Directional influences on global temperature prediction

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[1] There is growing evidence that major climate modes are involved in determining decadal variability in global mean temperature. These modes represent major oceanic and atmospheric signals and on decadal scales their collective interplay leads to climate shifts manifesting themselves as regime changes in global temperature trend. Here we investigate whether the collective role of these modes is extended within a regime, i.e. to shorter time scales. We apply nonlinear prediction in order to assess directional influences in the climate system. We show 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, we find 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. **Citation:** Wang, G., P. Yang, X. Zhou, K. L. Swanson, and A. A. Tsonis (2012), Directional influences on global temperature prediction, *Geophys. Res. Lett.*, *39*, L13704, doi:10.1029/2012GL052149.

1. Introduction

[2] The winter of 2011–2012 was a very strange winter for Northern Hemisphere. The contiguous United States (especially the Midwest and the east) experienced a very mild winter while Europe and parts of Asia a record breaking cold winter. A combination of a La Nina in the tropical Pacific and a positive phase of the North Atlantic Oscillation resulted in such an upper flow that kept the cold Arctic air away from the States and directed it over Europe. While it is well known that major climate modes/teleconnections can affect large regions of the planet thereby shaping up global temperature variability, we have only begun to understand the collective behavior of these modes and its effect on climate.

[3] Synchronization and coupling between climate modes has been lately implicated in the decadal variability of global temperature and in major climate shifts. In a series of papers [*Tsonis et al.*, 2007; *Swanson and Tsonis*, 2009; *Wang et al.*, 2009; *Tsonis and Swanson*, 2011] it has been demonstrated that the collective behavior of the network of four major climate modes (namely the Pacific Decadal Oscillation (PDO), the North Atlantic Oscillation (NAO), the El Niño/Southern Oscillation (ENSO), and the North Pacific Index (NPI)), can account for the decadal climate variability and all climate shifts observed in the instrumental record. While climate is in a regime characterized by a certain global temperature trend, this network may enter a state where the modes synchronize. It was found that in those cases where the synchronous state was followed by a steady increase in the coupling strength between the modes, the synchronous state was destroyed, and was followed by a climate shift and a new regime characterized by a reversed global temperature trend. Evidence for such type of behavior was also found in three climate simulations of forced (with CO_2) and control state-of-the-art models [*Tsonis et al.*, 2007] as well as in a set of proxy indices going back several centuries [*Tsonis and Swanson*, 2011]. The fact that this mechanism is found in both forced and control simulation suggests that this is an intrinsic mechanism of the climate system.

[4] While the above mechanism may explain climate shifts over decadal time scales, it does not address directional influences within a given regime. In other words, is the collective behavior of the modes important only in causing shifts or is it relevant at shorter time scales, for example seasonal or yearly time scales, during which there is no synchronization? An answer to this question will shed more light into the relationship between co-variability of major climate modes global temperature and may lead to improved predictions. This issue is addressed here.

2. Method

[5] One of the paramount issues in climate, as well as other areas of science, is extracting information flow from observed time series. This knowledge is pivotal in understanding the dynamical behavior of the system which we ultimately would like to predict accurately. Granger causality [*Granger*, 1969] has become one of the most important statistical approaches for achieving this task. According to Granger causality, given two simultaneously recorded time series x_i and y_i, where i = 1, N denotes sampling times, we say that y has causal influence on x if the variance of the prediction error of x given y is less than the variance of the prediction of x not given y. This means that if prediction of some output improves with the addition of an input, then the input Granger causes the output. In its original formulation Granger causality is based on linear prediction of stochastic time series. Here we consider time series which represent nonlinear dynamical systems. Because of that we will assess predictability improvements using nonlinear prediction methods.

[6] Let us assume that we have an observable (output) $x(t)$, t = 1,N from an unknown nonlinear dynamical system. It is common practice by now to use this time series and its

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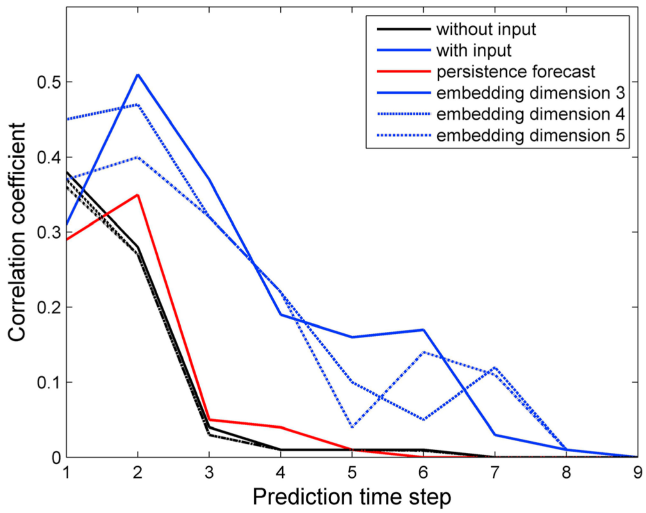

Figure 1. The correlation between predicted and actual values, for each embedding dimension, as a function of the prediction time step (in months) with (blue lines) and without (black lines) the influence of the inputs. The results using the non-skill method of persistence are also shown (red line). The results using all four inputs are superior as the results without inputs are basically the same as persistence (see text for more details).

successive time shifts (delays) as coordinates of a vector time series,

$$\boldsymbol{X}(t) = \{x(t), x(t-\tau), \ldots., x(t-(m_1-1)\tau\}$$

where m_1 is the dimensionality of the embedding space and τ an appropriate delay, in order to reconstruct the underlying attractor of the unknown system. Once this is done we can then estimate the various properties of the attractor (e.g., dimensionality, Lyapunov exponents [*Packard et al.*, 1980; *Casdagli et al.*, 1991]), as well as build a nonlinear prediction model of the form

$$\boldsymbol{x}(t+T) = f_T(\boldsymbol{x}(t)) \quad (1)$$

where f is some appropriate mapping and T the prediction time step [*Farmer and Sidorowich*, 1987; *Casdagli*, 1989]. Now suppose that this unknown system is in reality driven by an input whose influence is imprinted in x. If we don't have an idea of what this input is, then the best we can do is the above reconstruction and prediction method. If, however, we have an idea of what this input might be (for example, another time series $y(t)$) we can then attempt to model this input-output system via a delay coordinate reconstruction of the form

$$\boldsymbol{X}(t) = \{x(t), x(t-\tau), \ldots., x(t-(m_1-1)\tau; \\ y(t), y(t-\tau), \ldots., y(t-(m_2-1)\tau\}, t = 1, N$$

where m_2 is the embedding dimension of the input (i.e. the total embedding space is $m_1 + m_2$) and $N = n - (\max(m_1, m_2) - 1)\tau$ is the number of the points on the trajectory. Based on this trajectory, we may then build a model similar to (1) to predict the above process. The model is expressed as the map:

$$\boldsymbol{x}(t+T) = f_T(\boldsymbol{x}(t); \boldsymbol{y}(t)) \quad (2)$$

where f is again some desired mapping. The above prediction approach (which can be extended to consider more than one inputs), makes a prediction for one time step into the future (time step 1), then the predicted value is used to derive a new map to predict the next time step (i.e. time step 2), and so on.

3. Data Analysis and Results

[7] The above approach is very successful in improving prediction when inputs are included in "ideal" stationary systems such as the Lorenz system, the Henon map etc. (see auxiliary material) or nonstationary systems [*Wang et al.*, 2011].[1] Motivated by this, we examine here whether such approaches are successful when we only have measurements from systems whose formulation is unknown. More specifically we consider whether the above mentioned four major climate modes influence global mean temperature in the sense of *Granger* [1969]. These modes [*Mantua et al.*, 1997; *Hurrell*, 1995; *Philander*, 1990; *Trenberth and Hurrell*, 1994] represent regionally 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. Each of these modes involves different mechanisms over different geographical regions. Thus, we treat them as low-order nonlinear sub-systems of the grand climate system exhibiting complex dynamics. Indeed, some of their dynamics have been adequately explored and explained by simplified models, which represent subsets of the complete climate system and which are governed by their own dynamics. 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 [*Elsner and Tsonis*, 1993; *Schneider et al.*, 2002; *Marshall et al.*, 2001; *Suarez and Schopf*, 1998]. Monthly-mean values in the interval 1900–2007 are available for all modes. Note that major climate modes may be correlated to some degree as the action of one may (in a nonlinear way) trigger the action of another. Nevertheless, they represent different modes of variation. For example, NPI and PDO represent variability in the Northern Pacific Ocean but they correspond to variability of different fields, unlike NAO and AO (Arctic Oscillation), which represent the variability of the same field (surface pressure) in the North Atlantic Ocean.

[8] We first considered the values of the global temperature (which represent the output from the "unknown" system) and embedded it in dimensions 3–5 using τ = 1 month. For each embedding we used the first 103 years (1236 data points) to build the predictive model developed by [*Casdagli*, 1989] where f is assumed to be a polynomial of order two. The last four years (48 data points) were used for predictions

[1]Auxiliary materials are available in the HTML. doi:10.1029/2012GL052149.

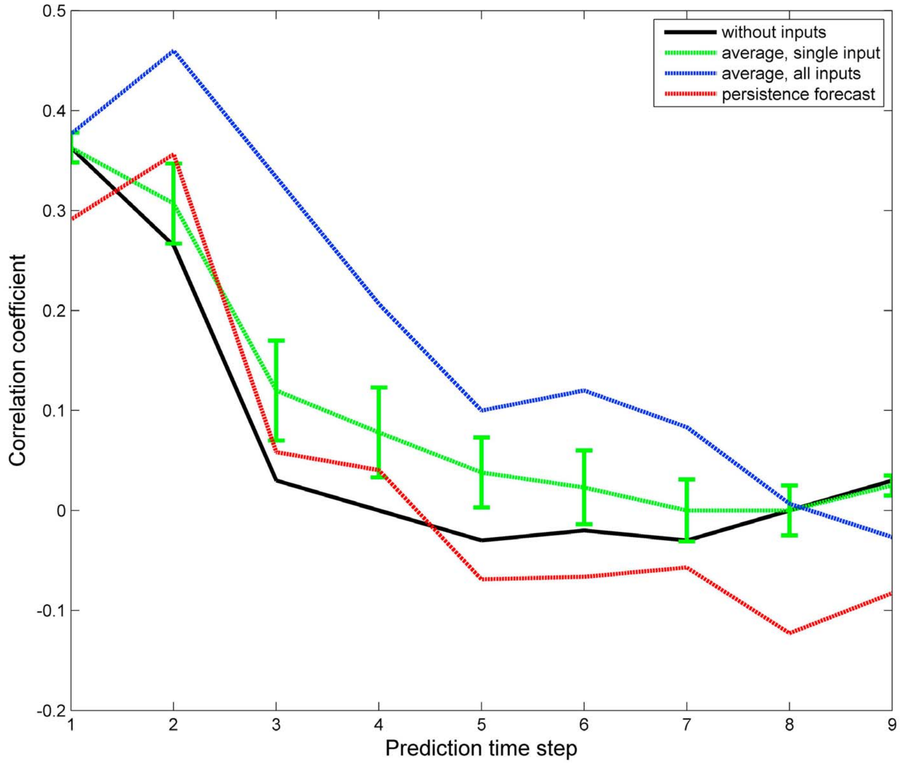

Figure 2. Average correlation coefficient as a function of prediction time step over the three embeddings. The black line is the average of the black lines in Figure 1 (not any input considered), the red line represent again persistence, and the broken blue line is the average of the blue lines in Figure 1 (all four inputs are considered). The green line is the average over the three embeddings and over the four modes acting individually. The bars on the green line indicate the one standard deviation. Clearly, the blue line stands above all other lines indicating that the improvement in predicting global temperature is the result of the collective behavior of the modes in the network and not a result of an individual dominant mode (see text for more details).

and to estimate the correlation coefficient between actual and predicted values, r(t), as a function of prediction time step, *r(t)*. The embedding dimension of the inputs is set to either 0 (i.e. equation (1) is used; the inputs are not taken into account in the predictive model), or 3–5 (i.e., equation (2) is used; the influence of the inputs is considered in the model). Figure 1 shows, for each embedding dimension, the prediction skill with and without the influence of the inputs. The results using the non-skill method of persistence (future values are the same as the terminal value in the reconstruction) are also shown. Note that for 5 variables and for a range of M possible embeddings for each variable, there exist M^5 combinations. Thus, to keep things simple, the embedding dimensions were set for all variables to either 3, or 4, or 5. Clearly, when the input of the four major modes is included prediction is dramatically improved. In fact, without the input, the predictive model is only as accurate as persistence. The average correlation over the prediction time step range 1–9 months is improved 125% –150% when the inputs are included. The improvement is also observed at embeddings 6 and 7, but due to sample limitations is not as good. In order to address possible effects of nonstationarities in the data we repeated the analysis with detrended data. The conclusions do not change significantly. These results establish for the first time Granger causality between major climate modes and global temperature variability over seasonal time scales.

[9] We then repeated the above analysis but now we used each mode alone as an input. Figure 2 shows the average correlation coefficient as a function of prediction time step over the three embeddings. The solid black line is the average of the black lines in Figure 1 (not any input considered), the red line represent again persistence, and the broken blue line is the average of the blue lines in Figure 1 (all four inputs are considered). The green line is the average over the three embeddings and over the four modes acting individually. The vertical green bars indicate the one standard deviation. While any individual input improves prediction compared to no input or to persistence, the blue line stands above all other lines indicating that the improvement in predicting global temperature is the result of the collective behavior of the modes in the network and not a result of an individual dominant mode. Note that ENSO was not particularly active for the forecast time period here; it is expected that predictability in global temperature arising from the linear ENSO signature will augment that shown here [*Trenberth et al.*, 2002].

[10] Nonlinear prediction has been very successful in identifying chaos and nonlinearity in data because, unlike other methods which exploit only a subset of the available points in the attractor, it uses all available points [*Sugihara and May*, 1990]. The fall-off in the correlation in nonlinear prediction, for short time steps (before r(t) → 0), is often used to differentiate between nonlinear dynamics (chaos)

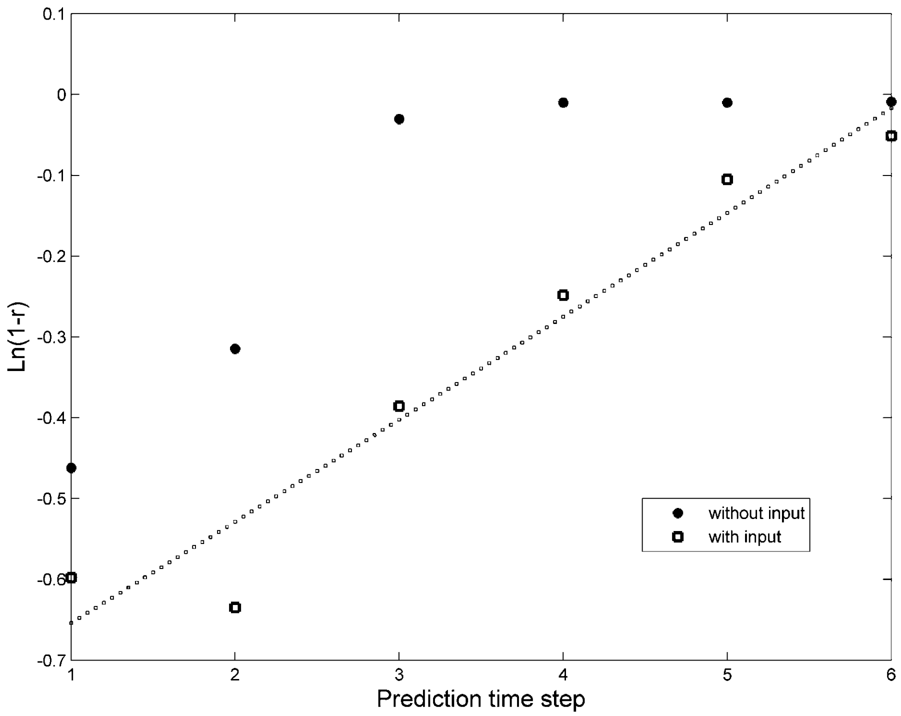

Figure 3. Logarithm of $1 - r(t)$ versus t for embedding dimension four and for $t = 1,6$ months (data from Figure 1). When the inputs are included (open squares) the fit is nearly linear unlike when the inputs are off (full circles). According to the *Tsonis-Elsner* test [*Tsonis and Elsner*, 1992], this indicates nonlinear dynamics (see text for more details).

and processes with red noise spectra and long range correlations such as fractional Brownian motions, which may "fool" algorithms for estimating dimensions or performing nonlinear prediction. According to the *Tsonis-Elsner* test [*Tsonis and Elsner*, 1992], a scaling $1 - r(t) \sim e^t$ (a straight line in a semi-log plot) indicates chaos, whereas a scaling $1 - r(t) \sim t^H$ (a curve in a semi-log plot) indicates random fractal sequences. Figure 3 shows (data from Figure 1) the logarithm of $1 - r(t)$ versus t for embedding dimension four and for $t = 1,6$ months. When the inputs are included (open squares) the fit is nearly linear unlike when the inputs are off (full circles). This provides additional evidence for our working hypothesis that the modes are low-order nonlinear subsystems of the grand climate system whose collective behavior strongly impacts global climate variability.

4. Conclusions

[11] Recent studies support the view that over time scales ranging from months to decades climate collapses into distinct subsystems and provide clues as to what these subsystems might be [*Tsonis et al.*, 2011]. To a large extend these subsystems identify with major oceanic and atmospheric signals and evidence is accumulating that the interaction between these subsystems may be largely responsible for the observed climate variability over decadal time scales [*Tsonis et al.*, 2007; *Swanson and Tsonis*, 2009; *Wang et al.*, 2009; *Tsonis and Swanson*, 2011; *Wyatt et al.*, 2011]. Here we show that inclusion of the NAO, PDO, ENSO, and NPI variability into a nonlinear prediction method largely improves the predictability of global temperature over seasonal time scales. Together with previous studies this result establishes causal directional influences between the co-variability of major oceanic and atmospheric modes and global temperature variability, suggesting a significant role of the major climate modes in shaping up global temperature not only over decadal time scales but over shorter time scales. Our results suggest that prediction schemes which incorporate modes as inputs may improve short (seasonal) predictions.

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