The Early Eocene Climate Optimum reconstructed with Bayesian multi-proxy integration

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# Abstract

Geochemical data such as oxygen isotopes (d18O), tetraether indices (TEX86) and magnesium calcium ratios (Mg/Ca) are routinely used to reconstruct ocean temperatures in deep time. However, limited spatial coverage and disagreements between geochemical proxies compromise the accuracy of these reconstructions. Geological data such as coral reefs, mangroves, and evaporites have the potential to supplement geochemical data by improving spatial coverage and constraining temperature estimates. Historically, these data have been used to qualitatively inform upon palaeoclimatic conditions at broad spatial scales, yet no transfer functions exist to convert geological data into temperature estimates. Quantitative temperature reconstructions have therefore not made use of these data. Here, we present a Bayesian hierarchical model to integrate geological data–with established temperature proxies–into a unified quantitative framework. We apply this approach to the early Eocene climatic optimum (EECO), the interval with the warmest sustained temperatures of the Cenozoic. Assuming the conservation of thermal tolerances of modern coral reefs and mangrove taxa, we establish broad sea surface temperature ranges for EECO coral reef and mangrove sites. We integrate these temperature estimates with the EECO geochemical shallow marine proxy record to model the latitudinal temperature gradient and its uncertainty. Our results confirm the presence of a flattened latitudinal temperature gradient and unusually high polar temperatures during the EECO. We show that the inclusion of ecological data can substantially reduce the uncertainty on temperature estimates in climate zones lacking geochemical data.

# Introduction

The geological record holds evidence for episodes in Earth history with fundamentally different climates than our current. Some episodes, for example the early Eocene, are thought to have been significantly warmer than the modern, potentially representing an analogue for extreme climate warming scenarios. Reconstructions of palaeoclimate commonly follow one of two approaches. Geochemical proxies such as oxygen isotopes (d18O), tetraether indices (TEX86) and magnesium calcium ratios (Mg/Ca) are used to derive palaeotemperature estimates for individual locations using experimentally derived transfer functions. Multiple local estimates are sometimes summarised to generate regional or global estimates, but this approach is prone to sampling bias (**Jones2022?**). Earth system models take a fundamentally different approach by modelling the climate-generating processes directly, reconstructing spatially resolved climate estimates for the entire glob.e This approach is, however, relying on proxy data to constrain the large number of possible model setups and ground truth the model output.

Hook -> Generic problem: - Reconstructing past climate important for understanding current/future global warming - Two main pathways: highly complex ESM <–> proxy compilations - Problems with proxy data: only provides a local picture (few local sites interpreted as global signal) - Problems with ESM (long time to run, very complex, a lot of assumptions on processes/doesn’t consider how they may change, need to be constrained with proxy data) - Lack of intermediate-complexity models to make full use of the proxy data

Specific problem: - exemplified with the EECO: proxies and ESM hard to reconcile, EECO important climate analogue - a lot of proxies recrystallised <–> unreliable data or lack of data

Solution: - Proxy-driven model (no strong assumptions on processes) - Integrate more data (quantify biological / geological information) - Integrate additional knowledge (constraints on such gradients)

Application: - EECO time of extreme warming - problem of the Early Eocene: - apply solution to EECO to constrain EECO lat. T gradient

Here:

Here, we present a Bayesian hierarchical model to integrate geological data—with established temperature proxies—into a unified quantitative framework. We apply this approach to the early Eocene climatic optimum (EECO), the interval with the warmest sustained temperatures of the Cenozoic. Assuming the conservation of thermal tolerances of modern coral reefs and mangrove taxa, we establish broad sea surface temperature ranges for EECO coral reef and mangrove sites. We integrate these temperature estimates with the EECO geochemical shallow marine proxy record to model the latitudinal temperature gradient and its uncertainty.

* EECO specific information
* Disagreement between GCM + geochem data

# Materials & Methods

## Geochemical data

**d18O.**

**d47.**

**Mg/Ca.**

**TEX86.**

## Ecological data

**Coral reefs.** Coral reefs built by zooxanthellate-bearing, shallow water corals are confined to the tropics - substropics. The coldest

**Mangroves.** Recent mangroves occur in the tropics - subtropics. Although many factors besides temperature determine the extent of mangrove distributions, empirical temperature limits have been established for the genera *Avicennia* and *Rhizophora*, with lower mean annual SST limits of 15.6 degC and 20.8 degC, respectively (**Quisthoudt2012?**). Both *Avicennia* and members of the Rhizophoraceae family were widespread in the early Eocene, but only *Avicennia* occurred in polar latitudes (**Suan2017?**; **Popescu2021?**). Assuming that Eocene members of these mangrove taxa had similar climatic requirements as their modern relatives, the presence and absence of *Avicennia* and Rhizophoraceae pollen can be used as a temperature proxy. To translate mangrove occurrences from the compilation by (**Popescu2021?**) to a quantitative temperature proxy, we allocate locations at which *Avicennia* pollen, but no Rhizophoraceae pollen were found, a mean temperature between the lower *Avicennia* and Rhizophoraceae limit (18.2 degC), with a standard deviation of 1.33 degC, thus placing 95 % of the probability density within that interval (see Fig. 1x). The range of temperatures in which both taxa occur in the modern is very wide (20.8 and 28 deC), hence occurrences of both *Avicennia* and Rhizophoraceae pollen were not used in the analysis.

[Fig 1: Map and distribution of proxy data and ecological data]

## Bayesian framework

**Model structure.** We model the mean temperature () at location as a function of absolute latitude () with a logistic regression (growth curve or Richard's curve) of the form:

where and denote the lower and upper asymptote, respectively, specifies the latitude of maximal growth, the most quickly with latitude, denotes the growth rate (Fig. 2), denotes the residual standard deviation, and denotes the number of locations.

We take a hierarchical approach and infer from individual temperature observations at location as

where is the number of observations at each location, and is the estimated standard deviation of the temperatures at location .

This structure implies that is not fixed at the mean of the temperatures of location , but is drawn (regularised) towards the overall logistic regression curve. The pull towards the regression curve tends to be high when is low, when the observations are scattered, and/or when the overall standard deviation is low. In practice, this has the desirable consequence that locations with few observations and large temperature differences between observations have less influence on the regression curve than well-sampled locations with consistent temperature observations.

**Priors.** In the Bayesian framework, priors need to be placed on the unknown parameters of a model. For and we use weakly informative inverse-gamma priors with shape parameter = … and scale parameter = … . Moderately changing these priors has little effect on the model outcome, which is desirable as we have little a-priori knowledge of these parameters. In contrast, we put informative priors on the regression coefficients , , and , based on basic physical principles. Specifically, we put a skew-normal prior on the lower asymptote , with … . This constrains to not be , which is the freezing point of sea water. We chose this distribution such that its mode is , slightly higher than the modern…

* logistic regression
* hierarchical model structure
* choice of priors (based on modern, see below)

[Fig. 2: Model structure and visualisation of parameters and priors]

## Model validation

[Fig. 3] - Modern data - Sample based on Eocene localities

## Model application

* Calculate lat gradient
* Calculate global T

[Fig. 4]

# Results

## Model validation

* Show that the modern gradient can be reproduced with Eocene sampling distribution [Fig 3 - Modern gradient]

## EECO reconstruction

* Show Eocene gradient
* Global t
* report lat gradient

## Fig 4 - compare Eocene gradient with previous reconstructions / ES models

* x1 Draw samples from the posterior gradient to get a latitudinal gradient of deg C / deg lat with uncertainty (intercept gradient at 0 and 90 deg lat)
* x2 generate global average temperature, and tropical, temperate, polar temperatures in a similar way, accounting for area

# Discussion

* x1 compare lat gradient to literature estimates, e.g. Zhang2019

# Conclusions

# Acknowledgements

# Author contributions

# Data accessibility

# References

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