

STATISTICAL POST-PROCESSING OF DUAL RESOLUTION ENSEMBLE FORECASTS

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WEATHER FORECASTING METHODS

Deterministic forecast of weather quantities: Gives a prediction based on the physical and chemical models of the atmosphere.

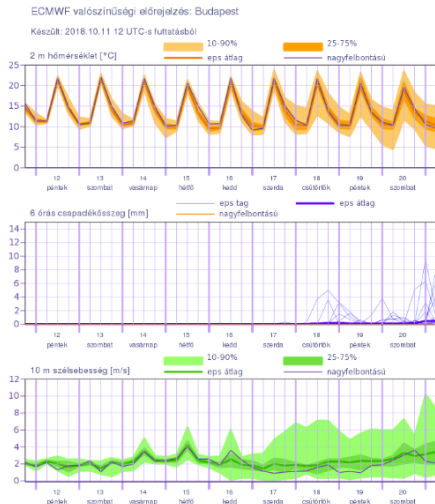


Bias due to:

- small amount of data;
- estimation methods;

The current state of the atmosphere can never be perfectly specified.

ENSEMBLE FORECAST



National Meteorological Service – www.met.hu

A collection of numerical weather prediction (NWP) model integrations; running the simulations with slightly different initial conditions and/or model variants.

The output is an ensemble forecast.

Advantage: provides an estimate of the uncertainty of the forecast.

Disadvantage: under- or overdispersion
→ calibration is needed

Leith, C. E. (1974) Theoretical skill of Monte-Carlo forecasts. *Mon. Wea. Rev.* 102, 409–418.

Palmer, T. N. (2002). The economic value of ensemble forecasts as a tool for risk assessment: From days to decades. *Q. J. R. Meteorol. Soc.* 128, 747–774.

European Centre for Medium-Range Weather Forecasts

- Hungary is a Member State since 1994
- A 52 member operational ensemble forecast system
 - 1 high resolution member
 - 1 control member
 - 50 perturbed members
- 2016–2025 Strategic Plan:
Increase the model grid resolution: 18 km → 5 km
Cost ratio: 1:50
- Partners: Martin Leutbecher and Zied Ben Bouallègue



DUAL RESOLUTION

HRES: (TCo639) 18 km high resolution ensemble of 50 members

LRES: (TCo399) 29 km low resolution ensemble of 200 members

Cost ratio of HRES:LRES $\sim 1:4$

Focus on finding **the optimal combination of dual resolution**

Optimality is based on cost efficiency; the analysed LRES-HRES combinations:

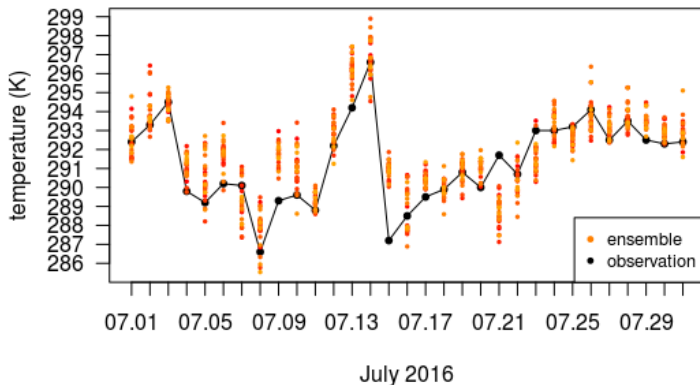
$(0, 50), (40, 40), (120, 20), (160, 10), (200, 0).$

Data

- Operational high resolution weather predictions from ECMWF ~ 4560 weather stations (MARS database)
- LRES testing data (ECMWF Research Department)
- Observations from SYNOP stations

ENSEMBLE FORECAST - ECMWF DATA

Ensemble forecasts - Debrecen



Initialization: 1 June 2016 - 31 August 2016

2 m surface temperature forecast of 1-5 days lead time.

ECMWF DATA - OROGRAPHIC CORRECTION

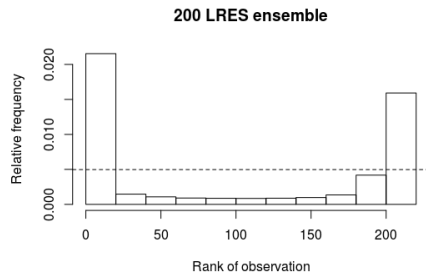
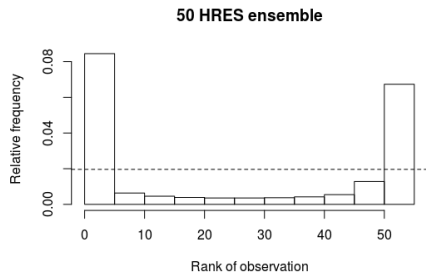
Observations are compared to forecasts at the nearest grid point of the native forecast grid.

Difference in altitude due to natural orography:

- observations: set at 2 m above surface (station height)
- predictions: altitude of a certain level of the atmosphere

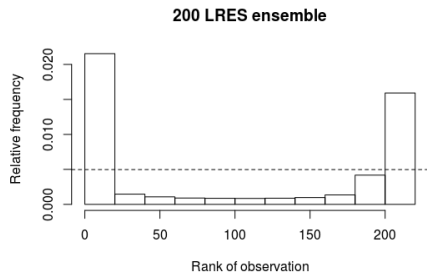
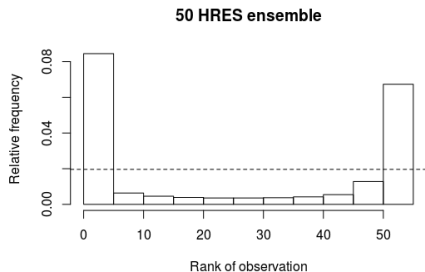
→ **orographic correction** is applied to the raw temperature forecasts accounting for height difference.

STATISTICAL POST-PROCESSING



Verification rank histograms of the ECMWF ensemble forecasts

STATISTICAL POST-PROCESSING



Verification rank histograms of the ECMWF ensemble forecasts

Statistical post-processing: Future predictions can be improved by fitting a suitable model to the ensemble based on previous predictions and validating observations.

EMOS - ENSEMBLE MODEL OUTPUT STATISTICS

EMOS model: fitting a single probability distribution to the ensemble forecast with parameters depending on the ensemble members.

X : temperature at a given time and location and forecast horizon

$\overline{f_1}, \overline{f_2}$ the mean of the predictions corresponding to the different resolution ensemble groups

Predicted distribution of temperature forecast:

$$\mathcal{N}(a + b_1\overline{f_1} + b_2\overline{f_2}, c + dS^2),$$

S^2 : is the empirical variance of the combined ensemble

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

MODEL FITTING - SCORING RULES

Estimation of the parameters: the optimal values of the mean of an appropriate scoring rule (e.g. CRPS) calculated on the training data.

CRPS – continuous ranked probability score

$$\text{CRPS}(F, y) := \int_{-\infty}^{\infty} [F(x) - \mathbb{1}_{\{y \leq x\}}]^2 dx,$$

F : distribution function for prediction y : verifying observations

Further scoring rules:

- Brier score (probability forecast);
- Quantile score (probability forecast);
- Mean Absolute Error (point forecast, e.g. median);
- Root Mean Squared Error (point forecast, e.g. mean).

TRAINING DATA

Length of the rolling training period: 30 days

Local approach For the estimation of the stations' parameters only the data from that station is used. Parameters differ for each station.

Global approach Estimation of the parameters use all of the training data; parameters are the same for all stations.

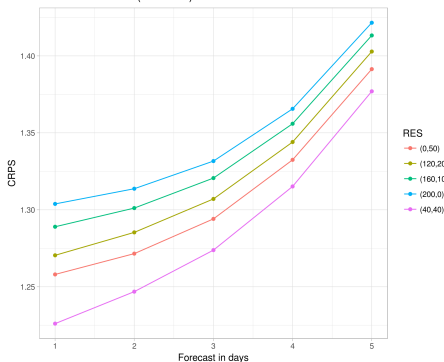
Semi-local approach¹

The stations are clustered based on their training data. Global approach for each cluster.

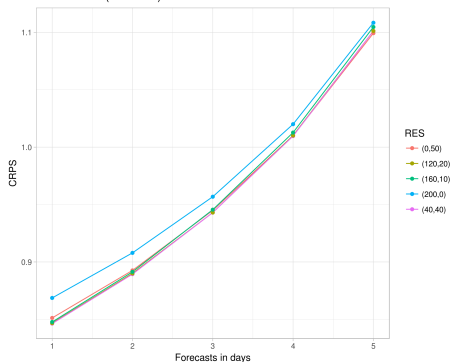
¹Lerch, S. and Baran, S., 2017. Similarity-based semilocal estimation of post-processing models. J. Roy. Stat. Soc. C 66, 29–51.

RESULTS - RAW ENSEMBLE AND EMOS

RAW ENSEMBLE (30 DAYS) CRPS



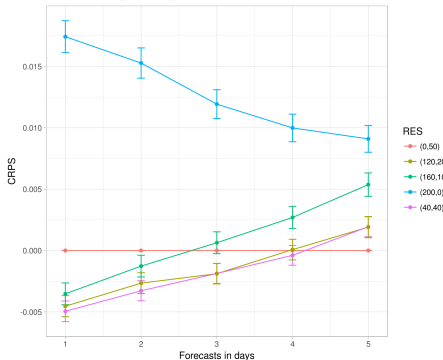
Local EMOS (30 DAYS) CRPS



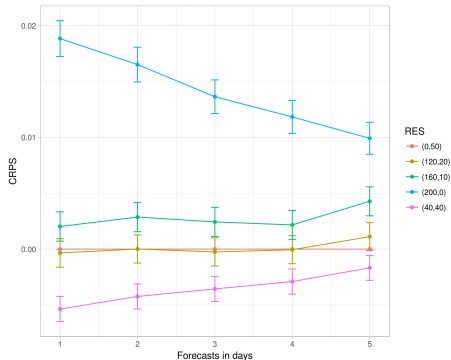
CRPS score results for 1-5 day forecasts with 30 day training period.

RESULTS - LOCAL AND SEMI-LOCAL ESTIMATION

Local EMOS (30 DAYS) CRPS



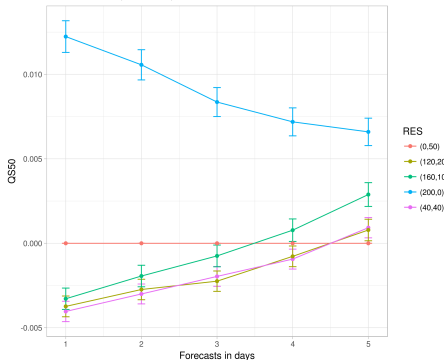
Semi-local EMOS (30 DAYS) CRPS



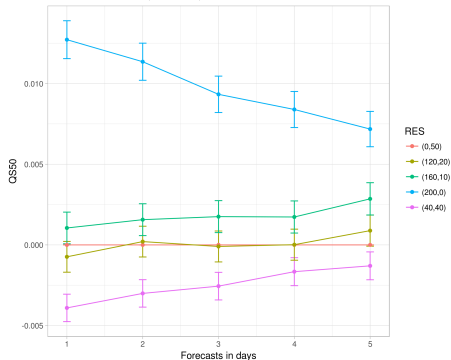
Difference between the CRPS score values and the reference (0,50) combination and the appropriate 95% confidence intervals.

RESULTS - LOCAL AND SEMI-LOCAL ESTIMATION

Local EMOS (30 DAYS) QS50



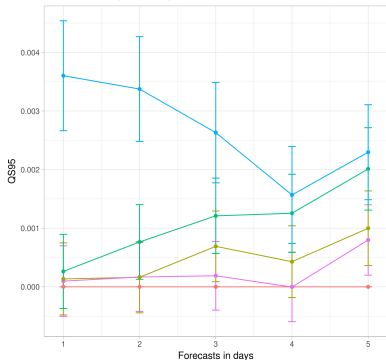
Semi-local EMOS (30 DAYS) QS50



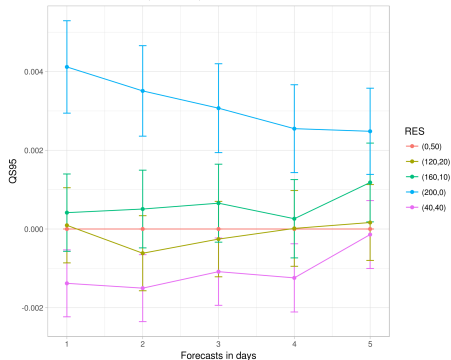
Difference between the QS50 score values and the reference (0,50) combination and the appropriate 95% confidence intervals.

RESULTS - LOCAL AND SEMI-LOCAL ESTIMATION

Local EMOS (30 DAYS) QS95



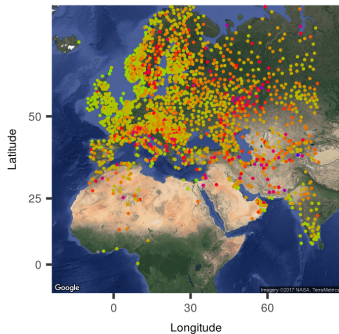
Semi-local EMOS (30 DAYS) QS95



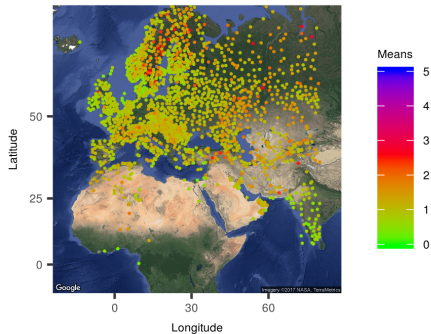
Difference between the QS95 score values and the reference (0,50) combination and the appropriate 95% confidence intervals.

RESULTS - OPTIMAL COMBINATION

RAW ENSEMBLE, MAE = 1.5048



EMOS, MAE = 1.205



The mean absolute error of the (40,40) ratio ensemble.

FURTHER RESEARCH

- Extending the data of 1 – 5 days forecasts with 6 – 15 days
- Model fitting to new winter data of the same year
- Implementation and analysis of a new model based on a combination of models for each resolution
- Different statistical post-processing method (BMA¹)

¹ Raftery, A. E., Gneiting, T., Balabdaoui, F. and Polakowski, M. (2005) Using Bayesian model averaging to calibrate forecast ensembles. Mon. Wea. Rev. 133, 1155–1174

Thank you for your attention!