Evaluation of re-calibrated decadal hindcast using a common verification framework

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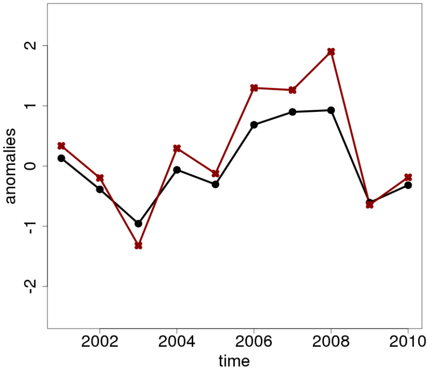
Introduction

- schematic figure
  - black: "observations" X
  - red: "model" Y

$$X = a + bY + \epsilon$$

[Gneiting et al., 2005, Sansom et al., 2016]



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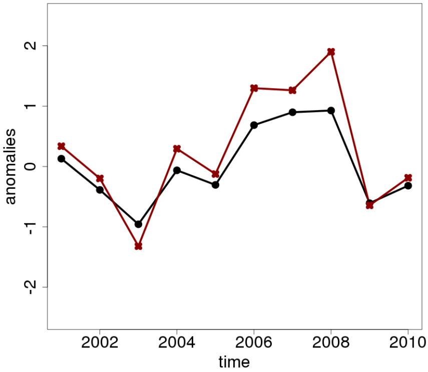

adjusted model $\hat{Y}$

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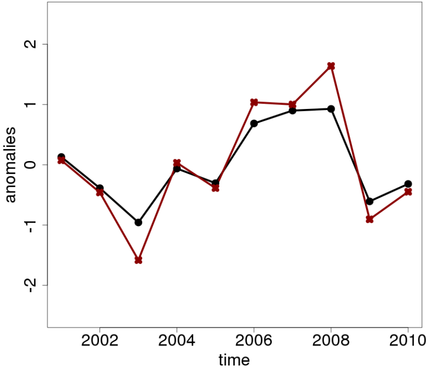

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adjusted model $\hat{Y}$
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$$\hat{Y} = \alpha + Y$$

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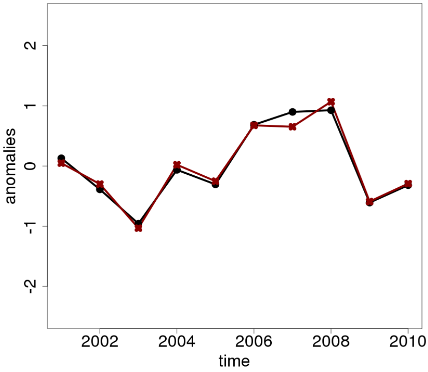

$$X = a + bY + \epsilon$$

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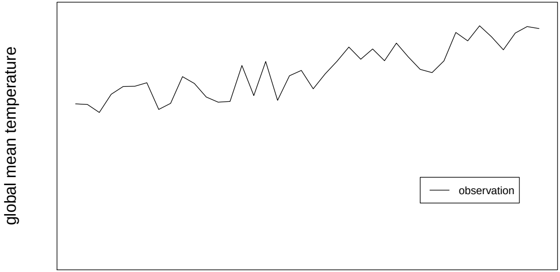
adjusted model $\hat{Y}$
mean and conditional bias

$$\hat{Y} = \alpha + \beta Y$$

Problem: initialization $\rightarrow$ lead time dependency

Problem: initialization → lead time dependency

schematic figure



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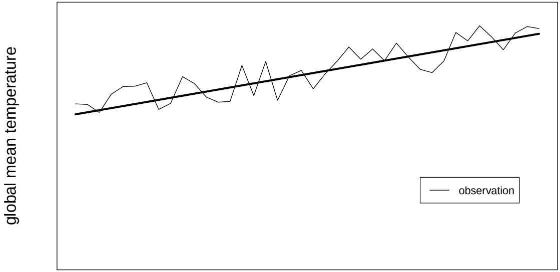

- linear trend

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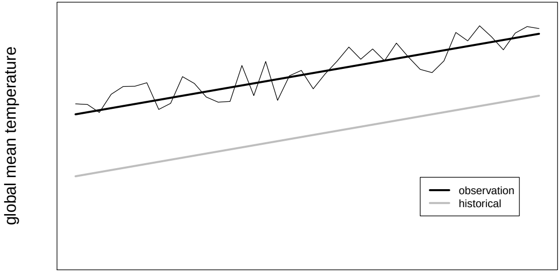

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- same model trend
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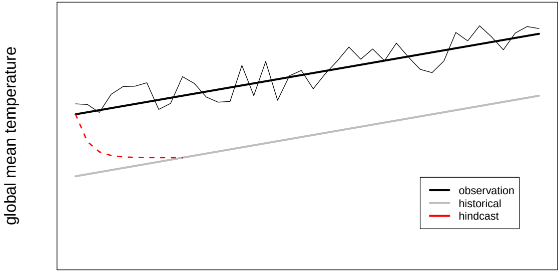

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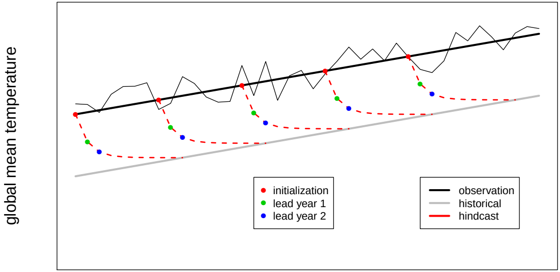

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- bias b depends on lead time τ
  - $\partial b / \partial \tau \neq 0$
  - drift
  - $\alpha(\tau)$, $\beta(\tau)$

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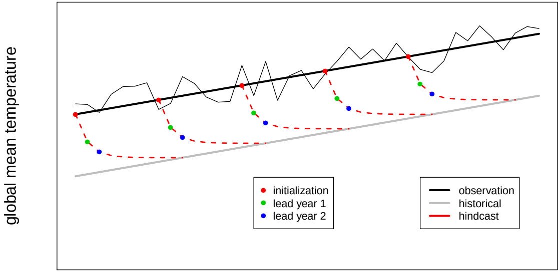

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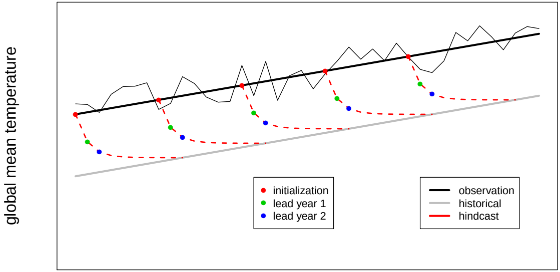

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  - fit curve to $b(\tau)$: parametric approach [Gangstø et al., 2013, Kharin et al., 2012, Pasternack et al., 2018]

Dependency on initialization time

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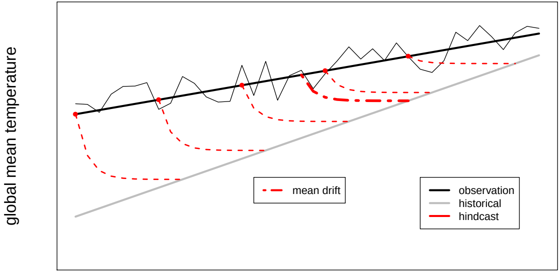

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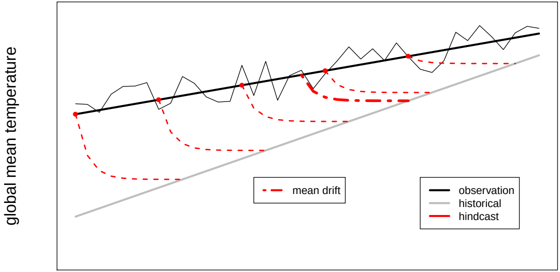

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- α and β can also depend on initialization time j [Kharin et al., 2012, Kruschke et al., 2015, Pasternack et al., 2018]
  - $\alpha(\tau, j)$, $\beta(\tau, j)$
  - trend adjustment

Adjustment approaches used in this study

α dependent on τ (DCPP recommendation) [Boer et al., 2016]

$\alpha_\tau = -\overline{Y}_\tau$; $\overline{(.)}$: long term mean $\tau = 1, ..., 10$

$\beta_\tau = 1$ $\rightarrow \alpha_1, ..., \alpha_{10}$

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α and β dependent on τ and j [Pasternack et al., 2018]

$$\alpha(j, \tau) = \sum_{k=0}^{3} \alpha_k(j)\tau^k$$

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find parameters $a_0, ..., a_7, b_0, ..., b_7$ that minimize CRPS using cross-validation leaving out 10 year block

Verification framework [Goddard et al., 2013]

mean square error (MSE)

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(Y_j - O_j)^2$$

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MSE forecast of MSE_Y

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Murphy and Epstein (1989)

with climatology as reference forecast: $R = \overline{O}$

$$\text{MSESS}(Y, \overline{O}, O) = r_{YO}^2 - \underbrace{\left[r_{YO} - \frac{s_Y}{s_O} \right]^2}_{\text{conditional bias}}$$

correlation r_{YO}

sample variance s_Y, s_O

Data: near surface temperature

Observation

- HADCRUT4
- 1960 - 2017

Hindcasts

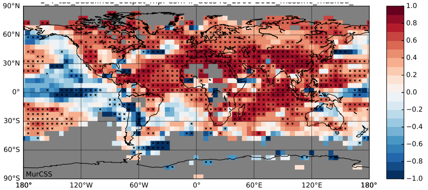
- Model: MPI-ESM-LR (T63)
- anomaly initialization ORAS4 reanalysis (ocean)
- 10 ensemble members
- Lead year 1-4 (average)

Adjustment [Boer et al., 2016], Ref: climatology

[c.f. Kadow et al., 2014, Marotzke et al., 2016]

$$\alpha_\tau = -\overline{Y}_\tau$$
$$\beta_\tau = 1$$

MSESS; best value: 1



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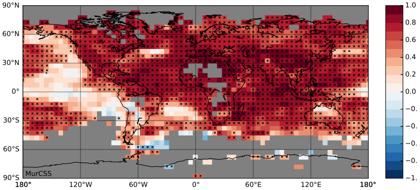
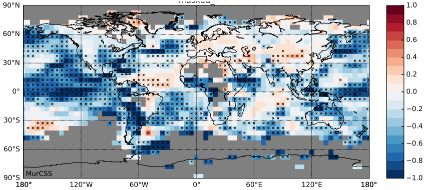


conditional bias; best value: 0



X : significantly different from zero

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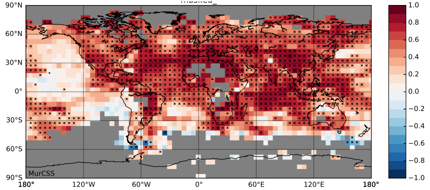

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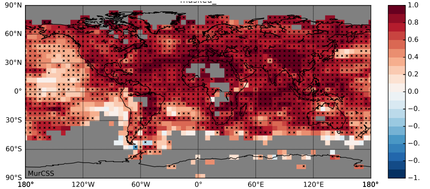

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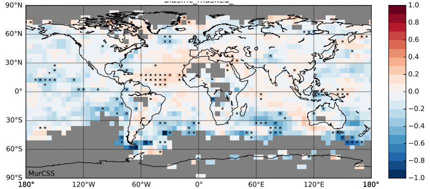

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Forecast uncertainty - ensemble spread

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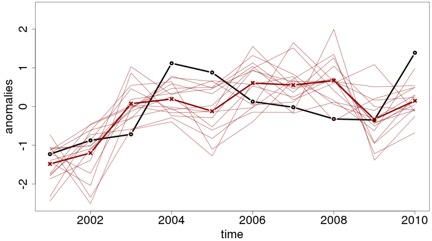

Ensemble mean $\{Y\}$

$$\{Y\} = \frac{1}{M} \sum_{k}^{M} Y_k,$$

$$\sigma^2_{\text{ens}} = \frac{1}{M-1} \sum_{i}^{M} (Y_k - \{Y\})^2$$

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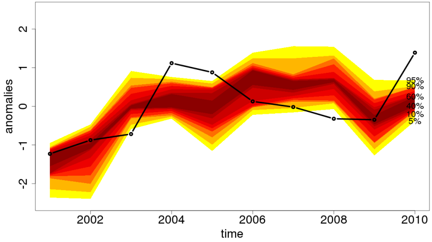

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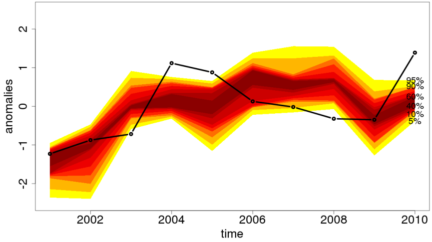

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Adjusted forecast distribution

$$\widehat{Y} \sim \mathcal{N}\left(\{\widehat{Y}\}, \gamma^2(j,\tau)\sigma^2_{\text{ens}}\right)$$

Ensemble spread adjustment

$CRPSS_{ES}$ [Goddard et al., 2013]

$CRPSS_{ES} \leq 0$
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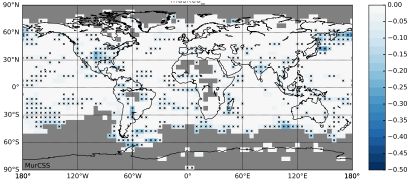
$$\gamma = 1$$

Pasternack et al. [2018]

$$\gamma^2(j,\tau) = log\left(\sum_{k=0}^{2}(c_{2k} + c_{2k+1}j)\tau^k\right)$$

$CRPSS_{ES}$



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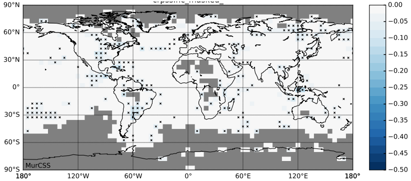

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lead time dependent anomaly (DCPP) α_τ is a robust adjustment but more sophisticated approaches $\alpha(\tau, j), \beta(\tau, j), \gamma(\tau, j)$ have potential for large skill improvement

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