To Bucket or not to Bucket? Analyzing the performance and interpretability of hybrid hydrological models with dynamic parameterization

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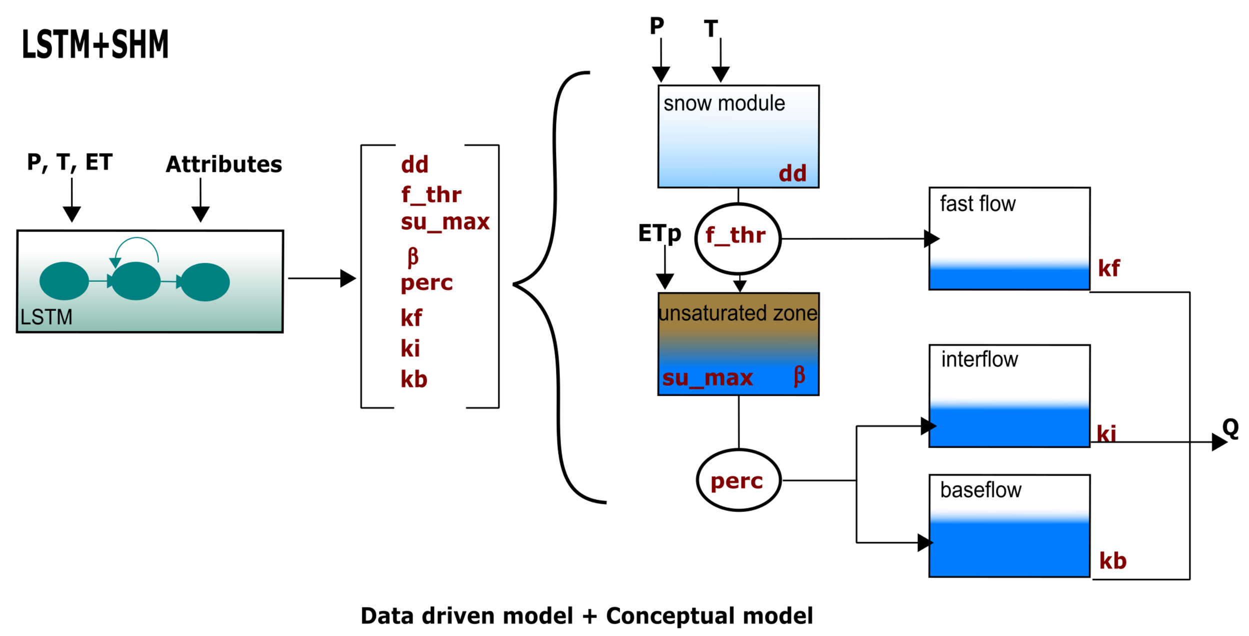
Introduction

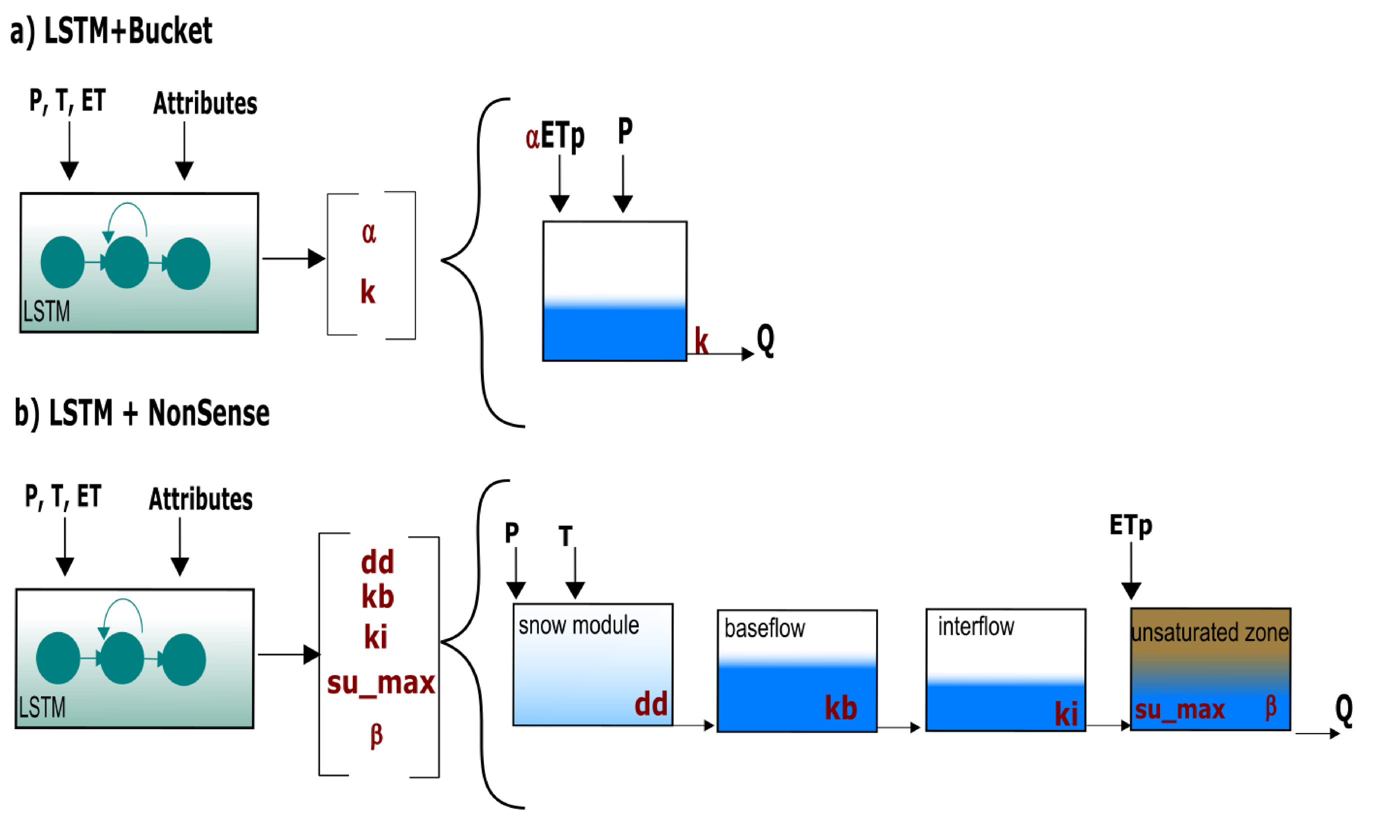
- Hydrological hybrid models have been proposed as an option to combine the enhanced performance of deep learning methods with the interpretability of process-based models.
- The dynamic parameterization of conceptual models using neural networks has shown high potential.
- We explored this method, using a subset of CAMELS-GB, to evaluate if the flexibility given by the dynamic parameterization overwrites the physical interpretability of the process-based part.

Methodology

1. Create a hybrid model



2. Assess how different forms of regularization affect the performance of the model



3. Analyze the internal states of the conceptual part to evaluate how much physical interpretability the model is keeping.

Results and discussion

Effect of different regularizations

- Hybrid models achieve similar performance (median-NSE) as stand-alone LSTM and outperform stand-alone conceptual models.
- The LSTM's dynamic parameterization can compensate for missing processes, and **the regularization provided is insufficient** to drop the model performance.

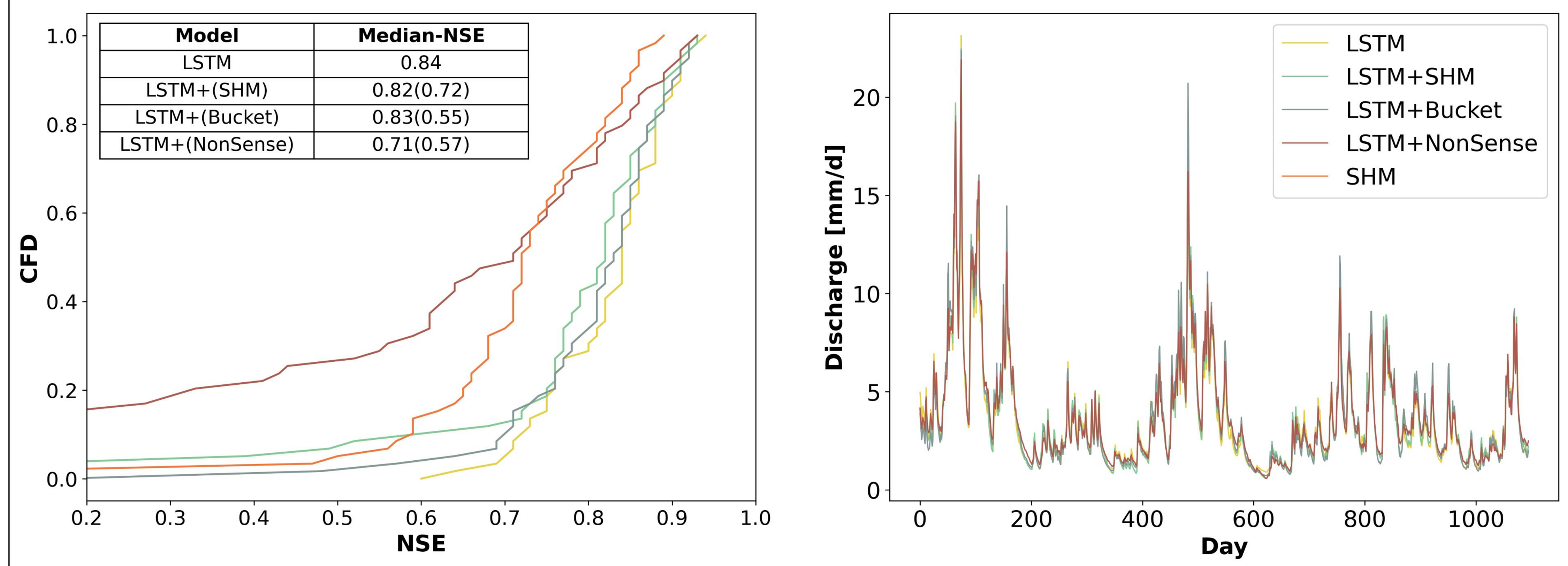


Figure 1. Left: Cumulative density functions of the NSE for the different models. Right: Specific discharge series in the testing period for basin ID 15006, simulated by the different models

Internal functioning of hybrid model

- We also analyzed the internal functioning of the LSTM+SHM, comparing it to external data and the stand-alone conceptual model.

Table 1. Median correlation of LSTM+SHM with external data and stand-alone SHM

Variable 1	Variable 2	Median - Correlation
LSTM + SHM (unsaturated zone)	ERA5-LAND swvl3	0.83
SHM (unsaturated zone)	ERA5-LAND swvl3	0.86
LSTM + SHM (unsaturated zone)	SHM (unsaturated zone)	0.96

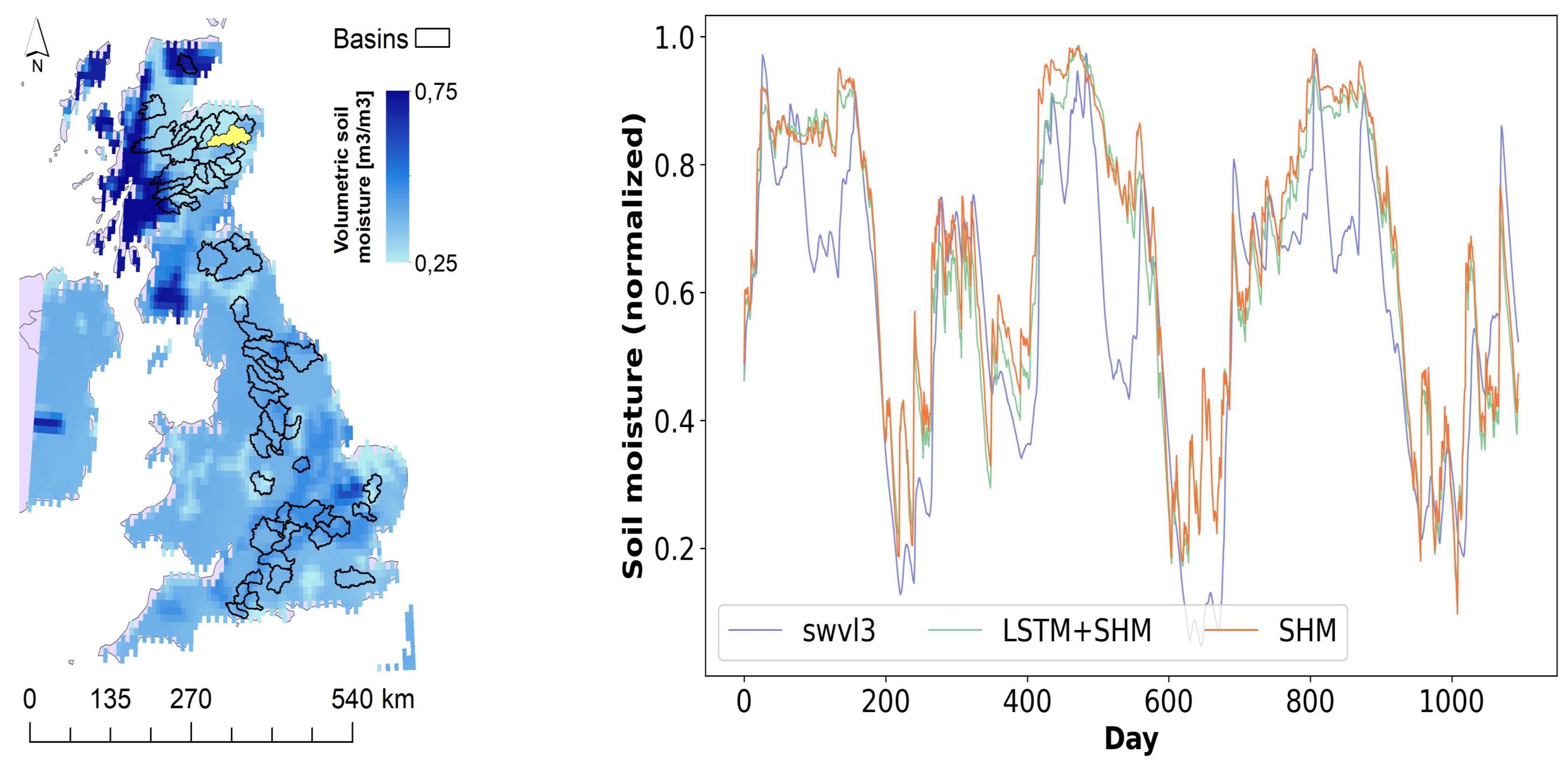


Figure 2. Left: ERA5-LAND swvl3 in the region on interest. Right: Soil moisture time series comparison during the testing period for basin ID 11001 (yellow basin in left figure)

Results and discussion

Internal functioning of hybrid model

Table 2. Proportions of discharge originating from each bucket for the different models

Bucket	LSTM + SHM (%)	SHM (%)
Fast flow	14	3
Interflow	59	66
Baseflow	27	31

- Lastly, we analyzed the parameter variation for the hybrid model

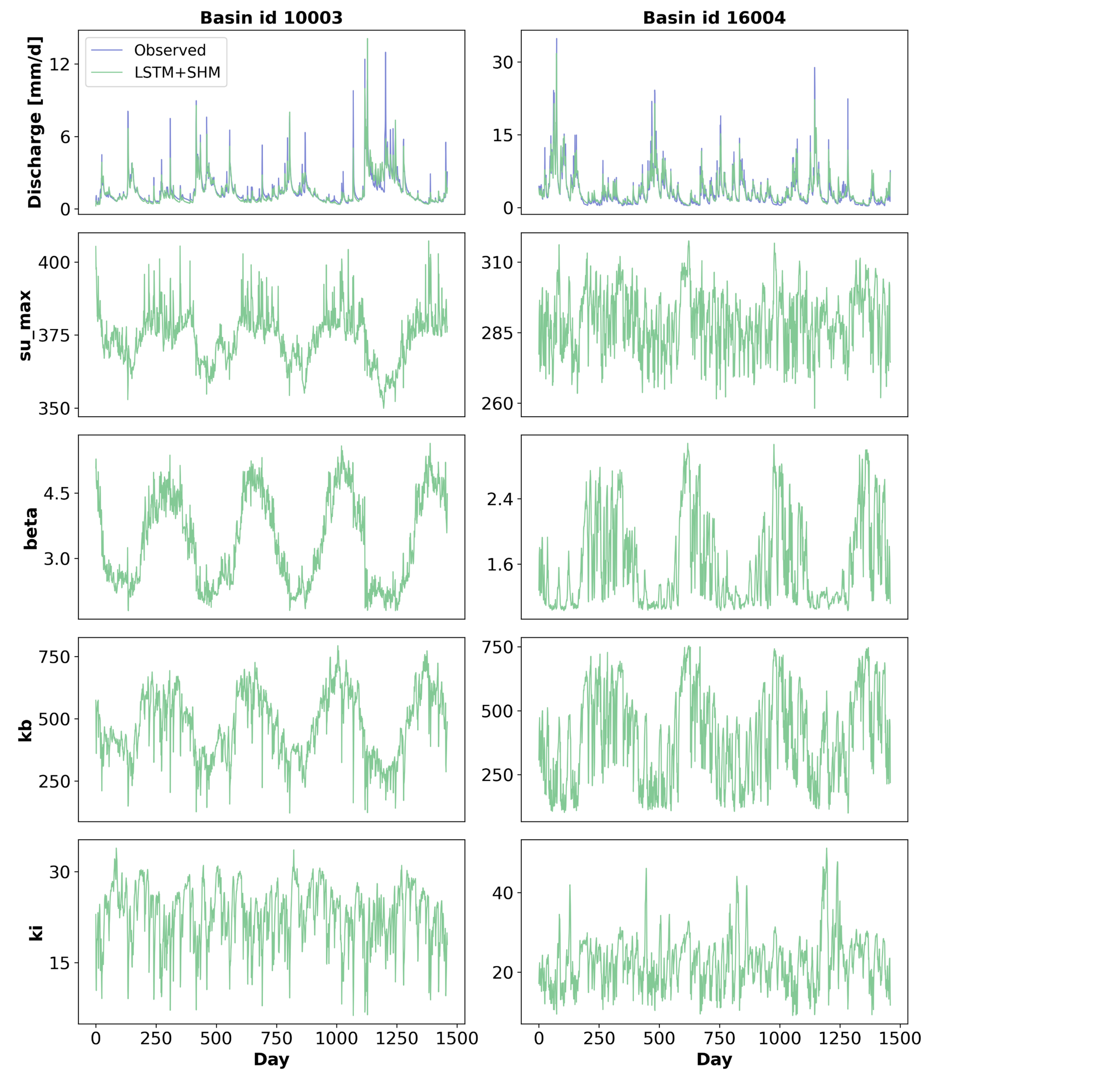


Figure 3. Time variation of parameters for basins 10003 (left column) and 16004 (right column). It should be noted that the Y-Axis ranges of the two basins differ

Conclusions

- The regularization given by the conceptual model is not strong enough to drop the predictive capability of the hybrid model, and missing processes can be outsourced to the data-driven part.
- If a well-tested model architecture is combined with a LSTM, the deep learning model can learn to operate the process-based model in a consistent manner.