Evaluating the performance of Long Short-Term Memory (LSTM) Networks for rainfall–runoff modelling in large catchments



JUSTUS-LIEBIG-UNIVERSITÄT GIESSEN

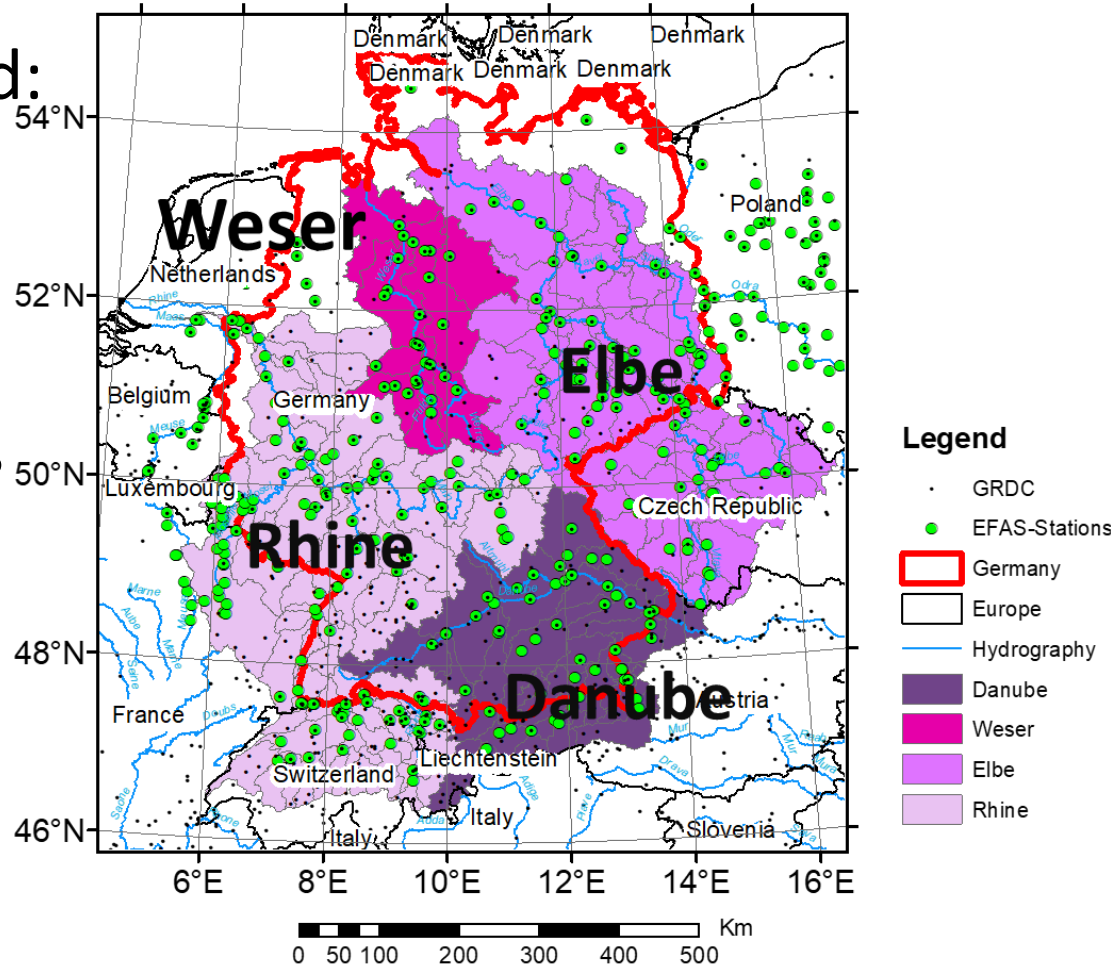
Edgar Fabián Espitia Sarmiento, Fatemeh Heidari, Qing Lin, Marc Vischer, and Elena Xoplaki

2022-09-06

1. Research question

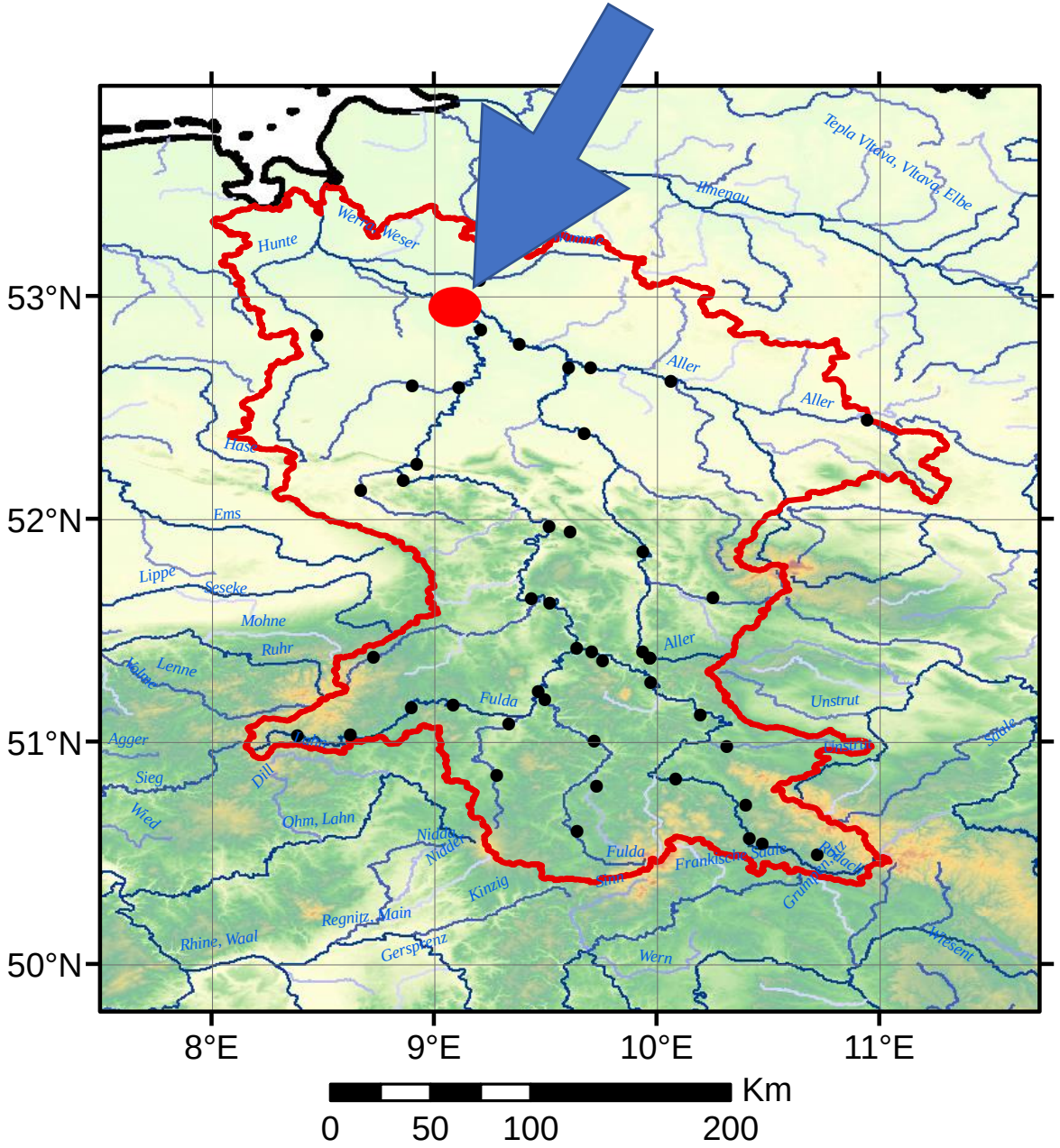
When a large catchment needs to be modelled:

- The performance of LSTM is suitable for rainfall-runoff modelling
- To what extent we can rely on these results and whether the involved physical processes are appropriately represented also at higher spatial resolutions?



2. Study area

River: WESER
Station: INTSCHEDE
Catchment area (km²): 37720



3. Data

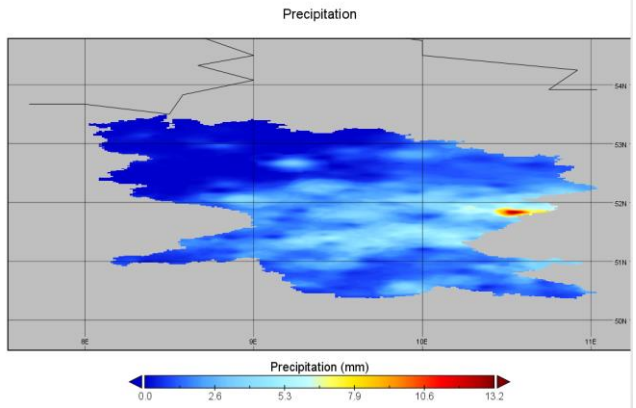
Meterological forcings

HYRAS

Air temperature max
Air temperature_mean
Air temperature min
Humidity
Precipitation
Radiation global

1990 – 2020
Spatial resolution: 1arcm
Time resolution: daily
10 calibration
10 Validation



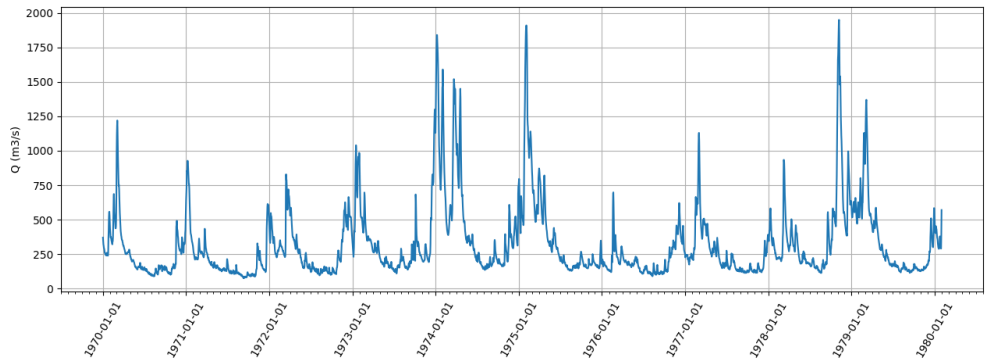


Hydrological observations

GRDC

Streamflow





4. Hydrological modelling

LISFLOOD model

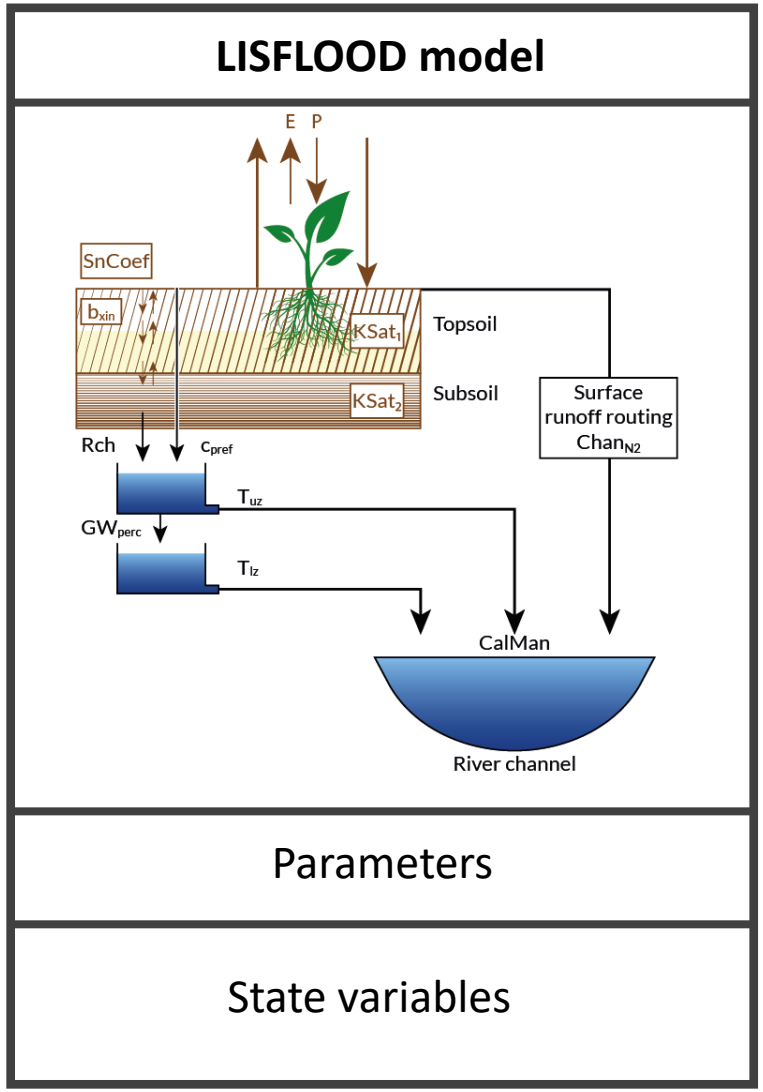
Time series data

Meteorological inputs
- **P**
- **ET0**
- **EW0**
- **ES0**
- **T_{avg}**

≈ Constant

Geographical inputs
- Land use
- Soil

Hydraulics
- H, W, L



Observed **streamflows**

Simulated **Streamflows**

Performance evaluation

4. Hydrological modelling

Calibration procedure LISFLOOD

Non-dominated Sorting Genetic Algorithm-II (NSGA-II)

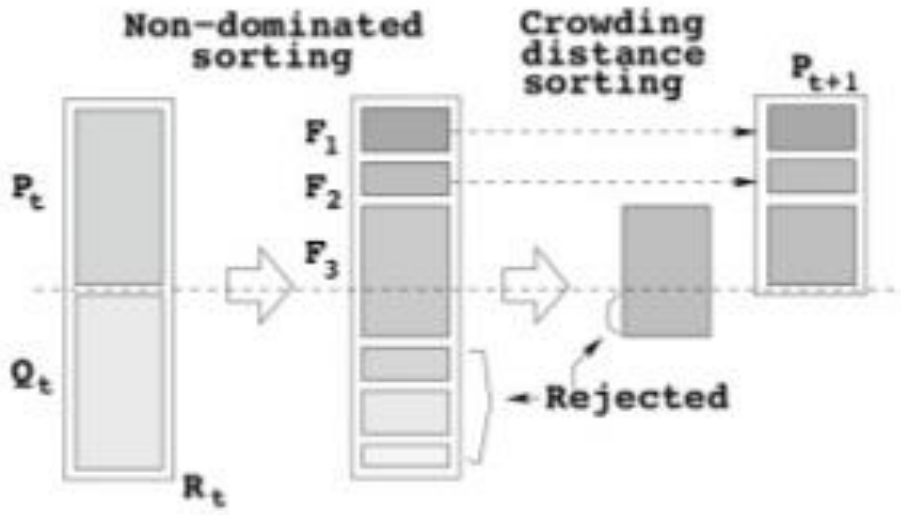


Figure: Non-dominated Selection [Deb et al. 2000]

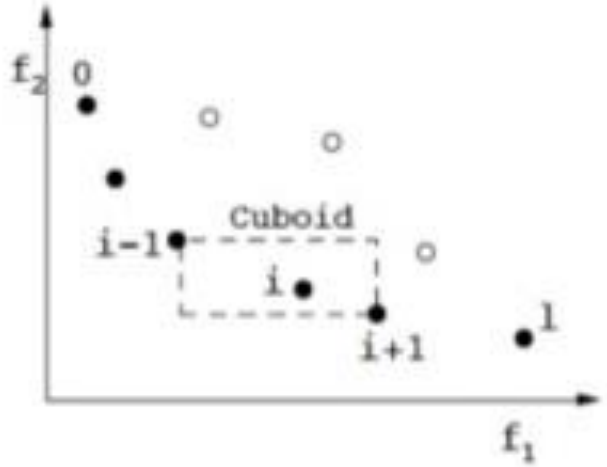
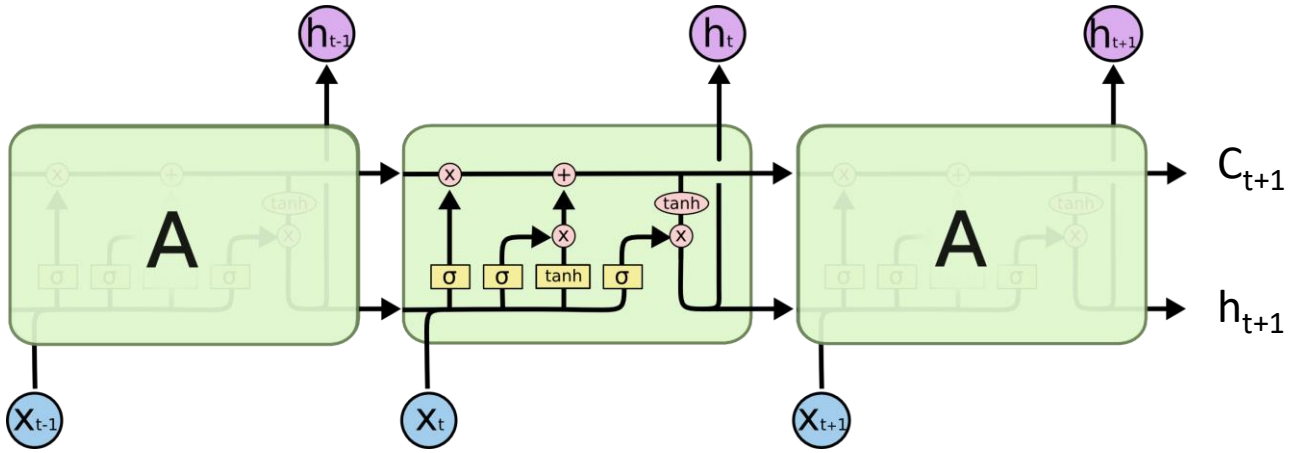


Figure: Crowding distance [Deb et al. 2000]

Source: https://esa.github.io/pagmo2/docs/cpp/algorithms/nsga2.html

4. Hydrological modelling

Long Short-Term Memory (LSTM)



Source: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

$$h_t = g\left(\mathbf{W}x_t + \mathbf{U}h_{t-1} + b\right)$$

$$f_t = \sigma\left(\mathbf{W}_\mathrm{f}x_t + \mathbf{U}_\mathrm{f}h_{t-1} + b_\mathrm{f}\right)$$

$$\tilde{c}_t = \tanh\left(\mathbf{W}_{\tilde{c}}x_t + \mathbf{U}_{\tilde{c}}h_{t-1} + b_{\tilde{c}}\right)$$

$$i_t = \sigma\left(\mathbf{W}_\mathrm{i}x_t + \mathbf{U}_\mathrm{i}h_{t-1} + b_\mathrm{i}\right)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

$$o_t = \sigma\left(\mathbf{W}_\mathrm{o}x_t + \mathbf{U}_\mathrm{o}h_{t-1} + b_\mathrm{o}\right)$$

$$h_t = \tanh(c_t) \odot o_t$$

4. Hydrological modelling

Hydrological model performance criteria

Modified Kling-Gupta Efficiency metric (KGE')

$$KGE' = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}$$

$$r_{xy} = \frac{\sum_i x_i y_i - n\bar{x}\bar{y}}{\sqrt{\sum_i x_i^2 - n\bar{x}^2}\sqrt{\sum_i y_i^2 - n\bar{y}^2}}.$$

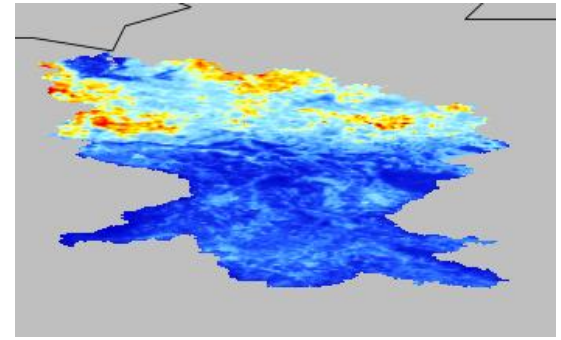
$$\gamma = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o} \qquad \beta = \frac{\mu_s}{\mu_o}$$

Nash–Sutcliffe model efficiency coefficient (NSE)

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q}_o\right)^2}$$

5. Preliminary results

LISFLOOD model parameters



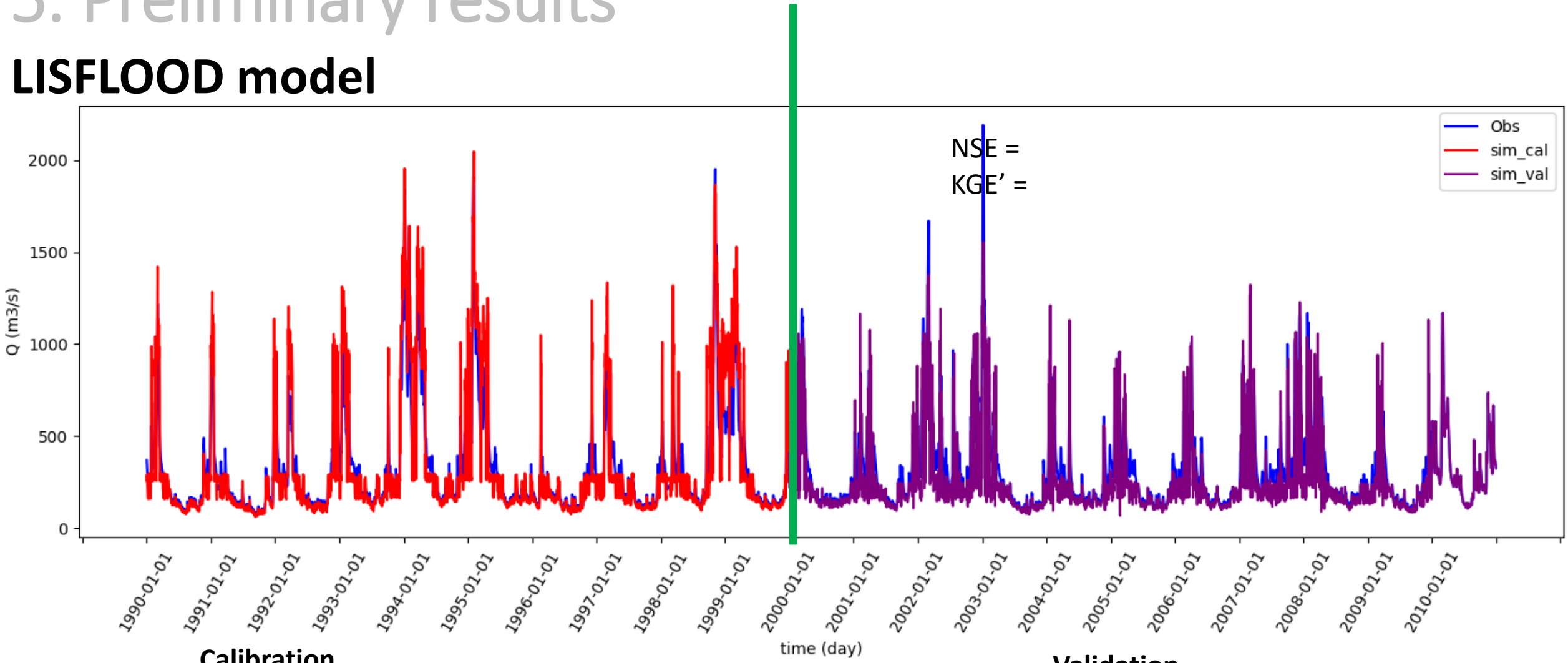
UpperZoneTimeConstant
LowerZoneTimeConstant
GwPercValue
GwLoss
LZThreshold
b_Xinanjiang
PowerPrefFlow
CalChanMan



SnowMeltCoef
CalChanMan2
adjust_Normal_Flood
ReservoirRnormqMult
AvWaterRateThreshold
QSplitMult
ChanBottomWMult
ChanDepthTMult
ChanSMult

5. Preliminary results

LISFLOOD model



Calibration

NSE = 0.76

KGE' = 0.75

r = 0.92 α =1.23 β = 1.04

Validation

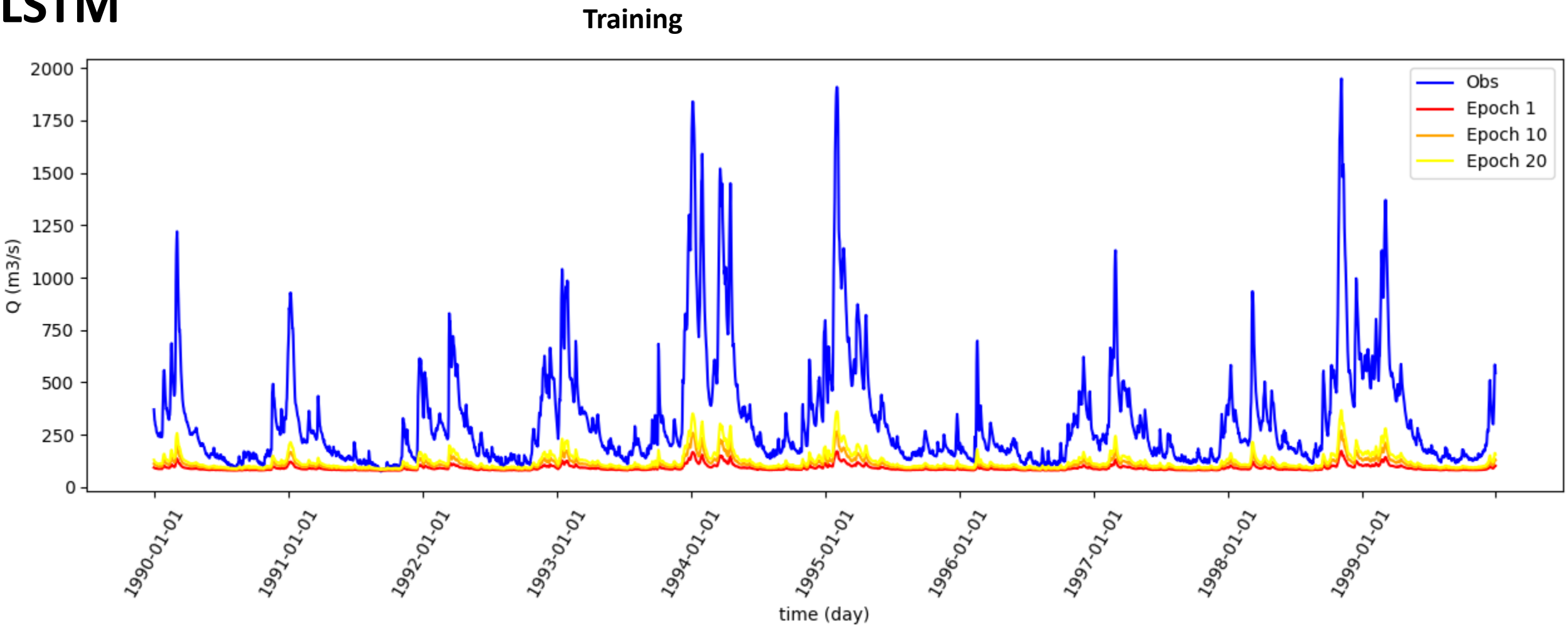
NSE = 0.66

KGE' = 0.74

r = 0.85 α =1.09 β = 0.81

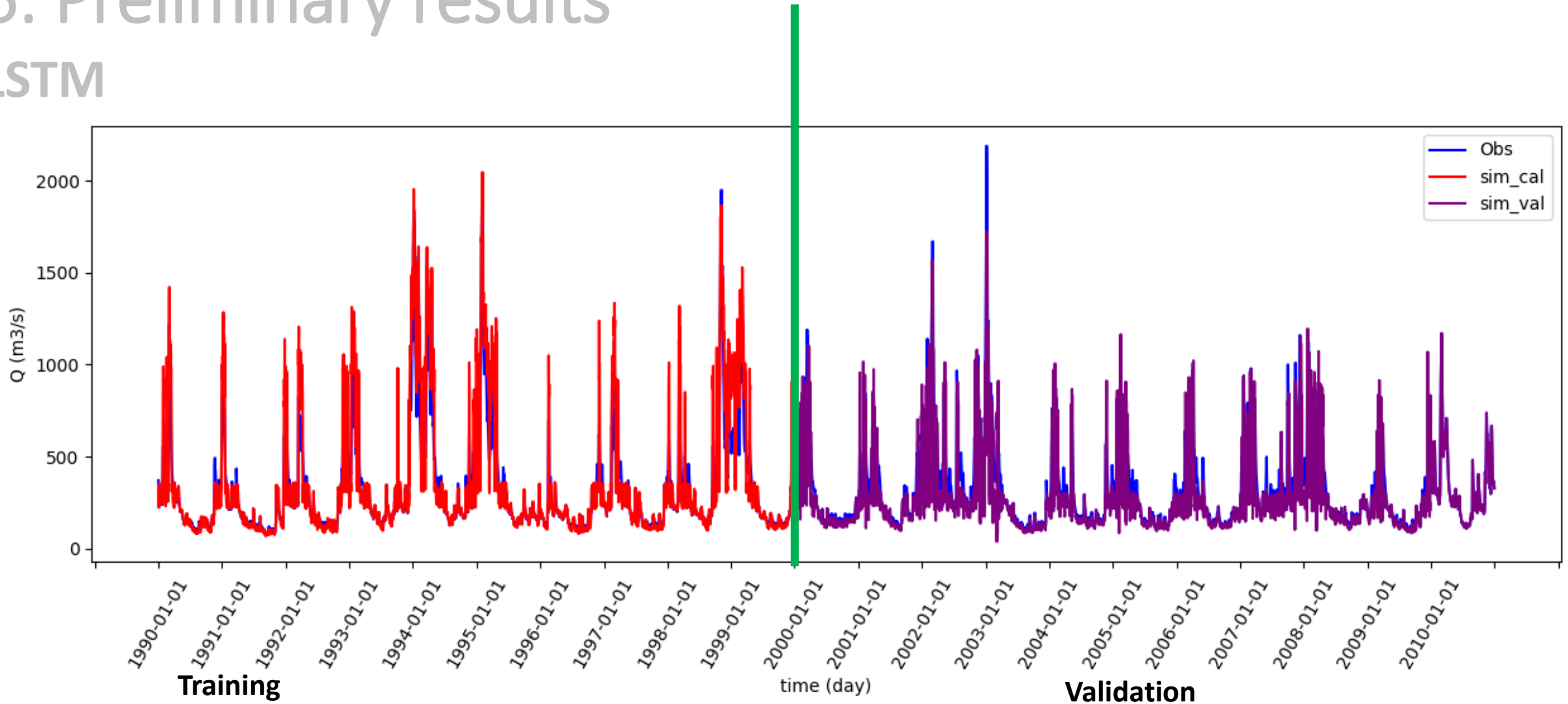
5. Preliminary results

LSTM



5. Preliminary results

LSTM



Training

NSE = 0.77

KGE' = 0.80

r = 0.94; α =1.16; β = 1.09

Validation

NSE = 0.68

KGE' = 0.78

r = 0.86 α =1.03 β = 0.84

5. Preliminary results

LISFLOOD vs LSTM

Validation

NSE = 0.66
KGE' = 0.74
r = 0.85 α =1.09 β = 0.81

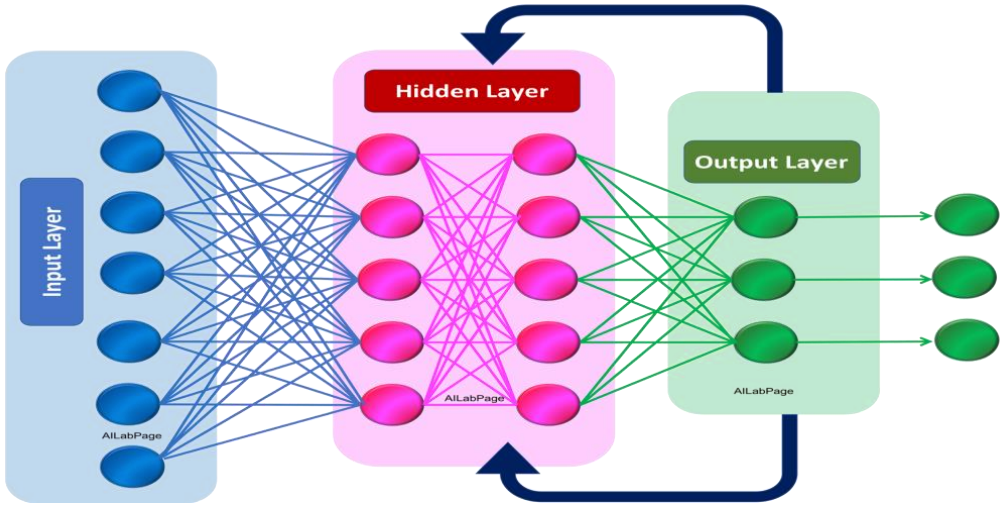
Validation

NSE = 0.68
KGE' = 0.78
r = 0.86 α =1.03 β = 0.84

Process Driven Models

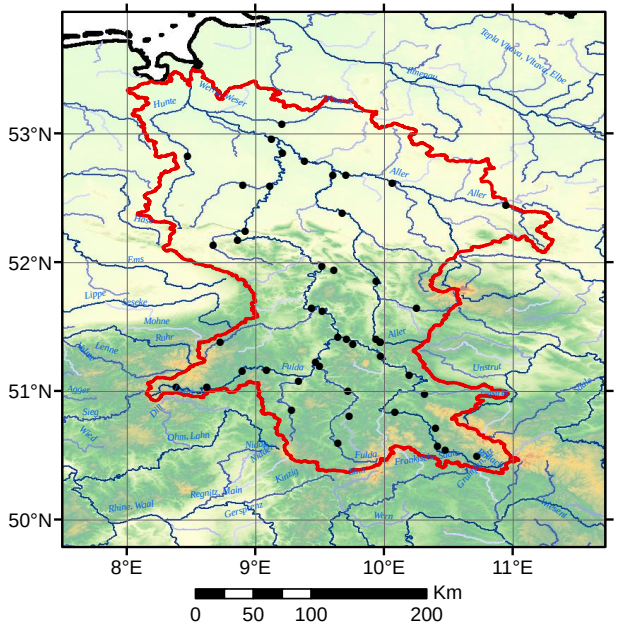


Data Driven Models



6. Further work

- Fine tunning Hydrological model LISFLOOD
- Fine tunning of the LSTM
- Include more hydrological station
- Include in the LSTM other meteorological forcings (**ET0, EW0, ES0**)



7. References

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE transactions on evolutionary computation, 6(2), 182-197.

Kratzert, Frederik, Daniel Klotz, Sepp Hochreiter, and Grey S. Nearing. "A Note on Leveraging Synergy in Multiple Meteorological Data Sets with Deep Learning for Rainfall–Runoff Modeling." *Hydrology and Earth System Sciences* 25, no. 5 (May 20, 2021): 2685–2703. https://doi.org/10.5194/hess-25-2685-2021.

Yang, Shuyu, Dawen Yang, Jinsong Chen, Jerasorn Santisirisomboon, Weiwei Lu, and Baoxu Zhao. "A Physical Process and Machine Learning Combined Hydrological Model for Daily Streamflow Simulations of Large Watersheds with Limited Observation Data." *Journal of Hydrology* 590 (November 2020): 125206. https://doi.org/10.1016/j.jhydrol.2020.125206.

Besaw, Lance E., Donna M. Rizzo, Paul R. Bierman, and William R. Hackett. "Advances in Ungauged Streamflow Prediction Using Artificial Neural Networks." *Journal of Hydrology* 386, no. 1–4 (May 2010): 27–37. https://doi.org/10.1016/j.jhydrol.2010.02.037.

Lees, Thomas, Marcus Buechel, Bailey Anderson, Louise Slater, Steven Reece, Gemma Coxon, and Simon J. Dadson. "Benchmarking Data-Driven Rainfall–Runoff Models in Great Britain: A Comparison of Long Short-Term Memory (LSTM)-Based Models with Four Lumped Conceptual Models." *Hydrology and Earth System Sciences* 25, no. 10 (October 21, 2021): 5517–34. https://doi.org/10.5194/hess-25-5517-2021.

Kratzert, Frederik, Daniel Klotz, Claire Brenner, Karsten Schulz, and Mathew Herrnegger. "Rainfall–Runoff Modelling Using Long Short-Term Memory (LSTM) Networks." *Hydrology and Earth System Sciences* 22, no. 11 (November 22, 2018): 6005–22. https://doi.org/10.5194/hess-22-6005-2018.

Hu, Youchuan, Le Yan, Tingting Hang, and Jun Feng. "Stream-Flow Forecasting of Small Rivers Based on LSTM," 2020. https://doi.org/10.48550/ARXIV.2001.05681.