Dear Dr. Ball,

We greatly appreciate your thoughtful comments and suggestions that helped us to improve the manuscript. Based on your comments, we have revised the manuscript accordingly and we believe that your comments have been addressed. In the following, we give a point-by-point reply to your comments.

(1) Reply to comment 1 regarding model calibration

Thanks for this critical and good comment. We agreed that high flows are more important in real-time flood forecasting. Actually the reason why we performed the two-step calibration (Section 3.4) is to better reproduce the high flows. We first calibrated the parameters based on the complete time-series of runoff observations using PEST, which fits both low and high flows. Then for the second step, we adjusted the parameters by trial and error approach, mainly according to high flows. Such straightforward but effective calibration strategy stroked a balance between the representativeness of the runoff data and the importance of large flood events, providing the reliable baseline to validate the XAJ-EB model in this study. We have revised the Section 3.4 to describe the calibration strategy we used clearly.

Moreover, by coupling the mass balance, we added more constrains to the XAJ model, which can help the model to reproduce more reliable hydrological processes in both flood and non-flood periods. As such, the complete time-series of runoff observations are necessary in order to evaluate Runoff/ET/LST from XAJ-EB under various hydrometeorological conditions. We also revised the introduction part to better justify our motivations.

We also added a separate section regarding the parameters calibration to address your concern (Section 4.3). Generally, runoff data including both dry and wet conditions is required to represent the various characteristics of the catchment, from which the stable and robust parameter values can be obtained (PERRIN et al., 2007; Razavi and Tolson, 2013; Singh and Bárdossy, 2012) . However, short-period runoff observations of wet period can be used for calibration if the data availability is poor, which is also able to provide acceptable calibration results (Kim and Kaluarachchi, 2009; Sun et al., 2016; Wang et al., 2017). In this study, the complete time-series of runoff observations are necessary, however, a more rigorous quantification of the uncertainties in parameters calibration is need for the XAJ and XAJ-EB model in subsequent studies.

(2) Reply to comment 2 regarding precipitation interpolation

Thanks for this question. The spatially-distributed precipitation is included in the meteorological forcing data, however, after evaluating against precipitation measured by gauges, we found that spatially-distributed precipitation is biased (Fang et al., 2017) . For this reason, we used the precipitation from 8 gauges instead.

Several approaches existed for spatially interpolating the precipitation from gauges, however, their performances and uncertainties depend on certain conditions including the pattern of precipitation, the characteristic of catchment, and the locations of gauges (Ball and Luk, 1998; Di Piazza et al., 2011; Zhang and Srinivasan, 2009). It's difficult to evaluate the performance of different interpolation approaches in LS since the true areal precipitation is theoretically not available. In this paper, the conventional Thiessen polygon approach was employed, this is because:

1) Thiessen polygon has been intensively used in the XAJ model for flood simulation and foresting (Xia and Zhang, 2009)
2) The potential uncertainties raising from the precipitation interpolation are not the major concern of this paper. Actually each interpolation approach can lead to uncertainties, which is difficult to evaluate in the study area since the true areal precipitation is theoretically not available.

We added the description of how we interpolate precipitation in the revised manuscript (Page 10 Line 30). The precipitation of gauges are interpolated to grids by following steps:

1) Thiessen polygons are generated according to the geographic locations of gauges;

2) Thiessen polygons are overlaid with element areas, and the precipitation of ith element area (Pi) is weighted by Thiessen polygons that intersected with it (the precipitation of green-filled element area in Figure 1 is determined by Thiessen polygons 1, 3, 4 and 5, taking their area as weight);

3) Grids belongs to the same element area i are assigned the same precipitation Pi.

using such scheme we can ensure that the areal mean precipitation of element area of both XAJ-EB and XAJ model are the same, and therefore the differences between two model are not result from the precipitation differences.

Xingnan Zhang
On behalf of all co-authors

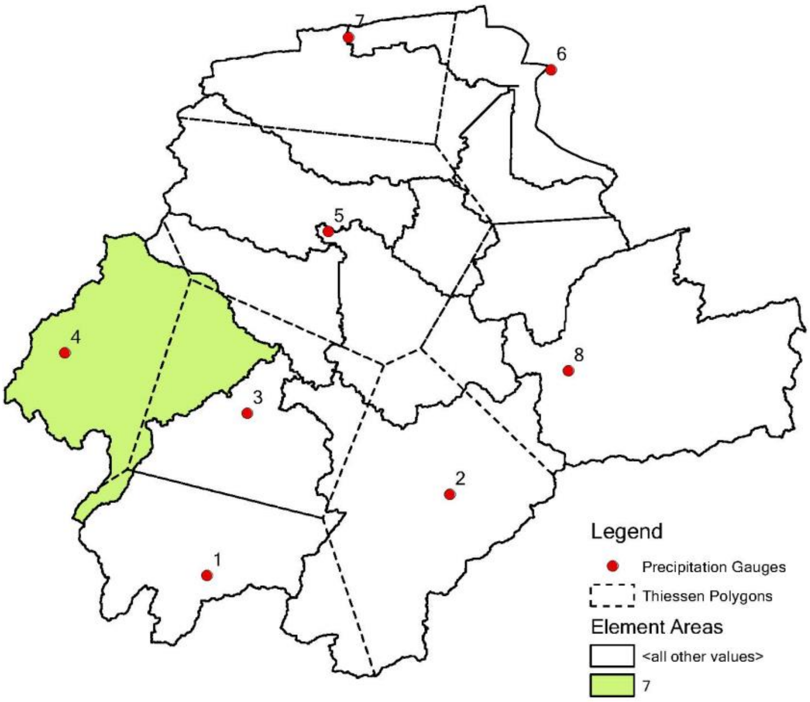

Figure 1. Sketch plot of precipitation calculation based on element areas and Thiessen polygons.

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