Can CNN-LSTM and lumped models improve (extreme) streamflow prediction of semi-distributed models? A comparative analysis of two hybrid frameworks

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This presentation participates in OSPP

EGU Outstanding Student & PhD candidate Presentation contest

1 Introduction

Background

- Effective decision-making in water resources management and environmental protection depends on addressing uncertainties and errors in hydrological modeling.
- Process-based models offer greater physical consistency, while data-driven models provide higher predictive accuracy.

Research gap

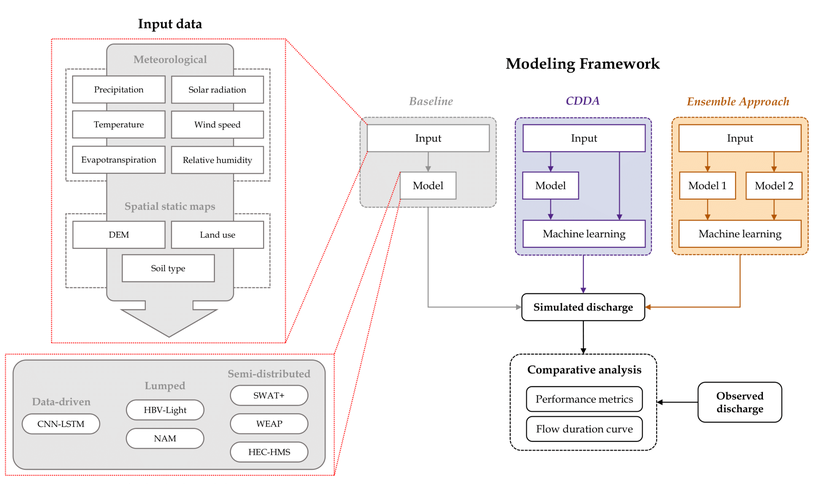
- Hybrid modeling is used in different frameworks without reaching consensus.
- The use of ensemble modeling from two conceptual models was not comprehensively investigated.

Research questions

- Can conceptual hydrological models learn from each other through Ensemble approach?
- Can Ensemble approach achieve higher accuracy than the Conceptual-Data-Driven Approach (CDDA) across different flow conditions?

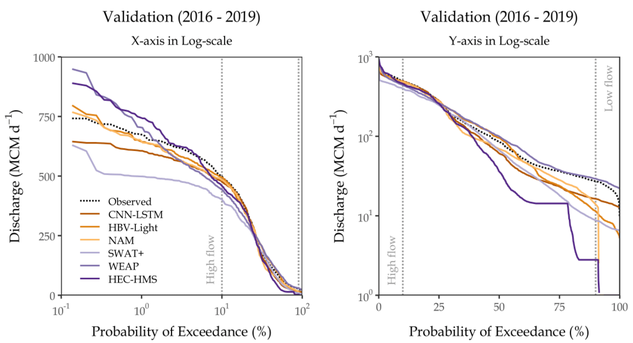
2 Methodology

- The analysis was conducted in the Upper Blue Nile Basin in Ethiopia over the period from 2002 to 2019. The basin area is approximately 176,000 km², with elevation ranging from 497 to 4200 m.a.s.l.
- Six conceptual models were employed: CNN-LSTM, HBV-Light, NAM, SWAT+, WEAP, and HEC-HMS.
- This study comprehensively compares two hybrid frameworks: the Conceptual-Data-Driven Approach (CDDA) and the Ensemble Approach.
- Two machine learning algorithms were tested within the hybrid models: Artificial Neural Networks (ANN) and Random Forest (RF).

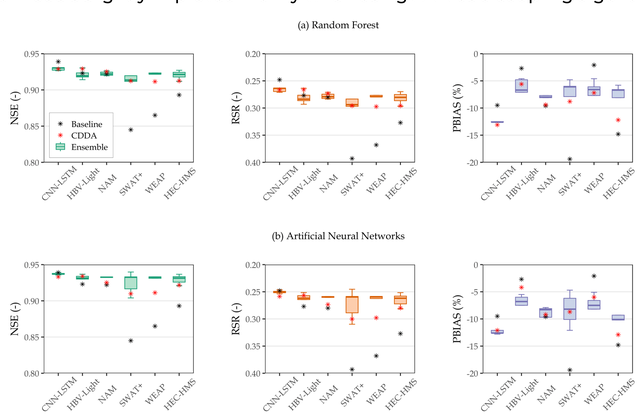


3 Results

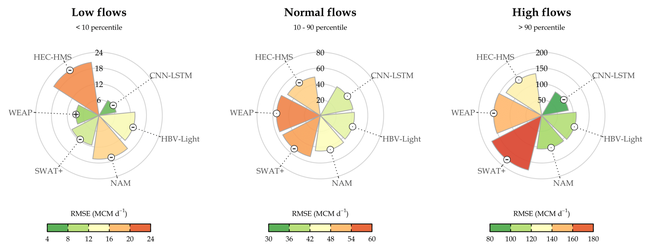
- Baseline: All models achieved NSE ≥ 0.85 during the validation period, with CNN-LSTM performing best (NSE = 0.94). However, performance varied across models, particularly for high and low flow conditions.



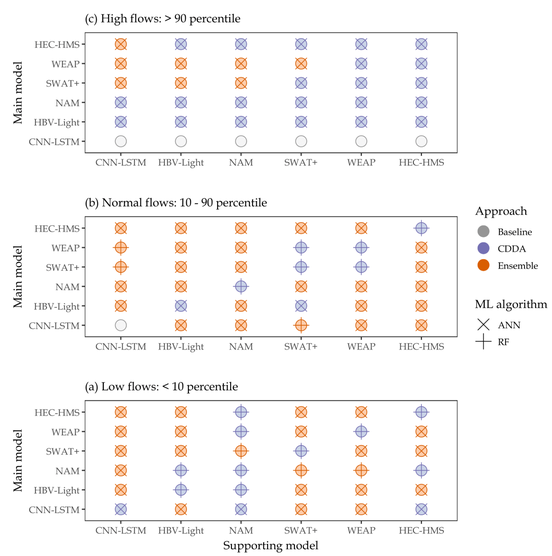
- Hybrid modeling: Both RF and ANN enhanced the streamflow predictions.
- Semi-distributed models exhibited the highest improvements across the metrics.
- Lumped models slightly improved mainly when using ANN as a coupling algorithm.



- Baseline: Both semi-distributed and lumped models tend to underestimate streamflow in low-flow conditions.
- Lumped models outperform semi-distributed models in normal and high-flow periods.



- Hybrid modeling: CDDA clearly outperforms baseline models in most cases, indicating that incorporating additional meteorological data enhances streamflow predictions.
- Ensemble models (orange circles) outperform both CDDA and baseline models.



4 Conclusion

- The ensemble model outperformed its standalone baseline models.
- The use of computationally efficient lumped models as supporting models within the Ensemble approach is more likely to enhance performance compared to semi-distributed models.
- For both hybrid models, deep learning techniques (ANN) were preferred over traditional machine learning algorithms (RF) as the coupling method.
- The Ensemble approach is robust to variations in supporting model selection, particularly under normal and high-flow conditions. However, for low-flow conditions, a more careful selection of the supporting model is required.