Review of “A novel method to identify sub-seasonal clustering episodes of extreme precipitation events and their contributions to large accumulation periods” by Jérôme Kopp1, Pauline Rivoire1, S. Mubashshir Ali1, Yannick Barton1, and Olivia Martius1

Main comment

The authors study the clustering of precipitation extremes and their relevance for accumulated precipitation extremes at the global scale. They use ERA5 data and aggregate precipitation over river catchments, which is the basis for an interesting study. They introduce metrics for investigating the above from a novel perspective.

I read the paper with high interest. I appreciate the effort done by the authors in providing graphics for explaining the procedure. However, unfortunately, I found the methodology very difficult to understand. In my view, the presentation of the methods, which is - together with the results - the fundamental aspect of the paper, requires a thorough revision. In fact, it is unclear to me from many points of views. In this context, I find it difficult to judge how well the metric captures the investigated physical processes and whether a more straightforward (easy to interpret) metric could have been designed.

After an improvement of the presentation, which should make everything clear to the reader (see specific comments below), I think that the following crucial aspects should be discussed thoroughly.

The authors propose a novel metric, hence high attention is required to the physical interpretation of (1) the defined metric (i.e., explain the reasoning beyond the choice of the metric based on simple physical arguments to the reader) and (2) the associated results. This is fundamental to allow the reader to well understand metric and results (and ultimately to maximise the impact of the work). On the same topic, as also states by the authors in the discussion, “a shortcoming of the method is the lack of a simple assessment of the significance of the clustering”. In fact, this shortcoming, combined with a non-clear (according to me) presentation/explanation of the metric, makes it difficult to interpret physically the spatial distribution of the clustering and its relevance for accumulated precipitation. I fully understand that the results are novel and, for this reason, it can be sometimes difficult to compare with previous literature, however, the authors should try to explain whether the results are consistent with some physical understanding/expectation. (I do provide some possible ways to go in this direction below.) This would help to make the work more robust. I hope that my comments can help the authors to improve the manuscript.

We thank the reviewer for their detailed and thoughtful review. In particular, pointing out the technical sections of the paper that were unclear, helped us greatly to improve the description of the methodology. We have addressed all comments pertaining to the description and interpretation of the methodology and propose a revised version of the corresponding sections (2.3, 2.4, 2.5 and 3.1) at the end of our reply. Suggested changes related to comments of those revised sections are not explicitly stated in each comment individually, but a reference is made to the new version of the corresponding section. We hope that this can improve the readability of our general answer. For comments related to the introduction and the discussion, changes are mentioned directly after the comment and highlighted in **bold font**.

Please note that the metrics S_f and S_f' are renamed S_cl (the clustering metric) and S_acc respectively, in the revised section and in our answers. The ratio S_cont is also renamed S_cont to highlight its measure of the contribution of clustering to accumulations:

Clustering Metric: $S_{cl} = \sum_{i \in Cl_n} n_w(i) \cdot q_i$

Accumulation Metric: $S_{acc} = \sum_{i \in Cl_{acc}} n_w(i) \cdot q_i$

Contribution Metric $S_{cont} = S_{cl} / S_{acc}$

Specific comments:

L25, I agree, but isn't the third point a consequence of the two above, so should not this presented in a non-parallel fashion?

Response: We agree that this third point could be a consequence of the first two.
Change: L25 **Therefore**, temporal dependence of precipitation…

- L31-40
"In these studies, clustering in time was assessed using the index of dispersion (variance-to mean ratio) of a one-dimensional homogeneous Poisson process model i.e., a Poisson process with a constant rate of occurrence (Cox and Isham, 1980)."
"All studies discussed above used statistical models to identify significant serial clustering of extreme events. However, none of those methods are able to directly identify individual clustering episodes."
"To our knowledge, no procedure exists that (1) automatically identifies individual serial clustering episodes of extreme (precipitation) events, and (2) subsequently uses the identified episodes to evaluate the clustering properties of a region."
Aren't Bevacqua et al. doing so (for precipitation from storms), i.e. introducing a counting-based procedure to identify individual clusters and avoid issues with the Poisson-process methods? Their approach does not rely on parametric distributions (related to your L275). If so, this should be acknowledged and the text fixed accordingly where necessary. Similarly, are Dacre and Pinto presenting counting based procedures as well?
(The two references are those in the original manuscript.)

Response: we thank the referee for pointing out the details of these references, which have now been acknowledged more specifically.

Changes:

L28 A number of previous studies have analyzed the statistical properties of the serial clustering of extreme events. Mailier et al. (2006); Vitolo et al. (2009) **and** Pinto et al. (2013) ~~and Bevacqua et al. (2020)~~ studied European winter storms…

L39 All studies discussed above used statistical models to identify significant serial clustering of extreme events. However, none of those methods are able to directly identify individual clustering episodes. **According to the review of Dacre and Pinto (2020), there are no widely used impact metrics used as a proxy for precipitation-related damage and only a recent study by Bevacqua et al. (2020) introduced a count-based procedure to identify individual cyclone clusters, combined with an impact metric based on precipitation accumulations**. ~~To our knowledge, no procedure exists that (1) automatically identifies individual serial clustering episodes of extreme (precipitation) events, and (2) subsequently uses the identified episodes to evaluate the clustering properties of a region~~. Here we propose a novel count-based procedure to….

L56 “Precipitation in ERA5 is a prognostic variable.”

I understand the sentence, however, I suggest to expand the text by mentioning the implication and what does that mean for a non-specialist (in a few words).

Response: we agree that this statement should be replaced by more precise explanations.

Change:

L56 ~~Precipitation in ERA5 is a prognostic variable.~~ **Precipitation is not directly constrained by observations in the ERA5 reanalysis data set as it stems from short-range numerical weather model forecasts. Consequently the quality of the precipitation data depends on the forecast quality. For our analysis primarily the timing of extreme precipitation events needs to be well represented. Rivoire et al. (2021) show that in the extratropics ERA5 captures the timing of extremes very well**.

L64. Can you explain better to the reader why you do this choice, i.e. using level 6? Thanks

Response: we agree that this should be better explained.

Changes: L64 We use level 6 of HydroBASINS for our study. **This choice is motivated further below.**

L70 We retained only catchments containing at least five ERA5 grid points for our analyses. **The choice of HydroBASINS level 6 and the removal of the smallest catchments allow us to focus our analysis on relatively large catchments (90% of the catchments are 3000 km^2 or larger).**

L70, “We retained only catchments containing at least five ERA5 grid points for our analyses.”

Does this mean that you consider only catchments with a catchment's area above about 5*25*25km? (I am assuming a resolution of 25km for the grid points.) If so, this means that you are considering relatively large catchments, where the clustering may be more important as they are responding slower to rainfall. If you agree (supported by a reference), this could be mentioned to reinforce your approach.

Response: we indeed want to focus our analysis on relatively large catchments because they are more sensitive to rainfall lasting for several days but cannot state an exact lower bound for their area. The East-West resolution of an ERA5 grid point (0.25°) is approximately 111km at the equator, 79km at 45°N/S or 44km at 67°N/S (Wikipedia). The catchment's area then depends on its latitude and on how the grid points are placed inside it.

Changes:

L70: We retained only catchments containing at least five ERA5 grid points for our analyses. The choice of HydroBASINS level 6 and the removal of the smallest catchments allow us to focus our analysis on relatively large catchments. **Such large catchments are sensitive to extended periods of heavy rainfall lasting for several days or longer (Westra et al. 2014) and consequently the impact of subseasonal clustering is likely to be more important for those catchments.**

New reference: Westra, S., Fowler, H. J., Evans, J. P., Alexander, L. V., Berg, P., Johnson, F., … Roberts, N. M. (2014). Future changes to the intensity and frequency of short-duration extreme rainfall. *Reviews of Geophysics*, *52*(3), 522–555. https://doi.org/10.1002/2014RG000464

L86, "After applying the declustering approach, a series of independent extreme daily precipitation events was defined". I understand that you end up with a time series of binary events (fig 3b). Specifying that would help the reader.

Response: we agree that it could help the reader to specify this point.

Change: L86 After applying the declustering approach, **a series of binary events of extreme precipitation was defined (Fig. 3b)**.

Depending on the local autocorrelation of the precipitation time series, after applying the high frequency declustering, you will end up having a different number of extreme events at different locations. Does this affect your final results, which may differ at different locations simply because of that? Please clarify/discuss.

As the second referee also raised a question regarding the runs declustering, we copied its question and our answer below in *italic* for completeness.

Response: we agree with the referee that the declustering reduces the number of extreme events differently at different locations. In a catchment where extreme precipitation is on average more persistent, the number of independent events retained after the declustering is smaller than in a catchment where extreme events have a short duration. The goal is to identify independent extreme events (ideally these are related to independent triggering weather systems). Note however that these differences in number are not relevant for our analysis as we focus on the clustering of independent events. We further limit our analysis to the top 50 clustering episodes for each catchment so the same number of episodes is used for all catchments (we checked that all catchments had 50 episodes with at least one (declustered) extreme event).

The sensitivity analysis presented in Fig. 9b also reveals that a change in the run length parameter r from 2 to 1 days resulted in the smallest differences in Sr. Not applying the declustering is equivalent to setting r = 0 days, and consequently this should have a very limited impact on our results and wouldn't affect our conclusions.

We also emphasize that the precipitation accumulations are not affected by the declustering, only the event counts.

2nd referee question: The runs declustering step needs more justification. I can understand its purpose for the case of slow-moving synoptic cyclones. But for the case of a multi-day sequence of afternoon severe convective storms, these are multiple events that are clustered rather than a single event.

We agree with the referee that by applying a runs declustering, our methodology will not pick up this specific scenario of a multi-day sequence of afternoon severe convective storms at the same grid-point. The spatial (0.25° lat/lon) and temporal (daily) resolutions of ERA-5 is too coarse to properly target convective scale precipitation, and we would miss many convective extremes. The present research is more targeted at the larger scale structures, such as mid-latitudes cyclones and cut-off lows. The runs declustering removes the short-term temporal dependence of extremes so as to focus exclusively on clustering at longer timescales (weekly and above).

That being said, it would be interesting to apply our approach to shorter time scales by using input data with a higher temporal and spatial resolution.

Change: L87 ***The runs declustering successively removes the short-term temporal dependence of extremes so as to focus exclusively on clustering at longer timescales (weekly and above). In this framework, a multi-day sequence of afternoon severe convective storms at the same grid-point would be reduced to a single event, while being composed of multiple independent events. This is not an issue because the present research is more targeted at the larger scale structures, such as mid-latitudes cyclones and cut-off lows. More importantly, the spatial (0.25° lat/lon) and temporal (daily) resolutions of ERA-5 are too coarse to properly target convective scale precipitation, and***

many convective extremes would be missed. Input data with a higher temporal and spatial resolution should be used to apply our approach to shorter time scales.

Could not Figure 3 and 4 be merged, i.e. keep only 4? The first two panels are *about* identical to Fig. 3. (They are not exactly identical as stated in the caption of Fig 4 given that there are no lines in panel 4b).

Response: we agree that merging the two figures could improve readability and remove redundant information.

Change: we have merged Fig. 3 and 4 into a new version of Fig. 3 (see new Fig. 3 in attached document).

Figure 4, Can be adding 14 days after the last day in the panel help to read the panels? (Such to be able to well understand why n14 is 0 in the last days in panel c.)

Response: we agree that this would improve the understanding.

Change: new Fig. 3 is modified accordingly. (see new section 2.3 in attached document)

L100, when you talk of extreme events in this section, I assume you refer to extreme events identified though the high frequency decluttering defined in the section above. Please make this clear/explicit.

Response: This is correct. Starting in section 2.3, extreme events are those identified after applying the runs declustering method. We made this point more explicit.

Change: in Table 3: Definition of n_w: Count of extreme events **(resulting from the runs declustering)** during a time window of w days. See also new section 2.3 in attached document)

L104, at the end, are windows centred or not? In Fig 4d, there is a centred window.

L105-106. You refer to Figure 4d. n14 is computed over the next 14 days, while acc14 is computed over a centred window. You explain why later, but it is confusing for the reader to find this in the Figure at this stage (as you refer to Figure 4d).

Response: we thank the referee for pointing out this possible point of confusion. The accumulations (acc_w) and the counts of extreme events (n_w) are both computed over the next w-1 days, that is: using a leading time window. In Fig. 4d (now 3d), the centred window corresponds to the days which are removed after the selection of an episode: we remove the days composing the episodes and also the previous w-1 days to strictly have independent episodes.

Change: see new section 2.3 in attached document.

L107-118, In my view, the explanation of the procedure needs major improvement. The statements below can help the reader to understand points where the text needs improvements.

Response: we thank the referee for their numerous suggestions and section 2.3 was reviewed by keeping those suggestions in mind. Please see the revised section and the new figures in the attached document.

L107 Add a sentence at the beginning of the paragraph explaining that through your procedure you aim at reducing the number of clustering episodes up to a number N_ep, to avoid having overlapped clusters. The reader is then able to read the step with this in mind and things will be easier to understand.

Response: We thank the referee for pointing out this possible point of confusion. Step (ii) of the algorithm is designed to avoid any overlapping between episodes, by removing w-1 days before and after the day selected at step (i). However, the reasons for limiting the number of selected clustering episodes to Nep are discussed at L177 and are not related to overlapping.

Change: see new section 2.3 in attached document.

L107 “highest count of extreme events”. What does “highest” mean? “Largest precipitation” The same with “largest”. It seems that there are two different thresholds involved in the selection, in addition to the constrain on N_ep and other thresholds. Please clarify.
Does changing these thresholds affect the results (in terms of matching between CI_n and CI_acc? (This is related to line 116)

Response: The highest count of extreme events means the largest value of n_w and the largest precipitation accumulations means the largest value of acc_w, with n_w and acc_w defined in the paragraph starting at L100. Hence, those values are not chosen and used as thresholds but are computed based on the underlying precipitation time series. The sole threshold is the yearly percentile used to define the extreme events (t, see section 2.2). A change in the parameters used to define the extreme events (e.g. the threshold t and the run length r) and in the time window length (w) will change n_w and acc_w and change CI_n and CI_acc. This sensitivity to the parameters is analysed in section 3.2 for Sr and is now further discussed in section 2.4.

Change: see new section 2.3 in attached document.

L113, do you mean you sort by the number of counts in extreme events, and if that is equal among clusters you then sort by precipitation?

Response: yes, this is how we proceed.

Change: see new section 2.3 in attached document.

L115. To me, it is unclear how CI_acc is obtained. You state: “This is done by applying steps (ii) to (iv) of our automated identification algorithm to the original precipitation time series.”
Hence, I would assume that you only apply steps ii to iv. Is this correct?
If so, this would imply that there is no association between CI_n and CI_acc, in the sense that CI_n and CI_acc can be associated with different dates as the two procedure are carried out independently (this seems in line with L164). In this context, I think that the sentence at line L122-124 is not necessarily obvious, and should be explained better to the reader.

Response: we thank the referee for pointing out this possible source of confusion. CI_acc is indeed obtained by applying steps ii to iv. The degree of similarity between CI_n and CI_acc is the key point in our method to evaluate the contribution of clustering to large accumulations. This degree of similarity is evaluated by doing a rank-by-rank comparison of the number of extreme events n_w in the episodes of CI_n with the episodes of CI_acc. If the episodes composing CI_acc and CI_n have the same n_w at each rank, then it means that the episodes with the largest number of extreme events are also leading to the largest accumulations. In this particular case, the contribution of clustering to accumulations is maximised. On the other hand, if any episode of CI_acc has less extreme events than the episode with the same rank in CI_n, then the contribution of clustering to accumulations is below the maximised contribution. The episodes selected in CI_n and CI_acc can be the same and ordered differently, but they can also differ. For example, this latter case could happen for catchments having episodes of large accumulations without extreme events. Assuming that the catchment has more than Nep episodes with at least an extreme event, those episodes would likely be selected in CI_acc but not in CI_n.

Change: see new section 2.3 in attached document.

L114, “The episodes picked out by the clustering episode identification and the extreme precipitation accumulation identification can be partly or completely identical. Examples of CIn and CIacc for the time series of Fig. 4 are shown in Table 1.”
- Is the example in the table one where they are identical or not? It seems they are in terms of dates (which I assume is not always the case - please clarify), but not in terms of rank. Please Clarify.
- If selecting episodes associated with different dates is possible (as I understand), I strongly suggest creating an example where this also occurs. This would help to avoid any confusion in this regard.

Response: in the example presented, the selected episodes are identical (they have the same starting date) but ordered differently in CI_n and CI_acc (their rank are not the same). We agree with the referee that an example where the two classifications are not composed of the exact same episodes would better illustrate the method and we modified it accordingly.

Change: see new Figures 3 and Table 1 in attached document.

L117. You refer to the table where Sr Sf S' is discussed but it has not been presented to the reader yet. This can be confusing.

Response: we agree with the referee that this can be confusing and made a reference to the section where the metrics are defined.

Change: see new section 2.3 in attached document.

L120, this sentence is not precise. I guess you mean that the clustering is present if the variance of the number of extreme events across CI_n is above a certain threshold.

Response: we thank the referee for pointing out this point of confusion. In contrast to the dispersion index, the CI_n classification does not contain explicit information on the variance. We moved the interpretation of the classifications from the beginning of section 2.4 to section 2.3. We explained in more details what the classifications represent and how they can be used to construct the metrics.

Change: see new section 2.3 in attached document.

L125 start a new paragraph before "We would like". ("We would like" is too colloquial in my personal view.)

Response: we agree with the referee's proposition. Section 2.4 now starts at L125.

L125 (now the first line of section 2.4): **Next we define** metrics that synthesize the properties of the two classifications **discussed in the previous section** and that will allow us to compare catchments.

After clarified things about the weights (see below), consider whether having their description in an appendix would help the reader. This could allow focusing directly on the metrics S. You should provide at around L 125 a general explanation on the way you are going to build the metrics S and why you need weights there. This should be before going into the details of the weights, which is a more technical aspect.

Response: we agree with the referee that the description of the weights should be moved in an appendix.

Change: L129 to L150 were moved in Appendix B.

L130, clarify the difference between "points" and "weights".

Response: The weights q_i are defined as explained in L140 (q_i = x_i/x_1) . However, there was an error in L142 to L148 where x_n was used instead of x_1 as the denominator. The definition could also be simplified by directly mentioning x_i instead of the definition of each x_i:

Change: L142 q_i = x_i/x_1 for all i.

The following questions all concern section 2.4 (L125 to L168). We also revised this section almost entirely and included it on pages 17-19 of our answer. For the sake of clarity we responded individually to each point but pointed to this revised section for the corresponding changes.

L132. Aren't the results therefore strongly sensitive to your choice of the weights? I mean, the condition "the difference between the ith place and the (i+1)th place should be larger than the difference between the (i+1)th place and the (i+2)th place"? This seems to be a very relevant point to discuss. For example, why isn't the difference between adjacent points always the same?

Response: We agree with the referee that this should be better explained. Regarding the choice of the weights: We have tried two other weighting schemes, also satisfying the two required properties: the inverse of the rank (1/1, ½, ⅓, etc…) and the inverse of the square root of the rank (1/1, 1/sqrt(2), 1/sqrt(3), etc.). The former gave slightly too much importance to the very first episodes of the classification and the latter gave almost identical results to the incenter method. In conclusion, our results are only slightly sensitive to the choice of the weighting scheme, as long as it satisfies the two desired properties.

The second property means that someone gaining a place (or a rank) should be rewarded more if the initial rank is higher, as improving at upper ranks is more challenging than improving at lower ranks.

Change: see new section 2.4 in attached document.

L140, what is lambda?

Response: lambda appears as a parameter in Sitarz (2013), which doesn't play a role in the definition of the scoring system and is set to 1.

Change: This parameter is no longer introduced.

About L150, You do not state explicitly whether qi is different in the two classifications.

Response: The weights q_i are the same in the two classifications. It is now stated explicitly in new section 2.4 in the attached document.

L150-155. Explain better to the reader why: “it measures how often sub-seasonal clustering episodes happen and how many extreme events these episodes contain”. (I appreciate the link to the metric phi in the next section, and I can somehow see why this happen. However, the reasoning beyond the choice of the metric should be provided clearly to the reader).

Response: We agree with the referee that this point deserves a more detailed explanation to avoid any confusion. The first metric S_cl is the weighted sum of the number of extreme events over all Nep episodes in the Cl_n classification. S_cl increases when the number of extreme events in any clustering episode increases. The increase in S_cl is more pronounced when the increase in the number of extreme events concerns the first episodes of the Cl_n classification (due to the weights). S_cl is then positively correlated to the number of extreme events in the considered clustering episodes.

Change: see new section 2.4 in attached document.

Does Sf depend on the high-frequency decluttering procedure, which - depending on the serial correlation of the precipitation - can lead to a different number of extremes at different catchments? If so, is it possible then to compare different catchments via Sf? In figure 8 you implicitly do such a comparison via selecting locations based on a global unique threshold for Sf.

Response: S_cl and S_acc both increase with the number of extreme events per episode so any parameter change which increases this number will also lead to an increase in S_cl and S_acc, generally speaking. An analysis of the sensitivity of S_cl showed that a lower threshold t, a shorter run length r and a larger window w led to a general increase in the values of S_cl. However, the sensitivity of S_cl and S_acc to the parameters does not affect our general conclusions. First, a change of parameters impacts all catchments, so while the scale of S_cl (or S_acc) is changed, the comparison of two catchments will result in the same conclusion in almost all cases. That is, a catchment with a relatively low (high) value of S_cl compared to other catchments for one parameter combination, will also have a relatively low (high) value for other combinations. This is supported by the fact that the correlation coefficient between S_cl and the index of dispersion remains high for all parameters combinations. Second, the sensitivity of S_cont (which depends on both S_cl and S_acc) to the parameters is explicitly assessed in section 3.2 and accounted for in our results.

Change: new Appendix C and new section 2.4 in attached document.

L160 Would the mean number of extreme events in the windows selected in Clacc divided by the total number of events provide information on the role of clustering for precipitation in a simpler fashion?

Response: By taking the mean number of extreme events, we lose all information on the rank of the episodes, and two catchments with an equal mean number of events could have different Cl_acc, and consequently different contributions of clustering to accumulation.

More specifically, an intuitive choice would be to use the sum or average of the number of extreme events over all (or a subset of) the episodes of Cl_n and Cl_acc as a basis for the metrics. However, such a choice would make us lose relevant information on how the episodes are ranked, and preclude a rank-by-rank comparison between classifications. This can be illustrated with the following theoretical example: let us consider a catchment where Cl_n is composed of 5 episodes, each with 3 extreme events, and 5 other episodes, each with 1 extreme event (i.e N_ep = 10). The average number of extreme events is 2. If Cl_acc is composed of the same episodes, then the average remains identical whatever the order of the episodes in Cl_acc and we cannot say anything about the contribution of clustering to accumulations by comparing the averages. For example, all episodes with 1 extreme event could have larger accumulations than those with 3 extreme events. There is a low contribution of clustering to accumulations in this case, and metrics based on averages would not be able to capture this feature. A metric based on average would also fail to capture some differences in the same classification between two catchments. This again can be illustrated with a theoretical example: let us consider catchment A where Cl_n is composed of 5 episodes: 1 with 5 extreme events, the 4 others without extreme event; and catchment B where Cl_n is composed of 5 episodes, each with 1 extreme event. In both cases the average number of extreme events is 1 but the clustering behaviour is different. Consequently, we need a way to properly account for the respective rank of each episode in both classifications.

Change: see new section 2.4 in attached document.

- Please present Sf, and explain it physically. Then S'f and explain what information it conveys from a physical point of view. Then present the ratio Sr.
- Especially, explain Sr in the context of the fact that Sf and Sf' may represent events associated with different dates (see comment above).

Response: We agree that S_cl, S_acc and S_cont should be better explained as they are the key metrics of our study.

The first metric S_cl is the weighted sum of the number of extreme events over all Nep episodes in the Cl_n classification. S_cl increases when the number of extreme events in any clustering episode increases. The increase in S_cl is more pronounced when the increase in the number of extreme events concerns the first episodes of the Cl_n classification (due to the weights). S_cl is then positively correlated to the number of extreme events in the considered clustering episodes. The second metric S_acc is computed the same way as S_cl, but using the episodes of the Cl_acc classification, where episodes are ranked according to their accumulations.

As S_cl and S_acc are computed using the same weights, their ratio S_cont can be used to make a rank-by-rank comparison and properly assess the contribution of clustering to large accumulations. S_cont is equal to 1 when S_acc = S_cl, i.e. when the two classifications have episodes with the same number of extreme events at identical ranks. In this case, the contribution of sub-seasonal clustering to large accumulations is maximised for the corresponding catchment. S_cont is equal to 0 when S_acc = 0, i.e. when all episodes in the S_acc classification contain no extreme events (n_w(i) = for all i in [1,Nep]). In this case, there is no contribution of sub-seasonal clustering to large accumulations (there is even no contribution of single extremes to large accumulations).

The episodes selected in Cl_n and Cl_acc can be the same and ordered differently, but they can also differ. For example, this latter case could happen for catchments having episodes of large accumulations without extreme events. Assuming that those catchments have more than N_ep episodes with at least one extreme event, those episodes would likely be selected in Cl_acc but not in Cl_n. In conclusion, S_cl and S_acc may indeed be calculated using different episodes composed of extreme events associated with different dates. However, this is not an issue here as having different episodes in Cl_acc and Cl_n just results in lower values of S_cont which is what we want to capture.

Change: see new section 2.4 in attached document.

- A suggestion is to use subscripts or superscripts "acc" and "n" for S such to clarify instantaneously when this is related to Cl_n and Cl_acc. This could help the reader.

Response: we thank the referee for this useful suggestion. S_cl and S_acc are renamed S_cl (the clustering metric) and S_acc respectively, throughout the new version of section 2.4. We also renamed the ratio S_cont as "S_cont" to highlight its measure of the contribution of clustering to accumulations.

Change: see new section 2.4 in attached document.

L205, Section 3.1. At the moment this section provides a description of the spatial pattern of the maps. Is it possible to provide some physical insights into the interpretation of the maps?

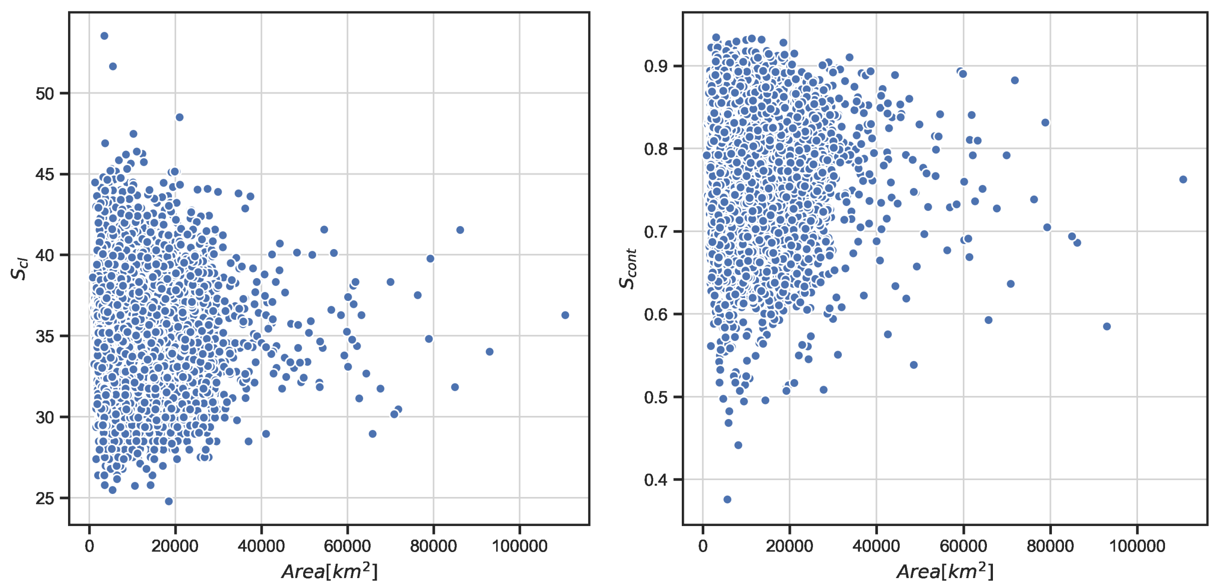
Response: we agree with the referee that this is a particularly interesting and relevant aspect. A detailed analysis of the drivers of subseasonal clustering is beyond the scope of this paper, whose focus is on introducing a new methodology. However, we now discuss the underlying structure of the precipitation time series for representative catchments (new Appendix A with examples) and we added references to existing literature.

Change: see new section 3.1 and Appendix A in attached documents.

L243: The physical drivers of the sub-seasonal clustering of extreme precipitation are numerous and a detailed analysis of the identified clustering patterns is beyond the scope of the present research. Generally speaking, sub-seasonal clustering of extremes requires either very stationary or recurrent conditions that locally provide the ingredients for heavy precipitation (lifting and moisture) (Doswell et al. 1996). In some areas, large-scale patterns of variability have found to be relevant, such as the North Atlantic Oscillation (e.g., Villarini et al., 2011; Yang and Villarini, 2019; Barton et al., in preparation), the El Niño Southern Oscillation (Tuel and Martius, 2021) or the variability of the extratropical storm-tracks (Bevacqua et al., 2020). However, in other areas the circulation patterns associated with clustering differ from the patterns of variability (Tuel and Martius, in preparation). We direct the interested readers to the above-mentioned publications.

L205, Section 3.1, feel free to consider whether the following can be interesting questions/aspects
to investigate or not. It is up to the authors.
- are results dependent on the catchment size?

Response: we analysed this question by computing the correlation between the catchment size and Sr and found no significant correlations. We agree with the referee that this could be briefly mentioned.



Change:
L242: **We investigated a potential link between the catchment size (in km2) and (1) the frequency of clustering episodes (Sn), and (2) their contribution to large accumulations (Sr), by computing the Spearman rank correlation coefficient, but found no significant correlations (not shown).**

- are results dependent on the (i) mean precipitation spatial variability or (ii) precipitation temporal
Variability?

Response: we agree with the referee that those could be interesting points to investigate and could mention them as potential future research questions in the discussion.

- Focussing on some catchments (through showing precipitation time series) where you do find opposite behaviours based on the S metrics could help the reader to better visualise the differences and see what the metric captures. This would also allow for describing some physical aspects leading/not leading to clustering (precipitation relevance) in the direction of Figure 11.

Response: we agree that showing examples would help the reader and thank the referee for this suggestion. The following 3 examples were added in a new Appendix A, see attached PDF):

- A catchment with a high value of S_n and a high value of S_cont (equivalent to a catchment where CI_n is similar to CI_acc, high clustering, high contribution)
- A catchment with a low value of S_n and a high value of S_cont (low clustering, high contribution of this low clustering)
- A catchment with a high value of S_n and a low value of S_cont (equivalent to a catchment where CI_n is not similar to CI_acc, high clustering, low contribution)

Change: new Appendix A containing 3 examples (see attached document).

L 220, (I see that you discuss this also in the final discussion). Can using an arbitrary percentile provide a good understanding of the spatial patterns?
For example, in the context of the metric phi, studies have looked at values significantly higher than zero, given that this implies clustering.
If based on theory it is not possible to define reference thresholds, is it possible based bootstrap procedures to define some thresholds for a “null case” to be used as a benchmark?

Response: We agree with the referee that using a bootstrap procedure could give precious insights on the significance of our results. We therefore tested the following hypothesis for each catchment (see new figure 6b below):

H0: The clustering episodes contain a number of extreme precipitation events (n_w) which is not higher than for a distribution of those extremes without temporal structure (random).

H1: The clustering episodes contain a number of extreme precipitation events (n_w) which is significantly higher than for a distribution of those extremes without temporal structure (random).

and we reject H0 if the observed value of S_cl is significantly greater than a given threshold. A rejection of H0 at a certain level of significance will be further noted as “significant sub-seasonal clustering” for simplicity. To this end, 1000 random samples were generated by doing permutations of the precipitation time series (i.e. each daily value is drawn only one time in each sample, without repetition, this way the distribution quantiles remain identical.). S_cl was calculated for each sample, using the initial parameters combination, and leading to an empirical distribution of S_cl values. An empirical cumulative distribution function (ECDF) was calculated from the S_cl empirical distribution, and an empirical p-value was obtained by evaluating the ECDF at the observed S_cl value: 1-ECDF(S_cl(obs)). At a 1% level, approx.

42% of the catchments (2729 out of 6466) show significant sub-seasonal clustering (Fig. 6b, catchments in red).

Interestingly, the whole S_cl empirical distribution is almost identical for each catchment, with a mean value around 31.42 (*note: this value cannot be used as a reference value as it depends on the choice of parameters (t, r and w*). This means that a selection of catchments based on a given level of significance can be well approximated by a selection based on relatively high observed S_cl values. In section 3, we select catchments pertaining either to the 1st (below the 25th percentile) or 4th quartile (above the 75th percentile) of the observed S_cl distributions for several parameter combinations. It allows for a rapid selection of catchments with rare or prevalent sub-seasonal clustering, whereas the permutation/resampling approach would have required more computational time. We compared the two selection methods and found only limited differences.

Many catchments have a very low p-value because we take an annual percentile for defining the extreme precipitation events. With this definition, catchments with strong seasonality in the precipitation (e.g. with extremes occurring during a "wet" season) will have their extreme events occurring only during a few months. A random permutation of the daily precipitation will redistribute the extremes equally during the year in most cases, corresponding to much lower values of S_cl. Taking seasonal percentiles would most likely result in fewer catchments having very low p-values. The implications of seasonality and the choice of an annual percentile are further discussed in section 4.

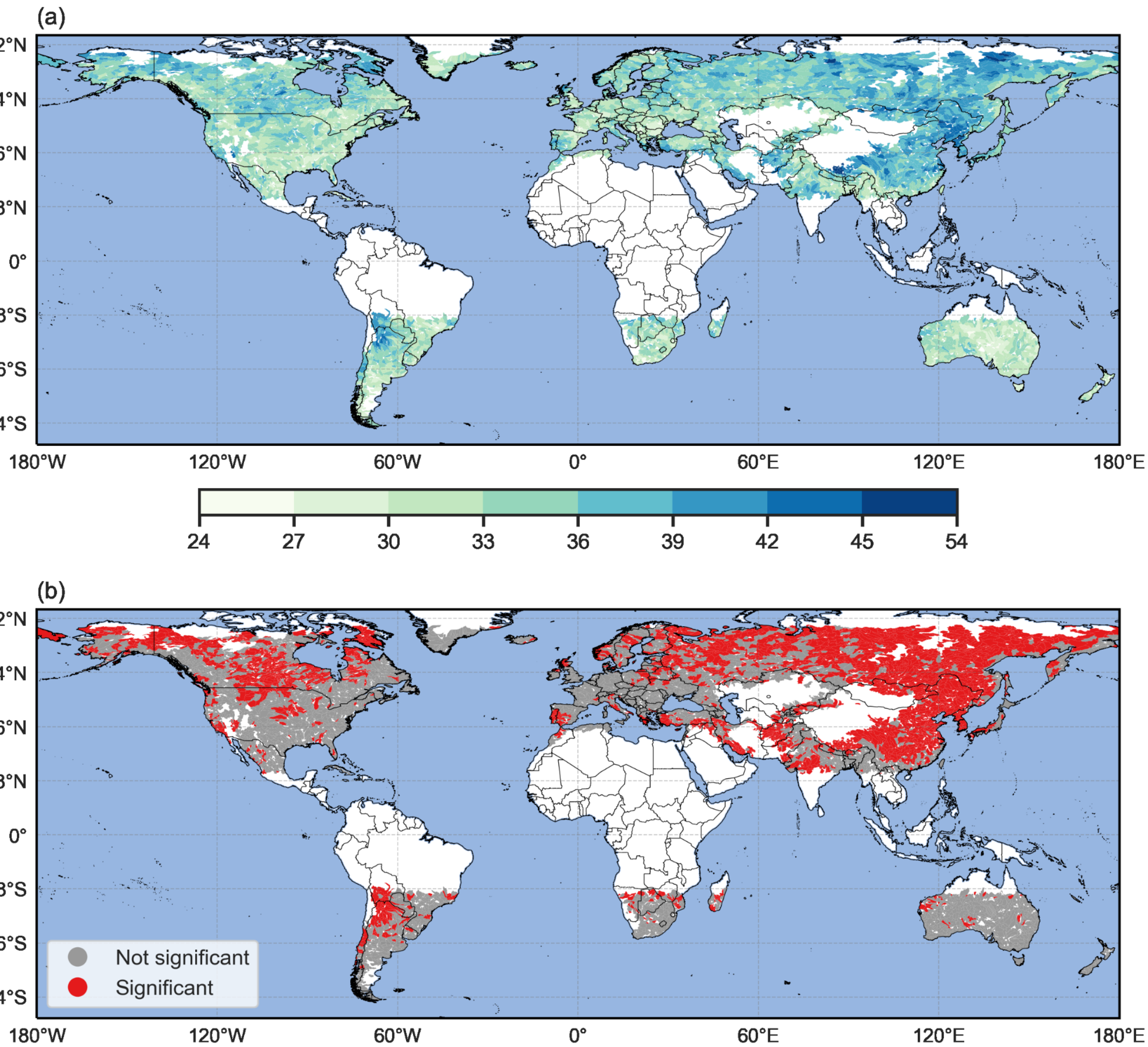


Fig. 6. Metric S_cl (a) and sub-seasonal clustering significance (b) by catchment, for r = 2 days, t = 99p, w = 21 days. In (a), high values of S_cl denote catchments where sub-seasonal clustering is prevalent. In (b), catchments where S_cl is significantly higher than for a distribution of extremes events without temporal structure are shown in red at the 1% level.

Change: revised section 2.5 in attached document, new figure 6b (previous figure 6b has been moved to Appendix E.

L289 ~~One shortcoming of our method is the lack of a simple assessment of the significance of the clustering~~. Our procedure introduces valuable practical refinements to the established methods.

Revised section 2.3 (Identification of sub-seasonal clustering episodes):

L100-118 **The identification of sub-seasonal clustering episodes is equivalent to searching for time periods (here 2 to 4 weeks) that contain several extreme precipitation events**. The first step is to count the number of independent extreme precipitation events (n_w) in a **running (leading)** time window of w days, after the runs declustering has been applied to the time series. This count is computed for each day of the time series over the next w − 1 days (not w, as the starting day is included in the time window length). In parallel, we calculate the running sum of daily precipitation (acc_w) over **the same leading** time window w. Time windows of w = 14, 21 and 28 days were investigated. **Fig. 3c and 3d show the values of n_21 and acc_21, corresponding to the time series of Fig. 3a**.

We then run an automated clustering episode identification algorithm that consists of the following steps: **(i) isolate the days with the largest value of n_w (highlighted in red in Fig. 3c). (ii) Among these days, retain the one with the largest accumulation acc_w (the purple bar in Fig. 3d). This selects a clustering episode which starts at the retained day and ends w-1 days later (shown by the red rectangle in Fig. 3a). The clustering episode identified in Fig. 3 contains four extreme events (n_21 = 4) and the related accumulation acc_21 is 275 [mm]. (iii) reduce the time series by removing all days within w − 1 days before and after the starting day of the selected episode (the purple window in Fig. 3d)**, to avoid further selected episodes from overlapping. **(iv) repeat steps (ii) and (iii) on the reduced time series to successively select the next episodes with the largest values of n_w and acc_w** until a predetermined number of episodes N_ep **= 50** is reached. The choice of N_ep is discussed below in greater detail, and **at this stage we emphasize that limiting the selection to 50 episodes is sufficient for our method**. This iterative selection results in the identification of 50 non-overlapping clustering episodes **sorted by the number of extreme events (n_w) and then by accumulations (acc_w)**. We denote this classification as Cl_n. **The left panel of Table 1 shows the Cl_n classification obtained for a subcatchment of the Tagus river in the Iberian Peninsula (HydroBASINS ID: 2060654920)**. **The Cl_n classification contains information about the frequency of sub-seasonal clustering. In a catchment where sub-seasonal clustering scarcely happens, Cl_n would typically be composed of a majority of episodes having a small number of extremes (e.g. n_w <=2). Whereas for a catchment where sub-seasonal happens frequently, Cl_n would be composed of several episodes with more extreme events (e.g. 2 <= n_w <= 6). Additional examples of catchments can be found in appendix A.**

In addition, we identify and classify the episodes with the **largest** precipitation accumulations as follows: we apply steps (ii) to (iv) of the automated identification algorithm to the **accumulation** time series. **This is equivalent to selecting episodes using the sole criteria of maximising acc_w (the 21-days accumulations) at each iteration**. **This second selection results in the identification of 50 non-overlapping episodes sorted by accumulations (acc_w)**. We denote this classification as Cl_acc. **The right panel of Table 1 shows the Cl_acc classification obtained for the same catchment as the left panel. All episodes listed in Table 1 are represented on the yearly timeline of Fig. 4 (in orange for Cl_n, in blue for**

CI_acc and in grey when they overlap), along with the timing of all extreme events (black dots). We note that the choice of a centred or lagged window, instead of a leading window, does not change the values of n_w and acc_w, except for the first and last w days of the time series. **This has no significant impact on the results**.

The degree of similarity between CI_n and CI_acc is the key point in our method to evaluate the contribution of clustering to large accumulations. This degree of similarity can be evaluated by doing a rank-by-rank comparison of the number of extreme events (n_w) in the episodes of CI_n with the episodes of CI_acc. If the episodes composing CI_acc and CI_n have the same n_w at each rank, then it means that the episodes with the largest number of extreme events are also leading to the largest accumulations. In this particular case, the contribution of clustering to accumulations is maximised. If an episode of CI_acc has fewer extreme events than the episode with the same rank in CI_n, then the contribution of clustering to accumulations is below the maximum contribution. The episodes selected in CI_n and CI_acc can be the same and ordered similarly or differently (they appear in grey in Fig. 4), but they can also differ (they appear in orange or blue in Fig. 4). The fifth columns of the left and right panel in Table 1 illustrate such a comparison, where the corresponding rank of each episode in the other classification is displayed. If the column is empty, it means that the episode is not present in the other classification. In this example, both classifications share the same first episode (n_w = 5), but their second and third episodes have different n_w. We also note the episodes without extreme events in CI_acc (at ranks 11, 24, 30,...). The additional examples in appendix A illustrate cases with different degrees of similarity between CI_n and CI_acc.

L121: ~~As a preliminary remark, we note that if the CIn classification of a given catchment has many clustering episodes that contain several extreme events, then sub-seasonal clustering is occurring frequently in that catchment. Similarly, if the two classifications CIn and CIacc have episodes with the same number of extreme events at identical ranks, this implies that the episodes with the largest number of extreme events correspond to the episodes with the largest precipitation accumulations. In this case, the contribution of sub-seasonal clustering to large precipitation accumulations is maximised.~~

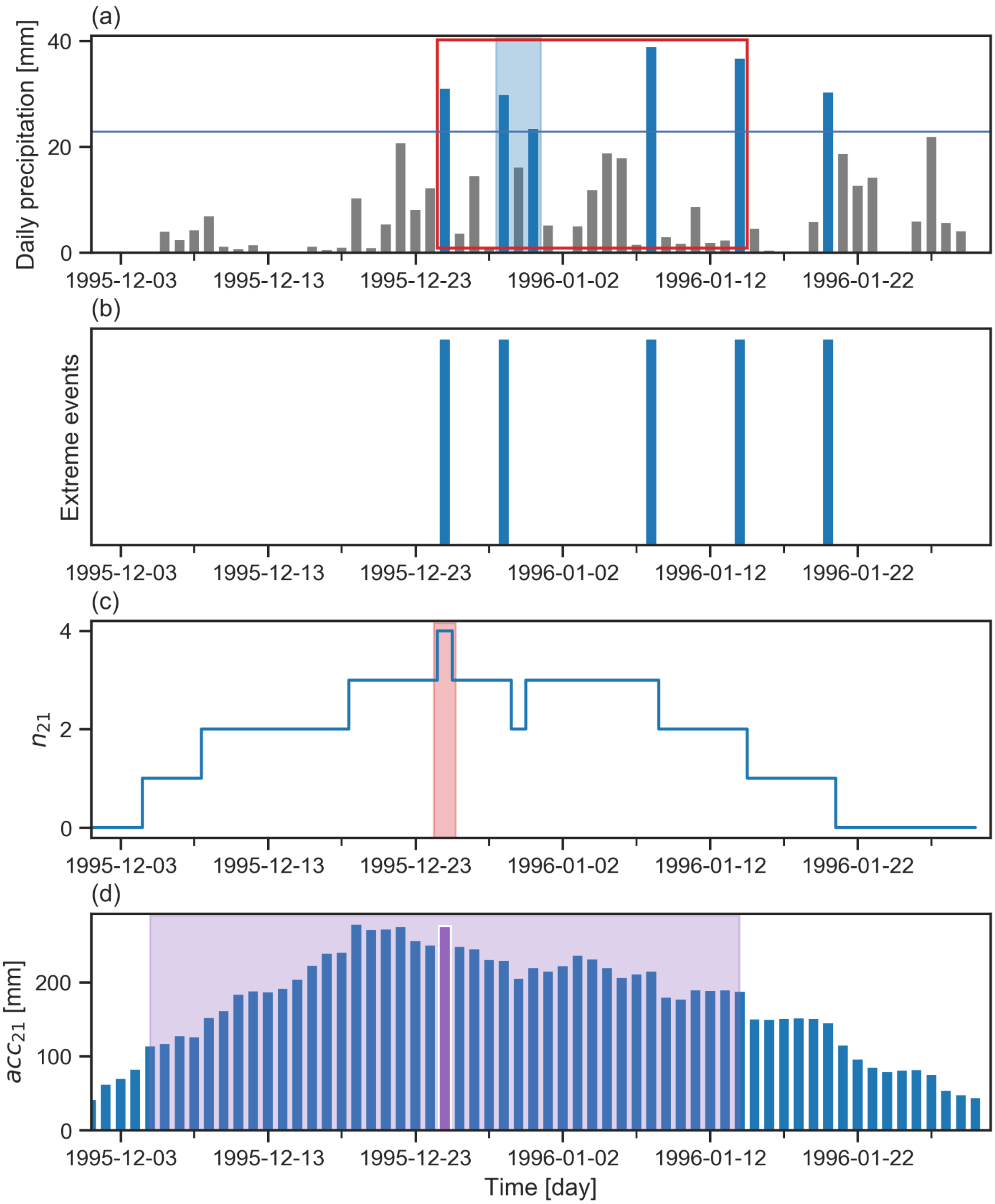


Fig. 3. Schematic illustration of the identification of a sub-seasonal clustering episode with w = 21 days. (a) Time series of daily precipitation with extreme precipitation days marked by blue bars; the horizontal blue line represents the threshold t (e.g. the 99th percentile) defining the extreme events; the light blue shading highlights a high-frequency cluster (r = 2 days) and the red rectangle denotes the clustering episode identified using the information of panel c and (d).

(b) Series of binary events of extreme precipitation obtained after applying the declustering approach to the daily precipitation. (c) Number of extreme precipitation events in a running (leading) time window of 21 days (n_21) based on the time series in panel (b); the light red shading indicates the day with the largest n21. (d) Precipitation accumulation in a running (leading) time window of 21 days (acc_21) derived from the time series of panel (a); the purple bar denotes the day with the largest acc21 among the days with highest n21; this day is the starting day of the selected clustering episode; all days within the light purple shading are removed from the initial time series in the next step of the selection algorithm.

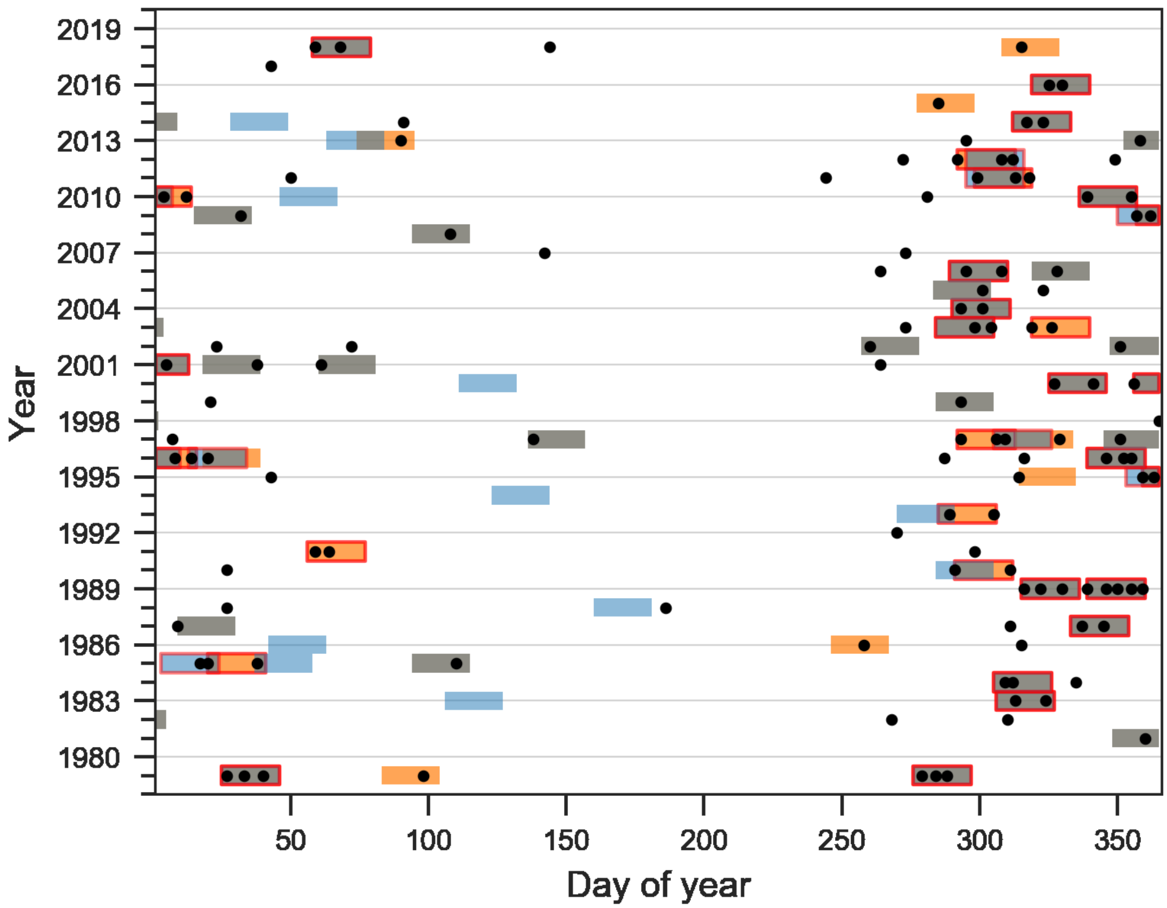


Fig. 4. For the catchment 2060654920, all extreme events are shown as black dots and 21-day episodes are highlighted by the colored rectangles. Episodes appearing in both classifications are shown in grey and those appearing only in the CI_n classification are shown in orange whereas those only in the CI_acc classification are shown in blue Episodes containing two or more extreme events (n_w >= 2) are highlighted with a red edge.

CIn					CIacc				
starting day	acc_21 [mm]	n_21	Rank CIn	Rank CIacc	starting day	acc_21 [mm]	n_21	Rank CIacc	Rank CIn
05.12.1989	281	5	1	1	05.12.1989	281	5	1	1
25.12.1995	275	4	2		19.12.1995	279	3	2	
23.12.2009	213	4	3		16.10.2006	275	2	3	11
25.01.1979	247	3	4	5	27.02.2018	255	2	4	12
11.11.1989	242	3	5	6	25.01.1979	247	3	5	4
04.12.1996	229	3	6	7	11.11.1989	242	3	6	5
03.10.1979	188	3	7	16	04.12.1996	229	3	7	6
19.10.1997	188	3	8		16.12.2009	220	3	8	
18.10.2012	161	3	9		21.12.2000	214	2	9	13
25.10.2011	141	3	10		02.11.1983	212	2	10	14
16.10.2006	275	2	11	3	15.02.2010	202	0	11	
27.02.2018	255	2	12	4	14.12.1981	196	1	12	28
21.12.2000	214	2	13	9	01.11.1997	191	2	13	
02.11.1983	212	2	14	10	20.11.2000	191	2	14	15
20.11.2000	191	2	15	14	13.01.1996	190	2	15	
20.01.1985	160	2	16		03.10.1979	188	3	16	7
02.12.2010	159	2	17	20	21.10.2012	169	2	17	
29.11.1987	154	2	18	23	06.02.1985	163	1	18	
16.10.2004	144	2	19	28	27.09.1993	161	1	19	
31.10.1984	142	2	20	29	02.12.2010	159	2	20	17
08.11.2014	141	2	21	31	11.10.1999	156	1	21	29
12.10.1993	139	2	22		13.12.2002	155	1	22	30
11.10.2003	135	2	23	36	29.11.1987	154	2	23	18
14.11.2016	118	2	24	48	04.03.2013	151	0	24	
25.02.1991	117	2	25		18.12.2013	150	1	25	32
18.10.1990	112	2	26		22.10.2011	147	2	26	
15.11.2003	85	2	27		01.03.2001	144	1	27	33
14.12.1981	196	1	28	12	16.10.2004	144	2	28	19
11.10.1999	156	1	29	21	31.10.1984	142	2	29	20
13.12.2002	155	1	30	22	11.02.1986	142	0	30	
18.01.1996	152	1	31		08.11.2014	141	2	31	21
18.12.2013	150	1	32	25	15.11.2006	138	1	32	35
01.03.2001	144	1	33	27	14.09.2002	137	1	33	36
15.03.2013	142	1	34		03.01.1985	137	2	34	
15.11.2006	138	1	35	32	10.10.2005	136	1	35	37
14.09.2002	137	1	36	33	11.10.2003	135	2	36	23
10.10.2005	136	1	37	35	11.10.1990	135	1	37	
03.04.2008	134	1	38	38	03.04.2008	134	1	38	38
09.01.1987	126	1	39	43	28.01.2014	133	0	39	
09.11.1997	122	1	40		03.05.1994	129	0	40	
15.01.2009	121	1	41	44	16.04.1983	128	0	41	
11.12.1997	120	1	42	45	20.04.2000	127	0	42	
18.01.2001	119	1	43	46	09.01.1987	126	1	43	39
04.04.1985	119	1	44	47	15.01.2009	121	1	44	41
16.05.1997	118	1	45	49	11.12.1997	120	1	45	42
04.10.2015	116	1	46		18.01.2001	119	1	46	43
04.11.2018	116	1	47		04.04.1985	119	1	47	44
03.09.1986	114	1	48		14.11.2016	118	2	48	24
24.03.1979	113	1	49		16.05.1997	118	1	49	45
10.11.1995	112	1	50		08.06.1988	117	0	50	

Table 1. Left panel: Episodes with the largest number of extreme events (n_21) retained in the CI_n classification for catchment with HydroBASINS ID: 2060654920 (corresponding to a subcatchment of the Tagus river in the Iberian Peninsula). Columns are (from left to right):

starting day of the episode, accumulation during the episode (acc_21), number of extreme events during the episode (n_21), rank of the episode (Rank Cl_n), rank of the episode in the Clacc (Rank Cl_acc), an empty Rank Cl_acc column means that the episode is not present in this classification. Right panel: Same as left panel but for episodes with the largest accumulations (acc_21) retained in the Cl_acc classification.

Revised section 2.4 (Metrics for sub-seasonal clustering):

Next we define metrics that synthesize the properties of the two classifications to compare catchments. An intuitive choice for the metrics would be to average the number of extreme events, however such a would result in a loss of information (see Appendix D for a more detailed discussion on this). We take a different approach, equivalent to defining a scoring system, where each episode is given a weight q_i depending on its rank in the classification, and this weight is used as a proportion factor for the number of extreme events in the episode. **We have many options for defining the weights. For example, taking the average over the N_ep episodes (as discussed in Appendix D) is the same as setting all weights equal to 1/N_ep.** Sitarz (2013) discusses a mathematical approach for defining a scoring system in sports, with two intuitively appealing properties. First, the first place should be rewarded more points than the second, and the second more than the third, and so on. In our case, rewarding more points is equivalent to giving a larger weight. Second, the difference between the ith place and the (i+1)th place should be larger than the difference between the (i+1)th place and the (i+2)th place. **The second property means that someone gaining a place (or a rank) should be rewarded more if the initial rank is higher, as improving at upper ranks is more challenging than improving at lower ranks**. We then follow the method of the incenter of a convex cone (Sitarz, 2013) to construct our weighting scheme (see Appendix B for a detailed description). **The same weight q_i is assigned to the ith episode of each classification (Cl_n and Cl_acc)**. **We have tried two other weighting schemes, also satisfying the two required properties: the inverse of the rank (q_i = 1/i) and the inverse of the square root of the rank (q_i = 1/sqrt(i)). The former gave slightly too much weight to the very first episodes of the classification and the latter gave almost identical results to the incenter method. Our results are hence only slightly sensitive to the choice of the weighting scheme, as long as it satisfies the two desired properties.**

We can now use each weight q_i as a proportion factor for the corresponding number of extreme events in the ith episode for both classifications **and derive the three following metrics:**

Clustering Metric: Scl = $\sum_{i \in Cl_n} n_w(i) \cdot q_i$

Accumulation Metric: Sacc = $\sum_{i \in Cl_{acc}} n_w(i) \cdot q_i$

Contribution Metric Scont = Scl / Sacc

The first metric S_{cl}, **called the clustering metri**c, is the weighted (q_i) sum of the number of extreme events ($n_w(i)$) over all episodes (i = 1 to 50) in the Cl_n classification. **S_{cl} is proportional to the number of extreme events in the clustering episodes. It is most sensitive to the number of extreme events in the first clustering episodes, which are given the largest weight. In section 2.5, we show that S_{cl} correlates well with the index of dispersion -- a widely used measure of clustering. Appendix A provides examples of catchments with high and low values of S_{cl} for illustration.**

The second metric S_{acc}, called the accumulation metric, is computed similar to S_{cl}, but using the episodes of the Cl_{acc} classification, where episodes were ranked according to their accumulations. As S_{cl} and S_{acc} are computed using the same weights, their ratio S_{cont} can be used to make a rank-by-rank comparison. S_{cont} is equal to 1 when $S_{acc} = S_{cl}$, i.e. when the two classifications have episodes with the same number of extreme events at identical ranks. S_{cont} is equal to 0 when $S_{acc} = 0$, i.e. when all episodes in the S_{acc} classification contain no extreme events (n_w(i) = for all i in [1,N_ep]). In this particular case, **subseasonal clustering does not contribute to large accumulation and there is even no contribution of single extremes to large accumulations.** In other cases, **a proper assessment of the contribution of clustering to large accumulations is done by considering both S_{cl} and S_{cont}. S_{cont} alone evaluates the similarity of the two classifications and catchments can have low values of S_{cl} (limited sub-seasonal clustering) and high values of S_{cont} at the same time**. The exact interpretation of intermediary values of S_{cont} requires looking at both classifications (Cl_n and Cl_{acc}) in detail to see where they differ from each other. **For example, if S_{cont}= 0.8, both classifications have a high degree of similarity, but it does not necessarily imply that 80% of the episodes are ranked equally. Appendix A provides examples of catchments having high and low values of S_{cont} as an illustration. We normalize S_{cont} to compare different catchments and to assess their sensitivity to the choice of the parameters.**

We now briefly address some technical points related to the definition of the metrics. We note that performing a regression between Cl_n and Cl_acc would be a more conservative approach in assessing their degree of similarity because it would require giving a unique identifier to each episode according to its starting day. In that case, the strength of the regression would be lowered when two episodes containing the same number of extreme events just swap their ranks in the two classifications. Such a change does not affect S_cont.

S_cl and S_acc both increase with the number of extreme events per episode so any parameter change which increases this number will also lead to an increase in Scl and

Sacc. Appendix C shows boxplots of S_cl for all parameter combinations. We see that a lower threshold t, a shorter run length r, and a larger window w lead to an increase in the values of S_cl. However, the sensitivity of S_cl and S_acc to the parameters does not affect our general conclusions. First, a change of parameters impacts all catchments, so while the scale of S_cl (or S_acc) is changed, the comparison of two catchments will result in the same conclusion in almost all cases. That is, a catchment with a relatively low value of S_cl compared to other catchments for one parameter combination will also have a relatively low value for other combinations and similarly for high values. Second, the sensitivity of S_cont to the parameters (which depends on both S_cl and S_acc) is explicitly assessed in section 3.2 and accounted for in our results.

[Continue at L177]

Appendix B: Calculation of the weights (new) - composed of L129 to L150.

Revised section 2.5: (Correlations with index of dispersion and significance test):

L185-197: unchanged

L197: ~~This is illustrated in Fig. 6, which shows Sf and phi for the initial parameter combination and where it can be seen that regions of high (low) Sf correspond to regions of high (low) phi. Figure 6a is further discussed in the results section.~~

L197: This is further illustrated in **Fig. 6a ad Fig. D1** in Appendix D, which respectively show a map of S_cl and a map of phi_hat for the initial parameters combination. A visual comparison of the two maps reveal that regions of high (low) S_cl correspond to regions of high (low) phi_hat.

An evident drawback of S_cl compared to phi_hat is the lack of a reference value above (below) which there is (no) clustering (phi_hat = 1). While we cannot derive such a reference value, we can still use a bootstrap based approach to assess how significant the value of Sn is for each catchment. More precisely, we tested the following hypothesis:

H0: The clustering episodes contain a number of extreme precipitation events (n_w) which is not higher than for a distribution of those extremes without temporal structure (random).

H1: The clustering episodes contain a number of extreme precipitation events (n_w) which is significantly higher than for a distribution of those extremes without temporal structure (random).

and we reject H0 if the observed value of S_cl is significantly greater than a given threshold. A rejection of H0 at a certain level of significance will be further noted as “significant sub-seasonal clustering” for simplicity. To this end, 1000 random samples

were generated by doing permutations of the precipitation time series (i.e. each daily value is drawn only one time in each sample, without repetition, this way the distribution quantiles remain identical.). S_cl was calculated for each sample, using the initial parameters combination, and leading to an empirical distribution of S_cl values. An empirical cumulative distribution function (ECDF) was calculated from the S_cl empirical distribution, and an empirical p-value was obtained by evaluating the ECDF at the observed S_cl value: 1-ECDF(S_cl(obs)). At a 1% level, approx. 42% of the catchments (2729 out of 6466) show significant sub-seasonal clustering (Fig. 6b, catchments in red).

Interestingly, the whole S_cl empirical distribution based on the random samples is almost identical for all catchments, with a mean value around 31.42. This means that a selection of catchments based on a given level of significance can be well approximated by a selection based on relatively high observed S_cl values. In section 3, we select catchments which are either below the 25th percentile or above the 75th percentile of the observed S_cl distribution for all catchments. It allows for a quick selection of catchments with rare or prevalent sub-seasonal clustering for each parameters combination, whereas the permutation/resampling approach would have required more computational time. We compared the two selection methods for the initial parameters combination and found only limited differences.

Many catchments have a very low p-value because we take an annual percentile for defining the extreme precipitation events. With this definition, catchments with strong seasonality in the precipitation (e.g. with extremes occurring during a "wet" season) will have their extreme events occurring only during a few months. A random permutation of the daily precipitation will redistribute the extremes equally during the year in most cases, corresponding to much lower values of S_cl. Taking seasonal percentiles would most likely result in fewer catchments having very low p-values. The implications of seasonality and the choice of an annual percentile are further discussed in section 4.

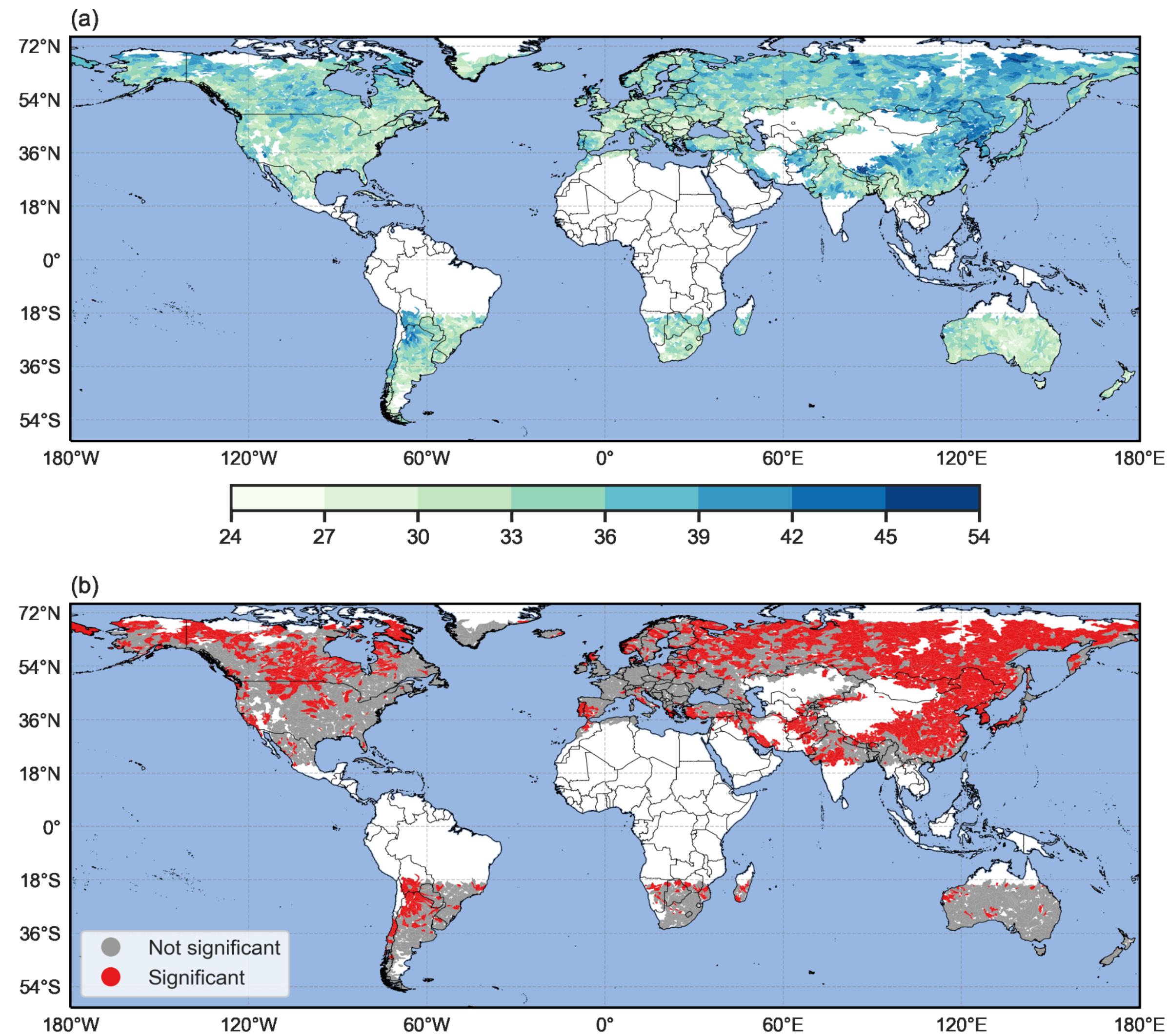


Fig. 6. Metric S_cl (a) and sub-seasonal clustering significance (b) by catchment, for r = 2 days, t = 99p, w = 21 days. In (a), high values of S_cl denote catchments where sub-seasonal clustering is prevalent. In (b), catchments where S_cl is significantly higher than for a distribution of extremes events without temporal structure are shown in red at the 1% level.

Revised section 3 (Results):

~~*First, world maps of the **clustering (Scl) and contribution (Scont) metrics** for all selected catchments are shown using the initial combination of parameters (r = 2 days, t = 99p, w = 21 days). These maps indicate regions where sub-seasonal clustering is prevalent. Then, the sensitivity of the sub-seasonal clustering to the parameter choice is assessed by testing 12 different parameter combinations: w = 14,21,28 days; u = 98p,99p; r = 1,2 days.*~~

3.1 Sub-seasonal clustering and its contribution to accumulations:

Sub-seasonal clustering is prevalent in catchments having high values of S_cl (see section 2.5). Such catchments are located in the east and northeast of the Asian continent (northeast of Siberia, northeast of China, Korean Peninsula, south of Tibet); between the northwest of Argentina and the southwest of Bolivia; in the northeast and northwest of Canada as well as in Alaska; and in the southwestern part of the Iberian Peninsula (Fig. 6a and 6b). Regions with low values of **S_cl** are located on the east coast of North America, on the east coast of Brazil, in central Europe, in South Africa, in central Australia, in New Zealand and in the north of Myanmar (Fig. 6a and 6b). Catchments with strongly contrasting values of **S_cl** are rarely found in close proximity, except for a group of catchments located northeast of the Himalayas (south of Tibet), and another group located southeast of the Himalayas (Bangladesh and Myanmar). The catchments to the north have high values of **S_cl**, whereas the neighbouring catchments to the south exhibit low values of **S_cl**.

~~Regions with large values of the relevance metric (Scont, see Fig. 7) are in the east and northeast of the Asian continent, west of India, central Australia and central North America. Areas with low values of Scont are located in central China, on the east coast of North America, in the south of Brazil and in France.~~

The contribution of sub-seasonal clustering to precipitation accumulations is analysed with both S_{cl} and S_{cont}. Catchments with high values of S_{cl} and S_{cont} are of special interest, because in these catchments, sub-seasonal clustering is prevalent and contributes substantially to large 21-days precipitation accumulations. We identify such catchments by considering those whose values of S_{cl} and S_{cont} are greater than the 75th percentile of their respective distribution for all catchments. The choice of the 75th percentile makes it possible to focus on the highest values, without being too restrictive, and follows the quick selection method mentioned in section 2.5. Catchments where sub-seasonal clustering is prevalent and contribute substantially to large accumulations are mainly concentrated over eastern and northeastern Asia (Fig. 7a). The largest continuous area of such catchments is located in northeastern China, in North and South Korea, Siberia and east of Mongolia. Other areas with several catchments of interest are central Canada, south California, Afghanistan, Pakistan, the southwest of the Iberian Peninsula, the north of Argentina and the south of Bolivia. Every continent includes groups of two to three or isolated catchements. **Appendix A1 contains detailed information for an example catchment with a strong seasonality located in northeastern China (S_{cl} = 41.14, S_{cont} = 0.93). Almost all extreme events happen between June and August, which make clustering episodes and periods of large accumulations more likely to overlap.**

We also identify catchments with values of S_cl below the 25th percentile and values of S_cont above the 75th percentile (Fig. 7b). Low values of S_cl mean that the clustering episodes identified by our algorithm contain a small number or even no extreme events, and high values of S_cont mean that those episodes lead to the largest accumulations. Such regions that exhibit rare clustering and where this rare clustering contributes substantially to large accumulations are the following: Taiwan, most of Australia, central Argentina, South Africa, south of Botswana and south of Greenland. **Again, every continent includes groups of two to three or isolated catchements**. Interestingly, the identified catchments are almost all located in the Southern hemisphere. **An example located in Australia is presented in detail in Appendix A2 (S_cl = 26.79, S_cont = 0.90). The extreme events are distributed throughout the whole year and only a limited number of episodes contain two or more extreme events.**

Finally, we identify regions with values of S_cl above the 75th percentile and values of S_cont below the 25th percentile (Fig. 7c). The high values of S_cl mean that the clustering episodes identified by our algorithm contain a relatively large number of extreme events, whereas the low values of S_cont mean that episodes leading to the largest accumulations contain a low number or even no extreme events. Such regions that exhibit prevalent clustering with a limited contribution to large accumulations are the following: the south of Tibet, the south of the Qinghai and west of the Sichuan Chinese provinces and central Bolivia. **Again, every continent includes groups of two to three or isolated catchements**. Only a few catchments exhibit this combination of high S_cl and low S_cont values, highlighting the importance of the clustering of extreme events for generating the largest accumulations for the majority of the catchments. **An example located in central China is presented in detail in Appendix A3 (Scl = 43.23, Scont = 0.59). The seasonality is present but less pronounced than in example A1: almost all extreme events happen between mid-May and September. However, in this case, clustering episodes and periods of large accumulations tend not to overlap as much as in Example A1. This is a particularly interesting feature, especially because the two different patterns exemplified by Appendix A1 and A3 happen in neighbouring regions.**

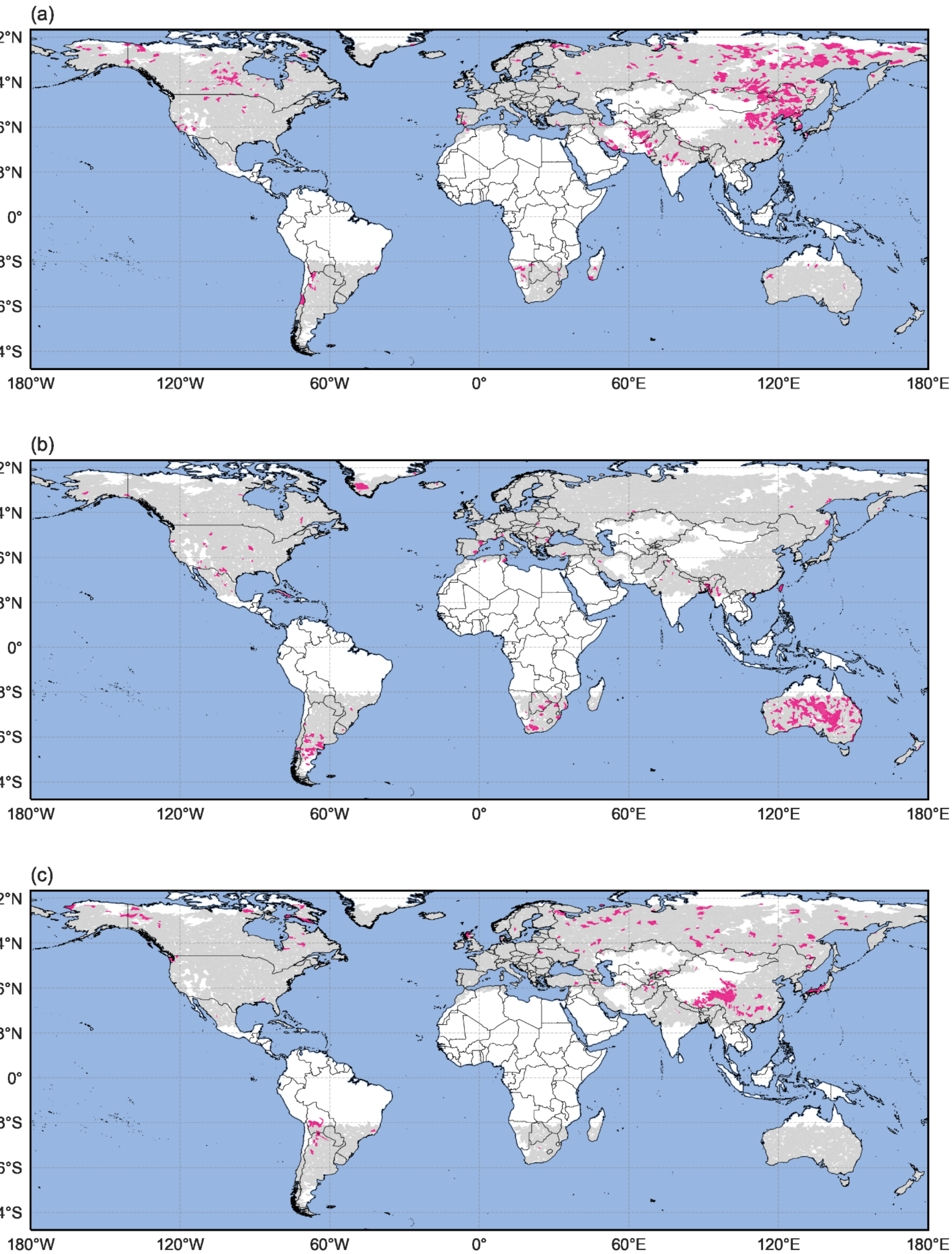


Fig. 7. (a) Catchments where S_{cl} and S_{cont} are both above the 75th percentile of their respective distribution (pink areas); (b) Catchments where S_{cl} < 25p and S_{cont} > 75p (pink areas); (c) Catchments where S_{cl} **>** 75p and S_{cont} **<** 25p (pink areas). In all panels, catchments in grey do

not satisfy the respective conditions, whereas catchments in white were excluded from the analysis according to the criteria defined in section 2.1.

We investigated a potential link between the catchment size (in km2) and both the clustering (S_cl) and the contribution metric (S_cont), by computing their Spearman rank correlation coefficient, but found no significant correlations (not shown).

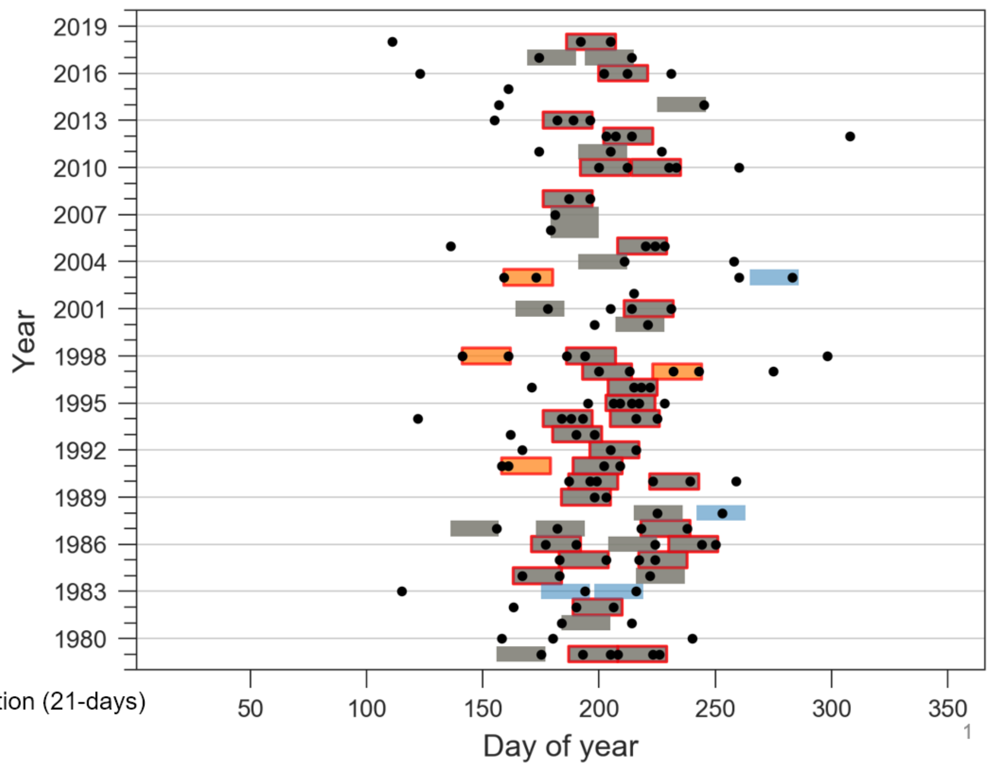
The physical drivers of the sub-seasonal clustering of extreme precipitation are numerous and a detailed analysis of the identified clustering patterns is beyond the scope of the present research. Generally speaking, sub-seasonal clustering of extremes requires either very stationary or recurrent conditions that locally provide the ingredients for heavy precipitation (lifting and moisture) (Doswell et al. 1996). In some areas, large-scale patterns of variability have found to be relevant, such as the North Atlantic Oscillation (e.g., Villarini et al., 2011; Yang and Villarini, 2019; Barton et al., in preparation), the El Niño Southern Oscillation (Tuel and Martius, 2021) or the variability of the extratropical storm-tracks (Bevacqua et al., 2020). However, in other areas the circulation patterns associated with clustering differ from the patterns of variability (Tuel and Martius, in preparation). We direct the interested readers to the above-mentioned publications.

Appendix A: Examples of catchments

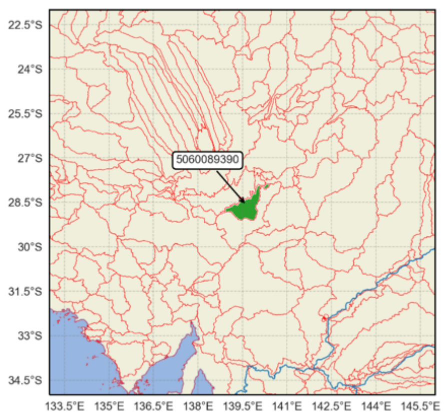
A1: Catchment with frequent subseasonal clustering contributing substantially to large accumulations (S_f = 41.14; S_r = 0.93)

Green area: catchment location (northeastern China).
Annotation: HydroBASINS number.
Red lines: HydroBASINS catchment boundaries.
Area: 9893.4 [km]
99th quantile: 30.16 [mm]
# of episodes with ≥ 2 extreme events : 34

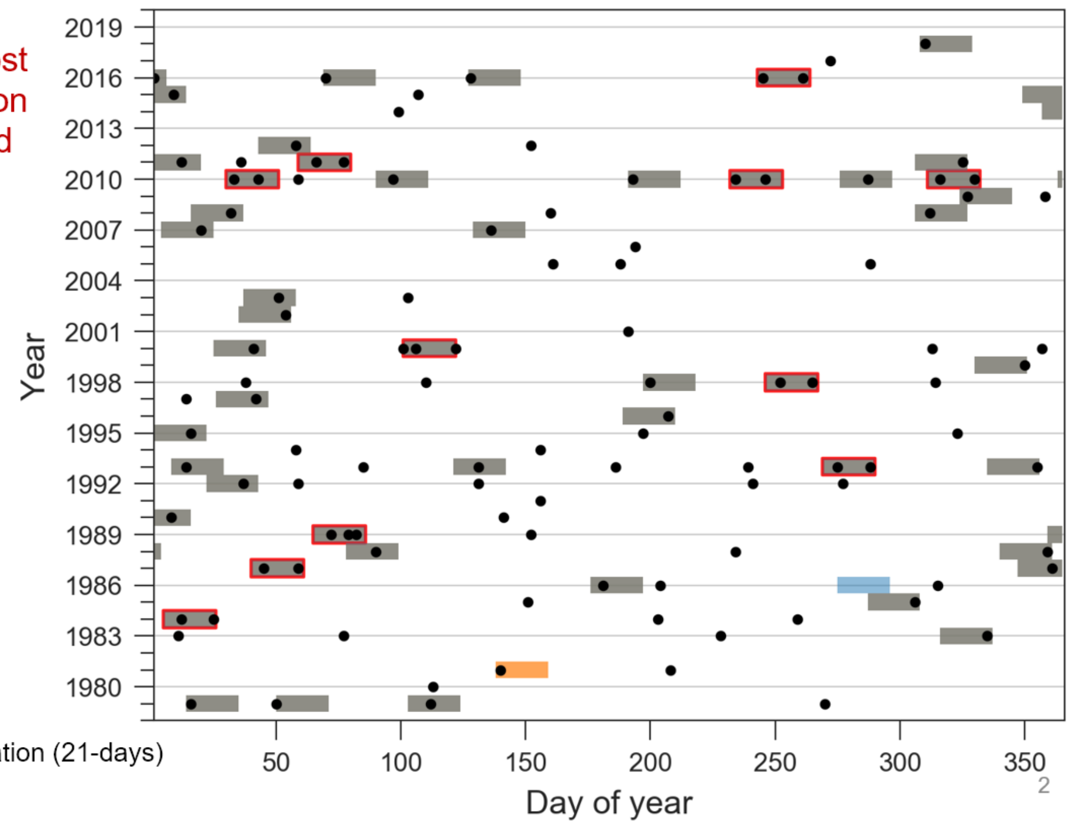
- Extreme events (> 99th percentile)
- Subseasonal clustering episode (21-days)
- Episode of large accumulation (21-days)
- Clustering episode contributing to large accumulation (21-days)
- Episode with ≥ 2 extreme events



A2: Catchment with rare subseasonal clustering contributing substantially to large accumulations* ($S_f = 26.79$; $S_r = 0.90$)



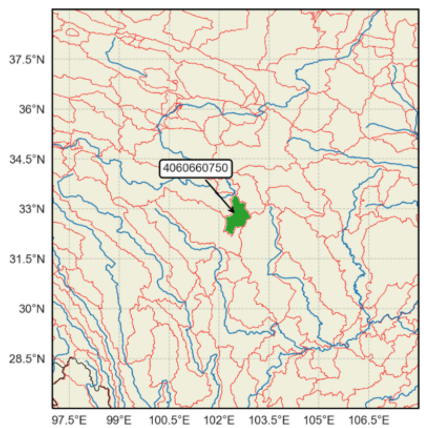
*in that case most of the contribution is due to isolated extreme events



Green area: catchment location (Australia).
Annotation: HydroBASINS number.
Red lines: HydroBASINS catchment boundaries.
Area: 7769.8 [km]
99th quantile: 12.10 [mm]
# of episodes with ≥ 2 extreme events : 11

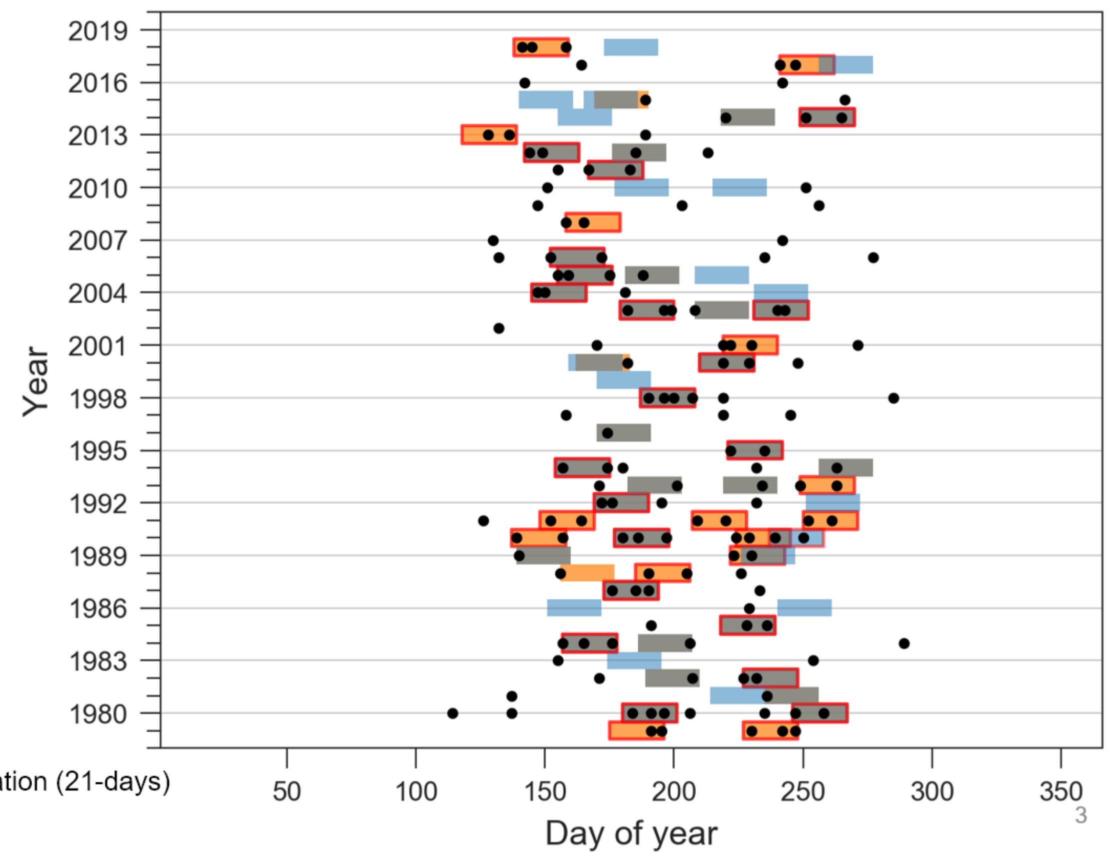
- Extreme events (> 99th percentile)
- Subseasonal clustering episode (21-days)
- Episode of large accumulation (21-days)
- Clustering episode contributing to large accumulation (21-days)
- Episode with ≥ 2 extreme events

A3: Catchment with frequent subseasonal clustering and limited contribution to large accumulations ($S_f = 43.23$; $S_r = 0.59$)



Green area: catchment location (central China).
Annotation: HydroBASINS number.
Red lines: HydroBASINS catchment boundaries.

Area: 5492 [km]
99th quantile: 17.31 [mm]
# of episodes with ≥ 2 extreme events : 35



- Extreme events (> 99th percentile)
- Subseasonal clustering episode (21-days)
- Episode of large accumulation (21-days)
- Clustering episode contributing to large accumulation (21-days)
- Episode with ≥ 2 extreme events

Appendix B: Calculation of the weights q_i

Sitarz (2013) assumes two intuitive conditions for a scoring system. First, he assigned more points for the first place than for the second place, and more for the second than for the third, and so on. Second, the difference between the ith place and the (i+1)th place should be larger than the difference between the (i+1)th place and the (i+2)th place. This is equivalent to considering the following set of points:

$$K = \left\{(x_1, x_2, \cdots, x_N) \in \mathbb{R}^N : x_1 \geq x_2 \geq \ldots \geq x_n \geq 0 \text{ and } x_1 - x_2 \geq x_2 - x_3 \geq \cdots \geq x_{N-1} - x_N\right\}$$

where x_1 denotes the points for first place, x_2 the points for second place,. . . , and x_N the points for Nth place. Any choice of points in K would satisfy the two conditions for a scoring system, however we would like to have a unique and representative value. The option chosen by Sitarz (2013) is to look for the equivalent of a mean value: the incenter of K. Formally, the incenter is defined as an optimal solution of the following optimization problem by Henrion and Seeger (2010):

$$\max_{x \in K \cap S_x} dist(x, \partial K)$$

where S_x denotes the unit sphere, dK denotes the boundary of set K and dist denotes the distance in the Euclidean space. By using the calculation presented in the Appendix of Sitarz (2013), and dividing by ~~the parameter lambda and~~ the points of the first place (x_1) to get the weights (q_i), we obtain:

$q_i = x_i/x_1$ for all i in [1,N]

The weight q_1 is always 1 but the values of weights q_2 to q_N depend on N and in our case N is the number of clustering episodes N_{ep}.

Appendix C:

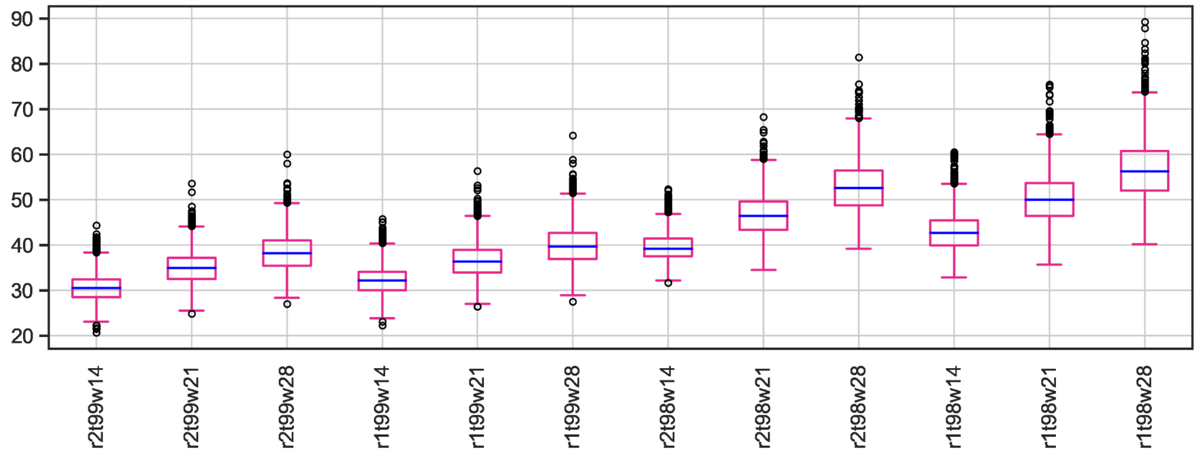


Fig. C1. Boxplots of S_cl for all catchments and parameters combinations. Boxes extend from the first (Q1) to the third (Q3) quartile values of the data, with a blue line at the median. The position of the whiskers is 1.5 * (Q3 - Q1) from the edges of the box. Outlier points past the end of the whiskers are shown with black circles.

Appendix D: Rationale behind the construction of the metrics

An intuitive choice to define the metrics (see section 2.4) is to use the sum or average of the number of extreme events over all (or a subset of) the episodes of Cl_n and Cl_acc. However, such a choice would result in a loss of relevant information on how the episodes are ranked, and preclude a rank-by-rank comparison between classifications. This can be illustrated with the following theoretical example: let us consider a catchment where Cl_n is composed of 5 episodes, each with 3 extreme events, and 5 other episodes, each with 1 extreme event (i.e., N_ep = 10). The average number of extreme events is 2. If Cl_acc is composed of the same episodes, then the average remains identical whatever the order of the episodes in Cl_acc and we cannot say anything about the contribution of clustering to accumulations by comparing the averages. For example, all episodes with 1 extreme event could have larger accumulations than those with 3 extreme events. There is a low contribution of clustering to accumulations in this case, and metrics based on averages would not be able to capture this feature. A metric based on average would also fail to capture some differences in the same classification between two catchments. This again can be illustrated with a theoretical example: let us consider catchment A where Cl_n is composed of 5 episodes: 1 with 5 extreme events, the 4 others without extreme event; and catchment B where Cl_n is composed of 5 episodes, each with 1 extreme event. In both cases the average number of extreme events is 1 but the clustering behaviour is different. Consequently, we need a way to properly account for the respective rank of each episode in both classifications.

Appendix E:

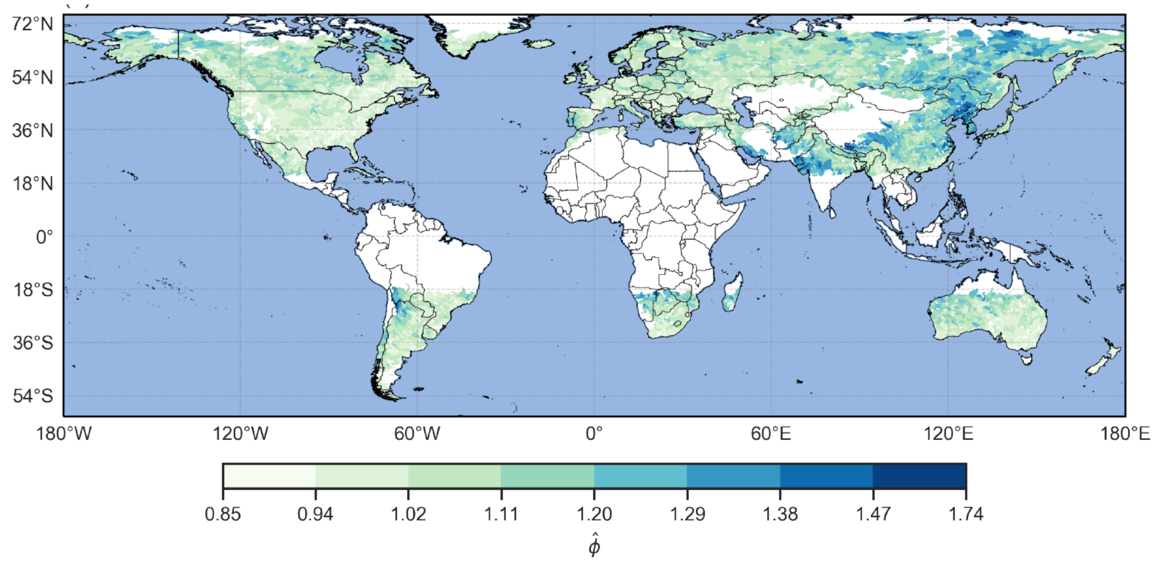


Fig. E1. Index of dispersion phi by catchment, for r = 2 days, t = 99p, w = 21 days. phi > 1 denotes catchments where extreme precipitation events are more clustered than random.

<u>New References:</u>

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Tuel A. and Martius O. (2021), A global perspective on the sub-seasonal clustering of precipitation extremes, submitted to Weather and Climate Extremes, in review. This manuscript is confidential but if reviewers want, we are happy to share it.