WAVES TO WEATHER

Postprocessing ensemble forecasts of wind gusts with a focus on European winter storms

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UP 1.3: Understanding and modelling of atmospheric hazards and severe weather phenomena

KIT

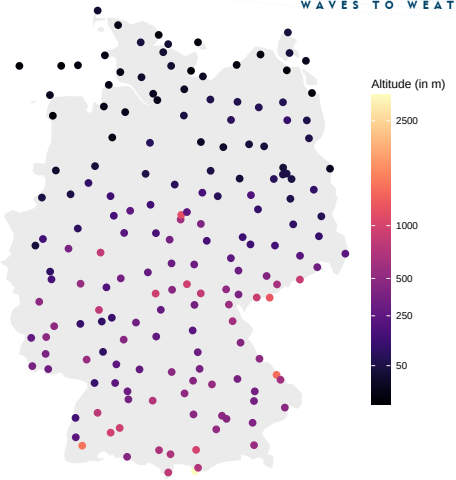
Agenda

1. Machine learning methods for postprocessing ensemble forecasts of wind gusts

2. Postprocessing in European winter storms

Data – COSMO-DE-EPS

- Location: Germany
- 20-member COSMO-DE-EPS.
- 2.8km horizontal resolution.
- 61 variables incl. wind gusts.
- Initialization time: 00 UTC.
- Lead times: 00 – 21h.
- Time range: 08/12/2010 – 31/12/2016.
- Training in 2010–2015, evaluation in 2016.
- Observations at 175 SYNOP stations.
- Forecasts taken from closest grid point.



Schulz, B. and Lerch, S. (2022): **Machine learning methods for postprocessing ensemble forecasts of wind gusts: A systematic comparison**, *Monthly Weather Review*, **150**, 235–257.

Setting

Goal: Find best postprocessing method for ensemble forecasts of wind gusts.

$\Rightarrow$ Review and comparison of existing postprocessing approaches

Basic methods:

Only wind gust ensemble

- EMOS
- MBM
- IDR

Separate model for each station!

ML benchmark:

Use additional predictors

- EMOS-GB
- QRF

Separate model for each station!

Neural networks:

Locally adaptive

- DRN
- BQN
- HEN

Joint model for **all** stations!

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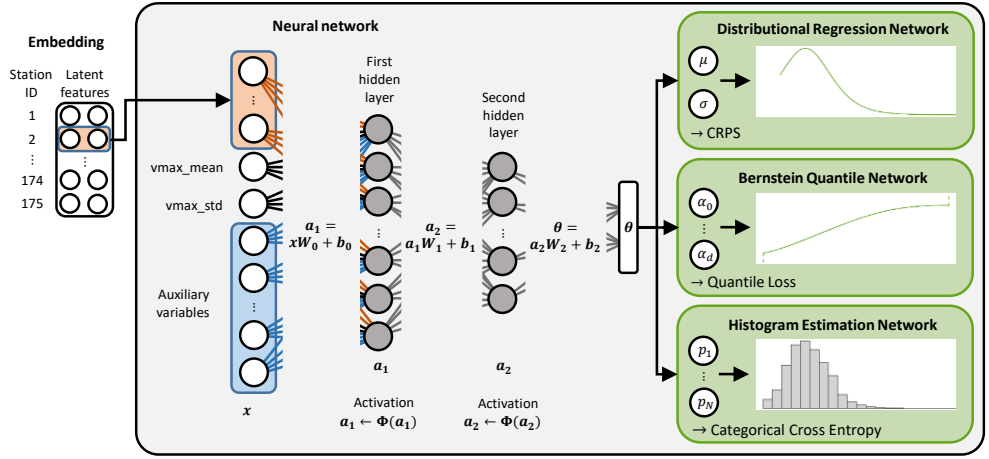
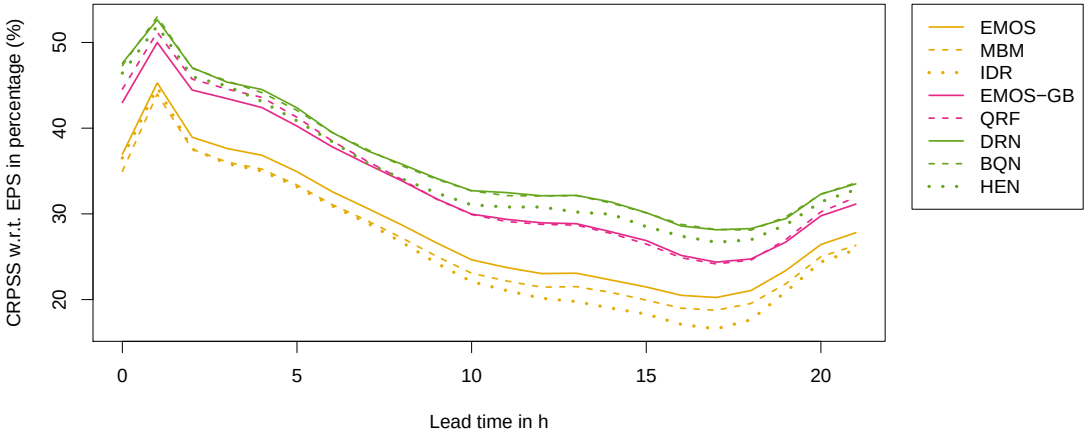
Locally Adaptive Networks



Schulz, B. and Lerch, S. (2022): **Machine learning methods for postprocessing ensemble forecasts of wind gusts: A systematic comparison**, *Monthly Weather Review*, **150**, 235–257.

CRPSS over Lead Time



CRPS skill of the postprocessing methods w.r.t. the ensemble dependent on the lead time. Training in 2010–2015, evaluation in 2016. Each method is applied for each lead time separately.

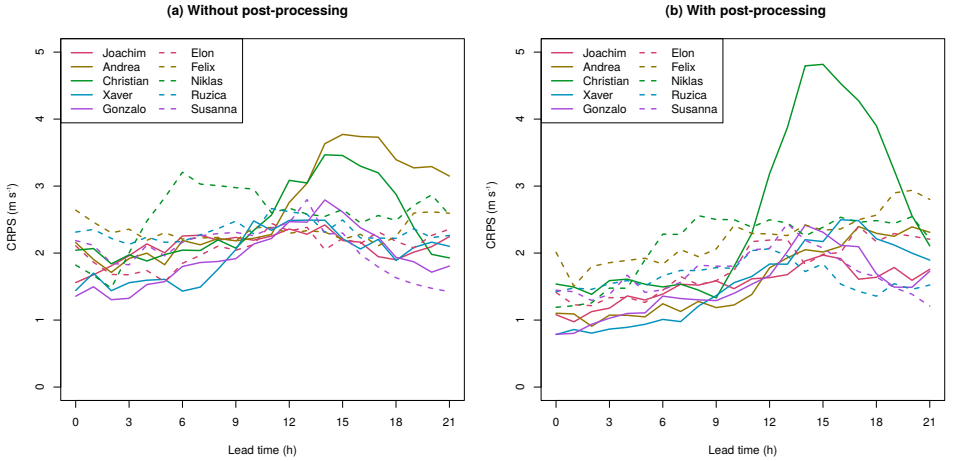
Higher means better.

Agenda

1. Machine learning methods for postprocessing ensemble forecasts of wind gusts

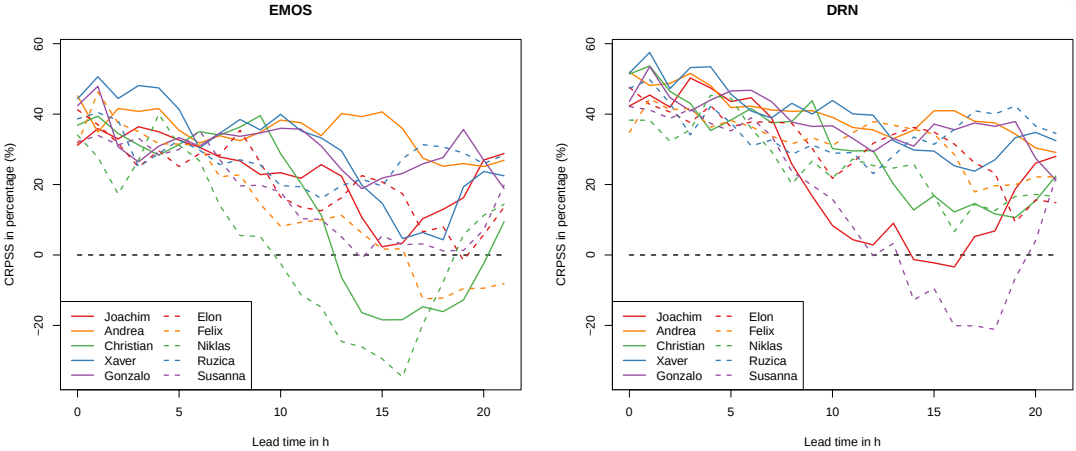
2. Postprocessing in European winter storms

Motivation: Deterioration through Postprocessing



Pantillon, F., Lerch, S., Knippertz, P. and Corsmeier, U. (2018): **Forecasting wind gusts in winter storms using a calibrated convection-permitting ensemble**, *QJRMS*, **144**, 1864–1881.

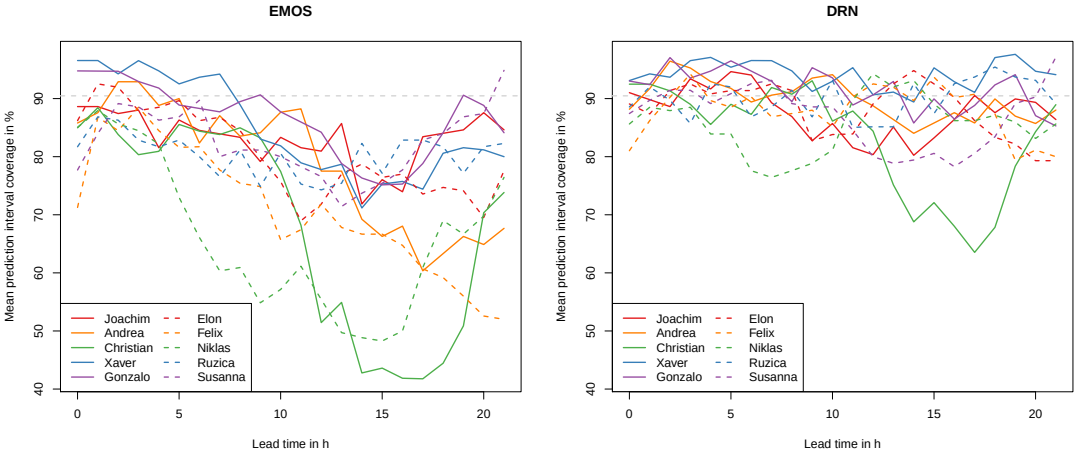
Skill in Winter Storms



CRPS skill of EMOS (left) and DRN (right) w.r.t. the ensemble dependent on the lead time. Training and evaluation via cross-validation. Each method is applied for each lead time separately.

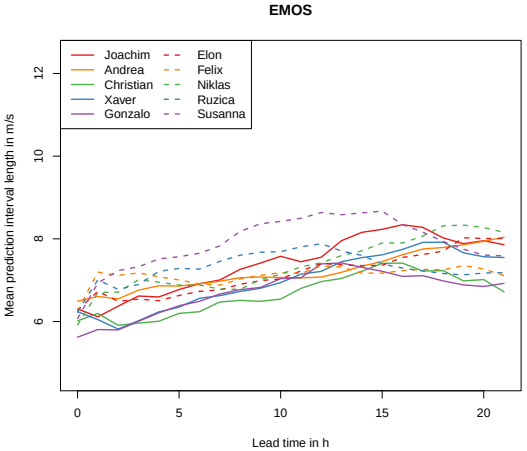
Higher means better.

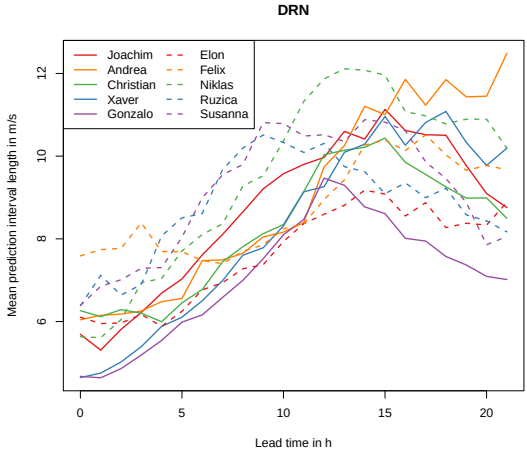
Reliability in Winter Storms



Prediction interval coverage of EMOS (left) and DRN (right) dependent on the lead time. Training and evaluation via cross-validation. Each method is applied for each lead time separately.

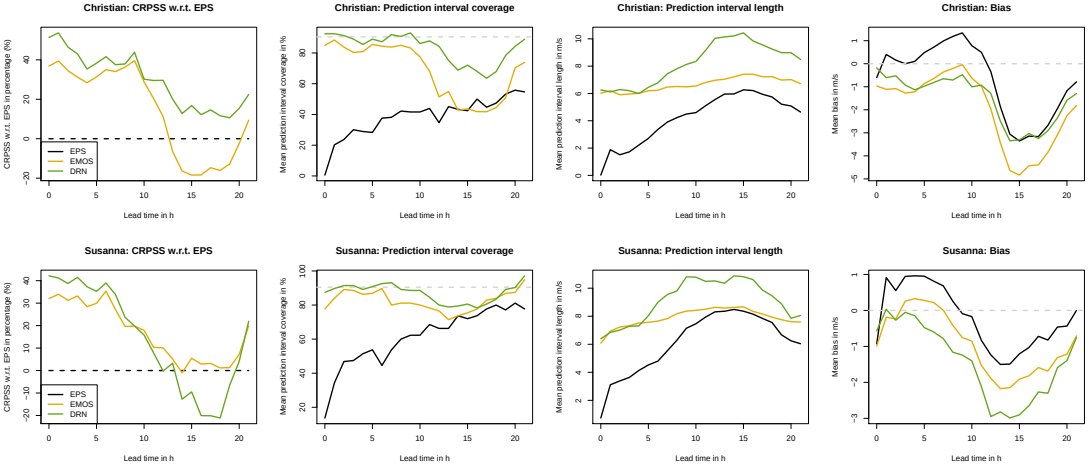
Forecast Uncertainty in Winter Storms





Prediction interval length of EMOS (left) and DRN (right) dependent on the lead time.
Training and evaluation via cross-validation. Each method is applied for each lead time separately.

Case studies: *Christian* and *Susanna*



CRPS skill w.r.t. ensemble forecasts, PI coverage, PI length and bias (left to right) of EMOS and DRN for *Christian* (top) and *Susanna* (bottom) dependent on the lead time.
Training and evaluation via cross-validation. Each method is applied for each lead time separately.

Conclusions and Outlook

Systematic comparison:

- Neural networks significantly outperform state-of-the-art benchmark methods.
- The neural networks learn **physically consistent** relations.

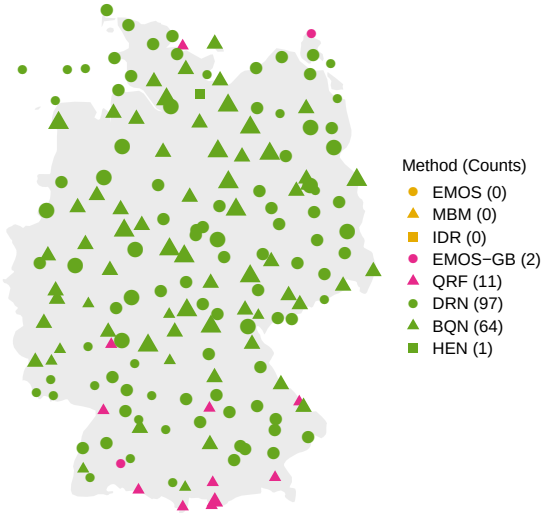
Winter storms:

- Neural networks outperform EMOS also within winter storms.
- Neural networks are **more reliable** and better represent the forecast uncertainty.
- Neural networks are still subject to a **forecast bust**.

Outlook:

- **Feature-dependent** forecast error analysis and postprocessing.

Backup — Stationwise Performance



Best method per location
in terms of the CRPS.

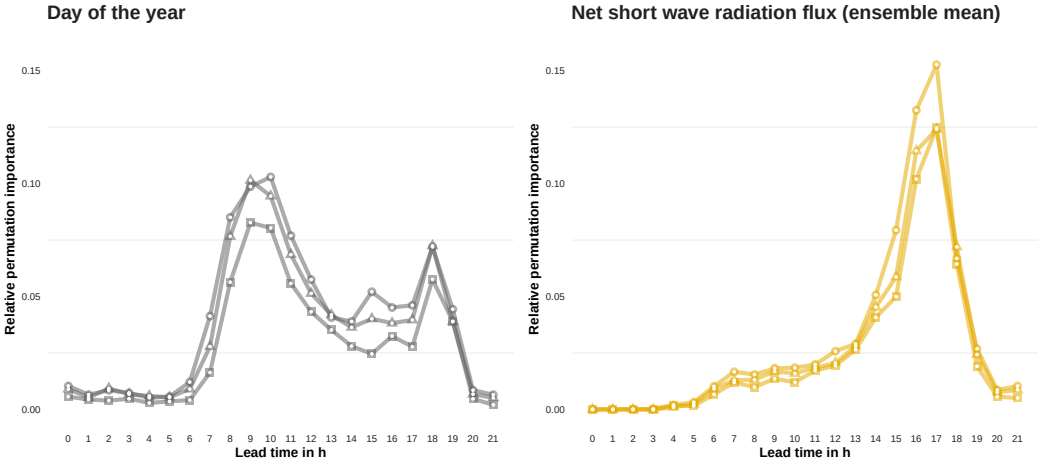
The larger the symbol,
the more significant the superiority.

Training in 2010–2015,
evaluation in 2016.

Each method is applied
for each lead time separately.

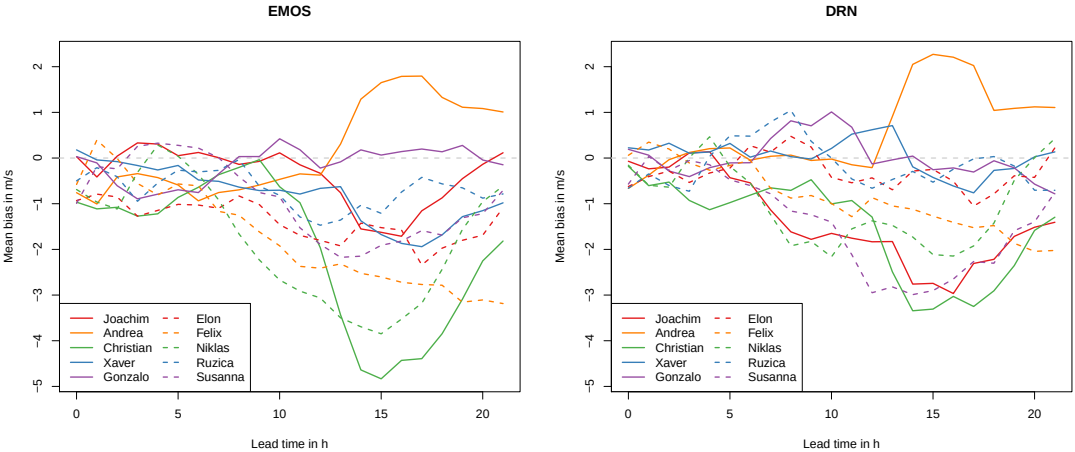
Locally adaptive networks
perform best at
162 of 175 stations (ca. 92.6%).

Backup — Importance of Predictor Variables



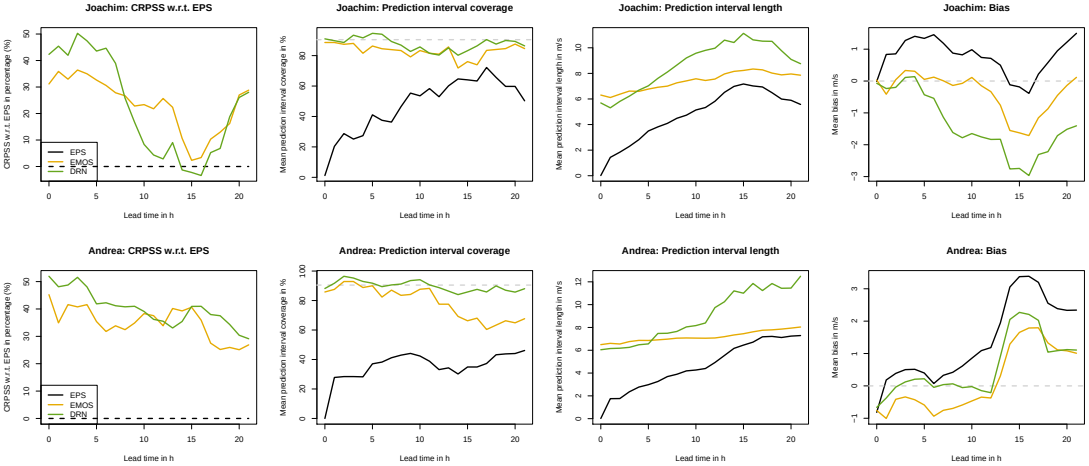
Relative **permutation importance** of the three network variants dependent on the lead time.
Higher means more important.

Backup — Forecast bias in Winter Storms



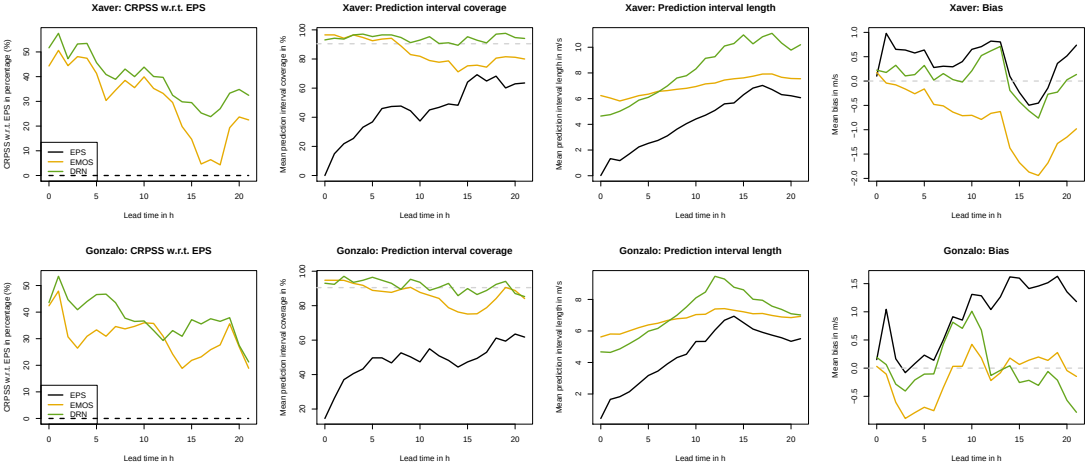
Mean forecast bias of EMOS (left) and DRN (right) dependent on the lead time.
Training and evaluation via cross-validation. Each method is applied for each lead time separately.

Backup — Case studies: *Joachim* and *Andrea*



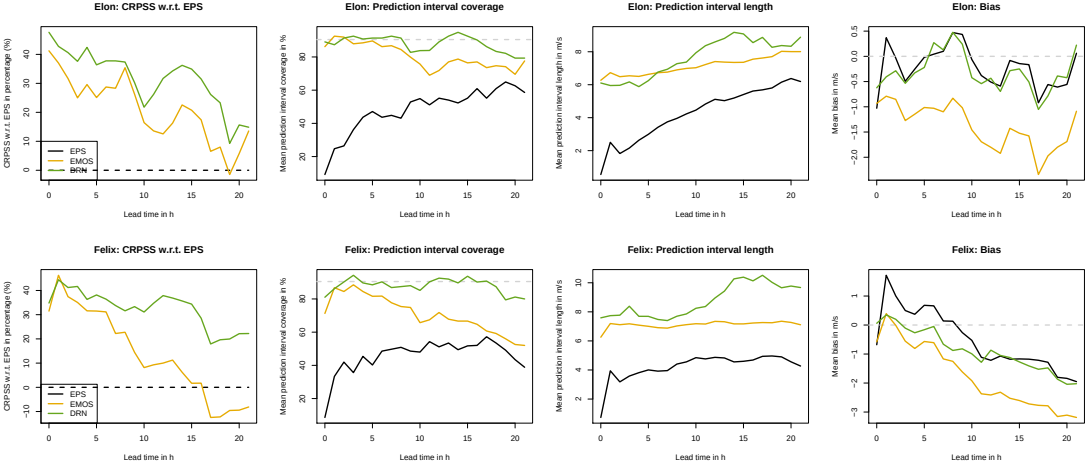
CRPS skill w.r.t. ensemble forecasts, PI coverage, PI length and bias (left to right) of EMOS and DRN for *Joachim* (top) and *Andrea* (bottom) dependent on the lead time.
Training and evaluation via cross-validation. Each method is applied for each lead time separately.

Backup — Case studies: *Xaver* and *Gonzalo*



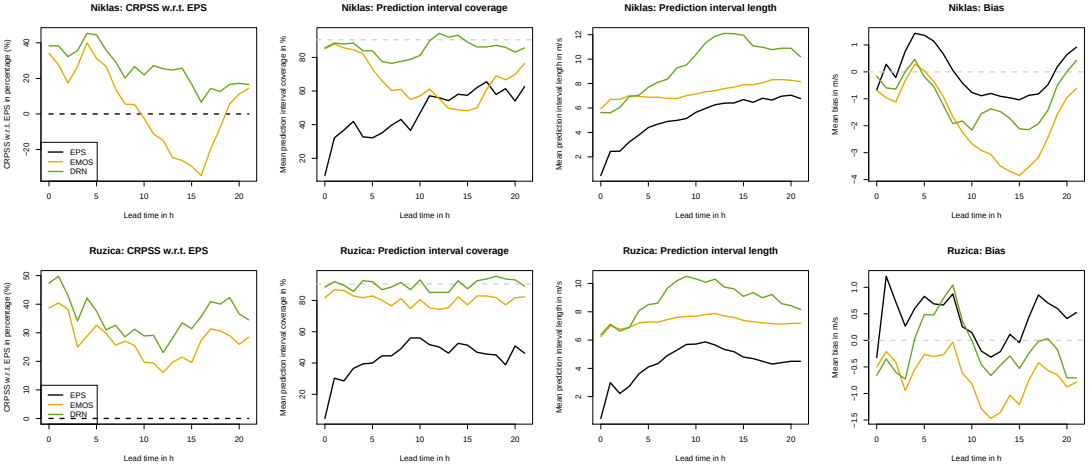
CRPS skill w.r.t. ensemble forecasts, PI coverage, PI length and bias (left to right) of EMOS and DRN for *Xaver* (top) and *Gonzalo* (bottom) dependent on the lead time.
Training and evaluation via cross-validation. Each method is applied for each lead time separately.

Backup — Case studies: *Elon* and *Felix*



CRPS skill w.r.t. ensemble forecasts, PI coverage, PI length and bias (left to right) of EMOS and DRN for *Elon* (top) and *Felix* (bottom) dependent on the lead time.
Training and evaluation via cross-validation. Each method is applied for each lead time separately.

Backup — Case studies: *Niklas* and *Ruzica*



CRPS skill w.r.t. ensemble forecasts, PI coverage, PI length and bias (left to right) of EMOS and DRN for *Niklas* (top) and *Ruzica* (bottom) dependent on the lead time.
Training and evaluation via cross-validation. Each method is applied for each lead time separately.