# Artificial detection of lower frequency periodicity in climatic studies by wavelet analysis demonstrated on synthetic time series

**Running head**: Wavelet artificial detection of periodicity in climatic studies

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## Abstract

The Continuous Wavelet Transform (CWT) is a frequently used tool to study periodicity in climate and other time series. Periodicity plays a significant role in climate reconstruction and prediction. In numerous studies, the use of CWT revealed Dominant Periodicity (DP) in climatic time series. Several studies suggested that these "natural oscillations" would even reverse global warming. It is shown here that the results of wavelet analysis for detecting DPs can be miss-interpreted in the presence of local singularities that are manifested in lower frequencies. This may lead to false DPs detection. In CWT analysis of synthetic and real-data climatic time series, with local singularities, CWT indicates on a low frequency DP even if there is no true periodicity in the time series. It is argued that this is an inherent general property of CWT. Hence, applying CWT to climatic time series should be re-evaluated and more careful analysis of the entire wavelet power spectrum is required, focusing on high frequencies as well. Thus, a cone-like shape in the wavelet power spectrum most likely indicates the presence of a local singularity in the time series rather than a DP, even if the local singularity has an observational or a physical basis. It is shown that analyzing the derivatives of the time series may be helpful in interpreting the wavelet power spectrum. Nevertheless, this is only a partial remedy that does not completely neutralize the effects caused by the presence of local singularities.

**Keywords:** Wavelet analysis, climate time-series, climate change, mother wavelet, Morlet, artificial periodicity, Fast Fourier Transform

## 1. Introduction

Spectral methods such as the Continuous Wavelet Transform (CWT, frequently named wavelet analysis) and the Fast Fourier Transform (FFT) have a special appeal for climate and paleo climate research because they can be used to detect periodicities in time series and other applications. CWT has therefore become a most common tool for the study of variations within climate time series, capable to analyse them with different timescales, which is imperative in climate reconstruction and prediction (Torrence and Compo, 1998). An appealing feature of CWT is its ability to analyse non-stationary time series, which is vital in climate research (Lau and Weng, 1995).

Recently, CWT was used in a plethora of climate and geophysical studies (e.g., Gray *et al.*, 2004; Knight *et al.*, 2005; Li *et al.*, 2011; DeLong *et al.*, 2012; Mccabe-Glynn *et al.*, 2013; Pike *et al.*, 2013; Cox *et al.*, 2014; Duan *et al.*, 2014; Kreppel *et al.*, 2014; Magee *et al.*, 2014; Soon *et al.*, 2014; Xu *et al.*, 2014; Burn *et al.*, 2015; Lee *et al.*, 2015; Wright *et al.*, 2015; Novello *et al.*, 2016; Sharma *et al.*, 2016). These studies have incorporated CWT as a primary tool, chosen from the many other signal analysis tools within the frequency domain. These authors have highlighted Dominant Periodicity (DP) in climatic, paleo climatic and geophysical time series, attributing them to natural origin (e.g., NAO, ENSO, PDO, solar cycles, solar irradiance, thermohaline circulation, etc.). Cone like shapes, expressing low frequency DPs in the wavelet power spectrum that emerged in the aforementioned studies have motivated the present work. It is stressed that low frequency DPs may suggest a long term climatic process as opposed to local high frequency features. Thus, low frequency DPs are appealing in improving predictability of the climate system.

Frequently, such studies detected DP's using a point wise significance testing procedure applied to the wavelet spectrum (Torrence and Compo, 1998). These authors have suggested that for a first order auto-regressive process with lag-1 auto-correlation, a theoretical normalized red-noise power spectrum can be computed. To obtain the 5% significance level, the red-noise power spectrum is multiplied by the 95% of a chi-square distribution with two degrees of freedom and then the result is divided by two to remove the degrees of freedom factor. The auto-correlation coefficient can be estimated by standard methods, e.g., Allen and Smith (1996) used in this study.

DPs are defined herein as a statistically significant region of the wavelet spectrum within a band of lower frequencies/periodicities (e.g., Figure 1). It is emphasized that these higher power regions extend in time and are not very local features in the power spectrum. As such, many climatic studies relate DPs to natural cycles of the climate system, as indicated above. However, point wise testing procedures applied to simultaneous testing of a large number of wavelet coefficients ignore the severe multiple testing problem and, therefore, typically result in detection of spurious patches in the wavelet power spectrum (e.g., Abramovich and Benjamini, 1995; Maraum *et al.*, 2007). When one performs a test at a specific significance level, by definition one rejects the null hypothesis at a certain percent (e.g., 5%) even if it is true. Thus, when performing a test many times, a certain percent would emerge as spuriously significant. This is referred to as the multiple testing problem mentioned above (Maraun and Kurths, 2004). Nevertheless, pointwise significance testing is still the most commonly used significance test in climate studies.

Several improved significance testing procedures were considered in the literature. Maraun *et al.* (2007) proposed an area wise significance test. The main disadvantage of this test is the complexity of the significance level calculation, which involves a root-finding algorithm. Liu *et al*. (2007) have addressed the bias problem in the estimate of the wavelet spectra in atmospheric and oceanic datasets. They have suggested a rectification procedure, which is the transform coefficient squared divided by the scale it associates with. Schulte *et al.* (2015) developed a Geometric method for significance testing in the wavelet domain. It was found that this method produces results similar to the area wise significance test (Schulte *et al.*, 2015) while being more computationally flexible and efficient. In a most recent study, the Geometric method was improved by a cumulative area wise significance testing procedure (Schulte, 2016). It was shown that the latter test implies higher statistical power in most cases, especially when the signal-to-noise ratio is high (Schulte, 2016).

The purpose of this paper is to show that the CWT, even after applying the aforementioned state-of-the-art methods, still often identifies artificial lower frequency DPs arising from local singularities in a time series that can lead to misinterpretation of the wavelet power spectrum. This observation is particularly important because of the enormous recent increase in the number of publications using wavelet analysis in climate research, from 15 publications per year in 1998 to about 550 in 2018 (Science Direct).

## 2. Data and methods

To demonstrate the detection of artificial DPs in the wavelet power spectrum we applied the state-of-the-art Cumulative Area Wise (Schulte, 2016) and the Geometric (Schulte *et al.*, 2015) significance testing procedures (www.mathworks.com/matlabcentral/fileexchange/ ) to six synthetic and four real climate time series:

1) A sine time series with a ~200 low frequency periodicity (Figure 1).

2) The sun-spot number time series (SILSO, World Data Center; Figure 2).

3) A local abrupt change (step) time series generated manually (Figure 3).

4) Stratospheric aerosol optical depth time series (Bourassa *et al.*, 2012; Figure 4).

5) A red noise time series (Figure 5).

6) The local abrupt change time series added to the red noise time series (Figure 6).

7) The sine time series added to the red noise time series (Figure 7).

8) The Pacific Decadal Oscillation (PDO) reconstruction (Mann *et al.*, 2009; Figure 8).

9) The daily Nino3.4 index for 12.7.2015 – 6.4.2018 (Reynolds *et al*., 2007; Figure 9).

10) A time series containing a few local abrupt changes added to red noise (Figure 10).

For all the examples, we applied the above advanced significance testing procedures of Schulte *et al.* (2015) and Schulte (2016), where we used the Morlet 6 "mother" wavelet, which is the most commonly used wavelet in geophysics. All time series were padded with zeros at the edges as typically recommended in geophysics. We used a red noise (see introduction) and the applied significance testing procedure were adapted correspondingly to such a noise background, by generating 1000 realizations of noisy samples from this surrogate distribution, using Monte-Carlo techniques. Red noise is a commonly used background in geophysics (Torrence and Compo, 1998; Maraun *et al.*, 2007; Schulte *et al.*, 2015; Schulte, 2016). It is noted that the null distribution (the time series is similar to a red-noise background) of the normalized area of a significance patch depends on the choice of null hypothesis, with, for red-noise processes, the normalized area increases with increasing lag-1 autocorrelation coefficients (Schulte *et al.*, 2015).

For the sake of comparison, the Fast Fourier Transform, and pointwise wavelet significance testing (Torrence and Compo, 1998) were also applied to the time series described above (Figure S1, S2, respectively). The bias rectification procedure (Liu *et* *al.*, 2007) was further applied to the synthetic time series before using the Cumulative Area Wise significance test (Schulte 2016; Figure S3). In addition, boundary conditions may be a considerable source of uncertainty in climate and other time series. Several options have been presented in the literature. For example, Lin and Franzke (2015) and Gallegati (2018) have extended their time series using a symmetric/anti-symmetric extension mode. No clear recommendation has yet been given for climate time series. Here, the effect of using zero padding is evaluated for the synthetic time series (Figure S4). We have further investigated the above mentioned time series using alternative "mother" wavelets including the Paul (Figure S5) and Dog (Figure S6) "mother" wavelets.

To better distinguish between real DPs and local abrupt changes, it may be helpful to apply wavelet-based tests to the derivative (the rate of change at each time step) of the original time series. Taking the derivative does not affect periodicity. On the other hand, it reduces regularity of a signal, and a local singularity would be stronger manifested at higher frequencies of the wavelet spectrum. See Mallat (2008, Section 6) for rigorous mathematical analysis.

## 3. Results

CWT should only detect periodicities in the Sine time series (Figure 1), in the sun-spot number time series (Figure 2; SILSO, World Data Center), and in the Sine time series with red noise (Figure 7) as shown in the Fast Fourier Transform analysis (Figure S1). However, the wavelet power spectrum indicates the presence of DPs in all considered time series (Figures 1-10). The detected periodicities in the wavelet power spectrum in Figures 3-6 and 8-10 are artificial and are caused by local abrupt changes in the time series. It should be stressed that local abrupt changes may represent a real physical change in the system. For example, the stratospheric aerosol optical depth attributed to volcanic eruptions is analyzed here (Figure 4; Bourassa *et al.*, 2012). Two major local abrupt changes that coincide with the large volcanic eruptions of Krakatoa in 1883 and of El Chicon and Mount Pinatubo in 1982 and 1991, respectively, produce DPs at the 10-12 year periods (Figure 4). The CWT accurately detects the local abrupt change location on high frequency scales (Figures 3c, e – 10c, e). However, in the lower frequencies, the patch expands in time (Figures 3c, e – 10c, e) and results in a lower frequency band in the wavelet power spectrum, that may be erroneously interpreted as indication of a DP in the time series. Furthermore, it seems that the

Cumulative Area Wise test is more susceptible to the emergence of lower frequency DPs than the Geometric test (Figures 3c, e – 10c, e).

Following our remarks at the end of Section 2, we analyzed also the wavelet spectrum of the original time series derivative. Figure 1d, f and 2d, f show that the derivative of the Sine time series and the sun-spot number time series, respectively, indeed leaves the low frequency periodicity intact. On the other hand, when there are local abrupt changes in the time series (e.g., Figure 6 and 10), using the derivative emphasizes the power at higher frequencies in the wavelet power spectrum and reduces the power in the lower frequency patches (Figure 6d, f and 10d, f). However, it still does not completely prevent detection of false DPs. This is further demonstrated in real reconstructed PDO and Nino3.4 time series (Figure 8d, f and 9d, f). Thus, using the derivatives is a partial remedy that does not completely neutralize the effects caused by the presence of local singularities.

It is further shown that the pointwise significance testing procedure (Torrence and Compo, 1998) also displays significant artificial low frequency DPs in the aforementioned time series (Figure S2). This test mostly does not find the high frequency scales as significant, in contrast to the area based tests (Schulte *et al*., 2015; Schulte 2016).

Rectifying the wavelet power spectrum may allow the comparison of spectral peaks across scales (Liu *et al*., 2007). However, for time series containing local abrupt changes, the Cumulative Area Wise significance test (Schulte 2016) finds the high frequency scales as significant but not the real DPs (Figure S3).

Figure S4 displays the effect of using zero padding on the synthetic time series used in this study. It is shown that using the zero padding procedure (Figure S4 left column) reduces boundary conditions in all aforementioned time series with respect to no padding (Figure S4 right column). It is stressed that zero padding is helpful wherever it smooths the time series at its boundaries, thus reducing the effect of local singularities. For example, the improvement in the boundary conditions is higher in the left side of the sine time series then in the right side (Figure S4a, b, respectively). Thus, no clear recommendation can be given for climate time series since the edge effects will highly depend on the analyzed time series edges. It is recommended to analyze time series with different extension procedures to give a better evaluation of edge effects.

Finally, it is found that the Morlet 6 "mother" wavelet is the least susceptible to the effect of local singularities on lower frequency DPs (Figures 1-10) with respect to the

Paul (Figure S5) and Dog (Figure S6) "mother" wavelets. Thus, we recommend using Morlet 6 for climate time series as earlier recommended (Torrence and Compo, 1998; Maraun *et al.*, 2007; Schulte *et al.*, 2015; Schulte, 2016).

Summarizing, we argue that local singularities, commonly present in climatic time series (e.g., Yosef *et al.*, 2018) can induce low-frequency power that may be interpreted as DPs. It is further stressed here that spectral methods have been used to quantify non-linearity in time series (May 1976). Such non-linearity can lead to abrupt changes in time series and in turn, period doubling bifurcations that will ultimately be exhibited as a cone like shape in the wavelet power spectrum (Weng and Lau, 1994).

We have demonstrated this problematic feature on synthetic time series and on real climatic series. However, it should be noted that any series containing local singularities would necessarily produce a DP at lower frequencies, as this is inherent to wavelet analysis (Holschneider 1995; Abramovich *et al.*, 2000; Mallat 2008).

## 4. Discussion

The results of using CWT for detecting periodicities in climate time series might be misleading, as demonstrated here on different synthetic as well as real climate time series. It is shown that the presence of a lower frequency band in the wavelet power spectrum does not necessarily indicate a real periodicity, but is often caused by local singularities in the time series (as shown in Figures 3-6 and 8-10). Note that one can think of CWT as a series of localized band-pass filters, where low frequencies correspond to large windows in the time domain. Therefore, local singularities would be necessarily manifested in the lower frequencies domain of the wavelet power spectrum (Holschneider, 1995; Abramovich *et al.*, 2000; Mallat, 2008). A finer analysis of the geometry of patch shapes is required to distinguish between a true DP and an abrupt change in a time series. The latter typically yields local maxima within a cone around its location that propagate along high frequencies in the wavelet spectrum (e.g., Mallat, 2008, Sections 6.1-6.2), while DPs are characterized by temporally long bands in the low frequency domain. In this case, one could think of some length test for a patch. The problem, however, is more challenging, as there is occasionally a series of local singularities with interfering cones that might look similar to a long band in the low frequency domain (Figures 8-10). Here, we suggest to use the derivative of a time series as an additional test to distinguish between real periodicity and low frequency bands in the wavelet power spectrum emerging from local singularities. However, it still does not completely prevent detection of false DPs.

Summarizing, in order to distinguish between various possible scenarios, a topological analysis of the entire wavelet power spectrum is required, focusing on high frequency as well. Accordingly, whenever a lower frequency dominant periodicity appears in the wavelet power spectrum, one should also analyze the higher frequency, to distinguish between a real periodicity and an artificial one, produced by local singularities. Cone-like shapes in the wavelet power spectrum, propagating from the higher to the lower frequencies, most likely indicate on an artificial DP. The rigorous theory for such an analysis is a topic for further research.

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**Legend to figures**

**Figure 1** A Sine time series (a) and the derivative of the sine time series (b) Continuous Wavelet Transform (CWT) applied with (c,d) Cumulative area wise (Schulte 2016) (e,f) Geometric (Schulte *et al.*, 2015) significance testing using a Morlet 6 "mother" wavelet. The Wavelet Power Spectrum is shown for both significance testing. The black contours are regions found to be significant at the 5% level with respect to a red noise background using 1000 realizations from a Monte Carlo experiment. The shaded regions mark the cone of influence in which boundary conditions become important. The Dominant Periodicities (DP) are marked in an arrow. DPs are a statistically significant region of the wavelet spectrum within a band of lower frequencies/periodicities. It is emphasized that these higher power regions extend in time and are not very local features in the power spectrum.

**Figure 2** Same as Figure 1 but for the sun-spot number time series (SILSO, World Data Center). Dominant Periodicities (DP) are marked in arrows.

**Figure 3** Same as Figure 1 but for a Local Abrupt Change time series. Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

**Figure 4** Same as Figure 1 but for the stratospheric aerosol optical depth time series (Bourassa *et al.*, 2012). Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

**Figure 5** Same as Figure 1 but for a red noise time series.

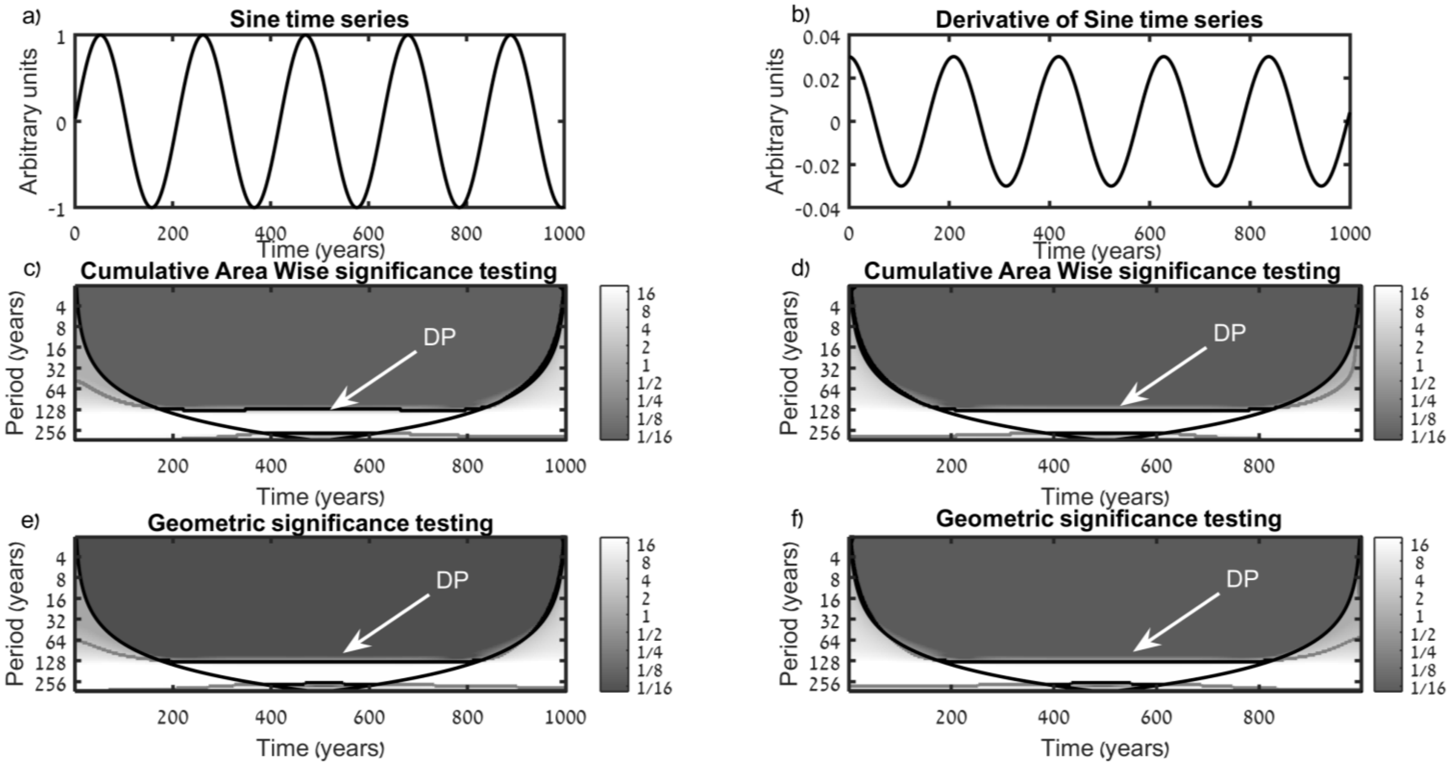
**Figure 6** Same as Figure 1 but for the red noise time series added to the Local Abrupt Change (LAC) time series. LAC and Dominant Periodicities (DP) are marked in arrows.

**Figure 7** Same as Figure 1 but for the sine time series added to the red noise time series. Dominant Periodicities (DP) are marked in arrows.

**Figure 8** Same as Figure 1 but for the reconstructed PDO (Mann *et al.*, 2009). Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

**Figure 9** Same as Figure 1 but for the Nino3.4 index 12.7.2015 – 6.4.2018. Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

**Figure 10** Same as Figure 1 but for a time series with a few Local Abrupt Changes (LAC) added to red noise.

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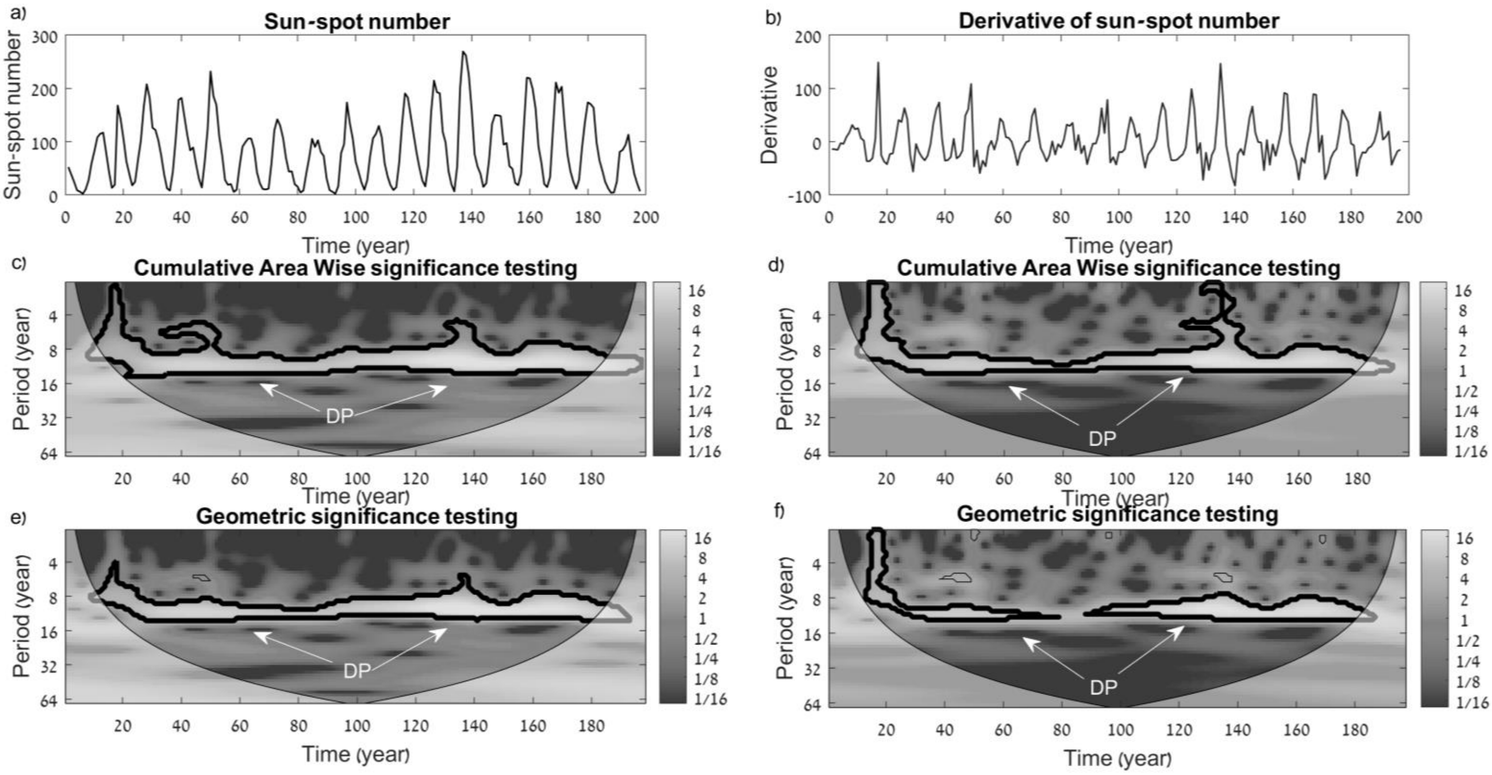


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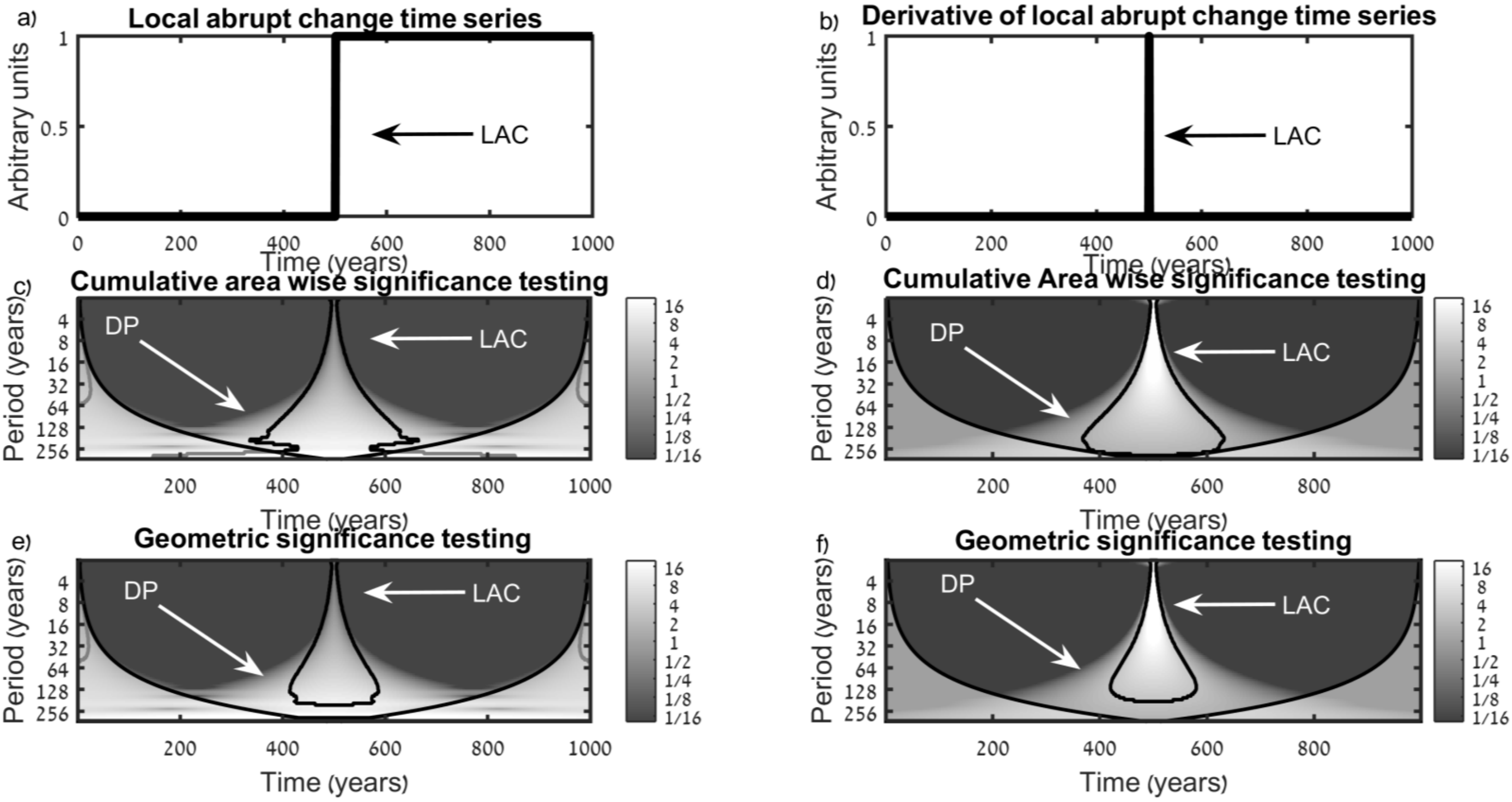


**Figure 3** Same as Figure 1 but for a Local Abrupt Change time series. Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

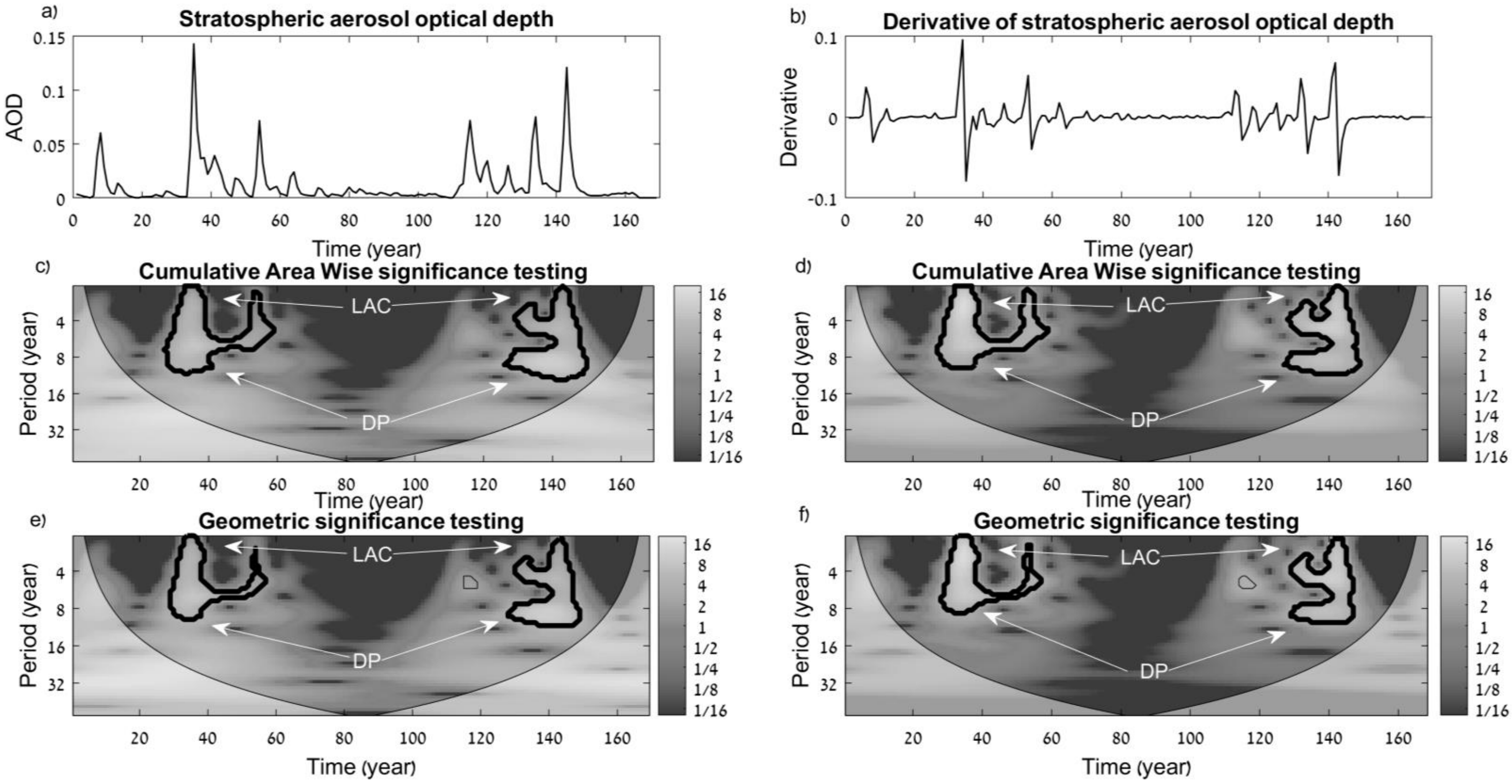


**Figure 4** Same as Figure 1 but for the stratospheric aerosol optical depth time series (Bourassa *et al.*, 2012). Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

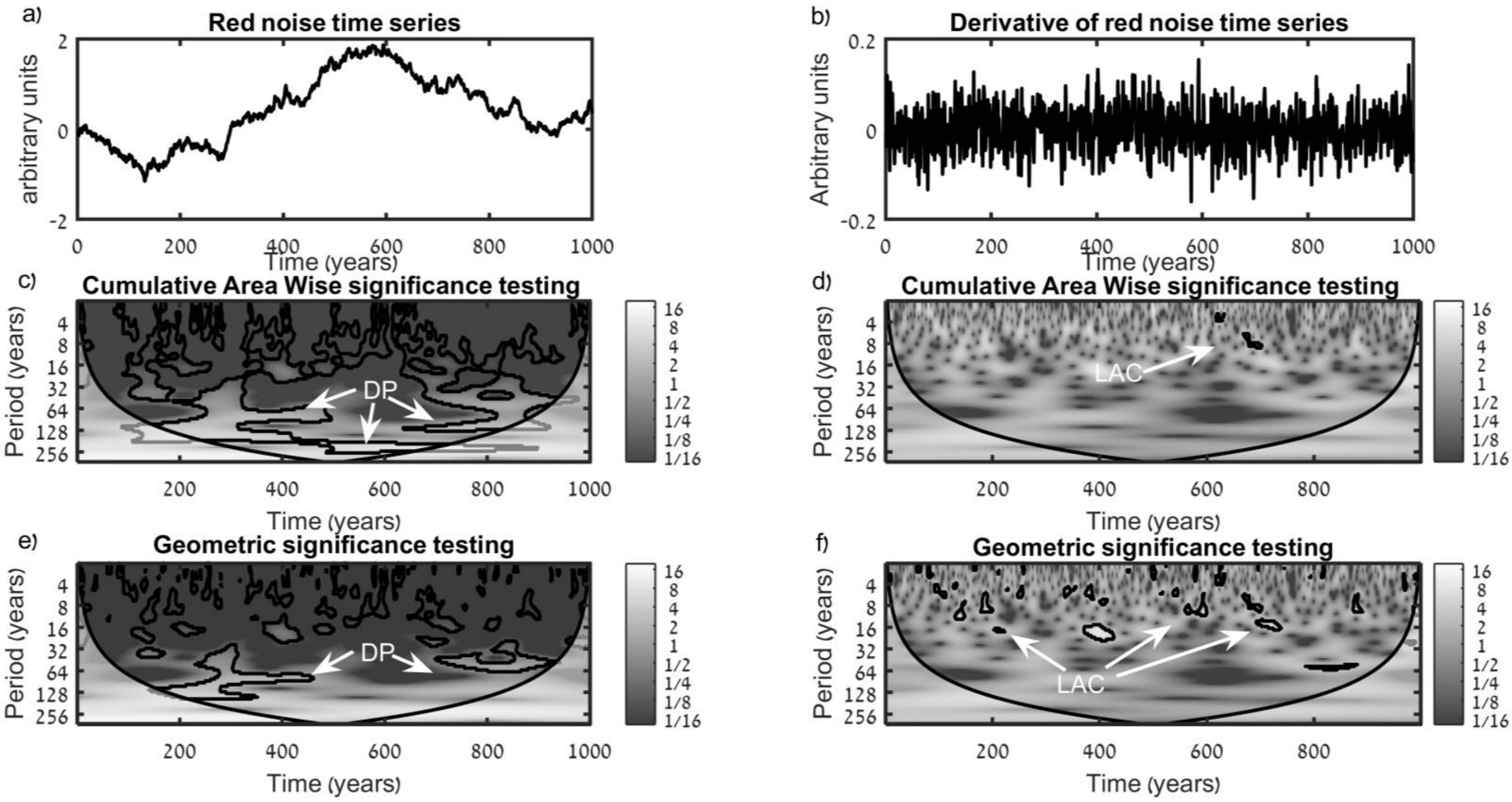


**Figure 5** Same as Figure 1 but for a red noise time series.

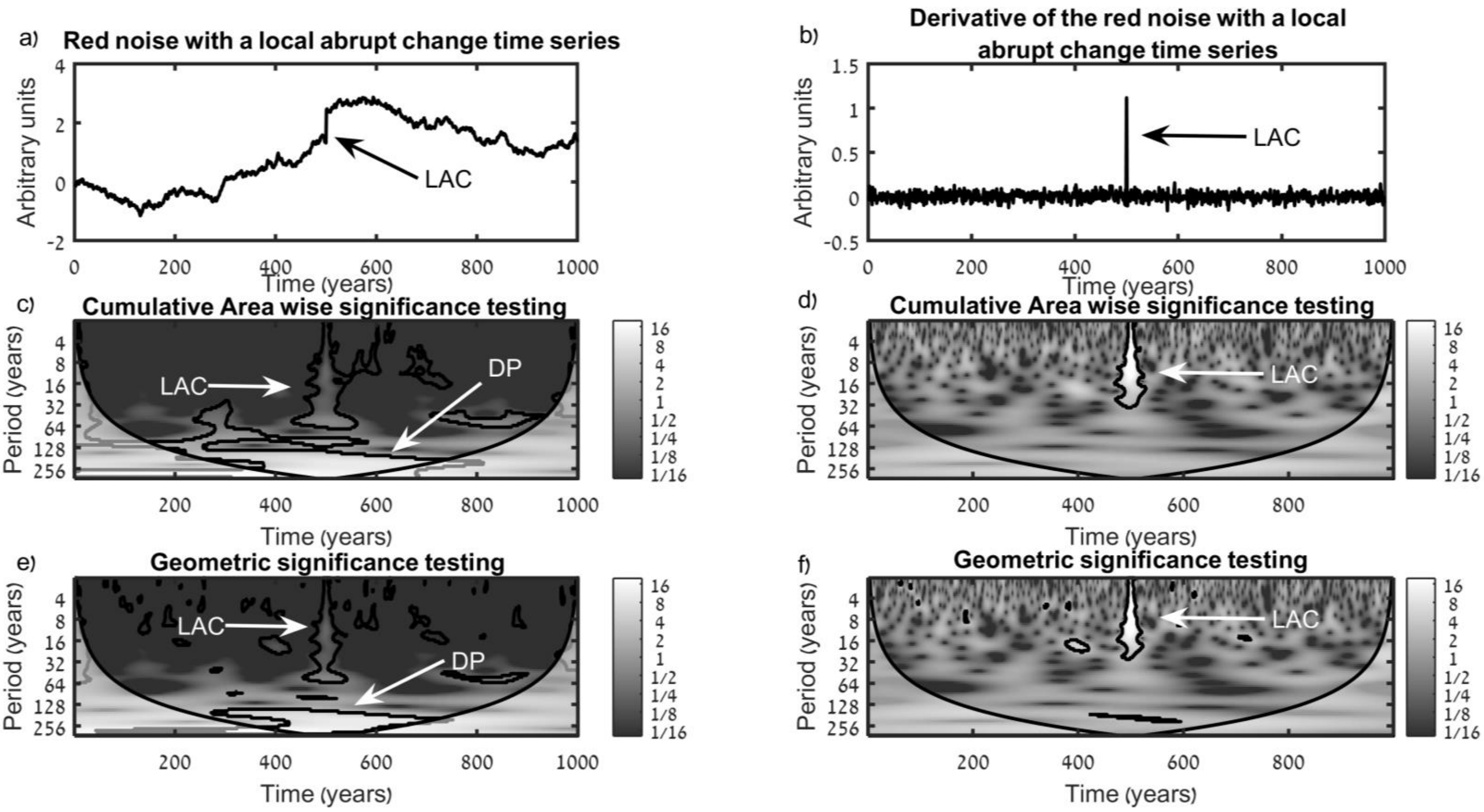


**Figure 6** Same as Figure 1 but for the red noise time series added to the Local Abrupt Change (LAC) time series. LAC and Dominant Periodicities (DP) are marked in arrows.

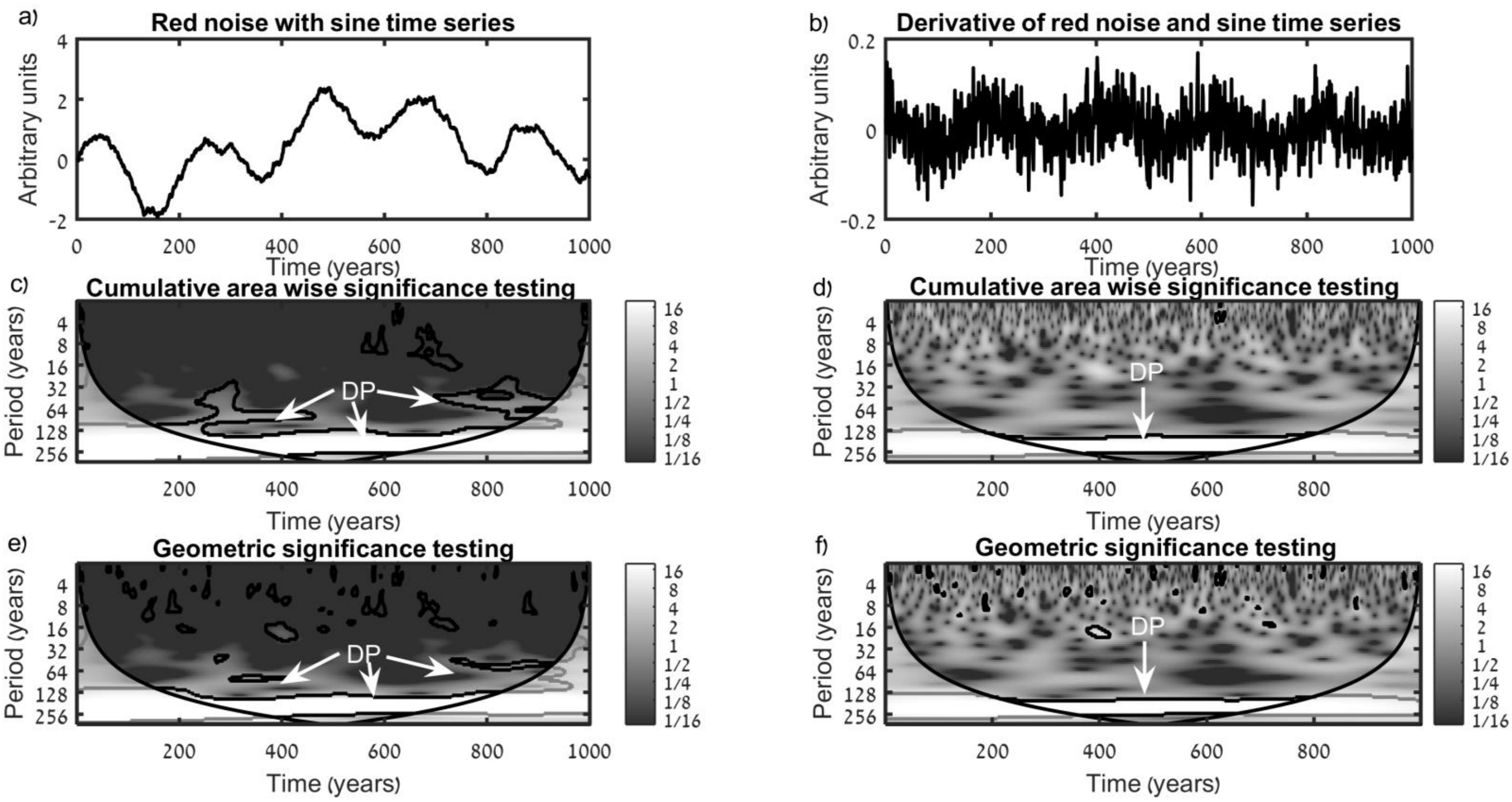


**Figure 7** Same as Figure 1 but for the sine time series added to the red noise time series. Dominant Periodicities (DP) are marked in arrows.

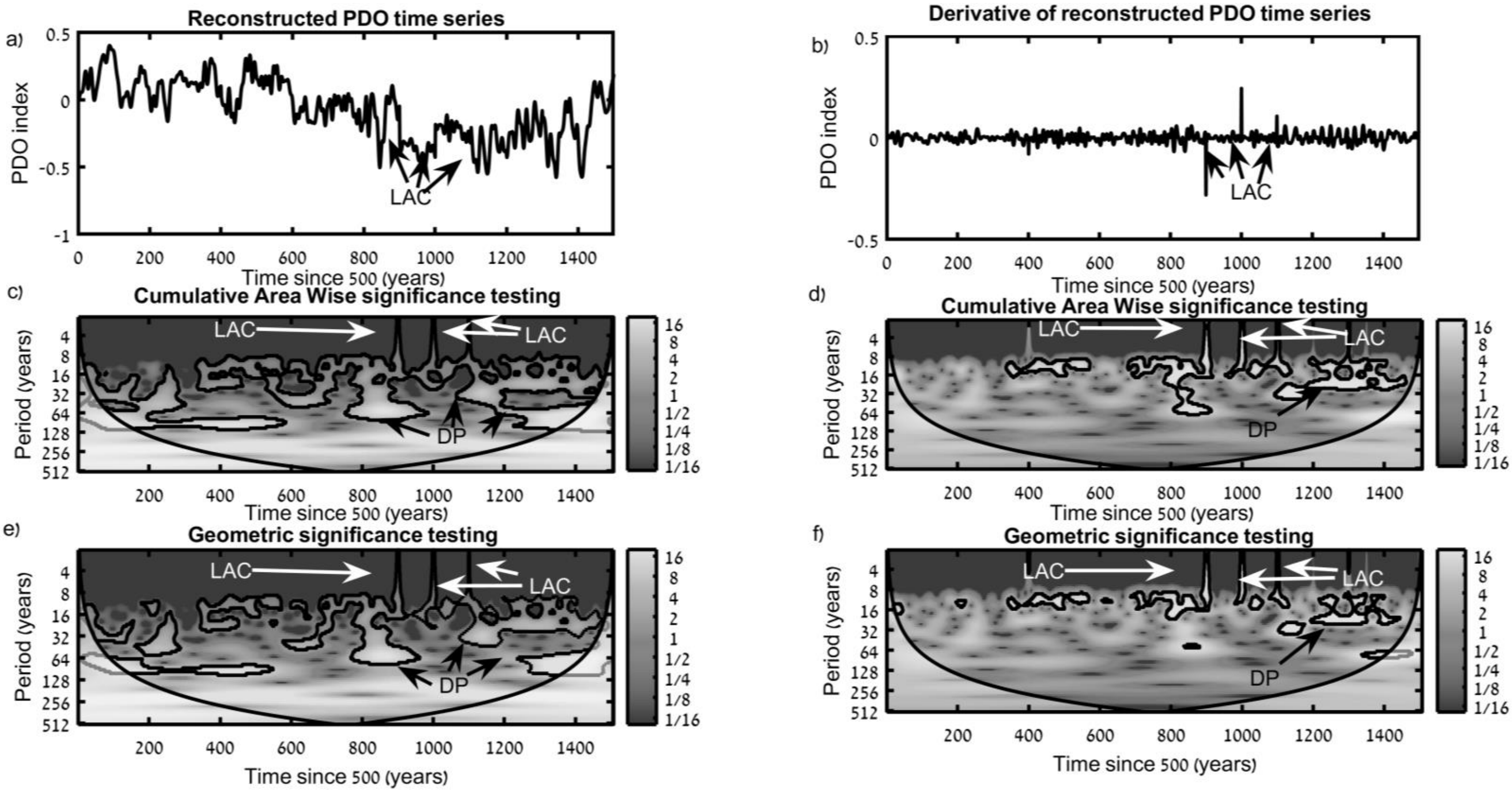


**Figure 8** Same as Figure 1 but for the reconstructed PDO (Mann *et al.*, 2009). Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

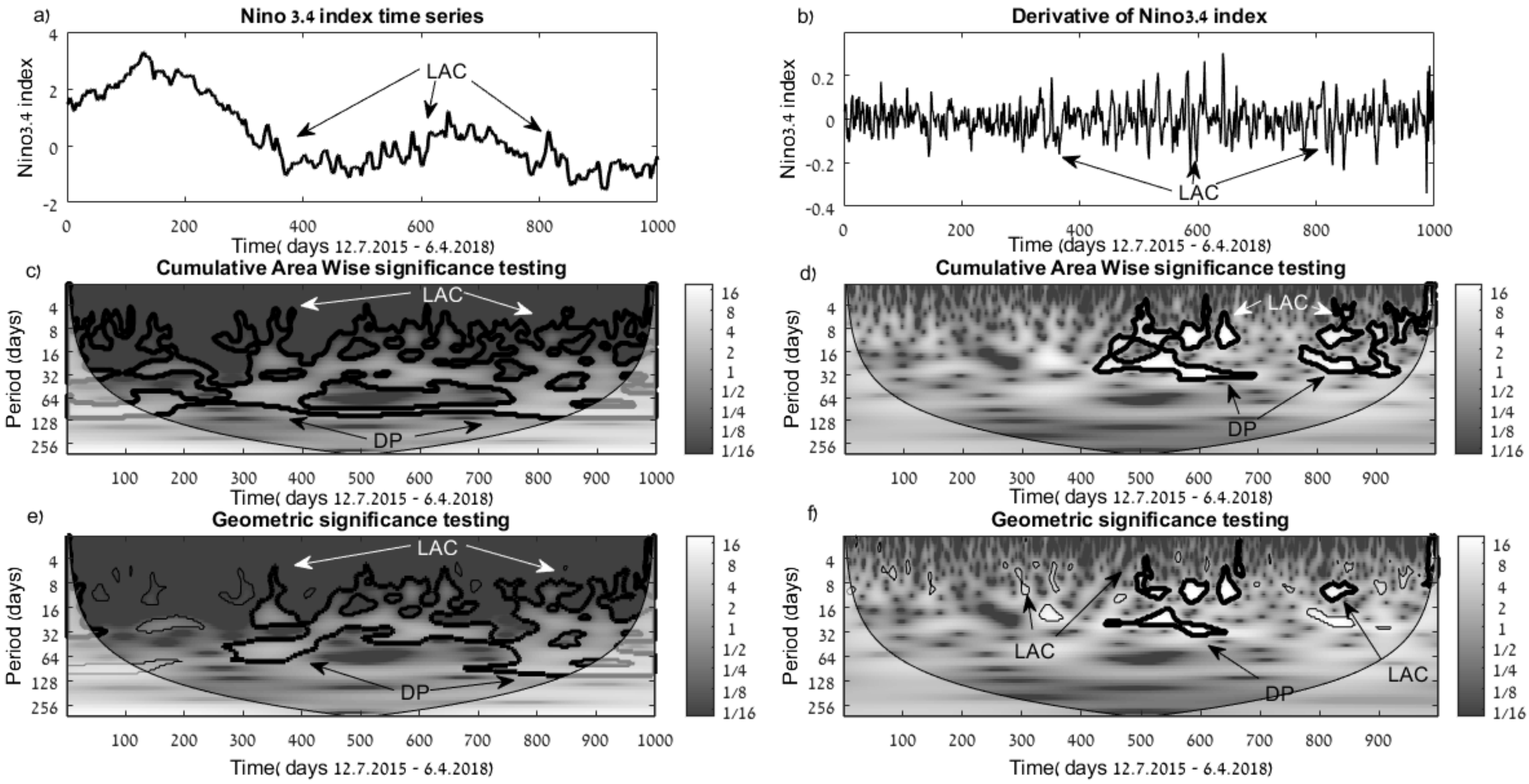


**Figure 9** Same as Figure 1 but for the Nino3.4 index 12.7.2015 – 6.4.2018. Local Abrupt Changes (LAC) and Dominant Periodicities (DP) are marked in arrows.

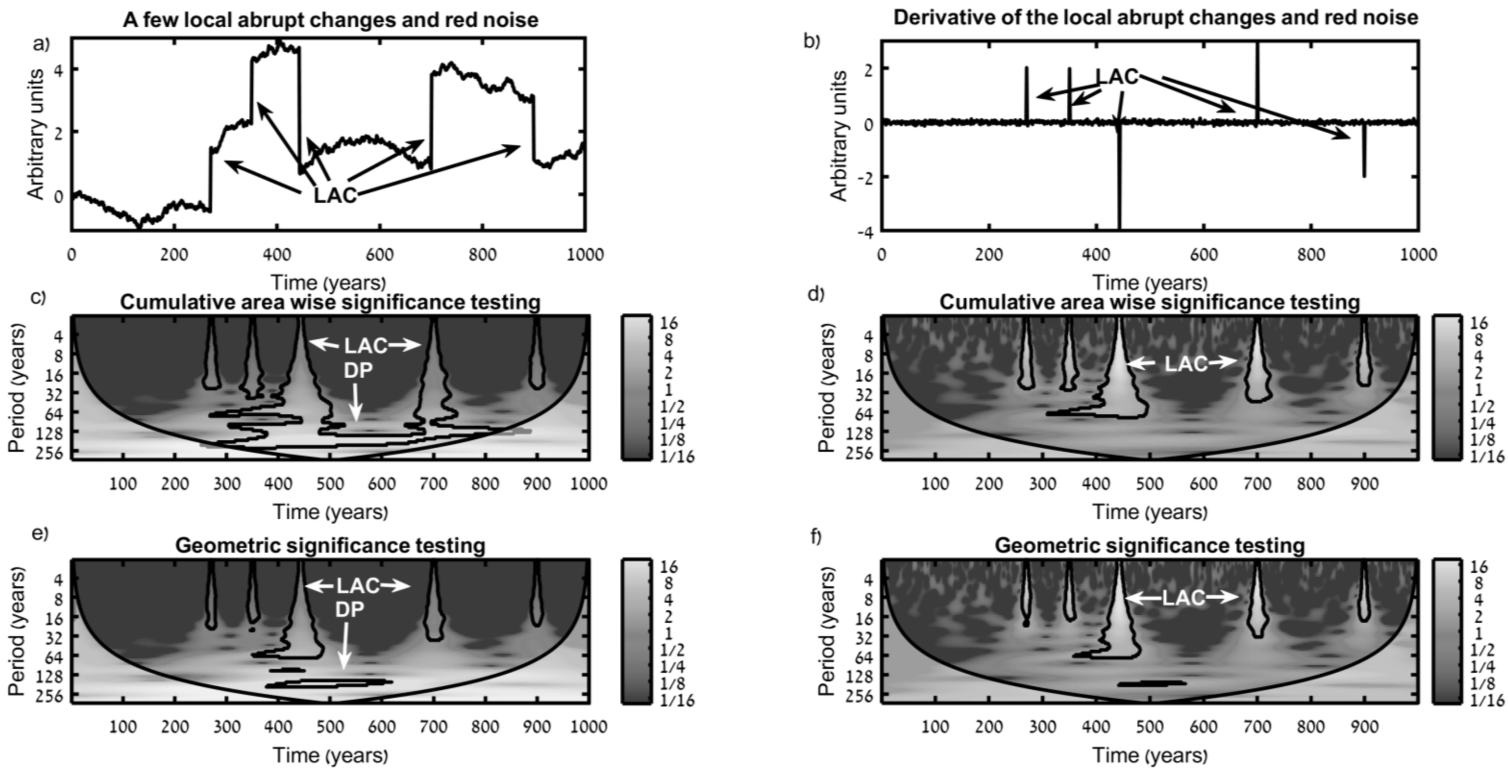


**Figure 10** Same as Figure 1 but for a time series with a few Local Abrupt Changes (LAC) added to red noise.