The potential of a hybrid framework including data driven approaches for hydrological forecasting

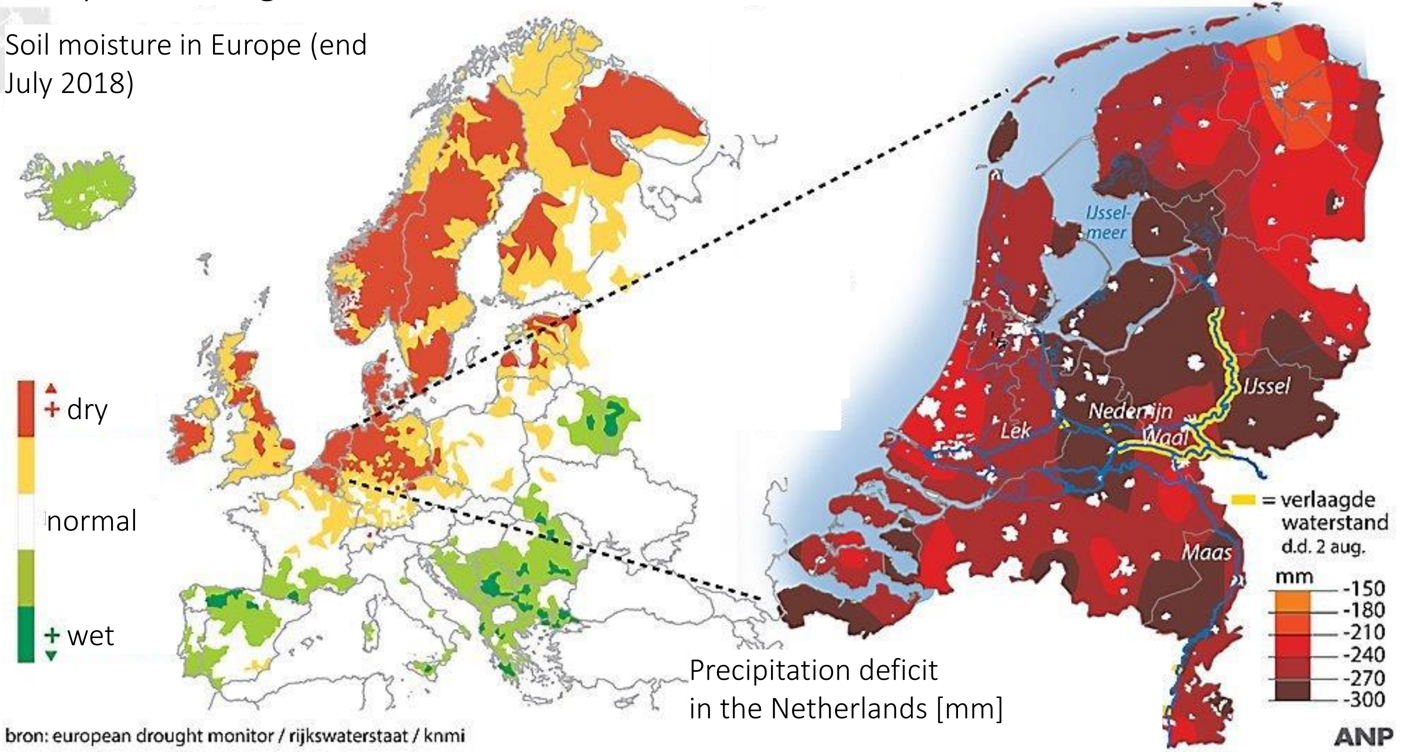
Sandra Hauswirth [1]
Marc F.P. Bierkens [1,2] Vincent Beijk [3] and Niko Wanders [1]

Affiliation: *1. Utrecht University,*
2. Deltares,
3. Rijkswaterstaat

Sharing is encouraged

Recent drought periods: A challenge to the Dutch hydrological system and water management

European drought situation, summer 2018

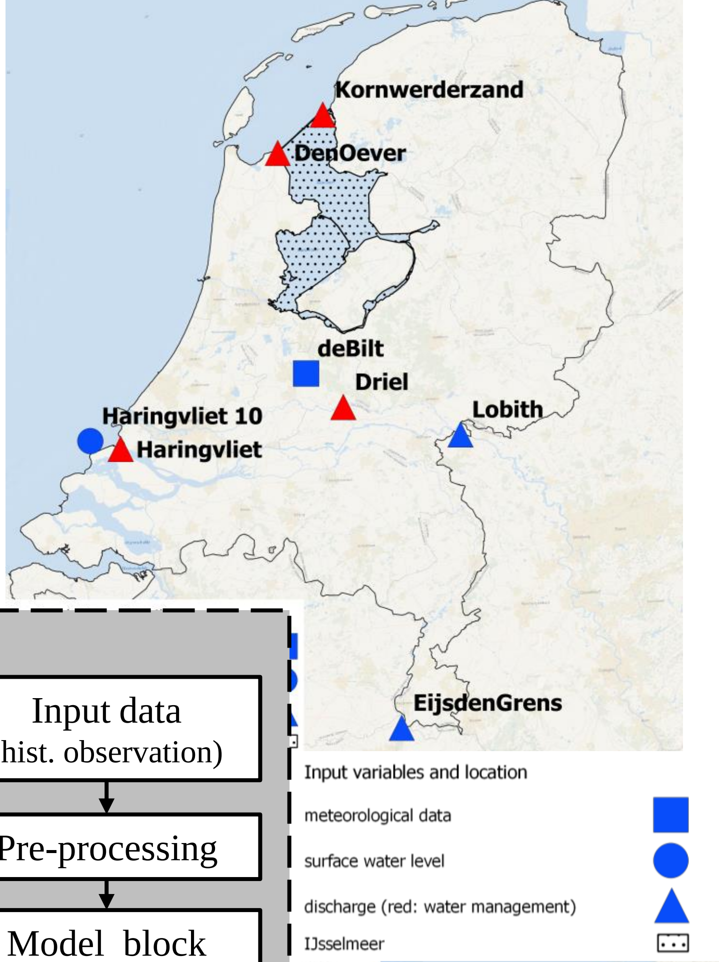


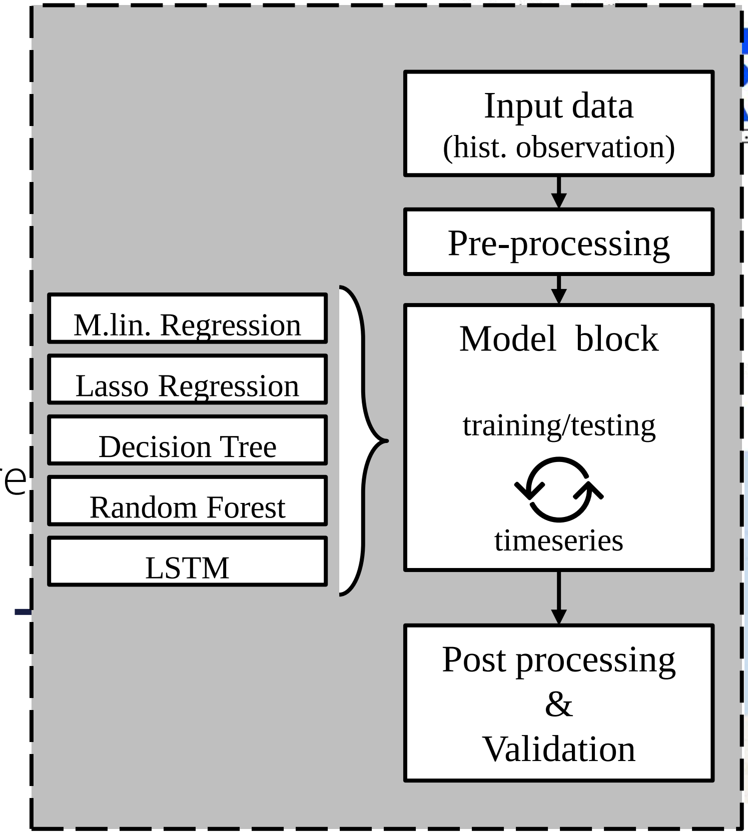
https://frieschdagblad.nl/2018/12/14/droge-zomer-kan-nog-heel-2019-na-ijlen

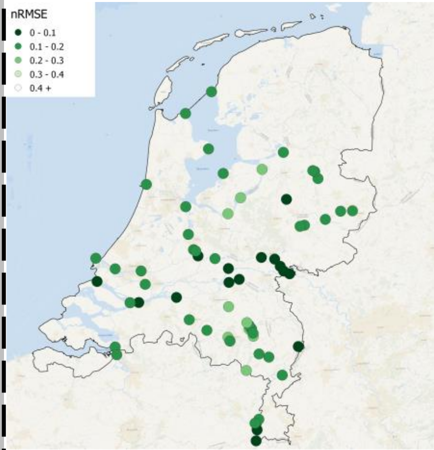
https://www.trouw.nl/nieuws/kan-de-nederlandse-natuur-nog-zo-n-droge-zomer-aan~bbf0e5c5/#&gid=1&pid=1

Model framework

- **simple** model framework to simulate hydrological variable
  - testing different ML models
  - each model/station locally **trained** on **historical observation**
  - 5 input variables:
    - Discharge (2 main rivers)
    - Precipitation and Evaporation
    - Sea/surface water level
  - Target variables:
    - discharge
    - surface water levels & surface water temperature
    - groundwater levels







Utrecht University

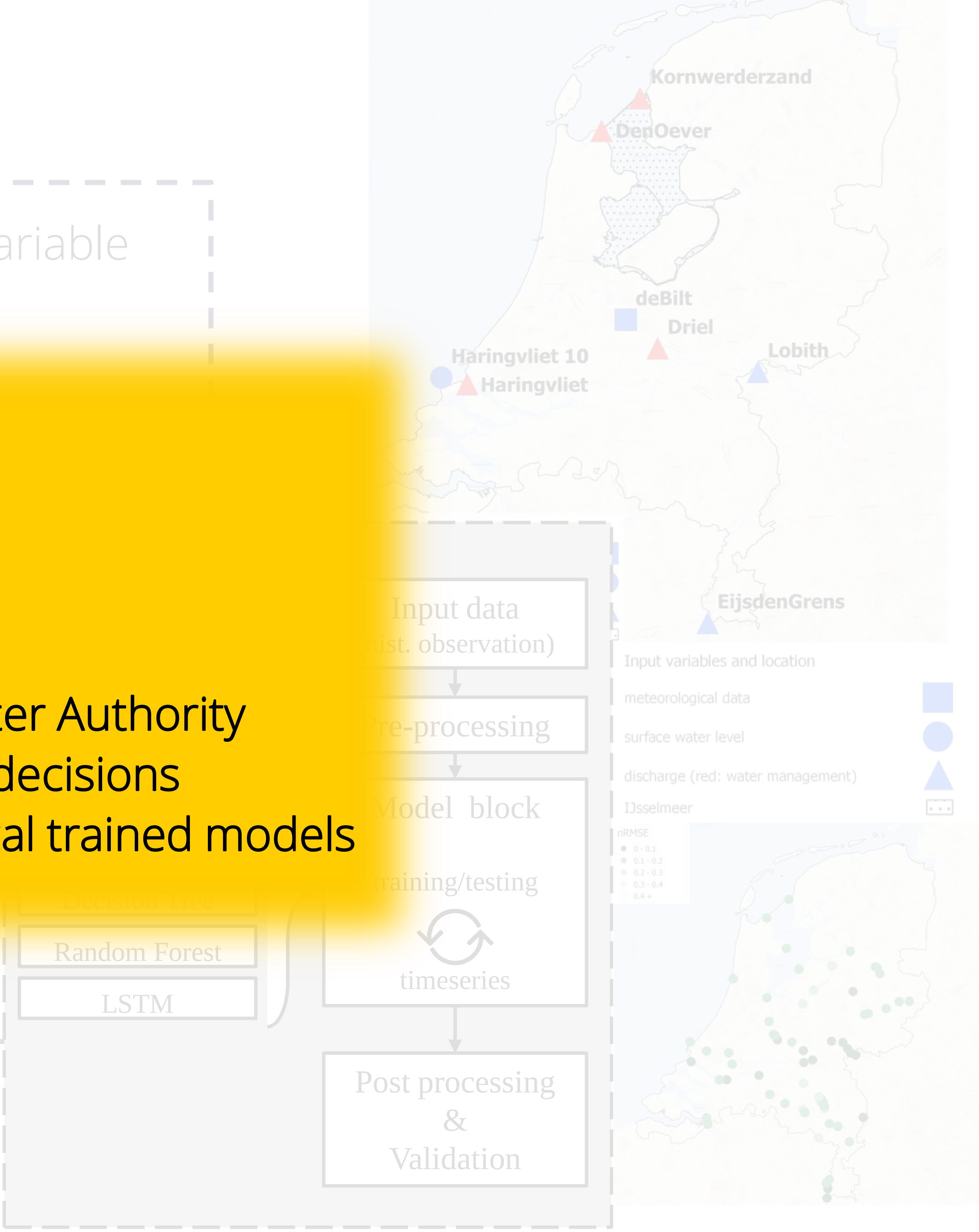
Hauswirth et al. (2021) Adv. Water Resour. DOI: https://doi.org/10.1016/j.advwatres.2021.104017

Model framework

- simple model framework to simulate hydrological variable
  - testing different ML models
    - surface water levels & surface water temperature
    - groundwater levels

- simple but flexible approach
  → exchange of input data

- Developed in interest for local application
  → working together with National Water Authority
  → exploration of water management decisions
  → monitoring network as basis for local trained models



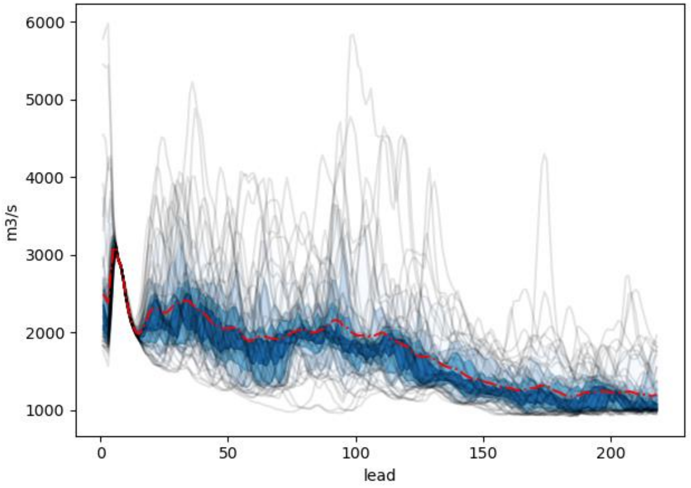
Utrecht University

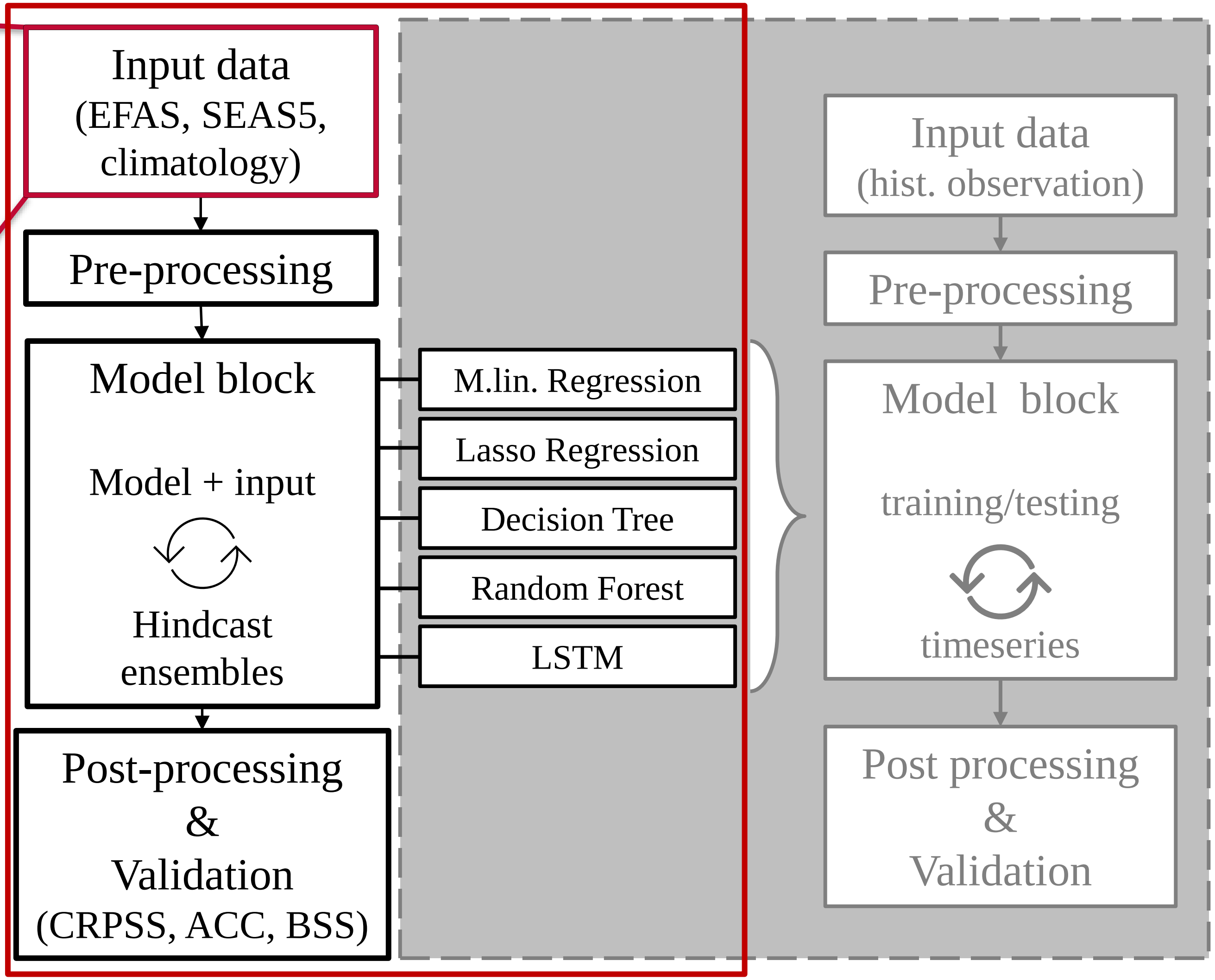
Hauswirth et al. (2021) Adv. Water Resour. DOI: https://doi.org/10.1016/j.advwatres.2021.104017

Model framework

- Seasonal reforecast data:
  - period 1993-2019,
  - 25 to 52 ensemble members,
  - 215 lead days
    - Precipitation (SEAS5)
    - Evaporation (calc. based on SEAS5)
    - Rhine discharge (EFAS)
    - Meuse discharge (EFAS)
    - Seawater level (climatology)

Example forecast discharge





Utrecht University

Hauswirth et al. (2021) Adv. Water Resour., Hauswirth et al. (2022) HESSD (in review)

Main interests

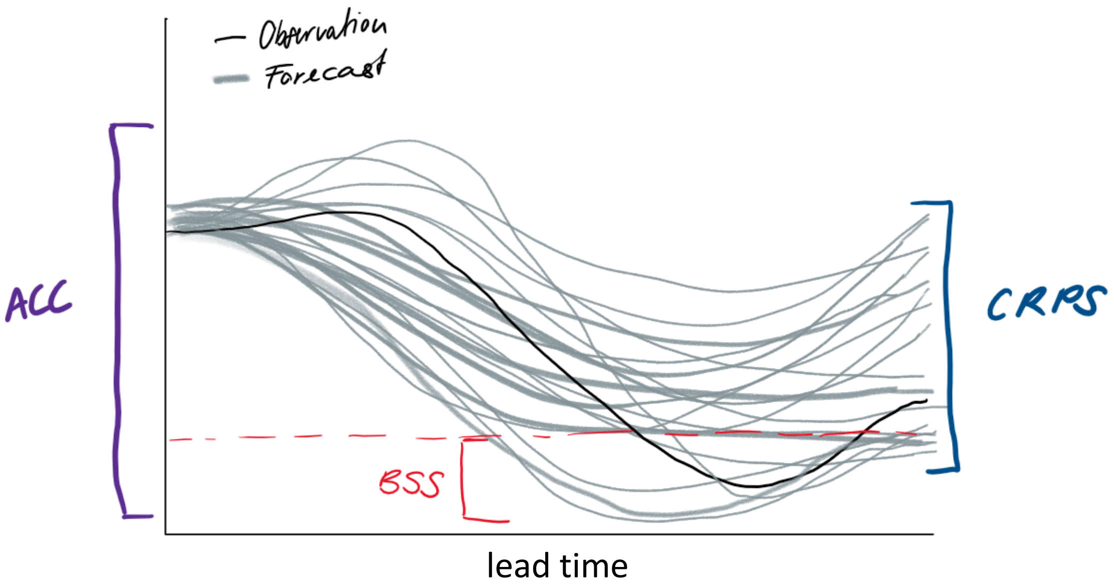
- How well does the ML framework perform in a hindcast setting?
- How skilful are our seasonal hindcasts?
- What are the strength and limitations of the hybrid framework?

Hindcast evaluation

- CRPS (Continuously Ranked Probability Score)
  ➢ To assess the reliability and the spread of a forecast

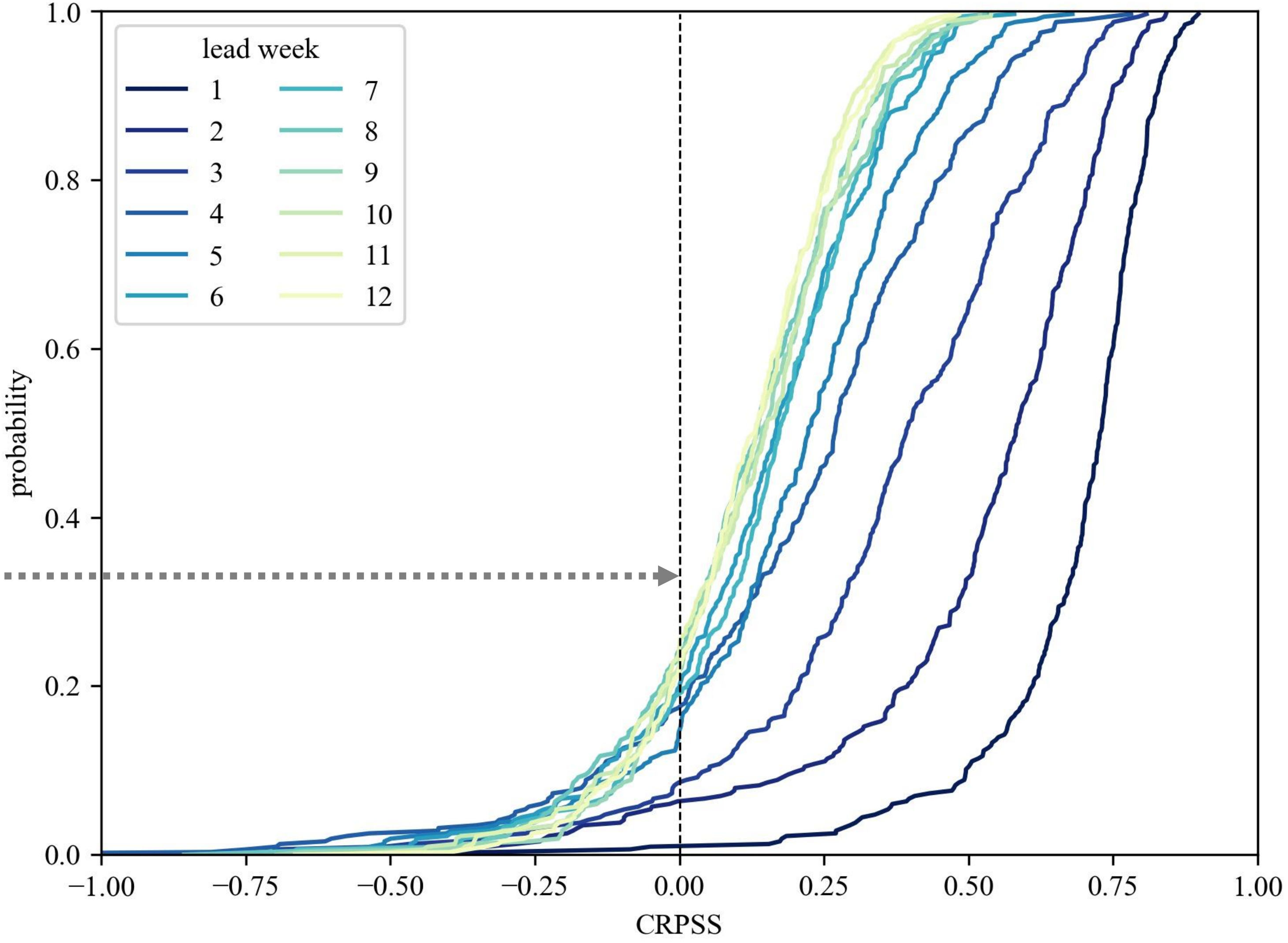
- ACC (Anomaly Correlation Coefficient)
  ➢ To measure the performance of the mean forecast

- BSS (Brier Skill Score)
  ➢ To determine the accuracy + the performance of the hindcasts for high and low flow periods (using a threshold)



How well does the ML framework perform in a hindcast setting?

- ➢ everything above 0 → better than climatological reference
- ➢ roughly 60% of all stations and models show a better performance than the climatological reference



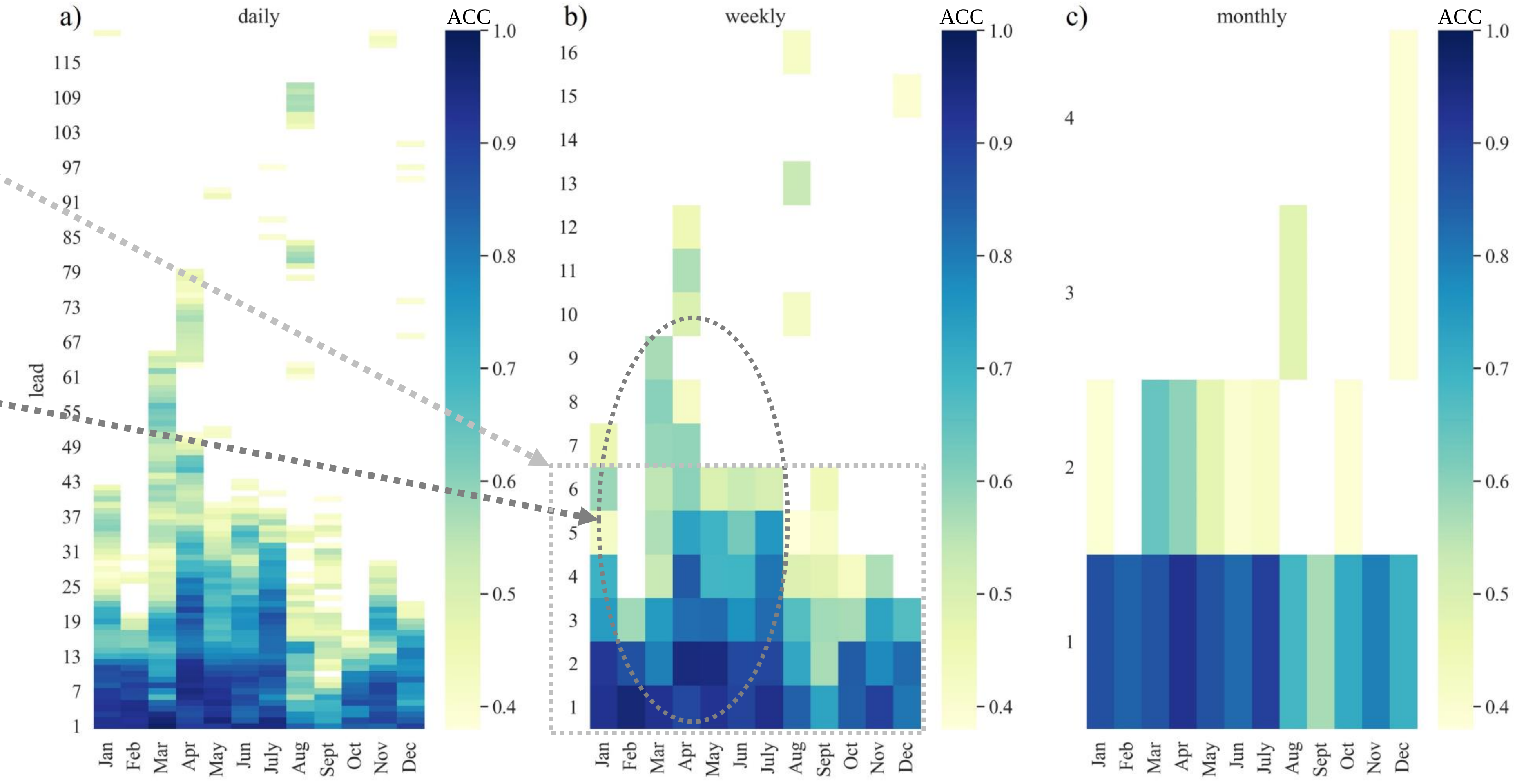
CRPSS (Continuously Ranked Probability Skill Score)

- ➢ To assess the reliability and the spread of a forecast

Hauswirth et al. (2022) HESSD (in review)

How skilful are our seasonal hindcasts?

- skilful forecasts for first few lead weeks (1-2 months)
- early spring skilful forecasts for lead 2-3 months
- captures snow melt dynamic



station: Hagestein Boven, discharge hindcast

ACC (Anomaly Correlation Coefficient)
- To measure the performance of the mean forecast

Hauswirth et al. (2022) HESSD (in review)

Utrecht University

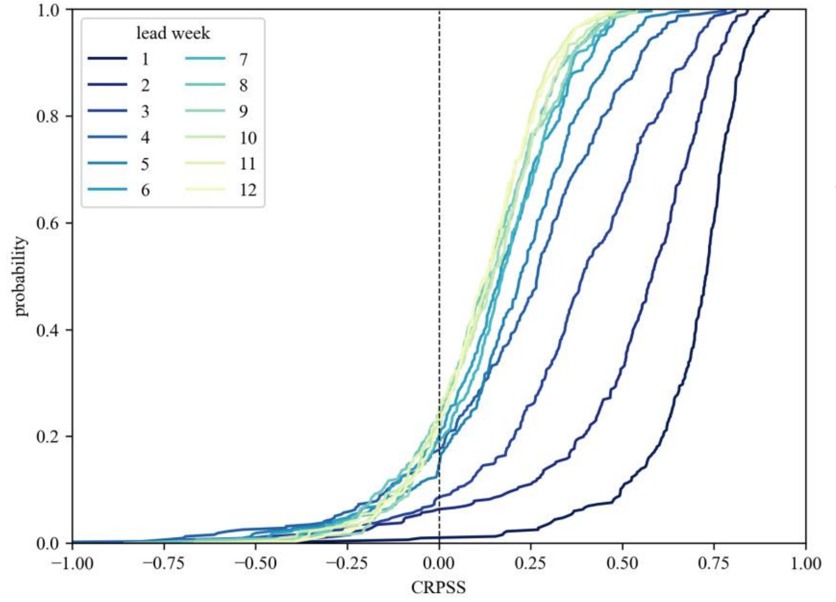
Limitations & Opportunities

- Data limitation (historical observations)
- Modelling choices (e.g. training/testing)
- Uncertainty of input data (seasonal reforecasts)
- Model limitations

+ Fast, less computational intensive than large scale physically based model
+ Spatial and temporal applicability
  + Local application and information
  + Temporal scales relevant to water managers

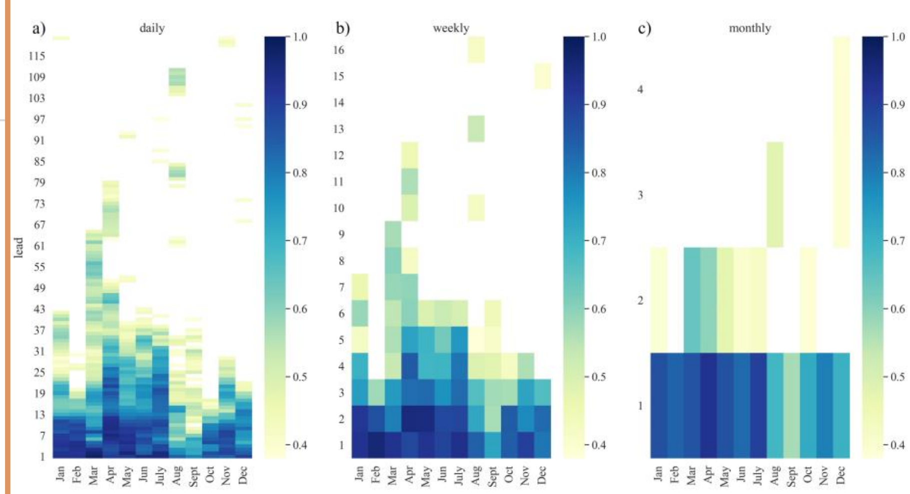
Thank you!

a) How well does the ML framework perform in a hindcast setting?
   - ✓ Outperforming climatological reference by ~ 60% (discharge)



a. CRPSS for discharge hindcasts

b) How skilful are our seasonal forecast?
   - ✓ Skilful for 1 month lead
   - ✓ Skilful up to 2-3 months in spring



b. ACC example station (daily, weekly, monthly temporal scale)

c) What are the strength and weaknesses of this hybrid framework

- Data limitation (historical observations)
- Modelling choices (e.g. training/testing)
- Uncertainty of input data (here seasonal reforecasts)
- Model limitations

\+ Fast, less computational intensive than large scale physically based model
\+ Spatial and temporal applicability
  \+ Local application and information
  \+ Temporal scales relevant to water managers

s.m.hauswirth@uu.nl @SandraHauswirth Hauswirth et al. (2022) HESSD (in review): https://doi.org/10.5194/hess-2022-89