

This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

Catchment classification: empirical analysis of hydrologic similarity based on catchment function in the eastern USA

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Received: 21 April 2011 – Accepted: 22 April 2011 – Published: 5 May 2011

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Published by Copernicus Publications on behalf of the European Geosciences Union.

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8, 4495–4534, 2011

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Abstract

Hydrologic similarity between catchments, derived from their similarity in how they respond to precipitation input, is the basis for classification, for transferability, for generalization and also for understanding the potential impacts of environmental change. An important question in this context is, in how far can widely available hydrologic information (precipitation-temperature-streamflow) be used to create a first order grouping of hydrologically similar catchments? We utilize a heterogeneous dataset of 280 catchments located in the Eastern US to understand hydrologic similarity in a 6-dimensional signature space across a region with strong environmental gradients. Signatures are defined as hydrologic response characteristics that provide some insight into the hydrologic function of catchments. A Bayesian clustering scheme is used to separate the catchments into 9 classes, which are subsequently analyzed with respect to their hydrologic, as well as climatic and landscape attributes. Based on the empirical results we hypothesize the following: (1) Streamflow elasticity with respect to precipitation is modified by the soil characteristics of a catchment. (2) Spatial proximity is a good first indicator of hydrologic similarity because of the strong control climate exerts on catchment function, and because it varies slowly in space.

1 Introduction

Catchments provide a sensible (though not the only possible) unit for a hydrological classification system. Despite the degree of uniqueness and complexity that each catchment exhibits (Beven, 2000), we generally assume that some level of organization and therefore a degree of predictability of the functional behavior of a catchment exists (Dooge, 1986). This organization may be a result of natural self-organization or co-evolution of climate, soils, vegetation and topography (Sivapalan, 2005). The uniqueness of catchments limits the success of hydrological regionalization, because some catchments will be outliers and not behave like the majority of catchments analyzed.

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There will therefore be constraints on the inclusion of ungauged catchments into any classification system. Hydrology has thus far not established a common catchment classification system that would provide order and structure to the global assemblage of these heterogeneous spatial units (McDonnell and Woods, 2004; Wagener et al., 2007) and which would provide a first order grouping of hydrologically similar catchments with implications for hydrological theory, observations and modeling (Gupta et al., 2008).

Identifying and categorizing dominant catchment functions as revealed through a suite of hydrologic response characteristics, such as can be extracted from observed streamflow-precipitation-temperature datasets, is one strategy to quantify the degree of similarity that may exist between catchments (Haltas and Kavvas, 2011; Lyon and Troch, 2010; McIntyre et al., 2005; Oudin et al., 2008, 2010; Samaniego et al., 2010). Understanding how and why certain functional behavior occurs in a given catchment would ultimately shed new light on the reasons for similarity or dissimilarity that is exhibited between catchments (Gottschalk, 1985; Dooge, 1986). A range of benefits would be obtained if both functions and their causes could be understood and formalized in a similarity framework, and therefore a classification scheme (Grigg, 1965, 1967):

1. To give names to things, i.e. the main classification step.
2. To permit transfer of information, i.e. regionalization of information.
3. To permit development of generalizations, i.e. to develop new theory.

In the light of increasing concerns about non-stationarity of the responses of hydrologic systems (Milly et al., 2008; Wagener et al., 2010), we add a fourth benefit:

4. To provide a first order environmental change impact assessment, i.e., the hydrologic implications of climate, land use and land cover change.

All four of the above listed benefits are objectives of a catchment classification system to achieve order, new understanding and predictive power. Achieving a generalization

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of knowledge beyond individual catchments or beyond a particular dataset has been a particular struggle in hydrology, as well as in other sciences related to the natural world (Beven, 2000; Harte, 2002). We believe that the task of catchment classification will be an essential element in this much hoped for generalization. But how should one define hydrologic similarity or dissimilarity in a catchment classification system? Past strategies for classification have largely focused on physical similarity (e.g., similarity in physical characteristics, or how the catchments look) or on similarity of some (narrowly defined) characteristic of the streamflow record (mainly based on flow regimes). Below we argue that both approaches fall short in achieving all of the four benefits listed above, and that the general idea of catchment function (Black, 1990; Sivapalan, 2005; Wagener et al., 2007) can bridge the gap between these strategies and in this way help fulfill the needs of a more general classification system.

Many previous studies grouped catchments based on their similarity in physical characteristics, such as soils, land cover, or topography. Winter (2001) introduced the idea of hydrologic landscapes, which are defined on the basis of similarity of climate, topography and geology, assuming that catchments that are similar with respect to these three criteria will behave similarly in a hydrological sense. Implementing this approach results in 20 non-contiguous regions when US catchments are clustered using over 40 000 units of about 200 km² size (Wolock et al., 2004). In a similar manner, Buttle (2006) suggests that, within a particular hydro-climatic region, three factors should provide first-order controls on the streamflow response of catchments: (1) typology – hydrologic partitioning between vertical and lateral pathways, (2) topology – drainage network connectivity, and (3) topography – hydraulic gradients as defined by basin topography. These studies make the implicit assumption that the physical (climate and landscape) properties considered are the dominant controls on the “hydrologic behavior” of a catchment and are therefore sufficient to group catchments that are hydrologically similar. However, Merz and Blöschl (2009) for example showed that land use, soil types, and geology did not seem to fully define the process controls on catchment behavior. In addition, the uniqueness problem discussed above will often lead

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to unexpected catchment behavior that is difficult to predict a priori. Therefore, to fully permit (hydrologic) information transfer and to achieve a generalization of the relationships between catchment attributes, climate and hydrologic responses, an explicit quantitative assessment of such relationships (a mapping) is required and has to be tested, rather than an implicit one as used above. Alternatively, assessing similarity in terms of certain streamflow characteristics has been particularly popular in aquatic ecology, due to the importance of flow characteristics for aquatic habitats (e.g. Poff et al., 2006; Olden and Poff, 2003; Monk et al., 2007), and in regime studies (e.g. Haines et al., 1988; Bower et al., 2004). However, these studies are typically not aimed at understanding the behavior of the catchment, and therefore the cause of a particular regime occurring beyond climatic differences between regions.

Black (1997) introduced the idea of hydrologic function, defined as the actions of the catchment exerted on the precipitation it collects. Wagener et al. (2007, 2008) expanded this idea by viewing catchments as non-linear space-time filters, which perform a set of common hydrologic functions, broadly consisting of the partitioning, storage, and release of water. Partitioning is defined as the process whereby incoming precipitation is partitioned at the land surface into several components (e.g. infiltration, interception and surface runoff). Storage refers to the mechanisms by which incoming precipitation is held in temporary storage before its eventual release from the catchment (e.g. soil moisture, groundwater or interception). Release of stored water is defined as the pathway (and state) through which water ultimately leaves the catchment (e.g. evaporation, transpiration or surface runoff). Wagener et al. (2007) suggested that (to a degree) these functional characteristics should be revealed and hence observable in selected signatures of the catchment responses to precipitation input, i.e. in characteristics of the streamflow hydrograph, soil moisture and vegetation patterns, and other hydrologic variables. Different observed characteristics will enable a more or less detailed view of catchment function. Other observations, e.g. isotopic tracers, likely provide more information on internal pathways than what could possibly be derived from streamflow data alone (e.g. McGlynn et al., 2003; Weiler et al., 2003; McGuire et

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al., 2005; Tetzlaff et al., 2009; Broxton et al., 2009). However, the limited availability of such tracer data makes it necessary to understand in how far more generally available data such as streamflow can provide first-order insight.

This paper provides the first cluster analysis with respect to hydrologic similarity across a large geographic region with strong environmental gradients. The objective is to understand how catchments group in this situation and whether a hypotheses regarding controls on similarity can be generated. Rather we use an empirical study to cluster catchments based on hydrologic similarity as defined by six key signatures. None of the signatures itself are novel, but their combined use to quantify hydrologic function, and hence hydrologic similarity is. The choice of streamflow as output variable, with all its limitations as discussed above, means that we can utilize many catchments, but are limited to a first order classification. Some functional equifinality, i.e. a limited ability to uniquely characterize hydrologic function, will necessarily remain. The results are valid within the hydro-climatic and landscape characteristic gradients in our dataset. We use the clustering result to speculate on more general signature controls that will have to be generalized through additional study, e.g. using numerical models as used by Carrillo et al. (2011).

2 Study catchments and data

A total of 280 catchments, spanning the eastern half of the United States, were used in this study. Catchments range in size from 67 km² to 10 096 km² (though only a few very large catchments are included), and show aridity indices (long-term potential evapotranspiration to precipitation rates) between 0.41 and 3.3, hence representing a heterogeneous dataset (See further details in supplemental material). They cover type 1 eco-regions 5, 8 and 9, which are defined as Northern Forests, Eastern Temperate Forests, and Great Plains, respectively (Omernik, 1987).

Time-series data of daily streamflow, precipitation, and temperature for all catchments were provided by the MOPEX project (Duan et al., 2006). The catchments

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within this dataset are minimally impacted by human influences. Streamflow information within this dataset was originally provided by the United States Geological Survey (USGS) gauges, while precipitation and temperature was supplied by the National Climate Data Center (NCDC). A total of 10 hydrologic years of data was used (1949 to 1958) in order to calculate the signatures. This time period was assumed to be long enough to capture climatic variability, but short enough to not be affected by climatic trends. To ensure precipitation quality, the MOPEX dataset sets a minimum acceptable precipitation gauge density within each catchment was defined following the equation,

$$N = 0.6A^{0.3} \quad (1)$$

where N is the number of precipitation gauges and A is the area of the catchment (km^2) (Schaake et al., 2000). The use of this guideline provides mean areal precipitation estimates at each time step and should result in less than 20% error 80% of the time (Schaake et al., 2006). The MOPEX dataset has been used widely for hydrologic model comparison studies (see references in Duan et al., 2006).

3 Signatures

Signatures should be characteristics of the hydrologic response that provide us with some insight into the functional behavior of the catchment. In this paper we will limit ourselves to signatures derived from widely available time-series information such as streamflow, precipitation, and temperature as the basis of a first-order analysis. These key signatures were chosen, from a much larger list of possible indices (see list in Yadav et al., 2007), following inspection and careful evaluation using both quantifiable measures of correlation between pairs of signatures and based on our understanding of a signature's hydrologic meaning, i.e., our theory as discussed below. The chosen signatures are: runoff ratio, baseflow index, snow day ratio, slope of the flow duration curve, streamflow elasticity, and rising limb density. In the remainder of this section we will provide a brief definition of each of the six signatures.

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3.1 Runoff ratio

Runoff Ratio (R_{QP} [-]) is defined as the ratio of long-term average streamflow, Q , to long-term average precipitation, P ,

$$F_{QP} = \frac{Q}{P} \quad (2)$$

5 It represents the long-term water balance separation between water exiting the catchment as streamflow and as evapotranspiration (assuming no net change in storage) (Milly, 1994; Olden and Poff, 2003; Poff et al., 2003, Sankarasubramanian et al., 2001; Yadav et al., 2007). A high runoff ratio identifies a catchment from which a large amount of water exits as streamflow (streamflow dominated or energy limited), whereas a low
10 value of runoff ratio identifies a large amount of water exiting the catchment as evapotranspiration (ET dominated or water limited).

3.1.1 Slope of the flow duration curve

The Flow Duration Curve (FDC) is a distribution of probabilities that streamflow is greater than or equal to a specified magnitude, and is typically derived from hourly or
15 daily (and sometimes monthly) streamflow data (e.g. Vogel and Fennesy, 1994; Jothityangkoon et al., 2001; Jencso et al., 2009). To calculate an index of flow of variability, the slope of the FDC (S_{FDC} [-]) is calculated between the 33rd and 66th streamflow percentiles, since at semi-log scale this represents a relatively linear part of the FDC (Yadav et al., 2007; Zhang et al., 2008). A high slope value indicates a variable flow
20 regime, while a low slope value means a more damped response. Damped response can arise as a result of a combination of persistent (wide-spread and year-round) rainfall and the dominance of groundwater contribution to streamflow. The signature is defined as,

$$S_{FDC} = \frac{\ln(Q_{33\%}) - \ln(Q_{66\%})}{(0.66 - 0.33)} \quad (3)$$

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where S_{FDC} is the slope of the flow duration curve, $Q_{33\%}$ is the streamflow value at the 33rd percentile, $Q_{66\%}$ is the streamflow value at the 66th percentile.

3.1.2 Baseflow index

Base Flow Index (I_{BF} [-]) is the ratio of long-term baseflow to total streamflow (e.g. Arnold et al., 1995; Vogel and Kroll, 1992; Kroll et al., 2004). A high value of I_{BF} defines a catchment with higher baseflow contribution, i.e. more water moving along long flow-paths through the catchment. A range of algorithms has been proposed and compared to perform a separation of quick flow and baseflow from observations of streamflow alone (Kroll et al., 2004; Eckhardt, 2005; Institute of Hydrology, 1980; Arnold et al., 1995; Arnold and Allen, 1999). In this study we use the one-parameter single-pass digital filter method (DFM) based on previous studies reported by Arnold et al. (1995) and Lim et al. (2005). We do not consider the specific choice of filter crucial in this study since we assume that an analysis of flow is only sufficient to detect the relative differences between catchments. The filter applied is defined as follows,

$$Q_{Dt} = cQ_{Dt-1} + \frac{1+c}{2}(Q_t - Q_{t-1}) \quad (4)$$

where $Q_{D,t}$ is the direct flow value at time-step t , Q_t is the total flow at time step t , and c is a parameter. The parameter

c was set at a value of 0.925 based on a comprehensive case study performed by Eckhardt (2007). The value of the baseflow $Q_{B,t}$ at time-step t is then given by,

$$Q_{Bt} = Q_t - Q_{Dt} \quad (5)$$

The baseflow index is therefore,

$$I_{BF} = \sum \frac{Q_B}{Q} \quad (6)$$

where the summation is carried out over all time steps of the study period.

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3.1.3 Inter-annual streamflow elasticity

Inter-annual streamflow elasticity (E_{QP} [-]) describes the sensitivity of a catchment's streamflow response to change in precipitation. It is calculated taking the inter-annual difference between annual streamflow divided by the inter-annual difference between annual precipitation, and is then normalized by the long-term runoff ratio. Based on the study by Sankarasubramanian et al. (2001) we assume that the median value is a good representative of the general variability, i.e.,

$$E_{QP} = \text{median} \left(\frac{dQ}{dP} \frac{P}{Q} \right) \quad (7)$$

where E_{QP} is the streamflow elasticity, dQ (dP) is the difference between the previous year's streamflow (precipitation) and the current year's streamflow (precipitation), P is the mean annual precipitation, and Q is the mean annual streamflow. The median value of E_{QP} is considered as a robust measure, since it filters out outliers, which may significantly affect the mean value (Sankarasubramanian et al., 2001; Sankarasubramanian and Vogel, 2003). E_{QP} is the percentage change in streamflow divided by the percentage change in precipitation. A value of 1 indicates that a 1% precipitation change leads to a 1% change in streamflow. A value greater or less than 1 would, respectively, define the catchment as being elastic, i.e., sensitive to change of precipitation, or inelastic, i.e., insensitive to a change of precipitation.

3.1.4 Snow day ratio

The snow day ratio (R_{SD} [-]) is defined as the number of days that experience precipitation when the average daily air temperature is below 2°C, divided by the total number of days per year with precipitation. This value provides an indicator of the amount of precipitation that falls and is stored as snow. It can be related to the seasonality of the catchment response (Woods, 2009). The ratio is defined as,

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$$R_{SD} = \frac{N_S}{N_P} \quad (8)$$

where N_S is the number of days with precipitation and a daily average temperature below 2°C , and N_P is the number of days with precipitation. A high value of R_{SD} suggests more snow storage with a significant impact on the intra-annual variability of streamflow.

3.2 Rising limb density

The sixth signature considered in this study is called Rising Limb Density (R_{LD}). R_{LD} describes the flashiness of the catchment response and is defined as the ratio of the number of rising limbs (N_{RL}) and the total amount of time the hydrograph is rising (T_R) (Morin et al., 2002; Shamir et al., 2005). The equation is given as,

$$R_{LD} = \frac{N_{RL}}{T_R} \quad (9)$$

R_{LD} is a descriptor of the hydrograph shape and smoothness without consideration for the flow magnitude. A small the signature value indicates a smooth hydrograph.

3.3 Other signatures tested

Other signatures have been tested as well (see Yadav et al., 2007), but were not included for different reasons (mainly correlation with other signatures). Examples include High Pulse Count, which was shown to correlate highly with the Slope of the FDC, and thus, was assumed to contain similar information. Similarly, signatures that measure the slope of the rising and falling limbs (such as a recession coefficient) were highly correlated with baseflow index. We also tested the nonlinearity of the recession, i.e. the $Q - dQ/dt$ relationship, which is the slope of the linear fit to the scatter between streamflow versus change of streamflow in time at log-log scale (Brutsaert and Nieber, 1977; Vogel and Kroll, 1992; Wittenberg and Sivapalan, 1999). While this

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signature contains valuable information about catchments, it was excluded because it caused the classification to be poor. One reason for this problem could be that there is no single value that fits this relationship well, but that it rather changes with season (McMillan et al., 2010).

3.4 4 Methods: cluster analysis

Cluster analysis is the process of grouping similar entities (catchments) according to one or more chosen similarity measures (signatures), while concurrently separating those that are different. There are three common types of clustering algorithms: agglomerative hierarchical clustering, k-means clustering, and fuzzy partition clustering.

All three strategies of unsupervised clustering require some subjective choices that define the clustering process, e.g. the distance metric used, and there is consequently not one single correct solution to this kind of analysis. The objective here is therefore to use an empirical analysis to investigate how the similarity between catchments defined by the six signatures might create groupings, not to derive at an ultimate classification result that would always depend on the choices we made. To account for the uncertainty in the classification process, we used a fuzzy partitioning algorithm that allows use to analyze the quality of the resulting classification.

The clustering algorithm used in this study is a fuzzy partitioning Bayesian mixture clustering algorithm implemented in the AutoClass C software package (version 3.3.4) (Stutz and Cheeseman, 1994; Cheeseman and Stutz, 1996; Archcar et al., 2009; Kennard et al., 2010). Bayesian mixture modeling is a probabilistic approach in which marginal likelihoods for different classification realizations are estimated and ranked against all other realizations. The classification with the highest posterior probability is ultimately chosen as the most likely realization (Webb, 2007). Each catchment is therefore assigned to a particular class with a certain probability, called here the probability of class assignment. A catchment could be allocated to different classes due to the probabilistic nature of the algorithm, and it is only the primary class assignment that is listed, which pertains to the class assignment with the highest probability. The

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the correlation value is largely created by the endmember values while there is much less correlation for the majority of catchments in the dataset. Hence both signatures are included further, but their correlation is considered during clustering.

Different spatial patterns for the six signatures can be seen in Fig. 2. Runoff ratio, RR, shows high values in the humid region along the Appalachian mountain and connected plateau regions, which decrease with increasing distance from this area, especially towards the central US (e.g. Sankarasubramanian and Vogel, 2003). Figure 2b shows that the smallest values of slope of the FDC are located on the southeastern side of the Appalachian mountain range and west of this area. Values of streamflow elasticity and rising limb density show much greater heterogeneity than the first two signatures (Fig. 2c and f). High values of baseflow index can be found along the Eastern coastal US and around the Great Lakes region (Fig. 2d), where more permeable soils and bedrock dominate (Wolock et al., 2004; Santhi et al., 2008). Values decrease when moving towards the east where soils and bedrock are more impermeable. As expected, the ratio of snow days correlates highly with latitude (Fig. 2e). These spatial patterns further underline the relative independence of the different signatures and attest to their suitability for the similarity analysis. Figure 2 also shows that, taken individually, there are strong regional patterns in the variations of several signatures (Runoff Ratio, Ratio of Snow Days, Baseflow Index, Slope FDC).

4.2 Cluster analysis

The cluster analysis was applied to all 280 catchments within the six-dimensional signature space. The analysis aimed at addressing the following questions: (1) How do the catchments group with respect to the signatures used? (2) What spatial patterns of clusters emerge? (3) What hypotheses regarding the function of catchments and what physical or climatic controls on this functional behavior can be derived?

The cluster analysis identified 9 different classes of varying size for the most likely classification. The classification process was repeated 20 times and the Adjusted Rand Index (ARI) between classification schemes of 15 of the 20 runs was above

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0.90. Furthermore, 7 of these 20 runs were found to be nearly identical and thus one of these 7 runs was used as the final classification. Results were also screened for extremely small or large classes, and for generally providing high probability of class memberships.

The heuristic measures calculated for the analysis are visualized in Fig. 3. Figure 3a shows the probability that a catchment belongs to the assigned class. The histogram indicates that the vast majority of catchments has probabilities above 0.9 and hence are very likely to be classified correctly. The number of catchments per class varied between 5 and 82 (Fig. 3b). All classes show a relatively high class strength (Kennard et al., 2010), i.e. the variability of signature values within each class is rather low. Classes 2 and 3 have the highest values, while those for class 5, 8, and 9 are somewhat lower.

The relative value of attribute influence of each signature describes the contribution of each signature to the classification. This measure represents the separation of classes due to each signature, and is calculated from the average Kullback-Leibler distance between attribute distributions in individual classes and the overall distribution found in the full dataset (Webb et al., 2007). The attribute influence increases as the variance between the signature mean of each class increases. Its values range from 1 (highest contribution) to 0 (no contribution). The order of signature influence on the clustering result was: Streamflow Elasticity (1), Ratio of Snow Days (0.98), Runoff Ratio (0.862), Slope of the FDC (0.462), Baseflow Index (0.462), and Rising Limb Density (0.201). These values suggest that all the signatures provided information for the classification, though RLD was not very influential. It also suggest that mainly climate-controlled signatures dominate the classification, further adding to the evidence supporting the dominant role climate has in controlling catchment behavior (see also Rosero et al., 2010).

Cluster results are shown as a box and whisker plots in Fig. 4 and as a spatial map with a corresponding heatmap in Fig. 5. The catchments in Fig. 4 are sorted from left to right by increasing median value of the signature shown. Catchments shown

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with a red border in Fig. 5a are those with primary class membership probability below 0.7. The heatmap in Fig. 5b further enables the comparison of signature patterns between the different classes. Figures 6 and 7 are used to analyze possible controls on the signature-based classes identified. Geographic location is used to structure the discussion of results, starting in the Northeastern US.

Catchments in the northeastern United States (class C2) are characterized by high ratios of streamflow to precipitation (high RQP) and large amounts of snow (high RSD) (Fig. 4). These catchments are located in humid continental climate with low energy availability and hence low evapotranspiration. Snow storage is important in controlling seasonal variability of runoff, i.e. these catchments have the highest ratio of snow days in the dataset. Catchments located in class C2 can be found in an area ranging from Maine to Pennsylvania. These catchments are the smallest in the dataset with the highest slope (max SLOPE and min DA), with long and frequent storms (max SD and NP), and the lowest maximum temperatures (TMAX). This class consists mainly of catchments with a very low precipitation seasonality index (PSI; Fig. 6), meaning that precipitation amounts are distributed relatively evenly throughout the year (a uniform distribution would be 0). PSI values are generally low for the eastern US (less than 0.6) and lowest in the Northeastern US, compared to the southwestern US where rain falls mainly in the winter (Pryor and Schoof, 2008). All catchments in this class are energy limited with the smallest aridity indices ($AI = PE/P$ below 1), suggesting that these catchments are controlled by low average energy availability throughout the year, but with strong seasonal variability, as well as a relative uniform distribution of moisture input in time.

Catchments slightly further to the south (in Pennsylvania and Virginia), cluster C3, extend westward to Indiana with lower runoff ratios (median of 40 % versus about 55 % for class C2) and less dominant snow storage, while the values of SFDC stay relatively similar to those catchments further north (Fig. 4). There are generally strong similarities in physical and climatic characteristics between the catchments of classes C3 and C2: they are the smallest catchments, with a high fraction of poorly drained soils

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(high HGC), the longest storm durations and the lowest aridity indices. Differences to the previous class are mainly topography and land use, since C3 catchments are at a lower elevation, with less slope, and have more agriculture with lower root zone depths (Fig. 6).

5 Within the extent of C3 catchments, a small collection of catchments from C9 are found in Northwest Ohio. This class is separated by a very low streamflow elasticity, along with the smallest variability of this signature of any class. Class 9 does show the lowest median value of Slope of the FDC, and the highest median value of Baseflow Index, however the variability of these signatures within this class is the largest of any
10 class. Class 9 also shows a larger amount of snow than C3, suggesting a climatic separation between these regions. Climatically, C9 experiences the lowest temperatures and shortest storm duration in the dataset, along with some of the highest precipitation seasonality found within the dataset.

Continuing southeastward down the Appalachian Mountain entering into North Carolina, we witness a decrease in the values of Ratio of Snow Days in class C1, although the variability of this signature increases in this class with the highest number of catchments. We also see a small decrease in the Slope of the FDC (and conversely, a slightly higher baseflow index). Catchments belonging to this class are spread along the same latitude and are mainly separated from classes C2 and C3 by a lower snow
20 day ratio (median of about 20 %, Fig. 4). From Fig. 6, we can also see that these catchments experience low precipitation seasonality index, a low amount of poorly drained soil along with high percentage of sand, and hence high soil permeability, as well as the lowest relief ratio (RRM) of all classes. Classes C1 and C5 (the next class further south) are the baseflow dominated catchments in the dataset.

25 In the catchments further south of class C1, i.e. cluster C5, we find a persistence of high IBF and low SFDC values. The number of snow days signature decreases even further, suggesting a climate-based separation between the classes C1 and C5. Catchments in C5 also have some of the lowest elasticity values (Fig. 4c), which is in line with their low flow duration curve slope (suggesting high storage in the catchment).

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The higher baseflow fraction creates a smaller streamflow response to changes in precipitation. Catchments within this class experience high maximum temperatures and large amounts of rainfall ($>1200 \text{ mm year}^{-1}$).

West of class C5, in the southern Mississippi river basin, are catchments of class C6. While climatically similar, e.g. similarly water limited with negligible snow as class C5, the baseflow index decreases, with decreasing percentage sand levels and deeper mean root zone depths (Fig. 6). This class is also quite similar to the catchments grouped in class C1, even though located further north, with respect to geologically controlled signatures (e.g. BFI), but with lower runoff ratio.

The catchments located furthest west in the study region (belonging to classes C8, C7 and C4) are characterized by the lowest runoff ratios, generally less than 20 percent of precipitation is released from the catchments as streamflow (Fig. 4a). These are water-limited catchments ($AI > 1$) that receive less precipitation than the other areas of the study region, while the fraction of snow increases when moving from south to north (C8 to C7 to C4) (Fig. 4e). The catchments of this class, along the western boundary of the study region, are approaching a more arid area of the Köppen classification system (Peel et al., 2007). This area also exhibits a high precipitation seasonality index, i.e. a non-uniform distribution of precipitation through the year. These catchments are located in areas that are primarily cultivated land use, demonstrated by a very higher percentage of agriculture found within 800 m of the stream (riparian zone) (Fig. 7). Catchments south of Iowa, class C7, exhibit the highest flow duration curve slopes, SFDC, and elasticity values, EQP, as well as the lowest baseflow indices in the dataset. The latter is likely related to the very low percent of soils classified as sand, and the highest fraction of very poorly drained soils.

4.3 Discussion

Overall it seems like the signatures that vary along a climatic gradient (RQP, EQP, RSD) are exerting a stronger control on separating the catchments into different classes than the signatures that are likely to be more impacted by topographic, geological and land

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cover gradients (IBF, SFDC, RLD). This highlights the problem with this type of empirical analysis in which the result is controlled by the gradients found in the dataset analyzed. Hence making it difficult to generalize beyond the data at hand. This further suggests that a general regionalization of signatures across the region might not be the best strategy for some of the signatures, but that the region has to be broken up into smaller subregions (Laaha and Blöschl, 2006). This degree of equifinality of controls might also be reduced if further variables characterizing the functional behavior of the catchments would be included. For example, one would expect tracer data to provide a better separation of flowpaths/residence times and hence enable a refinement of the hydrologic function of the catchments.

This conclusion was not unexpected and, as stated on the outset of this paper, no cluster analysis can produce a general classification system because the results are depending on the dataset used and subjective decisions made (mainly choice of algorithm and distance metric). However, the clustering results help to understand controls, enable us to derive a small number of hypotheses. One could analyze these hypotheses further in a more idealized setting (i.e. not empirical) to understand the generality of the results found here. Multiple authors have advocated the use of “virtual experiments” for this purpose, i.e. by analyzing modeled or synthetic realities rather than actual systems (e.g. Bashford et al., 2002; Weiler and McDonnell, 2004; Winter et al., 2004; van Werkhoven et al., 2008). So what does the empirical analysis above suggest? The main issue we focus on is the suggested variability of controls on similar hydrologic signatures, and hence on hydrologic function in the context of this paper.

Streamflow elasticity to changes in precipitation is modified by the permeability characteristics of a catchment. The results suggest that high elasticity values (clusters 8 and 7) relate to low BFI values and vice versa (clusters 9, 5, 2, 1) (Figs. 4 and 7). Cluster 8 and 7 have low %Sand and the highest percentage poorly drained soils (HGD), and hence the smallest potential for buffering precipitation variability. Clusters 5, 2 and 9 have high %Sand, and 5 and 2 also have a high percentage well drained soils (HGA), and therefore a high potential for buffering. This result is similar to the conclusions of

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Sankarasubramanian and Vogel (2003) who analytically derived a parameter (parameter b of the abcd model) they refer to as soil moisture holding capacity, which they found to buffer streamflow variability and that is considered regionalizable using soil permeability. The classes with the highest elasticity values (8, 4, 7) are also the classes with the shallowest roots (lowest RZD) and the lowest runoff ratio (highest fraction of evaporated precipitation). Class C2 on the other hand has the highest root zone depth and the highest runoff ratio (highest of precipitation becoming streamflow). This interaction between climate, soils and vegetation is also shown in Fig. 8. It shows that deep-rooted vegetation coincides with high runoff ratios (energy limited catchments), but only if the catchments have mainly poorly or very poorly drained soils. Results like these suggest a co-evolution of soil-climate-vegetation that is further explored numerically in Carillo et al. (2011).

Spatial proximity is a valuable first indicator of hydrologic similarity because it reflects the strong climatic control on catchment behavior and because varies slowly in space.

Many researchers have commented on the value (Merz and Blöschl, 2004; Parajka et al., 2005; Oudin et al., 2008) or lack of value (for example with respect to drought characteristics, see Tallaksen and van Lanen, 2004) of catchment spatial proximity in predicting hydrological similarity. The empirical results shown here suggest that spatial proximity clearly plays an important role as an indicator of similarity. However, the results also suggest that spatial proximity is reflecting similarity in other characteristics. The different clusters show strong spatial connectedness (clusters 47 and 2), show large patches with “outliers” (6, 5, 3, 8, 9), or are relatively widely distributed (1 and 6). Combining Figs. 4, 5 and 7, we can see that cluster 4 is a connected group of catchments with very low (high) values of runoff ratio (ratio of snow days), and with very little variability in both signatures. An analysis of Fig. 6 shows little variability and extreme (within the dataset) values in landscape (lowest root zone depth, highest % HGC and HGD) and climatic (lowest MAP, highest PSI) characteristics for this cluster. This result suggests that the catchments in this cluster are very different from the rest. Another connected cluster is C2 in the northeastern US, which exhibits the highest

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runoff ratio and the highest ratio of snow days. This cluster also shows extreme values with little variability, but this time mainly for climatic characteristics (lowest T_{MAX} and aridity index, AI; low PSI and highest N_p). It does also have the highest root zone depth. Cluster C5, on the other hand, has distributed patches in different parts of the study region. This cluster has the highest baseflow index values in the dataset (aside from C9), and shows little variability as well as the highest values for %Sand. At the same time, it shows considerable variability in climate (e.g. T_{MAX} and MAP) and landscape characteristics (%AG and RZD).

The discussion in this section supports the earlier statement that such an empirical analysis cannot be the endpoint for classification, but rather a step along the way. The focus on streamflow means that we are limited in the degree of detail regarding hydrologic function that we can extract from such an integrated measure. The limited availability of detailed descriptors of geology (certainly for a dataset covering a large region) suggests that we are also limited with respect to understanding subsurface controls (see similar issues in Oudin et al., 2008). And finally, the variability and environmental gradients in the dataset define what controls could even occur. There is of course no guarantee that different datasets, with different gradients, would not show other relationships between signatures and climate/landscape; or that these relationships would not change with the scale of analysis (Kennard et al., 2010). Therefore it is in the physical interpretation where the potential for generalization lies, rather than in the actual empirical result.

5 Conclusions

The lack of a generally accepted classification framework brought the question of what defines hydrologic similarity to the forefront. Wagener et al. (2007) suggested that a classification framework, which is both descriptive and predictive, be derived if it is based on the notion of catchment function and contains an explicit mapping between function (as observed in signatures), climate and landscape characteristics. Here we

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tested this idea in an empirical study utilizing 280 catchments across the Eastern US. This work provides insight into not only how and what catchments are hydrologically similar in the United States, but offers possible controls of such hydrologic behavior.

We defined six signatures derived from precipitation-temperature-streamflow data and used a Bayesian clustering algorithm to identify groups of similar catchments. Eleven clusters that showed a relatively good separation were identified. Spatially, most of the clusters showed some degree of connectivity suggesting that spatial proximity is a good indicator of similarity. It is likely that this is because climatic and some landscape characteristics change slowly in space. Further, the results suggest that permeable soils provide a buffer to how strongly a catchment responds to changes in climate. This result suggests that soil properties will modify the impacts of climate change on hydrologic regimes. And lastly, the empirical results suggest that the (central) slope of the flow duration curve is dominated by soil characteristics, rather than climate or other landscape attributes.

As with any study, there are certain limitations to our work presented here. First, we assume that catchment functional behavior is reflected in signatures that can be derived from streamflow. Others might argue that this is too integrated a measure and that tracer studies are required. While we agree that tracer studies would be helpful to reduce some of the functional equifinality found here, they are not widely available and we believe that a first order classification is helpful nonetheless. Certainly signatures such as flow duration curves (for example) have been used for many years to define the hydrologic character of catchments. It would be very interesting to study some of the catchments included here further with tracers to further distinguish their functional behavior. Second, the empirical and subjective nature of the cluster analysis itself of course limits the generality of our result. We believe that this issue can be helped by numerical experiments in which idealized systems are tested using catchment models.

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Supplementary material related to this article is available online at:
<http://www.hydrol-earth-syst-sci-discuss.net/8/4495/2011/hessd-8-4495-2011-supplement.zip>.

Acknowledgements. Support for this project was provided by the National Science Foundation under project EAR-0635998 “Understanding the Hydrologic Implications of Landscape Structure and Climate – Towards a Unifying Framework of Watershed Similarity”. Time series data used in this study was provided by the MOPEX project.

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Table 1. Explanation of physical and climatic properties used.

Variable	Description [units]	Minimum Value	Maximum Value
AG	Fraction of land used as agriculture within 800 m of the stream [-]	0.04	91.87
ELEV	Mean elevation of the catchment [m]	21.9	1212
HGA	Percentage of soil within the "A" Hydrologic Group (well drained soils). Soils are deep and well drained and, typically, have high sand and gravel content [%]	0	35.04
HGC	Percentage of soil within the "C" Hydrologic Group (poorly drained soils). The soil profiles include layers impeding downward movement of water and, typically, have moderately fine or fine texture [%]	0	91.77
HGD	Percentage of soil within the "D" Hydrologic Group (very poorly drained soils). Soils are clayey, have a high water table, or have a shallow impervious layer [%]	0	88.01
MAP	Mean annual precipitation [mm yr ⁻¹]	46.6	207.2
NP	Number of days with measurable precipitation per year [days]	46.7	167
PSI	Precipitation seasonality index, as defined by. A high value means that precipitation is seasonal, and a low value means that the precipitation is uniformly distributed throughout the year. X_n is the monthly precipitation for month n [-]	0.017	0.434
RRM	Relief ratio $(Elev_{median} - Elev_{min}) / (Elev_{max} - Elev_{min})$ [-]	0.059	0.705
RZD	Mean rootzone depth [m]	0.732	1.243
TMAX	Mean maximum monthly temperature within the dataset [°C]	10.4	28.7
DA	Contributing drainage area [km ²]	67	10096
P_{SIAE}	Capillary fringe height [cm]	12.2	71.36
LAI_{MAX}	Maximum Leaf Area Index based on vegetation type [-]	3.46	6.04
LAI_{DIFF}	Difference between the maximum Leaf Area Index (LAI_{MAX}) and the minimum Leaf Area Index (LAI_{MIN}) based on vegetation type [-]	1.619	5.146
NO200SIEVE	Percent soil passing through the No. 200 sieve. [%]	10.5	94.4
SAND	Percentage of sand found within the catchment. Used as a metric in hydrologic landscape regions and included as comparison [%]	4.60	89.45
SLOPE	Mean slope found within the catchment. Used as a metric in hydrologic landscape regions and included as comparison [%]	0.10	34
SD	Mean Storm duration, defined as when the precipitation starts and zero, increases, and decreases back to zero [hours]	3.88	6.93
AI	Aridity Index, defined as the ratio between mean annual Potential Evapotranspiration (PE) and Precipitation (P). PE was calculated using a modified Hamon algorithm (Dingman, 2002) [-]	0.490	2.95
$P-PE$	The difference between mean annual Precipitation and Potential Evapotranspiration. Used in hydrologic landscapes and included as a reference [m]	-0.564	1.083

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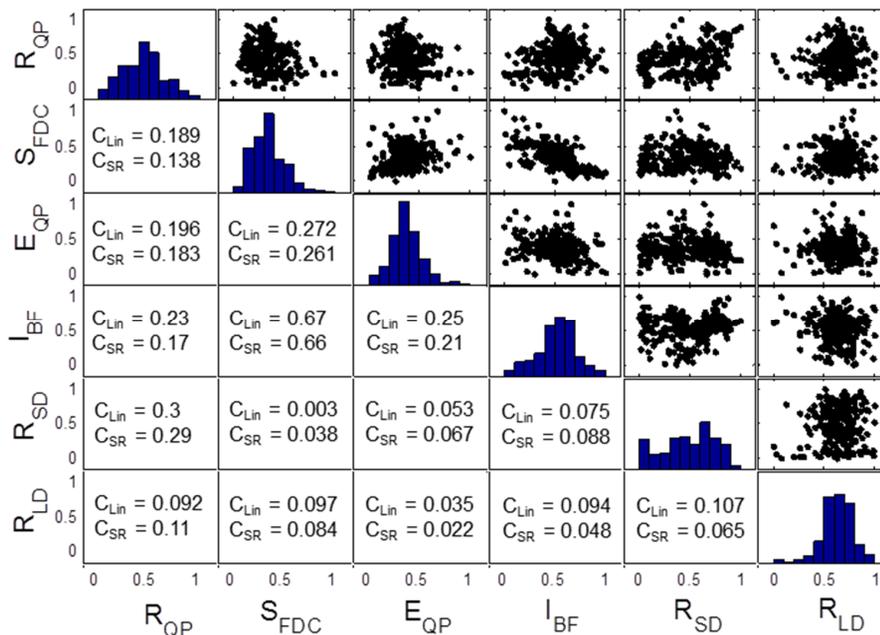


Fig. 1. Distributions of the individual signatures shown as histograms and of the correlation between the signatures shown as scatter plots as well as numerical values. Correlation (C) is calculated using linear correlation (Lin) and Spearman Rank (SR) correlation coefficients, both ranging from zero to one.

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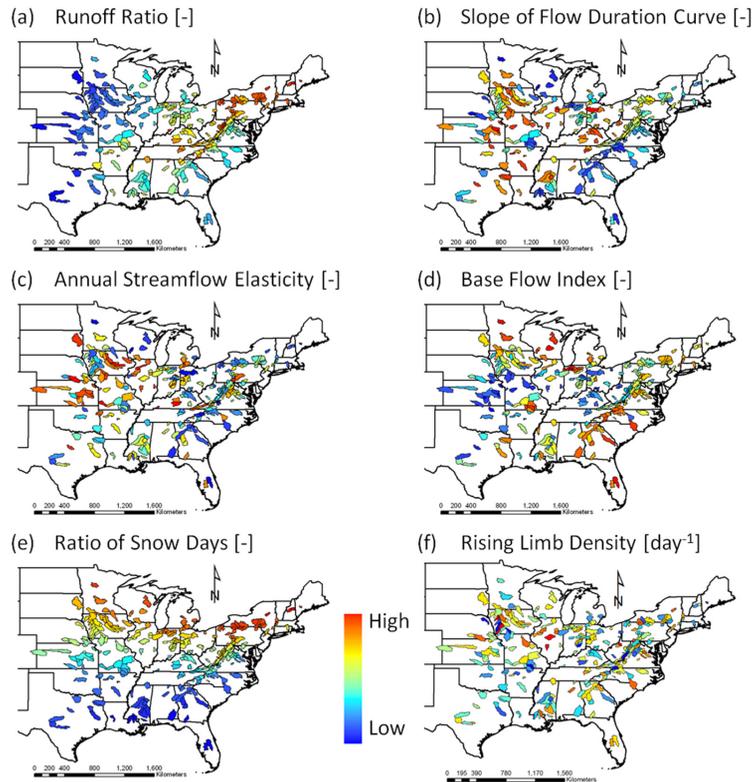


Fig. 2. Each map shows the spatial distribution of catchment signatures at each delineated catchment area. The color of the catchment corresponds to the high (red) and low (blue) values, as shown by the colorbar. Plots show spatial distributions of: **(a)** Mean annual runoff ratio (R_{QP}). **(b)** Slope of the FDC (S_{FDC}). **(c)** Streamflow elasticity (E_{QP}). **(d)** Base flow index (I_{BF}). **(e)** Ratio (or fraction) of snow days (R_{SD}). **(f)** Rising Limb Density (R_{LD}). The actual range in values can be found in supplemental material.

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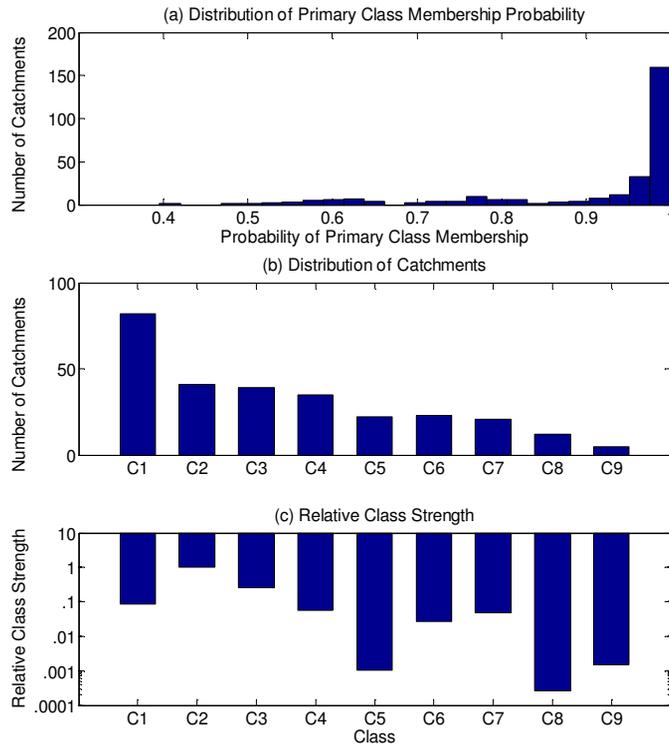


Fig. 3. (a) Distribution of the primary class membership probability for all 280 catchments. (b) Histogram of the number of catchments within each class. (c) Relative class strength. Measure of how similar catchments are in a particular class normalized to the strongest class (value of 1 is the strongest value, all other classes are less).

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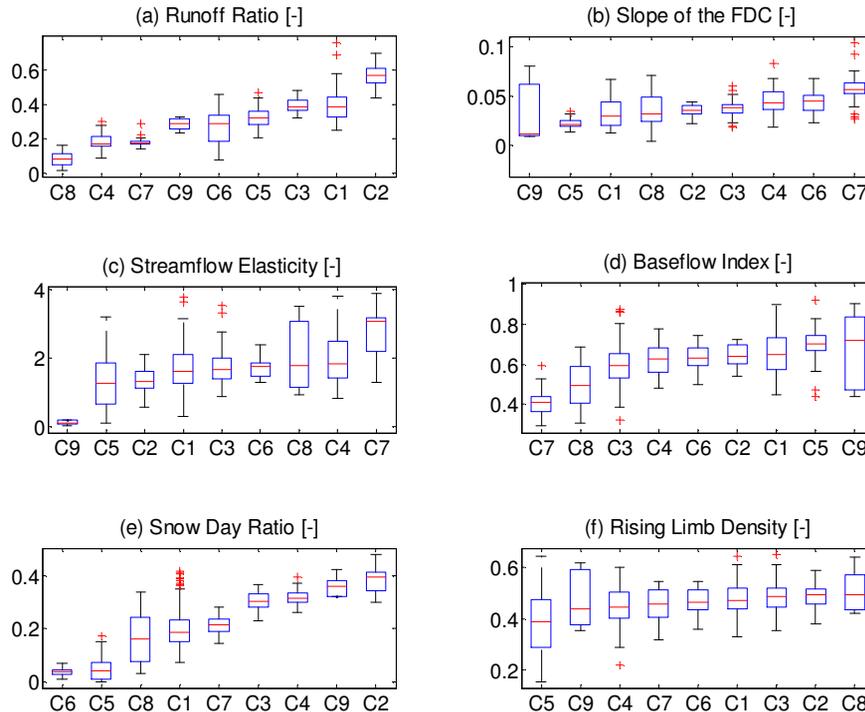


Fig. 4. Distribution of signature values for each class, ordering the class from low to high (left to right) by the median value. **(a)** Mean annual runoff ratio (R_{QP}). **(b)** Slope of the FDC (S_{FDC}). **(c)** Streamflow elasticity (E_{QP}). **(d)** Base flow index (I_{BF}). **(e)** Ratio (or fraction) of snow days (R_{SD}). **(f)** Rising Limb Density (R_{LD}).

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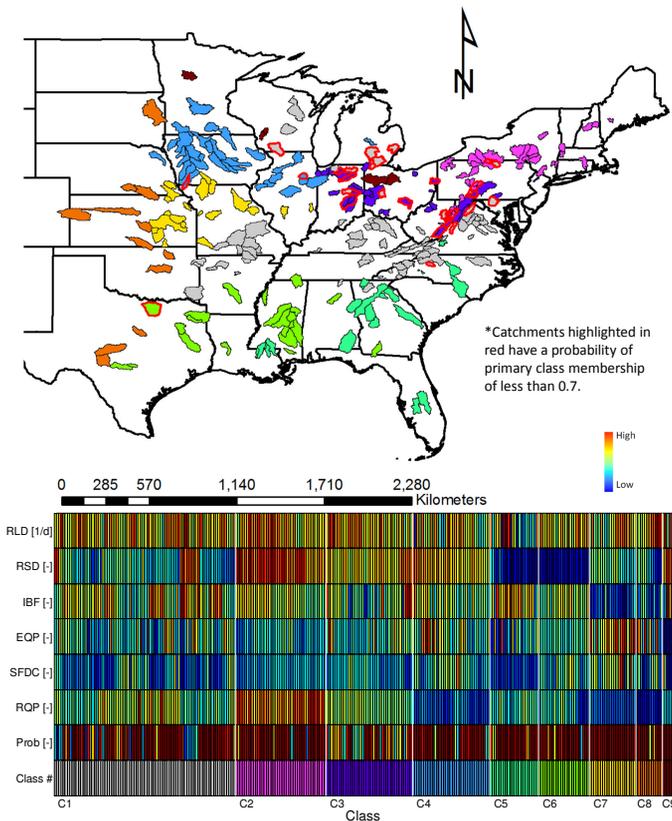


Fig. 5. The top figure represents the spatial distribution of catchments according to class. These catchments are color coded according to Class # in the lower part of the recursive pattern plot. The first 6 rows of the recursive pattern plot represent signature values (high values shown as red, low being blue). The 7th row indicates the probability of a catchment's primary class assignment. The 8th and last row represents the color code used in the map above.

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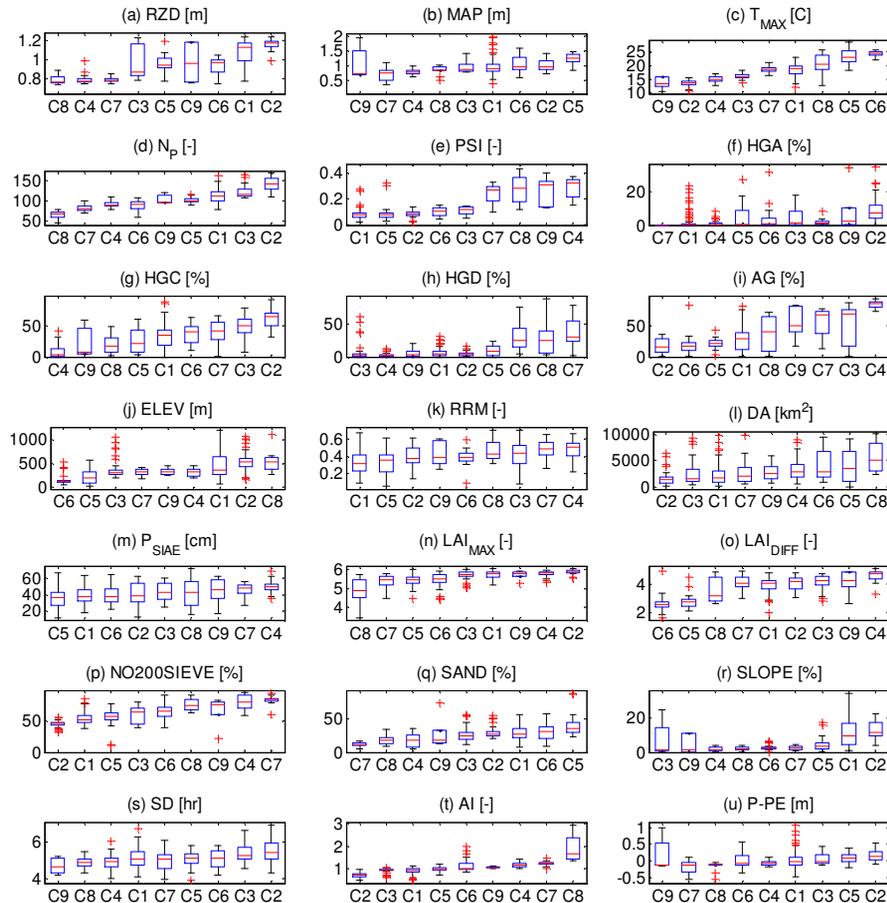


Fig. 6. Box-Whisker plots of the clusters with respect to landscape and climatic characteristics. Explanations of abbreviations can be found in Table 1.

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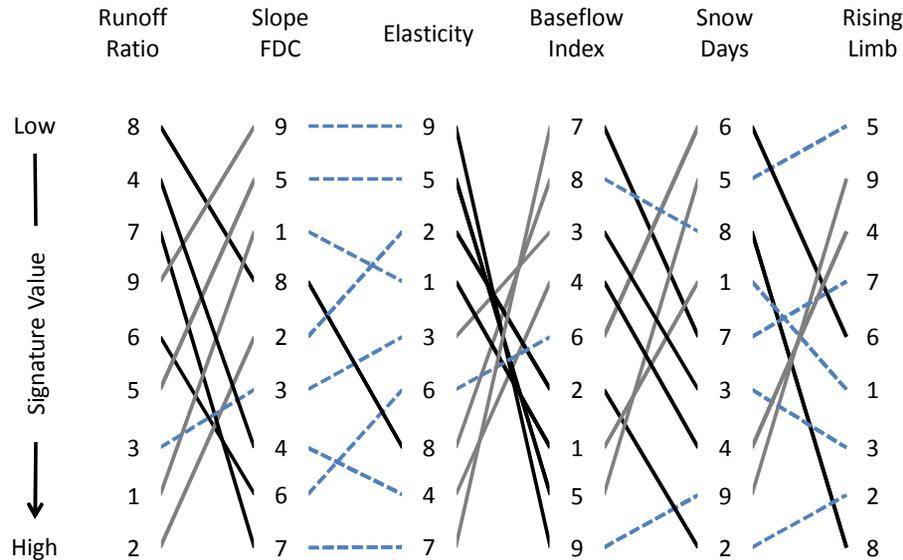


Fig. 7. Schematic representation to analysis the relationships between the rankings found in Fig. 4. Median signature values of each cluster are connected. Black is increasing, gray is decreasing and dashed suggests similar values from left to right. Cluster 9 consists only of five members and therefore has to be treated with care.

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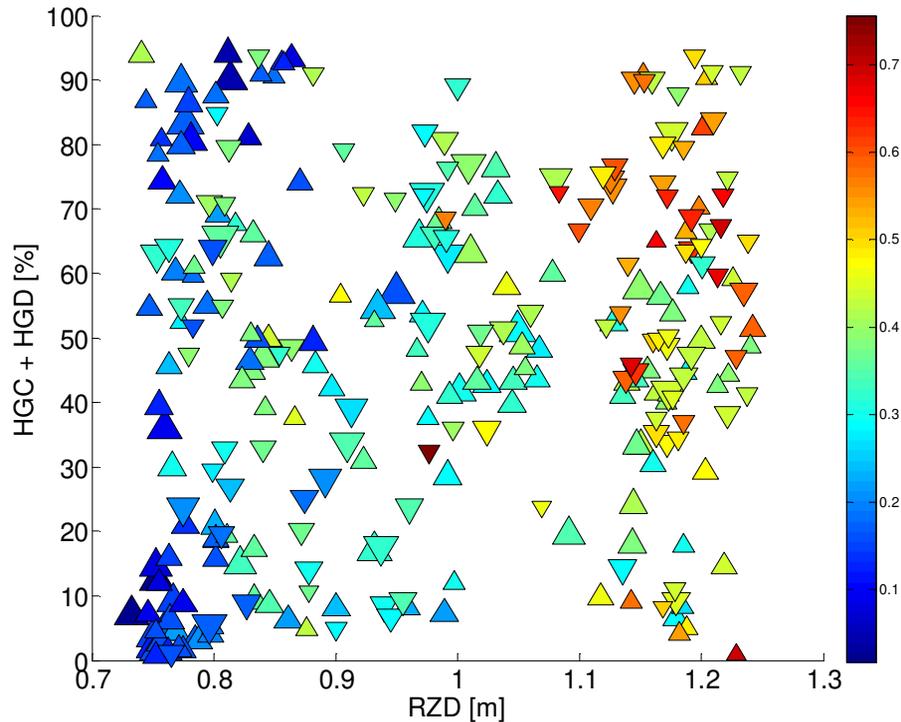


Fig. 8. Five-dimensional plot of signature runoff ratio versus soil, vegetation and climate characteristics. Triangles are color coded by Runoff Ratio. Size of triangles is proportional to drainage area (large point means large value). Triangles pointed upwards mean water limited catchments (pointed down means energy limited [$AI > 1$], upwards means water limited).

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