Incorporating Spatial Information Into Ensemble Post-processing via Autoencoder Neural Networks

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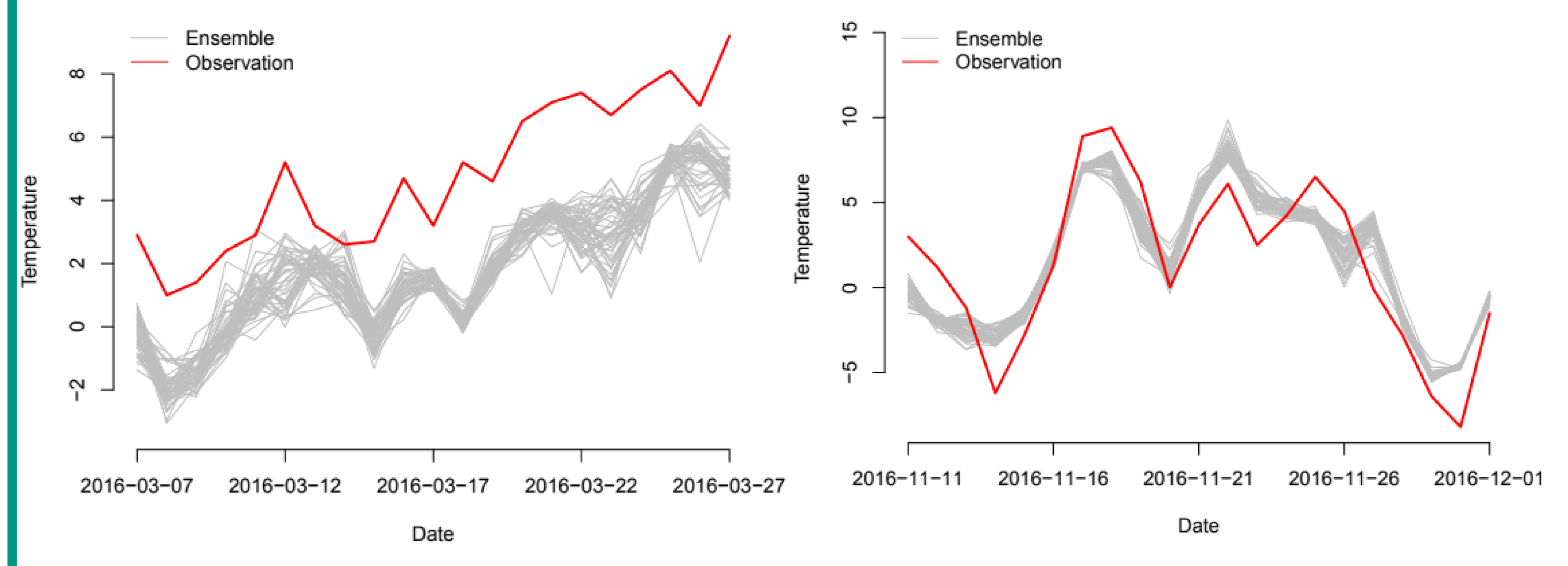
1. Post-processing ensemble weather forecasts

Ensemble simulations quantify uncertainties and produce probabilistic forecasts. However, systematic errors frequently occur and require correction.



Exemplary time series of ECMWF ensemble forecasts of 2m temperature at Frankfurt airport showing a clear bias (left) and a lack of spread of the ensemble (right).

Distributional regression models for statistical post-processing aim to correct such systematic errors.

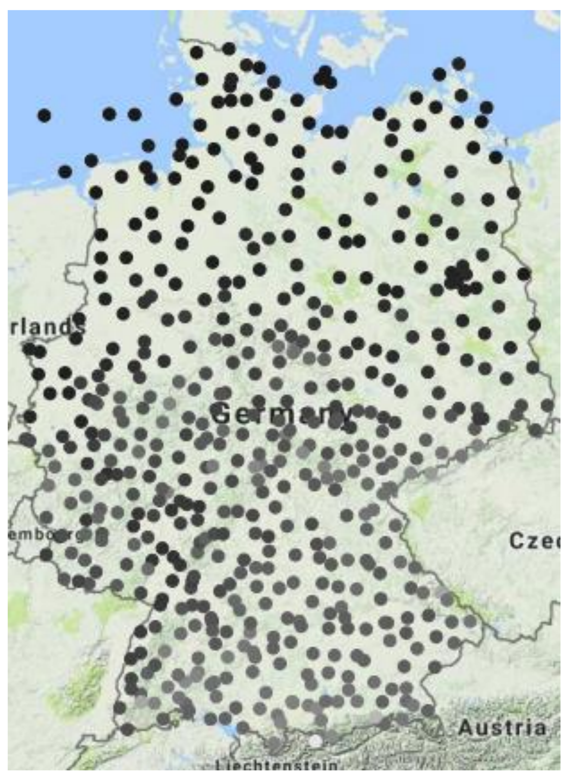
2. Data

10 years of forecast and observation data (2007-2016)

48 hours-ahead ECMWF 50-member ensemble forecasts of temperature (and 17 other variables)

Station observations at 537 locations over Germany

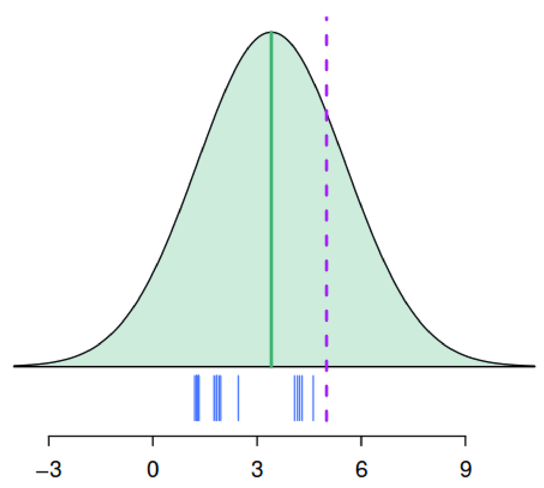
Data from 2016 is used as test set



3. Traditional methods for statistical post-processing

Ensemble Model Output Statistics (EMOS) approaches take the ensemble prediction from the physical model as input, and produce probability distributions as output.

For temperature, the probabilistic forecast takes the form of a Gaussian distribution.



$$y|\boldsymbol{X}^{t2m} \sim N_{(\mu,\sigma)},$$

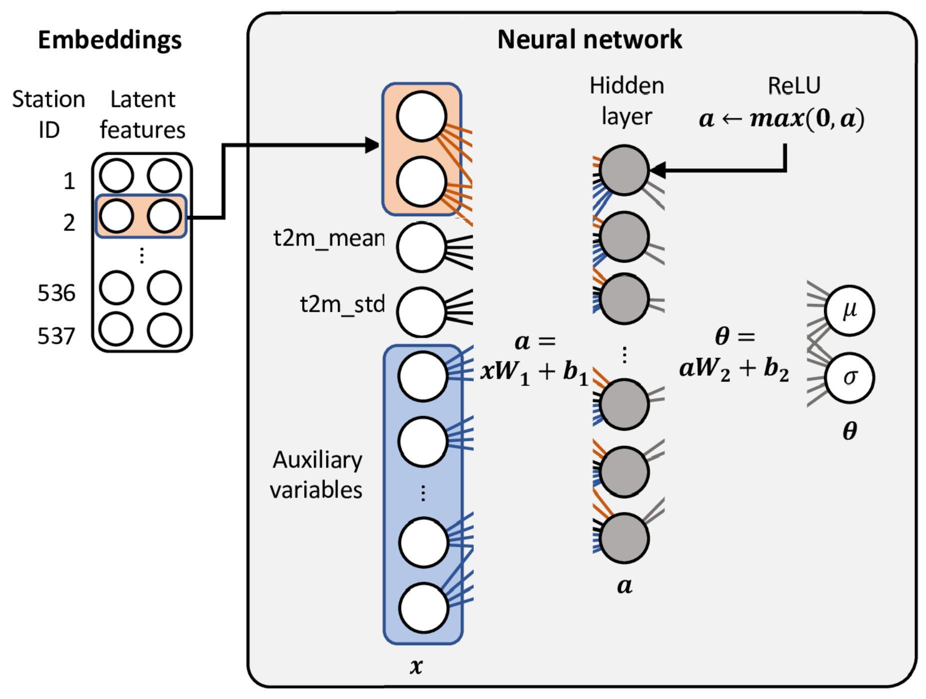
$$\mu = a + b \cdot \mathrm{mean}(\boldsymbol{X}^{t2m})$$

$$\sigma = c + d \cdot \mathrm{sd}(\boldsymbol{X}^{t2m})$$

4. Neural network-based post-processing

Rasp and Lerch (2018, https://doi.org/10.1175/MWR-D-18-0187.1) propose a new semi-parametric approach: Estimate distribution parameters directly as output of a neural network designed to

- learn arbitrary nonlinear relations between predictors and distribution parameters in an automated, data-driven manner
- generate local adaptivity in models estimated jointly for all locations



Input: NWP ensemble quantities (mean + std.dev.); station characteristics

Output: Distribution parameters

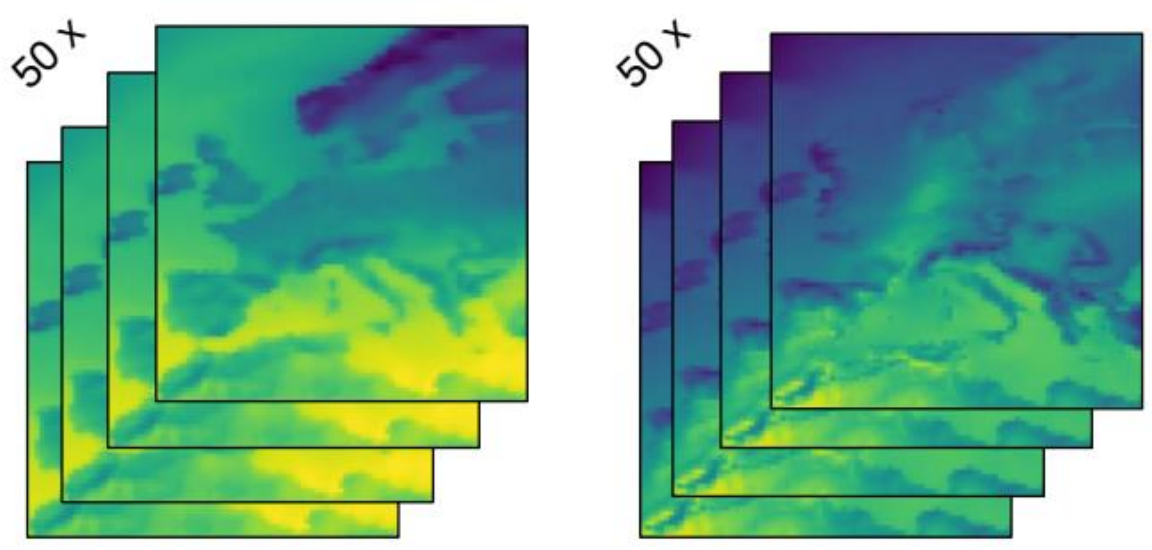
Embeddings generate local adaptivity

Mathematically principled loss function (CRPS) for distributional regression

5. Limitations of NN-based post-processing

The NN-based model from Rasp and Lerch (2018) shows significant improvements over state of the art benchmark models.

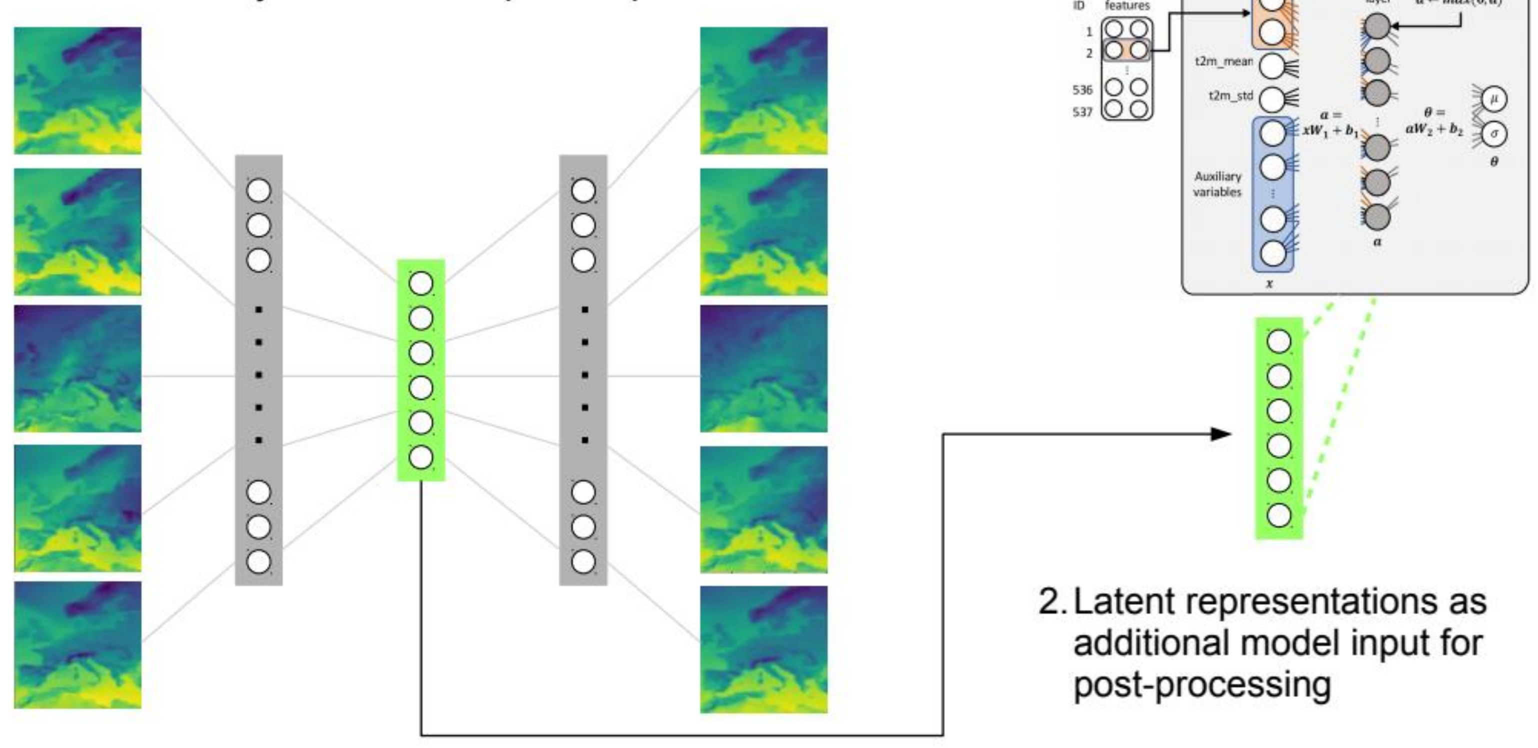
However, ensemble forecasts are gridded 2D fields of forecasts, which were interpolated to station locations.



The large-scale spatial structure and predictability information get lost in this interpolation step.

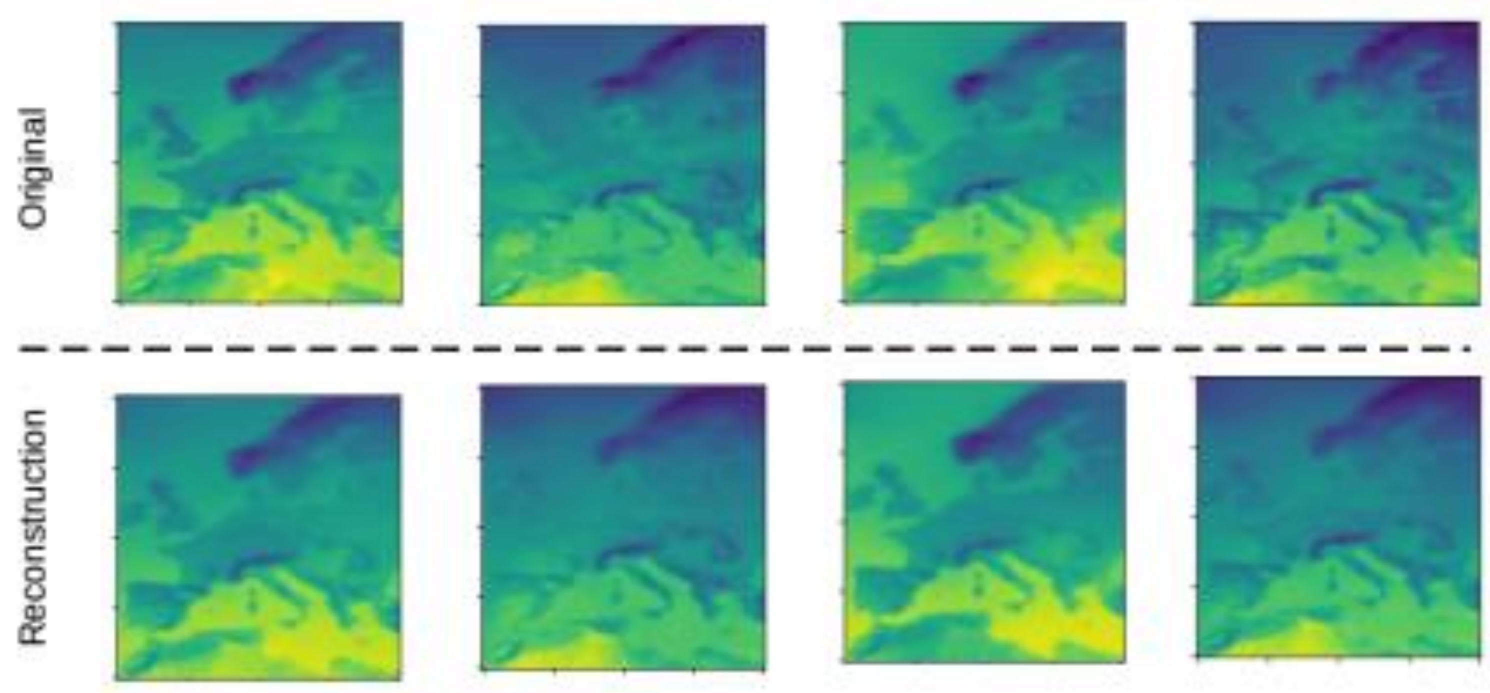
6. Convolutional autoencoders for incorporating spatial information into post-processing

1. Autoencoder neural networks for nonlinear dimensionality reduction of spatial input fields



2. Latent representations as additional model input for post-processing

7. Preliminary results



Random (test set) examples of original T2M forecast fields and reconstruction by convolutional AE with a latent dimension of 8.

CRPS: Continuous ranked probability score, lower is better

Model	Mean CRPS for training period 2015	2007–2015
Raw ensemble	1.16	1.16
Benchmark post-processing methods		
Local EMOS	0.90	0.90
Local EMOS with boosting	0.85	0.80
Local quantile regression forest	0.95	0.81
Neural network models		
Neural network with auxiliary predictors and station embeddings	0.82	0.78
Neural network with AE inputs (T2M)	**0.81**	**0.75**

Incorporating spatial information further improves predictive performance.

Quality of AE-representations strongly depends on the target variable and requires additional experiments, in particular to account for ensemble structure of the data.

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