

Parametric drift correction for decadal hindcasts on different spatial scales

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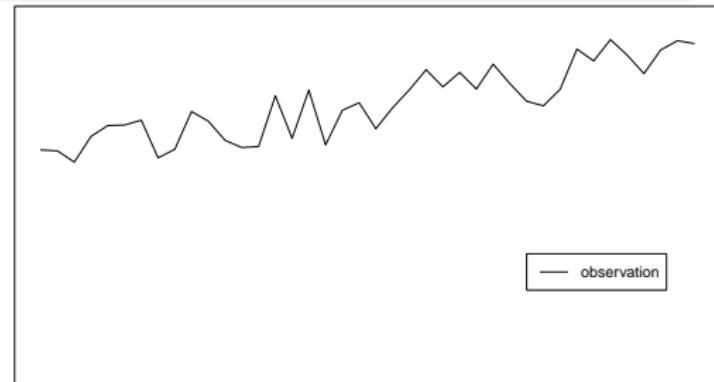
Introduction

Parametric drift correction on
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global mean temperature

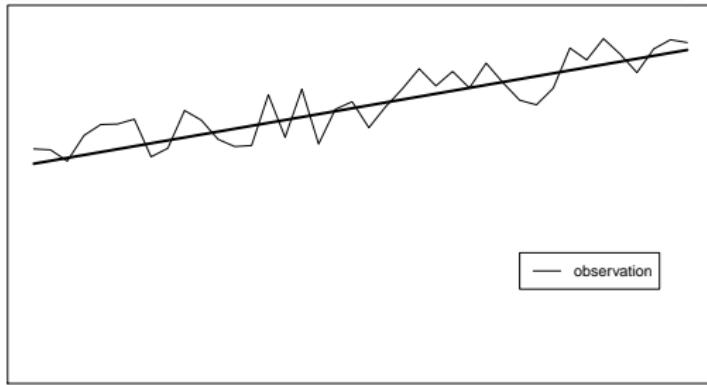


- random data

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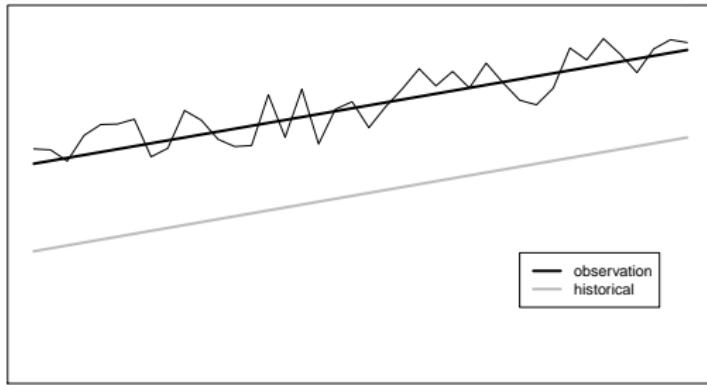


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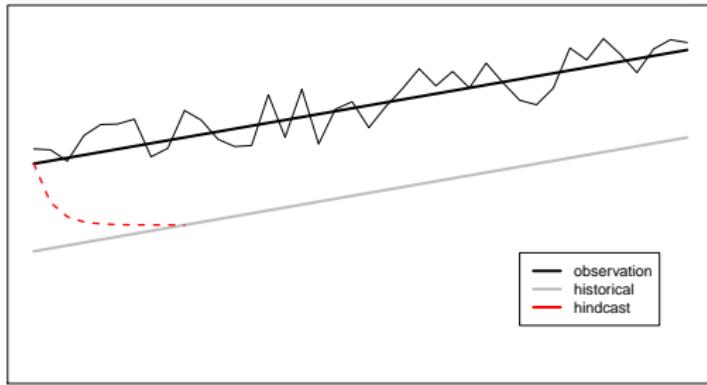


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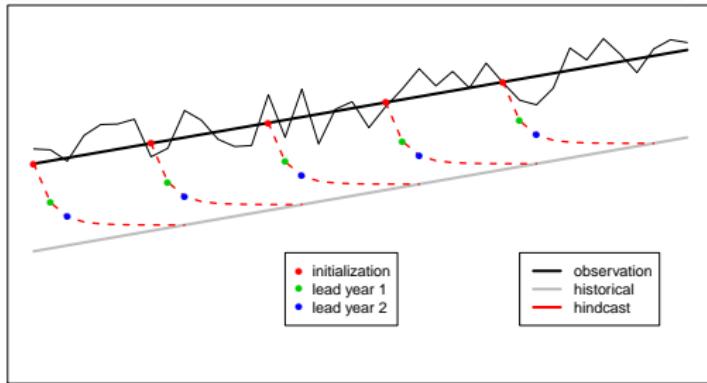
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Parametric **drift** correction on different spatial scales

- bias b depends on lead time τ
 - ▶ $\partial b / \partial \tau \neq 0$
 - ▶ drift

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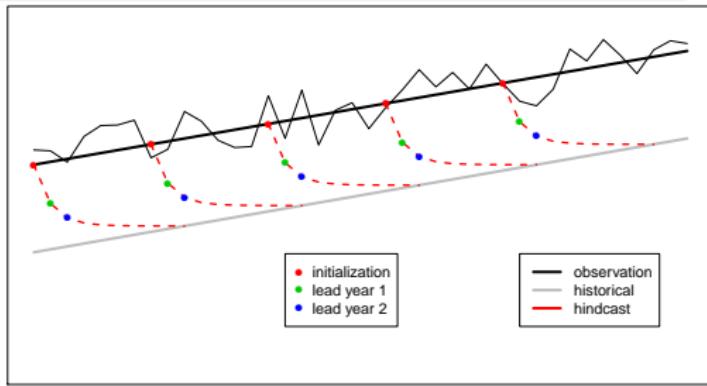


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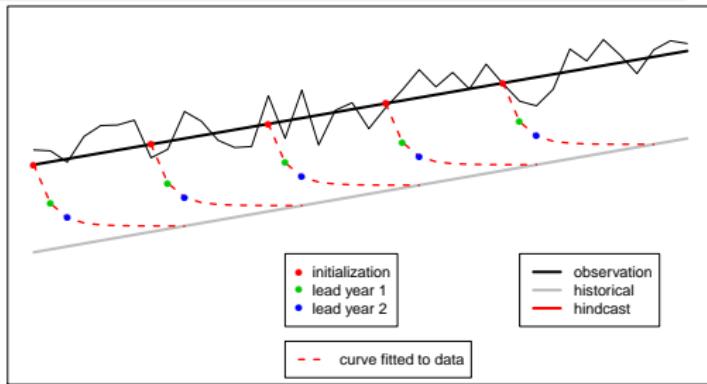
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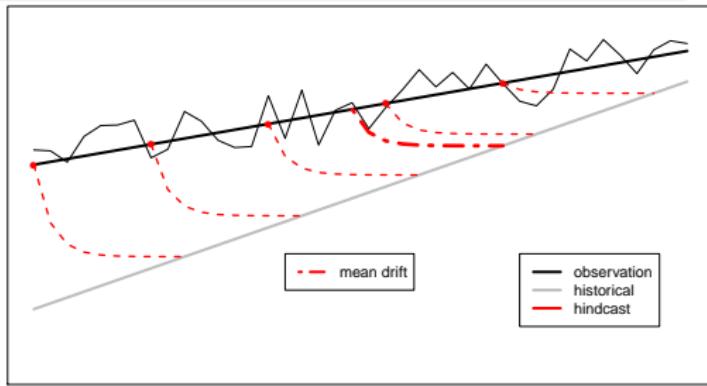
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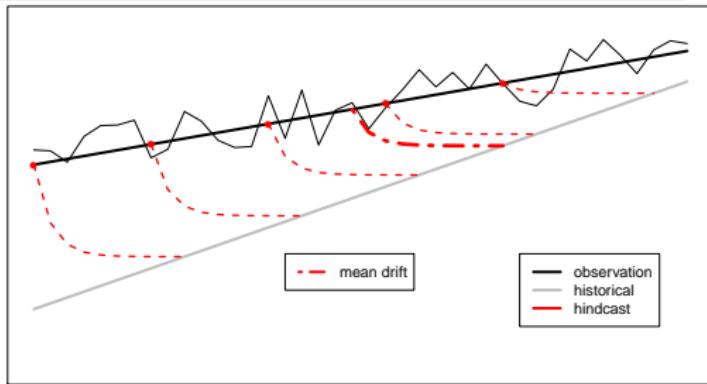
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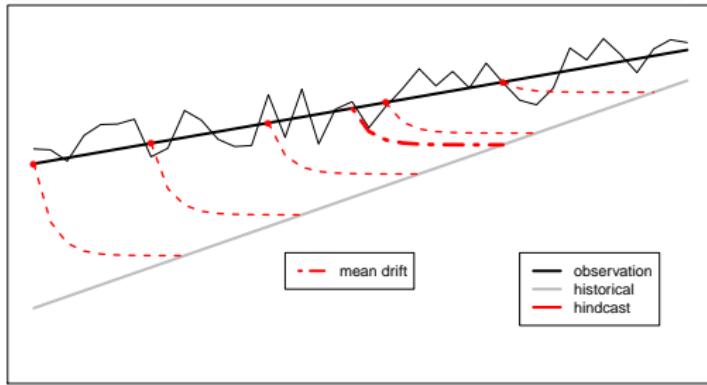
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- parameter depend on initialization time t [Kruschke et al., 2015]

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$$D(\tau, t) = a_0(t) + a_1(t)\tau + a_2(t)\tau^2 + a_3(t)\tau^3$$

et al., 2015]

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- potential problems on small scale are:
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- for global mean temperature [Kharin et al., 2012]
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- potential problems on small scale are:
 - ▶ data on small scale can be noisy: parameter estimation can be difficult
 - ▶ data on small scale can have wrong trend: correction approach can lead to artificial skill
- does the best choice of the parametric model depend on the spatial scale?

Data

- yearly mean near surface temperature (tas)

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observation

- **HadCRUT4** [Jones et al., 2012]
- $5^\circ \times 5^\circ$ grid

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model simulations

- **decadal hindcasts** with **MPI-ESM**, 10 ensemble members
- full-field initialized with ERA in the atmosphere and ORA S4 [Balmaseda et al., 2013] in the ocean
- integrated at T63: $\approx 1.85^\circ$ grid

Method: bias adjustment

- correction is done for yearly mean values
- leave one out for the adjustment

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parametric drift correction [Kruschke et al., 2015]

$$D(\tau, t) = a_0(t) + a_1(t)\tau + a_2(t)\tau^2 + a_3(t)\tau^3$$

$$D(\tau, t) = (b_0 + b_1 t) + (b_2 + b_3 t)\tau + (b_4 + b_5 t)\tau^2 + (b_6 + b_7 t)\tau^3$$

Method: verification

verification [Illing et al., 2014]

- using mean square error skill score (MSESS) comparing forecast (FC) and reference (REF)

$$\text{MSE} = \frac{1}{n} \sum_t (H_t - O_t)^2$$

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- FC: non-parametric, REF: climatology

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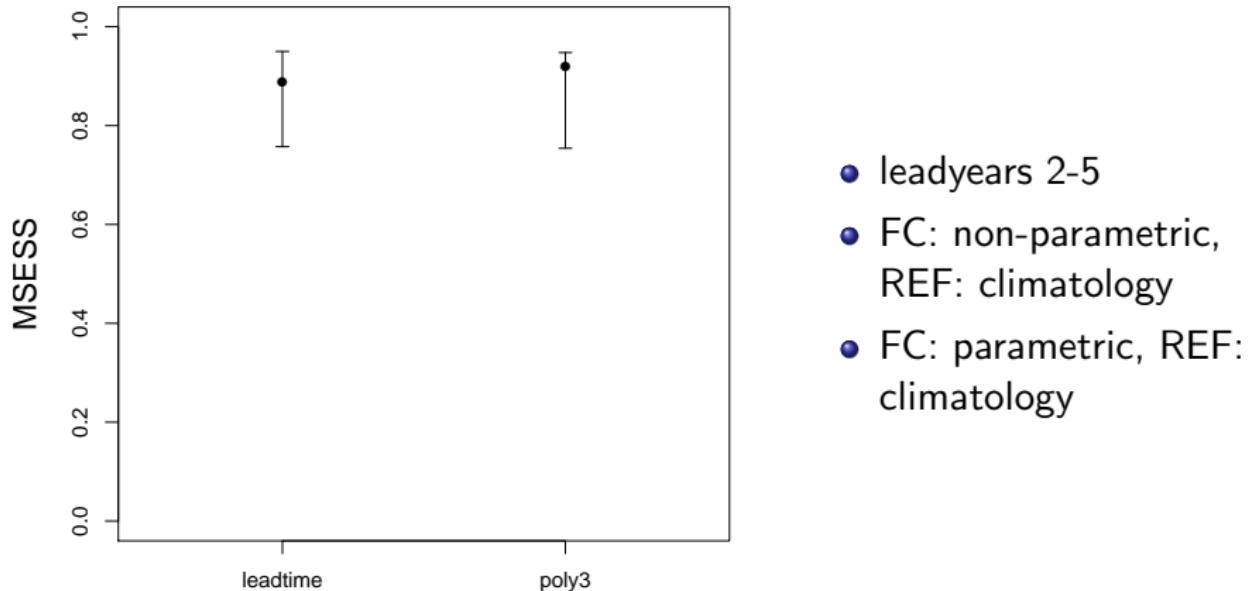
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- FC: parametric, REF: climatology
- FC: parametric, REF: non-parametric

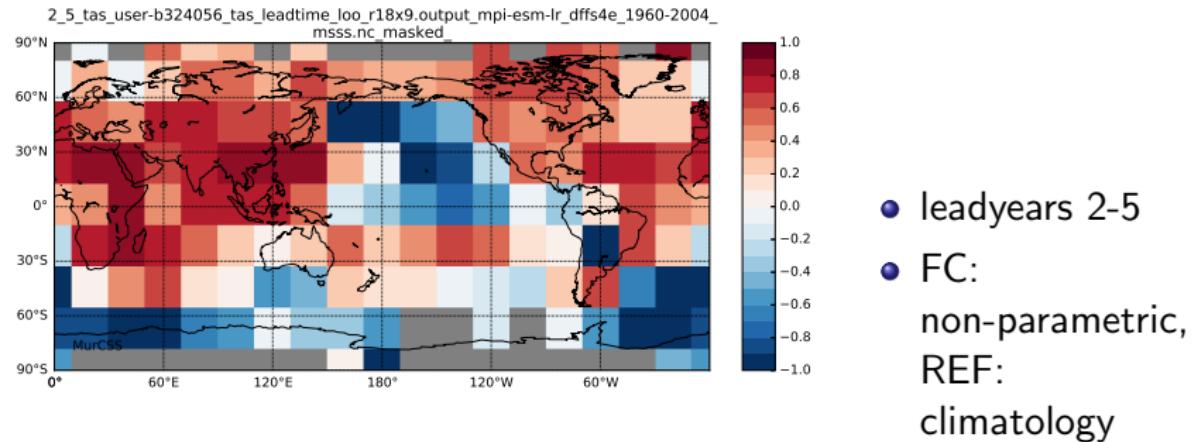
Results: global mean



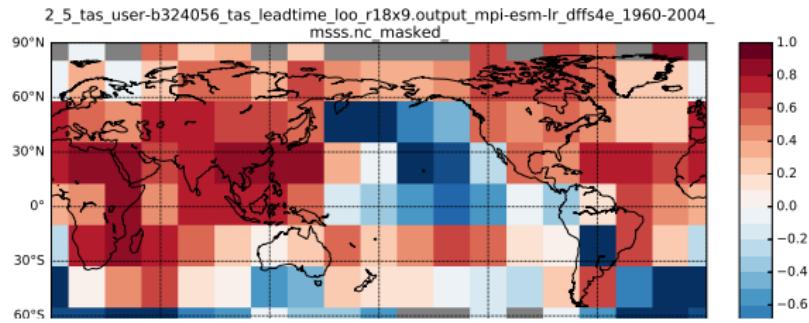
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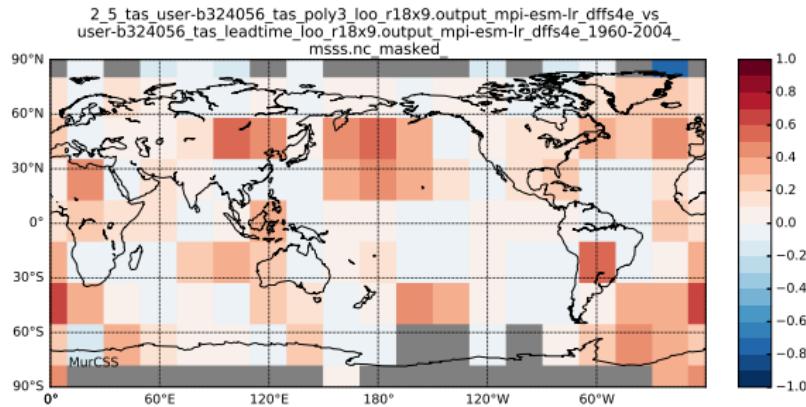
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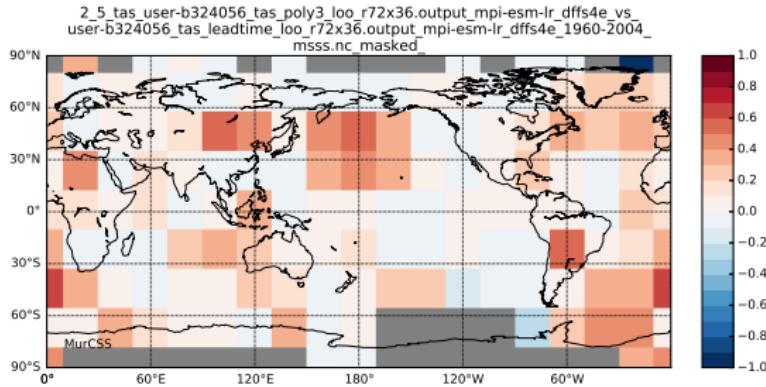


- leadyears 2-5
- FC:
non-parametric,
REF:
climatology
- FC: parametric,
REF:
non-parametric



Results: 20°grid

- Can parameters estimated on small scales?

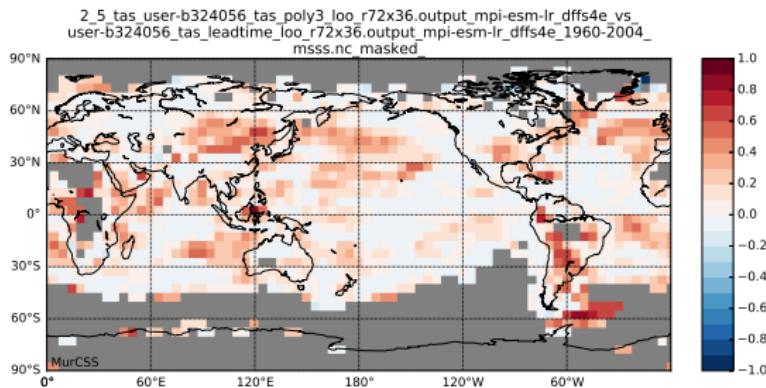


- leadyears 2-5
- FC: parametric,
- REF:
- non-parametric
- parameters are estimated on 5°grid

- Parameter estimation on different grids makes no difference

Results: 5°grid

- Adjustment and verification on small scale



- leadyears 2-5
 - FC: parametric,
REF:
non-parametric

- data quality?
 - does the forecast system has skill on the 5° grid boxes?

Results: different parametric models

which parametric model?

$$D_1(\tau, t) = (b_0 + b_1 t) + (b_2 + b_3 t)\tau + (b_4 + b_5 t)\tau^2 + (b_6 + b_7 t)\tau^3$$

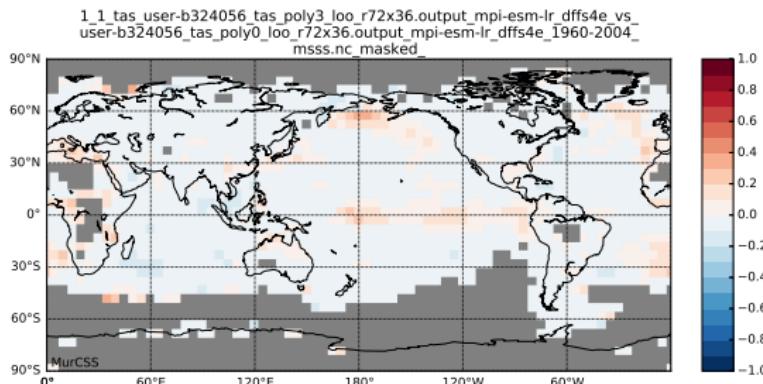
$$D_2(\tau, t) = (c_0 + c_1 t)$$

Results: different parametric models

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$$D_2(\tau, t) = (c_0 + c_1 t)$$



- leadyear 1
- FC: parametric D_1
- REF: parametric D_2 and non-parametric

- no difference on global scale
- small improvement on local scale

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parametric drift correction shows higher skill than non-parametric method

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Thank you

References

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