Low-Frequency Minimum Temperature Variability Throughout the Southeastern United States during the 1970s: Regime Shift or Phase Coincidence?

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LOW-FREQUENCY MINIMUM TEMPERATURE VARIABILITY THROUGHOUT THE SOUTHEASTERN UNITED STATES DURING THE 1970S: REGIME SHIFT OR PHASE COINCIDENCE?

By:

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<th>Description</th>
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<tr>
<td>°F</td>
<td>Degrees Fahrenheit</td>
</tr>
<tr>
<td>AMO</td>
<td>Atlantic Multidecadal Oscillation</td>
</tr>
<tr>
<td>EEMD</td>
<td>Ensemble empirical mode decomposition</td>
</tr>
<tr>
<td>ENSO</td>
<td>El Niño Southern Oscillation</td>
</tr>
<tr>
<td>EOF</td>
<td>Empirical orthogonal function</td>
</tr>
<tr>
<td>GCM</td>
<td>Global climate model</td>
</tr>
<tr>
<td>GrADS</td>
<td>Grid Analysis and Display System</td>
</tr>
<tr>
<td>LFS</td>
<td>Low-frequency signal</td>
</tr>
<tr>
<td>MAC</td>
<td>Modulated annual cycle</td>
</tr>
<tr>
<td>NCDC</td>
<td>National Climatic Data Center</td>
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<tr>
<td>PC</td>
<td>Principal component</td>
</tr>
<tr>
<td>PDO</td>
<td>Pacific Decadal Oscillation</td>
</tr>
<tr>
<td>PNA</td>
<td>Pacific/North American</td>
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<tr>
<td>SLP</td>
<td>Sea level pressure</td>
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<tr>
<td>SST</td>
<td>Sea surface temperature</td>
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<tr>
<td>TAC</td>
<td>Traditional annual cycle</td>
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ABSTRACT

The low-frequency signals (LFS) of climate variables such as temperature and pressure often contain variability as a result of the nonlinear and non-stationary nature of Earth's climate system. Occasionally, as in the case of the North Pacific climate regime shift of the mid-1970s, this variability appears in the form of an abrupt shift in climate states. Because such variability can have large impacts on agriculture, wildfire frequency/intensity, and ecological systems, it is important to pursue a more complete understanding of low frequency climate interactions. Previously, techniques such as fourier, windowed fourier, and wavelet analyses were used to extract the LFS. However, these techniques rely on an assumption of linearity, and thus when applied to nonlinear climate data, can potentially cloud the physical meaning of the extracted LFS.

In this study a recently developed adaptive and temporally local analysis method—ensemble empirical mode decomposition (EEMD)—is applied to extract the LFS from observed daily minimum temperature data. The analysis uses data from 115 weather stations scattered throughout North Carolina, South Carolina, Georgia, Alabama, and Florida for the period from 1955 through 2007. An EOF analysis of the minimum temperature LFS reveals a large drop in the first PC time series in the mid-1970s. Further EOF-based analysis of the low-frequency variability leads to different interpretations of the characteristics of surface temperature variability. Most notably, the widely recognized shift of low-frequency variability around the mid-1970s can be alternatively interpreted in the Southeastern United States as phase coincidence between individual quasi-oscillatory components of interannual to decadal timescales.
CHAPTER 1

INTRODUCTION

1.1 Background

Climate variability occurs on numerous temporal scales, ranging from annual and interannual to decadal and multidecadal. Decomposing a set of climate data into its frequency components provides valuable insights into the physical processes that may be affecting global or regional climate systems. Of the many modes of climate variability that occur, some that have piqued the interest of climate researchers in recent years are those that occur at interannual, decadal, and multidecadal frequencies. This low-frequency variability, examples of which include such physical phenomena as the El Niño Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the Atlantic Multidecadal Oscillation (AMO), must be better understood to improve regional and global climate prediction. For example, Tourre et al. (2001) applied a multi-taper method/singular value decomposition technique to SST and sea level pressure (SLP) data to examine patterns of coherent decadal and interdecadal climate signals in the Pacific Basin in an effort to improve climate prediction. Such research has the potential to help provide those within the scientific community with a more complete understanding of the climate system, and also to give those involved in operational climate prediction tools for improved forecasting. These improvements in climate forecasting may help alleviate the impacts of recurring drought/flood (Balmaseda et al. 1995).

In addition to providing crucial information and understanding for prediction purposes, analysis of the low-frequency signal (LFS) can be useful in examinations of past climate events. Filtering out the high-frequency signal and annual cycle associated with daily data allows the characteristics of interannual and decadal climate variability to be more easily identified. One such notable event that appears in low-frequency climate data and that will be the primary focus of the research presented in this paper has been referred to as the North Pacific climate “regime shift” of the mid-1970s (Tsonis et al. 2007). A shift is defined as an abrupt change in the characteristic state of a climate
system relative to the duration of the characteristic state or regime (Hare and Mantua 2000). A regime, by definition, must exist as the characteristic state for a decade or longer. A shift, however, occurs within one to two years.

Evidence for an apparent regime shift in the mid-1970s was clearly observed in changes in large-scale boreal winter circulation patterns in the North Pacific (Trenberth 1990; Graham 1994). These changes included a southward shift and intensification of the Aleutian Low, which resulted in numerous physical and biological impacts on a wide array of ocean and land ecosystems in the Pacific Northwest (Francis and Hare 1994; Anderson and Piatt 1999; McGowan et al. 2003). Trenberth (1990) found that from 1977 to 1988, averaged November through March pressures over the North Pacific were lower by 2 mb (Fig. 1.1). The short length of the time series used in the Trenberth (1990) study however, makes it difficult to draw conclusions regarding the existence of a shift. For example, if the time series in Fig. 1.1 is extended into the 1990s, it may indicate a more oscillatory pattern on a timescale similar to that of the Atlantic Multidecadal Oscillation. The potential role of low-frequency oscillatory components in the mid-1970s event will be a focal point in this research.

In addition to Trenberth’s work, Hare and Mantua (2000) used 69 biological time series in addition to 31 climatic time series to provide empirical evidence for a regime shift in the North Pacific. They discovered notable changes in SST, air temperature, fish recruitment, zooplankton mass, and numerous other variables in and around the North Pacific after the mid-1970s climate event. Several others have also examined the existence and nature of this apparent shift in climate regimes. Wallace et al. (1991) used a phase-space analysis to suggest that low-frequency climate oscillations appear to exhibit regime-like behavior, and Karspeck and Cane (2002) modeled the regime shift using a linear, wind-driven model. On the basis of these and other studies, the existence of North Pacific climate regime shift is generally accepted by climate scientists.

Although the importance of these observed changes in boreal winter circulation patterns are generally accepted as evidence for a regime shift, the actual causal mechanism for the shift continues to be debated. Trenberth (1990), for example, suggested that increased SSTs resulting from a series of three El Niño events and no corresponding La Niña events could alter North Pacific circulations. However, it was
also noted that this teleconnection alone could not explain the abrupt shift in the Aleutian Low given that the low remained strong even in non-El Niño years. Graham (1994) attributed the shift observed in the Pacific Northwest to changes in sea surface temperatures and organized convection over the tropical Pacific on the basis of evidence obtained through global climate model (GCM) experiments. Wu et al. (2005), however, attributed the North Pacific shift to a response to persistent wind stress anomalies in the previous decade. Additionally, several papers have discussed the need to examine whether the regime shift occurred through natural variability or as the result of an external—possibly anthropogenic—forcing (Trenberth 1990; Graham 1994).

Although many scientists have studied the mid-1970s regime shift with respect to the Pacific Northwest, regional studies that discuss the effects of this climate event elsewhere in the United States are less common. Trenberth (1990) briefly discussed an observed decrease in surface temperatures for the period 1977–1986 in the eastern United States, which is thought to have occurred in association with the Pacific/North American (PNA) teleconnection.

The PNA (Fig. 1.2) is an important atmospheric teleconnection that occurs on an interannual timescale and links upper tropospheric geopotential heights over the Northern Pacific Ocean to height fields in the continental United States (Leathers et al. 1991). The mean flow over the PNA region is characterized by a trough over the North Pacific, a ridge over the Rocky Mountains, and a trough over eastern North America. Departures from this mean flow include PNA anomaly centers over the North Pacific and the southeastern United States. Konrad (1998) showed that the Northwestern and Southeastern United States are two of the most highly correlated regions affected by the PNA. The deepening and southward migration of the Aleutian Low would result in more meridional flow across the continental United States as seen in Fig. 1.2. As Trenberth (1990) observed, these PNA anomalies would be associated with decreased heights across the southeastern United States. On the basis of this research then, it is reasonable to hypothesize that the climate event of the mid-1970s would have an impact on the climate of the southeastern United States. However, because the PNA occurs on an interannual timescale, there is a possibility that different quasi-oscillatory low-frequency components somehow interact to cause this climate event in the mid-1970s. Detailed
regional analyses focused on this event and the low-frequency patterns associated with it are sparse.

1.2 Motivation and Objectives

With the potential to impact crop production in numerous agricultural industries ranging from citrus to cotton to peanuts, climate variability and associated climate events are of great importance to the Southeastern United States. There has also been extensive urban expansion throughout the second half of the 20th century in areas such as Atlanta, Georgia, and Miami, Florida (Solecki 2001; Yang 2002). As climatic variables such as temperature and rainfall can have significant effects on energy consumption needs and urban planning, understanding the nature of climate variability in this region is of great importance. Additionally, wildfire frequency and intensity is known to vary greatly as a result of climate teleconnections (Brenner 1991; Beckage et al. 2003). Given the possible implications for agriculture and natural ecosystems in the area, a climate regime shift in the Southeastern United States associated with these events in the North Pacific would be an important feature of climate variability to understand. The research presented here seeks to understand the effects the mid-1970s North Pacific event may have had on the Southeastern United States. Using Trenberth’s (1990) observations of lower surface temperatures throughout this area as initial evidence, this study will use surface temperature data from the region of interest to analyze in greater detail the nature of this climate event. To attain this goal, an adaptive analysis technique (ensemble empirical mode decomposition) will be applied to accurately extract the LFS. Because the North Pacific event is generally thought to be associated with low-frequency variability (Wallace 1991; Minobe 1999), focusing on the low-frequency component of the temperature time series allows for clear identification of any large surface temperature decreases possibly associated with a regime shift.

The opportunity to use a modulated annual cycle (MAC) as the frame of reference for extracting the LFS is an important motivating factor for this research. In previous studies that examined temperature anomalies, the annual cycle was extracted from the dataset using either climatology, some kind of windowed filtering technique, or in some cases, was not extracted at all (Walsh and Richman 1981; Konrad 1998; Schneider et al.
In these studies the temperature anomalies were typically defined as deviations from a traditional annual cycle (TAC), which is the component of variability that is a function of month but not of year (Wu et al. 2008). Defined in this manner, the TAC does not experience changes in amplitude or frequency from year-to-year. Using this subjectively-defined TAC as a reference frame for defining climate anomalies therefore assumes that the climate system is stationary. However, because of nonlinear forcings, the climate system is known to exhibit nonstationary behavior. Because of these nonstationary and nonlinear characteristics, Wu et al. (2008) proposed a new reference frame in which to define the annual cycle. This modulated annual cycle (MAC), which can be extracted using the EEMD method previously mentioned, is allowed to vary in both amplitude and frequency. Unlike the subjectively-defined TAC, the locally-defined MAC is an intrinsic property of the data. Since the anomalies associated with the alternative reference frame of a MAC are different than those associated with a TAC, the physical explanations for the anomaly may be different (Wu et al. 2008). Figure 1.3 illustrates the confusion that can arise when using a TAC to define the annual cycle. When the anomaly is extracted by subtracting out the TAC, an oscillation of an annual timescale remains present in the anomaly. This is likely because, as a result of the nonlinear response of the climate system to the periodic forcing of the sun, the annual cycle exhibits changes in amplitude and frequency from year to year. Such modulation in amplitude and frequency is not captured by the TAC and is instead assumed to be part of the anomaly. This was demonstrated by examining the nature of ENSO phase locking to the annual cycle using the MAC as a frame of reference. On the basis of these results, which used the Pacific cold tongue index (CTI), Wu et al. (2008) suggested that the ENSO phase locking to the annual cycle may actually be a consequence of the TAC. He shows that the residual annual cycle, which is defined as the difference between the MAC and the TAC, has been considered in previous studies as part of the anomaly (based on a TAC). When viewed in the context of a MAC, however, this phase-locking is seen to be the superposition of the MAC onto interannual variability.

On the basis of the Wu et al. (2008) conclusions regarding the importance of the MAC, this research uses an MAC reference frame to examine the LFS temperature signal
in the Southeastern United States. What others may have interpreted as temperature anomalies in the TAC-defined reference frame may actually be included in the MAC in this analysis. Thus, the LFS extracted using the MAC as a frame of reference will appear different than the LFS extracted using the TAC as a frame of reference. Applying this climate reference frame rather than the traditionally defined reference frame will potentially lead to new physical explanations for low frequency climate variability, including any large changes observed during the mid-1970s, within the Southeastern United States.

In addition to examining the existence of regional changes in the minimum temperature LFS, this research seeks to better understand the nature of these changes in the Southeastern United States. The primary objective here is to determine whether any changes in the surface temperature signal that occurred during the mid-1970s can be attributed to either an actual shift in climate regimes or to mode interactions between two or more different low-frequency oscillations. For example, if the minimum temperature LFS appears to recover from any shifts experienced in the mid-1970s within a decade, phase-locking or phase-coincidence between multiple modes of climate variability may be possible explanations for the observed temperature changes. Similar mechanisms have been examined in association with the regime shift, but they have not been proposed as alternative explanations. For example, Minobe (1999) examined the role of interactions between bidecadal and pentadecadal climate oscillations in the North Pacific climate regime shift. Minobe suggested that the overall time scale for regime length is based on pentadecadal oscillations, whereas the rapid shifts from one regime to the next can be attributed to bidecadal variability. Although Minobe examined the oscillatory behavior associated with the climate event, he still maintained that the climate system underwent actual shifts in regimes (Fig. 1.4a). Were there shifts in the climate state, or instead were there simply interactions between low-frequency quasi-oscillatory climate modes? For example, Fig. 1.4b illustrates an interdecadal oscillation overlaid on the NPI time series Minobe used to depict the regime shifts of the 20th century. On the basis of this figure, it seems reasonable to hypothesize that the low-frequency components associated with climate variables may help to explain large apparent jumps in the climate system. The research presented in Minobe (1999) relied upon wavelet analysis to
identify the oscillations of interest. Although wavelet analysis is indeed an improvement upon previously used signal-processing methods such as fourier analysis and windowed fourier analysis, the data should be linear in order for such processes to provide physically meaningful results. Therefore, research that applies data related to a nonlinear climate system should employ adaptive analysis methods to obtain more physically relevant insights. In this respect, the use of an adaptive annual cycle such as the MAC described previously may allow for more physically meaningful conclusions. Despite imperfections in the signal-processing technique applied, the idea that the changes observed in the North Pacific could be related to climate mode interactions is a potentially important concept that will be investigated in this research.

We begin by applying ensemble empirical mode decomposition (EEMD) to surface temperature data within the region of interest. Once the LFS has been extracted, an empirical orthogonal functions/principal components (EOF/PC) analysis is applied to identify the primary modes of variance for the data. The EOF/PC analysis is then used to determine whether or not a climate regime shift occurred in the Southeastern United States. Following this, we perform a further decomposition of the first mode of variance (the first principal component) to gain insight into the nature of the mode interactions that compose the overall temperature signal. This is useful in determining the nature of any large changes that occurred within the region. In this manner we a) accurately extract the minimum temperature LFS, b) determine whether any large changes associated with the mid-1970s North Pacific events can be classified as a regime shift in the Southeastern United States, and c) identify important mode interactions that may explain events in the time period and region of interest. Insights gained from analyses such as these may help to improve climate prediction for this region and may also be useful in applications for other regional analyses.
Fig. 1.1. Mean North Pacific sea level pressures (SLPs) averaged over the months November–March from Trenberth (1990). The horizontal lines represent time series means for 1946–1976 and 1977–1987.

Fig. 1.2. 700 mb flow across the United States for positive (solid black line), negative (dashed line), and average (solid gray line) values of the PNA index from Leathers et al. (1991).
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CHAPTER 2

DATA

Minimum temperature data used in this research come from the National Climatic Data Center (NCDC) DSI-3200 dataset. The majority of the stations that make up this dataset are a part of the National Weather Service cooperative station network (National Climatic Data Center 2009). The NCDC DSI-3200 has already been used in a wide range of climatological research applications, including climate prediction studies using maximum and minimum temperature and drought classification investigations using rainfall data (Alfaro et al. 2006; Greene et al. 2008). As the use of these data in such research indicates, the DSI-3200 contains several important meteorological parameters ranging from daily precipitation totals to daily minimum and maximum temperatures. The NCDC data were subjected to a number of quality control measures including internal consistency checks and comparison against climatological limits and surrounding stations (National Climatic Data Center 2009). Aside from being subjected to these quality control measures, the dataset is completely unadjusted. Of the 8 000 active cooperating observing stations scattered throughout the United States, 115 from Alabama, Florida, Georgia, South Carolina, and North Carolina have been selected for use in this regional study (Fig. 2.1).

Minimum temperature, rather than maximum or average daily temperature, is chosen as the analysis parameter because of its impact on agriculture in the region (Tsai et al. 2002; Downton and Miller 1993; Rouse and Sherman 2002; Stewart and Guinn 1969). Additionally, there is significantly more variability within the minimum temperature data than is seen in maximum temperature data. Although many of these stations contain data from as far back as the 1890s, large gaps in much of these earlier data cannot be easily or accurately interpolated. Only stations containing gaps less than or equal to six months are considered. For this reason, the time period from 1 January 1955 through 31 December 2007 is chosen for the analysis.
Although the selection of this time period eliminates many of the larger multi-
year gaps, smaller data gaps that exist in the refined dataset still must be addressed.
Whereas a number of previous climate studies employed a spatial interpolation scheme to
account for gaps in the DSI-3200 (Williams 2010; Smith 2006), a temporal scheme is
selected for this project and applied to gaps of less than one year. Very few of the
selected stations, however, contain gaps of more than six months. This method is chosen
in part because of the spatial inhomogeneity of the selected stations. Figure 2.2 provides
an example of interpolated data for a station time series that contains the largest gaps in
the dataset. For a given date with missing data, for example, 2 January 1984, the
technique interpolates the missing point using a cubic spline based on all other data from
2 January. In this way, the missing data is first filled using a kind of climatological
method. Because low-frequency variability rather than high frequency variability is the
focus of this research, the interpolated points are smoothed using a running mean. After
all missing data are interpolated with the cubic spline, 31-day means centered at the
interpolated points are computed only for the interpolated portions of the time series. In
this manner any extreme values from the climatologically determined interpolated points
are smoothed to reflect the more temporally local characteristics of that point. The
accuracy of the interpolation scheme is tested by removing several existing data points,
applying the interpolation, and comparing the interpolated points to the true values. In
the first test, two days were removed, interpolated, and compared to the true values. The
test was also carried out for seven days and twenty days. As is evident in Fig. 2.3, the
interpolation process yields a smoothed, but still realistic estimate of a time series with
missing points. Estimated points fall within the range of the actual points.

As is often the case with climate data, the DSI-3200 contains imperfections. As
has already been noted, much of the earlier data must be eliminated because of large
gaps. This is particularly limiting in studies of low-frequency climate variability, which
require many decades’ worth of data to identify potentially important oscillations and
patterns of variability. In addition to this, changes in observation time, instrumentation,
and the surrounding environment can have noticeable effects on the data. Although most
of the stations used are rurally located, several are situated in areas that have experienced
some degree of urbanization within the past fifty years. For example, several stations
exist within the greater Atlanta area, which has seen significant urban and suburban development (Yang 2002). Such stations may show an urban heating effect in the temperature time series, although it is noted in the DSI-3200 literature that placement of the stations was carefully considered to avoid such effects. It should also be noted that stations containing data that deviated significantly from surrounding station data are not included in this analysis. Despite these imperfections, the DSI-3200 provides the necessary high spatial and temporal resolution temperature data that are required for this study.

Fig. 2.1. Station locations are indicated by black diamonds: 115 stations from the DSI-3200 data set are shown.
Fig. 2.2. An illustration of the temporal interpolation process applied to the raw minimum temperature observations for a station in Tuscaloosa, Alabama. The top panel shows a selected portion of time series following the first step of the interpolation in which the missing points are interpolated using a cubic spline (blue). The red dots indicate the original observation time series. Missing values in the original data are assigned a value of -99. In the middle panel a 30-day running mean is applied to the interpolated points to smooth the data (blue). The red dots again show the original data. The green boxes highlight an interpolated portion of the time series. The bottom panel shows the final interpolation for the entire time series.
Fig. 2.3. The temporal interpolation scheme was tested by removing 2 (top panel), 7 (middle panel), and 20 (bottom panel) data points from a time series, interpolating the time series for these missing data, and comparing the interpolated points to the actual points. Actual points are shown in black, and interpolated points are shown in red. The purple lines highlight the portion of the time series that was removed.
CHAPTER 3

METHODOLOGY

The methodology is broken down into a time domain analysis and a spatial domain analysis. The temporal analysis is carried out to extract the low-frequency components from the original set of 115 daily minimum temperature time series. We are interested in the frequency components of this data that vary on interannual to interdecadal timescales. To accomplish this goal, ensemble empirical mode decomposition is applied. This adaptive temporal analysis technique extracts the low-frequency signal from the daily minimum temperature time series. Following the temporal analysis, a separate analysis is carried out in the spatial domain. This analysis relies on the use of empirical orthogonal functions (EOFs) to examine the dominant spatial modes associated with the extracted low-frequency components. The EOF analysis is used to a) determine the spatial coherency of the dominant mode of variability, and b) examine whether the spatial structure associated with the dominant mode of variability changes significantly following the mid-1970s climate event. The remainder of this section will provide both a review of the methods applied.

3.1 Overview of Ensemble Empirical Mode Decomposition

As discussed earlier, the LFS is extracted in the context of a MAC. Thus, it is important to accurately extract the LFS without leaving the time domain or making any assumptions about the linearity or stationarity of the original minimum temperature data. Ensemble empirical mode decomposition (EEMD) is applied to accomplish this. The use of the temporally local EEMD method in the analysis is particularly relevant because many climate variables, which result from nonlinear forcings, exhibit nonstationary behavior. Although other methods have been applied in the past to extract the LFS, these techniques often rely on the underlying assumption of a stationary and linear dataset. For example, fourier analysis, although no doubt an important milestone in mathematical history, is not locally adaptive in the time domain and thus cannot be applied to time
series that exhibit nonstationary behavior. The windowed Fourier transform presented by Denis Gabor allows for nonstationary data, but can contain discontinuities and missing low frequencies (Wu and Huang 2009). These drawbacks prevent Gabor’s technique from being applicable in this study given the focus on low-frequency variability and the use of a MAC-based reference frame. More recently developed approaches such as singular spectrum analysis and wavelet analysis can also be applied to nonstationary time series, but do not handle nonlinear data well. (Huang and Wu 2008).

Unlike the aforementioned analysis methods, EEMD is a locally adaptive tool that can accurately decompose a time series of data into its various frequency components. Although not entirely local, EEMD does not rely on pre-determined basis functions and is thus a far more local method than the previously used methods discussed above. EEMD follows from empirical mode decomposition (EMD) as presented by Huang et al. (1998). Using EMD, the components are obtained from a time series $x(t)$,

$$x(t) = \sum_{j=1}^{n} c_j + r_n$$

(1)

In equation (1) the $c_j$ terms represent the components, and $r_n$ gives the residual data of $x(t)$ following the extraction of $n$ components (Wu and Huang 2009). The actual procedure by which data are decomposed using EMD relies on a sifting process that begins with creating an envelope around the data (Fig. 3.1). Local maxima (minima) are connected using a cubic spline to create the upper (lower) part of the envelope. The local mean of this envelope is then subtracted from the original data, and the result of this subtraction is treated as the data for which a new envelope is created. This procedure is repeated until the envelope is symmetric about a zero mean. The final data from this sifting serve as the first component. Figure 3.1 illustrates the extraction of the first component using this sifting process. Subsequent components are obtained by subtracting the first component from the original data and repeating the process. Although EMD is a useful adaptive method for extracting components from a given time series of data, problems arise involving mode mixing, in which a component contains oscillations of a different
frequency. Figure 3.2 provides an example of a component that contains mode mixing occurs as a result of signal intermittency and can cloud the physical meaning of a component (Huang and Wu 2008). These problems are resolved in EEMD by implementing the sifting process for an ensemble of noise-added signal (Wu and Huang 2009). In an EEMD, white noise is first added to the time series which is to be decomposed. After adding the noise, the components are obtained in a manner similar to that applied in EMD. This procedure is then repeated many times using a different white noise series for each repetition. At the end of this process, the ensemble mean of the components is computed and treated as the real solution. By taking the mean of the ensemble, the added white noise series cancel out, and the resulting components do not experience mode mixing.

In implementing the EEMD method for the minimum temperature data, this study uses 400 ensembles having a noise-signal ratio of 0.2. The decomposition results in 13 components of which the first 7 contain the high frequency signal, the 8th and 9th contain the annual cycle, and the final 4 contain the LFS. Figures 3.3 and 3.4 illustrate the EEMD process applied to one station. In Fig. 3.3, which depicts the decomposition for one ensemble member, mode mixing is present in the seventh and eighth components. As is evident in Fig. 3.4, when the ensemble mean is taken at the end of the EEMD procedure, mode mixing is not observed in the extracted components. By this process, the true nonstationary nature of the data is not forfeited during the decomposition. Since EEMD does not rely on any predetermined basis functions, the annual cycle exhibits many changes in amplitude from year to year. Because the temperature signal is affected by nonlinear radiational and dynamical forcings, it is reasonable to have such an amplitude-modulated annual cycle. The ability to extract the MAC is one of the benefits of applying EEMD.

Following the decomposition, the components that contain high-frequency oscillations are added and treated as the high-frequency signal. The annual cycle and LFS are similarly determined (Fig. 3.5). Once the high-frequency, annual cycle, and low-frequency signals are accurately extracted and summed for each of the 115 stations, the data can be used in an EOF/PC analysis, which will provide further insight into the nature
of the variability associated with minimum temperatures in the Southeastern United States. Only the low-frequency components will be used in the following analysis.

### 3.2 Empirical Orthogonal Functions Analysis

Following the decomposition of the original data, the EOFs are computed for the set of extracted low-frequency signals. EOF/PC analysis, first classified by Lorenz (1956), produces a set of orthogonal spatial patterns, or empirical orthogonal functions (EOFs), in addition to a set of uncorrelated time series, or principal components (PCs) (Hannachi et al. 2007). EOF/PC analysis has been used extensively in the atmospheric sciences to break down a complex set of data into a simpler set of uncorrelated eigenvectors. The eigenvalues give the variance carried by the corresponding eigenvectors. The purpose of this analysis is to find “uncorrelated linear combinations of the different variables that explain maximum variance” (Hannachi et al. 2007, p.3). Typically the first few eigenvectors account for the bulk of the variance in the data. On the basis of these dominant modes of variability determined in the EOF analysis, it may be possible to glean information about the physical behavior of the system that the data describes.

Mathematically, the EOF/PC analysis is carried out by first calculating the covariance matrix for an ordered set of mean-removed data (Monahan et al. 2009). For the data matrix \( \mathbf{X} \) with station time series of length \( n \), the covariance matrix, \( \mathbf{C} \) is calculated as follows:

$$
\mathbf{C} = \frac{1}{n} \mathbf{X} \mathbf{X}^T
$$

(2)

Following this calculation, the EOFs, \( \mathbf{e}_k \), and the corresponding eigenvalues, \( u_k \), are determined by solving the eigenvector problem,

$$
\mathbf{C} \mathbf{e}_k = \mathbf{e}_k u_k
$$

(3)
Multiplication of the original data matrix and the eigenvector matrix results in the PC time series, which describes the time evolution of the dominant mode. EOF/PC analysis, although more of a statistical tool than a physical tool, can still provide useful information about the primary modes of variability within a data set and can potentially lead to additional insights about the physical processes associated with these modes.

In this research, three separate EOF/PC analyses are executed. In the first EOF calculation, the mean-removed LFS from the minimum temperature station data are arbitrarily grouped into a matrix. The covariance matrix is calculated first, followed by calculations of the eigenvectors and PC time series. The percentage of variance that each PC explains is calculated using the eigenvalues of each eigenvector. This analysis is carried out for the entire dataset for the time period 1 January 1955 through 31 December 2007. To compare the dominant spatial modes from before and after the mid-1970s climate event, two more EOF analyses are carried out. The original mean-removed, low-frequency matrix is separated into two smaller matrices. The first matrix contains the data from 1 January 1955 through 12 December 1974, and the second matrix contains the data from 1 January 1975 through 12 December 2007. The covariance matrix, eigenvectors, PCs, and percentages are calculated separately for each of these matrices to easily compare the dominant modes of variability. The same arbitrary station order used in the first EOF analysis is used here.

Once the EOFs have been computed for each of the three cases previously described, the spatial structure of the eigenvectors is analyzed. To accomplish this, the station data, which are not evenly distributed throughout the study region, must be set to a grid. This is done using the “meshgrid” and “griddata” functions available in the MATLAB software package. A grid of 0.5° by 0.5° resolution from 24–37°N and 75–90°W is first created using “meshgrid.” The station data are then fitted to this grid using the “griddata” function with a v4 (MATLAB version 4 griddata method) fitting technique. The v4 gridding technique constitutes a minimum curvature method and results in a smooth interpolation. Fitting the station data to a grid allows the EOFs to be displayed in a grid-analysis software program such as GrADS, creating a visual display in which the EOFs before and after the mid-1970s are easily compared.
Figure 3.1. The EMD sifting process applied to a section of station minimum temperature data. The top panel shows the original station data (blue line) with envelope defined using a cubic spline that connects all local maxima and minima (red and green lines). The black line is the average of the red and green lines. The second panel shows the second sifting. Here the blue line is the result of the subtraction of the black line in the top panel from the original data. The sifting process continues until the bottom panel, in which the envelope is symmetric about a zero mean.
Fig. 3.2. An example of mode mixing from an EMD decomposition of minimum temperature station data. High frequency modes are appearing in an annual cycle mode.

Fig. 3.3. The resulting components of the EEMD sifting process for one ensemble member. Components range from high frequency in the first few plots, to low frequency in the last several plots.
Fig. 3.4. The final results of the EEMD process for the same time series decomposed in Fig. 3.3. The components shown here represent the ensemble mean taken from 400 ensemble members.
Fig. 3.5. Minimum temperature data from Plant City, Florida after the EEMD. The top plot contains the original data. The second plot contains the high-frequency components, which were obtained by summing the first 7 components. The third plot contains the annual cycle (8\textsuperscript{th} and 9\textsuperscript{th} components, summed), and the fourth plot contains the LFS (10\textsuperscript{th} through 13\textsuperscript{th} components, summed).
CHAPTER 4

RESULTS AND DISCUSSION

Following the extraction of the LFS using EEMD, the first set of EOFs and PC time series are calculated for all stations for the period 1955–2007. The results of this first EOF/PC analysis are given in Figs. 4.1, 4.2, and 4.3. An examination of the first eigenvector, depicted by the red line in Fig. 4.1, reveals a relatively uniform dominant spatial mode. Thus, the dominant mode exhibits significant spatial coherency for all 115 stations. When multiplied by the standard deviation of the first principal component (PC1), as has been done for the lines plotted in Fig. 4.1, this first eigenvector is positive and near 2 °F for all stations. The scaled second eigenvector, shown in blue in the top panel of Fig. 4.1, oscillates about the 0 °F line. Percentages calculated from the eigenvalues associated with the first and second modes reveal that the first mode accounts for 66.12% of the total variance, whereas the second mode accounts for 5.82% of the total variance. Thus, about two-thirds of the total variance is carried by the dominant spatial mode.

Figures 4.2 and 4.3 contain the PC time series for the first and second modes. As can be seen in Fig. 4.3, the normalized PC1 time series (bold red line) agrees well with the mean-removed low-frequency station data. This analysis will focus on the PC1 time series since this mode accounts for the largest percentage of the total variance. PC1, shown in red in Fig. 4.2, clearly captures the drop in surface temperatures in the mid-1970s that was described in Trenberth (1990). Normalized PC1 values drop from around 2 °F in 1974 to near -2.5 °F by the end of 1976. Although there are other fairly substantial jumps in the PC1 time series, this drop in temperature is the most dramatic decline observed within the time period examined.

Although it is evident that a large shift in minimum temperatures occurred throughout the Southeastern United States in the mid-1970s, a quick glance at the PC1 time series reveals that the temperatures gradually recover to their pre-1975 state. There does not appear to be a corresponding jump back to the warmer state following the mid-
1970s rapid drop in temperatures. Instead the signal steadily increases through the early and mid-1980s. By the mid-1980s, PC1 seems to have fully recovered from the dramatic temperature decrease that occurred a decade earlier. The cooler temperatures following the abrupt drop in the LFS in the mid-1970s are not maintained for longer than a decade. On the basis of this qualitative examination of PC1, it appears that the minimum temperature LFS does not indicate the occurrence of a regime shift in the Southeastern United States during the mid-1970s.

To more thoroughly examine the possibility that the mid-1970s large temperature drop in the Southeastern United States may not be attributable to an actual shift in climate regimes, the results of the EOF/PC analyses for the 1955–1974 time period (Group 1) are compared with those of the 1975–2007 time period (Group 2). The results of these analyses are presented in Figs. 4.4 and 4.5. The eigenvectors, shown in Fig. 4.4, reveal that the dominant spatial mode does not significantly change between Group 1 and Group 2. In Fig. 4.4 EOF 1 remains positive between 1-2 °F with only occasional jumps in both Group 1 and Group 2. Although not identical, the first eigenvectors still show a high degree of spatial coherency for both Group 1 and Group 2. Fig. 4.5 gives the first two PC time series for the EOFs in Fig. 4.4. In each group, the dominant spatial mode accounts for over two-thirds of the total variance (74.91% for Group 1, and 67.92% for Group 2). Because the variance carried by the first mode does not change considerably between the two time periods, the primary mode of variability does not appear to change following the mid-1970s temperature drop. Moreover, the Group 1 and Group 2 PCs again illustrate the apparent recovery of the minimum temperature LFS by the mid-1980s.

After the EOFs were calculated for an arbitrarily ordered matrix of stations, the station data were set to a grid to better examine the spatial structure of the EOFs. The resulting EOF maps for the entire time period, for Group 1, and for Group 2 are provided in Fig. 4.6. While the shading indicates some subtle variations in the spatial structure of Group 1 compared to that of Group 2, these differences are small in magnitude and primarily consist of noise. The overall spatial pattern of the first EOF remains largely unchanged between Group 1 and Group 2. The lack of significant change in the dominant spatial mode from Group 1 to Group 2 suggests that the background climate state did not undergo a shift in regimes in the Southeastern United States.
The PC1 time series for the entire period 1955–2007 is used in a final decomposition. Although EOF/PC analyses are purely statistical and do not yield physical results, because PC1 accounts for such a large fraction of the overall variance, it represents much of the variability contained in the minimum temperature LFS. Therefore, to gain insight into the nature of this variability on various low-frequency time scales, we can apply EEMD to the overall PC1 time series. The results of this final decomposition are shown in Fig. 4.7. The decomposition reveals that the first PC of the minimum temperature LFS contains significant phase coincidence among low-frequency oscillations of different time scales. In 1976, for example, at least four oscillatory components of interannual to decadal variability are decreasing toward a local minimum. The broad decadal oscillation shown at the bottom of Fig. 4.7 begins decreasing in 1972 and continues to a local minimum around 1979. The 11\textsuperscript{th} and 12\textsuperscript{th} IMFs also show fairly steep decreases in the mid-1970s. When added together, the simultaneous decreasing phases of these low-frequency components appears as the dramatic decrease seen in the PC1 time series. None of these oscillatory components appear to decrease to a new state, as would be the case in a regime shift.

This phase coincidence is not simply an artifact of the decomposition process, but is a true representation of the oscillatory components contained in the dominant mode of variability. This can be demonstrated by observing other portions of the PC1 time series that also display large drops, such as 1957–1958 and 1999–2001 (Fig. 4.8). The late-1950s drop, as seen in Figs. 4.7 and 4.8, still contains a large degree of phase coincidence; however, not all oscillatory components are decreasing as they were in the mid-1970s case. The broad decadal component at the bottom of Fig. 4.7 is increasing, and two other components are near local maxima. Similarly, in the case of the 1999–2001 drop there is an increasing component present among the other decreasing components. This illustrates that the mid-1970s event seems to be a specific case of phase coincidence among all oscillatory components contained in the dominant mode of the minimum temperature LFS.
Fig. 4.1. Eigenvector results from the first EOF/PC analysis for an arbitrarily ordered matrix of all 115 stations from 1 January 1955 through 31 December 2007. The first two eigenvectors (EOFs) are shown here, with EOF 1 shown in red and EOF 2 shown in blue. EOF 1 and EOF 2 have been multiplied by the standard deviation of their corresponding PC time series (18.35 and 5.44, respectively). The ordinate axis denotes the temperature in degrees Fahrenheit, and the abscissa gives the station number.

Fig. 4.2. PC time series associated with the first two eigenvectors for the period 1 January 1955 through 31 December 2007. PC1 is shown in red, and PC2 is shown in blue. PC1 and PC2 have been normalized by their respective standard deviations. The purple box indicates the approximate temporal location of the 1976 shift. Percentages have been calculated from the eigenvalues and give the total variance accounted for by the respective PC/EOF. The ordinate axis is given in degrees Fahrenheit, and the abscissa is given in years.

Fig. 4.3. The mean-removed, low-frequency signals for 1 January 1955 through 31 December 2007 from all 115 stations are plotted with the PC1 time series (scaled by a factor of 10) indicated by the bold red line. The ordinate axis is given in degrees Fahrenheit, and the abscissa is given in years.
Fig. 4.4. (a) Eigenvector 1 (red) and eigenvector 2 (blue) for Group 1, which contains station data for the time period 1 January 1955 through 31 December 1974. Eigenvectors 1 and 2 have been multiplied by the standard deviation of their corresponding PC time series (19.34 and 5.66, respectively). (b) Same as (a), but for Group 2, which contains station data for 1 January 1975 through 31 December 2007. The corresponding PC standard deviations are 17.88 and 5.96, respectively. The ordinate axis denotes the temperature in degrees Fahrenheit, and the abscissa gives the station number.

Fig. 4.5. (a) PC time series associated with eigenvectors 1 and 2 for Group 1. PC1 is shown in red, and PC2 is shown in blue. Percentages have been calculated from the eigenvalues to give the total variance accounted for by the respective PC/EOF. (b) Same as (a), but for Group 2. The ordinate axis is given in degrees Fahrenheit, and the abscissa is given in years.
Fig. 4.6. (top panel) First EOF for the gridded station data from 1955–2007. (bottom left) First EOF for Group 1, 1955–1974. (bottom right) First EOF for Group 2, 1975–2007. All figures are in the domain 26°–35°N and 75°–88°W. The colorbar is expressed in degrees Fahrenheit.
Fig. 4.7. IMFs 9-16 (low-frequency components) from the PC1 (1 January 1955 through 31 December 2007) decomposition using EEMD. The magenta line indicates the approximate location of the mid-1970s shift, and the green lines indicate two other significant drops in PC1. All components are plotted based on the same y-scale.

Fig. 4.8. The PC1 time series for the 1 January 1955 through 31 December 2007 time period. The green boxes indicate the two additional large decreases in temperature examined in the final decomposition of PC1.
CHAPTER 5

SUMMARY AND CONCLUSIONS

To examine the mid-1970s climate regime shift in the Southeastern United States, this study analyzed the minimum temperature LFS using regional station data. EEMD, which is a recently developed analysis tool that provides a locally adaptive means of decomposing time series, was applied to accurately extract the LFS. EEMD was chosen because, unlike many other filtering and decomposition methods, it can be used for nonstationary and nonlinear time series to extract the LFS in the context of a modulated annual cycle as opposed to the traditional annual cycle used in many previous studies. Additionally, EEMD results in a decomposed time series that doesn’t mix modes associated with the annual cycle and higher frequency variability. To identify the dominant mode of low-frequency variability and test the spatial coherency of the LFS throughout the Southeastern United States, an EOF/PC analysis was carried out using the extracted LFS. When calculated for the entire time period of 1955–2007, the first EOF indicated that the mean response to the dominant spatial mode was uniform throughout the study region. The PC1 time series contained a large drop in minimum temperatures coincident with the mid-1970s regime shift in the North Pacific, which is consistent with observations in Trenberth (1990). Although the PC1 time series indicated a dramatic decrease in temperatures in the mid-1970s, the cooler state was not maintained for more than a decade following the drop. When the data set was broken into two groups, with Group 1 containing data from 1955–1974 and Group 2 containing data from 1975–2007, the results show that the dominant spatial mode remained nearly the same both before and after the mid-1970s climate event. The first mode accounted for over two-thirds of the total variance in both Group 1 and Group 2. All these results suggest that the large drop in minimum temperatures during the mid-1970s in the Southeastern United States is not an indication of a regime shift.

To further examine the nature of the mid-1970s minimum temperature LFS decrease, an additional decomposition with EEMD was applied to the first principal
component time series for the 1955–2007 period. An examination of the last eight components of this final decomposition revealed strong phase coincidence among the five components with the largest magnitudes. This phase coincidence, which was shown to not be an artifact of the decomposition process, appears to account for the large drop in the minimum temperature LFS in the mid-1970s. Thus, an alternative explanation for the mid-1970s regime shift is simple phase coincidence among low-frequency oscillatory components. Although these results apply only to the Southeastern United States, future studies could apply similar techniques to other regional or global datasets to determine the nature of the mid-1970s event elsewhere.

Future work might also include an investigation into the physical modes of climate variability associated with the extracted oscillatory components shown in Fig. 4.6. For example, these components may be regressed against indices for ENSO and the PDO to examine the relative roles of these physical modes in the phase coincidence that occurred in the mid-1970s. Because the individual components of the PC1 time series decomposition are not constant in amplitude or frequency, it is difficult to use them in deterministic climate prediction applications. However, for probabilistic climate prediction purposes, it may be useful to have a better understanding of which physical processes are contained in these oscillatory components. Although it may be difficult to predict on the basis of these results, the use of the MAC as a reference frame for analyzing low frequency climate variability in the southeastern United States leads interesting insights into the nature of the mid-1970s climate event and demonstrates one of the many potential applications of this new frame of reference for studying climate.
REFERENCES


BIOGRAPHICAL SKETCH

Sarah Strazzo spent the first eighteen years of her life in the rural mountain town of Arnold, California. The occasional summer thunderstorms that would develop there are what initially piqued Sarah’s interest in the atmospheric sciences. By the time she was in the sixth grade, Sarah had acquired an impressive—some might say excessive—collection of photos of atmospheric phenomenon that she witnessed in Arnold. This aesthetic appreciation of meteorology became scientific when Sarah enrolled in the atmospheric science department at the University of California, Davis in 2005. While at Davis, Sarah had the opportunity to spend a summer conducting research in the atmospheric chemistry lab with Dr. Cort Anastasio. After four enjoyable years in the bicycle friendly oasis of Davis, California, she graduated with highest honors from UC Davis with a B.S. in atmospheric science.

Before heading to Tallahassee, Florida to pursue a graduate degree in meteorology at the Florida State University, Sarah travelled to Barrow, Alaska for the summer to work on a biometeorological research project with Dr. Walt Oechel and the Global Change Research Group. This experience fueled Sarah’s interest in meteorological research as well as her desire to reside in a warmer climate. After moving to Florida, Sarah enjoyed nearly two years of climate research under the guidance of Dr. Zhaohua Wu. Upon completing her Master’s of Science in meteorology, Sarah intends to pursue a Ph.D. in geography at the Florida State University.