New Insights on Land Surface-Atmosphere Feedbacks over Tropical South America at Interannual Timescales

Juan Mauricio Bedoya-Soto & Germán Poveda

Universidad Nacional de Colombia, Sede Medellín

Departamento de Geociencias y Ambiente, Medellín, Colombia

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Introduction

- Tropical South America (TropSA) concentrates a large amount of net radiation and water vapor.
- Intense heat and humidity fluxes dominate the interactions between soil and lower atmosphere.
- Soil moisture modulates diverse land-atmosphere feedbacks (LAFs); similarly, the rates of change between dry and wet conditions in the soil necessarily impact surface temperatures.

Introduction

- Interannual timescales are mainly controlled by ENSO (Trenberth et al., 1997, 2001, 2002, 2008; Wang, 1999, 2001; Wang et al., 2017).
- Known roles of land-surface interactions (Brubaker and Entekhabi, 1996; Koster et al., 2004; Xue et al., 2006; Bagley et al., 2014; Rocha et al., 2015; Ruscica et al., 2015; Kolstad et al., 2017; Zemp et al., 2017)

Introduction

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Analysis of feedback mechanisms in land-atmosphere interaction

Kaye L. Brubaker[1] and Dara Entekhabi
Ralph M. Parsons Laboratory, Massachusetts Institute of Technology, Cambridge

Abstract. The initiation of a hydrologic drought may depend on large-scale or teleconnective causes; however, local positive feedbacks in the land-atmosphere system are believed to contribute to the observed persistence and intensification of droughts. In this study a basic linearization technique is combined with a nonlinear stochastic model of land-atmosphere interaction to analyze and, more importantly, quantify feedback mechanisms that arise in the coupled water and energy balances at the land surface. The model describes land-atmosphere interaction by four coupled stochastic ordinary differential equations in soil moisture, soil temperature, mixed-layer humidity, and mixed-layer potential temperature. The solution is a physically consistent joint probability distribution. The steady and perturbation-induced parts of the model equations are decomposed into the dependence of each component physical process upon each model state. Because of the negative correlation between soil moisture and soil temperature, the physical mechanisms that serve to restore each state individually (largely soil moisture control of evaporation and temperature dependence of saturation specific humidity) act as significant anomaly-reinforcing mechanisms for the other state.

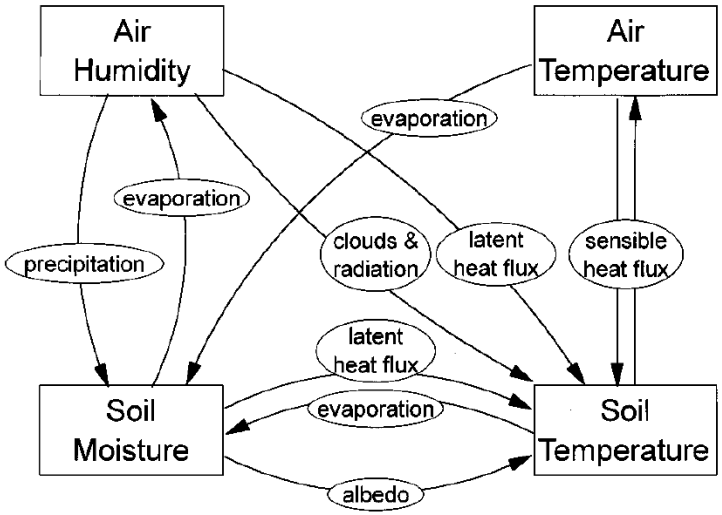
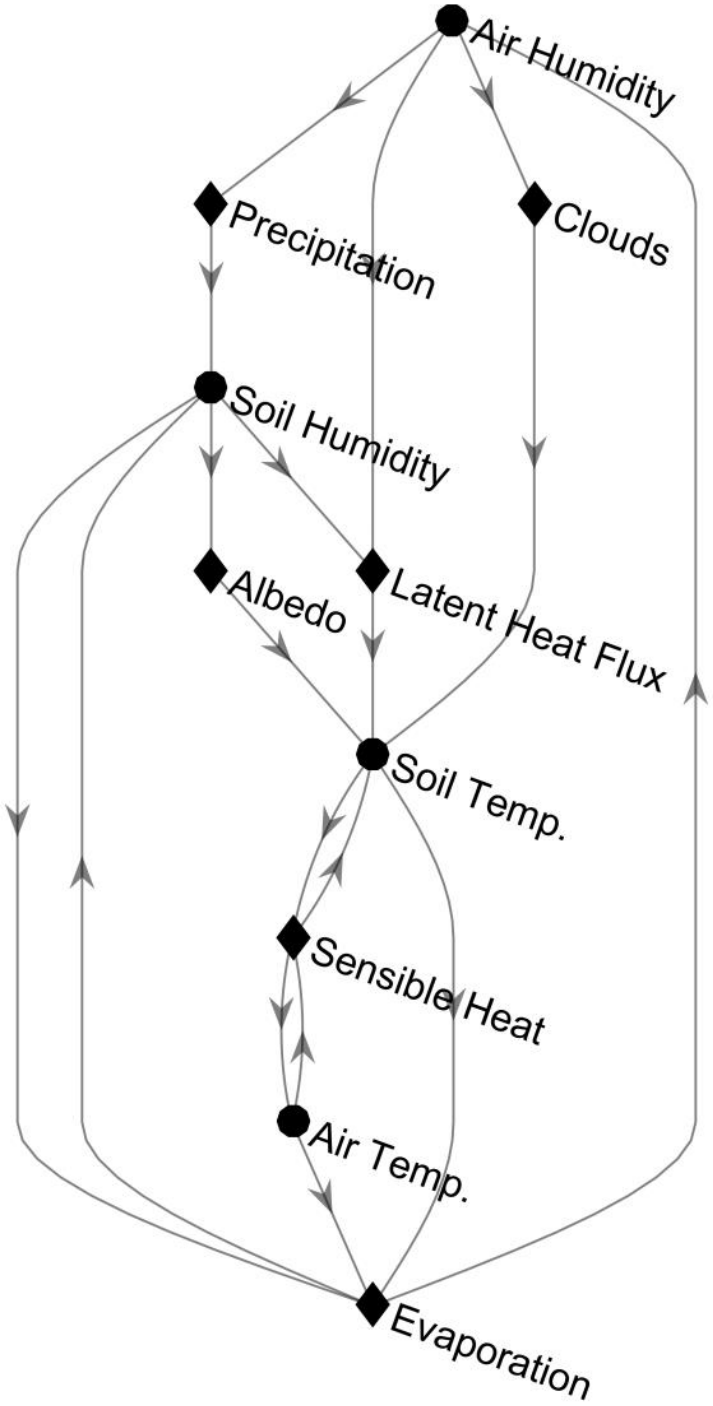


Figure 1. Conceptual diagram of well-known linkages among heat and moisture states in the soil and near-surface atmosphere.

Decomposition of the steady- and perturbation-forcing functions into the dependence of each component physical process upon each model state shows the following:

1. Soil moisture control of infiltration and of evaporation efficiency are self-restoring forces of comparable strength for the soil moisture state.
2. The temperature dependence of surface saturation specific humidity is a major factor in reinforcing soil moisture anomalies.
3. The individually strong, multiple (mostly radiative) effects of atmospheric humidity on ground temperature take opposite signs and cancel one another.
4. Soil moisture control of evaporation efficiency is the major mechanism by which the moisture state tends to reinforce temperature anomalies.
5. The temperature dependence of surface saturation specific humidity is a major self-restoring factor for the temperature state, and it exceeds the thermal radiation factor.
6. The buoyancy velocity is a significant recovery factor for temperature anomalies because it affects both the soil temperature and its coupling to air temperature. Soil temperature is positively correlated with temperature gradient anomalies; when the soil is anomalously warm, a strong gradient that enhances cooling also tends to be present.
7. Both the soil moisture and the soil temperature state are more susceptible to variations in wind speed (noise) when the system is dry than when it is moist.

It is well known that the soil moisture and soil temperature states are negatively correlated (cool/moist or warm/dry). These soil states communicate their covariability partially through local-scale interaction with the near-surface atmosphere. Because of the negative correlation between the states, the physical mechanisms that serve as restoring forces for each state individually (soil moisture control of evaporation and temperature dependence of saturation specific humidity) act as anomaly-enhancing positive feedback mechanisms for the other state. These feedback mechanisms are not apparent if the hydrologic variable soil moisture is considered alone. The coupled energy balance and energy states of the soil and near-surface atmosphere must be taken into account when seeking to understand and predict the persistence of hydrologic anom-



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Links structure with Graph Theory

- Conceptual scheme of interconnections among the main variables involved in the studied land surface-atmosphere feedbacks (LAFs), adapted as a graph from Brubaker and Entekhabi (1996), and hierarchized by number of connections of each variable.
- The state (process) variables are denoted as circles (diamonds) nodes.
- Evaporation is the most heterogeneous process involved in LAFs since it connects soil humidity with the other state variables

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Objectives

1. To study the essential role of Land Atmosphere Feedbacks and the mechanisms involved in water and heat anomalies in TropSA at interannual timescales.

2. To explore new tools to advance our understanding of land surface-atmospheric feedbacks in TropSA.

3. To integrate classical analyses of climatic fields with more recent methods of information theory and graph theory including linear and non-linear analysis.

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Data and Methods

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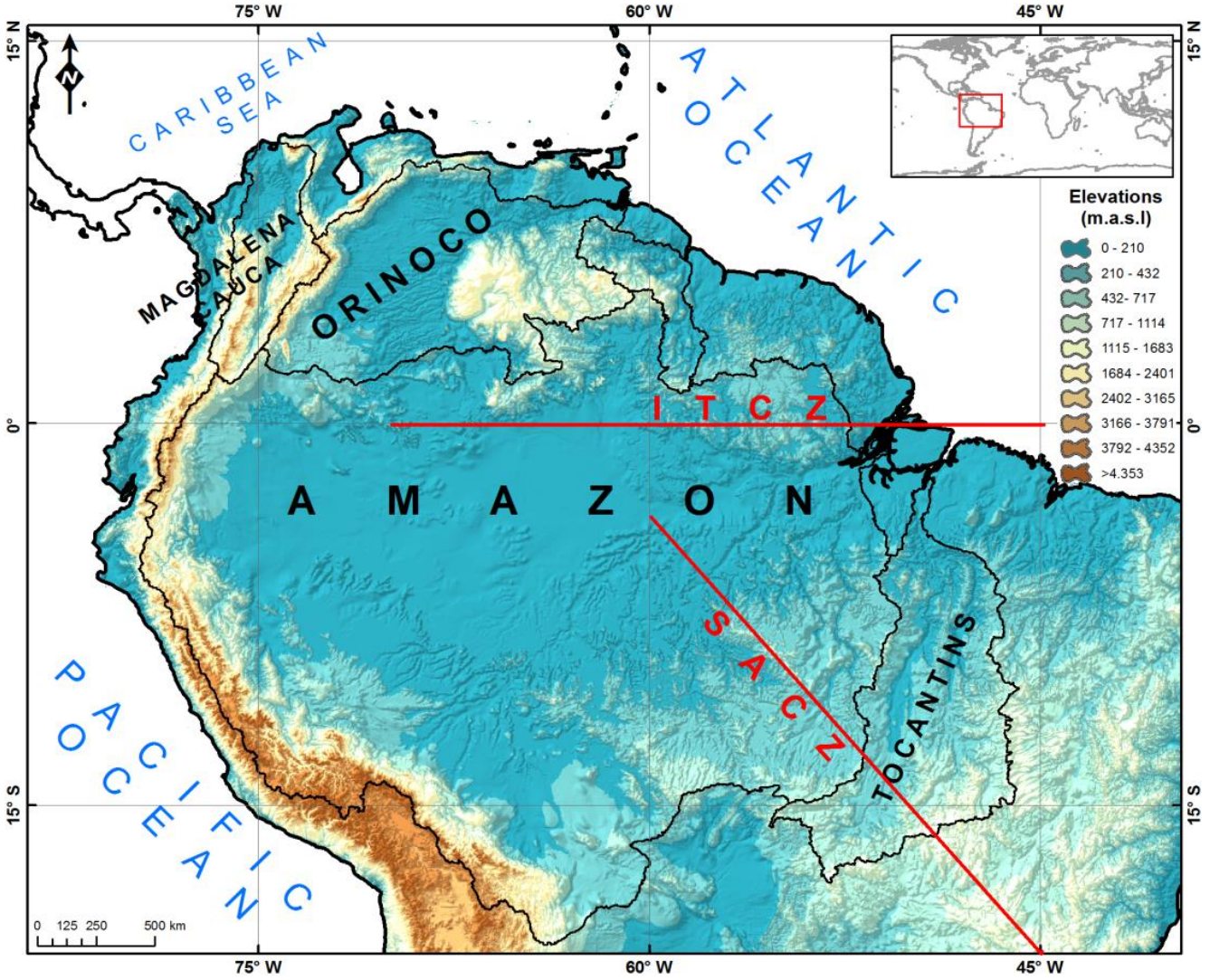
Study Region



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Data

Visualize and Download GPCC Products

GPCC Product	Spatial Resolution	Time Coverage	Possible Application
First Guess Monthly	*1.0°*	*2004 - present*	*drought monitoring*
First Guess Daily	*1.0°*	*2009 - present*	*analysis of extremes*
Monthly Monitoring Version 5	*1.0°, 2.5°*	*1982 - present*	*calibration of satellite data*
Full Data Monthly Version	*0.5°, 1.0°, 2.5°*	*1901 - 2013*	*hydrological studies*
Full Data Daily Version 1	*1.0°*	*1988 - 2013*	*analysis of extremes*
HOAPS/GPCC global daily precipitation Version 1	*0.5°, 1.0°, 2.5°*	*1988 - 2008*	*analysis of extremes*
HOMPRA Europe Version 1 (coming soon)	*1.0°*	*1951 - 2005*	

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- Potential vorticity
- Pressure levels
- ▸ Surface

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- Invariant
- Synoptic Monthly Means
- ▸ Monthly Means of Daily Means
- Monthly Means of Daily Forecast Accumulations

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- Home
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ERA Interim, Monthly Means of Daily Means

Please note that the fields shown on this interface are a subset of the ERA Interim dataset. The complete dataset (including wave fields) is available via the batch access. The full list of fields can be found here.

Select a list of months

Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016

Select All or Clear

Select parameter

- 2 metre dewpoint temperature
- 2 metre temperature
- 10 metre U wind component
- 10 metre V wind component
- 10 metre wind speed
- Albedo
- Boundary layer height
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Select date

Select a date in the interval 1979-01-01 to 2010-12-31

Start date: 1979-01-01 End date: 2010-12-31

Select a list of months

Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010

Select All or Clear

Select time

00:00:00 06:00:00 12:00:00 18:00:00

Select All or Clear

Select parameter

- Skin temperature
- Snow albedo
- Snow density
- Snow depth
- Soil temperature level 1
- Soil temperature level 2
- Soil temperature level 3
- Soil temperature level 4
- Temperature of snow layer
- Volumetric soil water layer 1
- Volumetric soil water layer 2
- Volumetric soil water layer 3
- Volumetric soil water layer 4

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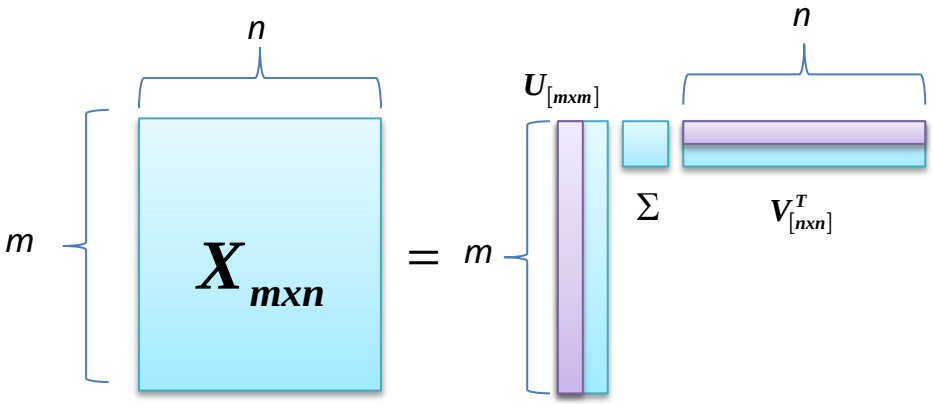
Data

- Soil moisture (VSW) from Era-Interim Land 1° x 1°
- Specific Humidity at 925 hPa (SH^{925}), 2m Temperature (T_{2m}) and Evaporation (EVP) from ERA-Interim 1° x 1°
- Precipitation (PRC) from GPCC 1° x 1°
- All climate fields period 1979-2010

Methods

- SVD, Entropy, and Noise Reduction: After standardized each variable and apply a Singular Value Decomposition (SVD), we select the representative modes of each variable at interannual time scale (noise reduction) using a criterion from the information theory (Entropy). 5 variables denoised.
- Maximum Covariance Analysis of Interannual Variability in TropSA: We apply a SVD on the covariance matrices thus establishing connections between all possible pairs of variables (10 possible combinations)
- Graph Models of LAF in Tropical South America at Interannual Timescales: Establishing connections among variables and defining relationship structure. We use linear and non-linear metrics as links.

SVD, Noise Reduction, and Entropy



X is the standardized time-space matrix for each variable

$$X_{mxn} = U_{[mxm]} \Sigma_{[mxn]} V^T_{[nxn]}$$

$$X_{mxn} = U_{[mxm]} \Sigma_{[mxn]} V^T_{[nxn]} = \sum_{i=1}^{\min(m,n)} u_i \sigma_i v_i^T = u_1 \sigma_1 v_1^T + u_2 \sigma_2 v_2^T + \ldots + u_m \sigma_m v_n^T$$

Truncated matrix of lower rank k

$$X \approx \hat{X}_{mxn} = U_{[mxk]} \Sigma_{[kxk]} V^T_{[nxk]} = \sum_{i=1}^{k} u_i \sigma_i v_i^T = u_1 \sigma_1 v_1^T + u_2 \sigma_2 v_2^T + \ldots + u_k \sigma_k v_k^T \quad con \quad k < r$$

Relative contribution of each singular factor

$$f_i = \sigma_i^2 \Big/ \sum_i \sigma_i^2$$

$$H_X = -\frac{1}{\log_2(\min\{n,m\})} \sum_{i=1}^{\min(n,m)} f_i \log_2 f_i$$

Entropy for each matrix k

Cummulated contribution $F_i = \sum_i f_i$

$$min(k) \rightarrow \sum_{i=1}^{k} f_i \geq E$$

Entropy criterion to select k and noise reduction

Maximum Covariance Analysis (MCA) with Interannual Variability in TropSA

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Covariance matrix

$$C_{XY} = \frac{1}{n-1}\hat{X}\hat{Y}^T$$

$$C_{XY\,[\,mxq\,]} = U_{[mxk]}\Sigma_{[kxk]}V^T_{[qxk]} = \sum_{i=1}^{k} u_i \sigma_i v_i^T$$

- The SVD of couple fields (MCA) identify only modes in which those are strongly coupled
- Converts a set of correlated variables to visualize the relationships between them
- Identify and order the dimensions where the data exhibit the greatest covariability
- Better approximation to the data using less dimensions

$$f_k^{XY} = \sigma_k^2 \Big/ \sum_i \sigma_i^2$$

Square covariance fraction of the k-factor of the MCA

$$x_k = u_k^T \hat{X}$$

$$y_k = v_k^T \hat{Y}$$

Expansion coefficients

We use the first k=3 Maximum Covariance States (***MCS$_k$***) to characterize the cumulative covariance and its space-time distribution

As a result we obtain 4 kind of maps

Symbol	Description of map
$\rho(x_k, \hat{Y})$	Correlation between vector x_k with each column vector of matrix $\hat{\mathbf{Y}}$
$\rho(y_k, \hat{X})$	Correlation between vector y_k with each column vector of matrix $\hat{\mathbf{X}}$
$\rho(x_k, \hat{X})$	Correlation between vector x_k with each column vector of matrix $\hat{\mathbf{X}}$
$\rho(y_k, \hat{Y})$	Correlation between vector y_k with each column vector of matrix $\hat{\mathbf{Y}}$

Non-Linear Dependence: Causality (Liang 2013, 2014, 2015)

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The **Liang**-Kleeman information flow: Theory and applications
XS Liang - Entropy, 2013 - mdpi.com
Abstract: Information flow, or information transfer as it may be referred to, is a fundamental notion in general physics which has wide applications in scientific disciplines. Recently, a rigorous formalism has been established with respect to both deterministic and stochastic
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Unraveling the cause-effect relation between time series
X San **Liang** - Physical Review E, 2014 - APS
Abstract Given two time series, can one faithfully tell, in a rigorous and quantitative way, the cause and effect between them? Based on a recently rigorized physical notion, namely, information flow, we solve an inverse problem and give this important and challenging
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Normalizing the causality between time series
X San **Liang** - Physical Review E, 2015 - APS
Abstract Recently, a rigorous yet concise formula was derived to evaluate information flow, and hence the causality in a quantitative sense, between time series. To assess the importance of a resulting causality, it needs to be normalized. The normalization is achieved
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PHYSICAL REVIEW E **90**, 052150 (2014)

Unraveling the cause-effect relation between time series

X. San Liang*
School of Marine Sciences, Nanjing University of Information Science and Technology (Nanjing Institute of Meteorology), Nanjing 210044 and China Institute for Advanced Study, Central University of Finance and Economics, Beijing 100081, China
(Received 8 June 2014; revised manuscript received 14 October 2014; published 24 November 2014)

Given two time series, can one faithfully tell, in a rigorous and quantitative way, the cause and effect between them? Based on a recently rigorized physical notion, namely, information flow, we solve an inverse problem and give this important and challenging question, which is of interest in a wide variety of disciplines, a positive answer. Here causality is measured by the time rate of information flowing from one series to the other. The resulting formula is tight in form, involving only commonly used statistics, namely, sample covariances; an

The rate of information (causality) flowing from a component, say, Y, to another, say, X, is the change rate of the marginal entropy of X, minus the same change rate but with the effect from Y instantaneously excluded from the system.

Absolute Causality formula:

$$T_{Y\to X} = \frac{C_{xx}C_{xy}C_{y,dx} - C_{xy}^2 C_{x,dy}}{C_{xx}^2 C_{yy} - C_{xx}C_{xy}^2}$$

where C_{xx}, C_{xy} y C_{yy} denote the possible covariances between series.

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Relative Causality (τ)

PHYSICAL REVIEW E **92**, 022126 (2015)

Normalizing the causality between time series

X. San Liang*

Nanjing University of Information Science and Technology (Nanjing Institute of Meteorology), Nanjing 210044, and China Institute for Advanced Study, Central University of Finance and Economics, Beijing 100081, China

(Received 18 January 2015; revised manuscript received 31 May 2015; published 17 August 2015)

Recently, a rigorous yet concise formula was derived to evaluate information flow, and hence the causality in a quantitative sense, between time series. To assess the importance of a resulting causality, it needs to be normalized. The normalization is achieved through distinguishing a Lyapunov exponent-like, one-dimensional phase-space stretching rate and a noise-to-signal ratio from the rate of information flow in the balance of the marginal entropy evolution of the flow recipient. It is verified with autoregressive models and applied to a real financial analysis problem. An unusually strong one-way causality is identified from IBM (International Business Machines Corporation) to GE (General Electric Company) in their early era, revealing to us an old story, which has almost faded into oblivion, about "Seven Dwarfs" competing with a giant for the mainframe computer market.

$$Z_{y\to x} = |T_{y\to x}| + \left|\frac{dH_y^*}{dt}\right| + \left|\frac{dH_y^{noise}}{dt}\right|$$

Marginal entropy

p and q are maximum likelihood estimators of Z

$$p = \frac{C_{yy}C_{x,dx} - C_{xy}C_{y,dx}}{\det(C)}$$

$$q = \frac{C_{yy}C_{x,dx} - C_{xy}C_{y,dx}}{\det(C)}$$

Relative Flow of Information or Relative causality

$$\tau_{y\to x} = \frac{|Z_{y\to x}|}{T_{y\to x}} * 100$$

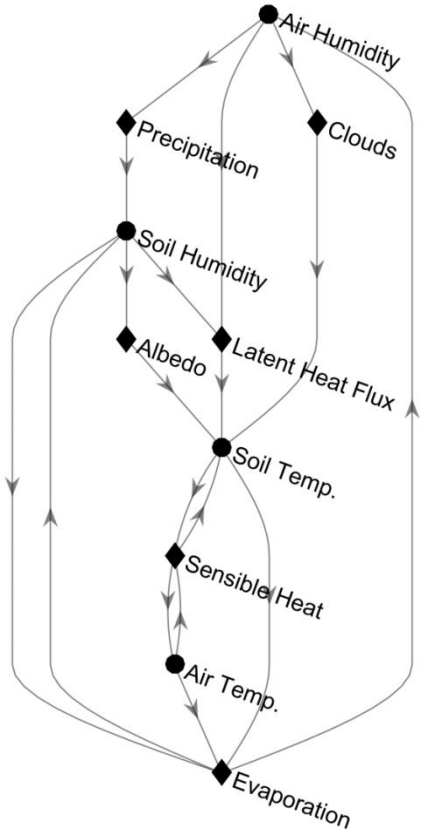
If the result is 100, ***x*** is 100% due to the flow of information from ***y***.

$$\left|\frac{dH_y^*}{dt}\right| = p$$

$$\left|\frac{dH_y^{Noise}}{dt}\right| = \frac{\Delta t}{2C_{xx}}(C_{dx,dx} + p^2C_{xx} + q^2C_{yy} - 2pC_{dx,x} - 2qC_{dx,y} + 2pqC_{xy})$$

Graph Theory

- Time series extracted from the MCA procedures were used to quantify linear (correlations) and nonlinear (causalities) metrics for different time lags among all pairs of variables.
- All sets of associations were summarized in the form of correlation and causality graphs in turn grouped according to their association degree with ENSO.
- This way, we analyzed how the LAFs over TropSA contribute to explain the simultaneous and lagged interannual anomalies over land and atmosphere.
- We also applied spectral analysis to infer links structure at each lag as a graph using the adjacency matrix



Authoritative sources in a hyperlinked environment
JM Kleinberg - Journal of the ACM (JACM), 1999 - dl.acm.org
Abstract The network structure of a hyperlinked environment can be a rich source of information about the content of the environment, provided we have effective means for understanding it. We develop a set of algorithmic tools for extracting information from the link structures of such environments, and report on experiments that demonstrate their effectiveness in a variety of context on the World Wide Web. The central issue we address ...
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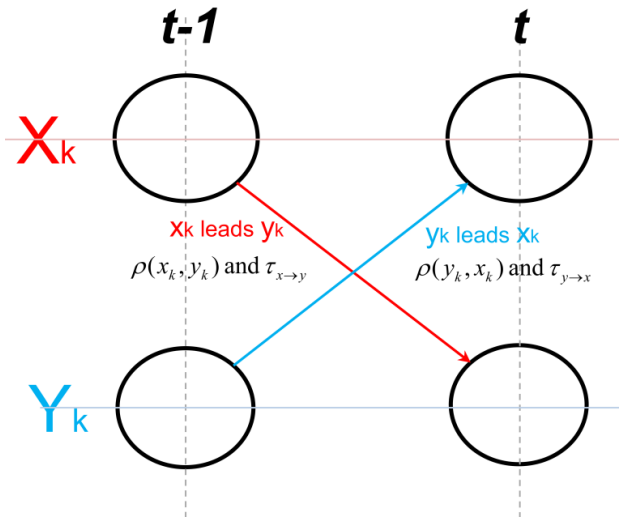
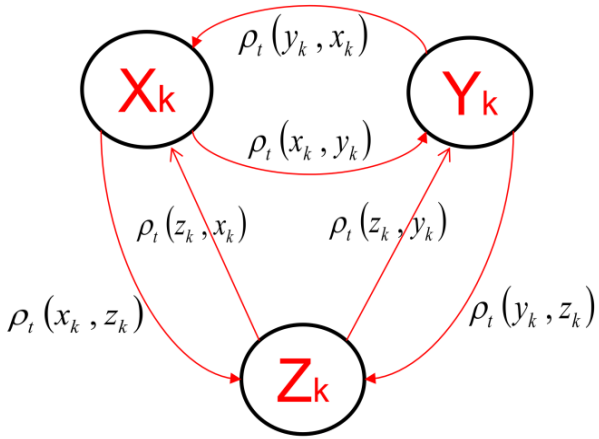
Adjacency Matrix of a Graph (Linear and Non-Linear Metrics as Edges)



Basic scheme of the interaction between two singular vectors resulting from a Maximum Covariance Analysis (MCA) between two variables X and Y for each mode k assuming 1 lag-month

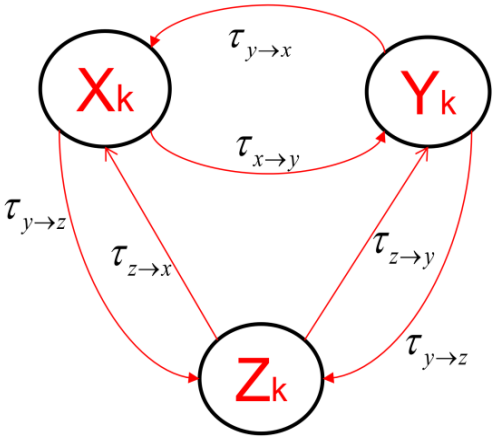
Graphs among three variables (X, Y, Z) with links denoting lagged correlations (top left) and causalities (top right) between variables/nodes.

Bottom panels include the structure of the graph's adjacency matrix, W, to illustrate the node-to-node connection that is established in each graph.



ρ_t : **Significant Correlations (P < 1%)**

$t = 1$ to 9 months lag



τ : **Causalities**

$t = 1$ to 9 months lag

$$W^{\rho}_{[ixj]} = \begin{array}{c} \\ X \\ Y \\ Z \end{array} \begin{array}{c} \begin{array}{ccc} X & Y & Z \end{array} \\ \begin{pmatrix} 0 & \rho_t(x_k, y_k) & \rho_t(x_k, z_k) \\ \rho_t(y_k, x_k) & 0 & \rho_t(y_k, z_k) \\ \rho_t(z_k, x_k) & \rho_t(z_k, y_k) & 0 \end{pmatrix} \end{array}$$

$$W^{\tau}_{[ixj]} = \begin{array}{c} \\ X \\ Y \\ Z \end{array} \begin{array}{c} \begin{array}{ccc} X & Y & Z \end{array} \\ \begin{pmatrix} 0 & \tau_{x\to y} & \tau_{x\to z} \\ \tau_{y\to x} & 0 & \tau_{y\to z} \\ \tau_{z\to x} & \tau_{z\to y} & 0 \end{pmatrix} \end{array}$$

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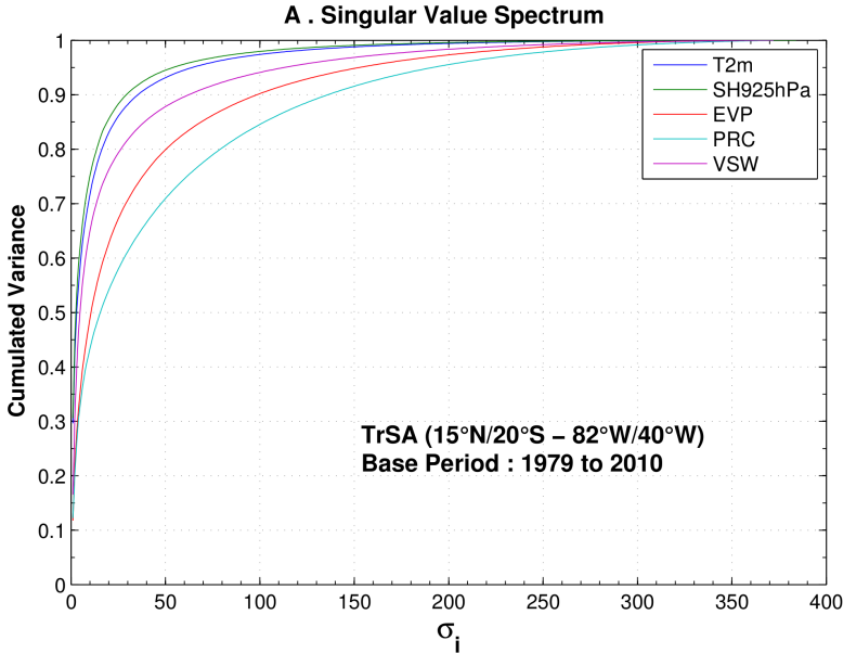
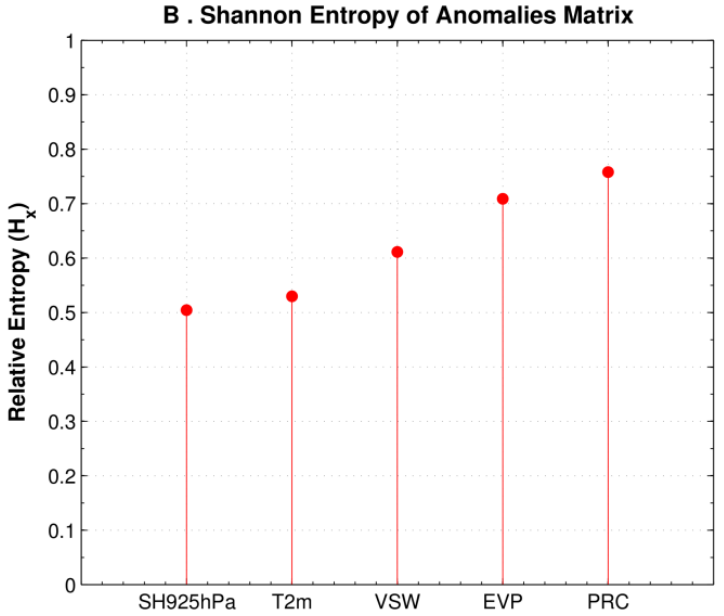
Results

Noise Reduction





Data Source	X_{mxn}	m (# of cells 1°)	n (# months)	$rank\ (X)$	f_1	f_2	H_x	k_H	f_{k_H}
GPCC	*Precipitation (PRC)*	1101	384	372	0.12	0.20	0.76	64	0.76
ERA-Interim	*Evaporation (EVP)*	1047		372	0.12	0.22	0.71	31	0.71
ERA-Interim Land	*Volumetric Soil Water Content (VSW)*	1039		348	0.16	0.31	0.61	9	0.63
ERA-Interim	*Air Temperature (T_{2m})*	1047		348	0.30	0.43	0.53	4	0.55
ERA-Interim	*Specific Humidity at 925 hPa (SH^{925})*	1047		348	**0.31**	0.45	0.50	3	0.53

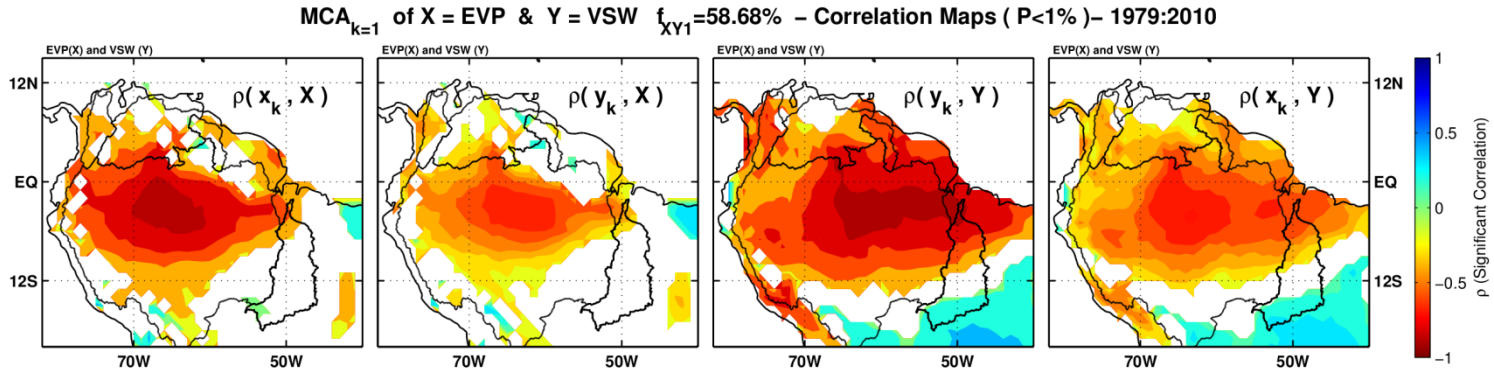
- A matrix ***X*** with low relative entropy (H_X) represents a variable controlled by few modes over TropSA at interannual timescales.
- State atmospheric variables SH^{925} and T_{2m} are the less complex variables of our datasets (64 and 31 k_H factors)
- Process variables (PRC and EVP) are the most

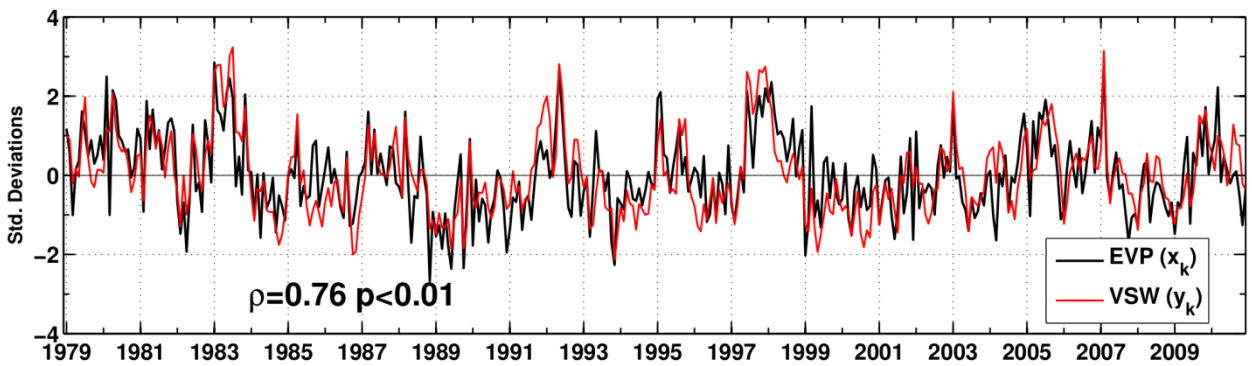
MCA over TropSA

C_{XY}		EMC_1		EMC_2		EMC_3		H_{XY}
$\hat{X}$	$\hat{Y}$	f_1^{XY} (F_1^{XY})	$\rho(x_1,y_1)$	f_2^{XY} (F_2^{XY})	$\rho(x_2,y_2)$	f_3^{XY} (F_3^{XY})	$\rho(x_3,y_3)$	
SH^{925}	**T_{2m}**	**0.78** (0.78)	0.95	0.16 (0.94)	0.96	0.06 (1.00)	0.94	0.09
EVP	**T_{2m}**	0.64 (0.64)	0.54	0.23 (0.87)	0.63	0.08 (0.95)	0.53	0.14
PRC	**SH^{925}**	0.63 (0.63)	0.75	0.29 (0.92)	0.51	0.08 (1.00)	0.49	0.12
EVP	**VSW**	0.59 (0.59)	0.76	0.18 (0.77)	0.62	**0.12** (0.89)	0.61	0.18
EVP	**SH^{925}**	0.59 (0.59)	0.52	0.31 (0.90)	0.60	0.10 (1.00)	0.51	0.13
PRC	**T_{2m}**	0.59 (0.59)	0.69	0.32 (0.91)	0.54	0.06 (0.97)	0.50	0.13
SH^{925}	**VSW**	0.58 (0.58)	0.67	**0.36** (0.94)	0.50	0.06 (1.00)	0.38	0.12
T_{2m}	**VSW**	0.57 (0.57)	0.62	0.33 (0.90)	0.55	0.06 (0.96)	0.55	0.14
EVP	**PRC**	0.42 (0.42)	0.70	0.34 (0.76)	0.72	0.11 (0.87)	0.70	**0.23**
PRC	**VSW**	0.41 (0.41)	0.77	0.36 (0.75)	0.77	0.08 (0.88)	0.78	0.20

- Set of reduced variables over TropSA (Table) to derive all possible pairs of truncated matrices for a crosslink analysis.
- We estimate a total of 10 covariance matrices
- The first *k=3* MCS_k characterize more than 85% of the cumulative covariance of each covariance matrix

- T_{2m} - SH^{925} (both state variables) has the to 78% of its total covariance in the first relative fraction
- PRC-EVP (42 %) and PRC-VSW (41 %) concentrate the lowest fraction in the first relative fraction





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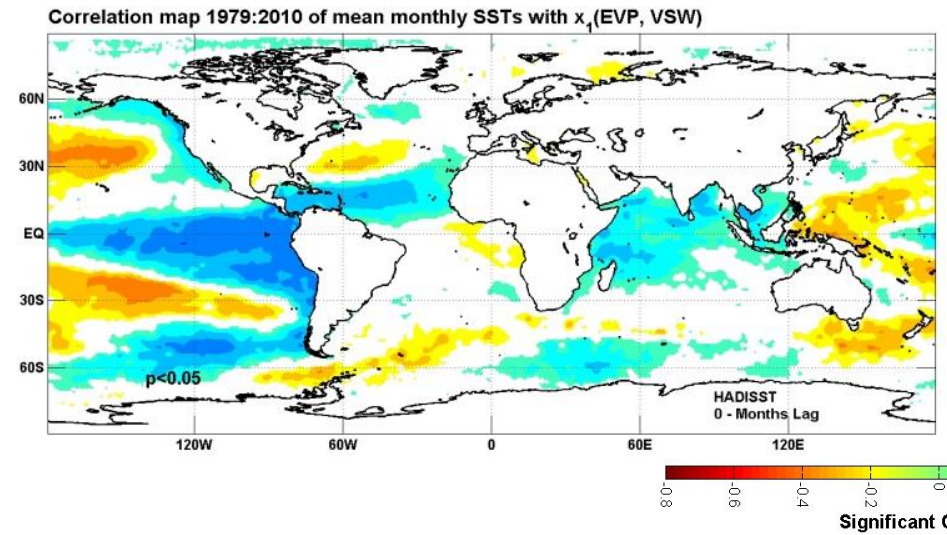
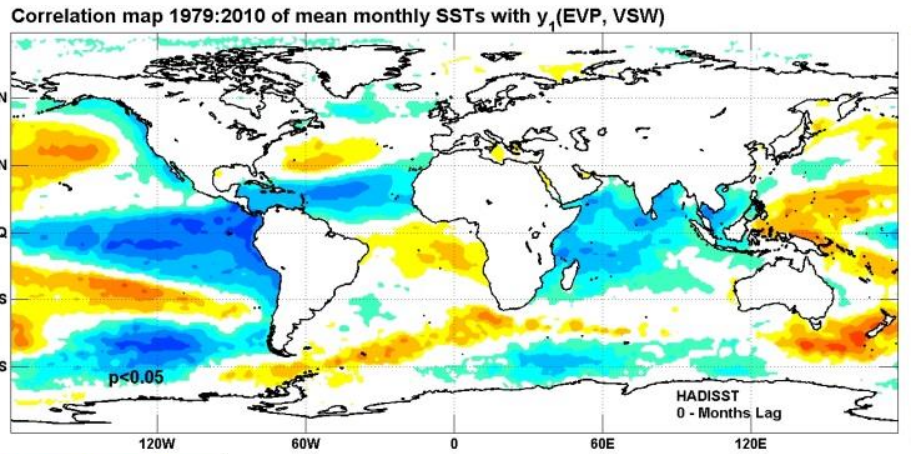
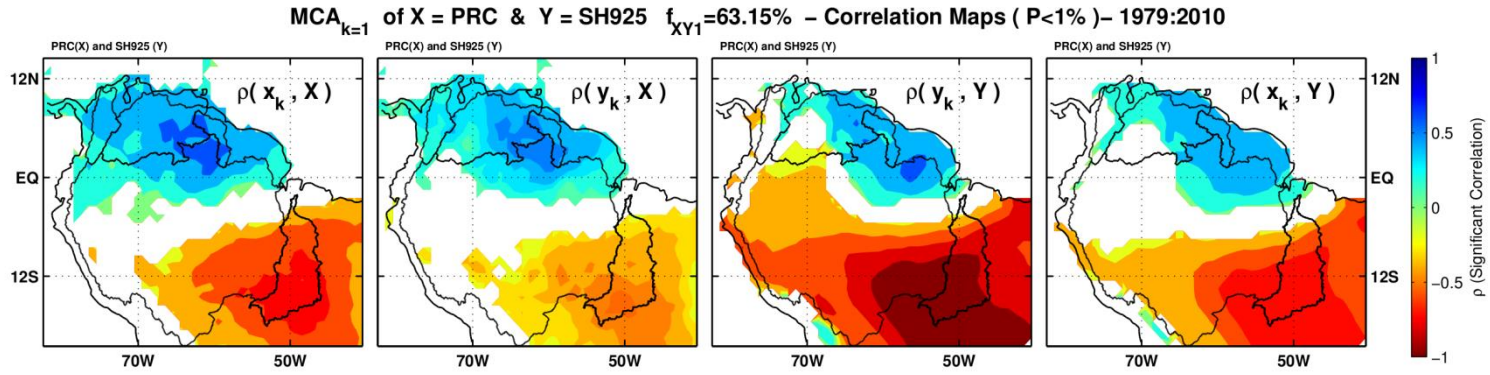
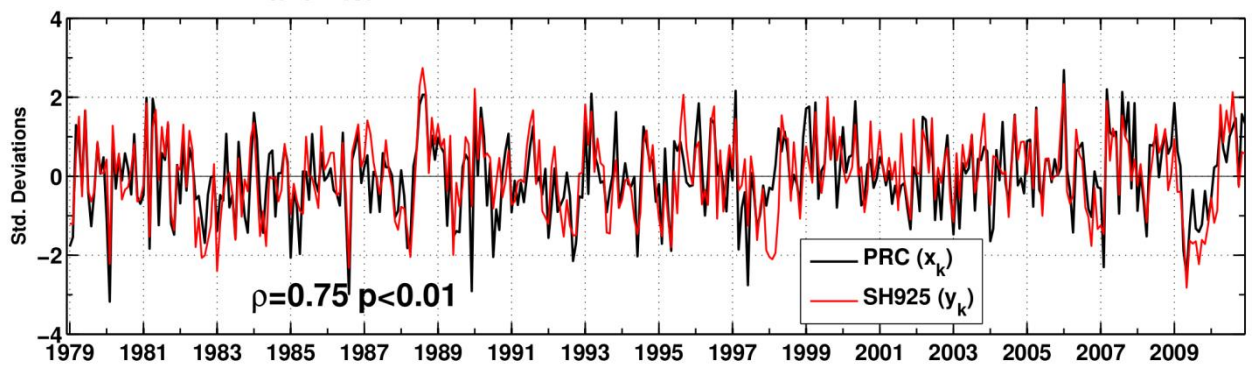
The core of interannual interactions of soil humidity and evaporation is located in the Amazon River basin, in connection with the Magdalena-Cauca River basin over north-western TropSA









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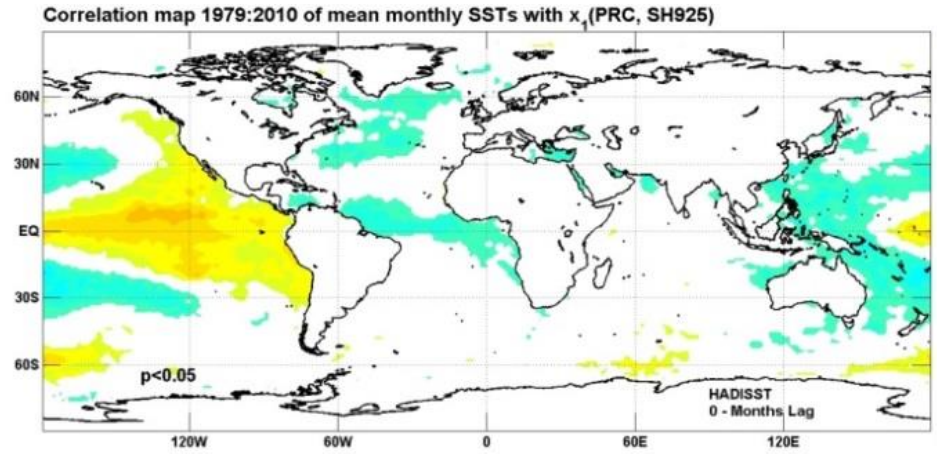
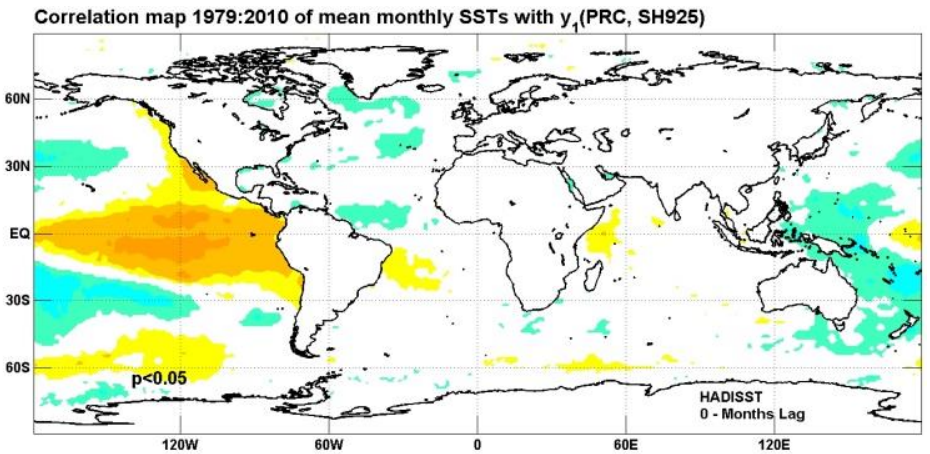
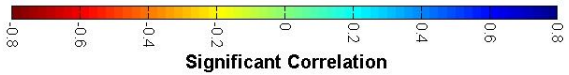
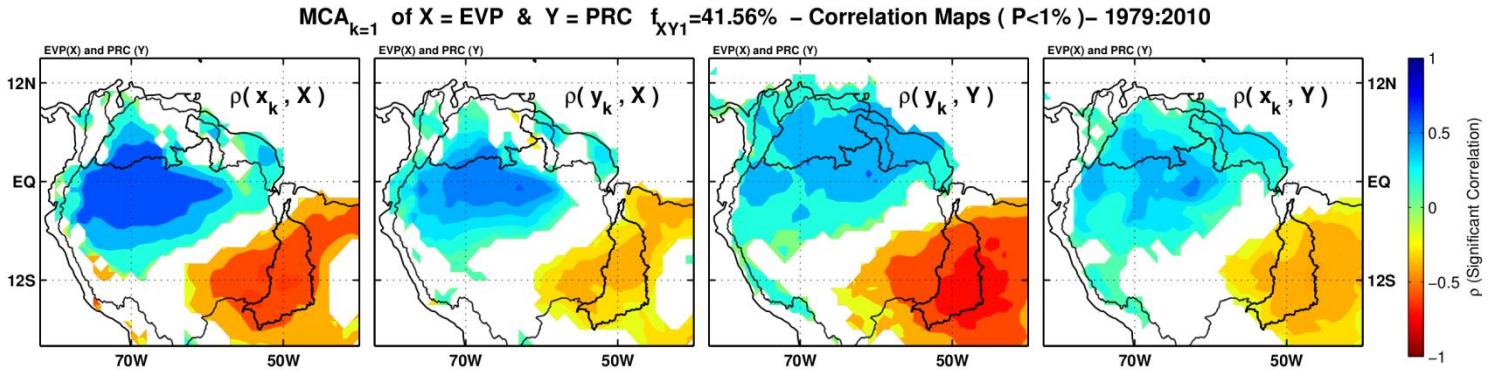
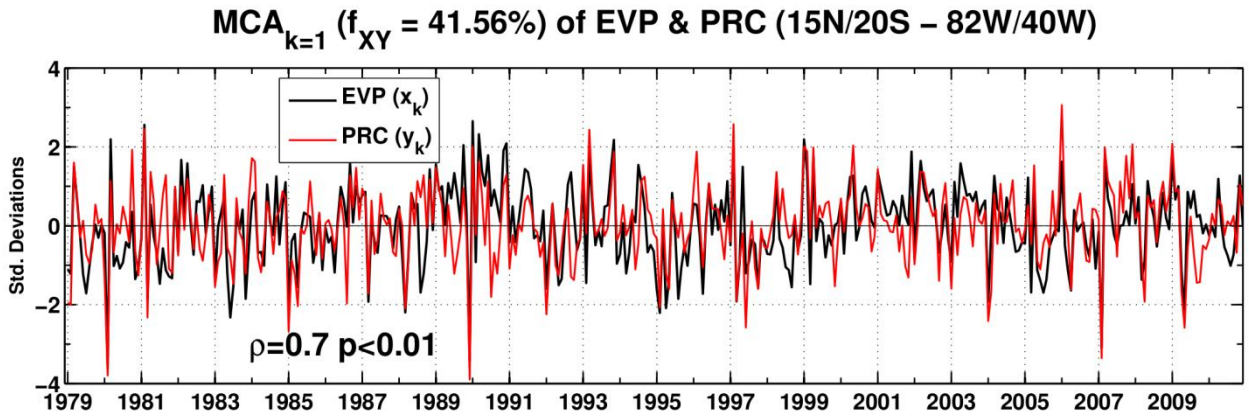
The spatial correlation pattern associated with this pair of variables (MCS_1 of SH^{925}-PRC) exhibits a dipole with one center in the northwest (direct correlations), and other in the southeast (inverse).



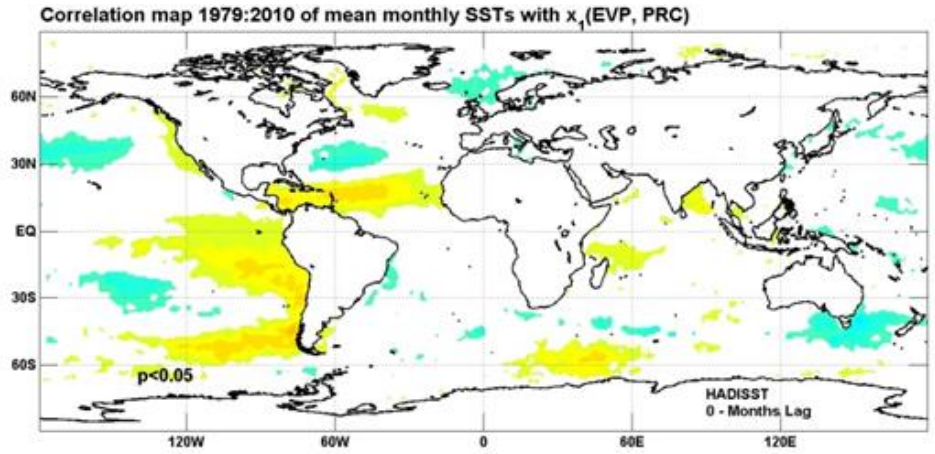


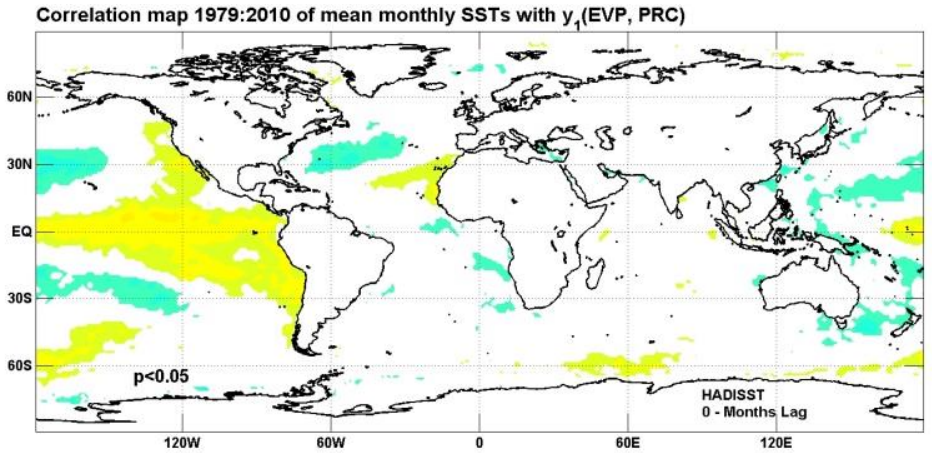


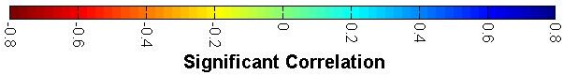




Correlations over the northern pole of the MCS1 of PRC-EVP are significant over the piedmont of Amazon-Orinoco River basins.







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Results (2)

Graphs with Linear Edges

ENSO-intensities Categorizing Interannual Oceanic Modes

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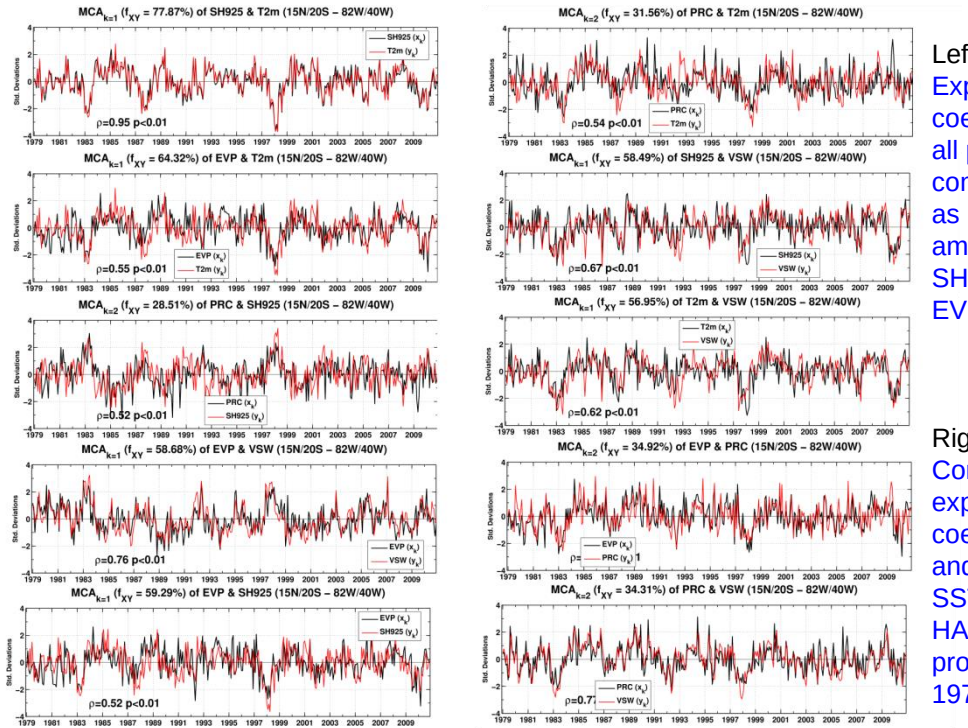
C_{XY}		MCS_1		MCS_2		MCS_3	
$\hat{X}$	$\hat{Y}$	$\rho(x_1, N3.4)$	$\rho(y_1, N3.4)$	$\rho(x_2, N3.4)$	$\rho(y_2, N3.4)$	$\rho(x_3, N3.4)$	$\rho(y_3, N3.4)$
SH^{925}	T_{2m}	-0.44	-0.50	0.15	0.13	-0.20	-0.17
EVP	T_{2m}	-0.48	-0.52	0.11	0.12	0.14	0.14
PRC	SH^{925}	-0.25	-0.31	0.40	0.45	-0.20	0.10
EVP	VSW	0.4	0.44	0.32	0.36	0.11	0.18
EVP	SH^{925}	-0.44	-0.44	0.20	0.21	0.22	0.05
PRC	T_{2m}	0.32	0.43	-0.32	-0.45	-0.17	0.03
SH^{925}	VSW	-0.43	-0.47	0.36	0.35	-0.10	-0.03
T_{2m}	VSW	-0.52	**-0.55**	-0.30	-0.21	-0.05	-0.09
EVP	PRC	-0.08	-0.19	-0.48	-0.4	-0.22	-0.31
PRC	VSW	0.3	0.37	-0.35	-0.4	0.21	0.21

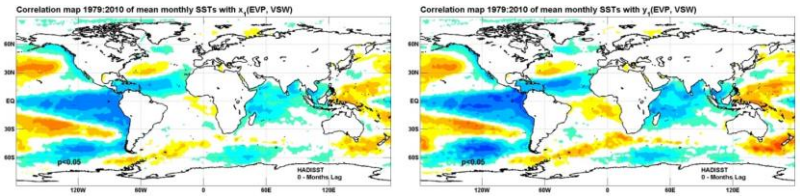
- Correlation between MCA series and Niño 3.4 index, for the MCS_k, k=1,2, and 3.
- High correlation values are denoted in blue, medium values in green and low values in red.



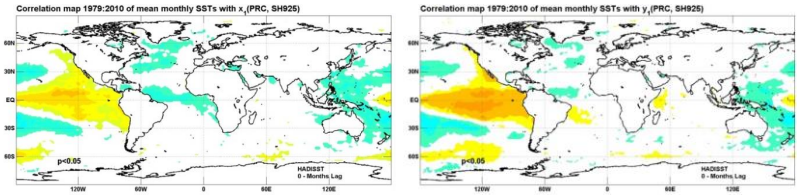
Left: Expansion coefficients for all possible combinations as pairs among VSW, SH925, T2m, EVP and PRC

Right: Correlations expansion coefficients x_k and y_k with SSTs from HADISST product period 1979-2010

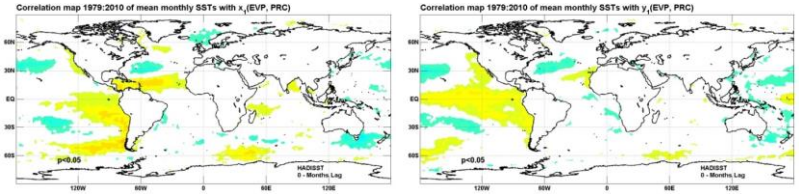
A. High ENSO - related $\mathbf{MCS}_1(EVP, VSW)$ $f_1^{XY} = 59\%$



B. Medium ENSO - related $\mathbf{MCS}_1(PRC, SH^{925})$ $f_1^{XY} = 64\%$



C. Low ENSO - related $\mathbf{MCS}_1(EVP, PRC)$ $f_1^{XY} = 42\%$



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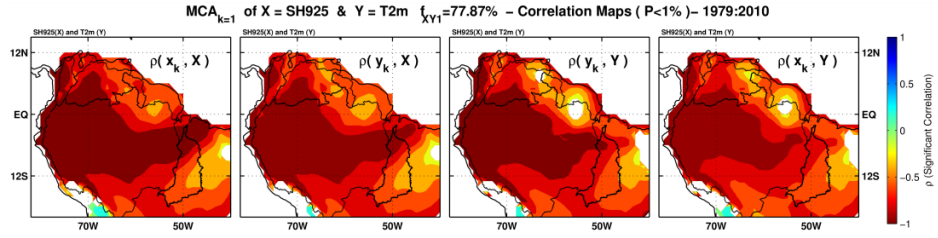
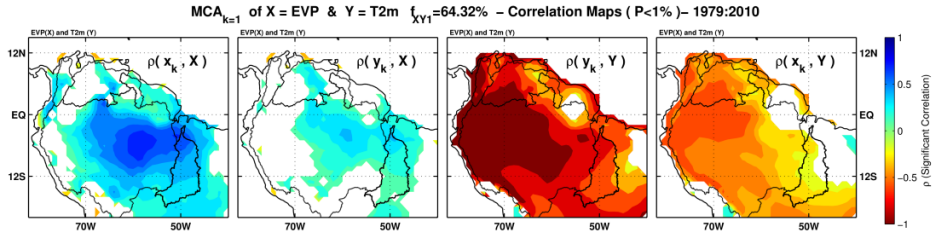
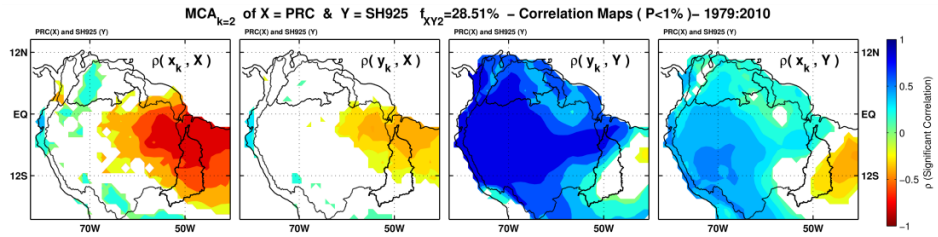
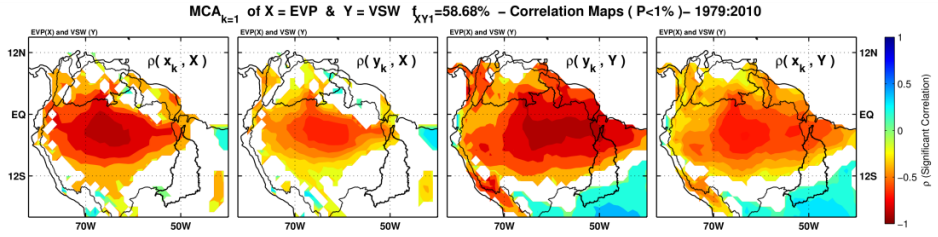
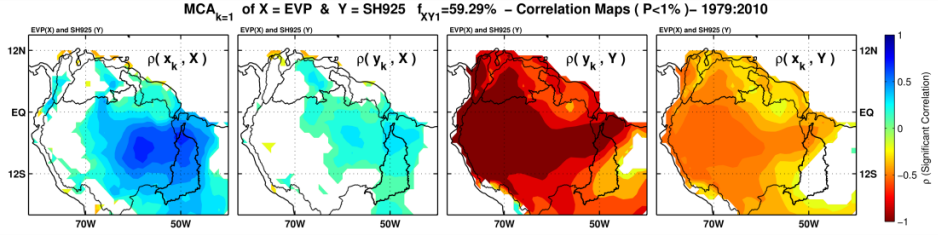




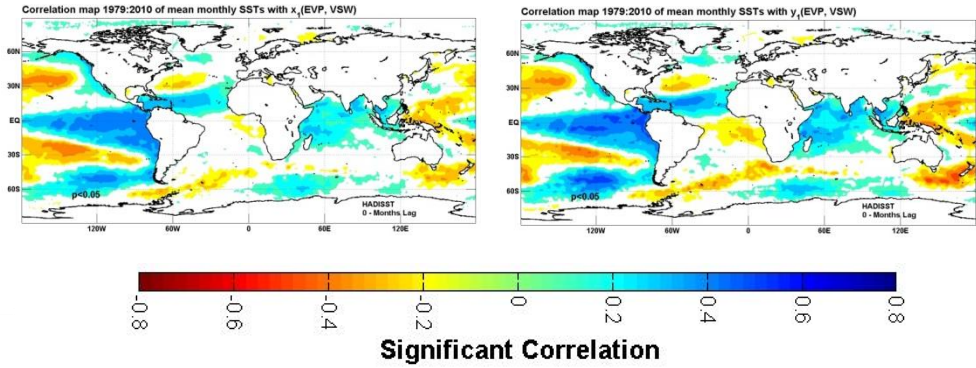






Symbol	Description of map
$\rho(x_k, \hat{Y})$	Correlation between vector x_k with each column vector of matrix $\hat{\mathbf{Y}}$
$\rho(y_k, \hat{X})$	Correlation between vector y_k with each column vector of matrix $\hat{\mathbf{X}}$
$\rho(x_k, \hat{X})$	Correlation between vector x_k with each column vector of matrix $\hat{\mathbf{X}}$
$\rho(y_k, \hat{Y})$	Correlation between vector y_k with each column vector of matrix $\hat{\mathbf{Y}}$

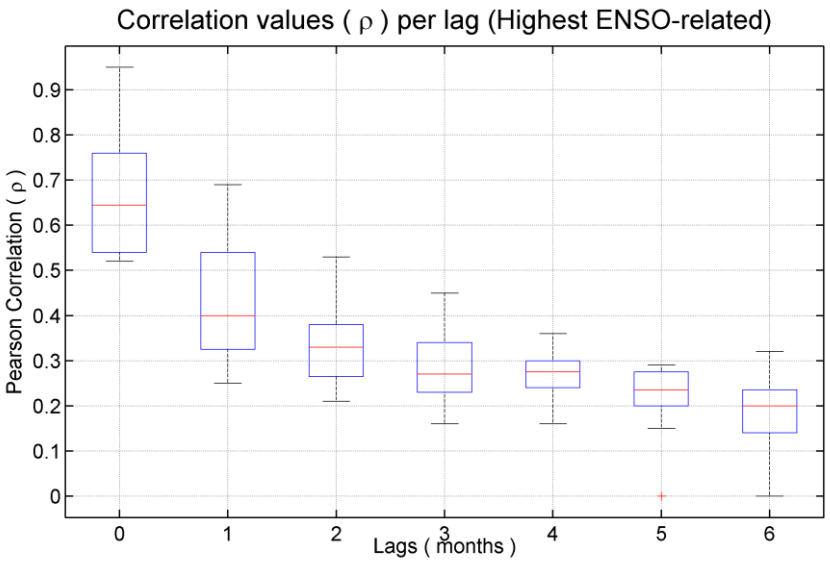
- Type of maps connected with high ENSO related MCS (See SSTs correlation maps at bottom)
- Correlation maps for the pairs SH^{925}-T_{2m} (Continental extent over TropSA), EVP-T_{2m}, PRC-SH^{925}, EVP-VSW, EVP-SH^{925}
- Generally, continental extent of significant correlations related with pairs including T_{2m} and SH^{925}

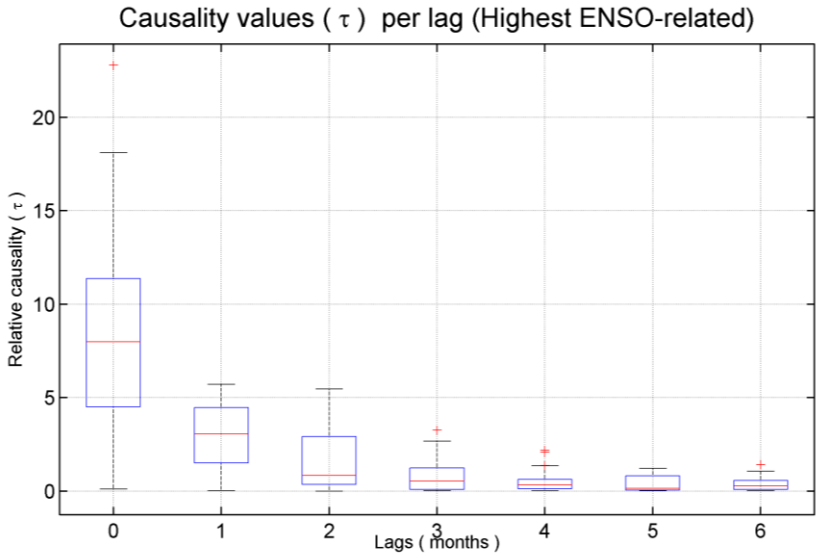


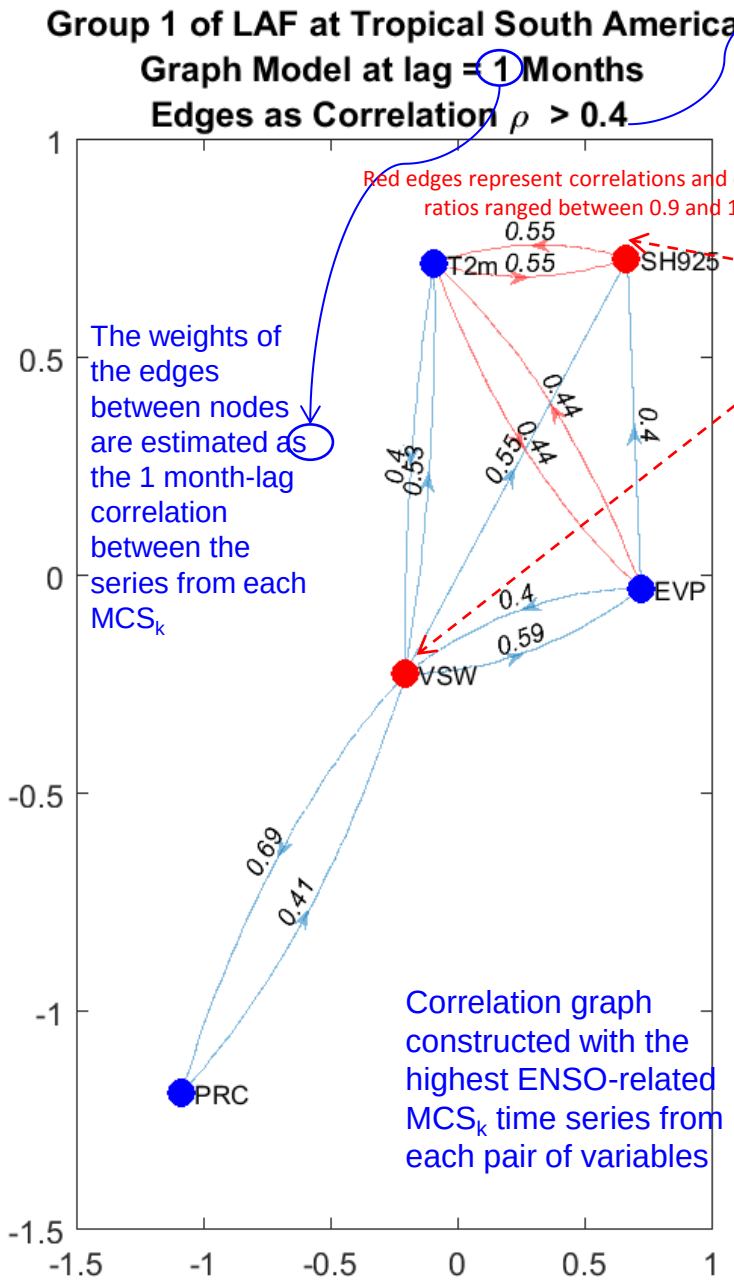
Thresholds to Define Weight of Graphs Edges

- We define a threshold for the edges magnitude to construct correlation and causality graphs.
- This allow us to study the strongest connections among the studied variables.
- In all cases, we select the percentile of 50% of the empirical probability distribution of causalities and correlations for each time lag.

Metric type	Mode	Lag						
		0	*1*	*2*	*3*	*4*	*5*	*6*
Correlation	Highest	0.64	0.4	0.33	0.27	0.275	0.235	0.2
Relative Causality (%)	ENSO-related	9.93	4.8	3.44	3.94	2.69	1.75	1.08



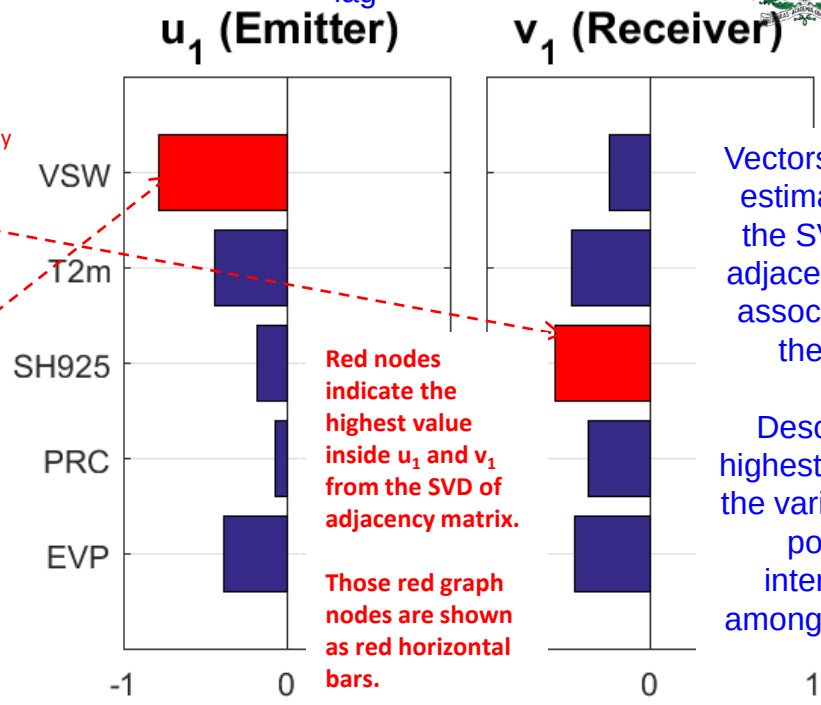




The weights of the edges between nodes are estimated as the 1 month-lag correlation between the series from each MCS_k

Correlation graph constructed with the highest ENSO-related MCS_k time series from each pair of variables

Threshold selected as the median of the empirical probability of all interactions at each lag

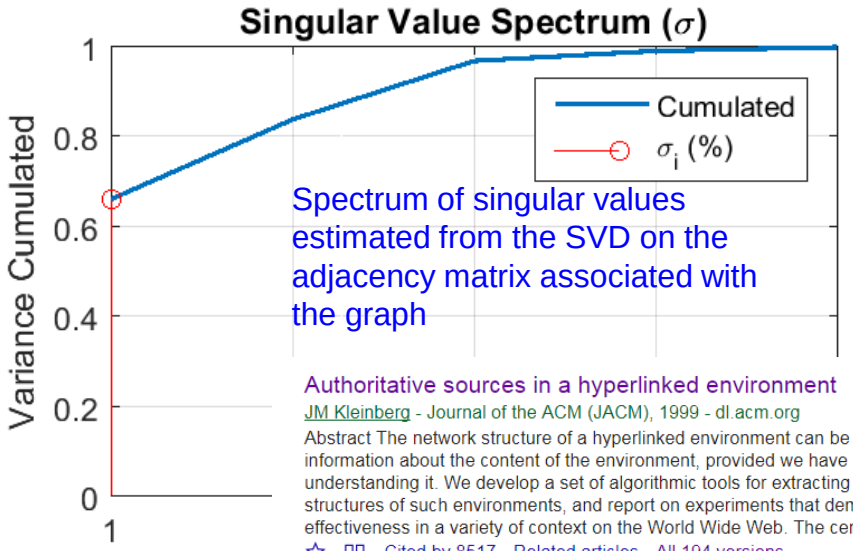


Red nodes indicate the highest value inside u_1 and v_1 from the SVD of adjacency matrix.

Those red graph nodes are shown as red horizontal bars.

Vectors u_1 and v_1 estimated from the SVD of the adjacency matrix associated with the graph

Describe the highest amount of the variance of all possible interactions among variables.



Spectrum of singular values estimated from the SVD on the adjacency matrix associated with the graph

Authoritative sources in a hyperlinked environment
JM Kleinberg - Journal of the ACM (JACM), 1999 - dl.acm.org
Abstract The network structure of a hyperlinked environment can be a rich source of information about the content of the environment, provided we have effective means for understanding it. We develop a set of algorithmic tools for extracting information from the link structures of such environments, and report on experiments that demonstrate their effectiveness in a variety of context on the World Wide Web. The central issue we address ...
☆ 99 Cited by 8517 Related articles All 194 versions

1 lag-month graph using a threshold of significant correlations higher than 0.4 (1979-2010)

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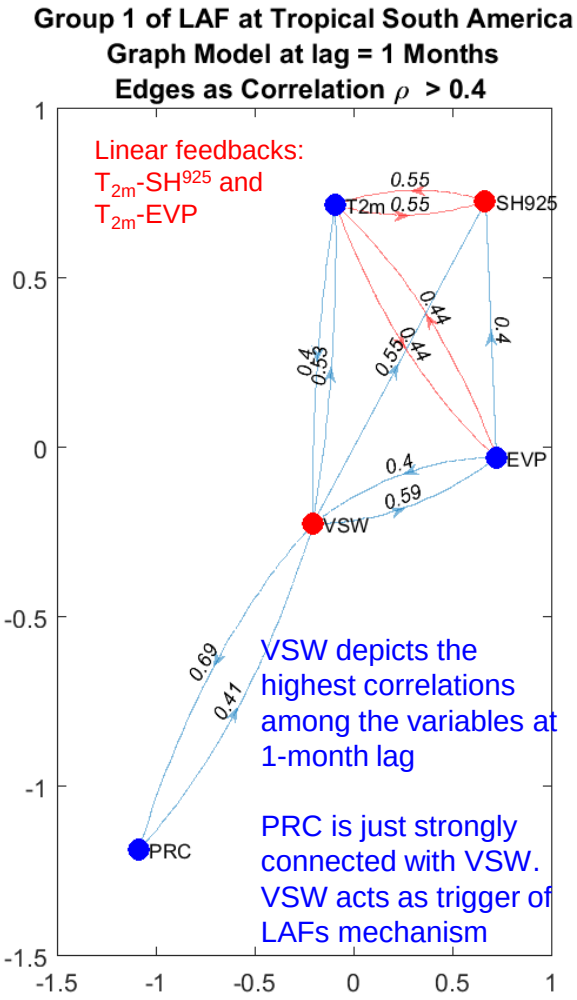
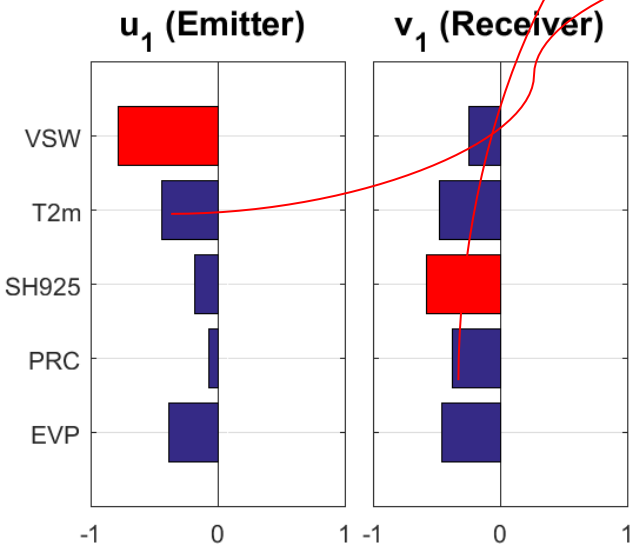
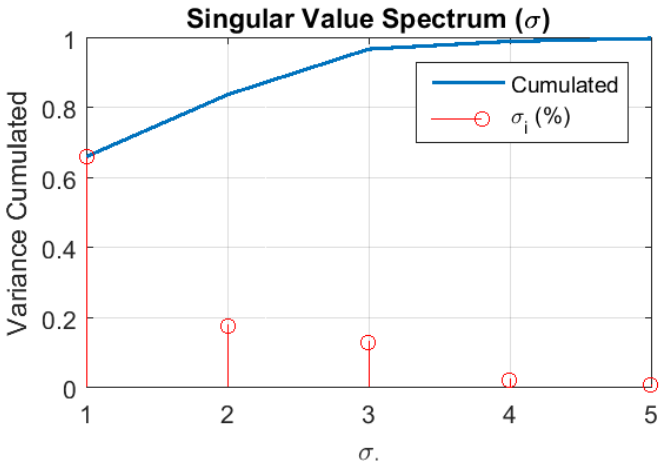
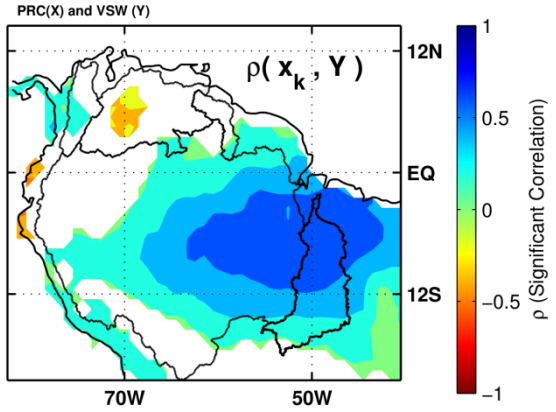






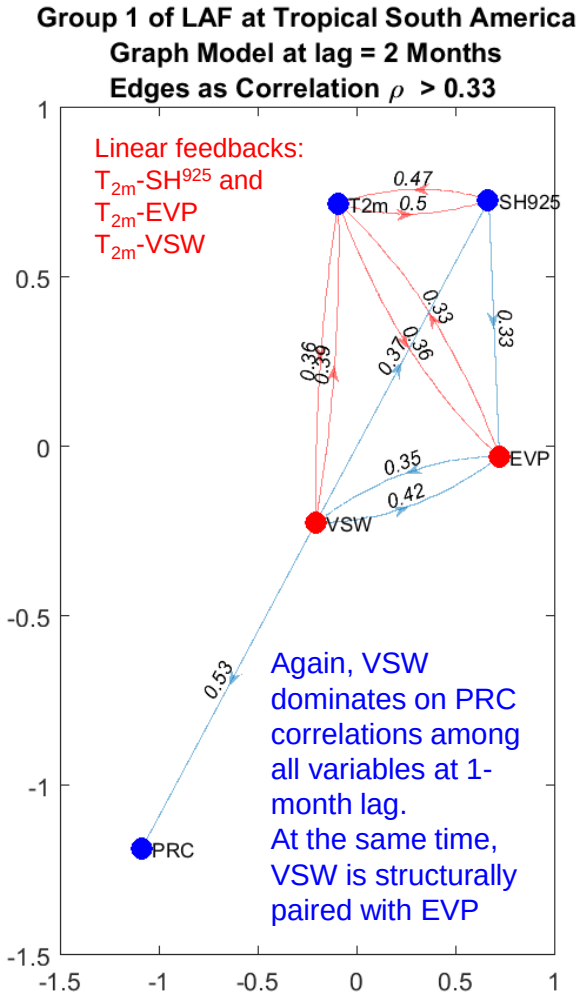
Volumetric Soil Water (best emitter) *is essential over Tropical South America to structurally feeds back specific humidity at 925 (best receiver) hPa under the group of highest ENSO-related Maximum Covariance States at 1 month-lag for linear metrics.*

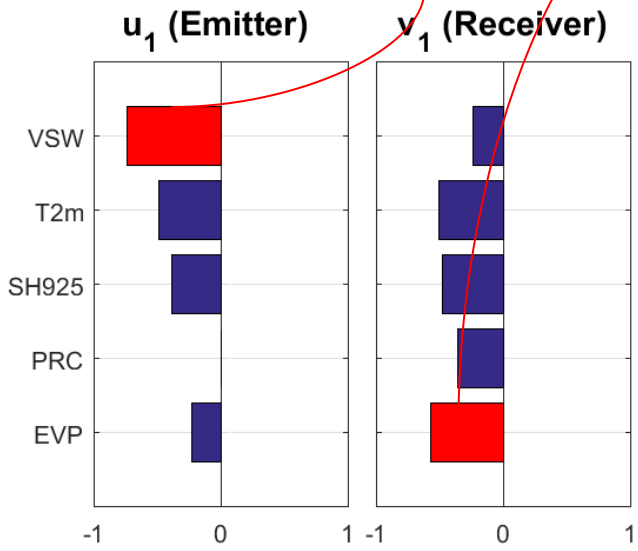
This links structure depicts the Land Atmosphere Feedbacks between state variables VSW and SH925

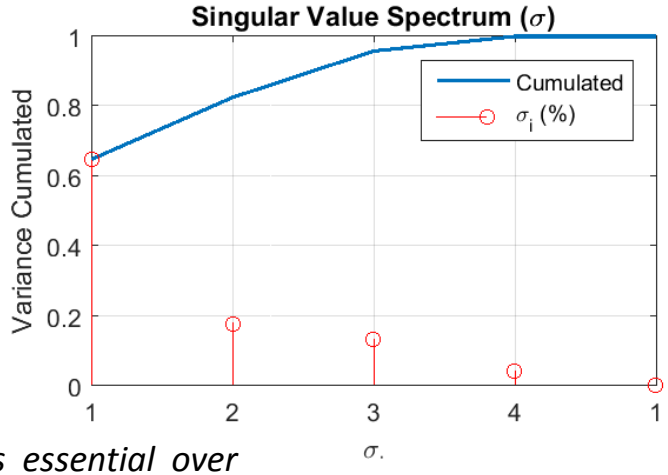


At 1 month-lag, VSW dominates linear relationships on PRC, EVP, SH925 and T2m at interannual time scales. It remarks the memory of this variable in the context of LAFs over TropSA

2 lag-month graph using a threshold of significant correlations higher than 0.33 (1979-2010)







Volumetric Soil Water (best emitter) *is essential over Tropical South America to structurally feeds back EVP (best receiver) under the group of highest ENSO-related Maximum Covariance States at 2 month-lag*

Again, but *at 2 month-lag,* ***VSW*** *is essential over Tropical South America to structurally as emitter of group of highest ENSO-related Maximum Covariance States*

At 2 month-lag, VSW dominates linear relationships on PRC, among EVP, SH^{925} and T$_{2m}$ at interannual time scales

3 lag-month graph using a threshold of significant correlations higher than 0.27 (1979-2010)

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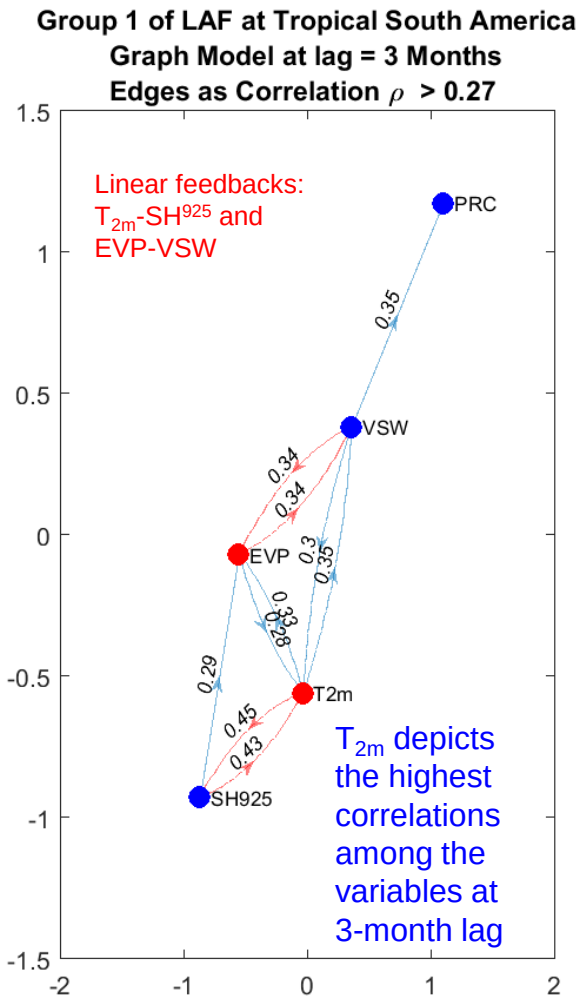

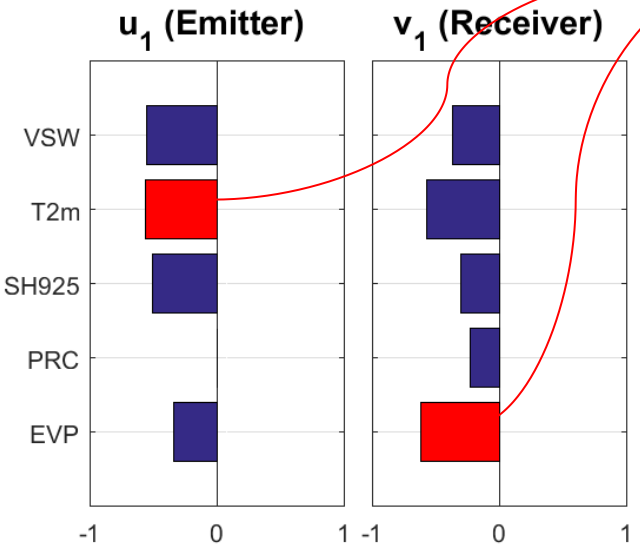

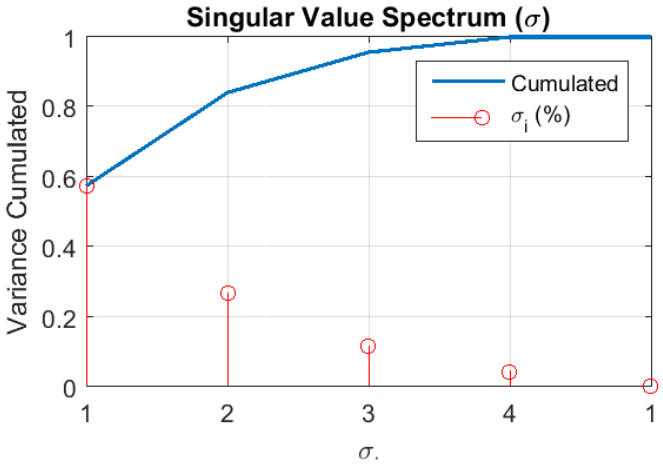

2m Temperature (best emitter) and VSW are *essential over Tropical South America to structurally feeds back EVP (best receiver) under the group of highest ENSO-related Maximum Covariance States at 3 month-lag.*

This links structure depicts the Land Atmosphere Feedbacks between state variable T_{2m} , VSW and EVP

VSW *connects PRC feeding back EVP over Tropical South America under the group of highest ENSO-related Maximum Covariance States at 3 month-lag*

At 3 month-lag, soil humidity dominates linear relationships on PRC, EVP, SH^{925} and T_{2m} at interannual time scales

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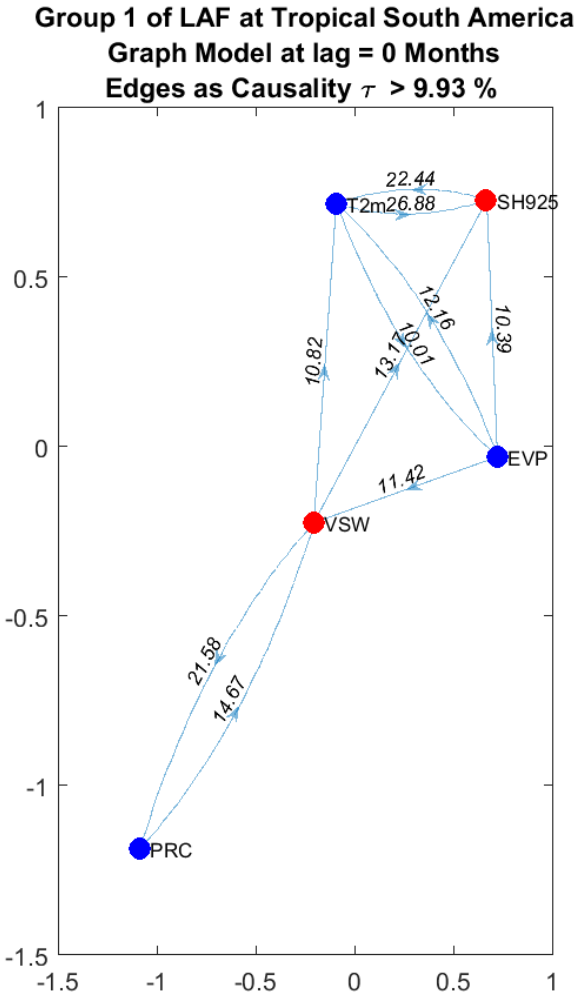
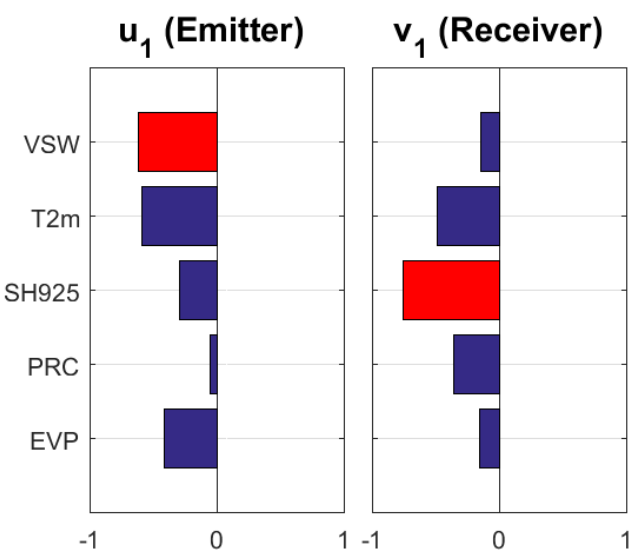
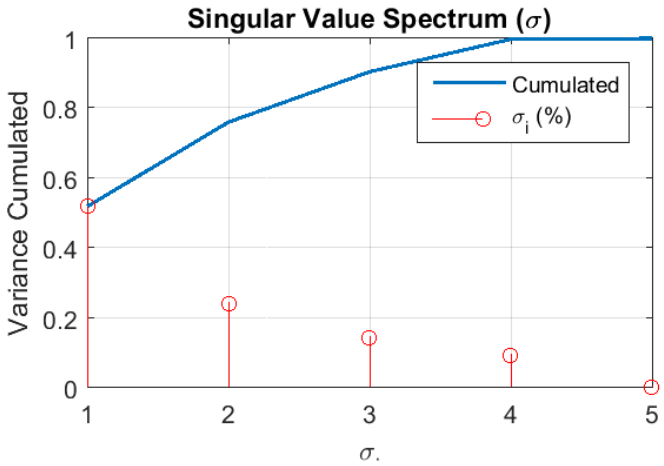
Results (3)

Graphs with Non-Linear Edges

0 lag-month graph using a threshold of relative causality higher than 9.93% (1979-







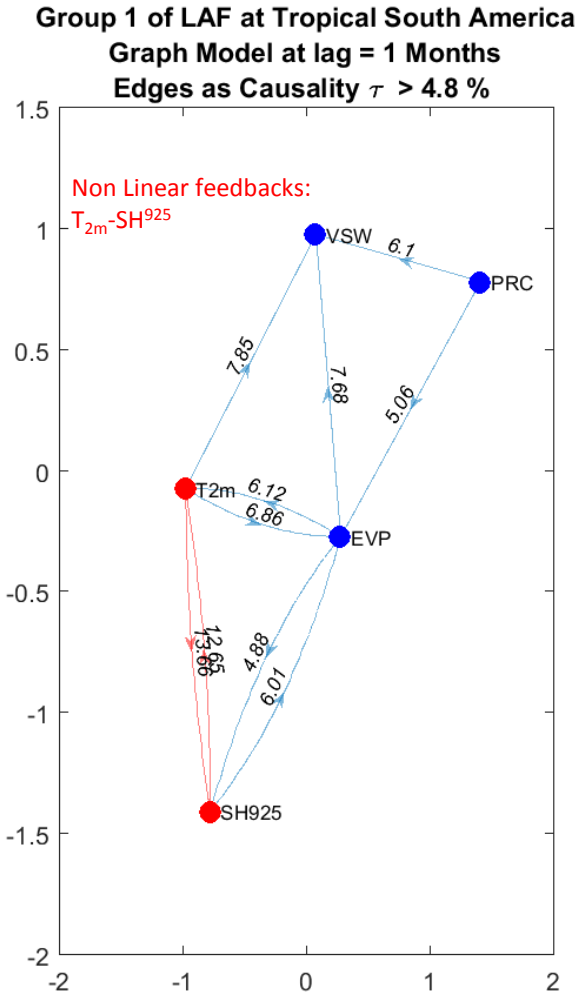
Volumetric Soil Water ***(best emitter)*** *is essential over Tropical South America to structurally feeds specific humidity at 925 hPa (best receiver) back under the group of highest ENSO-related Maximum Covariance States at 0 month-lag for non-linear metrics .*

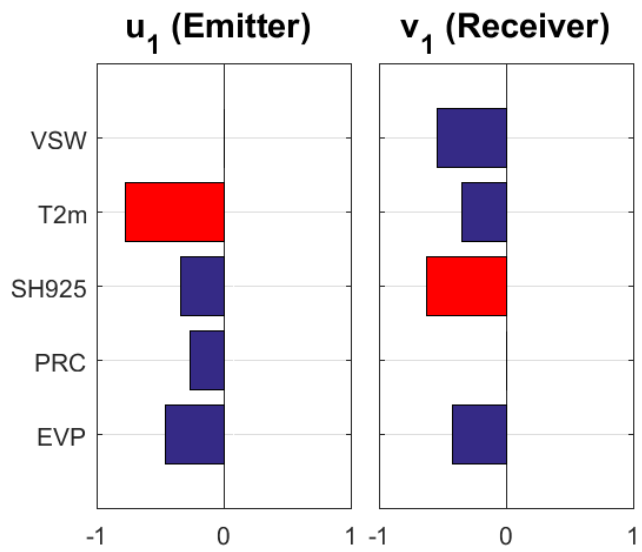
This links structure depicts the Land Atmosphere Feedbacks between state variables VSW-T_{2m} and SH^{925}

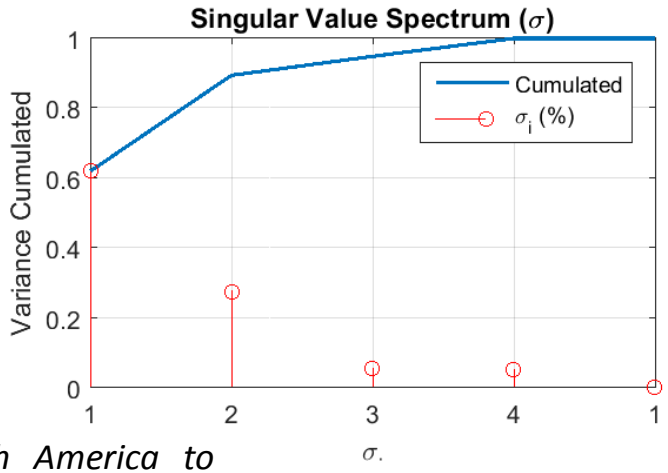
VSW *is essential over Tropical South America to structurally feeds back SH^{925} under the group of highest ENSO-related Maximum Covariance States at concurrent series (non-linear links)*

At 0 month-lag (concurrent), VSW dominates non-linear relationships on PRC, SH^{925} and T_{2m} at interannual time scales. However, EVP dominates on VSW.

1 lag-month graph using a threshold of relative causality higher than 4.8% (1979-







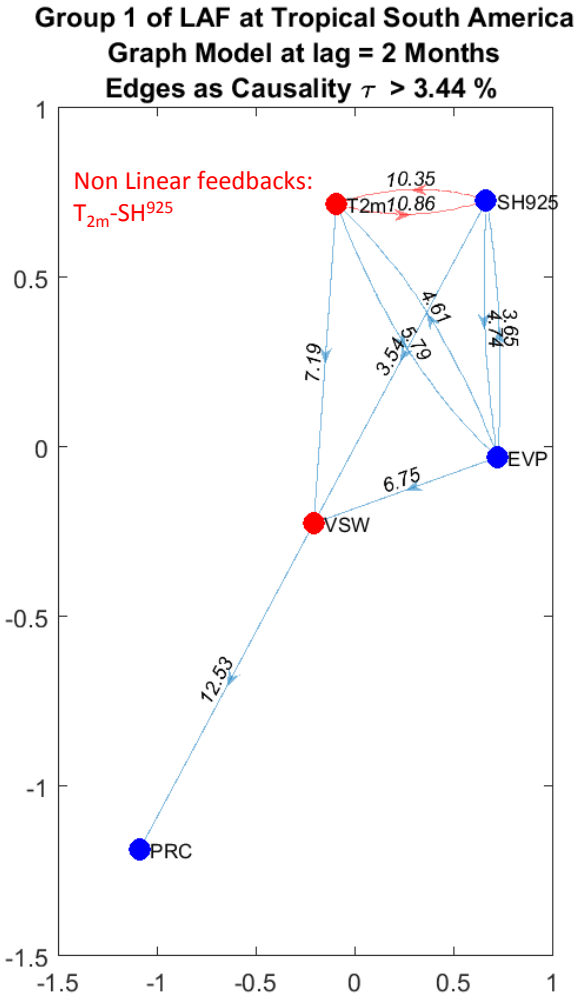
T_{2m} (best emitter) *is essential over Tropical South America that structurally feedbacks specific humidity at 925 hPa (best receiver) under the group of highest ENSO-related Maximum Covariance States at 1 month-lag.*

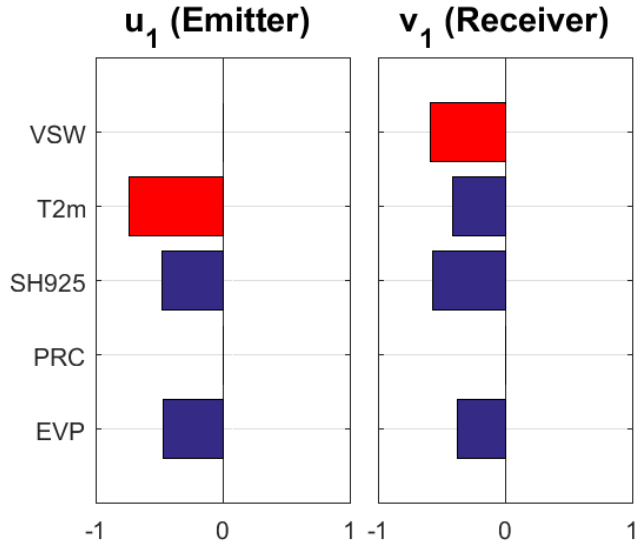
This links structure depicts the Land Atmosphere Feedbacks between state variables T_{2m} and SH^{925}

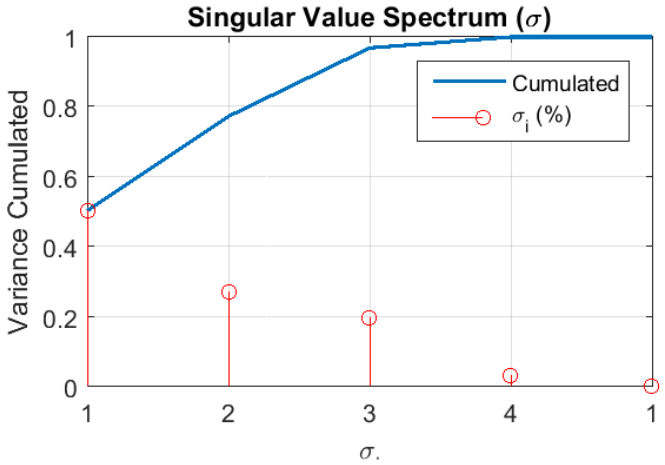
***T_{2m}** is essential over Tropical South America to structurally feeds back specific humidity under the group of highest ENSO-related Maximum Covariance States at 1 month-lag*

At 1 month-lag, EVP, PRC and T_{2m} dominates non-linear relationships on VSW and at interannual time scales

2 lag-month graph using a threshold of relative causality higher than 3.44% (1979-2010)







T_{2m} (best emitter) *is essential over Tropical South America that structurally feedback VSW (best receiver) hPa under the group of highest ENSO-related Maximum Covariance States at 2 month-lag.*

This links structure depicts the Land Atmosphere Feedbacks between state variables ***T_{2m}*** *and VSW*

T_{2m} *is essential over Tropical South America to structurally feeds back VSW under the group of highest ENSO-related Maximum Covariance States at 2 month-lag and non-linear links*

At 2 month-lag, VSW dominates non-linear relationships on PRC. At the same time, EVP and T_{2m} dominates on VSW at interannual time scales.

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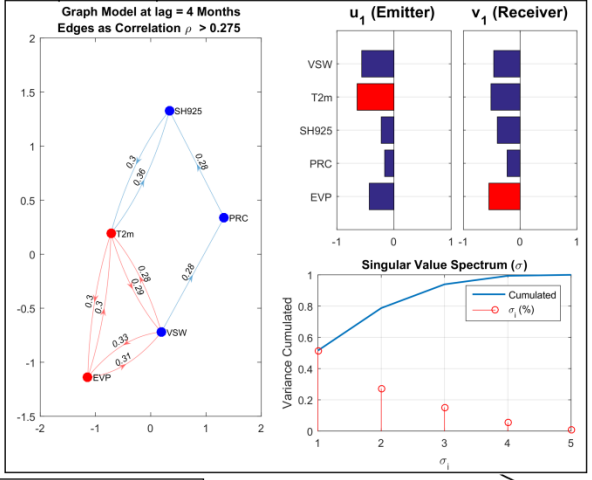
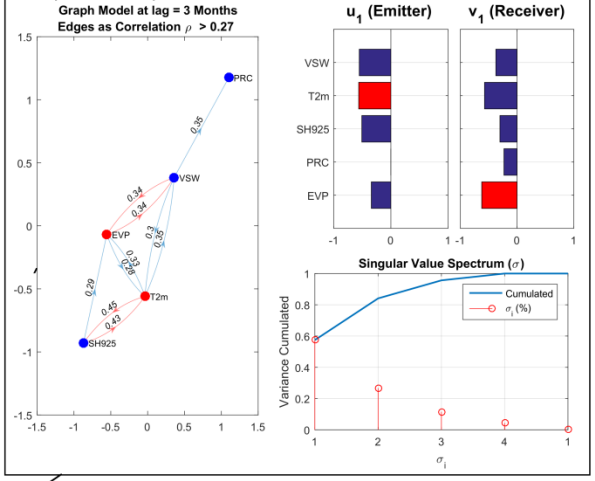
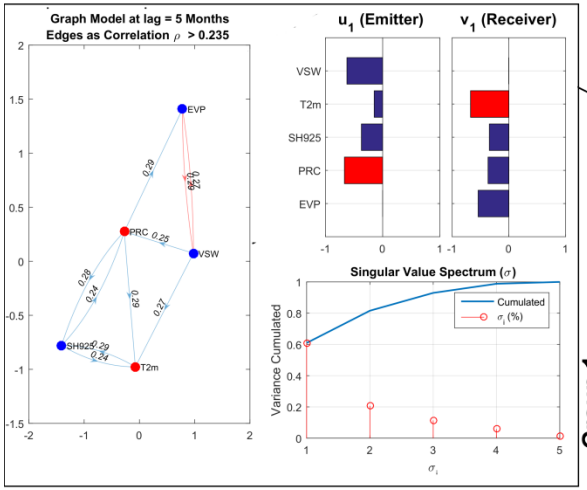
Results (4)

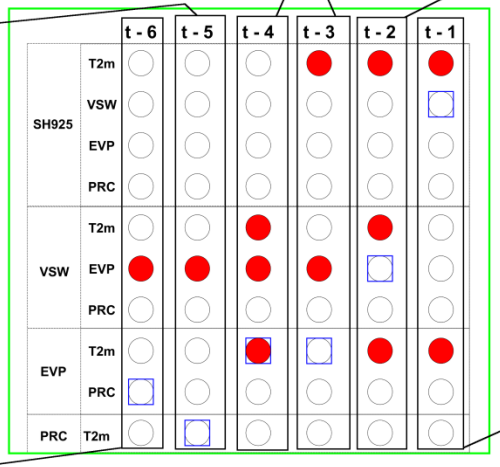
Comparing Graphs with Linear and Non-Linear Edges



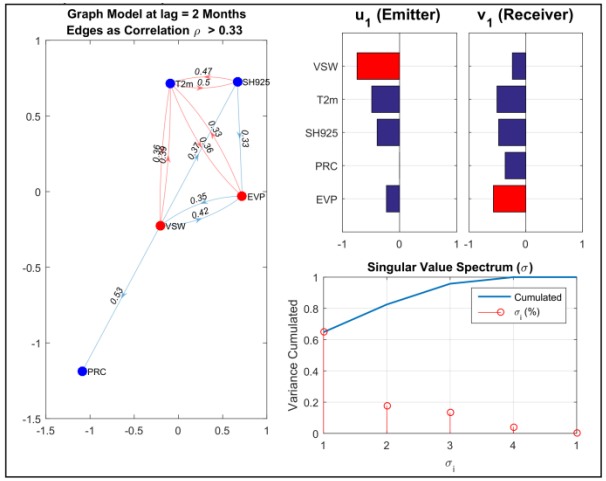


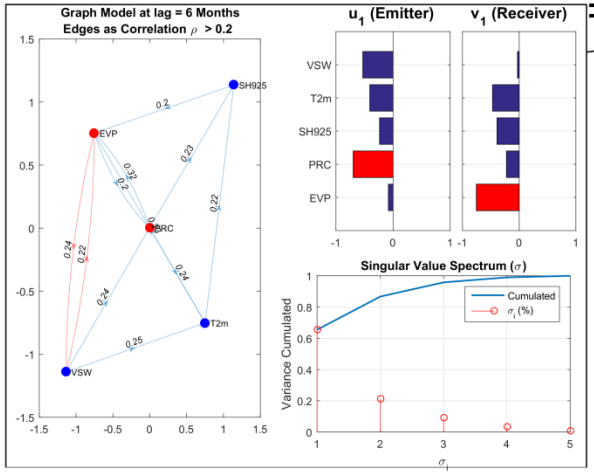


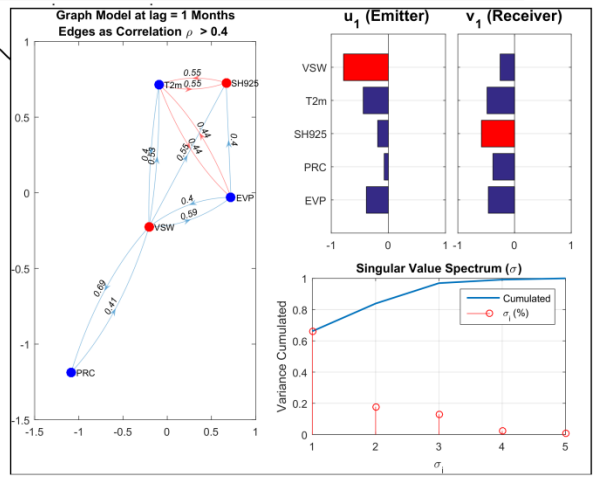
Correlation Graphs
Linear Coupling Edges



Group 1
High ENSO-related





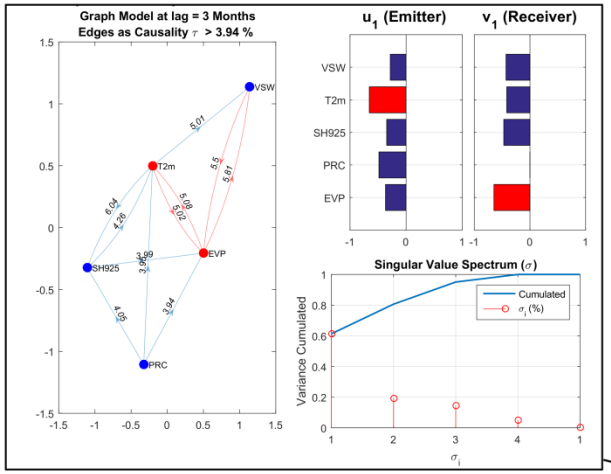


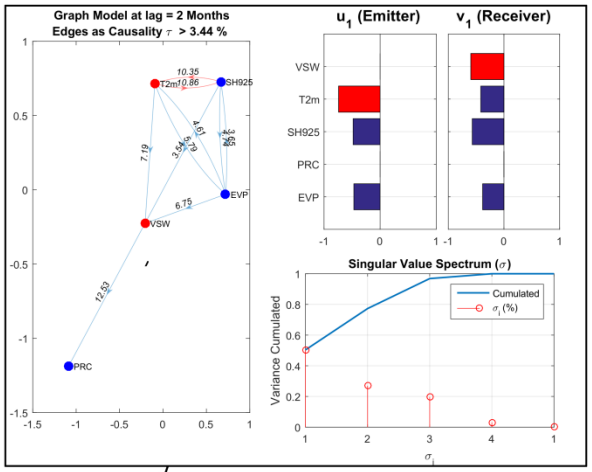
○ Graph's Edge

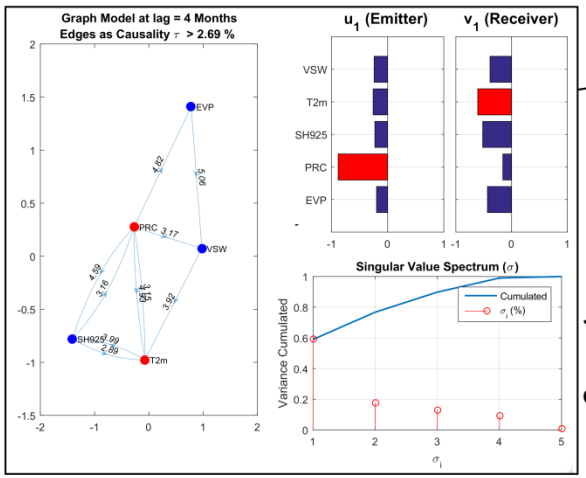
▢ Highest Value of main singular vectors u1 and v1 per each lag graph

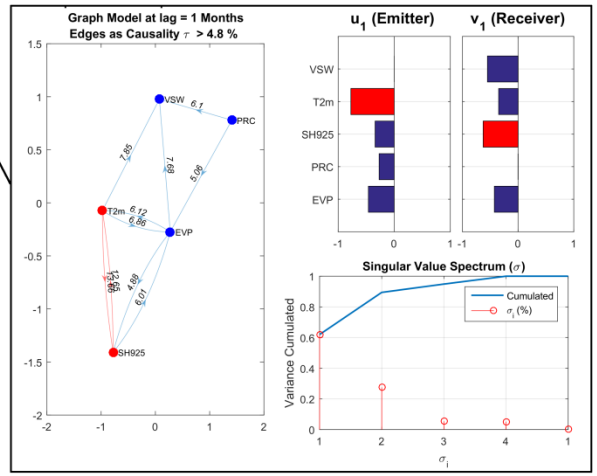
● Edges ratio of correlations or causalities ranging 0.9 - 1.1 per each lag graph

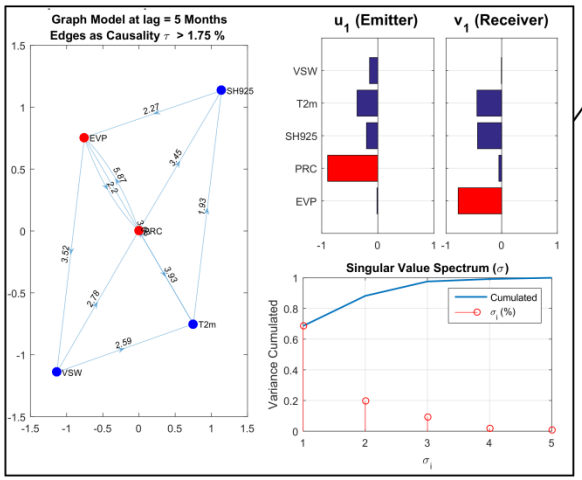
- VSW plays an important role as structural link at several time lags
- VSW provides the memory of the atmosphere-driven processes and their subsequent influence

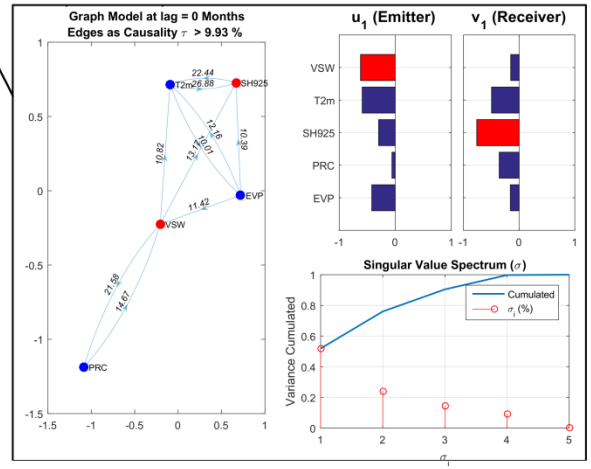




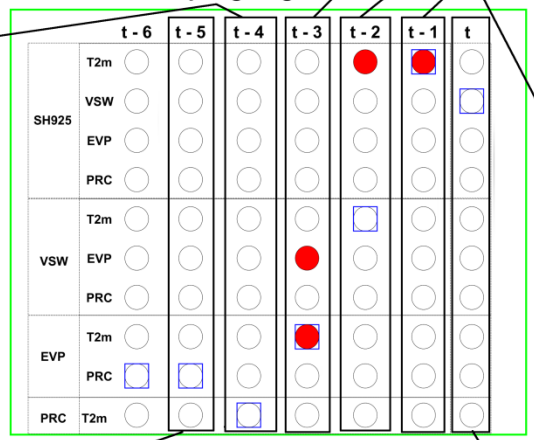








Causality Graphs
Non-Linear Coupling Edges



Group 1
High ENSO-related

Graph's Edge

Highest Value of main singular vectors u1 and v1 per each lag graph

Edges ratio of correlations or causalities ranging 0.9 - 1.1 per each lag graph

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Conclusions

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- The regulatory action of ENSO sets in a stronger memory and resilience of interactions among state and process variables. VSW is a key variable in defining the spatiotemporal patterns of PRC and EVP in TropSA at interannual timescales, and as such plays a major role in regulating LAFs at interannual timescales.
- We defined the dominant LAF spatiotemporal patterns by a pair-wise categorization of variables through Maximum Covariance Analysis (MCA)/Singular-Value Decomposition (SVD), with the aim of quantify the most salient factors associated with ENSO over TropSA. With such patterns, we evaluated the relational structure between state (T_{2m}, SH^{925}, and VSW) and process (PRC and EVP) variables using Graph Theory.
- The identified structure of correlations (linear) among variables differs from that derived from causalities (non-linear).
- Among the studied variables, T_{2m} and VSW exhibit the highest amount of linear feedbacks (correlation) including the one among them at 1 month-lag, and with process variables PRC and EVP.
- For both the simultaneous and lagged analysis, surface temperature (T_{2m}), as a state variable, activates non-linear associations with atmospheric moisture (SH^{925}) and soil moisture (VSW) among the high ENSO-related graphs (causality graphs).
- Under the ENSO influence, T_{2m} is not only a key variable to diagnose the dynamics of interannual LAFs but also has a substantial role on the dynamics and thermodynamics of the lower troposphere and soil interfaces over TropSA