High-Resolution Climate Field Reconstructions for Multidecadal Dynamic Analysis: Prospects and Challenges

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GloDecH Meeting – Wednesday, March 9th, 2011
Lamont-Doherty Earth Observatory of Columbia University
Spatiotemporal Reconstructions, Dynamic Inferences, and Model Validation

Mann et al., Global Signatures and Dynamical Origins of the Little Ice Age and Medieval Climate Anomaly, Science, 326, 2009.

Secular ENSO Behavior

AMO Variability and Consequences

Volcanism and Monsoons

MCA and LIA Dynamics and Causes

Drought Variability, Forcing and Impacts

Extremes

Global and Regional Climate Sensitivity

Characterize Decadal/Multidecadal Var.
NAO, El Nino and N. Am. Winters

Dec-Mar 1950-99 Snowfall Anomalies (inches/season)

Modern NINO3 and NAO Indices
Paleo-Modern NAO and NIN03 Indices

Cook, E. (2000), Niño-3 SST reconstruction, ITRDB, NOAA Paleoclimatology, CO.


Field Reconstructions for 1783–4 C.E.

**SLP DJF 1783–4**

**Temperature DJF 1783–4**

**PDSI JJA 1784**

Laki Eruption and the 1783–4 Winter

Benjamin Franklin (Paris, 1784): “…when the effect of the sun’s rays to heat the earth in these northern regions should have been greater, there existed a constant fog over all Europe, and a great part of North America…hence perhaps the winter of 1783-4 was more severe than any that had happened for many years…The cause of this universal fog is not yet ascertained…whether it was the vast quantity of smoke, long continuing, to issue during the summer from Hekla in Iceland, and that other volcano which arose out of the sea near that island…is yet uncertain.”

Atlantic Multidecadal Oscillation

AMO Oscillatory Period ~ 60–70 years

Monthly values for the AMO index, 1856-2009

SST and SLP
The Secular Behavior of ENSO

100-yr Trends in Zonal SST Gradients

- ECHO-g Control Run
- GFDL Control Run

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**Legend:**
- **SST Trend:** Change in surface sea temperature over 100 years.
- **Zonal SST Gradient:** Variation in temperature across the ocean's zonal axis.

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**Graphs:**
1. **ECHO-g Control Run:** Shows fluctuations in zonal SST gradients over 100 years.
2. **GFDL Control Run:** Displays similar data, focusing on temperature variations.
3. **Calendar Month SST Trend:** Illustrates trends across different calendar months.
4. **Zonal SST Gradient:** Graph depicting the spread of temperature data over years.

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**Analysis:**
- The ECHO-g Control Run exhibits significant variations in zonal SST gradients.
- The GFDL Control Run follows a similar pattern but with different magnitudes.
- The calendar month SST trend graph highlights fluctuations, possibly indicating seasonal effects.
- The zonal SST gradient graph suggests consistent variation over the years.
Millennial Climate Model Simulations

Coupled Model Intercomparison Project Phase 5 (CMIP5)

21 Modeling Groups Performing “Long-Term Experiments”

10 Groups Performing (multiple) Last Millennium Experiments
Field Reconstructions for 1783–4 C.E.

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Available CFRs for the Common Era
Which Ones Are CFRs?

Which Ones Are CFRs?

Mann et al., *Science*, 2009

Most Reconstruction Approaches: Multivariate Linear Regression

Calibration $\rightarrow T^C = BP^C + \varepsilon$

Reconstruction $\rightarrow T^R = BP^R$

- $T$ = Temperature Field
- $P$ = Proxies
- $C \rightarrow$ Calibration Interval
- $R \rightarrow$ Reconstruction Interval
Global CFRs: Reduced Space Regression Approaches

Ordinary Least Squares Estimator:

$$B = (TP^T)(PP^T)^{-1}$$

**BUT**, estimation of the B matrix works best when the system is overdetermined, that is, when the time dimension $n$ is much larger than the spatial dimension $m$, because the covariances are more reliably estimated.
Global CFRs: Reduced Space Regression Approaches

Ordinary Least Squares Estimator:

\[ B = \left( TP^T \right) \left( PP^T \right)^{-1} \]

Three Principal Choices

**Reduced Space Representation of \( T \) and \( P \):**

\[ T = U_t \Sigma_t V_t^T \]
\[ P = U_p \Sigma_p V_p^T \]

**Regularization of \( B \):**

\[ B = U_t \Sigma_t V_t^T V_p \Sigma_p^{-1} U_p^T \]
Important (Potentially Violated) Assumptions

- Proxy-Climate Connection is linear, stationary and univariate
- Target patterns are stationary and well-represented in the calibration interval
- Missing values are missing at random
- Climate teleconnections justify non-local connections between proxies and the target field
Employing Millennial GCM Simulations for Synthetic CFR Experiments

Model Data

Complete Spatial Fields

Mean Temperature (°K)

Continuous Time Series

Temperature Anomaly (K)

Time (years A.D.)

Model Subsampling

Target Field

Proxy Locations
Pseudoproxy Validation
Making Pseudoproxies

Signal

Temperature Anomaly (K)

57.5° N, 2.5° E

Stand. Dev. = 1

Time (years C.E.)

White Noise

SNR = 1.0

Stand. Dev. = 1
Correlation = 0.01

SNR = 0.5

Stand. Dev. = 2
Correlation = 0.01

SNR = 0.25

Stand. Dev. = 4
Correlation = 0.01

Time (years C.E.)
Making Pseudoproxies

Signal

Signal + White Noise

SNR = 1.0
Correlation = 0.71

SNR = 0.5
Correlation = 0.45

SNR = 0.25
Correlation = 0.25
NH Mean Performance

**MBH98 Method**


**RegEM - Ridge**


**RegEM - TTLS**

Mann et al., *J. Geophys. Res.*, 2007

**CCA**

Smerdon et al., *J. Clim.*, 2010
Global or Hemispheric Mean Evaluations of CFRs are not Enough

Another Way of Looking at It: Global Mean vs. ENSO3.4

Grid-Point Correlations

Pseudoproxy SNR: 0.5

MBH98

Ridge

RegEM-TTLS

CCA

Correlation (r)

Impact of Network Sampling

Mann et al. (1998) Network

Mann et al. (2008) Network

Synthetic Tree-Ring Experiments


Smerdon et al., Impact of tree-ring simulated pseudoproxies on reconstruction skill in climate field reconstructions, in prep.
CFRs and the Future

Work with what we’ve got

- Uncertainties, uncertainties, uncertainties...
- Expanded proxy networks
- Constrained CFRs targeting high skill regions
- Continued methodological testing

Work toward what we’ve not

- Process-based characterization of climate-proxy connections
- Local calibrations and error constraints
- Bayesian formulations
- Other climate variables (multivariate target fields)