Hydrol. Earth Syst. Sci., 21, 2863–2879, 2017
https://doi.org/10.5194/hess-21-2863-2017

Hydrology and Earth System Sciences
Open Access

Understanding hydrologic variability across Europe through catchment classification

Anna Kuentz[1], **Berit Arheimer**[1], **Yeshewatesfa Hundecha**[1], **and Thorsten Wagener**[2,3]

[1]Swedish Meteorological and Hydrological Institute, 601 76 Norrköping, Sweden
[2]Department of Civil Engineering, University of Bristol, BS8 1TR, Bristol, UK
[3]Cabot Institute, University of Bristol, Bristol, UK

Correspondence to: Anna Kuentz (anna.kuentz@smhi.se)

Received: 21 August 2016 – Discussion started: 29 August 2016
Revised: 3 March 2017 – Accepted: 21 April 2017 – Published: 12 June 2017

Abstract. This study contributes to better understanding the physical controls on spatial patterns of pan-European flow signatures – taking advantage of large open datasets for catchment classification and comparative hydrology. Similarities in 16 flow signatures and 35 catchment descriptors were explored for 35 215 catchments and 1366 river gauges across Europe. Correlation analyses and stepwise regressions were used to identify the best explanatory variables for each signature. Catchments were clustered and analyzed for similarities in flow signature values, physiography and the combination of the two. We found the following. (i) A 15 to 33 % (depending on the classification used) improvement in regression model skills when combined with catchment classification versus simply using all catchments at once. (ii) Twelve out of 16 flow signatures were mainly controlled by climatic characteristics, especially those related to average and high flows. For the baseflow index, geology was more important and topography was the main control for the flashiness of flow. For most of the flow signatures, the second most important descriptor is generally land cover (mean flow, high flows, runoff coefficient, ET, variability of reversals). (iii) Using a classification and regression tree (CART), we further show that Europe can be divided into 10 classes with both similar flow signatures and physiography. The most dominant separation found was between energy-limited and moisture-limited catchments. The CART analyses also separated different explanatory variables for the same class of catchments. For example, the damped peak response for one class was explained by the presence of large water bodies for some catchments, while large flatland areas explained it for other catchments in the same class. In conclusion, we find that this type of comparative hydrology is a helpful tool for understanding hydrological variability, but is constrained by unknown human impacts on the water cycle and by relatively crude explanatory variables.

1 Introduction

Hydrological systems exhibit a tremendous variability in their physical properties and in the hydrological variables we observe, such as streamflow and soil moisture patterns (Bloeschl et al., 2013). At the catchment scale, we assume (or at least hope) that the aggregated response behavior, e.g., the hydrograph, is related to average or dominating characteristics and that smaller-scale differences are less relevant. Although the extent of the validity of this assumption can be questioned (Beven, 2000; Oudin et al., 2010), it is the basis for statistical hydrology, where it allows us to regionalize certain flow characteristics related to floods or low flows. We generally make the same assumption in the search for a catchment classification framework where our aim is to group catchments that somehow exhibit similar hydrologic behavior (McDonnell and Woods, 2004). While the preferred classification system will depend to a degree on the specific objective of a study or the data availability, it is generally agreed upon that even the search for such an organizing principle is an important undertaking for hydrology (Wagener et al., 2007).

Many studies have attempted to organize the catchments we find across our landscape. Approaches include the use of physical and climatic characteristics (e.g., Winter, 2001;

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Brown et al., 2013; Buttle, 2006; Leibowitz et al., 2016), the use of hydrologic signatures (e.g., Ley et al., 2011; Olden et al., 2012; Sawicz et al., 2011; Singh et al., 2016), or the inclusion of water quality (Arheimer et al., 1996; Arheimer and Lidén, 2000). The advantage of the first approach is that physical characteristics such as topography and land cover are now available for any location on earth (though with varying quality of the data available), while the second approach groups catchments directly by the characteristic we mainly care about, i.e., their hydrologic behavior (see the discussion in Wagener et al., 2007). The disadvantages are that the first framework does not ensure that physically/climatically similar catchments will also behave similarly, while the second is not directly applicable to ungauged catchments. Furthermore, the two approaches do not necessarily group catchments in the same way since the datasets used for the classification are different. Therefore, one needs to derive functions that link flow characteristics and catchment attributes within each group of catchments classified in either way. Ultimately, we believe that a catchment classification framework has to achieve the advantages both approaches offer to be useful; i.e., it has to be applicable to any catchment and provide insight into its expected hydrological behavior.

Here we assume that flow signatures are one relevant way towards quantifying hydrological behavior and therefore form a sensible basis for a classification framework. They condense hydrologic information derived from streamflow observations (alone or in combination with other variables) (Sivapalan, 2005). The choice of the specific signatures used for classification can be guided by (i) the attempt to describe basic hydrological behavior (e.g., Ley et al., 2011; Sawicz et al., 2011; Trancoso et al., 2016); (ii) the need to relate to societally relevant issues such as floods and droughts (Wagener et al., 2008); (iii) the objective to characterize ecologically relevant characteristics of the catchment response (e.g., Olden et al., 2012); or (iv) in relation to subsequent hydrologic modeling (Euser et al., 2013; Hrachowitz et al., 2014; Donnelly et al., 2016). Studying differences and similarities in flow signatures as well as in catchment characteristics can also improve our understanding of hydrological processes under potential future conditions (Sawicz et al., 2014; Berghuijs et al., 2014; Pechlivanidis and Arheimer, 2015; Rice et al., 2015). Linking catchment descriptors (physical and climatic) and hydrological response signatures enables the inclusion of ungauged basins and provides the potential for assessing environmental change impacts across large domains.

Despite the significant worldwide research performed during many decades to both understand and predict hydrologic variability using physiography, work has largely addressed small or medium-sized and pristine catchments when delineating regions of similar flow controls (e.g., Yaeger et al., 2012; Ye et al., 2012; Patil and Stieglitz, 2012). Often different studies have resulted in conflicting relationships between some catchment responses and some of their physiographic controls, as a result of catchment size and geographical location. For instance, some studies have found that forest cover reduces catchment streamflow (e.g., Hundecha and Bárdossy, 2004; Brown et al., 2005; Buytaert et al., 2007), while an increase in streamflow has been found in some others (e.g., Bruijnzeel, 2004). It would, therefore, be worthwhile identifying the physiographic controls of catchment responses and their relationships using a consistent approach across a larger geographic domain, which is subdivided into catchments of different spatial scales. A large sample of observed data from different physiographical and hydrological conditions enables comparative analysis of dominant drivers for flow generation (Falkenmark and Chapman, 1989). No study so far, to our knowledge, has applied comparative hydrology at the continental scale, i.e., including large rivers with human alteration and ungauged basins.

Our study aims to explore and understand the physical controls on spatial patterns of pan-European flow signatures by taking advantage of large open datasets. We explore the relationships between catchment descriptors and flow signatures by analyzing 35 215 catchments which cover a wide range of pan-European physiographic and anthropogenic characteristics. A database of catchment descriptors for all catchments and of hydrologic signatures using 1366 flow gauges across Europe has been gathered. Based on this database, we make use of a set of established classification and regression approaches to learn more about physical controls of flow generation.

Our study is guided by the following science questions.

- To what extent can physiography explain similarities in flow signatures across Europe?
- What spatial pattern can be derived from combining similarity in flow signatures and physiography across the European continent?
- Which flow-generating processes can be attributed to regions with similar flow signatures?

2 Data and methods

This paper summarizes a complex workflow including numerous datasets, calculations, analyses and interpretations, which are summarized in Fig. 1. The data and methods are described in the following sub-sections.

2.1 Database of catchment descriptors and flow signatures

A database of catchment descriptors (climate, physical and human alteration) was compiled for 35 215 European catchments with a median size (total upstream area of the outlet) of 493 km^2, ranging from 1 to 800 000 km^2 (Fig. 2). The geographical domain (8.8 million km^2) was delineated according to plate tectonic borders and catchment borders all the way

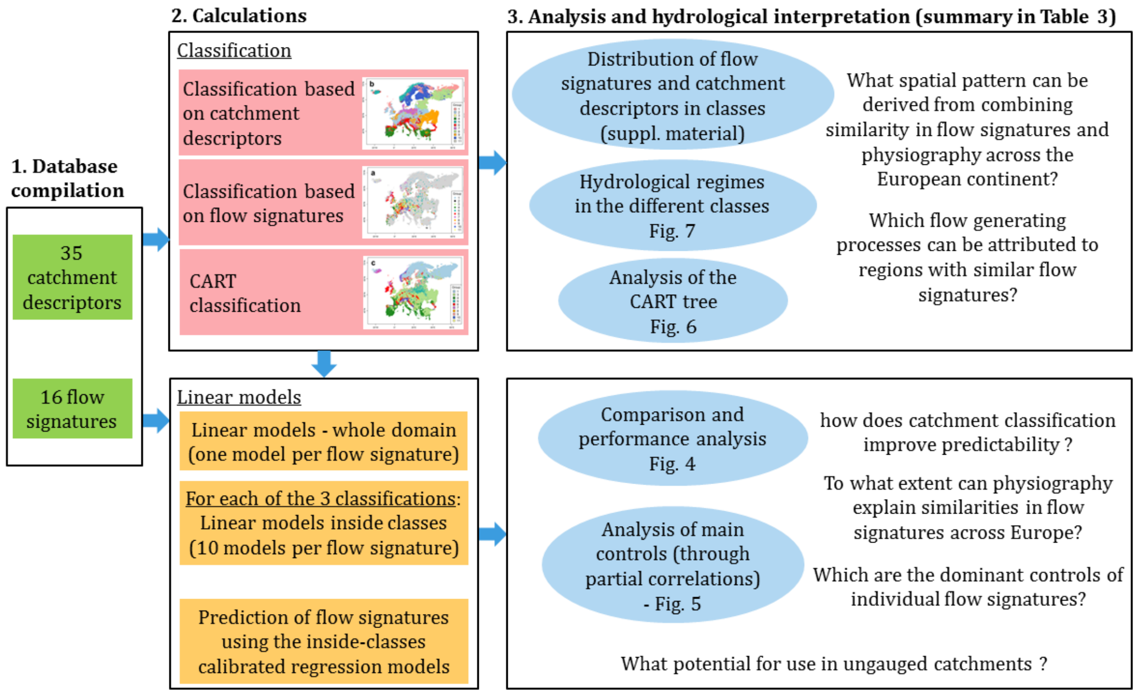

Figure 1. Flow chart of the different steps followed in the study.

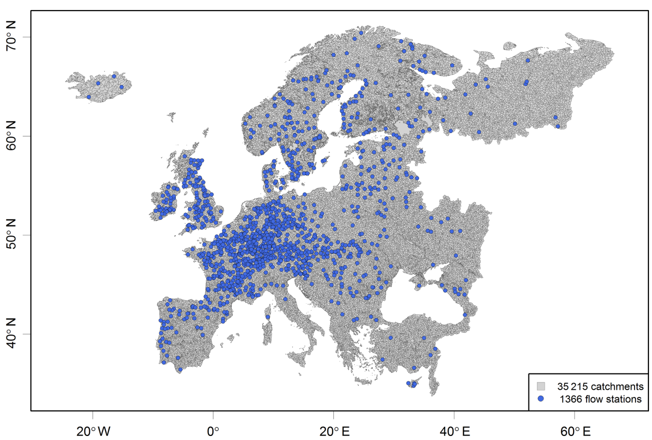

Figure 2. Spatial extent of the study showing catchment division and selected river gauges.

down to the European coast and to the Ural Mountains in the east.

For each catchment, 48 catchment descriptors were assigned using upstream topography, climate, soil types, land cover (including human alterations) as well as geology from open data sources (Table 1). Descriptors were estimated as spatial means of the upstream area and assigned to each catchment outlet.

Flow signatures were compiled using daily hydrograph time series of the Global Runoff data Center (GRDC) and European Water Archive (EWA) databases from initially 2690 flow gauges across our study domain selected based on agreement between catchment size in metadata and the delineation in pan-European hydrological model E-HYPE (Donnelly et al., 2012). A subsample of this database was selected for this study according to data availability. In order to ensure the reliability of the analyses of flow signatures, only gauging stations with at least 5 whole calendar years of continuous daily data have been selected (2016 stations). Others subsamples with longer time series (such as 10, 15, 20, 25, and 30 years) were extracted for result evaluation. No missing data were allowed over the period and the longest continuous time series was used at each gauge. This means that time periods differ between gauging stations, but consistent descriptors of precipitation and temperature were always used to match the observed period. Finally, all hydrographs of the resulting subset of flow gauges were visually checked for a 10-year period. This quality assurance mainly eliminated heavily regulated stations, obviously erroneous hydrographs or wrong time steps (e.g., monthly), still keeping stations with moderately altered flow. After this selection, the final set of streamflow stations used in the study included 1366 gauging stations.

For each river gauge, 16 flow signatures were computed (Table 2). The choice of flow signatures has been guided by a study by Olden and Poff (2003), which provides recommendations for selection of nine indices describing flow regimes with importance to hydro-ecology. In addition, five flow signatures commonly used in hydrology have been added for comparability (Qsp, CVQ, Q5, Q95, RBFlash) and two variables describing catchment response were calculated (RunoffCo and ActET).

2.2 Cluster analysis for catchment classification

We classified the catchments based on their similarities in (1) flow signatures for gauged sites only, (2) catchment descriptors, and (3) catchment descriptors selected from regression tree analysis of the classes identified using method 1.

For the first two analyses, we used the same clustering method. The catchments were grouped into classes of similar characteristics (of physiography or flow signatures, respectively) using a hierarchical minimum-variance clustering method. The method groups clustering objects (catchments) so that the within class variability is minimized using a combination of the k-means algorithm (Hartigan and Wong, 1979) and Ward's minimum-variance method (Ward, 1963). Clustering started with the k-means algorithm with a large number of classes (50) and classes were merged hierarchically using Ward's minimum-variance method. Two classes are merged in such a way that the increase in the sum of the within-class variance of the classification variables weighted by the respective class size across all classes is minimal. After each merging step, the k-means algorithm was applied to the reduced number of classes. The optimum number of classes was established by evaluating the changes in the sum of the weighted variance of the variables across all classes between successive merging steps. The point where the rate of change becomes steeper was set as the optimum number of classes.

We performed classification using 16 flow signatures and 35 of the catchment descriptors, which have some correlation with flow signatures (correlation significance tested on Pearson correlation using a t distribution with a threshold of 0.05). In order to reduce the effect of possible correlations between the different catchment descriptors or flow signatures, we applied principal component analysis (PCA). PCA enables derivation of a set of independent variables, which could be much fewer than the original variables, thereby reducing the dimensionality of the problem. The number of principal components selected for further classification was fixed so that they account for at least 80 % of the total variance of the original variables.

The third classification was done for all catchments – both gauged and ungauged, using a predictive regression tree, the so-called CART (Breiman et al., 1984), calibrated to match the classes identified with method 1. CART stands for classification and regression trees, and gathers algorithms based on recursive partitioning, aiming either at classifying a sample or at predicting a dependent variable (here the class of the flow station classification) based on a set of explanatory variables (here the set of catchment descriptors). At the different consecutive levels (nodes of the tree), two groups of catchments are divided based on a logical expression using one of the explanatory variables (dominant catchment descriptors). Our idea was to obtain a classification close to the one based on the flow signatures but available for the whole set of catchments. Using CART, a regression tree was first adjusted to predict the classes of the flow signature classification using criteria based on catchment descriptors, and then this tree was used in a predictive way to classify all catchments in the domain. It was calibrated using an automatic recursive partitioning based on methods described by Breiman et al. (1984) and provided in R package "rpart" (see Atkinson and Therneau, 2000). CART has been used previously for understanding controls on groupings of catchments in relation to their hydrologic behavior (e.g., Sawicz et al., 2014) or of hydrologic model parameters or model input and their regional predictors (e.g., Singh et al., 2014; Deshmukh and Singh, 2016).

2.3 Analysis of physiographic controls of flow characteristics

To examine the link between physiography and flow regimes across our geographical domain, matrices of correlation coefficients between all pairs of catchment descriptors and flow signatures were computed using three different correlations: Pearson correlation, Spearman correlation and distance correlation (e.g., Székely and Rizzo, 2009). Significance of correlations was tested based on a t distribution with a threshold of 0.05. This analysis, whose results are presented in Sect. A of the Supplement, revealed significant correlations between some of the variables, generally consistent with our a priori knowledge (e.g., Donnelly et al., 2016). However, a number of catchment descriptors did not show any significant relationship with any of the flow signatures and were thus removed from the set of variables for the rest of the analyses. These variables are written in grey color in Table 1.

The correlation matrices were accompanied by a visual analysis of scatterplots of all pairs of variables for quality control to avoid disinformation. Statistical distributions of flow signatures were plotted for different subsets of stream gauges according to the minimum length of the period of continuous daily data availability. Unrealistic values, such as runoff ratios above 1, identified gauging stations that were filtered out for the following analyses. Similarly, spatial distributions of all catchment descriptors and flow signatures were plotted as maps. Most of the maps show rather coherent patterns across Europe and could thus be compared to other sources and local knowledge for additional visual quality control.

To evaluate the importance of catchment classification, we compared the performance of multiple regression models when developed for the whole domain versus those where regressions were derived separately for each class of grouped catchments. For a given flow signature, models were explored using a stepwise regression with forward selection, starting from a simple model using only the best correlated descriptor (according to Pearson's linear correlation) and up

Table 1. Catchment descriptors and the original source of information. Type of descriptor is indicated in brackets after variable name (T: topography; LC: land cover; S: soil type; G: geology; C: climate). Variables marked with grey color were removed from the analysis because no significant correlation was found between these and the flow signatures (see Sect. 2.3).

Variable	Unit	Data source	Description
Area (T)	Km^2	SMHI: E-HYPE (Donnelly et al., 2016) http://hypeweb.smhi.se/	Total upstream area of catchment outlet
meanElev (T)	m	USGS: Hydrosheds and Hydro 1K (for latitude $>60°$; Lehner et al., 2008)	Mean elevation
stdElev (T)	m	(same as above)	Standard deviation of elevation
meanSlope (T)	–	(same as above)	Mean slope
Drainage density (T)	Km^{-2}	(same as above)	$\frac{\text{Total length of all streams}}{\text{Area}}$
10 land cover variables (LC)	–	CORINE; GLC2000 (Bartholomé and Belward, 2005; for areas not covered by CORINE, 2014); GGLWD (lake area, distribution, Lehner and Döll, 2004); EIM (EU-scale irrigation, Wriedt et al., 2009); GMIA (global-scale irrigation, Siebert et al., 2005)	% of catchment area covered by the following land cover types: water/glacier/urban/forest/agriculture/pasture/wetland/open with vegetation/open without vegetation/irrigated
7 soil variables (S)	–	ESD (Panagos, 2006); DSMW	% of catchment area covered by the following soil types: coarse soil/medium soil/fine soil/peat/no texture/shallow/moraine
21 geological variables (G)	–	USGS Geological maps of Europe and the Arabian Peninsula (Pawlewicz et al., 1997; Pollastro et al., 1999)	% of catchment area covered by the following geological classes: Cenozoic (Cz), Cenozoic–Mesozoic (CzMz), Cenozoic–Mesozoic intrusive (CzMzi), Cenozoic volcanic (Czv), Mesozoic (Mz), Mesozoic–Paleozoic (MzPz), Mesozoic–Paleozoic metamorphic (MzPzm), Mesozoic intrusive (Mzi), Mesozoic metamorphic (Mzm), Mesozoic volcanic (Mzv), Paleozoic (Pz), Paleozoic intrusive (Pzi), Paleozoic metamorphic (Pzm), Paleozoic–Precambrian (PzpCm), Paleozoic–Precambrian metamorphic (PzpCmm), Paleozoic volcanic (Pzv), intrusive (i), metamorphic (m), Precambrian (pCm), Precambrian intrusive (pCmi), Precambrian volcanic (pCmv)
Karst (G)	–	World Map of Carbonate Soil (2015) Outcrops V3.0 (University of Auckland)	% of catchment area marked as "carbonate outcrop" in the World Map of Carbonate Soil Outcrops V3.0
Pmean (C)	mm	WFDEI (Weedon et al., 2014)	Mean annual precipitation
SI.Precip (C)	–		Seasonality index of precipitation: $SI = \frac{1}{R} \cdot \sum_{n=1}^{12} \left\| \overline{x}_n - \frac{\overline{R}}{12} \right\|$ $\overline{x}_n$: mean rainfall of month n, $\overline{R}$: mean annual rainfall
Tmean (C)	°C	WFDEI (Weedon et al., 2014)	Mean annual temperature
AI (C)	–	Precipitation, temperature and wind from WFDEI (Weedon et al., 2014)	Aridity Index: PET/P, where PET is the potential evapotranspiration calculated with the Jensen–Haise algorithm (Jensen and Haise, 1963).

to a model including all descriptors. At each step, the descriptor giving the best improvement with respect to BIC (Bayesian information criterion) is added, and the algorithm stops when no further improvement can be obtained. The coefficient of determination of each model was then plotted and the final number of variables was determined based on this plot. For a given classification, as many models as the number of classes in the classification were calibrated for each

Table 2. Description of the 16 flow signatures studied.

Component of flow regime		variable	Unit	Description
Magnitude of flow events	Average flow conditions	skew	–	skewness = mean/median of daily flows
		Qsp	$\mathrm{L\,s^{-1}\,km^{-2}}$	mean specific flow
		CVQ	–	coef. of variation = SD/mean of daily flows
	Low flow conditions	BFI	–	Baseflow index: 7-day minimum flow divided by mean annual daily flow averaged across years
		Q5	$\mathrm{L\,s^{-1}\,km^{-2}}$	5th percentile of daily specific flow
	High flow conditions	HFD	–	High flow discharge: 10th percentile of daily flow divided by median daily flow
		Q95	$\mathrm{L\,^{-1}\,km^{-2}}$	95th percentile of daily specific flow
Frequency events of flow	Low flow conditions	LowFr	$\mathrm{year^{-1}}$	total number of low flow spells (threshold equal to 5 % of mean daily flow) divided by the record length
	High flow conditions	HighFrVar	–	coef. of var. in annual number of high flow occurrences (threshold 75th percentile)
Duration of flow events	Low flow conditions	LowDurVar	–	coef. of var. in annual mean duration of low flows (threshold 25th percentile)
	High flow conditions	Mean30dMax	–	mean annual 30-day maximum divided by median flow
Timing of flow events		Const	–	Constancy of daily flow (see Colwell, 1974)
Rate of change in flow events		RevVar	–	Coef. of var. in annual nb of reversals (change in sign in the day-to-day change time series)
		RBFlash	–	Richard–Baker flashiness: sum of absolute values of day-to-day changes in mean daily flow divided by the sum of all daily flows
Catchment response		RunoffCo	–	Runoff ratio: mean annual flow (in $\mathrm{mm\,yr^{-1}}$) divided by mean annual precipitation
		ActET	$\mathrm{mm\,yr^{-1}}$	Actual evapotranspiration: mean annual precipitation less mean annual flow (in $\mathrm{mm\,yr^{-1}}$)

of the 16 flow signatures, and their joint performances were evaluated. To be consistent, regression models were only analyzed for classes with more than 30 gauging stations, and therefore 17 gauging stations (from 2 classes of the catchment descriptor classification and 1 class of the flow signature classification) were removed from this analysis because they ended up in classes with fewer stations. In total, 480 regression models were developed in our analysis. For each classification method and flow signature, we explored the influence of different types of catchment descriptors by examining their partial correlations in the regression.

To gain better understanding of processes behind the hydrologic variability, we further examined similarities in both flow signatures and catchment descriptors for each of the classes based on the CART classification. Each class was described by geographical locations, most characteristic physiography and flow regime. Based on this analysis, hydrological interpretation was used to identify potential drivers of hydrological processes, which are dominant in each cluster. The analysis was assisted by several sources of information for classes and sub-classes, such as boxplots of variability in both flow signatures and catchment descriptors, matrices showing the median characteristics in each class, visualization of hydrographs in diagrams, and mapping spatial patterns geographically (most of this material is found in the Supplement).

3 Results and discussion

3.1 Catchment classifications

An automatic clustering based on flow signatures was performed first as explained in Sect. 2.2. We found that 11 classes were optimal for the database used in this study. The same number of classes was then chosen for the classification based on catchment descriptors. As described in Sect. 2, the third classification (through CART analysis) was based on the classes from the classification of flow signatures. However, class No. 2, which contains only four gauges (all situated in Cyprus), was excluded from the CART analysis for consistency. As a result, the classification derived from the CART tree only contains 10 classes (numbered 1 and 3–11).

During the CART analysis and classification, we found that 20 nodes in the tree was a good compromise to allow all 10 classes to be predicted while minimizing the complexity of the tree (to make the relationships between catchment descriptors and signatures interpretable) and maximizing the

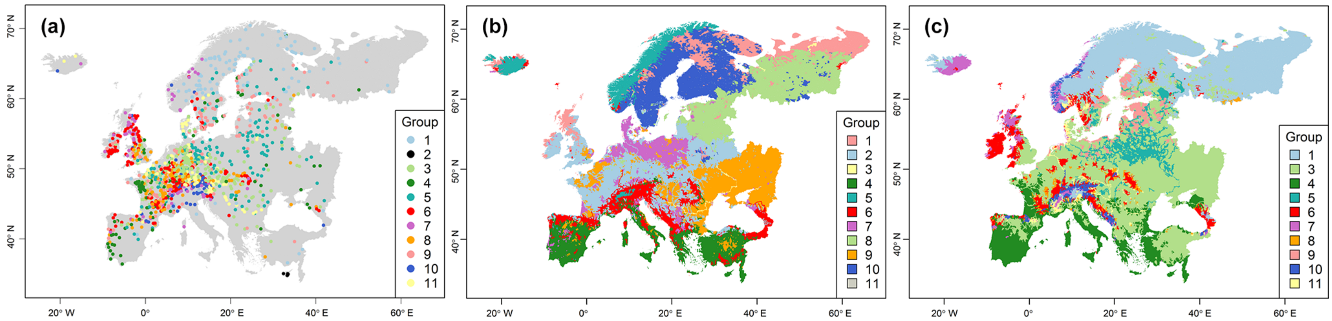

Figure 3. Spatial patterns of catchment classification across Europe based on **(a)** flow signatures at flow gauges, **(b)** catchment descriptors, and **(c)** a CART predictive regression tree.

probability of correct classification of catchments (relative error = 0.59; cross-validation error 0.69; minimum probability of correctly classified stations at a node = 0.35). The average percentage of correctly classified gauged catchments in each class was 60 % (ranging between 35 and 88 % across the leaf node; see Table A in the Supplement). It should be noted that one node (node 3a; see Fig. 6) contained more than a third of the catchments (13 645 catchments) and only 35 % of the gauges in that node were correctly classified. Efforts to further classify catchments in this node through an increase in the complexity of the tree did not result in a good compromise. Indeed, to reach a level of 40 % of correctly classified gauges at all nodes, the tree had to be detailed up to more than 400 nodes, making any hydrological interpretation of the splits impossible.

The first two classifications, based on clustering of either the flow signatures or the catchment descriptors alone, resulted in very different spatial patterns of similarity across Europe (Fig. 3; note that there is no correspondence between the numbering of the catchment classes used in maps a and b). Correspondence between the two classifications is not expected as the two classifications were performed using different sets of data. The third classification – where we predict the flow-based classification from the catchment descriptors – exhibits spatial patterns that are rather similar to the flow signature-based classification, which is expected since the former is derived from the latter through a CART predictive regression tree. Detailed discussion of results in terms of the classification based on flow signatures will, therefore, be focused on results obtained from the CART-based classification.

In order to analyze the specific characteristics of the different classes in terms of catchment descriptors and flow signatures, boxplots representing the distribution of each variable within the classes were plotted (see Sect. D.1 and D.2 of the Supplement). For the classification based on flow signatures (Fig. 3a), some clear distinctions appear between classes in terms of mean specific flow and coefficient of variation of daily flow. For example, class nos. 7 and 10 have the highest mean specific flows, while class nos. 2 and 4 have the highest coefficients of variation. Concerning the percentage of agricultural area, some classes cover a wide range of values (nos. 3, 4, 5, and 11), while others contain mostly catchments with low percentages of area covered by agriculture (nos. 1 and 7).

The spatial pattern in Fig. 3b (based on catchment descriptors) shows geographically coherent patterns, with for example class No. 6 bringing together mainly mountainous areas, No. 4 gathering southern warm catchments, and No. 7 representing plain regions of the Netherlands, northern Germany, Denmark and Poland. Analysis of the distribution of the different variables in the classes (see boxplots in Sect. D.2) showed for example that class No. 5, which is mainly located in western Norway and Iceland, gathers catchments with low mean temperatures and high mean precipitations with a high proportion of open areas without vegetation. In terms of flow signatures, these catchments have high mean and high flows, high runoff ratios and low actual evapotranspiration. Class No. 11 contains 323 catchments (mainly small lake catchments in northern Europe), but none of them corresponds to a stream gauge included in the study. Thus, no observations are available to characterize flow signatures for this class. Observations are limited as well for class No. 3 as only 13 of the 152 catchments that belong to this class (mainly large catchments corresponding to the downstream parts of big rivers flowing to the Black Sea and the Arctic Ocean) correspond to a flow station. These two classes were thus excluded from further analysis.

Only clustering using catchment descriptors or CART can be applied for the whole domain, i.e., in ungauged catchments. The CART-based catchment classification (Fig. 3c) was chosen for more detailed analysis (in Sect. 3.3) of similarities in flow-generation processes as the classes were more homogenous. When looking at the classification based on catchment descriptors, the average standard deviation of each catchment descriptor within all classes was estimated to be 0.71, and the average standard deviation of the flow signatures was 0.78. For the CART classification, these numbers are 0.76 for catchment descriptors and 0.67 for flow signatures. Hence, the former discriminates classes more in terms of physiography (0.71 versus 0.76 for the CART classification) and the CART classification discriminates classes more in terms of flow signatures (0.67 versus 0.78).

3.2 Using regression analysis to understand controls on individual signatures

As explained in Sect. 2.3, multiple regression models for signature prediction were developed both using the entire domain and within each group of the three classifications, and their results were compared. The regression constants are given for each of the 480 calibrated linear models in Sect. E of the Supplement. This analysis step provides us with two insights. First, what are the dominant controls on individual signatures? Second, how predictable are individual signatures given available catchment/climate descriptors? Figure 4 shows that developing regressions for each of the classes derived leads to better predictive performance than developing an individual regression for each signature using all catchments at once. This could be expected as using 10 models instead of only 1 increases the degree of freedom as the number of calibrated parameters increases. This result is consistent with previous findings (e.g., Almeida et al., 2016), which also found that single high performing regressions across large domains are difficult to achieve. On average, classification using catchment descriptors and CART improved the model performance by 14.7 % and flow signatures by 33 %. The latter yields the best results since this classification is based directly on the discriminating variables (flow signatures). There are few differences in terms of the performance of the models obtained using either the catchment descriptors or CART for classification, the later giving slightly better results for most of the variables (e.g., Q5, high flow discharge, high flow frequency variability, variability of reversals, flashiness, runoff ratio), but poorer results for baseflow index and low flow frequency. The performance of the regression models for the different flow signatures will be further discussed in Sect. 3.4.

The partial correlation analysis of the regression models shows that there are different controls for the different flow signatures (Fig. 5). The highlighted controls are rather similar across the different classification methods; i.e., the patterns seen in all three plots are very similar (Fig. 5a–c). This suggests that the identification of controls is robust, while the performances of the different regressions vary. Climatic descriptors play the most important role for most of the flow signatures, especially those related to average and high flows. For the baseflow index, geology is more important and, for the flashiness of flow, topography is the main control. Topography also plays an important role in low flow magnitude (Q5), being the main driver for this signature in some of the classes and for the global model. For most of the flow signatures, the second most important descriptor is generally land cover (mean flow, high flows, runoff coefficient, ET, variability of reversals).

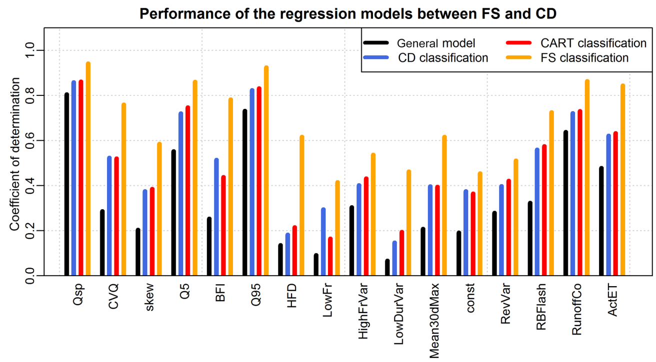

Figure 4. Performance of regression models when calibrated for each flow signature (Table 2) and applied over the whole domain with a general model or one per class, using catchment classification based on catchment descriptors (CD), flow signatures (FS) or regression trees (CART). Performance is evaluated over the whole set of flow gauges together even if different models are used in different classes.

The importance of the different controls varies across the classes (length of the boxplots in Fig. 5) and the main drivers for a given variable can also differ between classes (not shown in the figure). For example, climate is a strong driver for almost all signatures in class No. 4 (warm regions in southern Europe), while other drivers play an important role in other parts of Europe, for example in class nos. 7 (topography, land cover and geology are important), 9 (topography) and 10 (topography and land cover). This shows that the drivers behind hydrological responses vary between European regions.

The identified controls for the different flow signatures are generally consistent with the findings of previous studies conducted in different parts of the world. For instance, Longobardi and Villani (2008) and Bloomeld et al. (2009) found a strong relationship between the baseflow index and geology for the Mediterranean area and the Thames basin, respectively. Similarly, Holko et al. (2011) found out that the flashiness index is correlated with geology, catchment area and elevation as well as percentages of agricultural and forest land uses for catchments in Austria and Slovakia. For catchments across the US, Yaeger et al. (2012) found out that the upper tail of the flow duration curve is controlled more by precipitation intensity, while the lower tail is more controlled by catchment landscape properties such as soils and geology. For the same US dataset, Sawciz et al. (2011) showed that the runoff coefficient was dominated by aridity, and that the baseflow index was controlled by soil and geological characteristics. The influence of topography on the magnitude of low flow was also found by Donnelly et al. (2016) through a correlation analysis of a set of flow signatures and catchment descriptors across Europe.

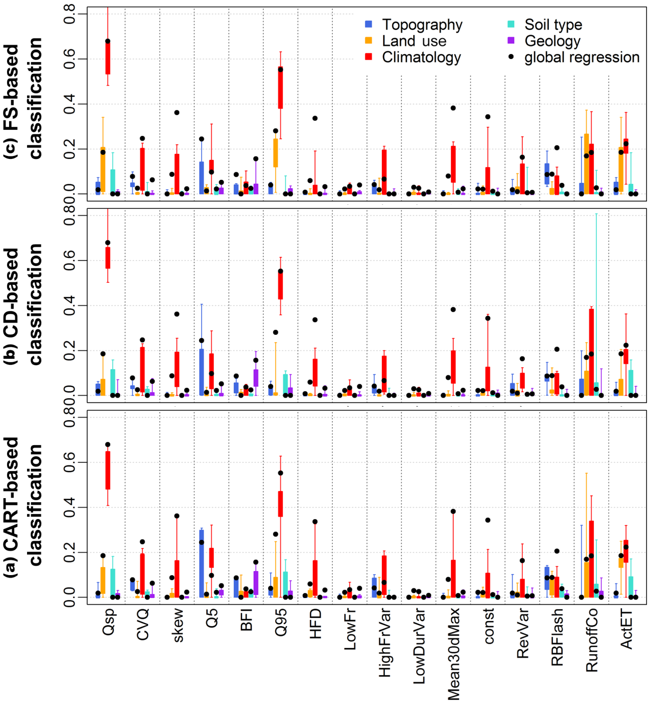

Figure 5. Partial R^2 of different types of descriptors (Table 1) used in the regression models for flow signatures (partial R^2 for the type of descriptors is the sum of partial R^2 of variables from that type used in the regression model). The boxplots show the range of values among the models calibrated in the different classes using the different catchment classification methods: **(a)** flow signatures at flow gauges, **(b)** catchment descriptors, and **(c)** CART predictive regression trees. The black point gives the value for the general model calibrated over the whole domain.

3.3 Hydrological interpretation of classes using CART

The regression tree classification (CART) enabled us to understand the main controls driving the separation into classes (rather than individual signatures), as it predicts the classes of flow signature combinations from the available catchment descriptors. In the resulting tree (Fig. 6), the main variable separating the different classes is the Aridity Index (AI) with a separating value close to 1. This purely empirical finding is nice, because this value separates the energy-limited catchments ($AI < 1$) from the moisture-limited catchments ($AI > 1$). As expected for classification over such a large domain, we therefore find climate to the first-order control. Mean temperature is the second separating variable, followed by variables describing soil types (peat, moraine), land cover (agriculture, open without vegetation, wetland, forest), topography (area, mean elevation) and climate (precipitation seasonality index, mean precipitation). This indicates the order of importance of catchment descriptors that control flow signatures moving from climate to other descriptors.

Some of the differences between the hydrographs within catchment classes and across catchment classes can be seen in Fig. 7, where we show examples of the observed time series. We found the following characteristics, which are summarized in Table 3 and further supported by results figures in Sect. C of the Supplement.

Class No. 1 has a rather smooth flow and seasonal flow pattern with a very pronounced spring flood peak. These catchments are located in a cold northern part of Europe and some parts of the Alps and Caucasus, characterized by spring snowmelt with some dampening in lakes and wetlands.

Class No. 3 is a very large (about 1/3 of the catchments) miscellaneous class without any distinct character. As explained in Sect. 3.1, efforts to further classify catchments in this class (and more specifically in node 3a) did not succeed.

Class No. 4 is characterized by very spiky hydrographs with high peaks and low baseflow. The flow regime exhibits high winter flows and low summer flows. Catchments are located in the Mediterranean region characterized by arid climate, flow seasonality and human impacts.

Class No. 5 shows relatively low flows with some influence of snowmelt (spring flood) for some catchments during some years. This is the northern part of central–eastern Europe characterized by low flashiness due to the large number of water bodies, low topographic slopes, and low elevation, which dampen the flow response.

Class No. 6 has very high peaks, especially during winter, and high flow periods in general: overall, flashy flow with a tendency to lower flow during summer and geographically scattered humid areas all over Europe.

Class No. 7 shows in general high and flashy flows: for most catchments these are higher winter flows, though for some catchments they are summer high flows instead, due to snowmelt and glacier melt (this is the class with the most glaciers; see Fig. G of the Supplement). This class encompasses wet and cold mountainous areas along the coasts in northwestern Europe and some humid parts of the Alps.

Class No. 8 is characterized by peaky flow throughout the year, with higher peaks in winter. This class consists of smaller headwater catchments in some warm and humid parts of central, southwestern and northeastern Europe.

Class No. 9 has rather low flow, with a snowmelt-dominated spring flood. Low amplitude but frequent short-term variability. These catchments are mainly in flat lands around the Baltic Sea and North Sea further characterized by forests, lakes and wetlands. Some catchments exhibit similar geological structures (Pz, pCmi; see Fig. K in the Supplement).

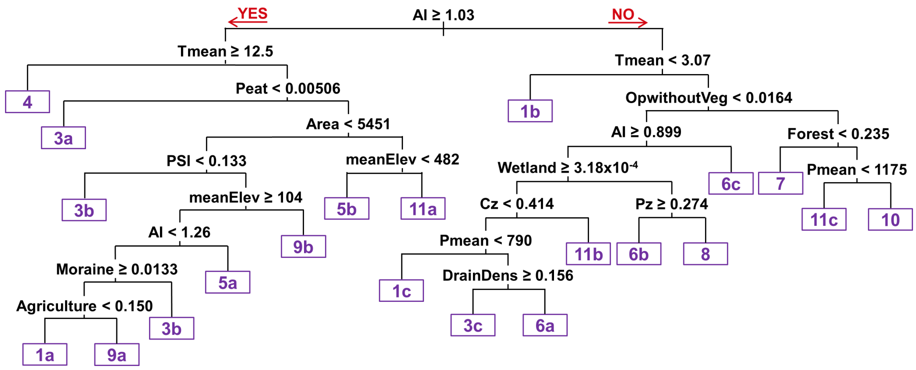

Figure 6. CART tree adjusted on the FS classification and used as a predictive tree for the CART classification.

Class No. 10 shows high flows with very high and frequent peaks, some tendency to peaks in spring, but also high flow during winter. Frequent short-term variability is common in these wet, high elevation and steep catchments across mountain ranges of Europe.

Class No. 11 is characterized by sustained high baseflow and some tendency to spring season peaks in some catchments, but overall low seasonality of flow. These catchments are close to mountains or in lower parts of large river basins. We suspect some outliers in this class when extrapolating the CART tree to the full European domain, as parts of the catchments in this class were not representative of the majority of river gauges in the same class (see Fig. M in the Supplement, showing that the gauged catchments in node 11b have different characteristics than those in nodes 11a and 11c).

The hydrological interpretations of the detected spatial patterns (Table 3) pointed to climate as the main control of the hydrological response in most classes (which is consistent with the Aridity Index as the main control in Fig. 6). This is highlighted by the notable influence of rainfall-driven river flow in class nos. 6, 7, and 8 (western and northern Europe) throughout the year, and during winter in 4 (southern and eastern Europe). The latter region is most obviously strongly affected by evapotranspiration, while snow-dominated regimes with a spring melt season are characteristic of class nos. 1, 7, and 9 and to some extent also nos. 5 and 10. These classes are found in the northern and mountainous parts of Europe.

Regarding landscape influence, dampening effects of river flow response are found in class nos. 1 and 5, due to the presence of many water bodies and vast flatland areas. Continuously strong baseflow is found in class nos. 9 and 11 through lateral flow, large catchment sizes or upstream mountainous areas. On the other hand, class nos. 7, 8 and 6b show fast response and low storage capacity, which could be attributed to their thin soils, high slopes or small catchment sizes.

Impact from hydropower production was found in class nos. 1, 9, and 10, which were all snow-dominated but showed redistribution of water during the year due to regulation and in some cases influence of short-term regulation. It should be noted that this effect was visible although the gauges from most regulated rivers were already excluded from the study (Sect. 2.1). Human alteration was also assumed to dominate the hydrological response in class No. 4, where the hydrographs did not look natural and irrigated areas are large (southern and eastern Europe).

Interestingly, some classes were found to have similar flow signatures but for different reasons. For instance, the damping of peak flows in class No. 5 could be caused by either the presence of water bodies (5b) or floodplains with a wider river channel (5a).

The insight gained from this classification analysis varies across the different parts of the European continent as the classes correspond to different percentages of area (Table 3), and for some classes we learned more than for others. The classification highlighted distinct patterns for most of the classes, some of them showing several outstanding signatures or physiography (e.g., nos. 1, 4, 7, and 10), while others had signatures with more average magnitude (e.g., nos. 6 and 8). On the other hand, about 1/3 of the catchments, covering 39 % of the studied area, could not be interpreted hydrologically, as they did not show similarities in flow signature values and showed only little similarity in catchment descriptors (within the 30th percentile of agriculture, moraine and one geological feature; see Table 3). For this part of Europe, we need to search for other or more detailed data of catchment descriptors for understanding the physical controls.

Previous studies have noted that large-scale databases are connected with uncertainties and may sometimes even be disinformative at high resolution (Donnelly et al., 2012; Kauffeldt et al., 2013), which may be a reason for some of the weak statistical relationships and difficulties in catchment classification. European hydrology is also very much affected by human alteration, which is probably not fully covered by the descriptors. Hence, there is still a need for further investigations to better understand hydrologic variability across Europe.

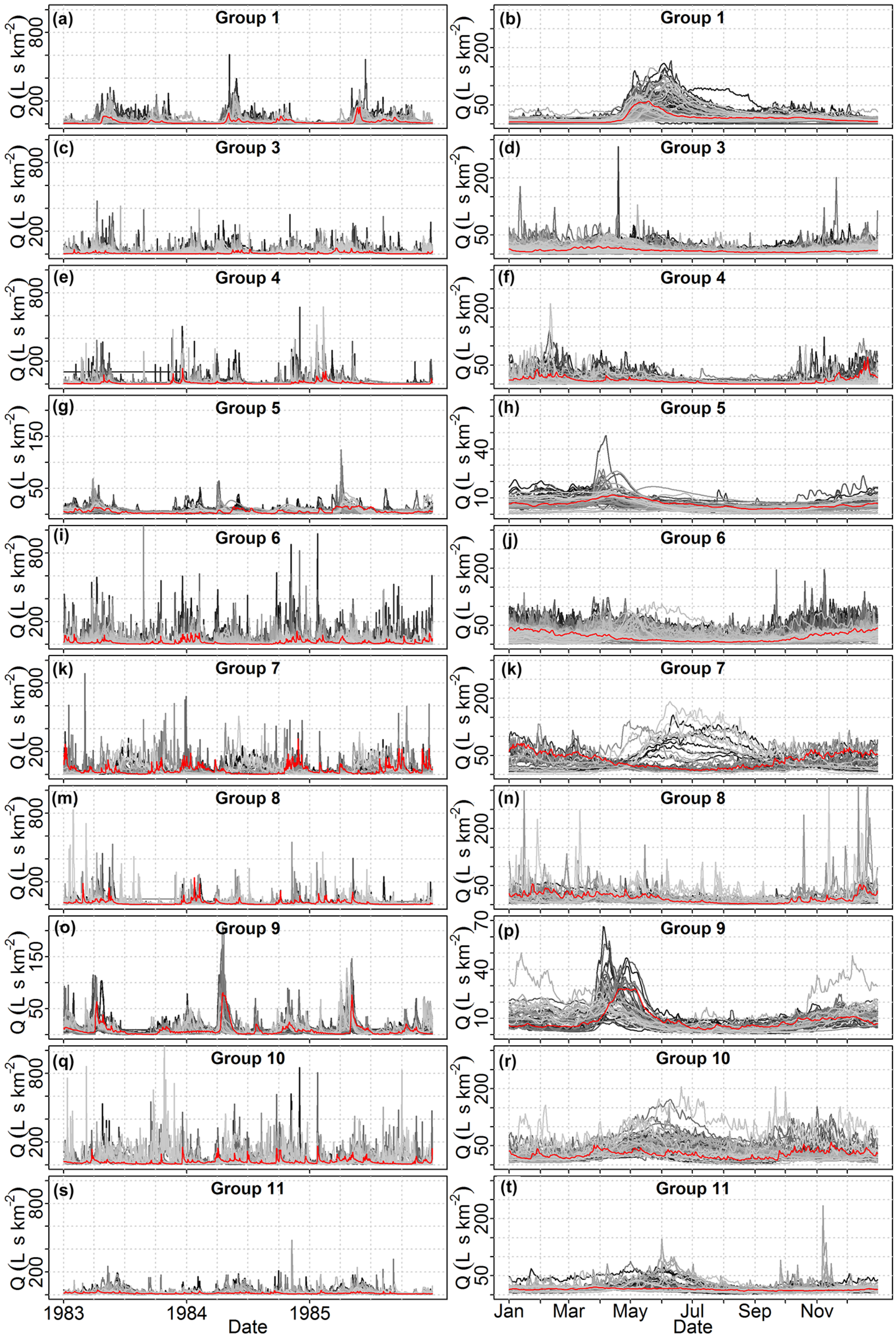

Figure 7. Three-year hydrographs (left) and average annual hydrographs based on > 5-year daily flows (right) at the stream gauges of the CART classification classes. Grey → black: all stream gauges belonging to the class; red: stream gauge where the flow signatures are closest to the class median flow signatures. Note that the scales are different for classes 5 and 9 and that this classification does not contain any class No. 2 as explained in Sect. 3.2.

Table 3. Summary of findings when using the CART tree to classify catchments (CART classification shown in Fig. 3c) and extracting the main features for each cluster. Appointed flow signatures (Table 1) and catchment descriptors (Table 2) have median values in the 30 % low/high percentile of the distribution over whole domain. Bold indicates median values in the 10 % low/high percentile. Supporting figures with boxplots and matrices of flow signatures and catchment descriptors as well as detailed maps of spatial patterns are found in the Supplement (in Sects. C.1, C.2 and C.3).

Class	Sample size		Flow signatures (FS)		Catchment descriptors (CD)		Spatial pattern	Dominant hydrological processes
	No. of catchments	No. of gauges	FS low	FS high	CD low	CD high	(% of map area)	
1	6878	112	RBFlash, ActET	RunoffCo, HighFrVar, Mean30 dMaxRevVar	Urban, agriculture, pasture, Medium AI, DrainDens, Pmean, Tmean,	Water, forest, wetland, OpwithVeg, peat, NoTexture, Moraine, PSI, pCm, PzpCmm	Northern and central Scandinavia, western Iceland, Russia. (22.8 %)	Snow-dominated flow regime with significant snowmelt during spring but rather even flow during the rest of the year due to dampening in lakes, wetlands and low actual evapotranspiration. Flow influenced by some hydropower regulation.
2	–	–		–	–	–	–	–
3	14282	536	–	–	–	Agriculture, Moraine, PzpCmm	Large coverage in western, central and eastern Europe. (38.8 %)	–
4	5112	91	Qsp, Q5, RunoffCo, BFI	CVQ, const, RBFlash, HFD, LowFr, skew, Mean30dMax	Forest, pasture	Agriculture, irrigated, moraine, Tmean, PSI, AI, PzpCmm	Southern and eastern parts of Europe. (15.0 %)	High ET and high human alteration of natural processes. Winter flow is dominated by precipitation, while summer flow is limited by evapotranspiration.
5	1765	72	Qsp, CVQ, Q95, RBFlash, RunoffCo, skew, HFD, Mean30dMax	BFI, HighFrVar, LowDurVar, RevVar	meanElev, stdElev, meanSlope, Pmean	area, Water, Agriculture, Coarse, Peat, Moraine, AI, Cz, PzpCmm	Mainly Poland, Belarus, and Lithuania; some in southern Sweden and Russia (5.6 %)	Water flow is dampened by large river channels and water bodies and flat lands. Some influence of snowmelt-driven flows. One sub-class (5b) is more controlled by water bodies and the other (5a) by surrounding flood plains.
6	3325	261	HighFrVar, RevVar	Qsp, Q95, RBFlash, RunoffCo	AI	Pasture, Moraine, Pmean, PzpCmm,	Rather scattered distribution: the British Isles, southern Scandinavia, Russia, lower regions of mountainous areas. (6.3 %)	Precipitation driven frequent peak flows. One sub-class with rapid response due small area and high slope (6b).
7	678	33	ActET, HighFrVar, LowDurVar, RevVar	Qsp, Q5, Q95, RBFlash, RunoffCo	Urban, Forest, Agriculture, Medium, DrainDens, Tmean, AI	stdElev, meanSlope, Wetland, peat, OpwithVeg, Pmean, OpwithoutVeg, NoTexture, Shallow, moraine, PzpCmm	Southeastern Iceland, Scotland, western Norway, some in the Alps. (2.4 %)	Low storage (in soil and water bodies) that generates quick response to rainfall. Most catchments have rainfall dominated flow but also some are snow and glaciers melt dominated.
8	670	63	BFI, HighFrVar	CVQ, RBFlash, ActET, skew, LowFr,	area, OpwithVeg, NoTexture	Pasture, moraine, Pmean, Tmean, Mz, PzpCmm,	Close to class No. 6 regions in the center of France, Carpathians and Russia. (1.6 %)	Fast response to precipitation since they are small headwater catchments with low storage capacity.
9	969	52	Q5, RBFlash, ActET	HFD, LowFr, LowDurVar, Mean30dMax, RevVar	meanElev, stdElev, meanSlope, Pasture, Pmean, Tmean	Water, forest, Wetland, peat, NoTexture, moraine, PzpCmm,	Around the Baltic Sea and along the North Sea and English Channel coast. (3.2 %)	Snow-dominated flow regime with significant snowmelt during spring. Indications of short-term regulations. Continuous contribution through lateral flow leading to a more sustained flow.
10	762	79	CVQ, skew, HFD, HighFrVar, Mean30dMax, RevVar	Qsp, Q5, Q95, RunoffCo, BFI, const	Agriculture, Tmean, AI	meanElev, stdElev, meanSlope, Pmean, OpwithVeg, PzpCmm, OpwithoutVeg, Shallow, Moraine,	Mountainous regions of western Norway, Pyrenees, Alps, Bosnia, Montenegro, a few in the Carpathians and Scotland. (2.3 %)	Regulated flow for hydropower production during winter but still with some tendency of spring flow.
11	774	67	CVQ, RBFlash, skew, HFD, Mean30dMax	Q5, BFI	–	area, meanElev, stdElev, meanSlope, Water, Irrigated, OpwithoutVeg, Coarse, Moraine, DrainDens, Cz, pCm, Pzi, PzpCmm	SE France, northeastern Italy, western Denmark, southeastern Norway, some in Sweden, large catchments of big rivers like the Rhine and Danube. (2.0 %)	Flow is governed by continuous supply from upstream storages either from large upstream areas or upstream mountains. (Note: some catchments (e.g., in Denmark) are not representative of the gauges in this class.)

3.4 Application of the results: predicting flow signatures over Europe

Figure 8 shows the result of predicted flow signatures using the regression models calibrated within each class of the CART classification. As shown in Fig. 4, the performances of these models are diverse: some flow signatures are well modeled (R^2 above 0.8 for mean specific flow and the 95th quantile, above 0.7 for the 5th quantile, runoff ratio, skewness of daily flow, mean 30-day maximum), but some other models perform very poorly (R^2 below 0.2 for low flow frequency and variability of low flow duration). It is well recognized that modeling low flows can be difficult (e.g., Nicolle et al., 2014; Donnelly et al., 2016; Zhang et al., 2015) and the correlation matrices (see Supplement) showed that these two flow signatures were poorly correlated with catchment descriptors. This highlights the difficulties in understanding process and physical controls to predict low flows with the datasets currently available to us.

The performances also vary from class to class (not shown here). Models are generally poor (most R^2 below 0.4, a few between 0.4 and 0.6) in class No. 3, which is a very large and miscellaneous class, but also for class nos. 6 and 8, which bring together mostly humid catchments rather scattered over the continent. On the other hand, the best performances are observed in class nos. 7, 10 and 11, containing a majority of mountainous or close to mountainous catchments. Good performances were also observed for at least some of the flow signatures in classes 1, 4 and 5 covering both northern Europe and arid Mediterranean regions.

Figure 8 shows that some negative values appear when applying the calibrated regression models to predict flow signatures. This is explained by the larger range of values of the predicting variables in the whole domain than in the subset of 1366 catchments with flow stations. For example, the predicted values for the 5th quantile of daily flow are negative in 2607 catchments (over the 35 215 modeled), most of them belonging to classes 3 and 4. In class No. 4, the regression for Q5 uses percentage of forest (positive coefficient) and mean temperature (negative coefficient) as the first two predictors. Some negative values appear when the model is applied to catchments with a low percentage of forest and a high mean temperature.

These mitigated results emphasize the empirical nature of these regression models (without process controls) and that they should not be applied outside of the observed ranges of catchment descriptors. However, these regression models help us in improving our understanding of European hydrological processes and identifying the dominant controls of the flow signatures in different parts of Europe (see Sect. 3.2). This understanding can be useful when building models that include physical reasoning.

One implication of the identified spatial pattern of flow characteristics and their dominant physiographic controls is that one can delineate regions of particular flow characteristics, for which part of the hydrograph is important. This could be related to the season or component of the hydrograph where the flow is more sensitive to the controlling physiographic attributes. In addition to establishing empirical relationships between the flow signatures and catchment descriptors, like we did in this work, this has a potential application in improving dynamical rainfall–runoff models across Europe. Design and results of process-based models should be coherent with empirical findings and, when applied on a large scale, they should thus be evaluated against empirical observations of large-scale spatial patterns, like the ones we provided in this paper.

Furthermore, our results could be applied to improve hydrological models, as patterns of flow signatures are used for defining regions globally for regional model calibration (Beck et al., 2016). We showed that regression predictions are improved by 15 % when establishing regressions for separate classes of catchment with similar signatures and controls (see Sect. 3.2). This knowledge could be valuable when estimating parameter values for continental-scale hydrological models. Currently, there is an emerging need for parameter estimation also in ungauged basins from several modeling communities (Archfield et al., 2015). For instance, traditional catchment models have recently been applied on a pan-European scale, e.g., SWAT (Abbaspour et al., 2015) and HYPE (Donnelly et al., 2016). Accordingly, global hydrological models are starting to develop rigorous calibration procedures (e.g., Müller Schmied et al., 2014). The new empirical knowledge we gained in this work could, for instance, be incorporated into the process description of such models. Processes that control the part of the hydrograph that is sensitive to given physiographic attributes can be parameterized and calibrated separately as functions of the physiographic attributes for the different catchment classes (Hundecha et al., 2016). This could ultimately improve the predictive ability of dynamic models in ungauged basins.

4 Conclusions

We set out to better understand hydrological patterns and their controls across the European continent by exploring similarities in flow signatures and physiography. Using open datasets and statistical analysis, we found it possible to attribute dominant flow-generating processes to specific geographical domains. From the analysis of catchment classification using similarities in 16 flow signatures and 35 catchment descriptors across Europe, we can conclude the following.

Physiography is significantly correlated with flow signatures at this large scale and catchment classification improves predictions of hydrologic variability across Europe (15 to 33 % – depending on the classification used – improvement in regression model skills). Different physiographical variables control different flow signatures, though climatic variables play the most important role for most of the flow signatures (12 out of 16). Topography is more important for flashiness and low flow magnitude, while geology is the main control for the baseflow index. All studied flow signatures were significantly correlated with at least one catchment descriptor.

Classes obtained by clustering of flow signatures can be predicted from catchment descriptors. On average, 60 % of the catchments were correctly classified in each class. In total, Europe could be divided into 10 hydrological classes with both similar flow signatures and physiography. The most important physiographic characteristic for predicting classes is

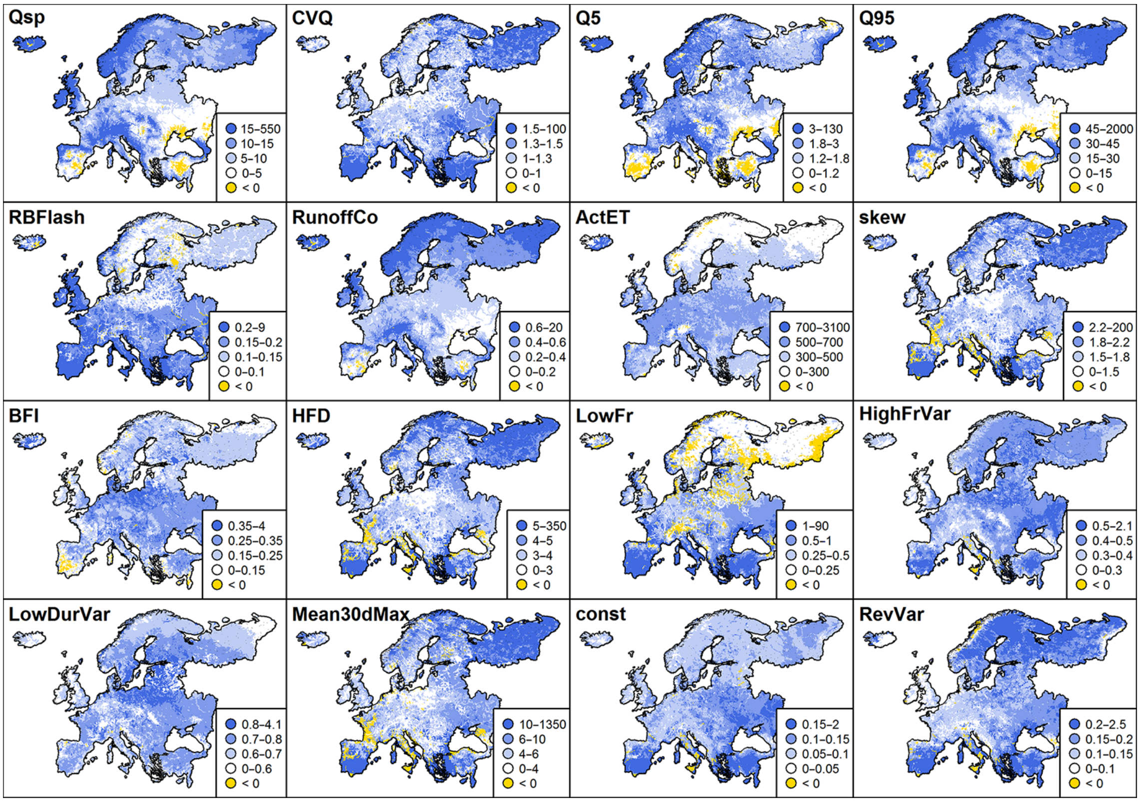

Figure 8. Predicted flow signatures using the regression models calibrated within classes of the CART classification (Fig. 3c). Note that the color intervals are adapted to each signature and do not have a constant size for a given signature: for a better readability they are based on the quartiles of the signature distribution. The coefficients of determination of these models are shown in Fig. 4.

the Aridity Index, which separates the energy-limited catchments from the moisture-limited catchments. Further explanatory variables include soil type, land cover, topography and other aspects of the climate/weather. The CART analyses also separated different explanatory variables for the same class of catchments. For example, the damped peak response for one class was explained by the presence of large water bodies for some catchments, while large flatland areas explained it for other catchments in the same class.

Interpretation of dominant flow-generating processes and catchment behavior (such as rainfall response, snowmelt, evapotranspiration, dampening, storage capacity, and human alterations) could explain the hydrologic variability across Europe to a large extent (61 % of the studied domain area). Distinct patterns with characterized flow signatures and processes appeared for some European regions (e.g., northern Europe, arid Mediterranean regions, mountainous areas), providing useful information for predictions in ungauged catchments in these areas. On the other hand, flow signatures from 1/3 of the catchments (mainly situated in central Europe) could not be classified or understood based on the catchment descriptors available for this analysis. These limitations of our large-scale study call for more detailed analysis with additional data in these areas.

Links between flow characteristics and physiography could potentially be used in spatial mapping of flow signatures (for instance, mean specific flow, the 5th and 95th quantiles, runoff ratio, skewness of daily flow, mean 30-day maximum) for ungauged basins, which might be used in hydrological modeling in the future. The 10 classes of similar catchments may facilitate model parameter estimation in pan-European hydrological models.

Open data sources enable new forms of comparative science and show large potential for research to generate new knowledge and hydrological insights encompassing variable environmental conditions. However, for Europe there is a lack of homogenous datasets for human impact on flows, such as local water management, abstractions and regulation schemes. There is thus still a need for opening up more public sector data for re-use and, especially, for compiling large-scale databases on the global or continental scales across administrative borders.

Data availability. Additional information on the experiment with protocols and links to data scripts are available at http://www.switch-on-vwsl.eu/. The data that support the findings of this study are available in Zenodo with the identifiers https://doi.org/10.5281/zenodo.581435 (Kuentz et al., 2017g) for the river flow gauge selection (shapefile); https://doi.org/10.5281/zenodo.581428 (Kuentz et al., 2017a) for the climatologic catchment descriptors; https://doi.org/10.5281/zenodo.581429 (Kuentz et al., 2017b) for the geologic catchment descriptors; https://doi.org/10.5281/zenodo.581430 (Kuentz et al., 2017c) for land use catchment descriptors; https://doi.org/10.5281/zenodo.581431 (Kuentz et al., 2017d) for soil types (catchment descriptors); https://doi.org/10.5281/zenodo.581432 (Kuentz et al., 2017e) for topographic catchment descriptors; https://doi.org/10.5281/zenodo.581433 (Stromback, 2017) for catchment delineation (shapefile) and https://doi.org/10.5281/zenodo.581434 (Kuentz et al., 2017f) for the flow signatures.

The Supplement related to this article is available online at https://doi.org/10.5194/hess-21-2863-2017-supplement.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This study was performed within EU FP7-funded project SWITCH-ON (grant agreement no. 603587), which explores the potential of open data for comparative hydrology and collaborative research, and promotes open science for transparency and reproducibility. All data, scripts and protocols are available in the SWITCH-ON Virtual Water-Science Laboratory at http://www.water-switch-on.eu for review. We would like to thank the Global Runoff Data Center (GRDC) for compiling, maintaining and sharing time series of river flow as monitored by national institutes. Much of the data used in this study were available from input files of the E-HYPE model; the authors therefore also wish to thank staff at the Hydrological Research unit at SMHI for previous efforts on data compilation; we would especially like to acknowledge the work by Kristina Isberg and Jörgen Rosberg.

Edited by: B. Schaefli
Reviewed by: M. C. Westhoff and two anonymous referees

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