Journal of Hydrology 560 (2018) 24–38

Contents lists available at ScienceDirect

Journal of Hydrology

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

Research papers

Parameter transferability within homogeneous regions and comparisons with predictions from a priori parameters in the eastern United States

Wafa Chouaib [a,*], Younes Alila [b], Peter V. Caldwell [c]

[a] Department of Forest Resources Management 2404, University of British Columbia, 2424 Main Mall, Vancouver, BC V6T 1Z4, Canada
[b] Department of Forest Resources Management 2030, 2424 Main Mall, Vancouver, BC V6T 1Z4, Canada
[c] USDA Forest Service, Southern Research Station, Center for Forest Watershed Research, Coweeta Hydrologic Lab, 3160 Coweeta Lab Road, Otto, NC 28734, USA

ARTICLE INFO

Article history:
Received 29 December 2017
Received in revised form 19 February 2018
Accepted 7 March 2018
Available online 8 March 2018
This manuscript was handled by Corrado Corradini, Editor-in-Chief, with the assistance of Mohsen M. Sherif, Associate Editor

Keywords:
Parameter transfer
Ungauged catchments
A priori parameters
Flow duration curve
Sacramento model

ABSTRACT

The need for predictions of flow time-series persists at ungauged catchments, motivating the research goals of our study. By means of the Sacramento model, this paper explores the use of parameter transfer within homogeneous regions of similar climate and flow characteristics and makes comparisons with predictions from a priori parameters. We assessed the performance using the Nash-Sutcliffe (NS), bias, mean monthly hydrograph and flow duration curve (FDC). The study was conducted on a large dataset of 73 catchments within the eastern US. Two approaches to the parameter transferability were developed and evaluated; (i) the within homogeneous region parameter transfer using one donor catchment specific to each region, (ii) the parameter transfer disregarding the geographical limits of homogeneous regions, where one donor catchment was common to all regions. Comparisons between both parameter transfers enabled to assess the gain in performance from the parameter regionalization and its respective constraints and limitations. The parameter transfer within homogeneous regions outperformed the a priori parameters and led to a decrease in bias and increase in efficiency reaching a median NS of 0.77 and a NS of 0.85 at individual catchments. The use of FDC revealed the effect of bias on the inaccuracy of prediction from parameter transfer. In one specific region, of mountainous and forested catchments, the prediction accuracy of the parameter transfer was less satisfactory and equivalent to a priori parameters. In this region, the parameter transfer from the outsider catchment provided the best performance; less-biased with smaller uncertainty in medium flow percentiles (40%–60%). The large disparity of energy conditions explained the lack of performance from parameter transfer in this region. Besides, the subsurface stormflow is predominant and there is a likelihood of lateral preferential flow, which according to its specific properties further explained the reduced efficiency. Testing the parameter transferability using criteria of similar climate and flow characteristics at ungauged catchments and comparisons with predictions from a priori parameters are a novelty. The ultimate limitations of both approaches are recognized and recommendations are made for future research.

1. Introduction

Estimates of stream flow are a prerequisite for solving a number of engineering and environmental problems (i.e., water quality and supply, flood control, and stream habitat assessment (Kokkonen et al., 2003). The accuracy of flow prediction in ungauged basins (PUB) is a central issue in hydrological modeling (Arsenault and Brissette, 2014; Ao et al., 2006; Sivapalan et al., 2003). When no flow records of sufficient length are available at the site of interest, regionalization techniques may be applied to derive such estimates (Kokkonen et al., 2003). Over the past decade, different studies have developed techniques for PUB, primarily via flow regionalization and model parameterization (Hrachowitz et al., 2013; Gan and Burges, 2006; Ren et al., 2016). Model parameterization in ungauged basins can be achieved using two primary approaches: parameter regionalization and a priori parameters determined from catchment properties (Hrachowitz et al., 2013). Despite the plethora of studies devoted to this topic, there is still no consensus regarding the most efficient approach for model parameterization in ungauged basins (Hrachowitz et al., 2013; Parajka et al., 2013; Razavi and Couillibaly, 2013).

Regionalization for PUB involves the following steps: (i) identification of homogeneous regions where several criteria of homogeneity can be used and (ii) data transfer (observed flow data or

* Corresponding author.
E-mail addresses: wafa.chouaib@alumni.ubc.ca (W. Chouaib), younes.alila@ubc.ca (Y. Alila), pcaldwell02@fs.fed.us (P.V. Caldwell).

https://doi.org/10.1016/j.jhydrol.2018.03.018
0022-1694/

calibrated parameters) between gauged and ungauged catchments of the same homogenous region. In parameter regionalization, the rainfall-runoff model is calibrated for all the study catchments with observed flows. Then, using a regionalization method, the parameters are transferred from the donor gauged catchments to the recipient ungauged catchments within the same region. To examine the potential predictive performance at ungauged catchments, the simulated flows from parameter transfer are compared with observed flows of recipient gauged catchments that play the role of ungauged catchments (i.e., Hundecha and Bárdossy, 2004; Jennings et al., 1994; Kokkonen et al., 2003; Norbiato et al., 2007).

The three most common methods used for parameter regionalization are the regression-based approach, spatial proximity, and physical similarity (i.e., Merz and Blöschl, 2004; Parajka et al., 2005; Sefton and Howarth, 1998; Young, 2006). The regression-based approach correlates the calibrated model parameters with physical properties of gauged catchments. The correlation is used to determine the model parameters in ungauged catchments (Merz and Blöschl, 2004). The spatial proximity approach consists of transferring parameters from neighboring catchments to the ungauged catchment, the rationale being that catchments close to one other should have similar hydrologic behavior (i.e., Oudin et al., 2008; Parajka et al., 2007). In physical similarity approach, the catchments with similar physical descriptors exhibit similar hydrologic behaviors (i.e., McIntyre et al., 2005). A common issue among the three regionalization approaches is less-than-satisfactory efficiency (i.e., Arsenault and Brissette, 2014) and a strong dependence on the complexity of the terrain and scale at which the relations are derived (Bock et al., 2015). The model parameter definitions are by nature ambiguous and difficult to determine from a small number of descriptors (i.e., physical and climatic characteristics) (Zhang et al., 2008). The lowest efficiency is obtained from the regression-based approach. The high correlation between model parameters and catchment descriptors does not guarantee efficient predictions (Kokkonen et al., 2003; Oudin et al., 2010a; Sefton and Howarth, 1998). Studies of spatial proximity and physical similarity have yielded no evidence of most efficient method (i.e., Oudin et al., 2008; Arsenault and Brissette, 2014). The spatial proximity has significant uncertainty due to a lack of representativeness of catchment data, rainfall as well as issues of identifiability of model parameters (Skøien and Blöschl, 2007). More measures other than distances between catchments are needed to refine the predictions. In physical similarity, the homogeneity of physical descriptors does not necessarily translate into representativeness of model parameters and flow response (Zhang et al., 2008).

The most important component of parameter regionalization—critical to obtaining satisfactory efficiency—is the identification of the geographic extent to which there is homogeneity in hydroclimate characteristics and therefore similarity in hydrologic response (Bock et al., 2015). Only a few recent studies have tested parameter transferability within homogeneous regions of similar hydroclimate characteristics. Using this approach, all catchments that are geographically located in the same homogeneous region received the same parameter set (i.e., Kim and Kaluarachchi, 2008; Bock et al., 2015). Likewise, for decades—in flood regionalization—flow data of gauged catchments determined the regional flood frequency distribution to predict floods at ungauged catchments of the same region (i.e., Farquharson et al., 1992; Mimikou and Gordios, 1989; Portela and Dias, 2005; Zrinji and Burn, 1994).

It is worth mentioning that one of the explanatory variables of hydroclimate similarity is the spatial proximity (Sawicz et al., 2011) due to the first-order effects of climate and topography on hydrologic response (Smakhtin, 2001; Ali et al., 2012). Therefore, similarity in hydroclimate characteristics combines to some extent criteria of spatial proximity and physical similarity but with more robust measures of similarity in hydrologic response. In Kim and Kaluarachchi (2008), each sub-basins of a large catchment (176,000 km^2) was the spatial extent of similarity in hydroclimate characteristics and the region to conduct parameter transfer. Bock et al. (2015) used flow data of gauged catchments to analyze model parameter sensitivity (PS) and geographically identify regions of similar PS that is indicative of similarity in model runoff processes. All catchments of the same region received the same parameter set. The approach yielded satisfactory efficiency of the mean monthly flow predictions (Bock et al., 2015). Additional research is needed to evaluate predictions of daily flow time series and provide alternatives to PS while meeting criteria of hydroclimate homogeneity in parameter regionalization.

The lack of consensus regarding the most efficient approach among the common parameter regionalization methods and the need for more in-depth investigation of parameter transfer within homogenous regions —of similar hydroclimate characteristics— prompted the research goals of this study. We investigate the parameter transferability of Sacramento model (SAC-SMA) in the eastern United States (US) using the geographically contiguous hydroclimatic regions determined by Sawicz et al. (2011). The homogeneous regions have the uniqueness of being identified based on criteria of similarity in climate and flow characteristics which adds to the novelty of our research in testing parameter transferability. Previous studies that tested parameter transferability of SAC-SMA used either criteria of spatial proximity in few catchments from US (Koren et al., 2003) or no specific criteria in few distant catchments (Gan and Burges, 2006).

Our primary objective was to quantify the gain in performance attained by the transfer of calibrated parameters from gauged catchments within homogeneous regions (TRANS_IN) relative to 1) model parameterized with a priori parameters derived from soil properties (APRIORI), and 2) model parameterized with transferred parameters from a single best performing catchment in the study area (TRANS_OUT).

We hypothesize that similarity in hydroclimate conditions will improve the efficiency of parameter transferability within homogeneous regions (TRANS_IN) relative to APRIORI and TRANS_OUT. TRANS_OUT is not meant to represent a regionalization scheme for PUB but instead aids to measure the gain in performance and reveal limitations of TRANS_IN. The comparison between TRANS_IN and APRIORI will identify the catchments' conditions where predictions from a priori parameters are better (worse) than predictions from the regionalization approach. We are unaware of other studies that make similar comparisons. Our goal is to provide insights into the usage of the parameter transfer within homogeneous regions and the a priori parameters for PUB in the U.S and elsewhere.

2. Study area and dataset

A total of 73 catchments from the Eastern US were used in this study. The catchments range in size from 67 km^2 to 8052 km^2 (20% of the catchments have sizes above 4000 km^2). The climate in the study region is mainly humid (Coopersmith et al., 2012). Perennial snow cover is absent for most catchments and does not exceed 3% of the surface area for individual catchments (Berghuijs et al., 2014). Time series data of daily streamflow, precipitation, and potential evapotranspiration (PET) for all catchments were provided by MOPEX project (Duan et al., 2006).

The data are freely available and were retrieved from the following website: www.nws.noaa.gov/oh/mopex/mo_datasets.htm.

The flows within this dataset are based on observed data collected by the United States Geological Survey (USGS). Precipitation is determined by means of weighted averaging using rain gage measurements and PRISM data (Schaake et al., 2006). The mean areal precipitation estimates result in limited errors (Schaake et al., 2006). The mean monthly precipitation has limited fluctuation through seasons (Coopersmith et al., 2012; Sawicz et al., 2011), whereas storm characteristics—in particular storm intensity—have systematic seasonal variation (Hershfield, 1961). Potential evapotranspiration (PET) was estimated on the basis of the NOAA Evaporation Atlas. The NOAA Atlas maps were derived by analysis of evaporation pan data (Schaake et al., 2006). The modified Hamon algorithm helped in calculations of the daily PET under the MOPEX project (Dingman, 2002; Sawicz et al., 2011). The MOPEX catchments are minimally impacted by the human influence.

3. The homogeneous regions in the study area and their specific characteristics

Over the last decade, PUB studies have worked to identify appropriate schemes for homogeneous regions (Hrachowitz et al., 2013). According to Wagener et al. (2007), the homogeneous regions should be physically meaningful and provide a means to assess the dominant controls on the streamflow patterns (McDonnell and Woods, 2004). We used the homogeneous regions identified by Sawicz et al. (2011) that have the ultimate goal of facilitating the predictions at ungauged catchments (Fig. 1a). The homogeneous regions are geographically contiguous and have been identified using six characteristics: the streamflow elasticity to precipitation, snow day ratio (SDR, the number of days per year where the precipitation is falling as snow), the baseflow index, runoff ratio, slope of the flow duration curve (FDC), and the slope of the hydrograph rising limb. The streamflow elasticity to precipitation and the climate were the most influential in the regionalization followed by the runoff ratio and the slope of the flow duration curve (Sawicz et al., 2011). The regionalization using the six characteristics employed the method of partitioning algorithm by Kennard et al. (2010). As mentioned in the introduction section, the novelty in Sawicz et al. (2011) is not in the characteristics themselves but in their combination to determine the homogeneous regions and, therefore, quantify the hydrologic similarity between the catchments. We maintain the same regions notations as in Sawicz et al. (2011): C1, C2, C3, C5 (Fig. 1(a)).

The SDR is generally low across the study area and increases with the increasing latitude (R^2 = 0.81, p-value < 0.001) (Fig. 1(b)). The largest median value is 25% obtained in C2 (Fig. 1(b)). In C3, the median value is 22%. In C1, it drops to 12% followed by 2% in C5 (Fig. 1(b)). The storms have longer duration in C1, C2, and C3 than in the region of C5 (Chouaib et al., 2018). The aridity index (AI) is the mean annual Potential Evapotranspiration (PET) by the mean annual precipitation (MAP) (Sawicz et al., 2011), describing the relative energy and water limitations on evapotranspiration of the catchments in each region (Fig. 1(c)).

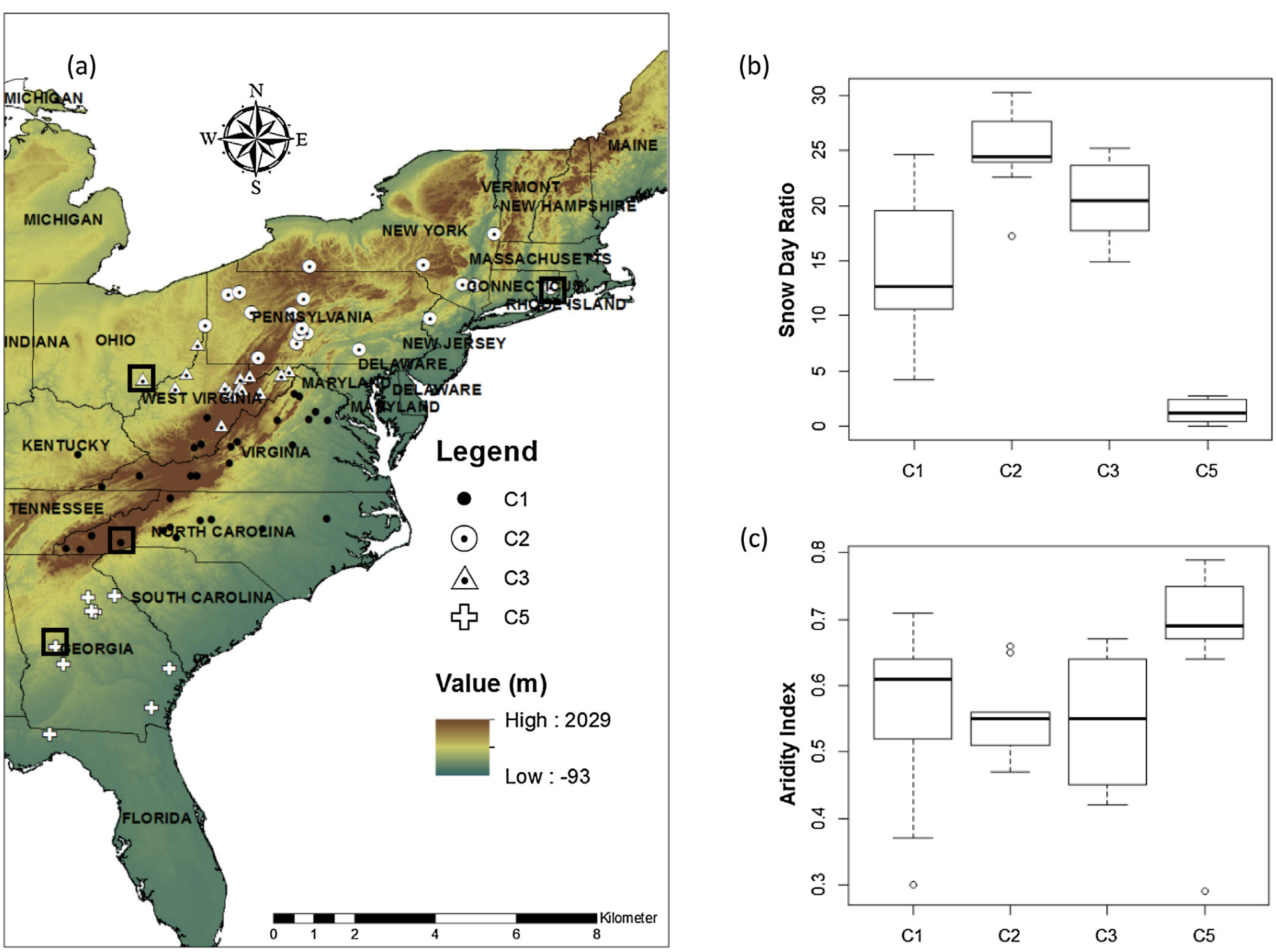

Fig. 1. (a) regions in the eastern US, the catchments highlighted in squares are the donor catchments in each region (b) whiskerplots of snow day ratio (SDR), (c) whisker plots of aridity index (AI).

The catchments in C2 and C3 are more energy limited (low PET) than the catchments in C1 and C5 (large PET) (Fig. 1(c)). The precipitation seasonality index (PSI) is nearly zero in all regions (Table 1). The forest cover proportions (FR) are large (Table 1). The smallest proportions of FR are in C5 where the median is 46% (Table 1). The median of agricultural lands is the largest in C5, but not exceeding 23.1% (Table 1). The proportions of open water and wetlands are small in all the regions (Table 1).

4. Methods

4.1. Overview

Our overall methodology included the following steps detailed below and summarized in the flowchart of Fig. 2:

Step 1: Performed model simulations for all catchments using a priori parameters (APRIORI), calculated fit statistics for the two periods we used for calibration and validation of SAC-SMA model.

Step 2: Calibrated the SAC-SMA model to optimize model performance for each catchment

Step 3: identified calibrated catchment with best performance in each region to be used as donor catchments for a parameter transfer scheme (TRANS_IN).

Step 4: performed model simulations using parameter transfer scheme TRANS_IN, calculated fit statistics during calibration and validation period

Step 5: performed model simulations using parameters from the single best performing catchment for all catchments irrespective of regions (TRANS_OUT), calculated fit statistics during calibration and validation period

Step 6: compared model performance for the parameter transfer scheme TRANS_IN to both APRIORI and TRANS_OUT simulations, interpret SAC-SMA parameters transferability with respect to catchment characteristics.

4.2. The SAC_SMA model

The SAC-SMA model has been applied worldwide, particularly in the different hydroclimate regimes of the United States (Koren et al., 2003). This model of thirteen parameters (all cited in the Appendix with their respective physical meaning) allows for detailed flow simulations dealing with runoff components, i.e., the direct runoff, surface runoff, interflow, and baseflow (Werkhoven et al., 2008). The SAC-SMA conceptual model has a two-soil-layer structure (Werkhoven et al., 2008). Each layer is made of tension and free water storages that interact to simulate the soil moisture and the runoff components (Koren et al., 2000, 2003). The tension water storages simulate the evapotranspiration (ET). The daily average PET from MOPEX data in addition to the daily precipitation are the inputs necessary for the flow simulations.

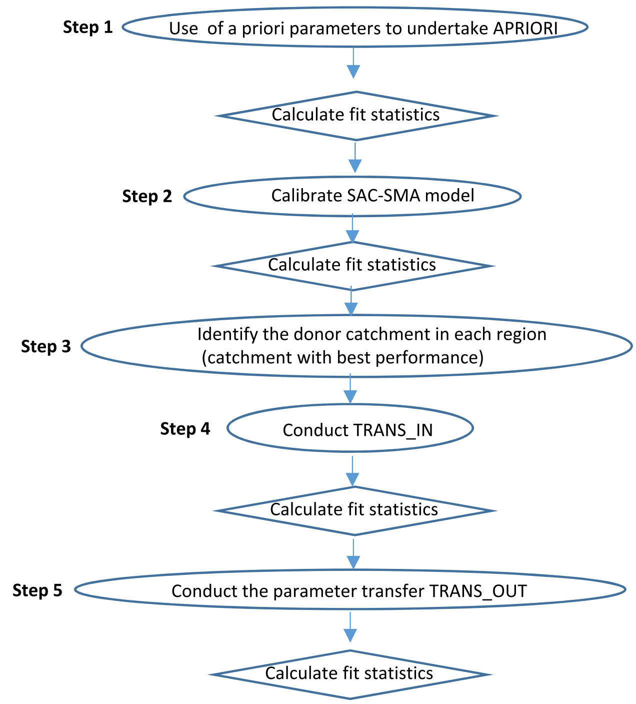

Fig. 2. The study framework summarized in 5 steps.

4.3. Model simulation with a priori parameters

The a priori parameters are determined from physical and empirical equations where the variables are mostly soil-derived (Koren et al., 2003). The soil-derived variables used in the physical and empirical equations of the a priori parameters are determined from the soil map of the State Soil Geographic Database (STATSGO) of 1×1 km grid. The soil map of this fine resolution was constructed via interpolations of the data obtained by soil sampling. In some regions, the soil sampling is done over large areas (once in 100 to 200 km^2) (Koren et al., 2003). The STATSGO provides at each grid estimates of θ_{wlt} (the water content at wilting point), θ_s (the water content at saturation), θ_{fld} (the water content at field capacity), and K_s (the hydraulic conductivity at saturation). These variables determines the a priori values of the parameters simulating the runoff processes in the upper layer (subsurface flow) and the lower layer of SAC-SMA (baseflow) (Duan et al., 2001; Koren et al., 2003). The a priori parameters are available in MOPEX

Table 1
Region's main descriptors.

Region	Statistics	Mean elevation (m)	slope (%)	Urban areas (%)	Forest (%)	Agriculture (%)	Open water (%)	Wetland (%)	MAP (mm)	PSI
	Min	76.7	2.0	1.9	39.2	0.3	0.00	0.00	982.1	0.026
C1	Max	1211.9	34.0	18.7	97.0	46.0	1.42	11.64	2072.0	0.45
	Median	547.8	14.3	6.6	66.8	19.8	0.27	0.07	1201.8	0.065
	Min	16.2	0.3	0.0	28.6	0.0	0.01	0.00	998.1	0.018
C2	Max	769.1	19.8	11.6	95.2	59.0	2.69	23.19	1520.2	0.127
	Median	424.3	10.2	4.0	74.0	10.8	0.41	1.20	1145.2	0.076
	Min	274.3	6.0	2.6	45.4	3.5	0.13	0.00	983.6	0.072
C3	Max	997.8	20.9	12.9	91.0	38.0	0.97	1.11	1385.5	0.117
	Median	655.8	17.9	5.5	82.9	9.4	0.53	0.07	1158.9	0.083
	Min	53.1	0.6	5.0	35.4	17.4	0.30	3.19	1206.0	0.032
C5	Max	269.6	4.8	15.8	55.7	31.3	1.35	19.66	1366.7	0.088
	Median	217.7	3.4	9.0	46.0	23.1	0.62	5.65	1284.6	0.066

dataset and are designed to serve as an estimation technique for ungauged catchments (Koren et al., 2003; Young, 2006). We evaluate the performance of the predictions from a priori parameters (APRIORI) using Nash–Sutcliffe (NS) coefficient (Nash and Sutcliffe, 1970), percent bias (PBIAS), mean monthly hydrograph (MMH), and the flow duration curve (FDC). We compare APRIORI to TRANS_IN. This comparison is fair as both approaches are designed to make PUB.

4.4. Model calibration

We calibrated the thirteen SAC-SMA model parameters using the Shuffle Complex algorithm (SCE-UA) with 10,000 iterations (Sorooshian et al., 1993). This algorithm is extensively used for SAC-SMA calibration to achieve different research goals, such as studying model parameter transferability (i.e., Gan and Burges, 2006) and building a large database for the continental United States (i.e., Newman et al., 2015). Similar to Gan and Burges (2006) and Koren et al. (2003), we constrained the calibration to the a priori value of each parameter that is available in MOPEX. This approach is termed 'constrained calibration strategy' (Gan and Burges, 2006; Koren et al., 2003) and it helps to maintain physical consistency and to reduce equifinality. We set ±35% as the range of deviations allowed from the a priori parameters. This range is larger than the range used in Koren et al. (2003) (i.e., ±25%). We set this interval to allow for more variability around the default parameters and in the parameters space which is used by the SCE-UA algorithm to find the global optimum. In this study the sample of catchments have limited effect of snow therefore we did not need to use the snow module of the SAC-SMA model. We calibrated SAC-SMA for each catchment over 15 years (January 1948–December 1963). Subsequently, we tested the model performance over an independent validation period of 36 years (January 1964–December 1999). The calibration adjusted model parameters to best match the daily simulated flows to the daily observed flows using an objective function that minimized the RMSE (Root Mean Square Error). We assessed the model performance using the NS coefficient and the PBIAS in mean flow (Moriasi et al., 2007).

4.5. Parameter transfer within homogeneous regions (TRANS_IN)

We investigated and evaluated a parameter regionalization scheme (TRANS_IN) to transfer parameter values from gauged to ungauged catchments within homogeneous regions for predictions of daily flow time series using SAC-SMA model.

In TRANS_IN, we designated one single donor catchment. After conducting the SAC-SMA model calibration, we determined the catchment in each region with the highest NS coefficient at calibration where the validation NS was quite stable and did not go below 85% of the calibration NS (i.e., Arsenault and Brissette, 2014). In Fig. 1(a), the donor catchment of each region is highlighted with a square. We transferred the parameter set of the designated donor catchment to any of the catchments located in the same region of homogeneous climate and flow characteristics (recipient catchments). Any ungauged catchment located in the same region uses the same parameter set to predict the flow data (Bock et al., 2015). Past studies demonstrated that using the parameter set of the catchment with the highest NS helped to attain better efficiency from the parameter transfer than transferring the median parameter set of multiple donor catchments (i.e., Kim and Kaluarachchi, 2008; Masih et al., 2010;Oudin et al., 2008). Evaluations of the predictive performance from TRANS_IN use the recipient catchments assuming they are ungauged. At individual catchments, the performance evaluation assesses the NS, PBIAS, predictions of the flow duration curve (FDC) and the mean monthly hydrograph (MMH). Besides, we assess the median percent error of several flow percentiles of the FDC (high and low flow percentiles) for a more in-depth evaluation.

4.6. Parameter transfer irrespective of the homogeneous regions (TRANS_OUT)

TRANS_OUT takes into account all of the heterogeneities in the eastern United States (i.e., catchment energy conditions, landscape properties, predominant runoff generation mechanism, storm characteristics). TRANS_OUT is not a regionalization scheme for PUB, instead it is used to assess the gain in efficiency from TRANS_IN. Our assessment of the gain in performance from the regionalization through comparisons of TRANS_IN with TRANS_OUT used the same performance measures we noted above (NS, PBIAS, MMH, and FDC). In TRANS_OUT, one donor catchment was used to parameterize all catchments for all the regions. The donor catchment had the highest NS among all 73 catchments.

Given that TRANS_IN employs the catchment with best NS in each of the four regions, thus the single best catchment across all regions is one of the four designated catchments for TRANS_IN. This catchment coincides with the donor catchment of TRANS_IN in C1.Therefore, TRANS_OUT is not applicable for C1. TRANS_OUT is a parameter transfer that includes all types of heterogeneities, therefore, comparisons of TRANS_IN with TRANS_OUT also reveal the extent at which the transferred parameters in TRANS_IN are representative of the catchments' conditions. Particularly when TRANS_IN and TRANS_OUT have comparable efficiency. This comparison, therefore, indicates the limitations of the parameter transferability within the homogeneous regions (TRANS_IN).

4.7. Interpretation of SAC-SMA parameters transferability

We interpret quantitatively the performance from the parameter transfer TRANS_IN and TRANS_OUT in order to determine the representativeness of transferred parameters to catchments' conditions in each region. First, we use the catchment descriptors (climate, soil properties, and elevation) and their measures of variation/inter-quantile variation to explain the satisfactory (lack of) efficiency of TRANS_IN in comparison with TRANS_OUT in each region. The catchment descriptors we employ are the AI, the mean elevation, and the soil hydrologic properties (HGC (low infiltration rates), HGB (medium infiltration rates), HGA (very large infiltration rates, see Wood and Blackburn (1984)). Second, we analyze the correlation of these descriptors with the latitude (soil hydrologic properties) and the mean elevation (AI) in order to further understand the geographical extent of the variation, and therefore deduce the effect on the parameter transferability. Furthermore, we complement our interpretations of the parameter transferability with analysis of the predominant runoff generation mechanism in each catchment, using the Topographic Index (TI) distribution. The prevalent runoff generation mechanism is indicative of the runoff processes. This information is supplementary to explain the representativeness of the transferred parameters in each region from the perspective of runoff processes. In the following, we explain our approach to calculate the TI distribution at catchment site.

TI represents the propensity of a point within a catchment to generate saturation excess overland flow (Beven and Kirkby, 1979) due to a topographic control on surface and subsurface flows (Rice and Hornberger, 1998). TI was first defined by Beven and Kirkby (1979) as follows:

$$\mathrm{TI} = \ln\left(\frac{a}{\tan\beta}\right) \quad (1)$$

where: TI is the topographic index of a point/pixel within a watershed;

a is the specific upslope area per unit contour length;
β is the local topographic slope angle acting at the point.

In this study, TI was calculated at the pixel level using a DEM of 30-m resolution and algorithms necessary for the determination of specific upslope area "a" and the local slope angle β (Rousseau et al., 2005; Hentati et al., 2010). The TI calculation uses the properties of the stream network, namely, the flow directions and the flow accumulation which both help to identify the riparian zone (see Hentati et al., 2010). The frequency of TI distribution was then determined for each catchment after classification of TI pixel values. The differences in the TI frequency distribution at the catchment scale illustrates the wide differences in topographic properties between study catchments and, consequently, the effect of topography on the flow response. According to Beven and Kirkby (1979) and Beven and Wood (1983), large values of TI in the tails of the distribution indicate the likelihood of runoff being generated by saturation excess overland flow, whereas smaller values in the tails hint to predominant subsurface processes in the runoff generation. The flow response depends also on the soil infiltration properties (Price, 2011; Ameli et al., 2015). Therefore, our analyses of the runoff generation mechanism using TI serve to reveal the predominant mechanism that is likely to take place as a direct response to topography while we acknowledge the effect of other factors (i.e., soil infiltration rate and permeability) on the flow response. We use the spatial pattern of the soil hydrologic properties as indicative of the soil infiltration rates and permeability (Wood and Blackburn, 1984).

5. Results and discussion

5.1. Performance of parameter transferability and a priori parameters

We represent the calibrated parameters' values of the donor catchment in each region in Table 2 (see Appendix). We used these calibrated parameters to conduct TRANS_IN in each region.

TRANS_IN outperformed the prediction from TRANS_OUT for all of the homogeneous regions except in C3. The improvements are mainly a higher median NS and/or less-biased predictions with lower variation (see the values of NS and PBIAS with their respective variation listed in parentheses in Table 3). On the other hand, TRANS_IN outperformed the APRIORI with a particularly higher efficiency and/or less-biased predictions except for C3 (Table 3). Below, we present the performance results for C1 and C5 followed by C2 and C3; the former two regions exhibited the highest performance in TRANS_IN.

In C1, TRANS_IN outperformed the APRIORI and led to predictions with higher median efficiency and limited bias (small median PBIAS in Table 3). The MMH and the FDC of a typical catchment exhibited a good fit of TRANS_IN and APRIORI with the observed flow (Fig. 3(a)). However, the median percent error of the FDC at several percentiles exhibited larger errors for APRIORI, particularly for the low and large flow percentiles (Fig. 4(a)).

In C5, TRANS_IN outperformed TRANS_OUT. The gain in performance due to TRANS_IN is mainly higher NS and less-biased predictions (Table 3). The MMH from the typical catchment did not exhibit a difference in performance between TRANS_IN and TRANS_OUT and the observed MMH (Fig. 3(b)). However, the FDC from TRANS_IN at the typical catchment had a better fit than the

Table 2
Parameters' values of the donor catchments in each region.

Catchment ID	Region	UZTWM	UZFWM	UZK	PCTIM	ADIMP	ZPERC	REXP	LZTWM	LZFPM	LZFSM	LZSK	LZPK	PFREE
03,443,000	C1	61.3925	34.7632	0.3578	0.0918	0.3043	87.8953	1.4921	170.9203	29.2026	140.0720	0.1469	0.0145	0.1300
11,270,000	C2	42.7346	25.1386	0.3367	0.0750	0.3994	72.3811	2.1382	352.2244	20.0474	158.3974	0.1141	0.0235	0.0606
03,159,500	C3	76.0213	24.1819	0.3146	0.0857	0.3023	118.9506	2.1983	125.4961	36.9895	71.9652	0.0597	0.0055	0.2061
02,347,500	C5	22.3412	36.4631	0.8884	0.0801	0.3044	50.6779	2.0854	137.5428	41.0259	223.0901	0.1613	0.0203	0.1327

UZTWM: Upper zone tension water maximum storage, mm; UZFWM: Upper zone free water maximum storage, mm; UZK: Upper zone free water withdrawal rate, d^{-1}; PCTIM: Percent permanent impervious area,%; ADIMP: Percent area contributing as impervious when saturated,%; ZPERC: Maximum percolation rate under dry conditions, dimensionless; REXP: Percolation equation exponent, dimensionless; PFREE: Percent of percolation going directly to lower zone free water,%; LZTWM: Lower zone tension water maximum storage, mm; LZFPM: Lower zone free water primary maximum storage, mm; LZFSM: Lower zone free water supplementary maximum storage, mm; LZPK: Lower zone primary withdrawal rate, d^{-1}; LZSK: Lower zone supplementary withdrawal rate, d^{-1}

Table 3
Average NS and PBIAS statistics of the different simulations across regions in calibration and validation periods.

Cluster NS	Period	APRIORI	TRANS_IN	TRANS_OUT
C1	Calibration	0.691 (0.075)	0.711 (0.079)	N/A
C1	Validation	0.681 (0.088)	0.710 (0.067)	N/A
C2	Calibration	0.604 (0.060)	0.604 (0.056)	0.622 (0.056)
C2	Validation	0.617 (0.081)	0.588 (0.049)	0.604 (0.064)
C3	Calibration	0.623 (0.065)	0.625 (0.058)	0.646 (0.070)
C3	Validation	0.590 (0.133)	0.631 (0.068)	0.645 (0.063)
C5	Calibration	0.749 (0.074)	0.762 (0.060)	0.757 (0.059)
C5	Validation	0.707 (0.108)	0.771 (0.066)	0.705 (0.034)
PBIAS (%)				
C1	Calibration	0.0245 (5.458)	0.483 (4.255)	N/A
C1	Validation	−0.550 (4.841)	0.711 (0.079)	N/A
C2	Calibration	−10.168 (5.549)	0.780 (0.032)	−5.044 (5.934)
C2	Validation	−9.319 (7.226)	−9.867 (6.318)	−7.123 (7.051)
C3	Calibration	−4.213 (6.246)	−4.416 (6.178)	0.557 (4.663)
C3	Validation	−3.835 (6.243)	−11.688 (9.519)	−3.665 (4.177)
C5	Calibration	−5.761 (9.076)	−1.966 (7.646)	−8.706 (9.727)
C5	Validation	2.078 (11.009)	−3.458 (6.866)	−4.800 (4.272)

*() numbers between parentheses refer to the standard deviation of the NS values across catchments in each cluster

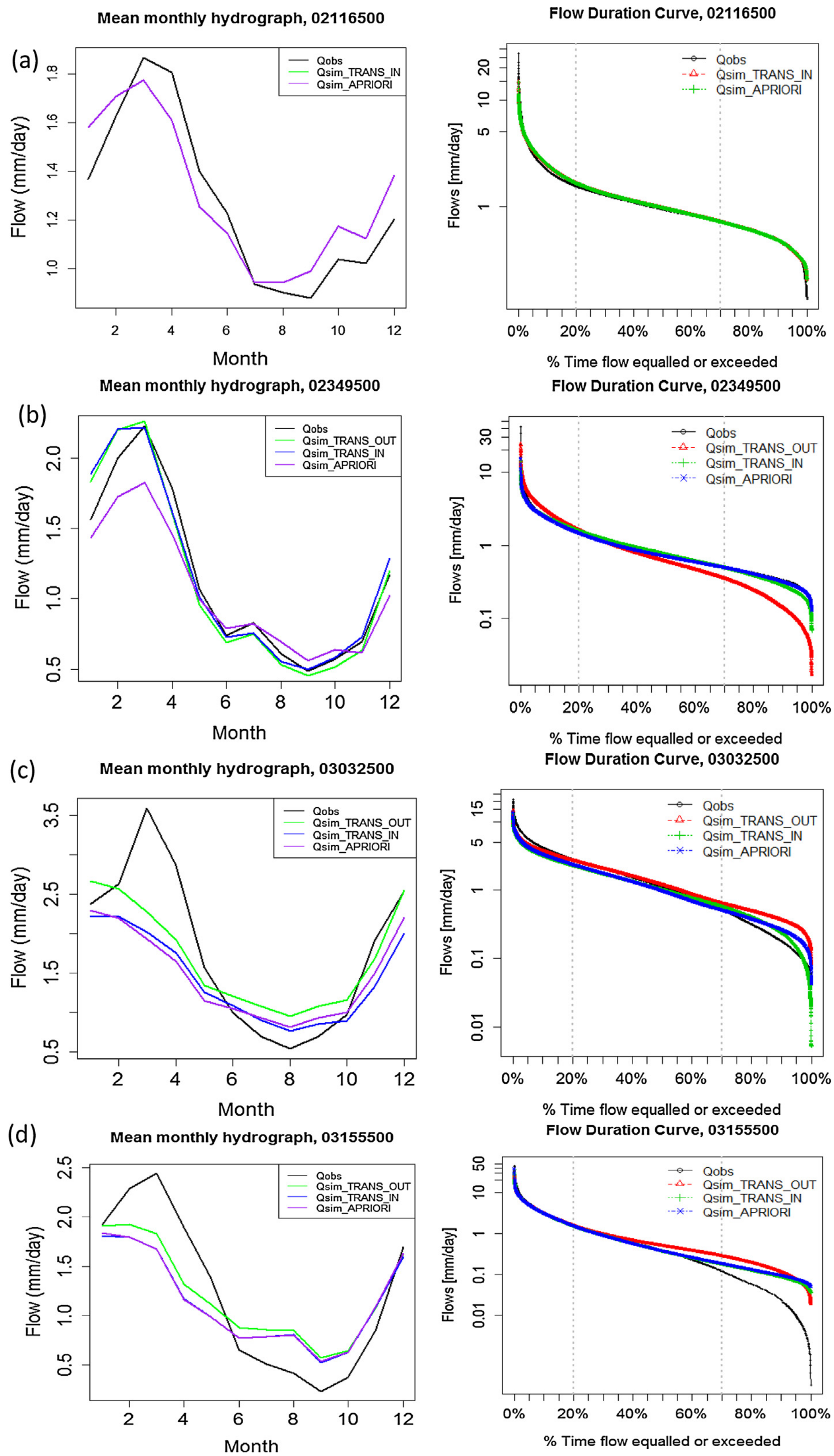

Fig. 3. (a) mean monthly hydrograph (MMH) and FDC of a typical catchment from C1 with NS 0.80, 0.74 at APRIORI, and TRANS_IN, respectively, (b) MMH and FDC in a typical catchment from C5 with NS 0.79, 0.78, 0.73 at APRIORI, TRANS_IN, and TRANS_OUT, respectively, (c) MMH and FDC in a typical catchment from C2 with NS 0.55, 0.6, 0.55 at APRIORI, TRANS_IN, and TRANS_OUT,respectively, (d) MMH and FDC in a typical catchment from C3 with NS 0.7, 0.72,0.71 at APRIORI, TRANS_IN, and TRANS_OUT, respectively.

FDC from TRANS_OUT (Fig. 3(b)). The median percent errors of the FDC in TRANS_OUT were larger for all of the flow percentiles compared with TRANS_IN (particularly until the 75th percentile).

The APRIORI remained less efficient and more biased (see the large values of PBIAS with larger variation listed in Table 3). The MMH predicted by APRIORI in a typical catchment underestimates

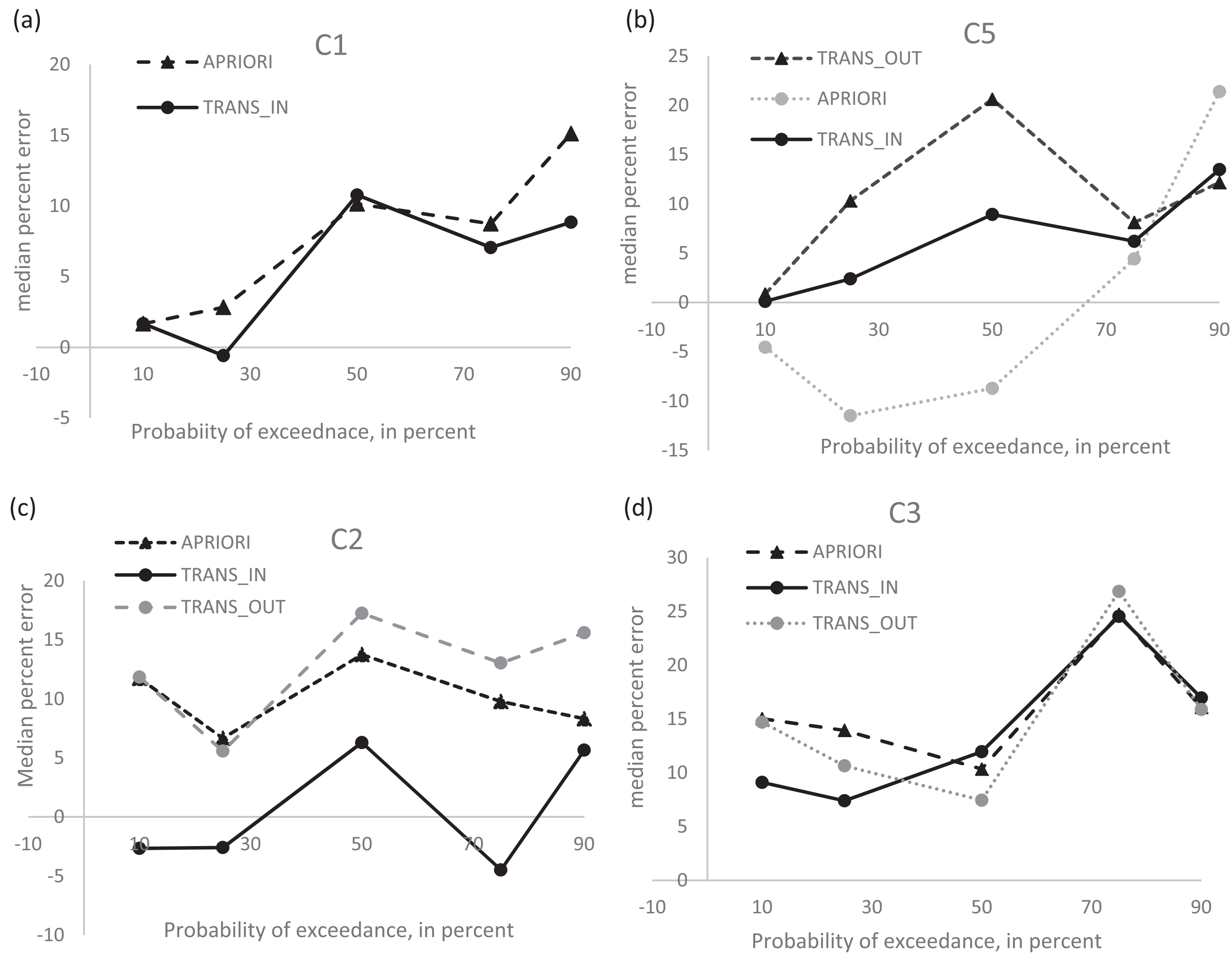

Fig. 4. The median percent error of the FDC at several flow percentiles (10%, 25%, 50%, 75%, and 90%) in each region.

the large flows compared with the observed MMH and the one predicted from TRANS_IN (Fig. 3(b)). The predicted FDC from APRIORI in the same typical catchment deviates at the upper and lower tails from the observed FDC and from the FDC predicted using TRANS_IN (Fig. 3(b)). The median percent errors of the FDC are larger than those obtained from TRANS_IN in most of the percentiles (Fig. 4(b)).

In C2 and C3, the predictions from TRANS_IN were either of limited bias compared with those of TRANS_OUT (C2) or were outperformed by those of TRANS_OUT (C3). Below, we present the performance of parameter transferability in both regions that we compare with APRIORI.

In C2, located in the northeastern US, the improvement of TRANS_IN compared with TRANS_OUT (see the less-biased predictions listed in Table 2) was not visible from the typical MMH (Fig. 3(c)) contrarily in the typical FDC (the FDC from TRANS_OUT deviated from the observed FDC at the upper and the lower tails (Fig. 3(c)).

The limited bias of TRANS_IN led to smaller median percent errors of the FDC than TRANS_OUT (Fig. 4(c)). APRIORI was less efficient and more biased than TRANS_IN but slightly more efficient than TRANS_OUT (Table 3). These findings are clear in the predictions of FDCs and values of the median percent errors (Fig. 3(c) and 4(c), respectively). We noted more errors in the FDC predictions with APRIORI than with TRANS_IN. These results highlight that a priori parameters are less representative of the catchment conditions in C2 than the transferred parameters by TRANS_IN.

In C3, contrarily to previous regions, TRANS_OUT outperformed TRANS_IN and APRIORI (higher median NS and lower PBIAS of smaller variation during the calibration and validation periods; Table 3). TRANS_IN and APRIORI had similar performance in C3 (Table 3). The differences in the efficiency were not visible based on the typical MMH and the typical FDC. All predicted FDCs deviated from observed FDCs at the lower tail (Fig. 3(d)). However, the median percent errors of the FDC revealed the differences in efficiency between TRANS_IN, TRANS_OUT and APRIORI. The larger efficiency of TRAN_OUT yielded better predictions than TRANS_IN and APRIORI, mainly, medium flows of the FDC (particularly between 30% and 70% of the exceedance probability) and was comparable to TRANS_IN and APRIORI at low and high flow percentiles (Fig. 4(d)).

5.2. Evaluation, interpretation and discussion of parameter transferability and a priori parameters

Below, we interpret and discuss the performance results for C1 and C5 followed by C2 and C3.

The good performance of TRANS_IN in C1 indicates that the transferred parameters are representative of the catchments

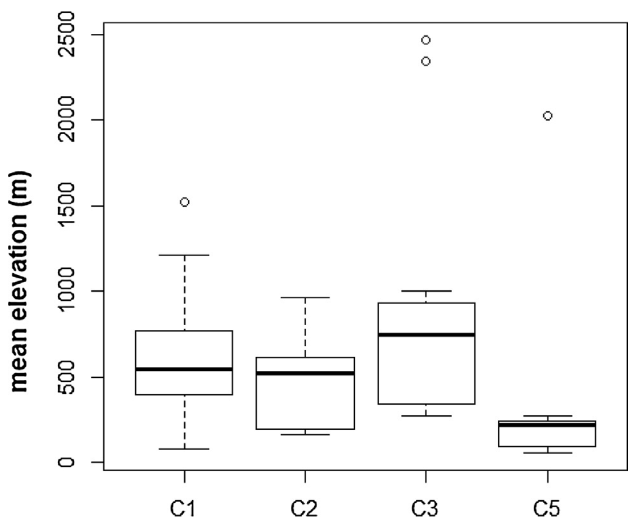

Fig. 5. The mean catchment elevation in each region.

conditions. In this region, most of the catchments are at low elevation, and a few are located in Appalachian Mountains (Fig. 1(a) and 4). We found that AI was statistically correlated with the mean elevation (R^2 = 0.33, p-value < 0.0001). This relation is mainly explained by the PET decrease with elevation as found in Swift et al. (1988). The change in AI with elevation was not large according to the small inter-quantile range and the median value (Fig. 1 (c)). In C1, the catchments have similar energy conditions and are mostly water limited. The energy conditions are important for flow predictions as PET is one of the inputs in SAC-SMA model. Parameters' transfer between catchments of similar energy conditions has a large effect on TRANS_IN efficiency. We note that most of soils in C1 are well-drained (mainly HGB with some proportions of HGC (Figs. 6 and 7(b) and (c)). A saturation excess overland flow dominates in majority of catchments (Fig. 8). The subsurface storm flow is prevalent in few catchments at high elevations. All of which helps to explain the satisfactory prediction from TRANS_IN in C1. In conditions of predominant saturation excess overland flow, the large infiltration rates lead to an increase in the groundwater level which enhances the groundwater contribution, mainly the surface flow from the saturated areas and base flow. The saturated surface flow and base flow are both determined by the groundwater level (Huang et al., 2016). In the few catchments where subsurface storm flow is dominant and soils are well-drained, the groundwater contribution is also important as a result of recharge in the vadose zone. According to isotope hydrology, in steep terrain with conductive soils, the new infiltrating water pushes the old subsurface runoff to induce stream flow in the channel (i.e., Buttle, 1994). This understanding demonstrates that groundwater contribution is important in catchments of C1 and is consistent with the base flow index (BFI) being large in this region (Sawicz et al., 2011). The similarity in the groundwater effect between catchments further explains the efficiency from TRANS_IN and supports the claim that transferred parameters are representative of catchment conditions in C1.

Considering the smaller efficiency of APRIORI, we suggest that the soil-derived values of the a priori parameters are less representative of the catchments' conditions in C1 than the regionalization approach.

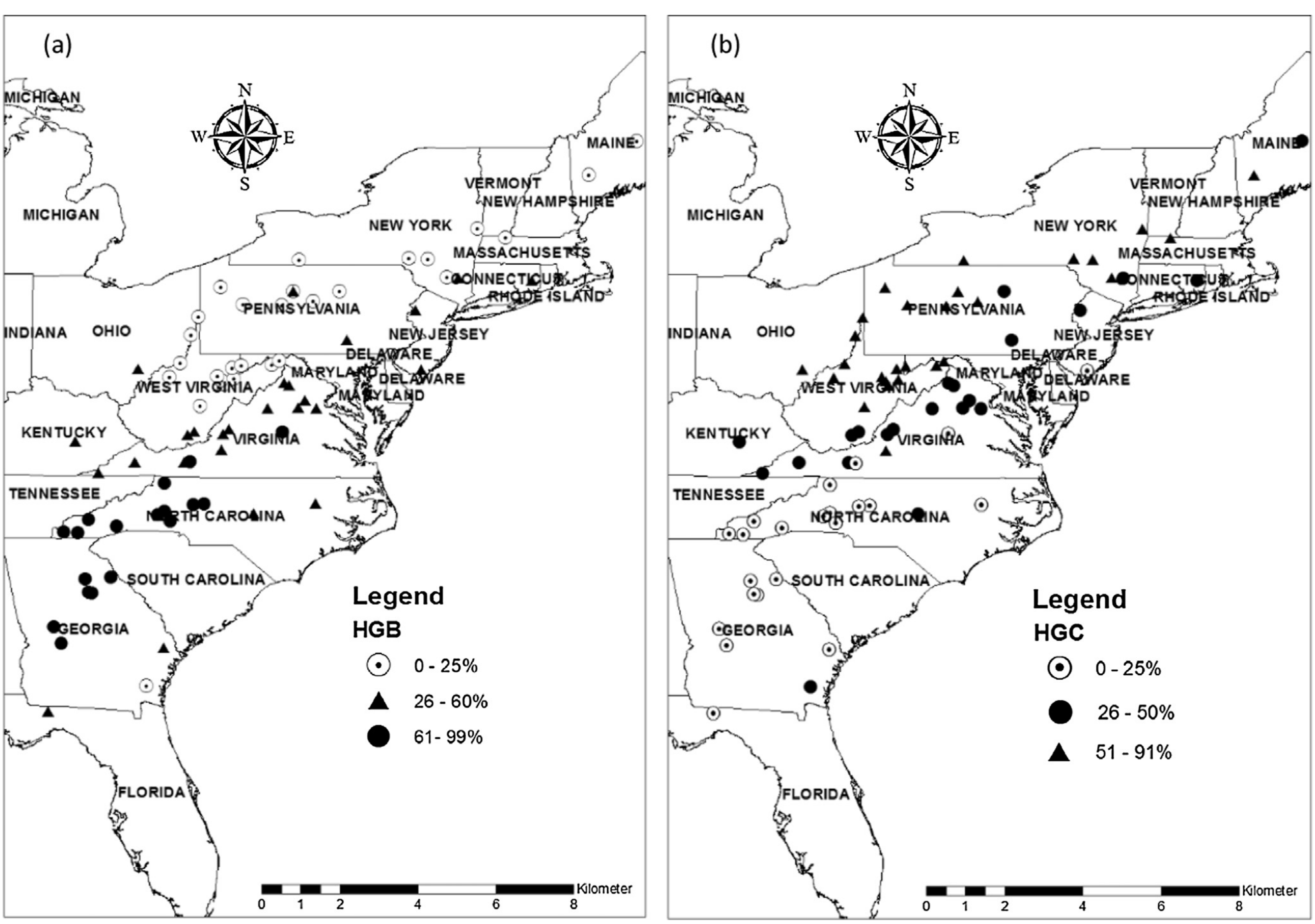

Fig. 6. (a) spatial pattern of HGB soil proportions; (b) spatial pattern of HGC soil proportions across the eastern United States.

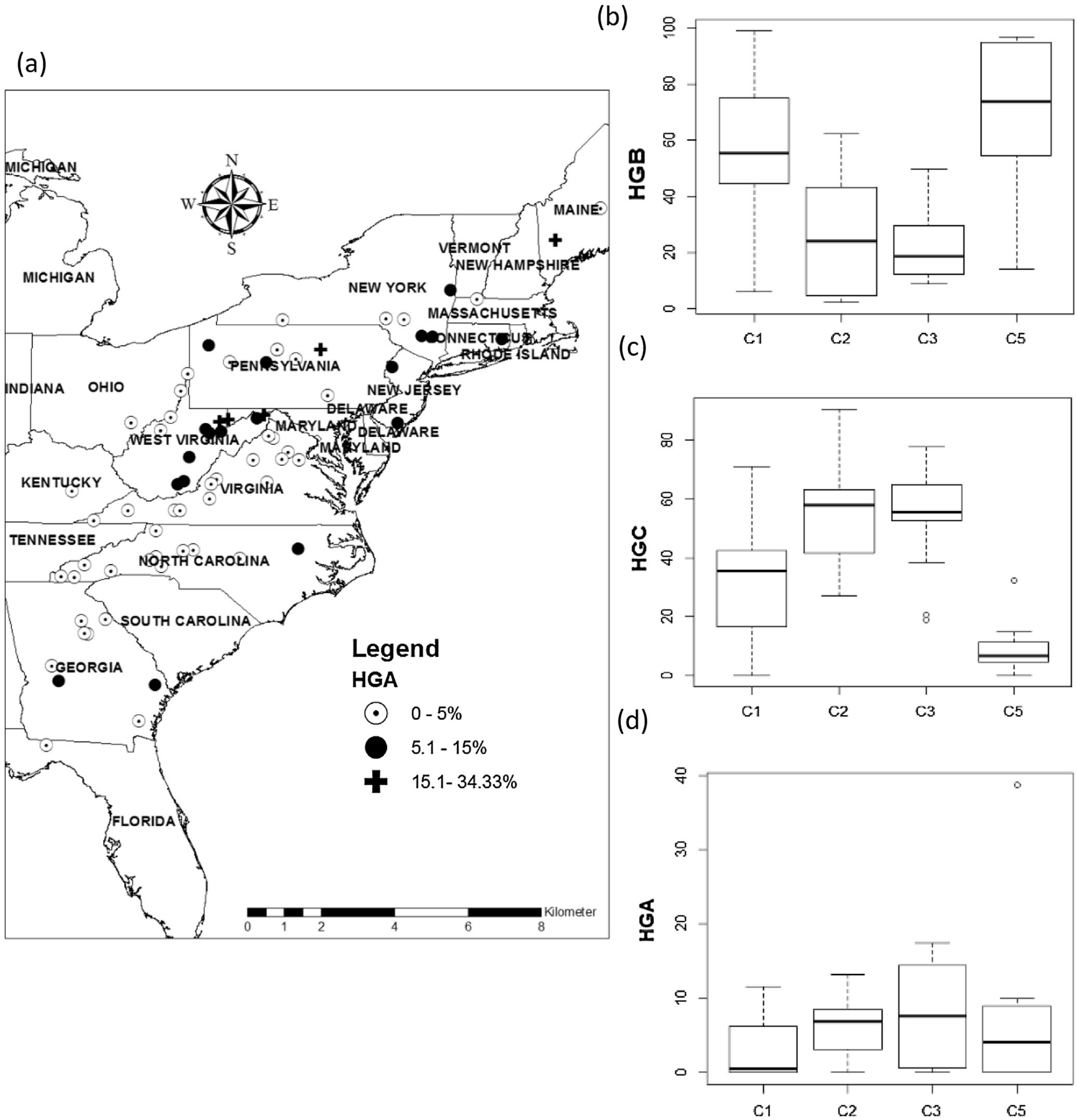

Fig. 7. (a) spatial pattern of HGA soil proportions; (b) whisker plots of HGC soil proportions across the regions; (c) whisker plots of HGB soil proportions across the regions; (d) whisker plots of HGA soil proportions across the regions.

The catchments in C5 are all located at low elevations with the exception of one catchment of higher elevation (see the outlier in Fig. 5 and refer to the Digital Elevation Model shown in Fig. 1(a)). Provided that AI is correlated to mean elevations (p-value < 0.0001), there is homogeneity in the energy conditions where all C5 catchments are water limited with a very small inter-quantile range of AI (Fig. 1(c)). Only one catchment is energy limited (see the outlier in Fig. 1(c)). Saturated excess overland flow is prevalent in C5 catchments of well-drained soils (HGB soil proportions are dominant compared with HGC except in one catchment: Figs. 6 and 6(a), (b)). Likewise the catchments in C1, these characteristics of runoff processes and soil enhance the groundwater contribution and are consistent with BFI being the largest (larger than in C1) and the flow being the most mitigated (the smallest slope of the FDC), as stated in Sawicz et al. (2011). The catchments' conditions and predominant runoff generation mechanism explained the large efficiency of TRANS_IN not affected by the presence of one outlier (visible in Figs. 1(c) and 7(c)). Transferring parameters from an outsider catchment (TRANS_OUT) (the catchment belong to C1) leads to poor efficiency in the predictions due to differences between C1 and C5, although the donor catchment in TRANS_OUT is the closest to C5 (Fig. 1(a)). The catchments in C5 have (i) the shortest duration of storms, (ii) the most stringent water-limited conditions (Fig. 1(c)) (iii), the lowest elevations (Fig. 5), and (iv) the smallest HGC proportions (Fig. 7(c)). In conditions of the predominant saturation excess, these attributes generate flows with

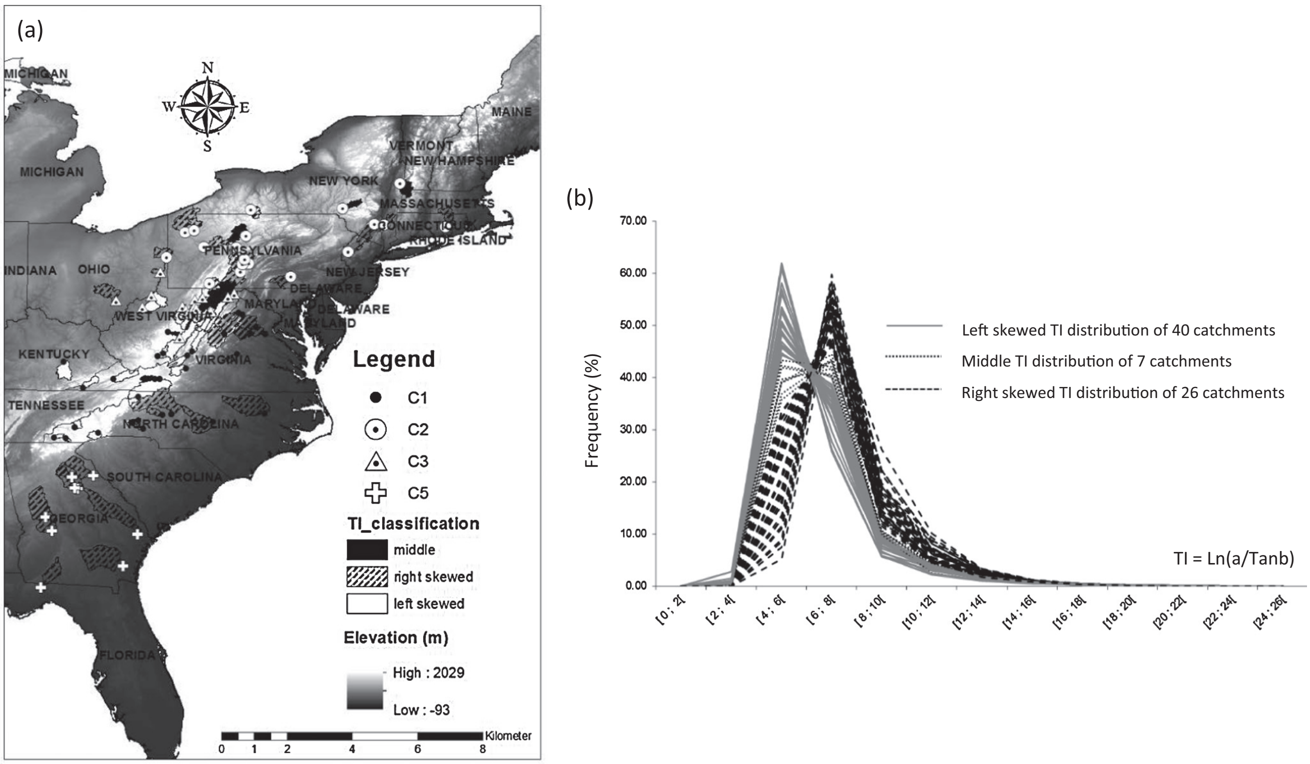

Fig. 8. (a) spatial distribution of TI groups designated as TI classification in the map (b) frequency distribution of topographic index per catchment.

characteristics different from those of C1. It has been shown that climate factors interact with the runoff generation mechanism and influence the runoff response where, for instance, the semi-arid conditions fosters the dominance of infiltration-excess surface runoff (Huang et al., 2016).

In C2, the less-biased predictions from TRANS_IN and the lack of efficiency of TRANS_OUT are pertinent and reveals the extent to which the catchments are hydrologically similar and the transferred parameter by TRANS_IN are representative of catchments' conditions.

The catchments' properties in C2 and their differences from C1 explain the gain in performance associated with TRANS_IN compared with TRANS_OUT. In C2, most of the catchments are energy limited (except two outliers) with a small range of variation compared with C1 (Fig. 1(c)). Hence, C2 have homogeneous energy conditions with lower median AI than in C1. There is a very small range of variation in the value of snow day ratio (SDR) in C2 (Fig. 1(b)), which further illustrates the homogeneity in climate and its effect on runoff response and subsequently on TRANS_IN efficiency. The SDR, although it is small in C2 (median 25%), is influential on the runoff response (Singh and xu, 1997; Ye et al., 2012). In this region of the northeast, the soils are mostly poorly drained (the HGC proportions are the largest, Figs. 6(a) and 7(c)). The runoff generation mechanism in C2 is mainly dominated by saturation excess (Fig. 8). Very few catchments belong to the middle category of the TI (Fig. 8) where saturation excess and the subsurface storm flow are equivalent in their effect on the flow response (Beven and Kirkby, 1979; Beven and Wood, 1983). Therefore, the interaction of the homogeneous climate, soil, and energy characteristics with the runoff generation mechanism (primarily saturation excess) fosters the hydrologic similarity between catchments and explains the efficient performance of TRANS_IN. An example of interaction between climate, landscape properties and runoff generation mechanism is presented in Bronstert et al. (2002). The differences between C1 and C2 lead to differences in the flow response (the catchments in C2 have steeper slope of the FDCs than those in C1; see Sawicz et al. (2011)), and the lack of efficiency of TRANS_OUT further demonstrates that parameters of one donor catchment with best predictions are representative of catchments' conditions in C2.

In C3, the poor efficiency of TRANS_IN compared with TRANS_OUT indicates some level of heterogeneity and explains the lower performance of the parameter regionalization (TRANS_IN). In C3, although the catchments are energy limited (low PET), the AI is characterized by large variations and a large inter-quantile range, suggesting that the catchments have heterogeneous energy conditions (Fig. 1(c)). There are catchments that are more energy limited (low PET) and others that are more water limited (high PET). The PET is one of the inputs into the SAC-SMA model.

Hence, the transfer of parameters that are calibrated in different conditions of energy and water does not help to attain high efficiency. All catchments in C3 are forested (Table 1) and mountainous with higher elevations than other regions (Figs. 1(a) and 5). There is also large variation in the mean elevation among catchments (Fig. 5). The soils are poorly drained (Fig. 6) with the lowest proportions of HGB (Fig. 7(b)) and among the highest proportions of HGC (Fig. 7(c)). According to the TI analysis, subsurface storm flow dominates in C3 (Fig. 8). The disparity in the mean elevation likely leads to differences in the response provided that the hydraulic gradient is proportional to the topographic gradient in mountainous catchments (Butt et al., 2001). Moreover, in similar conditions of runoff generation mechanism and within forested mountainous catchments there is a likelihood of preferential flow (McDonnell et al., 2007; Weiler and McDonnell, 2007). The dominant subsurface storm flow and the non-uniformity of the soil porosity with depth are among the factors that result in preferential flow. The non-uniformity in the soil porosity is related to the macropores resulting from the decayed/living roots and from the biological activity that fosters preferential pathways in the subsurface zone (Bonell, 1993). In all of the forested mountainous catchments dominated by subsurface storm flow from other regions (C1 and C2), lateral preferential flow is likely. However, likelihood of such flow is even higher in C3 because (i) the physiography is more complex (i.e., it has the steepest topography, the highest elevation, the lowest proportion of HGB) and (ii) the HGA soils (characterized by very large infiltration rates) have the largest proportions with the largest inter-quantile range (Figs. 6 and 7(d)). Consequently, non-uniformity in the porosity and the preferential pathways is more probable in C3, which results in a more pronounced effect of preferential flow, and further explains the low performance from TRANS_IN.

Current physically based and conceptual models—including SAC-SMA—often ignore the effect of preferential flow (Weiler and McDonnell, 2007). Therefore, we recognize its effect as a source of uncertainty in other predictions from C3 (APRIORI, TRANS_OUT). In ideal conditions where the preferential flow is simulated by the model structure, the parameter transfer within C3 (TRANS_IN) will not lead to high performance because (i) of the same reasons noted above related to the disparity in the catchment conditions, and (ii) the nature of preferential flow being specific to characteristics of each catchment (the density of preferential pathways changes as a result of soil texture/porosity, the root zone density, and the density of decayed/living roots) (Brammer and McDonnell, 1996; Bronstert, 1999; McDonnell et al., 2007; Weiler and McDonnell, 2007). Additional research is necessary to properly simulate lateral preferential flow and investigate techniques to measure the differences/similarities in the effects of this peculiar flow between catchments in the same region.

The relatively better performance of TRANS_OUT in C3 (only for medium flow percentiles) might refer to the outsider donor catchment (located in C1) being spatially close to catchments in C3 where dominant runoff generation mechanisms are the same (the subsurface stormflow dominates the donor catchment of TRANS_OUT and the catchments in C3, Figs. 1 and 8).

The results from TRANS_OUT and the likelihood of preferential flow indicate limitations of the parameter regionalization and suggest the need for other measures of similarity to relocate the catchments in C3. We propose adding other characteristics in the regionalization to assess the effect of preferential flow that can be complemented by physically based measures of soil characteristics (i.e., porosity, permeability) and other measures related to PET (i.e., AI) in order to reduce the heterogeneity in energy conditions. Improving the efficiency from the parameter regionalization in regions of very complex landscape properties is a research venue that requires in-depth investigations.

In the eastern United States, the spatial pattern of soils led us to notice that HGC proportions are correlated with the latitude. This relation is statistically significant ($R^2 = 0.47$, $r = -0.68$, p-value < 0.001). The latitude explains 47% of the HGC variation in the eastern United States. It is difficult to conjecture the reasons for this tight correlation, but the geology structure that interacts with the topography and climate agents (i.e., storm characteristics) may be the potential factors. The climate and soil hydrologic properties (HGC proportions) are correlated with latitude in eastern US and both contribute to the flow response (Wagener et al., 2007). They can be used to identify the homogeneous regions. However, the performance from the parameter transfer would probably not be as efficient as the parameter regionalization approach investigated in the current study. The climate and the physical descriptors do not capture the effect of interaction between all factors contributing to the flow response (i.e., climate, soil texture, runoff generation mechanism, groundwater, porosity, preferential pathways) (Troch et al., 2013).

Note that a previous regional study by Oudin et al. (2010b) demonstrated that only 60% of the hydrologically similar catchments are physically similar. The overlap was statistically significant. In 40% of the catchments classified based on physical similarity, the parameters are not transferable. This finding supports our claim of using catchments' characteristics that capture the interaction between all factors contributing to the flow response in the regionalization scheme. We conjecture that the more the effect of interaction is captured, the more efficient are the predictions from the parameter transfer.

Our study demonstrates that when MMHs do not exhibit differences between several predictions, the FDCs have diverse shapes according to analyses of the median percent error in each simulation. Consequently, two main facts emerge concerning FDC use: (i) it reveals the bias effect on flow simulation inaccuracy and (ii) it is advantageous for a more reliable parameter transfer assessment, which is urgently needed for accurate PUB. Several past PUB studies have regarded FDC as a fundamental daily stream flow statistic (Archfield et al., 2013). For example, Kapangaziwiri et al. (2009, 2012) analyzed FDCs to assess predictions from parameter regionalization. Masih et al. (2010) delineated regions of homogenous hydrologic behavior based on similarity of the FDC. Farmer et al. (2014) used the FDC of gauged basins to predict flow percentiles in ungauged basins using nonlinear spatial interpolations. We therefore suggest using the FDC to better assess PUB in combination with the efficiency measures of NS and PBIAS.

Our assessments using FDC suggest giving new paradigms in the evaluation of model prediction a try. The use of summary metrics involving measures of the FDC (i.e., slope of the FDC, rising limb density, declining limb density) in Sadegh et al. (2015) and Vrugt and Sadegh (2013) showed great promises for prediction evaluations. It ensured that simulated response depicts accurately the observed flow behaviors. This finding is consistent with our results; FDC being more efficient in prediction evaluation than MMH and classic residual-based metrics. The problem resides in the convoluted error residuals of the observed and the simulated time-series. According to Sadegh et al. (2015), the summary metrics have the advantage to be relatively insensitive to forcing data errors, which is particularly desirable in the context of non-stationarity. The summary metrics, therefore, avoid proclaiming non-stationarity for the wrong reasons (errors on the rainfall data) (Sadegh et al., 2015).

5.2.1. Which approach to use for PUB, the a priori parameters or the parameter regionalization?

In all the regions, the comparisons of the efficiency from parameter transfer with APRIORI highlighted the uncertainty in using the a priori parameters to make PUB compared to a parameter regionalization approach. The lowest performance (low median NS and high PBIAS) from APRIORI was in C2 and C3 (Table 3).

APRIORI was equivalent to TRANS_IN in C3 where TRANS_IN was the least efficient across the regions. This finding does not allow to recommend the use of a priori parameters for PUB. Slightly better predictions from APRIORI occurred in the catchments from C1 and C5 (Table 3) but never exceeded TRANS_IN. This finding suggests that a priori parameters in C2 and C3 have among the highest uncertainty and are less representative of the catchments' conditions. The complex landscape properties of C3 and C2 (i.e., the steepest topography with the finest soil texture) suggests that the poor performance of APRIORI is related to the larger uncertainty in soil-data interpolations from STATSGO. This uncertainty may relate to the lack of soil sampling in several regions with complex terrain (Koren et al., 2003). More research is required to further analyze the uncertainty in the SAC-SMA a priori parameters and their effect on flow predictions. Our findings suggests that it is better to use a parameter regionalization approach, similar to what we present in this study, for PUB. Future research would consider comparing predictions from a priori parameters with predictions from other regionalization approaches (i.e., regression, spatial proximity, similarity in physical properties) to further evaluate the use of SAC-SMA a priori parameters in predictions at ungauged catchments.

5.3. Comparisons with previous studies

Comparisons of the efficiency results with findings from other studies demonstrate that none of the catchments had predictions as poor and as biased as those reported by Gan and Burges (2006). These authors used the same model to investigate the parameter transferability over geographically distant MOPEX catchments. These differences demonstrate the benefit of using hydrologically "similar" catchments for the parameter transfer. Our results outperform predictions from the spatial proximity, which provided better predictions than the physical similarity in a study by Oudin et al. (2008). The median NS attained 0.77 in our study, but it did not exceed 0.7 for spatial proximity and 0.69 for physical similarity in Oudin et al. (2008). In Arsenault and Brissette, (2014) the efficiency of the physical similarity did not exceed 0.75 at individual catchments. This efficiency is lower than the value of 0.85, the maximum we obtained in this study at individual catchments.

Despite the limitations, the effect of interaction which is captured by the climate and flow characteristics used in the regionalization, explain the better performance we obtained compared with separate use of spatial proximity and physical similarity criteria.

Note that Oudin et al. (2008) considered the spatial proximity and physical similarity as complementary and that the average of flow simulation from both approaches can be used to improve the prediction efficiency. Given the satisfactory performance we obtained in this study and the fact that homogeneous regions implicitly combine aspects of spatial proximity and physical similarity, the proposition of Oudin et al. (2008) suggesting to combine predictions from two regionalization methods may represent a worth-testing approach to investigate in future studies. This so-called "multiregionalization scheme" requires identification of a priori regionalization approaches to obtain the average of flow simulation leading to the best performance after combination (Oudin et al., 2008).

Our prediction performance was consistent with other studies transferring the parameters between hydrologically similar catchments. Bock et al. (2015) obtained a median NS of 0.76 from the parameter transfer within regions of similar parameter sensitivity. The performance in individual catchments in our study exceeded the maximum value of 0.78 reported by Masih et al. (2010) who used the criterion of similarity in the FDC for parameter regionalization.

6. Conclusions

This paper evaluated the performance from the parameter transfer within homogeneous regions of similar climate and flow characteristics. Subsequently, it compared the performance from the parameter regionalization to the prediction efficiency from the soil-derived a priori parameters that are designed to make predictions at ungauged catchments. The study was conducted in the eastern US using 73 catchments. We employed the SAC-SMA model and the geographically contiguous regions determined by Sawicz et al. (2011) using climate and flow characteristics.

Our results showed that parameter transfer within homogeneous regions reduced the bias and increased the predictions efficiency (it reaches a median NS of 0.77 and a NS of 0.85 at individual catchments). The use of the FDC was advantageous in revealing the effect of bias on the flow simulation inaccuracy. The satisfactory efficiency from the transferred parameters within the homogeneous regions was fostered by the similarity in the effect of interaction between climate, physiographic characteristics and predominant runoff generation mechanism. The use of the flow characteristics in the regionalization helped to capture the similarity in the effect of interaction.

The transferred parameters within homogeneous regions outweighed in performance the soil derived a priori parameters. Therefore, it is better to use a regionalization approach to make predictions at ungauged catchments.

In one region of very complex landscape properties (i.e., forested mountainous catchments, steepest topography, higher fraction of the poorly drained soils) and heterogeneous energy conditions, the predictions from the a priori parameters had equivalent efficiency to those from transferred parameters within this region. Both had poor performance. The use of the transferred parameters from an outsider donor catchment slightly improved the predictions (i.e., more accurate predictions of the medium flow percentiles). This finding underlined the limitations of the parameter regionalization that affected the efficiency from the parameter transfer. The limitations of the approach are in part caused by differences in the energy conditions between the catchments of this specific region and the likelihood of lateral preferential flow that fostered the heterogeneity between the catchments in this region.

From this perspective, there is a room to improve the parameter regionalization within similar conditions of the catchments, where we propose to add other measures of similarity in the regionalization. Examples the aridity index, and measures of the effect of preferential flow that can be supported by specific measures of soil characteristics (i.e., porosity, permeability).

Expanding our study to larger datasets will have the potential to provide further insights on parameter regionalization using similarity in climate and flow characteristics. More limitations of the parameter regionalization are related to the implications of climate variability and change on the homogeneity in each region and consequently on parameter transferability. This limitation remains unexplored and it is recommended in future research related to parameter regionalization.

Acknowledgements

We thank the three anonymous reviewers for their careful reading of our manuscript and their many insightful comments and suggestions.

Funding

W. Chouaib is grateful for the Islamic Development Bank who funded her PhD studies at the University of British Columbia. This study was partially funded by internal awards of the Faculty of Forestry: [Weldwood of Canada Limited H. Richard Whittall, 2016], [Mary and David Macaree, 2015], and [Peter Rennie Memorial Award, 2017]) and the NSERC Discovery Grant of Dr. Younes Alila (RGPIN 194388-11).

Authors' contribution

W. Chouaib analyzed the data and wrote the manuscript. Y. Alila supervised both the content and interpretations of this work and edited the manuscript. P.V Caldwell helped with fruitful discussions on the findings and edited the manuscript.

Appendix A.

See Table 2.

References

Ali, G., Tetzlaff, D., Soulsby, C., McDonnell, J.J., Capell, R., 2012. A comparison of similarity indices for catchment classification using a cross-regional dataset. Adv. Water Resour. 40, 11–22.

Ameli, A.A., Craig, J.R., McDonnell, J.J., 2015. Are all runoff processes the same? Numerical experiments comparing a Darcy-Richards solver to an overland flow-based approach for subsurface storm runoff simulation. Water Resour. Res. 51 (12), 10008–10028.

Ao, T., Ishidaira, H., Takeuchi, K., Kiem, A.S., Yoshitari, J., Fukami, K., Magome, J., 2006. Relating BTOPMC model parameters to physical features of MOPEX basins. J. Hydrol. 320 (1), 84–102.

Archfield, S.A., Pugliese, A., Castellarin, A., Skøien, J.O., Kiang, J.E., 2013. Topological and canonical kriging for design flood prediction in ungauged catchments: an improvement over a traditional regional regression approach? Hydrol. Earth Syst. Sci. 17, 1575–1588. http://dx.doi.org/10.5194/hess- 17- 1575- 2013.

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.

Berghuijs, W.R., Sivapalan, M., Woods, R.A., Savenije, H.H., 2014. Patterns of similarity of seasonal water balances: A window into streamflow variability over a range of time scales. Water Resour. Res. 50 (7), 5638–5661.

Beven, K., Wood, E.F., 1983. Catchment geomorphology and the dynamics of runoff contributing areas. J. Hydrol. 65 (1), 139–158.

Beven, K.J., Kirkby, M.J., 1979. A physically based, variable contributing area model of basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. Hydrol. Sci. J. 24 (1), 43–69. https://doi.org/10.1080/02626667909491834.

Bock, A.R., Hay, L.E., McCabe, G.J., Markstrom, S.L., Atkinson, R.D., 2015. Parameter regionalization of a monthly water balance model for the conterminous United States. Hydrol. Earth Syst. Sci. Discuss. 12 (9), 10023–10066. https://doi.org/10.5194/hessd-12-10023-2015.

Bonell, M., 1993. Progress in the understanding of runoff generation dynamics in forests. J. Hydrol. 150 (2–4), 217–275.

Buttle, J.M., 1994. Isotope hydrograph separations and rapid delivery of pre-event water from drainage basins. Prog. Phys. Geogr. 18 (1), 16–41.

Butt, T., Russell, P., Turner, I., 2001. The influence of swash infiltration–exfiltration on beach face sediment transport: onshore or offshore? Coast. Eng. 42 (1), 35–52.

Brammer, D.D., McDonnell, J.J., 1996. An evolving perceptual model of hillslope flow at the Maimai catchment. Adv. Hillslope Process. 1, 35–60.

Bronstert, A., Niehoff, D., Bürger, G., 2002. Effects of climate and land-use change on storm runoff generation: present knowledge and modelling capabilities. Hydrol. Process. 16 (2), 509–529.

Bronstert, A., 1999. Capabilities and limitations of detailed hillslope hydrological modelling. Hydrol. Process. 13 (1), 21–48.

Coopersmith, E., Yaeger, M.A., Ye, S., Cheng, L., Sivapalan, M., 2012. Exploring the physical controls of regional patterns of flow duration curves-Part 3: A catchment classification system based on regime curve indicators. Hydrol. Earth Syst. Sci. 16 (11), 4467.

Chouaib, W., Caldwell, P.V., Alila, Y., 2018. Regional variation of flow duration curves in the eastern United States: process-based analyses of the interaction between climate and landscape properties. J. Hydrol. 559, 327–346.

Dingman, S.L., 2002. Physical hydrology. Prentice Hall, Boca Raton, p. 646.

Duan, Q., Schaake, J. and Koren, V., 2001. A priori estimation of land surface model parameters. Land Surface Hydrology, Meteorology, and Climate: Observations and Modeling, pp. 77–94.

Duan, Q., Schaake, J., Andreassian, V., Franks, S., Goteti, G., Gupta, H.V., Gusev, Y.M., Habets, F., Hall, A., Hay, L., Hogue, T., 2006. Model Parameter Estimation Experiment (MOPEX): An overview of science strategy and major results from the second and third workshops. J. Hydrol. 320 (1), 3–17.

Farmer, W.H., Archfield, S.A., Over, T.M., Hay, L.E., LaFontaine, J.H., Kiang, J.E., 2014. A comparison of methods to predict historical daily streamflow time series in the southeastern United States (No. 2014–5231), U.S. Geological Survey Scientific Investigations Report.

Farquharson, F.A.K., Meigh, J.R., Sutcliffe, J.V., 1992. Regional flood frequency analysis in arid and semi-arid areas. J. Hydrol. 138, 487–501.

Gan, T.Y., Burges, S.J., 2006. Assessment of soil-based and calibrated parameters of the Sacramento model and parameter transferability. J. Hydrol. 320 (1), 117–131.

Hentati, A., Kawamura, A., Amaguchi, H., Iseri, Y., 2010. Evaluation of sedimentation vulnerability at small hillside reservoirs in the semi-arid region of Tunisia using the Self-Organizing Map. Geomorphology 122 (1), 56–64.

Hershfield, D.M., 1961. Rainfall frequency atlas of the United States for durations from 30 minutes to 24 hours and return periods from 1 to 100 years. US Department of Commerce, Weather Bureau. Washington D.C., Technical Report No. 40.

Hrachowitz, M., Savenije, H.H.G., Blöschl, G., McDonnell, J.J., Sivapalan, M., Pomeroy, J.W., Arheimer, B., Blume, T., Clark, M.P., Ehret, U., Fenicia, F., 2013. A decade of Predictions in Ungauged Basins (PUB)—a review. Hydrol. Sci. J. 58 (6), 1198–1255.

Huang, P., Li, Z., Chen, J., Li, Q., Yao, C., 2016. Event-based hydrological modeling for detecting dominant hydrological process and suitable model strategy for semi-arid catchments. J. Hydrol. 542, 292–303.

Hundecha, Y., Bárdossy, A., 2004. Modeling of the effect of land use changes on the runoff generation of a river basin through parameter regionalization of a watershed model. J. Hydrol. 292 (1), 281–295.

Oudin, L., Kay, A., Andréassian, V., Perrin, C., 2010a. Are seemingly physically similar catchments truly hydrologically similar? Water Resour. Res. 46 (11), W11558. https://doi.org/10.1029/2009WR008887.

Jennings, M.E., Thomas Jr., W.O., Riggs, H.C., 1994. Nationwide Summary of US Geological Survey Regional Regression Eqs. for Estimating Magnitude and Frequency of Floods for Ungauged Sites, 1993. USGS Water-Resources Investigations Report 94-4002, p. 196.

Kapangaziwiri, E., Hughes, D., Wagener, T., 2009. Towards the development of a consistent uncertainty framework for hydrological predictions in South Africa. IAHS Publ. 333, 84.

Kapangaziwiri, E., Hughes, D.A., Wagener, T., 2012. Incorporating uncertainty in hydrological predictions for gauged and ungauged basins in southern Africa. Hydrol. Sci. J. 57 (5), 1000–1019.

Kennard, M.J., Mackay, S.J., Pusey, B.J., Olden, J.D., Marsh, N., 2010. Quantifying uncertainty in estimation of hydrologic metrics for ecohydrological studies. River Res. Appl. 26 (2), 137–156.

Kim, U., Kaluarachchi, J.J., 2008. Application of parameter estimation and regionalization methodologies to ungauged basins of the Upper Blue Nile River Basin, Ethiopia. J. Hydrol. 362 (1), 39–56.

Kokkonen, T.S., Jakeman, A.J., Young, P.C., Koivusalo, H.J., 2003. Predicting daily flows in ungauged catchments: model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina. Hydrolog. Process. 17 (11), 2219–2238.

Koren, V., Smith, M., Duan, Q., 2003. Use of APRIORI parameter estimates in the derivation of spatially consistent parameter sets of rainfall-runoff models. Calibration Watershed Models, 239–254.

Koren, V.I., Smith, M., Wang, D., Zhang, Z., 2000. Use of soil property data in the derivation of conceptual rainfall-runoff model parameters. In: 15th Conference on Hydrology, Long Beach. American Meteorological Society, USA (Paper 2.16).

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.

McDonnell, J.J., Woods, R., 2004. On the need for catchment classification. J. Hydrol. 299 (1–2), 2–3.

McDonnell, J.J., Sivapalan, M., Vaché, K., Dunn, S., Grant, G., Haggerty, R., Hinz, C., Hooper, R., Kirchner, J., Roderick, M.L., Selker, J., 2007. Moving beyond heterogeneity and process complexity: A new vision for watershed hydrology. Water Resour. Res. 43 (7), W07301. https://doi.org/10.1029/2006WR005467.

McIntyre, N., Lee, H., Wheater, H., Young, A., Wagener, T., 2005. Ensemble predictions of runoff in ungauged catchments. Water Resour. Res. 41 (12), W12434. https://doi.org/10.1029/2005WR004289.

Merz, R., Blöschl, G., 2004. Regionalisation of catchment model parameters. J. Hydrol. 287 (1), 95–123.

Mimikou, M., Gordios, J., 1989. Predicting the mean annual flood and flood quantiles for ungauged catchments in Greece. Hydrol. Sci. J. 34 (2), 169–184.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I—A discussion of principles. J. Hydrol. 10 (3), 282–290.

Newman, A.J., Clark, M.P., Sampson, K., Wood, A., Hay, L.E., Bock, A., Viger, R.J., Blodgett, D., Brekke, L., Arnold, J.R., Hopson, T., 2015. Development of a large-sample watershed-scale hydrometeorological data set for the contiguous USA: data set characteristics and assessment of regional variability in hydrologic model performance. Hydrol. Earth Syst. Sci. 19 (1), 209–223.

Norbiato, D., Borga, M., Sangati, M., Zanon, F., 2007. Regional frequency analysis of extreme precipitation in the eastern Italian Alps and the August 29, 2003 flash flood. J. Hydrol. 345 (3), 149–166.

Oudin, L., Kay, A., Andréassian, V., Perrin, C., 2010b. Are seemingly physically similar catchments truly hydrologically similar? Water Resour. Res. 46, W11558. https://doi.org/10.1029/2009WR008887.

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), W03413. https://doi.org/10.1029/2007WR006240.

Parajka, J., Merz, R., Blöschl, G., 2005. A comparison of regionalisation methods for catchment model parameters. Hydrol. Earth Syst. Sci. Discussions 9 (3), 157–171.

Parajka, J., Blöschl, G., Merz, R., 2007. Regional calibration of catchment models: Potential for ungauged catchments. Water Resour. Res. 43 (6), W06406. https://doi.org/10.1029/2006WR005271.

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.

Portela, M.M., Dias, A.T., 2005. Application of the index-flood method to the regionalization of flood peak discharges on the Portugal mainland. WIT Trans. Ecol. Environ. 83.

Price, K., 2011. Effects of watershed topography, soils, land use, and climate on baseflow hydrology in humid regions: a review. Progr. Phys. Geogr. 35 (4), 465–492.

Razavi, T., Coulibaly, P., 2013. Classification of Ontario watersheds based on physical attributes and streamflow series. J. Hydrol. 493, 81–94.

Ren, H., Hou, Z., Huang, M., Bao, J., Sun, Y., Tesfa, T., Leung, L.R., 2016. Classification of hydrological parameter sensitivity and evaluation of parameter transferability across 431 US MOPEX basins. J. Hydrol. 536, 92–108.
Rice, K.C., Hornberger, G.M., 1998. Comparison of hydrochemical tracers to estimate source contributions to peak flow in a small, forested, headwater catchment. Water Resour. Res. 34 (7), 1755–1766.
Rousseau, A.N., Hentati, A., Tremblay, S., Quilbé, R. and Villeneuve, J.P., 2005. Computation of the topographic index on 16 watersheds in Quebec (No. R800f). INRS, Centre Eau, Terre et Environnement.
Sadegh, M., Vrugt, J.A., Xu, C., Volpi, E., 2015. The stationarity paradigm revisited: hypothesis testing using diagnostics, summary metrics, and DREAM (ABC). Water Resour. Res. 51 (11), 9207–9231.
Sawicz, K., Wagener, T., Sivapalan, M., Troch, P.A., Carrillo, G., 2011. Catchment classification: empirical analysis of hydrologic similarity based on catchment function in the eastern USA. Hydrol. Earth Syst. Sci. 15 (9), 2895–2911.
Schaake, J., Cong, S., Duan, Q., 2006. The US MOPEX data set. IAHS Publ. 307, 9.
Smakhtin, V.U., 2001. Low flow hydrology: a review. J. Hydrol. 240 (3), 147–186.
Sefton, C.E.M., Howarth, S.M., 1998. Relationships between dynamic response characteristics and physical descriptors of catchments in England and Wales. J. Hydrol. 211 (1), 1–16.
Singh, V.P., Xu, C.Y., 1997. Sensitivity of mass transfer-based evaporation equations to errors in daily and monthly input data. Hydrol. Process. 11 (11), 1465–1473.
Sivapalan, M., Takeuchi, K., Franks, S.W., Gupta, V.K., Karambiri, H., Lakshmi, V., Liang, X., McDonnell, J.J., Mendiondo, E.M., O'connell, P.E., Oki, T., 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.
Skøien, J.O., Blöschl, G., 2007. Spatiotemporal topological kriging of runoff time series. Water Resour. Res. 43, W09419. https://doi.org/10.1029/2006WR005760.
Sorooshian, S., Duan, Q., Gupta, V.K., 1993. Calibration of rainfall-runoff models: application of global optimization to the Sacramento Soil Moisture Accounting Model. Water Resour. Res. 29 (4), 1185–1194.
Swift Jr, L.W., Cunningham, G.B., Douglass, J.E., 1988. Climatology and hydrology. In: Forest hydrology and ecology at Coweeta (pp. 35–55). Springer, New York.
Troch, P.A., Carrillo, G., Sivapalan, M., Wagener, T., Sawicz, K., 2013. Climate-vegetation-soil interactions and long-term hydrologic partitioning: signatures of catchment co-evolution. Hydrol. Earth Syst. Sci. 17 (6), 2209.
van Werkhoven, K., Wagener, T., Reed, P., Tang, Y., 2008. Characterization of watershed model behavior across a hydroclimatic gradient. Water Resour. Res. 44 (1), W01429. https://doi.org/10.1029/2007WR006271.
Vrugt, J.A., Sadegh, M., 2013. Toward diagnostic model calibration and evaluation: Approximate Bayesian computation. Water Resour. Res. 49 (7), 4335–4345.
Wagener, T., Sivapalan, M., Troch, P., Woods, R., 2007. Catchment classification and hydrologic similarity. Geography compass 1 (4), 901–931.
Weiler, M., McDonnell, J.J., 2007. Conceptualizing lateral preferential flow and flow networks and simulating the effects on gauged and ungauged hillslopes. Water Resour. Res. 43 (3), W03403. https://doi.org/10.1029/2006WR004867.
Wood, M.K., Blackburn, W.H., 1984. An evaluation of the hydrologic soil groups as used in the SCS runoff method on rangelands. J. Am. Water Resour. Assoc. 20 (3), 379–389.
Ye, S., Yaeger, M., Coopersmith, E., Cheng, L., Sivapalan, M., 2012. Exploring the physical controls of regional patterns of flow duration curves–Part 2: role of seasonality, the regime curve, and associated process controls. Hydrol. Earth Syst. Sci. 16 (11), 4447–4465.
Young, A.R., 2006. Stream flow simulation within UK ungauged catchments using a daily rainfall-runoff model. J. Hydrol. 320 (1), 155–172.
Zrinji, Z., Burn, D.H., 1994. Flood frequency analysis for ungauged sites using a region of influence approach. J. Hydrol. 153, 1–21.
Zhang, Z., Wagener, T., Reed, P., Bhushan, R., 2008. Reducing uncertainty in predictions in ungauged basins by combining hydrologic indices regionalization and multiobjective optimization. Water Resour. Res. 44(12), W00B04. doi:10.1029/2008WR006833.