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Lead time continuous statistical post-processing of ensemble weather forecasts

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Numerical weather prediction (NWP) models usually output their forecasts at a multiplicity of different lead times. For example, the Met Office ensemble prediction system for the UK (MOGREPS-UK) predicts atmospheric variables on a 2.2km grid for up 126h on hourly and sub-hourly timesteps. Even though for applications, information is often required on this range of lead times, many post-processing methods in the literature are either applied at fixed lead time or by fitting individual models for each lead time. This is also the case in systems used in practice such as the Met Office IMPROVER system. However, this is 1) computationally expensive because it requires the training of multiple models if users are interested in information at multiple lead times and 2) prohibitive because it restricts the training data used for training post-processing models and the usability of fitted models.

In this work we investigate lead time dependence of ensemble post-processing methods by looking at ensemble forecasts in an idealized Lorenz96 system as well as temperature forecast data from the Met Office MOGREPS-UK system. First, we investigate the lead time dependence of estimated model parameters in non-homogenous Gaussian regression (NGR -- a standard ensemble post-processing technique) and find substantial smoothness. Secondly, we look at the usability of models fitted for one lead time and employed at another to then thirdly fit models that are “lead time continuous”, meaning they work for multiple lead times simultaneously by including lead time as a covariate using spline regression. We show that these models can achieve similar performance to the classical “lead time separated” models, whilst saving substantial computation time. Fourthly and finally we make first steps towards the development of a cheap computational model including seasonality and working continuously over the lead time, needing to be fit only once.