Connectivity, Topology and Dynamics in Climate Networks

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Abstract

In a recently proposed approach for inferring patterns and (tele)connections in climate system **multivariate time series** are turned into **complex networks** (Tsonis & Roebber, 2004, Yamasaki et al., 2008, Donges et al., 2009).

- Constructing climate networks, vertices are either meteorological stations, or nodes of the grid of gridded field of a meteorological variable (air temperature, pressure, geopotential heights).
- Taking two time series of the variable one defines an edge and its weight as a suitable measure of dependence (connectivity) between those two time series.
- Accounting for the bias due to dynamical memory (serial correlations) in an connectivity measure (absolute cross-correlation) markedly changes the network topology and allows to observe previously hidden phenomena in climate network evolution.

Bias in connectivity depends on dynamics

- Autoregressive process

$$y_t = c\sum_{k=1}^{10} a_k y_{t-k} + \sigma e_t, \qquad (1)$$

where $a_{k=1,\dots,10} = 0,0,0,0,0,.19,.2,.2,.2,.2$, $\sigma = 0.01$ and e_t are Gaussian deviates with zero mean and unit variance

- **Entropy rate**; dynamical entropy

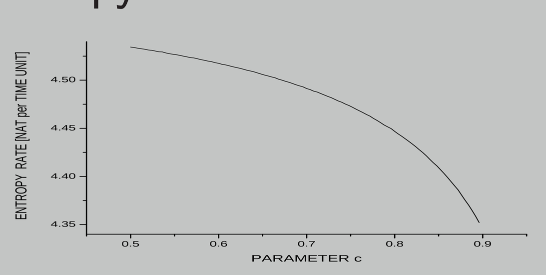
$$h = \lim_{n\to\infty}\frac{1}{n}H(Y(1),\dots,Y(n)) \qquad (2)$$

- Dynamical systems: *Kolmogorov-Sinai entropy*
- For a Gaussian process with spectral density function $f(\omega)$

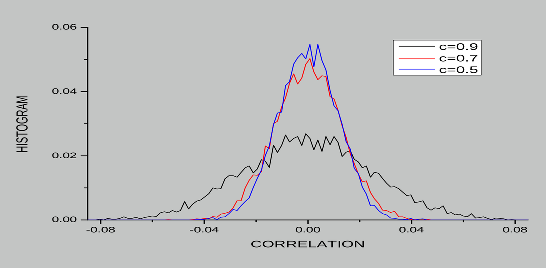
$$h_G = \frac{1}{2\pi}\int_{-\pi}^{\pi}\log f(\omega)d\omega \qquad (3)$$

- Parameter c influence on

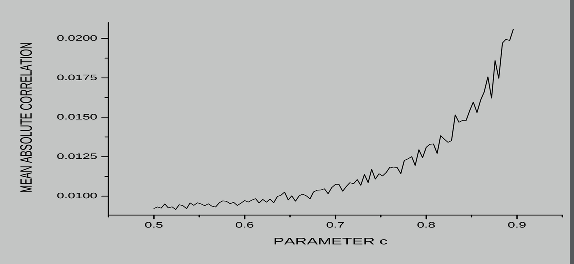
Entropy rates



histogram of correlations



mean absolute correlations

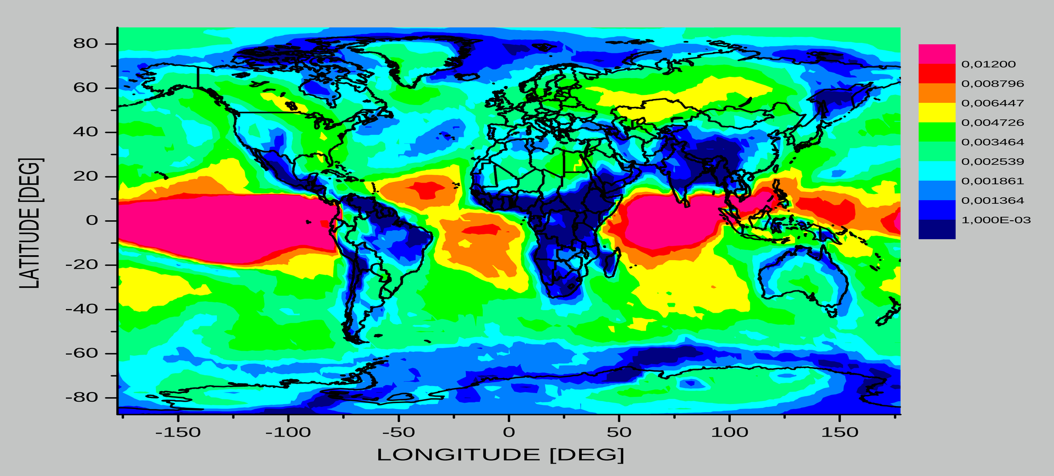


of INDEPENDENT realizations of (1)

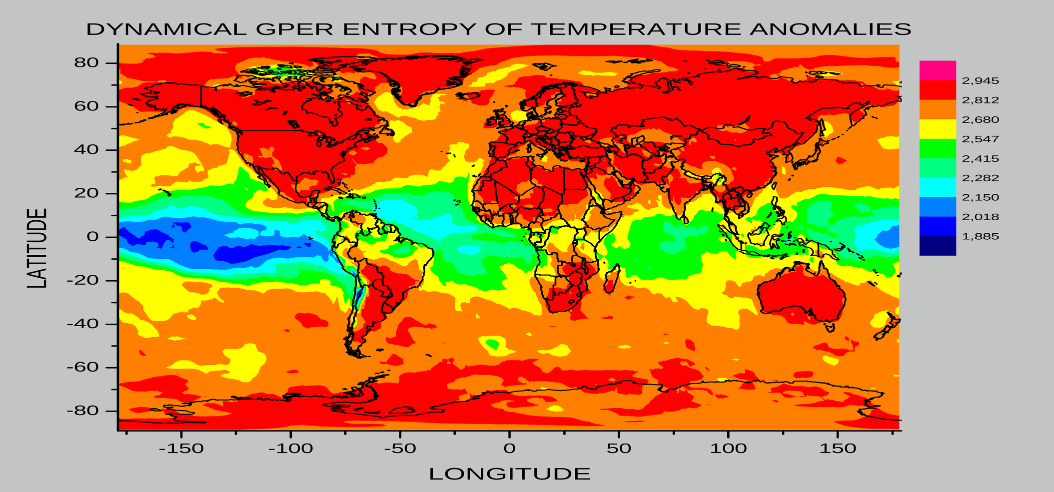
Connectivity vs dynamics in climate networks

- **Multivariate time series** $\longrightarrow$ **networks**
- Here: NCEP/NCAR surface air temperature **anomalies**
- grid 2.5° x 2.5° $\longrightarrow$ 10^4 nodes
- Pearson correlation $\longrightarrow$ weighted network
- thresholding $\longrightarrow$ binary network $\longrightarrow$ graph-theoretical analysis

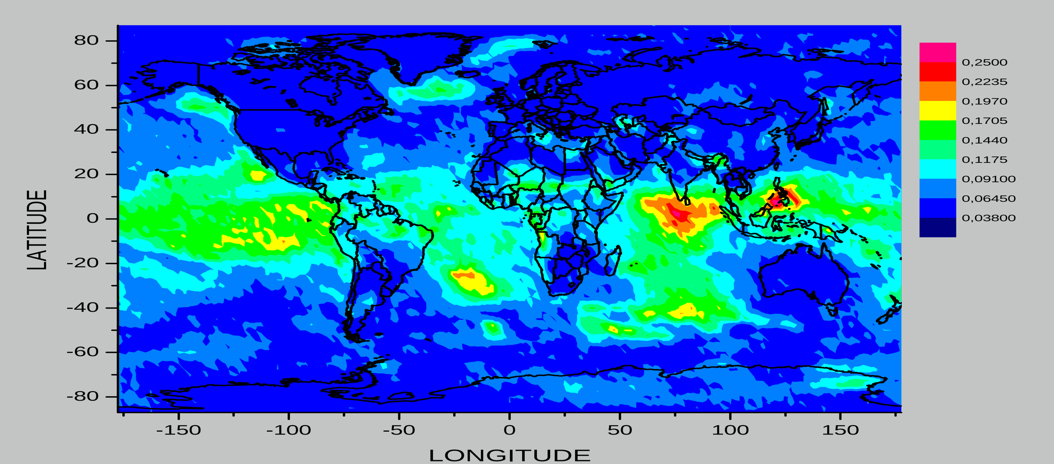
Area Weighted Connectivity for NCEP/NCAR SATA – thresholding of **absolute correlations** to $\varrho = 0.005$.



Entropy rate (dynamical entropy, inverse to regularity) of NCEP/NCAR SATA time series for each node.



Mean absolute correlation of each node NCEP/NCAR SATA time series with its independent FT surrogate data (Paluš, 2007).

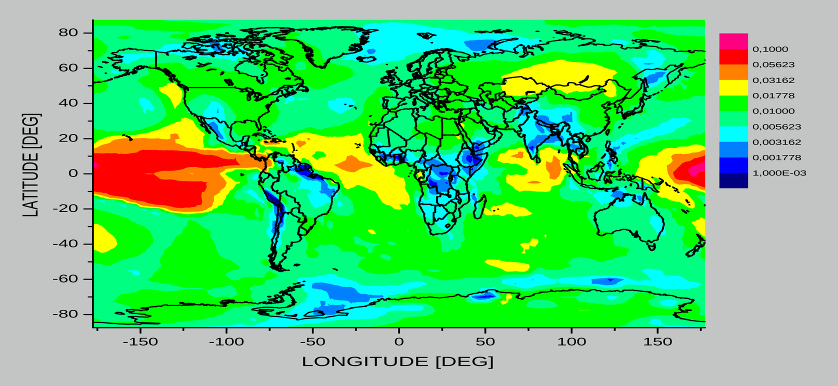


- Regularity of dynamics (autocorrelation) of a time series influences its dependence measures with other series. Different regularity leading to different bias in connectivity estimates is demonstrated using mean connectivity of a time series with its own univariate surrogate data (i.e., independent realizations of the same process).

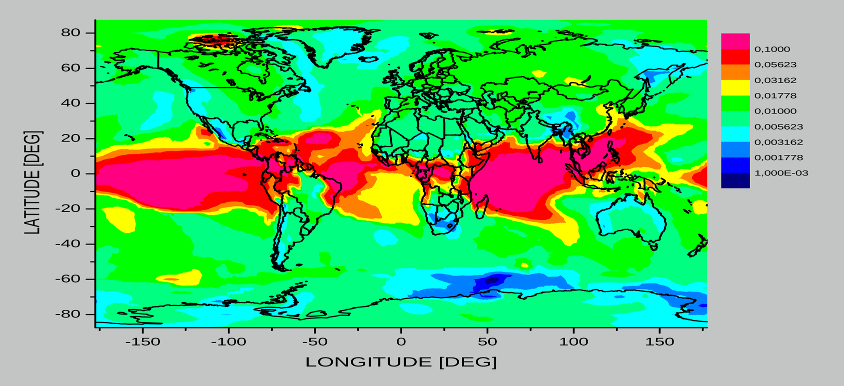
Connectivity or dynamics

- Following the study of Tsonis & Swanson (2008), below we present **Area Weighted Connectivity** for

negative ENSO phase

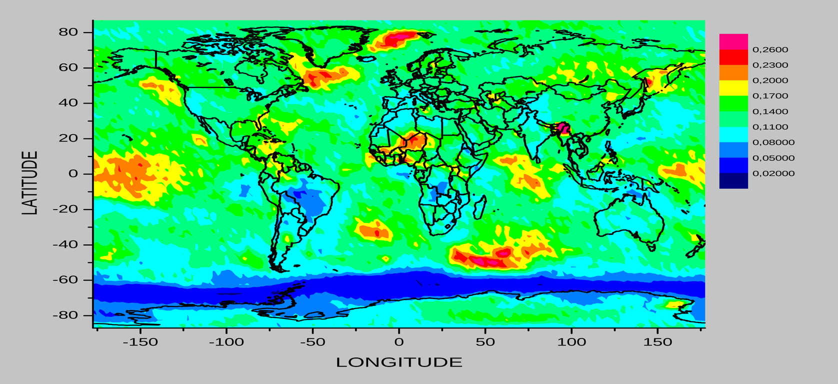


positive ENSO phase

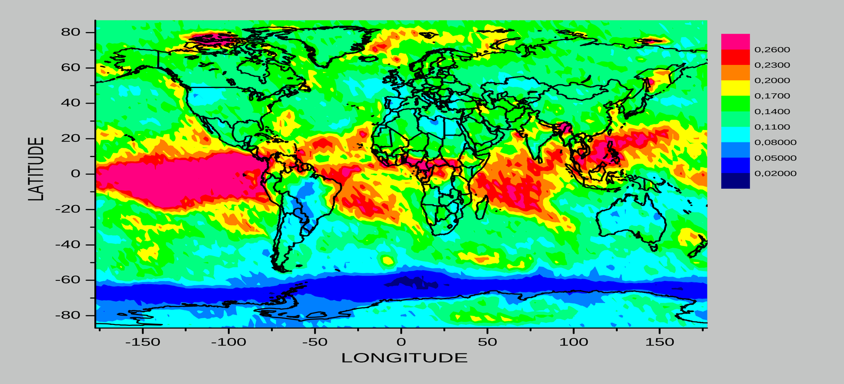


- in comparison with **mean absolute correlations** SATA w/ FT surrogates for

negative ENSO phase



positive ENSO phase



- ENSO influence can be explained by the dynamics rather than by connectivity.

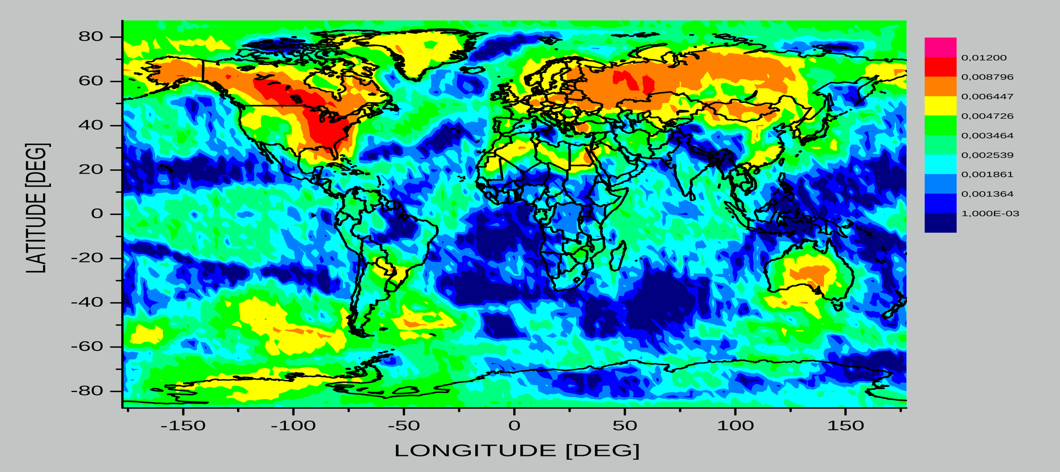
Correcting the biased connectivity

- Correction for dynamics (serial correlations) by using **Z-score**
- For each link a statistical test with FT surrogate data evaluated:

$$Z_{i,j} = \frac{c_{i,j} - mean[c_{i,j}(surr)]}{SD[c_{i,j}(surr)]}$$

Z-score $Z_{i,j}$ used instead of $c_{i,j}$ for the link weights

Area Weighted Connectivity, for NCEP/NCAR SATA, $\varrho = 0.005$, thresholding **Z-score** for absolute correlations + FT surrogate data

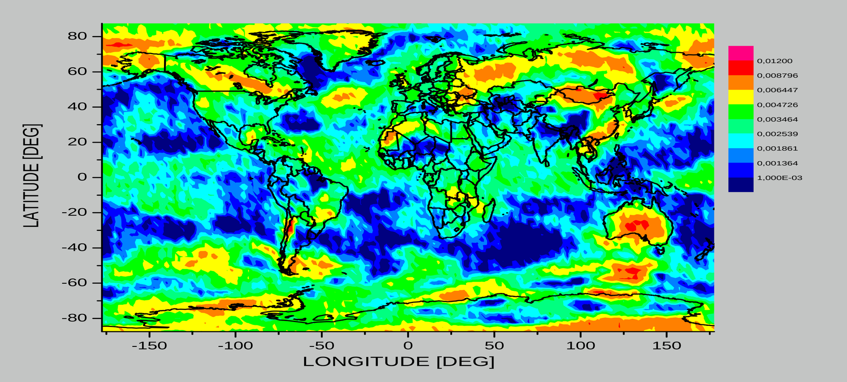


- Correcting the bias by using the Z-scores changes topology of the climate network – the "most connected" areas move from the tropics to NH areas influences by the North Atlantic Oscillation (NAO).

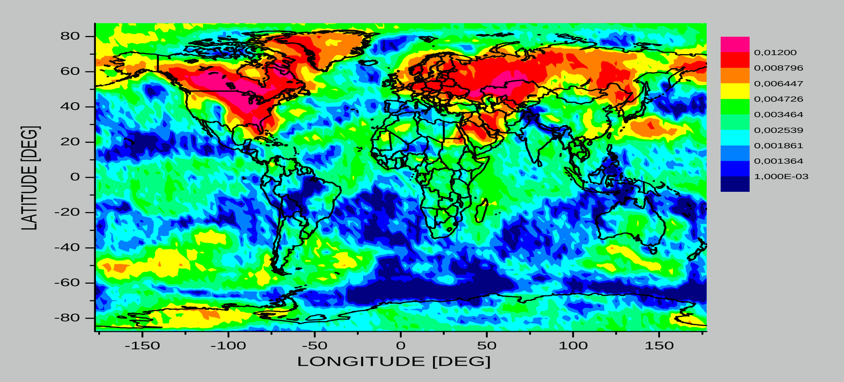
Climate networks with corrected connectivity

- Considering possible influence of NAO and solar activity, below we present **Area Weighted Connectivity** for

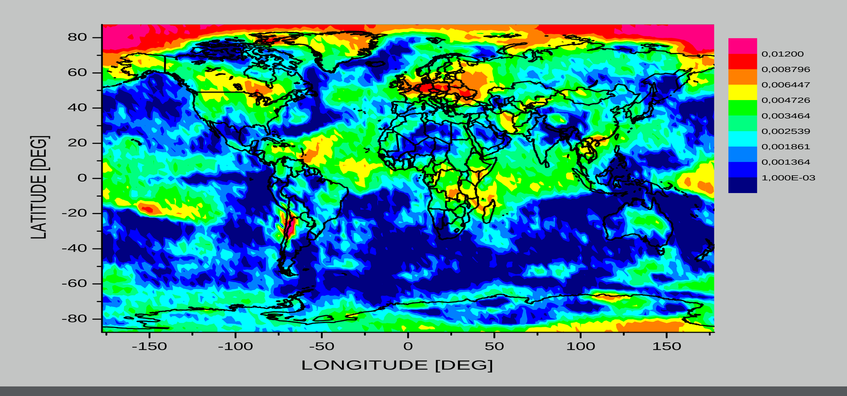
negative NAO phase



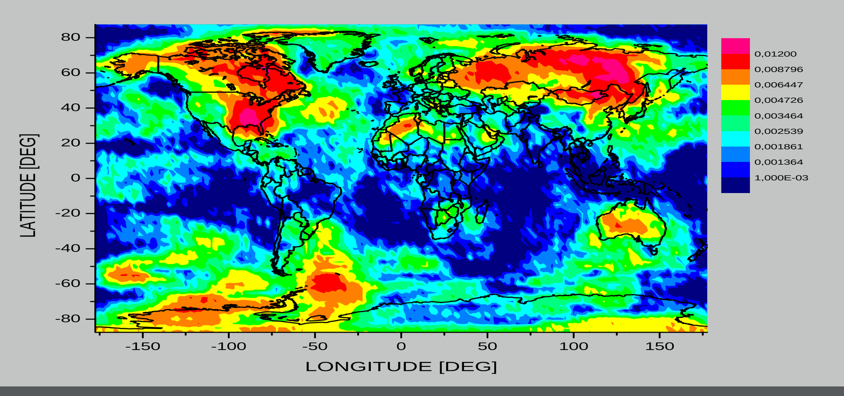
positive NAO phase



low solar activity



high solar activity



Conclusion

- Bias-corrected connectivity measure uncovers increased connectivity due to stronger transport of air masses during the positive NAO phase (Marshall et al., 2001) and larger NAO extent during high solar activity (Kodera, 2002).
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