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Transient coupling relationships of the Holocene Australian monsoon

Thomas Stemler†, Fiona McRobie‡ and Karl-Heinz Wyrwoll‡

†School of Mathematics and Statistics, The University of Western Australia
35 Stirling Highway Crawley, Perth, 6009 Australia
‡School of Earth and Enviroment, The University of Western Australia
35 Stirling Highway Crawley, Perth, 6009 Australia
Email: thomas.stemler@uwa.edu.au

Abstract—The northwest Australian summer monsoon owes a notable degree of its interannual variability to interactions with other regional monsoon systems. Therefore, changes in the nature of these relationships may contribute to variability in monsoon strength over longer time scales. Previous attempts to evaluate how proxy records from the Indonesian-Australian monsoon region correspond to other records from the Indian and East Asian monsoon regions, as well as to El Niño-related proxy records, have been qualitiative, relying on 'curve-fitting' methods. Here, we seek a quantitative approach for identifying coupling relationships between paleoclimate proxy records, employing statistical techniques to compute the interdependence of two paleoclimate time series. We verify the use of complex networks to identify coupling relationships between modern climate indices. This method is then extended to a set of paleoclimate proxy records from the Asian, Australasian and South American regions spanning the past 9,000 years. The resulting networks demonstrate the existence of coupling relationships between regional monsoon systems on millennial time scales, but also highlight the transient nature of teleconnections during this period. In the context of the northwest Australian summer monsoon, we recognise a shift in coupling relationships from strong interhemispheric links with East Asian and ITCZ-related proxy records in the mid-Holocene to significantly weaker coupling in the later Holocene. Although the identified links cannot explain the underlying physical processes leading to coupling between regional monsoon systems, this method provides a step towards understanding the role that changes in teleconnections play in millennial- to orbital-scale climate variability.

1. Introduction

The northwest Australian summer monsoon, and the related circulation over the Maritime Continent (i.e. the Indonesian-Australian summer monsoon – IASM), is a critical feature of the global low latitude circulation. It provides a global heat source, and is the primary region of latent heat release associated with both the Southern Oscillation and the Madden-Julien Oscillation (MJO). Despite its importance, the Australian summer monsoon, occurring over the northwest Kimberley region of Australia, is relatively shallow, with sensible heating only observed below 750 hPa. Monsoon precipitation is relatively low, with annual November to April precipitation over northwestern Australia ranging from a mean of 1200mm (Kimberley Coastal Camp) in the northwest, to 500mm at the south (Jubilee Downs, Broome), over a distance of some 500km. Such a relatively weak monsoon system, located at the southern margins of the more general IASM regime, should be sensitive to changes in forcing mechanisms acting at both the global and regional scale, and over short and long time scales.

While a range of considerations come into play , the dominant control on the Australian summer monsoon relates to the controlling role of the thermal land–sea contrast that manifests itself in the heat lows that develop during the summer months. IASM strength is also tied to the latitudinal position of the Intertropical Convergence Zone (ITCZ), separating equator-ward easterlies from poleward westerlies. The monsoon regime is characterised by summer rainfall associated with low-level westerlies that extend from the equator to around 15°S. The position of these westerlies is associated with the monsoon trough, representing a broad zone of strong convective activity with generally westerly inflow and characterised by the occurrence of monsoon depressions and tropical cyclones, defining the southern edge of the IASM region. With the progression of the seasons there is a northward displacement of the ITCZ, such that by the boreal summer it is located well to the north of the Maritime Continent, and is now associated with the East Asian summer monsoon.

It is the onset of westerly flow which defines the Australian summer monsoon circulation, and 'active' monsoon phases are linked to the MJO, resulting in strong convective activity and precipitation over the monsoon region. Interhemispheric interactions between the IASM and the Northern Hemisphere are provided by cold surges emanating directly out of the East Asian winter monsoon, and leading to strong convective activity in the South China Sea and over the wider IASM region. It has also been suggested that these cold surges may also be directed into the Arabian Sea, enhancing MJO activity, which provides a link with the Northern Hemisphere. These relationships make it clear that the present IASM is driven by an ensemble of regional and global scale climate controls.

When considered over longer time scales, additional drivers at both the global and regional scale need to be introduced. Milankovich insolation forcing of global monsoon systems has been long recognised. Coupled ocean-atmospheric modelling studies have sought to explain the response of the northwest Australian monsoon to direct insolation forcing. These results suggest that although precession dominates changes in Northern Hemisphere monsoon strength, the Australian monsoon response is also significantly impacted by ocean temperature feedbacks and tilt forcing. Some suggest that the enhanced Australian monsoon at 11,000 years BP, contrary to reduced summer insolation, is due to a combination of sea surface temperature feedbacks and inflows from a strong East Asian winter monsoon.

The interconnected nature of these coupling relationships provides evidence for the 'global monsoon' model as advocated in recent literature. This concept has been advanced to portray monsoon activity as a single body of tropical convection migrating about the equator according to seasonal heating, and tied closely to the positioning of the ITCZ . Over longer time scales, a coherent response of regional monsoons to Milankovich insolation forcing is noted. Using an accelerated transient simulation spanning 284,000 years, the authors display a positive response in regional monsoon systems to orbital forcing, with lead/lag relationships driven by local land and sea surface temperature feedbacks. As such, the global monsoon model has been extended to the paleoclimate context to describe this somewhat synchronous response to orbital forcing as well as abrupt events such as the Heinrich Stadials.

Here, we use complex network theory to analyse relationships between the northwest Australian summer monsoon, related monsoon systems and likely forcing climate states. We explore these relationships within the context of the 'global monsoon', and through this we seek to separate global, interconnected relationships and drivers from more local controls. Using this approach, we attempt to establish the changing nature of the dynamical coupling relationships of the Australian summer monsoon over Holocene time scales.

2. Methods

Complex network theory offers a method for identifying coupling relationships and long-range teleconnections by connecting 'similar' data sets. As such, it provides a suitable approach to assess interactions between monsoon systems within the context of the global monsoon. By defining a measure of similarity between climate time series, climate networks have been shown to provide insight into dynamical interactions beyond the scope of traditional statistical analysis. Measures of similarity include linear cross-correlation, mutual information, and event synchronisation between extremes. Applying complex network methods to modern climate data is relatively straightforward, due to the availability of gridded datasets and high-density observation networks, but they also provide a powerful technique for analysing paleoclimate time series. This is demonstrated by K. Rehfeld who developed a paleoclimate network of the Indian and East Asian summer monsoons covering the past 1,100 years, demonstrating distinct changes in network structure between the Medieval Warm Period, Little Ice Age and present day. The application of these techniques is facilitated by the development of a Matlab toolbox (http://tocsy.pik-potsdam.de/nest.php). Here, we first construct a climate network using modern convective indices to demonstrate the veracity of complex network theory to identify dynamically-based coupling relationships between climate systems. We then develop a method for creating paleoclimate networks using a range of proxy records. The resulting paleoclimate networks identify linkages at the global and regional scale, and demonstrate the transient nature of coupling relationships of the northwest Australian monsoon region throughout the Holocene.

2.1. Data

Our main aim is to capture coupling relationships of the Holocene Australian summer monsoon, but we first test the suitability of complex networks to identify dynamically-based coupling relationships using modern climate data. Seasonal convective indices are constructed using monthly values for 1948–2013 of mid-tropospheric (500mb) vertical velocity (ω), a surrogate for convection (NCEP Reanalysis data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their web site at http://www.esrl.noaa.gov/psd/).

Following this, paleoclimate networks are produced for rolling 3,000 year windows at millennial intervals over the period 9,000 years BP to Present. We select proxy records (Table 2) within the broad Indian Ocean-Pacific region according to high temporal resolution and low age uncertainty, as per K. Rehfeld. Although one prefers a database comprised of a single proxy for reasons of comparability, one is often constrained by the number of proxy records available. We therefore combine speleothem, titanium , sediment and multi-proxy data sets. The IASM region is represented in the proxy record database by two speleothem records, G09 (Liang Luar, Flores) and D13 (Cave KNI-51, northwest Australia), both of which are interpreted as capturing monsoon precipitation trends and variation. The Chinese speleothem δ^{18}O records (D05, H08, D10) have each been interpreted as a proxy for precipitation changes driven by the East Asian summer monsoon, while the Lake Huguang Maar record has been discussed in the context of the East Asian winter monsoon and coupled to the IASM region in the modern climate through cold surges. We also include two widely used proxy records: the titanium concentration series from the Cariaco basin (H01) has been cited in studies in the context of Holocene ITCZ positioning, and the Laguna Pallacocha sediment record

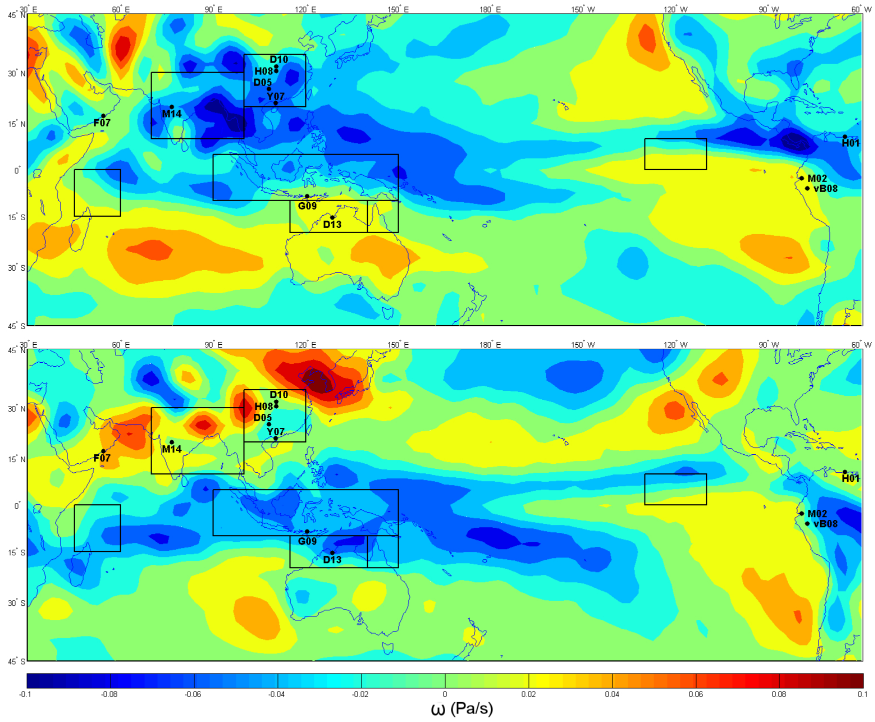

Figure 1: a) DJF 1981–2010 500mb ω (NCEP Reanalysis). Also shown are the location of the boxes over which 500mb omega is averaged to produce modern convective indices (see Table 1), and the location of proxies; b) As above, for JJA.

Table 1: Modern climate data

Code	Location	Lat/Lon Bounds	Season
NWAus	Northwest Australia	10-20°S; 115-140°E	DJF
NEAus	Northeast Australia	10-20°S; 140-150°E	DJF
MC	Maritime Continent	5°N-10°S; 90-150°E	DJF
IO	Western Indian Ocean	0-15°S; 45-60°E	DJF
ISM	Indian summer monsoon region	5-25°N; 70-100°E	JJA
EASM	East Asian summer monsoon region	10-20°N; 100-120°E	JJA
EEP	East Equatorial Pacific	0-10°N; 230-250°E	DJF

Table 2: Proxy records used in this analysis

Code	Location	Lat/Lon	Proxy Type	Reference	Average Time Step (years)
F07	Qunf Cave, Oman	17.17°N, 54.30°E	Speleothem δ^{18}O	Fleitmann et al., 2007	7.7
M14	Lonar Lake, India	19.98°N, 76.51°E	Multi-proxy	Menzel et al., 2014	18.8
H08	Heshang Cave, China	30.45°N, 100.42°E	Speleothem δ^{18}O	Hu et al., 2008	7.8
D05	Dongge Cave, China	25.28°N, 108.08°E	Speleothem δ^{18}O	Dykoski et al., 2005	14.7
Y07	Lake Huguang Maar, China	21.15°N, 110.28°E	Ti concentration of lake sediment	Yancheva et al., 2007	0.8
D10	Sanbao Cave, China	31.67°N, 110.43°E	Speleothem δ^{18}O	Dong et al., 2010	10.2
G09	Liang Luar Cave, Indonesia	8.52°S, 120.43°E	Speleothem δ^{18}O	Griffiths et al., 2009	10.1
D13	Cave KNI-51, Australia	15.30°S, 128.62°E	Speleothem δ^{18}O	Denniston et al., 2013	6.2
M02	Laguna Pallacocha, Ecuador	2.77°S, 79.23°W	Red colour intensity of lake sediment	Moy et al., 2002	0.8
vB08	Cueva del Tigre Perdido, Peru	5.94°S, 77.31°W	Speleothem δ^{18}O	van Breuklen et al., 2008	19.4
H01	Cariaco Basin	10.70°N, 65.17°W	Ti concentration of marine sediment	Haug et al., 2001	5.6

from Peru (M02) is a very widely used proxy for changes in El Niño intensity and frequency over the last 12,000 years.

2.2. Constructing complex networks

Estimating correlations between paleoclimate records is fraught with difficulty, and therefore an intuitive qualitative curve-fitting approach is typically employed. We apply methods widely accepted by statistical physicists which have been successfully applied in the context of financial markets, solar activity, disease dynamics, and pigeon interactions in flight. In a climate or paleoclimate context, one may envisage such a network as a number of nodes, each corresponding to the site of a climate or paleoclimate data set. If a statistically significant 'similarity' between two data sets is found, then an edge is drawn between the two nodes. More formally, for a database of n time series, denoted X_i, we may describe the set of nodes as $V = \{v_i : i \in [n]\}$, and the set of edges is given by $E = \left\{e_{i,j}\right\}$ where $e_{i,j} = 1$ is X_i and X_j are found to be statistically significantly 'similar', and $e_{i,j} = 0$ otherwise.We define similarity between two time series, X_i and X_j, by mutual information, a nonlinear, symmetric (and thus non-directional) measure of how much information is shared between the two time series. Mutual information, $I(X_i, X_j)$ is given by:

$$I(X_i, X_j) = \sum_{x_i \in X_i} \sum_{x_j \in X_j} p(x_i, x_j) \log \left(\frac{p(x_i, x_j)}{p(x_i) p(x_j)} \right)$$

where $p(x_i)$ is the probability mass function of random variable X_i, and $p(x_i, x_j)$ is the joint probability mass function of X_i and X_j.

Paleoclimate time series are often distributed along irregular time intervals due to sampling constraints. To account for this, a Gaussian kernel is used to 'match' data in paired paleoclimate time series. K. Rehfeld demonstrate that this reduces bias in the resulting mutual information estimate compared to linear interpolation. We use the Matlab toolbox to produce estimates of Gaussian kernel weighted mutual information, $I_G(X_i, X_j)$. This method does not produce symmetric estimates of I_G, but these asymmetric estimates do not imply directionality in the network, and are simply due to the unequal sampling rates of the two paleoclimate time series (Rehfeld et al., 2011). We therefore define:

$$I_G(X_i, X_j) = max(I_G(X_i, X_j), I_G(X_j, X_i))$$

We use a Monte Carlo approach to define statistically significant coupling relationships. For each modern or paleoclimate data set we generate a synthetic time series uncoupled to the others. Following Rehfeld et al., we use an autoregressive model with one lag, Brownian motion with drift, to model the modern data sets and all but one of the paleoclimate data sets. The parameters – linear drift and constant diffusion – are estimated from the observed time series through linear regression. This time series is initially regularly spaced, and we downsample according to the time steps of the original, observed data set. The Laguna Pallacocha record from Ecuador (M02) is not well suited to be modelled by Brownian motion. This time series is comprised of a number of large events which are registered well above a baseline level of near zero. We therefore introduce a Poisson process, to model the event time series defined by the 90% quantile in the Laguna Pallacocha record. This event time series is well approximated by a Poisson process ($\chi^2 = 1.85$, $p = 10.12$, at a 95% significance level).

Having constructed networks for the paleoclimate database (Table 2) at 3,000 year windows throughout the last 9,000 years, we seek to evaluate changes in network density and structure. This may be attempted through a number of measures provided by graph theory (Newman, 2010). The *degree*, d_i, of a node, v_i, describes the number of edges incident to the node, providing a description of how coupled the time series at v_i is to other records in the network. Similarly, the *network average degree*, d_n, is given by:

For a full version of the paper and references please see Fiona McRobie et al. Transient coupling relationships of the Holocene Australian monsoon, Quaternary Science Reviews 121, pp. 120131, doi:10.1016/j.quascirev.2015.05.011 (2015).