Improved Fields of Satellite-Derived Ocean Surface Turbulent Fluxes of Energy and Moisture

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1. Introduction

Air-sea turbulent fluxes determine the exchange of momentum, heat, freshwater, and gas between the atmosphere and ocean. These exchange processes are critical to a broad range of research questions spanning length scales from meters to thousands of kilometers and time scales from hours to decades. The estimation of surface turbulent fluxes from satellite is challenging and fraught with considerable errors. We are working to reduce these errors and to create high quality gridded products for studies of the energy and moisture budgets. We have made excellent progress in preliminary retrievals, and in understanding several causes for biases. We are to reduce these biases prior to producing the gridded flux product.

Surface fluxes are defined as the rate per unit area at which something (e.g., energy or moisture) is transferred across the air/sea interface. Wind- and buoyancy-driven surface fluxes are called surface turbulent fluxes because the mixing and transport are due to turbulence. Examples of nonturbulent processes are radiative fluxes (e.g., solar radiation) and precipitation. Turbulent fluxes are strongly dependent on wind speed; therefore, observations of wind speed are critical for the calculation of all turbulent surface fluxes. We utilize bulk algorithms to calculate the fluxes from satellite observations of winds, sea surface temperature, atmospheric temperature, and atmospheric humidity. Surface pressure is also needed to calculate the air density. Our early efforts assume global averaged sea level pressure. When we construct our gridding product, this assumption will be improved because the gridding technique (develop through separate funding for surface vector winds and fluxes from ship observations) uses vector and scalar winds observations to determine a pressure field.

The bulk algorithms for sensible heat (H), evaporation (E), and latent heat (Q) are given below. The air density (ρ) is dependent on surface air pressure, air temperature (T_{10}), and humidity (q_{10}).

$$H = -\rho\, C_p\, \theta_* \,|\mathbf{u}_*| \approx \rho\, C_p\, C_H (\mathrm{T}_{\mathbf{10}} - \mathrm{T}_{\mathbf{s}})\, |(\mathbf{U}_{\mathbf{10}} - \mathbf{U}_{\mathbf{s}})|, \tag{1}$$

$$E = -\rho\, q_* \,|\mathbf{u}_*| \approx \rho\, C_E (q_{\mathbf{10}} - q_{\mathbf{s}})\, |(\mathbf{U}_{\mathbf{10}} - \mathbf{U}_{\mathbf{s}})|, \tag{2}$$

$$Q = -\rho\, L_\mathrm{v}\, q_* \,|\mathbf{u}_*| \approx L_v\, E, \tag{3}$$

The other key variable is the surface wind shear ($\mathbf{U}_{\mathbf{10}} - \mathbf{U}_{\mathbf{s}}$), which is closely related to friction velocity ($\mathbf{u}_*$; the square root of the kinematic stress). The scaling terms θ_* and q_* are analogous to u_*, C_p is the specific heat of air, and L_v is the latent heat of vaporization. The transfer coefficients (C_D, C_H, C_E) account for differences in scale and include variability in $\mathbf{u}_*$ (and

similar terms) due to atmospheric stratification and sea state that is not included in the air/sea differences.

Sea surface temperatures are also sufficiently well observed for most turbulent surface flux applications (Donlon et al., 2007). In contrast, near-surface atmospheric humidity and temperature have historically been difficult to retrieve via remote sensing methods because of the much larger signal from the ocean surface. Sea surface temperature (SST), and atmospheric temperature and humidity have been retrieved using linear combinations of the observed radiances. One of the great difficulties of atmospheric temperature and humidity observations is they are retrieved with frequencies that are quite sensitive to liquid water (i.e., excessive cloud cover), resulting in a lack of data in many areas that have very active weather and large fluxes (see Ebsenson et al. (1993) for a description of problems with moisture retrievals). There have been considerable improvements (discussed below) in the last decade. The great improvement for SST observations (Donlan et al. 2007) has been intercalibration of may SST sensors. New techniques for retrieving atmospheric temperature and humidity (Jackson et al. 2006, 2009; Roberts et al. 2010; section 3c) have lead to considerable improvements in accuracy over a wider range of conditions, and are used by use to calculate more accurate inputs to bulk algorithms.

2. Historical Challenges and Recent Improvements

Historical challenges in observing air-sea fluxes include insufficient sampling, biases, large random errors in air temperature, and no accounting for how surface water waves modify fluxes. A lack of intercalibration has also been a tremendous problem, resulting in spurious trends and variability that have more to do with the observing system than any natural processes. Intercalibration of winds and sea surface temperatures has been greatly improved in recent years. Intercalibration for atmospheric temperature and humidity is just beginning. Errors related to surface pressure are very small in comparison to other problems; therefore, improved estimation of surface pressure has had a low priority.

3. Results

a. Example Surface Turbulent Fluxes

Below are examples of latent and sensible heat fluxes from two strong storms (Fig. 1). These fluxes are calculated from the Roberts et al. (2010) retrievals of air temperature and humidity, diurnally varying SST (a product under development based on NASA support from a non-NEWS program), and winds from SSMI. A neural net technique was used to mimic the COARE3.0 bulk flux algorithm.

One obvious problem with satellite retrieved fluxes is gaps in coverage due to excessive cloud cover in some regions. In the case of these storms (Fig. 1), areas of relatively strong fluxes are missed. We anticipate that changes in winds and SST will be much more important than changes in atmospheric temperature and moisture within these gaps. The GHRSST project is working on producing accurate SSTs. Winds must be interpolated with knowledge of the relevant physics, rather than simply statistics. We are completing our NASA OVWST based activities in that area. The wind, for the flux fields developed for NASA NEWS, will be used as test cases for the development of this wind product. It is anticipated that air temperature and humidity can be more easily extrapolated; however, this extrapolation will likely be the dominant

source of error in these fluxes. Our efforts should remove a large fraction of the bias due to ignoring these storms. We will attempt to examine this bias.

b. Diurnal Cycle

We have found that the use of diurnally varying sea surface temperatures removes a roughly 10Wm^{-2} monthly-averaged bias in regional latent heat fluxes. The region depends on the model used to determine latent heat fluxes and the model for diurnal warming; further work should greatly reduce the significance of these differences.

c. Observations for bulk parameterizations

The bulk formulas (Eq 1-3) are typically tuned to earth relative wind speeds; however, satellite winds are tuned to equivalent neutral winds (Ross et al. 1985; Bourassa et al. 2010) which are an approximation for friction velocity. If these satellite winds are treated as earth relative winds, there are seasonal and regional biases (admittedly small compared to prior problems). However, these biases can easily be removed, and will be removed in our product.

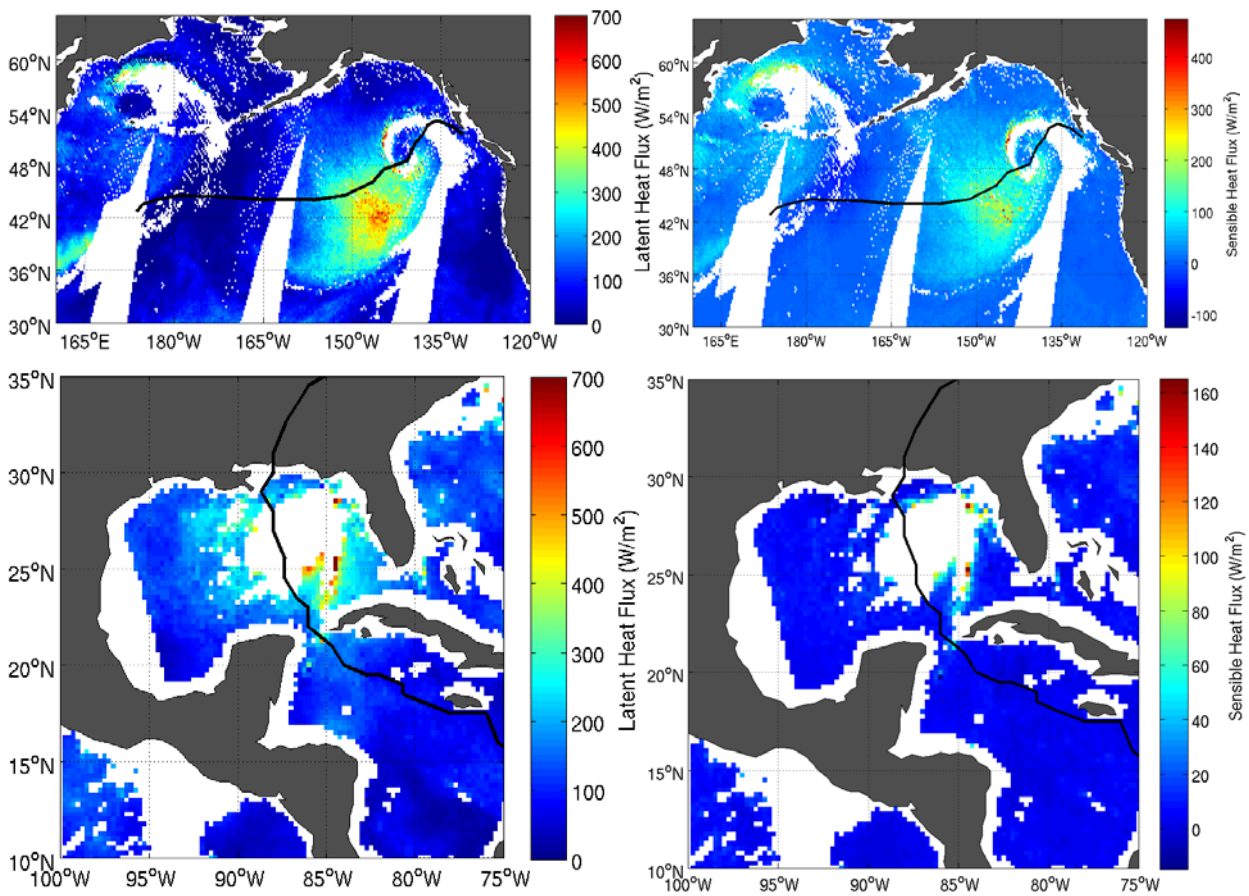

Figure 1: Satellite-based estimates of the latent heat flux (left column) and sensible heat flux (right column) for an intense mid-latitude storm (top row) and Hurricane Ivan, 2004 (bottom row). The black line is the storm track. Missing values occur where there was too much

precipitation, masking out much of the interesting area for hurricanes, but much less of a problem for fluxes behind mid-latitude storms. These fluxes were calculated as part of the development process for the SeaFlux gridded fluxes.

The quality of our temperature and humidity retrievals are shown below (Fig. 2), with examples from the storms shown in Fig. 1. These images have some suggestion of problems associated with excessive atmospheric moisture, resulting in questionable retrievals. We are collaborating on the testing of the retrievals in comparison to surface truth from buoys are research vessels. For the vast majority of conditions, these retrievals are remarkably impressive, and should contribute to a great reduction in biases in heat fluxes and evaporation!

Air/sea differences in air temperature and humidity are shown in Fig. 3. Preliminary evaluation by the SeaFlux developers is remarkably encouraging. The air/sea temperature differences associated with cold air outbreaks are well represented! Such outbreaks follow warm core seclusions (the high latitude example in the figures), and can be seen (Fig. 2) as the cold and dry air transport south of the storm track. The associated large air/sea temperature differences (Fig. 3) contribute to extremely large fluxes in the wake of these storms.

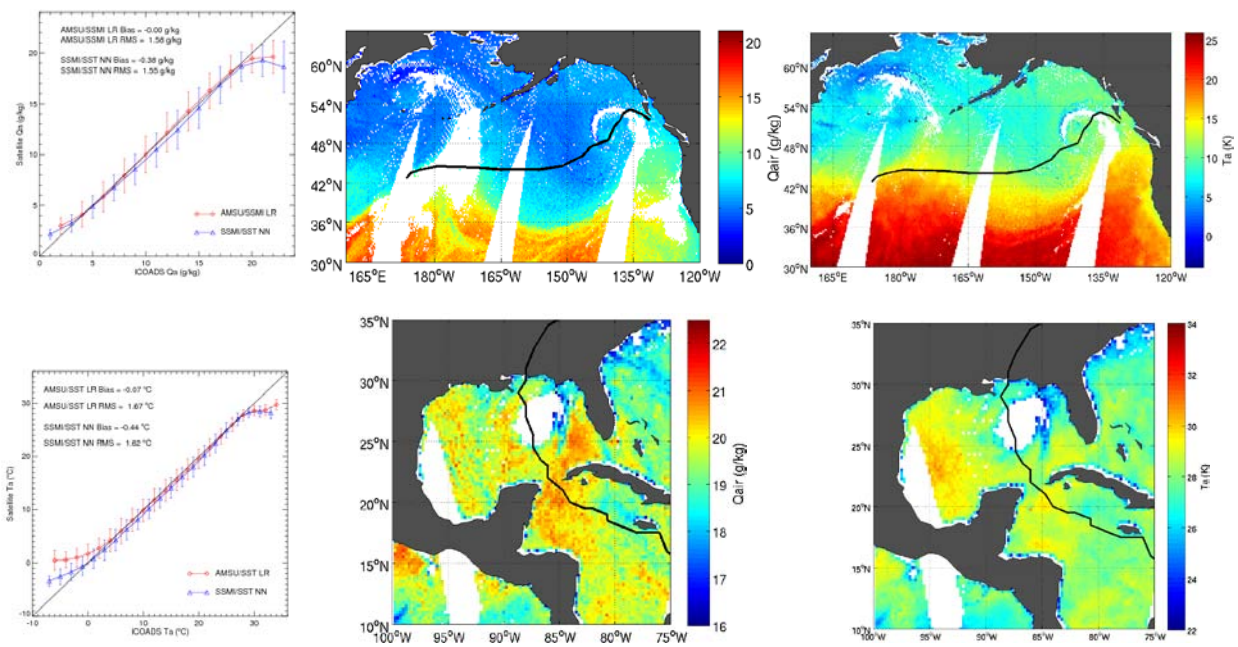

Figure 2. Validation of satellite retrievals of humidity at a height of 10 m above the water surface (top left) and air temperature at the same height (bottom left); and examples of humidity (middle column) and air temperature (right column) for the same cases as in Fig. 2.

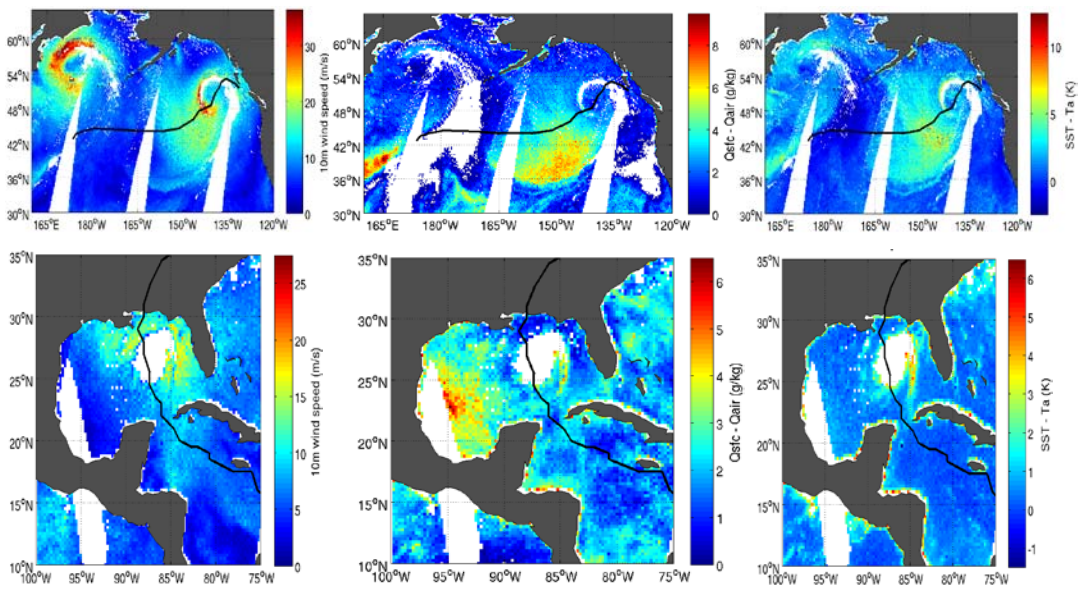

Figure 3. Wind speeds (left column), air/sea differences in humidity (middle column) and air/sea differences in air temperature (right column) for the same cases as in Fig. 2. The fluxes are proportional to these wind speeds and differences. The wind speeds are from Remote Sensing Systems v6 SSMI product.

d. Tuning of Bulk Algorithms

We have also improved the calibration of latent heat fluxes. We have found that noise in the observed stress, passed through several non-linear manipulations, contributes to roughly a 10 Wm^{-2} bias in the tropical latent heat fluxes. The distribution of observation based estimated of roughness length was very well modeled by adding realistic noise to stresses based on the COARE3.0 model for wind derived stress (Griffin 2010). Our technique removes highly questionable observations, resulting in a data set that is better suited for tuning flux models. The biases associated with the original parameterization is clearly seen in Fig. 4. This bias is well within prior uncertainty in turning parameters. Small changes in these parameters can correct the biases (Fig. 5).

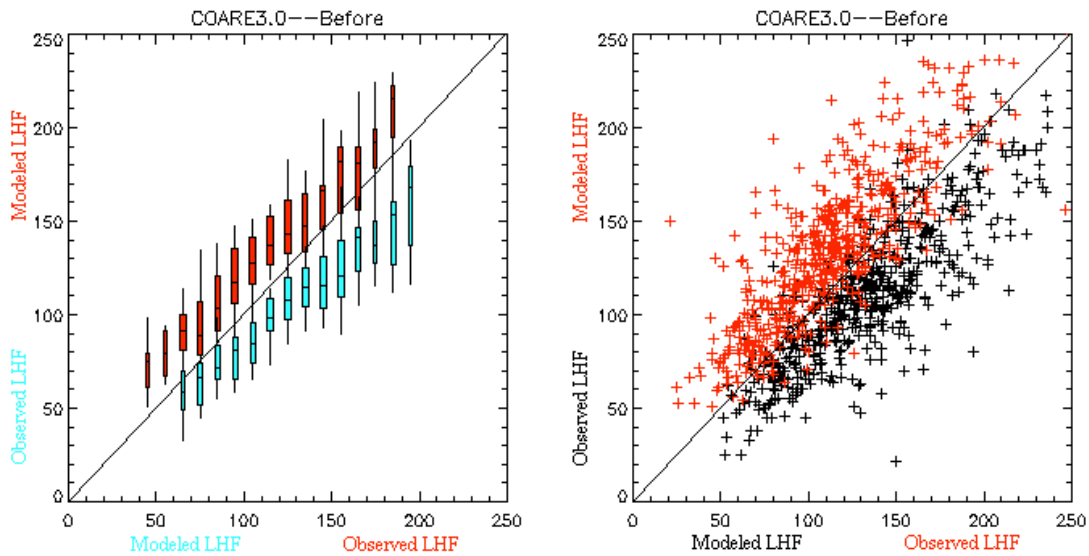

Figure 4. Scatter plots and box plots of the LHF values from the original parameterizations. The data for the scatter plots is first plotted with the observed as the x-axis and modeled as the y-axis (red). The axes are then reversed and the data is plotted again (blue and black). The box plots are created from these scatter plots. The box plots represent the 10th, 25th, median, 75th, and 90th percentile. The widths of the boxes correspond to the number of data points contained within. The wider the box, the more data points are included. The farther the box plots are from the 1:1 line, the more bias is present in the data. Any slope that is seen in the data is indicative of large random errors in the value that is being binned or a non-constant systematic error.

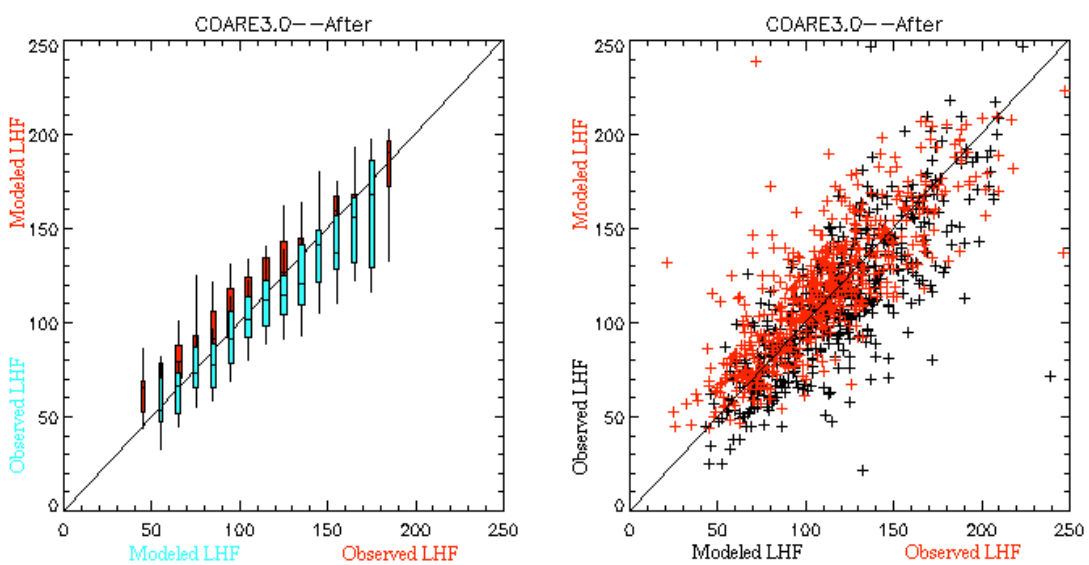

Figure 5. Same as fig. 4, but with the modeled LHFs calculated from the parameterizations with the new changes applied to the z_{0q} calculations.

Summary

We are improving estimates of surface turbulent fluxes of heat and moisture. Improvements include improved sampling, improved retrievals of inputs to bulk algorithms, improved treatment of satellite derived winds, and improved parameterization in the bulk algorithms.

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