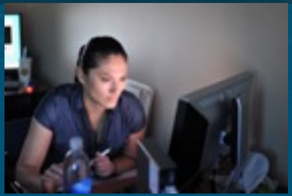
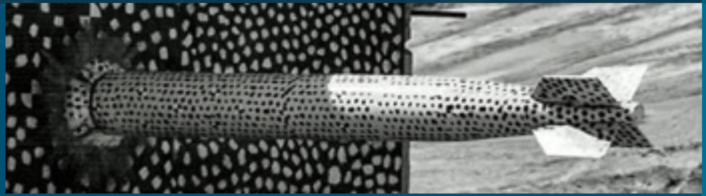
Learning Why: Data-Driven Causal Evaluations of Climate Models





Presented by

J. Jake Nichol, University of New Mexico and Sandia National Labs

Problem

The Earth's climate is a highly complex system and high-dimensional coupled Earth system models are essential to predict future climate.

Evaluation and analysis of climate model output and observational data must use a holistic approach that considers the many temporal interdependencies in the system.

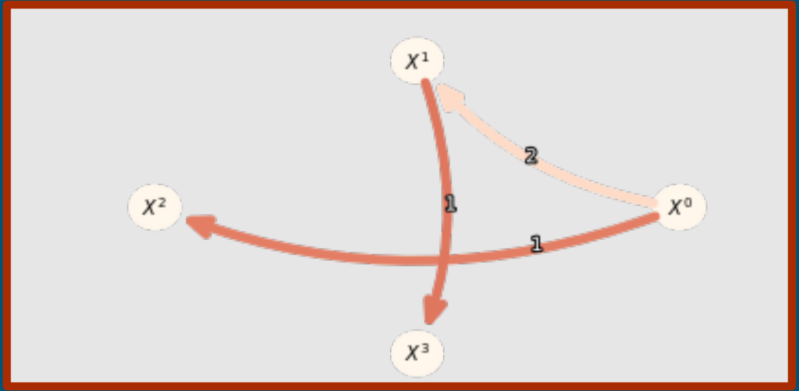
Currently, most climate data are evaluated with correlation, regression, and spectral analysis methods. These are hard to interpret holistically, they are not causal, and they can lead to spurious inferences.

Climate model development and climate science are hindered by relatively simplistic evaluation methods. We need more informative methods for evaluating and comparing climate models.

Causal Discovery

Finding causal relationships in data:

- Ideally found via controlled, randomized experiments.
- Expense, complexity, ethics, or uniqueness can render experimentation infeasible.
- Under appropriate **assumptions**, Markov equivalence classes can be found.
  - Based on conditional independence relationships.
- Recovered Markov equivalence classes may contain multiple partially directed, acyclic graphs representing the discovered causal structure.



Assumptions

Faithfulness/stableness: independencies in the data arise by an underlying causal structure, not by coincidence.

Causal Sufficiency: all of the common causes are represented in the variables measured.

Causal Markov condition: for a node *n*, it is independent of all nodes *n* is not directly linked to, conditional on the set of *n*'s parents.

Causal Discovery

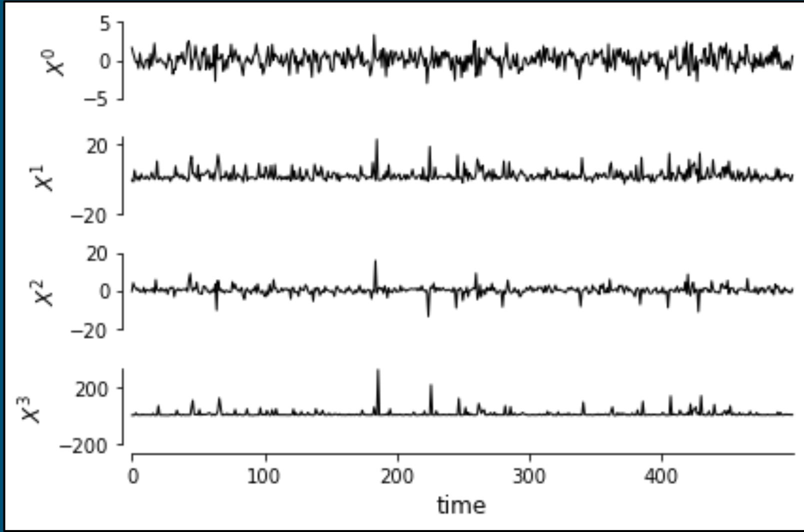
Temporal causal relations

$$X_t^0 = \eta_t^0$$
$$X_t^1 = 2.0(X_{t-2}^0)^2 + \eta_t^1$$
$$X_t^2 = 0.5(X_{t-1}^0)^3 + \eta_t^2$$
$$X_t^3 = 0.6(X_{t-1}^1)^2 + \eta_t^3$$

Variables X^0, X^1, X^2, X^3
Noise terms η^i

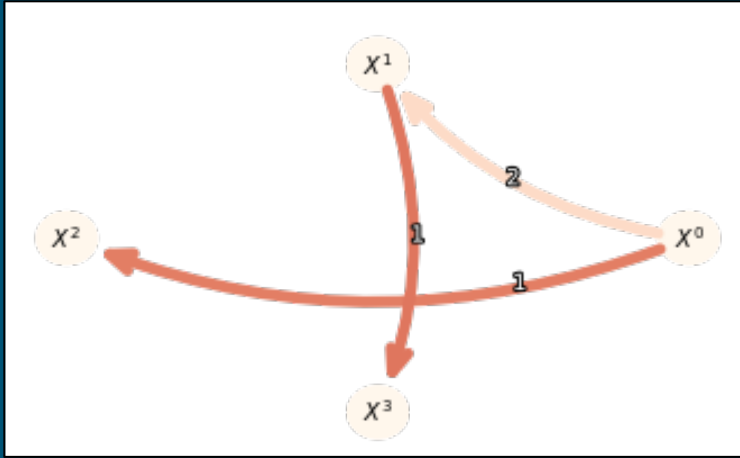
=

Time series



Causal network learning algorithm, such as PC[1]

Causal graph



1. Spirtes P, Glymour C. An Algorithm for Fast Recovery of Sparse Causal Graphs. Social Science Computer Review. 1991;9(1):62-72. doi:10.1177/089443939100900106

Specific Methodology

Peter-Clark Momentary Conditional Independence PCMCI[2]:

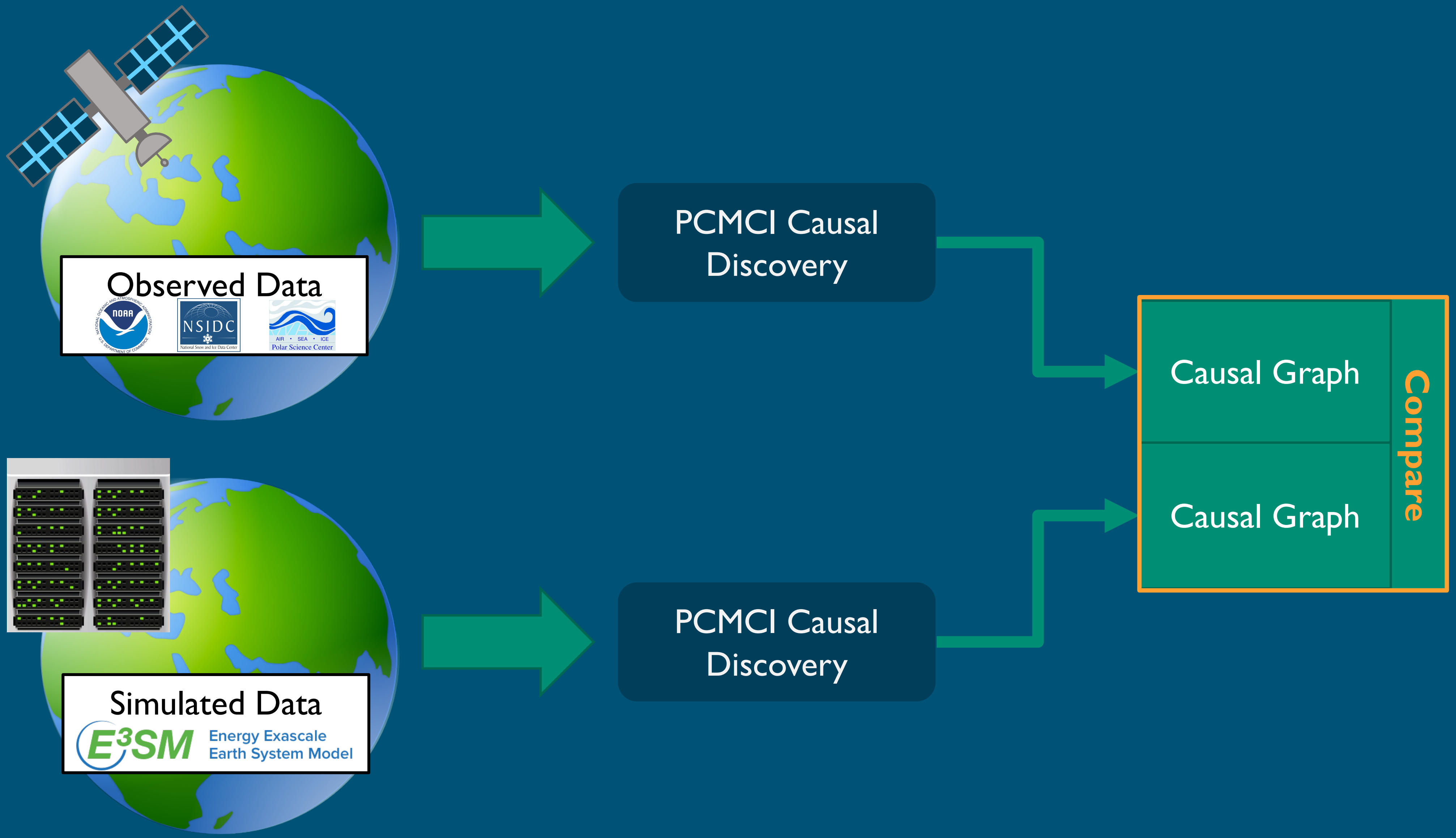
Note: starts with fully connected undirected graph of variables and their lags

1) PC (named after authors): condition selection
   - Identify relevant conditions $\mathcal{P}(X_t^j)$ for all time series variables (including lags of each time series)
   - Markov set discovery algorithm based on PC causal network discovery
   - Removes irrelevant conditions for each of the N variables by iterative independence tests
   - May include false positives

2) MCI tests:
   - Test whether $\mathcal{P}(X_{t-\tau}^i \rightarrow X_t^j)$ for all variables i,j and all lags τ
   - Accepts relations with greater than threshold significance
   - Addresses PC's false-positives for highly inter-dependent time series

[2] Jakob Runge, Peer Nowack, Marlene Kretschmer, Seth Flaxman, and Dino Sejdinovic. 2019. Detecting and quantifying causal associations in large nonlinear time series datasets. Retrieved from http://advances.sciencemag.org/

Specific Methodology



Arctic Climate Data

Monthly Means

Air Temperature | Cloud Coverage

Longwave Radiation Flux

Precipitation | Sea Ice Extent

Shortwave Radiation Flux

Sea Ice Extent | Sea Ice Volume

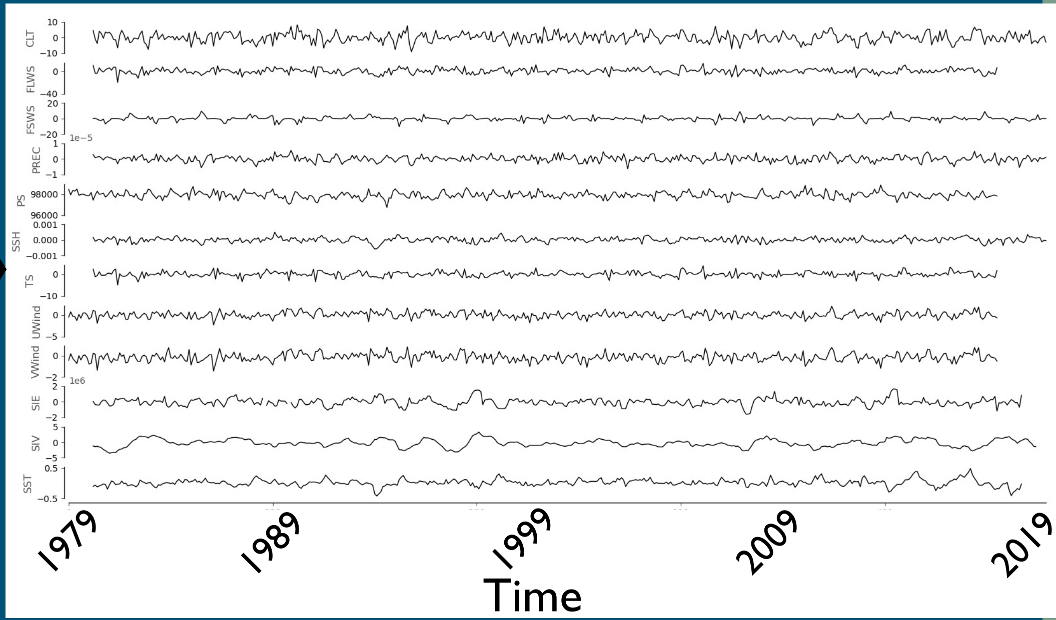
Sea Surface Temperature

Surface Pressure

Zonal Wind | Meridional Wind

12-month-lag differencing for stationarity

Stationary time series



Sea ice data https://nsidc.org/data/G02202/versions/2, Meier, *et al.* (2013)

Atmosphere reanalysis data https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html, Kanamitsu, *et al.,* (2002)

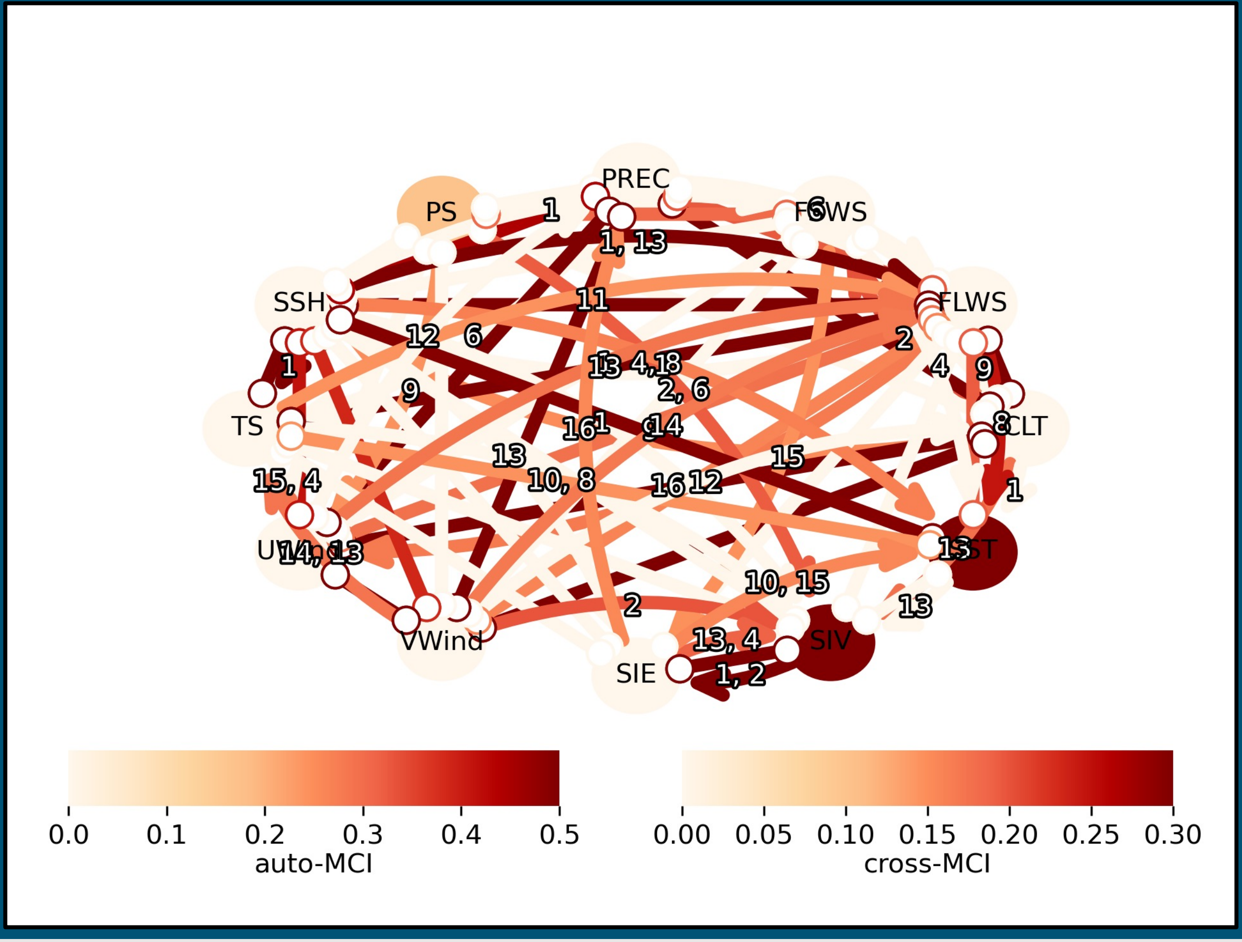
Sea surface temperature https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.ersst.v4.html, Huang, *et al.* (2014).

Preliminary Results for Observational Data

Resulting graphs are highly interconnected and difficult to interpret visually.

Many variables are correlated, though there are significant causal arrows inferred.

Need to use metrics to describe and compare resulting causal graphs.



Lines with circles indicate correlated, but non-spurious relationships (if assumptions hold).

Nodes' Auto-MCI indicates the momentary conditional independence of each node with itself.

Links' Cross-MCI indicates the momentary conditional independence of the two linked nodes.

Next Steps and Discussion

- Determine the best conditional independence test for our data and parameterize methods
  - Available tests include the linear partial correlation, nonlinear gaussian process regression and distance correlation, and nonlinear conditional mutual information estimated with k-nearest-neighbors.
- Determine useful metrics for comparing resulting causal models
  - Ideas include: F1 score, node/edge degrees

- Once major differences are found between graphs computed by observed and simulated datasets, we can take a closer look to see which variable links are contributing to the differences.
- This will help to explain why E3SM's simulation of the Arctic climate is different from what we observe year to year and provide guidance for future model improvements.