Journal of Hydrology 573 (2019) 855–871

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Predicting hourly flows at ungauged small rural catchments using a parsimonious hydrological model

Aynalem T. Tsegaw[a,*], Knut Alfredsen[a], Thomas Skaugen[b], Tone M. Muthanna[a]

[a] Department of Civil and Environmental Engineering, Norwegian University of Science and Technology (NTNU), S.P. Andersensvei 5, N-7491 Trondheim, Norway
[b] Hydrology Department, Norwegian Water Resources and Energy Directorate (NVE), PO Box 5091, Oslo 0301, Norway

ARTICLE INFO

This manuscript was handled by Marco Borga, Editor-in-Chief, with the assistance of Yasuto Tachikawa, Associate Editor

Keywords:
Small ungauged catchments
Prediction of hourly flow
Recession parameters
Regionalizations
Distance distribution dynamics (DDD)
rainfall-runoff model

ABSTRACT

Streamflow data is important for studies of water resources and flood management, but an inherent problem is that many catchments of interest are ungauged. The lack of data is particularly the case for small catchments, where flow data with high temporal resolution is needed. This paper presents an analysis of regionalizing parameters of the Distance Distribution Dynamics (DDD) rainfall-runoff model for predicting hourly flows at small-ungauged rural catchments. The performance of the model with hourly time resolution has been evaluated (calibrated and validated) for 41 small gauged catchments in Norway (areas from 1 km^2–50 km^2). The model parameters needing regionalization have been regionalized using three different methods: multiple regression, physical similarity (single-donor and pooling-group based methods), and a combination of the two methods. Seven independent catchments, which are not used in the evaluation, are used for validation of the regionalization methods. All the three methods (the multiple regression, pooling-group, and combined methods) perform satisfactorily ($0.5 \leq KGE < 0.75$). The combined method (which combines multiple regression and pooling-group) performed slightly better than the other methods. Some model parameters, namely those describing recession characteristics, estimated by the regionalization methods, appear to be a better choice than those estimated locally from short period of hydro-meteorological data for some test catchments. The single-donor method did not perform satisfactorily. The satisfactory performance of the combined method shows that regionalization of DDD model parameters is possible by combining multiple regression and physical similarity methods.

1. Introduction

Streamflow is important information for water resources management applications such as flood risk management, water resources planning, and environmental impact assessment (Parajka et al., 2013; Westerberg et al., 2014). However, most of the catchments that we are interested in are ungauged which makes a method to predict flow in ungauged catchments an important prerequisite (Bloschl et al., 2013; Parajka et al., 2013; Tegegne and Kim, 2018). Reliable estimation of continuous streamflow in ungauged catchments has remained a fundamental challenge in hydrology, although significant insights have been gained in recent years (Steinschneider et al., 2014; Wagener and Wheater, 2006; Wagener et al., 2004). To solve the challenges posed by ungauged catchments, a number of predictive tools have been developed and tested [e.g. data driven models, such as multiple linear regression (MLR), autoregressive moving average (ARMA), and artificial neural networks (ANNs); lumped models (e.g., Hydrologiska Byråns for Vattenbalansavdelning model (HBV)); distributed models (e.g., MIKE-SHE) and statistical regionalization] that allow objective and quantitative decision-making with respect to water resources management, but considerable uncertainties remain (Sivapalan et al., 2003). The International Prediction in Ungauged Basins (PUB) initiative recommends the use of an appropriate model structure for predicting flow in ungauged catchments (Blöschl et al., 2013), and the choice of appropriate model structure helps in reducing predictive uncertainty (Son and Sivapalan, 2007). Flash floods are usually localized disasters that occur in small catchments with response times of a few hours or even less (Borga et al., 2007). The short lead time and small area collectively enhance the difficulty of flood management in such catchments (Miao et al., 2016). In addition, small catchments and short time scales are the most under-observed and problematic in terms of prediction and design, and should be identified as a priority in water resource and flood

* Corresponding author.
E-mail addresses: aynalem.t.tasachew@ntnu.no, aynalemtassachew1982@gmail.com (A.T. Tsegaw), knut.alfredsen@ntnu.no (K. Alfredsen), ths@nve.no (T. Skaugen), tone.muthanna@ntnu.no (T.M. Muthanna).

https://doi.org/10.1016/j.jhydrol.2019.03.090
Received 3 October 2018; Received in revised form 14 March 2019; Accepted 25 March 2019
Available online 29 March 2019

management (Spence et al., 2013).

Water resource management problems are increasingly approached using continuous time rainfall-runoff modelling (Lamb and Kay, 2004; Swain and Patra, 2017), rather than the traditional statistical or event-based models. Simple concept models such as the rational formula and its more sophisticated derivatives are criticized for containing parameters which are difficult to estimate (e.g. the runoff coefficient) or for being founded upon questionable assumptions (e.g. identical return period for precipitation and resulting peak flow) (Viviroli et al., 2009). The advantage of continuous simulation approaches is that the catchment moisture state prior to the flow-producing rainfall event is implicitly incorporated within the modeling framework provided that the model produces reasonable simulations (Pathiraja et al., 2012). Furthermore, getting the right answers for the right reasons is crucial for getting the right answers at all, if conditions shift beyond the range of prior experience (due to extreme precipitation events, climate change, or shifts in land use) (Kirchner, 2006).

Catchment size has an effect in hydrological modelling, and hydrological responses of small catchments are likely to be different from and more variable than those of large catchments (Pilgrim et al., 1982). Small catchments need to be modelled using shorter time steps (Blöschl and Sivapalan, 1995; Bronstert, 2003; Vormoor and Skaugen, 2013; Wetterhall et al., 2011). Until the 1990s, hydrologists had to rely mostly on data with a daily time step, e.g. accumulated rainfall amounts recorded once a day by observers, and this caused limitations to the applicability of rainfall–runoff models for problems (e.g. flooding) needing short time steps (Blöschl and Sivapalan, 1995; Creutin and Obled, 1980). However, over the last two decades, the availability of hourly and even sub-hourly data is increasing in many countries, especially with the implementation of automatic rain gauge networks and rainfall radars (Berne and Krajewski, 2013; Creutin and Borga, 2003).

A rainfall-runoff model is one of the tools used to predict flows in ungauged catchments (Nruthya and Srinivas, 2015). This method requires estimation of the model parameters using regionalization (Zhang et al., 2014). There are different types of rainfall-runoff hydrological models and regionalization methods. One method may work well for one type of model and another method may work well for another model in different regions (Razavi and Coulibaly, 2013) because each model has its own unique characteristics and respective applications (Devi et al., 2015). Conceptual rainfall-runoff models, such as HBV and Identification of Unit Hydrographs and Component Flows from Rainfall, Evaporation and Stream Data (IHACRES) have emerged as the most frequently used models for estimating continuous stream flow at ungauged catchments (Razavi and Coulibaly, 2013). The three commonly used regionalization methods are regression, physical similarity and spatial proximity (Bao et al., 2012; Bárdossy, 2007; Merz and Blöschl, 2004; Oudin et al., 2008; Parajka et al., 2005). Some hydrologists have tried to compare and evaluate the methods, but the results are not consistent (Kay et al., 2006; McIntyre et al., 2005; Oudin et al., 2008; Young, 2006; Zhang and Chiew, 2009). Young (2006) regionalized the Probability Distributed Model (PDM) in 260 catchments in the UK and found that the regression method was more accurate than the spatial proximity method. Skaugen et al. (2015) regionalized the Distance Distribution Dynamics (DDD) model in 84 catchments ranging from small to large sizes in Norway using daily data and found that multiple regression equations performed well in predicting flows at ungauged catchments. Kay et al. (2006) tried to compare the performance of regression and physical similarity methods with two models [PDM and Time–Area Topographic Extension (TATE)] for 119 catchments across the UK but did not obtain consistent results. For the PDM, physical similarity was more accurate, but regression outperformed physical similarity for TATE. Merz and Blöschl (2004) found that the multiple regression method of regionalization at 308 catchments in Austria, using HBV model involving 11 calibration parameters, gave significantly poorer results than the spatial proximity method. Oudin et al. (2008) used two lumped rainfall-runoff models with daily data on 913 French catchments and found that when a dense network of gauging stations is available, the spatial proximity method provides the best regionalization solution, while the regression method shows the least satisfactory results, and the physical similarity method is in between the two others in accuracy. Magette et al. (1976) used 21 catchments in USA in the regionalization of six selected parameters of the Kentucky Watershed Model (KWM) using hourly data and found that a multiple regression method was successful in estimating model parameters from catchment descriptors, but a simple linear regression model was unsuccessful. Kokkonen et al. (2003) used 13 catchments in North Carolina, USA, in the regionalization of six parameters of IHACRES model with daily data and found that the arithmetic mean method of regionalization gave poorer results than regression and similar hydrologic behavior methods.

The major goal of the international PUB initiative was to reduce the uncertainty in the prediction of runoff by shifting away from tools that require calibration and curve fitting to tools that need little or no calibration (parsimonious models) (Spence et al., 2013). The PUB synthesis book states that the starting point for predicting the runoff hydrograph in ungauged catchments using rainfall–runoff models is the choice of an appropriate model structure (Blöschl et al., 2013). Sivapalan et al. (2003) pointed out that for predicting flow at ungauged catchments, it is important to challenge and overcome the potential problem posed by the “uniqueness in place” (Beven, 2000) of catchments. It is hence important that the hydrologic models are parametrically efficient (parsimonious), and their parameters are identifiable from the available catchment data (Young and Romanowicz, 2004). DDD is a parsimonious rainfall-runoff model with few calibration parameters recently developed by Skaugen and Onof (2014), and many of its other parameters can be estimated from the topography and land use of a catchment (Skaugen and Onof, 2014). Previous experience in using DDD for estimation of flow at ungauged catchments with daily data showed satisfactory results (Skaugen et al., 2015). Since DDD is one of the hydrological models which has features acknowledged for prediction of flow at ungauged catchments, we used it in this study.

During the calibration of hydrological models, it is common and probable that multiple calibration periods yield multiple optimum parameter sets. Different sets of optimum parameter values may yield similar performances, and this is designated as “equifinality” (Beven, 2006). Since conceptual hydrological models can be viewed as an empirically derived combination of mathematical operators describing the main features of an idealized hydrological cycle, one cannot rely on a uniquely determined model parameter set or model prediction (Kuczera and Parent, 1998). Consequently, attention should be given to uncertainties in hydrological modelling. Prediction uncertainties in hydrological modelling arise from a variety of sources, such as errors associated with input data and data for calibration, imperfection in model structure, calibration accuracy and uncertainty in model parameters (Benke et al., 2008; Jin et al., 2010; Montanari, 2011). In this study, uncertainty of the calibrated model parameters has been addressed.

Most of the regionalization methods applied so far are based on daily temporal resolution in catchments ranging from small to large sizes (Masih et al., 2010; Merz et al., 2006). Hailegeorgis et al. (2015) and Viviroli and Seibert (2015) have done regionalization studies with hourly resolution, but the studies are not specific to small catchments. Response times of small catchments are typically less than 24 h, and thus for flood forecasting purposes, hydrological models are required to provide simulations at high temporal resolution (Reynolds et al., 2017). Therefore, regionalization of model parameters for small catchments with sub-daily time resolution is important.

In this study, we have regionalized the DDD model parameters for small catchments with hourly time resolution in order to predict flows at ungauged rural small catchments in Norway. The specific research objectives are:

1. To evaluate the performance of the DDD rainfall-runoff hydrological model on rural small catchments with hourly temporal resolution (areas from 1 km^2–50 km^2). It includes the selection of parameters to calibrate, or to fix, the model goodness of fit and uncertainties in the calibration parameters.
2. To evaluate multiple regression-based regionalization against a physical similarity-based regionalization method.
3. To analyze and assess whether there is a combined regression and physical similarity method for regionalizing DDD model parameters.

2. Study area and data

Forty-one gauged small rural catchments located across Norway are used in the study. We selected the catchments from the Norwegian Water Resources and Energy Directorate (NVE) HYDRA II database of gauged catchments. Our definition of a small catchment follows that of Fleig and Wilson (2013) with an upper area limit of 50 km^2. The number of catchments is limited by the availability of hydro-meteorological data with the required temporal resolution of 1 h and a length of record that makes calibration possible. Seven additional gauged catchments, which are not used in the model calibration, have been used in validation. Fig. 1 shows the location of the study and test catchments.

Time series of precipitation, temperature and discharge are the main input data for running and calibrating the DDD model. Precipitation and temperature are based on a 1 × 1 km gridded product of the Norwegian Meteorological Institute (http://thredds.met.no/thredds/catalog.html) with hourly temporal resolution (Lussana et al., 2016). Since the data is available from 2010 onwards, we have used a total of five years of data for calibration and validation. The DDD model uses distributed precipitation and temperature data as input for the model's 10 elevation zones extracted from the hypsographic curve of a catchment. The elevation of the center of each temperature and precipitation grid cell has been extracted from the 10 × 10 m digital elevation model (DEM) of Norway. For the model elevation zone that contains more than one grid cell, mean of the values of temperature and precipitation is used. Hourly discharge data have been obtained from the Norwegian Water Resources and Energy Directorates (NVE) HYDRA II database.

The constant model parameters during the simulation period are derived from an analysis of hydro-meteorological, topographical and land use data for a catchment using GIS. The source of the topography and land use data is the Norwegian Mapping Authority (www.statkart.no). The 10 × 10 m DEM, the river network and the 1: 50 000 scale land use data have been retrieved and used in the study. The DEM has been re-conditioned to the naturally occurring river network using the DEM reconditioning tool from Arc Hydro to create a hydrologically correct terrain model that can improve the accuracy of watershed modeling (Li, 2014). The re-conditioned DEM is further used to determine the distance distributions of hill slopes and river networks as needed by DDD.

3. Methodology

3.1. Model structure

The DDD model is written in R programming language (R Core and Team, 2017) and currently runs operationally with daily and three-hourly time steps at the Norwegian flood forecasting service at NVE. Subsurface and dynamic runoff are the two main modules of the model.

The volume capacity of the subsurface water reservoir, W (mm), is shared between a saturated zone with volume S (mm) and an unsaturated zone with volume D (mm). If the saturated zone is high, the unsaturated volume has to be small (Skaugen and Onof, 2014). The actual water volume present in the unsaturated zone is described as Z (mm). The subsurface state variables are updated after evaluating whether the current soil moisture, Z(t), together with the input of rain and snowmelt, G(t), represent an excess of water over the field capacity, R, which is fixed at 30% (R = 0.3) of D(t) (Skaugen and Onof, 2014). If G(t) + Z(t) > R*D(t), then the excess water X(t) is added to S(t).

$$\text{Excess water} \quad X(t) = Max\left\{\frac{G(t)+Z(t)}{D(t)} - \mathrm{R},\ 0\right\}D(t) \tag{1}$$

$$\text{Groundwater} \quad \frac{dS}{dt} = X(t) - Q(t) \tag{2}$$

$$\text{Soil water content} \quad \frac{d\,Z}{dt} = G(t) - X(t) - Ea(t) \tag{3}$$

$$\text{Soil water zone} \quad \frac{dD}{dt} = -\frac{dS}{dt} \tag{4}$$

$$\text{Potential evapotranspiration} \quad Ep = cea * T \tag{5}$$

$$\text{Actual evapotranspiration} \quad Ea = Ep * \frac{S+Z}{W} \tag{6}$$

$Q(t)$ is runoff, and $Ea(t)$ is the actual evapotranspiration which is estimated as a function of potential evapotranspiration and the level of storage. A degree hour factor (cea) is positive for positive temperature (T) and zero for negative temperature. Ea is drawn from Z. This is indeed a simplification, but experience from Skaugen and Onof (2014) shows that the evapotranspiration routine in DDD calculates similar values to the approach used in HBV (Bergström, 1976). A recession analysis of the observed runoff from the catchment is used to estimate the catchment scale fluctuations of storage (the capacity of the subsurface water reservoir, W, see Skaugen and Mengistu, 2016).

The dynamics of runoff in DDD has been derived from the catchment features using a GIS combined with runoff recession analysis. The method for describing the runoff dynamics of a catchment is built on the distance distribution derived from the catchment topography. The distances from the points in the catchment to the nearest river reach are calculated for marsh and soil (non-marsh) parts of a hillslope. Previous studies in more than 120 catchments in Norway showed that the exponential distribution described the hillslope distance distribution well, and the normal distribution described well the distances between points in the river network and outlet of a catchment (Skaugen and Mengistu, 2016; Skaugen and Onof, 2014). Fig. 2 shows a map of the distance distributions of the marsh and soil (non-marsh) parts of the hillslope and river network for the Valen catchment and the corresponding empirical cumulative distribution functions. Fig. 3 shows the structure of the DDD model. All GIS work is done with ArcMap 10.3, and the recession analysis is done using the R script.

In the model, water is conveyed through the soils to the river network by waves with celerity determined by the actual storage, S(t), in the catchment (Skaugen and Mengistu, 2016; Skaugen and Onof, 2014). The celerity associated with the different levels of subsurface storage is estimated by assuming exponential recessions with parameter Λ in the equation $Q(t) = Q_0 \Lambda e^{-\Lambda(t-t_0)}$, where Q_0 is the peak discharge immediately before the recession starts. Λ is the slope of change per time (t) of the recession in the log-log space and calculated using Eq. (7). The distribution of Λ is modeled using a two-parameter gamma distribution.

$$\Lambda(t) = \frac{\log(Q(t)) - \log(Q(t+\Delta t))}{\Delta t} \tag{7}$$

The celerity, v, is calculated as a function of Λ using Eq. (8).

$$v = \frac{\Lambda\, d_{mean}}{\Delta t} \tag{8}$$

d_{mean} is the mean of the distances from points in the catchment to the nearest river. The capacity of the subsurface reservoir W (mm), is divided into storage levels i corresponding to the quantiles of the distribution of Λ under the assumption that the higher the storage, the higher the value of Λ. Each storage level is further assigned a celerity

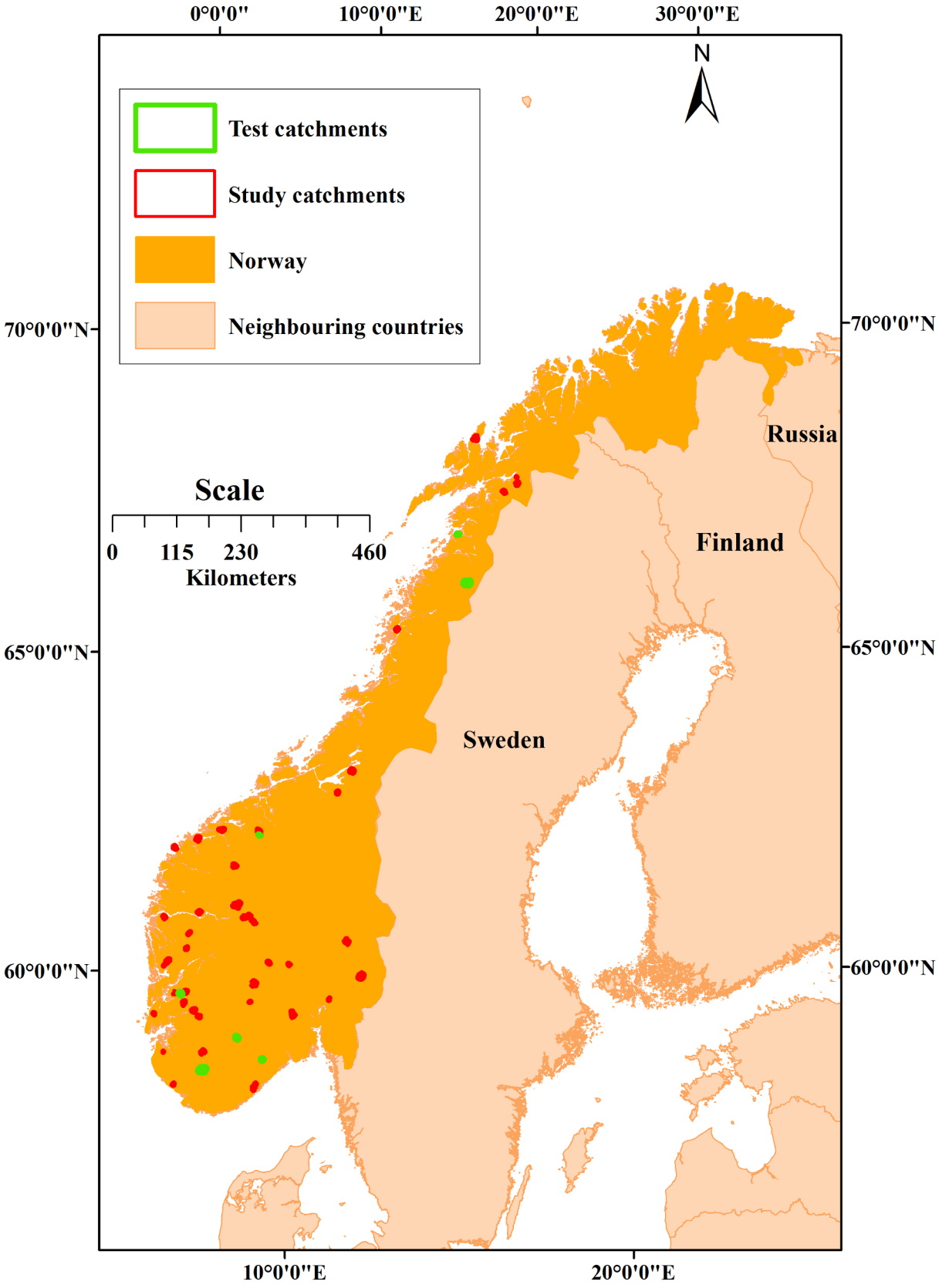

Fig. 1. Locations of the study and test catchments used in Norway.

$\nu_i = \frac{\lambda_i \, d_{mean}}{\Delta t}$ (see Eq. (8)), where λ_i is the parameter of the unit hydrograph for the individual storage level i, and estimated such that the runoff from several storage levels will give a unit hydrograph equal to the exponential unit hydrograph with a parameter Λ_i. With the assumption that the recession and its distribution carry information on the distribution of catchment-scale storage, we can consider that the

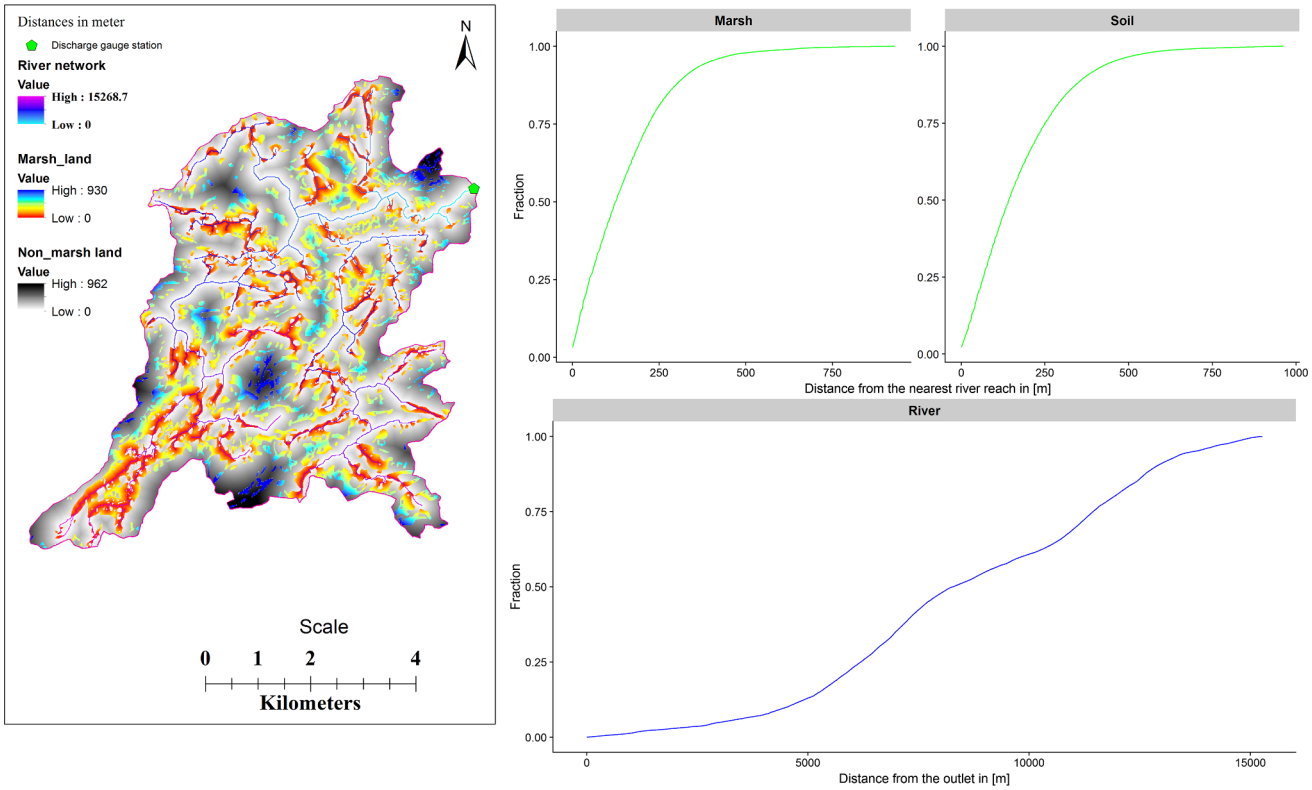

Fig. 2. Map of distance distribution of marsh, non-marsh (soil) part of hill slope and river network and the corresponding empirical cumulative distribution functions for catchment Valen.

temporal distribution of catchment-scale storage, S(t), is a scaled version to that of Λ. S(t) is calculated using Eq. (9), and its distribution is modelled using a two-parameter gamma distribution.

$$S(t) = \frac{Q(t)}{1 - e^{-\Lambda(t)}} \tag{9}$$

3.2. Model parameters and calibration

The model has three main groups of parameters. The first group are those determined by model calibration against observed discharge (the upper 5 in Table 1), the second group are those estimated from observed hydro-meteorological data (the lower 4 in Table 1 and the upper 3 in Table 2), and the third group are those estimated from geographical data (all in Table 2 except the upper 3). The calibration of the

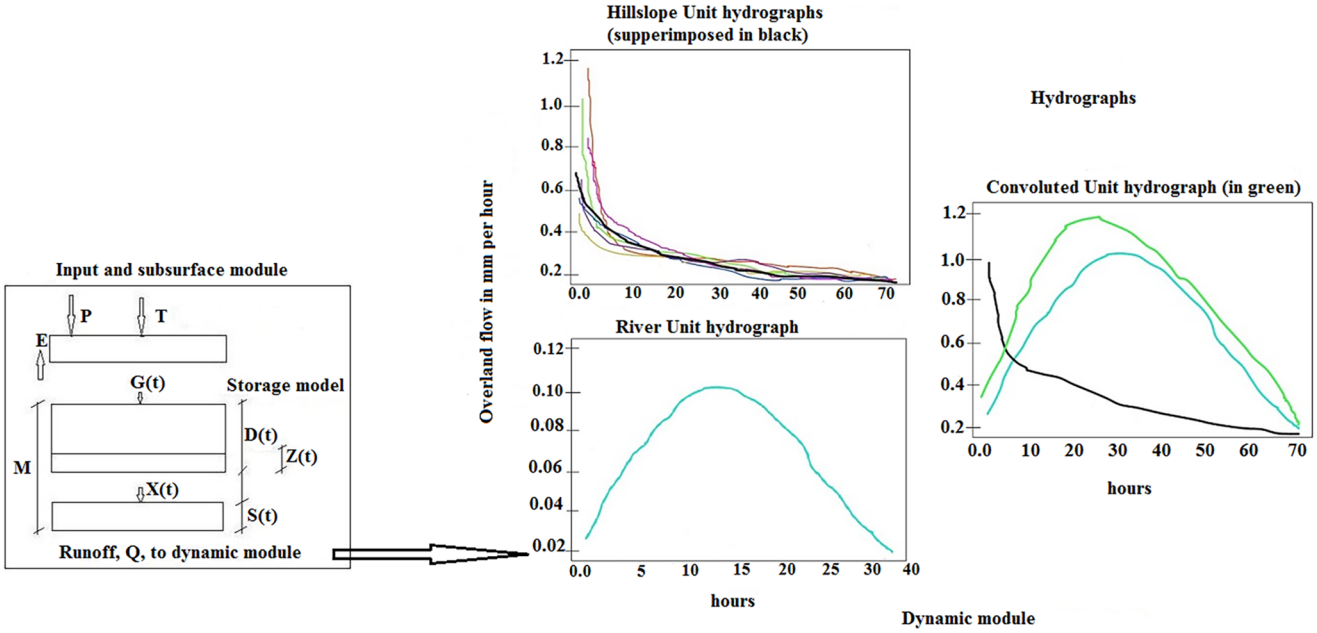

Fig. 3. Structure of the Distance Distributions Dynamics model adapted from Skaugen and Onof (2014). Left panel: the storage model and right panel: hydrographs of hillslope and river.

Table 1
List of nine model parameters needing regionalization.

Parameters	Description of the parameter	Method of estimation	Unit	Intervals of calibration
pro	Maximum liquid water content of snow	Calibration	fraction	0.03 — 0.1
cx	Degree hour factor for snow melt	Calibration	mm $^{\circ}C^{-1} h^{-1}$	0.05 — 1.0
CFR	Degree hour factor for refreezing	Calibration	mm $^{\circ}C^{-1} h^{-1}$	0.001 — 0.01
cea	Degree hour factor for evapotranspiration	Calibration	mm $^{\circ}C^{-1} h^{-1}$	0.01 — 0.1
rv	Celerity for river flow	Calibration	meter/second	0.5 — 1.5
Gshape	Shape parameter of λ	Recession analysis of observed runoff	Positive real number	not calibration parameter
Gscale	Scale parameter of λ	Recession analysis of observed runoff	Positive real number	not calibration parameter
GshInt	Shape parameter of Λ	Recession analysis of observed runoff	Positive real number	not calibration parameter
GscInt	Scale parameter of Λ	Recession analysis of observed runoff	Positive real number	not calibration parameter

model is performed using the probability particle swarm optimization (PPSO) algorithm (Lu and Han, 2011). The Kling-Gupta efficiency criteria (KGE) has been used as an objective function for the calibration (Gupta et al., 2009), and the KGE and BIAS (ratio of the mean of simulated to observed discharge) have been used to evaluate the calibrated results. In addition, the hydrographs of all catchments are visually inspected.

The calibration intervals of the parameters are set based on literature and experience in using the DDD model (Skaugen and Mengistu, 2016; Sælthun, 1996). Since cea and degree hour factor for snow melt (Cx) are sensitive to the temporal resolution, we used the DDD model calibration results from 84 catchments with daily time step (Skaugen et al., 2015) as a starting point, and literature review for setting the intervals of hourly time step. The mean celerity for river flow (rv) has a standard value of 1 m/s in using DDD with catchments ranging from small to large sizes (Skaugen and Mengistu, 2016) with daily time steps, but it has been calibrated with an interval of plus or minus 0.5 m/s of the standard value for hourly resolution. From experience and field measurements, we have set the calibration interval of maximum liquid water content of snow (pro) between 3% and 10% (Fierz et al., 2009; Saloranta, 2012).

For the 41 study catchments, we have calibrated the model on 2–3 years of data and validated on 1–2 years. The selection of the period is mainly based on the availability of flow and gridded precipitation and temperature data. The gridded precipitation data in Norway is highly uncertain due to rugged terrain and few precipitation stations in elevated areas. The data used does not include the correction for undercatch due to the wind, and the relation between the precipitation and elevation is introduced only locally around the station locations. As a result, the predicted precipitation field may potentially underestimate the actual precipitation, especially at higher elevations where the station network is sparser such as at the mountainous region of the southern part of Norway (Frauenfelder et al., 2017; Lussana et al., 2018). Accordingly, we introduced a precipitation correction factor to take this into account so that the long-term water balance is correct. The correction factor is applied to those catchments that give BIAS less than 0.8, and the correction factor is the ratio of long-term mean annual discharge to mean of simulated discharge. For purely ungauged catchments, the long-term mean annual discharge is estimated from a gridded map of average annual runoff for Norway for the period 1961–1990 (Beldring et al., 2003). The threshold temperature for rain or snow and snow melt are fixed with a value of 0.5 °C and 0.0 °C, respectively, based on literature (Saloranta, 2012; Skaugen, 1998). This is done to avoid regressed parameters that do not have a clear physical relationship with any of the catchment descriptors, but which can be fixed on a physical or an empirical basis. Removing parameters from calibration also strengthens the parsimony of the model. Table 1 lists the nine model parameters needing regionalization (five calibrated and four estimated from recession analysis), and Table 2 lists the non-regionalized model parameters. The snow routine in DDD has two non-regionalized parameters. The shape parameter (a0) and the decorrelation length (d) of the gamma distribution of snow and snow water equivalent (SWE) (Skaugen and Weltzien, 2016) are estimated from the previous calibration of 84 catchments in Norway (Skaugen et al., 2015).

3.3. Uncertainty analysis of calibrated parameters

We calibrated the model using probability particle swarm optimization (PPSO) algorithm with 500 calibration runs for each study catchment and sampled sets of parameters from the calibration runs for uncertainty analysis. To select behavioral sets of parameters, we used a threshold KGE value of 70th percentile (a value below which at least

Table 2
Non-regionalized model parameters which are unique to the local catchment of interest.

Symbol of parameters	Description of the Parameter	Method of estimation
a0	Parameter for new spatial distribution of SWE, shape parameter	From spatial distribution of observed precipitation
d	Parameter for new spatial distribution of SWE, decorrelation length	From spatial distribution of observed precipitation
MAD	Long term mean annual discharge	From long term observed mean annual flow data
area	Catchment area	GIS
maxLbog	Maximum distance of marsh land portion of hillslope	GIS
midLbog	Mean distance of marsh land portion of hillslope	GIS
bogfrac	Areal fraction of marsh land from the total land uses	GIS
zsoil	Areal fraction of DD for soils (what area with distance zero to the river)	GIS
zbog	Areal fraction of distance distribution for marsh land (what area with distance zero to the river)	GIS
midFl	Mean distance (from distance distribution) for river network	GIS
stdFL	Standard deviation of distance (from distance distribution) for river network	GIS
maxFL	Maximum distance (from distance distribution) for river network	GIS
maxDl	Maximum distance (from distance distribution) of non-marsh land (soils) of hill slope	GIS
midDL	Mean distance (from distance distribution) of non-marsh land (soils) of hill slope	GIS
midGl	Mean distance (from distance distribution) for Glacial	GIS
stdGl	Standard deviation of distance (from distance distribution) for Glacial	GIS
maxGl	Maximum distance (from distance distribution) for Glacial	GIS
Hypsographic curve	11 values describing the quantiles 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100	GIS

Table 3
Statistics of the catchment descriptors (CDs) of the study catchments used in the regionalization.

S.no	Catchment Descriptors	Symbol	Minimum	Maximum	Average	Unit
1	Topographic					
1.1	Area	A	1	50.7	28.2	km^2
1.2	Mean of grid to grid slope	M_g	8	64.8	28.4	%
1.3	Mean of elevation	M_e	59.6	1372	654	m
1.4	Mean of non-marsh land distance from the river	M_s	131.1	434.2	236.7	m
1.5	Mean of marsh land distance from the river	M_m	0	389.4	140.1	m
1.6	Mean of river length from the outlet	M_r	421.3	11422.5	5459.6	m
1.7	Standard deviation of river length from the outlet	S_r	262	5583.6	2531.2	m
1.8	River Slope	R_s	7.5	146	49	m/km
2	Land Uses					
2.1	Lake	L	0	13.6	5.63	%
2.2	Effective lake	L_e	0	11	2.3	%
2.3	Bare mountain	B	0	93.7	48.2	%
2.4	Cultivated land	C	0	35	1.8	%
2.5	Forest	F	0	94.3	32.7	%
2.6	Marsh land	M	0	28.9	4.6	%
2.7	Urban	U	0	1.5	0.1	%
2.8	Glacial	G	0	5.1	0.3	%
3	Hydro-meteorological					
3.1	Mean annual precipitation	M_p	679	3090	1543	mm
3.2	Mean annual temperature	M_t	−2.5	7.2	2.6	°C
3.3	Specific discharge	S_q	11.3	150.8	58	$l/(s*km^2)$

70% of the values lie) from the 500 runs for each study catchment. Evaluating several thousand calibration runs with an hourly resolution at 41 study catchments is computationally costly. To check whether the 500 runs used in the calibration give different behavioral sets from several thousand calibration runs, we ran the model with 2000 runs at one catchment, and 5000 and 10,000 runs at another catchment. All the study catchments are run with the behavioral sets of parameters, but the results are presented only for four randomly selected catchments. For each timestep, we sampled the number of discharge values equal to the number of behavioral parameter sets for each catchment, and the minimum and maximum discharges are used to estimate the width of the uncertainty bounds.

3.4. Regionalization methods

We used 41 catchments with KGE greater than or equal to 0.55 for the regionalization of the model parameters. For the three regionalization methods used in this study, 19 catchment descriptors (CDs) readily available from catchment data are used at the start and later refined based on their significance in estimating model parameters (Table 3). Since the selected catchments are widely spread across Norway, the spatial proximity method of regionalization may not be favored and is not considered in this study (Oudin et al., 2008). Validation of the regionalization methods is done assuming a selected number of gauged catchments to be ungauged and then comparing simulated runoff (using the regionalized parameters) with observed runoff.

3.4.1. Multiple regression method

The multiple regression equations, which are used to relate the CDs with the model parameters, are fitted to the calibrated model parameters of the 41 catchments. We used a stepwise regression procedure for building the regression model. We build the model from 19 candidate CDs by entering and removing CDs in a stepwise manner into the regression model until there is no convincing reason to enter or remove any more. Before starting to use the step wise procedure, we removed a CD which is highly correlated with another CD(s). To identify the correlation between the CDs, we have plotted the scatter plot matrix of the CDs (predictors). When R-Squared of correlation between two CDs is greater than or equal to 0.5, they are considered as highly correlated. The stepwise procedure is described in detail as follows:

i) We set a significance level of 0.2 for deciding when to enter into and remove from the stepwise model. We set the significance level so that it is not too difficult to enter CDs into the model and not too easy to remove CDs from the model.
ii) We fit each of the one-predictor models that regress each model parameter with all CDs one by one. Example: celerity of river flow (rv) against bare mountain (B), rv against forest (F), etc.
iii) Of those predictors (CDs) whose ***P***-value is less than 0.2, the first predictor introduced to the stepwise model is the CD that has the smallest ***P***-value. Accordingly, bare mountain is the first predictor for celerity of river flow.
iv) If no predictor (CD) has a ***P***-value less than 0.2, stop fitting the regression model (CFR is a typical example for this step).
v) Now, we fit each of the two-predictor models that include the first CD as a predictor. Example: rv on B and Rs, rv on B and U, etc.
vi) Of those predictors whose ***P***-value is less than 0.2, the second predictor put in the stepwise model is the predictor that has the smallest ***P***-value. For the celerity of river flow (rv), river slope was deemed the “best” second predictor, and it is therefore entered into the stepwise model.
vii) Now, since the bare mountain was the first predictor, we step back and see if entering river slope into the stepwise model somehow affects the significance of the bare mountain predictor. That is, check whether the ***P***-value of bare mountain is less than 0.2 or not. If the ***P***-value is less than 0.2, the first predictor (bare mountain) is retained in the stepwise model.
viii) Continue the steps as described above until adding an additional predictor does not yield a ***P***-value below the significant level chosen.

Both linear and non-linear (logarithmic) forms of the response variables (model parameters needing regionalization) and predictors (CDs) are tested in the regression model. If the non-linear values contribute significantly, then the non-linear form is retained in the model with the transformed value.

3.4.2. Physical similarity method

The physical similarity method relies on the assumption that the same parameter set should be successful in physically similar catchments (Merz and Blöschl, 2004; Oudin et al., 2008; Parajka et al., 2005; Zhang and Chiew, 2009). The transfer can be made from one or several

donor catchments on the basis of a chosen similarity method (McIntyre et al., 2005). The method transfers entire parameter sets from gauged to ungauged catchments instead of establishing links between model parameters and CDs. In this study, we used two types of physical similarity methods i.e. single-donor based, and pooling-group based. We used 12 CDs (2 hydro-climatic, 4 land uses, 3 topographic and 3 that can describe the runoff dynamic processes in DDD). The CDs used are: area, mean elevation, mean of soil (non-marsh land) distance from a river, mean of marsh land distance from the river, mean of river distance from outlet, river slope, effective lake percentage, forest, urban, mean annual precipitation, specific discharge and bare mountain.

For the single-donor type, we used a rank accumulated method of physical similarity in selecting a donor catchment to a test catchment (Oudin et al., 2008; Zhang and Chiew, 2009). For each CD, the catchment with the most similar descriptor to the test catchment is assigned rank 1, the catchment with the second most similar descriptor is assigned rank 2, and so on. When two or more catchments have the same value of CDs with the test catchment, they have been assigned the same rank. The rank numbers of CDs have been added for each of the study catchments. Each CD used for regionalization is given equal weight in the ranking system (Oudin et al., 2008). All the 41 catchments are considered in the selection of the most similar catchment to each of the 7 test catchments. The single gauged catchment with the smallest total rank is used as a donor catchment.

In the pooling-group type, the parameters for an ungauged site are estimated from the calibrated parameters of a pooling-group, i.e., a set of gauged catchments considered to be most similar to the target ungauged catchment in terms of some set of CDs (Kay et al., 2006, 2007). Kay et al. (2006) defined physical similarity by Euclidean distance in a space of CDs that was determined for each model parameter as shown in Eq.10.

$$dist_{a,\ b} = \sqrt{\sum_{j=1}^{J}\left(\frac{X_{a,j} - X_{b,j}}{\sigma_{x,j}}\right)^2} \tag{10}$$

where j indicates one of a total of J CDs (12 in this study), $X_{a,j}$ is the value of that CD at the a^{th} test catchment, $X_{b,j}$ is the value of the CD at b^{th} study catchment, and $\sigma_{x,j}$ is the standard deviation of the CD across all the N study catchments (41 in this study). Kay et al. (2007) suggests that around a 10-member pooling group is preferable to a much larger number, particularly when many CDs are used to define Euclidean distance for the pooling group. K(7 in this study) closest neighbors (minimum distance) are selected to create a pooling group for the test catchments.

After identifying the pooling group, the estimate of the model parameter at the test catchment a (α_a^{PG}) is calculated as a weighted average of the corresponding parameters from the study catchments in the pooling group. Kay et al. (2007) stated that it is more appropriate to write the expression for the model parameter as a weighted average of the estimated parameter values, α_m, for all catchments (N) as shown in Eq. (11).

$$\alpha_a^{PG} = \frac{\sum_{m=1}^{N} h_{am}\alpha_m}{\sum_{m=1}^{N} h_{am}} \tag{11}$$

Catchments not in the pooling group are given a weight h_{am} equal to zero, but those in the pooling are assigned weights to reflect their importance which is based on the distance measure $dist_{a,\ b}$ as defined in Eq. (10). The weights of the pooling group members are estimated by Eq. (12).

$$h_{am} = 1 - \ S_{am} \tag{12}$$

where

$$S_{am} = \begin{cases} dist_{a,\ b}/dist_{a,\ max} & for\ linearly\ decreasing\ weights \\ (dist_{a,\ b}/dist_{a,\ max})^2 & for\ quadratically\ decreasing\ weights \end{cases}$$

Where $dist_{a,\ max}$ is set to be 10% larger than the maximum distance of a pooling group member from the test catchment, a. In this study, we used a linear weight assigning method.

3.4.3. Combined method

The 9 model parameters needing regionalization come from two groups with different estimation methods. In the combined method, the new parameter set is derived by combining regression and physical similarity methods, i.e., when regression is used for the first group, physical similarity is used for the second group and vice versa.

4. Results

4.1. Calibration

To evaluate the performance of the DDD model in calibration and validation, we used the KGE, BIAS and visual inspection of hydrographs. The model performs satisfactorily ($0.5 \leq KGE < 0.9$) both for the study (for calibration and validation) and for the test catchments (for calibration). The minimum and maximum KGE values during calibration of the study catchments are 0.55 and 0.89 respectively while the median is 0.71. The minimum and maximum KGE values during validation are 0.4 and 0.88 respectively while the median is 0.66. The median BIAS value for calibration and validation is 0.88. As stated in Thiemig et al. (2013), $0.75 \leq KGE < 0.9$ is good, $0.5 \leq KGE < 0.75$ is intermediate and $0.0 \leq KGE < 0.5$ is poor. When validating, 5, 27 and 9 study catchments show poor, intermediate and good KGE values respectively. Except for one catchment, all test catchments give satisfactory calibration results. The visual inspection of the hydrographs shows underestimation of floods caused by heavy precipitation.

4.2. Uncertainty of calibrated parameters

From parameter samples of different sizes at two of the study catchments, the frequency histograms and dotty plots of the behavioral calibrated parameters show the same optimal value for the different sizes. Fig. 4(a) and (b) show the histogram and dotty plot for one calibrated parameter (celerity of river flow), respectively. The results show that we have the same value of optimal parameter at 500, 5000 and 10,000 iterations, and hence a sample size of 500 appears to be sufficient for the uncertainty analysis of calibrated parameters.

The frequency histograms of behavioral calibrated parameters for the 41 study catchments are analyzed. The results of histograms (pro, cea, rv and cx) for the four randomly selected study catchments are shown in Fig. 5(a) to (d). The histograms show that the calibrated parameters have a well-identifiable modal value. The parameters max out the calibration interval except for rv. For each timestep, we used discharge values simulated from 170, 156, 183 and 179 behavioral parameter sets in the calibration period to plot the uncertainty bounds for the catchments with identification numbers (ID) 6.10, 19.107, 73.27 and 123.29 respectively. Examples of simulated ranges and observed discharges are shown in Fig. 6.

4.3. Regionalization results

4.3.1. Regression method

The multiple regression equations are shown in Eqs. (13)–(20). The overall multiple regression model for CFR is statistically insignificant, hence the mean of the 41 calibrated catchments (0.007) has been used as the regionalized model parameter. For catchments with a CD value of zero in a logarithmic expression, a value of 1 has been assigned. The units of the model parameters are presented in Table 1. There is a probability that parameters estimated using the multiple regression equations can lie outside of the calibration intervals. In this case, we will use the nearest boundary value from the calibration interval.

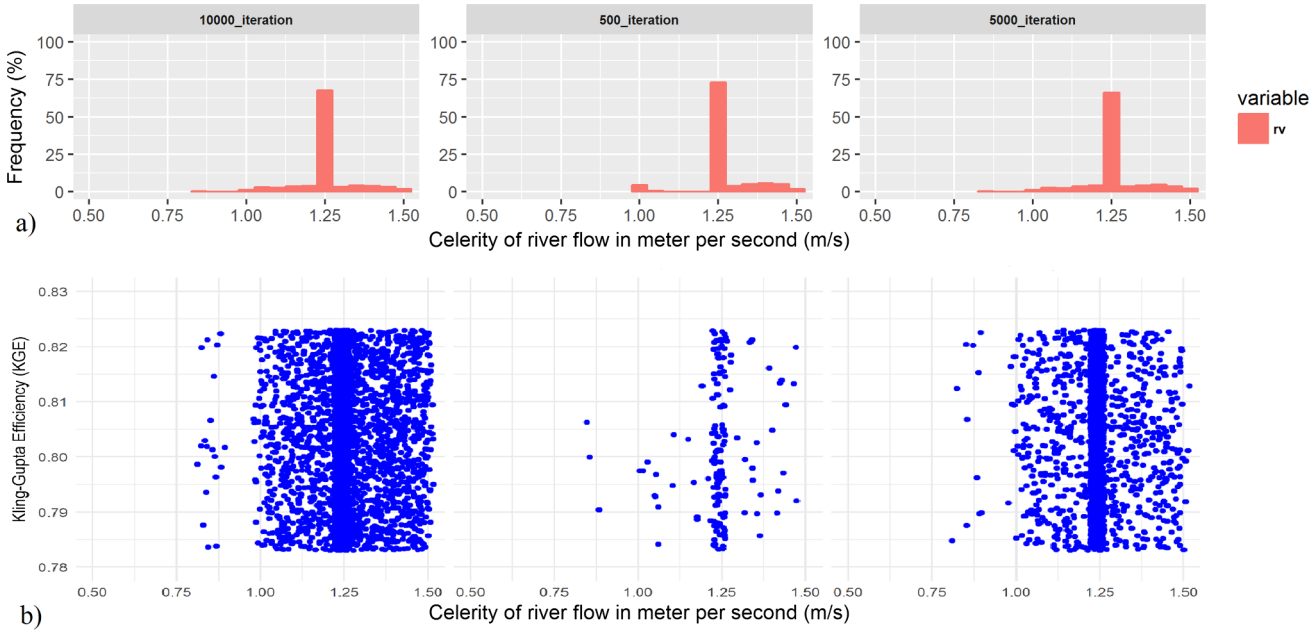

Fig. 4. Frequency histogram and dotty plot of celerity of river flow for three different sample sizes at the study catchment with identification number 19.107.

$$Pro = 0.017 + 0.026\log(M_m) - 0.066\log(M_s) + 0.038\log(M_r) + 0.013\log(M_e) - 0.029U \quad (13)$$

$$Cx = \exp(-4.2 + 0.41\log(M_e) + 0.87\log(M_p) - 0.95\log(M_s)) \quad (14)$$

$$Cea = \exp(-8.78 + 0.28\log(M_e) + 1.17\log(M_p) - 0.26\log(M_m) + 0.22\log(M_r) + 0.003F) \quad (15)$$

$$rv = 0.83 + 0.05\log(R_s) + 0.003B \quad (16)$$

$$Gscale = \exp(-5.12 - 0.12L_e + 0.22\ln(S_q) + 0.3\log(M_e)) \quad (17)$$

$$Gshape = 0.82 + 0.0005M_p - 0.009S_q \quad (18)$$

$$GshI = 2.047Gshape - 0.658 \quad (19)$$

$$GscI = 0.49Gscale - 0.0014 \quad (20)$$

The standardized residuals of the regression model for the response variables show a distribution close to normal (Fig. 7). Fig. 7 shows that few large and small values deviate from the approximated straight line of normal probability plot while many of the residuals lie along the straight line. Fig. 8 shows the actual (calibrated and estimated from observed hydro-meteorological data) and predicted values of the response variables with the multiple regression model. The standard error of estimate is a measure of the accuracy of the regression model predictions and informs how much uncertainty is associated with the model prediction. The standard error result of the regression model shows that there is uncertainty in the predicted values. Table 4 presents the summary of the multiple correlation coefficient (R^2), their significance and standard errors for the 41 catchments used in the regionalization. The non-parametric Spearman rank correlation was used (Seibert, 1999).

4.3.2. Physical similarity method

For the single-donor type, Table 5 summarizes the smallest total rank used to select a donor catchment. For the pooling-group type, we analyzed different numbers of group members (3–20) to get an overview on the dependency of KGE values on the number of group members. The KGE values are slightly sensitive to the number of group members (Table 6). Table 7 presents the seven pooling-group members for test catchment 19.79, with Euclidian distance, the weights and the weighted-average value (regionalized value) for celerity of river flow (rv).

4.3.3. Combined method and comparison of methods

The DDD model parameters needing regionalization are two groups. The first group is estimated from calibration, and the second group is estimated from observed hydro-meteorological (described in detail under Section 3.4.3). Table 8 presents the regionalized model parameters using the three methods (physical similarity, multiple regression and combined) for one of the test catchments (ID 25.32) and compares with the calibrated parameters and parameters derived from recession.

The KGE and BIAS performance results for the three regionalization methods are presented in Table 9. KGE and BIAS values have an optimum value of 1. Fig. 9 presents the observed and predicted hydrographs using the three regionalization methods for two of the test catchments, and Table 10 compares the performance of calibration against regionalization methods.

5. Discussion

5.1. Model performance and parameters

The evaluation of calibration and validation results shows that the DDD model performs satisfactorily, but we have observed underestimation of floods caused by heavy precipitation events. The main reason for the underestimation of floods is likely an underestimation of the higher precipitations in the gridded data. Comparisons of the gridded precipitation with gauged data for the Svarttjønnbekken (ID 123.29 and area 3.6 km^2) and Hokfossen (ID 123.28 and area 8.1 km^2) catchments show that the gridded value is lower than the gauge-recorded data for several floods. Since we do not have rain gauges installed within the other small catchments used, we have to rely on the gridded data for the nationwide study. Another reason could be the assumption that the GIS- derived model parameters are constant during low, medium and high flows. The distance distributions of the marsh land and soil (non-marsh) land of hillslope and the distance distribution of the river network could be different during the three flow conditions. During heavy precipitation events (that can cause damaging floods), the river network transporting overland flow could increase and produce faster runoff generation, and it will be a topic for further investigation.

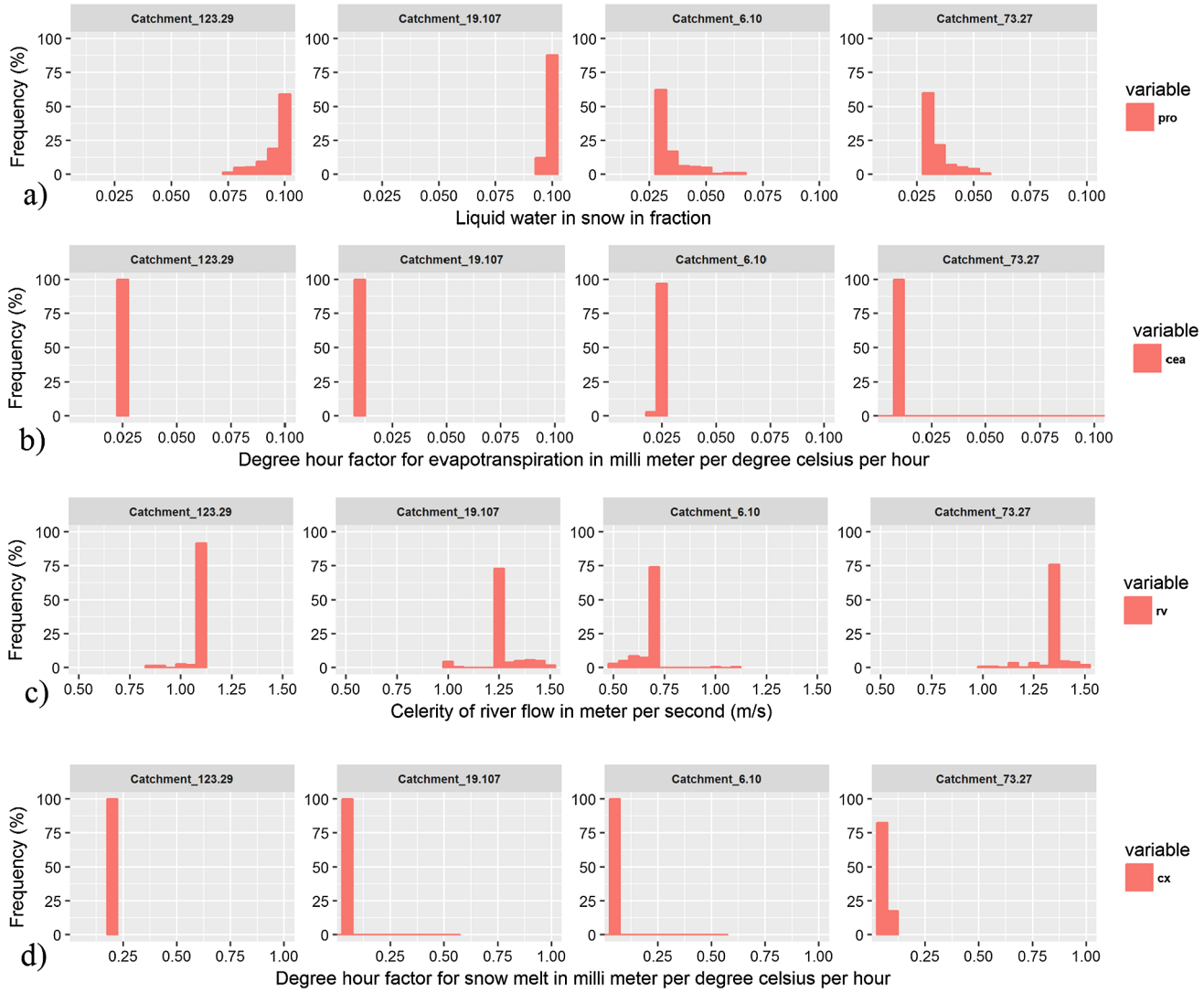

Fig. 5. Frequency histograms of liquid water in snow (pro), degree hour factor for evapotranspiration (cea), degree hour factor for snow melt (cx) and celerity of river flow (rv).

5.2. Uncertainty of calibrated parameters

Both the dotty plots and the frequency histograms of the 5000 and 10,000 sample sizes have the same shape and distribution as the 500-sample size for the behavioral parameters. The histograms and dotty plots of the river flow celerity for the catchment with ID 19.107 [Fig. 4(a) and (b)] show that the optimum celerity parameter is identifiable and has the same value (1.25 m/s) for sample sizes of 500, 5000 and 10000. Similar findings have been obtained using sample sizes of 500 and 2000 at another study catchment.

The calibrated parameters show one clear peak or most frequent value for almost all the study catchments even if the peak is at the extreme boundaries of the calibration interval for some parameters. The sharp and peaked distributions are associated with well-identifiable parameters, and the parameter estimates can unambiguously be inferred as modal values, while flat distributions indicate more parameter uncertainty (Blasone et al., 2008; Jin et al., 2010). The identifiability of the parameters and their small uncertainty resulted in the narrow width of uncertainty bounds (the difference between the maximum and minimum discharge for each hour). The small uncertainty of the calibrated model parameters reduces uncertainty in the model predictions at ungauged catchments. Two model parameters (degree hour factor for evapotranspiration and snow melt) show sharp, peaked and skewed distribution to the lower boundary of the calibration intervals. Since the intervals are set based on experience, field results and literature, the skewness indicates that we can get a higher performance criteria (KGE) if we let the calibration parameters go beyond the specified intervals. However, we believe that gaining a higher KGE value in these cases comes with a cost of less realistic model parameters, and it was decided to keep the parameter intervals within a reasonable value.

5.3. Regionalization methods

5.3.1. Multiple regression and physical similarity

The multiple regression performs satisfactorily in regionalizing the DDD model parameters, despite the uncertainty in the regression model. The pooling-group method also performs satisfactorily in regionalizing the model parameters despite the slight sensitivity of the method to the number of pooling-group members.

Significant correlations have been obtained between model parameters and CDs for the regression equations. Effective lake percentage, mean annual precipitation, specific discharge and mean elevation of the catchments are used to estimate the shape and scale parameters of λ and Λ. The scale parameter of λ is correlated with the effective lake percentage, the mean elevation and the specific discharge in the catchment. The shape and scale parameters of Λ are highly correlated

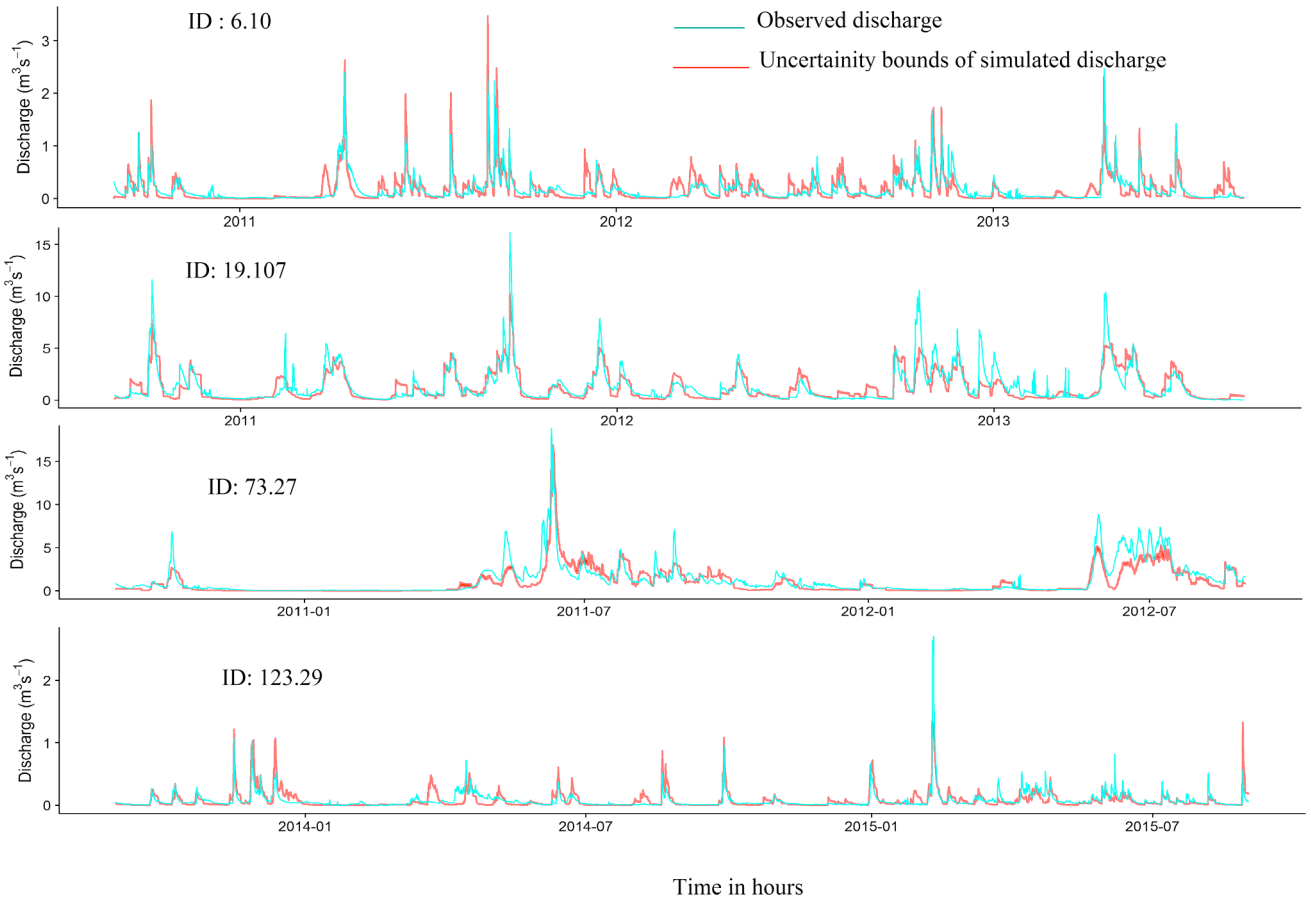

Fig. 6. Uncertainty bounds of DDD simulations due to calibrated parameters and observed discharges at four of the study catchments selected randomly.

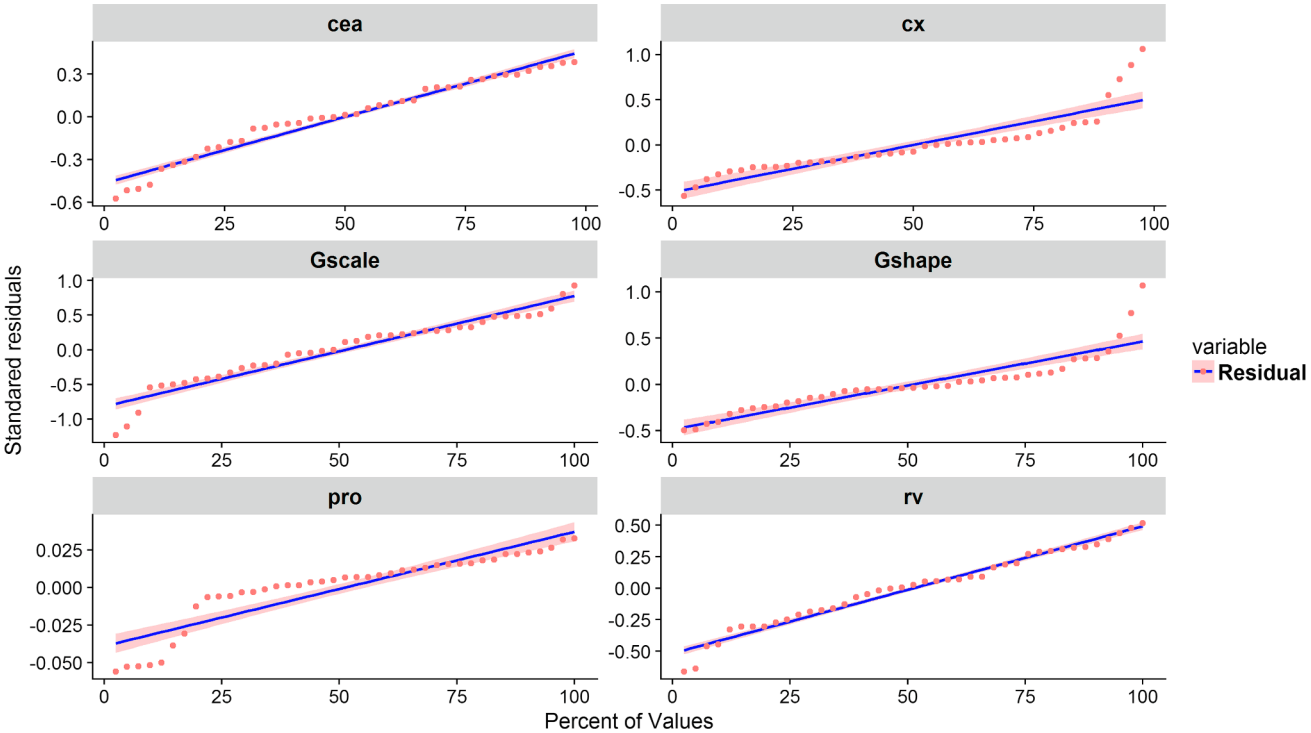

Fig. 7. Normal probability plots of the standard residuals of the multiple regression model.

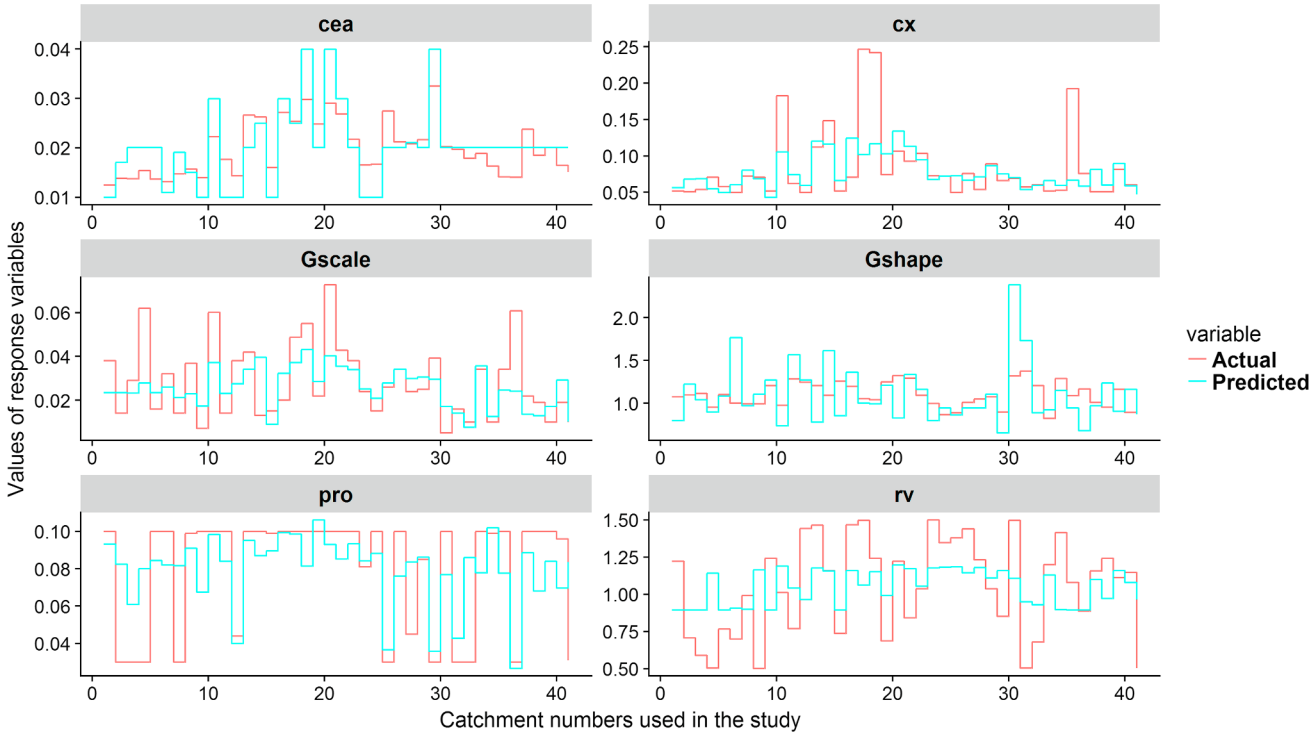

Fig. 8. Actual and predicted values of the response variables using the multiple regression model.

Table 4
Summary of the multiple correlation coefficient of determination (R^2), their significance (*p-value*) and standard error of the study catchments.

Parameter	Description of the parameter	R^2	Significance (p-value)	Standared Error
pro	Liquid water in snow	0.4	0.01	0.03
cx	Degree hour factor for snow melt	0.42	0.0001	0.35
cea	Degree hour factor for evapotranspiration	0.51	0.0001	0.28
rv	Celerity for river flow	0.14	0.06	0.3
Gshape	Shape parameter of λ	0.2	0.03	0.32
Gscale	Scale parameter of λ	0.43	0	0.5
GshInt	Shape parameter of Λ	0.97	0	0
GscInt	Scale parameter of Λ	0.98	0	0
CFR	Degree hour factor for refreezing	The regression model is statistically insignificant		

with the shape and scale parameters of λ (0.98 and 0.99, respectively). This correlation is expected since the latter is derived from the former (see Skaugen and Onof, 2014). Accordingly, we estimate the shape and scale parameters of Λ from the shape and scale parameters of λ with multiple linear regression.

The performance of the multiple-regression method in this study strengthens the statement that relating model parameters to catchment characteristics offers a possibility for estimating hydrological model parameters to predict flow at ungauged catchments (Magette et al., 1976). The results obtained in this paper are consistent with what Magette et al. (1976) obtained using 21 catchments in USA in the regionalization of six selected parameters of the KWM hydrological model using hourly data. They found that the hydrological model with the regressed parameters was successful in predicting flow at ungauged small catchments. The satisfactory performance of the multiple regression equations is in agreement with the recent results of Skaugen et al. (2015) who used daily data on small and large catchments in Norway. The finding that multiple-regression method gives better regionalization is also supported by Young (2006) who compares multiple-regression against a nearest-neighbor-based method. The performance of the multiple- regression method is also supported by the study results of Post and Jakeman (1999). They regressed six IHACRES model parameters from six landscape attributes, and the predictions made at the daily stream flow at ungauged catchments gave very good results for some catchments.

The pooling-group type performs better than the single-donor type for group members ranging from 3 to 20. The pooling group performance is as good as the multiple regression if we vary the number of members in the pooling group (Table 6) for each test catchment (e.g. if we take catchment ID of 19.79 and 104.22, a pooling group of 17 and 7 members gives as good KGE as the multiple regression, respectively). If we select fixed number of group members, multiple regression performs

Table 5
Summary of the smallest total rank and the donor catchments for the 7 test catchments.

Test catchments	ID	Area(km^2)	Donor catchments	ID	Area(km^2)	Smallest total rank
Gravå	19.79	6.3	Hangtjern	12.212	11.2	94
Knabåni	25.32	49.1	Jogla	26.26	31.1	123
Kjemåvatn	163.7	36.6	Viertjern	16.127	46.6	116
M.Mardalsvan	104.22	13.5	Nysetvatn	74.24	28.8	124
Fjellhaugen	42.16	7.3	Fjellanger	63.12	12.8	100
Tjellingtjernbekken	18.11	2.1	Gramstaddalen	29.7	1	98
Strandå	165.6	23.3	Laksåbru	168.3	26.8	108

Table 6
KGE values of different numbers of members of the pooling-group based physical similarity.

ID	Multiple regression	Number of members of the pooling-group based physical similarity												
		3	4	5	6	7	8	9	10	12	15	17	20	Max KGE
18.11	0.44	0.36	0.35	0.35	0.39	0.41	0.41	0.41	0.42	0.42	0.42	0.41	0.41	**0.42**
19.79	0.67	0.44	0.41	0.61	0.64	0.63	0.64	0.65	0.64	0.65	0.69	0.67	0.69	**0.69**
25.32	0.74	0.7	0.71	0.71	0.72	0.72	0.7	0.69	0.69	0.68	0.68	0.68	0.68	**0.72**
42.16	0.75	0.71	0.72	0.72	0.72	0.72	0.73	0.73	0.73	0.72	0.72	0.72	0.72	**0.73**
104.2	0.65	0.56	0.58	0.61	0.61	0.62	0.59	0.56	0.55	0.53	0.53	0.61	0.51	**0.62**
163.7	0.75	0.71	0.73	0.7	0.65	0.66	0.67	0.68	0.67	0.67	0.68	0.68	0.67	**0.73**
165.6	0.57	0.6	0.6	0.61	0.6	0.6	0.62	0.61	0.61	0.62	0.62	0.62	0.62	**0.62**
Mean	**0.65**	**0.58**	**0.59**	**0.62**	**0.62**	**0.62**	**0.62**	**0.62**	**0.62**	**0.61**	**0.62**	**0.63**	**0.61**	**0.65**

Table 7
Pooling-group based method of physical similarity for the celerity of river flow at test catchment with catchment identification number (Cat.ID) 19.79.

ID of Pooling group members	Euclidean distance ($dist_{a,b}$)	Celerity of river flow(rv)	Linearly decreasing weights(S_{am})	Weights of the pooling group members(h_{am})	h_{am} * rv
29.7	2.26	1.44	0.589	0.411	***0.594***
12.212	2.26	0.70	0.590	0.410	***0.286***
123.29	2.47	1.08	0.645	0.355	***0.384***
6.1	2.65	0.71	0.690	0.310	***0.219***
16.66	3.05	0.99	0.795	0.205	***0.203***
174.3	3.47	1.15	0.903	0.097	***0.111***
8.6	3.49	0.59	0.909	0.091	***0.053***
The weighted average of the estimated celerity of river flow will be the ratio between the two as stated in Eq. (11). Therefore, the regionalized value of rv using the pooling-group based physical similarity method is **1.851/1.88 = 0.99 m/s**				$\sum_{m=1}^{41} h_{am} r_v$	***1.851***
				$\sum_{m=1}^{41} h_{am}$	**1.880**

slightly better than the pooling group method. We selected 5, 7 and 10 members for further analysis. A group of 7 members performs as well as a group of 10 members. The group of 5 members performs slightly lower than the groups of 7 and 10 members. Finally, the group of 7 members is considered an optimal size of the pooling-based physical similarity in this study.

The performance of the pooling-group method in this study adds to the confirmation that the method can be applied for regionalization in different regions with different rainfall-runoff hydrological models. Regionalization results from 119 catchments across England, Wales and Scotland (46 with hourly data,73 with daily data and size ranging from 1 km^2 to 1200 km^2), showed that pooling-group method performed best with the conceptual hydrological model Probability Distributed Model (PDM), (Kay et al., 2006). Bao et al. (2012) regionalized Variable Infiltration Capacity (VIC) model parameters using multiple-regression and multiple-donor (5 donors) physical-similarity methods at 55 catchments of China and found that the multiple donor performed better than multiple regression.

5.3.2. Combined method

Generally, the combined method (which uses recession parameters estimated from multiple regression and calibrated parameters from the pooling-group method of physical similarity) performs slightly better than multiple-regression and physical-similarity methods (Table 9). The better performance of the combined method shows that multiple-regression is slightly better than pooling-group method in estimating the recession parameters while the pooling method is slightly better than the regression method in estimating the calibrated model parameters.

The hydrographs are also used for evaluation of the performance of the regionalization methods in addition to the KGE and BIAS. The hydrographs in Fig. 9 show that the combined method predicted the magnitude and the shape of the observed hydrographs better than the multiple- regression and pooling-group methods of regionalization. The floods are underestimated in both the presented hydrographs. When we look at the hydrograph of the catchment with ID of 25.32, the combined method predicted the timing and magnitude of the 2014 summer flood better than the pooling-group method, but the pooling-group method of

Table 8
Summary of model parameters estimated from three methods of regionalization for a test catchment ID 25.32. For combined method, values in italic are transferred with regression while the remainder is transferred using physical similarity.

Model Parameters	Calibration and runoff Recession analysis		Regression	Physical similarity		Combined (pooling and regression)
	Calibration	Recession		Single donor	Pooling group	
pro	0.1	…	0.1	0.1	0.09	0.09
cx	0.1	…	0.137	0.183	0.14	0.14
CFR	0.01	…	0.007	0.01	0.01	0.01
cea	0.02	…	0.014	0.03	0.02	0.02
rv	0.5	…	1.11	1.013	1.15	1.15
Gshape	…	1.139	1.187	0.735	0.9	*1.187*
Gscale	…	0.055	0.034	0.06	0.04	*0.034*
GshInt	…	1.521	1.771	0.899	1.2	*1.771*
GscInt	…	0.024	0.015	0.029	0.02	*0.015*

Table 9
Summary of comparisons of the regionalization methods using KGE and BIAS. The green shows the best KGE values (close to 1) while the blue shows the best BIAS value (close to 1).

S.no	Test catchment	ID	Area (km^2)	Regression method		Physical similarity method				Combined method							
										Recession parameters from regression				Recession parameters from physical similarity			
						Single donor		Pooling group (7 members)		Single donor		Pooling group		Single donor		Pooling group	
				BIAS	KGE	BIAS	KGE	BIAS	KGE	BIAS	KGE	BIAS	KGE	BIAS	KGE	BIAS	KGE
1	Gravå	19.79	6.3	1.04	0.67	1.09	0.33	1.04	0.58	1.06	0.6	1.03	0.67	1.09	0.34	1.04	0.58
2	Knabåni	25.32	49.1	0.8	0.74	0.75	0.66	0.77	0.72	0.75	0.66	0.77	0.7	0.75	0.66	0.8	0.75
3	Kjemåvatn	163.7	36.6	0.9	0.75	0.9	0.59	0.87	0.67	0.88	0.75	0.9	0.76	0.9	0.59	0.9	0.66
4	M.Mardalsvatn	104.22	13.5	0.72	0.65	0.72	0.53	0.74	0.6	0.69	0.63	0.74	0.65	0.74	0.56	0.72	0.6
5	Fjellhaugen	42.16	7.3	0.83	0.75	0.79	0.63	0.79	0.72	0.79	0.72	0.79	0.72	0.8	0.71	0.84	0.75
6	Tjellingtjernbekken	18.11	2.1	1.47	0.44	1.51	0.2	1.46	0.34	1.46	0.45	1.4	0.5	1.49	0.26	1.49	0.31
7	Strånda	165.6	23.3	1.13	0.57	1.06	0.6	1.06	0.6	1.07	0.58	1.08	0.59	1.06	0.6	1.12	0.58
Mean				*0.98*	*0.65*	*0.97*	*0.51*	*0.96*	*0.60*	*0.96*	*0.63*	*0.96*	*0.66*	*0.98*	*0.53*	*0.99*	*0.60*
Standard deviation				*0.26*	*0.12*	*0.28*	*0.17*	*0.25*	*0.13*	*0.27*	*0.1*	*0.23*	*0.09*	*0.27*	*0.17*	*0.26*	*0.15*

regionalization has a KGE value of 0.72 while the combined method has a KGE value of 0.71.

The combined method combines the advantages from the two methods of regionalizations used in this study (physical similarity and multiple regression). Kokkonen et al. (2003) states that exploiting merely relationships between calibrated model parameters and CDs can result in a decrease in regionalization performance. Physical similarity has an advantage of transferring the entire calibrated model parameters from one or few gauged to ungauged catchments (Arsenault and Brissette, 2014; McIntyre et al., 2005; Oudin et al., 2010; Parajka et al., 2005). The recession parameters describe the integrated information of how different factors influence the runoff process (Fiorotto and Caroni, 2013). Recession parameters are used in the DDD model to estimate the subsurface storage capacity (Skaugen and Mengistu, 2016), and they can also be used to model streamflow recession for regionalization and prediction (Stoelzle et al., 2013). Vogel and Kroll (1996) state that regression procedures for estimating hydrograph recession parameters generally work well, which is supported by our findings in that the

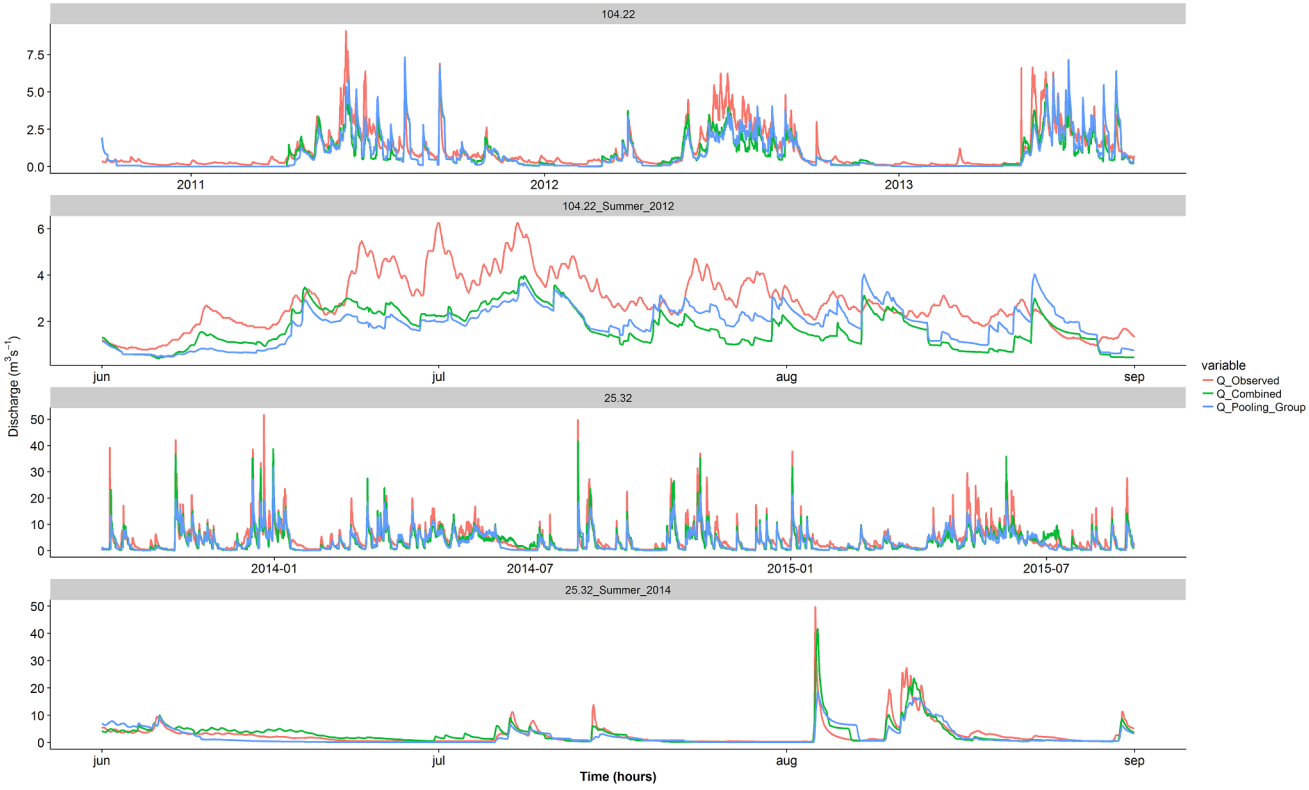

Fig. 9. Observed and predicted hydrographs using multiple regression, pooling group and combined methods of regionalization at two test catchments.

Table 10
Comparison of the KGE performance of calibration with the satisfactorily performing regionalization methods (the green shows KGE values of methods are better than calibration or the KGE values of calibration are better than methods).

S.no	Test catchment	ID	Area (km^2)	Calibrated		Regression method		Physical Similarity method		Combined (recession parameters from regression and calibrated from pooling)	
								Pooling group (7 members)			
				BIAS	KGE	BIAS	KGE	BIAS	KGE	BIAS	KGE
1	Gravå	19.79	6.3	1.02	0.39	1.04	**0.67**	1.04	**0.58**	1.03	**0.67**
2	Knabåni	25.32	49.1	0.79	0.66	0.8	**0.74**	0.77	**0.72**	0.77	**0.7**
3	Kjemåvatn	163.7	36.6	0.86	**0.77**	0.9	0.75	0.87	0.67	0.9	0.76
4	M.Mardalsvatn	104.22	13.5	0.75	0.55	0.72	**0.65**	0.74	**0.6**	0.74	**0.65**
5	Fjellhaugen	42.16	7.3	0.82	0.7	0.83	**0.75**	0.79	**0.72**	0.79	**0.72**
6	Tjellingtjernbekken	18.11	2.1	1.22	**0.55**	1.47	0.44	1.46	0.34	1.4	0.5
7	Strånda	165.6	23.3	1.05	**0.63**	1.13	0.57	1.06	0.6	1.08	0.59
Mean				0.93	0.61	*0.98*	*0.65*	*0.96*	*0.60*	*0.96*	*0.66*
Standard deviation				0.17	0.12	*0.26*	*0.11*	*0.25*	*0.13*	*0.23*	*0.09*

recession parameters estimated using multiple regression are slightly better than those estimated by physical similarity. It must be noted, however, that the recession parameters derived from the regression method are estimated from hydrographs of 41 study catchments while that of the pooling-group method are derived from hydrographs of only 7 study catchments.

The regionalized recession parameters of DDD model (estimated by pooling-group, multiple regression and combined method) are, in some cases, better than the recession parameters estimated locally from a short period of hydro-meteorological data. This is the case for four of the test catchments and makes the performance of the regionalization methods better than the calibration result for the four catchments (Table 10). The main reason that the single-donor type of physical similarity performs the poorest is that the recession parameters in the single donor type are estimated from hydrographs of a single catchment while that of a pooling group and multiple regression are estimated from hydrographs of 7 and 41 catchments respectively. The other reason is probably the long distance between donor and test catchments.

The main limitation of this study is related to the precipitation data, mainly how heavy precipitation events are represented. As discussed previously, there are studies which show that the gridded data set has uncertainties and smooths out peaks (Lussana et al., 2018). To reduce the uncertainty in the precipitation, we have introduced a precipitation correction factor as mentioned in the methodology section, and we estimate the precipitation correction factor for ungauged catchments using a daily specific runoff map of Norway produced by NVE (*https://atlas.nve.no*). Another limitation is related to the use of the daily spatial variations of precipitation data for the gamma distributed snow parameters. Skaugen et al. (2015) used observed, daily precipitation data from rain gauges to estimate the snow distribution parameters of DDD. In this study, we assume that the daily spatial variation of precipitation is similar to that of hourly variation, and we used the parameters from the 84 calibrated catchments in Skaugen et al. (2015) due to the lack of sufficient rain gauges with hourly temporal resolution. One source of uncertainty in this study that is not yet quantified is the lack of long-term discharge data with hourly resolutions for estimating the runoff recession parameters, as they are sensitive to the length of the time series.

6. Conclusions

The results of our study show that the DDD model performs satisfactorily both during the calibration and validation periods for small rural catchments in Norway (area $< 50\,km^2$) with hourly temporal resolution. The model underestimates floods generated by heavy precipitation events, and a method to improve the simulation of peak floods should be further investigated.

The calibrated parameters in the DDD model are identifiable and show small uncertainty in our analysis. The uncertainty bound of DDD simulations due to the calibrated parameters is narrow, which shows that the uncertainty due to calibrated parameters for predicting flow using hourly temporal resolution is small, and this also indicates that the model is suitable for regionalization.

Both the multiple-regression and pooling-group methods performed satisfactorily (except for one test catchment, both methods gave a KGE performance between 0.5 and 0.75). The combined method (which uses recession parameters estimated from multiple-regression and calibrated parameters from the pooling-group method of physical similarity) performed slightly better than the pooling-group and multiple-regression methods. Therefore, the combined method of regionalization is recommended as a method for estimation of flow at small rural ungauged catchments with hourly resolution in Norway. The recession parameters estimated by the three regionalization methods are, for some catchments, better than those estimated from a short period of hydro-meteorological data.

The parameter parsimonious rainfall-runoff hydrological model (DDD) has a capability of generating continuous flow data at ungauged small rural catchments with hourly temporal resolution using regionalized model parameters. The satisfactory performance of the combined method shows that regionalization of DDD model parameters is possible by combining multiple- regression and physical-similarity methods.

Declaration of interests

None.

Acknowledgments

The authors would like to acknowledge Cristian Lussana of the Norwegian Meteorological Institute for providing information on how to access and process the 1 × 1 km spatial and 1-hour temporal resolution gridded precipitation and temperature data for Norway. We would like to acknowledge Abebe Girmay also for his support in processing the gridded data. The authors also acknowledge and appreciate the anonymous reviewers, despite their busy schedules, have taken out time to read the manuscript and give us feedback, which helped a lot for the improvement of the manuscript. Finally, the authors gratefully acknowledge the financial support by the Research Council of Norway and several partners through the Centre for Research-based Innovation "Klima 2050" (see www.klima2050.no).

References

Arsenault, R., Brissette, F.P., 2014. Continuous streamflow prediction in ungauged basins: the effects of equifinality and parameter set selection on uncertainty in regionalization approaches. Water Resour. Res. 50 (7), 6135–6153. https://doi.org/10.1002/2013WR014898.

Bao, Z., Zhang, J., Liu, J., Fu, G., Wang, G., He, R., et al., 2012. Comparison of regionalization approaches based on regression and similarity for predictions in ungauged catchments under multiple hydro-climatic conditions. J. Hydrol. 466-467, 37–46. https://doi.org/10.1016/j.jhydrol.2012.07.048.

Bárdossy, A., 2007. Calibration of hydrological model parameters for ungauged catchments. Hydrol. Earth Syst. Sci. 11 (2), 703–710. https://doi.org/10.5194/hess-11-703-2007.

Beldring, S., Engeland, K., Roald, L.A., Sælthun, N.R., Voksø„ A., 2003. Estimation of parameters in a distributed precipitation-runoff model for Norway. Hydrol. Earth Syst. Sci. 7(3). https://doi.org/10.5194/hess-7-304-2003.

Benke, K.K., Lowell, K.E., Hamilton, A.J., 2008. Parameter uncertainty, sensitivity analysis and prediction error in a water-balance hydrological model. Math. Comput. Modell. 47 (11), 1134–1149. https://doi.org/10.1016/j.mcm.2007.05.017.

Bergström, S., 1976. Development and application of a conceptual runoff model for Scandinavian catchments. Department of Water Resources Engineering, Lund Institute of Technology, University of Lund, Lund.

Berne, A., Krajewski, W.F., 2013. Radar for hydrology: Unfulfilled promise or unrecognized potential? Adv. Water Resour. 51 (Supplement C), 357–366.

Beven, K.J., 2000. Uniqueness of place and process representations in hydrological modelling. Hydrol. Earth Syst. Sci. Discuss. 4 (2), 203–213.

Beven, K.J., 2006. A manifesto for the equifinality thesis. J. Hydrol. 320 (1), 18–36. https://doi.org/10.1016/j.jhydrol.2005.07.007.

Blasone, R.-S., Madsen, H., Rosbjerg, D., 2008. Uncertainty assessment of integrated distributed hydrological models using GLUE with Markov chain Monte Carlo sampling. J. Hydrol. 353 (1), 18–32. https://doi.org/10.1016/j.jhydrol.2007.12.026.

Blöschl, G., Sivapalan, M., 1995. Scale issues in hydrological modelling: a review. Hydrol. Process. 9 (3–4), 251–290. https://doi.org/10.1002/hyp.3360090305.

Bloschl, G., Sivapalan, M., Wagener, T., Viglione, A., Savenije, H., 2013. Runoff Prediction in Ungauged Basins : Synthesis across Processes, Places and Scales. Cambridge University Press, Cambridge.

Blöschl, G., Sivapalan, M., Wagener, T., Viglione, A., Savenije, H., 2013. Runoff prediction in ungauged basins: synthesis across processes, places and scales. Cambridge University Press, Cambridge.

Borga, M., Boscolo, P., Zanon, F., Sangati, M., 2007. Hydrometeorological analysis of the 29 August 2003 flash flood in the eastern Italian Alps. J. Hydrometeorol. 8 (5), 1049–1067. https://doi.org/10.1175/JHM593.1.

Bronstert, A., 2003. Floods and climate change: interactions and impacts. Risk Anal. 23 (3), 545–557.

Creutin, Borga, M., 2003. Radar hydrology modifies the monitoring of flash-flood hazard. Hydrol. Process. 17 (7), 1453–1456. https://doi.org/10.1002/hyp.5122.

Creutin, Obled, C., 1980. Modeling spatial and temporal characteristics of rainfall as input to a flood forecasting model. IAHS-AISH Publication 129 In: Hydrological forecasting. Proc. Oxford symposium. International Association of Hydrological Sciences, Washington DC, pp. 41–49.

Devi, G. K., Ganasri, B. P., & Dwarakish, G. S., 2015. A review on hydrological models. International conference on water resources, coastal and ocean engineering (ICWRCOE'15) (Vol. 4).

Fierz, C., R.L, A., Y, D., P, E., Greene, E., McClung, D., et al., 2009. The international classification for seasonal snow on the ground (UNESCO, IHP (International Hydrological Programme)–VII, Technical Documents in Hydrology, No 83; IACS (International Association of Cryospheric Sciences) contribution No 1).

Fiorotto, V., Caroni, E., 2013. A new approach to master recession curve analysis. Hydrol. Sci. J. 58 (5), 966–975. https://doi.org/10.1080/02626667.2013.788248.

Fleig, A. K., & Wilson, D., 2013. The Natural Hazards Project - 5 Flood and Surface Water Flooding Retrieved from Oslo, Norway.

Frauenfelder, R., Solheim, A., Isaksen, K., Romstad, B., Dyrrdal, A. V., Ekseth, K. H. H., et al., 2017. Impacts of extreme weather events on transport infrastructure in Norway. In: Natural Hazards and Earth System Sciences Discussions, 1-24. doi:10.5194/nhess-2017-437.

Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. J. Hydrol. 377 (1), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003.

Hailegeorgis, T.T., Abdella, Y.S., Alfredsen, K., Kolberg, S., 2015. Evaluation of regionalization methods for hourly continuous streamflow simulation using distributed models in boreal catchments. J. Hydrol. Eng. 20 (11). https://doi.org/10.1061/(ASCE)HE.1943-5584.0001218.

Jin, X., Xu, C.-Y., Zhang, Q., Singh, V.P., 2010. Parameter and modeling uncertainty simulated by GLUE and a formal Bayesian method for a conceptual hydrological model. J. Hydrol. 383 (3), 147–155. https://doi.org/10.1016/j.jhydrol.2009.12.028.

Kay, A.L., Jones, D.A., Crooks, S.M., Calver, A., Reynard, N.S., 2006. A comparison of three approaches to spatial generalization of rainfall–runoff models. Hydrol. Process. 20 (18), 3953–3973. https://doi.org/10.1002/hyp.6550.

Kay, A.L., Jones, D.A., Crooks, S.M., Kjeldsen, T.R., Fung, C.F., 2007. An investigation of site-similarity approaches to generalisation of a rainfall-runoff model. Hydrol. Earth Syst. Sci. https://doi.org/10.5194/hess-11-500-2007.

Kirchner, J.W., 2006. Getting the right answers for the right reasons: linking measurements, analyses, and models to advance the science of hydrology. Water Resour. Res. 42 (3), n/a-n/a. https://doi.org/10.1029/2005WR004362.

Kokkonen, T., Jakeman, Anthony J., Young, Peter C., Koivusalo, Harri J., Blöschl, G., Vertessy, R., Zhang, L., 2003. Predicting daily flows in ungauged catchments: model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina. Hydrol. Processes 17 (11), 2219–2238. https://doi.org/10.1002/hyp.1329.

Kuczera, G., Parent, E., 1998. Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. J. Hydrol. 211 (1/4), 69–85. https://doi.org/10.1016/S0022-1694(98)00198-X.

Lamb, R., Kay, A.L., 2004. Confidence intervals for a spatially generalized, continuous simulation flood frequency model for Great Britain. Water Resour. Res. 40 (7), n/a-n/a. https://doi.org/10.1029/2003WR002428.

Li, Z., 2014. Watershed modeling using arc hydro based on DEMs: a case study in Jackpine watershed. Environ. Syst. Res. 3 (1), 11. https://doi.org/10.1186/2193-2697-3-11.

Lu, Q., Han, Q.-L., 2011. A probability particle swarm optimizer with information-sharing mechanism for odor source localization. IFAC Proc. 44 (1), 9440–9445. https://doi.org/10.3182/20110828-6-IT-1002.00507.

Lussana, C., Ole Einar, T., & Francesco, U., 2016. seNorge v2.0: an observational gridded dataset of tempperature for Norway. METreport, 108.

Lussana, C., Saloranta, T., Skaugen, T., Magnusson, J., Einar Tveito, O., Andersen, J., 2018. SeNorge2 daily precipitation, an observational gridded dataset over Norway from 1957 to the present day. Earth Syst. Sci. Data 10 (1), 235–249. https://doi.org/10.5194/essd-10-235-2018.

Magette, W.L., Shanholtz, V.O., Carr, J.C., 1976. Estimating selected parameters for the Kentucky Watershed Model from watershed characteristics. Water Resour. Res. 12 (3), 472–476. https://doi.org/10.1029/WR012i003p00472.

Masih, I., Uhlenbrook, S., Maskey, S., Ahmad, M.D., 2010. Regionalization of a conceptual rainfall–runoff model based on similarity of the flow duration curve: a case study from the semi-arid Karkheh basin, Iran. J. Hydrol. 391 (1), 188–201. https://doi.org/10.1016/j.jhydrol.2010.07.018.

McIntyre, N., Lee, H., Wheater, H., Young, A., Wagener, T., 2005. Ensemble predictions of runoff in ungauged catchments. Water Resour. Res. 41 (12), n/a-n/a. https://doi.org/10.1029/2005WR004289.

Merz, Blöschl, G., Parajka, J., 2006. In: Regionalization Methods in Rainfall-runoff Modelling using Large Catchment Samples. IAHS-AISH Publication, pp. 117–125.

Merz, Blöschl, 2004. Regionalisation of catchment model parameters. J. Hydrol. 287 (1), 95–123. https://doi.org/10.1016/j.jhydrol.2003.09.028.

Miao, Q., Yang, D., Yang, H., Li, Z., 2016. Establishing a rainfall threshold for flash flood warnings in China's mountainous areas based on a distributed hydrological model. J. Hydrol. 541, 371–386. https://doi.org/10.1016/j.jhydrol.2016.04.054.

Montanari, A., 2011. Uncertainty of Hydrological Predictions (pp. 459–478).

Nruthya, K., Srinivas, V.V., 2015. Evaluating methods to predict streamflow at ungauged sites using regional flow duration curves: a case study. Aquat. Procedia 4, 641–648. https://doi.org/10.1016/j.aqpro.2015.02.083.

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), n/a-n/a. https://doi.org/10.1029/2007WR006240.

Oudin, L., Kay, A., Andréassian, V., Perrin, C., 2010. Are seemingly physically similar catchments truly hydrologically similar? Water Resour. Res. 46 (11). https://doi.org/10.1029/2009WR008887. n/a-n/a.

Parajka, J., Merz, R., Bloeschl, G., 2005. A comparison of regionalisation methods for catchment model parameters. Hydrol. Earth Syst. Sci. Discuss. 2 (2), 509–542. https://doi.org/10.5194/hessd-2-509-2005.

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 (5), 1783–1795. https://doi.org/10.5194/hess-17-1783-2013.

Pathiraja, S., Westra, S., Sharma, A., 2012. Why continuous simulation? The role of antecedent moisture in design flood estimation. Water Resour. Res. 48 (6), n/a-n/a. https://doi.org/10.1029/2011WR010997.

Pilgrim, D.H., Cordery, I., Baron, B.C., 1982. Effects of catchment size on runoff relationships. J. Hydrol. 58 (3), 205–221. https://doi.org/10.1016/0022-1694(82)90035-X.

Post, D., Jakeman, A.J., 1999. Predicting the daily streamflow of ungauged catchments in S.E. Australia by regionalising the parameters of a lumped conceptual rainfall-runoff model. Ecol. Model. 123.

R Core Team., 2017. R: A Language and Environment for Statistical Computing. doi:http://www.R-project.org/.

Razavi, T., Coulibaly, P., 2013. Streamflow prediction in ungauged basins: review of regionalization methods. J. Hydrol. Eng. 18 (8), 958–975. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000690.

Reynolds, J.E., Halldin, S., Xu, C.Y., Seibert, J., Kauffeldt, A., 2017. Sub-daily runoff predictions using parameters calibrated on the basis of data with a daily temporal resolution. J. Hydrol. 550, 399–411. https://doi.org/10.1016/j.jhydrol.2017.05.012.

Sælthun, N. R., 1996. The "Nordic" HBV model. Description and documentation of the model version developed for the project Climate Change and Energy production. (ISBN 82-410-0273-4). Retrieved from Oslo.

Saloranta, T.M., 2012. Simulating snow maps for Norway: description and statistical evaluation of the seNorge snow model. Cryosphere 6 (6), 1323–1337. https://doi.org/10.5194/tc-6-1323-2012.

Seibert, J., 1999. Regionalisation of parameters for a conceptual rainfall-runoff model. Agric. For. Meteorol. 98–99, 279–293. https://doi.org/10.1016/S0168-1923(99)00105-7.

Sivapalan, M., Takeuchi, K., Franks, S.W., Gupta, V.K., Karambiri, H., Lakshmi, V., 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. https://doi.org/10.1623/hysj.48.6.857.51421.

Skaugen, T., Mengistu, Z., 2016. Estimating catchment-scale groundwater dynamics from recession analysis – enhanced constraining of hydrological models. Hydrol. Earth Syst. Sci. 20 (12), 4963–4981. https://doi.org/10.5194/hess-20-4963-2016.

Skaugen, T., Onof, C., 2014. A rainfall-runoff model parameterized from GIS and runoff data. Hydrol. Process. 28 (15), 4529–4542. https://doi.org/10.1002/hyp.9968.

Skaugen, T., Weltzien, I.H., 2016. A model for the spatial distribution of snow water equivalent parameterized from the spatial variability of precipitation. Cryosphere 10 (5), 1947. https://doi.org/10.5194/tc-10-1947-2016.

Skaugen, T., Peerebom, I. Olaf, Nilsson, A., 2015. Use of a parsimonious rainfall–run-off model for predicting hydrological response in ungauged basins. Hydrol. Process. 29 (8), 1999–2013. https://doi.org/10.1002/hyp.10315.

Skaugen, T., 1998. Studie av skilletemperatur for snø ved hjelp av samlokalisert snø pute, nedbør- og temperaturdata NVE RAPPORT nr. 11.

Son, K., Sivapalan, M., 2007. Improving model structure and reducing parameter uncertainty in conceptual water balance models through the use of auxiliary data. Water Resour. Manage. 430.

Spence, C., Whitfield, P.H., Pomeroy, J.W., Pietroniro, A., Burn, D.H., Peters, D.L., St-Hilaire, A., 2013. A review of the Prediction in Ungauged Basins (PUB) decade in Canada. Can. Water Res. J./Revue canadienne des ressources hydriques 38 (4), 253–262. https://doi.org/10.1080/07011784.2013.843867.

Steinschneider, S., Yang, Y.-C.E., Brown, C., 2014. Combining regression and spatial proximity for catchment model regionalization: a comparative study. Hydrol. Sci. J. https://doi.org/10.1080/02626667.2014.899701.

Stoelzle, M., Stahl, K., Weiler, M., 2013. Are streamflow recession characteristics really characteristic? Hydrol. Earth Syst. Sci. 17 (2), 817–828. https://doi.org/10.5194/hess-17-817-2013.

Swain, J.B., Patra, K.C., 2017. Streamflow estimation in ungauged catchments using regionalization techniques. J. Hydrol. 554, 420–433. https://doi.org/10.1016/j.jhydrol.2017.08.054.

Tegegne, G., Kim, Y.-O., 2018. Modelling ungauged catchments using the catchment runoff response similarity. J. Hydrol. 564, 452–466. https://doi.org/10.1016/j.jhydrol.2018.07.042.

Thiemig, V., Rojas, R., Zambrano-Bigiarini, M., De Roo, A., 2013. Hydrological evaluation of satellite-based rainfall estimates over the Volta and Baro-Akobo Basin. J. Hydrol. 499, 324–338. https://doi.org/10.1016/j.jhydrol.2013.07.012.

Viviroli, D., Mittelbach, H., Gurtz, J., Weingartner, R., 2009. Continuous simulation for flood estimation in ungauged mesoscale catchments of Switzerland – part II: parameter regionalisation and flood estimation results. J. Hydrol. 377 (1), 208–225. https://doi.org/10.1016/j.jhydrol.2009.08.022.

Viviroli, D., Seibert, J., 2015. Can a regionalized model parameterisation be improved with a limited number of runoff measurements? J. Hydrol. 529, 49–61. https://doi.org/10.1016/j.jhydrol.2015.07.009.

Vogel, R., Kroll, C., 1996. Estimation of baseflow recession constants. Water Resour. Res. 10.

Vormoor, K., Skaugen, T., 2013. Temporal disaggregation of daily temperature and precipitation grid data for Norway. J. Hydrometeorol. 14 (3), 989–999. https://doi.org/10.1175/JHM-D-12-0139.1.

Wagener, T., Wheater, H. S., & Gupta, H. V., 2004. Rainfall-Runoff Modelling in Gauged and Ungauged Catchments.

Wagener, T., Wheater, H.S., 2006. Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty. J. Hydrol. 320 (1), 132–154. https://doi.org/10.1016/j.jhydrol.2005.07.015.

Westerberg, I.K., Gong, L., Beven, K., Seibert, J., Semedo, A., Xu, C., Halldin, S., 2014. Regional water balance modelling using flow-duration curves with observational uncertainties. Hydrol. Earth Syst. Sci. 18 (8), 2993. https://doi.org/10.5194/hess-18-2993-2014.

Wetterhall, F., Cloke, H., Pappenberger, F., Wetterhall, F., 2011. Effects of temporal resolution of input precipitation on the performance of hydrological forecasting. Adv. Geosci. 29, 21–25.

Young, A.R., 2006. Stream flow simulation within UK ungauged catchments using a daily rainfall-runoff model. J. Hydrol. 320 (1), 155–172. https://doi.org/10.1016/j.jhydrol.2005.07.017.

Young, A.R., Romanowicz, R.J., 2004. PUB and data-based mechanistic modelling: the importance of parsimonious continuous-time models. International Environmental Modelling and Software Soc.(Proceedings fo the iEMSs 2004 international congress: complexity and integrated resouces management). 214-224.

Zhang, Y., Chiew, F.H.S., 2009. Relative merits of different methods for runoff predictions in ungauged catchments. Water Resour. Res. 45 (7), n/a-n/a. https://doi.org/10.1029/2008WR007504.

Zhang, Y., Vaze, J., Chiew, F.H.S., Teng, J., Li, M., 2014. Predicting hydrological signatures in ungauged catchments using spatial interpolation, index model, and rainfall–runoff modelling. J. Hydrol. 517 (Supplement C), 936–948. https://doi.org/10.1016/j.jhydrol.2014.06.032.