Causal Discovery as a novel approach for climate model evaluation

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Abstract

The recently developed causal discovery algorithm called PCMCI (Runge et al., 2019) estimates the time-lagged causal dependency structures from multiple time series and is adapted to properties of Earth System time series data. One recent study used PCMCI to evaluate models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Nowack et al., 2020).

Here, we first reproduce and discuss the results found in Nowack et al. before highlighting possible directions of future work, such as the application of the same method to the more recent CMIP6 archive. For this, we re-evaluate CMIP5 models against a reanalysis dataset as a proxy for observations. We use PCMCI on dimension-reduced meteorological reanalysis data and the CMIP5 ensembles data. The resulting causal networks represent teleconnections in each of the CMIP5 climate models. The model performance in representing realistic teleconnections is then assessed by comparing its causal network to the one obtained from meteorological reanalysis. We are able to reproduce the relationship between the networks F1-score (measures presence and absence of links) and precipitation change over land found in Nowack and al.,2020. In addition, we find a similar relationship between the networks weights similarity metric (measures similarity of causal link strengths) and precipitation change over land.

1 - Input data and preprocessing

Input data:

- Variable: Sea Level Pressure (SLP)
- Time period: 1979-2014
- Frequency: 3-day averaged
- Datasets: NCEP reanalysis dataset (reference dataset) and historical runs of CMIP5 models

Preprocessing: regridding to reference dataset, detrending, anomalizing, time separation of seasons (DJF,MAM,JJA,SON).

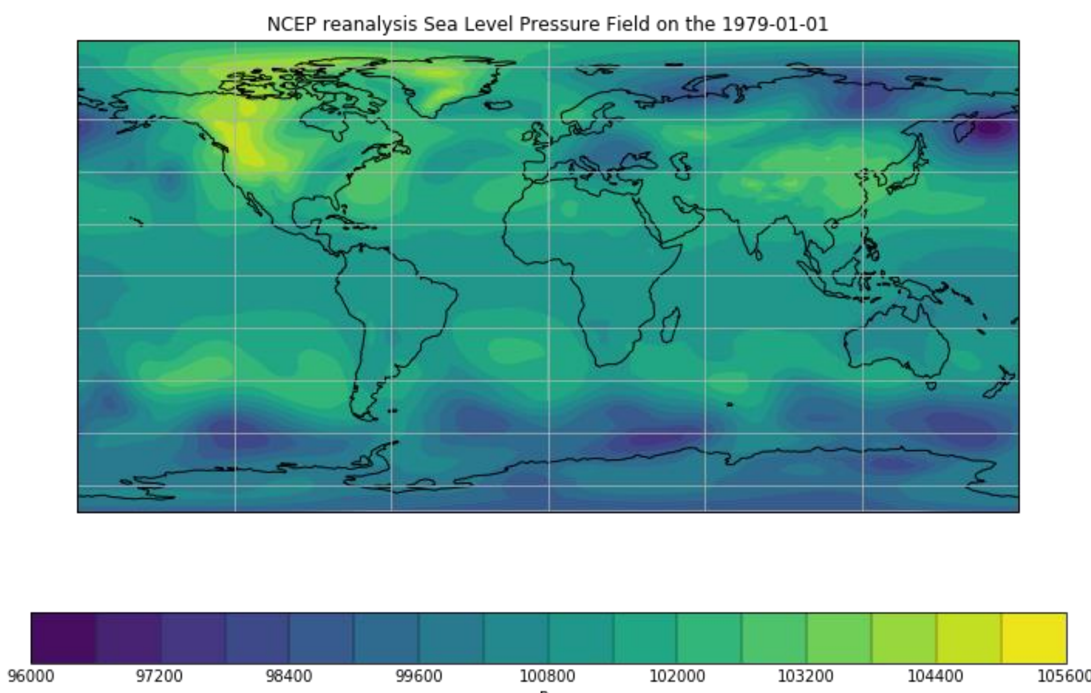

Figure 1 Example of input data : NCEP sea level pressure field for the 1st of January 1979. Preprocessing has not been applied yet.

2 - Dimensionality reduction

Why do we need to reduce dimension of the input data ?
Causal discovery methods lose detection skill for large numbers of variables, especially considering our interest in multiple time lags. We therefore reduce the spatial dimension to a set of 50 components.

Dimensionality reduction technique, PCA-Varimax:
For each season:

- We perform a spatial PCA (also known as EOF) on the reference dataset.
- Then, we rotate the PCA components using a Varimax rotation. The rotated components are more spatially confined.
- We apply the PCA-Varimax transformation learned on the reference datasets to the CMIP5 models' data. We keep the first 50 components.

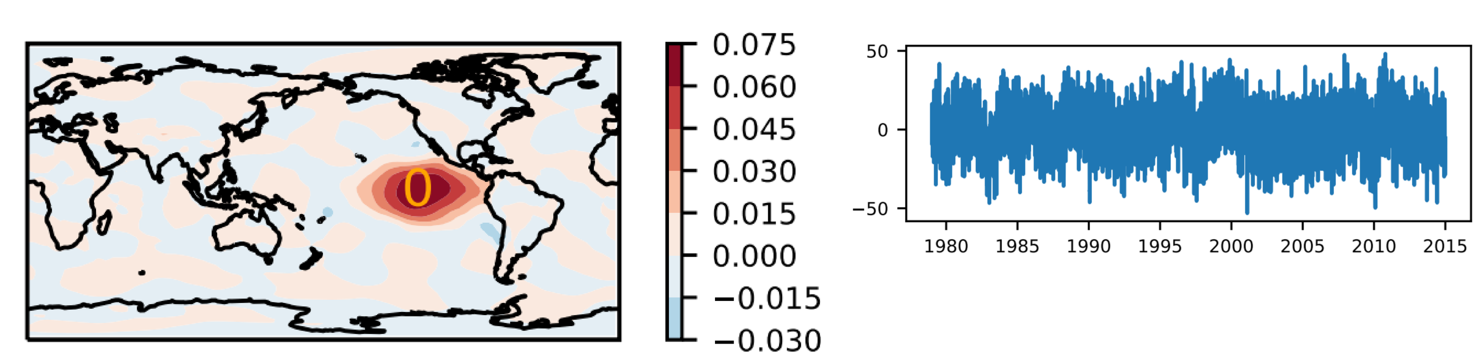

Figure 2 First PCA-Varimax component of the preprocessed NCEP SLP dataset (1979-2014) for season DJF. We can derive a time series for each component.

3 - Causal discovery

Causal discovery methods aim at retrieving the causal dependencies in the input data. Here, we use **PCMCI** (Runge et al., 2019). It allows to efficiently reconstruct causal graphs from high-dimensional time series datasets and model the obtained causal dependencies.

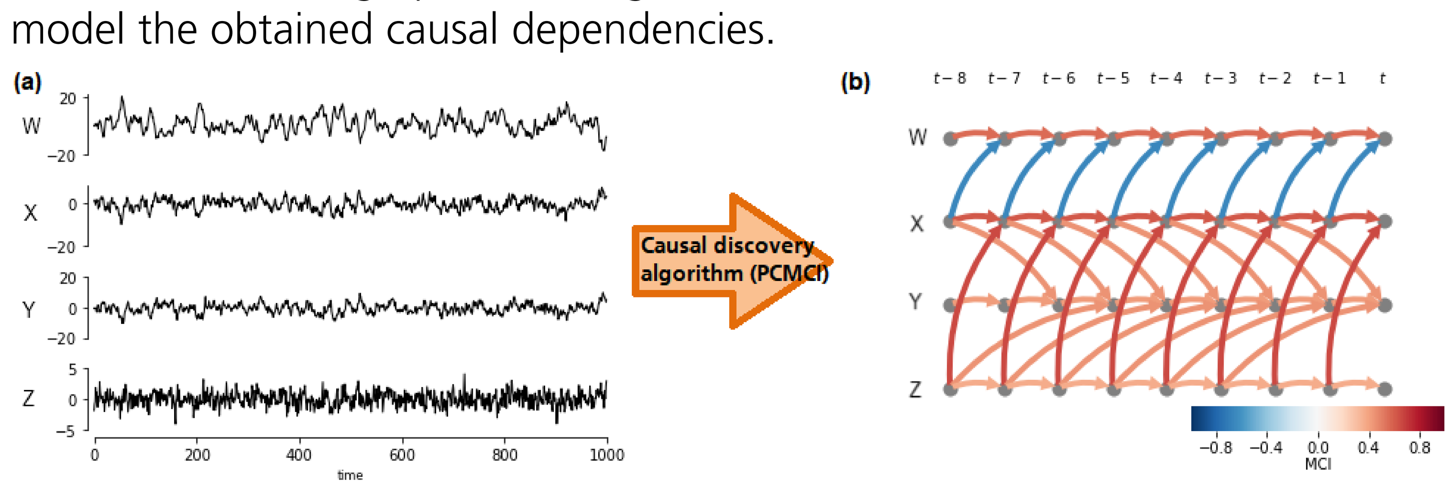

Figure 3 Example of an application of PCMCI (Runge et al., 2019). (a) Simulated time series of four variables linked by time-lagged linear dependencies. (b) Output graph of the PCMCI Causal Discovery algorithm exhibiting found time-lagged dependencies and their strengths.

4 – Global workflow

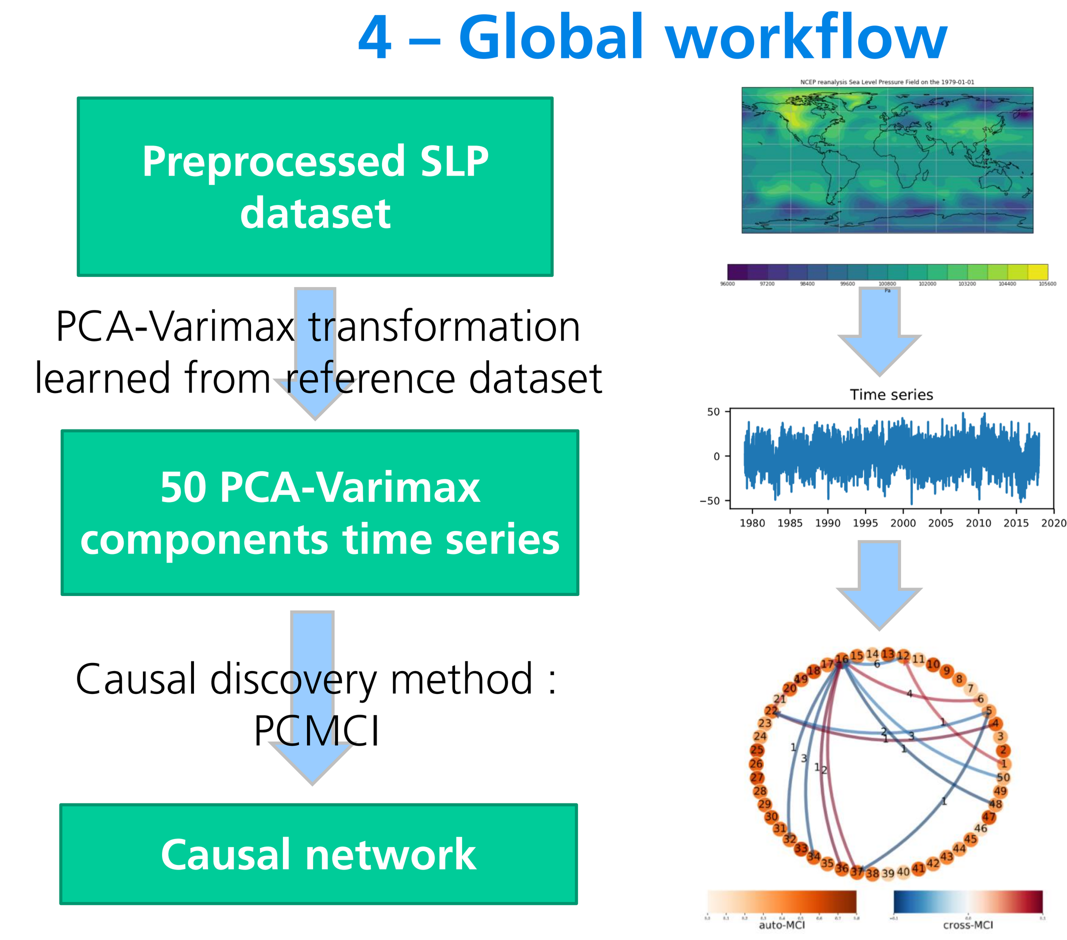

Figure 4 Workflow applied to obtain a causal network from each preprocessed SLP dataset. There are (#Seasons × #CMIP models and reference dataset) preprocessed datasets in total. This yields the same number of causal networks.

Results

We access model skill in network by measuring similarity between the model's causal network and the reference NCEP causal network using two measures : a F1-score (like in Nowack et al.) and a Weight similarity metric (newly introduced measure). The correlations between model skill in networks and historical precipitation representation lead to investigate a relationship between the model skill and the projected land precipitation change of the model.

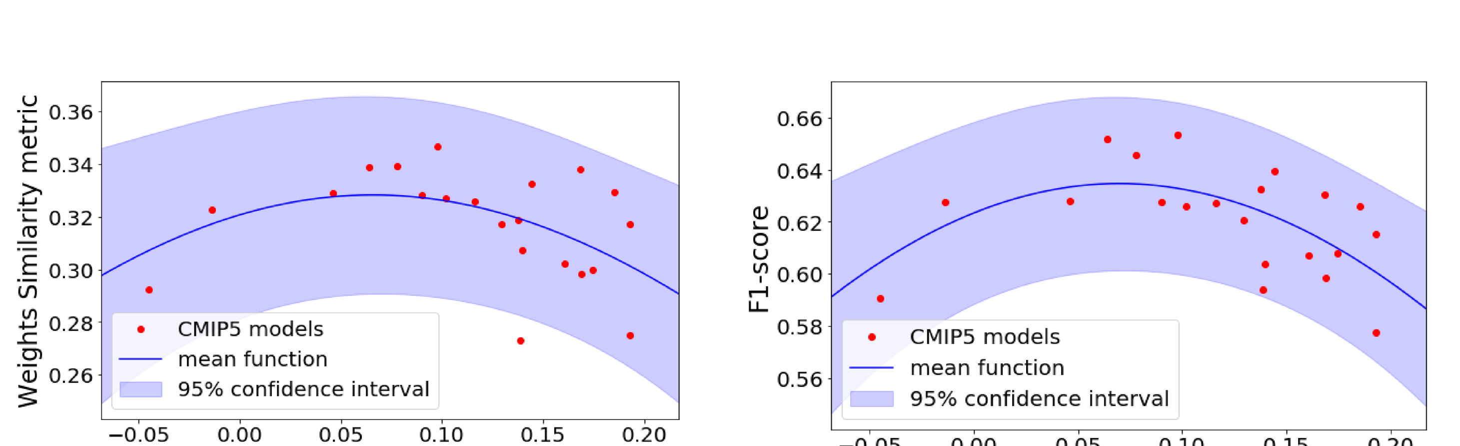

Figure 4 (left) Weights similarity metric of CMIP5 models causal network versus projected precipitation change over land. (right) F1-score versus projected land precipitation change. The land precipitation change is taken as the difference between 1860-1910 and RCP8.5 2050-2100. The curves are fitted using a Gaussian Process Regression.

Outlook from Nowack et al., 2020

Our relationship is similar to the one found in Nowack et al., 2020. In this paper, the causal networks are constructed using 1948-2017 data.

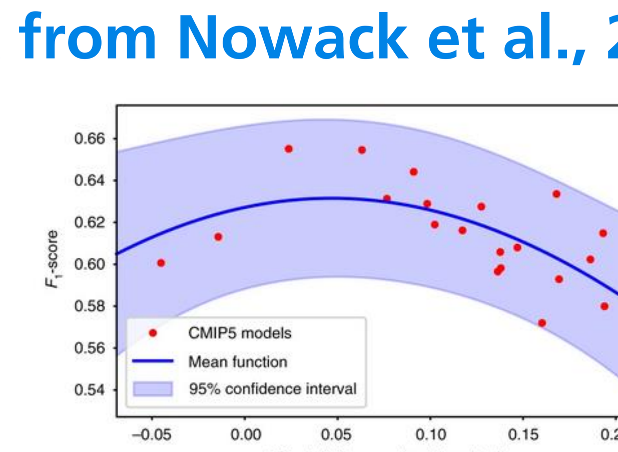

Figure 5 Excerpt from Nowack et al., 2020: F1-score versus projected land precipitation change. The precipitation change is taken as the difference between 1860-1910 and RCP8.5 2050-2100. The curve is fitted using a Gaussian Process Regression.

Future works

- Apply the same workflow to CMIP6 data archive and ERA-Interim,
- Test more causal network similarity measures,
- Develop a weighing scheme based on the model skill/projected precipitation change over land relationship.

References

J. Runge, P. Nowack, M. Kretschmer, S. Flaxman, D. Sejdinovic, Detecting and quantifying causal associations in large nonlinear time series datasets. Sci. Adv. 5, eaau4996 (2019). DOI: 10.1126/sciadv.aau4996

Nowack, P., Runge, J., Eyring, V. *et al.* Causal networks for climate model evaluation and constrained projections. *Nat Commun* **11**, 1415 (2020). https://doi.org/10.1038/s41467-020-15195-y

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