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A regional parameter estimation scheme for a pan-European multi-basin model

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ABSTRACT

Study region: Europe.
Study focus: A semi-distributed continuous hydrological model, HYPE, was applied to model daily stream flows in more than 35,000 subcatchments across Europe. A stepwise regionalization approach was implemented to estimate different groups of model parameters. HRU based parameters were estimated first for each soil and landuse class, respectively. Lake and reservoir parameters were estimated separately. Catchments were grouped based on similarity of their characteristics and model parameters defined at a catchment scale were then regionalized for each group as functions of the catchment characteristics by simultaneously calibrating the model for a number of catchments to concurrently optimize the overall model performance and the functional relationships between the parameters and the catchment characteristics. Calibration was performed at 115 discharge stations and the approach was validated at 538 independent stations.
New hydrological insights for the region: Parameters could be linked to catchment descriptors with good transferability, with median NSE of 0.54 and 0.53, and median volume error of −1.6% and 1.3% in the calibration and validation stations, respectively. Although regionalizing parameters for different groups of catchments separately yielded a better performance in some groups, the overall gain in performance against regionalization using a single set of regional relationships across the entire domain was marginal. The benefits of separate regionalization were substantial in catchments with considerable proportion of agricultural landuse and higher mean annual temperature.

1. Introduction

Proper management of freshwater resources requires quantification of the spatial and temporal distribution of available freshwater in its different compartments of the earth. This is often achieved through implementation of hydrological models, which have different levels of complexity, depending on the specific purpose to which they are to be applied, input data available, and resource availability (e.g. Singh, 1995; Refsgaard et al., 2010; Pechlivanidis et al., 2011; Hrachowitz et al., 2013). Although such assessment is usually performed at a catchment or river basin level, there is an increasing need for a more integrated assessment across regions at continental and global scales as society is becoming more and more integrated and resources need to be managed in a coordinated way.

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Continental and global scale assessment of water resources have been performed in the past using macro-scale hydrological models (eg. Yates, 1997; Vörösmarty et al., 2000; Alcamo et al., 2003; van Beek et al., 2011). Such models have a rather coarse spatial resolution and low accuracy. In recent years, however, there has been a shift towards more detailed and higher resolution models for assessment of water resources at regional and continental scales (Arnold et al., 1999; Schuol et al., 2008; Arheimer et al., 2012; Donnelly et al., 2016; Pechlivanidis and Arheimer, 2015; Rakovec et al., 2016).

Implementation of more detailed hydrological models at large scale often requires calibration of the models at a large number of subbasins across the model domain to account for the spatial variability of the model parameters (e.g. Graham, 1999; Abbaspour et al., 2015). This entails a huge computational effort and requires availability of catchment response observations, such as discharge data, with a sufficient spatial and temporal coverage, limiting prediction in ungauged subbasins. One possible solution to ease these requirements is incorporating a regionalization approach, in which model parameters estimated in carefully selected gauged donor catchments are transferred to other catchments based on their similarity with the catchments where the model has been calibrated (see Parajka et al., 2013 for a review of the different methods).

A number of research efforts have been put on developing strategies to relate model parameters to measurable catchment properties using different approaches. One group of approaches uses an assumption that catchments that are spatially close to one another tend to be similar in their characteristics and hydrological behaviors and therefore parameters of the models employed to simulate their flows (e.g. Li et al., 2009; Gottschalk et al., 2011). Using such an assumption, model parameters are transferred from calibrated nearby catchments. Another group of approaches groups catchments based on catchment physiographic and/or hydrological similarities using different catchment properties and flow indices to transfer model parameters (e.g. Johansson, 1992; Arheimer and Brandt, 1998; Merz and Blöschl, 2004; Lee et al., 2005; Parajka et al., 2005; Lindström et al., 2005; Seibert and Beven, 2009; Bulygina et al., 2011). A third group of approaches follows a strategy in which regression based models are established between model parameters and several catchment characteristics and flow indices from a number of catchments for which the model is calibrated independently (e.g. Abdulla and Lettenmaier, 1997; Seibert, 1999; Wagener and Wheater, 2006; Pechlivanidis et al., 2010; Singh et al., 2012).

One of the problems associated with the regression based approach is that because of the problem of equifinality (Beven and Binley, 1992), it may be difficult to obtain a unique set of parameters in the individual catchments, potentially making it difficult to come up with a strong relationship between the model parameters and catchment properties. In order to address this problem, a regional calibration approach, which treats the model calibration and fitting of the relationship between the model parameters and catchment attributes simultaneously, has been pursued by some researchers (Fernandez et al., 2000; Hundecha and Bárdossy, 2004; Hundecha et al., 2008; Samaniego et al., 2010; Kumar et al., 2013; Wallner et al., 2013). In this approach, the functional form of the relationship between the model parameters and catchment characteristics is assumed a-priori and model calibration is done for a number of catchments simultaneously to estimate the parameters of the functions relating the model parameters and the catchment characteristics.

Each of the methods listed above has their own advantages and shortcomings. The proximity and similarity based methods are easier to implement in that the entire set of parameters are assumed to be the same in all ungauged catchments where the parameters are transferred to. However, they ignore the possible variability of the catchment characteristics between the different catchments. The regression based method enables estimation of a unique set of parameters for each catchment based on their catchment characteristics. However, as mentioned in the previous paragraph, the equifinality problem makes it difficult to achieve a strong relationship between model parameters and catchment characteristics. The regional calibration approach eases this problem, but at a higher computational cost. See Blöschl et al. (2013) for a review of the different methods.

In the present work, we brought together some elements from the different groups of approaches in order to exploit their advantages and achieve robust parameter regionalization. To that end, we grouped catchments into homogeneous groups using catchment classification and performed regional calibration separately for each group by simultaneously calibrating the model for multiple catchments within each group while concurrently estimating the regional relationship between the model parameters and the catchment descriptors whose form is assumed a-priori. The rationale behind combining the two approaches lies in the following:

A regional model calibration approach, in which model calibration and estimation of the relationship between model parameters and catchment characteristics is performed simultaneously, needs a prior assumption of the functional form of the relationship between the model parameters and the catchment descriptors (eg. Hundecha and Bárdossy, 2004; Samaniego et al., 2010). If this approach is implemented over a large spatial domain, where the variability of the catchment descriptors is large, the assumed function may fail to capture the inherent relationship over the full range of variability of the catchment characteristics. Reducing the variability of the catchment characteristics over which the relationship is established by grouping catchments of similar catchment characteristics would reduce this risk and could lead to a stronger relationship. On the other hand, regionalization approaches that are based on catchment similarity have usually been pursued by directly transferring parameters from calibrated catchments to other similar catchments. This has been performed either from a single catchment or from a group of catchments through averaging the parameters estimated at individual catchments (eg. Parajka et al., 2005), or by simultaneously calibrating selected catchments of a homogeneous group established through catchment classification (eg. Pagliero et al., 2014). Nevertheless, despite their homogeneity, catchments in the same group still exhibit some variability in their catchment characteristics. Therefore, estimating the model parameters as functions of the catchment characteristics within a group would improve the parameter estimation.

We tested the benefits of using this new parameter estimation scheme for the HYdrological Predictions for the Environment (HYPE) model (Lindström et al., 2010) set up for the pan-European region and referred to as E-HYPE (Donnelly

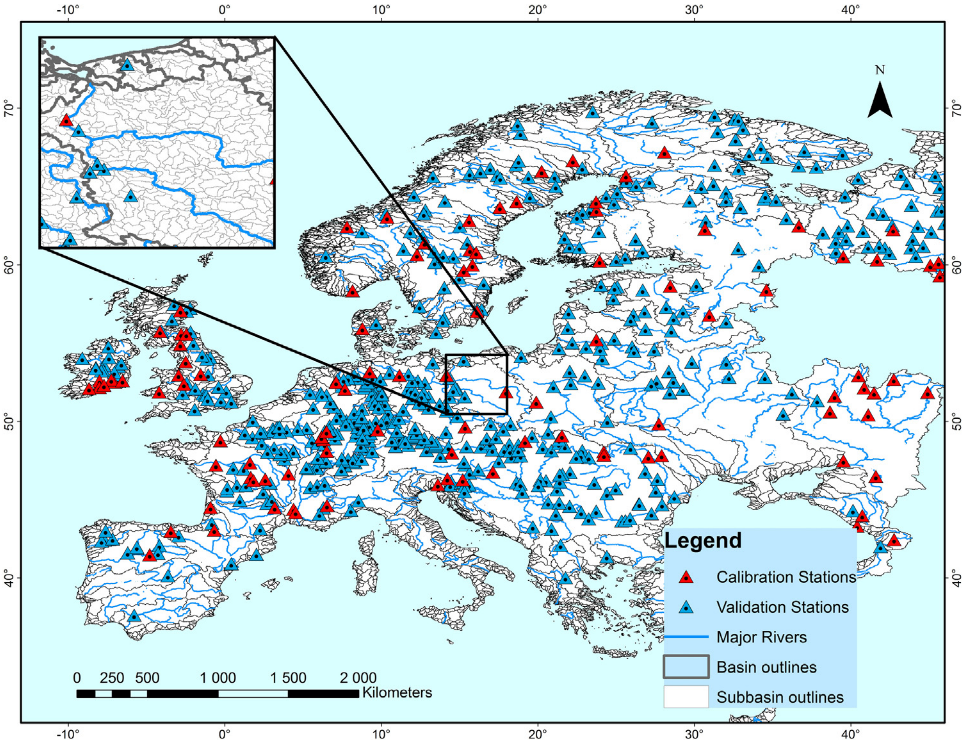

Fig. 1. Model domain with subdivision into smaller subcatchments shown for portion of the domain.

et al., 2016), which is a large-scale multi-basin model run operationally for several purposes. Current uses include flood forecasting across the continent (EFAS and WET, see http://hypeweb.smhi.se/), estimating inflow of water and substances to oceanography models, soil-water forecasts for gardening companies and climate change impact assessments, e.g. for hydropower companies. HYPE has also been used for scientific studies to test hypotheses using a large sample of catchments (Donnelly et al., 2016; Pechlivanidis and Arheimer, 2015). The overall aim of the present study is to improve the model performance through a refined calibration and parameter regionalization for a large geographical domain with a high diversity of catchment characteristics. We specifically aimed to address the following research questions:

- Does introducing a functional relationship between the model parameters and catchment descriptors in a simultaneous calibration scheme for a group of general parameters that would otherwise be assigned constant values improve the E-HYPE model performance in ungauged basins?
- Can one achieve stronger regional relationships and better model performance when classifying catchments into homogeneous groups and derive the regional relationships separately for each group compared to deriving the relationships across the full model domain?

2. Data and method

The HYPE model was setup for the pan European domain, which covers an area of 8.8 million km^2 and was subdivided into 35,408 subcatchments with an average size of 248 km^2 (Fig. 1). The model setup is referred to as E-HYPE and it is a further development of the previous version v2.1 (Donnelly et al., 2016). The version used in this work is v3.0.

2.1. Data

A range of open data sources were used in setting up the model (see Table 1). River networks and subcatchments were delineated using WWF's Hydrosheds data (Lehner et al., 2008) for the model domain south of 60° latitude and from Hydro1 K (Verdin, 1997) further north. Hydrological response units (HRUs) were derived from landuse and soil data obtained from different sources. Landuse was derived from the CORINE landuse data and GlobCover data (Arino et al., 2008) where CORINE does not have coverage. Lakes and reservoirs were extracted from GLWD (Lehner and Döll, 2004) and GranD (Lehner et al., 2011) data sets respectively. Irrigated areas were identified from GMIA (Siebert et al., 2010) and MIRCA (Portmann et al., 2010) data sets. Soil types were derived from the European Soil Database, ESDB (Panagos, 2006) and Digital Soil Map of the World (DSMW) data sets. 8 soil types and 15 landuse classes were used in the model setup and based on their combination, a

Table 1
Data used for model setup and their database.

Data	Database	Source link	Reference	Resolution
Subcatchments and river networks	Hydrosheds	http://hydrosheds.cr.usgs.gov/index.php	Lehner et al., (2008).	15 arc-second
	Hydro1K (>60 °N)	https://lta.cr.usgs.gov/HYDRO1K	Verdin (1997)	1 × 1 km2
Precipitation, temperature	WATCH (WFDEI)	http://www.eu-watch.org/data_availability	Weedon, et al.(2014)	0.5° (approx 50 km)
Observed discharge	GRDC	http://www.bafg.de/GRDC/EN/02_srvcs/21_tmsrs/riverdischarge_node.html;jsessionid=C22E2022D049900355DDB9C3C6502A6E.live1042	GRDC (2014)	Daily Daily Daily Daily
	EWA	http://www.bafg.de/GRDC/EN/04_spcldtbss/42_EWA/ewa_node.html	EWA (2013)	Daily
	BHDC	http://www.smhi.se/sgn0102/bhdc/	BHDC (2008)	Daily
	SMHI	http://vattenwebb.smhi.se/station/	SMHI (2014)	Daily
	Spanish authorities	–	–	Daily
Snow data	GlobSnowFSUS	http://www.globsnow.info/index.php?page=Snow_Water_Equivalent	–	25 km
		http://nsidc.org/data/g01170	–	–
Potential evapotranspiration	MODIS	ftp://ftp.ntsg.umt.edu/pub/MODIS/Mirror/MOD16/	Mu et al., 2011	1 × 1 km2
LandUse	CORINE	http://www.eea.europa.eu/data-and-maps/data/corine-land-cover-2000-clc2000-seamless-vector-database-1	–	100 × 100m
		http://www.eea.europa.eu/data-and-maps/data/corine-land-cover-2006-raster		
	GlobCover	http://due.esrin.esa.int/page_globcover.php	Arino et al. (2008).	300 × 300 m
	GLWD	http://worldwildlife.org/pages/global-lakes-and-wetlands-database	Lehner and Döll (2004)	–
	GranD	http://www.gwsp.org/products/grand-database.html	Lehner et al. (2011)	–
	GMIA	http://www.fao.org/nr/water/aquastat/irrigationmap/index.stm	Siebert et al. (2010)	5.5 min (approx. 10 km at equator).
Irrigation	GMIA	http://www.fao.org/nr/water/aquastat/irrigationmap/index.stm	Siebert et al. (2010)	1.5 min (approx. 10 km at equator).
	MIRCA	https://www.uni-frankfurt.de/45218023/MIRCA	Portmann et al. (2010)	2.5 min (approx. 10 km at equator).
Soil	ESDB 1 × 1 km	http://eusoils.jrc.ec.europa.eu/ESDB_Archive/ESDB_data_1k_raster_intro/ESDB_1k_raster_data_intro.html	Panagos (2006)	1 km × 1 km
	ESDB 10 × 10 km	http://eusoils.jrc.ec.europa.eu/ESDB_Archive/rasterarchive/ESDBv2_ETRS_LAEA_raster_archive.html	Panagos (2006)	10 km × 10 km
	DMSW	http://www.fao.org/geonetwork/srv/en/metadata.show?id=14116		–

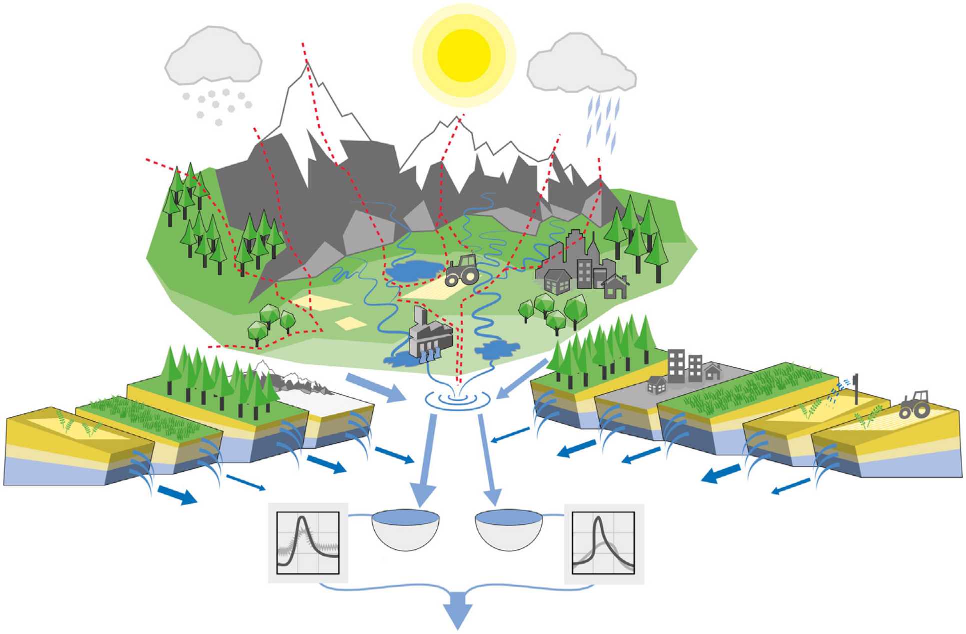

Fig. 2. Schematic representation of the HYPE model processes.

maximum of 75 HRUs were identified. Daily discharge data at more than 3000 gauging stations were obtained from different sources (Table 1). A subset of the gauging stations was used in this work – 115 discharge stations were used for calibration while 538 independent stations were used for model validation (see Section 2.5 for the selection procedure).

The WFDEI meteorological forcing data set, an observation corrected reanalysis (Weedon et al., 2014) for the period 1979–2010 was used for model calibration and validation. The dataset provides daily gridded meteorological records with approximate grid size of 2500 km^2 which is approximately 10 times greater than the subcatchment resolution. For each subcatchment, the daily precipitation was taken from the grid center nearest to the subcatchment centroid, while the magnitude was rescaled on the monthly basis so that the monthly total precipitation equals the area weighted mean total precipitation of all grid cells whose portions fall within the subcatchment. Temperature was computed as the area weighted average of the values at the grid cells that are within the subcatchment.

2.2. Hydrological model

The hydrological model employed in this study, HYPE, is a continuous process-based model, which simulates components of the catchment water cycle at a daily or hourly time step. The model is a semi-distributed conceptual model, in which a river basin may be subdivided into multiple subcatchments, which are further subdivided into homogeneous hydrological response units (HRUs) based on combined soil type and landuse classes (Fig. 2). Normally, model outputs are generated at the subcatchment outlet. The model has conceptual routines for most of the major land surface and subsurface processes (e.g. including snow/ice accumulation and melting, evapotranspiration, surface and macropore flow, soil moisture, discharge generation, groundwater fluctuation, aquifer recharge/discharge, irrigation, abstractions and routing through rivers, lakes and reservoirs) that are controlled by a number of parameters (Table 2) that are often linked to physiography to account for spatial variability and need to be estimated through calibration. The snow accumulation and melt process is modeled using the degree-day method with landuse dependent parameters. A fraction of rainfall or snowmelt infiltrates into the topsoil, which is limited by a soil type dependent maximum rate (*mactrinf*). If the soil moisture in the upper soil layer exceeds a threshold for macropore flow (*mactrsm*), part of the remaining water forms macropore flow that is controlled by a soil type dependent runoff coefficient *macrate*. Part of the remaining water is transformed into surface runoff using a soil dependent coefficient *srrate*. The remaining water forms a surface pool and overland flow is computed using a landue dependent recession coefficient *srrcs*. Potential evapotranspiration (PET) is estimated using the modified Jensen-Haise model (Oudin et al., 2005), whose parameters (k_c) are landuse dependent. PET is achieved only if the actual soil moisture exceeds a large proportion (*lp*) of the soil field capacity and for soil moisture below this limit, the actual evapotranspiration decreases linearly to zero at wilting point. Runoff from the soil zone is computed when the soil moisture exceeds field capacity using soil type dependent recession coefficients *rrcs*. Water percolates from upper to lower soil layers when the soil moisture in the upper layer exceeds field capacity and the rate is determined using a soil type dependent percolation parameter *mperc*. The ground water level is estimated based on the level in the soil zone where the pore space is filled.

Table 2
Different groups of model parameters and the basis of their regionalization.

Process	Parameter	Units	Min	Max
Soil type based				
Water holding	Fraction of soil water available for PET (wcfc)	–	0.05	0.5
	Wilting point as fraction of soil depth (wcwp)	–	0.05	0.5
	Effective porosity as fraction of soil depth (wcep)	–	0.05	0.5
Percolation	Maximum percolation capacity (mperc)	mm/d	5	120
Recession	Soil recession coefficient (rrcs)	–	0.05	0.6
Surface runoff	Threshold for macro pore flow (mactrinf)	mm/day	0	100
	Threshold soil water as fraction of soil depth for macro pore flow and surface runoff (mactrsm)	–	0	1
	Fraction of macro pore flow (macrate)	–	0.05	0.5
	Fraction of surface runoff (srrate)	–	0.05	0.5
Landuse based				
Evapotranspiration	Crop coefficient used to scale reference PET (k_c)	–	0.8	1.2
Snow	Threshold temperature for snowmelt (ttmp)	°C	0	0
	Degree-day factor (cmlt)	mm/d °C	1	4
Surface runoff	Recession coefficient for surface runoff (srrcs)	–	0.01	0.2
Catchment scale				
Evapotranspiration	Threshold soil water for activation of PET (lp)	%	0.8	1
	Temperature correction for elevation in relation to mean subcatchment elevation (tcelevadd)	°C/100m	0	0.7
	Adjustment factor for PET (cevpcorr)	–	−0.2	0.2
	Adjustment factor for temperature (tempcorr)	–	−0.2	0.2
Precipitation	Threshold elevation for precipitation adjustment (pcelevth)	m	–	–
	Adjustment factor for precipitation with elevation (pcelevadd)	mm/100m	0	5
Flood speed	Clelerity of flood wave (rivvel)	m/s	0.5	1.5
	Fraction of delay in water course (damp)	–	0.4	0.7
Recession	Correction factor for soil recession coefficient (rrcscorr)	–	−0.2	0.2
	Slope dependent recession coefficient in the upper soil layer (rrcs3)	–	0.0	0.1
Lakes and reservoirs				
Lake Rating curves	Lake recession factor (gratk)	–	1	2
	Exponent parameter to lake depth (gratp)	–	1	100

The generated discharge is routed through each subcatchment and between subcatchments using a river routing routine which simulates attenuation and delay using a flow wave and delay parameters *rivvel* and *damp*, respectively. If lakes and reservoirs are present within a subcatchment, the flow is routed in the lake or reservoir using a rating curve with parameters *gratk* and *gratp*.

2.3. Catchment classification

As a first step in our parameter regionalization framework, we classified catchments into different groups of similar characteristics based on a set of catchment physiographic and climate descriptors. Different descriptors have different process controls on different flow signatures and the objective of the classification is to group catchments with different dominant catchment response behaviors that are controlled by their catchment descriptors (Sawicz et al., 2011; Olden et al., 2012). All descriptors were derived from readily measurable and available data such as topographic, soil and land cover data, as well as climate data. We selected a set of catchment descriptors that are expected to influence the hydrological response of a catchment partly based on an evaluation of how catchment characteristics affect aspects of observed discharge in Europe (Donnelly et al., 2016), but extended to include more descriptors. In total, we used 21 catchment physiographic and climate descriptors as a basis for catchment classification: catchment area, mean catchment elevation, mean catchment slope, 9 landuse classes, 7 soil types, mean annual catchment precipitation and temperature. There could be significant correlation between some of the descriptors. Hence, we employed principal component analysis to derive variables that are independent and have less dimensionality than the original descriptors.

Catchments were grouped into groups of similar characteristics using a hierarchical minimum-variance clustering method, since the method keeps the within group variability to a minimum. To this end, we employed the k-means algorithm (Hartigan and Wong, 1979) with a large number of groups (100 groups in this work) and hierarchically merged groups using Ward's minimum variance method (Ward Jr., 1963). Two groups are merged in such a way that the increase in the sum of the within group variance of the descriptors weighted by the respective group size across all groups is the minimum. After each merging step the k-means algorithm was applied to the reduced number of groups. The optimum number of groups was established by evaluating the changes in the total weighted variance of the catchment descriptors across all groups between successive merging steps. The point where the rate of change becomes steeper was set as the optimum number of groups.

2.4. Model parameter regionalization

2.4.1. Base-line regionalization

HYPE has several parameters that can be grouped into different categories based on how they are estimated and regionalized (Table 2). Calibration is normally carried out in a stepwise manner by estimating parameters of each group at a time (Arheimer and Lindström, 2013; Donnelly et al., 2016; Pechlivanidis and Arheimer, 2015). The HRU parameters, which are soil or landuse type dependent, are first estimated for each soil and landuse type by calibrating the model for a group of representative gauged subcatchments for which the dominant soil or landuse type is the one whose parameters are estimated. The parameters thus estimated are applied everywhere in the model domain since they are soil or landuse type specific. In the second step, subcatchment scale parameters, which are not directly linked to soil or landuse type, are estimated by calibrating the model for all subcatchments used to calibrate the first group of parameters. These parameters are set to be constant across the entire model domain. These include rating curves for lakes and reservoirs. However, the rating curves can be estimated for individual lakes where discharge gauging stations are collocated with lakes.

In the current model version (E-HYPE v.3.0), the landuse dependent evapotranspiration parameters were estimated against satellite based (MODIS global dataset, Mu et al., 2011) PET data. The HYPE model PET parameters were optimized for each landuse type so that HYPE modeled annual PET matches the MODIS PET within the entire model domain. The landuse dependent snow accumulation and melt parameters were also estimated for each landuse type so that the model estimated snow depth matches the GlobSnow snow depth data. The other HRU parameters that are defined based on landuse or soil type were estimated for each landuse or soil type by calibrating the model simultaneously for a set of selected gauged catchments in each catchment group identified through catchment classification at a time and repeating the procedure iteratively. Parameters that are not defined based on landuse and soil types were adjusted manually such that certain features of the hydrographs, such as time shift, which are modelled using the routing parameters, are corrected. These parameters were calibrated and regionalized in detail at the next step of model calibration described in Section 2.4.2. General parameters that control flows out of lakes and dam regulation were calibrated using a set of subcatchments with significant proportion of lakes or regulation and used as default parameters. For those rivers in Europe most affected by lake and reservoir processes and sufficiently gauged, these parameters were individually tuned to the nearest downstream gauge. In total 39 gauging stations were used for individual calibration of lakes and reservoirs in 8 river systems.

2.4.2. Introduced regional parameter estimation scheme

We introduced a calibration strategy, where the general parameters that are set constant throughout the model domain in the standard calibration procedure of HYPE are estimated as functions of a set of catchment descriptors. Each catchment will then have a unique set of these parameters that are regionalized based on the catchment characteristics. We employed a method similar to a regionalization approach outlined in Hundecha and Bárdossy (2004), in which a linear relationship between a model parameter and a set of catchment descriptors is assumed a-priori and the coefficients of the linear function are estimated during model calibration. While assumption of linearity of the relationships is attractive due to its simplicity, the relationship could deviate from linearity if the catchment descriptors show a large variability, which is the case in a large-scale model setup such as the present work. Therefore, we performed the estimation for each parameter separately in each group of catchments established through catchment classification. Since the catchments were grouped into different groups based on their catchment descriptors, the variability of the catchment descriptors within each group is much less than the corresponding variability across the entire model domain. Therefore, it is assumed that the error that could result from a linearity assumption would be reduced by regionalizing the parameters separately for each group of catchments.

The catchment descriptors used in the regionalization of the parameters were initially set based on prior knowledge of the controls of the processes they describe (e.g. Strömqvist et al., 2012; Donnelly et al., 2016; Pechlivanidis and Arheimer, 2015). See also Section 3.2 for which descriptors were used as a basis of regionalization for the different parameters. Descriptors to which the parameters did not show sensitivity during the estimation procedure were subsequently left out and the relationships with the remaining descriptors were refined through a subsequent estimation.

To investigate the value of separate regionalization for each group of catchments, we compared the results with a reference regionalization approach, where a single set of regionalization equations, which were estimated by simultaneously calibrating the model for all the calibration catchments obtained by merging all groups of catchments, were applied across the entire model domain (hence accounting for the entire heterogeneity in the domain). Finally, we compared the model performance after introducing the new regional parameter estimation scheme with the results from the base-line model (standard HYPE parameter estimation).

2.5. Parameter estimation and model evaluation

2.5.1. Parameter estimation strategy

Estimation of the model parameters was performed using a set of daily discharge stations. The calibration period was set to 1980–1999 with 1979 used as a spin-up period. Since many stations do not have a complete data set over this period, we filtered stations to exclude those with a maximum of 60% missing data. Furthermore, selection of the stations was guided by the need to have the entire subcatchments draining to the given station belong to the same class of catchment groups (See Section 3.1). In addition, since the climate drivers for each subcatchment were estimated from grid based data and the small scale variability may not be well represented, we set a minimum drainage area of 1000 km^2 for the selected stations. There were 115 stations that meet these criteria and we used all of them for model calibration.

At each stage of model calibration, simultaneous calibration was performed to all stations of the calibration set within a given catchment group. We employed the sum of Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970) at each of the stations as a basis of the objective function. However, this could lead to unbalanced model performance at the different stations since a poor performance at some stations could be offset by a good performance at others. Therefore, we used an objective function that gives more emphasis to the station where the performance is the poorest (see Hundecha and Bárdossy, 2004):

$$Obj = \sum_{i=1}^{N} NSE_i + N minNSE \tag{1}$$

where N is the number of stations, $minNSE$ is the minimum of the NSE_i values. A combination of automatic calibration and manual tuning was employed in the process of estimation of the soil, landuse and the catchment scale parameters. We employed the DE-MC algorithm (Ter Braak, 2006) for automatic calibration with 200 generations of 100 parallel chains at each step of calibration. The median values of the last 100 generations were used as estimates of the optimum parameter values.

2.5.2. Evaluation of the regionalized model

The regional parameterization established using the calibration set of stations was tested using a set of independent validation stations that were not used during the model calibration. We selected 538 stations that were not highly influenced by anthropogenic alterations by screening those stations known to be influenced by regulation and manually inspecting the remaining stations for unusual hydrographs. To group the validation stations into the different groups of catchments, we computed the percentages of the catchment areas draining to the stations belonging to the different groups and assigned the station to the group that has more than a 50% share of the drainage area. Those stations to which there is no group with more than 50% contribution to the upstream area were treated as belonging to a new group representing inhomogeneous conditions (mixed).

We employed NSE and relative volume error, which is defined as the percentage bias of the modeled average daily flow against the observed to evaluate the model performance in both the calibration set and validation set of catchments. Furthermore, we evaluated the model performance in terms of its ability in reproducing different features of the daily hydrograph by using a set of flow signatures. We compared the modelled and observed mean specific daily flow (Qmean), the daily specific flows that are exceeded 5% (Q95) and 95% (Q05) of the number of days to characterize the overall daily, high flow, and low flow, respectively. Furthermore we compared the modelled and observed coefficient of variation (CV) of the daily flow to evaluate the models ability to capture the variability of the daily flow.

3. Results and discussion

3.1. Catchment classification

Application of principal component analysis on the 21 catchment descriptors resulted in 12 principal components accounting for 86% of the total variability and these were used for catchment classification. Following the procedure outlined in Section 2.3, we ended up with 16 groups of catchments. This can be seen in Fig. 3, where the change in the sum of the weighted variance of the principal components that are used for the classification across all groups between successive merging steps shows a sharp change when the number of groups is 16.

Generally, the catchment groups display spatial coherence across the study domain with a visible north-south distinction (Fig. 4a). Analysis of the distributions of the different catchment descriptors employed in the classification (Fig. 4b) shows that much of the variability between the groups comes from the landuse and soil types. In addition, catchments in the Alps and Norway with high elevation are grouped into a few classes, highlighting the added importance of elevation in the classification. However, as the classification is dominated by landuse and soil types, there are also catchments in low lying areas that are grouped together with the high elevation catchments. This is reflected by the higher variability of the distribution of elevation in such groups (see for instance groups 3, 12, 14 and 16 in Fig. 4b). Each of the groups is characterized by one or two dominant landuse and soil types. The distribution of mean annual precipitation within the catchment groups closely follows that of the elevation, with a bit higher median value and higher variability in groups where the high elevation catchments are grouped. On the other hand, mean annual temperature displays a clear north-south gradient, with a higher variability within groups made up of catchments located in both northern and southern Europe, such as group 12. Catchment area has similar distribution within all groups and thus plays little role in the classification.

The fact that the dominant controls for the catchment classification are landuse and soil types was exploited in the regionalization of the model parameters. Since there are one or two dominant landuse and soil types in each group of

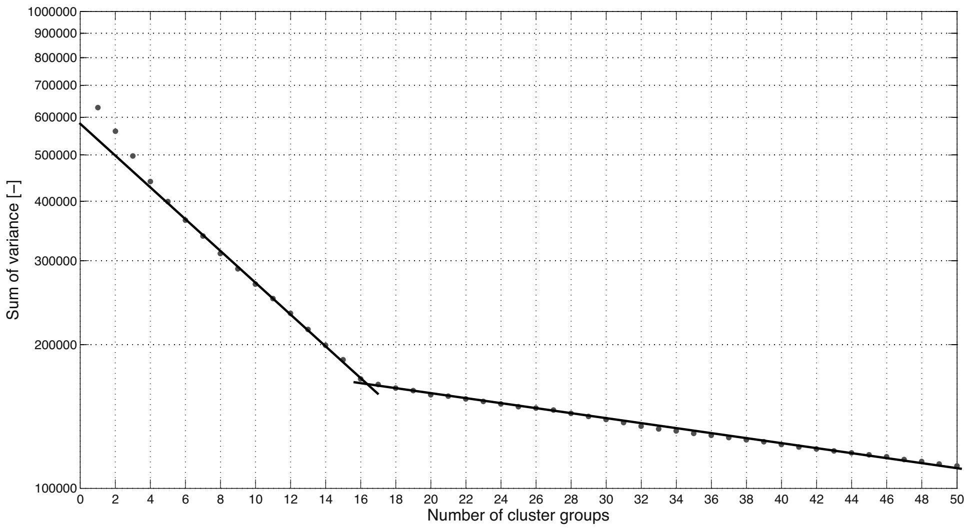

Fig. 3. Sum of within group variances of the principal components of catchment descriptors weighted by the respective group size at each stage of the hierarchical clustering procedure of the catchment classification.

Table 3
Number of stations used for calibration and spatial validation in different groups of catchments.

Group No.	Calibration set				Validation set			
	No. Stats	Min. area	Max. area	Avg. area	No. Stats	Min. area	Max. area	Avg. area
1	11	955	5202	2248	31	1170	194376	18162
2	4	920	5510	2225	73	1033	97780	15880
3	7	1060	2240	1368	24	1107	13733	4505
4	2	1920	14100	8010	13	1020	54700	9423
5	18	903	5560	1774	25	1036	6983	2464
6	20	1000	2418	1597	31	1010	19920	2964
7	20	908	4160	1696	64	1026	36275	5622
8	2	2780	3062	2921	7	1110	12000	3726
9	16	995	5090	2007	73	1010	285000	21276
10	0	–	–	–	0	–	–	–
11	5	1110	8538	2759	7	1704	14191	5224
12	1	1142	1142	1142	4	1755	7074	3459
13	0	–	–	–	0	–	–	–
14	9	908	5915	2128	19	1100	26084	6347
15	0	–	–	–	0	–	–	–
16	0	–	–	–	1	7380	7380	7380
Mixed	–	–	–	–	166	1119	807000	76510

catchments, estimation of the landuse and soil type based parameters was performed by separately calibrating a group of parameters for catchments belonging to a single group at a time and refining the estimates iteratively.

There were too few calibration stations (Table 3) in some of the catchment groups to allow a reasonable estimation of the catchment scale parameters using a regional relationship. Therefore, for estimation of the catchment scale parameters, we manually merged some of the catchment groups that have similar distributions of their catchment descriptors. We merged groups with less than 5 stations with groups that have similar dominant landuse and soil types and more than 5 stations. This resulted in 8 groups (Table 4) with a slightly modified distribution of the dominant catchment descriptors within the merged groups, showing somewhat less variability than within the group in the original classification with the highest variability (Fig. 5). Note that the original classification was used for estimation of the HRU parameters since the groups have more distinct landuse and soil class distribution.

3.2. Regional relationships between parameters and catchment descriptors

Table 5 shows that the catchment descriptors to which the catchment scale parameters are sensitive are mostly linked to soil type, mean catchment slope, up-stream area or mean catchment elevation. Table A1 also shows the correlation coefficients between the parameters and catchment descriptors for each group of catchments. It should be noted that some of the catchment-scale parameters, such as the evapotranspiration and recession parameters, have mainly the effect of modulating the soil and landuse parameters, as these were estimated during the first step to calibrate the base-line model

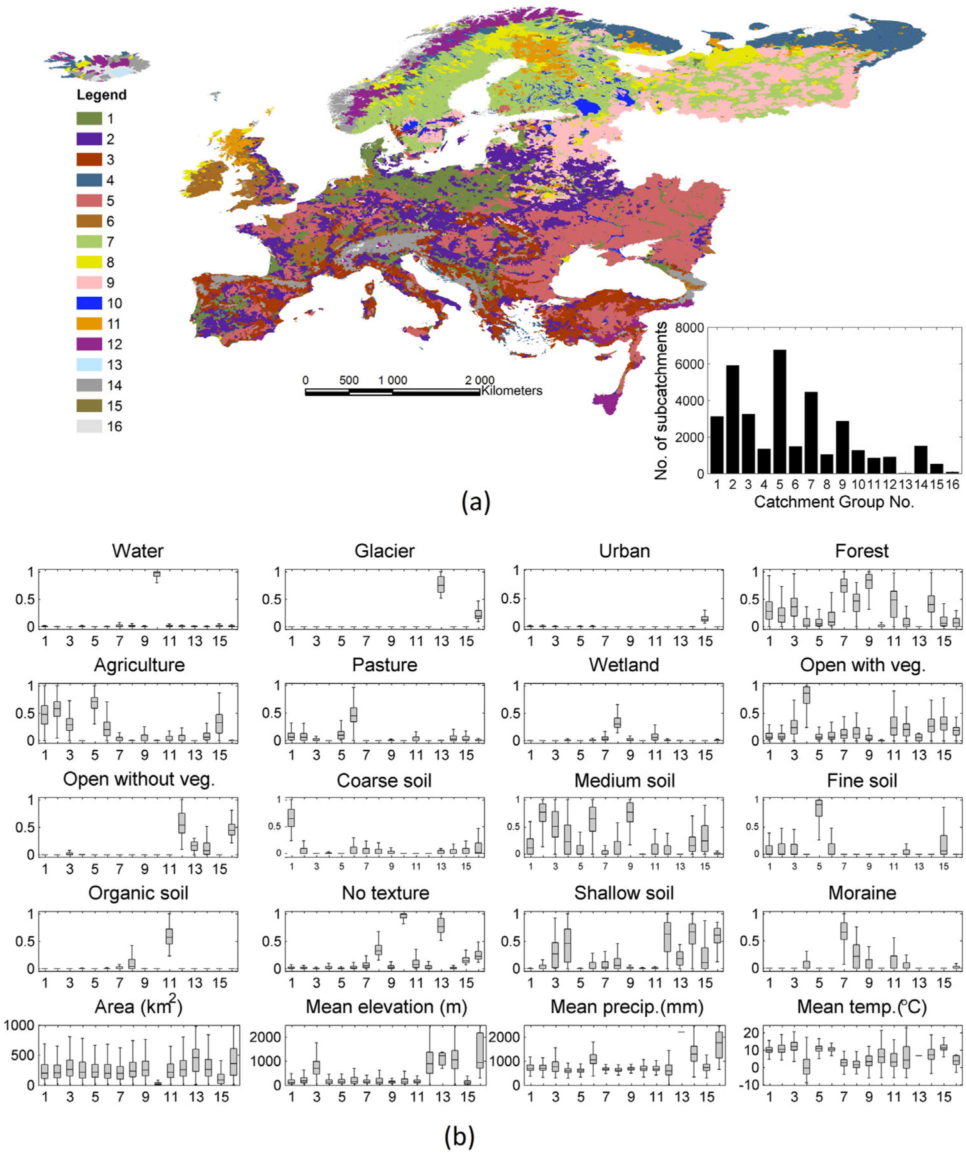

Fig. 4. (a) Spatial pattern of catchment groups and their frequency distribution, and (b) distribution of the different catchment descriptors in each of the groups (landuse and soil types are shown as fractional proportions).

Table 4
Original groups of catchments merged together to form a new grouping for regionalization of catchment scale parameters and the number of stations in the new groups of catchments.

New group ID.	Merged groups	Calibration set				Validation set			
		No. Stats	Min. area	Max. area	Avg. area	No. Stats	Min. area	Max. area	Avg. area
A	1,2	16	920	5510	2242	132	1033	194376	18367
B	3,4,12	9	1060	14100	2758	45	1020	54700	5723
C	5	18	903	5560	1774	25	1036	6983	2464
D	6,15	20	1000	2418	1597	32	1010	19920	3105
E	7,8,11	27	908	8538	1984	89	1026	36275	5593
F	9	16	995	5090	2007	73	1010	285000	21276
G	13,14,16	9	908	5915	2128	26	1100	26084	7219
H	10	0	–	–	–	0	–	–	–
Mixed	–	–	–	–	–	116	1119	807000	101502

Table 5
Catchment scale model parameters and catchment descriptors they are regionalized with.

Process	Parameter	Catchment descriptors used for regionalization						
		Catchment group ID						
		A	B	C	D	E	F	G
Evapotranspiration	lp	% coarse soil % medium soil	% medium soil	% fine soil % agriculture	–	–	–	% medium soil % shallow soil
	tcelevadd	0.6	0.6	0.6	0.6	0.6	0.6	0.6
	cevpcorr	% forest %agriculture	% forest % agriculture % open area	% forest % agriculture % pasture	% forest % agriculture % pasture	–	% forest % open area	% forest % agriculture % pasture % open area
	tempcorr	–	–	–	–	–	–	–
Precipitation	pcelevth	450m	1000m	250m	400m	–	–	950m
	pcelevadd	Mean elevation	Mean elevation	Mean elevation	Mean elevation	–	–	Mean elevation
Flood speed	rivvel	Slope Upstream area	Slope Upstream area	Slope Upstream area	Slope Upstream area	Slope	Slope Upstream area	Slope Upstream area
	damp	Slope Upstream area	Slope Upstream area	Upstream area	Slope	–	–	Slope Upstream area
Recession	rrcscorr	% coarse soil % medium soil	–	% medium soil % fine soil	–	–	–	% medium soil % shallow soil
	rrcs3	% coarse soil % medium soil	% coarse soil % medium soil % shallow soil	% medium soil % fine soil	% medium soil % fine soil % shallow soil	–	% medium soil % moraine	–

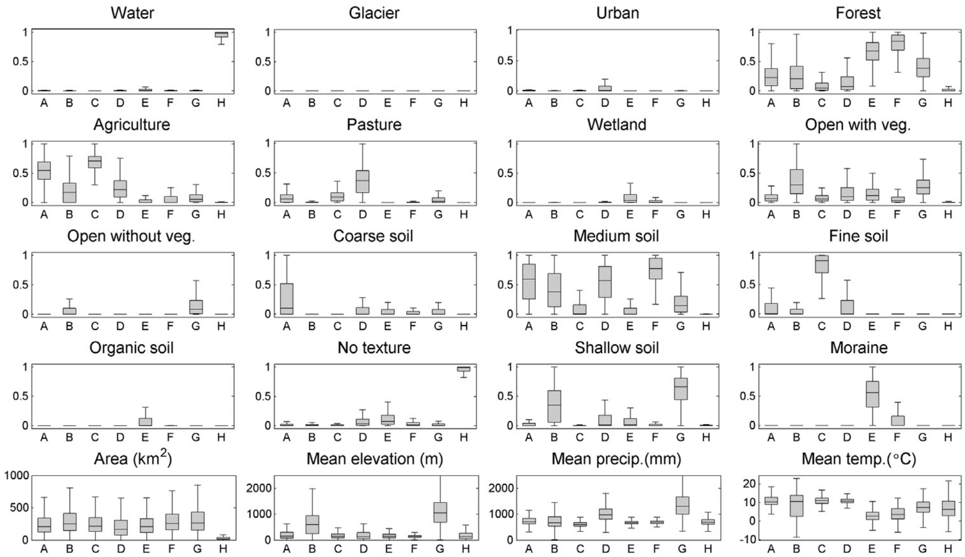

Fig. 5. Distributions of catchment descriptors in the different catchment groups that are formed after merging some of the classes for regionalization of catchment scale parameters (landuse and soil types are shown as fractional proportions).

(Section 2.4.1). Others, such as the flood propagation parameters, pertain to processes whose parameters have not been properly calibrated in the previous step.

The parameters that control evapotranspiration (*lp* and *cevpcor*) were regionalized based on the proportions of the soil type and landuse within each group of catchments. For the parameter *lp*, which controls the threshold for activation of the full potential PET in the soil root zone, strong relationships were obtained with the proportion of soil types in some of the groups. Only in group C does proportion of landuse (agriculture) show a strong correlation with this parameter. No strong correlation was obtained with either landuse or soil type in three of the groups (D, E, and F), which are mainly located in the northern part of Europe. The parameter *cevpcor*, which adjusts the potential evapotranspiration, was found to have a strong correlation with proportions of the dominant landuses in most groups, except in group E, where no adjustment was needed. The landuse dependent parameter k_c that controls PET was estimated using satellite data (See Section 2.4.1). However, the landuse characteristics in different parts of the model domain could have different features and, therefore, *cevpcor* adjusts the PET for a possible variation of the landuse characteristics in different catchment groups.

The adjustment parameters for soil recession were regionalized using proportions of the soil types making up the group. While the parameter *rrcs3*, which adjusts the upper soil layer recession as a linear function of mean catchment slope shows a strong correlation with some of the soil types in most groups, the parameter *rrcscorr*, which adjusts the recession in all layers, was found to be strongly correlated with proportions of soil types only in groups A, C, and G. Groups A and C consist of catchments that are mainly located in the southern and central parts of Europe, while group G consists of high elevation catchments in the Alps and Norway.

The threshold elevation above which precipitation correction is needed (*pcelevth*) was set constant for each group and it varies between the different groups. Generally, the threshold gets higher in catchments where the elevations are high (B and G) and the rate of correction with elevation (*pcelevadd*), which was also set constant for a given group, is lower in these catchment groups compared to low lying catchments. Similarly the rate of correction for temperature (*tcelevadd*) was set constant for each group. However, temperature correction did not lead to any noticeable increase in model performance. Therefore, the parameter was not regionalized in order to reduce the number of parameters used for model calibration and was instead assigned a default lapse rate value everywhere. The same was done to the catchment temperature adjustment factor *tempcorr*.

The flood propagation parameters were regionalized based on total upstream area and mean catchment slope (Table 5). Generally, both the flood celerity parameter (*rivvel)* and the damping parameter (*damp)* show a strong correlation to both descriptors in most catchment groups (Table A1). However *damp* shows no variation with respect to both the slope and upstream area in the mainly flat areas of northern Europe (groups E and F) where possibly lakes dominate routing more than slope and area.

3.3. Evaluation of the regionalized model in terms of NSE and volume error

Fig. 6 shows that there is some variation in the distribution of the performances, especially the NSE, between the different catchment groups. The relative volume error has a fairly similar distribution across all groups, with a general tendency of the model to underestimate the total discharge volume in the calibration catchments, except in groups A and F. In the validation

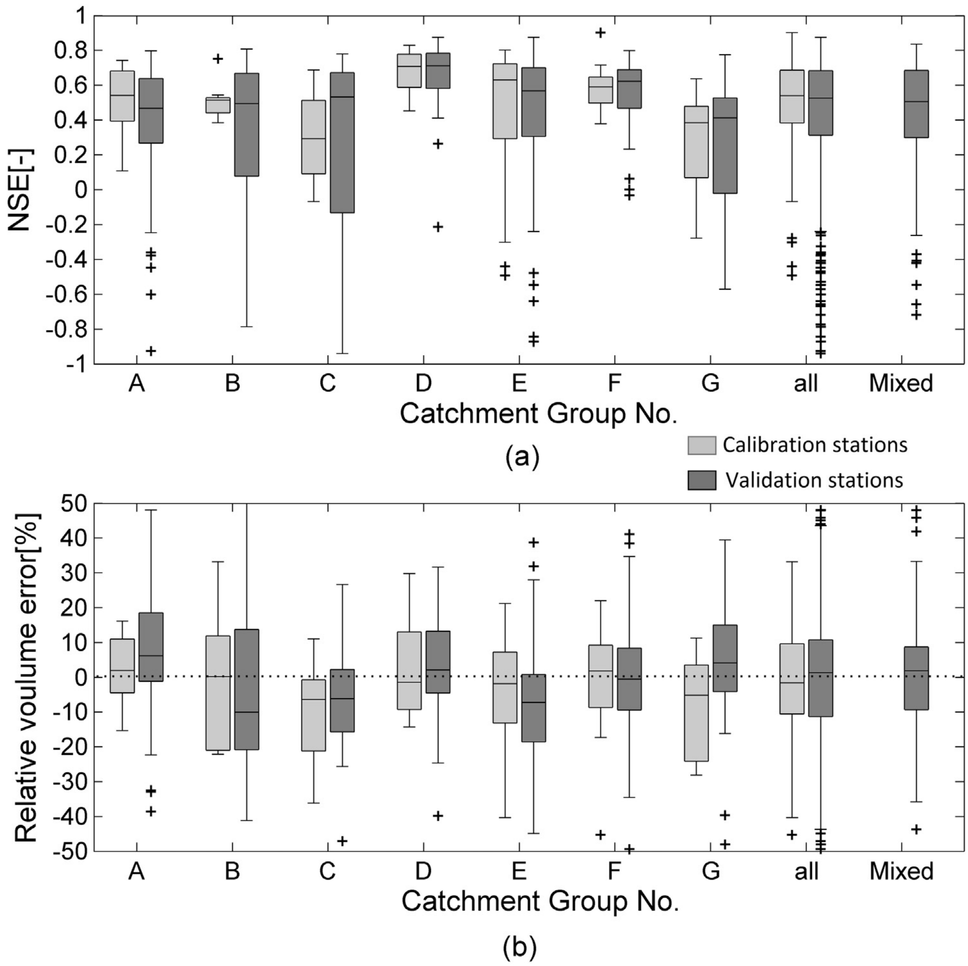

Fig. 6. Distribution of performance measures at the stations used for calibration and validation of the different catchment groups (number of stations within each class shown in Table 4).

catchments, however, the model slightly overestimates the discharge for most groups. However, the median relative error across all stations is only within ±2% in both the calibration and validation sets of catchments.

The available data in the period after the calibration period at many of both the calibration and validation stations is not enough to allow a reasonable temporal validation of the regionalized model. Therefore, we computed the performance measures at the validation stations for all available data over 1980–2010. In order to use the calibrated model as reference for comparison, we present the performance in the calibration set of stations over the calibration period.

Model performance is the highest in group D, both in the calibration and validation sets, with high NSE values and low volume error and less variability in performance between stations (Fig. 6). The catchments in this group are characterized by a predominantly medium texture soil and pasture landuse with some agriculture and forest. Most of the catchments in this group are located in the low lying areas of Western Europe and the British isles (Fig. 7), with a relatively high mean annual precipitation and less variability of temperature. The performance is generally the lowest in group C, with a median NSE of 0.3 in the calibration set and the flow being underestimated in almost all catchments with a median relative error of −12%. Group C constitutes catchments with predominantly fine soil and agricultural landuse. They span a diverse region across central and Eastern Europe as well as south Western Europe (Fig. 7). They are characterized by low lying areas with low mean annual precipitation and high mean annual temperature. They generally have lower flows with higher variability (See section 3.4). This highlights the relatively poor model performance under an arid setting. The overall performance when all the calibration sets of catchments in all groups are pooled together is reasonably acceptable, with median NSE and relative volume error of 0.54 and −1.6%, respectively.

The median NSE values in the validation set of catchments are comparable with the corresponding values in the calibration set in most groups. They are slightly lower in groups A and E and considerably higher in group C than in the corresponding calibration sets; however, the scatter across stations is higher in most groups (Fig. 6). Note that there are more stations in the validation set than in the calibration set in each group and the catchments draining to the validation stations do not all

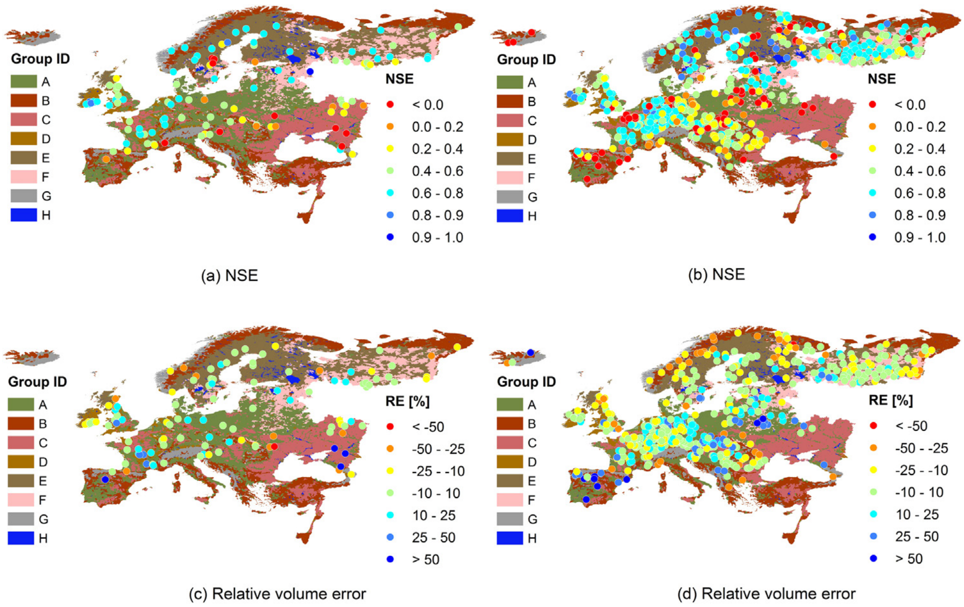

Fig. 7. Spatial patterns of NSE and Relative volume errors at the calibration (a and c) and validation (b and d) stations.

belong to the same group and hence are more heterogeneous, as we have set a 50% area rule to decide the membership of the stations (see section 2.5.2). This consequently leads to a higher spread in the model performance. However, the median values and variability of the relative volume error across stations within a given group are not very much different between the calibration and validation sets in most groups. The median NSE is similar to that of the calibration set (0.53 versus 0.54) with slightly higher spread between stations, while the distribution of the relative volume error is similar both in the calibration and validation sets with median values of −1.6% and 1.3%, respectively. The performance at stations that could not be grouped in any of the catchment groups, because none of the groups account for at least 50% of the upstream area, has a similar distribution of performance with that of the entire validation set of catchments. Overall, this indicates that the model parameters are robust enough for predictions in ungauged basins within the model domain with comparable skills, notwithstanding regional differences.

Generally, the regionalized model performance in terms of NSE shows a north-south gradient, with the performance decreasing southwards. Catchments located in the north, such as groups E and F, are characterized by a predominantly forest landuse and lower mean annual temperature, while those in the southern part, such as A and C are predominantly of agricultural landuse with higher mean annual temperature.

3.4. Evaluation of the regionalized model in terms of flow signatures

The model reproduces different flow signatures related to the long term mean, variability, and extremes with different levels of accuracy (Fig. 8). The model skill to predict the flow signatures varies between the different groups of catchments and could thus be linked to catchment characteristics.

As shown in Fig. 8, catchment groups A and C generally have lower mean (Qmean) and high flow (Q95) values while those in group G have the highest. Groups A and C are characterized by dominantly agricultural catchments with some forest landuse. While group A has a predominantly coarse to medium soil texture, group C has a predominantly fine soil. Both groups have a low mean annual precipitation and high mean annual temperature with little variation between the catchments making up the group. Catchments in group G have a predominantly forest landuse with some open land. The soil layer is mainly shallow with less storage, meaning that there is less water available for evapotranspiration and hence higher flow. In addition, the mean annual precipitation in this group of catchments is the highest among all the catchment groups. In all the other groups, the flows are generally variable across the catchments within each of the group. Generally, except in group C where there is a general underestimation, Qmean is slightly overestimated in catchments with lower mean flows while it is underestimated in catchments with higher flows within most catchment groups. No systematic bias in relation to flow magnitude is apparent in the estimation of Q95 within all groups. The low flows (Q05), on the other hand, are estimated with overestimation in catchments with lower low flows and underestimation in those with higher low flows.

Coefficient of variation of the daily flow shows less distinct variation between the different groups of catchments except that catchment group C has the highest value than the others, while the other groups have similar variation. The model estimates this signature with less bias compared to the other three signatures, which are related to magnitude of flows. However, the spread in the prediction is high across the entire range of variability of the values.

3.5. Value of catchment classification in parameter regionalization

Fig. 9 shows that both the median and upper quartile values of the NSE got lower in most catchment groups when parameters were regionalized without catchment classification. The model performance deteriorated the most in group C, where the flow displays the highest variability and the model performance was the lowest, with the median NSE dropping from 0.29 to 0.21 at the calibration stations and from 0.55 to 0.46 at the validation stations. Similarly, the distribution of NSE at all stations showed a slight shift to the lower side when regionalization was performed without catchment classification. The pattern of the difference in performance in the validation set of stations within most groups was similar with that of the corresponding calibration set of stations.

In terms of the relative volume error, regionalization with catchment classification led to less model bias in the calibration set of stations in all groups of catchments compared to regionalization without catchment classification. While the median error values were similar in most of the groups except within a few groups where the absolute median value showed improvement under classification based regionalization, the spread between the lower and upper quartiles were reduced in most of the groups and this tendency was also seen when all stations were pooled together. At the validation stations, however, the performance in terms of volume error was not consistently better in all groups under the classification based regionalization. It got better in group C, while little or no improvement was observed in most other groups. It got worse in groups B and G, which are groups that constitute high elevation catchments located both in the north and southern parts of the model domain. These groups are characterized by a wide variability of many of their catchment characteristics. Although the model performance showed improvement in the calibration set, transferring parameters to the validation set may not lead to improvement in all catchments consistently due to the wide variability of the catchment characteristics. The volume error distributions when all the validation stations were pooled together were also similar under both approaches.

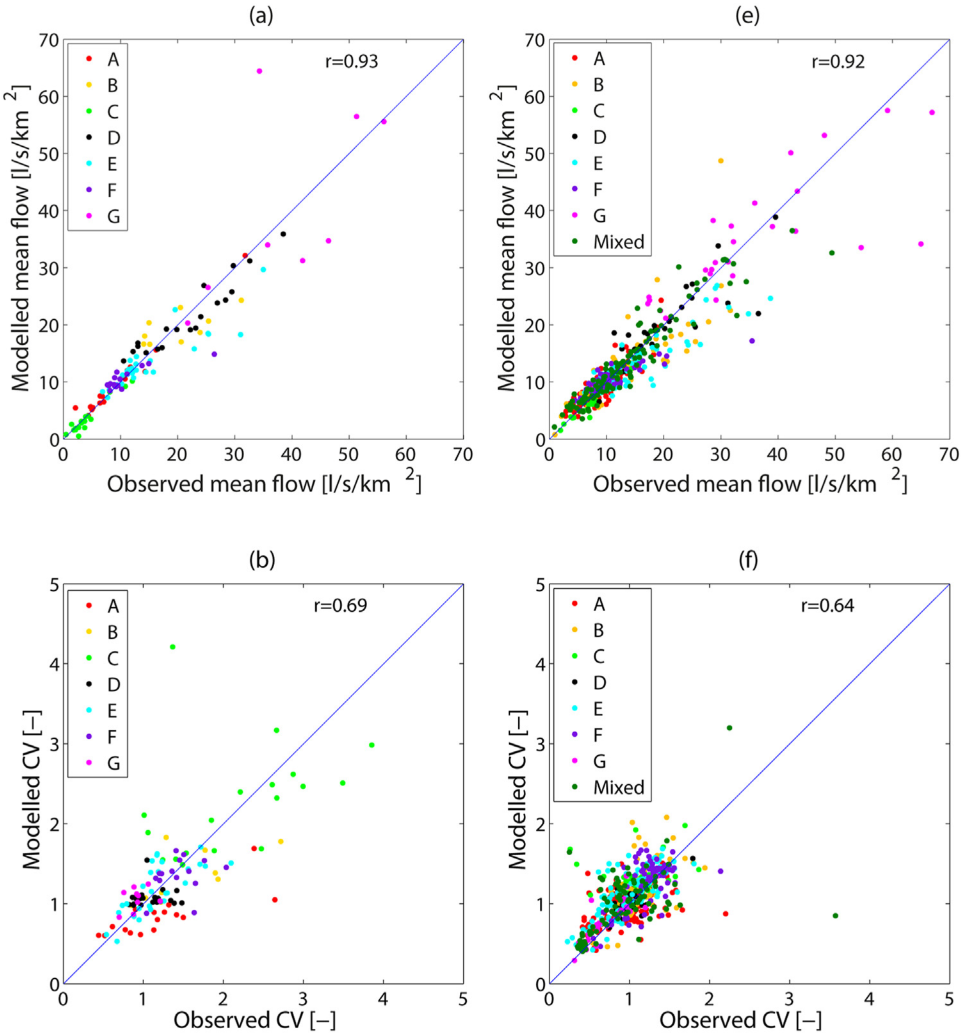

Fig. 8. Scatter plots of simulated vs. observed flow signatures in the calibration (a–d) and validation (e–h) stations within different catchment groups.

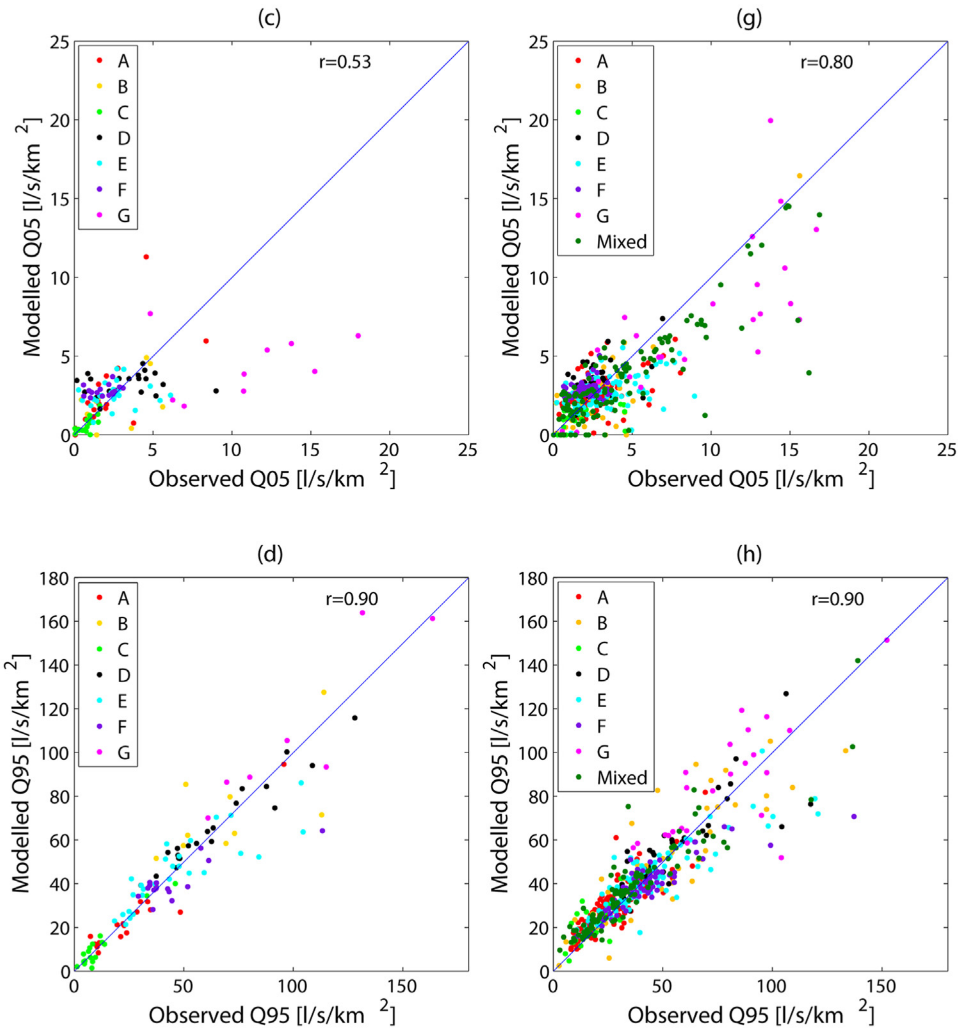

Fig. 8. Scatter plots of simulated vs. observed flow signatures in the calibration (a–d) and validation (e–h) stations within different catchment groups.

Also in terms of volume error, the performance improved the most in group C when regionalization was performed with classification, with the median volume error going down from −10.6% to −6.4% at the calibration stations and from −12% to −6% at the validation stations.

Overall, the classification based regionalization yielded considerably better model prediction in some of the catchment groups, such as in groups C and D, while the improvement against regionalization without classification in the other groups was marginal. The distribution of the NSE and volume error when all stations were pooled together was also slightly better under a classification based regionalization approach.

Regarding the improvement of model performance by introducing the regional parameter-estimation scheme for the catchment scale model parameters in the stepwise calibration, Fig. 10 shows that the model performance in terms of NSE improved at stations where the model performance was good under the base-line model calibration. However it got worse at those stations where the performance was very low. The median performance, nevertheless, got slightly better. In terms of volume error, regionalization clearly led to a better performance, especially at those stations where the flow was under-estimated under the base-line model calibration. The median volume error reduced from −5% at both the calibration and validation stations to ±2%.

Our finding that the employed regionalization scheme improved for sites where the model works well while it got worse at sites where the performance is the least could be suggestive of the possibility that other factors than parameter values might have led to the poor performance at these locations. Such factors can be erroneous or inconsistent input data, poor model forcing or human alterations. It is well known that the routing from the Hydrosheds database and the gridded meteorological products are far from perfect for Europe (Donnelly et al., 2012; Kauffeldt et al., 2013). Moreover, most of Europe is significantly affected by water regulation, irrigation, abstractions, channel strengthening, etc, which is probably

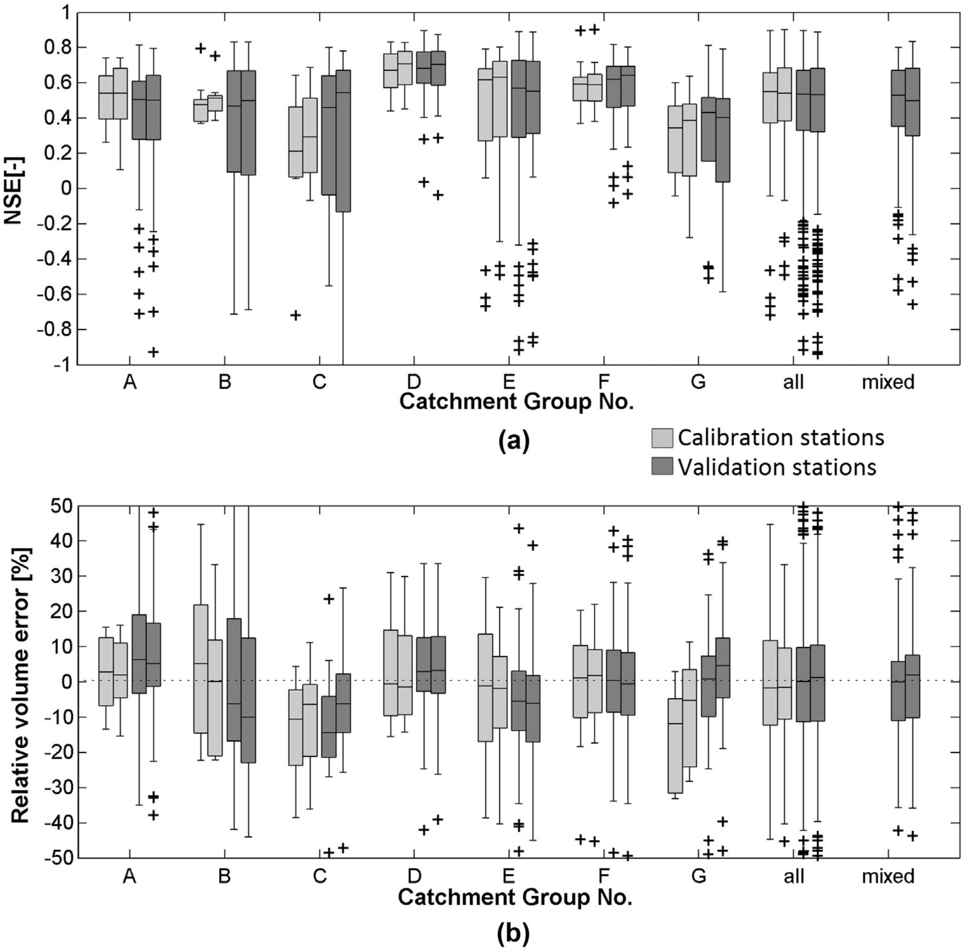

Fig. 9. Distribution of NSE (a) and RE (b) within the different catchment groups during the calibration period when regionalization of catchment scale parameters was performed without and with catchment classification (left side boxes in each group of stations: regionalization without classification, and right side boxes: regionalization with classification).

not fully described in the global databases at the resolution used in the E-HYPE model. This highlights the importance of more detailed spatial data across Europe to improve model parameter values and model structure.

4. Conclusions

By introducing a regional parameter-estimation scheme for the catchment scale parameters based on catchment physiography within a stepwise calibration procedure in the E-HYPE version 3.0, we found that:

- Regionalizing the model parameters as a function of catchment descriptors can improve prediction skills of a processed-based model. For E-HYPE this was especially valid for sites where the model is already performing well. The eventual success of the tested regional parameter-estimation scheme is influenced both by climate and human influence on the catchments.
- For some groups of catchments with similar physiography, stronger relationships between model parameters and catchment descriptors could be achieved with higher model performance than if regionalization was done for the full geographical domain. However, the overall performance for the full model domain did not improve much by introducing homogeneous groups and derive the regional relationship separately for each group.
- The properties of soil, land use and to some extent elevation were the most distinct physiographical characteristics for classification of catchment similarities across Europe. The strongest relationships between E-HYPE model parameters and catchment characteristics were found for soil, slope, up-stream area or elevation, to which model performance of flow signatures could also be linked.

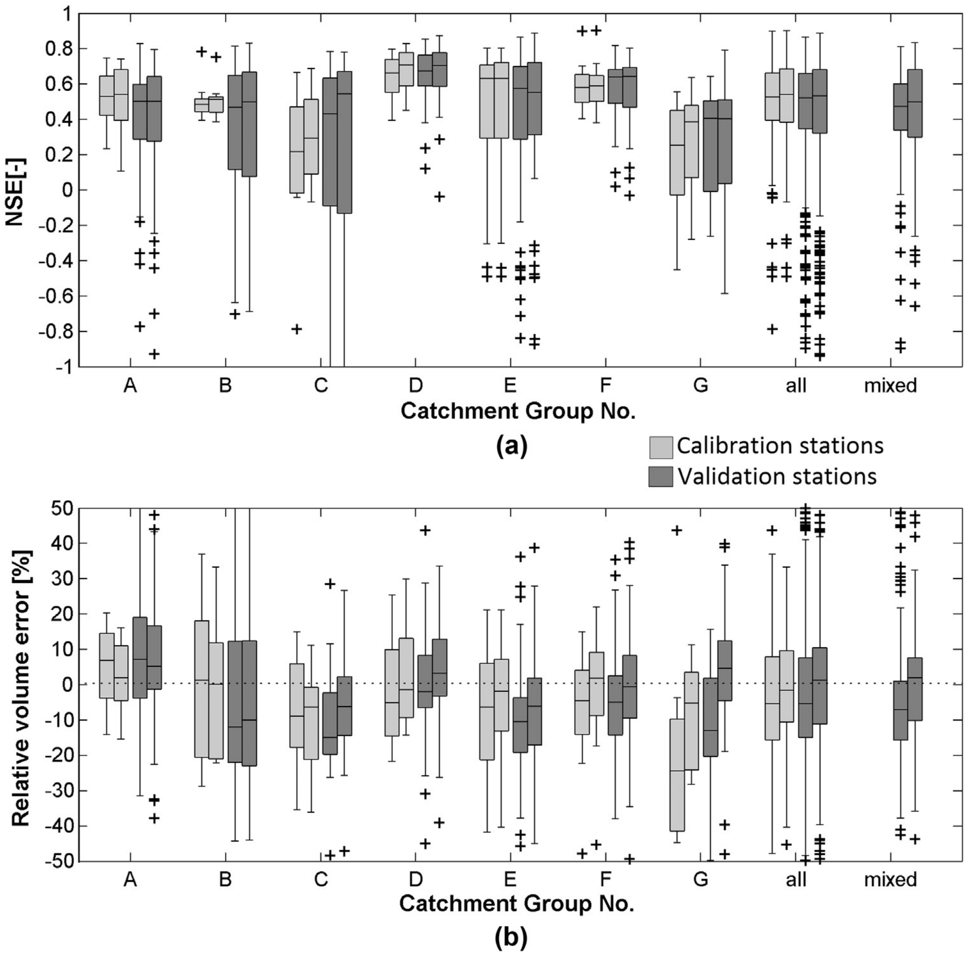

Fig. 10. Distribution of NSE (a) and RE (b) within the different catchment groups during the calibration period under base-line calibration and when regionalization of catchment scale parameters was performed with catchment classification (left side boxes in each group of stations: base-line calibration, and right side boxes: regionalization with classification).

The implemented regionalization scheme was found to allow transferability of parameters from a limited set of calibration stations to other locations without a need to calibrate a large number of catchments in a multi-basin setup of large scale modeling and to further enable modeling in ungauged catchments. The model performance in catchments that were not used for the derivation of the regional parameters was comparable with that of the catchments used for model calibration and parameter regionalization.

Conflict of interests

The authors declare there is no conflict of interest.

Acknowledgements

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Appendix A.

Table A1
Correlation coefficients between the optimum catchment scale model parameters and the different catchment descriptors (A value is shown as bold if the catchment descriptor is used as a basis of regionalization for the corresponding parameter and is significant at 5%).

Parameter	Group ID	Catchment descriptors																		
		cathment area (km2)	Mean elevation (m)	Mean slope	Water (%)	Glacier (%)	Urban (%)	Forest (%)	Agricluture (%)	Pasture (%)	Wetland (%)	Open with vegit. (%)	Open without vegit (%)	Coarse soil (%)	Medium soil (%)	Fine soil (%)	Organic soil (%)	No texture (%)	Shallow soil (%)	Moraine (%)
lp	A	0.06	−0.14	−0.06	0.14	0.02	0.11	0.07	−0.15	0.07	0.17	0.04	0.00	**0.38**	**−0.80**	0.17	0.22	0.23	0.17	0.11
	B	−0.01	−0.01	−0.19	0.16	0.16	−0.03	−0.22	−0.19	−0.15	0.20	0.06	0.15	0.12	**−0.94**	0.16	0.03	0.25	0.15	0.18
	C	0.06	0.02	0.14	−0.01	0.20	0.16	−0.08	**−0.41**	0.12	0.00	−0.10	0.22	0.20	−0.12	**−0.64**	0.13	0.23	0.07	0.23
	D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	E	0.14	0.10	0.09	0.01	0.06	−0.14	0.12	0.08	0.19	0.18	0.09	−0.02	−0.15	0.07	0.21	0.22	0.07	0.01	0.10
	F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	G	0.08	0.06	0.11	0.13	0.00	−0.03	0.13	0.16	−0.03	−0.10	−0.11	−0.16	0.11	**0.49**	0.08	0.15	−0.11	**0.38**	0.03
tcelevadd	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	G	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
cevpcorr	A	−0.03	0.00	−0.15	0.02	0.00	0.14	**−0.74**	**0.83**	−0.19	−0.02	0.17	0.05	−0.23	0.22	0.04	−0.16	0.06	0.06	−0.09
	B	0.05	0.34	0.35	−0.09	−0.02	0.21	**0.35**	**0.86**	0.20	−0.17	**−0.79**	−0.04	−0.03	0.18	0.19	−0.20	−0.12	−0.16	−0.22
	C	−0.03	0.08	−0.29	0.03	0.00	−0.02	**−0.72**	**0.93**	**−0.47**	0.02	−0.17	0.13	−0.04	0.00	0.09	−0.04	0.02	−0.20	−0.11
	D	−0.12	0.21	0.11	0.04	0.02	0.19	**0.41**	**0.60**	**−0.92**	−0.21	0.17	0.06	−0.03	−0.22	0.17	−0.22	0.22	0.15	0.07
	E	−0.13	−0.02	0.04	0.08	0.01	0.06	0.07	0.15	0.00	−0.19	−0.08	−0.07	0.03	−0.15	0.06	−0.08	−0.14	−0.07	0.13
	F	0.03	−0.10	0.04	0.12	0.00	0.18	**−0.83**	0.25	0.20	0.08	**0.91**	0.07	0.04	−0.17	0.08	0.11	0.15	0.16	−0.03
	G	0.29	−0.02	−0.15	0.13	0.14	−0.09	**−0.78**	**−0.52**	**−0.39**	0.13	**0.34**	**0.63**	0.08	−0.17	−0.11	0.04	0.14	−0.12	0.20
tempcorr	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	F	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	G	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
pcelevth	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	B	−0.04	−0.32	−0.05	−0.10	−0.10	0.16	0.33	0.30	0.15	−0.17	0.26	−0.88	0.03	0.38	−0.11	0.09	−0.19	−0.28	−0.13
	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	E	0.10	−0.03	0.06	−0.08	−0.01	−0.04	−0.58	0.09	0.32	0.47	0.30	0.13	−0.09	0.16	−0.01	0.75	0.42	−0.09	−0.72
	F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	G	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A1 (*Continued*)

Parameter	Group ID	Catchment descriptors																		
		cathment area (km2)	Mean elevation (m)	Mean slope	Water (%)	Glacier (%)	Urban (%)	Forest (%)	Agriclture (%)	Pasture (%)	Wetland (%)	Open with vegit. (%)	Open without vegit (%)	Coarse soil (%)	Medium soil (%)	Fine soil (%)	Organic soil (%)	No texture (%)	Shallow soil (%)	Moraine (%)
pcelevadd	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.01	0.00	0.00	0.00	0.00	0.00
	B	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00
	C	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00
	D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	E	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	G	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
rivvel	A	**0.27**	0.11	**0.33**	0.32	0.00	0.05	0.09	−0.15	−0.01	0.01	0.06	0.06	0.06	−0.10	0.11	−0.12	0.14	−0.03	−0.03
	B	**0.33**	0.13	**0.33**	0.03	0.13	−0.13	−0.20	−0.20	−0.10	0.06	−0.20	0.29	−0.03	−0.20	0.10	−0.11	0.11	0.21	0.07
	C	**0.30**	−0.07	**0.47**	0.21	−0.01	0.09	0.06	−0.07	−0.09	0.16	−0.02	0.01	0.16	0.02	−0.18	−0.01	0.19	0.04	0.00
	D	**0.39**	−0.07	**0.39**	0.20	0.04	0.26	0.01	0.10	−0.21	−0.10	0.12	0.07	0.04	−0.15	0.05	−0.08	0.20	0.06	0.01
	E	0.09	0.22	**0.38**	−0.03	0.00	0.00	−0.12	−0.10	0.06	0.15	0.13	0.12	0.02	0.04	0.00	−0.07	0.15	0.12	−0.21
	F	**0.36**	−0.13	**0.36**	−0.04	0.00	0.04	−0.09	−0.01	0.04	0.09	0.11	0.03	0.33	−0.14	0.02	0.00	0.05	−0.05	−0.02
	G	**0.51**	−0.06	**0.41**	0.27	−0.05	0.12	−0.02	0.17	0.01	−0.06	−0.12	−0.05	0.04	0.11	0.13	−0.03	0.17	−0.20	−0.02
damp	A	**−0.22**	0.11	**−0.27**	−0.14	0.01	−0.07	0.01	0.05	−0.03	−0.06	0.00	−0.02	−0.08	0.13	−0.10	0.06	−0.19	0.05	0.00
	B	**0.30**	−0.22	**−0.26**	0.07	−0.20	0.13	0.11	0.18	0.05	−0.05	0.17	−0.47	0.09	0.20	−0.07	0.09	0.00	−0.22	−0.06
	C	**0.28**	−0.08	−0.07	0.26	0.00	0.09	0.06	−0.06	−0.09	0.16	−0.02	0.01	0.17	0.02	−0.18	−0.01	0.42	0.04	0.00
	D	−0.19	−0.64	**−0.78**	0.12	0.02	0.23	−0.26	0.21	0.02	0.03	0.11	0.01	0.13	−0.21	0.10	0.14	0.24	−0.11	0.04
	E	−0.13	−0.14	−0.20	0.06	0.01	0.01	0.21	0.02	−0.23	−0.17	−0.18	−0.12	0.03	−0.03	0.04	−0.41	−0.24	−0.04	0.41
	F	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	G	**−0.32**	0.30	**0.91**	−0.25	−0.02	−0.08	0.03	0.17	0.05	−0.14	−0.05	0.01	−0.02	0.02	0.26	−0.02	−0.19	0.01	−0.04
rrcscorr	A	−0.04	−0.02	−0.02	−0.04	0.01	−0.07	0.24	−0.22	0.02	−0.02	0.01	0.01	**0.90**	**−0.55**	−0.17	−0.03	−0.07	−0.20	−0.07
	B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	C	0.01	0.09	−0.01	**−0.23**	0.00	**−0.21**	−0.18	0.13	0.12	−0.16	−0.04	0.08	−0.19	**−0.45**	**0.86**	0.09	−0.15	−0.17	−0.12
	D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	E	0.09	0.05	−0.08	−0.03	−0.01	−0.04	−0.24	−0.16	−0.09	0.70	−0.12	0.07	0.01	0.08	−0.02	−0.22	0.16	0.11	−0.17
	F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	G	0.21	−0.24	−0.17	0.27	0.43	−0.04	−0.29	−0.20	−0.12	0.30	0.11	0.18	0.20	**−0.88**	**−0.32**	0.02	0.15	0.17	0.17
rrcs3	A	0.01	−0.04	−0.01	−0.02	0.00	0.02	0.13	−0.12	0.06	−0.02	−0.03	−0.02	**0.62**	**−0.83**	0.18	−0.07	−0.02	−0.21	−0.10
	B	0.04	0.13	0.05	0.07	0.13	−0.15	−0.14	−0.21	−0.15	0.12	−0.21	0.19	**−0.46**	**−0.38**	0.17	−0.09	0.14	**0.28**	0.08
	C	0.01	0.07	−0.02	−0.21	0.00	−0.21	−0.17	0.11	0.13	−0.14	−0.03	0.09	−0.21	**−0.58**	**0.91**	0.13	−0.19	−0.17	−0.10
	D	0.08	0.14	0.14	−0.22	−0.05	−0.21	0.12	0.22	−0.02	−0.14	−0.07	0.01	−0.20	**−0.62**	**0.76**	**−0.47**	−0.01	**−0.48**	−0.21
	E	0.11	0.01	−0.06	−0.05	−0.01	−0.05	−0.11	−0.11	0.03	0.10	−0.01	0.10	−0.02	0.13	−0.02	−0.04	0.15	0.08	−0.21
	F	−0.09	−0.10	−0.06	−0.07	0.00	0.08	−0.03	0.09	0.04	−0.10	0.00	0.00	0.10	**−0.36**	−0.02	−0.10	−0.12	−0.07	**−0.38**
	G	−0.05	0.13	0.12	−0.08	−0.18	−0.01	0.05	0.21	0.11	0.08	−0.16	−0.10	0.20	0.19	0.22	0.02	−0.17	−0.11	0.15

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ejrh.2016.04.002.

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