Probabilistic Quantitative Precipitation Forecasting Using Ensemble Model Output Statistics

Michael Scheuerer

Institute of Applied Mathematics

November 2012

Universität Heidelberg

supported by

Deutscher Wetterdienst

1. From Forecast Ensembles to Predictive Distributions
2. A distribution family for precipitation and model fitting
   - The left-censored generalized extreme value distribution
   - Ensemble Model Output Statistics (EMOS)
   - Model fitting
3. Incorporating Neighbourhood Information
   - Displacement errors
   - Ensemble model output statistics for neighbourhoods
4. Data Example
   - Setup for training and verification
   - Brier Skill Scores and CRP Skill Scores
   - Reliability Diagrams
5. Directions for Improvement

From forecast ensembles to predictive distributions

We present a statistical post-processing method that transforms ensemble forecasts into a full predictive distribution. The goal of statistical post-processing is to

- maximize the sharpness of the predictive distributions
- subject to calibration

Sharpness refers to the spread of the predictive distributions. It is a *property of the forecasts only*.

From forecast ensembles to predictive distributions

We present a statistical post-processing method that transforms ensemble forecasts into a full predictive distribution. The goal of statistical

post-processing is to

- maximize the sharpness of the predictive distributions
- subject to calibration

Sharpness refers to the spread of the predictive distributions. It is a *property of the forecasts only*.

Calibration refers to the statistical compatibility between the predictive distributions and the observations. It is a *joint property of the forecasts and the observations*.

From forecast ensembles to predictive distributions

We present a statistical post-processing method that transforms ensemble forecasts into a full predictive distribution. The goal of statistical

post-processing is to

- maximize the sharpness of the predictive distributions
- subject to calibration

Our approach is guided by the paradigm that one should

- make optimal use of the *information* contained in the ensemble
- not rely on any assumption about ensemble forecasts being draws from some unknown distributions

1 From Forecast Ensembles to Predictive Distributions

2 A distribution family for precipitation and model fitting
- The left-censored generalized extreme value distribution
- Ensemble Model Output Statistics (EMOS)
- Model fitting

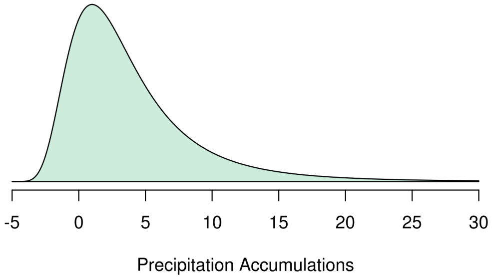
3 Incorporating Neighbourhood Information
- Displacement errors
- Ensemble model output statistics for neighbourhoods

4 Data Example
- Setup for training and verification
- Brier Skill Scores and CRP Skill Scores
- Reliability Diagrams

5 Directions for Improvement

A distribution family for precipitation

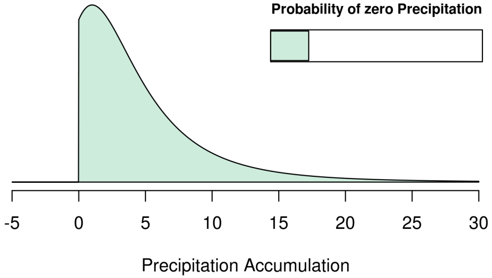
We model precipitation amounts by a generalized extreme value (GEV) distribution...



- positive skew ✓
- heavy right tail ✓
- non-negative ✓
- may be equal to zero with positive probability ✓

A distribution family for precipitation

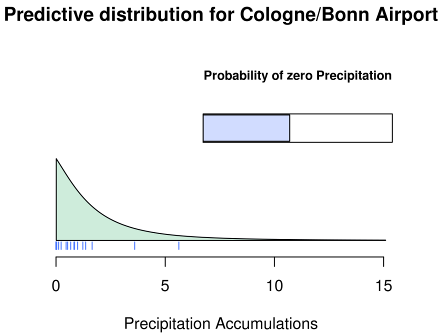
We model precipitation amounts by a generalized extreme value (GEV) distribution...

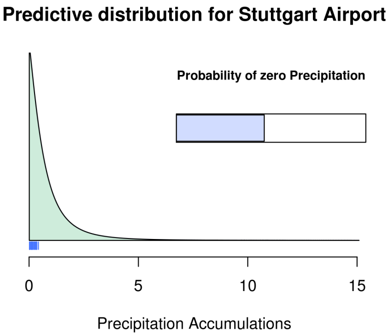


- positive skew ✓
- heavy right tail ✓
- non-negative ✓
- may be equal to zero with positive probability ✓

...which we consider to be *left-censored at zero*.

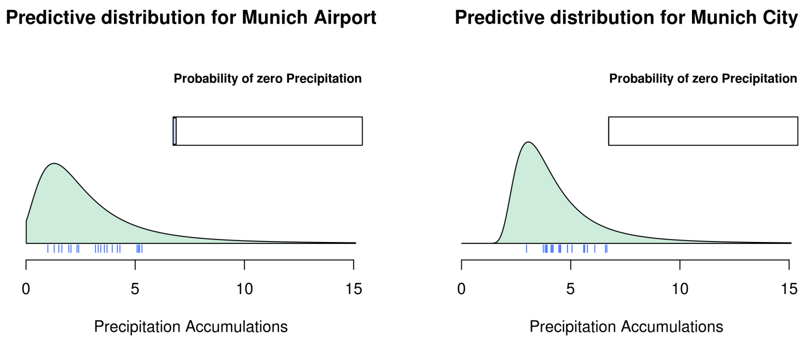
Censored GEV type predictive distributions in practice





Predictive distributions of precipitation accumulations on June 11, 2011 between UTC 12:00 and UTC 18:00 at different locations.

Censored GEV type predictive distributions in practice



Predictive distributions of precipitation accumulations on June 11, 2011 between UTC 12:00 and UTC 18:00 at different locations.

Ensemble Model Output Statistics (EMOS)

We parametrize the censored GEV by three parameters m, σ and ξ which represent location, scale and shape. The two former will be linked to certain statistics of the ensemble forecasts $f_{s1}, \ldots, f_{sK}$ at site s:

- $\bar{\mathbf{f}}_s := \frac{1}{K}\sum_{k=1}^{K} f_{sk}$ (ensemble mean)
- $\overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}} := \frac{1}{K}\sum_{k=1}^{K} \mathbf{1}_{\{f_{sk}=0\}}$ (fraction of zero precipitation members)
- $\mathrm{MD}(\mathbf{f}_s) := \frac{1}{K^2}\sum_{k,k'=1}^{K} |f_{sk} - f_{sk'}|$ (ensemble mean difference)

Specifically, we let

$$m = \alpha_0 + \alpha_1 \cdot \bar{\mathbf{f}}_s + \alpha_2 \cdot \overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}}, \qquad \sigma = \beta_0 + \beta_1 \cdot \mathrm{MD}(\mathbf{f}_s)$$

with parameters $\alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \xi$ to be estimated from training data.

Ensemble Model Output Statistics (EMOS)

We parametrize the censored GEV by three parameters m, σ and ξ which represent location, scale and shape. The two former will be linked to certain statistics of the ensemble forecasts $f_{s1}, \ldots, f_{sK}$ at site s:

- $\overline{\mathbf{f}}_s := \frac{1}{K} \sum_{k=1}^{K} f_{sk}$ (ensemble mean)
- $\overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}} := \frac{1}{K} \sum_{k=1}^{K} \mathbf{1}_{\{f_{sk}=0\}}$ (fraction of zero precipitation members)
- $\mathrm{MD}(\mathbf{f}_s) := \frac{1}{K^2} \sum_{k,k'=1}^{K} |f_{sk} - f_{sk'}|$ (ensemble mean difference)

Specifically, we let

$$m = \alpha_0 + \alpha_1 \cdot \overline{\mathbf{f}}_s + \alpha_2 \cdot \overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}}, \qquad \sigma = \beta_0 + \beta_1 \cdot \mathrm{MD}(\mathbf{f}_s)$$

with parameters $\alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \xi$ to be estimated from training data.

Ensemble Model Output Statistics (EMOS)

We parametrize the censored GEV by three parameters m, σ and ξ which represent location, scale and shape. The two former will be linked to certain statistics of the ensemble forecasts $f_{s1}, \ldots, f_{sK}$ at site s:

- $\overline{\mathbf{f}}_s := \frac{1}{K}\sum_{k=1}^{K} f_{sk}$ (ensemble mean)
- $\overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}} := \frac{1}{K}\sum_{k=1}^{K} \mathbf{1}_{\{f_{sk}=0\}}$ (fraction of zero precipitation members)
- $\mathrm{MD}(\mathbf{f}_s) := \frac{1}{K^2}\sum_{k,k'=1}^{K} |f_{sk} - f_{sk'}|$ (ensemble mean difference)

Specifically, we let

$$m = \alpha_0 + \alpha_1 \cdot \overline{\mathbf{f}}_s + \alpha_2 \cdot \overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}}, \qquad \sigma = \beta_0 + \beta_1 \cdot \mathrm{MD}(\mathbf{f}_s)$$

with parameters $\alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \xi$ to be estimated from training data.

Ensemble Model Output Statistics (EMOS)

We parametrize the censored GEV by three parameters m, σ and ξ which represent location, scale and shape. The two former will be linked to certain statistics of the ensemble forecasts $f_{s1}, \ldots, f_{sK}$ at site s:

- $\overline{\mathbf{f}}_s := \frac{1}{K} \sum_{k=1}^{K} f_{sk}$ (ensemble mean)
- $\overline{\mathbf{1}_{\{\mathbf{f}_s = 0\}}} := \frac{1}{K} \sum_{k=1}^{K} \mathbf{1}_{\{f_{sk}=0\}}$ (fraction of zero precipitation members)
- $\mathrm{MD}(\mathbf{f}_s) := \frac{1}{K^2} \sum_{k,k'=1}^{K} |f_{sk} - f_{sk'}|$ (ensemble mean difference)

Specifically, we let

$$m = \alpha_0 + \alpha_1 \cdot \overline{\mathbf{f}}_s + \alpha_2 \cdot \overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}}, \qquad \sigma = \beta_0 + \beta_1 \cdot \mathrm{MD}(\mathbf{f}_s)$$

with parameters $\alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \xi$ to be estimated from training data.

Ensemble Model Output Statistics (EMOS)

We parametrize the censored GEV by three parameters m, σ and ξ which represent location, scale and shape. The two former will be linked to certain statistics of the ensemble forecasts $f_{s1}, \ldots, f_{sK}$ at site s:

- $\overline{\mathbf{f}}_s := \frac{1}{K} \sum_{k=1}^{K} f_{sk}$ (ensemble mean)
- $\overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}} := \frac{1}{K} \sum_{k=1}^{K} \mathbf{1}_{\{f_{sk}=0\}}$ (fraction of zero precipitation members)
- $\mathrm{MD}(\mathbf{f}_s) := \frac{1}{K^2} \sum_{k,k'=1}^{K} |f_{sk} - f_{sk'}|$ (ensemble mean difference)

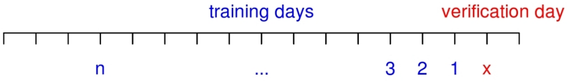
Specifically, we let

$$m = \alpha_0 + \alpha_1 \cdot \overline{\mathbf{f}}_s + \alpha_2 \cdot \overline{\mathbf{1}_{\{\mathbf{f}_s=0\}}}, \qquad \sigma = \beta_0 + \beta_1 \cdot \mathrm{MD}(\mathbf{f}_s)$$

with parameters $\alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \xi$ to be estimated from training data.

Model fitting

To obtain the post-processing parameters for a certain day, we consider forecasts and observations during the preceding n days.



A standard tool for quantitative assessment of the quality of probabilistic forecasts are the so-called scoring rules.

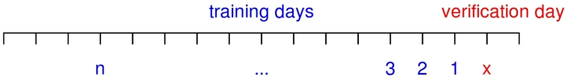
A scoring rule $s(F, y)$ assigns a numerical score to to each pair (F, y), where F is the predictive distribution and y is the verifying observation. We consider negatively oriented scores, i.e. the smaller the better.

$\Rightarrow$ suggests the following estimation procedure:

Choose the parameters with minimal score in the training period.

Model fitting

To obtain the post-processing parameters for a certain day, we consider forecasts and observations during the preceding n days.



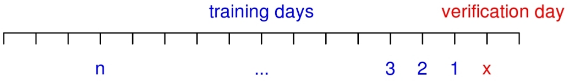
A standard tool for quantitative assessment of the quality of probabilistic forecasts are the so-called scoring rules.
A scoring rule $s(F, y)$ assigns a numerical score to to each pair (F, y), where F is the predictive distribution and y is the verifying observation.
We consider negatively oriented scores, i.e. the smaller the better.

$\Rightarrow$ suggests the following estimation procedure:

Choose the parameters with minimal score in the training period.

Model fitting

To obtain the post-processing parameters for a certain day, we consider forecasts and observations during the preceding n days.



A standard tool for quantitative assessment of the quality of probabilistic forecasts are the so-called scoring rules.
A scoring rule $s(F, y)$ assigns a numerical score to to each pair (F, y), where F is the predictive distribution and y is the verifying observation.
We consider negatively oriented scores, i.e. the smaller the better.

$\Rightarrow$ suggests the following estimation procedure:

Choose the parameters with minimal score in the training period.

Model fitting

In our method we use the continuous ranked probability score (CRPS)

$$crps(F, y) = \int_0^\infty \left((F(t) - \mathbf{1}_{[y,\infty)}(t) \right)^2 dt$$

The CRPS is ideal for precipitation because

- it is *only moderately sensitive* to *single forecasts that are very far off*
- it can deal with the fact the predictive distribution for precipitation has both a *discrete* and a *continuous component*

For our left-censored GEV, a *closed form expression* for the CRPS can be calculated which makes estimation *computationally efficient*.

Model fitting

In our method we use the continuous ranked probability score (CRPS)

$$crps(F, y) = \int_0^\infty \left((F(t) - \mathbf{1}_{[y,\infty)}(t)\right)^2 dt$$

The CRPS is ideal for precipitation because

- it is *only moderately sensitive* to *single forecasts that are very far off*
- it can deal with the fact the predictive distribution for precipitation has both a *discrete* and a *continuous component*

For our left-censored GEV, a *closed form expression* for the CRPS can be calculated which makes estimation *computationally efficient*.

Model fitting

In our method we use the continuous ranked probability score (CRPS)

$$crps(F, y) = \int_0^\infty \left((F(t) - \mathbf{1}_{[y,\infty)}(t)\right)^2 dt$$

The CRPS is ideal for precipitation because

- it is *only moderately sensitive* to *single forecasts that are very far off*
- it can deal with the fact the predictive distribution for precipitation has both a *discrete* and a *continuous component*

For our left-censored GEV, a *closed form expression* for the CRPS can be calculated which makes estimation *computationally efficient*.

1. From Forecast Ensembles to Predictive Distributions

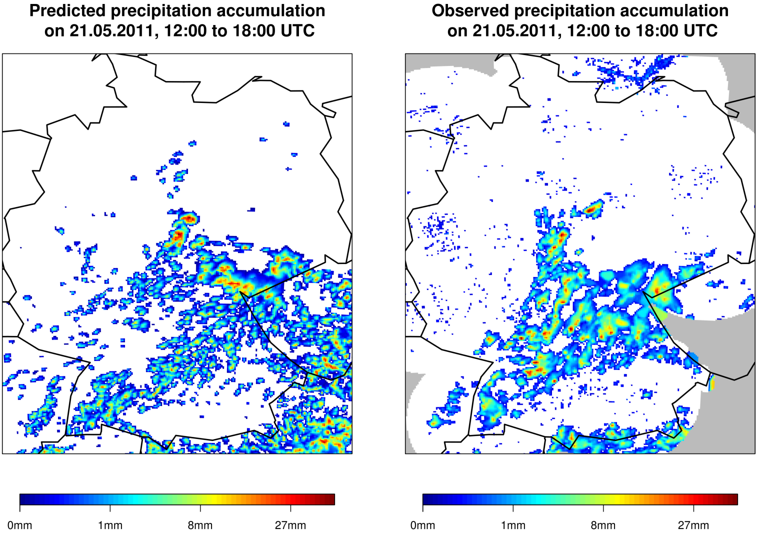
2. A distribution family for precipitation and model fitting
   - The left-censored generalized extreme value distribution
   - Ensemble Model Output Statistics (EMOS)
   - Model fitting

3. Incorporating Neighbourhood Information
   - Displacement errors
   - Ensemble model output statistics for neighbourhoods

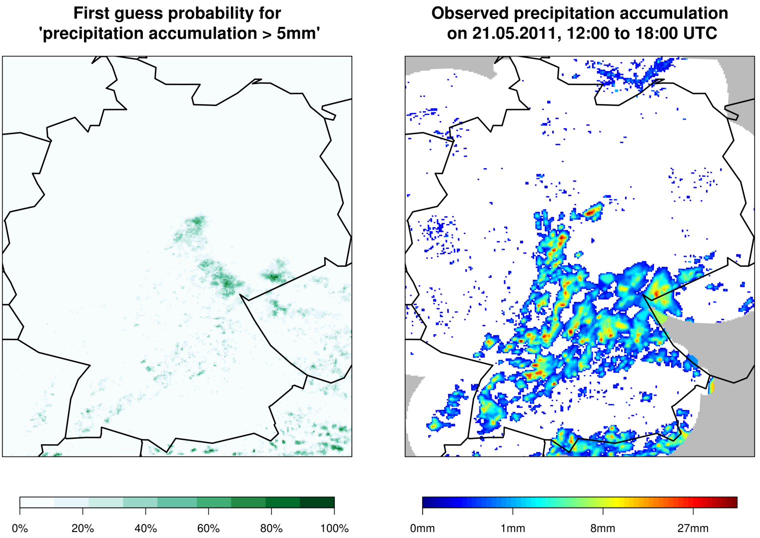
4. Data Example
   - Setup for training and verification
   - Brier Skill Scores and CRP Skill Scores
   - Reliability Diagrams

5. Directions for Improvement

The issue of displacement errors



The issue of displacement errors



Ensemble model output statistics for neighbourhoods

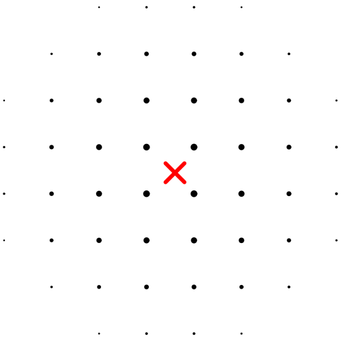
The problem of 'qualitatively correct' but displaced precipitation forecasts can be mitigated by passing from $f_{s1}, \ldots, f_{sK}$ to *weighted averages*

$$f_{\mathcal{N}(s),1} = \sum_{x \in \mathcal{N}(s)} w_x^{(s)} f_{x1}$$

$$\vdots \qquad \vdots$$

$$f_{\mathcal{N}(s),K} = \sum_{x \in \mathcal{N}(s)} w_x^{(s)} f_{xK}$$

with $$\sum_{x \in \mathcal{N}(s)} w_x^{(s)} = 1, \quad \forall s$$



where $\mathcal{N}(s)$ is the neighbourhood of the location s of interest.

Ensemble model output statistics for neighbuorhoods

The above ensemble model output statistics become

- $\bar{\mathrm{f}}_{\mathcal{N}(s)} := \frac{1}{K}\sum_{k=1}^{K} f_{\mathcal{N}(s),k}$ (mean weighted neighbourhood average)
- $\overline{\mathbf{1}_{\mathcal{N}(s),\{\mathrm{f}_x=0\}}} := \frac{1}{K}\sum_{k=1}^{K}\sum_{x\in\mathcal{N}(s)} w_x^{(s)}\,\mathbf{1}_{\{f_{xk}=0\}}$

  (mean weighted fraction of zero precipitation members)
- $\mathrm{MD}\left(\mathbf{f}_{\mathcal{N}(s)}\right) := \frac{1}{K^2}\sum_{k,k'=1}^{K}\left|f_{\mathcal{N}(s),k} - f_{\mathcal{N}(s),k'}\right|$

  (mean difference of weighted neighbourhood averages)

Following our guideline of making *optimal use of the information in the ensemble* ***and*** *in the neighbourhood*, we use the additional statistic

- $\overline{\mathrm{MD}_{\mathcal{N}(s)}(\mathrm{f}_x)} := \frac{1}{K}\sum_{k=1}^{K}\sum_{x,x'\in\mathcal{N}(s)} w_x^{(s)} w_{x'}^{(s)}\left|f_{xk} - f_{x'k}\right|$

  (mean neighbourhood weighted mean differences)

Ensemble model output statistics for neighbuorhoods

The above ensemble model output statistics become

- $\bar{\mathbf{f}}_{\mathcal{N}(s)} := \frac{1}{K}\sum_{k=1}^{K} f_{\mathcal{N}(s),k}$ (mean weighted neighbourhood average)
- $\overline{\mathbf{1}_{\mathcal{N}(s),\{\mathbf{f}_x=0\}}} := \frac{1}{K}\sum_{k=1}^{K}\ \sum_{x\in\mathcal{N}(s)} w_x^{(s)}\ \mathbf{1}_{\{f_{xk}=0\}}$

  (mean weighted fraction of zero precipitation members)
- $\mathrm{MD}\left(\mathbf{f}_{\mathcal{N}(s)}\right) := \frac{1}{K^2}\sum_{k,k'=1}^{K}\left|f_{\mathcal{N}(s),k} - f_{\mathcal{N}(s),k'}\right|$

  (mean difference of weighted neighbourhood averages)

Following our guideline of making *optimal use of the information in the ensemble **and** in the neighbourhood*, we use the additional statistic

- $\overline{\mathrm{MD}_{\mathcal{N}(s)}(\mathbf{f}_x)} := \frac{1}{K}\sum_{k=1}^{K}\ \sum_{x,x'\in\mathcal{N}(s)} w_x^{(s)} w_{x'}^{(s)}\ \left|f_{xk} - f_{x'k}\right|$

  (mean neighbourhood weighted mean differences)

Ensemble model output statistics for neighbourhoods

The location and scale parameters m and σ of the left-censored GEV are linked to these statistics via

$$m = \alpha_0 + \alpha_1 \cdot \bar{\mathbf{f}}_{\mathcal{N}(s)} + \alpha_2 \cdot \overline{\mathbf{1}_{\mathcal{N}(s),\{\mathbf{f}_x=0\}}}$$

$$\sigma = \beta_0 + \beta_1 \cdot \mathrm{MD}\left(\mathbf{f}_{\mathcal{N}(s)}\right) + \beta_2 \cdot \overline{\mathrm{MD}_{\mathcal{N}(s)}(\mathbf{f}_x)}$$

As before, the parameters $\alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \beta_2, \xi$ are estimated from training data via *minimum CRPS estimation*.

We assess the performance of this method with forecasts from the COSMO-DE-EPS and compare results for different neighbourhood sizes.

Ensemble model output statistics for neighbourhoods

The location and scale parameters m and σ of the left-censored GEV are linked to these statistics via

$$m = \alpha_0 + \alpha_1 \cdot \bar{\mathbf{f}}_{\mathcal{N}(s)} + \alpha_2 \cdot \overline{\mathbf{1}_{\mathcal{N}(s),\{\mathbf{f}_x = 0\}}}$$

$$\sigma = \beta_0 + \beta_1 \cdot \mathrm{MD}\left(\mathbf{f}_{\mathcal{N}(s)}\right) + \beta_2 \cdot \overline{\mathrm{MD}_{\mathcal{N}(s)}(\mathbf{f}_x)}$$

As before, the parameters $\alpha_0, \alpha_1, \alpha_2, \beta_0, \beta_1, \beta_2, \xi$ are estimated from training data via *minimum CRPS estimation*.

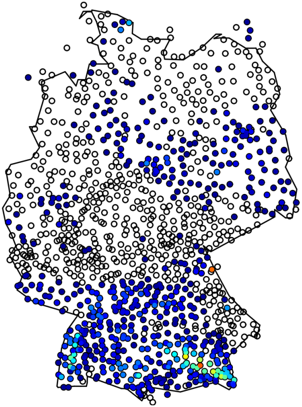
We assess the performance of this method with forecasts from the COSMO-DE-EPS and compare results for different neighbourhood sizes.

1. From Forecast Ensembles to Predictive Distributions
2. A distribution family for precipitation and model fitting
   - The left-censored generalized extreme value distribution
   - Ensemble Model Output Statistics (EMOS)
   - Model fitting
3. Incorporating Neighbourhood Information
   - Displacement errors
   - Ensemble model output statistics for neighbourhoods
4. Data Example
   - Setup for training and verification
   - Brier Skill Scores and CRP Skill Scores
   - Reliability Diagrams
5. Directions for Improvement

Data example: 6h precipitation accumulations over Germany

We apply the above EMOS method to the COSMO-DE-EPS forecasts (initialization time 0:00 UTC) of precipitation accumulations from 12:00 UTC to 18:00 UTC.

- forecast period: 01.01.2011 to 31.12.2011
- rolling 30 day training period
- training and verification with station data ($\sim$ 1100 SYNOP stations in Germany)
- left-censored GEV fitted and applied with identical parameters over the whole domain



Brier Scores and CRP skill scores for the different methods

We first compare our basic EMOS method (no neighbourhood information) with extended logistic regression (Wilks, 2009) and Bayesian model averaging (BMA) (Sloughter et al., 2007).

The following skill scores show the *improvement over the raw ensemble*:

	BSS	0mm	5mm	10mm	15mm	CRPSS
extended LR		7.9%	4.4%	4.8%	4.4%	5.2%
BMA		4.2%	0.8%	2.2%	3.1%	2.4%
EMOS		5.5%	4.6%	5.7%	4.0%	5.4%

$\Longrightarrow$ our basic method is competitive

Brier Scores and CRP skill scores for the different methods

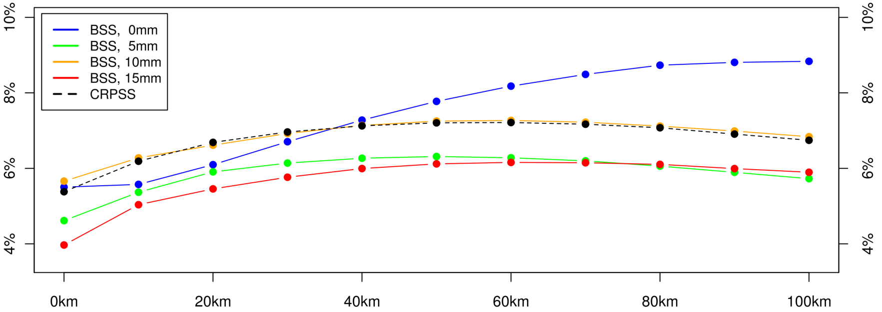
We first compare our basic EMOS method (no neighbourhood information) with extended logistic regression (Wilks, 2009) and Bayesian model averaging (BMA) (Sloughter et al., 2007).

The following skill scores show the *improvement over the raw ensemble*:

	BSS	0mm	5mm	10mm	15mm	CRPSS
extended LR		7.9%	4.4%	4.8%	4.4%	5.2%
BMA		4.2%	0.8%	2.2%	3.1%	2.4%
EMOS		5.5%	4.6%	5.7%	4.0%	5.4%

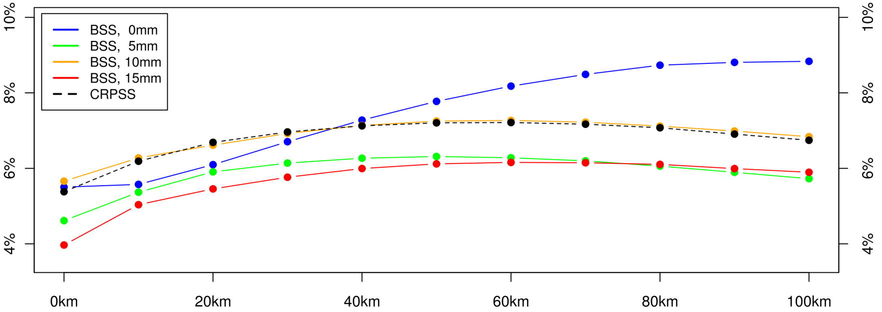
$\Longrightarrow$ our basic method is competitive

Brier and CRP skill scores for different neighbourhoods



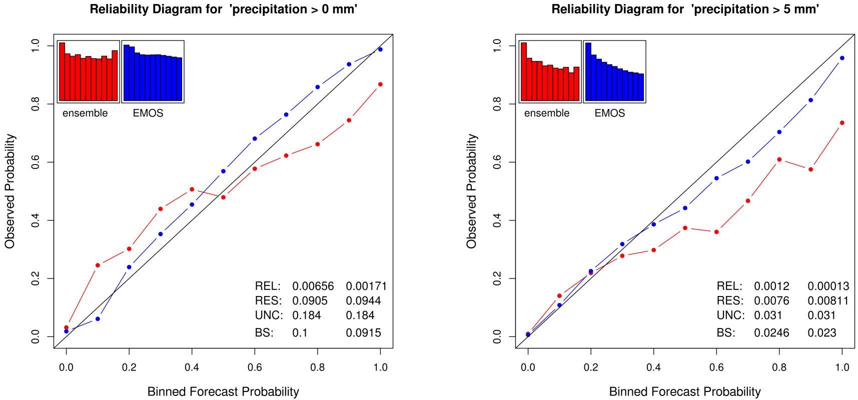
- skill first increases with neighbourhood size and then decreases again
- maximal skill for 60km radius: CRPSS 7.2% (basic EMOS: 5.4%)

Brier and CRP skill scores for different neighbourhoods



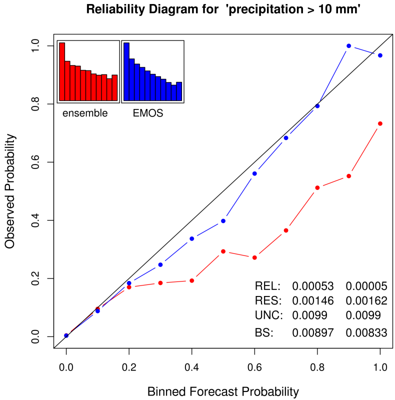
- skill first increases with neighbourhood size and then decreases again
- maximal skill for 60km radius: CRPSS 7.2% (basic EMOS: 5.4%)

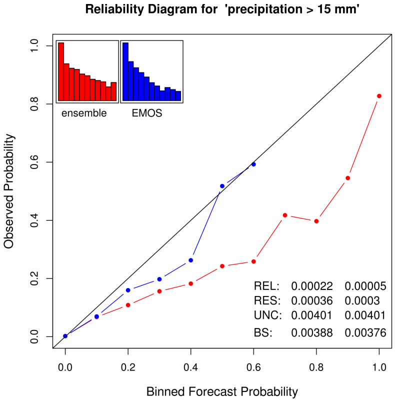
Reliability Diagrams: low and moderate thresholds



Reliability diagrams for 6h precipitation accumulations. Data are aggregated over all stations and all days of the verification period.

Reliability Diagrams: high and extreme thresholds





Reliability diagrams for 6h precipitation accumulations. Data are aggregated over all stations and all days of the verification period.

1. From Forecast Ensembles to Predictive Distributions
2. A distribution family for precipitation and model fitting
   - The left-censored generalized extreme value distribution
   - Ensemble Model Output Statistics (EMOS)
   - Model fitting
3. Incorporating Neighbourhood Information
   - Displacement errors
   - Ensemble model output statistics for neighbourhoods
4. Data Example
   - Setup for training and verification
   - Brier Skill Scores and CRP Skill Scores
   - Reliability Diagrams
5. Directions for Improvement

Directions for Improvement

- prevent the smoothing out of orography-related precipitation when averaging over neighbourhoods ✓
- weight the ensemble members according to their skill
- regime-dependent post-processing parameters?
- spatially varying post-processing parameters?
- modeling spatial dependence between forecast locations
  → *poster by Roman Schefzik and talk by Tilmann Gneiting on "Ensemble Copula Coupling"*

Thanks for listening!

Directions for Improvement

- prevent the smoothing out of orography-related precipitation when averaging over neighbourhoods ✓
- weight the ensemble members according to their skill
- regime-dependent post-processing parameters?
- spatially varying post-processing parameters?
- modeling spatial dependence between forecast locations
  $\rightarrow$ *poster by Roman Schefzik and talk by Tilmann Gneiting on "Ensemble Copula Coupling"*

Thanks for listening!

Directions for Improvement

- prevent the smoothing out of orography-related precipitation when averaging over neighbourhoods ✓
- weight the ensemble members according to their skill
- regime-dependent post-processing parameters?
- spatially varying post-processing parameters?
- modeling spatial dependence between forecast locations
  → *poster by Roman Schefzik and talk by Tilmann Gneiting on "Ensemble Copula Coupling"*

Thanks for listening!

Directions for Improvement

- prevent the smoothing out of orography-related precipitation when averaging over neighbourhoods ✓
- weight the ensemble members according to their skill
- regime-dependent post-processing parameters?
- spatially varying post-processing parameters?
- modeling spatial dependence between forecast locations
  → *poster by Roman Schefzik and talk by Tilmann Gneiting on "Ensemble Copula Coupling"*

Thanks for listening!

Directions for Improvement

- prevent the smoothing out of orography-related precipitation when averaging over neighbourhoods ✓
- weight the ensemble members according to their skill
- regime-dependent post-processing parameters?
- spatially varying post-processing parameters?
- modeling spatial dependence between forecast locations
  → *poster by Roman Schefzik and talk by Tilmann Gneiting on "Ensemble Copula Coupling"*

Thanks for listening!

Directions for Improvement

- prevent the smoothing out of orography-related precipitation when averaging over neighbourhoods ✓
- weight the ensemble members according to their skill
- regime-dependent post-processing parameters?
- spatially varying post-processing parameters?
- modeling spatial dependence between forecast locations
  $\rightarrow$ *poster by Roman Schefzik and talk by Tilmann Gneiting on "Ensemble Copula Coupling"*

Thanks for listening!

Directions for Improvement

- prevent the smoothing out of orography-related precipitation when averaging over neighbourhoods ✓
- weight the ensemble members according to their skill
- regime-dependent post-processing parameters?
- spatially varying post-processing parameters?
- modeling spatial dependence between forecast locations
  $\rightarrow$ *poster by Roman Schefzik and talk by Tilmann Gneiting on "Ensemble Copula Coupling"*

Thanks for listening!

Literature I

Friederichs, P. and Thorarinsdottir, T. L.
Forecast verification for extreme value distributions with an application to probabilistic peak wind prediction.
arXiv:1204.1022, 2012.

Gebhardt, C., Theis, S.E., Paulat, M., Bouallègue, Z. Ben
Uncertainties in COSMO-DE precipitation forecasts introduced by model perturbations and variation of lateral boundaries.
Atmos. Res., 100:168–177, 2011.

Gneiting, T., Raftery, A. E., Westveld, A. H. , Goldman, T.
Calibrated probabilistic forecasting using ensemble model output statistics and minimum CRPS estimation.
Mon. Weather Rev.,133:1098–1118, 2005.

Gneiting, T., Balabdaoui, F. and Raftery, A.E.
Probabilistic forecasts, calibration and sharpness.
J. R. Statist. Soc. B, 69:243–268, 2007.

Literature II

Sloughter, J.M., Raftery, A.E., Gneiting, T., and Fraley, C.
Probabilistic quantitative precipitation forecasting using Bayesian model averaging.
Mnthly Weath. Rev., 135:3209–3220, 2007.

Wilks, D.S.
Extending logistic regression to provide full-probability-distribution MOS forecasts.
Meteor. Applic., 16:361–368, 2009.