A multi-model multi-analysis limited area ensemble: calibration issues

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MUSE
a Multimodel-multianalysis ensemble

4 LAMs:
- BOLAM - MM5
- RAMS1 - RAMS2

2 I.C & B.C.:
- AVN 12Z - ECMWF 12Z

Area:
13.5W-34N / 24.5E-54.5N

Spatial Resolution:
0.25°

Fct time range:
+72h (by 6 h steps)

Integration period:
15/10/2002 to 15/04/2003 (183 days)

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Measured data

The calibration assessment is done for a continuous variable with a relatively simple PDF. Namely, the 2m temperature.

For the 186 days, all 6-hourly measured data were collected from 21 ground meteorological stations located in Sardinia.

These stations were singled out from the whole network (about 60 stations), because they were the sole having no missing data.
NOTE.
The variability of the spread-skill relationship across the forecast time steps reflects on the RMSE of the deterministic forecasts and on the calibration outcomes.
Why calibrate?

The ensemble is under-dispersive and the single forecasts are clearly not equi-probable. Calibration should reduce the under-dispersion, provide a suitable weight for each member and, hopefully, increase the sharpness of the resulting distribution.
Calibration methods - 1

- **Bayesian Model Averaging (BMA)**

\[ p(o|f_1, \ldots, f_K) = \sum_{m=1}^{M} w_m G_m(o|f_m) \quad \text{where} \quad G(o|f_m) = \mathcal{N}(a_m + b_m f_m, \sigma_m^2) \]

\( w_m \) and \( \sigma_m \) are estimated by maximum likelihood and in a further step the variance is refined minimizing the Continuous Ranked Probability Score,

\[ CRPS = \frac{1}{K} \sum_{j=1}^{K} \int_{-\infty}^{+\infty} \left( F_j(z) - H(z - t_j) \right)^2 \, dz, \]

over the training period. \( F(z) \) is the Cumulative Distribution Function of \( G \) while \( H \) is the Heaviside function.

Ref.: A. E. Raftery et al. - MWR 2005
Calibration methods - 2

- **Ensemble model output statistics (EMOS)**

  The EMOS PDF is expressed as:

  \[ \mathcal{N}(\alpha + \beta_1 f_1 + \ldots + \beta_K f_K; \gamma^2 + \delta^2 S^2) \]

  the coefficients are calculated minimizing the CRPS over the training period

- **Modified ensemble model output statistics (EMOS\(^+\))**

  CRPS minimization iterated: after each step models associated to negative \(\beta_i\) are drop out from the next iteration. The process stops when all \(\beta_i\) left are positive. Id est: ensemble retains only forecasts providing a skilful contribution.

Ref.: T. Gneiting et al. - MWR 2005
Calibration methods - 3

- **Dressing kernel**

The covariance of the stochastic values $\eta$ to be added to the dynamical forecasts $f$, is calculated in a way that renders the, seasonally averaged, variance of the dressed ensemble and that of the observation, indistinguishable. That is to say that:

$$\eta^T \eta = (\bar{f}_i - \bar{o}_i)^T (\bar{f}_i - \bar{o}_i) - \sigma_i^2$$

with $F_{dress} = f + \eta$ then

(sampling mean and variance of true forecast PDF)  
(observations)

The means are taken over all forecast-observation occurrences in the training period.

The number of perturbations to be added to each dynamical forecast was set to 32.

Ref.: Wang and Bishop - QJRM 2005
Training period

- The training period is a sliding-window varying from time step to time step. To define it, a few quantities used to evaluate the calibration quality (the rank histogram, the PDF's coverage and width, the RMSE for the related deterministic forecasts) were used.

- In practice the chosen interval length is such that a longer training period do not bring any improvement on the calibration scores.

- In this case this happens between 60 and 90 days. In the following results are based on a 90 days training period.

- In order to test the robustness of the techniques and its independence from the training set, all the calculation were also accomplished swapping training and testing periods. The final results did not change.
Calibration: rank histograms (+66h)

- **raw**
  - Relative frequency bars for ranks 0 to 10.
  - Perfect calibration line.

- **emos and emos+**
  - Relative frequency bars for ranks 0 to 10.
  - EMOS and EMOS+ lines.

- **dressing**
  - Relative frequency bars for ranks 0 to 10.
  - Perfect calibration line.

- **bma**
  - Relative frequency bars for ranks 0 to 10.
  - Perfect calibration line.
Calibration: rank histograms (+72h)

- raw
- emos and emos+
- dressing
- bma
Calibration: rank histograms (all steps)

"Root mean square error" outliers

Root mean square error

0.014
0.018
0.011
0.011
0.021
0.032
Calibration: coverage and width

Coverage
(ref. value 7/9 → 0.778)

Width
(Confidence interval 0.778)
Calibration: coverage and width

Rank Histogram (+72h)

Coverage

Rank Histogram (+66h)

Width
BMA weights

BMA global averaged weights

test period: 90 days
Expectation values

The expectation value of the PDFs for BMA, EMOS and EMOS*, and the “dressed" ensemble mean are deterministic forecasts on their own.

For instance for BMA is: $\mu_{\text{BMA}} = \sum_{m=1}^{K} w_m (a_m + b_m f_m)$

Scores like RMSE and MAE have been calculated for all of them and compared to the likes of: each ensemble member, the “unbiased" ensemble mean and the “super-ensemble”.

Why so?

The hope was to unveil a behaviour so good to gain for free, and for a system which inherently lacks it, a reference (control) forecast directly from the calibration method.
Deterministic forecasts

RMSE
(test period 90 days)
Conclusions

- Calibration for 2m temperature works well both with BMA and DRESSING. (Easy the extension to temperature at pressure levels and to other continuous variables as MSLP, geopotential, etc.)

- BMA shows more consistent results than DRESSING across the forecast time steps, especially for the external intervals (outliers). Moreover, BMA weights are directly interpretable in terms of probabilities.

- Deterministic scores for the expectation values of calibration methods, the “dressed” ensemble mean, the “unbiased” ensemble mean and the super-ensemble are similar. All of them outperform, on average, the best model. Therefore, once a calibration method is chosen, it is argued that the expectation value can be used as reference/control forecast for the ensemble.
Future work

- Calibration is going to be implemented on MUSE (needs a good amount of computer power)

- SPITLOMS: a ECMWF special project (SAR – CRS4 – Italian MetService) aimed at exploring the potential of longer and more structured training periods.

- Calibration for wind and precipitation is going to be shortly addressed (need a careful analysis of the underlying PDF and probably, for precipitation, longer training sets).