Real-time bias correction of an atmospheric general circulation model

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Motivation and plan

Is there a relationship between model *"fidelity"* and model *"skill"*?

- CCCma's AGCM3 (Scinocca et al. 2008)
- a method to construct real-time corrections to reduce model bias is introduced.
- two sets of AMIP-type ensemble simulations ("hindcasts") with and without bias-correcting terms are discussed.
- changes in model co-variability and skill on *seasonal* time scale are examined.

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Methodology

Consider a dynamical model:

$$\frac{\partial X}{\partial t} = F(X)$$

where X represents the model state, $F(X)$ is the model tendency (advection, physics, etc.)
The goal is to find a r.h.s. term g

$$\frac{\partial X}{\partial t} = F(X) + g$$

that reduces model bias $\overline{X} - \overline{X}_{\mathrm{obs}}$.

Empirical correction

$$\frac{\partial X}{\partial t} = F(X) + g$$

DelSole et al. (2008), Yang et al (2008) refer to this approach as *"empirical correction"*.

- DelSole et al. (2008) consider several strategies for estimating g. The best strategy is based on 24-hr error tendencies.
- The forecast bias is generally reduced (except for U and V).
- None of the considered methods consistently improves skill (may be model dependent). Caveats: JJA only, short 10-yr runs.

Relaxation runs

Relaxation runs: 5-member ensemble AMIP-type runs with AGCM3 by relaxing model solution to ERA interim reanalysis:

$$\frac{\partial X}{\partial t} = F(X) - \frac{1}{\tau}(X - X_R)$$

where X_R is ERA interim reanalysis.

- VORT, DIV, TEMP, and SHUM are relaxed.
- τ=36hrs for VORT, DIV, TEMP, and τ=72hrs for SHUM. (for τ=24–36hrs, $|X - X_R| \approx |X_{R1} - X_{R2}|$)
- Only larger scales are relaxed with full strength (T1-T21). (Gaussian filter for T22-T63 with half-decay at ≈T35).
- Weaker relaxation near the model top above ≈100hPa.

Empirical bias correction:

$$g = -\frac{\overline{(X - X_R)}^{AC}}{\tau}$$

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AMIP-type runs

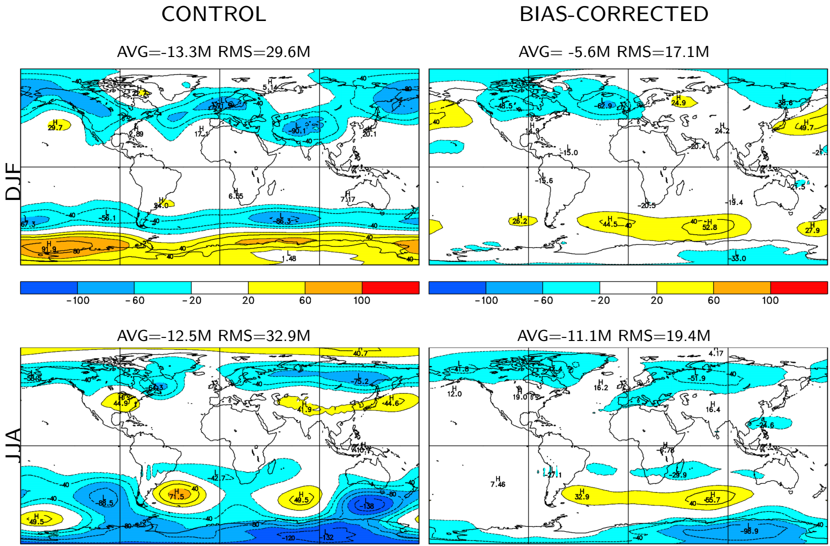
- *Control* runs: 10-member ensemble of AMIP runs with AGCM3 for years 1959-2008:

$$\frac{\partial X}{\partial t} = F(X)$$

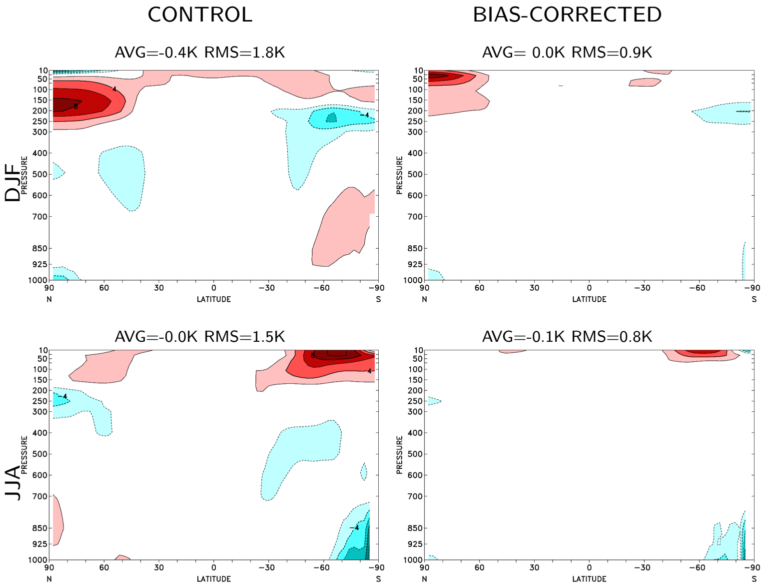
- *Bias-corrected* runs: 10-member ensemble of AMIP runs with AGCM3 by adding the climatological tendency term g:

$$\frac{\partial X}{\partial t} = F(X) + g$$

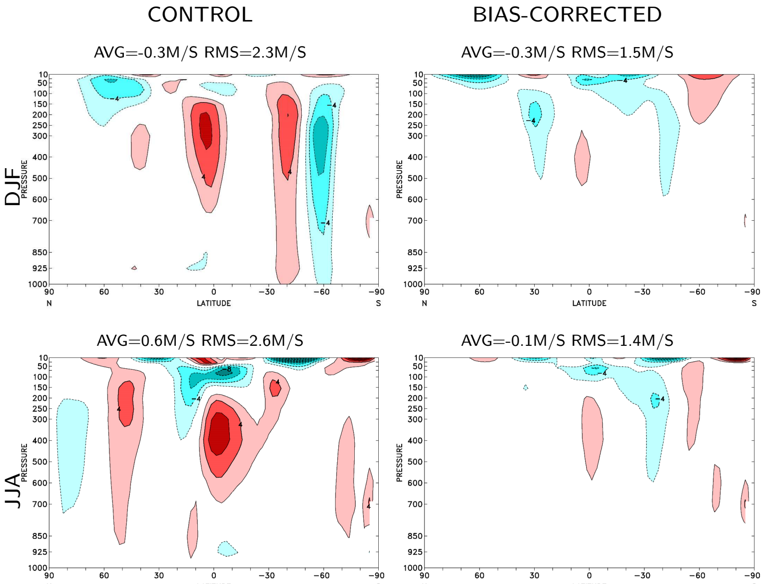
Z500 bias vs ERA interim, 1989-2008



Zonal TEMP bias vs ERA interim, 1989-2008



Zonal U bias vs ERA interim, 1989-2008

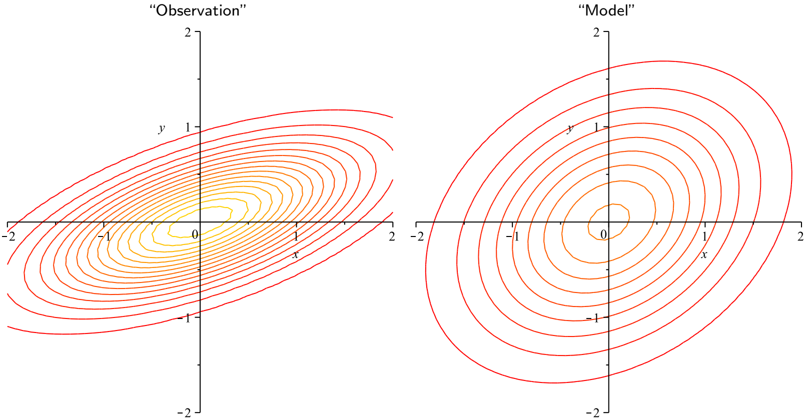


Conclusion 1

The model climatology is improved.

Multivariate normal distribution

Variability distribution on monthly to seasonal time scales is assumed to be multivariate normal:



Kullback-Leibler (KL) divergence

Kullback-Leibler divergence (also information divergence, information gain, or relative entropy) is a non-symmetric measure of the difference between two probability distributions P and Q.

$$D_{\mathrm{KL}}(P \| Q) = \int p(x) log \frac{p(x)}{q(x)} dx$$

Typically P represents the "true" distribution of data, or observations. Q typically represents a model distribution.

For two *multivariate normal* distributions $N_p(\Sigma_p)$ and $N_q(\Sigma_q)$:

$$D_{\mathrm{KL}}(N_p \| N_q) = \frac{1}{2} \left(\log_e \left(\frac{\det \Sigma_q}{\det \Sigma_p} \right) + \mathrm{tr} \left(\Sigma_q^{-1} \Sigma_p \right) - N \right)$$

where Σ_q and Σ_q are the auto-covariance matrices.

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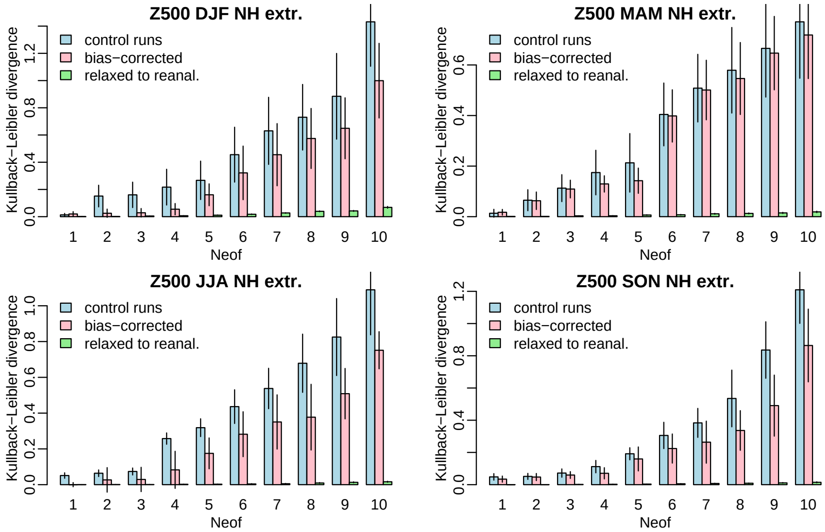
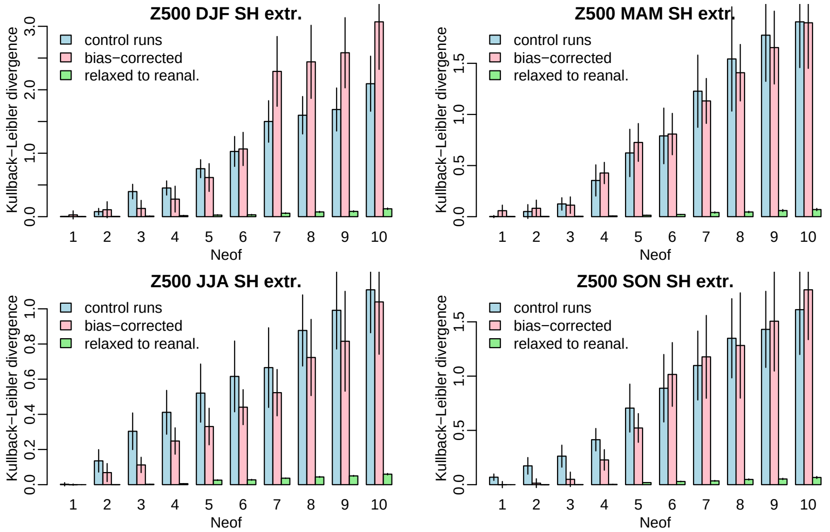
D_{KL}, Z500, NH Extratropics, 1959-2008



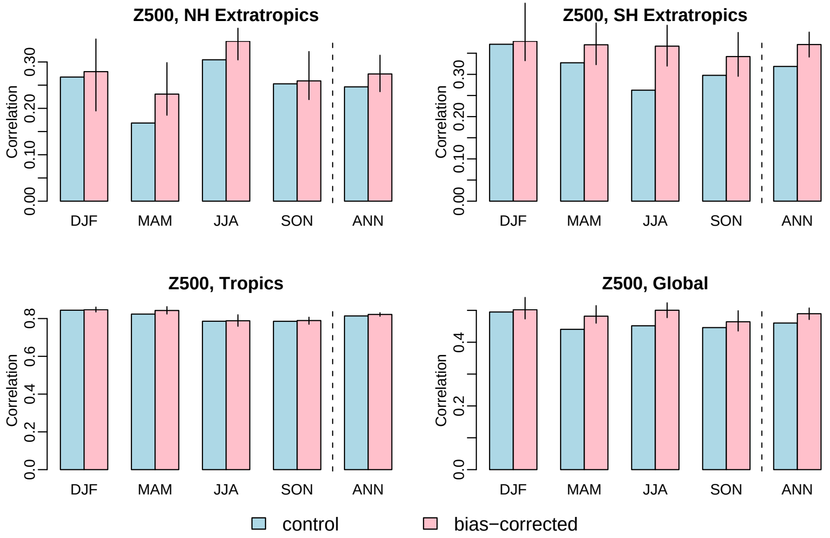
D_{KL}, Z500, SH Extratropics, 1959-2008



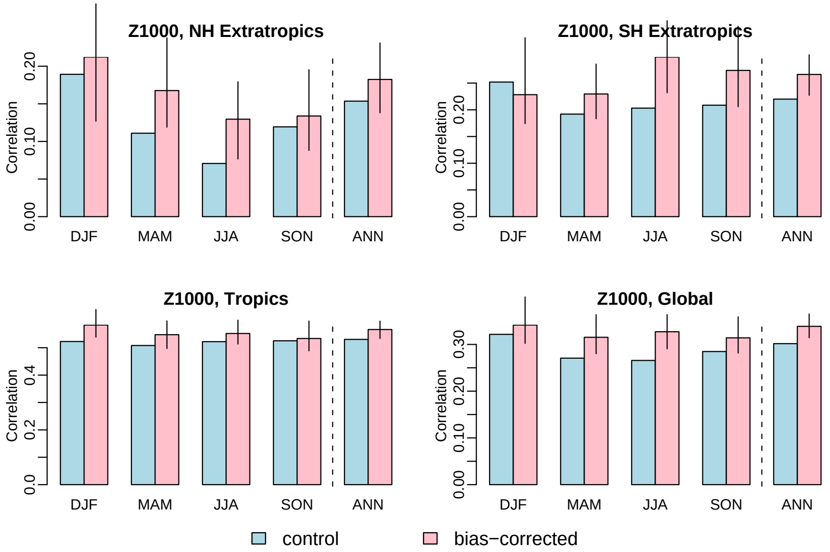
Conclusion 2

Interannual co-variability is generally improved.

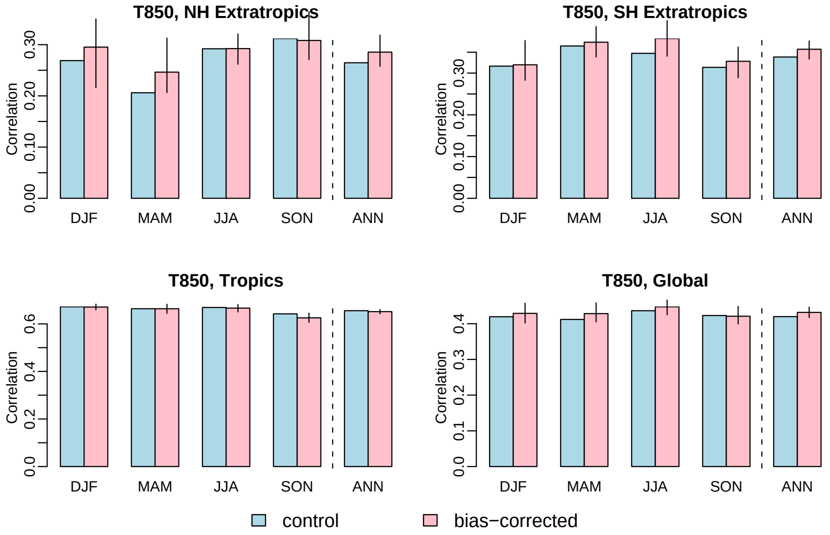
Correlation, Z500, 1959-2008



Correlation, Z1000, 1959-2008



Correlation, T850, 1959-2008



Conclusion 3

Skill of seasonal “hindcasts” is modestly improved.

Conclusions

- The presented method reduces climatological biases in AGCM3.
- Interannual atmospheric co-variability is generally improved.
- Potential skill of seasonal hindcasts is modestly improved.

It isn't unreasonable to expect that models with smaller bias produce more skillful seasonal predictions.

Outlook:

- Are results reproducible in AGCM4?
- Can a similar approach be implemented in a coupled model?
  - run-time bias-correcting tendencies are not conservative.
  - how to bias-correct OGCM?

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