Assimilation of Southern Hemisphere proxy records into a climate modelling framework

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1. Introduction

- The reconstruction of past climatic fields, such as temperature and surface pressure, is a critical challenge within palaeoclimatology.
- Data assimilation is a particularly promising approach, combining the dynamical information encoded within climate models with the real-world information recorded by natural archives.
- Here, we explore the potential of data assimilation by assimilating Southern Hemisphere proxy records into a climate model.

2. Data and methods

- We employ an off-line approach to data assimilation (Matsikaris et al., 2015). A large ensemble of climate model simulations is generated. Palaeoclimate information is then assimilated by calculating a weighted ensemble mean, based on an assessment of model skill.
- To generate an ensemble, we use the CSIRO Mk3L climate system model to complete 25 transient simulations of the global climate. Each simulation is driven by past changes in the Earth's orbit, greenhouse gases, solar irradiance and volcanic eruptions.
- The records chosen for assimilation are the three Southern Hemisphere continental-scale temperature reconstructions generated by the PAGES 2k Consortium (Figure 1).

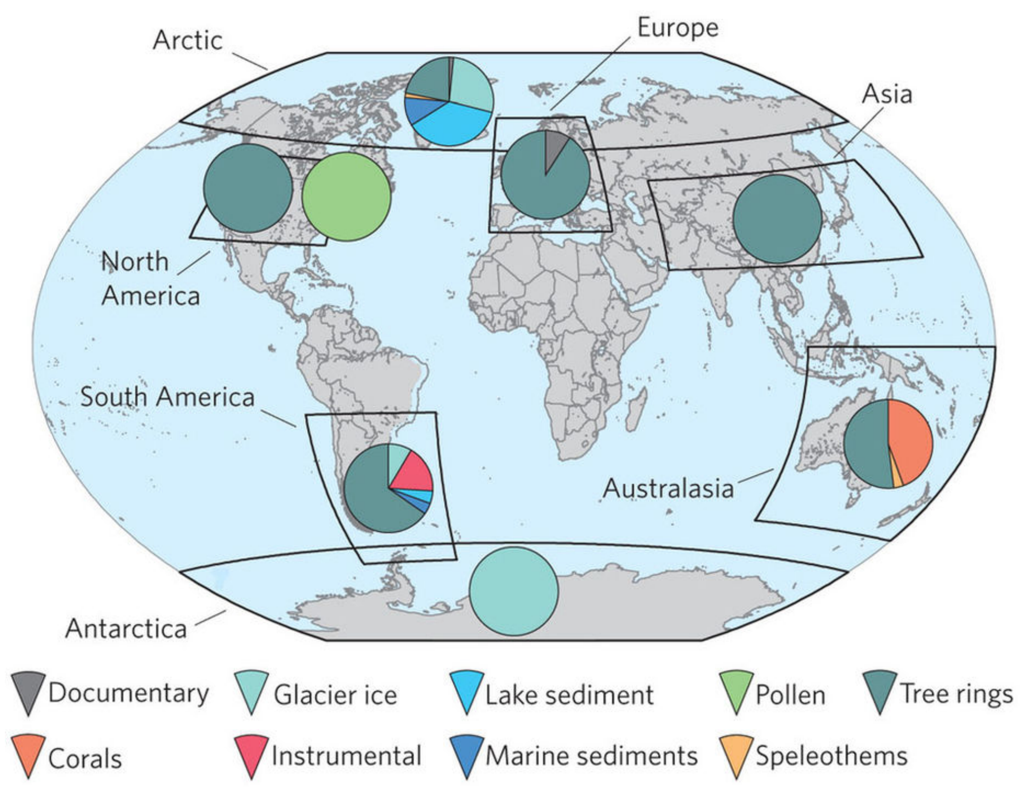

Figure 1. The continental-scale reconstructions generated by PAGES 2k Consortium (2013).

- The error in each simulation is given by (van Leeuwen, 2009):

$$E(t) = [\mathbf{x}(t) - \hat{\mathbf{x}}(t)]^{\mathrm{T}} \mathbf{R}^{-1} [\mathbf{x}(t) - \hat{\mathbf{x}}(t)]$$

- $\mathbf{x}$ is the reconstructed temperature, $\hat{\mathbf{x}}$ is the simulated temperature and $\mathbf{R}$ is the error covariance matrix for the reconstructions.
- The errors are calculated separately for each calendar year. Each simulation is then weighted proportionally to $e^{-\frac{1}{2}E(t)}$.
- The output of this data assimilation provides climate field reconstructions spanning the period from 1001 to 1995 CE.

3. Potential skill

- We first assess the potential skill of data assimilation using a perfect model approach. Each simulation in turn is taken as "reality". Data assimilation is used to reproduce this "reality", with the "observed" temperatures for each of the three Southern Hemisphere regions assimilated into the remaining ensemble members. The coefficient of efficiency (CE; Cook et al., 1994) is used to assess skill.
- Figure 2a shows that the model has considerable skill at reproducing surface air temperature (SAT), even without data assimilation. This can be attributed to external forcing by volcanic eruptions.
- Data assimilation adds considerable skill at mid- and high latitudes in the Southern Hemisphere, particularly over Antarctica (Figures 2c and 2f). However, in the case of mean sea level pressure (MSLP), the assimilation degrades skill elsewhere.

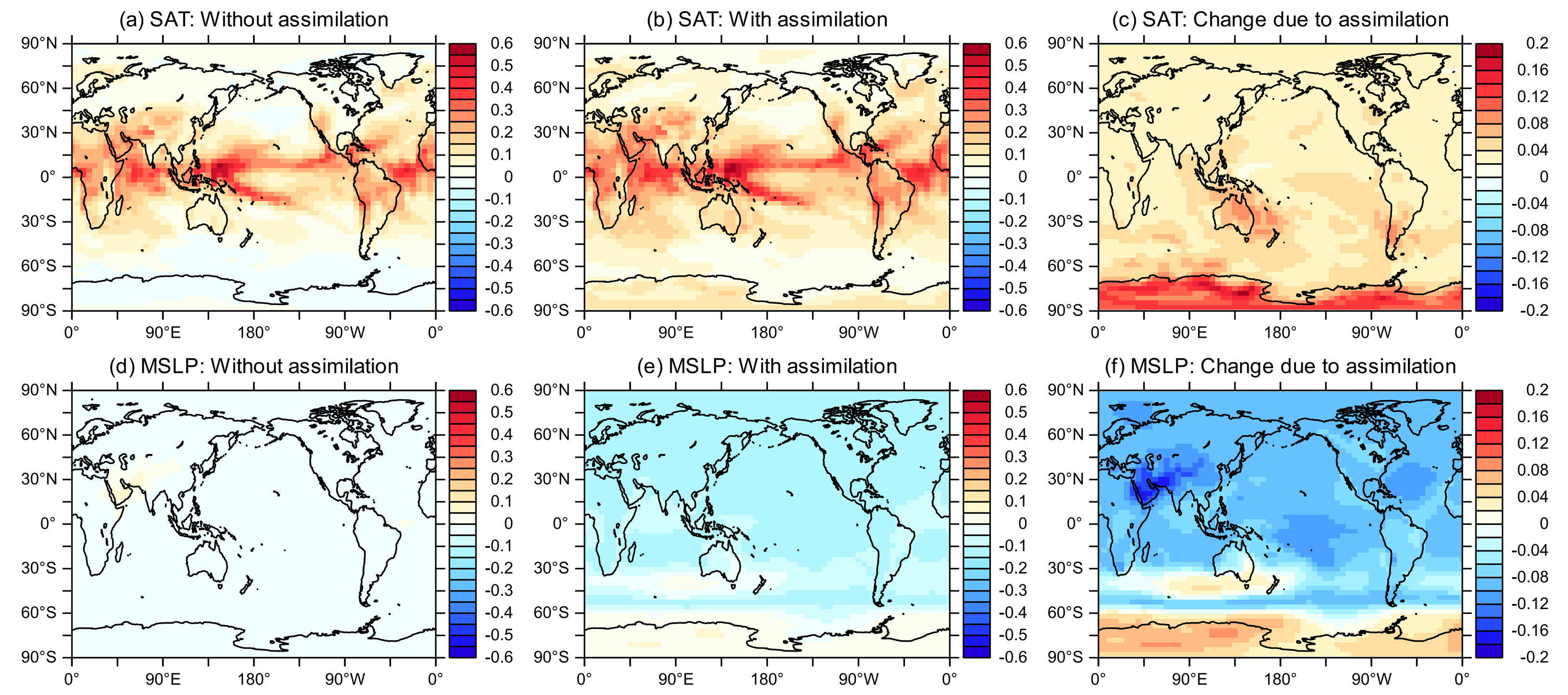

Figure 2. Coefficient of efficiency for a perfect model assessment over the period 1001–1850 CE.

- We can also use the perfect model approach to assess how the skill of data assimilation depends upon the size of the model ensemble.
- Figure 3 shows that at least three model simulations are required to reproduce Antarctic SAT with a CE greater than zero, which indicates that the assimilation has skill. Data assimilation is less skillful at reproducing the Southern Annular Mode (SAM) Index, with at least six simulations required to ensure a positive CE.
- Our results suggest that little additional skill would be gained by increasing the size of the model ensemble to more than 25.

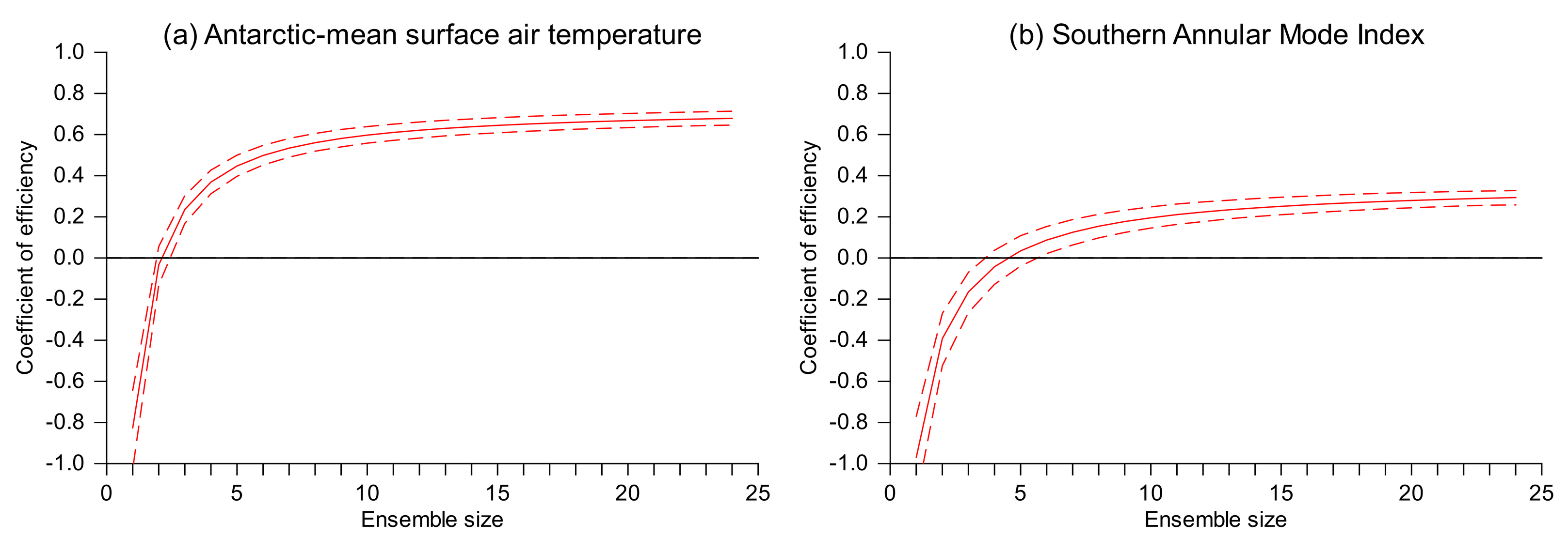

Figure 3. CE as a function of the ensemble size, determined using a perfect model assessment over the period 1001–1850 CE. Dashed lines indicate the 95% confidence intervals.

4. Results of data assimilation

- We can now use data assimilation to reconstruct past climatic fields. Figure 4 shows reconstructed Medieval Climate Anomaly (1001–1250 CE) minus Little Ice Age (1401–1700 CE) anomalies for surface air temperature (SAT) and mean sea level pressure (MSLP).
- Data assimilation has little impact on the SAT anomalies, although it does reduce the magnitude of the warming over Antarctica.
- However, data assimilation has a notable impact on the MSLP anomalies in the Southern Hemisphere. The assimilation indicates lower MSLP over Antarctica and higher MSLP at ∼40°S, corresponding to a more positive phase of the SAM.

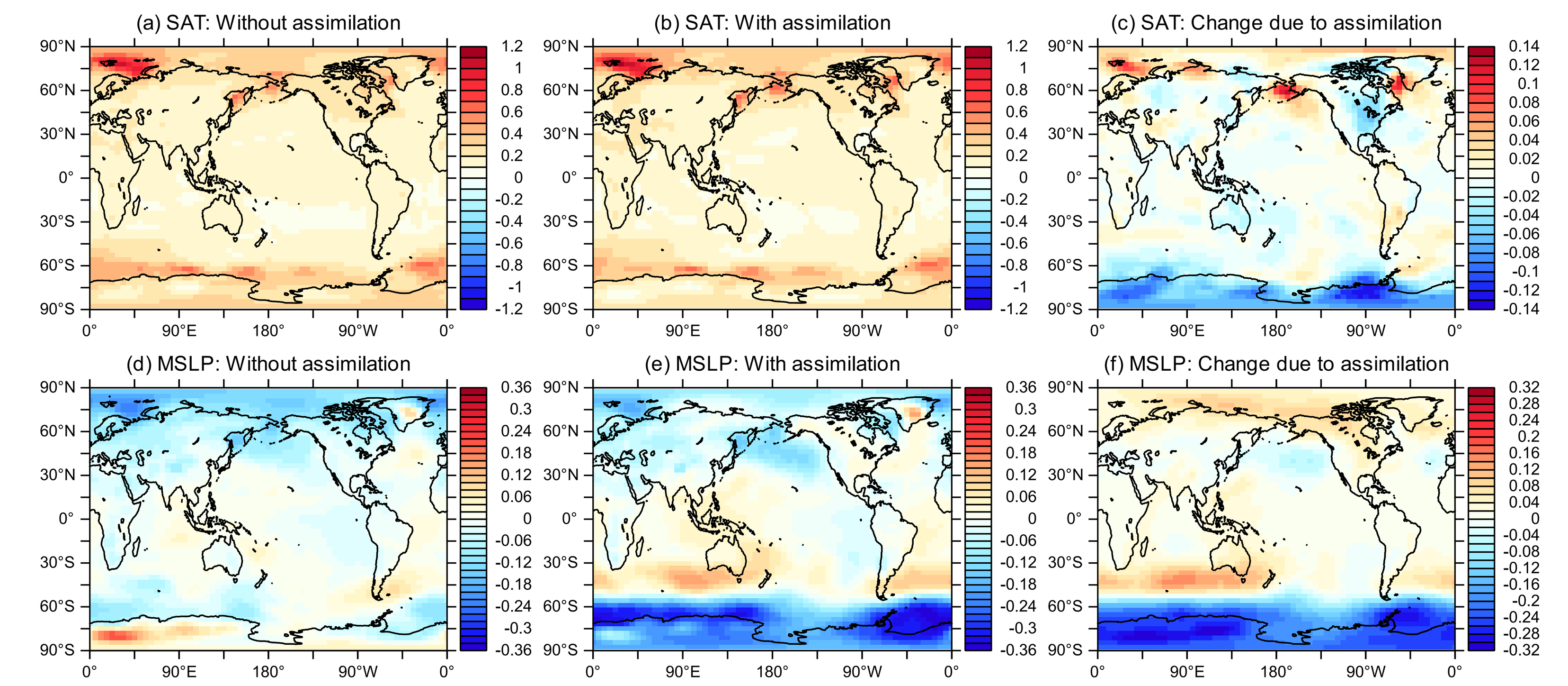

Figure 4. Reconstructed anomalies for the Medieval Climate Anomaly (1001–1250 CE) minus the Little Ice Age (1401–1700 CE): surface air temperature (°C) and mean sea level pressure (hPa).

- Inspired by the above results, we use the assimilation to diagnose past changes in the SAM Index (Gong and Wang, 1999).
- The model simulates a negative phase of the SAM during the last millennium. Data assimilation causes the SAM to become even more negative, with a rapid shift towards the present state over the last ∼200 years. A negative SAM during the last millennium is consistent with the reconstruction of Abram et al. (2014).

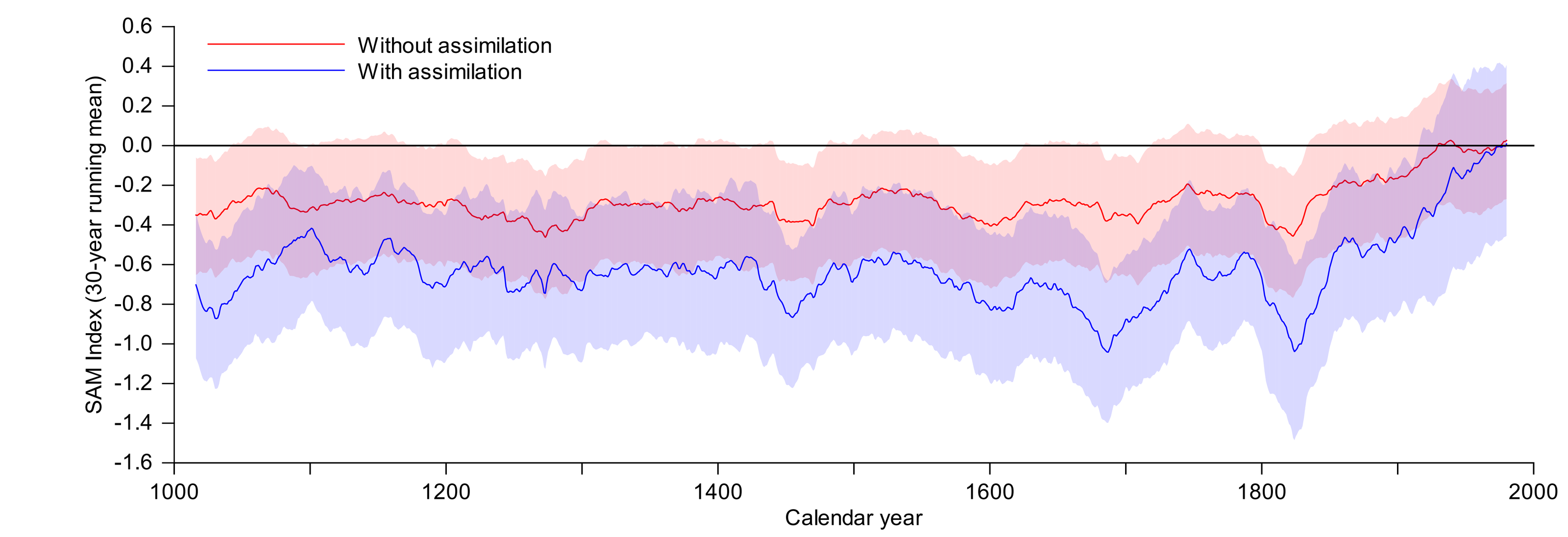

Figure 5. Reconstructed values for the Southern Annular Mode Index, with (blue) and without (red) data assimilation. Shading indicates the 95% confidence intervals.

References

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