EGUSPHERE-2023-660: Inferring heavy tails of flood distributions from common discharge dynamics

Response to Reviewers

We thank the Editor and the Reviewer for providing comments and suggestions. We have incorporated their comments in the revised version of the manuscript and answered each point below. The Reviewers' comments are in black font while our replies are in blue font. Text in the original version is reported in red, with revisions in dark-blue italics. L_o refers to the line number of the original version of the manuscript, whereas L_r refers to the tracked-revised version.

Editor:

Thank you for the revised manuscript. Reviewer #1 has highlighted a number of issues that should be addressed before final publication can be considered. One of the issues is the title of the manuscript which the review considers too generic. Other issues include concerns over application to short record-lengths and evidence of chosen distributions being appropriate. I copy the points here and would ask you to respond to each one and make appropriate changes to the manuscript accordingly

Thank you for the concise review summary. Following your and the reviewer's comments regarding the title, we have improved it to be more precise. The new title is: "*Inferring heavy tails of flood distributions through hydrograph recession analysis*". The title summarizes the main contribution of this work, which is the introduction of a newly proposed method for inferring heavy-tailed flood behavior from the analysis of hydrograph recessions. We have also addressed all the remaining comments of the reviewer and made appropriate modifications in the manuscript, as outlined below.

Reviewer #1:

The Authors have addressed all comments from the previous review; please see my replies to initiate a scientific discussion with the aim of improving the manuscript. I understand the method applied here and the implications this may have for probability fitting of streamflow flood events; however, I kindly disagree with the title of this paper, which I think is too generic and does not reflect the applied methodology and the literature review on the heavy-tails of flood distributions. Please see my replies to each of the Authors' comments:

As requested, we have revised the title to make it more specific. The new title is "*Inferring heavy tails of flood distributions through hydrograph recession analysis*". The title summarizes the main contribution of this work, which is the introduction of a newly proposed method for inferring (predicting) heavy-tailed flood behavior from the analysis of hydrograph recessions.,

1) Thank you for the clarification; I understand the applied methodology, however, please note that since there are strong indications that daily precipitation does always follow the Poisson distribution but rather a heavy-tail (not stretched exponential) one, then this means that the derived flood distribution may not always can be represented by the derived expression (which is based on other processes, like soil-moisture, but also highly depends on the assumed Poisson distribution for the daily precipitation). This is a strong

limitation of the presented methodology and should be emphasized in the analysis and results as well as reflected in the title of the paper.

We have emphasized that we represent daily precipitation as a Poisson process (see L_r*86-87*), and the limitations linked to this choice, at lines L_r*93-98* and L_r*372-373*:

L_r*93-98: "The description of daily rainfall as a Poisson process is grounded in extensive literature (e.g., Cox and Isham, 1988; Rodriguez-Iturbe et al., 1999; Porporato et al., 2004; Yunus et al., 2017). Some studies (e.g., Papalexiou et al., 2013) however argued that heavier-tailed distributions better represent the tail of rainfall records. The chosen rainfall description may thus affect the resulting statistical properties of streamflow. Nevertheless, a recent review of the state-of-the-art (Merz et al., 2022) on this topic stresses that although the tail of precipitation matters, this is not the dominant factor which determines the tail of streamflow and flood distributions, as catchment processes."*

L_r*372-373: "We acknowledge that assumptions underlying the method (e.g., the description of daily rainfall as a Poisson process) may influence the identification of heavy-tailed behaviors."*

We have also modified the title to make it more specific and thus address a previous comment of the reviewer. However, we consider that it is inappropriate to emphasize such a detail as the underlying distribution of precipitation in the title of the paper. As we clarified in our previous reply to the reviewer and in the manuscript at lines L_r*93-99*, a recent review of the state-of-the-art (Merz et al., 2022) on this topic shows that the tail of the rainfall distribution is not a dominant control of the tail of streamflow and flood distributions.

2) Regarding the Authors reply "It is important to note that the stretched exponential distribution offers greater flexibility in terms of tail behavior compared to the exponential distribution. Depending on its parameters, the stretched exponential distribution can exhibit either a light-tailed or heavy-tailed behavior, whereas the exponential distribution always exhibits a light-tailed behavior." and "We acknowledge that the description of precipitation and runoff generation mechanisms incorporated in PHEV does not encompass the entirety of potential rainfall-runoff processes. However, the chosen representation is firmly rooted in established scientific frameworks that have undergone extensive testing through numerous case studies over the past decades.", it is important to note that regardless of the PHEV methodology or any other deterministic or semi-empirical models, one should also compare this to what the actual data show, i.e., what the actual runoff distribution is, as derived from distribution-fitting of thousand of streamflow stations by adjusting for the length and for the auto-correlation of this process. The largest so-far such analysis on the streamflow timeseries is done by Dimitriadis et al. (2021), where is shown that the Pareto-Burr-Feller distribution captures well the daily (and that of smaller resolutions) streamflow (as far as I am aware; maybe, more recent research exists in the literature that derives different results, and so, I kindly ask the Authors to cross-check this; for example, Basso et al., 2023, the analysis includes fewer stations and does not fit in a classical manner the observed marginal distribution but rather uses a different methodology based on hydrograph recessions). This is another limitation that it is not emphasized in the paper, and one may argue why applying this "discharge dynamics" that does not start from the observed rainfall distribution and does not end-up in a standard runoff distribution shown from a simple fitting in thousands of runoff distribution in the literature. I am not suggesting the Authors to change their methodology but emphasize on its limitations (both in the title and in the paper).

We agree with the reviewer that "regardless of the PHEV methodology or any other deterministic or semi-empirical models, one should also compare this to what the actual data show". This is indeed what we do in Fig. 1 and 2, where we compare the indications given by the proposed method of whether the distribution tail is heavy or not with results from empirical analyses of datasets of daily flows, peak flows and monthly maxima (see, e.g., the method's results on the x-axes versus the results of empirical data analyses on the y-axes of Fig. 2; L_r*240-242, 246*) while accounting for the length of observed data, which may impair the capability of the latter approaches to identify heavy-tailed distributions (e.g., lines L_r*179-180, 201-203, 226-231, 255-258*). We instead disagree with the reviewer's claim that benchmarking must be done by comparing runoff distributions, and that any other type of benchmarking on data (like the one we perform) would constitute a limitation. In this regard, we would like to stress that the objective of this work is not to propose a standard probability distribution for streamflow or floods, as done by Dimitriadis et al. (2021) and several others before (e.g., Vogel et al., 1993; Merz and Thieken, 2009; Saf, 2009; Rahman et al., 2013; Kousar et al., 2020). Conversely, our goal is to test against data the inference capabilities of a process-based index of heavy-tailed behavior identified from a description of runoff generation processes in river basins. We apologize if this was not clear from the previous version of the manuscript, and further clarify it at lines L_r*67-71*). This assessment and the results of this study confirm good capabilities of the index to predict heavy-tailed behavior in streamflow and flood distributions.

The advantage of inferring tail behavior by mean of the proposed method instead than, e.g., by identifying distributions that mimic well the observed data frequency through fitting is similar to the advantages amply discussed in recent years of metastatistical (i.e., which infer extremes of hydrological variables from ordinary values; Marani and Ignaccolo, 2015) versus classical extreme value approaches (i.e., where a distribution is typically fitted on sample of maxima or peaks over a certain threshold). Fitting approaches provide accurate descriptions of the samples used to fit the distribution (as expected), but they are also known to be highly sensitive to the specific data record used for fitting (Hu et al., 2020), resulting in large uncertainties where predictions or extrapolations are needed (see, e.g., Gaume, 2006; Zorzetto et al., 2016). Methods that rely on a characterization of ordinary values (e.g., metastatistical approaches) or common discharge dynamics (as, e.g., Basso et al., 2021; Basso et al., 2023; or the current method) are instead less affected by the specific sample considered (because they characterize the underlying statistical properties of the population from which extremes emerge, or the dynamics of the system) and can therefore provide reliable predictions with shorter data records (see, e.g., Zorzetto et al., 2016; Marani and Ignaccolo, 2015; Lombardo et al., 2019; Hu et al., 2023). This is a clear advantage of these approaches compared to simple fitting of distributions to data records. It also explains why these approaches can provide reliable inference from short record (see reviewer's comment number 4), i.e., because they do not rely on fitting the available datasets, but instead aim at characterizing well the underlying dynamics of the system which are responsible for the emergence of tail behaviors.

To clarify and incorporate these points, we have modified the original statements ($L_0$61-$L_0$70) to L_r*63*-L_r*81* in the manuscript:

$L_0$61-$L_0$70: "This study aims to investigate whether a suitable descriptor of the tail behavior of flood distributions exists by exploring the intrinsic hydrological dynamics of the flow regime. Currently, widely-used metrics for tail behavior estimation of flood distributions do not incorporate such a physical description, to the best of our knowledge. Using this descriptor as a proxy for estimating heavy-tailed flood behavior, rather than relying solely on statistical analysis of extreme events, we aim to bridge this gap and improve the accuracy and reliability of tail behavior estimation for flood distributions. We begin the analysis with a mechanistic description of hydrological processes. We subsequently distinguish between the key processes generating heavy and nonheavy tailed behavior of flood distributions and propose a physical descriptor for heavy-tailed flood behavior which is based on common streamflow dynamics. We verify its ability to identify heavy-tailed flood behavior and its robustness in datasets with decreasing lengths through numerous case studies across Germany, encompassing various climate and physiographic characteristics. This confirms the practical transferability and stability of the descriptor."

L_r63-L_r81: "This study aims to investigate whether a suitable descriptor of the tail behavior of flood distributions exists by exploring the intrinsic hydrological dynamics of the flow regime. Currently, widely-used metrics for tail behavior estimation of flood distributions do not incorporate such a physical description, to the best of our knowledge. Instead of proposing a standard probability distribution for streamflow or floods, as done by several others before (e.g., Vogel et al., 1993; Merz and Thieken, 2009; Saf, 2009; Rahman et al., 2013; Kousar et al., 2020; Dimitriadis et al., 2021), our goal is to test against data the inference capabilities of the proposed index of heavy-tailed behavior identified from a description of runoff generation processes in river basins. As mentioned earlier, classical fitting methods for assessing tail behavior are known to be highly sensitive to the specific data record used for fitting. This study presents an alternative method for inferring heavy-tailed flood behavior by characterizing well the underlying dynamics of the system which are responsible for the emergence of tail behavior. This approach has the potential to enhance the accuracy and reliability of tail behavior estimation for flood distributions because it does not solely rely on fitting the available datasets.

To achieve this, we begin the analysis with a mechanistic description of hydrological processes. We subsequently distinguish between the key processes generating heavy and nonheavy tailed behavior of flood distributions and propose a physical descriptor for heavy-tailed flood behavior which is based on common streamflow dynamics. We verify its ability to identify heavy-tailed flood behavior and its robustness in datasets with decreasing lengths through numerous case studies across Germany, encompassing various climate and physiographic characteristics. This confirms the practical transferability and stability of the descriptor."

3) I am concerned about how is it possible to derive the tail-index of a distribution from so small records; for example, in Figure 3d, it is shown that consistency is very strong for the a-index even in a couple of years of data, and remains high (and almost constant) for the entire range of data-length. This comes in contrast to many papers in the literature that deals with extreme probability fitting and the estimation of the tain-index of streamflow (please see Koutsoyiannis, 2022, for a review on extremes, which is the most recent review in the literature regarding the extremes; and please include papers that deal with runoff extremes, and not with precipitation extremes, since as mentioned by the Authors, this paper is dedicated in the former and not the latter process), and so, it would require a very strong analysis and amount of data to challenge it. In other words, how is it possible that the hydrograph-recession methodology and the tail a-index show so good results regardless of the data-length, which should (by definition) depend on the data-length (i.e., without much data, the amount of extreme events is smaller, and thus, there should be a threshold length below which the applied methodology fails to robustly estimate the tail-index and the other parameters of the runoff distribution). This major issue should be further discussed and supported in the current analysis.

We regret that, notwithstanding repeated claims of the reviewer to have understood the methods applied in this study (see the first paragraph and the first numbered comment of the review), these were clearly not well enough explained yet, as revealed by this comment. We apologize for this and try to improve the explanations in the revised manuscript (lines *L_r328-L_r339*) and in the following reply.

First, results provided by "literature that deals with extreme probability fitting and the estimation of the tail index of streamflow" are strongly dependent on the data length exactly because distributions are fitted to data. This guarantees satisfactory metrics of goodness-of-fit, but limited prediction capabilities beyond the fitted sample. The issue has been largely discussed in the literature, both for what concern the estimation of extreme values (see, e.g., Miniussi and Marra, 2021) and in other fields (e.g., hydrological models; Kirchner et al., 2006). We do not fit our method on observed samples (i.e., the available records of floods). Instead, we use observed samples to assess the prediction performance of our method.

The method employed in this study is based on deriving flood behavior from daily streamflow dynamics. Therefore, when working with shorter data series, such as 10 years, we do not use flood maxima over 10 years for distribution fitting. Instead, we analyze the daily streamflow dynamics over this 10-year period to infer flood behavior. The number of hydrograph recessions here used to estimate the value of the index of tail behavior (i.e., the median value of a), which is on average 109 (48-170 is the 0.05-0.95 quantile range) for each case study, decreases with shorter data lengths, as those analyzed in Fig. 3 of the study. As the reviewer expects, also the performance of the proposed method decreases with decreasing data length, but does so at a slower rate than approaches relying on fitting of a limited sample of extremes (see Fig. 3d). We explain such a result at lines *L_r333-L_r339* of the revised text:

L_r333-L_r339: "This result is possible because the proposed index infers heavy-tailed behavior from common discharge dynamics through the analysis of hydrograph recessions, instead of fitting probability distributions to short records of extreme values as conventional approaches do. This allows for a more effective use of information contained in the data. For example, in the two years sample we analyze a median number of 4 hydrograph recessions (which is not a large number), but these recessions have an average length of 8 days, which is sufficient to robustly characterize typical discharge dynamics of the rivers (Biswal and Marani, 2010; Dralle et al., 2017). Literature also evidenced that the variability of the hydrograph recession exponent across events is limited (Biswal and Marani, 2010), which makes possible to reliably characterize it from few hydrograph recessions only."

4) Thank you for the clarification; it seems to me that "hydrograph recession" method strongly depends on the specific runoff timeseries examined in each case, since a deterministic law is directly applied to the data. Please mention how many parameters (Ki and ai) are used in this methodology (from how many values the median a and K are estimated), and why not apply the standard method of statistical methods (e.g., through probability-fitting or fitting through moments). Also, please check the consistency of this methodology in terms of the marginal probability distribution, e.g., by generating many runoff timeseries with the same parameters and lengths, applying the hydrograph-recession method, and see whether the same a-index is approximately estimated.

The median values of *a* and *K* are estimated from a median number (across case studies) of 109 hydrograph recessions (the 0.05-0.95 quantile range of the number of recessions analyzed for each case study is 48-170). These values are now reported at lines *L_r169-L_r172* of the manuscript, as requested.

L_r169-L_r172: "The median value of all the a_i computed for a case study is the estimated value of a, here used to represent the average nonlinearity of a catchment response. The value is obtained from the

analysis of 48 to 170 (0.05-0.95 quantile range; median number of 109) hydrograph recessions for each case study."

In the context of this study (i.e., process-based descriptions of the emergence of streamflow probability distributions, here used to infer their heavy versus nonheavy tailed behaviors) the standard parameter estimation approach does not consist in fitting probability distributions to empirical frequency distributions of data (as it is, instead, for statistics and other branches of the hydrological science). The standard approach is rather the estimation of the parameters from the observed data series, e.g., through hydrograph recession analyses (see, e.g., Botter et al. 2007a; Ceola et al., 2010; Müller et al., 2014; Basso et al., 2015). One recent study (Santos et al., 2019) tested the possibility to estimate parameters directly by fitting the probability distribution to data records (as suggested by the reviewer). However, previous study demonstrated the robustness of the adopted procedure to estimate median values of *a* (Dralle et al., 2017). This procedure (i.e., no fitting of the distribution) allows for retaining the physical meaning of the parameters, which would otherwise be lost in the fitting exercise. For these reasons we prefer to retain the chosen parameter estimation method.

The suggestion of checking the consistency of the parameter estimation method is very reasonable. Several works were carried out in the past to this purpose (see, e.g., Shaw and Riha, 2012; Dralle et al., 2015; Dralle et al., 2017; Jachens et al. 2020; Biswal, 2021). For this reason, we would prefer not to repeat analyses that are already available in the literature. The analyses highlight the limited variability of the hydrograph recession exponent across recessions (which also helps explaining why few recession are enough to robustly estimate its value) (e.g., Shaw et al., 2013; Bart and Hope, 2014; Biswal, 2021). They also recommend the analyses of single recessions instead of the whole point cloud (Jachens et al., 2020), and suggest the selection of the median *a* among the a_i of all recessions as a suitable method to estimate a representative value of *a* (Biswal and Marani, 2010; Mutzner et al., 2015; Roques et al., 2017; Dralle et al., 2017; Jachens et al., 2020). To improve the clarity of the manuscript, we have included the additional details:

L_r160-L_r166: "This approach is widely recognized as a standard practice in the field (e.g., Wittenberg, 1999; Biswal and Marani, 2010; Krakauer and Temimi, 2011; Troch et al., 2013; Pauritsch et al., 2015; Jepsen et al., 2016; Sharma et al., 2023). Recent studies have suggested estimating this power law relationship for individual recession events rather than aggregating them, in order to enhance the representation of observed recession behavior. Fitting a single power-law relationship to the aggregated data points from all observed recessions often results in an underestimation of the observed hydrograph recession behavior (Biswal and Marani, 2010; Basso et al., 2015; Karlsen et al., 2019; Jachens et al., 2020; Tashie et al., 2020a; Biswal, 2021)."

L_r174-L_r178: "It's worth mentioning that a previous study (Dralle et al., 2017) demonstrated the robustness of the adopted procedure for estimating the median value of event-based recession exponents, and the selection of the median value is suggested as a suitable method to estimate the representative hydrograph recession characteristics of a catchment (e.g., Biswal and Marani, 2010; Shaw et al., 2013; Bart and Hope, 2014; Mutzner et al., 2015; Roques et al., 2017; *Dralle et al., 2017*; *Jachens et al., 2020)."*

Although we would prefer not to repeat the theoretical analysis suggested by the reviewer, a similar analysis aimed at evaluating the consistency of the estimated recession exponent across different data series is reported in Fig. 3. There, the observed data series is randomly resampled 30 times (without substitution) for each of the 34 different data lengths ranging from 2 to 35 years and each case study (as outlined in the manuscript *L_r285-L_r292*). The results highlight that the estimated median values of *a* are rather consistent across different data samples (see line *L_r308-L_r311* in the manuscript) and data length. To enhance the clarity, we have improved the text in the manuscript:

L_r285-L_r292: "For all three indices ($a, UTR, and\ \xi$), we estimate their values for data lengths decreasing from 35 (i.e., the shortest entire record length in the dataset) to 2 years. …For each case study, we obtain 30 samples with the assigned test length from the entire data series using resampling without substitution (to avoid the results with a strong dependency on the specific streamflow time series). For each test length, we calculate the median values of the indices estimated from these samples"

5) I am also skeptical about the selection of the power-law relationship between the rate of change of streamflow in time, dq/dt, and the magnitude of streamflow q. Please show how this is fitted through the recorded runoff and whether indeed a power-law relationship (and not so many other hydrograph models in the literature; see the works by H.E. Beck, e.g., Beck et al., 2013) is the most applicable for the examined runoff timeseries.

Beck, H. E., van Dijk, A. I. J. M., Miralles, D. G., de Jeu, R. A. M., Sampurno Bruijnzeel, L. A., McVicar, T. R., & Schellekens, J. (2013). Global patterns in base flow index and recession based on streamflow observations from 3394 catchments. Water Resources Research, 49, 7843–7863. https://doi.org/10.1002/2013WR013918.

The study mentioned by the reviewer (Beck et al., 2013) analyzes base flow recessions (i.e., the first 5 days after a peak are excluded from the analysis) by using a linear reservoir model. A non-linear reservoir model (which is mirrored by power-law hydrograph recessions) as the one we adopted in our study includes the linear reservoir model as a particular case. However, numerous studies showed that the non-linear model is more suitable to characterize the entire hydrograph recession starting from the peak as done in our study (as opposed to only base flow, as done by Beck et al., 2013) (see, e.g., Jachens et al., 2020; Tashie et al., 2020a, which show that the exponent of hydrograph recession is always above one).

The use of a power-law to describe the relation between the rate of change of streamflow in time, dq/dt, and the magnitude of streamflow q was first introduced by Brutsaert and Nieber (1977) and since then became a standard in hydrograph recession analyses, as indicated at lines *L_r158-L_r161* (see, e.g., the review of Troch et al. (2013), and Wittenberg (1999), Biswal and Marani (2010), Krakauer and Temimi (2011), Pauritsch et al. (2015), Jepsen et al. (2016), Sharma et al. (2023)). This is stated at lines ***L_r158-L_r178*** of the manuscript, which read:

L_r158-L_r178: "The proposed index is derived from hydrograph recession analysis. The hydrograph recession is typically described by a power law relationship between the rate of change of streamflow in time, dq/dt, and the magnitude of streamflow q (Brutsaert and Nieber, 1977). This approach is widely recognized as a standard practice in the field (e.g., Wittenberg, 1999; Biswal and Marani, 2010; Krakauer and Temimi, 2011; Troch et al., 2013; Pauritsch et al., 2015; Jepsen et al., 2016; Sharma et al., 2023). Recent studies have suggested estimating this power law relationship for individual recession events rather than aggregating them, in order to enhance the representation of observed recession behavior. Fitting a single power-law relationship to the aggregated data points from all observed recessions often results in an underestimation of the observed hydrograph recession behavior (Biswal and Marani, 2010; Basso et al., 2015; Karlsen et al., 2019; Jachens et al., 2020; Tashie et al., 2020a; Biswal, 2021). In line with these studies, we calculate the recession exponent for each individual event and then take the median exponent across all events as the representative value for a given case study. In particular, a power law is used to represent hydrograph recessions of a single event i, $dq/dt = -K_i \cdot q^{a_i}$, where t denotes the unit time, K_i and a_i denote the estimated coefficient and exponent of hydrograph recessions for event i, respectively. The median value of all the a_i computed for a case study is the estimated value of a, here used to represent the average nonlinearity of a catchment response. The value is obtained from the analysis of 48 to 170 (0.05-

0.95 quantile range; median number of 109) hydrograph recessions for each case study. Hydrograph recessions are composed of ordinary peak flows and the following streamflow values decreasing for a minimum duration of five days (Biswal and Marani, 2010). The proposed index of heavy-tailed flood behavior can thus be estimated based on commonly available daily discharge observations. It's worth mentioning that a previous study (Dralle et al., 2017) demonstrated the robustness of the adopted procedure for estimating the median value of event-based recession exponents, and the selection of the median value is suggested as a suitable method to estimate the representative hydrograph recession characteristics of a catchment (e.g., Biswal and Marani, 2010; Shaw et al., 2013; Bart and Hope, 2014; Mutzner et al., 2015; Roques et al., 2017; Dralle et al., 2017; Jachens et al., 2020)."

Besides being widely applied in the literature, physical reasons support the use of such a model. For example, Biswal and Marani (2010) showed that power-law hydrograph recessions results from a description of the drainage process of riparian unconfined aquifers. Mutzner et al. (2013) also reached the same result by investigating how the geometry of saturated areas contributing to discharge varies in time.

For all these reasons, we cannot understand the skepticism of the reviewer and hold unnecessary to provide further justifications (in addition to lines L_r*158*-L_r*178*) of the adoption of a power-law relation between dq/dt and q in this study.

We appreciate the thorough review and hope that the modifications made to the manuscript, together with our replies, are satisfactory.

Please notice that in addition to addressing all the comments, we have also made the following adjustments in the manuscript:

(1) The colors in the figures are adjusted to ensure they are color-blind friendly, following the journal assistant's guidance.

(2) Author contributions.

(3) Additional modifications to the text beyond those outlined above have been made to enhance the manuscript. Please refer to the following lines for specific changes: L_r*12, 26-29, 46-47, 48-49, 52, 141, 150, 186, 195, 323, 326-332, 350-351, 364, 368, 370, 375, 397-400, 407, 444***.**

(4) All the newly referenced literature has been incorporated into the revised version.

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