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**Technical Note:
Characterizing
hydrologic change**

K. A. Sawicz et al.

Technical Note: Characterizing hydrologic change through catchment classification

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Abstract

In recent years there has been an intensive search for suitable strategies to organize and classify the very heterogeneous group of catchments that characterize our landscape. One strand of our work has focused on testing the value of hydrological signatures derived from widely available hydro-meteorological observation for this catchment classification effort. In this study, we classify 314 catchments across the contiguous US using six signature characteristics for a baseline decade (1948–1958) into 12 distinct clusters. We develop a regression tree to re-classify these catchments for subsequent decades. This activity allows us to assess the movement of catchments between clusters in time, and therefore to assess whether their hydrologic similarity/dissimilarity changes. We found situations where catchments belonging to one class would diverge into multiple classes, and conversely cases where catchments from different classes would converge into a single one. Finally, we attempt to interpret the changes observed to identify the causes for this temporal variability in hydrologic behavior. Generally, the change in both directions was most strongly related to changes in the water balance characteristics of catchments with an aridity index close to one. Changes to climate characteristics of catchments – mean annual precipitation, length of winter or seasonality of precipitation throughout the year – seem to explain most of the observed class transitions between slightly water-limited and slightly energy-limited states. Inadequate temporal information on other time-varying aspects such as land use change made it difficult to disentangle causes for change further.

1 Introduction

The topic of catchment classification has seen steep rise in interest in recent years suggesting that there is significant interest in making progress regarding this topic (McDonnell and Woods, 2004; Wagener et al., 2007). Approaches to catchment classification can be based on physical catchment characteristics (Winter, 2001; Wolock,

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2004; Gharari et al., 2011; Cheng, 2012), on streamflow characteristics (Olden et al., 2011; Ley et al., 2011; Corduas, 2011), or on environmental tracers (Flury and Wai, 2003; Tetzlaff et al., 2009). These different strategies each have advantages and disadvantages. Tracers provide more insight, but are not widely available. Physical characteristics are (essentially) available everywhere, but we have to make assumptions about how they control hydrologic behavior and we lack suitable subsurface descriptors (Winter, 2001). Streamflow observations are widely available in developed countries where dense observational networks exist – though their information content regarding catchment functions is limited (Carrillo et al., 2011). Ultimately, any classification system needs to enable a mapping between climate, physical characteristics and hydrological behavior – while being widely applicable (Wagener et al., 2007). Here we follow the strategy introduced in Sawicz et al. (2011) who established similarity between catchments on the basis of hydrologic signatures derived from widely available observations of streamflow, temperature and precipitation. The authors used a Bayesian clustering algorithm to understand hydrologic similarity and dissimilarity across 280 catchments located in the Eastern half of the US. Hydrologic similarity was defined as closeness in a six-dimensional signature space.

As the topic of catchment classification is increasing in interest, there is the recognition of the increasing nonstationarity of the hydrological cycle, mainly due to climate and land use change (e.g., Milly et al., 2008). Land use changes occur due to urbanization (Martin et al., 2012), forest clearance (Andreassian, 2004), and agricultural demands/practices (Parton et al., 2005; Mahmood et al., 2006). These changes alter the functional behavior of catchments in terms of how these systems partition, store and release water (Wagener et al., 2007). Climate change will increasingly create new boundary conditions in which catchments will evolve. We start to realize that climate change can alter the behavior of catchments in intricate ways (e.g., Rosero et al., 2010; Merz et al., 2011). Land use change will have a more immediate impact in many cases, though our predictive ability regarding how this change manifests itself in hydrological characteristics is not often obvious. Any catchment classification system therefore has

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to account for these changes, or alternatively, any classification framework should help in shedding light on how and why catchments are changing. Therefore classification provides one possible option for new ways of hydrological investigations in a changing world (Wagener et al., 2010).

In this paper, we combine the topics of catchment classification and environmental change to investigate in how far a signature-based classification can provide insight into the consequences of and the reasons for the changing behavior of catchments in time. To achieve this objective we re-classify 314 catchments located across the US for four consecutive decades. We assume that a decade is both required and sufficient to reasonably estimate signature values for classification. Cluster analysis and decision tree models used are based on six different hydrologic signatures. We attempt to identify how catchment classification, and therefore hydrologic similarity, changes through time and provide mechanistic explanations for the change identified in our study region.

2 Data and study catchments

The 314 catchments selected for this study are a subset of the MOPEX database (Duan et al., 2005). Only catchments with at least 95 % data availability across all four selected periods (1948–1958; 1958–1968; 1968–1978; 1978–1988) were included in the investigation. Catchments that were already heavily impacted by human activity during the baseline decade were excluded from the analysis a priori through visual inspection. The spatial density of catchments available through the MOPEX initiative is much higher in the Eastern US than in the Western US. Further details on the dataset can be found in our previous study (Sawicz et al., 2011). The MOPEX database includes daily streamflow data from USGS hydro-climatic data network, daily precipitation and temperature data from the Natural Resources Conservation Service SNOTEL and the National Climate Data Center, soil texture data from STATSGO, and vegetation classification information from the University of Maryland. The USDA provided information about land cover (agriculture, impervious area, forest) at 5 yr intervals at the state level.

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Falcone et al. (2010) collated information about stream network characteristics, geology, number of dams, soil, and topography that were used here for further analysis (Table 1).

3 Methods

3.1 Signatures

Six signatures were calculated from long-term records of daily streamflow, air temperature, and precipitation observations per catchment for four decadal periods: (1) 1948–1958 (baseline), (2) 1958–1968, (3) 1968–1978, and (4) 1978–1988. We use the hydrologic year rather than the calendar year to remove the impacts of carry-over of water storage between calendar years. The US hydrologic year spans from 1 October of a given year to 30 September of the following year. Signatures were chosen to capture catchment behavior at annual, seasonal and daily timescales, and to capture hydrological behavior for averages and extremes. All signatures are briefly described below. For a more detailed discussion of these signatures see Sawicz et al. (2011).

The signatures used here are:

- Runoff Ratio (R_{QP} , [-]), the long term water balance represented by the ratio of long-term average streamflow (Q) to long-term average precipitation (P).
- Baseflow index (I_{BF} , [-]), the portion of streamflow classified as baseflow, which represents a measure of the volume of water taking longer flow paths through the catchment. In this study we use the one-parameter single-pass digital filter method based on previous studies as reported by Arnold et al. (1995) and Lim et al. (2005).
- Slope of the flow duration curve (S_{FDC} , [-]), the slope between the 66 % and the 33 % flow exceedance percentiles, which is an indicator of streamflow variability.

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- Ratio of snow days (R_{SD} , [-]), the ratio of precipitation events that occur when mean daily temperature is below 2°C to the total number of precipitation events. This signature is a proxy for flow seasonality and the importance of snow storage.
- 10th Percentile Streamflow (Q_{10} , [-]) is the ratio of daily streamflow that is exceeded 10% of the time normalized by the mean streamflow. This signature is a measure of high flows.
- 90th Percentile Streamflow (Q_{90} , [mm]) is simply the value of daily streamflow that is exceeded 90% of the time. This signature is a measure of low flows.

3.2 Clustering algorithm

The method chosen for this study is a fuzzy partitioning Bayesian mixture clustering algorithm implemented in the AutoClass C software package (version 3.3.4) (Stutz and Cheeseman, 1995; 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 et al., 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 (i.e., highest probability) class assignment that is listed. The number of classes is automatically decided during the clustering process. The input variables characterizing the catchments, i.e., the signatures, were log transformed and modeled as normally distributed continuous variables with an associated degree of uncertainty. Additionally, these variables are scaled such that the magnitude differences between signatures do not cause any additional weighting in the calculation of the distance metric.

Due to the probabilistic nature of the AutoClass-C algorithm, classification realizations will slightly change over multiple runs. We use the Adjusted Rand Index to test

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the stability of the results across these different realizations (ARI, Rand, 1971; Hubert and Arabie, 1985). The ARI takes a value of 0, if the agreement between two classification outcomes is no better than mere chance, and 1, if there is perfect agreement between the two classification results. While a range of different clustering algorithms is available, the chosen algorithm has been shown to be effective with respect to its use in environmental studies (Reidy Liermann et al., 2012; Kennard et al., 2010; Sawicz et al., 2011).

3.3 Decision tree

A CART analysis of the results for the baseline time period (1948–1958) was performed using all six signatures to predict the class assignment generated from the AutoClass cluster result. The stopping criteria used to prune the tree was 10-fold cross validation. Limitations to the CART analysis, resulting from simplistic splits and a small number of catchments constrained to two groups (C10 and C11), were adjusted manually to improve accuracy and value of the analysis.

4 Results and discussion

4.1 Catchment classification for baseline decade (1948–1958)

The AutoClass cluster analysis produced 12 different classes as shown in Fig. 1. Classes that were formed exhibited in most cases strong spatial patterns. We can use the normalized influence measure discussed in the methods section to quantify the importance of a signature for the clustering result. The signatures influenced the cluster analysis in descending order [Signature (Normalized Influence Measure)]: R_{QP} (1.00), R_{SD} (0.807), S_{FDC} (0.626), I_{BF} (0.626), Q_{90} (0.626), and Q_{10} (0.501). The spatial patterns found are generally similar to the ones identified in Sawicz et al. (2011), though some differences can be seen due to the differences in signatures used and in

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catchments included (i.e., we use a larger and more diverse set of catchments in this study).

We discuss the classification for the baseline period in detail, while we subsequently only discuss class changes for the other periods. Qualitative statements regarding whether signature values and physical/climatic characteristics are high and low are only made in relation to other catchments within our dataset (Fig. S2 and Supplement). Clearly visible as a single group is a collection of small catchments in the North-East and along the North facing side of the Appalachians, which reflect an energy-limited hydrology (Group 0). Group 1 on the other hand consists of large agricultural catchments that have significant snow storage during the winter while their summers are very dry. A more widely spread cluster of catchments is found along the south-east coast of the US and is characterized by the permeable geology of this region, exhibiting therefore flat flow duration curves (FDC) and relatively high baseflows (Group 2) (Bloomfield et al., 2009). These catchments experience storms of short duration with dry summers resulting in significant low flow periods. Just below this cluster, we can identify a group of catchments on the south-facing slopes of the Appalachians with low high flows, Q_{10} , and high low flows, Q_{90} (Group 3). This group of catchments is also characterized by quite a flat FDC. Catchments of Group 4 are located further inland and at lower elevations. These are low aridity catchments with very variable flows and little baseflow due to rather impermeable soils. Group 5 is a cluster located on the southern side of the Great Lakes. These lakes control the climate of the region and the catchments show very low FDC slopes, while they have the highest baseflow indices. Catchments in the coastal region of the western US are small, steep and have permeable soils (Group 6). They show the highest $P-PE$ differences (P : Precipitation, PE : Potential Evapotranspiration) of the dataset along with the highest topographic slopes and elevation differences. They are snow dominated and exhibit the highest runoff ratios. Group 7 shows an interesting split between a few catchments in the western US and a bigger cluster in the central US. These catchments are characterized by impermeable soils, which cause a flashy response, while their aridity indices are close to 1.

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Group 8 consists of mountainous catchments with the highest elevations in the Northern US. These are heavily snow-dominated catchments (highest ratio of snow days) with a very damped (highest percentage sand in soils) and delayed response to precipitation input. The largest catchments are part of Group 9. These are located in the central and southwestern US and have an ET-dominated climate (lowest precipitation) (ET: evapotranspiration). Group 10 is made up of catchments at the lowest elevation, which experience the highest temperatures and exhibit very low summertime flows. The last cluster of catchments (Group 11) has the highest aridity indices (lowest runoff ratio), the lowest high flows (Q_{10}) and lowest baseflow indices. This hydrologic behavior is caused by high air temperature, low precipitation and low permeability soils.

4.2 CART analysis to understand class separations

Figure 3 shows the decision tree that resulted from a CART analysis of the classification for the baseline decade discussed above. A total of 285 catchments (91 %) could be assigned via the decision tree for the original AutoClass classification, which resulted in 21 different end nodes (some classes have more than one end node). The presence of more end nodes than classes is an artifact of the CART analysis itself and the way it organizes information. Mapping these nodes on the classification leads to an assignment accuracy ranging from 100 to 76 % for all classes (Fig. 4).

There are a number of thresholds within the decision tree that mark key transitions between different classes. The runoff ratio threshold of 0.295 represents a primary separation between wet and dry catchments within the classification. The Pike–Turc equation that can be used to estimate R_{QP} from estimates of P/PE is defined as follows,

$$R_{QP} = 1 - \frac{1}{\left(1 + \left(\frac{P}{PE}\right)^2\right)^{\frac{1}{2}}}. \quad (1)$$

Interestingly, when applying this Turc-Pike relationship, a RQP value of 0.295 represents an expected aridity index (P/PE) of 1.0. This threshold can therefore be

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interpreted as the separation between water limited ($R_{QP} < 0.295$) and energy limited ($R_{QP} > 0.295$) catchments. This threshold value was achieved purely as a result of the empirical Autoclass cluster analysis and the CART analysis.

For the slope of the flow duration curve, S_{FDC} , the primary separation, at 0.045 and 0.049, is virtually the same on both branches of the classification system. S_{FDC} values less than this threshold value correspond to a more “filtered or damped response” whereas larger values correspond to a more “flashy response”. S_{FDC} represents the distribution of flow values of different magnitude, and will be influenced by any changes in the distribution of precipitation events or by land use change that can alter how a catchment partitions water at the land surface.

The ratio of snow days, R_{SD} , threshold of 0.225 can be interpreted as the length of winter conditions. With the exception of the catchments in the western US, which experience a dramatically different distribution of precipitation (dominant winter precipitation), there is a clear relationship between R_{SD} and the length of time between the first day of freezing and first day of thawing. A R_{SD} value of 0.225 equals approximately 4 months of snow conditions (less than 0.225 can be considered to be a short winter, and greater than 0.225 can be considered a long winter). Unlike the other signature thresholds, there is more than one R_{SD} threshold present in the decision tree. A threshold of 0.125 corresponds to a duration of about 3 months. A threshold of 0.465 corresponds to 5–6 months of winter conditions.

The low flow characteristic, Q_{90} , only appears in the decision tree to separate catchments that have zero flow periods from those that show perennial streamflow, at a threshold of 0.005. This corresponds to a separation between perennial or near perennial catchments ($Q_{90} > 0.005$) and intermittent streams ($Q_{90} < 0.005$), i.e., those that experience streamflow less than 90 % of the time.

4.3 Signature values during the four decades

A wide range of climatic and physical catchment characteristics impacts catchment signature values (Wagener et al., 2007). Disentangling these influences simultaneously

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for a large number of catchments is likely to be very difficult given the lack of time series describing land use patterns such as urbanization (e.g., Martin et al., 2012) and due to the heterogeneity of characteristics found within a catchment (especially those that are poorly described like sub-surface characteristics). Nonetheless we will characterize the changes observed, and make an attempt here to explain some of the identified changes. We focus in a parallel study on how some of these shortcomings of empirical studies can be overcome by physically-based modeling (Troch et al., 2013).

We briefly discuss the potential impact of both climate and land use change on hydrologic signatures, before we analyze what changes in signature values can be observed in our dataset. Between 1948 and 1988, different parts of the US experienced varied changes in land use, including urbanization, logging and vegetation clearance, and expanding agricultural cover (Woodbury et al., 2006). These changes altered catchment behavior by impacting precipitation patterns, partitioning, storage and release of water. Logging for example can allow more water to be stored in the soil while simultaneously decreasing the amount of water leaving a catchment through evapotranspiration, therefore impacting runoff ratio (Woodbury et al., 2006). Changes in agricultural extent will impact catchment behavior by altering partitioning at the land surface (for example changing S_{FDC}) or by altering the distribution of quick versus slow flow paths (B_{FI}). Increasing agricultural activity likely increases evapotranspiration (impacting R_{QP}), changes soil water retention (impacting R_{QP} , B_{FI} , S_{FDC} , Q_{90}) and may change the length and distribution of flow paths (impacting B_{FI}). Changes to both average and extreme climate conditions will also alter catchment behavior. Runoff ratio is varying through changes in average air temperature and precipitation. Changes to S_{FDC} are influenced by the frequency, intensity, or distribution of precipitation events, as this impacts the overall distribution of streamflow events. As the FDC information used (for the signature defined in this paper, S_{FDC}) is derived from the central 33 % of the hydrograph, the S_{FDC} signature is less unaffected extreme flood and drought events. Greater damping in the catchment as reflected by lower S_{FDC} values might occur if the precipitation regime of a catchment becomes more evenly distributed (Yeager et al., 2012), or

due to the additional retention of water in the catchment from increasing snow storage. Warmer winter air temperatures on the other hand will reduce snow storage, resulting in less delayed streamflow response (time between precipitation falling and runoff occurring) and removing the presence of large spring melt events in the streamflow time series.

We can examine how the six signatures vary across the four decades (Table 1) to inform us of general trends. As an average across all catchments, R_{QP} shows little variation across the four decades, though some catchments experience large changes between periods ($\pm 15\%$ of the total range). If we examine the degree of change between decades, we find that delta values (change of signature values between decades) are more or less normally distributed between each period, with mean values slightly below zero from the first to second and third to fourth periods, and slightly positive between the second and third periods. R_{SD} is similarly invariant on average, but some catchments change by $\pm 13\%$ between periods and with a noticeable negative skew for the delta values between periods 1 and 2 (the remaining differences show normal distributions). B_{FI} changes exhibit normal distributions with consistently positive means between each of the 4 decades (with a maximum mean of 1.3% found between periods 2 and 3). Change values in B_{FI} are greater than R_{QP} and R_{SD} with maximum inter-period variability reaching 25–30% of the range over time. S_{FDC} change values exhibit a slightly negative skew between each period and consistently negative means (most extreme center of mass value of -4% between periods 1 and 2). The largest value of S_{FDC} change reaches -47% of the total range. The distribution of changes to Q_{90} values is positively skewed. However, catchments that have the highest values also show the greatest variability ($\sim 30\%$). Q_{10} , which is not present in the decision tree, shows the highest variability through time, with mean values of -1 , -11 , and 2% between periods 1 and 2, 2 and 3, and 3 and 4, respectively. Q_{90} and Q_{10} are expected to exhibit the most inter-period variability because they define events that occur rarely (flood and drought conditions) whereas the other 4 signatures either capture flow conditions that are more common (S_{FDC}), or capture longer time scale averages (B_{FI} , R_{QP} ,

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R_{SD}). R_{QP} , B_{FI} , and S_{FDC} all show the least variability during the final transition phase, whereas R_{SD} , Q_{90} , and Q_{10} show the least variability between period 1 and 2. R_{QP} , B_{FI} , R_{SD} , Q_{10} , and Q_{90} experience the highest variability between periods 2 and 3, while we found the highest variability for S_{FDC} between periods 1 and 2. The variability found suggests that to split the analysis up into different geographical regions is sensible, which is therefore how the following section is structured.

4.4 Interpretation of change by region

Change in catchment class assignment can be organized as three transition phases between each of the four decades studied. We identify groups of catchments that change class assignment between decades, rather than focusing on individual catchments in isolation, to better understand broader patterns of change. Trying to explain the change occurring in each individual catchment would be infeasible. During the first transition phase (between period 1 and 2), four spatially interesting class changes occur. The second and third transition phases both exhibit two spatially interesting class changes. The groups of catchments that we emphasized, along with the remaining changing catchments are shown in Fig. 5a–c.

4.4.1 Transition phase 1 (1948–1958 to 1958–1968)

The first group of catchments we analyze is located in the Midwest/Great Lakes area. Its members transition from a number of different classes (C0, C3, C4, C5, C7) to a single class, (C1, indicated by dark green; Figs. 5, 1a). These changes in hydrologic similarity can be explained by changes to runoff ratio, R_{QP} (C0, C3, and C4), and to low flows, Q_{90} (C7). For the latter, a small increase in average precipitation (5%) changes C7 (blue) catchments to C1 catchments via a slight increase in Q_{90} . The intra-annual variability of precipitation on average does not change during this transition period, so it is a general increase of precipitation that seems to explain the increase in Q_{90} . These catchments are located across Missouri, Oklahoma, and Kansas and exhibit

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high percentages of agricultural land use (57.5 % for Kansas, 42.5 % in Missouri, and 34 % in Oklahoma). However, the change in Q_{90} does not seem to be affected by the change of land use as changes to agricultural cover between these two periods of time are inconsistent across these three states, with Missouri agricultural land showing an increase, Oklahoma cover a decrease, and the Kansas cover remaining constant. The primary reasons for this shift appear to be the increase in precipitation (from period 1 to period 2) and a less seasonal precipitation distribution across the year, i.e., more summer rainfall (Pryor and Schoof, 2008).

Shifts in catchments from one class to many or from many classes to one between phases often seem to be tied to shifts between water and energy limited conditions. Initially, the primary catchments that split into classes C0, C3, C4, and C5 because of differences in values of S_{FDC} , B_{FI} , and R_{SD} . The energy-limited catchments are further separated from the water-limited catchments in C1 (dark green) during the baseline period. However, the dissimilarity in S_{FDC} , B_{FI} , and R_{SD} values became secondary to the common shift of the aridity index to a water-limited state, and the corresponding change in runoff ratio, R_{QP} , resulting in catchments from many classes shifting to a single class. The primary cause of this decrease in R_{QP} values was found to be a decrease in total annual precipitation (mean annual decrease of about 8 %).

Catchments located in Virginia diverge from class C3 (cyan) into classes C1 and C0 (Figs. 5, 1b). The shift from C3 to C1, caused by a decrease in R_{QP} values, is most likely driven by an average 9 % decrease in precipitation across these catchments. In contrast, catchments that transition from C3 to C0 do so due to higher values of ratio of snow days (R_{SD}) (increasing past the 0.225 threshold), which corresponds to a two week increase in winter length. The increase in R_{SD} values is caused by a decrease in air temperature by an average of 0.7 °C. All catchments transitioning from class C3 to C1 and C0 experience the same mean increase in their R_{SD} values (average of 0.03). However, the initial R_{SD} values vary from 0.14 to 0.22. This increase results in a divergence of classes since the R_{SD} values for the second period (range of 0.17 to 0.25) now fall on either side of the CART threshold of 0.225. In this case, the

catchments transitioning to C0 are located directly on the Appalachian mountain range (higher elevations) whereas the catchments transitioning to C1 are found directly east of the mountain range (lower elevations).

Southeastern US catchments, originally part of class C4 (orange), transition to C2 mainly due to a change in S_{FDC} (4 catchments) (Figs. 5, 1c). The behavioral distinction between these classes is S_{FDC} , which shows a more damped response in these catchments during the second period, as opposed to a more flashy response in the baseline period (3 of the 4 catchments experience a decrease of over 10% of the observable range). These catchments experience a mean precipitation seasonality index (PSI [-], a measure of seasonality of precipitation) across all catchments of 0.21 during the first period and 0.19 during the second period (Pryor and Schoof, 2008). This represents a 2.4% decrease in the seasonality of precipitation throughout the year which may contribute, as a minor part, to the damped response.

The last observed shift for this first transition phase occurs through parts of Arkansas, Mississippi, and Alabama, where catchments in classes C2 and C4 transition to class C3 (Figs. 5, 1d). Catchments transitioning from C4 show a decrease in S_{FDC} (which again indicates a more damped response as was seen in area 1c). These catchments experience a decrease in PSI, from an average of 0.19 in the first period to 0.165 in the next period. However even though the mean value of these catchments are decreasing, two of the four catchments do not experience any change in PSI implying that there must be other causes for the decrease in S_{FDC} . They do not transition to C2, as they experience a higher value of R_{SD} than those in 1c. Catchments, which transition from C2 to C3, experience an increase in R_{SD} due to a 2-week average lengthening of the winter season per year.

4.4.2 Transition phase 2 (1958–1968 to 1968–1978)

Catchments belonging to C1 (dark green) in the second period experience transitions to a number of classes (C0, C3, C4, and C5; Fig. 5b, groups 2a and 2c), shifting from water to energy-limited conditions due to an increase in R_{QP} . The cause of this shift

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can be attributed to an average increase of annual precipitation of 0.24 mm day^{-1} . This transition is seen both in areas 2a and 2c, which cover the Midwest/Great Lakes region and the eastern slopes of the Appalachian Mountains.

Catchments located in West Virginia and Kentucky belonging to class C4 (orange) experience a shift from a flashy response in the second period to a more damped response in the third period, quantified by a decrease in the SFDC values for these catchments (Figs. 5b, 2b). Catchments transition to C0 (yellow) and C3 (cyan), depending on whether the value of RSD for each of these catchments is above (C3) or below (C0) the 0.225 regression tree threshold. These catchments experience a relatively large decrease in PSI (0.20 in period 2 vs. 0.14 in period 3), which indicates that the cause of the decrease in S_{FDC} are caused by a less seasonal precipitation regime.

4.4.3 Transition phase 3 (1968–1978 to 1978–1988)

Changes occurring between the third and fourth periods are primarily due to shifts between water and energy limited conditions across the Midwest. Despite close spatial proximity, the northern portions of Iowa experience a slight increase in precipitation (2% from the prior period), while the southern portion of Iowa, the eastern portion of Illinois, and all catchments in Missouri and Arkansas experience a decrease (3% from the prior period) in precipitation. These changes result in proportional shifts in R_{QP} values and hence in class transitions. Catchments located in central to northern Iowa (Figs. 5, 3a) transition from C0 (yellow) to C5 (dark red), while the remaining catchments of interest transition from C3 (cyan) to C1 (dark green). Changes in R_{QP} values that cause these transitions are much smaller than those found in other phases though (± 1 to 2%). These transitions therefore highlight how slight changes in climate may result in different shifts in behavior for neighboring catchments. Although land-use in this general area is dominated by agriculture, there is no substantial change in agricultural land-use at the state level during the 3rd transition period, and no general trends were found that suggested agriculture had an effect on R_{QP} .

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Strong spatial patterns were found for groups of catchments that transition between classes for similar reasons, albeit the magnitudes of those changes differ in relation to the catchments proximity to thresholds in signature space. As described above, changes to climatic forcing are primarily responsible for spatial patterns of shifts in catchment behavior. However, there are a number of catchments that did not experience behavioral shifts found in other similar catchments. These later catchments have experienced changes in signature values for reasons that we are unable to quantify at present. Catchments along the western coast experience a high climatic gradient as well as variable local physical features. In order to interpret the control of class transition in these catchments over time, we require additional temporal information quantifying changes in how vegetation, land use, and human activity change. Information such as the Leaf Area Index is currently being recorded at relatively coarse spatial and temporal scales (e.g., MODIS, GRACE) and only for the past decade, therefore limiting its applicability to long-term studies.

5 Conclusions and open questions

Classification can be a valuable tool for understanding catchment scale hydrological change. It can be used to characterize temporal and spatial changes in similarity and dissimilarity between catchments, and provide a general indicator of the sensitivity of catchments to change. In this study, we utilize six streamflow-based signatures of hydrologic behavior at annual, seasonal, and daily time scales to classify catchment behavior across the US. We find that catchments experienced changes to all six signatures to differing degrees at different times.

The initial classification for the baseline decade (1948–1958) resulted in 12 clusters that separated distinctly due to differences in hydrological behavior as expressed by the differences in signature values. We subsequently analyzed how much other decades deviate from this initial classification by re-classifying the catchments using a decision-tree established for the baseline period. The first transition phase, taking

place between 1948–1958 and 1958–1968, showed just over 40 catchments changing class, spatially ranging from Oklahoma/Nebraska to Virginia. The second transition phase, taking place between 1958–1968 and 1968–1978, with a similar number of class changing catchments, most experiencing large changes (5–10 %) in values of the R_{QP} and the S_{FDC} . During the last transition phase, taking place between 1968–1978 and 1978–1988, only about half as many catchments changed class, and they were located solely in the Midwest. Generally, climate was found to be a primary control on catchment behavior when comparing catchments at the decadal scale. Change in climatic characteristics – mean annual precipitation, length of winter period, intra-annual seasonality of precipitation – had the strongest impact on changes in catchment behavior. While we were able to explain some of the changes found, e.g., the regular switch between energy- and water-controlled regimes for catchments close to an aridity index of one, other temporal variability could not be explained as well with the information available, for example changes to the flow duration curve slope, S_{FDC} . Land-use, although likely to be important in how a catchment filters water, was not found to provide valuable information in describing the change in hydrologic behavior (most likely due to limited information available at the catchment scale). The difficulty in explaining some of the changes based on an empirical analysis alone, as attempted here, might also partially relate the rather moderate changes observed. Martin et al. (2012) for example showed that urbanization in the order of 15 % of the catchment area could be required to detect a significant change in signature characteristics. Most of the signature changes observed here are rather small, in the order of 5–10 %.

Some open questions therefore remain, such as: (1) to what degree does the climate-vegetation (land use) interaction matter in explaining changing behavior? (2) What space-time resolution of physical and climatic information is needed to capture the change in hydrologic behavior? (3) How can we effectively use watershed models to disentangle the reasons for the observed change in hydrologic behavior?

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Supplementary material related to this article is available online at:
<http://www.hydrol-earth-syst-sci-discuss.net/10/6599/2013/hessd-10-6599-2013-supplement.pdf>.

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Table 1. Minimum, mean, and maximum values for the six signature classes across each of the four periods.

Period	RQP [-]			BFI [-]			SFDC [-]		
	min	mean	max	min	mean	max	min	mean	max
1	0.02	0.37	1.00	0.29	0.64	0.96	0.01	0.037	0.103
2	0.01	0.36	1.00	0.28	0.65	0.95	0	0.033	0.088
3	0	0.40	0.99	0.31	0.66	0.96	0	0.031	0.073
4	0	0.39	0.90	0.31	0.66	0.96	0.01	0.031	0.080

Period	RSD [-]			Q_{10} [-]			Q_{90} [mm]		
	min	mean	max	min	mean	max	min	mean	max
1	0	0.26	0.64	0.44	2.24	3.53	0	0.17	1.71
2	0	0.27	0.61	0.65	2.21	3.43	0	0.19	1.97
3	0	0.28	0.66	0.44	1.79	3.9	0	0.23	1.97
4	0	0.27	0.64	0.45	1.88	4.1	0	0.20	1.43

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Classification for Baseline Decade (1948-58)

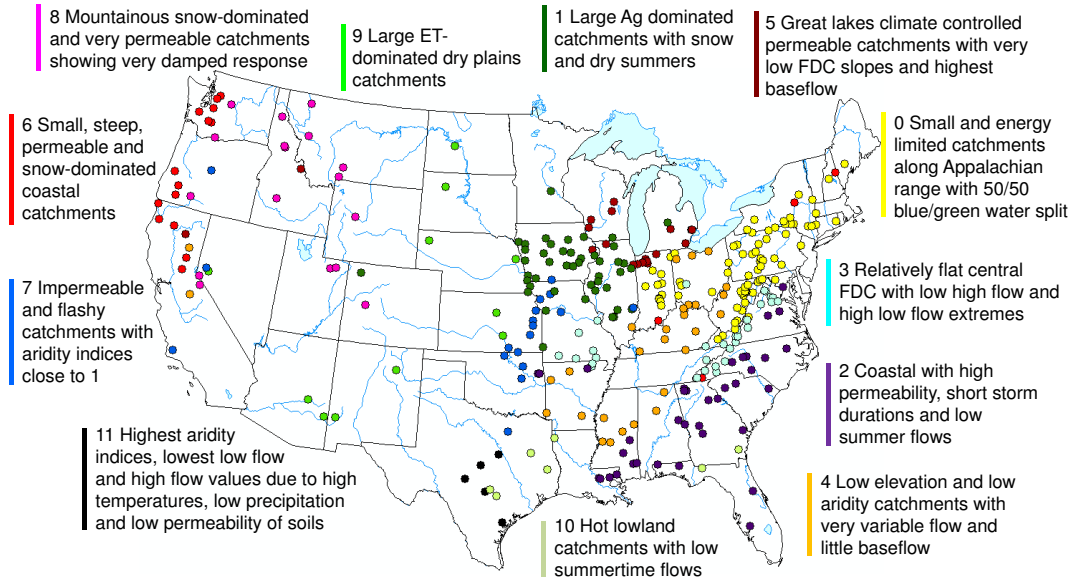


Fig. 1. Results of cluster analysis based on 6 hydrological signatures as described by their physical and climatic properties.

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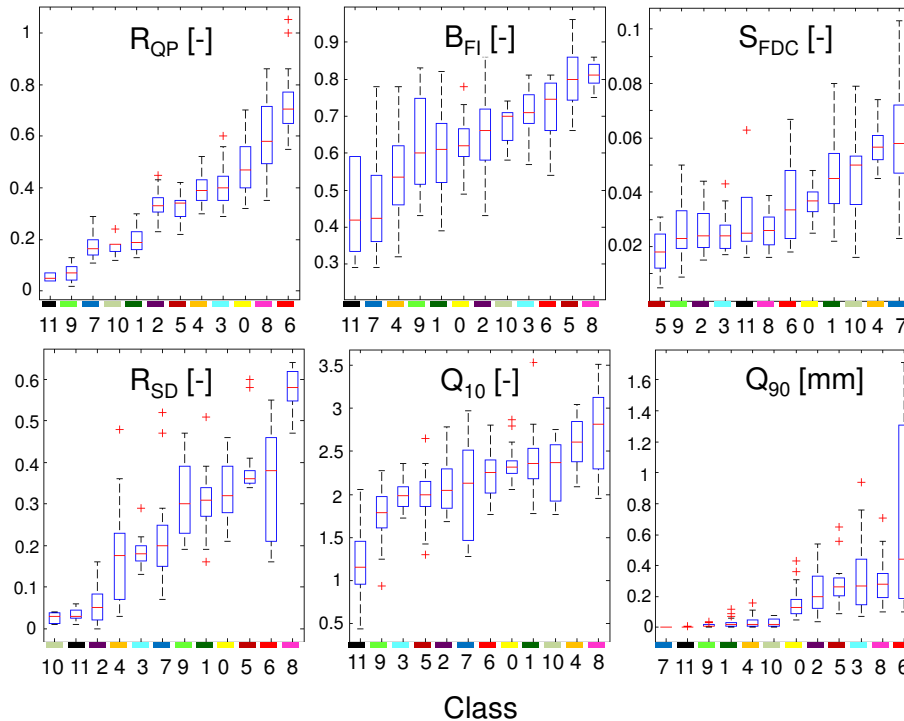


Fig. 2. Box–Whisker plots of signature characteristics for each cluster.

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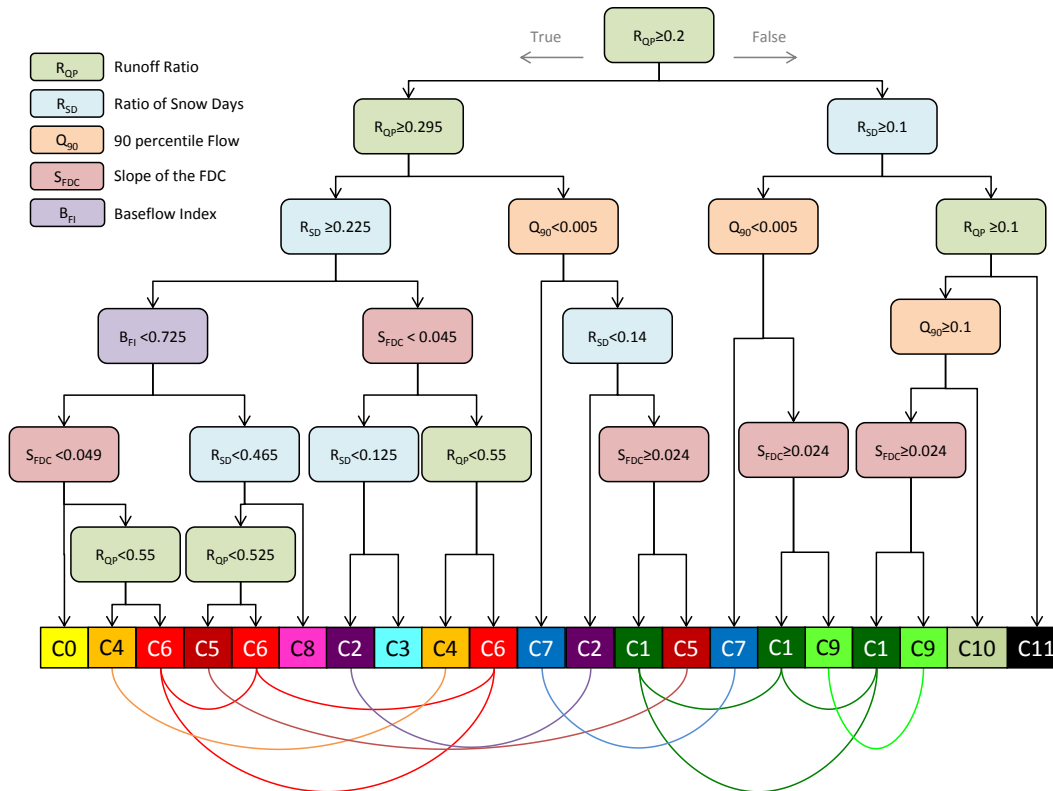


Fig. 3. CART decision tree showing what physical and climatic characteristics control the classification, including separation thresholds.

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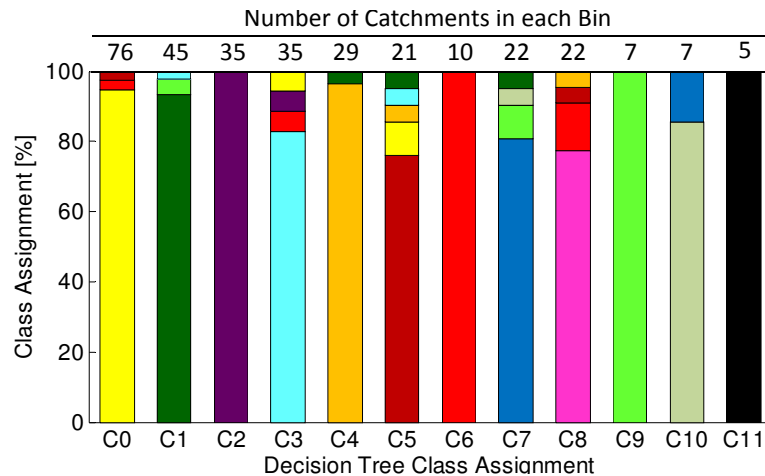


Fig. 4. Analysis of CART analysis results with respect to the percentage of classes that have been assigned (correct assignment: min is 76 %; avg. is 91 %). Colors are used to show miss-classification through CART.

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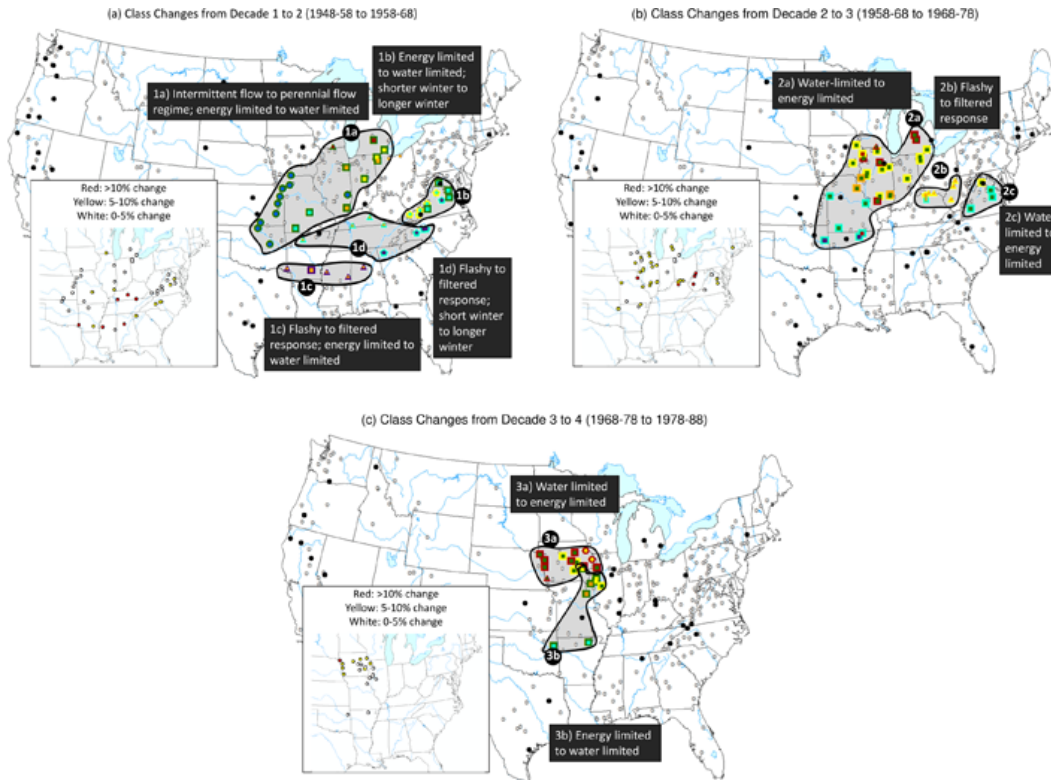


Fig. 5. Maps highlighting those catchments that change class assignment from one decade to the next, including interpretation of change. The inner color of each marker describes the initial class (see Fig. 1 for color scheme legend) and the boarder color describes the new class in which catchments transition during the decade under study. A catchment with a key change in S_{FDC} is visualized as a triangle, in R_{SD} as a pentagon, in R_{QP} as a square, and Q_{90} as a circle.