A23P-3056: Linear and Nonlinear Causality in Monthly Atmospheric and Ocean Time-Series.

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INTRODUCTION

- In meteorology, identification of teleconnections between climatic phenomena plays an important role in the validation of atmospheric models which are used for weather and climate prediction and for the development of future climate scenarios.
- In order to evaluate the connectivity between climatic phenomena, correlation analysis is often used, but this type of analysis may lead to oversimplified relationships, which does not imply causality between different scales of time.
- In this work, Partial Directed Coherence (PDC) and kernel non-linear Partial Directed Coherence (*kn*PDC) were used to infer the influence between atmospheric compartments (atmosphere and ocean), allowing the detection of linear and non-linear connections, respectively, between variables representative of important climatic variability modes.

DATA AND METHODOLOGY

Climate Indices (1950 to 2018)

National Oceanic and Atmospheric Administration (NOAA)

PSA index: defined by the 2nd (PSA1) and 3rd (PSA2) EOF of the monthly mean 500hPa geopotential anomalies (Mo, 2000).

Groups of climatic indicators

El Niño-Southern Oscillation (ENSO); Atlantic Multidecadal Oscillation (AMO); Pacific Decadal Oscillation (PDO); Atlantic Interhemispheric SST Gradient (GTA)	Antarctic Oscillation (AAO); Pacific Decadal Oscillation (PDO); Pacific-South American (PSA1 and PSA2)

Inference of the linear or nonlinear couplings between the climatological patterns

Partial Directed Coherence (PDC) [1]	Nonlinear Partial Directed Coherence kernel (*kn*PDC) [2]

We represent the input series $\{x_i(n)\}_{n=1}^{N}$ (input space) through a Kernel Vector Autoregressive (kVAR) model, such as in (Massaroppe and Baccalá, 2019)

$$\langle \phi(x(n)) | = \sum_{r=1}^{p} A_k \langle \phi(x(n-k)) | + \langle \tilde{w}(n) |,$$

where

- $\{\langle \tilde{w}(n) |\}_{n\in\mathbb{Z}} \sim i.i.d.\, WN(0, \sum_{\langle \tilde{w}(n) \rangle})$
- $\phi : \mathbb{X} \rightarrow \mathbb{F}$ represents a nonlinear mapping (Parzen, 1959), such that $\mathbb{E}\{\langle \phi[x_i(n)] | \phi[x_i(n-k)] \rangle\} = \mathbb{E}\{\kappa[x_i(n), x_i(n-k)]\}$;
- $\kappa(\cdot)$: a Mercer kernel;
- $\langle \cdot \mid \cdot \rangle$: Dirac's ´bracket´ notation.

The *kernel-nonlinear*-Partial Directed Coherence is defined, in the phase space, as

$$_{\kappa\eta}\pi_{ij}(f) = \frac{\bar{A}_{ij}(f) \Big/ \sqrt{\sigma_{ii}}}{\sqrt{\bar{a}_j^H(f) \sum_{\langle \tilde{w}(n) \rangle}^{-1} \bar{a}_j(f)}}$$

where

- $\bar{A}_{ij}^{\phi}(f) = \delta_{ij} - \sum_{r=1}^{p} a_{ij}^{\phi}(r) e^{-i2\pi f r}$, $(i^2 = -1)$;
- $a_{ij}^{\phi}(r)$ are the coefficients of an adequately adjusted *k*VAR model;
- $\bar{a}_j(f)$ represent the columns of the $\left[\bar{A}_{ij}^{\phi}(f)\right]$ matrix.

PDC is similarly defined and can be seen in (Baccalá et al.,2013).

RESULTS

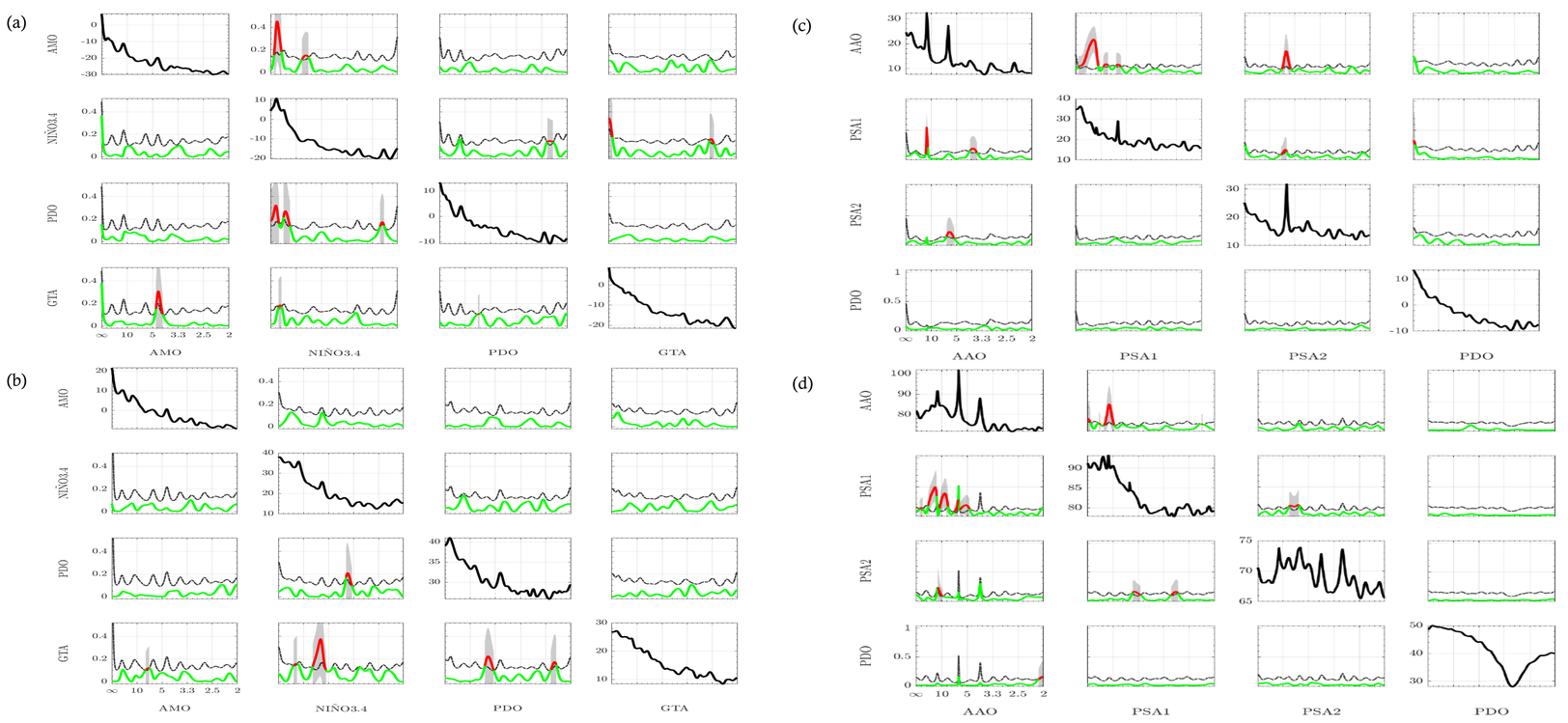

Fig. 1. The black plot represents the (pseudo-) spectral density of the series in dB; the red line represents the statistically significant PDC / *kn*PDC values; the dashed black line represents Patnaik's threshold approximation (Baccalá et al., 2013); the green line the statistically non-significant PDC / knPDC values. Therefore, using 1% significance level, the figures depict, respectively: (a) PDC for time series set (AMO, Niño 3.4, PDO and GTA) using an autoregressive model of order p = 48, (b) *kn*PDC for the time series set (AMO, Niño 3.4, PDO and GTA), using the polynomial kernel $[\boldsymbol{k}(\boldsymbol{x},\boldsymbol{y}) = (\boldsymbol{x}.\boldsymbol{y})^2]$ and using a *kernel*-autoregressive model of order p = 24, (c) *kn*PDC for the time series set (AAO, PSA1, PSA2 and PDO) and using an autoregressive model of order p = 48, (d) *kn*PDC for the time series set (AAO, PSA1, PSA2 and PDO) and using the polynomial kernel $[\boldsymbol{k}(\boldsymbol{x},\boldsymbol{y}) = (\boldsymbol{x}.\boldsymbol{y})^2]$ and using a *kernel*-autoregressive model of order p = 24.

It is observed that ENSO influences all other analyzed climate variability patterns (AMO, PDO and GTA) as indicated in other studies concerning extratropic teleconnections between Atlantic and Pacific oceans, where ENSO exerts greater influence on the North Atlantic (Rodríguez-Fonseca et al. , 2016; García-Serrano et al., 2017). Similar studies have observed the causal relationship between the Pacific (Niño 3) and the Atlantic (TNA) (Builes-Jaramillo et al., 2018). In addition, Fig.1b also shows that PDO has a nonlinear causal relationship with GTA, evidencing that the Pacific exerts influence in the Atlantic.

Furthermore, the results obtained by PDC and knPDC suggest that SO also causes PDO and are related linearly (Fig.1a) and nonlinearly (Fig.1b). Theoretical studies (Ramirez et al., 2017) also support this conclusion from a theoretical point of view.

The results also indicate to linear and nonlinear relationships between AAO ← → PSA1 and AAO ← → PSA2. The *kn*PDC analysis also indicates causality between PDO and AAO in agreement with some studies that suggest the influence of PDO on AAO in summer and late winter (Pezza et al., 2007; Goodwin et al., 2016).

DISCUSSION AND CONCLUSIONS

The causality analysis suggests that ENSO causes AMO and AITG causes PDO, highlighting the non-linear relations ENSO → PDO and ENSO → AITG. Furthermore, we observe the influences PDO → AITG and PDO → AAO, evidencing the energy transfer from the Pacific to the Atlantic Ocean. In addition, PDC and *kn*PDC techniques results suggest that some indices have non-linear interaction, emphasizing the use of non-linear machine learning techniques, e.g., deep learning, that are able to capture these variations.

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