Lead time continuous post-processing of ensemble weather forecasts

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Introduction

Ensemble post-processing corrects biases and dispersion errors in ensembles of numerical weather prediction (NWP) models to yield *well calibrated* and *sharp* predictions. Even though forecasts are usually required by end users on a range of different lead times, many post-processing methods in the literature are either applied at a single lead time or by fitting a separate statistical model for each one. This however is:

1) Computationally expensive: if I am interested in multiple lead times it requires the training of multiple models.
2) Prohibitive: it restricts the training data used for training post-processing models and the usability of fitted models.

Questions

1. How do parameters of typical post-processing methods like Nonhomogeneous Gaussian Regression (NGR) vary over the lead time?

2. Is it possible to fit models that work continuously over the lead time, that
   a. achieve equal performance as separated models and
   b. save computational costs?

Methods & Data

Data:

- MOGREPS-G forecasts of 2m temperature and 10m wind speed (averaged over 10mins), 01/04/2019-01/04/2022, initialized at 00 UTC.
- Forecasts bilinearly interpolated and verified at 30 measurement stations in the UK.
- Lead times: T+06 to T+198 (8.25 days).

Methods:

- We fit NGR models separately for each lead time (t) as baseline and compare them with lead time continuous models we construct. We use a normal distribution for temperature[1] and a truncated normal for wind speed[2], so model: $Y_t \sim N(\mu_t, \sigma_t^2)$ or $Y_t \sim N_0(\mu_t, \sigma_t^2)$. The models are fit by minimizing the Continuous Ranked Probability Score (CRPS).
- We need to account for seasonality in the models. We do that in two ways:
  1) Add day of year (doy) as a covariate in the model. Training set: 01.04.2019-31.12.2020, testing set: 01.01.2021-01.04.2022.
  2) Train and apply models in a running window. Running window length of 40 days.

Results

1) Accounting for seasonality within the model:

We build lead time continuous models of the following form:

$$\mu_t = \alpha + \beta m_t + \kappa_1 \text{tod} \cdot \sin(2\pi \cdot \text{doy}/366) + \kappa_2 \text{tod} \cdot \cos(2\pi \cdot \text{doy}/366) + \text{tod} + t,$$
$$\log(\sigma_t) = \gamma + \delta \log(s_t) + \kappa_3 \text{tod} \cdot \sin(2\pi \cdot \text{doy}/366) + \kappa_4 \text{tod} \cdot \cos(2\pi \cdot \text{doy}/366) + \text{tod} + t,$$

here tod is a factor for the time of day accounting for the diurnal cycle, t stands for the lead time and doy for day of year. We compare these models to ones fitted separately to each lead time (t):

$$\mu_t = \alpha_t + \beta_t m_t + \kappa_{1,t} \sin(2\pi \cdot \text{doy}/366) + \kappa_{2,t} \cos(2\pi \cdot \text{doy}/366)\,,$$
$$\log(\sigma_t) = \gamma_t + \delta_t \log(s_t) + \kappa_{3,t} \sin(2\pi \cdot \text{doy}/366) + \kappa_{4,t} \cos(2\pi \cdot \text{doy}/366)\,.$$

Results:

1. The lead time continuous models achieve equal performance to the lead time separated ones (Fig. 1: temperature, Fig. 2: wind speed) measured in terms of CRPS, but only use around a 50% of the computation time.
2. The interaction between diurnal cycle (time of day) and seasonality is crucial for the model performance. Experiments with splines do not show much evidence for nonlinear lead time effects.

2) Accounting for seasonality in running window:

We build lead time continuous models of the following form, fitted in a running window:

$$\mu_t = \alpha + \beta m_t + \text{tod} + t,$$
$$\log(\sigma_t) = \gamma + \delta \log(s_t) + \text{tod} + t,$$

We compare these to lead time separated models (not including tod nor lead time t):

$$\mu_t = \alpha_t + \beta_t m_t,$$
$$\log(\sigma_t) = \gamma_t + \delta_t \log(s_t).$$

Results:

1. The lead time continuous models have similar performance to the separated models at earlier lead times, but improved performance at later ones, measured in terms of CRPS (Fig. 3: temperature, Fig. 4: wind speed). Furthermore they save substantially on computation time: 0.417s vs. 1.482s per location, running window (~70% saving).
2. Removing lead time (t) as a main effect does improve performance for later lead times but worsens it at earlier ones for temperature (not shown). This is difficult to account for using splines. For wind speed the performance stays equal.
3. Merging data across lead times allows to reduce the training window size which again leads to improved performance probably due to faster adaptation to seasonality or regimes (Fig. 5).

1) Seasonality within the model

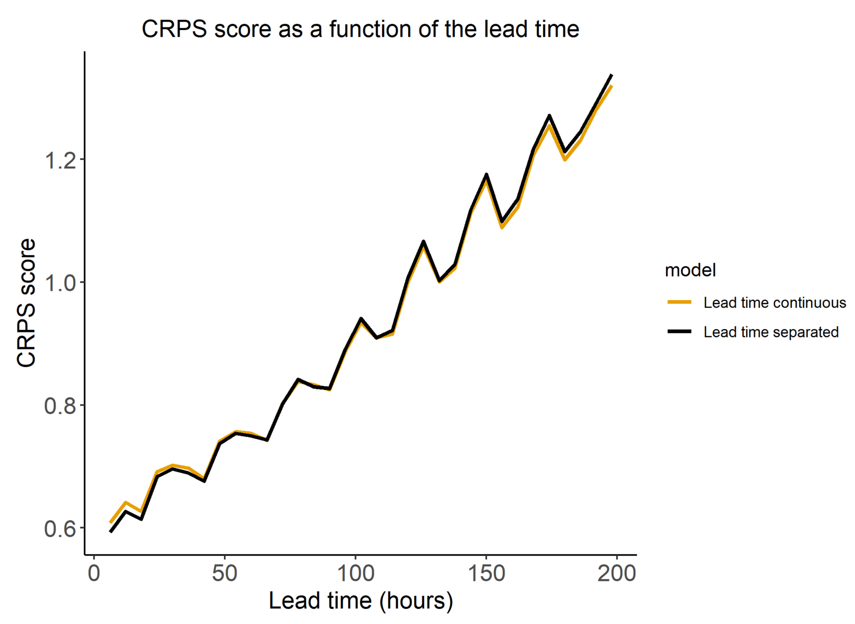


Fig. 1: temperature

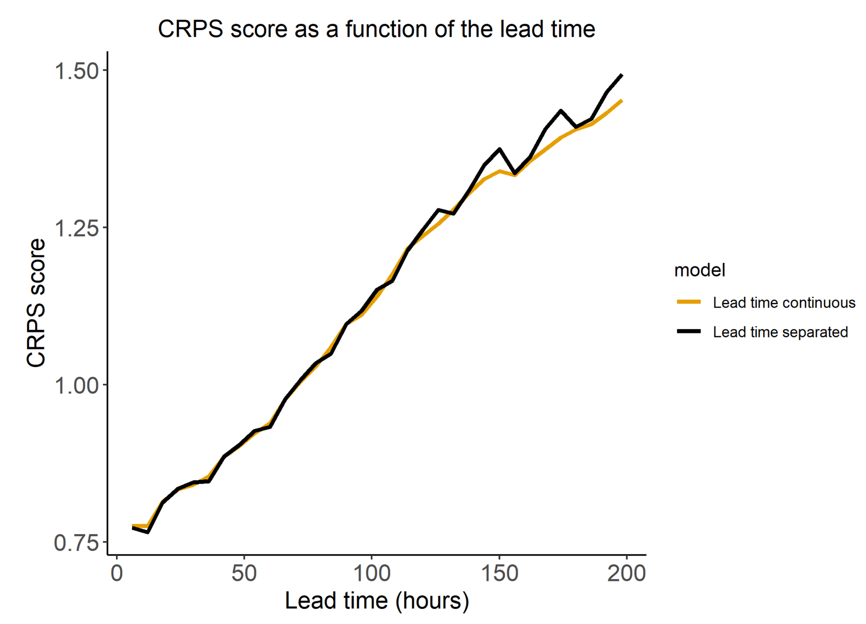


Fig. 2: wind speed

2) Seasonality in running window

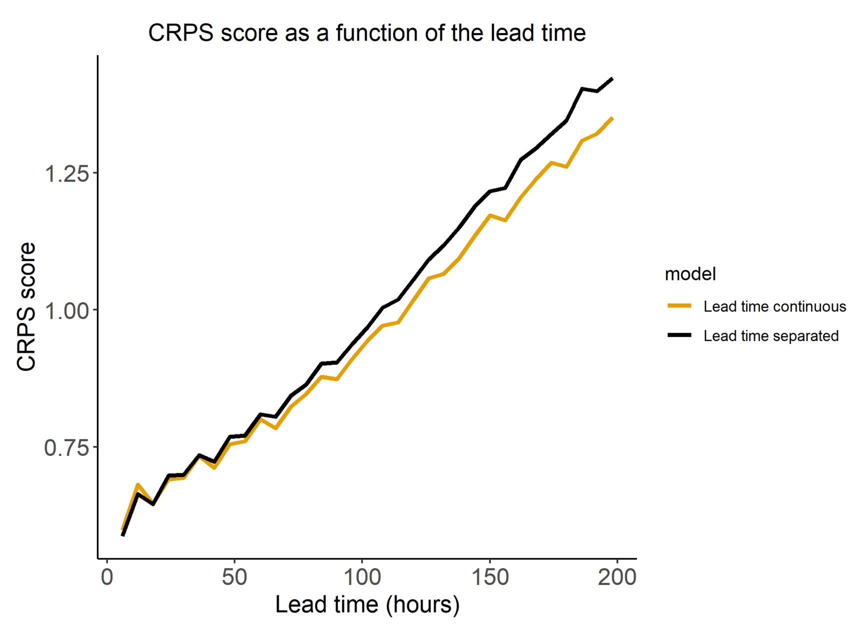


Fig. 3: temperature

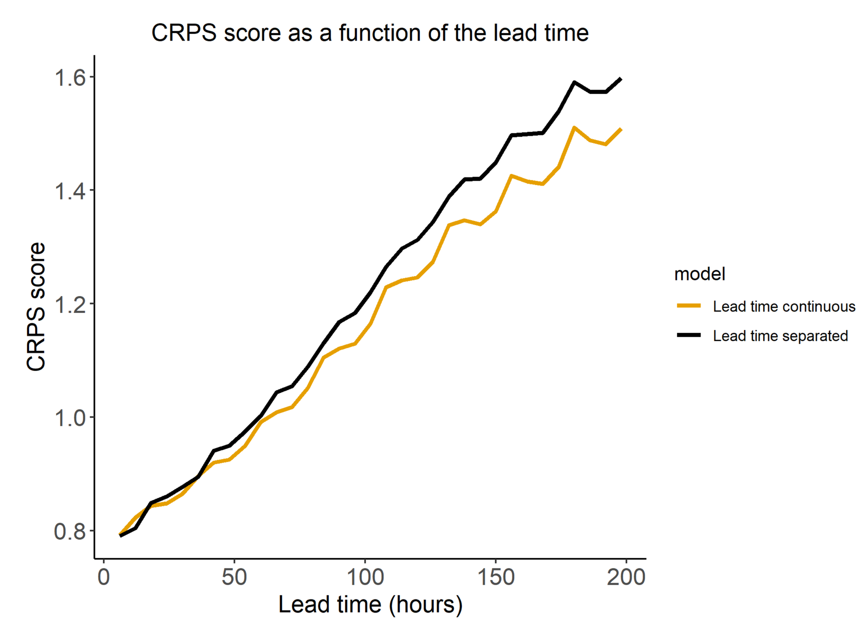


Fig. 4: wind speed

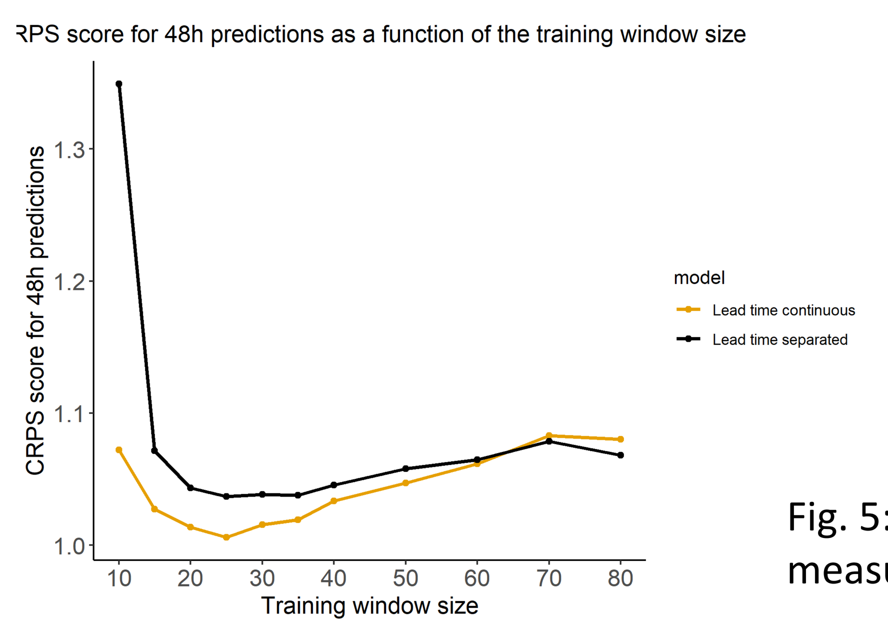
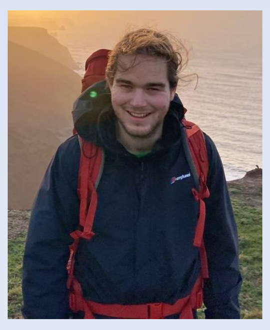


Fig. 5: temperature -- one measurement station

Conclusions

- A lot of research in post-processing of ensemble weather forecasts has focused on building models for separate lead times.
- We show that it is easily possible to build models that work continuously over the lead time which save substantially on computation time and can even have improved performance.
- The computational cost for post-processing is generally minor compared to the one for NWP model generation. However,
  - in machine learning based post-processing methods it can become considerable,
  - merging across lead times allows for more efficient utilization of the data which is of interest for data intensive methods from machine learning.



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References

[1] Gneiting, T. *et al.* (2005) 'Calibrated Probabilistic Forecasting Using Ensemble Model Output Statistics and Minimum CRPS Estimation', *Monthly Weather Review*, 133(5), pp. 1098–1118.
[2] Scheuerer, M. and Möller, D. (2015) 'Probabilistic wind speed forecasting on a grid based on ensemble model output statistics', *The Annals of Applied Statistics*, 9(3), pp. 1328–1349.