Royal Netherlands
Meteorological Institute
*Ministry of Infrastructure
and Water Management*

# Added seasonal forecasting skill from land surface parameterization detail

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**For efficient management of a Dutch surface water reservoir, (sub)seasonal forecasts of the fluxes going in and out of the reservoir would be very helpful. Previous research has shown promising streamflow forecast skills, which can be exploited to forecast discharge or river IJssel, the main influx. We analyse multiple seasonal discharge forecasts with different underlying hydrological models, bias-correct them using quantile mapping and analyse various metrics of the forecast quality.**

## Background

For efficient management of a Dutch surface water reservoir, (sub)seasonal forecasts of the fluxes going in and out of the reservoir would be very helpful. Local meteorology is known to be poorly predictable, but for river discharge, the main influx, higher forecast skills have been shown. We investigate to what extent the level of detail in hydrological modelling affects forecast skill.

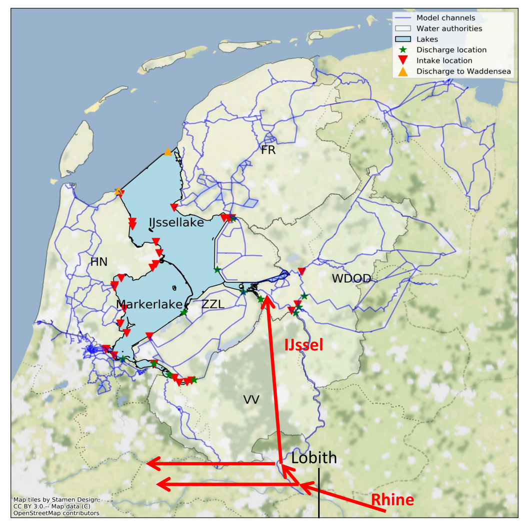



***Figure 1:*** *IJssellake with the river IJssel (a distributary of the Rhine) flowing into it.*

## Data

We collected streamflow (re)forecasts from ECMWF SEAS5, EFAS and SMHI-HYPEWeb for the location Lobith, where the river Rhine enters the Netherlands (Figure 1). About 15% of the Rhine discharge (during low discharge) enters the IJssel lake through the IJssel. For ECWMF, we aggregated the runoff from the ECMWF model over the Rhine catchment. In EFAS, the hydrological model LISFLOOD is run at 5x5 km$^2$ and SMHI-HYPEWeb is based on the semi-distributed HYPE model, with an average catchment size of 1000 km$^2$ (Arheimer et al., 2020). We consider reforecasts from 1993-2015 and operational forecasts for the (exceptionally dry) summer of 2018.

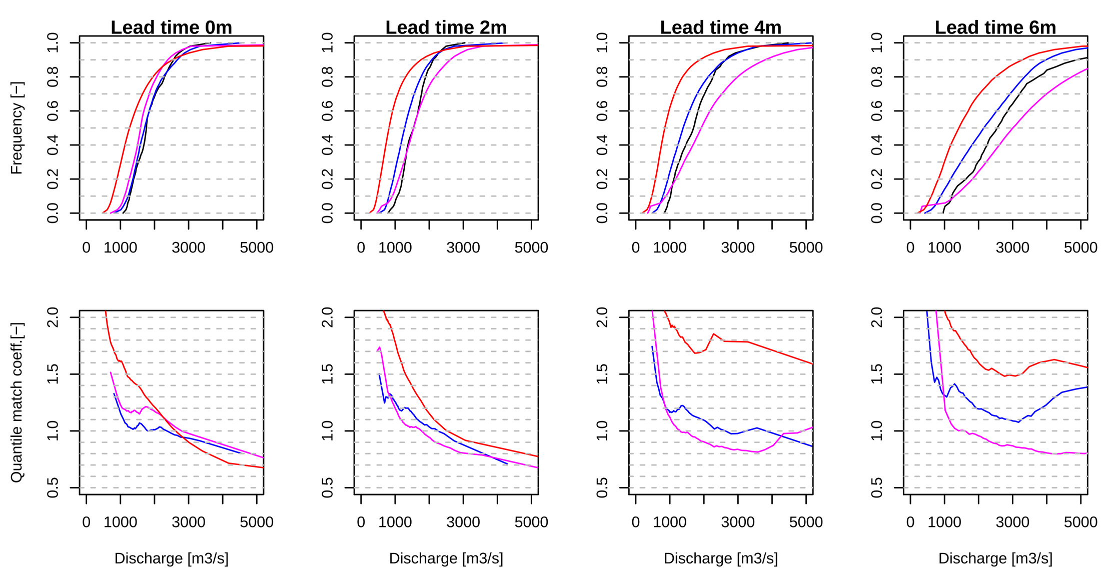



***Figure 2:*** *Quantile mapping for forecasts starting at July 1$^{st}$. Upper row shows CDF of EFAS (blue), HYPE (magenta), ECMWF (red) and observations (black) for lead times of 0, 2, 4 and 6 months where 0 indicates average discharge over an entire month, forecasted at the first of that month. The lower row shows the resulting multiplication factors.*

## Bias correction

We apply quantile-mapping for bias-correcting the hindcasts, by calculating the Cumulative Density Function (CDF) by counting occurences in 2% percentile bins (as in e.g. Wetterhall et al., 2015). Per bin, this results in a multiplication factor using which the forecasts are corrected (Figure 2).

## Metrics

For all hindcasts, with and without bias correction, we calculated a number of metrics on each target month and lead time of monthly aggregated discharge values (Arnal et al., 2018; Figure 3), using observed discharge climatology as a benchmark.

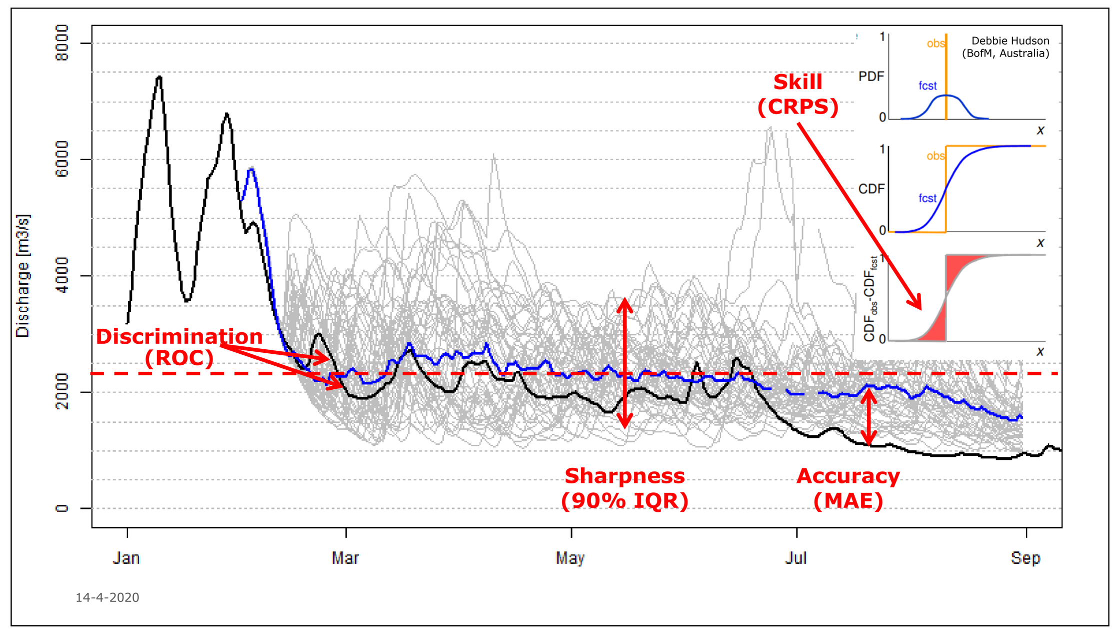



***Figure 3:*** *Schematic representation of forecast metrics.*

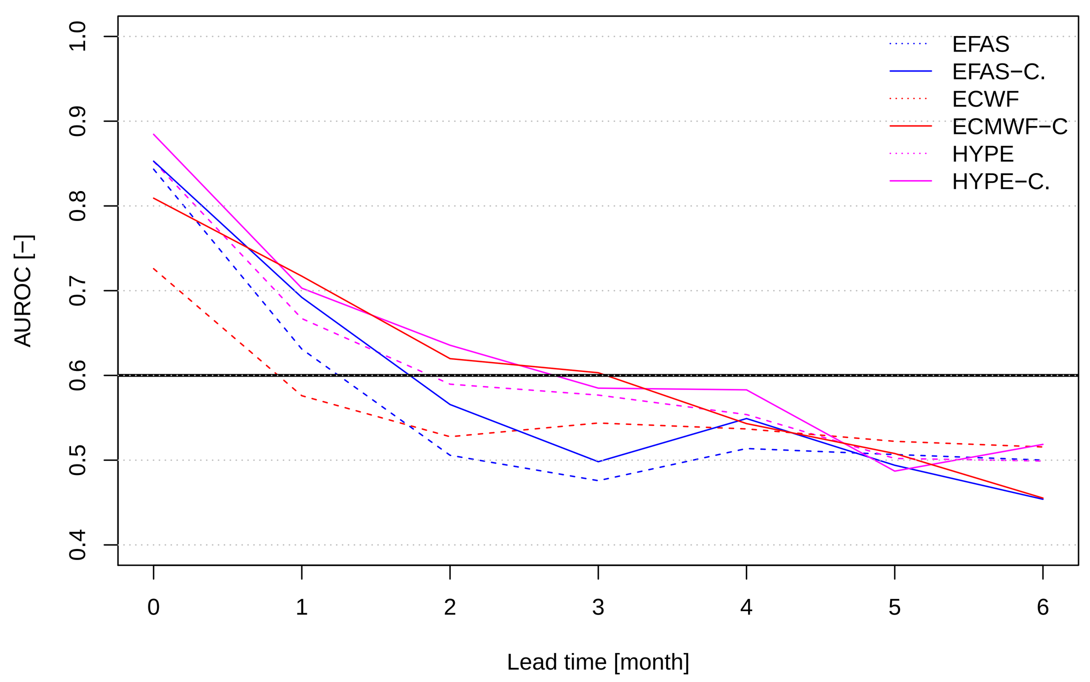
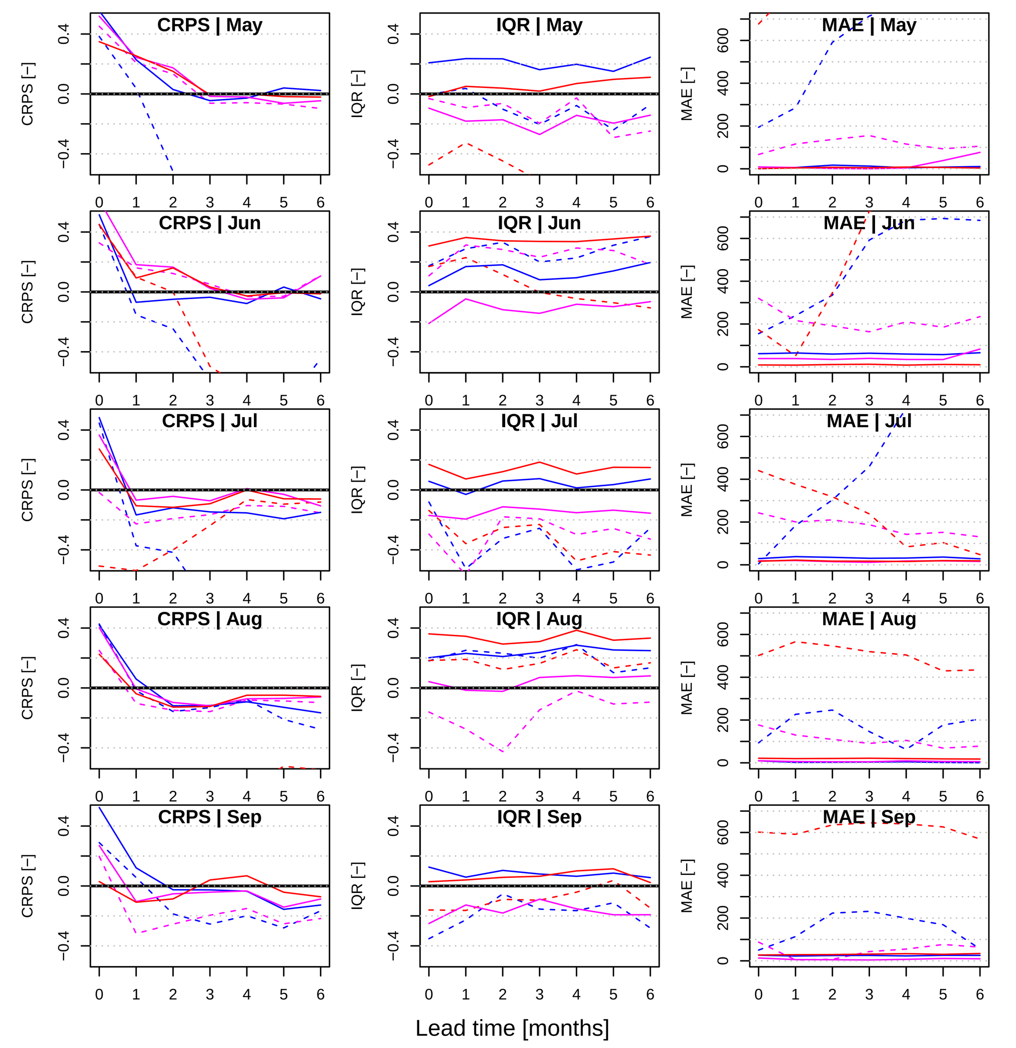



***Figure 4:*** *CRPS (left), IQR (right), MAE (left) and AUROC (bottom) for all hindcasts, with and without bias correction. For the first four, forecasts for the relevant (dry season) months are shown.*

## Results for hindcasts

Figure 4 shows the metrics as a function of lead time, for selected target months. The threshold for defining the AUROC is underexceedence of the lower tercile (33% percentile) of the observations in a given month.




Largest skill is present in spring and early summer, when discharge seems predictable up to four months ahead. Presumably this is due to the Alpine snow pack. Later in the summer, when discharge is rain-dominated, the skill is much lower and deteriorates after about 2 months. Still this is higher than when precipitation alone is considered. The bias correction improves the sharpness, and as expected, the accuracy of the forecast to a large degree: both the spread and the bias become much smaller. Also the CRPS increases by bias-correction. Here we see an interesting difference between the datasets: earlier in summer HYPE and ECMWF have higher and longer skills, whereas in late summer EFAS shows the highest values.

## Summer of 2018

For EFAS and ECMEF SEAS5, we also use operational forecasts for the summer of 2018. We bias-corrected the forecasts using the multiplication factor from earlier. Figure 6 show the observed streamflow with ensemble means of EFAS and ECMWF, both corrected and uncorrected. Also a tercile plot is shown, where the blue bars indicate the probability of underexceedence of the lower tercile, where horizontally the lead time is shown in months.

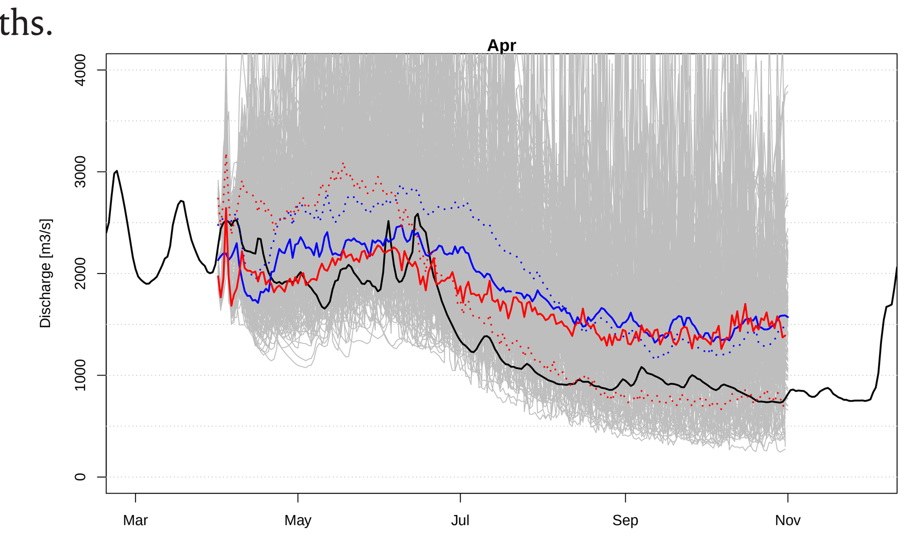



***Figure 5:*** *Example of operational forecasts for 2018. Shown forecasts are for April 1$^{st}$ 2018, together with observations. The grey area indicates the spread over all forecasts.*

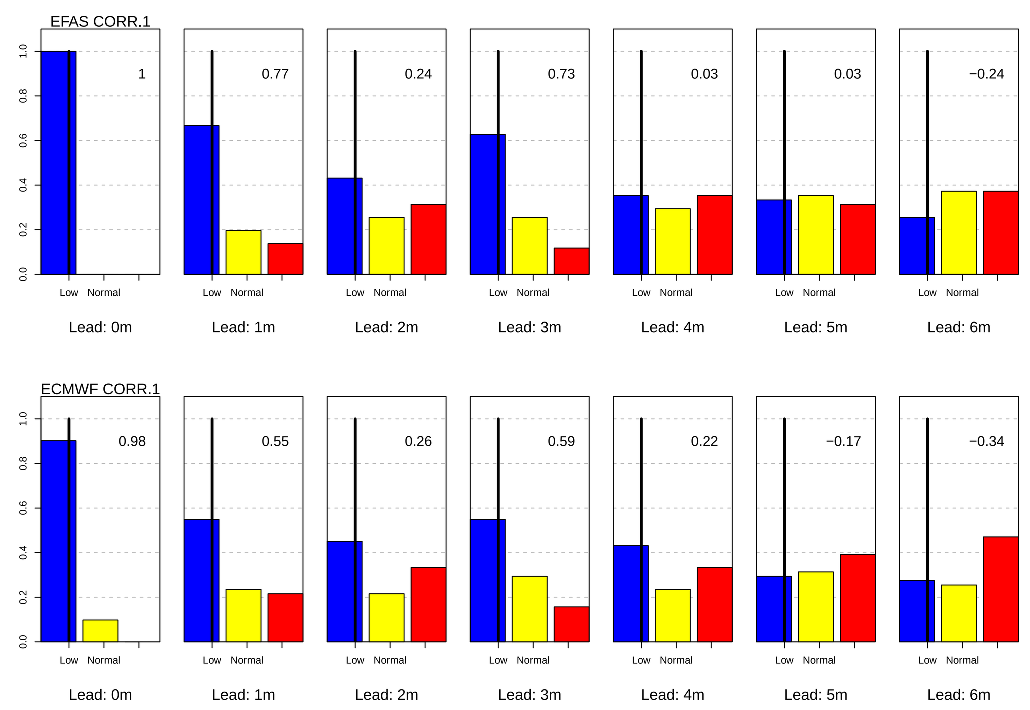



***Figure 6:*** *Example of a probabilistic display: the blue bar indicates underexceedence of the lower tesrcile, i.e., below normal discharge. The black line is the observed realistation, the number indicates the RPSS, consistent with those thresholds. EFAS (top) and ECMWF (bottom) are shown, both bias-corrected.*

Discharge in 2018 was exceptionally low, so that bias correction in fact worsened the forecast late in summer. Still, in this case some skill was present up to 4 months ahead.

## Conclusion and outlook

Depending on the season, there is indeed forecast skill streamflow forecasts up to 3, sometimes 4 months ahead. EFAS seems to have higher skill in late summer, SMHI-HYPEWeb in spring, possibly hinting at differences in snow modelling. Next, we plan to include WFLOW, a distributed high-resolution hydrological model, forced by ECMWF SEAS5, and explore statistical postprocessing tools other than quantile mapping.

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*-Wetterhall et al., 2015, Seasonal predictions of agro-meteorological drought indicators for the Limpopo basin, Hydrol. Earth Syst. Sci., 19, 2577–2586.*
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