The benefit of pre- and postprocessing streamflow forecasts for 119 Norwegian catchments, evaluated within the frame of an operational flood-forecasting system

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Ensemble forecasts are often biased and under-dispersed, and we investigate how processing schemes can improve flood forecasts

In this presentation we aim at answering the following research questions

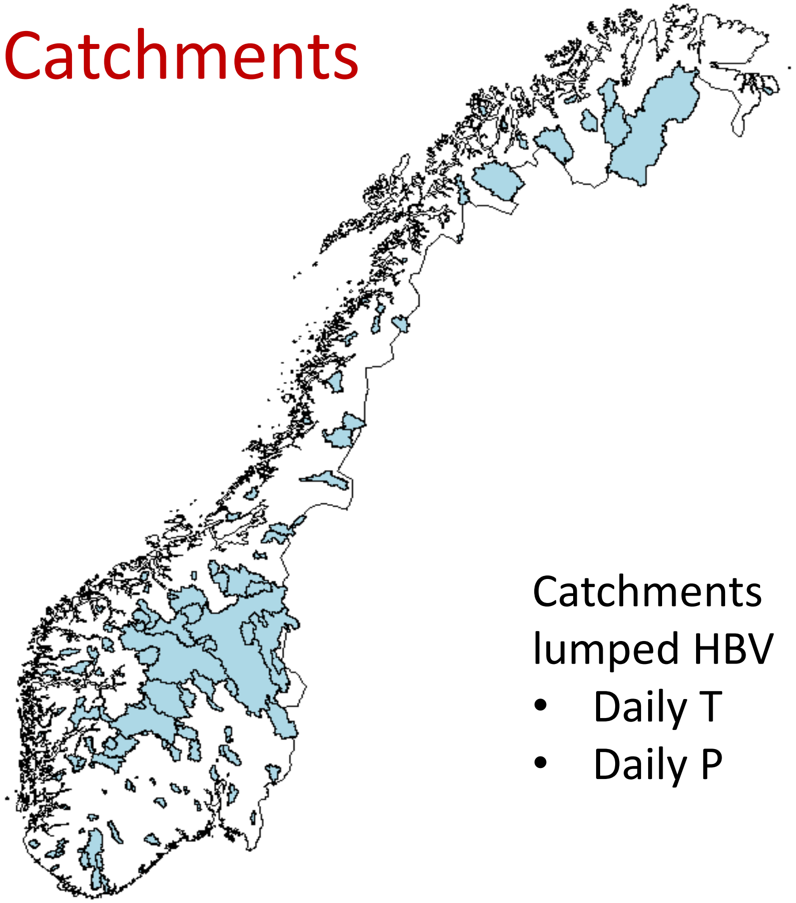
- Are there differences in the performance of correction/processing schemes when applied to all the data compared to the flood situations of the study?
- Can we detect any regional or seasonal patterns?

ECMWF-ENS temperature and precipitaion are forced the operational HBV model for flood-forecasting catchments in Norway

Input data

ECMWF[1] ensemble forecasts
- 2014.01.01 to 2015.12.31
- 51 ensemble members
- 9 daily values
- Temperature (T) and precipitation (P)

Catchments



Catchments lumped HBV
- Daily T
- Daily P

HBV[2] - model

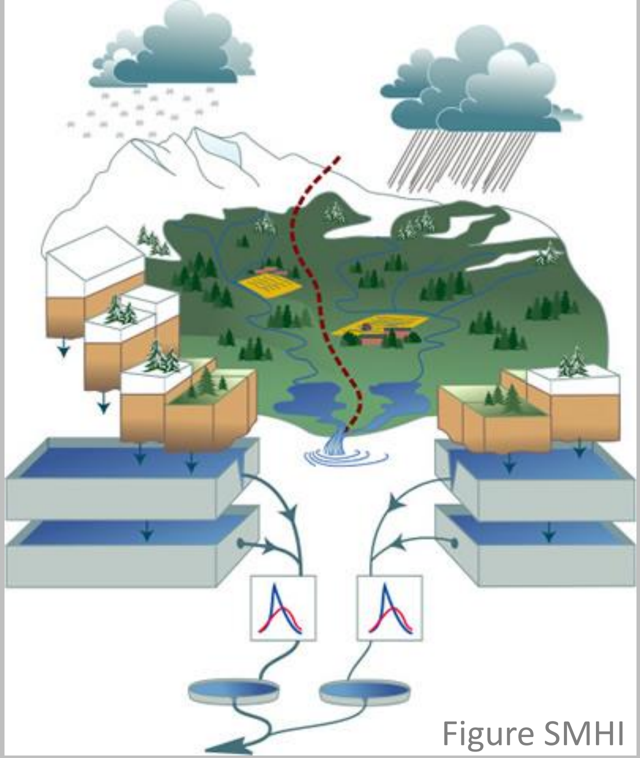
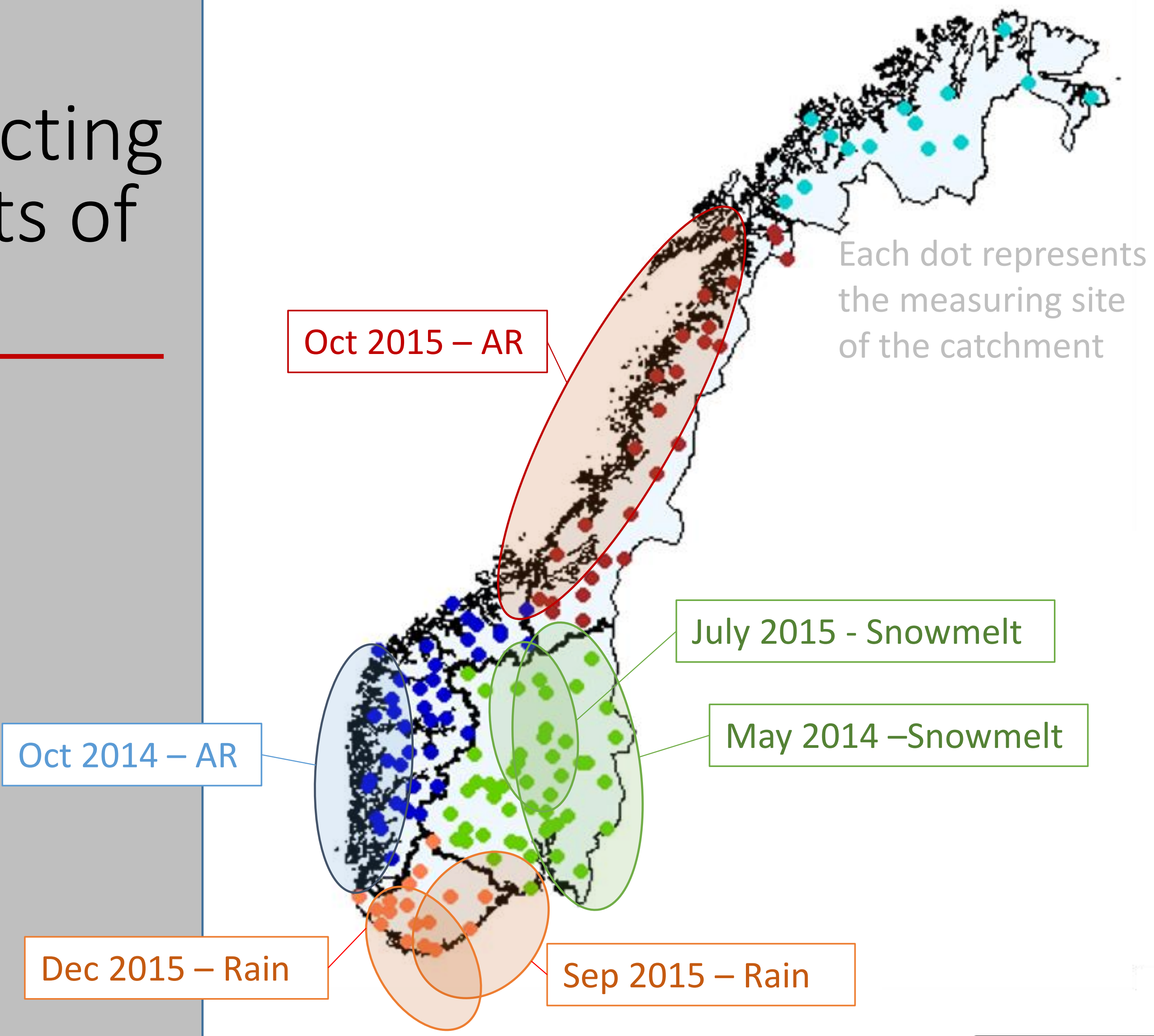


Figure SMHI

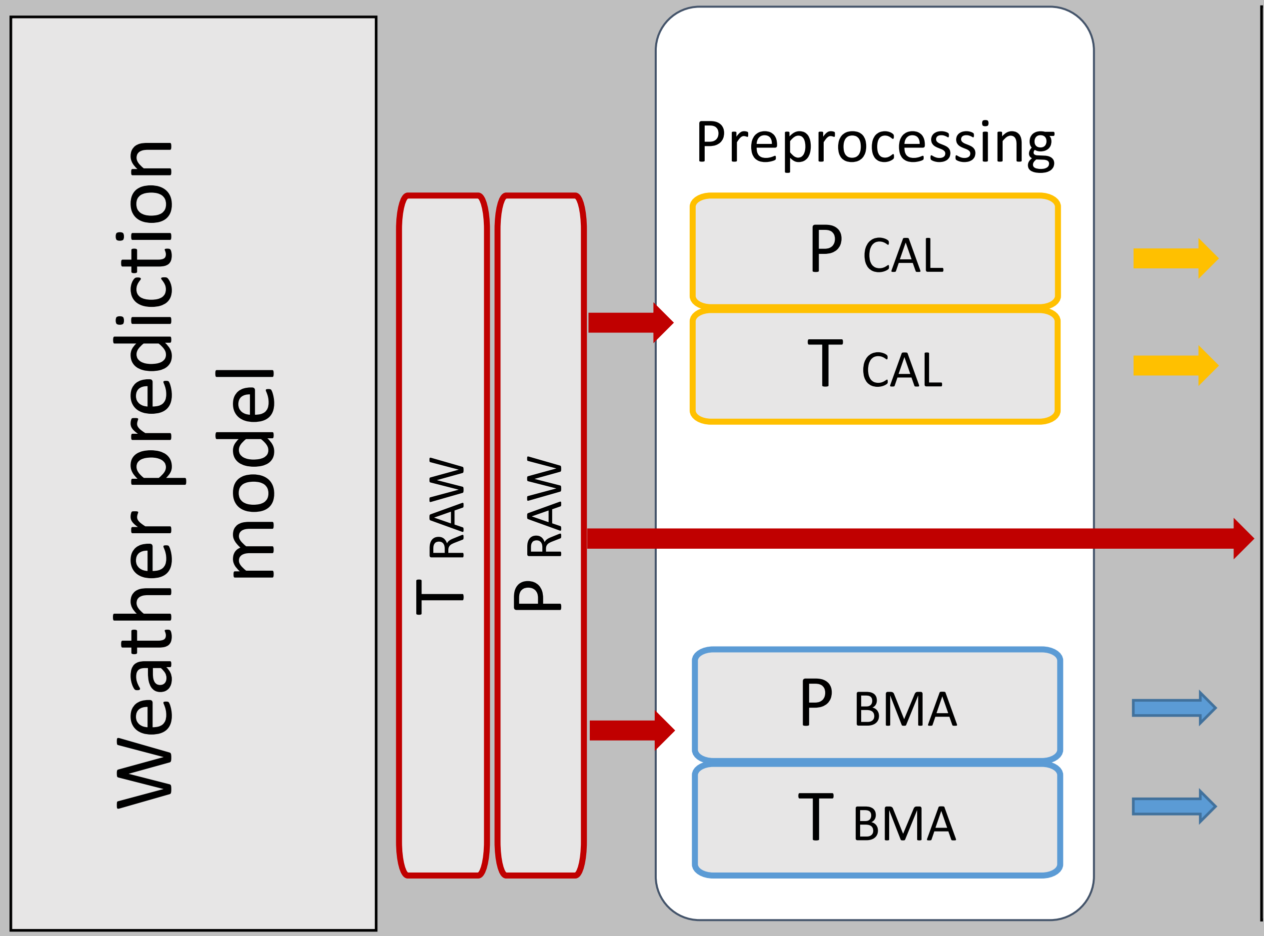
In 2014 and 2015 there were several floods affecting catchments in large parts of Norway

Typical flood generating processes

Snowmelt: often spring floods inland and high elevations
Rain induced: autumn and summer showers
Atmospheric rivers (AR) are responsible for the most extreme floods affecting western, coastal Norway



The ECMWF ensemble T and P are used raw and applied different preprocessing schemes



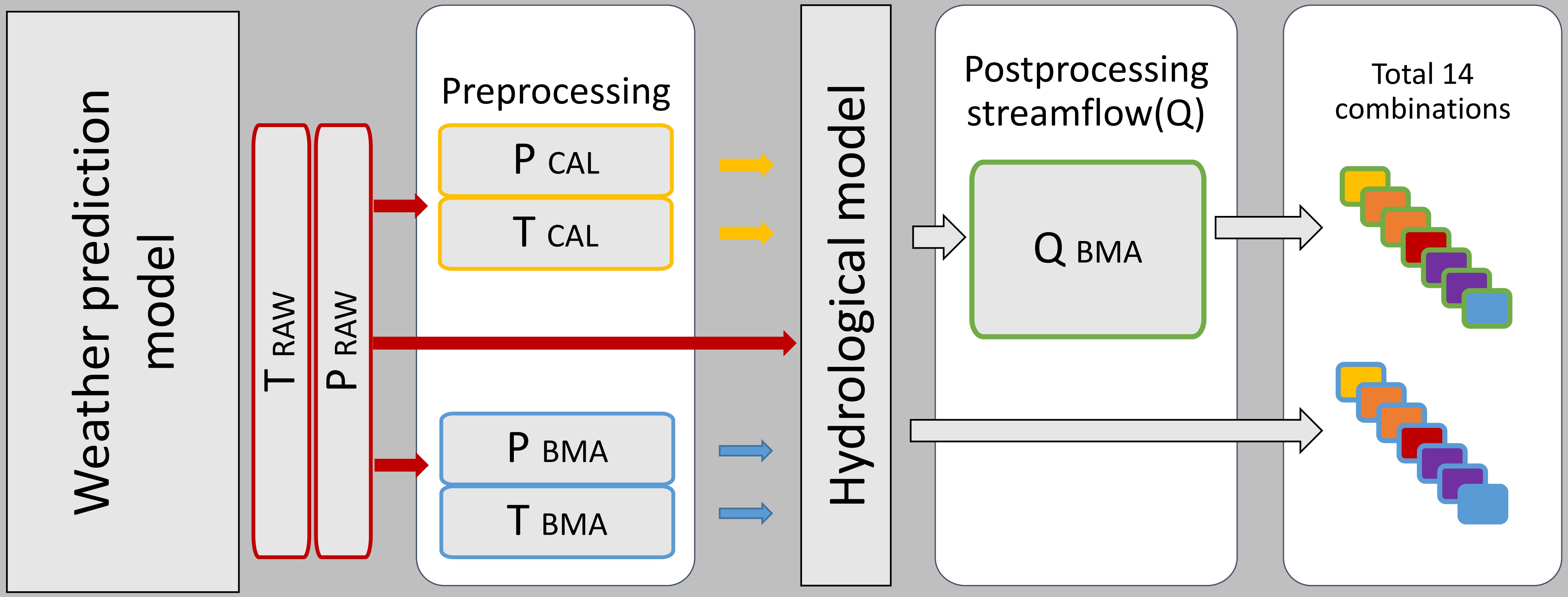
CAL[3] refers to the calibration method applied to the operational ensemble forecast by Met Norway[3] in the period 2014 and 2015, and includes:

- Quantile mapping applied to temperature (T)
- Zero adjusted gamma distribution applied to precipitation (P)

BMA[4] refers to Bayesian model averaging applied to the catchment average values

- Normal distribution was chosen for temperature
- Zero adjusted gamma distribution for precipitation

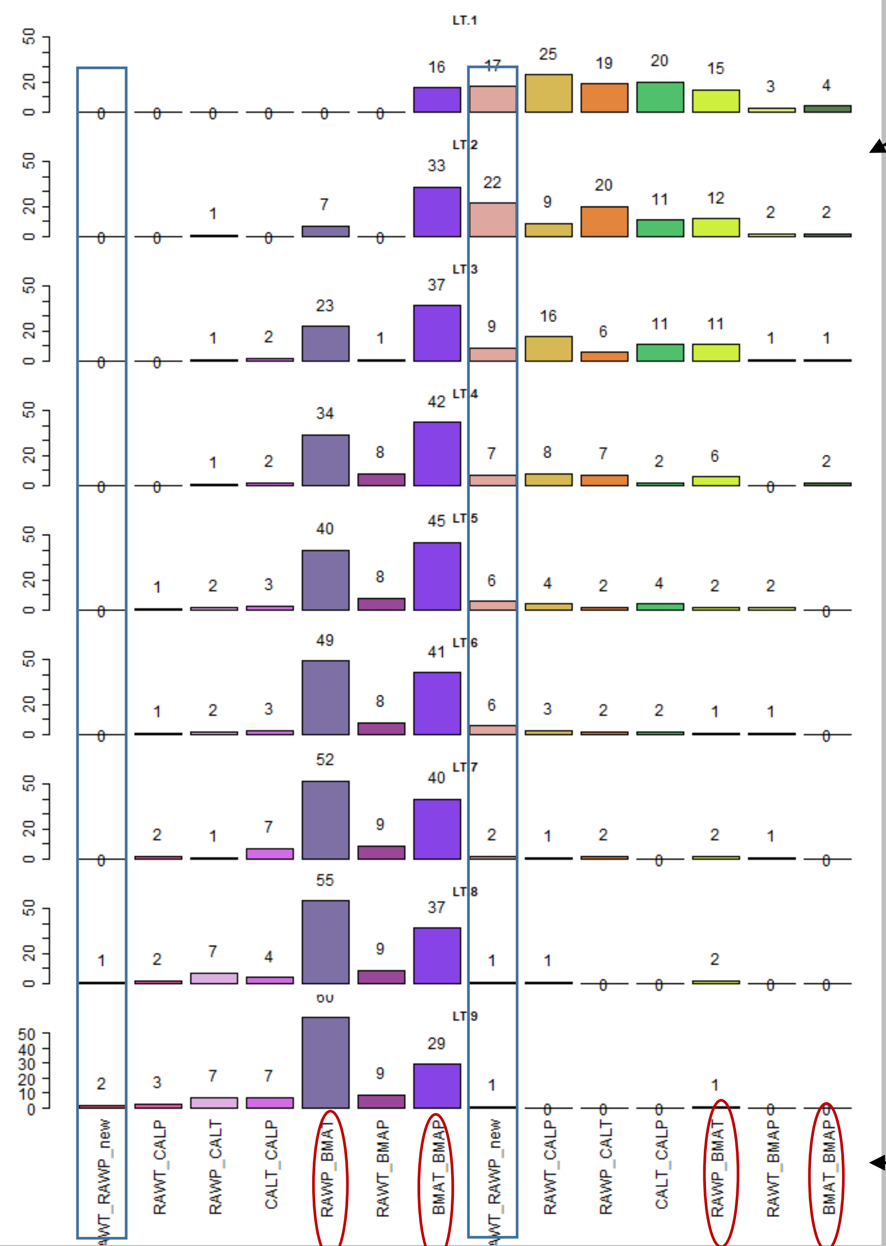
Combinations of T and P are forced the HBV models. Box-cox transformed streamflow is applied BMA, which enables an evaluation of the added effect of postprocessing



Best schemes for 119 catchments all data, vs 79 catchments only floods

Pre | Pre + Post

Lead-time 1 to 9



All data

Only days with Floods

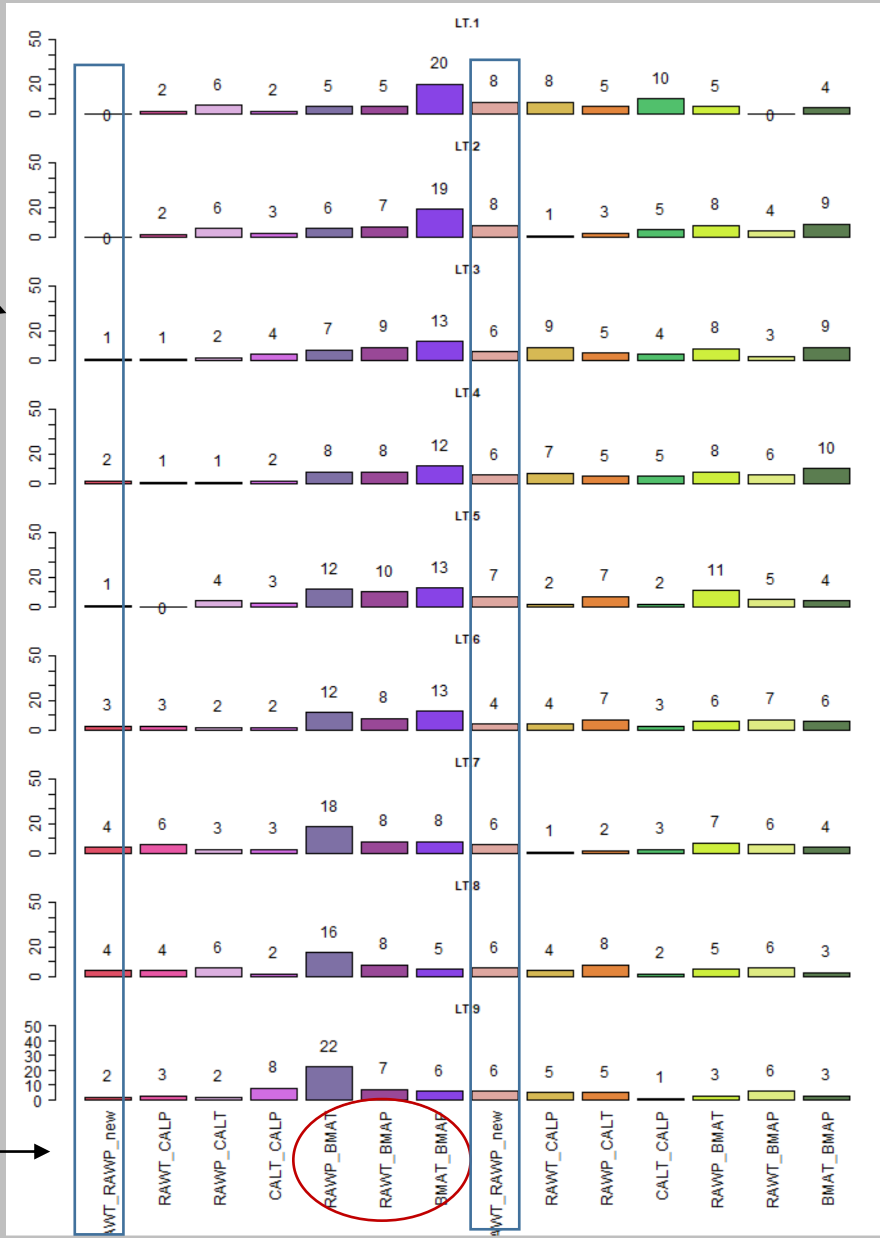
Each bar in the histogram indicates the number of catchments that achieved the best CRPS(5) for the processing scheme

✓ The best processing schemes for all data were not necessarily the best for flood data

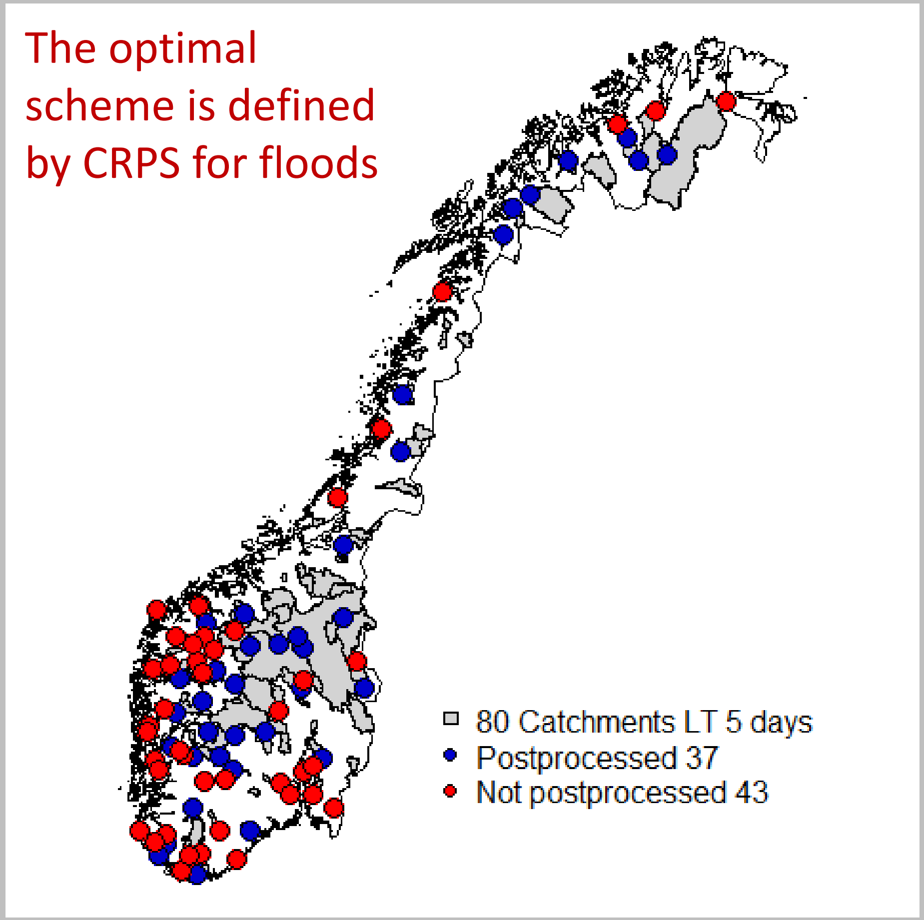
Processing schemes

Pre | Pre + Post

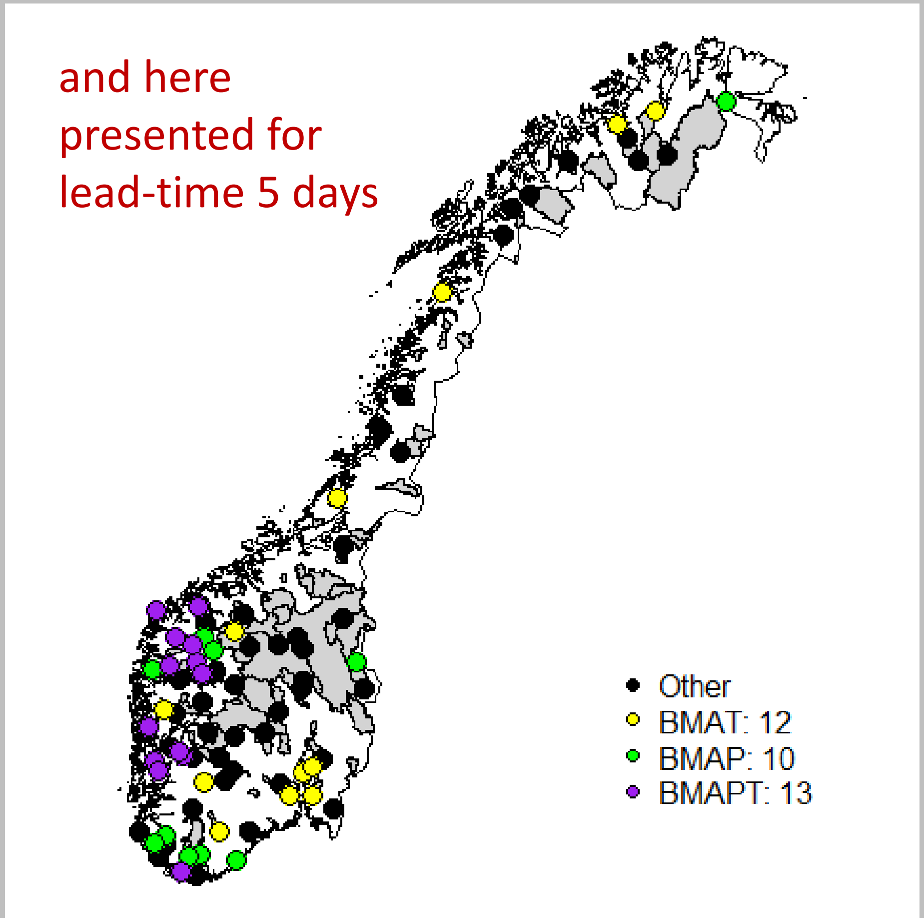
Lead-time 1 to 9



The spatial distribution of optimal schemes indicates that the success depends on location



Postprocessing (blue) has effect for inland and high elevated catchments, less for the coastal catchments

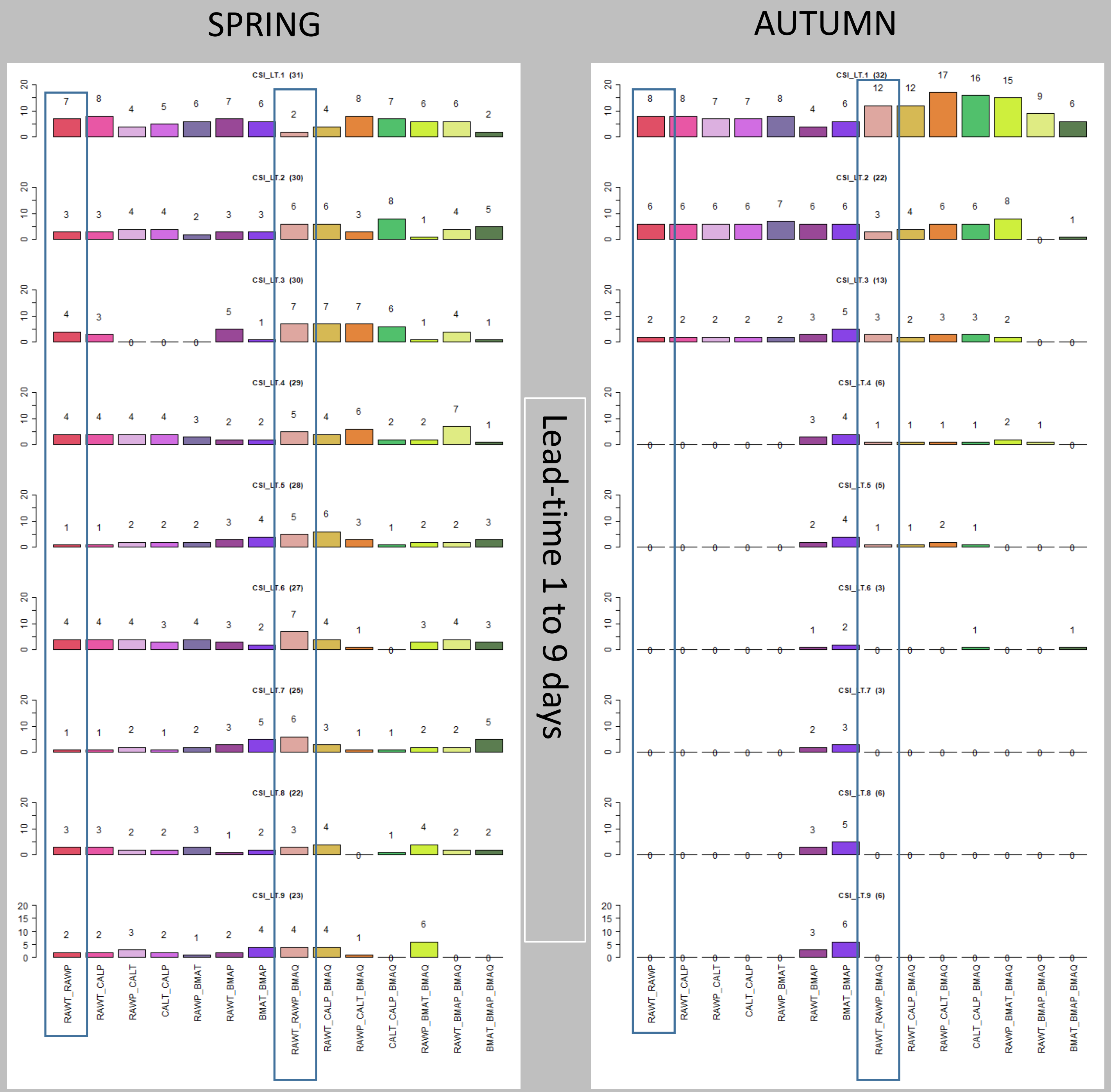


Preprocessing P alone and in combination with T improves the coastal flood forecasts

To assess the seasonal differences in predictability, we used the critical success index (CSI[(6)])

The CSI indicate success for predictions exceeding pre-defined flood threshold. In this set-up multiple schemes can be successful for each evaluated catchment.

Each bar indicates the number of catchments that achieved the best CSI for each processing scheme



- ✓ Spring has a longer predictability for more schemes
- ✓ In autumn there is almost no predictability beyond 2-3 days

Main findings

- The best processing schemes for all data were not necessarily the best for flood data
  - Especially the effect of postprocessing is less pronounced for floods
- We find regional differences in how the applied schemes improve the flood predictions (CRPS)
  - Coastal versus inland areas
- The ensemble forecasts are less good at predicting autumn floods, and especially for longer lead-times
  - emphasis should hence be focused on methods to improve autumn precipitation and floods forecasting
- Flood forecasts **do** benefit from pre- and/or postprocessing
  - the optimal processing approaches does, however, depend on region, catchment and season

References

1) ECMWF. Set III - Atmospheric model Ensemble 15-day forecast (ENS). Retrieved from https://www.ecmwf.int/en/forecasts/datasets/set-iii, 2018a.

2) Beldring, S.: Distributed Element Water Balance Model System.Norwegian Water Resources and Energy directorate, report 4, 40 pp, Oslo, 2008.

   2) Bergstrom, S.: Development and application of a conceptual runoff model for Scandinavian catchments. Swedish Meteorological and Hydrological Institute, 1976.

3) https://github.com/metno/gridpp/

4) Raftery, A. E., Gneiting, T., Balabdaoui, F. and Polakowski, M.: Using Bayesian model averaging to calibrate forecast ensembles. Monthly Weather Review, 133(5), 1155-1174, 2005.

   4) Sloughter, J. Mc Lean, et al. Probabilistic quantitative precipitation forecasting using Bayesian model averaging. Monthly Weather Review, 135.9: 3209-3220, 2007.

5) Gneiting, T., Raftery, A. E., Westveld III, A.H., and Goldman, T.: Calibrated Probabilistic Forecasting Using Ensemble Model Output Statistics and Minimum CRPS Estimation. Monthly Weather Review, 133(5), 1098-1118, 2005.

6) Jolliffe, Ian T., and David B. Stephenson, eds. Forecast verification: a practitioner's guide in atmospheric science. John Wiley & Sons, 2012.

Thank you!

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