

## Improvement in air–sea flux estimates derived from satellite observations

Abderrahim Bentamy<sup>a,\*</sup>, Semyon A. Grodsky<sup>b</sup>, Kristina Katsaros<sup>c</sup>, Alberto M. Mestas-Nuñez<sup>d</sup>,  
 Bruno Blanke<sup>e</sup> & Fabien Desbiolles<sup>a,e</sup>

<sup>a</sup> Laboratoire d'Océanographie Spatiale (LOS), Institut Français pour la Recherche et l'Exploitation de la Mer (IFREMER), France

<sup>b</sup> Department of Atmospheric and Oceanic Science, University of Maryland, College Park, MD, USA

<sup>c</sup> Rosenstiel School of Marine and Atmospheric Science, University of Miami, Miami, FL, USA

<sup>d</sup> Department of Physical and Environmental Sciences, Texas A&M University-Corpus Christi, Corpus Christi, TX, USA

<sup>e</sup> Laboratoire de la Physique des Océans (LPO), UMR 6523 CNRS-Ifremer-IRD-UBO, France

\*: Corresponding author : Abderrahim Bentamy, email address : [abderrahim.bentamy@ifremer.fr](mailto:abderrahim.bentamy@ifremer.fr)

### Abstract:

A new method is developed to estimate daily turbulent air–sea fluxes over the global ocean on a 0.25° grid. The required surface wind speed ( $w_{10}$ ) and specific air humidity ( $q_{10}$ ) at 10 m height are both estimated from remotely sensed measurements.  $w_{10}$  is obtained from the SeaWinds scatterometer on board the QuikSCAT satellite. A new empirical model relating brightness temperatures ( $T_b$ ) from the Special Sensor Microwave Imager (SSM/I) and  $q_{10}$  is developed. It is an extension of the author's previous  $q_{10}$  model. In addition to  $T_b$ , the empirical model includes sea surface temperature (SST) and air–sea temperature difference data. The calibration of the new empirical  $q_{10}$  model utilizes  $q_{10}$  from the latest version of the National Oceanography Centre air–sea interaction gridded data set (NOCS2.0). Compared with mooring data, the new satellite  $q_{10}$  exhibits better statistical results than previous estimates. For instance, the bias, the root mean square (RMS), and the correlation coefficient values estimated from comparisons between satellite and moorings in the northeast Atlantic and the Mediterranean Sea are  $-0.04 \text{ g kg}^{-1}$ ,  $0.87 \text{ g kg}^{-1}$ , and 0.95, respectively. The new satellite  $q_{10}$  is used in combination with the newly reprocessed QuikSCAT V3, the latest version of SST analyses provided by the National Climatic Data Center (NCDC), and 10 m air temperature estimated from the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalyses (ERA-Interim), to determine three daily gridded turbulent quantities at 0.25° spatial resolution: surface wind stress, latent heat flux (LHF), and sensible heat flux (SHF). Validation of the resulting fields is performed through a comprehensive comparison with daily, *in situ* values of LHF and SHF from buoys. In the northeast Atlantic basin, the satellite-derived daily LHF has bias, RMS, and correlation of  $5 \text{ W m}^{-2}$ ,  $27 \text{ W m}^{-2}$ , and 0.89, respectively. For SHF, the statistical parameters are  $-2 \text{ W m}^{-2}$ ,  $10 \text{ W m}^{-2}$ , and 0.94, respectively. At global scale, the new satellite LHF and SHF are compared to NOCS2.0 daily estimates. Both daily fluxes exhibit similar spatial and seasonal variability. The main departures are found at latitudes south of 40° S, where satellite latent and sensible heat fluxes are generally larger.

## 1. Introduction

---

Accurate turbulent air–sea fluxes (i.e. momentum, latent heat, and sensible heat) are of great interest in regard to a wide variety of air–sea interaction issues. The main sources of such fluxes over the global ocean are numerical weather prediction (NWP) models, voluntary observing ships (VOSs), and remotely sensed data.

For over a decade, several scientific groups have been developing direct and inverse methods, algorithms, and procedures to calculate long time series of surface winds, wind stress, specific air humidity, and latent and sensible heat fluxes; representative data sets include the Japanese Ocean Flux data sets with the Use of Remote sensing Observations (J-OFURO) (Kubota et al. 2002), the Goddard Satellite-based Surface Turbulent Fluxes (GSSTF) (Chou et al. 2003), the Objectively Analysed Air–Sea Fluxes (OAFLUX) (Yu, Weller, and Sun 2004), the Institut Français pour la Recherche et l'Exploitation de la Mer (IFREMER) (Bentamy et al. 2003, 2008), and the Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Data (HOAPS) (Anderson et al. 2010). These satellite fluxes are widely used by the scientific community for various purposes such as forcing ocean circulation models (e.g. Ayina et al. 2006), studying the spatial and temporal variability associated with the El Niño Southern Oscillation (ENSO) (e.g. Mestas-Nuñez, Bentamy, and Kristina 2006), or employing an enhanced spatial and temporal sampling provided by remote techniques to evaluate intra-seasonal variability (e.g. Grodsky et al. 2009). Even though the results of these investigations have increased our understanding of air–sea interactions, further improvements of satellite-based fluxes are still required.

A number of studies assessing the quality of turbulent fluxes have been published in recent years. By comparing latent heat fluxes (LHFs) from buoys and satellites, Bourras (2006) has found that the overall accuracy is of the order of 20–30%, whereas the required error for a quantitative use over the global oceans should be lower than 10%. He has concluded that the main LHF error sources are related to the accuracy of the specific air humidity ( $q$ ) and surface wind speed ( $w$ ). Tomita and Kubota (2006) have investigated the accuracy of satellite-based LHF through comparisons with buoy and NWP estimates. In the tropics, the main source of buoy and satellite LHF discrepancy is attributed to the accuracy of satellite  $q$ , whereas around Japan the LHF discrepancy is associated with the accuracy of both  $w$  and  $q$ . They both have concluded that the improvement in satellite LHF estimation requires improvements in remotely sensed  $w$  and  $q$ .

1 at global and regional scales. Santorelli *et al* (2011) have conducted detailed accuracy investigations  
2 of IFREMER and OAFLUX latent and sensible heat fluxes as well as of basic bulk variables (10  
3 m wind speed,  $W_{10}$ ; 10m specific air humidity,  $Q_{a10}$ ; 10 m air temperature,  $T_{a10}$ ; and SST) using  
4 standard moored buoy and dedicated-experiment scientific data. Their conclusions generally agree  
5 with the studies mentioned earlier. In particular, they emphasized that the improvement of satellite  
6 fluxes should include the improvement of the interpolation method used to calculate gridded fields  
7 over the global ocean to better reflect conditions during synoptic-scale storms and fronts.

8 Following the suggested recommendations improving the fluxes, the present study aims at  
9 enhancing the following three aspects: the determination of  $Q_{a10}$  retrievals over global oceans, the  
10 accuracy of bulk variables as well as of the turbulent fluxes themselves, and the spatial and  
11 temporal resolutions of the flux fields. This study takes advantage of the availability of the new air-  
12 sea interaction datasets estimated from the updated International Comprehensive Ocean-  
13 Atmosphere Data Set (ICOADS) (Berry *et al.*, 2011), and of the new QuikSCAT wind retrievals  
14 (Fore *et al.*, 2011) .

15 A description of the various datasets used is given in section 2 and the method retrieving  $Q_{a10}$   
16 from satellite radiometer measurements is presented in section 3. The validation of the resulting  
17 flux field analyses is provided and discussed in sections 4 and 5. Finally, section 6 presents the  
18 summary, conclusion, and perspective study.

19

## 20 **2. Data**

21 The main basic bulk variables required for turbulent flux estimations are surface wind speed  
22 ( $W$ ), specific air humidity ( $Q_a$ ), specific surface humidity ( $Q_s$ ), air temperature ( $T_a$ ), and sea  
23 surface temperature (SST) . Moored buoys, ships, and NWP models provide valuable estimates of  
24 these variables with various spatial and temporal resolutions. They are used in this study for the  
25 calibration and/or validation of satellite retrievals at local, regional, and global scales.

### 26 **2.1 Scatterometer data**

27 To ensure homogeneity of  $W$  and its variability, this study employs only wind retrievals from  
28 SeaWinds scatterometer onboard QuikSCAT. The QuikSCAT scatterometer principle is described in  
29 many scientific papers. Readers may find complete description in (JPL, 2006) including instrument  
30 physics, retrieval and ambiguity removal methods, rain detection and flagging techniques, and  
31 quality control procedures. Briefly, QuikSCAT is a rotating antenna with two differently polarized  
32 emitters: the H-pol with incidence angle of  $46.25^\circ$  and V-pol with incidence angle of  $54^\circ$ . The inner  
33 beam has a swath width of about 1400km, while the outer beam swath is 1800km width. QuikSCAT

1 scatterometer is a Ku band radar. Therefore, rain has a substantial influence on its measurements.  
2 Previous studies showed that the rain impact may attenuate the scatterometer signal, resulting in  
3 wind speed underestimation, or change the surface shape due to raindrop impacts leading to W  
4 overestimation in the retrieved winds. QuikSCAT wind products involve several rain flag  
5 determined from the scatterometer observations and from the collocated radiometer rain rate  
6 onboard other satellites.

7 This study uses a new QuikSCAT wind retrievals indicated as QuikSCAT V3  
8 (<ftp://podaac.jpl.nasa.gov/OceanWinds/quikscat/preview/L2B12/v3/>). They are made available by  
9 Jet Propulsion Laboratory (JPL)/ Physical Oceanography Distributed Active Archive Center  
10 (PODAAC) scientific team (Fore *et al*, 2011). QuikSCAT V3 products are calculated based on the  
11 use of a geophysical model function ensuring the consistency with winds retrieved from microwave  
12 radiometers such as Special Sensor Microwave Imager (SSM/I) and WindSat (Ricciardulli *et al*,  
13 2011). Wind retrievals are provided over QuikSCAT swath at Wind Vector Cell (WVC) of 12.5km  
14 spatial resolution. This new scatterometer product is assumed improving wind speed performance in  
15 rain and at high wind speed conditions.

16 The accuracy of the QuikSCAT V3 data is determined through various comparisons with  
17 buoy wind measurements, QuikSCAT V2 retrievals, and with remotely sensed winds derived from  
18 the ASCAT scatterometer onboard Metop-A satellite. The main findings (not shown) are that the  
19 comparison results meet those obtained previously (Bentamy *et al*, 2012). QuikSCAT V3 and  
20 QuikSCAT V2 exhibit similar comparison results versus buoys. ASCAT and QuikSCAT V3 statistics  
21 are of the same order as ASCAT and QuikSCAT V2. Discrepancies characterizing ASCAT and  
22 QuikSCAT V2 comparisons are found for ASCAT and QuikSCAT V3. For instance, the most  
23 significant discrepancies are found at tropical and high latitudes. QuikSCAT V3 are corrected and  
24 improved when compared with (Bentamy *et al*, 2012) results.

## 25 **2.2 Radiometer data**

26 The special sensor microwave imager (SSM/I) measurements used in this study are the same  
27 as in (Bentamy *et al*, 2003 and 2008). The SSM/I radiometers onboard the Defense Meteorological  
28 Satellite Program (DMSP) F11, F13, F14, and F15 satellites provide measurements of the surface  
29 brightness temperatures (T<sub>b</sub>) at frequencies 19.35, 22.235, 37, and 85 GHz (hereafter referred to as  
30 19, 22, 37, and 85 GHz), respectively. Horizontal and vertical polarization measurements are taken  
31 at 19, 37, and 85 GHz. Only vertical polarization is available at 22 GHz. Due to the choice of the  
32 channels operating at frequencies outside strong absorption lines (for water vapor 50-70 GHz), the  
33 detected radiation is a mixture of radiation emitted by clouds, water vapor in the air and the sea  
34 surface, as well as radiation emitted by the atmosphere and reflected at the sea surface. Brightness

1 temperature measurements as well as the associate geophysical parameters are provided by Global  
2 Hydrology Resource Center (GHRC) (<http://ghrc.msfc.nasa.gov/> )  
3

## 4 **2.3 Buoys**

5 Data from a number of moored buoys located in different basins are used for the ground truth  
6 validation. These include 8 Atlantic moorings off the French and England coasts maintained by UK  
7 Met-Office and/or Météo-France (MFUK), 96 moorings off the Atlantic and Pacific U.S coasts  
8 maintained by the National Data Buoy Center (NDBC), 66 moorings of the TAO/TRITON array in  
9 the equatorial Pacific, and 13 moorings of the PIRATA network in the equatorial Atlantic.  
10 TAO/TRITON and PIRATA will be hereafter referred as tropical buoys. Meteorological buoy data  
11 are hourly average. Measurement height varies between 3m and 10m depending on mooring  
12 configuration Buoy wind, specific air humidity, air temperature are converted to the standard height  
13 of 10m using the COARE3.0 algorithm of Fairall *et al.* (2003). The latter is also used to estimate  
14 buoy turbulent fluxes.

## 15 **2.4 NOCS data**

16 A new daily mean air-sea interaction gridded dataset (Berry *et al.*, 2011) is provided by the  
17 National Oceanography Centre Southampton and referred as NOCS Flux Dataset v2.0 (NOCS2.0).  
18 They are available over global ocean with a spatial resolution of 1° in longitude and latitude. Daily  
19 parameters such as  $W_{10}$ ,  $Q_{a10}$ ,  $T_{a10}$ , SST, Latent heat (LHF) and sensible (SHF) are provided with  
20 uncertainty estimates. The accuracy of NOCS2.0 gridded parameters was investigated trough  
21 various comparisons including buoy, satellite, and numerical model data. For instance the  
22 comparison with buoys deployed and maintained by the Woods Hole Oceanographic Institution  
23 (WHOI) Upper Ocean Processes Group (UOP) indicates that the mean difference (NOCS2.0 –  
24 WHOI UOP) of  $W_{10}$  and  $Q_{a10}$  are about 0.30m/s and 0.40g/kg, respectively (Table II of Berry *et al.*,  
25 2011)

## 26 **2.5 Era Interim**

27 Era-Interim (Simmons *et al.*, 2006) refers to the re-analyses of atmospheric parameters  
28 produced by the European Center for Medium Weather Forecasts (ECMWF). It uses 4D-variational  
29 analysis on a spectral grid. This re-analysis covers the period from 1989 to the present day. The  
30 ERA-Interim data used in this study was obtained from the ECMWF data server on a fixed grid of  
31 0.75°. The main parameters used in this study are specific air humidity and air temperature at 2m,  
32 available at synoptic times (00h:00, 06h:00, 12h:00, 18h:00 UTC), converted to  $Q_{a10}$  and to  $T_{a10}$  ,

1 respectively, utilizing the COARE3.0 model (Fairall *et al*, 2003). The quality of  $Q_{a10}$  and of  $T_{a10}$  is  
2 checked through comparisons with MFUK, TAO, and PIRATA buoy estimates. The main finding  
3 of interest for this study, is that Era Interim  $T_{a10}$  are underestimated for buoy  $T_{a10}$  exceeding 20°C.  
4 A bias correction is determined from linear regression between Era Interim and buoy  $T_{a10}$   
5 estimates.

## 6 **2.6 Collocation**

7 For  $Q_a$  calibration purpose, SSM/I, NOCS2.0, Era Interim and SST are collocated in space  
8 and time. SST data are version 2 of IO daily analyses (Reynolds *et al*, 2007) with a spatial  
9 resolution of 0.25° in longitude and latitude. Common collocation procedure is utilized. Era interim  
10  $Q_{a10}$  and  $T_{a10}$  occurring within 50km and 3 hours from SSM/I cell location and time, respectively,  
11 are bi-linearly interpolated at SSM/I cell. SSM/I brightness temperatures and NOCS2.0  $Q_{a10}$   
12 occurring same day are matched such as the spatial difference is less than 100km. Same collocation  
13 approach is used for SSM/I  $T_b$  and daily SST, except that the spatial difference criteria is 25km.

## 14 **3. Specific Air Humidity Improvement**

### 15 **3.1 Retrieving specific air humidity from satellite measurements**

16 Based on the collocated SSM/I and ICOADS data, several authors assessed the relationship  
17 between satellite brightness temperatures ( $T_b$ ) and in-situ specific air temperature ( $Q_a$ ) (e.g.  
18 Kubota *et al*, 2008; Jackson *et al*, 2009). The former is mainly related to the quite linear relationship  
19 between specific air humidity and the column integrated water vapor content (WV) obtained from  
20 satellite microwave radiometers (Schultz *et al*, 1993). SSM/I  $T_b$  measurements are sensitive to WV  
21 especially in 19v, 19h, 22v, and 37v channels. In (Bentamy *et al*, 2003) the development of a  
22 SSM/I-based method for the retrieval of  $Q_a$  from brightness temperatures is based on a model  
23 determined from the collocated SSM/I  $T_b$  and COADS  $Q_a$  over a limited oceanic areas of the North  
24 Atlantic and of the eastern equatorial Pacific oceans, and during a limited period (1996 – 1998).  
25 This model was successfully used by several groups for  $Q_a$  estimation from SSM/I or from AMSRE  
26 measurements as well as to assess a new development of  $Q_a$  models (e.g. Anderson *et al*, 2010;  
27 Kubota *et al*, 2008; Jackson *et al*, 2009). However, Grodsky *et al* (2009), and Santorelli *et al* (2011)  
28 underlined the need for improvement of the remotely sensed specific air humidity. To achieve such  
29 enhancement, the new updated and enhanced NOCS2.0 data are used as references for a new  $Q_{a10}$   
30 modeling. For instance Figure 1 shows the difference between NOCS2.0 and the previous version  
31 of satellite  $Q_{a10}$  of Bentamy *et al*. (2003) as a function of satellite-derived  $Q_{a10}$  and for five  
32 NOCS2.0 SST ranges. The findings (Figure 1) suggest including SST as a variable in a satellite

1 Qa<sub>10</sub> model. Furthermore, the investigation of NOCS2.0 and satellite Qa<sub>10</sub> differences indicates a  
 2 stratification dependency. The latter would be an indication of the modification of the relationship  
 3 between WV and Qa as a function of stratification variability. Therefore, the new Qa model  
 4 includes terms related to SST and to the difference between 10m air and sea surface temperatures  
 5 ( $\Delta T$ ).

$$6 \quad Qa_{10} = f_1(TB_{19V}) + f_2(TB_{19H}) + f_3(TB_{22V}) + f_4(TB_{37V}) + g(SST) + h(\Delta T) \quad (1)$$

7 The functions  $f_1, f_2, f_3, f_4, g$ , and  $h$  are determined through a maximum likelihood procedure based  
 8 on the use of collocated data: SSM/I F11 Tb, NOCS2.0 Qa<sub>10</sub>, SST, and Era Interim Ta<sub>10</sub>. Only  
 9 matchups occurring during January, April, August, and September 2005 are used. Due to the strong  
 10 correlation between WV and brightness temperatures and between specific air humidity and sea  
 11 surface temperature, Qa<sub>10</sub> (eq. 1) is mainly weighted by functions  $f_1, f_2, f_3, f_4, g$ . On overall, the  
 12 term  $h(\Delta T)$  has a small impact. However, it maintains the bias between NOCS2.0 and satellite Qa  
 13 close to zero with respect to air-sea temperature difference.

14

15 **Insert Figure1**

16

### 17 ***3.2 Daily analysis***

18 One of the main goals of this study is to estimate daily 10m specific air humidity from  
 19 remotely sensed data with same spatial resolution as the gridded daily wind fields (see the following  
 20 section). All available and valid brightness temperature measurements from F11, F13, F14, and F15  
 21 satellites during 2005 – 2007 period are used. For each day and for each individual SSM/I swath  
 22 cell, valid brightness temperatures (instantaneous), and the spatially closest daily averaged SST and  
 23 6-hourly 10m air-temperature are selected. Specific air humidity is estimated based on (eq. 1). Due  
 24 to time differences and accuracy characteristics (Meisnner *et al*, 2001) of brightness temperatures  
 25 derived from various instruments may contribute to a non consistency between Qa derived from (1)  
 26 and actual values expected to be used for daily gridded specific air humidity calculation. To reduce  
 27 the non-consistency impact, auxiliary information providing a mean description of Qa during a  
 28 given day is also used. It is derived from 6-hourly Era Interim Qa estimates. The following linear  
 29 relationship between retrievals (Qa<sub>10</sub>) and auxiliary data is assumed:

30

$$31 \quad E(Qa_{10}(x,y,t)) = \alpha_0 + \beta_1 Qa_{mod}(x,y,t) \quad (2)$$

32 Where  $x, y$ , and  $t$ , state for spatial and temporal coordinates.  $\alpha_0$  and  $\beta_1$  are coefficients to be

1 estimated. Operator  $E$  states for mathematical mean (conventional first moment).  $Q_{a_{10}}$  indicates  
 2 Era Interim  $Q_{a_{10}}$  collocated in space and time with each individual satellite retrieval. (2) is known  
 3 as external drift constraint (Wackernagel, 1998).

4 The objective method aiming to calculate gridded daily specific air humidity from retrievals is  
 5 quite similar to the method used for daily ASCAT wind field analyses (Bentamy *et al*, 2011).  
 6 Briefly, daily satellite  $Q_a$  is estimated based on the following assumption:

$$7 \quad Q_{a_{sat}} = \frac{1}{(t_b - t_a)} \int_{t_a}^{t_b} \left( \sum_{j=1}^N \lambda_j (Q_{a_{10}}(x_j, y_j, t)) \right) dt + \varepsilon \quad (3)$$

8 With unbiased constraint  $\sum_{j=1}^N \lambda_j = 1$  and external drift constraint (2)

9  $Q_{a_{10}}(x_j, y_j, t)$  indicates the  $j$ th  $Q_{a_{10}}$  retrieval available over a given satellite swath cell with  
 10 geographical coordinates  $(x_j, y_j)$  and at time  $t$ .  $t_a$  and  $t_b$  indicate the time interval falling within  
 11 00h:00mn:00sec and 23h:59mn:59sec when retrievals are available.  $N$  is the retrieval number  
 12 selected for daily analysis calculation.

13  $\lambda$  is the weighting vector to be estimated. It is the solution of the following linear system:

$$14 \quad \left\{ \begin{array}{l} 15 \quad \sum_{j=1}^{j=N} \lambda_j C_{ij} - \mu_1 - \mu_2 Q_{a \text{ mod } i} = C_{i0} \quad \text{for } i = 1, N \\ 16 \quad \sum_{j=1}^{j=N} \lambda_j = 1 \\ 17 \quad \sum_{j=1}^{j=N} \lambda_j Q_{a \text{ mod } j} = Q_{a \text{ mod } 0} \end{array} \right.$$

18  $C_{ij}$  stands for covariance matrix between  $Q_a$  observations, while  $\mu_1$  and  $\mu_2$  are the Lagrangian  
 19 terms used to take into account the unbiased and external drift constraints. Index 0 indicates grid  
 20 point where daily analysis is performed.

21 The objective method requires parameterization of the spatial and temporal covariance  
 22 structure of specific air humidity. It is determined from retrievals occurring during January, April,  
 23 July, and October 2005 over the global ocean between 55°S and 55°N.

### 24 **3.3 Satellite daily $Q_{a_{10}}$ Accuracy**

25 The quality of the resulting satellite daily 10m  $Q_a$  estimates ( $Q_{a_{sat}}$ ) is mainly investigated  
 26 through comprehensive comparisons with daily averaged 10m specific air humidity ( $Q_{abuoy}$ ) from  
 27 buoys during the 2005 – 2007 period when the new  $Q_{a_{sat}}$  and the old  $Q_{a_{sat\_old}}$  are both available.



1 Daily buoy estimates are calculated as arithmetic mean of all valid hourly data. For each day of the  
2 period, all daily buoy and satellite data separated by less than 25 km are selected. Consequently,  
3 2910 collocations from MFUK, and 16999 from tropical networks, with specific air humidity  
4 ranging from 2g/kg to 25 g/kg met all the collocation quality control criteria. The buoy-satellite  
5 comparisons are complimented by comparisons with daily ship data from NOCS2.0 for the two  
6 regions: low humidity region in the midlatitude North Atlantic and in the Mediterranean sea 20°W-  
7 10°E, 35°N – 60°N, and more humid region in the tropical Atlantic 70°W-10°E, 15°S-15°N. These  
8 regions are selected based on the ground truth mooring locations. The northern region hosts the  
9 MFUK moorings while the tropical region hosts the PIRATA mooring array. In addition, the quality  
10 of daily satellite Qa analysis is investigated on the global scales through comparisons with daily  
11 estimates from NOCS2.0 and Era Interim. Only the 2007 NOCS2.0 Qa are used for the global  
12 comparisons because these data were excluded from the calibration of Qa model (eq. 1).

13 Even though buoy as well as ship Qa data are used as ground truth references, both sources  
14 may have uncertainties mainly related to hygrometer type, measurement height, and to solar  
15 radiation contamination (Kent *et al*, 2007). The assessment of quality of the reference data is  
16 beyond the topic of this paper.

17 To limit possible impacts of sampling errors of in-situ data, comparisons are limited to Qa  
18 with relative random error less than 10%. Most of cases (>95%) when this error exceeds 10% occur  
19 in dry conditions  $Qa < 4\text{g/kg}$  happening at MFUK buoys. The statistics established for these specific  
20 cases yields an overestimation of satellite  $Qa_{10}$ .

21 Figure 2a and 2b illustrate validation results obtained for MFUK and tropical moorings,  
22 respectively. The statistics characterizing buoy and satellite comparisons are estimated. Table 1  
23 provides the biases and standard deviations (Std) of buoy and satellite differences (in this order),  
24 and correlation coefficients (Cor). The statistics associated with the performance of daily Qa from  
25 (Bentamy *et al*, 2003), indicated as Qasat\_old, are also provided. The updated daily satellite Qasat  
26 gives a good representation of daily in-situ Qa estimates. Correlation coefficients between tropical  
27 and satellite, and between MFUK and satellite daily Qa are of 0.85 and 0.95, respectively. At  
28 MFUK buoy locations, correlation coefficient varies between 0.92 and 0.95 leading to no  
29 significant location dependence. Even though at tropical locations, correlation coefficients are quite  
30 high, better results are found at buoys moored off the equatorial area where polar-orbiting satellite  
31 sampling is better than at low latitudes. NOCS2.0 and satellite Qa comparisons (Table 1) indicate  
32 similar correlation results.

33

34 **Insert Figure2**

35

1 Biases for the new Qa product are low (Table 1) and are not statistically significant. Bias increases  
2 for low and high mooring Qa (Figure 2a and b) indicating slight overestimation and  
3 underestimation, respectively, which is also evident from the regression fit lines in Figure 2.  
4 However, the bias always stays within the one standard deviation corridor. Therefore, the bias  
5 behavior as a function of buoy Qa ranges may be related in part to the collocation procedures (both,  
6 satellite data coverage and Qa depend on latitude), to differences in estimates of daily average buoy  
7 and satellite Qa, and to the impact of difference in the buoy and satellite temporal and spatial  
8 sampling schemes. Similar bias dependencies on Qa are present in comparisons with NOCS2.0 Qa  
9 (Figures 2c and 2d). Biases at buoy locations (where at least one year of collocated data are  
10 available) display weak geographical variations. Air humidity bias varies from -0.10g/kg to  
11 0.10g/kg at the midlatitude MFUK locations, but the bias range increases in more humid tropical  
12 conditions where it varies from -0.30g/kg to 0.30g/kg at the tropical mooring locations, except at  
13 the 125°W, 2°S TAO mooring where the bias is anomalously strong reaching 0.90g/kg.

14 Standard deviation (STD) of daily satellite and in-situ (buoy and ship) specific air humidity is  
15 also weaker at midlatitudes and increases in the tropics (Table 1) changing from 0.79g/kg to  
16 1.05g/kg. It depicts weak changes among buoy locations with the exception of higher values in the  
17 Mediterranean Sea where STD is about 1.10g/kg. At the two Mediterranean MFUK locations  
18 atmospheric conditions are strongly variable. For instance, STD of specific air humidity measured  
19 by MFUK buoy moored in the Mediterranean Sea is twice as strong as that at the Atlantic MFUK  
20 moorings. Better satellite data sampling is needed to STD between satellite and buoy data in the  
21 Mediterranean Sea.

22 The newly developed algorithm used to estimate satellite daily specific air humidity provides  
23 significant improvements compared to the previous one (Bentamy *et al*, 2003). Indeed, statistics  
24 characterizing comparisons between buoy and satellite, as well as NOCS2.0 and satellite clearly  
25 state that results are better for the updated Qasat in various study regions (Table 1). For instance,  
26 RMS difference values (estimated from bias and standard deviation values) are reduced by factor  
27 exceeding 50% between new and old daily satellite Qa estimates.

28 At global scale, the updated Qasat are compared with daily averaged 10m Qa from NOCS2.0  
29 (Qanocs). The two Qa sources are collocated in space and time. For each day, Qasat values are  
30 linearly interpolated over Qamod grid map. The resulting collocated daily data are used to estimate  
31 monthly, seasonal, and annual statistical parameters, such as mean and standard deviation of each  
32 Qa product, mean and RMS differences, and correlation coefficient between Qanocs and Qasat (in  
33 this order). Only results derived from collocated data occurring during 2007 are shown. They are  
34 not used for calibration procedure dealing with the determination of the retrieval model (eq. 1).

35 Spatial variability of specific air humidity from the two products exhibit very similar features

1 for monthly as well as for seasonal and annual scales. The former are highly related to sea surface  
2 temperature and precipitation spatial patterns and meet the main known specific air humidity spatial  
3 distribution characteristics (Jackson *et al*, 2009). For instance, Figure 3 illustrates Qasat spatial  
4 patterns estimated for winter (December-January-February (DJF)), spring (March-April-May  
5 (MAM)), summer (June-July-August (JJA)), and autumn (September-October-November (SON))  
6 north hemisphere seasons (NH). Qa values exceeding 18 g/kg are mainly found along the  
7 convergence zones in the tropical Atlantic, Pacific and Indian Ocean. High values reaching or  
8 exceeding 19g/kg are depicted in the western Pacific zone (warm pool) throughout the year, in the  
9 tropical and north eastern Indian Ocean areas during spring and summer seasons, respectively, and  
10 in the Caribbean and Gulf of Mexico during summertime. The seasonal variations result in  
11 significant differences between NH winter and summer specific air humidity estimates. They reach  
12 6g/kg off north eastern oceanic regions, north of the Indian Ocean, Gulf of Mexico, over the entire  
13 Mediterranean sea, off the northwestern African coasts, and southeastern Indian Ocean. Such  
14 spatial and seasonal patterns are likely closely related to those of SST.

15

### 16 **Insert Figure3**

17

18 The spatial patterns of differences between NOCS2.0 and satellite Qa during NH winter and  
19 summer seasons are shown in Figure 4. Panels on top and on bottom illustrate bias and standard  
20 deviation differences, respectively. The new Qasat daily estimates reduce the discrepancies between  
21 in-situ and satellite in term of mean difference as well as in term of variability. Indeed, previous  
22 studies reported that IFREMER (old version) specific air humidity is 1g/kg underestimated  
23 compared to ICOADS over the intertropical ocean (Jackson *et al*, 2009), whereas is slightly  
24 overestimated over subtropical oceanic areas. Both statistical parameter spatial distributions (Figure  
25 4) do not exhibit significant geophysical pattern dependency. More than 84% and 95% of Qa  
26 difference values are lower than 1g/kg and 1.5g/kg, respectively. Whereas the associated standard  
27 deviation values are lower than 2g/kg for 95% of total grid points. Most of the differences  
28 exceeding 1g/kg are found in the southern ocean and/or in regions where NOCS2.0 Qa error exceed  
29 1.3g/kg associated with issues related to sampling by ships (Berry *et al*, 2011). Excluding these  
30 poorly sampled regions leads to an improvement of NOCS2.0 and satellite comparisons. More than  
31 95% of differences do not exceed 1.20g/kg. At regional scales, two areas located in northwestern  
32 Atlantic and Pacific oceans and likely related to Gulf Stream and Kuroshio currents are depicted  
33 during NH winter season. Specific air humidity is assumed to be low (Figure 4) due to continental  
34 cold air outbreaks. These discrepancies might be partly related to the uncertainties of the retrieval  
35 model (eq. 1) at some specific locations and for some local atmospheric and oceanic conditions.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32

**Insert Figure4**

## 4. Daily Wind Fields

Surface wind speeds and directions may be retrieved from scatterometer and radiometers. In this study only QuikSCAT V3 retrievals are used. As mentioned in section 2, they are corrected with respect to (Bentamy *et al*, 2012) results. The calculation of daily gridded wind fields from scatterometer wind observations is performed using same objective method used for the estimation of daily ASCAT wind fields (Bentamy *et al*, 2011). The resulting wind field accuracy is investigated through the comparisons with daily-averaged winds from MFUK, NDBC, PIRATA, RAMA, and TAO moored buoy estimates. The main statistics characterizing scatterometer and buoy daily wind speeds and direction comparisons are summarized in Table 2. The overall statistics indicate that the daily scatterometer wind fields compare well to daily-averaged buoy data. The rms differences do not exceed 2m/s and 20°, which are the scatterometer specifications for wind speed and direction, respectively. For in-situ and scatterometer daily winds higher than 3m/s no significant bias trend is found. For lower wind speed ranges, scatterometer winds tend to be slightly overestimated compared to buoys. The wind direction biases are relatively small. Despite of difference in buoy and scatterometer sampling schemes used for the estimation of daily winds, correlation values attest that satellite daily winds reproduce fairly well in-situ estimates. The lowest correlation value is found for Tropical buoy and satellite wind comparisons due to the low wind speed conditions distribution in these specific oceanic regions.

## 5. Turbulent Fluxes

Daily surface wind stress and the associated zonal and meridional wind stress components, surface latent and sensible heat fluxes are estimated over global ocean from daily winds (section 4), specific air humidity (section 3), sea surface temperature and air temperature, utilizing COARE3.0 bulk parameterization (Fairall *et al*, 2003). SST are daily OI analyses (Reynolds et al, 2007), while  $T_{a10}$  are daily averaged estimates calculated from Era Interim analyses (section 2). The calculations of the gridded bulk variables and turbulent flux fields are performed over global ocean with a spatial resolution of 0.25° in longitude and latitude. One should notice that flux fields spatial and temporal resolutions are consistent with SST analyses.

The quality of the new flux fields is first examined through comparisons with turbulent fluxes estimated from moored buoy daily-averaged bulk variables. Most of the NDBC buoys do not

1 provide measurements of specific air humidity (or relative humidity). They are calculated from air  
2 and dew point measurements. Daily turbulent fluxes are estimated utilizing COARE 3.0  
3 parameterization. Therefore, any departures between buoy and satellite daily fluxes highlight  
4 differences in the daily bulk variables. In this paper statistics related to the comparisons between  
5 buoy and satellite daily wind stress ( $\tau$ ), latent (LHF) and sensible (SHF) heat fluxes are provided  
6 (Table 2). They are calculated from collocated buoy and satellite data during the 2005 – 2007  
7 period.

8 As expected, buoy and satellite daily wind stress exhibit quite similar comparison results that  
9 found for wind speed (Table 2). This is clearly attested by the correlation coefficient values.  
10 Furthermore, the negative bias values are associated with the small overestimation of satellite wind  
11 speeds.

12 Daily satellite LHF is slightly underestimated in comparison with buoy data. The biases from  
13 the MFUK, NDBC, and tropical moorings are  $5\text{W/m}^2$ ,  $13\text{W/m}^2$ , and  $2\text{W/m}^2$ , respectively,  
14 correspondingly 7%, 12%, and 1% of the mean buoy LHF. Again we find rather high temporal  
15 correlation of satellite and in-situ turbulent fluxes (Table 2), which tend to decrease in the tropics.  
16 Remaining sampling issues result in moderately strong RMS errors ( $\sim 30\text{W/m}^2$  for MFUK and  
17 tropical moorings and somewhat stronger  $37\text{W/m}^2$  in the Atlantic western boundary sampled by  
18 NDBC moorings). The positive (buoy-minus-satellite) LHF biases at MFUK and NDBC locations  
19 are mainly related to the underestimation of high  $\text{LHF} > 200\text{W/m}^2$  at low  $Q_a$  and/or for high winds.  
20 In fact, the satellite  $Q_a$  is higher than in-situ  $Q_a$  in dry conditions (Figure 2) that leads to LHF  
21 underestimation. Excluding cases with buoy  $Q_a < 3\text{g/kg}$  reduces satellite LHF biases down to  $4\text{W/m}^2$   
22 (MFUK) and  $6\text{W/m}^2$  (NDBC) while the RMS error reduces to  $25\text{W/m}^2$  (MFUK) and  
23  $29\text{W/m}^2$  (NDBC).

24 Satellite daily SHF has high correlation with in-situ data at extratropical locations and  
25 somewhat reduced correlation in the tropics (Table 2). The biases at MFUK and NDBC moorings  
26 are lower than  $2\text{W/m}^2$  in magnitude, which are negligible. In the tropics where time mean SHF is  
27 weak, satellite SHF is overestimated by  $4\text{W/m}^2$ . This departure is related to the underestimation of  
28 air temperature in warm and humid conditions (not shown). These comparisons show improvements  
29 of the new satellite SHF. Indeed, the previous version of SHF (Bentamy *et al*, 2007) was biased by  
30 more than  $10\text{W/m}^2$  according to Stantorelli *et al* (2011) .

31 For global comparisons we select NOCS2.0 daily LHF and SHF with uncertainties lower than  
32  $40\text{W/m}^2$  and  $20\text{W/m}^2$ , respectively. The above thresholds are the median values of NOCS2.0 LHF  
33 and SHF errors. They are chosen in order to keep enough in situ data for comparisons.  
34 Consequently, most of selected NOCS2.0 data are located in northern basins. The lowest NOCS2.0

1 data sampling is in the tropics and in the southern latitudes. In particular, there is a factor 20  
2 between sampling lengths at 40°N and 40°S. The spatial distribution of the seasonal mean  
3 NOCS2.0 minus satellite LHF does not show any systematic basin scale patterns. The highest  
4 positive differences (NOCS2.0 – satellite > 30W/m<sup>2</sup>) are found in the Mediterranean Sea year  
5 around, and in the western boundaries during local winter. To summarize NOCS2.0 and satellite  
6 LHF comparisons, Figures 5 and 6 show zonally average fluxes stratified by basins. The two LHF  
7 data have similar latitudinal dependencies, especially in the north where in-situ data coverage is  
8 better. For both datasets the zonal mean LHF exceeds 100W/m<sup>2</sup> in the trade wind zones (Figures 5  
9 and 6) where rather strong winds and dry air are both present. The seasonal variability, which is  
10 pronounced in the Atlantic and Pacific, is associated with stronger winds in local winter. Both,  
11 NOCS2.0 and satellite LHF indicate maxima along 40°N and 36°N in the Atlantic and Pacific,  
12 respectively during winter season (Figure 5) reflecting contributions from high LHF in the western  
13 boundaries associated with winter storms. These high LHF are absent in local summer (Figure 6).  
14 Locally weak LHF is present year around along the equator in the Atlantic and Pacific due to lower  
15 winds and rather cold SST in the eastern cold tongue regions. The lowest LHF is found at high  
16 latitudes due to cold SST and related low air humidity. Due to the sampling issues, the discrepancies  
17 between NOCS2.0 and satellite LHF are stronger in southern oceans. For instance near 40°S in the  
18 Atlantic and Indian Oceans they exceed 30W/m<sup>2</sup> in boreal summer (Figure 6). Lower ship-based  
19 LHF may be linked to the need to avoid stormy sea. Indeed, 90% of NOCS2.0 daily LHF along  
20 40°S in the Indian Ocean are lower than 50W/m<sup>2</sup>, but this percentage is only of 20% for satellite  
21 daily LHF.

### **Insert Figures 5 and 6**

24 Zonally average sensible heat fluxes from NOCS2.0 and satellite exhibit qualitatively similar  
25 behavior (Figures 7 and 8). Both SHF estimates do not exceed 20W/m<sup>2</sup> in the tropics and increases  
26 towards the midlatitudes of the winter hemisphere. The highest sensible heat loss occurs around  
27 40°N in the Atlantic and Pacific in boreal winter due to high winds and strong air-sea temperature  
28 difference ( $\Delta T$ ) in the western boundary regions. The northern SHF amplification is not present in  
29 local summer reflecting significant seasonal drop in the storm track activity. Though the two SHF  
30 are highly correlated, satellite SHF is higher than NOCS2.0. The difference is apparent during local  
31 winter. It increases up to 25W/m<sup>2</sup> in the north Pacific between 30N and 40°N (Figure 7). Even  
32 higher differences occur in the South Ocean in austral winter (Figure 8). Discrepancies between  
33 NOCS2.0 and satellite SHF are more pronounced during summer season in regions located south of  
34 40°S, where satellite SHF exhibits much more seasonal variation than NOCS2.0. Summertime

1 departures found at high southern latitudes are mainly associated with differences in wind speeds  
2 and to the poor temporal and spatial samplings of NOCS2.0 daily data and missing strong wind  
3 events, which are avoided by ships.

4 **Insert Figures 7 and 8**

5

## 6 6. Conclusion

7 The presence of notorious biases in the previous version of the IFREMER turbulent fluxes of  
8 Bentamy *et al.* (2003) requires improvement of the product. The availability of the new air-sea  
9 interaction gridded dataset (NOCS2.0) calculated from ICOADS data, allows an opportunity for  
10 satellite-derived turbulent flux enhancement over global ocean. The new version of the IFREMER  
11 satellite turbulent air-sea fluxes is based on improved air humidity (Qa) retrieval scheme, improved  
12 scatterometer wind retrievals, and adopting air temperature from Era Interim air temperature.

13 The core of the air humidity retrieval scheme remains unchanged. It is based on the statistical  
14 relationship between the microwave brightness temperatures and Qa, which in turn is based on the  
15 quasi-linear relationship between Qa and water vapor content (Schultz *et al.*, 1993). But, direct  
16 application of this retrieval algorithm in Bentamy *et al.* (2003) results in SST-dependent Qa bias.  
17 This suggests including of SST as a parameter of satellite Qa retrieval model. Furthermore, the  
18 analysis of Qa bias reveals a dependence on the atmospheric stratification that reflects  
19 modifications in the relationship between water vapor content and Qa over the ocean SST fronts.  
20 Therefore, the new Qa retrieval algorithm includes SST and the air-sea temperature difference terms  
21 along with traditional microwave brightness terms. The retrieval model parameters are fitted using  
22 global in-situ data from the bias corrected version of ICOADS (NOCS2.0). The new satellite Qa  
23 has a reduced bias with in situ data that nor longer depicts the large scale patterns (dry tropics and  
24 wet subtropics) found in the previous IFREMER product.

25 The objective method developed and used for the estimation of daily surface wind analyses  
26 from scatterometer retrievals is adopted for the calculation of gridded daily Qa over global ocean  
27 with a spatial resolution of  $0.25^\circ$  in latitude and longitude. The validation of daily Qa estimates  
28 shows good statistic comparisons with daily Qa from moorings in the North Atlantic Ocean and in  
29 the tropical zones. The RMS values are about 1g/kg while correlation coefficients exceed 0.85.  
30 Similar results are obtained from the comparisons versus daily NOCS2.0 not used in the  
31 development of the satellite Qa model.

32 Using of the improved Qa retrieval, surface wind speed from the newly reprocessed

1 QuikSCAT data (QuikSCAT V3), 10m air temperature estimated from Era Interim re-analyses,  
2 results in significant improvement of the global turbulent fluxes. Daily satellite LHF is slightly  
3 underestimated in comparison with in-situ buoy data. LHF bias at the midlatitudes locations  
4 (MFUK and NDBC moorings) is  $5\text{W/m}^2$  (or 7% of the mean buoy LHF) and  $13\text{W/m}^2$  (12%),  
5 respectively. It decreases to  $2\text{W/m}^2$  (1%) at the tropical moorings. SHF is slightly overestimated by  
6  $2\text{W/m}^2$  (11%) at MFUK, by  $2\text{W/m}^2$  (7%) at NDBC, and by  $4\text{W/m}^2$  (51%) at the tropical moorings.  
7 At global scale, satellite-derived LHF and SHF exhibit similar spatial and temporal patterns that  
8 derived from NOCS2.0. Global comparisons between NOCS2.0 and satellite suggest that both, LHF  
9 and SHF exceed in-situ values in the storm track belts during local winter, which are particularly  
10 evident at high southern latitudes. The increased difference in the south is in part explained by the  
11 poor temporal and spatial samplings of NOCS2.0 daily data and missing strong wind events, which  
12 are avoided by ships. Indeed, 90% of NOCS2.0 daily LHF along  $40^\circ\text{S}$  in the Indian Ocean are  
13 lower than  $50\text{W/m}^2$ , but this percentage is only of 20% for satellite daily LHF.

14 The statistical comparisons between in-situ (moorings and NOCS2.0) and satellite bulk  
15 variables and turbulent fluxes assess the improvement of the new calculations with regards to the  
16 previous IFREMER satellite flux accuracy. In future, flux calculation will be first performed for the  
17 whole QuikSCAT period (August 1999 – November 2009). The spatial and temporal patterns of the  
18 resulting flux fields will be investigated and compared to those derived from satellite observations  
19 such as HOAPS, from blended data such as AOFLUX, or from meteorological re-analyses such as  
20 Era Interim. The extension of the calculation to the periods of the European Satellite Remote  
21 Sensing satellites ERS-1 and ERS-2 (March 1992 – January 2001), and of ASCAT (February 2007 –  
22 Present) is expected.

23

24 **Acknowledgements.** This research was supported by TOSCA (Terre, Océan, Surfaces  
25 continentales, Atmosphère) and SIMED ((Simulation de la MEDiterranée) projects, and by the  
26 NFS grant *ATM0631685*NASA. We thank D. Crozé-fillon, F. Paul, and J. F. Piollé and  
27 IFREMER/CERSAT for data processing support. The authors are grateful to ECMWF,  
28 EUMETSAT, CERSAT, JPL, NOAA, NOCS, Météo-France, NDBC, PMEL, and UK MetOffice for  
29 providing numerical, satellite, and in-situ data used in this study.



1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34

## References

Andersson A., K. Fennig, C. Klepp, S. Bakan, H. Graßl, and J. Schulz, 2010:  
The Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Data - HOAPS-3,  
*Earth Syst. Sci. Data*, **2**, 215-234, doi:[10.5194/essd-2-215-2010](https://doi.org/10.5194/essd-2-215-2010).

Ayina L. H., A. Bentamy, A. Mestas-Nunez, G. Madec, 2006: The impact of satellite winds and  
latent heat fluxes in a numerical simulation of the tropical Pacific Ocean. *Journal of Climate*,  
**19**(22), 5889-5902. <http://dx.doi.org/10.1175/JCLI3939.1>

Bentamy A., K. Katsaros, A. Mestas-Nuñez, W. Drennan, E. Ford, H. Roquet, 2003: Satellite  
estimates of wind speed and latent heat flux over the global oceans. *Journal Of Climate*,  
**16**(4), 637-656. [http://dx.doi.org/10.1175/15200442\(2003\)016<0637:SEOWSA>2.0.CO;2](http://dx.doi.org/10.1175/15200442(2003)016<0637:SEOWSA>2.0.CO;2)

Bentamy A., L-H Ayina, W. Drennan, K. Katsaros, A. Mestas-nuñez, and R. T. Pinker, 2008: 15  
years of ocean surface momentum and heat fluxes from remotely sensed observations.  
FLUXNEWS, No 5, World Climate Research Program, Geneva, Switzerland, 14-16

Bentamy A., D. Croizé. Fillon, 2011: Gridded Surface Wind Fields from Metop/ASCAT  
Measurements. *Inter. Journal of Remote Sensing*, **33**, pp 1729-1754.

Bentamy, A., S. A. Grodsky, J. A. Carton, D. Croizé-Fillon, and B. Chapron, 2012: Matching  
ASCAT and QuikSCAT Winds, *J. Geoph. Res.*, doi:10.1029/2011JC007479,

Berry, D.I. and E.C. Kent, 2011, Air-sea fluxes from NOCS2.0: the construction of a new gridded  
dataset with uncertainty estimates. *Int. J. Climatol.* ([CLIMAR-III Special Issue](#)), **31**, 987-  
1001 ([doi:10.1002/joc.2059](https://doi.org/10.1002/joc.2059)).

Bourras D., 2006: Comparison of Five Satellite-Derived Latent Heat Flux Products to Moored  
Buoy Data. *Journal of Climate*, Vol. 19, 2006, pp. 6291-6313. doi:10.1175/JCLI3977.1

Chou, S.-H., E. Nelkin, J. Ardizzone, R. M. Atlas, and C.-L. Shie, 2003: Surface turbulent heat and  
momentum fluxes over global oceans based on the Goddard satellite retrieval, version 2  
(GSSTF2). *J. Climate*, **16**, 3256–3273.

Fairall, C.W., E.F Bradley, J.E. Hare, A.A. Grachev, and J.B. Edson (2003), Bulk parameterization  
of air-sea fluxes: updates and verification for the COARE3.0 algorithm, *J. Climate*, **16**, 571-  
591.

Fore A., B. Stiles, R. S. Dunbar, B. Williams, A. Chau, L. Ricciardulli, F. Wentz, T. Meissner and  
E. Rodridguez, 2011: Point-wise wind retrieval and ambiguity removal improvements for the  
QuikSCAT climatological data set. International Ocean Vector Wind Science Team Meeting  
Annapolis, Maryland, USA, 9-11 May 2011  
(<http://coaps.fsu.edu/scatterometry/meeting/past.php#2011>)

1 Grodsky S. A., A. Bentamy, J. A. Carton, R. T. Pinker, 2009: Intraseasonal Latent Heat Flux Based  
2 on Satellite Observations. *Journal of Climate*, 22(17), 4539-4556.  
3 <http://dx.doi.org/10.1175/2009JCLI2901.1>

4 Jackson, D. L., G. A. Wick, and F. R. Robertson, 2009: Improved Multisensor Approach to  
5 Satellite-retrieved Near-surface Specific Humidity Observations. *J. Geophys. Res.*, D16303,  
6 doi:10.1029/2008JD011341.

7 JPL, 2006: QuikScat science data product user's manual (version 2.0). Jet Propulsion Laboratory  
8 Publ. D-18053, Pasadena, CA, 84pp. (Available online at <http://podaac.jpl.nasa.gov/quikscat>)

9 Kent E., S. D. Woodruff, and D. I. Berry, 2007: Metadata from WMO Publication No. 47 and an  
10 assessment of Voluntary Observing Ship observation heights in NOCS2.0. *J. Atmos. Oceanic*  
11 *Technol.*, 24, 214–234.

12 Kubota, M., N. Iwasaka, S. Kizu, M. Konda & K. Kutsuwada , 2002: Japanese ocean flux data sets  
13 with use of remote sensing observations (J-OFURO), *J. Oceanogr.*, 58, 213-225.

14 Ricciardulli L. and F. Wentz, 2011: Reprocessed QuikSCAT (V04) wind vectors with Ku-2011  
15 geophysical model function. Remote Sensing Systems Technical Report 043011  
16 ([http://www.ssmi.com/qscat/qscat\\_Ku2011\\_tech\\_report.pdf](http://www.ssmi.com/qscat/qscat_Ku2011_tech_report.pdf))

17 Meissner, T., D. K. Smith and F. J. Wentz, 2001: A 10-Year Intercomparison Between Collocated  
18 Special Sensor Microwave Imager Oceanic Surface Wind Speed Retrievals and Global  
19 Analyses, *Journal of Geophysical Research*, 106(C6), 11731-11742.

20 Mestas-Nuñez A., A. Bentamy, K. Kristina, 2006: Seasonal and El Nino variability in weekly  
21 satellite evaporation over the global ocean during 1996-98. *Journal Of Climate*, 19(10),  
22 2025-2035. <http://dx.doi.org/10.1175/JCLI3721.1>

23 Reynolds, R.W., T.M. Smith, C. Liu, D.B. Chelton, K.S. Casey, M.G. Schlax (2007), Daily High-  
24 Resolution-Blended Analyses for Sea Surface Temperature. *J. Climate*, 20, 5473-5496.

25 Santorelli, A., R. T. Pinker, A. Bentamy, W. Drennan, K. Katsaros, J. Carton, and A. Mestas-  
26 Nunez, 2011. *J. Geophys. Res.*, 116, Article Number: C09028 DOI: 10.1029/2010JC006927

27 Schulz, J., P. Schlüssel, and H. Grassl, 1993: Water vapour in the atmosphere boundary layer over  
28 oceans from SSM/I measurements. *Int. J. Remote. Sensing*, 14, 2773-2789.

29 Tomita,H. and M. Kubota, 2006: An analysis of the accuracy of Japanese Ocean Flux data sets with  
30 Use of Remote sensing Observations(J-OFURO) satellite-derived latent heat flux using  
31 moored buoy data,*J. Geophys. Res*, 111, C07007, doi:10,1029/2005 JC003013, 2006.

32 Wackernagel, H., 1998. Multivariate geostatistics. *Springer*, Berlin, 291pp.

33 Yu, L., R. A. Weller, and B. Sun, 2004: Improving latent and sensible heat flux estimates for the  
34 Atlantic Ocean (1988-1999) by a synthesis approach. *J. Climate*, 17, 373–393.

# 1 Tables

Table 1 : Statistical parameters of differences between daily buoy (MFUK, TAO, PIRATA, RAMA) and satellite specific air humidity estimated for the period 2005 –2007. Bias, STD, and Cor stand for mean and standard deviation difference (Buoy minus satellite) values, and correlation coefficients, respectively. Bias and Std are in g/kg units.

	Length	Qasat			Qasat_old		
		Bias	STD	Cor	Bias	Std	Cor
MFUK	2910	-0.04	0.87	0.95	-0.20	1.43	0.90
TAO/PIRATA/RAMA	16999	-0.10	1.05	0.85	0.88	1.62	0.75
NOCS2.0(MFUK)	67104	0.23	0.79	0.95	0.42	1.57	0.88
NOCS2.0(Tropical)	129341	0.27	1.05	0.83	0.74	1.55	0.73

2  
3  
4  
5

Table 2: : Statistical parameters of differences between daily buoy (MFUK, NDBC, TAO, PIRATA, RAMA(Tropical)) and satellite wind speeds (Speed in m/s), wind directions (direction in degree), wind stress amplitude (Stress in dyn/m<sup>2</sup>), latent (LHF) and sensible (SHF) heat fluxes (in W/m<sup>2</sup>). Numbers to the right of mooring names are sampling length of buoy and satellite collocated daily data.

	MFUK(12146)			NDBC(28048)			Tropical(49843)		
	Bias	STD	Cor.	Bias	STD	Cor.	Bias	STD	Cor.
Speed	-0.36	1.58	0.92	-0.27	1.09	0.94	-0.25	1.25	0.85
Direction	0	19	1.76	-5	23	1.74	-4	17	1.65
Stress	-0.01	0.07	0.92	-0.01	0.04	0.95	-0.01	0.03	0.85
LHF	5	27	0.89	13	37	0.89	2	31	0.79
SHF	-2	10	0.94	-2	10	0.96	-4	6	0.77

6

1

## 2 **Figure captions**

- 3
- 4 • Figure 1 : NOCS2.0 minus satellite  $Q_{a10}$  difference as a function of satellite  $Q_{a10}$ . Lines are  
5 average difference in 1g/kg satellite  $Q_{a10}$  bin for data grouped in the five SST bins. Satellite  
(Ifremer)  $Q_{a10}$  is from Bentamy et al (2003).
  - 6 • Figure 2 : Daily-averaged specific air humidity from buoys (MFUK(a) and Tropical(b)) and  
7 satellites. Panels c and d show companion comparisons with daily NOCS2.0  $Q_a$  from the  
8 two areas surrounding MFUK and tropical arrays, respectively. Black and red lines are  
9 perfect and symmetrical linear fit, respectively. Inner and outer dashed lines show one and  
10 two standard deviations of in-situ minus satellite  $Q_a$ , respectively. Numbers in the color  
11 bars represent the number of collocated data per 0.50g/kg bins. Only bins such as the  
12 number of collocated data exceeding a threshold (30 for mooring and 100 for NOCS2.0  
13 comparisons) are shown. The rest of collocated data are shown in gray dots.
  - 14 • Figure 3: North hemisphere winter (DJF), spring (MAM), summer(JJA), and fall (SON)  
15 mean  $Q_{a10}$  patterns estimated from daily satellite analyses for the period: 2005 – 2007
  - 16 • Figure 4: Seasonal patterns of mean (top) and standard deviation (bottom) differences  
17 between daily NOCS2.0 and satellite  $Q_{a10}$  estimated for 2005 – 2007 wintertime (DJF) and  
18 summertime(JJA).
  - 19 • Figure 5: North hemisphere winter (DJF), spring (MAM), summer(JJA), and fall (SON)  
20 mean  $Q_{a10}$  patterns estimated from daily satellite analyses for the period: 2005 – 2007.
  - 21 • Figure 6: As Figure 5 for summertime
  - 22 • Figure 7: Latitudinal averages of NOCS2.0 (red color) and satellite (blue color) of SHF  
23 estimated over the Atlantic (left), the Pacific (middle), and the Indian (right) oceans for  
24 2005-2007 wintertime.
  - 25 • Figure 8: As Figure 7 for summertime
- 26

1 **Figures**

2

3

4

5

6

7

8

9

10

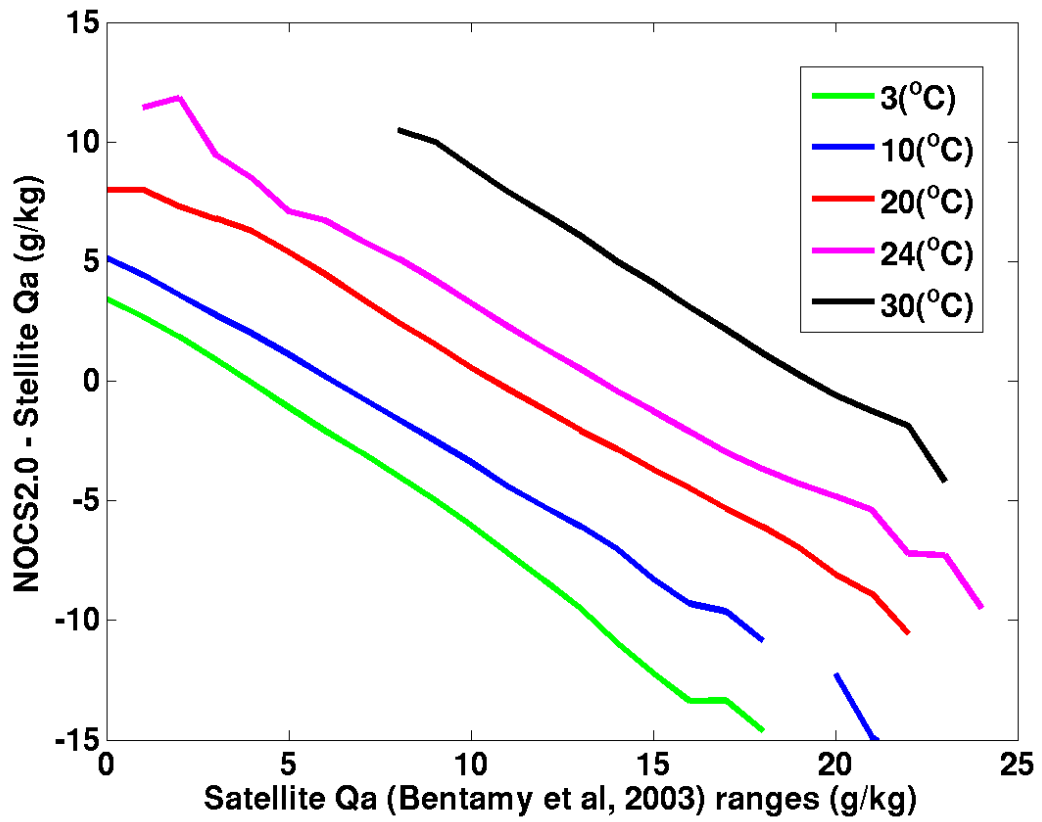
11

12

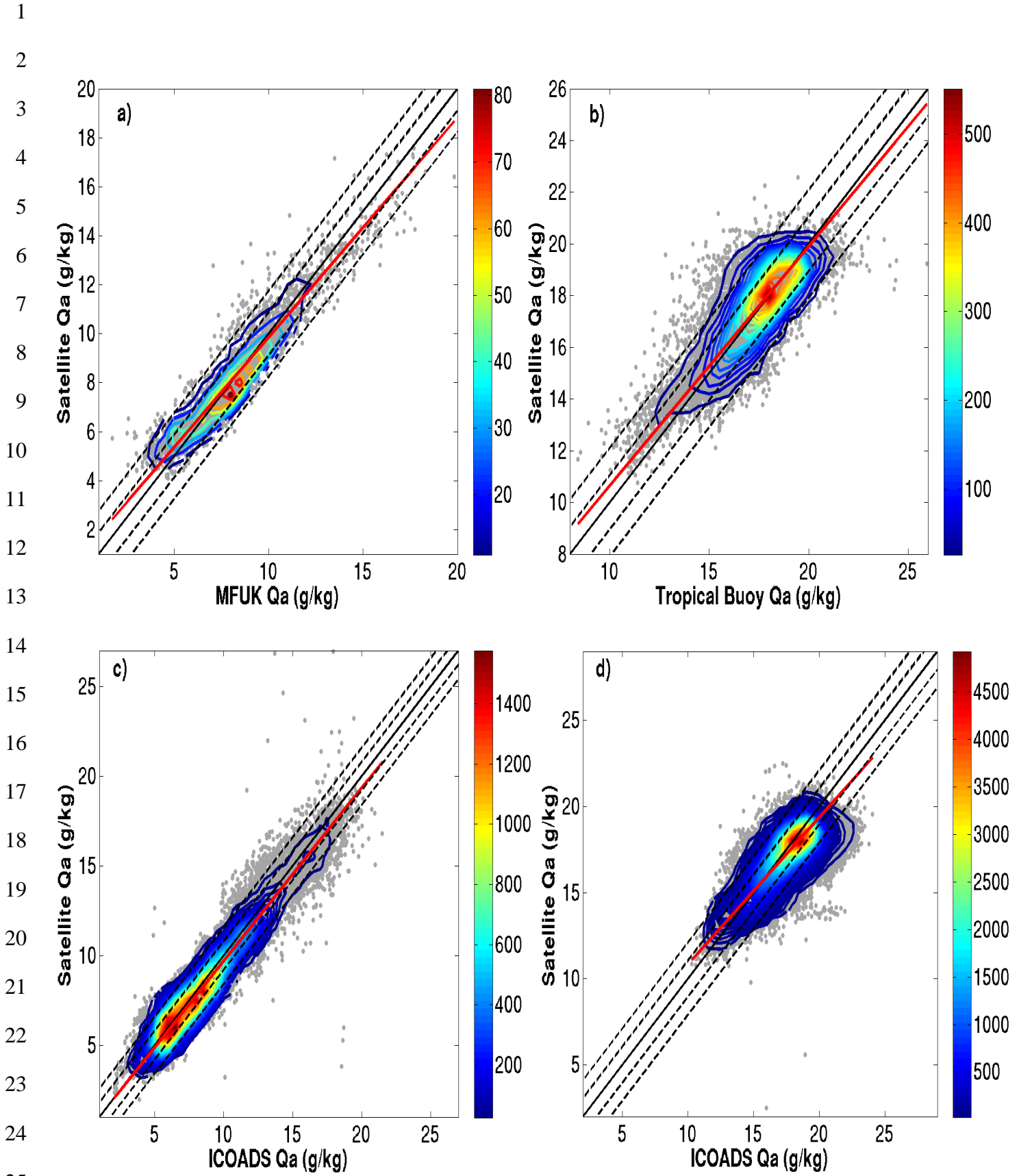
13

14

15

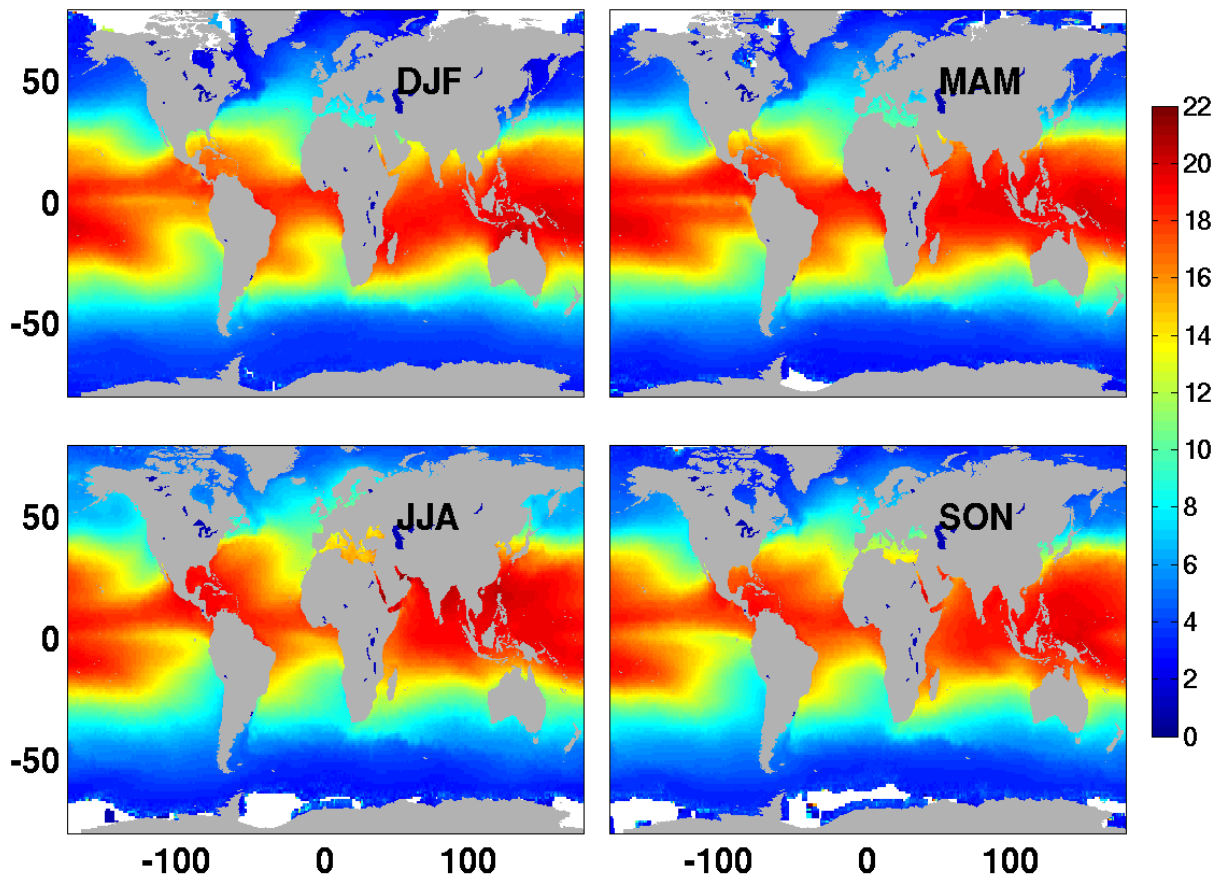


**Figure 1** : NOCS2.0 minus satellite  $Q_{a10}$  difference as a function of satellite  $Q_{a10}$ . Lines are average difference in 1g/kg satellite  $Q_{a10}$  bin for data grouped in the five SST bins. Satellite (Ifremer)  $Q_{a10}$  is from Bentamy et al (2003).



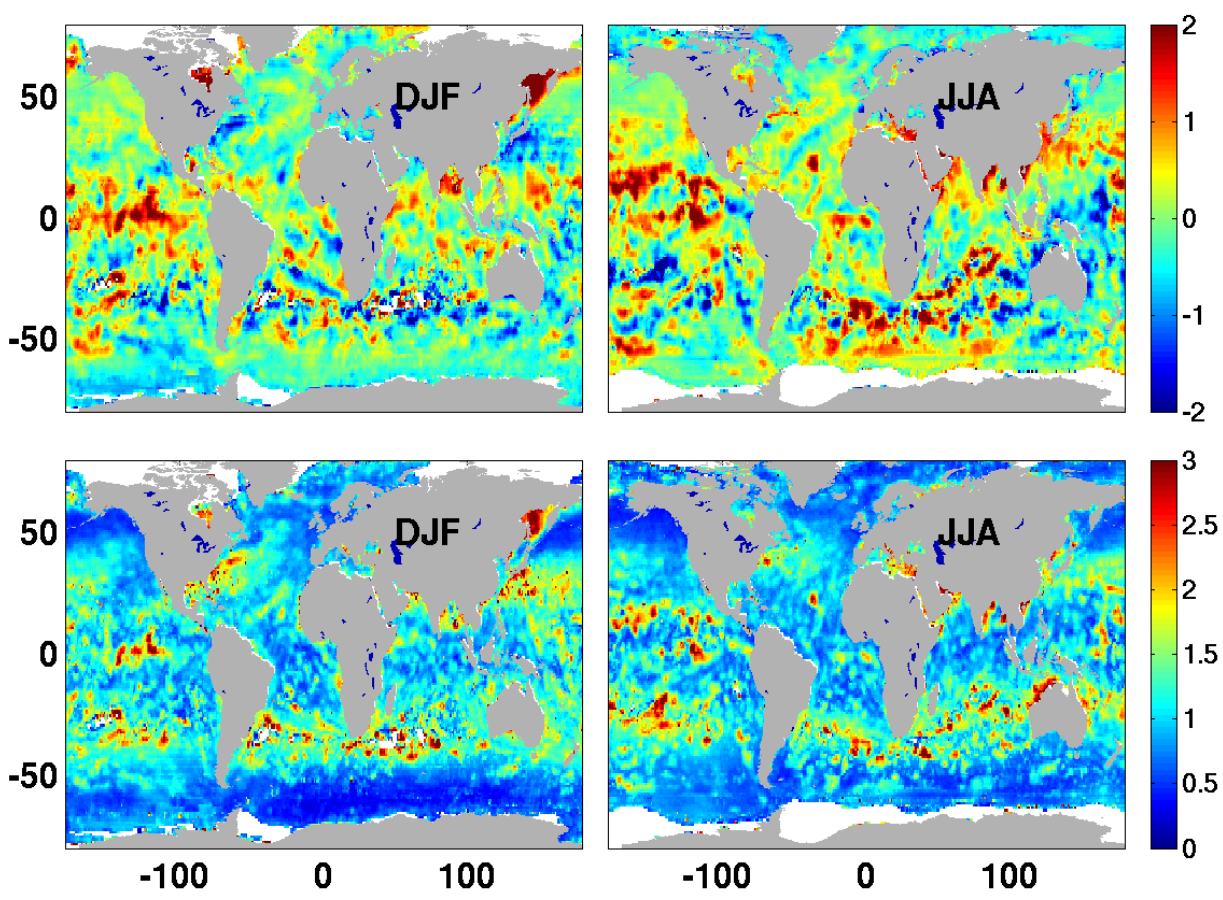
**Figure 2** : Daily-averaged specific air humidity from buoys (MFUK(a) and Tropical(b)) and satellites. Panels c and d show companion comparisons with daily NOCS2.0 Qa from the two areas surrounding MFUK and tropical arrays, respectively. Black and red lines are perfect and symmetrical linear fit, respectively. Inner and outer dashed lines show one and two standard deviations of in-situ minus satellite Qa, respectively. Numbers in the color bars represent the number of collocated data per 0.50g/kg bins. Only bins such as the number of collocated data exceeding a threshold (30 for mooring and 100 for NOCS2.0 comparisons) are shown. The rest of collocated data are shown in gray dots.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27



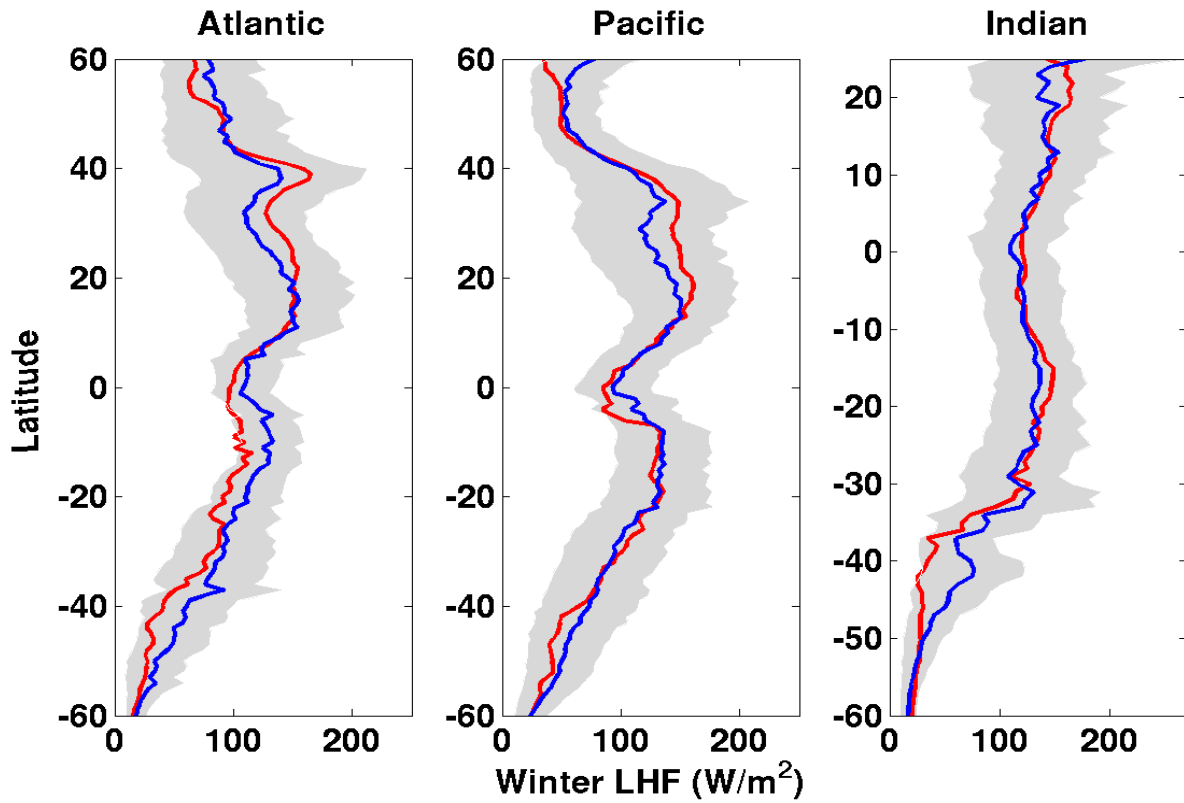
**Figure 3** : North hemisphere winter (DJF), spring (MAM), summer(JJA), and fall (SON) mean  $Q_{a10}$  patterns estimated from daily satellite analyses for the period: 2005 – 2007.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23

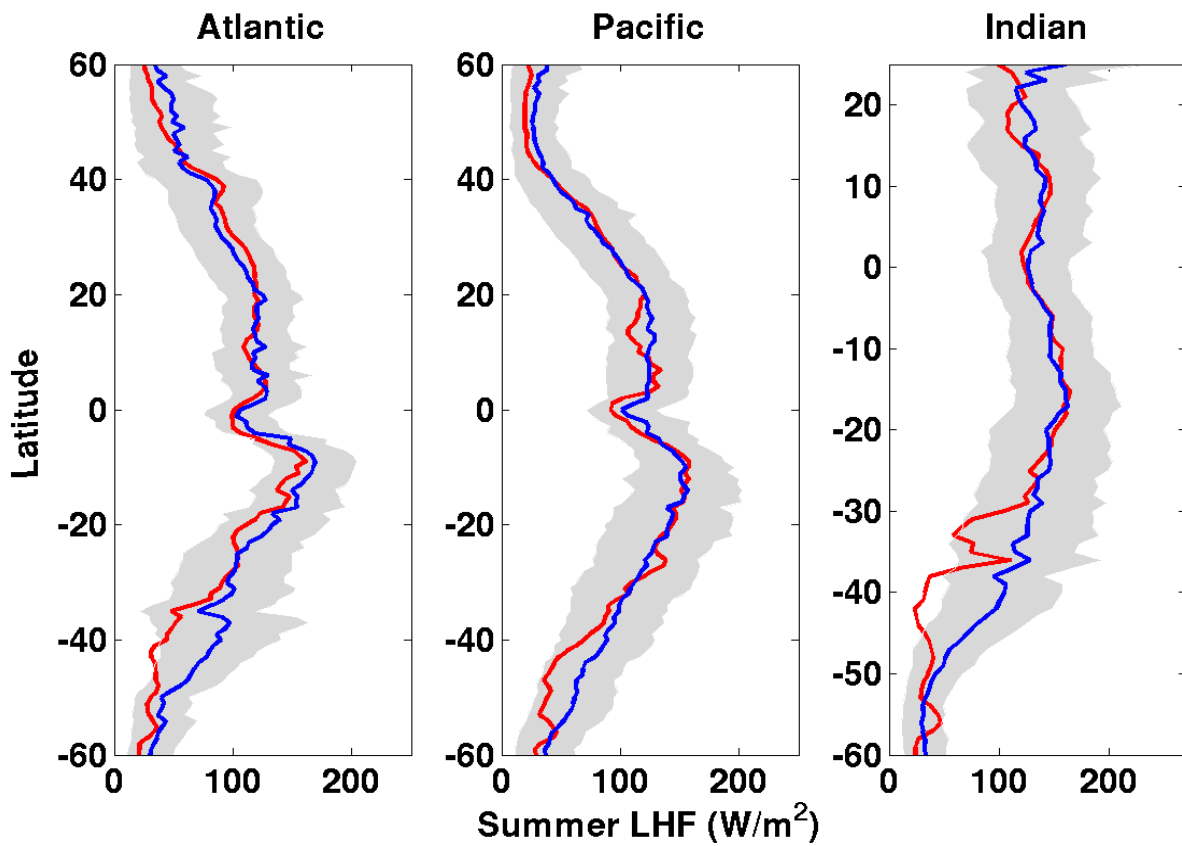


**Figure 4** : Seasonal patterns of mean (top) and standard deviation (bottom) differences between daily NOCS2.0 and satellite  $Q_{a10}$  estimated for 2005 – 2007 wintertime (DJF) and summertime(JJA).



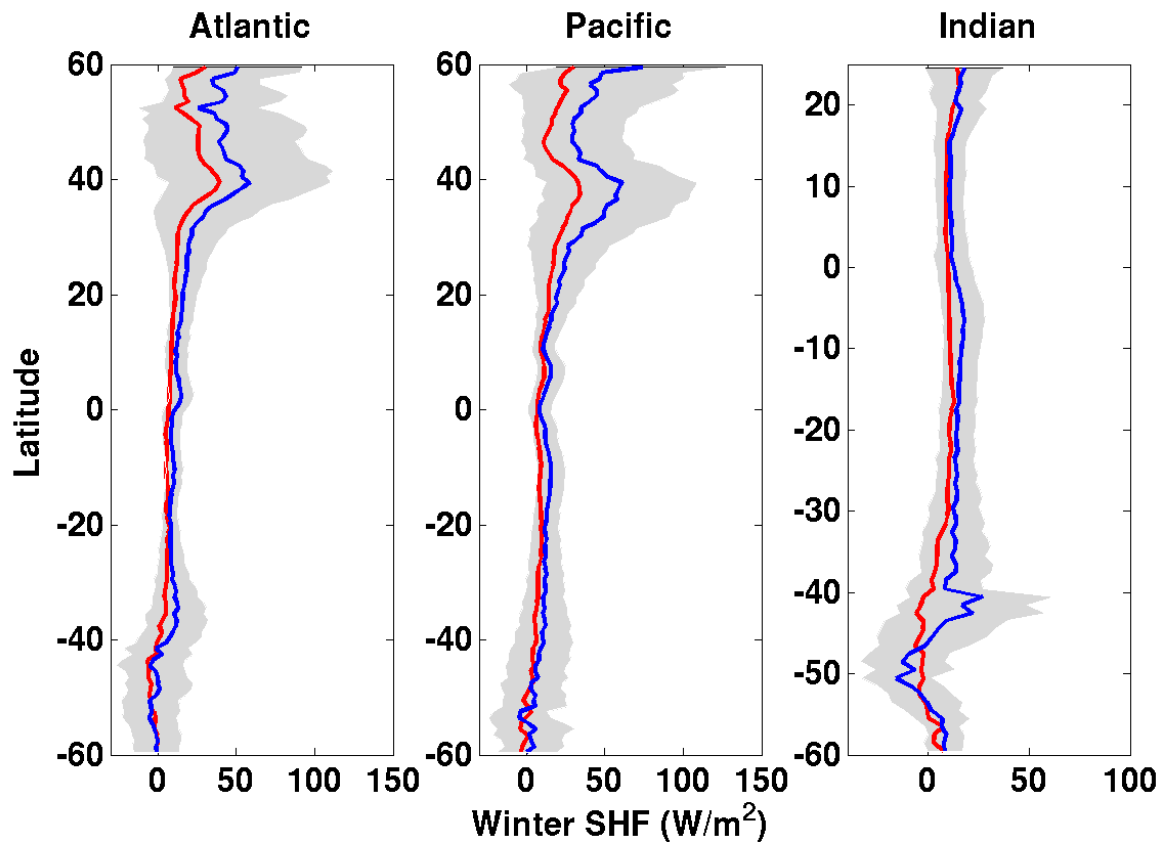


**Figure 5** : Latitudinal averages of NOCS2.0 (red color) and satellite (blue color) of LHF estimated over the Atlantic (left), the Pacific (middle), and the Indian (right) oceans for 2005-2007 wintertime.

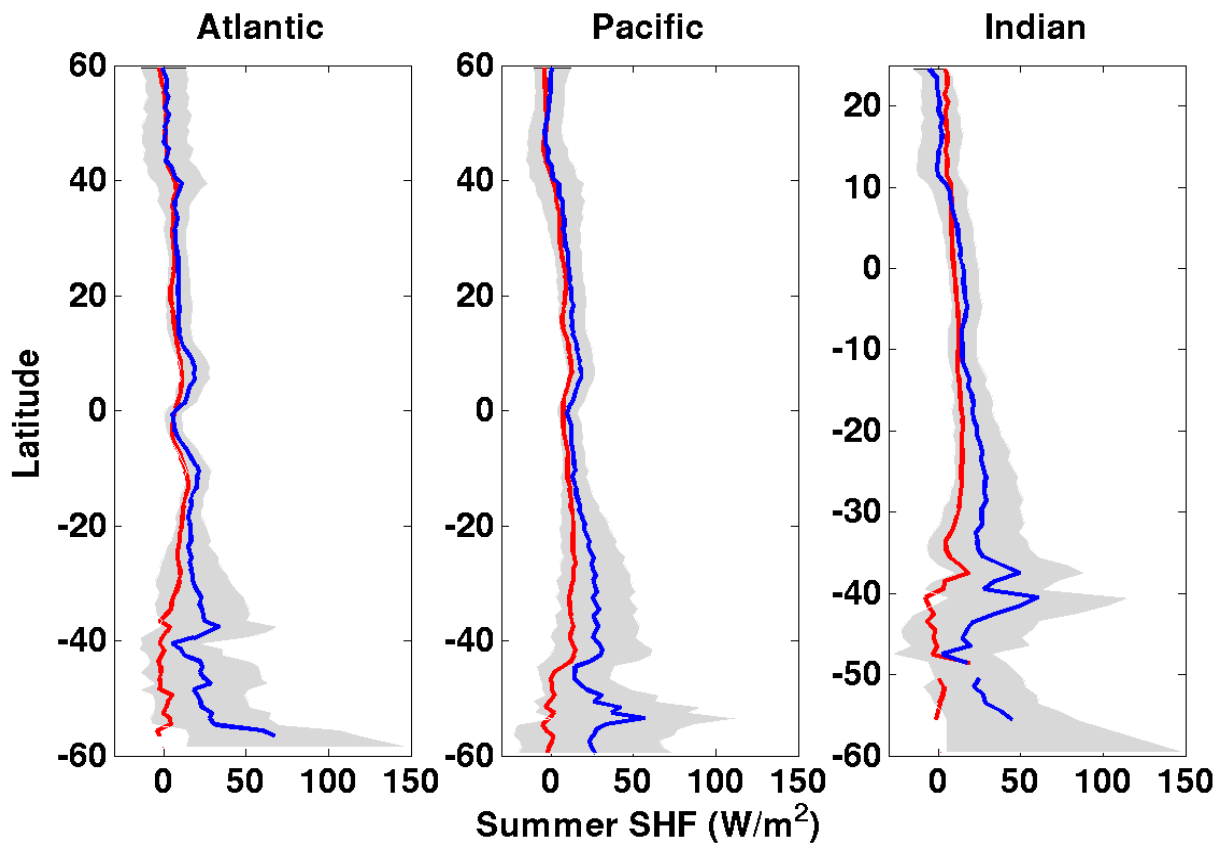


**Figure 6** : As Figure 5 for summertime

1  
2



**Figure 7** : : Latitudinal averages of NOCS2.0 (red color) and satellite (blue color) of SHF estimated over the Atlantic (left), the Pacific (middle), and the Indian (right) oceans for 2005-2007 wintertime.



**Figure 8** : As Figure 7 for summertime.