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Zentrum für Umweltforschung
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Spatially-distributed Deep Learning for rainfall-runoff modelling and system understanding

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The Elbe catchment

- 4th largest river catchment of EU
- Strong flood events in 2002, 2006, 2013
- Low-flow period 2003, 2005

→ Need for accurate prediction of streamflow

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Methods

- Streamflow prediction from E-OBS gridded dataset of precipitation + temperature
- Transfer Convolutional-LSTM Architecture to Hydrology
- Aim: Exploit spatio-temporal patterns in gridded climate data
- Baseline models:
    - Spatially-distributed Physical model (mHM: Samaniego L., R. Kumar, S. Attinger (2010))
    - Non-spatially distributed LSTM on catchment means

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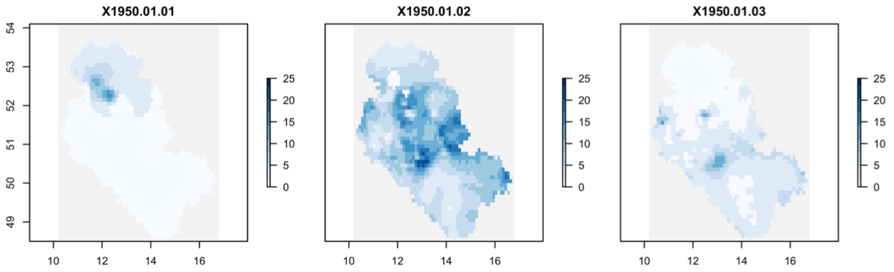
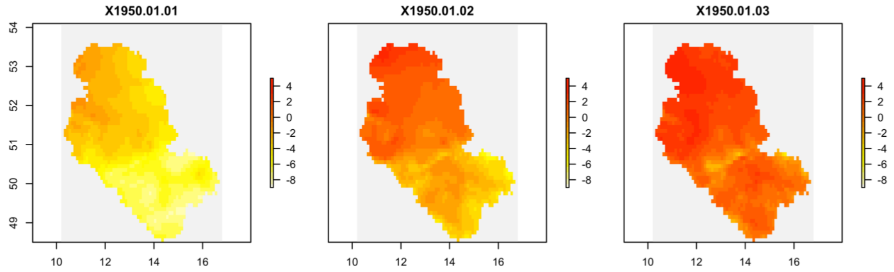
Data

Precipitation [mm/d]

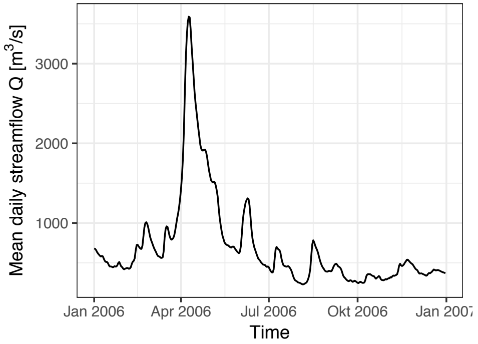


Air temperature [°C]



Input

- 1950 – 2013
- Daily mean values
- Spatial Resolution 0.1°



ConvLSTM

Patterns:
- Spatial
- Temporal

Target

ConvLSTM

Uncertainty Quantification:

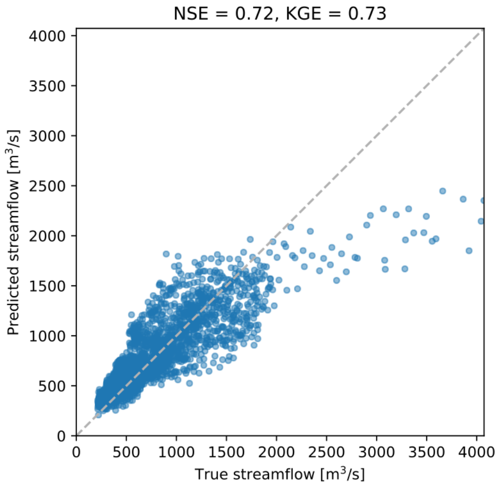
- Aleatoric uncertainty by estimating standard deviation in gaussian loss function (Kendall & Gal, 2017)
- Epistemic uncertainty: Drop-out in inference

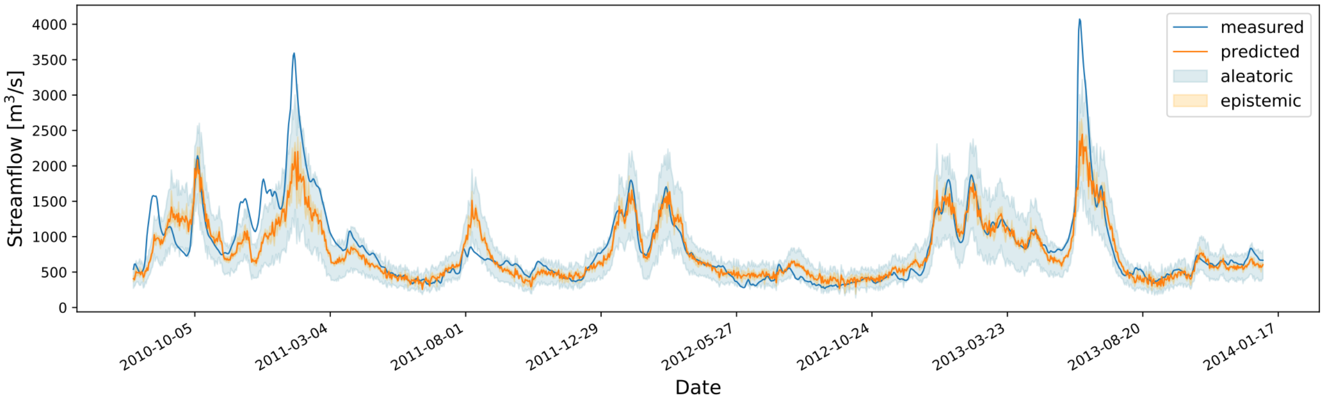
ConvLSTM

Strided convolution operations (instead of pooling)

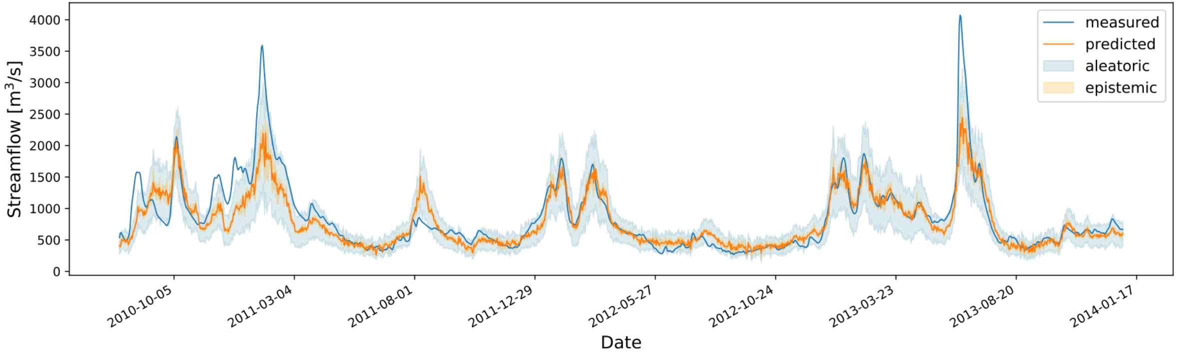
Results: ConvLSTM

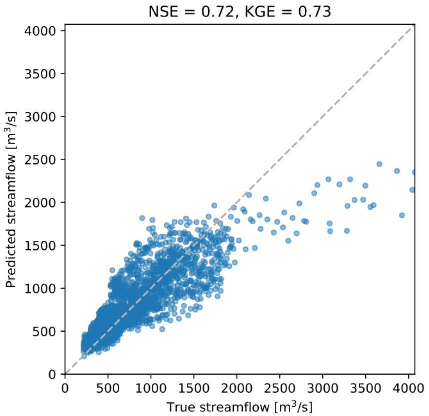
- Accurate modelling of dynamics
- Meaningful uncertainty bands
- Oscillations
- Underestimation of peak flows



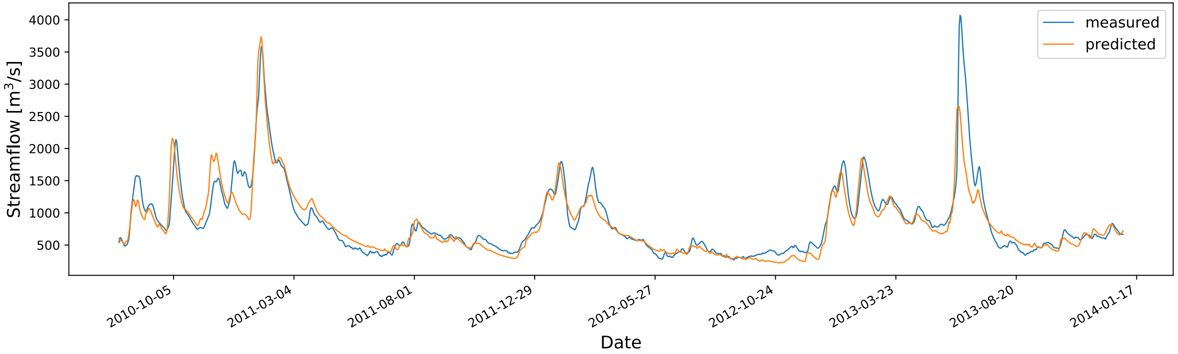


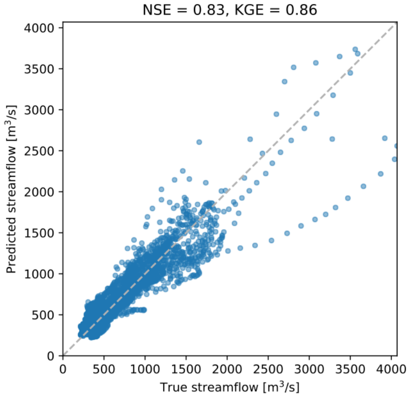
Results: ConvLSTM vs. Physical Model





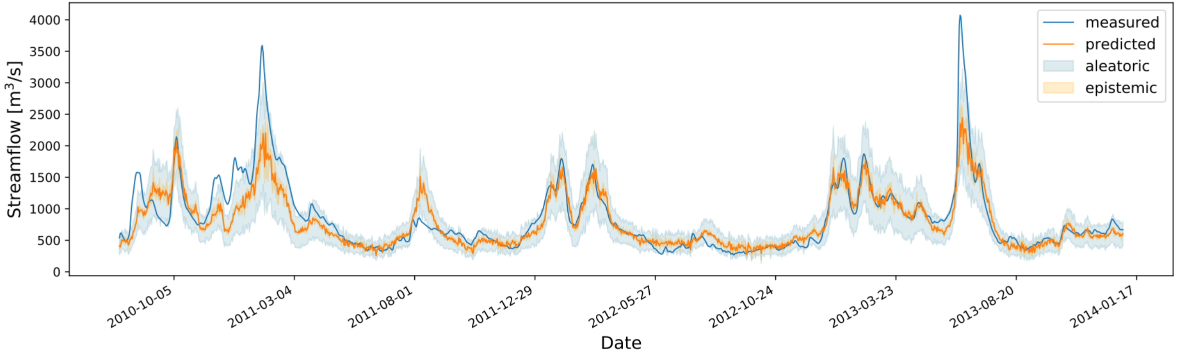
ConvLSTM

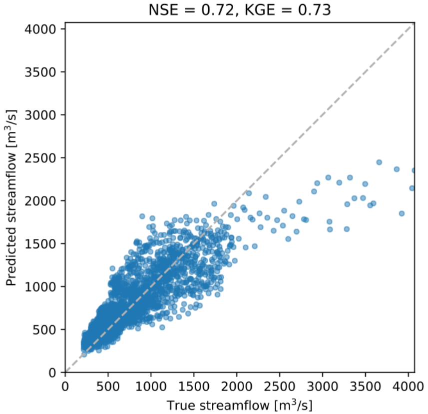




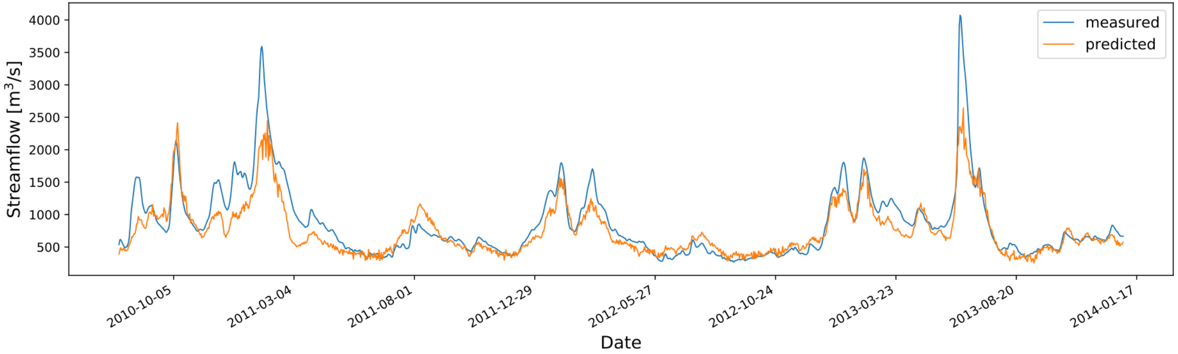
Physical

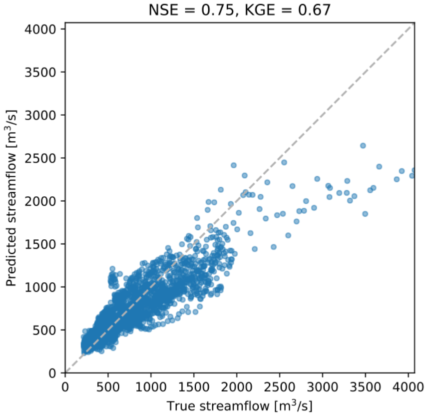
Results: ConvLSTM vs. LSTM





ConvLSTM





LSTM

Results: Summary

- Deep Learning allows for accurate prediction incl. uncertainty from 2 inputs
- Similar predictions to physical model but oscillations
- Non-spatially distributed LSTM achieves similar accuracy as spatially-distributed ConvLSTM

→ Flexibility of DL does not guarantee more accurate predictions

→ Spatial patterns not exploited / not relevant

Results: Discussion

→ Spatial patterns not exploited / not relevant

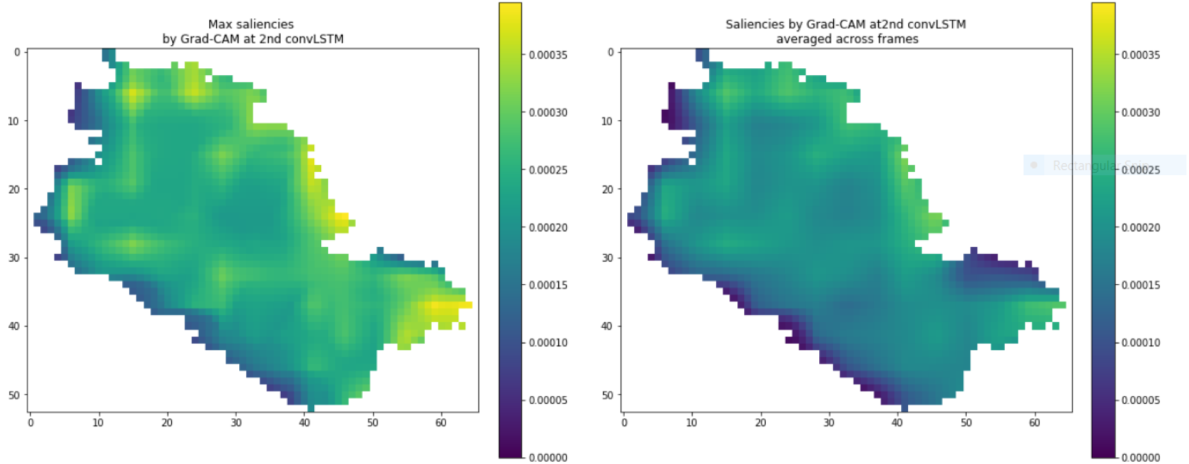
Possible explanations:

- Uncertainty in E-OBS gridded dataset
- Short-comings in model training / architecture
- Similar to known issue in process-based modelling:

  Lumped models might be more accurate than distributed models

Outlook

- Systematic Hyperparameter tuning
- Analyze: Reasons for limited use of spatial information
- Interpretation: Saliency Maps
    - Runoff-relevant subregions in catchment
    - Relevant time-lags
- Apply on real-time Remote-Sensing Data



References

- Cornes, R., G. van der Schrier, E.J.M. van den Besselaar, and P.D. Jones. 2018: An Ensemble Version of the E-OBS Temperature and Precipitation Datasets, J. Geophys. Res. Atmos., **123**. doi:10.1029/2017JD028200
- Samaniego L., R. Kumar, S. Attinger (2010): Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. Water Resour. Res., 46,W05523, doi:10.1029/2008WR007327.