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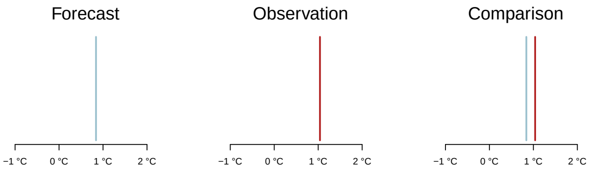
Remember the past: A comparison of time-adaptive training schemes for non-homogeneous regression

Moritz N. Lang, Sebastian Lerch, Georg J. Mayr, Thorsten Simon, Reto Stauffer, and Achim Zeileis

Probabilistic forecasting

Point forecast



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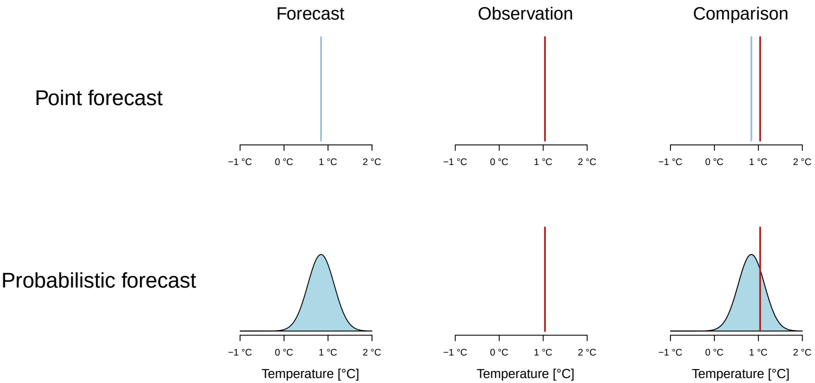
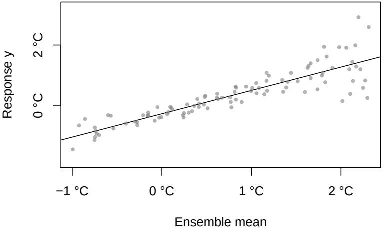


- Probabilistic forecasts quantify the uncertainty of the predictions.
- Aims: Calibration and sharpness.

Non-homogeneous or distributional regression



- Response y is assumed to follow a predefined parametric distribution, e.g., normal distribution.
- The two distribution parameters location and scale are expressed by a **linear function of covariates** $x_1 \dots x_{(k+l)}$:

$$y \sim \mathcal{N}(\mu, \sigma)$$

$$\mu = \beta_0 + \beta_1 \cdot x_1 + \dots + \beta_k \cdot x_k$$

$$\log(\sigma) = \gamma_0 + \gamma_1 \cdot x_{(k+1)} + \dots + \gamma_l \cdot x_{(k+l)}$$

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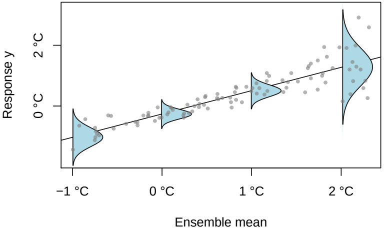

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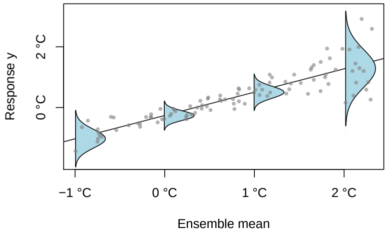

- Response y is assumed to follow a predefined parametric distribution, e.g., normal distribution.
- The two distribution parameters location and scale are expressed by the **ensemble mean** *m* and **ensemble standard deviation** *s* of the corresponding NWP of the response:

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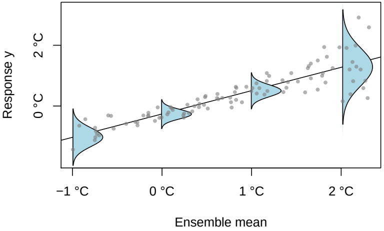

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$\Rightarrow$ **How to account for seasonally varying regression coefficients?**

Time adaptive training schemes

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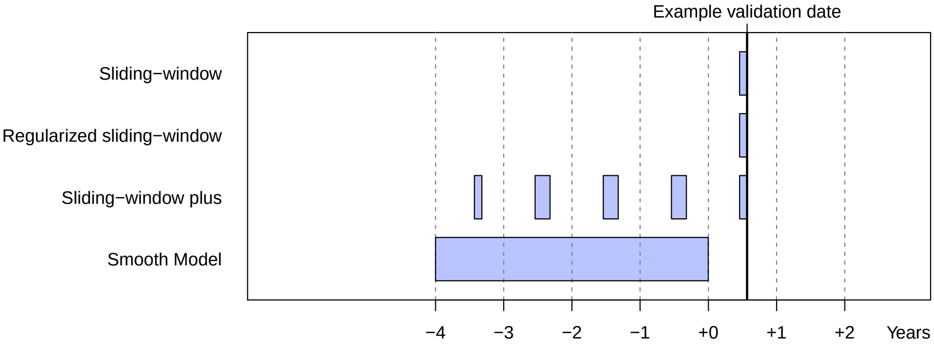
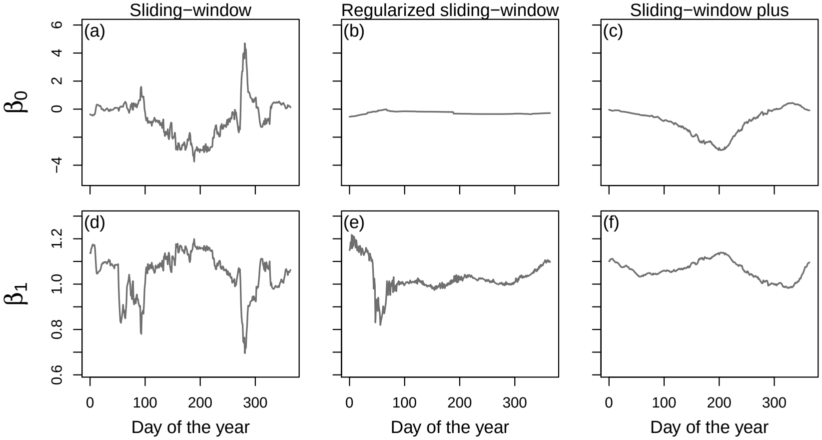
- **Regularized sliding-window** adds regularization in model estimation.
- **Sliding-window plus** uses $2n$ days centered around the same calendar day over all previous years for model training.
- **Smooth model** uses all available days for model training by allowing coefficients to smoothly evolve over the year.

Time adaptive training schemes



Surface temperature forecasting

Location parameter



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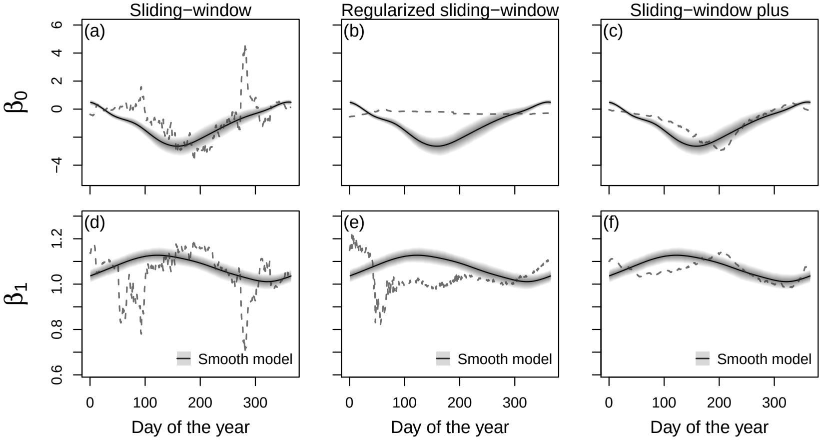
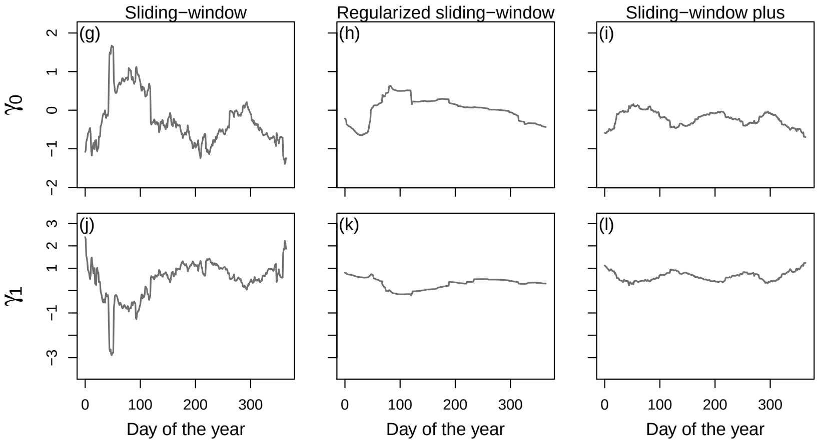


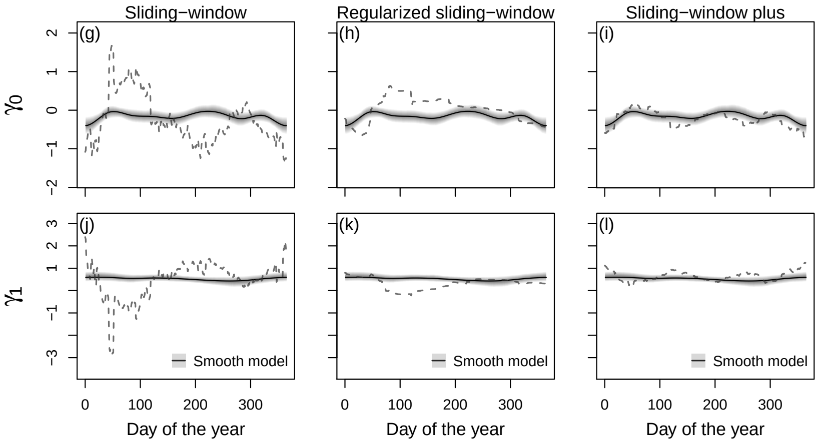
Surface temperature forecasting

Scale parameter



Surface temperature forecasting

Scale parameter



Surface temperature forecasting

Validation setup

Response:

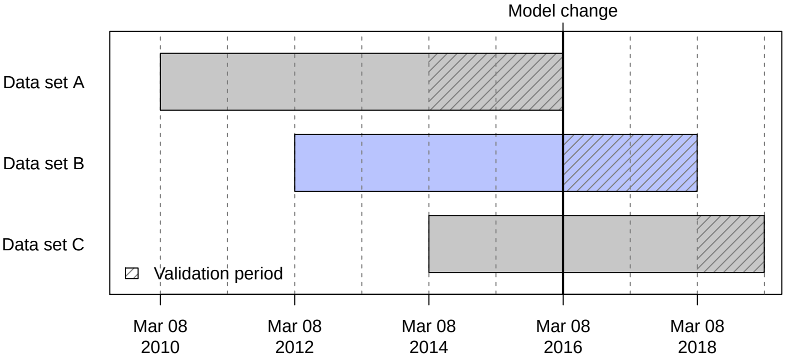
- 2 m temperature forecasts at five weather stations located in the plain of northern Germany.

Covariates:

- Ensemble mean m and the ensemble standard deviation s of bilinearly interpolated 2 m temperature forecasts issued by the ECMWF.
- Considered forecast steps from $+12$ to $+72$ h, at a 12-hourly temporal resolution (00:00 UTC run).

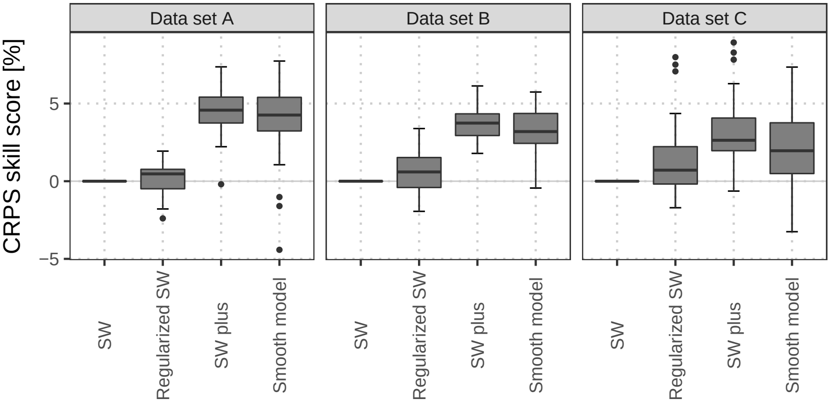
Surface temperature forecasting

Validation setup



Surface temperature forecasting

Validation results



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- In case of certain ensemble model changes, using multiple years of training data is still superior to the classical sliding-window approach.
- Reducing the variance of the regression estimates appears to be more important than adjusting rapidly for changing forecast biases.

References

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