Non-stationary bias in climate predictions

6th Climateurope Webinar

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Introduction

- bias *adjustment*
  - we do not know the truth
  - assume bias of observation/reanalysis to be smaller than bias of prediction model

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  - assume bias of observation/reanalysis to be smaller than bias of prediction model
- deviation between model and observation

Bias adjustment is important

- for comparison between model and observation
- to reduce uncertainty
- to enhance prediction skill
- communication

Difference of "observations" and "model"

- random data

- black: "observations"
- red: "model"

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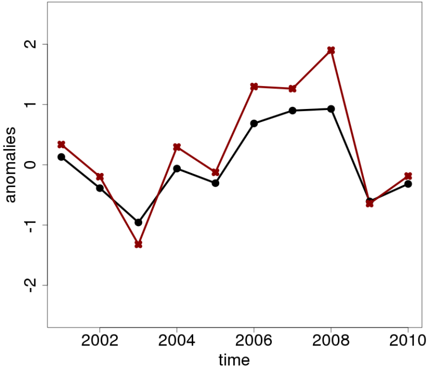
time series



Difference of "observations" and "model"

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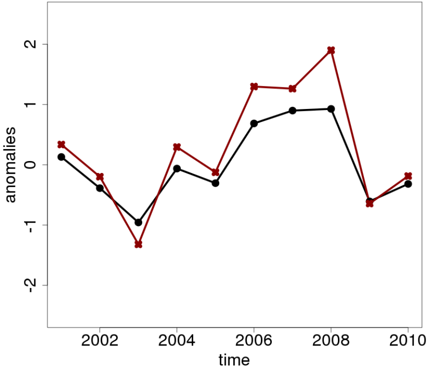
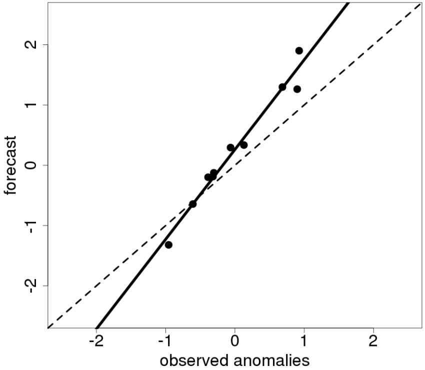
time series



scatter plot



mean bias adjustment

- random data
  - black: "observations"
  - red: "model"

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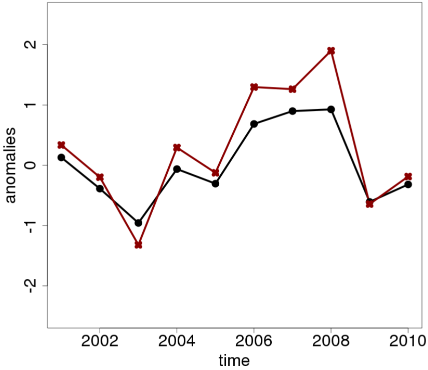

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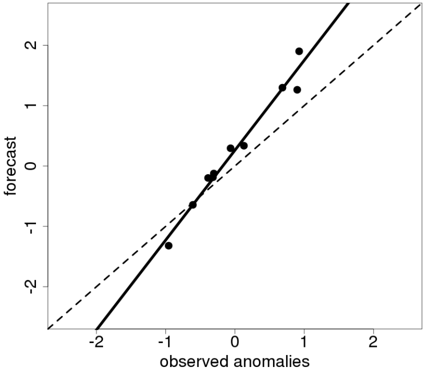
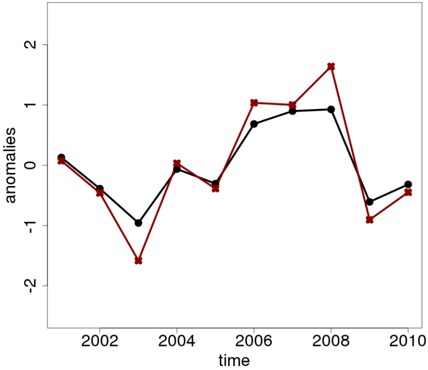


$$\hat{f}(t) = \alpha + f(t)$$

mean bias adjustment

- random data
  - black: "observations"
  - red: "model" (mean bias adjusted)

time series



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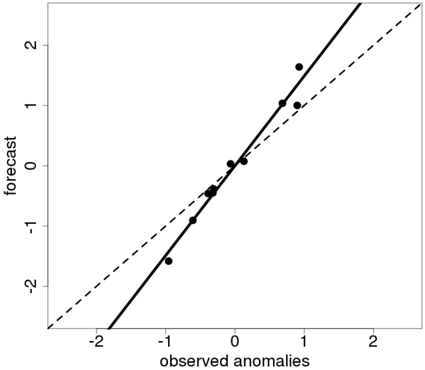
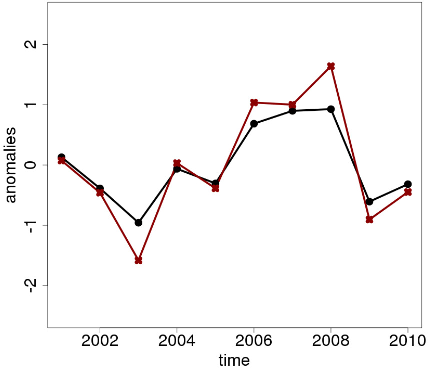


$$\hat{f}(t) = \alpha + f(t)$$

conditional bias adjustment

- random data
  - black: "observations"
  - red: "model"

time series



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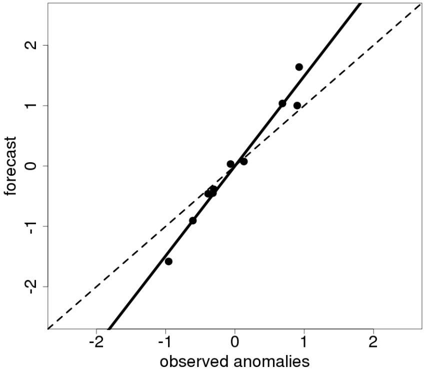
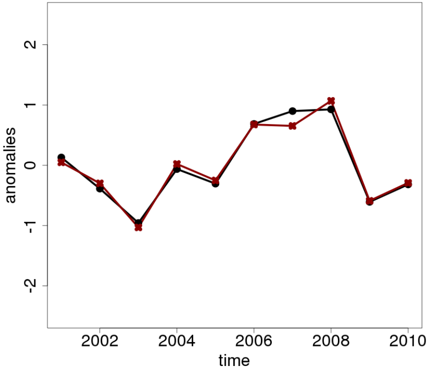


$$\hat{f}(t) = \alpha + \beta f(t) \qquad \text{(assuming normal distribution)}$$

conditional bias adjustment

- random data
  - black: "observations"
  - red: "model" (conditional and mean bias adjusted)

time series



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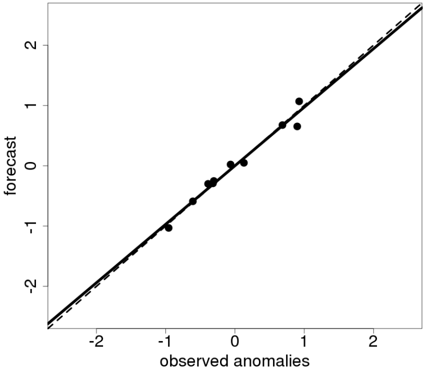

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bias depends on lead time: drift

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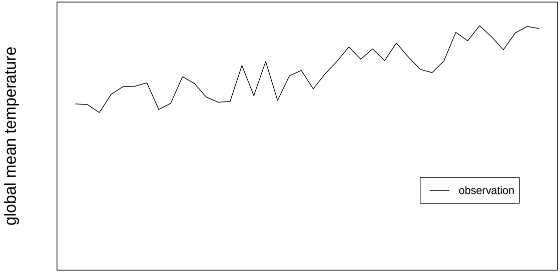

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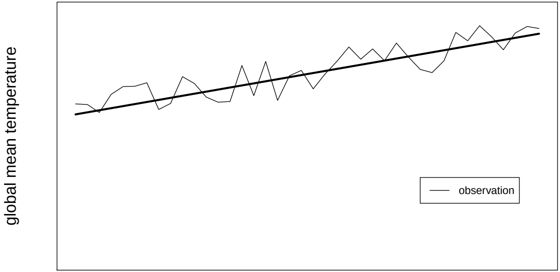

- random data
- linear trend

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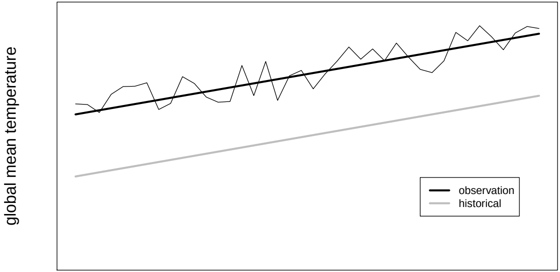

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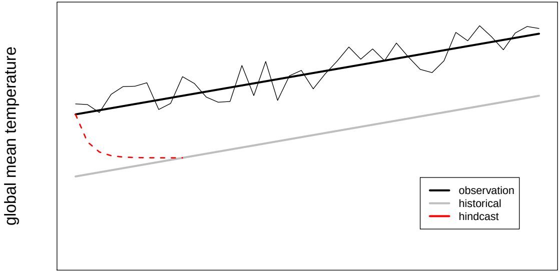

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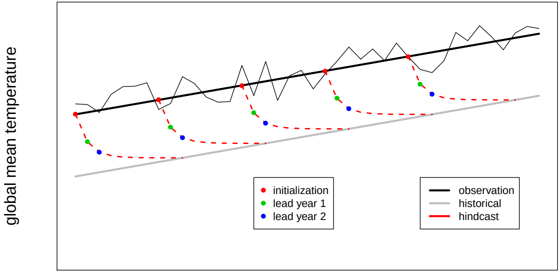

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  - $\partial b / \partial \tau \neq 0$
  - drift

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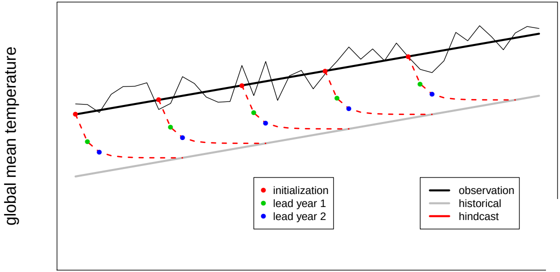

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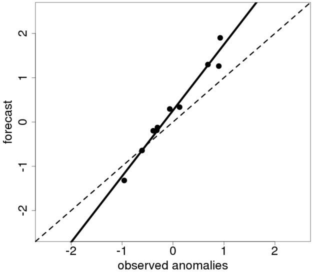
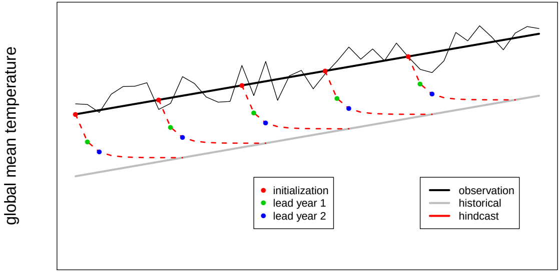


Climate prediction $\rightarrow$ initialization

bias depends on lead time: drift



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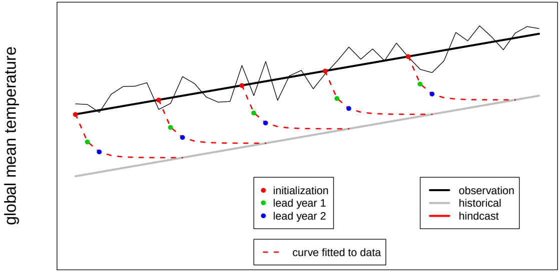
Climate prediction → initialization

bias depends on lead time: drift



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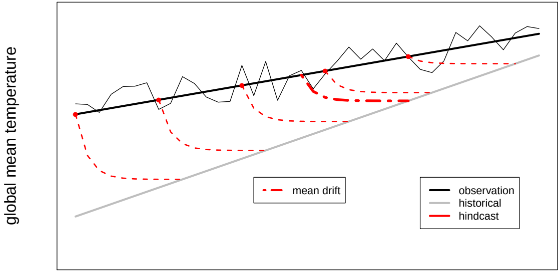
Climate prediction $\rightarrow$ initialization

bias depends on lead time: drift



- random data
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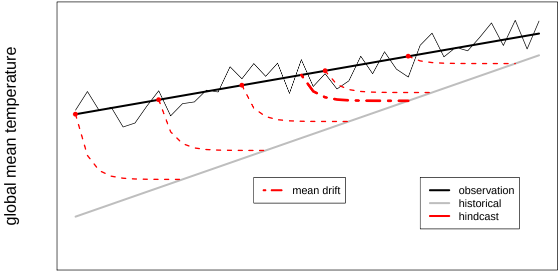
- fit curve to $b(\tau)$: parametric approach
- α and β can also depend on initialization time t

Anomaly initialization



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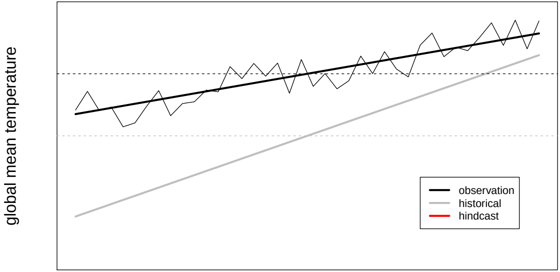

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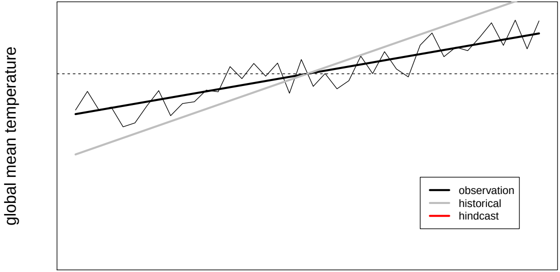
Anomaly initialization



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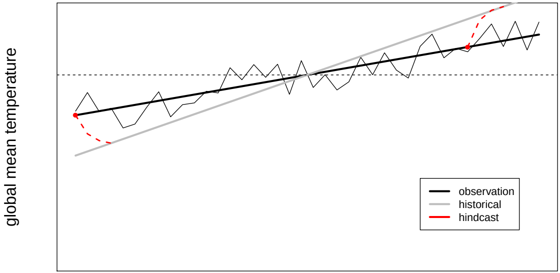
Anomaly initialization



- random data
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- model run with external forcing
- initialized decadal forecast (anomaly)

- Idea: model stays at its climate state
- different climatology of model and observations
- using anomalies for initialization
- nevertheless, there can be a drift
  - no mean drift
  - different drift for different initialization times

Bias adjustment: dependency on (τ, t) I

separate trend adjustment for each lead time: non-parametric

- Kharin et al. [2012]
- Fučkar et al. [2014]

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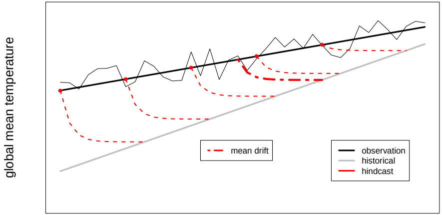
parametric approach: $\alpha(\tau, t)$ [Kruschke et al., 2015]

$$\begin{aligned}\alpha(\tau, t) &= a_0(t) + a_1(t)\tau + a_2(t)\tau^2 + a_3(t)\tau^3 \\ &= (b_0 + b_1 t) + (b_2 + b_3 t)\tau + (b_4 + b_5 t)\tau^2 + (b_6 + b_7 t)\tau^3\end{aligned}$$



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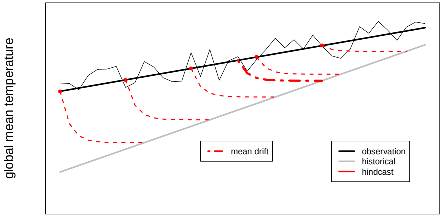
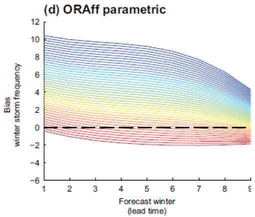
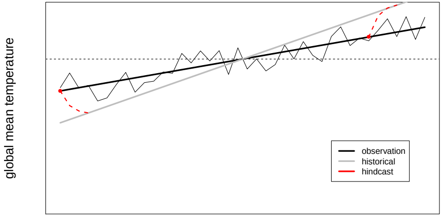


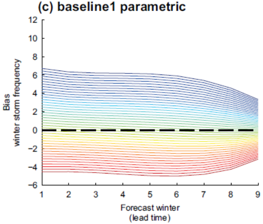


Bias of storm frequency in the NA.
Color: initialization time: blue early, red most recent
Kruschke et al. [2015]

Bias adjustment: dependency on (τ, t) II

Anomaly initialization:





Bias of storm frequency in the NA.
Color: initialization time: blue early, red most recent
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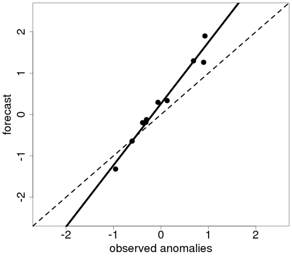
- positive bias for early years
- negative bias for most recent years
- almost no bias for mid period

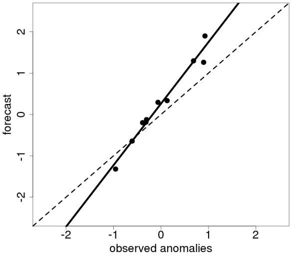
Summary

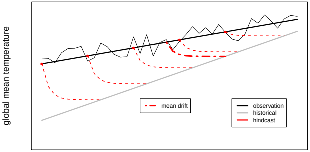
- mean and deviation of the distribution depends on lead time τ



Summary

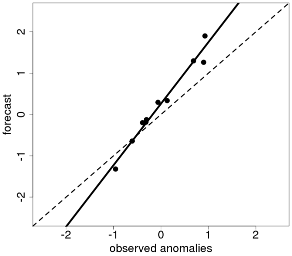
- mean and deviation of the distribution depends on lead time τ
- drift can be different for different initialization times

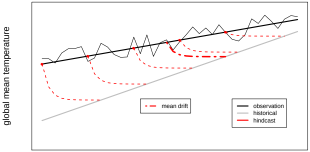


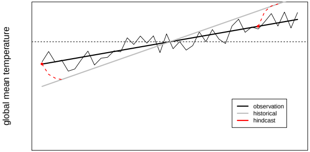


Summary

- mean and deviation of the distribution depends on lead time τ
- drift can be different for different initialization times
- this can also be the case for anomaly initialized forecast systems







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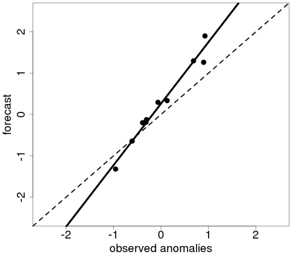
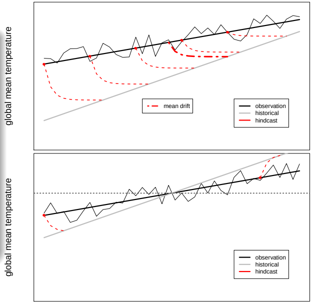


for analysis, interpretation of forecast

- useful to know the bias behavior
- adjustment enhances skill and reduces uncertainty



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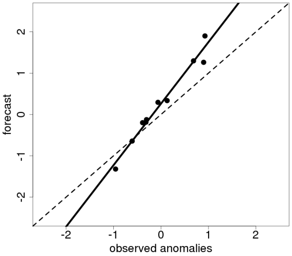

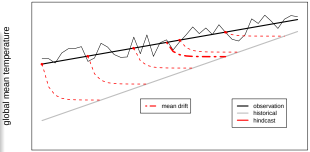

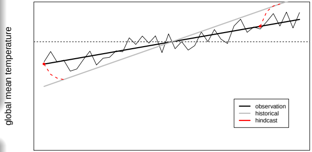

for analysis, interpretation of forecast

- useful to know the bias behavior
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Thank you

Genereal Questions I

Which challenges for climate modeling and observations are raised by climate services?

- providing data with small bias
  - *observations*
    - long time series (validation and climate diagnostic)
    - small scale
    - full 4D information
  - *model data*
    - resolution: modeling events with high impacts (society) often need high resolution
    - including complex processes
    - computationally expensive

Genereal Questions II

What are the barriers that prevent a faster development of a climate services market?

- technical issue
  - analysis is highly complex concerning the amount of data
- which time scales are relevant?

References

G. J. Boer, D. M. Smith, C. Cassou, F. Doblas-Reyes, G. Danabasoglu, B. Kirtman, Y. Kushnir, M. Kimoto, G. A. Meehl, R. Msadek, W. A. Mueller, K. E. Taylor, F. Zwiers, M. Rixen, Y. Ruprich-Robert, and R. Eade. The decadal climate prediction project (dcpp) contribution to cmip6. *Geoscientific Model Development*, 9(10):3751–3777, 2016. doi: 10.5194/gmd-9-3751-2016. URL http://www.geosci-model-dev.net/9/3751/2016/.

Neven S. Fučkar, Danila Volpi, Virginie Guemas, and Francisco J. Doblas-Reyes. A posteriori adjustment of near-term climate predictions: Accounting for the drift dependence on the initial conditions. *Geophysical Research Letters*, 41(14):5200–5207, 2014. ISSN 1944-8007. doi: 10.1002/2014GL060815. URL http://dx.doi.org/10.1002/2014GL060815.

R Gangsto, AP Weigel, MA Liniger, and C Appenzeller. Methodological aspects of the validation of decadal predictions. *Clim Res*, 55(3):181–200, 2013. URL http://www.int-res.com/abstracts/cr/v55/n3/p181-200/.

V. V. Kharin, G. J. Boer, W. J. Merryfield, J. F. Scinocca, and W.-S. Lee. Statistical adjustment of decadal predictions in a changing climate. *Geophysical Research Letters*, 39(19):n/a–n/a, 2012. ISSN 1944-8007. doi: 10.1029/2012GL052647. URL http://dx.doi.org/10.1029/2012GL052647. L19705.

Tim Kruschke, Henning W. Rust, Christopher Kadow, Wolfgang A. Müller, Holger Pohlmann, Gregor C. Leckebusch, and Uwe Ulbrich. Probabilistic evaluation of decadal prediction skill regarding northern hemisphere winter storms. *Meteorologische Zeitschrift*, pages –, 01 2015. URL http://dx.doi.org/10.1127/metz/2015/0641.

Margit Pattantyús-Ábrahám, Christopher Kadow, Sebastian Illing, Wolfgang A. Müller, Holger Pohlmann, and Wolfgang Steinbrecht. Bias and drift of the medium-range decadal climate prediction system (miklip) validated by european radiosonde data. *Meteorologische Zeitschrift*, 25(6):709–720, 12 2016. doi: 10.1127/metz/2016/0803. URL http://dx.doi.org/10.1127/metz/2016/0803.