

# Forecasting the error: a statistical postprocessing approach

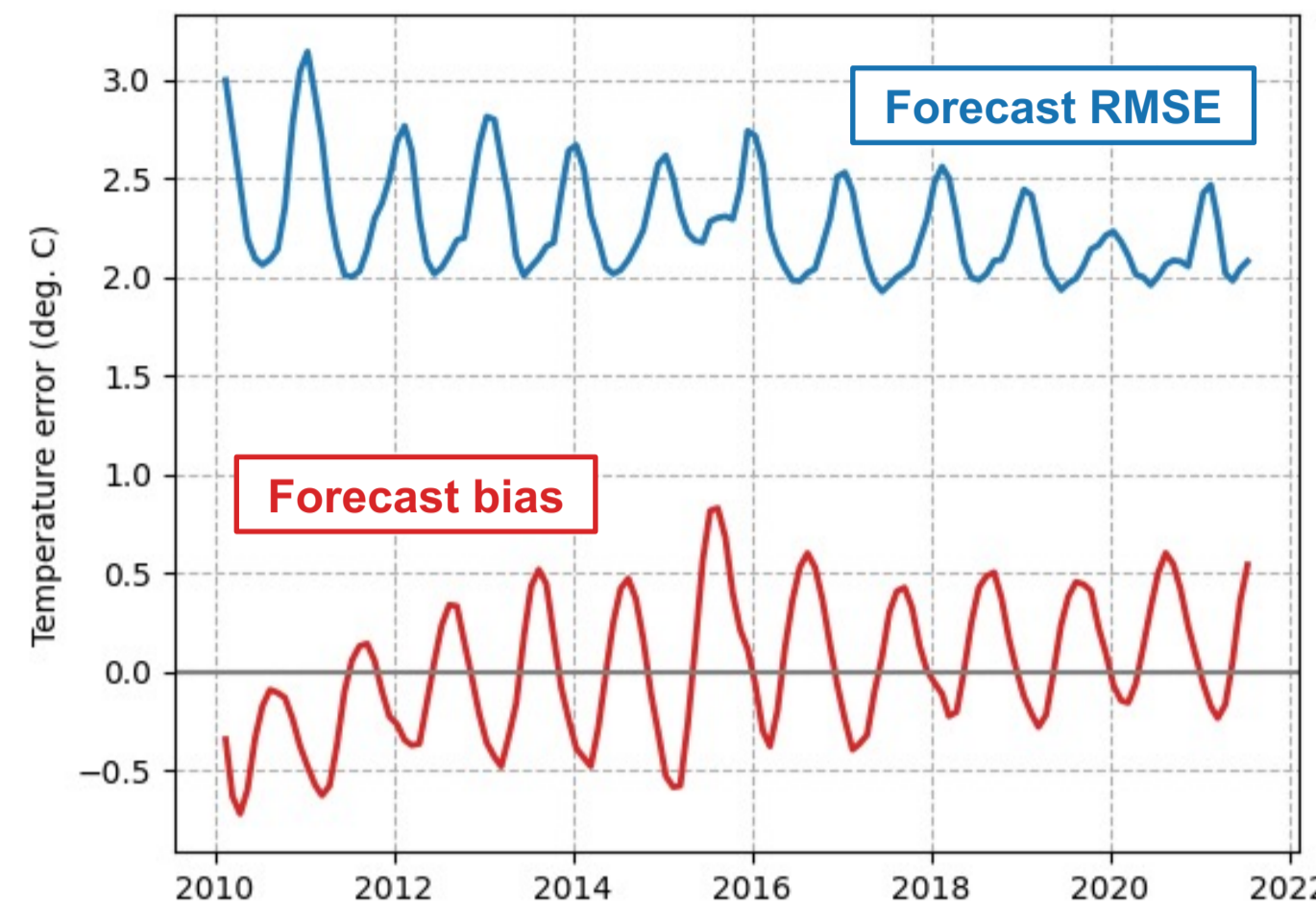
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## Systematic errors in IFS

Long-standing biases affect the operational medium-range forecasts of **2m temperature** as illustrated here aside.

Numerical weather prediction systems like IFS struggle in producing **bias-free forecasts** of near-surface variables (such as temperature, wind, ..), even at short lead times.

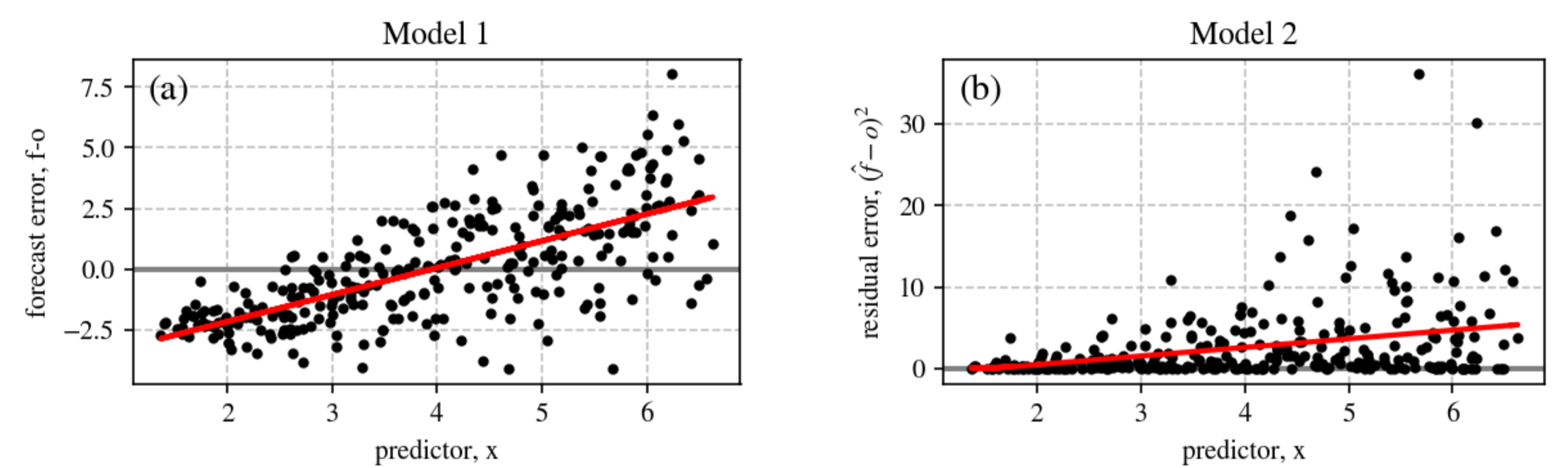


Can statistical postprocessing based on ML be part of the solution?

- **Statistical postprocessing:** "Learning from past errors to correct current forecasts"
- **Machine learning (ML):** set of state-of-the-art tools for training statistical models and making predictions based on large datasets.

## 2 Models

A **synthetic example** using linear regression: the forecast error (*forecast-observation*) is expressed as a function of a predictor  $x$ . **Model 1** provides the best estimate of the error as a function of  $x$  (red line). The residual error corresponds to the squared distance between the red line and the black dots. As a second step, **Model 2** is built to capture the residual error as a function of the predictor  $x$ .

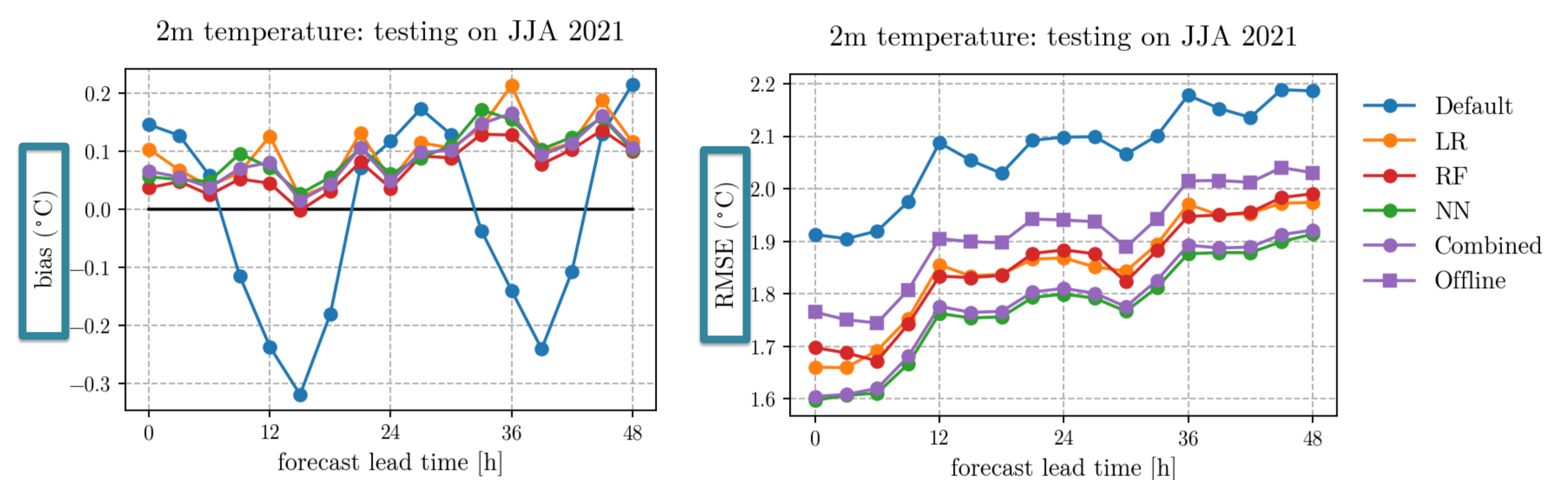


➤ Model 1: **forecast correction**, Model 2: **uncertainty quantification**.

## Testing, comparing, and combining ML models

ML models are trained to predict **situation-dependent bias** and uncertainty of the high-resolution IFS global forecasts. **Input:** forecast error and corresponding predictors from around the globe following a global approach. **Output:** statistical models able to deliver postprocessed forecasts **at any points on the globe**.

- **LR:** linear regression
- **RF:** random forest
- **NN:** neural network
- **Combined:** a combination of the 3 above-mentioned models
- **Offline:** state-independent predictors only (orography, day of the year,...)



## Predictor selection and model interpretability

**Predictor selection** involves:

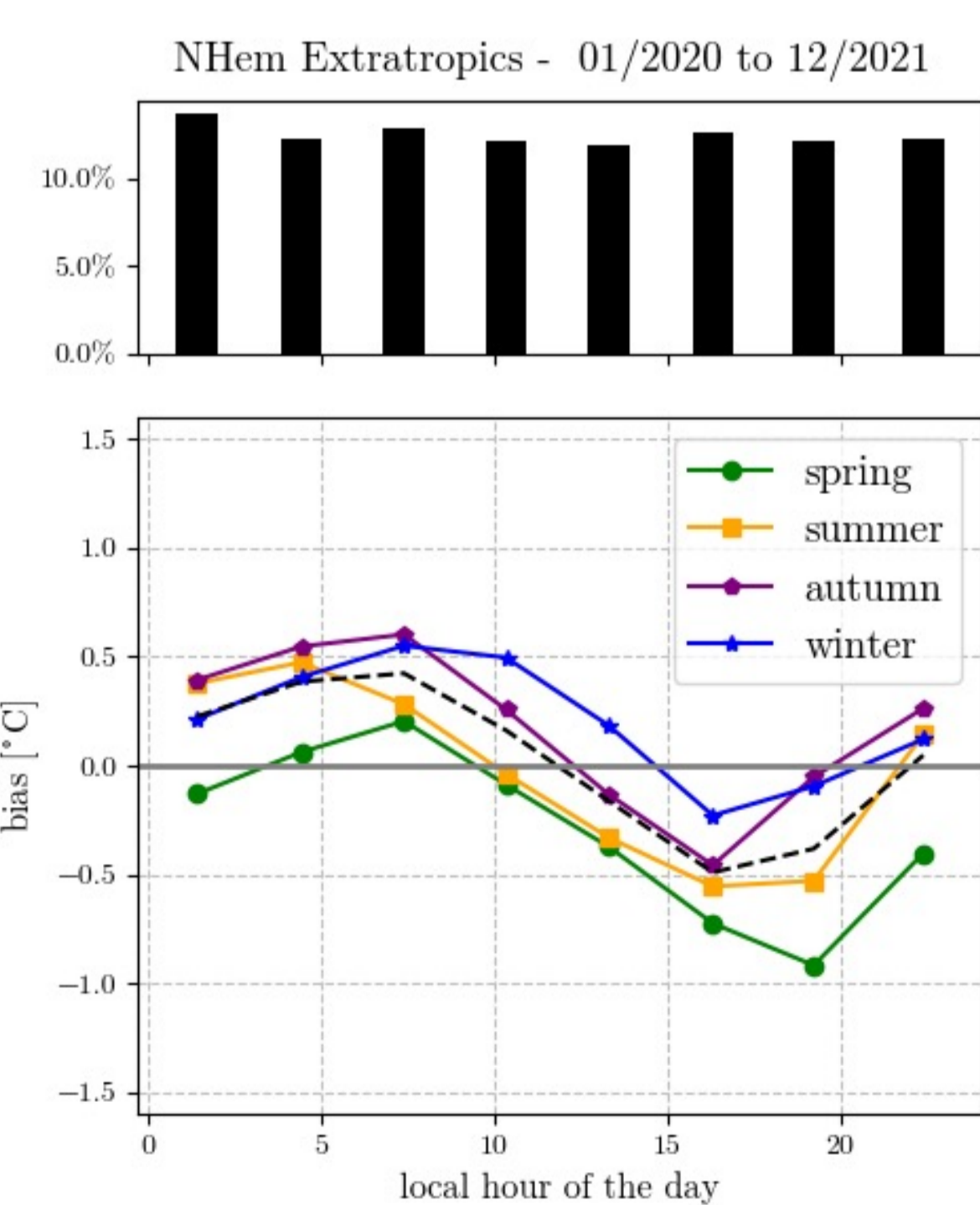
- domain expert knowledge
- literature review
- statistical techniques
- a lot of testing
- ...

**Model interpretability** is based on:

- predictor importance
- backwards stepwise selection
- estimation of predictor variation impact on predictions
- ...

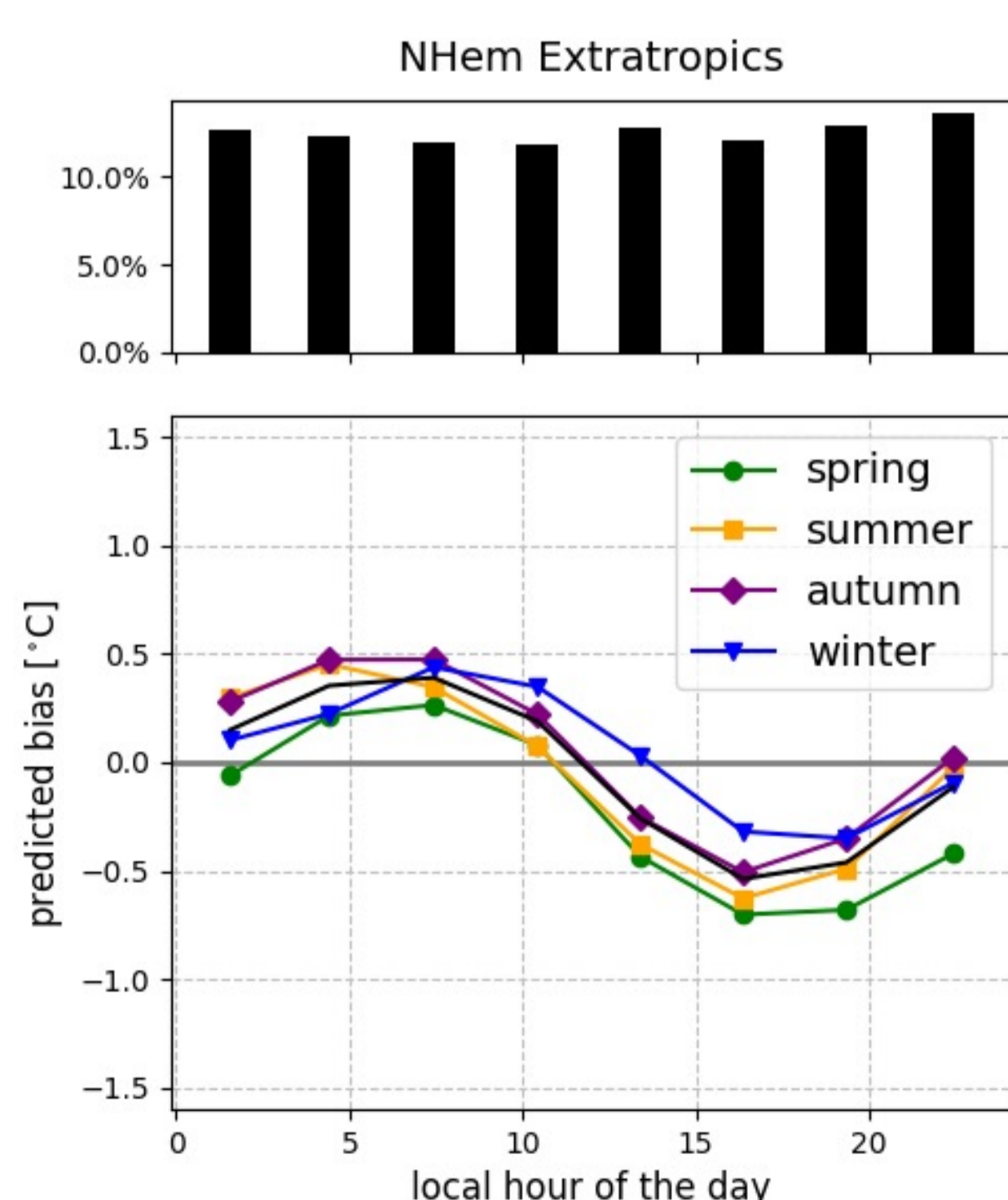
**Conditional Verification Plot**

➤ helps model error diagnosis and can motivate choice of predictors



**Partial Dependence Plot (PDP)**

➤ shows the (marginal) effect a covariate has on the predicted outcome



observed bias

ML-modelled bias

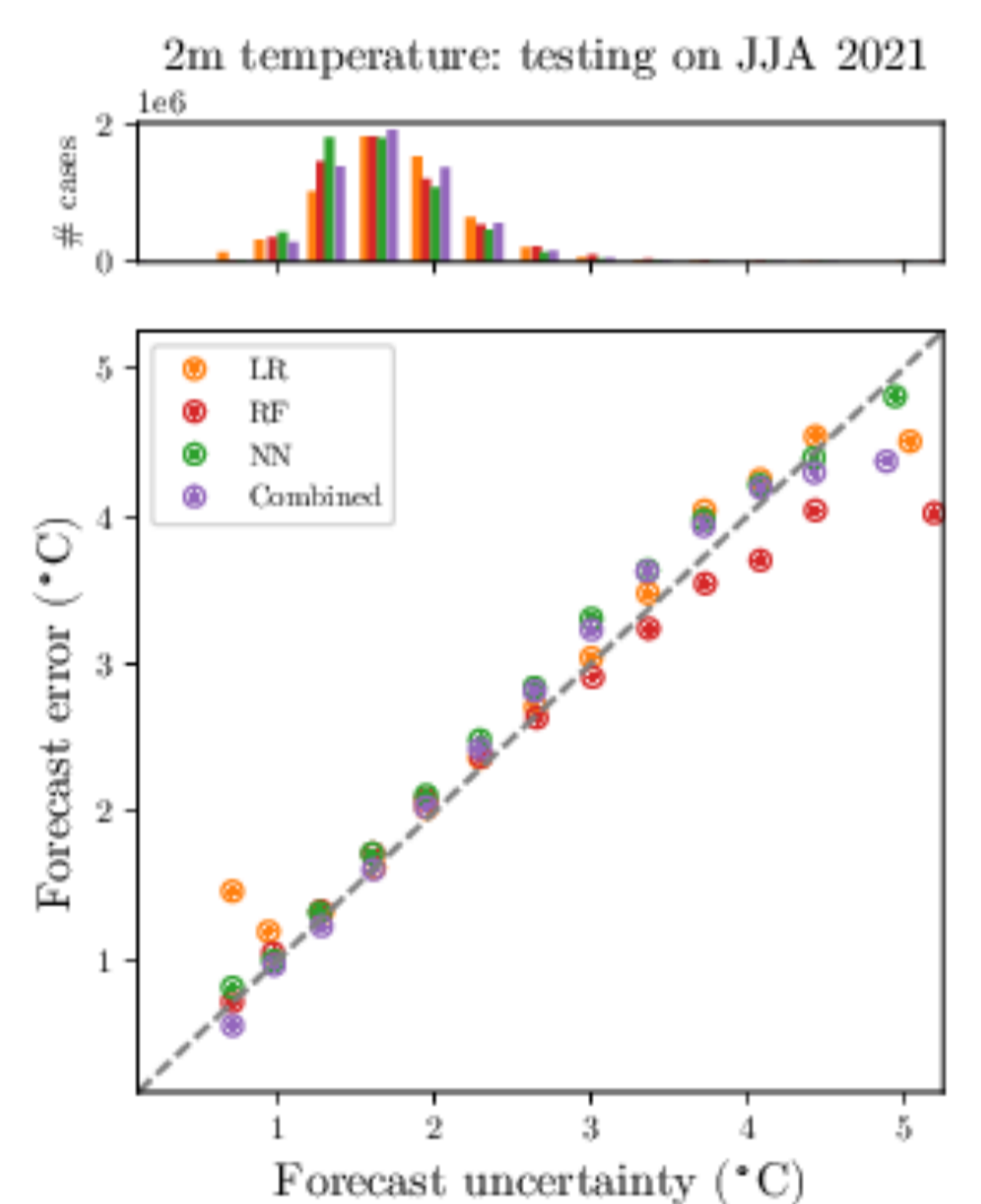


Benefit from similarities between **verification tools** and **ML interpretability tools** to build trust in ML-solutions.

## Forecast reliability

**Statistical consistency** between predicted forecast uncertainty and actual forecast error is called **reliability**. This forecast attribute is tested using **reliability plots**.

➤ **Fig.:** the forecast uncertainty (x-axis) corresponds to the square root of the residual error prediction, the actual forecast error (y-axis) corresponds to the RMSE of the bias-corrected forecast. Perfect reliability is indicated with a dashed diagonal line. The histogram shows the number of cases in each forecast uncertainty category.



## Key findings

- **Postprocessed forecasts accuracy** does not depend so much on the choice of the ML method but more crucially on the selection of predictors, the size of the training/test datasets, and the quality control applied to the data.
- **ML-based solutions** for forecast postprocessing exist with different levels of complexity in terms of practical implementation. **State-independent postprocessing** configurations that only rely on predictors available before the start of the forecast are simple to implement and easy to maintain.
- Good performance of statistical models for **uncertainty quantification** opens new horizons for the generation of calibrated probabilistic weather forecasts based on statistical models.

## More results?

Ben Bouallegue Z, Cooper F, Chantry M, Düben P, Bechtold P, Sandu I, 2022. Statistical modelling of 2m temperature and 10m wind speed forecast errors. ECMWF Tech. Memo. 896.

