

Evaluating Proxy Influence in Paleoclimate Reconstructions

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INTRODUCTION

Climate Field Reconstructions (CFR)

CFRs attempt to estimate spatiotemporal fields of climate variables over a historical period. CFRs are an important tool for studying the mechanisms of climate change

Data Assimilation (DA)

DA methods are a type of CFR that combines climate models with proxies. Proxies can include tree rings, ice cores, and corals. DA methods are advantageous because of their inherent uncertainty quantification with ensembles.

Proxy Influence

It is not known how much the proxies influence reconstructions over the base climate model. If reconstructions are just a product of the climate model then climate change forecasts based on DA are not fully incorporating historical data.

Statistical Challenge

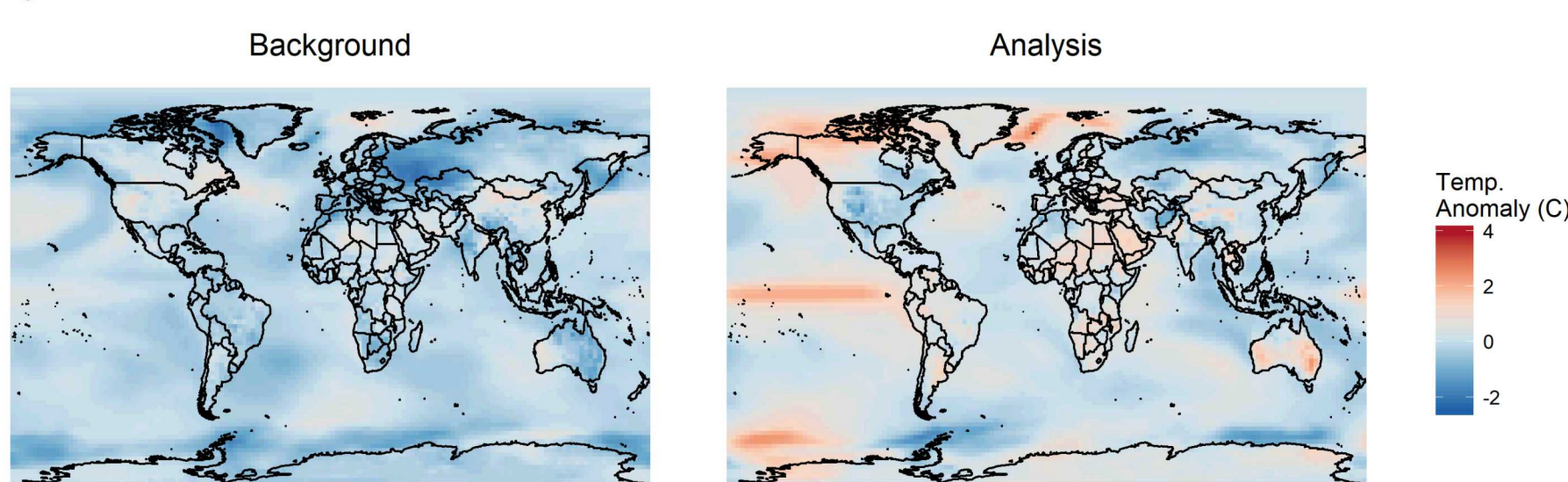
Use a specifically designed DA experiment to isolate proxy influence and recast the climatological problem as comparing two sets of spatiotemporal random fields. Use Functional Data Analysis and Data Depth to compare their distributions.

PROJECT GOALS

1. Develop a new statistical test for comparing the distribution of two sets of random fields.
2. Quantify and assess the influence of proxies in assimilated CFRs .

DATA

- Background: 100 fields on 144 x 96 grid points.
- Analysis: 100 fields on 144 x 96 grid points over 998 years



METHOD

Data and Hypothesis

- Observe $X_1, \dots, X_n \sim P$ and $Y_1, \dots, Y_m \sim Q$
- $H_0: P = Q; H_A: P \neq Q$

Depth Definitions

- Define the Univariate Tukey depth

$$D(x(t), P_t) = 1 - |1 - 2P_t(x(t))|$$

- Define the Integrated Tukey depth

$$D(x, P) = \int_{[0, 1]^p} D(x(t), P_t) dt$$

- For each X_k define the two empirical measures

$$\hat{F}_X(x_k) = \frac{1}{n} \sum_{i=1}^n 1(D(X_i, P_n) \leq D(x_k, P_n))$$
$$\hat{G}_Y(x_k) = \frac{1}{m} \sum_{i=1}^m 1(D(Y_i, P_n) \leq D(x_k, P_n))$$

- Measure the outlyingness of P over Q with

$$K_P(X, Y) = \max_{x_k \in X} |\hat{F}_X(x_k) - \hat{G}_Y(x_k)|$$

- For each Y_k define the two empirical measures

$$\tilde{F}_X(x_k) = \frac{1}{n} \sum_{i=1}^n 1(D(X_i, P_n) \leq D(y_k, P_n))$$
$$\tilde{G}_Y(x_k) = \frac{1}{m} \sum_{i=1}^m 1(D(Y_i, P_n) \leq D(y_k, P_n))$$

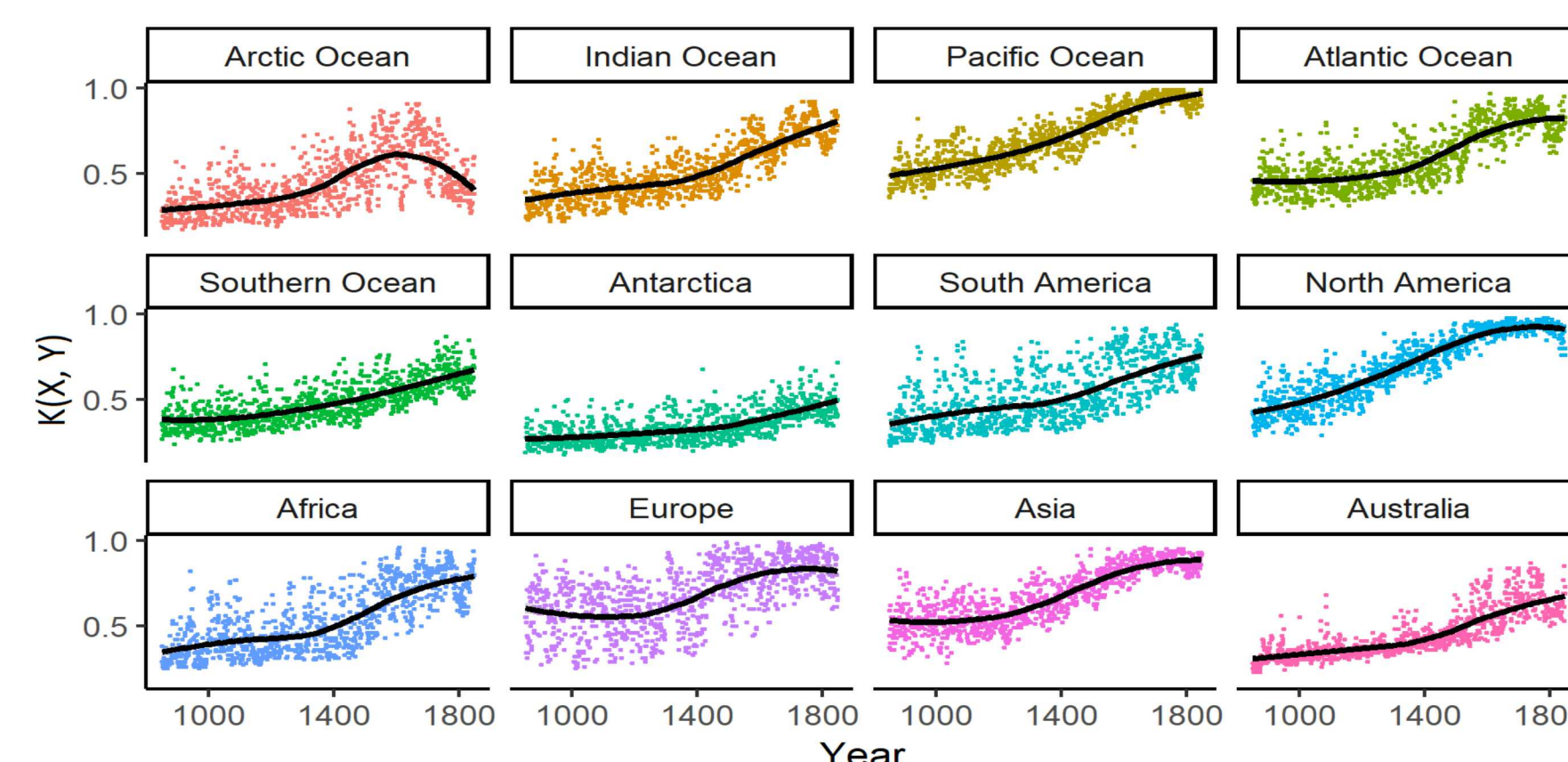
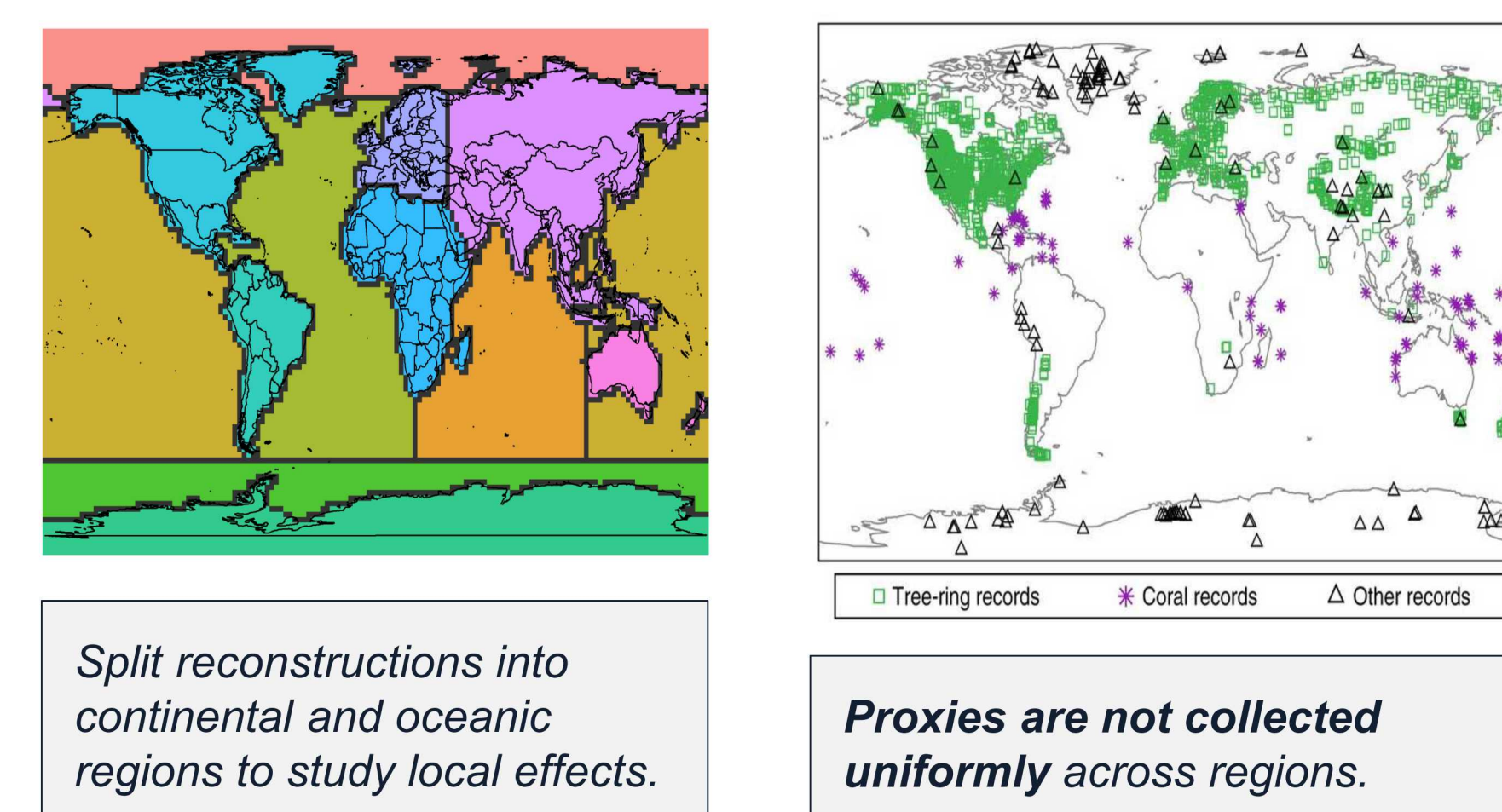
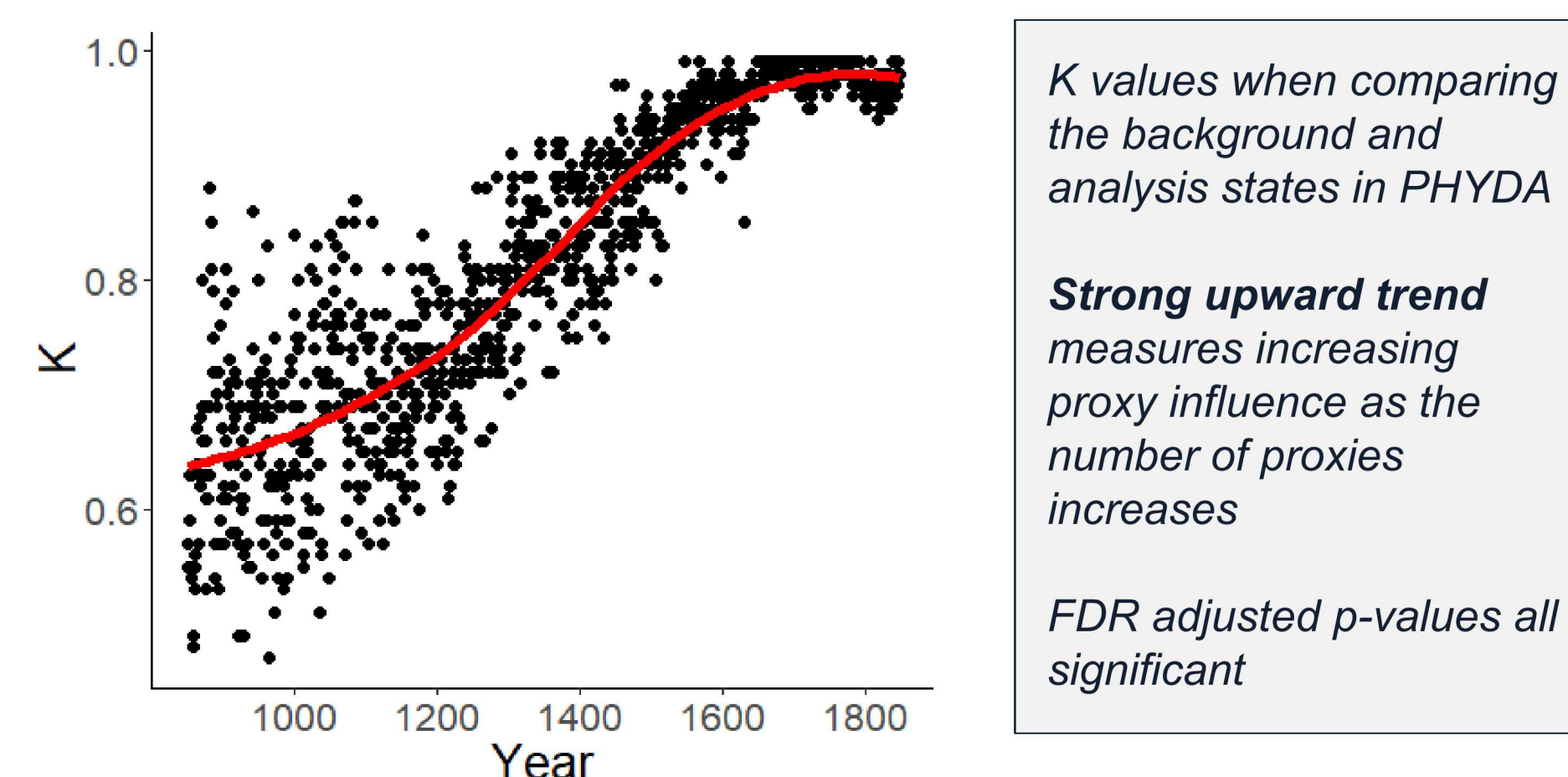
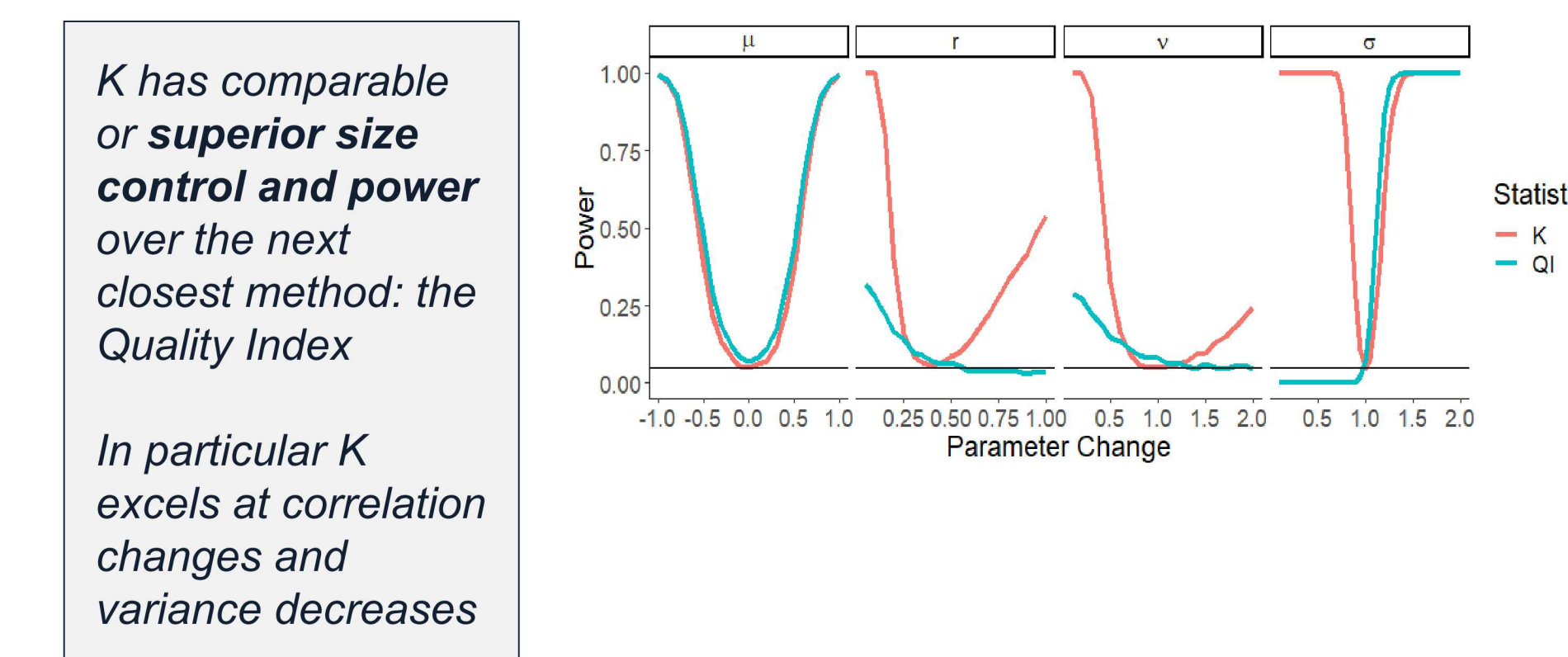
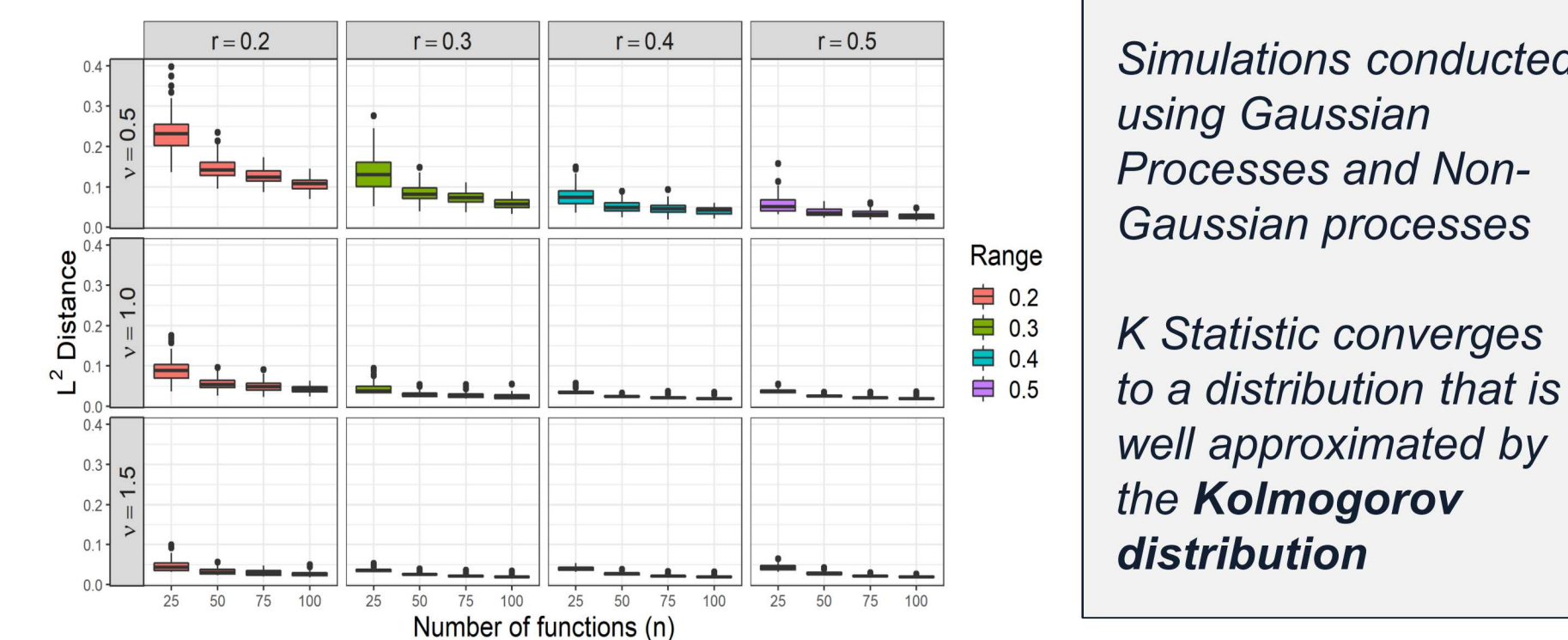
- Measure the outlyingness of Q over P with

$$K_Q(X, Y) = \max_{y_k \in Y} |\tilde{F}_X(y_k) - \tilde{G}_Y(y_k)|$$

Test Statistic

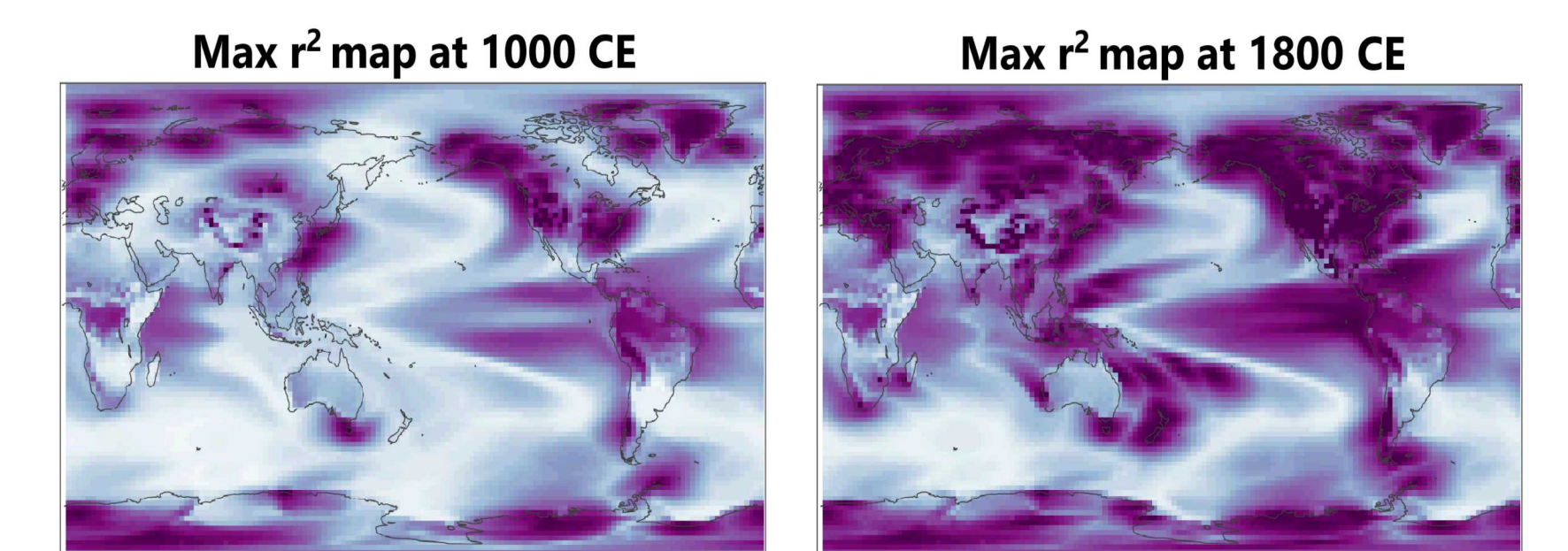
$$K(X, Y) = \max\{K_P(X, Y), K_Q(X, Y)\}$$

RESULTS



PROXY CORRELATION

- Some regions experience strong proxy influence despite a lack of local proxies, such as the Pacific.
- Lack of local proxies can be compensated for by strong correlation with regions with numerous proxies.



- Climate in the Pacific is highly connected with climate in North America due to the El-Niño Southern Oscillation.
- Teleconnection and local connection strength increases over time as more proxies become available for reconstruction.

CONCLUSIONS

- Strong evidence of divergence between the background and analysis states associated with PHYDA.
- Degree of separation depends on geographic location and time period.
- Increasing proxy information is associated with a commensurate influence over the reconstructions.
- Influence of the model prior is minimized as proxy networks become considerably more dense.

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