

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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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.

C1

Comment

1. Precipitation information

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?

2. Size of evaluation window

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 $2 \cdot n$ in the forward and backward scheme to make the window size consistent?

3. Probability threshold of event

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?

4. Automation of the method

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?

C2

5. Detection of snowmelt event

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?

6. Comparison with existing method

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.

7. Potential usage of the method

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)?

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