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Evolving Climate Networks

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Abstract—We propose a method to reconstruct and analyse an evolving complex network from data generated by a spatio-temporal dynamical system. We study reanalysis surface air temperature data by different complex network measures. This approach reveals a rich internal structure in complex climate networks and allows to study the stability of the climate network and the impacts of teleconnections (e.g., El Niño/ Southern Oscillation). Moreover, the betweenness analyis uncovers peculiar wave-like structures of high information flow, that can be related to global surface ocean currents.

1. Introduction

Climate dynamics is related to spatio-temporal variability on different scales. Various approaches for spatio-temporal analysis are in use for a better understanding of the climate variability, like wavelet or EOF analysis [6, 8]. More recently, the complex network approach has been suggested for a spatio-temporal interaction analysis of climate data [9, 17, 20]. The complex network paradigm has proven to be a fruitful tool for the investigation of complex systems in various areas of science, e.g., the internet and world wide web in computer science, food webs, gene expression and neural networks in biology, and citation networks in social science [5, 16, 19]. The intricate interplay between the structure and dynamics of real networks has received considerable attention [5]. Particularly, synchronisation arising by the transfer of dynamical information in complex network topologies has been studied intensively [3]. The application of complex network theory to climate science is a young field, where only few studies have been reported recently [9, 10, 17, 20]. The vertices of a climate network are identified with the spatial grid points of an underlying global climate data set. Edges are added between pairs of vertices depending on the degree of statistical interdependence between the corresponding pairs of anomaly time series taken from the climate data set. Climate networks enable novel insights into the topology and dynamics of the climate system over many spatial scales ranging from local properties as the number of first neighbours of a vertex v (the degree centrality) to global network measures such as the clustering coefficient or the average path length. For example, the betweenness centrality uncovers peculiar wave-like structures of high energy flow, that can be related to global surface ocean currents [9]. These insights are conceptually new and cannot be obtained using classical methods of climatology such as principal component analysis (PCA) or singular spectrum analysis (SSA) of anomaly fields [12, 18], because these are by design local in a network sense and are not suitable to study local flow measures depending on a global network topology.

Because the climate is changing in time, it is obvious, that the climate network should also change in time, i.e., the correlation structure of climatological fields cannot generally be considered to be stationary in a statistical sense. This is related to the concept of evolving complex networks (dynamically changing networks), which have received increasing interest in the last years, as real systems often exhibit variations in the ensembles of elements (vertices) and interrelations (edges) [2, 4, 13]. Evolving networks are marked by the emergence of information, rich dynamics and structure formation, e.g., collective behaviour between some of the elements. They can switch between stability and instability, leading to new qualitative behaviour like robustness or vulnerability. Evolving complex networks have been successfully studied to investigate failure propagation in power-grids [1] or hierarchical structures in the brain [16, 21].

2. Data and data pre-processing

We utilise the 6-hourly global surface air temperature (SAT) field to construct climate networks, that allows to directly capture the complex dynamics on the interface between ocean and atmosphere due to heat exchange and other local processes. SAT, therefore, enables us to study atmospheric as well as oceanic dynamics using the same climate network. We use reanalysis data provided by the National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) [15]. A data set consists of a regular spatio-temporal grid with time series $x_i(t)$ associated to every spatial grid point i at latitude λ_i and longitude ϕ_i. The data starts at January 1948 and ends at December 2009 (744 months). The latitudinal and longitudinal resolution is $\Delta\lambda = \Delta\phi = 2.5$ ($N = 10,224$ vertices).

To minimise the bias introduced by solar forcing common to all time series in the data set, we calculate anomaly time series $a_i(t)$ from the $x_i(t)$, i.e., remove the mean annual cycle by phase averaging. Furthermore, the anomaly time series are normalised to zero mean and unit variance, and the data field is transformed from the cartesian grid to an icosahedral grid (in order to avoid the bias due to the higher grid point density at the poles).

3. Methodology

The climate interaction network is a representation of the interactions or interrelations I_{ij} between the time series at the grid points i and j. Such interactions can be measured, e.g., by cross correlation $I_{ij} = C_{ij}$ (as done by Yamasaki et al. [20]) or mutual information (MI) $I_{ij} = M_{ij}$ [9]. MI is a measure from information theory, that can be interpreted as the excess amount of information generated by falsely assuming the two time series a_i and a_j to be independent, and is able to detect linear as well as nonlinear relationships [14]. MI can be estimated using

$$M_{ij} = \sum_{\mu\nu} p_{ij}(\mu,\nu) \log \frac{p_{ij}(\mu,\nu)}{p_i(\mu) p_j(\nu)}, \qquad (1)$$

where $p_i(\mu)$ is the probability density function (PDF) of the time series a_i, and $p_{ij}(\mu,\nu)$ is the joint PDF of a pair (a_i, a_j).

By definition, I_{ij} is symmetric, so that $I_{ij} = I_{ji}$. We can also evaluate time delayed correlation and MI. This is appropriate when studying climate networks on smaller time scales using data sets with (sub-)diurnal resolution [20].

We now construct the climate interaction network by thresholding the interrelation matrix I_{ij}, i.e., only pairs of vertices (i, j) that satisfy $I_{ij} > \tau$ are regarded as linked, where τ is the threshold. Using the Heaviside function $\Theta(x)$, the adjacency matrix A_{ij} of the climate network is given by $A_{ij} = \Theta\left(I_{ij} - \tau\right) - \delta_{ij}$, where δ_{ij} is the Kronecker delta (subtracted in order to remove self-loops). If we consider time delayed interrelations, we choose the maximum value of interrelations within the range of considered time delays and apply the threshold on this maximal value. The resulting climate network is an undirected and unweighted simple graph (A_{ij} inherits its symmetry from I_{ij}). The threshold τ can be chosen as a fixed value or on dependence of a desired edge density. As the network characteristics (e.g., betweenness centrality) depend on the choice of the threshold τ, it is sometimes desirable to constrain the edge density $\rho = 2E/(N(N-1))$, where E gives the total number of edges [9], and to use a corresponding threshold $\tau = \tau(\rho)$. It was shown recently, that the backbone of the climate network is most clearly observed at small ρ with corresponding large threshold τ, that is very unlikely to be exceeded by chance, and that was reassured using various significance tests [9].

Following the idea of evolving networks we divide the reanalysis data into short time epochs and construct the climate networks from these epochs. This way we get a time evolving complex network $A_{ij}(t)$ and can analyse the time variation of the topology of the interaction patterns and heat transfer in the global climate system.

The climate interaction network can be characterised by global and local network statistics. Several of them have been analysed for climate networks [9, 17, 20].

In order to study the stability of a climate network, Yamasaki et al. have suggested to study the number of robust edges [20]. A robust edge is defined as an edge which remains in the evolving network for some time k. Formally, we calculate a matrix

$$R_{ij}(t) = \prod_{t'=t-k}^{t} A_{ij}(t'), \qquad (2)$$

containing only such edges lasting a period of at least k time steps. Here we consider a period of $k = 250$ days. The number of robust edges n is then calculated by the sum over this matrix $n(t) = \sum_{ij} R_{ij}(t)$.

Donges et al. have studied the betweenness centrality (BC) of a climate interaction network [9]. BC includes global topological information by relying on shortest paths between pairs of vertices (communication through the network concentrates on shortest paths). There are σ_{ij} shortest paths connecting i and j. Vertex v is an important mediator for communication in the network, if it is traversed by a large number of all existing shortest paths. Mathematically, the betweenness BC_v can be expressed by

$$BC_v = \sum_{i,j\neq v}^{N} \frac{\sigma_{ij}(v)}{\sigma_{ij}}, \qquad (3)$$

where $\sigma_{ij}(v)$ gives the number of shortest paths from i to j, that include v [11], and is normalised by σ_{ij}. Because the shortest paths contain only edges corresponding to pairs of highly dynamically interrelated time series, BC is a local measure of dynamical information flow. Since we use it to analyse a temperature field we interpret BC more fundamentally as a measure of the flow of energy (heat).

4. Results

The number of robust edges n in the climate network has been calculated from a network based on cross correlation and a threshold $\tau = 2\sigma_{\hat{C}_{ij}(t)}$ (where $\sigma_{\hat{C}_{ij}(t)}$ is the standard

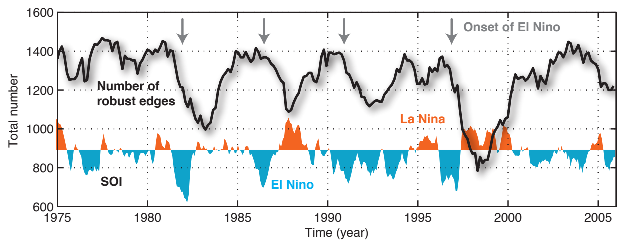

Figure 1: Number of robust edges n of the global climate network and El Niño/ Southern Oscillation index (SOI). The number of robust edges decreases significantly after the onset of an El Niño event (grey arrows).

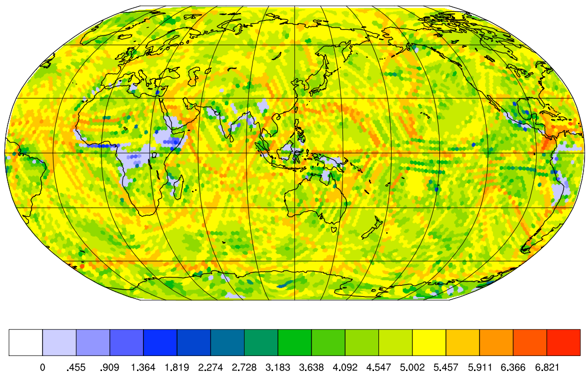

Figure 2: Betweenness centrality BC_v for the time epoch 3.10.1987–3.10.1989 which includes a strong La Niña year (logarithmic scale).

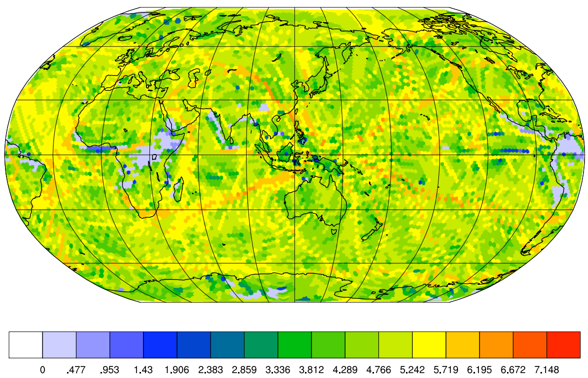

Figure 3: Betweenness centrality BC_v for the time epoch 3.10.1992–3.10.1993 which is about one year after the eruption of the Pinatubo vulcano (logarithmic scale).

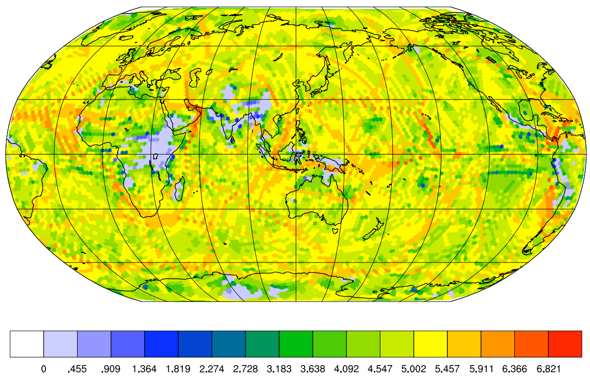

Figure 4: Betweenness centrality BC_v for the time epoch 2.1.1996–2.1.1998 which includes a strong El Niño year (logarithmic scale).

deviation of the cross correlation function between i and j normalised by its largest value [20]). n varies significantly for the studied period (Fig. 1). Moreover, we find that the sudden decrease of n is strongly related to the onset of El Niño events. After an El Niño event, the global climate regime needs several years to recover to the former number of robust edges.

For the calculation of BC_v, we have used MI and fixed the edge density at $\rho = 0.001$. The time evolving calculation of BC_v reveals a strong temporal variation also of this measure (Figs. 2–4). Furthermore, the spatial variation of BC_v forms characteristic patterns and obviously unveils paths of strong interactions and interrelations, which we can interpret as important transport paths (of energy or heat) within the climate network. For example, the year 1993 after the eruption of the Pinatubo volcano in 1991 is remarkable (Fig. 3). Paths of higher betweenness start at the site of the volcano and spread out over this part of the Earth. Comparing a typical El Niño with a La Niña years reveals structural differences in the interconnectivity, i.e., in the teleconnection patterns, in the climate system, and, thus, highlights the regional and global impact of the El Niño/ Southern Oscillation (Figs. 2, 4).

In analogy with the internet, we call the network of these channels of high energy flow the *backbone of the climate network*. Several of the backbone features which lie over the oceans coincide with well known ocean currents [9]. Temperature anomalies in sea surface temperature (SST) are advected by the surface ocean currents and transfered to the SAT field via heat flux coupling. Therefore, ocean currents provide a physical mechanism for the transport of energy on localised linear structures over large distances. In [9] it was shown that the betweenness field is neither correlated to SAT-SST gradients, nor is it statistically strongly related to the fields of degree and closeness centrality. Therefore we can underline that the backbone structures observed in climate networks are neither a trivial response to local anomalies in the SST-SAT gradient nor artifacts of chains of hubs with high degree and/or closeness centrality (highly spatially interrelated regions).

5. Conclusions

We have demonstrated the application of the evolving complex networks approach for a spatio-temporal analysis of global climate field data. Applying this approach we have been able to analyse the global stability of the climate regime and to unveil pathways of strong interactions and interrelations (teleconnections). By studying the number of robust edges we have found that the El Niño/ Southern Oscillation strongly reduces the dynamical interconnectivity within the global climate regime after the onset of El Niño events. The betweenness centrality underlines such changes by depicting pathways of heat exchange. For example, just after the eruption of the volcano Pinatubo, these pathways have been centred around the volcano underlying that the eruption had a major impact on the global air surface temperature field.

It is important to realise that our complex network approach is an essential ingredient in the discovery of the climate backbone. For example, the main advantage of betweenness is that it takes into account the global network topology of pairwise interrelationships between regions. However, the classical linear methods (PCA, SSA, etc. [12, 18]) widely applied to disclose teleconnection patterns in climatology use information about next neighbours at each grid point, and are, therefore, only local from a complex network point of view. Our method is promising to study the impact of extreme events such as strong El Niños, extreme Monsoons or volcanic eruptions on the topology of climate interaction networks. In the future it will thereby allow us to obtain new insights into the individual local signature of changes in the energy and information flow structure and stability of the climate system.

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