Comparison between Global Latent Heat Flux Computed from Multisensor (SSM/I and AVHRR) and from In Situ Data

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ABSTRACT

The accurate estimate of the latent heat flux (LHF) is important to understand better the coupling between the atmosphere and the ocean and their respective circulation. In the near future, the availability of satellite-derived datasets over long periods will allow us to perform studies that, so far, have only been possible with historic in situ datasets. Therefore, a natural issue to explore is how the computation derived from both data types agree on LHF estimates. Comprehensive Ocean–Atmosphere Data Set (COADS) on one hand and satellite-derived parameters on the other hand are input to a similarity theory-based model and treated in completely equivalent ways to compute global latent heat flux. In order to compute latent heat flux exclusively from satellite measurements, an empirical relationship ($Q-W$ relationship) is used to compute the air mixing ratio from Special Sensor Microwave Imager precipitable water $W$ and a new one is derived to compute the air temperature also from retrieved $W$ ($T-W$ relationship). First analyses indicate that in situ and satellite LHF computations compare within 40%, but systematic errors increase the differences up to 100% in some regions. By investigating more closely the origin of the discrepancies, the spatial sampling of ship reports has been found to be an important source of error in the observed differences. When the number of in situ data records increases (more than 20 per month), the agreement is about 50 W m$^{-2}$ rms (40 W m$^{-2}$ rms for multiyear averages). Limitations of both empirical relationships and $W$ retrieval errors strongly affect the LHF computation. Systematic LHF overestimation occurs in strong subsidence regions and LHF underestimation occurs within surface convergence zones and over oceanic upwelling areas. The analysis of time series of the different parameters in these regions confirms that systematic LHF discrepancies are negatively correlated with the differences between COADS and satellite-derived values of the air mixing ratio and air temperature. To reduce the systematic differences in satellite-derived LHF, a preliminary ship–satellite blending procedure has been developed for the air mixing ratio and air temperature. The $T-W$ relationship is not used any more and the air temperature is computed by adding the 3-yr-averaged COADS air-sea temperature difference to the satellite SST maps. The method to get the air mixing ratio is based on a weighted combination of COADS and satellite values according to the number of COADS observations available. After the blending process is applied, large improvements are observed in the Northern Hemisphere where both datasets are complementary. At midlatitudes, the blending procedure does not modify LHF values since satellite and COADS air mixing ratio do not differ by more than the expected satellite uncertainty (1 g kg$^{-1}$). In the eastern and northern part of the basin, where the air mixing ratio difference is large and ship observations are numerous, blended LHF values are efficiently corrected toward in situ estimates compensating for the limitations of $Q-W$ relationship. In the Southern Hemisphere, the number of in situ observations rarely exceeds four values per month, and without “ground truth,” more confidence is given to the satellite-derived values. Statistically, the rms difference drops to 28 W m$^{-2}$ when 20 ship observations are available, which is likely a good approximation of the lowest bound of the blended LHF uncertainty compared with optimal in situ estimates. However, along the eastern boundaries in the southern oceans, local differences are expected to be much larger.

1. Introduction

Latent heat flux (LHF) represents one of two dominant components in energy exchanges between the ocean and the atmosphere. It mostly balances energy from shortwave solar flux, the other important component in air–sea heat exchanges. While shortwave flux is associated with the direct warming process of the earth’s surface, latent heat exchange first occurs as a transfer of water vapor from ocean to atmosphere, also called evaporation. Then, by condensing, water vapor releases latent heat in the atmosphere and provides the energy to feed atmospheric circulation, particularly in tropical regions.

Most of the studies carried out to estimate the evaporation field on a global scale have used only historical ship reports (Bunker 1976, 1988; Hastenrath and Lamb 1977, 1979; Hsiung 1986). Depending on which date these studies were performed, they rely on either the original Tape Deck Family-11 dataset (also called TD-1100), the updated version, or the Comprehensive

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Ocean–Atmosphere Data Set (COADS). They differ by regions, time periods covered by the data, and the timescale of variability studied by the authors. For instance, Bunker has built a climatic atlas of surface energy fluxes with the TD-1100 dataset for the North (Bunker 1976) and South Atlantic Ocean (Bunker 1988). Using the same dataset, Hastenrath and Lamb computed the components of the heat budget for the tropical Atlantic (Hastenrath and Lamb 1977) and the Indian Oceans (Hastenrath and Lamb 1979). Hsiung (1986) preferred to use an extended version of the TD-1100 file to compute global net surface energy fluxes. The most recent studies using in situ data (Oberhuber 1988; Cayan 1992) relied on COADS. They provided an assessment of the accuracy of the LHF as well as a description of their long-term variability on a global scale.

These studies have improved our knowledge of the spatial variations of the evaporation field but some doubts still remain about the adequacy of ship sampling and about the way the in situ measurements were performed. For instance, part of the southern global ocean is never sampled because it is far from shipping lanes. Also ships avoid storm systems; thus extreme situations are rarely observed, resulting in too weak gradients of atmospheric quantities. Adequate estimation of monthly mean turbulent flux, such as evaporation, requires more than 20 samples per month (e.g., Luther and Harrison 1984; Taylor 1984), which are available only north of 20°N and along coasts and shipping lanes in the Southern Hemisphere (see Fig. 9b).

Besides the sampling problem, the quality of ship reports has been a main concern. Instruments on some volunteer ships were found to be poorly maintained and incorrectly operated. Differences in measuring methods also caused systematic errors. Sea surface temperature may be measured from a bucket or from engine intakes (at various depths and various proximities to the ship's engine). Ship structure usually distorts the airflow of the immediate environment and affects wind speed measurements acquired by anemometers. When wind estimates are made by visual estimate of the sea state, Isemer and Hasse (1991) showed that the relation used to convert them into physical quantities introduces systematic underestimation of wind speed. The corresponding error in the monthly mean evaporation reaches up to 50 W m⁻², between 0° and 40°N in the Atlantic Ocean (Isemer and Hasse 1987). This error mainly concerns the pre–World War II marine reports and does not strongly affect the studies performed by Hsiung (1986) or Cayan (1992). The other results from long-term computations on the evaporation field, however, are expected to contain biases because of this problem.

An alternative to using ship measurements is the use of satellite data. But in this case the air mixing ratio and air temperature needed to compute the LHF are not directly accessible by satellite measurements. Liu (1984) suggested an empirical relationship to compute the air mixing ratio from satellite measurements of integrated water vapor content. He applied his method to study the variability of moisture and latent heat flux in the tropical Pacific Ocean (Liu 1988) using retrieved precipitable water, sea surface temperature, and wind speed from Nimbus-7 Scanning Multichannel Microwave Radiometer (SMMR). Eymard et al. (1989) computed two months of satellite-derived LHF with SMMR data in the Pacific and in the Atlantic with the same method and compared the results with those derived from the analysis of the European Centre for Medium-Range Weather Forecasts (ECMWF) model. They concluded that the method is valid overall but pointed out important local differences in the Atlantic Ocean that they credited to SMMR retrieval problems and a local failure of the relationship. Subsequently, the Special Sensor Microwave/Imager (SSM/I) sensor has been providing similar data and opportunity to update these results with a longer dataset.

The objective of this paper is to quantify to what extent in situ and satellite-based estimation of global LHF agree, and, when large discrepancies are found, to investigate the source of these discrepancies. To accomplish this objective, we computed the LHF globally, using Liu's parameterization (Liu et al. 1979) both on a set of SSM/I-derived and on a set of COADS-observed parameters over the same period and compared the results. This approach was chosen to illustrate the influence of the dataset on LHF retrievals and because Liu's parameterization has been recognized as being, potentially, the best one, particularly for tropical regions under low wind speed conditions (Godfrey and Beljaars 1991). A similar analysis using SSM/I and COADS data was conducted recently by Esbensen et al. (1993). The present analysis was made independently and prior to the publication of the results by Esbensen et al., and both the differences in the approach and the resulting general agreement of the conclusions are presented here. Our study can be considered an extension of the results of Esbensen et al. (1993) since it is based on the complete SSM/I F-08 dataset (July 1987–March 1991) and involves comparisons of long-term temporal series and multyear averages of the fluxes. While their study provides an analysis in terms of the atmospheric physics of the systematic differences observed between both flux computations, we propose a blended approach to build a dataset combining the advantages of both in situ and satellite data.

The datasets are presented in detail in section 2. Section 3 introduces the method used to compute the LHF and compares the input parameters from the COADS and SSM/I datasets. In section 4, monthly averaged evaporation maps obtained from both computations are presented and compared. In section 5, differences are discussed with respect to the problems that each
type of data is subject to, and possible sources for the discrepancies are reviewed. In an attempt to compensate for these difficulties, we propose a ship–satellite blending method and perform the analysis on two input parameters in section 6. Statistics on the blended LHF product are computed, and the improvements are discussed. Finally, our conclusions and recommendations are presented in section 7.

2. Datasets

We have used two different datasets to estimate the LHF. One is composed of in situ measurements only, while the other is retrieved exclusively from satellite measurements.

a. COADS marine surface data

COADS is the result of a project initiated to collect available historical ocean–atmosphere marine reports and merge them into a unique database. Marine reports, including local weather observations and records of various oceanic and atmospheric quantities near the sea surface and within the atmospheric boundary layer, have been regularly collected by ships over the oceans since 1854. In the 1960s, it was decided to convert all the independent marine report card decks available at that time into one standard format. This became the Tape Deck Family-11 dataset, now called TD-1100, that was, until recently, the database of choice to perform global climate studies. In the early 1970s, the marine data were collected and processed independently by different countries as part of the Historical Sea Surface Temperature (HSST) Data Project. Some processed data were older and not in the original TD-1100 database, but most of them were already included. Finally in the mid-1980s, several other datasets—buoy data or more recent ship data—became available. Previous historical datasets were then merged with these new marine data to create the COADS dataset (Slutz et al. 1985; Woodruff et al. 1987).

COADS provides a complete range of products. These are the outputs, at different stages, of the quality-controlled processing applied to each individual marine report input into the database. The Monthly Summaries Trimmed Grouped (MSTG) product stays at the end of this processing flow. The first step of primary processing is to convert all the data into a common format in order to sort and to eliminate duplicates. Each report is also checked for internal consistency and extreme values. The data are summarized in monthly and decadal scales on $2^\circ \times 2^\circ$ boxes, and statistics are computed for the unflagged values from the initial test. These statistics are used to define the limits used to “trim” the variables in a second statistical screen. In this test, values for a given box that fall outside a 3.5 standard deviation interval centered on the long-term median value are rejected. The monthly average of the selected values is then computed in each box and stored in the Monthly Summaries Trimmed (MST) files. The secondary process puts the MST files in a more convenient format, grouping the related variables into the same file. These files constitute the MSTG product.

We have acquired the MSTG files for the SSM/I–F08 period and extracted air temperature, air mixing ratio, sea surface temperature (SST), and wind speed in order to compute the LHF. The range of the values is, respectively, $-21^\circ$–$35^\circ$, $0.6$–$27.7$ g kg$^{-1}$, $-1.9^\circ$–$34.0^\circ$C, and $0$–$22.6$ m s$^{-1}$ for the four parameters. It must be noted that the parameters are treated independently and that, consequently, the average value of each parameter for a given box is not computed with the same number of samples. Surface measurements are routinely acquired and more numerous than near-surface measurements. This problem can cause systematic errors for air–sea difference quantities that are then calculated from data that are not all collocated in time. In the present study, air–sea humidity differences may be of concern in regions of strong and permanent sea surface temperature gradients.

b. Satellite-derived data

1) Wind speed and precipitable water

The wind speed and precipitable water fields are part of the global SSM/I ocean monthly products (Wentz 1992a). They were obtained by averaging individual values into monthly $1^\circ \times 1^\circ$ bins. Before that, a model (Wentz 1983, 1992b) was used to retrieve these geophysical quantities from brightness temperatures measured at each of the four SSM/I frequencies. The temporal coverage extends from July 1987 to December 1991, with an interruption between 2 December 1987 and 12 January 1988 during which time the SSM/I sensor was turned off. The month of December 1987 is therefore missing. The precipitable water takes a value varying from 0 to 7.5 g cm$^{-2}$ with an expected rms error less than 0.2 g cm$^{-2}$ (F. J. Wentz 1993, personal communication). The possible range of wind speed is 0–30 m s$^{-1}$, with an rms error of 1 m s$^{-1}$ (F. J. Wentz 1993, personal communication). An illustration of the $U$ and $W$ fields is presented in Fig. 1 [panels (a) and (b)]. These maps represent 3-yr averages of monthly mean SSM/I products for the month of January.

2) Sea surface temperature

The sea surface temperature fields are part of the multichannel sea surface temperature (MCSSST) data product derived from the AVHRR (Smith 1992). It consists of weekly files over the global ocean with a spatial resolution of about $0.175^\circ$ square. For each grid
FIG. 1. Three-year-averaged monthly mean maps of (a) precipitable water $W$, (b) wind speed $U$, and (c) sea surface temperature SST for January.

point, the average of AVHRR measurements is computed, and the number of observations is stored. Open areas are filled by interpolating the valid observations surrounding such areas with an iterative Laplacian relaxation technique. In this case, the number of observations is set equal to 1. We acquired the data between July 1987 and March 1991 for both the surface temperature values and the number of measurements.

In order to have consistent spatial and temporal resolutions for all the satellite variables, we computed
monthly averages by combining four or five weekly fields encompassing the SSM/I month period. The first weekly field is chosen so that its first day is the closest in time to the first day of the month. Therefore, the maximum shift between the SSM/I monthly mean and the SST averaging period is 3 days. The variability of the SST over these few days is negligible compared with the monthly mean signal, and this time lag does not introduce any significant error in the computation of the LHF. We then spatially averaged the SST fields using a linear interpolation scheme taking the 12 closest observation points to the interpolation grid point. The process was applied twice: the first time degraded the resolution to 0.5°, and the second degraded the resolution, again, to 1°. In this way, all the grid points available at the original resolution within a 1° × 1° cell were used to compute the monthly mean value. As with wind speed and precipitable water, the 3-yr-averaged map for January is shown in Fig. 1c. The SST values range from 0.5° to 34.2°C. The claimed error level in the satellite-derived SST is 0.6°C (Strong and McClain 1984).

3. Latent heat flux computation

a. Exchange fluxes and similarity theory

The most common way to compute the momentum and energy fluxes at the ocean–atmosphere interface is to use the aerodynamic bulk formulas. They link momentum flux τ (also called wind stress), water vapor flux E, and sensible heat flux H between the ocean and the atmosphere to the quantities U, Q, and T (wind speed, air mixing ratio, and air temperature) through the transfer coefficients C_D, C_E, and C_H:

\[ \tau = \rho C_D (U_s - U_a)^2 \]  
\[ E = \rho C_E (U_s - U_a) (Q_s - Q_a) \]  
\[ H = \rho C_H (U_s - U_a) (T_s - T_a) \] (3)

The subscripts (s and a) denote that the quantities are taken at the ocean–atmosphere interface or within the atmospheric layer above it, respectively. The product of \( E \) with the latent heat of vaporization (2.5 × 10^6 J kg\(^{-1}\)) gives the LHF. The main problem with this parameterization is the choice of values for the coefficients \( C_D, C_E, \) and \( C_H, \) which vary with the wind speed and the stability of the atmosphere (Large and Pond 1981, 1982; Smith 1988).

We have adopted another approach based on the similarity theory that implicitly takes into account boundary layer stability. This is equivalent to using the previous formulation with transfer coefficients that now depend on surface features and meteorological quantities. Our goal here is not to give an exhaustive description of this method but rather to illustrate its use. One can find a more detailed theoretical description and discussion in Businger (1975) and Liu et al. (1979). The similarity theory relies on the assumption that the functional behavior of the profiles of \( U, Q, \) and \( T \) close to the surface should have a common form since they are each affected by the same forces at the same time. Knowledge about the relationship between the stability of the atmosphere, surface roughness length, and gradient for wind speed provides the constraint to derive an equation predicting the behavior of the wind speed profile within the boundary layer:

\[ \frac{U(z) - U_s}{U^*} = 2.5 \left[ \ln \left( \frac{z}{z_0} \right) - Y_U(I_{mo}) \right] \] (4)

By similarity, equations can also be derived for \( Q \) and \( T \):

\[ \frac{T(z) - T_s}{T^*} = 2.2 \left[ \ln \left( \frac{z}{z_T} \right) - Y_T(I_{mo}) \right] \] (5)

\[ \frac{Q(z) - Q_s}{Q^*} = 2.2 \left[ \ln \left( \frac{z}{z_Q} \right) - Y_Q(I_{mo}) \right] \] (6)

Variables \( U^*, T^*, \) and \( Q^* \) are, respectively, the friction velocity, temperature scale, and humidity scale, which can all be expressed as a function of \( \tau, E, \) and \( H. \) The altitude is \( z. \) The stability functions \( Y_{U,T,Q} \) express the dependence of the profiles on the stability of the atmosphere through the Monin–Obukhov stability parameter \( I_{mo}. \) This parameter takes negative values in case of instability (e.g., convective processes in the boundary layer), positive values in case of stability (e.g., stratified boundary layer), and is equal to 0 in the neutral case. In this last case, the stability functions cancel, and (4)–(6) yield the classical logarithmic variation of the parameters with the altitude in the boundary layer.

Parameters \( z_0, z_T, \) and \( z_Q \) are, respectively, the roughness lengths for velocity, temperature, and humidity. They describe the sea surface as it is seen by turbulent phenomena and define the lower boundary of the region where the similarity theory is valid. Their values are functions of \( \tau \) and the fluid properties through the Reynolds number and the viscosity of the fluid. Very close to the air–sea interface, the molecular constraints become more important. They change the temperature and velocity distributions and modify the lower boundary values \( z_0, z_T, \) and \( z_Q. \) Liu et al. (1979) developed a model including these constraints in air–sea exchanges parameterization.

Because of the assumption of the diabatic profiles [(4)–(6)], the validity of the model is restricted to wind speed greater than about 0.5 m s\(^{-1}\) so that a logarithmic layer exists between the molecular layer and the region where stability effects are important. Below, Godfrey and Beljaars (1991) have shown that the model can still be valid by extrapolating the minimum flux estimates, always obtained at the lower limit of
validity, toward zero wind speed. In practical application, effective wind speed rarely lies below the threshold of validity, and we have used Liu’s original model in a slightly modified version that includes satellite-derived air temperature [see section 2b(2) below] and rejects LHF computation for wind speed smaller than 0.5 m s\(^{-1}\).

b. Computation method with satellite observations

Finding \(\tau, E,\) and \(H\) are obtained by solving the system of (4)–(6) in which \(U^*, T^*,\) and \(Q^*\) are the unknowns. The system is solved by iteration until the correct value of \(I_{\text{mo}}\), fitting the given vertical gradient of wind, temperature, and humidity between \(z_0\) and the altitude \(z\), has been found.

The inputs are \(U, T,\) and \(Q\) at the surface and at a given height, \(z = a\). At the surface, the temperature SST can be retrieved from satellite measurements. The wind speed \(U_a\) is equal to 0, and the air mixing ratio \(Q_a\) can be computed from the SST, assuming the air is saturated. Within the boundary layer, the wind speed \([U_a = U(a)]\) can be retrieved from satellite measurements, but the air temperature \([T_a = T(a)]\) and air mixing ratio \([Q_a = Q(a)]\) are unavailable. The determination of these two parameters, but particularly \(Q_a\), is at the heart of the satellite-based method to obtain LHF.

1) Satellite-derived air mixing ratio \(Q_a\)

Liu (1984) demonstrated that over periods longer than a few weeks mean precipitable water \(W\) is an adequate predictor of \(Q_a\). He proposed a polynomial relationship to compute \(Q_a\) as a function of \(W\), which he refined a few years later using a more extended dataset of radiosonde measurements (Liu 1986). This statistical relationship (hereafter \(Q-W\) relationship) has been evaluated over the global ocean by comparison with the radiosonde dataset from field experiments (Hsu and Blanchard 1989), with ship reports (Liu 1988) and with an atmospheric general circulation model (Liu et al. 1992). The results have demonstrated an overall accuracy of 1 g kg\(^{-1}\) rms of the relation but also pointed out limitations over some identified regions.

Figures 2a and 2b represent the 3-yr-averaged maps of the \(Q_a\) difference between the satellite-derived and COADS values \((Q_a^{\text{SSM/I}} - Q_a^{\text{COADS}})\) for January and July. A 3-yr average for each month is computed by averaging the monthly mean maps over the 3 years (1988–90) common to both datasets. Most of the values range within \(±1\) g kg\(^{-1}\), but larger negative and positive discrepancies are also observed.

Negative differences (SSM/I values smaller than COADS by 2 g kg\(^{-1}\) or more) are observed in winter, across the northern Pacific and Atlantic Oceans between 10° and 30°N. Also, in both oceans, the eastern part of the basins (off the coasts of California and west Africa) features the largest magnitude \((\Delta Q = -3\) g kg\(^{-1}\)). The Arabian Sea shows strong discrepancies in January. Similar patterns are found in the Southern Hemisphere, in July (austral winter) off the west coast of southern Africa, and in the southern Indian Ocean between 20° and 30°S. Differences in the southeastern Pacific are observed both in January and July, with a larger magnitude in July, however.

During summer, \(Q_a^{\text{SSM/I}}\) values exceed \(Q_a^{\text{COADS}}\) values by more than 2 g kg\(^{-1}\) in the northern ocean off Baja California and in the eastern equatorial Pacific and Atlantic Oceans. In the Pacific Ocean, the region extends southward along the coast of Peru. In the Southern Hemisphere, differences are observed in January along the west coast of southern Africa.

Liu et al. (1992) also found similar discrepancies between \(Q_a\) from SSM/I and ECMWF fields, as did Eymard et al. (1989) off the west coast of Africa by comparing SMMR and ECMWF fields of precipitable water. While some of the regions with positive differences were expected because of the limitations of the \(Q-W\) relation, the regions with a \(Q_a^{\text{SSM/I}}\) deficit did not appear with such a large magnitude in any previous comparison. Recently, Esbensen et al. (1993) brought this problem to light by performing a comparison between \(Q_a\) values from COADS and those deduced from SSM/I for one particular year. The agreement of present multyear averaged differences with their results demonstrates a recurrence of the problem.

2) Satellite-derived air temperature \(T_a\)

When the relative humidity is known, the Clausius–Clapeyron relation can be used to obtain the air temperature. Liu (1988) took a constant value of relative humidity equal to 80% for his study in the tropical regions. Esbensen et al. (1993) decided not to account for the atmospheric stability for the purposes of comparing in situ and satellite LHF estimates. In our case, since we want to include the stability dependence and extend the computation globally, we chose to deduce \(T_a\) from \(W\). To that end, we used a nonlinear regression scheme to fit an empirical function through radiosonde measurements of \(T_a\) and \(W\). Individual soundings have first been checked for quality leading to a set of 30 stations, globally distributed (Petty and Katsaros 1992). We removed four stations located in ice-covered regions so that the final dataset is as representative as possible of open ocean conditions in latitudes ranging from 55°S to 64°N. We then computed the monthly average of \(T_a\) measurements and \(W\) values to reduce the scatter in the data and the random error of the variation of height, whether it is at the lowest sounding level or at the level of ships. Information about ships shows that the average height of instrumentation is
around 20 m (Cardone et al. 1990), which is the height we assigned to $T_a$ in the LHF computation. Finally, a function with the shape

$$T_a = a_1\left(1 - \frac{a_2}{a_3 + W^2}\right)^{1/2}$$

was fitted through averaged values by adjusting the coefficients $a_1$, $a_2$, and $a_3$. Figure 3 shows the scatter plot of $T_a$ (K) versus $W$ (kg m$^{-2}$), and the best fit we obtained (hereinafter called $T$–$W$ relationship). The corresponding values of the coefficients are given in Table 1. The rms of the residual is 1.88 K.

As we did previously for $Q_a$, we mapped the 3-yr-averaged difference $T_{a \text{ SSM/I}} - T_{a \text{ COADS}}$ for January and July (Fig. 4). The overall agreement between the two estimates is ±2°C, but larger positive and negative discrepancies are found at the same locations and with the same sign as in the maps of $Q_a$ differences.

The similarity between the difference distribution was predictable since the same global statistical approach was applied to obtain both relationships. With typical values of $U = 7$ m s$^{-1}$, $Q_a = 13$ g kg$^{-1}$, $T_a = 18^\circ$C, and SST = 23°C, a typical mixing ratio difference $Q_a - Q_a$ is about 5 g kg$^{-1}$. Then, a difference of 1 g kg$^{-1}$ in $Q_a$ translates in a difference of approximately 30 W m$^{-2}$ in the LHF. All the other parameters being unchanged, a 2°C departure in $T_a$ translates into a 6 W m$^{-2}$ error. When both quantities are underestimated (overestimated) at the same time, the differences combine to yield an overestimation (underestimation) of the LHF.

In summary, the model's input parameters are wind speed, sea surface temperature, and precipitable water that can be obtained from satellite measurements. The wind speed at the interface is taken equal to 0, and the mixing ratio is computed from the sea surface tem-
temperature, assuming the air is saturated. Finally, the air mixing ratio and the air temperature are computed from precipitable water, using \( Q - W \) and \( T - W \) relationships. According to the intercomparison between COADS- and SSM/I-derived values of \( Q_a \) and \( T_a \) parameters, we expect the LHF computations to disagree in some regions. Our objective, however, still remains to compute first LHF exclusively with satellite data. In the next sections, we will discuss how \( Q_a \) and \( T_a \) differences influence the LHF estimates and how to correct for these differences.

4. COADS and SSM/I latent heat flux intercomparison

Forty-five monthly mean maps of LHF have been computed from July 1987 to March 1991 using the satellite-derived variables. These maps have an original resolution of 1° between 70°S and 70°N. We also derived maps over the same period and meridional extent with the COADS data at 2° resolution. The resolution of the satellite-derived maps is degraded afterward to match the COADS one.

A first assessment of the satellite-derived computation with respect to the COADS values is made by computing the differences between each pair of monthly LHF values available. The histogram of the distribution \( \text{LHF}_{\text{SSM/I}} - \text{LHF}_{\text{COADS}} \) is plotted in Fig. 5 along with the associated best Gaussian fit (solid line). The mean and standard deviations are \(-1.9 \pm 64.8 \text{ W m}^{-2} \) (55% rms difference), which suggests that the two computations strongly disagree.

A better understanding of the spatial distribution is given by looking at the 3-yr-averaged maps. The maps for January and July are presented in Figs. 6 and 7. In each figure, the upper panel (a) is obtained using sat-elite data, the middle panel (b) is obtained with COADS data, and the bottom one (c) is the averaged relative difference expressed as the percentage of the COADS LHF: \(( \text{LHF}_{\text{SSM/I}} - \text{LHF}_{\text{COADS}} ) / \text{LHF}_{\text{COADS}} \).

The spatial coverage differs strongly between satellite and in situ maps, especially in the Southern Hemisphere, and prevents any comparison between the two LHF estimates south of 40°S. The lack of data in the southeastern Pacific makes it difficult south of 20°S in this region. One also observes unsampled regions in the central Pacific Ocean, whose extent changes slightly with the seasons. It has to be noted that the problem is even more crucial when individual monthly mean maps are compared directly.

The qualitative agreement between the maps is good in the sense that similar structures are found at the same location and at the same time during the year. Quantitatively, the maps roughly divide into 1) regions where the computations compare within 40%, which corresponds to the random error level, and 2) regions with high positive or negative differences (100% and more) due to additional systematic errors in these regions.

The systematic positive LHF differences are mainly concentrated in high-evaporation regions during wintertime. In the Northern Hemisphere, in January (Fig. 6c), we observe four regions differing by more than 80% from the COADS estimates: the Pacific Ocean north of 40°N, the regions off the coast of California and west Africa, and the Arabian Sea. Similarly, in the Southern Hemisphere in July, along the west coast of southern Africa (Fig. 7c), the satellite-derived LHF has a magnitude about two and a half times larger than that of COADS LHF. Comparison is difficult in the southeastern Pacific, but the grid points available also show high positive differences around 90% in January and July. Other cases with differences around 60% of COADS estimates are found in the southern Indian Ocean, about 30°S in July.

Systematic negative differences (40%–80%) are located in low evaporation regions, between 10°S and 10°N in relation with ITCZ seasonal changes, and over oceanic upwelling areas. In the eastern equatorial Atlantic, differences are found between 0° and 10°S in January (Fig. 6c), while larger differences (more than 80%) are located north of the equator in July (Fig. 7c). Seasonal variations are not so clearly observed in the eastern equatorial Pacific, where the negative differences are rather constant in magnitude and stationary.

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<th>Table 1. Regression coefficients.</th>
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along the coast of Peru in connection with oceanic upwellings. At higher latitudes, differences are also observed in summertime off the coast of Baja California, along the western coast of southern Africa, and north of 40°N.

Esbensen et al. (1993) have observed similar differences in both August 1987 and February 1988 monthly LHF maps. However, their results also show an important disagreement between SSM/I and COADS LHF in winter in the central Pacific between 10° and 30°N, which does not appear as clearly in our results. By analyzing the monthly maps of differences for the four years, we have verified that this region experienced its largest differences in 1988. The other regions, and especially the coastal areas, do not have such interannual variations and, therefore, appear more clearly in the long-term average.

To assess whether these LHF differences are significant, we estimated the random error of satellite-derived LHF using a Monte Carlo method. The three input quantities—$U$, SST, and $W$—have been modified at each grid point by adding a random value selected from a white noise distribution with zero mean and variance set to the rms error of each parameter (see section 2b). The procedure has been repeated several hundred times for each month, and the output LHF fields are averaged. An estimate of the LHF error computation due to the noncorrelated error of the input parameters is then given by the ratio of the standard deviation to the averaged LHF map. The distribution error (Fig. 8) is represented by two Gaussian functions (solid line) overlapping around 50%. The mean and standard deviation of the first one are 30% ± 9% and characterize the random error in the regions between 40°S and
40°N. The second Gaussian function (64% ± 7%) is associated with higher latitude regions. In the latter, the LHF error is much higher because the random error of the parameters is close to the value of the parameters itself.

5. Discussion

It is encouraging to note that the random differences we observe in Figs. 6c and 7c are close to the upper limit of the error computation. However, the magnitude of the differences, particularly the systematic differences, are still very high and require a closer look.

In order to do that, the percentage of times (with respect to the 45 maps) that the difference between the two computations is less than the error computation level has been mapped (Fig. 9a). The characteristic pattern of shipping tracks can be easily recognized, especially in the Indian Ocean and Southern Hemisphere. As a confirmation, Fig. 9b presents the average number of measurements acquired for specific humidity over the same period. The correlation between the two maps shows that, as the number of in situ data increases, the agreement between the two LHF computations improves. From these maps, we estimated that 20 observations on a monthly average are required to achieve agreement better than 30%, during at least 75% of the time. By selecting the pixel values with the required number of observations, absolute agreement now becomes 50 W m⁻² rms to be compared to 65 W m⁻², when the requirement on the number of observations is relaxed (Fig. 5). The differences between the long-term averages decreased from 54 to 40 W m⁻² rms.

Therefore, the spatial sampling appears to be an important source in the random differences observed between the two LHF computations.

In some regions, however, where high positive or negative error is observed, agreement is reached only about 30% of the time, even when the number of ship records exceeds 20. It is particularly clear in the Northern Hemisphere, along the coasts of California and west Africa, as well as in the Arabian Sea. In these regions, it is highly likely that satellite-derived computations fail. As expected, the LHF differences in these regions are correlated with patterns observed in the \( Q_a \) and \( T_a \) difference maps. A comparison between Figs. 2a, 4a, and 6c, and Figs. 2b, 4b, and 7c shows that the regions with systematic positive LHF discrepancies are associated with regions where \( Q_a \) and \( T_a \) SSM/I-derived values are smaller than COADS values by at least 2 g kg⁻¹ and 6°C, respectively. Similarly, smaller satellite-derived values compared with COADS LHF values are observed where satellite-derived parameters exceed COADS parameters by similar amounts.

A strong correlation also exists between differences in global LHF distribution and the index introduced by Prabhakara et al. (1979) to highlight the effect of large-scale atmospheric motion on water vapor. Stephens (1990) mapped the multiyear average of this index using SMMR data. As computed in his study, negative index values are related to dry air advection or subsidence, whereas positive index values reveal convectively active regions and moisture convergence areas. By comparing the difference in \( Q_a \), \( T_a \), and LHF with the global distribution of this index, it appears that \( Q_a \) and \( T_a \) are underestimated (LHF is overestimated) in strong subsidence regions mostly during wintertime and underestimated (underestimated) in moisture convergence zones.

To better understand how systematic differences develop in the long-term average, we plotted the time series of each input parameter, the \( Q_a - Q_s \) difference, and the LHF (Figs. 10–12). In each panel, a star represents one monthly COADS value and a diamond represent one monthly satellite-derived value. As a reference, Fig. 10 shows the time series at 41°N, 321°E in the Atlantic Ocean where the in situ sampling is very dense, and no systematic differences are observed. The agreement between all the parameters is good, especially for \( Q_a \) and \( T_a \), for which the statistical relationships give a very satisfactory result in this case. The rms difference of the LHF is 31 W m⁻².

If we now plot the time series for a grid point located in any of the subsidence regions, we obtain very different results. As an example, Fig. 11 shows the time series in the Arabian Sea (19°N, 65°E). This figure clearly indicates that \( Q_a \) and \( T_a \) are systematically underestimated nine months out of the year (October–May). In the other subsidence regions, large discrepancies usually occur over a shorter time period (Jan-
ity—May). During the same period $Q_a$ (Fig. 11d) does not agree as well as for the reference case and $Q_s - Q_a$ (Fig. 11e) shows very large discrepancies. The LHF disagreement (Fig. 11f) is, therefore, large and equal to 117 W m$^{-2}$ rms.

Esbensen et al. (1993) explained the $Q_a$ differences by the departure of the regional vertical humidity profile with respect to the global average distribution assumed in the $Q-W$ relation. Indeed, in comparison with the vertical distribution of water vapor in pre-
vailing subsidence regime, a profile representative of a global average situation has less water vapor within the boundary layer and more above. The $Q-W$ relationship, therefore, will tend to underestimate $Q_e$. Horizontal advection of dry air will have a similar effect, and we observe that the regions affected are close to arid land areas, where dry air and aerosol input over the ocean are very important (Pye 1987). When both processes (subsidence and horizontal advection) strongly combine, as during the northeast monsoon in the Arabian Sea and in the Bay of Bengal, the differences have the largest magnitude. Temperature inver-
sion is also associated with subsidence. In comparison with this regional characteristic the $T-W$ relationship based on a global averaged lapse rate will underestimate $T_a$.

The comparison between $Q_a$ fields produced by the ECMWF model and those predicted by the $Q-W$ relation with $W$ model values (Liu et al. 1992) showed that the difference introduced by using the relation can account for as much as 2–4 g kg$^{-1}$ (depending on the region) of the observed differences in $Q_a$. Therefore, although accounting for the largest amount of the $Q_a$ differences, the entire amount cannot be explained only by the failure of the $Q-W$ relationship. The fact that these differences also occur when comparing SSM/I data with COADS suggests that the values of precipitable water may be doubtful too. Sun (1993) studied the impact of the simplifying assumptions introduced in the SSM/I retrieval algorithm. Sun’s maps even show a slight overestimation of $W$, which would have a further tendency to increase the difference between $Q_a$ SSM/I and COADS fields by 1.5–2 g kg$^{-1}$.

As far as the regions with large negative LHF differences are concerned, we have documented (Fig. 12) a grid point off the Baja California coast (25°N, 243°E). In this case $Q_a$ (Fig. 12a) and $T_a$ (Fig. 12b) are regularly overestimated during summer months (June–September), which yields an underestimation of the LHF (Fig. 12f). Liu et al. (1992), by comparing the $Q_a$ fields from SSM/I with those computed by the ECMWF model, demonstrated that the $Q-W$ relationship does not apply in the northern ocean, off Baja California, and, to a lesser extent, off the coast of West Africa.

In these regions, the global profile has more water vapor near the surface and less above (Esbensen et al. 1993). Different processes can lead to this situation depending on the region. At high latitudes and over upwelling regions, it is more likely that saturation near the surface prevents the humidity from reaching the values predicted by the $Q-W$ relationship. In the northern Pacific Ocean, the difference $Q_a - Q_w$ becomes negative and the LHF cannot be performed. In the convergence zone, the development of vertical convection leads to an increase in the thickness of the mixed layer. For the same amount of total water vapor content, distribution over a thicker layer will have a tendency to reduce the humidity close to the surface, in comparison with the average state assumed in the $Q-W$ relationship. Again, the use of the relation leads to an overestimation of $Q_a$. Finally, for the coastal regions of California and Africa, Sun’s results (Sun 1993) also showed that retrieval error contributes to the overestimation of $Q_a$.

6. Blended analysis

Owing to the problems just mentioned with $Q-W$ and $T-W$ relationships and the need to have a global field of LHF, further investigation is required to produce optimal fields with the available data. There are a number of potential approaches, and a possible improvement relies on the combination of in situ and satellite datasets. The concept has already been used and implemented in a more sophisticated way to analyze SST fields (e.g., Reynolds 1988). In the present study, the idea supporting the blended analysis is simply to compute a weighted value of $Q_a$ and $T_a$ from the gridded in situ and satellite values by taking into account both dataset limitations mentioned previously: the in situ sampling and the systematic errors of satellite retrievals.

a. Description of the method

First, the bias between satellite and COADS estimates of $Q_a$ is computed for the entire dataset selecting the grid points with more than 20 COADS observations. The bias, equal to 0.68 g kg$^{-1}$ with COADS having the larger values, is then added to the satellite values, and monthly mean unbiased differences are computed. The next step is the calculation of blended quantities. Our criterion is to compute blended values when the unbiased difference between in situ and satellite estimates of $Q_a$ is larger than 1 g kg$^{-1}$; this value corresponds to the random error level of the $Q-W$ relationship. While it would be possible to use COADS data as soon as one observation is available, our earlier results suggest that COADS data may not be representative when the sampling is limited. Consequently, we chose an approach that combines the two datasets through a weighting process based on the number of COADS observations available:
\[ X_{a \text{BLENDED}} = \left(1 - \frac{1}{N_{\text{obs}}^{1/2}}\right) X_{a \text{COADS}} + \left(\frac{1}{N_{\text{obs}}^{1/2}}\right) X_{a \text{SSM/I}} \]  

(8)

In this expression, \(X\) is either \(Q\) or \(T\) and \(N_{\text{obs}} \geq 1\) is the number of observations that were used to compute the \(Q_{\text{COADS}}\) or \(T_{a \text{COADS}}\) grid value. The \(N_{\text{obs}}^{-1/2}\) shape of the coefficients is in agreement with the dependence of the monthly COADS parameter standard errors on the data density (Morissey 1990). According to (8), satellite and in situ data make equal contributions to the blended values when \(N_{\text{obs}} = 4\). Above 20 in situ observations, more than 80% of the blended value comes from the in situ measurements. Thus, this assumes that ship observations are favored over satellite ones when the number of observations from both types is equal.

This procedure is applied to the 1° × 1° fields of \(Q_a\) and \(T_a\) that are computed from precipitable water at that resolution with the statistical relationships. Over the 45 months, 53% of the data points are selected for the blending process. COADS fields are transformed to the same resolution by duplicating four times each grid value. This way, the statistics of the COADS fields are unchanged.

We have also considered another method to compute blended values of \(T_a\). Previous climatological results (e.g., Esbensen and Kushnir 1981) have shown that global air–sea temperature difference varies within ±1°C with little seasonal variations. Slightly larger values (3°–4°C) are systematically observed over the west boundary currents. The quite homogeneous distribution and small variability of the air–sea temperature difference allows us to try a global statistical approach.
to calculate $T_a$ from satellite SST. In order to account for the geographical distribution as best as possible, we first computed the 3-yr COADS average of the air–sea temperature difference and then calculated $T_a$ monthly blended field as the sum of individual monthly satellite SST and the corresponding long-term COADS air–sea difference average. A 3-yr average is preferred to the individual monthly COADS air–sea temperature difference field in order to have the most complete coverage.

The blended value of $Q_a$ as computed from (8) and both types of blended $T_a$ values are compared with $Q_a$ and $T_a$ COADS values, respectively. Figure 13a is the same as Fig. 2a for the difference $Q_a^{\text{blended}} - Q_a^{\text{COADS}}$. Global distribution of the difference now ranges within $\pm 1$ g kg$^{-1}$. As expected,
systematic differences have been reduced, especially in the Northern Hemisphere where the in situ sampling is appropriate. The band of negative differences across the Atlantic and Pacific Oceans has disappeared, and the maxima in the Arabian Sea, off the coast of California and West Africa, are now smaller than 2 g kg$^{-1}$. The resulting differences in the Southern Hemisphere, although less marked, are significant in the central Indian Ocean, off the west coast of South America, and southern Africa where the disagreement does not exceed 3 g kg$^{-1}$ any more. An improvement is also observed in the overestimated areas, within the ITCZ, off the coast of Baja California, Peru, and southern Africa in summer (not shown).

Figure 13b represents difference $T_{a}^{\text{BLENDED}} - T_{a}^{\text{COADS}}$ with $T_{a}^{\text{BLENDED}}$ computed from (8). Again the improvement is obvious comparing to the original computation (Fig. 4a). Regions identified with important discrepancies now differ by 2°C at most. Finally, the
last panel (Fig. 13c) represents $T_{a}^{BLENDED} - T_{a}^{COADS}$ with $T_{a}^{BLENDED}$ computed from satellite SST. The agreement is better than previously and the difference only rarely exceeds $+1^\circ$C. Difference larger than $2^\circ$C exist only in the northwestern part of the Atlantic and Pacific. Patterns in the Arabian Sea and along the west coast of the North American and African continents have disappeared and more significant improvement

is observed in the southeastern Pacific. Results are similar in July. Overall the $T_{a}^{BLENDED}$ computed from COADS air–sea temperature difference is in better agreement with $T_{a}^{COADS}$.

Our procedure essentially comes down to having confidence in satellite-derived wind and SST, since the blending procedure is applied only to $Q_{a}$ and $T_{a}$. This confidence seems justified by looking at reported results.
in the literature (Halpern et al. 1994). The blending could be extended to other parameters or based on fields that are already blended, such as SST analysis from the Climate Analysis Center (Reynolds 1988).

b. Blended LHF fields

We have recalculated LHF monthly maps with \( Q_a^{\text{BLENDED}} \) fields produced as described above and \( T_a^{\text{BLENDED}} \) fields produced from SST (Fig. 13c). Wind speed and SST fields are unchanged from the original computation.

To assess the improvement resulting from the blended procedure, we have evaluated, anew, LHF time series for the locations that were previously discussed. Figures 14a and 14b represent the blended time series of \( Q_a \) and \( T_a \) (triangles), along with the \( Q_a \) unbiased differences (crosses), and the number of observations (squares) for temperature as an indicator of the quality of the sampling for both \( Q_a \) and \( T_a \). To facilitate com-
parisons with previous results, we also have repeated the COADS and satellite time series (respectively, the solid and dashed line) of Figs. 10a and 10b. Over the Atlantic Ocean, the blending analysis does not markedly modify the parameter values, since the agreement was good originally. Most of the time, the $Q_a$ unbiased difference is smaller than the threshold (dotted line), indicating that $Q_{a,SSM/1} - Q_{a,COADS}$ values do not differ significantly from the $Q_{a,SSM/1}$ error. In this case, $Q_{a,SSM/1}$ is not changed. Several points, however, at the beginning of the time series, during summer 1988, and at the end of the time series do not agree so well. The number of observations is large (40–50, in general), and the blended values are, therefore, practically equal to the COADS values. Results for temperature (Fig. 14b) are also very satisfactory, although in this particular case the agreement would be better if $T_a$ had been computed from Eq. (8). The blended LHF is plotted in Fig. 14c. We still
observe some discrepancies that result from wind speed, especially during fall 1988 (Fig. 10c), and SST disagreement through $Q_a$ (Fig. 10d). Most of the time, blended values are between the two others computations and appear as a good compromise: the blended process clearly removes outliers (October 1987) and smooths LHF values while preserving the variability observed by satellite (winter 1990/91). At this particular grid point, the rms of the difference between blended and COADS monthly LHF is only 24 W m$^{-2}$.

The fluxes in the Arabian Sea are illustrated in Fig. 15. During the fall, winter, and spring seasons, we observed an important underestimation of humidity and colder air temperature, as derived by satellite (dashed lines). The blending process, implemented with a satisfactory sampling (20–25 observations), compensates for most of the differences in $Q_a$ (Fig. 15a) and $T_a$ (Fig. 15b). Differences in $T_a$ are slightly larger in summer because of an SST disagreement. The LHF computations (Fig. 15c)
are now in satisfactory agreement during these periods. However, there are still large differences in summer because of discrepancies in the wind speed (Fig. 11c) and, above all, in $Q_v$ (Fig. 11d). Because of that, the rms of the LHF, although decreased by more than 50%, is still high (53 W m$^{-2}$). Similar wind speed discrepancies have been observed and discussed by Halpern et al. (1994), and SST errors appear now to be the main limiting factor in this region.
The last time series for the region off the coast of California is presented in Fig. 16. It is, in fact, an illustration of the two main problems encountered: an underestimation during winter, such as in the Arabian Sea, and an overestimation of air parameters during summer. Therefore, the blending procedure is applied for almost all the $Q_a$ values of the time series. After processing, the blended values of $Q_a$ and $T_a$ (Figs. 16a and 16b) follow COADS time series variations quite closely. Values are still offset by about 1 g kg$^{-1}$ because the number of in situ observation (around 10) allows, at most, 70% of the COADS values in the result. The LHF agreement is significantly improved, with an rms error equal to...
30 W m\(^{-2}\) (by comparison with 81 W m\(^{-2}\) before blending; see Fig. 12f).

To have a global view of the blended LHF, we finally produced 3-yr-averaged maps. Figure 17 shows the maps for January and July. By comparing them with Figs. 6a and 7a, we observe a general decrease in LHF magnitude. Most of the changes occur in the Northern Hemisphere and within the trade wind region where in situ information is available. The most spectacular improvements, as we discussed previously, are observed over the eastern part of the three basins. Changes are also observed in the southeastern Pacific along the coast of South America where values no longer exceed 200 W m\(^{-2}\). The global rms of the monthly mean difference (Fig. 5) is now 40 W m\(^{-2}\) and goes down to 28 W m\(^{-2}\) when 20 in situ observations are available, showing a significant improvement in the satellite-derived LHF estimates.

It must be noted that we used the COADS data as our reference to evaluate both the satellite-derived and
Fig. 16. Same as Fig. 14 off the coast of California.

the blended (satellite plus ship) LHF fields. The bias and rms error discussed are expressed by comparison with this dataset and, therefore, do not represent absolute error estimation since COADS-based estimates also contain uncertainties. Wilkerson and Earle (1990) compared reports from transient ships with measurements from 47 buoys at various locations and found the ship-buoy differences in wind speed, air temperature, and sea surface temperature to be 1–2 m s\(^{-1}\), 1.1°C, and 0.1°C, respectively, and the standard deviations 3.5–4 m s\(^{-1}\), 4.3°C, and 3.5°C, respectively. These errors translate to substantial errors in LHF derived from ship reports. The choice of the COADS dataset has been made because it is the one on which most of the recent climatological studies have been based. Nevertheless, other LHF fields could have been chosen for comparison, such as one produced by an atmospheric general circulation model. Since no field really exists as “ground truth,” we are limited to intercomparisons with other fields.
7. Conclusions

We have computed global monthly maps of latent heat flux over three years based on COADS and SSM/I data. In the first part, two statistical relations have been used to derive relevant parameters from satellite precipitable water fields, and both parameter types, satellite-derived and in situ, have been input into a model that is based on similarity theory to compute the LHF. The satellite-derived maps show consistently high values of latent heat flux in the region of the trade winds in both hemispheres and all oceans. The signature of western boundary currents is clear, and the highest values are observed in the Arabian Sea and the Gulf of Bengal. Minimum LHF is observed in the low-level convergence zones, especially in the eastern Pacific and Atlantic Oceans.

The overall rms difference between SSM/I and COADS LHF shows that the two computations differ by about 65 W m$^{-2}$ rms (55%). Analysis of the long-term averaged differences between both flux estimates indicates that, in fact, a random component (about 40%) and a systematic component (up to 150% in particular regions) of that error level exist. Both types of errors exceed the estimated accuracy of the satellite-derived LHF obtained by propagating parameter errors in the model. A closer comparison demonstrates that an important source of random differences is the sampling of COADS data. When the number of observations is sufficient (>20), the global rms difference drops down to 50 W m$^{-2}$.

Systematic differences in the LHF are found to correlate with differences in the air mixing ratio $Q_a$ and air temperature $T_a$, as derived from satellite fields with the statistical relationships. The LHF is overestimated in strong subsidence regions, mostly during the winter season in association with the underestimation of $Q_a$.
and $T_a$. The LHF is underestimated mainly in the atmospheric convergence zones and the oceanic upwelling regions all year long and also in the Northern Ocean, off the coast of Baja California, and West Africa, in summer. In these regions, $Q_a$ and $T_a$ are overestimated.

Limitations of both statistical relationships are mostly responsible for these systematic errors, but retrieval errors also combine with other error sources in the coastal area to contribute to $Q_a$ and $T_a$ overestimation. The limitations are explained by the departure of local vertical profiles of water vapor and temperature from the average vertical distribution assumed in the empirical relationships. [See Esbensen et al. (1993) for a discussion on $Q-W$ relationship.]

In an attempt to improve the global LHF estimate, a ship–satellite blending procedure has been developed for the parameters $Q_a$ and $T_a$. For $Q_a$, the blending procedure consists in a combination of satellite and ship values when the difference in $Q_a$ exceeds the random error level of the parameter. The combination is weighted by the number of COADS observations available. The comparison between blended and COADS LHF shows much improvement in the regions previously identified as having large, systematic differences. For $T_a$ we compared two methods: 1) we computed it the same way as we did for $Q_a$ values, and 2) we added the long-term average of the COADS air-sea temperature difference to the satellite SST values. The latter method has been found to give a better global agreement with $T_a$ COADS values and selected to built $T_a$ blended fields. LHF maps are computed anew with both blended parameters. Overall, the blended LHF is found to agree within 28 W m$^{-2}$ with COADS computations when the in situ sampling is good enough. This corresponds to the effects of $Q_a$ differences, which are now no larger than 1 g kg$^{-1}$, but also to differences in SST and wind for the two datasets.

Two aspects are important in a blending procedure: the numerical technique employed and the choice of weighting functions associated with each type of dataset. The numerical technique tested here for $Q_a$ is rather simple and preliminary. Also, we chose to give the maximum weight for satellite observations of SST and wind (no ship observation is used), but more limited weights to $Q_a$ and $T_a$, which we believe are more difficult to obtain from satellite observations. Blending satellite and ship observations is possible only where ship data are available. However, there are regions such as the Southern Hemisphere where we believe errors may exist in satellite-derived fluxes. It is indeed imperative to examine carefully the LHF determination in the southeastern part of the oceans where large values are computed. This is particularly true if one is to use this blended LHF for freshwater exchange estimations. The present overall level of uncertainty in the LHF quoted above is now getting small enough to attempt such studies, provided few systematic errors exist.

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REFERENCES


