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To link to this article DOI: http://dx.doi.org/10.1175/JCLI-D-17-0652.1

Publisher: American Meteorological Society

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

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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 ($Q_{\text{net}}$) 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 ($Q_{\text{SW}}$) and latent heat flux ($Q_{\text{LH}}$), with non-negligible biases up to $\sim 75$ W m$^{-2}$. The $Q_{\text{SW}}$ and $Q_{\text{LH}}$ are the largest drivers of the observed $Q_{\text{net}}$ 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 $Q_{\text{net}}$ by 40-60 W m$^{-2}$ compared with in situ estimates from a moored buoy near 0$^\circ$, 80.5$^\circ$E. Their results suggested that the accumulation of these deficiencies in heat flux over time could result in 2 $^\circ$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 ($\varepsilon$) and thus calculate $q_a$, as per Bolton (1980):

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

(1)

where $p$ is surface pressure and $\varepsilon = 0.622$ 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 $1^\circ \times 1^\circ$, 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 $1^\circ \times 1^\circ$ horizontal grid.

TropFlux is a blended (reanalysis-based) product of air-sea fluxes and associated meteorological variables over the global tropical oceans, from $30^\circ$S to $30^\circ$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:

$$
\Psi_{tf}(x,y,t) = a(\Psi(x,y,t) - \Psi_{\text{mean}}(x,y)) + b(x,y) + \Psi_{\text{mean}}(x,y)
$$

where $\Psi_{tf}$ is the corrected ERA-I variable, $\Psi$, and the long term mean is $\Psi_{\text{mean}}$. 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 $1^\circ \times 1^\circ$ 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. $\Delta T$ and $\Delta q$ 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:

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

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

where $\alpha$ is a constant albedo value of 0.055, SWR is the incoming downwelling radiation, $\varepsilon$ is the emissivity constant (0.97), $\beta$ is the Stefan Boltzmann constant ($5.67 \times 10^{-8}$), $T_s$ 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, $\Delta T$, the air-sea humidity difference, $\Delta q$, 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):

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

(5)

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

(6)

where $x$, $y$ and $\sigma_x$, $\sigma_y$ 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 \(\Delta T\) are much lower than those for either \(SST\) or \(T_d\) (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 \(\Delta q\) 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 (~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 $\Delta T$ 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 sur-
prising as it had relatively poor skill for $\Delta q$ (Fig. 2d). TropFlux underestimates $\Delta q$ 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 $\Delta q$ 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 $\Delta T$ 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 $Q_{LH}$: $\Delta q$ 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 $\Delta q$ and $Q_{LH}$ is lower (Fig. 4a) as $\Delta q$ and $V$ are anti-correlated (Fig. 4g). This anti-correlation is well-captured by ERA-I (Fig. 4h) with a slight overestimate of $\Delta q$. The TropFlux corrections result in a underestimation of $\Delta q$, but despite this the $Q_{LH}$ agrees reasonably with b28, perhaps due to the gustiness adjustment to wind in the flux calculation.

$\Delta T$ 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 $\Delta T$. ERA-I is biased toward unstable atmospheric conditions ($\Delta T$ 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) $\Delta q$, and $Q_{SH}$ variability is mostly driven by $\Delta T$. Results here suggest errors/biases in $Q_{LH}$ originate from both the wind field and the $\Delta q$ 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 $\Delta T$. $Q_{SW}$ 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$^\circ$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 (~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$^\circ$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 $\pm 45$ 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 ob-
served $Q_{SW}$, 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, \( \Delta T \), air-sea humidity difference, \( \Delta q \), 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\(^{\circ}\)N, 90\(^{\circ}\)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 ex-
tend 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.

Acknowledgments. The NERC BoBBLE project supported ASF and ECK (NE/L013835/1), BGMW (NE/L013827/1), and SCP (NE/L013800/1). PNV thanks the Ministry of Earth Sciences, Govt. of India for funding under the BoBBLE project. The authors thank the US National Oceanic and Atmospheric Administration (NOAA)/Pacific Marine Environ-
mental Laboratory (PMEL) and National Institute of Oceanography (NIO) for access to RAMA buoy data (https://www.pmel.noaa.gov/tao/drupal/disdel/). The authors would also like to acknowledge the European Centre for Medium Range Weather Forecasting for ERA-Interim data access (http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=pl/); the Computational and Information Systems Laboratory Research Data Archive (https://rda.ucar.edu) for access to the reanalysis datasets JRA-55 and CFSR; the Global Modeling and Assimilation Office (GMAO) and the GES DISC for the dissemination of MERRA-2 (https://disc.sci.gsfc.nasa.gov/daac-bin/FTPSubset2.pl); and, ESSO-INCOIS for TropFlux data access (http://www.incois.gov.in/tropflux/). The TropFlux data is produced under a collaboration between Laboratoire d’Oceanographie: Experimentation et Approches Numeriques (L’OCEAN) from Institut Pierre Simon Laplace (IPSL, Paris, France) and National Institute of Oceanography/CSIR (NIO, Goa, India), and supported by Institut de Recherche pour le Developpement (IRD, France). TropFlux relies on data provided by the ECMWF Re-Analysis interim (ERA-I) and ISCCP projects. The interpolated OLR and NCEP Reanalysis data were provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their website at http://www.cdc.noaa.gov/. The BSISO data were provided by the Apec Climate Centre through their website: http://www.apcc21.net/ser/moni.do?lang=en. The authors are grateful to Dr. Shoji Hirahara of JMA for the JRA-55 daily SST data. The matlab version of the COARE3.0 algorithm was used to estimate the uncertainty in the RAMA turbulent fluxes: ftp://ftp.etl.noaa.gov/BLO/Air-Sea/bulkalg/cor3.0/. The authors are also grateful for the helpful insight and comments from three anonymous reviewers.
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<table>
<thead>
<tr>
<th>Product</th>
<th>Input SST</th>
<th>Resolution</th>
<th>Period</th>
<th>Reference</th>
<th>Flux method</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERA-Interim</td>
<td>See Dee et al. (2011)</td>
<td>-Sub-daily (3, 6-hourly)</td>
<td>1979 to present</td>
<td>Dee et al. (2011)</td>
<td>Model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.75° X 0.75°</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TropFlux*</td>
<td>Bias corrected ERA-I</td>
<td>-Daily</td>
<td>1979 to present</td>
<td>Kumar et al. (2012)</td>
<td>COARE 3.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-1.0° X 1.0°</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JRA-55</td>
<td>COBE SST</td>
<td>-Sub-daily (3, 6-hourly)</td>
<td>1979 to present</td>
<td>Kobayashi et al. (2015)</td>
<td>Model</td>
</tr>
<tr>
<td></td>
<td>(Ishii et al. 2005)</td>
<td>-0.56° X 0.56°</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.5° X 0.625°</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CFSR</td>
<td>See Saha et al. (2011)</td>
<td>-Sub-daily (6-hourly)</td>
<td>1979 to 2011</td>
<td>Saha et al. (2010)</td>
<td>Model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.5° X 0.5°</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>CFSv2: 2011 to pres.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RAMA array</td>
<td>Observed</td>
<td>-Sub-daily (1-hourly fluxes; 2-min radiation data; 10-min surface meteorological data)</td>
<td>2007 to present</td>
<td>McPhaden et al. (2009)</td>
<td>COARE 3.0</td>
</tr>
</tbody>
</table>

*Blended products are typically used in conjunction with reanalysis data to improve the spatial and temporal coverage of the dataset.
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.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>SST</td>
<td>±0.02°C</td>
</tr>
<tr>
<td>V</td>
<td>±0.2 m s^{-1}</td>
</tr>
<tr>
<td>T_a</td>
<td>±0.2°C</td>
</tr>
<tr>
<td>q_a</td>
<td>±0.2 g kg^{-1}</td>
</tr>
<tr>
<td>ΔT</td>
<td>±0.2°C</td>
</tr>
<tr>
<td>Δq</td>
<td>±0.28 g kg^{-1}</td>
</tr>
<tr>
<td>Q_{SH}</td>
<td>±2.5 W m^{-2}</td>
</tr>
<tr>
<td>Q_{LH}</td>
<td>±7.3 W m^{-2}</td>
</tr>
</tbody>
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