

Annual Cycle and Prediction of Interannual Variability

Zhaohua Wu

*Department of Meteorology & Center for Ocean-Atmospheric Prediction Studies
Florida State University, Tallahassee, FL*

1. Some Issues of Climate Prediction

There are four major issues that we concerned in this talk. The first one is the reference frame for climate anomaly. Current climate prediction of interannual variability starts mostly with what is called climate anomaly, which is the deviation of a climate variable from its reference frame, often its annual cycle. Traditionally, this annual cycle is taken to be an exact repeat of itself year after year. Such defined reference frame for climate anomaly has several drawbacks: (1) The repetitive annual may not reflect well the intrinsic nonlinearity of the climate system, especially under external forcing, for we are concerning the annual cycle of a climate variable which is the response of nonlinear climate system to external forcing rather than the periodicity of the external forcing itself; (2) The traditional annual cycle defined uses an a priori determined episode of a climate data, e.g., from 1960 to 1990. This a priori determined episode is not backed by any physical reason; rather, it is just for convenience. This ‘convenience’ unfortunately brings inconvenience, for we can define annual cycles of other episodes with equal validation. Following the way of defining traditional annual cycle, we can define numerous versions annual cycles as well as numerous versions of anomaly; and (3) When the anomaly with a traditional annual cycle is examined more carefully, we would find that the anomaly may still contain “annual cycle”, which leads to the conceptual inconsistency for the anomaly.

Recently, Wu et al. (2008) has proposed an alternative reference frame for climate anomalies, the modulated annual cycle (MAC) that allows the annual cycle to change from year to year, for defining anomalies. The MAC is temporally locally determined so that it is unique and has some “absoluteness” for any given climate time series. Moreover, the temporally locality of MAC also bypasses stationarity and linear assumptions of a climate time series often used in the majority of climate studies, and hence, the anomaly being defined is also unique. The MAC reference frame has been demonstrated to have many advantages in our understanding of climate system by Wu et al. (2008). For examples, the re-emergence mechanism may be alternatively interpreted as an explanation of the change of the annual cycle instead of an explanation of the interannual to interdecadal persistence of SST anomalies; the ENSO phase locking can largely be attributed to the residual annual cycle (the difference of the MAC and the corresponding traditional annual cycle) contained in the traditional anomaly, and, therefore, can be alternatively interpreted as a part of the annual cycle phase locked to the annual cycle itself. It was also shown in Wu et al. (2008) that using MAC as a reference framework for anomaly can bypass the difficulty brought by concepts such as “decadal variability of summer (or winter) climate” for understanding the low-frequency variability of the climate system.

The second major issue is what the predictable part of a climate variable, e.g., the sea surface temperature at Niño3.4 region, is for short term (for example, one year) climate prediction. A time series of climate variable contains noise, sub-annual high frequency variability, changing annual cycle, interannual and longer timescale variability, and secular trend. For variability of different timescales, the physical reasons that lead to the variability of particular timescales may be different. A handy example is the SST at Niño3.4 region, of which the sub-annual variability and the changing annual cycle may have more to do with (in large-scale view) the direct response of the tropical upper ocean to solar radiation while the interannual variability has more to do with the atmosphere-ocean coupled instability and equatorial wave dynamics, a relatively slowly evolving physical process.

To further explain the concept of the predictability of climate system, we use string-mass-pendulum system under random forcing, which is sketched in Figure 1. Suppose that the cube of large mass move leftward or rightward slowly and the small ball swings fast, the actual position of the ball of the pendulum can

be determined by the position of the cube and the position of ball with respect to the balance point of the pendulum. In the case of no random forcing, the positions are quite predictable for both the cube and the small ball with respect to the balance point of the pendulum, and thereby the actual position of the small ball. When there is moderate random forcing, due to the large inertia of the cube, its left-rightward oscillation would not be affected much, therefore, the position of the cube is still predictable. However, the position of small ball with respect to the balance point of the pendulum is affected significantly by the random forcing, and, therefore, is not predictable.

A relevant question is whether an accurate prediction model of the small ball based on the historical record of the position of the small ball can be constructed. Due to different physical processes (string-mass system and pendulum system) hidden in the record of the small ball and to the lack of a priori knowledge of the hidden string-mass system and pendulum system and the random forcing, a simple oscillatory model may not explain the position data and can not predict the position of small ball well. The inference of this argument is that we should be less ambitious: instead of trying to predict the exact location of small ball, we rather focus on the prediction of the location of the predictable part, the location of the cube. The implication of this analogue for short term climate prediction is: We should try to isolate the predictable part, the relatively low-frequency part of the climate data and make prediction of that, and leave out the hardly predictable high frequency part.

The third major issue is from data analysis perspective, as displayed in Figure 2. Suppose that the blue line is a climate index. If we construct a statistical model, e.g., a Markov model, directly based on this index and use that to predict the exact value of the index for future, we can not predict well. However, if we separate the two components, which have exact functional forms (with the simple physical mechanisms), we can predict both the functional forms separately with accuracy. As a consequence, we can predict the blue line accurately. This synthetic example implies that for a climate time series, we may obtain a better prediction based on the predictions of individual components of the time series.

The last major issue is related to the non-stationarity of the climate data. In many statistical prediction models, which are constructed based on the data over the whole temporal domain, stationarity is a pre-requirement. However, if the climate data was generated by non-stationary processes, the stationarity assumption used in the construction of a model would lead to significant error of prediction. In such a case, a non-stationary approach may lead to a significantly improved prediction.

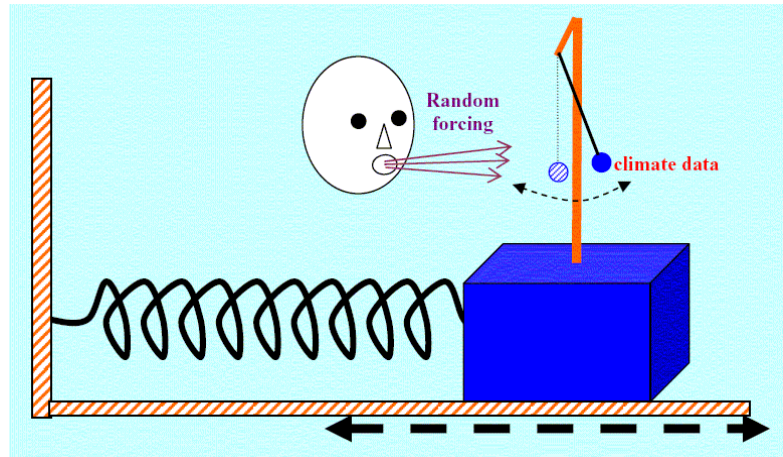


Fig. 1. A string-mass system analogue of climate data.

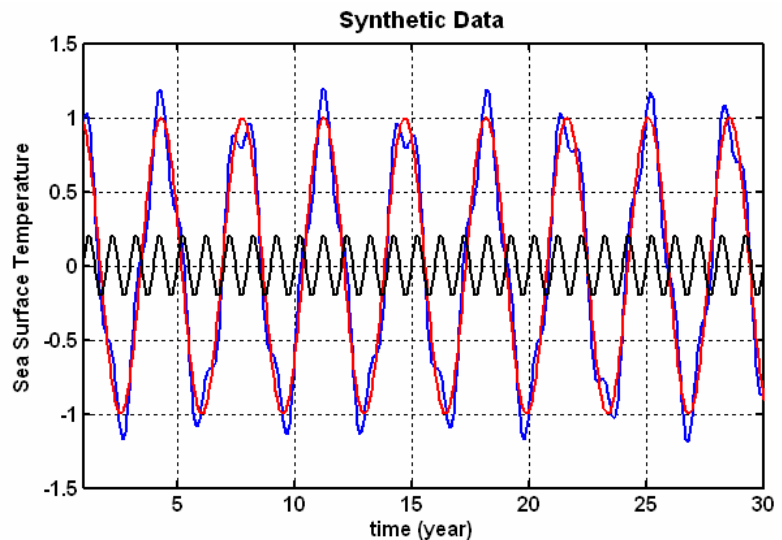


Fig. 2. The schematics of a synthetic climate data (blue line) and its components (red and black lines, two sinusoidal waves of different frequency).

2. An Alternative Prediction Scheme

Based on the discussions in the previous section, we constructed an alternative type of prediction scheme to the traditional statistical models. The new scheme is illustrated in Figure 3. In Figure 3, the black line is the interannual and lower frequency components of cold tongue index (CTI), an index defined based on equatorial SST of central and eastern Pacific. We use the Ensemble Empirical Mode Decomposition (Huang et al. 1998, Huang and Wu 2008, Wu and Huang 2009) to decompose the black line into oscillatory components of different frequency and obtain both the instantaneous amplitude and the instantaneous frequency for each component. Suppose that we want to predict the index for 1989, we first predict the instantaneous amplitude of each component for the year by using cubic spline extrapolation based on the instantaneous amplitude of previous years. By using the instantaneous frequency of the Dec. 1988 for each component, we predict the oscillatory component one by one.

Based on this scheme, we make prediction of interannual timescale and longer timescale part of CTI for year 1967 to 1999. Figure 4 presents the result of the retrospective prediction from each month during the period. In each prediction, the prediction duration is one year. In general, the prediction results are quite promising, which can be validated by the closeness of the green lines to the red line (which is the part of interannual and longer timescales of CTI). The predictions seem to have systematic errors: for certain years, the predictions are consistently higher than the index values while in the other periods, the predictions are consistently lower than index values. Such systematic errors may be reduced if other potential correction schemes are designed and used.

References

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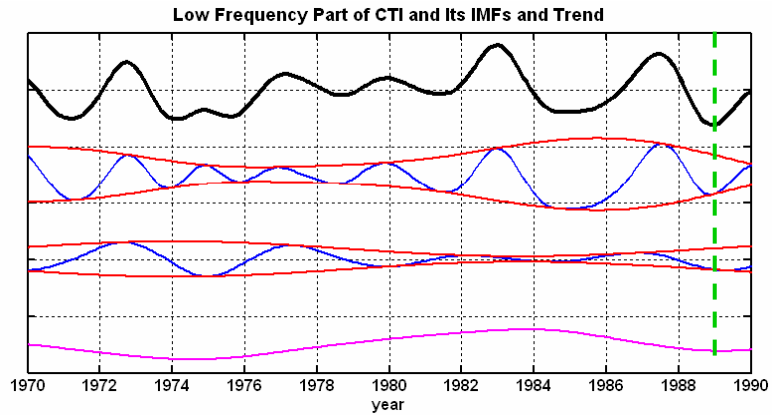


Fig. 3. The part of interannual and longer timescales of the cold tongue index (black line) and its oscillatory components (blue lines and magenta line). The red lines are upper and lower envelopes. The green dashed line corresponding to Jan. 1989.

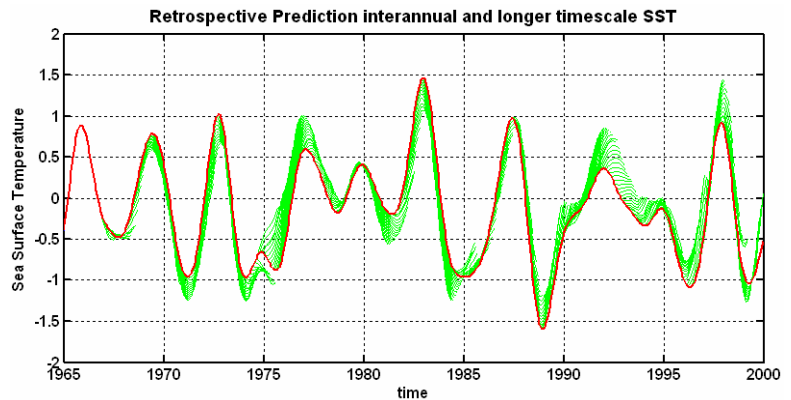


Fig. 4. The retrospective prediction of the part of cold tongue index of interannual and longer timescales (red line). The predictions from each month are displayed by green lines.