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Hydrology and Earth System Sciences
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Discussions

Interactive comment on "Identifying rainfall-runoff events in discharge time series: A data-driven method based on Information Theory" *by* Stephanie Thiesen et al.

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We thank Dr. Yiwen Mei for reviewing our article and providing his feedbacks. Following, we have addressed all of his comments and discussed them. The observations were very helpful to identify some unclear issues regarding the method application.

Summary: This manuscript describes a flood event identification method based on information theory. The idea of using data-based method in automatic event identification is novel; and few studies investigated event identification method for hourly flow time series. I am overall supportive of this research but I have some major concerns that need to be addressed by the authors. At this stage, I would assign major revision to

the manuscript.

1. Precipitation information

Comment 1: Results of the manuscript show that precipitation at the current time step is not an informative predictor for flood event. I think this makes sense because there is always a lag time for the excess rainfall to travel to the outlet of the catchment. This has also been pointed out by Mei and Anagnostou (2015) with an event time lag parameter. Therefore, could a cumulative precipitation quantity that is produced based on a window with some size before the current time step help?

Response 1: We agree that aggregated precipitation is a potentially very useful predictor for event detection and will likely improve the results. The choice of predictors is an interactive and incremental process, and besides aggregated precipitation there may be other predictors which may eventually improve the results obtained so far. Thus, since the main point of the paper is to introduce the method without necessarily finding the perfect predictive model, and since precipitation data are often not available for analysis, we consider that the presented application is sufficient to demonstrate the potential of the approach. We suggest adding to a revised version of the manuscript a short discussion on the potential of using aggregated precipitation as a predictor.

2. Size of evaluation window

Comment 2: Fig. 4: clearly, the window sizes are different in the center scheme to the forward and backward one and I observed different patterns of the conditional entropy with number of time step involved. I wonder why the authors did not use 2*n in the forward and backward scheme to make the window size consistent?

Response 2: We have designed this parameter in a way such as to explore all possible window sizes at the finest resolution, while avoiding problems such as centering with odd window sizes. The "n" for each predictor was selected individually, and only displayed simultaneously on the same graph. The suggestion by the referee can be met by simply using window size as x-axis position instead of "n" in the graph. We suggest that neither of the two choices entails a particular advantage or disadvantage. Thus, considering that the results are clearly visible and that the results will remain the same, we prefer to keep it as it is.

3. Probability threshold of event

Comment 3: Clearly, the selection of an optimal probability threshold is essential of the proposed method but the authors did not introduce a method of doing so. The only description is on P14 L10-15 and given the relatively short demonstration period, the authors arbitrarily select 75%. I wonder could such a threshold change with a) increasing number of time step and b) different basins?

Response 3: Indeed the threshold could be optimized, and it might be different for different datasets. We chose 75% as a threshold rather ad hoc, and only to demonstrate that it is possible to convert by choosing threshold the probabilistic prediction to a binary one if so desired. If there is no particular reason to do so, it will always be better to keep the probabilistic result as the binary transformation includes loss of information. That said, we agree with the referee that if a binary result is desired, the choice of threshold can and should be found by optimization. If the editor finds this a useful addition, we will do the related analysis (optimization by maximizing the number of hits in a contingency table) and add it to the manuscript. This will add about $\frac{3}{4}$ of a page to the manuscript (contingency table plus explanations).

4. Automation of the method action

Comment 4: It can be seen from Figure 7 that there exist time steps associated with probability lower than 75% within the manually-identified events. This means that event identified by a user-defined fixed probability threshold are different than the manually identified one (i.e. the automatic one will have more events due to the existence of more separation time steps). So, do the authors have a method to skip those very-short discontinuous time steps so as to form longer events in an automatic manner?

Response 4: We agree that in general it is desirable to have non-interrupted events of realistic length, but would like to mention that for some use-cases it is not relevant (e.g. if only the number of time steps classified as event is of interest). However, we see the use-cases where this property is of interest. There are several ways to address this in our method: The first is to include a memory effect in the classification by applying a recursive predictor ep(t-1). Comparable to a Markov model, this helps the model to better 'stick' to a classification after a transition from event to no-event or vice versa. While we already present and discuss such a model in the manuscript, the memory effect could be further enhanced if required by adding more recursive predictors (t-2, t-3, etc.). An alternative option would be to increase event coherence in a postprocessing step with an autoregressive model, with model parameters found by maximizing agreement with the observed events. We prefer the first method as it simply adds more predictors instead of adding another model component. We suggest describing these two options in a revised version of the manuscript.

5. Detection of snowmelt event

Comment 5: The authors show that the algorithm fell to detect the snowmelt event. I wonder is the inclusion of additional predictor can potentially help to extract the snowmelt event? For example, by adding in the in-situ or remote sensing-based observation of snow depth/extend, ground temperature and date of year, could the snowmelt event be identified?

Response 5: One of the strengths of the data-based approach we describe is that it accepts any kind of additional predictors such as air temperature, nitrate concentrations, etc. We agree with the referee that snow depth (or depth change) could be a potentially very useful predictor to identify snowmelt events. As mentioned in comment #1, we suggest that doing so would add another facet of application to the manuscript, but would not add to the method description as such. We therefore suggest adding a brief discussion of this topic in a revised version of the manuscript, but not an application.

6. Comparison with existing method

Comment 6: I think a comparison with the existing event identification methods could help to reveal the values of this newly-developed data-based method. If the authors would like to compare with Mei and Anagnostou (2015) method they may find the matlab codes on our GitHub profile (https://github.com/YiwenMei/Hydro_Seper). Another way to verify the method is to demonstrate the patterns of flood event parameters (e.g., runoff coefficient, time lag, baseflow) of events identified by the method.

Response 6: We agree that a comparison with existing method adds a valuable additional perspective to the study. If the Editor agrees, we will apply the Mei and Anagnostou method and compare results to the binary transforms of our probabilistic predictions via contingency tables and time-series plots. This will add at least one page to the manuscript.

7. Potential usage of the method

Comment 7: I did not see descriptions on potential usage of this method. Can this method be used to construct flood event database like for example the Shen et al. (2017, Comprehensive Database of Flood Events in the Contiguous United States from 2002 to 2013) constructed by the Characteristic Points Method introduced in Mei and Anagnostou (2015)?

Response 7: Given sufficient data to learning, we believe it is possible to construct such a database with our method. For each gauge in the database an individually optimized set of predictors could be identified. In addition, since we are dealing with a data-driven approach and avoiding parametrizations such as equations or indexes, the more event categories we aspire to classify, the more data will be required. Potential usages of the method were mentioned at the beginning of the introduction (P2 L8-34). We suggest adding the usage suggested by the referee to it.

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