**Title:** Streamflow indices to identify catchment drivers of hydrograph
**Author(s):** Jeenu Mathai and Pradeep Mujumdar
**MS No.:** hess-2021-307
**MS type:** Research article

We sincerely thank Dr. Wouter Knoben (Reviewer #1) and the anonymous reviewer (Reviewer#2) for reviewing the manuscript and offering valuable critical comments to improve the manuscript. We provide here our responses to their comments.

**Comments of Reviewer #1:**

The manuscript "Streamflow indices to identify catchment drivers of hydrograph" by Mathai and Mujumdar estimates six streamflow indices for 621 stations in the U.S. and investigates their correlation with 15 catchment attributes, taken from the CAMELS data set in a spatial context. This study aims at identifying the drivers of streamflow indices, by distinguishing indices related to the rising and falling limbs of the hydrographs, i.e., implicitly related to different processes. The idea of the study is potentially very interesting however, in my opinion, the analyses, results and discussion presented should be further expanded and developed in order to be considered suitable for publication. The manuscript is overall well written, but I have some specific comments/suggestions regarding the organisation of some sections/figures.

**Response:** We sincerely thank you for the encouraging remarks and for giving us an opportunity to revise our manuscript.

Please find my specific comments below.

**Major comments:**

1. Methods: the method section is partly unclear (lines 85-93) and further explanations are needed. How are the diurnal increments of streamflow obtained (line 85)? How is the Weibull distribution fitted to the data (line 86)? How are the recession coefficient b1 and b2 obtained (the description of these two indices is missing)? How are the correlation coefficients, presented in the result section, calculated? Please clarify these aspects in the method section and provide references.

**Response:** We apologize for the lack of clarity in the text. To obtain the diurnal increments of streamflow for wet days [Fig 1 (a)], we first identify the hydrologic state of the stream (ascension and recession) (Mathai and Mujumdar, 2019). To determine the hydrologic state of a stream - increasing (wet) or decreasing (dry) - on a given day, a time series of diurnal increments is extracted by differencing the original time series with its one-day lagged time series. The positive increments are identified as diurnal increments for wet days (ascension limb).

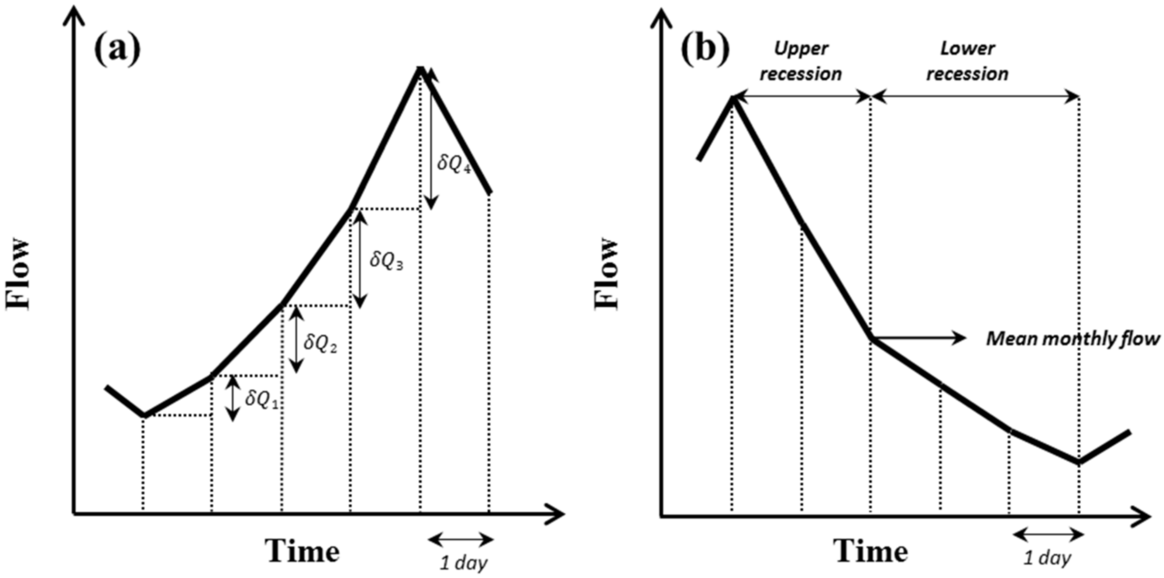


Fig 1. Schematic representation of flow series (a) ascension limb and (b) recession limb.

The diurnal increments (indicating $\delta Q$) of the ascension limb (wet days) are fitted with an appropriate probability density function. The Weibull distribution is proven to be a reasonable fit as an extreme value distribution to the diurnal increments of the streamflow (Stagge and Moglen, 2013; Szilagyi et al., 2006). The Weibull pdf is positive only for positive values of $x$, and is zero otherwise. For strictly positive values of the scale parameter $a$ and shape parameter $b$, the density function is given by

$$f(x;a,b) = \begin{cases} \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-(x/a)^b} & x \geq 0, \\ 0 & x < 0\,, \end{cases}$$

where $a > 0,\ b > 0$. The shape and scale parameters of the Weibull distribution are estimated for each catchment from the observed diurnal increments of the streamflow.

The steps to obtain recession coefficients $b_1$ and $b_2$ are explained below (Mathai and Mujumdar, 2019):

Modeling of the recession limb (dry days) of the daily hydrograph is carried out in two stages to capture the underlying dynamics of the flow (Aksoy, 2003; Aksoy and Bayazit, 2000). Practically, the upper recession [Fig 1 (b)] corresponds to the rapid flow following a storm event and the lower recession corresponds to the baseflow recession (Stagge and Moglen, 2013). Barnes (1939) represented the emptying of water from the basin after a storm with an exponential recession given as,

$$Q_t = Q_0 e^{-bt}$$

where $b$ is the recession coefficient, $t$ is time, $Q_t$ is the flow $t$ days after the peak and $Q_0$ is the peak flow. Mean flow value is chosen as an appropriate measure (Sargent, 1979) to divide the recession into two stages.

The limbs with a peak flow value greater than the observed mean flow value are considered as upper recessions and those with peak flow values smaller than the observed mean as lower recessions. The upper recession is assumed to take the form of:

$$Q_t = Q_0 e^{-b_1 t}$$

where $b_1$ is the recession coefficient for the upper part of the recession limb, $t$ is the number of days after the peak, $Q_t$ is flow $t$ days after the peak, $Q_0$ is the preceding peak flow. The lower recession is assumed to take the form of:

$$Q_t = Q_0^* e^{-b_2 (t-t^*)}$$

where $b_2$ is the recession coefficient for the lower part of the recession limb, $t^*$ is the time from the start of the lower recession, $Q_0^*$ is the initial flow in the lower part of the recession.

The recession expressions for upper and lower recession are fitted by regressing $\ln(Q_t/Q_0)$ versus $t$ and $\ln(Q_t/Q_0^*)$ versus $t - t^*$ respectively. These linear regressions are performed on each individual recession sequence. The average of the upper/lower recession parameters is taken as the upper/lower recession parameter of that catchment (on daily time series data).

In the results section, we used Spearman rank correlation for the correlation analysis (in Tables 3 and 4 of the manuscript). Green-colored coefficients represent positive correlation, and the red-colored correlation coefficients represent negative correlation. Only significant values of correlations are provided in the table, which results in some columns being blank in Table 3 and Table 4.

2. In the manuscript too much space is given, in my opinion, to the presentation of the CAMEL database and the related catchment attributes or clustering of stations. Three figures (Figure 3, Figure 4 and Figure S1) and two tables (Table 2 and Table S1) of the manuscript are directly taken from other publications (in some cases the figures are copy-pasted, and the source is cited, and in other cases the data is simply re-plotted compared to the original publication and the source is cited). I would suggest significantly reducing the room (both text and figures/tables) allocated to these “non-original” parts of the manuscript by, e.g. combining, condensing and reworking (or removing) the above cited figures and tables.

**Response:** Thank you for the valuable suggestions. Figure 4, which depicts topographic characteristics of CAMELS catchments across the CONUS, will be moved to the Supplement section. Table 2 in the manuscript will also be moved to the Supplement. Because the spatial maps are interpreted using Figure 3 in the results section, we wish to keep Figure 3 in the manuscript. We prefer to keep Figure S1/Table S1 in the Supplement rather than eliminating them since we use the clusters provided by Jehn et al. (2020) to interpret the results.

3. The correlation analysis between the streamflow indices and the catchment attributes (pages 16-19, Section 6.2 and 6.3), which should represent the main focus of the paper, is carried out in a bit too simplistic and superficial way. The only results presented in Section 6.2 are two correlation matrices (where the authors do not specify how the correlation coefficients are calculated) and the analysis in the ‘climate index space’ (Section 6.3, figure 9) merely consists in plotting the streamflow indices as a function of two (arbitrarily chosen) climate indices.

Further and more rigorous analyses should be added (e.g. are the correlations significant?) in order to properly investigate the processes represented by the time-irreversibility-based indices and to support the authors' statements. The discussion of the results is poor, and Section 6 is limited to the mere description of the figures/tables. A discussion or interpretation of the processes behind the obtained results would be advisable.

**Response:** We are grateful to you for your insightful recommendations and comments. We acknowledge that the discussion part is weak due to the lack of discussion of the processes that underpin the correlations. We will add an interpretation of the processes behind the correlations to the discussion section to improve it.

In the results section (Section 6.2), we used Spearman rank correlation for the correlation analysis (in Tables 3 and 4 of the manuscript). Green-colored coefficients represent positive correlation, and the red-colored correlation coefficients represent negative correlation. Table 3 and Table 4 have certain columns that are blank because only significant correlation values are provided in the table. We will clarify in the revised manuscript.

**Specific comments:**

Lines 71-74 about the novelty of the study would better fit at the end of the introduction section.
**Response:** We thank you for the suggestion. We will now move the main novelty part to the end of the introduction section.

Table 1: there is an apparent change in terminology (i.e. "rising limb" and "ascension limb" are used in the description of different indices). Please use consistent terminology throughout the manuscript.
**Response:** Thanks for pointing out this mistake. We will use consistent terminology throughout the manuscript.

Figure 2: 3 rising limbs are taken into account in the RLD denominator, but only 2 are considered in the RLD numerator. Why is that? How do the authors take into account rising/falling limbs that fall only partly into the analysed period? Please specify it also in the text of the method section.
**Response:** Thanks for pointing out this mistake. The numerator is also 3. We will correct the numerator in the revised manuscript. In this study, we consider entire daily time series of a particular station and identify the state of the stream as ascension or recession. The limbs that correspond to the ascension state are considered rising limbs, while those belonging to the recession state are considered falling limbs.

Figure 2: please align the labels of the time intervals to the centre of corresponding segments.
**Response:** Thanks for pointing out this mistake. We will follow the suggestion and include a modified figure in the revised manuscript.

Section 3 (contributions of the study) and Section 4 (motivation of the study) would be better placed at the end of the introduction. The description of the Camel dataset and corresponding catchment attributes (currently in Section 4) would be better placed in the Data section 5.

**Response:** Thank you for the suggestions. We will move Section 3 (Contributions of the study) and Section 4 (Motivation to extend to large sample hydrology) to the end of the introduction section. The text (lines 137-147) will appropriately move to Data Section 5.

Line 105: "to identify the key drivers of streamflow hydrographs" or "to identify the key drivers of streamflow indices"?

**Response:** "to identify the key drivers of streamflow hydrographs" is used in the Line 105. The main goal of the study is to identify the key drivers of streamflow hydrograph (rising and falling limbs) in terms of catchment attributes (eg. mean slope, aridity, fraction of precipitation falling as snow).

Line 110: what do the author mean by "attribute class"? It's not clear to me.

**Response:** Thank you so much for bringing this up. The attribute class is a broad classification of attributes based on a particular aspect/feature. *Topography, climate, and soil* are examples of attribute classes.

A data set of attributes for 671 catchments in the contiguous United States is presented using a series of maps (CAMELS dataset- Addor et al., 2017) to describe six main classes of attributes at the catchment scale: topography, climate, streamflow, land cover, soil, and geology. In this study, we present a new attribute class of ***streamflow indices related to rising and falling limbs.***

Line 180: "the landscape of each catchment is described using multiple attributes […]" I believe that the attributes of Table 2 are representative of broader catchment features than landscape (e.g. climate)

**Response:** We apologize for the lack of clarity in the text. Table 2 summarizes the various attributes of CAMELS dataset used in the analysis. We will remove the text (line 180) and move Table 2 to the Supplement section.

Line 186-191: line numbers are mistakenly written into the last column of the table

**Response:** Thanks for pointing out this mistake. We will correct this in the revised manuscript.

Line 192: how are "high precipitation days" defined?

**Response:** High precipitation days are defined as days that have precipitation ≥ five times the mean daily precipitation (Addor et al., 2017). 'high_prec_freq' is the frequency of high precipitation days (≥ 5 times mean daily precipitation). Unit is days $yr^{-1}$. We will add this description in Table 2.

Section 6.1: several statements in this section are not justified by the results and figures presented by the authors. This occurs e.g., in lines 219-220 "these clusters … respectively", lines 221-222 "as these clusters … rapid snowmelt", lines 226-229 "These catchments ... forest.", lines 321-232 "This is because … regions", lines 238-239 "This is due to… regions", lines 240-241 "dominant with … snowmelt" and line 246. Please support your statements with additional figures/results.

**Response:** We thank you for this advice. We acknowledge that we did not provide adequate supporting references for the statements.

For Section 6.1, the features/characteristics of the 10 clusters provided by Jehn et al. (2020) are used to interpret the findings of the results. For explaining these statements, *lines 219-220 "these clusters … respectively", lines 221-222 "as these clusters … rapid snowmelt", lines 226-229 "These catchments ... forest.", lines 321-232 "This is because … regions", lines 238-239 "This is due to… regions", lines 240-241 "dominant with … snowmelt" and line 246* – we start by identifying the regions in the United States where high/low values of streamflow indices occur. The dominant catchment attributes of these identified regions are also identified using corresponding clusters. Finally, the streamflow indices and the dominant catchment attribute are related to interpret the process behind the obtained findings.

We will add these discussions in the manuscript.

*in lines 219-220:* We found the regions with the highest rising limb densities, as well as the dominant catchment characteristics in these clusters: high forest proportion, low aridity, and a high frequency of high precipitation events (Jehn et al., 2020). The higher the forest proportion, therefore, higher is the precipitation intercepted, resulting in shallow rising limbs. A high frequency of high precipitation episodes, on the other hand, can result in more rising limbs and higher rising limb densities.

*lines 221-222: Reproduced from the manuscript* [Northwestern Forested Mountains (Clusters 3, 4), located in the mountains of the western US, experience low values of rising limb density as these clusters are characterized by a dominant summer peak of discharge caused by rapid snowmelt (Fig. 6.a)].

In these clusters, we identified regions with low rising limb densities and the main catchment characteristics as dominant summer discharge peaks induced by quick snowmelt (Jehn et al., 2020). A long lag time and shallow rising limb might be caused by snow on the ground; hence low values of rising limbs might be caused by a longer lag time.

*lines 226-229: Reproduced from the manuscript* [Clusters (5, 7) over the Northwestern Forested Mountains of CONUS experience very high values of rising limb scale parameters. These catchments have the highest discharge, especially in the early summer, due to a combination of high precipitation and snowmelt (Jehn et al., 2020). Further, the region in the Continental US which receives the highest precipitation is included in Cluster 5 (Jehn et al., 2020). Again, Cluster 7 with high values of rising limb scale parameter is characterized by high fraction of precipitation falling as snow (Jehn et al., 2020)].

High precipitation and snowmelt might result in a large outflow. Higher discharges can create higher values of rising scale parameters because the rising limb scale parameter regulates the magnitude of the rising limb.

*lines 231-232: Reproduced from the manuscript* [Low values of rising limb scale parameters are shown by Clusters 2, 8, 9. This is because of low water availability, low snow fraction precipitation falling as snow, and high evaporation experienced in these regions].

Low discharge and thus lower rising limb scale parameters can be caused by excessive evaporation, low water availability, and a low snow fraction of precipitation falling as snow.

*lines 238-239: Reproduced from the manuscript* [All the catchments located in the Southern states of the US (Cluster 9), Great Plains and North American deserts (Cluster 8), and the Central Plains (Cluster 2) characterize low values of rising limb shape parameters (Fig. 6.c). This is due to low water availability, low snow fraction precipitation falling as snow, low leaf area index, and high evaporation experienced in these regions].

Low discharge- long lag time and thus lower rising limb shape parameters can be caused by excessive evaporation, low water availability, and a low snow fraction of precipitation falling as snow.

*lines 240-241: Reproduced from the manuscript* [High values of rising limb shape parameters are seen in Clusters 3, 4 (Fig. 6.c) located in the Northwestern Forested Mountains of the western US, dominant with a summer peak of discharge caused by rapid snowmelt].

The rapid snowmelt can cause flashy hydrographs with high values of rising limb shape parameters.

*line 246: Reproduced from the manuscript* [Clusters 6, 7 over Marine West Coast Forests and Western Cordillera smaller falling limb densities (Fig. 8.a). This is due to less presence of forest cover in these arid regions].

Our interpretation is that the falling limb density shows a positive association with the arid climate.

We considered the clusters provided by Jehn et al. (2020) for this study. Even though the CAMELS dataset provides an excellent overview of many kinds of catchments in contrasting climatic and topographic regions, a comprehensive dataset like CAMELS does not allow easy to find a conclusive set of clusters to explain catchment hydrologic behavior. In order to tackle this difficulty, we transformed the streamflow indices and presented them in clusters that represent distinct hydrological behavior which facilitates the interpretation of hydrological processes easier. The ten clusters represent groups of catchments with distinct hydrological behavior and have distinct spatial patterns as well. The clusters presented by Jehn et al. (2020) are formed based on agglomerative hierarchical clustering with ward linkage on the principal components of the hydrological signatures. The hydrological signatures that are identified with the highest spatial predictability are used to cluster 643 catchments from the CAMELS dataset.

Captions of Figures and tables: the captions of the manuscript often contain the description of the results presented in the figure/table (Figure 4, 5, 6, 7, 8, 9 and Table 3, 4). This is not needed. Please place the description of the figure/table in the main text.
**Response:** We thank you for your remarks. The description of the figures/tables (Figure 4, 5, 6, 7, 8, 9 and Table 3, 4) will be removed during the revision and will be placed in the text as advised.

I would suggest combining Figure 5/6 and 7/8 into one figure with multiple panels (i.e., one figure with the current Figure 5 and 6, and another figure with the current figure 7 and 8). This is because the message conveyed by figures 5 and 6 and by figures 7 and 8 is similar and complementary (they present spatial patterns and spatial clusters) and it would be easier for the reader to have comparable results in a more compact form.
**Response:** We thank you for your suggestion. We will combine Figures 5/6 and 7/8 and provide a more compact form for easy readability.

Table 3 and Table 4: Reading the tables would be easier if rows and columns were inverted (i.e. transposed table). I would also suggest merging table 3 and 4 for a more rapid and direct comparison.
**Response:** We thank you for your suggestion. We will incorporate this change in the revised manuscript.

Section 6.2: the streamflow indices are here referred to as "Flow descriptors". Please use consistent terminology throughout the manuscript.
**Response:** Thanks for pointing out this mistake. We will correct this text in the revised manuscript.

Section 6.3: Why only 2 climate attributes (aridity and snow fraction) are considered?
**Response:** Thank you for raising this concern. We acknowledge that we chose these two climate attributes (aridity and snow fraction) rather arbitrarily in the study, out of the many possible attributes.

The climatic indices indicate a more substantial influence on hydrological signatures than the topographic, soil, land cover, and geological attributes combined (Addor et al., 2018). Additionally, the findings of Jehn et al. (2020) highlighted that the climate appears to be the most critical factor influencing hydrological behavior in the CAMELS dataset as a whole, and depending on the location, aridity, snow, or seasonality are most important.

Therefore, we attempted to determine how widely streamflow indices differ across US catchments in terms of aridity and snow fraction.

Section 6.3: The clusters G1, G2, G3 are arbitrarily chosen by re-grouping 10 pre-existing clusters. The reasons of this choice are not fully clear to me and this double clustering creates some confusion in this section. Perhaps the authors could use a clustering algorithm or better justify this choice.

**Response:** We are sorry for the lack of clarity in the text.

Clusters 5, 6, 7, 1, 10 are characterized by a low fraction of precipitation falling as snow and humid climate, whereas Clusters 3, 4 have humid climate experiencing a high fraction of precipitation falling as snow (Please refer Fig. 9.a in the manuscript). Clusters 2, 8, 9 are featured by a low fraction of precipitation falling as snow and arid climate (Fig. 9.a in the manuscript).

The three categories mentioned above are referred to as G1, G2, and G3, respectively. These three are the possible combinations with climate attributes- the aridity and fraction of precipitation falling as snow.

G1- a low fraction of precipitation falling as snow and humid climate
G2- humid climate experiencing a high fraction of precipitation falling as snow
G3- a low fraction of precipitation falling as snow and arid climate
The fourth combination of arid climate and a high fraction of precipitation falling as snow does not happen in actual cases.

We then tried to group the 10 clusters in the above categories to understand better how streamflow indices behave in these climate attribute combinations.

The title of Section 6.3 is unclear
**Response:** The title of Section 6.3 is Streamflow Indices with Attributes of Climate. As the climate is the most important factor in the US for the hydrological behavior for the CAMELS dataset (Jehn et al., 2020), the influence of climatic factors on streamflow indices is studied in this section. We will modify the title of Section 6.3 to 'Influence of Climate Attributes on Streamflow Indices'.

## Comments of Reviewer #2:

### Manuscript summary

This study attempts to investigate the relationship between statistical descriptors of catchment properties (e.g mean elevation, mean aridity, forest fraction, etc) and statistical properties of the rising limbs and recessions of streamflow hydrographs. The study uses 671 catchments from the CAMELS dataset and a subset of 15 of the CAMELS' attributes. The study uses six streamflow indices/signatures; three of which describe properties of rising limbs and three of which describe properties of recessions. The signatures are the rising and falling limb density, and four parameters that are found by respectively fitting a Weibull function to the rising limbs of each catchment and two exponential regressions to the falling limbs of each catchment. Values for these six signatures are correlated with values of the 15 catchment attributes and these correlations are summarized. Part of the analysis is performed with the catchments grouped into 10 clusters defined in other work and part of the analysis is performed without this division into clusters.

**Summary of comments**

I have provided a summary of my thoughts about this manuscript here. I have also uploaded an annotated PDF with additional comments. Some overlap exists between the summary here and the individual comments in the annotated PDF.

*Novelty*

The introduction is currently missing an overview of what is already known about drivers of rising limbs and recessions. Currently no knowledge gap is defined and this makes it somewhat difficult to assess the novelty of this paper. A literature review and definition of knowledge gap should be added to the paper.

**Response:** Thank you your valuable review of our manuscript. Specifically, we thank you for pointing out the limitation on literature review. We will include a summary of the literature review to address the concern. We agree that a considerable work exists on identifying drivers, we provided this approach as an alternate/complementary procedure to understand the drivers of rising limbs and recessions using indices related to rising and falling limbs.

We have also responded to the comments in the annotated PDF.

In my opinion, the paper currently does not provide what the title indicates, namely a way to identify the catchment drivers of hydrograph[s]. Instead, the paper merely shows that certain catchment attributes in the CAMELS data correlate with certain streamflow signatures. The fact that these attributes and signatures show correlations is not particularly instructive for hydrologic understanding unless it can be explained why these correlations exist. This connection is currently not discussed in the paper, apart from a single mention on line 250. Multiple papers already exist that investigate the relationship between CAMELS attributes and a variety of other things (model performance, streamflow signatures, catchment similarity, etc), and unless hypotheses about the catchment processes that explain the correlations seen in this paper are added and tested, the main novelty of this paper seems to be that we now know that the CAMELS attributes correlate with four previously unseen streamflow signatures. In my opinion this is not enough to warrant publication.

**Response:** We thank you for the critical concerns raised. Reviewer #1 also has raised similar concerns.

Since this concern relates closely to that of Reviewer# 1 on Section 6.1, our response to the specific comments of reviewer #1 on Section 6.1 above may kindly be examined, in this context (reproduced below for convenience). In particular, we would like to state that we have drawn interpretations based on the Jehn et al., 2020 paper. We will add these discussions in the revised manuscript. We will also improve the literature review in the revised manuscript to include earlier relevant work on CAMELS attributes.

--- Reviewer # 1 Comment on Section 6.1 and our Response ----

Section 6.1: several statements in this section are not justified by the results and figures presented by the authors. This occurs e.g., in lines 219-220 “these clusters … respectively”, lines 221-222 “as these clusters … rapid snowmelt”, lines 226-229 “These catchments ... forest.”, lines 321-232 “This is because … regions”, lines 238-239 “This is due to… regions”, lines 240-241 “dominant with … snowmelt” and line 246. Please support your statements with additional figures/results.

**Response:** We thank you for this advice. We acknowledge that we did not provide adequate supporting references for the statements.

For Section 6.1, the features/characteristics of the 10 clusters provided by Jehn et al. (2020) are used to interpret the findings of the results. For explaining these statements, *lines 219-220 “these clusters ... respectively”, lines 221-222 “as these clusters ... rapid snowmelt”, lines 226-229 “These catchments ... forest.”, lines 321-232 “This is because ... regions”, lines 238-239 “This is due to… regions”, lines 240-241 “dominant with ... snowmelt” and line 246* – we start by identifying the regions in the United States where high/low values of streamflow indices occur. The dominant catchment attributes of these identified regions are also identified using corresponding clusters. Finally, the streamflow indices and the dominant catchment attribute are related to interpret the process behind the obtained findings.

We will add these discussions in the manuscript.

*in lines 219-220:* We found the regions with the highest rising limb densities, as well as the dominant catchment characteristics in these clusters: high forest proportion, low aridity, and a high frequency of high precipitation events (Jehn et al., 2020). The higher the forest proportion, therefore, higher is the precipitation intercepted, resulting in shallow rising limbs. A high frequency of high precipitation episodes, on the other hand, can result in more rising limbs and higher rising limb densities.

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High precipitation and snowmelt might result in a large outflow. Higher discharges can create higher values of rising scale parameters because the rising limb scale parameter regulates the magnitude of the rising limb.

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Low discharge and thus lower rising limb scale parameters can be caused by excessive evaporation, low water availability, and a low snow fraction of precipitation falling as snow.

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The rapid snowmelt can cause flashy hydrographs with high values of rising limb shape parameters.

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Our interpretation is that the falling limb density shows a positive association with the arid climate.

We considered the clusters provided by Jehn et al. (2020) for this study. Even though the CAMELS dataset provides an excellent overview of many kinds of catchments in contrasting climatic and topographic regions, a comprehensive dataset like CAMELS does not allow easy to find a conclusive set of clusters to explain catchment hydrologic behavior. In order to tackle this difficulty, we transformed the streamflow indices and presented them in clusters that represent distinct hydrological behavior which facilitates the interpretation of hydrological

processes easier. The ten clusters represent groups of catchments with distinct hydrological behavior and have distinct spatial patterns as well. The clusters presented by Jehn et al. (2020) are formed based on agglomerative hierarchical clustering with ward linkage on the principal components of the hydrological signatures. The hydrological signatures that are identified with the highest spatial predictability are used to cluster 643 catchments from the CAMELS dataset.
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*Methods*
The paper does a good job of explaining what was done but it is somewhat incomplete in explaining why various choices are made and how certain methods are implemented. For example:

Why are these six signatures chosen? Why not other ones?
**Response:** We have considered signatures directly associated with rising limbs and recession limbs. This distinction can help us easily distinguish the underlying processes associated with the steeper ascending and gradual descending limbs of the hydrograph. And therefore, we consider only these six signatures.

Why is only a subset of the CAMELS catchment attributes used and why specifically were those 15 attributes selected? How much independent information is contained in these 15 attributes?
**Response:** Thank you very much for raising this concern. Note that not all of the CAMELS attributes are used in this study. We used the same attributes in each class of vegetation, topography, soil, geology, climate which are consistent with the study of (Jehn et al., 2020), where they cluster 643 catchments from the CAMELS dataset using hydrological signatures with the highest spatial predictability (Addor et al., 2018).

The attributes used in the different classes are:

1) climate: aridity, frequency of high-precipitation events, fraction of precipitation falling as snow, precipitation seasonality
2) vegetation: forest fraction, green vegetation fraction maximum, leaf area index (LAI) maximum
3) topography: mean slope, mean elevation, catchment area
4) soil: clay fraction, depth to bedrock, sand fraction
5) geology: subsurface porosity, subsurface permeability.

We also acknowledge that we have not performed analysis on CAMELS attributes to exclude the redundant information. These catchment attributes are chosen because they are relatively easy to obtain, which will allow a transfer of this approach to other groups of catchments worldwide (Jehn et al., 2020). Jehn et al. (2020) also describe the resulting 10 clusters concerning their *behavior, location, and attributes*, used in this study to interpret the results.

Why are the catchments divided into clusters for part of the analysis and why these clusters specifically?

**Response:** Even though the CAMELS dataset provides an excellent overview of many kinds of catchments in contrasting climatic and topographic regions, a large dataset such as CAMELS renders interpretations from analyses a little difficult. In order to tackle this difficulty, we transformed the streamflow indices and presented them in clusters that represent distinct hydrological behavior which facilitates the interpretation of hydrological processes easier.

We also acknowledge that the findings depend on the size of the clusters and catchment attributes considered.

We considered the clusters provided by Jehn et al. (2020). The reason for choosing these clusters is illustrated below:

The clusters presented by Jehn et al. (2020) are formed based on agglomerative hierarchical clustering with ward linkage on the principal components of the hydrological signatures. The hydrological signatures identified as those with the highest spatial predictability are used to cluster 643 catchments from the CAMELS dataset. The ten clusters that resulted represent groups of catchments with distinct hydrological behavior and capture the diversity since they closely follow ecological regions.

How are the number of rising limbs and number of falling limbs determined?

**Response:** The definition of rising limb density and falling limb density is as follows:

RLD is defined as the ratio of the number of rising limbs and the cumulative time of rising limbs.

$$\mathrm{RLD} = \frac{\mathrm{N_{RL}}}{\mathrm{T_R}}$$

FLD is defined as the ratio of the number of falling limbs and the cumulative time of falling limbs.

$$\mathrm{FLD} = \frac{\mathrm{N_{FL}}}{\mathrm{T_F}}$$

The calculation of rising limbs and falling limbs is illustrated through an example as follows:

Suppose there are 10 days and corresponding streamflow states as follows:

| Days | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| States | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |

State 1- represents a wet day, and state 0, a dry day. In the above example, a rising limb (first three days) is followed by a recession limb (next three days), and then it is further followed by a rising limb of four days. If there is no increase or decrease in the flow with respect to the previous day, it is reckoned as part of the recession limb. We then take the ratio of all the rising limbs in a time series to the cumulative time of rising limbs. A similar procedure is used to determine the falling limb density.

How are the Weibull and exponential regressions fitted to rising and falling limbs respectively?
**Response:** Please see our response to major comment # 1 of the reviewer #1 (reproduced here for convenience):

We sincerely apologize for the lack of clarity in the text. To obtain the diurnal increments of streamflow for wet days [Fig 1 (a)], we first identify the hydrologic state of the stream (ascension and recession) (Mathai and Mujumdar, 2019). To determine the hydrologic state of a stream - increasing (wet) or decreasing (dry) - on a given day, a time series of diurnal increments is extracted by differencing the original time series with its one-day lagged time series. The positive increments are identified as diurnal increments for wet days (ascension limb).

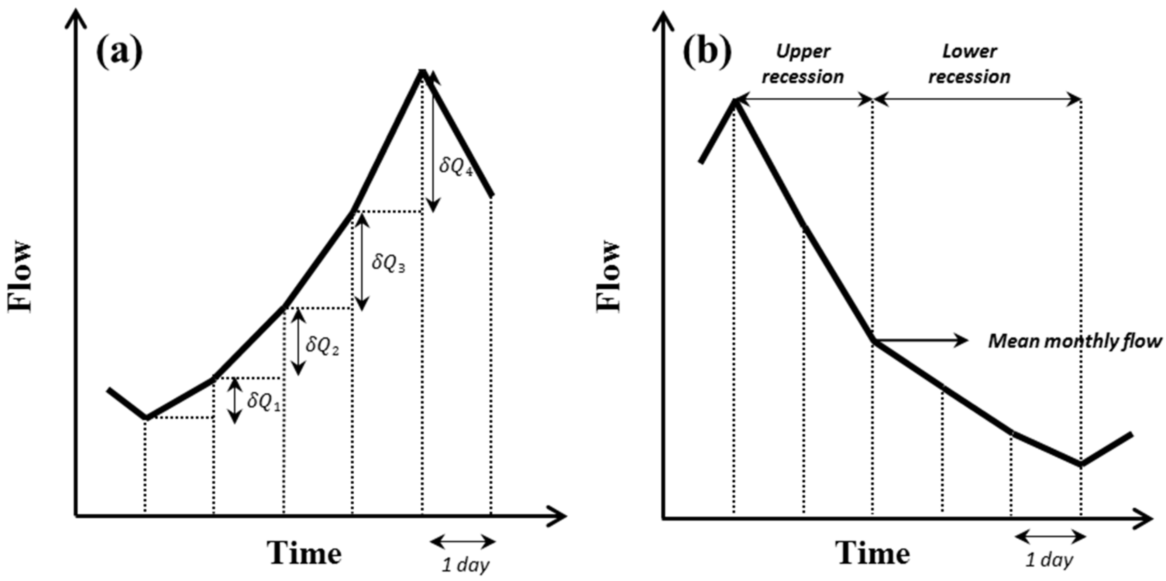


Fig 1. Schematic representation of flow series (a) ascension limb and (b) recession limb.

The diurnal increments (indicating $\delta Q$) of the ascension limb (wet days) are fitted with an appropriate probability density function. The Weibull distribution is proven to be a reasonable fit as an extreme value distribution to the diurnal increments of the streamflow (Stagge and Moglen, 2013; Szilagyi et al., 2006). The Weibull pdf is positive only for positive values of $x$, and is zero otherwise. For strictly positive values of the scale parameter $a$ and shape parameter $b$, the density function is given by

$$f(x;a,b) = \begin{cases} \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-(x/a)^b} & x \geq 0, \\ 0 & x < 0\,, \end{cases}$$

where $a > 0,\ b > 0$. The shape and scale parameters of the Weibull distribution are estimated for each catchment from the observed diurnal increments of the streamflow.

The steps to obtain recession coefficients $b_1$ and $b_2$ are explained below (Mathai and Mujumdar, 2019):

Modeling of the recession limb (dry days) of the daily hydrograph is carried out in two stages to capture the underlying dynamics of the flow (Aksoy, 2003; Aksoy and Bayazit, 2000). Practically, the upper recession [Fig 1 (b)] corresponds to the rapid flow following a storm event and the lower recession corresponds to the baseflow recession (Stagge and Moglen, 2013). Barnes (1939) represented the emptying of water from the basin after a storm with an exponential recession given as,

$$Q_t = Q_0 e^{-bt}$$

where $b$ is the recession coefficient, $t$ is time, $Q_t$ is the flow $t$ days after the peak and $Q_0$ is the peak flow. Mean flow value is chosen as an appropriate measure (Sargent, 1979) to divide the recession into two stages.

The limbs with a peak flow value greater than the observed mean flow value are considered as upper recessions and those with peak flow values smaller than the observed mean as lower recessions. The upper recession is assumed to take the form of:

$$Q_t = Q_0 e^{-b_1 t}$$

where $b_1$ is the recession coefficient for the upper part of the recession limb, $t$ is the number of days after the peak, $Q_t$ is flow $t$ days after the peak, $Q_0$ is the preceding peak flow. The lower recession is assumed to take the form of:

$$Q_t = Q_0^* e^{-b_2(t-t^*)}$$

where $b_2$ is the recession coefficient for the lower part of the recession limb, $t^*$ is the time from the start of the lower recession, $Q_0^*$ is the initial flow in the lower part of the recession.

The recession expressions for upper and lower recession are fitted by regressing ln $(Q_t/Q_0)$ versus $t$ and ln $(Q_t/Q_0^*)$ versus $t - t^*$ respectively. These linear regressions are performed on each individual recession sequence. The average of the upper/lower recession parameters is taken as the upper/lower recession parameter of that catchment (on daily time series data).

How accurate are these fits for each catchment and what does this mean for the resulting correlations with catchment attributes?

**Response:** From the literature, it can be seen that the Weibull distribution is proven to be a reasonable fit as an extreme value distribution to the *diurnal increments* of the streamflow (Stagge and Moglen, 2013; Szilagyi et al., 2006). We admit that the distribution fits in this study were not checked for accuracy, and only an assumption is made on the distribution.

The rising limb scale and shape parameters are obtained after the Weibull distribution is fitted to the diurnal increments of the streamflow. The scale parameter controls the magnitude of the increasing limb, whilst the shape parameter reflects the flashiness of the increasing limb. The scale parameter is related to the magnitude of storm events which mirrors the general shape of flows in the stream. As a result, correlating these parameters with catchment attributes reveals which catchment attributes drive the magnitude and flashiness of rising limbs.

Which correlations are shown in Tables 3 and 4? Why are some correlations missing in these tables?

**Response:** In the results section (Section 6.2), we used Spearman rank correlation for the correlation analysis (in Tables 3 and 4 of the manuscript). Green-colored coefficients represent positive correlation, and the red-colored correlation coefficients represent negative correlation. Table 3 and Table 4 have certain columns that are blank because only significant correlation values are provided in the table.

*Manuscript flow*

The manuscript is well-written but may benefit from some restructuring. For example, Section 3 ("Contributions of this study") could be moved to be part of the introduction.
**Response:** Thank you for the valuable suggestions. We will move Section 3 (Contributions of the study) to the end of the introduction section.

As far as I can tell, Section 6.1 relies quite heavily on descriptions of clusters in Jehn et al. (2020). To fully understand the results shown in 6.1 the reader currently needs to flip back and forth between the current manuscript and searching through Jehn et al. (2020). I suggest to make this easier for the reader by showing/reproducing the relevant data that supports these catchment/cluster descriptions in the current manuscript or in the Supporting Information if space is an issue.
**Response:** Thank you for this valuable suggestion. In order to better explain and interpret the spatial variability of streamflow indices shown in Section 6.1, we have used the cluster classification provided by Jehn et al. (2020). We will include the relevant details of the clusters (clusters, location, behavior, and dominating catchment attributes) in the manuscript to make it easy for the reader to follow the results.

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