# An interaction network perspective on global sea surface temperature variability WCRP Latin America

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### How can we explain global temperature variability?



- Forcing (natural or anthropogenic)
- Internal variability (ENSO, AMO, etc.)

SST spatial signature

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### How can we explain global temperature variability?



Figure: Variance of SST for periods longer than a year from HadISST.

- Detect SST *spatial patterns of variability* from gridded observations or simulations?
- Analyze their relationship with global temperature variability?

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### 2 Detecting spatial patterns of variability using correlation networks



3 Results of the SST networks

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### Data and processing

- Observations (HadISST): 140 years of monthly SST anomalies on a  $1^\circ$  grid
- *Processing*: 1 year (interannual) and 8 years (decadal) low-pass filtered linearly detrended SST anomalies
- Grid: Sinusoidal,  $\theta_{EQ} = 2^{\circ}$ ,  $\lambda = 2^{\circ} \Rightarrow N = 6280$  grid points.



# Empirical Orthogonal Functions (EOF)

### The Pearson Sample Correlation Matrix

The elements of the *Pearson correlation* matrix R of a dataset D are defined as:

$$r_{ij} = \frac{\sum_{k=1}^{L} (d_i(t_k) - \mu_i) (d_j(t_k) - \mu_j)}{\sigma_i \sigma_j}$$

#### Definition

The EOFs  $\mathbf{e}_{\mathbf{i}}$  are the *eigen-vectors* of the correlation matrix. They form an orthogonal basis *E* and maximize the variance of the projected time-series.

$$RE = E\Lambda$$

# EOF analysis of HadISST



 Only the first mode can be associated with a known pattern of variability (ENSO)

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• Regional modes are absent.

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# The Complex Network Framework

### Motivation

Focus on the *relationship* between the time series associated with the grid-points.

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# The Complex Network Framework

#### Motivation

Focus on the *relationship* between the time series associated with the grid-points.

#### Definition

A *network* is defined by a set of *nodes*  $(n_k)_{1 \le k \le N}$  and a set of *edges*  $(e_i)_{1 \le k \le E}$  linking the nodes.



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### How to determine if two climate time series are linked?

• Estimate the correlation matrix R of the dataset

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- Estimate the correlation matrix R of the dataset
- Choose a threshold to keep only significant and strong correlations, here  $\tau = 0.4$

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#### Link definition

Node (grid-point)  $n_i$  is linked to node  $n_j$  iff  $|r_{ij}| > \tau$ .

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The network is thus characterized by the *adjacency matrix A*:

$$a_{ij} = \Theta(|r_{ij}| - \tau) - \delta_{ij}$$



### Degree centrality of the interannual network

#### Definition of the degree centrality

Number of nodes in the network node  $n_i$  is connected to.



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### Degree centrality of the interannual network



Part of the pattern is similar to the dominant EOF, but other centers of action are present, though not distinguishable.

# Community structure of the interannual network

#### Definition of communities

Groups of nodes tightly connected to each other and sparsely connected to the rest of the network.



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# Community structure of the interannual network

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Communities can be associated with known patterns (El Niño/Southern Oscillation, Atlantic Multidecadal Oscillation)

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# Connectivity to communities of the interannual network

#### Definition

The connectivity of node  $n_i$  to community  $C_j$  is the percentage of nodes in the community  $C_j$  node  $n_i$  is connected to.



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# Connectivity to communities of the interannual network



- The first community is well defined
- The map is similar to a correlation map, but no index had to be subjectively defined.

### Community structure of the decadal network

All time series are now 8-years low-pass filtered.



- The tropical Pacific community (TP) is weaker
- Communities in the Indian Ocean-West Pacific (IWP) and North Atlantic (NA) also have a large number of links.

# Relationship between communities and Global Surface Temperatures

 Global Surface Temperature averages taken from NOAA (Ocean only, Land only and Ocean + Land)



# Relationship between communities and Global Surface Temperatures

 Global Surface Temperature averages taken from NOAA (Ocean only, Land only and Ocean + Land)

• Community time-series are calculated from spatial averages of the time-series of the nodes of each community.



#	Ocean + Land	Land	Ocean
TP	0.52	0.47	0.50
IWP	0.84	0.77	0.78
NA	0.65	0.49	0.67





# Conclusion

- The network approach allows to detect spatial patterns of variability on different spatial and temporal scales
- Three dominant patterns of decadal variability exist in the Indian Ocean-West Pacific, the North Atlantic and the tropical Pacific
- The patterns of the Indian Ocean-West Pacific and North Atlantic are strongly correlated to global surface temperatures







Thank you for your attention.

Tantet, A., Dijkstra, H. A. (2014). An interaction network perspective on the relation between patterns of sea surface temperature variability and global mean surface temperature. Earth System Dynamics



Figure: The Malvinas and Brazil currents confluence (Piola & Matano 2001).

# How to choose the threshold

- $\bullet$  Should only allow correlations significant at an  $\alpha$  significance level
- Should only allow "strong" correlations.

#### Moving block bootstrap test

Test the sample correlation of X and Y against the sample correlations of  $(X_b^*)_{1 \le b \le B}$  and  $(Y_b^*)_{1 \le b \le B}$  where the  $X_b^*$  and  $Y_b^*$  are resamples of X and Y by blocks of length L.

Allows to conserve the *distributions* of X and Y as well as there *auto-correlation*. In our case, L = 20 years.

# The Infomap community detection algorithm

#### Principle

Find a partition of the network minimizing the code length needed to code the paths of random walkers evolving in the network.

#### Algorithm

- *t*<sub>0</sub>: Assign each node to its own group.
- *t<sub>k</sub>*: move each node to the neighbouring module giving the largest decrease of the map equation until no move generates a decrease.
- *t<sub>l</sub>*: build a new network with these modules and repeat *t<sub>k</sub>* to find the next level.

Remark: the number of communities is not known a priori!



Figure: Lagged correlations between the IWP and the GLST. IWP leading for positive lags.

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# Rotated EOF

#### The Normal Varimax Rotation

Combine the EOFs (rotate) to minimize the spatial variance of the squared amplitudes of the rotated EOFs (thus favoring regional modes).

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# Rotated EOF



- The first EOF still bears the signature of ENSO
- Regional modes are present such as the Indian Ocean-West Pacific (IWP) and North Atlantic (NA).

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