Nonlin. Processes Geophys., 19, 559–568, 2012
www.nonlin-processes-geophys.net/19/559/2012/
doi:10.5194/npg-19-559-2012

Nonlinear Processes in Geophysics

Review article
"On the origins of decadal climate variability: a network perspective"

A. A. Tsonis and K. L. Swanson

Atmospheric Sciences Group, Department of Mathematical Sciences, University of Wisconsin-Milwaukee, Milwaukee, WI 53201-0413, USA

Correspondence to: A. A. Tsonis (aatsonis@uwm.edu)

Received: 29 May 2012 – Revised: 9 August 2012 – Accepted: 3 September 2012 – Published: 1 October 2012

Abstract. This review is a synthesis of work spanning the last 25 yr. It is largely based on the use of climate networks to identify climate subsystems/major modes and to subsequently study how their collective behavior explains decadal variability. The central point is that a network of coupled nonlinear subsystems may at times begin to synchronize. If during synchronization the coupling between the subsystems increases, the synchronous state may, at some coupling strength threshold, be destroyed shifting climate to a new regime. This climate shift manifests itself as a change in global temperature trend. This mechanism, which is consistent with the theory of synchronized chaos, appears to be a very robust mechanism of the climate system. It is found in the instrumental records, in forced and unforced climate simulations, as well as in proxy records spanning several centuries.

1 Introduction

The flow chart in Fig. 1 provides the outline of this review. The story starts in the mid 1980s when new and exciting approaches to nonlinearly analyze time series made their appearance in atmospheric sciences. At that time very few in the atmospheric sciences community had heard terminology such as fractals, chaos theory, strange attractors, and the like. Soon reports of fractality and low dimensionality in climate records and other geophysical data begun to surface. These climate records represented dynamics over different time scales ranging from very long (thousands of years; Nicolis and Nicolis, 1984) to very short (hours; Tsonis and Elsner, 1988). Virtually every report suggested underlying attractors of dimensions between 3 and 8. These early results suggested that climate variability may indeed be described by relatively few differential equations. This resulted in both enthusiasm and hope that climate variability may be tamed after all, and in fierce opposition. Fortunately, this tug of war did not eliminate interest in this new theory; rather it led to a deeper understanding of the nonlinear character of nature and to new insights about the properties of the climate system. This review is a small part of what we have learned so far and it largely draws from our work over the years.

The initial opposition to those dimension estimates seemed to be that in all these studies the sample size was simply too small. While this issue has been debated extensively (Smith, 1988; Nerenberg and Essex, 1990; Tsonis, 1992; Tsonis et al., 1994), it still remains contentious. In a sense, it is naïve to imagine that our climate system (a spatially extended system of infinite dimensional state space) is described by a grand attractor let alone a low dimensional attractor. If that were true, then all observables representing different processes should have the same dimension, which is not likely the case based on the myriad of reported dimensions. In Tsonis and Elsner (1989), it was suggested that if low dimensional attractors exist they are associated with subsystems each operating at different space and/or time scales. In his study on dimension estimates, Lorenz (1991) concurs with the suggestion of Tsonis and Elsner (1989). These subsystems may be nonlinear and exhibit a variety of complex behaviors. All subsystems are connected with each other, as in a web, with various degrees of connectivity. Accordingly, any subsystem may transmit information to another

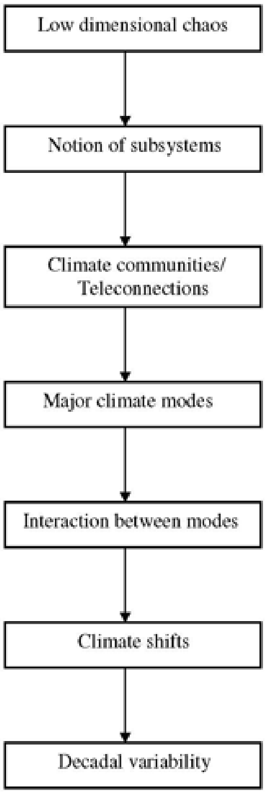

Fig. 1. Flow chart of the outline of this review.

subsystem thereby perturbing its behavior. This information plays the role of an ever present external noise, which perturbs the subsystem and, depending on the connectivity of a subsystem to another subsystem, the effect can be dramatic or negligible. Subsystems with weak connectivities will be approximately independent and as such they may exhibit low dimensional chaos. It is also possible that the connectivity between subsystems may vary in time and this effect may dictate the variability of the climate system.

Thus, evidence of low dimensional chaos leads to the notion of climate subsystems. Given this, the question arises. If subsystems exist in the climate system what are they and what physics can we infer from them?

2 Searching for subsystems

Answers on the nature, geographical basis, and physical mechanisms underlying these subsystems are provided by recent developments in graph theory and networks. Networks relate to the underlying topology of complex systems with many interacting parts. They have found many applications in many fields of sciences. In the interest of completeness, a short introduction to networks is offered next.

A network is a system of interacting agents. In the literature an agent is called a node. The nodes in a network can be anything. For example, in the network of actors, the nodes are

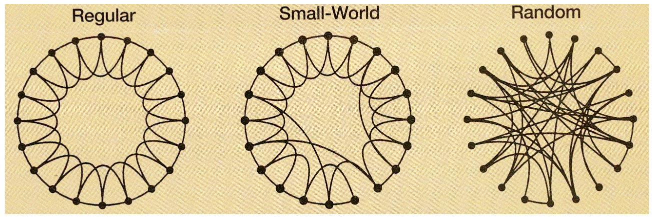

Fig. 2. Illustration of a regular, a small-world and a random network (after Watts and Strogatz, 1998).

actors that are connected to other actors if they have appeared together in a movie. In a network of species, the nodes are species that are connected to other species they interact with. In the network of scientists, the nodes are scientists that are connected to other scientists if they have collaborated. In the grand network of humans, each node is an individual, which is connected to people he or she knows. There are four basic types of networks.

a. Regular (ordered) networks

   These networks are networks with a fixed number of nodes, each node having the same number of links connecting it in a specific way to a number of neighboring nodes (Fig. 2, left panel). If each node is linked to all other nodes in the network, then the network is a fully connected network. When the number of links per node is high, regular networks have a high (local) clustering coefficient. In this case loss of a number of links does not break the network into non-communicating parts. In this case the network is stable, which may not be the case for regular networks with small local clustering. Also, unless networks are fully connected, they have a large diameter. The diameter of a network is defined as the maximum shortest path between any pair of its nodes. It relates to the characteristic path length, which is the average number of links in the shortest path between two nodes. The smaller the diameter, the easier is the communication in the network.

b. Classical random networks

   In these networks the nodes are connected at random (Fig. 2, right panel). In this case the degree distribution is a Poisson distribution (the degree distribution, p_k, gives the probability that a node in the network is connected to k other nodes). The problem with these networks is that they have very small clustering coefficient and thus are not very stable. Removal of a number of nodes at random, may fracture the network into non-communicating parts. On the other hand, they are characterized by a small diameter. Far away nodes can be connected as easily as nearby nodes. In this case information may be transported all over the network much more efficiently than in ordered networks. Thus, random networks exhibit efficient information transfer but they are not stable.

c. Small-world networks

In nature we should not expect to find either very regular or completely random networks. Rather we should find networks that are efficient in processing information and at the same time are stable. Work in this direction led to a new type of network, which was proposed twelve years ago by the American mathematicians Duncan Watts and Steven Strogatz and is called small-world network (Watts and Strogatz, 1998). A small-world network is a superposition of regular and classical random graphs. Such networks exhibit a high degree of local clustering but a small number of long-range connections making them as efficient in transferring information as random networks. Those long-range connections do not have to be designed. A few long-range connections added at random will do the trick (Fig. 2, middle panel). The degree distribution of small-world networks is also a Poisson distribution.

d. Networks with a given degree distribution.

The small-world architecture can explain phenomena such as the six-degrees of separation (most people are friends with their immediate neighbors but we all have one or two friends a long way away), but it really is not a model found often in the real world. In the real world, the architecture of a network is neither random nor small-world, but rather comes in a variety of distributions such as truncated power-law distributions, Gaussian distributions, power-law distributions, and distributions consisting of two power-laws separated by a cutoff value (for a review see Strogatz, 2001). The most interesting and common of such networks are the so-called scale-free networks. Consider a map showing an airline's routes. This map has a few hubs connecting with many other points (super nodes) and many points connected to only a few other points, a property associated with power law distributions. Such a map is highly clustered, yet it allows motion from a point to another far away point with just a few connections. As such, this network has the property of small-world networks, but this property is not achieved by local clustering and a few random connections. It is achieved by having a few elements with a large number of links and many elements having very few links. Thus, even though they share the same property, the architecture of scale-free networks is different than that of small-world networks. Such inhomogeneous networks have been found to pervade biological, social, ecological, and economic systems, the internet, and other systems (Albert et al., 1999; Liljeros et al., 2001; Jeong et al., 2001; Pastor-Satorras and Vespignani, 2001; Bouchaud and Mezard, 2000; Barabasi and Bonabeau, 2003). These networks are referred to as scale-free because they show a power-law distribution of the number of links per node. Lately, it was also shown that, in addition to the power-law degree distribution, many real scale-free networks consist of self-repeating patterns on all length scales (Song et al., 2005). These properties are very important because they imply some kind of self-organization within the network. Scale-free networks are not only efficient in transferring information, but due to the high degree of local clustering they are also very stable (Barabasi and Bonabeau, 2003). Because there are only a few super nodes, chances are that accidental removal of some nodes will not include the super nodes. In this case the network would not become disconnected. This is not the case with weakly connected regular or random networks (and to a lesser degree with small-world networks), where accidental removal of the same percentage of nodes makes them more prone to failure (Barabasi and Bonabeau, 2003).

The topology of the network can reveal important and novel features of the system it represents (Albert and Barabasi, 2002; Strogatz, 2001; da F. Costa et al., 2007). One such feature is communities (Newman and Girvan, 2004). Communities represent groups of densely connected nodes with only a few connections between groups. It has been conjectured that each community represents a subsystem, which operates relatively independent of the other communities (Arenas et al., 2006). Thus, identification of these communities can offer useful insights about dynamics. In addition, communities can be associated to network functions such as in metabolic networks where certain groups of genes have been identified that perform specific functions (Holme et al., 2003; Guimera and Amaral, 2005). Recently, concepts from network theory have been applied to climate data organized as networks with impressive results (Tsonis et al., 2006, 2007, 2008; 2011; Tsonis and Swanson, 2008; Yamasaki et al., 2008; Gozolchiani et al., 2008; Swanson and Tsonis, 2009; Elsner et al., 2009).

Figure 3 is an example of a climate network showing the area weighted connectivity (number of edges) at each geographic location for the 500 hPa height field. More accurately it shows the fraction of the total global area that a point is connected to. This is a more appropriate way to show the architecture of the network because the network is a continuous network defined on a sphere (see Tsonis et al., 2006 for details). These data are derived from the global National Center for Environmental Prediction/ National Center for Atmospheric Research (NCEP/NCAR) atmospheric reanalysis data set (Kistler et al., 2001). In Fig. 3 we observe two very interesting features. In the tropics it appears that all nodes possess more or less the same (and high) number of connections, which is a characteristic of fully connected networks. In the extratropics it appears that certain nodes possess more connections than the rest, which is a

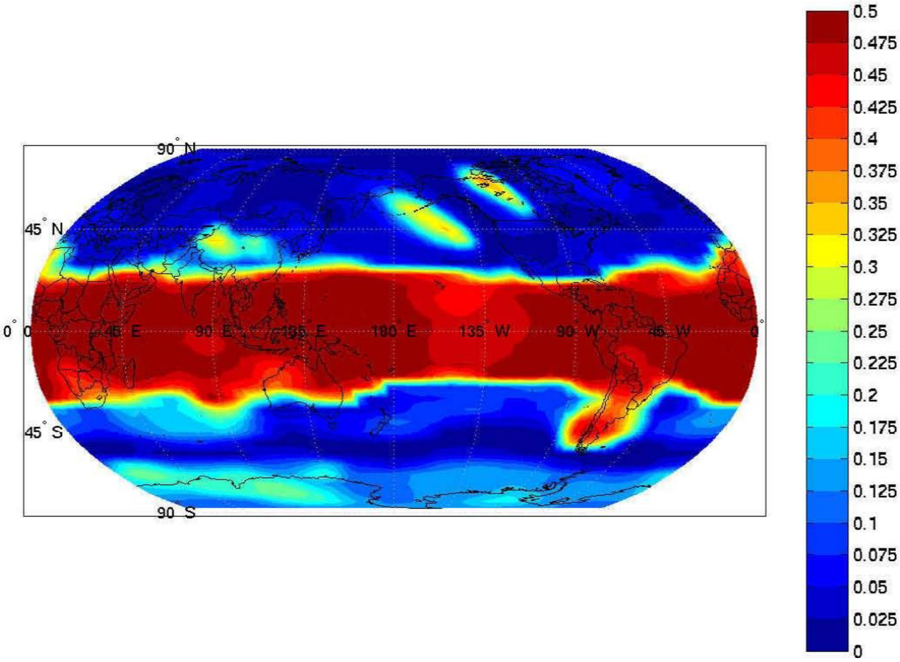

Fig. 3. Total number of links (connections) at each geographic location. More accurately it shows the fraction of the total global area that a point is connected to. This is a more appropriate way to show the architecture of the network because the network is a continuous network defined on a sphere. The uniformity observed in the tropics indicates that each node possesses the same number of connections. This is not the case in the extratropics where certain nodes possess more links than the rest. The definition of a link is based on cross-correlations at lag zero (r) between the time series of any pair of points (nodes). Note that since the values are monthly anomalies, there is very little autocorrelation in the time series. A pair is considered as connected if the absolute value of their cross-correlation $|r| \geq 0.5$. This criterion is based on parametric and non-parametric significance tests. According to the t-test, a value of $r = 0.5$ is statistically significant above the 99 % level. In addition, randomization experiments where the values of the time series of one node in a pair are scrambled and then are correlated to the unscrambled values of the time series of the other node indicate that a value of $r = 0.5$ will not arise by chance. The choice of $r = 0.5$ while it guarantees statistical significance is somewhat arbitrary. We find that while other values might affect the connectivity structure of the network, the effect of different correlation thresholds (between 0.4 and 0.6) does not affect the conclusions. Obviously, as the threshold $|r| \to 1$ we end up with a random network and as $r \to 0$ we remain with just one fully connected community. The use of the correlation coefficient to define links in networks is not new. Correlation coefficients have been used to successfully derive the topology of gene expression networks (Farkas et al., 2003) and to study financial markets (Mantegna, 1999). Other ways to define a link exist. Donges et al. (2009a, b), for example, have used the mutual information instead when they construct the networks. We believe that any way to define a link is adequate if it delineates features of the system. In our case it is consistent with the known features in the climate systems, such as ENSO, NAO, PNA, etc.

characteristic of scale-free networks. In the Northern Hemisphere, we clearly see the presence of regions where such super nodes exist in China, North America and Northeast Pacific Ocean. Similarly, several super nodes are visible in the Southern Hemisphere. These differences between tropics and extratropics have been delineated in the corresponding degree distributions, which suggest that indeed the extratropical network is a scale-free network characterized by a power law degree distribution (Tsonis et al., 2006). As is the case with all scale-free networks, the extratropical network is also a small-world network (Tsonis et al., 2006).

An interesting observation in Fig. 3 is that super nodes may be associated with major teleconnection patterns. For example, the super nodes in North America and Northeast Pacific Ocean are located where the well-known Pacific North America (PNA) pattern (Wallace and Gutzler, 1981) is found. In the Southern Hemisphere, we also see super nodes over the southern tip of South America, Antarctica and South Indian Ocean that are consistent with some of the features of the Pacific South America (PSA) pattern (Mo and Higgins, 1998). Interestingly, no such super nodes are evident where the other major pattern, the North Atlantic Oscillation (NAO) (Thompson and Wallace, 1998; Pozo-Vazquez et al., 2001; Huang et al., 1998) is found. This, however, does not indicate that NAO is an insignificant feature of the climate system. Since NAO is not strongly connected to the tropics, the high connectivity of the tropics with other regions is masking NAO out (Tsonis et al., 2008). Indeed if we consider only the extratropics the resulted network is dominated by NAO (Fig. 4).

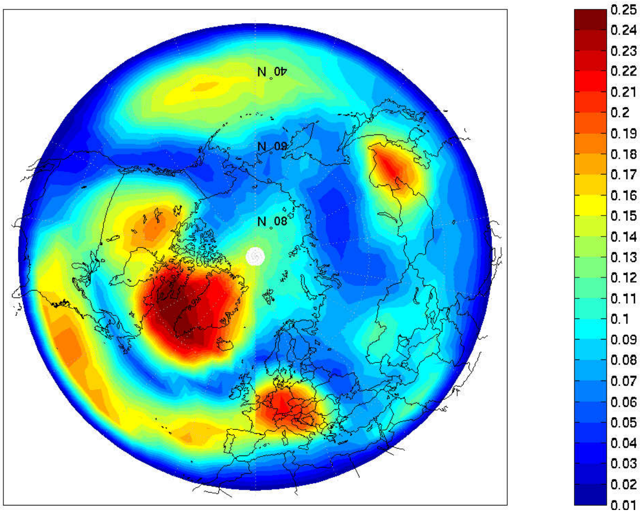

Fig. 4. Same as Fig. 3 but only for the extratropics (north of 30°).

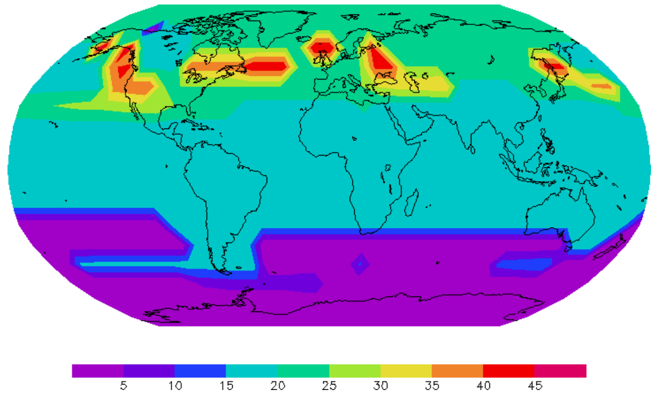

Fig. 5. Community structure of the network in Fig. 3. The number below the shading key indicates the total number of communities (see text for more details).

This is also indicated by the community structure of the 500 hPa network (Fig. 3) shown in Fig. 5 (for details see Tsonis et al., 2011). The total number of communities is 47. Many of these communities, however, consist of very few points in the boundaries between a small number of dominant communities (think of a country whose population is dominated by two races but also includes small groups of other races). Evidently the effective number of communities is, arguably, four (delineated as purple, blue, green, and yellow-red areas). We observe that three of the effective four communities correspond to a latitudinal division 90° S–30° S, 30° S–30° N, and 30° N–90° N. This three-zone separation is not a trivial separation into Northern Hemisphere winter, Southern Hemisphere summer, and the rest of the world, because when we repeat the analysis with yearly averages rather than seasonal values, we also see evidence of this three-zone separation. This separation is consistent with the transition from a barotropic atmosphere (where pressure depends on density only; appropriate for the tropics-subtropics) to a baroclinic atmosphere (where pressure depends on both density and temperature; appropriate for higher latitudes). Another possibility is that it reflects the well known three-zone distribution of variance of the surface pressure field. Within the third community (green area) another community (yellow-red) is embedded. This community is consistent with the presence of major atmospheric teleconnection patterns such as the Pacific North America (PNA) pattern and the North Atlantic Oscillation (NAO) (Wallace and Gutzler, 1981; Barnston and Livezey, 1987). We note here that NAO (which has been lately suggested of being a three-pole pattern rather than a dipole; Tsonis et al., 2008) and AO (Arctic Oscillation; Thompson and Wallace, 1998) are often interpreted as manifestations of the same dynamical mode, even though in some cases more physical meaning is given to NAO (Ambaum et al., 2001). In any case, here we do not make a distinction between NAO and AO. We note that similar results are obtained for other observed fields (such as the surface air temperature and sea level pressure, where influences of ENSO and PDO are present) as well as in model simulated fields (Tsonis et al., 2011). We note that in spatially extended systems it is possible that spatial correlation may produce spurious small-world networks (Bialonski et al., 2010; Hlinka et al., 2012; Paluš et al., 2011). For our climate networks, we have shown (Tsonis et al., 2011) that the network structure derived from spatio-temporal surrogate data on a sphere, which are spatially correlated with a decorrelation distance of 3000 km, is not consistent with the network structure of the observed fields. This provides confidence that our networks and their structures are not an artifact of spatial correlations

In summary, the results outlined in this section suggest that climate networks are characterized by supernodes and a small number of communities, which relate to major teleconnection patterns/climate modes. Having established this, we proceed with our discovery of a mechanism for climate shifts based on the interaction of major climate modes.

3 Interaction between subsystems

One of the most important events in recent climate history is the climate shift in the mid-1970s (Graham, 1994). In the Northern Hemisphere 500-hPa atmospheric flow, the shift manifested itself as a collapse of a persistent wave-3 anomaly pattern and the emergence of a strong wave-2 pattern. The shift was accompanied by sea-surface temperature (SST) cooling in the central Pacific and warming off the coast of western North America (Miller et al., 1994). The shift brought sweeping long-range changes in the climate of the Northern Hemisphere. Incidentally, after the dust settled, a new long era of frequent El Niño events superimposed on a sharp global temperature increase begun. While several possible triggers for the shift have been suggested and investigated (Graham, 1994; Miller et al., 1994; Graham et al., 1994), the actual physical mechanism that led to this shift is not clear. Understanding the dynamics of such phenomena is essential for our ability to make useful prediction of climate change. A major obstacle to this understanding is the extreme complexity of the climate system, which makes it difficult to disentangle causal connections leading to the observed climate behavior.

First a network from four major climate indices was constructed. The indices represent the Pacific Decadal Oscillation (PDO), the North Atlantic Oscillation (NAO), the El Niño/Southern Oscillation (ENSO), and the North Pacific Index (NPI) (Barnston and Livezey, 1987; Hurell, 1995; Mantua et al., 1997; Trenberth and Hurrell, 1994). These indices represent regional but dominant modes of climate variability, with time scales ranging from months to decades. NAO and NPI are the leading modes of surface pressure variability in northern Atlantic and Pacific Oceans, respectively, the PDO is the leading mode of SST variability in the northern Pacific and ENSO is a major signal in the tropics. Together these four modes capture the essence of climate variability in the Northern Hemisphere. Each of these modes is assumed to represent a subsystem involving different mechanisms over different geographical regions. Indeed, some of their dynamics have been adequately explored and explained by simplified models, which represent subsets of the complete climate system and are governed by their own dynamics (Elsner and Tsonis, 1993; Schneider et al., 2002; Marshall et al., 2001; Suarez and Schopf, 1998). For example, ENSO has been modeled by a simplified delayed oscillator in which the slower adjustment time scales of the ocean supply the system with the memory essential to oscillation. Monthly-mean values in the interval 1900–2000 are available for all indices (http://jisao.washington.edu/data sets, for NAO, PDO and El Nino, http://climatedataguide.ucar.edu/guidance/north-pacific-index-npi-trenberth-and-hurrell, for NPI).

An important aspect in the collective behavior of coupled nonlinear oscillators is synchronization and coupling strength. The theory of synchronized chaos predicts that in many cases when such systems synchronize, an increase in coupling between the oscillators may destroy the synchronous state and alter the system's behavior (Heagy et al., 1995; Pecora et al., 1997). It should be noted that in those studies, coupling strength is determined by a parameter that is allowed to increase and the focus is in the perfect synchronization among the modes (i.e., the cross-correlation between outputs of the synchronized coupled systems is one), rather than weaker types of synchronization, such as phase synchronization (Boccaletti et al., 2002; Maraun and Kurths, 2005) or clustered synchronization (Zhou and Kurths, 2006), which are also important in climate interactions. In view of this theory, we investigated whether our climate modes synchronize and when they do how synchronization relates to coupling strength between the modes. It is vital to note that synchronization and coupling are not interchangeable; for example, it is trivial to construct a pair of coupled simple harmonic oscillators whose displacements are in quadrature (and hence perfectly uncorrelated), but whose phases are strongly coupled (Vanassche et al., 2003). In our case, synchronization is defined from the sum of cross-correlations of all pairs in the network over a sliding time window, and coupling is measured by how well the phase between pairs of climate modes is predicted using information about the current phase (Tsonis et al., 2007). Note that according to our definition of coupling strength, if the modes are perfectly synchronized, their states are equivalent and thus coupling strength cannot increase further. Since our network of modes represents signals of a complex physical system where noise is also present, synchronization cannot be perfect but statistically significant (for details see Tsonis et al., 2007). As such it is possible for the modes to enter into a synchronized state in a period when the coupling strength is decreasing and that desynchronization may not happen when coupling strength is maximum.

The results from the observations are summarized in Fig. 6. This figure shows the yearly anomaly values of global temperature (blue negative anomalies, red positive anomalies). The black solid line is a smoothed version of this record. It is evident from the smoothed version that on decadal time scales there are times when the global temperature trend is shifting from negative to positive and vice-versa. These shifts are superimposed on a low frequency signal known as global warming. Here we are not interested on the origins of the low frequency signal. Rather we are interested in the departures from this signal over decadal time scales. The part of the black line that is colored yellow indicates that the four climate modes are synchronized during a period when the coupling between the modes is *not* increasing. The part colored green indicates periods when the modes are synchronized and the coupling is increasing. Thus, we see that the network synchronized six times in the periods 1908–1913, 1921–1925, 1932–1943, 1952–1957, 1975–1979, and 1998–2003. In the periods 1921–1925, 1932–1938, 1952–1957 synchronization is not associated with an increasing coupling strength and no change in the temperature trend is taking place. However, in the periods 1908–1913, 1939–1943, 1975–1979, and 1998–2003 synchronization is associated with an increase in coupling strength. As the modes keep on synchronizing and the coupling strength keeps on increasing, at some coupling threshold the synchronized state is destroyed and climate shifts into a new state characterized by a reversal in global temperature trend. This mechanism appears to be an intrinsic mechanism of the climate system as it is found in both control and forced climate simulation (Tsonis et al., 2007; Wang et al., 2009). It also appears to be a very robust mechanism. In all 13 synchronization events found in the observations and model simulations, once the modes begin to synchronize while the coupling is increasing, desynchronization and the impeding shift happen at some coupling

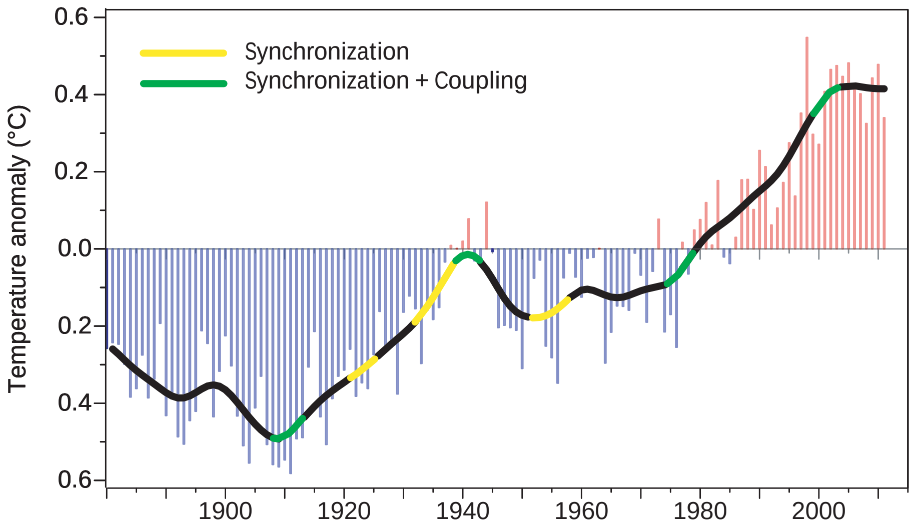

Fig. 6. Summary of synchronization events, coupling between the modes during these events, and climate shifts. See text for details.

strength threshold. Due to noise/uncertainties in the data, synchronization cannot be perfect and this threshold is not always the same or always maximum at desynchronization. Once the modes are desynchronized, the coupling may continue to increase as the modes may fall into phase with each other. This is consistent with the general theory of synchronized chaos where coupling strength may keep on increasing after desynchronization. No shift ever occurred when during the synchronous state the coupling strength was decreasing. Lately Tsonis and Swanson (2011) extended their analysis to consider proxy data for climate modes going back several centuries. While noise in the proxy data in some cases masks the mechanism, it was found that significant coherence between both synchronization and coupling and global temperature exists. These results provide further support that the mechanism discussed here for climate shifts is a robust feature of the climate system.

The above results refer to the collective behavior of the four major modes used in the network. As such they do not offer insights on the specific details of the mechanism. For example, do small distance values (strong synchronization) result from all modes synchronizing or from a subset of them? When the network is synchronized, does the coupling increase require that all modes must become coupled with each other? To answer these questions, Wang et al. (2009) split the network of four modes into its six pair components and investigated the contribution of each pair in each synchronization event and in the overall coupling of the network. It was found that one mode is behind all climate shifts. This mode is the NAO. This North Atlantic mode is without exception the common ingredient in all shifts and when it is not coupled with any of the Pacific modes no shift ensues. In addition, in all cases where a shift occurs NAO is necessarily coupled to north Pacific. In some cases it may also be coupled to the tropical Pacific (ENSO) as well, but in none of the cases is NAO only coupled to ENSO. Thus, results indicate that not only is NAO the instigator of climate shifts but that the likely evolution of a shifts has a path where the north Atlantic couples to north Pacific, which in turn couples to the tropics. Solid dynamical arguments and past work offer a concrete picture of how the physics may play out. NAO with its huge mass re-arrangement in north Atlantic affects the strength of the westerly flow across mid-latitudes. At the same time through its twin, the arctic Oscillation (AO), it impacts sea level pressure patterns in the northern Pacific. This process is part of the so-called intrinsic mid-latitude Northern Hemisphere variability (Vimont et al., 2001, 2003). Then this intrinsic variability through the seasonal footprinting mechanism (Vimont et al., 2001, 2003) couples with equatorial wind stress anomalies, thereby acting as a stochastic forcing of ENSO. This view is also consistent with a recent studies showing that PDO modulates ENSO (Gershunov and Barnett, 1998; Verdon and Franks, 2006). Another possibility of how NAO couples to north Pacific may be through the five lobe circumglobal waveguide pattern (Branstator, 2002). It has been shown that this waveguide pattern projects onto NAO indices and its features contribute to variability at locations throughout the Northern Hemisphere. Finally, North Atlantic variations have been linked to Northern Hemisphere mean surface temperature multidecadal variability through redistribution of heat within the northern Atlantic with the other oceans left free to adjust to these Atlantic variations (Zhang et al., 2007)[1]. Thus, NAO, being the major mode of variability in the northern Atlantic, impacts both ENSO vari-

[1] In Elsner (2007) it is shown that global temperature Granger causes (leads) North Atlantic SST. It may be that the discrepancy between these two studies lies in the bi-directionality between the two variables, which is often the case in Granger causes.

ability and global temperature variability. Recently, a study has shown how ENSO with its effects on PNA can, through vertical propagation of the Rossby waves influence the lower stratosphere and how in turn the stratosphere can influence NAO through downward progression of Rossby wave (Ineson and Scaife, 2009). These results coupled with our results suggest the following 3-D super-loop: NAO → PDO → ENSO → PNA → stratosphere → NAO, which captures the essence of decadal variability in the Northern Hemisphere and possibly the globe.

This co-variability of climate modes and its influence on global temperature has recently been confirmed by a different approach. Wyatt et al. (2011) analyzed the lagged covariance structure of a network of climate indices and discovered the so called stadium wave; a sequence of lagged atmospheric and oceanic teleconnections leading to Northern Hemisphere temperature reversals every about 30 yr. Lately, Wang et al. (2012) investigate whether the collective role of these modes is extended within a regime, i.e., to shorter time scales. They applied nonlinear prediction in order to assess directional influences in the climate system. They showed evidence that input from four major climate modes from the Atlantic and Pacific improves the prediction of global temperature and thus these modes Granger cause global temperature. Moreover, they found that this causality is not a result of a particular mode dominating but a result of the nonlinear collective behavior in the network of the four modes.

4 Conclusions

The above synthesis describes some new approaches that have been applied lately to climate data. The findings presented here and in the references may settle the issue of dimensionality of climate variability over decadal scales, as they support the view that over these scales, climate collapses into distinct subsystems whose interplay dictates decadal variability. At the same time these results provide clues as to what these subsystems might be. As such, while weather may be complicated, climate may be complex but not complicated. Moreover, it appears that the interaction between these subsystems may be largely responsible for the observed decadal climate variability. A consequence of these results is that a dynamical reconstruction directly from a small number of climate modes/subsystems may be attempted to extract differential equations, which model the network of major modes. Such an approach may provide an alternative and direct window to study decadal variability in climate. Work in this area is in progress and will be reported in the future elsewhere.

Acknowledgements. This work was supported by the Department of Energy, USA, grant DE-SC0005305.

Edited by: J. Kurths
Reviewed by: two anonymous referees

References

Albert, R. and Barabasi, A.-L.: Statistical mechanics of complex networks, Rev. Mod. Phys., 74, 47–101, 2002.

Albert, R., Jeong, H., and Barabasi, A.-L.: Diameter of the World Wide Web, Nature, 401, 130–131, 1999.

Ambaum, M. H. P., Hoskins, B. J., and Stephenson, D. B.: Arctic Oscillation or North Atlantic Oscillation?, J. Climate, 14, 3495–3507, 2001.

Arenas, A., Diaz-Guilera, A., and Perez-Vicente, C. J.: Synchronization reveals topological scales in complex networks, Phys. Rev. Lett., 96, 114102, doi:10.1103/PhysRevLett.96.114102, 2006.

Barabasi, A.-L. and Bonabeau, E.: Scale-free networks, Scientific American, 288, 60–69, 2003.

Barnston, A. G. and Livezey, R. E.: Classification, seasonality, and persistence of low-frequency atmospheric circulation patterns, Mon. Weather Rev., 115, 1083–1126, 1987.

Bialonski, S., Horstmann, M.-T., and Lehnertz, K.: From brain to earth and climate systems: Small-worldnetworks or not?, Chaos, 20, 013134, doi:10.1063/1.3360561, 2010.

Boccaletti, S., Kurths, J., Osipov, G., Valladares, D. J., and Zhou, C. S.: The synchronization of chaotic systems, Phys. Reports, 366, 1–101, 2002.

Bouchaud, J.-P. and Mezard, M.: Wealth condensation in a simple model of economy, Physica A, 282, 536–540, 2000.

Branstator, G.: Circumglobal teleconnections, the jet stream waveguide, and the North Atlantic Oscillation, J. Climate, 15, 1893–1910, 2002.

da F. Costa, L., Rodrigues, F. A., Travieso, G., and Villas Boas, P. R.: Characterization of complex networks: a survey of measurements, Adv. Phys., 56, 167–242, 2007.

Donges, J. F., Zou, Y., Marwan, N., and Kurths, J.: The backbone of the climate network, EPL, 87, 48007, doi:10.1209/0295-5075/87/48007, 2009a.

Donges, J. F., Zou, Y., Marwan, N., and Kurths, J.: Complex networks in climate dynamics, Euro. Phys. J. 174, 157–179, 2009b.

Elsner, J. B.: Granger causality and Atlantic hurricanes, Tellus 59A, 476–485, 2007.

Elsner, J. B. and Tsonis, A. A.: Nonlinear dynamics established in the ENSO, Geophys. Res. Lett. 20, 213–216, 1993.

Elsner, J. B., Jagger, T. H., and Fogarty, E. A.: Visibility network of United States hurricanes, Geophys. Res. Lett., 36, L16702, doi:10.1029/2009GL039129, 2009.

Farkas, I. J., Jeong, H., Vicsek, T., Barabási, A.-L., and Oltvai, Z. N.: The topology of the transcription regulatory network in the yeast Saccharomyces cerevisiae, Physica A, 318, 601–612, 2003.

Gershunov, A. and Barnett, T. P.: Interdecadal modulation of ENSO teleconnections, B. Am. Meteorol. Soc., 79, 2715–2725, 1998.

GFDL CM2.1 development team: GFDL's CM2 global coupled climate models, Parts 1–4, J. Climate, 19, 643–740, 2006.

Girvan, M. and Newman, M. E. J.: Community structure in social and biological networks, Proc. Natl. Acad. Sci. USA, 99, 7821–7826, 2002.

Graham, N. E.: Decadal scale variability in the tropical and North Pacific during the 1970s and 1980s: Observations and model results, Clim. Dynam., 10, 135–162, 1994.

Graham, N. E., Barnett, T. P., Wilde, R., Ponater, M., and Schubert, S.: On the roles of tropical and mid-latitude SSTs in forcing interannual to interdecadal variability in the winter Northern Hemisphere circulation, J. Climate, 7, 1500–1515, 1994.

Gozolchiani, A., Yamasaki, K., Gazit, O., and Havlin, S.: Pattern of climate network blinking links follow El Nino events, Europhys. Lett., 83, 28005, doi:10.1209/0295-5075/83/28005, 2008.

Guimera, R. and Amaral, L. A. N.: Functional cartography of complex metabolic network, Nature, 433, 895–900, 2005.

Heagy, J. F., Pecora, L. M., and Carroll, T. L.: Short wavelength bifurcations and size instabilities in coupled oscillator systems, Phys. Rev. Lett., 74, 4185–4188, 1995.

Hlinka, J., Hartman, D., and Palus, M.: Small-world topology of functional connectivity in randomly connected dynamical systems, Chaos, in press, arXiv:1206.3963v1, http://arxiv.org/abs/1206.3963v1, 2012.

Holme, P., Huss, M., and Jeong ,H.: Subnetwork hierarchies of biochemical pathways, Bioinformatics, 19, 532–543, 2003.

Huang, J. P., Higuchi, K., and Shabbar, A.: The relationship between the North Atlantic Oscillation and El Nino Southern Oscillation, Geophys. Res. Lett., 25, 2707–2710, 1998.

Hurrell, J. W.: Decadal trends in the North Atlantic oscillation regional temperature and precipitation, Science, 269, 676–679, 1995.

Ineson, S. and Scaife, A. A.: The role of the stratosphere in the European climate response to El Nino, Nat. Geosci., 2, 32–36, 2009.

Intergovernmental Panel on Climate Change: Climate change 2001 – The scientific basis. Contribution of working group I to the third assessment report of the Intergovernmental Panel on Climate Change, edited by: Houghton, J. H., Ding, Y., Griggs, D. J., Noguer, M., van der Linden, P. J., Dai, X., Maskell, K., and Johnson, C. A., Cambridge University Press, UK, 2001.

Jeong, H., Mason, S., Barabasi, A.-L., and Oltvai, Z. N.: Lethability and centrality in protein networks, Nature, 411, 41–42, 2001.

Kistler, R., Kalnay, E., Collins, W., Saha, S., White, G., Woollen, J., Ghelliah, M., Ebisuzaki, W., Kanamitsu, M., Kousky, V., van den Dool, H., Jenne, R., and Fiorino, M.: The NCEP/NCAR 50-year reanalysis: monthly means, CD-ROM and documentation, B. Am. Meteorol. Soc., 82, 247–267, 2001.

Liljeros, F., Edling, C., Amaral, L. N., Stanley, H. E., and Aberg, Y.: The web of human sexual contacts, Nature, 411, 907–908, 2001.

Lorenz, E. N.: Dimension of weather and climate attractors, Nature, 353, 241–244, 1991.

Mantegna, R. N.: Hierarchical structure in financial markets, Eur. Phys. J. B, 11, 193–197, 1999.

Mantua, N. J., Hare, S. R., Zhang, Y., Wallace, J. M., and Francis, R. C.: A Pacific interdecadal climate oscillation with impacts on salmon production, B. Am. Meteorol. Soc., 78, 1069–1079, 1997.

Maraun, D. and Kurths, J.: Epochs of phase coherence between El Nino/Southern Oscillation and Indian monsoon, Geophys. Res. Lett., 32, L15709, doi:10.1029/2005GL023225, 2005.

Marshall, J., Kushnir, Y., Battisti, D., Chang, P., Czaja, A., Dickson, R., Hurrell, J., McCartney, M., Saravanan, R., and Visbeck, M.: North Atlantic climate variability: Phenomena, impacts and Mechanisms, Int. J. Climatol., 21, 1863–1898, 2001.

Miller, A. J., Cayan, D. R., Barnett, T. P., Craham, N. E., and Oberhuber, J. M.: The 1976-77 climate shift of the Pacific Ocean, Oceanography, 7, 21–26, 1994.

Mo, K. C. and Higgins, R. W.: The Pacific-South America modes and tropical convection during the southern hemisphere winter, Mon. Weather Rev., 126, 1581–1596, 1998.

Nerenberg, M. A. H. and Essex, C.: Correlation dimension and systematic geometric effects, Phys. Rev. A , 42, 7065–7074, 1990.

Newman, M. E. J. and Girvan, M.: Finding and evaluating community structure in networks, Phys. Rev. E, 69, 226113, doi:PhysRevE.69.026113, 2004.

Nicolis, C. and Nicolis, G.: Is there a climatic attractor?, Nature, 311, 529–532, 1984.

Paluš, M., Hartman, D., Hlinka, J., and Vejmelka, M.: Discerning connectivity from dynamics in climate networks, Nonlin. Processes Geophys., 18, 751–763, doi:10.5194/npg-18-751-2011, 2011.

Pastor-Satorras, R. and Vespignani, A.: Epidemic spreading in scale-free networks, Phys. Rev. Lett., 86, 3200–3203, 2001.

Pecora, L. M., Carroll, T. L., Johnson, G. A., and Mar, D. J.: Fundamentals of synchronization in chaotic systems, concepts, and applications, Chaos, 7, 520–543, 1997.

Pozo-Vazquez, D., Esteban-Parra, M. J., Rodrigo, F. S., and Castro-Diez, Y.: The association between ENSO and winter atmospheric circulation and temperature in the North Atlantic region, J. Climate, 14, 3408–3420, 2001.

Schneider, N., Miller, A. J., and Pierce, D. W.: Anatomy of North Pacific Decadal Variability, J. Climate 15, 586–605, 2002.

Smith, L. A.: Intrinsic limits on dimension calculations, Phys. Lett. A, 133, 283–288, 1988.

Song, C., Havlin, S., and Makse, H. A.: Self-similarity of complex networks, Nature, 433, 392–395, 2005.

Strogatz, S. H.: Exploring complex networks, Nature, 410, 268–276, 2001.

Suarez, M. J. and Schopf, P. S.: A delayed action oscillator for ENSO, J. Atmos. Sci. 45, 549–566, 1998.

Swanson, K. L. and Tsonis, A. A.: Has the climate recently shifted?, Geophys. Res. Lett., 36, L06711, doi:10.1029/2008GL037022, 2009.

Thompson, D. W. J. and Wallace, J. M.: The Arctic Oscillation signature in the wintertime geopotential height and temperature fields, Geophys. Res. Lett., 25, 1297–1300, 1998.

Trenberth, K. E. and Hurrell, J. W.: Decadal atmospheric-ocean variations in the Pacific, Clim. Dynam., 9, 303–319, 1994.

Tsonis, A. A.: Chaos: From Theory to Applications. Plenum, New York, 1992.

Tsonis, A. A. and Elsner, J. B.: The weather attractor over very short time scales, Nature, 33, 545–547, 1988.

Tsonis, A. A. and Elsner, J. B.: Chaos, strange attractors and weather, B. Am. Meteorol. Soc., 70, 16–23, 1989.

Tsonis, A. A. and Elsner, J. B.: Mapping the channels of communication between the tropics and higher latitudes in the atmosphere, Physica D, 92, 237–244, 1996.

Tsonis, A. A. and Swanson, K. L.: Topology and predictability of El Nino and La Nina networks, Phys. Rev. Lett., 100, 228502, doi:10.1103/PhysRevLett.100.228502, 2008.

Tsonis, A. A. and Swanson, K. L.: Climate mode co-variability and climate shifts, Int. J. Bifurcat. Chaos, 21, 3549–3556, doi:10.1142/S0218127411030714, 2011.

Tsonis, A. A., Triantafyllou, G. N., and Elsner, J. B.: Searching for determinism in observed data: a review of the issues involved, Nonlin. Processes Geophys., 1, 12–25, doi:10.5194/npg-1-12-1994, 1994.

Tsonis, A. A., Swanson, K. L., and Roebber, P. J.: What do networks have to do with climate?, B. Am. Meteorol. Soc., doi:10.1175/BAMS-87-5-585, 87, 585–595, 2006.

Tsonis, A. A., Swanson, K. L., and Kravtsov, S.: A new dynamical mechanism for major climate shifts, Geophys. Res. Lett., 34, L13705, doi:10.1029/2007GL030288, 2007.

Tsonis, A. A., Swanson, K. L., and Wang, G.: On the role of atmospheric teleconnection in climate, J. Climate, 21, 2990–3001, 2008.

Tsonis, A. A., Wang, G., Swanson, K. L., Rodrigues, F. A., and da F. Costa, L.: Community structure and dynamics in climate networks, Clim. Dynam., 37, 933–940, doi:10.1007/s00382-010-0874-3, 2011.

Vanassche, P., Gielen, G. G. E., and Sansen, W.: Behavioral modeling of (coupled) harmonic oscillators, IEEE Trans. Comp. Des. Int. Circ., 22, 1017–1027, 2003.

Verdon, D. C. and Franks, S. W.: Long-term behavior of ENSO interactions with the PDO over the past 400 years inferred from paleoclimate records, Geophys. Res. Lett., 33, L06712, doi:10.1029/2005GL025052, 2006.

Vimont, D. J., Battisti, D. S., and Hirst, A. C.: Footprinting: A seasonal connection between the tropics and mid-latitudes, Geophys. Res. Lett., 28, 3923–3926, 2001.

Vimont, D. J., Wallace, J. M., and Battisti, D. S.: The seasonal footprinting mechanism in the Pacific: Implications for ENSO, J. Climate, 16, 2668–2675, 2003.

Wallace, J. M. and Gutzler, D. S.: Teleconnections in the geopotential height field during the northern hemisphere winter, Mon. Weather Rev., 109, 784–812, 1981.

Wang, G., Swanson, K. L., and Tsonis, A. A.: The pacemaker of major climate shifts, Geophys. Res. Lett., 36, L07708, doi:10.1029/2008GL036874, 2009.

Wang, H. and Fu, R.: Influence of ENSO SST anomalies and water storm-tracks on the interannual variability of the upper tropospheric water vapor over the Northern Hemisphere extratropics, J. Climate, 13, 59–73, 2000.

Watts, D. J. and Strogatz, S. H.: Collective dynamics of “small-world” networks, Nature, 393, 440–442, 1998.

Wyatt, M. G., Kravtsov, S., and Tsonis, A. A.: Atlantic multidecadal oscillation and northern hemisphere’s climate variability, Clim. Dynam., doi:10.1007/s00382-011-1071-8, 38, 929–949, 2011.

Yamasaki, K., Gozolchiani, A., and Havlin, S.: Climate networks around the globe are significantly affected by El Nino, Phys. Rev. Lett., 100, 228501, doi:10.1103/Phys.Rev.Lett.100.228501, 2008.

Zhang, R., Delworth, T. L., and Held, I. M.: Can the Atlantic Ocean drive the observed multidecadal variability in northern hemisphere mean temperature?, Geophys. Res. Lett., 34, L02709, doi:10.1029/2006GL028683, 2007.

Zhou, C. S. and Kurths, J.: Dynamical weights and enhanced synchronization in adaptive complex networks, Phys. Rev. Lett., 164102, 96, doi:10.1103/PhysRevLett.96.164102, 2006.