ESoWC 2019

MATEHIW // MAchine learning TEchniques for High-Impact Weather

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20.09.2019

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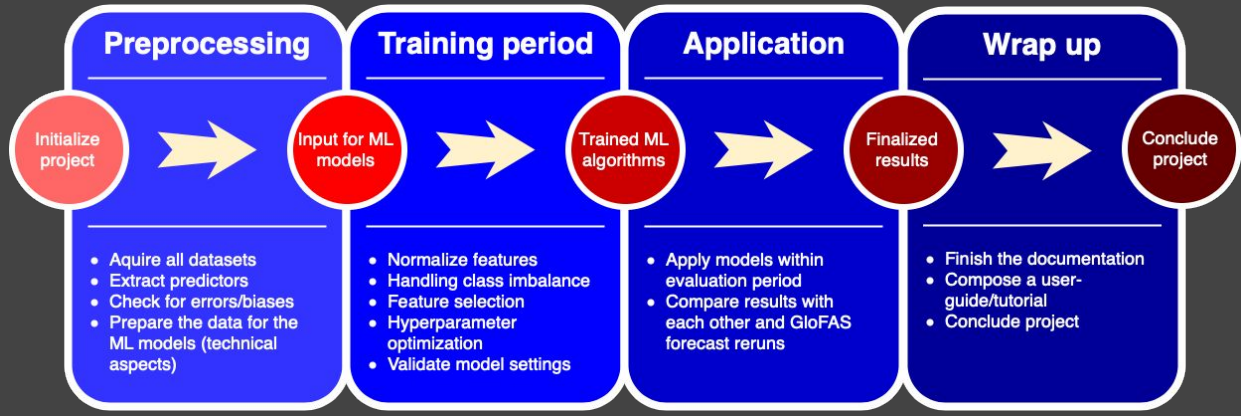


Motivation & goal

Modeling river discharge => high-dimensional problem: many meteorological/ hydrological parameters important with complex interactions => coupled dynamical models.

- Can statistical connections based on ML techniques with comparable skill be established?

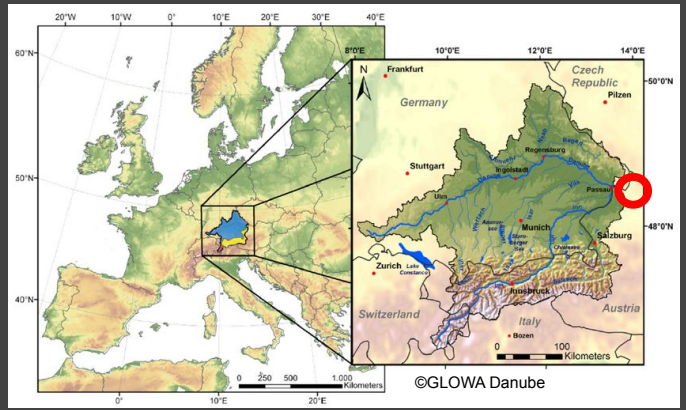
➔ Explorative comparison study: investigate flood forecasting capability of ML techniques (with data from ECMWF/Copernicus)

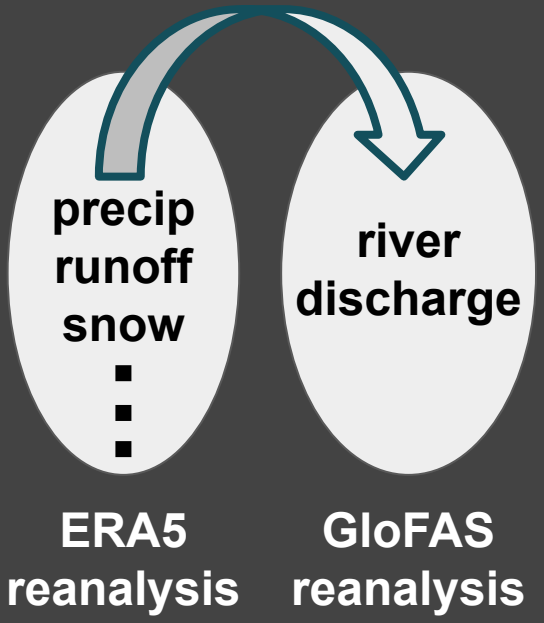
➔ Code and documentation for interested peers (open source and reproducible)

ECMWF

Principal model design

- Determine point of interest (for discharge forecasts)
- Find upstream area
- Spatially average features in the corresponding area
- Predictand: discharge at specified point





Data // Download

- Daily resolution; spatial domain of interest
- Predictor data from ERA5
  via the Climate Data Store API for python
- Predictand data from GloFAS
  - Reanalysis
  - 4 Forecast reruns for a flooding event

  directly from the GloFAS team via FTP

GLOFAS
Global Flood Awareness System

Notebook: 1.03_data_overview.ipynb

ECMWF

Data // Preprocessing

CDO (Climate data operator) used for processing raw (hourly) data

Generate:

- daily averages
- daily accumulated precipitation
- extract data from bounding box (spatial region)
- merge into one .nc file

Setup and doc (mpimet): link

Python implementation:
https://pypi.org/project/cdo/

Notebook: 1.04_preprocessing_with_cdo.ipynb

Feature selection // Heatmap

- Filter method: Correlation analysis

ERA5 variables:

runoff

large-scale precipitation

convective precipitation

total-column water vapor

soil water content layer 1

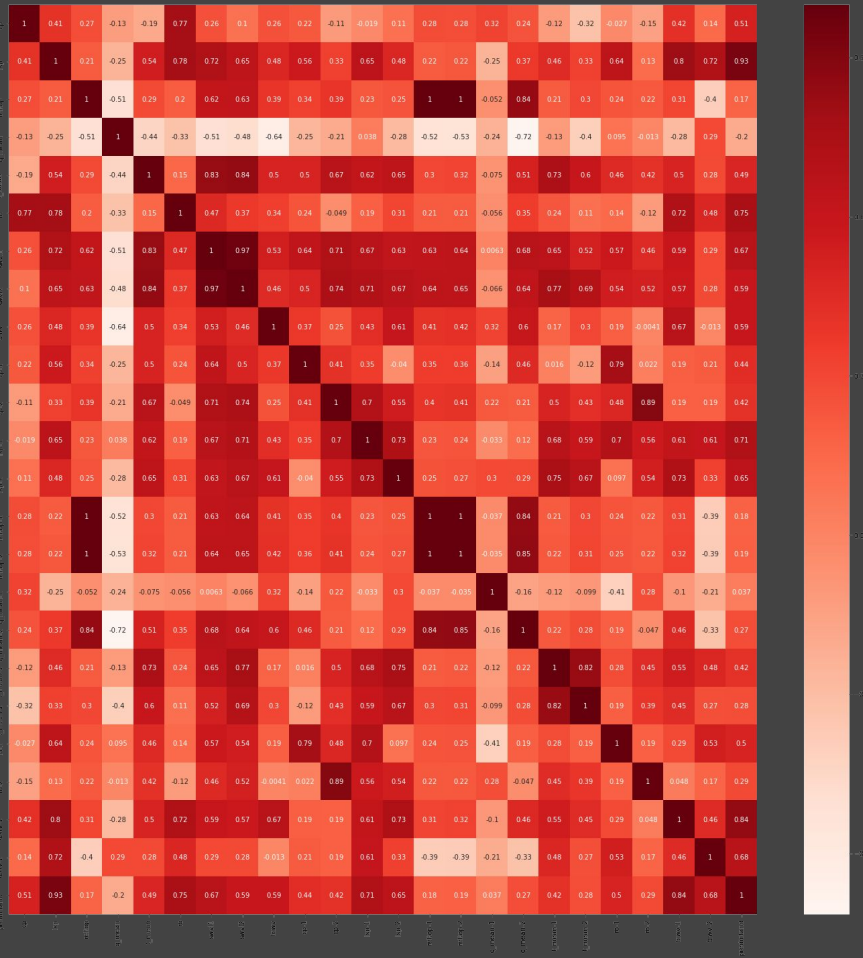
Δ snowdepth

relative topography

snowdepth

soil water content layer 2

=> same time as well as time shifted



Notebook: 2.01_feature_selection.ipynb

Feature selection // Relevant parameters

- Filter method: Correlation analysis (Heatmap)
  - precipitation (convective as well as large-scale)
  - time-lagged precipitation
  - runoff
  - soil water content layer 1

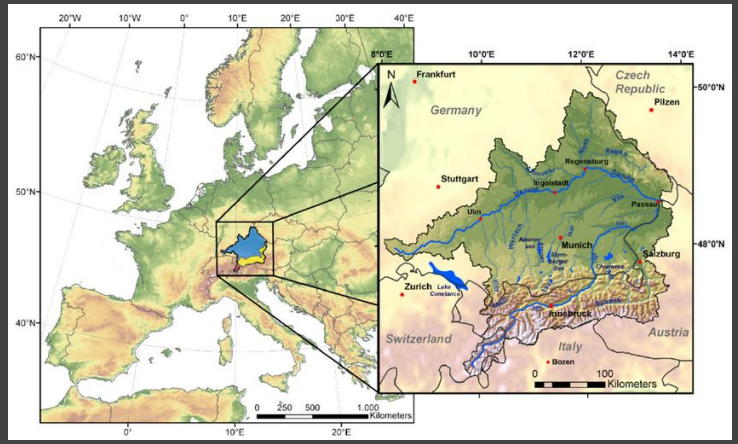
★ Total column water vapor high correlation, BUT collinearity with precipitation!

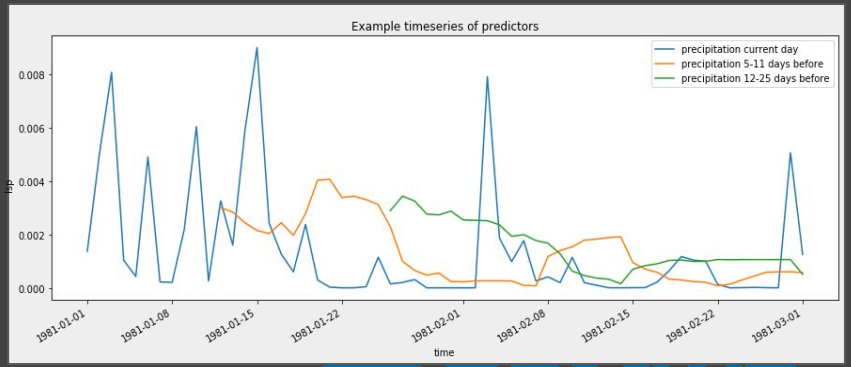
★ Time-lagged runoff high corr, BUT collinearity to itself (non time-lagged)!

Notebook: 2.01_feature_selection.ipynb

Feature selection // Engineering

- Only consider data in the given catchment
- Average features
- Shift time (time-lagged features)
- Specially treated: Precipitation (large-scale)
  - Aggregation over time large time periods
  - captures long memory effects
  - up to 180 days into the past



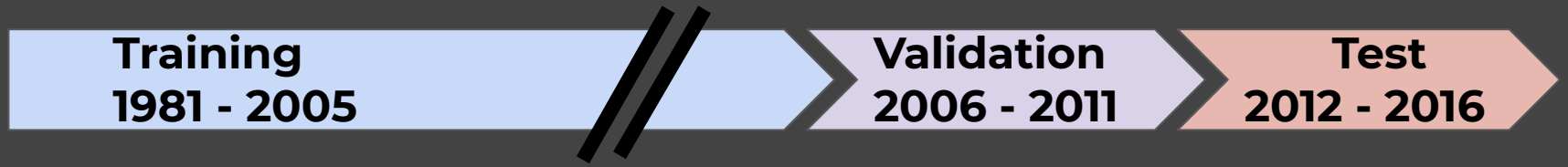


Notebook: [2.05_prepare_data_for_the_models.ipynb]

ML model setup // Overview

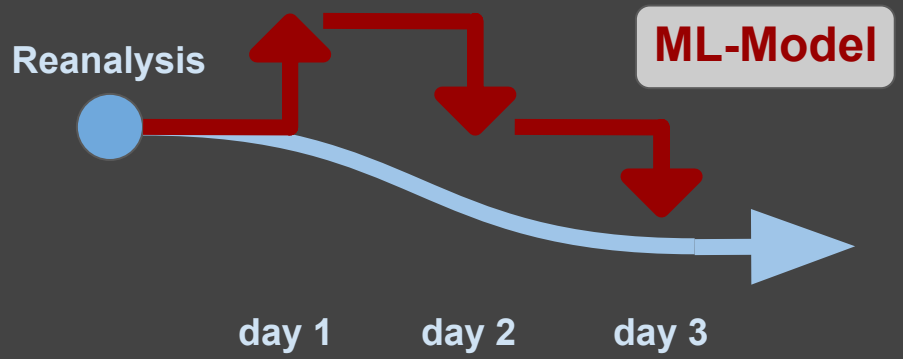
Models:

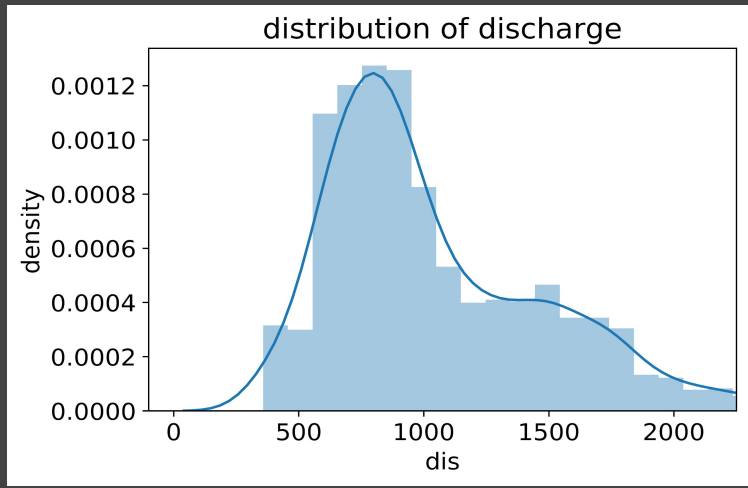
- LinearRegressionModel via scikit learn
- SupportVectorRegressor via scikit learn
- GradientBoostingRegressor via scikit learn
- Time-Delay Neural Net via Keras

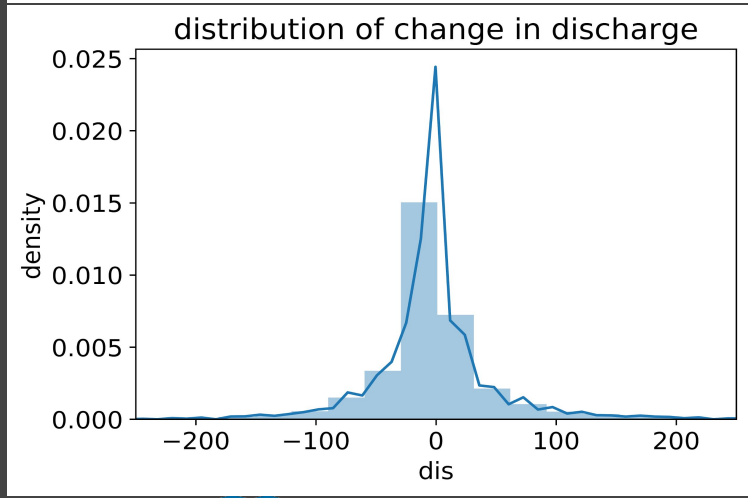


ML model setup // Overview

- River discharge non-normal distribution => Predict change in discharge
- 14-day forecast: Reanalysis baseline + cumulative sum of predicted change





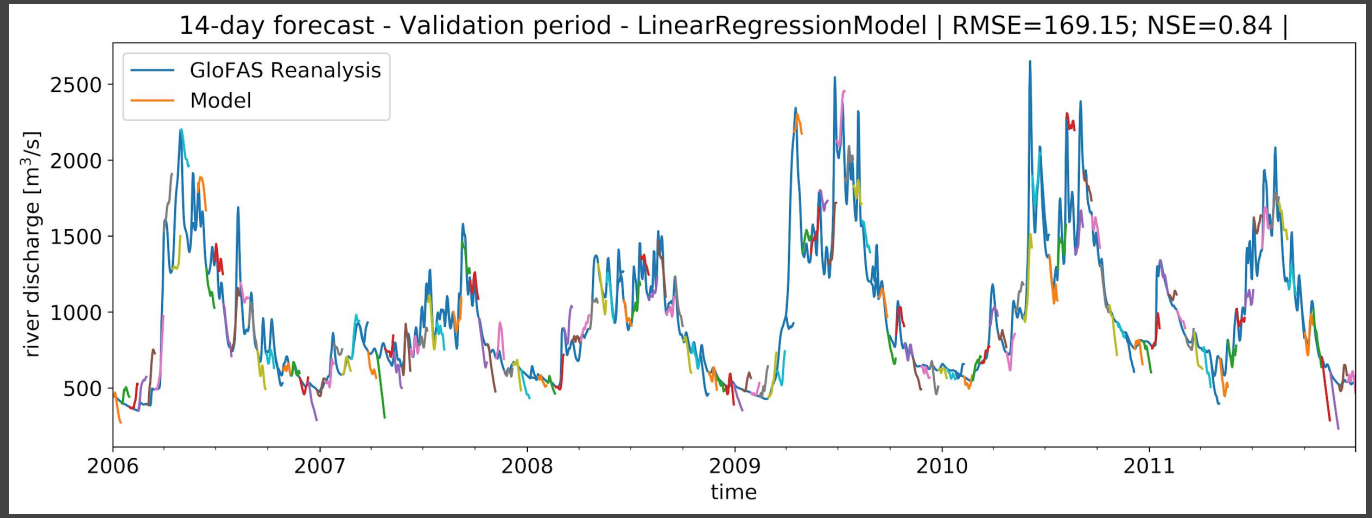


ML model setup // LinearRegressionModel

Hyperparameter optimization:

- Standard OLS Linear Regression does not have any hyperparameters ✓

RMSE	NSE
169 m^3/s	0.84



Notebook: 3.02_LinearRegression.ipynb

ML model setup // SupportVectorRegressor

Hyperparameter optimization: via GridSearch

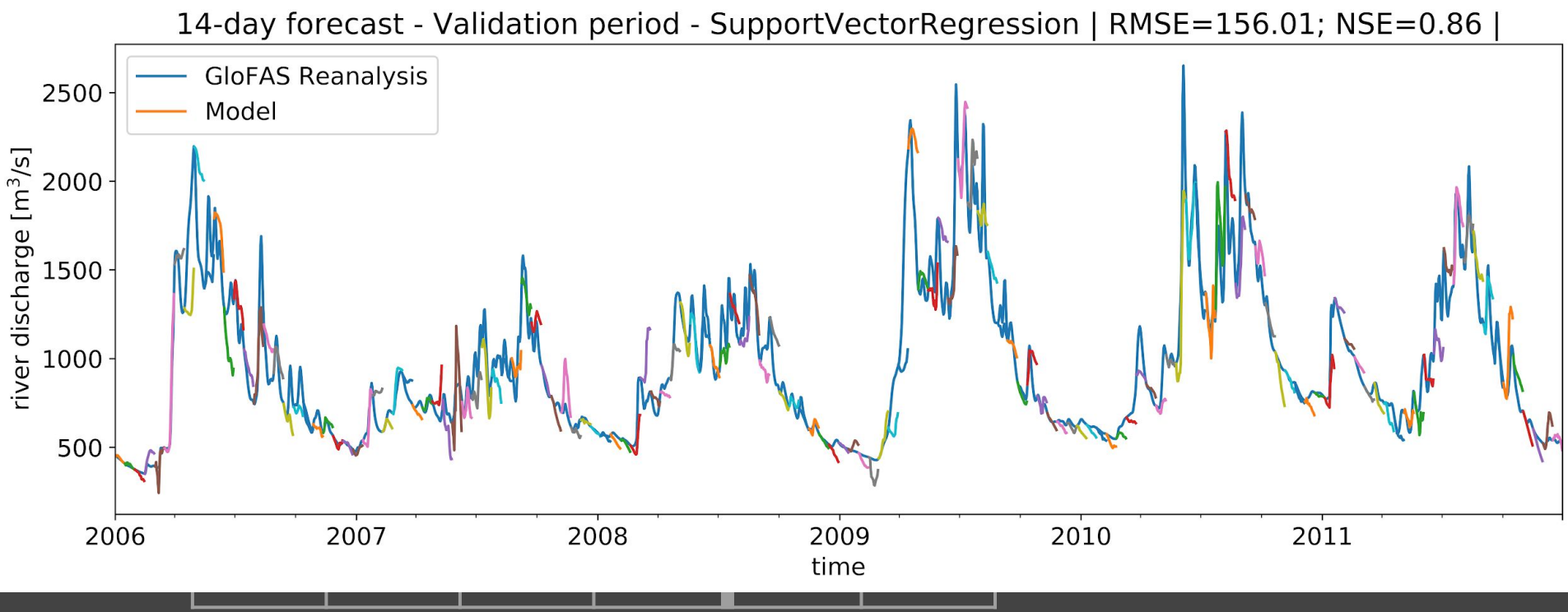
- kernel: rbf, poly
- C: [1, 10, 100]
- epsilon: [0.01, 0.1, 1]
- degree (if poly): [1, 2, 3, 4, 5]

Best setting:

kernel	C	epsilon	degree	**RMSE**	**NSE**
poly	100	0.01	3	**156** m^3/s	**0.86**

Notebook: [3.03_SupportVectorRegression.ipynb]

ML model setup // SupportVectorRegressor



Notebook: [3.03_SupportVectorRegression.ipynb]

ML model setup // GradientBoostingRegressor

Hyperparameter optimization: via GridSearch

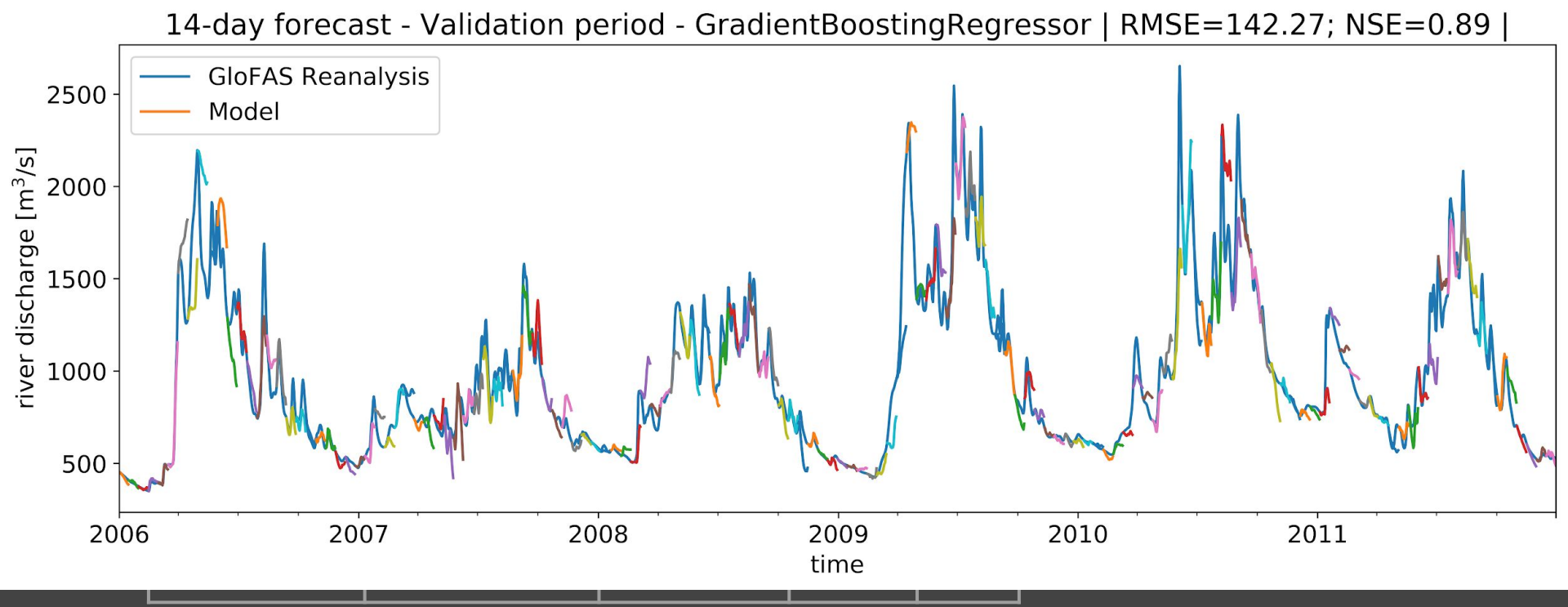
- n_estimators: [10, 50, 100, 200, 300]
- learning_rate: [0.05, 0.1, 0.2]
- max_depth: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15]

Best setting:

n_estimators	learning_rate	max_depth	**RMSE**	**NSE**
200	0.1	5	**142** m^3/s	**0.89**

Notebook: [3.04_GradientBoost.ipynb]

ML model setup // GradientBoostingRegressor

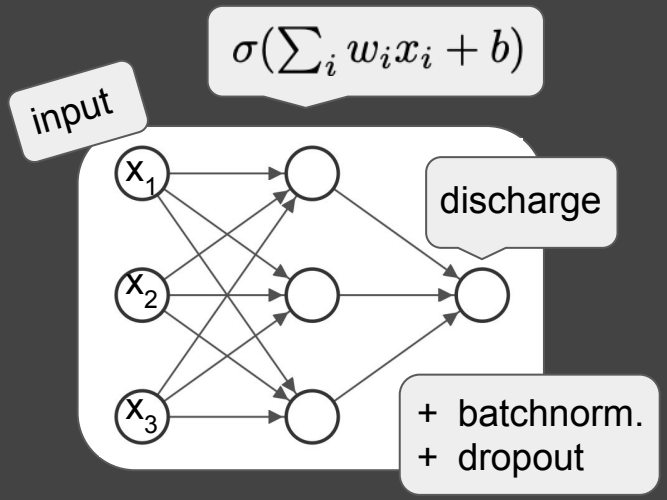


Notebook: [3.04_GradientBoost.ipynb]

ML model setup // Time-Delay Neural Net

Hyperparameter optimization:

- Number of hidden layers: 1 - 4
- Number of nodes per layer: [4, 8, 16, 32]
- Dropout: 10% - 50%



Best setting:

one hidden layer, 64 nodes (1281 free parameters)

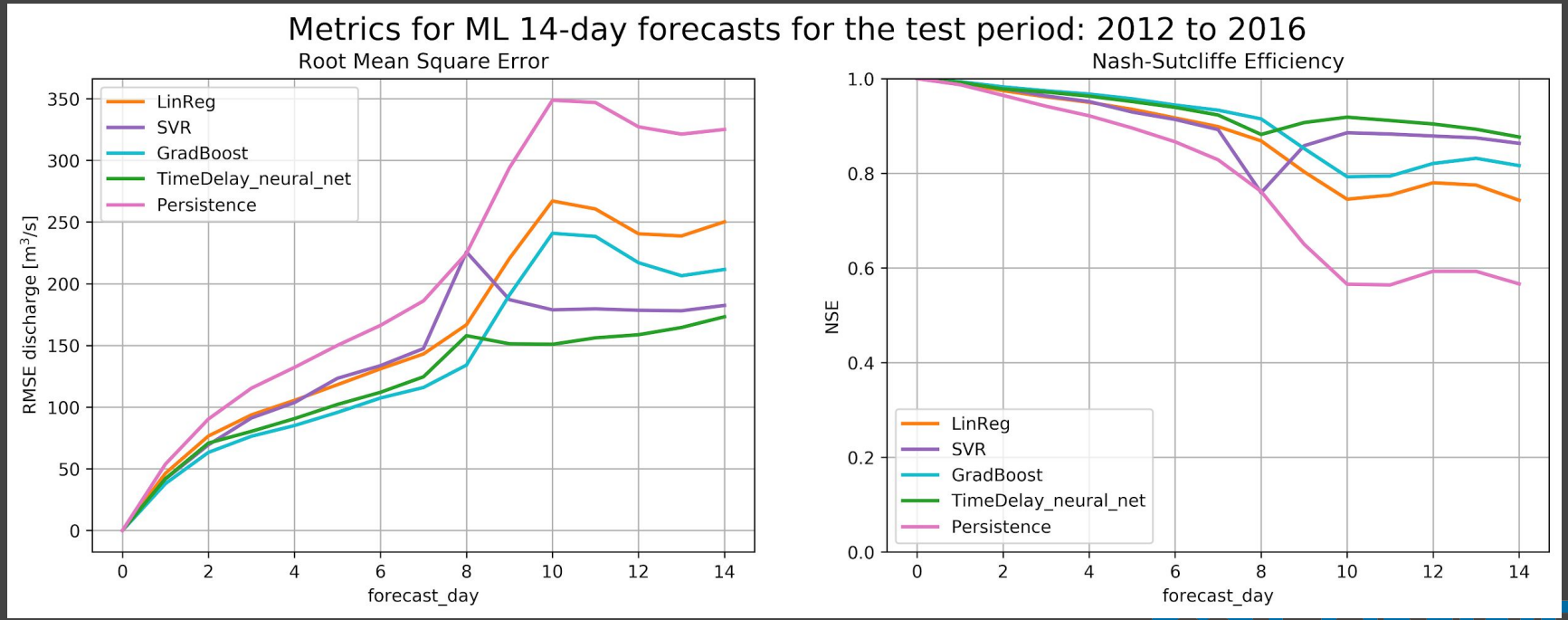
with batch size 90 days, tanh activation, 2 min training on 4 cores

RMSE	NSE
126 m^3/s	**0.93**

Notebook: [3.05_Time-delay_neural-net.ipynb]

Results // Model comparison in the full test period

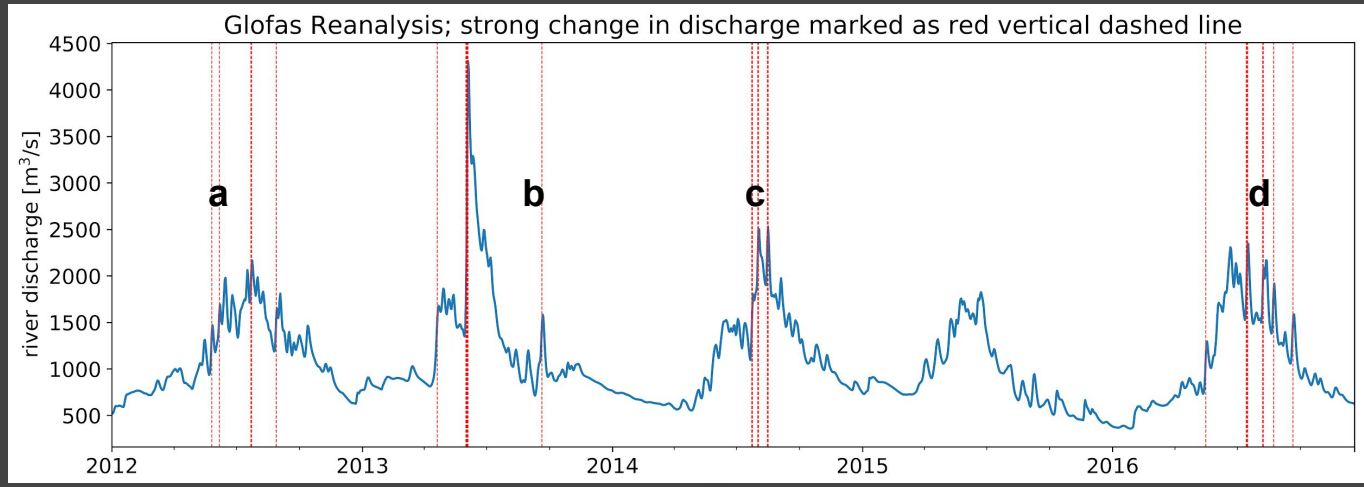
14-day forecasts over the full test period: Best model => Time-delay neural net



Notebook: [3.06_model_evaluation.ipynb]

Results // Samples: rapid changes in discharge

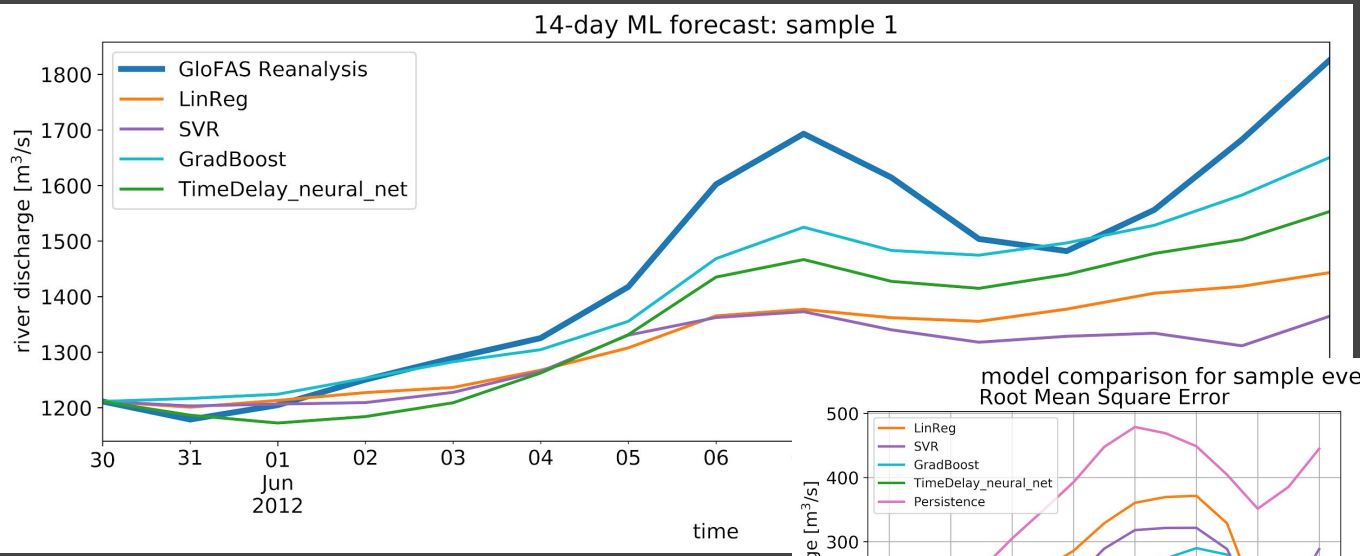
- 14-day forecast samples
- Init times:
  a. 30.06.2012
  b. 22.10.2013
  c. 03.08.2014
  d. 23.08.2016



- Flooding event 2013 => more detailed case study

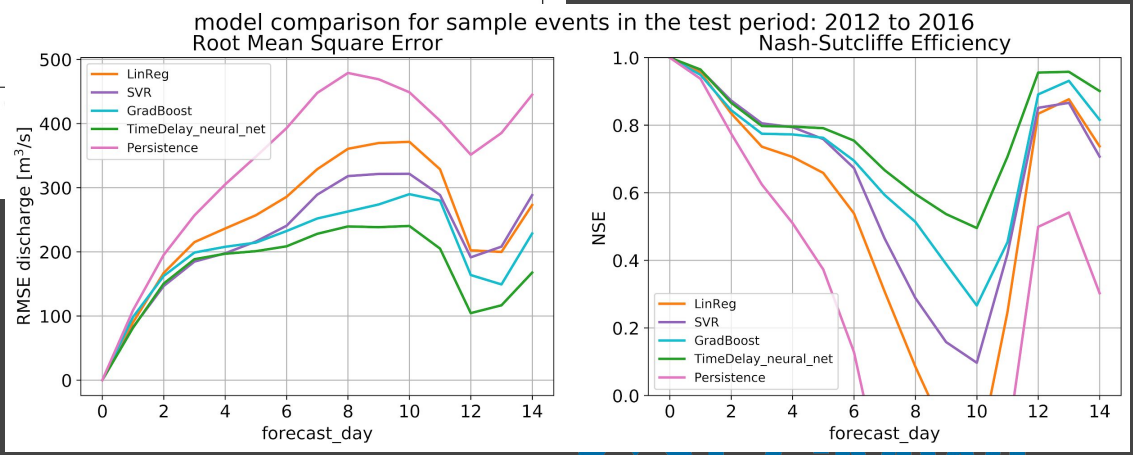
Notebook: 3.06_model_evaluation.ipynb

Results // Samples: rapid changes in discharge



<= metrics
for sample period a)

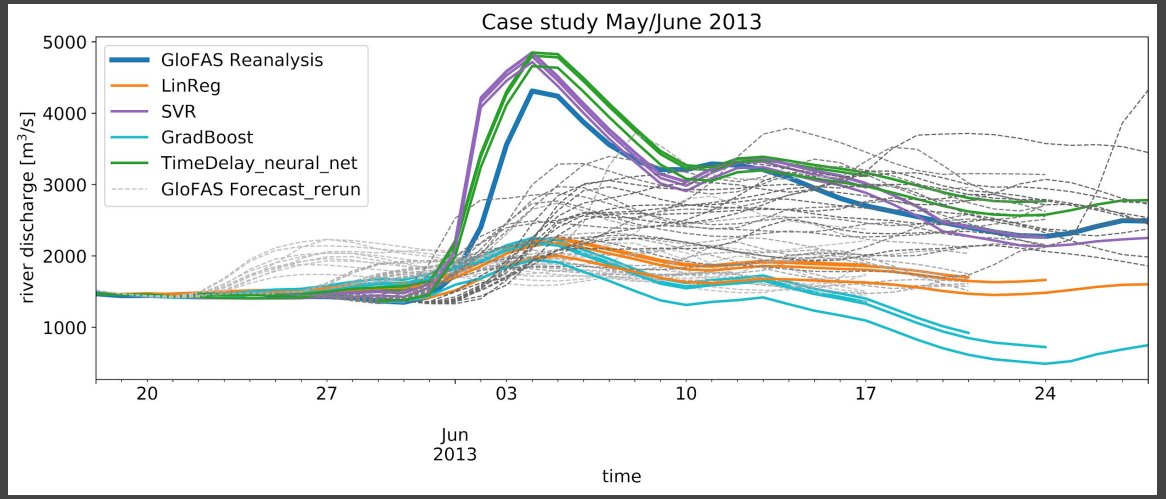
metrics for all 4
sample periods together =>



Notebook: [3.06_model_evaluation.ipynb]

Results // Case study: 2013 European Flood

- Reruns are forecast-driven
- ML is Reanalysis-driven



➔ Time-delay neural net & Support Vector Reg. perform best

➔ Grad. Boost. & Lin. Reg. Model show no significant increase in discharge (shape is quite fine, but amplitude not)

Notebook: 3.06_model_evaluation.ipynb

Conclusion

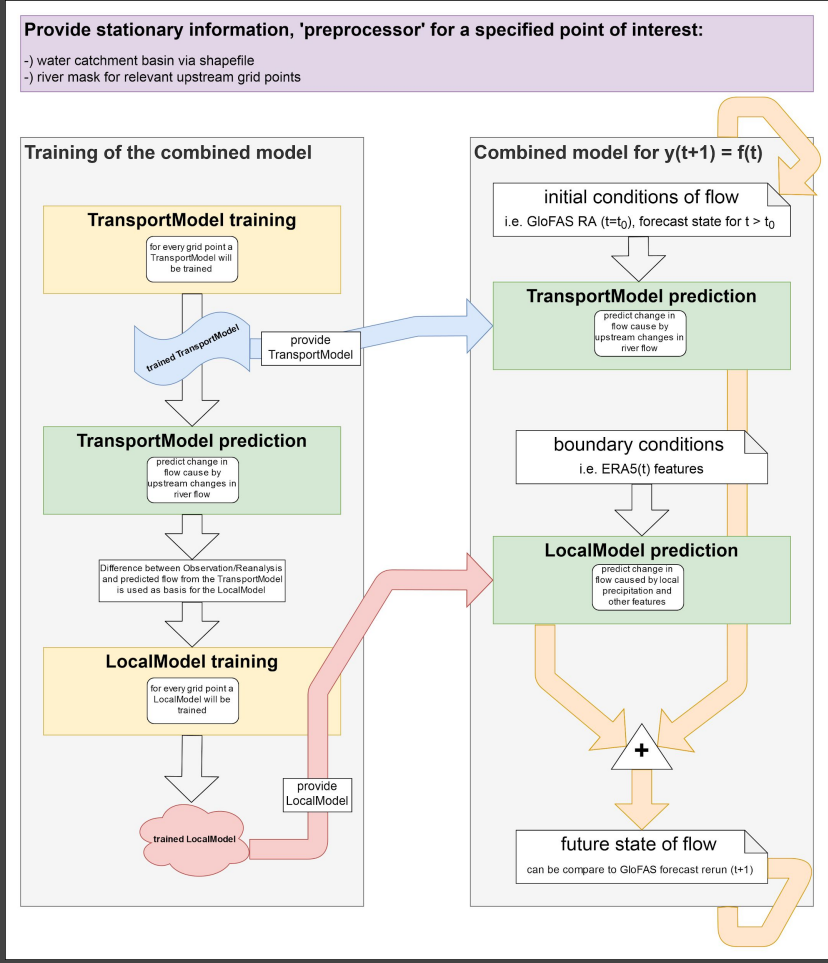
- The TD-NN and SVR models:
  - are able to predict an extreme flooding event, despite their relatively simple setting,
  - may provide cheap additional information to assist forecasts.
- LR and GBR were not able to predict an adequate increase in discharge (although in general GBR performed about as good as TD-NN and SVR)

Additional tuning of models → neural nets exhibit the most theoretical potential due to a lot of possible improvements in the base architecture

Notebook: 3.06_model_evaluation.ipynb

Outlook

- Incorporate stationary information
  - e.g. catchment specific variables in a CNN or an LSTM as Embedding
- More comprehensive case study in different kinds of catchments (surface characteristics)
- Coupled model: Concept idea



Github: github.com/esowc/ml_flood

Nbviewer: [link]

Acknowledgements

Big thanks go to   

- Our mentors: Claudia Vitolo, Julia Wagemann and Stephan Siemens,
  for always providing helpful comments
- Esperanza Cuartero,
  for communicating the results
- The University of Vienna, Dept. of Meteorology and Geophysics,
  for office and server access
- ECMWF-Copernicus,
  for setting up ESoWC and providing such an opportunity!