Deep Neural Networks for the reconstruction of near-surface hourly temperature

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Norwegian Meteorological Institute

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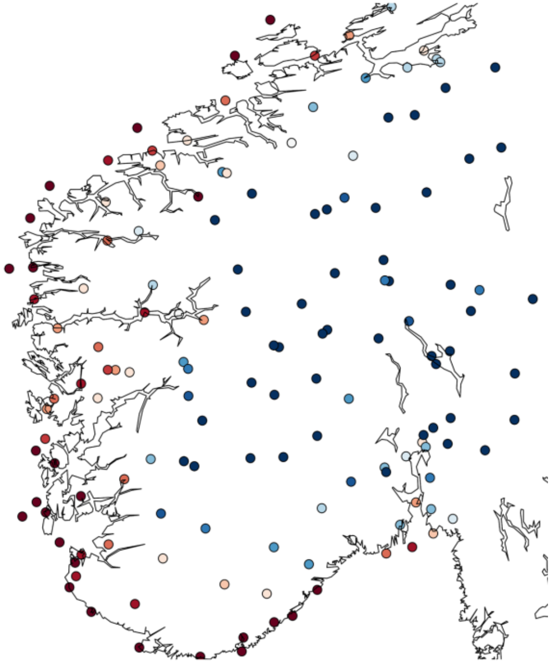
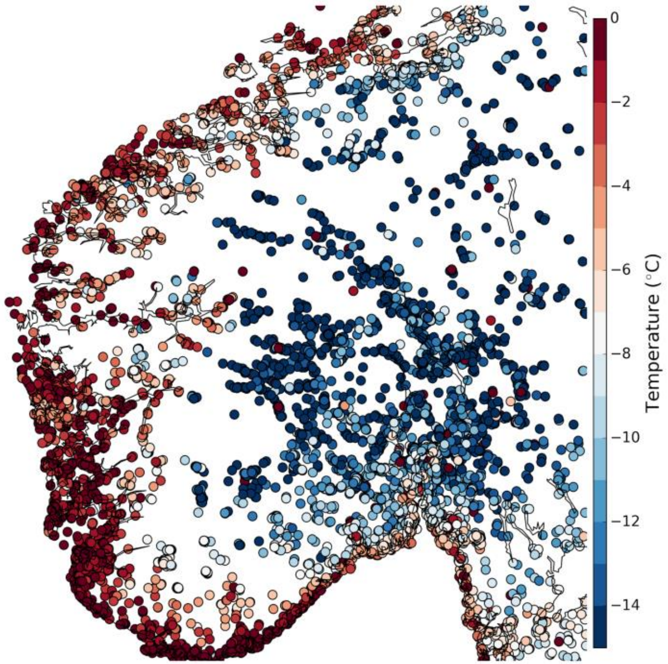
DMW 2025, Oslo

In-situ Observations

- Netatmo's station density is roughly 50 times greater than MET Norway's (e.g. see hourly temperature in the figure)



MET Norway



Netatmo

Source: netamo.com

Extreme events

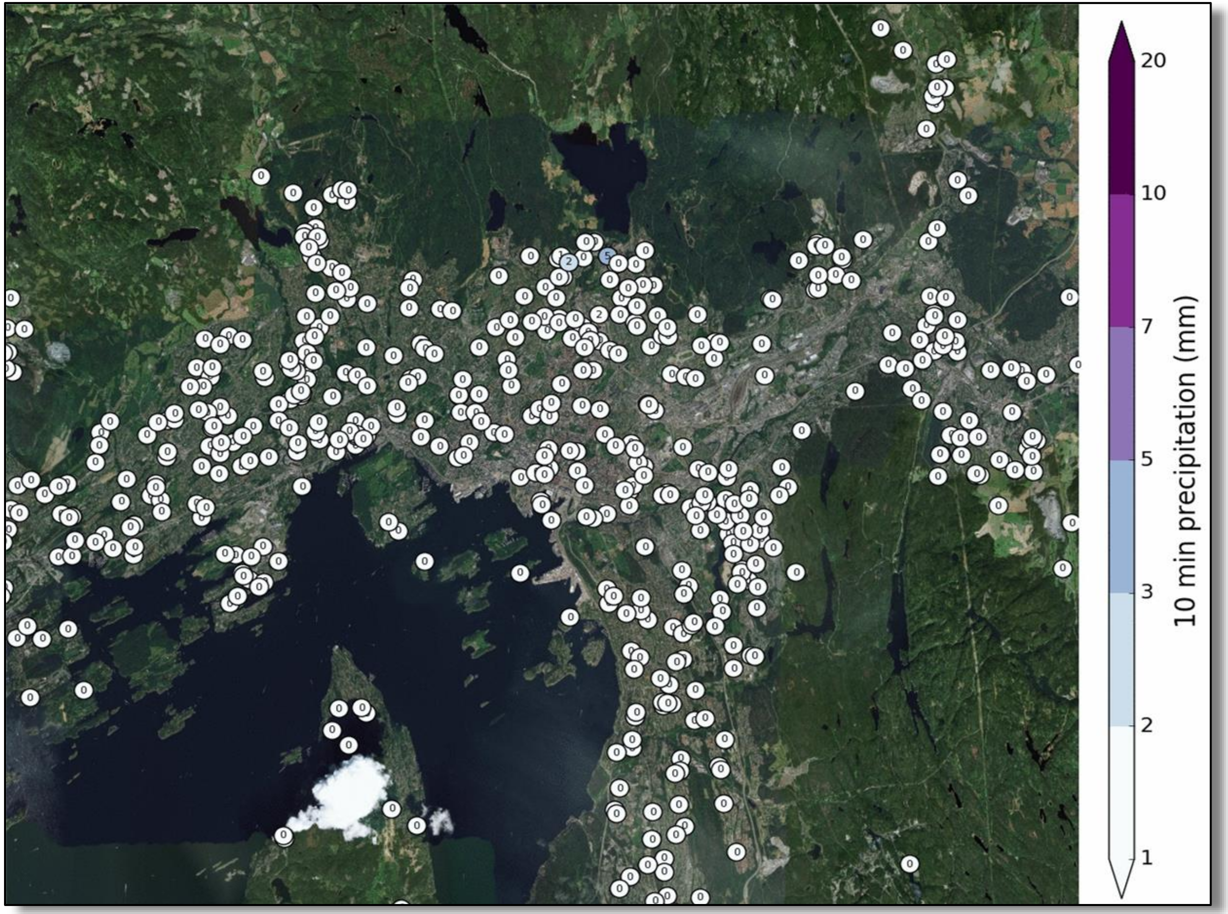
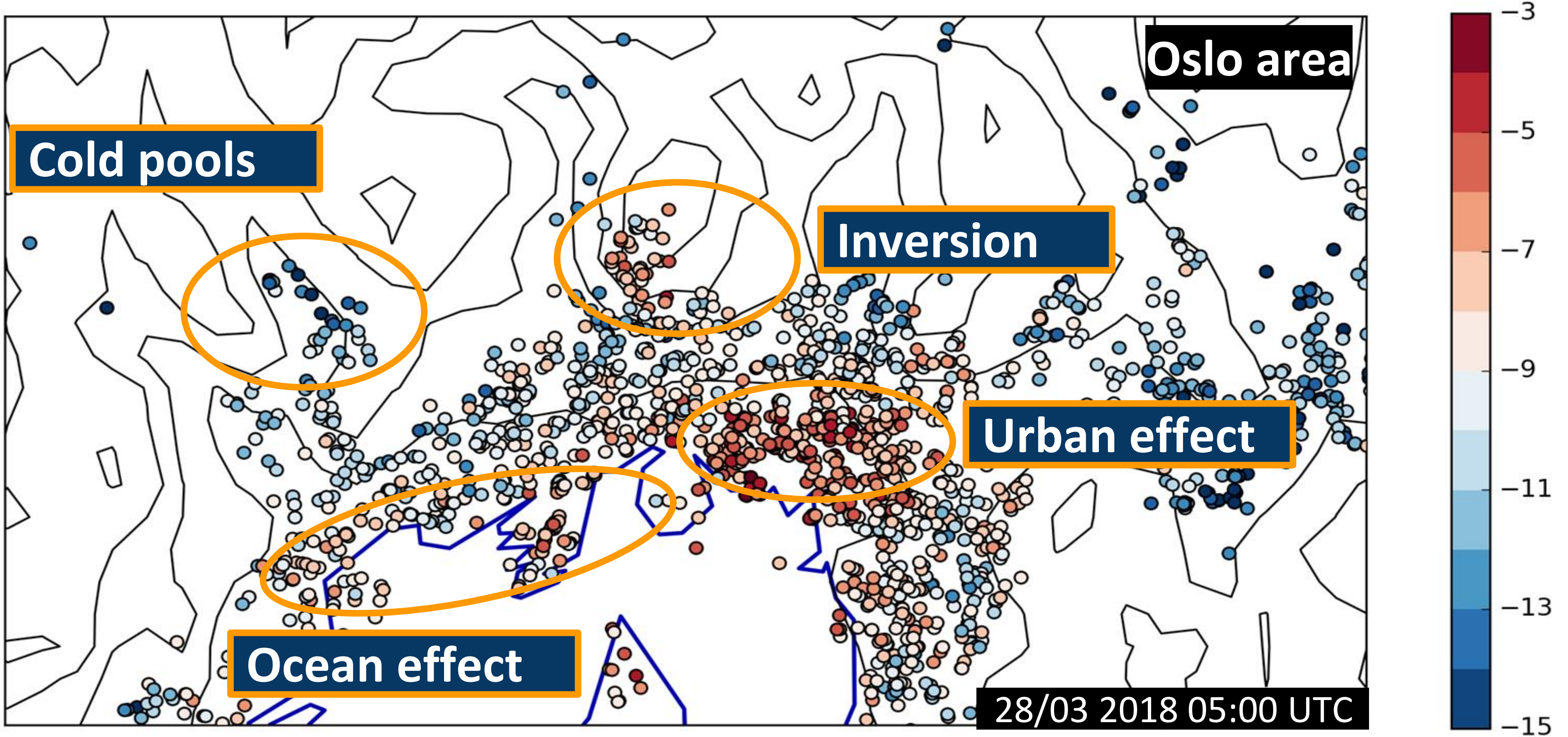
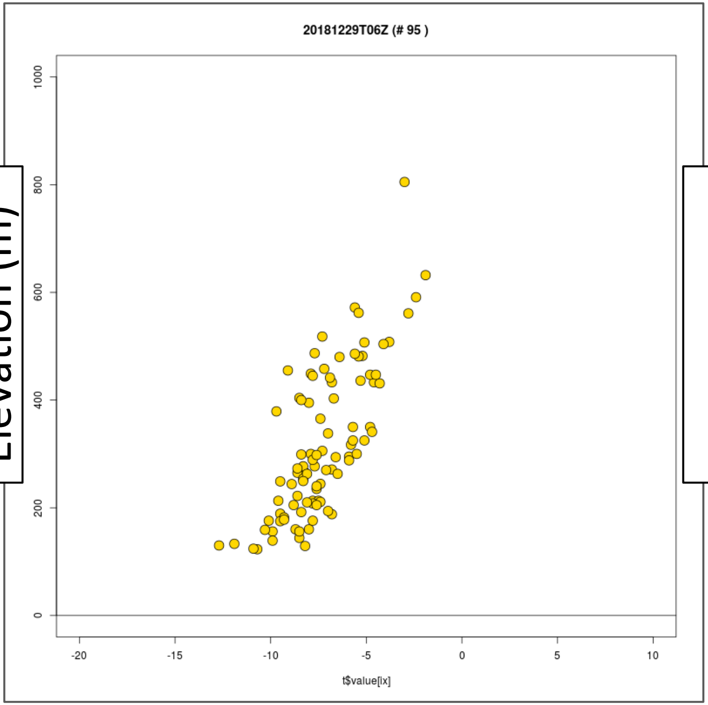


Photo: Audun Braastad / NTB Scanpix

Local weather conditions are better described with more observations

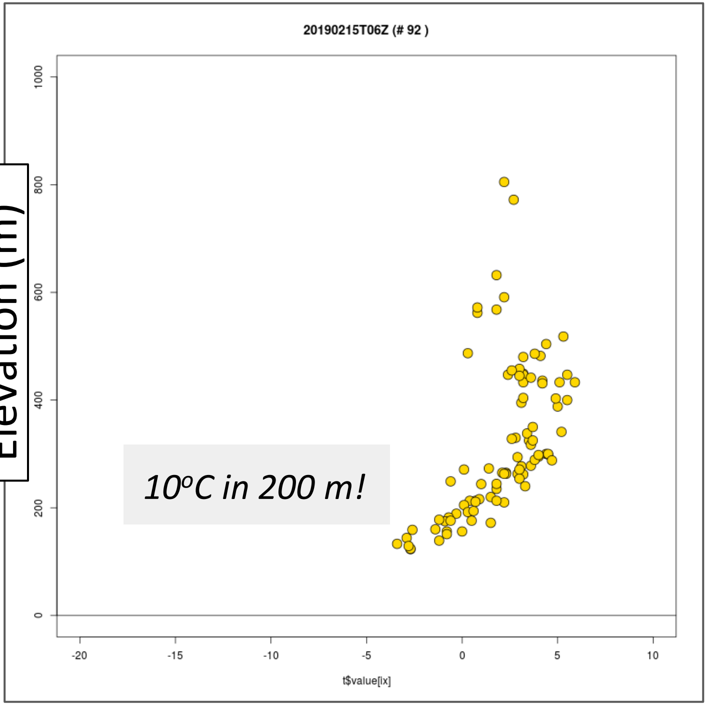


Small-scale processes Temperature inversion in a valley



Elevation (m)

Temperature (°C)

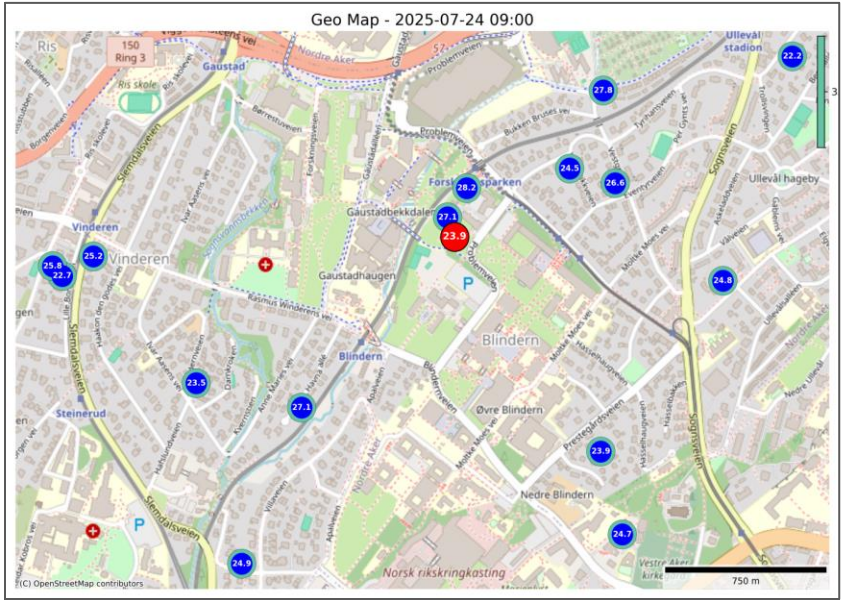


Elevation (m)

10°C in 200 m!

Temperature (°C)

Hourly Temperatures or Precipitation from the nearest observation stations



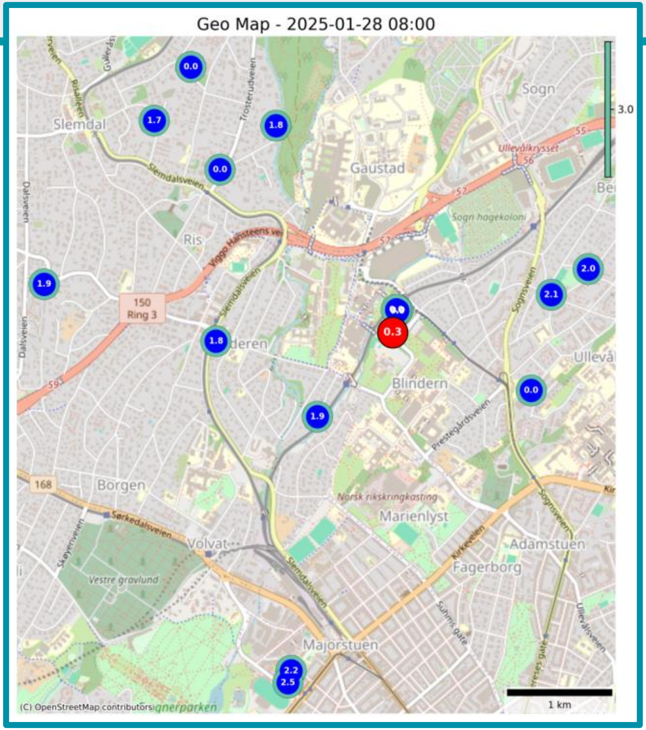
Obs: 27.9 ^{o}C ; Pred: 23.9 ^{o}C. One of the largest deviations

Can we reconstruct a value at a target location (red dot) using data from the 15 nearest stations (gray dots) in a sparse in-situ observational network?

The dataset uses the network of MET Norway stations, plus private stations (Netatmo) in the Fennoscandia region.

Target Application: Automatic Data Quality Control of thousands of observations per hour.

Hourly Temperatures or Precipitation from the nearest observation stations



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The dataset uses the network of MET Norway stations, plus private stations (Netatmo) in the Fennoscandia region.

Target Application: Automatic Data Quality Control of thousands of observations per hour.

Obs: 2.4 mm/h ; Pred: 0.3 mm/h. One of the largest deviations

Probabilistic Predictions from the nearest observation stations

Quantile function as a linear combination
(x=input variables, τ=quantile level):

$$\mathcal{Q}(\tau, x) = \sum_{j=0}^{d} \alpha_j(x) B_{jd}(\tau)$$

Method: Quantile function regression based on neural Networks. All quantiles are modeled simultaneously through a flexible quantile function Q(τ,x).
the regression coefficients $\alpha_j(x)$ vary with the input variables while the basis functions only depend on the quantile level τ.

Basis functions: Bernstein polynomials
(d=degree of the Bernstein polynomials):

$$B_{jd} = \binom{d}{j} \tau^j (1-\tau)^{d-j}$$

j=0,1,...,d

Bremnes, J. B. (2020).
Monthly Weather Review, *148*(1), 403-414.

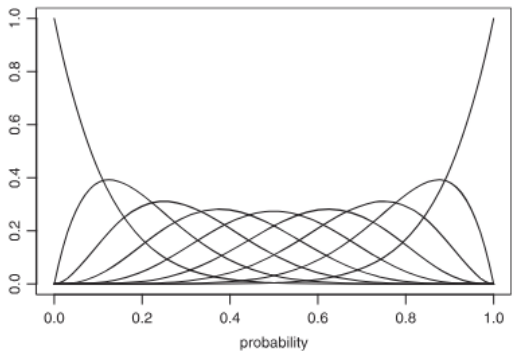
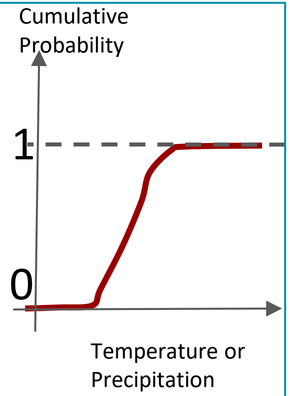


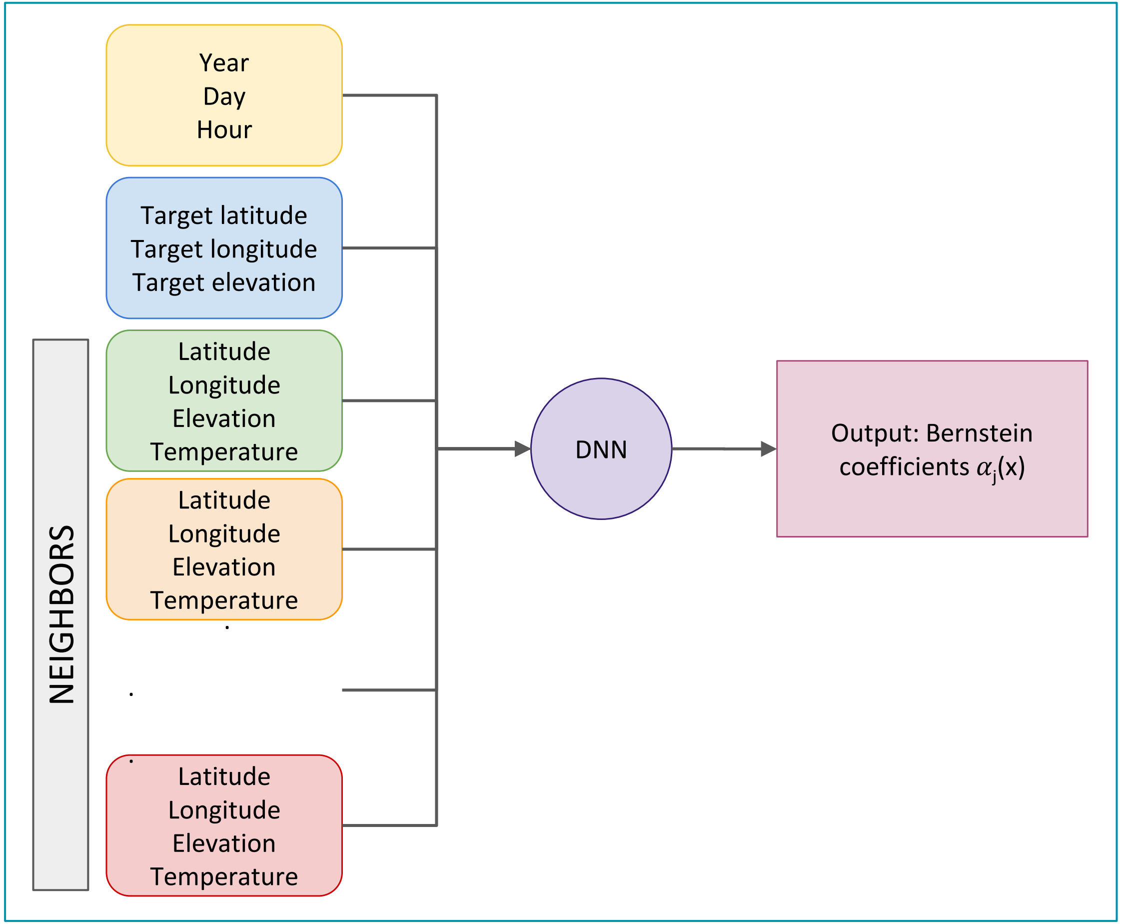
FIG. 2. Bernstein polynomial basis functions of eighth degree.

$* \quad \alpha_j(x) =$

regression coefficients obtained from the DNN



Probabilistic Predictions from the nearest observation stations



Training Setup:

Inputs: 52 features (using 15 neighbors, distances, time encoding)

Layers: 4 fully connected layers with size 128

Outputs: 9, since we limit the linear combination to the 8th Bernstein polynomial

Batch size: 128

Optimizer: Adam

Learning rate: 1e-4

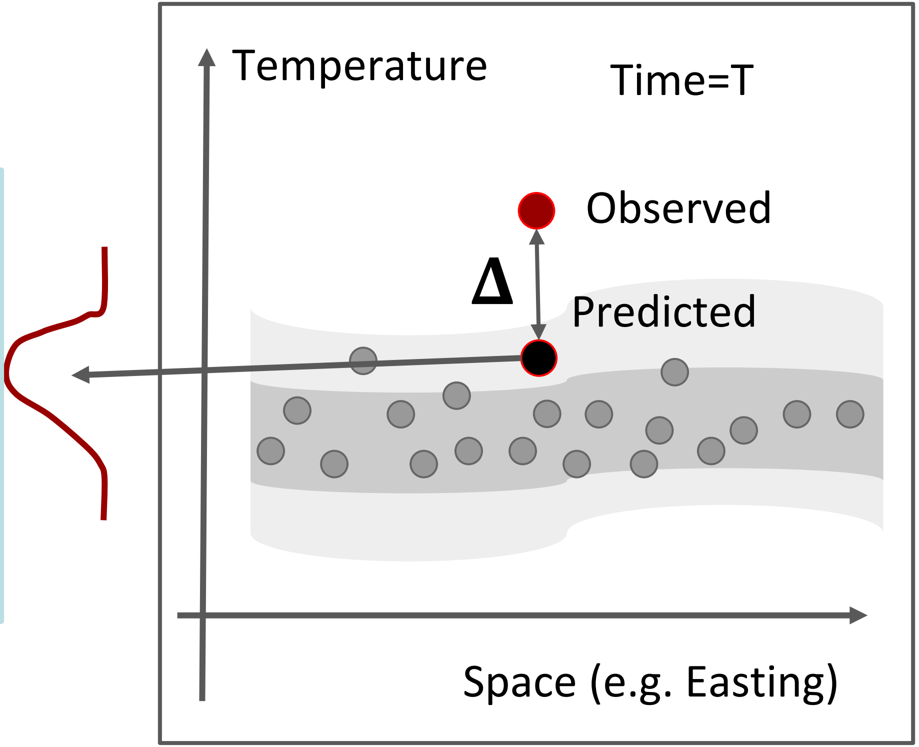
Epochs: 500

Training Strategy: Train one model per month: We might expand later to include multiple/all months

Spatial Consistency Test, current implementation

Step 1

Neural Network with quantile cost function to predict the full distribution of Temperature at a location

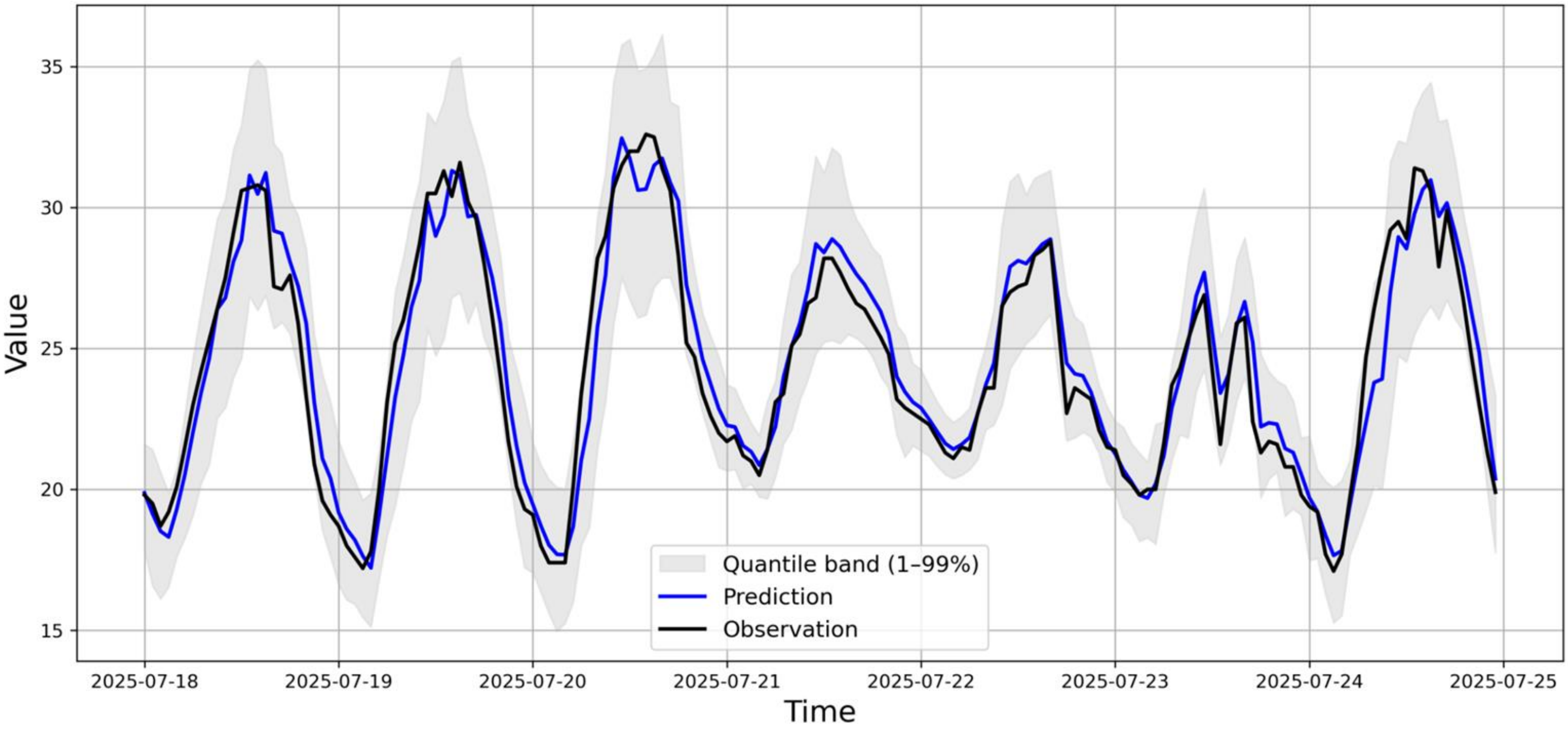


Step 2

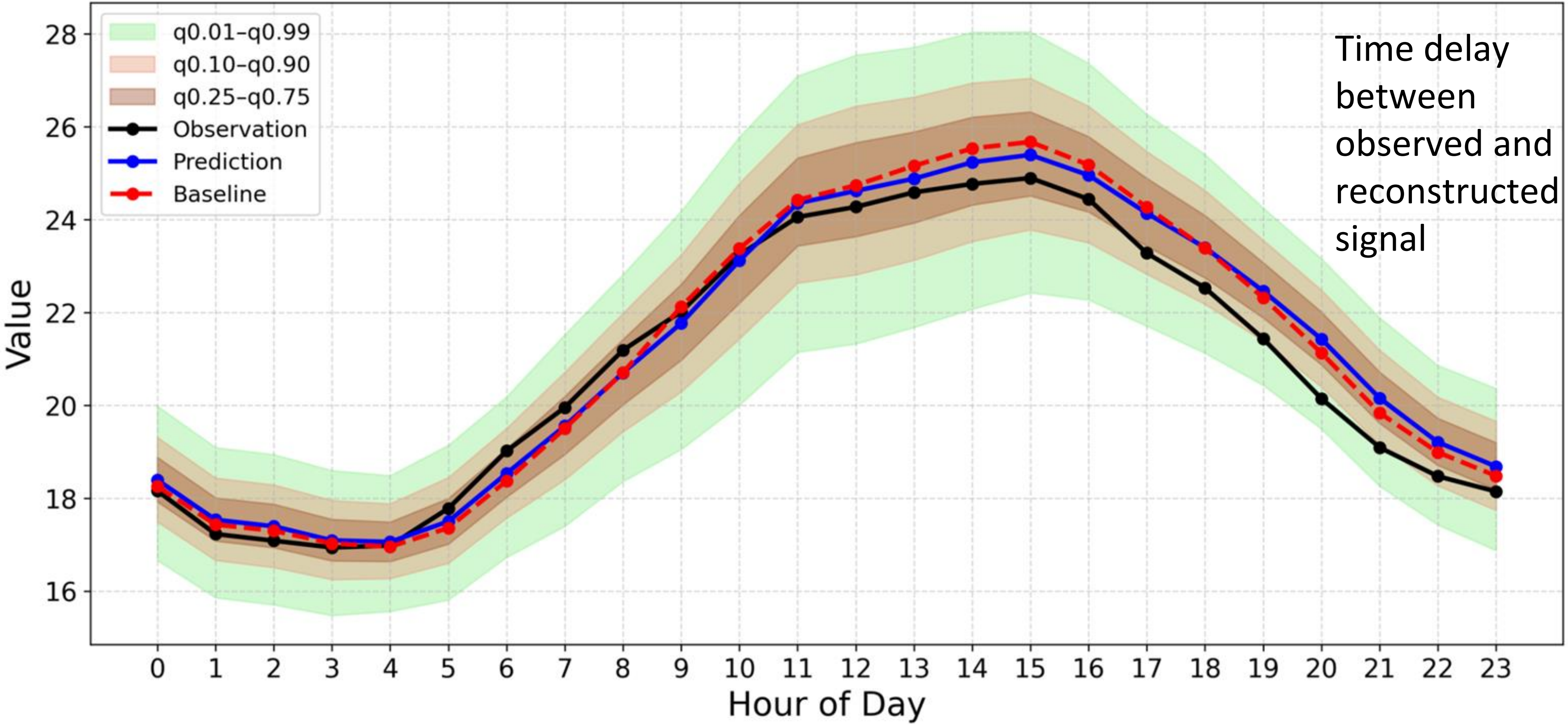
Classification of good/bad observations by choosing thresholds based on quantiles of the predicted temperature probability distributions (as done by *Alerskans et al. 2022*)

Hourly Temperature

Example: Oslo time series (July 2025)

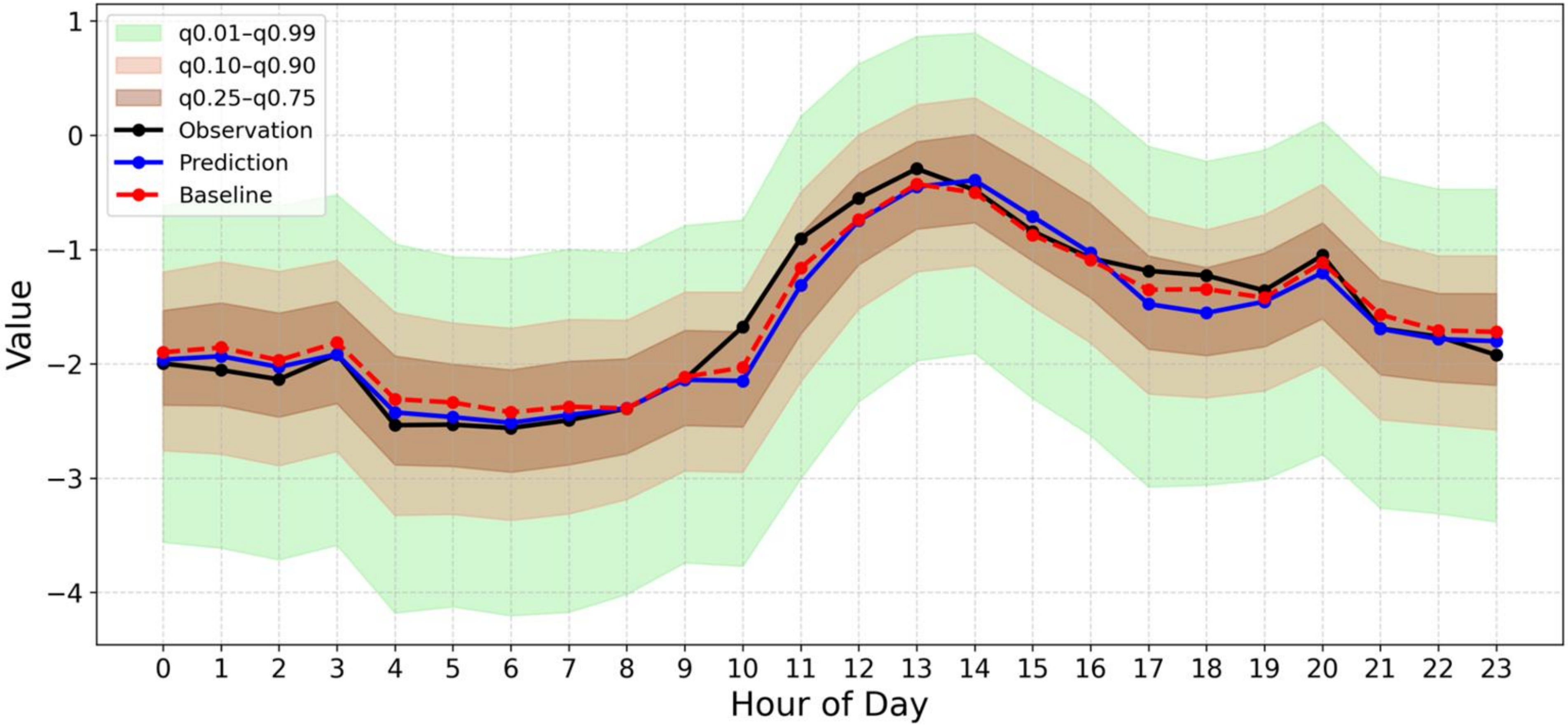


Oslo typical day (July)

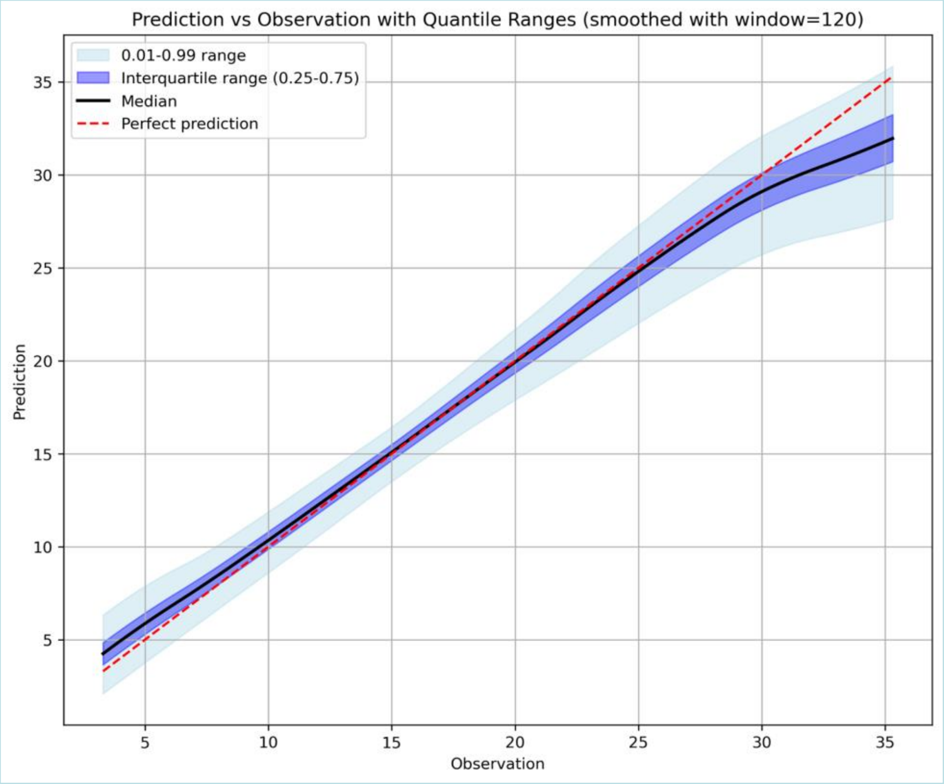


Time delay between observed and reconstructed signal

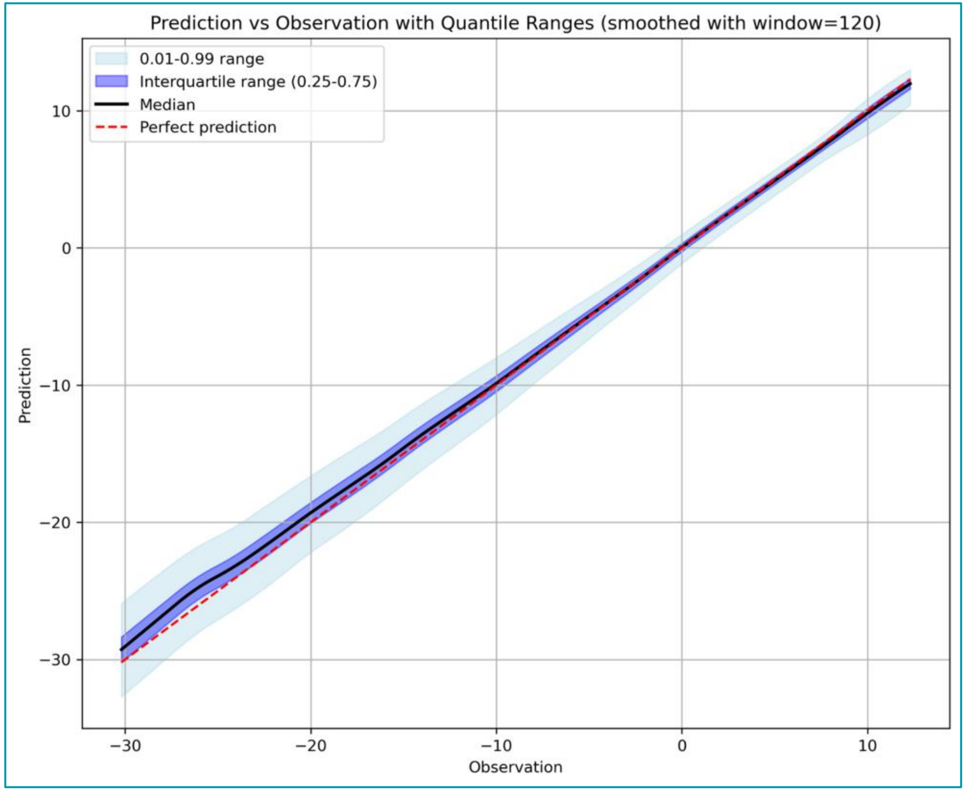
Oslo typical day (January)



Predicted versus Observed with quantile ranges

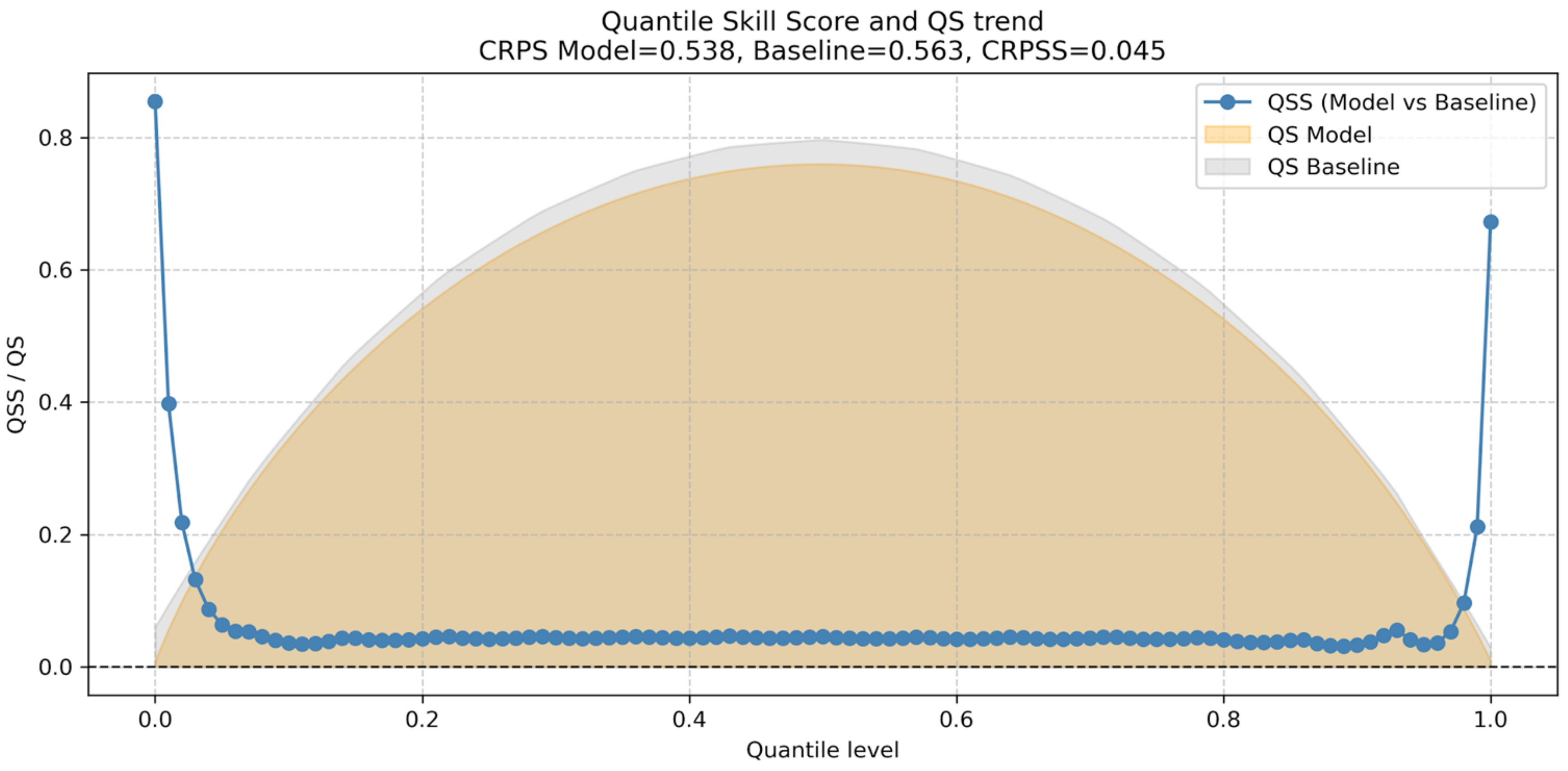


Summer 2025



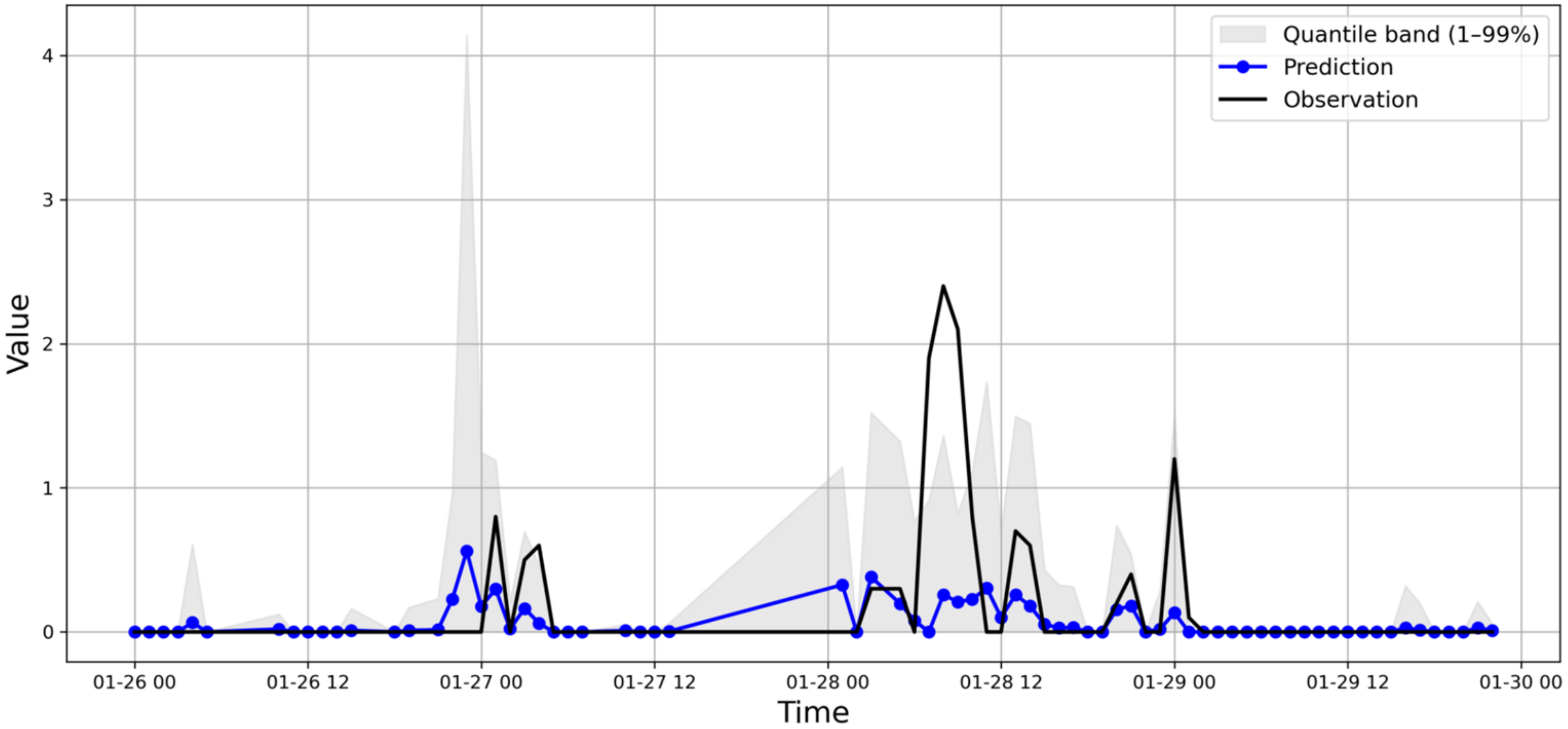
Winter 2025

Temperature: Quantile Skill Score



Hourly Precipitation

Oslo: january precipitation time series



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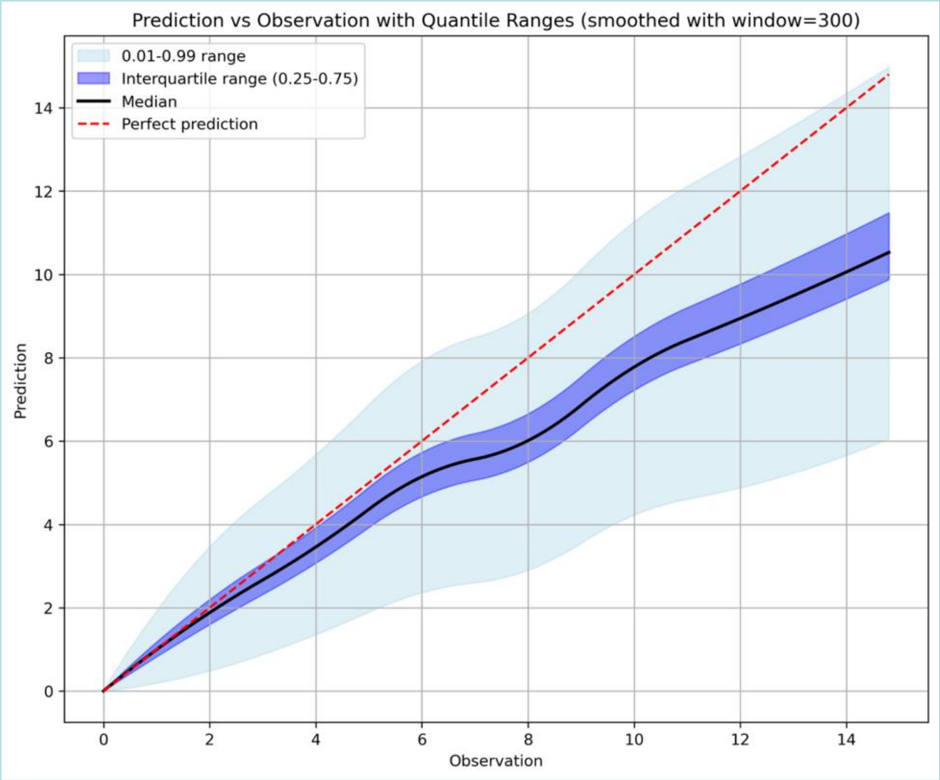

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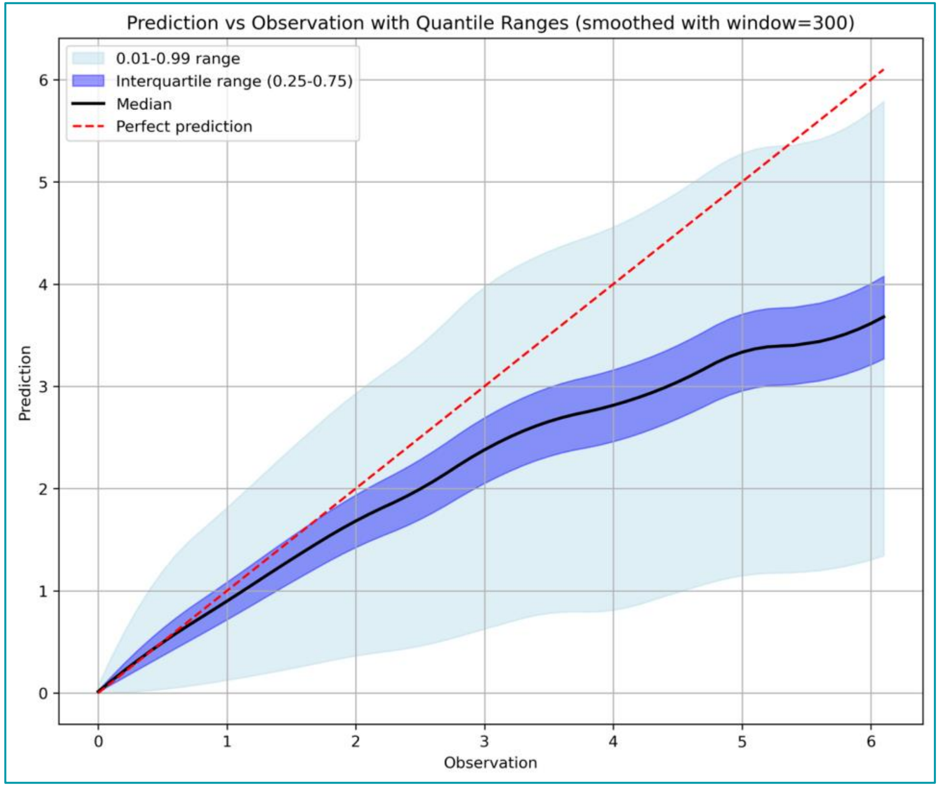
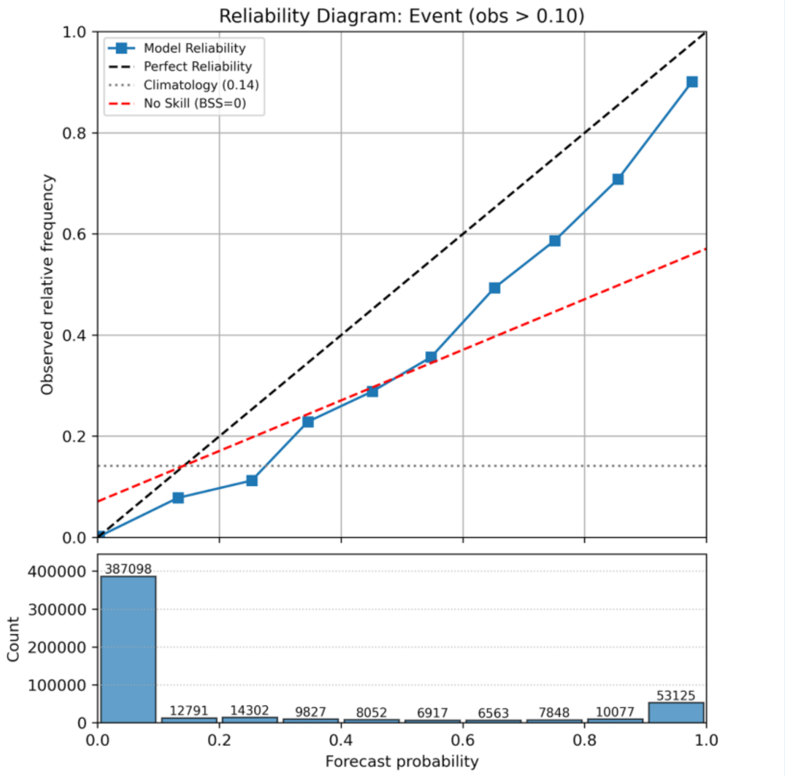
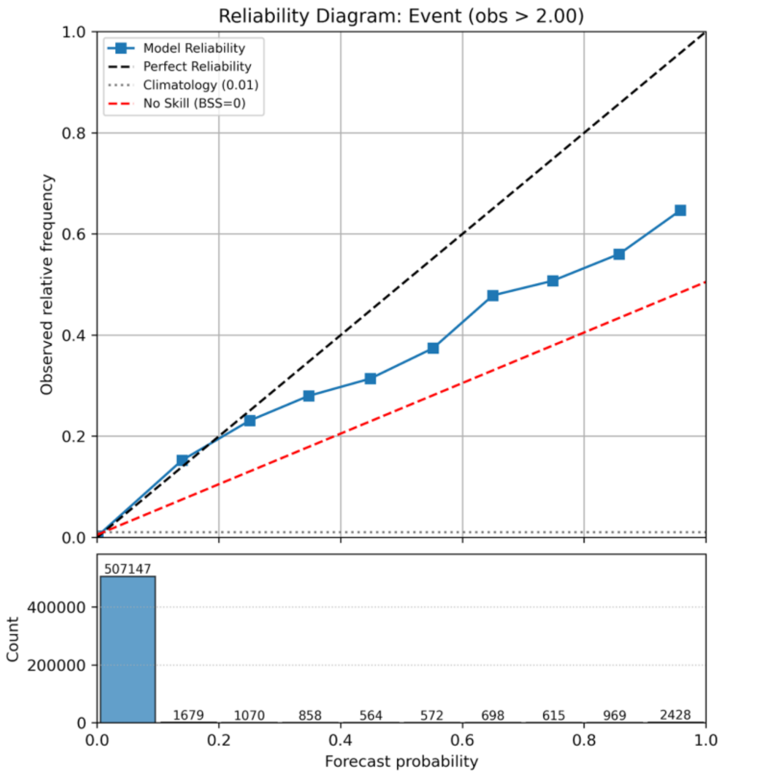


Winter 2025

Reliability Diagrams January 2025





Conclusions

Preliminary Results

- We use a method for probabilistic predictions using a deep neural network. It can predict several near-surface atmospheric variables and has been well tested in post-processing numerical model output.
- For temperature, the probabilistic predictions are useful for data quality control, even when using only a few input datasets such as the closest neighbours.
- For precipitation, additional context information is likely needed, for example from reanalysis data.
- In the future, we plan to use probabilistic predictions for automatic data quality control and explore how to select thresholds based on estimated distribution quantiles.