We would like to thank the reviewers for their constructive comments on the manuscript "Using hydrological and climatic catchment clusters to explore drivers of catchment behavior."

(comments of the referees are printed in blue, responses of authors are held in black, added text to the manuscript is in italic)

Response to Reviewer #1 (Anonymous)

Jehn et al made substantial improvements to the manuscript based on the first review round. Analyses were added, and the results are now better embedded in the literature and compared to existing classification strategies. There is, however, still one question that remains after reading the manuscript, which I will discuss below.
Major:
The added analyses provide valuable glimpses on what exactly explains the differences among the different catchment clusters, but it does not become exactly clear what characterizes each cluster. This is of course the result of the approach taken; rather than classifying starting off from process-understanding (or expert opinion, if you will), the authors chose to start off with just the data, and from there derive clusters using PCA, subsequently trying to characterize the found clusters. Although I don't think this approach is by definition is invalid (i.e., in principle nothing is wrong with this approach), for me as a modeler frequently working with large sample data, I am not sure if I would use the classification presented because I wouldn't know how to interpret the subsequent results.
For large sample studies, catchments often need to be clustered because different types of catchment behavior are not equally represented in the large-sample data set. Therefore, catchment classifications are highly valuable. But how you will classify the catchments depends on the research question. If aridity is expected to have a big impact on what is studied, it would perhaps be better to cluster the catchments on aridity, if snow is of substantial importance for the process studied, the catchments can be clustered on their snow fraction.

As you stated, it is impossible to find a set of clusters that can be used for all applications and indeed, if you are only interested in aridity or snow, the clusters discussed in this study here will probably be of little use. However, our study does not claim to provide clusters that can be used in every case. Rather, we created clusters based on hydrological signatures with a clear hydrological meaning as discussed by Addor et al. 2018. Doing so, we capture the overall hydrological behavior of the catchments. An example use case for such clusters would be the research into parameter transferability between catchments, as those rely on hydrological similarity between catchments. As of now, Jan Seibert is using the clusters discussed in this study (and other metrics) to transfer parameters between catchments.
The main goal of our study is of a more exploratory nature. It is often assumed that catchments are mainly (or even solely) driven by their climatic forcing. However, if this were the case, using hydrologically derived clusters, should always result in a uniform climate in those clusters. We challenged this assumption by clustering according to hydrological similarity and then exploring a) which catchment attributes seem to be the most important one in each cluster and b) how those clusters can be found again in a climatic clustering. As shown by our study, climate does not seem to be the single driver for all catchments and we probably should take a deeper look on how the climatic forcing is shaped by the catchment attributes.
To make this intent of our study more clear, we added the following to the introduction (before the last section of the introduction):

In addition, if the climate is the dominant driver of catchment behavior, clustering catchments based on their hydrological behavior should result in clusters with a uniform climate.

The point is that for the classification presented in the manuscript, it is unclear where they are clustered on, and therefore the application for large sample studies remains unclear.

We have reorganized and partly rewritten section 2.2 Data analysis, to make it clearer what the clusters are based on. The whole section now reads as follows:

2.2 Data analysis

The workflow of the data analysis considers a data reduction approach with a principal component analysis and a subsequent clustering of the principal components, similar to Kuentz et al. (2017) and McManamay et al. (2014). For the principal component analysis and the clustering, we used the Python package sklearn (0.19.1). The code is available at GitHub (Jehn, 2018). Validity was checked by a random selection of 50 and 75 % of all catchments. We found that the overall picture stayed the same (not shown). In all further analysis, we used all catchments to get a sample as large as possible to be able to make statements that are more general.

Calculation of the principal component analysis

The principal components were calculated from the six hydrological signatures described above (Table 1). We used a principal component analysis on the hydrological signatures to remove correlations between the single hydrological signatures. We only used principal components that together account for at least 80% of the total variance of the hydrological signatures, which resulted in two principal components. Those two principal components contain the uncorrelated information of all hydrological signatures used and thus can be seen as describers of the overall hydrological behavior. Therefore, catchments with similar principal components have similar hydrological behavior.

Evaluating the connection between the principal components and the catchment attributes

1) *First, we calculated quadratic regressions between the two principal components and the catchment attributes (with the principal component as the dependent variable). This resulted in one coefficient of determination (R^2) for each pair of principal component and catchment attribute (e.g. PC 1 and aridity).*
2) *We then weighted the R^2 by the explained variance of the principal components. This addresses the differences in the explained variance of the principal components (e.g., PC 1 explained 75% of the variance, PC 2 explained 19% of the variance).*
3) *The weighted coefficients of determination of the principal components were subsequently added to obtain one coefficient of determination for every catchment attribute.*

Quadratic regression was selected as interactions in natural hydrological systems are known to have unclear patterns and can therefore often not be fitted with a simple straight line (Addor et al., 2017; Costanza et al., 1993). This was done first for the whole dataset and then for all clusters separately. This procedure captures the pattern on the catchment attributes in the PCA space of the hydrological signatures (for examples of this pattern see Figure A1).

Clustering the principal components

The principal components of the hydrological signatures were clustered following agglomerative hierarchical clustering with ward linkage (Ward, 1963), similar to previous studies (Kuentz et al., 2017; Li et al., 2018; Yeung and Ruzzo, 2001). From those studies, Kuentz et al. (2018) provides the largest set with over 35,000 catchments. They also clustered their catchments in a PCA space of a range of hydrological signatures. To select the number of clusters, they used the elbow method (and two other methods to validate their *results) and found that ten or eleven clusters (depending on the method) were most appropriate for their data. Due to the similarity in the clustered data and the larger database of Kuentz et al. (2018), we also used ten clusters. Those ten clusters represent groups of catchments with distinctly different hydrological behavior.*

It would be really helpful if every cluster has a clear signature or characteristic that distinguished it from other clusters, and as such would ease the interpretation of large-sample study results. Sort of related to this point is the choice of the six hydrological signatures. It is clear why these were selected (Addor et al), but question remains how different the clusters would be if different / fewer signatures were used. Related to the previous point; if one is interested in high flows, this researcher might prefer a cluster solely based on the 95% flow quantile. Another point, remarked by the authors, is that a low-flow signature is not accounted for, for reasons explained in Addor et al., but that makes again the results more difficult to interpret – do the clusters represent the flow with focus on higher discharge ranges?

The clusters do have typical signatures and characteristics. They are described in Table 2 and to more depth in the appendix. It is true though, that those clusters are somewhat fuzzy in their membership. However, this is exactly one of the sticking points of our study: If we use the hydrological signatures described as most hydrologically meaningful and we still are not able to create crisp clusters, than this means in turn that solely relying on climate or single catchment attributes to cluster catchments is not a reliable way to find similar catchments. We also stress this and the choice of the hydrological signatures in the last section of the conclusion.

In other words, for which type of studies should this classification be used?

As mentioned above, the classification is for exploratory purposes and we test the several aims outlined at the end of the introduction. Still, possible use cases for this clustering are testing hydrological models in contrasting environments with a focus on either parameter transferability or testing different model structures and their transferability. As each cluster represents catchments that have similar behavior over a range of hydrological signatures and thus hydrological behavior, parameters and model structures should be transferable. As discussed in the conclusions, the results of this study can also be used to point to further research. We think it is quite worthwhile to explore if a less clear climatic signal is caused by intra-catchment variability of the climate or a larger influence of other catchment attributes.

Minor:
p.11 l.220: 'We link this to a less strong climatic signal in those regions' – it is unclear to me what you mean by this. Please clarify / reformulate.

We reformulated the sentence:

We link this to the signal of the climatic forcing being more influenced by other catchment attributes, which results in a less clear connection between hydrological behavior and climate.

p.17 l.301: 'For example, the signature 'mean half flow date' can be seen as a measure of seasonality' – I disagree with this statement. This for instance of a catchment with the same flow throughout the whole year, the half flow date will be in the middle of the year. Now think of a catchment with a very clear seasonality and the discharge peak halfway the year; also here the half flow date will be in the middle of the year. Half flow date does not say anything about the variation over the seasons. Therefore, I believe that the last part of section 3.5 requires reformulation.

We removed this statement and the sentence that refers to it.

Although the manuscript generally reads well and has a nice flow to read, there are some minor typo's/language edits that can be resolved. Small example of typo and language edit is p.19 l.317 last word ('catchment') should be plural, and the 'Still' (p.19 l.328) does not precede a 'Nevertheless' (p.19 l.329) really well.

Changed as proposed.

Summarizing, my main issue is that it remains unclear how the classification should be used and can help in interpreting large-sample studies. If the authors are able to clarify this, it would be nice if the cluster numbers along with the CAMELS catchment ID would be shared publicly for others to use.

The cluster numbers together with the catchment IDs and the climatic indices are already available in the supplement of this paper. To make this clearer we now refer to it in the data availability section.

Response to Reviewer #2 (Andrew Newman)

I appreciate the extensive revisions to this article. I believe the authors have taken the reviewer comments to heart and the revised article is much improved. The comparisons to the Köppen-Geiger climate classes and the Knoben et al. (2018) indices are interesting. There are a few remaining errors and clarifications that need to be addressed.

Specific comments:

Line 176: "including obviously different climates". I think the opposite is also true: part of the reason basins that are very far away end up in the same cluster is that they may actually have very similar climates. Of course the authors' statement is also true, sometimes basins with different climates have similar hydrologic signatures.

We replaced "obviously" with "sometimes very" to emphasis this.

Even though the catchments might be far away from each other, the interplay of different catchment attributes and driving factors, including sometimes very different climates, can lead to similar (equifinal) discharge behavior.

Line 291-293. It is unclear to me what exactly these lines are referring to. Is it discussing clusters that have weak or strong climate signal in the attributes?

Those lines discuss that clusters where we could identify the most important catchment attributes, where also those that tend to have a clearer pattern in the climate index space. In contrast, clusters without a clearly identifiable most important catchment attribute, have catchments in all regions of the climate index space. We rephrased the section to:

This is in line with our analysis of the most influential catchment attributes for this cluster, as we identified aridity as the main driver. Contrastingly, clusters where we could not identify a clear dominating catchment attribute, e.g. Cluster 4 (located in the Northwestern Forested

Mountains and Florida) (Figure 5), also have no clear clustering in the climate index space. The catchments of those clusters can be found in the space of the climatic indices of Knoben et al. (2018) with very different aridity, seasonality and fraction of the precipitation falling as snow.

Figure 8. In the panels, is the aridity label flipped? It seems that basins with high daily flow or wet clusters (e.g. cluster 6) end up with negative values, or more arid? That seems incorrect.

We double-checked the figure and it is correct. The position of e.g. cluster 6 on the aridity scale is probably caused by the seasonality and the way the aridity is calculated. Knoben et al. (2018) calculate a moisture index for every month separately and then take the mean of all months as a measure of aridity. The catchments in question probably have mostly arid month and then some with quite a lot of precipitation. Cluster 6 for example has very low mean summer discharge, but quite high mean winter discharge. In addition, the mean discharge is sensitive to extreme values in the high flows, which seems to be more common in the more arid catchments.

Using hydrological and climatic catchment clusters to explore drivers of catchment behavior

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Abstract.

The behavior of every catchment is unique. Still, we seek for ways to classify them as this helps to improve hydrological theories. In this study, we use hydrological signatures that were recently identified as those with highest spatial predictability to clusters 643 catchments from the CAMELS data set. We analyze the connections between the resulting clusters and the catchment attributes and relate this to the co-variability of the catchment attributes. To explore whether the observed differences result from clustering catchments by either climate or hydrological behavior, we compare the hydrological clusters to climatic ones. We find that aridity is more important for hydrological behavior in the eastern US, while it is the amount of snow in the West. In the comparison of climatic and hydrological clusters, we see that the widely used Koeppen-Geiger climate classification is unsuitable to find hydrologically similar catchments. However, in comparison with a novel, hydrologically based continuous climate classifications, some clusters follow the climate classification very directly, whilst others do not. From those results, we conclude that the signal of the climatic forcing can be found more explicitly in the behavior of some catchments than in others. It remains unclear if this is caused by a higher intra-catchment variability of the climate or a higher influence of other catchment attributes, overlaying the climate signal. Our findings suggest that very different sets of catchment attributes and climate can cause very similar hydrological behavior of catchments - a sort of equifinality of the catchment response.

1 Introduction

Every hydrological catchment is composed of a unique combination of topography and climate, which makes their discharge heterogeneous. This, in turn, makes it hard to generalize behavior beyond individual catchments (Beven, 2000). Catchment classification is used to find patterns and laws in the heterogeneity of landscapes and climatic inputs (Sivapalan, 2003). Historically, this classification was often done by simply using geographic, administrative or physiographic considerations.

However, those regions proved to be not sufficiently homogenous (Burn, 1997). Therefore, it was proposed to use seasonality measures with physiographic and meteorological characteristics, but it was deemed difficult to obtain those information for a large number of catchments (Burn, 1997), even if only simple catchment attributes (e.g. aridity) are used (Wagener et al., 2007). Nonetheless, in the last decade datasets with hydrologic and geological data were made available, comprising information of hundreds of catchments around the world (Addor et al., 2017; Alvarez-Garreton et al., 2018; Newman et al., 2014; Schaake et al., 2006). This is a significant step forward as those large sample datasets can generate new insights, which are impossible to obtain when only a few catchments are considered (Gupta et al., 2014). Different attributes have been used to classify groups of catchments in those kind of datasets: flow duration curve (Coopersmith et al., 2012; Yaeger et al., 2012), catchment structure (McGlynn and Seibert, 2003), hydro-climatic regions (Potter et al., 2005), function response (Sivapalan, 2005) and more recently, a variety of hydrological signatures (Kuentz et al., 2017; Sawicz et al., 2011; Toth, 2013). Quite often, climate has been identified as the most important driving factor for different hydrological behavior (Berghuijs et al., 2014; Kuentz et al., 2017; Sawicz et al., 2011). Still, it is also noted that this does not hold true for all regions and scales (Ali et al., 2012; Singh et al., 2014; Trancoso et al., 2017). In addition, a recent large study of Addor et al. (2018) has shown that many of the hydrological signatures often used for classification, are easily affected by data uncertainties and cannot be predicted using catchment attributes. Another recent study by Kuentz et al. (2017) used an extremely large datasets of 35,000 catchments in Europe and classified them using hydrological signatures. For their classification, they used hierarchical clustering and evaluated the result of the clustering by comparing variance between different numbers of clusters. They were able to find ten distinct classes of catchments. However, Kuentz et al. (2017) used some of the signatures identified to have a low spatial predictability by Addor et al. (2018). In addition, one third of their catchments was aggregated in one large class with no distinguishable attributes. Overall, we conclude that no large sample study exists that uses only hydrological signatures with a good spatial predictability. In addition, if the climate is the dominant driver of catchment behavior, clustering catchments based on their hydrological behavior should result in clusters with a uniform climate.

Therefore, we selected the best six hydrological signatures with spatial predictability to classify catchments of the CAMELS (Catchment Attributes and MEteorology for Large-Sample Studies) dataset (Addor et al., 2017). Those six hydrological signatures are evaluated together with the fifteen catchment attributes that were shown to have a large influence on hydrological signatures (Addor et al., 2018). The connection between the hydrological signatures and the catchment attributes is determined by using quadratic regression of the principal components (of the hydrological signatures) and the catchment attributes. This will help to explore, if a clustering with hydrological signatures that have a high predictability in space, provides hydrologically meaningful clusters and how those are related to catchment attributes. In addition, we compare the hydrologically derived clusters with climatic clusters and determine the spatial distance between the most hydrologically similar catchments. This will determine if grouping catchments by climate or by hydrologic behavior will yield the same results and explore the validity of considering spatial distance as a measure of similarity between catchments.

2 Material and Methods

2.1 Data base

This work is based on a detailed analysis of catchment attributes and information contained in hydrological signatures. The CAMELS data set contains 671 catchment in the continental united states (Addor et al., 2017) with additional meta information such as slope and vegetation parameters. For our study, we used a selection of the available meta data ~~(Table 1)~~. We excluded all catchments that had missing data, which left us with 643 catchments. Those catchments come from a wide spectrum of characteristics like different climatic regions, elevations ranging from 10 to almost 3,600 m a.s.l. and catchment areas ranging from 4 to almost 26,000 km². To ensure an equal representation of the different catchment attributes classes (climate, topography, vegetation, soil, geology) we used three attributes per class. *Climate*: aridity, frequency of high precipitation events, fraction of precipitation falling as snow; *Vegetation*: forest fraction, green vegetation fraction maximum, LAI maximum; *Topography*: mean slope, mean elevation, catchment area; *Soil*: clay fraction, depth to bedrock, sand fraction; *Geology*: dominant geological class, subsurface porosity, subsurface permeability. Those catchment attributes were chosen due to their ability to improve the prediction of hydrological signatures (Addor et al., 2018) and because they are relatively easy to obtain, which will allow a transfer of this method to other groups of catchments world-wide.

Hydrological signatures cover different behaviors of catchments. However, many of the published signatures have large uncertainties (Westerberg and McMillan, 2015) and lack in predictive power (Addor et al., 2018). Therefore, we used the six hydrological signatures with the best predictability in space (Table 1) (Addor et al., 2018). Those signatures were calculated for all catchments. Due to this selection, no signatures that capture low flow behavior were used, as those signatures have a very low spatial predictability.

Table 1: Applied hydrological signatures on the discharge data of the CAMELS data set (Addor et al., 2018).

Signature	Unit
Mean annual daily discharge	mm d^{-1}
Mean winter daily discharge (Nov. – Apr.)	mm d^{-1}
Mean half-flow date; Date on which the cumulative discharge since October first reaches half of the annual discharge	day of year
95 % Flow quantile (high flow)	mm d^{-1}
Runoff ratio	-
Mean summer daily discharge (May – Oct.)	mm d^{-1}

2.2~~3~~ Data analysis

The workflow of the data analysis considers a data reduction approach with a principal component analysis and a subsequent clustering of the principal components, similar to Kuentz et al. (2017) and McManamay et al. (2014). For the principal component analysis and the clustering, we used the Python package sklearn (0.19.1). The code is available at GitHub (Jehn, 2018). Validity was checked by a random selection of 50 and 75 % of all catchments. We found that the overall picture stayed the same (not shown). In all further analysis, we used all catchments to get a sample as large as possible to be able to make statements that are more general.

Calculation of the principal component analysis

The principal components were calculated from the six hydrological signatures described above (Table 1). We used a principal component analysis on the hydrological signatures to remove correlations between the single hydrological signatures. We only used principal components that together account for at least 80% of the total variance of the hydrological signatures, which resulted in two principal components. Those two principal components contain the uncorrelated information of all hydrological signatures used and thus can be seen as describers of the overall hydrological behavior. Therefore, catchments with similar principal components have similar hydrological behavior.

Evaluating the connection between the principal components and the catchment attributes

~~We evaluated the connection between the principal components and the catchments attributes with the following procedure:~~

1) First, we calculated quadratic regressions between the two principal components and the catchment attributes (with the principal component as the dependent variable). This resulted in one coefficient of determination (R^2) for each pair of principal component and catchment attribute (e.g. PC 1 and aridity).
2) We then weighted the R^2 by the explained variance of the principal components. This addresses the differences in the explained variance of the principal components (e.g., PC 1 explained 75% of the variance, PC 2 explained 19% of the variance).
3) The weighted coefficients of determination of the principal components were subsequently added~~,~~ to obtain one coefficient of determination ~~regression~~ for every catchment attribute.

Quadratic regression was selected as interactions in natural hydrological systems are known to have unclear patterns and can ~~cannot~~ therefore often not be fitted with a simple straight line (Addor et al., 2017; Costanza et al., 1993). This was done first for the whole dataset and then for all clusters separately. This procedure captures the pattern on the catchment attributes in the PCA space of the hydrological signatures (for examples of this pattern see Figure A1).

Clustering the principal components

The principal components of the hydrological signatures were clustered following agglomerative hierarchical clustering with ward linkage (Ward, 1963), similar to previous studies (Kuentz et al., 2017; Li et al., 2018; Yeung and Ruzzo, 2001). From those studies, Kuentz et al. (2018) provides the largest set with over 35,000 catchments. They also clustered their catchments in a PCA space of a range of hydrological signatures. To select the number of clusters, they used the elbow method (and two other methods to validate their results) and found that ten or eleven clusters (depending on the method) were most appropriate for their data. Due to the similarity in the clustered data and the larger database of Kuentz et al. (2018), we also used ten clusters. Those ten clusters represent groups of catchments with distinctly different hydrological behavior.

~~For the principal component analysis and the clustering we used the Python package sklearn (0.19.1). The code is available at GitHub (Jehn, 2018). Validity was checked by a random selection of 50 and 75 % of all catchments. We found that the overall picture stayed the same (not shown). In all further analysis, we used all catchments to get a sample as large as possible to be able to make statements that are more general.~~

3 Results and Discussion

3.1 Impacts of catchment attributes on discharge characteristics in the whole dataset

First we examined the weighted R^2 of the catchment attributes for the whole dataset. This analysis shows not only differences in their score between the single attributes, but also between the different classes of catchment attributes (Figure 1). Attributes related to climate (aridity) and vegetation (forest fraction) get the highest scores. With the exception of the mean slope, the first seven catchment attributes are all related to climate and vegetation. The last seven attributes on the other hand are all related to soil and geology, except the catchment area. They also show much lower scores of the weighted R^2. This indicates that soil and geology are less important for the chosen hydrological signatures. Similar patterns were also found by (Yaeger et al., 2012). They stated climate as the most important driver for the hydrology.

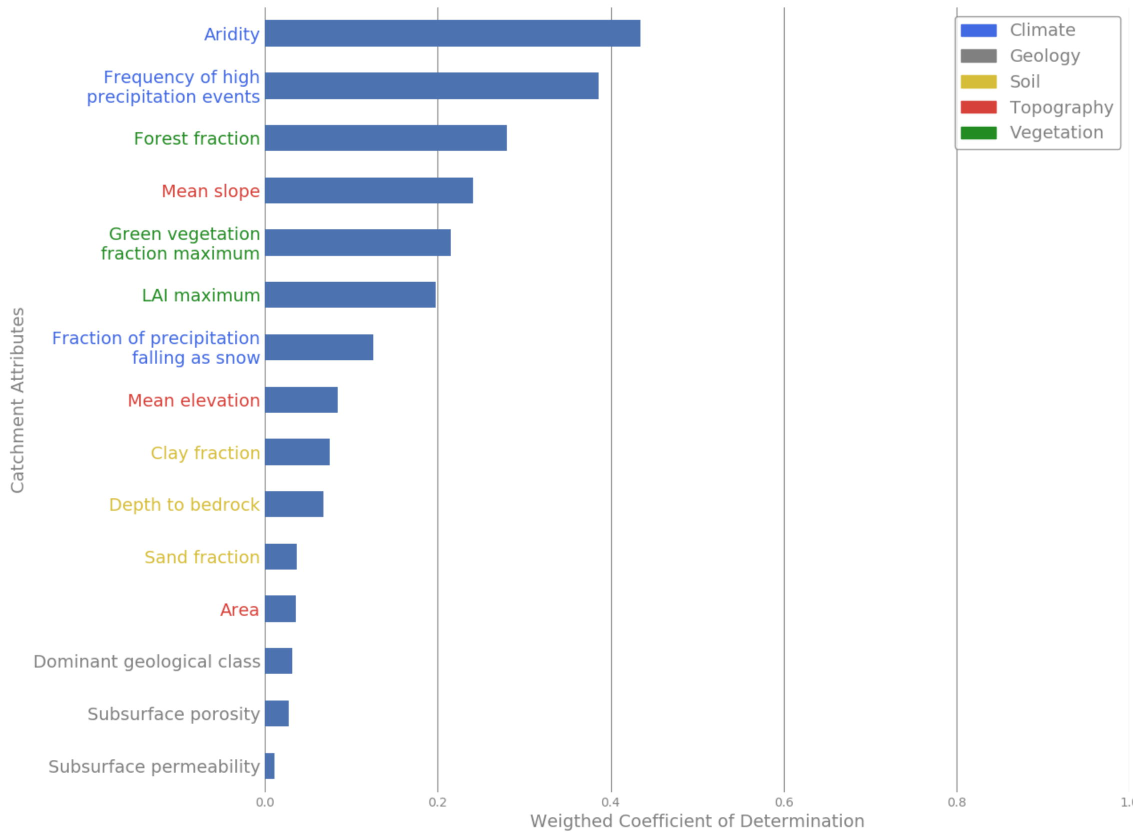


Figure 1: Importance of catchment attributes evaluated by quadratic regression for all considered catchments. Attributes colored according to their catchment attribute class.

However, they also unraveled that low flows are mainly controlled by soil and geology. The minor importance of soil and geology in our study might therefore be biased by the choice of hydrological signatures, which excluded low flow signatures due to their low predictability in space. Nevertheless, our study probably captures a more general trend as we used a larger dataset and more hydrologically meaningful hydrological signatures (Addor et al., 2018). Addor et al. (2018) also explored the influence of different catchment attributes in the CAMELS dataset on discharge characteristics. They found that climate has the largest influence on discharge characteristics, well in agreement with Coopersmith et al. (2012). The latter also used a large group of catchments in the continental United States from the MOPEX dataset. They conclude that the seasonality of the climate is the most important driver of discharge characteristics. However, Coopersmith et al. (2012) only analyzed the flow duration curve, which has a mediocre predictability in space and it is therefore more unclear what it really depicts (Addor et al., 2018). Overall, this study here is in line with other literature in the field. Using the weighted R^2 reliably detects climatic forcing as the most important for the discharge characteristics for a large group of catchments. This can probably be extrapolated to most catchments in the continental US without human influence, as the CAMELS dataset contains large samples of undisturbed catchments (Addor et al., 2017). In the next step, we will test whether these relations also hold for the clusters of the catchments.

3.2 Relation of the principal components and the hydrological signatures

The rivers considered in this study show a wide range in hydrological signatures. This is visible in the clusters of principal components of the hydrological signatures (Figure 2).Most of the rivers are opposite of the loading vectors (the loading vectors are shown as arrows). This shows that most rivers have relatively low values for all hydrological signatures and only some, more extreme rivers, have higher values for specific hydrological signatures. Most typical for the overall behavior of the river are the hydrological signatures mean annual discharge and Q95 (high flows), as they have a strong correlation with the first principal component. For the second principal component, the mean half-flow date (an indicator for seasonality) has the highest correlation. Therefore, the first principal component can be seen as a measure of overall discharge and amount of high flows, while the second principal component can be seen as a measure of seasonality in the discharge.

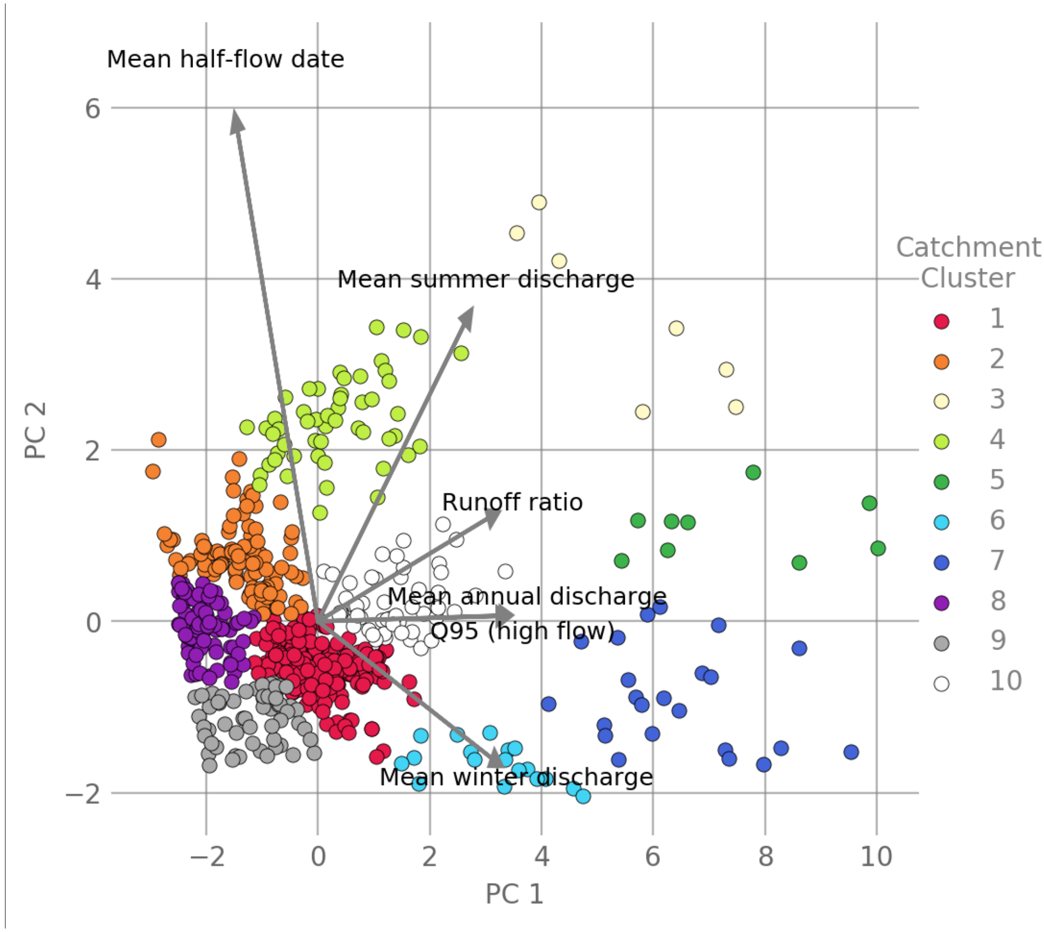


Figure 2: Biplot of the principal components (PC). Colors indicate the cluster of the catchment.

3.3 Exploration of the catchment clusters

The catchment attributes in the CAMELS and similar large scale datasets often show a pattern that resembles climatic zones (Addor et al., 2018; Coopersmith et al., 2012; Yaeger et al., 2012). The picture is less clear for the hydrological catchment clusters presented. This is directly observable in the spatial distribution of the clusters (Figure 3). Usually the 100th meridian is seen as the dividing climatic line in the US, splitting the country in a semi-arid west and a humid east.

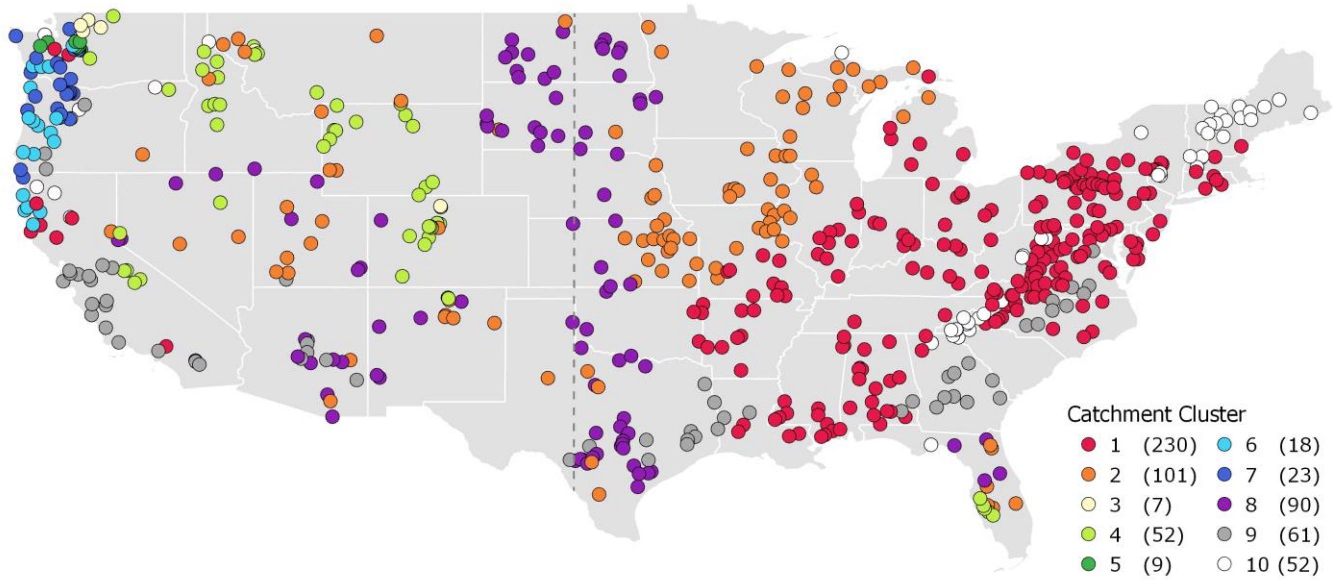


Figure 3: Locations of the clustered CAMELS catchments in the continental US. Dotted line marks the 100th meridian.

This split can also be found in some of the clusters depicted in Figure 3. Cluster 3, 4, 5, 6 and 7 are all located mainly in the West, while Cluster 1 and 10 are in the East. However, the remaining Clusters 2, 8 and 9 have roughly similar amounts of catchments in both regions. The catchments in the eastern half of the United States form large spatial patterns of similar behavior, while the catchments in the west are a lot patchier. The descriptions of the catchment clusters are summarized in Table 2. A further detailed description of the clusters can be found in the appendix, together with figures showing the distribution of hydrological signatures (Figure A2) and catchment attributes (Figure A3) in the clusters. A list of all catchments with index, position and cluster classification is given in the supplementary material.

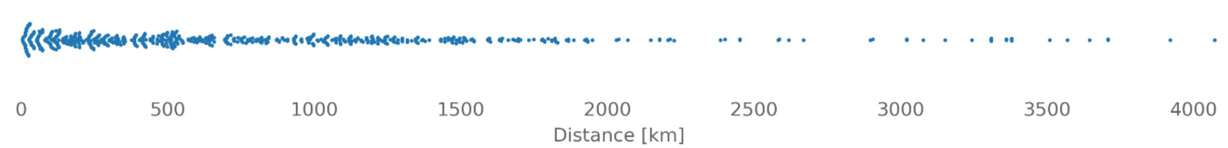


Figure 4: Swarm plot of the real world distances of all catchments to the most hydrologically similar catchment (based on their distance in the PCA space of the hydrological signatures).

In addition, similar catchments can be quite far away from each other (Figure 4). Sometimes, the catchment with the most similar signature was found as far as 4000 km away (almost the entire longitudinal distance of the continental US). This explains why spatial proximity seems to be important in some studies that look into explanations of catchment behavior (Andréassian et al., 2012; Sawicz et al., 2011), but not in others (Trancoso et al., 2017). This also indicates that clustering by using spatial proximity might only work in regions like the eastern US, where the behavior of rivers changes gradually. The finding that the most similar catchment (based on their hydrological signatures) can be far away, also explains the behavior of clusters that contain catchment quite distant from each other (e.g. Cluster 4). Even though the catchments might be far away from each other, the interplay of different catchment attributes and driving factors, including ~~obviously~~ sometimes very different climates, can lead to similar (equifinal) discharge behavior.

The derived importance of the catchment attributes in the clusters is highly variable and partly differs from the order of importance in the overall dataset (compare Figure 1 and Figure 5). For Cluster 1 (Southeastern and Central Plains), 6 (Marine West Coast Forests), 8 (Great Plains and Deserts) and 9 (Southern states) aridity has the clearest connection to the clusters. However, this is not the case for the remaining catchment clusters. For Cluster 3 (Northwestern Forested Mountains), 4 (Northwestern Forested Mountains and Florida) and 7 (Western Cordillera) the clearest connection is to the fraction of precipitation falling as snow. However, for Cluster 3, and 4 many other catchment attributes have a weighted R^2, which is almost as high as the one for the fraction of precipitation falling as snow.

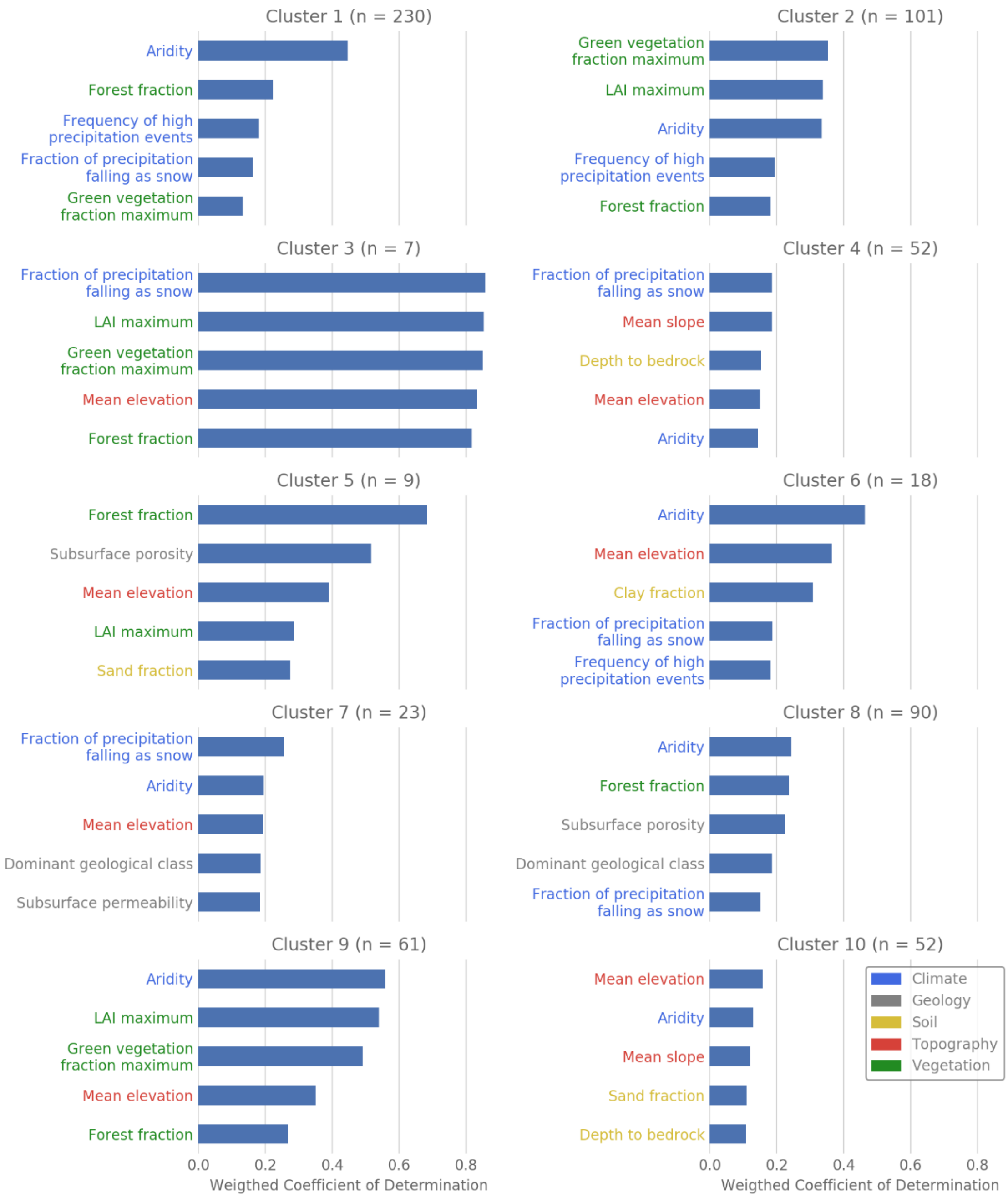


Figure 5: Importance of the catchment attributes evaluated by the quadratic regression. For the catchment clusters. Attributes colored according to their catchment attribute class.

In addition, all catchment attributes have a high weighted R^2 in Cluster 3, while the weighted R^2 is low for all catchment attributes in Cluster 4. For the remaining clusters, it is green vegetation maximum (Cluster 2, Central Plains), forest fraction (Cluster 5, Northern Marine West Coast Forest) and mean elevation (Cluster 10, Appalachian Mountains). Overall, the western clusters (west of the 100th meridian) have the highest weighted R^2 with the:

Fraction of precipitation falling as snow (Cluster 3, 4, 7)

Forest fraction (Cluster 5)

Aridity (Cluster 6)

The eastern clusters (east of the 100th meridian) with the:

Aridity (Cluster 1)

Mean elevation (Cluster 10)

The clusters equally present in west and east with the:

Green vegetation fraction maximum (Cluster 2)

Aridity (Cluster 8, 9)

In the next step, we linked the abovementioned findings to the differences between the correlations of the catchment attributes with each other in the eastern and western parts of the continental US (Figure 6). While aridity is the most important catchment attribute, when looking at all catchments at the same time (Figure 1), this does not hold true for most of the single clusters (Figure 5). Yet, the factors with the highest weighted coefficient of correlation might simply be proxies for aridity. To test this, we scrutinized the correlation between the catchment attributes with each other, separated by East and West (Figure 6). The western US (Figure 6a) and eastern US (Figure 6b) show high differences in the way the catchment attributes correlate with each other (Figure 6c). The main differences are in the mean elevation, the fraction of precipitation falling as snow, and the LAI maximum. For example, in the western US the mean elevation has a high correlation (r = 0.8) with the fraction of precipitation falling as snow. In the eastern US however, this correlation is much smaller (r = 0.4). This is probably caused by the overall higher elevation in the western US. In addition, in the western US, the fraction of the precipitation falling as snow does not correlate with the aridity (r = 0.1), while the forest fraction does (r = -0.8). Thus, the forest fraction is linked very directly to the climate in this region. Therefore, aridity (and the highly correlated forest fraction) have the highest weighted R^2 in two out of the five clusters in the western US. Only two clusters are mostly located in the eastern US (Cluster 1 and 10). Here, aridity and the mean elevation have the highest weighted R^2 with the hydrological behavior. The mean elevation has a medium correlation with the aridity. Hence, the hydrological behavior in the eastern US is most highly correlated with aridity, which is not the case for the western US. There, the fraction of precipitation falling as snow is more prevalent. Those results imply that aridity is a good indicator for the discharge characteristics in the eastern US and only mediocre in the West.

Overall, we found that it is relatively easy to link the dominating catchment attributes to the hydrological behavior, in some regions of the US. However, it is more challenging in others. We link this to the signal of the climatic forcing being more influenced by other catchment attributes, which results in a less clear connection between hydrological behavior and climate~~We link this to a less strong climatic signal in those regions~~. This hints that climate and catchment attributes are more intertwined in those areas and indicates regions where different types of hydrological model structures are needed. Furthermore, it indicates regions where hydrological predictions in ungauged basins (Hrachowitz et al., 2013) can become very challenging, as the interplay of the available meteorological- and catchment-attributes data cannot sufficiently explain the hydrological characteristics.

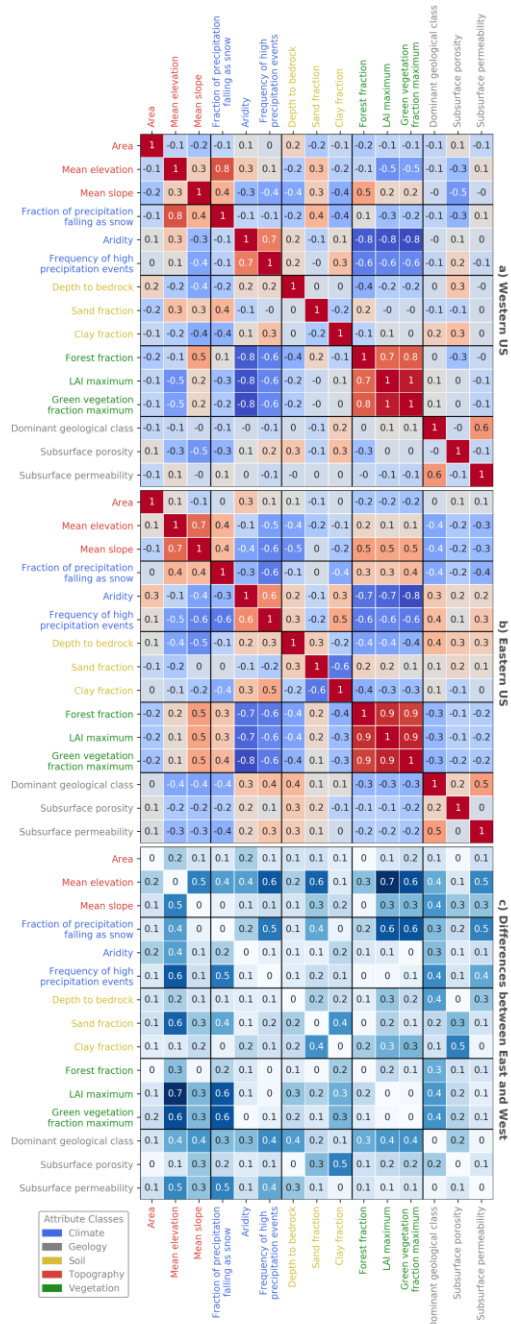


Figure 6: Correlation of all catchment attributes for western (a) and eastern (b) US and absolute differences in correlation between the eastern and western US. Eastern and western is defined by the 100th meridian.

Table 2: Properties of the catchment clusters. Typical signatures/attributes refers to the signature/attribute of the cluster with the lower coefficient of variation scaled by the mean coefficient of variation of the whole dataset. Dominating attribute refers to the catchment attribute that has the highest weighted R^2.

Cluster	n	Main Region	Typical signature	Typical attribute and their manifestation	Dominating attribute
1	230	Southeastern and Central Plains	Low mean winter discharge	Low aridity	Aridity
2	101	Central Plains (with scattered catchments all over western US)	High mean half-flow date	Mid to low depth to bedrock	Green vegetation fraction maximum
3	7	Northwestern Forested Mountains	High mean summer discharge	High forest fraction	Fraction of precipitation falling as snow
4	52	Northwestern Forested Mountains and Florida	High mean half-flow date	Mid frequency of high precipitation events	Fraction of precipitation falling as snow
5	9	Northern Marine West Coast Forests	High mean summer discharge	Very high forest fraction	Forest fraction
6	18	Marine West Coast Forests	Mid runoff ratio	Very high forest fraction	Aridity
7	23	Western Cordillera (Part of Marin West Coast Forests)	High mean winter discharge	Very high forest fraction	Fraction of precipitation falling as snow
8	90	Great Plains and North American Deserts	Mid mean half-flow date	High frequency of high precipitation events	Aridity
9	61	All southernmost states of the US	Low mean half-flow date	High frequency of high precipitation events	Aridity
10	52	Appalachian Mountains	Low mean winter discharge	High forest fraction	Mean elevation

3.4 Differences in clusters in comparison with other hydrological clustering studies

Compared to the clustering results of Kuentz et al. (2017), who derived their cluster from European catchments by an analogous method, some similarities can be found. Like them, this study here also found one cluster (Cluster 2) that does not have any distinct character. However, only around one sixth of the CAMELS catchments belongs to this Cluster 2, while Kuentz et al. (2017) had one third of their catchments in a cluster without distinct features. Therefore, our selection of hydrological signatures seems to allow a better identification of hydrological similarities. However, all catchments in CAMELS are mostly without human impact (Addor et al., 2017), while many catchments in the study of Kuentz et al. (2017) are under human influence. This influence might overlay potentially apparent patterns. Kuentz et al. (2017) also found two clusters that contain mostly mountainous catchments. These show a similar behavior to Cluster 3 (Northwestern Forested Mountains) and Cluster 10 (Appalachian Mountains) found in Figure 3. The main difference between their findings and this study here is Cluster 8, as it contains very arid catchments (with some being located in deserts). Obviously, this cluster cannot be found in Europe as Europe has no real deserts. Still, there is some similarity with their cluster of Mediterranean catchments as both are dominated by aridity. Summarizing, in their study and this study catchments are mainly clustered in groups of desert/arid catchments, mountainous catchments, mid height mountains with high forest shares, wet lowland catchments and one cluster of catchments that do not show a very distinct behavior and therefore do not fit in the other clusters (Table 2). One possible explanation for this unspecific behavior might that many catchments have one or two important attributes that dictate most of their behavior, but which are different from other cluster members. For example, desert catchments are relatively easy to identify, as they are dominated by heat and little precipitation. A European upland catchment on the other hand have several more influences such as snow in the winter, heat in the summer, varying land use and strong impact of seasonality. Here, many influences overlap each other and make it thus difficult to identify a single causes, see also the discussion by Trancoso et al. (2017) that goes in a similar direction. Those overlapping influences are probably also the reason why catchment classification studies often find clusters where one or two cluster that include a large number of catchments, while most other cluster only contain few catchments (Coopersmith et al., 2012; Kuentz et al., 2017). Therefore, it is quite difficult to confirm the 'wish' of the hydrological community to have homogenous catchment groups with only a few outliers (e.g. (Burn, 1997)), because catchments are complex systems with a high level of self–organization arising from co-evolution of climate and landscape properties, including vegetation (Coopersmith et al., 2012). Accordingly, it requires many separate clusters to separate those multi-influence catchments into homogenous groups. Still, the cluster found here might capture much of the variety present in the United States, as they roughly follow ecological regions (McMahon et al., 2001), which has been stated as a hint of a good classification (Berghuijs et al., 2014). In addition, this study shows that using clusters derived from principal components of hydrological signatures create meaningful groups of catchments with similar attributes (Figure A2, A3). Those clusters also show distinct spatial patterns (Figure 3). Similar results were also found in other studies that used the same method (Kuentz et al., 2017; McManamay et al., 2014), but based them on partly different hydrological signatures. Therefore, the principal components of hydrological signatures can be used as a measure of similarity between catchments. They represent the "essence" of all hydrological signatures used. Our results also show that it is difficult to link those catchment clusters to simple averaged measures of catchment attributes. While some clusters have very clear connections to the attributes, others have no catchment attribute that could easily explain the behavior of the catchments. This hints, that some catchments are easier to explain (in a hydrological sense) than others. Those difficulties might be an artifact of the averaged catchment attributes or be caused by complex catchment reaction, forced by intertwined climate and catchment attributes. Which in turn, might indicate an equifinality of catchment response.

3.5 Comparing catchment clusters based on hydrological behavior and climate

Besides hydrological behavior, climate is often used to sort catchments into similar groups (e.g. Berghuijs et al., 2014; Knoben et al., 2018). Therefore, we are interested if both approaches deliver comparable results. To evaluate this, we contrasted our results to the commonly used Koeppen-Geiger climate classification (Beck et al., 2018) (Figure 7) and recently published approach of Knoben et al. (2018), who sorted climate along three continuous axis of aridity, seasonality and fraction of precipitation falling as snow (Figure 8). The resulting clusters based on climate and hydrology should be the same, if climate is the dominating driver of hydrological behavior in every catchment. Yet, this is not the case for the Koeppen-Geiger classification. In every hydrological cluster are at least two different climates regarding the Koeppen-Geiger classification, ranging up to eight different climatic regions for Cluster 2 and 8 (those even include deserts and very cold regions). Thus, the Koeppen-Geiger classification seems unable to capture the essential drivers of hydrological behavior. A critique also raised in other studies (e.g. Haines et al. (1988); Knoben et al. (2018)).

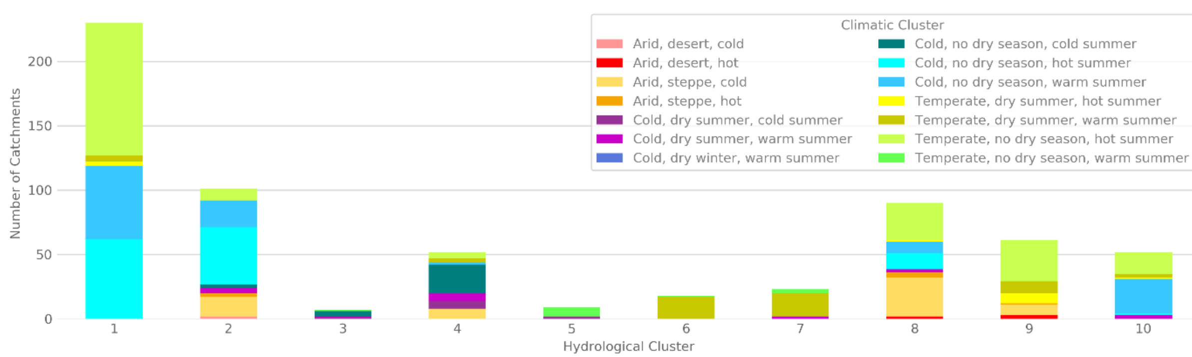
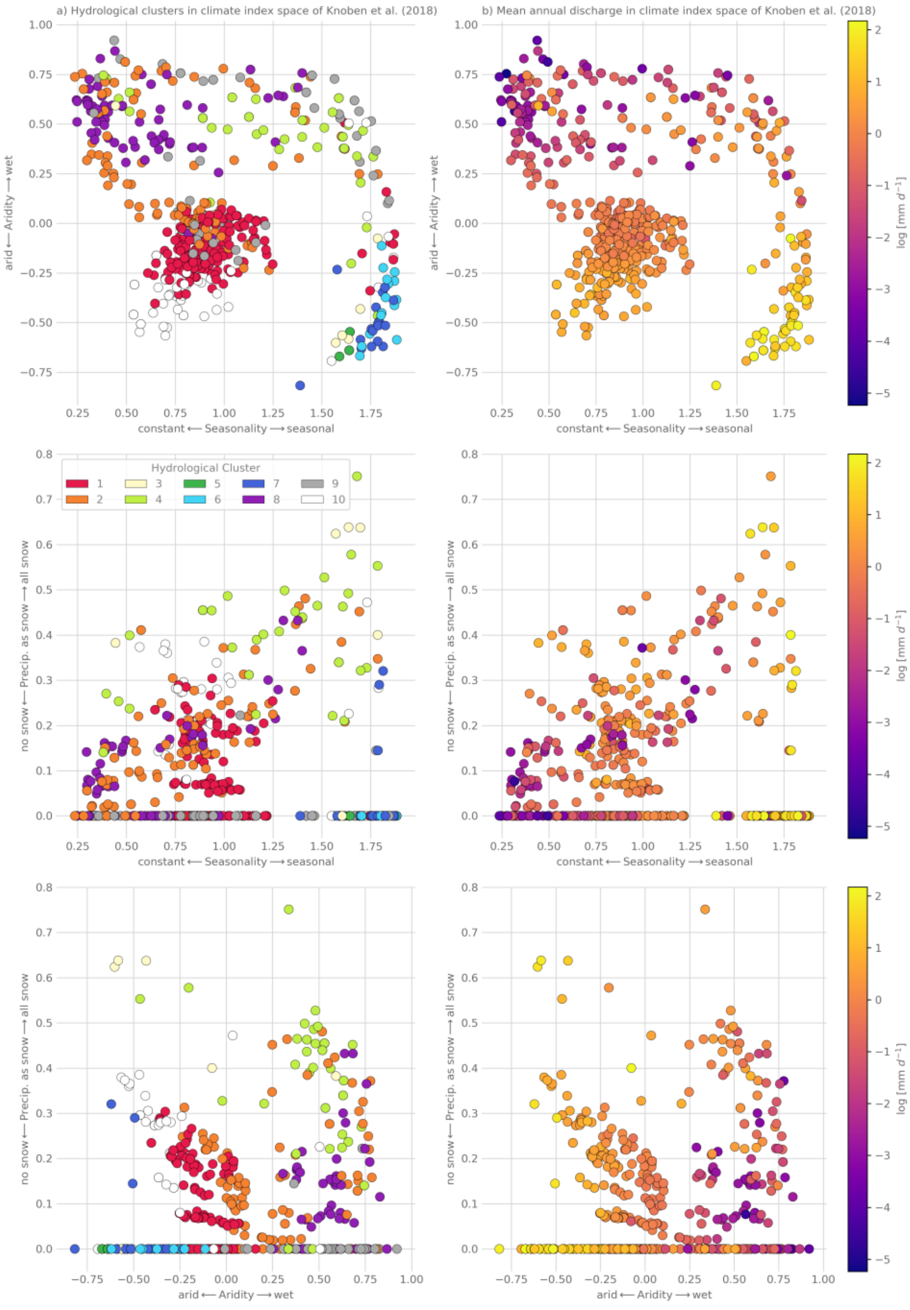


Figure 7: Membership of Koeppen-Geiger clusters (Beck et al. (2018)) in the hydrological clusters.

The picture is less clear concerning the climatic index space of Knoben et al. (2018) (Figure 8a). Due to the continuous nature of the approach of Knoben et al. (2018), there are no clear boundaries as in the Koeppen-Geiger classification. Still, there are some emerging patterns. For example, according to the approach of Knoben et al. (2018) Cluster 1 is mainly defined by a relatively arid climate, with some seasonal variability and little to no snow. This is in line with our analysis of the most influential catchment attributes for this cluster, as we identified aridity as the main driver. Contrastingly, clusters where we could not identify a clear dominating catchment attribute, ~~if we~~ e.g. ~~look at~~ Cluster 4 (located in the Northwestern Forested Mountains and Florida) (Figure 5), also have no clear clustering in the climate index space. ~~Catchments with this hydrological behavior~~ The catchments of those clusters can be found in the space of the climatic indices of Knoben et al. (2018) with very different aridity, seasonality and fraction of the precipitation falling as snow. There seem to be regions were the forcing signal of the climate is transferred more directly to a streamflow response than in others. However, this does not mean that climate is unimportant in those regions. Either the climate forcing signal is changed more through other attributes of the catchment, or the mean values describing the climate do not properly reflect the variability of the climate in the single catchments. This leads to less clear correlation between the climate and the hydrological behavior. Interestingly, when we look at the single hydrological signatures in the climate index space (Figure 8b, A4) we see a very clear connection between the single hydrological signatures and the climate. This direct connection of the signatures used was also found by Addor et al. (2018). Our results and the comparison show that the complex hydrological behavior, captured in a range of hydrological signatures, does not simply follow the climate only, even though the individual signatures do. ~~This is even more remarkable, as the signatures used are linked to climate directly. For example, the signature "mean half flow date" can be seen as a measure of seasonality.~~ Still, all signatures combined seem to capture a dynamic, which is climatic in origin, but is shaped through the attributes of the catchments (like vegetation and soils (Berghuijs et al., 2014)). Therefore, to find truly similar catchments, using climate characteristics only, is probably not sufficient.



325 **Figure 8: a) Comparison of the hydrological clustering of this study with the climate index space of Knoben et al. (2018). Single dots show the catchments and are colored by their hydrological clusters. b) Mean annual discharge for all catchments in the climate index space of Knoben et al. (2018). Single dots show the catchments and are colored according to the value of the mean annual discharge. The log of the mean annual discharge is used to show the relative differences between the catchments. For a depiction of all hydrological signatures used, see Figure A4.**

4 Summary and conclusion

This study explored the influence of catchment attributes on the discharge characteristics in the CAMELS dataset. We found that over the whole dataset climate (especially aridity) is the most important factor for the discharge characteristics. This changes when we take a closer look at clusters that are derived from specific hydrological signatures. For the clusters in the eastern US, aridity is still the most important catchment attribute. In the western US however, the amount of snow is more important. In addition, in the western catchments the hydrological behavior is less correlated with the remaining catchment attributes. It seems like the clear climatic signal in the east is dampened in the west. This might be caused by a higher influence of other catchment attributes like elevation and vegetation. A similar effect can be found, when we compare how catchments align along hydrological and climatic axes. While some hydrological clusters align along a relatively narrow range of values of the climatic indices, others are found in very contrasting climates. Summarizing, there are differences of how directly the signal of forcing climate can be found again in the hydrological behavior. This explains why catchments often show a surprisingly similar behavior across many different climate and landscape properties (Troch et al., 2013) and why the most hydrologically similar catchment can be hundreds of kilometers away.

The aggregated data used in this study might level out the variability of the catchment attributes in the single catchment, but it also indicates that there is a kind of equifinality in the behavior of catchments. Different sets of intertwined climate forcing and catchment attributes could lead to a very similar overall behavior, not unlike to hydrological models that produce the same discharge with different sets of parameters.

We acknowledge that the results are dependent on the amount and size of the clusters, the catchment attributes considered and the hydrological signatures used. Still, we think that the CAMELS dataset offers an excellent overview of different kinds of catchments in contrasting climatic and topographic regions. ~~Nevertheless~~However, it seems that even a comprehensive dataset like CAMELS, does not allow an easy way to find a conclusive set of clusters for catchments. For future research, it might be a worthwhile pathway to include measures of spatial variability of the climate in the single catchments. This might help to prove, if a less clear climatic signal is caused by intra-catchment variability of the climate or a larger influence of other catchment attributes.

Data availability

The CAMELS dataset can be found at https://ncar.github.io/hydrology/datasets/CAMELS_timeseries and is described in Addor et al. (2017). The cluster numbers together with the CAMELS catchment ID and the climatic indices can be found in the supplement of this paper.

Code availability

The code used for this study can be found at Jehn (2018).

Author contribution

FUJ, LB, TH and PK conceived and designed the study. FUJ did the data analysis. All authors aided in the interpretation and discussion of the results and the writing of the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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References

Addor, N., Newman, A. J., Mizukami, N. and Clark, M. P.: The CAMELS data set: catchment attributes and meteorology for large-sample studies, Hydrology and Earth System Sciences, 21(10), 5293–5313, doi:10.5194/hess-21-5293-2017, 2017.

Addor, N., Nearing, G., Prieto, C., Newman, A. J., Le Vine, N. and Clark, M. P.: A ranking of hydrological signatures based on their predictability in space, Water Resources Research, doi:10.1029/2018WR022606, 2018.

Ali, G., Tetzlaff, D., Soulsby, C., McDonnell, J. J. and Capell, R.: A comparison of similarity indices for catchment classification using a cross-regional dataset, Advances in Water Resources, 40, 11–22, doi:10.1016/j.advwatres.2012.01.008, 2012.

Alvarez-Garreton, C., Mendoza, P. A., Boisier, J. P., Addor, N., Galleguillos, M., Zambrano-Bigiarini, M., Lara, A., Puelma, C., Cortes, G., Garreaud, R., McPhee, J. and Ayala, A.: The CAMELS-CL dataset: catchment attributes and meteorology for large sample studies – Chile dataset, Hydrology and Earth System Sciences, 22(11), 5817–5846, doi:10.5194/hess-22-5817-2018, 2018.

Andréassian, V., Lerat, J., Le Moine, N. and Perrin, C.: Neighbors: Nature's own hydrological models, Journal of Hydrology, 414–415, 49–58, doi:10.1016/j.jhydrol.2011.10.007, 2012.

Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A. and Wood, E. F.: Present and future Köppen-Geiger climate classification maps at 1-km resolution, Scientific Data, 5, 180214, doi:10.1038/sdata.2018.214, 2018.

Berghuijs, W. R., Sivapalan, M., Woods, R. A. and Savenije, H. H. G.: Patterns of similarity of seasonal water balances: A window into streamflow variability over a range of time scales, Water Resources Research, 50(7), 5638–5661, doi:10.1002/2014WR015692, 2014.

Beven, K. J.: Uniqueness of place and process representations in hydrological modeling, Hydrology and Earth System Sciences, 4(2), 203–213, 2000.

Burn, D. H.: Catchment similarity for regional flood frequency analysis using seasonality measures, Journal of Hydrology, 202(1–4), 212–230, doi:10.1016/S0022-1694(97)00068-1, 1997.

Coopersmith, E., Yaeger, M. A., Ye, S., Cheng, L. and Sivapalan, M.: Exploring the physical controls of regional patterns of flow duration curves - Part 3: A catchment classification system based on regime curve indicators, Hydrology and Earth System Sciences, 16(11), 4467–4482, doi:10.5194/hess-16-4467-2012, 2012.

Costanza, R., Wainger, L., Folke, C. and Mäler, K.-G.: Modeling Complex Ecological Economic Systems: Toward an Evolutionary, Dynamic Understanding of People and Nature, in Ecosystem Management, pp. 148–163, Springer New York, New York, NY., 1993.

Gupta, H. V., Perrin, C., Blöschl, G., Montanari, A., Kumar, R., Clark, M. and Andréassian, V.: Large-sample hydrology: a need to balance depth with breadth, Hydrology and Earth System Sciences, 18(2), 463–477, doi:10.5194/hess-18-463-2014, 2014.

Haines, A. T., Finlayson, B. L. and McMahon, T. A.: A global classification of river regimes, Applied Geography, 8(4), 255–272, doi:10.1016/0143-6228(88)90035-5, 1988.

Jehn, F. U.: zutn/Catchment-Classification: Release for Zenodo, , doi:10.5281/zenodo.2203639, 2018.

Knoben, W. J. M., Woods, R. A. and Freer, J. E.: A Quantitative Hydrological Climate Classification Evaluated With Independent Streamflow Data, Water Resources Research, 54(7), 5088–5109, doi:10.1029/2018WR022913, 2018.

Kuentz, A., Arheimer, B., Hundecha, Y. and Wagener, T.: Understanding hydrologic variability across Europe through catchment classification, Hydrology and Earth System Sciences, 21(6), 2863–2879, doi:10.5194/hess-21-2863-2017, 2017.

Li, C., Cao, J., Nie, S.-P., Zhu, K.-X., Xiong, T. and Xie, M.-Y.: Serum metabolomics analysis for biomarker of Lactobacillus plantarum NCU116 on hyperlipidaemic rat model feed by high fat diet, Journal of Functional Foods, 42, 171–176, doi:10.1016/j.jff.2017.12.036, 2018.

McGlynn, B. L. and Seibert, J.: Distributed assessment of contributing area and riparian buffering along stream networks: TECHNICAL NOTE, Water Resources Research, 39(4), doi:10.1029/2002WR001521, 2003.

McMahon, G., Gregonis, S. M., Waltman, S. W., Omernik, J. M., Thorson, T. D., Freeouf, J. A., Rorick, A. H. and Keys, J. E.: Developing a Spatial Framework of Common Ecological Regions for the Conterminous United States, Environmental Management, 28(3), 293–316, doi:10.1007/s0026702429, 2001.

McManamay, R. A., Bevelhimer, M. S. and Kao, S.-C.: Updating the US hydrologic classification: an approach to clustering and stratifying ecohydrologic data: US HYDROLOGIC CLASSIFICATION, Ecohydrology, 7(3), 903–926, doi:10.1002/eco.1410, 2014.

Newman, A., Sampson, K., Clark, M., Bock, A., Viger, R. and Blodgett, D.: A large-sample watershed-scale hydrometeorological dataset for the contiguous USA, , doi:10.5065/D6MW2F4D, 2014.

Potter, N. J., Zhang, L., Milly, P. C. D., McMahon, T. A. and Jakeman, A. J.: Effects of rainfall seasonality and soil moisture capacity on mean annual water balance for Australian catchments: WATER BALANCE OF AUSTRALIAN CATCHMENTS, Water Resources Research, 41(6), doi:10.1029/2004WR003697, 2005.

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

Schaake, J., Cong, S. Z. and Duan, Q. Y.: The US MOPEX data set, IAHS-AISH, 307, 9–28, 2006.

Semenova, O. and Beven, K.: Barriers to progress in distributed hydrological modelling: Invited Commentary, Hydrological Processes, 29(8), 2074–2078, doi:10.1002/hyp.10434, 2015.

Singh, R., Archfield, S. A. and Wagener, T.: Identifying dominant controls on hydrologic parameter transfer from gauged to ungauged catchments – A comparative hydrology approach, Journal of Hydrology, 517, 985–996, doi:10.1016/j.jhydrol.2014.06.030, 2014.

Sivapalan, M.: Prediction in ungauged basins: a grand challenge for theoretical hydrology, Hydrological Processes, 17(15), 3163–3170, doi:10.1002/hyp.5155, 2003.

Sivapalan, M.: Pattern, Process and Function: Elements of a Unified Theory of Hydrology at the Catchment Scale, in Encyclopedia of Hydrological Sciences, edited by M. G. Anderson and J. J. McDonnell, John Wiley & Sons, Ltd, Chichester, UK., 2005.

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

Trancoso, R., Phinn, S., McVicar, T. R., Larsen, J. R. and McAlpine, C. A.: Regional variation in streamflow drivers across a continental climatic gradient, Ecohydrology, 10(3), e1816, doi:10.1002/eco.1816, 2017.

Troch, P. A., Carrillo, G., Sivapalan, M., Wagener, T. and Sawicz, K.: Climate-vegetation-soil interactions and long-term hydrologic partitioning: signatures of catchment co-evolution, Hydrology and Earth System Sciences, 17(6), 2209–2217, doi:10.5194/hess-17-2209-2013, 2013.

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

Ward, J. H.: Hierarchical Grouping to Optimize an Objective Function, Journal of the American Statistical Association, 58(301), 236–244, doi:10.1080/01621459.1963.10500845, 1963.

Westerberg, I. K. and McMillan, H. K.: Uncertainty in hydrological signatures, Hydrology and Earth System Sciences, 19(9), 3951–3968, doi:10.5194/hess-19-3951-2015, 2015.

Yaeger, M., Coopersmith, E., Ye, S., Cheng, L., Viglione, A. and Sivapalan, M.: Exploring the physical controls of regional patterns of flow duration curves – Part 4: A synthesis of empirical analysis, process modeling and catchment classification, Hydrology and Earth System Sciences, 16(11), 4483–4498, doi:10.5194/hess-16-4483-2012, 2012.

Yeung, K. Y. and Ruzzo, W. L.: Principal component analysis for clustering gene expression data, Bioinformatics, 17(9), 763–774, doi:10.1093/bioinformatics/17.9.763, 2001.

Appendix

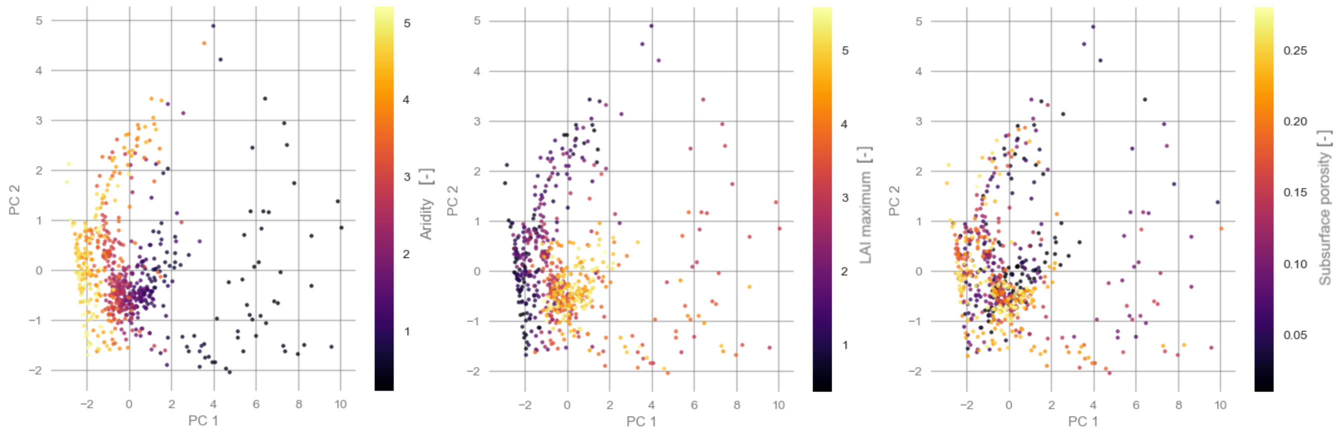


Figure A1: Patterns of catchment attributes in the PCA space of the hydrological signatures.

A 1.1 Detailed description of the catchment clusters

Cluster 1 is defined by a high cover of vegetation. In addition, most catchments are located at low elevations, experience little snow and have a deep bedrock. Hydrologically these catchments have little discharge. They are mainly located in the Southeastern and Central Plains and therefore get relative high rainfall (> 1000 mm year). Their low discharge is probably caused by the low elevation those catchments are located, groundwater discharge and the high evaporation of the forests. Cluster 1 also contains the largest amount of catchments from all cluster (n = 230). So over one third of the catchments in CAMELS show a relatively similar behavior.

Cluster 2 most typical attribute in comparison with the other catchments is its depth to the bedrock. However, concerning the catchment attributes cluster 2 is undefined as it contains catchments of most regions of the continental United States (with a focus on the Central Plains). The hydrological signatures on the other hand show a clearer pattern. Here, the mean winter discharge, Q95 and the mean annual discharge have a narrow range. This shows that catchments with very different attributes can produce very similar discharge characteristics, as the different attributes seems to cancel each other out in their influence on the discharge.

Cluster 3 is the smallest cluster with only seven catchments. Those are all located in the Northwestern Forested Mountains. Their most distinct feature is their uniform high cover with forest. They also experience high precipitation events only seldom and precipitation is snow half of the time. Hydrologically their most distinct features is their very high mean summer discharge and high runoff ratio, which is probably caused by the large amounts of snow these catchments receive.

Cluster 4 is also located in the Northwestern Forested Mountains, with the exception of four catchments that are located in Florida. This again is an example of different catchment attributes being able to create similar discharge characteristics concerning their signatures, while having different catchment attributes. The catchments have overall low discharge and few high flow events, while their catchment attributes vary widely, especially in all attributes that are related to elevation (e.g. fraction of precipitation falling as snow).

Cluster 5, has only few catchments (n = 9). They are all located at regions in the northern part of the Marin West Coast Forests. This is the region in the continental US that receives the highest precipitation (> 2000 mm year). This is mirrored in their discharge characteristics. These catchments have the highest discharge in the whole dataset, especially in the summer. They are also uniformly covered by almost 100 % of forest. They also experience only few high precipitation events as they get rain and snow more or less constantly in the same amount.

Cluster 6 catchments are also located in the Marine West Coast Forest, but cover the whole region and not only the northern part like Cluster 5. The catchments are very similar in their attributes and discharge characteristics to Cluster 5, with the exception of a lower discharge and runoff ratio. This might be caused by a slightly lower precipitation in comparison with Cluster 5.

Cluster 7 is also located in the same region as Cluster 5 and 6 (Marine West Coast Forests). Concerning the catchment attributes and the discharge characteristics, it is located between Cluster 5 and 6. So, Cluster 5 to 7 all cover the same region and differ in their mean summer discharge, which is caused by slight variations in elevation and location.

Cluster 8 is the overall most arid cluster catchments. All of the catchments are located in western parts of the Great Plains and in the North American Deserts. They are shaped by an overall little availability of water and high evaporation, which is shown in the very low mean annual discharge and runoff ratio. This also results in low values for the LAI. However, the frequency of high precipitation events is high.

Cluster 9 covers all southern states of the United States. The catchments here are quite similar to Cluster 8, but show a lower seasonality (as indicated by their lower half flow date) and a higher forest cover and green vegetation.

Cluster 10 catchments are located in the Appalachian Mountains. The mean elevation higher than most other clusters and the catchments also have low aridity and a very high forest cover. Their discharge characteristics is similar to the Marine West Coast Forests of Cluster 5 to 7. However, they receive less water than those catchments and experience a higher seasonality (as indicated by the higher mean half-flow date).

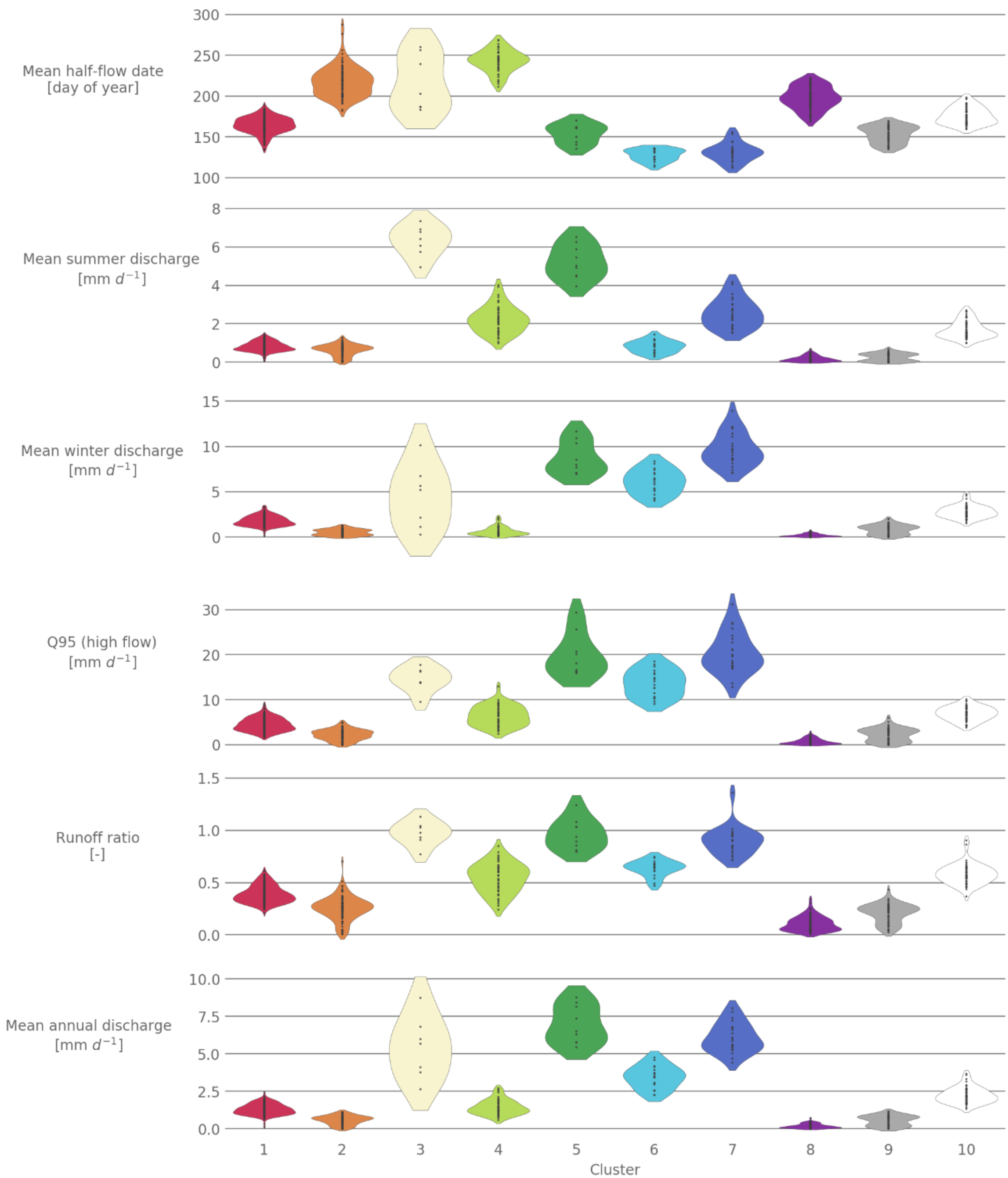
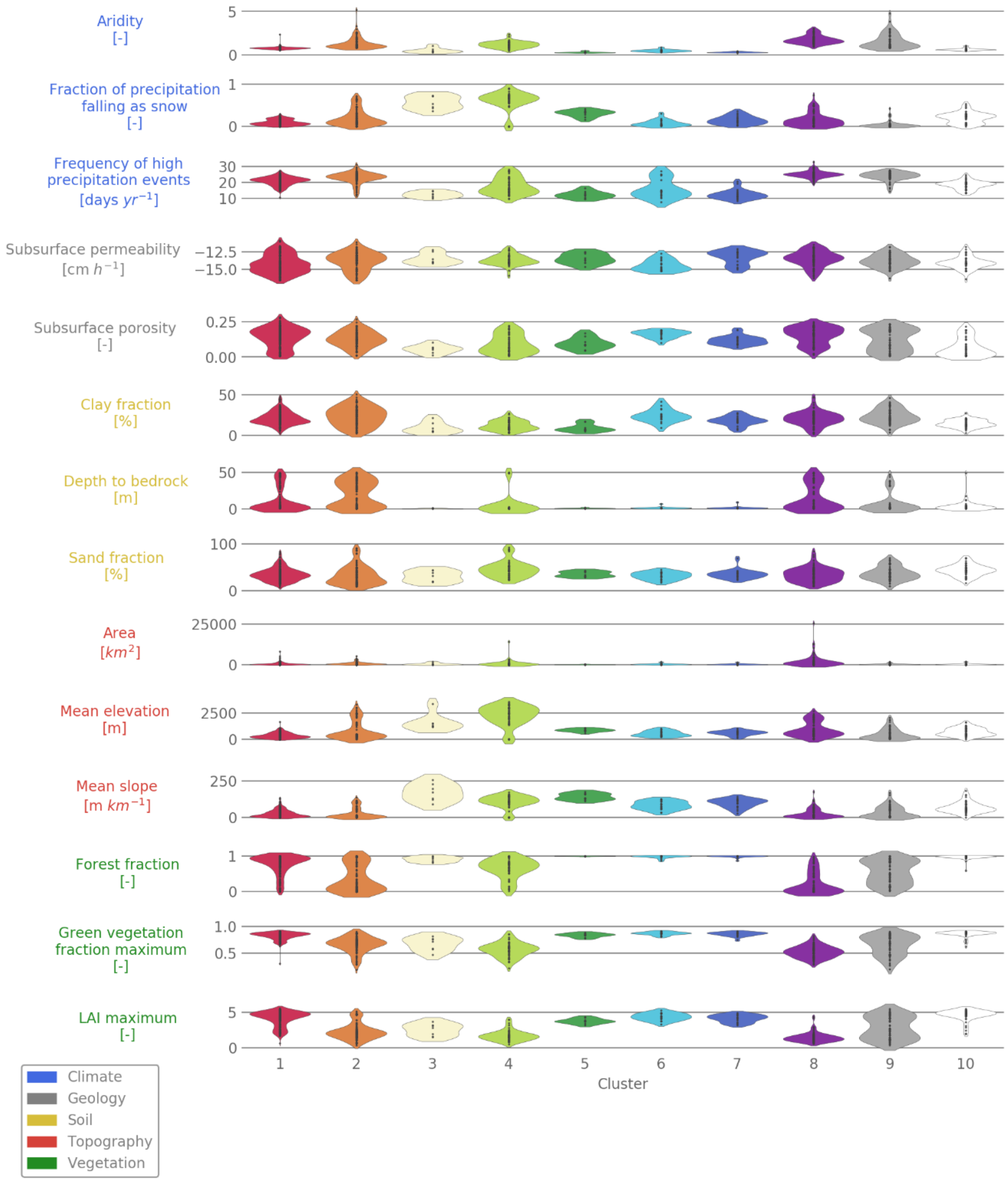


Figure A2: Violin plot of the hydrological signatures sorted by catchment clusters. Single dots in the violins indicate the single catchments.



525 **Figure A3: Violin plots of the catchment attributes sorted by catchment clusters. Single dots in the violins indicate the single catchments.**

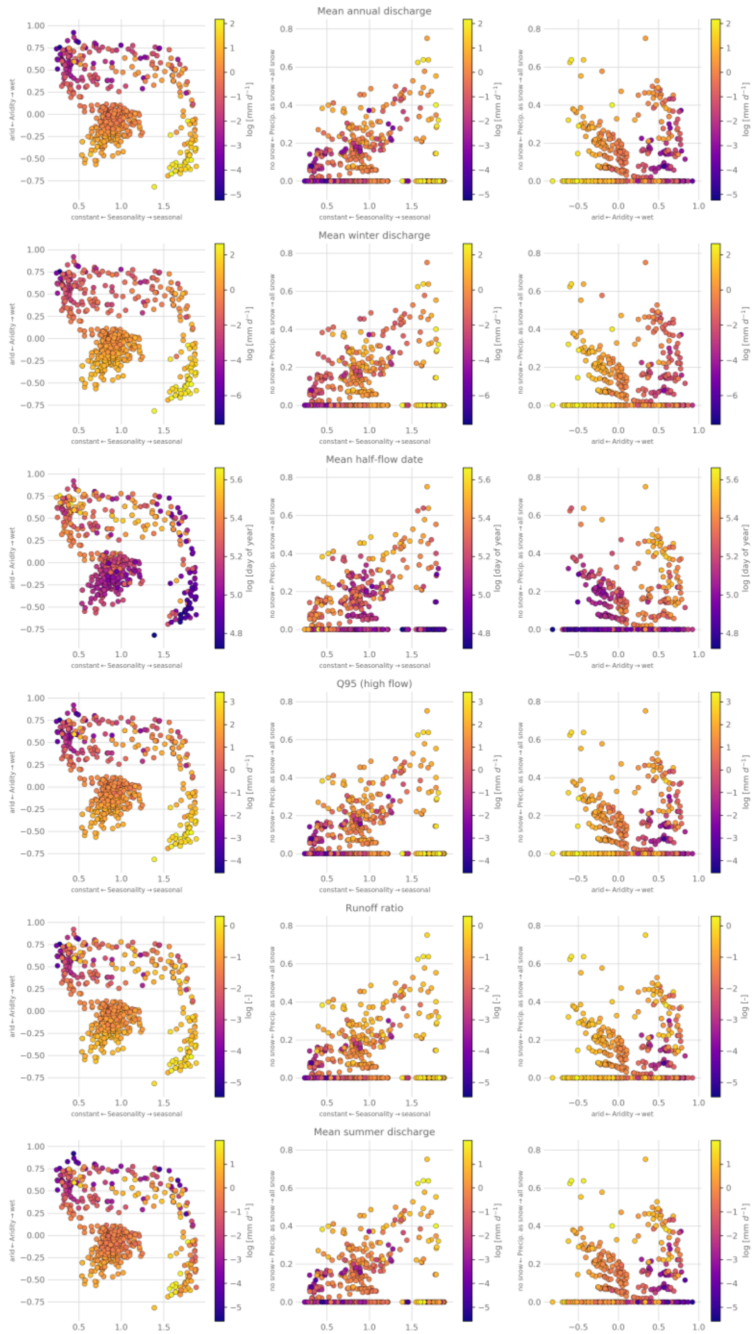


Figure A4: Hydrological signatures for all catchments in the climate index space of Knoben et al. (2018). Single dots show the catchments and are colored according to the value of the mean annual discharge. The log of the signatures is used to show the relative differences between the catchments.