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Comparison of Five Satellite-Derived Latent Heat Flux Products to Moored Buoy Data

DENIS BOURRAS

CETP-CNRS-IPSL, UMR 8639, Vélizy-Villacoublay, France

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ABSTRACT

Five satellite products of latent heat flux at the sea surface were compared to bulk fluxes calculated with data from 75 moored buoys, on almost 36 successive months from 1998 to 2000. The five products compared are the Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Dataset (HOAPS-2), the Japanese Ocean Flux Datasets with Use of Remote Sensing Observations (J-OFURO), the Jones dataset, the Goddard Satellite-Based Surface Turbulent Fluxes, version 2 (GSSTF-2), and the Bourras-Eymard-Liu dataset (BEL). The comparisons were performed under tropical and midlatitude environmental conditions, with three datasets based on 66 Tropical Atmosphere-Ocean array (TAO) buoys in the tropical Pacific, nine National Data Buoy Center (NDBC) buoys off the U.S. coasts, and four Met Office/Météo-France (UK-MF) moorings west of the United Kingdom and France, respectively. The satellite products did not all compare well to surface data. However, for each in situ dataset (TAO, NDBC, or UK-MF) at least one satellite product was found that had a good fit to surface data, that is, an rms deviation of 15-30 W m⁻². It was found that HOAPS-2, J-OFURO, GSSTF-2, and BEL satellite products had moderate systematic errors with respect to surface data, from -13 to 26 W m⁻², and small biases at midlatitudes (6-8 W m⁻²). Most of the satellite products were able to render the seasonal cycle of the latent heat flux calculated with surface data. The estimation of near-surface specific humidity was found to be problematic in most products, but it was best estimated in the HOAPS-2 product. GSSTF-2 and J-OFURO strongly overestimated the surface flux variations in time and space compared to surface data and to a flux climatology. With respect to TAO data, Jones fluxes yielded good results in terms of rms deviation (27 W m⁻²) but also presented a large systematic deviation. Overall, for application of the satellite fluxes to the world oceans, it was found that HOAPS-2 was the most appropriate product, whereas for application to the Tropics, BEL fluxes had the best performance in rms with respect to TAO data (24 W m⁻²).

1. Introduction

Turbulent heat fluxes at the air-sea interface are required for analyzing the upper-ocean heat budget, initializing ocean models, diagnosing atmosphere models, and thus improving our understanding of the climate system.

The heat budget of the sea surface is the sum of four fluxes. Two radiation fluxes, namely the solar and infrared fluxes, and two turbulent fluxes, the latent heat flux (LHF) and the sensible heat flux. LHF is associated with vertical humidity exchanges across the interface, while the sensible heat flux is related to temperature exchanges. LHF is generally 7 times larger than the sensible heat flux, and ranks second (\sim 130 W m⁻²) in the global heat budget of the ocean surface. The magnitudes of the other fluxes are $\sim 200 \text{ W m}^{-2}$ for the incoming solar flux, $\sim 60 \text{ W m}^{-2}$ for the infrared flux, and $\sim 10 \text{ W m}^{-2}$ for the sensible heat flux.

Two-dimensional flux fields may be derived from in situ data such as moored buoys, research vessels, or merchant ships (e.g., Woodruff et al. 1998). However, this approach cannot produce fields at a time resolution shorter than a month, because data are too sparse. A promising technique consists of using spaceborne observations, because of their large and nearly constant spatial and temporal sampling of the world oceans.

Radiation fluxes can be derived from satellite data with a good accuracy of about 10% (Frouin and Chertock 1992). In contrast, estimation of LHF or of the sensible heat flux from satellite data is still a research topic, because they depend on near-surface air specific humidity and air temperature that cannot be accurately estimated from satellite data. This paper focuses on

Corresponding author address: Denis Bourras, 10-12, Avenue de l'Europe, 78140 Vélizy-Villacoublay, France. E-mail: denis.bourras@cetp.ipsl.fr

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estimation of LHF, which is a priority because it is 7 times larger than the sensible heat flux in the earth's surface energy budget, averaged over one year for the world oceans.

A bulk parameterization is often used for quantifying LHF. It is written as

$$L_E = \rho L_V C_E U_A (Q_S - Q_A), \tag{1}$$

where ρ is air density, L_{ν} is the latent heat of vaporization, and U_A and Q_A are wind magnitude and specific humidity at altitude z_A , respectively. Altitude z_A must be smaller than 20–30 m so that U_A is measured in the surface boundary layer where (1) is valid (Businger et al. 1971). Here, Q_S is the specific humidity at the sea surface and is assumed to be 98% of the saturation humidity at the sea surface temperature (SST). In (1), C_E is a coefficient that depends in part on wind speed and dynamical stability of air, which is itself a function of air-sea temperature difference. Air temperature is referred to as T_A hereafter.

The SST may be estimated from satellite data. Its rms accuracy is 0.3° C, which translates into 5 W m⁻² in terms of LHF, according to observations of the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR; Kilpatrick et al. 2001). For U_A , accuracy is 1-2 ms⁻¹ with the Special Sensor Microwave Imager (SSM/I) or the Quick Scatterometer (QuikSCAT) spaceborne scatterometer (Ebuchi et al. 2002). This corresponds to an error of ~15 W m⁻² in LHF. For Q_A , the error is 1–2 g kg⁻¹, or 15–30 W m⁻² in LHF, which is large. Here, C_E is often assumed to be constant in satellite products, because T_A is unknown. If not, an iterative bulk algorithm more complex than (1) can be used for calculating more accurate fluxes (e.g., Fairall et al. 2003). Note that several other variables [e.g., sea level pressure (SLP) and radiation fluxes] may be used as inputs of such iterative algorithms.

Several satellite sensor-derived LHF datasets are already available to the community of LHF users, namely the new version of the Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Dataset (HOAPS-2), the Japanese Ocean Flux Datasets with Use of Remote Sensing Observations (J-OFURO), the Jones et al. (1999) tropical flux dataset (named "Jones" in the following), the Goddard Satellite-Based Surface Turbulent Fluxes, version 2 (GSSTF-2), and the Bourras–Eymard–Liu (Bourras et al. 2002, hereafter BEL) global flux dataset, respectively. They are all based on different bulk algorithms and satellite inversion techniques. Some of the available products were already compared to surface data. For instance, Chou et al. (2004) recently compared their GSSTF-2 LHF estimates to accurate surface measurements from several research cruises. They found an rms deviation of 6.5 W m^{-2} for monthly flux estimates, which is excellent. Next, Chou et al. (2004) compared the monthly GSSTF-2 fluxes to a global flux product based on in situ data (Da Silva et al. 1994) and to HOAPS-2 monthly fluxes, over 1992-93. Chou et al. (2004) concluded that their product was likely to be more realistic than the other products. Kubota et al. (2003) compared J-OFURO to HOAPS (first version), GSSTF (first version) and the Da Silva et al. (1994) dataset for 1992-93. Their main result is that HOAPS and Da Silva et al. (1994) products are smaller in the Tropics in comparison with GSSTF and J-OFURO. Their overall conclusion is that they "could not know which product was closer to the truth since they only carried out intercomparisons of the products." This is clearly insufficient for flux users. What is expected is a quantitative comparison between satellite flux products on the one hand, and a statistically significant amount of constant quality surface fluxes on the other hand. The study of Bentamy et al. (2003) complies with this approach. They compared weekly satellite flux estimates to surface data derived from moored buoys in three areas during nine months (October 1996–June 1997). They found that the accuracy of their LHF estimates was ~ 30 W m⁻². Unfortunately, they did not compare their product to other satellite products.

Overall, to the best of our knowledge, the available satellite flux products were never all quantitatively compared to long-term surface data. The present paper provides a simple intercomparison of five monthly flux products, and an attempt to validate these products with respect to moored buoy data from 1998 to 2000.

The satellite and in situ flux datasets are presented in sections 2 and 3, respectively. Next, the satellite products are compared to buoy fluxes in section 4. A temporal analysis is presented in section 5, followed by an analysis of individual bulk variables (section 6), a spatial analysis (section 7), and a discussion (section 8).

2. Satellite datasets

The flux products described in this section are monthly LHF fields from HOAPS-2, J-OFURO, Jones, GSSTF-2, and BEL flux datasets, respectively. Another flux dataset by Bentamy et al. (2003) was available. However, it was left out of the comparison because it is an 8-day product, from which monthly LHF estimates could not be rigorously calculated.

a. HOAPS-2

Monthly HOAPS-2 LHF fields are available from January 1987 to December 2000 (Schulz et al. 1997).

The technique used for deriving LHF estimates from satellite sensor data in HOAPS-2 consists of estimating the SST from radiances measured by the AVHRR, which is a passive infrared sensor. Next, U_A and Q_A are inferred from the SSM/I, which is a passive microwave radiometer. The SSM/I measures brightness temperatures (TBs) at several frequencies ranging from 19 to 85 GHz, in two polarizations, vertical and horizontal. The techniques used for obtaining U_A and Q_A are statistical algorithms, or in fact statistical relationships between TBs and U_A or Q_A . The algorithm used for estimating Q_A is described in Bentamy et al. (2003), while the algorithm for U_A is unpublished. Air temperature is assumed to be the average of air temperature estimates calculated with two methods. In the first method, air temperature corresponds to 80% of relative humidity, whereas in the second, air temperature is $SST + 1^{\circ}C$. After the bulk variables are obtained, a bulk algorithm (Fairall et al. 1996) is applied for calculating the HOAPS-2 LHF estimates. Spatial resolution of the

b. J-OFURO

Fully described in Kubota et al. (2002), J-OFURO is based on SSM/I TBs for deriving U_A and Q_A (Wentz 1994 and Schlussel et al. 1995, respectively). The SST is from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis project. The NCEP–NCAR SST is a blend between in situ and satellite SST (Reynolds and Smith 1994). In the bulk algorithm used for J-OFURO (Kondo 1975), air temperature and SLP were not accounted for. Flux data have a 1° latitude × 1° longitude spatial sampling.

HOAPS-2 flux product is 0.5° latitude $\times 0.5^{\circ}$ longitude.

c. Jones

This dataset, described in Jones et al. (1999), covers the Tropics from 30°S to 30°N in latitude. LHF were obtained using satellite-derived estimates of T_A and Q_A , wind speeds from SSM/I (Wentz 1994), and SLP and SST from the NCEP-NCAR reanalysis project, from July 1987 to December 2001. The bulk algorithm is from Liu et al. (1979). For deriving T_A and Q_A , Jones et al. (1999) created a statistical relationship between two types of data with an artificial neural network method. First, they used surface measurements (T_A and Q_A) from the Tropical Atmosphere–Ocean array (TAO) of moored buoys from January 1991 to September 2002 (McPhaden 1995) and observations of the Pilot Research Moored Array in the Tropical Atlantic (PIRATA) during January 1998-September 2002. Next, they extracted SSM/I products of total precipitable water (TPW), cloud liquid water (CLW), rain rate (RR) and surface wind speed (Wind) from July 1987 to April 2003 (Wentz 1994). The daily SST fields, originally available at 2.5° latitude \times 2.5° longitude, were interpolated with a bilinear method to 0.25° latitude \times 0.25° longitude. The training of the algorithm and its validation were performed on the period January 1991–September 2002. After that, 15 yr of data (July 1987–April 2003) were processed to obtain LHF estimates.

d. GSSTF-2

The GSSTF-2 dataset provides monthly mean, global ocean, 1° latitude × 1° longitude gridded surface fluxes, from July 1987 to December 2000. SSM/I surface wind speeds and total precipitable water from the SSM/I (Wentz 1997), as well as SST, air temperature, and SLP from the NCEP–NCAR reanalysis, were used; Q_A was derived from SSM/I data with the algorithm of Chou et al. (1997). The bulk algorithm used is described in Chou (1993).

e. BEL

In the four datasets described above, the technique used for deriving LHF estimates from satellite sensor data consisted of deriving the SST either from infrared sensors or from a mix between in situ and satellite SSTs on one hand, and other bulk variables from SSM/I TBs on the other hand. After the bulk variables were obtained, a bulk algorithm was applied for calculating the flux.

Recently, BEL used an alternate technique. They found a nonlinear statistical relationship between satellite TBs and LHF. For BEL, the motivation was twofold. First, in HOAPS-2, GSSTF-2, Jones, and J-OFURO, the SSM/I TBs were used twice for estimating LHF: once for U_A and another time for Q_A . Therefore, a straightforward relationship between SST, TBs, and the LHF could help increase the accuracy of LHF estimates. Second, the TBs might contain more information on LHF than initially thought. For instance, the TB signal should depend on T_A , according to the radiative transfer theory. Overall, BEL thought it was conceptually better to create a single satellite algorithm for estimating LHF.

The BEL dataset contains LHF estimates derived from a combination of instantaneous SSM/I-F14 TBs and AVHRR SSTs. Two flux products were created, one that uses daily AVHRR SSTs and another based on 8-day- (7 days since 2002) averaged AVHRR SSTs. For the present comparison, the 8-day SST product was selected because it had a better spatial coverage, which



Average number of data per pixel per month (8-day product) over 1998-2000

FIG. 1. Number of data available per pixel in the BEL product. (a) 8-day and (b) 1-day AVHRR SST estimates were used in combination with instantaneous SSM/I TB. (c) The difference between the averaged LHF over 1998–2000 obtained with the 1-day and the 8-day products.

Longitude (°)

is shown in Figs. 1a,b. The average number of data available at each grid point per month is 55 for the 8-day product (or 1.86 per day), whereas it is just 32 per month for the 1-day product (or 1.01 per day). In the 1-day product, areas that are systematically underrep-

resented because of the presence of clouds contain 15 points per month, which is half the average value. The consequences on LHF can be large depending on the region considered. The 1998–2000 average differences between monthly LHF values calculated with the 1-day

SST and the 8-day SST are presented in Fig. 1c. They are small in the Tropics but exceed -30 W m^{-2} west of Australia and near the coasts of Peru, and in the northwest of the Atlantic Basin. In contrast, differences of $+30 \text{ W m}^{-2}$ are noticeable off the coasts of Senegal, Mauritania, and Portugal, among others.

The BEL LHF estimates are available from 1 March 1997 to 31 December 2003 at a spatial resolution of 0.3° latitude $\times 0.3^{\circ}$ longitude. The algorithm used is based on an artificial neural network fully described in BEL. The learning of the neural network algorithm was performed with a combination of European Centre for Medium-Range Weather Forecasts (ECMWF) analyses, in situ observations from the TAO array of buoys, and SSM/I TBs. The neural network was applied to every combination of instantaneous SSM/I-TB and 1- or 8-day AVHRR SST. Next, the flux estimates were averaged over time periods of 1 month.

3. In situ data

The in situ data used are LHF values derived from moored buoy data, from 1998 to 2000. Turbulent fluxes from moored buoys may be less reliable than data collected during field experiments, since instruments on buoys are often selected based on cost, reliability, and resistance to harsh conditions rather than accuracy. Nevertheless, moored buoy data are a unique opportunity to evaluate satellite products on time scales larger than a month.

Seventy-nine moored buoys were used. They are divided into three groups representative of various environmental conditions, namely, 66 buoys of the TAO array in the equatorial Pacific (Fig. 2b), 4 buoys located off the French and English coasts and operated by the Met Office and/or Météo-France, the French meteorological office (UK-MF hereafter; Fig. 2a), and 9 moored buoys from the National Data Buoy Center (NDBC), placed along the coast of the United States (Fig. 2c). Seven of the NDBC buoys are located in the Gulf of Mexico, where the SST is generally large; one buoy is placed off the West Coast at 32°N; and one buoy is located off the East Coast, experiencing often dry westerly winds blowing from the continent. This is a small selection of NDBC buoys usually close to the coast to satisfy two criteria: first, they have to measure relative humidity (or equivalently the dewpoint temperature), which is not easy for most buoys farther from the U.S. and Hawaiian coasts; second, reliable satellite products had to be available at their site. Satellite LHF estimates are generally avoided within 1° or 2° from shore because of the sidelobe effect, resulting from a parasite signal from the large emissivity on land received as a secondary signal by the antenna. To avoid a coastal bias in satellite estimates, one defines a so-called land–sea mask, where no estimate is produced.

All selected buoys measured SST and meteorological variables such as U_A , the dewpoint temperature, and T_A at heights ranging from 3 to 5 m. For each dataset, quality flags were available, which were used to filter data. The time sampling of buoy data is 1 h for NDBC and UK-MF buoys. For the TAO array, it is either 10 min or 1 h, depending on the buoy selected. To produce a homogeneous set of monthly fluxes, daily TAO data were used instead of a mix of 10-min and 1-h data. Nevertheless, it was checked that the results presented in the present manuscript did not significantly differ according to the choice of time sampling of TAO data (not shown). A bulk algorithm (Fairall et al. 2003) was then applied to the measured bulk variables for calculating fluxes. Last, the daily TAO (hourly NDBC and UK–MF) fluxes obtained were averaged over time periods of 1 month. No flux was calculated when some of the required data were not available, except in the Tropics where TAO buoys did not measure SLP before April 2000. For this reason, SLP was set to 1010 hPa with TAO data. Various options are available in the bulk algorithm used, among which is the type of calculation for sea surface temperature. For buoy data, SST is measured below the surface (several meters) and should therefore be corrected in order to calculate the so-called skin SST that should be used instead, as input of the bulk algorithm. Unfortunately, the SST correction requires several inputs that are not available from most buoy data, such as the infrared or the solar downwelling flux. For this reason, the SST correction was disabled in the algorithm for obtaining the results that will be presented in the next three sections. However, the impact of the SST correction on the results will be discussed in the last section. Note also that we did not consider buoy data for which less than 10 out of 30 daily data (300 out of 720 hourly data) were available per month, in order to ensure an acceptable representativeness of the monthly fluxes calculated.

4. Comparison of satellite and in situ LHFs

a. Methodology

It is a challenge to perform a fair comparison between satellite LHF products because they were all prepared at different spatial resolutions, different flux algorithms were used, and some of the buoy data used for the validation were already used in several products, either for adjusting the statistical retrieval algorithms, or directly as inputs of these algorithms. For example,



FIG. 2. Location of the moored buoys used for validation of the satellite products. (a), (b) The numbers correspond to official buoy names.

some of the TAO data were used in the Jones and BEL flux datasets whereas TAO data are used in the present manuscript for validating these satellite products. Next, the Jones, J-OFURO, and GSSTF-2 products are based on SSTs that are not independent from the moored buoys (section 2). Last, for GSSTF-2, air temperature and SLP are not independent from buoy data. The characteristics of the satellite products and their known correlation with the validation data used hereafter are reported in Tables 1 and 2. In the following, we try our

best to minimize—or at least mention—any problem of this kind.

The validation was conducted as follows. At each buoy location and for each month, all available satellite estimates of the LHF within a radius of 0.5° were selected and averaged. Then, the averaged satellite estimates were compared to in situ fluxes. LHF estimates were not always available at each selected buoy location because of differences among the five satellite products in terms of land–sea masks, bulk algorithms,

		TABLE 1. Char	acteristics of the five f	lux datasets.		
	BEL	GSSTF-2	HOAP	S-2	J-OFURO	Jones
Time extent Spatial sampling SST	Apr 1997-Dec 2003 0.3° × 0.3° AVHRR (Kilhortrick et al 2001)	Jul 1987–Dec 2000 $1^{\circ} \times 1^{\circ}$ NCEP	Jan 1987–Dec 200 0.3° × 0.3° AVHRR (Kilpatri	$\begin{array}{c c} 0 & Jan 19 \\ 1^{\circ} \times 1 \\ 1^{\circ} \times 1 \end{array}$ ick et al. 2001) NCEP	92-Dec 2000	Jan 1991–Dec 2002 0.25° × 0.25° NCEP
$egin{array}{c} Q_A \ U_A \ T_A \ { m SLP} \ { m SLP} \end{array}$	(wilpation of al. 2001)	SSM/I (Chou et al. 1997) SSM/I (Wentz 1997) NCEP NCEP	SSM/I (Bentamy e SSM/I (unpublishe Satellite (unpublis Unknown	et al. 2003) SSM/I ed) SSM/I ihed)	(Schlussel et al. 1995) (Wentz 1994)	SSM/I (Jones et al. 1999) SSM/I (Wentz 1994) SSM/I (Jones et al. 1999) NCEP
Satellite flux algorithm Bulk algorithm Product reference	SSM/I/AVHKK Bourras et al. (2002) Bourras (2000) This article	Chou et al. (1993) Chou et al. (2003)	Fairall et al. (1996 Unpublished	t) Kondo Kubot	o (1975) a et al. (2002)	Liu et al. (1979) Jones et al. (1999)
TABLE 2. Known corr	elation between five satelli	ite products and the moored	l buoy data plus the bu applicable.	ulk algorithm used for val	lidation of the satellite	products. N/A means not
	BEI	Γ	GSSTF-2	HOAPS-2	J-OFURO	Jones
Known correlation with	Yes	Ye	s (NCEP SST) Yes	(AVHRR SST adjusted	Yes (NCEP SST)	Yes (NCEP SST, Q_A , and T_A

	BEL	GSSTF-2	HOAPS-2	J-OFURO	Jones
Known correlation with TAO data	Yes (LHF algorithm adjusted to TAO in 1998)	Yes (NCEP SST)	Yes (AVHRR SST adjusted to TAO)	Yes (NCEP SST)	Yes (NCEP SST, Q_A , and T adjusted to TAO)
Known correlation with	Possibly	Yes (NCEP T_A	Yes (AVHRR SST adjusted	Yes (NCEP SST)	N/A
NDBC data	(LHF algorithm adjusted to ECMWF analyses)	and SST)	to NDBC)		
Known correlation with UK-MF data	Possibly, in 1998 (ECMWF analyses)	No	No	No	N/A
Known correlation with	No	No	Possibly, Fairall et al. (1996)	No	No
Fairall et al. (2003)					

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or quality flags. As a result, the number of collocated buoy-satellite fluxes available for validation strongly depended on the satellite product considered. For instance, with the NDBC buoy dataset there were 563, 177, 291, and 427 collocated situations available for validation of the BEL, HOAPS-2, GSSTF-2, and J-OFURO fluxes, respectively. As this affected the results, it was decided to select only the situations that were common to the four products, namely, 177 situations with the NDBC dataset. The same technique was used for selecting TAO and UK-MF validation data, which resulted in 1742 and 122 situations, respectively. As a consequence, TAO data will be overrepresented and UK-MF and NDBC data will be underrepresented in the following comparisons. In other words, the comparisons will be statistically more reliable in the Tropics than at midlatitudes.

b. Comparison between satellite products and buoy fluxes

In this section, four satellite flux products (BEL, GSSTF-2, HOAPS-2, and J-OFURO) are successively compared to TAO, UK–MF, and NDBC data. Jones flux estimates are compared only to TAO data, as UK–MF or NDBC surface data are not the tropical domain of Jones (section 2).

1) TAO

The comparisons between TAO buoy fluxes and five satellite products (BEL, GSSTF-2, HOAPS-2, J-OFURO, and Jones) are presented in Fig. 3. The rms deviations found between satellite products and buoy fluxes range from 24 (BEL fluxes) to 41 W m⁻² (J-OFURO), which is acceptable. However, it shows that there may be significant differences depending on the product considered.

Systematic deviations (or biases) between satellite products and TAO fluxes are in the range of 10–49 W m⁻², which is moderate to large (7%–30%). A large bias does not necessarily matter for regional application of the fluxes, either because it can be corrected (e.g., adjusted to available in situ fluxes) or because the information sought after might be in the spatial variations of LHF (e.g., Bourras et al. 2004). However, it is a serious issue in global application of the satellite products. HOAPS-2 fluxes have the smallest bias (10 W m⁻²). In addition, HOAPS-2 performs well in terms of correlation coefficient (0.74) and rms deviation (29 W m⁻²).

In spite of their larger bias with respect to TAO fluxes (24 W m⁻²), BEL fluxes have a good correlation coefficient (0.76) and the best rms deviation (24

W m⁻²). This could be related to the fact that 1997–98 TAO data were used for adjusting the flux algorithm used in the BEL satellite product. To clarify this point, another comparison between BEL and TAO was performed, in which only data more recent than 1998 were considered, namely, 1999-2002. The rms deviation found was 22.3 W m⁻², which hardly differed from the rms found in Fig. 3a. In addition, the correlation coefficient (0.76) and the systematic deviation (24.7 W m^{-2}) were almost unchanged when the 1998 TAO data were not accounted for, in spite of a number of collocated situations (2433) larger than for the 1998–2000 dataset (1747). We conclude that BEL fluxes compare generally well to TAO fluxes because the algorithm was adjusted to the environmental conditions of the TAO array of buoys. Nevertheless, Fig. 3a reveals a threshold (100 W m^{-2}) below which the bias of BEL fluxes increases by $\sim 15 \text{ W m}^{-2}$. This is confirmed by the slope of the first-degree polynomial fit of BEL fluxes to TAO fluxes, which is smaller than unity (0.70). The other products have slopes of first-degree fit to the surface data in the range of 0.86–0.89, which is larger and thus better than the slope found with BEL fluxes.

GSSTF-2 and J-OFURO have identical behavior with respect to buoy data. They present a large scatter that increases with LHF values and a large overestimation of LHF values larger than 100 W m⁻². Jones fluxes have an rms deviation of 27 W m⁻² with respect to TAO fluxes, which is good. They also present the highest correlation coefficient with respect to TAO data (0.76). However, the systematic deviation between Jones fluxes and TAO data is 49 W m⁻², which is 5 times larger compared to the systematic deviation found for HOAPS-2 fluxes.

2) UK-MF

Fluxes from BEL, GSSTF-2, HOAPS-2, and J-OFURO compare well to UK-MF buoy data, as shown in Fig. 4. Indeed, the rms deviations found range from 15 to 22 W m⁻², which is 2–26 W m⁻² smaller than with TAO data. GSSTF-2 fluxes have the largest rms (22 W m^{-2}) and present the largest bias (26 W m^{-2}) with respect to UK-MF data. In contrast, the rms is the smallest for HOAPS-2 fluxes, which also have a negligible bias with respect to UK-MF fluxes. It is necessary to recall that the smaller rms deviation found for UK-MF data compared to TAO data is not only related to changes in geographical location, but also to a different number of collocated situations (122). With a larger number of collocated situations for the UK-MF dataset, the rms deviation between satellite and buoy data could be larger.



FIG. 3. Comparison of five satellite LHF products to monthly fluxes calculated with moored buoys data from the TAO array in the equatorial Pacific from 1998 to 2000.



FIG. 4. Comparison of four satellite LHF products to fluxes from four moored buoys operated by Météo-France and the Met Office, off the coasts of the United Kingdom and France over 1998–2000.

3) NDBC

Figure 5 presents the comparison between four satellite products and NDBC buoy fluxes. None of the four products presents a good fit to buoy fluxes, although the correlation coefficients are good for all the products (0.80–0.90). The rms deviation of GSSTF-2 and HOAPS-2 fluxes with respect to surface fluxes is ~30 W m⁻², whereas it is 10 W m⁻² larger for J-OFURO and BEL fluxes. Biases are reasonable and range from -13 (HOAPS-2) to 7 W m⁻² (BEL). However, the slope of linear fit to surface data strongly differs from one satellite product to another. The slope is 0.51 for BEL, which implies that they fail to render part of the natural variability of the fluxes. It also suggests that their systematic error strongly depends on the flux value. The slope of linear fit to surface data is 0.63-0.73 for the three other products, which is better than for BEL. HOAPS-2 has the best fit to surface data in terms of rms deviation (30 W m⁻²), but the slope of linear fit to surface data is smaller by 7% than with GSSTF-2 fluxes. Thus, GSSTF-2 fluxes are the best compromise in rms deviation, bias, and slope of linear fit with respect to NDBC data.

5. Temporal analysis

To get a further insight into the behavior of the five satellite flux products with respect to moored buoy data, it is interesting to compare time series of satellite and surface fluxes, as presented hereafter for TAO, NDBC, and UK–MF data, respectively.



FIG. 5. Comparison of four satellite LHF products to data from four NDBC buoys over 1998–2000.

Only 15 out of the 66 TAO buoys were selected for analyzing the temporal variations of the fluxes, because time series were incomplete for the remaining 51 buoys, that is, less than 30 monthly fluxes were available out of 36 months of data (36 corresponds to 12 months multiplied by 3 yr from 1998 to 2000). We present statistics (average and rms deviation) calculated for the 15 available TAO buoy time series. In Fig. 6a, the overall biases of the satellite products with respect to TAO data were subtracted in order to emphasize the temporal variations of the fluxes. The biases were shown in section 4 and will be further discussed in section 8. Figure 6a indicates that HOAPS-2 fluxes correctly render the time variations of TAO data (in average and for 15 buoys). The behavior of BEL fluxes is close to HOAPS-2 fluxes, with a trend to underestimate the flux variations. This is more evident at months 4 and 16–17, and after month 31, when BEL fluxes depart from TAO data. The consequence is that time variations of BEL fluxes are smaller than time variations of TAO fluxes. Jones fluxes approximately reproduce the time variations of buoy data, but they occasionally overestimate or underestimate the fluxes calculated with TAO data. As a result, the systematic deviation of Jones fluxes with respect to TAO data is variable in time and is in the range of -10 to +20 W m⁻². GSSTF-2 and J-OFURO have a similar behavior with respect to surface data, namely, they strongly overestimate the variate the variate the variate the variate the variate the variate variate the variate vari



FIG. 6. Time series of satellite and buoy fluxes over 1998–2000. (a) Flux estimates (which are an average over 15 locations of the TAO array of buoys for each month) minus their average over the entire time period (36 months). (b) The rms deviation of the flux for each month over the 15 locations of the TAO array.

tions of the fluxes up to a factor 2. GSSTF-2, J-OFURO, BEL, HOAPS-2, and TAO fluxes all present time variations that can be interpreted as three seasonal cycles (Fig. 6a), which is good. The seasonal cycle also appears in Jones fluxes, though it is hardly present in the first six months of 1998. Interestingly, Jones fluxes also present a 2-month time lag with respect to TAO data in Fig. 6a, after month 25.

Figure 6b shows time series of the rms deviation of the flux over 15 TAO buoys, for each month, which provides a spatial view of the evolution of satellite and TAO fluxes. In other words, Fig. 6b is indicative of the diversity of the flux values through the TAO array, for each month. GSSTF-2 and J-OFURO fluxes overestimate the rms deviation of the TAO fluxes, as could be expected from the results above. BEL fluxes follow, yet underestimate the rms deviation of TAO fluxes. In contrast, HOAPS-2 and Jones fluxes slightly overestimate the variability of the rms of TAO fluxes. These results suggest that HOAPS-2 and Jones products are in good agreement with surface data in terms of spatial variations. For Jones, it indicates that spatial variations are better rendered than time evolution of the flux (Figs. 6a,b).

In two out of the four UK–MF buoys, more than 30 months of data were available for analyzing the time variations of the flux. They are represented in Fig. 7, in which we clearly distinguish three seasonal cycles in each product. However, peak deviations between satellite and surface fluxes exceed 40 W m⁻² in Fig. 7. The most apparent departure from UK–MF data occurs with BEL and GSSTF-2, which is coherent with the larger rms deviation of these products with respect to UK–MF data, found in section 4, compared to HOAPS-2 or J-OFURO.

Times series were sufficiently represented for two NDBC buoys located in the Gulf of Mexico (more than 30 months of data out of 36 were available for comparison), namely, buoys 42039 and 42040. Although the two NDBC buoys are close to each other (less than 200 km apart), the behavior of the satellite fluxes with respect to surface fluxes is quite different at these two sites, as



FIG. 7. Time series of satellite and buoy fluxes over 1998–2000 for two UK–MF buoys. The average of the flux over the whole time series was subtracted from the data for each product.

shown in Fig. 8. For buoy 42039, time series of the surface fluxes are correctly rendered by the four satellite products, whereas the time variations of satellite and surface fluxes markedly differ by up to 70 W m⁻² for buoy 42040, especially during the first 18 months (Fig. 8b). According to Fig. 8a, most satellite products tend to underestimate the flux variations, which is consistent with the slopes of linear fit that were equal to 0.51-0.73 in Fig. 4. Figure 8b also reveals that GSSTF-2 fluxes clearly depart from the other products at months 0, 17–19, and 27–30, which comes as a surprise because GSSTF-2 fluxes had the best fit to surface data in Fig. 4. To explain this difference, one has to study the deviation between GSSTF-2 and surface data in terms of bulk variables.

6. Analysis of bulk variables

The results presented in sections 4 and 5 revealed discrepancies between satellite-derived fluxes and buoy data. To explain them, it is necessary to investigate the deviation between satellite and surface data in terms of bulk variables, namely wind, Dalton number (C_E) , Q_S , and Q_A . Unfortunately, individual bulk variables are not available for most products. For instance, no bulk variable can be given along with products such as BEL, since the flux is calculated with a direct relationship between satellite radiances and flux data. Bulk variables are available for two products only: HOAPS-2 and GSSTF-2. The analysis presented hereafter is carried out for these two products. Such an analysis is useful for two reasons. On the one hand, HOAPS-2 fluxes are in good agreement with surface data (sections 4 and 5). Therefore, the comparison to surface data in terms of bulk variable should reveal which bulk variable is still an issue with the most accurate satellite products available. On the other hand, there were unanswered questions regarding the singular behavior of GSSTF-2 fluxes with respect to NDBC fluxes.

The analysis of bulk variables from satellites and surface data was performed as follows. It is hypothesized that the differences between satellite and surface bulk in terms of bulk variables and flux are small with re-



FIG. 8. Same as in Fig. 7, but for two NDBC buoys.

spect to the values of these variables. The first step is to differentiate (1), which is written as

$$dL_{E} = \left(\frac{\partial L_{E}}{\partial C_{E}}\right) dC_{E} + \left(\frac{\partial L_{E}}{\partial U_{A}}\right) dU_{A} + \left(\frac{\partial L_{E}}{\partial Q_{A}}\right) dQ_{A} + \left(\frac{\partial L_{E}}{\partial Q_{S}}\right) dQ_{S},$$
(2)

where

$$\begin{cases} \frac{\partial L_E}{\partial C_E} = \rho L_V U_A (Q_S - Q_A) \\ \frac{\partial L_E}{\partial U_A} = \rho L_V C_E (Q_S - Q_A) \\ \frac{\partial L_E}{\partial Q_S} = \rho L_V C_E U_A \\ \frac{\partial L_E}{\partial Q_A} = -\rho L_V C_E U_A. \end{cases}$$
(3)

In a second step, one considers that

 $\begin{cases} dL_E = L_E(\text{satellite}) - L_E(\text{buoy}) \\ dC_E = C_E(\text{satellite}) - C_E(\text{buoy}) \\ dU_A = U_A(\text{satellite}) - U_A(\text{buoy}) \\ dQ_A = Q_A(\text{satellite}) - Q_A(\text{buoy}) \\ dQ_S = Q_S(\text{satellite}) - Q_S(\text{buoy}). \end{cases}$ (4)

Last, (2), (3), and (4) can be rewritten as

$$dL_E = Q_{C_E} + Q_{U_A} + Q_{Q_A} + Q_{Q_S} = Q_{\text{tot}},$$

where the "Q terms" are the contributions (W m^{-2}) to the deviation between satellite and surface fluxes. Hereafter, the analysis of the Q terms is presented in terms of time series from January 1998 to December 2000, for TAO and UK–MF and NDBC data, respectively.

a. TAO

The analysis in Q terms for TAO is presented in Fig. 9. The purple line in Fig. 9a is the difference between satellite and surface flux (referred to as "control" in the following). Ideally, it should be superimposed on the



FIG. 9. Analysis of Q terms over 15 TAO buoys for HOAPS-2 and GSSTF-2 satellite products.

black line that represents the sum of the Q terms (Q_{tot}) . If not, the analysis in Q terms is not valid, because the difference between satellite and reference flux is too large with respect to the flux value. According to Fig. 9a, the largest deviation between the control and Q_{tot} is \sim 5 W m⁻², which indicates that there is a good agreement between the two curves, or equivalently that the analysis in Q terms is valid. The overall average of Q_{tot} is on the order of 10 W m^{-2} , which is coherent with section 4 findings. It does not vary much in time, which is a success for HOAPS-2. However, the time series of the individual Q terms presented in Fig. 9a reveal that the stationarity of Q_{tot} mainly results from the fact that Q_S and Q_A are underestimated by ~10 and ~15 W m⁻², respectively. Note that an overestimation of Q_A would have led to a negative Q_{Q_A} . Note Q_{U_A} and Q_{C_E} vary from 1998 to 2000, but are positive in average, which means that they are overestimated.

Figure 9b presents the analysis in Q terms for GSSTF-2 fluxes. As in Fig. 9a, the control (in purple)

closely follows the curve of Q_{tot} , which validates the analysis. The systematic deviation of GSSTF-2 fluxes with respect to TAO fluxes varies from -10 to +30 W m^{-2} , which is large and coherent with what was found in sections 4 and 5, namely that time variations of GSSTF-2 fluxes are exaggerated compared to surface data. Indeed positive systematic deviations in Fig. 9b correspond to flux extrema in Fig. 7. Here Q_{tot} is positive on average ($\sim 10 \text{ W m}^{-2}$) and its time variations are almost totally explained by those of $Q_{\mathcal{Q}_{\mathrm{A}}},$ which means that the estimation of Q_A is the main issue with GSSTF-2 in the Tropics. Note Q_{Q_s} is also underestimated (-20 W m^{-2}), whereas C_E is overestimated. Surprisingly, $Q_{U_{\perp}}$ shows variations very well correlated with those of Fig. 9a, for HOAPS-2, whereas they use a different wind retrieval algorithm (Table 1).

b. UK-MF

The Q term analysis for individual UK–MF buoys is presented in Fig. 10. It strongly differs according to the



FIG. 10. Analysis of Q terms for two UK-MF buoys.

satellite product considered. For HOAPS-2, the deviations between satellite and surface fluxes are small and Figs. 10a,c reveal that all Q terms contribute to the deviation. One may notice however that Q_{U_A} is systematically positive, on the order of 10 W m⁻². For GSSTF-2, the deviation between satellite and surface fluxes is almost entirely explained by deviations in Q_A (Q_{Q_A}), which is strongly underestimated, as was already found with TAO data (previous paragraph).

c. NDBC

Figure 11 presents the analysis in Q terms for NDBC buoys, a dataset for which HOAPS-2 and GSSTF-2 had similar performances according to the results reported in section 3. The variability of Q_{tot} is much more complicated to explain with NDBC data than with TAO or UK-MF data, because the Q terms all contribute to $Q_{\rm tot}$, not equally, but one at a time. It is especially noticeable for buoy 42039 (Figs. 11a,c). However, it was found in section 4 that the satellite flux product could render the seasonal cycle of the latent heat flux present in the surface data, which is already good. For buoy 42040, the seasonal cycle was missed in several satellite products, among which were HOAPS-2 and GSSTF-2. This is most noticeable in the first 18 months of the time series. Curves in Fig. 11 show that the deviation between satellite and surface data are mostly related to Q_{O_A} , which strongly fluctuates and reverses its sign several times during the 36-month period.

7. Spatial analysis

Five maps of satellite-derived latent heat fluxes averaged over 1998-2000 are presented in Fig. 12. Although a comparison between satellite products is not a validation, it is useful for better visualizing the respective behavior of the satellite products analyzed in the previous sections. In addition, it was found interesting to compare the satellite products to the National Oceanography Centre (NOC) climatology (Grist and Josey 2003), presented in Fig. 13. Figures 12 and 13 show common spatial patterns, such as large fluxes in the Tropics, as well as large flux values over warm surface ocean currents, such as the Kuroshio and the Gulf Stream. HOAPS-2 and BEL flux distributions are in good agreement. BEL fluxes are larger than HOAPS-2 fluxes in regions of small fluxes such as upwelling regions or the ITCZ, and also in the Arabian Sea, in the northern Indian Ocean, and in the eastern Mediterranean, which is consistent with NOC fluxes. GSSTF-2 and J-OFURO have spatial patterns that match those of HOAPS-2, except that spatial flux contrasts are exaggerated, which one could possibly relate to the fact that these two products overestimate the variations of TAO fluxes (sections 4, 5, and 6). Note however that the patterns of large flux values in the Indian Ocean west of Australia from GSSTF-2, J-OFURO, and Jones are in better agreement with the climatology than HOAPS-2 or BEL, which underestimate the flux in this region. Jones fluxes present some singular spatial patterns, such as relatively large LHF values in the Gulf of Guinea, which are present neither in the climatology nor in the other satellite products. A noticeable feature in Fig. 12 is the presence of wavy patterns in the GSSTF-2 product, which are not present in all the oceans. An analysis of the spatial patterns of individual bulk variables revealed that Q_s [based on NCEP SST according to Chou et al. (2003)] was the bulk variable in which similar waves could be seen. Figure 14 shows the difference between HOAPS-2 Q_s , which has smoother spatial variations, and GSSTF-2 Q_s values. It clearly shows unrealistic waves propagating, in various directions depending on the basin considered.

8. Discussion

Five satellite products of LHF were compared to bulk fluxes calculated with data from 79 moored buoys on almost 36 successive months from 1998 to 2000. The comparisons were performed under various environmental conditions, namely, tropical regions with the TAO array of buoys and midlatitudes with nine NDBC buoys and four UK–MF buoys. Comparisons to TAO, UK–MF, and NDBC were done with 66, 5, and 9 buoys, resulting in 1747, 122, and 177 satellite/buoy collocated situations available for comparison, respectively. This suggests that the results found in this paper are statistically representative of tropical and equatorial flux conditions. In contrast, comparisons to NDBC and UK–MF buoys rather give clues on the accuracy of the satellite products at midlatitudes than firm conclusions.

a. Rms deviation between satellite and surface data

The comparison of five satellite products to TAO indicated that the rms deviations with respect to surface data ranged from 24 to 29 W m⁻² for three products, BEL, Jones, and HOAPS-2, whereas they were 36–41 W m⁻² for the other products (GSSTF-2 and J-OFURO). The comparison of four satellite products to UK–MF also gave encouraging results, that is, rms deviations in the range of 15–22 W m⁻². In contrast, the comparison to NDBC buoys gave slightly larger rms deviations from 30 to 39 W m⁻². Overall, the comparisons performed between satellite products and buoy



FIG. 11. Analysis of Q terms for two NDBC buoys in the Gulf of Mexico.





FIG. 12. Latent heat flux in average from 1998 to 2000 for five satellite products.



FIG. 13. Latent heat flux from the NOC climatology.

data indicated that HOAPS-2 compared generally better to TAO, UK–MF, and NDBC data than the other products did, in terms of bias, rms, and correlation. We also conclude that the comparison between satellite products and moored buoy data is a success. Indeed, buoy data are appropriate for the comparisons to satellite products, since rms deviations as low as 15 W m⁻² and correlation coefficients as large as 0.90 were found with respect to satellite products. Note, however, that the accuracy of surface fluxes calculated with moored buoy data cannot be accurately known.

The best rms deviations found are 24 (BEL), 15 (HOAPS-2), and 30 (HOAPS-2) W m⁻² for TAO, UK–MF, and NDBC data, respectively, which is quite low since they correspond to a 15%–30% relative error (15% for TAO). These reinforce previous results by Esbensen et al. (1993), who compared satellite fluxes to surface data for several months between 1987 and 1988 and found an rms deviation of ~30 W m⁻². Bentamy et al. (2003) also found similar relative errors, which confirms the present results. The reader should be informed that the rms deviations found between satellite and buoy data are not necessarily equal to the rms ac-

curacy of the satellite fluxes. Instead, it is likely that the rms accuracy of the satellite products be on the order of half the rms deviations found above. For example, let us estimate the rms accuracy of BEL fluxes in the Tropics, based on the rms deviation found between BEL fluxes and TAO data (21 W m^{-2}). If the distributions of BEL and TAO fluxes are assumed to be Gaussian and if the rms error in satellite fluxes, one may show with Monte Carlo simulations that the rms accuracy of BEL fluxes is a mere 10 W m^{-2} (e.g., Bourras et al. 2003).

b. Analysis of time series

A temporal analysis revealed that four satellite products (GSSTF-2, BEL, J-OFURO, and HOAPS-2) were able to render the time variations of the surface fluxes calculated with TAO and UK–MF data. However, the seasonal cycle was less well represented in Jones data.

It was found that BEL fluxes tend to slightly underestimate the spatial and temporal variations of the flux compared to TAO and UK–MF data. On the opposite, GSSTF-2 and J-OFURO largely overestimate the flux variations of TAO and UK–MF data.



FIG. 14. Difference in surface specific humidity between HOAPS-2 and GSSTF-2.

Time series of satellite fluxes compared to two NDBC buoys gave mixed results. For one buoy, the seasonal cycles rendered by the satellite products were noisy, but in good agreement with surface data. For a second buoy located 200 km downwind from the first one and closer to the coast, the satellite products did not perform well.

c. Systematic deviations between satellite and surface data

Biases of the satellite products with respect to TAO data are in the range (-13;+26) W m⁻² for GSSTF-2, HOAPS-2, BEL, and J-OFURO, which is acceptable. In contrast, the Jones product has a stronger bias, 49 W m^{-2} , with respect to TAO data. The reader should be informed that the biases found strongly depend on the bulk algorithm used for calculating the buoy fluxes. Indeed, strong discrepancies still exist among the available bulk algorithms. Fairall et al. (2003) was selected in the present study because it was found to be "one of the least problematic flux algorithms" in a recent study (Brunke et al. 2003). However, such a ranking is always questionable because of the lack of available validation data and for multiple technical reasons, among which are the heterogeneity of the instruments used and the flux measurement platforms used for collecting data. In addition, the values of the calculated fluxes strongly depend on the options selected in the bulk algorithm. For instance, the Fairall et al. (2003) algorithm was not used with an option of skin SST correction that should have been used if radiation fluxes were available (section 3). To check the robustness of the biases found with satellite products with respect to surface data, another algorithm (Bourras 2000) was used for calculating the TAO fluxes. The biases found were even smaller with the Bourras (2000) algorithm, namely, 2-15 W m^{-2} , than with the Fairall et al. (2003) algorithm (not shown). This is a reminder that the estimates of the systematic errors presented in this manuscript strongly depend on the bulk algorithm used with no current agreement on the best one.

Nevertheless, it is interesting to discuss the spatial variations of the systematic deviations between satellite and surface data. Indeed, it was found in section 4 that they varied according to the dataset considered. For instance, the bias of HOAPS-2 fluxes with respect to surface data was 0 W m⁻² with respect to UK–MF, -13 W m⁻² with respect to NDBC data, and +10 W m⁻² with respect to TAO. To explain such differences, it is necessary to analyze the systematic deviations of satellite-derived individual bulk variables with respect to surface data, for the three datasets (TAO, NDBC, and UK–MF).

d. Analysis of individual bulk variables

Such an analysis was carried out with GSSTF-2 and HOAPS-2 products only, because bulk variables were not available in the other products. It was shown that the estimation of Q_s and Q_A are the main concern with TAO data, for both HOAPS-2 and GSSTF-2. For Q_s , the monthly bias was remarkably stationary (Fig. 9), which suggests that it could possibly be corrected in future versions of the satellite products. Indeed, it depends on the bulk algorithm chosen (and the options selected in the latter algorithm), on the calibration of the satellite-derived SSTs used, or both. For Q_A , the conclusion depends on the satellite product considered. The systematic deviation found for HOAPS-2 fluxes presents reasonable fluctuations that correspond to 5–25 W m⁻² in Q_{Q_4} . In contrast, time variations of the deviation between $GSSTF-2 Q_A$ and TAO data are unacceptably large (-10 to +35 W m⁻² in terms of $Q_{O_{1}}$). This indicates that the Q_A estimates used in GSSTF-2 have some deficiencies in the Tropics.

The same analysis was performed with UK–MF data. It revealed that GSSTF-2 fluxes were again strongly affected by the lack of accuracy of their Q_A estimates, whereas Q_A was almost not a problem with HOAPS-2.

In the Gulf of Mexico (NDBC buoys), the analysis revealed that deviations between satellite and surface data in terms of C_E , Q_A , U_A , and Q_S were all occasionally responsible for the discrepancy between satellite and NDBC fluxes. It was also noticed that the contribution of Q_A to the error budget was larger than the contribution of the other bulk variables. Altogether, these results show that the geophysical signal is difficult to invert with satellite data in the region of the two NDBC buoys.

Overall, the analysis of the deviations between individual bulk variables from satellites and buoys clearly indicates that the estimation of Q_A is problematic in satellite products. This gives clues for explaining the different systematic deviations of HOAPS-2 fluxes with respect to TAO, NDBC, and UK-MF data. Indeed, a Q_A algorithm is no more and no less than a statistical relationship between the integrated water vapor content in the atmosphere and Q_A . As a result, a typical vertical humidity profile is assumed. In the Tropics (TAO area), humidity can be found at altitudes larger than in the hypothetic profile, leading to an underestimation of Q_A (for the same integrated humidity content, surface humidity is smaller if moist air is present at larger altitudes). A profile presenting an opposite extradry tendency at larger altitudes would result in overestimating satellite-derived Q_A (Fig. 5), as could be the case in the Gulf of Mexico.

Let us recall that the analysis was performed with GSSTF-2 and HOAPS-2 bulk variables only, which means that no conclusion can be drawn for BEL, Jones, or J-OFURO.

e. Spatial analysis

The spatial patterns of satellite-derived fluxes are consistent with those present in a flux climatology. However, it appears that GSSTF-2 fluxes and J-OFURO strongly overestimate LHF in the Tropics, with respect to the climatology. This is consistent with the overestimation of large fluxes with respect to TAO data that were found in GSSTF-2 and J-OFURO. This was also found by Kubota et al. (2003), who wrote that "HOAPS and Da Silva et al. (1994) products are underestimated in the Tropics compared to GSSTF and J-OFURO," except that the sentence should be rewritten as "GSSTF-2 and J-OFURO are strongly overestimated with respect to known reference data." In addition, the present results show that GSSTF-2 produces less realistic flux estimates than HOAPS-2, a possibility that was not clearly seen by Chou et al. (2004), according to whom GSSTF-2 was likely to be more realistic than HOAPS-2 and the Da Silva et al. (1994) product.

In addition, the spatial analysis performed in the present manuscript revealed apparently unrealistic wave patterns in the GSSTF-2 flux product. The same waves were present in the Q_s fields delivered with the GSSTF-2 product. The Q_s fields come from NCEP fields, according to Chou et al. (2003). Note that the waves were not present in GSSTF-2 wind or Q_A fields.

f. Conclusions

The results presented in this manuscript indicate that deviations between satellite and surface data strongly depend on the satellite product selected and on the surface data considered (location and bulk algorithm used). Therefore, flux users may wonder whether or not satellite fluxes should be used, and if yes, which one should be used. The answer depends on the intended use of the satellite fluxes and on the time and space scales under investigation.

If mesoscale spatial variations of the LHF are analyzed, several studies have shown that satellite fluxes are helpful to identify air-sea interaction processes (e.g., Bourras et al. 2004). The present paper shows that spatial variations of the flux follow those calculated with TAO data with an accuracy that is better than 16 W m⁻², calculated as the maximum deviation between HOAPS-2 and TAO fluxes in Fig. 6b. It represents a 15% relative error, which is reasonable.

The analysis of time series also revealed that several

satellite flux products performed well. For instance, the rms deviation between BEL and TAO fluxes in Fig. 6a is only 4.4 W m⁻². However, it can be larger, depending on the region considered, namely 36 W m⁻² for NDBC and 15 W m⁻² with UK–MF buoys. The discrepancy found is a function of the vertical distribution of humidity in the atmosphere, which is a major issue with the current satellite sensors used.

For the same reason, satellite fluxes have regional systematic errors. For instance, our results show that biases with respect to surface data vary by $\sim 25 \text{ W m}^{-2}$ depending on the region under consideration (TAO, UK–MF, or NDBC).

One may conclude that satellite fluxes can already be used for studying mesoscale air-sea interaction processes in several regions. The results found in the present manuscript suggest that satellite fluxes are not yet appropriate for a quantitative use over the world oceans, because their overall accuracy is on the order of 20%-30%. These figures would have to be decreased by 5%-10% before the use of satellite fluxes would become obvious to all users. This goal may be achievable with the use of more sophisticated Q_A retrieval algorithms in the future (only microwave imagers were used so far for estimating surface humidity). However, satellite products are already competitive with respect to flux climatology or output fields from weather forecasting models, the accuracy of which strongly depends on the availability of data in the assimilation/interpolation process.

Overall, for application of the fluxes over the world oceans, our results show without ambiguity that HOAPS-2 fluxes are the most adequate satellite product. For regional studies concerning the Tropics, our results suggest that BEL fluxes also perform well.

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