Combining a rainfall–runoff model and a regionalization approach for flood and water resource assessment in the western Po Valley, Italy

Alessio Cislaghi[1,2] *, Daniele Masseroni[1], Christian Massari[3], Stefania Camici[3], and Luca Brocca[3]

[1] *Department of Agricultural and Environmental Sciences (DiSAA), University of Milan, Milan, Italy*

[2] *Centre of Applied Studies for the Sustainable Management and Protection of Mountain Areas (Ge.S.Di.Mont), University of Milan, Brescia, Italy*

[3] *Research Institute for Geo-Hydrological Protection, National Research Council, Perugia, Italy*

* Corresponding author, Alessio Cislaghi:

Department of Agricultural and Environmental Sciences (DiSAA), Università degli Studi di Milano, via Celoria 2, 20133, Milan, Italy. Phone: +39 02 503 16903; Fax: +39 02 503 16911. E-mail address: alessio.cislaghi@unimi.it

Abstract Selecting the best structure and parameterization of rainfall–runoff models is not straightforward and depends on a broad number of factors. In this study, the "Modello Idrologico Semi-Distribuito in continuo" (MISDc) was tested on 63 mountainous catchments in the western Po Valley (Italy) and the optimal model parameters were regionalized using different strategies. The model performance was evaluated through several indexes analysing hydrological regime, high-flow condition and flow–duration curve (FDC). In general, MISDc provides a good fit behaviour with a Kling-Gupta Efficiency index greater than 0.5 for 100% and 84% of cases for calibration and validation respectively. Concerning the regionalization, spatial proximity approach is the most accurate solution obtaining satisfactory performance. Lastly, the predicted FDCs showed an excellent similarity with the observed ones. Results encourage to apply MISDc over the study area for flood forecasting and for assessing water resources availability thanks to the modest computational efforts and data requirements.

Keywords ungauged catchments; parameter set regionalization; flow–duration curve; catchment descriptors; flood-risk management

1 Introduction

Simulating reliable continuous streamflow has been an essential and common objective for the scientific hydrological community since the middle of the 20th century (Boughton and Droop, 2003, Brocca *et al.*, 2011, Loukas and Vasiliades, 2014). Such an issue is of paramount importance for addressing engineering and environmental problems, which span from designing hydraulic structures to flood-risk assessment and stormwater management, from forecasting the climatic and anthropogenic effects on water resources to assessing economic benefits from hydropower production. Rainfall–runoff (RR) models are the most common tools for the prediction of discharge and estimation of water balance (Beven, 2012). The scientific literature contains a large number of RR models, characterized by different levels of complexity and data requirement (Chiew *et al.*, 1993, Kampf and Burges, 2007a, Knapp *et al.*, 1991, Singh and Woolhiser, 2002). Many authors proposed exhaustive classification schemes to sort through many existing mathematic models used in hydrology at the catchment scale (Clarke, 1973, Dawdy and O'Donnell, 1965, Refsgaard, 1990, Todini, 1988). One of the most comprehensive classifications was introduced by Kampf and Burges (2007b), who subdivided RR models according to the spatial structure (lumped, semi-distributed or distributed), the time representation (continuous or discrete event-based), or the hydrological processes description (physically meaningful or data driven). Despite significant advances in watershed science and hydrological modelling, the discussion regarding RR model accuracy and reliability is a topic of increasing research interest and remains a current challenge. Four key points could motivate this: (a) the difficulty to select the most appropriate and accurate RR model, (b) the data availability to calibrate and to validate the parameters, (c) the model predictive uncertainties, and (d) the computational time (Perrin *et al.*, 2001, Sorooshian and Gupta, 1983, Todini, 2011).

In addition, hydrologists have been facing a fundamental challenge in flood forecasting in ungauged and/or poorly gauged basins for many decades. Indeed, the International Association of Hydrological Sciences (IAHS) launched the Prediction in Ungauged Basins (PUB) initiative covering the decade 2003–2012 aimed to foster major advances in our capacity to make predictions in areas with poor coverage of hydrological data (Seibert and Beven, 2009, Sivapalan *et al.*, 2003). In this respect, since the 1970s, experts in watershed science have been attempting to develop regionalization strategies to describe similar hydrological behaviours between catchments at different spatial scale (Abdulla and Lettenmaier, 1997, Brutsaert and Nieber, 1977, Egbuniwe and Todd, 1976, Jarboe and Haan, 1974, Klemeš, 1986, Tasker, 1989, Weeks and Ashkanasy, 1983). Later, the term "regionalization" identified mathematical and computational methodologies enable to transfer models parameters from hydrologically similar catchments to a catchment of interest (Blöschl and Sivapalan, 1995). In particular, in the case of ungauged catchments where measurements (i.e.

streamflow time series) are not available and therefore it is not possible to calibrate only RR models, regionalization approaches remain the most low-cost and popular solutions for predicting continuous streamflow (He *et al.*, 2011, James, 1972, Magette *et al.*, 1976, Manley, 1978, Samuel *et al.*, 2011, Wagener *et al.*, 2004). Despite particular attention and scientific progress on this topic, there is no universal regionalization method for a given region (Samuel *et al.*, 2011, Zhang and Chiew, 2009).

A large variety of regionalization approaches has been proposed, developed and applied to catchments worldwide with different landscape, morphology, climate and size: each with its specific advantages and inherent drawbacks (Blöschl, 2013, He *et al.*, 2011, Hrachowitz *et al.*, 2013, J. Parajka *et al.*, 2013, Razavi and Coulibaly, 2013, Zhang and Chiew, 2009). Such methods can be summarized in three main categories. The first category includes the regression-based analyses (Young, 2006) that consist in developing *a posteriori* relationships between catchment descriptors (physiographic and climatic) and model parameter values calibrated on gauged catchments. Despite regression-based analyses are simple to implement, they request an accurate knowledge of catchment attributes and RR data availability of several catchments inside the same region under investigation. The second category comprises the distance-based regional approaches, or spatial-proximity methods, that represent the earliest attempts to regionalize the parameters of a hydrological model (Egbuniwe and Todd, 1976, Merz and Blöschl, 2004, Oudin *et al.*, 2008, Parajka *et al.*, 2005). Such regionalization schemes consist in transferring parameter sets calibrated at the closest neighbour catchments to the ungauged target assuming that neighbouring catchments have a similar hydrological response. The performance of such methods mainly depends on the number and the spatial distribution of the donor catchments (Oudin *et al.*, 2008). The last scheme of regionalization approaches combines a synthesis of the spatial-proximity approach and the regression-based approach. Indeed, these strategies are based on the similarity between an ungauged catchment and one or more gauged donor catchments in terms of physical attributes (Burn and Boorman, 1993, McIntyre *et al.*, 2005). They essentially transfer the model parameters from gauged to ungauged catchments, which are not necessary spatially closer, based on a similarity measure of physiographic catchment characteristics. In this method, the catchment characteristics are similar to those of the regression approach, but the regionalization model structure is different as no assumption of linearity is made. In addition, the complete set of model parameters is usually transposed from one or more donor catchments to the catchment of interest in this approach, while in the regression case, the parameters are usually regionalized independently from each other.

Against this background, combining an accurate RR model with a reliable regionalization method to accurately predict continuous streamflow, floods and water resource availability in ungauged catchments is a primary objective, in particular in those areas where flood-risk assessment and sustainable water resource management appear desirable (Burges, 1998). A typical example is the Upper Po River catchment located in northern Italy and including a flourishing agricultural, urbanized-industrialized plain and wide natural mountain areas. This large territory is prone to multiple natural hazards including floods (Mysiak *et al.*, 2013), landslides (Guzzetti and Tonelli, 2004), snow avalanches (Viglietti *et al.*, 2010), land subsidence (Carminati and Martinelli, 2002) and seasonal drought (Strosser *et al.*, 2012). Such hydrological hazards appear to be strongly correlated with the physiographic setting and mainly affect mountainous areas, alluvial plains and valley floors, with maximum values along Alpine valleys, where flood and landslide risks co-exist with a high urban density (Lari *et al.*, 2009). This fact was highlighted by the Italy's Regional Civil Protection Agencies as well as the integrated programme for the mitigation of natural hazard evaluations (years 2007–2010). Specifically, since 1906, floods have caused 421 fatalities (Guzzetti, 2000); the hydrogeological risk mitigation costs for the period 2007–2010, incurred by public administrations in the Upper Po River basin, amounted to 500 million euros (mainly intended for the protection of urban areas from landslides, floods and avalanches). In this respect, recent actions, aimed to combine the detection of hazard-prone areas with smart low-impact urban planning, appear indispensable to prevent the damages caused by the ever more frequent extreme weather (Ercolani *et al.*, 2018, Luino *et al.*, 2012).

Moreover, there are significant requirements from the agricultural, hydropower and drinking water management sectors. In particular, ggriculture needs roughly two-thirds of all the available water resource for irrigation and is the largest water user in Italy (Masseroni *et al.*, 2017a). Meanwhile hydropower sector manages the regulated reservoirs and strongly influences the water availability over the plain (Giuliani *et al.*, 2016, Ravazzani *et al.*, 2015).

On the basis of the above considerations, the application of a hydrological model over a large set of sub-catchments of the Po River Valley is strongly encouraged, especially by regional water protection authorities, in order to ensure a high level of flood-risk prevention and water allocation over the territory. In particular, hydrological modelling is an essential instrument to support the emergency activities during extreme meteorological events and to estimate the amount of water described by the flow–duration curve (FDC). FDCs are a widely used measure in various applications related to water resource management (e.g. hydropower generation, irrigation systems, monitoring of stream pollution, fluvial erosion) (Foster, 1934, Vogel and Fennessey, 1994, 1995, Wolman and Miller, 1960).

Therefore, the main purposes of this work are: (a) to evaluate the performance of a simple hydrological RR model applied over 63 Alpine and pre-Alpine catchments uniformly distributed in northwestern Italy; (b) to construct FDCs using streamflow predictions and compare them with those obtained by measured records; and (c) to adopt different regionalization strategies for predicting parameter sets for ungauged or poorly gauged catchments and, therefore, for simulating streamflow to compare regionalization approaches and determine their performance.

2 Materials and methods

2.1 RR model

2.1.1 Model structure

This study applies a lumped version of a simple RR model, named "*Modello Idrologico Semi-Distribuito in continuo*" MISDc, developed by Brocca et al. (2010, 2011a). This conceptual model was originally designed as supporting instrument for the civil protection activities to predict flood events at an hourly time scale in central Italy (Brocca *et al.*, 2013). Later, it was widely used in different contexts across Europe (Barbetta *et al.*, 2017, Camici *et al.*, 2011, 2014, Ciabatta *et al.*, 2016, Loizu *et al.*, 2018, Massari e*t al.*, 2015a, 2015b, Masseroni *et al.*, 2017b). The MISDc model incorporates a soil water balance model (Brocca *et al.*, 2008), the Soil Conservation Service - Curve Number (Chow, 1959), and a routing module (RM) (Melone *et al.*, 2001). The first two modules simulate the soil water content $W(t)$ and, as a consequence, the surface runoff r(t), the saturation excess se(t) and the subsurface runoff sb(t). In addition, two packages simulating snowmelt and glacier melt are integrated the soil water balance model of MISDc. The last three components contribute to generate the discharge at the outlet through the simulation of transferring processes described by the geomorphological instantaneous unit hydrograph (GIUH; Gupta *et al.*, 1980) and by a linear reservoir approach. Figure 1 shows a schematic representation and Appendix A reports a more detailed summary, including the main equations.

2.1.2 Model parameters and calibration process

The MISDc model includes 12 model parameters: the initial condition of soil water content, $W(\mathrm{t}_0)$ (Appendix A1, Eq. (A1)); the maximum water capacity of the soil layer, W_{max} (i.e. field capacity term; Eq. (A1)); the initial abstraction coefficient, λ (Eq. (A2)); the parameter of the relationship between the saturation degree and the soil retention, a (Eq. (A3)); the correction factor for actual evapotranspiration b (Eq. (A5)); the saturated hydraulic conductivity K_{s} (Eqs ((A6)) and (A7)); the exponent of drainage component, m (Eqs (A6) and (A7)); the fraction of drainage that transforms into subsurface runoff, ϑ (Eqs (A6) and (A7)); the degree-day coefficients, $C_{m\text{-snowpack}}$ and $C_{m\text{-glaciers}}$ for the melting process of snowpack and glaciers (Eqs (A11) and (A12)); the constant referring to the flow of water at the base of glaciers k_{glaciers} (Eq. (A12)); and the coefficient of lag–area relationship, η (Eq. (A14)). Each model parameter can vary within a range of admissible values derived by other applications of MISDc over many catchments worldwide (Camici *et al.*, 2018, Massari *et al.*, 2015b, Masseroni *et al.*, 2017b), as reported in Table 1.

The calibration of the MISDc model parameters requires rainfall, air temperature and streamflow time series as input data. The calibration process consists in adopting a standard gradient-based automatic optimization method implemented in the MATLAB software package (‘fmincon’ function; MATLAB R2016b, The MathWorks, Inc., Natick, Massachusetts, United States). This algorithm is particularly suitable and efficient for a limited number of model parameters and enables one to maximize an objection function. In this case, the objective function is the difference between the unity and the modified Kling-Gupta efficiency statistic dimensionless, KGE′, proposed by Gupta *et al.* (2009) and later adjusted by Kling *et al.* (2012). Based on the decomposition of the Nash-Sutcliffe efficiency coefficient (NS; Nash and Sutcliffe 1970) into three distinctive components represented by correlation, conditional bias and unconditional bias (Murphy, 1988, Węglarczyk, 1998), it assumes the value of 1 when the models perfectly simulates the observed data.

The KGE′ is easily formulated by computing the Euclidean distance of these three terms, as given by equation (1).

$$KGE' = 1 - \sqrt{\left[\frac{\sum_{t=1}^{N}(Q_{\text{obs},t}-\mu_{\text{obs}})\,(Q_{\text{sim},t}-\mu_{\text{sim}})}{\sqrt{\sum_{t=1}^{N}(Q_{\text{obs},t}-\mu_{\text{obs}})^2(Q_{\text{sim},t}-\mu_{\text{sim}})^2}}-1\right]^2+\left(\frac{\mu_{\text{sim}}}{\mu_{\text{obs}}}-1\right)^2+\left[\frac{\sqrt{\sum_{t=1}^{N}(Q_{\text{sim},t}-\mu_{\text{sim}})^2}}{\sqrt{\sum_{t=1}^{N}(Q_{\text{obs},t}-\mu_{\text{obs}})^2}}\frac{\mu_{\text{obs}}}{\mu_{\text{sim}}}-1\right]^2} \quad (1)$$

In Eq. (1), $Q_{\text{obs},t}$ and $Q_{\text{sim},t}$ are the observed and simulated discharge, respectively, at time t and N is the total number of hourly observations, where μ_{obs} and μ_{sim} is the mean of the observed and simulated discharges.

The KGE′ criterion offers interesting diagnostic insights, taking into account the temporal dynamics and the distribution of the streamflow time series (Camici *et al.*, 2018, Dick *et al.*, 2015, Massari *et al.*, 2018, Thirel *et al.*, 2015).

2.1.3 Model performance of continuous stemflow predictions

Three widely used indices were applied to determine the performance of the RR model. The first is NS, also known as the efficiency index, useful to evaluate differences in the continuous simulation of streamflow.

$$\mathrm{NS} = 1 - \frac{\sum_{t=1}^{N}\left(Q_{\mathrm{obs},t} - Q_{\mathrm{sim},t}\right)^2}{\sum_{t=1}^{N}\left(Q_{\mathrm{obs,t}} - \mu_{\mathrm{obs}}\right)^2} \qquad (2)$$

The second index is the ANSE, an adapted version of NS, well-suited for high streamflow conditions (Guex, 2001, Hoffmann *et al.*, 2004):

$$\mathrm{ANSE} = 1 - \frac{\sum_{t=1}^{N}\left(Q_{\mathrm{obs},t} + \mu_{\mathrm{obs}}\right)\left(Q_{\mathrm{sim},t} - Q_{\mathrm{obs,t}}\right)^2}{\sum_{t=1}^{N}\left(Q_{\mathrm{obs},t} + \mu_{\mathrm{obs}}\right)\left(\mu_{\mathrm{obs}} - Q_{\mathrm{obs},t}\right)^2} \quad (3)$$

The third criterion applied here is the absolute volume error, VE, commonly used to evaluate the RR model ability for simulating runoff volume (Merz and Blöschl, 2004):

$$\mathrm{VE} = \frac{\left|\sum_{t=1}^{N} Q_{\mathrm{sim},t} - \sum_{t=1}^{N} Q_{\mathrm{obs},t}\right|}{\sum_{t=1}^{N} Q_{\mathrm{obs},t}} \cdot 100 \qquad (4)$$

Once the above performance scores were calculated, a framework for statistical interpretation of hydrological model performance developed by Ritter and Muñoz-Carpena (2013) was used to assess the goodness of fit and classify into four different performance classes. These are: ‘unsatisfactory’ (KGE′, NS, ANSE < 0.5), ‘satisfactory’ (0.5 < KGE′, NS, ANSE < 0.65), ‘good’ (0.65 < KGE′, NS, ANSE < 0.75) and ‘very good’ (KGE′, NS, ANSE > 0.75). Moreover, the model performance was evaluated according to the volume differences, as follows: ‘unsatisfactory’ (VE > 15%), ‘satisfactory’ (10% < VE < 15%), ‘good’ (5% < VE < 10%) and ‘very good’ (VE < 5%).

2.1.4 Model performance of FDC predictions

For a complete assessment of the MISDc model performance, observed and simulated long-term, FDCs are compared. The FDC is the cumulative frequency curve that shows the percentage of time during which the discharge is equalled or exceeded (Foster, 1934). The FDCs were computed considering all datasets of observations to overcome the problem related to gap filling (Castellarin *et al.*, 2004, 2007). To verify the accuracy of the model (Yilmaz *et al.*, 2008), three diagnostic signature measures were adopted:

2.1.4.1 Percent bias in the FDC mid-segment slope, BiasFMS:

$$\mathrm{BiasFMS} = \frac{\left[\log\left(q_{\mathrm{sim},m1}\right) - \log\left(q_{\mathrm{sim},m2}\right)\right] - \left[\log\left(q_{\mathrm{obs},m1}\right) - \log\left(q_{\mathrm{obs},m2}\right)\right]}{\log\left(q_{\mathrm{obs},m1}\right) - \log\left(q_{\mathrm{obs},m2}\right)} \cdot 100 \qquad (5)$$

where q_{obs} and q_{sim} are the sorted time series of observed and simulated flows, whereas $m1$ and $m2$ are the lowest and highest flow exceedance probabilities (0.2 and 0.7, respectively) within the mid-segment of the FDC.

2.1.4.2 Percent bias in the FDC high-segment volume, BiasFHV:

$$\mathrm{BiasFHV} = \frac{\sum_{h=1}^{H}(q_{\mathrm{sim},h} - q_{\mathrm{obs},h})}{\sum_{h=1}^{H} q_{\mathrm{obs},h}} \cdot 100 \quad (6)$$

where h =1, 2, …, H is the flow index for flows with exceedance probability lower than 0.02.

2.1.4.3 Percent bias in the FDC low-segment volume, BiasFLV:

$$\mathrm{BiasFLV} = \frac{\sum_{l=1}^{L}[\log(q_{\mathrm{sim,l}}) - \log(q_{\mathrm{sim,L}})] - \sum_{l=1}^{L}[\log(q_{\mathrm{obs,l}}) - \log(q_{\mathrm{obs,L}})]}{\sum_{l=1}^{L}[\log(q_{\mathrm{obs,l}}) - \log(q_{\mathrm{obs,L}})]} \cdot 100 \quad (7)$$

where l = 1, 2, …, L is the index of the flow value located within the low-flow segment (0.7–1.0 flow exceedance probability of the FDC) and L represents the index for the minimum flow.

In accordance with the literature (Herbst *et al.*, 2009, Mendoza *et al.*, 2015, Pfannerstill *et al.*, 2014), the results are classified as 'satisfactory' when a bias value is less than 30%; conversely, a result is 'unsatisfactory' when the bias is greater than 30%.

2.2 Regionalization strategies

In this study, different regionalization strategies were adopted to assess which one is the most suitable for a large and various area. Table 2 presents a summary of the selected methods and a brief description of each is reported below.

2.2.1 Regionalization using spatial-proximity approaches

The spatial-proximity methods consist in transferring model parameters from neighbouring catchments to the ungauged one. The main concept of this group of methods is that catchments that are close to each other will have a similar hydrological response as the climate and catchment conditions will only vary smoothly in space and the differences arise only from random factors (Merz and Blöschl, 2004, Parajka *et al.*, 2005, Razavi and Coulibaly, 2013). Although such approaches are very attractive, they strongly depend on the spatial density of the gauged catchments (Oudin *et al.*, 2008). Several authors have proposed and developed different adjustments for this methodology (Drogue and Khediri, 2016). The most common are the inverse distance weighted (IDW) and the arithmetic mean (AM) techniques. The IDW method is a multivariate interpolation approach, which is based on the inverse spatial distance between catchment centroids (IDW_C) or outlets (IDW_O), as first proposed by Shepard (1968) and given by:

$$U_j = \sum_{i=1}^{M-1} W_{j,i} P_i = \sum_{i=1}^{M-1} \left(\frac{\mathrm{gd}_{j,i}^{-2}}{\sum_{i=1}^{M-1} \mathrm{gd}_{j,i}^{-2}} \right) P_i \qquad (5)$$

where U_j indicates the model parameters of the ungauged catchment j, P_i represents the calibrated model parameters of the gauged catchment i, $W_{j,i}$ is the weighted function, M is the number of donor catchments and $gd_{j,i}$ is the geographical distance between two centroids/outlets of gauged to ungauged catchments.

$$\mathrm{gd}_{j,i} = \sqrt{\left(X_j - X_i\right)^2 + \left(Y_j - Y_i\right)^2} \qquad (6)$$

where X_j, Y_j, and X_i, Y_i are the geographical coordinates of the centroids/outlet of the of gauged to ungauged catchments.

The AM method is an alternative approach, which evaluates the arithmetic mean of parameter sets calibrated for all the available input data time series of the gauged catchments (global mean, AM_g) or only of those located in an area delimited by a circumference of a specific radius, for example 25 or 50 km (Parajka *et al.*, 2005), from the ungauged catchment centroid (AM_{25} or AM_{50}).

$$U_j = \frac{1}{D-1} \sum_{i=1}^{D-1} P_i \qquad (7)$$

where D is the donor catchments inside a region or a portion of it.

2.2.2 Regionalization using regression-based methods

The regression-based techniques are the simplest and most popular methodologies in applied hydrology (He *et al.*, 2011, Oudin *et al.*, 2008, Razavi and Coulibaly, 2013). Regression is a statistical tool that enables one to relate the model parameters (dependent variables) to catchment attributes (independent variables). Although catchment attributes should be selected among the factors that drive the hydrological response of a catchment (Kokkonen *et al.*, 2003), there is no standard set of them and they are largely different across numerous studies (Bocchiola *et al.*, 2010, Cheng *et al.*, 2006, McIntyre *et al.*, 2005, Merz and Blöschl, 2004, Post, 2009, Seibert, 1999, Wagener and Wheater, 2006). Such attributes include meteorological (e.g. mean annual precipitation, maximum daily annual precipitation, average temperature) and physiographic information (e.g. position of the catchment outlet or centroid, area, stream length, percentage of area covered by grass, forest, urban, roads, buildings or water, soil types, soil permeability). The methods belonging to the regression-based regionalization can be grouped into linear multiple ('level-level') and nonlinear multiple regression ('level-log', 'log-level', 'log-log') according to the subdivision proposed by He *et al.* (2011).

2.2.3 Regionalization using physical-similarity approaches

The physical-similarity approaches are based on the concept that the model parameters can be transferred from gauged to ungauged catchments according to the similarity of their physical and climatic attributes. This perception implies that the model parameters reflect the hydrological behaviour of the catchment (Oudin *et al.*, 2010, Sawicz *et al.*, 2011). A wide variety of studies have used this type of regionalization (e.g. Oudin *et al.*, 2008, Samuel *et al.*, 2011, Zhang and Chiew, 2009). In this study, two alternatives are applied.

The first approach (PhyS), simple and immediate, provides the model parameters of ungauged basins using, directly, all the available datasets and defining a metric of physical similarity *d*, i.e. a weighted Euclidean distance between the catchment attributes of the ungauged site *j* and the other catchments *i* =1, …, *M*–1 (He *et al.*, 2011) as follows:

$$d_{j,i} = \sqrt{\sum_{k=1}^{m} w_k \left(A_{k,j} - A_{k,i}\right)^2} \qquad (8)$$

where w_k is the weight associated with the *k*th normalized physical descriptor *A*. In fact, each attribute has to ensure the same importance regardless of its range. In the general case, in which all descriptors are considered to be equally important, w_k is set to 1 (Garambois *et al.*, 2015, Kay *et al.*, 2006, Oudin *et al.*, 2008, Parajka *et al.*, 2005, Zhang and Chiew, 2009). Then, the model parameters are estimated replacing $gd_{j,i}$ with $d_{j,i}$ in Eq. (5).

The second approach consists in catchment classification (CC, Di Prinzio *et al.*, 2011). It includes, indiscriminately, all the calibrated model parameters for all the available gauged catchments into the regionalization procedure, dividing them into groups and subgroups, hydrologically similar, identified by the prominent physical characteristics (Di Prinzio *et al.*, 2011). Different procedures have been developed within the topic of CC, but most hydrologists have adopted the clustering technique (e.g. Razavi and Coulibaly, 2013). In this study, the applied methodology is a two-level approach that combines a self-organizing map (SOM) and a hierarchical clustering (i.e. the inner squared distance Ward's method). This allows one to deal with a high-dimensional dataset and to group it into the most appropriate number of classes, reducing noise and outliers (Ley *et al.*, 2011, Vesanto and Alhoniemi, 2000). Such a CC is described in detail by Boscarello *et al.* (2016) and adopted to group catchments inside the Upper Po River basin. Once all study catchments have been grouped into a smaller number of classes according to their physical similarities, a regional set of RR model parameters for each class is estimated using an arithmetic mean of model parameters of the catchment of the same class, or, alternatively, using a similarity metric (combining Eqs (5) and (8)). For simplicity, such strategies are hereafter named as CC with arithmetic mean (CC_{pm}) and CC with physical similarity measure (CC_{pd}) respectively.

2.2.4 Cross-validation and assessment of regionalization methods

The performance of each regionalization approach was validated following the leave-one-out cross-validation scheme, as described in many hydrological studies (e.g. Merz and Blöschl, 2004, Oudin *et al.*, 2008, Parajka *et al.*, 2005, Samuel *et al.*, 2011). This validation technique consists in considering each catchment of the available dataset, in turn, as ungauged and in applying the regionalization approach on the remaining ones.

3 Case study

3.1 Hydro-geomorphological features

The study area includes 63 basins and sub-catchments of the western Po Valley and covers approximately 16 000 km^2 (Fig. 2 and Appendix B). The study catchments are predominantly located in the western chain of Italian Alps and pre-Alps, with areas ranging from 15 to 2300 km^2 and an average elevation of between 210 and 2100 m a.s.l. Mountains cover half of this area, whereas the remaining part is characterized by a large plain. The particular morphology has created a typical torrential hydrographic system composed of numerous tributaries of the Po River. The annual regime of the western Po River is characterized by two different periods: a low-water phase in winter and summer and a high-water phase in autumn, when an intensification of rainstorms usually occurs, and spring, due to the contribution of the snowmelt processes, especially at high altitudes (Ravazzani *et al.*, 2015). The precipitation regime according to the Köppen-Geiger climate classification (Kottek *et al.*, 2006, Peel *et al.*, 2007) belongs to the temperate/cool continental class, featuring seasonal continuous snow cover above 1000 m a.s.l. Mean annual precipitation ranges from 680 to 1700 mm, while the average annual temperature is about 8°C, with a minimum in January and a maximum in August.

Concerning the lithological point of view, the plain is composed of different lithological units (Ravazzani *et al.*, 2015): (a) a soil thickness of 20–50 m deep composed of alluvial deposits with gravelly-sandy texture where it is possible to detect an unconfined productive aquifer, (b) an alternation between silty-clayey and gravelly-sandy horizons (i.e. fluvial-lacustrine deposits), and (c) a marine origin sediment unit with fine texture. In the shallower unconfined aquifer, the groundwater level is variable, particularly under the plain and during the irrigation period. In many cases, the groundwater table can reach a few centimetres from the ground, especially where rice is cultivated or where the resurgences are operated (mainly between the Ticino and Adda rivers).

Approximately 65% of the territory is devoted to agriculture, although urbanized areas have been expanding by about 45% since 1954 (Bocchi *et al.*, 2012). The water in the agrarian lands is delivered by a network of artificial channels of different sections and order, which extends for over 10 000 km across the plain, diverting water from the main rivers to the fields. Therefore, it is clear that there is a strong interdependence between irrigation requirements in the plain and water availability in the Alps and this affects the management of water resources in both contexts.

3.2 Dataset

Meteorological and hydrological data were collected at a half-hourly time step by the telemetric monitoring system managed by the Regional Agencies for the Protection of the Environment (ARPA). Available data included observations from more than 400 raingauges and thermometric sensors, and 63 hydrometric stations (see Fig. 2) from 1 January 2000 to 31 December 2010 (i.e. 10 years of observations). The selected hydrometric stations are not influenced by artificial channels or other water management structures. The available data from five gauged stations, belonging to the meteorological network of ARPA Lombardy, cover the period from 1 January 2004 to 31 December 2014. The water level in the rivers was converted to flow thanks to a stage–discharge relationship provided by the Regional Agency for each hydrometric station. The dataset was subdivided with approximately 50% of data for model calibration and validation respectively.

The time series of data (i.e. precipitation, temperature, discharge) were analysed in order to verify their goodness and to detect missed values, malfunction of instruments, multiple change points and/or trends. A preliminary exploratory scan enabled us to verify the completeness of the time series. Furthermore, a particular procedure for the detection of multiple abrupt change points in daily time series (MAC-D; Rienzner and Gandolfi, 2013) was adopted to detect an unknown number of breaks and/or outliers.

Concerning the RR modelling, input data of hourly precipitation and temperature measured by the meteorological station network were computed by the Thiessen polygon method (Thiessen, 1911) for each analysed catchment.

To implement the regression-based and physical-similarity regionalization strategies (Section 2), a set of 27 catchment attributes was selected (Table 3). Topographic characteristics were derived from a digital elevation model (DEM) with a spatial resolution of 20 m, land-use properties from the Corine Land Cover map (downloaded from the European Environmental Agency, EEA[1]), soil properties from the regional lithological and geological maps, and climate indices from the available meteorological data. The data are freely available on the regional website of Piedmont[2] and Lombardy[3] region and on the Italian National Institute for Environmental Protection and Research (ISPRA) website [4].

The choice of the most representative catchment descriptors is not easy because an extremely large set of physical properties is used in the hydrological literature and, in most cases, is led by empirical remarks (Carrillo *et al.*, 2011, Sanborn and Bledsoe, 2006, Sawicz *et al.*, 2011, Toth, 2013, Wagener *et al.*, 2007, Yadav *et al.*, 2007). Thus, to avoid redundancies in independent variables for the regression, several studies conducted a selection through correlation matrix, step-wise regression and principal component analysis (Sefton and Howarth, 1998). In this study, the procedure consisted in: (a) providing an exhaustive overview of physiographic, topographic (DEM-derived), land-use and soil property variables; (b) evaluating such catchment descriptors using the available data (Table 3); (c) building a correlation matrix between all pairs of catchment descriptors using the Pearson correlation coefficient ρ (Pearson, 1895); (d) grouping the catchment attributes that were found to be correlated with $|\rho| > 0.70$; and (e) selecting only one from each correlated group.

4 Results

4.1 Model performance of continuous streamflow predictions

The application of MISDc provided good predictions of streamflow time series for the greater part of analysed catchments in the study area. For simpler comparison with the performance of other RR models given in the literature, the indicators were calculated using the daily averages from hourly streamflow time series. The best performance of the MISDc model shows values of KGE′ > 0.5 for

---

[1] http://dataservice.eea.europa.eu/
[2] http://www.geoportale.piemonte.it/
[3] http://www.geoportale.regione.lombardia.it/
[4] http://www.isprambiente.gov.it/

100% of cases in calibration and for 84.1% of cases in validation (Fig. 3(a)). In particular, 90.5% and 44.4% of catchments, respectively, fall into the best performing class, i.e. 'very good'. The median value of KGE′ is 0.883 for the calibration period (range: 0.579 to 0.973), whereas for the validation period the median KGE′ is 0.715 (range: –0.295 to 0.886) (Fig. 3(b)). The MISDc model produced poor predictions in the validation period: only six out of 63 catchments were highlighted by the presence of outliers inside the boxplots in Fig. 3(b).

The NS, ANSE and VE criteria were used as additional indicators of model performance. The NS values reflect the results achieved by the KGE′ scores. Only 11.1% and 22.2% of cases in the calibration and validation datasets, respectively, are in the worst performance class (Fig. 4). Likewise, the results in terms of ANSE are encouraging: for 95.2% and 88.9% of basins, an ANSE value of >0.50 was obtained in calibration and validation, respectively. In particular, 79.4% and 61.9% of ANSE values fall in the 'very good' performance class. The VE values partially agree with the other criteria: 90.5% and 52.4% of cases in calibration and validation, respectively, are in at least the 'satisfactory' class. In fact, 30 cases show unsatisfactory results, with VE > 15%. Analysing the distribution of ANSE values, the accuracy and reliability of the MISDc model is confirmed (Fig. 5(a)). The range of values varies from 0.356 to 0.996 in calibration and from –0.448 to 0.950 in validation (median: 0.854 and 0.736, respectively). In terms of NS, the median value is 0.760 in the calibration period (range: 0.219 to 0.968), whereas in the validation period the median NS is 0.639 (range: –0.258 to 0.890) (Fig. 5(b)). In terms of VE, the results are promising (Fig. 5(c)). The median values of VE are 2.40% and 14.10% for calibration and validation, respectively (range: 0.05–49.92% and 0.21–92.00%, respectively). In particular, the worst VE, excluding the five outliers, was 44.25%.

Figure 6 shows the model results for four river sections. The discrepancies between observed and modelled discharge are low, in both calibration and validation periods (see KGE′ values in Fig. 3). In particular, the model was found to be reliable in reproducing both the peak and the shape of the observed hydrographs, mainly during high-flow conditions that are of great interest for flood simulation events.

4.2 Model performance of FDC predictions

The assessment of the stream frequency regime was evaluated by constructing the mean annual FDCs. To estimate their accuracy and reliability, each FDC simulated using MISDc was compared to the observed one.

The results are 'satisfactory', considering that the value of BiasFMS was 26.44% ± 14.76% for the complete dataset (Fig. 7). The best performance was obtained analysing the portion of FDC that describes the highest values of discharge, i.e. the floods for which the value of BiasFHV was 11.52% ± 7.12%. Conversely, larger discrepancies were underlined in simulating the low streamflow and in particular the baseflow: the values of BiasFLV was over 41%. In Fig. 8, the comparisons between observed and simulated FDCs are shown for the same four gauged catchments as in Fig. 6.

4.3 Comparison between regionalization strategies

This section shows the model performance of MISDc coupled with the selected regionalization strategies, estimating a series of indicators (i.e. KGE′, NS, ANSE and VE) of simulated daily streamflow, average of hourly predictions. Prior to applying several regionalization models (i.e. the spatial-proximity, regression-based and physical-similarity approaches), it was important to prevent possible error propagation due to a poor calibration process or an over-parameterization of the RR model. On this point, Goswami *et al.* (2007), mentioning the work of Andréassian *et al.* (2003), emphasized that over-parameterization, dependency on input data bias and lack of systematic link between parameter precision and model efficiency are the three main factors that complicate the regionalization of a conceptual RR model. For this reason, it was necessary to examine the calibrated parameter sets and to analyse the catchment descriptors to be included in the regionalization strategies. The correlation analysis between all pairs of the model parameters revealed a lack of correlation ($|\rho| < 0.38$), except for a weak correlation, with $|\rho| = 0.44$ between ϑ and K_s (shown in in the Supplementary Material, Table S1). In addition, a further correlation analysis was performed to verify that the model parameters were uncorrelated, while the procedure described in Section 2.3.2 was carried out to identify a limited number of catchment descriptors, removing those that were highly correlated with other ones. Thus, the catchment descriptors were grouped into highly-correlated classes with $|\rho| > 0.70$ and, for each group, only one of them were designated to be included in the regionalization techniques to avoid intrinsic redundancy. The correlation matrix is reported in the Supplementary Material (Table S2), whereas the 12 uncorrelated catchment attributes, as reported in Table 4, were: AREA (catchment landform), Z_m (topographic index derived by DEM), CN and URB (land use), HIGHp and LOWp (catchment soils), MAP, Dstd, PVAR, MMA and RWD (climatic).

The model performance results for the different regionalization techniques applied to the ungauged catchments showed a moderate worsening with respect to the results obtained for the gauged ones in the validation process, as expected. In terms of median values of KGE′, the AM_{25}, AM_{50}, and MLR2 (i.e. level-log model) produced better results among the regionalization methods (Fig. 9), with a reduction in accuracy with respect to the results of the validation process of 13.4%, 19.1%, and 20.9%, respectively. The range of median values of KGE′ was from 0.346 (for MLR3) to 0.609 (for AM_{25}). In particular, MLR3 showed the poorest model performance, with a median value of KGE′ that was approximately 50.8%.

The distributions of NS values for the different regionalization strategies was similar to those obtained calculating the KGE′ scores. The range varied from 0.474 (for CC_{pd}) to 0.559 (for MLR1) (Fig. 10). In contrast, all the regionalization procedures provided good performance on the prediction of high discharge time series (Fig. 11), with a reduction in accuracy of, at most, 10%. The median values of ANSE varied from 0.660 (for CC_{pd}) to 0.732 (MLR1). Moreover, AM_{25} showed positive performance, with a median of ANSE equal to 0.724. Estimating the errors in streamflow volume, AM_{25} is clearly the most competitive, with the results of the validation process having a median of VE of 15.0% (Fig. 12). However, IDWc, PhyS, MLR3 and MLR4 obtained the worst results, with VE values that exceeded 20%.

To assess the performance in constructing the FDCs, the three scores BiasFMS, BiasFHV and BiasFLV were evaluated (Table 5). All the regionalization strategies showed satisfactory results, with BiasFMS values for validation varying from 28.2% to 35.4% compared to 26.4% obtained through the calibration of the parameter sets. The ranges of BiasFHVs and BiasFLVs were 18.1–32.5% and 52.7–69.5%, respectively. As expected, the best performance was obtained with AM_{25} and MLR1, while the worst was obtained using the physically-based and catchment classification approaches.

5 Discussion

5.1 Model performance

Several studies have applied the hydrological RR model MISDc as an excellent predictor of streamflow time series for flood forecasting, water resource assessment, climate change and impact projection (Barbetta *et al.*, 2017, Camici *et al.*, 2014, Loizu *et al.*, 2018, Massari *et al.*, 2015a). This model provided robust and accurate results with relatively slight differences between observed and simulated discharge at the gauged outlet sections of investigated catchments. In a recent review, Masseroni *et al.* (2017b) underlined how in 25% of tested catchments, the MISDc model performance was excellent, with values of NS greater than 0.85. In particular, the median NS calculated on all tested catchments was 0.6, whereas 70% of basins provided NS greater than 0.5.

This is consistent with our results, which show satisfactory achievements in the majority of gauged catchments, i.e. MISDc obtained NS > 0.5 in 77.8% of the validation dataset. Moreover, this work verifies a particular propensity of the MISDc model for flood forecasting (Barbetta *et al.*, 2017, Brocca *et al.*, 2013, Masseroni *et al.*, 2017b). This accuracy has been demonstrated by applying the hydrological model on a large number of study catchments in the Upper Po River basin, a mountainous area often subject to hydrogeological hazard, and by adopting a particular performance score for high flows, i.e. ANSE.

However, it is possible to note a moderate degree of uncertainty in terms of volume, as already discussed in Masseroni *et al.* (2017b). Indeed, the results emphasize quite a wide range of VE (1–92%), showing difficulty in predicting streamflow during periods without precipitation. This probably depends on a less accurate simulation of the baseflow, or of the snow and glacier melting processes. Moreover, such a problem was emphasized by analysing the FDCs and calculating the index BiasFLV (Fig. 7).

These results emphasize that the MISDc model is competitive in relation to more complex hydrological models. In particular, similar results have been produced by many authors adopting fully distributed hydrological models (e.g. Ercolani and Castelli, 2017, Montaldo *et al.*, 2007, Rabuffetti *et al.*, 2009). In addition, a significant advantage of MISDc is the excellent ratio between the accuracy in predicting streamflow time series and the computational time.

This makes it suitable for long simulations to evaluate the impact of climate change, for evaluating differences in discharge according to weather forecasts and for implementing a risk management database to extend over large areas, as proposed by Brocca *et al.* (2013).

5.2 Spatial distribution of model performance

Following suggestions by Boscarello et al. (2016), the evaluation of a potential spatial trend of model performance is an interesting analysis, which might reveal if there are catchment characteristics that provoke poor results. The gauged catchments were grouped into the four performance classes according to KGE′ values, and the results are reported on the map in Fig. 13. It is clear that there is no evidence of a spatial trend: the worst performance was uniformly distributed over the study area. All correlations (ρ) between KGE′ and catchment descriptors reported in Table 3 showed, on average, a value of $|\rho| < 0.25$ in validation. Moreover, there is an equal distribution among catchments with low performance in the Piedmont and Lombardy regions (about 83.0% and 87.5 respectively).

5.3 Comparison between regionalization performance

In this study, the differences among the regionalization strategies are not so evident. The results show that the spatial proximity approaches, in particular the arithmetic mean approaches, performed best. In particular, the first was clearly AM_{25} (i.e. the arithmetic mean method applied to a portion of a region within a radius of 25 km). This method obtained the best results in terms of all the performance indices: 58.7% of cases with KGE′, 61.9% with NS, 85.7% with ANSE and 52.4% with VE were classified as, at least, satisfactory. Considering the KGE′ values as a measure of comparison, AM_{50} and MLR2 (level-log) produced the next best results, with 60.3% of them satisfactory. Instead, the regression-based models MLR3 (log-level) and MLR4 (log-log) showed the poorest predictions, with approx. 60% of cases classified as unsatisfactory. Moreover, the spatial-proximity approaches based on the inverse distance and physical similarity achieved inaccurate results: only one out of two cases provided satisfactory performance. This situation is certainly motivated by the construction of MISDc, which can be classified as a physically meaningful approach, but not as physically- and spatially-distributed model. Another clear indication is given by the performance of the combination between MISDc and regionalization strategies on the prediction of high streamflow: indeed, ANSE was greater than 0.5 in at least 74.6% of cases for the worst performance of regionalization approach (i.e. MLR4).

Although many hydrologists mainly investigated the various regionalization approaches, their studies did not reach a shared conclusion and clearly indicate that there is not a universal procedure (e.g. McIntyre *et al.*, 2005, Merz and Blöschl, 2004, Oudin *et al.*, 2008, Razavi and Coulibaly, 2017, Zhang and Chiew, 2009). However, several regional investigations have shown favourable performance using the spatially-based regionalization models, such as IDW or kriging, an advanced geo-statistical procedure; three examples of these are the studies of Oudin *et al.* (2008), Samuel *et al.* (2011) and Swain and Patra (2017). The first authors calibrated a 10-parameter RR model with a large set of data consisting of streamflow time series of 913 French catchments (10–9390 km^2). Samuel *et al.* (2011) coupled the 11-parameter RR model (HBV, Bergström, 1976) with the 3-parameter lumped conceptual RR model (MAC) and regionalized them for 111 large catchments (100–100 000 km^2) located in Ontario (Canada). Finally, Swain and Patra (2017) used the 18-parameter SWAT model on 32 large catchments (728–23501 km^2) in eastern and southeastern India. Such evidence is supported also by our results, which achieved the best performance using the local arithmetic mean strategy belonging to the spatial-proximity class, although our study was conducted using a different RR model and tested on catchments covering an overall area of approx. 16 000 km^2. In addition, the indications of our study confirm the pioneering study of Merz and Blöschl (2004), who simulated the water balance dynamic using the HBV model on 308 catchments (3–5000 km^2) in Austria. They obtained good results using the average model parameters of the nearest upstream and downstream gauged catchments and adopting kriging, and poor results using multiple regression-based strategies. A similar outcome was obtained by Parajka *et al.* (2005) and Jin *et al.* (2009) using the HBV model on 320 Austrian catchments (10–9770 km^2) and on 13 nested natural sub-catchments of the Dongjang basin in South China (100–1000 km^2), respectively.

Conversely, our results are in disagreement with many works that adopted one of the most extensively used hydrological model, IHACRES (the acronym for Identification of unit Hydrographs And Component flows from Rainfall, Evapotranspiration and Streamflow data), developed by the Institute of Hydrology and the Australian (National University) Centre for Resource and Environmental Studies (Jakeman *et al.*, 1990). In fact, the regression-based approaches, including linear, nonlinear or multiple models, seem to provide accurate estimation of model parameters (Croke *et al.*, 2004, Kokkonen *et al.*, 2003, Post, 2009, Post and Jakeman, 1999, Sefton and Howarth, 1998, Young, 2006). Moreover, other studies support the application of the combination of different regionalization techniques. McIntyre *et al.* (2005) observed an improvement in the established procedure of regressing parameter values against numeric catchment descriptors, using a conceptual RR model on 127 catchments in the UK (1–1700 km^2). Viviroli *et al.* (2009a, 2009b) developed a 12-parameter conceptual process-based hydrological system for 49 catchments (10–1000 km^2) in Switzerland and adopted a combination among the classical regionalization models (spatially-based, physical-similarity and regression). Bao *et al.* (2012) coupled a meso-scale land surface model and different regionalization strategies on 55 large Chinese catchments (2582–121 972 km^2). An alternative solution was presented by Razavi and Coulibaly (2017), who combined diverse regionalization strategies and two hydrological RR models and applied them to 90 catchments (85.5–91 802 km^2) in Ontario (Canada), classified with non-linear data-driven classification techniques. They indicated the feed-forward neural network as the best regionalization method, and very competitive with the spatial-proximity methodologies.

According our results and the background literature, it is clear that the reliability of the hydrological regionalization approaches for flow assessment in ungauged catchments by regional analysis depends on: (a) the choice of RR model, (b) the quality and quantity of available data at gauged stations, and (c) the knowledge of the physiographic characteristics of the catchments under study. Despite the fact that, currently, there is not a universal procedure and common consensus, we suggest that regionalization approaches remain the key solution that can enable us to apply hydrological RR models to derive streamflow time series from rainfall and temperature data over any catchment without a hydrological station.

6 Conclusions

Appropriate and reliable streamflow knowledge is a key-issue for correctly addressing a wide range of applications, from flood prevention to water resource management, from engineering design of hydraulic structures to restoration of ecosystem services. Especially in the western Po River basin, in northern Italy, the application of RR models for accurate flow assessments over a large set of catchments is strongly encouraged by the regional water protection authorities to ensure a high level of flood prevention and rational water allocation over the territory. To address these issues, in this work, the lumped MISDc rainfall–runoff model was applied over 63 uniformly distributed Alpine and pre-Alpine basins located in the northwestern part of the Upper Po River basin. The performance of the model was promising: almost the 85% of catchments produced values of KGE′ greater than 0.5 and 45% produced values greater than 0.75, while approximately 62% of cases gave an ANSE greater than 0.75 the in validation period. The performance in terms of volume error (VE) was satisfactory, even if around the 90% and 52% of tested catchments in calibration and in validation, respectively, revealed a VE of less than 15%.

In general, the analysis carried out on available time series shows good performance in terms of reproducing the FDCs: on average, the indices used to assess the performance on the mid-segment slope and the high-segment volume of FDC were below 30% and 10%, respectively. Conversely, poorer performance was found in analysing the low-segment volume of FDCs, with a bias of approx. 41%.

Lastly, the local arithmetic mean regionalization offered a reliable solution for ungauged catchments, providing good performance in all indices, with KGE′, NS, ANSE and VE being satisfied in 58.7%, 61.9%, 85.7% and 52.4% of cases.

Further developments will focus on the improvement of the performance of the MISDc model in predicting low streamflow and dry periods for the management of irrigation water resources, changing the error criterion in calibration (for example using VE or BiasFLV), even if this is at the expense of the prediction of floods. Moreover, a customization of MISDc will integrate the proposed model, especially improving the simulation of the snow and glacier melting processes. In particular, if the present version includes the degree-day method and predicts the behaviour of the accumulation and the melting of the snowpack and the melting of glaciers, further elaboration can address the use of a more specific approach using snow maps captured by automatic measuring stations.

Further works on this topic will be dedicated to systematically applying the MISDc model over those mountainous areas, as sources of water, to enable us to determine the availability of water resources for the irrigation requirements of the plain, in accordance also with future precipitation and temperature change scenarios.

Acknowledgements

We wish to thank Eng. Secondo Barbero (ARPA Piemonte), Dr Lorenzo Craveri (ARPA Lombardia), Prof. Gian Battista Bischetti and Prof. Claudio Gandolfi for their scientific and technical support as experts of hydrological science, Dr Michele Rienzner and Dr Sandra Cesari de Maria (University of Milan) for their suggestions for managing and analysing hydro-meteorological data, and the Associate Editor Prof. Shaochun Huang and the two anonymous reviewers for their detailed comments that have helped us to improve the manuscript.

References

Abdulla, F. A. and Lettenmaier, D. P., 1997. Application of regional parameter estimation schemes to simulate the water balance of a large continental river. *Journal of Hydrology*, **197**(1), 258–285.

Andréassian, V., Rojas-Serna, C., Michel, C., Perrin, C., Mouelhi, S. and Loumagne, C., 2003. Is the regionalization of conceptual rainfall–runoff models impossible? Presented at the EGS - AGU - EUG Joint Assembly (6-11 April 2003, Nice, France). *Geophysical Research Abstracts*, 4, 4175.

Bao, Z., Zhang, J., Liu, J., Fu, G., Wang, G., He, R., Yan, X., Jin, J., and Liu, H., 2012. Comparison of regionalization approaches based on regression and similarity for predictions in ungauged catchments under multiple hydro-climatic conditions. *Journal of Hydrology,* **466–467**, 37–46. doi:10.1016/j.jhydrol.2012.07.048

Barbetta, S., Coccia, G., Moramarco, T., Brocca, L. and Todini, E., 2017. The multi temporal/multi-model approach to predictive uncertainty assessment in real-time flood forecasting. *Journal of Hydrology,* **551**, 555–576. doi:10.1016/j.jhydrol.2017.06.030

Bergström, S., 1976. Development and application of a conceptual runoff model for Scandinavian catchments (No. 7). SMHI Hidrologi, 134. Norrköping, Sweden: Lund University.

Beven, K. J., 2012. *Rainfall–runoff modelling: the primer*, 2nd ed. Chichester, West Sussex ; Hoboken, NJ: Wiley-Blackwell.

Blöschl, G. and Sivapalan, M., 1995. Scale issues in hydrological modelling: a review. *Hydrological Processes*, **9**(3–4), 251–290. doi:10.1002/hyp.3360090305

Blöschl, G., 2013. *Runoff prediction in ungauged basins: synthesis across processes, places and scales*. Cambridge University Press.

Bocchi, S., La Rosa, D. and Pileri, P., 2012. Agro-ecological analysis for the EU Water Framework Directive: an applied case study for the river contract of the Seveso basin (Italy). *Environmental Management*, **50**(4), 514–529. doi:10.1007/s00267-012-9925-3

Bocchiola, D., Mihalcea, C., Diolaiuti, G., Mosconi, B., Smiraglia, C. and Rosso, R., 2010. Flow prediction in high altitude ungauged catchments: a case study in the Italian Alps (Pantano Basin, Adamello group). *Advances in Water Resources*, **33**(10), 1224–1234. doi:10.1016/j.advwatres.2010.06.009

Boscarello, L. A., Ravazzani, G., Cislaghi, A. and Mancini, M., 2016. Regionalization of flow-duration curves through catchment classification with streamflow signatures and physiographic–climate Indices. *Journal of Hydrological Engineering*, **21**(3), 05015027. doi:https://doi.org/10.1061/(asce)he.1943-5584.0001307

Boughton, W. and Droop, O., 2003. Continuous simulation for design flood estimation—a review. *Environmental Modelling & Software*, **18**(4), 309–318. doi:10.1016/S1364-8152(03)00004-5

Brocca, L., Barbetta, S., Melone, F., Moramarco, T., 2010. A continuous rainfall–runoff model derived from investigations in a small experimental basin, in: *Status and Perspectives of Hydrology in Small Basins* (Proceedings of the Workshop Held at Goslar-Hahnenklee, Germany, 30 March–2 April 2009). Wallingford, UK: International Association of Hydrological Sciences IAHS Publ. 336, 179–186.

Brocca, L., Liersch, S., Melone, F., Moramarco, T. and Volk, M., 2013. Application of a model-based rainfall–runoff database as efficient tool for flood risk management. *Hydrology and Earth System Sciences*, **17**(8), 3159–3169. doi:10.5194/hess-17-3159-2013

Brocca, L., Melone, F. and Moramarco, T., 2008. On the estimation of antecedent wetness conditions in rainfall–runoff modelling. *Hydrological Processes,* **22**(5), 629–642. doi:10.1002/hyp.6629

Brocca, L., Melone, F. and Moramarco, T., 2011. Distributed rainfall-runoff modelling for flood frequency estimation and flood forecasting. *Hydrological Processes*, **25**(18), 2801–2813.

Brutsaert, W. and Nieber, J. L., 1977. Regionalized drought flow hydrographs from a mature glaciated plateau. *Water Resources Research,* **13**(3), 637–643. doi:10.1029/WR013i003p00637

Burges, S. J., 1998. Streamflow prediction: capabilities, opportunities, and challenges. *Hydrologic Sciences: Taking Stock and Looking Ahead* 101–134.

Burn, D. H. and Boorman, D. B., 1993. Estimation of hydrological parameters at ungauged catchments. *Journal of Hydrology,* **143**(3–4), 429–454.

Camici, S., Brocca, L., Melone, F. and Moramarco, T., 2014. Impact of climate change on flood frequency using different climate models and downscaling approaches. *Journal of Hydrological Engineering,* **19**(8), 04014002–1:15. doi:10.1061/(ASCE)HE.1943-5584.0000959

Camici, S., Ciabatta, L., Massari, C. and Brocca, L., 2018. How reliable are satellite precipitation estimates for driving hydrological models: a verification study over the Mediterranean area. *Journal of Hydrology,* **563**, 950–961. doi:10.1016/j.jhydrol.2018.06.067

Camici, S., Tarpanelli, A., Brocca, L., Melone, F. and Moramarco, T., 2011. Design soil moisture estimation by comparing continuous and storm-based rainfall–runoff modeling. *Water Resources Research*, **47**(5). doi:10.1029/2010WR009298

Carminati, E. and Martinelli, G., 2002. Subsidence rates in the Po Plain, northern Italy: the relative impact of natural and anthropogenic causation. *Engineering Geology,* **66**(3), 241–255.

Carrillo, G., Troch, P. A., Sivapalan, M., Wagener, T., Harman, C. and Sawicz, K., 2011. Catchment classification: hydrological analysis of catchment behavior through process-based modeling along a climate gradient. *Hydrology and Earth System Sciences,* **15**(11), 3411–3430. doi:10.5194/hess-15-3411-2011

Castellarin, A., Camorani, G. and Brath, A., 2007. Predicting annual and long-term flow-duration curves in ungauged basins. *Advances in Water Resources,* **30**(4), 937–953. doi:10.1016/j.advwatres.2006.08.006

Castellarin, A., Galeati, G., Brandimarte, L., Montanari, A. and Brath, A., 2004. Regional flow-duration curves: reliability for ungauged basins. *Advances in Water Resources,* **27**(10), 953–965. doi:10.1016/j.advwatres.2004.08.005

Cheng, Q., Ko, C., Yuan, Y., Ge, Y. and Zhang, S., 2006. GIS modeling for predicting river runoff volume in ungauged drainages in the Greater Toronto Area, Canada. *Computer Geosciences,* **32**(8), 1108–1119. doi:10.1016/j.cageo.2006.02.005

Chiew, F. H. S., Stewardson, M. J. and McMahon, T. A., 1993. Comparison of six rainfall–runoff modelling approaches. *Journal of Hydrology,* **147**, 1–36.

Chow, V. T., 1959. *Open channel hydraulics*. McGraw-Hill Book Company, Inc; New York.

Ciabatta, L., Brocca, L., Massari, C., Moramarco, T., Gabellani, S., Puca, S. and Wagner, W., 2016. Rainfall–runoff modelling by using SM2RAIN-derived and state-of-the-art satellite rainfall products over Italy. *International Journal of Applied Earth Observation and Geoinformation,* **48**, 163–173. doi:10.1016/j.jag.2015.10.004

Clarke, R. T., 1973. A review of some mathematical models used in hydrology, with observations on their calibration and use. *Journal of Hydrology,* **19**(1), 1–20.

Corbari, C., Ravazzani, G., Martinelli, J. and Mancini, M., 2009. Elevation based correction of snow coverage retrieved from satellite images to improve model calibration. *Hydrology and Earth System Sciences,* **13**(5), 639–649.

Croke, B. F. W., Merritt, W. S. and Jakeman, A. J., 2004. A dynamic model for predicting hydrologic response to land cover changes in gauged and ungauged catchments. *Journal of Hydrology,* **291**(1–2), 115–131. doi:10.1016/j.jhydrol.2003.12.012

Dawdy, D. R. and O'Donnell, T., 1965. Mathematical models of catchment behavior. *Journal of the Hydraulics Division ASCE,* **91**(4), 123–137.

Di Prinzio, M., Castellarin, A. and Toth, E., 2011. Data-driven catchment classification: application to the pub problem. *Hydrology and Earth System Sciences,* **15**(6), 1921–1935. doi:10.5194/hess-15-1921-2011

Dick, J. J., Tetzlaff, D., Birkel, C. and Soulsby, C., 2015. Modelling landscape controls on dissolved organic carbon sources and fluxes to streams. *Biogeochemistry* **122**(2–3), 361–374. doi:10.1007/s10533-014-0046-3

Doorenbos, J. and Pruitt, W. O., 1977. Background and development of methods to predict reference crop evapotranspiration (ETo). *Append. II FAO-ID-24* 108–119.

Drogue, G. and Khediri, W. B., 2016. Catchment model regionalization approach based on spatial proximity: Does a neighbor catchment-based rainfall input strengthen the method? *Journal of Hydrology – Regional Studies*, **8**, 26–42. doi:10.1016/j.ejrh.2016.07.002

Egbuniwe, N. and Todd, D. K., 1976. Application of the Stanford watershed model to Nigerian watersheds. *JAWRA Journal of the American Water Resources Association,* **12**(3), 449–460.

Ercolani, G. and Castelli, F., 2017. Variational assimilation of streamflow data in distributed flood forecasting. *Water Resources Research,* **53**(1), 158–183. doi:10.1002/2016WR019208

Ercolani, G., Chiaradia, E. A., Gandolfi, C., Castelli, F. and Masseroni, D., 2018. Evaluating performances of green roofs for stormwater runoff mitigation in a high flood risk urban catchment. *Journal of Hydrology,* **566**, 830–845. doi:10.1016/j.jhydrol.2018.09.050

Famiglietti, J. S. and Wood, E. F., 1994. Multiscale modeling of spatially variable water and energy balance processes. *Water Resources Research,* **30**(11), 3061–3078. doi:10.1029/94WR01498

Foster, H. A. (1934) Duration curves. *Transactions of the ASCE*, 99, 1213–1267.

Garambois, P. A., Roux, H., Larnier, K., Labat, D. and Dartus, D., 2015. Parameter regionalization for a process-oriented distributed model dedicated to flash floods. *Journal of Hydrology,* **525**, 383–399. doi:10.1016/j.jhydrol.2015.03.052

Giuliani, M., Li, Y., Castelletti, A. and Gandolfi, C., 2016. A coupled human-natural systems analysis of irrigated agriculture under changing climate. *Water Resources Research,* **52**(9), 6928–6947. doi:10.1002/2016WR019363

Goswami, M., O'Connor, K. M. and Bhattarai, K. P., 2007. Development of regionalisation procedures using a multi-model approach for flow simulation in an ungauged catchment. *Journal of Hydrology,* **333**(2–4), 517–531. doi:10.1016/j.jhydrol.2006.09.018

Guex, F., 2001. *Modélisation hydrologique dans le bassin versant de l'Alzette (Luxembourg), régionalisation des paramètres d'un modèle global.* Travail pratique de Diplôme, Ecole Polytechnique Fédérale de Lausanne 67.

Gupta, H. V., Kling, H., Yilmaz, K. K. and Martinez, G. F., 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology,* **377**(1–2), 80–91. doi:10.1016/j.jhydrol.2009.08.003

Gupta, V. K., Waymire, E. and Wang, C. T., 1980. A representation of an instantaneous unit hydrograph from geomorphology. *Water Resources Research,* **16**(5), 855–862.

Guzzetti, F., 2000. Landslide fatalities and the evaluation of landslide risk in Italy. *Engineering Geology,* **58**(2), 89–107.

Guzzetti, F. and Tonelli, G., 2004. Information system on hydrological and geomorphological catastrophes in Italy (SICI): a tool for managing landslide and flood hazards. *Natural Hazards and Earth System Science,* **4**(2), 213–232.

He, Y., Bárdossy, A. and Zehe, E., 2011. A review of regionalisation for continuous streamflow simulation. *Hydrology and Earth System Sciences,* **15**(11), 3539–3553. doi:10.5194/hess-15-3539-2011

Herbst, M., Gupta, H. V. and Casper, M. C., 2009. Mapping model behaviour using Self-Organizing Maps. *Hydrology and Earth System Sciences* **13**, 393–409.

Hoffmann, L., El Idrissi, A., Pfister, L., Hingray, B., Guex, F., Musy, A., Humbert, J., Drogue, G., Leviandier, T., 2004. Development of regionalized hydrological models in an area with short hydrological observation series. *River Research and Applications*, **20**(3), 243–254. doi:10.1002/rra.774

Hrachowitz, M., Savenije, H. H. G., Blöschl, G., McDonnell, J. J., Sivapalan, M., Pomeroy, J. W., Arheimer, B., Blume, T., Clark, M.P., Ehret, U., Fenicia, F., Freer, J.E., Gelfan, A., Gupta, H.V., Hughes, D.A., Hut, R.W., Montanari, A., Pande, S., Tetzlaff, D., Troch, P.A., Uhlenbrook, S., Wagener, T., Winsemius, H.C., Woods, R.A., Zehe, E., and Cudennec, C., 2013. A decade of Predictions in Ungauged Basins (PUB)—a review. *Hydrological Sciences Journal*, **58**(6), 1198–1255. doi:10.1080/02626667.2013.803183

Jakeman, A. J., Littlewood, I. G. and Whitehead, P. G., 1990. Computation of the instantaneous unit hydrograph and identifiable component flows with application to two small upland catchments. *Journal of Hydrology*, **117**(1–4), 275–300. doi:10.1016/0022-1694(90)90097-H

James, L. D., 1972. Hydrologic modeling, parameter estimation, and watershed characteristics. *Journal of Hydrology*, **17**(4), 283–307.

Jarboe, J. E. and Haan, C. T., 1974. Calibrating a water yield model for small ungauged watersheds. *Water Resources Research*, **10**(3), 256–262.

Jin, X., Xu, C., Zhang, Q. and Chen, Y. D., 2009. Regionalization study of a conceptual hydrological model in Dongjiang basin, south China. *Quaternary International*, **208**(1–2), 129–137. doi:10.1016/j.quaint.2008.08.006

Kampf, S. K. and Burges, S. J., 2007. Parameter estimation for a physics-based distributed hydrologic model using measured outflow fluxes and internal moisture states. *Water Resources Research*, **43**(12), W12414. doi:10.1029/2006WR005605

Kampf, S. K. and Burges, S. J., 2007. A framework for classifying and comparing distributed hillslope and catchment hydrologic models. *Water Resources Research*, **43**(5), W05423. doi:10.1029/2006WR005370

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

Klemeš, V., 1986. Operational testing of hydrological simulation models. *Hydrological Sciences Journal,* **31**(1), 13–24. doi:10.1080/02626668609491024

Kling, H., Fuchs, M. and Paulin, M., 2012. Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. *Journal of Hydrology,* **424–425**, 264–277. doi:10.1016/j.jhydrol.2012.01.011

Knapp, H. V., Durgunoglu, A. and Ortel, T. W., 1991. A review of rainfall–runoff modeling for stormwater management (No. SWS Contract Report 516), 96. Illinois State Water Survey - Hydrology Division. [online] http://www.isws.illinois.edu/pubdoc/cr/iswscr-516.pdf

Kokkonen, T. S., Jakeman, A. J., Young, P. C. and Koivusalo, H. J., 2003. Predicting daily flows in ungauged catchments: model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina. *Hydrological Processes*, **17**(11), 2219–2238. doi:10.1002/hyp.1329

Kottek, M., Grieser, J., Beck, C., Rudolf, B. and Rubel, F., 2006. World map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift,* **15**(3), 259–263. doi:10.1127/0941-2948/2006/0130

Lari, S., Frattini, P., and Crosta, G. B., 2009. Integration of natural and technological risks in Lombardy, Italy. *Natural Hazards and Earth System Science,* **9**(6), 2085–2106.

Ley, R., Casper, M. C., Hellebrand, H. and Merz, R., 2011. Catchment classification by runoff behaviour with self-organizing maps (SOM). *Hydrology and Earth System Sciences,* **15**(9), 2947–2962. doi:10.5194/hess-15-2947-2011

Loizu, J., Massari, C., Álvarez-Mozos, J., Tarpanelli, A., Brocca, L. and Casalí, J., 2018. On the assimilation set-up of ASCAT soil moisture data for improving streamflow catchment simulation. *Advances in Water Resources,* **111**, 86–104. doi:10.1016/j.advwatres.2017.10.034

Loukas, A. and Vasiliades, L., 2014. Streamflow simulation methods for ungauged and poorly gauged watersheds. *Natural Hazards and Earth System Science,* **14**(7), 1641–1661. doi:10.5194/nhess-14-1641-2014

Luino, F., Turconi, L., Petrea, C. and Nigrelli, G., 2012. Uncorrected land-use planning highlighted by flooding: the Alba case study (Piedmont, Italy). *Natural Hazards and Earth System Science,* **12**(7), 2329–2346. doi:10.5194/nhess-12-2329-2012

Magette, W. L., Shanholtz, V. O. and Carr, J. C., 1976. Estimating selected parameters for the Kentucky watershed model from watershed characteristics. *Water Resources Research,* **12**(3), 472–476.

Manley, R. E., 1978. Simulation of flows in ungauged basins. *Hydrological Science Bulletin,* **23**(1), 85–101. doi:10.1080/02626667809491772

Martinec, J., 1960. The degree-day factor for snowmelt runoff forecasting. In: *Proceedings of General Assembly of Helsinki Commission on Surface Waters*. Wallingford, UK: International Association of Hydrological Sciences, IAHS Publ. 51, 468–477.

Massari, C., Brocca, L., Ciabatta, L., Moramarco, T., Gabellani, S., Albergel, C., De Rosnay, P., Puca, S. and Wagner, W., 2015a. The use of H-SAF soil moisture products for operational hydrology: flood modelling over Italy. *Hydrology* **2**(1), 2–22. doi:10.3390/hydrology2010002

Massari, C., Brocca, L., Tarpanelli, A. and Moramarco, T., 2015b. Data assimilation of satellite soil moisture into rainfall–runoff modelling: a complex recipe? *Remote Sensing,* **7**(9), 11403–11433. doi:10.3390/rs70911403

Massari, C., Camici, S., Ciabatta, L. and Brocca, L., 2018. Exploiting satellite-based surface soil moisture for flood forecasting in the Mediterranean area: state update versus rainfall correction. *Remote Sensing,* **10**(2), 292. doi:10.3390/rs10020292

Masseroni, D., Ricart, S., Cartagena, F. de, Monserrat, J., Gonçalves, J., Lima, I. de, Facchi, A., Sali, G., and Gandolfi, C., 2017a. Prospects for improving gravity-fed surface irrigation systems in mediterranean European contexts. *Water* **9**(1), 20. doi:10.3390/w9010020

Masseroni, D., Cislaghi, A., Camici, S., Massari, C. and Brocca, L., 2017b. A reliable rainfall–runoff model for flood forecasting: review and application to a semi-urbanized watershed at high flood risk in Italy. *Hydrology Research*, **48**(3), 726–740. doi:10.2166/nh.2016.037

McIntyre, N., Lee, H., Wheater, H., Young, A. and Wagener, T., 2005. Ensemble predictions of runoff in ungauged catchments. *Water Resources Research,* **41**(12). doi:10.1029/2005WR004289

Melone, F., Corradini, C. and Singh, V. P., 2002. Lag prediction in ungauged basins: an investigation through actual data of the upper Tiber River valley. *Hydrological Processes*, **16**(5), 1085–1094. doi:10.1002/hyp.313

Melone, F., Neri, N., Morbidelli, R. and Saltalippi, C., 2001. A conceptual model for flood prediction in basins of moderate size. *Applied Simulation and Modelling, IASTED Acta Press, Marbella (SP),* 461–466.

Mendoza, P. A., Clark, M. P., Barlage, M., Rajagopalan, B., Samaniego, L., Abramowitz, G. and Gupta, H., 2015. Are we unnecessarily constraining the agility of complex process-based models? *Water Resources Research,* **51**(1), 716–728. doi:10.1002/2014WR015820

Merz, R. and Blöschl, G., 2004. Regionalisation of catchment model parameters. *Journal of Hydrology,* **287**(1–4), 95–123. doi:10.1016/j.jhydrol.2003.09.028

Montaldo, N., Ravazzani, G. and Mancini, M., 2007. On the prediction of the Toce alpine basin floods with distributed hydrologic models. *Hydrological Processes,* **21**(5), 608–621. doi:10.1002/hyp.6260

Mysiak, J., Testella, F., Bonaiuto, M., Carrus, G., De Dominicis, S., Ganucci Cancellieri, U., Firus, K., and Grifoni, P., 2013. Flood risk management in Italy: challenges and opportunities for the implementation of the EU Floods Directive (2007/60/EC). *Natural Hazards and Earth System Science*,**13**(11), 2883–2890. doi:10.5194/nhess-13-2883-2013

Nash, J. E. and Sutcliffe, J. V., 1970. River flow forecasting through conceptual models. Part I - A discussion of principles. *Journal of Hydrology,* **10**(3), 282–290.

Oudin, L., Andréassian, V., Perrin, C., Michel, C. and Le Moine, N., 2008. Spatial proximity, physical similarity, regression and ungaged catchments: A comparison of regionalization approaches based on 913 French catchments. *Water Resources Research*, **44**(3), W03413. doi:10.1029/2007WR006240

Oudin, L., Kay, A., Andréassian, V. and Perrin, C., 2010. Are seemingly physically similar catchments truly hydrologically similar? *Water Resources Research*, **46**(11), W11558. doi:10.1029/2009WR008887

Parajka, J., Viglione, A., Rogger, M., Salinas, J. L., Sivapalan, M. and Blöschl, G., 2013. Comparative assessment of predictions in ungauged basins - Part 1: Runoff-hydrograph studies. *Hydrology and Earth System Sciences,* **17**(5), 1783–1795. doi:10.5194/hess-17-1783-2013

Parajka, Juraj, Merz, R. and Blöschl, G., 2005. A comparison of regionalisation methods for catchment model parameters. *Hydrology and Earth System Sciences*, **9**(3), 157–171.

Pearson, K., 1895. Note on regression and inheritance in the case of two parents, *Proceedings of the Royal Society of London*, 240–242. https://doi.org/10.1098/rspl.1895.0041

Peel, M. C., Finlayson, B. L. and McMahon, T. A., 2007. Updated world map of the Köppen-Geiger climate classification. *Hydrology and Earth System Sciences Discussions* **4**(2), 439–473.

Perrin, C., Michel, C. and Andréassian, V., 2001. Does a large number of parameters enhance model performance? Comparative assessment of common catchment model structures on 429 catchments. *Journal of Hydrology*, **242**(3), 275–301.

Pfannerstill, M., Guse, B. and Fohrer, N., 2014. Smart low flow signature metrics for an improved overall performance evaluation of hydrological models. *Journal of Hydrology* **510**, 447–458. doi:10.1016/j.jhydrol.2013.12.044

Post, D. A., 2009. Regionalizing rainfall–runoff model parameters to predict the daily streamflow of ungauged catchments in the dry tropics. *Hydrology Research*, **40**(5), 433–444. doi:10.2166/nh.2009.036

Post, D. A. and Jakeman, A. J., 1999. Predicting the daily streamflow of ungauged catchments in S.E. Australia by regionalising the parameters of a lumped conceptual rainfall–runoff model. *Ecological Modelling,* **123**, 91–104.

Rabuffetti, D., Ravazzani, G., Barbero, S. and Mancini, M., 2009. Operational flood-forecasting in the Piemonte region–development and verification of a fully distributed physically-oriented hydrological model. *Advances in Geosciences,* **17**(17), 111–117.

Raduła, M. W., Szymura, T. H. and Szymura, M., 2018. Topographic wetness index explains soil moisture better than bioindication with Ellenberg's indicator values. *Ecological Indicators,* **85**, 172–179. doi:10.1016/j.ecolind.2017.10.011

Ravazzani, G., Barbero, S., Salandin, A., Senatore, A. and Mancini, M., 2015. An integrated hydrological model for assessing climate change impacts on water resources of the Upper Po River basin. *Water Resources Management,* **29**(4), 1193–1215. doi:10.1007/s11269-014-0868-8

Razavi, T. and Coulibaly, P., 2013. Streamflow prediction in ungauged basins: review of regionalization methods. *Journal of Hydrological Engineering,* **18**(8), 958–975. doi:10.1061/(ASCE)HE.1943-5584.0000690

Razavi, T. and Coulibaly, P., 2017. An evaluation of regionalization and watershed classification schemes for continuous daily streamflow prediction in ungauged watersheds. *Canadian Water Resources Journal,* **42**(1), 2–20. doi:10.1080/07011784.2016.1184590

Refsgaard, J. C., 1990. Terminology, modelling protocol and classification of hydrological model codes. In: *Distributed Hydrological Modelling*, 17–39. Heidelberg, Germany: Springer.

Rienzner, M. and Gandolfi, C., 2013. A procedure for the detection of undocumented multiple abrupt changes in the mean value of daily temperature time series of a regional network. *International Journal of Climatology*, **33**(5), 1107–1120. doi:10.1002/joc.3496

Ritter, A. and Muñoz-Carpena, R., 2013. Performance evaluation of hydrological models: Statistical significance for reducing subjectivity in goodness-of-fit assessments. *Journal of Hydrology*, **480**, 33–45. doi:10.1016/j.jhydrol.2012.12.004

Samuel, J., Coulibaly, P. and Metcalfe, R. A., 2011. Estimation of continuous streamflow in Ontario ungauged basins: comparison of regionalization methods. *Journal of Hydrologic Engineering* **16**(5), 447–459. doi:10.1061/(ASCE)HE.1943-5584.0000338

Sanborn, S. C. and Bledsoe, B. P., 2006. Predicting streamflow regime metrics for ungauged streamsin Colorado, Washington, and Oregon. *Journal of Hydrology*, **325**(1–4), 241–261. doi:10.1016/j.jhydrol.2005.10.018

Sawicz, K., Wagener, T., Sivapalan, M., Troch, P. A. and Carrillo, G., 2011. Catchment classification: empirical analysis of hydrologic similarity based on catchment function in the eastern USA. *Hydrology and Earth System Sciences*, **15**(9), 2895–2911. doi:10.5194/hess-15-2895-2011

Sefton, C. E. M. and Howarth, S. M., 1998. Relationships between dynamic response characteristics and physical descriptors of catchments in England and Wales. *Journal of Hydrology*, **211**(1), 1–16.

Seibert, J., 1999. Regionalisation of parameters for a conceptual rainfall–runoff model. *Agricultural and Forest Meteorology*, **98–99**, 279–293. doi:10.1016/S0168-1923(99)00105-7

Seibert, J. and Beven, K. J., 2009. Gauging the ungauged basin: how many discharge measurements are needed? *Hydrology and Earth System Sciences*, **13**(6), 883–892.

Shepard, D., 1968. A two-dimensional interpolation function for irregularly-spaced data, *Proceedings of the 23rd ACM National Conference. ACM*, pp. 517–524.

Singh, V. P. and Woolhiser, D. A., 2002. Mathematical modeling of watershed hydrology. *Journal of Hydrological Engineering*, **7**(4), 270–292.

Sivapalan, M., Takeuchi, K., Franks, S. W., Gupta, V. K., Karambiri, H., Lakshmi, V., Liang, X., McDonnell, J.J., Mendiondo, E.M., O'Connell, P.E., Oki, T., Pomeroy, J.W., Schertzer, D., Uhlenbrook, S., and Zehe, E., 2003. IAHS Decade on Predictions in Ungauged Basins (PUB), 2003–2012: Shaping an exciting future for the hydrological sciences. *Hydrological Sciences Journal*, **48**(6), 857–880. doi:10.1623/hysj.48.6.857.51421

Sorooshian, S. and Gupta, V. K., 1983. Automatic calibration of conceptual rainfall-runoff models: The question of parameter observability and uniqueness. *Water Resources Research*, **19**(1), 260–268.

Strosser, P., Dworak, T., Garzon Delvaux, P. A., Berglund, M., Schmidt, G., Mysiak, J., Kossida, M., Iacovides, I., and Ashton, V., 2012. Gap analysis of the water scarcity and droughts policy in the EU European Commission. *European Commission*, **Tender ENV.D.1/SER/2010/0049**, 206.

Swain, J. B. and Patra, K. C., 2017. Streamflow estimation in ungauged catchments using regionalization techniques. *Journal of Hydrology*, **554**, 420–433. doi:10.1016/j.jhydrol.2017.08.054

Tarboton, D.G., 1994. Measurements and modeling of snow energy balance and sublimation from snow, *International Snow Science Workshop*, Snowbird, Utah, November 1, 1994. Snowbird, Utah U.S.A.

Tarboton, D.G., Chowdhury, T.G., Jackson, T.H., 1995. A spatially distributed energy balance snowmelt model. In: K.A. Tonnessen, M.W. Williams and M. Tranter, eds. *Biogeochemistry of seasonally snow-covered catchments* (3-14 June 1995 Boulder, CO. USA). Wallingford, UK: International Association of Hydrological Sciences, IAHS Publ. 228, 141–155. https://iahs.info/uploads/dms/iahs_228_0141.pdf [Accessed 4 Nov. 2019]

Tasker, G.D., 1989. Regionalization of low flow characteristics using logistic and GLS regression. In: M.L. Kavvas, ed. *New directions for surface water modelling* (Proceedings of the Baltimore Symposium, May 1989). Wallingford, UK: International Association of Hydrological Sciences, IAHS Publ. 181, 323–332. https://iahs.info/uploads/dms/iahs_181_0323.pdf [Accessed 4 Nov. 2019]

Thiessen, A.H., 1911. Precipitation averages for large areas. *Monthly Weather Review*, **39**(7), 1082–1084.

Thirel, G., Andréassian, V., Perrin, C., Audouy, J.-N., Berthet, L., Edwards, P., Folton, N., Furusho, C., Kuentz, A., Lerat, J., Lindström, G., Martin, E., Mathevet, T., Merz, R., Parajka, J., Ruelland, D., and Vaze, J., 2015. Hydrology under change: an evaluation protocol to investigate how hydrological models deal with changing catchments. *Hydrological Sciences Journal*, **60**(7–8), 1184–1199. doi:10.1080/02626667.2014.967248

Todini, E., 1988. Rainfall–runoff modeling - past, present and future. *Journal of Hydrology,* **100**, 341–352.

Todini, E., 2011. History and perspectives of hydrological catchment modelling. *Hydrology Research*, **42**(2–3), 73. doi:10.2166/nh.2011.096

Toth, E., 2013. Catchment classification based on characterisation of streamflow and precipitation time series. *Hydrology and Earth System Sciences,* **17**(3), 1149–1159. doi:10.5194/hess-17-1149-2013

Troutman, B. M. and Karlinger, M. R., 1985. Unit hydrograph approximations assuming linear flow through topologically random channel networks. *Water Resources Research*, **21**(5), 743–754.

Vesanto, J. and Alhoniemi, E., 2000. Clustering of the Self-Organizing Map. *IEEE Transactions on Neural Networks,* 11, 586–600. Helsinki University of Technology. https://aaltodoc.aalto.fi/handle/123456789/2257 [Accessed 4 Nov. 2019]

Viglietti, D., Letey, S., Motta, R., Maggioni, M. and Freppaz, M., 2010. Snow avalanche release in forest ecosystems: A case study in the Aosta Valley Region (NW-Italy). *Cold Regions Science and Technology,* **64**(2), 167–173. doi:10.1016/j.coldregions.2010.08.007

Viviroli, D., Mittelbach, H., Gurtz, J. and Weingartner, R., 2009. Continuous simulation for flood estimation in ungauged mesoscale catchments of Switzerland – Part II: Parameter regionalisation and flood estimation results. *Journal of Hydrology,* **377**(1–2), 208–225. doi:10.1016/j.jhydrol.2009.08.022

Viviroli, D., Zappa, M., Schwanbeck, J., Gurtz, J. and Weingartner, R., 2009. Continuous simulation for flood estimation in ungauged mesoscale catchments of Switzerland – Part I: Modelling framework and calibration results. *Journal of Hydrology,* **377**(1–2), 191–207. doi:10.1016/j.jhydrol.2009.08.023

Vogel, R. M. and Fennessey, N. M., 1994. Flow-duration curves. I: New interpretation and confidence intervals. *Journal of Water Resources Planning and Management,* **120**(4), 485–504.

Vogel, R. M. and Fennessey, N. M., 1995. Flow-duration curves. II: A review of applications in water resources planning. *Water Resources Bulletin,* American Water Resources Association **31**(6), 1029–1039.

Wagener, T., Sivapalan, M., Troch, P. and Woods, R., 2007. Catchment classification and hydrologic similarity. *Geography Compass* **1**(4), 901–931. doi:10.1111/j.1749-8198.2007.00039.x

Wagener, T., Wheater, H. and Gupta, H. V., 2004. *Rainfall–runoff modelling in gauged and ungauged catchments*. World Scientific.

Wagener, T. and Wheater, H. S., 2006. Parameter estimation and regionalization for continuous rainfall–runoff models including uncertainty. *Journal of Hydrology,* **320**(1–2), 132–154. doi:10.1016/j.jhydrol.2005.07.015

Weeks, W. D. and Ashkanasy, N. M., 1983. Regional parameters for the Sacramento model: a case study, 183. Presented at the Hydrology and Water Resources Symposium 1983: Preprints of Papers, Institution of Engineers, Australia.

Wolman, M. G. and Miller, P., 1960. Magnitude and frequency of forces in geomorphic processes. The *Journal Of Geology,* **68**(1), 54–74.

Yadav, M., Wagener, T. and Gupta, H., 2007. Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins. *Advances in Water Resources,* **30**(8), 1756–1774. doi:10.1016/j.advwatres.2007.01.005

Yilmaz, K. K., Gupta, H. V. and Wagener, T., 2008. A process-based diagnostic approach to model evaluation: application to the NWS distributed hydrologic model. *Water Resources Research,* **44**(9). doi:10.1029/2007WR006716

Young, A. R., 2006. Stream flow simulation within UK ungauged catchments using a daily rainfall–runoff model. *Journal of Hydrology,* **320**(1–2), 155–172. doi:10.1016/j.jhydrol.2005.07.017

Zhang, Y. and Chiew, F. H. S., 2009. Relative merits of different methods for runoff predictions in ungauged catchments. *Water Resources Research,* **45**(7). doi:10.1029/2008WR007504

Table 1. Description, unit and range of the model parameters that have to be calibrated in MISDc.

Model parameters	Description	Unit	Range
Soil water balance (SWB)			
$W(t_0)$	Initial condition of soil water content		
W_{max}	Maximum water capacity of the soil layer	mm	100-1000
K_s	Saturated hydraulic conductivity	mm h^{-1}	0.01-20
M	Exponent of drainage component	-	5-60
Θ	Fraction of drainage versus interflow	-	0-1
B	Correction factor for actual evapotranspiration	-	0.4-2
$C_{m\text{-snowpack}}$	Degree-day factor for snowpack	mm h^{-1} °C^{-1}	0.1-3
$k_{glacier}$	Constant factor for glaciers melting	mm h^{-1}	0-0.0002
$C_{m\text{-glacier}}$	Degree-day factor for glaciers	mm h^{-1} °C^{-1}	0.1-3
Soil Conservation Service – Curve Number (SCS-CN)			
λ	Initial abstraction coefficient	-	0.0001-0.2
a	Parameter of $S(t)$ versus $W(t)$ relationship	-	1-4
Routing module (RM)			
η	Lag-time parameter	-	0.5-6.5

Table 2. List of regionalization approaches compared in this work.

Regionalization strategy	Method	Approach	Abbreviation
Spatial-proximity	Inverse spatial distance	From the centroid	IDW_c
		From the outlet	IDW_o
	Arithmetic mean technique	Global mean	AM_g
		Local mean (50 km)	AM_{50}
		Local mean (25 km)	AM_{25}
Regression-based	Linear multiple regression	level-level model	MLR1
	Nonlinear multiple regression	level-log model	MLR2
		log-level model	MLR3
		log-log model	MLR4
Physical-similarity	Distance inside the n-dimensional space of the n physical attributes	Euclidean distance	PhyS
	Catchment classification	Using arithmetic mean	CC_{pm}
		Using physical similarity measure	CC_{pd}

Table 3. Overview of geographic, physiographic, climatic and geological variables used in previous catchment classifications and/or regionalization studies.

Descriptor	Abbreviation	Unit	Source	Min	Max
Longitude (WGS 84 / UTM zone 32N)	X_s	-	Gauged station information	346505	612401
Latitude (WGS 84 / UTM zone 32N)	Y_s	-	Gauged station information	4885566	5130276
Curve Number	CN	-	Combination of available data	66.0	80.8
Area	A_C	km^2	DEM	15.9	2335.4
Stream length	L	km	DEM	5.52	112.74
Mean elevation	Z_m	m	DEM	241.6	2104.5
Minimum elevation	Z_{min}	m	DEM	72.8	950.5
Maximum elevation	Z_{max}	m	DEM	377.6	4427.3
5th percentile elevation	Z_5	m	DEM	104.28	1189.43
95th percentile elevation	Z_{95}	m	DEM	336.69	3152.88
Average slope	SL	deg	DEM	0.70	33.99
Topographic wetness index (details in Raduła et al., 2018)	TWI	-	DEM	5.54	13.03
Percentage of catchment covered by mountains (Z > 600 m)	MOUN	-	DEM	0.00	1.00
Percentage of catchment covered by arable land and permanent crops	AGR	%	Corine land cover map	0.96	92.48
Percentage of catchment covered by forested land	WOOD	%	Corine land cover map	6.57	99.00
Percentage of catchment covered by artificial areas	URB	%	Corine land cover map	0.00	40.84
Mean cumulated annual precipitation	MAP	mm	Meteorological data	518.5	2007.4
Standard deviation of cumulated annual precipitation	Dstd	mm	Meteorological data	111.8	637.9
Coefficient of variation in annual precipitation	PVAR	-	Meteorological data	0.117	0.593
Number of days with precipitation	NP	-	Meteorological data	81	241.5
Mean annual maximum 1-hour precipitation	MMA	mm	Meteorological data	7.21	51.35

Ratio of precipitation in wettest month to that of the driest	RWD	-	Meteorological data	17.38	164.31
Average monthly temperature	Tmo	°C	Meteorological data	3.10	13.23
Percentage of soil with high permeability within the catchment (sand and loamy sand)	HIGHp	%	Lithological and geological maps	0.00	98.65
Percentage of soil with median permeability within the catchment (silt loam and silty clay loam)	MEDp	%	Lithological and geological maps	0.60	100.00
Percentage of soil with low permeability within the catchment (silt clay and clay)	LOWp	%	Lithological and geological maps	0.00	85.91
Mean field capacity	FC	mm	Lithological and geological maps	0.164	0.76

Table 4. Grouping of catchment descriptors according to the procedure described in Section 2.3.2. The catchment descriptors with a high linear correlation ($|\rho| > 0.70$) are grouped. Numbered brackets show the correlated groups, while the asterisk indicates lack of correlation with the other attributes. Underlined response characteristics were selected for the regionalization.

Correlated group	Catchment descriptors
[1]	<u>AREA</u>, L
[2]	<u>Z_m</u>, Z_{min}, Z_{max}, SLOPE, MOUN, TWI, Z_5, Z_{95}, WOOD, AGR, FC, NP, Tmo, X_s
[3]	<u>HIGHp</u>, MEDp
[4]	<u>MAP</u>, Y_s
[*]	<u>CN</u>, <u>URB, LOWp, Dstd</u>, <u>PVAR</u>, <u>MMA</u>, <u>RWD</u>

Table 5. Comparison of three performance indicators (BiasFMS, BiasFHV and BiasFLV) estimated for the ungauged catchments using the investigated regionalization techniques.

	IDWc	IDWo	AMg	AM_{50}	AM_{25}	MLR1	MLR2	MLR3	MLR4	PhyS	CC_{pm}	CC_{pd}
BiasFMS (%)	33.1	34.1	28.9	31.5	28.2	31.7	29.8	34.6	32.6	32.2	35.4	32.2
BiasFHV (%)	25.9	25.0	31.1	25.5	19.2	18.1	24.4	23.2	24.6	32.5	27.9	31.2
BiasFLV (%)	63.9	64.2	57.1	62.4	52.7	55.3	57.8	55.3	58.2	59.9	62.3	69.5

Figure captions

Figure 1. Schematization of the lumped version of MISDc incorporating the Soil Water Balance Model, the Soil Conservation Service Curve Number, and the Routing module.

Figure 2. Locations of gauged hydrological and meteorological stations in the western Po Valley, Italy.

Figure 3. KGE′ values in calibration (KGE'_{cal}) and in validation (KGE'_{val}): (a) frequency of the four performance classes and (b) statistical distribution.

Figure 4. Distribution of gauged catchments into the four performance classes considering ANSE, NS and VE as scores in calibration (subscript cal) and validation (subscript val) periods.

Figure 5. Boxplots of model performances in terms of ANSE, NS and VE values in calibration (cal) and validation (val) periods. The value in bold (red) text is the median of each boxplot.

Figure 6. Comparison between the observed Q_{obs}, and simulated Q_{sim}, discharge (lower panel) for calibration and validation periods at four different gauged river stations: (a) San Martino (no. 25), (b) Villafranca (no. 31), (c) Passobreve (no. 36), and (d) Carrù (no. 44). The upper panel shows the temporal pattern of rainfall rate.

Figure 7. Boxplots of model performance in terms of BiasFMS, BiasFHV and BiasFLV. The value in bold (red) text is the median of each boxplot.

Figure 8. Observed (grey line) and simulated (blue line) FDCs for four gauged river stations: (a) San Martino (no. 25), (b) Villafranca (no. 31), (c) Passobreve (no. 36), and (d) Carrù (no. 44).

Figure 9. Comparison of KGE′ values of ungauged catchments using the investigated regionalization technique. The value in bold (red) text is the median of each boxplot.

Figure 10. Comparison of NS values of ungauged catchments using the investigated regionalization technique. The value in bold (red) text is the median of each boxplot.

Figure 11. Comparison of ANSE values of ungauged catchments using the investigated regionalization techniques. The value in bold (red) text is the median of each boxplot.

Figure 12. Comparison of VE values of ungauged catchments using the investigated regionalization techniques. The value in bold (red) text is the median of each boxplot.

Figure13. Spatial distribution of model performances in terms of KGE′ index values.

Appendix A

Here, we provide a brief description of the lumped version of the semi-distributed continuous RR model *Modello Idrologico Semi-Distribuito in continuo*, MISDc, developed by Brocca et al. (2011a). MISDc consists of three principal components: the soil water balance (SWB), the Soil Conservation Service - Curve Number method (SCS-CN) and the routing module (RM). The SWB is based on equation (A1).

$$\begin{cases} \frac{\mathrm{d}W(t)}{\mathrm{d}t} = \mathrm{lp}(t) - r(t) - e(t) - [g(t) + \mathrm{bf}(t)] + \mathrm{swe}_{\mathrm{snowpack}}(t) + \mathrm{swe}_{\mathrm{glacier}}(t) & W(t) \leq W_{\max} \\ W(t) = W_{\max} & \text{otherwise} \end{cases} \quad \text{(A1)}$$

In equation (A1), $W(t)$ is the soil water content at time t, $\mathrm{lp}(t)$ is the liquid precipitation, $r(t)$ is the effective rainfall (i.e. the superficial runoff), $e(t)$ is the evapotranspiration rate, $g(t)$ and $\mathrm{bf}(t)$ indicate the drainage rate due respectively to interflow and deep percolation, $\mathrm{swe}_{\mathrm{snowpack}}(t)$ is the melting of snowpack, $\mathrm{swe}_{\mathrm{glacier}}(t)$ is the melting of glaciers, and $W_{\max}$ the maximum water capacity of the soil layer.

The model assumes that the surface soil layer is a spatially-lumped system with the following characteristics:

- r(t) is calculated through the SCS-CN method (Chow, 1959), as follows:

$$r(t) = \frac{[\mathrm{lp}(t) - \lambda\, S(t)]^2}{\mathrm{lp}(t) - \lambda\, S(t) + S(t)} \quad \text{(A2)}$$

where λ is the initial abstraction coefficient and $S(t)$ is the soil potential maximum retention.

- $S(t)$ and the saturation degree, i.e. the difference between $W_{\max}$ and $W(t)$, are related by a linear relationship:

$$S(t) = a[W_{\max} - W(t)] \quad \text{(A3)}$$

- $e(t)$ mainly controls the soil moisture temporal pattern without precipitation and is represented by a linear relationship depending on the potential evapotranspiration $\mathrm{ET}p(t)$ and the soil saturation through the empirical formulation (Doorenbos and Pruitt 1977):

$$e(t) = \mathrm{ET}_p(t) \frac{W(t)}{W_{\max}} \quad \text{(A4)}$$

$$\mathrm{ET}_p(t) = -2 + b\{\xi[0.46T_a(t) + 8.13]\} \quad \text{(A5)}$$

where $T_a(t)$ is the air temperature, b is the correction factor for actual evapotranspiration and ξ is the percentage of total daytime hours;

- $g(t)$ is the percolation that is a percentage of the drainage term described by the relationship (Famiglietti and Wood 1994):

$$g(t) = \theta\, K_s \left[\frac{W(t)}{W_{\max}}\right]^m \qquad \text{(A6)}$$

where K_s is the saturated hydraulic conductivity, m is the exponent of the drainage component, and θ is the fraction of drainage that percolates.

- $\mathrm{bf}(t)$ is the subsurface runoff, i.e. the interflow:

$$\mathrm{bf}(t) = (1-\theta)K_s \left[\frac{W(t)}{W_{\max}}\right]^\theta \qquad \text{(A7)}$$

- $\mathrm{swe}(t)$ indicates the snowmelt package that was specifically added to the original version of MISDc developed by Brocca *et al*. (2010, 2011a) in this study. The snowmelt model includes the melting of the snowpack, the melting of glaciers and snow accumulation dynamics on both the snowpack and the glaciers (Tarboton, 1994, Tarboton *et al*., 1995). It starts partitioning the total precipitation in the liquid $P_{liq}(t)$ and solid $P_{sol}(t)$ components:

$$\begin{cases} P_{\mathrm{liq}}(t) = \alpha_P\, P(t) \\ P_{\mathrm{sol}}(t) = (1-\alpha_P)\, P(t) \end{cases} \qquad \text{(A8)}$$

where α_P is a coefficient computed by:

$$\begin{cases} \alpha_{\mathrm{P}} = 0 & T_{\mathrm{a}} \le T_{\mathrm{inf}} \\ \alpha_{\mathrm{P}} = 1 & T_{\mathrm{a}} \ge T_{\mathrm{sup}} \\ \alpha_{\mathrm{P}} = \frac{T_{\mathrm{a}}-T_{\mathrm{inf}}}{T_{\mathrm{sup}}-T_{\mathrm{inf}}} & T_{\mathrm{inf}} \le T_{\mathrm{a}} \le T_{\mathrm{sup}} \end{cases} \qquad \text{(A9)}$$

where T_{inf} and T_{sup} are the calibration parameters that are set to 0°C, as suggested by Corbari *et al.* (2009).

The melting process is based on the degree-day concept (Martinec, 1960), which assumes a melt rate proportional to the difference between $T_a(t)$ and a predefined threshold temperature $T_b(t)$, as follows:

$$\begin{cases} s_{\mathrm{acc}}(t) = s_{\mathrm{acc}}(t-1) + P_{\mathrm{sol}}(t) & T_{\mathrm{a}} \leq T_{\mathrm{sup}} \\ s_{\mathrm{acc}}(t) = s_{\mathrm{acc}}(t-1) - \mathrm{swe}(t) = s_{\mathrm{acc}}(t-1)[1 - \mathrm{Cm}\left(T_a - T_{\mathrm{sup}}\right)] & T_{\mathrm{a}} > T_{\mathrm{sup}} \end{cases} \quad \text{(A10)}$$

where s_{acc} is the accumulated snow layer and Cm is the degree-day coefficient.

This methodology is applied separately for the melting processes of the snowpack and the glaciers, as follows:

$$\mathrm{swe}_{\mathrm{snopack}}(t) = s_{\mathrm{acc-snowpack}}(t-1)\mathrm{Cm}_{\mathrm{snowpack}}(T_{\mathrm{a}} - T_{\mathrm{sup}}) \quad \text{(A11)}$$

$$\mathrm{swe}_{\mathrm{glaciers}}(t) = k_{\mathrm{glaciers}} + s_{\mathrm{acc-glaciers}}(t-1)\mathrm{Cm}_{\mathrm{glaciers}}(T_{\mathrm{a}} - T_{\mathrm{sup}}) \quad \text{(A12)}$$

where the subscripts indicate the type of melting process and k_{glaciers} is a constant referred to the flow of water at the base of glaciers.

The direct runoff hydrograph $H(t)$ at the outlet station is given by the convolution of $r(t)$ and the instantaneous unit hydrograph (IUH), $h(t)$, as follows:

$$H(t) = A_C \int_0^t r(\tau)\, h(t-\tau)\, d\tau \quad \text{(A13)}$$

where A_C is the catchment area and τ is an auxiliary variable for time

The geomorphological IUH is derived according to the methodology proposed by Gupta *et al.* (1980) and through a linear reservoir approach for the sub-catchments, assuming a lag time that can be evaluated by (Melone *et al.* 2002):

$$L = \eta 1.19 A_C^{0.33} \quad \text{(A14)}$$

where L is the lag time and η is the coefficient of lag time relationship.

Finally, the direct runoff hydrograph, $Q(t)$ is calculated through a diffusive routing approach (Troutman and Karlinger, 1985), which takes all the contributions of the streamflow at the catchment outlet.

$$Q(t) = \sum \int_0^t r(\tau)\, h(t-\tau)\, \mathrm{d}\tau \quad \text{(A15)}$$

Appendix B

Table B1. Details of the 63 basins and sub-catchments of the western Po Valley used in the study.

Gauge station	River	Province	Code	Longitude	Latitude	Area (km^2)	Elevation (m a.s.l.)	Average slope (°)	MAP (mm)
Gavardo	Chiese	BS	1	612401	5049768	386.63	706.73 (169-2000)	26.02	1356.484354
Gera Lario	Adda	CO	2	531834	5110833	2335.4	1809.8 (179-4023)	28.28	1412.380883
Lozza	Olona	VA	3	489790	5069162	66.43	423.25 (265-992)	9.11	1353.678106
Castellanza	Olona	VA	4	492782	5050408	141.06	360.49 (190-992)	5.88	1345.836099
Cantù-Asnago	Serenza	CO	5	507810	5062779	46.37	340.87 (261-610)	4.58	1340.856098
Peregallo	Lambro	MB	6	523311	5053559	300.62	439.39 (184-1457)	11.11	1398.242161
Caslino d'Erba	Lambro	CO	7	518045	5075784	76.97	713.3 (257-1457)	22.91	1586.57
Brembate di Sopra	Brembo	BG	8	545718	5062020	772.56	1154.81 (199-2916)	26.89	1476.450365
Bovegno	Mella	BS	9	598193	5070535	88.32	1300.09 (525-2201)	28.95	1325.455737
Darfo Boario Terme	Oglio	BS	10	589758	5080335	1329.41	1649.04 (176-3539)	28.36	1150.054545
Lambrugo	Lambro	CO	11	519380	5067757	223.03	492.15 (199-1457)	13.84	1409.574734
Camerata Cornello	Brembo	BG	12	551077	5082983	408.37	1440.27 (376-2916)	30.08	1714.486159
Ponte Cene	Serio	BG	14	563859	5070401	463.3	1325.74 (342-3049)	28.1	1424.471552
Gandellino	Serio	BG	15	573384	5095337	102.47	1884.4 (731-3049)	33.99	2007.414286
Molteno	Bevera	LC	16	523871	5069985	42.61	381.85 (246-879)	7.89	1373.323174
Chiavenna	Mera	SO	17	528981	5130276	192.37	1956.78 (296-3280)	28.25	1770.542936
Brandizzo	Malone	TO	20	409800	5003812	312	464.75 (192-1965)	4.13	1130.802
Front	Malone	TO	21	395359	5015296	153.05	667.59 (271-1965)	5.58	1295.519
Germagnano Borgo	Stura di Vi?	TO	22	377061	5011309	232.07	1764.91 (647-3334)	13.48	1208.35
La Loggia	Chisola	TO	23	395185	4980749	444.21	352.99 (223-1346)	1.87	924.196
Lanzo	Stura di Lanzo	TO	24	380981	5013880	635.15	1752.85 (491-3346)	13.5	1281.709
Moncalieri	Sangone	TO	25	395894	4983882	252.1	733.65 (226-2389)	4.92	1036.6
Parella	Chiusella	TO	26	405964	5030308	158.05	1301.49 (280-2517)	10.41	1406.646
Perrero	Germagnasca	TO	27	355060	4978655	195.05	1914.36 (767-2817)	12.46	1034.73
San Martino	Chisone	TO	28	364405	4971649	574.15	1721.23 (458-2980)	12.39	1035.444

Pont	Soana	TO	30	390595	5030737	218.05	1922.28 (666-3039)	13.99	1294.095
San Benigno	Orco	TO	31	406312	5011060	874.22	1545.16 (210-3646)	11.49	1227.847
Santena	Banna	TO	32	403909	4977517	373.23	288.53 (232-516)	0.7	717.688
Torino-Stura di Lanzo	Stura di Lanzo	TO	35	398252	4996118	927.27	1346.83 (216-3346)	10.43	849.211
Torino-Dora Riparia	Dora Riparia	TO	36	399093	4992176	1328.29	1634.22 (225-3376)	12.58	1233.321
Trana	Sangone	TO	37	375548	4988109	133.04	1115.13 (381-2389)	8.35	1101.385
Villafranca	Pellice	TO	38	381345	4963168	1016.34	1475.88 (254-2980)	10.91	1081.357
Carisio	Elvo	VC	41	437994	5029760	257.11	605.2 (177-2320)	4.83	1279.9
Cossato	Strona	BI	42	436246	5046480	57.02	643.82 (265-1375)	5.61	1575.803
Pray	Sessera	BI	43	439375	5058122	121.04	1161.18 (444-2294)	8.57	1756.883
Quinto Vercellese	Cervo	VC	44	451011	5025503	996.44	511 (138-2320)	3.6	1281.222
Passobreve	Cervo	BI	45	425025	5053441	80.03	1502.24 (666-2276)	12.39	1730.268
Varallo	Mastallone	VC	46	442188	5075482	145.04	1306.06 (583-2217)	9.39	1774.76
Vigliano	Cervo	BI	47	430619	5044911	160.06	1148.42 (310-2276)	9.39	1643.049
Candoglia	Toce	VCO	48	455208	5091406	1589.27	1723.39 (203-4427)	15.47	1571.15
Momo	Agogna	NO	49	464707	5046499	161.07	328.5 (209-715)	1.25	1378.548
Novara	Agogna	NO	50	467980	5030915	221.1	285.97 (142-715)	0.97	1276.212
Busca	Maira	CN	51	379303	4930201	596.29	1667.5 (488-3096)	10.1	734.5753
Camerana	Bormida	CN	52	432986	4920844	268.27	769.87 (397-1283)	4.54	995.048
Carrù	Pesio	CN	53	411139	4924109	334.28	825.95 (300-2483)	5.47	1067.402
Farigliano	Tanaro	CN	55	412708	4929896	1540.7	943.97 (248-2483)	6.09	1052.156
Fossano	Stura di Demonte	CN	56	398627	4930852	1339.92	1598.48 (329-2936)	10.34	1122.081
Garessio	Tanaro	CN	57	421307	4894775	156.44	1581.9 (932-2437)	9.46	1123.39
Piantorre	Tanaro	CN	58	418166	4918796	545.82	1068.22 (371-2437)	7.48	1080.444
Mondovì	Ellero	CN	59	406019	4915890	178.16	1089.75 (428-2428)	6.02	1135.993
Monterosso	Grana	CN	60	366583	4918710	109.07	1561.76 (785-2454)	9.87	777.2961
Polonghera	Varaita	CN	62	389173	4961955	626.32	1354.54 (244-3468)	8.12	857.741
Rocchetta	Belbo	CN	64	434523	4942717	94.08	589.19 (325-787)	2.82	518.532
Castelnuovo	Belbo	AT	65	454038	4960719	372.32	336.1 (120-787)	2.21	725.215
Mombaldone	Bormida	AT	67	447204	4935282	440.44	496.55 (209-1145)	3.32	951.102
Arquata	Scrivia	AL	69	490563	4947691	328.33	684.97 (318-1371)	4.89	1310.63
Basaluzzo	Orba	AL	70	474018	4957174	739.73	479.47 (126-1243)	3.36	1176.784

Cartosio	Erro	AL	71	454038	4935729	207.21	530.39 (248-1163)	3.42	1066.278
Casal Cermelli	Orba	AL	72	470870	4964453	826.8	444.28 (100-1243)	3.06	1132.212
Cassine	Bormida	AL	73	463785	4955435	1586.53	496.59 (116-1283)	3.51	896.475
Guazzora	Scrivia	AL	74	490257	4986144	977.92	542.2 (72-1568)	4.07	1034.28
Volpedo	Curone	AL	75	498652	4970401	170.15	626.13 (184-1493)	4.66	720.7034
Serravalle	Scrivia	AL	76	488987	4952418	665.65	693.24 (218-1568)	5.25	586.2606
Murialdo	Bormida di Millesimo	SV	77	432869	4905986	139.15	890.83 (599-1283)	5.28	1008.38