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

Jan Verkade 1 2 3, James Brown 4, Albrecht Weerts 1 5 and Paolo Reggiani 6

November 2014 HEPEX meeting © ECMWF

1 Deltares, Delft, The Netherlands
2 Delft University of Technology, The Netherlands
3 Rijkswaterstaat River Forecasting Service, Lelystad, The Netherlands
4 Hydrologic Solutions Ltd, Southampton, United Kingdom
5 Wageningen University and Research Centre, The Netherlands
6 University of Siegen, Germany
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)
Setting the scene

- hydrologic forecasting
- ensemble prediction
- reduction of predictive uncertainties
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

Predicted forcings (e.g. P,T,E-ensembles) → Bias-correct forcings ("pre-process") → Predicted streamflow ensembles

Predicted forcings (e.g. P,T,E-ensembles) → Predicted streamflow ensembles
Observations from the E-OBS dataset (www.ecad.eu/E-OBS/)
## 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-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, 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. ~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
- 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)
Post-processing ECMWF precipitation and temperature ensemble reforecasts for operational hydrologic forecasting at various spatial scales

J.S. Verkade a,b,c,*, J.D. Brown d, P. Reggiani a,e, A.H. Weerts a,f

a Deltares, PO Box 177, 2600 MH Delft, The Netherlands
b Ministry of Infrastructure and the Environment, Water Management Centre of The Netherlands, River Forecasting Service, Lelystad, The Netherlands
c Delft University of Technology, Delft, The Netherlands
d Hydrologic Solutions Limited, Southampton, United Kingdom
e RWTH Aachen University, Aachen, Germany
f Wageningen University and Research Centre, Hydrology and Quantitative Water Management Group, Wageningen, The Netherlands

ARTICLE INFO

Article history:
Received 20 January 2013
Received in revised form 21 July 2013
Accepted 28 July 2013
This manuscript was handled by Konstantine P. Georgakakos, Editor-in-Chief, with the assistance of Ashish Sharma, Associate Editor

Keywords:
Bias-correction
Post-processing

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


Contact details

Jan Verkade
jan.verkade@deltares.nl

James Brown
james.brown@hydrosolved.com

Slides are available via twitter.com/janverkade