Reply to the Reviewers' Comments

We would like to thank the Editor and the Referees for reviewing the revised version of our paper. We acknowledge that one reviewer suggests publication of our manuscript in the present form, while the second reviewer suggests rejection.

While we appreciate the constructive approach adopted by the Editor, and felt very comfortable with the first round of the review process, we would like to kindly point out that we do feel uncomfortable with the second review round. The reason is that one **new** review (the report by Reviewer #2 in the second round) is not open and therefore the review process is not transparent as it should be (according to the journal's policy).

The problem is originated by the fact that a **new** reviewer was involved in the second review round (who did not respond to the invitation to review the paper in the first round). Therefore, his/her report in the second round is actually a **first round review**, which should be open and therefore publicly available. In fact, according to our understanding of the journal's policy, the second review round aims to assess whether the criticism expressed in the public review was successfully addressed or not. New criticism by a new reviewer should not be expressed. In fact, the email we received after the publication of our paper in HESS-D reads as (cut and pasted text is reported between asterisks, with relevant text in red):

----- Mensaje reenviado de editorial@copernicus.org -----Fecha: Tue, 3 Apr 2018 09:11:07 +0200 (CEST) De: editorial@copernicus.org Asunto: hess-2018-134 (author) - manuscript available for public review and discussion

You are receiving the following email copy due to your co-authorship of the manuscript hess-2018-134. The original message was sent to the contact author defined upon manuscript registration. Please contact us in case of any discrepancies with regard to the manuscript.

Dear Theano Iliopoulou,

We are pleased to inform you that your following manuscript has been posted as a discussion paper in HESSD, the scientific discussion forum of HESS:

OMISSIS

As soon as the open discussion phase is over, no more referee comments or short comments will be accepted. During the following final response phase, however, you will have the opportunity to post final author comments. Before submitting a revised version of your manuscript for publication in HESS, you are obliged to have answered all referee comments and relevant short comments in one or more author comments in the discussion forum of your paper.

OMISSIS

We decided to submit our paper to HESS because we appreciate the transparency of the open review process and we appreciate the opportunity of the public reply to the reviewer comments. If a **new reviewer**, and therefore a **new report**, is involved in the second round, the distinguishing feature of the open review system vanishes. This is particularly relevant in this case as we do not agree with the **new** concerns that were raised by the reviewer in the second review round and therefore we would like to have the opportunity to publicly reply. We are confident that the Editor

will recognize that our reply below is providing interesting arguments that, therefore, deserve to be known by the community.

Furthermore, we would like to stress that the audience would never know the real reason why the paper was not published if the review is not made open and our paper is finally rejected. This would be in contrast with the essential feature of the open review, namely, transparency.

Finally, we would like to point out that the second-round policy that was adopted here may stimulate reviewers to skip the first review round to avoid open publication of their report, therefore annihilating the benefit of submitting papers to HESS.

Therefore, we kindly ask the Editor that the review report by Reviewer #2, alongside with the present document which reports our replies, is published in the open discussion of the first review round. We believe that publication of reviews is important to keep the editorial process of HESS fully transparent.

Here below we reply to the concerns of Reviewer #2.

Reply to Reviewer #2

In the following, the comments of the Reviewer are copied in italic.

We first reply to the **general comment** of the Reviewer that reads as:

In the author's own words, the results are often 'expected' and the discussion section mostly 'confirms' previous work and understanding of what is controlling catchment streamflow.

First, we feel it is necessary to clarify that the results were mostly not "expected". In fact, we use the term "expected" several times in the paper to highlight the conjectures that led us to design our experiment. In fact (lines and text refer to the revised version of the paper from the first round reviews):

- at line 130 we write "We use the mean flow in the previous month as a robust proxy of 'storage' in the catchment that is expected to reflect the state of the catchment, i.e., wetter/drier than usual";
- at line 156 we write "...as lakes and glaciers are expected to increase catchment storage thus affecting persistence";
- at line 173 we write "Geological features are expected to be linked to persistence properties...";
- at line 188 we write "We expect the presence of multi-collinearity among the explaining variables and therefore Principal Component....";
- at line 520 we write "The former result may be explained considering that increased evapotranspiration (higher temperature) is expected to dry out LFS flows....";
- at line 532 we write "However, in the glacier dominated regime of western Alpine and central Austrian catchments this is not expected to be [equivalent to "expected not to be"] a relevant driver of higher correlation".

In other cases, we highlight that the results were **not** "expected". In fact:

- at line 338 we write "...indicates that it is not a key determinant of correlation";
- at line 347 we write "The impact of lake area (Fig. S1a) on correlation for LFS and HFS is not significant but positive...";

- at line 374 we write "Therefore, a spatially consistent pattern does not clearly emerge...";
- at line 384 we write "Figure S2 in the Supplement shows that there is not a prevailing pattern in either case...";
- at line 408 we write "Presence of lake, glaciers, karstic and Flysch areas do not appear significantly effective at a 5 % significance level.";

Finally, only in some cases we indeed point out that the results confirmed our expectation and/or the outcome of previous studies. For instance:

- at line 464 we write "As expected from Eq. (3) and (4), the variance of the updated (conditioned) distribution decreases while the mean value increases.";
- at line 479 we write "This result was expected since the LFS correlation refers to average flow while the HFS correlation is related to rapidly occurring events." Please note that this sentence is relevant to our reply to comment #2 below.

Indeed, when we found a potentially interesting result we tried to provide physically based reasoning, and/or review of the previous literature, to give further support to our findings, namely, to provide evidence that they are not merely due to "noise". This is what a rigorous scientific approach requires, rather than a sign of "conspiracy" (see the unfortunate wording that is used by the Reviewer in his/her comment #2 that is copied below).

Actually, we do see the fact that results confirm our previous conjectures as a positive outcome. When a deductive approach is used, the scientist first elaborates a conceptual reasoning to explain what is observed. In this case, we did observe that **peak flows in the high flow season** (HFS) are often preceded by high **mean flows in the previous month**. Therefore, in a previous work we decided to explore the correlation between the two random variables above (highlighted in bold) for two rivers only. The results confirmed our expectation. Therefore, the present contribution aims to (1) extend the analysis to the low flow in the LFS, (2) extend the analysis to several other rivers, and (3) explore the physical drivers of river memory.

About the latter issue, we of course needed to select physically based metrics to explain correlation. We conjectured what physical properties (metrics) may determine correlation and therefore elaborated an expectation. We therefore designed the experiment precisely with the aim to confirm our conjecture. The Reviewer seems to imply that confirmation of conjectures (expectations) makes the results meaningless. We regret to report that we disagree. Rather, confirmation of expectations means that the experiment is well designed.

1. The following aspects of the methodology are unclear: For the HFS, the max daily discharge in the 3-month HFS is chosen. Is this value distinct from the max yearly discharge? In most cases, I suspect not. If the max discharge is in the second month of the HFS, does the lag-1 represent the correlation with the previous months mean discharge (also technically in the 3 month HFS), or with the last month before the onset of the HFS? If it is the latter, then the analysis is no longer technically a lag-1 analysis, and the study could be a big mix of lag-1, lag-2 and even lag-3 analyses that are all confused as representing a lag-1 value. Of course, it could be argued that you wish to be outside the HFS season for the correlation analysis, but what is the value of having inconsistent time periods in your lag analysis, especially given how sensitive the correlation will be to changing lag lengths? Moreover, what if a single catchment has max discharge always moving between the first and third month of the HFS over all the years of record? This will have a large impact on the 'lag-1' correlation even before any hydrological interpretations are involved. Some clarification on the mechanics of this analysis would really help.

Strictly speaking, the Reviewer is right, but a mixed lag is not infrequent in hydrological analysis. As an example when we examine daily maximum discharges of consecutive years, we usually speak about the average time lag which is one year, but in fact this is mixed and varies between 1 day (if the max values were observed in 1 Jan of one year and 31 Dec of the previous year) to 730 days (if the max values were observed in 31 Dec of one year and 1 Jan of the previous year). In our view the important thing is to clarify the terminology and the methodology, and consistently define the related random variables. This does not necessarily require that data are sampled at regular time step or that the time distance of consecutive high flow events is constant.

In our case, we rigorously define in the paper the random variables which we consider. For instance, for the HFS they are:

- Peak flow in the high flow season (with arbitrary but rigorously identified length);
- Mean flow in the previous months.

We also clearly define that we denote with lag-1 the correlation between the peak flow in the HFS and the average flow in the previous month, before the onset of HFS. In the same way we define lag-2 correlation and so on. We regret to report that we do not agree with the criticism of the Reviewer and therefore did not make any major change to the manuscript in this respect. However, we have added this further clarification in the revised manuscript: "In the case of HFS, a correlation is sought between the maximum daily flow occurring in the HFS period and the mean flow in the previous months, before the onset of HFS." (Line 128-129).

2. The authors do not consider how the design of their study may have conspired to control the reported results before referring to a myriad of hydrological explanations. The core issue is one of signal vs noise. The LFS lag analysis uses a correlation between mean values that are by definition weighted by the central tendency of the data being considered, whereas the HFS uses a correlation between a max value and a mean, which is by design a far noisier signal, and hence displays little to no correlation with other variable throughout the study. Can the authors image a scenario where this would not be an expected result?

We fully agree with the Reviewer that correlation between monthly data is expected to be higher with respect to correlation between local variables like peak flow. This is precisely the reason why the correlation that we found between peak flow in high flow season and average flow in previous month is a relevant (and not expected) result. It implies timely predictability of the probability distribution of peak flows, which is a relevant finding.

As for the low flows, we demonstrated that the correlation that we found is higher than the correlation computed for the whole set of monthly data. This means that focusing on the specific correlation of the monthly flow for the LSF season and the monthly flows of the previous months again allows us to improve predictability of low flows. Again, this is not an expected result. In both cases, we found that there is a specific signal that emerges above other signals and noise. Please note: it's not just a question of signal versus noise, which highlights an oversimplified view of the inherent processes. It's a matter of recognizing a specific signal – namely, correlation between previous monthly flows and LFS low flows and HFS peak flow – over other signals (monthly correlation, for instance, for the LFS) and random components.

Turning to the physical explanation that we sought, we do not see the reason why the fact that the results were expected would downgrade their value (please see our reply to the Reviewer's general comment above). Therefore we rebut the statement that we designed the experiment by "conspiring" (a very unfortunate term, as we already remarked) in order to obtain expected results. Again, the experiment was based on our preliminary conjectures that are in turn based on conceptual and

physical reasoning. The fact that the results confirm expectation is a confirmation that the experiment was well designed. For what reason should we investigate possible physical explanations that are not expected to be sound?

Still, we would like to point out once again that many of the explanatory metrics we investigated turned out to be not effective on the correlation, such as, for instance, the presence of lakes and glaciers for the HFS, catchment elevation, flysch areas and so on. Therefore, not all of our results were expected.

To mitigate the concern of the Reviewer, we changed the wording throughout the manuscript to avoid many repetitions of the term "expected". We also made changes in the Discussion section to better highlight the purpose of the analysis and underline more some of the most important and less expected results. The relevant sentences of the revised manuscript (copied at the end of the present report) read:

- At line 482: "We also aim to investigate physical drivers for correlation <u>and quantify their</u> relative impact on correlation magnitude."
- At line 486: "We found that increasing basin area and baseflow index are associated with increasing seasonal streamflow correlation, <u>yet the latter has a stronger impact</u>."
- At line 492: "Our results additionally point out that catchment storage induces mild positive correlation, not only for low discharges which are directly governed by base flow, but also for high flows, which is less anticipated."
- At line 509: "In fact, our finding that increased wetness has a negative impact on seasonal memory of both high and low flows, extends the above results to the seasonal scale and interestingly, to both types of extremes."
- At line 513: "We also confirm the role of lakes in determining higher catchment storage and therefore positive correlations for the LFS, which has <u>only</u> been reported for annual persistence in a few sites (Zhang et al., 2012)."
- 3. Related to point 2, the authors use a suite of metrics, many of which (P, SR, BFI) have a natural correlation with HFS and LFS since they are either derived from the same data or help generate it. The HFS analysis produces such a noisy signal that no result can be found, and this is hardly a surprising result (as mentioned above). LFS is not as noisy, and so displays better correlations. The heart of the paper is then to say that the correlations are better with hydrological processes that will also natural reduced the noise, e.g. higher groundwater flow subsidies and snowmelt, and worse correlations with processes and drivers that have increased noise. Again, can the authors think of a situation where this would not be an expected result?

First, we believe there is a misunderstanding here. We did find that correlation for the HFS season is relevant and helpful to improve predictability. Please see Section 4.2 and 7. Therefore there is indeed a signal that we discovered over what the Reviewer terms "noise". Furthermore, we demonstrated that such correlation is explained by catchment area, precipitation and catchment storage in general. Therefore we regret to report that we cannot agree with the statement that "*The heart of the paper is then to say that the correlations are better with hydrological processes that will also natural reduced the noise*" (sic). The heart of our paper is stated in the last sentence of the abstract: "Our findings suggest that there is a traceable physical basis for river memory which in turn can be statistically assimilated into high- and low-flow frequency estimation to reduce uncertainty and improve predictions for technical purposes."

Furthermore, we do not understand the criticism by the Reviewer "*natural correlation with HFS and LFS since they are either derived from the same data or help generate it*". For instance, we analyzed the correlation between rainfall and river flow. Would the fact that rainfall generates river flow make the analysis of their correlation meaningless? We regret to say that we cannot agree.

4. Given these factors, it is unclear what processes or understanding can be revealed by such an analysis, since the study is producing most of the results by design, rather than by hydrological insight. In this sense the analysis in this manuscript obscures the actual hydrology, for example if you just plot actual baseflow on the maps in Figures 7 and 8 a clearer pattern of the hydrological controls on low flows would be revealed (or indeed baseflow against elevation, as documented by a lot of previous work). Surely, the LFS lag analysis only obscures these key hydrological drivers rather than making them clearer or easier to understand? I think this is also clearly shown in the discussion section, which is highly speculative about general processes and mostly confirms the results of previous workers rather than adding new understanding.

We are glad that the Reviewer recognizes the value of previous studies that analyzed the correlation between baseflow and low flow, even if both baseflow and low flows are "*derived from the same data*". We believe our contribution provides relevant new findings such as:

- We confirmed **by referring for the first time to a large set of basins** that the peak flow probability distribution and the low flow probability distribution can be usefully updated in real time one or more months in advance through data assimilation.
- The physical drivers of predictability of low flows and high flows are **quantitatively identified for the first time for the chosen variables** (please note that graphical depictions may provide a more immediately clear representation, as we all know, but do not allow a quantitative assessment unless a quantitative relationship is provided, as we did).

5. I don't see the value or utility of section 7, it is incredibly short and not at all mentioned in the discussion section, therefore its completely unclear what we have learnt from this exercise, or in what context it's results should be considered. This asymmetry is considerable given it has more length devoted to describing the methodology than anything else in the paper (section 2.3). However, after reading it a couple of times I found this to be the most interesting part of the paper, since it asks an interesting question about how you would expect HFS or LFS to change based on obtaining the new average discharge for the previous month (an update). However, this seems to have already been published and discussed in detail by Aguilar et al (2017), so what is the utility of the very brief repetition of the same work on a single river in this study? Given the results and methodology are far closer to Aguilar et al. (2017) than the rest of the submitted manuscript, it seems entirely out of place and only confirms their previous work.

We agree with the Reviewer that the application presented in Section 7 (which arguably is not *"incredibly short"*) whose theoretical basis is presented in section 2.3, is similar to what is presented by Aguilar et al. However, we refer here to a different river which has a higher memory with respect to the case studies previously analyzed and we also present a LFS application for the same river. Therefore we believe the case studied here is technically interesting. Sections 2.3 and 7 are titled "Technical experiment: Real-time updating of the frequency distribution of high and low flows" and "Real-time updating of the frequency distribution of high and low flows for the Oise River". They are meant to be a technical example. They do not present a scientific advance in the strict sense, but we believe they are an interesting addition to the paper. However, we may easily remove section 7 (and therefore section 2.3) if the Editor feels that they are redundant.

Our replies to the minor comments of the Reviewer follows here below.

Figure 10 c, no colour scale provided

We do not understand the comment as in our vision there is colour scale.

131: I don't understand the basis of correlating LFS with the mean flow of the previous month on the expectation this is a robust proxy for storage. If you define the LFS as the month with the lowest flow, then by definition the previous months will have higher flow, so how will this be a robust proxy for storage? In fact, you will be correlating against months that could also be included in the definition of HFS, which we would not suggest are a good indicator of storage.

Perhaps we missed the exact meaning of the comment, but in any case mass balance and energy balance apply to fluid mechanics and therefore river flow formation. Mass balance suggests that storage is related to river flow. The Reviewer, may refer to a simple conceptual model like the bucket model, where higher storage implies higher discharge and the river flow is clearly a proxy for storage. Besides, the Reviewer may feel free to use better proxies in his/her studies.

154: "SR (m3 s–1 km–2) is computed as the mean daily flow of the river standardized by the size of its basin area. It may be an important physical driver as it is an indicator of the catchment's wetness" – so this basically says that runoff can be considered as an indicator of how wet a catchment is. This is like saying rainfall can be considered an indicator of how much water is falling from the sky, hopefully the authors can see the silliness of such a statement without further explanation.

We are negatively surprised by the offensive tone used by the anonymous Reviewer. We do not see the reason why specific runoff should not be related to catchment wetness or aridity.

479: "This result was expected since the correlation refers to average flow while the HFS correlation is related to rapidly occurring events" See major points 2 -4, the design of the study is a major control on the results reported here rather than actual hydrological processes.

We regret to confirm that we fully disagree with the idea that an experiment should not be designed according to physical basis and scientific reasoning.

We respectfully submit a revised version of our paper. We regret to report that we do not agree with the criticism of the Reviewer and therefore did not make any major change to the manuscript in this respect, but only small clarifications (discussed above). We rely on the Editor assessment, in particular for the opportunity of keeping (or not) Section 7 and 2.3.

With our best regards,

Theano Iliopoulou, Cristina Aguilar, Berit Arheimer, María Bermúdez, Nejc Bezak, Andrea Ficchì, Demetris Koutsoyiannis, Juraj Parajka, María José Polo, Guillaume Thirel and Alberto Montanari

1 A large sample analysis of European rivers on seasonal river flow correlation

- 2 and its physical drivers
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27 Abstract

28 The geophysical and hydrological processes governing river flow formation exhibit persistence 29 at several timescales, which may manifest itself with the presence of positive seasonal 30 correlation of streamflow at several different time lags. We investigate here how persistence 31 propagates along subsequent seasons and affects low and high flows. We define the High Flow 32 Season (HFS) and the Low Flow Season (LFS) as the three-month and the one-month periods 33 which usually exhibit the higher and lower river flows, respectively. A dataset of 224 rivers from 34 six European countries spanning more than 50 years of daily flow data is exploited. We compute 35 the lagged seasonal correlation between selected river flow signatures, in HFS and LFS, and the 36 average river flow in the antecedent months. Signatures are peak and average river flow for HFS 37 and LFS, respectively. We investigate the links between seasonal streamflow correlation and various physiographic catchment characteristics and hydro-climatic properties. We find 38 39 persistence to be more intense for LFS signatures than HFS. To exploit the seasonal correlation 40 in the frequency estimation of high and low flows, we fit a bivariate Meta-Gaussian probability 41 distribution to the selected flow signatures and average flow in the antecedent months in order to condition the distribution of high and low flows in the HFS and LFS, respectively, upon river 42 43 flow observations in the previous months. The benefit of the suggested methodology is 44 demonstrated by updating the frequency distribution of high and low flows one season in

45 advance in a real-world case. Our findings suggest that there is a traceable physical basis for

46 river memory which in turn can be statistically assimilated into high- and low-flow frequency

47 estimation to reduce uncertainty and improve predictions for technical purposes.

- 49 Keywords: seasonal streamflow correlation, river memory, persistence, real-time flow
- 50 forecasting, floods, low flows, meta-Gaussian

51 1. Introduction

52 Recent analyses for the Po River and the Danube River highlighted that catchments may exhibit significant 53 correlation between peak river flows and average flows in the previous months (Aguilar et al., 2017). Such 54 correlation is the result of the behaviours of the physical processes involved in the rainfall-runoff 55 transformation that may induce memory in river flows at several different time scales. The presence of long-term persistence in streamflow has been known for a long time since the pioneering works of Hurst 56 57 (1951) and has been actively studied ever since (e.g. Koutsoyiannis, 2011; Montanari, 2012; O'Connell et 58 al., 2016 and references therein). While a number of seasonal flow forecasting methods have been explored in the literature (e.g. Bierkens and van Beek, 2009; Dijk et al., 2013), attempts to explicitly exploit 59 60 streamflow persistence in seasonal forecasting through information from past flows have been in general 61 limited. Koutsoyiannis et al. (2008) proposed a stochastic approach to incorporate persistence of past flows 62 into a prediction methodology for monthly average streamflow and found the method to outperform the 63 historical analogue method (see also Dimitriadis et al., 2016 for theory and applications of the latter) and 64 artificial neural network methods in the case of the Nile River. Similarly, Svensson (2016) assumed that the 65 standardized anomaly of the most recent month will not change during future months to derive monthly flow forecasts for 1-3 months lead time and found the predictive skill to be superior to the analogue 66 67 approach for 93 UK catchments. The abovementioned persistence approach has also been used 68 operationally in the production of seasonal streamflow forecasts in the UK since 2013, within the framework of the Hydrological Outlook UK (Prudhomme et al. 2017). A few other studies have included 69 70 past flow information in prediction schemes along with teleconnections or other climatic indices (Piechota 71 et al., 2001; Chiew et al., 2003; Wang et al., 2009). Recently, it was shown that streamflow persistence, 72 revealed as seasonal correlation, may also be relevant for prediction of extreme events by allowing one to 73 update the flood frequency distribution based on river flow observations in the pre-flood season and reduce 74 its bias and variability (Aguilar et al., 2017). The above previous studies postulated that seasonal

75 streamflow correlation may be due to the persistence of the catchments storage and/or the weather, but no
76 attempt was made to identify the physical drivers.

The present study aims to further inspect seasonal persistence in river flows and its determinants, by 77 78 referring to a large sample of catchments in 6 European countries (Austria, Sweden, Slovenia, France, Spain and Italy). We focus on persistence properties of both high and low flows by investigating the 79 80 following research questions: (i) what are the physical conditions, in terms of catchment properties, i.e. 81 geology and climate, which may induce seasonal persistence in river flow? And, (ii) can floods and 82 droughts be predicted, in probabilistic terms, by exploiting the information provided by average flows in 83 the previous months? These questions are relevant for gaining a better comprehension of catchment 84 dynamics and planning mitigation strategies for natural hazards. To reach the above goals, we identify a set 85 of descriptors for catchment behaviours and climate, and inspect their impact on correlation magnitude and 86 predictability of river flows.

A few studies have analysed physical drivers of streamflow persistence on annual and deseasonalized monthly and daily timeseries (Mudelsee, 2007; Hirpa et al., 2010; Gudmundsson et al., 2011; Zhang et al., 2012; Szolgayova et al., 2014; Markonis et al., 2018) but the topic has been less studied on intra-annual scales relevant to seasonal forecasting of floods and droughts.

To demonstrate the high practical relevance of the identified seasonal correlations we present a technical experiment for one of the studied rivers (Section 7) in which the frequency distribution of both high and low flows is updated one season in advance by exploiting real-time information on the state of the catchment.

95 2. Methodology

The investigation of the persistence properties of river flows focuses separately on both high and low discharges and is articulated in the following steps: (a) identification of the high- and low-flow seasons; (b) correlation assessment between the peak flow in the high flow season (average flow in the low-flow season) and average flows in the previous months; (c) analysis of the physical drivers for streamflow persistence and its predictability through a Principal Component Analysis; (d) real-time updating of the frequency distribution of high and low flows for a selected case study with significant seasonal correlation by employing a Meta-Gaussian approach. The above steps are described in detail in the following sections.

103 2.1 Season Identification

104 Season identification is performed algorithmically to identify the High Flow Season (HFS) and Low Flow 105 Season (LFS) for each river time series. For the estimation of HFS, we employ an automated method 106 recently proposed by Lee et al. (2015), which identifies the high flow season as the three-month period 107 centred around the month with the maximum number of occurrences of Peaks Over Threshold (POT), with 108 the threshold set to the highest 5% of the daily flows. To evaluate the selection of HFS, a metric constructed as the Percentage of Annual Maximum Flows (PAMF) captured in the HFS is used. The 109 PAMFs are classified in subjective categories of "poor" (<40%), "low" (40-60%), "medium" (60-80%) 110 111 and "high" (>80%) values, denoting the probability that the identified HFS is the dominant high-flow season in the record. If the identified peak month alone contains 80% or more of annual maxima flows, a 112 113 uni-modal regime is assumed and the identification procedure is terminated. In all other cases, the method 114 allows for the search of a second peak month and the identification of a minor HFS but we do not further 115 elaborate on this analysis here because we are only interested in the most extreme seasons for the purpose 116 of predicting high and low flows.

The method proposed by Lee et al. (2015) has several advantages that make it suitable for the purpose of this research. Most importantly, it is capable of handling conditions of bi-modality, which is usually a major issue for traditional methods like, e.g., directional statistics (Cunderlik et al., 2004). A potential limitation is the assumption of symmetrical extension of HFS around the peak month, along with the uniform selection of its length (3-month period). The degree of subjectivity in the evaluation of the second HFS is another limitation, which is not relevant here as we focus on the main HFS. LFS is herein identified as the one-month period with the lowest amount of mean monthly flow. An alternative approach of estimating the relative frequencies of annual minima of monthly flow and selecting the month with the highest frequency as LFS is also considered.

126 2.2 Correlation analysis and physical interpretation through Principal Component Analysis

127 2.2.1 Correlation analysis

In the case of HFS, a correlation is sought between the maximum daily flow occurring in the HFS period and the mean flow in the previous months, before the onset of HFS. For LFS, correlation is computed between the mean flow in the LFS itself and the mean flow in the previous months. We use the mean flow in the previous month as a robust proxy of 'storage' in the catchment that is expected to reflect the state of the catchment, i.e., wetter/drier than usual. Since we are interested in seasonal persistence, we compute the Pearson's correlation coefficient up to 9-month lag for HFS and 11-month lag for LFS.

134 2.2.2 Analysis of physical drivers

135 a. Catchment, geological and climatic descriptors

136 An extensive investigation is carried out to identify physical drivers of seasonal streamflow correlation, in

137 terms of catchment, geological and climatic descriptors.

As catchment descriptors, we consider the basin area (*A*), the Baseflow Index (BI), the mean specific runoff (SR), the percentage of basin area covered by lakes (percentage of lakes, PL) and glaciers (percentage of glaciers, PG) and altitude as candidate explanatory variables for streamflow correlation.

141 The area A (km²) is primarily investigated as it is representative of the scale of the catchment, under 142 the assumption that in larger basins the impact of the climatological and geophysical processes affecting 143 river flow becomes more significant and may lead to a magnified seasonal correlation.

BI is considered based on the assumption that high groundwater storage may be a potential driver of correlation. BI is calculated from the daily flow series of the rivers following the hydrograph separation procedure detailed in Gustard et al. (2009). Flow minima are sampled from non-overlapping 5-day blocks of the daily flow series and turning points in the sequence of minima are sought and identified when the 90% value of a certain minimum is smaller or equal to its adjacent values. Subsequently, linear interpolation is used in between the turning points to obtain the baseflow hydrograph. The BI is obtained as the ratio of the volume of water beneath the baseflow separation curve versus the total volume of water from the observed hydrograph, and an average value is computed over all the observed hydrographs for a given catchment. A low index is indicative of an impermeable catchment with rapid response, whereas a high value suggests high storage capacity and a stable flow regime.

SR $(m^3 s^{-1} km^{-2})$ is computed as the mean daily flow of the river standardized by the size of its basin area. It may be an important physical driver as it is an indicator of the catchment's wetness. PL (%) and PG (%) are investigated for the Swedish and Austrian catchments, respectively, as lakes and glaciers are expected to increase catchment storage thus affecting persistence. Lake coverage data are based on cartography and available from the Swedish Water Archive (https://www.smhi.se/), while glacier coverage data are estimated from the CORINE land cover database (https://www.eea.europa.eu/publications/COR0landcover).

The effect of catchment altitude is also inspected using relief maps from the Shuttle Radar Topography Mission (SRTM) data (http://srtm.csi.cgiar.org/). The data are available for the whole globe and are sampled at 3 arch-seconds resolution (approximately 90 meters). Topographic information is available for all catchments located at latitude lower than 60 degrees north while a 1 km resolution digital elevation model is available for Austria.

As geological descriptors we consider the percentage of catchment area with the presence of flysch (percentage of flysch, PF) and karstic formations (percentage of karst, PK) for Austrian and Slovenian catchments, respectively, for which this type of information is available. A subset of Austrian catchments is characterised by the dominant presence of flysch, a sequence of sedimentary rocks characterized by low permeability, which is known to generate a very fast flow response. Karstic catchments, characterized by the irregular presence of sinkholes and caves, are also known for having rapid response times and complex behaviour; e.g. initiating fast preferential groundwater flow and intermittent discharge via karstic springs (Ravbar, 2013; Cervi et al., 2017). Geological features are expected to bepresumed to be _-linked to
persistence properties also because geology is the main control for the baseflow index across the European
continent (Kuentz et al. 2017). PK (%) and PF (%) are estimated from geological maps of Slovenia and
Austria, respectively.

As climatic descriptors, the mean annual precipitation P (mm year⁻¹) and the mean annual 177 178 temperature T ($^{\circ}$ C) are selected. Corresponding gridded data are retrieved from the Worldclim database 179 (http://www.worldclim.org/) at a spatial resolution of 10 minutes of degree (approximately 18.55 km). We 180 note that low mean temperature regimes are also associated with snow, the presence of which is also 181 considered in the interpretation of the results. We also adopt as climatic descriptor the De Martonne index 182 (De Martonne, 1926), IDM, which is given by IDM = P/(T + 10), and enables classification of a region 183 into one of the following 6 climate classes, i.e., arid (IDM \leq 5), semi-arid (5 < IDM \leq 10), dry sub-humid 184 $(10 < IDM \le 20)$, wet sub-humid $(20 < IDM \le 30)$, humid $(30 < IDM \le 60)$ and very humid $(IDM \ge 60)$. 185 Additionally, the Köppen-Geiger climatic classification (Kottek et al., 2006) of the rivers is assessed.

186 b. Principal Component Analysis

187 To identify what catchment, physiographic and climatic characteristics may explain river memory we attempt to regress the seasonal streamflow correlation against the physical descriptors introduced above. 188 189 We expect the presence of multi-collinearity among the explaining variables and therefore Principal Component Analysis (PCA; Pearson, 1901; Hotelling, 1933) was applied to construct uncorrelated 190 191 explanatory variables. In essence, PCA is an orthonormal linear transformation of p data variables into a 192 new coordinate system of $q \le p$ uncorrelated variables (principal components, PCs) ordered by decreasing 193 degree of variance retained when the original p variables are projected into them (Jolliffe, 2002). Therefore, 194 the first principal axis contains the greatest degree of variance in the data, while the second principal axis is 195 the direction which maximizes the variance among all directions orthogonal to the first principal axis and so on. Specifically, let x be a random vector with mean μ and correlation matrix Σ , then the principal 196 197 component transformation of x is obtained as follows:

198 $y = C^T x'$

where y is the transformed vector whose kth column is the kth principal component (k = 1, 2..p), C is the $p \times p$ matrix of the coefficients or loadings for each principal component and x' is the standardized x vector. Standardization is applied in order to avoid the impact of the different variable units on selecting the direction of maximum variance, when forming the PCs. The y values are the scores of each observation, i.e. the transformed values of each observation of the original p variables in the kth principal component direction.

PCA has useful descriptive properties of the underlying structure of the data. These properties can be efficiently visualized in the biplot (Gabriel, 1971), which is the combined plot of the scores of the data for the first two principal components along with the relative position of the p variables as vectors in the twodimensional space. Herein, the distance biplot type (Gower and Hand, 1995), which approximates the Euclidean distances between the observations, is used. Variable vectors coordinates are obtained by the coefficients of each variable for the first two principal components. After construction of the PCs, a linear regression model is explored for the case of HFS and LFS lag-1 correlation.

212 2.3 Technical experiment: Real-time updating of the frequency distribution of high and low flows 213 In order to evaluate the usefulness of the information provided by the one-month-lag seasonal correlation 214 for flow signatures in HFS and LFS, we perform a real-time updating of the frequency distribution of high 215 and low flows based on the average river flow in the previous month. A similar analysis for the high flows 216 was carried out by Aguilar et al. (2017) for the Po and Danube Rivers. In principle, this is a data 217 assimilation approach, since real-time information, i.e. observations of the average river flow, is used in 218 order to update a probabilistic model and inform the forecast of the flow signature of the upcoming season. In detail, a bi-variate meta-Gaussian probability distribution (Kelly and Krzysztofowicz, 1997; 219 220 Montanari and Brath, 2004) is fitted between the observed flow signatures, i.e., peak flow in the HFS, Q_P and average flow in the LFS, Q_L, and the average flow in the pre-HFS and LFS months, Q_m, respectively. 221 222 The peak HFS flow and the average LFS flow are the dependent variables and are extracted as the peak

(1)

river discharge observed in the previously identified HFS and the average river discharge observed in the previously identified LFS, respectively. The average flow in the month preceding the HFS and the LFS is the explanatory variable in both cases. In the following, random variables are denoted by underscore and their outcomes are written in plain form.

227 The normal quantile transform, NQT (Kelly and Krzysztofowicz, 1997), is used in order to make the 228 marginal probability distribution of dependent and explanatory variables Gaussian. This is achieved as follows: a) the sample quantiles Q are sorted in increasing order e.g. $Q_{m_1}, Q_{m_2} \dots Q_{m_n}$, b) the cumulative 229 230 frequency, e.g. FQ_{m_i} is computed via a Weibull plotting position, and c) the standard normal quantile, e.g., NQm, is obtained as the inverse of the standard normal distribution for each cumulative frequency, e.g., 231 232 $G^{-1}(FQ_{m_i})$. Therefore, all sample quantiles are discretely mapped into the Gaussian domain. To get the 233 inverse transformation for any normal quantile, we connect the points in the above mapping with linear 234 segments. The extreme segments are extended to allow extrapolation outside the range covered by the 235 observed sample.

In the Gaussian domain, a bivariate Gaussian distribution is fitted between the random explanatory variable $\underline{NQ_m}$ and the dependent variables $\underline{NQ_P}$ and $\underline{NQ_L}$ by assuming stationarity and ergodicity of the variables. We define the generic random variable $\underline{NQ_{fs}}$ to represent any dependent flow signature, i.e.; $\underline{NQ_P}$ and $\underline{NQ_L}$ in our case. Then, the predicted signature at time *t* can be written as:

(2)

240
$$\operatorname{NQ}_{fs}(t) = \rho(\underline{NQ}_{m}, \underline{NQ}_{fs}) \operatorname{NQ}_{m}(t-h) + \operatorname{N}\varepsilon(t)$$

where $\rho(\underline{NQ_m}, \underline{NQ_{fs}})$ is the Pearson's cross correlation coefficient between $\underline{NQ_m}$ and $\underline{NQ_{fs}}$, *h* is the selected correlation lag with *h* = 1 in the present application, and N_E(*t*) is an outcome of the stochastic process <u>N</u>_E, which is independent, homoscedastic, stochastically independent of <u>NQ_m</u> and normally distributed with zero mean and variance $1-\rho^2(\underline{NQ_m}, \underline{NQ_{fs}})$. Then, the joint bivariate Gaussian probability distribution function is defined by the mean ($\mu(\underline{NQ_m}) = 0$ and $\mu(\underline{NQ_{fs}}) = 0$), the standard deviation ($\sigma(\underline{NQ_m}) = 1$ and $\sigma(\underline{NQ_{fs}}) = 1$) of the standardized normalized series, and the Pearson's cross correlation coefficient between the normalized series, $\rho(\underline{NQ_m}, \underline{NQ_{fs}})$. From the Gaussian bivariate probability properties, it follows that for 248 any observed NQ_m(t - h) the probability distribution function of <u>NQ_{fs}(t)</u> conditioned on NQ_m is Gaussian,

249 with parameters given by:

$$250 \quad \mu(\underline{NQ_{fs}}(t)) = \rho(\underline{NQ_{m}}, \underline{NQ_{fs}}) \ NQ_{m}(t-h) \tag{3}$$

(4)

251
$$\sigma(NQ_{fs}(t)) = (1 - \rho^2(NQ_m, NQ_{fs}))^{0.5}$$

To derive the probability distribution of $\underline{Q}_{fs}(t)$ conditioned to the observed $Q_m(t-h)$, we first apply the 252 253 inverse NQT, i.e., we use linear segments to connect the points of the previous discrete quantile mapping of 254 the original quantiles into the Gaussian domain, and accordingly, obtain $Q_{fs}(t)$ for any NQ_{fs}(t). 255 Subsequently, we estimate the parameters of an assigned probability distribution for the obtained quantiles 256 in the untransformed domain. This is referred to as the updated probability distribution of the considered 257 flow signature ($\underline{NQ_P}$ and $\underline{NQ_L}$ in our case). We use the Extreme Value Type I distribution for the peak 258 flows and calculate the differences in the magnitude of estimated maxima for a given return period between the unconditioned and the updated distribution. The latter is conditioned by the 95% sample quantile of the 259 260 observed mean flow in the previous month. To model the low flows we use the lognormal distribution, 261 which was found to exhibit the best fit for the river in question among other typical candidates for average 262 flows, i.e. the Weibull and the Gamma distribution. The low flows are conditioned by the lower 5% sample 263 quantile of the observed mean flow in the previous month.

264 3. Data and catchments description

265 The dataset includes 224 records spanning more than 50 years of daily river flow observations from gauging stations, mostly from non-regulated streams. A few catchments are impacted by regulation. 266 267 Among the 224 rivers, 108 are located in Austria, 69 in Sweden, 31 in Slovenia, 13 in France, 2 in Spain and one in Italy. Catchment areas vary significantly, the largest being the Po River basin in Italy (70 091 268 km²) and the smaller being the Hålabäck River basin in Sweden (4.7 km²). The geographical location of the 269 270 river gauge stations as well as their climatic classification are shown in Fig. 1. Most of the examined rivers belong to either a warm temperate (C) or a boreal/snow climate (D) with a subset impacted by polar 271 272 climatic conditions (E), according to the updated World Map of the Köppen-Geiger climate classification 11

273 (Fig. 1) based on gridded temperature and precipitation data for the period 1951-2000 (Kottek et al., 2006). More specifically, the majority of French, Slovenian and approximately one third of the Swedish basins 274 275 belong to the warm temperate Cfb category characterized by precipitation distributed throughout the year 276 (fully humid) and warm summers. The rest of the Swedish catchments are impacted by a Dfc climatic type, i.e. a snow climate, fully humid with cool summers. The Austrian catchments belonging to the region 277 278 impacted by the European Alps have the most complicated regime due to their topographic variability. At 279 the lowest altitudes, Cfb is the prevailing regime, but as proximity to the Alps increases, a Dfc regime 280 dominates and progressively, in the highest altitude basins, the climate becomes a polar tundra type (Et), 281 characterized primarily by the very low temperatures present. The characteristics of all the climatic regimes 282 of the studied rivers are given in the legend of Fig. 1. A summary of the river basins under study in terms of 283 the selected descriptors is also provided in Table 1, showing that the investigated rivers cover a wide range 284 of catchment area sizes, flow regimes and climatic conditions.

285 It is relevant to note that 16 of the Austrian rivers are subject to regulation, which may alter the 286 persistence properties of river flows. This relates to generally 'mild' forms of regulation, i.e. upstream 287 regulation with very low degree of flow attenuation, hydropower operations and flow diversions to and 288 from the basin. A preliminary examination of these rivers did not reveal any significant change during time 289 of the flow regime. The presence of regulation does not preclude the exploitation of correlation for 290 predicting river flows in probabilistic terms, but may affect the analysis of physical drivers, as it may 291 enhance or reduce persistence in the natural river flow regime. Given that detailed information is generally 292 lacking on the impact of regulation (Kuentz et al. 2017), we assume stationarity of the river flows for all the 293 catchments herein considered and additionally, assume that river management does not significantly affect the identification of the physical drivers. 294

4. River memory analysis for the considered case studies

297 4.1 Season Identification

Approximately half of the 224 rivers are characterized by at least one high-flow season with medium or 298 299 higher significance (PAMF(HFS) \geq 60%). Among them, very strong unimodal regimes (PAMF(HFS) \geq 300 80%) are observed in 63 rivers, the majority of which are located in Sweden. For 25% of the rivers, a high-301 flow season of low significance is found (PAMF(HFS) between 40-60%), while for the remaining 25% the 302 high-flow distribution looks uniform along the year. Bi-modality regimes are found with low and moderate 303 significance in rivers located mostly in Austria and Sweden, but we focus here on the major high-flow 304 season, as we are interested in the most extreme events. A minor HFS analysis would be perhaps relevant 305 in other regions of the world where bimodal flood regimes are more prominent, as suggested by the 306 analysis of Lee et al. (2015).

Regarding the LFS identification, the two considered approaches (see Section 2.1) agree for 139 out of 224 stations but the first method, i.e. the one-month period with the lowest amount of mean monthly flow is selected as being more relevant to the purpose of computing mean flow correlations.

310 4.2 Seasonal correlation

311 LFS correlation is markedly higher than the corresponding HFS correlation for lags 1-5 and its median remains higher than 0 for more lags (see Fig. 2). For the case of HFS correlation, we focus only on the most 312 313 significant first lag, for which 73 rivers are found to have correlation significantly higher than 0 at 5% 314 significance level. In Fig. 3, the autocorrelation of the whole monthly series is compared to the LFS 315 correlation for lag of 1 and 2 months, in order to prove that the seasonal correlation for LFS is significantly 316 higher than its counterpart computed by considering the whole year. The latter is also confirmed by the 317 Kolmogorov-Smirnov test for both LFS lags (corresponding p-values, $p_{lag1} < 2.2 \times 10^{-6}$ and $p_{lag2} < 2.2 \times 10^{-6}$ 318 for the null hypothesis that the LFS correlation coefficients are not higher than the corresponding values for 319 the monthly series autocorrelation; Conover, 1971).

Figure 4 shows the spatial pattern of HFS and LFS streamflow correlations. It is interesting to notice the emergence of spatial clustering in the correlation magnitude, which implies its dependence on different spatially varying physical mechanisms. For example, for HFS, a geographical pattern emerges within France, since the highest correlation coefficients are located in the northern part of the country, which is characterized by oceanic climate and higher baseflow indexes.

325 5. Physical interpretation of correlation

To attribute the detected correlations to physical drivers, we define 6 groups of potential drivers of seasonal correlation magnitude, which are: basin size, flow indices, presence of lakes and glaciers, catchment elevation, catchment geology, and hydro-climatic forcing. For some of the descriptors the information is available for a few countries only.

In what follows, we will use the term "positive (negative) impact on correlation" to imply that an increasing value of the considered descriptor is associated to increasing (decreasing) correlation. For each descriptor, we also report between parentheses the Spearman's rank correlation coefficient r_s (Spearman, 1904) between its value and the considered (LFS or HFS) correlation, and the p-value of the null hypothesis $r_s = 0$. Spearman's coefficient is adopted in view of its robustness to the presence of outliers and its capability of capturing monotonic relationships of non-linear type.

336 5.1 Catchment area – Descriptor A

Figure 5 shows that there is only a weak positive impact of the catchment area (log-transformed) on correlation for HFS ($r_s = 0.17$, p = 0.01) but a more significant positive one for LFS ($r_s = 0.27$, $p = 5.5 \times 10^{-1}$ 5). The presence of relevant scatter in the plots also indicates that it is not a key determinant of correlation.

340 5.2 Flow indices – Descriptors BI and SR

The effect of the BI and SR is shown in Fig. 6. BI (Fig. 6a) appears to be a marked positive driver for LFS ($r_s = 0.6$, $p = 1.8 \times 10^{-23}$) while its effect for HFS is less clear, being weakly positive ($r_s = 0.21$, p = 0.001).

For SR (Fig. 6b), it appears that both LFS and HFS streamflow correlations drop for increasing wetness (r_s = -0.4, p = 4 × 10⁻¹⁰ and r_s = -0.28, p = 2.8 × 10⁻⁵ respectively).

345 5.3 Presence of lakes and glaciers – Descriptors PL and PG

Detailed information on the presence of lakes is available for the 69 Swedish catchments while areal 346 347 extension of glaciers is known for the 108 Austrian catchments. Figure S1 in the Supplement shows that the 348 impact of lake area (Fig. S1a) on correlation for LFS and HFS is not significant but positive ($r_s = 0.10$, p =349 0.399 and $r_s = 0.12$, p = 0.347). The results for glaciers show a positive impact for LFS ($r_s = 0.28$, p = 0.28, p =350 0.081) but negative for HFS ($r_s = -0.34$, p = 0.032). For a meaningful interpretation, these results should be 351 considered in conjunction with the seasonality of flows for the Austrian catchments. Low flows for the glacier-dominated catchments are typically occurring in winter months, when glaciers are not contributing 352 353 to the flow (Parajka et al., 2009). Thus the observed result for LFS is more likely portraying the impact of 354 low temperature (low evapotranspiration) and snow accumulation, the latter generally being a slowly 355 varying process. For HFS, which is typically occurring in the summer months for the considered 356 catchments, flows are mainly determined by snowmelt which is associated to large variability and reduced 357 persistence (Fig. S1b).

358 5.4 Catchment elevation

359 The areal coverage of the SRTM data is limited to 60 degrees north and 54 degrees south and therefore, 360 data for the northern part of the Swedish catchments are not available. The rest of the rivers are divided in 361 three regions based on proximity: Region I including the central and eastern part of the Alps and 362 encompassing Austrian, Slovenian and Italian catchments; Region II showing the western part of the Alps and encompassing French and Spanish territory; and Region III including the southern part of Sweden. 363 364 Figure 8 shows elevation maps along with the location of gauge stations and magnitude of correlations. 365 Elevation seems to enhance LFS correlation which is more evident in the mountainous Region I (Fig. 7). 366 For HFS correlation there is not a prevailing pattern.

367 In the case of Austrian catchments, a 1 km resolution digital model is also used to extract information on elevation. Figure 8 confirms that there is a positive correlation pattern emerging with elevation for LFS. 368 369 Based on local climatological information, it can be concluded that the spatial pattern for LFS correlation is 370 reflective of the timing and strength of seasonality of the low flows in Austria, where dry months occur in 371 lowlands during the summer due to increased evapotranspiration and in the mountains during winter 372 (mostly February) due to snow accumulation which is characterised by stronger seasonality compared to 373 the lowlands flow regime (Parajka et al., 2016; see Fig. 1). Concerning HFS in the same region, high flows 374 are significantly impacted by the seasonality of extreme precipitation (Parajka et al., 2010), which is highly 375 variable, with the exception of the rivers where high flows are generated by snowmelt. Therefore, a 376 spatially consistent pattern does not clearly emerge.

377

378 5.5 Catchment geology – Descriptors PK and PF

Two different geological behaviours are identified which may impact river correlation. We first focus on 21 Slovenian catchments (out of 31) where more than 50% of the basin area is characterised by the presence of karstic aquifers (percentage of karstic areas $PK \ge 50\%$). Figure 9 shows boxplots of the estimated lag-1 correlation coefficient for both HFS and LFS against rivers where PK < 50%. It is clear that there is a significant decrease in correlation where karstic areas dominate for both for HFS and LFS.

In a second analysis, we focus on Austrian catchments and investigate the relationship between correlation and percentage of Flysch coverage, PF. Figure S2 in the Supplement shows that there is not a prevailing pattern in either case ($r_s = 0.13$, p = 0.6 for LFS and $r_s = -0.19$, p = 0.446 for HFS).

387 **5.6** Atmospheric forcing – Descriptors *P* and *T*

Figure 10 shows the lag-1 HFS and LFS correlations against estimates of the annual precipitation P and annual mean temperature T as well as the De Martonne index IDM. LFS correlation appears to be more sensitive than HFS to the above climatic indices, showing a decrease with increasing temperature and also a

decrease with increasing precipitation ($r_s = -0.44$, $p = 3.1 \times 10^{-12}$ for P and $r_s = -0.57$, $p = 1.8 \times 10^{-20}$ for 391 HFS correlation 392 *T*). is scarcely sensitive to these variables (r_s = -0.17, p = 0.011 for P and r_s = 0.08, p = 0.208 for T). The IDM (Fig. 10 c) shows a mild decrease of both 393 394 LFS ($r_s = -0.06$, p = 0.368) and HFS correlation with increasing IDM ($r_s = -0.17$, p = 0.01), while for the latter there seems to be a clearer trend (lower correlation with higher IDM) in very humid areas (dark blue 395 396 points in Fig. 10c).

397

398 5.7 Physical drivers of high correlation

399 To gain further insights into the results we select the 20 catchments with the highest streamflow seasonal correlation coefficients for both HFS and LFS periods in order to investigate their physical characteristics 400 401 in relation to the remaining set of rivers. Table 2 summarizes statistics for selected descriptors in order to 402 identify dominant behaviours. We also compare the number of rivers with distinctive features, i.e. lakes N_L 403 (number of rivers with lakes), glaciers N_G (number of river with glaciers), flysch N_F (number of rivers with 404 flysch formations) and karst $N_{\rm K}$ (number of rivers with karstic areas) for the highest correlation group with 405 those obtained from 1000 randomly sampled 20-catchment groups from the whole set of considered 406 catchments to assess whether higher correlation implies distinctive features.

407 By focusing on HFS, one can notice that the catchments with higher seasonal correlation are characterised by larger catchment area, higher baseflow index and temperature with respect to the 408 409 remaining catchments, and lower specific runoff, precipitation and wetness. Presence of lake, glaciers, karstic and Flysch areas do not appear significantly effective at a 5% significance level. More robust 410 411 considerations can be drawn for the LFS: higher seasonal correlation is found for larger catchments with 412 higher baseflow index and lower specific runoff, precipitation and wetness. Decreasing temperature is 413 strongly associated with higher correlation for the LFS. The presence of lakes plays a significant role both for lag-1 and lag-2 correlations with the latter being also significantly influenced by presence of glaciers. 414

415 6. Principal component analysis of the predictors and linear regression

416 We attempt to fit a linear regression model to relate correlation to physical drivers, in order to support 417 correlation estimation for ungauged catchments. To avoid the impact of multicollinearity in the regression 418 while additionally summarizing river information, we apply PCA (see Section 2.2). Although correlation 419 effects are efficiently dealt with via the PCA, we avoid including highly correlated variables in the analysis. For example, the De Martonne Index, Precipitation and SR are mutually highly correlated (all Pearson's 420 421 cross-correlations are higher than 0.6) and therefore we only consider the SR in the PCA because it shows a 422 more robust linear relationship with correlation magnitude. We select A, BI, SR and T as the variables to be 423 considered in the PCA. A log transformation is applied on the basin area to reduce impact of outliers. Table 424 3 shows the coefficients estimated for each component (the loadings) and the explained variance. The first 425 principal component is primarily a measure of BI; the second principal component mostly accounts for T426 and the third principal component accounts for A. There is an evident geographical pattern emerging by the 427 visualization of countries in the biplot (Fig. 11). Slovenian rivers cluster towards the direction of increasing 428 SR and T, whereas Swedish rivers towards the opposite direction of increasing BI and decreasing T. 429 Austrian rivers, which are the majority, are the most diverse. The first two components together explain the 430 70% of the total variability in the data.

431 Naturally, the statistical behaviour of the indices reflects the known local controls for certain rivers.
432 For example, the observed lowest BI in Slovenia is consistent with the presence of karstic formations for
433 the majority of the Slovenian rivers, as is the higher BI in Sweden and Austria, which is related to the
434 presence of lakes and glaciers in both countries.

In the case of HFS, all the examined linear models (combinations of ln *A*, SR, BI, *P*, *T*, IDM predictors) failed in explaining the streamflow correlation magnitude. On the contrary, the linear regression model performs fairly well in explaining the correlation for LFS, with an adjusted R^2 value of 0.58 and an F-test returning a p-value < 2.2 ×10⁻¹⁶. The coefficients for the first three PCs are found significantly different from zero at a 0.1% significance level and are included in the regression (see Table 4). The 440 highest coefficient is obtained for the first PC, which mostly accounts for BI importance. Diagnostic plots from linear regression for LFS are shown in Fig. 12. There is no clear violation of the homoscedasticity 441 442 assumption in linear regression, apart from the presence of a limited number of outliers. There is a certain 443 departure from normality in the lower tail of the residuals, which relates to the fact that the model performs better in the area of higher seasonal streamflow correlations and overestimates the lower correlations. 444

445

7. Real-time updating of the frequency distribution of high and low flows for the Oise River 446

447 We apply the technical experiment (see section 2.3) for high and low flows to the Oise River in France and 448 assess the difference in the estimated flood and low-flow magnitudes. We update the probability 449 distribution of high and low flows after the occurrence of the upper 95% and lower 5% sample quantile of 450 the observed mean flow in the previous month, respectively.

The Oise River (55 years of daily flow values) at Sempigny in France has a basin area of 4320 km² and its 451 452 gauging station at Sempigny is part of the French national real-time monitoring system (https://www.vigicrues.gouv.fr/), which is in place to monitor and forecast floods in the main French rivers. 453 454 The selected river has a high technical relevance since it experiences both types of extremes with large 455 impacts. For instance, a severe drought event in 2005 led to water restrictions impacting agriculture and 456 water uses in the region (Willsher, 2005), while the river originated an inundation during the 1993 flood 457 events in northern and central France, which was one of the most catastrophic flood-related disasters in Europe in the period 1950-2005 (Barreldo, 2007). It is characterized by HFS correlation $\rho = 0.54$, which is 458 459 the 3rd largest lag-1 correlation for the HFS in our dataset and LFS correlation $\rho = 0.80$, which stands for the 70% quantile of the sample lag-1 correlation for LFS. 460

A visual inspection of the residuals plots is also performed (Fig. 13a, b) in order to evaluate the 461 assumption of homoscedasticity of the residuals of the regression models given by Eq. (2). The residuals do 462 not show any apparent trend and therefore the Gaussian linear model is accepted. Figure 13 (c, d) shows the 463 464 conditioned and unconditioned probability distributions of peak and low flows in the Gaussian domain. As 465 expected <u>follows</u> from Eq. (3) and (4), the variance of the updated (conditioned) distributions decreases
 466 while the mean value increases.

After application of the inverse NQT the conditioned peak flows are modelled through the EV1 467 distribution and compared to the unconditioned (observed) peak flows. The corresponding Gumbel 468 probability plot for conditioned and unconditioned distributions is shown in Fig. 13e. For the return period 469 470 of 200 years, the updated distribution shows a 6% increase in the flood magnitude for the Oise River (307.7 m³ s⁻¹ to 326.44 m³ s⁻¹). Likewise, the conditioned low flows are modelled through the lognormal 471 472 distribution. The two cumulative distribution functions are compared in Fig. 13f showing a major departure 473 in the estimated quantiles for the updated distribution; the occurrence of the predefined 5% quantile flow in the pre-LFS month induces a decrease of the exceedance probability of an average LFS flow of 15 m³ s⁻¹ 474 475 from a prior 43% (according to the unconditioned model) to 1%.

476 8. Discussion

477 The methodology presented herein aims to progress our physical understanding of seasonal river flow persistence for the sake of exploiting the related information to improve probabilistic prediction of high and 478 479 low flows. The correlation of average flow in the previous months with LFS flow and HFS peak flow was 480 found to be relevant, with the former prevailing on the latter. This result was expected foreseen since the 481 LFS correlation refers to average flow while the HFS correlation is related to rapidly occurring events. We 482 also aim to investigate physical drivers for correlation and quantify their relative impact on correlation 483 magnitude. Therefore, a thorough investigation of the geophysical and climatological features of the 484 considered catchments was carried out.

We found that increasing basin area and baseflow index are associated with increasing seasonal streamflow correlation, yet the latter has a stronger impact. To this respect, Mudelsee (2007), Hirpa et al. (2010) and Szolgayova et al. (2014a) also found positive dependencies of long-term persistence on basin area, Markonis et al. (2018) found a positive impact too but for larger spatial scales (> 2×10^4 km²), while Gudmunsson et al. (2011) found basin area to have negligible to no impact to the low-frequency 20 components of runoff. Our results additionally point out that catchment storage induces mild positive
correlation, not only for low discharges which are directly governed by base flow, but also for high flows.
which is less anticipated.

Previous studies also pointed out that correlation increases for groundwater-dominated regimes (Yossef et al., 2013; Dijk et al., 2013; Svensson, 2016) and slower catchment response times (Bierkens and van Beek, 2009), which concurs with the impact of baseflow index found herein as well as with the observed impact of fast responding karst areas. The latter findings are also in agreement with our conclusion that correlation decreases for increasing rapidity of river flow formation, which for instance occurs in the presence of karstic areas and wet soils, which explains why persistence decreases with high specific runoff; as also confirmed by other studies (Gudmundsson et al., 2011; Szolgayova et al., 2014).

500 Other contributions also reported higher streamflow persistence in drier conditions, either relating to lower specific runoff or mean areal precipitation estimates (Szolgayova et al., 2014; Markonis et al., 2018). 501 502 It was postulated that this is due to wet catchments showing increased short-term variability compared to 503 drier catchments (Szolgayova et al., 2014) and having a faster response to rainfall due to saturated soil. A 504 similar conclusion has been reached by other previous studies reporting that low humidity catchments are 505 more sensitive to inter-annual rainfall variability (Harman et al., 2011), therefore leading to enhanced 506 persistence. Yet, these studies refer to generally humid regions and cannot be extrapolated to more arid 507 climates. A related conclusion is proposed by Seneviratne et al. (2006) who found the highest soil moisture 508 memory for intermediate soil wetness. These results do not contrast with our findings, which refer to a wide 509 range of climatic conditions. In fact, our finding that increased wetness has a negative impact on seasonal memory of both high and low flows, extends the above results to the seasonal scale and interestingly, to 510 both types of extremes. 511

512 We also confirm the role of lakes in determining higher catchment storage and therefore positive 513 correlations for the LFS, which has <u>only</u> been_reported for annual persistence in a few sites (Zhang et al., 514 2012). 515 The effect of snow cover for lag-1 LFS correlation is also revealed by the Austrian catchments. The mountainous rivers, directly affected by the process of snow accumulation, exhibit winter LFS and higher 516 517 correlation than the rivers in the lowlands, which are more prone to drying out due to evapotranspiration in 518 the hotter summer months. The inspection of elevation data confirmed the role of high altitudes in increasing LFS correlation, which is likely related to storage effects due to snow accumulation and gradual 519 520 melting. In this respect, Kuentz et al. (2017) found that topography exerts dominant controls over the flow 521 regime in the larger European region, controlling the flashiness of flow, and being a particularly important 522 driver for other low flow signatures too. In fact, topography may affect the flow regime directly, through 523 flow routing, but also indirectly, because of orographic effects in precipitation and hydroclimatic processes 524 affected by elevation (e.g. snowmelt and evapotranspiration).

525 Regarding atmospheric forcing, we find LFS correlation to be negatively correlated to mean areal temperature and annual precipitation. The former result may be explained considering that increased 526 527 evapotranspiration (higher temperature) is expected-likely to dry out LFS flows while snow coverage 528 (lower temperature) was found to be associated with higher LFS correlation. An apparently different 529 conclusion was drawn by Szolgayova et al. (2014a) and Gudmundsson et al. (2011), who reported 530 increasing persistence with increasing mean temperature postulating that snow-dominated flow regimes 531 smooth out interannual fluctuations. Yet, it should be noted that they refer to interannual variability while 532 we refer here to seasonal correlation and therefore to shorter time scales, which imply a different dynamic 533 of snow accumulation and snowmelt; latitude may also play a relevant role in this, since in southern Europe 534 the complete ablation of snow can occur more than once during the cold season, and sublimation may 535 account for 20-30% of the annual snowfall (Herrero and Polo, 2016), decreasing the amount of snowmelt and impacting LFS flows in the summer season. 536

Snowmelt mechanisms are found to increase predictive skill during low-flow periods in some other
studies (Bierkens and van Beek, 2009; Mahanama et al., 2011; Dijk et al., 2013). However, in the glacierdominated regime of western Alpine and central Austrian catchments, it is unlikely that this is not expected

to be a relevant driver of higher correlation, since low flow is occurring in the winter months. Yet the mountainous, glacier-dominated rivers still show increased LFS correlation compared to rivers in the lowlands, which agrees well with other studies that have found less uncertainty in the rainfall-runoff modelling in this regime owing to the greater seasonality of the runoff process and the decreased impact of rainfall compared to the rainfall-dominated regime of the lowlands (e.g Parajka et al., 2016).

Although the considerable uncertainty of areal precipitation estimates should be acknowledged, the contribution of annual precipitation interestingly complements the negative effect of increasing specific runoff –which is highly correlated to *P* estimates– on the correlation magnitude for both LFS and HFS. This outcome confirms that catchments receiving significant amount of rainfall do show less correlation than drier regimes <u>as discussed before</u>.

550

551 9. Conclusions and outlook

This research investigates the presence of persistence in river flow at the seasonal scale, the associated physical drivers and the prospect for employing the related information to improve probabilistic prediction of high and low flows by exploring a large sample of European rivers. The main findings are summarized below:

- Rivers in Europe show persistent features at the seasonal timescale, manifested as correlation between
 high- and low-flow signatures, i.e. peak flows in HFS and average flows in LFS respectively, and
 average flows in the previous month. LFS correlation <u>Correlation for LFS signatures</u> is found
 consistently higher than HFS correlation.
- Seasonal correlation shows increased spatial variability together with spatial clustering.
- Storage mechanisms, groundwater-dominated basins and slower catchment response time, as reflected
 by large basin areas, high baseflow index and the presence of lakes, amplify <u>seasonal</u> correlation. On

the contrary, correlation is lower in quickly responding karstic basins, and increased wetnessconditions, as revealed by high specific runoff.

Low mean areal temperature is associated with higher LFS correlation owing to the weaker drying-out
 evapotranspiration force and the mechanism of snow accumulation in higher altitudes. Higher mean
 areal precipitation is associated with lower LFS predictability, possibly due to the presence of saturated
 conditions and increased short-term variability in wetter climates.

• The drivers of LFS predictability are easier to identify and allow for the opportunity to construct regression models for possible application to ungauged basins (see Section 6).

HFS and LFS correlation may directly serve for the probabilistic prediction of 'extremes', i.e. high and
 low flows, as increased correlation can be exploited in various stochastic models. Such an application
 was performed in Section 7 in a data assimilation setting for a river of marked technical relevance.

574 Regarding the latter, once a significant correlation is identified, it may be exploited in other model 575 variants as well, e.g. adding more dependent variables of lagged flow and/or coupling with other relevant 576 explanatory variables, such as teleconnections or antecedent rainfall, in multivariate prediction schemes. 577 Indeed, the presence of river memory at the seasonal scale represents a possible opportunity to improve the 578 prediction of water-related natural hazards by reducing uncertainty of associated estimates and allowing 579 significant lag time for decision-making and hazard prevention. Besides the high relevance for extremes, 580 this type of seasonal predictability could also be of interest to water resources management by, for instance, 581 exploring the memory properties of a minor HFS.

The inspection of the physical basis, apart from advancing our understanding of the catchment dynamics and enabling predictions in ungauged basins, is highly important as it may also guide the search for other dependent variables and build confidence in the formation of process-based stochastic models (Montanari and Koutsoyiannis, 2012). A large sample of indices was herein inspected, yet data are majorly needed to allow for more certain and generalized conclusions worldwide. An important note is the presence of regulation, the effect of which, due to lack of objective data, is not completely understood. However, the 588 opportunity of exploiting correlation is not affected by the presence of regulation, provided that the

589 management of river flow does not change in time.

590 We conclude that our results point out that river memory provides interesting information that holds 591 both theoretical and operational potential to improve the understanding and prediction of extremes, support

592 decision-making and increase the level of preparedness for water-related natural hazards.

593 Data and Code availability

The data and code used in this study may be made available to the readers upon request to the corresponding author.

596 Competing interests

597 The authors declare that they have no conflict of interest.

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730 Tables

729

731 Table 1 Summary statistics of the river descriptors. Summary statistics for PL, PG and PF variables are computed

732 only for the subset of catchments with positive values (the total number of catchments is also reported in brackets).

- PK is used as a categorical variable (PK is either higher or lower than 50% of catchment area), therefore sample
- statistics are not computed in this case, but the number of stations with $PK \ge 50\%$ is reported as 'positive' presence of karst.

Descriptor (Units)	A (km ²)	BI (-)	SR (m ³ s ⁻¹ km ⁻²)	PL (%)	PG (%)	PF (%)	PK (-)	P (mm year ⁻¹)	<i>Т</i> (°С)	IDM (-)
Min	4.7	0.29	0.004	0.5	0.1	0.3	-	444	-1.8	29.41
Max	70091	0.99	0.088	19.5	56.5	100	_	1500	13.7	153.40
Standard	5904 3	0 14	0.018	4 04	15 54	32.56	_	288 22	3 59	24 53
deviation	0,0,00	011	0.010		10101	02100		200122	0.07	21100
Sample size	224	224	224	69 [69]	39 [108]	18 [108]	21 [31]	224	224	224

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Table 2 Differences in the mean values between the descriptors of the 20-highest correlation river group for HFS and

LFS vs the remaining rivers (204). NL, NG, NF and NK columns contain the absolute number of rivers in the higher

correlation group with the specific descriptor (presence of lake, glacier, flysch and karst) with * denoting

significance at 5% significance level (two-sided test) and brackets containing the mean value from the 1000

resampled 20-catchment subsets.

Descriptor (Units)	<i>A</i> (km ²)	BI (-)	SR (m ³ s ⁻¹ km ⁻²)	N _L (-)	N _G (-)	N _F (-)	N _K (-)	P (mm year ⁻¹)	<i>Т</i> (°С)	IDM (-)
HFS lag1	+38.7%	+9.6%	-36.5%	5 [6]	5 [3]	1 [2]	1 [2]	-6.7%	+11.7%	-11.3%
LFS lag1	+358%	+20.2%	-47.3%	17* [6]	3 [3]	0 [2]	0 [2]	-37.9%	-80%	-17.3%
LFS lag2	+139.7%	+18.9%	-40.8%	12* [6]	7* [3]	0 [2]	0 [2]	-26.5%	-64.2%	-8.8%

Table 3 Loadings of the three Principal Components for ln A, SR, BI and T. The explained variance of each PC is

denoted in parenthesis.

Predictor variables	PC1 (42.5%)	PC2 (28.2%)	PC3 (17%)	PC4 (12.2%)	
ln A	-0.486	-0.427	0.748	0.145	
SR	0.48	0.483	0.652	-0.332	
BI	-0.619	0.262	-0.11	-0.731	
Т	0.385	-0.718	-0.04	-0.577	

Table 4 Summary of Linear Regression results for the LFS model. *** indicate a 0.1% significance level.

Predictor	Estimate	Standard Error	t value	Pr(> t)	Adjusted	F-statistic
riculator	Lotiniate	Standard Error	t vuide	11(> t)	rajustea	1 statistic

			\mathbb{R}^2	
0.659407	0.008557	77.065	< 2 ×10 ⁻¹⁶ *** 0.58	334 104.2
-0.110632	0.006577	-16.820	$< 2 \times 10^{-16***}$	p-value:
0.031761	0.008070	3.936	0.000111***	$< 2.2 \times 10^{-16}$
-0.038999	0.010388	-3.754	0.000223***	
	0.659407 -0.110632 0.031761 -0.038999	0.659407 0.008557 -0.110632 0.006577 0.031761 0.008070 -0.038999 0.010388	0.659407 0.008557 77.065 -0.110632 0.006577 -16.820 0.031761 0.008070 3.936 -0.038999 0.010388 -3.754	R^{2} 0.659407 0.008557 77.065 <2 ×10 ^{-16***} 0.58 -0.110632 0.006577 -16.820 <2 ×10 ^{-16***} 0.031761 0.008070 3.936 0.000111*** -0.038999 0.010388 -3.754 0.000223***

758 Figures



Figure 1. Updated Köppen-Geiger climatic map for period 1951–2000 (Kottek et al., 2006) showing the location of
 the 224 river gauge stations.





Figure 2. Boxplots of seasonal correlation coefficient against lag time for HFS (left panel) and LFS (right panel) analysis for the 224 rivers. The lower and upper ends of the box represent the 1st and 3rd quartiles, respectively, and the whiskers extend to the most extreme value within 1.5 IQR (interquartile range) from the box ends; outliers are plotted as filled circles.

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Figure 4. Spatial distribution of the lag-1 correlation coefficients for HFS (left) and LFS (right) analysis. Legend
 shows the color assigned to each class of correlation for the data.



Figure 5. Scatterplots of lag-1 HFS (bottom panel) and LFS (top) streamflow correlation versus the natural logarithm of basin area ln *A*.



Figure 6. Scatterplots of lag-1 HFS (bottom panels) and LFS streamflow correlation (top panels) versus baseflow
 index BI (a) and specific runoff SR (b).



Figure 7. Relief maps from SRTM elevation data for the HFS and LFS lag-1 correlations of the rivers. Note that
 elevation scale is different for each region. Legend shows the colour assigned to each class of correlation for the data.



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Figure 8. Digital elevation model of the Austrian river network depicting the spatial distribution of lag-1 positive correlation for HFS (left) and lag-1 positive correlation for LFS (right). Legend shows the colour assigned to each class of correlation for the data.







Figure 10. Scatterplots of lag-1 HFS and LFS correlation versus annual precipitation P (a), mean annual temperature T (b), and Index De Martonne IDM (c).







axes along with the vectors (brown arrows) representing the coefficients of the baseflow index BI, specific runoff SR,

natural logarithm of basin area ln A and mean annual temperature T variables when projected on the principal axes. Scores for the rivers are plotted in different colors corresponding to each country of origin and 68% normal







827 Figure 13. Conditioning the frequency distributions for high and low flows for the Oise River. Plots of the

residuals of the linear regression given by Eq. (2) for the HFS (a) and LFS (b) models. Probability

829 distribution of the unconditioned normalized peak flows NQ_P (solid line) and the normalized peak flows

\$30 NQ_P-conditioned to the occurrence of the 95% quantile (dotted line) for the HFS (c) and probability

831 distribution of the unconditioned normalized low flows NQ_L (solid line) and the normalized low flows NQ_L

834 EV1 distribution and conditioned to the occurrence of the 95% quantile (red line) for the HFS (e) and

835 cumulative distribution function of the unconditioned low flows Q_L (black line) and the low flows Q_L

modelled by the lognormal distribution and conditioned to the occurrence of the 5% quantile (red line) for

837 the LFS (f).