Analysis of MJO Wind-Flux Feedbacks in the Indian Ocean Using RAMA Buoy Observations

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Abstract

Observations spanning 2004 – 2012 from two Research Moored Array for African-Asian-
Australian Monsoon Analysis and Prediction (RAMA) buoys along the equator in the Indian
Ocean are used in conjunction with Tropical Rainfall Measuring Mission (TRMM) and Global
Precipitation Climatology Project (GPCP) rainfall measurements to assess the relative
importance of surface latent heat fluxes to intraseasonal convection. This work is motivated by
previous observational and modeling studies that have suggested the importance of wind induced
surface fluxes to the dynamics of the Madden-Julian Oscillation (MJO).

Intraseasonal variability is isolated in two ways: 1) 20-100 day bandpass filtering and 2)
using global MJO indices. Results are compared between the well-established Realtime
multivariate index (i.e. RMM) and a new outgoing longwave radiation only based index (i.e.
OMI). Linear regression shows latent heat flux anomalies to be between 5%-10% of precipitation
anomalies. Mesoscale and synoptic scale wind variability have negligible impact on
intraseasonal latent heat flux anomalies. Results derived from both simple intraseasonal filtering
and using global MJO indices indicate that precipitation leads latent heat flux on the order of a
few days. Sensitivity tests using smoothed wind speed or thermodynamics (i.e. air temperature,
relative humidity, and sea surface temperature) to compute latent heat flux show wind speed
variability explains most of the latent heat flux variability on intraseasonal timescales. A similar
conclusion is found via linearization of the latent heat flux formula. In the context of theoretical
estimates of convective moisture discharge from the column, these results confirm the potential
of wind induced latent heat fluxes to aid destabilization of MJO convection.

Keywords: Madden-Julian Oscillation; intraseasonal oscillation; surface flux; wind speed;
precipitation; TRMM; GPCP; Indian Ocean; buoy
1. Introduction

Observationally, the Madden-Julian Oscillation (MJO) is well described as the dominant mode of tropical intraseasonal (30 – 90 day) variability consisting of a large envelope (O(1000 km)) of multiscale convective cloud elements (e.g. Nakazawa 1995) that frequently, but not always, initiates over the Indian Ocean (e.g. Salby and Hendon 1994, Matthews 2008) and propagates slowly eastward (~ 5 m s\(^{-1}\); Madden and Julian 1972 and Zhang 2005 and references therein). Precipitation decays over the central Pacific, while the wind and moisture signals associated with the MJO continue to circumnavigate the globe (e.g. Knutson and Weickmann 1987, Kikuchi and Takayabu 2003, Kiladis et al. 2009, Haertel et al. 2014).

From an Eulerian perspective, as the canonical MJO evolves from suppressed to active convective conditions, low-level winds transition from easterly to westerly (with opposite signed upper level winds), low-level moisture builds vertically, and the fractional contribution of various cloud types shift (e.g. Lin and Johnson 1996, Kiladis et al. 2005, Benedict and Randall 2007, Powell and Houze 2013, Johnson and Ceisielski 2014). Narrow deep convective clouds along with shallow convection give way to wide (more organized) convection followed by anvil clouds (Riley et al. 2011, Morita et al. 2006, Powell and Houze 2013, Barnes and Houze 2013, Zuluga and Houze 2013, Xu and Rutledge 2014). While general circulation models (GCMs) have been able to reproduce these observed characteristics of the MJO with varying degrees of success (e.g. Grabowski 2003, Maloney and Sobel 2004, Benedict and Randall 2009, Kim et al. 2009, Maloney et al. 2010; Chikira 2014) no consensus exists on a theory that completely explains the spatial scale, initiation and propagation of the MJO. As such, the MJO remains an ideal target phenomenon to further understanding of convective and large-scale interactions and the importance of air-sea coupling.
The original linear theory of wind induced surface heat exchange (i.e. WISHE; Neelin et al. 1987 and Emanuel 1987) proposed that a positive feedback between wind, surface fluxes, and convection could initiate and maintain the MJO. While the details of the original theory have been disproven given that the active conditions of the MJO, with deep organized convection, are accompanied by anomalous low-level westerlies (e.g. Lin and Johnson 1996) as opposed to easterlies as the theory predicted, the general idea of surface flux feedbacks being important to MJO destabilization has not been disproven as recently emphasized in a review article by Sobel et al. (2010).

This study aims to quantify the relative importance of wind induced surface latent heat fluxes to precipitation associated with the MJO. This work builds from previous observational and modeling work (i.e. Maloney and Esbensen 2005 and 2007, Back and Bretherton 2005, Araligidad and Maloney 2008, Maloney 2009, and DeMott et al. 2014) that has suggested the importance of wind-induced fluxes for destabilizing the MJO, and supports a recent body of work referred to as moisture mode theory (e.g. Raymond and Fuchs 2007 and 2009, Sugiyama 2009a,b, Sobel et al. 2010, and Sobel and Maloney 2012).

Maloney and Esbensen (2003) noted the plausible importance of latent heat flux anomalies to the feedback between MJO convection and the low-level circulation in the east Pacific warm pool. Subsequent model simulations by Maloney and Sobel (2004) and Maloney and Esbensen (2005) further supported the importance of surface fluxes to intraseasonal convection both in the Indo-Pacific warm pool and the east Pacific. Maloney and Sobel (2004) found that wind-induced flux variability in their GCM simulations was necessary to produce realistically large intraseasonal precipitation amplitude. This result was reproduced by Maloney and Esbensen (2005) for the east Pacific warm pool. In GCM mechanism denial experiments,
Sobel et al. (2008; 2010) and Maloney et al. (2010) demonstrated that removing intraseasonal flux variability strongly diminished tropical intraseasonal variability.

On a tropics wide scale, Back and Bretherton (2005) showed a positive correlation between precipitation and latent heat flux anomalies, especially in regions of high specific humidity. Araligidad and Maloney (2008; hereafter AM08) and Maloney and Esbensen (2007) found a similar positive correlation at intraseasonal timescales using Tropical Ocean Global Atmosphere (TOGA) Tropical Atmosphere Ocean (TAO) buoy data and Tropical Rainfall Measuring Mission (TRMM) rainfall measurements over the west and east Pacific, respectively. Additionally, Kiranmayi and Maloney (2011) showed a positive covariance between reanalysis precipitation and surface fluxes. Maloney and Esbensen (2005) showed in both observational and model results that east Pacific intraseasonal latent heat flux anomalies are about 10% of intraseasonal precipitation anomalies (their Fig. 11). AM08 found a slightly higher ratio from observations in the west Pacific – intraseasonal LHFLX anomalies were between 18%-24% of intraseasonal precipitation anomalies.

The importance of surface fluxes over the Indian Ocean relative to MJO convection was analyzed during the CINDY/DYNAMO (i.e. Cooperative Indian Ocean Experiments on Intrasesional Variability in the Year 2011; Dynamics of the MJO) field campaign (Yokoi et al. 2014, Moum et al. 2014). Yokoi et al. (2014) focused on surface fluxes associated with sub-mesoscale convection. By examining the evolution of fluxes from pre-convective to convective to recovery MJO periods, they concluded that both sensible and latent heat flux contributed to the overall increase in surface fluxes during convective periods, though latent heat flux more so than sensible heat flux. Additionally, they noted latent heat fluxes were more wind-driven while sensible heat fluxes were driven more by air-sea temperature differences. Using observations
from the R/V Revelle (nominally located at 0°, 80.5°E) and the 0° 80.5°E RAMA buoy during CINDY/DYNAMO, Moum et al. (2014) found that the arrival of MJO active phases were related to westerly wind bursts and an increase in surface latent heat fluxes, which helped the ocean surface transition from a net heating to a net cooling as the MJO evolved from suppressed to active conditions (their Figs. 2 and 7).

We extend the observational analysis of AM08 and Maloney and Esbensen (2007) to the Indian Ocean using the Research Moored Array for African-Asian-Australian Monsoon Analysis and Prediction (RAMA) buoys and independent precipitation measurements from TRMM and the Global Precipitation Climatology Project (GPCP). Extending previous latent heat flux (LHFLX) vs. precipitation analyses, but for the Indian Ocean, is warranted since the Indian Ocean is the main area of MJO initiation and development (e.g. Salby and Hendon 1994, Matthews 2008). DeMott et al. (2014) argue that Indian Ocean air-sea coupled processes are critical for the subsequent global evolution of the MJO. Additionally, it is important to assess if and how the LHFLX vs. precipitation relationship changes as the MJO propagates eastward across the Indian Ocean to the Pacific Ocean. This work compliments CINDY/DYNAMO studies by not only overlapping with the campaign time period, but also extending the analysis of fluxes to time periods substantially before and after the campaign.

If an important link between intraseasonal LHFLX and precipitation anomalies is suggested, it supports the moisture mode theory of the MJO. The theory works under the assumption of weak temperature gradients (WTG) in the tropics in which temperature tendencies are assumed to be negligible to first order (Sobel and Bretherton 2000, Sobel et al. 2001). As the theory’s name suggests, convective dynamics are controlled by processes that regulate free-tropospheric moisture. These regulatory processes include cloud radiative feedbacks and surface
flux feedbacks. Moist static energy (MSE) anomalies are equivalent to latent heat anomalies under WTG theory, and hence MSE budgets can be used to diagnose the dynamics of a moisture mode (e.g. Maloney 2009, Hannah and Maloney 2011, Andersen and Kuang 2012, and Chikira 2014). When enhanced MJO convection occurs, the sum of column processes, horizontal advection, and MSE sources (e.g. surface fluxes) should be positive to support moisture anomalies and maintain the MJO (e.g. Back and Bretherton 2006, Raymond et al. 2009). The unique role of moisture to MJO dynamics separates it from other convectively coupled waves, such as Kelvin waves, which are more strongly controlled by temperature variations (Raymond and Fuchs 2009, Riley et al. 2011, Yasunaga and Mapes 2012a,b). When examining the intraseasonal MSE budget in a GCM, Maloney (2009) found that LHFLX and horizontal advection of MSE were the two dominant terms, although the importance of LHFLX as a destabilization mechanism is strongly model dependent (e.g. Andersen and Kuang 2012). Using DYNAMO sounding observations, Sobel et al. (2014) found surface fluxes to be important to the MSE budget for the October and November 2011 MJO events, despite radiative fluxes being the dominant term. Such results motivate the current observational work to document the importance of wind induced LHFLX to the MJO in the Indian Ocean.

The following section describes the data and methods. Section 3 shows the relationship between intraseasonal Indian Ocean latent heat flux anomalies and precipitation and results of sensitivity experiments that attribute flux anomalies to wind speed anomalies. Section 4 focuses on the latent heat flux-precipitation relationship derived from two global MJO indices. Section 5 discusses the implication of the results and concludes the paper.

2. Data and Methods
2.1 RAMA buoy data

The RAMA buoy array consists of 23 operational moored buoys in the Indian Ocean basin (McPhaden et al. 2009, http://www.pmel.noaa.gov/tao/rama). Two buoys along the equator at 80.5°E and 90°E were subjectively chosen to use in this study based on their continuity of high time resolution data compared to other RAMA buoys, and their location in a region relevant to MJO dynamics (e.g. Hendon and Salby 1994, Matthews 2008, Yoneyama et al. 2013). Of all the RAMA buoys, the 0° 90°E buoy has the largest amount of high-resolution data needed to compute surface fluxes. The 0°, 80.5°E buoy has about 60% of the amount of data the 0°, 90°E buoy has, but was chosen for analysis because it sits along the same latitude as the 90°E buoy. Since both buoys are located along the equator, we simply distinguish the two buoys by their longitude for the remainder of the paper. Both buoys are ATLAS (autonomous temperature line acquisition system) moorings deployed by the National Oceanographic and Atmospheric Association Pacific Marine Environmental Laboratory (NOAA-PMEL) in collaboration with the Indian National Center for Ocean Information Services (NIO) and the Indian Ministry of Earth Sciences in 2004. Both moorings measure air temperature (T), relative humidity (RH), wind velocity, downwelling shortwave (SW) radiation and rain between 3-4 m above mean sea level and sea surface temperature (SST) at 1 m below the sea surface (McPhaden et al. 2009). Rainfall is measured with a self-siphoning rain gauge (Serra et al. 2001). The 80.5°E mooring additionally records downwelling longwave (LW) radiation and barometric pressure (McPhaden et al. 2009). We used the high-resolution meteorological and radiation data collected at 10- and 2-minute intervals, respectively. The LW and SW radiation data were re-binned to 10-minute resolution to be consistent with the meteorological variables.
The TOGA Coupled Ocean-Atmosphere Response Experiment (COARE) flux bulk algorithm version 3.0 was used to compute surface LHFLX and sensible heat fluxes (SHFLX; Fairall et al. 2003) from the 10 minute fields. The flux algorithm contains sub-models that calculate the cool skin and warm layer ocean temperatures to estimate the actual sea surface interface (vs. 1 m depth) temperature (Fairall et al. 2003). Both LW and SW radiation are inputs to these sub-models. However, since the 90°E buoy has no LW information, the LW radiation correction was neglected for both buoys when calculating LHFLX and SHFLX. Comparing LHFLX and SHFLX computed with and without LW radiation for the 80.5°E buoy revealed little change in final values – O(1 Wm$^{-2}$), O(0.1 Wm$^{-2}$) for LHFLX and SHFLX, respectively (not shown). In extreme cases, neglecting the LW correction did cause a substantial change in LHFLX and SHFLX values with a difference of 15 Wm$^{-2}$ and 3 Wm$^{-2}$, respectively. However, the importance of these few times with substantial differences is diminished on the intraseasonal timescale and our results are not sensitive to the LW correction. Surface flux output from the algorithm was averaged to daily timescales.

Figure 1 shows the time series of daily averaged surface fluxes for the 80.5°E buoy from 2008 – 2012 and from 2004 – 2012 for the 90°E buoy. Although the 80.5°E buoy has been in place since 2004, no high-resolution data were available until 2008. Likewise, no high-resolution data were available from the 90°E buoy until 2004. Gaps in the surface flux record occur when either wind, air temperature, SST, RH or a combination of the variables were missing. Since we are interested in intraseasonal timescales, linear interpolation was used between data gaps less than or equal to 10 days when doing analysis. After interpolation, the 80.5°E buoy has three continuous time periods – 333 days from 8 August 2008 to 6 July 2009, 213 days from 27 August 2009 to 27 March 2010, and 119 days from 27 July 2012 to 22 November 2012. The
90°E buoy also has three continuous periods – 133 days from 8 November 2004 to 20 March 2005, 902 days from 30 July 2009 to 17 January 2012, and 220 days from 1 May 2012 to 6 December 2012 (Fig. 1). Since LHFLX is about an order of magnitude larger than SHFLX (black vs. grey lines in Fig. 1) our analysis in Section 3 focuses on LHFLX.

2.2 Rain Products

We use rain measurements from the RAMA buoys (mentioned above), TRMM 3B42, and GPCP. Using three somewhat independent rainfall sources emphasizes the robustness of the results, while pointing out differences in the three products (Section 3). Both TRMM 3B42 and GPCP data were obtained from the Goddard Space Flight Center Global Precipitation Analysis website (http://precip.gsfc.nasa.gov/).

TRMM 3B42 is a merged precipitation product providing 3-hourly rainfall measurements at 0.25° x 0.25° resolution, which we average to 1° x 1° resolution to be consistent with GPCP resolution (discussed below). Input to TRMM 3B42 includes passive low earth orbit microwave satellite data, geosynchronous earth orbit (GEO) infrared (IR) satellite data, TRMM Combined Instrument (TCI) estimates, the GPCP monthly rain gauge analysis, and the Climate Assessment and Monitoring System (CAMS) monthly rain gauge analysis (Huffman et al. 2007). We use version 7 of TRMM 3B42, which includes several updates from previous versions detailed online (Huffman and Bolvin 2014). For GPCP, we use version 1.2 of the 1° x 1° daily combination product. GPCP combines GEO and low Earth-orbit IR measurements with TIROS Operational Vertical Sounder (TOVS) and Atmospheric Infrared Sounder (AIRS) measurements to estimate global rainfall (Huffman et al. 2001). Both TRMM 3B42 and GPCP measurements
were interpolated to each buoy point. TRMM 3B42 was additionally averaged to daily
timescales.

Figure 2 shows daily rainfall from each of the three rain data sources for the 80.5°E buoy.

GPCP values appear systematically lower than buoy and TRMM 3B42 values. This is likely do
to the lower effective horizontal resolution of the GPCP product. However, all three products
have reasonable agreement in capturing rainy vs. dry periods. For example, all three products
show similar rain oscillations from about days 550 to 700. However, the buoy data records little
rainfall around day 850, while both TRMM and GPCP record several rain events, indicating the
buoy must have been on the periphery or outside the precipitating systems.

2.3 Global MJO indices

The real time multivariate MJO (RMM) index, developed by Wheeler and Hendon
(2004), classifies each day in the tropics as representing one of eight MJO phases. Each phase
represents the general geographical location of deep convection associated with the MJO as it
propagates eastward. The index is derived from the leading pair of EOFs of the combined fields
of 15°S – 15°N averaged outgoing longwave radiation (OLR) and 200-hPa and 850-hPa zonal
wind once the annual, interannual, and ENSO signals have been removed from each variable.
Projection of daily averaged OLR and upper and lower zonal winds on to the leading EOF pair
results in a principal component pair (PC), referred to as the RMM1 and RMM2 time series, that
effectively describe the spatial and temporal evolution of the MJO. Because RMM1 leads
RMM2 by about 10 – 15 days, eastward MJO propagation is indicated as counterclockwise
rotation when plotted in standardized RMM1-RMM2 phase space (see Fig. 7 Wheeler and
Hendon).
An index recently developed by Kiladis et al. (2014) focuses solely on convection to describe the tropics-wide daily phase of the MJO. Their index uses only 30 – 96 day filtered OLR averaged over 20°S – 20°N for eastward propagating zonal wavenumbers to define the MJO and is therefore referred to as the OLR MJO index (OMI). Like RMM, OMI is an all season MJO index based on EOF analysis. For all years between 1979 and 2012, an EOF analysis is computed centered on each day of the year using a 121-day sliding window. This results in 365 eigenvector pairs, which represent the eastward propagation of the MJO. 20 – 96 day filtered OLR, containing both eastward and westward zonal wavenumbers from each day in the historical data record, is then projected onto the spatial EOFs for the corresponding day of the year. An MJO phase diagram, similar to the RMM phase diagram, can then be constructed by plotting the normalized PC components against each other. We have made OMI phases directly comparable to RMM phases by switching the OMI PC ordering and reversing the sign of the first OMI PC (i.e. OMI(PC2) = RMM(PC1) and -OMI(PC1) = RMM(PC2)), as advised by Kiladis et al. (2014).

3. Intraseasonal LHFLX-precipitation relationship

3.1 Relationship of 20 – 100 day LHFLX and precipitation anomalies

Each continuous time chunk of the LHFLX and precipitation time series for the 80.5°E and 90°E buoy were subject to a 20 – 100 day non-recursive Lanczos bandpass filter with 60 weights. Figs. 3 and 4 show scatterplots of precipitation anomalies (in energy units) versus LHFLX anomalies for the indicated precipitation source for the 80.5°E and 90°E buoys, respectively. Note that only every fourth day is plotted, yet statistics are calculated using all available days. These plots are similar to Fig. 3 of AM08 and Fig. 8 of Maloney and Esbensen.
expect here precipitation is plotted on the x-axis and LHFLX on the y-axis, which is a more relevant convention in the context of moisture mode theory (Raymond et al. 2009).

The black solid line is the linear best-fit line that minimizes the chi-square error statistic. The correlation and regression coefficients are labeled in the top left of each panel. Correlation coefficients are statistically significant at the 90% level for all precipitation vs. LHFLX anomalies, except using the buoy precipitation anomalies at the 80.5°E buoy. Significance was determined following AM08 using a Student’s t-test. Degrees of freedom (DOF) for the purpose of assessing the correlation coefficient significance were determined by dividing the number of days that went in to each plot by 40 – the approximate length of an MJO event. For both buoy locations, the correlation and regression coefficients between LHFLX and TRMM and GPCP rain sources are similar (cf. 3b,c and 4b,c).

The black bars on each plot indicate the 90% confidence intervals for the means of 200 Wm\(^{-2}\) wide precipitation bins, where means are indicated by black dots. Bins are centered on -300 Wm\(^{-2}\), -100, Wm\(^{-2}\), 0 Wm\(^{-2}\), 100 Wm\(^{-2}\), and 300 Wm\(^{-2}\) and confidence limits were computed using the t-statistic. DOFs for each 200 Wm\(^{-2}\) bin were found by estimating the number of independent MJO events per bin. To do this, we made use of the average characteristics of the MJO as described by the RMM indices. Data in each bin were assigned RMM phases and ordered according to date. Consecutive days in each bin were assumed to belong to the same MJO event. Non-consecutive days belonged to the same MJO event if the time span between the data were below an allowable “phase gap threshold”. The “phase gap threshold” was defined as eight times the phase difference between the non-consecutive days. Eight represents the approximate number of days spent in each RMM phase (choosing five or ten changed the error bars very little). For example, at the 90°E buoy, May 2-3 and May 21-23, 2010 fall into the
same LHFLX bin. May 2\textsuperscript{nd} and 3\textsuperscript{rd} are in RMM phase 2, while the 21\textsuperscript{st} – 23\textsuperscript{rd} are in phase 6.

Eight times the phase difference between the two sets of days means there may be up to 32 days separating the two sets of days for both sets to occur in the same MJO event. Given there are 18 days between the two dates, it seems plausible that the days in between experienced phases 3 – 5.

A check on days May 4-20 confirm those days did in fact experience phases 3 – 5. This method of determining DOFs is slightly stricter than Maloney and Esbensen (2007) and AM08 in which a 10-day or larger time span between non-consecutive days was essentially the requirement for counting independent MJO events.

At the 80.5°E buoy, regression coefficients indicate LHFLX anomalies are about 5% of TRMM and GPCP precipitation anomalies (Fig. 3b,c). At the 90°E buoy, LHFLX anomalies are between 7% and 8% of TRMM and GPCP precipitation anomalies, respectively (Fig. 4b,c). At both buoys, LHFLX anomalies are a slightly smaller percentage of buoy precipitation anomalies compared to the two merged precipitation products – only about 4% and 6% for the 80.5°E and 90°E buoy, respectively (Figs. 3a and 4a). The difference in the relationship between LHFLX anomalies and buoy precipitation anomalies versus TRMM and GPCP anomalies is perhaps not surprising given the buoy is a single point measurement and TRMM and GPCP are area averaged values before interpolating to the buoy point location. The LHFLX-TRMM and GPCP precipitation relationships for the two Indian Ocean buoys are similar to what AM08 found using two west Pacific TOGA TAO buoys and TRMM precipitation in that both regions show a positive relationship between precipitation and LHFLX. However, the ratio of LHFLX anomalies to precipitation anomalies associated with the Indian Ocean buoys are about a third as large as the ratio AM08 found (i.e. ~7% vs. 20%).
Previous studies estimated that deep convection discharges column MSE by vertical advection at a rate of about 20% of precipitation in warm pool regions and about 14% over the Maritime Continent (Yu et al. 1998). Recent MSE analysis by Sobel et al. (2014) for the DYNAMO MJO events found a similar rate of MSE discharge by vertical advection during peak MJO activity – between 10-20% of precipitation (their Fig. 8a, 9a). This suggests that LHFLX anomalies may be sufficient to destabilize the MJO in the west Pacific, as AM08 postulated, but may not be large enough, on their own, for MJO destabilization in the Indian Ocean, although they may still play a significant role. Radiation feedbacks may be important to complete the destabilization process (e.g. Andersen and Kuang 2012; Chikira 2014). In fact, Lin and Mapes (2004) found anomalous column-integrated cloud radiative heating to be about 10%-15% of precipitation anomalies in the west Pacific. If a similar cloud radiative heating anomaly is observed in the Indian Ocean, LHFLX and cloud radiative feedbacks together could be enough to destabilize the MJO. Future studies will use CERES (i.e. Clouds and the Earth’s Radiant Energy System) data to quantify radiative heating relative to precipitation over the Indian Ocean.

3.2 Sensitivity of LHFLX to wind vs. air-sea humidity differences

To quantify the importance of intraseasonal LHFLX to wind speed relative to thermodynamic variability, sensitivity tests were conducted where LHFLX was recomputed twice using selective smoothing to the input time series to the COARE flux algorithm. In one re-computation, the high-resolution wind speed was smoothed using a 50-day running average while the thermodynamic (i.e. SST, RH, and air T) time series remained the same. A 50-day running mean effectively removes MJO-timescale wind variability is the wind field. In the other computation, the wind speed was smoothed while the thermodynamic time series were not.
The intraseasonal LHFLX-precipitation anomaly relationship remains qualitatively similar to the full LHFLX field (i.e. positively correlated) at each buoy when LHFLX was computed with the intraseasonally smoothed thermodynamic variables and the original (i.e. unsmoothed) wind speed (Fig. 5a, b). Only scatterplots using TRMM precipitation are shown since TRMM and GPCP are so similar. Correlation and regression coefficients increase at each buoy and for all rain products. LHFLX and TRMM anomalies are still significantly correlated at the 90% level. Regression coefficients increase by about 40% and 60% between LHFLX and the TRMM rainfall, such that LHFLX anomalies are now approximately 7.5% and 11% of precipitation anomalies for the 80.5°E and 90°E buoys, respectively.

When intraseasonally smoothed winds are used to compute LHFLX, the LHFLX-precipitation anomaly relationship on intraseasonal timescales fundamentally changes (Fig. 5c, d). Correlation and regression coefficients are now negative at both buoys. In this sensitivity run, only the correlation coefficient at the 90°E buoy is statistically significant at the 90% level when LHFLX is compared to TRMM precipitation. We note that when only a 20-day running average was used to smooth the wind time series the relationship between intraseasonally filtered LHFLX and precipitation remained similar as to when the two unsmoothed time series were used to calculate LHFLX (i.e. similar to Figs. 3 and 4).

Physically, the computation of LHFLX with complementary smoothed time series indicates that intraseasonal LHFLX anomalies are primarily wind driven. That is, the positive relationship between intraseasonal LHFLX anomalies and precipitation anomalies is primarily explained by wind variability. Other studies have also found LHFLX anomalies to be primarily wind driven (Jones and Weare 1996; Maloney and Esbensen 2007; AM08; Grodsky et al. 2009; Yokoi et al. 2014). Thermodynamic variability, on the other hand, largely opposes or damps the
positive relationship between intraseasonal LHFLX anomalies and precipitation anomalies (Fig. 5). Accordingly, examination of the spread along the LHFLX anomaly axis in the top and bottom panels of Fig. 5 vs. Figs. 3b and 4b indicate thermodynamic variability decreases the spread of LHFLX anomalies compared to the spread that would exist if wind variability were acting alone. The change in standard deviation among various LHFLX computations verifies the visual differences seen between Figs. 3b and 4b and Fig. 5. The standard deviation of LHFLX increases from 15.5 Wm$^{-2}$ to 20.7 Wm$^{-2}$ and from 17.9 Wm$^{-2}$ to 23.7 Wm$^{-2}$ at the 80.5° and 90°E buoys, respectively, when the smoothed thermodynamic fields are used to compute LHFLX. Conversely, the standard deviation of LHFLX decreases from 15.5 Wm$^{-2}$ to 10.6 Wm$^{-2}$ and from 17.9 Wm$^{-2}$ to 11.5 Wm$^{-2}$ at the 80.5°E and 90°E buoys, respectively, when the smoothed wind field is used to compute LHFLX. Further evidence of the relative importance of wind vs. thermodynamic variability to MJO fluxes is given in Section 4.

### 3.3 Coherence and phase relationship between precipitation and LHFLX

To further quantify the relationship between intraseasonal LHFLX and precipitation and more deeply explore the effects of wind speed vs. thermodynamic variability to LHFLX, we examine the coherence and phase relationship between the paired time series. Figure 6 shows the coherence squared between precipitation and LHFLX computed using the original (i.e. unsmoothed wind speed or thermodynamics) time series for each buoy location. The cross spectrum and power spectrum were calculated for 100-day long segments and then averaged together to estimate the coherence squared and phase relationship over the entire time series. The 80.5°E buoy has six 100-day segments, while the 90°E buoy has twelve (Fig. 1). As a consistency check, coherence was also calculated for the longest continuous timespan at each
buoy and then subject to re-binning of adjacent periods. Both methods gave similar results, but we show coherence computed via segments as that method maximized the usable portion of each time series. The dotted line indicates the 95% confidence level following Biltoft and Pardyjak’s (2009) coherence significance test (their Eq. 3). DOF were estimated as two times the number of 100-day segments.

At the 90°E buoy, a broad peak in coherence exists between LHFLX and both TRMM precipitation and GPCP spanning intraseasonal timescales, with maximum coherence squared near 0.7 in the intraseasonal band (Fig. 6a). The average coherence between the intraseasonal band (i.e. 20 – 100 days) is near 0.4, which is above the statistically significant line. At intraseasonal timescales, precipitation leads LHFLX by about a day at shorter intraseasonal periods to several days at longer intraseasonal periods (Fig. 6b). Results are similar at the 80.5°E buoy when using TRMM precipitation, although the significant peak in coherence occurs in a narrower period range (Fig. 6c, d). Coherence between LHFLX and GPCP at the 80.5°E buoy shows no significant peak. Limited data at the 80.5°E buoy (i.e. half as many 100-day segments at the 90°E buoy) may explain the lack of significant coherence.

The lead lag relationship of LHFLX and precipitation is consistent with Shinoda et al. (1998), Jones et al. (1998), and Robertson and Roberts (2012), but contrary to Zhang (1996). Using the European Centre for Medium-Range Weather Forecasts (ECMWF) surface analysis to calculate LHFLX and outgoing longwave radiation (OLR) to approximate deep convection, Shinoda et al. (1998) found LHFLX to lag maximum convection by about three days over the western Pacific and Indian Ocean between 2.5°S-7.5°S for the average of 10 MJO events with an approximate cycle length of 50-days (their Figs. 9 and 10). Jones et al. (1998) also used ECMWF reanalyses to estimate LHFLX and OLR as a deep convective proxy and found that over the west...
Pacific and Indian Ocean LHFLX anomalies maximize when westerly winds are strongest, about one to two pentads (5-day averages) after convection. Robertson and Roberts (2012) looked at tropical intraseasonal variability from both Modern-Era Retrospective analysis for Research and Applications (MERRA) reanalysis and observations from TRMM and the OAFlux dataset (i.e. objectively analyzed air-sea fluxes for the global ocean; Yu and Weller 2007) from 2000 to 2007 and found LHFLX lagged precipitation in both. Zhang (1996), however, found surface heat fluxes slightly lead precipitation in the 30 – 90 day frequency band. His paper looked at area averaged surface fluxes over a subset of the TAO buoys in the west Pacific relative to high cloud cover (i.e. a proxy for deep precipitation) estimates from geostationary satellites. These differences may indicate the relationship between surface fluxes and precipitation changes as the MJO moves eastward. Indeed, Zhang (2005) discussed four models on the phase relationship between MJO convection and surface fluxes as convection propagates eastward. Over the Indian Ocean, Model I depicts convection in between westerlies to the west and easterlies to the east, while the Pacific Ocean more resembles Model II with convection and strong westerlies in phase (Zhang 2005 Fig 6). Alternatively, the use of different precipitation estimates and areal averaging may explain the differences, as TRMM 3B42 estimates are arguably more accurate than geostationary satellites alone at identifying deep convection.

Figure 7 is analogous to Fig. 6, except LHFLX was calculated using the smoothed (i.e. 50-day running average) thermodynamics (i.e. SST, air T, and RH). Using the smoothed time series reduces the number of 100-day segments at each buoy by two. Little difference exists between Fig. 6 and 7, which means most of the coherence is explained via wind variability and reinforces the conclusion that LHFLX variations on intraseasonal timescales are predominately wind driven. The coherence plot using the smoothed high-resolution wind speed is much noisier.
than the coherence plot using LHFLX computed with the smoothed thermodynamics and coherence is generally not statistically significant (not shown). However, the phase relationship between LHFLX and precipitation at intraseasonal timescales changes substantially when the smoothed wind speed time series is used to compute LHFLX (not shown). The thermodynamic component of LHFLX increasingly leads precipitation from the short to long end of the intraseasonal period range (i.e. 20 – 100 days). These results are consistent with Fig. 5a, b that showed a negative correlation between filtered LHFLX and precipitation when LHFLX was computed using the smoothed wind speed time series, but a positive relationship when smoothed thermodynamics were used to compute LHFLX (Fig. 5c, d).

3.4 Importance of mesoscale variability to the MJO

The importance of mesoscale wind variability to LHFLX variability associated with the MJO is now evaluated in light of the large body of literature that has highlighted the importance of mesoscale convection to tropical dynamics (e.g. Esbensen and McPhaden 1996, Houze 2004, Mapes et al. 2006, Del Genio 2012) and specifically the MJO (e.g. Moncrieff 2004, and Riley et al. 2011). We only test one small piece of the possible mesoscale influence on tropical dynamics, in particular the effect of mesoscale effects on intraseasonal surface flux variability. Following Maloney and Esbensen (2007), the effect of mesoscale variability is minimized by computing LHFLX from wind speed reconstructed from daily averaged wind vectors. Figure 8 shows the precipitation-LHFLX relationship at each buoy for LHFLX calculated using daily averaged vector winds. Only results using GPCP are shown as that was the only rain product for the 80.5°E buoy that showed a relationship that was significantly different than zero at the 90% level. Similar to Maloney and Esbensen (2007), the precipitation-LHFLX relationship resembles
the relationship using LHFLX computed from the full wind field, (cfs. 3c, 4c, and 8a,b) but with
decreased regression and correlation coefficients. Regression coefficients decrease by
approximately 22% and 12% for the 80.5°E and 90°E buoy, respectively. The reduction in
regression and correlation coefficients indicates mesoscale gustiness contributes to the
precipitation–LHFLX relationship, but does not fully explain the relationship. Back and
Bretherton (2005) and Araligidad (2007) came to similar conclusions by using area averaged
QuickSCAT wind vectors to compute wind speed to minimize the effects of wind variations
associated with mesoscale convective variability. These results do not rule out the importance of
mesoscale convection to MJO dynamics. Vertical momentum transport by mesoscale
circulations, which is not addressed here, could be an important driver of MJO dynamics and the
grid-scale vector wind (e.g. Moncrieff 2004). Rather, the contribution of mesoscale gustiness to
intraseasonal LHFLX variability is small.

Wind speed was also constructed from three day averaged wind vectors and used to
determine LHFLX anomalies (Fig. 8 c,d). The three-day average (effectively a six day low pass
filter) eliminates much of the synoptic-timescale wind variability, which was shown by Maloney
and Esbensen (2007) to contribute strongly to the intraseasonal wind speed signal in the east
Pacific. The LHFLX-precipitation correlation remains qualitatively similar to the original
LHFLX-precipitation scatter plots (Figs. 3c and 4c) and those derived from LHFLX calculated
from daily mean vector winds (Fig. 8a, b). At the 80.5°E buoy, regression and correlation
coefficients are similar compared to when daily vector winds were used, while the coefficients
increase slightly at the 90°E buoy. The phase relationship between precipitation and LHFLX
remained the same when mesoscale and synoptic scale variability were minimized (not shown).
This is similar to what Araligidad (2007) found in the west Pacific using TAO buoys.
4. LHFLX-precipitation relationship using MJO global indices

The LHFLX-precipitation relationship is now considered for the OMI (Kiladis et al. 2014) and RMM (Wheeler and Hendon 2004) global MJO indices (discussed in Section 2.3). Each day in the LHFLX and precipitation time series was assigned an RMM and OMI phase. Only days that had an OMI or RMM amplitude greater than or equal to one were retained for analysis, as the amplitude one is a common threshold for classifying RMM MJO events (e.g. Wheeler and Hendon 2004). The average LHFLX and precipitation value was then computed for each phase. Phase anomalies were then calculated as deviations from the all-phase mean of each respective variable.

Figure 9 shows the LHFLX versus precipitation phase anomalies for the 80.5°E buoy for all precipitation sources for both global MJO indices (RMM phases left column, OMI phases right column). Phase values are represented by their corresponding phase number. The number of days each phase experienced is given in Table 1. Large black numbers in Fig. 9 indicate phase anomalies where the original two time series were subject to a 20 – 100 day Lanczos filter, whereas anomalies indicated by small grey numbers were computed with the raw, unfiltered LHFLX and precipitation time series. Using the filtered time series makes results clearer, but does not qualitatively alter the interpretation of the results as discussed below. Index anomalies using the filtered vs. non-filtered time series will simply be referred to as filtered and non-filtered RMM and OMI phases, respectively. As before, precipitation values have been converted to energy units to be synonymous with LHFLX units.

Little variation exists among the precipitation sources for a given MJO index (i.e. compare rows in each column of Fig. 9). Using the filtered time series, both indices show an
elliptical counterclockwise progression of precipitation- LHFLX anomalies with the major axis of the ellipses where the diagonal one unit of LHFLX to ten units of precipitation line would be. The plots indicate that depending on which global index is evaluated, precipitation and LHFLX have either a lag-lead relationship, with precipitation leading LHFLX anomalies by about one phase, or are in phase. For example, for filtered and non-filtered RMM phases at 80.5°E, precipitation anomalies maximize during phase 2, while LHFLX anomalies peak one phase later during phase 3 (Fig. 9, left column). Filtered and non-filtered OMI shows both LHFLX and precipitation anomalies peaking during phase 3. However, the lead-lag relationship is still noticeable between other OMI phases (Fig. 9, right column). Results using the unfiltered time series do not have as clean an elliptical progression of anomalies, but still indicate a similar relationship between LHFLX and precipitation anomalies (i.e. small grey numbers on Fig. 9).

Focusing on the results from the filtered time series, LHFLX anomalies range between 5%-13% of precipitation anomalies at the time of peak precipitation amplitude, which is similar to the relationship between precipitation and LHFLX in Figs. 3 and 4 where intraseasonally filtered time series were compared. The elliptical shape, though, indicates that the ratio of LHFLX anomalies to precipitation anomalies changes throughout an MJO cycle. Only if phase anomalies fell along the x-y diagonal would LHFLX consistently be about 10% of precipitation anomalies. However, one could argue that for assessing MJO destabilization and the ability of fluxes to help maintain the MJO active phase, we are most concerned with the strength of LHFLX anomalies at the time of peak precipitation.

Comparing the LHFLX-precipitation relationship between RMM and OMI phases, RMM has less variability in LHFLX and precipitation through an MJO cycle (Fig. 9 - left vs. right columns). Also, individual OMI phases are shifted slightly clockwise relative to the RMM
phases. The most noticeable shift for results using the filtered time series occurs perhaps during phases 3 and 8 (large black numbers). RMM phases 3 and 8, when GPCP precipitation is used, are centered near a LHFLX value of 13 Wm$^{-2}$ and a precipitation value of 90 Wm$^{-2}$ for phase 3 and a LHFLX value of -8 Wm$^{-2}$ and precipitation value of -30 Wm$^{-2}$ for phase 8 (Fig. 9c large black numbers). OMI phases 3 and 8 (large black numbers), however, are centered near a LHFLX-precipitation value pair of 19 Wm$^{-2}$ and 170 Wm$^{-2}$ and 8 Wm$^{-2}$ and -110 Wm$^{-2}$, respectively.

Figure 10 is the same as Fig. 9 except for the 90°E buoy. Anomalies computed using the filtered time series have an elliptical shape, while the anomalies from the unfiltered time series have a more erratic progression, similar to the 80.5°E buoy (cf. 9 and 10). During precipitation maxima, LHFLX anomalies range between 6%-16% of precipitation anomalies, which is a slightly larger range than at the 80.5°E buoy. There are slight phase variations in LHFLX-precipitation anomalies between the two buoys. Precipitation and LHFLX anomalies are largest during phases 3 and 4, respectively, at the 90°E buoy compared to phases 2 and 3 at the 80.5°E buoy. Given the phase numbers represent the approximate physical location of eastward propagating deep convection associated with the MJO, buoys farther east should, by design, have maximum precipitation values at later phases. Another subtle difference is that maximum OMI LHFLX anomalies at the 90°E buoy do not coincide with the maximum precipitation anomalies, as the two did for the 80.5°E buoy during phase 3. Rather, precipitation anomalies are largest during phase 3 for results from filtered and unfiltered time series, while LHFLX anomalies are largest during phase 4 for filtered time series and phase 5 for the unfiltered time series. Given the 90°E buoy has about twice as much data as the 80.5°E buoy, it is difficult to conclude if the
Differences between buoy locations and among a given buoy site but for different MJO indices are perhaps explained by the unique ways in which the RMM and OMI indices define the MJO. Since OMI phases are solely based on convection and does not have a global wind dependence, perhaps the relationship between LHFLX and precipitation is expected to remain constant as MJO convection moves eastward. Low-level and upper-level wind signals influence the RMM index, and the phase relationship of the winds and precipitation changes as the MJO moves through RMM physical space, perhaps leading to alterations in the LHFLX-precipitation relationship as the MJO envelope moves east.

4.1 Linearization of the LHFLX formula across global MJO indices

The relative importance of wind speed variability vs. thermodynamic variability across global MJO phase is achieved by linearization of the LHFLX bulk formula. This analysis supports the findings in Section 3a above. Through Reynolds decomposition the following is obtained:

\[ LH' = \rho LC_H \left( \bar{v} \Delta q + \bar{v}' \Delta q' + (v \Delta q')' \right), \tag{1} \]

where \( \rho \) is the density of near-surface air, \( L \) is the latent heat of vaporization, and \( C_H \) is the exchange coefficient, \( v \) is daily averaged buoy wind speed, and \( \Delta q \) is the difference between daily averaged surface saturation specific humidity and daily averaged boundary layer specific humidity. Overbars represent averages over an entire MJO cycle (i.e. RMM and OMI phases 1 – 8), while primes represent the deviation of individual phase averages from the all-phase mean. \( \rho LC_H \) was prescribed as a constant such that the average ratio of actual LHFLX anomalies to
linearized LHFLX anomalies across all global phases is equal to one. A similar decomposition was done by Maloney and Esbensen (2005).

Figure 11 shows each component of Eq. 1 (red and blue lines), except for the third term inside the brackets that is negligible, along with LHFLX anomalies calculated from the COARE algorithm (black line) across RMM phases for the 80.5°E buoy (panel a) and the 90°E buoy (panel b). Panels (c) and (d) are the same as (a) and (b) except for OMI phases. Note, LHFLX computed using the COARE flux algorithm and precipitation anomalies are the same values as those shown in Figs. 9 and 10 using the unfiltered time series (small grey numbers). The dashed line in each panel is the sum of the first two terms inside the brackets of Eq. 1 and shows how good the linear approximation matches the COARE algorithm. At both buoys and for both MJO indices, the component of the linearized LHFLX anomalies due to wind speed variability (i.e. first term inside brackets of Eq. 1 and red line in panels (a) and (b) explains nearly all the variability in LHFLX anomalies. The component due to air-sea humidity difference variability (i.e. second term inside bracket of Eq. 1 and blue lines) is generally out of phase with and smaller than the wind speed variability term and total LHFLX anomalies. Irrespective of MJO index or phase, air-sea humidity differences act most of the time to reduce LHFLX anomalies, though the percent reduction is not consistent across phases and in a few instances even enhances LHFLX anomalies. For example, during RMM phase 6 at the 90°E buoy the two terms nearly cancel each other – the first term (red line) is 2.9 Wm⁻², while the second term (blue line) is -2.6 Wm⁻². In phase 7, however, air-sea humidity differences reduce total LHFLX anomalies by only 2.5%. Further, during OMI phase 1 at the 90°E buoy (Fig. 11d) both terms of Eq. 1 are negative (red and blue lines) so the air-sea humidity differences (blue line) actually enhances total LHFLX anomalies by nearly 23%. Shinoda et al. (1998) also showed that the reduction in
LHFLX anomalies via air-sea humidity differences is not consistent across MJO phases (their Fig. 12), though this conclusion was not explicitly stated in their paper.

These results from the linearization of the LHFLX formula are consistent with the sensitivity experiments shown in Fig. 5 where the correlation between LHFLX and precipitation was explained primarily via wind speed variations, while thermodynamic variations damped or opposed the positive correlations. The dominance of wind speed to LHFLX variations was also found in Shinoda et al. (1998), Maloney and Esbensen (2005) and Araligidad and Maloney (2008). Maloney and Esbensen (2005), though, found the air-sea humidity difference term to have negligible impact on total LHFLX variations for their model simulations of the boreal summertime intraseasonal oscillation (ISO) over the east Pacific. Their model did not have an interactive ocean and only fixed SSTs, which may explain the irrelevance of air-sea humidity differences. They also noted an asymmetry in LHFLX anomalies between building vs. decaying ISO phases. Similar asymmetries are noticeable between phases 1 and 8 at the 90°E buoy, but are not apparent for the 80.5°E buoy (Fig. 11). Perhaps if the 80.5°E buoy had more data, an asymmetry would also appear. As such, firm conclusions cannot be made about the asymmetry of LHFLX anomalies in building vs. decaying phases of the MJO over the Indian Ocean.

5. Summary and Discussion

Observations from two RAMA buoys along the equator at 80.5°E and 90°E were used to calculate LHFLX anomalies on intraseasonal timescales. LHFLX anomalies were related to intraseasonal precipitation anomalies obtained from the buoys and two merged satellite products, GPCP and TRMM, interpolated to the buoy points to assess the importance of LHFLX for maintaining convection on intraseasonal timescales. We found intraseasonal LHFLX and
precipitation anomalies to be positively correlated for both buoys and all rain data sources, with LHFLX anomalies between 4% and 8% of precipitation anomalies depending on buoy location and rain data (Figs. 3 and 4). The contribution of intraseasonal LHFLX anomalies to precipitation anomalies for these Indian Ocean buoys is lower than previous results derived from the Pacific. Results from Maloney and Esbensen (2007) but for buoys in the east Pacific along 95°W, found LHFLX anomalies to be between 20%-50% of precipitation anomalies. Likewise, AM08 found a LHFLX-precipitation relationship around 20% for two buoys in the west Pacific along 165°E. In both Maloney and Esbensen (2007) and AM08, the linear regressions were computed with LHFLX as the independent variable and precipitation as the dependent variable, however. In this study, the independent and dependent variable are reversed because we are interested in the magnitude of LHFLX at peak precipitation, with consequences for the destabilization of the MJO. If LHFLX is retained as the independent variable and precipitation the dependent variable, the fraction of LHFLX anomalies to precipitation anomalies for the two Indian Ocean buoys used here are similar to Maloney and Esbensen (2007) and AM08 at around 20%. Assessing the relationship with LHFLX as the dependent variable produces similar results to those derived from composite analysis using globally defined MJO phases when assessing the strength of LHFLX anomalies relative to maximum precipitation (Figs. 9 and 10). Plots were also made for the 8°S 80.5°E buoy to see how the relationship of the precipitation-LHFLX relationship varies away from the equator. The 8°S 80.5°E buoy has a continuous time span of high-resolution data between 22 August 2008 and 8 July 2012. Scatterplots (similar to Fig. 3) reveal a weakly negative relationship between filtered precipitation and LHFLX anomalies (not shown). Only the correlation coefficient between buoy precipitation and LHFLX is statistically different from zero at the 90% confidence level.
Contrasting the results from the 8°S buoy with its equatorial counterpart reveals that the relationship between precipitation and LHFLX is not consistent across latitudes. Rather, LHFLX anomalies may only be important for locally supporting MJO convection on or very close to the equator, and even there, the magnitude of the flux anomaly may not be sufficient in itself to destabilize the MJO. Phase relationship plots between intraseasonal precipitation and LHFLX show that the 8°S 80.5°E buoy lies near a region where the lead-lag relationship between precipitation and LHFLX is not statistically significant and near a transition latitude where the relationship switches from precipitation leading LHFLX to LHFLX leading precipitation (Charlotte DeMott, personal correspondence 2014). 8°S is also where the mean surface zonal wind changes sign from westerlies near the equator to easterlies further south. Maloney and Esbensen (2007) showed a similar inconsistency between LHFLX and precipitation for some regions of the east Pacific as the two variables had a negative (albeit, not statistically significant) relationship at the 8°N, 110°W buoy where mean winds were easterly, unlike mean westerlies further east.

Examining the composite precipitation-LHFLX relationship using global MJO indices also showed a positive relationship between the two variables at the equatorial buoys. During the convectively active MJO phase, LHFLX anomalies were anomalously positive, while suppressed phases had negative anomalies. Similar to the linear regression analysis, LHFLX anomalies were between 5%-13% of precipitation anomalies during MJO phases associated with maximum rainfall (Figs. 9 and 10). The percentage of LHFLX anomalies to precipitation anomalies varies depending on MJO phase as indicated by the elliptical progression of anomalies in Figs. 9 and 10. Maloney (2009) also showed that the relationship between surface fluxes and precipitation for NCAR CAM3 simulations varied through the lifecycle of the model MJO, though that
finding was not explicitly stated, with LHFLX being about 20% of precipitation during maximum rainfall (his Fig. 7).

In the context of moisture mode theory that requires support from column moistening processes to maintain the moisture anomaly that supports MJO convection, LHFLX anomalies of a value 4-13% of precipitation are likely important. However, surface fluxes are only one source of column moisture. A careful diagnoses of other terms in the MSE budget is necessary to reveal how important surface fluxes are relative to other processes affecting the moisture tendency (e.g. vertical advection and radiative feedbacks). A highly idealized theoretical analysis of Yu et al. (1998) suggested that the export of column MSE by vertical motions associated with deep convection occurs at a rate of ~20% of precipitation over the west Pacific warm pool and southeast Indian Ocean and at a rate of ~14% of precipitation near the Maritime Continent. In more recent findings, Sobel et al. (2014) showed vertical advection discharges column MSE at a rate of between 10-20% of precipitation at the peak of the 2011 DYNAMO MJO events. Therefore, our results – that LHFLX anomalies are between 4%-13% of precipitation anomalies – suggest the LHFLX anomalies are a non-negligible moisture source for MJO convection and contribute to the destabilization and maintenance of the MJO, but alone are not sufficient to overcome export of column MSE by convection. Previous studies have suggested that cloud-radiative feedbacks may also be important for destabilizing MJO convection (e.g. Andersen and Kuang 2012). Lin and Mapes (2004) estimated cloud-radiative heating to be about 10-15% of intraseasonal precipitation over the west Pacific. Tropics wide, Kiramayi and Maloney (2011) showed that the combination of intraseasonal surface and radiative fluxes in NCEP and ERA reanalysis data are positively correlated with and slightly lag intraseasonal precipitation with radiative flux anomalies larger than surface flux anomalies. More work is needed with reanalysis
products, sounding datasets, and high resolution models to determine more exactly the magnitude of MSE discharge associated with MJO convection and the threshold that diabatic MSE sources need to meet to help destabilize the MJO, if it is indeed a moisture mode. The effects of horizontal advection also need to be considered, as anomalous advective drying shows a non-zero covariance with MJO convection (e.g. Kiranmayi and Maloney 2011; Kim et al. 2014; Chikira 2014).

Sensitivity experiments with the COARE algorithm and a linear partitioning of LHFLX anomalies into wind-driven and thermodynamic contributions as a function of global MJO index phase both showed LHFLX anomalies associated with the two equator Indian Ocean buoys to be primarily wind driven, while slightly damped by air-sea humidity differences. The dominance of wind variability to LHFLX anomalies supports the notion that wind-induced surface fluxes are important to MJO convection in the Indian Ocean as previously noted by AM08 for the west Pacific and Maloney and Esbensen (2007) for the east Pacific.

Coherence analysis between 20 – 100 day filtered precipitation and LHFLX time series showed LHFLX anomalies lag precipitation anomalies on the order of days in the intraseasonal band (Fig. 6). Similar results were found using MJO global indices. At the 90°E buoy, the evolution of both RMM and OMI phases showed precipitation anomalies peaking in phase 3 with LHFLX peaking one phase later during phase 4 (Fig. 10). At the 80.5°E buoy, precipitation anomalies peaked during phase 2 with peak LHFLX following in phase 3 for RMM phases, while OMI phases showed both variables peaking during phase 3 (Fig. 9). This lag-lead relationship for the Indian Ocean buoys is consistent with previous findings for the Indian Ocean and Pacific basin (Shinoda et al. 1998; Jones et al. 1998; and Robertson and Roberts 2012) and has important implications for the time scale (or propagation) of the MJO. Maloney (2009) and
Kiranmayi and Maloney (2011) suggested that the fact that LHFLX is in phase or slightly lags precipitation effectively slows down MJO propagation, as the discharge of column MSE is retarded compared to if horizontal and vertical advection of MSE were acting alone. The idealized model of Sobel and Maloney (20012; 2013) suggested a similar effect of fluxes on propagation.

A natural question to ask when comparing RMM and OMI results is: How similar is the classification of phase and amplitude between the two indices? That is, is the evolution of precipitation and LHFLX anomalies for RMM and OMI phases (Figs. 9 and 10) reflecting the same events? Table 1 indicates how many days had synonymous RMM and OMI phase classifications. For example, at the 90°E buoy there are 24 days where both RMM and OMI say Phase 4 of an MJO event with amplitude ≥ 1 is occurring, which is approximately 26% of the RMM days and about 34% of the OMI days that occurred in Phase 4. Overall, overlap percentage per phase ranges from about 8% - 40% depending on phase, buoy, and index. If phase classification is ignored and just the number of RMM and OMI days that both have amplitude greater than or equal to one is compared, the overlap percentage is much higher (i.e. greater than 50%; Table 1, bottom row). This indicates the two indices are generally describing similar MJO events, but classifying days of the same event in different phases. Despite the different classifications of the two indices, they arrive at similar descriptions of the evolution of precipitation and LHFLX for composite MJO events. A similar overlap percentage was found by Kiladis et al. (2014) when they compared initiation dates for primary MJO events; between 7%-24% of RMM and OMI dates matched for initiation windows of +3 days to +14 days. It will be interesting to see if future studies that look at both RMM and OMI indices find a similar conclusion as we do here, that though the two indices may classify days differently in MJO
phase or amplitude, they give the same statistical description of the MJO. Repeating the global MJO index analysis but for the western and eastern Pacific TAO buoys is one way forward to test the robustness of the results between the two indices.

Further analysis using QuikSCAT wind retrievals over the Indian Ocean would benefit this work, as QuikSCAT enables the relationship between wind speed and precipitation to be diagnosed over a wider area than the single buoy points used here (Back and Bretherton 2005; AM08). However, QuikSCAT would only allow the wind component of the LHFLX to be assessed. Longer continuous records of in-situ flux observations would also be beneficial for diagnosing wind-flux feedbacks on convection. Cloud resolving model (CRM) simulations are another avenue to further study the importance of wind-induced LHFLX to intraseasonal precipitation. Future work, by the authors and collaborators, will include CRM simulations of MJO variability to isolate the importance of wind-flux feedbacks at various scales (e.g. convective, meso-, synoptic scale). Sensitivity experiments will control the strength of wind-induced LHFLX feedbacks to convection, including complete denial of wind-flux feedbacks, to test results found here and in other previous studies. Results of the observational work presented here and future model work are useful to the development of the Cyclone Global Navigation Satellite System (CYGNSS), which is scheduled to launch in 2016 with a mission to provide high temporal and spatial scale measurements of ocean surface wind.

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References


List of Figures

Figure 1 – LHFLX and SHFLX for the 80.5°E (top panel) and 90°E (bottom panel) buoys.

Figure 2 – Rainfall estimates from the 80.5°E buoy (a), GPCP (b), and TRMM 3B42 (c). GPCP and TRMM were interpolated to the buoy point. See text for more details.

Figure 3 – Scatterplots of anomalous LHFLX vs. anomalous (a) buoy, (b) TRMM, and (c) GPCP precipitation at the 80.5°E buoy. Anomalies are relative to each continuous time chunk in Fig. 1. Asterisks represent one day in the data record, where only every fourth day has been plotted. The solid line is the linear best-fit line that minimizes the chi-squared error statistic. Red dots indicate the mean of 20 Wm⁻² wide LHFLX bins, while the error bars are the 90% confidence limit for each bin computed using the t-statistic. See text for explanation and example on how DOF for the best-fit line and for each LHFLX bin were calculated.

Figure 4 – Same as figure 3, except for 90°E.

Figure 5 – TRMM Precipitation-LHFLX relationship when LHFLX is computed using smoothed thermodynamics (top) and smoothed winds (bottom) for 80.5°E (left) and 90°E (right).

Figure 6 – (a) Coherence squared between LHFLX and TRMM (solid line) and GPCP (dashed line) at the 90°E buoy. (b) Phase relationship between LHFLX and TRMM (diamond) and GPCP (asterisks) precipitation. (c) Same as a, except, for the 80.5°E buoy. (d) Same as b, except for the 80.5°E buoy. See text for details on how coherence was calculated.

Figure 7 – same as Fig. 6 except for LHFLX was computed using the smoothed (i.e. 50-day running averaged) thermodynamics.

Figure 8 – Scatterplots of LHFLX anomalies and GPCP precipitation anomalies when LHFLX was computed using wind speed calculated from (a, b) daily averaged wind vectors at the 80.5°E and 90°E buoy, respectively. (c, d) Same as a and b, but using 3-day averaged wind vectors to compute LHFLX anomalies.

Figure 9 – LHFLX vs. precipitation anomalies for RMM (a-c) and OMI (d-f) phase at the 80.5°E buoy. Phase anomalies are calculate as deviations form the all phases (i.e. phases 1-8) mean. Grey small numbers are phases using unfiltered time series, while black large numbers are phases using 20-100 day Lanczos filtered time series. (a, d) show buoy precipitation anomalies, while (b, e) show TRMM and (c, f) show GPCP precipitation anomalies.

Figure 10 – Same as figure 9, expect for the 90°E buoy.

Figure 11 – Composite LHFLX anomalies and linearized LHFLX terms for (a) RMM MJO phases at the 80.5°E buoy, (b) RMM MJO phases at the 90°E buoy. (c) and (d) are the same as (a) and (b) except for OMI phases. Bar represent average over an entire MJO cycle (i.e. all 8 RMM or OMI phases), while primes represent intraseasonal variations. See text for more details.
List of Tables

Table 1 – The number of days in each RMM and OMI phase for the 80.5°E and 90°E buoy. Also given, is the number of matching days between the two indices per phase and what percentage those matching days are of all the days in each phase. Values for the 90°E buoy are given in parentheses. Values in the total row, matching days column indicate how many days, independent of phase, qualified as both an RMM and OMI MJO event.
Table 1 – The number of days in each RMM and OMI phase for the 80.5°E and 90°E buoy. Also given, is the number of matching days between the two indices per phase and what percentage those matching days are of all the days in each phase. Values for the 90°E buoy are given in parentheses. Values in the total row, matching days column indicate how many days, independent of phase, qualified as both an RMM and OMI MJO event.

<table>
<thead>
<tr>
<th>Phase</th>
<th>RMM 80.5° (90°)</th>
<th>OMI 80.5° (90°)</th>
<th>Matching Days</th>
<th>Percent RMM days</th>
<th>Percent OMI days</th>
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<tbody>
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<td>Phase 1</td>
<td>42 (107)</td>
<td>26 (64)</td>
<td>8 (9)</td>
<td>19% (8%)</td>
<td>31% (14%)</td>
</tr>
<tr>
<td>Phase 2</td>
<td>57 (90)</td>
<td>61 (65)</td>
<td>20 (18)</td>
<td>35% (20%)</td>
<td>33% (28%)</td>
</tr>
<tr>
<td>Phase 3</td>
<td>51 (83)</td>
<td>56 (96)</td>
<td>13 (23)</td>
<td>25% (28%)</td>
<td>23% (24%)</td>
</tr>
<tr>
<td>Phase 4</td>
<td>58 (92)</td>
<td>33 (71)</td>
<td>9 (24)</td>
<td>16% (26%)</td>
<td>24% (34%)</td>
</tr>
<tr>
<td>Phase 5</td>
<td>59 (82)</td>
<td>30 (40)</td>
<td>12 (8)</td>
<td>20% (10%)</td>
<td>40% (20%)</td>
</tr>
<tr>
<td>Phase 6</td>
<td>50 (90)</td>
<td>54 (89)</td>
<td>9 (11)</td>
<td>18% (12%)</td>
<td>17% (12%)</td>
</tr>
<tr>
<td>Phase 7</td>
<td>67 (65)</td>
<td>61 (83)</td>
<td>25 (17)</td>
<td>37% (26%)</td>
<td>41% (20%)</td>
</tr>
<tr>
<td>Phase 8</td>
<td>55 (72)</td>
<td>51 (70)</td>
<td>9 (12)</td>
<td>16% (17%)</td>
<td>18% (17%)</td>
</tr>
<tr>
<td>Total</td>
<td>439 (681)</td>
<td>372 (578)</td>
<td>288 (383)</td>
<td>66% (56%)</td>
<td>77% (66%)</td>
</tr>
</tbody>
</table>
Figure 1 – LHFLX and SHFLX for the 80.5°E (top panel) and 90°E (bottom panel) buoys.
Figure 2 – Rainfall estimates from the 80.5°E buoy (a), GPCP (b), and TRMM 3B42 (c). GPCP and TRMM were interpolated to the buoy point. See text for more details.
Figure 3 – Scatterplots of anomalous LHFLX vs. anomalous (a) buoy, (b) TRMM, and (c) GPCP precipitation at the 80.5°E buoy. Anomalies are relative to each continuous time chunk in Fig. 1. Asterisks represent one day in the data record, where only every fourth day has been plotted. The solid line is the linear best-fit line that minimizes the chi-squared error statistic. Red dots indicate the mean of 20 Wm-2 wide LHFLX bins, while the error bars are the 90% confidence limit for each bin computed using the t-statistic. See text for explanation and example on how DOF for the best-fit line and for each LHFLX bin were calculated.
Figure 4 – Same as figure 3, except for 90°E.
Figure 5 – TRMM Precipitation-LHFLX relationship when LHFLX is computed using smoothed thermodynamics (top) and smoothed winds (bottom) for 80.5°E (left) and 90°E (right).
Figure 6 – (a) Coherence squared between LHFLX and TRMM (solid line) and GPCP (dashed line) at the 90°E buoy. (b) Phase relationship between LHFLX and TRMM (diamond) and GPCP (asterisks) precipitation. (c) Same as a except, for the 80.5°E buoy. (d) Same as b, except for the 80.5°E buoy. See text for details on how coherence was calculated.
Figure 7 – same as Fig. 6 except for LHFLX was computed using the smoothed (i.e. 50-day running averaged) thermodynamics.
Figure 8 – Scatterplots of LHFLX anomalies and GPCP precipitation anomalies when LHFLX was computed using wind speed calculated from (a, b) daily averaged wind vectors at the 80.5°E and 90°E buoy, respectively. (c, d) Same as a and b, but using 3-day averaged wind vectors to compute LHFLX anomalies.
Figure 9 – LHFLX vs. precipitation anomalies for RMM (a-c) and OMI (d-f) phase at the 80.5°E buoy. Phase anomalies are calculated as deviations from the all phases (i.e. phases 1-8) mean. Grey small numbers are phases using unfiltered time series, while black large numbers are phases using 20-100 day Lanczos filtered time series. (a, d) show buoy precipitation anomalies, while (b, e) show TRMM and (c, f) show GPCP precipitation anomalies.
Figure 10 – Same as figure 9, except for the 90°E buoy.
Figure 11 – Composite LHFLX anomalies and linearized LHFLX terms for (a) RMM MJO phases at the 80.5°E buoy, (b) RMM MJO phases at the 90°E buoy. (c) and (d) are the same as (a) and (b) except for OMI phases. Bar represent average over an entire MJO cycle (i.e. all 8 RMM or OMI phases), while primes represent intraseasonal variations. See text for more details.