A comparative study of statistical post-processing methods for the calibration of ensemble forecasts

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Motivation

- Ensembles are not perfect, they are subject to deterministic and probabilistic biases
- Statistical post-processing can correct many of these errors
- Optimise sharpness subject to calibration!

Conclusions

- After post-processing with EMOS and BMA, forecasts are calibrated (see histograms)
- CRPS improved by ~16% for temperature and ~11% for wind speed (site-specific)
- EMOS + ECC provides calibrated and physically realistic forecast fields

Methods

Ensemble Model Output Statistics (EMOS)

Step 1: Model observation conditional on the ensemble mean and variance using a standard probability distribution

$$Y \mid X_1, \ldots, X_M \sim \mathcal{N}\left(a + \beta^2 \cdot \overline{X},\ \gamma^2 + \delta^2 \cdot S^2\right)$$
$$Y \mid X_1, \ldots, X_M \sim \mathcal{N}^0\left(a + \beta^2 \cdot \overline{X},\ \gamma^2 + \delta^2 \cdot S^2\right)$$

Fig. 1: TOP: Surface temperature/normal distribution
BOTTOM: 10 m wind speed /normal distribution truncated in zero

Step 2: Estimate coefficients by minimising the CRPS over a rolling training period (~25-40 days)

Step 3: Apply coefficients to most recent ensemble forecast

Bayesian Model Averaging (BMA)

Step 1: Model observation conditional on the ensemble forecasts using standard probability distributions

$$Y \mid X_1, \ldots, X_M \sim \sum_{m=1}^{M} w_m \cdot \mathcal{N}\left(a_m + b_m \cdot X_m, \sigma^2\right)$$
$$Y \mid X_1, \ldots, X_M \sim \sum_{m=1}^{M} w_m \cdot \Gamma\left(\alpha_m, \beta_m\right)$$

Fig. 2: TOP: Surface temperature/normal distribution
BOTTOM: 10 m wind speed/gamma distribution

Step 2: Estimate weights, coefficients and variance by applying linear regression and maximum likelihood (EM algorithm) over a rolling training period (~25-40 days)

Step 3: Apply to most recent ensemble forecast

Ensemble Copula Coupling (ECC)

Preserves physical consistency from the ensemble, between sites, weather parameters, time steps, ...

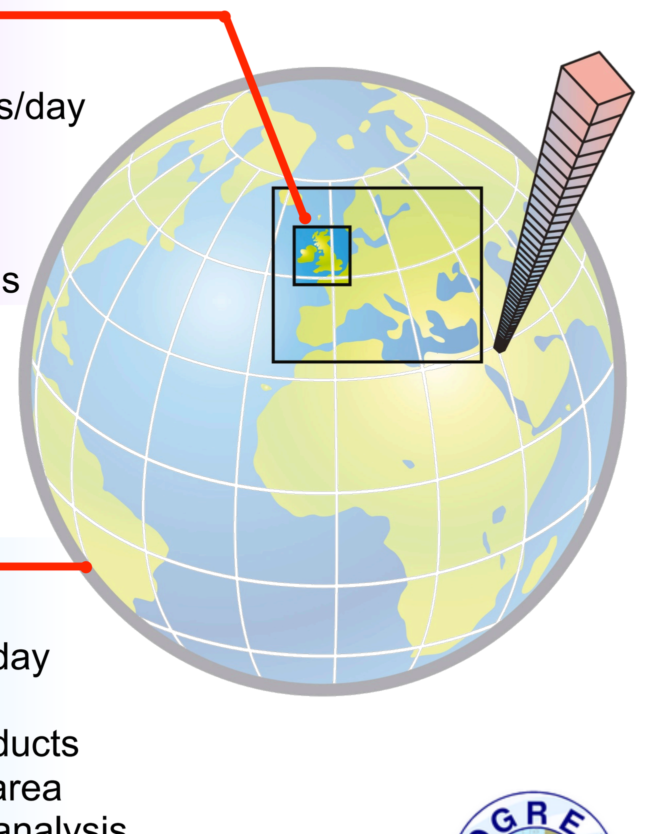
Step 1: Apply univariate calibration method, e.g. EMOS, BMA

Step 2: Draw a sample from the post-processed predictive distribution

Step 3: Rearrange the sample according to the rank order structure of the raw ensemble

NWP Models

MOGREPS-UK
- 2.2km 70 Levels
- 36 hour forecast 4 times/day
- 12 members
- **Here:** forecasts at 152 observation sites
- Compared to station obs



MOGREPS-G
- 33km 70 Levels
- 7 day forecast 4 times/day
- 12 members
- 24 member lagged products
- **Here:** restricted to UK area
- Compared to ECMWF analysis

Site-specific forecasts

CRPS: the lower the better!
Histograms: the flatter the better!

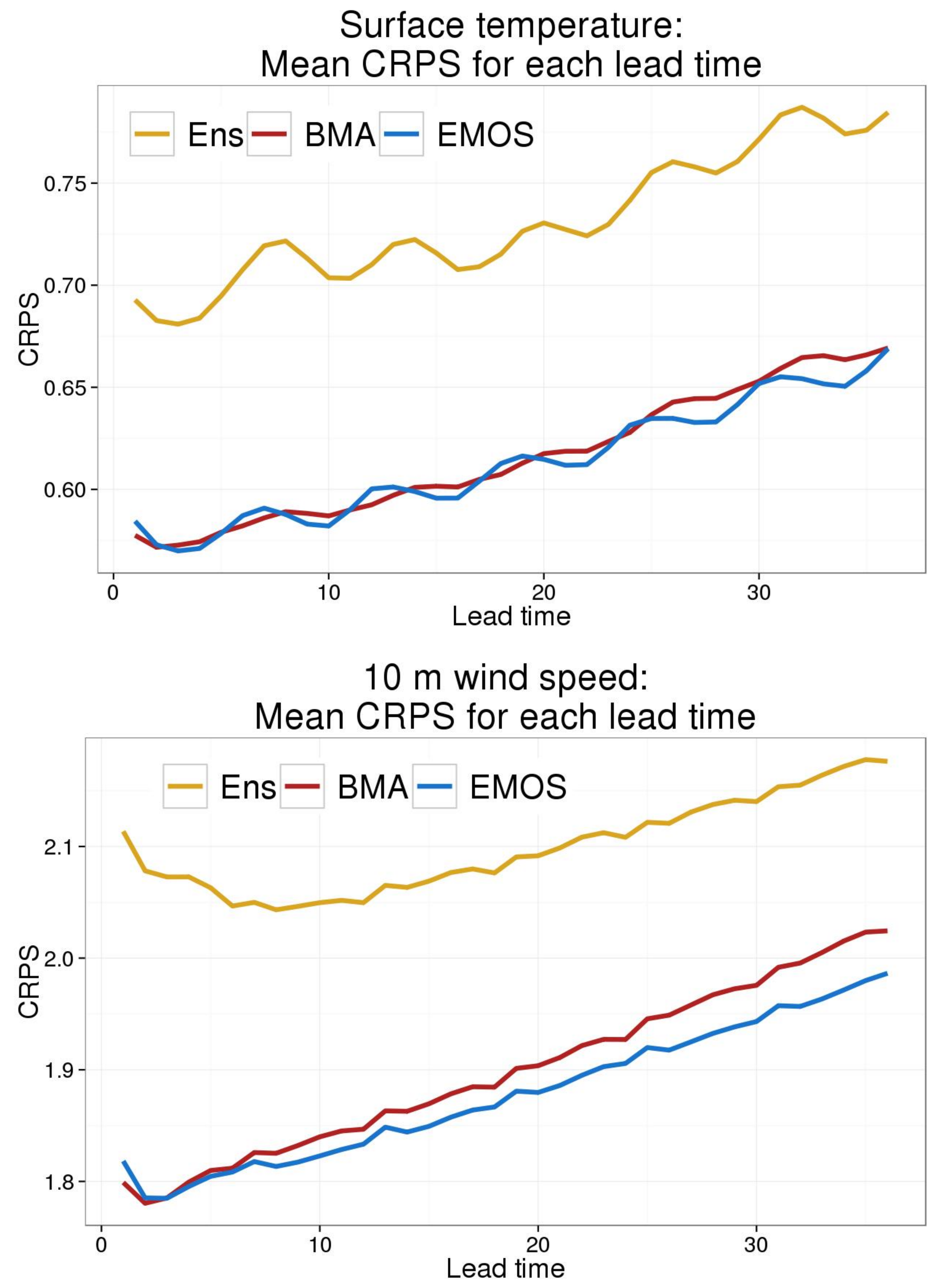


Fig. 3: Mean CRPS values for each MOGREPS-UK lead time, data from 10/2013 to 09/2014
TOP: surface temperature
BOTTOM: 10 m wind speed

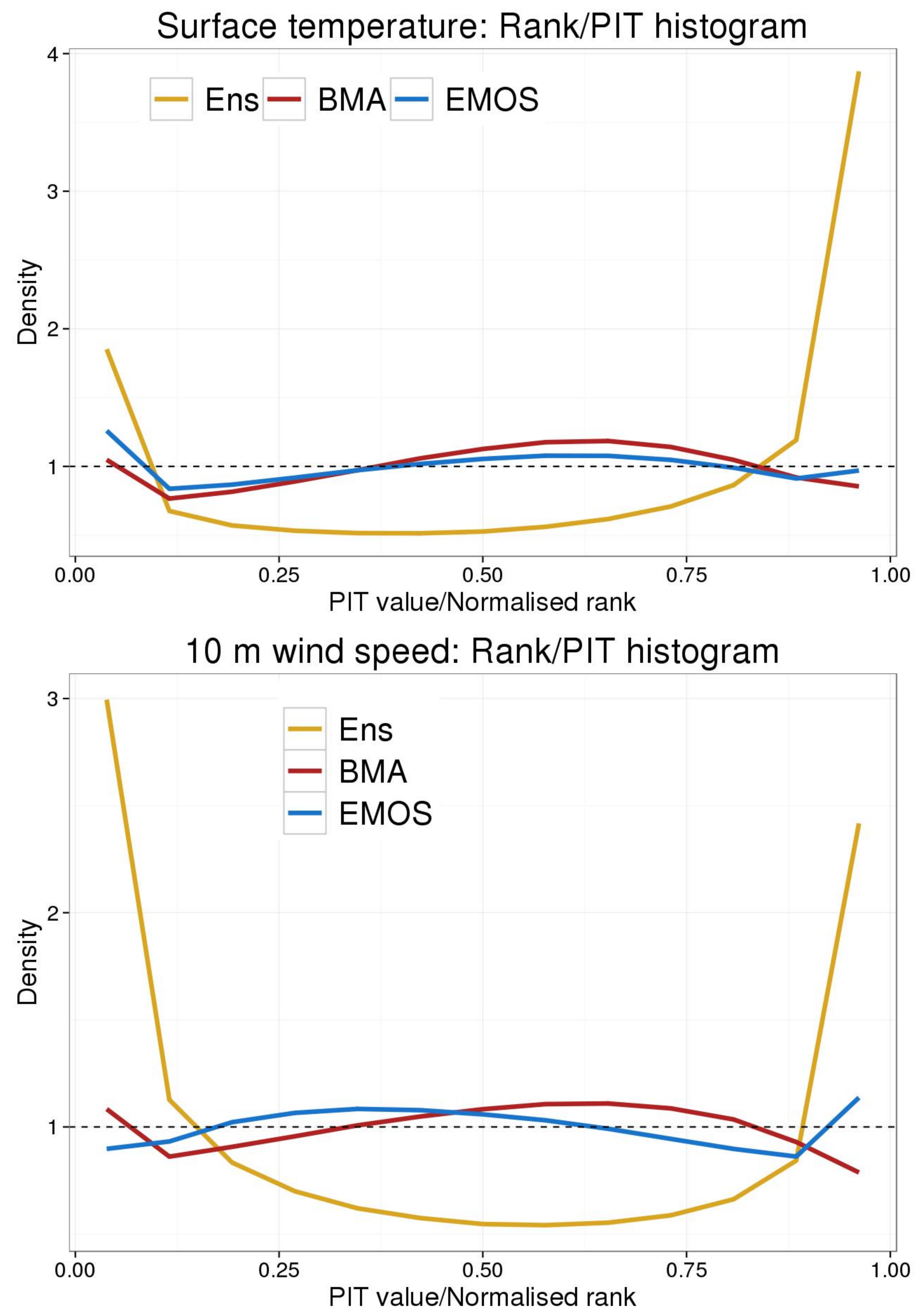


Fig. 4: Rank and PIT histograms aggregated over all sites, model runs and lead times from 10/2013 to 09/2014
TOP: surface temperature
BOTTOM: 10 m wind speed

Gridded forecasts

Data (surface temperature):
MOGREPS-G restricted to the UK area
00 UTC run, 24 hours ahead
07/2013 – 05/2014

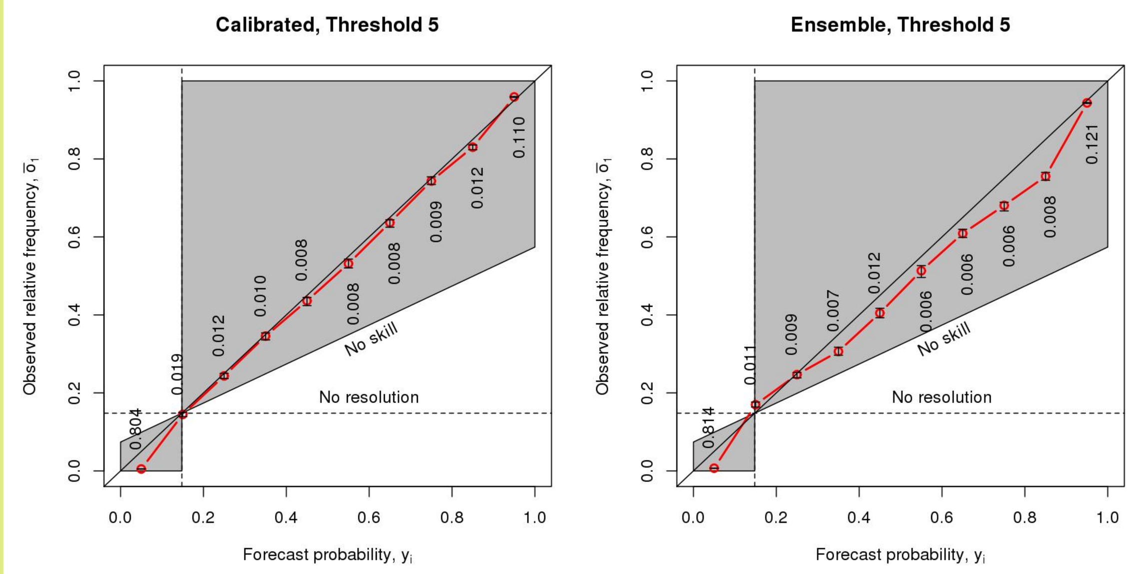


Fig. 5: Attribute (reliability) diagram for MOGREPS-G raw surface temperature forecasts (right) and EMOS calibrated forecasts (left). The threshold is 5° C.

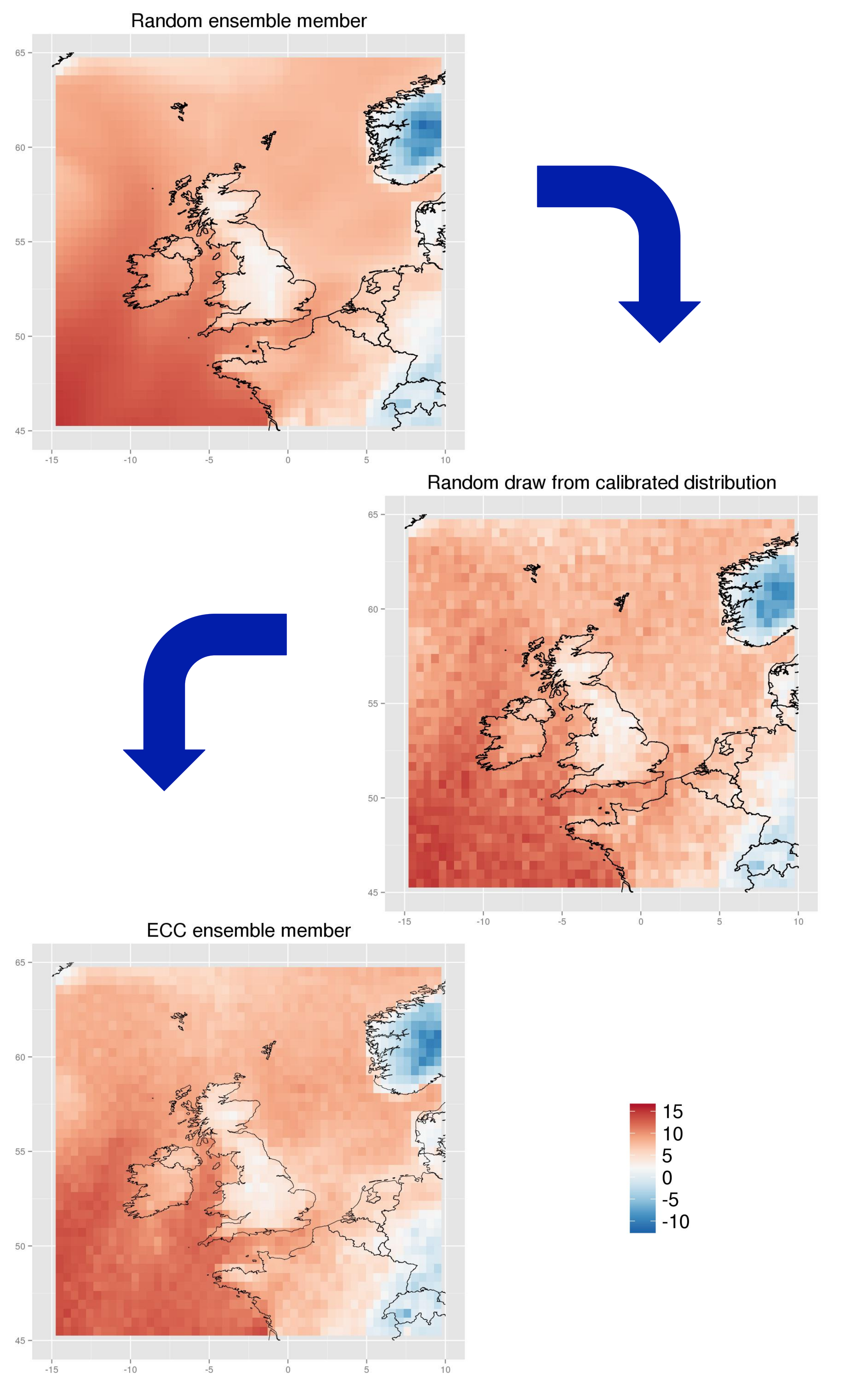


Fig. 6: Applying ECC: From one ensemble member (top) to a random draw from the EMOS calibrated distribution (middle) to a calibrated, physically realistic forecast field (bottom) (18/12/2013)

References

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