Runoff prediction in ungauged catchments in Norway: comparison of regionalization approaches

Xue Yang, Jan Magnusson, Jonathan Rizzi and Chong-Yu Xu

ABSTRACT

Runoff prediction in ungauged catchments has been a challenging topic over recent decades. Much research have been conducted including the intensive studies of the PUB (Prediction in Ungauged Basins) Decade of the International Association for Hydrological Science. Great progress has been made in the field of regionalization study of hydrological models; however, there is no clear conclusion yet about the applicability of various methods in different regions and for different models. This study made a comprehensive assessment of the strengths and limitations of existing regionalization methods in predicting ungauged stream flows in the high latitudes, large climate and geographically diverse, seasonally snow-covered mountainous catchments of Norway. The regionalization methods were evaluated using the water balance model – WASMOD (Water And Snow balance MODeling system) on 118 independent catchments in Norway, and the results show that: (1) distance-based similarity approaches (spatial proximity, physical similarity) performed better than regression-based approaches; (2) one of the combination approaches (combining spatial proximity and physical similarity methods) could slightly improve the simulation; and (3) classifying the catchments into homogeneous groups did not improve the simulations in ungauged catchments in our study region. This study contributes to the theoretical understanding and development of regionalization methods.

Key words | Norway, regionalization comparison, runoff prediction, ungauged catchments

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INTRODUCTION

Runoff prediction plays an important role in engineering design and water resources management (Parajka *et al.* 2013). For regions with availability of stream flow data, runoff is commonly predicted using a hydrological model calibrated using observed input and stream flow data. However, hydrological models cannot directly work in regions where observed runoff data are unavailable for model calibration (Oudin *et al.* 2008; He *et al.* 2011). Since many catchments lack discharge measurements, the International Association of Hydrological Sciences (IAHS) established a 'Decade on Predictions in Ungauged Basins (PUB): 2003–2012' with the goal of improving hydrological PUB (Sivapalan *et al.* 2003). During that period, a wide range of methods

were developed to predict discharge in catchments lacking observations (e.g. Xu 2003; Merz & Blöschl 2004; Young 2006; Parajka *et al.* 2007). Achievements of the PUB Decade and remaining challenges in the field of runoff PUB were reported in the review paper by Hrachowitz *et al.* (2013).

Even though the concept of PUB was formally introduced in 2003, many researchers started much earlier on developing and testing methods for PUB (Jarboe & Haan 1974; Jones 1976; Magette *et al.* 1976; Hughes 1989; Servat & Dezetter 1993; Xu 1999a). A key step in hydrological regionalization is transferring the parameter values of a hydrological model determined from gauged 'donor'

catchments to a target ungauged catchment lacking measurements.

Regionalization methods can be divided into distance-based (spatial proximity, physical similarity) and regression-based approaches, according to He *et al.* (2011). At the same time, Kriging is a geostatistical interpolation method and has been applied in many regionalization studies (e.g. Vandewiele & Elias 1995; Samuel *et al.* 2011; Ssegane *et al.* 2012). Egbuniwe & Todd (1976) used the spatial proximity method, which relies on the assumption that neighboring catchments behave similarly. By applying this method, the model parameter set of the target catchment is retrieved from the nearest gauged catchment. Furthermore, the method was extended by interpolating the parameter values using, for example, Inverse Distance Weighting (IDW) or Kriging (e.g. Merz & Blöschl 2004; Parajka *et al.* 2005). One of the most popular regionalization methods is the regression technique (Xu 1999a; Young 2006; Oudin *et al.* 2008). In this method, regression is used for establishing a relationship between calibrated model parameter values and the so-called catchment descriptors (e.g. soil properties or land-use characteristics, etc.). Regression relationships are then used for estimating the parameters of the hydrological model for the target catchment (e.g. Sefton & Howarth 1998; Kokkonen *et al.* 2003; Xu 2003). Another important method is the physical similarity method, which assumes that catchments with similar physical characteristics have the same hydrological response. In this method, the parameter set from the most physically similar donor catchment or catchments is transferred to the target catchment using the so-called similarity indices (e.g. Kokkonen *et al.* 2003; McIntyre *et al.* 2005; Merz *et al.* 2006; Parajka *et al.* 2007; Wagener *et al.* 2007; Zhang & Chiew 2009). In recent years, techniques combining the methods presented above have been proposed in order to improve the estimation: for instance, the integrated similarity method proposed by Zhang & Chiew (2009) and the coupled regionalization approach developed by Samuel *et al.* (2011).

Even though the aforementioned methods have been applied and validated in different regions, there is no clear conclusion as to under which conditions the different methods are applicable (e.g. Parajka *et al.* 2005; Oudin *et al.* 2008; Reichl *et al.* 2009; He *et al.* 2011; Samuel *et al.* 2011; Razavi & Coulibaly 2013; Salinas *et al.* 2013; Viglione *et al.* 2013). The lack of consistent conclusion is due to several different aspects. Firstly, the concept and structure of hydrological models, which are selected subjectively by authors based on their study area and study objective, are different; secondly, there is significant diversity and heterogeneity in the study catchments in terms of geography, climate, geology, land use and topography, etc.; thirdly, there is a lack of knowledge on which physical characteristics of the catchment play a dominant role in determining different model parameters; and finally, the subjective choice of evaluation criteria for donor catchment selection differs and affects the result. Parajka *et al.* (2013) reviewed a large range of studies participating in the PUB project showing, by statistical results, that regionalization methods perform better in humid regions than arid regions. This result was obtained based on 75 assessments in different climate regions and the conclusion is also supported by many other studies (e.g. McIntyre *et al.* 2005; Bao *et al.* 2012). Parajka *et al.* (2013) made a second comparison among regionalization methods, showing that spatial and physical similarity methods perform better than the regression method. This conclusion is supported by many comparison studies, such as Merz & Blöschl (2004), who applied the Hydrologiska Byråns Vattenbalansavdelning (HBV) model in Austria and concluded that estimation for ungauged catchments from the spatial neighbors' information is better than Kriging, and regression approaches performed the worst. Another study of Parajka *et al.* (2005), which used the same model in similar catchments in Austria, showed that the physical similarity method produced better results than regression, IDW and other averaging methods, and Kriging gave the best result. However, 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. Bao *et al.* (2012) applied the Akaike Information Criterion (AIC) to a set of 55 catchments distributed in China and compared the performance of physical similarity-based and regression-based regionalization methods. Results indicated that the physical similarity-based methods produced an overall higher accuracy than regression-based methods, especially for arid regions. Using 260 catchments from the UK, Young (2006) concluded that the regression method performed better than the proximity method based on a single physiographically nearest donor catchment.

However, in another study, Kay *et al.* (2007) compared regression and physical similarity methods using 119 catchments in the UK by applying two models (Probability Distributed Model (PDM) and Time–Area Topographic Extension (TATE) model), and found that results are model dependent: the physical similarity method performed better for PDM and the regression method is better for TATE.

Rather than using traditional single regionalization methods, some studies have introduced so-called combination methods and compared them with single methods, showing some improvements in the combination results. For instance, Zhang & Chiew (2009) concluded that the integrated similarity method gave the best simulation followed by physical similarity, while spatial proximity produced the least satisfying simulation for 210 catchments in Austria by using the Xinanjiang model. Similarly, Samuel *et al.* (2011) produced the best simulation by using the coupled regionalization method in Canada with the McMaster University (MAC)-HBV model, compared to a large set of regionalization methods (Kriging, IDW, regression, physical similarity and global mean of model parameters). However, results from Arsenault *et al.* (2015), who compared two kinds of combination methods (the regression-augmented spatial proximity and the regression-augmented similarity methods with the multiple linear regression method) with spatial proximity and physical similarity methods in Canada, did not show any improvement from using combination methods.

Not only is there no consistent conclusion that can be drawn on the preference of regionalization methods, but also there are fewer regionalization studies that have been carried out for catchments at high latitudes and these studies usually used only one regionalization method (e.g. Beldring *et al.* 2003; Seibert & Beven 2009; Samuel *et al.* 2011; Vormoor *et al.* 2011; Hundecha *et al.* 2016). Furthermore, large parts of high latitude regions (e.g. Scandinavia, northern Russia and Canada) lack hydrological observations. The aim of this study is, therefore, to assess whether regionalization methods that are typically used for regions at lower latitudes can give reliable results for watersheds in Norway, which stretch from approximately 58 to 71°N (excluding Svalbard and Jan Mayen), and are characterized by very large precipitation amounts along the west coast (sometimes over 3,000 mm per year), whereas the interior of the country shows much lower precipitation amounts (500 to 1,000 mm per year). In the high mountainous areas of Norway, a large fraction of precipitation falls as snow and many watersheds show a pronounced nival-fluvial runoff regime. Thus, the characteristics of our study region differ greatly from the areas assessed in previously cited inter-comparison studies of hydrological regionalization methods (e.g. Parajka *et al.* 2005, 2013; Merz *et al.* 2006; Oudin *et al.* 2008; Samuel *et al.* 2011). In this study, we evaluated the most widely-used regionalization methods in the literature, including the distance-based similarity regionalization methods (spatial proximity methods, physical similarity methods and combination methods), Kriging and the regression-based approaches. Successively, we evaluated whether these methods give better results if we cluster different regions according to climate. This test was performed because of the strong meteorological gradients over the country and the high range of latitudes.

In order to reduce the influence of equifinality problems and the inter-dependence of model parameters to a minimum, and to provide an objective comparison of the regionalization, we chose a simple water balance model – the WASMOD (Water And Snow balance MODeling system) (Xu 2002). Previous studies have shown that the model parameters are statistically independent and normally distributed (Xu 2001), and the model parameters can be related to catchment physical characteristics in different regions of the world (Xu 1999a, 2003; Müller-Wohlfeil *et al.* 2003; Kizza *et al.* 2013). This paper also serves as the first study that evaluates and compares the most used regionalization methods in a high latitude, seasonally snow-covered mountainous region. The results of the study will not only provide a scientific basis and practical guidelines for water balance mapping in Norway at the special resolution higher than what is possible based only on observation data, but will also contribute to the advancement of knowledge in regionalization studies of high latitude mountainous regions.

MATERIAL AND METHODS

Study area

In this study, a set of 118 independent catchments are selected in Norway, which is located in northern Europe

on the western and northern part of the Scandinavian Peninsula. Norway has a long and rugged coastline, spans 13 degrees of latitude, from approximately 58°N to 71°N (see Figure 1), and covers an area of around 385,000 km² (excluding Svalbard and Jan Mayen). Climate conditions vary greatly within the country (see climate descriptor distributions in Figure 1), from a wet maritime climate along the coast towards drier conditions in the interior. The mean annual temperature ranges from about 7°C in the south to

about −2°C in the inland areas of northern Norway and the high-altitude areas in the central parts of the country. The average annual precipitation is about 1,000 mm with large spatial variations. In particular, the southern parts of Norway display a strong precipitation gradient, from more than 3,000 mm per year in the western parts to around 700 mm per year in the inland regions in the east. As a result, the runoff hydrographs in Norway show quite different spatial patterns. For example, high flows or floods
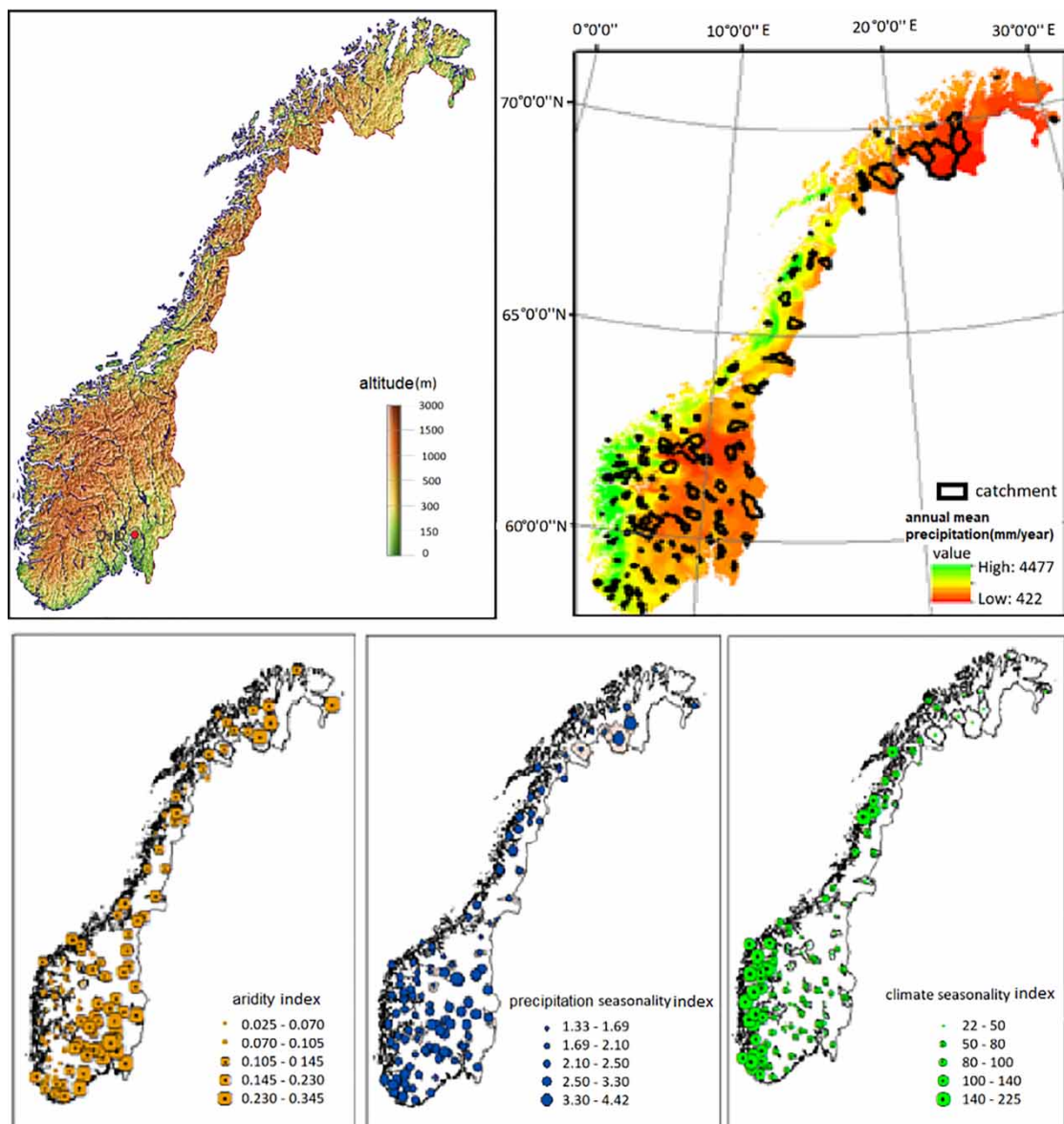
Figure 1 │ Study area and catchments (top panels) and climate descriptors: aridity index (bottom left), precipitation seasonality index (bottom middle) and climate seasonality index (bottom right). See Table 1 for summary statistics and definitions of the indices.

depend on high precipitation that occurs during November and December in western regions, and the time changes to October for southern and south-eastern regions. However, high flow or flood is dominated by snow melting occurring in spring (April-June) for inland regions and during summer (July-August) in mountainous regions.

Data

In this study, we use monthly runoff data spanning the period from September 1997 to August 2014. The size of the catchments varies from approximately 3 to 5,620 km^2, while the majority of the catchments (98 out of 118) are smaller than 500 km^2. The climate data for our rainfall-runoff model (monthly data of mean air temperature and total precipitation) are interpolated grid data with a resolution of 1 km retrieved from the seNorge dataset, produced by the Norwegian Meteorological Institute.

In the study, the catchment descriptors proposed by He et al. (2011) are used. We classify the catchment descriptors according to: (1) climate indices derived from meteorological variables such as precipitation and temperature; (2) terrain characteristics, for example average slope of the catchment, computed from digital elevation models; (3) land use, being the proportion information for five categories; and (4) soil indices, being the fractions of area covered by each soil infiltration capacity class, which are defined by the Geological Survey of Norway (2015). The catchment descriptors used in the study are summarized in Table 1. Generally, for climate indices, precipitation, temperature and aridity indices are applied (Merz & Blöschl 2004; McIntyre et al. 2005). However, in Norway, the precipitation and temperature distributions are not spatially uniform, therefore we added precipitation and temperature seasonality into climate indices as well, using the method proposed by Bull (2009).

Hydrological model

Numerous models have been developed in past decades. Few of these are applicable across scales and in ungauged basins because model structures, and/or model parameters are highly correlated, resulting in parameter-identifiability problems and poor performance in regionalization studies.

Table 1 | Summary of catchment descriptors used in this study

	Mean	Median	Minimum	Maximum
Area (km^2)	333	137	2.84	5,620
Climate indices				
Mean annual precipitation (mm)	1,075	1,695	722	4,477
Precipitation seasonality indices[1]	2.3	2.2	1.3	4.4
Mean annual temperature (°C)	1.9	1.5	−2.4	7.2
Temperature seasonality indices[2]	18.9	18.7	12.5	27.4
Aridity indices[3]	0.14	0.12	0.02	0.35
Climate seasonality indices[4]	74	59	23	225
Terrain characteristics				
Mean slope (°)	11	10	2	26
Elevation range (m)	936	880	171	2,036
Mean elevation (m)	717	690	90	1,471
Mean topographic index (ln(m))	15.1	15	11	19
Land use				
Artificial (%)	0.4	<0.001	0.0	8.0
Agriculture (%)	3.6	0.8	0.0	57.6
Forest (%)	86.0	89.2	34.8	100.0
Wetland (%)	6.6	2.2	0.0	41.6
Waterbody (%)	3.3	2.5	0.0	15.1
Soil infiltration capacity[5]				
Well suited (%)	0.1	<0.001	0.0	7.8
Medium suited (%)	2.0	1.3	0.0	10.4
Little suited (%)	18.8	9.8	0.0	81.4
Unsuitable (%)	27.2	26.1	0.0	90.7
Not classified (%)	42.2	37.4	0.0	98.7

[1]Precipitation seasonality indices: the ratio between the three consecutive wettest and driest months for each watershed.
[2]Temperature seasonality indices: the mean temperature of the hottest month minus the mean temperature of the coldest month in °C.
[3]Aridity indices: the ratio between annual mean precipitation and potential evapotranspiration for each watershed (Budyko 1974; Arora 2002).
[4]Climate seasonality indices: $|\delta_P - \delta_{E_p} R|$, δ_P is half of amplitude of precipitation, δ_{E_p} is half of amplitude of potential evaporation and R is aridity indices (Ross 2003).
[5]Soil infiltration capacity is measured by the 'suitability for infiltration' based on soil types and geology, which is classified as 'Most suited', 'Medium suited', etc. Infiltration rate is a function of water content and soil properties (Elliot 2010).

These considerations justify the use of simple conceptual models, with few parameters that are physically relevant and statistically independent, in regionalization studies. In this study, we use the monthly hydrological model

WASMOD presented by Xu (2002). This model is well suited for hydrological regionalization studies for several reasons. First, it has six parameters in total including the snow module, which is usually sufficient for reliably reproducing discharge in humid regions. Second, the model parameters are typically independent and statistically significant after calibration (Xu 2001). This feature is very important for parameter regionalization, which is negatively influenced by parameter equifinality and interdependences (Seibert 1999; Merz & Blöschl 2004). Third, the different versions of the model have been well-tested and applied in many watersheds in Europe, Asia and Africa and in global water balance studies (e.g., Vandewiele *et al.* 1991, 1992; Xu 1997, 2002; Widén-Nilsson *et al.* 2007; Li *et al.* 2013, 2015). Finally, and more importantly, several publications have reported its transferability in non-stationary climate conditions (Xu 1999b) and in ungauged basins in other regions of the world (e.g. Xu 1999a, 2003; Müller-Wohlfeil *et al.* 2003; Kizza *et al.* 2013).

The principal equations of the model are shown in Table 2. The parameters a_1 and a_2 are two threshold temperature parameters with $a_1 \geq a_2$. Snow melting begins when air temperature is higher than a_2, snowfall stops when air temperature is higher than a_1. Both snowfall and snow melting are allowed to take place when temperature is between a_1 and a_2 due to the lumping of time and space. Parameter a_3 is used to convert long-term average monthly potential evapotranspiration to actual values of monthly potential evapotranspiration. It can be eliminated from the model if potential evapotranspiration data are available or calculated using other methods. Parameter a_4 determines the value of actual evapotranspiration that is an increasing function of potential evapotranspiration and available water. Parameter a_5 controls the proportion of runoff that appears as 'base flow', a_6 is a non-negative parameter related to topography and soil conditions (Xu 2002). Previous studies (e.g. Xu 1999a, 2003) and a preliminary parameter sensitivity analysis performed in this study show that Parameter a_3 is relatively stable and it has been set to 0.005 in this regionalization study. Therefore, we only have five parameters in WASMOD with model parameter ranges given in Table 3.

Model calibration and assessment criteria

The model parameters are calibrated by minimizing the sum of squared errors (*sse*) between simulated and observed discharge:

$$sse = \sum_{i=1}^{n}(Q_{sim.i} - Q_{obs.i})^2 \tag{1}$$

where $Q_{sim.i}$ is the simulated monthly runoff, $Q_{obs.i}$ is the observed data and the sum runs over all n time-steps.

The calibration was performed in two steps. First, we used a Monte Carlo method for finding a global minimum of the objective function. We sampled the parameter values within ranges given in Table 3. Then, we used a local search algorithm (Lagarias *et al.* 1998) to refine the results obtained by the Monte Carlo method.

To evaluate the performance of the model and regionalization methods, we used the square root transformed Nash-Sutcliffe Efficiency (NSE_{sqrt}) as the evaluation

Table 2 | Principal equations of the WASMOD

Snow fall	$s_t = p_t \left\{ 1 - \exp\left[-(c_t - a_1)/(a_1 - a_2)\right]^2 \right\}^+$	(E1)
Rainfall	$r_t = p_t - s_t$	(E2)
Snow storage	$sp_t = sp_{t-1} + s_t - m_t$	(E3)
Snowmelt	$m_t = sp_t \left\{ 1 - \exp\left[(c_t - a_2)/(a_1 - a_2)\right]^2 \right\}^+$	(E4)
Potential evap	$ep_t = (1 + a_3(c_t - c_m))ep_m$	(E5)
Actual evap	$e_t = \min\left[ep_t\left(1 - a_4^{w_t/ep_t}\right), w_t \right]$	(E6)
Slow flow	$b_t = a_5\left(sm_{t-1}^+\right)^2$	(E7)
Fast flow equation	$f_t = a_6\left(sm_{t-1}^+\right)^{0.5}(m_t + n_t)$	(E8)
Total computed runoff	$d_t = b_t + f_t$	(E9)
Water balance equation	$sm_t = sm_{t-1} + r_t + m_t - e_t - d_t$	(E10)

where: $w_t = r_t + sm_{t-1}^+$ is the available water; $sm_{t-1}^+ = \max(sm_{t-1}, 0)$ is the available storage; $n_t = r_t - ep_t(1 - e^{-(r_t/ep_t)})$ is the active rainfall; p_t and c_t are monthly precipitation and air temperature, respectively; ep_m and c_m are long-term monthly average potential evapotranspiration and air temperature, respectively; $a_i = (1, 2, \ldots, 6)$ are model parameters with $a_1 \geq a_2$, $0 \leq a_4 \leq 1$, $a_5 \geq 0$ and $a_6 \geq 0$.

Table 3 | Parameter interval for WASMOD

Parameter	a_1	a_2	a_4	a_5	a_6
Interval	[0 5]	[−5 0]	[0 0.02]	[0 0.001]	[0 1]

criterion. Unlike *NSE*, which gives more weight to peak flow errors, NSE_{sqrt} emphasizes the overall agreement between observed and simulated streamflow (Seiller *et al.* 2012; Peña-Arancibia *et al.* 2015).

$$NSE_{sqrt} = 1 - \frac{\sum_{i=1}^{n} \left(\sqrt{Q_{sim.i}} - \sqrt{Q_{obs.i}} \right)^2}{\sum_{i=1}^{n} \left(\sqrt{Q_{obs.i}} - \overline{\sqrt{Q_{obs.i}}} \right)^2} \qquad (2)$$

$NSE_{sqrt} = 1$ indicates a perfect agreement between simulated and observed discharges, and if $NSE_{sqrt} < 0$ the average observed discharge is a better predictor than the model.

We assessed the model performance by splitting the complete data period into two sub-periods, spanning from September 1997 to August 2006 and from September 2006 to August 2014, respectively. First, we calibrated the model using the runoff data from the first period and evaluated the model results using the data from the second period. Afterwards, we swapped the calibration and evaluation periods and performed the same analysis. For each period, we used the first 36 months as the warm-up for the model since the initial states were unknown.

Description of regionalization methods

For distance-based approaches, the model parameter set is directly transferred from the donor to the target catchment. For regression-based approaches, on the other hand, the regression equation is transferred to target catchment. This equation is estimated by regression methods between the calibrated parameters of the hydrological model (dependent variables) and catchment descriptors (independent variables) in gauged catchments.

The regionalization methods evaluated in this study include: (1) distance-based approaches which include (i) spatial proximity methods based on geographical distance, (ii) physical similarity methods based on catchment characteristics and (iii) combination methods combining spatial proximity and physical similarity methods; (2) Kriging; and (3) regression-based methods.

For distance-based methods, when we choose more than one donor catchment, there are two different approaches to

transfer the model parameter set from donor catchments (Oudin *et al.* 2008):

(a) Parameter option: the model parameters from the donor catchments are first averaged and then used to run the model for the target catchment.
(b) 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. Thus, this method uses the unmodified parameter sets from the gauged catchments for the ungauged one.

Spatial proximity approach

The spatial proximity approach has been frequently used for modeling discharge in ungauged catchments. The method works under the assumption that catchments close to one another show more similar hydrological characteristics than those further apart from each other due to gradual and smooth changes in climate and catchment conditions in space (Merz & Blöschl 2004; Oudin *et al.* 2008).

To find the geographic neighbors, we use the Euclidean distance D_{td} between the donor and target catchments:

$$D_{td} = \sqrt{(x_t - x_d)^2 + (y_t - y_d)^2} \qquad (3)$$

where x_t, x_d and y_t, y_d stand for the target and donor catchment positions under the Universal Transverse Mercator (UTM) coordinate system and D_{td} is the distance between them. The target catchment is denoted by t, and the donor catchment in denoted by d.

We tested the two different approaches for choosing the number of donor catchments. When using one donor catchment, the parameter and output averaging options obviously give the same results for the target catchment. For the case of more than one donor catchment, we combine the model parameters or model output by using either (a) the arithmetic mean or (b) the inverse distance weighted (IDW) method, which is calculated by the following equation:

$$W_{d\_i} = \frac{(1/D_{td\_i})}{\sum_{i=1}^{n} (1/D_{td\_i})} \qquad (4)$$

where D_{td_i} is the distance from the donor catchment i to the target catchment, and n stands for the total number of donor catchments.

Physical similarity approach

Physical similarity methods are based on catchment attributes such as mean elevation, forest cover types and soil types (e.g. Kokkonen *et al.* 2003; Parajka *et al.* 2005; Samuel *et al.* 2011; Samuel *et al.* 2012). These methods are based on the observation that catchments that are far apart from each other may still show similar hydrological behavior (e.g. Pilgrim 1983). For the spatial proximity methods, all donor catchments are selected based only on the spatial distance without any information about catchment attributes (McIntyre *et al.* 2005; Oudin *et al.* 2008). For the physical similarity approach, on the other hand, the donor catchments are selected based on their attributes under the assumption that catchments with similar attributes may behave similarly in terms of hydrological processes (Acreman & Sinclair 1986; Merz *et al.* 2006; Kay *et al.* 2007).

Several similarity indices, computed from catchment attributes, have been used in regionalization studies (e.g. Burn & Boorman 1993; Kay *et al.* 2007; Oudin *et al.* 2008). In this study, we used the similarity index from Burn & Boorman (1993), which is calculated using the following formula:

$$SI_{td} = \sum_{i=1}^{k} \frac{\left| CD_{d,i} - CD_{t,i} \right|}{\Delta CD_i} \tag{5}$$

where CD is the catchment descriptor, d denotes the donor catchment, t denotes the target catchment, k is the total number of catchment descriptors and ΔCD_i is the range of ith catchment descriptor.

For the case of more than one donor catchment, as in the case of the spatial proximity method, we combine the model parameters or model output by using either (a) the arithmetic mean or (b) the inverse similarity weighted (ISW) method (Heng & Suetsugi 2014), which is similar to IDW but uses the physical similarity index instead of the distance between the target and donor catchment:

$$W_{d\_i} = \frac{(1/SI_{td\_i})}{\sum_{i=1}^{n} (1/SI_{td\_i})} \tag{6}$$

where SI_{td_i} is the physical similarity between donor catchment i and the target catchment, and n stands for the total number of donor catchments.

Combination methods

Spatial proximity and physical similarity methods use either information about the spatial location or physical attributes of watersheds. In order to improve the results from those two methods, some studies have combined both approaches (e.g. Zhang & Chiew 2009; Samuel *et al.* 2011). Zhang & Chiew (2009) treated the distance as an additional catchment attribute together with two catchment descriptors. The authors used the rank-accumulated similarity index to select the most similar donor catchment and then applied the output averaging method to predict discharge for the target catchments (Inte-AVE). Samuel *et al.* (2011) proposed a coupling between the spatial proximity (IDW) and physical similarity (Phys-IDW) approaches. In this method, donor catchments are first selected using physical similarity and afterwards the distance between the donor and target catchment is used for combining the model results using the output averaging approach.

In this study, we applied four combination methods. The first two methods (Inte-AVE and Phys-IDW) are the same as described above. Furthermore, we included two additional methods: (1) Spat-ISW approach, in which we first used the spatial distance to select the donor catchments and then used the inverse physical similarity between the donor and target catchments as the weight to transfer information from several donor catchments; and (2) Comb-ISW approach, in which we first used physical similarity indices to select donor catchments and then used the inversed similarity as the weight to transfer information from several donor catchments.

Kriging

In this study, we used ordinary Kriging in comparison with other methods. Ordinary Kriging is based on the theory of regionalized variables (Matheron 1973) and assumes that the process consists of a trend component and a spatially correlated random component (Vormoor *et al.* 2011). The

Kriging estimator is:

$$O_t = \sum_{i=1}^{n} w_i * O_{di} \tag{7}$$

where O_t is runoff in the ungauged target catchment, O_{di} is the model output value from i^{th} gauged donor catchment, and w_i is the interpolation weight estimated by the variogram model at every ungauged site (for more details, see Vormoor *et al.* (2011)). Differently to distance-based similarity methods, we only use Kriging to interpolate the output option for target catchment.

Regression methods

The regression method is one of the most popular regionalization methods (Xu 1999a, 2003; Young 2006; Oudin *et al.* 2008). In this method, functions are established between model parameters and catchment descriptors for the donor catchments. These functions, together with the catchment descriptors of the target catchment, allow for prediction of runoff in ungauged basins. The regression methods assume that: (a) a well-behaved relationship exists between the observable catchment characteristics and model parameters; and (b) the catchment descriptors used in regression provide information relevant to hydrological behavior at ungauged sites (see Merz *et al.* (2006) for further details).

In this study, we used two different regression methods: (a) stepwise regression and (b) principal component analysis (PCA) with multiple regression methods to find functions between catchment descriptors and model parameters. This study assumes that all catchment descriptors shown in Table 1 are related to parameters of WASMOD. For the stepwise regression approach, we applied Bayesian information criterion (BIC) and bidirectional elimination, with a significant improvement of the fit at 0.05 significance level for adding the variable and at 0.1 insignificant deterioration of the model fit for deleting the variable. PCA is a statistical procedure that uses orthogonal transformations to convert a set of observations of possibly correlated variables into a set of linearly uncorrelated variables, called principal components. The number of principal components is less than or equal to the number of original variables. After selecting catchment descriptors, the multiple regression method was applied to estimate the function between model parameters and selected catchment descriptors in gauged donor catchments. These functions were used for estimating parameters in the ungauged locations.

Catchment classification method

Several studies have shown a strong relationship between the homogeneity of the data and the performance of regionalization methods (Blöschl & Sivapalan 1995; Oudin *et al.* 2008). In our study area, the climate conditions vary greatly from wet maritime climate along the coast to drier conditions in the interior. In order to increase the reliability of conclusions and test the preferences of regionalization methods to climate conditions, we used a cluster method to classify the catchments into five groups based on the climate descriptors presented in Table 1.

We classify the catchments in this study using the K-Mean clustering method, which is a non-hierarchical clustering method. For this classification method, the first step is to calculate the centroids for each cluster; then, calculate the distance between points and centroids, which aims to assign the points to the closest cluster. This assignment is dynamic in that all points can change the cluster after being assigned to it, and this process is repeated until all points are assigned to a cluster (Carvalho *et al.* 2016). In our study, we used the ArcGIS grouping analysis (e.g. Assunção *et al.* 2006; Duque *et al.* 2007), which makes use of the K-Means algorithm. Specifically, we did not define the spatial constraints and initial seed locations when using Euclidean distance. The distance calculation includes six factors: mean monthly precipitation, mean monthly temperature and their seasonalities, aridity indices and climate seasonality indices.

Regional model parameter set method

This method uses the catchment classification presented above. Within each group a regional model parameter set was determined by the following steps:

(1) Set an objective function, which is used to select the best performing parameter set for the group. In this study, the objective function is:

$$OBJ = \max\left(\frac{1}{n}\sum_{i=1}^{n}NSE_{sqrt_i}\right) = max(OBJ_i) \qquad (8)$$

where n is the total number of catchments in each group; i^{th} catchment's calibrated model parameter set is applied to other catchments and the simulation result is NSE_{sqrt_i}.

(2) Calculate result of each parameter set OBJ_i.

(3) Select the ith parameter set as the regional (group) model parameter set, which produced the maximum OBJ_i.

This method is different from other regionalization methods as all ungauged catchments will apply the same model parameter set within one group. It is based on catchment classification and applies a regional parameter set for ungauged catchments. This method is denoted in this study as reg-MP for grouped climate regions.

Summary of experiments performed in this study

Regionalization methods tested in our study are summarized in Table 4. They collectively cover a wide range of methods presented in earlier studies (e.g. Parajka *et al.* 2005; Oudin *et al.* 2008; Zhang & Chiew 2009; Samuel *et al.* 2011; Bao *et al.* 2012), as well as new combinations of those methods (see combination methods). The performance of each regionalization approach is assessed using a leave-one-out cross-validation scheme as applied in many other regionalization studies (e.g., Merz & Blöschl 2004; Parajka *et al.* 2005; Laaha & Blo 2006; Leclerc & Ouarda 2007). Furthermore, we also assessed the regionalization methods at two different spatial levels:

- At the countrywide level (hereafter called the global level), we treat each of the 118 catchments as if it was ungauged and the remaining 117 catchments as the pool of donor catchments available for the regionalization methods. These results are denoted as global regionalization methods.

Table 4 │ Summary of regionalization methods used in this study

Regionalization method	Options	Weighting method	Number of donors	Abbreviation
Spatial proximity	Parameter option	Mean IDW	1 and 4	
	Output option	Mean IDW		Spat-1 Spat-AVE Spat-IDW
Physical similarity	Parameter option	Mean ISW	1 and 3	Phys-1
	Output option	Mean ISW		Phys-AVE Phys-ISW
Combination methods	Output option	ISW IDW Mean ISW	3	Spat-ISW Phys-IDW Inte-AVE Comb-ISW
Kriging	Output option		20	Kriging
Regression	Stepwise PCA			Stpws-reg PCA-reg
Regional model parameter*	Parameter option			Regional-par

Regional model parameter*: only used for climate regions comparison.
Spat-1 and Phys-1 stand for one donor catchment.

- At the climate regional level (hereafter called the regional level), the donor catchment pool is reduced from the countrywide selection to different climate regions. We repeat all the regionalization methods applied globally into each regional group. These results are denoted as regional regionalization methods.

RESULTS AND DISCUSSION

Model cross-validation results

The model calibration and validation results for the split-sample test are shown in Figure 2. When tuning the model parameters using runoff data from the second period (2006–2014), the median value of NSE_{sqrt} is equal to 0.86 for the calibration and 0.81 for the validation period; while using the first period (1997–2006) for optimizing the model, the NSE_{sqrt} value decreases to 0.83 for the calibration period and to 0.80 for the
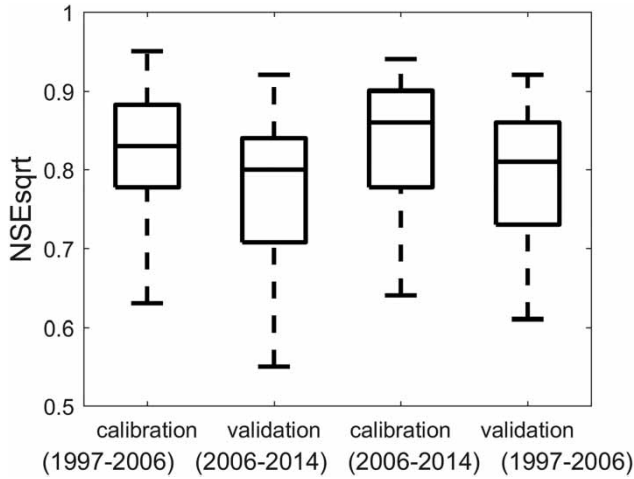
Figure 2 │ WASMOD calibration and validation performance in Norway.

Assessment of regionalization methods at the global level

Relationship between model performance and number of donor catchments

Figure 3 shows the model performance for different number of donor catchments for the spatial proximity and physical similarity methods, both for the parameter and output averaging options. For the spatial proximity method, the model performance increases quickly with the number of donor catchments for the output averaging option. For the parameter averaging option, the performance increases from one to four donor catchments followed by a decrease between four and eight donors. For the physical similarity method, the output averaging option shows the highest performance when using six donor catchments, whereas nine donor catchments produces the best model results for the parameter averaging option. However, the difference in performance for varying the number of donor catchments is small, shifting within a range of 0.02 for the physical similarity method.

In order to compare two options in one method, it is preferable to select the same number of donor catchments. However, since both input data and model structure are affected by uncertainty (e.g. Liu & Gupta 2007; Oudin *et al.* 2008), and considering the balance of performance and uncertainty, we selected four and three donor catchments for spatial and physical similarity methods, respectively.
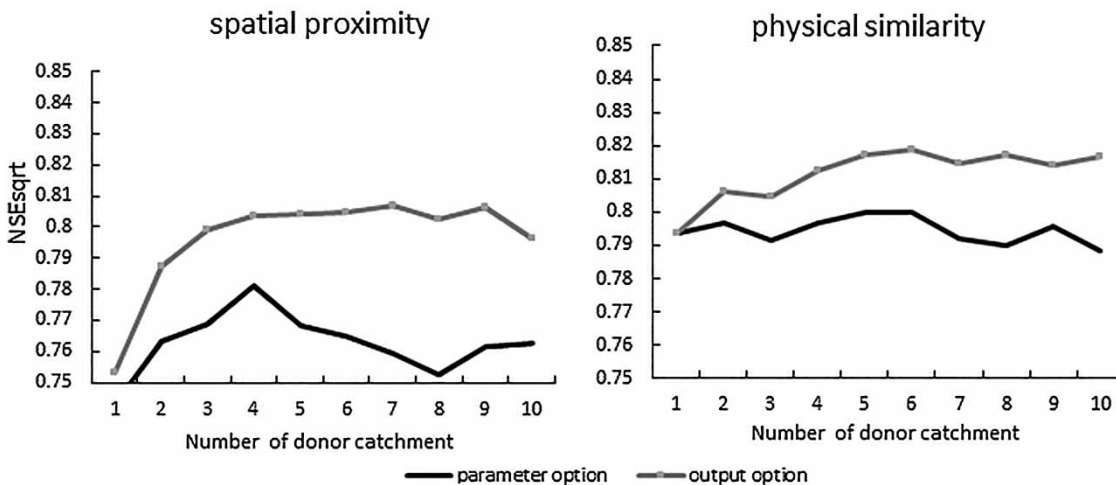
validation period. Overall, the model shows slightly better results when using data from the second instead of the first period for calibration. The reason that the calibration of the second period is better than that of the first period might be because the data quality in the second period is better than in the first period, since more stations are available in interpolating the grid precipitation data in the second period. In the following sections, we use the calibrated model parameters from the second period to test different regionalization methods.

Figure 3 │ Relationship between donor catchment number and performance.

Further, we selected three donor catchments for the combination method (four donor catchments would have affected the performance for physical similarity).

The number of donor catchments in this study is less than the number of donor catchments used by previous studies (Oudin *et al.* 2008; Zhang & Chiew 2009; Bao *et al.* 2012; Arsenault *et al.* 2015) because of a relatively low density of catchments compared with those studies. In addition, the climate conditions and topographic characteristics have variations in different regions within the country, leading to more spatially heterogeneous catchments. This result is consistent with Bao *et al.* (2012), who applied five donor catchments in a big hydro-climatic region with low catchment density.

Comparison of the parameter and output averaging option

The two options used in regionalization methods performed differently (Merz & Blöschl 2004; Oudin *et al.* 2008; Heng & Suetsugi 2014). Figure 4 gives the comparison of parameter and output averaging options using the arithmetic mean and IDW. For both spatial proximity and physical similarity methods, the output option shows better results than the parameter option. The difference in median NSE_{sqrt} value using the arithmetic mean and IDW of model outputs or parameters is small, in particular for the physical similarity method. The most robust results, in terms of minimum NSE_{sqrt} value, are given by output averaging using IDW.

This result is consistent with many previous studies (e.g. Parajka *et al.* 2005; Oudin *et al.* 2008; Zhang & Chiew 2009), which illustrates that the influence of parameters interaction is unavoidable. Hereafter, we will only apply output averaging since this method appears to produce better results than parameter averaging.

The results for all regionalization approaches examined at the global level are shown in Figure 5 and Table 5. For spatial proximity and physical similarity, we choose the optimal results given by the analysis presented above.

For the distance-based similarity methods, the performance increases when going from one to multiple donor catchments, in particular for spatial proximity (the median NSE_{sqrt} value increases from 0.75 to 0.80). This result is consistent with earlier studies showing the benefit of using multiple donor catchments (Samuel *et al.* 2011; Li *et al.* 2014; Arsenault *et al.* 2015), especially for watersheds with low efficiency (comparing the result between one and multiple donor catchments in Table 5). That is because multiple donor catchments can avoid strong errors of simulations by smoothing the response with other sources (Oudin *et al.* 2008).

Different weighting approaches do not greatly affect the performances. According to the median NSE_{sqrt} value, there is no difference between the two weighting approaches in the spatial proximity method and a small rise (0.003) for the ISW approach in physical similarity. This result is different from Zhang *et al.* (2015), whose results show further improved performance by IDW than the simple average
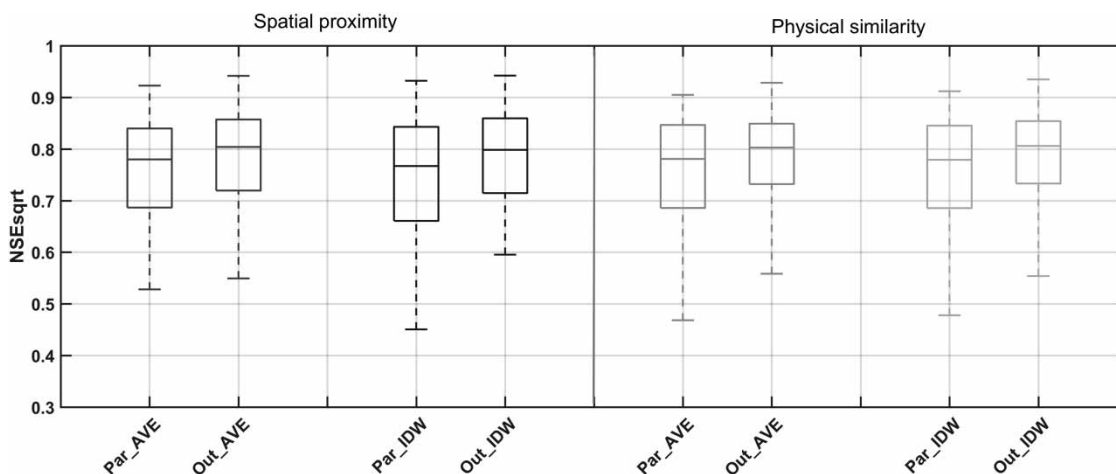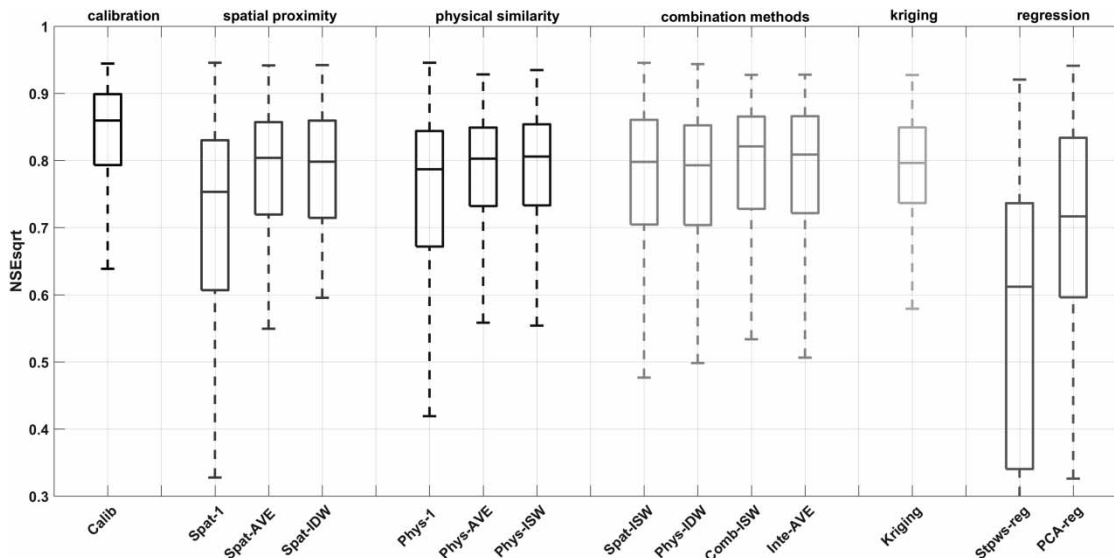

Figure 4 │ Parameter option and output option comparison.

Figure 5 | Performance of regionalization methods at the global level.

Table 5 | Performance of regionalization methods at global level

Method	Median	No.75*	Method	Median	No.75
Calibration	0.860	99	Spat-ISW	0.798	77
Spat-1	0.753	59	Phys-IDW	0.793	73
Spat-AVE	0.804	79	Comb-ISW	0.821	83
Spat-IDW	0.798	77	Inte-AVE	0.809	81
Phys-1	0.787	72	Kriging	0.796	81
Phys-AVE	0.803	81	Stpws-reg	0.612	28
Phys-ISW	0.806	81	PCA-reg	0.717	51

No.75*: The number of catchments when the NSE_{sqrt} is above 0.75.

approach using the spatial proximity method. This difference may be caused by: (a) a small difference in distances between donor and target catchments, which results in a small difference in the weights used in IDW; and (b) the fact that the number of donor catchments is smaller in our study than in the study by Zhang *et al.* (2015). As in the performances of the physical similarity method, the Comb-ISW approach performs better (0.012) than Inte-AVE because of weighting methods. This result is different from the conclusion drawn by Heng & Suetsugi (2014), which may be related to the distance or similarity differences among all the donor catchments. In our case, the distance or similarity difference among donor catchments is relatively small,

which means the weighting fractions are similar among all donor catchments. As a result, there is no obvious difference between the two weighting methods in our study.

For comparison of combination approaches, the Comb-ISW approach performs best, whereas the other three methods show similar performances to spatial proximity and physical similarity methods. This result supports the previous conclusion that the combination approach can improve the classical distance-based similarity methods (e.g. Zhang & Chiew 2009; Samuel *et al.* 2011; Heng & Suetsugi 2014). However, the Phys-IDW approach shows the worst performance in this study, which is opposite to results shown by Zhang & Chiew (2009) and Samuel *et al.* (2011), who concluded that the Phys-IDW approach outperformed other regionalization methods in their studies. This may be because we use a different set of similarity indices and the distances among all donor catchments change a lot. As a result, the weights influenced the result and showed a difference to the arithmetic mean.

The regression methods showed the lowest performance among all methods (Figure 5). For stepwise regression, the median NSE_{sqrt} value is equal to 0.61 and the corresponding value for PCA-regression is equal to 0.72. These performances are similar to those found by Skaugen *et al.* (2015) who predicted runoff in ungauged

catchments in southern Norway by a multiple regression method. In that study, they used a daily step, a parsimonious rainfall-runoff model and built the regression function using data from 84 catchments and tested in 17 independent catchments. Even though the datasets and models are different, the performances are similar. The PCA regression method produces a better result than stepwise regression, likely because the PCA regression method builds a relationship between model parameter values and uncorrelated catchment descriptors.

For the difference in performance between Phys-ISW and Comb-ISW, which is due to the inclusion of geographical distance in the Comb-ISW method, we can conclude that the geographic distance plays a major role in regionalization. This may be one of the reasons why spatial proximity methods perform well in our case.

Summarizing our results at the global level, the best performance is obtained by applying the combination method – the Comb-ISW method – followed by a group of distance-based similarity methods and Kriging, while the regression methods showed the worst performance.

Figure 6 displays, for each catchment, which regionalization method produced the best result. As with the previous results, the spatial and physical similarity methods show better results than the regression approach in most watersheds. The regression method produces better results than the remaining methods for a few catchments mainly located at high elevations in the innermost parts of southern Norway. The spatial proximity method shows the best performance in 53 catchments, whereas the physical similarity method outperforms the other methods in 46 catchments. Catchments where spatial proximity performs best are mainly located in regions where the climate seasonality and precipitation are close to the median for the whole study region (climate seasonality index is on average 70 for this group of catchments and annual mean precipitation is 1,842 mm). Meanwhile, the seasonality index rises to 88 and annual mean precipitation increases to 2,271 mm on average for catchments where physical similarity performed best. On the other hand, regression methods produced the best simulations in catchments with low climate seasonality (55 for mean climate seasonality index) and yearly precipitation (1,630 mm). These catchments are located at the highest mean elevation.
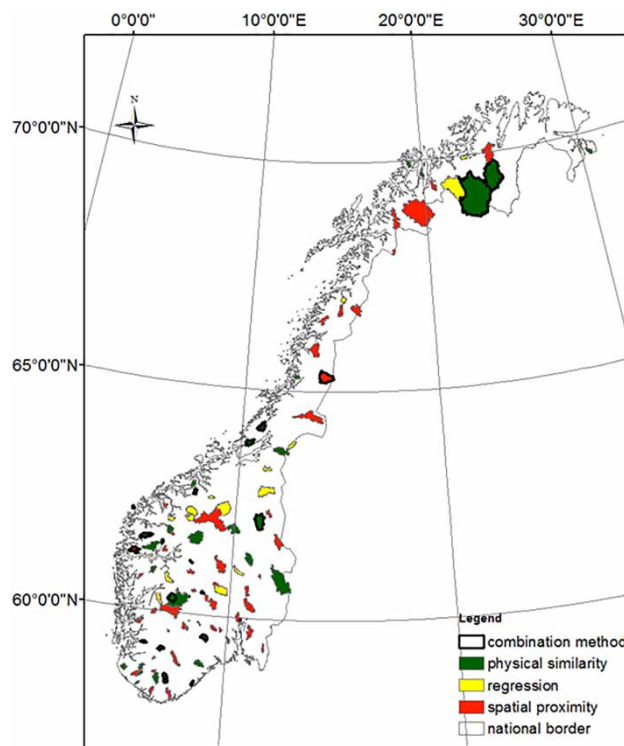

Figure 6 | Spatial distribution of best performing methods. For each catchment, the color indicates which of the three standard regionalization methods (physical similarity, regression, spatial proximity) produced the best results. Catchments where the combination method outperformed the three other methods are highlighted by a thick black border.

Note that even though we can identify the method that performed best for each catchment from Figure 6, the average NSE_{sqrt} difference between spatial proximity and physical similarity methods is just about 0.06. This is possibly related to the low stream gauge network density in our study, as it is not easy to decide which approach is the most appropriate when the stream gauge network density is lower than 60 stations per 100,000 km^2 (Oudin *et al.* 2008).

Catchment classification

Figure 7 displays the result of the catchment classification based on climate indices. The climate of catchments belonging to groups 3 and 4 is characterized by larger precipitation amounts and higher temperatures (see Figure 1 and Table 6). Those watersheds are mainly located in the western parts of southern Norway. Catchments in group 5 are exclusively situated on higher elevations in southern Norway on the
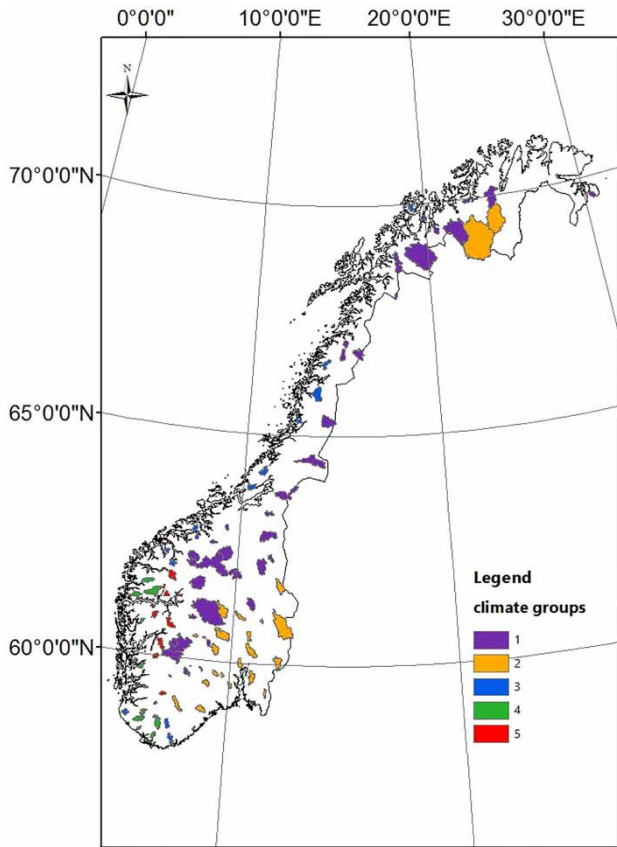
Figure 7 │ Climate regions classification in Norway.

Table 6 │ Climate characteristics for different groups identified in the catchment classification

	Group 1	Group 2	Group 3	Group 4	Group 5
Number of catchments	43	25	20	17	13
Precipitation (mm/month)	109	110	206	291	221
Temperature (°C)	−0.03	2.82	4.18	3.79	0.16
Aridity index	0.13	0.25	0.13	0.08	0.05
Seasonality index	45.3	53	88	146	99
Area (km^2)	453	547	129	127	111
Slope (°)	9.7	6.2	13.7	14	16
Elevation (m)	904	545.2	412	552	1,112
Normalized elevation range*	1.41	1.85	2.08	1.40	0.56

*Normalized elevation range: Difference between maximum and minimum elevation divided by mean elevation.
The numbers indicate the average values for each group.

transition zone where precipitation starts to decline from west to east (see also Figure 1). Those catchments exhibit higher precipitation amounts, whereas temperature is markedly lower than for the watersheds in groups 3 and 4. Catchments in group 1 are located either in the mountainous regions in southern Norway, or at higher latitudes (above 68°N). The climate in those watersheds is dry and cold. Finally, catchments in group 2 are mostly located in the driest and relatively warm south-eastern parts of Norway.

Assessment of regionalization methods using climate regions

Figure 8 shows the NSE_{sqrt} values from calibration and global and regional regionalization results. The calibration results show NSE_{sqrt} values range between 0.76 and 0.89. The highest median value is from group 5, which is 0.01 higher than group 1. The third ranked value is 0.86 for group 4, being 0.04 higher than group 3. Group 2 displays the lowest value.

Overall, selecting donor catchments from regions with a similar climate does not strongly improve the model performance. For the distance-based similarity methods, group 5 produces the biggest difference while the differences within the other four groups are relatively small. In most cases, the regional results do not show better performance than the global results, which means that the geographic factors are as important as climate factors in these kinds of climate regions. For the regression methods, the differences in median NSE_{sqrt} value between the results of global and regional regressions in all groups are within 0.02. The global regression methods build the relationship based on 117 catchments and the regional regression methods use information from catchments within each group to produce the relationship. However, the difference between global and regional result is small, which illustrates that the regression methods are not strongly dependent on number of catchments. For instance, there are only 13 catchments in group 5 and both regional regression methods perform with better results than the global regression methods.

The best performing method differs among the five groups. For group 1 catchments, the regional Spat-AVE approach produces the highest median NSE_{sqrt} value and
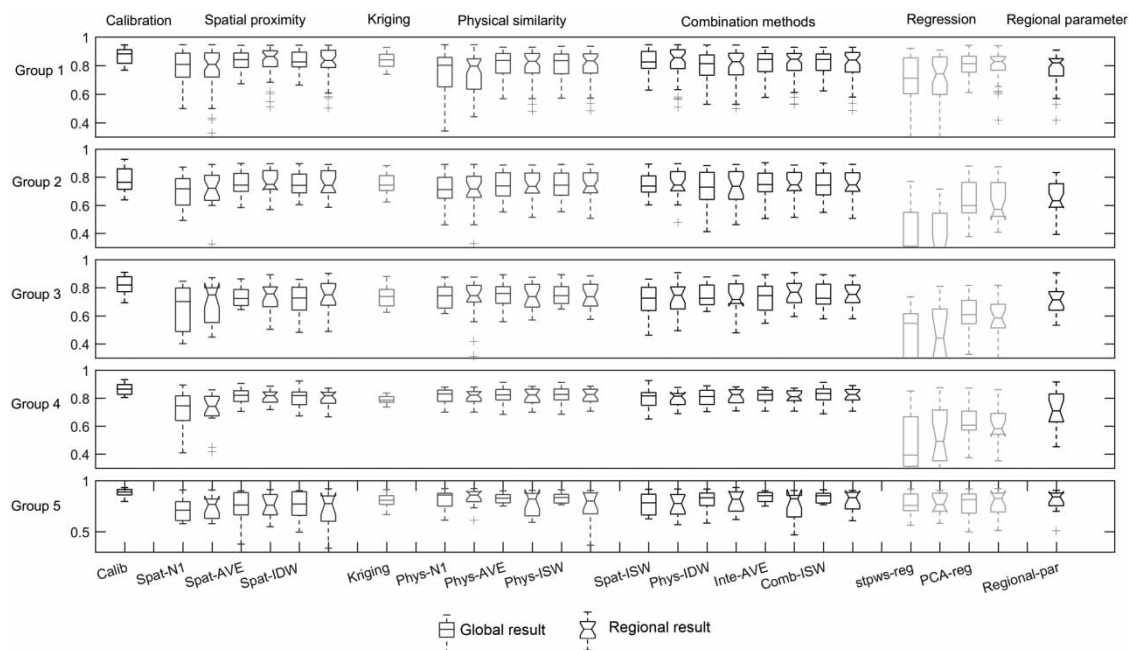
Figure 8 | Comparison of NSEsqrt values for regionalization methods within five different climate regions.

combination approaches are on average better than other methods. For group 2 catchments, the global Phys-AVE approach is the best and physical similarity approaches give similar simulations to combination approaches. The global Inte-AVE approach performs the best in group 3 and most global approaches perform equally as well as regional ones. For group 4 catchments, apart from regression methods, the other methods all perform well and the best performing approach is Comb-ISW. The Kriging method performs robustly well for all groups; the regional model parameter method performs better than regression methods for most groups.

Generally, the distance-based similarity approaches perform much better than regression approaches in all groups. In addition, the PCA regression approach produces acceptable results (median NSE_{sqrt} value is higher than 0.58). Finally, the regional regression can further improve the simulation if the global regression performs well, which means that the linear relationship between model parameter and catchment descriptors is validated. In general, the results of regionalization methods in this study are better than most of the similar studies reported in the literature, confirming the hypothesis set up earlier that simple models with statistically independent parameters are less

affected by equifinality and consequently have a better chance to be successful for hydrological regionalization.

CONCLUSIONS

This study aims at evaluating the performances of regionalization methods in Norway, a region located at high latitude, characterized by a large climate gradient and with seasonally snow-covered mountainous catchments. The comparison was made at two levels: globally, over all catchments in Norway; and regionally, in catchment groups defined according to climate indices.

The study results show that the best regionalization approach in Norway is the combination approach (Comb-ISW), being slightly better than Kriging and other distance-based similarity approaches. The worst approach is stepwise regression.

In this study, only the Comb-ISW approach showed better simulation and the other three combination approaches showed similar performances to classical single approaches. All the distance-based similarity approaches perform well in most humid regions in Norway.

The comparison of regionalization methods on the regional and global levels shows that classifying catchments into homogeneous groups before regionalization does not improve the simulation in Norway, while it is worth testing these conclusions in regions with more catchments and different climate diversity.

ACKNOWLEDGEMENTS

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