Geophysical Research Abstracts
Vol. 19, EGU2017-11366, 2017
EGU General Assembly 2017

Overcoming autocorrelation biases for causal inference in large nonlinear geoscientific time series datasets

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Causal discovery methods for geoscientific time series datasets aim at detecting potentially causal statistical associations that cannot be explained by other variables in the dataset.
A large-scale complex system like the Earth presents major challenges for methods such as Granger causality. In particular, its high dimensionality and strong autocorrelations lead to low detection power, distorting biases, and unreliable hypothesis tests. Here we introduce a reliable method that outperforms current approaches in detection power and overcomes detection biases, making it suitable to detect even weak causal signals in large-scale geoscientific datasets. We illustrate the method's capabilities on the global surface-pressure system where we unravel spurious associations and find several potentially causal links that are difficult to detect with standard methods, focusing in particular on drivers of the NAO.