IMPACTS OF SEASONAL ADJUSTMENT METHODS IN ENSO STUDIES

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Abstract

The El Niño/Southern Oscillation (ENSO) is the most important natural part of the global climate variability and is also a primary source for inter-annual climate variability. Two key indicators of ENSO phenomenon: Southern Oscillation Index (SOI) and the Niño Regional Sea Surface Temperature (SST) Indices measure the ENSO fluctuations over the atmosphere and the ocean, respectively. The values of both indicators are based on anomalies with the annual cycle signals removed (seasonal adjustment) from the data.

Annual cycle signals are usually estimated by the climatological values based on either the whole time period or a selected base period. Either of them would lead to time independent climatological estimates, which is a weak assumption, and the resulting anomalies may alter the conclusions on certain ENSO related phenomena, which are sensitive to the anomaly values.

We compare the climatological seasonal adjustment methodology with three other methods, STL (Loess based Seasonal-Trend Decomposition), DWT (Discrete Wavelet Transform) and EEMD (Ensemble Empirical Mode Decomposition), evaluate their performances, and provide guidelines on which seasonal adjustment methods to choose for handling seasonal variability in climate data processing under different circumstances.

This study also shows that the impacts of seasonal adjustment methods on the correlations analysis between the ENSO atmospheric indicator and the oceanic indicator, and the interpretation of ENSO temporal-spatial patterns are substantial. (a) DWT and EEMD provide a prominent measurement of the correlations among climatic variables and therefore enhance the capabilities of analyzing the relationships among different natural phenomena with inter-annual temporal scales. (b) Inconsistent conclusions on the Eastward-shifting of ENSO peak time over tropical and sub-tropical Pacific obtained from the four seasonal adjustment methods suggests that when one analyzes the inter-decadal variation of ENSO signal, one should choose a seasonal adjustment method with caution since the temporal-spatial patterns could be affected. Applying both fixed and modulated seasonal adjustment methods for the study of temporal-spatial pattern is suggested to achieve a convincing consistent conclusion.

Key Words: El Niño Southern Oscillation (ENSO), Annual Cycle, Sea Surface Temperature (SST)

1. Introduction

The El Niño/Southern Oscillation (ENSO) is the most important natural part of the global climate variability. It is also a primary source for inter-annual climate variability. The ENSO phenomenon is characterized by the appearance of extensive warm surface water over the tropical-subtropical Pacific at 2-7 year intervals (Lau et al. 2000). This phenomenon is featured by the sea surface temperature (SST) and pressure fluctuation occurring in the basins of the central and eastern tropical Pacific and the Indian Ocean (Trenberth 2002). During ENSO events, the dramatic changes in precipitation, temperature, and water vapor patterns in region over the whole world lead to severe natural disasters. Hence, it is vital to develop accurate ENSO measurement, monitor the phase and strength of ENSO events, study ENSO temporal and spatial distribution characteristics, and further understand the intrinsic changing trend of ENSO and its impacts on other natural phenomena.

The two key indicators of ENSO phenomenon are the Southern Oscillation Index (SOI) and the Niño Regional Sea Surface Temperature (SST) Indices, which measure the ENSO fluctuations over the atmosphere and ocean, respectively (Bjerknes 1969). SOI is defined as the difference between deseasonalized, normalized sea-level pressure (SLP) anomalies over Tahiti and Darwin. Niño Regional SST indices are defined as the area-averaged SST anomalies over Niño regions. High negative values of SOI are usually associated with high positive values of SST anomalies indicating a warm event of ENSO called El Niño. The counterpart is called La Niña. Due to the limitation of SOI on spatial dimension, Niño Regional SST indices have become the most popular indicators for monitoring the ENSO events.

In the meteorological scientific community, the legacy approach of seasonal adjustment for anomaly measurement is to treat the seasonal cycle (annual cycle) as a fixed mean effect that does not change every year. The mean of the seasonal cycle is estimated by averaging the climate variable for each individual month over all the available years or over a specified period. These means, called the climatology, are then subtracted from the original data to characterize variability from the mean seasonal cycle. In the following sections, we call this method as the Legacy method.

Obviously, the global mean (the climatology calculated over all the available year) is not appropriate for SST anomaly measurement because it can be distorted by extreme SST values due to the irregular strength of ENSO events. As a result, the SST mean is highly skewed. Moreover, the mean is time dependent because including new data as time goes on will alter the mean values. In order to avoid the skewed time-dependent means, scientists employ base periods to calculate the climatology. The SST records over a selected base period are more representative and not severely impacted by other climatic oscillations.

The base period used to calculate SST anomalies is not unique. For example, the 30-year period between 1961 and 1990 was once suggested by the World Meteorological Organization (WMO) and has been used as the base period in the adjusted optimum interpolation SST analysis (Smith and Reynolds 1998) at National Oceanic and Atmospheric Administration (NOAA). Shea et al. (1992) suggested that the 30-year period between 1950 and 1979 is a good base period because it avoids introduced errors due to the shift from uninsulated-bucket temperatures to ship injection (Folland et al. 1984), and avoids the SST warmings in the Tropics, which began with the 1982-1983 ENSO event (Smith et al. 1994). This base period is considered the most representative records in last century. The most recent updated SST climatology is defined on the base period between 1971 and 2000 because scientists consider SST observations in 1990s having better quality than those in 1960s. This base period is currently used by NOAA National Weather Service (NWS) to calculate Niño Regional SST indices.

It is not difficult to notice the disadvantage of using climatology to measure seasonal cycle in order to extract the anomalies. First, the selection of base period for SST climatology is very subjective. It is based on scientists' experiences and understanding of historical trends to decide the length and temporal location of base period. Second, with the continuous acquisition of new SST observations, the time series are reshaped and scientists need to make timely update on the base period, resulting variation and inconsistency into the SST anomaly measurement. A comparison by Reynolds and Smith (1995) shows that even though the choice of SST climatology might not obscure a moderate to strong El Niño or La Niña event, the exceeding 0.5°C differences between the SST anomalies based on different climatology can lead to confusion about the existence of weak warm or cold ENSO conditions.

Besides the shortcomings of utilizing climatology for seasonal cycle measurement and SST anomalies extraction discussed above, the issue on whether the climatic seasons need to be identical each year was raised. Many studies have shown that the season is the complex nonlinear response of atmosphere, land and oceans (Meyers 1982) and therefore it should not necessarily stay the same from year to year. Significant variations in seasonality have been found in many climate indicators, such as temperature, pressure, and wind (Van Loon et al. 1993; Thomson 1995). Using climatology to extract anomalies ignores the variability of seasonality and mixes up the annual cycle with inter-annual variations, which could mislead researchers in understanding results from ENSO studies.

To improve anomaly extraction accuracy, one has to take into account the seasonal variability. Scientists have explored many alternative methods to capture the variations in seasonal shape. Thomason (1995) measured the seasonal variations using a complex demodulation and suggested that the change in seasonal cycle may be caused by changes in the Sun's luminosity and greenhouse gas. Gu and Philander (1995) suggested that the amplitude of the seasonal cycle is affected by interannual variations in the depth of the thermoncline and in the intensity of the trade winds by using wavelet transform to catch modulation of seasonal cycle. Setoh et al. (1999) employed wavelet analysis to reveal the seasonal cycle changes in ENSO signals between two epochs: 1950-1978 vs.1979-1997 and observed the eastward shifting of ENSO episodes over central and east Pacific ocean. Wu et al. (2008) recommended ensemble empirical mode decomposition (EEMD) to extract the seasonal signal, so one can remove all possible annual and sub-harmonics variations from the original time series.

Although several methodologies have been proposed to measure the seasonal cycle by allowing the seasonal cycle to change from year to year, there is, however, no consensus within the scientific community as to which methodology best captures the seasonal variations. Issues are raised regarding these methodologies, such as (1) their differences and similarities, (2) the effects of methodology implementation on the analysis results, (3) whether there exists a best approach among these methodologies to measure the variations in seasonality, and (4) if the answer to (3) is 'no,' whether one can match a circumstance to the most suitable methodology to apply.

This paper intends to provide a comprehensive interpretation of the seasonal adjustment methodologies for anomaly measurement associated with ESNO studies. Section 2 introduces the SST and SOI data products used in this research. Section 3 describes the seasonal adjustment methodologies that are implemented to measure the seasonal variations. Section 4 evaluates the performances of various seasonal adjustment methods and compares them at both absolute and relative values through Niño regional SST indices comparison, the correlation with SOI, and ENSO temporal-spatial distribution patterns. Section 5 draws the conclusions.

2. Data Sets

The SST datasets used in this study are Hadley Centre Global Sea Surface Temperature (HadISST) datasets, available from National Center for Atmospheric Research (NCAR) website. The data product provides the 1° by 1° latitude and longitude spatially complete, monthly SST analysis for 1871 to date (Rayner et al. 2006).

The SST anomalies based on Niño-1+2, Niño-3, Niño-3.4, and Niño-4 regions in central and eastern equatorial Pacific are calculated since they are most common indices to monitor ENSO events (e.g., Handley et al. 2003; Barnston et al. 1997; Trenberth & Stepaniak 2001).

The monthly SOI is calculated based on standardized sea level pressure difference between Tahiti and Darwin, Australia and has been considered as an optimal index that combines the SO into one series. The correlation coefficient between SST indices and SOI is around -0.67 based on the Legacy method. A sustained negative SOI and positive SST indicate an El Niño episode. Conversely, a lasting positive SOI and negative SST indicate a La Niña Event.

The SOI datasets as well as the SLP values for Tahiti and Darwin are available from the website of Climate & Global Dynamics Division (CGD). In this study, the SOI values are calculated based on the same algorithm used by Ropelewski and Jones (1987) but with different seasonal adjustment methods for anomalies.

3. Methods for Seasonal Adjustment

Different methods for obtaining anomaly values are used for studies of climate related phenomena, and the challenging task is the seasonal variation modeling. Cleveland (1990) stated that there exists an intrinsic ambiguity in the definition of seasonal variation. In fact, this ambiguity is true for all seasonal decomposition procedures (Carlin and Dempster 1989). Moreover, seasonal variation highly depends on the characteristics of time series. Data from different problems could have very different shape of seasonal variation. For example, the seasonality of an economic time series is not only influenced by the climatic change, but also impacted by holiday calendars. Hence, to successfully separate seasonal, trend and other cyclical variations and to avoid seasonal and other components competing for variation, not only depend on the selection of models, but also rely on the choice of model input parameters. In this paper, four seasonal adjustment methods, the so called legacy method, the seasonal–trend decomposition procedure based on loess (STL), Discrete Wavelet Transform (DWT) and Ensemble Empirical Mode Decomposition (EEMD) procedure are discussed.

- **Legacy Method**

The Legacy method is to treat the seasonal cycle as a fixed mean effect that does not change every year. The mean of the seasonal cycle, called climatology, is estimated by averaging a climate variable for each individual month over a specified period. These means are then subtracted from the original data to characterize variability from the mean seasonal cycle. The methodology is simple and straightforward, but unavoidably has drawbacks previously described. In this work, this method is used as a benchmark to compare to other seasonal adjustment methods. The anomaly estimation from the legacy method is calculated as:

$$Anomaly_{Legacy} = MA_3\left(Y - S_{Legacy}\right), \tag{1}$$

where MA_3 represents the 3 month moving average, Y represents the original time series and S_{legacy} is the climatology, the mean of a climate variable for each individual month over the base period 1971-2000.

- **Seasonal–Trend Decomposition Based on Loess (STL)**

STL is a filtering procedure for decomposing a time series into trend, seasonal, and remainder components (Cleveland et al. 1990), or in short, $Y=S+T+R$, where Y is the data, S is the seasonal component, T is the trend component, and R is the remainder. STL has a simple and efficient computer implementation that consists of a sequence of applications of the loess (local weighted regression) smoothers (Cleveland & Devlin 1988).

STL consists of two recursive procedures: an inner loop nested inside an outer loop. The seasonal and trend components are updated in each pass of inner loop. Each pass of the outer loop consists of a group of the inner loops followed by a computation of robustness weights. The robustness weights are used in the next run of inner loop to reduce the impacts of transient and aberrant abnormal behavior on the trend and seasonal components.

The anomaly estimation from STL method is calculated as:

$$Anomaly_{STL} = MA_3\left(Y - S_{STL}\right) \tag{2}$$

and S_{STL} is the estimated seasonal component from STL procedure. STL algorithm provides the flexibility in specifying the amounts of variation in the trend and seasonal components through the inner loop. It also captures the robust trend and seasonal components that are not distorted by transient, aberrant behavior in the data using the robustness weights in the outer loop.

One difficult with the STL is that there are many parameters involved in the procedure. Selecting the appropriate parameters is important as it could significantly affect the amount of seasonal variation (the smoothness of seasonal component). STL algorithm has six parameters. They are (1) $n_{(i)}$: the number of passes in the inner loop; (2) $n_{(o)}$: the number of passes in the outer loop; (3) $n_{(p)}$: the number of observations in each cycle of the seasonal component; (4) $n_{(l)}$: the smoothing parameter for the low-pass filter; (5) $n_{(t)}$: the smoothing parameter for the trend component; and (6) $n_{(s)}$: the smoothing parameter for the seasonal component. The disciplines to choose values for these parameters are given in Cleveland et al. (1990). Only one of the parameters, $n_{(s)}$, is discussed below.

The values of $n_{(s)}$ affect the smoothness of each cycle-subseries, series of monthly values of the same month in all years. The choice of $n_{(s)}$ also determines the variation in the data that makes up the seasonal component. A STL diagnostic graphical method such as the seasonal-diagnostic plot could be helpful to decide $n_{(s)}$. Fig. 1 shows the seasonal-diagnostic plot for the Niño-3.4 SST time series with different $n_{(s)}$. As $n_{(s)}$ increases, the resulting cycle-subseries becomes smoother. When $n_{(s)}$ goes to infinite, each cycle- subseries becomes a horizontal line with no variance, which implies the seasonal component estimated from STL becomes a climatology, that is, the mean of the climate variable for each individual month over all the available years. In many situations, the final decision for $n_{(s)}$ value is based on knowledge about the mechanism generating the series and the goal of analysis.

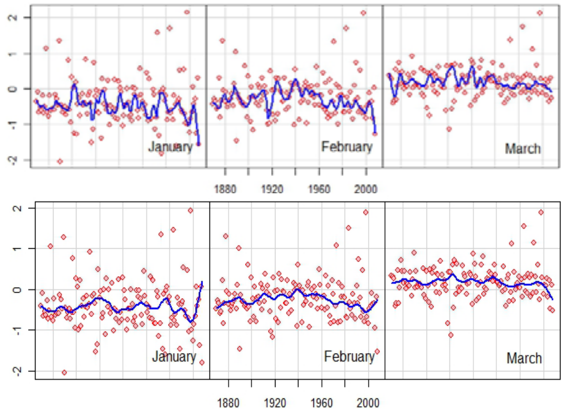

Fig. 1. Seasonal-Diagnostic Plot for Niño-3.4 SST time series with $n_{(s)}$ = 7 (top panel) and $n_{(s)}$ = 15 (bottom panel). The ordinate of each panel is the temperature in °C. The lines represent the normalized seasonal component by the global mean. The dots are the normalized seasonal component plus the remainder.

- **Discrete Wavelet Transform (DWT)**

DWT transforms a discrete signal into a discrete wavelet representation, and DWT algorithms are easy to implement and computationally efficient. DWT uses one high-pass filter and one low-pass filter to transform the time series into one set of detail coefficients (cD_1) and one set of approximation coefficients (cA_1). This transformation is usually applied recursively on the approximation coefficients until the desired number of iterations is reached. At the end of the iterations, one obtains $cA_i, cD_i, cD_{i-1}, ..., cD_1$, where i is the number of iterations. After one decides which scale of cD needs to be removed, the approximated signal is reconstructed using only the approximation coefficients and the rest of the detail coefficients. This algorithm allows us to reconstruct the signal using only the desired scales by removing certain scale details from the original series.

The equation to estimate the anomaly using DWT is

$$Anomaly_{DWT} = A_i - mean(A_i), \tag{3}$$

where A_i is the i-th level approximation and i (the number of decomposition levels for DWT) should be determined so that the seasonal signals are removed in the detail functions of the previous levels (Yu 2010). In this work, Daubechies 7, an asymmetric and orthogonal wavelet basis, is chosen to perform DWT (Kaiser 1994) using Matlab 'Wavedec' function (Mallat 1989).

- **Ensemble Empirical Mode Decomposition (EEMD)**

Empirical Mode Decomposition (EMD) (Huang et al. 1998) is a method of breaking down a signal without leaving the time domain. It is a powerful tool for adaptive multiscale analysis of nonstationary signals. The process is useful for analyzing natural signals, which are most often non-linear and non-stationary. EMD filters out functions, which form a complete and nearly orthogonal basis for the original signal. The functions, known as Intrinsic Mode Functions (IMFs), are sufficient to describe the signal, even though they are not necessarily orthogonal. The fact that the functions into which a signal is decomposed are in the time-domain and of the same length as the original signal allows varying frequency in time to be preserved.

The process of EMD is known as “sifting through envelopes” (Huang et al. 1998). Through this process, a time series is decomposed in to a group of IMF components and a remainder, which is either very small or monotonic, and the whole decomposition is guaranteed to be completed with a finite number of modes (Rilling 2003). In the EMD process, high frequency signals will be picked up first. The process can stop at any level, and of course, the remainder in this case contains low frequency signals.

One problem with EMD is the mode mixing as an IMF consisting of oscillations of dramatically different scales, or more than one IMFs containing signal of the same or comparable scales (Wu and Huang 2009). Ensemble Empirical Mode Decomposition (EEMD), a noise-assisted data analysis method, is an enhanced version of EMD designed primarily for solving the mode-mixing problem (Wu and Huang 2009). In EEMD, a random white noise with zero mean and variance α^2 is added to the original data before applying the EMD procedure. The EMD steps are repeated n times and the ensemble IMFs from the n samples will be the resulting IMFs.

The standard deviation of error introduced into the final ensemble IMFs is $\alpha' = \alpha/sqrt(n)$, and α and n are the key parameters affecting the decomposition results of EEMD. If α is too small, the noise may not affect the local extrema enough to solve the mode-mixing issue. When α is too big, significant noise will be brought into the data if the ensemble sample size n is not big enough. However, if large α has to be introduced, we can increase the ensemble sample size n in order to make α' trivial.

The equation to estimate anomaly using EEMD is given as

$$Anomaly_{EEMD} = r_i - mean(r_i), \qquad (4)$$

where r_i is the i-th level residue and i is the number of decomposition levels for EEMD that is decided by a computational algorithm (Yu 2010).

4. Sensitivity of ENSO to Season Adjustment Methods

To analyze the impacts of seasonal adjustment methods on the ENSO studies, two types of comparison are performed to capture the whole picture. One is absolute value comparison, which is to directly compare the values of SST anomaly estimations (e.g., Thomson 1995; Trenberth 1997; Trenberth et al. 2001). The other is relative values comparison by comparing SST anomaly estimations through a pattern or distribution (*e.g.*, Rasmusson & Carpenter 1982; Wang 1995).

Four seasonal adjustment methods are carried out to estimate SST and SLP anomalies. Both Niño regional SST indices and SOI are processed using SST and SLP anomalies derived by these methods. The effects of the seasonal adjustment methods on the amplitude of SST anomaly values are examined by performing a direct comparison on the SST anomaly values; recalculating the correlation coefficients between Niño regional SST indices and SOI; and investigating the temporal-spatial distributions based on CWT and PCA and the sensitivity of the ENSO temporal-spatial patterns to the seasonal adjustment methods (Yu 2010). Only selected results on the direct value comparison, correlation coefficients, and the spatio-temporal patterns are briefly described here.

The parameters selected are based on a hypothesis testing mechanism and the testing results. The specific values for $n_{(s)}$ are 11 for Niño-3.4 SSTA and 17 and 13 for Darwin and Tahiti SLP, respectively in STL procedure. In EEMD, α is 0.8 for Nino-3.4 index and 0.6 for SLP, and the sample size (n) is 400 for all cases. Three levels are chosen for both DWT and EEMD methods (i=3). The base periods for the legacy method are 1971-2000 for SST and 1951-80 for SLP, respectively.

- **Direct Comparison**

Unlike STL, DWT and EEMD separate not only the 12-month periodic harmonic but also all sub-annual signals from the original SST time series. Therefore, SST anomalies from DWT and EEMD are smoother than those processed by the Legacy and STL methods. The wavelet power spectrum show nearly zero wavelet power for high frequency signals in DWT and EEMD spectrum maps with the removal of all sub-annual variations (see Fig. 4). Hence, the three months running mean is not necessary for SST anomaly estimations for DWT and EEMD. Fig. 2 shows the time series of Niño-3.4 SSTA index from 1870 to 2008 processed by all four seasonal adjustment methods. Compared to the Legacy method and STL,,both DWT and EEMD methods result in smoother time series and smaller amplitude.

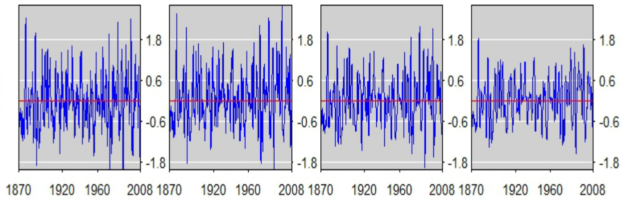

Fig. 2. Niño-3.4 SSTA Index (°C) Time Series over 1870-2008 using Legacy, STL, DWT and EEMD (from left to right) methods.

- **Correlation**

The correlation coefficient between SOI and SST anomalies measures how closely SO and El Niño phenomenon correlates. For example, Hanley et al. (2003) examined the different Niño Regional SST indices by correlating those indices with SOI. By evaluating the correlation coefficients between Niño regional SST indices and SOI, both processed by different seasonal adjustment methods, one can examine whether seasonal adjustment methods have an impact on the correlation measurement between the two climatic indicators. Both Pearson’s product moment coefficient (parametric) and Spearman’s rank correlation coefficient (nonparametric) are employed because Pearson’s coefficient can be adversely affected when there are outliers and it can only measure linear relationships between variables. Both correlation measures give very similar results here, and therefore, only the results of Pearson’s correlation coefficients between SOI and Niño-3.4 SST index are given in Table 1. Associated with each correlation value, a 95% confidence interval (CI) based on the bootstrap simulation is also given.

The correlation result suggests that different seasonal adjustment methods have significant impacts on the correlation measurement. For example, the correlation coefficient between Niño-3.4 SST index and SOI computed from Legacy method is -0.62 with [-0.65, -0.59] 95% confidence interval. By using either DWT or EEMD method, the correlation coefficient is increased to -0.82 with [-0.84, -0.8] 95% confidence interval. Our study further suggests that modulated seasonal component estimation using a seasonal adjustment method, provides a more explicit measurement of the correlations among climatic variables and therefore enhance the analysis of relationships among natural phenomena. The impacts of different seasonal adjustment methods on correlation coefficients also are applicable to the analysis to teleconnection (Glantz 1991; Trenberth 1997) and the climate network (Tsonis et al. 2006; 2008).

Table 1. Pearson Correlation Coefficient (CC) values and confideence interval (95% CI) between SOI and Niño-3.4 SST Index.

Methods	CC	95% CI
Legacy	-0.62	[-0.65, -0.59]
STL	-0.74	[-0.76, -0.71]
DWT	-0.82	[-0.84, -0.80]
EEMD	-0.82	[-0.84, -0.80]

- **Eastward-Shifting of ENSO Spatial Pattern**

The EOF analysis results show empirically that the choice of seasonal adjustment methods does not affect the spatio-temporal patterns. However, if one were to monitor the changes of spatio-temporal patterns along either spatial or temporal domain, the seasonal adjustment method needs to be carefully chosen. In this work, the eastward-shifting of ENSO spatial pattern is investigated to highlight this point.

The length, strength, regime of ENSO events was changed significantly after 1976. Comparisons on the earlier (1950-1978) and later (1979-1992) ENSO epochs have been discussed in many papers (e.g. Nitta and Yamada 1989; Mitchell and Wallace 1996; Setoh et al. 1999). Compared to the ones before 1976, scientists stated that the 'later' ENSO episodes (after 1976) have longer timescale, increased SST anomalies over central and eastern tropical Pacific, and the eastward-shifted regime where the peak of ENSO event occurred.

Fig. 3 shows the wavelet power spectrum of CWT for the averaged SSTA based on the legacy method along every 10^o longitude band between 5^{o}N-5^{o}S latitude. There are three major ENSO epochs in the 1971-1973, 1986-1988, and 1997-1998 time frames with strong wavelet power in the 2-8 years commonly known ENSO periods. The events during 1970s started to peak in the central Pacific between 140^{o}W-130^{o}W and the events after 1980 have the highest intensity in the eastern Pacific starting at 100^{o}W-90^{o}W. However, the results from the EEMD based SSTA in Fig. 4 show that all three epochs tend to peaked at the same longitude band, 100^{o}W-90^{o}W. As mentioned before, the results based on STL are similar to those based on the legacy method and the results from DWT are similar to those based on EEMD.

This observation implies that the seasonal variation causes the eastward shifting of ENSO peak time as the removal of seasonal variations from SST using DWT and EEMD largely weakens the eastward-shifting phenomenon. This implication suggests that there is doubt on whether there truly exists the eastward shifting in the regime of ENSO peak time as the inter-decadal variation of ENSO signal or the eastward shifting could just be a result of the inter-annual variation of seasonal cycle.

The above discussion underscores the importance of seasonal adjustment method for anomaly measurement when analyzing a changing process of phenomena associated with ENSO. The best way to validate the analysis result is to draw consistent conclusion by comparing results obtained from both legacy and DWT/EEMD methods.

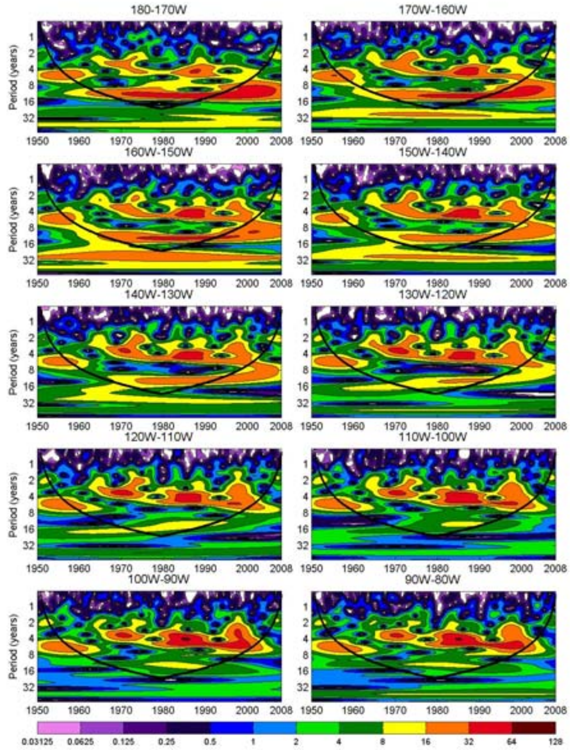

Fig. 3. Wavelet power spectrum for SSTA time series based on the Legacy method. The heavy black line is the 'cone-of-influence' line (Torrence & Compo 1998).

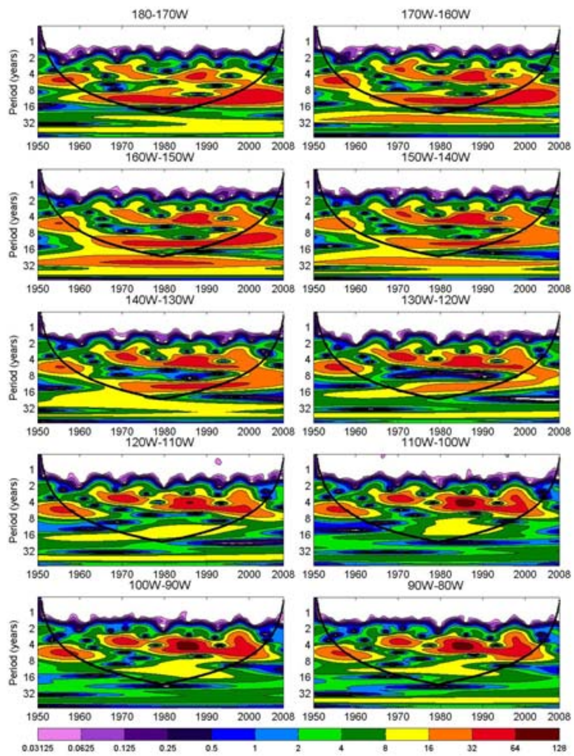

Fig. 4. Same as Fig. 3 except for SSTA based on EEMD method.

5. Concluding Remarks

Compared to the Legacy method and STL, DWT and EEMD have smoother estimations of SST anomalies as they remove both annual and sub-annual variations from the original data. They also provide a prominent measurement of the correlations among climatic variables and therefore enhance the capabilities of analyzing the relationships among different natural phenomena with inter-annual temporal scales. The four seasonal adjustment methods show the different spatial location of the emerging peak time of ENSO epochs over tropical and sub-tropical Pacific, and the results suggest that when analyzing the inter-decadal variation of ENSO signal, one should carefully choose a seasonal adjustment method since the temporal-spatial patterns could be affected. Applying both fixed and modulated seasonal adjustment methods for the study of temporal-spatial pattern is suggested in order to obtain a convincing consistent conclusion. The same strategy should be applied to study the regional and local impacts of ENSO and other inter-annual climate events.

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