Passive microwave remote sensing of surface turbulent fluxes: the role of clouds and statistics

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- Regression Approaches
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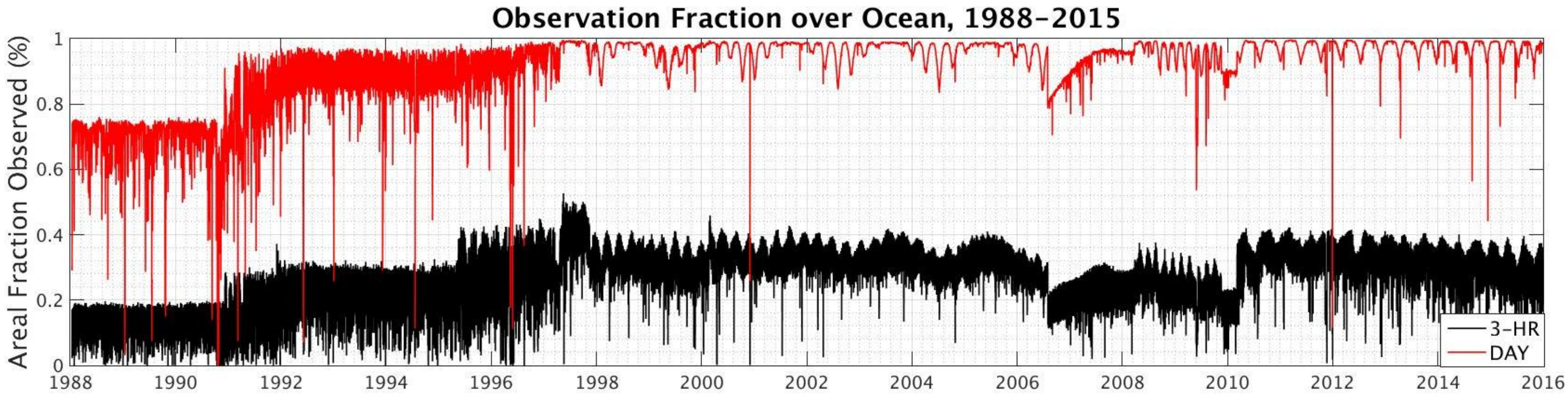
Motivation

- The turbulent latent heat flux (LHF) and sensible heat fluxes (SHF) are critical components of the Earth's energy and water cycle.
- *Results from the recent NASA Energy and Water Cycle Study (NEWS) Climatology indicate LHF/Evap requires the largest adjustments to balance the water and energy cycle as estimated from current state-of-the-art component estimates.*
- In-situ surface observations from buoys and voluntary observing ships (VOS) constitute a valuable source of direct observations of surface meteorology required to estimate fluxes. However, they offer incomplete coverage. Satellite based estimates provide an alternative approach with more complete global coverage every 1-2 days.



Background

Bulk flux algorithms relate the turbulent fluxes to near-surface meteorology

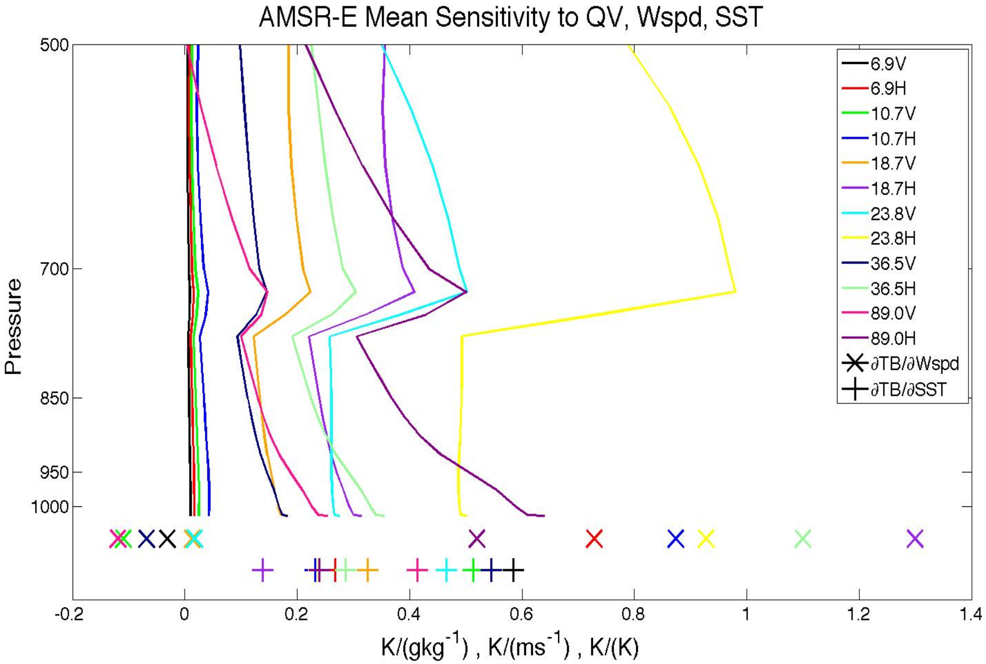
$$LHF = F(U10, Qair, Qsfc(SST), Tair)$$

$$SHF = F(U10, SST, Tair)$$

- Estimating the fluxes over the global (ice-free) oceans reduces to i) retrieving each of the near-surface bulk variables and application of a suitable bulk-flux algorithm (e.g. COARE 3.0).

Satellite Assets & Algorithms

- Each of these parameters have been retrieved using passive microwave observations:
  - SSM/I,SSMIS,WindSat,TMI, AMSR-E, GMI, AMSU-A
- 10-m Tair and Qair (i.e. at a specific level) show only moderate direct sensitivity (unlike SST/U10). Information on these surface-layer parameters is thus more indirect.



Regression Approaches

Physical/Semi-Empirical/Empirical

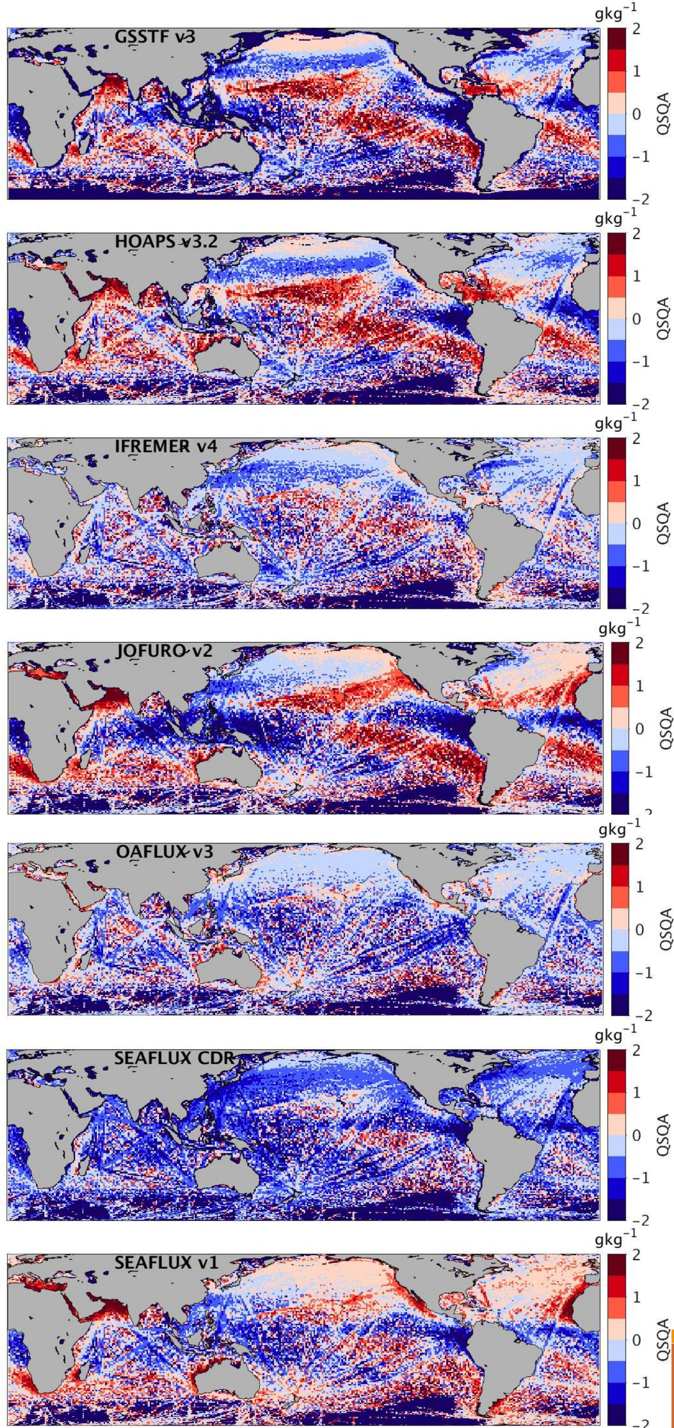
- Remote Sensing Systems (RSS) Geophysical Model
  - Use surface emissivity and atmospheric transmission model to simultaneously retrieve parameters including wind speed, cloud liquid water, precipitation, and sea surface temperature (for certain sensors)
- Bayesian and Constrained linear inversion methods (e.g. GPROF, sounding inversion)
- Obtain a (hopefully large) paired — in space and time — training dataset of observed response variable and independent parameters (e.g. brightness temperatures) and attempt to model the relationship.

$$(SST, U10, Qa, Ta,) = F(TB_{10HV}, TB_{19HV}, TB_{22V}, TB_{37HV}, TB_{85HV})$$

From statistical decision theory, finding a "best" model for predicting a response variable— under squared error loss— results in the optimal solution (Hastie et al. 2009):

$f(x)=E(Y|X=x)$, ***i.e. the conditional expectation***

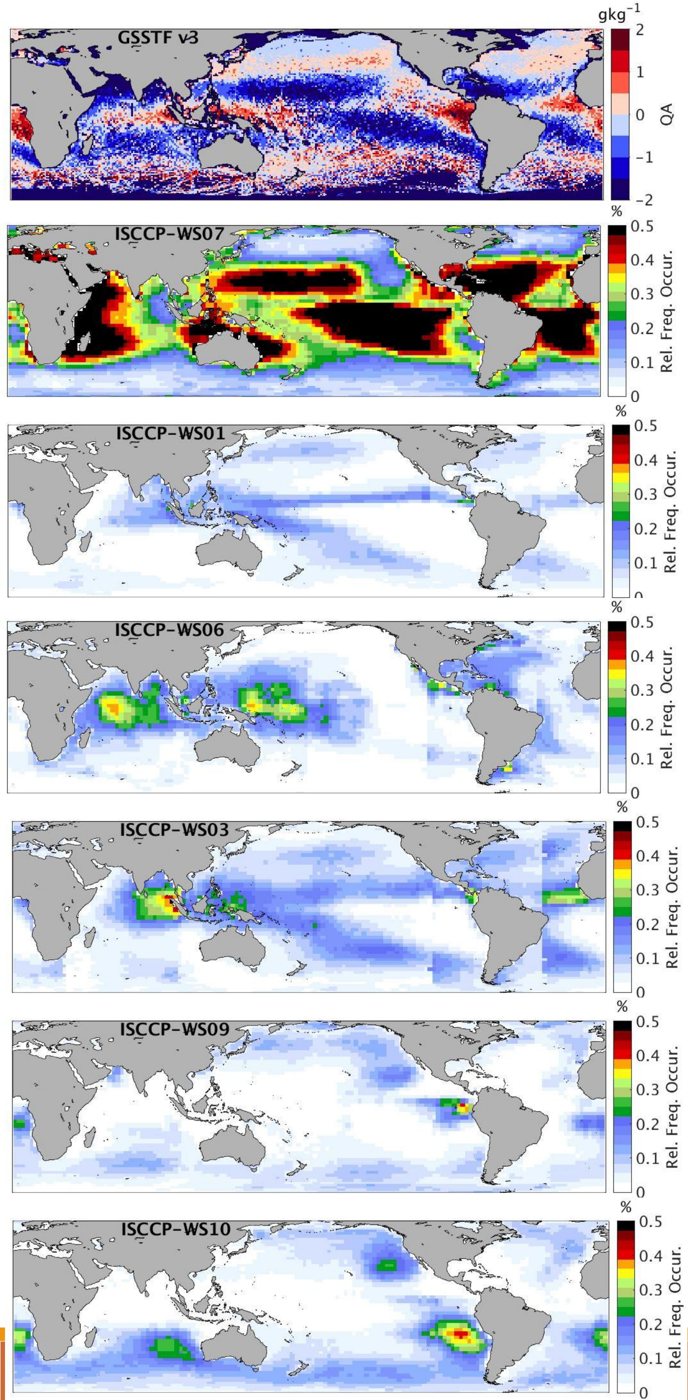
- Direct empirical methods make assumptions on the form form of these conditional relationships and then training parameters of the model using the paired dataset.
- All current satellite-based latent heat flux products use some form of empirical regression for specific humidity and/or wind speed, air temperature, sea surface temperature.



How are we doing?

- The different products show strong regional patterns of biases in relation to surface observations (IVAD)
- QSQA biases are driven primarily by differences in the near-surface humidity retrievals rather than SST
- GSSTF v3, HOAPS v2, and JOFURO v2 all show similar large scale patterns of bias, 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 Cloud Weather States



- The structure in the retrieval (Qa, top) biases appear to be co-aligned with patterns of cloud weather states (WS)
- WS are defined using ISCCP joint cloud top pressure / cloud-optical depth histograms.
- Large biases are seen regions associated with deep convection and thick stratocumulus decks
- Large biases are also seen aligned well with Global WS 7 (Tselioudis et al. 2012)
  - Mostly clear, w/ thin boundary layer cloudy
  - Thus, it is not simply a problem of cloud liquid water contamination

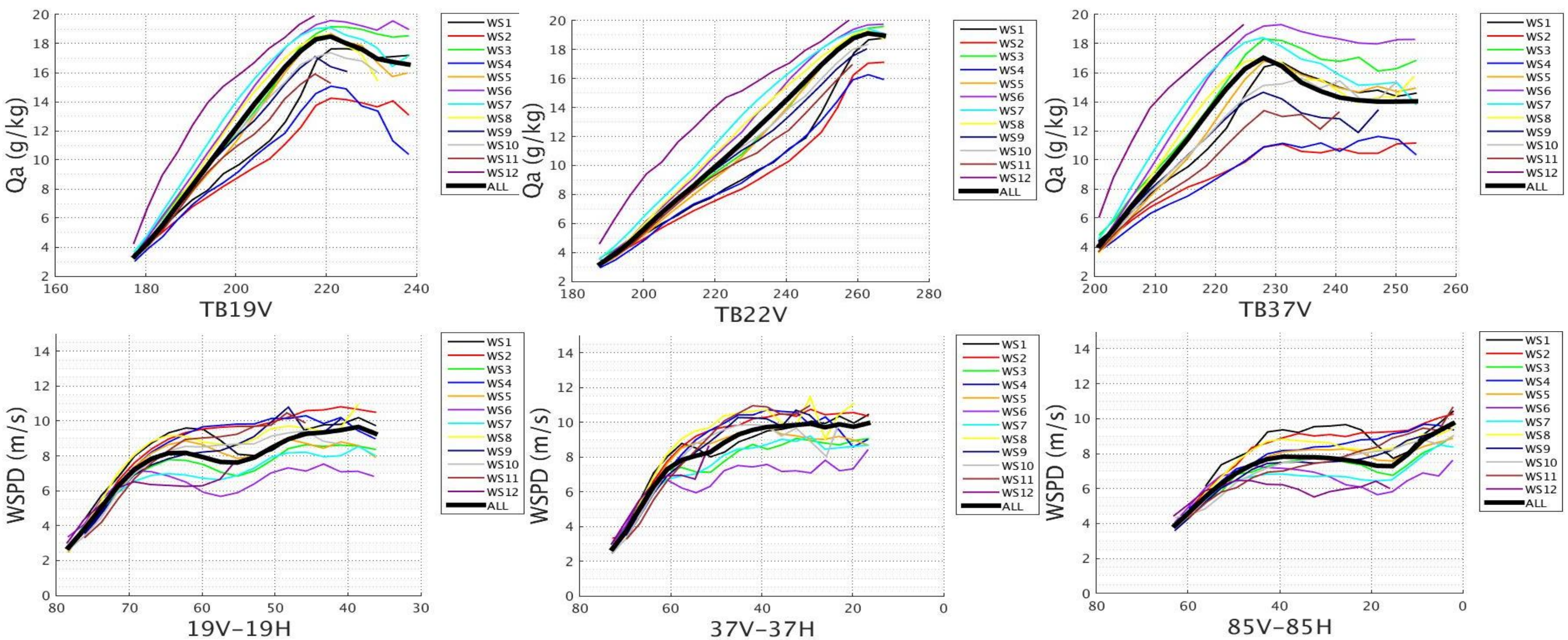
Weather states and passive microwave empirical retrievals

- Near-surface humidity, air temperature, and wind speed retrievals show strong regime dependent conditional biases

- *When the underlying component of the conditional biases are regionally dependent, the application of retrievals based on the "global" training dataset will result in regional biases*

Recall: $f(x) = E(Y|X = x)$, *i.e. the conditional expectation*

Binned Qair and U10 vs. observed F15 TBs



Moving Forward – Option #1 : Brute Force

- Develop empirical retrievals for each of the underlying cloud weather states. Using an external *a priori* weather state dataset, select the appropriate empirical algorithm to use.
- Alternatively, use an *a priori* weather state identifier directly as an input in an empirical algorithm.

Pros

- Explicitly accounts for the underlying conditional dependence that is missed when disregarding this source of variability.

Cons

- What is the source of this independent, *a priori* cloud weather state? There is no guarantee of their availability or consistency (e.g. ISCCP WS only presently extend to 2009 and are produced at a coarse spatial resolution.
- Where are you going to get all of the *in situ* observations to provide robust training dataset for each and every single regime. Recall, many of the individual regime peak relative frequency of occurrence are on the order of 20-30% over a small region!
- How do you ensure consistency of retrieved data *a posteriori* when coming from multiple different algorithms?

Moving Forward – Option #2: Clear-sky empirical retrievals

- First, passive microwave provide direct information on the clouds in the atmospheric FOV; hence we have several geophysical products for cloud liquid water and precipitation.
- Second, from a radiative transfer perspective we expect the "signal" of atmospheric water vapor and temperature to be contained in the "clear-sky" component of the observed brightness temperature.
- We propose to decompose the observed brightness temperature, TB_{obs} , into its clear-sky and cloudy-residual components, estimate TB_{clr} using the passive microwave observations, remove its contribution and retrieve the surface parameters:

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

$$\mathbf{TB_{cld} = F(TB10HV_{obs}, TB19HV_{obs}, TB22V_{obs}, TB37HV_{obs}, TB85HV_{obs})}$$

$$\mathbf{(SST, U10, Qa , Ta,) = F(TB10HV_{clr}, TB19HV_{clr}, TB22V_{clr}, TB37HV_{clr}, TB85HV_{clr})}$$

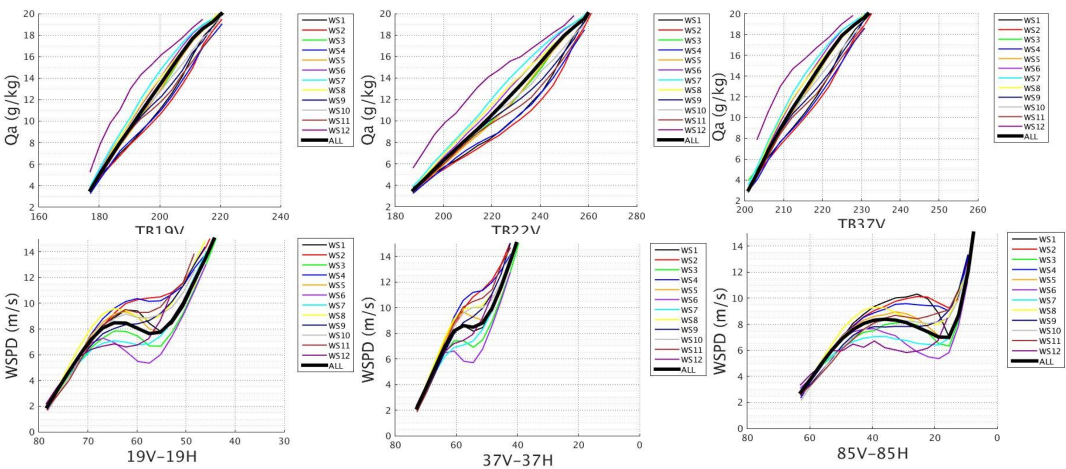
<u>Pros</u>

- Attempt to remove the confounding impact of clouds
- Homogenizes the underlying conditional distribution between surface parameters and input parameters

<u>Cons</u>

- Dependent on the accuracy of the TB_{cld} estimates
- Conditional dependence may still exist: some weather states occur in naturally warmer/more moist environments. Must account for this somehow?

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



Moving Forward – Option #3: Physical Model-based Retrievals

- Studies such as Schulz et al. (1994) have show there is explicit dependence on lower-*layer* quantities (e.g. lowest 500m) in passive microwave channels.
- If we empirically cloud correct the observed brightness temperatures — *and trust that correction* — then we can design, iterative constrained linear or Bayesian inversion retrievals based on the clear sky radiative transfer (e.g. with first-guess parameters).

Pros

- Directly tied to physical principles of remote sensing of atmospheric and surface parameters — not just a statistical relationship
- Can directly account for other uncertainties in the inversion problem including accounting for inter-sensor differences: Earth incidence angles, Noisy sensors, etc.
- Provides a consistent framework for moving between passive microwave imagers and sounders.
- Can take advantage of extensive literature on optimization approaches

Cons

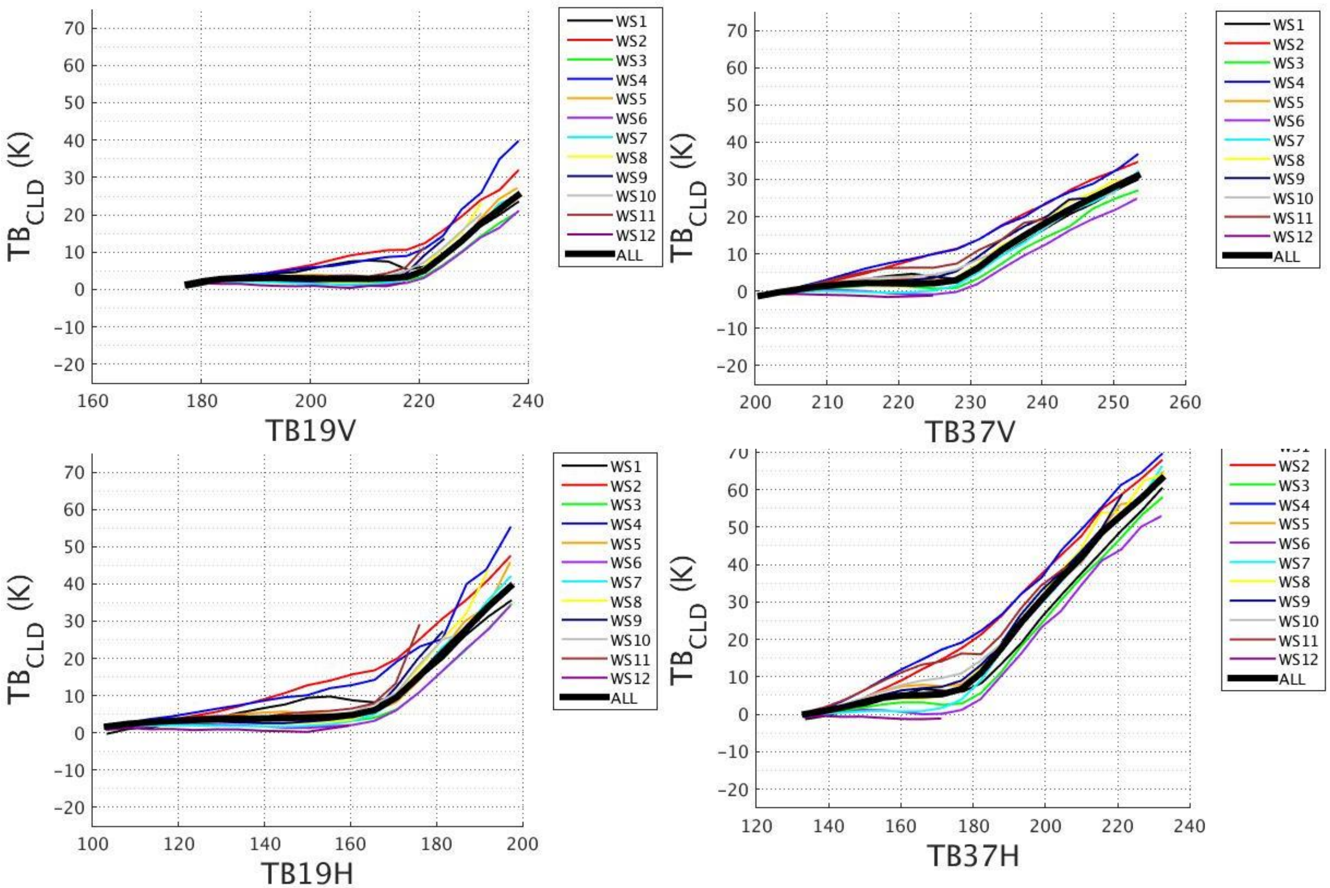
- Dependent on the accuracy of the TB_{cld} estimates (unless of course you design to retrieve TBcld as well).
- Dependent on the physical sensitivity of the observations to the atmospheric layer properties.
    - For example, if only 500m layers are able to be skillfully retrieved, then you still must estimate 10-m values from that 500m layer quantity. However, this relationship may itself be more stable/less conditionally dependent than the direct regressions.

Summary

- Global turbulent latent and sensible heat fluxed can be estimated reliability from passive microwave satellite retrieved near-surface meteorology.
- Each of the primary avenues for estimating the near-surface meteorology can be posed in terms of a “regression approach” in which the conditional expectation is being estimated in a different manner.
- Empirical regression approaches — the current standard used in satellite-based turbulent fluxes — exhibit strong regional biases in comparison to independent observational data. These biases are strongly co-aligned with large-scale weather states.
- We have shown that the biases can directly result from strong underlying deviations of the conditional (on weather state) distributions from the “pooled” distribution.
- We have proposed 3 specific paths forward and discussed pros and cons of each.

It is our conclusion that removing the cloudy-sky component for empirical regressions or performing a more complete physical-model based retrieval should be pursued.

Extras



TB19V
TB37V
TB19H
TB37H
TBCLD (K)
WS1
WS2
WS3
WS4
WS5
WS6
WS7
WS8
WS9
WS10
WS11
WS12
ALL

ISCCP Weather States