Enhancements of Air-Sea Fluxes Derived from Satellite Observations

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Improvements of Air-Sea Fluxes Derived from Satellite Observations

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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 ($q_{a10}$) at 10m height are both estimated from remotely sensed measurements. $w_{10}$ is obtained from SeaWind scatterometer on board the QuikSCAT satellite. A new empirical model relating brightness temperatures (Tb) from Special Sensor Microwave/Imager (SSM/I) and $q_{a10}$ is developed. It is an extension of the author’s previous $q_{a10}$ model. In addition to Tb variables, the empirical model includes sea surface temperature (SST) and air–sea temperature difference. The calibration of the new empirical $q_{a10}$ model utilizes $q_{a10}$ from the latest version of the National Oceanography Centre air-sea interaction gridded dataset (NOCS2.0). Compared to mooring data, the new satellite $q_{a10}$ exhibits better statistical results than previous estimates. For instance, the bias, the root mean square (RMS), and correlation coefficient values estimated from comparisons between satellite and moorings in the north east Atlantic and the Mediterranean Sea are -0.04 gkg⁻¹, 0.87 gkg⁻¹, and 0.95, respectively. The new satellite $q_{a10}$ 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 10m air temperature estimated from the European Centre for Medium Weather Forecasts (ECMWF) re-analyses (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 Wm⁻², 27 Wm⁻², and 0.89, respectively. For $shf$, the statistical parameters are -2 Wm⁻², 10 Wm⁻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 40°S where satellite latent and sensible heat fluxes are generally larger.

Keywords: scatterometer, radiometer, surface wind, specific air humidity, air-sea interaction, turbulent fluxes
1. Introduction

Accurate turbulent air-sea fluxes (i.e. momentum, latent heat, and sensible heat) are of great interest for a wide variety of air-sea interaction issues. The main sources of such fluxes over the global ocean are numerical weather prediction models (NWP), voluntary observing ships (VOS), 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 datasets 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 Analyzed Air-Sea Fluxes (OAFLUX) (Yu et al. 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 El Niño-Southern Oscillation (ENSO) (e.g. Mestas-Núñez et al. 2006), or employing an enhanced spatial and temporal sampling provided by remote techniques to evaluate the intra-seasonal variability (e.g Grodsky et al. 2009). Even though the results of these investigations have increased our understanding of air-sea interaction process, further improvements of satellite-based fluxes are still required.

A number of studies aiming at assessing the quality of turbulent fluxes have been published in recent years. By comparing latent heat fluxes (lhf) 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 (qa) and surface wind speed (W). Tomita et al. (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 qa, whereas around Japan the lhf discrepancy is associated with the accuracy of both W and qa. They both have concluded that the improvement of satellite lhf estimation requires improvements of the remotely sensed W and qa at global and regional scales. Santorelli et al. (2011) have conducted detailed accuracy investigations of IFREMER and OAFLUX latent and sensible heat fluxes as well as of basic bulk variables (10 m wind speed, w10; 10m specific air humidity, qa10; 10 m air temperature, ta10; and SST) using standard moored buoy and scientific data from dedicated-experiments. Their conclusions generally agree with the studies mentioned earlier. In particular, they emphasized that the improvement of satellite fluxes should include the improvement of the interpolation method used to calculate gridded fields over the global ocean to better reflect conditions during synoptic-scale storms and fronts.

Following the suggested recommendations for improving the fluxes, the present study aims at enhancing the following three aspects: the determination of qa10 retrievals over the global oceans, the accuracy of bulk variables and the associated turbulent fluxes, and the spatial and temporal resolutions of the flux fields. This study takes advantage of the availability of the new air-sea interaction datasets estimated from the updated International Comprehensive Ocean-Atmosphere Data Set (ICOADS) (Berry et al. 2011), and of the new QuikSCAT wind retrievals (Fore et al. 2011).

The statistical parameters defined by Bentamy et al. (2011a), aiming to characterize differences between in-situ and satellite data, are used to assess the quality of satellite bulk variables and fluxes.
2. Data

The main basic bulk variables required for turbulent flux estimations are surface wind speed \( w \), specific air humidity \( qa \), specific surface humidity \( gs \), air temperature \( ta \), and sea surface temperature (SST). Moored buoys, ships, and NWP models provide valuable estimates of these variables with various spatial and temporal resolutions. They are used in this study for the calibration and/or validation of satellite retrievals at local, regional, and global scales.

2.1 Scatterometer data

To ensure homogeneity of W and its variability, this study employs only wind retrievals from SeaWinds scatterometer onboard QuikSCAT. The QuikSCAT scatterometer principle is described in many scientific papers. Readers may find complete description in (JPL, 2006) including instrument physics, retrieval and ambiguity removal methods, rain detection and flagging techniques, and quality control procedures. Briefly, QuikSCAT is a rotating antenna with two differently polarized emitters: the H-pol with incidence angle of 46.25° and V-pol with incidence angle of 54°. The inner beam has a swath width of about 1400km, while the outer beam swath is 1800km width. QuikSCAT scatterometer is a Ku band radar. Therefore, rain has a substantial influence on its measurements. Previous studies showed that the rain impact may attenuate the scatterometer signal resulting in wind speed underestimation, or raindrop impacts may change the sea surface shape resulting in overestimation of the retrieved winds. Results from Portabella et al. (2012) indicate that rain backscatter contributes to the scatterometer signal resulting generally in wind speed overestimation; intense rain causes overestimates of 15-20 m/s for cross-track winds of. So, rain attenuation dominates over rain backscatter for extreme winds. QuikSCAT wind products include several rain flags determined from the scatterometer observations and from the collocated radiometer rain rate onboard other satellites.

This study uses new QuikSCAT wind retrievals called QuikSCAT V3 (ftp://podaac.jpl.nasa.gov/OceanWinds/quickscat/preview/L2B12/v3/). They are made available by Jet Propulsion Laboratory (JPL)/ Physical Oceanography Distributed Active Archive Center (PODAAC) scientific team (Fore et al. 2011). QuikSCAT V3 products are calculated through use of a geophysical model function ensuring the consistency with winds retrieved from microwave radiometers such as Special Sensor Microwave/Imager (SSM/I) and WindSat (Ricciardulli et al. 2011). QuikSCAT wind retrievals are provided over swaths at a Wind Vector Cell (WVC) of 12.5km spatial resolution. This new scatterometer product is assumed to improve wind speed performance in rain and at high wind speed conditions.

The accuracy of the QuikSCAT V3 data is determined through various comparisons with buoy wind measurements, QuikSCAT V2 retrievals, and with remotely sensed winds derived from the C-band, ASCAT scatterometer onboard Metop-A satellite. The main findings (not shown) are that the comparison results meet those obtained previously (Bentamy et al. 2012). QuikSCAT V3 and QuikSCAT V2 exhibit similar comparison results versus buoys. ASCAT and QuikSCAT V3 statistics are of the same order as ASCAT and QuikSCAT V2. Similar discrepancies characterizing ASCAT and QuikSCAT V2 comparisons are found for ASCAT and QuikSCAT V3. For instance, the most significant discrepancies are found at tropical and high latitudes. QuikSCAT V3 are improved when compared with the earlier results reported by (Bentamy et al. 2012). We expect that the remaining discrepancies between the C-band radar and the Ku-band radar wind retrievals are inherent in their characteristics including the radars’ penetrating wavelengths and back-scatter interactions with surface waves at different wavelengths. Such effects would be pronounced in low wind speed regimes and at certain values of SST.
2.2 Radiometer data

The special sensor microwave imager (SSM/I) measurements used in this study are the same as in (Bentamy et al. 2003 and 2008). The SSM/I radiometers onboard the Defense Meteorological Satellite Program (DMSP) F11, F13, F14, and F15 satellites provide measurements of the surface brightness temperatures (Tb) at frequencies 19.35, 22.235, 37, and 85 GHz (hereafter referred to as 19, 22, 37, and 85 GHz), respectively. Horizontal and vertical polarization measurements are taken at 19, 37, and 85 GHz. Only vertical polarization is available at 22 GHz. Due to the choice of channels operating at frequencies outside strong absorption lines (for water vapor 50-70 GHz), the detected radiation is a mixture of radiation emitted by clouds, water vapor in the air and the sea surface, as well as radiation emitted by the atmosphere and reflected at the sea surface. Brightness temperature measurements as well as the associated geophysical parameters are provided by Global Hydrology Resource Center (GHRC) (http://ghrc.msfc.nasa.gov/).

2.3 Buoys

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

2.4 NOCS data

A new daily mean air-sea interaction gridded dataset (Berry et al. 2011) is provided by the National Oceanography Centre Southampton and referred as NOCS Flux Dataset v2.0 (NOCS2.0). The gridded values are available over global ocean with a spatial resolution of 1°×1°. Daily parameters such as \( w_{10} \), \( qa_{10} \), \( ta_{10} \), SST, latent (\( lh \)) and sensible (\( sh \)) heat fluxes are provided with uncertainty estimates. The accuracy of NOCS2.0 gridded parameters was investigated through various comparisons including buoy, satellite, and numerical model data. For instance the comparison with buoys deployed and maintained by the Woods Hole Oceanographic Institution (WHOI) Upper Ocean Processes Group (UOP) indicates that the mean difference (NOCS2.0 – WHOI UOP) of \( w_{10} \) and \( qa_{10} \) are about 0.30 ms\(^{-1}\) and 0.40 gkg\(^{-1}\), respectively (Table II of Berry et al. 2011).

2.5 Era Interim

Era-Interim (Simmons et al. 2006) refers to the re-analyses of atmospheric parameters produced by the European Center for Medium-Range Weather Forecasts (ECMWF). It uses 4D-variational analysis on a spectral grid. This re-analysis covers the period from 1989 to the present. The ERA-Interim data used in this study was obtained from the ECMWF data server on a fixed grid of 0.75°. The main parameters used in this study are specific air humidity and air temperature at 2m, available at synoptic times (00h:00, 06h:00, 12h:00, 18h:00 UTC), that are converted to \( qa_{10} \) and to \( ta_{10} \), respectively, utilizing the COARE3.0 model (Fairall et al. 2003). The quality of \( qa_{10} \) and of \( ta_{10} \) is checked through comparisons with MFUK, TAO, and PIRATA buoy estimates. The main finding of interest for this study, is that Era Interim \( ta_{10} \) are underestimated for buoy \( ta_{10} \) exceeding 20°C. A bias correction is determined from linear regression between Era Interim and buoy \( ta_{10} \) estimates.
2.6 Collocation

For $qa$ calibration purpose, values of $qa$ and SST from the SSM/I, NOCS2.0, Era Interim are collocated in space and time. SST data are from version 2 of the Optimum Interpolated (OI) daily SST analyses (Reynolds et al. 2007) with a spatial resolution of 0.25°. A common collocation procedure is utilized. Era interim $qa_{10}$ and $ta_{10}$ occurring within 50km and 3 hours of an SSM/I cell location and time, respectively, are bi-linearly interpolated in both space and time at the SSM/I cell. SSM/I brightness temperatures and NOCS2.0 $qa_{10}$ occurring the same day are matched if the spatial difference is less than 100km. The same collocation approach is used for SSM/I Tb and daily SST, except that the spatial difference criteria is 25km.

3. Specific Air Humidity Improvement

3.1 Retrieving specific air humidity from satellite measurements

Based on the collocated SSM/I and ICOADS data, several authors have assessed the relationship between satellite brightness temperatures (Tb) and in-situ specific air temperature (e.g. Kubota et al. 2008; Jackson et al. 2009). The former is mainly related to the linear relationship between specific air humidity and the column integrated water vapor content ($wv$) obtained from satellite microwave radiometers (Schultz et al. 1993). SSM/I Tb measurements are sensitive to $wv$ especially in 19v, 19h, 22v, and 37v channels. In Bentamy et al. 2003, the development of a SSM/I-based method for the retrieval of $qa_{10}$ from brightness temperatures is based on a model determined from collocated SSM/I Tb and COADS $qa_{10}$ over limited oceanic areas of the North Atlantic and eastern equatorial Pacific, and during a limited period (1996 – 1998). This model was successfully used by several groups for $qa_{10}$ estimation from SSM/I or from AMSRE measurements as well as to assess development of new $qa$ models (e.g. Anderson et al. 2010; Kubota et al. 2008; Jackson et al. 2009). However, Grodsky et al. (2009), and Santorelli et al. (2011) underlined the need for improvement of the remotely sensed specific air humidity. To achieve such enhancement, the newly updated and enhanced NOCS2.0 data are used as references for new $qa_{10}$ modeling. For instance, Figure 1 shows the difference between NOCS2.0 and the previous version of satellite $qa_{10}$ of Bentamy et al. (2003) as a function of satellite-derived $qa_{10}$ and for five NOCS2.0 SST ranges. The findings (Figure 1) suggest including SST as a variable in a satellite $qa_{10}$ model. Furthermore, the investigation of NOCS2.0 and satellite $qa_{10}$ differences indicates a stratification dependency. The latter would be an indication of the modification of the relationship between $wv$ and $qa$ as a function of stratification variability. Therefore, the new $qa_{10}$ model includes terms related to SST and to the difference between 10m air and sea surface temperatures ($\Delta T$).

$$qa_{10} = f_1(Tb_{19v}) + f_2(Tb_{19h}) + f_3(Tb_{22v}) + f_4(Tb_{37v}) + g(SST) + h(\Delta T)$$  \hspace{1cm} (1)

The functions $f_1$, $f_2$, $f_3$, $f_4$, $g$, and $h$ are determined through a maximum likelihood procedure based on the use of collocated data: SSM/I F11 Tb, NOCS2.0 $qa_{10}$, SST, and Era Interim $ta_{10}$. Only matchups occurring during January, April, August, and September 2005 are used for $qa_{10}$ model calibration, thus leaving the remaining in-situ data for the verification purposes. Due to the strong correlation between $wv$ and brightness temperatures, and the correlation between specific air humidity and sea surface temperature, $qa_{10}$ (equation (1) is mainly weighted by functions $f_1$, $f_2$, $f_3$, $f_4$, $h$, $g$. Overall, the term $h(\Delta T)$ has a small impact. However, it maintains the bias between NOCS2.0 and satellite $qa_{10}$ close to zero with respect to air-sea temperature difference.

Insert Figure1
3.2 Daily analysis

This study aims at estimating daily 10m specific air humidity from radiometer retrievals. However, one should assess the meaning of daily averaged qa based on the use of limited remotely sensed observations. Indeed, local equator crossing times of the SSM/I at the ascending node are about 19h for F11, 18h for F13, 20h (1999) and 17h (2009) for F14, and 21h (2000) and 18h (2009) for F15. Such radiometer orbit characteristics lead to a limited observations during morning and evening local times. The impact of the radiometer sampling scheme on the accuracy of the calculation of qa daily estimates is evaluated using hourly buoy qa data. For each buoy, two kinds of daily-averaged estimates are calculated. First, \( \bar{q}_a^{b} \) is determined as an arithmetic mean of all available daily measurements (generally 24 hourly data), whereas the second \( \bar{q}_a^{s} \) is calculated as an arithmetic mean of hourly buoy qa collocated in space (distance less than 25km) and time (separation time less than 1h) with radiometer passes. The differences between \( \bar{q}_a^{b} \) and \( \bar{q}_a^{s} \) are investigated based on the use of MFUK and Tropical buoy qa measurements (Figures not shown).

In the Eastern Atlantic and the Mediterranean Sea, \( \bar{q}_a^{b} \) and \( \bar{q}_a^{s} \) differences, estimated at each buoy location, exhibit similar behaviors. The mean differences are low (0.18 gkg\(^{-1}\)) indicating that \( \bar{q}_a^{s} \) are slightly underestimated when compared to \( \bar{q}_a^{b} \). The associated root mean square (RMS) values are lower than 0.40 gkg\(^{-1}\). In the tropical basins, where specific air humidity values are maximum, the mean differences are close to zero, and RMS values do not exceed 0.40 gkg\(^{-1}\). The results characterizing \( \bar{q}_a^{b} \) and \( \bar{q}_a^{s} \) differences do not exhibit any significant geophysical pattern, except at a buoy located near coast in the Mediterranean Sea. Therefore, we conclude that daily average air humidity based on the particular temporal sampling of satellite observations deviates from the ‘true’ daily mean by no more than 0.18 gkg\(^{-1}\). The magnitude of this bias is below the characteristic error of satellite qa, as can be seen below.

These results allow the determination of daily averaged 10m specific air humidity from radiometer brightness temperature measurements. They are estimated as gridded fields with the same spatial resolution as the gridded daily wind fields (see the following section). All available and valid brightness temperature measurements from F11, F13, F14, and F15 satellites during 2005 – 2007 period are used. For each day and for each individual SSM/I swath cell, valid brightness temperatures (instantaneous), and the spatially closest daily averaged SST and 6-hourly 10m air-temperature are selected. Specific air humidity is estimated based on (equation 1). Time differences and accuracy characteristics (Meisnner et al. 2001) of brightness temperatures derived from various instruments may contribute to a non-consistency between \( qa_{10} \) derived from (1) and actual values expected to be used for the daily gridded specific air humidity calculation. To reduce the non-consistency impact, auxiliary information providing a mean description of \( qa_{10} \) during a given day is also used. It is derived from 6-hourly Era Interim qa estimates. The following linear relationship between retrievals (\( qa_{10} \)) and auxiliary data is assumed

\[
E(qa_{10}(x,y,t)) = \alpha_0 + \beta_1 \ qamod(x,y,t)
\]  

(2)

where \( x, y, \) and \( t, \) represent spatial and temporal coordinates, and \( \alpha_0 \) and \( \beta_1 \) are coefficients to be estimated. The operator \( E \) is the mathematical mean (conventional first moment). \( qamod \) indicates Era Interim \( qa_{10} \) collocated in space and time with each individual satellite retrieval. Equation (2) is known as the external drift constraint (Wackernagel, 1998).
The objective method aiming to calculate gridded daily specific air humidity from retrievals is quite similar to the method used for daily ASCAT wind field analyses (Bentamy et al. 2011b). Briefly, daily satellite $qa_{10}$ ($qasat$) is estimated based on the following assumption:

$$ qasat = \frac{1}{(t_b - t_a)} \sum_{j=1}^{N} \lambda_j (qa_{10}(x_j, y_j, t)) dt + \varepsilon $$

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

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

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

$$ \begin{aligned}
\sum_{j=1}^{N} \lambda_j C_{ij} - \mu_1 - \mu_2 Qamodi &= C_{i0} \quad \text{for } i = 1, N \\
\sum_{j=1}^{N} \lambda_j &= 1 \\
\sum_{j=1}^{N} \lambda_j Qamod_j &= Qamod_0
\end{aligned} $$

$C_{ij}$ stands for the covariance matrix between $qa_{10}$ observations, while $\mu_1$ and $\mu_2$ are the Lagrangian terms used to take into account the unbiased and external drift constraints. Index 0 indicates the grid point where daily analysis is performed.

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

### 3.3 Accuracy of the satellite daily specific air humidity

The quality of the resulting daily, satellite $qa_{10}$ estimates ($qasat$) is mainly investigated through comprehensive comparisons with daily averaged 10m specific air humidity ($qa_{buoy}$) from buoys during the 2005 – 2007 period when the new $qasat$ and $qasat_{old}$ are both available. Daily buoy estimates are calculated as an arithmetic mean of all valid hourly data. For each day of the period, all daily buoy and satellite data separated by less than 25 km are selected. Consequently, 2910 collocations from MFUK, and 16999 from tropical networks, with specific air humidity ranging from 2 gkg$^{-1}$ to 25 gkg$^{-1}$ met all the collocation quality control criteria. The buoy-satellite comparisons are complimented by comparisons with daily ship data from NOCS2.0 for two regions: a low humidity region in the midlatitude North Atlantic and Mediterranean sea 20°W-10°E, 35°N – 60°N, and more a humid region in the tropical Atlantic 70°W-10°E, 15°S-15°N. These regions are selected based on the ground truth mooring locations. The northern region hosts the MFUK moorings while the tropical region hosts the PIRATA mooring array. In addition, the quality of daily satellite $qa$ analysis is investigated on global scales through comparisons with daily estimates from NOCS2.0 and Era Interim. Only the 2007 NOCS2.0 $qa_{10}$ are used for the global comparisons because these data were excluded from the calibration of $qa_{10}$ model (1).
Even though buoy as well as ship \( qa_{10} \) data are used as ground truth references, both sources may have uncertainties mainly related to hygrometer type, measurement height, and to solar radiation contamination (Kent et al. 2007). The assessment of quality of the reference data is beyond the scope of this paper.

To limit possible impacts of sampling errors of in-situ data, comparisons are limited to \( qa \) with relative random error less than 10%. Most of the cases (>95%) when this error exceeds 10% occur in dry conditions \((qa_{10} < 4 \text{ g kg}^{-1})\) at the MFUK buoys. The statistics established for these specific cases yields an overestimation of satellite \( qa_{10} \).

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

**Insert Figure2**

The biases for the new \( qa_{10} \) product are low (Table 1) and are not statistically significant. Biases increase for low and high \( qa_{10} \) at mooring locations (Figure 2a and b) indicating slight overestimation and underestimation, respectively, which is also evident from the regression fit lines in Figure 2. However, the bias always stays within the one standard deviation corridor. Therefore, the bias behavior as a function of buoy \( qa_{10} \) ranges may be partly related to the collocation procedures (satellite data coverage and \( qa_{10} \) depend on latitude), to differences in estimates of daily-averaged buoy and satellite \( qa_{10} \), and to difference in the buoy and satellite temporal and spatial sampling schemes. The highest departure between daily-averaged buoy and satellite \( qa_{10} \) are depicted in the Pacific warm pool region. Satellite \( qa_{10} \) tend to be overestimated compared to in-situ estimates. Furthermore, buoy \( qa_{10} \) exhibit higher temporal variability than that reported from satellite \( qa_{10} \). Similar bias dependencies on \( qa_{10} \) are present in comparisons with NOCS2.0 \( qa_{10} \) (Figures 2c and 2d). Biases at buoy locations (where at least one year of collocated data are available) display weak geographical variations. Air humidity bias varies from -0.10 g kg\(^{-1}\) to 0.10 g kg\(^{-1}\) at the midlatitude MFUK locations, but the bias range increases in more humid tropical conditions when it varies from -0.30 g kg\(^{-1}\) to 0.30 g kg\(^{-1}\) at the tropical mooring locations, except at the 125°W, 2°S TAO mooring where the bias is anomalously strong reaching 0.90 g kg\(^{-1}\). The bias analysis indicates that the \( qa_{10} \) model (equation (1) works better in extra tropical area, where most of the water vapor is trapped near surface and assessing the relationship between \( wv \) and \( qa \).

However, the \( qa_{10} \) model is less accurate in regions of active convection where water vapor may exist aloft and is related to atmospheric processes that are not highly correlated to surface fluxes, especially at a daily scale.

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

The newly-developed algorithm used for estimating satellite daily specific air humidity provides significant improvements over the previous one (Bentamy et al. 2003). Indeed, statistics characterizing comparisons between buoy and satellite, as well as NOCS2.0 and satellite clearly show that results are better for the updated \( qa_{sat} \) in various study regions (Table 1). For instance, RMS difference values between the new and old daily satellite \( qa_{10} \) estimates (estimated from bias and standard deviation values) are reduced by more than 50%.

At global scale, the updated \( qa_{sat} \) are compared with daily-averaged 10m \( qa \) from NOCS2.0 (\( qa_{nocs} \)). The two \( qa_{10} \) sources are collocated in space and time. For each day, \( qa_{sat} \) values are linearly interpolated over \( qa_{mod} \) grid map. The resulting collocated daily data are used to estimate monthly, seasonal, and annual statistical parameters, such as mean and standard deviation of each \( qa \) product, mean and STD differences, and correlation coefficient between \( qa_{nocs} \) and \( qa_{sat} \) (in this order). Only results derived from collocated data occurring during 2007 are shown. They are not used for calibration procedure dealing with the determination of the retrieval model (equation (1)).

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

**Insert Figure 3**

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

Insert Figure 4

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. 2011b). 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. Bias and STD are mean and standard deviation values of differences between buoy and satellite data, respectively. Cor is the correlation coefficient. For wind direction, Cor is estimated as vector correlation (Bentamy et al. 2011b). It varies between -2 and +2. The overall statistics indicate that the daily scatterometer wind fields compare well to daily-averaged buoy data. The RMS differences do not exceed 2 ms\(^{-1}\) and 20°, which are the scatterometer specifications for wind speed and direction, respectively. For in-situ and scatterometer daily winds higher than 3 ms\(^{-1}\) 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 differences in buoy and scatterometer sampling schemes used for the estimation of daily winds, correlation values attest that satellite daily winds reproduce in-situ estimates fairly well. The lowest correlation value is found for Tropical buoy and satellite wind comparisons due to the low wind speed conditions within 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 the COARE3.0 bulk parameterization algorithm (Fairall et al. 2003). SST are from the daily OI analyses (Reynolds et al. 2007), while \(t_a\) 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. The spatial and temporal resolutions of the flux fields are consistent with SST analyses.

The quality of the new flux fields is first examined through comparisons with turbulent fluxes estimated from daily-averaged, buoy bulk variables. Most of the NDBC buoys do not provide measurements of specific air humidity (or relative humidity). They are calculated from air and dew point measurements. Daily turbulent fluxes are estimated utilizing COARE 3.0 parameterization. Therefore, any departures between buoy and satellite daily fluxes highlight differences in the daily bulk variables. In this paper statistics related to the comparisons between buoy and satellite daily wind stress (\(\tau\)), latent (\(lhf\)) and sensible (\(shf\)) heat fluxes are provided (Table 2). They are calculated from collocated buoy and satellite data during the 2005 – 2007 period.
As expected, buoy and satellite daily wind stress exhibit quite similar comparison results that found for wind speed (Table 2). This is clearly illustrated by the correlation coefficient values. Furthermore, the negative bias values are associated with the small overestimation of satellite wind speeds.

Daily satellite $\text{lhf}$ is slightly underestimated in comparison with buoy data. The biases from the MFUK, NDBC, and tropical moorings are 5 Wm$^{-2}$, 13 Wm$^{-2}$, and 2 Wm$^{-2}$, respectively, which corresponds to a 7%, 12%, and 1% of the mean buoy $\text{lhf}$. Again we find rather high temporal correlation of satellite and in-situ turbulent fluxes (Table 2), which tend to decrease in the tropics. Remaining sampling issues show moderately strong RMS errors, i.e. ~30 Wm$^{-2}$ for MFUK and tropical moorings and 37 Wm$^{-2}$ in the Atlantic western boundary sampled by NDBC moorings. The positive (buoy minus satellite) $\text{lhf}$ biases at MFUK and NDBC locations are mainly related to the underestimation of high $\text{lhf}$ (>200 Wm$^{-2}$) at low qa and/or for high winds. In fact, the satellite qa is higher than in-situ qa in dry conditions (Figure 2) that leads to $\text{lhf}$ underestimation. Excluding cases with buoy qa < 3 gkg$^{-1}$ reduces the satellite $\text{lhf}$ biases down to 4 Wm$^{-2}$ (MFUK) and 6 Wm$^{-2}$ (NDBC) while the RMS error reduces to 25 Wm$^{-2}$ (MFUK) and 29 Wm$^{-2}$ (NDBC).

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

For global comparisons we select NOCS2.0 daily $\text{lhf}$ and $\text{shf}$ with uncertainties lower than 40 Wm$^{-2}$ and 20 Wm$^{-2}$, respectively. The above thresholds are the median values of NOCS2.0 $\text{lhf}$ and $\text{shf}$ errors. They are chosen in order to keep enough in situ data for comparisons. Consequently, most of selected NOCS2.0 data are located in northern basins. The lowest NOCS2.0 data sampling is in the tropics and in the southern latitudes. In particular, there is a factor of 20 between sampling lengths at 40°N and 40°S. The spatial distribution of the seasonal mean NOCS2.0 minus satellite $\text{lhf}$ does not show any systematic basin scale patterns. The highest positive differences (NOCS2.0 – satellite > 30 Wm$^{-2}$) are found in the Mediterranean Sea year round, and in the western boundaries during local winter. To summarize, Figures 5 and 6 show NOCS2.0 and satellite $\text{lhf}$ comparisons of zonally-averaged fluxes stratified by ocean basin. The two $\text{lhf}$ products have similar latitudinal dependencies, especially in the north where in-situ data coverage is better. For both datasets the zonal mean $\text{lhf}$ exceeds 100 Wm$^{-2}$ in the trade wind zones (Figures 5 and 6) where rather strong winds and dry air are both present. The seasonal variability, which is pronounced in the Atlantic and Pacific, is associated with stronger winds in local winter. Both, NOCS2.0 and satellite $\text{lhf}$ indicate maxima along 40°N and 36°N in the Atlantic and Pacific, respectively, during the winter season, (Figure 5) reflecting contributions from high $\text{lhf}$ in the western boundaries associated with winter storms. These high $\text{lhf}$ are absent in local summer (Figure 6). Locally weak $\text{lhf}$ is present year around along the equator in the Atlantic and Pacific due to lower winds and rather cold SST in the eastern cold tong regions. The lowest $\text{lhf}$ is found at high latitudes due to cold SST and related low air humidity. Due to the sampling issues, the discrepancies between NOCS2.0 and satellite $\text{lhf}$ are stronger in southern oceans. For instance near 40°S in the Atlantic and Indian Oceans, they exceed 30 Wm$^{-2}$ in boreal summer (Figure 6). Lower ship-based $\text{lhf}$ may be linked to the need to avoid stormy seas. Indeed, 90% of NOCS2.0 daily $\text{lhf}$ along 40°S in the Indian Ocean are lower than 50 Wm$^{-2}$, but this percentage is only of 20% for satellite daily $\text{lhf}$.

Insert Figures 5 and 6

Zonally-averaged sensible heat fluxes from NOCS2.0 and satellite exhibit qualitatively similar behavior (Figures 7 and 8). Both $\text{shf}$ estimates do not exceed 20 Wm$^{-2}$ in the tropics and...
increases towards the midlatitudes of the winter hemisphere. The highest sensible heat loss occurs around 40°N in the Atlantic and Pacific in boreal winter due to high winds and strong air-sea temperature difference (ΔT) in the western boundary regions. The northern shf amplification is not present in local summer reflecting a significant seasonal drop in the storm track activity. Though the two shf are highly correlated, satellite shf is higher than NOCS2.0. The difference is apparent during local winter. It increases up to 25 Wm⁻² in the north Pacific between 30N and 40°N (Figure 7). Even higher differences occur in the Southern ocean in austral winter (Figure 8). Discrepancies between NOCS2.0 and satellite shf are more pronounced during summer season in regions located south of 40°S, where satellite shf exhibits much more seasonal variation than NOCS2.0. Summertime departures found at high southern latitudes are mainly associated with differences in wind speeds and with poor temporal and spatial samplings of NOCS2.0 daily data and missing strong wind events, which are avoided by ships.

Insert Figures 7 and 8

6. Conclusion

The presence of biases in the Bentamy et al. (2003) version of the IFREMER turbulent fluxes required improvement of the product. The availability of the new air-sea interaction gridded dataset (NOCS2.0) calculated from the height-adjusted ICOADS data allows for enhancement of satellite-derived, turbulent fluxes over the global ocean. The new version of the IFREMER satellite, turbulent air-sea fluxes is based on a synergy of remote sensing and atmospheric reanalysis data. It includes a new improved air humidity retrieval scheme, new QuikSCAT V3 scatterometer winds, and adopts $T_a$ from the ECMWF Era-Interim atmospheric reanalysis.

The core of the air humidity retrieval scheme remains unchanged. It is based on the statistical relationship between the microwave brightness temperature and $qa_{10}$, which in turn is based on the quasi-linear relationship between $qa_{10}$ and the integral atmospheric water vapor content (Schultz et al., 1993). But, the direct application of this retrieval algorithm in Bentamy et al. (2003) results in a SST-dependent $qa_{10}$ bias. This suggests including SST as an additional parameter in the satellite $qa_{10}$ retrieval algorithm. Furthermore, the analysis of $qa_{10}$ bias reveals a dependence on the atmospheric stratification that reflects modifications in the relationship between water vapor content and $qa_{10}$ over ocean SST fronts. Therefore, the new $qa_{10}$ retrieval algorithm developed in this paper includes SST and the air-sea temperature difference terms along with the traditional microwave brightness terms. The retrieval algorithm parameters are fitted using the global in-situ data from the bias corrected version of ICOADS (NOCS2.0). The new satellite $qa_{10}$ has a reduced bias that no longer depicts the large scale patterns (dry tropics and wet subtropics) found in the previous IFREMER product.

All satellite observations are objectively mapped on a daily 0.25° x 0.25° grid following Bentamy et al. (2011). The validation of daily gridded $qa_{10}$ shows good comparisons with in-situ, daily mean mooring measurements in the North Atlantic and tropics. The RMS values are about 1 g kg⁻¹, while the correlation coefficients exceed 0.85. Similar results are obtained from the comparisons with daily NOCS2.0 data not used in the development of the satellite retrieval model.

Daily satellite lhf is slightly underestimated in comparison with in situ buoy data. The lhf bias (buoy minus satellite) is 5 Wm⁻² (or 7% of the mean buoy lhf) and 13 W m⁻² (12%) at the midlatitudes locations (MFUK and NDBC moorings), respectively. It decreases to 2 Wm⁻² (1%) at the tropical moorings. shf is slightly overestimated by 2 Wm⁻² (11%) at MFUK, by 2 Wm⁻² (7%) at NDBC, and by 4 Wm⁻² (51%) at the tropical moorings. At global scale, the satellite-derived lhf and shf exhibit similar spatial and temporal patterns as those derived from NOCS2.0. Global comparisons between NOCS2.0 and satellite suggest that both lhf and shf exceed in-situ values in the storm track belts during local winter, which are particularly evident at high southern latitudes.
The increased difference in the south is in part explained by the poor temporal and spatial samplings of NOCS2.0 daily data and missing strong wind events, which are avoided by ships. Indeed, 90% of NOCS2.0 daily $lhf$ along 40°S in the Indian Ocean is lower than 50 Wm$^{-2}$, but this percentage is only of 20% for satellite daily $lhf$.

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

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References


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](http://dx.doi.org/10.1175/JCLI3939.1)


## 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\(^{-1}\) units.

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Table 2: Statistical parameters of differences between daily buoy (MFUK, NDBC, TAO, PIRATA, RAMA(Tropical)) and satellite wind speeds (Speed in m s\(^{-1}\)), wind directions (direction in degree), wind stress amplitude (Stress in dyn/m\(^2\)), latent (lhf) and sensible (shf) heat fluxes (in W m\(^{-2}\)). Numbers to the right of mooring names are sampling length of buoy and satellite collocated daily data.

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Figure captions

- Figure 1: NOCS2.0 minus satellite $qa_{10}$ difference as a function of satellite $qa_{10}$. Lines are average difference in 1g/kg satellite $qa_{10}$ bin for data grouped in the five SST bins. Satellite (Ifremer) $qa_{10}$ 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 0.50 gkg$^{-1}$ 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.

- Figure 3: North hemisphere winter (December-January-February (DJF)), spring (March-April-May (MAM)), summer(June-July-August (JJA)), and fall (September-October-November (SON)) mean $qa_{10}$ patterns estimated from daily satellite analyses for the period: 2005 – 2007. Color indicates $qa_{10}$ values in gkg$^{-1}$.

- Figure 4: Seasonal patterns of mean (top) and standard deviation (bottom) differences between daily NOCS2.0 and satellite $qa_{10}$ estimated for 2005 – 2007 wintertime (DJF) and summertime(JJA). Color indicates mean and STD values in gkg$^{-1}$

- Figure 5: North hemisphere winter (DJF), spring (MAM), summer (JJA), and fall (SON) mean $qa_{10}$ patterns estimated from daily satellite analyses for the period: 2005 – 2007.

- Figure 6: As in Figure 5 but for summertime

- 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 in Figure 7 but for summertime
**Figures**

![Graph showing NOCS2.0 minus satellite qa10 difference as a function of satellite qa10. Lines are average difference in 1 g kg⁻¹ satellite qa10 bin for data grouped in the five SST bins. Satellite (IFREMER) qa10 is from Bentamy et al (2003).](image)

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Figure 6: As Figure 5 but for summertime.
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