



Interactive and Mutual Information among low-frequency variability modes of a quasi-geostrophic model

Carlos Pires (1) and Rui Perdigão (2)

(1) Universidade de Lisboa, Instituto Dom Luiz (IDL) - Faculdade de Ciências - DEGGE, Lisboa, Portugal (cpires@fc.ul.pt, +351 217500886), (2) Institute of Hydraulic and Water Resources Engineering, Vienna University of Technology, Vienna, Austria

We assess the Shannon multivariate mutual information (MI) and interaction information (IT), either on a simultaneous or on a time-lagged (up to 3 months) basis, between low-frequency modes of an atmospheric, T63, 3-level, perpetual winter forced, quasi-geostrophic model. For that purpose, Principal Components (PCs) of the spherical-harmonic components of the monthly-mean stream-functions are used. Every single PC time-series (of 1000 years length) is subjected to a prior Gaussian anamorphosis before computing MI and IT. That allows for unambiguously decomposing MI into the positive Gaussian (depending on the Gaussian correlation) and the non-Gaussian MI terms. We use a kernel-based MI estimator. Since marginal Gaussian PDFs are imposed, that makes MI estimation very robust even when using short data. Statistically significant non-Gaussian bivariate MI appears between the variance-dominating PC-pairs of larger space and time-scales with evidence in the bivariate PDF of the mixing of PDFs centered at different weather regimes. The corresponding residual Gaussian MI is due to PCs being uncorrelated and to the weak non-Gaussianity of monthly-based PCs. The Gaussianized PCs in the tail's variance spectrum (of faster variability) do not much differ from Gaussian independent white noises. Trivariate MI $I(A,B,C)$ (also known as total correlation) is computed among simultaneous and time-lagged PCs: A,B,C as well as the interaction information: $IT(A,B,C)=I(A,B|C)-I(A,B)=I(A,C|B)-I(A,C)=I(B,C|A)-I(B,C)$ along with their Gaussian and non-Gaussian counterparts where conditional MI is used. The corresponding non-Gaussian term allows for quantifying nonlinear predictability and causality. For example, we find interactive variable triads of positive non-Gaussian IT where $A=X(t+\tau)$, $B=Y(t+\tau)$, $C=Z(t)$ where t is time, τ is time-lag and X,Y,Z are arbitrary PCs. Typically it works when X,Y are nearly independent while Z(t) is a mediator variable taking the role of a precursor predictor of the XOR gate of X(t+tau) and Y(t+tau). Examples of this kind of nonlinear 'threesome' predictability are shown in chaotic low-order models as well as in stochastic models forced by multiplicative noise. Negative IT occurs when both X and Y are dependent via the third variable Z. IT works also as a proxy of a nonlinear Granger causality diagnostic when $A=X(t)$, $B=Y(t)$ and $C=Y(t+\tau)$. Positively interacting geographic triads are interpreted as triadic teleconnections in the climatic system, which are potentially useful for long range forecasting.