Post-processing ECMWF precipitation and temperature ensemble reforecasts for operational hydrologic forecasting

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These slides are available from twitter.com/janverkade

(see www.hepex.org)

Summary conclusions

- Postprocessing of temperature, precipitation forecasts improves skill
- Quality improvement does **not** proportionally propagate to streamflow forecasts
- We believe this is due to:
  - non-linearities in rainfall to runoff processes
  - presence of storages
  - inadequate space-time modelling using Schaake shuffle
- These results are largely in line with those obtained in similar studies (Zalachori et al., 2012; Kang et al., 2010)

Introduction I

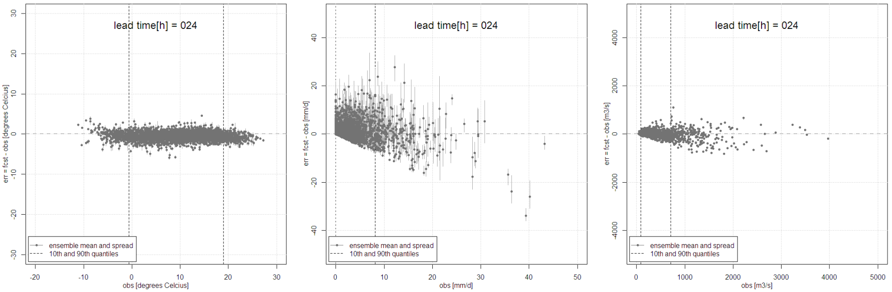
Setting the scene

- hydrologic forecasting
- ensemble prediction
- reduction of predictive uncertainties

Introduction II

Problem statement

- Numerical Weather Prediction products (NWP)
- propagation of biases



Introduction III

Statistical post-processing

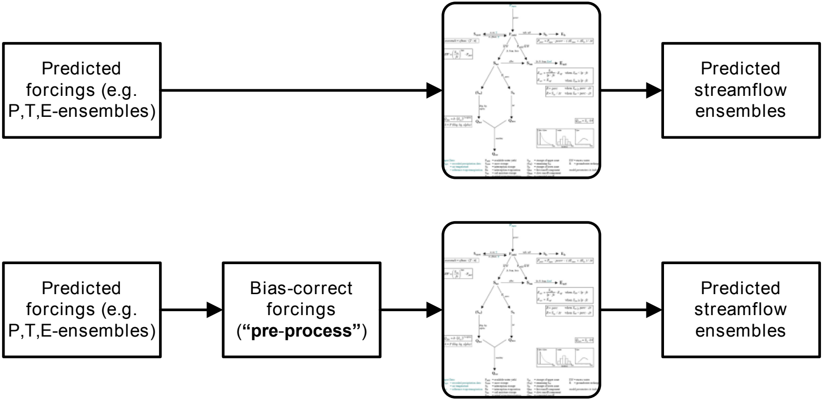
- often applied to streamflow forecasts directly
- can be applied to NWP also ('pre-processing')

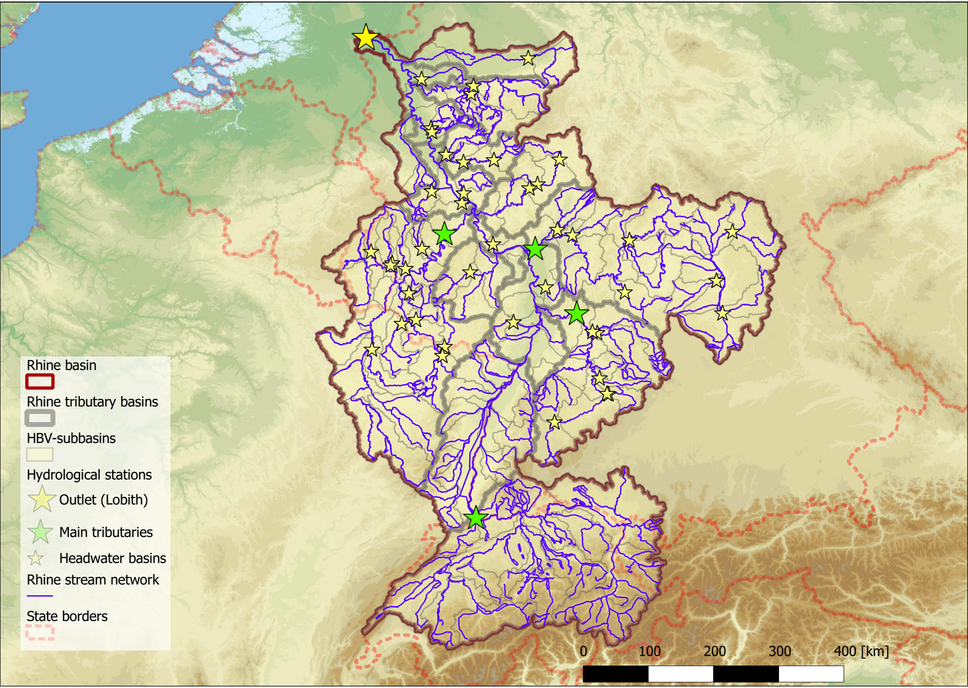
Research question

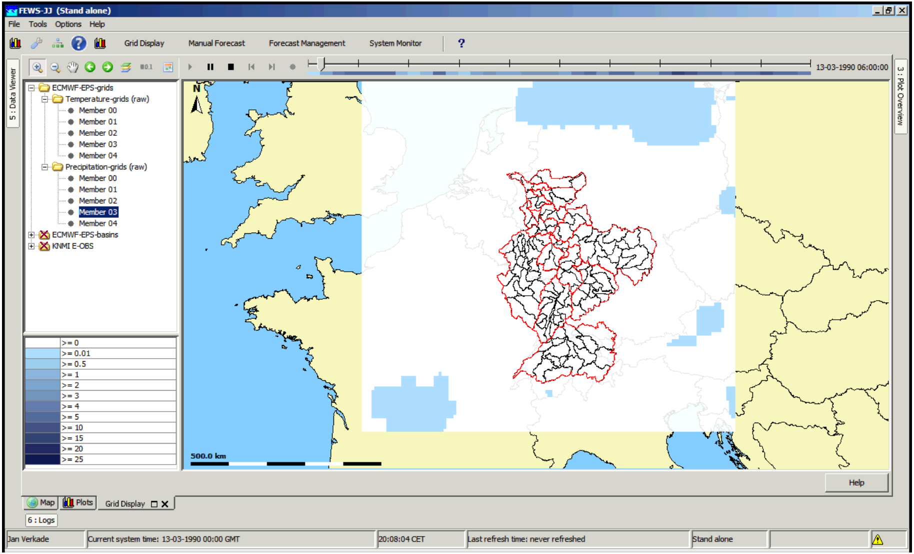
To which extent can biases (mean, spread) in streamflow forecasts be addressed through post-processing of the forcing ensembles?

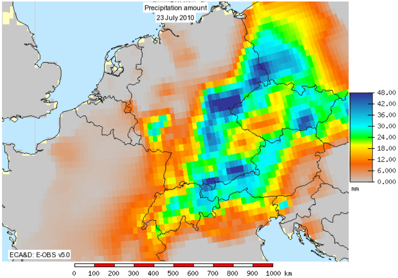
1. To what extent are the 'raw' forcing ensembles biased?
2. How do these biases propagate to streamflow ensembles?
3. Can quality of 'raw' forcing ensembles be improved by post-processing?
4. Does this quality improvement proportionally translate to streamflow ensembles?

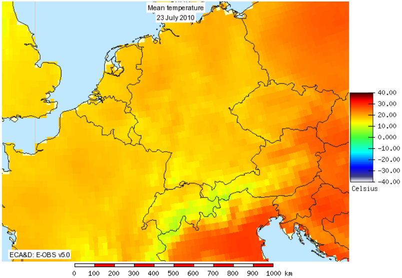
Research design




Rhine basin
Rhine tributary basins
HBV-subbasins
Hydrological stations
Outlet (Lobith)
Main tributaries
Headwater basins
Rhine stream network
State borders
0
100
200
300
400 [km]


FEWS-JJ (Stand alone)
File Tools Options Help
Grid Display
Manual Forecast
Forecast Management
System Monitor
13-03-1990 06:00:00
5 : Data Viewer
3 : Plot Overview
ECMWF-EPS-grids
Temperature-grids (raw)
Member 00
Member 01
Member 02
Member 03
Member 04
Precipitation-grids (raw)
Member 00
Member 01
Member 02
Member 03
Member 04
ECMWF-EPS-basins
KNMI E-OBS
>= 0
>= 0.01
>= 0.5
>= 1
>= 2
>= 3
>= 4
>= 5
>= 10
>= 15
>= 20
>= 25
N
500.0 km
Help
Map
Plots
Grid Display
6 : Logs
Jan Verkade
Current system time: 13-03-1990 00:00 GMT
20:08:04 CET
Last refresh time: never refreshed
Stand alone





Observations from the E-OBS dataset (www.ecad.eu/E-OBS/)

Bias-correction principles and techniques I

Temperature

- quantile-to-quantile transform
- linear Gaussian regression

Precipitation

- quantile–to–quantile transform
- logistic regression (Hamill et al., 2008)

Bias-correction principles and techniques II

Principles of conditional techniques

- Predictand Y = observed temperature, precipitation or streamflow. Assumed unbiased!
- Potential predictors $X = \{X_1, \ldots, X_5, \ldots, X_m\}$; biased.
- The bias—corrected forecast:

$$F(y|x_1, \ldots, x_m) = P[Y \leq y \mid X_1 = x_1, \ldots, X_m = x_m] \, \forall y$$

- for each lead—time and each location separately
- After bias-correction: "Schaake Shuffle" (Clark et al., 2004) to maintain spatial and temporal patterns ("traces")

Bias-correction principles and techniques III

Combinations of techniques used

- Uncorrected temperature, precipitation ensemble forecasts (raw–raw)
- Quantile-to-quantile transformed temperature, precipitation forecasts (qqt–qqt)
- linear Gaussian regression (temperature) and logistic regression (precipitation) (lin–log)

Ensemble verification

- Verification against simulations!
- Skills shown are relative to sample climatology
- Metrics expressed as function of P
- Metrics shown here:
  - Relative Mean Error
  - Brier's probability skill score
  - Mean Continuous Ranked Probability *skill* Score
  - Relative Operating Characteristic *skill* score
- metrics computed using Ensemble Verification System (Brown et al., 2010)

Verification graphs

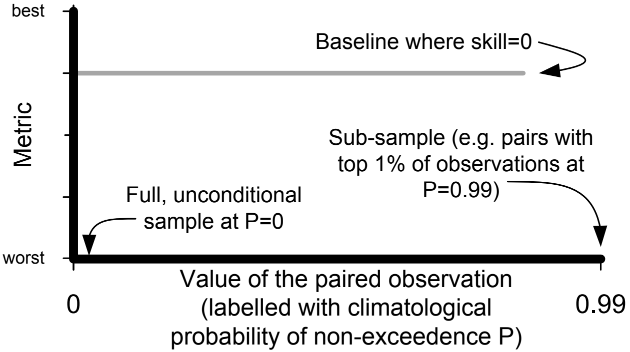
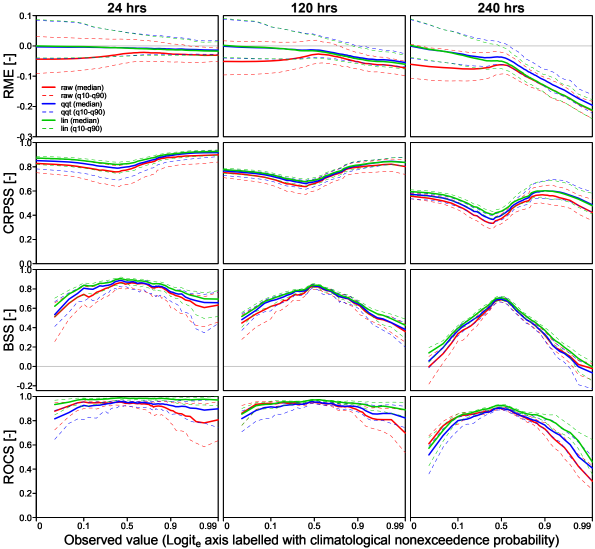


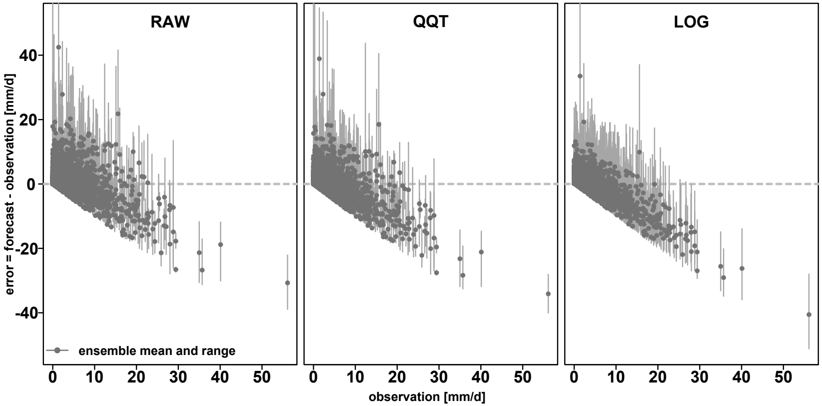
Figure: Sample verification plot

Temperature



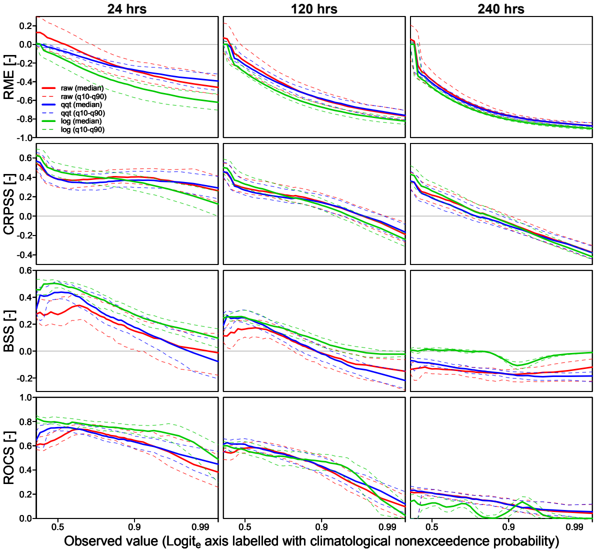
Temperature, 134 basins

Precipitation I



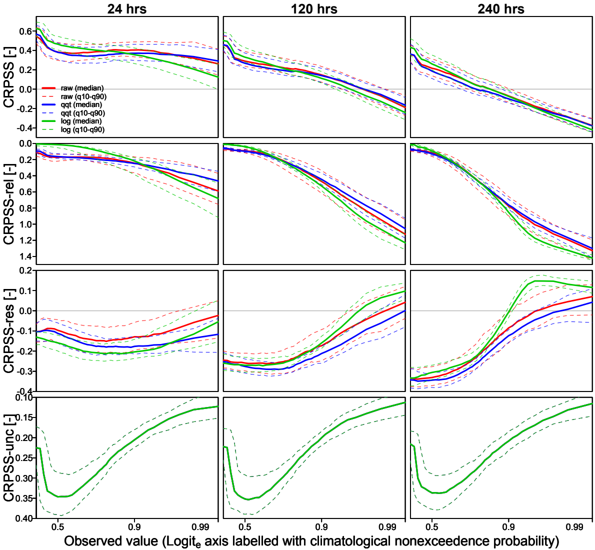
Precipitation, I-RN-0001, 72-hour lead time (in Neckar basin)

Precipitation II



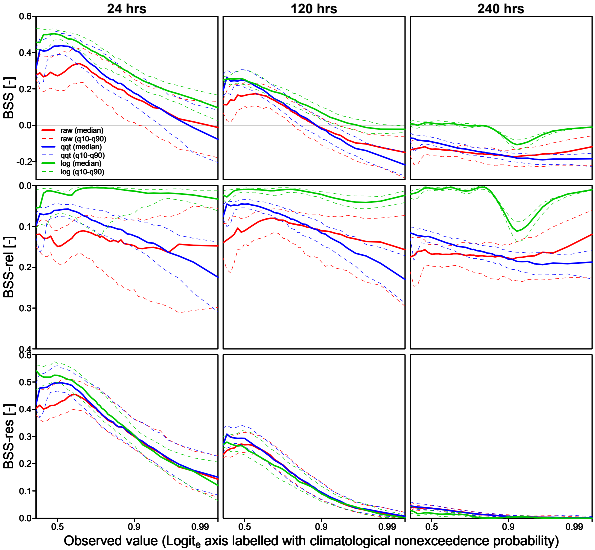
Precipitation, 134 basins

Precipitation III



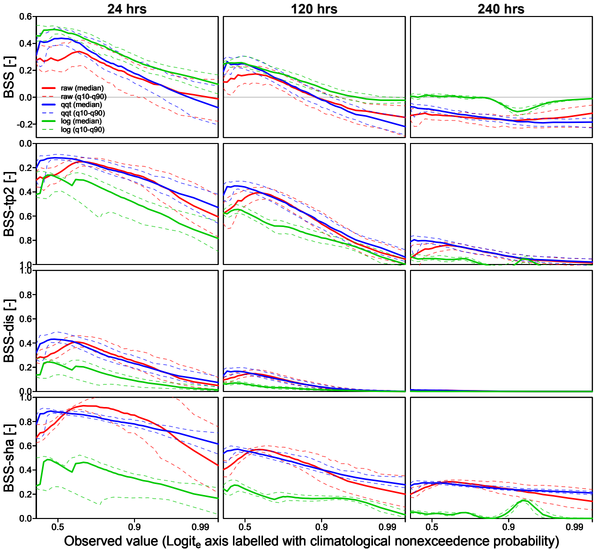
Precipitation, 134 basins, CRPSS

Precipitation IV



Precipitation, 134 basins, BSS Type I

Precipitation V



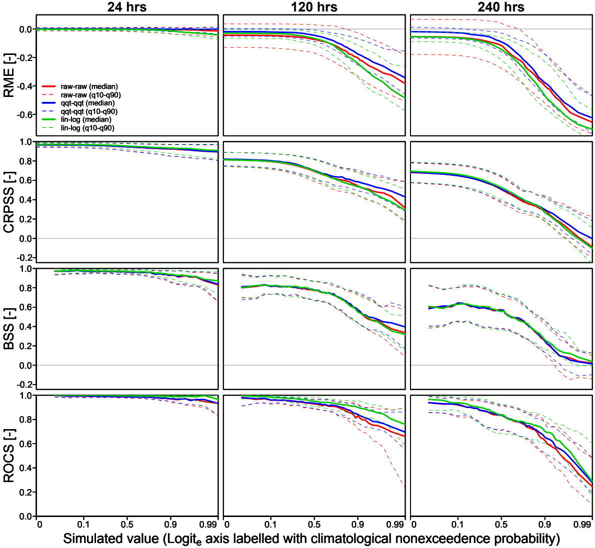
Precipitation, 134 basins, BSS Type II

Streamflow I

Three spatial scales:

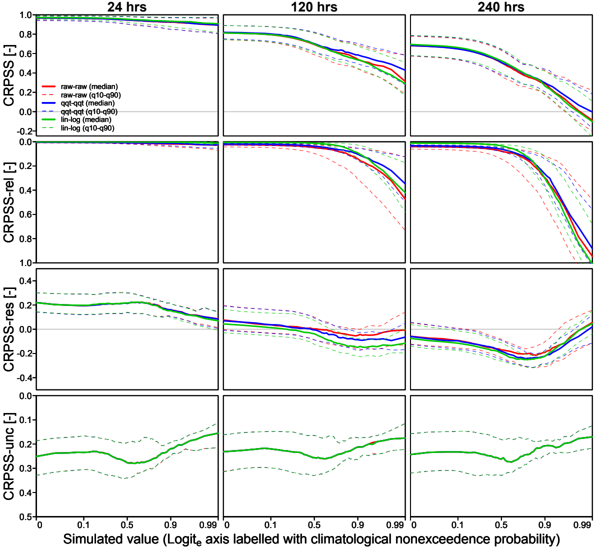
1. Basin outlet at Lobith
2. Four main tributaries: Main, Moselle, Neckar, Swiss Rhein
3. $\sim$40 headwater basins

Streamflow II



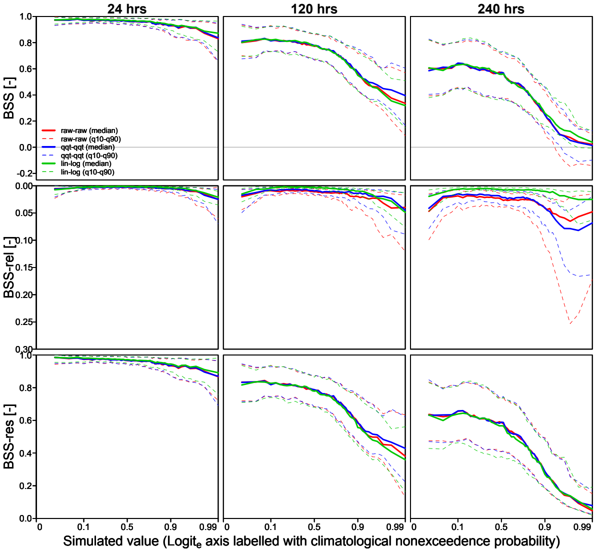
Streamflow, 43 headwater basins

Streamflow III



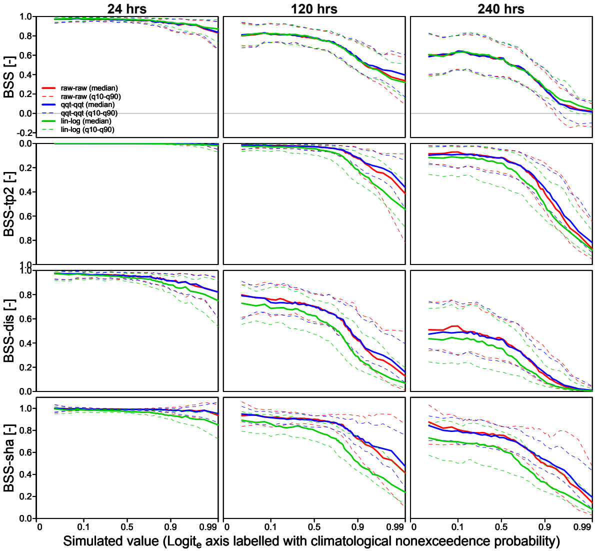
Streamflow, 43 headwater basins, CRPSS

Streamflow IV



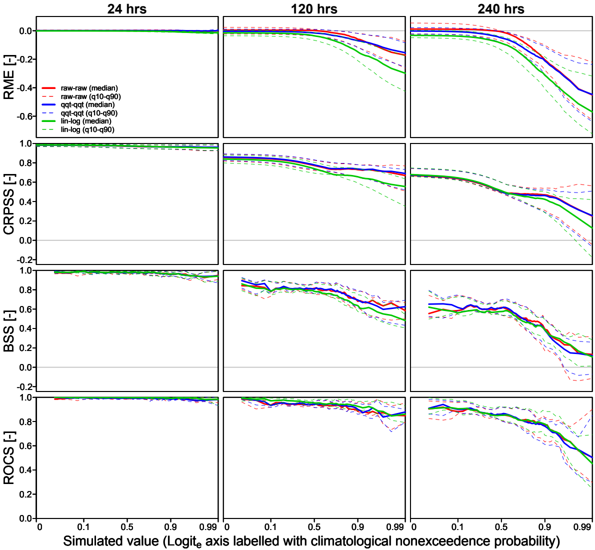
Streamflow, 43 headwater basins, BSS Type I

Streamflow V



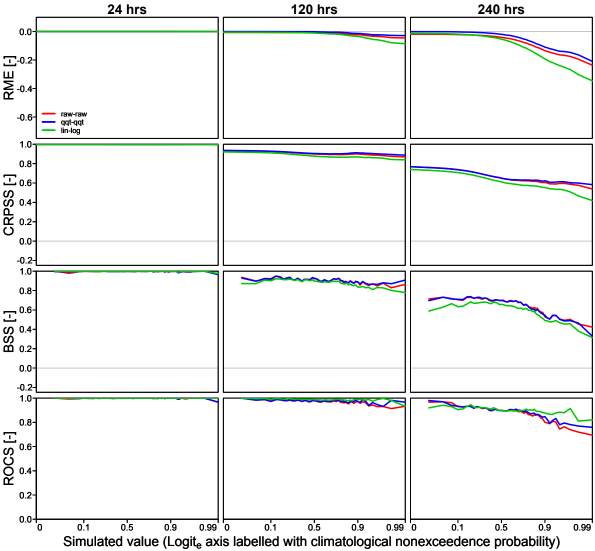
Streamflow, 43 headwater basins, BSS Type II

Streamflow VI



Streamflow, 4 tributaries, BSS Type II

Streamflow VII



Streamflow, Rhine outlet at Lobith

Summary conclusions

- Postprocessing of temperature, precipitation forecasts improves skill
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  - presence of storages
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Post-processing ECMWF precipitation and temperature ensemble reforecasts for operational hydrologic forecasting at various spatial scales ☆

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SUMMARY

The ECMWF temperature and precipitation ensemble reforecasts are evaluated for biases in the mean, spread and forecast probabilities, and how these biases propagate to streamflow ensemble forecasts. The forcing ensembles are subsequently post-processed to reduce bias and increase skill, and to investigate whether this leads to improved streamflow ensemble forecasts. Multiple post-processing techniques are used: quantile-to-quantile transform, linear regression with an assumption of bivariate normality and logistic regression. Both the raw and post-processed ensembles are run through a hydrologic model of the river Rhine to create streamflow ensembles. The results are compared using multiple verification metrics and skill scores: relative mean error, Brier skill score and its decompositions, mean continuous ranked probability skill score and its decomposition, and the ROC score. Verification of the streamflow ensembles is performed at multiple spatial scales: relatively small headwater basins, large tributaries and the Rhine outlet at Lobith. The streamflow ensembles are verified against simulated streamflow, in order to isolate the effects of biases in the forcing ensembles and any improvements therein. The results indicate that the

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