Physics-Informed AI-based Modelling for Flood Early Warning Systems

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Introduction

- Today, many early warning systems are introduced in which advanced deep learning, recurrent neural network or ensemble-based data mining techniques are applied to provide more accurate and reliable flood forecasting [1].
- A novel addition in this community is the physics-informed neural network models (PINN), integrating physical principles and constraints into architecture of data driven models [2].

Methodology

PINN-based ensemble multi-class data mining model, inspired by [3] is developed for the application of UDS (Figure 1). In addition to conventional inputs such as rainfall intensity, duration, session, and soil moisture, two physics-informed rainfall inputs - namely, the potential future return period of current rainfall and the current return period class - are incorporated (Figure 2). This model is verified by the case study located in the UK (Figure 3)

Result

The results indicate a substantial improvement in hit rates - from 67% to 88% - compared to a benchmark model. Notably, time lags in the correct detection of water level classes, are halved on average, reducing from 2-timstep intervals. More specifically, the rate of event underestimation decreases from 7% to 2%, showcasing that the new method has the potential to reduce false alarms in EWS. The application of PINN is currently limited to using only physics-informed input data. However, a promising avenue for future exploration involves extending this approach to adjusting hyperparameters of data-driven models with physics equations.

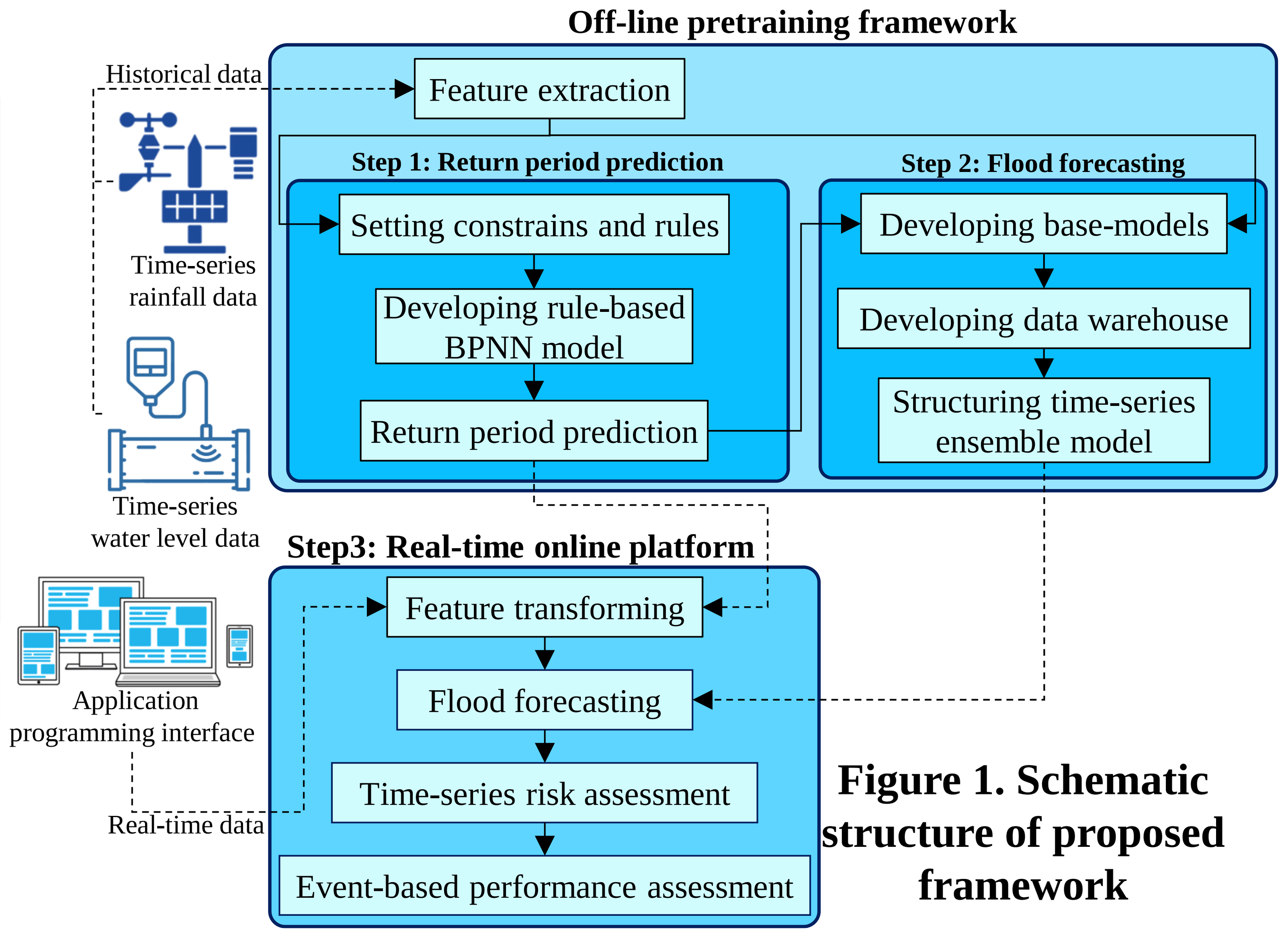

Figure 1. Schematic structure of proposed framework

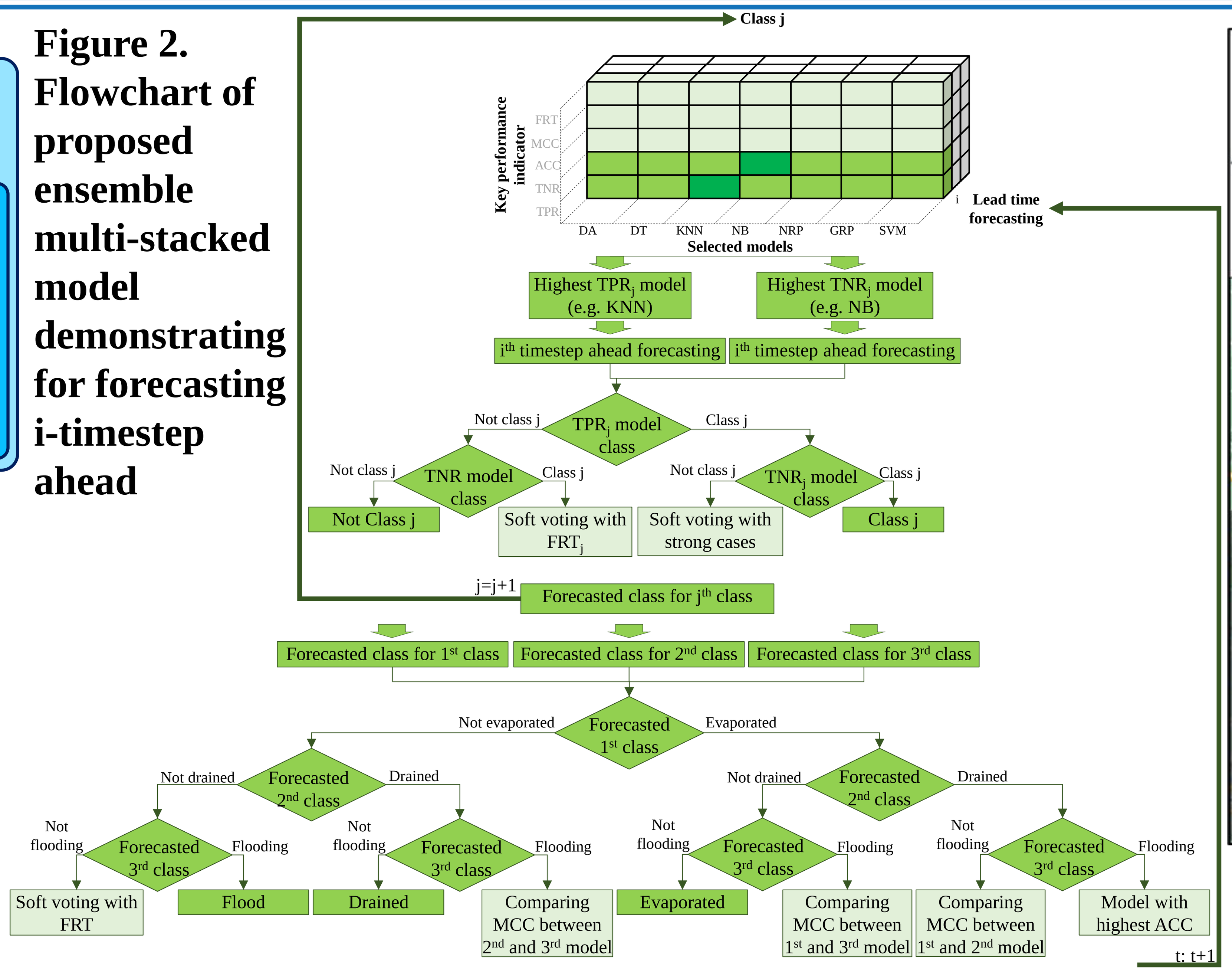

Figure 2. Flowchart of proposed ensemble multi-stacked model demonstrating for forecasting i-timestep ahead

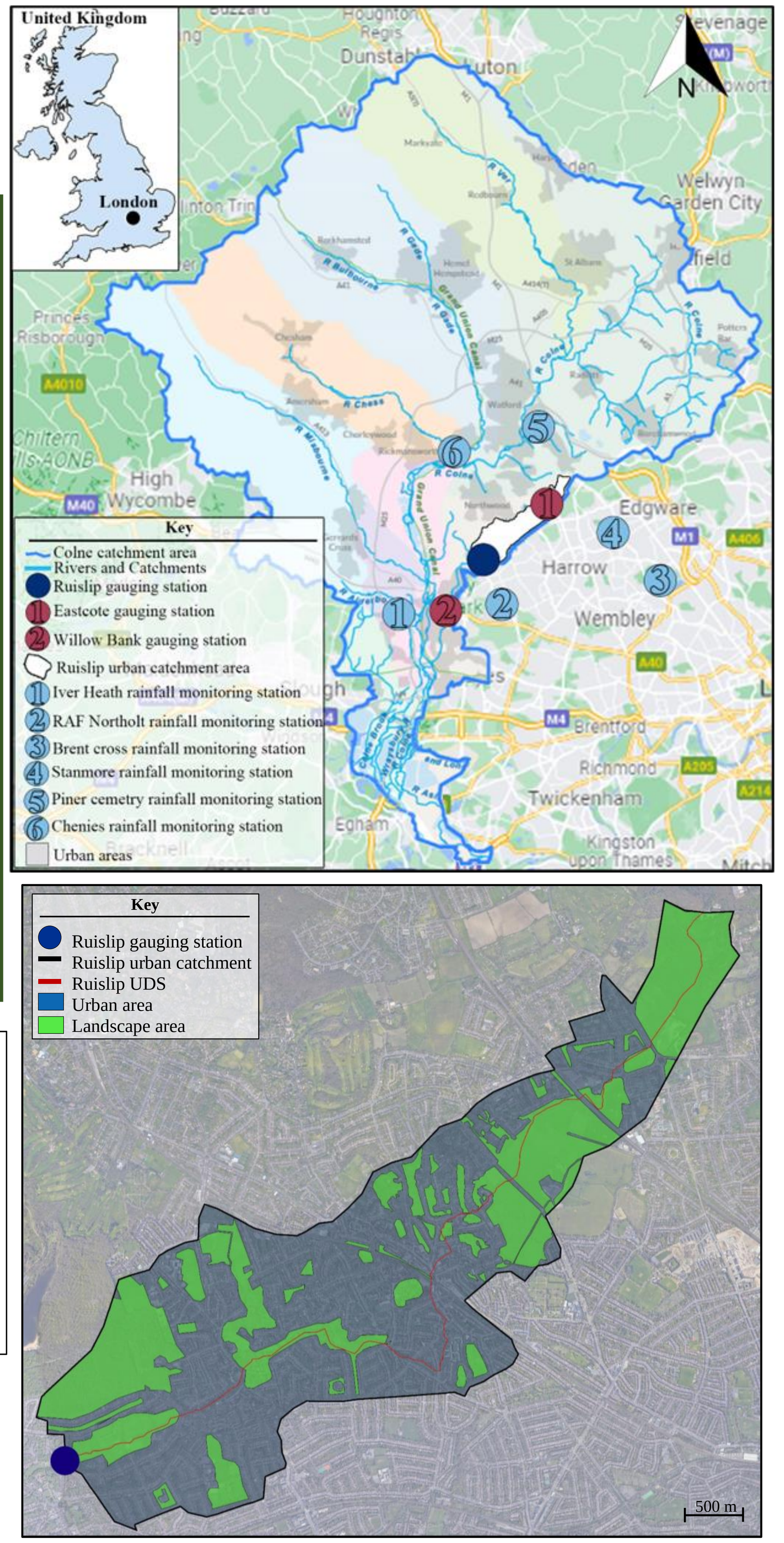

Figure 3. Geographical location of the pilot study: (top) location of catchment and monitoring stations, and (bottom) layout catchment

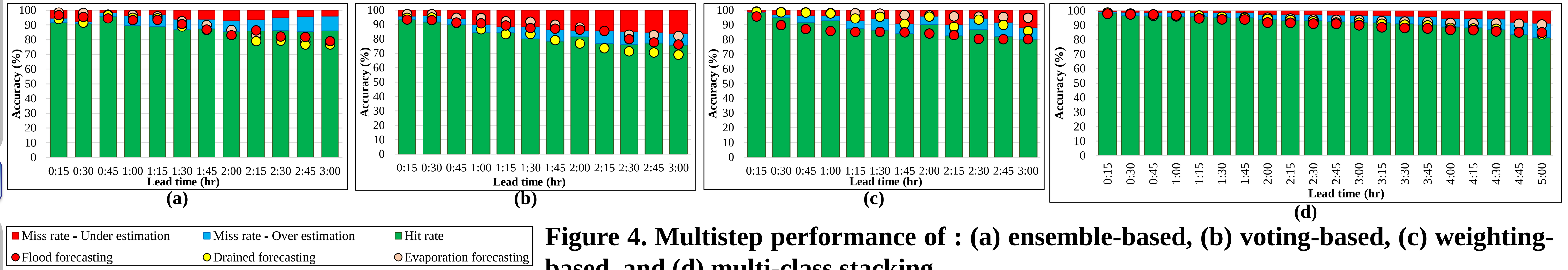

Figure 4. Multistep performance of : (a) ensemble-based, (b) voting-based, (c) weighting-based, and (d) multi-class stacking

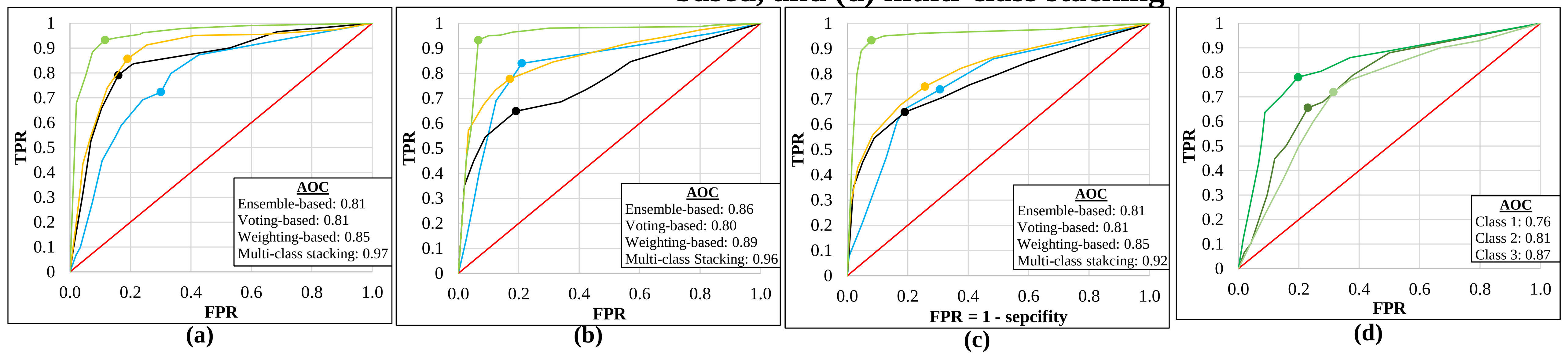

Figure 5. ROC and AOC of: (a) flood class in 3hrs ahead, (b) drained class in 3hrs ahead, (c) evaporation class in 3hrs ahead, and (d) different classes forecasted by multi-class stacking model in 5hrs ahead

References

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