

EGU23-9726, updated on 07 Jun 2023 https://doi.org/10.5194/egusphere-egu23-9726 EGU General Assembly 2023 © Author(s) 2023. This work is distributed under the Creative Commons Attribution 4.0 License.



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

Tanja Morgenstern<sup>1</sup>, Jens Grundmann<sup>2</sup>, and Niels Schütze<sup>3</sup>

<sup>1</sup>Technische Universität Dresden, Hydrology and Meteorology, Hydrology, Dresden, Germany (tanja.morgenstern@tudresden.de)

<sup>2</sup>Technische Universität Dresden, Hydrology and Meteorology, Hydrology, Dresden, Germany (jens.grundmann@tudresden.de)

<sup>3</sup>Technische Universität Dresden, Hydrology and Meteorology, Hydrology, Dresden, Germany (niels.schuetze@tudresden.de)

Floods are among the most frequently occurring natural disasters in Germany. Therefore, predicting their occurrence is a crucial task for efficient disaster management and for the protection of life, property, infrastructure and cultural assets. In recent years Deep Learning methods gained popularity on the research field on flood forecasting methods – Long Short-Term Memory (LSTM) networks being part of them.

Efficient disaster management needs a fine temporal resolution of runoff predictions. Past work at TU Dresden on LSTM networks shows certain challenges when using input data with hourly resolution, such as systematically poor timing in peak flow prediction (Pahner et al. (2019) and Morgenstern et al. (2021)). At times, disaster management even requires flood forecasts for hitherto unobserved catchments, so in total a regionally transferable rainfall-runoff model with a fine temporal resolution is needed. We derived the idea for a potential approach from Kratzert et al. (2019) and Fang et al. (2021): they demonstrate that LSTM networks for rainfall(R)-runoff(R)-modeling benefit from an integration of multiple diverse catchments in the training dataset instead of a strictly local dataset, as this allows the networks to learn universal hydrologic catchment behavior. However, their training dataset consists of daily resolution data.

Following this approach, in this study we train the LSTM networks using single catchments ("local network training") as well as combinations of diverse catchments in Saxony, Germany ("regional network training"). The training data (hourly resolution) consist of area averages of observed precipitation as well as of observed discharge at long-term observation gauges in Saxony. The gauges belong to small, fast-responding Saxon catchments and vary in their hydrological and geographical properties, which in turn are part of the network training as well.

We show the preliminary results and investigate the following questions:

• With a finer temporal resolution than daily values, characteristics of flood waves become more pronounced. Concerning the detailed simulation of flood waves, do regional LSTM-based R-R-

models enable more accurate and robust flow predictions compared to local LSTM-based R-R-models – especially for rare extreme events?

• Are regional LSTM-based R-R-models – trained at this temporal resolution – able to generalize to unobserved areas or areas with discharge observations unsuitable for network training?

## References

Fang, K., Kifer, D., Lawson, K., Feng, D., Shen, C. (2022). The Data Synergy Effects of Time-Series Deep Learning Models in Hydrology. In: Water Resources Research (58). DOI: 10.1029/2021WR029583

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

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

Pahner, S., Mietrach, R., Schütze, N. (2019): Flood Forecasting in small catchments: a comparative application of long short-term memory networks and artificial neural networks. DOI: 10.13140/RG.2.2.36770.89286.