Overview on SeaFlux

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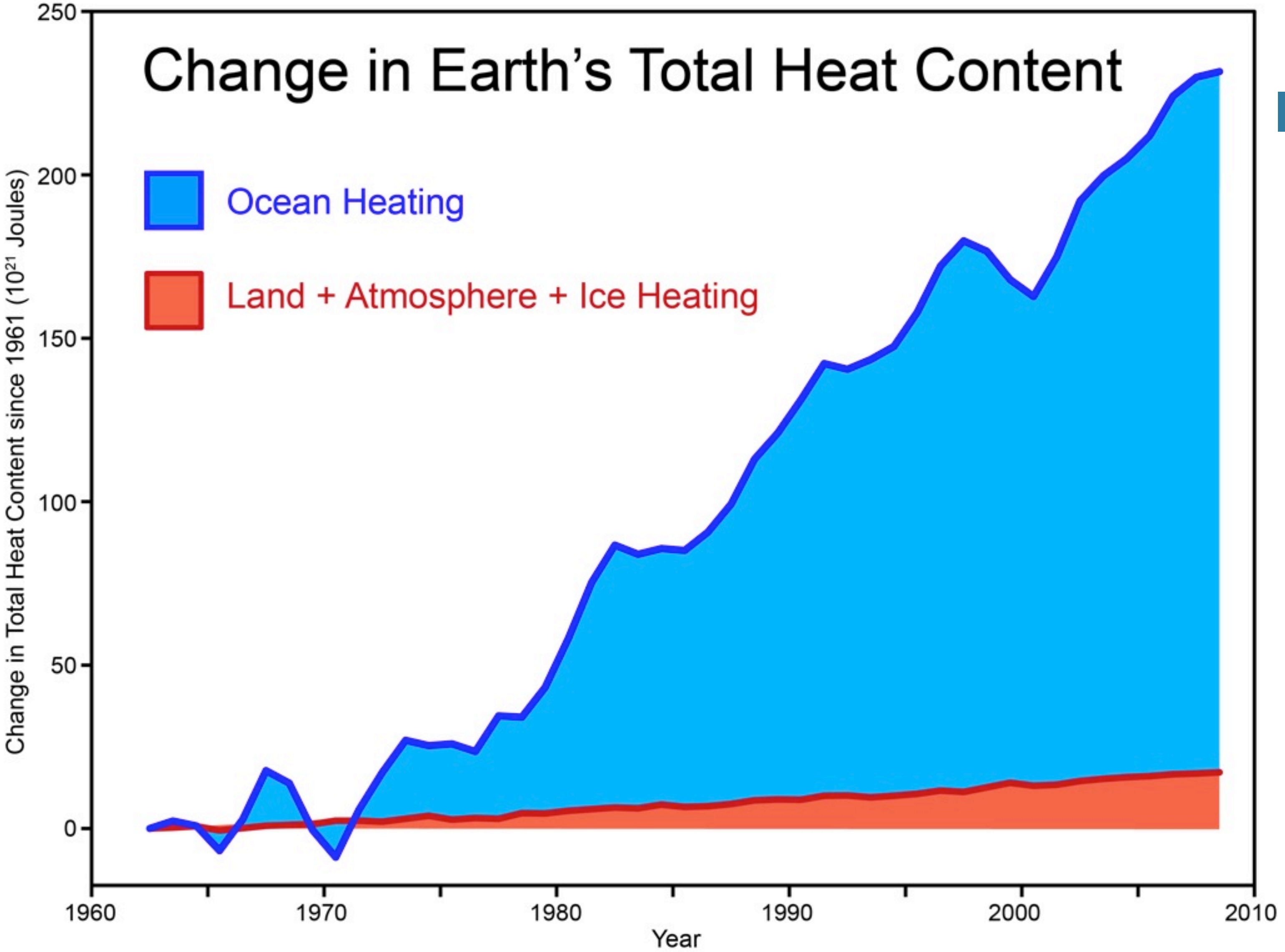
With Brent Roberts, MSFC

And Jeremiah Brown, Principal Scientific Computing

5th GDAP Meeting

29 November – 1 December 2016

Washington, DC



Church et al., 2011

Under WCRP Data Advisory Council (WDAC)

- Discussion of need for coordination and highlighting surface flux issues
  - Land, ocean, ice
  - Biogeochemical, heat, moisture, momentum
  - Turbulent, radiative
  - In situ, remote
- "promote a stronger dialogue and profile of flux efforts across WCRP and with sister programmes "
- Formed Surface Flux Task Team (C. A. Clayson/Brian Ward, chairs)
  - Cuts across GEWEX, CLIVAR, other WCRP groups
  - Members:
    - Carlos Jimenez (Observatoire de Paris, land, satellite, obs;
    - Jim Edson (U. Conn, ocean, obs);
    - Pierre-Philippe Mathieu (ESRIN, satellite);
    - Peter Gleckler (LLNL, modeling);
    - Ronald Buss de Souza (National Institute for Space Research, Brazil, ocean, obs)
    - Paul Stackhouse (NASA Langley, radiative fluxes, satellite, scientist extraordinaire);
    - Hans Peter Schmid (Karlsruhe Inst. Tech., biosphere, obs);
    - Anton Beljaars (ECMWF, land, modeling);
    - Saigusa Nobuko (Japan, National Inst. for Env. Studies, land, obs);
    - Petra Heil (University of Tasmania, sea ice, obs, remote sensing, modeling);

SeaFlux

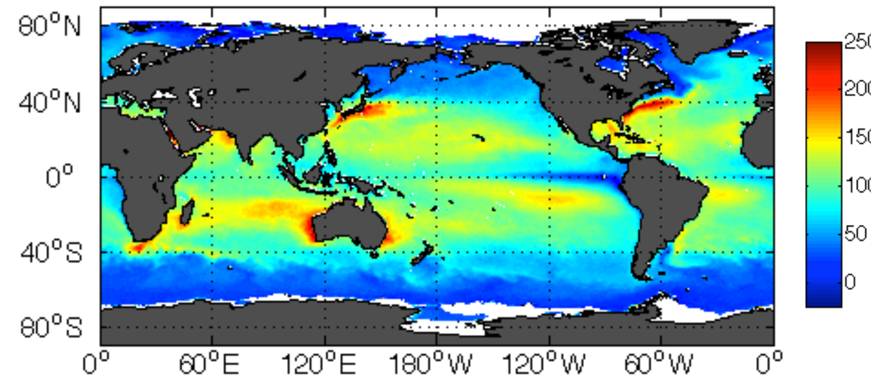
- International project under the auspices of the GEWEX Data and Assessments Panel: *to improve our understanding and determination of ocean surface turbulent fluxes*
- Our main questions:
  - What is feasible in terms of resolution and length-of-time series for satellite data?
  - Can we produce a high resolution dataset using satellites that is better than conventional climatology and NWP products?
  - What are the best methods for creating this dataset?
  - How do the different datasets perform under varying applications?
- Elements of the project include:
  - Evaluation of global flux products
  - Providing library of flux datasets and in situ data sets for easy comparisons by researchers
  - Production of a high-resolution (1^{o}, 3 hourly) turbulent flux dataset

SeaFlux CDR version 2

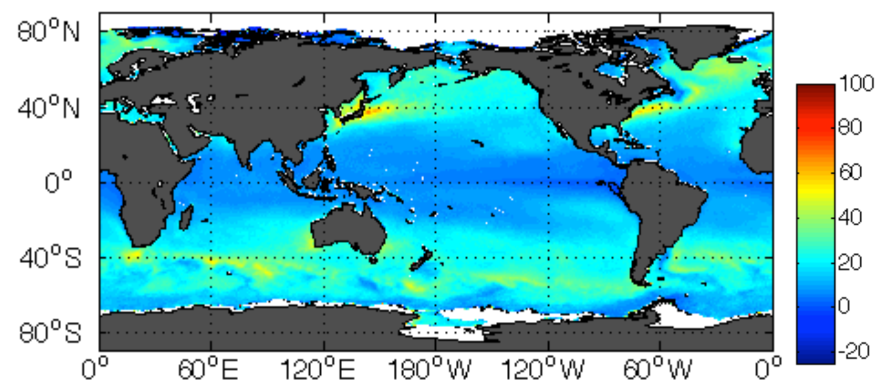
- Near-surface air temperature, humidity, and winds
  - Based on Roberts et al. (2010) neural net technique
    - CLW content used to remove rain-contamination (except for F08)
    - F10 – F18, pixels segregated by clear/cloudy sky
    - One neural net for F08, two for all others (total)
  - SSM/I and SSMIS from CSU FCDR
- SST
  - Pre-dawn based on Reynolds OISST
  - Diurnal correction
  - Uses SRB, CERES, FLASHFlux for radiation, HOAPS, GPCP for precipitation
- Land mask from NOAA GSHHG, ice mask from AVHRR ice fraction, ISCCP ice shelf
- Uses neural net version of COARE
- Gap-filling methodology -- use of MERRA2 variability – 3 hour

- Available from 1988 through mid-2016

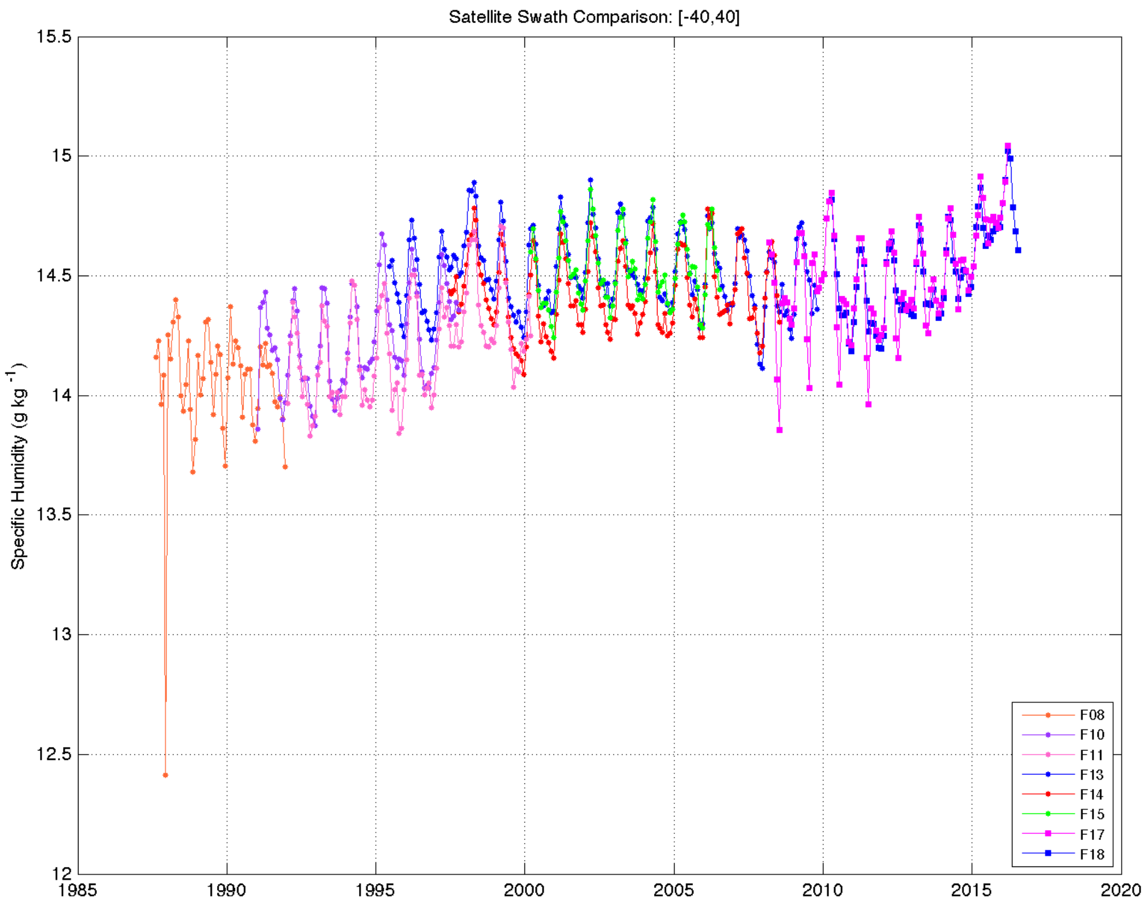
1999 Latent Heat Flux



1999 Sensible Heat Flux



Changes with satellites



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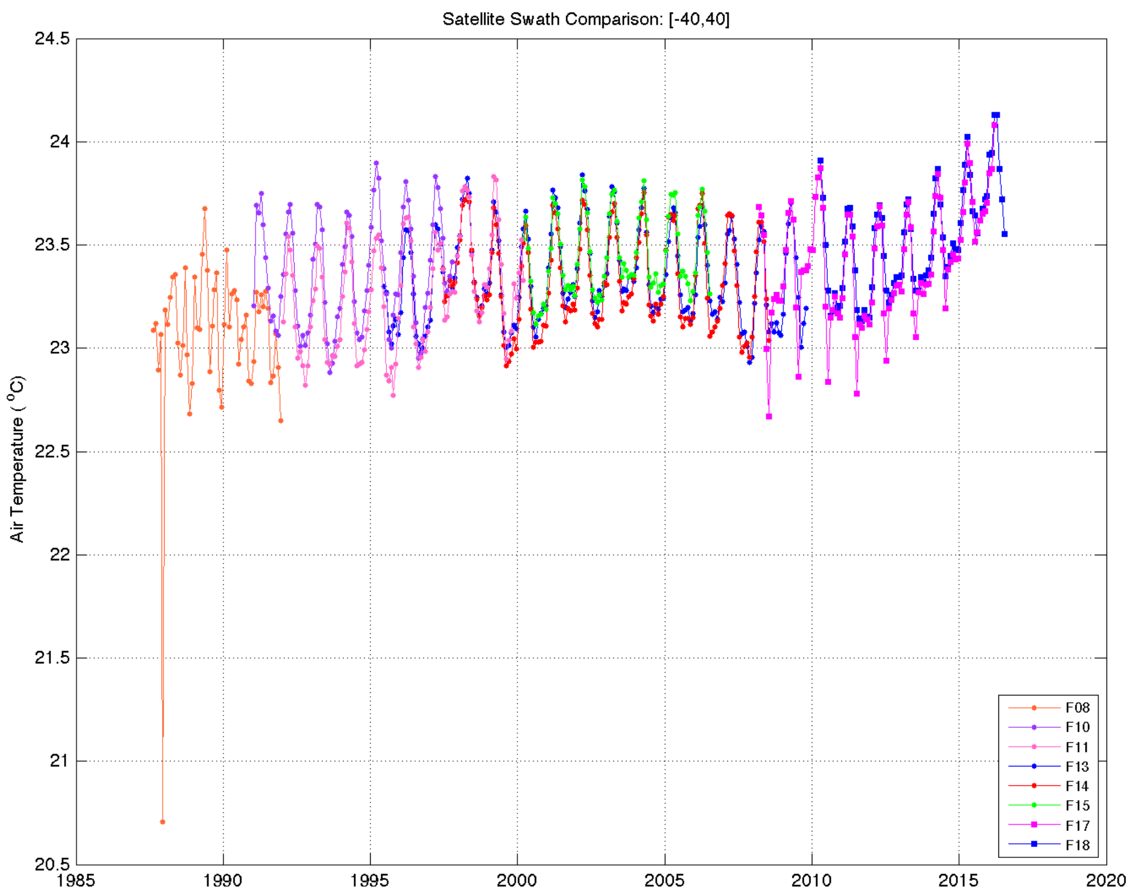

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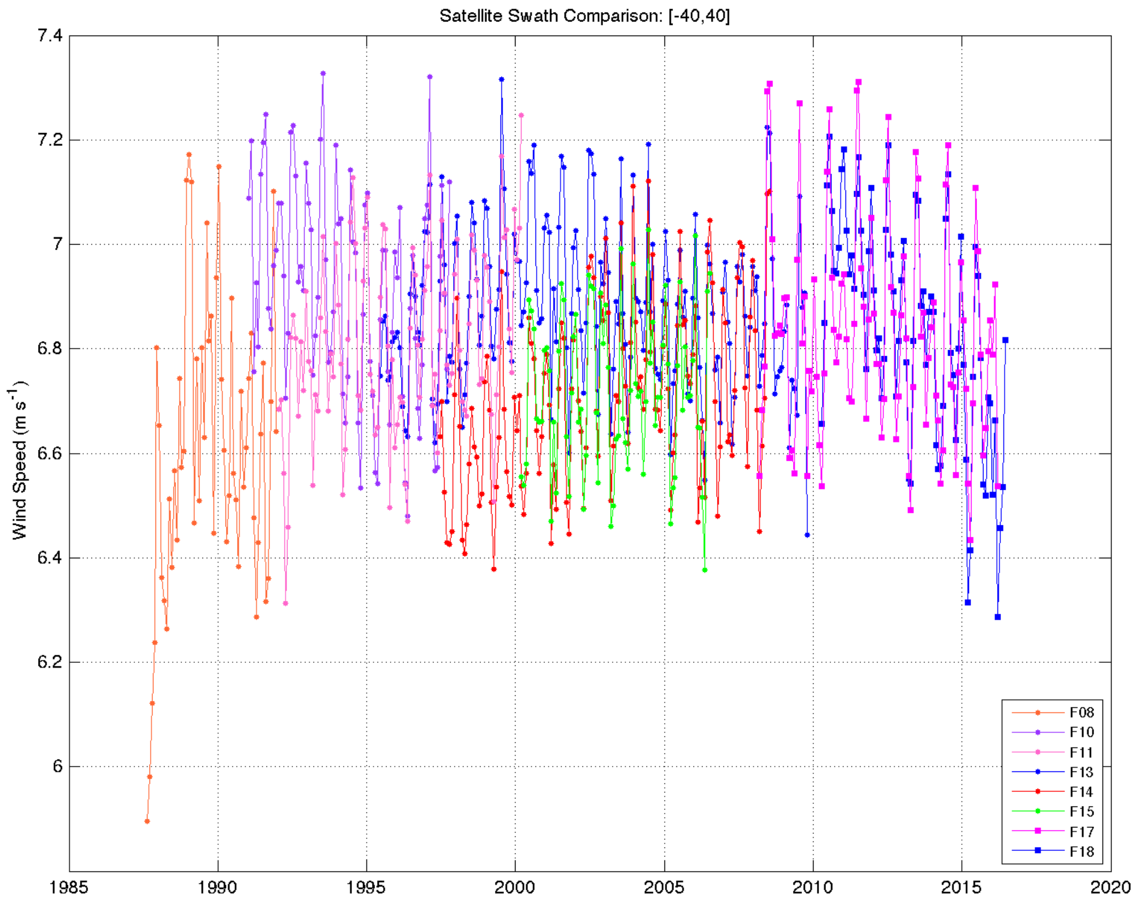
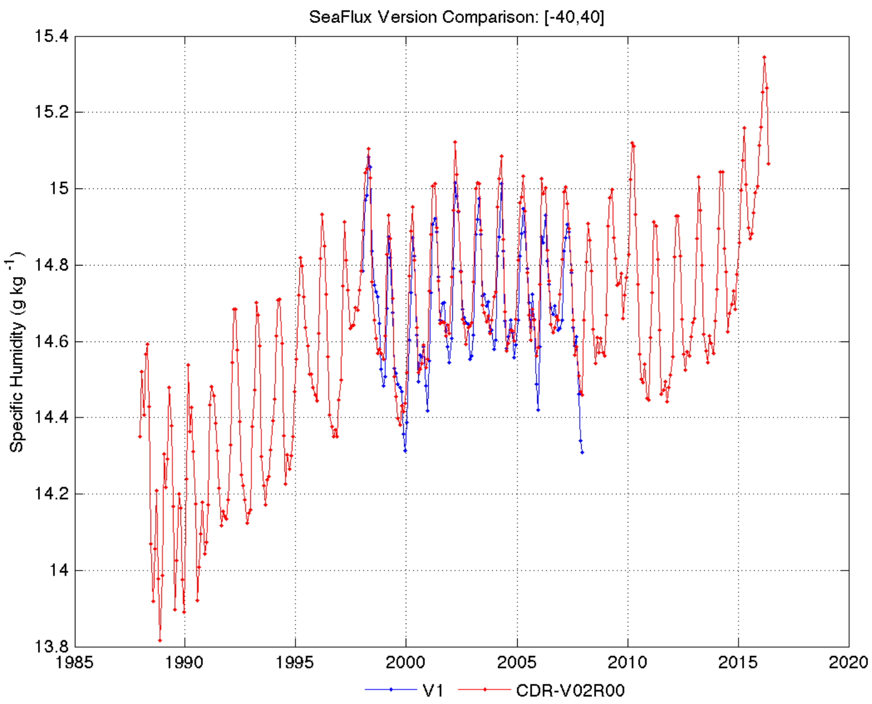
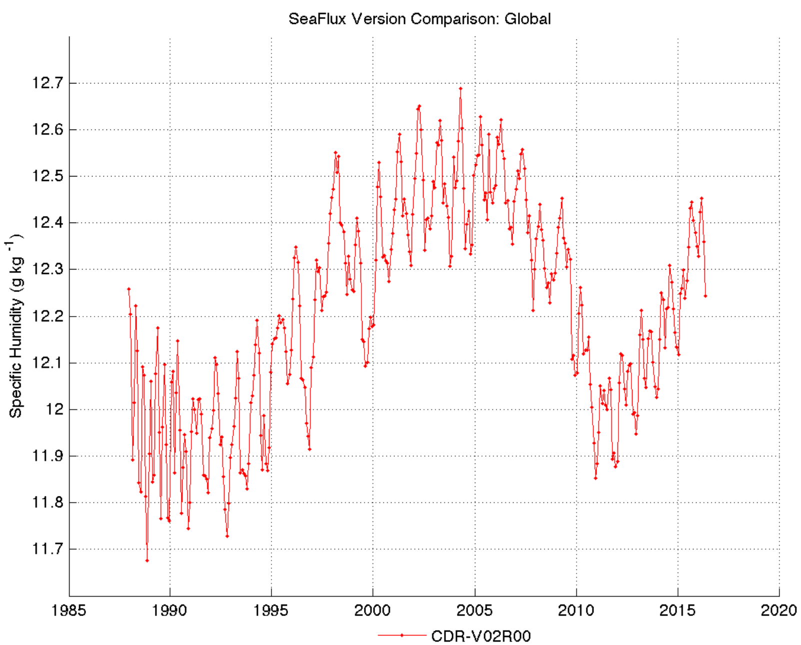


Qa variability

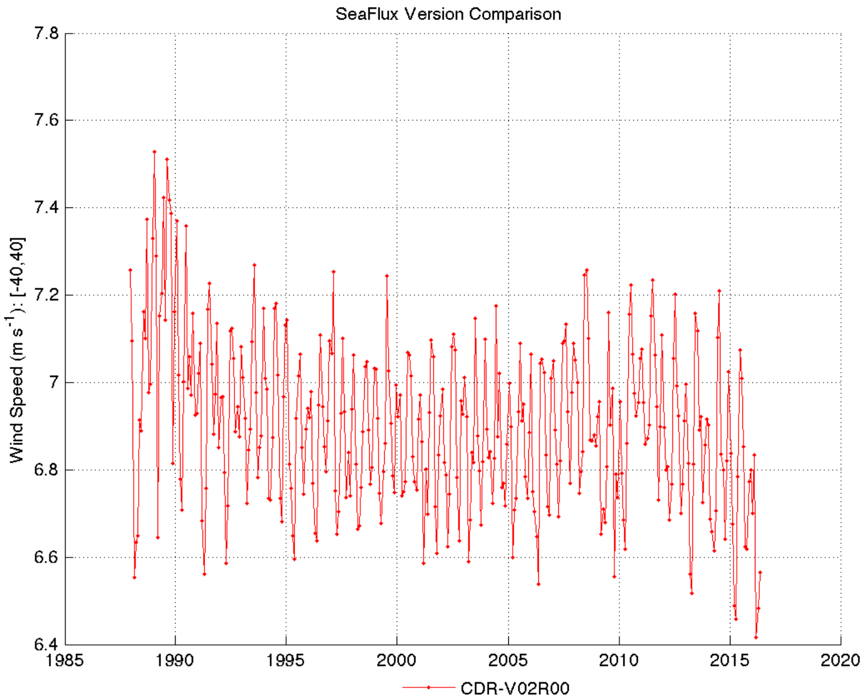


40 N – 40 S average (area weighted)



Global ocean average (area weighted)

Wind Speed variability



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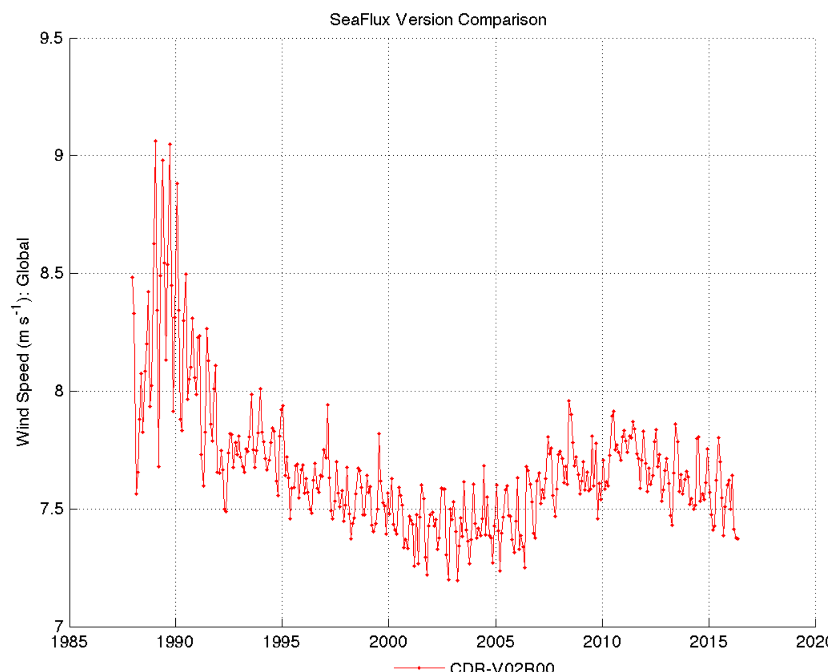
Global ocean average
(area weighted)



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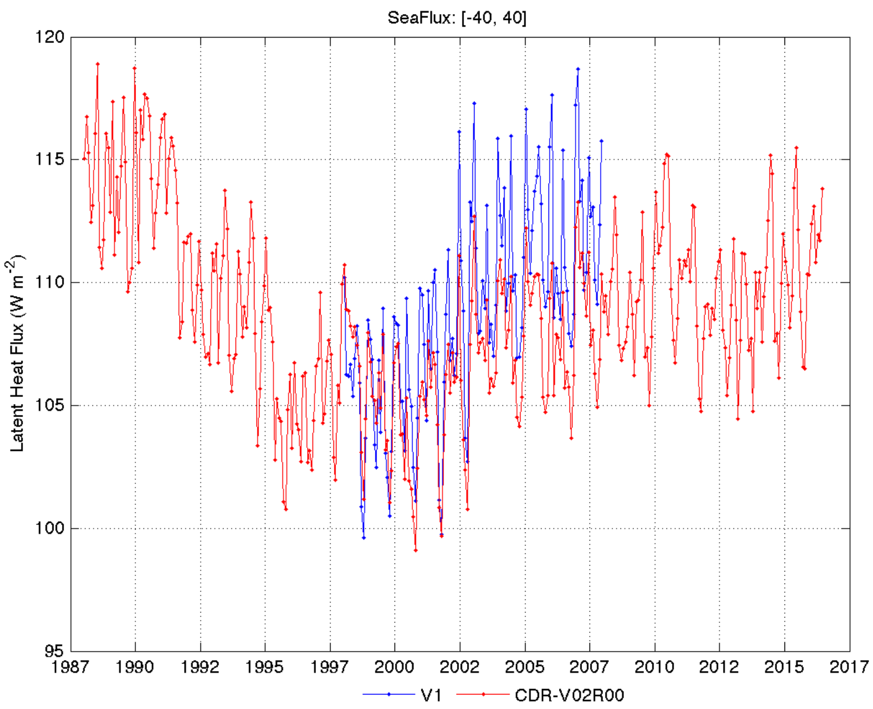

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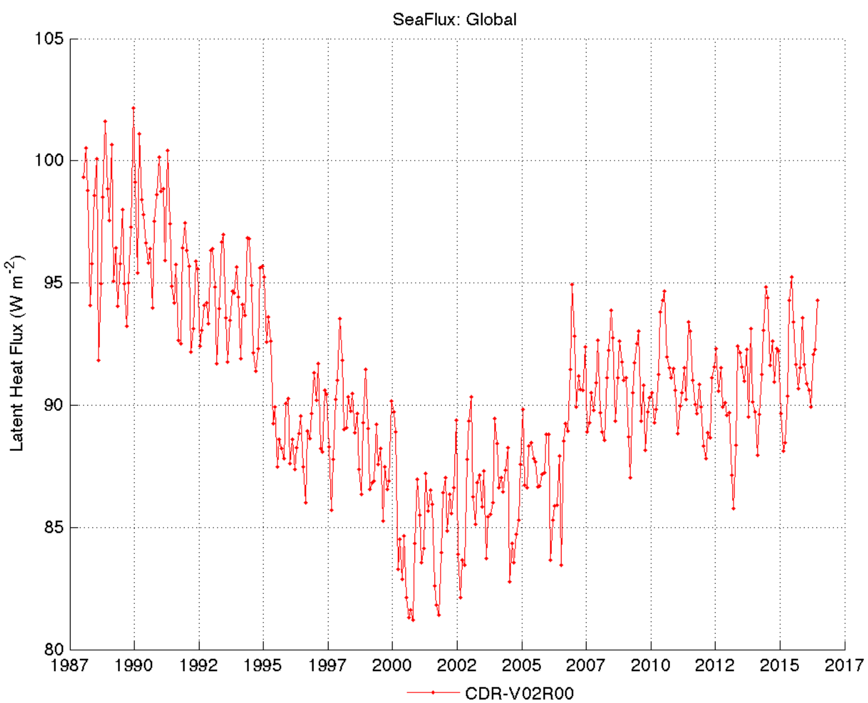
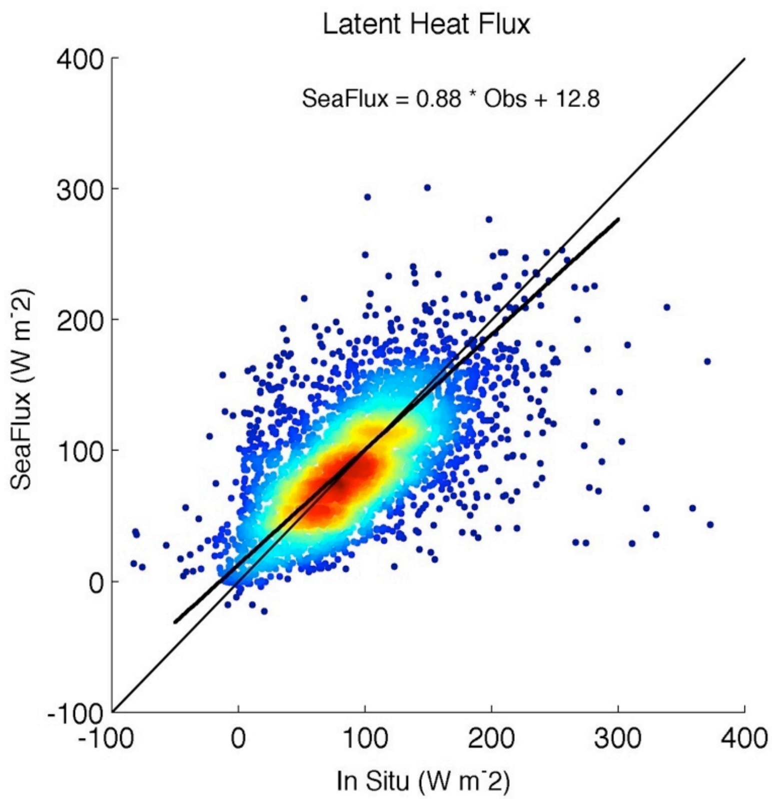


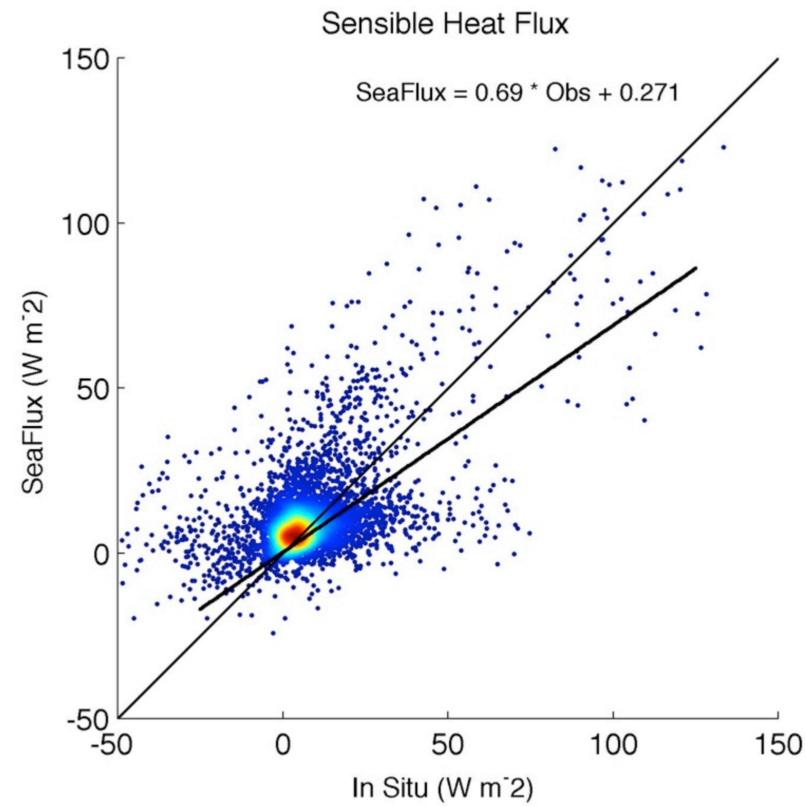
Global ocean average (area weighted)

Comparisons with eddy covariance fluxes



Bias: 2.1 W m^{-2}

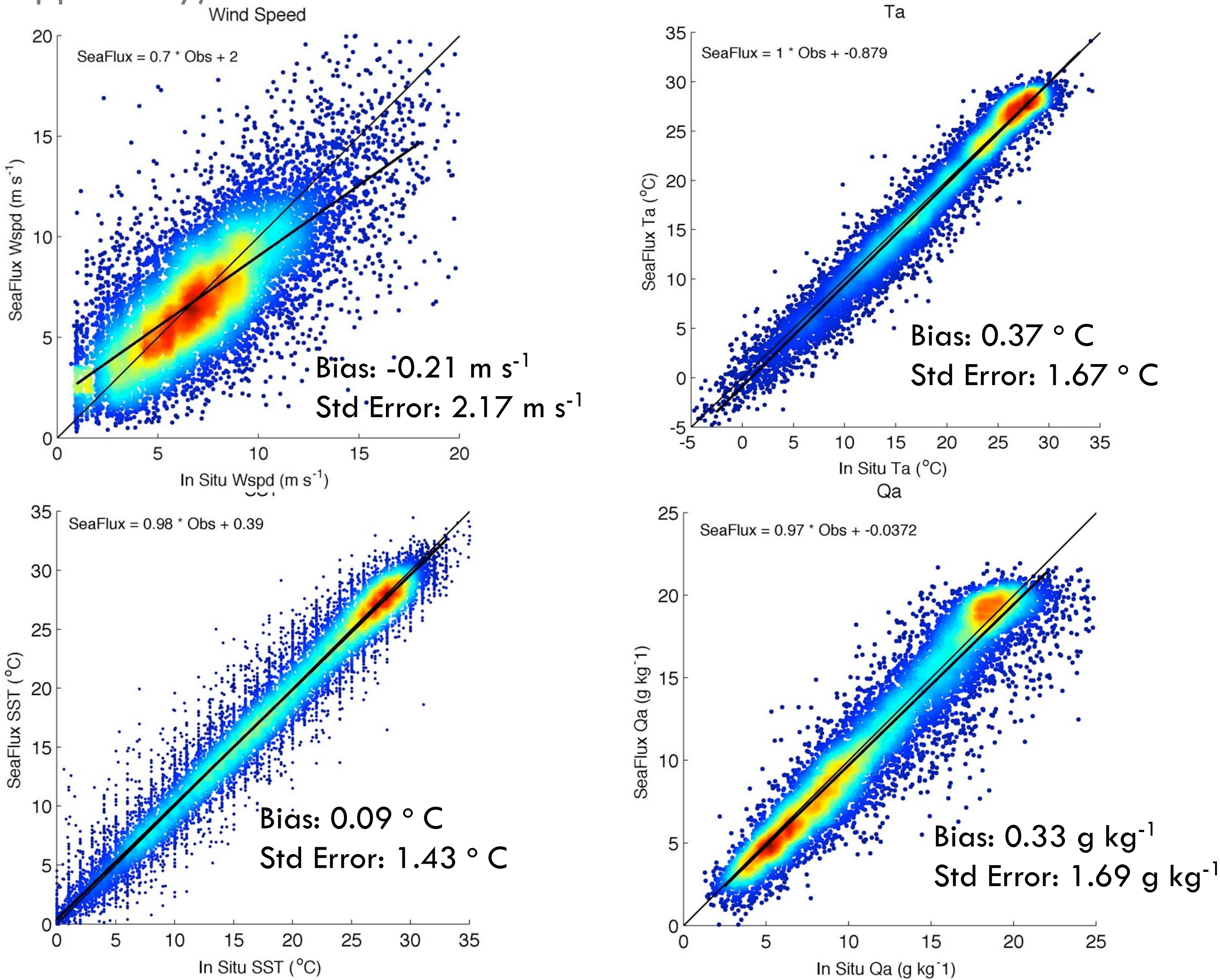
Std Error: 38 W m^{-2}



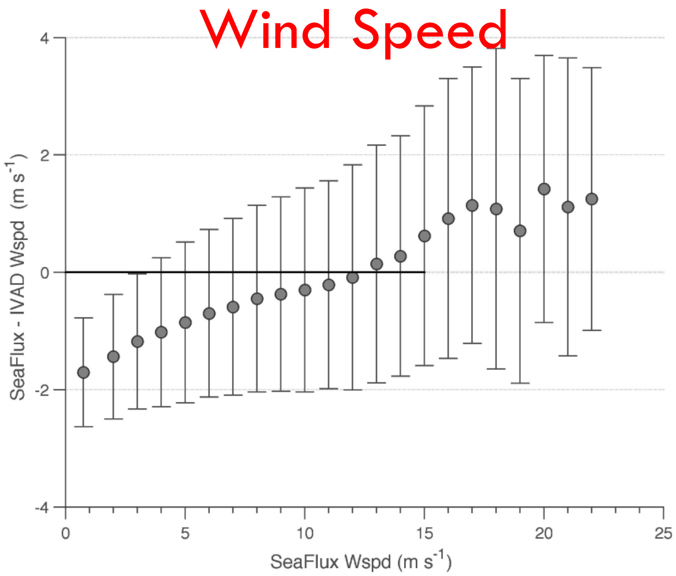
Bias: -3.1 W m^{-2}

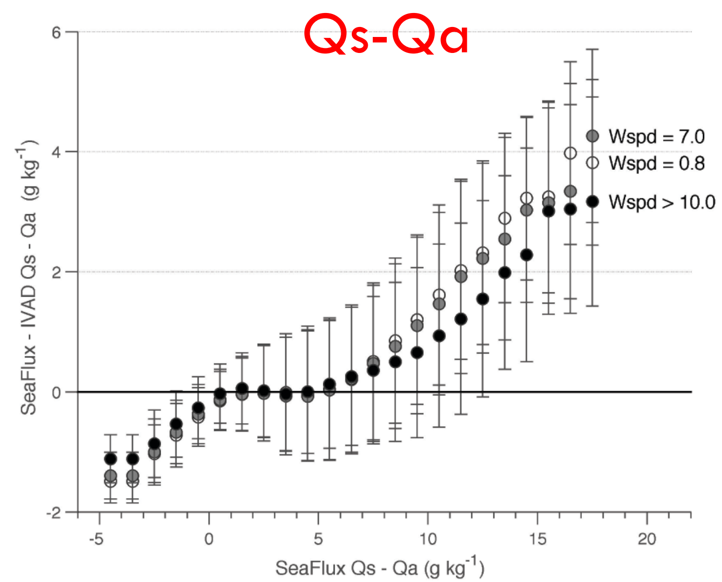
Std Error: 13.2 W m^{-2}

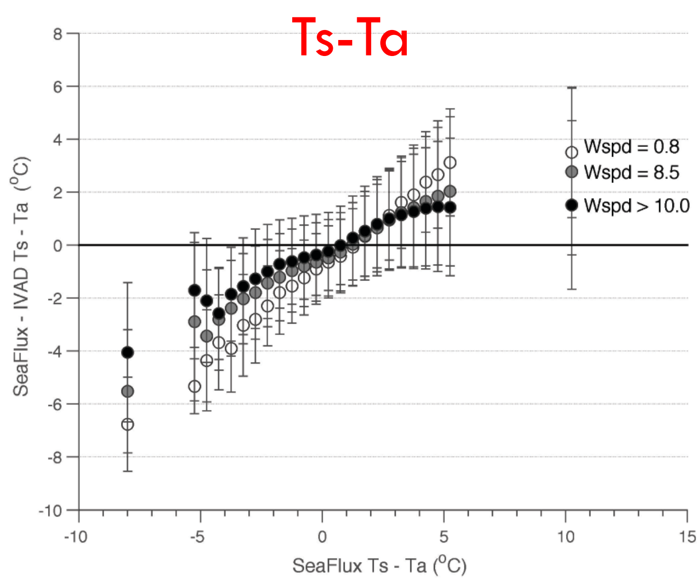
Comparison of SeaFlux derived parameters with ICOADS Value-Added Database (ships of opportunity)



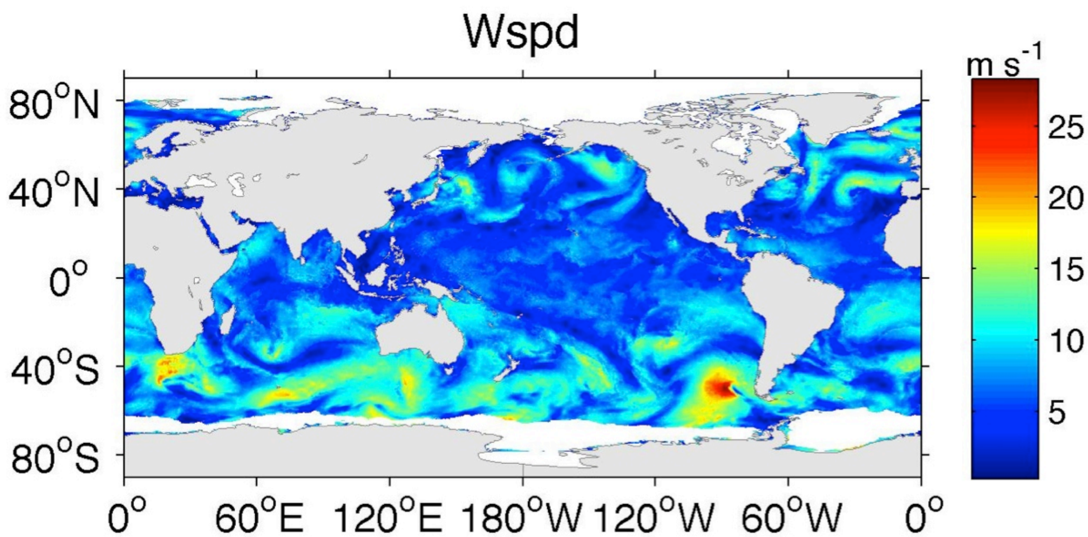
Evaluating uncertainty using IVAD data

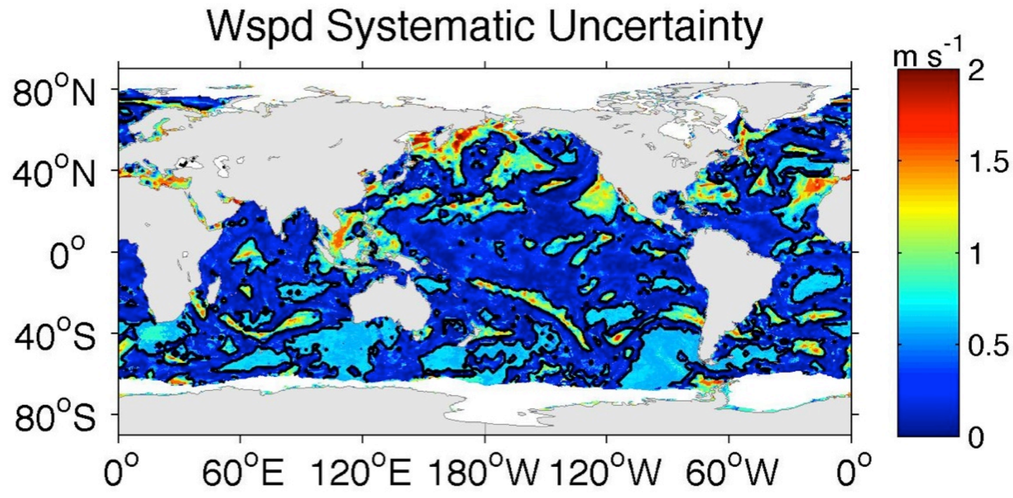


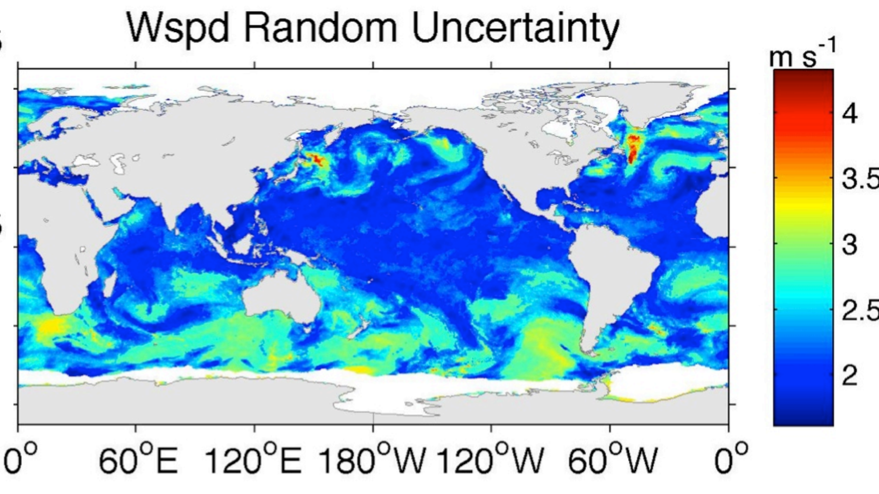




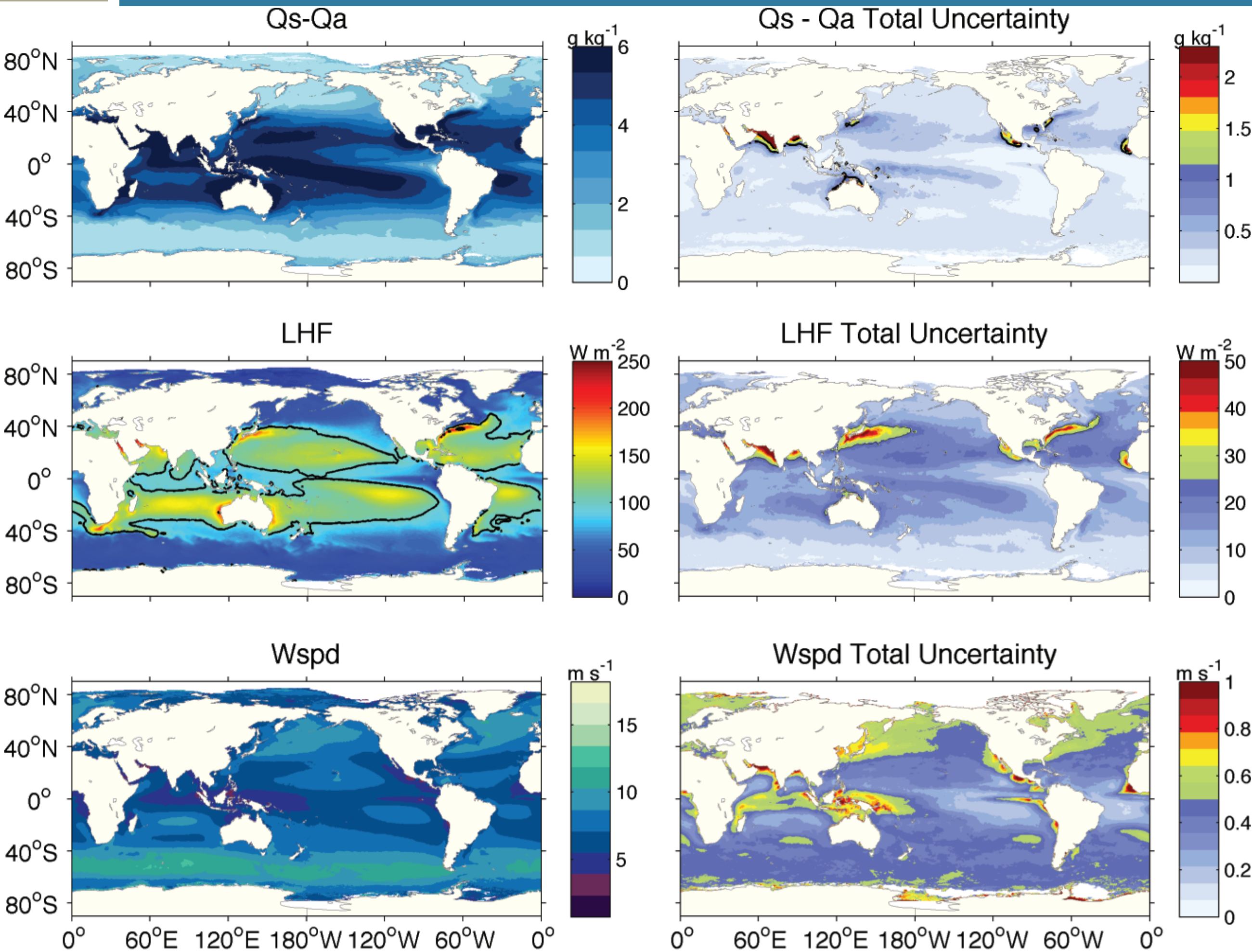
Instantaneous error estimates







Uncertainty estimates of 10-year means



Variable	Global uncertainty
LHF (W m^{-2})	8.2 (9%)
SHF (W m^{-2})	4.2 (24%)
Windspeed (m s^{-1})	0.39 (5.2%)
Qa (g kg^{-1})	0.45 (4.0%)
SST (^{o}C)	0.12 (< 1%)
Ta (^{o}C)	0.35 (2%)
Ts - Ta (^{o}C)	0.44 (33%)
Qs - Qa (g kg^{-1})	0.27 (8.2%)

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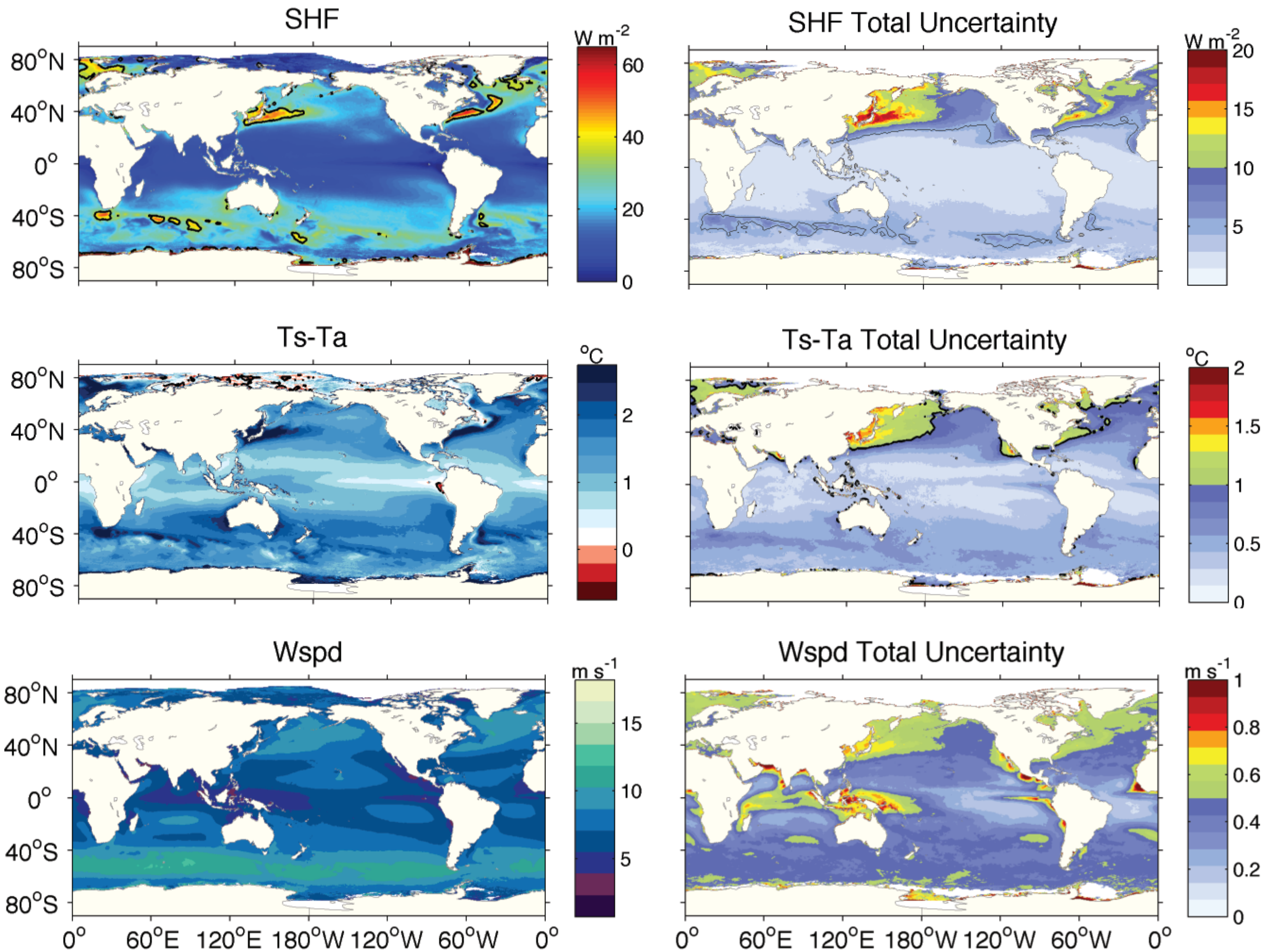

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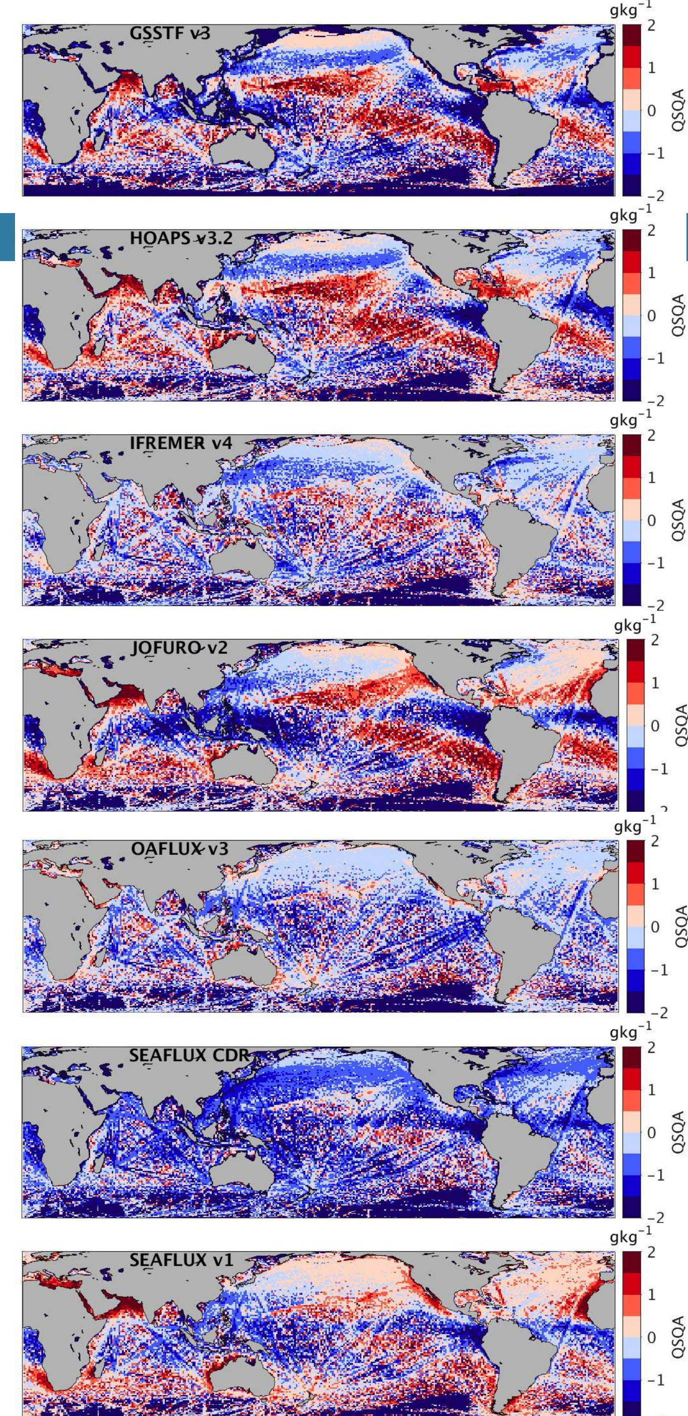
Regional biases (Qs-Qa)

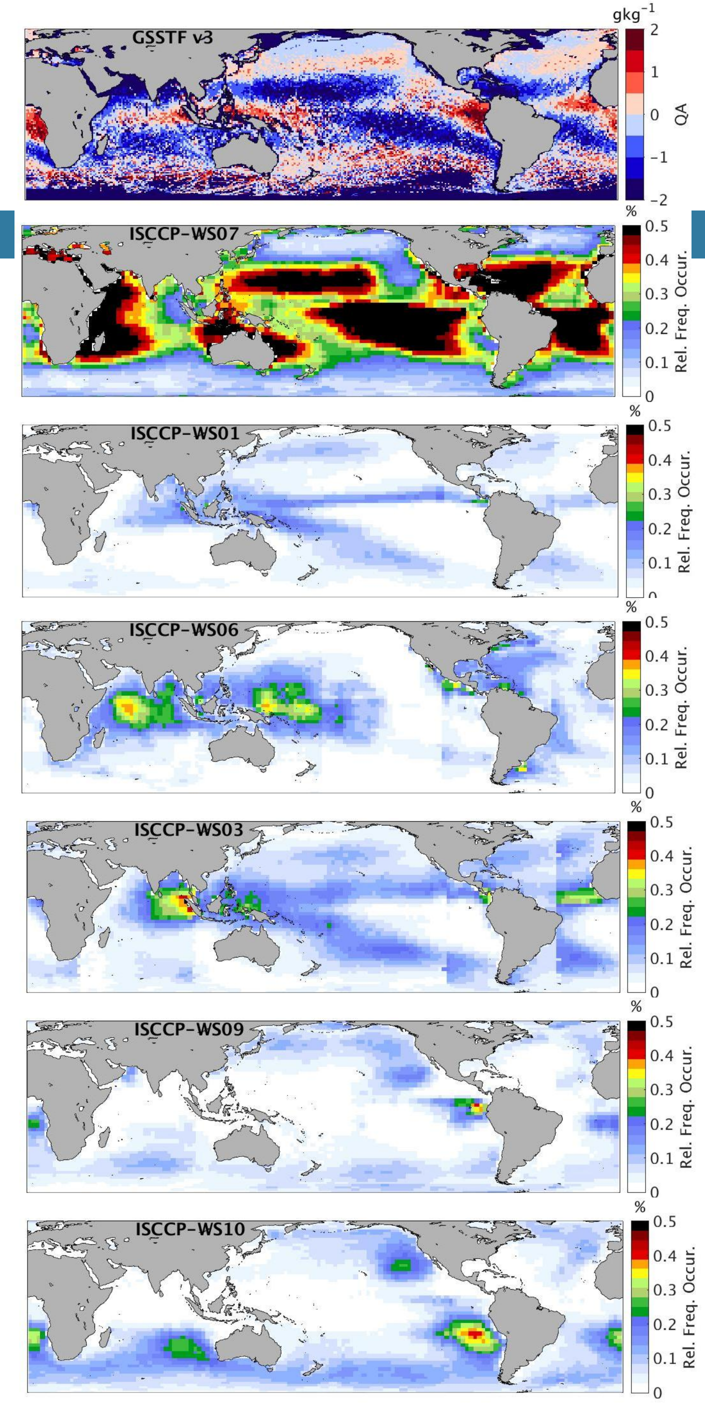
- Different products show strong regional patterns of biases compared to IVAD
- QSQA biases are driven primarily by differences in Qa retrievals rather than SST
- GSSTF v3, HOAPS v2, and JOFURO v2 all show a similar large scale pattern of biases, with strong regional signatures over the subtropical trade wind regimes and West Pacific STCZ
- IFREMER v4 and SeaFlux-V1 show muted regional signature, but they are still evident



Retrieval biases and weather states

- The structure in the retrieval (Qa, top) biases appear to be co-aligned with patterns of cloud weather states (defined by ISCCP cloud-top histograms)

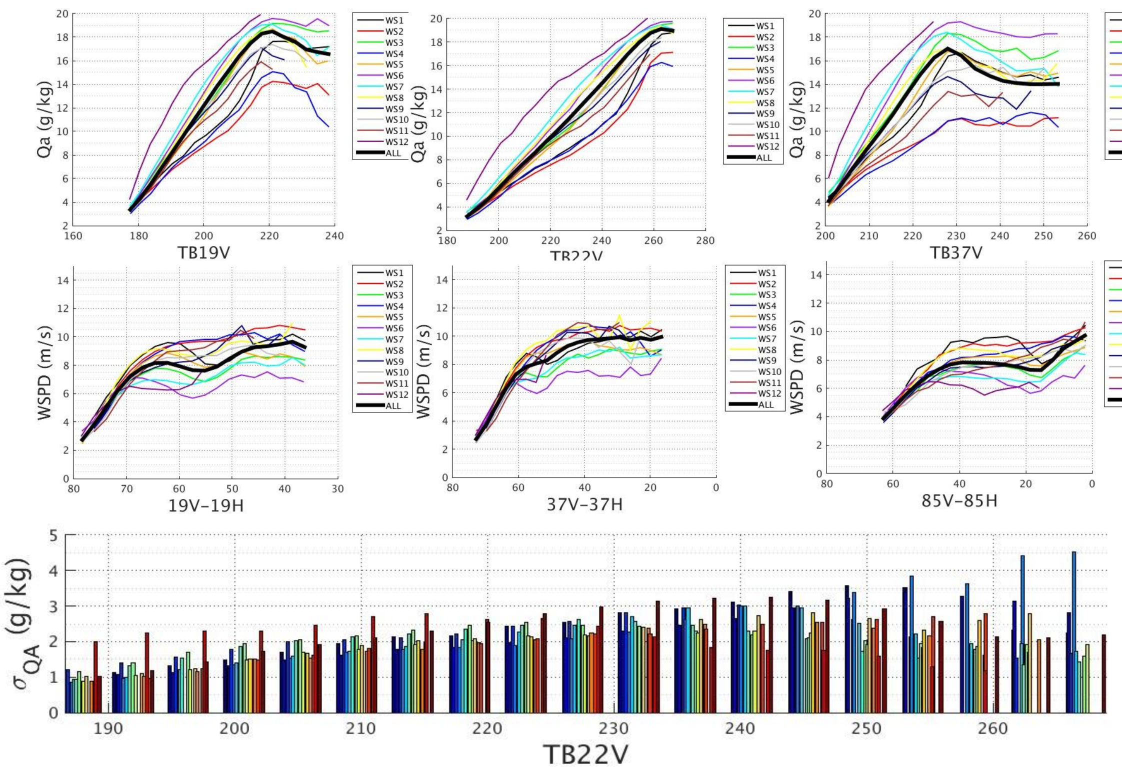
- The largest biases in several of the Qa retrievals are aligned best with Global WS 7 (Tselioudis et al. 2012) – mostly clear, with thin boundary layer clouds



Cloud impacts on passive microwave empirical retrieval algorithms

- Near-surface Qa, Ta, and wind speed retrievals show strong regime-dependent conditional biases
- Conditional-RMS also appears dependent on cloud weather state, but to lesser extent
- *When the underlying component of the conditional biases are regionally dependent, it is likely the application of "grouped" retrievals will result in regional biases*

Binned Qa and Wspd vs. observed F15 TBs



New opportunities

- Passive microwave provide direct information on the clouds in atmospheric FOV
- We can decompose the observed , TB_{obs}, into clear-sky and cloudy-residual components

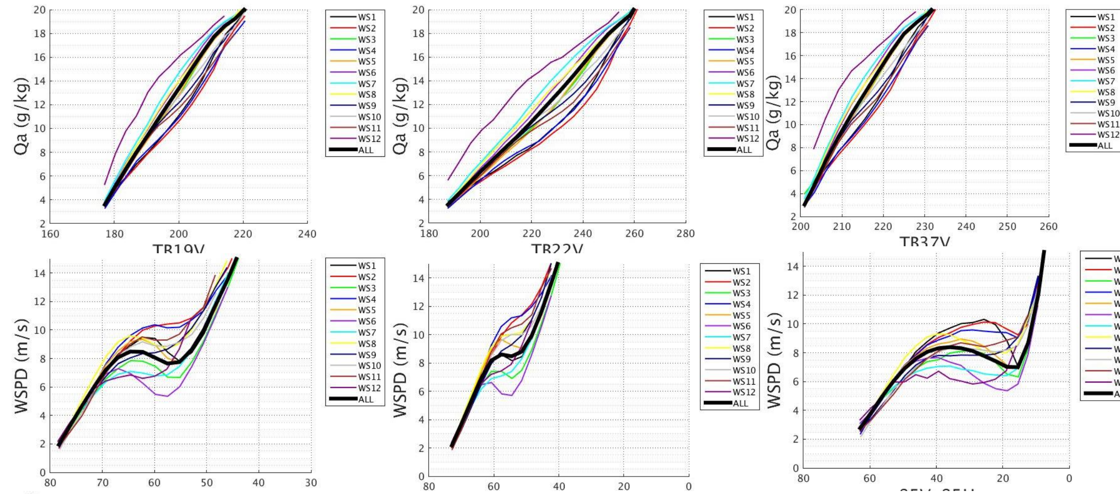
$$TB_{obs} = TB_{clr} + TB_{cld}$$

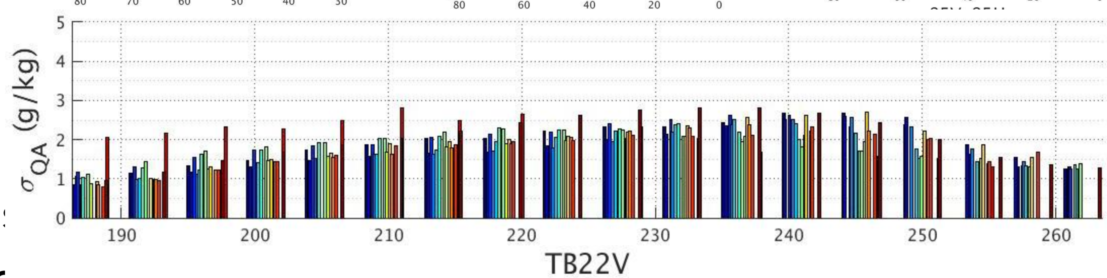
- Then retrieve using

$$\{Qa,Ta,Wspd,SST\} = F^{-1}(TB_{clr})$$

- Conditional-bias and RMS of near-surface parameters against the Clear-Sky TB appear smaller and more consistent across all of the weather regimes

Binned Qa and Wspd vs. Clear-Sky simulated F15 TBs





Final thoughts

There are multiple challenges at present for the development of accurate, precise, and consistent climate data records of turbulent latent and sensible heat fluxes.

- Large conditional/regional biases affect current remote sensing based estimates of near-surface air temperature and humidity, particularly under different cloud regimes
- Changes in the passive microwave observing system can generate anomalous variability in estimated turbulent fluxes:
- New advances are being made to address the development of climate-quality turbulent fluxes from remote sensing, including:
  1. Data Fusion
  2. New sensor development
  3. New approaches to handling cloud impacts on microwave TBs
  4. Improved sampling and analysis/blending techniques