Improving probabilistic forecast skill by calibrating site-specific and gridded ensemble forecasts

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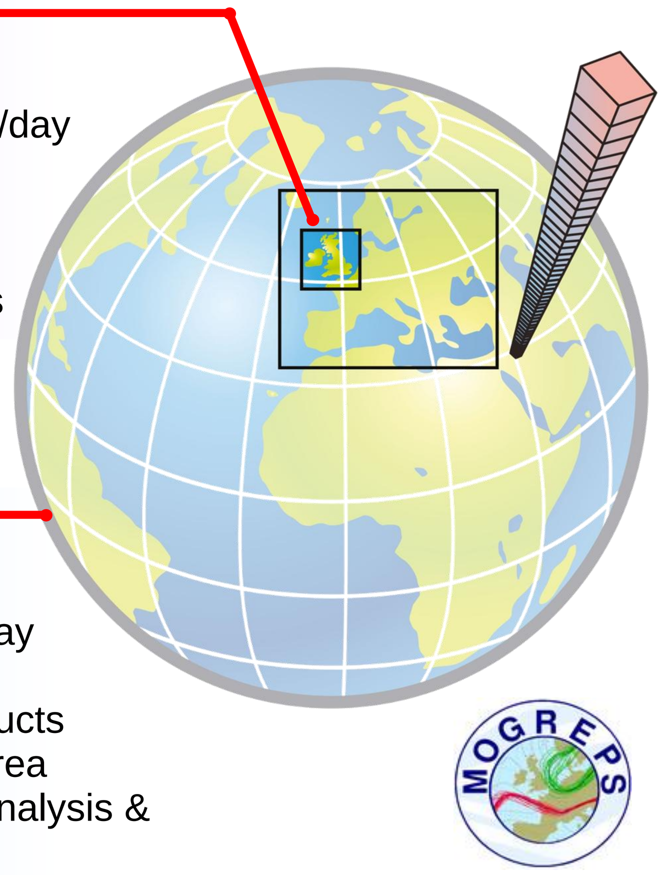
Motivation

- Ensembles comprise multiple runs of a numerical weather model with perturbations in initial conditions and physical processes
- They provide a flow-dependent quantification of forecast uncertainties
- Unfortunately they are not perfect and subject to deterministic and probabilistic biases
- Statistical post-processing can correct many of these errors
- **Optimise sharpness subject to calibration!**
  - Calibration: Statistical consistency between forecasts and observations
  - Sharpness: Concentration of the forecast distribution
- But: Statistical methods can destroy physical dependency structure, therefore we need additional techniques like Ensemble Copula Coupling

NWP ensembles at the Met Office

MOGREPS-UK
- 2.2km 70 Levels
- 36 hour forecast 4 times/day
- 12 members
- **Here:** forecasts at 151 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 & 2km nowcast analysis

References

Gneiting et al. (2005), Mon. Weather Rev., 133, 1098-1118
Thorarinsdottir and Gneiting (2010), J. R. Stat. Soc.: Series A, 173, 371-388
Raftery et al. (2005), Mon. Weather Rev., 133, 1155-1174
Sloughter et al. (2010), JASA, 105, 25-35
Schefzik et al. (2013), Statist. Sci., 28, 616-640

Methods

Ensemble Model Output Statistics (EMOS)

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

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

Figure 1: EMOS models for temperature (top) and wind speed (bottom)

Step 2: Estimate coefficients by minimising the CRPS over a rolling training period (25 days regional, 40 days local, 15 gridded)

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

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

Figure 2: BMA models for temperature (top) and wind speed (bottom)

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

Site-specific trial

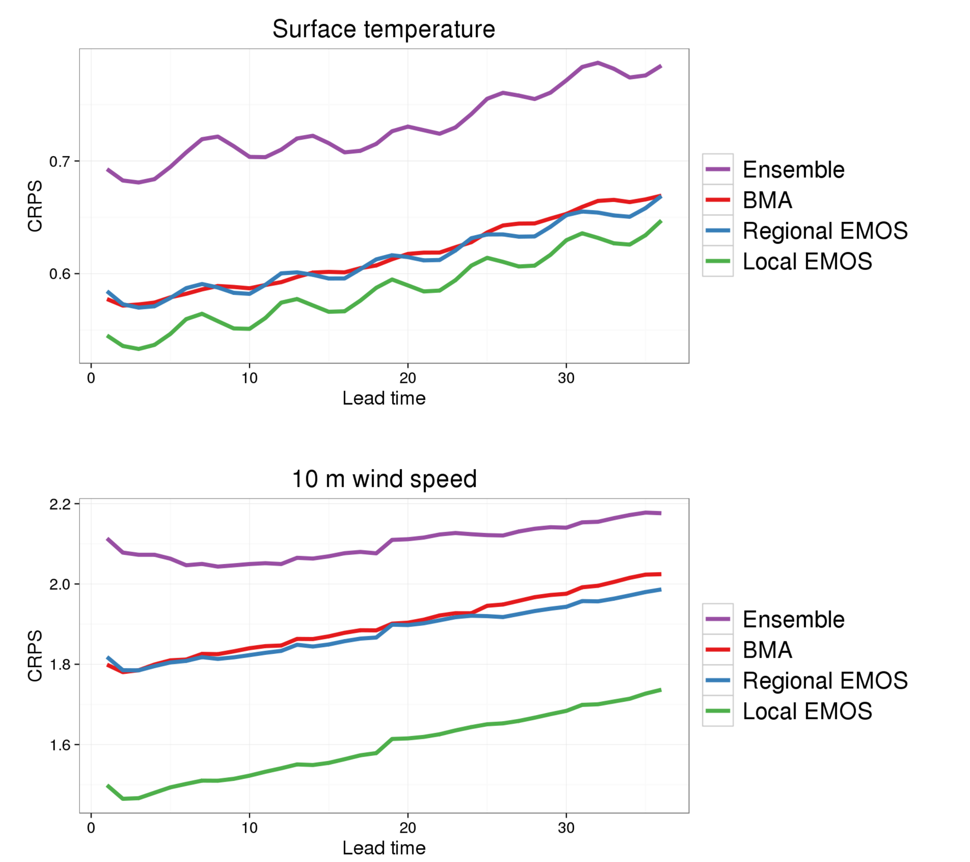


Figure 3: Mean CRPS over lead time, for temperature (top) and wind speed (bottom)

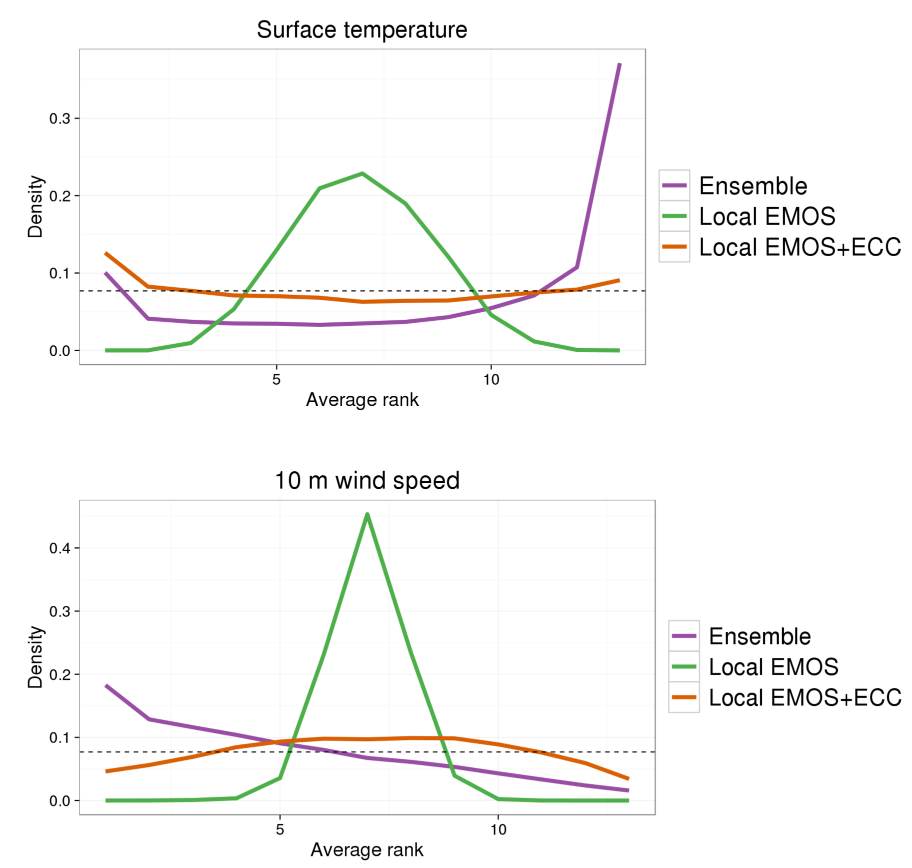


Figure 4: Average Rank histogram, showing spatial calibration, for temperature (top) and wind speed (bottom)

Gridded trial (on-going)

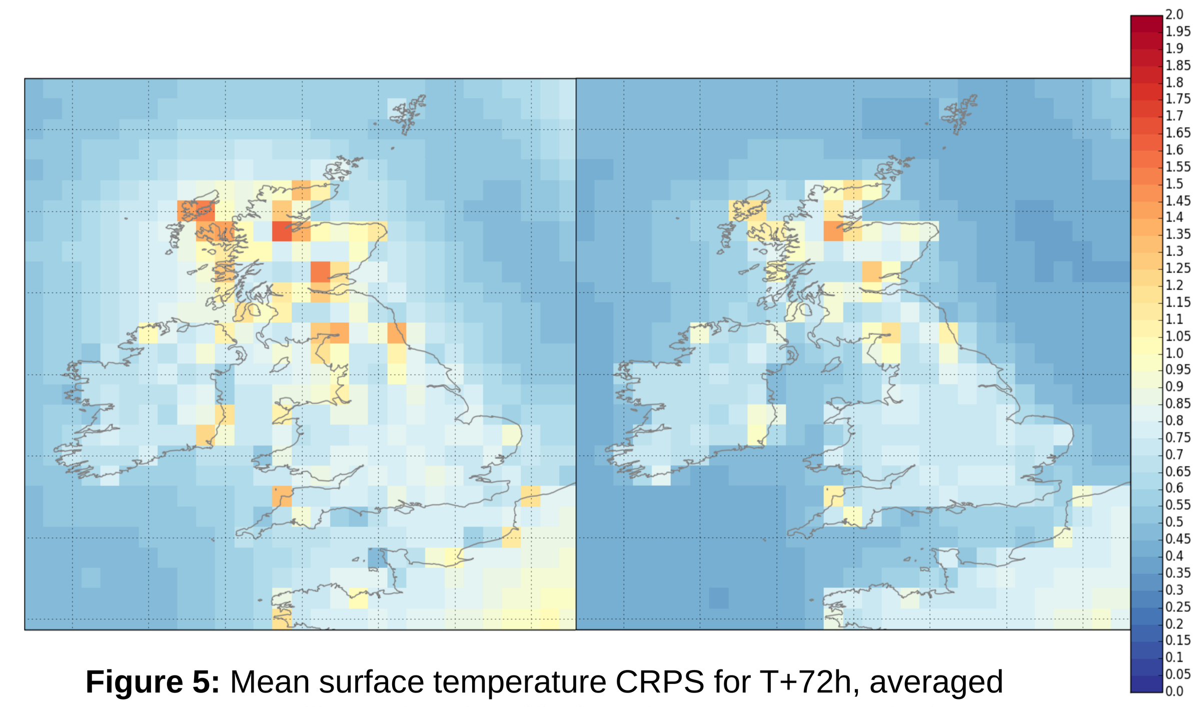


Figure 5: Mean surface temperature CRPS for T+72h, averaged over 1 year. Calibrated and verified against ECMWF analysis.
Left: Raw MOGREPS-G
Right: Calibrated with EMOS
CRPS for grid squares was reduced through calibration, especially along the coast, where we have a large bias due to e. g. the coarse model resolution.

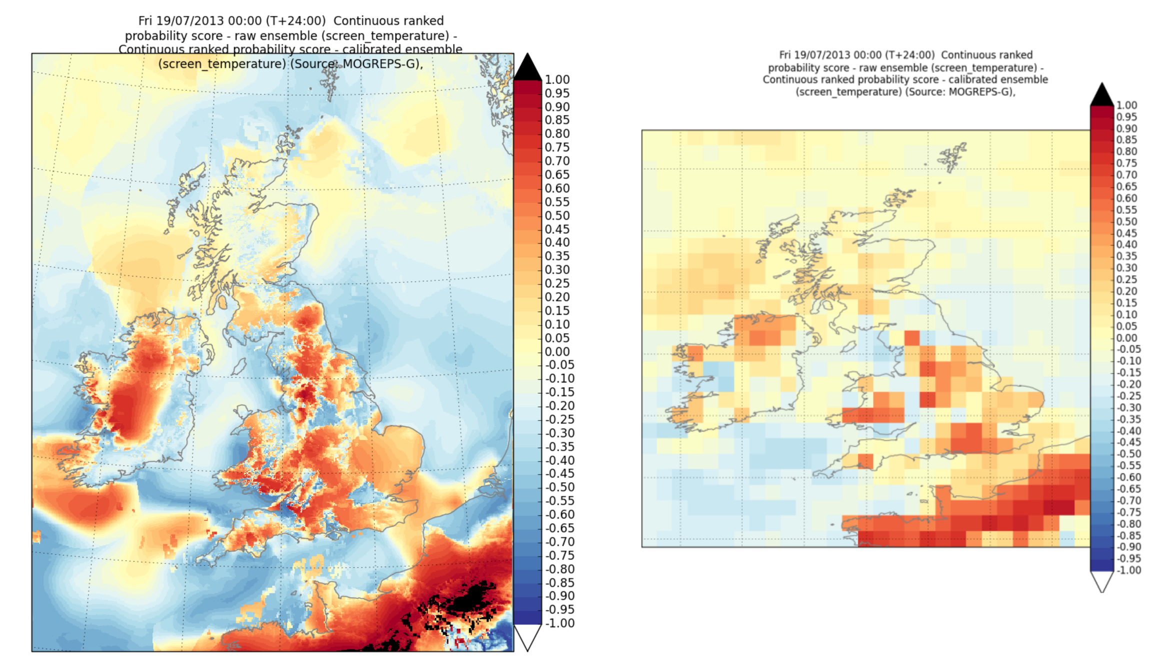


Figure 6: Case study, night-time temperature in summer
Difference in surface temperature CRPS for T+24h, valid at 19/07/2013 00Z (Raw MOGREPS-G – calibrated EMOS)
Left: Calibrated and verified against 2km nowcast analysis
Right: Calibrated and verified against 0.5° ECMWF analysis
Larger errors (> 2° C) in the ensemble in southern and eastern parts of England, over the Pennines and in north-west France have been significantly reduced by calibrating.

Conclusion: Improvement for temperature / wind speed

Raw ensemble → (15.7% / 9.6%) → BMA → (0.5% / 1.1%) → Regional EMOS → (4.4% / 15.2%) → Local EMOS → (6.6% / 5.2%) → Local EMOS + ECC

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