. He et al., 2011; Oudin et al., 2008; Parajka et al., 2005; Reichl et al., 2009; Samuel et al., 2011). However, models with higher complexity and more parameters will likely be more influenced by over-parameterization and equifinality problems (e.g. Li et al., 2009; Merz and Blöschl, 2004; Schoups et al., 2008; Seibert, 1999; Wagener et al., 2007), and the results might therefore lose generality. Thus, a model with few parameters that are physically relevant and statistically independent should be an advantage (Yang et al., 2018a). Considering these criteria, we selected a lumped conceptual rainfall-runoff model called WASMOD (Water And Snow balance MODeling system). Presented by Xu et al. (1996) and Xu (2002), WASMOD only has six parameters in total including the snow module and the model parameters are validated to be typically independent and statistically significant after calibration (Xu, 2001, 2003). The model equations are shown in Table 3. Because of the simple structure and few model parameters, the model has been used and validated in many different climate regions in the world (e.g. Li et al., 2015, 2013; Widén-Nilsson et al., 2007; Xu and Halldin, 1997; Xu and Singh, 2002). Additionally, the model has also been applied in different regionalization

Table 2
Information about climate models and their corresponding climate indices applied as catchment descriptors in this study. The Mean, Minimum and Maximum values are computed from 108 study catchments. Value A/ Value B shows the data for two periods, where A is for the past period (1976–2005) and B is for future period (2071–2100).

		CNRM-CM5-RCA4	EC-EARTH-RCA4	HADGEM2-RCA4	IPSL-CM5A-RCA4	MPI-ESM-RCA4
Precipitation (mm/year)	Mean	1925/2301	1933/2318	1947/2330	1952/2404	1953/2277
	Min. ~Max.	500~4844/663~6142	499~4900/670~5957	510~4945/693~5711	505~4923/716~6259	514~4977/643~5888
Temperature (°C)	Mean	1.4/5.5	1.5/6.3	1.6/7.0	1.4/6.2	1.5/5.2
	Min. ~Max.	(−3.4) ~ 6.5/1.2~10.2	(−3.3) ~ 6.7/2.1~10.7	(−3.3) ~ 6.7/3.2~11.3	(−3.5) ~ 6.6/1.7~10.6	(−3.5) ~ 6.7/1.2~10.0
Precipitation seasonality index (1)	Mean	2.19/2.08	2.16/2.06	2.15/2.25	2.18/2.22	2.22/2.23
	Min. ~Max.	1.62~3.01/1.31~3.38	1.48~3.36/1.43~3.24	1.46~2.89/1.51~3.52	1.54~3.22/1.49~3.33	1.53~3.02/1.43~3.19
Temperature seasonality index (2)	Mean	17.3/16.3	17.7/16.5	16.6/17.8	17.2/17.1	17.3/16.9
	Min. ~Max.	10.5~26.3/9.6~23.6	10.2~26.8/9.8~21.9	9.8~26.3/10.4~24.0	10.3~26.8/9.8~22.5	10.0~26.7/9.2~24.7
Aridity index (3)	Mean	0.28/0.48	0.27/0.54	0.27/0.63	0.26/0.52	0.26/0.47
	Min. ~Max.	0.05~0.92/0.07~1.30	0.05~0.85/0.09~1.43	0.05~0.89/0.10~1.70	0.05~0.85/0.08~1.45	0.05~0.86/0.07~1.27
Climate seasonality index (4)	Mean	62.8/83.6	63.3/83.8	66.7/109.1	65.1/86.9	70.4/90.9
	Min. ~Max.	18~195/22~312	22~207/20~265	19~224/19~326	24~213 /35~257	21~240/34~280
Institute of global climate models		CNRM	EC-EARTH consortium	The Met Office Hadley Centre	L'Institut Pie-simon Laplace, France	Max-Planck-Institute fur Meteorologie, Germany

(1) Precipitation seasonality index: the ratio between the three consecutive wettest and driest months for each catchment Bull (2009).
(2) Temperature seasonality index: the mean temperature of the hottest month minus the mean temperature of the coldest month Bull (2009).
(3) Aridity index: the ratio between annual mean precipitation and potential evapotranspiration for each catchment Budyko (1974); Arora (2002).
(4) Climate seasonality index: $|\delta_p - \delta_{E_p} R|$, δ_p is half of amplitude of precipitation, δ_{E_p} is half of amplitude of potential evaporation and R is aridity index Ross (2003).

studies (Xu, 1999b; Xu, 2003; Muller-Wohlfeil et al., 2003; Yang et al., 2018a) and climate change studies (Xu, 1999c; Li et al., 2015).

Table 4 shows the parameter ranges used for the calibration of WASMOD. The parameters a_1 and a_2 are two temperature threshold parameters used in snow routine. Parameter a_3 is used for the computation of potential evapotranspiration. Parameter a_4 determines the value of actual evapotranspiration, which is related to potential evapotranspiration and available water. Parameters a_5 and a_6 influence the generation of streamflow, where a_5 influences base flow and a_6 the fast flow. The base flow parameter should be higher in forested areas than in open areas or sandy soil, and the fast flow parameter should increase with the degree of urbanization, average basin slope, and drainage density (Xu, 2002).

3.1.2. Model calibration and evaluation

As most of the model parameters cannot be directly determined from field measurement, model calibration is an essential process for parameter estimation by optimising an objective function. A traditional split-sample test was conducted for model evaluation, aiming to test the model validity in different periods (Coron et al., 2012; Wang et al., 2017) In our study, we divided the observation period from 1976 to 2005 into two distinct periods: 1976–1990 and 1991–2005. Both periods are used for calibration and validation in turn. For the period of 1976–1990, the yearly mean precipitation is approximately 1885 mm and the yearly mean air temperature is 0.94 °C. Precipitation equals approximately 2000 mm and temperature is 1.94 °C in the period 1991–2005. Thus, temperature has increased by approximately 1 °C and precipitation has increased by about 6% from the first to the second period.

In this study, the model parameters are optimised to maximise the NSE-bias objective function (Viney et al., 2009), which is a weighted combination of Nash and Sutcliffe efficiency (Nash and Sutcliffe, 1970) and a logarithmic function of bias given by:

$$F = NSE - 5*|\ln(1 + Pbias)|^{2.5} \tag{1}$$

where *Pbias* is the bias and *NSE* denotes the Nash–Sutcliffe efficiency, which are shown in Eqs. (2) and (3), respectively. Eq. (1) can effectively maximise NSE while at the same time minimize the bias (Vaze et al., 2010).

$$Pbias = 100*\frac{\bar{Q}_{sim} - \bar{Q}_{reference}}{\bar{Q}_{reference}} \tag{2}$$

where $Q_{reference}$ represents the observed runoff and Q_{sim} represents the simulated runoff.

$$NSE = 1 - \frac{\sum (Q_{sim} - Q_{reference})^2}{\sum (Q_{reference} - \bar{Q}_{reference})^2} \tag{3}$$

NSE ranges between $-\infty$ and 1.0, where a value equals to one indicates a perfect model fit, and values smaller than zero indicate that the mean observed value is a better predictor than the simulated value.

For model calibration, we first used a Monte-Carlo method to find the best range of model parameters and then used a local search algorithm (Lagarias et al., 1998) to refine the result. For the Monte-Carlo step, we used 10,000 sets of parameters randomly sampled according to the ranges defined in Table 4. For model evaluation, we applied NSE and Pbias as criteria, since they can assess the simulation from different aspects. Following Moriasi et al. (2007), we classify model performance into four categories using the limits shown in Table 5.

3.2. Description of regionalization methods

Information from gauged basin, so-called donor catchments, are often used for predicting runoff in ungauged basins (Kleeberg, 1992; Blöschl and Sivapalan, 1995; Petroselli et al., 2018). Regionalization methods can help to select the best donor catchments for one particular ungauged target catchment. The regionalization methods evaluated in

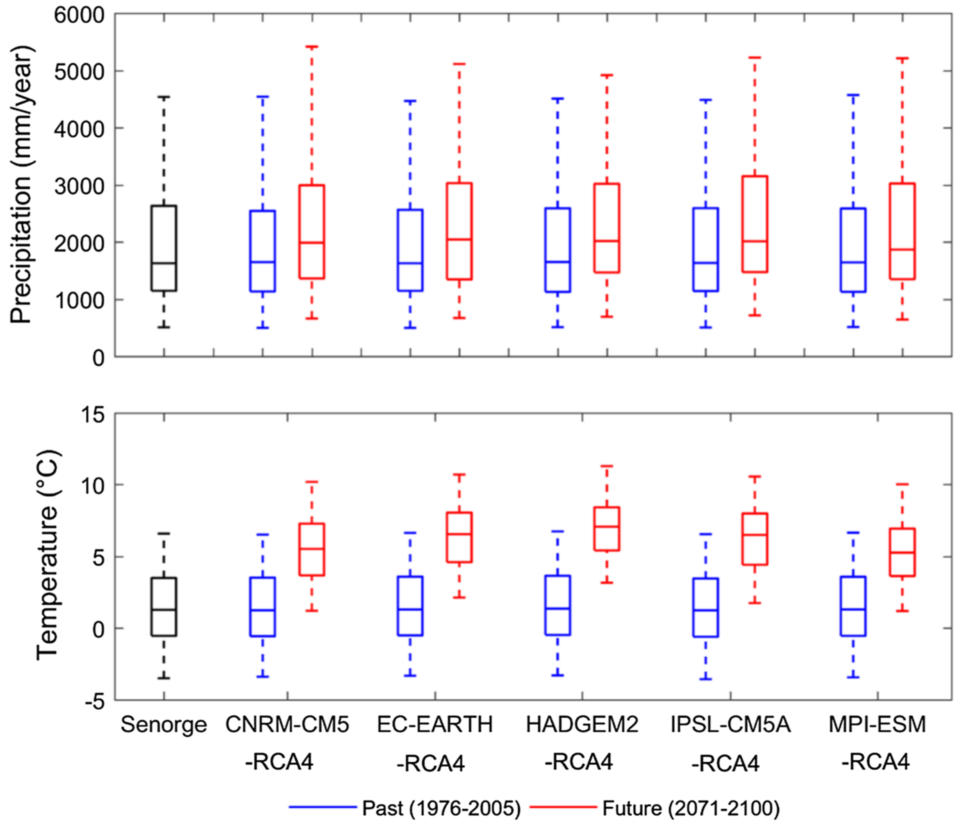

Fig. 2. Precipitation and temperature comparison over 108 catchments. The SeNorge dataset is denoted by black, the climate data for the past period by blue, and for the future period by red color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Principal equations of the WASMOD.

Variables	Equations
Snowfall (mm/month)	$S_t = P_t*\{1 - exp[-(T_a - a_1)/(a_1 - a_2)]^2\}^+$
Rainfall (mm/month)	$r_t = P_t - S_t$
Rainfall (mm/month)	$SP_t = SP_{t-1} + S_t - m_t$
Snowpack (mm)	$m_t = SP_t*\{1 - exp[-(T_a - a_1)/(a_1 - a_2)]^2\}^+$
Potential evap. (mm/month)	$ep_t = a_3*(T_a^+)^2$
Actual evap. (mm/month)	$e_t = \min(w_t*(1 - \exp(-a_4*ep_t), ep_t)$
Available water (mm/month)	$w_t = r_t + sm_{t-1}^+$
Slow flow (mm/month)	$b_t = a_5*(sm_{t-1}{}^+)^2$
Available storage (mm)	$sm_{t-1}^+ = max(sm_{t-1}, 0)$
Fast flow equation (mm/month)	$f_t = a_6*(sm_{t-1}{}^+)^{0.5}*(m_t - n_t)$
Active rainfall (mm/month)	$n_t = r_t - ep_t*(1 - e^{-(r_t/ep_t)})$
Total computed runoff (mm/month)	$d_t = b_t + f_t$
Water balance equation (mm)	$sm_t = sm_{t-1} + r_t + m_t - e_t - d_t$

Where, P_t – monthly precipitation (mm/month); T_a – air temperature (°C/month); t – time; a_i are model parameters, i = 1, 2, ⋯,6.

Table 4
Parameter ranges for WASMOD.

Parameter	a1	a2	a3	a4	a5	a6
Range	[0 5]	[−5 0]	[0 2]	[0 1]	[0 0.001]	[0 1]

this study include: (a) spatial proximity method based on geographical distance; (b) physical similarity method based on catchment characteristics similarity; and (c) Principal Component Regression (PCR) method.

Spatial proximity and physical similarity methods are regarded as distance-based regionalization methods by He et al. (2011) for transferring parameter information from donor to target catchments. In a previous study, three donor catchments produced the best performance of the distance-based regionalization methods for our study area (Yang et al., 2018a). We therefore use the same number of donor catchments in this study. Additionally, we applied two different approaches for using the regionalized model parameters in the hydrological model: the so-called parameter option and output option (Oudin et al., 2008; Yang et al., 2018a). For parameter option approach, the model parameters from the donor catchments are first averaged and then used to run the model for the target catchment. While, in the output option, the model is first run using the parameters from the donor catchments on the target catchment and the outputs from the model are then averaged. In total, four distance-based methods are applied in this study: (a) the spatial proximity method with parameter option (SP-par); (b) the spatial proximity method with output option (SP-out); (c) the physical similarity method with parameter option (Phy-par); and (d) the physical similarity method with output option (Phy-out).

Table 5
Classification of model performance into categories with limits following Moriasi et al. (2007) for Pbias and NSE.

Criteria	Performance class			
	Very good	Good	Satisfactory	Unsatisfactory
NSE (-)	> 0.75	0.65–0.75	0.55–0.65	< 0.55
|Pbias| (%)	< 10	10–15	15–25	> 25

Unlike the distance-based regionalization methods, for the regression methods the regression equations are transferred to target catchment. These equations are established by regression methods between the calibrated parameters of the hydrological model (dependent variables) and catchment descriptors (independent variables) in gauged catchments (Yang et al., 2018a). In this study, principal component regression (PCR) method is applied, which is a combination of principal component analysis (PCA) with multiple regression methods. According to the PCA statistical procedure, a set of observations of possibly correlated variables is converted into a set of linearly uncorrelated variables (called principal components) by orthogonal transformations. Based on these new principal components, a multiple regression method is used to determine the function between model parameters and selected catchment descriptors in gauged donor catchments. Finally, these functions are applied in ungauged locations to estimate the model parameters, which will be used in the hydrological model to predict the streamflow.

For details about the methods used in this study, see Yang et al. (2018a). The catchment descriptors for physical similarity and regression methods have been summarized in Tables 1 and 2.

3.3. Evaluating the transferability of regionalization methods

3.3.1. Performance of regionalization methods

We determine the performance of the regionalization methods using leave-one-out cross-validation, which is a commonly used strategy in many regionalization studies (e.g. Oudin et al., 2008; Parajka et al., 2013; Samuel et al., 2011). For each station, we compute the performance of each regionalization method using a so-called reference simulation since there is no observed runoff available for the future period. For the reference simulation, we use a model simulation applying the parameters obtained directly from the local calibration (see defined in Table 5), i.e. not involving any regionalization methods and drive the model with the bias-corrected climate data for all runoff simulations for both the past and future period (see Section 2.2.2). Our reference simulation follows a very typical approach for assessing climate change impacts on runoff (e.g. Chiew et al., 2009; Niemann and Eltahir, 2005; Xu, 1999c; Zheng et al., 2009; Guo et al., 2018). This method assumes that hydrological models calibrated for the historical period are also valid for use in the future period with possibly different climate conditions (Vaze et al., 2010). Following this assumption, we use the reference simulation to judge which regionalization method provides the best prediction of runoff for the future period. We compute the performance of the regionalization methods using the NSE and Pbias measures presented in Section 3.1.2.

3.3.2. Transferability of regionalization methods

Once we have determined the performance of regionalization methods, we test how sensitive the long-term runoff predictions in ungauged basins is to the choice of regionalization methods. The sensitivity is measured as the change in performance of the regionalization methods from the past (1976–2005) to the future (2071–2100) period. Since NSE and Pbias evaluates the agreement between the regionalized and reference simulation from different aspects, we need an additionally simple but comprehensive index to rank regionalization methods. The proposed ranking index (RI) is based on the probability of good performance (as described in Section 3.1.2) as:

$$RI_i = \frac{1}{m}\sum_{k=1}^{m}\left(0.5*\int_{0.65}^{1} f_{NSEik}\, d_{NSE} + 0.5*\int_{-15}^{15} f_{Pbiasik}\, d_{Pbias}\right) \tag{4}$$

where f_NSE_{ik} and f_Pbias_{ik} stand for the probability density functions of NSE and Pbias for regionalization method i and climate model k. As mentioned before, we applied five regionalization methods and five climate models, thus $m = 5$, k and $i = 1, 2, 3, 4, 5$. Since the ranking index is based on probability of good performance, higher values indicate better performance within each period and the optimal value is 1.

In summary, we evaluate the transferability of the regionalization methods using three different performance criteria. A small change in performance of the regionalization method from the past to the future period indicates a good transferability capacity of the method for different climate conditions.

3.4. Quantifying the uncertainty contributions from climate models and regionalization methods

The uncertainty in predictions of hydrological impact of climate change by hydrological models stems from different sources, such as model parameters, input data, climate models and hydrological model structural (e.g. Meresa and Romanowicz, 2017, Wine et al., 2018; He et al., 2018). The assessment of uncertainty contributions can help managers of water resources to understand the projections in more depth, and make better decisions than when this information is neglected (Winkler, 2016). For the uncertainty analysis presented below, we applied data from all five climate models presented in Section 2.2.2 and the five regionalization methods outlined in Section 3.2. We quantify the uncertainties stemming from climate models and regionalization methods for yearly average runoff over 2071–2100 for all 108 study catchments.

We use variance decomposition to compute the contributions to the total uncertainty from the climate models and regionalization methods. In this study, we follow the approach described in Déqué et al. (2007, 2012). The total variance of runoff V_{total}, can be splitted into the three different contributions as:

$$\mathrm{V_{total}} = \mathrm{V_{climate}} + \mathrm{V_{regionalization}} + \mathrm{V_{interaction}} \tag{5}$$

where $V_{climate}$ and $V_{regionalization}$ are the individual parts of the variance explained by the climate models and regionalization methods, respectively. $V_{interaction}$ is the variance due to the interaction between climate models and regionalization methods. Statistically, interaction effects occur when the effect of one factor depends on the levels of the second factor. In our case, this can occur when the response of the regionalization methods depends on the selection of climate models. The variances in Eq. (5) can be computed as:

$$\mathrm{V_{climate}} = \frac{1}{5}*\sum_{i=1}^{5}(\bar{R}_{i.} - \bar{R})^2 \tag{6}$$

$$\mathrm{V_{regionalization}} = \frac{1}{5}*\sum_{j=1}^{5}(\bar{R}_{.j} - \bar{R})^2 \tag{7}$$

$$\mathrm{V_{interaction}} = \frac{1}{5}*\frac{1}{5}*\sum_{i=1}^{5}\sum_{j=1}^{5}(R_{ij} - \bar{R}_{i.} - \bar{R}_{.j} + \bar{R})^2 \tag{8}$$

where R_{ij} is runoff simulation from climate model i and regionalization method j. $\bar{R}$ represents the yearly average runoff simulation of all samples. $\bar{R}_{i.}$ and $\bar{R}_{.j}$ are the average runoffs with respect to climate model i and regionalization method j. For more details, see Déqué et al. (2007, 2012).

4. Results

4.1. Evaluation of model performance by split-sample test

Fig. 3 shows the performance of WASMOD using a split-sample experiment. The median NSE value for the calibration period 1976–1990 is 0.86 and the 25% quantile value is approximately 0.8, which means that the model performance is higher than 0.8 for 75% of the catchments. For the validation period 1991–2005, the median NSE value is 0.75 and the 25% quantile value is around 0.70. The median Pbias is close to zero during the calibration period 1976–1990, and for the validation period, it is approximately −6.5%, and the interval between 75% and 25% quantile increases from 4 to 12%. When calibrating the model for the period 1991–2005, the model results are almost unbiased with an NSE value approximately equals to 0.84. For the validation period 1976–1990, the median NSE value is 0.78 and the bias is 3.0%. In addition, from the calibration to validation period, the

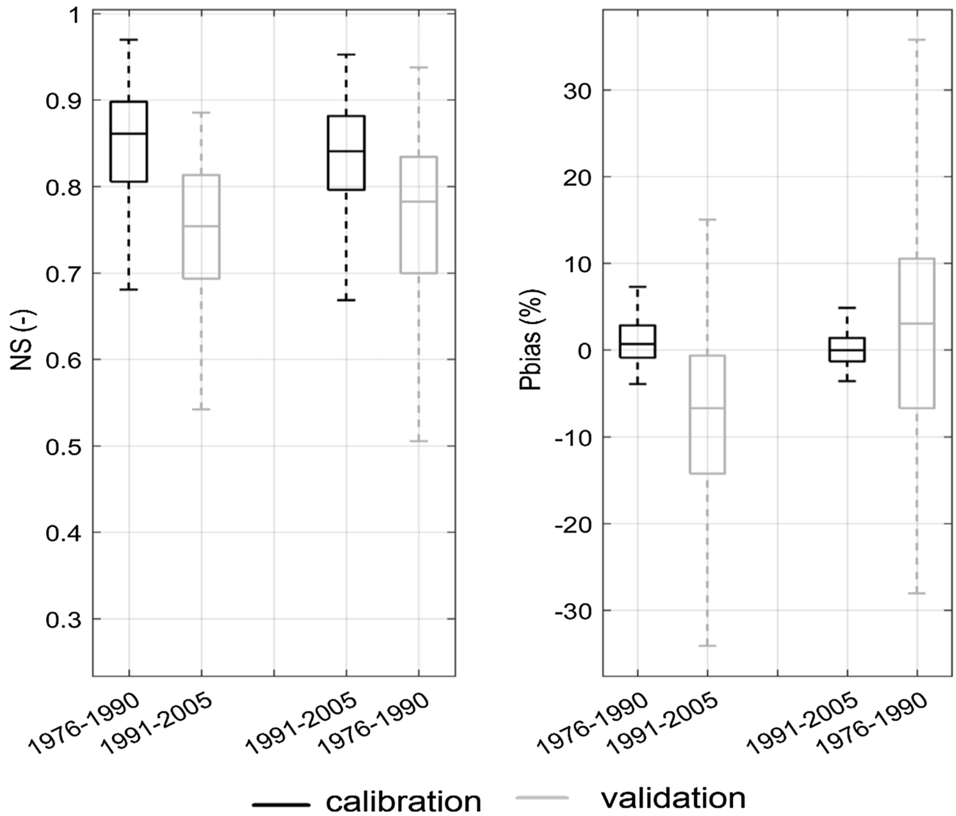

Fig. 3. Split-sample test showing the model performance of WASMOD for all 108 study catchments.

50% interquartile range (the interval between the 75% and 25% interquartile values) increases from 0.08 to 0.14 for NSE and from approximately 3% to 18% for the Pbias. According to the suggested performance classification by Moriasi et al. (2007), the model performance can be considered as very good for calibration and good for validation.

Fig. 4a shows a map with model performance for the calibration period 1976–1990. The catchments with highest performance (NSE greater than 0.85) are mainly located in the interior area rather than the coastal regions. There are more than 50% catchments with NSE values larger than 0.85. For the validation period 1991–2005, the model performance generally decreased (Fig. 4b). Many stations with poorer performance are located along the coast, whereas catchments with higher performance are often situated inland. For the validation period, about half of the catchments show NSE values higher than 0.75, and 8 catchments show NSE values higher than 0.85.

4.2. Transferability evaluation of regionalization methods

4.2.1. Visual difference between regionalization methods in different climates

All climate models show increased temperature and precipitation in the future compared to the past period (see Section 2.2.2). To illustrate

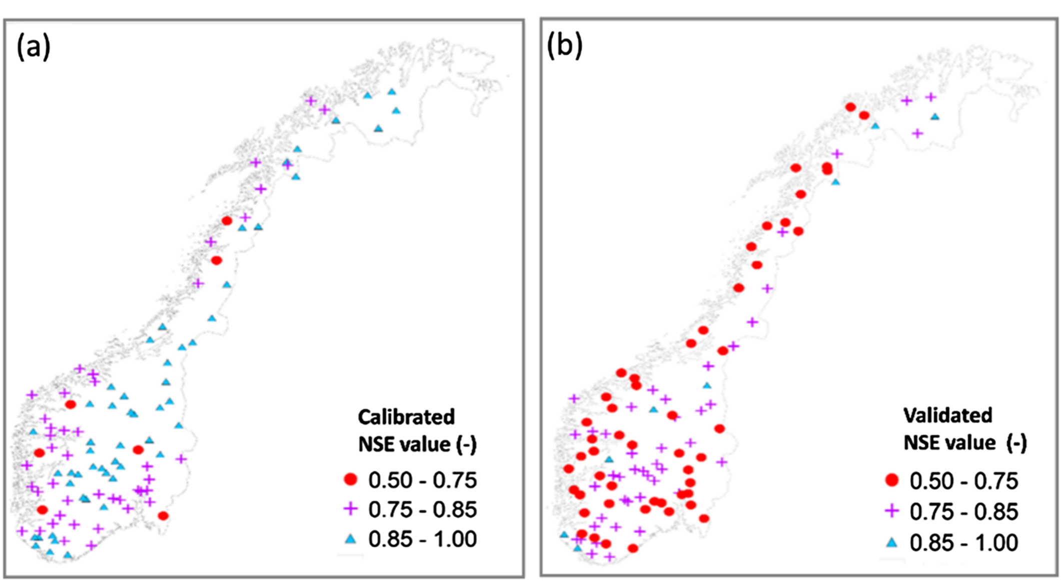

Fig. 4. Map showing the performance of WASMOD: (a) NSE values for the calibration period 1976–1990; (b) NSE values for the validation period 1991–2005.

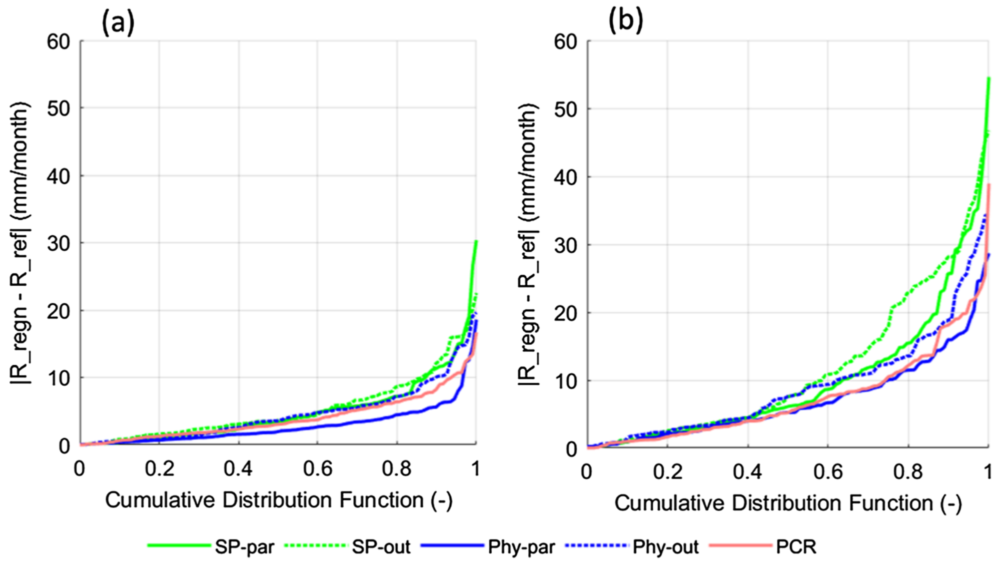

Fig. 5. Absolute difference in monthly mean runoff between the regionalized and reference simulations for the past (panel a) and future (panel b) period for the five regionalization methods. The figure shows these differences as a cumulative distribution function for the 108 study catchments.

how this change in climate influences the runoff simulations, we show the difference, in terms of cumulative distribution functions, between the regionalized and reference simulations for the past (1976–2005) and future period (2071–2100) in Fig. 5. The results are calculated based on the 30-year averaged monthly runoff for the 108 study catchments, and using the EC-EARTH-RCA4 climate model, whose precipitation and temperature data are closest to the ensemble mean spanned by the five individual models.

Comparing Fig. 5a and b, we first see that the absolute difference between the regionalized and reference runoffs shows a large increase from past to future period for all regionalization methods. For instance, the maximum absolute difference in runoff between the regionalized and reference simulation is around 30 mm/month for the past period, but has increased to about 55 mm/month for the future period. The largest increase occurs for the spatial proximity methods. Second, the difference between the regionalization methods themselves tends to increase in the future compared to the past period (i.e. the range between the methods increases). Therefore, we conclude that the regionalized simulations will differ more between each other for the future period, which indicates that the selection of regionalization method will largely influence the accuracy of runoff predictions in ungauged basins.

4.2.2. Evaluation of regionalization methods by Nash-Sutcliffe values

Fig. 6 shows the probability density functions (PDF) of NSE values for the five regionalization methods and five climate models during both periods. First, all regionalization methods perform worse in the future than in the past period. For instance, the mode value of NSE decreased and the probability density of high NSE values dropped from the past to future period based on data from all five climate models. Second, the decrease in performance varies between the regionalization methods and climate models. Third, by using different climate models, the differences of regionalization method performances are not substantial, which can be seen from median of NSE values over 108 catchments for each regionalization method (see right panel in Fig. 6). Thus, we conclude that the different climate models have small influence on the performance of the regionalization methods. Finally, among all regionalization methods, the Phy-par method performed best during both periods for all climate models (compare the PDF curves in the third panel from the left and the median NSE values in the right panel of Fig. 6).

4.2.3. Evaluation of regionalization methods by Pbias values

Fig. 7 shows probability density functions (PDF) of the simulated percentage bias (Pbias) for the different regionalization methods and climate models for the 108 study catchments. Foremost, the probability density curves change from narrow in the past to wide in the future period for all regionalization methods. This pattern indicates that there are more catchments with higher errors in the future simulations than in the past period, which can also see from the standard deviation of Pbias values increases between the two periods (right panel in Fig. 7). This result is consistent with the results presented in Fig. 6 where NSE was used as performance criterion. The different climate models have a small influence on the performance of the individual regionalization methods (compare the rows in Fig. 7 for each regionalization method). Typically, the shapes of the PDFs for the future period are similar between the climate models for each regionalization method. Furthermore, the difference in mode values between the two periods is always smaller than 5%, which also suggests that the choice of climate model has small influence on the regionalization performance in terms of Pbias. When comparing the different regionalization methods, we find that the Phy-par method shows the smallest change in mode value between two periods (see third column from the left and the right panel in Fig. 7). At the same time, this method also shows lowest standard deviation of Pbias for the future period (see right panel in Fig. 7). Thus, the Phy-par method seems best suited for projections of average runoff.

In the following, we examine how the Pbias in the past period relates to the Pbias in the future period. Fig. 8 shows the Pbias in modelled runoff by the five regionalization methods from the past to the future period using data from EC-EARTH-RCA4. Overall, there is a strong positive correlation between the Pbias for the past and future period. Thus, biases given by the regionalization methods will likely persist from the past to future period. Moreover, the value of the Pbias for the past period is generally smaller than for the future period. For example, the Pbias by SP-par method varies within a range from −25 to 15% for the past period, but the spread increases to a range from −45 to 35% for the future period. In this case, the uncertainty in simulated mean annual runoff due to the regionalization methods increases from the past to the future period. Comparing the methods in both periods, the physical similarity approaches show similar spread in both periods, whereas the other methods display larger differences (compare with results presented in Section 4.2.3).

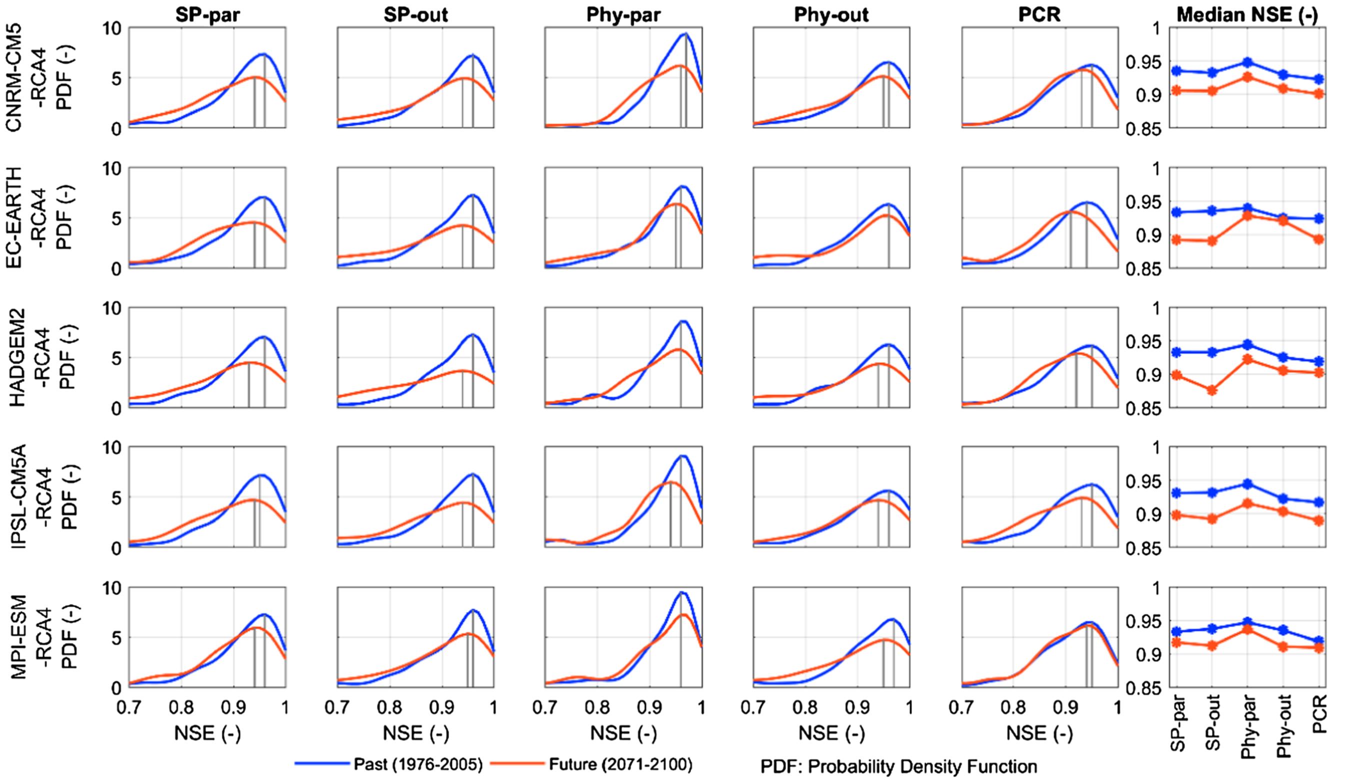

Fig. 6. Probability density functions (PDF) showing NSE values from five regionalization methods and five climate models for the past (1976–2005) and future (2071–2100) period. Each PDF contains data from the 108 study catchments. The grey vertical lines show the mode for each distribution. The right panel shows the median of the NSE values from the 108 catchments for the different regionalization methods for both periods.

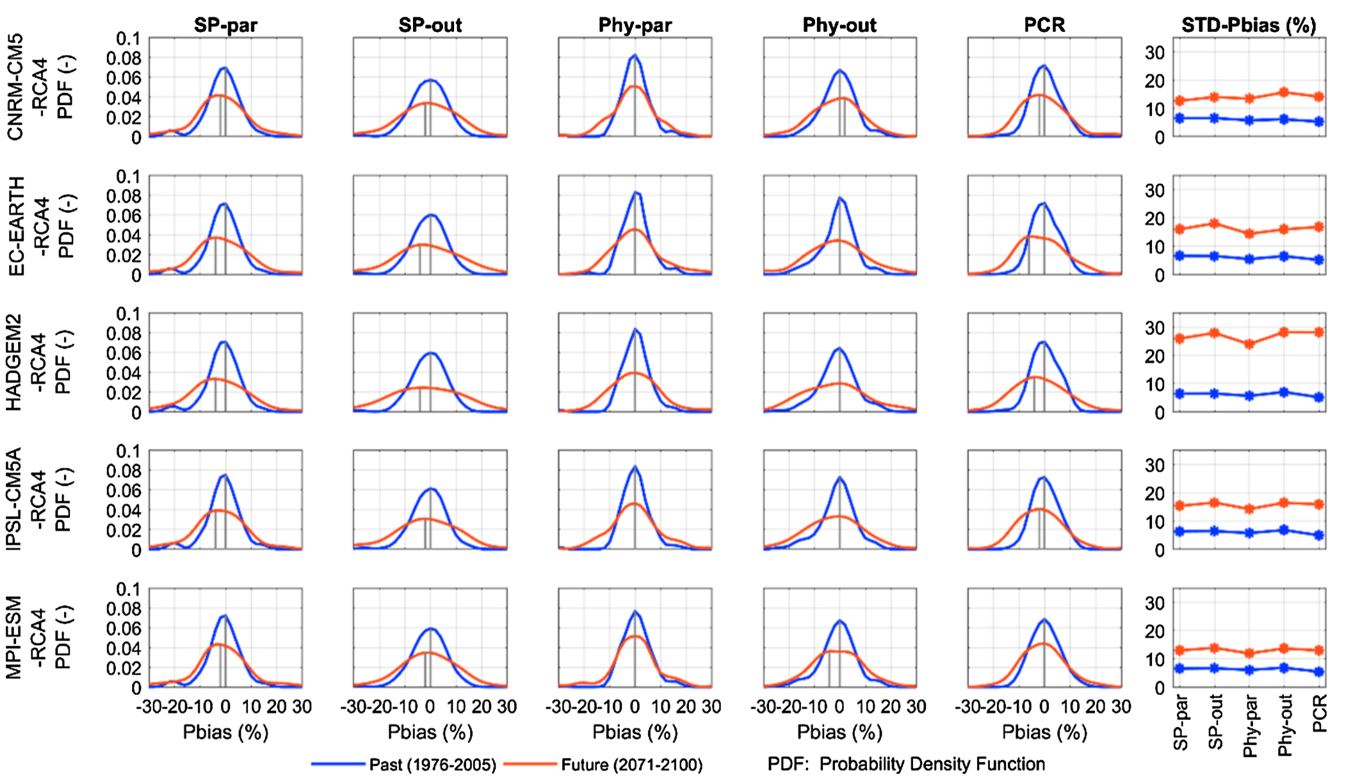

Fig. 7. Probability density functions (PDF) showing Pbias values from five regionalization methods and five climate models for the past (1976–2005) and future (2071–2100) period. Each PDF contains data from the 108 study catchments. The grey vertical lines show the mode for each distribution. The right panel shows the standard deviation of the Pbias values from the 108 study catchments for the different regionalization methods for both periods.

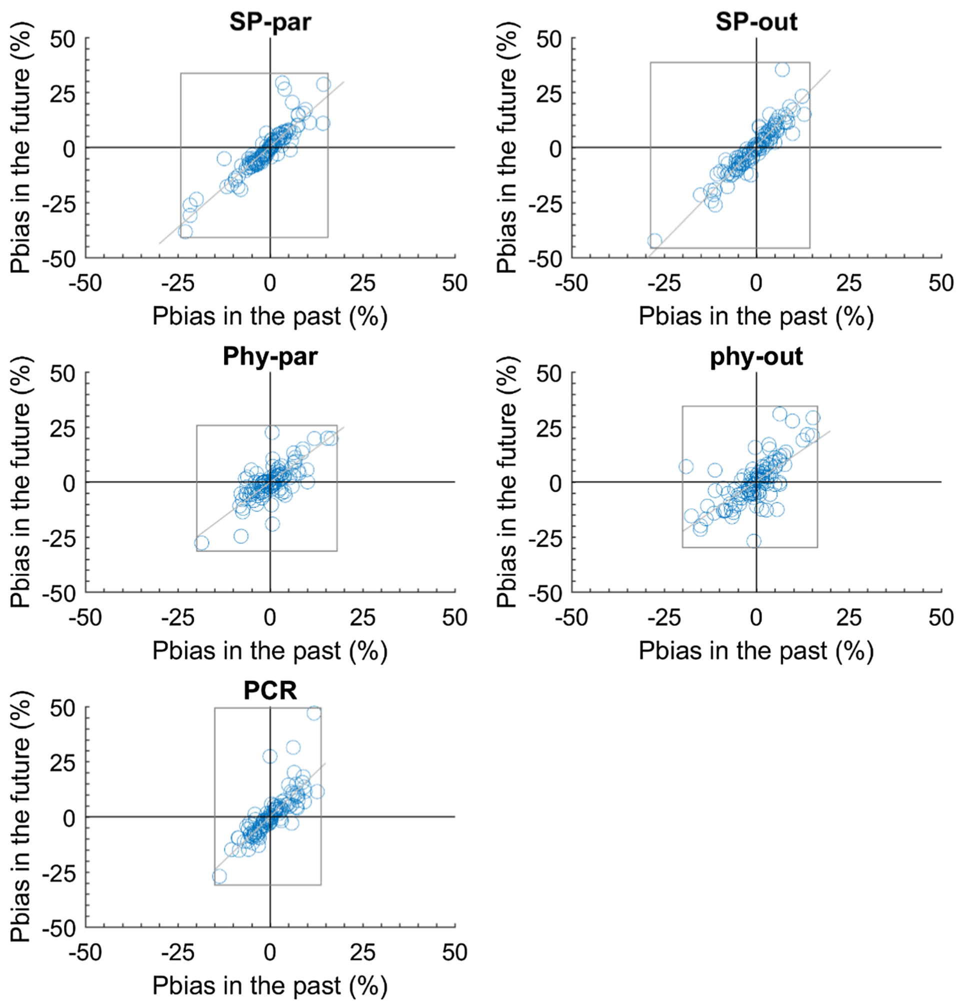

Fig. 8. Scatter plots showing the Pbias for the future period against the past period for the 5 different regionalization methods.

4.2.4. Evaluation of regionalization methods by ranking index

Table 6 shows the ranking of the regionalization methods using the index (RI) proposed in Section 3.3.2. As the evaluation criterion is probability-based higher values mean better performance than lower values. First, the probability of being good performance for all regionalization methods in the future is lower than in the past period, with an average decrease in RI of approximately 9.3%. This result is consistent with those shown in Figs. 6 and 7, indicating that all regionalization methods will have higher likelihood of producing worse simulations in the future. Second, the difference in RI between the regionalization methods increases from 7.14% (= (0.939–0.875)/0.939 * 100) for the past period to 10.8% (= (0.918–0.825)/0.918 * 100) for the future period. These results are in line with those presented in Section 4.2.1 (see Fig. 5). Third, when comparing the regionalization methods in the past period, the RI value for SP-par approach (0.875) is smaller than for all other methods. For the future period, both spatial proximity methods show lower RI values (less than 0.8) than other methods, where the remaining methods all utilize catchment descriptors. This result is partly related to the diversity of catchments characteristics in this study; the spatial proximity methods do not seem able to capture the large variability in parameter values through space. Finally, from the transferability aspect, the Phy-par approach shows the smallest decrease (7.14%) of probability for good performance from the past to the future period, whereas the SP-out and Phy-out methods show the largest decreases (higher than 10%). Thus, we conclude that the physical similarity method with the parameter option has the best transferability among all. The transferability of regression method (PCR) is moderate when considering all methods.

Table 6
Performance and ranking of regionalization methods by evaluation criteria RI.

	Multiple criterion *RI*		Ranking		Decrease of RI (%)
	Past	Future	Past	Future	
SP-par	0.875	0.793	5	4	9.37
SP-out	0.918	0.722	2	5	10.46
Phy-par	0.939	0.872	1	1	7.14
Phy-out	0.907	0.809	4	3	10.80
PCR	0.918	0.825	2	2	9.04

4.3. Contribution of uncertainty from climate models and regionalization methods

Fig. 9 shows boxplots of the variance decomposition for the predicted mean annual runoff for the 108 study catchments. The contribution of the uncertainty from the climate models and regionalization methods varies strongly between the catchments (from less than 10% to more than 90%). Overall, the climate models show a larger contribution to the uncertainty (median variance fraction equals to 51%) compared to the regionalization methods (median variance fraction equals to 40%). The contribution of the interaction term between the climate models and regionalization methods is, on the other hand, of much smaller importance.

Fig. 10 shows a map of the variance decomposition results

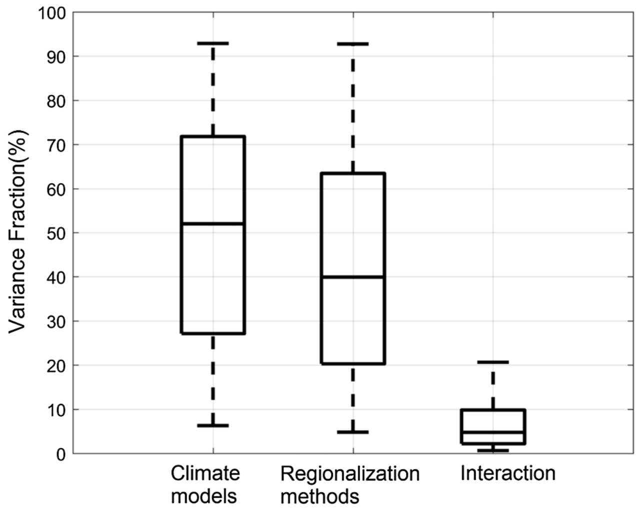

Fig. 9. Contribution of uncertainty from climate change models and regionalization methods, and their interaction for the 108 study catchments.

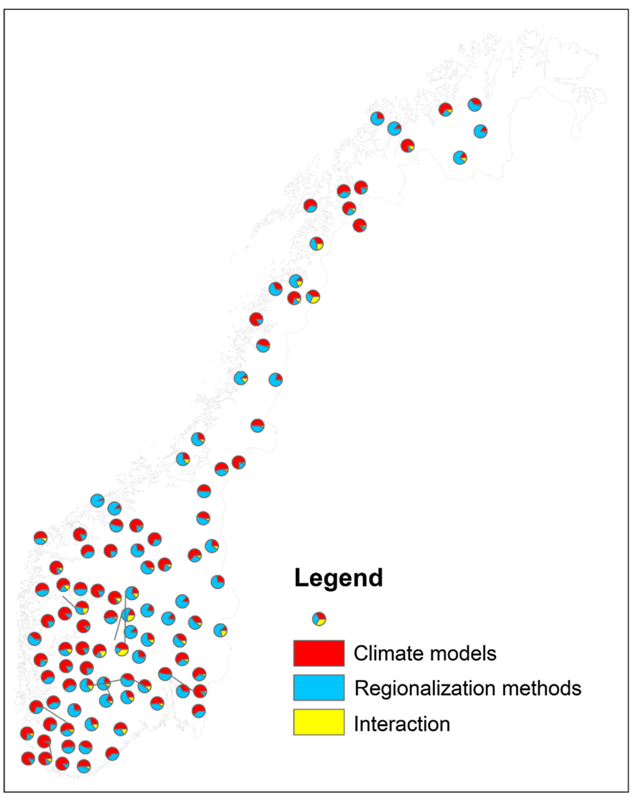

Fig. 10. Map showing the fraction of uncertainty given by the climate models and regionalization methods to yearly average runoff during 2071–2100 for the 108 study catchments.

displaying the uncertainty contributions from climate models and regionalization methods for the individual catchments. The uncertainty contributions vary largely between the basins, which is consistent with other studies (e.g. Mendoza et al., 2016; Sunyer et al., 2015). The regionalization methods typically dominate the uncertainty in most of the south-eastern catchments, and also in many of the catchments in middle and northern Norway. For the remaining catchments, the climate models typically dominate the uncertainty in predicted mean annual runoff. In almost all catchments, the contribution of the interaction term between the climate models and regionalization methods is small with few exceptions. Therefore, we can conclude that, for most catchments, the mean yearly runoff predictions from regionalization simulations do not depend on the selection of climate models.

Catchments where the total uncertainty in the runoff predictions is dominated by the climate models tend to be located in coastal areas, where precipitation is higher than in the inland regions. Fig. 11a displays the difference in uncertainty contributions between the climate models and regionalization methods against yearly mean precipitation for all study catchments. When precipitation is higher than 3400 mm/year, the climate models give higher uncertainty than the regionalization methods. At the same time, the standard deviation in projected precipitation between the climate models also increases with precipitation amount (Fig. 11b). Note that both panels use data from all climate model data during the future period (2071–2100). From the results in Fig. 11, it can be summarized that, for catchments with high precipitation amounts or high variability of simulated precipitations between climate models, the climate models dominate the total uncertainty of the runoff predictions. However, for catchments with precipitation lower than 3400 mm/year, climate models and regionalization methods both can dominate the total uncertainty of the runoff predictions. Thus, we can conclude that the uncertainty contribution from regionalization methods is comparable with climate models for catchments with precipitation amounts lower than 3400 mm/year in our study region.

Fig. 12 shows the normalized variances for climate models and regionalization methods computed using Eqs (6) and (7) for simulated annual mean runoff. The normalized variance for climate models is calculated by dividing $V_{climate}$ for each catchment by the maximum value of $V_{climate}$ for all catchments (see also Eqs. (6–8)). The same normalization is performed for the variance of the regionalization methods. The normalized variances are much higher, often a factor 10 or more, in the coastal areas than the interior regions. In the regions with high variances, the climate models overall produce higher uncertainties than the regionalization methods. These regions are characterized by higher precipitation amounts than the interior regions (compare with Fig. 1), and the differences in projected precipitation by the climate models dominate over the parameter uncertainty given by the different regionalization methods. On the contrary, the variances from both climate models and regionalization methods are considerably smaller in the interior regions and some northern basins (see also inset maps in Fig. 12). For many of these catchments the variance given by the regionalization methods exceeds the variance given by the climate models. This result may be due to the lower precipitation magnitude and variability observed in these regions (compare with Fig. 1b and Fig. 11b). Thus, for areas with low precipitation amounts and variability, the predicted runoff is more sensitive to variations in model parameter values given by the different regionalization methods than small changes in precipitation due to differences between climate models.

5. Discussion

5.1. Model performance

According to our results, there are more than 50% catchments whose NSE values are higher than 0.85, which is regarded as very good according to the classification presented by Moriasi et al. (2007). With a split-sample test, the model transferability can be assessed under different conditions, including changes in climate (Klemeš, 1986). In our case, yearly mean precipitation has increased with approximately 115 mm and temperature has increased approximately 1 °C from the period 1976–1990 to 1991–2005. Our split-sample test shows that NSE values are higher than 0.7 and absolute values of Pbias are lower than 15% for approximately 75% of catchments. These high model performances indicate that the model is able to predict changes in runoff conditions under changing climate conditions. The ability of WASMOD for simulating runoff for different climate conditions has also been

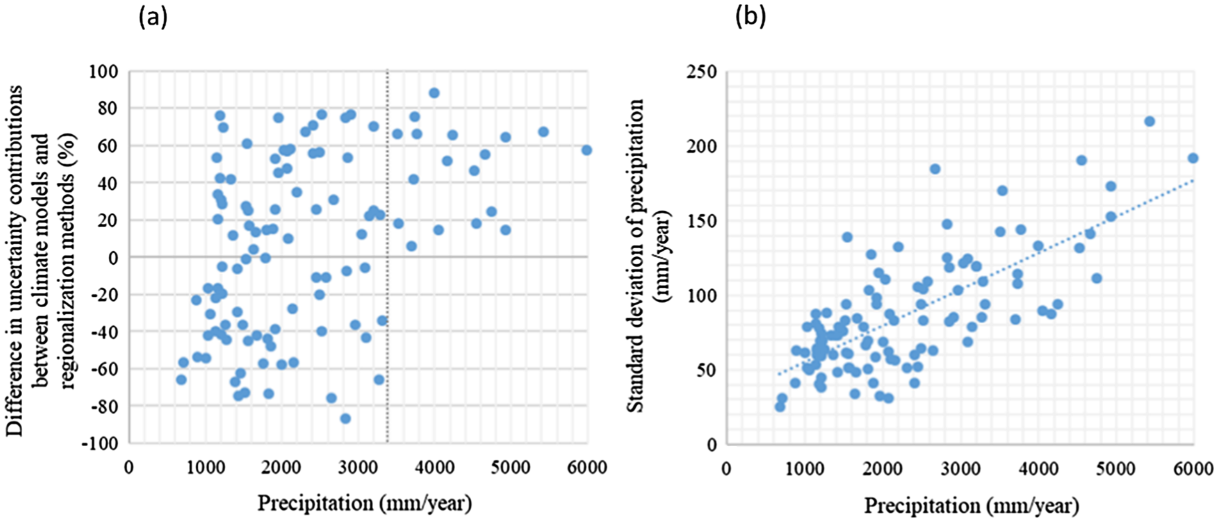

Fig. 11. (a) Scatter plots showing the difference in fraction of uncertainty given by the climate models and regionalization methods versus yearly average precipitation, and (b) correlation between precipitation amount and its variability. The results presented in this figure are computed using data from all five climate models during 2071–2100.

validated by Xu (1999c).

5.2. Transferability of regionalization methods under climate change

In this study, we assessed the transferability of five regionalization methods under climate change. We find that the capacity of the regionalized simulations to match the reference simulation declined from the past to the future period. This behaviour may partly be explained by the argument from Petheram et al. (2012), who concluded that the correlation between catchment descriptors and the model performance becomes weaker for prediction than calibration mode. In some cases, our results showed systematic differences for the regionalization methods between the past and future period. For example, we found a positive correlation in the percentage bias (Pbias) of simulated runoff

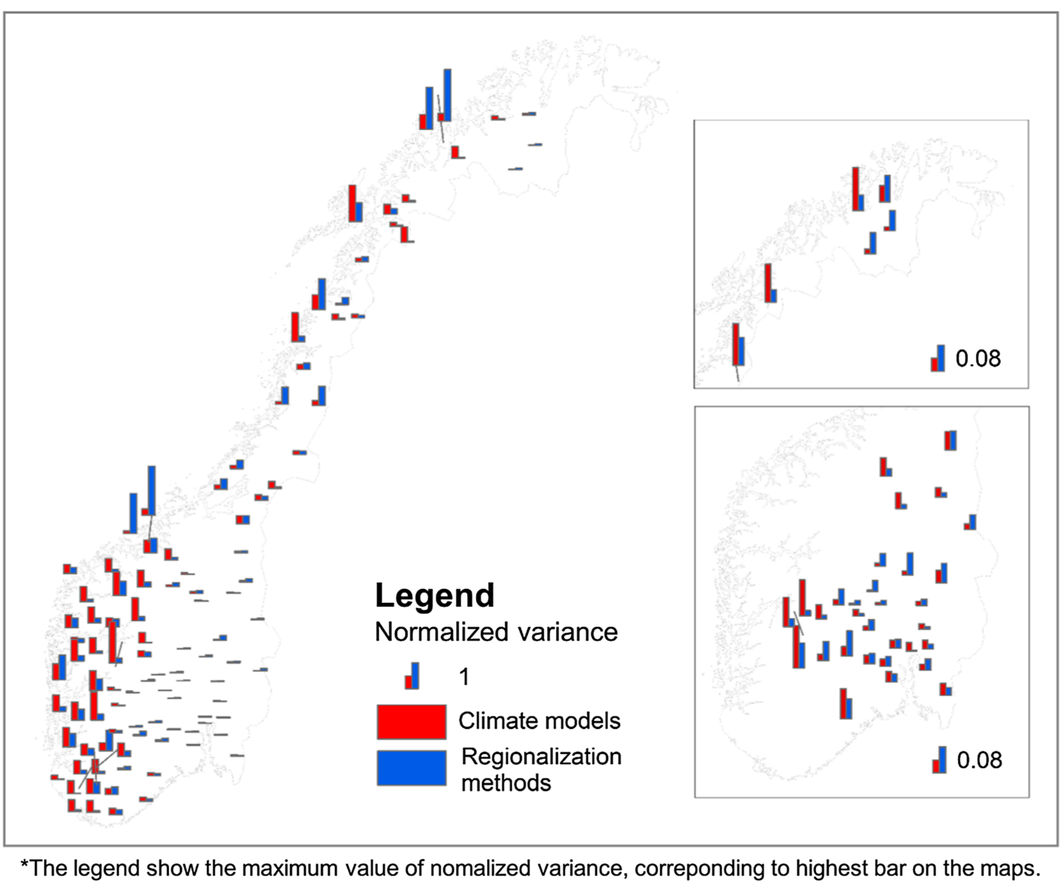

Fig. 12. Normalized variances from climate models and regionalization methods for the future (2071–2100) period over the 108 study catchments to the yearly runoff predictions. The bar height is proportional to the normalized variances ranging from 0 to 1 for the country-wide map, whereas it ranges from 0 to 0.08 for the two inset maps.

between the two periods (Fig. 8). According to this result, we can deduce that for catchments where the regionalization method overestimates runoff for the past period will likely also overestimate runoff for the future period. This has important implication for the choice of regionalization method when aiming for accurate predictions of average future runoff. Moreover, the difference between the runoff simulations obtained by all regionalization methods appears to increase from the past to the future period. Thus, for predicting runoff for the future period it is very important to select the methods with lowest uncertainty. Our results are similar to simulations using different hydrological models for gauged basins. Those simulations also tend to be more similar for the past historical period than the future projection period (e.g. Jiang et al., 2007).

Each regionalization method performs differently under changed climate conditions. Using our ranking index, we find that the physical similarity methods perform better than the spatial proximity methods for both periods (see Table 6). Here, the spatial proximity methods performs worse than in other studies (e.g. Oudin et al., 2008), which may partly be explained by the fact that our network of available donor catchments has a lower density than in previous studies. The density of donor catchments is considered as an important factor to impact the efficiency of spatial proximity methods (Lebecherel et al., 2016). For the future period, all regionalization methods that utilize catchment descriptors showed a better match with the reference simulation than the spatial proximity methods, which only consider distance information. From the past to future period, the Phy-par approach shows the smallest decrease of the ranking index, followed by regression and SP-par methods, and the largest drops are for SP-out and Phy-out methods. This result indicates that transferring model parameters as a whole set (output option) is most sensitive to changes in climate, and therefore less robust than the remaining methods evaluated.

5.3. Contribution of uncertainty from climate models and regionalization methods

As mentioned in many studies, future predictions include uncertainty (e.g. Beven et al., 2010; Koutsoyiannis et al., 2007). In this study, we quantified the contribution of uncertainty from climate models, regionalization methods and their interaction for predictions of runoff. Our analysis, based on data from 108 catchments, shows that overall the climate models contribute more to the total uncertainty than the regionalization methods. This result is, to some extent, supported by earlier studies, which have shown that the uncertainty stemming from climate models is larger than from the downscaling methods and/or hydrological models (e.g. Addor et al., 2014; Chen et al., 2011; Etter et al., 2017; Osuch et al., 2016; Sunyer et al., 2015). The interaction influence is considerably smaller and can almost be neglected, which indicates that climate models and regionalization methods work almost independently from each other for runoff predictions. While, as our result is based on 108 catchments, the result shows large variability between the catchments. The climate models contribute most to the total uncertainty in coastal areas whereas the regionalization methods dominate the uncertainty in some inland regions. The catchments where the uncertainty is dominated by climate models show higher precipitation amounts and variability than for the regions where the regionalization methods dominate the uncertainty. Furthermore, the variance map shows that the uncertainty due to climate models shrinks considerably from the coast to inland, whereas the variance by regionalization methods changes within a relatively narrow range for all catchments. Thus, the regionalization methods dominate the total uncertainty in the inland regions because the climate models contribute considerably less to the uncertainty there than in the coastal regions. In summary, contribution of climate models to future prediction uncertainty is related to the precipitation amount and its variability. In addition, for regions with less precipitation or lower precipitation variability, the uncertainty from regionalization methods cannot be neglected and can even be the dominant factor.

6. Conclusions

In this study, we evaluated the transferability of five regionalization methods for climate change studies using five different climate models. The regionalization methods were tested against a reference simulation using locally calibrated parameters. We also analysed whether the regionalization methods or the climate models dominated the total uncertainty in the predictions. The study was performed using data from 108 catchments in Norway, a seasonally snow-covered region with mountainous terrain. The main conclusions from the study are summarized in the following points:

- The match between simulations from all regionalization methods and the reference declined from the past to the future period. While, the performance in the future is positively correlated to the performance in the past period.
- From past to future period, the physical similarity method with the parameters averaged from the donor catchments (Phy-par) performs best, whereas the distance-based methods with output averaging option (SP-out and Phy-out), are more sensitive to climate change impact. The difference between the regionalised simulations tends to increase in the future compared to the past period.
- For the runoff predictions of the future period, the main source of uncertainty depends on catchment attributes. The climate models appear to contribute most to the total uncertainty for basins with high amounts and variability in precipitation, whereas the regionalization methods tend to dominate the uncertainty in catchments with lower amounts and variability in precipitation.

7. Declarations of interest

None.

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References

Addor, N., Rössler, O., Köplin, N., Huss, M., Weingartner, R., Seibert, J., 2014. Robust changes and sources of uncertainty in the projected hydrological regimes of Swiss catchments. Water Resour. Res. 50, 7541–7562.
Arora, V.K., 2014. The use of the aridity index to assess climate change effect on annual runoff. J. Hydrol. 265, 164–177.
Beven, K., Leedal, D., Alcock, R., 2010. Uncertainty and good practice in hydrological prediction sources of uncertainty in hydrological prediction. Vatten 66, 159–163.
Blöschl, G., Sivapalan, M., 1995. Scale issues in hydrological modelling: a review. Hydrol. Process. 9, 251–290.
Bull, W.B., 2009. Tectonically Active Landscapes. Wiley-Blackwell, Chichester, pp. 326.
Brugan, H.I., Aksoy, H., 2018. Annual flow duration curve model for ungauged basins. Hydrol. Res.
Budyko, M.I., 1974. Climate and Life. Academic Press, Orlando, FL, pp. 508.
Broderick, C., Matthews, T., Wilby, R.L., Bastola, S., Murphy, C., 2016. Transferability of hydrological models and ensemble averaging methods between contrasting climatic periods. Water Resour. Res. 52, 8343–8373.
Chen, J., Brissette, P., Poulin, A., Leconte, R., 2011. Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed. Water Resour. Res. 47, 1–16.
Chiew, F.H.S., Teng, J., Vaze, J., Post, D.A., Perraud, J.M., Kirono, D.G.C., Viney, N.R., 2009. Estimating climate change impact on runoff across southeast Australia : method, results, and implications of the modeling method. Water Resour. Res. 45, 1–17.

Coron, L., Andre, V., Perrin, C., Lerat, J., Vaze, J., Bourqui, M., Hendrickx, F., 2012. Crash testing hydrological models in contrasted climate conditions : an experiment on 216 Australian catchments. Water Resour. Res. 48, 1–17.
Déqué, M., Rowell, D.P., Lüthi, D., Giorgi, F., Christensen, J.H., Rockel, B., Jacob, D., Kjellström, E., De Castro, M., Van Den Hurk, B., 2007. An intercomparison of regional climate simulations for Europe : assessing uncertainties in model projections. Clim. Change 50, 53–70.
Déqué, M., Somot, S., Goodess, C.M., Jacob, D., Lenderink, G., Christensen, O.B., 2012. The spread amongst ENSEMBLES regional scenarios : regional climate models, driving general circulation models and interannual variability. Clim. Dyn. 38 (5–6), 951–964.
Etter, S., Addor, N., Huss, M., Finger, D., 2017. Climate change impacts on future snow, ice and rain runoff in a Swiss mountain catchment using multi-dataset calibration. J. Hydrol. Reg. Stud. 13, 222–239.
Gleick, P.H., 1986. Methods for evaluating the regional hydrologic impacts of global climatic changes. J. Hydrol. 88, 97–116.
Guo, Y.X., Fang, G.H., Wen, X., Lei, X.H., Yuan, Y., Fu, X.Y., 2018. Hydrological responses and adaptive potential of cascaded reservoirs under climate change in Yuan River Basin. Hydrol. Res nh2018165.
Hanssen-Bauer, I., Førland, E.J., Haddeland I., Hisdal H., Mayer S., Nesje A., Nilsen J.E.Ø., Sandven S., Sandø A.B., Sorteberg A., Ådlandsvik B., 2017. Climate in Norway 2100 – A Knowledge Base for Climate Adaptation.
He, Y., Bárdossy, A., Zehe, E., 2011. A review of regionalization for continuous streamflow simulation. Hydrol. Earth Syst. Sci. 15, 3539–3553.
He, S.K., Guo, S.L., Liu, Z.J., Yin, J.B., Chen, K.B., Wu, X.S., 2018. Uncertainty analysis of hydrological multi-model ensembles based on CBP-BMA method. Hydrol. Res. https://doi.org/10.2166/nh.2018.160.
Hewitson, B., Daron, J., Crane, R., Zermoglio, M., Jack, C., 2014. Interrogating empirical-statistical downscaling. Clim. Change 122, 539–554.
Hrachowitz, M., Savenije, H.H.G., Blöschl, G., McDonnell, J.J., Sivapalan, M., Pomeroy, J.W., Arheimer, B., Blume, T., Clark, M.P., Ehret, U., Fenicia, F., Freer, J.E., Gelfan, A., Gupta, H.V., Hughes, D.A., Hut, R.W., Montanari, A., Pande, S., Tetzlaff, D., Troch, P.A., Uhlenbrook, S., Wagener, T., Winsemius, H.C., Woods, R.A., Zehe, E., Cudennec, C., 2013. A decade of Predictions in Ungauged Basins (PUB)—a review. Hydrol. Sci. J. 58 (6), 1198–1255.
IPCC, 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In: Core Writing Team, R.K. Pachauri and L.A. Meyer (Eds.). IPCC, Geneva, Switzerland, 151 pp.
Jansson, A, Tveito, O E, Pirinen, P, Scharling, M., 2007. NORDGRID – A Preliminary Investigation on the Potential for Creation of a Joint Nordic Gridded Climate Dataset. met.no Report 03/2007 Climate.
Jiang, T., Chen, Y.D., Xu, C.-Y., Chen, X., Chen, X., Singh, V.P., 2007. Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China. J. Hydrol. 336, 316–333.
Kleeberg, A., 1992. Untersuchungen zur Phosphorfreisetzung und der Phosphorverteilung in Sedimenten der Oberwarnow. Dissertation, Universität Rostock, Fachbereich Biologie.
Klemeš, V., 1986. Operational testing of hydrological simulation models. Hydrol. Sci. J. 31 (1), 13–24.
Koutsoyiannis, D., Efstratiadis, A., Georgakakos, K.P., 2007. Uncertainty assessment of future hydroclimatic predictions : a comparison of probabilistic and scenario-based approaches. J. Hydrometeorol. 8, 261–281.
Kupiainen, M., Jansson, C., Samuelsson, P., Jones, C., Willén, U., Hansson, U., Ullerstig, A., Wang, S., Döscher, R., 2014. Rossby Centre REGIONAL Atmospheric model, RCA4. Rossby Center News Letter.
Lagarias, J.C., Reeds, J.A., Wright, M.H., Wright, P.E., 1998. Convergence properties of the Nelder-Mead simplex method in low dimensions. SIAM J. Optim. 9, 112–147.
Lebecherel, L., Andréassian, V., Perrin, C., 2016. On evaluating the robustness of spatial-proximity based regionalization methods. J. Hydrol. 539, 196–203.
Li, C.-Z., Zhang, L., Wang, H., Zhang, Y.-Q., Yu, F.-L., Yan, D.-H., 2012. The transferability of hydrological models under nonstationary climatic conditions. Hydrol. Earth Syst. Sci. 16, 1239–1254.
Li, L., Xia, J., Xu, C.-Y., Chu, J.-J., Wang, R., 2009. Analyse the sources of equifinality in hydrological model using GLUE methodology. Hydroinformatics in hydrology, hydrogeology and water resources. In: Proceedings of Symposium, JS.4, pp. 130–138.
Li, L., Ngongondo, C.S., Xu, C.-Y., Gong, L., 2013. Comparison of the global TRMM and WFD precipitation datasets in driving a large-scale hydrological model in southern Africa. Hydrol. Res. 44, 770.
Li, L., Diallo, I., Xu, C.-Y., Stordal, F., 2015. Hydrological projections under climate change in the near future by RegCM4 in Southern Africa using a large-scale hydrological model. J. Hydrol. 528, 1–16.
Mendoza, P.A., Mizukami, N., Ikeda, K., Clark, M.P., Gutmann, E.D., Arnold, J.R., Brekke, L.D., Rajagopalan, B., 2016. Effects of different regional climate model resolution and forcing scales on projected hydrologic changes. J. Hydrol. 541, 1003–1019.
Meresa, H.K., Romanowicz, R.J., 2017. The critical role of uncertainty in projections of hydrological extremes. Hydrol. Earth Syst. Sci. 21, 4245–4258.
Merz, R., Blöschl, G., 2004. Regionalization of catchment model parameters. J. Hydrol. 287, 95–123.
Mohr, M., 2009. Comparison of Version 1.1 and 1.0 of Gridded Temperature and Precipitation Data for Norway. met.no Note19/2009*.
Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.
Muller-Wohlfeil, D.-L., Xu, C.-Y., Iversen, H.L., 2003. Estimation of monthly river discharge from danish catchments. Nordic Hydrol. 34 (4), 295–320.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I—a discussion of principles. J. Hydrol. 10 (3), 282–290.
Niemann, J.D., Eltahir, E.A.B., 2005. Sensitivity of regional hydrology to climate changes, with application to the Illinois River basin. Water Resour. Res. 41, 1–15.
Osuch, M., Lawrence, D., Meresa, H.K., Napiorkowski, J.J., 2016. Projected changes in flood indices in selected catchments in Poland in the 21st century. Stoch. Environ. Res. Risk Assess. 31 (9), 2435–2457.
Oudin, L., Kay, A., Andráassian, V., Perrin, C., 2010. Are seemingly physically similar catchments truly hydrologically similar? Water Resour. Res. 46, 1–15.
Oudin, L., Andréassian, V., Perrin, C., Michel, C., Le Moine, N., 2008. Spatial proximity, physical similarity, regression and ungaged catchments: a comparison of regionalization approaches based on 913 French catchments. Water Resour. Res. 44 (3), 1–15.
Parajka, J., Blöschl, G., Merz, R., 2007. Regional calibration of catchment models: potential for ungauged catchments. Water Resour. Res. 43, W06406.
Parajka, J., Merz, R., Blöschl, G., 2005. A comparison of regionalization methods for catchment model parameters. Hydrol. Earth Syst. Sci. Discuss. 2, 509–542.
Parajka, J., Viglione, A., Rogger, M., Salinas, J.L., Sivapalan, M., Blöschl, G., 2013. Comparative assessment of predictions in ungauged basins-Part 1: runoff-hydrograph studies. Hydrol. Earth Syst. Sci. 17, 1783–1795.
Petheram, C., Rustomji, P., McVicar, T.R., Cai, W.J., Chiew, F.H.S., Vleeshouwer, J., Van Niel, T.G., Li, L.T., Cresswell, R.G., Donohue, R.J., Teng, J., Perraud, J.M., 2012. Estimating the impact of projected climate change on runoff across the tropical savannas and semiarid rangelands of northern Australia. J. Hydrometeorol. 13 (2), 483–503.
Petroselli, A., Vojtek, M., Vojteková, J., 2018. Flood mapping in small ungauged basins: a comparison of different approaches for two case studies in Slovakia. Hydrol. Res. https://doi.org/10.2166/nh.2018.040. in press.
Razavi, T., Coulibaly, P., 2013. Streamflow prediction in ungauged basins: review of regionalization methods. J. Hydrol. Eng. 18, 958–975.
Reichl, J.P.C., Western, A.W., McIntyre, N.R., Chiew, F.H.S., 2009. Optimization of a similarity measure for estimating ungauged streamflow. Water Resour. Res. 45, 1–15.
Ross, W., 2003. The relative roles of climate, soil, vegetation and topography in determining seasonal and long-term catchment dynamics. Adv. Water Resour. 30, 1061.
Salinas, J.L., Laaha, G., Rogger, M., Parajka, J., Viglione, A., Sivapalan, M., Blöschl, G., 2013. Comparative assessment of predictions in ungauged basins-Part 2: flood and low flow studies. Hydrol. Earth Syst. Sci. 17, 2637–2652.
Samuel, J., Coulibaly, P., Metcalfe, R.A., 2011. Estimation of continuous streamflow in Ontario Ungauged basins: comparison of regionalization methods. J. Hydrol. Eng. 16, 447–459.
Schoups, G., van de Giesen, N.C., Savenije, H.H.G., 2008. Model complexity control for hydrologic prediction. Water Resour. Res. 44, W00B03.
Seibert, J., 1999. Regionalization of parameters for a conceptual rainfall-runoff model. Agric. For. Meteorol. 98–99, 279–293.
Seneviratne, S.I., Nicholls, N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., Zhang, X., 2012. Changes in climate extremes and their impacts on the natural physical environment. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 109–230.
Sivapalan, M., Takeuchi, K., Franks, S.W., Gupta, V.K., Karambiri, H., Lakshmi, V., Liang, X., McDonnell, J.J., Mendiondo, E.M., O'Connell, P.E., Oki, T., Pomeroy, J.W., Schertzer, D., Uhlenbrook, S., Zehe, E., 2003. IAHS decade on Predictions in Ungauged Basins (PUB), 2003–2012: shaping an exciting future for the hydrological sciences. Hydrol. Sci. J. 48 (6), 857–880.
Sunyer, M.A., Hundecha, Y., Lawrence, D., Madsen, H., Willems, P., Martinkova, M., Vormoor, K., Bürger, G., 2015. Inter-comparison of statistical downscaling methods for projection of extreme precipitation in Europe. Hydrol. Earth Syst. Sci. 19, 1827–1847.
Teutschbein, C., Seibert, J., 2010. Regional climate models for hydrological impact studies at the catchment scale: a review of recent modeling strategies. Geogr. Comp. 4, 834–860.
Teutschbein, C., Seibert, J., 2013. Is bias correction of regional climate model (RCM) simulations possible for nonstationary conditions? Hydrol. Earth Syst. Sci. 17, 5061–5077.
Tveito, O.E., Bjørdal, I., Skjelvåg, A.O., Aune, B., 2005. A GIS-based agro-ecological decision system based on gridded climatology. Meteorol Appl. 12 (1), 57–68.
Vaze, J., Post, D.A., Chiew, F.H.S., Perraud, J., Viney, N.R., Teng, J., 2010. Climate non-stationarity – Validity of calibrated rainfall – runoff models for use in climate change studies. J. hydrol. 394, 447–457.
Viglione, A., Parajka, J., Rogger, M., Salinas, J.L., Laaha, G., Sivapalan, M., Blöschl, G., 2013. Comparative assessment of predictions in ungauged basins – Part 3: runoff signatures in Austria. Hydrol. Earth Syst. Sci. 17, 2263–2279.
Viney, N.R., Perraud, J., Vaze, J., Chiew, F.H.S., Post, D.A., Yang, A., 2009. The usefulness of bias constraints in model calibration for regionalization to ungauged catchments. In: Proc.18th World IMACS/MODSIM Congress. International Environmental Modelling and Software Society, Cairns, Australia, pp. 3421–3427.
Vormoor, K., Lawrence, D., Schlichting, L., Wilson, D., Kwok, W., 2016. Evidence for changes in the magnitude and frequency of observed rainfall vs snowmelt driven floods in Norway. J. Hydrol. 538, 33–48.
Wagener, T., Sivapalan, M., Troch, P., Woods, R., 2007. Catchment classification and hydrologic similarity. Geogr. Compass 1, 1–31.
Wang, L., van Meerveld, H.J., Seibert, J., 2017. When should stream water be sampled to be most informative for event-based, multi-criteria model calibration? Hydrol. Res.

48 (6), 1566–1584.
Widén-Nilsson, E., Halldin, S., Xu, C.-Y., 2007. Global water-balance modelling with WASMOD-M: parameter estimation and regionalization. J. Hydrol. 340, 105–118.
Wine, M.L., Cadol, D., Makhnin, O., 2018. In ecoregions across western USA streamflow increases during post-wildfire recovery. Eviron. Res. Lett. 13 (1), 14.
Winkler, J.A., 2016. Embracing complexity and uncertainty. Ann. Am. Assoc. Geograph. 106 (6), 1418–1433.
Xu, C.-Y., Seibert, J., Halldin, S., 1996. Regional water balance modelling in the NOPEX area: development and application of monthly water balance models. J. Hydrol. 180, 211–236.
Xu, C.-Y., Halldin, S., 1997. The effect of climate change on river flow and snow cover in the NOPEX area simulated by a simple water balance model. Nordic Hydrol. 28 (4/5), 273–282.
Xu, C.-Y., 1999a. From GCMs to river flow: a review of downscaling techniques and hydrologic modeling approaches. Prog. Phys. Geog. 23 (2), 229–249.
Xu, C.Y., 1999b. Estimation of parameters of a conceptual water balance model for ungauged catchments. Water Resour. Manage. 13, 353–368.
Xu, C.-Y., 1999c. Operational testing of a water balance model for predicting climate change impacts. Agr. Forest Meteorol. 99, 295–304.
Xu, C.-Y., 2001. Statistical analysis of a conceptual water balance model, methodology and case study. Water Resour. Manage. 15, 75–92.
Xu, C.-Y., 2002. The water and snow balance modeling system. In: Singh, V.J., Frevert, D.K. (Eds.), Mathematical Models of Small Watershed Hydrology and Applications. Water Resources Publications LLC, Highlands Ranch, CO, US, pp. 555–590 (Chapter 17).
Xu, C.-Y., Singh, V.P., 2002. Cross-comparison of mass-transfer, radiation and temperature based evaporation models. Water Resour. Manage. 16, 197–219.
Xu, C.-Y., 2003. Testing the transferability of regression equations derived from small subcatchments to a large area in central Sweden. Hydrol. Earth Syst. Sci. 7, 317–324.
Xu, C.-Y., Widén, E., Halldin, S., 2005. Modelling hydrological consequences of climate change – progress and challenges. Adv. Atmos. Sci. 22 (6), 789–797.
Yang, X., Magnusson, J., Rizzi, J., Xu, C.-Y., 2018a. Runoff prediction in ungauged catchments in Norway: comparison of regionalization approaches. Hydrol. Res. 49 (2), 487–505.
Yang, P., Xia, J., Zhan, C.S., Chen, X.J., Qiao, Y.F., Chen, J., 2018b. Separating the impacts of climate change and human activities on actual evapotranspiration in Aksu River Basin ecosystems. Northwest China. Hydrol. Res. https://doi.org/10.2166/nh.2018.136.
Young, A.R., 2006. Stream flow simulation within UK ungauged catchments using a daily rainfall-runoff model. J. Hydrol. 320, 155–172.
Zheng, H., Zhang, L., Zhu, R., Liu, C., Sato, Y., Fukushima, Y., 2009. Responses of streamflow to climate and land surface change in the headwaters of the Yellow River Basin. Water Resour. Res. 45, 1–9.