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Understanding changes in environmental time series with time-frequency causality analysis

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Understanding causal effect relationships between the different variables in dynamical systems is an important and challenging problem in different areas of research such as attribution of climate change, brain neural connectivity analysis, psychology, among many others. These relationships are guided by the process generating them. Hence, detecting changes or new patterns in the causal effect relationships can be used not only for the detection but also for the diagnosis and attribution of changes in the underlying process.

Time series of environmental time series most often contain multiple periodical components, e.g. daily and seasonal cycles, induced by the meteorological forcing variables. This can significantly mask the underlying endogenous causality structure when using time-domain analysis and therefore results in several spurious links. Filtering these periodic components as preprocessing step might degrade causal inference. This motivates the use of time-frequency processing techniques such as Wavelet or short-time Fourier transform where the causality structure can be examined at each frequency component and on multiple time scales.

In this study, we use a parametric time-frequency representation of vector autoregressive Granger causality for causal inference. We first show that causal inference using time-frequency domain analysis outperforms time-domain analysis when dealing with time series that contain periodic components, trends, or noise. The proposed approach allows for the estimation of the causal effect interaction between each pair of variables in the system on multiple time scales and hence for excluding links that result from periodic components.

Second, we investigate whether anomalous events can be identified based on the observed changes in causal relationships. We consider two representative examples in environmental systems: land-atmosphere ecosystem and marine climate. Through these two examples, we show that an anomalous event can indeed be identified as the event where the causal intensities differ according to a distance measure from the average causal intensities. Two different methods are used for testing the statistical significance of the causal-effect intensity at each frequency component.

Once the anomalous event is detected, the driver of the event can be identified based on the analysis of changes in the obtained causal effect relationships during the time duration of the event and consequently provide an explanation of the detected anomalous event. Current research efforts are directed towards the extension of this work by using nonlinear state-space models, both statistical and deep learning-based ones.