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Nonlinear features of Northern Annular Mode variability

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HIGHLIGHTS

- Nonlinear features of daily NAM variability are quantified.
- Two measures reach the same conclusion.
- Nonlinear features in NAM variation are significant at lower pressure levels.

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ABSTRACT

Nonlinear features of daily Northern Annular Mode (NAM) variability at 17 pressure levels are quantified by two different measures. One is nonlinear correlation, and the other is time-irreversible symmetry. Both measures show that there are no significant nonlinear features in NAM variability at the higher pressure levels, however as the pressure level decreases, the strength of nonlinear features in NAM variability becomes predominant. This indicates that in order to reach better prediction of NAM variability in the lower pressure levels, nonlinear features must be taken into consideration to build suitable models.

1. Introduction

The North Atlantic Oscillation (NAO)/ Arctic Oscillation (AO) is the dominant pattern of climate variability affecting North Atlantic region and western Europe [1]. The pattern mentioned above also has been taken as the near-surface Northern Annular Mode (NAM) [2–4], since NAM has been defined separately at each isobaric level from Earth's surface through the stratosphere [2]. NAM contains a broad spectrum of variations [5], however fundamental mechanisms determining the evolution of NAM are still far from being elucidated over each scale. For example, previous studies have found out that NAO index possesses distinct behaviors over a range of timescales and there is no one process that can likely account for all variabilities [1,5,6]. It has been suggested that the yearly NAO index is a stationary process with long-range correlation rather than a non-stationary random walk [5], although there are structured components, they can only explain less than 15% of the variations in the NAO index itself [7]. And that is why some scientists have obtained bad predictive performance when using pink noise as a model of yearly NAO index [8,9]. Furthermore, the dynamics of NAO is also associated with intra-seasonal time scales, which leads to the results that the daily NAM(NAO) index exhibits distinct behaviors from the yearly data [1,6,10,11]. Predominant nonlinear features are found in daily NAM (NAO) index: (i) Auto-regressive models fail to describe the daily NAM index at 1000 hPa and the spectra of daily NAM index are more consistent with low-order chaos [6], (ii) The duration of NAO pattern is extremely different over different phases [10].

According to the studies above, we find that the strength of nonlinear features may change for 1000 hPa NAM variability on the different time scales. However it is not clear whether the strength of nonlinear features in NAM variability is different

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at different pressure levels for a given time scale range. As we all know, the stratospheric harbingers may be a superior predictor of tropospheric weather regimes [2–4], therefore better understanding of nonlinear feature of NAM variability at different pressure levels is really necessary because only in this way we can build more suitable statistical model and make skillful climate prediction.

The nonlinear features of NAM index series can be quantified by two different kinds of approaches. Firstly, nonlinearity could result in an asymmetry of certain statistical properties under time reversal, therefore temporal irreversibility of time series is an important indirect quantitative assessment of nonlinearity [12,13]. A stationary process $x(t)$ is said to be time reversible if for every n, the series $\{x_1, \ldots, x_n\}$ and $\{x_n, \ldots, x_1\}$ have the same joint probability distributions [14]. More importantly, we need to address that quantifying the nonlinearity by means of time irreversibility has been widely applied to study nonlinear features in observational time series from various fields, such as physiology [15–18]. What is more, several statistical tests have been developed toward detection and quantification of irreversibility in time series [16–20]. Most recently, Lacasa and his colleges developed a method [19] based on horizontal visibility graph [21], which is an algorithmic variant of visibility graphs [22]. Without extra amount of ad hoc information for symbolization procedure, they show that irreversible dynamics results in an asymmetry between the probability distributions of the numbers of incoming and outgoing links in directed horizontal visibility graphs (DHVG) of given time series [18,19]. Therefore, in this paper we will characterize the nonlinear features of NAM variability at each pressure level through time series irreversibility by using the DHVG method. Secondly, nonlinear feature can be quantified by the nonlinear correlation, where original series x_i will be decomposed into magnitude series $|\triangle x_i| \equiv |x_{i+1} - x_i|$. If long-range correlation is found in the magnitude series $|\triangle x_i|$, and then this means the underlying process possesses the characteristics of nonlinearity [23–27]. Thus, here we will use detrended fluctuation analysis (DFA) [28,29] to quantify the strength of long-range correlation in time series. If the root mean square fluctuation function, $F(s)$, is proportional to s^{α}, where s is the window scale, the series is long range correlated. For a random series, $\alpha = 0.5$, while for long-range correlated series, $\alpha > 0.5$.

The rest of the paper is organized as follows. In Section 2, we will make a brief introduction to the data sets used in this paper. The results will be discussed in Section 3. In Section 4, discussions and conclusions are made.

2. Data

The data used in this study are daily and monthly mean temperatures and geo-potential height fields of the period of 1948–2010 from 1000 hPa to 10 hPa. The data are downloaded from National Centers for Environmental Prediction-National Center for Atmospheric Research(NCEP/NCAR) reanalysis project and are applied to calculate NAM index just like what Baldwin et al. have done [2]. Next, we calculate the climatological annual cycle of the NAM index as the average of the same of each year at each latitude, longitude, pressure level. And then this annual cycle is subtracted to obtain anomalies from 20 °N to the North Pole. The wintertime (December–February) monthly mean data are used to calculate the leading Empirical Orthogonal Function (EOF) spatial pattern [10]. Here a separate EOF is made for each pressure level. Daily values of the NAM, spanning over the entire 63-year data record, are calculated for each pressure level by projecting daily geo-potential anomalies onto the leading EOF patterns. In order to compare the features of daily NAM index at the 17 pressure levels, we normalize the NAM index on each level by subtracting its mean value and dividing standard deviation over the whole span. Four typical daily normalized NAM indices over four pressure levels are presented in Fig. 1(a), where we can see there are marked different behaviors in NAM variations over the different pressure levels. In order to remove the non-stationary variations of NAM index at the lower pressure levels during the cold seasons, day-to-day difference in NAM index $\triangle \mathrm{NAM}_i = \mathrm{NAM}_{i+1} - \mathrm{NAM}_i$ is chosen to be analyzed. The nonlinear correlation can be estimated from the normalized variable $|\triangle \mathrm{NAM}|$, where its seasonal cycle has been subtracted and its standard deviation has been divided. Four typical normalized $|\triangle \mathrm{NAM}|$ indices at four pressure levels are presented in Fig. 1(b), where we can see that the marked variations at the lower pressure levels during the cold seasons have been nearly eliminated and the behaviors on both higher and lower pressure levels are close to each other.

3. Results

3.1. DFA results

First of all, we analyze the normalized NAM and $|\triangle \mathrm{NAM}|$ index series to learn about the long-range correlation and nonlinear correlation hidden in the variations of NAM index. Due to non-overlapping annual cycle for each year in the NAM variation, we cannot totally eliminate the effect of the annual cycle in the normalized NAM index by the usual normalized procedure. From the DFA results for NAM index at each pressure level, we cannot find a scaling range extending far enough to estimate the long-range correlation exponent α. The lower the pressure level is, the more predominant cross-over in scaling range, see Fig. 2(a). Since the long-range correlation of NAM variation is not the focus of this paper, we will not give further analysis on it. However, different from DFA result of NAM variations, extended scaling ranges are found for $|\triangle \mathrm{NAM}|$ variations at each pressure level, see Fig. 2(b). Furthermore, in order to compare the DFA results from different pressure levels, we estimate the DFA scaling exponent $\alpha_{|\triangle \mathrm{NAM}|}$ on each pressure level from 10 days to 1.5 years, which is also the range connecting NAM variations from higher frequencies to lower frequencies. And most important, the DFA scaling exponent, $\alpha_{|\triangle \mathrm{NAM}|}$, is not constant for all 17 pressure levels, at the higher pressure levels, $\alpha_{|\triangle \mathrm{NAM}|}$ is close to 0.5, which indicates there