TECHNISCHE UNIVERSITÄT DRESDEN

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Abstract

Flood Forecasting with Deep Learning LSTM Networks: Local vs. Regional Network Training Based on Hourly Data

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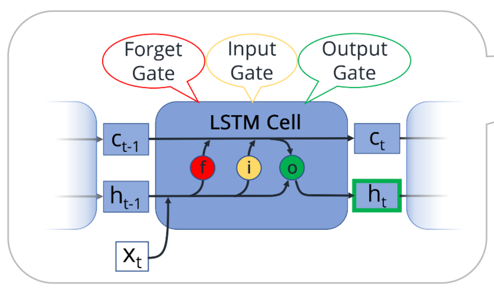
Motivation

"Local" Network Training:
The model is trained on data from one specific catchment ➔ specialisation
prior studies done with local network training: Morgenstern et al. 2021 [5]

"Regional" Network Training:
The model is trained on data from a diverse group of catchments in a region ➔ generalisation
➔ The model potentially learns universal system behaviour and is able to do forecasts for "unknown" catchments
➔ Increasing the amount of relevant data in training potentially improves discharge forecasts

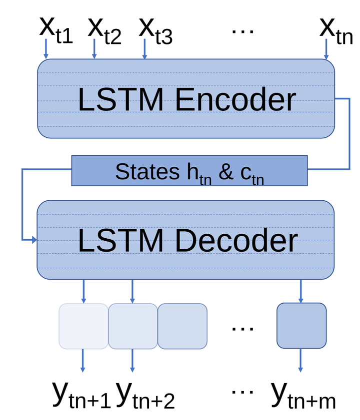
Model: LSTM Encoder-Decoder

LSTM = Long Short-Term Memory [1, 2]
(Artificial Neural Network for efficient and sequential processing of input sequences)



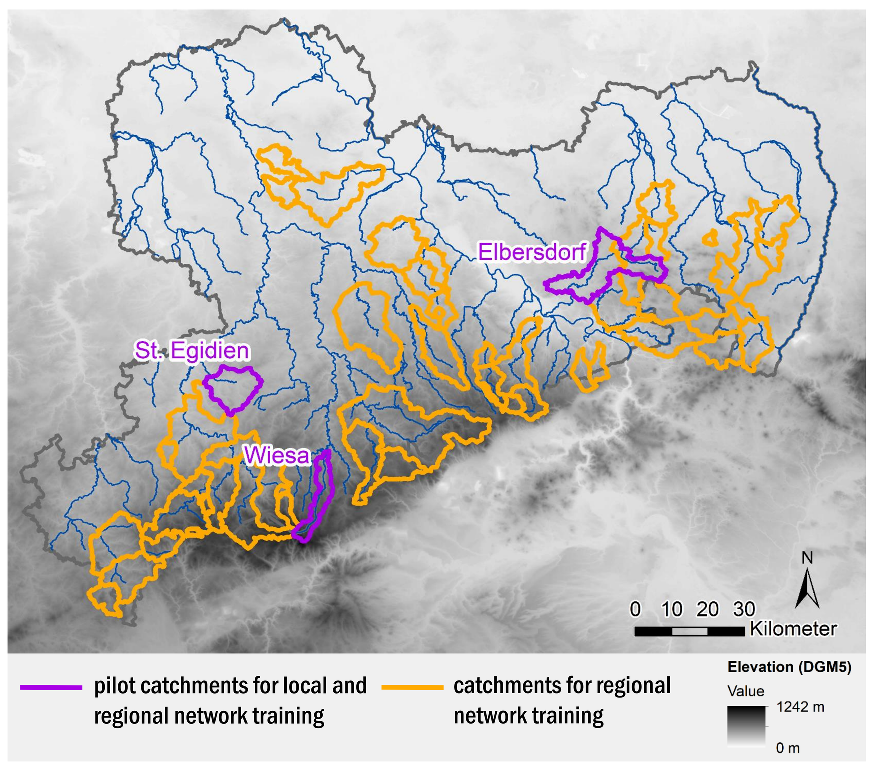
x_t, y_t ... Input-/Output signal (at timestep t)
h_t ... Hidden State (at timestep t)
c_t ... Cell State (at timestep t)

The architecture: LSTM Encoder-Decoder [3]



Data

Case Study: 52 Catchments in Saxony, Germany



Dynamic Input Data

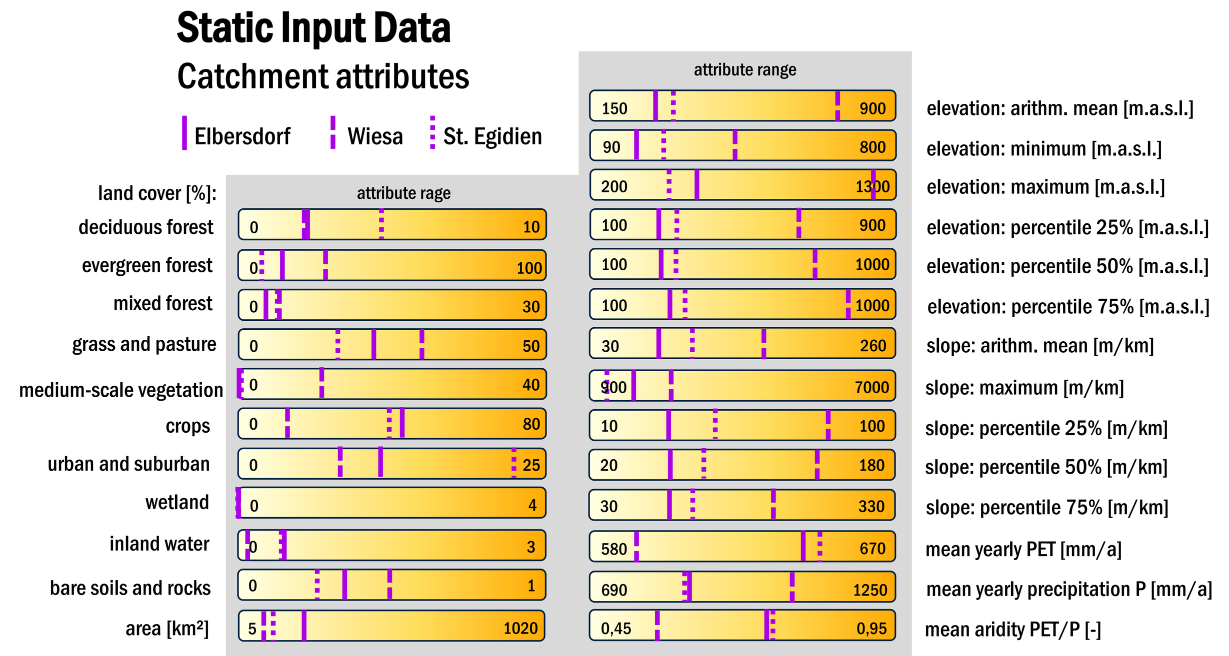
- local training dataset
- **precipitation** observations (RADOLAN RW) in hourly resolution as area average of catchment
- **discharge** observations in hourly resolution
- event based training

- regional training dataset: all 52 catchments
- meaningful catchment attributes necessary in regional network training for sensible categorisation / estimate of catchment responsiveness
- attribute selection: based on sensitive catchment characteristics from paper of Kratzert et al. 2019 [4] (experiments done on CAMELS dataset with daily resolution) + land cover attributes
- scaled attributes concatenated to dynamic input features

- regional training dataset without the pilot catchments

Static Input Data

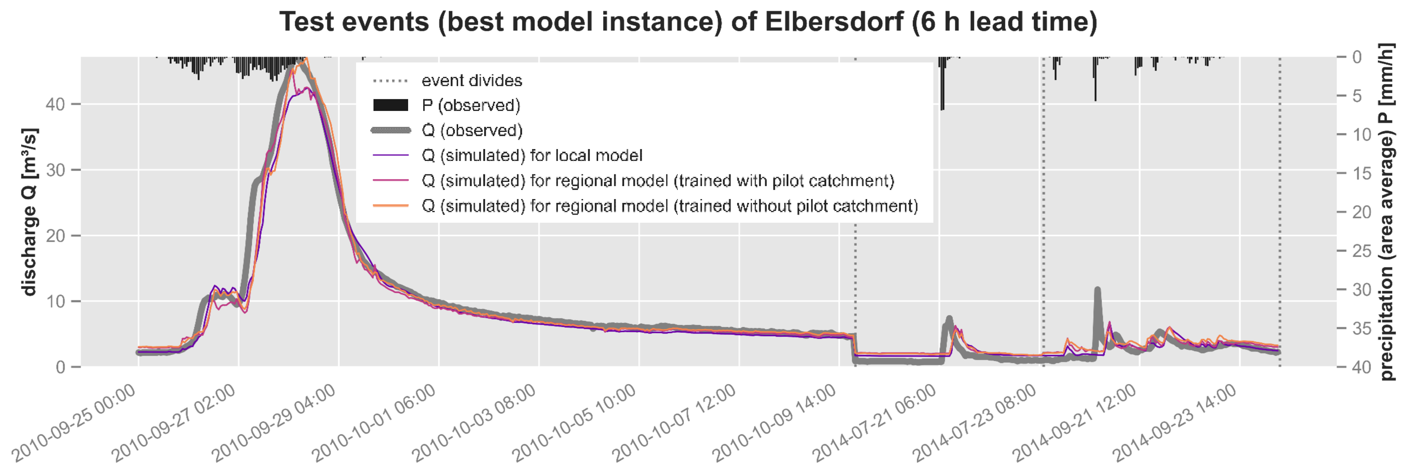
Catchment attributes



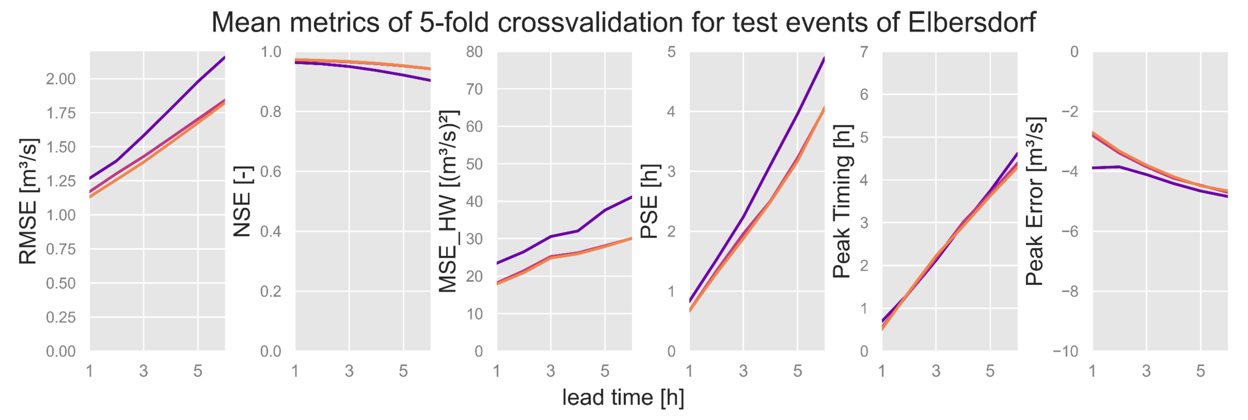
Results and Conclusion

RMSE = Root Mean Square Error (optimum = 0)
NSE = Nash Sutcliffe Efficiency (optimum = 1)
MSE_HW = Mean Square Error with special weight on peak flow range (optimum = 0)
PSE = Phase Shift Error, temporal shift of simulation (optimum = 0)
Peak Timing = Timing Error of peak flow (optimum = 0)
Peak Error = Magnitude Error of peak flow (optimum = 0)

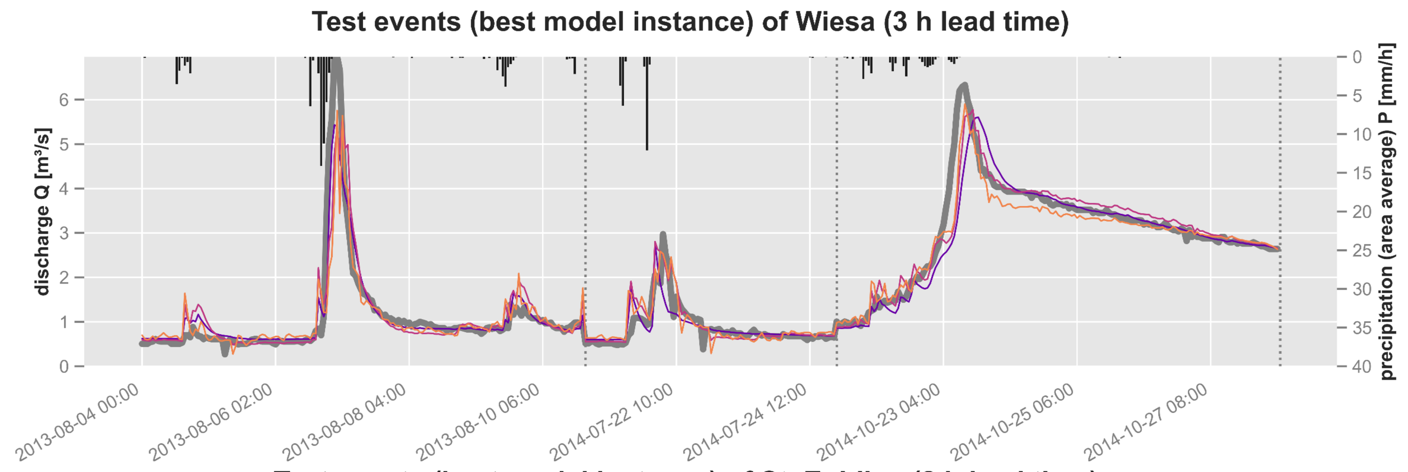
Test events (best model instance) of Elbersdorf (6 h lead time)



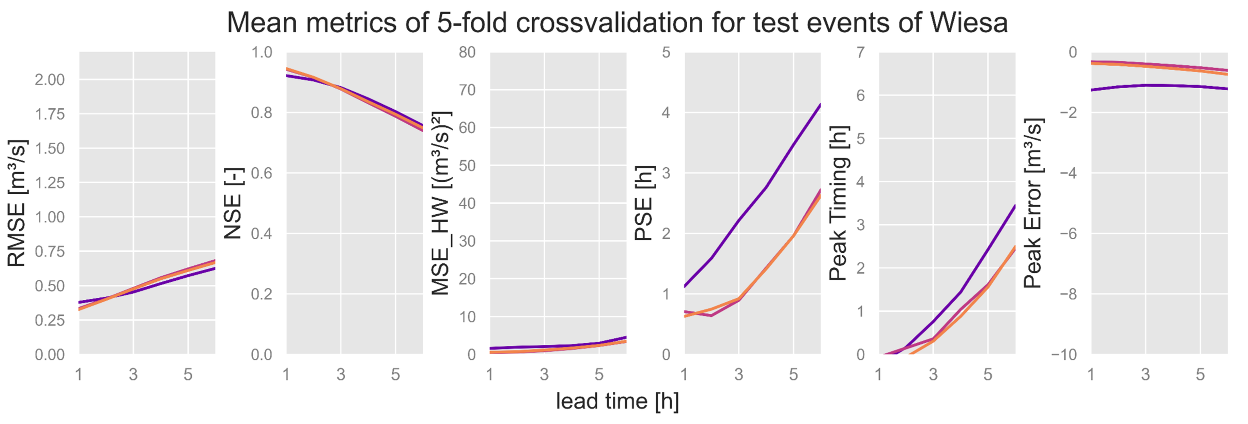
Mean metrics of 5-fold crossvalidation for test events of Elbersdorf



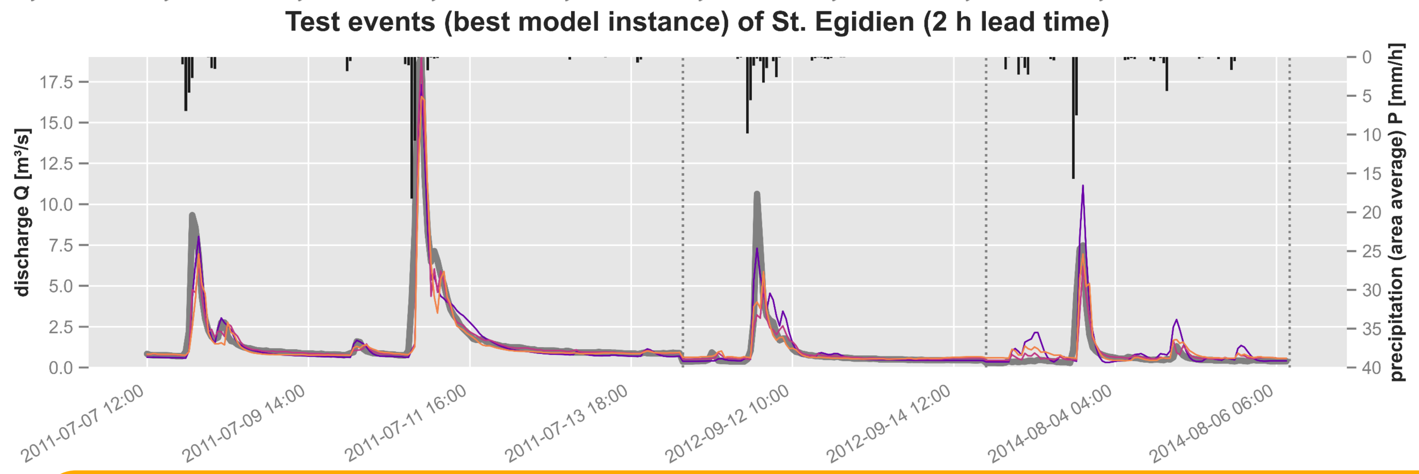
Test events (best model instance) of Wiesa (3 h lead time)



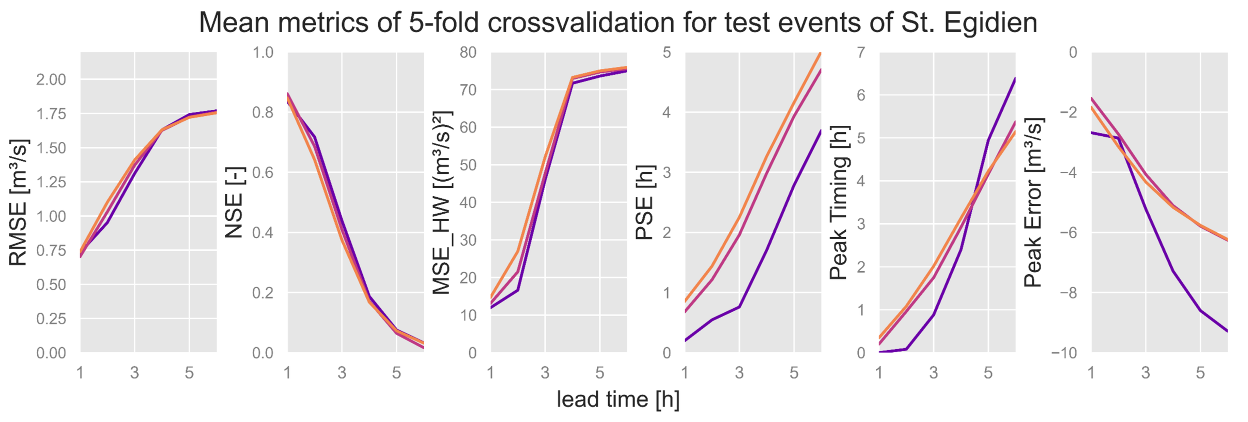
Mean metrics of 5-fold crossvalidation for test events of Wiesa



Test events (best model instance) of St. Egidien (2 h lead time)



Mean metrics of 5-fold crossvalidation for test events of St. Egidien



Findings:

Within the mean response time of the catchment (here: lead time of depicted hydrograps) there is **potential for better discharge forecasts with both regional models.** The regional model trained without the pilot catchment produces equally satisfactory results as the regional model trained with it.

Hypothesis:

The learned universal behaviour of the selection of Saxon catchments suffices for the prediction of flood events in "unknown" catchments in this region and within the range of the learned catchment attributes, thus indicating the **generalisation abilities** of regional models.

Findings:

The hydrographs of both regional models **oscillate** at catchment Wiesa, thus reducing the apparent reliability and robustness of their prediction. Many oscillations correlate with discharge impulses (dynamic input feature).

Hypotheses:

first: Regional models may be more reactive to discharge input as it is most **correlative to the target variable** (discharge) and increasing the diversity of training catchments may amplify this effect as other variables vary more in their correlation to the target discharge.

second: Wiesa has a **smaller range of discharge** values. **Absolute values** of discharge observation oscillations may be comparable to other catchments, their **relative size and impact however increases** with decreasing discharge range. Regional models may be used to smaller relative oscillations in input.

Outlook:

➔ big potential of regional network training, especially for "unknown" catchments
- Inclusion of other relevant catchment attributes (e.g. catchment shape factors)
- Analysis of sensitivity and impact of catchment attributes

[1] Hochreiter, S.; Schmidhuber, J. (1997): Long short-term memory. In: Neural computation 9 (8), S. 1735–1780. DOI: 10.1162/neco.1997.9.8.1735
[2] Gers, F. A.; Schmidhuber, J.; Cummins, F. (2000): Learning to forget: continual prediction with LSTM. In: Neural computation 12 (10), S. 2451–2471. DOI: 10.1162/089976600300015015
[3] Sutskever, I.; Vinyals, O.; Le, Q. V. (2014): Sequence to Sequence Learning with Neural Networks. Online verfügbar unter http://arxiv.org/pdf/1409.3215v3
[4] Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. Hydrology and Earth System Sciences (23), S. 5089–5110. DOI: 10.5194/hess-23-5089-2019
[5] Morgenstern, T., Pahner, S., Mietrach, R., Schütze, N. (2021): Flood forecasting in small catchments using deep learning LSTM networks. DOI: 10.5194/egusphere-egu21-15072

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