Variability of Air–Sea Interactions over the Indian Ocean Derived from Satellite Observations

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ABSTRACT

Novel ways of monitoring the large-scale variability of the southwest monsoon in the Indian Ocean are presented using multispectral satellite datasets. The fields of sea surface temperature (SST), surface latent heat flux (LHF), net surface solar radiation (SW), precipitation (P), and SW $-\ LHF$ over the Indian Ocean are analyzed to characterize the seasonal and interannual variability with special emphasis on the period 1988–90. It is shown that satellite data are able to make a significant contribution to the multiplatform strategy necessary to describe the large-scale spatial and temporal variability of air–sea interactions associated with the Indian Ocean Monsoon. The satellite data analyzed here has shown for the first time characteristics of the interannual variability of air–sea interactions over the entire Indian Ocean. Using monthly means of SST, LHF, SW, P, and the difference SW $-\ LHF$, the main features of the seasonal and interannual variability of air–sea interactions over the Indian Ocean are characterized. It is shown that the southwest monsoon strongly affects these interactions, inducing dramatic exchanges of heat between air and sea and large temporal variations of these exchanges over relatively small timescale (with regards to typical oceanic timescales). The analyses indicate an overall good agreement between satellite and in situ (ship) estimates, except in the southern Indian Ocean, where ship sampling is minimal, the disagreement can be large. In the latitudinal band of 10°N–15°S, differences in climatological in situ estimates of surface sensible heat flux and net longwave radiation has a larger influence on the net surface heat flux than the difference between satellite and in situ estimates of SW and LHF.

1. Introduction

The Indian Ocean is the locus of one of the largest seasonally occurring meteorological events: the southwest summer monsoon (June–September). The onset, duration, and intensity of the Indian monsoon are strongly determined by planetary-scale processes such as the large-scale solar radiation heating of the Indian subcontinent, the upper-level Tibetan anticyclone, the monsoon trough, and the cross-equatorial flow off the eastern coast of Africa (Hastenrath 1995). In addition, the large-scale solar radiation heating of the Arabian Sea (Gautier 1986; Mohanty et al. 1994), sea surface temperature (SST) distribution (Rao and Goswamy 1988), moisture buildup in the Arabian Sea resulting from both local evaporation and cross-equatorial moisture flow (Doherty and Newell 1984), and slowly northward traveling 30–50-day oscillations (Hartmann and Michelsen 1989; Gautier and Di Julio 1990) are important processes that modulate the monsoon variability.

Due to the large variability of the Indian monsoon over wide ranges of space and timescales, its optimal monitoring requires a multiplatform strategy. Each platform makes a unique contribution along with its own limitations. For instance, observations from ship and moored buoys can provide in situ measurements needed to resolve important air–sea interaction processes. In contrast, these observations have limited spatial and temporal resolutions. On the other hand, satellite observations, as it will be shown later, offer the unique opportunity to sample large oceanic areas with high temporal resolution. The accuracy of satellite estimates, however, have to be compared against in situ observations so that reliable estimates are assessed.

The objective of this paper is to demonstrate that recent advances in satellite remote sensing, which now allow a quantitative description of many geophysical fields to describe the interactions between the ocean and the atmosphere, can make a significant contribution to the multiplatform strategy of observing the Indian monsoon. The main features of large-scale air–sea interactions determined from long-term ship-based climatologies in the Indian Ocean can be observed from satellite data. We use data produced by different groups (SST, wind, total precipitable water, and precipitation), as well as parameters computed with our recently developed algorithms. These include net surface solar short wave radiation (SW), latent heat flux (LHF), and heat budget...
in the Indian Ocean. The data used and methods applied are described in section 2. The spatial structure of air–sea interface fluxes is discussed in section 3, and the analysis of their temporal variability is presented in section 4. Section 5 shows a spatial–temporal statistical analysis to characterize the physical associations involved in precipitation, surface heat fluxes, and SST over the Indian Ocean. The surface heat budget is discussed in section 6 on the basis of satellite estimates and other climatological studies. The last section offers a discussion and conclusions.

2. Data and methods

Data from several satellites and different sensors are used in this study. These include visible and infrared data from geostationary (Geostationary Operational Environmental Satellite) and polar-orbiting satellites (Advanced Very High Resolution Radiometer, AVHRR), and microwave data from the Special Sensor Microwave Imager (SSM/I) aboard the Defense Meteorological Satellite Program. These data have been processed to derive geophysical parameters following procedures that have become relatively standard and accepted by the scientific community. These procedures are only briefly introduced when we discuss each parameter used in this study. While each geophysical parameter computed has a different spatial and temporal resolution that depend on the data used to derive it and the platform on which the sensor is located, all fields presented here have been reduced to monthly averages mapped to a regular grid with 2.5° lat × 2.5° long resolution. The domain investigated covers the entire Indian Ocean and adjacent regions and extends from 35°S to 30°N and from 25° to 135°E.

The SST field derives from the reanalysis optimal interpolation scheme produced by the National Centers for Environmental Protection (NCEP). The analysis is produced daily and weekly on a 1° spatial resolution and utilizes in situ data from ships and buoys and bias-corrected satellite SST data (Reynolds and Smith 1994). Monthly averages for the period January 1984–December 1993 are used.

The precipitation (P) data are provided by the Global Precipitation Climatology Project (GPCP) described by Janowiak and Arkin (1991). It is available in the form of monthly averages (mm day⁻¹) at 2.5° lat × 2.5° long resolution and has been computed using infrared data from geostationary and polar-orbiting satellites over the period 1986–94. This particular dataset was chosen over one derived from microwave observations because it contains data over both land and ocean.

The SW at the surface is a new product computed using data from the International Satellite Cloud Climatology Project (ISCCP) C1 data (Rossow et al. 1988) and processed with the method of Gautier et al. (1980). This method of computing SW has been successfully tested under many different atmospheric and cloud regimes (e.g., Gautier and Frouin 1985; Bates and Gautier 1989; Gautier and Frouin 1992). The net surface SW radiation thus obtained has been compared with estimates by Pinker and Laszlo (1992) and Darnell et al. (1992), the presently used methods for estimating this parameter for the World Climate Program. A high correlation coefficient (over 0.95 for both) and a small root-mean-square difference (around 12 W m⁻²) (Wang 1994) have been found between our computations and their datasets. The surface shortwave radiation fluxes are available as monthly averages from 1984 to 1990 constrained in time only by the availability of the ISCCP data. Additional details on the last model version can be found in Gautier and Landsfeld (1997).

LHF is derived by the method of Jourdan and Gautier (1995), which is a blending of satellite calculations with Comprehensive Ocean–Atmosphere Data Set (COADS) derived parameters (Woodruff et al. 1987). The inputs to compute LHF satellite estimation only are the following: SST (from NCEP analysis), total precipitable water (W), and surface wind speeds (U). The last two parameters are derived from the SSM/I (Wentz 1994). The computation of the saturation specific humidity (Qₘ) is done using SST (NCEP), whereas the near-surface specific humidity (Qₜ) is derived from the empirical relationship of Liu (1986). The satellite estimates of air temperature and air mixing ratio are blended with COADS values weighted by the number of observations in the COADS fields. These blended fields become the final model inputs [see Jourdan and Gautier (1995) for details]. This monthly LHF has been found to agree well with LHF estimated from COADS observations in regions where these observations are sufficiently numerous (above 20 observations per month) to be representative of the area covered. Globally, the rms difference between the blended satellite–COADS LHF and COADS is 33.5 ± 18.1 W m⁻², whereas in the Indian Ocean it is 43.8 ± 19.6 W m⁻².

3. Air–sea interaction spatial variability

The spatial variability of the air–sea fluxes [SW, LHF, and (SW – LHF)] as well as P and SST is now analyzed in detail for the three years (1988–90) in which all datasets overlap. In the following discussion our convention will be to refer to seasons in the Northern Hemisphere. Figure 1 shows the mean fields of precipitation and SW for the winter (December–February) and summer (June–September) seasons. Seasonal means have been chosen to represent the different phases of the monsoon and are rather representative of what occurs during each month of the particular monsoon phase. The precipitation field shows well-known climatological features—that is, precipitation is maximum over the maritime continent during the winter season (Fig. 1a) but shifts toward India and the Bay of Bengal during summer (Fig. 1b). As expected, the mean net shortwave radiation at the surface reaches its maximum during the
summer season (Figs. 1c and 1d). However, since the net shortwave radiation at the surface is determined not only by the sun’s position, but also by clouds, a close correspondence can be found between the fields of precipitation and SW. During the winter season, Fig. 1c, when precipitation is maximum over the maritime continent, the net shortwave radiation is maximum over the southern Indian Ocean and minimum over the maritime continent. In contrast, during the summer season (Fig. 1d), the net shortwave radiation is maximum over the northeastern coast of Africa and minimum over most of the central and southern Indian Ocean. Only minima of insolation are expected to be highly correlated with precipitation, since these minima correspond to clouds that strongly reflect and absorb solar radiation, and therefore to clouds that have large amounts of liquid water and hence a high probability for rain. On the other hand, considering the technique with which the precipitation is computed, widespread precipitation will also correspond to extensive cirrus anvils, which are the outflow regions of deep convection. For these regions, SW will likely be higher than for the core of the deep convective regions. In summary, we can expect the strongest correspondence in the core regions of the deep convection but also a significant relationship in the outflow region, which surrounds the deep convective core.

To compare our satellite-derived products with existing climatological data, we computed the difference between the two largest terms in the heat budget, SW and LHF, at the ocean’s surface. This is done because there is presently no simple way to accurately compute the two other terms composing the net heat flux, net longwave radiation (LW), and sensible heat fluxes ($S_e$), from satellite data alone. This estimate [hereafter (SW − LHF)] includes most of the variability associated with the net surface heat flux. The mean and standard deviation of the difference of the first two terms (SW − LHF) and the sum of the second two terms ($S_e + LW$) is 76.1 ± 56.6 W m$^{-2}$ and 67.5 ± 13.0 W m$^{-2}$, respectively. The mean fields of LHF and (SW − LHF) are shown in Fig. 2. In the Arabian Sea, Bay of Bengal, and China Sea, a strong annual cycle is seen in LHF, reaching its maximum during the winter season (Fig. 2a). In contrast, during the summer season (Fig. 2b), LHF reaches very high values over the southern Indian Ocean due to high wind speeds in the unobstructed
4. Temporal variability

a. Seasonal cycle

To examine the temporal variability of air–sea interaction processes over the Indian Ocean in more detail, we have produced time–latitude diagrams for two meridional cross sections. The first section is taken along longitudes 60°E–65°E and passes through the Arabian Sea; the second section is taken along 85°–90°E over the Bay of Bengal. For completeness, we show the time variability of the P, SW, LHF, (SW − LHF), and SST fields for the available data record. Figure 3 shows the cross section along 60°–65°E (Arabian Sea), and Fig. 4 describes the cross section along 85°–90°E (Bay of Bengal). Strong seasonal variations are observed in all fields. Most notably, the seasonal variations in precipitation over the Bay of Bengal are much stronger than over the Arabian Sea (Figs. 3a and 4a). The SW fluxes (Figs. 3b and 4b) cover a period extending from 1984 through 1990. This time series length allows us to put our three years of extensive study into a longer-term context. The meridional cross sections in the Arabian Sea and Bay of Bengal are dominated by strong seasonal variability due to clouds and sun angle. Surface LHF (Figs. 3c and 4c) also exhibit pronounced seasonal variations, reaching maximum amplitudes during the monsoon season. Consistent with other studies (Mohanty et al. 1994), significant heating and cooling are observed...
over the Arabian Sea and Bay of Bengal as it can be inferred from seasonal variations in surface (SW – LHF) (Figs. 3d and 4d) and SST (Figs. 3e and 4e).

**b. Interannual variability**

Figure 5 shows the time–latitude variation of the previous fields through the Arabian Sea after removing the annual cycle. Anomalies were computed by subtracting the long-term monthly climatology from each month and for each field. Positive anomalies of precipitation (Fig. 5a) are observed throughout the Arabian Sea during the summer of 1988. Indeed, from the longer time series of precipitation available to us, we have determined that the summer monsoons of 1988, 1989, and 1990 have the first, second, and fourth highest annual precipitation averages, respectively, out of the eight available years of data (not shown). Also of interest is the fact that the summer monsoons of 1987 and 1988 are considered drought and flood years, respectively, and have been investigated in detail in other studies (Krishnamurti et al. 1989; Krishnamurti et al. 1990).

Figure 5b shows the time–latitude variation of SW anomalies. Positive anomalies of up to 20 W m\(^{-2}\) in SW over the equator are observed prior to the flood summer season of 1988, consistent with the negative anomalies in precipitation over those regions. During the summer monsoon of 1988 there are strong (>10 W m\(^{-2}\)) negative anomalies of SW across the entire Arabian Sea and southern Indian Ocean. The latitudinal variations of LHF anomalies over the southern Indian Ocean (Fig. 5c) show positive anomalies of about 25–50 W m\(^{-2}\) during the flood summer season of 1988. Figure 5d shows (SW – LHF) anomalies as a function of time and latitude. Negative anomalies are observed over the Arabian Sea during the flood summer season of 1988. This predominance of LHF over net SW is consistent with previous studies that suggest that during flood years, there is cooling trend in the Arabian Sea (Mohanty et al. 1994). Significant positive SST anomalies (Fig. 5e) are seen during 1987 and 1991 over most of the Arabian Sea. The results shown above indicate that satellite-derived surface heat fluxes are helpful to
describe the large-scale seasonal and interannual variability over oceanic regions.

5. Air–sea interaction processes

In this section, we study in more detail the relationships between precipitation, surface heat fluxes, and SST over the Indian Ocean during 1988–90. We first examine the pointwise temporal correlations between pairs of fields. These correlations allow us to assess the processes at work over seasonal timescales. We have estimated the number of degrees of freedom to be approximately 20 in these three years of data, and therefore correlations larger than (smaller than) 0.4 (−0.4) are significant at 95% significance level. Figure 6a shows the correlation between time series of precipitation and SW. Over most of the northern Indian Ocean, significant negative correlations are observed, indicating that an increase (decrease) in precipitation is correlated with a decrease (increase) in SW. This is not unexpected for the tropical regions, where precipitation is usually associated with areas of deep convection and extended cirrus anvils (tropical cloud clusters), as discussed earlier. Regions of positive correlation exist in the Pacific Ocean north of 20°N and along the southeastern African coast. These might be explained by the cloud types encountered in these regions, which are less tropical (vertically extending and associated with precipitation) and more stratiform. The relationship between precipitation and LHF is shown in Fig. 6b. Over most of the central and northern Indian Ocean, where precipitation is climatologically intense, correlations are positive although small. This indicates that, over monthly timescales, tropical precipitation is weakly associated with local evaporation, and moisture convergence is the dominant source for precipitation. In addition, intraseasonal variations are intense in the equatorial Indian Ocean and other studies indicate that the eastward propagation of convective anomalies are followed by an increase in LHF due to westerly wind bursts (Jones et al. 1998). Areas of negative correlation are found south of 10°S and inspection of individual time series (not shown) indicates that the negative correlations arise primarily from the seasonal cycle. Precipitation in the southern Indian Ocean is largest during austral summer, whereas latent heat flux is largest during austral winter. Fur-
thermore, precipitation in the southern Indian Ocean results mostly from moisture advection and vertical lifting, which is more typical of subtropical regions.

To evaluate the role of the net surface heat flux on the evolution of SST, we have computed the correlation between (SW – LHF) and the rate of change of SST \(\frac{d}{dt}(\text{SST})\) (Fig. 6c). Positive correlations are observed over all of the Indian Ocean, suggesting that the mixed layer evolves following a rather standard pattern, whereby local effects are dominant and the processes are mostly one-dimensional. In contrast, correlations are small over the equatorial Indian Ocean indicating that dynamical oceanic processes are at play. In addition, near the Somali coast, the absence of significant correlations indicates that SST changes are strongly affected by ocean dynamics and to a lesser extent by surface heat fluxes. The coast of Somalia is characterized by coastal upwelling that forms at the onset of the southwest monsoon. This period has been shown to be characterized by one of the largest changes in surface heat flux that exists over the tropical regions (Gautier et al. 1988) from strongly positive (dominated by solar irradiance) before the onset to strongly negative (dominated by LHF). Finally, the relationships between SST and precipitation are shown in Fig. 6d. Areas of positive correlation exist over the southern Indian Ocean, parts of the Arabian Sea, the Bay of Bengal, and South China Sea, suggesting that, as SST increases, precipitation will increase. Over most of the equatorial Indian Ocean, where precipitation is most intense, only a small region of negative correlations is observed, indicating that an increase in SST is associated with a decrease of precipitation, which seems to be related to the threshold SST limit of 28.5°C discussed next.

Much attention has been paid to the relationship between tropical convection and SST over the last few years to clarify, in particular, the proposed super greenhouse effect introduced by Ramanathan and Collins (1992), but mostly to help refine general circulation model parameterizations of deep convection. Waliser et al. (1993) and Waliser and Graham (1993) have shown, for instance, that different relationships exist depending on the SST regime. Below 28.5°C, there is a positive correlation between SST and deep convection, whereas...
above that threshold the correlation is small to negative, suggesting that a feedback mechanism exists in the ocean–atmosphere system to limit SST. To gain further insight on these mechanisms, Fig. 7a shows the distribution of precipitation intensity as a function of SST and LHF for the years 1988–93 and all available data in the Indian Ocean, while Fig. 7b shows the histogram of SST and LHF. Figure 7c shows the average monthly mean precipitation and standard deviation as a function of LHF (solid line) and the corresponding histogram of the number of observations (dashed line). Similarly, Fig. 7d shows the average monthly mean precipitation and standard deviation as a function of SST (solid line) and the number of observations (dashed line). Consistent with previous studies, precipitation increases with SST up to about 28.5°–29°C and then decreases sharply. In addition, precipitation is more frequent, on average, with low values of LHF (100–150 W m⁻²). In a recent study, Zhang et al. (1995) investigated the relationship between precipitation and surface evaporation over short and long timescales over the tropical Pacific Ocean. They point out that on timescales of several days, convection is associated with high surface evaporation due to increased surface wind speeds and surface humidity deficit. In contrast, on timescales of months and longer, precipitation is associated with low surface evaporation, which arises from the dominance of low surface wind speeds over surface humidity deficit regions. The proposed mechanism is that at high SST, tropical convection is intense and is associated with increased low-level convergence, and therefore decreased surface wind speeds and surface evaporation. Such mechanism has also been noted to occur on timescales related to the Madden–Julian Oscillation (Jones and Weare 1996).

The dependence of LHF on surface specific humidity deficit (Qₛ − Qₐ) is illustrated in Fig. 8a, which shows the average monthly mean LHF and standard deviation as a function of (Qₛ − Qₐ) (solid line) and the number of observations (dashed line). Similarly, the dependence of LHF on surface wind speed is shown in Fig. 8b. As expected, LHF increases with (Qₛ − Qₐ) and surface wind speed. However, on average, LHF is more frequently observed with (Qₛ − Qₐ) on the order of 5–7 g kg⁻¹, whereas surface wind speeds are in the range of 4–8 m s⁻¹. The variations of SST as a function of SW and LHF are observed in Figs. 9a and b, respectively.
On average, SST shows a large increase with SW from about 100 to 220 W m\(^{-2}\), and then shows a slight decrease from 220 to about 300 W m\(^{-2}\). In contrast, SST shows a smoother dependence with LHF, increasing with LHF from 20 to about 90 W m\(^{-2}\) and slowly decreases with increasing LHF. Although these results do not show evidence in favor or against the thermostat hypothesis (Ramanathan and Collins 1992), they do suggest that SST may be more sensitive to SW variations than to LHF variations.

6. Surface heat flux

Another way to look at air–sea interactions is to compute the net surface heat flux. The spatial and temporal variability of the surface heat flux indicates where and over what timescale the ocean is heated (or cooled) by the atmosphere. Historically, the only available surface heat flux climatologies have been derived from ship observations. Based on simple (bulk) parameterizations to derive the four terms composing the heat flux (the solar radiation flux, the longwave radiation flux, the latent heat flux, and the sensible heat flux), these ship-based climatologies generally lack in space and time sampling. In particular, large areas of the Southern Hemisphere are seldom monitored by ships. As an illustration of this deficiency, one of the most comprehensive databases available for air–sea interactions studies, the Comprehensive Ocean–Atmosphere Data Set (Woodruff et al. 1987) has very few observations on an average month over most of the Indian Ocean. Figure 10 shows the highest (air temperature) and least (air mixing ratio) sampled parameters used to determine the latent heat flux and represents the percentage of time a particular grid cell had greater than 20 samples month\(^{-1}\) over a 14-yr period (1980–93). Clearly, only places along the well-traveled ship lanes consistently have 20 or more observations per month, whereas the sampling is rather poor over the western, eastern, and southern Indian Ocean. For the surface air mixing ratio the situation is even more critical with over 60% of grid points in the Indian Ocean never meeting this criteria of 20 samples month\(^{-1}\) (black regions in Fig. 10b).

While until this point of our discussion, it has not been necessary to address the absolute accuracy of our results, this becomes essential when using the surface
heat flux to compare with other datasets. Uncertainty estimates of climatological products are always difficult to perform because of the lack of standards to which to refer. Ship-based climatologies have been the most intensely scrutinized because of their availability, but even the most thorough studies (e.g., Glecker and Weare 1997; Large and Doney 1996) are limited to evaluating the impact of uncertainties on the input terms to the parameterizations. Neither the quality of the parameterizations applied nor the impact of the uneven spatial and temporal distribution of ship observations have really been fully addressed. Climatologies based on these limited ship datasets nevertheless form the basis of our present knowledge of the ocean–atmosphere heat exchanges. If the poor sampling leads to a bias in some regions, such as the southern Indian Ocean, this may mean that our understanding of how the heat is redistributed by the ocean in this region of the world is partly flawed.

The poor spatial and temporal coverage of ship observations can be overcome with the more evenly distributed satellite observations. This may arguably be at the expense of the measurement accuracy. When satellite-derived fluxes are compared with ship-based fluxes using the same parameterizations, satellite fluxes show small discrepancies (~30 W m⁻² for the LHF, e.g., Jourdan and Gautier 1994; 10–20 W m⁻² for shortwave (Bishop and Rossow 1991)). However, when similar comparisons are performed in regions poorly sampled by ships, the results are much worse, suggesting that the ship-based climatologies in these regions are strongly influenced by the spatial and temporal interpolations performed with insufficient knowledge of the local spatial-temporal variability. Whereas the satellite-derived fluxes may have their own weaknesses, they nevertheless contain little spatial and temporal bias and offer a synoptic view of the atmosphere–ocean interface conditions over these large but still poorly observed regions.

a. The difference \( SW - LHF \)

Based on our satellite database, we can compute only the difference of the largest terms: the solar radiation flux and the latent heat flux (\( SW - LHF \)). Maps of this difference (\( SW - LHF \)) obtained from our satellite datasets have been compared with Oberhuber (1988, hereafter O88) and Hastenrath and Lamb (1979, hereafter HL79) climatologies in Figs. 11, 12, and 13, but from a different perspective.
Figure 10 shows the percentage of time each grid cell has greater than 20 samples month$^{-1}$ over the 14-yr period 1980–93: (a) air temperature and (b) air-mixing ratio.

Figure 11 shows that the mean difference ($SW - LHF$) is smaller for the satellite estimate than either of the two climatology estimates. The difference is greatest in the northernmost Indian Ocean and in the southern Indian Ocean around 20°–25°S. Some of these differences can be easily explained by looking at each individual term, but it is much more difficult to determine which of the satellite or ship-derived dataset is correct because of the differences in spatial and temporal sampling. The lower value south of 15°S reflects higher satellite LHF estimates in the south central Indian Ocean. Overall the satellite ($SW - LHF$) map agrees well with both O88 and HL79 maps in basic features. It, however, tends to disagree as the result of enhancement of both extremes. It can easily be argued that the difference in extremes results from the fact that individual years are expected to have larger extreme values of geophysical parameters than long-term averages.

Looking at the seasonal evolution of ($SW - LHF$), Fig. 12, again shows agreement between satellite estimate and those of O88 and HL79 on the main features of ($SW - LHF$) variability. All three datasets show LHF dominating SW in the southern Indian Ocean during May–July with the zero contour ($LHF = SW$) extending up to ~15°S.

Another way to evaluate ($SW - LHF$) is to compute the total energy exchanged (1°$^{-1}$ lat band) by multiplying the mean zonal ($SW - LHF$) by the area of that latitude band. The area considered extends from 25°N to 35°S and from 25° to 120°E long, excluding the South China Sea, the Persian Gulf, and the Red Sea [note the difference from the published curves in Hastenrath (1980), which included the China Sea]. Figure 13, which presents a comparison of the total energy computed from different datasets shows (i) a smaller value of energy exchanged in the northern Indian Ocean than that computed from ship observations, (ii) good agreement in the equatorial Indian Ocean, and (iii) a much smaller satellite estimated value in the southern Indian Ocean. Considering the minimal ship sampling in the southern Indian Ocean, but also the expected LHF overestimation from the satellite data in the central part of this region,
FIG. 12. Monthly mean SW $-\text{LHF}$ as a function of latitude for the same sources of data shown in Fig. 11: (a) satellite, (b) O88, and (c) HL79. Contours are 50 W m$^{-2}$. Dark shading indicates negative values, and light shading values greater than 100 W m$^{-2}$. Thick black line denotes zero contour.

FIG. 13. Total SW $-\text{LHF}$ (1°$^{-1}$ of latitude) of (10$^{14}$ W) for three datasets: satellite (solid), O88 (dotted), and HL79 (dashed) with positive values indicating a gain of energy by the ocean.

it is difficult to conclude which one provides the best estimation. The important aspect to remember, however, is that this difference will induce a huge discrepancy when computing the meridional oceanic heat transport from the divergence of the net surface heat flux.

b. The net surface heat flux

The net surface heat flux is however unlike the difference (SW $-\text{LHF}$) just discussed. It is the sum of four terms. At present, there is no available method to derive the remaining two terms, LW and $S_e$, from satellite observations. One way to derive a net surface heat flux that has a better spatio-temporal coverage in the Southern Hemisphere than ship-based climatologies and is optimally based on satellite computations is to estimate the LW flux and the sensible heat flux from ship data only. To that effect, it is often argued that this is reasonable, since these two terms are individually small compared to the other two terms (the solar radiation flux SW and the latent heat flux LHF). Figure 14, which presents the contribution of the other two terms composing the heat budget ($S_e - \text{LW}$) to the total energy exchanged (1°$^{-1}$ band), shows otherwise. Although both climatologies are derived from ship observations, differences between them exist and are probably due to differences in time period, data quality control, and, most important, to different physical parameterizations. The two most interesting aspects of this figure are (i) the relatively large difference between ($S_e + \text{LW}$) in HL79 and O88 and (ii) the increase of the ($S_e + \text{LW}$) component southward of the equator for both datasets. The mean difference of the combined two terms ($\sim$11 W m$^{-2}$) results in a difference [between the two estimations of ($S_e + \text{LW}$)] as high as 0.1 $\times$ 10$^{14}$ W (1°$^{-1}$ lat). The ship-based ($S_e + \text{LW}$) products compared here disagree by a significant amount, and it is difficult to
conclude the superiority of either product. While they disagree in magnitude, they both suggest a similar increase of the \((S_e + LW)\) component southward of the equator, likely as a result of increased sensible heat flux due to the intense winds observed over the southern Indian Ocean. When comparing Figs. 13 and 14 it is clear that the \((SW - LHF)\) and \((S_e + LW)\) components have comparable magnitude. The implication of this result is that, contrary to what is often postulated, it is not possible to neglect the \((S_e + LW)\) term when computing the net heat budget.

Finally, to evaluate the range of the present estimates of the net heat flux over the Indian Ocean (\(SW - LHF - LW - S_e\)), we have combined the satellite (\(SW - LHF\)) with the two climatological \((S_e + LW)\) datasets. Figure 15 shows the zonal total heat budget (\(SW - LHF - LW - S_e\)). The dotted and dashed lines represent the zonal average of surface heat fluxes as estimated by O88 and HL79, respectively. The solid and dot–dashed lines represent the zonal average of surface heat fluxes using satellite (\(SW - LHF\)) estimates and \((LW + S_e)\) from O88 and HL79, respectively. A good agreement is found between 15°S and 10°N. In contrast, the satellite estimates tend to be lower than the climatology in the northern and southern Indian Ocean. The above results show that, except over the southern Indian Ocean where differences are large, the satellite (\(SW - LHF\)) estimates are situated within the envelop of similar estimations made from in situ data.

7. Summary and conclusions

The objective of this study was to show that satellite data can make a significant contribution in building an observational database for the Indian monsoon and the associated processes of air–sea interaction in the Indian Ocean. Currently, the satellite data record is only beginning to reach the decadal timescale, whereas ship observations are available for over half a century. The main strength of satellite data is their high spatial and temporal sampling, particularly over the southern Indian Ocean where ship observations are minimal. Over the Indian Ocean the average sampling for parameters from ships is on the order of 8 per month per 2° grid cell. On the same space/time scale, the sampling of SSM/I sensor with a 25-km footprint is on the order 2000! This sample number can be even higher for sensors with higher resolution such as the AVHRR used to determine SST.

Our analysis of the net surface heat flux using satellite estimates indicates features rather similar to those already known from ship observations in the northern and equatorial Indian Ocean, but significant differences in the southern Indian Ocean. In this part of the world our knowledge of air–sea interactions is minimal. Satellite data suggest that the ocean acquires much less heat per degree of latitude than ship data suggest. This difference reaches \(0.22 \times 10^{14}\) W around 25°S. This discrepancy has serious implications if we compute the meridional oceanic heat transport from the divergence of the net surface heat flux. Indeed, when this is done with the combined satellite and ship data discussed in the previous section, the direction and magnitude of the heat transport is con-
sistent with our present knowledge in the northern and equatorial Indian Ocean, but large differences are found in the southern Indian Ocean.

We will only be able to answer questions relative to air–sea interactions in the southern Indian Ocean when we can improve the satellite-based estimates in this remote and poorly traveled region. Field experiments will be necessary to validate the satellite algorithms and explore the physical processes in that region. Satellite data have already afforded us a preliminary look at the variability of the dominant air–sea interaction processes, but much more work is needed to acquire confidence in the new datasets that will be collected by the forthcoming national or international multisensor orbiting platforms such as the Earth Observing System.

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