Joint inversion of proxy system models to reconstruct paleoenvironmental time series from heterogeneous data

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# Abstract

Paleoclimatic and paleoenvironmental reconstructions are fundamentally uncertain because no known proxy is a direct record of a single environmental variable of interest; all proxies are sensitive to multiple forcings. One productive approach to reducing proxy uncertainty is the integration of information from multiple proxy systems with complimentary, overlapping sensitivity to environmental one or more target variables. Most such analyses are conducted in an ad-hoc fashion, either through qualitative comparison to assess the similarity of single-proxy reconstructions or through step-wise quantitative interpretations where one proxy is used to constrain a variable relevant to the interpretation of a second proxy. Here we propose a formal framework for the integration of multiple proxies via the joint inversion of proxy system models. The “Joint Proxy Inversion” (JPI) method provides a statistically robust approach to producing self-consistent interpretations of multiproxy datasets, allowing full and simultaneous assessment of all proxy and model uncertainties to obtain quantitative estimates of past environmental conditions. Other benefits of the method include the ability to use independent information on climate and environmental systems to inform the interpretation of proxy data, to fully leverage information from unevenly- and differently-sampled proxy records, and to obtain refined estimates of proxy model parameters that are conditioned on paleo-archive data. Application of JPI to the marine Mg/Ca and δ18O proxy systems at two distinct timescales demonstrates many of the key properties, benefits, and sensitivities of the method, and produces new, statistically-grounded reconstructions of Neogene ocean temperature and chemistry from previously published proxy data. We suggest that JPI is a universally applicable method that can be implemented using proxy models of wide-ranging complexity to generate more robust, quantitative understanding of past climatic and environmental change.

# Introduction

Paleoenvironmental reconstructions, including reconstructions of past climate, provide a powerful tool to document the sensitivity of Earth systems to forcing, characterize the range of natural responses associated with different modes of global change, and identify key mechanisms governing these responses. Throughout the vast majority of the planet’s history, however, estimates of environmental conditions can only be obtained through proxy reconstructions. Proxy data are, as their name implies, indirect recorders of the environmental conditions we hope to estimate, and the estimates they provide are plagued by substantial, often poorly characterized, uncertainty.

The simplest proxy reconstructions typically focus on a single environmental variable of interest, inverting experimental or natural calibration datasets to obtain quantitative estimates of that variable and treating residual variance in the calibration as ‘noise’. In reality, however, no proxy system exists that is sensitive only to a single paleoenvironmentally-relevant variable, the majority of this noise reflects the uncharacterized influence of other environmental variables on the proxy system. Fossil leaf assemblages exhibit characteristic variability that can be associated with mean annual air temperature, but also appears to be influenced by annual temperature range and diverges among floras separated by long periods of independent evolution (REF). The saturation state of alkenones produced by marine phytoplankton is a sensitive recorder of water temperature, but is also strongly controlled by cell growth rate and size (REF). Even recently emerging clumped isotope techniques, which are in theory a direct recorder of the temperature of carbonate mineral formation, can be affected by factors such as kinetic growth-rate effects and poorly constrained, potentially variable offsets between the environment of carbonate formation and more commonly targeted atmospheric temperature conditions (Passey et al. 2010). Failure to recognize and consider the sensitivity of proxies to multiple environmental factors leads to two important problems in traditional proxy interpretations. First, considering only a single environmental variable in our interpretations maximizes the uncertainty in our reconstructions, which could be reduced if the influence of other variables is described and constrained. Second, unacknowledged sensitivity to multiple variables creates potential for biased proxy interpretations if variation in these variables is non-random over the period being reconstructed.

One productive approach to resolving the second issue is the development and use of proxy system models in the interpretation of proxy data (REFS). These models represent an attempt to mathematically describe the complex of environmental, physical, and biological factors that control how environmental signals are sampled, recorded, and preserved in proxy measurements. Several recent reviews and perspectives are available discussing the concepts underlying proxy system models and different ways that they have been applied to proxy interpretation, ranging from substitution for empirical calibrations in inverse estimation of environmental signals to formal integration within climate model data assimilation schemes (Evans et al. 2013). A growing number of proxy system models and modeling systems are being developed (e.g., Tolwinski-Ward et al. 2011, Stoll et al. 2012, Dee et al. 2015), and useful models span a range of complexity from empirically-constrained regressions to fully mechanistic, theory-based formulations. Key to any such model is accurate representation of uncertainty in each model component, which allows even relatively simple, potentially incomplete models to be used to obtain reconstructions with quantifiable uncertainty bounds.

Reducing the uncertainty of quantitative paleoenvironmental reconstructions requires adding constraints to proxy interpretations, as exemplified by the increasingly common development of multi-proxy reconstructions. In situations where two or more proxies share sensitivity to common or complimentary environmental variables, it stands to reason that the information provided by each can be used to refine interpretation of the multi-proxy suite. In practice, a variety of approaches have been used. Commonly, multi-proxy integration has been qualitative and focused on confirmation: trends reconstructed using one proxy system are cross-checked against a second, providing increased confidence in the reconstruction if and when the patterns match (e.g., Grauel et al. 2013). In other cases, proxies have been combined quantitatively, but usually in a stepwise fashion: one proxy system is used to estimate an environmental variable to which it is sensitive, and those reconstructed values are then used to constrain the interpretation of a second proxy formed at the same time (e.g., Fricke et al. 1998, Lear et al. 2000). Although it provides a simple strategy to combining complimentary proxy information, this approach does not fully leverage overlapping information that may be contained in multiple systems that respond to common forcing, is not conducive to robust quantification of uncertainty, and requires that both proxies sample coeval paleoenvironmental conditions.

Here we propose a general approach to proxy interpretation that leverages the benefits of proxy models and provides a formal statistical framework for proxy integration. The method, which we call Joint Proxy Inversion (JPI), cast in a Bayesian inferential framework, uses Markov Chain Monte Carlo methods to invert a hierarchy of proxy-system and environmental timeseries models. These models are simultaneously conditioned on proxy data and calibration datasets to obtain posterior estimates of the target paleoclimate timeseries with quantifiable uncertainty that accounts for all model components. We first describe the framework as applied to joint inversion of the marine Mg/Ca and δ18O proxy systems, and then present applications of JPI to two such datasets recording paleoceanographic conditions at two different timescales. These applications provide a platform allowing us to illustrate and discuss merits and limitations of JPI relevant to its broader application.

# Methods

## Data

## Proxy model

## Environmental model

# Results and Discussion

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