A Global and Tropical Quasi-Decadal Oscillation of the Atmosphere and Ocean

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Submitted to the Department of Earth, Atmospheric and Planetary Sciences
in Partial Fulfillment of the Requirements for the Degree of
Bachelor of Science in Earth, Atmospheric and Planetary Sciences
at the Massachusetts Institute of Technology
May 6, 2011

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Abstract

An oscillatory, quasi-periodic signal with a period of around 10 years was found in radiosonde- and satellite-measured datasets of lower stratospheric temperature. Power spectrum analysis and Fourier decomposition were used to characterize the temporal and vertical manifestations of the signal, while EOF analyses were used to analyze its spatial characteristics. The oscillation was found to be unrelated to the solar activity cycle, while it displayed coherence with similar oscillatory signals in ENSO, PDO and AMO indices, as well as with a quasi-decadal signal in SST data. Finally, the quasi-decadal signal in lower stratospheric temperature was found to have a small but measurable contribution to the signal of tropical cyclone potential intensity in the Atlantic MDR.
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1 Introduction

The purpose of this research is the investigation and characterization of an observed, quasi-decadal, oscillatory signal in lower stratospheric temperature. This investigation aims to elucidate the dynamics governing the phenomenon by establishing connections with other known physical climate mechanisms. It also seeks to determine the effects of the temperature cycle on phenomena of tropospheric weather and climate; in particular, tropical cyclones.

1.1 Background

The lower stratosphere plays an important role in regulating the weather and climate of the Earth. Because of its proximity to the tropopause, the properties of the lower stratosphere can have significant effects throughout the atmosphere, including at the Earth’s surface. The quasi-decadal oscillation of lower stratospheric temperature is studied to better understand the role of the lower stratosphere in atmospheric dynamics and its effects on global weather and climate.

1.1.1 Tropical cyclones and potential intensity

A major way in which the lower layer of the stratosphere can directly affect tropospheric weather events lies in the evolution of tropical cyclones. As dictated by potential intensity theory, the values of maximum allowable near-surface wind speed in tropical cyclones can be well approximated by the equation

$$V_{\text{max}}^2 \approx \frac{C_k}{C_D} \frac{T_s - T_0}{T_0} (k_0^* - k),$$

where $C_k$ and $C_D$ are transfer coefficients of momentum and enthalpy, respectively; $T_s$ is the temperature of the sea surface; $T_0$ is the outflow temperature at the top of the cyclone; $k_0^*$ is the saturation enthalpy of the sea surface; and $k$ is the enthalpy of the air in the boundary layer (Bister and Emanuel 1998, Emanuel 2003). Therefore, it is clear that the outflow temperature at the top of a tropical cyclone can be an important limiting factor on its intensity. Emanuel (2003) notes that a typical height for the outflow region of mature tropical cyclones is between 10 to 15 km. In the tropics, this height range falls within the lower portion of the stratosphere. Therefore, for mature tropical cyclones, the temperature of the lower stratosphere can be treated as the outflow temperature of the storm. Since outflow temperature is known to be a limiting factor on potential intensity, it can be concluded that lower stratospheric temperature is a modulating factor for the intensity of tropical cyclones.

This mechanism is cited in a 2008 study by Elsner and Jagger, in which the authors find a statistically significant connection between solar activity and Atlantic hurricane counts.
Here, the authors postulate that increased solar activity warms the lower layer of the stratosphere, thereby decreasing the difference between hurricane inflow and outflow temperatures, and lowering the maximum potential intensity of tropical cyclones. Since the solar cycle has a period of around 11 years (Labitzke and Van Loon 1988), variations in solar activity could therefore cause a quasi-decadal signal in lower stratospheric temperature, as well as in tropical cyclone activity.

This study examines the degree to which the solar signal is observable particularly in the lower layer of the stratosphere, whose temperature is of specific relevance to tropical cyclone potential intensity.

1.1.2 Non-solar mechanisms for lower stratospheric temperature modulation

Aside from variations in solar activity, other physical mechanisms for modulation of lower stratospheric temperature are relevant for the characterization of the quasi-decadal oscillation of the temperature of the lower stratosphere. While the amount of existing literature on this subject is limited, a few studies have documented processes that are known to affect lower stratospheric temperature. Through analysis of numerical model output, Shine et. al. (2003) find that ozone depletion and changes in flux of water vapor from the troposphere are factors responsible for cooling temperatures in the lower stratosphere. Furthermore, time-series of lower stratospheric temperatures were also found to be influenced by stratospheric warming following major volcanic events. Two such recent events were the eruptions of El Chichón in Mexico in 1982 and Mount Pinatubo in the Philippines in 1991. The temperature of the lower stratosphere increased significantly after each of these volcanic events (Shine et. al. 2003). For this reason, several studies of stratospheric temperature trends chose to omit data for up to two years following each eruption (Randel and Cobb 1994; Shine et. al. 2003).

Another mechanism known to affect the temperature of the lower stratosphere is the Quasi-Biennial Oscillation (QBO) (Labitzke and Van Loon 1988). The QBO is an oscillation of zonal winds in the tropical stratosphere whose period is about 26 months. The profile of alternating easterly and westerly winds moves downward through the lower stratosphere, causing the direction of tropical zonal winds to reverse every 24 to 30 months (Lindzen and Holton 1968). Holton and Tan (1980) discover a relationship between the QBO and the polar vortex, showing that zonal mean geopotential height is higher during the easterly phase of equatorial QBO. Furthermore, Gray et. al. (2001) find that the effects of the Holton-Tan relationship on stratospheric temperatures are modified by the 11-year solar cycle. However, this result is refuted by Hu and Tung (2002), as well as by Lu et. al. (2008). Still, Salby and Callaghan (2000) shows that the QBO is itself modified by the solar activity cycle. Finally, Labitzke and Van Loon (1988) show that stratospheric temperature data must be grouped
by QBO phase in order to detect a solar signal.

1.1.3 Tropospheric quasi-periodic climate oscillations

While the QBO exists in the stratosphere and affects the dynamics and temperature of the lower stratospheric layer, it is also possible that other quasi-periodic climate oscillations in the troposphere could affect the temperature above the tropopause. One such oscillation is the El Niño-Southern Oscillation (ENSO). ENSO is characterized by the oscillation of sea surface temperatures (SSTs) in the tropical Pacific Ocean, and it has an average period of about 5 years (Rasmusson and Wallace 1983). However, while characterized by Pacific SSTs, ENSO also has a range of atmospheric manifestations. The Southern Oscillation Index (SOI), which is the index of ENSO phase and strength, is computed from the difference in atmospheric surface pressure between Tahiti and Darwin, Australia (Rasmusson and Wallace 1983). Furthermore, ENSO events have consequences for weather on a global scale. Strong ENSO events are known to be associated with sharp changes in rainfall amounts in Asia, Europe, and North and South America (Grove 1998), as well as tropical cyclone activity (Saunders et. al. 2000; Tang and Neelin 2004). Finally, Compagnucci et. al. (2000) find the presence of a lower stratospheric temperature response to ENSO events, with warm SST anomalies being associated with warming in the lower stratosphere.

Another such climate oscillation is the Pacific Decadal Oscillation (PDO). The PDO is observed as a fluctuation of SSTs in the extratropical North Pacific Ocean, and its oscillations occur on interdecadal timescales, changing phase about every 5 to 15 years. The PDO index, which is the index of PDO phase and strength, is defined by the time history of the leading eigenvector of North Pacific SST (Mantua et. al. 1997). While the PDO has only recently been observed and studied, there are mechanisms known to contribute to its forcing. These mechanisms include ENSO, variability of the Aleutian low, and advection by oceanic Rossby waves (Schneider and Cornuelle 2005). Therefore, the PDO can be considered a result of a superposition of several contributing atmospheric and oceanic phenomena.

The Atlantic Multidecadal Oscillation (AMO) is another tropospheric climate oscillation with effects on weather and climate. With an observed period of 65-70 years, the AMO is manifested in SSTs in the North Atlantic Ocean (Schlesinger and Ramankutty 1994). Specifically, the AMO index is calculated from a detrended weighted average of North Atlantic SSTs. The AMO is known to have effects in Northern Hemispheric rainfall, temperature, and tropical cyclone activity (Zhang and Delworth 2006). However, there is no documentation of AMO effects in the stratosphere, as previous studies on AMO focus primarily on tropospheric and oceanic phenomena.

Other quasi-periodic climate oscillations with documented effects in the troposphere include the North Atlantic Oscillation (NAO), which is manifested as an oscillation in atmo-
spheric pressure and is known to affect the positions of climatic pressure systems (Hurrell 1995), and the Atlantic Meridional Mode (AMM), which is characterized by SST fluctuations in the Atlantic Ocean inter-tropical convergence zone, and is known to have strong connections to Atlantic tropical cyclone activity (Vimont and Kossin 2007).

The Arctic Oscillation (AO) is another dominant oscillation of the tropospheric atmosphere, and is manifested in atmospheric pressure variations at middle and high latitudes. However, the AO is neither periodic nor quasi-periodic (Lorenz 1951; Thompson and Wallace 1998).

1.2 Motivation

While the existence of such a signal in lower stratospheric temperature has been previously documented (Labitzke and Van Loon 1988, Salby and Callaghan 2000), there has been little research into the dynamics that govern this phenomenon, its spatial manifestation, or its effects on tropospheric weather and climate. Therefore, this research aims to more fully characterize the observed quasi-decadal signal in lower stratospheric temperature, as well as its connections with other atmospheric, oceanic, and climatic phenomena. This study thereby aims to contribute to the construction of a more complete scientific understanding of stratospheric processes, their interactions with the troposphere, and the dynamics of the atmosphere as a whole.

The possible connection between the quasi-decadal oscillation in lower stratospheric temperature and tropical cyclones provides an additional motivation for this study. Should such a connection be found to exist, the characterization of the quasi-decadal temperature signal could lead to an enhanced understanding of tropical cyclones. Since tropical cyclones are among the most costly and deadly of natural phenomena (Emanuel 2003), an increased understanding of the factors governing their dynamics and intensity could lead to better tropical cyclone prediction, thereby decreasing the risk to life and property posed by these storms.

1.3 Approach

To characterize the quasi-decadal oscillation in lower stratospheric temperature, two types of observed temperature data are utilized. First, to identify the signal, temperature data from radiosondes are used. Since radiosondes take measurements at a series of discrete, pre-determined pressure levels, this data can be effectively employed to determine the level at which the quasi-decadal signal is most strongly observed. Here, the method of Fourier spectral analysis is used to identify signals whose periods are on the order of about 10 years. Furthermore, since the Rossby radius of deformation $L_R = NH/f$ is inversely proportional
to the Coriolis parameter $f$ (Thorpe and Emanuel 1985), it has relatively high values in
the low-latitude tropics. Furthermore, since the stratification $N$ is large in the stratosphere,
the radius of deformation will be particularly large for points in the stratospheric tropics
(Emanuel 2010). Therefore, although radiosonde data represent point measurements, tem-
perature data from radiosondes in the tropical stratosphere can be taken to be representative
of much larger areas.

However, to analyze the spatial patterns in which the quasi-decadal oscillation is man-
ifested, a dataset with full coverage of the spatial domain is required. Therefore, lower
stratospheric temperature data from remote sensing satellites is utilized. Although these
datasets have a shorter temporal domain than those from radiosondes, the regularity and
completeness of their spatial domain enable spatial analyses of the quasi-decadal signal to
be carried out using these data.

To conduct spatial analysis on the lower stratospheric temperature data, the method of
empirical orthogonal functions (EOFs) is used. Using EOFs, the temperature data can be
decomposed into its principal components, each of which has an associated time series and
spatial loading pattern. The same procedure is applied to satellite SST datasets, and the
principal components of each are compared to determine connections.

To investigate connections with other climatic oscillations, a low-pass Fourier filter is
applied to the temperature data to isolate the quasi-decadal signal. This filtered data is
then compared to filtered time series of the indices of the major quasi-periodic climate
oscillations.

Finally, the lower stratospheric temperature data and SST data are used in conjunction
with pressure data to calculate tropical cyclone potential intensity, and the same Fourier
and EOF analysis is conducted on the new potential intensity dataset.

2 Methods

2.1 Spectral analysis

To identify the quasi-decadal signal in lower stratospheric temperature, spectral analysis was
performed on tropical radiosonde data. Monthly average radiosonde temperature data were
acquired from the National Environmental Satellite, Data, and Information Service (NES-
DIS) Radiosonde Atmospheric Temperature Products for Assessing Climate (RATPAC). The
RATPAC-B dataset was downloaded from the website of the National Climatic Data Center
(NCDC) for both 00Z and 12Z observation times.

The RATPAC stations in San Juan, Puerto Rico; Bangkok, Thailand; Bogotá, Colombia;
Jeddah, Saudi Arabia; and Majuro, Marshall Islands were selected for spatial analysis, since
each station is located in the tropical northern hemisphere and has good temporal data
coverage. Bash shell scripts were used to extract the data for each station from the main RATPAC data files. Year, month, and temperature data were then extracted from the segregated station data files and written to new data files by pressure level. The codes used to do this can be found in get_[station name].sh and cleanup_[station name].sh, respectively, in Appendix A.1. The data used had a temporal range from January 1979 to May 2010.

For each RATPAC station, a set of .txt files was created by cleanup_[station name].sh. Each of these files was then imported into MATLAB, thereby creating a matrix containing the time and temperature data for each pressure level. Finally, the MATLAB script psa.m was used to perform a Fourier transform on the temperature datasets, and calculate their power spectra.

The temperature data from the 70 hPa level from each RATPAC station were analyzed, since this is the RATPAC observation level closest to the lower stratospheric outflow level of tropical cyclones. The power spectra of 70 hPa temperature data were calculated and plotted for each station. Next, since San Juan is located in the Atlantic tropical cyclone basin, its RATPAC station was singled out for additional analysis. To get a sense of the vertical structure of the quasi-decadal temperature signal throughout the stratosphere, the power spectra of RATPAC temperature data at the 30, 50, 70, and 100 hPa levels were calculated for San Juan.

The same spectral analysis was then performed on daily total solar irradiance (TSI) data from the Active Cavity Radiometer Irradiance Monitor (ACRIM). ACRIM data from November 18, 1978 through April 14, 2010 were acquired and imported into MATLAB, and psa.m was used to compute the Fourier transform and calculate the power spectrum of TSI.

### 2.2 Low-pass filtering of radiosonde and TSI data

To determine whether the quasi-decadal signals in lower stratospheric temperature and solar activity are coherent, a Fourier low-pass filter was applied to each dataset. For each tropical RATPAC station previously selected for spectral analysis, the temperature time series from the 70 hPa level was imported into MATLAB. The MATLAB script hf_filter.m was then used to apply a low-pass Fourier filter to the dataset. Within hf_filter.m, the data were detrended, and high frequency oscillations were then removed from each time series by computing the Fourier transform of the time series, zeroing values corresponding to frequencies higher than .2 yr⁻¹, and computing the inverse Fourier transform.

The same low-pass filter was then applied to ACRIM TSI data on which spectral analysis was previously performed, again using hf_filter.m. The resulting filtered TSI time series was then plotted against the filtered RATPAC time series from each tropical station in order to make a graphical comparison.
2.3 Satellite temperature data analysis

To analyze the spatial patterns of the quasi-decadal signal in lower stratospheric temperature, satellite data with full coverage of the global domain were required. Therefore, brightness temperature data from the National Oceanic and Atmospheric Administration (NOAA) Microwave Sounding Units (MSU) were obtained from Remote Sensing Systems. Specifically, monthly data from the MSU channel “Temperature Lower Stratosphere” (TLS) from December 1979 through June 2010 were used.

To investigate connections with SST and tropical cyclones, satellite SST data were also used. The dataset used was monthly NOAA Optimum Interpolation SST (OISST), downloaded from the NOAA Earth System Research Laboratory (ESRL). The OISST data used had a temporal range of December 1981 through June 2010.

2.3.1 Spectral analysis of satellite data

To identify the quasi-decadal signal in satellite lower stratospheric temperature data, a power spectrum analysis was performed on MSU TLS data using the MATLAB script tls-psa.m. In tls-psa.m, the temperature data were averaged over their spatial domain, and a power spectrum analysis was performed on the resulting time series using psa.m.

The same process was applied to the OISST data using the MATLAB script oisst-psa.m. In oisst-psa.m, OISST data were imported into MATLAB and run through a land-sea mask. Those values in the sea were then averaged over the spatial domain for each time step, and a power series analysis was conducted on the resulting time series using psa.m.

2.3.2 EOF analysis

To conduct EOF analyses on the satellite datasets, the data were first filtered to remove high-frequency signals. Since the datasets were now three-dimensional (time and two spatial dimensions), a new MATLAB script was written to filter data in the two spatial dimensions with respect to variations in the time dimension. Specifically, for each data point in the two-dimensional spatial grid, a Fourier low-pass filter was applied to the temperature time series, thus resulting in a dataset whose two spatial dimensions remained, but in which high-frequency temporal variations had been removed. This script, hf_filter_2D.m, can be found in Appendix A.2. After filtering the MSU TLS and OISST data with hf_filter_2D.m, the filtered data were written to netCDF files for EOF processing.

The netCDF data were then opened with GrADS. In GrADS, the EOF script created by Matthias Munnich of UCLA was used (see eof.gs in Appendix A.3). For a given dataset, the EOF script calculated and returned the time series and loading patterns of the first 12 principal components of the dataset over a specified spatial and temporal domain, as
well as the percentage of the total variance of the data for which each principal component accounted. Several EOF analyses were performed on the MSU TLS and OISST datasets:

### 2.3.2.1 Entire domain

EOF analyses were performed on the MSU TLS and OISST datasets over the entire spatial domain (the globe). The time series of their principal components were imported into MATLAB. The MSU TLS and OISST time series were then plotted in conjunction with each other, and with indices of ENSO, PDO, and AMO to which the Fourier low-pass filter in `hf_filter.m` had been applied. The time series of the ENSO and AMO indices were obtained from ESRL, while the PDO index was obtained from the University of Washington. The loading patterns of the principal components of MSU TLS and OISST were also plotted on global maps and graphically compared.

### 2.3.2.2 Atlantic main development region

The same process of EOF analysis was repeated for the filtered datasets with the spatial domain for the EOFs restricted to the main development region (MDR) of tropical cyclones in the Atlantic Ocean. The Atlantic MDR is defined as the rectangle bounded by 6°N, 18°N, 60°W, and 20°W (Emanuel 2007). The resulting principal component time series of MSU TLS and OISST were again imported into MATLAB and plotted against each other, and their loading patterns were again graphically output in map form.

### 2.3.2.3 Unfiltered data

Three-dimensional arrays of MSU TLS and OISST data were written to netCDF files without first being filtered to remove high-frequency signals. The netCDF files were then opened in GrADS, and the `eof.gs` script was used to conduct EOF analyses. The resulting principal component time series were imported into MATLAB and plotted in conjunction with unfiltered indices of ENSO, PDO, and AMO. Again, the loading patterns of the principal components of MSU TLS and OISST were plotted on maps.

### 2.3.2.4 Time-averaged data

Instead of applying the Fourier low-pass filter to raw temperature datasets, 10-year averages were first calculated for MSU TLS and OISST, with each average calculated backward in time. These averages were calculated such that for each grid point at a given time step, the temperature value was given by an arithmetic mean of the 10 most recent temperature
values for that month (for example, the 10 most recent July temperature values) at that point. This was accomplished through the MATLAB scripts tls_mean.m and oisst_mean.m. These scripts are reprinted in Appendix A.2. After applying hf_filter_2D.m to each of the time-averaged datasets, the resulting three-dimensional variables were saved to netCDF files. These files were then opened in GrADS, and eof.gs was used to compute the principal components of each. The time series of the principal components were imported into MATLAB and plotted with each other, and the loading patterns were again represented graphically in maps.

2.4 Potential intensity calculations

To investigate connections between the quasi-decadal oscillation in lower stratospheric temperature and tropical cyclone activity, potential intensity data were calculated using the MSU TLS and OISST data. Since entropy was more readily calculable than enthalpy with the data available, potential intensity was calculated with an alternate from of the expression given in Equation 1:

\[ |V_{max}|^2 = \frac{T_s - T_0}{T_0} T_s (S_0^* - S_{600}^*), \]

where \( S_0^* \) is the saturation entropy of the sea surface, and \( S_{600}^* \) is the saturation entropy of the air at the 600 hPa level. Here, the value of saturation entropy is given by

\[ S^* = c_p \ln(T) + \frac{L_v q^*}{T} - R_{dry} \ln(p), \]

where \( c_p = 1005 \) J/kg/K is the specific heat capacity of air, \( L_v = 2.5 \times 10^6 \) J/kg is the latent heat of vaporization of water, \( R_{dry} = 287 \) J/kg/K is the specific gas constant of dry air, \( T \) and \( p \) are temperature and pressure, respectively, and \( q^* \) is the saturation specific humidity as given by

\[ q^* = 0.622 \frac{e^*}{p - e^*}, \]

and the saturation partial pressure \( e^* \) is given by

\[ e^* = (6.112 \text{ hPa}) \exp\left(\frac{17.67T_C}{243.5^\circ C + T_C}\right), \]

where \( T_C \) is the temperature in Celsius.

A MATLAB script was written to create a three-dimensional (time and two spatial dimensions) array of potential intensity using MSU TLS data for \( T_0 \), and OISST data for \( T_s \).
Other quantities required to carry out the potential intensity calculation were $p_0$ and $T_{600}$ ($p_{600}$ data was not needed, since the atmospheric pressure at the 600 hPa pressure level is necessarily 600 hPa). For the $p_0$ and $T_{600}$ datasets, data from the NCEP/National Center for Atmospheric Research (NCAR) Reanalysis dataset were used. To gather these data, the MATLAB scripts `temp_monthly.m` and `pres_monthly.m` were created. These scripts are called from `potential_intensity.m`, which gathers all required data, interpolates the data such that all datasets share the same grid dimensions, and performs the potential intensity calculation. These scripts are reproduced in Appendix A.2. A potential intensity dataset was created in MATLAB by executing `potential_intensity.m`.

After the potential intensity dataset was created, it was analyzed using the same EOF techniques applied to MSU TLS and OISST. First, the low-pass Fourier filter was applied using `hf_filter_2D.m` to isolate the quasi-decadal variability of the potential intensity signal. The resulting dataset was then saved to a netCDF file and opened in GrADS. The EOF script `eof.gs` was then used to compute the principal components of the filtered potential intensity data, and their corresponding loading patterns. The EOF process was conducted both over the entire spatial domain, and with the spatial domain limited to the Atlantic MDR. The resultant time series were imported to MATLAB and compared to the results of the MSU TLS and OISST EOF analysis. Similarly, the EOF loading patterns for potential intensity were also graphically output in map form.

Finally, to determine the extent to which the quasi-decadal signal in potential intensity can be expressed as a linear combination of the quasi-decadal SST and lower stratospheric temperature signals, time series of MSU TLS, OISST, and potential intensity were created in which the Fourier-filtered values over the Atlantic MDR were spatially averaged to create one-dimensional datasets. This was accomplished by way of the MATLAB script `mdr_data.m`, which is reproduced in Appendix A.2. Next, the script `find_coeffs.m` was written and used to determine the coefficients of the MSU TLS and OISST signals that would minimize the root mean square difference between the linear combination of those signals and the potential intensity signal. The MATLAB function `corrcoef` was then used to determine the correlation coefficients of each of the signals, individually, and their linear combination, with the potential intensity signal.

3 Results

3.1 Spectral analysis

The results of the power spectrum analysis of northern hemispheric tropical RATPAC temperature and ACRIM TSI data are shown below. Figure 1 shows the power spectra of the 70 hPa temperature time series from January 1979 through May 2010 at each analyzed sta-
tion, Figure 2 shows the power spectra at different stratospheric pressure levels in San Juan, Puerto Rico, and Figure 3 shows the power spectrum for ACRIM TSI.

Figure 1: Power spectra of temperature data from the Bangkok, Thailand; Bogotá, Colombia; Jeddah, Saudi Arabia; Majuro, Marshall Islands; and San Juan, Puerto Rico RATPAC radiosonde stations at the 70 hPa pressure level.
Figure 2: Power spectra of temperature data from the San Juan, Puerto Rico RATPAC radiosonde station at the 30, 50, 70, and 100 hPa pressure levels.
3.2 Low-pass filtering of radiosonde and TSI data

The results of the application of the Fourier low-pass filter to northern hemispheric tropical RATPAC temperature and ACRIM TSI data are shown in Figure 4.
Figure 4: Time series of filtered 70 hPa RATPAC temperature data (blue) and ACRIM TSI data (red) for Bangkok, Thailand; Bogotá, Colombia; Jeddah, Saudi Arabia; Majuro, Marshall Islands; and San Juan, Puerto Rico over the period from December 1979 to June 2010.
3.3 Satellite temperature data analysis

3.3.1 Spectral analysis of satellite data

The results of the spectral analysis of satellite MSU TLS and OISST data are shown in Figures 5 and 6.

Figure 5: Power spectrum of MSU TLS data.
3.3.2 EOF analysis

An EOF analysis was successfully conducted on the full spatial range of MSU TLS data that had been filtered in both spatial dimensions with the Fourier low-pass filter. Table 1 shows the result of this analysis. Furthermore, the time series and loading pattern of the first principal component of MSU TLS data are shown in Figures 7 and 8, respectively. Data for the remaining principal components are located in Appendix B.1.

Figure 6: Power spectrum of OISST data.
Table 1: Eigenvalues and % variance values for first 12 principal components of filtered MSU TLS data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1496.6</td>
<td>45.799</td>
</tr>
<tr>
<td>2</td>
<td>799.67</td>
<td>24.471</td>
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<tr>
<td>3</td>
<td>372.44</td>
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<td>5</td>
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<td>6</td>
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<td>2.8708</td>
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<td>7</td>
<td>53.005</td>
<td>1.6220</td>
</tr>
<tr>
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<td>39.735</td>
<td>1.2159</td>
</tr>
<tr>
<td>9</td>
<td>25.706</td>
<td>0.78666</td>
</tr>
<tr>
<td>10</td>
<td>20.551</td>
<td>0.62890</td>
</tr>
<tr>
<td>11</td>
<td>16.644</td>
<td>0.50934</td>
</tr>
<tr>
<td>12</td>
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<td>0.40965</td>
</tr>
</tbody>
</table>
Figure 7: Time series of first principal component of filtered MSU TLS data.
Figure 8: Loading pattern of first EOF of filtered MSU TLS data.

An EOF analysis was also successfully conducted on the full spatial range of OISST data that had been filtered in both spatial dimensions with the Fourier low-pass filter. Table 2 shows the result of this analysis. Furthermore, the time series and loading pattern of the first principal component of OISST data are shown in Figures 9 and 10, respectively. Data for the remaining principal components are located in Appendix B.1.
Table 2: Eigenvalues and % variance values for first 12 principal components of filtered OISST data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1211.5</td>
<td>32.915</td>
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<td>2</td>
<td>595.04</td>
<td>16.165</td>
</tr>
<tr>
<td>3</td>
<td>517.60</td>
<td>14.062</td>
</tr>
<tr>
<td>4</td>
<td>295.38</td>
<td>8.0248</td>
</tr>
<tr>
<td>5</td>
<td>242.33</td>
<td>6.5835</td>
</tr>
<tr>
<td>6</td>
<td>235.02</td>
<td>6.3850</td>
</tr>
<tr>
<td>7</td>
<td>180.12</td>
<td>4.8934</td>
</tr>
<tr>
<td>8</td>
<td>150.57</td>
<td>4.0906</td>
</tr>
<tr>
<td>9</td>
<td>141.16</td>
<td>3.8351</td>
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<td>10</td>
<td>112.07</td>
<td>3.0446</td>
</tr>
<tr>
<td>11</td>
<td>7.2492×10⁻⁴</td>
<td>1.9694×10⁻⁵</td>
</tr>
<tr>
<td>12</td>
<td>6.3224×10⁻⁴</td>
<td>1.7176×10⁻⁵</td>
</tr>
</tbody>
</table>
Figure 9: Time series of first principal component of filtered OISST data.
Additionally, an EOF analysis was successfully conducted on filtered MSU TLS data whose spatial domain was confined to the Atlantic MDR. Table 3 shows the result of this analysis. Furthermore, the time series and loading pattern of the first principal component are shown in Figures 11 and 12, respectively. Data for the remaining principal components are located in Appendix B.2.
Table 3: Eigenvalues and % variance values for first 12 principal components of filtered MSU TLS MDR data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.350</td>
<td>98.699</td>
</tr>
<tr>
<td>2</td>
<td>0.20998</td>
<td>0.81756</td>
</tr>
<tr>
<td>3</td>
<td>6.9858×10^{-2}</td>
<td>0.27199</td>
</tr>
<tr>
<td>4</td>
<td>1.6994×10^{-2}</td>
<td>6.6167×10^{-2}</td>
</tr>
<tr>
<td>5</td>
<td>1.3387×10^{-2}</td>
<td>5.2122×10^{-2}</td>
</tr>
<tr>
<td>6</td>
<td>7.6985×10^{-3}</td>
<td>2.9973×10^{-2}</td>
</tr>
<tr>
<td>7</td>
<td>5.5811×10^{-3}</td>
<td>2.1730×10^{-2}</td>
</tr>
<tr>
<td>8</td>
<td>3.9083×10^{-3}</td>
<td>1.5216×10^{-3}</td>
</tr>
<tr>
<td>9</td>
<td>2.2855×10^{-3}</td>
<td>8.8988×10^{-3}</td>
</tr>
<tr>
<td>10</td>
<td>1.8410×10^{-3}</td>
<td>7.1680×10^{-3}</td>
</tr>
<tr>
<td>11</td>
<td>1.4850×10^{-3}</td>
<td>5.7821×10^{-3}</td>
</tr>
<tr>
<td>12</td>
<td>9.7203×10^{-4}</td>
<td>3.7845×10^{-3}</td>
</tr>
</tbody>
</table>

26
Figure 11: Time series of first principal component of filtered MSU TLS MDR data.
Figure 12: Loading pattern of first EOF of filtered MSU TLS MDR data.

An EOF analysis was also successfully conducted on filtered OISST data whose spatial domain was confined to the Atlantic MDR. Table 4 shows the result of this analysis. Furthermore, the time series and loading pattern of the first principal component are shown in Figures 13 and 14, respectively. Data for the remaining principal components are located in Appendix B.2.
Table 4: Eigenvalues and % variance values for first 12 principal components of filtered OISST MDR data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>41.977</td>
<td>90.611</td>
</tr>
<tr>
<td>2</td>
<td>2.0927</td>
<td>4.5173</td>
</tr>
<tr>
<td>3</td>
<td>1.3070</td>
<td>2.8213</td>
</tr>
<tr>
<td>4</td>
<td>0.33403</td>
<td>0.72103</td>
</tr>
<tr>
<td>5</td>
<td>0.18472</td>
<td>0.39874</td>
</tr>
<tr>
<td>6</td>
<td>0.12757</td>
<td>0.27538</td>
</tr>
<tr>
<td>7</td>
<td>0.11103</td>
<td>0.23967</td>
</tr>
<tr>
<td>8</td>
<td>7.9591E-02</td>
<td>0.17180</td>
</tr>
<tr>
<td>9</td>
<td>6.1259E-02</td>
<td>0.13223</td>
</tr>
<tr>
<td>10</td>
<td>5.1496E-02</td>
<td>0.11115</td>
</tr>
<tr>
<td>11</td>
<td>6.7202E-06</td>
<td>1.4506E-05</td>
</tr>
<tr>
<td>12</td>
<td>3.8984E-06</td>
<td>8.4150E-06</td>
</tr>
</tbody>
</table>
Figure 13: Time series of first principal component of filtered OISST MDR data.
Another EOF analysis was successfully conducted on the full spatial range of MSU TLS data without first applying the Fourier filter. Table 5 shows the result of this analysis. Furthermore, the time series and loading pattern of the seventh principal component are shown in Figures 15 and 16, respectively. Data for the remaining principal components are located in Appendix B.3.
Table 5: Eigenvalues and % variance values for first 12 principal components of unfiltered MSU TLS data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>388950</td>
<td>88.444</td>
</tr>
<tr>
<td>2</td>
<td>20882</td>
<td>4.7484</td>
</tr>
<tr>
<td>3</td>
<td>7207.3</td>
<td>1.6389</td>
</tr>
<tr>
<td>4</td>
<td>4815.7</td>
<td>1.0950</td>
</tr>
<tr>
<td>5</td>
<td>3908.6</td>
<td>0.88881</td>
</tr>
<tr>
<td>6</td>
<td>3223.1</td>
<td>0.73293</td>
</tr>
<tr>
<td>7</td>
<td>1646.8</td>
<td>0.37449</td>
</tr>
<tr>
<td>8</td>
<td>1382.3</td>
<td>0.31433</td>
</tr>
<tr>
<td>9</td>
<td>813.74</td>
<td>0.18504</td>
</tr>
<tr>
<td>10</td>
<td>696.21</td>
<td>0.15831</td>
</tr>
<tr>
<td>11</td>
<td>465.31</td>
<td>0.10580</td>
</tr>
<tr>
<td>12</td>
<td>452.11</td>
<td>0.10280</td>
</tr>
</tbody>
</table>
Figure 15: Time series of seventh principal component of unfiltered MSU TLS data.
An EOF analysis was also successfully conducted on the full spatial range of OISST data without first applying the Fourier low-pass filter. Table 2 shows the result of this analysis. Furthermore, the time series and loading pattern of the fourth principal component are shown in Figures 17 and 18, respectively, and the time series and loading pattern of the sixth principal component are shown in Figures 19 and 20. Data for the remaining principal components are located in Appendix B.3.
Table 6: Eigenvalues and % variance values for first 12 principal components of unfiltered OISST data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12909</td>
<td>84.522</td>
</tr>
<tr>
<td>2</td>
<td>4995.1</td>
<td>3.2706</td>
</tr>
<tr>
<td>3</td>
<td>4128.0</td>
<td>2.7029</td>
</tr>
<tr>
<td>4</td>
<td>1739.6</td>
<td>1.1390</td>
</tr>
<tr>
<td>5</td>
<td>1104.3</td>
<td>0.72309</td>
</tr>
<tr>
<td>6</td>
<td>766.50</td>
<td>0.50188</td>
</tr>
<tr>
<td>7</td>
<td>583.49</td>
<td>0.38204</td>
</tr>
<tr>
<td>8</td>
<td>467.80</td>
<td>0.30630</td>
</tr>
<tr>
<td>9</td>
<td>413.60</td>
<td>0.27081</td>
</tr>
<tr>
<td>10</td>
<td>343.62</td>
<td>0.22499</td>
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<tr>
<td>11</td>
<td>327.94</td>
<td>0.21472</td>
</tr>
<tr>
<td>12</td>
<td>298.18</td>
<td>0.19524</td>
</tr>
</tbody>
</table>
Figure 17: Time series of fourth principal component of unfiltered OISST data.
Figure 18: Loading pattern of fourth EOF of unfiltered OISST data.
Figure 19: Time series of sixth principal component of unfiltered OISST data.
Finally, an EOF analysis was successfully conducted on 10-year time-averaged, filtered MSU TLS data. Table 7 shows the result of this analysis. Furthermore, the time series and loading pattern of the first principal component are shown in Figures 21 and 22, respectively. Data for the remaining principal components are located in Appendix B.4.
Table 7: Eigenvalues and % variance values for first 12 principal components of time-averaged, filtered MSU TLS MDR data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>593.48</td>
<td>54.526</td>
</tr>
<tr>
<td>2</td>
<td>395.95</td>
<td>36.378</td>
</tr>
<tr>
<td>3</td>
<td>83.506</td>
<td>7.6722</td>
</tr>
<tr>
<td>4</td>
<td>6.4806</td>
<td>0.59541</td>
</tr>
<tr>
<td>5</td>
<td>5.6099</td>
<td>0.51541</td>
</tr>
<tr>
<td>6</td>
<td>1.6942</td>
<td>0.15565</td>
</tr>
<tr>
<td>7</td>
<td>1.1521</td>
<td>0.10585</td>
</tr>
<tr>
<td>8</td>
<td>0.54470</td>
<td>5.0045×10^{-2}</td>
</tr>
<tr>
<td>9</td>
<td>2.8750×10^{-4}</td>
<td>2.6415×10^{-5}</td>
</tr>
<tr>
<td>10</td>
<td>2.4499×10^{-4}</td>
<td>2.2509×10^{-5}</td>
</tr>
<tr>
<td>11</td>
<td>2.4499×10^{-4}</td>
<td>2.2509×10^{-5}</td>
</tr>
<tr>
<td>12</td>
<td>2.4499×10^{-4}</td>
<td>2.2509×10^{-5}</td>
</tr>
</tbody>
</table>
Figure 21: Time series of first principal component of time-averaged, filtered MSU TLS MDR data.
Figure 22: Loading pattern of first EOF of time-averaged, filtered MSU TLS MDR data.

The EOF analysis was also successfully conducted on 10-year time-averaged, filtered OISST data. Table 8 shows the result of this analysis. Furthermore, the time series and loading pattern of the first principal component are shown in Figures 23 and 24, respectively. Data for the remaining principal components are located in Appendix B.4.
Table 8: Eigenvalues and % variance values for first 12 principal components of time-averaged, filtered OISST data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>605.07</td>
<td>56.450</td>
</tr>
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<td>396.72</td>
<td>37.012</td>
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<td>37.649</td>
<td>3.5125</td>
</tr>
<tr>
<td>4</td>
<td>14.922</td>
<td>1.3921</td>
</tr>
<tr>
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<td>10.866</td>
<td>1.0138</td>
</tr>
<tr>
<td>6</td>
<td>6.6368</td>
<td>0.61918</td>
</tr>
<tr>
<td>7</td>
<td>5.5860×10^{-4}</td>
<td>5.2115×10^{-5}</td>
</tr>
<tr>
<td>8</td>
<td>5.1799×10^{-4}</td>
<td>4.8326×10^{-5}</td>
</tr>
<tr>
<td>9</td>
<td>4.3678×10^{-4}</td>
<td>4.0749×10^{-5}</td>
</tr>
<tr>
<td>10</td>
<td>3.5557×10^{-4}</td>
<td>3.3173×10^{-5}</td>
</tr>
<tr>
<td>11</td>
<td>3.1496×10^{-4}</td>
<td>2.9384×10^{-5}</td>
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<tr>
<td>12</td>
<td>3.1496×10^{-4}</td>
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</tr>
</tbody>
</table>
Figure 23: Time series of first principal component of time-averaged, filtered OISST MDR data.
3.4 Potential intensity calculations

After calculating a dataset of tropical cyclone potential intensity using MSU TLS and OISST data, the Fourier filter was applied, and an EOF analysis was successfully performed on the resulting data over the entire spatial domain. Table 9 shows the result of this analysis. Furthermore, the time series and loading pattern of the first principal component are shown in Figures 25 and 26, respectively. Data for the remaining principal components are located in Appendix B.5.
Table 9: Eigenvalues and % variance values for first 12 principal components of filtered potential intensity data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
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<td>1</td>
<td>12632</td>
<td>27.121</td>
</tr>
<tr>
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<td>8812.1</td>
<td>18.919</td>
</tr>
<tr>
<td>3</td>
<td>6459.4</td>
<td>13.868</td>
</tr>
<tr>
<td>4</td>
<td>4016.0</td>
<td>8.622</td>
</tr>
<tr>
<td>5</td>
<td>3146.6</td>
<td>6.755</td>
</tr>
<tr>
<td>6</td>
<td>3025.4</td>
<td>6.495</td>
</tr>
<tr>
<td>7</td>
<td>2868.0</td>
<td>6.157</td>
</tr>
<tr>
<td>8</td>
<td>2093.3</td>
<td>4.494</td>
</tr>
<tr>
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</tr>
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<td>3.2066×10^{-3}</td>
<td>6.8845×10^{-6}</td>
</tr>
<tr>
<td>12</td>
<td>3.2066×10^{-3}</td>
<td>6.8845×10^{-6}</td>
</tr>
</tbody>
</table>
Figure 25: Time series of first principal component of filtered potential intensity data.
Figure 26: Loading pattern of first EOF of filtered potential intensity data.

Table 10 shows the result of the same EOF analysis performed on the filtered potential intensity dataset with the spatial domain limited to the Atlantic MDR. Furthermore, the time series and loading pattern of the first principal component are shown in Figures 27 and 28, respectively. Data for the remaining principal components are located in Appendix B.6.
Table 10: Eigenvalues and % variance values for first 12 principal components of filtered MDR potential intensity data.

<table>
<thead>
<tr>
<th>EOF number</th>
<th>eigenvalue</th>
<th>% variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>544.40</td>
<td>64.210</td>
</tr>
<tr>
<td>2</td>
<td>172.31</td>
<td>20.323</td>
</tr>
<tr>
<td>3</td>
<td>72.041</td>
<td>8.4970</td>
</tr>
<tr>
<td>4</td>
<td>27.250</td>
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<td>5</td>
<td>9.7541</td>
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<td>9.1793</td>
<td>1.0826</td>
</tr>
<tr>
<td>7</td>
<td>4.7931</td>
<td>0.56533</td>
</tr>
<tr>
<td>8</td>
<td>3.8641</td>
<td>0.45576</td>
</tr>
<tr>
<td>9</td>
<td>2.7751</td>
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</tr>
<tr>
<td>10</td>
<td>1.4699</td>
<td>0.17337</td>
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<tr>
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<td>12</td>
<td>4.8748×10^{-5}</td>
<td>5.7497×10^{-6}</td>
</tr>
</tbody>
</table>
Figure 27: Time series of first principal component of filtered MDR potential intensity data.
Finally, the filtered MSU TLS, OISST, and potential intensity datasets were spatially averaged over the MDR, and the resulting signals were optimized in an attempt to express the potential intensity signal as a linear combination of TLS and SST data. The MATLAB script `find_coeffs.m` yielded the coefficients in Table 11. The linear combination coefficients for MSU TLS and OISST are henceforth denoted $\kappa_{TLS}$ and $\kappa_{SST}$, respectively, and each has units of $\text{m s}^{-1} \text{K}^{-1}$.

Table 11: Optimal coefficients for a linear combination of filtered MSU TLS and OISST to reconstruct the potential intensity signal in the Atlantic MDR.

<table>
<thead>
<tr>
<th>signal</th>
<th>coefficient ($\kappa$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSU TLS</td>
<td>-0.3339</td>
</tr>
<tr>
<td>OISST</td>
<td>6.4898</td>
</tr>
</tbody>
</table>
The correlation coefficients of each signal and their optimal linear combination with the potential intensity signal are given in Table 12.

<table>
<thead>
<tr>
<th>signal</th>
<th>correlation coefficient (r)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSU TLS</td>
<td>-0.6364</td>
</tr>
<tr>
<td>OISST</td>
<td>0.8397</td>
</tr>
<tr>
<td>$\kappa_{TLS} ; TLS + \kappa_{SST} ; SST$</td>
<td>0.8410</td>
</tr>
</tbody>
</table>

### 4 Analysis

#### 4.1 Temperature power spectra

To identify the quasi-decadal signal in lower stratospheric temperature, power spectrum analyses were conducted on data from several RATPAC stations. As shown in Figure 1, the power spectra for 70 hPa-level radiosonde temperature data from the RATPAC stations in Bangkok, Thailand; Bogotá, Colombia; Jeddah, Saudi Arabia; and Majuro, Marshall Islands each exhibit their strongest peaks at frequencies corresponding to periods of around 5 years. However, the power spectra for Bogotá, Jeddah, Majuro, and San Juan, Puerto Rico also exhibit peaks at periods of around 10 years. At San Juan, this is the strongest spectral peak. The existence of spectral peaks at frequencies corresponding to periods of around 10 years thereby confirms the existence of a lower stratospheric temperature signal whose period is around 10 years at each RATPAC station, with the exception of the Bangkok station.

The Majuro RATPAC station exhibits the strongest quasi-decadal peak of all five stations surveyed. However, the period corresponding to this peak is noticeably shorter than those of the other stations. Of the remaining stations, Bogotá has the strongest 10-year peak, followed by San Juan and Jeddah. The differing heights of the spectral peaks at different geographic locations may imply a spatial dependence of the quasi-decadal temperature signal. However, this power spectrum analysis alone is not sufficient to draw this conclusion, since other spatial factors could be responsible for the amplification of the other peaks at certain stations, thereby reducing the relative strength of the 10-year signals there.

The spectral analysis of temperature data from different pressure levels at the San Juan RATPAC station offers further evidence of a quasi-decadal signal. Figure 2 shows spectral peaks at frequencies corresponding to periods of around 10 years for each of the pressure levels analyzed. The signal is strongest at the 50 hPa level, and in fact the 10-year peak at this level is nearly three times stronger than the peaks at the other pressure levels analyzed.
Next, the 30 hPa and 70 hPa levels exhibit similar peaks to each other, while the 100 hPa temperature data exhibits the weakest of the four 10-year peaks. This result provides a profile of the vertical manifestation of the quasi-decadal oscillation in stratospheric temperature. Although for this radiosonde station, the quasi-decadal signal is strongest at the 50 hPa level, this study focuses on temperature data for the 70 hPa level because this is the RATPAC observation level closest to the lower stratospheric outflow level of tropical cyclones.

Power spectrum analyses were also conducted for the MSU TLS and OISST satellite temperature data. Figure 5 shows the power spectrum for MSU TLS data, which exhibits a small peak at a period of around 5 years, and a larger peak at a period of around 10 years. This is consistent with the RATPAC result showing a signal in lower stratospheric temperature whose period is around 10 years. However, this result considers temperature data from the entire global domain, while the earlier RATPAC result considered only point measurements at each radiosonde observing station. Therefore, while spatial characteristics of the 10-year signal cannot be inferred from this result, the result confirms that the quasi-decadal lower stratospheric temperature signal is not confined to the regions sampled by the five RATPAC stations from which data were analyzed.

The power spectrum for OISST also exhibits peaks at frequencies corresponding to periods of around 5 and 10 years, as shown in Figure 6. However, for OISST, these two spectral peaks are of roughly the same magnitude. Also, while the two peaks correspond to periods that are around 5 and 10 years, the actual periods at which peaks occur somewhat shorter than 5 and 10 years, respectively. Therefore, while a quasi-decadal oscillation in SST may be related to that of lower stratospheric temperature, there is not sufficient evidence in the result of the spectral analysis of OISST to support that conclusion.

4.2 Solar activity

The power spectrum analysis of ACRIM TSI data, shown in Figure 3, exhibits a strong peak at a frequency corresponding to a period of slightly more than 10 years. This is consistent with the fact that the solar activity cycle is known to have a period of about 11 years. Furthermore, the spectral peak in TSI data at a period of around 10 years is consistent with similar peaks exhibited by RATPAC and MSU TLS lower stratospheric temperature data.

However, the results of the application of the Fourier low-pass filter to RATPAC lower stratospheric temperature data and ACRIM TSI provide evidence of incoherence of the solar cycle signal with that of lower stratospheric temperature. Figure 4 shows that the filtered RATPAC 70 hPa temperature data exhibit significantly different periods at each radiosonde station. Furthermore, while several of the troughs and peaks in the filtered RATPAC are coherent with those of filtered TSI, others fail to display coherence with the solar data. For example, while the filtered Bogotá and Jeddah time series display coherence with that of
TSI in 1986 and 1996, respectively, those same time series later display incoherence with the solar data after the year 2000. Therefore, these results indicate the lack of a significant relationship between the solar activity cycle and the quasi-decadal oscillation in lower stratospheric temperature.

4.3 EOFs of satellite temperature data

4.3.1 Global domain

EOF analyses were conducted for filtered MSU TLS and OISST temperature data over their entire spatial domains to analyze the principal components of the decadal-scale temperature signals, and their spatial manifestations. For the filtered TLS data, the first EOF accounts for 45.80% of the total variance. As shown in Figure 8, the loading pattern of the first EOF is fairly zonally symmetric, with higher values near the Equator and North Pole, and lower values near the South Pole. However, the highest values of this loading pattern are located in the Pacific Ocean on either side of the Equator, and near the southern coast of Alaska.

For filtered OISST data, the first EOF accounts for 32.92% of the total OISST variance. As shown in Figure 10, its loading pattern is much less zonally symmetric than that of the first EOF of TLS. The lowest negative values are located in the Pacific Ocean near the west coasts of the Americas, and along the Equator away from the continents. The highest positive values are located in the western North Pacific and eastern North Atlantic.

The spatial loading pattern of the first EOF of OISST in the Pacific Ocean is similar to the pattern of SST regressed on the PDO index as described by Mantua et. al. (1997). Therefore, the time series of the first principal components of MSU TLS and OISST data are plotted in Figure 29 against a time series of PDO index to which the Fourier low-pass filter has been applied.
Figure 29: Time series of the first principal components of MSU TLS (red) and OISST (blue) against a time series of filtered PDO index (green).

The three time series have coherent peaks in 1990, 2001, and 2007, as well as coherent troughs in 1993 and 2005. This result therefore implies a connection between the quasi-decadal oscillation in lower stratospheric temperature and variability in SST associated with the PDO.

The loading pattern of the first EOF of OISST is also similar to the SST anomaly associated with ENSO, as described by Rasmusson and Wallace (1983). Therefore, the time series of the first principal components of MSU TLS and OISST data are plotted in Figure 30 against a time series of ENSO index to which the Fourier low-pass filter has been applied.
Here, the negative of the ENSO index is plotted to make coherence more apparent. The three resulting time series also have coherent peaks in 1990, 2001 and 2007, as well as coherent troughs in 1993 and 2005. This result therefore implies a connection between the quasi-decadal oscillation in lower stratospheric temperature and variability in SST associated with ENSO.

However, the statistical significance of these results are called into question by the fact that each of these principal components accounts for less than 50% of the net variance of its respective filtered temperature dataset. The signals interpreted here could therefore be insignificant with respect to the cumulative variance of the remaining principal components. Therefore, while there appears to be some connection between the quasi-decadal oscillation in lower stratospheric temperature and variability in SST associated with PDO and ENSO, that variability may not make a major overall contribution to the quasi-decadal signal in the
stratosphere.

4.3.2 Atlantic MDR

The results of the EOF analysis of the satellite temperature data whose spatial domain is restricted to the Atlantic MDR can be interpreted similarly. For MSU TLS data, the first EOF accounts for 98.70% of the total variance. As shown in Figure 12, its lowest values are at the western edge of the MDR, while higher values are found toward the northern edge. Similarly, for OISST data, the first EOF accounts for 90.61% of the total SST variance. As shown in Figure 14, its highest values are at the southwest and northeast corners of the MDR, and the lowest values are at the southeast corner.

The time series of the first principal components of filtered MSU TLS and OISST MDR data are plotted in Figure 31.

![Figure 31: The time series of the negative of the first principal component of MDR MSU TLS (red) is plotted against the time series of the first principal component of MDR OISST (blue).](image)

Here, the negative time series of the first principal component of MSU TLS is plotted to make coherence with OISST more apparent. The two time series now have coherent peaks
in 2006, as well as coherent troughs in 1992. However, the remainder of the extrema in the TLS time series occur approximately 1 to 2 years sooner than those in the SST time series. Therefore, a lagged relationship is found to exist between the quasi-decadal oscillation in lower stratospheric temperature and SST variability in the Atlantic MDR, with the SST signal lagging that of lower stratospheric temperature by about 0-2 years.

Since the first principal components of the global temperature datasets were found to have a connection with PDO, the first principal components of the MDR temperature datasets are plotted against a filtered time series of PDO index in Figure 32.

![Figure 32: The time series of the negative of the first principal component of MDR MSU TLS (red) is plotted against the time series of the first principal component of MDR OISST (blue) and a time series of filtered PDO index (green).](image)

In this case, neither of the first principal component time series of MSU TLS and OISST exhibit coherence with the filtered PDO index time series. Therefore, PDO is not found
to contribute to the first principal components of the quasi-decadal oscillations of SST and lower stratospheric temperature data in the Atlantic MDR. This is expected, since the PDO is observed primarily in the Pacific Ocean, not the Atlantic.

The first principal components of the MDR temperature datasets are next plotted against a filtered time series of AMO index in Figure 33.

Figure 33: The time series of the negative of the first principal component of MDR MSU TLS (red) is plotted against the time series of the first principal component of MDR OISST (blue) and a time series of filtered AMO index (green). Here, the AMO index time series is amplified by a factor of 7 to give it a similar magnitude to the two principal component time series.

The filtered AMO index exhibits coherence with the first principal components of filtered MSU TLS and OISST data in the MDR. Coherent peaks occur in 1989, 1999, and 2006, while coherent troughs occur in 1986, 1994, and 2008. Therefore, a lagged relationship
is found in the Atlantic MDR between the quasi-decadal oscillation in lower stratospheric temperature and variability in SST associated with the AMO. Since each of the first principal components of temperature data accounts for over 90% of the net variance of its respective filtered dataset over the MDR, this connection is much more statistically robust than the global connection with PDO. However, since the AMO is by definition a measure of North Atlantic SSTs, the connection between AMO and OISST is somewhat of a trivial result, and the connection between AMO and TLS remains a result of the underlying connection between lower stratospheric and sea surface temperatures.

4.3.3 Unfiltered data analysis

Over the global domain, the results of EOF analyses for unfiltered satellite temperature datasets are consistent with known characteristics of SST and TLS temperature signals. For both MSU TLS and OISST, their first principal components are consistent with the annual cycle. For MSU TLS, the annual cycle accounts for 88.44% of the total variance, and for OISST, the annual cycle accounts for 84.52% of the total variance. Thus, the unfiltered TLS and SST datasets are dominated by annual variability not pertinent to the quasi-decadal oscillation.

As shown in Figure 16, the loading pattern of the seventh principal component of unfiltered MSU TLS data has its highest values at high latitudes in each hemisphere. Figure 15 shows that the time series of the EOF exhibits sharp drops in 1983 and 1992, each of which persists for about 2 years. The timings of these drops are consistent with the major volcanic eruptions of El Chichón in 1982 and Mt. Pinatubo in 1991, respectively. Thus, it can be concluded that stratospheric warmings from major volcanic eruptions constitute the seventh principal component of unfiltered TLS data. This EOF accounts for 0.37% of the total variance in MSU TLS.

As shown in Figure 18, the loading pattern of the fourth principal component of unfiltered OISST data has its lowest negative values in a strip extending westward along the Equator from the west coast of South America. This pattern is similar to the SST anomaly associated with ENSO (Rasmusson and Wallace 1983). Therefore, the time series of the fourth principal component of unfiltered OISST is compared with ENSO index in Figure 34.
Figure 34: The negative of the time series of fourth principal component of unfiltered OISST (blue) is plotted against a time series of ENSO index (red).

Here, the negative of the fourth principal component of OISST is plotted to make coherence with ENSO more apparent. The two time series are very closely coherent, and thus the ENSO signal is found to constitute the fourth EOF of unfiltered OISST data. This EOF accounts for 1.14% of the total variance. This result is also expected, since ENSO index is calculated from tropical Pacific SSTs.

As shown in Figure 20, the loading pattern of the sixth principal component of unfiltered OISST data has its highest values in the North Pacific Ocean near the south coast of Alaska. Since this is similar to the SST pattern associated with PDO, the time series of the sixth principal component of OISST is compared with PDO index in Figure 35.
Here, the negative of the sixth principal component of OISST is plotted to make coherence with PDO more apparent. While the two time series have coherent peaks in 1983, 1988, and 1997, and a coherent trough in 1992, the time series become very closely coherent after 2002. However, the PDO index from University of Washington uses OISST data to calculate PDO starting with the year 2002. Therefore, it is expected that the two time series would be closely coherent, and it can be concluded that the PDO signal constitutes the sixth principal component of OISST. This EOF accounts for 0.50% of the total variance.

4.3.4 Time-averaged data analysis

The EOF results for filtered, time-averaged MSU TLS and OISST data are similar to those of filtered, non-averaged temperature data over the global domain. However, the effect of
the time average is an overall smoothing of the results. For time-averaged, filtered MSU TLS data, the first EOF accounts for 54.53% of the total variance. As shown in Figure 22, the loading pattern of this EOF is very zonally symmetric, with its lowest values exhibited near the South Pole, and its highest values near the Equator, and at high latitudes in each hemisphere.

For time-averaged, filtered OISST data, the first EOF accounts for 56.45% of the total variance. As shown in Figure 24, the loading pattern of this EOF exhibits its lowest values near the western boundaries of the North Atlantic and North Pacific Oceans.

The time series of the first principal components of time-averaged, filtered MSU TLS and OISST data are compared in Figure 36.

Figure 36: The time series of the first principal component of time-averaged, filtered MSU TLS (red) is compared with the negative of the first time series of the first principal component of time-averaged, filtered OISST data (blue).

Here, the negative of the time series of the first EOF of OISST is plotted to make coherence with TLS more apparent. The two time series have coherent peaks in 2002 and 2007, and a coherent trough in 2004. However, the two time series are less closely coherent earlier in the time domain. This result is therefore inconclusive regarding the relationship between temperature in the lower stratosphere and SST on a global scale.

Furthermore, while the first principal components of MSU TLS and OISST now account for greater than 50% of the total variability of each dataset, the cumulative variance of
the remaining principal components is still relatively high. Additionally, the execution of a 10-year time average reduced the temporal domains of each temperature dataset from around 30 years to around 20 years. For quasi-decadal oscillations, each time series can then only sample about two cycles. Therefore, only limited conclusions can be drawn from this analysis.

4.4 Potential intensity

After performing the potential intensity calculation, the initial results were generated by an EOF analysis. The first EOF of the potential intensity dataset to which the Fourier low-pass filter was applied accounted for 27.1% of the total variance. As shown in Figure 26, the loading pattern of this EOF is similar to that of the first EOF of filtered OISST, shown in Figure 10. Therefore, the time series of the first EOF of filtered potential intensity is compared to those of the first EOFs of OISST and MSU TLS in Figure 37.

![Figure 37](image)

Figure 37: The time series of the first principal component of filtered MSU TLS (red) is plotted with the time series of the first principal component of filtered OISST (blue), and the first principal component of filtered calculated potential intensity data (green).

These three time series have coherent peaks in 1989, 2001, and 2007, as well as coherent troughs in 1993 and 2004. Therefore, the first principal component of potential tropical
cyclone shares a connection with those of SST and lower stratospheric temperature on a global scale.

The nature of this connection in the Atlantic MDR is determined by the results of the Atlantic MDR EOF analysis of potential intensity data. The first EOF of filtered potential intensity data whose spatial domain is restricted to the Atlantic MDR accounts for 64.21% of the total variance. As shown in Figure 28, the loading pattern for this EOF exhibits its largest values at the southwestern and northeastern boundaries of the region, while the lowest values are found around the middle latitudes of the region, at around 30ºW.

The time series of the first principal component of Atlantic MDR potential intensity data is again compared to those of the first principal components of MSU TLS and OISST over the same region in Figure 38.

Figure 38: The time series of the first principal component of filtered MDR MSU TLS (red) is plotted with the time series of the first principal component of filtered MDR OISST (blue), and the first principal component of filtered MDR calculated potential intensity data (green).

The three time series again exhibit coherence. Specifically, the three series have coherent peaks in 1989, 1997, and 2005, while they have a coherent trough in 1992. However, the curve corresponding to the first principal component of potential intensity is much more closely coherent with that of OISST data than with that of MSU TLS data. It can therefore be concluded that potential intensity, SST, and lower stratospheric temperature exhibit a connection in the Atlantic MDR, although the connection between SST and potential inten-
sity is stronger than that between lower stratospheric temperature and potential intensity. This result is more statistically significant than the global result, since each of the three first EOFs accounts for at least 60% of the total variance of their respective temperature datasets.

The results of the linear reconstruction of the quasi-decadal potential intensity signal from those of SST and TLS in Atlantic MDR-averaged values provide further information on the relationship between potential intensity and the temperature of the lower stratosphere. First, the values of the linear combination coefficients $\kappa_{\text{TLS}}$ and $\kappa_{\text{SST}}$, as shown in Table 11, indicate the relative strengths of each quasi-decadal temperature signal in constructing the potential intensity signal. First, the fact that $\kappa_{\text{TLS}}$ is negative while $\kappa_{\text{SST}}$ is positive confirms the expected result that increases in SST will increase potential intensity of tropical cyclones, while increases in TLS increase the outflow temperatures of hypothetical cyclones, thereby decreasing their potential intensity. Next, the relative magnitudes of each term indicate the strength of each temperature signal in contributing to the potential intensity signal. The ratio of the magnitudes of the two coefficients is given by

$$\frac{|\kappa_{\text{TLS}}|}{|\kappa_{\text{SST}}|} = 0.05145.$$  

Therefore, while there is a contribution to the potential intensity signal from the quasi-decadal stratospheric temperature signal in the Atlantic MDR, the magnitude of its contribution is roughly 5% of that of the SST signal.

Figure 39 shows the time series of each individual MDR-averaged filtered temperature signal, their optimal linear combination, and the MDR-averaged filtered potential intensity signal. The linear reconstruction of potential intensity is coherent with the observed signal in both phase and amplitude. The optimal linear combination of the TLS and SST signals is therefore a reasonable approximation of the observed potential intensity signal.

The correlation coefficients of each individual temperature signal, and their linear combination, with the potential intensity signal, as shown in Table 12 and Figure 39, also provide information on the connection between the quasi-decadal signal in lower stratospheric temperature and the potential intensity of tropical cyclones. Again, as expected, the negative value of $r$ for MSU TLS data indicates that the quasi-decadal lower stratospheric temperature oscillation is anticorrelated with the potential intensity signal, while the positive value of $r$ for OISST indicates a positive correlation between SST and potential intensity. Additionally, the correlation between SST and potential intensity is stronger than the anticorrelation between lower stratospheric temperature and potential intensity. Finally, the optimal linear combination of the TLS and SST signals exhibits a stronger correlation with the potential intensity signal than does either signal individually. However, the difference between the value of $r$ for the optimal linear combination of TLS and SST data and the value of $r$ for
SST data alone is given by the value

$$\Delta r = 0.0013.$$  \hspace{1cm} (7)

Therefore, the inclusion of TLS data with the SST signal improves the correlation with potential intensity by around 0.13%. Thus, the quasi-decadal signal in lower stratospheric temperature makes a small, but non-negligible contribution to the signal of tropical cyclone potential intensity in the Atlantic MDR. Finally, since the correlation coefficient $r = 0.8410$ of the optimal linear combination of SST and TLS data with potential intensity is significantly less than 1, there must be other signals contributing to the construction of the potential intensity signal in this region.

It is important to note, however, that the coherent nature of the TLS and SST datasets is detrimental to the robustness of this result. Since the two quasi-decadal temperature signals have similar phases, it can be assumed that they are not independent signals. Therefore, especially if their relationship is causal, their resulting linear combination may be, to some extent, an amplification of only a single signal. It is therefore difficult to be certain from which signal the strengths of the correlations truly arise given the results of this analysis.
5 Discussion

The investigation of the quasi-decadal oscillation of lower stratospheric temperature by this study yielded several results concerning the characterization of the signal, its relationship with the solar activity cycle, its connections with other known climatic oscillations, and its effects on tropical cyclone activity.

5.1 Characterization of the lower stratospheric temperature signal

The existence of an oscillatory, quasi-decadal signal in lower stratospheric temperature is confirmed by the spectral analyses of lower stratospheric temperature data. For RATPAC data, four of the five tropical radiosonde stations surveyed recorded spectral peaks at the 70 hPa level at frequencies corresponding to periods near 10 years. Furthermore, the power spectrum of satellite-observed MSU TLS data exhibits a distinct spectral peak at a period just above 10 years. These results confirm the existence of an observable, oscillatory signal in lower stratospheric temperature whose period is around 10 years.

Vertically, the signal is observed at several levels in the stratosphere above the tropical Atlantic Ocean. Of the pressure levels at which radiosonde measurements were taken, the signal is found to be strongest at the 50 hPa level, nearer to the middle of the stratosphere, and weakest at the 100 hPa level, nearer to the tropopause. However, extensive study of the vertical profile of the quasi-decadal signal in lower stratospheric temperature was not undertaken by this research.

Although the quasi-decadal period of the lower stratospheric temperature signal is consistently found throughout the global domain, the strength and phase of the signal is found to vary spatially. The most significant principal component of the signal is found to vary primarily with latitude. Additionally, the amplitude of this component is found to be notably greater in the northern hemisphere, and in the Pacific Ocean. This conclusion suggests possible connections with tropospheric and oceanic climate oscillations such as PDO, ENSO, and AMO, which may be governing the spatial manifestation of the lower stratospheric temperature signal.

5.2 Lack of coherence with solar activity cycle

Although the quasi-decadal nature of the oscillatory signal in lower stratospheric temperature is consistent with the quasi-decadal period of the solar activity cycle, analysis of Fourier-filtered radiosonde temperature and TSI data shows a lack of coherence between the two signals. At each radiosonde station, the temperature and solar activity signals exhibit different periods and incoherence of phase. Therefore, it is concluded that the quasi-decadal signal in lower stratospheric temperature is not related to the 11-year cycle in solar activity.
This result refutes the role of lower stratospheric temperature as a pathway for modulation of tropical cyclone counts by solar activity, as proposed by Elsner and Jagger (2008). Since the solar cycle is not responsible for the quasi-decadal oscillation in lower stratospheric temperature, variations in solar activity cannot be modulating the outflow temperatures of tropical cyclones on a quasi-decadal basis. Therefore, if the observed relationship between the solar cycle and hurricane counts is causal, there must exist some other mechanism by which this modulation takes place.

5.3 Connections with tropospheric and oceanic climatic oscillations

The results of the EOF analyses of MSU TLS and OISST data suggest connections between the quasi-decadal oscillation in lower stratospheric temperature and several climatic oscillations in the troposphere and ocean. The strongest of these connections discovered by this study is that of lower stratospheric temperature with SST and AMO in the Atlantic Ocean MDR. Although the AMO has an overall period of 65-70 years, higher frequency oscillations in the AMO index are observed to occur on a decadal scale. Since the AMO is calculated from North Atlantic Ocean SSTs, the coherence of AMO with SSTs in the Atlantic tropical cyclone basin is hardly revelatory. However, since each of these time series exhibits coherence with the quasi-decadal signal in lower stratospheric temperature, these data exhibit a connection of AMO with the stratosphere that has not been previously documented. Still, this study has not explored whether AMO has a causal relationship with the quasi-decadal oscillation in lower stratospheric temperature, or, more importantly, the nature of the physical relationship between the oscillatory signals in lower stratospheric and sea surface temperatures in this region.

Another conclusion drawn from the EOF analyses is the existence of a connection between the lower stratospheric temperature oscillation with SST and PDO on a global scale. This connection is not found to be as statistically robust as that of AMO in the MDR. However, this may be due to the fact that the analyses were conducted over a global domain, of which the domain of the PDO comprises only a part. Still, the time series and loading patterns of MSU TLS and OISST support the existence of this connection. However, since the PDO is interpreted as a superposition of several other contributing phenomena, the significance of this connection in terms of inferring physical mechanisms contributing to the quasi-decadal oscillation in lower stratospheric temperature may be limited.

Similarly, a connection is found between the lower stratospheric temperature oscillation, SST, and ENSO on a global scale. Again, since the region in which ENSO is primarily manifested comprises only the Pacific, EOF analyses over the global domain captured a weaker statistical relationship between these signals. Still, the time series and loading patterns of
MSU TLS and OISST again support the existence of this connection. Since ENSO is known to be a contributing phenomenon to PDO, this conclusion may be related to the result that a global connection exists with PDO. In any event, however, this conclusion again does not determine whether ENSO or PDO have causal relationships with the quasi-decadal lower stratospheric temperature oscillation, and whether the sea surface is used as a pathway for a physical mechanism for modulation of one by the other.

For each of the aforementioned connections found through EOF analysis, a stronger coherence is found between the climatic indices and SST than is found between the indices and the lower stratospheric temperature oscillation signal. Therefore, further investigation is required to determine whether there is a direct link between the quasi-decadal oscillation in lower stratospheric temperature and climatic oscillations in the troposphere and ocean, or if these connections are byproducts of a deeper relationship between the temperatures of the sea surface and the lower stratosphere.

Additionally, the EOF analyses of MSU TLS and OISST data yield the conclusions that ENSO and PDO signals are principal components of global SST, while a signal of major volcanic eruptions is a principal component of lower stratospheric temperature. These conclusions are consistent with prior knowledge about modulation of SST and lower stratospheric temperature, and therefore confirm the expected results.

5.4 Effects on tropical cyclone activity

The results of the potential intensity calculations yield conclusions on the effect of the quasi-decadal signal in lower stratospheric temperature on tropical cyclone activity. First, the largest principal components of Fourier-filtered TLS, SST, and potential intensity data are found to be coherent both for the global domain and for the MDR of tropical cyclones in the Atlantic basin. This evidence supports the hypothesis that the quasi-decadal oscillation in lower stratospheric temperature could be modulating the potential intensity of tropical cyclones, since the coherence of their signals implies a possible physical relationship.

Next, the results of the linear reconstruction of the potential intensity signal from TLS and SST data in the Atlantic MDR yields further information on the nature of the relationship between the lower stratospheric temperature signal and potential intensity of tropical cyclones. Since the optimal linear combination of quasi-decadal MSU TLS and OISST signals is able to reasonably approximate the signal in observed potential intensity of the same frequency, it can be concluded that the quasi-decadal temperature signals in both the sea surface and the lower stratosphere make some contribution to the potential intensity signal in that region.

Further conclusions about the contribution of the lower stratospheric temperature signal to potential intensity are drawn from the values of the linear combination coefficients $\kappa$. 

70
and correlation coefficients $r$. The first of these conclusions is that the contribution from the TLS signal has opposite sign from that of the signal of potential intensity. Secondly, the contribution of the lower stratospheric temperature oscillation to the potential intensity signal is small—roughly 5% of that of SST—but not negligible. Therefore, the quasi-decadal oscillation in lower stratospheric temperature is found to have a measurable effect on the potential intensity of tropical cyclones in the Atlantic MDR. However, this conclusion is made with the reservation that the robustness of this result may be compromised by the possibility that both TLS and SST signals are manifestations of a single oscillatory, quasi-decadal signal.

5.5 Research limitations and errors

One possible source of error in this study stems from the use of RATPAC temperature data from the 00Z observation time. Utilizing data from the same observation time does not introduce any error when considering a single station, but when considering radiosonde stations in different geographic locations, a spatial bias could be created due to the fact that some stations have every observation taken during the day, while others have all observations taken at night. While the magnitude of this error is unknown, it could be resolved by taking an arithmetic mean of 00Z and 12Z temperature data for each monthly mean RATPAC data point.

Another possible source of error from RATPAC data is the existence of voids in the radiosonde dataset. While RATPAC temperature time series were interpolated to fill in any missing values, there are varying levels of missing data at different RATPAC stations. Therefore, a bias could be introduced due to the fact that certain radiosonde stations have higher levels of missing data. However, this bias should not be significantly large given the assumption that missing data are randomly distributed, and the fact that RATPAC stations with large amounts of missing data were not used.

Finally, the largest limitation of this study lies in the limited temporal domain provided by satellite data. Since the technology to acquire remotely sensed temperature data from satellites was only put into use in the late 1970s and early 1980s, the satellite temperature datasets available for this study incorporate a maximum of only about 30 years of data. Since the lower stratospheric temperature signal being studied is oscillatory with a period of around 10 years, the satellite temperature data can encompass a maximum of 3 cycles. There is some question in regard to whether this is enough data to draw statistically significant conclusions about the nature of the oscillation and its interactions with other atmospheric phenomena. This short time domain becomes especially constraining when a 10-year time average is applied to the satellite temperature data, and the maximum number of encompassed cycles drops to 2. However, utilizing the full 30 years of satellite data should be sufficient to at
least draw qualitative conclusions about the quasi-decadal oscillation in lower stratospheric temperature.

5.6 Future research

There are several areas unexplored by this study that could be addressed by future research. First, a study could characterize the vertical manifestation of the quasi-decadal temperature signal in the stratosphere. While this study addressed the power spectra of radiosonde temperature data at a single RATPAC station, another study could identify the levels at which the quasi-decadal signal is strongest and weakest over a wider spatial range. This data could then be used to further analyze the connections between the quasi-decadal temperature cycle and other atmospheric phenomena.

Another possibility for future research lies in the selection of spatial domains for statistical analyses. While the EOF analyses in this study were restricted to the global domain and the Atlantic MDR, similar analyses could be conducted for the same data in other regions of the globe. For instance, whether the degree to which the % variance of the first EOF of MSU TLS and OISST rises or falls if the spatial domain is restricted to the North Pacific, where the PDO is manifested, could be investigated. Furthermore, while connections between the quasi-decadal oscillation in lower stratospheric temperature and the potential intensity signal were studied in the Atlantic MDR, similar techniques could be applied to data from the MDRs for the other major tropical cyclone basins to determine whether the results of this study are universal to all tropical cyclone basins.

Finally, another study could work to develop physical models for the interactions documented here of the signal in lower stratospheric temperature with other atmospheric and oceanic processes. While this study has found several connections between the quasi-decadal oscillation in lower stratospheric temperature and other atmospheric and oceanic phenomena, it has been unable to determine the physical mechanisms through which these relationships occur. A study to determine these mechanisms would be very beneficial to improving the understanding of the quasi-decadal oscillation in lower stratospheric temperature.

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Appendix A  Scripts and codes

A.1  Bash scripts

A.1.1  get_bangkok.sh

#!/bin/bash

cd ~/data
if [ -e bangkok_monthly_00z.txt ]; then
  rm bangkok_monthly_00z.txt;
fi

while read LINE; do
  WMO=$(echo $LINE | cut -d ' ' -f 17)
  if [[ $WMO == 48455 ]]; then
    echo $LINE >> bangkok_monthly_00z.txt
  fi
done < RATPAC-B-monthly-00Z.txt

A.1.2  cleanup_bangkok.sh

#!/bin/bash

cd ~/data
if [ -e bangkok/850mb_00z.txt ]; then
  rm bangkok/*_00z.txt;
fi

while read LINE; do
  YEAR=$(echo $LINE | cut -d ' ' -f 2)
  MONTH=$(echo $LINE | cut -d ' ' -f 3)
  T_850=$(echo $LINE | cut -d ' ' -f 4)
  T_700=$(echo $LINE | cut -d ' ' -f 5)
  T_500=$(echo $LINE | cut -d ' ' -f 6)
  T_400=$(echo $LINE | cut -d ' ' -f 7)
  T_300=$(echo $LINE | cut -d ' ' -f 8)
  T_250=$(echo $LINE | cut -d ' ' -f 9)
  T_200=$(echo $LINE | cut -d ' ' -f 10)
  T_150=$(echo $LINE | cut -d ' ' -f 11)
  T_100=$(echo $LINE | cut -d ' ' -f 12)
  T_70=$(echo $LINE | cut -d ' ' -f 13)
  T_50=$(echo $LINE | cut -d ' ' -f 14)

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T_30=$(echo $LINE | cut -d ' ' -f 15)

if [ $YEAR -ge 1979 ]; then
  if [[ $T_850 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_850" >> bangkok/850mb_00z.txt
  fi
  if [[ $T_700 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_700" >> bangkok/700mb_00z.txt
  fi
  if [[ $T_500 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_500" >> bangkok/500mb_00z.txt
  fi
  if [[ $T_400 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_400" >> bangkok/400mb_00z.txt
  fi
  if [[ $T_300 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_300" >> bangkok/300mb_00z.txt
  fi
  if [[ $T_250 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_250" >> bangkok/250mb_00z.txt
  fi
  if [[ $T_200 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_200" >> bangkok/200mb_00z.txt
  fi
  if [[ $T_150 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_150" >> bangkok/150mb_00z.txt
  fi
  if [[ $T_100 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_100" >> bangkok/100mb_00z.txt
  fi
  if [[ $T_70 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_70" >> bangkok/70mb_00z.txt
  fi
  if [[ $T_50 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_50" >> bangkok/50mb_00z.txt
  fi
  if [[ $T_30 != 999.00 ]]; then
    echo "$YEAR$MONTH$T_30" >> bangkok/30mb_00z.txt
  fi
fi
done < bangkok_monthly_00z.txt

The remaining shell scripts get_[station name].sh and cleanup_[station name].sh are identical to get_bangkok.sh and cleanup_bangkok.sh, where everywhere in the code, the word bangkok is replaced with the name of each individual RATPAC station.
A.2 MATLAB scripts

A.2.1 psa.m

function [pxx period] = psa(t_data)

% Function to calculate the power spectrum of a set of RATPAC TLS, SST, or TSI data whose temporal domain is from January 1979 to May 2010.
% Vince Agard
% June 2010

% create time scales in terms of fractions of years
% t_data(:,4)=t_data(:,1)+(t_data(:,2)-.5)/12;
% t=1979:1/12:t_data(length(t_data),4);
% t=t';
% t=t_data(:,1);

% get T values and interpolate to fill in any missing values
% x=interpl(t_data(:,4),t_data(:,3),t);
% x=t_data(:,3);

% uncomment for TSI data
% t=1980+t_data(:,4)/365.25;
% x=t_data(:,2);

% uncomment for TLS, OISST data
t=t_data(:,1);
x=t_data(:,2);

x=detrend(x);
n=length(x);
t=t-t(1);

% perform Fourier transform and calculate power spectrum
p=abs(fft(x))/(n/2);
if mod(n,2)
    pxx=p(1:(n-1)/2).^2;
else
    pxx=p(1:n/2).^2;
end
% frequency and period
freq=[0:n/2-1]/t(n);
period=1./freq;

% generate plots
figure
plot(t_data(:,1),t_data(:,2))
xlabel('year')
ylabel('temperature anomaly (K)')
figure
plot(period,pxx)
xlabel('period (years)')
ylabel('signal power')

A.2.2 hf_filter.m

% Function HF_FILTER
% Function to remove high-frequency signals from a data series.
% Vince Agard
% June 2010

function [time filtered] = hf_filter(t_data)

% get T or TSI values and interpolate to fill in any missing values
if numel(t_data(1,:)) == 3 % RATPAC data
    % create time scales in terms of fractions of years
    t_data(:,4)=t_data(:,1)+(t_data(:,2)-.5)/12;
    time=1979+.5/12:1/12:t_data(length(t_data),4);
    time=time';
    x=interpl(t_data(:,4),t_data(:,3),time);
    fs=12;
elseif numel(t_data(1,:)) == 4 || numel(t_data(1,:)) == 2 % TSI or NCEP data
    x=t_data(:,2);
    time=t_data(:,1);
    fs=365;
elseif numel(t_data(1,:)) == 1 % Monthly NCEP
    x=t_data;
    time=1948:1/12:1948+(length(x)-1)/12;
    time=time';
    fs=12;

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end
x=detrend(x);
n=length(x);

% perform Fourier transform
f=fft(x);
freq=fs*(mod(((0:n-1)+floor(n/2)),n)-floor(n/2))/n;

% eliminate high-frequency signals
for j=1:n
    if abs(freq(j)) > .2
        f(j)=0;
    end
end
filtered=real(ifft(f));

A.2.3  tls_psa.m

XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
% Function TLS_PSA
%
% Function to apply a land-sea mask to MSU TLS data, average it over the
% spatial domain, and perform a power spectrum analysis.
%
% Vince Agard
% June 2010
XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

function [time m_tls] = tls_psa()
nc=netcdf('/meteor/disk7/agard/grads-1.9b4/data/rss_tb_maps_ch_tls_v3_2.nc',...
         'nowrite');
tls=nc{'brightness_temperature'}(:,:,:);
time=1979+11/12:12:1979+389/12;
time=time';
m_tls=0;
for j=12:numel(tls(:,:,1))-6
    numdata=0;
total=0;
    for lat=1:numel(tls(1,:,1))
        for lon=1:numel(tls(1,1,:))
            if tls(j,lat,lon) ~= -9999  % don't add missing values
                numdata=numdata+1;
total=total+tls(j,lat,lon);
            end
        end
    end
    m_tls(j)=total/numdata;
end

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numdata = numdata + 1;
total = total + tls(j, lat, lon);
end
end
m_tls(j-11) = total/numdata; % average TLS value
end
m_tls = m_tls';
psa([time m_tls])
end

A.2.4 oisst_psa.m

function [time m-sst] = oisst_psa()
%
% Function OISST_PSA
% %
% Function to apply a land-sea mask to OISST data, average it over the % spatial domain, and perform a power spectrum analysis.
% %
% Vince Agard
% June 2010
% %

nc = netcdf('/meteor/disk7/agard/grads-1.9b4/data/sst.mnmean.nc','nowrite');
nc2 = netcdf('/meteor/disk7/agard/grads-1.9b4/data/lsmask.nc','nowrite');
sst = nc{'sst'}(:, :, :);
sst = sst.*.01;
land = nc2{'mask'}(:, :, :); % land mask
time = 1981+11/12:1/12:1981+353/12;
time = time';
m_sst = 0;
for j = 1:numel(sst(:, 1, 1))
    % substitute -999 for land values
    sst(j, :, :) = squeeze(sst(j, :, :)).*land + ((land-1).*999);
    numdata = 0;
total = 0;
    for lat = 1:numel(sst(1, :, 1))
        for lon = 1:numel(sst(1, 1, :))
            if sst(j, lat, lon) == -999
                numdata = numdata + 1;
                total = total + sst(j, lat, lon);
            end
        end
    end
end
m_sst(j)=total/numdata; % average SST value
end
m_sst=m_sst';
psa([time m_sst])
end

A.2.5 hf_filter_2D.m

function filtered = hf_filter_2d(t_data)

_fs=12;

z=detrend(z);
n=length(t_data(:,1));

f=fft2(t_data);
freq=fs*(mod(((0:n-1)+floor(n/2)),n)-floor(n/2))/n;

f(j,:,:)=0;
end

filtered=real(ifft2(f));

A.2.6 tls_mean.m

function Y Function HFFILTER_2D
Y Function to remove high-frequency signals from a data series.
Y Vince Agard
Y June 2010

function filtered = hf_filter_2d(t_data)

% get T or TSI values and interpolate to fill in any missing values
fs=12;

z=detrend(z);
n=length(t_data(:,1));

% perform Fourier transform
f=fft2(t_data);
freq=fs*(mod(((0:n-1)+floor(n/2)),n)-floor(n/2))/n;

% eliminate high-frequency signals
for j=1:n
  if abs(freq(j)) > .2
    f(j,:,:)=0;
  end
end

filtered=real(ifft2(f));
function [tseries dseries] = tls_mean()

nc=netcdf('/meteor/disk7/agard/grads-1.9b4/data/rss_tb_maps_ch_tls_v3_2.nc','nowrite');
tb=nc{'brightness-temperature'}(:,:,:);
months=nc{'months'}(:);
time=1978+months./12;
time=time(12:length(time)-6);
tb=tb(12:length(tb)-6,4:69,:);

% take monthly 10-year means
for j=121:length(time)
    dseries(j-120,:,:)=squeeze(mean(tb(j-120:12:j,:,:)));
end
tseries=time(121:length(time));
tseries=tseries';
end

A.2.7  oisst_mean.m

function [tseries dseries] = oisst_mean()

nc=netcdf('/meteor/disk7/agard/grads-1.9b4/data/sst.mnmean.nc','nowrite');
nc2=netcdf('/meteor/disk7/agard/grads-1.9b4/data/lsmask.nc','nowrite');
sst=nc{'sst'}(:,:,:);
sst=sst.*.01;
land=nc2{'mask'}(:,:,:); % land mask
time=nc{'time'}(:);
A.2.8 temp_monthly.m

% Function TEMPMONTHLY
% Function to compile several years of NETCDF pressure-level temperature data into a single matrix in which monthly values are averaged.
% Vince Agard
% June 2010

function [yr mo dseries] = temp_monthly()

% initialize variables
yrseries=(1:12)';
moseries=(1:12)';
aseries=0;
year0=1978;

for year=year0:2010
    fprintf('Getting temperature data from %i...
',year);
    march=60;  % first day of March
    leap=mod(year-1948,4);
    if leap==0
        march=61;  % leap year
    end

    % get temperature data from NetCDF file
    nc=netcdf(strcat('/halo/disk30/reanal/NCEP-NCAR-reanalysis/dailyavgs/pressure/air.','...
        ,int2str(year),'.nc'),'nowrite');
    air=nc{'air'}(:,:,:);
    air=air.*.01+477.66;
end
X average over 70mb MDR

\% air\_series=mean(mean(air(:,13,30:35,121:137),3),4);
\% air\_series=air(:,13,:,:);  \% 70mb
air\_series=air(:,5,:,:);

\% calculate monthly averages
yrseries(1:12)=year;
clear aseries;
aseries(1,:,:)=squeeze(mean(air\_series(1:31,:,:,:),1));
aseries(2,:,:)=squeeze(mean(air\_series(32:march-1,:,:,:),1));
aseries(3,:,:)=squeeze(mean(air\_series(march:march+30,:,:,:),1));
aseries(4,:,:)=squeeze(mean(air\_series(march+31:march+60,:,:,:),1));
aseries(5,:,:)=squeeze(mean(air\_series(march+61:march+91,:,:,:),1));
aseries(6,:,:)=squeeze(mean(air\_series(march+92:march+121,:,:,:),1));
aseries(7,:,:)=squeeze(mean(air\_series(march+122:march+152,:,:,:),1));
aseries(8,:,:)=squeeze(mean(air\_series(march+153:march+183,:,:,:),1));
aseries(9,:,:)=squeeze(mean(air\_series(march+184:march+213,:,:,:),1));
aseries(10,:,:)=squeeze(mean(air\_series(march+214:march+244,:,:,:),1));
aseries(11,:,:)=squeeze(mean(air\_series(march+245:march+274,:,:,:),1));
aseries(12,:,:)=squeeze(mean(air\_series(march+275:march+305,:,:,:),1));
aseries=squeeze(aseries);

if year==year0
    yr=yrseries;
    mo=moseries;
    dseries=aseries;
else
    yr=[yr; yrseries];
    mo=[mo; moseries];
    dseries=[dseries; aseries];
end

A.2.9 pres\_monthly.m

% Function PRES\_MONTHLY
% Function to compile several years of NETCDF surface pressure data into
% a single matrix in which monthly values are averaged.
% Vince Agard
% June 2010
function [yr mo dseries] = pres_monthly()

% initialize variables
yrseries=(1:12)';
moseries=(1:12)';
aseries=0;
year0=1978;

for year=year0:2010
    fprintf('Getting pressure data from...
',year);
march=60; % first day of March
leap=mod(year-1948,4);
if leap==0
    march=61; % leap year
end

% get temperature data from NetCDF file
nc=netcdf(strcat(...
    '/halo/disk30/reanal/NCEP-NCAR-reanalysis/dailyavgs/surface/pres.sfc.'...
    ,int2str(year),'.nc'),'nowrite');
pres=nc{'pres'}(::,::);
pres=pres./10+3676.5;

% calculate monthly averages
yrseries(1:12)=year;
clear pseries;
pseries(1,:,:) = squeeze(mean(pres(1:31,:,:),1));
pseries(2,:,:) = squeeze(mean(pres(32:march-1,:,:),1));
pseries(3,:,:) = squeeze(mean(pres(march:march+30,:,:),1));
pseries(4,:,:) = squeeze(mean(pres(march+31:march+60,:,:),1));
pseries(5,:,:) = squeeze(mean(pres(march+61:march+91,:,:),1));
pseries(6,:,:) = squeeze(mean(pres(march+92:march+121,:,:),1));
pseries(7,:,:) = squeeze(mean(pres(march+122:march+152,:,:),1));
pseries(8,:,:) = squeeze(mean(pres(march+153:march+183,:,:),1));
pseries(9,:,:) = squeeze(mean(pres(march+184:march+213,:,:),1));
pseries(10,:,:) = squeeze(mean(pres(march+214:march+244,:,:),1));
pseries(11,:,:) = squeeze(mean(pres(march+245:march+274,:,:),1));
pseries(12,:,:) = squeeze(mean(pres(march+275:march+305,:,:),1));
pseries=squeeze(pseries);

if year==year0
    yr=yrseries;
    mo=moseries;
    dseries=pseries;
else
    yr=[yr; yrseries];
end
A.2.10 potential_intensity.m

% Function potential_intensity

function [time lat lon intensity] = potential_intensity()

% get NCEP/NCAR 600mb reanalysis temp
[yr_ncep mo_ncep ncep] = temp_monthly();
nc0 = netcdf(fullfile('/halo/disk30/reanal/NCEP-NCAR-reanalysis/dailyavg/pressure/air.2009.nc'), 'nowrite');
t_ncep=yr_ncep+mo_ncep/12;
t_ncep=t_ncep(48:390);
ncp=ncp(48:390,:,:);  % narrow time domain to match that of OISST
lat_ncp=nc0{'lat'}(:);
lon_ncp=nc0{'lon'}(:);

% get NCEP/NCAR reanalysis sfc pressure
[yr_pres mo_pres pres] = pres_monthly();
nc = netcdf(fullfile('/halo/disk30/reanal/NCEP-NCAR-reanalysis/dailyavg/surface/pres.sfc.2009.nc'), 'nowrite');
t_pres=yr_pres+mo_pres/12;
t_pres=t_pres(48:390);
pres=pres(48:390,:,:);  % narrow time domain to match that of OISST
lat_pres=nc{'lat'}(:);
lon_pres=nc{'lon'}(:);

% get MSU TLS data
nc1 = netcdf(fullfile('/meteor/disk7/agard/grads-1.9b4/data/rss_tb_maps_ch_tls_v3.2.nc'), 'nowrite');
tls = nc1{'brightness_temperature'}(:,:, :) ;  
mo_tls = nc1{'months'}(:, :);  
t_tls = 1978 + mo_tls . / 12;  
t_tls = t_tls (48:390);  
tls = tls (48:390, :, :);  % narrow time domain to match that of OISST  
lon_tls = nc1{'longitude'}(:);  
lat_tls = nc1{'latitude'}(:);  

% get OISST data  
nc2 = netcdf('/meteor/disk7/agard/grads-1.9b4/data/sst.mnmean.nc', 'nowrite');  
sst = nc2{'sst'}(:, :, :);  
sst = sst .* .01 + 273.15;  % convert to K  
t_sst = nc2{'time'}(:);  
t_sst = t_sst . / 365.25 + 1800;  
lat_sst = nc2{'lat'}(:);  
lon_sst = nc2{'lon'}(:);  

% get land mask  
nc3 = netcdf('/meteor/disk7/agard/grads-1.9b4/data/lsmask.nc','nowrite');  
land = nc3{'mask'}(:,:);  

% flip MSU latitudes  
tls = flipdim(tls, 2);  
lat_tls = flipdim(lat_tls, 1);  

% interpolate everything to MSU grid  
sst = interp3(lat_sst, t_sst, lon_sst', sst, lat_tls, t_tls, lon_tls');  
land = round(interp2(lon_sst, lat_sst', land, lon_tls, lat_tls'));  
ncep = interp3(lat_ncep, t_ncep, lon_ncep', ncep, lat_tls, t_ncep, lon_tls');  
pres = interp3(lat_pres, t_pres, lon_pres', pres, lat_tls, t_pres, lon_tls');  

% plot sample interpolated data to check proper interpolation has occurred  
% surf(lon_tls, lat_tls, squeeze(sst(100, :, :)))  
% figure  
% surf(lon_tls, lat_tls (5:65), squeeze(tls (100, 5:65, :)))  
% figure  
% surf(lon_tls, lat_tls, squeeze(ncep (100, :, :)))  
% figure  
% surf(lon_tls, lat_tls, squeeze(pres (100, :, :)))  

% narrow latitude range to crop out void MSU data near poles  
lat = lat_tls (3:69);  
lon = lon_tls;  
time = t_tls;  
tls = tls (:, 3:69,:);  
sst = sst (:, 3:69,:);
land=land(3:69,:);
ncep=ncep(:,3:69,:);
pres=pres(:,3:69,:);

% potential intensity constants
cp=1005;  % m^2/s^2/K
lv=2.5e6;  % m^2/s^2
rd=287;  % J/kg/K

% calculate potential intensity
e_star_sfc=6.112*exp(17.67*(sst-273.15)./(243.5+sst-273.15));
e_star_600=6.112*exp(17.67*(ncep-273.15)./(243.5+ncep-273.15));

q_star_sfc=.622*e_star_sfc./(pres-e_star_sfc);
q_star_600=.622*e_star_600./(600-e_star_600);

s_star_sfc=cp*log(sst)+lv*q_star_sfc./sst-rd*log(pres);
s_star_600=cp*log(ncep)+lv*q_star_600./ncep-rd*log(600);

v_squared=(sst-tls)./tls.*sst.*(s_star_sfc-s_star_600);
v_squared=max(v_squared,0);

intensity=sqrt(v_squared);

% apply land mask
for j=1:length(t-tls)
    intensity(j,:,:)=squeeze(intensity(j,:,:)).*land+((land-1).*999);
end
end

A.2.11 mdr_data.m

% Function MDR_DATA
% Function to acquire GISST and potential intensity data for the MDR, apply the low-pass filter, and perform spatial averages.
% Vince Agard
% April 2011
function [time fa_sst fa_tls fa_intensity] = mdr_data()
% calculate potential intensity data
[time lat lon intensity] = potential_intensity;

% open OISST data
nc=netcdf('/meteor/disk7/agard/grads-1.9b4/data/sst.mnmean.nc','nowrite');
nc2=netcdf('/meteor/disk7/agard/grads-1.9b4/data/lsmask.nc','nowrite');
sst=nc{'sst'}(:,:,1);
sst=sst.*.01;
land=nc2{'mask'}(:,:,1);

% open TLS data
ncl=netcdf('/meteor/disk7/agard/grads-1.9b4/data/rss_tb_maps_ch_tls_v3_2.nc','nowrite');
tls=ncl{'brightness-temperature'}(:,:,1);
mo_tls=ncl{'months'}(:,:,1);
t_tls=1978+mo_tls./12;
t_tls=t_tls(48:390);
tls=tls(48:390,:,:);

% restrict spatial domain to MDR
% 6N to 18N
% 60W to 20W
intensity=intensity(:,:,27:32,121:137);
sst=sst(:,:,72:85,300:341);
land=land(72:85,300:341);
tls=tls(:,:,39:44,120:137);

% apply filter
f_intensity=hf-filter_2D(intensity);
f_sst=hf_filter_2D(sst);
f_tls=hf_filter_2D(tls);

% initialize output variables
fa_sst=0;
fa_tls=0;
fa_intensity=0;

% average over spatial domain
for j=1:numel(sst(:,:,1))

% substitute -999 for SST land values
f_sst(j,:,:)=squeeze(f_sst(j,:,:)).*land+((land-1).*999);
end
numdata=0;

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```matlab
sst_total=0;
tls_total=0;
intensity_total=0;

% iterate through each SST data point
for k=1:numel(f_sst(1,:,1))
    for l=1:numel(f_sst(1,1,:))
        if f_sst(j,k,l) ~= -999
            numdata=numdata+1;
            sst_total=sst_total+f_sst(j,k,l);
        end
    end
end

% iterate through each TLS data point
for k=1:numel(f_tls(1,:,1))
    for l=1:numel(f_tls(1,1,:))
        tls_total=tls_total+f_tls(j,k,l);
    end
end

% iterate through each intensity data point
for k=1:numel(f_intensity(1,:,1))
    for l=1:numel(f_intensity(1,1,:))
        intensity_total=intensity_total+f_intensity(j,k,l);
    end
end

% perform averages
fa_sst(j)=sst_total/numdata;
fa_tls(j)=tls_total/numel(f_tls(1,:,1));
fa_intensity(j)=intensity_total/numel(f_intensity(1,:,1));
end

% vertical orientation
fa_sst=fa_sst';
fa_tls=fa_tls';
fa_intensity=fa_intensity';
end

A.2.12 find_coeffs.m
```

% Function FIND_COEFFS
% Function to estimate the optimal linear combination of TLS and SST
% time series to express potential intensity. Uses crude, brute-force
% methodology.

% Vince Agard
% April 2011

function [a b] = find_coeffs(sst, tls, intensity)

% initialize variables
a=0;
b=0;
min_rms=999;

% iterate through possible coefficients
for j=6.4:.0001:6.6
    for k=-.5:.0001:-.3
        % calculate RMS difference between linear combo and actual data
        rms=sqrt(mean((j*sst+k*tls-intensity).^2));
        if rms < min_rms
            a = j;
            b = k;
            min_rms=rms;
        end
    end
end
end

A.3 GrADS script

A.3.1 eof.gs

* * Compute Empirical Orthogonal Functions (EOFs) *
* * The current GrADS dimension environment is used for the *
* estimation of the covariance matrix. *
* * EOFs and PCs are written to separate grads file pairs. *
* *
* *
* USAGE: [run] eof [options ]<fld>
*
* with
*   fld: Input field (GrADS expression).
* Options:
*   -neof <# eof> : Number of EOFs (default: 12)
*   -npc <# pc> : Number of PCs (default: # eof)
*   -tinc <tinc> : Time increment (default: 1)
*   -nper <nper> : Minimal percent of defined data values required
*                  for a grid point to be considered in the EOF calculation
*                  (default: 70 %)
*   -o <prefix> : Prefix for output files: (default: first 6 characters
*                 of <fld>)
*
* Normalization: Variance(PCS)=1
*
* NOTES:
*   i) The data are not weighted. Use cos(lat*3.141/180) for a simple
*      area weight.
*   ii) The program is not well tested for inputs with data gaps.
*       Please let me know if you get wrong results with for such input.
*   iii) Try avoiding GrADS's cyclic continuation for global data.
*       Otherwise the cyclic points are weighted twice.
*
* (c) Matthias Munnich (munnich@atmos.ucla.edu)
*
* Example session: Compute tropical Pacific EOF of Reynolds sst
* in file "sst.mmmean.nc"
*
* ga-> sdfopen sst.mmmean.nc
* ga-> set lat -30 30
* ga-> set lon 140 280
* ga-> set time jan1982 dec2000
* ga-> eof sst

function eof(arg)
*  
* get options
*  
rc=parsearg(arg)
if (rc = 1)
   return
endif

gxstate()
*  
* Checks
* tdim=(._te-_ts+1)/._tinc
  if(tdim<2)
    say 'Fatal error: Only one time step.'
    usage()
    return
  endif
  *
  * write input data files
  *
  'set gxout fwrite'
  'set fwrite eof_in.gad'

  say ' Writing data to transfer file...'
  tt=_ts
  'set t _ts'
  'd _fld'
  tt=tt+_tinc
  tdim=1
  while (tt<=_te)
    'set t tt'
    'd _fld'
    tt=tt+_tinc
    tdim=tdim+1
  endwhile

  'disable fwrite'
  'set gxout contour'
  * say ' Data written.'

  *
  * Compute EOFs and PCs
  *
  'set t _ts'
  'c'
  say ' Executing eofudf binary ...'
  say ',
  * say 'd eofudf(_fld','tdim','_neof','_npc','_nper','_outb')'
  'd eofudf(_fld','tdim','_neof','_npc','_nper','_outb')'
  if(rc != 0)
    say ' eof.gs: First call of eofudf returned Error. STOP'
  return
  endif

  *
  * get time info from a UDF transfer file with varying time
* 'set x 1'
  'set y 1'
  'set z 1'
  'set t \_ts \_ts+1
  say ' Writing time info to CTLs...'
* suppress display output:
  'set gxout fwrite'
  'set fwrite /dev/null'
* say '
  d eofudf('\_fld',-\_tinc')'
  'd eofudf('\_fld',-\_tinc')'
  'disable fwrite'
  'set gxout contour'
*
  Reset environment
*
  'set lon \_lons \_lone
  'set lat \_lats \_late
  'set lev \_levs \_leve
  'set t \_ts \_te

'!\rm -f eof_in.gad eofudf.in eofudf.out eofudfpa.out'
return

*************************************************************
function gxstate()
*
  Get dimension information as global var \_xs,\_xe,...
*
  'query dim'
  dinf = result
  lx = sublin(dinf,2)
  ly = sublin(dinf,3)
  lz = sublin(dinf,4)
  lt = sublin(dinf,5)
  if ( subwrd(lx,7) = 'to')
    _lons = subwrd(lx,6)
    _lone = subwrd(lx,8)
    _xs = subwrd(lx,11)
    _xe = subwrd(lx,13)
  else
    _lons = subwrd(lx,6)
    _lone = subwrd(lx,6)
    _xs = subwrd(lx,9)
    _xe = subwrd(lx,9)
endif
if ( subwrd(ly,7) = 'to')
   _lats = subwrd(ly,6)
   _late = subwrd(ly,8)
   _ys = subwrd(ly,11)
   _ye = subwrd(ly,13)
else
   _lats = subwrd(ly,6)
   _late = subwrd(ly,6)
   _ys = subwrd(ly,9)
   _ye = subwrd(ly,9)
endif
if ( subwrd(lz,7) = 'to')
   _levs = subwrd(lz,6)
   _leve = subwrd(lz,8)
   _zs = subwrd(lz,11)
   _ze = subwrd(lz,13)
else
   _levs = subwrd(lz,6)
   _leve = subwrd(lz,6)
   _zs = subwrd(lz,9)
   _ze = subwrd(lz,9)
endif
if ( subwrd(lt,7) = 'to')
   _tims = subwrd(lt,6)
   _time = subwrd(lt,8)
   _ts = subwrd(lt,11)
   _te = subwrd(lt,13)
else
   _tims = subwrd(lt,6)
   _time = subwrd(lt,6)
   _ts = subwrd(lt,9)
   _te = subwrd(lt,9)
endif
return
***************************************************************************
function parsearg(arg)
* Defaults
  _neof=12
  _aper=70
  _npse=-1
  _verb=0
  _tinc=1
  _outb=''

i=1
word=subwrd(arg,i)
if(word = '')
    usage()
    return 1
endif

while (substr(word, 1, 1) = '-')
    if (word = '-neof')
        i=i+1
        _neof=subwrd(arg, i)
    else
        if (word = '-npc')
            i=i+1
            _npc=subwrd(arg, i)
        else
            if (word = '-nper')
                i=i+1
                _nper=subwrd(arg, i)
            else
                if (word = '-o' | word = '-outname')
                    i=i+1
                    _outb=subwrd(arg, i)
                else
                    if (word = '-v' | word = '-verbos')
                        _verb = 1
                    else
                        if(word = '-tinc')
                            i=i+1
                            _tinc=subwrd(arg, i)
                        else
                            say 'Unknown option: "word"',
                            usage()
                            return 1
                        endif
                    endif
                endif
            endif
        endif
    endif
endif
i=i+1
word=subwrd(arg, i)
endwhile

 fld=subwrd(arg, i)
if(_outb = '')
    _outb=substr(_fld, 1, 6)
endif
if(_fld == '')
  say ' Fatal: Missing field expression'
  usage()
  return 1
endif
if(_verb>0)
  printopt()
endif
return 0

*****************************************************************************
function printopt()
  say '   Number of EOFs:' _neof
  say '   Number of PCs:' _npc
  say '   Time increment:' _tinc
  say '   Required % of good data:' _nper
  say '   Output files basename:' _outb
  say '   Field undef:' _undef
  say '   Field file is XDF:' _xdf
  say '   EOF of :'_fld
  * say '   Verbose:' _verb
return

*****************************************************************************
function usage()
  say '   EOF: Compute Empirical Orthogonal Functions (EOFs)'
  say '         eof.gs Version 0.154'
  say '   ',
  say '   USAGE: eof [options] fld'
  say '   ',
  say '   with '
  say '      fld: Input field (GrADS expression).'
  say '   ',
  say '   OPTIONS: '
  say '      -neof <# eof> : Number of EOFs (default: 12)'
  say '      -npc <# pc> : Number of PCs (default: # eof)'
  say '      -tinc <tinc> : Time increment (default: 1)'
  say '      -nper <nper> : Minimal percent of defined data values required '
  say '      for a grid point to be considered in the EOF calculation'
  say '      (default: 70 %)'
  say '      -o <prefix> : Prefix for files: (default: first 6 characters of <fld>)
  say '   NOTES: '
  say '      i) The data are not weighted. Use cos(lat*3.141/180) for a simple'
  say '      area weight.'
  say '      ii) The program is not well tested for inputs with data gaps.'
  say '      Please let me know if you get wrong results with for such input.'
  say '      (c) Matthias Munnich (munnich@atmos.ucla.edu)'

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return

*********************************************
*********************************************
Appendix B  Full EOF results

B.1  Filtered temperature data

Figure 40: Time series of principal components of filtered MSU TLS data.
Figure 41: Loading patterns of EOF of filtered MSU TLS data.
Figure 42: Time series of principal components of filtered OISST data.
Figure 43: Loading patterns of EOFs of filtered OISST data.
B.2 Filtered MDR temperature data

Figure 44: Time series of principal components of filtered MSU TLS MDR data.
Figure 45: Time series of principal components of filtered MSU TLS MDR data.
Figure 46: Time series of principal components of EOFs of filtered OISST MDR data.
Figure 47: Loading patterns of EOFs of filtered OISST MDR data.
B.3 Unfiltered temperature data

Figure 48: Time series of principal components of unfiltered MSU TLS data.
Figure 49: Loading patterns of EOFs of unfiltered MSU TLS data.
Figure 50: Time series of principal components of unfiltered OISST data.
Figure 51: Loading patterns of EOFs of unfiltered OISST data.
B.4 Filtered, time-averaged temperature data

Figure 52: Time series of principal components of time-averaged, filtered MSU TLS data.
Figure 53: Loading patterns of EOFs of time-averaged, filtered MSU TLS data.
Figure 54: Time series of principal components of time-averaged, filtered OISST data.
Figure 55: Loading patterns of EOFs of time-averaged, filtered OISST data.
B.5 Filtered potential intensity data

Figure 56: Time series of principal components of filtered potential intensity data.
Figure 57: Loading patterns of EOFs of filtered potential intensity data.
B.6 Filtered MDR potential intensity data

Figure 58: Time series of principal components of filtered MDR potential intensity data.
Figure 59: Loading patterns of EOFs of filtered MDR potential intensity data.