

Post-processing of multi-model ensemble river discharge forecasts using censored EMOS

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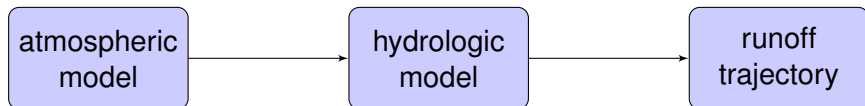
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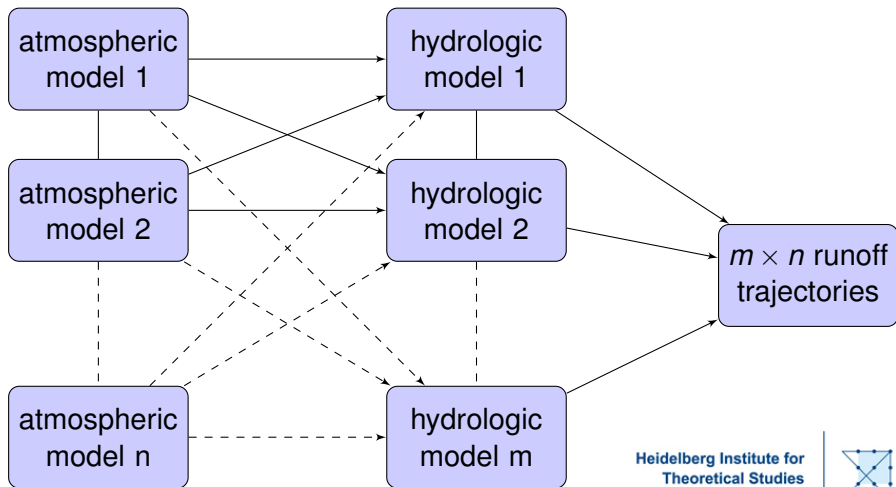


Deterministic hydrologic forecasts



- Problem: statements on **uncertainty** impossible
- Generate **ensemble forecasts** by using several models, model configurations, and initial and boundary conditions.

Hydrologic ensemble forecasts



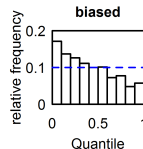
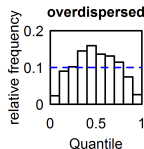
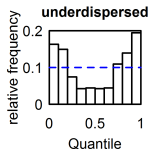
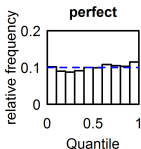
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Post-processing of ensemble forecasts

Main goals by Gneiting & Raftery (2007):

■ Well **calibrated**,



Hypothetical PIT histograms

■ and **sharp** probabilistic forecasts.

Hydrologic post-processing example

Joint project with the BfG on post-processing of ensemble forecasts for river Rhine:

- The BfG forecasting system censors forecast and observed runoff values below a specific threshold (i.e. $5 \text{ m}^3/\text{s}$).

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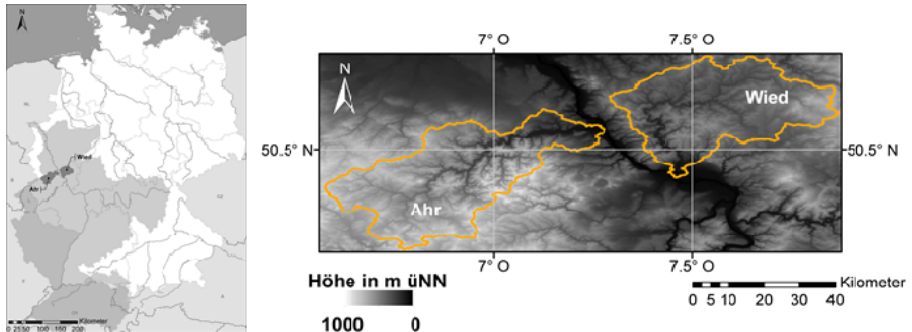
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- Standard post-processing methods rely mostly on continuously distributed variables (very often Gaussian).
- There is a need for a post-processing method for censored data:
→ Ensemble Model Output Statistics (EMOS) by Gneiting et al. (2005) is very suitable for this purpose due to its flexibility and simplicity

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Considered catchments

For testing the censored EMOS method we have selected the rivers Wied and Ahr:



Source: Bundesanstalt für Gewässerkunde (BfG), Koblenz (2013).

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Considered catchments: censoring

Percentage of censored observations (obtained from the climatology from 1.11.1998 to 31.10.2008):

gauge	catchment	area [km ²]	% censored
Altenahr (ALTE)	Ahr	746	72%
Friedrichsthal (FRIE)	Wied	680	55%

Meteorological forcing

The hydrologic raw ensemble is obtained by running the HBV-96 model several times using the following meteorological input ensembles¹:

name	# members	lead-times	spatial resolution ~
COSMO-LEPS	16	1-114 h	10 km
DWD-GME	1 (det.)	1-174 h	20 km
DWD-MER	1 (det.)	78 h (174 h)	7 km (20 km)
ECMWF-IFS	1 (det.)	1-240h	16 km

¹ DWD-MER stands for a model run based on COSMO-EU forcing up to lead-time 78 h and on DWD-GME thereafter.

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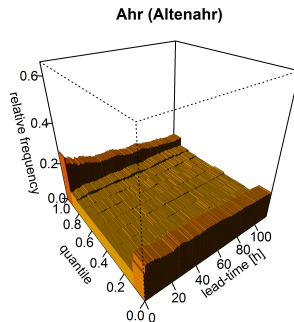
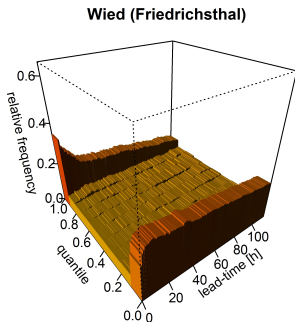
→ A hydrologic raw ensemble of size
19 covering lead-times 1-114 h.

Post-processing design

- Hydrologic re-forecasts from 01.11.2008 to 25.10.2011.
- Post-process the forecasts for each lead-time separately.
- Seasonal training and verification periods:

verification period	training period
November 2008	SON 2009, SON 2010, SO 2011
DJF 2008/2009	DJF 2009/2010, DJF 2010/2011
MAM 2009	MAM 2010, MAM 2011
.	.
.	.
.	.
SO 2011	November 2008, SON 2009, SON 2010

Calibration raw ensembles: 3D PIT



→ strong underdispersion

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Censored EMOS: model I

Procedure:

- Box-Cox transformation in order to meet normality assumption
- subtract the censoring threshold
- use the following left-censored (Gneiting et al., 2004) and right-truncated distribution (Thorarinsdottir & Gneiting, 2010):

$$P(Y \leq y \mid \bar{f}_1, \dots, \bar{f}_K) = \begin{cases} 0 & \text{if } y < 0 \\ \frac{\Phi(\frac{y-\mu}{\sigma})}{\Phi(\frac{v-\mu}{\sigma})} & \text{if } 0 \leq y \leq v \\ 1 & \text{if } y > v \end{cases}, \quad \text{where } \rightarrow$$

Censored EMOS: model II

$$P(Y \leq y \mid \bar{f}_1, \dots, \bar{f}_K) = \begin{cases} 0 & \text{if } y < 0 \\ \frac{\Phi(\frac{y-\mu}{\sigma})}{\Phi(\frac{v-\mu}{\sigma})} & \text{if } 0 \leq y \leq v \\ 1 & \text{if } y > v \end{cases}, \quad \text{where}$$

- y : forecast runoff
- \bar{f}_k : model forecasts, mean value if from an ensemble
- v : upper threshold: 2 times the maximum of the climatology, also Box-Cox transformed \rightarrow prevents unrealistic high forecast quantiles
- $\sigma^2 = c_1 + c_2 S^2$ (S^2 : variance among all raw forecast members)
- censoring threshold is set to zero
- $\mu \rightarrow$ see next slide

Censored EMOS: model III

- Due to the right-truncation the location parameter μ has to fulfill:

$$\mathbb{E}[Y|Y \leq v] := \sum_{k=1}^K w_k \bar{f}_k + a \overline{\mathbb{1}_{f=0}} = \mu - \sigma \frac{\varphi(\frac{v-\mu}{\sigma})}{\Phi(\frac{v-\mu}{\sigma})}, \quad \text{where}$$

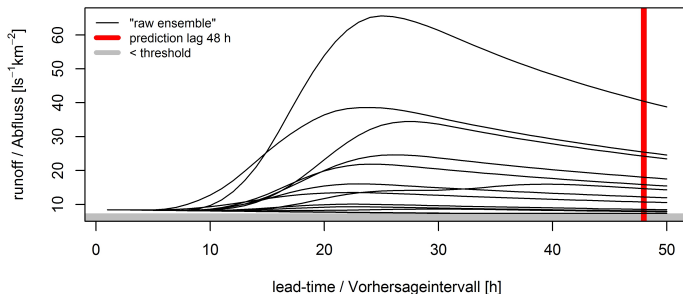
- w_k : weight of model k
- $\overline{\mathbb{1}_{f=0}}$: proportion of ensemble means \bar{f}_k that equal the lower threshold value (see Scheuerer, 2013)
- $\sigma = \sigma_0$ if $\overline{\mathbb{1}_{f=1}}$
- Parameters are estimated using minimal Continuous Ranked Probability Score (CRPS) estimation.

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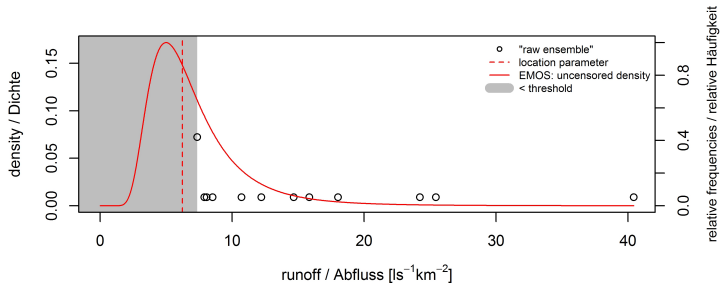
Censored EMOS: illustration I

Example forecast initialized on 5.9.2009 06:00 CET:



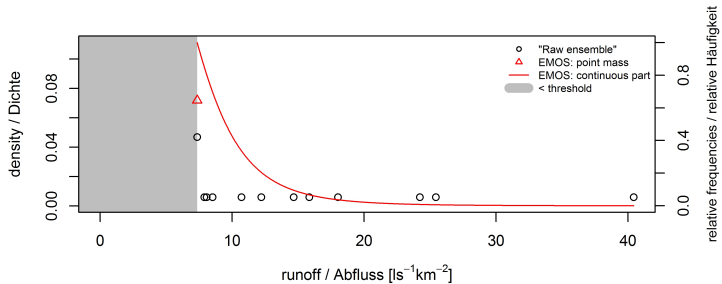
Censored EMOS: illustration II

Uncensored model pdf:



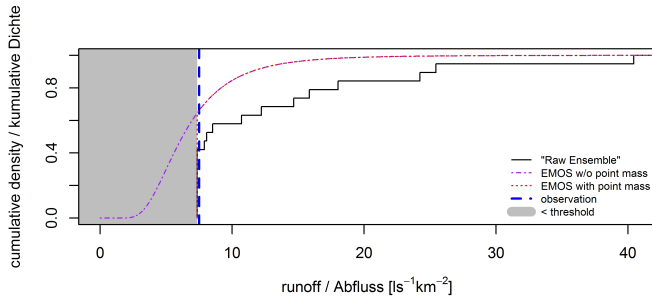
Censored EMOS: illustration III

Censored model pdf:

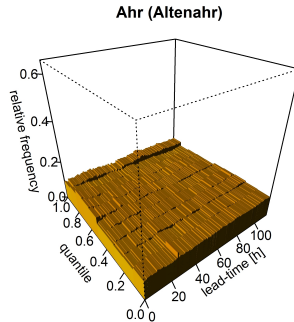
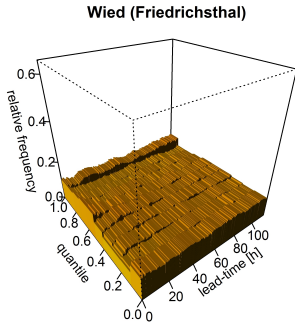


Censored EMOS: illustration IV

Censored model cdf:



Results: 3D PIT EMOS



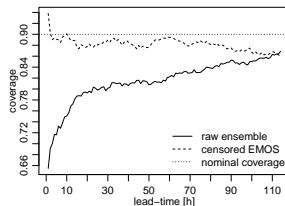
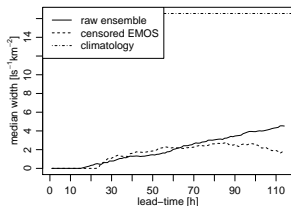
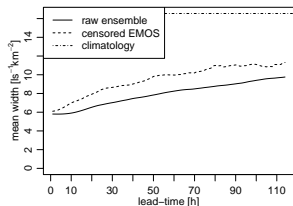
→ well calibrated

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Results: sharpness Wied

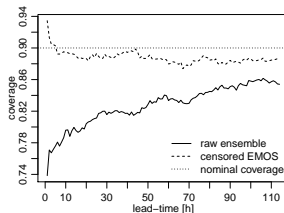
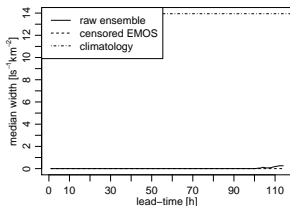
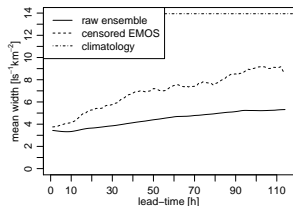
From left to right: Mean prediction width, median prediction width and associated coverage of 90% prediction intervals:



→ quite sharp

Results: sharpness Ahr

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→ quite sharp

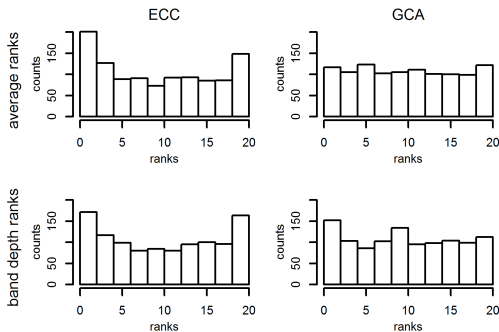
Multivariate calibration

Consider **temporal dependencies** among lead-times by:

- using a moving average of EMOS parameters (here: sliding window of size 5)
- using Copula approaches to consider correlation structure among lead-times:
 - Random **Ensemble Copula Coupling** that conserves the rank order structure of the raw ensemble (Scheffzik et al., 2013)
 - **Gaussian Copula approach** (GCA) that conserves the covariance structure estimated from the observations in the training period (Pinson & Girard, 2012)

Results: multivariate calibration Wied

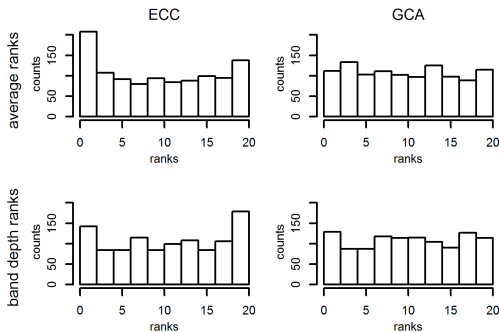
Average and band depth rank histograms (Thorarinsdottir et al., 2013):



→ GCA outperforms ECC in terms of correlation structure

Results: multivariate calibration Ahr

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Summary

- Statistical post-processing based on censored multi-model ensemble runoff forecasts yields **appropriate predictive distributions**.
- Censored EMOS improves **calibration** while not deteriorating **sharpness** much for the two examples considered.
- There exist straightforward methods for modeling of the **temporal dependencies**.
- GCA outperforms ECC in our example:
→ Are thus training observations better **predictors of correlation structure** than the raw ensemble?

References

- [1] T. Gneiting et al., Report to the Washington Technology Center, May 2004.
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- [7] M. Scheuerer, *Quarterly Journal of the Royal Meteorological Society*, DOI:10.1002/qj.2183, 2013.
- [8] T. L. Thorarinsdottir & T. Gneiting, *Journal of the Royal Statistical Society (Series A)*, 173 : 371–388, 2010.
- [9] T. L. Thorarinsdottir et al., *arXiv:1310.0236*, 2013.