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Quantifying space-time patterns of precipitation importance for flood generation via interpretability of deep-learning models

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This study proposes a new approach for quantitively assessing the importance of precipitation features in space and time to predict streamflow discharge (and, hence, sensitivity). For this, we combine well-performing deep-learning (DL) models with interpretability tools.

The DL models are composed of convolutional neural networks (CNNs) and long-short term memory (LSTM) networks. Their input is precipitation data distributed over the watershed and taken back in time (other inputs, meteorological and watershed properties, can also be included). Its output is streamflow discharge at a present or future time. Interpretability tools allow learning about the modeled system. We used the Integrated Gradients method that provides a level of importance (IG value) for each space-time precipitation feature for a given streamflow prediction. We applied the models and interpretability tools to several watersheds in the US and India.

To understand the importance of precipitation features for flood generation, we compared spatial and temporal patterns of IG for high flows vs. low and medium flows. Our results so far indicate some similar patterns for the two categories of flows, but others are distinctly different. For example, common IG mods exist at short times before the discharge, but mods are substantially different when considered further back in time. Similarly, some spatial cores of high IG appear in both flow categories, but other watershed cores are featured only for high flows. These IG time and space pattern differences are presumably associated with slow and fast flow paths and threshold-runoff mechanisms.

There are several advantages to the proposed approach: 1) recent studies have shown DL models to outperform standard process-based hydrological models, 2) given data availability and quality, DL models are much easier to train and validate, compared to process-based hydrological models, and therefore many watersheds can be included in the analysis, 3) DL models do not explicitly represent hydrological processes, and thus sensitivities derived in this approach are assured to represent patterns arise from the data. The main disadvantage of the proposed approach is its limitation to gauged watersheds only; however, large data sets are publicly available to exploit sensitivities of gauged streamflow.

It should be stressed out that learning about hydrological sensitivities with DL models is proposed

here as a complementary approach to analyzing process-based hydrological models. Even though DL is considered black-box models, together with interpretability tools, they can highlight hard or impossible sensitivities to resolve with standard models.