European Commission

Will post-processing always improve my forecasts?

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Sharing Geoscience Online

And some explanations to why it sometimes doesn't happen

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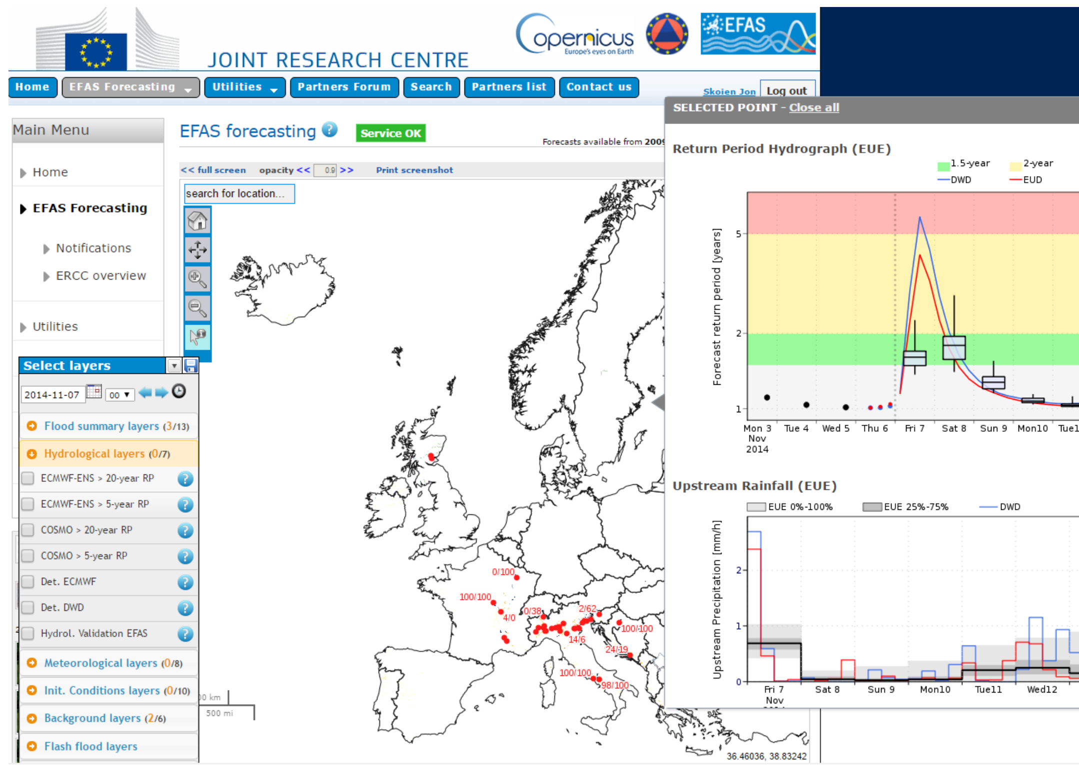
Context

- European Flood Awareness system (EFAS) based on runoff ensemble forecasts
- Operational forecasts of flood levels for Europe
- 1-10 days probabilistic forecasts
- National HydroMet services as partners
- Part of Copernicus Emergency Management Service (EU)



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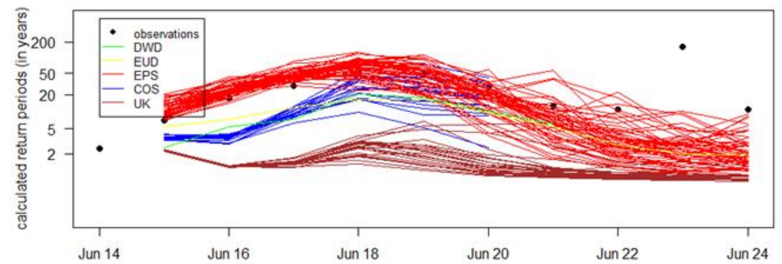
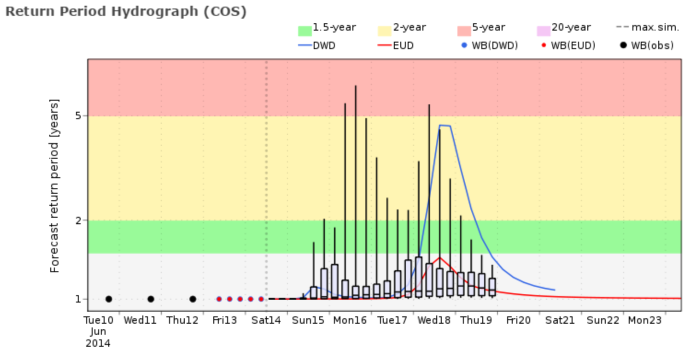
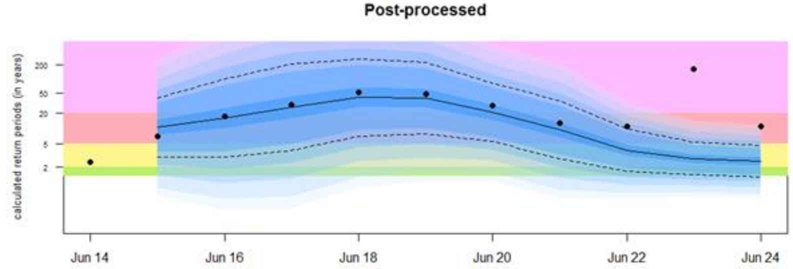
Post-processing of ensemble forecasts

- Usually recommended
- Should reduce biases and dispersion errors (ensemble variance too large/too small)
- Here: Using Ensemble Model Output Statistics (EMOS) on continental scale hydrological ensembles (LISFLOOD), based on different meteorological forecasts (ensemble from ECMWF and COSMO, deterministic from ECWMF and DWD)
- NOTE: We're comparing with simulated runoff (based on observed precipitation), not runoff observations





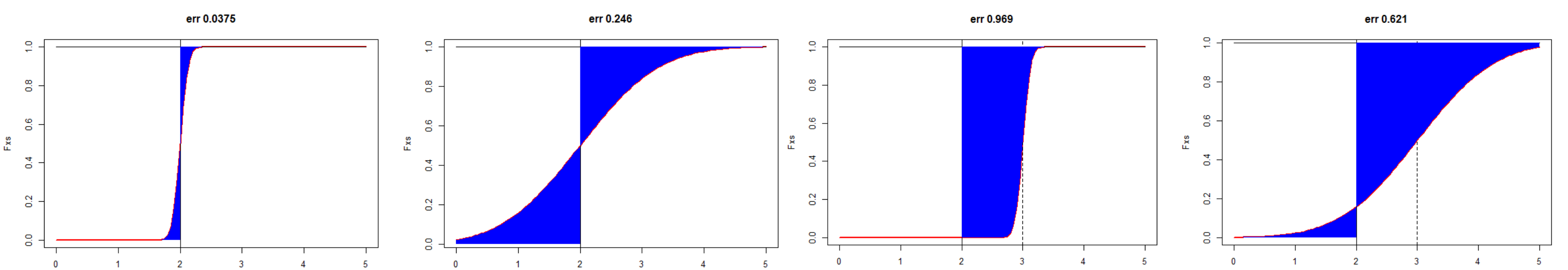


Calibrating with Ensemble Model Output Statistics (EMOS-method)

- Not all forecasters are equally good, best prediction as weighted mean
- Variance as function of ensemble variance - correct dispersion errors

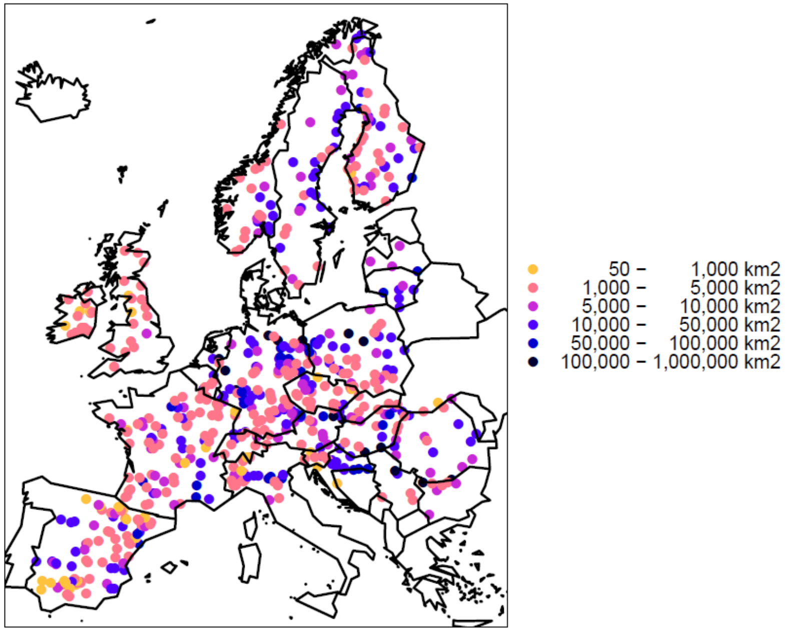
$$Y = a + b_1X_1 + b_2X_2 + \cdots + b_nX_n + e$$
$$Var(e) = c + dS^2$$

- Minimizing Continuous Ranked Probability Score (CRPS) – which is a combination of prediction error and dispersion error (variance too high or too low – there should be a reasonable relationship between prediction variance and prediction error)
- CRPS-errors in blue below. The two panels to the left have correct forecasts, the two panels to the right with prediction errors. Panels 1 and 3 have low prediction variance, panels 2 and 4 have large prediction variance.



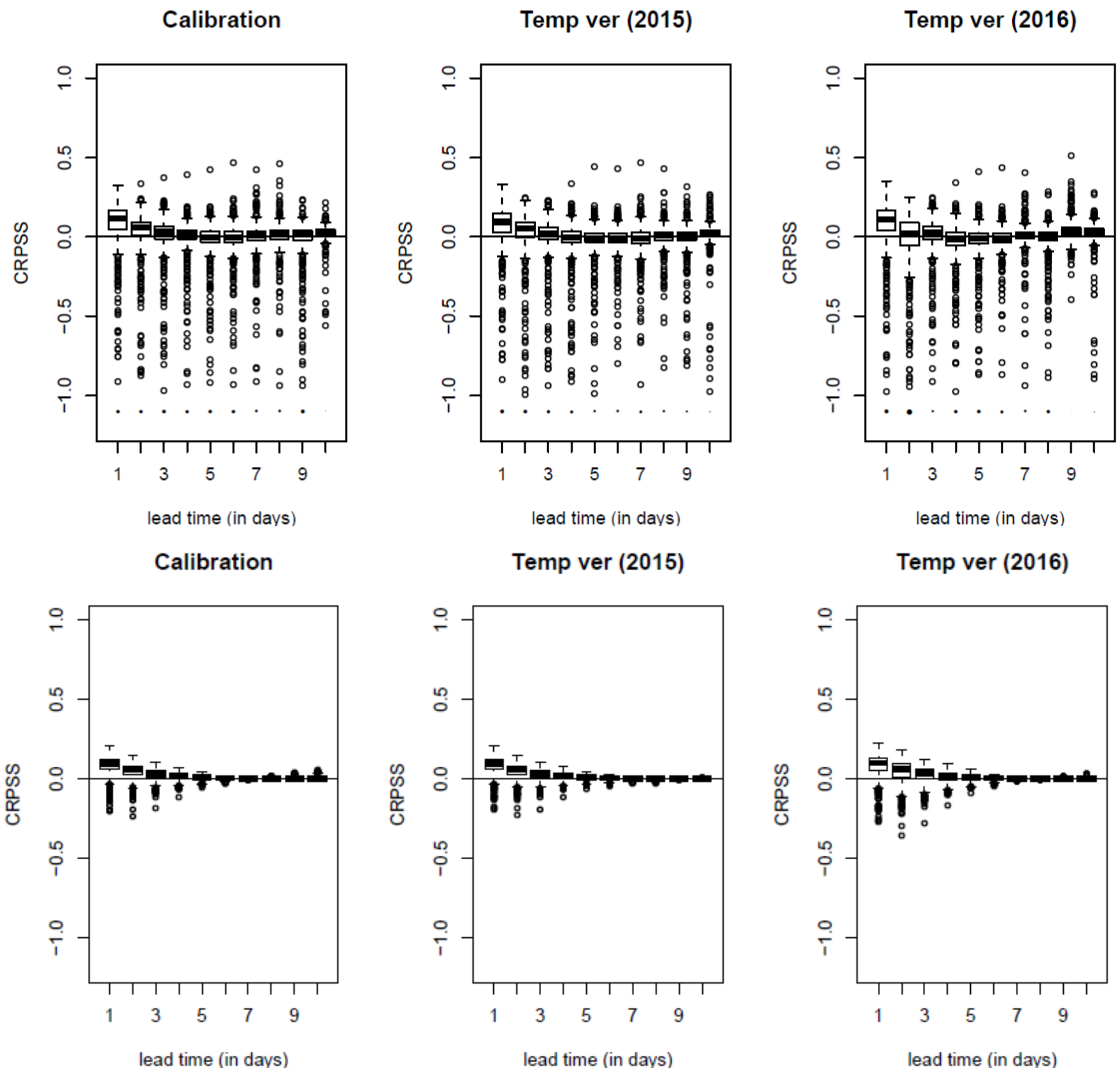
Calibration and validation

- Simulated runoff data from observed precipitation and from weather forecasts from more than 600 stations in Europe for 2015-2017
- Using Continuous Ranked Probability Skill Score (CRPSS) as a measure of the improvement from post-processing.
- CRPSS compares CRPS-errors for raw ensemble and post-processed ensemble.
- CRPSS is above 0 when the post-processed distribution is better than the raw ensemble (up to 1).
- Calibrating for each year separately. Post-processing ensembles from 2017 with calibrated parameters from 2016 as validation.



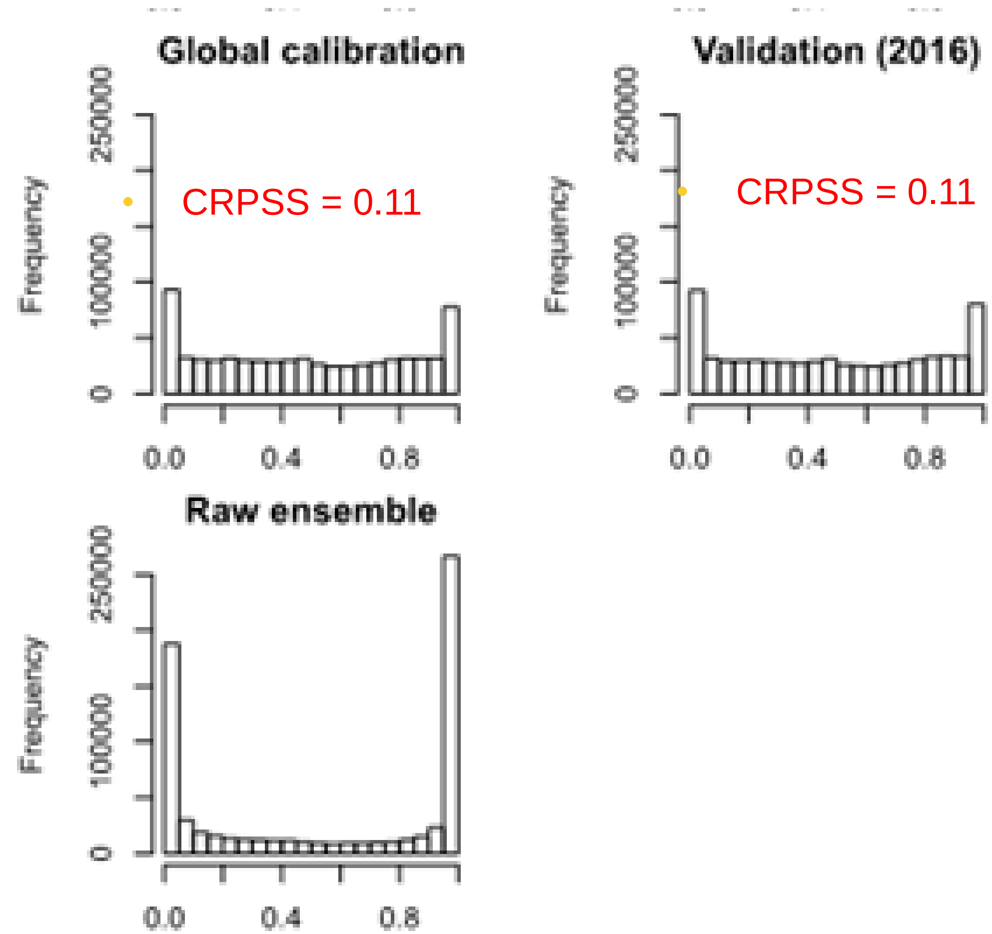
CRPSS-results

- Calibration and validation results from EMOS
- Only some improvement for short lead times
- Only variance inflation parameter fitted in the lowest panels – similar results



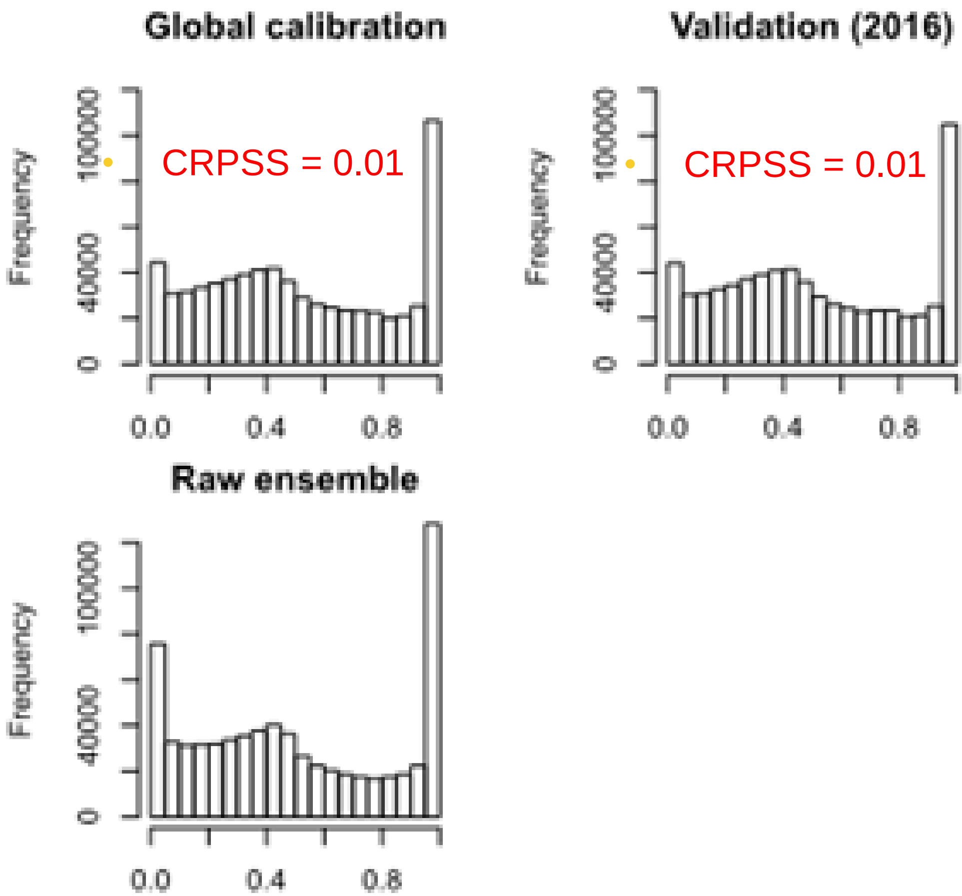
PIT-diagram of raw ensemble and post-processed distribution – 1 day lead time

- Probability integral transform diagrams is a check on how the observations plot in the predictive distribution of the ensemble. It should ideally have a uniform distribution.
- The raw ensemble is strongly underdispersed (bottom)
- PIT-diagrams of post-processed distribution are more uniform, validation almost as good as calibration
- CRPSS around 0.1 (~ 10% improvement)



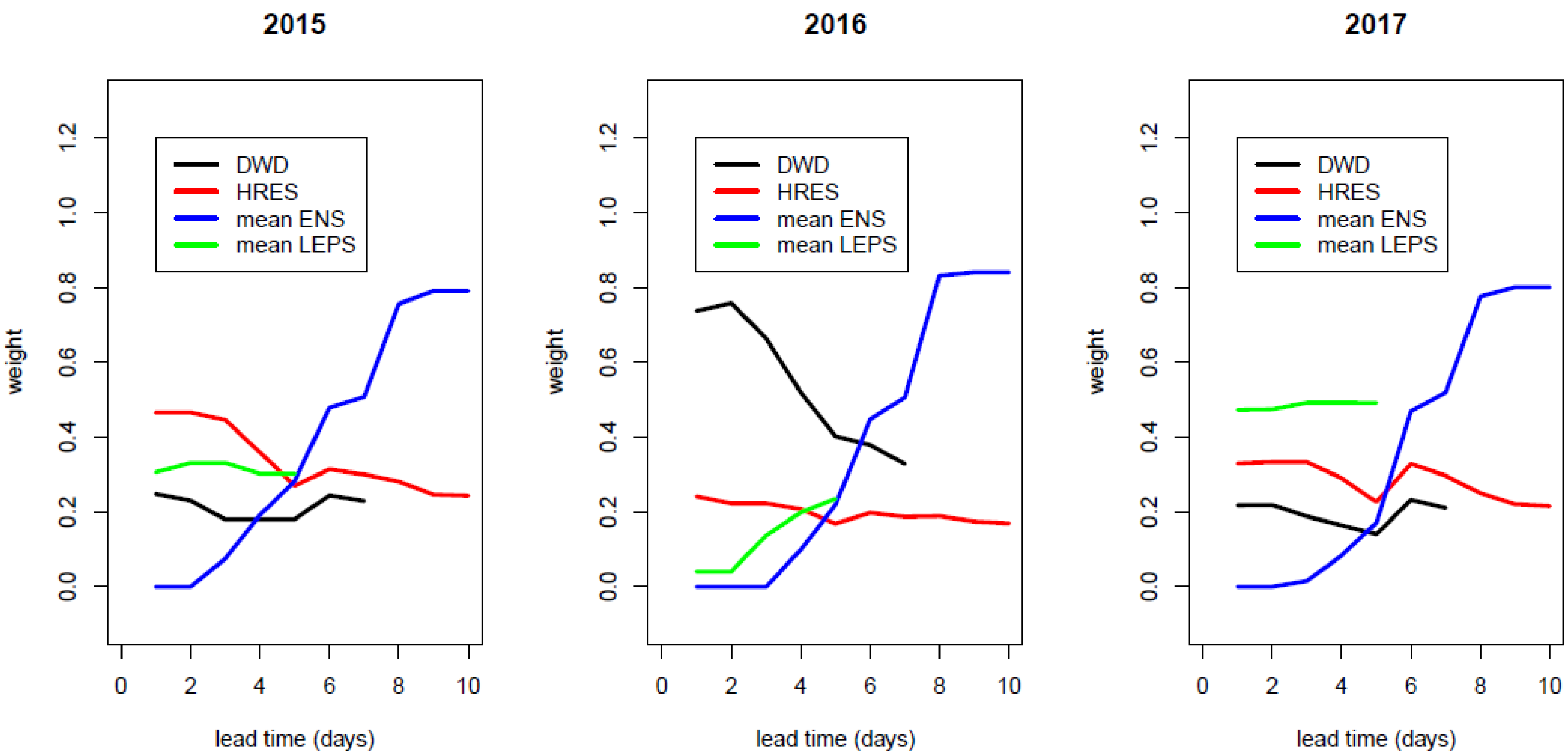
PIT-diagram of raw ensemble and post-processed distribution – 7 days lead time

- The PIT diagram of the raw ensemble is almost trimodal (bottom)
- The variance post-processing is not able to reduce the underdispersion without simultanously increasing the peak in the middle – best fit is to leave the variance as it is.
- CRPSS is close to zero
- The ensemble for 7 days lead time is mainly from ECMWF, so mixing methods as Bayesian Model Averaging (BMA) would probably not improve.



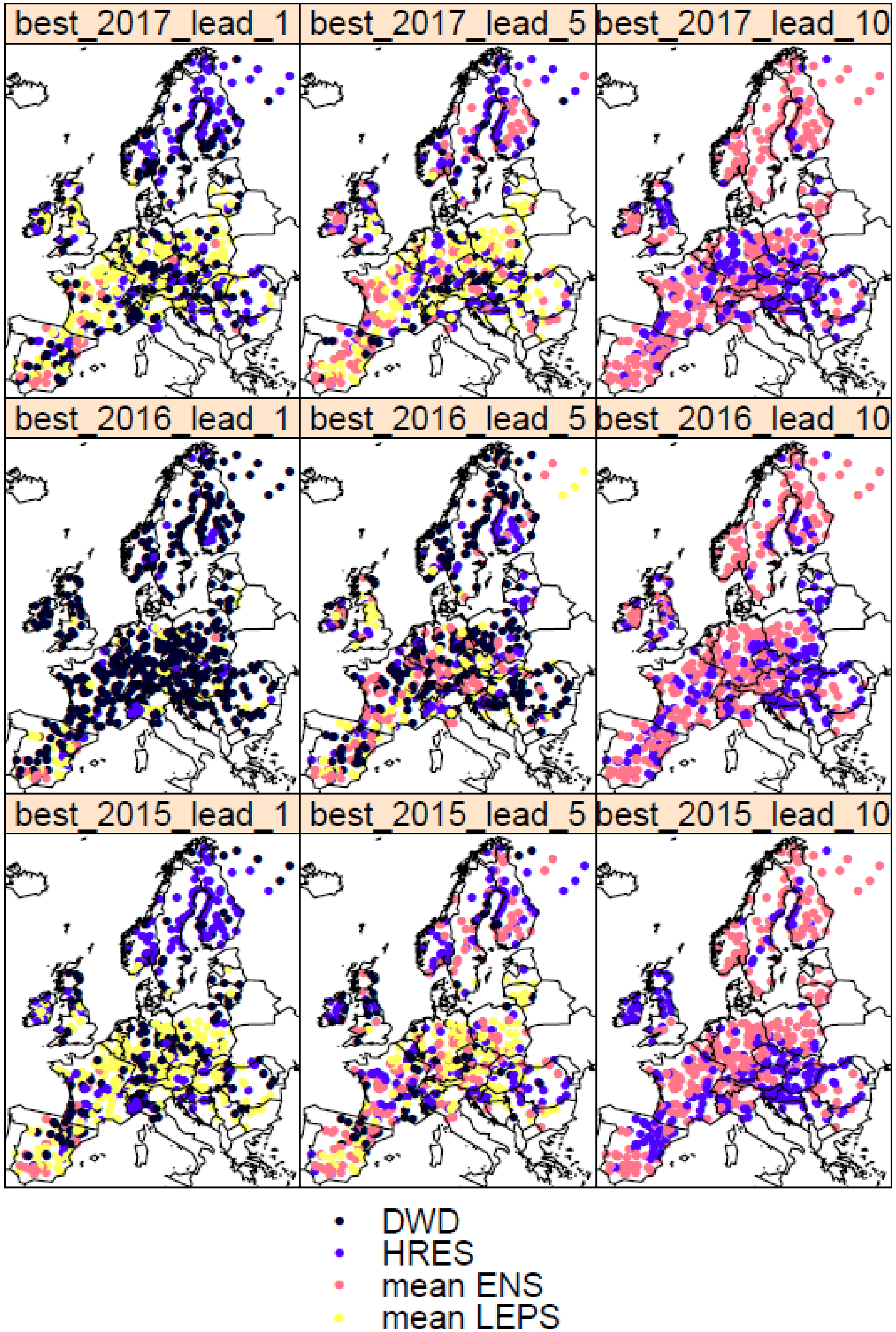
Weights change from year to year

- There is little consistency in the calibrated weights for each forecast between the different years
- The best set of weights for the calibration year is not necessarily the best set for the validation year



Analysing NSE

- We computed Nash-Sutcliffe efficiency for each forecast, each station and for each year.
- The figure shows which forecast gave highest NSE for each station and each year for lead times 1, 5 and 10 days.
- Some spatial patterns visible for individual years, but not between years



Conclusions

- Post-processing helps for lead time 1-3 days in our case, but not for the remaining days
- Bias correction seems unnecessary for this application. Maybe also as a result of using simulated runoff for comparison (this is done as EFAS is focusing on return periods, not on the runoff itself). However, there could still have been a bias between meteorological observations and forecasts.
- There are no forecasts that consistently give better results for different years. We have tried shorter calibration/verification periods, with same result.
- The variance is underestimated by the model for short lead times. Post-processing can help in this case.
- The ensembles for long lead times have a multi-modal distribution, which cannot be easily fixed by the solution we have tested here.

Keep in touch

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Thank you

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