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Exploring the physical controls of regional patterns of flow duration curves – Part 3: A catchment classification system based on seasonality and runoff regime

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Abstract

Predictions of hydrological responses in ungauged catchments can benefit from a classification scheme that can organize and pool together catchments that exhibit a level of hydrologic similarity, especially similarity in some key variable or signature of interest.

- Since catchments are complex systems with a level of self-organization arising from co-evolution of climate and landscape properties, including vegetation, there is much to be gained from developing a classification system based on a comparative study of a population of catchments across climatic and landscape gradients. The focus of this paper is on climate seasonality and seasonal runoff regime, as characterized by
- the ensemble mean of within-year variation of climate and runoff. The work on regime behavior is part of an overall study of the physical controls on regional patterns of Flow Duration Curves (FDCs), motivated by the fact that regime behavior leaves a major imprint upon the shape of FDCs, especially the slope of the FDCs. As an exercise in comparative hydrology, the paper seeks to assess the regime behavior of 428 catch-
- ¹⁵ ments from the MOPEX database simultaneously, classifying and regionalizing them into homogeneous or hydrologically similar groups. A decision tree is developed on the basis of a metric chosen to characterize similarity of regime behavior, using a variant of the Iterative Dichotomiser (ID3) algorithm to form a classification tree and associated catchment classes. In this way, several classes of catchments are distinguished,
- in which the connection between the catchments' regime behavior and climate and catchment properties becomes self-evident. Only four similarity indices are entered into the algorithm, all of which are obtained from smoothed daily regime curves of climatic variables and runoff. Results demonstrate that climate seasonality plays the most significant role in the classification of US catchments, with rainfall timing and climatic
- aridity index playing somewhat secondary roles in the organization of the catchments. In spite of the tremendous heterogeneity of climate, topography, and runoff behavior across the continental US, 331 of the 428 catchments studied are seen to fall into only six dominant classes.





1 Introduction

This work is aimed at developing a catchment classification system that will help organize a large population of catchments within the continental US into homogeneous groups on the basis of climate seasonality and runoff regime. The work is part of a

- ⁵ broader study aimed at better understanding of the physical controls of the Flow Duration Curve (FDC). It has been motivated by the observation that a catchment's regime curve (ensemble mean of the within-year variation of runoff) has a major impact on the shape of the FDC (Yokoo and Sivapalan, 2011), thus serving as the connective tissue between high and low flows that appear at the extreme ends of the FDC.
- ¹⁰ Through numerical simulations with a physically-based rainfall-runoff model applied to hypothetical catchments, Yokoo and Sivapalan (2011) showed that the FDC of total runoff can be partitioned into two components, i.e., the FDC of the surface (or fast) flow and that of subsurface (or slow) flow. This result has been further confirmed by the comprehensive analysis of the FDCs of some 200 catchments located within the
- ¹⁵ continental US by Cheng et al. (2012). Yokoo and Sivapalan (2011) further argued that while both the fast and slow flow components are driven by different climate and landscape properties, the FDC of the slow, subsurface flow component closely resembles and could be more easily reproduced from the catchment's regime curve. If this is true, then spatial variations of the regime curve, and associated climatic and landscape con-
- trols that result from their interactions, could help explain the regional patterns of the FDCs within the continental US. So while understanding of the process controls of the regime behavior is important in its own right, it is also valuable for understanding the controls of the FDC.

Catchments everywhere are highly variable, displaying enormous complexity, with a large number of degrees of freedom, which makes it very difficult to make general statements about their responses. Yet, despite substantial heterogeneity and the complexity of their responses exhibited by observations, experience with modeling studies and predictions indicates that at the catchment scale simple models with a small number





of parameters can describe the majority of catchment responses (Sivapalan, 2003). This has encouraged hydrologists to aspire to organize and classify catchments into homogeneous or similar groups on the basis of a small number of explanatory variables, and as a vehicle towards generating improved understanding and predictions

- (Dooge, 1986; Blöschl and Sivapalan, 1995; McDonnell and Woods, 2003). Due to the self-organization of climatic and landscape features arising from their co-evolution, and their impact on multi-scale process interactions and feedbacks, any catchment classification system must be necessarily holistic. A variety of classification approaches and techniques, both inductive and deductive, are reviewed by Olden et al. (2011). Wa-
- gener et al. (2007) proposed a classification system that is based on similarity of key signatures of catchment runoff response. The characteristic signatures included, with decreasing timescale, are inter-annual variability, regime curve (i.e., mean within-year variability of runoff), and the flow duration curve (FDC). There has been considerable success in developing similarity measures and catchment classification on the basis
- of mean annual runoff, expressed in terms of the Budyko curve and the aridity index (Budyko, 1974; Zhang et al., 2001). The focus on the regime curve in this paper is a natural extension to establish the basis for similarity of catchment responses. Whereas the competition between water available and energy available governs similarity at the annual timescale, the shape of the regime curve is governed additionally by the rela-
- tive timing of precipitation and potential evaporation, and the ability of the landscape to store and release water. Roughly 75 yr ago, the Koppen-Geiger climate classification system attempted to classify climates using basic information on the variability of precipitation and temperature (Koppen and Geiger, 1936), which was recently updated by Peel et al. (2007). The classification of regime behavior presented in this paper can be
- seen as a precursor to a possible extension of the Koppen-Geiger climate classifica-25 tion towards classification of catchment responses. The work presented in this paper continues similar work, using the essentially the same datasets, aimed at classification of catchments located within eastern half of the US on the basis of several signatures such as the runoff ratio, the slope of a flow duration curve, or streamflow elasticity

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(Sawicz et al., 2011). This was followed by a comparative study of several catchments based on detailed physically-based modeling that can account for differences in topography, soil types, geomorphology, and vegetation (Carillo et al., 2011).

- The regime behavior of catchments, characterized in this paper on the basis of daily time series data for precipitation, potential evaporation and runoff, represents a combination of the key climate features (relative magnitudes and timing of precipitation and potential evaporation), and runoff (the magnitude and timing) that provides insights into storage and release processes involved in the transformation between precipitation and runoff. These key components of regime behavior represent similarity indices
- that allow grouping of similar catchments into homogeneous classes. We would thus consider two catchments with similar climates and similar landscape controls to produce similar regime behavior. Guided by the results from Yokoo and Sivapalan (2011) and Cheng et al. (2012), in this work, we will construct a catchment classification system based on regional patterns of variability of regime curves, with the expectation that
- it may help to explain regional patterns of the FDCs as well. The classification will be achieved by objective data-driven procedures that ultimately produce homogeneous groups of catchments, based on a metric of similarity formed from four key features associated with regime behavior and following a recursive, binary splitting process. These partitions will produce a decision tree that, at its root, will contain over 400 catchments
 and at its terminal nodes will contain clusters of similar catchments in terms of regime
- behavior.

This paper is one paper of a four-part series whose aim is to better understand the physical drivers of observed regional patterns of the FDCs. The paper by Cheng et al. (2012) approached the problem empirically, by fitting a mixed-gamma distribution to

the FDC of not only total runoff but also the fast flow and slow components of runoff, as well as the corresponding precipitation inputs, for 200 catchments across the continental US. This work revealed regional patterns in the parameters of the gamma distribution and their underlying climatic and landscape controls. It also provided empirical evidence to support the hypothesis offered by Yokoo and Sivapalan (2012) about the





scientific value of partitioning of total runoff into slow and fast components. On the other hand, the paper by Ye et al. (2012) adopted a top-down modeling approach to explore the process controls of the regime curve (i.e., mean within-year variability of runoff), providing an alternative perspective to the data-based classification that is the main
 focus of this paper. Ye et al. (2012) highlighted regional variations of regime behavior governed by differences in aridity and the relative seasonality of precipitation and potential evaporation. These are compounded by differences in the manner in which

- catchments store and release water, including delays due to groundwater and snow.
 The top-down modeling strategy adopted by Ye et al. (2012) enabled them to not only
 discover dominant processes in different regions of the continental US, but also demonstrated that the same process may be dominant in different regions. Finally, Yaeger et al. (2012) provided a synthesis of the insights gained from the empirical study of FDCs by Cheng et al. (2012), the process-based modeling of regime curves carried out by Ye et al. (2012), and the results of the data-based catchment classification presented
- in this paper, with a particular focus on developing a process based understanding of the climatic and landscape controls of the FDCs. In particular, in order to aid development of physically meaningful regionalization of FDCs on the basis of these insights, Yaeger et al. (2012) carried out further meta-analyses, including the three-way mapping between the alternative approaches that have been followed in these three parallel
 studies.

This paper begins with a discussion of hydrologic similarity, focused on similarity of regime behavior, which encapsulates the mean within-year variability of key climatic variables (i.e., relative magnitude and timing of precipitation and potential evaporation) as well the relative timing of runoff. Four key indices that will be used to quantify

hydrologic similarity are also presented and justified. This section is followed by a detailed presentation of the methodology used to construct the decision tree, including the similarity metrics used and a demonstration of the Iterative Dichotomiser (ID3) clustering algorithm. The results of the implementation of the decision tree will be presented next, discussing each of four quadrants of the tree in detail, and focusing upon





six pivotal clusters that happen to describe the majority of the catchments analyzed. Having established clusters of similar catchments, the robustness of the classification tree is verified by reconstructing the decision tree using a 200-catchment subset of the 400 catchment database used initially to develop the catchment classification.

⁵ The paper will conclude with an hydrologic assessment of the catchment classification achieved, including lessons learned and questions left for future work.

2 Similarity of regime behavior

Since the focus of this paper is on the catchment's regime behavior, two catchments will be considered hydrologically similar if their regime behavior can be deemed similar. In this paper, four key similarity indices will be used to characterize the similarity 10 of regime behavior, and are defined and discussed in detail later in this section. These include (i) aridity index, a measure of aridity that, to first order, determines the annual water balance, (ii) a seasonality index that guantifies the strength of seasonal variability of precipitation within the year, (iii) the timing (mean date) of precipitation peak within the year, and (iv) the timing (mean date) of runoff peak within the year. Since the 15 climate of the continental US is such that the seasonal variation of energy (and temperature) is relatively uniform across the country, the timing of precipitation is effectively a measure of the phase difference between the seasonality of precipitation and potential evaporation. On the other hand, the timing of the runoff peak (especially in relation to precipitation and potential evaporation) captures the mechanisms of storage (in soil 20 water or snow storage) and release (in terms of subsurface drainage or snowmelt). In this sense the similarity indices provide a first order mapping towards the regional variations in dominant processes highlighted in the parallel study of Ye et al. (2012).





2.1 An example of regime behavior

Figure 1 presents the daily regime curves of precipitation, potential evaporation, total runoff (and its partitioning into fast flow and slow flow components) for a Midwestern-American catchment, located in Kansas. The fast and slow flow components were obtained by the application of a standard baseflow separation procedure (Lyne and Hollick, 1979; Sivapalan et al., 2011; Cheng et al., 2012). The left image (Fig. 1a) is obtained, using MOPEX daily data from 1948 to 2001 (Sivapalan et al., 2011; Cheng et al., 2011)¹, using ensemble averaging by calendar day. While this image does provide useful information about the within-year (daily) variability of the chosen variables, for
the purpose of catchment classification in this paper, a sliding, 30-day moving average is generated, as shown in Fig. 1b. Equation (1) captures this smoothing,

$$P_{i} = \frac{\sum_{i=15}^{i+15} P_{i}}{\sum_{i=15}^{i+15} (1)}$$

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where P_i represents the average precipitation for day *i* of the year; as a point of clarification, this calculation is circular. In classifying catchments on the basis of the daily regime curves of climatic and runoff data, in this paper we will focus upon images like this one (Fig. 1b) for all 428 catchments within the MOPEX database (Duan et al., 1992). The proposed classification scheme will be built around four key indices, each extracted from the smoothed regime curves of the type presented in Fig. 1b.

2.2 Similarity indices used

²⁰ In the spirit of Koppen-Geiger, a key objective of this research is the classification of regime behavior using an absolute minimum quantity of data, on the basis of four very



(1)



¹MOPEX data obtained from http://voda.hwr.arizona.edu/mopex/

simple and widely available similarity indices. To estimate these four indicators, three daily time series are required: precipitation, potential evaporation, and total runoff. The first index is the aridity index (E_p/P), the ratio of annual potential evaporation to annual precipitation; it measures the competition between energy available and water avail-⁵ able, and is seen as a good first-order indicator of runoff ratio (ratio of annual runoff

- to annual precipitation). The seasonality index and maximum day of precipitation are both estimated from daily precipitation time series. The seasonality index measures the strength of within-year (seasonal) variability of precipitation, and is zero if the precipitation is uniform throughout the year. The timing of rainfall peaks is a reflection of the
- ¹⁰ phase difference between the timing of precipitation peak and that of potential evaporation (Milly, 1994), given that in the continental US timing of potential evaporation peak is uniform spatially. Finally, the timing of maximum runoff accounts for the response of catchment to the interactions between precipitation and potential evaporation. The timing of runoff allows for differences in storage and release processes between dif-15 ferent regions, owing to distinctions in topography, snowfall, snow storage and melt
- processes, and also differences in the physiological responses of vegetation.

These four variables are chosen not only because they are succinct descriptors of processes that underpin seasonality of runoff, but also because they represent the minimum amount of information that is needed to classify regime behavior within the continental US. In essence, the four indices represent answers to the following four questions:

- "Is this catchment very humid, somewhat humid, temperate, somewhat arid, or very arid?"
- "Is rainfall relatively consistent year-round, somewhat seasonally dependent, or highly seasonally dependent?"
- "When, during the year, is rainfall greatest?"

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- "When, during the year, is streamflow greatest?"





Once the classification system is established, even approximate or fuzzy answers to these questions can help towards a first-order classification of regime behavior, subject to further data collection and analysis.

2.2.1 Aridity index: dry or wet?

⁵ Figure 1 shows that in this catchment in Kansas, the daily potential evaporation rate is almost uniformly in excess of the daily precipitation rate throughout the year. The aridity index (E_p/P) is estimated by summing the mean daily rates of potential evaporation (PE) over the 365-day time series and dividing it by the sum of the mean daily precipitation rates over the same 365-day period. The aridity index thus measures the competition between energy available and water available annually: $E_p/P > 1$ for arid (dry) catchments whereas $E_p/P < 1$ for humid (wet) catchments.

Figure 2 presents regional patterns of the aridity index for 428 catchments belonging to the MOPEX database. It shows that eastern catchments tend to be largely humid (except in the south), whereas Midwestern catchments tend to be mostly semi-arid, becoming more arid as they approach the Rocky Mountains and the desert south-west, and becoming humid again in the Pacific Northwest. Essentially one finds systematic east–west (and north–south) trends in the aridity index, compounded by some outliers in the south-east and north-west.

2.2.2 Seasonality index: is precipitation uniform or periodic?

- Figure 1 presented a catchment whose precipitation and also runoff response exhibited significant seasonality, with rainfall being much higher during the summer than during winter months. This is a feature exhibited by a significant number of catchments belonging to the MOPEX database. Potential evaporation is also highly seasonal, although in this case there is very little phase difference between precipitation and potential evaporation are likely.
- ²⁵ oration. The relative magnitudes of precipitation and potential evaporation are likely to have an impact on runoff regime, and must be accounted for in the classification





scheme. Walsh and Lawler (1981) defined a seasonality index for precipitation on the basis of average monthly rainfall values, which in essence is a measure of within-year variance. In this paper we use an adaptation of Walsh and Lawler to accommodate the 365-day smoothed precipitation regime curve as follows:

$${}_{5} \quad \frac{\sum_{i=1}^{365} \left| P_{i} - \frac{\sum_{i=1}^{365} P_{i}}{\frac{2}{365}} \right|}{\sum_{i=1}^{365} P_{i}}$$

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where P_i represents the value obtained from Eq. (1). The seasonality index helps to distinguish those regions in which precipitation is highly variable seasonally from those in which rainfall is comparatively uniform throughout the year.

Figure 3 presents the spatial distribution of the estimated seasonality index across
 the USA. In the eastern part of the country, precipitation is fairly uniform year-round with the exception of three catchments located in southern Florida. Moving westward, the seasonality index tends to increase displaying moderate seasonality in the Midwest (mid-continent) and peaking in those catchments near the Pacific. While there are a few catchments that do not follow this trend in the northern Rocky Mountains, the general
 trend remains consistent.

2.2.3 Day of peak precipitation: in-phase or out-of-phase with respect to PE?

With the seasonality index defining the strength of seasonal variability of precipitation, another key feature is the timing of the maximum precipitation within the year. In this case, the metric we use is the date (from 1 to 365) on which the smoothed precipitation regime curve has its peak. Given that the timing of the peak of potential evaporation is uniform throughout continental US, the timing of the precipitation peak serves to focus attention to the phase difference between these climate variables, i.e., whether



(2)



precipitation seasonality is in phase with that of potential evaporation (e.g., precipitation peaks during June or July), is out-of-phase (precipitation peaks during December or January), leading PE somewhat (precipitation peak during Spring months) or lagging PE somewhat (precipitation peak during Fall months). As an aside, it is important

- that this similarity index be estimated from a regime curve obtained with a suitably long moving window to avoid mischaracterizing a catchment. These distinctions are important, since the phase differences between the seasonality of water input and energy input impact storage and release mechanisms, and can thus impact the magnitude and timing of runoff as well.
- Figure 4 presents the distribution of the day of maximum precipitation using a circular color coding, i.e., if the day of maximum precipitation happens to fall on 31 December for a catchment, then the similarity index is quite similar to another catchment with its precipitation peak falling on 2 January, even though the timing index will be "365" for the first catchment and "2" for the second catchment. Although numerical values are different, they are actually similar with respect to the timing of the precipitation peak.
 - The color coding reflects this similarity.

In this case, the east-to-west trends seen in the case of aridity index and seasonality index no longer hold. Although the Midwestern regions see precipitation peak in the late-Spring to early-Summer, there is much more variability across the continent,

²⁰ creating smaller clusters that are less-defined by longitude and latitude alone. The southern Appalachians are quite different from their northern, snowy counterparts, the Pacific coast displays a notable gradient north to south, and several catchments in the monsoon-influenced southwest distinguish themselves from their snowmelt-driven neighbors to the north, and their hurricane-influenced neighbors to the east.

25 2.2.4 Day of peak runoff: role of catchment storage and release processes

Analogous to the day of peak precipitation, the day of peak runoff (1–365) is the final piece to the classification puzzle. In this case, the differences between the catchments reflect not only the magnitude and phase differences between precipitation and





potential evaporation, but also the transformations that happen at the land surface (storage and release processes, including below-ground soil and groundwater processes and above-ground snow storage and snowmelt), as illustrated by Milly (1994).

- The results are presented in Fig. 5, once again using a color coding scheme that is circular (1–365). As with the day of peak precipitation, we observe clusters that are not solely longitude- or latitude-driven, including considerable local variations that may reflect landscape heterogeneity. The Pacific Northwest distinguishes itself due to the out-of-phase relationship between precipitation (peaks during winter) and potential evaporation (peaks during summer). In the Midwest and along the east coast there is considerable heterogeneity, and in some cases even adjacent catchments show differences in runoff timing. Along the Appalachian mountains in the eastern half of the continent, runoff peaks appear in early spring, presumably driven by melting snow and
 - 3 Developing a catchment classification system: decision trees, similarity metrics, and clustering algorithms

3.1 Decision trees for grouping catchments

spring rainfall.

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The goal of this section is to describe the methodology adopted in this paper to "group" catchments exhibiting similar *regime behavior*, and separate them from those that are different. Figures 2 through 5 also exhibited certain regional trends across the continen-

tal USA with respect to each of the 4 similarity indices we had considered, and some level of clustering. In the same way, if the regime curves of the type presented in Fig. 1, generated for each of the 428 catchments in the MOPEX database, are superimposed upon a large map of the USA, one could see regional trends, including the emergence of distinct clusters of similar regime behaviors (at least qualitatively). Is there a connection or possible mapping between the former and the latter? Our hypothesis in this





paper is that a combination of the 4 similarity indices governs the regime behavior and can be the basis of their classification.

Considering that ultimately we want to develop a catchment classification system on the basis of regime behavior, and the fact that we have 4 different similarity indices that might collectively determine similarity of regime behavior, how can we develop a

- that might collectively determine similarity of regime behavior, how can we develop a robust classification system? One way to develop such a classification system is by recourse to "decision trees" that can recursively divide the 428 catchments into self-similar groups in such a way that, at each step in the decision tree, the variability of a catchment attribute within each group is less than the variability between groups. This requires a suitable metric.
- requires a suitable metric a mathematical definition of similarity (of regime behavior) that can be deployed for any group of catchments a metric that encompasses the four key indices.

3.2 Metric of regime similarity

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Each of the four similarity indices, seasonality index (*S*), the aridity index (*A*), day of peak precipitation (τ_p) and maximum runoff day (τ_q) show considerable variability across the catchments, which can be expressed in terms of a variance measure. For *S* this is straightforward, with the estimation of the standard deviation obtained from:

$$\sigma_{\rm S} = \sqrt{\frac{\sum\limits_{i=1}^{n} \left(S_i - \mu_{\rm S}\right)^2}{n-1}}$$

where S_i is the seasonality index for catchment *i*, μ_S is the its mean over all catch-²⁰ ments, and *n* = 428 is the number of catchments. An analogous estimate can be obtained for the standard deviation of the aridity index, σ_A .

In contrast, for τ_p and τ_q , this estimation is not as straightforward. This is due to the circularity of the timing of the two peaks (i.e., 1–365), as in the case of four catchments whose values for τ_p are 361, 364, 359, and 3. To overcome this, we transform τ_p and



(3)



 τ_q into new variables C_1 and C_2 both of which naturally fall between -1 and +1, and overcome the circularity problem.

$$C_1 = \sin\left(\frac{\tau_p}{365} \cdot 2\pi\right), \quad C_2 = \cos\left(\frac{\tau_p}{365} \cdot 2\pi\right). \tag{4}$$

By estimating σ_{C_1} and σ_{C_2} , the standard deviations of C_1 , and C_2 , respectively, we can then estimate the standard deviation of τ_p , σ_{τ_p} , as follows:

$$\sigma_{\tau_{\rm p}} = \sqrt{\sigma_{C_1}^2 + \sigma_{C_2}^2}.$$
(5)

The standard deviation of $\tau_{\rm q},$ expressed as σ_{τ_Q} can be estimated in an analogous manner.

In summary, for the four similarity indices outlined, their between-catchment variability across the entire MOPEX database of 428 catchments are characterized by $\sigma_{\rm S}$, $\sigma_{\rm A}$, $\sigma_{\tau_{\rm P}}$, and $\sigma_{\tau_{\rm Q}}$ respectively. To ensure that no one index overwhelms the others by virtue of its numerical scales, the variance of each index, whether it contains all 428 catchments or a smaller subset of them, is normalized by the four constants listed above. For any group of *m* catchments, we define a new quantity, *E*, the metric of regime similarity associated with that group, as follows:

$$E = \sqrt{\left(\frac{\sigma_{\mathrm{S},m}}{\sigma_{\mathrm{S}}}\right)^{2} + \left(\frac{\sigma_{\mathrm{A},m}}{\sigma_{\mathrm{A}}}\right)^{2} + \left(\frac{\sigma_{\tau_{\mathrm{P},m}}}{\sigma_{\tau_{\mathrm{P}}}}\right)^{2} + \left(\frac{\sigma_{\tau_{\mathrm{q},m}}}{\sigma_{\tau_{\mathrm{q}}}}\right)^{2}}.$$
(6)

Essentially, the regime similarity metric, E, is a representative measure of the combined within-group variance of the four similarity indices for any group of m catchments, with equal weights attached to each of the similarity indices.

20 3.3 Clustering algorithm: iterative dichotomiser algorithm (ID3)

Classification trees offer a straightforward approach for grouping objects on the basis of similarity or variance measures (Brieman et al, 1984). Such tools are routinely included





in many statistical programming packages (Brieman et al., 1993). The clustering or grouping algorithm used in this paper is the *iterative dichotomiser* (ID3) algorithm developed by Quinlan (1986), which was re-coded from scratch as part of this research. This algorithm has found classification applications in forest resource management

Aertsen et al., 2011), crop identification for soil management (Pena-Barragan et al., 2011), mapping of arid rangeland vegetation (Brodley and Freidl, 1997; Lailiberte et al., 2007), and prediction of the failure of business ventures (Li et al., 2010).

The algorithm's implementation is explained next. Given all 428 catchments, choose a value of any one of the four indices (e.g., seasonality index) with which to partition all catchments. This will yield two clusters – those with a statistic (i.e., seasonality

index) above that value and those with a statistic below that value. Iterate over four possible similarity indices to choose the value of one of these indices that minimizes the regime similarity metric, *E*, and weighted by the number of constituents in each subsequent class (as explained next). Repeat recursively until either value of *E* can no longer decrease significantly or these clusters become too small. The first split, atop

the decision tree is offered in detail in the following paragraphs. By definition, the normalized value of the variance of the entire distribution of any independent variable is equal to unity. Substituting into Eq. (6) to obtain the value of *E* of the initial data belonging to 428 catchments yields:

20
$$E = \sqrt{(1)^2 + (1)^2 + (1)^2 + (1)^2} = \sqrt{4} = 2.$$

When all 428 catchments were assessed, although each of the four similarity indices was considered, the best-performing splitting criterion turned out to be a seasonality index of 0.2564. There are 266 catchments with seasonality index values less than 0.2564 and 162 with seasonality indices that exceed 0.2564. The new value of the regime similarity index, E, is now calculated as follows:

 $E^{'} = 266 \left(E_{\text{S} \le 0.2564} \right) + 162 \left(E_{\text{S} > 0.2564} \right).$

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(7)

(8)



In this case, $E_{S \le 0.2564}$ denotes the regime similarity metric of the set of catchments for which $S \le 0.2564$ (266 in all) and $E_{S>0.2564}$ represents the similarity metric of the set of catchments for which S > 0.2564 (162 in all). In each term of Eq. (8), Eq. (6) is now used to estimate *E* for only the sub-groups of 266 and 162 respectively. Substituting into Eq. (8) this gives, after the first split:

E' = [266(1.1838) + 162(2.1992)]/428 = 1.5681.

5

This represents the minimum possible value of *E* after one single split. Thus what began with an *E* value of 2 has now improved to 1.5681. It is worth noting that one branch, the one with more seasonal catchments, actually displays greater "disorder" than the entire dataset. However, given that 266 of the 428 catchments begin to cluster significantly (i.e., E = 1.1838), the small increase in the disorder of the remaining 162 is justified.

At this point, the algorithm as described above can be repeated recursively, locating an optimal split criterion at each node by choosing from one of the four similarity ¹⁵ indices, thus branching outward down the tree. Splitting ceases when it is determined that the catchments within a given terminal node are maximally similar – no further splitting will decrease the regime similarity metric significantly, or there is only a single catchment left at that node (and thus *E* is zero). In some cases, there are very few

catchments left in a given node to be split with an obvious pair of clusters. In such cases, adopting different splitting criteria might yield the same two groups. In these rare cases, a manual choice of splitting is invoked to choose the most appropriate class delineator.

4 Results: what patterns emerge, and where are the largest clusters?

We now present the results of the application of the clustering algorithm presented above, describing the breakdown developing at each level of the decision tree. For presentation purposes, depending on the magnitudes of the similarity indices at which the



(9)



splits occur, we divide each similarity index into several (3 to 5) distinct and meaningful classes. The combination of these classes then produces the nomenclature we need to describe the catchment classes at each level.

Nomenclature for catchment classes 4.1

The nomenclature we have adopted is letter-based, using up to 5-letters of the alphabet 5 to characterize the range of values of each of the four similarity indices; these are presented below.

4.1.1 Codes for aridity index

- V = "Very-Humid",
 $E_p/P < \sim 0.5$

 H = "Humid",
 $\sim 0.5 < E_p/P < \sim 0.75$

 T = "Temperate",
 $\sim 0.75 < E_p/P < \sim 1.2$

- S = "Somewhat Arid", $\sim 1.2 < E_p/P < \sim 2$
- A = "Arid", $\sim 2 < E_p/P$

4.1.2 Codes for seasonality index 10

- *S* < ~0.25 L = "Low Seasonality",
- = "Intermediate Seasonality", $\sim 0.25 < S < \sim 0.5$
- ~0.5 < S X = "eXtreme Seasonality",

4.1.3 Codes for day of precipitation peak

- = "June", Max rainfall occurs in early or mid-summer (not necessarily in June). J
- = "Winter", Max rainfall occurs in winter (mid-February or March). W
- В = "Blizzard", Max rainfall in late November (to mid-February).
- Ρ = "Printemps", Max rainfall during spring.

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4.1.4 Codes for day of runoff peak

- Q = Max runoff during summer months. Early June through August.
- F = "Fall/Hurricane season". Generally in September/October. Uncommon (TX and FL).
- M = "Melt", Spring melt, usually at a peak in April, May, or early June.
- C = "Cold runoff", max runoff occurring from early February to before April.
- D = "December", max runoff during December/January or early February.

The classes described above can theoretically describe $3 \times 5 \times 4 \times 5 = 300$ different combinations of the similarity indices (and associated catchment groupings) although,

as will become apparent soon, an overwhelming majority of those combinations will never occur. Indeed we will show that the first 6 most dominant classes will encompass 331 of the 428 catchments.

4.2 Initial split: top of the classification tree

The classification tree begins with the complete database of 428 MOPEX catchments. As mentioned before, the population of 428 catchments is split recursively into smaller, more homogeneous groups, being named along the way depending on the value(s) of the similarity indices at play at each split. After the very first split, the dataset is divided into two large clusters, which are not terminal nodes, but rather, are intermediate nodes, and these are further split into four clusters, and so on. After each split, the resulting pair of clusters begins to receive a more detailed code using the letters above,

depending on the value of the similarity index that is in play at each split.

Seasonality turned out to be the single most important factor in creating order in the 428 catchments in the MOPEX database at the first level. Two clusters emerged: one characterized by catchments with a low seasonality index (L) and the other character-

²⁰ ized by catchments with a "not low" seasonality index. This is shown in Fig. 6, with the left branch labeled "L" and the right branch labeled "*" because it could be either an "I"





or an "X" type of seasonality. The transfer of the first level split onto a map of the US makes the classes resulting from the first split easy to understand hydrologically, as seen in Fig. 7.

- The results presented in Fig. 7 indicate that the seasonality index, after only one ⁵ binary split, effectively partitions continental US geographically in a meaningful way. In the eastern part of the country, rainfall is relatively uniform throughout the year, from New England in the northeast, down the Appalachian Mountains to the Ozarks, stretching into the Midwest. Only three eastern catchments in this database, those in Florida, deviate from this pattern, as they see large amounts of rainfall during a ¹⁰ warm, humid, hurricane-influenced summer/autumn and considerably less during the winter. In the western US, excluding a handful of catchments in the northern Rocky
- Mountains, every catchment displays considerable seasonal variability of precipitation, from the Midwestern catchments characterized by a precipitation that is in phase with potential evaporation to the Pacific coast catchments in which the precipitation regime is out-of-phase with respect to that of potential evaporation.

The second split criterion, for the lower seasonality, eastern catchments (colored blue in Fig. 7), is the timing (day) of precipitation peak while for the more seasonal, western catchments, the split criterion becomes the aridity index (see Fig. 3). For less seasonal catchments, the dividing date falls on 1 June, for the more seasonal catchments, the

- dividing aridity index is roughly 1.9. This leads to four classes, as shown in Fig. 6, one of which (LJ) is a terminal node. The transfer of these four clusters after two consecutive splits of the original dataset, on to the map of the US is presented in Fig. 8. The results presented in Fig. 8 show an east-west division based on the seasonality index at the first level, a northeast-southwest split occurs in the eastern (non-seasonal) region via
- the timing of rainfall, while in the west, a split based on aridity index distinguishes the Pacific Northwest and the northern Midwest catchments from the remaining western catchments.





4.3 Four quadrants of the classification tree

The four main clusters of similar climatic regions obtained in the second level will be further split by the recursive algorithm outlined above until smaller, very similar climate

clusters remain. The details of this are not presented here for reasons of brevity; only
 the resulting final classification tree is presented. Even here, because of the size of the resulting tree, it is most easily viewed in portions, which we call quadrants, relating to the major clusters formed at the end of the level two splits. In what follows, each quadrant of the classification tree is presented and discussed in detail.

4.3.1 1st quadrant: low seasonality, max precipitation before 1 June

- Figure 9 presents the expansion of the 1st quadrant. Six climate regions describe the 119 catchments that comprise this group. The most populous group, "LWC" contains 52 catchments, 50 of which are located in the south-eastern states. While this terminal grouping has been obtained without the use of the aridity index, using only seasonality and the timings of precipitation and runoff, the 52 catchments all display $E_p/P < 0.87$,
- ¹⁵ displaying a tight cluster of humid catchments where rainfall and runoff peak in February or March. The second-most populated group is "LPC", containing 29 catchments from the eastern Midwest. Once again, although the aridity index has not been used as a split criterion to obtain this cluster, the 29 catchments have similar E_p/P values, near or slightly below one. This class is distinguished from LWC by virtue of maxi-
- ²⁰ mum rainfall occurring later in the spring. A third, well-populated cluster is found in 28 "LPM" catchments located in the south-eastern regions of the Midwest where rainfall and runoff both peak during springtime. The "LBMH" catchment in Montana, which seems unusual for its geography given its low seasonality, and humidity ($E_p/P \sim 0.67$), 3 "LBMS" catchments from Colorado and Montana which are similar to the LBMH odd-
- ity, only considerably drier $(1.17 < E_p/P < 1.66)$, and 6 "LPQ" catchments, also from the mountain west (Wyoming) where rainfall peaks in the spring instead of the winter, round out this quadrant.





4.3.2 2nd quadrant: low seasonality, max precipitation after 1 June

This quadrant becomes fully organized with only two criteria for splitting, leaving 147 catchments which all carry the "LJ" designation. Although the maximum date on which runoff occurs is not used to create this class, 145 of the 147 catchments observe ⁵ maximum runoff between mid-February and late-April (the remaining two peaks occur in the first week of May). In fact, 124 of the 147 catchments peak between the second week of March and the first week of April. Furthermore, although once again the aridity index is not used to generate this cluster, all 65 catchments fall between $E_p/P \sim 0.5$ and $E_p/P \sim 1.05$. This class of catchments defines the mid-Atlantic and Appalachian regions of the US, extending into the eastern Midwest. This quadrant of the tree, albeit expressed as a single node, is illustrated in Fig. 10.

4.3.3 3rd quadrant: higher seasonality, non-arid

This quadrant of the tree is the most diverse by a considerable margin. The criteria for this quadrant are, to reiterate, the seasonality index >0.2564 and an aridity index $(E_{\rm p}/P)$ below 1.9. Some 128 catchments meet these conditions and are further seg-15 mented into 12 terminal nodes as shown in Fig. 11 (note that two terminal nodes classify to the common Midwestern climate of "ITC"). However, despite the apparent complexity, two climates describe 75 of the 128 catchments. The first, and most common, "ISQJ" contains 39 catchments in the Midwest and southern Midwest. The second most common, "ITC", is guite similar to the previous grouping geographically, although it is 20 more humid and maximum runoff arrives sooner. This class contains 36 catchments from the Midwest and northern Midwest. The remaining clusters, partitioning the Pacific Northwest, consist of 6 humid catchments from northern California and Oregon ("XHD"), 7 catchments in Idaho ("IHM"), 6 extremely humid catchments in Washington ("XVM"), 10 more temperate catchments in the pacific northwest from Washington, 25 ("XTM"), 3 extremely humid catchments in Washington ("IVD"), which differ from their "XVM" counterparts by virtue of their lower seasonality index, and winter runoff peak,





3 Floridian catchments ("ITF"), which are truly unlike any others in the US, 7 drier Midwestern catchments with early runoff peaks ("ISCJ"), 3 drier southern Californian catchments ("XSC"), and 6 drier southern Californian/Nevadan catchments with later runoff peaks ("XSMB").

⁵ The terminal nodes in the 3rd quadrant contain 10 or fewer catchments, describing certain niche climates of US. These mini-clusters often describe several catchments that are very similar to each other, but quite different from their neighbors.

4.3.4 4th quadrant: higher seasonality, arid

In this final quadrant, the 34 remaining catchments are further divided into five terminal nodes. The most common classification ("IAQ") contains 16 catchments, a miscellaneous assortment of the country's most arid locations, including 10 from the southwest, 5 from the Midwest, and one remarkably arid catchment in Wyoming (the mountain west). The remaining clusters consist of three Californian catchments that represent the driest American Pacific climates ("XADB"), the northern Midwestern "badlands", six

extremely arid catchments in Nebraska and North and South Dakota ("XACJ"), a cluster of seven arid southwestern catchments, one oddity in the Pacific northwest, ("IACJ"), shielded from the Pacific coast by the Cascade mountains, and three arid catchments in Texas characterized by runoff peaks occurring as late as the fourth week of October ("IAF"). Figure 12 presents the final quadrant.

20 4.4 Summary of the resulting catchment classification and the "Big 6" classes

In total, the classification tree yielded 24 terminal nodes, depicting 24 distinct classes according to the criteria we have used. The geographic representation of these 24 classes on a map of the continental US is presented in Fig. 13, revealing distinct regional associations of many of the major catchment classes.

²⁵ However, of the 428 catchments which comprise the MOPEX dataset, 331 can be described by only 6 climate classes, namely "LWC", "LPC", "LPM", "LJ", "ITC", and





"ISQJ", which we call the "Big 6". There are only two other groupings that contain 10 or more catchments. While admittedly, this could be due in part to the makeup of the MOPEX dataset, which contains more catchments in certain regions than in others, it still suggests that while 300 different classifications are theoretically possible using the

⁵ coding system adopted here, over 77 % of the catchments are well described by 2 % of the possible classes, and the entire dataset is captured by 8 % of all possible classes.

Three of the "Big 6" are found within the 1st Quadrant (LWC, LPC, and LPM). The catchments belonging to these three classes are characterized by limited seasonality, and are essentially catchments with pre-spring maximum rainfall and runoff (LWC),

- 10 catchments with pre-spring peak runoff, but mid-Spring maximum rainfall (LPC) and catchments with springtime rainfall and runoff peaks (LPM). The entire set of catchments in the 2nd quadrant (belonging to the terminal LJ class) is clearly the fourth member of the "Big 6". These catchments display limited seasonality, humid climates, and peak runoff during the springtime, and peak rainfall during the summertime. The
- ¹⁵ final two members of the "Big 6" are found in the 3rd quadrant, namely ISQJ and ITC (and none of the classes in the 4th quadrant constitute the "Big 6"). The two Midwestern classes, ISQJ and ITC, both contain catchments with rainfall that is in phase with potential evaporation. However, the ISQJ catchments are notably more arid, with E_p/P averaging roughly 1.5, as opposed to an average of roughly 1 for ITC. As a result of the
- ²⁰ more temperate climate, the ITC group displays peak runoff during early spring, when stored water from winter has thawed. On the other hand, ISQJ, characterized by drier soils shows its runoff peak in late-May or June, at the same time as its precipitation peak.

4.5 Robustness of classification: recurrent, dominant clusters

²⁵ When classification systems are generated using recursive, splitting algorithms (those that minimize variance at each stage without concern for future splits), there is a tendency to over-fit one's data. Although variance is minimized at every stage, ensuring that we do not split a group of catchments without purpose, caution is required to





prevent fitting the noise inherent in the dataset rather than true patterns. To this end, the same algorithm was applied to a 197-catchment subset of the larger, 428-catchment dataset. These 197 catchments were chosen due to their comparatively richer datasets (fewer missing days, more complete years, etc). Indeed, this is the dataset that has ⁵ been employed by Ye et al. (2012), Cheng et al. (2012), and Yaeger et al. (2012) in the accompanying papers that are all focused on exploring the physical controls of the FDCs from different perspectives.

Although naturally there are subtle differences in the tree that is formed in the latter case, the important features of the tree remain unchanged (not presented for reason of brevity). Using the notion of quadrants, as described in the previous section, the first quadrant is not only characterized by lower seasonality and peak rainfall before 1 June (the same date as the 428-catchment tree), but also contains six total terminal nodes as well. Furthermore, the three most common classes from that quadrant of the 428-catchment tree and their number of constituents ("LWC" – 52, "LPC" – 29, and "LPM" – 28) are mirrored in the most common classes in the 197-catchment tree as well ("LWC" – 21, "LPC" – 11, and "LPMT" – 7). The additional letter T from the subset tree is the result of slightly different sequences of the splitting, yielding essentially, the same groups.

The second quadrant of the 197-catchment tree, like the 428-catchment tree, contains the single class "LJ", now composed of 65 catchments rather than 147. The remaining two quadrants also show some differences, this likely resulting from the nature of the dataset. Unfortunately, given the challenges associated with data gathering in more arid catchments, many of the catchments characterized by substantial missing data are found in the nation's more arid locations. As a result, the 428-catchment tree

²⁵ contains a much higher proportion of arid catchments (thus, the second split criterion, for more seasonal catchments is E_p/P). Conversely, the 197-catchment tree contains a smaller proportion of arid catchments, and thus, splits on the maximum day of precipitation to define its third and fourth quadrants. Despite this, the two most common classes on this side of the 428-catchment tree ("ISQJ" – 39 and "ITC" – 36), still find





their parallels in the 197-catchment tree ("ISQJ" – 15 and "IJTC" – 20). The remaining, less common groups do display some overlap, although in this case differences appear simply because certain groups are not represented at all in the 197-catchment subset, or find themselves folded into other classes. Despite these minor distinctions,
once again, a nearly identical "Big 6" again defines over 70% of all catchments and the tree's general structure remains intact. This demonstrates that not only is the classification system intuitively satisfying in its simplicity, but is robust to alterations in the dataset.

The most effective argument for the success of this classification system lies in its ability to validate the initial hypothesis – that simple climatic regime indicators lead to clusters of similar runoff behavior. Each cluster of runoff regimes is presented in Fig. 14, demonstrating regional self-similarity. While certain clusters with larger numbers of catchments (notably LJ) do display some variance among their constituents, the overall pattern of runoff timing associated with each catchment still remains intact.

15 **5** Conclusions

This paper has presented the application of a clustering algorithm (i.e., Iterative Dichotomizer or ID algorithm) for classifying catchments across the continental US with respect to their climatic seasonality and regime behavior (i.e., mean within-year variation of runoff). The classification was achieved by assessing the catchments in terms

- of a metric of regime similarity, *E*, which is a composite measure estimated on the basis of the magnitudes of four similarity indices: (i) a seasonality index of precipitation, (ii) aridity index, (iii) timing of maximum precipitation, and (iv) timing of maximum runoff. The clustering algorithm was applied to 428 catchments across the continental US belonging to the MOPEX dataset.
- The clustering algorithm identified 24 distinct classes. Even though the classification was achieved with just 4 numbers from each catchment (similarity indices), and only the max date of the runoff regime curve was used, the regime behavior for each of the





classes showed distinct differences between classes and strong similarity within. This confirms the power of the simple classification scheme for predicting regime behavior across the continental US, subject to the limitations of the geographical extent of the dataset and coverage across the country. Considering that three of the four indices
 ⁵ used to construct the classification tree are based upon climate, it comes as no surprise

that climate's impact is readily apparent. Just as Koppen-Geiger delineated the nation into clusters of climatic similarity a century ago, climate still dominates the hydrologic landscape, creating distinct, hydrologically similar clusters.

The resulting classes also display strong regional associations and patterns, which is very valuable to further explore the climatic and landscape controls underlying the resulting catchment classes. Whether the final group is IHM, with seven catchments all located in the state of Idaho or ITF, with three catchments all located in Florida, or IAF, with three catchments located in one region of Texas, these groups are not only numerically similar, but geographically contiguous as well in many cases.

- ¹⁵ Despite the enormous heterogeneity of catchments represented in the MOPEX dataset, just six classes (the so-called "Big 6") accounted for over 77 % of the catchments. The classification system is found to be robust, producing the same recurring six clusters even with a smaller subset of the full dataset. Each of the recurring, dominant six classes displays distinct characteristics that suggest their own set of hydro-
- logic drivers. In the Midwest, the aridity index determines whether runoff is driven by the spring thaw of water frozen in soil storage (ITC) or by the arrival of summer rains (ISQJ). In the south-east, runoff timing in late-winter (LWC and LPC) or early-Spring is governed by the temperatures in and around the Applachian Mountains. In the northeast, spring runoff is likely the result of melting of snow (LJ). In the area in which the
- south-eastern US merges with the Midwest, seasonality begins to appear strongly, and runoff is driven by springtime rainfall (LPM). In addition to these "Big 6" clusters, other smaller, niche climates display distinct behaviors. From the monsoon-driven southwest (XACJ), where precipitation occurs mainly in a narrow band of summer months, to the extremely humid Pacific Northwest where runoff peaks are driven by extreme winter





rainfall (IVD) or the melting of snowcaps in the spring (XVM), the US exhibits a tremendously heterogeneous group of catchments.

The analyses presented in this paper have identified catchment groupings that are similar in terms of their runoff regime. What makes them similar? Their regime curves
⁵ certainly suggest as much, but does that imply similar dominant processes? The accompanying paper by Ye et al. (2012) explores their regime behavior from a process perspective, by adopting a top-down modeling approach. Is there a recognizable mapping between the catchment classification found in this paper and the classification of dominant processes highlighted in Ye et al. (2012). Furthermore, this paper has been
¹⁰ motivated by our quest to explore the physical controls of the Flow Duration Curve

- (FDC), considering that the regime curve provides a major connective tissue between the high flow and low flow ends of the FDC. Cheng et al. (2012) presented an empirical analysis of the regional patterns of FDCs across the continental US, and their physical controls. Is there a connection between the regional groupings of catchments
- ¹⁵ based on the regime curve, and regional patterns of variation of the FDCs. The accompanying synthesis paper by Yaeger et al. (2012) addresses these questions through cross comparisons between the results of each of these three studies to draw general conclusions about the physical and process controls of the regime curve and the Flow Duration Curve, helping to discover not only which catchments are similar, but also *why* they are similar.

Finally, it is important to acknowledge the limitations inherent in the classification system presented. Although the continental US represents a diverse and rich array of climate conditions and landscape features, it is natural that it does not contain every conceivable combination of climate and landscapes. It may very well be the case that

²⁵ such climates exist on other continents. It is to be hoped that future efforts will integrate global climate data into an enhanced tree, duplicating this work on a larger, multinational scale. Secondly, while the classification system classified 428 gauged catchments (including information on runoff timing) into distinct classes, without a further effort to incorporate catchment or landscape features that impact on runoff generation,





especially runoff timing, application to ungauged catchments is not feasible. This calls for further research that will overcome this major limitation of this study.

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Fig. 2. Spatial distribution of the aridity index (E_p/P) .







Fig. 3. Spatial distribution of the seasonality index.







Fig. 4. Spatial patterns of the day of peak precipitation Day (1–365).











Fig. 6. The top 2 layers of the classification tree (terminal node shown in blue).







Fig. 7. 1st split, low seasonality (blue) and higher seasonality (orange).







Fig. 8. 2nd split: low seasonality and earlier precipitation peak (dark blue), low seasonality and later precipitation peak (light blue), higher seasonality and non-arid (yellow), higher seasonality and arid (red).







Fig. 9. Low seasonality, early precipitation peak: expanded (terminal nodes in blue).







Fig. 10. Low seasonality, late precipitation peak: expanded (terminal node).

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Fig. 11. Higher seasonality, non-arid: expanded (terminal nodes in blue).



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Fig. 12. Higher seasonality, arid: expanded (terminal nodes in blue).







Fig. 13. All classes.





Fig. 14. Clusters of runoff regimes.



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