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Analysis of the 10–20-Day Intraseasonal Oscillation in the Indian Ocean Using Surface Winds from Composite Satellite Data

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ANALYSIS OF THE 10–20-DAY INTRASEASONAL OSCILLATION IN THE INDIAN OCEAN USING SURFACE WINDS FROM COMPOSITE SATELLITE DATA

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ABSTRACT

The 10–20-day mode of surface winds is examined in the Indian Ocean, with special reference to the Arabian Sea, the Bay of Bengal, and the equatorial Indian Ocean during a strong (1994), weak (2002), and normal (1995) Indian summer monsoon. The winds are from the Cross Calibrated Multi-Platform (CCMP) gridded wind product version 2.0. Results indicate the 10–20-day mode of latitudinally averaged surface winds have zonal propagation in the western Indian Ocean (west of 75°E) and the signal appears stationary in the eastern Indian Ocean (east of 75°E) during May through September. The meridional propagation of the 10–20-day mode of longitudinally averaged surface winds appears weak during summer monsoon periods. The 10–20-day mode of surface winds in the Arabian Sea and the Bay of Bengal is more energetic than in the equatorial Indian Ocean. The signal of the 10–20-day mode appears more robust during a strong monsoon than during a weak monsoon in the Arabian Sea; however, no significant difference is found in the Bay of Bengal and equatorial Indian Ocean between strong and weak monsoons. Ensemble empirical mode decomposition (EEMD) analysis is used on a time series from the Arabian Sea to create an index for the 10–20-day mode in surface winds. Using this index, 75 cases of 15-phase 10–20-day events are identified and used to create composites of surface winds. Through these composites, a positive surface wind anomaly is found to appear at 60°E, centered on 15°S, and propagate zonally eastward to 90°E before reflecting back to propagate westward and then disperse off the coast of Madagascar. It is proposed that this oscillating positive wind anomaly is a feature of the southernmost cell of the 10–20-day convective double-cell structure that has extended farther south into the southern Indian Ocean and that this mode connects the Arabian Sea and southern Indian Ocean through the Somali Jet and surface winds.
CHAPTER 1

INTRODUCTION

Every year, from the end of May through September, India experiences a massive influx of precipitation known as the Indian Summer Monsoon. With over a billion residents and much of India’s agriculture largely dependent on rains from the monsoon, forecasting and characterizing it has become a large area of study in the earth sciences over the last several decades. Indian Monsoon research has largely been divided between those investigating the monsoon itself and those investigating larger-scale patterns associated with it. This latter category predominantly is concerned with oscillations, ranging from intraseasonal to climatic timescales.

Intraseasonal oscillations (ISOs) are often overlooked in comparison to larger-scale phenomena, such as El Niño and the Southern Oscillation (ENSO), as they operate on a much smaller scale and thus research into them has been limited. One exception, and the one that has received the lion’s share of attention, is the Madden-Julian Oscillation (MJO) because it impacts weather and climate globally (Madden and Julian 1971). The MJO is typically said to range from 30–60 or 40–70 days (depending on the source) and it is dominant in boreal winter (Kikuchi et al. 2012).

Still, other intraseasonal oscillations that are not the MJO are often overlooked even though they are critically important to tropical and monsoonal dynamics. Tropical intraseasonal oscillations exhibit mostly on the timescales of 30–60 days and 10–20 days (Fig. 1). The primary non-MJO 30–60-day mode of variability is the boreal summer intraseasonal oscillation, commonly referred to as the ISO, BSISO, or quasi-monthly mode of variability (Kikuchi et al. 2012; Wang et al. 2006). Another mode of the boreal summer ISO occurs with a period of either 15–30 or 10–30 days, depending on the source, and it is also referred to as either an ISO or BSISO (Kikuchi et al. 2012). Most studies thus far have focused on these two modes.

The other mode of variability is the 10–20-day mode, which will be the focus of this study. The 10–20-day mode is referred to by many names: the quasi-biweekly mode (QBM), the quasi-biweekly oscillation (QBWO), or simply an intraseasonal oscillation (ISO). As a disambiguation and to avoid the overlapping acronyms that plague this field of research, here we will refer to it as the 10–20-day mode of variability.
Several studies have investigated how tropical ISOs affect Indian summer monsoon rainfall (Pai et al. 2009; Kikuchi et al. 2012; Suhas et al. 2013; Lee et al. 2013). The 10–20-day mode is usually represented by the westward propagation from the western North Pacific to about 70°E, captured by outgoing longwave radiation (OLR), winds at 850 mb or 200 mb, and precipitation (Krishnamurti and Ardunay 1980; Chen and Chen 1993; Chatterjee and Goswami 2004; Kikuchi and Wang 2009). The 10–20-day mode captured by surface winds in the Indian Ocean has thus far not been the focus of much research, particularly during strong and weak monsoons. The present study is an attempt to provide some preliminary results regarding the strength and propagation of the 10–20-day mode based on high-quality surface wind products.

Intraseasonal Oscillations (ISOs)

![Diagram of Intraseasonal Oscillations (ISOs)](image)

Figure 1. An overview of tropical intraseasonal oscillations (ISOs) active in the Indian Ocean and related to the Indian Monsoon.

1.1 Overview of the 10–20-day Mode

The 10–20-day mode of variability was first characterized by Murakami (1976) as the dominant control over the active and break cycle of the monsoon. The active phase takes the form of a mesoscale cyclonic circulation that forms over the Bay of Bengal, with warm temperature anomalies in the upper troposphere and cold anomalies in the lower troposphere. During the break phase, an anticyclone forms over the Bay of Bengal and the local atmospheric temperature anomalies are reversed (Murakami 1976).
This active and break cycle was further analyzed by Krishnamurti and Ardanuy in 1980, who used wavenumber power spectra analysis to determine that this mode was westward propagation, (Fig. 2). This composite power spectra of wavenumbers was taken from composites of surface pressure data over India. Through their analysis, the authors were able to discern the dominant modes of variability for each of the wavenumbers. They found that there is a dominant westward propagating mode in the 10–20-day timeframe for wavenumbers 3–6. This is clearly shown in Fig. 2, where most of the wavenumbers rapidly expand in power around the 10 day mark. The authors also identified a number of other notable prominent modes of variability. They found that the 20- to 30-day range also had a substantial signal for wavenumbers 3–6, suggestive of the BSISO. In lower wavenumbers, they found that synoptic-scale weather (the 3–6-day mode) had rapid westward propagation for wavenumber 1. The 30- to 40-day range had strong eastward propagation in wavenumbers 1 and 2, indicative of the MJO.

Figure 2. From Krishnamurti and Ardanuy (1980), composite power spectra for six wavenumbers taken originally from surface pressure data. The difference taken for any given wavenumber at a frequency between left (westward) and right (eastward) of zero power describes signal propagation. Waves are quasi-stationary when the left side and right side are equal.

Through time-longitude analysis, their study found that the 10–20-day mode could be characterized by a pressure rise or fall between -5 and +5 days, (Fig. 3). Using this analysis, the authors went further to test the predictability of the 10–20-day mode with regards to active and
break cycles of the monsoon, using 25 test cases. In seven of those test cases, predictability failed. Thus, they found that a linear extrapolation of wave phase cannot predict breaks in the monsoon. This research was critically important for the study of the 10–20-day mode, as it identified it as a major contributor to variability and wavenumber power with respect to the monsoon, and it described the patterns of pressure changes associated with this mode.

Further research into the 10–20-day mode revealed that it had a distinct double-cell structure. (Fig. 4; Chen and Chen 1993). This double-cell consists of either a pair of highs or lows, similar to the findings of Krishnamurti and Ardanuy (1980; Fig. 3). The northernmost cell of this structure was found to be between 15°N and 20°N, whereas the southernmost cell was found to be roughly around the equator, if closer to 5°S. The vertical structure of the double-cell was found to

Figure 3. From Krishnamurti and Ardanuy (1980), a time-longitude diagram of wavenumbers 3–6 taken from composite surface pressure (mb). Shading denotes areas of low pressure and white areas denote areas of high pressure.
have a local Hadley circulation that connected the two cells, and that Hadley cell did not change phase in the troposphere. The entire structure was found to propagate west, with the northern cell propagating along the monsoon trough and delivering significant rainfall, which is attributed to this active and break cycle. This study also showed that the 10–20-day mode has a zonal wavelength of 6000 km and a propagation speed of 4 or 5 m/s, (Chen and Chen 1993).

![Figure 4. From Chen and Chen (1993), Hovmöller diagram of time-latitude 850 mb meridional winds averaged between 75°E and 95°E, with positive wind values shaded and contoured at a 1 m/s interval.](image)

While multiple studies have showed the 10–20-day mode has a clearly defined structure, none addressed the mechanism for the oscillation. Like many oscillations, there has been no hard and fast reason given for why the 10–20-day mode occurs. If it was a purely stochastic system attributed to natural variability, then it would not have such well-defined features and patterns characteristic of a proper oscillation. What, then, was the cause of these 10–20-day signals?

This question remained unanswered for another decade, as most research into the 10–20-day mode consisted of structural or wavenumber analysis. It was not until 2004 that we began to get a better understanding of to how the 10–20-day mode was generated in the Indian Ocean when Chatterjee and Goswami (2004) created composites of the 10–20-day mode in outgoing longwave radiation (OLR) and 850 mb winds (Fig. 5). Their analysis further confirmed the double-cell structure found by Chen and Chen (1993). Based on vortex size from these composites, they determined that the signal’s half-wavelength was on the order of 3000 km and the phase speed was
4.5 m/s, further confirming previous findings. The authors also found that the structure was similar to that of a northward translated equatorial Rossby Wave centered at 5°N.

Figure 5. From Chatterjee and Goswami (2004), 10-year composites for Boreal summer with OLR anomalies (shaded) and 850 mb winds (vectors; m/s) for: a) phase 8 of their 15-phase method, b) phase 1 with opposite shading, and c) relative vorticity of composite winds as a function of phase.
The Chatterjee and Goswami study further explored the equatorial Rossby Wave avenue, using a 2½ layer model to discover that the 10–20-day mode is an equatorial Rossby Wave made unstable through a wave-boundary layer-CISK mechanism, (Fig. 6; Chatterjee and Goswami 2004).

![Figure 6](image)

*Figure 6. From Chatterjee and Goswami (2004), a schematic illustrating Wave-Boundary Layer-CISK, where $\omega_e$ is the BL convergence (solid (dashed) contours for positive (negative) values), $\zeta_c$ is the curl of baroclinic vorticity, and $\theta$ is potential temperature.*

Through model analysis, the Chatterjee and Goswami study was able to demonstrate that the 10–20-day mode is a convectively coupled equatorial Rossby Wave translated north to 5°N during boreal summer. They also were able to show that the vertical structure has both barotropic and baroclinic components. This convectively coupled equatorial Rossby Wave is driven unstable by moist convective feedbacks when translated north by the dynamic equator, where absolute vorticity is equal to zero (Chatterjee and Goswami 2004).

With convectively coupled equatorial Rossby Waves established as a reasonable mechanism for the 10–20-day mode, the next logical question is where the equatorial Rossby Waves originate from. A 2009 study by Kikuchi and Wang answered this question in a massive
global study of the 10–20-day mode (Kikuchi and Wang 2009). Their composite study used 1088 cases from 1979–2005 of boreal summer 10–20-day events to characterize, with EEOF analysis, the propagation of the mode from the Pacific Ocean into the Indian Ocean following the Asian Monsoon using OLR anomalies, NASA’s Tropical Rainfall Measurement Mission (TRMM) precipitation, and 850 mb winds (Figs. 7 and 8). They were able to identify the source of the equatorial Rossby Waves as convection over the western Pacific Warm Pool and further break down the exact sequence of events leading to the 10–20-day mode observed in the Indian summer Monsoon periods.

![Figure 7. From Kikuchi and Wang (2009), 10–20-day events identified by tracking location, a) ensemble of contours of b) initial, c) mature, and d) dissipation locations (shaded, contours).](image)

The convective anomaly generated over the equatorial western Pacific emerges at day -4, moves west until day 0, and then moves northwest until day +4. This convective anomaly constitutes the northern cell and is what triggers the Rossby Wave response in both hemispheres at day 4. In the western Indian Ocean, another convective anomaly emerges to form the southern half of the double-cell structure, and at day 0 they merge to properly form the double-cell with a northwest/southeast convective band. The double-cell then propagates northwest until it dissipates over the Arabian Sea and central/southern Indian Ocean.
Figure 8. From Kikuchi and Wang (2009), the lifecycle of the Asian Monsoon summer 10–20-day oscillation, with bandpass filtered OLR anomalies (contoured), 850 mb winds (vectors), and TRMM precipitation (shaded).
CHAPTER 2

DATA

In this study, we use the Cross-Calibrated Multi-Platform ocean surface wind vector analyses (CCMP V2.0) produced by Remote Sensing Systems to analyze the surface winds over the Indian Ocean. CCMP V2.0 is a composite satellite dataset of microwave scatterometers, radiometers, buoys, and European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim Reanalysis derived winds on a 0.25°x0.25° grid with 6-hourly temporal spacing from 1990–2015, (Atlas et al. 2011; Wentz et al. 2015; Remote Sensing Systems).

Scatterometers are active microwave sensors on satellites that are often employed to determine winds over water, especially oceans. Scatterometers send a microwave signal down to the water as the instrument passes over an area and the signal Bragg scatters off of small surface water waves on larger ocean waves. The instrument then captures the signal that returns to the satellite (backscatter) at multiple angles, which is then translated using model functions in order to determine equivalent neutral winds and direction at 10 m above sea level (Agruez et al. 2005; Bourassa 1998). Equivalent neutral wind speed is current relative and dependent on atmospheric stability and ocean currents. There are multiple definitions, though the most effective in scatterometry is that which is calculated with stress using friction velocity (the square root of the kinematic stress) and surface roughness length determined with atmospheric stratification considered, but in the calculation of the equivalent neutral winds the stratification term is set to zero. Depending on the atmospheric stratification, or air-sea temperature gradient, the differences between equivalent neutral wind and a traditional wind are roughly ~0.5 m/s, (Kara et al. 2008; Bourassa 1998; Tang and Liu 1996). A further difference is that equivalent neutral winds are relative to the ocean surface current, whereas traditional winds are relative to the fixed earth.

Microwave radiometers are passive sensors that, like scatterometers, can infer winds only over water. These instruments are also satellite mounted, but measure brightness temperature rather than backscatter. Radiometers use the brightness temperature to infer emissivity as a function of equivalent neutral wind speed at 10 m, which is then fed back into a radiative transfer and emissivity model to derive wind speed from these ocean brightness temperatures (Atlas et al. 2011; Reul et al. 2012). Older designs of radiometers have their drawbacks, as they become less
effective beyond wind speeds of ~15 m/s; however, recently flown longer wavelength radiometers perform quite well in high wind speeds (Reul et al. 2012).

CCMP employs the variational analysis method to blend the data from multiple scatterometers, radiometers, buoys, and ECMWF ERA-Interim Reanalysis winds. Satellite observational data is validated through the ocean moored buoys to within 0.8 m/s agreement. The variational analysis method is then used to assimilate the satellite and buoy wind speed observations with reanalysis 10 m winds from ECMWF. The result of this blending of data is the CCMP wind product (Atlas et al. 2011; Hoffman et al. 2003).

The CCMP dataset has sufficient resolution to allow us to capture the 10–20-day timescale, as well as spatial features on a synoptic scale. As it primarily takes data from ocean waves and sources, however, this dataset does have the drawback of not providing data over land. As much of the 10–20-day mode of variability occurs over land, and as monsoonal rainfall over India is the primary concern of most studies, the CCMP dataset is not the ideal for every study. However, in this study, we are primarily concerned with surface winds over ocean basins, not in rainfall totals, and so the CCMP V2.0 dataset is appropriate.

It should be noted that, because the surface winds are derived at least in part from scatterometers and radiometers, much of the surface wind data being recorded may not be purely representative of traditional surface winds. While surface winds do not encounter a barrier at coastlines and reflect back, ocean waves do. And so, it is possible that there are reflected signals around coastlines of waves, modifying the surface current, which is in turn interpreted as changes to surface winds. The reflected waves have much too long a wavelength to directly alter the satellite measurements of winds. While perhaps not purely reflective of surface wind characteristics in this case, these waves may still provide helpful insights into the nature of air-sea interactions with the relevant mode of variability for the purpose of this study.
CHAPTER 3
SIGNAL IDENTIFICATION AND ANALYSIS

3.1. Signal Identification and Energy

To begin our analysis, it is first useful to determine the strength of the 10–20-day signal in the Indian Ocean and the smaller basins that comprise it. As the 10–20-day mode is noted to have elements in the Bay of Bengal, Arabian Sea, and equatorial Indian Ocean, all three of these basins are spectrally analyzed for this signal (Chen and Chen 1993; Kikuchi and Wang 2009). To further decompose this signal, we compare the strength of the 10–20-day mode for strong, weak, and normal monsoon years based on monsoon rainfall (Zheng et al. 2016)

3.1.1. Methodology

Time series were created for each of the relevant basins in the greater Indian Ocean: the Arabian Sea (52°E-72°E x 0°N-20°N), Bay of Bengal (80°E-95°E x 5°N-20°N), and equatorial Indian Ocean (40°E-105°E x 20°S-10°N). These basins were further reduced into time series from 1990-2015. The Arabian Sea was latitudinally averaged between 10°N and 15°N, the Bay of Bengal between 10°N and 15°N, and the equatorial Indian Ocean between 20°S and 10°N.

3.1.1.1. Wavelet spectral analysis

Using these three time series as the input, continuous wavelet transforms are created, (Grinsted et al. 2004). Wavelets are functions with a zero mean (detrended) localized in frequency and time and are dependent on timestep (Δt) and frequency step (Δω). Time series undergoing continuous wavelet transforms analysis must be detrended and have a uniform timestep, with the time series being the only input for the function. For wavelet analysis both the time series (x) and frequency (ω0) are considered to be dimensionless. There are different shapes of wavelets and a variety of different ways of applying a continuous wavelet transform. In this study, the Morlet wavelet (ω0 = 6) is used, (Grinsted et al. 2004). This wavelet ($\psi_0(x)$) is defined as:

\[
\psi_0(x) = \pi^{-\frac{1}{4}} e^{i\omega_0 x} e^{-\frac{1}{2}x^2}
\]

The continuous wavelet transforms effectively applies the wavelet as a bandpass filter to the time series, stretched temporally and by scale, with units of normalized energy, defined as wavelet power. Wavelets by nature have edge effects, the size of which are determined by the size
of the time series being analyzed and the length of the period of oscillation. Shorter time series being analyzed for longer periods of oscillation will have strong edge effects, and therefore a large cone of uncertainty. The cone of uncertainty is the area of the continuous wavelet transform where edge effects cause power to fall below $e^{-2}$ times the original value compared to the edge value. Effectively, the cone of influence visually shows the areas of the continuous wavelet transform which have a large amount of uncertainty due to the length of the time series. A time series cannot confidently have high power in periods longer than the time series itself, and the shorter the period compared to the length of the time series, the higher the confidence will be. Statistical significance of signals with a stationary process within the transform can be obtained compared to the background power spectrum (Grinsted et al. 2004). For the purpose of this study, continuous wavelet transform analysis is performed to determine the relative energy of the 10–20-day signal compared to others, as well as to determine if the signal is statistically significant.

### 3.1.1.2. Monsoon strength

To assess the differences between strong and weak monsoon years on the 10–20-day mode of variability, three years were chosen for comparative analysis. Based on the India Meteorological Department rainfall totals analyzed by Zheng et al. 2016, 1994 was chosen as the strong monsoon year, 1995 was chosen as a normal monsoon year, and 2002 was chosen as the weak monsoon year. 1995 was chosen as “normal” as the rainfall totals were close to the 1901-2013 mean, (Zheng et al. 2016; Fig. 9).

*Figure 9. From Zheng et al. (2016), annual India Meteorological Department summer (JJAS) monsoonal rainfall totals compared to 1901-2013 mean value. Red denotes high precipitation monsoon years, blue denotes low precipitation monsoon years.*
Using the time series for the Indian Ocean during these three years, continuous wavelet transforms were then created for April-October to assess how the monsoon strength might impact the frequency and strength of the 10–20-day events and signal.

### 3.1.2. Results and Discussion

There are many oscillations and modes of variability active in and around the Indian Ocean on a variety of time scales, including ENSO, the MJO, and the BSISO. The continuous wavelet transforms for 1990-2015 for the Arabian Sea, Bay of Bengal, and Indian Ocean are reflective of this, (Fig. 10). In all three basins, the dominant mode of variability is on the order of 6-18 months to 95% significance. This mode is an order of magnitude longer than the oscillation we are interested in, however. There is reasonably high power across longer, seasonally dependent modes of variability, especially in the Arabian Sea and Bay of Bengal, though few have statistical significance. The 10–20-day range appears to have varied energy that is strongly basin dependent. In the Arabian Sea, this window has reasonably high power throughout the time series, including reasonably consistent, seasonally dependent, statistical significance. Both the Indian Ocean and Bay of Bengal, however, have only medium power even during the correct time of year, with sporadic statistically significant patterns.

This analysis suggests that the 10–20-day signal is spatially dependent, as well as seasonally dependent. This is to be expected, as the 10–20-day mode of variability is associated with the summer monsoon in India, and thus is unlikely to have a strong signal in the winter months. This does, however, beg the question of how monsoon strength impacts these oscillations.

As the 10–20-day mode of variability is responsible for the break and active phases of the monsoon, it is a reasonable hypothesis that stronger monsoon seasons would contain stronger signals for the active and break cycles, (Krishnamurti and Ardanuy 1980; Murakami 1976). Continuous wavelet transforms of 1994, 1995, and 2002 from April through October are used to test this hypothesis, taking 1994 to be a strong monsoon, 1995 to be a normal monsoon, and 2002 to be a weak monsoon, (Fig. 11). In comparing these three wavelet transforms, it is clear that all have a signal present in the 10–20-day range, though there is high energy on the BSISO time-scale. This 10–20-day signal is most energetic May-September in all three years, corresponding with monsoon season. While 2002 and 1995 both have areas of reasonably high power and statistical significance sporadically for this mode of variability, 1994 has both reasonably consistent high
power and statistical significance. This suggests that the 10–20-day signal is more prominent during strong monsoon years.

Figure 10. Continuous wavelet transforms for the Arabian Sea, Bay of Bengal, and equatorial Indian Ocean, 1990-2015.
3.2. Signal Variability

Having used wavelet analysis to identify dominant modes of variability in each basin in the previous section, it is next important to determine how strong the 10–20-day signal is in each basin and how this signal strength is influenced by monsoon strength. To do this, the 10–20-day signal is isolated and then statistically compared to the overall surface wind signal in each basin.

3.2.1. Methodology

3.2.1.1. Bandpass filtering

To isolate the 10–20-day signal, a Butterworth 4\textsuperscript{th} order recursive time filter is used to bandpass filter the data (Krishnamurti et al. 2017). The data is double filtered, front to back and then back to front to avoid edge effects and obtain a more accurate output. Single filtering data (e.g., only filtering in the forward direction) will have not insignificant edge effects due to initial conditions and will produce a largely incorrect signal, with anomalously large oscillations produced at the edges. Double filtering the data solves this initial condition problem and compensates for the edge effects, having zero phase distortion. The double filtering function extrapolates the ends of the time series for the purpose of the filter and filters the time series both front to back and back to front while treating these extrapolations as the new endpoints. These extrapolations are then removed for the final product is the bandpass filtered data, (Gustafsson 1996). The 4\textsuperscript{th} order Butterworth filter’s response function is given by:
\[ W(Z) = \frac{a(1-Z^2)}{1+b_1Z+b_2Z^2} \]

where \( W(Z) \) is the response function of the form: \( Z = e^{-\omega \Delta T} \), \( \omega \) is the frequency, \( \Delta T \) is the sampling interval in seconds, and \( a, b_1, \) and \( b_2 \) are constants that determine filter sharpness, (Krishnamurti et al. 2017).

**3.2.1.2. Linear regression**

Unfiltered latitudinally averaged time series are compared with bandpass filtered time series for each basin in each year. The Arabian Sea is latitudinally averaged between 10°N and 15°N, the Bay of Bengal between 10°N and 15°N, and the equatorial Indian Ocean between 20°S and 10°N. Linear regression is performed to determine the relative strength of the 10–20-day signal in each basin for strong, normal, and weak monsoon years. To do this, the unfiltered surface winds for all three years in each basin are plotted against their bandpass filtered counterparts, creating a scatterplot. A linear trendline is then fitted to each scatterplot and the coefficient of determination \( (R^2) \) calculated for each. \( R^2 \) describes the percent variation of regression explained by a trendline.

**3.2.1.3. Spectral analysis**

Beyond wavelets, another form of spectral analysis is the periodogram. Periodograms plot frequency versus power for a given time series, decomposing all the frequencies present within a time series compared to how powerful that signal is. Periodograms allow us to identify which frequencies or periods are most energetic and dominant within a time series for the duration of the entire time series. Unlike wavelets, periodograms do not show us when within a time series a particular period is dominant but has the advantage of allowing us to quantitatively determine the precise periods that are most energetic. Similar to wavelets, this form of spectral analysis can only be performed on detrended time series with even timesteps.

In this study, this form of spectral analysis will be often used to decompose frequencies of time series and is applied in this section to time series for the Arabian Sea for the strong, normal, and weak monsoon years.

**3.2.2. Results and Discussion**

Given that the active and break phases of the monsoon associated with the 10–20-day mode are characterized by mesoscale cyclones over the Bay of Bengal, it would be expected that this
basin would present the strongest 10–20-day signal of the three basins, and that this signal would be most prominent in both strong and weak monsoon years. Comparative analysis of the unfiltered surface wind time series and the bandpass filtered time series would seem to suggest that this is not necessarily the case (Fig. 12). Though the Bay of Bengal has the most clearly defined monsoon season of the three basins, and experiences the greatest overall surface wind variability, the 10–20-day signal does share this range of variability. There are a number of notable peaks and troughs in each season that clearly line up, but overall, the time series are only loosely related to one another.

Figure 12. Unfiltered surface wind time series for the Arabian Sea, Bay of Bengal, and equatorial Indian Ocean in 2002, 1995, and 1994 (black; m/s) compared with their 10–20-day bandpass filtered counterparts (blue; m/s).
The surface winds in the equatorial Indian Ocean are not well characterized by the 10–20-day mode of variability. Regardless of monsoon strength, the signal strength remains low, suggesting that for this basin, other modes of variability are more dominant. This result is somewhat surprising given that the southernmost cell of the double-cell structure characteristic of this mode of variability occurs around the equator and that the given bounds for the equatorial Indian Ocean should have encompassed at least one cell. Given how large the basin is, however, it is possible that most of the signal was drowned out by other modes of variability. As it has been noted previously, the equatorial Indian Ocean has a very low 10–20-day signal, despite being the location of much of it, (Kikuchi and Wang 2009). This lack of signal is reflected in low signal strength shown.

Though the Bay of Bengal and equatorial Indian Ocean are where the majority of the 10–20-day mode of variability have been noted to take place in studies that focused on rainfall, it is the Arabian Sea that is best described by the 10–20-day mode for winds. The winds in the Arabian Sea remain energetic most of the year, though they do experience a slight increase during monsoon season. What is most notable about the Arabian Sea surface winds, however, is not the magnitude, but the clearly defined 10–20-day mode of variability apparent in them, even in the unfiltered winds. Of the three basins, the Arabian Sea also has the highest amplitude 10–20-day bandpass filtered winds, reflective of the strength of this 10–20-day mode in the Arabian Sea.

Unlike the other basins, which have no clear distinction between monsoon strength, the filtered winds in the Arabian Sea see a distinct increase in magnitude during strong monsoon years. While not the basin where the signal is generated, the Arabian Sea is the demise location for many of the mesoscale systems that comprise the 10–20-day mode over India. It is therefore likely that increased number of these events in the stronger (normal and weak) monsoon years accounts for the increased (decreased) variability captured by the signal.

The discrepancy between the basins is most clearly shown in Fig. 13, with the corresponding R² values given for each correlation presented. It is immediately clear from these that the equatorial Indian Ocean and Bay of Bengal experience a statistically insignificant seasonal difference in variance explained by the 10–20-day mode, and that a low amount of variability can be explained by the 10–20-day mode. In the equatorial Indian Ocean, this value ranges from 6% to almost 9%, but remains extremely low. The Bay of Bengal is only slightly better, ranging from
8% to 13%. It is therefore extremely likely that another mode of variability, such as the BSISO or MJO, is predominantly responsible for surface wind variations in these basins.

The Arabian Sea shows a great deal of seasonal variation. 2002, the weak monsoon year, had a staggering 22% of the variance explained by the 10–20-day mode, which is nearly twice that of the highest amount of variability explained in the Bay of Bengal and equatorial Indian Oceans. This variance drops slightly down to 19% for normal monsoon years. During a strong monsoon year, however, more than 40% of surface wind variability can be attributed to this 10–20-day mode.

![Figure 13. Linear regression and corresponding correlation coefficients of unfiltered and 10–20-day bandpass filtered surface winds for the Arabian Sea, Bay of Bengal, and equatorial Indian Ocean in 2002, 1995, and 1994.](image)

Given the relative prominence of the 10–20-day signal in the Arabian Sea, it is then important to determine just how dominant this mode of variability is in the Arabian Sea. Spectral
analysis for the strong, weak, and normal cases shows that there are two dominant modes of variability in the Arabian Sea: a ~200-day period and the 10–20-day period, (Fig. 14). This ~200-day period was previously noted in Section 1 as being a dominant mode of variability in all the basins. During 1994—the strong monsoon year—however, the 10–20-day mode became even more prominent than this ~200-day mode. This suggests that the 10–20-day mode is strongly related to monsoon strength in the Arabian Sea.

These results, while surprising, are critically important to this study and have implications in a much broader context, for modeling and operational studies. The relative dominance of this mode of variability on surface winds in the Arabian Sea, especially during a strong monsoon season, suggests that any model analysis that does not properly capture or take into account the 10–20-day mode of variability over the Arabian Sea could be missing up to 40% of the surface wind variability.

![Figure 14. Periodograms of Arabian Sea surface winds averaged from 10°N-15°N in 2002, 1995, and 1994.](image)
CHAPTER 4

SIGNAL PROPAGATION

The 10–20-day mode of variability as characterized by rainfall is known to be a westward propagating system of Rossby Waves generated by convection in the Western Pacific and Bay of Bengal with a meridional double-cell structure that moves northwest over India, with demise regions in the Arabian Sea and southern Indian Ocean, (Chatterjee and Goswami 2004; Chen and Chen 1993). In this section, we will explore how well surface winds adhere to this model of signal propagation.

4.1. Methodology

To better understand how the surface wind signal propagates across the Indian Ocean, Hovmöller diagrams for both latitude and longitude are created. The 10–20-day bandpass filter is applied to the 1994, 1995, and 2002 wind data over the Indian Ocean to create these diagrams in both the directions and isolate signal propagation. Time-latitude propagation analysis is performed for the entire Indian Ocean basin, taken to be 40°S-30°N and time-longitude propagation is performed for 40°E-105°E. This longitude analysis is then repeated for the Arabian Sea, between 50°E and 75°E.

4.2. Results and Discussion

At first glance, the unfiltered time-latitude plots for strong, normal, and weak monsoon years appear identical, (Fig. 15). Onset of the monsoon in May and its demise in late September are both clearly observed in these unfiltered Hovmöller diagrams. The positive wind anomalies during monsoon season have a double-cell structure centered around the equator with some northward propagation from south to north, almost entirely contained within the tropics (30°N-30°S). The relatively inactive region at the equator between these positive wind anomaly regions may be interpreted as the intertropical convergence zone (ITCZ). Upon closer inspection, it would also appear that the winds in 2002—the weak monsoon year—are slightly stronger than those in the normal or strong monsoon years.

The bandpass filtered time-latitude plots lack the seasonal definition of their unfiltered counterparts, (Fig. 15). These are characterized predominantly by northward propagation of
signals across the equator and stationary signals. Outside of the monsoon season described by the unfiltered winds, there is some southward propagation north of the equator. During the monsoon season, there is predominantly either stationary or with northward propagation.

![Time-latitude Hovmöller diagrams of Indian Ocean surface wind magnitude averaged longitudinally 40°E to 105°E for April-October 2002, 1995, and 1995, both unfiltered (left; m/s) and with a 10–20-day 4th order Butterworth bandpass filter (right; m/s).](image)

Figure 15. Time-latitude Hovmöller diagrams of Indian Ocean surface wind magnitude averaged longitudinally 40°E to 105°E for April-October 2002, 1995, and 1995, both unfiltered (left; m/s) and with a 10–20-day 4th order Butterworth bandpass filter (right; m/s).

There are two real potential sources of this northward propagation. The double-cell structure of the 10–20-day mode in other variables has one cell slightly south of the equator and one centered 15-20°N of the equator and this propagates northwest, (Chen and Chen 1993). For northward propagation signals that originate at or around the equator, this may be the source. The other potential source of this northward propagation stems from the mean, large scale wind pattern over the Indian Ocean, (Loshnigg and Webster 2000). These winds originate around 15°S of the equator as easterlies, turn north near Africa, and then curve to become westerlies around 15°N.
Given the longitudinal averaging of these Hovmöllers, it is possible that the northward propagation seen across the equator is due to anomalously strong shifts in these winds.

Figure 16. Time-longitude Hovmöller diagrams of Indian Ocean surface wind magnitude averaged latitudinally, both unfiltered (left; m/s) and 10–20-day bandpass filtered (right; m/s) surface winds for April-October 2002, 1995, and 1994. Signal propagation in filtered diagram denoted by black lines.
The time-longitude Hovmöller diagrams for all three monsoon years clearly show the onset and demise of the monsoon season, (Fig. 16). Immediately clear is the difference between the eastern and western Indian Ocean with respect to surface winds. West of 75°E has consistently positive wind anomalies throughout the year, though they increase in strength during the monsoon season. There is some eastward propagation visible in all the years and very little, if any, westward propagation. East of 75°E has a clearly defined monsoon season, with positive wind anomalies occurring only during those months. This is, perhaps, unsurprising given the seasonal changes in the overall winds in the Indian Ocean. The southeastern Indian Ocean experiences a peak in surface winds during the boreal summer months and a relative decrease in winds during boreal winter, which may be reflective of this seasonality, (Loschnigg and Webster 2000).

Much as with the unfiltered winds, the filtered winds had a clear division between the eastern and western Indian Ocean. East of 75°E is almost entirely stationary with some westward and eastward propagation. This westward propagation may be due to the double-cell structure and mesocyclones characteristic of this mode as they move to the northwest over India from the Bay of Bengal, though it would not account for the eastward propagation also apparent, particularly in the western half of the ocean.

Given that the 10–20-day mode is a westward propagating system, it is therefore curious that much of the signal propagation west of 75°E in the Indian Ocean would be eastward propagating, and thus, following the conclusions of Chapter 3, the Arabian Sea is isolated, where an eastern and westward coupled pattern becomes apparent, (Fig. 17). This phenomenon becomes less of a mystery when the nature of the data used is then considered. As CCMP V2.0 is derived from surface ocean currents, it is therefore not unreasonable to suggest that the signal being presented is not purely surface winds, but also of surface ocean waves. It is then proposed that the eastward propagating signal of the 10–20-day mode of variability is not reflective of surface winds, but of ocean currents that are reflected westward propagating waves. This would seem to be supported by the apparent coupling of eastward and westward propagating signals in Figs. 16 and 17.

This theory would be not unlike the Delayed Oscillator Theory (DOT) for ENSO in the Pacific Ocean. The DOT proposes that westward propagating Equatorial Rossby Waves reach the western boundary of the Pacific Ocean and are reflected back eastward as Equatorial Kelvin Waves, (Kirtman 1997; Suarez and Schopf 1988). Previous studies have even applied this theory
to the Indian Ocean when studying ENSO, (White and Tourre 2007). Given that the 10–20-day mode of variability is characterized by westward propagating Rossby Waves, that the e-folding distance for equatorial Kelvin Waves encompasses the East African Coast of the Arabian Sea used in this study, and that the period of oscillation of equatorial Kelvin Waves is 16 days, it is then proposed that the eastward propagation seen west of 75°E in the Arabian Sea shown in these Hovmöllers is due to the reflection of Rossby Waves as equatorial Kelvin Waves in the surface ocean currents.

Figure 17. Time-latitude Hovmöller diagram for unfiltered (left; m/s) and 10–20-day bandpass filtered (right; m/s) surface winds over the Arabian Sea for April-October 1994. Signal propagation in filtered diagram denoted by black lines.
Another possible explanation, which may not be mutually exclusive, follows the lifecycle of the 10–20-day mode set forth by Kikuchi and Wang (2009). In their model for development, the southernmost cell of the double-cell structure originates as a convective anomaly in the western Indian Ocean, (Fig. 8; Kikuchi and Wang, 2009). This convective anomaly then propagates east until it couples with the northern cell and moves westward. And as the Arabian Sea is the demise location for many of these double-cell events, that would account for the westward propagation that often follows an eastward event. It is therefore possible that the east/west pairings of signals shown here is a combination of multiple signals, both in the form of equatorial Kelvin Waves and these convective anomalies moving back and forth across India.
CHAPTER 5
INDEX AND COMPOSITES

5.1 Empirical Mode Decomposition Analysis and Creation of an Index

Creating a standardized index for a mode of variability allows for identification of spatial pattern of variable for that mode. Indices of this type provide a threshold of sorts that may be used to decide if an event has occurred, or in other cases, to determine the phase of an oscillation. The most famous index of this type is the Southern Oscillation Index (SOI), with negative and positive phases corresponding to La Niña and El Niño conditions. In creating an index for the surface winds for the 10–20-day mode of variability, we may identify events and compile these events into composites—a compilation of events into a mean case—so that the variability and associated dynamics may be characterized.

Previous studies have employed empirical orthogonal function (EOF) analysis to characterize and create indices for rainfall in the 10–20-day mode of variability, as well as other, similar ISOs in the Indian Ocean and elsewhere, (Chatterjee and Goswami 2004). EOF analysis was attempted for this study, but it was concluded that the EOF approach captures only a small fraction of the variance associated with the 10–20-day signal in surface winds that was found with a bandpass filter near zero variance was explained by the first two principle components on a five-year time scale. Due to this, it is concluded that EOF analysis is perhaps not the best tool to use in analyzing such irregular variability because these patterns are irregular and inconsistent.

5.1.1. Methodology

5.1.1.1. Ensemble empirical mode decomposition (EEMD)

Instead of EOF analysis, an ensemble empirical mode decomposition (EEMD; Wu and Huang 2009) is employed to characterize the 10–20-day mode of variability. EEMD analysis is simple to use and interpret, provides an easily understood breakdown of the signals in a time series, and works on all time series. Unlike EOF analysis and Fourier decomposition, which assume stationary, linear processes, EEMD can accommodate nonlinear and nonstationary processes, (Lee et al. 2011; Huang and Wu 2008; Wu and Huang 2004; Wu and Huang 2009).

As EOF decomposes a time series into a number of principal components, EEMD analysis decomposes a time series into intrinsic mode functions (IMFs). IMFs must meet two criteria. First,
the number of extrema (local minimums and local maximums) and zero crossings in a series must not differ by more than one. Second, for any given data point, the mean value of the envelopes defined by the local maxima and local minima respectively must equal zero, (Huang and Wu 2008; Lee et al. 2011). Conveniently, a time series need not be detrended prior to analysis.

EEMD creates IMFs through a sifting process with added white noise and multiple ensemble members, to the end of decomposing the original time series, eliminating background noise, and smoothing. The only input is a one-dimensional array as a function of time, e.g., x(t), (Huang and Wu 2008; Lee et al. 2011). The number of ensemble members and standard deviation must also be given, (Huang and Wu 2009). To begin the sifting process, all local minima and maxima (extrema) are identified and connected with lines, commonly a cubic spline function, forming an upper and lower envelope respectively. The difference between the input and the mean of the upper and lower envelopes is called the first protomode, the result of the first sifting.

Sifting is repeated using this protomode to satisfy multiple coordinate systems, as changing coordinate systems may introduce more extrema. With each successive sift, the protomode is updated and treated as a new time series for the next iteration. This process is repeated for multiple iterations until the updated protomode can meet the criteria for an IMF and a stopping criterion is met. When this stopping criterion is met, the updated protomode becomes the first IMF and the residual is treated as a new time series for the process to be repeated, (Huang and Wu 2008).

There are different types of stopping criteria for sifting, and in this study, the Cauchy-type stopping criteria is employed. The Cauchy-type stopping criteria is given by a Cauchy-type convergence—the normalized squared difference between two sifting operations that must be less than a scalar convergence criterion, (Huang and Wu 2008; Wang et al. 2010). In this study, 0.2 is used as the convergence criterion.

When the stopping criterion is met during the sifting process, what remains is the first IMF, which is the repeatedly sifted protomode, and a residual. This residual, i.e. the original time series minus the first IMF, is then treated as the new time series for the next iteration of the sifting process, and this continues until the residual becomes a monotonic function with no zeroes, where no further IMFs can be extracted. The first IMF contains the shortest period of oscillation present in the original time series, with each successive IMF containing a longer period of oscillation and the residual being either a trend or a constant, (Huang and Wu 2008).
Regular empirical mode decomposition analysis of this form is susceptible to mode mixing and aliasing, and thus it is better to use the ensemble empirical mode decomposition which functions similarly, merely adding in white noise at the beginning of the sifting process and utilizing a specified number of ensemble members to exhaust all possible solutions, (Wu and Huang 2009). The sifting process, or empirical mode decomposition, is repeated for each ensemble member and the resulting IMFs are averaged across ensemble members to create the final IMFs. In this experiment, we use 100 ensemble members. These EEOF IMFs are much more stable and result in a much-improved decomposition with real physical meaning. The process is adaptive and without harmonics, and thus EEMD can be used reliably to analyze nonstationary and nonlinear processes. That being said, if the noise in a time series is of the time scale as the signal being analyzed, EEMD cannot remove the noise, (Wu and Huang 2004; Wu and Huang 2009).

5.1.1.2. Index creation

Figure 18. Periodograms for IMF 4 (left) and IMF 5 (right) of the EEMD for Arabian Sea Surface Winds 10°N-15°N from 1990-2015.

To create an index for the 10–20-day mode of variability in surface winds required to identify events and create our composites, similar methodology for index creation is followed from Chatterjee and Goswami 2004, using EEMD analysis rather than EOF analysis for the full time series 1990-2015 for the Arabian Sea averaged over 10-15°N. Of the 14 IMFs given by the analysis, IMF 4 and IMF 5 are the only ones whose frequency decomposition encompass the desired time
frame for the 10–20-day mode of variability, (Fig. 18). IMF 4 and IMF 5 are then combined into one time series that is scaled to its own standard deviation. When compared to the 10–20-day bandpass filtered time series of winds, it is found that this new IMF time series explains ~63% of the variance. This is a gross improvement over the EOF time series, which had a near zero $R^2$ value, even when bandpass filtered; but the percentage of variance explained is not so large that a bandpass filter can be said to produce an identical result. Our normalized IMF time series is then lightly filtered to eliminate any remaining noise, thereby creating our index.

5.1.1.3. Wavelet coherence

![Wavelet Coherence](image)

*Figure 19. Wavelet coherence of 10–20-day bandpass filtered Arabian Sea surface winds 10°N-15°N from 1990-2015 and IMF derived normalized time series.*

To further analyze the coherence of the IMF time series and the filtered winds, wavelet coherence analysis is performed, (Grinsted et al. 2004). Building off of the continuous wavelet transform described in Section 1 of Chapter 3, wavelet coherence is analogous to taking to
correlation coefficient of two time series at different frequencies through time. More specifically, it describes how coherent two cross wavelet transforms are in time frequency space. A cross wavelet transform of two time series is defined mathematically as: \( W_{XY} = W_X W_Y^* \), where \( X \) and \( Y \) are time series and \( * \) denotes the complex conjugate of the time series. Cross wavelet transforms describe common periods of oscillation between two time series in time frequency space and are represented in wavelet power, as with the continuous wavelet transform, and also have a cone of influence. In addition, cross wavelet transforms describe the phase angle in regions of >95% significance, (Grinsted et al. 2004). The phase angle denotes the difference in phase between two time series, where an arrow to the right (left) signifies being in (out of) phase and pointing up or down describes lag. Phase angles are also employed in the wavelet coherence analysis. Statistical significance for wavelet coherence is estimated through Monte Carlo methods. The two time series are found to be coherent and in phase for the duration of the period of record, (Fig. 19).

5.1.2. Results and Discussion

The EEMD analysis of the Arabian Sea time series yields 14 IMFs and a residual, fully decomposing the time series, (Fig. 20). Though IMFs 4 and 5 encompass the 10–20-day mode that is of interest to this study, the other IMFs also contain notable signals. Spectral analysis of each IMF yields the spread of frequencies present in each, where frequency is taken to be in units of 1/day. IMF 1 has only one peak centered on 1 day and represents daily data, or the diurnal cycle. IMF 2 had a much greater spread of frequencies, with the most falling between 1-5 days, representative of weather. IMF 3 is centered primarily on 3-10 days, which is suggestive of synoptic weather and monsoon trough. IMF 4 was centered on 5-20 days and IMF 5 was centered on 12-50 days, encompassing the entire 10–20-day mode. This longer period for IMF 5, however, means that much of its variability may encompass other oscillations, such as the BSISO. IMF 6 spans 25-100 days, containing the BSISO and MJO. Other IMFs contain annual, seasonal, decadal, and even multidecadal signals.

EEMD analysis allows us to combine IMFs 4 and 5 and create a normalized index for the 10–20-day mode of variability in surface winds, (Fig. 21). While the 10–20-day mode is characterized by rainfall, it is still important to understand how surface winds vary on this time scale. Having a wind-based index is critically important for identifying events and creating
composites, which in turn allow us to better understand the dynamics behind the variability seen in the time series.

**Figure 20.** EEMD analysis for full Arabian Sea unfiltered time series 1990-2015. The original time series (signal), all 14 IMFs, and the residual are shown. Time on the x-axis is given in Julian days.

**Figure 21.** A 26-year standardized index for 10–20-day mode in surface winds over the Arabian Sea based on bandpass filtered IMF 4 and IMF 5 from EEMD analysis.
5.2. Composite Creation and Analysis

Composites, which are the subject of this section, are essentially a mean amalgamation of many or all events over a given period of time that produces a typical case for that event. The threshold for an event—with an event in this case being one cycle of the 10–20-day mode of variability—is given by an index. Having developed an index for the 10–20-day mode of variability in the previous section, here composites will be created and analyzed for their dynamics.

5.2.1. Methodology

Using the index created in the previous section, events can now be identified. Using this index, peaks and troughs at least 5 days apart from one another are first identified. Whereas the work of Chatterjee and Goswami (2004) used one standard deviation as the threshold for identification of peaks and troughs to create their composites from their index, we use 0.85 standard deviations as the threshold for peak identification as it doubles the number of cases usable in analysis. The advantages of reducing this threshold are well illustrated in Fig. 22. The few extremes identified with one standard deviation are shown in the top figure and the additional extremes identified with a threshold of 0.85 shown in bottom. By reducing the threshold to 0.85 standard deviations, the number of identified peaks is increased from 43 using 1 standard deviation to 88, effectively doubling the number of available cases.

Cases are further refined to require both a peak and a trough to exceed the 0.85 standard deviation threshold, be in Indian Summer Monsoon season (May–September), and have a distance between points between 5 and 10 days. 75 cases between 1990 and 2015 are identified and averaged to create the composite case, (Fig. 23). Error is greatest for days 6 and 7, due to the difference in oscillation length between cases. While the average case length was 13.5 days, there was a range between 12 and 16 days, allowing for the greater errors at the beginning and end of the oscillation. Case length was kept constant so as to maintain uniformity of cases and retrieve a mean wind field. The range of days is fixed around day 0, following the methodology of Chatterjee and Goswami (2004). The other area of increased error was at the peak, caused by differences in event magnitude. It should be noted, however, that the 1 standard deviation error was still only 0.1 standard units of the index, suggesting that cases overall are relatively consistent, except in duration.
Figure 22. Index with identified peaks and troughs using a 1 standard deviation threshold (top) and 0.85 (bottom). Reducing the threshold doubled the number of peaks from 43 to 88.

Figure 23. Composite signal of 75 oscillation events from 1990-2015 (black) with one standard deviation error (blue).

To identify phases of the oscillation, phase 8 is chosen to be the peak of the oscillation, following Chatterjee and Goswami (2004). The average space between peaks and troughs is 6.75 days, and so phases 1 and 15 are chosen to be ±6.75 days respectively. The intervening phases are chosen to occur at evenly spaced intervals throughout the ~14-day oscillation. Composites are then expanded to the overall basin to assess the associated dynamics. Wind vectors, relative vorticity,
and divergence are calculated using the zonal and meridional wind corresponding to the 75 filtered cases, for which this analysis is repeated.

As this composite creation methodology was designed for use with EOF analysis, it is validated by recreating the composites by beginning at the troughs instead of the peaks, e.g. choosing phase 1 to be the first trough. The resulting composites show no significant changes from the original composites, and thus the methodology used is determined to be reasonable and valid.

Bandpass filtering of composite fields is accomplished using a two-dimensional Gaussian-weighted moving window, averaging bandpass filter, following the Greene (2017) methodology of the two-dimensional data filter (Greene 2017). The 4th order Butterworth bandpass filter used for time series filtering was not used for image filtering as it inaccurately resulted in only stationary signals in a two-dimensional space that is unreflective of natural variability. Instead, the Gaussian bandpass filter is used, (Hale 2006). A Gaussian filter in two dimensions approximates the contribution of each point on a grid to a weighted Gaussian curve around a center point. In the case of a bandpass filter, this Gaussian filter method highlights signals in between the upper and lower wavelength bounds of the filter, thereby isolating the signal, (Greene 2017). Input is based on data grid spacing and the wavelength bounds of the bandpass filter. As previous studies have noted the wavelength of the 10–20-day mode of variability as being 6000 km, a bandpass filter is used centered on this 6000 km wavelength, (Chatterjee and Goswami 2004; Chen and Chen 1993).

5.2.2. Results and Discussion

Given the results of previous sections, it is anticipated that the majority of activity seen in the composites would occur in the Arabian Sea. Previous studies (Murakami 1976; Chatterjee and Goswami 2004) suggest that most variability would occur in the Bay of Bengal region. In viewing the composite breakdown of all 15 phases of the 10–20-day mode identified, the signal that is most apparent occurs not in the Arabian Sea, but in the southeastern Indian Ocean, (Fig. 24). Little appears to change between phases 1 and 3. During these three days, there is a modest positive wind anomaly in the southern Indian Ocean centered around 60°S off the coast of Madagascar and a negative wind anomaly between the equator and 5°N. In phase 4, however, there is a substantial increase in the positive wind anomalies at 15°S between 55°E and 85°E. This positive anomaly continues to grow in strength for phases 5-7, becoming more clearly defined and shifting eastward several degrees. At day 0—phase 8 and the peak of the composite curve—the positive anomaly
has its greatest values between 75°E and 90°E. After day 0, the wind anomaly begins to rapidly weaken. By phase 12, the positive anomaly has lost most of its defined structure and the energy begins to disperse westward towards Madagascar. This progression of phases has the overall effect of having a large positive wind anomaly at 15°S slosh back and forth across the basin, taking roughly seven days to cross each way and reaching its peak magnitude in the eastern portion of the basin.

![Figure 24](image.png)

*Figure 24. 26-year composites of the 10–20-day mode of variability of surface wind anomalies (shaded; m/s) with wind vectors (black arrows; m/s).*

Given the relative disconnect between the southeastern Indian Ocean and the Arabian Sea, it is helpful to consider the large-scale winds and ocean currents active in the Indian Ocean. The surface wind vectors follow that of climatology, by in large, moving west along 15°S, recurving north along the Somali Coast, and then moving eastward around the coast and around India. These wind vectors follow a very similar pattern throughout the phases of the 10–20-day mode, (Fig. 25). It is possible, then, that this positive wind anomaly that develops feeds into the Somali Jet and
Somali Current along the coast of Africa and into the Arabian Sea, strengthening the surface wind signal seen there. This can be seen in the composites, as a positive wind anomaly off the horn of Africa as the large anomaly in the southeast strengthens and then disperses, (Figs. 24 and 25). This pulsing of the Somali Jet along with the 10–20-day mode suggests a strong connection between this mode of variability and variability of the Somali Jet.

The emergence of the signal at -4 days could be due to convective anomalies emerging out of the Western Pacific that trigger a Rossby Wave response in both hemispheres, (Kikuchi and Wang 2009). Given the longitudes at which it forms and then reverses direction, however, it would seem to follow, almost perfectly, the path of the southernmost cell of the convective double-cell structure characteristic of this mode that is reflected in 850 mb wind, OLR, and precipitation, (Chatterjee and Goswami 2004; Chen and Chen 1993; Kikuchi and Wang 2009). Given that the vortex southernmost cell forms at ~5°S of the equator, this would suggest that this wind anomaly is reflective of this convective southernmost cell, which is centered farther south than the vortex double-cell, (Chatterjee and Goswami 2004; Chen and Chen 1993; Kikuchi and Wang 2009).

![Figure 25. Phases 1, 8, and 15 of composite wind anomalies (shaded; m/s), with overlaid wind vectors (black vectors; m/s). Black arrows indicate signal propagation.](image)

The convective double-cell structure is not well reflected in the unfiltered surface wind anomalies but is more apparent in the filtered winds in the eastern half of the basin, (Figs. 26 and 27). In the bandpass filtered wind anomaly composites, the large anomaly in the southern Indian Ocean appears as it does in the unfiltered wind field. The life cycle of this wind anomaly between
10°S and 15°S can be clearly seen in the filtered composites as it develops over the 15 phases, first beginning to truly appear in phase 4 (day -4), and then largely dissipating by phase 12 (day +4), which is largely consistent with the movement and lifecycle of the southernmost cell, (Kikuchi and Wang 2009). Though the complete convective double-cell structure itself is not as readily apparent in filtered surface winds as it is in OLR or TRMM precipitation, it is suggested by the positive wind anomalies, which follow a similar pattern to the OLR anomalies of past studies, (Fig. 28; Chatterjee and Goswami 2004; Kikuchi and Wang 2009). OLR anomalies are not entirely consistent on past studies with regards to the location of the northern cell or anomalies to the direct east and west of India, but both patterns are reflected in the filtered surface winds, suggesting that both have some degree of merit. Discrepancies between all three studies can be largely attributed to data used and the manner in which the composites were created, (Chatterjee and Goswami 2004; Kikuchi and Wang 2009). Additionally, OLR anomalies can be seen over land, whereas CCMP surface winds cannot, and thus the seemingly isolated patterns on either side of India may be more reflective of a greater anomaly encompassing most of the area, such as the northernmost cell.

Figure 26. Bandpass filtered composite surface wind anomalies (shaded; m/s) with wind vectors (black vectors; m/s)
The increased activity in the Arabian Sea could be reflective of the increased winds caused by the southern wind anomaly, the presence of the southernmost cell forming, and the nature of the Arabian Sea as the demise region for the double-cell structure. Previous studies have shown consistent OLR and precipitation anomalies over the Arabian Sea throughout, and so it is likely that the consistent winds over the Arabian Sea visible in our filtered composites are, at least in part, a product of these, (Figs. 26 and 27; Kikuchi and Wang 2009).

The filtered surface wind anomalies are more fluid and encompass a larger area than the OLR anomalies. This is likely due to the nature of surface winds compared to precipitation or OLR, namely that OLR and precipitation have distinct edges, that define them from the clearer air around them, whereas surface winds lack this definition.

Figure 27. Phases 1 and 8 of bandpass filtered composite winds (shaded; m/s) with overlaid wind vectors of filtered winds (black vectors; m/s). Black oval indicates area with vortex double-cell structure and OLR anomalies in Fig. 5 from Chatterjee and Goswami (2004). Green oval indicates area with convective double-cell structure and OLR anomalies in Fig. 8 from Kikuchi and Wang (2009).

To further describe these composite fields, divergence and relative vorticity are calculated for both the filtered and unfiltered wind fields, (Figs. 28 and 29). The unfiltered are characterized by a large swath of convergence between 15°S and 10°N and then a region of divergence outside
of those bounds. These unfiltered divergence fields do not appear to change significantly between phases, (Fig. 28). The filtered divergence, however, changes a great deal between phase 1 and phase 8. In phase 1, the majority of the basin is characterized by a relatively weak divergent wind field, but there are stronger areas of convergence around India, into the Arabian Sea and Bay of Bengal and in the southeast Indian Ocean. The convergent fields around India correspond with areas of OLR in previous studies, suggesting that this may reflect some degree of convection, (Chatterjee and Goswami 2004; Kikuchi and Wang 2009). The divergence field for phase 8 shows a strengthening of this pattern of convergence in the northern Indian Ocean and its extension farther into the Bay of Bengal. In the southern Indian Ocean, there is a large area of strong convergence 60°E and 80°E, which corresponds to the western half of the strong southern surface wind anomaly associated with the southernmost cell, once more suggesting convection.

Figure 28. Divergence fields of unfiltered (left; shaded; $10^{-4}$1/s) and bandpass filtered (right; shaded; $10^{-7}$1/s) surface winds, overlaid with wind vectors (black vectors).
Figure 29. Relative vorticity fields of unfiltered (left; shaded; $10^{-4}$ 1/s) and bandpass filtered (right; shaded; $10^{-4}$ 1/s) surface winds, overlaid with wind vectors (black vectors).

Even more so than the divergence fields, unfiltered vorticity fields for phase 1 and phase 8 show a clear pattern centered on 15°S, with most positive vorticity occurring south of 15°S, (Fig. 29). This is consistent with the divergent wind field shown in Fig. 28, with the area between 10°N and 15°S roughly coinciding with a large area of stagnant wind that is likely the result of an area of high pressure. In the filtered images, the southern Indian Ocean has a large swath of positive vorticity in phase 1, more similarly to the unfiltered vorticity. Phase 8 has an area of strong positive vorticity roughly between 60°E and 80°E, in the same region of the convergent anomaly in the
filtered divergent field. Like the area around India, this area corresponds to OLR and TRMM precipitation anomalies from past studies, further suggesting that this area is reflective of convection and the southernmost cell of the double-cell structure, (Chatterjee and Goswami 2004; Kikuchi and Wang 2009). The most notable feature, however, in both the unfiltered and filtered vorticity fields, particularly in phase 8, is the positive vorticity at 30°S. This is suggestive of convection in the Southern Ocean and clearly influences the overall wind and convective patterns in the Indian Ocean associated with the this 10–20-day mode.

The results of our composite analysis suggest that the southernmost cell of the convective double-cell structure associated with the 10–20-day mode in the Indian Ocean is not confined to the equator, but has a mode in surface wind that is centered on 15°S and forms east of Madagascar, propagates eastward across the basin to 90°E, and then reflects back as a Rossby Wave, propagating westward across the basin before the energy disperses east of Madagascar, largely traveling up the Somali Coast into the Arabian Sea. This mechanism would explain the east and westward propagating signals seen in the Hovmöller diagrams in Chapter 4, as well as provide a plausible connection between the northern and southern halves of the greater Indian Ocean basin, (Figs. 15 and 16). This theory would also support the double-cell structure observed and characterized by past studies, extending it further into the southern hemisphere and to include surface winds, (Chatterjee and Goswami 2004; Kikuchi and Wang 2009).
CHAPTER 6

CONCLUSION

The 10–20-day mode of variability in the Indian Ocean is one of the most prominent intraseasonal oscillations related to the Indian Monsoon and is largely responsible for the active and break cycles of precipitation over India. Continuous wavelet transform spectral analysis showed that while a 6- to 18-month oscillation is the dominant mode of variability in the Indian Ocean, Arabian Sea, and Bay of Bengal, the 30- to 60-day and 10–20-day modes are the most prominent on intraseasonal time scales. Further statistical analysis showed that the 10–20-day mode could explain on average, less than 10% of the total surface wind variability in the Indian Ocean and Bay of Bengal, regardless of monsoon strength, suggesting that it not the 10–20-day mode, but rather the 15- to 30-day or 30- to 60-day modes that are more dominant in these basins. The Arabian Sea, however, showed significant seasonal variability, with 19% and 22% of surface wind variance being explained by the 10–20-day mode during normal (1995) and weak (2002) monsoon years respectively. During a strong monsoon year (1994), the Arabian Sea had more than 40% of the surface wind variance explained by the 10–20-day mode, suggesting a relative dominance of the 10–20-day mode of variability in the Arabian Sea, especially during strong monsoon years.

Signal propagation analysis showed that the majority of the activity in the 10–20-day mode occurs west of 75°E, with further analysis suggesting that there is a reflection around 60°E between eastward and westward propagating signals, as seen in the Arabian Sea and overall basin time-longitude Hovmöller diagrams. As the western Indian Ocean is the genesis region for the southernmost cell of the double-cell, convectively coupled Rossby Wave structure associated with the 10–20-day mode, this was suggested as a possible source of the eastward propagation, with the demise of the system resulting in the westward propagation.

Ensemble empirical mode decomposition analysis was performed on a time series from the Arabian Sea and from the resulting IMFs 4 and 5, a normalized index was created for the 10–20-day mode in surface winds. This index was used to construct composite wind fields based on 75 10–20-day events identified by the index. Given the robustness and simplicity of EEMD analysis compared to EOF analysis, we propose it as an alternative method of signal analysis for nonstationary, irregular period signals such as that of the 10–20-day mode.
Through these composites, a large positive wind anomaly was discovered to be in the southern Indian Ocean, centered on 15°S and forming off the eastern coast of Madagascar around 60°E. This wind anomaly moves eastward until it reaches 90°E, at which point it changes direction and moves westward, dissipating near Madagascar and its genesis region. This pattern was already noted in the Hovmöller diagram analysis and bears a striking resemblance to the activity of the southernmost cell of the double-cell structure. We therefore propose that this positive wind anomaly is a feature of the southernmost cell of the convective double-cell structure in the southern Indian Ocean, as supported by OLR and TRMM precipitation anomalies noted by previous studies, (Chatterjee and Goswami 2004; Kikuchi and Wang 2009).

In addition to this double-cell structure, the Somali Jet pulses along with the 10–20-day mode, suggesting a strong connection between the Somali Jet and this mode of variability. This pulsing of the Somali Jet, along with the fact that these composites were based primarily off of winds in the Arabian Sea, suggests a connection between the southern and northern Indian Oceans through this mode of variability via the Somali Jet.

In the divergence and relative vorticity fields, it is apparent as well that there is a connection to the Southern Ocean and convection in the Southern Ocean. This convection ties into the southernmost cell of the convective cell structure and likely contributes to the overall variability seen on this time scale. As it is austral winter in the southern hemisphere during this Indian Summer Monsoon season, it is possible that mid-latitude cyclonic activity in the Southern Ocean contributes to the 10–20-day mode seen in the Indian Ocean. If found to be true in further research, this would connect the Southern Ocean to the Indian Ocean, Somali Jet, and Arabian Sea. Further research, however, will need to further investigate this possible connection and its consequences.
Figure 30. Additional composite images of unfiltered surface wind anomalies.
Figure 30 – Continued
Figure 30 – Continued
APPENDIX B

ENSO ANALYSIS

To briefly assess the impact of ENSO on the 10–20-day mode, Niño 3.4 SSTs and DMI are compared to the Arabian Sea filtered time series. NCEP NOAA Niño 3.4 SSTs and ESRL DMI are used for this analysis, (NOAA ESRL). Seasonal averages are taken for both variables and then averaged for each year. These time series are then compared to a time series of Arabian Sea surface wind variance, taken from the R² value between each unfiltered and filtered time series from 1990–2016. Linear regression is performed between each variable and the wind variance time series.

Figure 31. Comparison of ENSO variability and Arabian Sea surface wind variance 1990–2016. A) Cross wavelet transform of Arabian Sea surface wind variance as explained by the 10–20-day oscillation and Winter Niño 3.4 SST anomalies. B) Time series of Arabian Sea surface wind variance (orange) and Niño 3.4 SSTs (teal) with corresponding correlation coefficient. C) Cross wavelet transform of Arabian Sea surface wind variance as explained by the 10–20-day oscillation and Summer DMI. D) Time series of Arabian Sea surface wind variance (orange) and Summer DMI (green) with corresponding correlation coefficient.
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BIOGRAPHICAL SKETCH

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