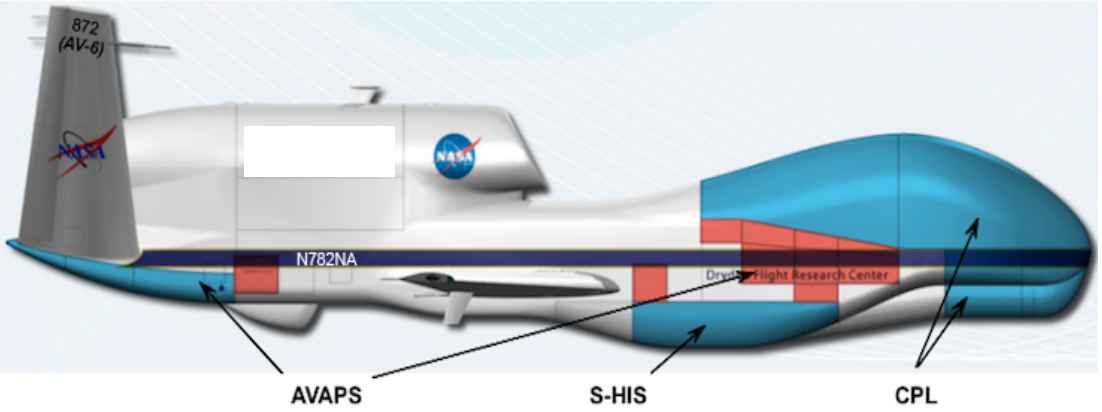
Validation of the CLARREO Linear Retrieval Algorithm Using Airborne Field Campaign Satellite, Aircraft, Radiosonde, and Dropsonde Measurements

W. Smith Sr., N. Smith, M. Yesalusky, E. Weisz, H. Revercomb, A. Larar. J. Taylor, X. Liu, D. Zhou



May 2013 Suomi-NPP Aircraft Campaign

SHIS, NAST-I, NAST-M, MASTER/AVIRIS on ER-2

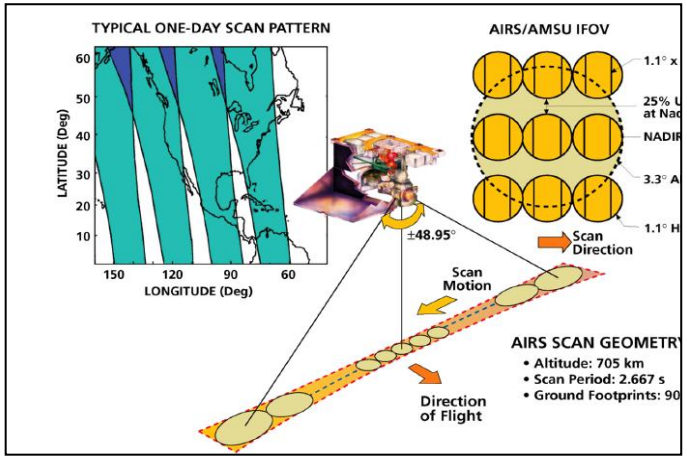
September-October, 2014 Hurricane and Severe Storm Sentinel (HS3)

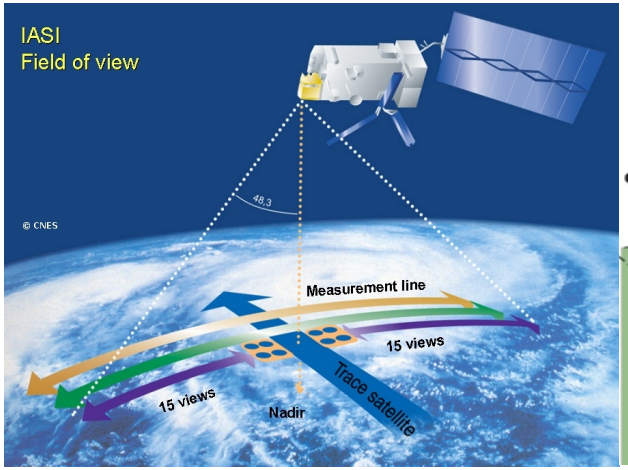
Dropsondes, SHIS, and Lidar on Global Hawk

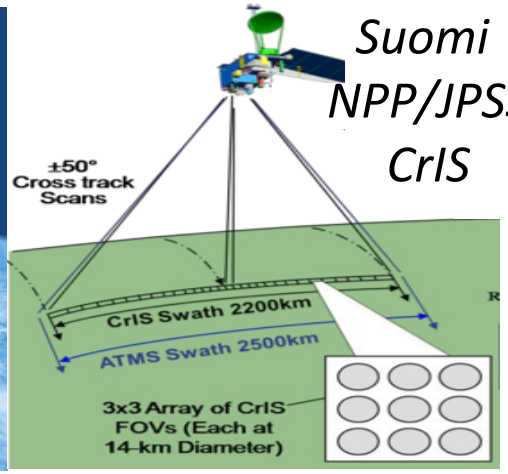
CLARREO SDT Meeting

National Institute of Aerospace, October 28-30, 2014

Comparison of Climate Variables from Hyperspectral Satellite Instruments







Instrument	Spatial resolution	spectral res. (cm^{-1})	spectral rng. (cm^{-1})	spatial sampling
AIRS (2002 -)	3x3 13.5-km (50 km)	~1200 resolving power	645-2700	Contiguous Cross-track scan
IASI-A (2006 -) **IASI-B (2012 -)**	2x2 12.0-km (50 km)	0.25	645-2760	Contiguous Cross-track Scan
CrIS (2011 -)	3 x 3 13-km (50 km)	0.6	645-2700	Contiguous Cross-track

The Dual Regression Retrieval Algorithm

Global Clear Soundings

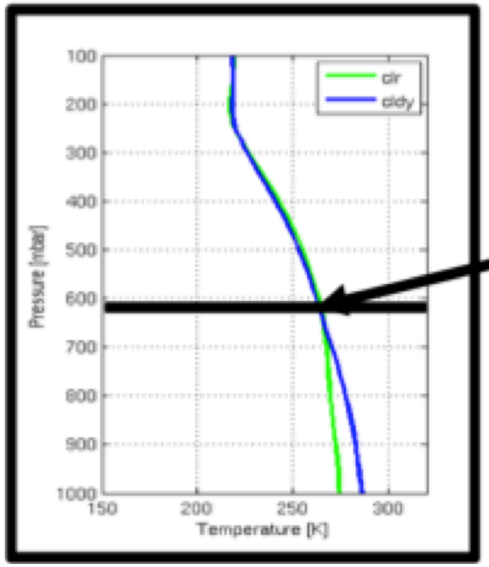
Radiances
(calculated with clear FM)

Clear trained EOF regression results

Global Cloudy Soundings

Radiances
(calculated with cloudy FM)
8 cloud height classes (100-900 hPa)

Cloud trained EOF regression results



Cloud Top Altitude

level where T(cloudy)>T(clear) for $p>p_{cld}$

Final Profile

- *clear-trained above,*
- *cloud-trained below cloud level*

* Smith, W. L., E. Weisz, S. Kirev, D. K. Zhou, Z. Li, and E. E. Borbas (2012), Dual-Regression Retrieval Algorithm for Real-Time Processing of Satellite Ultraspectral Radiances. *J. Appl. Meteor. Clim., 51*, Issue 8, 1455-1476.

CLARREO - State Parameter Climate Retrieval Monitoring Climate Change from Polar Soundings

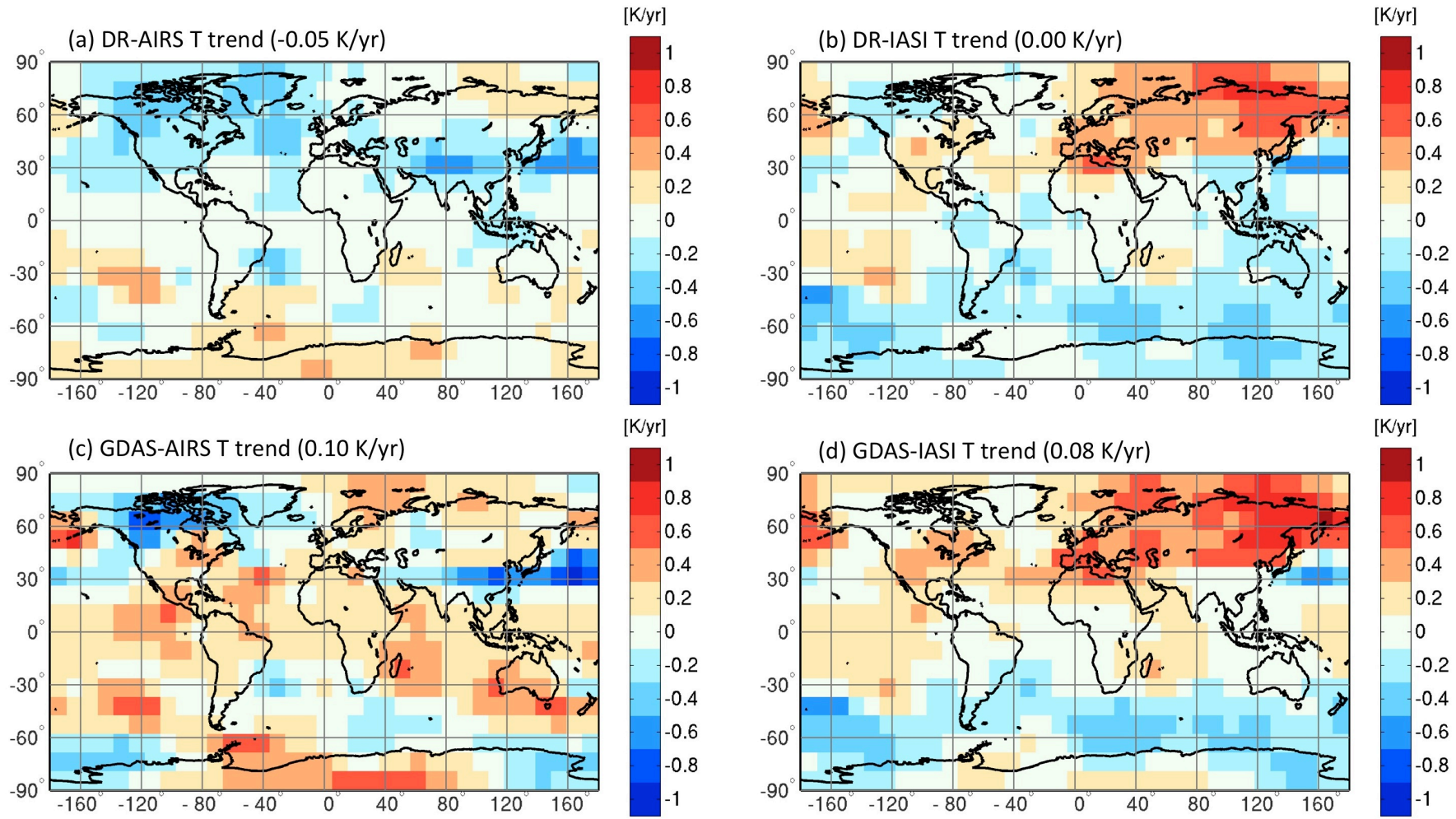
Desirable Features of a Climate Variable Retrieval Algorithm*:

- ***Linear dependence on radiance spectra***
  - Variation depends only on radiance (i.e., no other input variables)
- ***All sky***
  - clear and cloudy (0 - 100%)
- ***Independent of Field-of-View (FOV) size***
  - Can be applied to different instruments
- ***Retrieval Variables***
  - *Surface :* temperature & spectral emissivity
  - *Atmosphere :* T, H_2O, and O_3 profiles & CO_2 ppm
  - *Cloud :* height and optical thickness

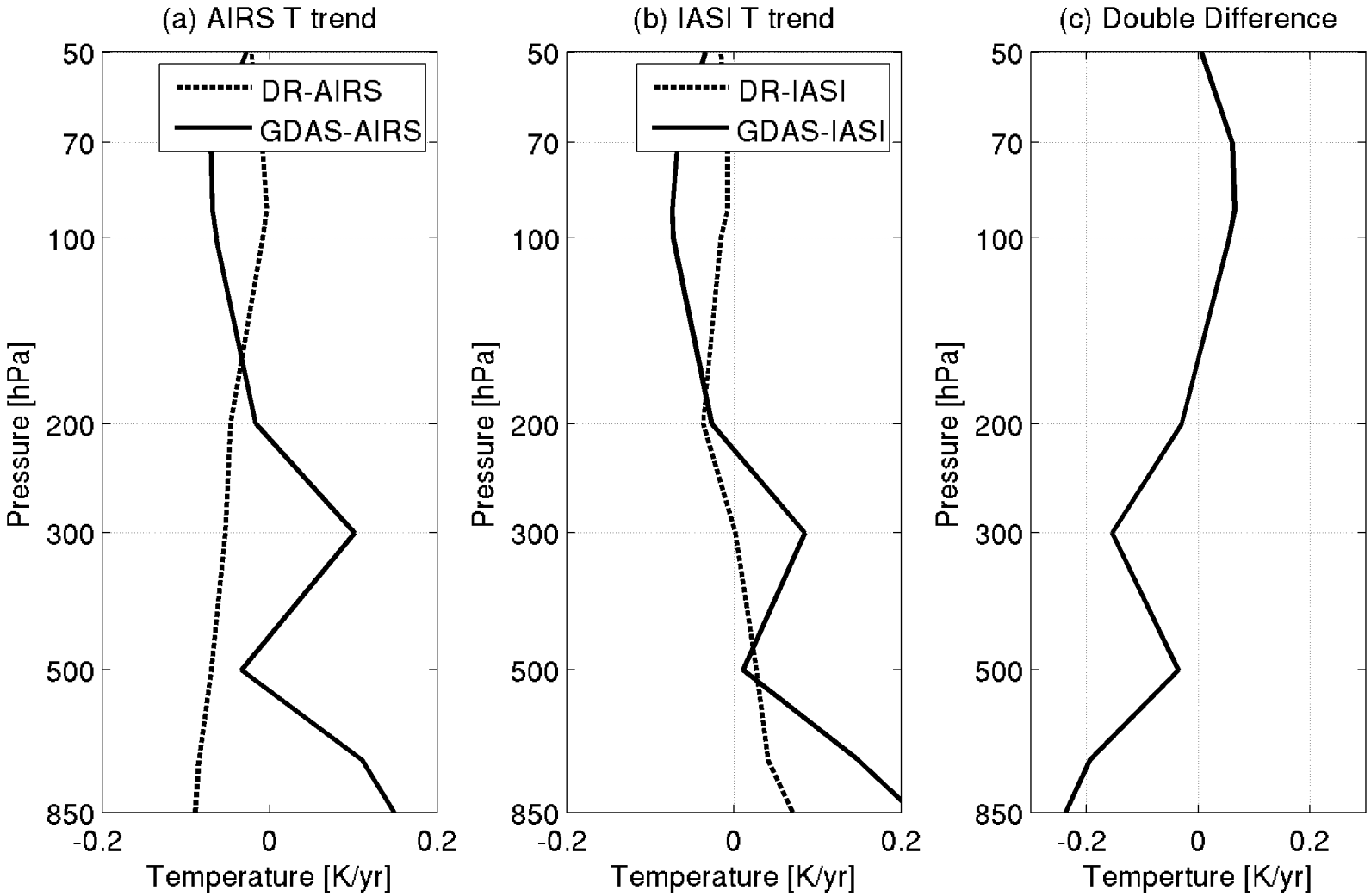
*Smith, W. L., E. Weisz, S. Kirev, D. K. Zhou, Z. Li, and E. E. Borbas (2012), Dual-Regression Retrieval Algorithm for Real-Time Processing of Satellite Ultraspectral Radiances. *J. Appl. Meteor. Clim., 51*, Issue 8, 1455-1476.

Dual Regression CLARREO Studies

2008 -2012 AIRS Vs IASI 300 hPa Trends

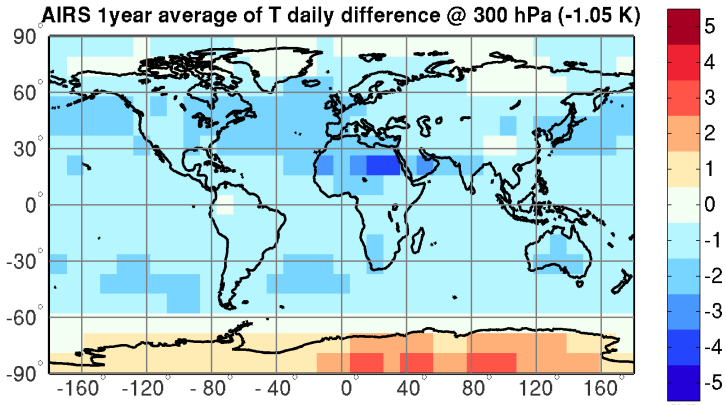


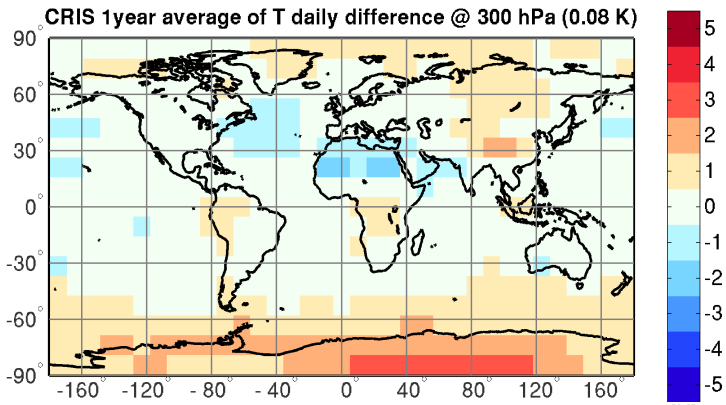
5-year (2008-2012) Annual Trend Profiles

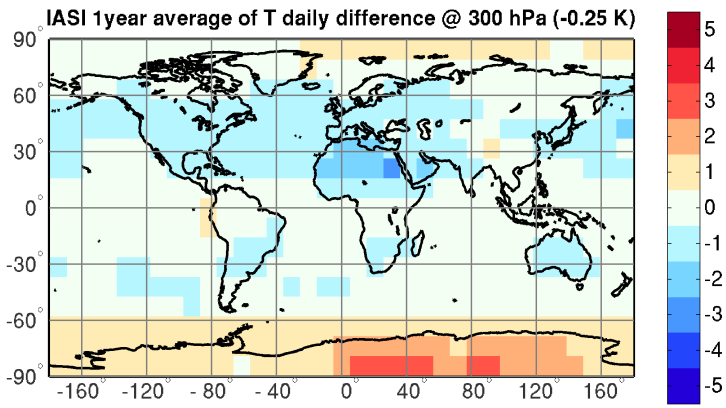


AIRS, CrIS and IASI – GDAS Annual Means (2012)

300 hPa





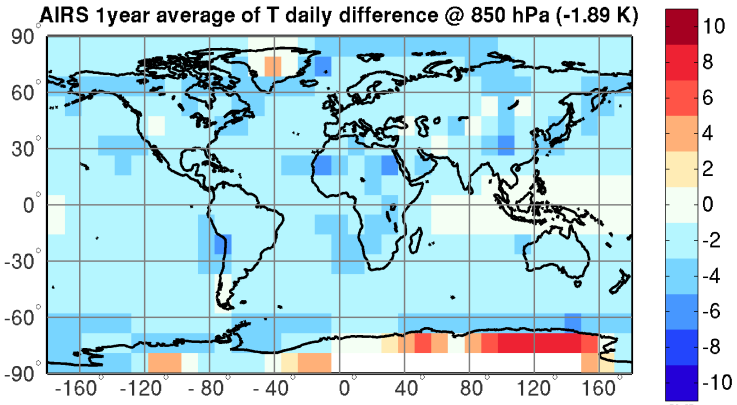


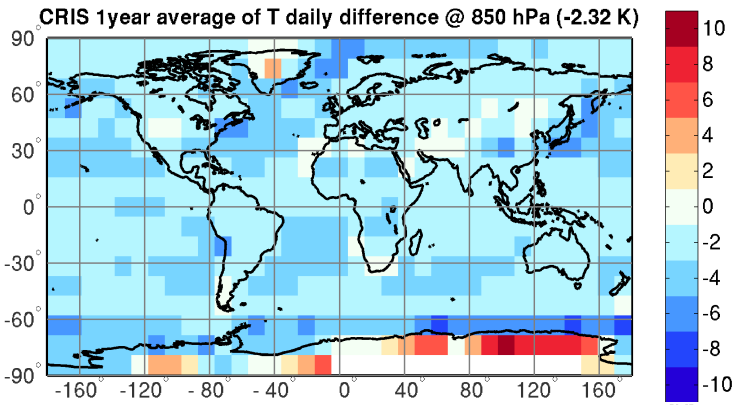
13:30
AIRS

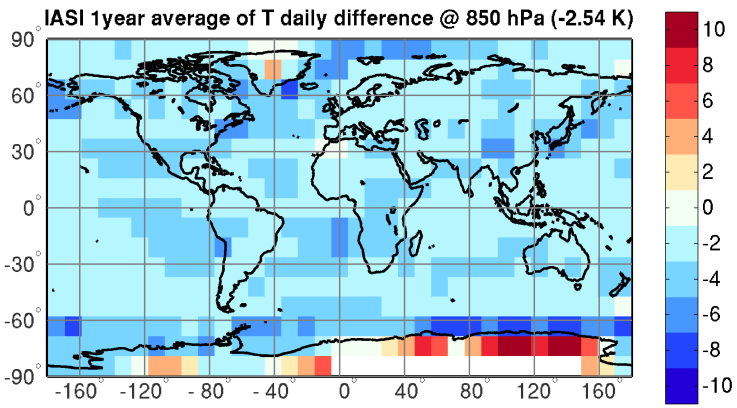
13:30
CrIS

09:30
IASI

850 hPa





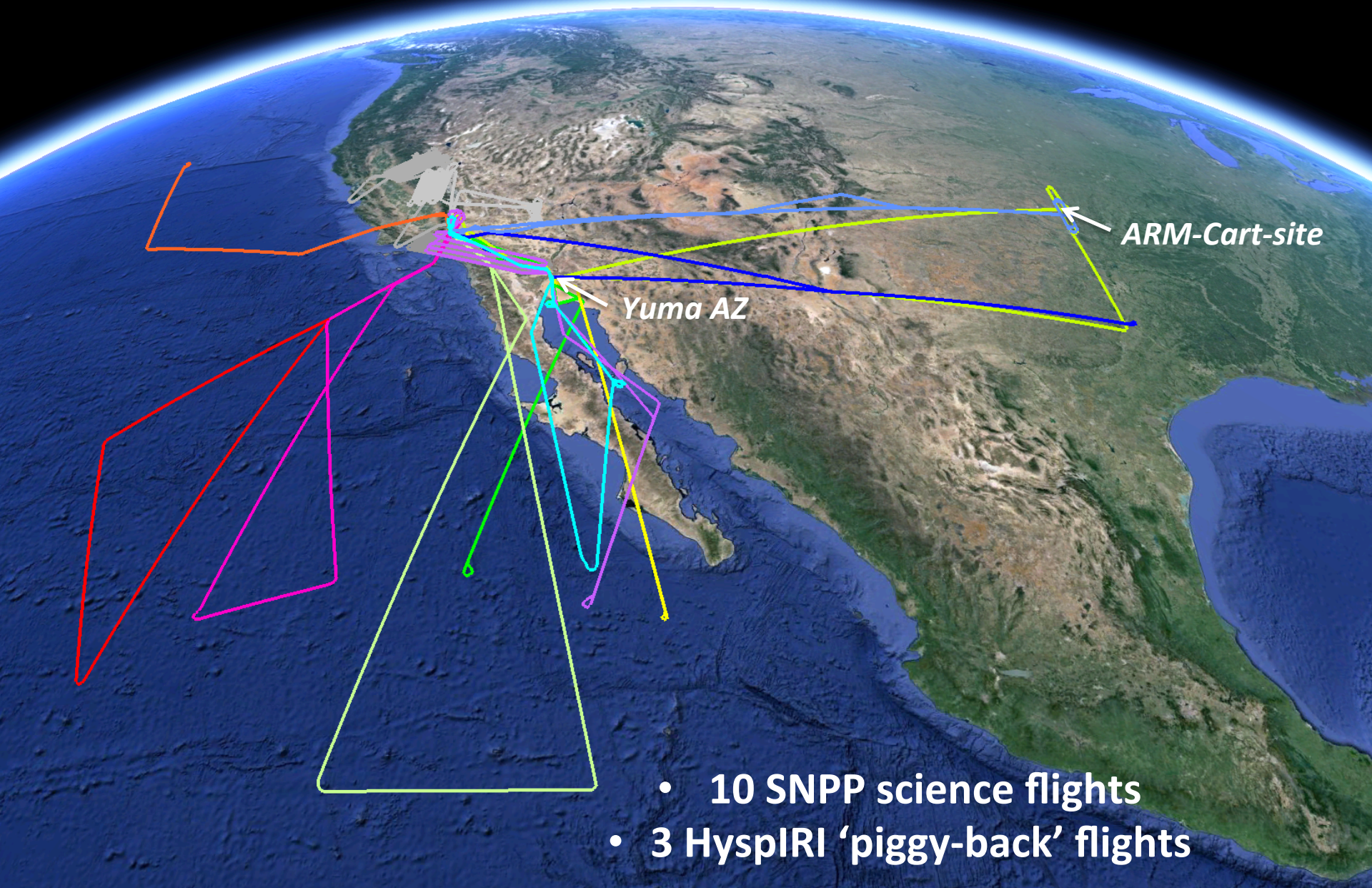


Sources of Retrieval Error

- **Statistical Bias due to Vertical Null Space Error**
- **Planetary Boundary Layer (PBL) Errors over Land Surfaces due to Complex Terrain Conditions**
- **Undetected Cloud Attenuation (i.e., optically thin Cirrus)**

Improvements in DR Algorithm Being Made on the Basis of Airborne Validation Campaign Ground "Truth" Data

Suomi-NPP Cal/Val Flight Tracks



- 10 SNPP science flights
- 3 HyspIRI 'piggy-back' flights

SNPP Cal/Val Validation Sites

Yuma Arizona

32.6 N, 114.5 W

Lamont Ok

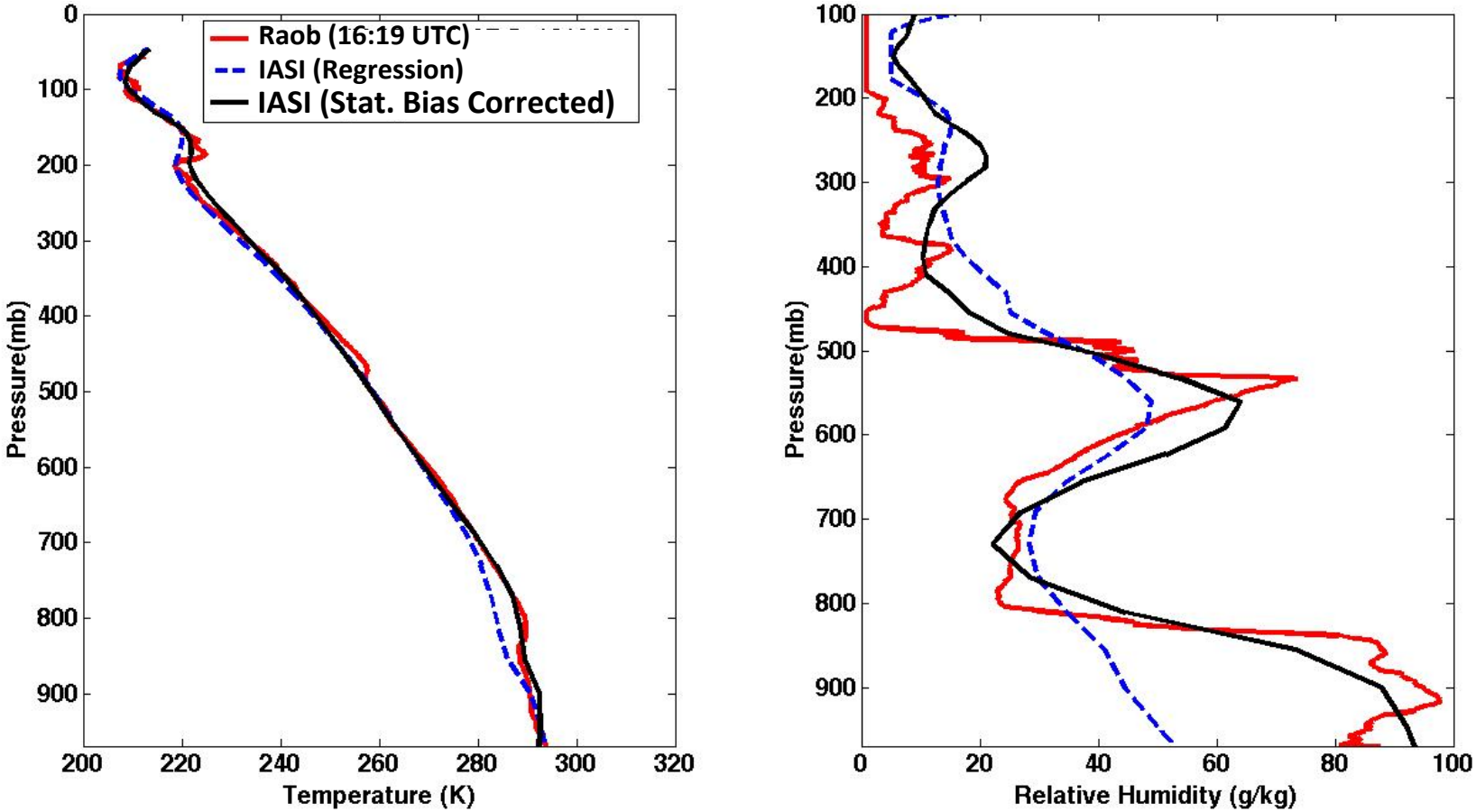
36.6 N, 97.5 W

Physical Correction Using Forecast Model Profile

Problem: DR method uses a statistical training data set. Imperfect skill, due to lack of vertical resolution in radiances, leads to local statistical bias.

Solution: Calculate radiances from forecast profile (FP) and perform DR retrieval using simulated "Truth" radiances. Retrieval Error = Statistical Bias.

Statistical Bias = FP – FP radiance Retrieval



Surface Correction

- **For this study PCRTM simulated radiances are used to derive the regression coefficients from a climatological data set assuming a "black (i.e., ε =1)" surface with the skin temperature equal to the air temperature**

Thus, the observed radiances must be "corrected" for the real non-black skin/air temperature contrast surface condition. This is performed using an iterative scheme where the surface correction is performed using:

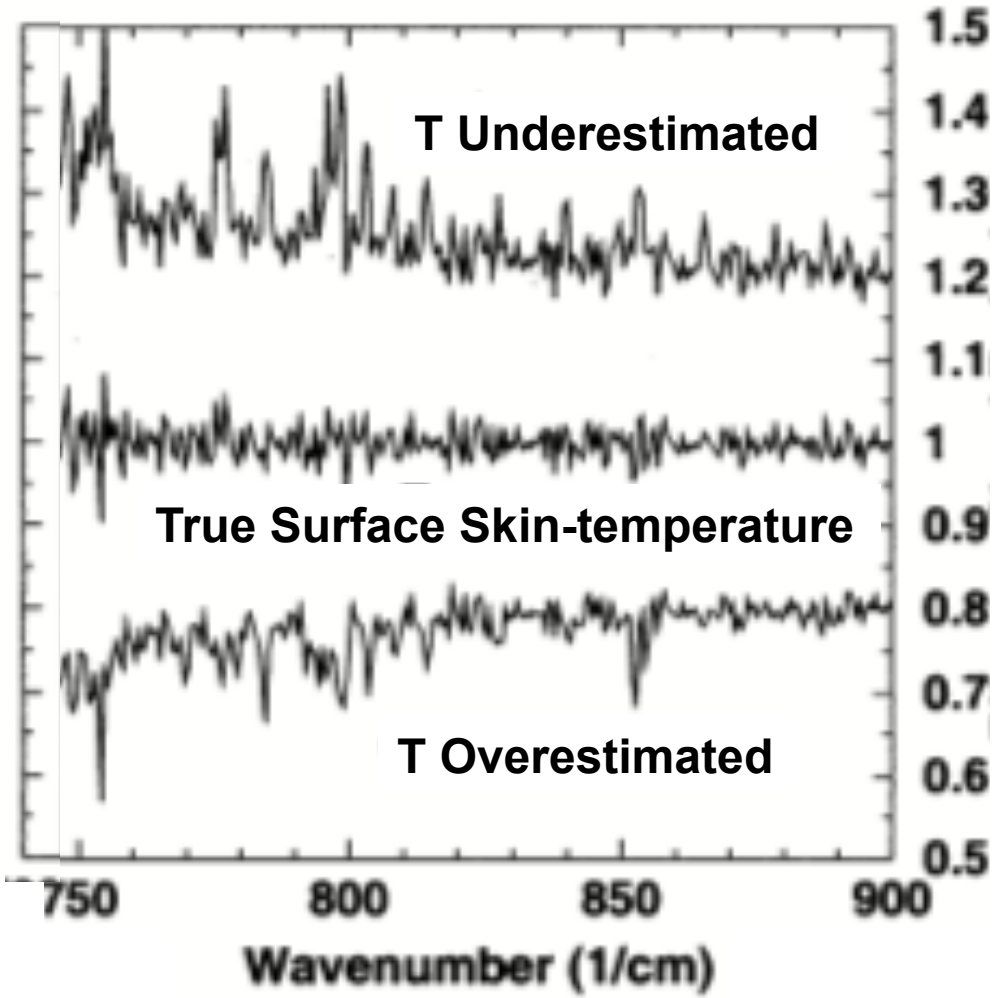
$$R_m(\varepsilon=1;T_s=T_a) = R_m(\varepsilon, T_s, T_a) - [R_c(\varepsilon, T_s, T_a) - R_c(\varepsilon=1, T_s=T_a)]$$

where the calculated radiances are defined from an iterated guess atmospheric and surface state. The surface emissivity and skin temperature are determined using the "minimum emissivity variance" technique described below. The initial guess for this process comes the operational GFS model forecast

Emissivity Minimum Variance Technique

$$R = \varepsilon B(T_s)\tau_s + (1-\varepsilon)R_{sky}\tau_s + R_{atm}$$

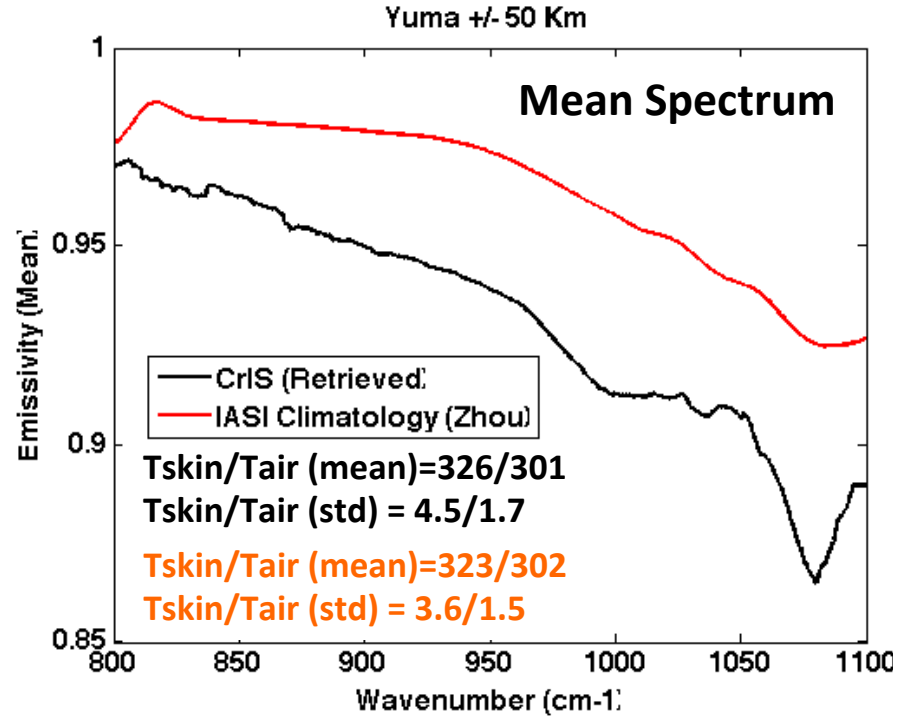
$$\varepsilon(\sigma, T_s) = [R_m - R_{atm} - R_{sky}\tau_s] / [B(T_s) - R_{sky}]\,\tau_s$$

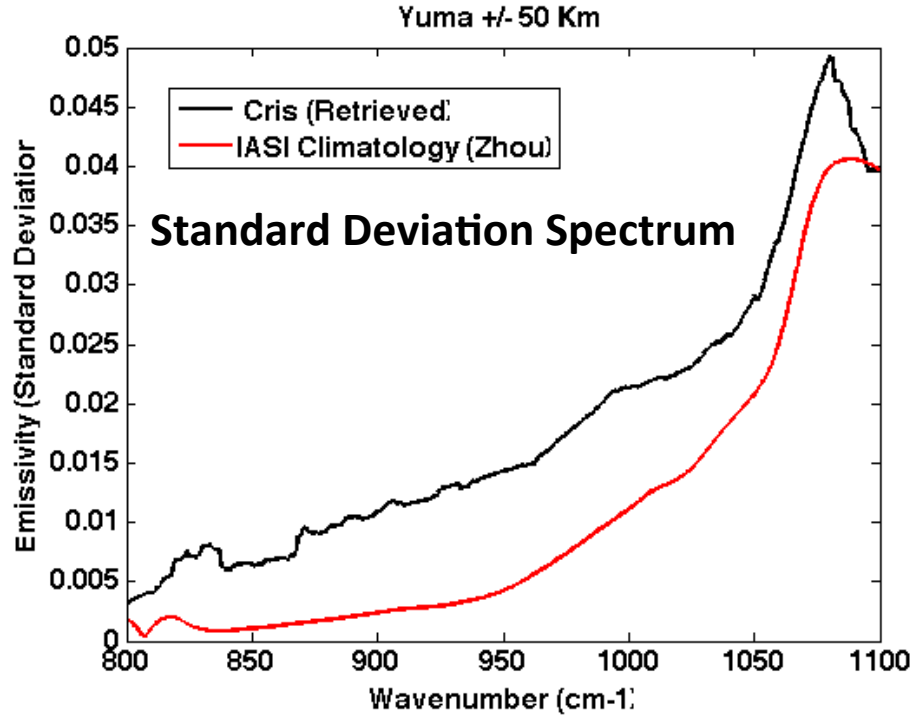


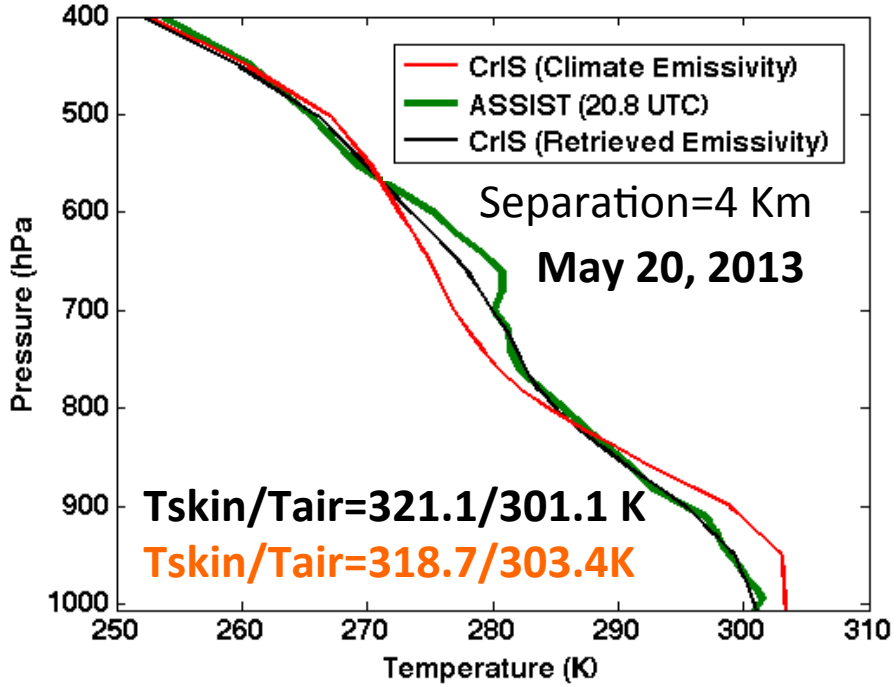
In computing the emissivity, the surface skin temperature must be assumed. If the assumed skin temperature is incorrect, the atmospheric emission spectral lines will be visible in the computed emissivity causing the local variance to be too high.

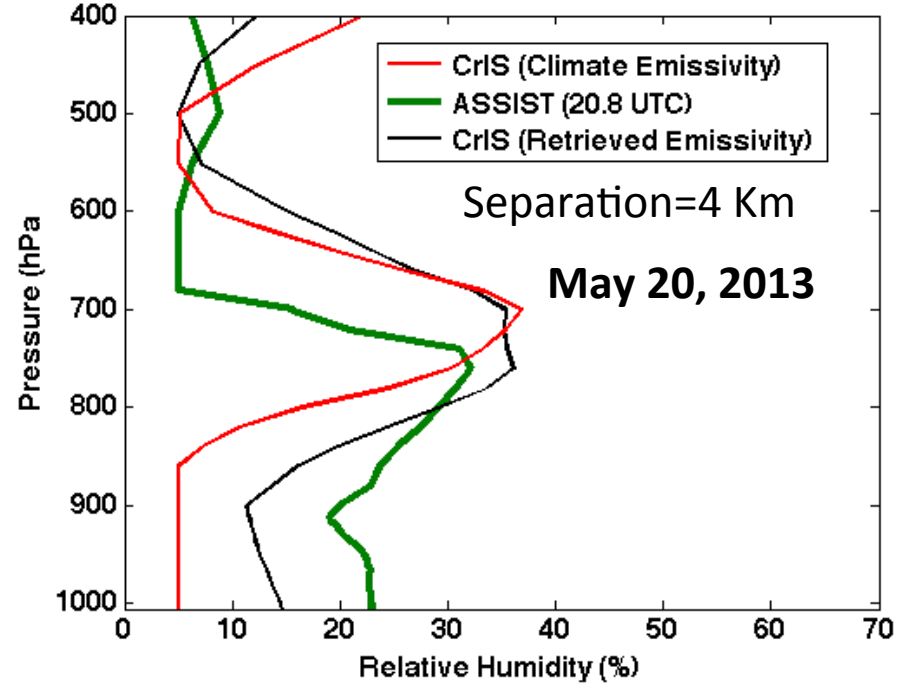
Therefore, the correct surface skin temperature is that for which

$$\int \left|\frac{\partial e(T)}{\partial \sigma}\right| d\sigma = \text{Min}$$

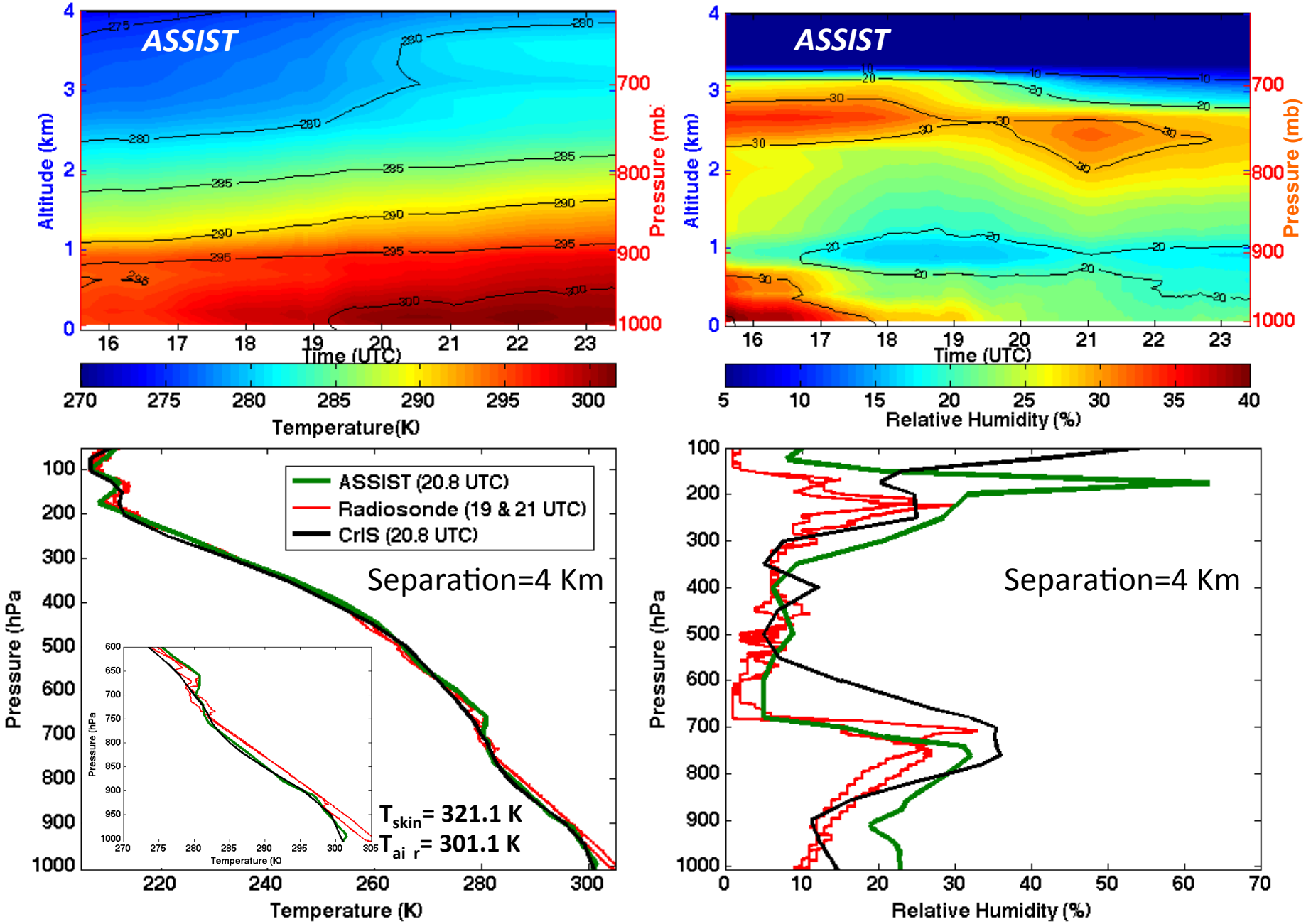

Yuma +/- 50 Km
Mean Spectrum
CrIS (Retrieved)
IASI Climatology (Zhou)
Tskin/Tair (mean)=326/301
Tskin/Tair (std) = 4.5/1.7
Tskin/Tair (mean)=323/302
Tskin/Tair (std) = 3.6/1.5
Emissivity (Mean)
Wavenumber (cm-1)


Yuma +/- 50 Km
Cris (Retrieved)
IASI Climatology (Zhou)
Standard Deviation Spectrum
Emissivity (Standard Deviation)
Wavenumber (cm-1)

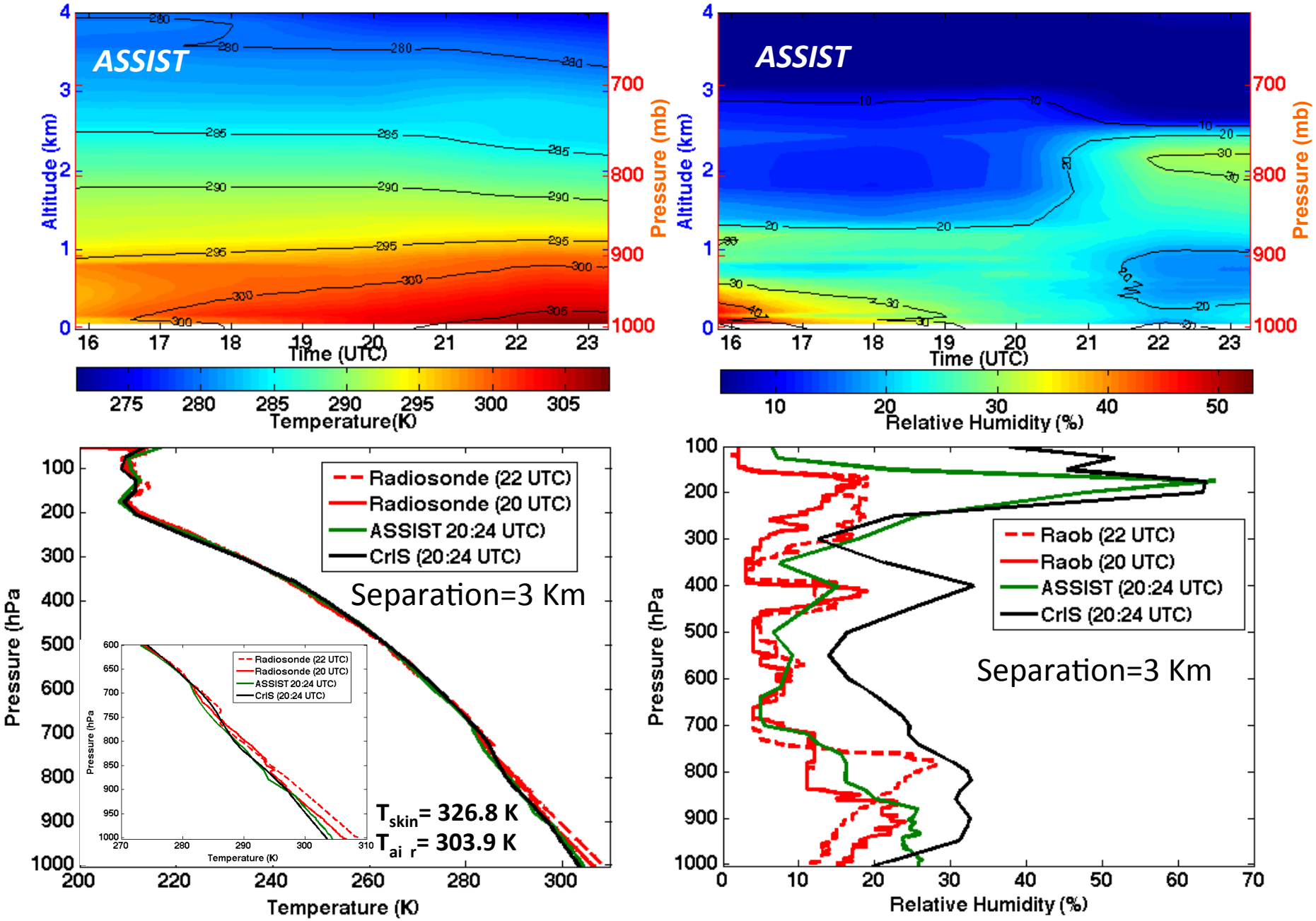

CrIS (Climate Emissivity)
ASSIST (20.8 UTC)
CrIS (Retrieved Emissivity)
Separation=4 Km
May 20, 2013
Tskin/Tair=321.1/301.1 K
Tskin/Tair=318.7/303.4K
Pressure (hPa)
Temperature (K)


CrIS (Climate Emissivity)
ASSIST (20.8 UTC)
CrIS (Retrieved Emissivity)
Separation=4 Km
May 20, 2013
Pressure (hPa)
Relative Humidity (%)

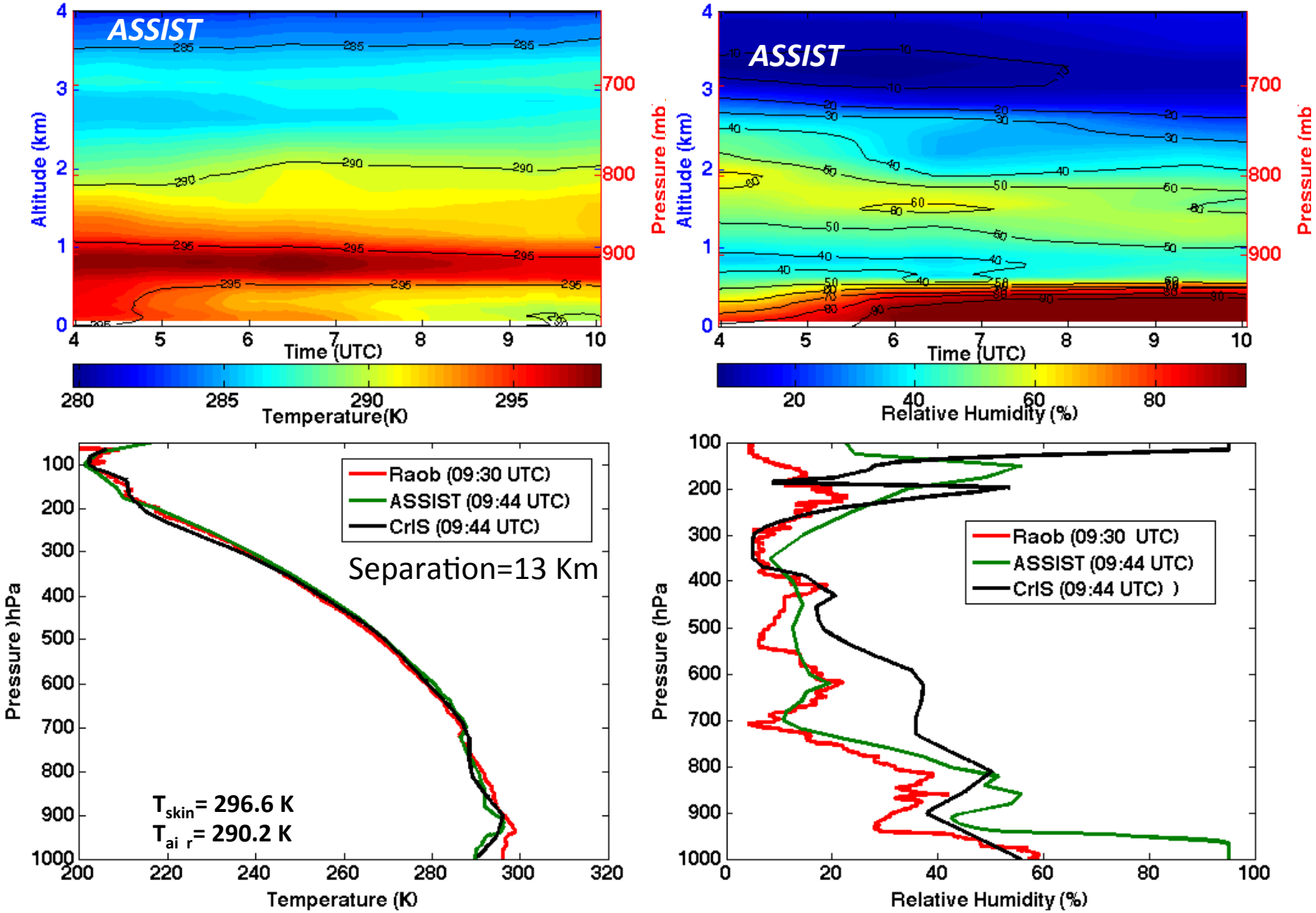
Yuma AZ Example (May 20, 2013)



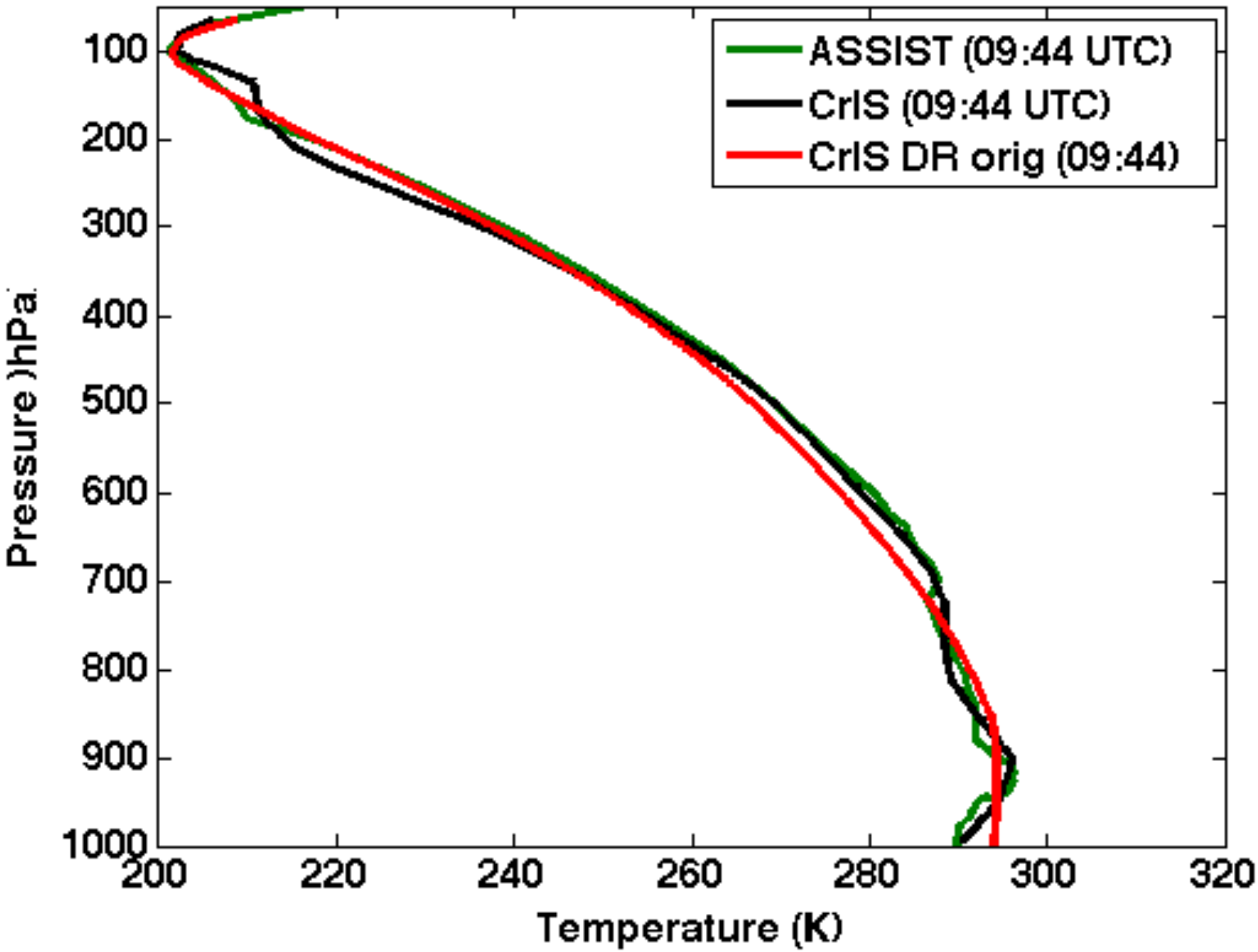
Yuma AZ Example (May 16, 2013)

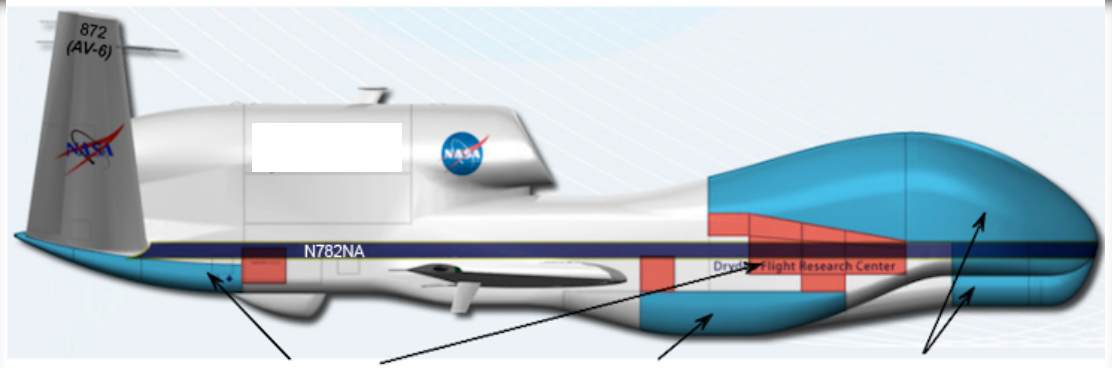


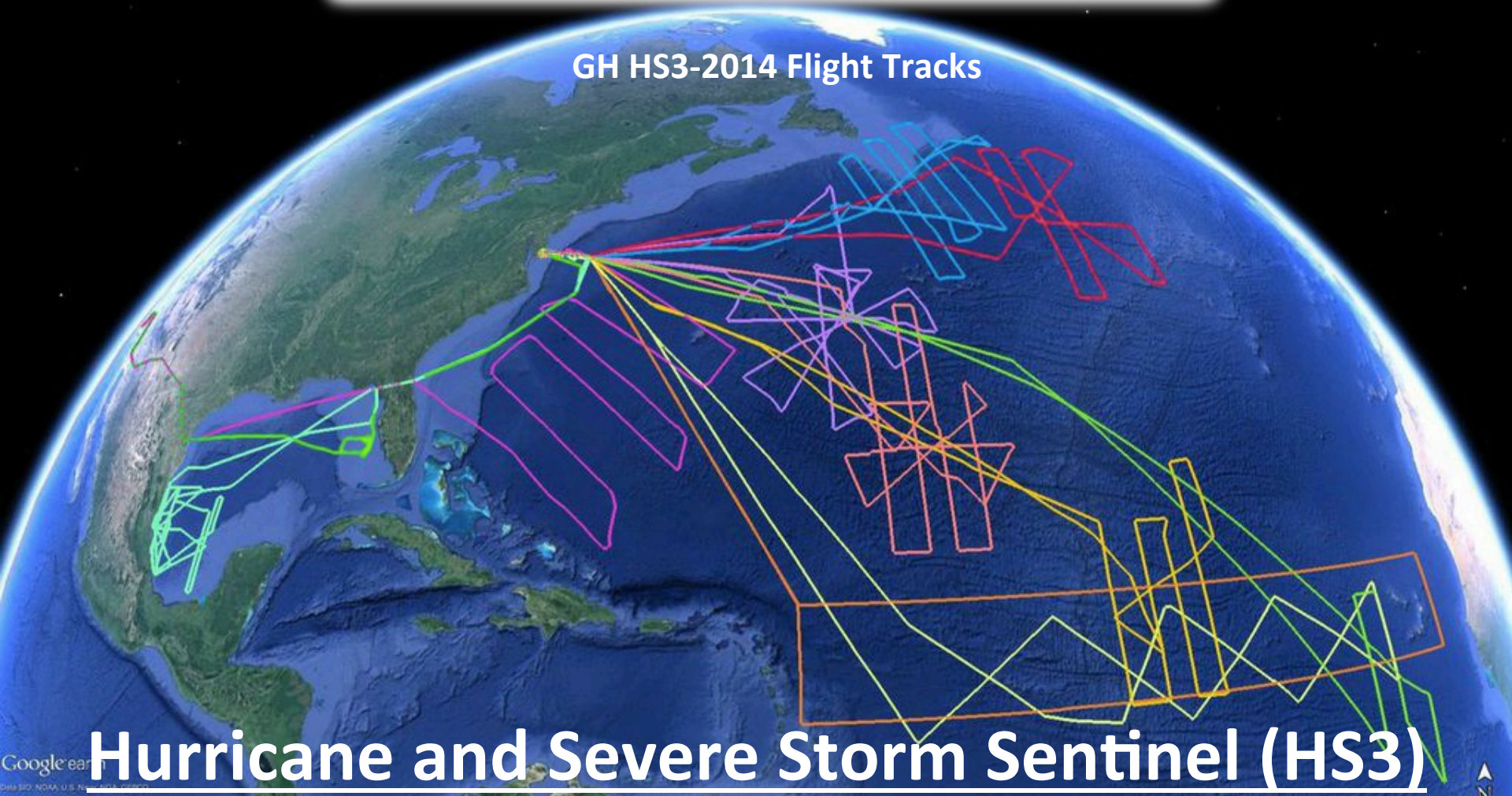
Yuma AZ Night Example (May 30, 2013)



Yuma AZ New DR Vs Original DR (May 30, 2013)

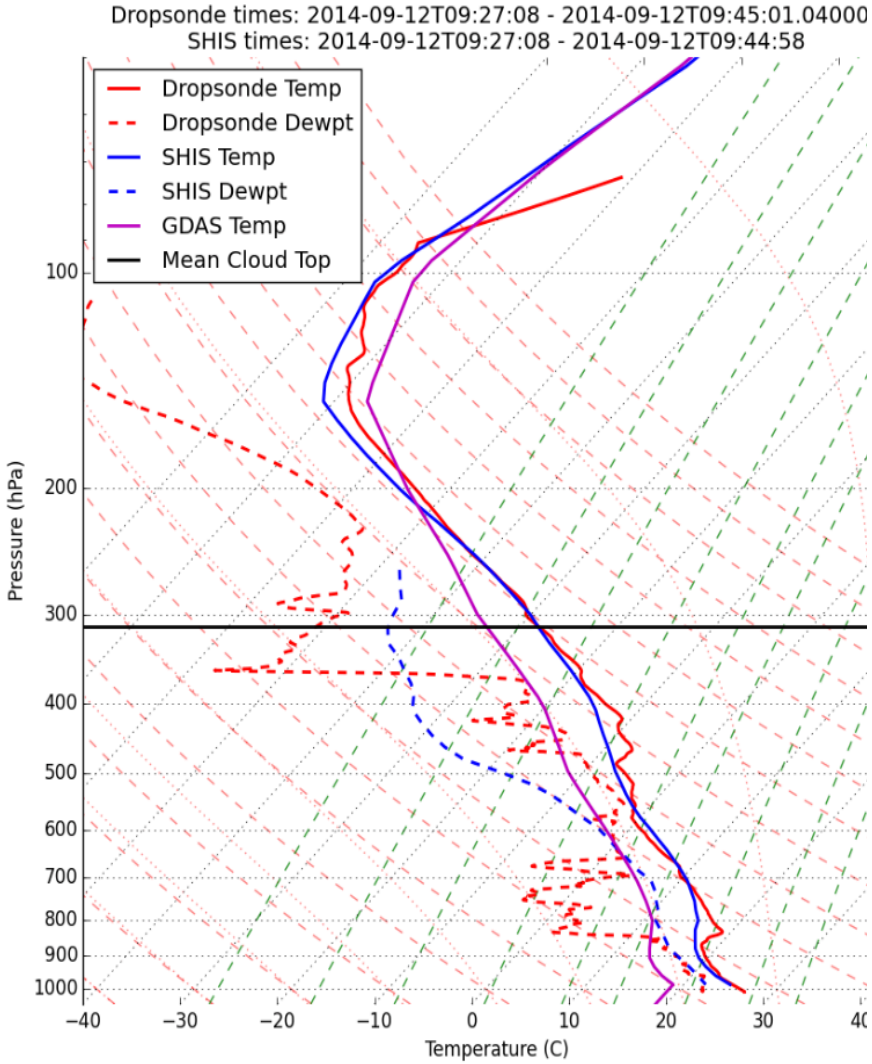


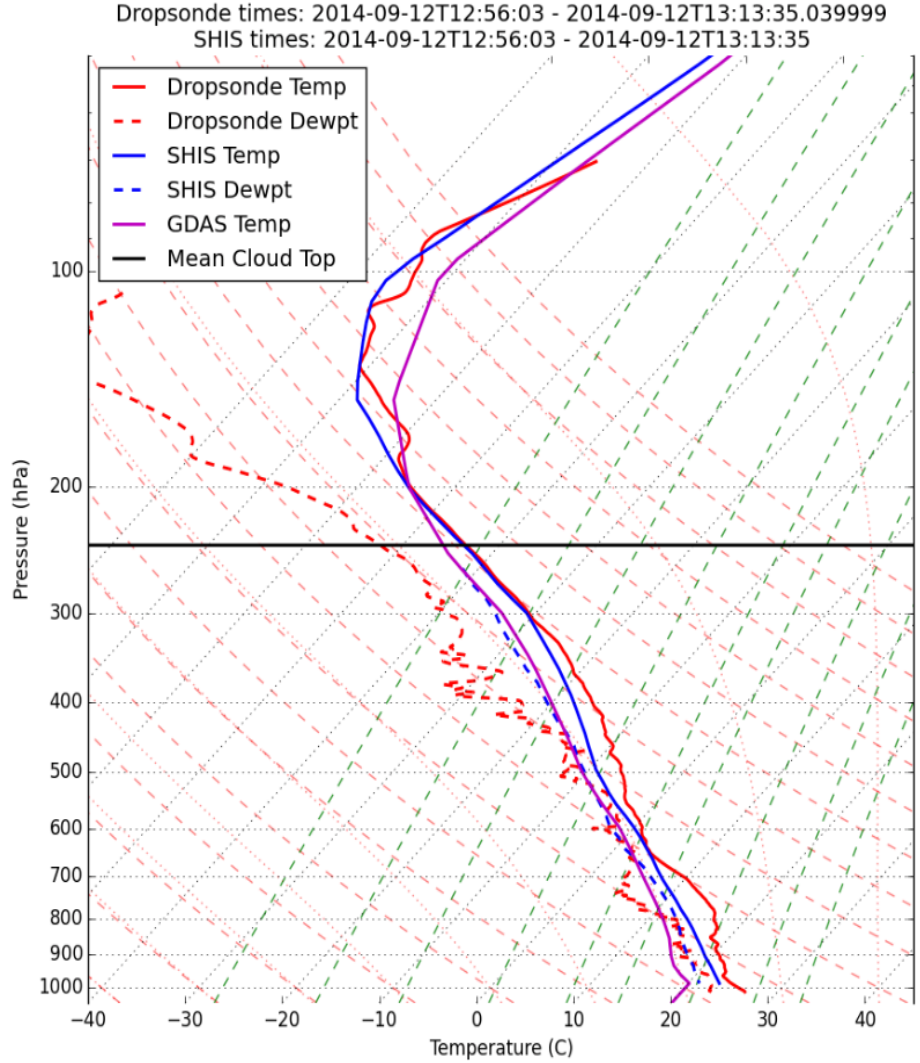




Hurricane and Severe Storm Sentinel (HS3)

Typical Real-time Comparisons of SHIS Vs Dropsonde





(1) SHIS much better than the GDAS Profiles used for the Bias Correction
(2) Often a cold bias exists believed to be due to undetected cirrus cloud attenuation

Cloud Attenuation Detection and QC

Undetected clouds attenuation (e.g., thin cirrus) always produces a cold bias in the single FOV Dual Regression Retrieval

$$mT_w(p) = \text{mean}\,[T_w(p) >= mT(p)];$$

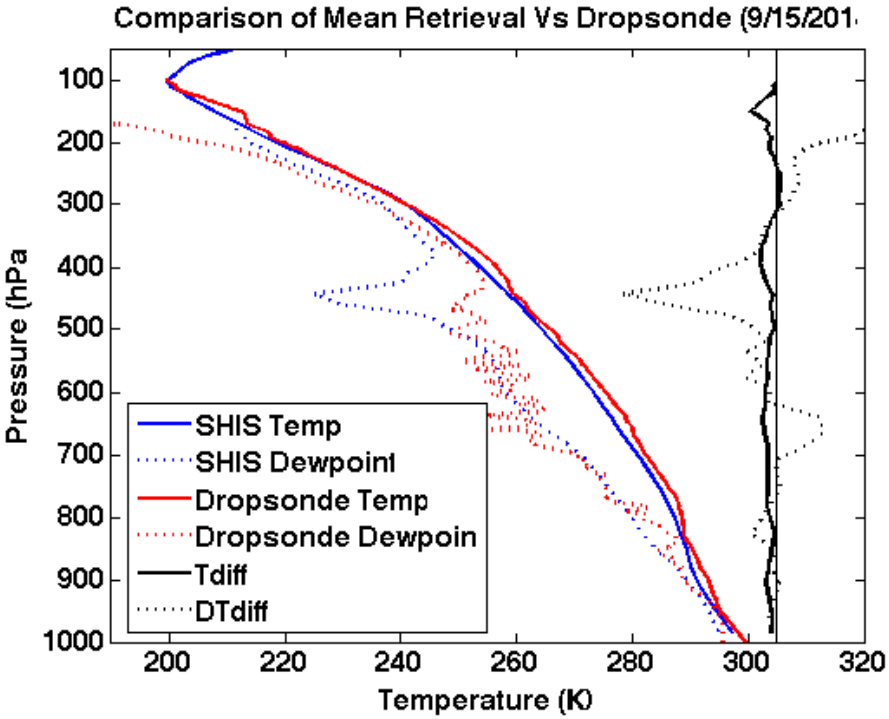
$$f(p) = [(mT_w(p) - mT(p)] / [mT_w(strat) - mT(strat)] - 1$$

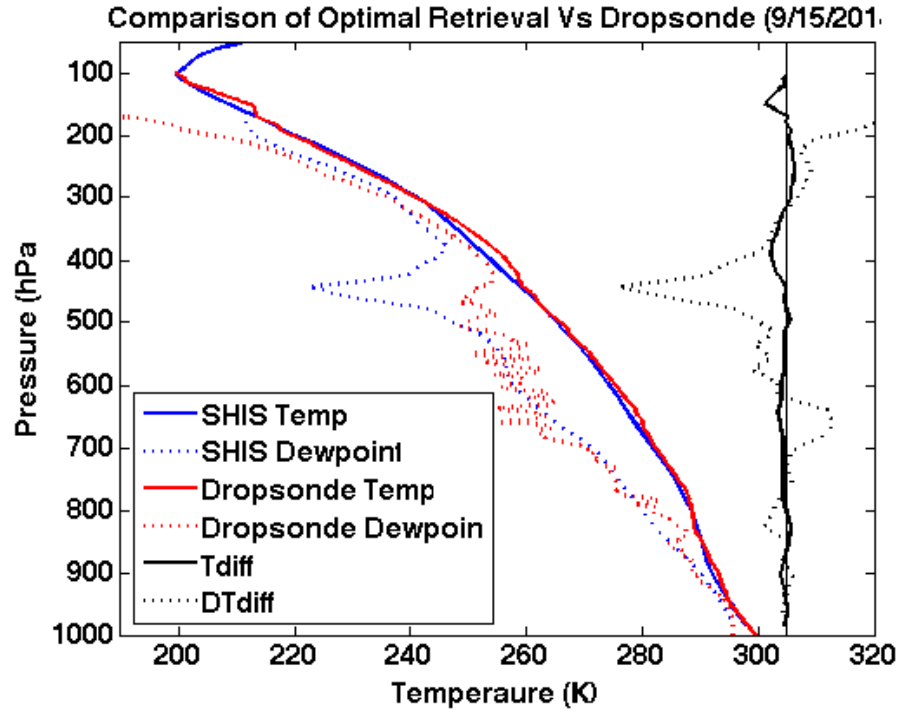
Where: strat = above cloud 30 – 150 hPa layer

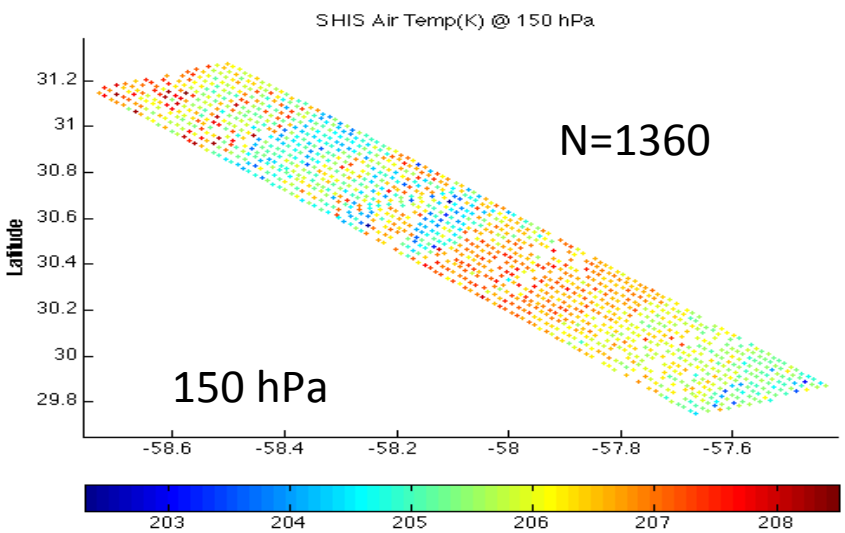
$$0 \le f(p) \le 1$$

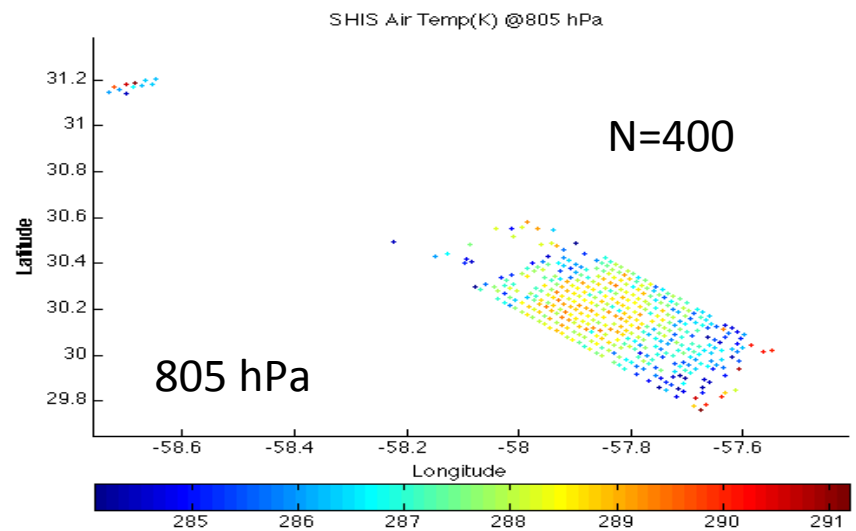
$$T(p) = f(p) * mT_w(p) + [1 - f(p)] * mT(p)$$

Example (September 15, 064859 UTC)

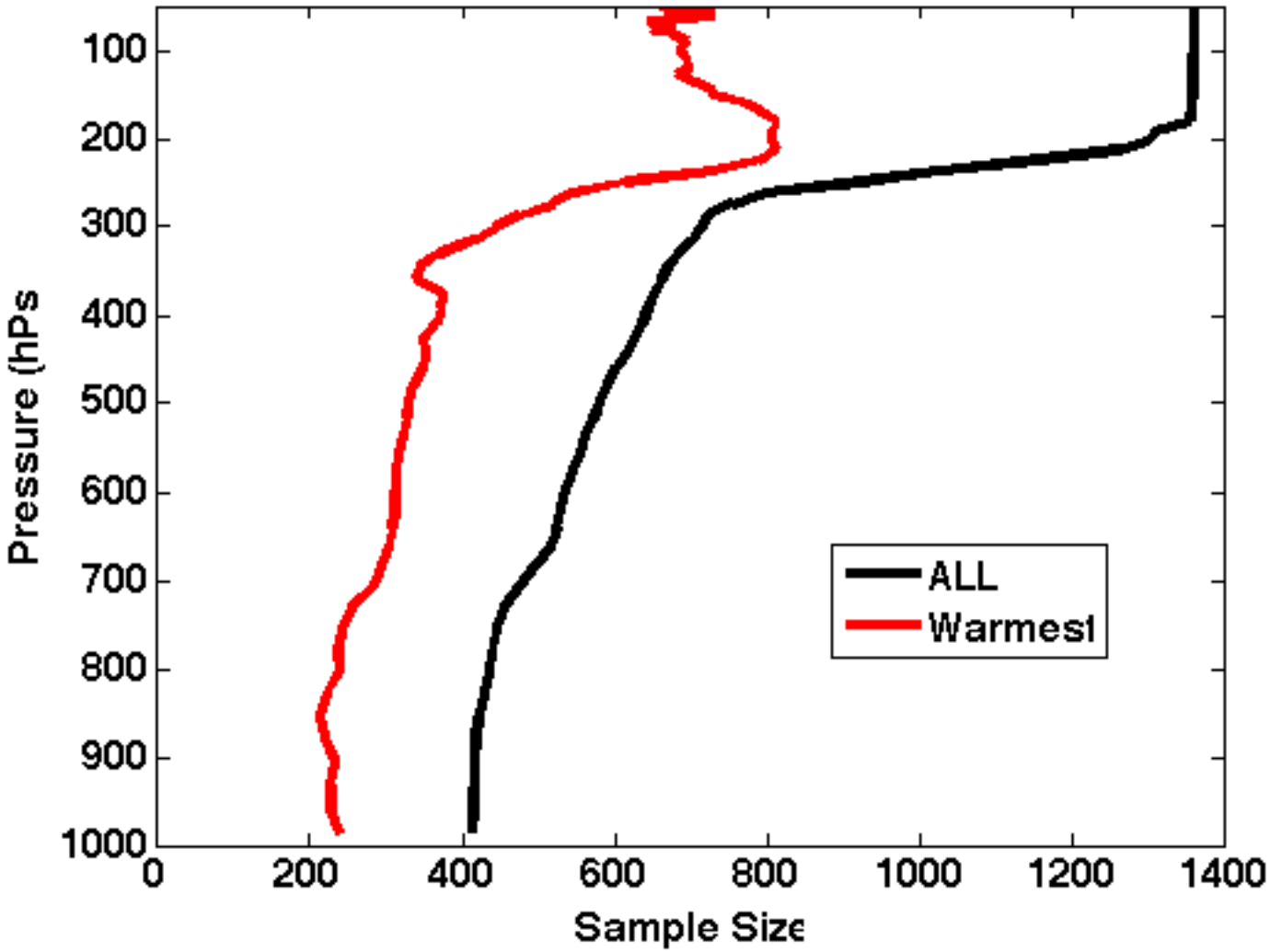




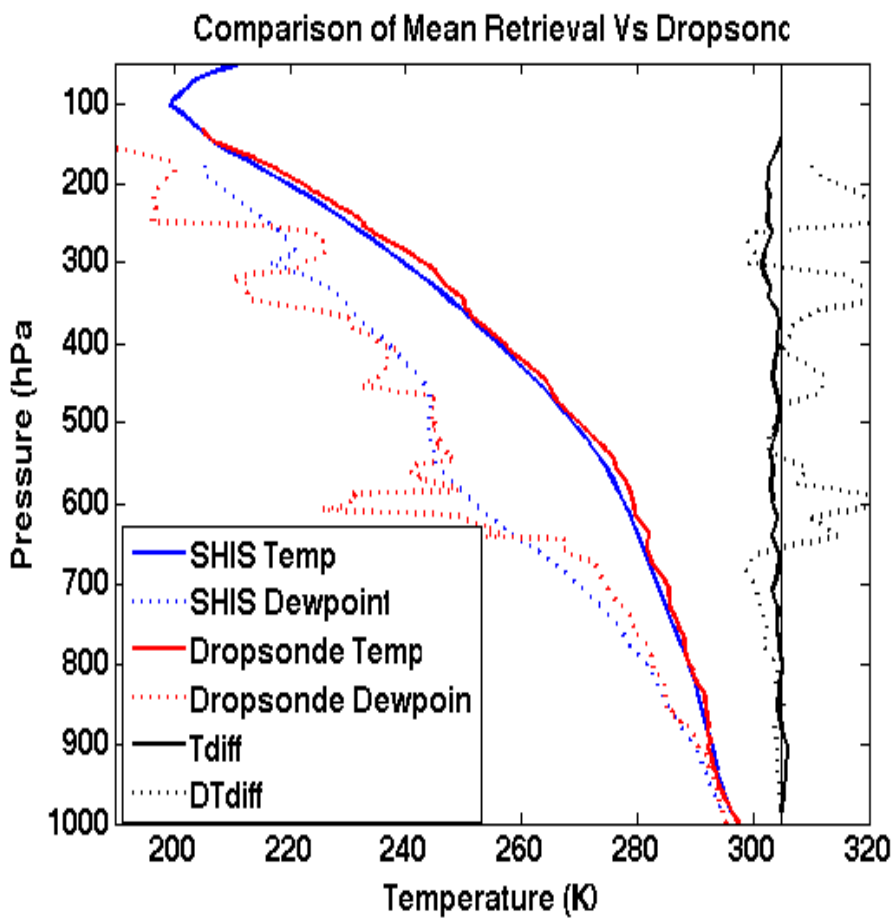


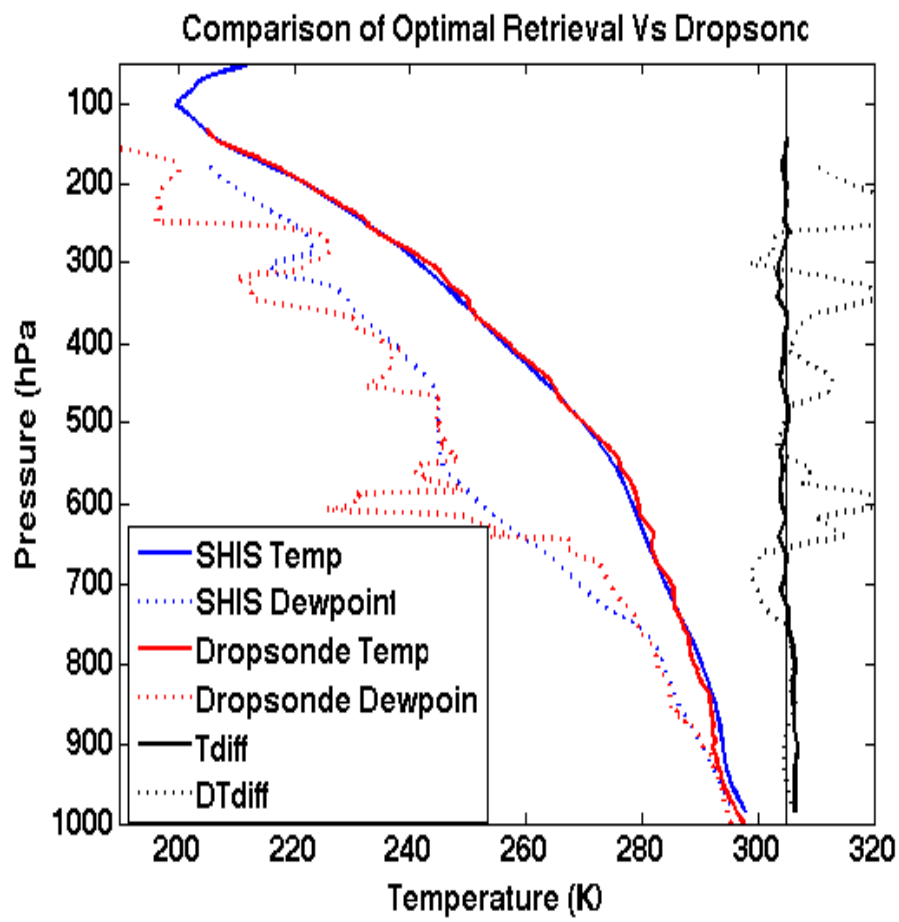


Retrieval Samples
Example (September 15, 064859 UTC)

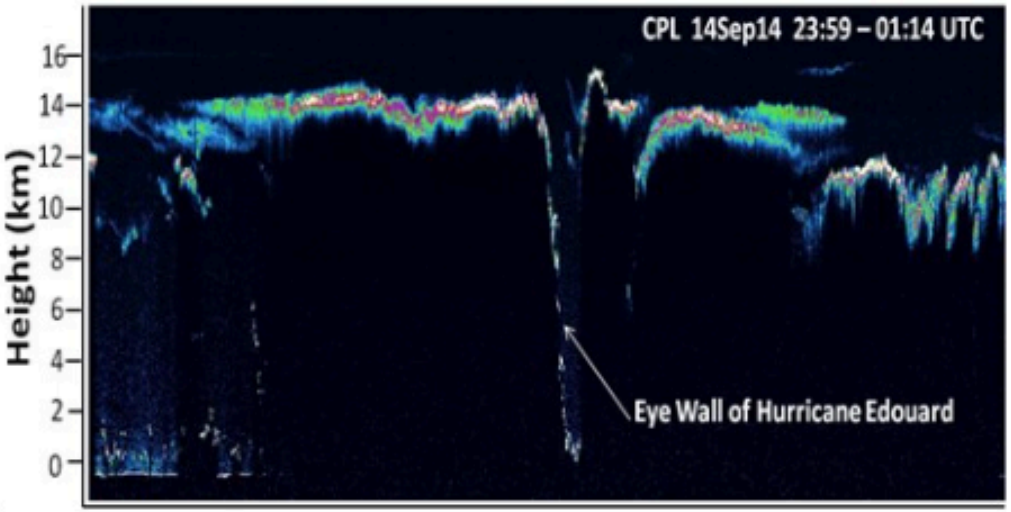


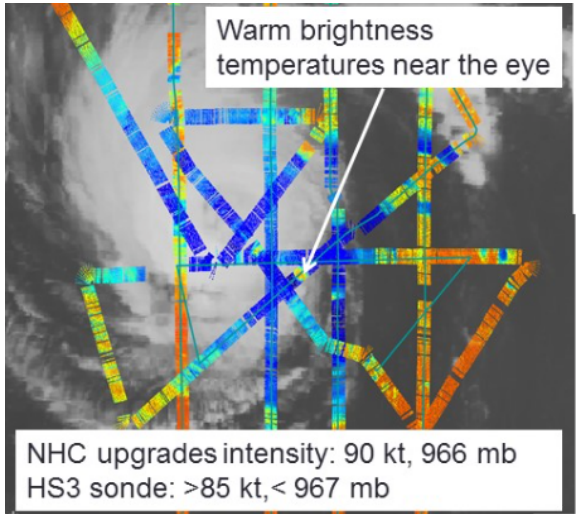
Example (September 18, 160433 UTC)

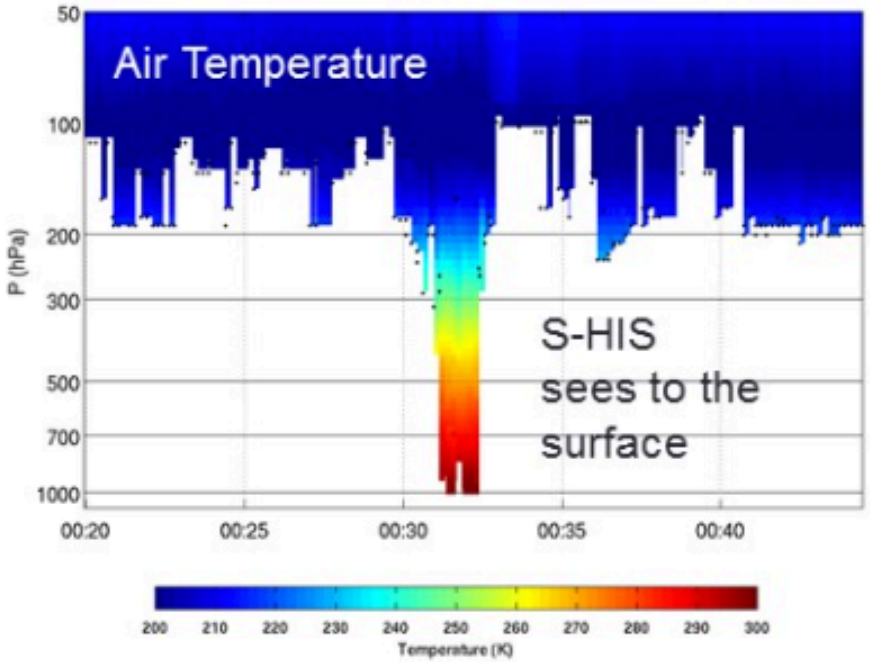


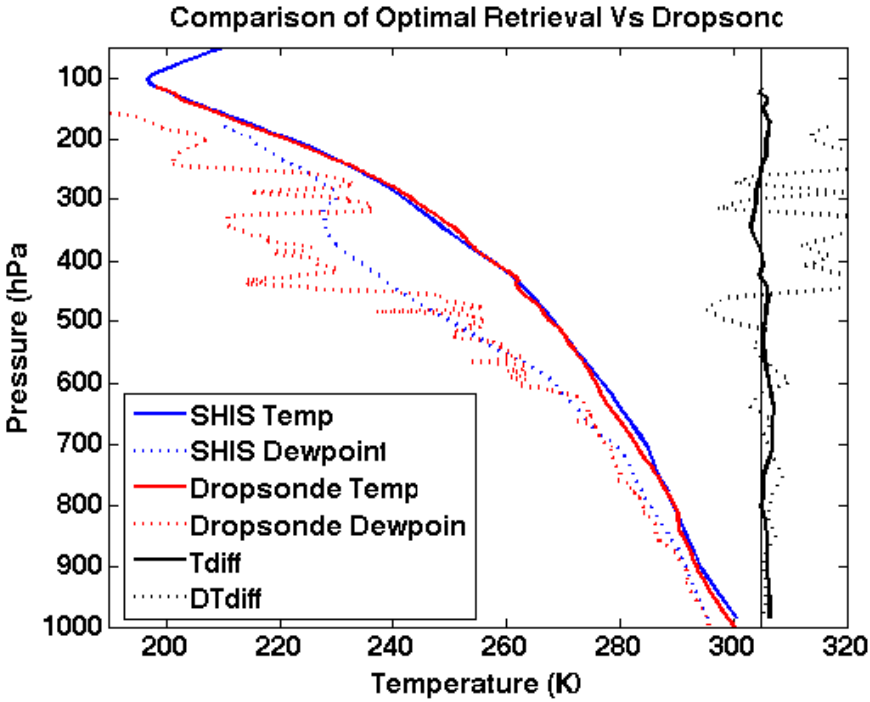


Hurricane Edouard (September 14, 2014)









Summary and Conclusions

- Improvements in DR Retrievals have been validated using ASSIST/AERI and radiosonde data obtained at the Yuma AZ and Lamont OK (ARM) SNPP ground truth sites.

- It is shown that for desert locations (e.g., Yuma AZ) the accuracy of the retrieval in the lower troposphere is highly dependent on the accuracy of surface emissivity.

- Retrievals obtained using a physical retrieval of surface emissivity and skin temperature compare well with ASSIST/AERI PBL and free troposphere radiosonde measurements

- The NASA GH HS3 campaign provides a wealth of dropsonde ground truth data for validating hyperspectral sounding retrievals

- For Climate applications, cloud attenuation cold bias must be detected and eliminated. Techniques have been defined to discard inaccurate retrievals when computing space and time averages so as to insure accurate climate trend analysis.

- **Publication:** Smith N, W. Smith Sr., E. Weisz, and H. Revercomb : " A Characterization of Systematic Uncertainty in Satellite Hyperspectral Retrieval Records at Climate Scales", to be submitted to JCAM (October 2014)

Thank You for Your Attention