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Intraseasonal Variability of Air-Sea Fluxes over the Bay of Bengal during the Southwest Monsoon

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ABSTRACT

In the Bay of Bengal (BoB), surface heat fluxes play a key role in monsoon dynamics and prediction. The accurate representation of large-scale surface fluxes is dependent on the quality of gridded reanalysis products. Meteorological and surface flux variables from five reanalysis products are compared and evaluated against in situ data from the RAMA moored array in the BoB. The reanalysis products: ERA-Interim (ERA-I), TropFlux, MERRA-2, JRA-55 and CFSR are assessed for their characterisation of air-sea fluxes during the southwest monsoon season (JJAS). ERA-I captured radiative fluxes best while TropFlux captured turbulent and net heat fluxes (Q_{net}) best, and both products outperformed JRA-55, MERRA-2 and CFSR, showing highest correlations and smallest biases when compared to the in situ data. In all five products, the largest errors were in shortwave radiation (Q_{SW}) and latent heat flux (Q_{LH}), with non-negligible biases up to $\sim$75 W m^{-2}. The Q_{SW} and Q_{LH} are the largest drivers of the observed Q_{net} variability, thus highlighting the importance of the results from the buoy comparison. There are also spatially coherent differences in the mean basin-wide fields of surface flux variables from the reanalysis products, indicating that the biases at the buoy position are not localized. Biases of this magnitude have severe implications on reanalysis products ability to capture the variability of monsoon processes. Hence, the representation of intraseasonal variability was investigated through the boreal summer intraseasonal oscillation and we found that TropFlux and ERA-I perform best at capturing intraseasonal climate variability during the southwest monsoon season.

1. Introduction

Circulation in the Indian Ocean is governed by monsoon variability (Lau et al. 2012; Weller et al. 2016). In the Bay of Bengal (BoB), sea surface temperature (SST) and heat flux are the key components in southwest (SW) monsoon behavior (Vecchi and Harrison 2002; Parampil et al. 2010; Vialard et al. 2011). The mechanism via which the surface net heat fluxes (Q_{net}) impact SST variability is linked to the BoB barrier layer (Duncan and Han 2009). During the summer, a combination of increased precipitation and river runoff in the northern BoB contributes to the formation of a highly stratified surface barrier layer that sits above the thermocline and below the mixed layer base (Vinayachandran et al. 2002). The summer barrier layer acts to inhibit processes such as entrainment, vertical advection and upwelling, which result in surface Q_{net} having a greater impact on the intraseasonal SST variability (Duncan and Han 2009).

The importance of the Q_{net} as a driver of summer SST variability in the BoB (Duncan and Han 2009; Lau et al. 2012) is also shown in observations and ocean models, where summer intraseasonal oscillations (ISO) of SST are forced mainly by heat flux variability, with occasional contributions from vertical mixing and entrainment at the base of the mixed layer (Schiller and Godfrey 2003; Waliser 2006; Girishkumar et al. 2017). Both models and observations indicate that the intraseasonal oscillation of the northern Indian Ocean SST impacts the large-scale atmospheric wind field, temperature, humidity and the active–break cycle of monsoon convection (Vecchi and Harrison 2002; Waliser 2006; Yang et al. 2008). Studies suggest that fluctuations in SST, driven by surface heat fluxes (Q_{net}), can be used as an indicator/proxy for the forecast of active and break periods in the monsoon (Vecchi and Harrison 2002; Parampil et al. 2010). Consequently, the accurate measurement and representation of SST and Q_{net} are critical in understanding and predicting

SW monsoon processes over the BoB (Vialard et al. 2011), and monsoon variability and dynamics (Vecchi and Harrison 2002).

Several studies have reported significant differences between flux products and in situ data in the Indian Ocean (e.g., Yu et al. 2007; McPhaden et al. 2009; Kumar et al. 2012; Goswami et al. 2014; Weller et al. 2016). McPhaden et al. (2009) found that then-current numerical weather prediction (NWP) products underestimated Q_{net} by 40-60 W m^{-2} compared with in situ estimates from a moored buoy near 0°, 80.5°E. Their results suggested that the accumulation of these deficiencies in heat flux over time could result in 2 °C errors in SST. Kumar et al. (2012) compared reanalysis products with moored buoy data in the global tropical oceans to create a blended flux product, TropFlux, which is based on fields from the best performing product: the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim (ERA-I) (Dee et al. 2011). They found that older reanalyses had larger biases and rms differences than ERA-I when compared to the in situ data. Yu et al. (2007) compared NWP, reanalysis and blended products for annual, seasonal and interannual time scales in the Indian Ocean and found differences between 53 and 108 W m^{-2} for daily averaged measurements. Goswami et al. (2014) showed that the coupled Climate Forecast System Reanalysis (CFSR) product does not accurately simulate monsoon intraseasonal variability. These studies highlight significant shortcomings with reanalysis fields in the Indian Ocean and suggest that the accumulated errors found in reanalysis and blended products could lead to significant deficiencies in their representation of Indian Ocean processes.

To determine whether any reanalysis product gives a robust representation of monsoon processes, particularly in the BoB, it is important to understand their individual performance in representing air-sea fluxes and related meteorological parameters, such as SST, surface wind speed (V), air temperature (T_a), and specific humidity (q_a). The products examined in this work include the atmospheric global reanalysis products: ERA-I (Dee et al. 2011), the National Aeronautics and Space Administrations (NASA) Modern Era Retrospective-Analysis for Research and Applications v2 (MERRA-2) (Rienecker et al. 2011), the Japanese Meteorological Agency (JMA) Japanese 55-year Reanalysis (JRA-55) (Kobayashi et al. 2015), the National Centers for Environmental Prediction (NCEP) CFSR (Saha et al. 2010), and the air-sea flux product focused on the tropical oceans, TropFlux (Kumar et al. 2012). The products are assessed using in situ data from the Research Moored Array for African-Asian-Australian Monsoon Analysis and Prediction (RAMA) (McPhaden et al. 2009). The BoB is a region where monsoon processes are still not fully understood (Weller et al. 2016) and in situ data are sparse (Vinayachandran et al. 2018), making gridded reanalysis products hard to verify.

Section 2 gives a brief overview of the datasets used in this paper, including four reanalysis products, a blended product, and in situ data. The analysis and discussion of air-sea fluxes in the BoB for the SW monsoon season (JJAS) is presented in sections 3, 4 and 5. There is a comparison of reanalysis products with in situ data from RAMA buoys in the BoB for interannual variability (section 3), an in-depth analysis of individual flux components (section 4), and an evaluation of the reanalysis products characterisation of basin-wide air-sea fluxes and the associated intraseasonal variability from the boreal summer intraseasonal oscillation (section 5). A summary is given in section 6.

2. Data and Methods

The characterisation of air-sea fluxes in the BoB from flux products is investigated using meteorological (SST, V, T_a, q_a) and flux parameters [shortwave radiation (Q_{SW}), longwave radiation (Q_{LW}), sensible heat flux (Q_{SH}), latent heat flux (Q_{LH}) and Q_{net}] from four reanalysis products, one blended product, and in situ data from the RAMA moored array. The surface fluxes from the reanalysis products are model fluxes, turbulent fluxes for RAMA and TropFlux are calculated from meteorological parameters following Fairall et al. (2003), radiative fluxes are measured by RAMA and derived as described in Kumar et al. (2012) for TropFlux. In all reanalysis (and blended) datasets, T_a and q_a are provided at 2 m height above sea level, and V is provided at 10 m. The in situ buoy data measures T_a and q_a at 3 m, and V at 4 m, which are adjusted to 2 m and 10 m respectively using COARE v3.0 algorithm (Fairall et al. 2003). Note, q_a is not available from ERA-I or at the RAMA sites. Instead, we use dewpoint temperature from ERA-I and relative humidity in the case of RAMA, from which we derive the vapour pressure (e) and thus calculate q_a, as per Bolton (1980):

$$q_a = \left[\varepsilon \frac{e}{p - e(1 - \varepsilon)} \right] \times 1000 \tag{1}$$

where p is surface pressure and ε = 0.622 is the ratio of the molecular masses of water vapour and dry air. Similarly the specific humidity at the sea surface, q_s, is computed from SST as per equation (1), where the saturation specific humidity is assumed to be at 98% saturation at the SST.

Data were obtained at the temporal resolutions described in section 2a for the summer periods (JJAS) from 2007 to 2015 and then daily averaged, as daily resolution is adequate for resolving intraseasonal variability which is the primary mode of variability for monsoonal processes. In the following sections, both meteorological and flux variables from the reanalysis data have been regridded to 1° x 1°, by linear interpolation, where necessary. The data products used in this paper are briefly described here and in Table 1.

a. Reanalysis and blended products

ERA-I is a global atmospheric reanalysis product from the ECMWF (Dee et al. 2011). The ERA-I data assimilation system uses 4-dimensional variational analysis (4D Var), with an improved hydrological cycle and quality control compared with the previous ECMWF reanalysis product: ERA-40 (Berrisford et al. 2011). The mean state variables used here are from the analysis field (step 0) at 6-hourly time intervals and the flux variables are from the forecast field (step 12) at 3-hourly time intervals. All variables are obtained on a 1° x 1° horizontal grid.

TropFlux is a blended (reanalysis-based) product of air-sea fluxes and associated meteorological variables over the global tropical oceans, from 30°S to 30°N (Kumar et al. 2012, hereafter KP12). TropFlux uses ISCCP satellite cloud data (Zhang et al. 2004) to compute Q_{SW}, and bias-adjusted ERA-I (Dee and Uppala 2009) data to compute SST, V, T_a, q_a and Q_{LW} as per:

$$\Psi_{tf}(x,y,t) = a(\Psi(x,y,t) - \overline{\Psi}(x,y)) + b(x,y) + \overline{\Psi}(x,y) \tag{2}$$

where Ψ_{tf} is the corrected ERA-I variable, Ψ, and the long term mean is $\overline{\Psi}$. The amplitude, a, and bias, b, adjustments of the TropFlux variables are based on a comparison between the reanalysis product and in situ data from the Global Tropical Moored Buoy Array (McPhaden 2010). The turbulent fluxes were computed using the COARE v3.0 algorithm (Fairall et al. 2003) on the corrected daily-averaged input variables and, since TropFlux computes heat fluxes from daily averaged data, a gustiness correction is applied to the surface wind speed parameter to compensate for the higher frequency ($<$ 1 day) fluctuations in wind speed, which result in underestimations in the flux variability based on results of Cronin et al. (2006). The cool skin and warm layer calculations in COARE v3.0 are switched off (Kumar et al. 2012). The gustiness correction is applied to the surface wind speed parameter only for the computation of turbulent heat fluxes. The TropFlux data are served as daily means, on a 1° x 1° horizontal grid. The spatially homogeneous amplitude adjustment (a) acts to increase the variance of all the parameters in ERA-I around their long term values. We note that TropFlux adjusts ERA-I meteorological parameters based on measurements from the Global Tropical Moored Buoy Array, however, only data to the end of 2009 was available at the time TropFlux was produced. At this time the RAMA array had only recently been established: measurements at b28 started in November 2006, with b26 and b27 being added a year later. The observational constraints will therefore be dominated by the longer-established moorings in the Pacific, and to a lesser extent, in the Atlantic.

JRA-55 is the second global atmospheric reanalysis product produced by the JMA (Kobayashi et al. 2015), built to improve upon JRA-25 (Onogi et al. 2007). JRA-55 has a new longwave radiation scheme, increased spatial resolution, and uses variational bias correction (VarBC) and 4D Var analysis. The data used here are on a 0.56° x 0.56° grid using analysis fields for the mean state variables and 3-hourly averages for the flux variables.

MERRA-2 is a global atmospheric reanalysis of the satellite period produced by NASA (Bosilovich et al. 2015), and updated from the original MERRA product (Rienecker et al. 2011). MERRA-2 uses an updated atmospheric data assimilation system: the Goddard Earth Observing System (GEOS-5) with a 3D Var algorithm. Important updates to MERRA-2 since the original MERRA product also include an updated observing system with more satellite observations, and an aerosol analysis (Bosilovich et al. 2015). The MERRA-2 data has a spatial resolution of 0.5° latitude by 0.625° longitude on 72 levels. Here, the mean state variables are at 1-hourly, instantaneous, single-level diagnostics and the flux variables are 1-hourly, time-averaged, radiation diagnostics.

CFSR is a coupled ocean-atmosphere reanalysis product created by the NCEP (Saha et al. 2010). The Coupled Forecast System model that CFSR uses includes a spectral atmospheric model and the Modular Ocean Model from the Geophysical Fluid Dynamics Laboratory. The atmospheric model has a spatial resolution of 0.5° x 0.5° on 37 vertical levels, and the ocean model has a resolution of 0.5° on 40 vertical levels. CFSR was completed for the period of 1979 to 2009 and was later extended to 2011. In 2011, CFSv2 was implemented as a continuation of CFSR (Saha et al. 2011). As CFSv2 uses the same model as CFSR, the CFSv2 product is treated as an extension of CFSR and CFSv2 is hereafter implied in any mention of CFSR. The data were available at 6-hour forecast field for mean state variables and at 6-hour averaged field for flux variables.

All reanalysis products assimilate ocean observations from fixed mooring arrays, including the Global Tropical Moored Array (McPhaden 2010).

b. In situ data: the RAMA array

RAMA is an array of moored buoys in the Indian Ocean that provide atmospheric and oceanographic data for the study of ocean circulation, air-sea interactions and monsoon dynamics (McPhaden et al. 2009). The types of moored buoys relevant for this study within the RAMA network are the surface and enhanced surface moorings. The enhanced surface moorings are Autonomous Temperature Line Acquisition System (ATLAS) moorings with additional sensors for pressure and longwave radiation measurements designed for measuring complete air-sea interactions, and are denominated flux reference sites. In the BoB, there are two surface moorings located at 8°N, 90°E (designated b26) and 12°N, 90°E (b27), and one enhanced surface mooring at 15°N, 90°E (b28).

Meteorological variables used include SST (measured at 1 m below sea surface), V (measured at 4 m above sea surface and converted to 10 m height by the data providers), T_a (measured at 3 m above sea surface and adjusted to 2 m), and relative humidity (measured at 3 m above sea surface and adjusted to 2 m), T_a and pressure from which q_a is computed as per equation (1). All height adjustments use the COARE v3.0 algorithm as per Fairall et al. (2003). Table 2 shows the uncertainties for the meteorological variables (SST, V, T_a, humidity), which correspond to the Next Generation ATLAS Mooring Sensors accuracies listed on the NOAA/PMEL website, https://www.pmel.noaa.gov/gtmba/sensor-specifications. These accuracies are based on calibrations for pre-deployment and post-recovery. ΔT and Δq uncertainties are calculated using quadrature (Table 2).

The air-sea flux variables are computed using the COARE 3.0b algorithm (Fairall et al. 2003; Cronin et al. 2006) by data providers. Net radiative fluxes, also calculated by providers, were calculated from measured downwelling components following Cronin et al. (2006) such that:

$$Q_{SW} = (1-\alpha) \times SWR \tag{3}$$

$$Q_{LW} = \varepsilon(\beta \times T_s^4 - LWR) \tag{4}$$

where α is a constant albedo value of 0.055, SWR is the incoming downwelling radiation, ε is the emissivity constant (0.97), β is the Stefan Boltzman constant (5.67×10^{-8}), T_s is the skin temperature (K) and LWR is the incoming downwelling longwave radiation. For the turbulent fluxes, biases from daily resolved wind speed in the RAMA fluxes (computed using COARE 3.0) are minimized by applying a gustiness correction in the wind speeds prior to their use in the bulk flux calculations as per Cronin et al. (2006). We estimated the turbulent flux uncertainties (Table 2) from the standard deviation of differences between RAMA turbulent fluxes (calculated using hourly data input for the COARE3.0 algorithm, including cool skin and warm layer effects) and turbulent fluxes estimated from RAMA meteorological variables perturbed with the instrument uncertainties (input data was daily averaged in the COARE3.0 algorithm, and as per Cronin et al. (2006) cool skin and warm layer effects were turned off). We note that there is a mean difference of 0.13 and 2.25 $W\ m^{-2}$ for Q_{SH} and Q_{LH} respectively when comparing turbulent fluxes estimated from hourly averaged data (cool skin and warm layer effects turned on) and daily averaged data (cool skin and warm layer turned off). Subsets of RAMA data can be obtained from the TAO Project Office of NOAA/PMEL, where meteorological and flux variables are available at high (up to 10 min) resolution. All meteorological and flux variables are presented in this paper averaged to give daily resolution.

The RAMA moorings in the BoB have been operational since 2007; however, issues in buoy maintenance affect data return resulting in intermittent data coverage (McPhaden 2010). Fig. 1 shows the availability of parameters used in this study at b28. As b27 and b26 are not flux reference sites, pressure (hence q_a) and Q_{LW} are not available at these buoy locations (not shown here). The most comprehensive coverage occurs at site b28, with almost complete data return in SST. Noticeable gaps for the remaining variables occur mostly during 2007, 2008, 2011, 2012 and (for $V$and turbulent fluxes only) 2013. Due to the data limitation at sites b27 and b26, the following time series analysis using reanalysis products and the RAMA buoys will focus only on data from site b28.

3. Evaluation of meteorological and flux variables

In this section, the five data products are evaluated against in situ data from the RAMA buoy b28 in the BoB for the summer months (JJAS), from 2007 to 2015. We evaluate the meteorological parameters important for calculation of turbulent fluxes: SST, V, T_a and q_a, as well as the air-sea temperature difference, ΔT, the air-sea humidity difference, Δq, the turbulent fluxes, Q_{SH} and Q_{LH}, the radiative fluxes, Q_{SW} and Q_{LW}, and the Q_{net}. In the following section, meteorological variables are further investigated to understand their impact on the turbulent fluxes in this region and the causes for disparities in the products' ability to represent surface fluxes.

Individual daily values of the surface fluxes and associated variables for each of the products are compared to RAMA b28 using four metrics. Firstly the differences (product - b28) and their 95% confidence intervals (calculated using a t test implemented in R using function t.test (R Core Team 2015)) are presented (Fig. 2a). Second, the Pearson product moment correlation coefficients for each product with b28 and their 95% confidence intervals (calculated in R using function cor.test) are presented (Fig. 2b). Fig. 2c shows the variance ratio of the parameters with their 95% confidence interval (calculated using an F test implemented in R using function var.test). Fig. 2d combines these metrics to give skill scores for each product and variable (Wallcraft et al. 2009). Skill scores are an established way to assess the quality of numerical weather forecasts (Murphy 1988) and are based on the correlation between the product being assessed and a reference standard, penalized for disagreement in mean values and variance ratio. Thus, if we denote x_i $(i = 1,...,n)$ as the observations and y_i $(i = 1,...,n)$ as a data product for a sample of n, we can define the linear correlation, R, and skill score, SS, between x_i and y_i as per Murphy (1988):

$$R = \frac{1}{n}\sum_{i=1}^{n}\frac{(x_i - \mathbf{x})(y_i - \mathbf{y})}{(\sigma_x\ \sigma_y)} \tag{5}$$

$$SS = R^2 - [R - \frac{\sigma_y}{\sigma_x}]^2 - [\frac{(\mathbf{y} - \mathbf{x})}{\sigma_x}]^2 \tag{6}$$

where $\mathbf{x}$, $\mathbf{y}$ and σ_x, σ_y are the sample mean and standard deviation of x_i and y_i, respectively. Skill scores of 1 demonstrate perfect agreement between the data products and the observed data. Perfectly correlated data with a 25% underestimate of variance and a bias of magnitude of 25% of the variance would have a skill score of 0.5. Negative skill scores typically arose in our comparison due to substantial underestimates of variance combined with large mean differences, although there were also some low correlation values.

Sea surface temperature For SST, all reanalysis products show fairly strong correlations with RAMA b28 (Fig. 2b). ERA-I shows the largest offset (-0.37 °C), followed by MERRA-2 (-0.20 °C), both underestimating the in situ SST (Fig. 2a). Both these reanalyses use the OSTIA foundation SST product (Donlon et al. 2012) in the period of our analysis so are expected to have colder SSTs than a standard near-surface estimate. MERRA-2 uses OSTIA after 2006 and ERA-I from February 2009, The reason for the difference between the SST for these products is therefore not clear; their agreement improves from 2009 but remains 0.2 °C (not shown). JRA-55 SST agrees well with b28, with the smallest bias and highest correlation (Fig. 2b, 0.90), giving the highest skill in reproducing the b28 SST (Fig. 2d), despite an underestimate of the variance (Fig. 2c). The coupled product CFSR also shows a good representation of the observed SST. We note that the CFSR SST is constrained through a relaxation coefficient at the sea surface (i.e. model SST is nudged toward observed SST), which counteracts any drift in the model related to error in the surface fluxes (Xue et al. 2011). On the other hand, JRA-55, MERRA-2, and ERA-I are atmosphere-only reanalysis products with prescribed SST fields (Table 1).

Surface wind speed V shows the highest correlation (≥ 0.9) across all products with V from RAMA b28. TropFlux and MERRA-2 V are closest to that from b28. ERA-I and JRA-55 underestimate and CFSR overestimates the observed V (Fig. 2a). Variance ratios are around one, apart from CFSR, which shows significantly greater variance in V than b28 (Fig. 2c). V shows the best skill scores across the variables with ERA-I, TropFlux and JRA all having skill scores of about 0.9 (Fig. 2d).

Air Temperature The highest T_a correlations are observed with ERA-I, TropFlux and JRA-55 (≥ 0.83) and the lowest correlation with MERRA-2 (0.62) (Fig. 2b). ERA-I has the largest offset (-0.38 °C), the other products are within 0.1 °C of b28 (Fig. 2a). TropFlux significantly overestimates the variance, and MERRA-2 and CFSR significantly underestimate the variance (Fig. 2c). Overall JRA-55 shows the best skill, followed by TropFlux (Fig. 2d).

Specific humidity The products all struggle with reproducing the observed q_a. Kumar et al. (2012) found that ERA-I underestimated q_a, and attributed more than half of that estimate to a cold bias in T_a and the remainder to an underestimate in the relative humidity. However their adjustment to q_a for ERA-I for TropFlux results in an overestimate at b28. Skill scores are all less than 0.2, resulting from a combination of modest correlations (< 0.8), large mean biases (> 0.3 g kg^{-1}), and a large underestimate of the variance. Our results show a CFSR dry bias also previously observed in the maritime continent and western Pacific by Wang et al. (2011) and overall dry bias found in ERA-I when compared to research vessel data (Brunke et al. 2011).

Air-sea temperature difference For all products except ERA-I, the skill scores for ΔT are much lower than those for either SST or T_a (Fig. 2d). JRA-55 performs best, combining a small bias (Fig. 2a) with the strongest correlation (Fig. 2b) and is the only product to make a reasonable estimate of the variance (Fig. 2c).

Air-sea humidity difference The skill scores for Δq for ERA-I, JRA-55 and MERRA-2 are larger than their respective skill scores for q_a, but the best skill score is only 0.5 for MERRA-2 (Fig. 2d). Modest correlations combined with large biases for most products (Fig. 2a) and a very significant underestimate of variance (Fig. 2c) give poor skill overall.

Shortwave radiation For all products apart from TropFlux, biases in Q_{SW} (and Q_{LW}) are directly linked to its radiation schemes, spatial distribution and aerosol properties (Dee et al. 2011). TropFlux Q_{SW} uses observed cloudiness data from ISCCP up until the end of 2007 (when it was last available), and the ISCCP mean seasonal cycle and adjusted using NOAA outgoing longwave radiation (OLR) thereafter (KP12). TropFlux and ERA-I show the highest correlations ($\sim$0.7) with the observed Q_{SW} (Fig. 2b) and the highest overall skill (Fig. 2d). All of the products underestimate Q_{SW} apart from CFSR which overestimates by more than 70 W m^{-2}. MERRA-2 and CFSR show the lowest correlations (Fig. 2b) and highest biases (Fig. 2a). Positive bias in CFSR Q_{SW} in the tropics has been previously catalogued by Wang et al. (2011) due to an underestimate of cloudiness. MERRA-2s underestimation of Q_{SW} has been similarly linked to its cloud scheme (general difficulties capturing irradiance variability) in a study by Boilley and Wald (2015). All of the products significantly underestimate the variability of Q_{SW} (Fig. 2c).

Longwave radiation The skill scores for Q_{LW} are very low, with only ERA-I achieving a positive score (Fig. 2d). All products underestimate the variance (Fig. 2c) and for all of the products other than ERA-I the biases are large relative to the variability resulting in low skill.

Sensible heat flux TropFlux has the most skill due to a relatively high correlation of 0.79, a small bias of slightly over 1 W m^{-2} but overestimates the variance. ERA-I and JRA-55 have negative skill scores due to large biases and overestimates of variance. The poor skill in JRA-55 is hard to understand as it performed best at reproducing ΔT and showed high skill for V.

Latent heat flux TropFlux is the only product to have a positive skill score for Q_{LH}. This is surprising as it had relatively poor skill for Δq (Fig. 2d). TropFlux underestimates Δq but shows only a small underestimate in Q_{LH} which may indicate that the gustiness parameter used by TropFlux in the transfer coefficients may be acting to compensate for low Δq with an enhanced wind effect in the flux calculation. MERRA-2s large overestimation of Q_{LH} can be attributed to the fact that MERRA-2 has humidity (dry) bias problems related to forecast model spin up/down (Kobayashi et al. 2015). The large Q_{LH} bias apparent in CFSR has been observed on a global scale (larger evaporative cooling, in general) and is linked to the dry bias over the equatorial Indian Ocean (Wang et al. 2011) and the erroneously strong winds (Fig. 2a).

Net heat flux TropFlux has the highest skill in reproducing Q_{net}. CFSR does better than expected, despite having negative skill scores for 3 of the 4 flux components, and ERA-I is the only other product to have a positive skill score (Fig. 2d). ERA-I, JRA-55 and MERRA-2 all have too much heat loss from the ocean. TropFlux and CFSR all show a mean net heat gain by the ocean of 30-35 W m^{-2} over JJAS of 2007-2015, whereas ERA-I, JRA-55 and MERRA-2 all show a net heat loss of between -20 to -50 W m^{-2} (not shown here). We note that biases in turbulent and radiative fluxes cancel out in the Q_{net} from CFSR and (to a smaller degree) TropFlux. However, biases (mostly) in Q_{SW} and Q_{LH} carry over considerably in the Q_{net} biases estimated from ERA-I, JRA-55 and MERRA-2. Thus the blended product, TropFlux, captures the observed Q_{net} with greater skill than the reanalysis products.

Similar results are found between the reanalysis products and in situ data at other BoB RAMA buoy locations: 90°E, 12°N (b27; Fig. S1) and 90°E, 8°N (b26; Fig. S2). Based on the 4 metrics presented here, SST and V perform consistently well at all 3 locations; T_a struggles showing lower correlations and poorer skill scores at b27 and b26 (more so than at b28) and as a result ΔT and Q_{SH} are similarly poorly represented across most products. For Q_{LH}, results are consistently poor and only TropFlux shows a skill score greater than zero. Last, Q_{SW} performs similarly between products for all 3 buoys, i.e. ERA-I and TropFlux are able to reasonable reproduce Q_{SW} while remaining products perform poorly based on mean differences, correlations, variance ratio and skill score.

Based on the four metrics presented here, we find that ERA-I captures radiative fluxes best while TropFlux is better at capturing the turbulent and net heat fluxes. In general, however, Q_{SW} and Q_{LH} (and Q_{net} by association) are the variables that are the hardest to capture across all products. This is evident in the low correlations, large biases and low skill scores. Since errors in Q_{net} can cause large errors in SST in the BoB and affect the accurate representation of monsoon processes from reanalysis products, the next section investigates the flux components in more depth.

4. Surface Fluxes at RAMA flux reference site b28

SST variability in the BoB is mainly driven by surface heat fluxes (Sengupta and Ravichandan 2001). Accurate representation of meteorological variables and the associated fluxes in reanalysis products is therefore crucial for the correct representation of monsoon related variability. The individual components of surface heat fluxes are further investigated here.

Fig. 3 shows scatterplots of the Q_{net} vs each flux component from RAMA b28, ERA-I, TropFlux, JRA-55, MERRA-2 and CFSR. Individual daily means are plotted as points and contour lines enclose 10% and 50% of points in the each joint distribution (calculated with R function HPDregionplot in the emdbook package, Bolker (2008)). Fig. 3a shows the relationship between Q_{SW} and Q_{net} at b28. Q_{SW} is the main driver of Q_{net} with a strong positive correlation (r=0.93). Q_{LW} is anticorrelated with Q_{net} (r=-0.58, Fig. 3b) as increased cloud cover reduces the heat gain by the ocean by Q_{SW} and reduces the heat loss by the ocean by Q_{LW}. Both Q_{LH} and Q_{SH} are positively correlated with Q_{net} (r=0.68, 0.63 respectively, Fig. 3c,d) but Q_{LH} is an order of magnitude larger.

ERA-I shows similar correlations to b28, the correlations for the radiative components (Q_{SW} and Q_{LW}) being slightly less correlated with Q_{net} than for B28 and the turbulent components (Q_{LH} and Q_{SH}) more correlated. The underestimate of variability in Q_{SW} and Q_{LW} by ERA-I is clear in Figs. 3e, f, and the overestimate of Q_{LH} and resulting bias in Q_{net} in Fig. 3g. The adjustments applied to ERA-I to give TropFlux perform well for the turbulent fluxes (Figs. 3k, l) given better alignment of the distributions in addition to reducing biases. However the radiative estimates from TropFlux are worse than ERA-I. TropFlux Q_{SW} is constructed from ISCCP, until 2007, and bias corrected ISCCP mean seasonal cycle and NOAA OLR to present; hence, TropFlux Q_{SW} biases are likely linked to the algorithm used in KP12. TropFlux Q_{SW} shows improved (higher) variability, but shifts the peak of the distribution to even lower values than ERA-I (compare Figs. 3e, i). The adjustments applied to ERA-I Q_{LW} to give TropFlux give worse performance compared with b28 (Figs. 3f, j).

The remaining 3 products (JRA-55, MERRA-2 and CRSR, Figs. 3m-x) all show poor agreement with the relationships between the flux components and Q_{net}, as expected from the skill scores presented in Fig. 2. The exception is the good agreement shown for CFSR Q_{SH} (Fig. 3x) but only due to the compensating biases in CFSR Q_{net}.

De-constructing turbulent fluxes into their meteorological components provides further insight into differences among products, and helps determine if errors and biases in Q_{SH} (Q_{LH}) at the buoy location (Fig. 2a) originate from errors in the wind field or air-sea contrasts in temperature (humidity). Fig. 4a-f shows scatterplots of Q_{LH} vs the individual components of Q_{LH}: Δq and V. The largest contributing factor to Q_{LH} variability across all products is V, where increases in V are linked with increases in Q_{LH} (Fig. 4d). The correlation between Δq and Q_{LH} is lower (Fig. 4a) as Δq and V are anti-correlated (Fig. 4g). This anti-correlation is well-captured by ERA-I (Fig. 4h) with a slight overestimate of Δq. The TropFlux corrections result in a underestimation of Δq, but despite this the Q_{LH} agrees reasonably with b28, perhaps due to the gustiness adjustment to wind in the flux calculation.

ΔT is the strongest control on Q_{SH} (Fig. 4j) with V contributing little to the variability (Fig. 4m) of Q_{SH}. This is consistent with the finding that Q_{SH} variability is particularly sensitive to SST fluctuations (compared to Q_{LH}) in the tropical Indian Ocean at intraseasonal time scales (DeMott et al. 2014). Both ERA-I (Fig. 4k) and TropFlux (Fig. 4l) overestimate the variability in ΔT. ERA-I is biased toward unstable atmospheric conditions (ΔT positive) and TropFlux over-represents stable conditions. The TropFlux Q_{SH} is strongly skewed compared to b28, but the representation of Q_{SH} is overall better than ERA-I (Fig. 2d). The relationship between the radiative flux components at b28 (Fig. 4s) is better captured by ERA-I (Fig. 4t) than TropFlux (Fig. 4u).

In general, Q_{net} is largely driven by Q_{SW} and Q_{LH}; Q_{LH} variability is driven by V and (to a lesser extent) Δq, and Q_{SH} variability is mostly driven by ΔT. Results here suggest errors/biases in Q_{LH} originate from both the wind field and the Δq and, as Q_{SH} shows negligible dependence on V, the biases from the observed Q_{SH} are more likely to be linked with errors in the ΔT. Q_{SW} and Q_{LH} are the variables the reanalysis and blended products have the most difficulty reproducing (Section 3).

5. Air-Sea fluxes across the Bay of Bengal

a. Mean fields

In this section, air-sea fluxes at all points in the BoB from the reanalysis products are compared to determine how much of the variability observed at the RAMA buoy sites is localized.

Figure 5 shows turbulent fluxes from five data products averaged over the summer (JJAS) monsoon season, from 2007 to 2015, across the BoB. The Q_{SH} values from JRA-55 and (to a lesser extent) ERA-I show higher negative (upward) flux values, indicating greater heat loss from ocean to atmosphere, than the other 3 products. This is consistent with biases seen in section 3 (Fig. 2a), where JRA-55 and ERA-I overestimated the observed Q_{SH}. Differences in spatial gradients between products occur near b28 (black square, Fig. 5), where TropFlux, ERA-I and CFSR show a larger gradient decreasing from east to west across the buoy, and MERRA-2 and JRA-55 show almost no gradient. Other spatial differences are apparent in the patterns across coastal waters of the BoB, such as the region around Sri Lanka and the east coast of India, where only TropFlux and CFSR show regions of positive Q_{SH} (i.e. heat gain to the ocean). (We note the smaller contour range in Q_{SH} values, -20 to 20 W m^{-2} compared with Q_{LH}, -200 to 0 W m^{-2}). For the mean Q_{LH} field, all products show a region of strong Q_{LH} centred on the southern part of the BoB, sandwiched between the equator and 10°N, covering the zonal extent of the basin. This pool of elevated Q_{LH} in the southern BoB appears largest and strongest in JRA-55 and CFSR, and in TropFlux the pool is shifted further south and is considerably weaker compared to the remaining reanalysis products. Near b28 most products show a strong gradient in Q_{LH} decreasing from south to north, though in JRA-55 this gradient is slightly more sloped in the southwest to northeast direction. These patterns are consistent with the mean and standard deviation of the Q_{SH} and Q_{LH} from all products (Fig. S3). Combining these results with the biases and skill scores from section 3, where it was shown that Q_{LH} from TropFlux underestimates the observed Q_{LH} at b28 and the reanalysis products all overestimate the observed Q_{LH} by a wide margin on the order of 50 to 75 W m^{-2}, suggests TropFlux captures turbulent fluxes best, and the erroneously enhanced Q_{LH} seen at the b28 location in ERA-I, JRA-55, MERRA-2 and CFSR shows large-scale coherence across the BoB.

In section 3, Q_{SW} was shown to have some of the largest biases in the reanalysis products when compared with the in situ Q_{SW} from RAMA b28 data. It follows that in Fig. 6, the mean Q_{SW} fields over the BoB show a wide range in Q_{SW} values ($\sim$100 to 250 W m^{-2}), differing quite substantially between products: CFSR and MERRA-2 show higher and lower values, respectively, of Q_{SW} when compared to ERA-I, TropFlux and JRA-55. The mean Q_{SW} field across the BoB depicts regions of high Q_{SW} in the vicinity of Sri Lanka and southwest of the southernmost tip of India, from the equator to 5°N in ERA-I, in TropFlux and JRA-55, but not in the MERRA-2 or CFSR products, consistent with dry slot in the rain shadow of Sri Lanka (Puvaneswaran and Smithson 1991). Since the smallest biases (which are negative) were observed in JRA-55 and ERA-I in section 3 (Fig. 2a), these results suggest TropFlux and (to a greater degree) MERRA-2 values are underestimating the observed Q_{SW} across the basin, while CFSR is overestimating them across the basin on an order of 70 W m^{-2}. CFSR also shows the greatest departure from the spatial patterns across the BoB than any of the other products, failing to capture the region of high Q_{SW} around Sri Lanka and southeast India (Fig. S3). The difference in the range of Q_{LW} values across products is considerably smaller, consistent with section 3, where it was shown that the Q_{LW} had some of the smallest biases among the flux components (Fig. 2a). The mean field for Q_{LW} appears to show a more consistent pattern in spatial gradients from all products across the BoB, compared to Q_{SW} (Fig. 6; right hand column). In general, there is a high to low (south to north) gradient in Q_{LW} across the BoB.

Q_{net} for ERA-I, JRA-55 and MERRA-2 depict large heat loss in the central and southern regions of the BoB (Fig. S4), which is consistent with the results shown in section 3 (Fig. 2). TropFlux and CFSR, on the other hand, depict a net heat gain by the ocean all across the basin and strongest in the southwest and northern parts of the basin. In particular, values for Q_{net} in CFSR are the product of errors in the Q_{LH} and Q_{SW} components cancelling out. Since the patterns of variability are generally similar across the basin for all products (Fig. 6), results from section 3 wherein TropFlux underestimates observed Q_{LW} and all remaining products overestimate the observed Q_{LW} at RAMA b28 (Fig. 2a) are taken to be representative of the basin wide biases in the BoB.

b. Monsoon Variability: The Boreal Summer Intraseasonal Oscillation

In the previous sections, the performance of the reanalysis products in simulating the day-to-day variability at a point location in the BoB (sections 3, 4) and the time-mean spatial patterns over the BoB (section 5a) was assessed. Another necessary capability of a reanalysis product is that it should be able to simulate the main spatial and temporal patterns of variability within a given region, as these modes are the likely sources of potential predictability in a forecast system that uses reanalysis products as a forcing input. The boreal summer intraseasonal oscillation (BSISO) is one of the primary modes of variability associated with the Asian summer monsoon (Webster et al. 1998; Lee et al. 2013). The BSISO is also known as the Monsoon Intraseasonal Oscillation (MISO; Suhas et al. 2013), and was first identified as northward-propagating 30-60-day bands of clouds and convection over India by, e.g., Sikka and Gadgil (1980). It is often recognised as the northern summer counterpart to the Madden-Julian Oscillation (MJO; Madden and Julian, 1994).

Here the BSISO index from Lee et al. (2013) is used to assess the representation of boreal summer intraseasonal variability from the reanalysis products.

Similar to the MJO (Wheeler and Hendon 2004), the BSISO indices are constructed from multivariate empirical orthogonal function analysis of satellite OLR and the 850-hPa zonal wind fields from NCEP-DOE reanalysis in the region of the Asian summer monsoon (Lee et al. 2013). The first two principal components (PC) of the BSISO form the BSISO1, which corresponds to the northward propagating component of the summer monsoon and has a 30–60 day period (Wang et al. 2005). The third and fourth PC of the BSISO form the BSISO2, which is the northward/northwestward component of the monsoon, usually associated with the pre-monsoon and monsoon onset periods, and has a period of 10-20 days (Kikuchi and Wang 2010). Here we focus on the 30–60 day northward propagating BSISO, i.e. the BSISO1.

The BSISO1 mode is divided into eight phases, each phase covering one-eighth of the cycle (Lee et al. 2013). During phase 1, a zonally elongated band of enhanced atmospheric convection lies over the equatorial Indian Ocean, while a band of suppressed convection extends from India southeastward across the BoB, southeast Asia and into the equatorial western Pacific (Fig. 7). Over phases 2, 3 and 4, the band of enhanced convection moves northward and eastward, while the suppressed convection retreats to the northeast and contracts. A second band of suppressed convection then starts to develop over the equatorial Indian Ocean, such that the anomalies at phase 5 are approximately the opposite sign to those at phase 1 (a half cycle earlier). The new band of suppressed convection then propagates northeastward during phases 6, 7, and 8. Finally, enhanced convection re-establishes itself over the equatorial Indian Ocean again in phase 1, and the next cycle begins.

The BSISO1 composites here are constructed using an index of BSISO1 phases (1–8) based on satellite OLR and 850hPa zonal wind fields as described in Lee et al. (2013) and made available through the APEC Climate Centre data portal: http://www.apcc21.net/ser/casts.do?lang=en. For each variable V, wind direction, Q_{SW}, Q_{LH} and Q_{net}, daily anomalies were computed from the monthly mean for the monsoon season (JJAS) 2007 to 2015. Then, each day during the study period was allocated to one of the eight BSISO1 phases, or was discarded if the overall BSISO1 amplitude was weak (i.e., $\sqrt{PC1^2+PC2^2} < 1$). Data from each product were averaged over the days in each phase to obtain the eight phase composites of the life cycle.

The BSISO1 representations in each reanalysis product are first validated against the *in situ* data at the RAMA b28 location. Fig. 8 shows the median, interquartile range, 95% confidence intervals and outliers for V, wind direction, Q_{SW}, Q_{LH} and Q_{net} from the in situ data and the ERA-I, TropFlux and CFSR products at each phase of the BSISO1 life cycle. During phase 1 (2) all products overestimate (underestimate) the observed BSISO1 V and, in general, all do a reasonable job of capturing the observed V during BSISO1 phases 3 to 8 (Fig. 8a-d). The prevailing surface winds remain approximately from the south west during JJAS, as measured by the buoy and in all the products at the buoy location (Fig. 8e-h). The change in surface wind direction through the cycle is less well represented in the products. During phases 1 through 3, the buoy shows winds becoming more southerly, whereas all of the products show a change to more westerly winds during these phases.

The RAMA Q_{SW} measurements show high median values in phases 1 to 3 (Fig. 8i), during the convectively suppressed part of the BSISO1 cycle in the northern BoB (Fig. 7). As the enhanced convection moves into the BoB, cloud cover increases and the Q_{SW} values decrease during phases 4, 5 and 7. Although the reanalysis products do reproduce this qualitative pattern, they all underestimate the amplitude of the Q_{SW} variability associated with the BSISO1 (Fig. 8j-l). In particular, ERA-I and TropFlux tend to underestimate (overestimate) highs (lows) in the observed Q_{SW} within a range of ±45 W m^{-2}; meanwhile though CFSR also generally underestimates the amplitude of the variability, it grossly overestimates Q_{SW} values (associated with BSISO1) in comparison with the observed Q_{SW}, with up to values of 75 W m^{-2}. These results are consistent with section 3, where it was shown that ERA-I and (to a lesser degree) TropFlux reasonably estimated the observed Q_{SW}, based on skill score; and, CFSR showed large positive biases, low correlation and poor skill score for Q_{SW}. Hence, in an ocean model forced by one of these products, the heating of the ocean surface by Q_{SW} during the suppressed convective phase, and the cooling during the active convective phase of the BSISO1 would both be severely misrepresented.

The systematic error apparent in Q_{SW} is compensated to a certain degree by a systematic error in Q_{LH} of similar magnitude (Fig. 8n-p). The Q_{LH} at the RAMA b28 location shows low median Q_{LH} values in phases 1 to 3, indicating reduced cooling of the ocean surface, and higher Q_{LH} values from phases 5 to 7, indicating increased cooling of the ocean surface (Fig. 8m). The TropFlux product does best at capturing the Q_{LH} BSISO1 variability and magnitude. The other data products appear to generally capture the observed variability correctly; however, both ERA-I and (to a greater extent) CFSR largely overestimate the median values of the observed Q_{LH}, indicating erroneously high cooling of the ocean surface. The significantly reduced bias in NHF from CFSR throughout all phases (Fig. 8t) indicates the systemic error in Q_{SW} is being largely compensated for by the systemic error in Q_{LH}. Hence, in the case of CFSR and (to much smaller extent) TropFlux, the erroneous strong cooling of the ocean surface from high Q_{LH} values offsets the erroneous high heating of the ocean surface from the Q_{SW} values. ERA-I generally captures the observed BSISO1 Q_{net} variability; however, the Q_{SW} and Q_{LH} offsets add up and yield a Q_{net} of a sign opposite to the observed, consistent with Fig. 2.

ERA-I has a similar pattern of Q_{SW} and Q_{LH} biases, but the magnitude of errors is smaller in comparison to CFSR. The blended product, TropFlux, shows similar offsets in the Q_{SW}; however, its Q_{LH} and Q_{net} is more realistic and appears to capture best the observed BSISO1 Q_{SW} and Q_{LH}

variability. These results are consistent with section 3, where it was showed that in general ERA-I does better at capturing radiative fluxes and TropFlux captures turbulent and net heat fluxes best. To calculate Q_{SW}, TropFlux uses observed cloudiness data from ISCCP up until 2009 (when it was last available), and the ISCCP mean seasonal cycle and NOAA OLR thereafter (KP12); while the four reanalysis products use their internally generated cloud fields, which are dependent on their convective and microphysical parameterization schemes. This highlights the well-known major errors in these schemes (e.g. Boilley and Wald 2015). These errors clearly impact intraseasonal variability as well as the mean fields.

Fig. 9 shows composites of daily anomalies from the monthly mean for the summer season (JJAS) from 2007 to 2015 for Q_{SW}, Q_{LH}, V and q_a during the most extreme phases, 2 and 5, of the BSISO1 life cycle over the BoB from TropFlux (shaded) and ERA-I (contour lines). During phase 2, both products depict large positive Q_{SW} anomalies in the northern BoB, and negative Q_{LH} and V anomalies in the eastern BoB (Fig. 9 a, b, c), indicating clear skies and suppressed convection in that region. In phase 5, the anomalies have flipped sign, and there is an elongated zonal band of negative Q_{SW} anomalies, and positive Q_{LH} and V anomalies across the BoB, indicating enhanced convection, in agreement with the BSISO1 life cycle from NOAA OLR and NCEP wind fields (Fig. 7) and the BSISO1 life cycle at the RAMA b28 location (Fig. 8). Generally, both TropFlux and ERA-I consistently capture the correct patterns of variability associated with the BSISO1 at phase 2 and 5 (see Fig. 7). However, ERA-I shows weaker Q_{SW} anomalies and stronger Q_{LH} anomalies than TropFlux, consistent with results observed at the RAMA b28 location that suggest TropFlux is more accurate at this location (Fig. 8).

In contrast, the BSISO1 life cycles of Q_{SW} and Q_{LH} in JRA-55, MERRA-2 and CFSR are shown to be noisier (Fig. 10) than their counterparts in TropFlux and ERA-I, especially during phase 5. During phase 5, usually characterized by a zonal band of enhanced convection in the northern

BoB, JRA-55 only captures a weakened band of negative Q_{SW} anomalies in the northernmost and easternmost parts of the BoB (Fig. 10d). In MERRA-2, the BSISO1 signal is barely perceptible from the Q_{SW}, and in CFSR the band of Q_{SW} variability is weakened and shifted south (Fig. 10e, f). CFSR further shows exaggeratedly high positive Q_{LH} anomalies that compensate for the Q_{SW} bias. The diminished Q_{SW} variability in MERRA-2 can likely be attributed to the MERRA-2 negative bias, low correlation and poor skill score in Q_{SW} (Fig. 2). The difficulties of MERRA-2, JRA-55 and CFSR in capturing the BSISO1 signal across the basin is consistent with their difficulties capturing the BSISO1 variability at RAMA b28 (Fig. 8) and can be directly attributed to the products difficulties in representing surface fluxes, as seen in the previous sections (i.e. section 3, 4). In general, TropFlux and ERA-I captured the observed BSISO1 Q_{SW} best, and TropFlux captured the observed BSISO1 Q_{LH} and Q_{net} best; both products depicted a life cycle composite which was encouragingly similar to the Lee et al. (2013) OLR life cycle (Fig. 8).

Finally, we note that with low wind speeds and high radiation, the effectiveness of the radiation shields on the T_a and humidity sensor decreases (Anderson and Baumgartner 1998). Anderson and Baumgartner (1998) estimated that for naturally ventilated sensors, errors of up to 3.4°C in the mean daytime temperature could lead to biases of 22 $W\ m^{-2}$ in the turbulent fluxes. Here the T_a and humidity sensor aboard the ATLAS moorings used multi-plate radiation shield and are naturally ventilated, hence high radiation and low wind speeds may result in less effective radiation shields (Freitag et al. 2001). Specifically, manufacturer estimates that for radiation above 1080 $W\ m^{-2}$ and winds at or below 3 $m\ s^{-1}$, the temperature bias can increase from 0.2°C to 0.4°C (Freitag et al. 2001). During phase 1 of the BSISO1, when wind speeds drop to 3 $m\ s^{-1}$ and the solar radiation is quite high due to suppressed convection, there are greater chances of T_a errors occurring due to failing radiation shields. However, careful examination of the T_a anomalies per phase (not shown here) suggests there are no significant T_a errors. The high wind speed during the majority of the phases (2 through 8) decreases the chances of radiation shields contributing to the overall error.

6. Summary and Conclusions

In this study, five data products are analysed and compared with in situ data from a moored array in the BoB to determine how well the reanalysis products characterise air-sea fluxes and intraseasonal variability during the SW monsoon season. Specifically, meteorological parameters, SST, V, T_a and q_a, air-sea temperature difference, ΔT, air-sea humidity difference, Δq, and fluxes, Q_{SW}, Q_{LW}, Q_{SH}, Q_{LH} and Q_{net} from ERA-I, TropFlux, JRA-55, MERRA-2 and CFSR were evaluated for JJAS from 2007–2015, and compared with in situ data from the RAMA surface flux reference site at 15°N, 90°E, denoted b28. In general, most products did reasonably well at representing the meteorological variables, though q_a had the lowest correlations, highest biases and lowest skill scores across all products (Fig. 2). TropFlux and ERA-I performed best, while the coupled product, CFSR, exhibited some of the largest biases. From the flux variables, Q_{SW} and Q_{LH} were shown to be the main drivers of the observed Q_{net} variability, but were also the two variables the products had the most difficulty capturing. Correlations were lowest for the radiative fluxes and Q_{SH}, and there were non-negligible biases in the range of 50 W m^{-2} in Q_{SW}. For Q_{LH}, all products other than TropFlux overestimated the observed Q_{LH} by at least 40 W m^{-2}, while the TropFlux bias was $\sim$10 W m^{-2}. In general, based on mean biases, correlations and skill scores, ERA-I was shown to capture radiative fluxes best, while TropFlux better captured turbulent and latent heat fluxes. Skill scores indicated poor performance for Q_{LH} and the radiative fluxes in MERRA-2 and CFSR, and we note that for the coupled ocean-atmosphere product CFSR, these biases canceled each other out in the Q_{net}.

The temporal mean fields for the fluxes across the BoB were investigated in section 5a, where various discrepancies were observed in the spatial patterns among the products. For Q_{SH}, the patterns were consistent across ERA-I, TropFlux and CFSR, though JRA-55 and ERA-I had large negative biases, indicating erroneously high heat loss to the atmosphere and therefore erroneous cooling of the sea surface. Patterns of Q_{LH} variability were generally consistent across all products (i.e. a region of high Q_{LH} in the southwest corner of the BoB), though values ranged on the order of 40 W m^{-2} between the reanalysis products. For Q_{SW}, ERA-I outperformed the other three products by a wide margin (CFSR, in particular, showed much higher values and different spatial gradients than the other products). Differences in Q_{LH} and Q_{SW} in the reanalysis products were generally attributed to differences or issues with the internally-generated cloud fields/schemes (e.g. Wang et al. 2011; Boilley and Wald 2015). For Q_{LW}, though spatial gradients were consistent, correlations high and biases small, skill scores were low (except for ERA-I) across all products. In general, results from the temporal mean field indicate results at the b28 location are not localized, and biases of similar magnitude to those seen at b28 will be widespread across the BoB. Further, the biases in the fluxes implied by the meteorological parameters at b28 are likely representative of the magnitude of biases observed in other regions in the basin, in the temporally-averaged fields.

The BSISO1 index, representative of the northward propagating component of the summer monsoon (with a 30–60 day periodicity), was used to test the ability of the different products to represent the principal mode of atmospheric variability in the BoB in this season, in particular in the representation of Q_{SW} and Q_{LH} in ERA-I, TropFlux, and CFSR. Comparison with RAMA b28 suggested TropFlux and ERA-I most reliably captured surface flux variability compared with the observed BSISO1 Q_{SW} cycle at 15°N, 90°E; however, TropFlux captured the variability and magnitude of the observed Q_{LH} and Q_{net} best. The analysis of the mean fields, the comparison with BSISO1 at b28, and comparison with Lee et al. (2013) satellite OLR maps allows us to extend this confidence over the entire BoB. Thus, both TropFlux and ERA-I appear to best represent the variability of the surface fluxes at RAMA b28 and across the entire BoB basin. Conversely, MERRA-2, CFSR and JRA-55 struggled to capture the climatic variability associated with the BSISO1, with weak Q_{SW} variability at the location of RAMA b28 suggesting that the convective signal is poorly represented in these products, while the over-estimation of Q_{LH} variability suggests erroneous surface wind and humidity fields. Hence, we infer inability to accurately capture or reproduce the surface fluxes at b28 or at mean field levels shows that the MERRA-2, CFSR and JRA-55 products will similarly struggle to capture variability associated with the boreal summer monsoon.

As air-sea fluxes have been shown to be key players in monsoon variability (Vecchi and Harrison 2002), caution is advised when selecting a data product to represent monsoonal processes. This study has highlighted significant and critical deficiencies in reanalysis flux products from the accumulated errors observed in the meteorological parameters and surface fluxes specific to the southwest monsoon time period and have yet to be verified for the entire seasonal cycle. In general, ERA-I and TropFlux were shown to outperform MERRA-2, JRA-55 and CFSR; ERA-I represented radiative fluxes best, while TropFlux better captured turbulent and net heat fluxes. Based on findings shown here, this analysis recommends TropFlux and ERA-I as the best available products for the study of air-sea fluxes and intraseasonal variability over the BoB during the SW monsoon, or for the forcing of ocean models during boreal summer in the tropical Indian Ocean.

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TABLE 1. Summary of reanalysis, blended* and in situ products used in this study.

Product	*Input SST*	*Resolution*	*Period*	*Reference*	*Flux method*
ERA-Interim	See Dee et al. (2011)	-Sub-daily (3, 6-hourly) -0.75° X 0.75°	1979 to present	Dee et al. (2011)	Model
TropFlux*	Bias corrected ERA-I	-Daily -1.0° X 1.0°	1979 to present	Kumar et al. (2012)	COARE 3.0
JRA-55	COBE SST (Ishii et al. 2005)	-Sub-daily (3, 6-hourly) -0.56° X 0.56°	1979 to present	Kobayashi et al. (2015)	Model
MERRA-2	See Bosilovich et al. (2015)	-Sub-daily (1-hourly) -0.5° X 0.625°	1980 to present	Bosilovich et al. (2015)	Model
CFSR	See Saha et al. (2011)	-Sub-daily (6-hourly) -0.5° X 0.5°	1979 to 2011 CFSv2: 2011 to pres.	Saha et al. (2010) Saha et al. (2011)	Model
RAMA array	Observed	-Sub-daily (1-hourly fluxes; 2-min radiation data; 10-min surface meteorological data)	2007 to present	McPhaden et al. (2009)	COARE 3.0

TABLE 2. Summary of documented (SST, V, T_a, and q_a) uncertainties (McPhaden et al. 2009) and calculated (ΔT, Δq, Q_{SH}, and Q_{LH}) uncertainties from the RAMA buoy instruments.

Measurement	*Uncertainty*
SST	$\pm 0.02°C$
V	± 0.2 m s^{-1}
T_a	$\pm 0.2°C$
q_a	± 0.2 g kg^{-1}
ΔT	$\pm 0.2°C$
Δq	± 0.28 g kg^{-1}
Q_{SH}	± 2.5 W m^{-2}
Q_{LH}	± 7.3 W m^{-2}

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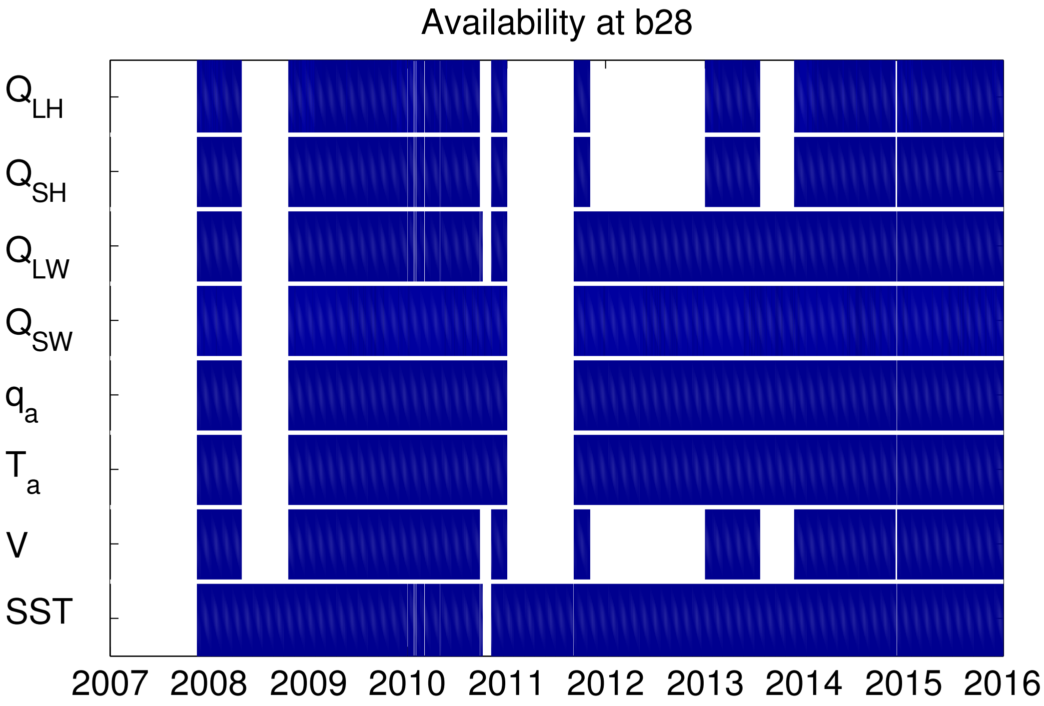
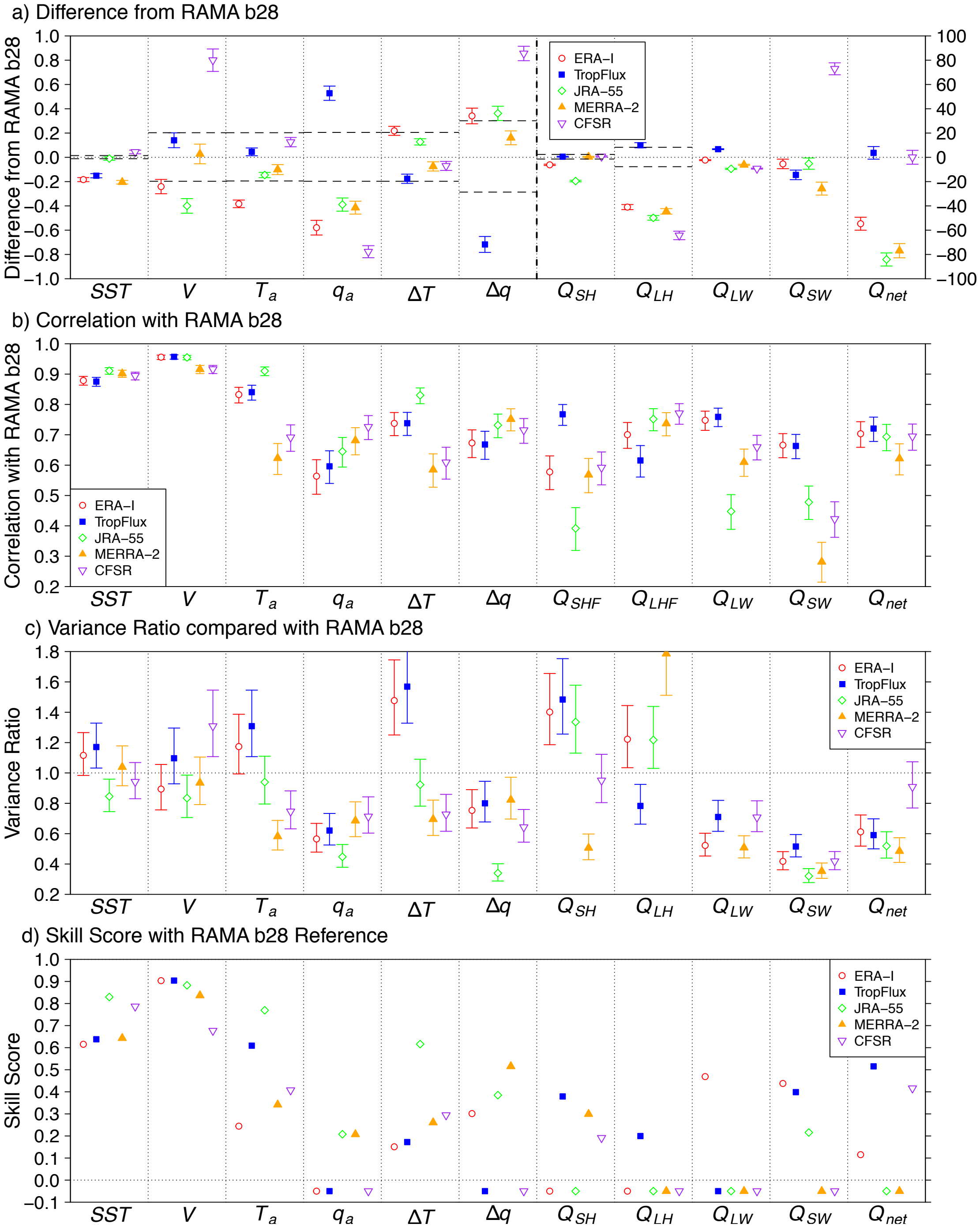


881 FIG. 1. Availability of data at buoy site b28 (15°N and 90°E b28) for meteorological and flux parameters
882 used in this study.


a) Difference from RAMA b28

b) Correlation with RAMA b28

c) Variance Ratio compared with RAMA b28

d) Skill Score with RAMA b28 Reference

FIG. 2. Difference (product - RAMA; a), correlation (b), variance ratio (c), and skill score (d) for reanalysis products (ERA-I, TropFlux, JRA-55, MERRA-2 and CFSR) against data from RAMA b28. The 95% confidence intervals are shown in the difference, correlation and variance ratio metrics. The variables evaluated are the meteorological, SST (°C), V (m s^{-1}), T_a (°C), q_a (g kg^{-1}), ΔT (°C), Δq (g kg^{-1}), and flux, Q_{SW} (W m^{-2}), Q_{LW} (W m^{-2}), Q_{SH} (W m^{-2}), Q_{LH} (W m^{-2}), Q_{net} (W m^{-2}), for the summer (JJAS) from 2007 to 2015. Panel (a) shows uncertainties as per Table 2 indicated by the horizontal dashed lines, and a split scale to differentiate between meteorological and flux parameters.

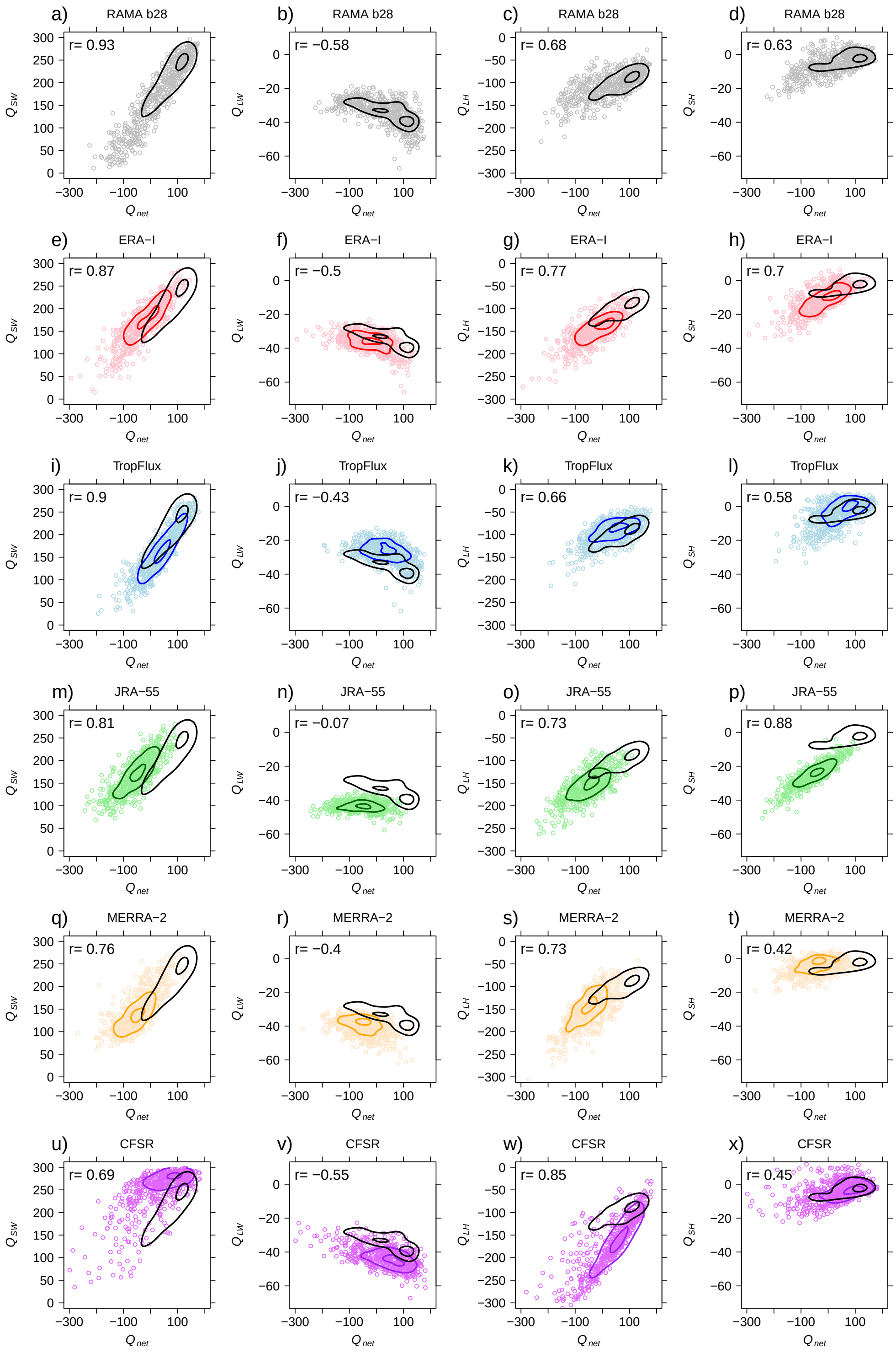


FIG. 3. Scatterplots for Q_{net} vs each of Q_{SW}, Q_{LW}, Q_{SH} and Q_{LH} (all units in W m^{-2}) from RAMA buoy observations (a, b, c, d), ERA-I (e, f, g, h), TropFlux (i, j, k, l), JRA-55 (m, n, o, p), MERRA-2 (q, r, s, t) and CFSR (u, v, w, x) at site b28 (8°N and 90°E). Contour lines enclose the 10% and 50% of points in each joint distribution. RAMA contour lines (black) are repeated for comparison.

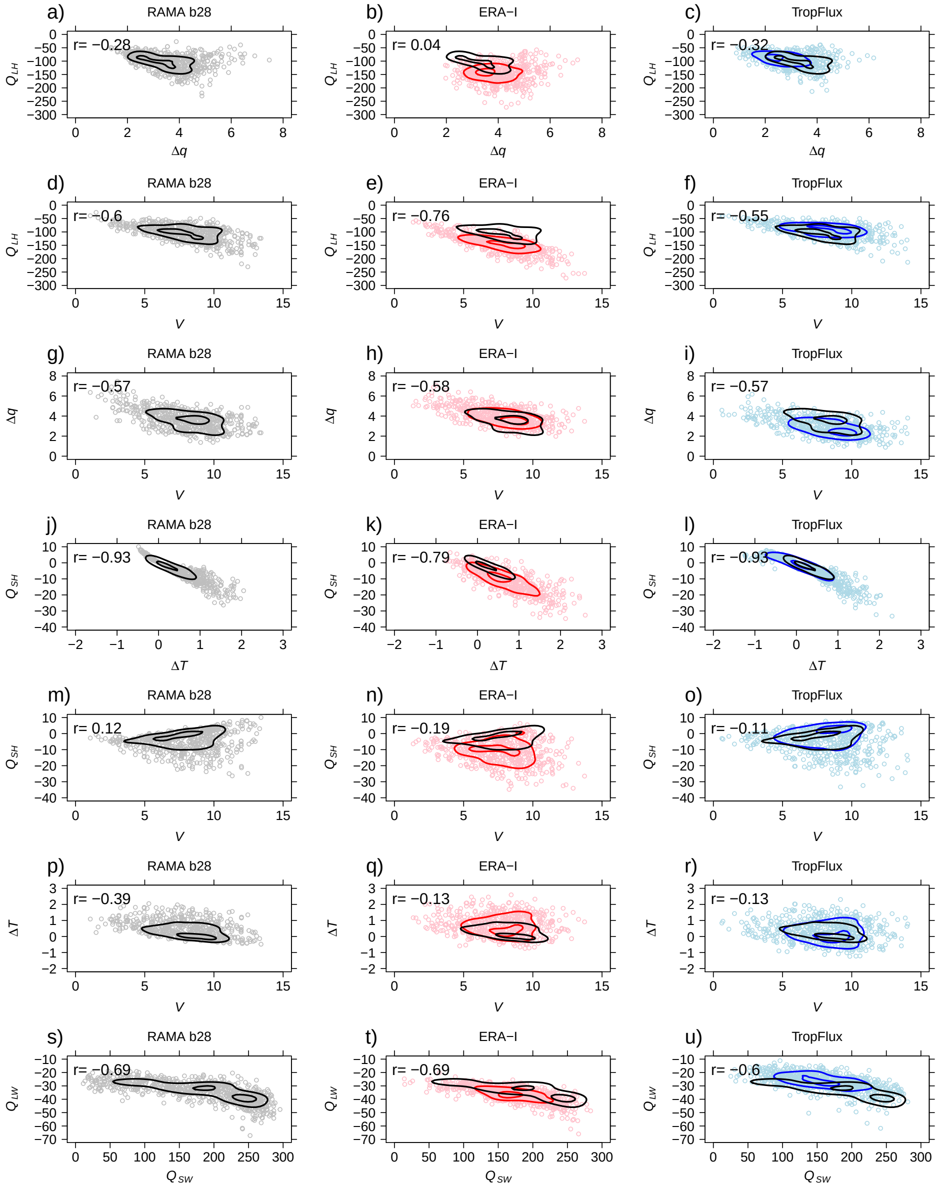


FIG. 4. Scatterplots of Q_{LH} (W m^{-2}) vs Δq (g kg^{-1}), Q_{LH} (W m^{-2}) vs V (m s^{-1}), Δq (g kg^{-1}) vs V (m s^{-1}), Q_{SH} (W m^{-2}) vs ΔT (°C), Q_{SH} (W m^{-2}) vs V (m s^{-1}), ΔT (°C) vs V (m s^{-1}), and Q_{LW} (W m^{-2}) vs Q_{SW} (W m^{-2}) from RAMA buoy observations (left column), ERA-Interim (center column) and TropFlux (right column) at site b28 (8°N and 90°E). Contour lines enclose the 10% and 50% of points in each joint distribution. RAMA contour lines (black) are repeated for comparison.

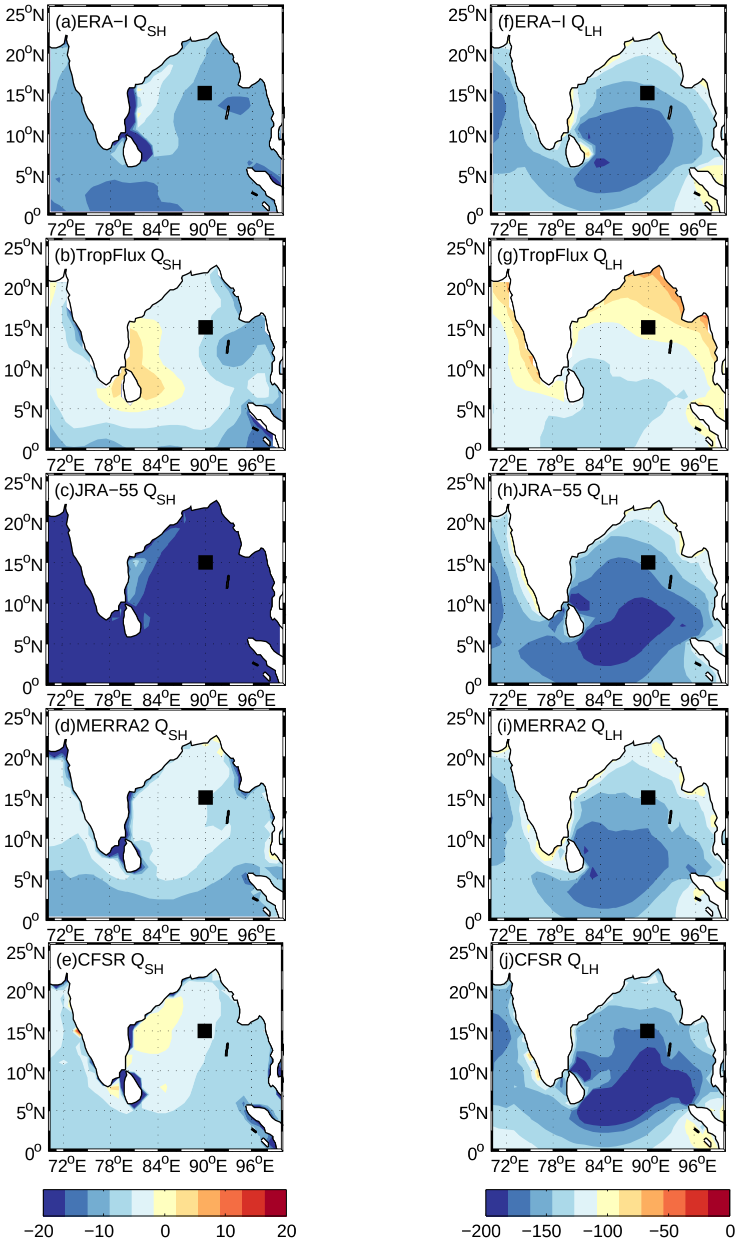


FIG. 5. Mean Q_{SH} (left column; W m^{-2}) and Q_{LH} (right column; W m^{-2}) for ERA-I (a, f), TropFlux (b, g), JRA-55 (c, h), MERRA-2 (d, i), and CFSR (e, j). All fields are averaged for the SW monsoon season (JJAS) from 2007 to 2015. The black square indicates the location of the RAMA buoy, b28, in the Bay of Bengal.

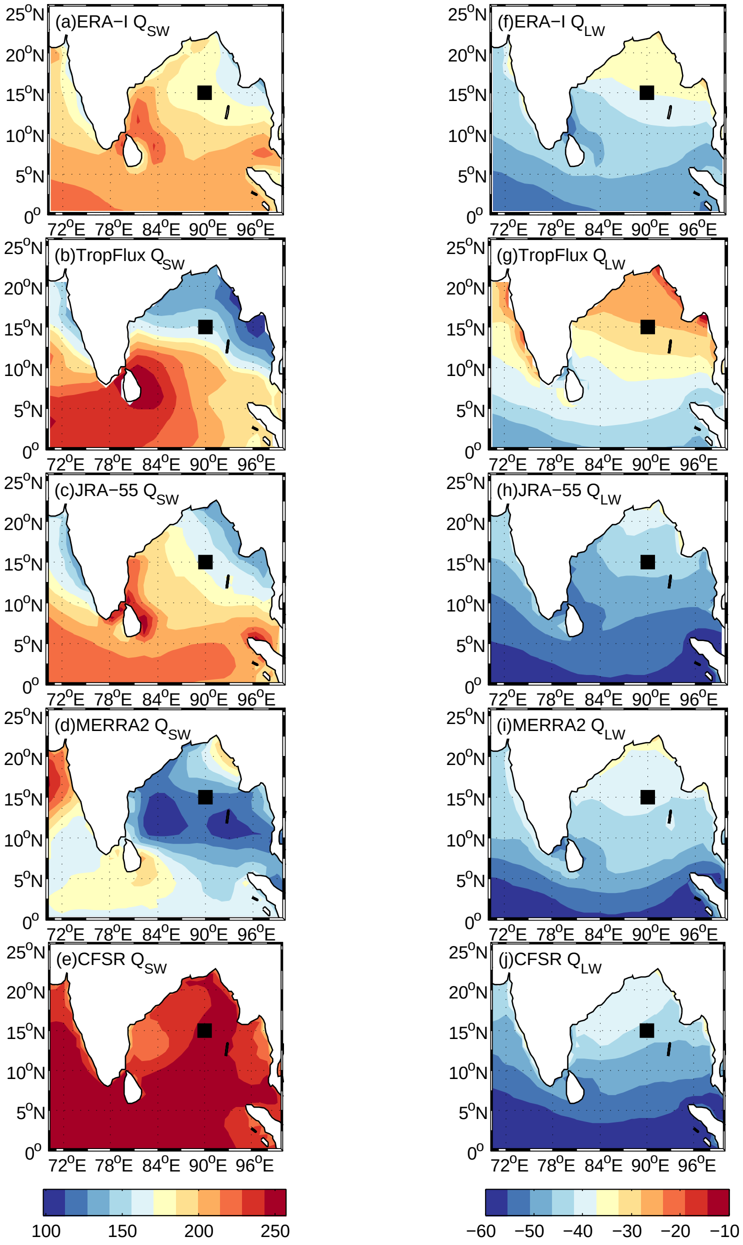


FIG. 6. Same as in Fig. 5 but for radiative fluxes.

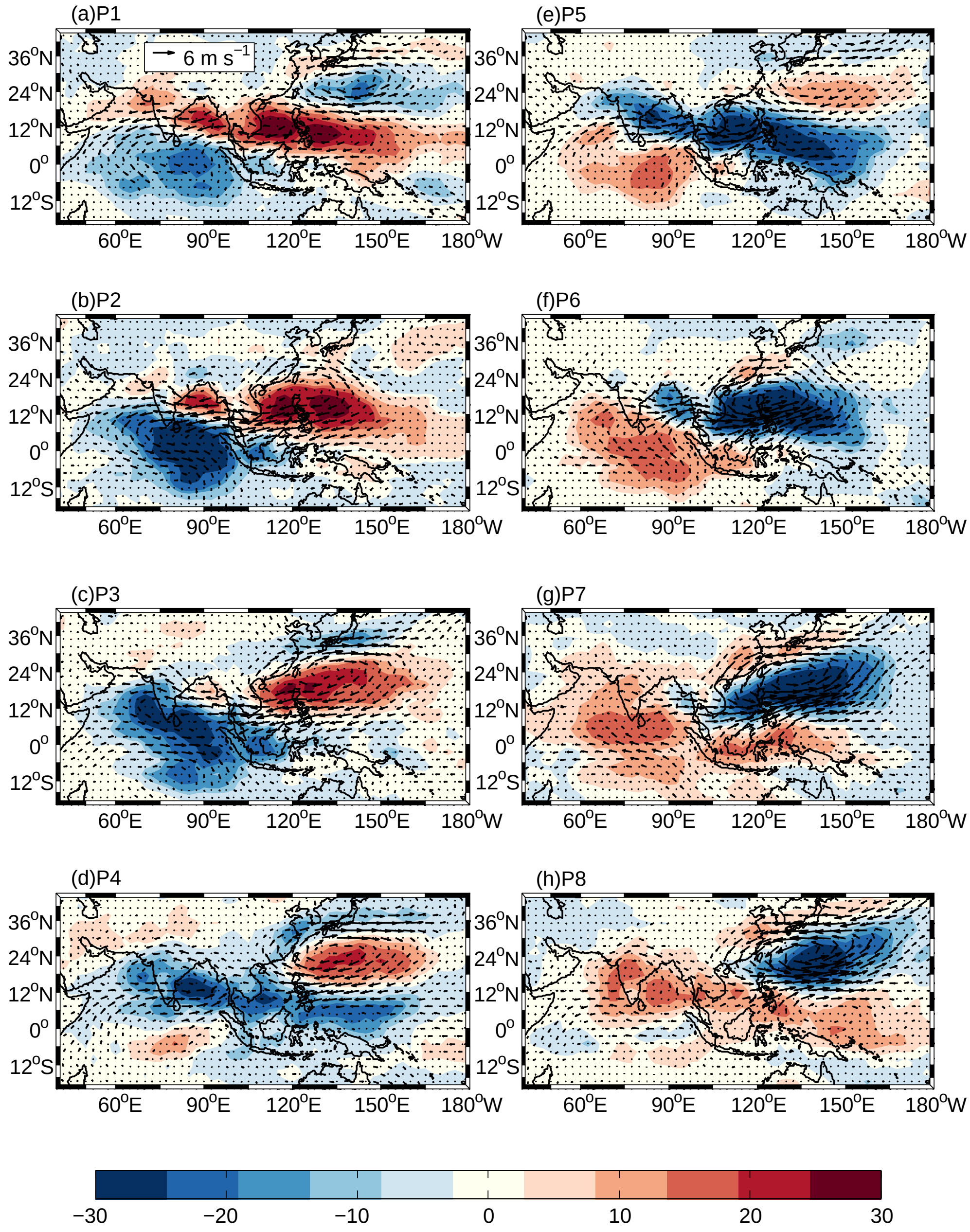


FIG. 7. BSISO 1 life cycle composite of NOAA OLR anomalies (shaded; W m^{-2}) and NCEP-DOE 850-hPa wind anomalies (vector; m s^{-1}).

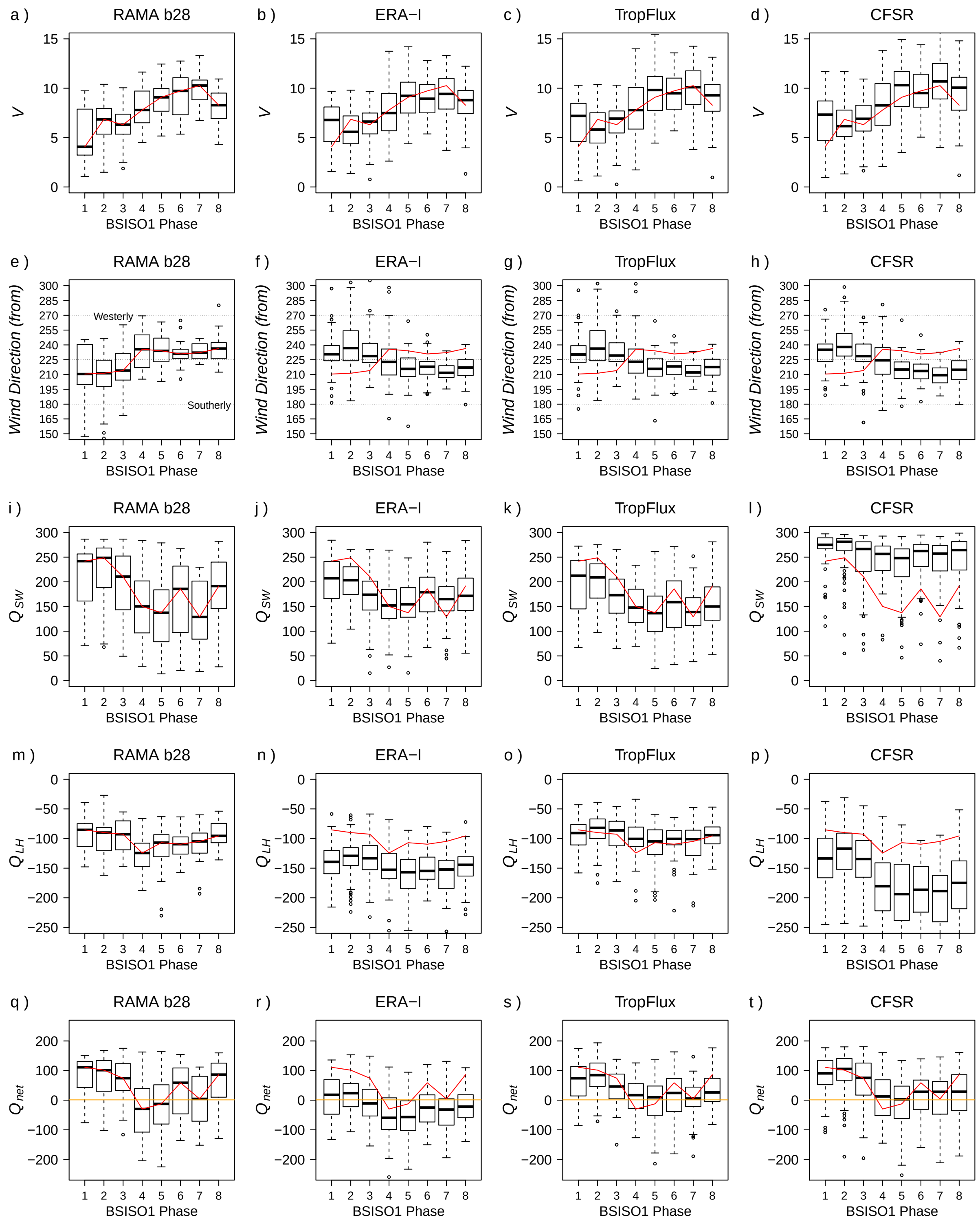


FIG. 8. Median, interquartile range, 95% confidence interval, and outliers for V (m s^{-1}), wind direction (°), Q_{SW} (W m^{-2}), Q_{LH} (W m^{-2}), and Q_{net} (W m^{-2}) vs BSISO1 phases (1 to 8) from RAMA b28 (a, e, i, m, q), ERA-I (b, f, j, n, r), TropFlux (c, g, k, o, s), and CFSR (d, h, l, p, t). The red line is the RAMA b28 median line, repeated for comparison.

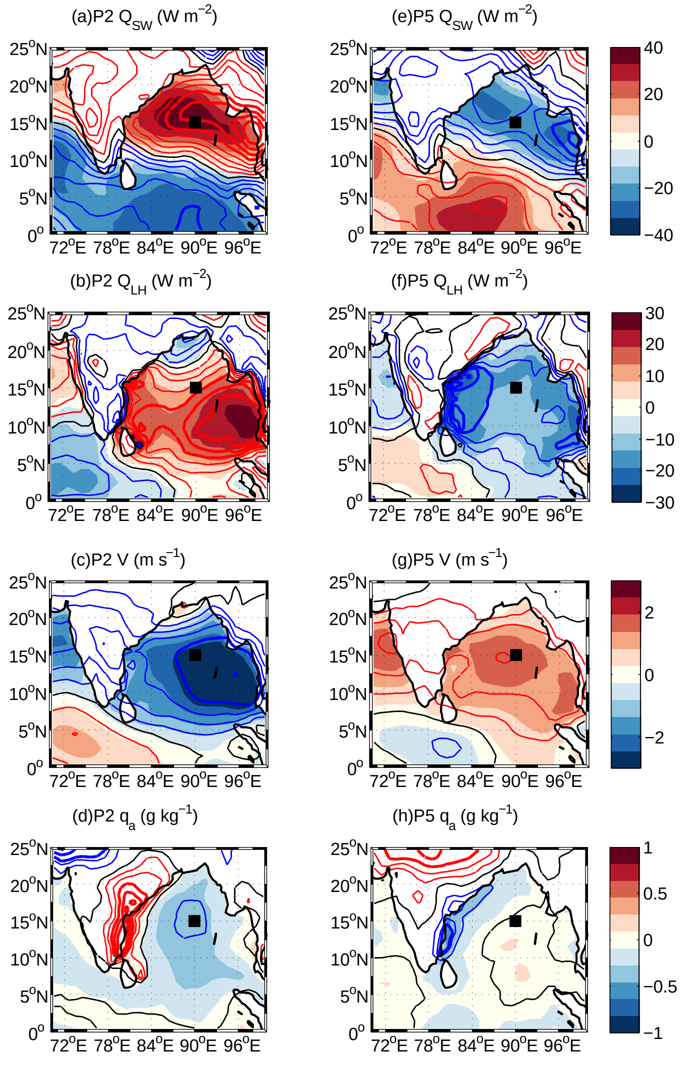


FIG. 9. Composite of phase 2 (left column) and phase 5 (right column) of the BSISO1 life cycle. TropFlux (shaded) and ERA-I (contour lines) Q_{SW} anomalies at phase 2 (a) and phase 5 (e); Q_{LH} anomalies at phase 2 (b) and 5 (f); V anomalies at phase 2 (c) and 5 (g); and, q_a anomalies at phase 2 (d) and 5 (h). ERA-I Q_{SW} contour lines range from -40 to 40 W m^{-2} and Q_{LH} contour lines range from -30 to 30 W m^{-2}, with 5 W m^{-2} intervals. ERA-I V contour lines range from -3 to 3 m s^{-1}, with 0.5 m s^{-1} intervals. ERA-I q_a contour lines range from -1 to 1 g kg^{-1}, with 0.2 g kg^{-1} intervals. The black square indicates the location of the RAMA buoy 28.

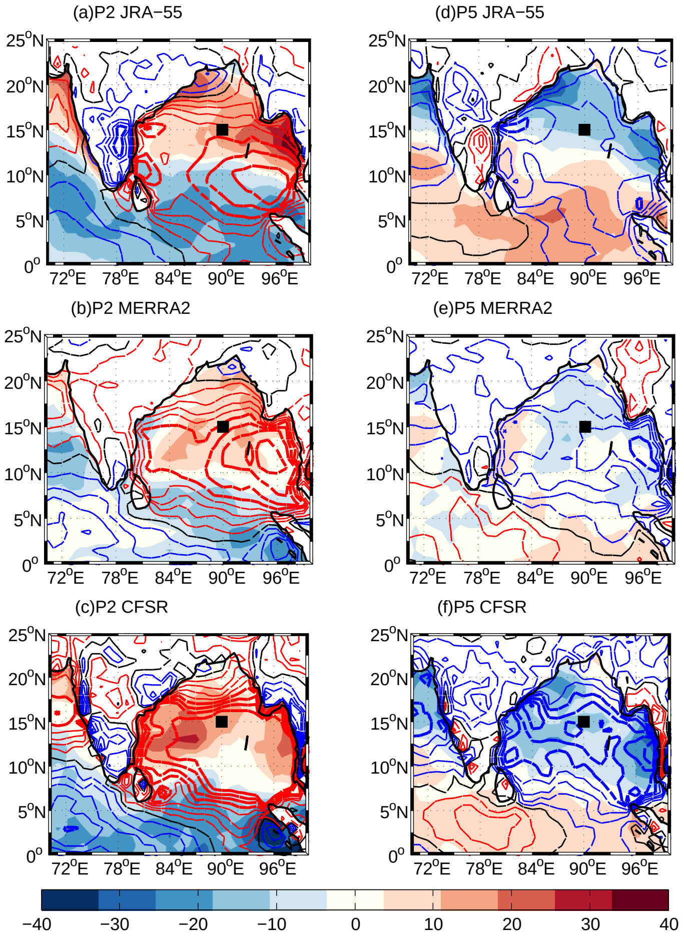


FIG. 10. Phase 2 (left column) and 5 (right column) of the Q_{SW} (shading) and Q_{LH} (contour line) anomalies from JRA-55 (a, d), MERRA-2 (b, e), and CFSR (c, f) based on the BSISO1 phases. Q_{LH} contour lines range from -40 to 40 W m^{-2}, with 5 W m^{-2} intervals. The black square indicates the location of the RAMA buoy 28. All units in W m^{-2}.