# Ensemble postprocessing for probabilistic quantitative precipitation forecasts

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universitätbonn

Deutscher Wetterdienst
*Wetter und Klima aus einer Hand*
DWD

## High-resolution limited-area mesoscale NWP models

- Describe mesoscale processes in an explicit way
- Predict weather with potential for hazardous impacts (high-impact weather)

## Ensemble Prediction Systems (EPS)

- Quantify uncertainty (initial/boundary conditions, model error)
- Statistically meaningful probabilistic forecasts

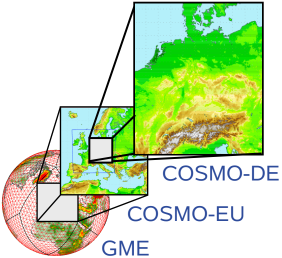
## Probabilistic postprocessing

- Integral part of an EPS
- Ensemble spread and forecast skill
- Verification

# COSMO*-DE

Convection-permitting NWP model operated by DWD (Baldauf et al., 2011)

- 2.8 km grid spacing and non-hydrostatic
- No parameterization of deep moist convection
- Assimilation of radar precipitation using latent heat nudging
- Forecast time of 21 hours initialized every 3h
- Designed to predict "high-impact" weather




DWD (2010)

* Consortium for Small-scale Modeling

# COSMO-DE-EPS

Ensemble prediction system at DWD

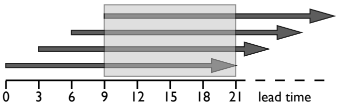
- 20 members, initialized every 3h (21h-forecasts)
- Boundary conditions and perturbed physics (GEBHARDT ET AL., 2011)
- Initial condition perturbations (PERALTA ET AL., 2012)
- Pre-operational since December 2010 - operational since May 2012

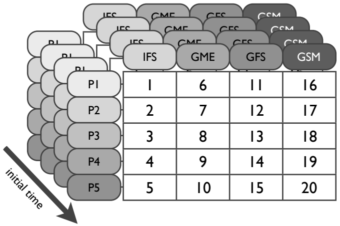
| COSMO-DE-EPS operational | IFS | GME | GFS | GSM |
|---|---|---|---|---|
| mean entrainment rate for shallow convection | 1 | 6 | 11 | 16 |
| critical value for normalized over-saturation | 2 | 7 | 12 | 17 |
| scaling factor boundary layer for heat (min) | 3 | 8 | 13 | 18 |
| scaling factor boundary layer for heat (max) | 4 | 9 | 14 | 19 |
| maximal turbulent length scale | 5 | 10 | 15 | 20 |

# Lagged average forecasts

## Time-lagged ensemble (HOFFMAN AND KALNAY, 1983)

- Rapidly updated NWP model / ensemble member
- Forecasts from overlapping prediction period



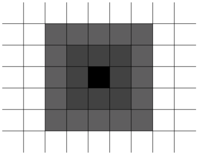




**LAF** – 4 time-lagged COSMO-DE forecasts
**EPS** – 20 members
**TLEPS$_{20}$** – 5 members x 4 time-lagged forecasts
**TLEPS$_{80}$** – 20 members x 4 time-lagged forecasts

# First Guess – Probabilities and Quantiles

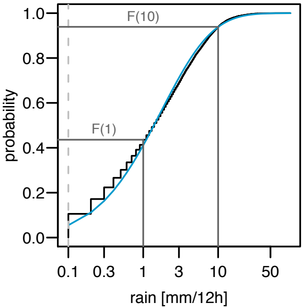
Most simple postprocessing

- First guess probability of precipitation: **fgPOP**
- First guess probability of threshold exceedance: **$\mathbf{fgPOT}_u$**
  $\longrightarrow$ relative frequencies of the ensemble members
- First guess quantile $\tau \in [0, 1]$: **$\mathbf{fgQ}_\tau$**
  $\longrightarrow$ order statistics of the ensemble members
- others ...



**+ neighborhood method** (Theis et al., 2005)
Spatial neighborhood of $5 \times 5$ gridboxes

# Postprocessing – learning from history and data




**Logistic regression**:

$$\pi = 1 - F_Y(u \mid \mathbf{X}) = \mathrm{logit}^{-1}(\beta^T \mathbf{X})$$

**Variable selection with Lasso**

(TIBSHIRANI, 1996):

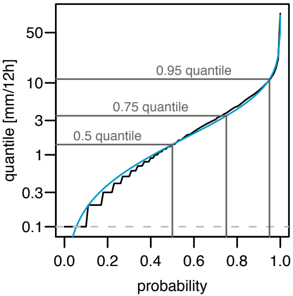
$$\sum_j \mid \beta_j \mid \leq \lambda\,, \quad \lambda \geq 0$$

**Brier score (BS)**:

$$S_{BS}(y, F_Y, u) = (\pi - \mathbb{I}_{y>u})^2$$

$\longrightarrow$ decomposition (reliability, resolution)

# Postprocessing – learning from history and data




**Quantile regression**:
$$q_\tau = F_Y^{-1}(\tau \mid \mathbf{X}) = \beta_\tau^T \mathbf{X}$$

**Censored quantile regression**:
$$q_\tau = F_Y^{-1}(\tau \mid \mathbf{X}) = \max(0, \beta_\tau^T \mathbf{X})$$

**Bayesian quantile regression and variable selection**: work in progress

**Quantile score (QS)**:
$$S_{QS}(y, F_Y, \tau) = \rho_\tau(y - q_\tau)$$

$$\rho_\tau(v) = \begin{cases} \tau v & \text{for } v > 0 \\ (\tau - 1)v & \text{for } v \leq 0 \end{cases}$$

$\longrightarrow$ decomposition (reliability, resolution)

BENTZIEN AND FRIEDERICHS, 2013 (in prep.)

# Bayesian inference for censored quantile regression

(YU AND STANDER, 2007)

Likelihood based on asymmetric Laplace distribution

$$L_\tau(\mathbf{y} \mid \boldsymbol{\beta}_\tau) = \tau^N (1-\tau)^N \exp\left\{ -\sum_{n=1}^{N} \rho_\tau(y_n - max[0, \boldsymbol{\beta}_\tau^T \mathbf{x}_n]) \right\}$$

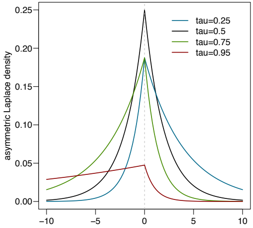
Variable selection using independent zero-mean Laplace priors (Lasso)

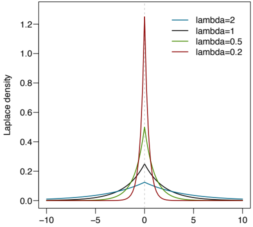
$$\pi(\boldsymbol{\beta}_\tau \mid \lambda) = \left(\frac{1}{2\lambda}\right)^P \exp\left\{ -\frac{1}{\lambda} \sum_{j=1}^{P} \mid \beta_{\tau,j} \mid \right\}$$

For a given $\lambda$, the posterior is given by

$$\pi(\boldsymbol{\beta}_\tau \mid \mathbf{y}) \propto L_\tau(\mathbf{y} \mid \boldsymbol{\beta}_\tau)\, \pi(\boldsymbol{\beta}_\tau \mid \lambda)$$

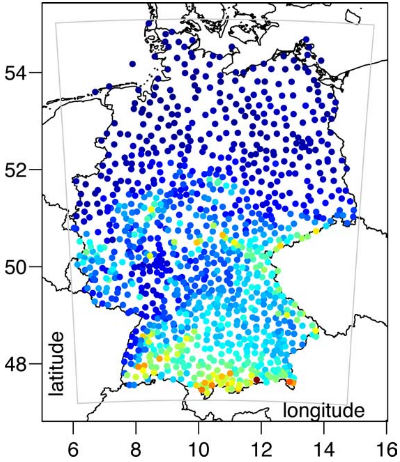
Estimates of $\boldsymbol{\beta}_\tau$ are obtained via Markov Chain Monte Carlo and a single-component Metropolis algorithm.



# Observational Sites

- **Precipitation**
- 12-hour accumulation between 12 and 24 UTC
- ∼1000 rain gauges
- 01/2011 - 12/2011
- PoP, PoT, and quantiles

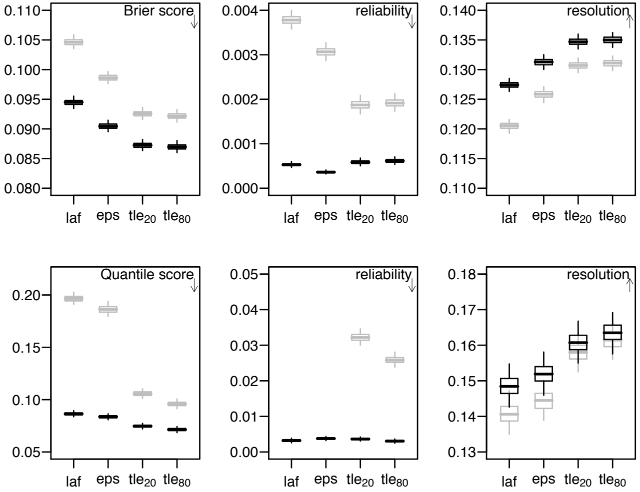


## Scores – Decomposition

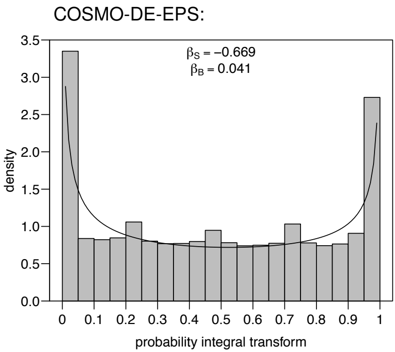
— first guess — postprocessing

Probability of precipitation

99% Quantile



# The benefit of time-lagging




Beta-Score (KELLER AND HENSE, 2011):

$\beta_S > 0\,(< 0)$: overestimation (underestimation) of ensemble spread

$\beta_B > 0\,(< 0)$: bias towards higher (lower) values

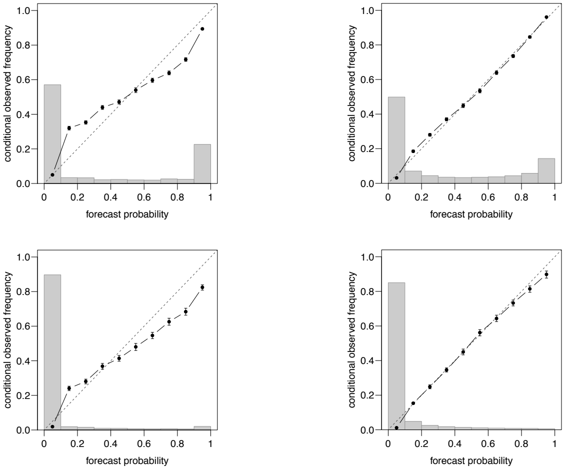
## Reliability

first guess:

logistic regression:

Probability of precipitation

Probability of precipitation **above 5mm**

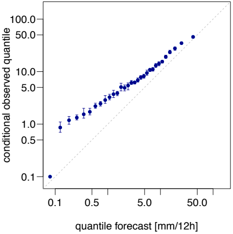


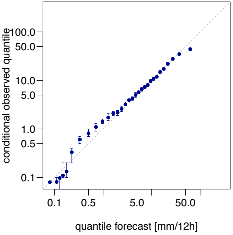
## Reliability

first guess:

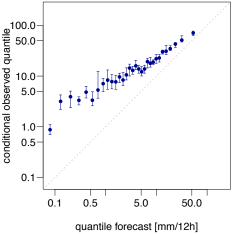
quantile regression:

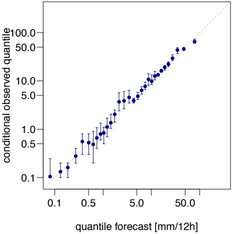
99% Quantile



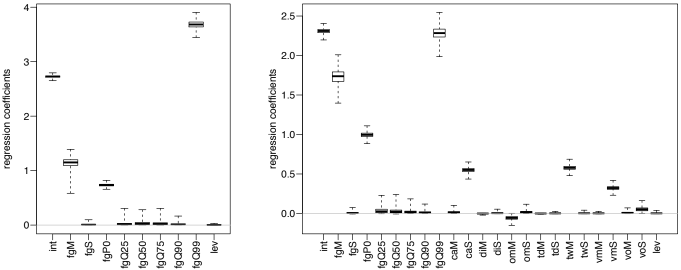




99.9% Quantile



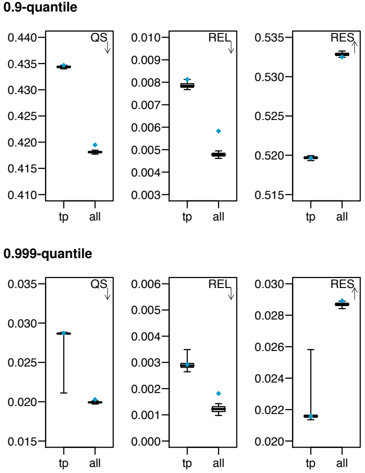
## LASSO – variable selection for quantile regression (0.9-quantile)




- Complexity of the model depends on the lasso parameter
- Selection of suitable predictors from total precipitation
- Influence of other meteorological variables (cape, tdiv_hum, twater, vmax$_{10m}$; divergence, vorticity and omega in 850hPa)

## LASSO – variable selection for quantile regression

- Out-of-sample verification for spring/summer 2011
- Bayesian and frequentistic quantile regression with selected covariates
- Additional covariates (besides totprec):
  - → increase resolution (information content)
  - → improve reliability (calibration)



## LASSO – variable selection for quantile regression

| $\tau$ | fgPoP | fgM | fgS | $fgQ_{25}$ | $fgQ_{99}$ | vmax | cape | twater | |
|---|---|---|---|---|---|---|---|---|---|
| 0.25 | ✓ | ✓ | | ✓ | | ✓ | | | |
| 0.50 | ✓ | ✓ | | ✓ | | ✓ | | | |
| 0.75 | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | |
| 0.90 | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | omega,vorticity |
| 0.99 | ✓ | | ✓ | | ✓ | (✓) | ✓ | ✓ | tdiv_hum |
| 0.999 | ✓ | | ✓ | | ✓ | | ✓ | ✓ | |

- Additional covariates improve predictive performance during spring/summer → vmax, cape, twater
- Larger impact on higher quantiles

# Take home messages

- Postprocessing is indispensable for reliable probabilistic forecasts
- Probabilistic guidance may be obtained from deterministic system by time-lagging and neighborhood extension (BENTZIEN AND FRIEDERICHS, 2012)
- EPS increases forecast skill – time-lagging and neighborhood extension always beneficial
- Variable selection via the Lasso in a Bayesian framework
  - $\longrightarrow$ selection of predictive covariates (besides total precipitation)
  - $\longrightarrow$ positive impact on reliability and resolution

# References 1/2

[1] M. Baldauf, A. seifert, J. Förstner, D. Majewski, M. Raschendorfer, and T. Reinhardt, "Operational convective-scale numerical weather prediction with the COSMO model: description and sensitivities," *Monthly Weather Review*, vol. 139, pp. 3887–3905, 2011.

[2] S. Bentzien and P. Friederichs, "The decomposition of the quantile score," *(in prep.)*, 2013.

[3] S. Bentzien and P. Friederichs, "Generating and calibrating probabilistic quantitative precipitation forecasts from the high-resolution NWP model COSMO-DE," *Weather and Forecasting*, vol. 27, no. 4, pp. 988–1002, 2012.

[4] P. Friederichs and A. Hense, "Statistical downscaling of extreme precipitation events using censored quantile regression," *Monthly Weather Review*, vol. 135, pp. 2365–2378, Jun. 2007.

[5] C. Gebhardt, S. E. Theis, M. Paulat, and Z. Ben Bouallègue, "Uncertainties in COSMO-DE precipitation forecasts introduced by model perturbations and variations of lateral boundaries," *Atmospheric Research*, vol. 100, pp. 168–177, 2011.

# References 2/2

[6] R. N. Hoffman and E. Kalnay, "Lagged average forecasting, an alternative to Monte Carlo forecasting," *Tellus*, vol. 35, pp. 100–118, 1983.

[7] J. D. Keller and A. Hense, "A new non-Gaussian evaluation method for ensemble forecasts based on analysis rank histograms," *Meteorologische Zeitschrift*, vol. 20, no. 2, pp. 107–117, Apr. 2011.

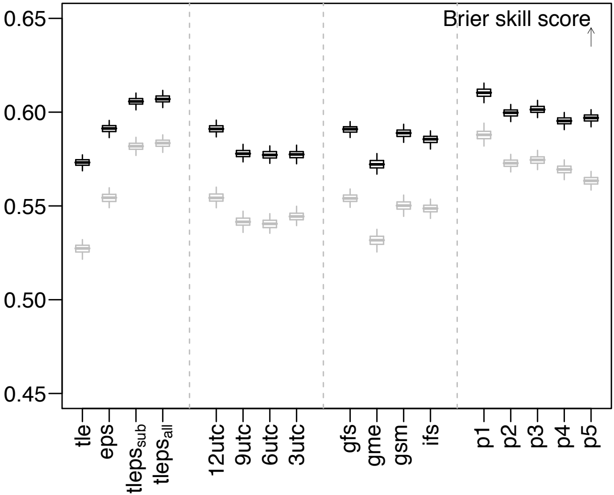
[8] C. Peralta, Z. Ben Bouallègue, S. E. Theis, C. Gebhardt, and M. Buchhold, "Accounting for initial condition uncertainties in COSMO-DE-EPS," *Journal of Geophysical Research*, vol. 117, 2012.

[9] S. E. Theis, A. Hense, and U. Damrath, "Probabilistic precipitation forecasts from a deterministic model: a pragmatic approach," *Meteorological Applications*, vol. 12, pp. 257–268, 2005.

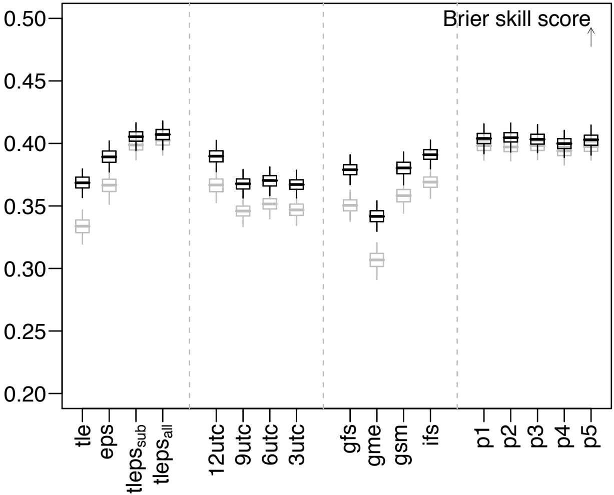
[10] R. J. Tibshirani, "Regression shrinkage and selection via the Lasso," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.

[11] K. Yu and J. Stander, "Bayesian analysis of a Tobit quantile regression model," *Journal of Econometrics*, vol. 137, no. 1, pp. 260–276, Mar. 2007.

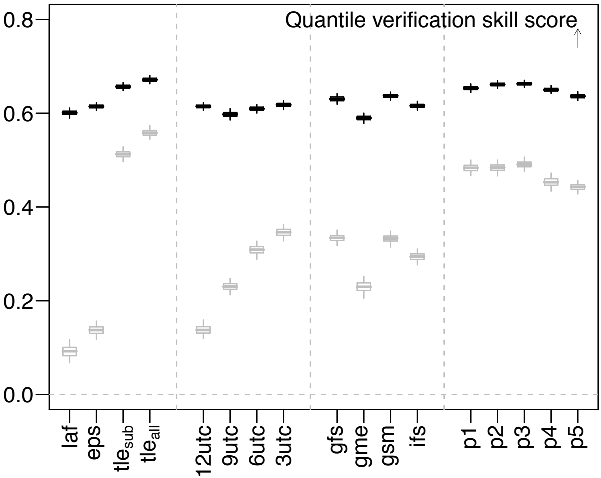
## Skill scores – PoP



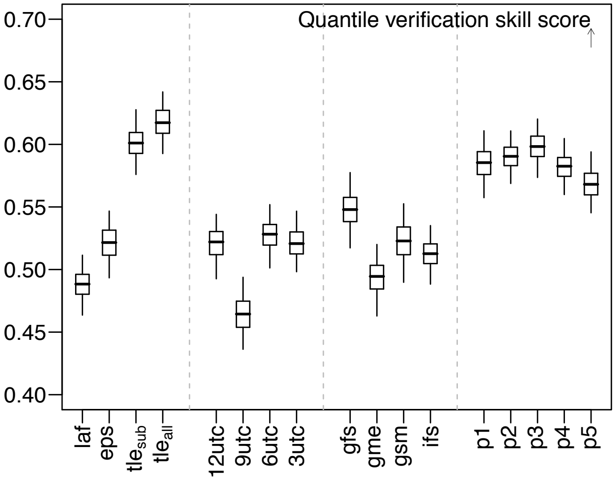
## Skill scores – $PoT_{5mm}$



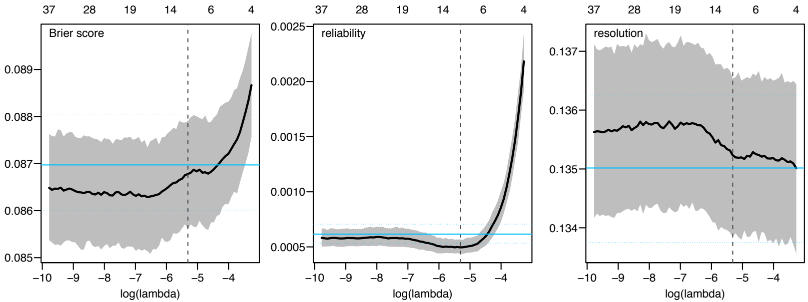
## Skill scores – 99% Quantile



## Skill scores – 99.9% Quantile



## LASSO – variable selection for logistic regression (PoP)




- Complexity of the model depends on the lasso parameter
- Selection of lasso parameter $\lambda$ via cross-validation
- Minimize Brier score, reliability, ...

## LASSO – variable selection for logistic regression (PoP)

- 44 variables
- Selection of covariates
- Shrinkage of regression coefficients

Regression coefficients from cross-validation: