Machine Learning Methods for Postprocessing Ensemble Forecasts of Wind Gusts

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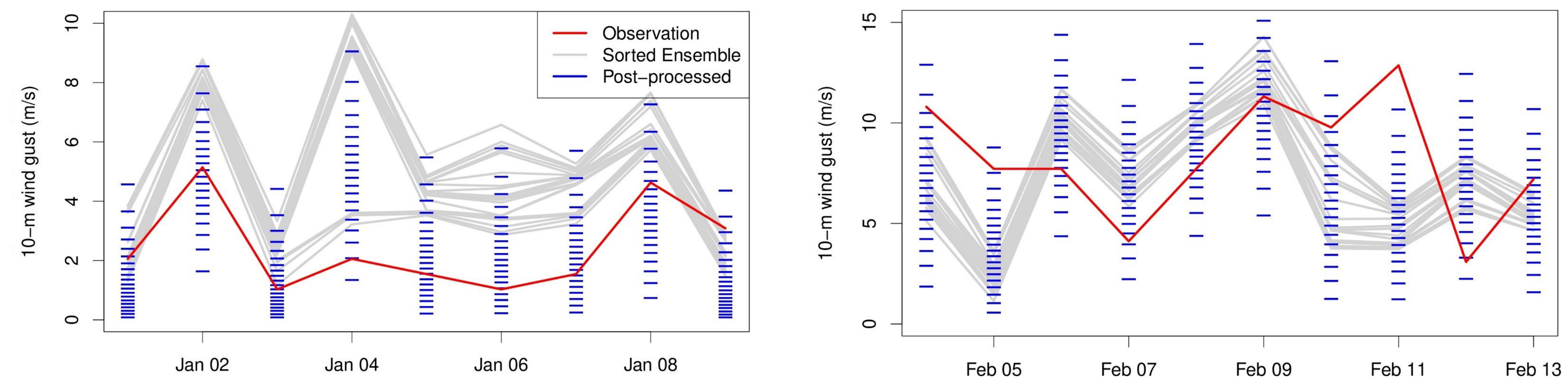
ENSEMBLE POSTPROCESSING OF WIND GUSTS

Ensemble forecasts are subject to systematic biases and dispersion errors, which can be corrected with **statistical postprocessing**. We postprocess wind gust ensemble forecasts with a focus on European winter storms.



COSMO-DE-EPS forecasts subject to bias (left) and dispersion errors (right) and postprocessed EMOS forecasts.

As a first step towards regime-dependent postprocessing for wind gusts, we systematically compared eight postprocessing methods (Schulz and Lerch, 2021).

ENSEMBLE AND OBSERVATIONAL DATA

- 20-member COSMO-DE-EPS
- Initialization time: 00 UTC
- Ensemble forecasts of 61 variables
- Time range: 08/12/2010–31/12/2016
- Lead times: 0–21h
- Observations at 175 SYNOP stations

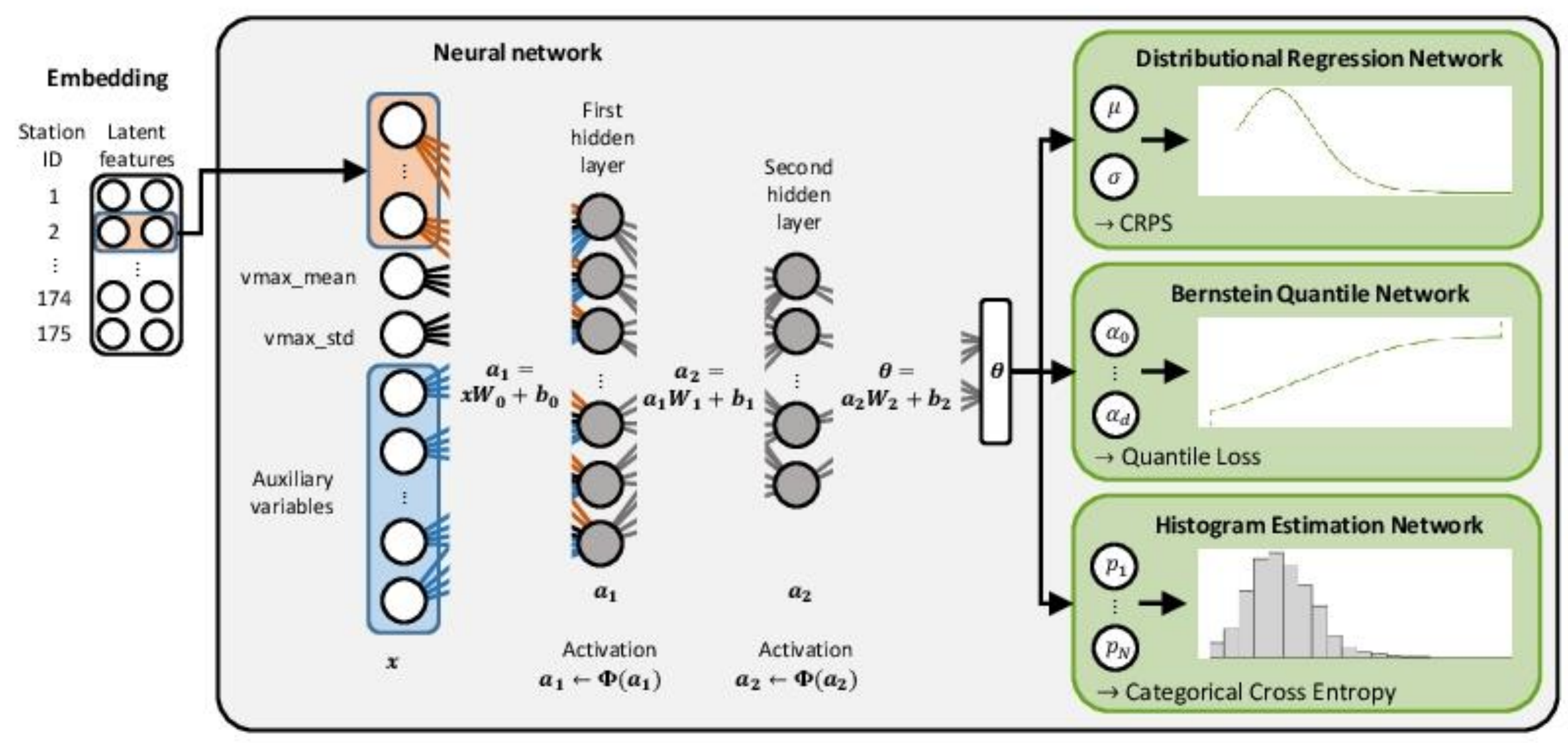
NEURAL NETWORKS

We consider three variants of neural network-based postprocessing that use a **common network architecture** but differ in the forecast form and loss function.

Locally adaptive networks:

Via station embedding, only one model needs to be estimated for all stations.

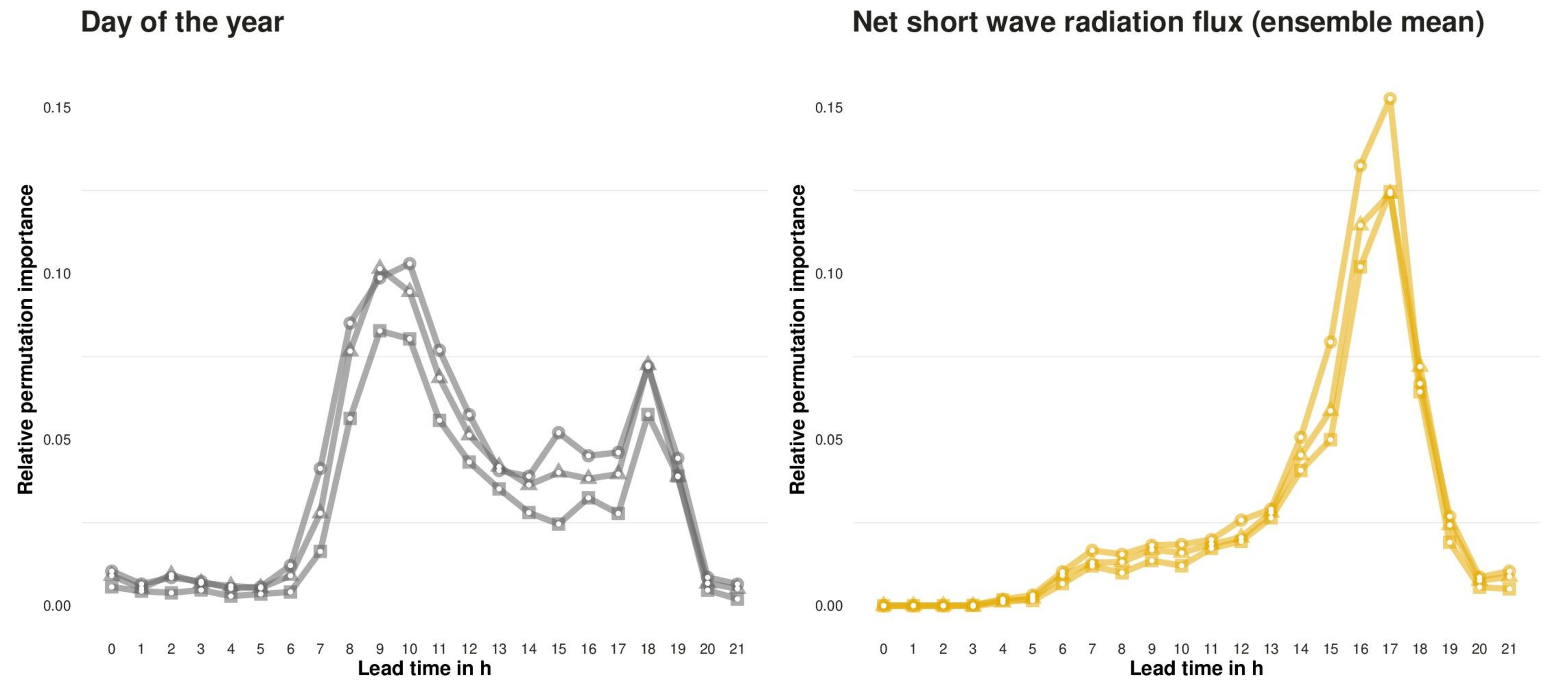
- Distributional Regression Network (DRN)
- Bernstein Quantile Network (BQN)
- Histogram Estimation Network (HEN)



Framework for neural network-based postprocessing.

FEATURE IMPORTANCE

The machine learning methods learn **physically consistent** relations, as exemplified for the neural network approaches. The day of the year is an important predictor in the morning and evening, radiation is important during the evening transition of the planetary boundary layer.



Feature importance of the day of the year (left) and the ensemble mean of the net short wave radiation flux (right) for the three network variants dependent on the lead time. **Higher means more important.**

POSTPROCESSING BENCHMARKS

All postprocessing benchmark techniques are **locally estimated**, i.e. a separate model is fitted for each station.

Statistical methods:

Only the ensemble forecasts of wind gusts are used as predictors.

- Ensemble Model Output Statistics (EMOS)
- Member-by-Member Postprocessing (MBM)
- Isotonic Distributional Regression (IDR)

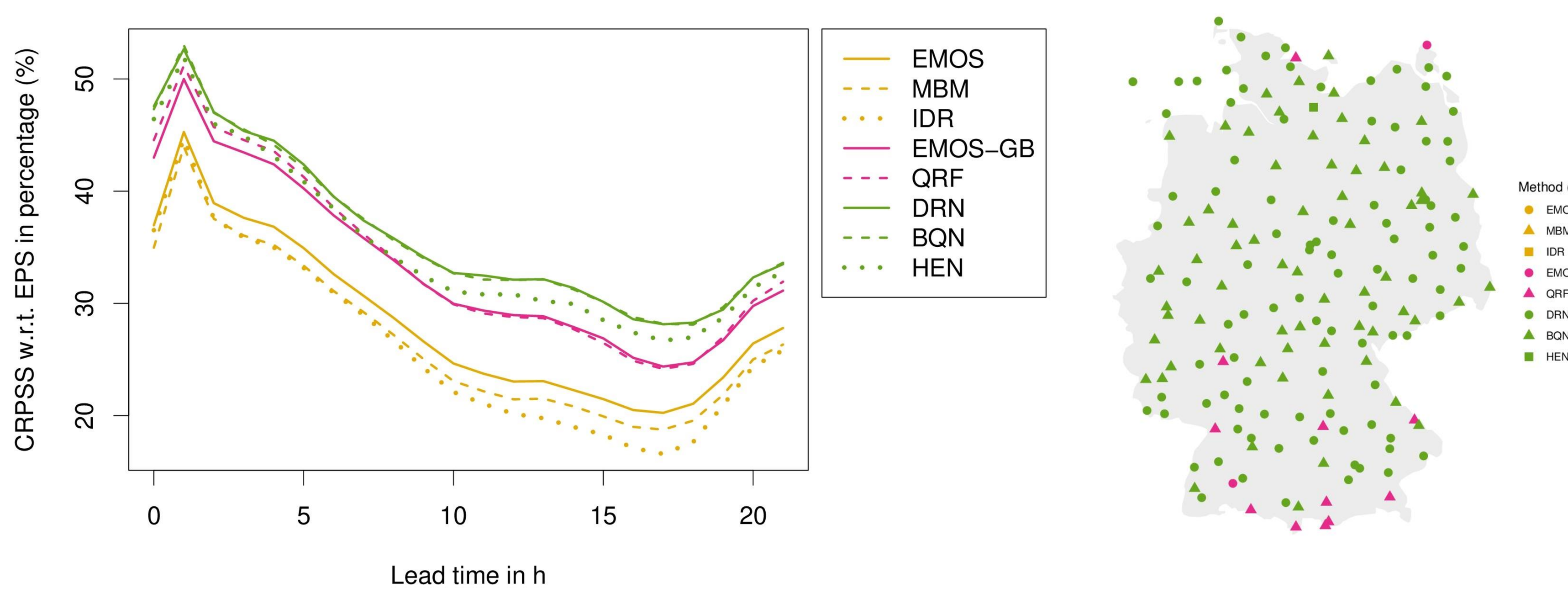
Machine learning methods:

Incorporation of additional predictors feasible.

- Gradient Boosting extension of EMOS (EMOS-GB)
- Quantile Regression Forests (QRF)

COMPARISON OF POSTPROCESSING METHODS

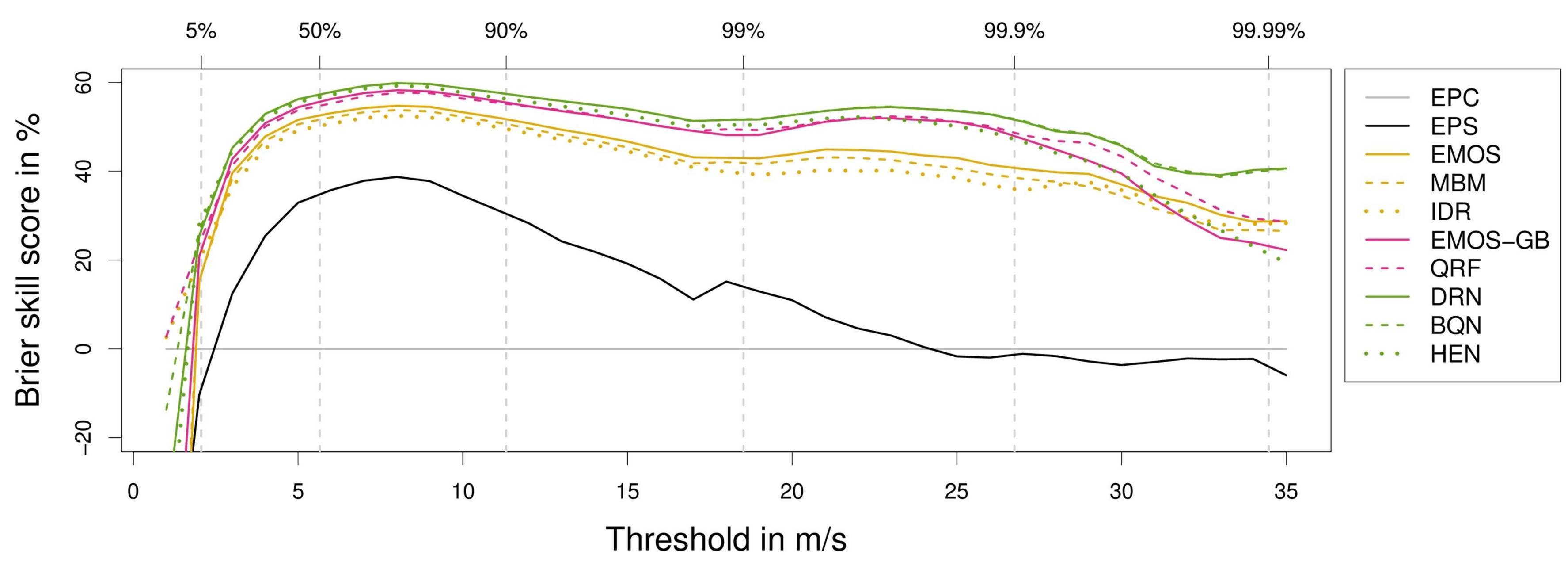
Training from **2010–2015** for each lead time separately, evaluation in **2016**.



Left: Skill of the methods w.r.t. the EPS in terms of the CRPS dependent on the lead time. **Higher means better.**
Right: Best method at each station in terms of the CRPS, averaged over all lead times.

Results in terms of the continuous ranked probability score (CRPS):

- Overall, the postprocessing methods improve the predictive performance w.r.t. the ensemble prediction system (EPS) by **20–50%**.
- The machine learning methods that **incorporate additional predictors** consistently outperform the statistical benchmarks by 5–10%.
- The **neural network**-based approaches perform best.
- The locally adaptive networks, which estimate **one model for all 175 stations**, perform best at more than 90% of the stations.



Skill of the methods w.r.t. the extendend probabilistic climatology (EPC) in terms of the BS dependent on the threshold. **Higher means better.** The quantiles of the observed wind gusts are indicated by the vertical lines.

Results in terms of the Brier score (BS):

- Similar results to the CRPS, again the **networks are superior**.
- While the skill of the EPS vanishes the larger the thresholds become, the skill of the postprocessing methods **remains high**.

REFERENCES

Schulz, B. and Lerch, S. (2021): Machine learning methods for postprocessing ensemble forecasts of wind gusts: A systematic comparison. *Monthly Weather Review*, in press.