

ON THE MULTI-DECADAL OSCILLATION OF ATLANTIC TROPICAL STORM ACTIVITY

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Abstract. Long term Atlantic tropical storm activity is described by the time series of the yearly Accumulated Cyclone Energy (ACE) Index for the time interval 1851-2007. ACE is a measure of total wind energy for North Atlantic basin and land falling tropical cyclone activity. Since the ACE index reflects a combination of storm intensity and duration it is a better measure of overall activity and likely damage than the number of either basin or land falling tropical storms or hurricanes. The yearly ACE time series is non-stationary, and one step toward detecting possible long-term quasi-periods is to detrend the original data. In this paper, we use a procedure for data transformation by which ACE index is fitted in least square sense with polynomials of increasing order, followed by detrend. It is shown that, with some approximation, the obtained time series is cyclostationary, and a multi-decadal oscillation is detectable, as indicated by the power spectrum analysis.

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1. INTRODUCTION

The North Atlantic tropical storm (ATS) and hurricane activity typically occurs during June-November (also called hurricane season), due in part to increased sea surface temperature, which favors cyclone development and intensification [5, 7, 9, 16]. An average hurricane season features approximately 9 named storms, with a standard deviation of 4 (a tropical named storm has a maximum sustained surface wind of at least 39 mph, while a hurricane has a maximum sustained surface wind of at least 74 mph; 1 mph = 1.609344 km/h = 0.44704 m/s). In this context, “Named storms” refers to all tropical storms, hurricanes, and subtropical storms and such distinction is made to

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exclude mid-latitude cyclones. A measure of the North Atlantic tropical cyclone total seasonal activity is the Accumulated Cyclone Energy (ACE) index. The “total seasonal activity” describes the collective intensity and duration of Atlantic named storms occurring during a given season. The ACE index is a wind energy index, defined as the sum of the squares of the maximum sustained surface wind speed measured every six hours for all named systems while they are at least tropical storm strength. The annual number of named storms, NS, and the ACE Index show significant inter-annual variability, a positive trend over the time interval 1851-2007, and oscillatory component at multi-decadal scale. These time series, as many others encountered in Geosciences, exhibit non-stationarity, and are generally too short for detection of well defined multi-decadal quasi-periodicities. Additional problems are related to possible non-homogeneities caused by changes in the observing systems in the last over 150 years. To analyze such non-stationary time series, one step is to create approximate stationary (or cyclostationary) time series. In this process, the removal of the time series trend is an important transformation [6, 20].

The number of Atlantic tropical storms show a strong trend in the last few decades. It has been debated that this trend has possibly been influenced by global warming [4, 3, 15, 19]. Thus, the evolution of ATS activity in the future may be influenced by competing factors such as global warming and internal dynamics of the atmosphere-ocean system [11]. The goal of this paper is to report results from a new technique of approximation of non-stationary time series used for ATS activity analysis at multi-decadal time scales.

2. METHOD

We examine time series of Atlantic tropical storm annual data from 1851-2007. We use annual data, since in this study we focus on variations on multi-decadal time scales. Inter-annual variability and significant variations on periods of less than a decade are not considered here. The yearly number of ATS is based on National Oceanic and Atmospheric Administration (NOAA) re-analysis project (see [12, 13]). The project is concerned with tropical cyclones of the North Atlantic Ocean, Caribbean Sea and Gulf of Mexico. Observed quantities analyzed in the present study, most of which are from the hurricane re-analysis available for each year include: (1) number of tropical named storms (NS); (2) number of hurricanes (H), defined as tropical storm with surface wind speed larger than 74 mph; (3) number of major hurricanes (MH) defined as hurricanes of category 3, 4, and 5 (surface wind speed larger than 111 mph); (4) accumulated cyclone energy (ACE) index [1]. The classification of hurricanes in 5 categories is based on the widely used scale defined by Saffir and Simpson [17]. We present the distributions of the Pearson correlation coefficients, $r(a, b)$, between variables a and b , obtained by the bootstrapping method, resampling 50000 times the original time series. Bootstrapping is a

statistical technique for estimating the sampling distribution of an estimator by sampling with replacement from the original sample set (Figure 1). The purpose is to derive robust estimates of the correlation coefficient [2].

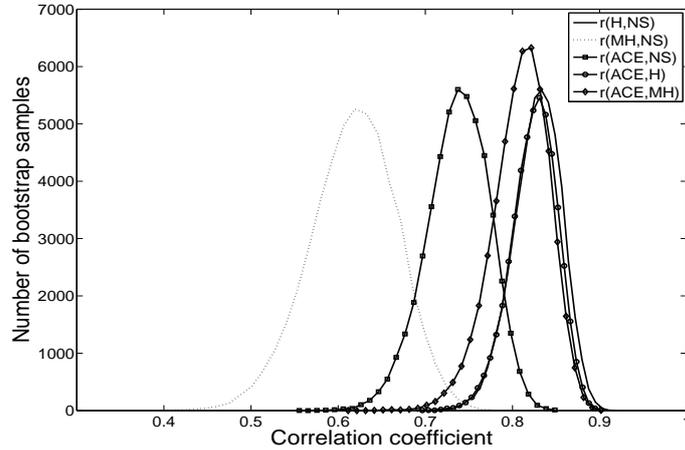


Fig. 1. Distribution of the correlation coefficient between pairs of variables shown in parenthesis. For example, $r(H, NS)$ represents the correlation coefficient between the number of hurricanes (H) and the total number of storms (NS).

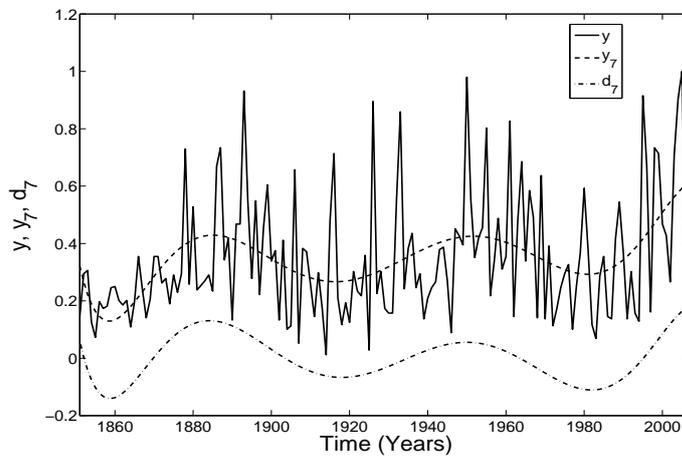


Fig. 2. The normalized ACE Index (y), the 7-order polynomial least square fit (y_7), and the detrended (d_7) time series versus time.

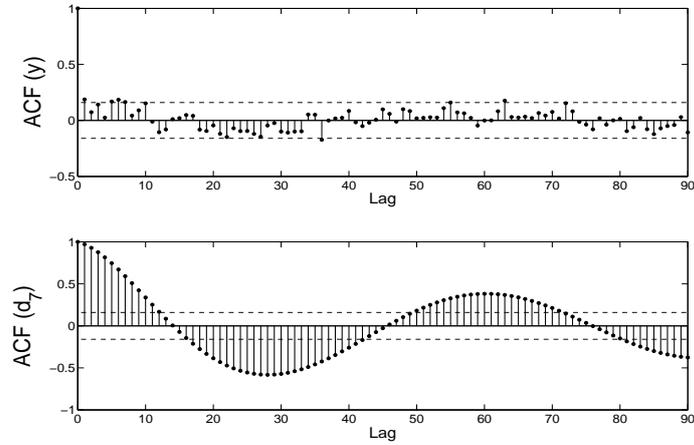


Fig. 3. Autocorrelation function of y and d_7 versus lag (in years).

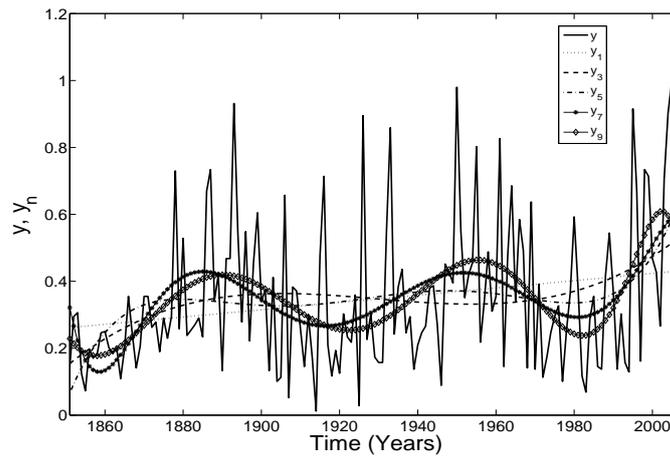


Fig. 4. The annual normalized ACE Index (y), and its n -order polynomial least square fit time series (y_n), versus time.

3. RESULTS

We determined that there is significant, positive correlation between NS, H, MH, and ACE as shown in Figure 1. We note that all correlation coefficients (r) are substantial, with a lower correlation coefficient $r(\text{MH}, \text{NS})$ between the number of major hurricanes and the number of tropical storms. By contrast, ACE seems highly correlated with MH and H and somehow less correlated with NS. This confirms that ACE is indeed a better quantification of the effects of the most intense hurricanes. In the light of these results, we limit

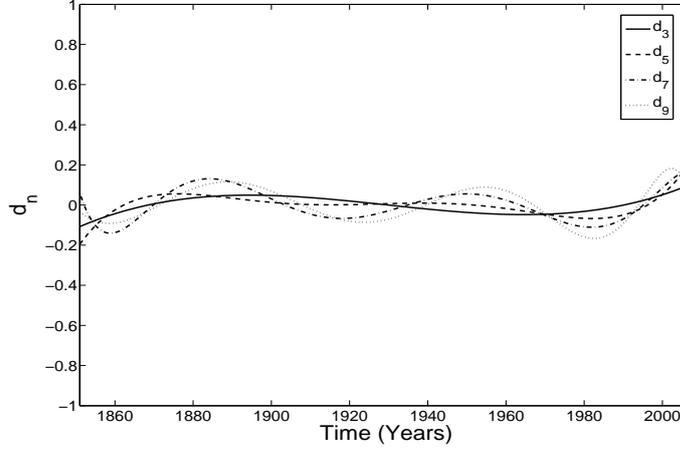


Fig. 5. Detrended n -order polynomial least square fit of the normalized ACE, d_n . (By definition $d_n = y_n - x_n$, where x_n is the linear fit of y_n).

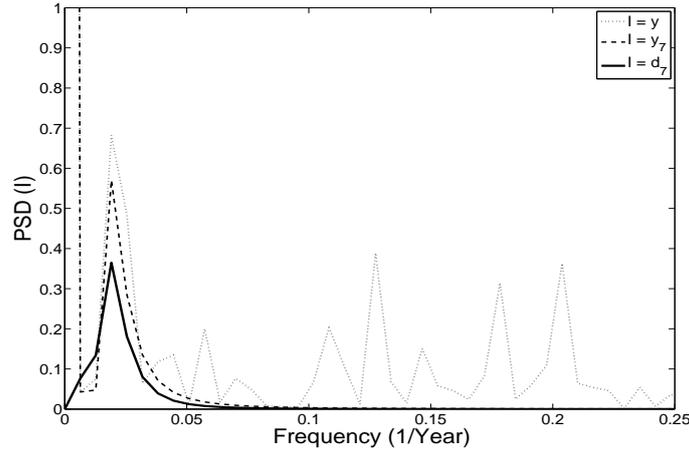


Fig. 6. Power spectrum density of y , y_7 and d_7 . We note that $\text{PSD}(y)$ shows spikes at high frequency, while $\text{PSD}(y_7)$, and $\text{PSD}(d_7)$ show spikes only at low frequency (corresponding to a multi-decadal oscillation with average quasi-period of about 65 years).

our presentations to the variable ACE, while the methodology used here can be easily applied to any variable from the re-analysis data set. The results for the other variables described above, are similar.

In the following, we denote the original ACE Index by y_0 , and $y_{\max} = \max(y_0)$. Thus, $y = y_0/y_{\max}$ is the normalized ACE index which will be used in this study. Since we are concerned here only with variability on multi-decadal time scales of y , we generate time series that are approximations of

the original data set. The method used to generate these approximations of y is to take the n -order polynomial least squares fit (LSF) of y , and the result is denoted by y_n . Thus, for example, y_1 is the first order polynomial LSF of y , also known as linear trend of the time series. We note that low order n (between 1 and 5) will provide a good description of the linear trend in the data, while high order n (greater than 20, for example) tends to describe the data in greater detail, close to the original data set. We expect that for a relatively low order n , the y_n is a good approximation of the trend and possibly major oscillatory components in the data. This is valid for relatively short time series, that contains only few oscillations of the presumed quasi-periodic process. For time series that contain a large number of oscillations of the quasi-periodic process, the power spectrum analysis is generally sufficient to detect without ambiguity the quasi-periods.

To find out the appropriate polynomial order, we calculate y_n with $n = 1, 2, 3, \dots, 30$, and monitor the total absolute residual of the approximation. The total absolute residual of the n -order approximation is given by the sum $\sum_1^N |y - y_n|$, where N is the number of terms in the time series y , and n is the order of the polynomial. By increasing n we find that the total absolute residual decreases with n , and becomes approximately stationary for $n \geq 7$. For n between 10 and 30 there is a lower rate of change in the total absolute residual.

We find that y_n , for $n = 7, 8$ or 9 , provide a good approximation of y variations at multi-decadal time scales. The next step in our analysis is to detrend y_n (which is obtained by removing the linear trend from y_n). Thus, the new time series, denoted d_n , are defined by $d_n = y_n - x_n$, where x_n is the linear fit of y_n . The resulted time series d_n is a better approximation of the oscillations at large time scales. In the following we illustrate results for $n = 7$ polynomial LSF of y . Figure 2 shows that normalized ACE, y , has significant inter-annual variability, some apparent oscillatory component and a positive trend, especially in the last few decades. Firstly, we note that the time series, y_7 , is a fit of ACE, which tends to represent ATS variations at time scales over a decade. Secondly, we note that y_7 has a positive trend, so y_7 is detrended to produce the time series d_7 as described above. Thus, d_7 shows the oscillatory part of y at decade time scales and is closer to a stationary time series (or, more exactly to a cyclostationary time series). We note that polynomial fit cannot be used outside the range of time interval considered, and also that high order polynomial fit does not necessarily improve data representation and can lead to large residuals especially at the extremes of the time series.

To illustrate the periodic structure of y and d_7 , we calculate the autocorrelation function (ACF) of y and d_7 (Figure 3). We note that $\text{ACF}(y)$ is noisy, and strongly influenced by inter-annual and short term variability in y . In contrast, $\text{ACF}(d_7)$ has significant periodicity with approximate period between 60 and 70 years.

Figure 4 illustrates the annual normalized ACE Index (y), and its n -order polynomial least square fit (LSF) time series (y_n), versus time. Only several selected n -order polynomials are shown, for figure clarity. Generally, we found that low n -order polynomial LSF produce a good approximation of the linear trend, while for n between 7 and 10, we obtain a better representation of the oscillatory component at multi-decadal time scale. We experimented with high order polynomials, up to $n = 30$.

Figure 5 shows the detrended n -order polynomial least square fit of the normalized ACE, d_n . Orders 5 to 9 show an aspect close to cyclostationary time series. This aspect is further explored in Figure 6, using the power spectrum density (PSD) representation of the time series. PSD can reveal the most relevant quasi-periods in a time series. One source of uncertainty in determination of quasi-period is caused by the short time series. Another source of miss-interpretation is the presence of significant trend in the data. Such feature appears as a very large “period” in the PSD (see Figure 6, PSD for the original y series). We note also that PSD(y) shows spikes at high frequency, corresponding to shorter quasi-periodicities in the ACE index, due to short term oscillations in the ocean-atmosphere system, as well as due to noise. In contrast, PSD(y_7), and PSD(d_7) show spikes only at low frequency (corresponding to a multi-decadal oscillation with average quasi-period of about 65 years). There is large uncertainty in the value of quasi-period, due in part that our time series has only 157 terms, but the value found here is consistent with other evaluations reported in literature [8, 10, 14, 18]. Results show that our method of polynomial LSF, followed by detrend, produces a PSD that is free of the effects of trend, and free of the effects of high frequency signals in the analyzed time series.

4. CONCLUSIONS

Time series of annual data from 1851-2007 for the normalized Accumulated Cyclone Energy (ACE) index (y), shows distinct features of a non-stationary time series. Firstly, the series has a significant linear trend, due to possible intensification of Atlantic tropical storm activity in the last few decades, and in part due to possible non-homogeneities in the data, caused by changes in observation systems. Secondly, the time series has also very strong inter-annual variability, as well as intense variability at times scales less than a decade. Thirdly, the time series has indication of multi-decadal oscillation, of intensity that seems largely masked by the high frequency oscillations. To detect the multi-decadal oscillatory component, we perform a series of transformations intended to filter the short term variations, and the trend. Thus, we find n -order polynomial least squares fit (LSF) of y , are more representative for multi-decadal oscillations, for n between 7 and 10. We detrend the obtained time series, and we find that the remaining time series has a distinct quasi-period of about 65 years, as shown by power spectrum analysis. The method

has potential applications in time series analysis that manifest low-frequency signals, masked by more intense high frequency signals.

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