Past, Present, and Future Infrared Radiance Assimilation at the Global Modeling and Assimilation Office

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The Problem of Data Assimilation

While there are many sources of error in Numerical Weather Prediction, one of, if not the, largest is the characterization of the initial conditions (or analysis)

The issues of atmospheric analysis are fairly simple to comprehend, but difficult to address

- Billions of model variables
  - Simply: T, q, u, v, p, ps
  - Complexly (and realistically): qv, convective and large scale ql & qi, aerosol components, w/ω, etc.
  - Resolutions approaching single-kilometer scales globally
- Millions of observations, recently eclipsing 5 million observations actively assimilated per 6 hours

How do we blend the model fields with the observations?

The Problem of Data Assimilation

Very, very basically, we average the two together, weighted inversely by their respective errors

- Observations with large error will carry little weight, and vice versa
- This would maybe work if we observed every variable at every point

In practice, there are many issues at hand

- All points are not observed, so cross-correlations are used to attempt to spread information horizontally, vertically, and across variables
  - Mass and wind observations must be in balance
- Most observations are not even measuring the variables we are trying to analyze
  - T, q, u, v, etc. aren't the analyzed variables
  - The bulk of the modern observing system is satellite radiances

The Variational Approach

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \frac{1}{2}(\mathbf{y}_o - H(\mathbf{x}))^T\mathbf{R}^{-1}(\mathbf{y}_o - H(\mathbf{x}))$$

$$\mathbf{y} - H(\mathbf{x}) = \mathbf{y} - (H(\mathbf{x_b}) + \mathbf{H}\delta\mathbf{x})$$

H(**x**) transforms the background/guess state to observation space

- If in the same space, as simple as an interpolation
- If in different space, *H* can be radiative transfer (radiances), a projection of the wind

To solve the minimization, the *H* operator is linearized about the background state to form **H**

- To compensate for nonlinearities, multiple linearizations, or outer loops, are performed in the analysis solution

The Impact of the Variational Approach

It was the use of Variational methods that collapsed forecast skill gaps between hemispheres

These methods allowed for the effective assimilation of satellite radiances

- The linearization of radiative transfer
- real meteorological information of the background fields

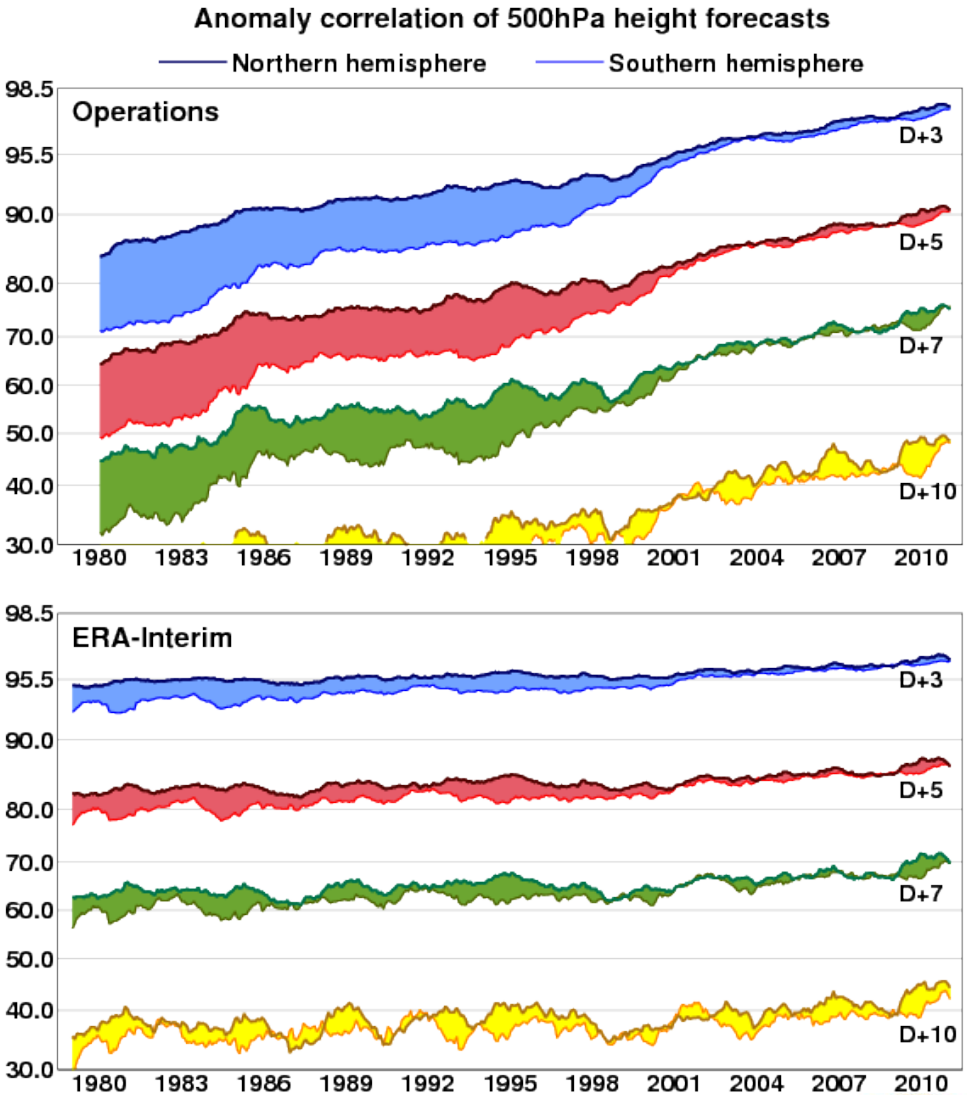
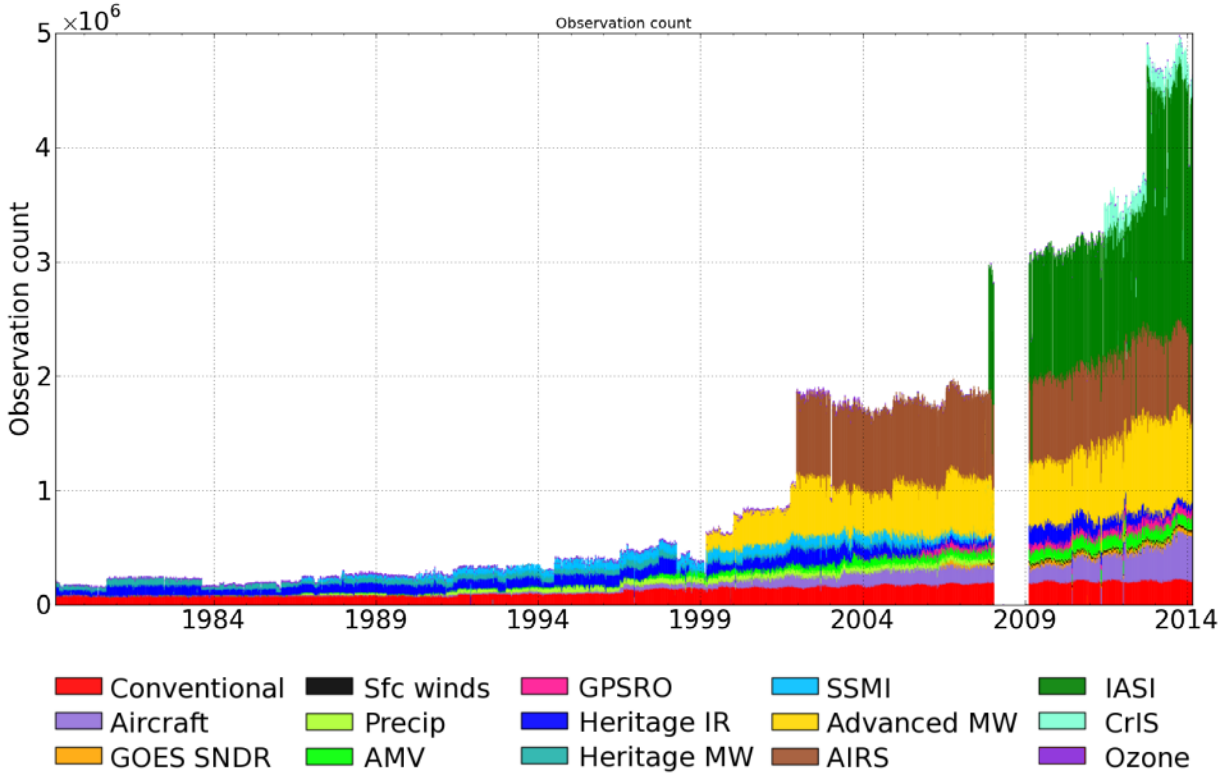


Figure from ECMWF

Observations as a Function of Time

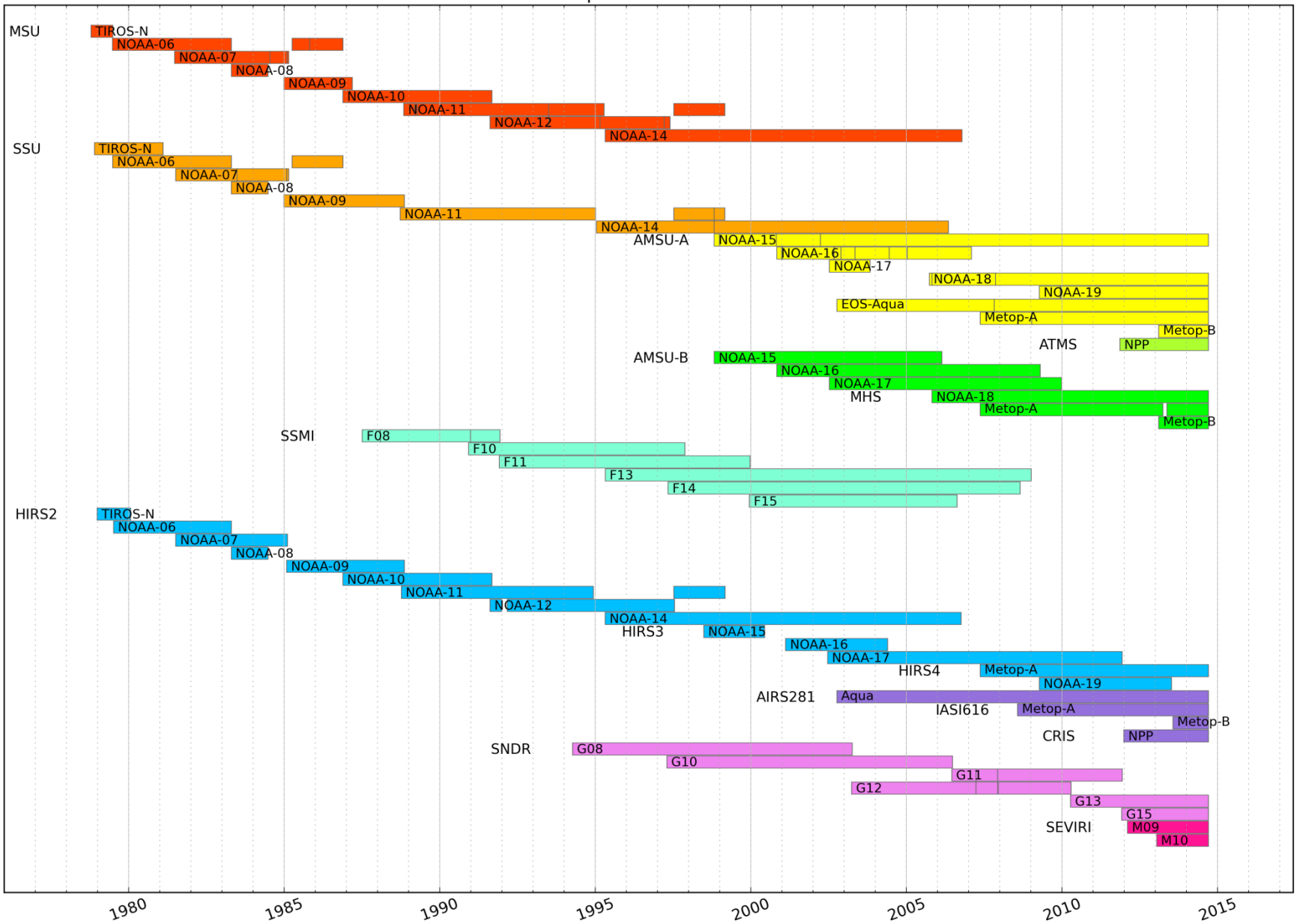
Observations assimilated per 6-hr cycle



The vast majority of observations over the modern era (1979-onward) are of satellite origin

- Since 2002, infrared observations account for ~65% of observations

MERRA2 Input - Satellite Radiances

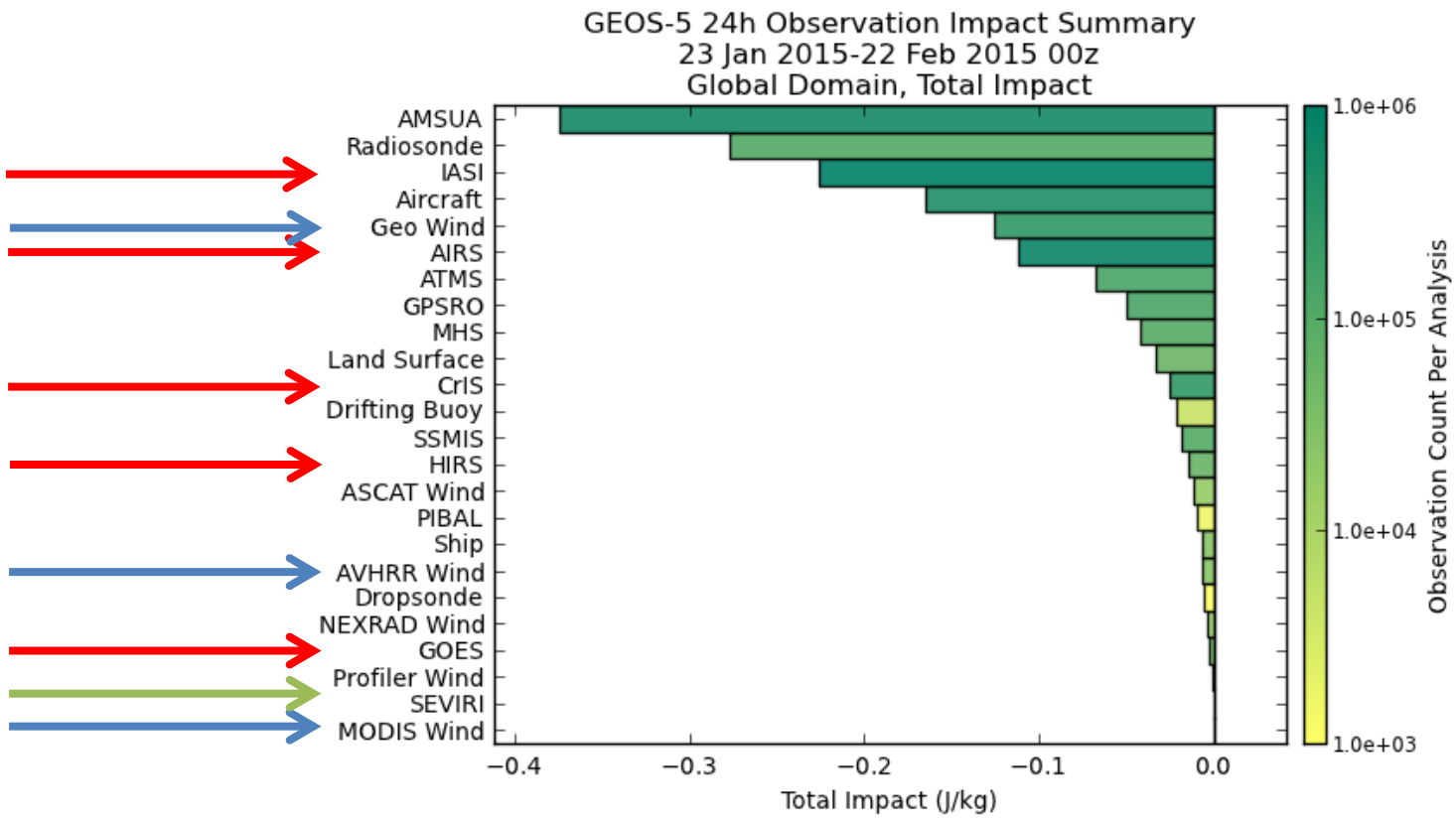


Infrared Satellite Observations

IR observations are generally classified into measurements from imagers and sounders

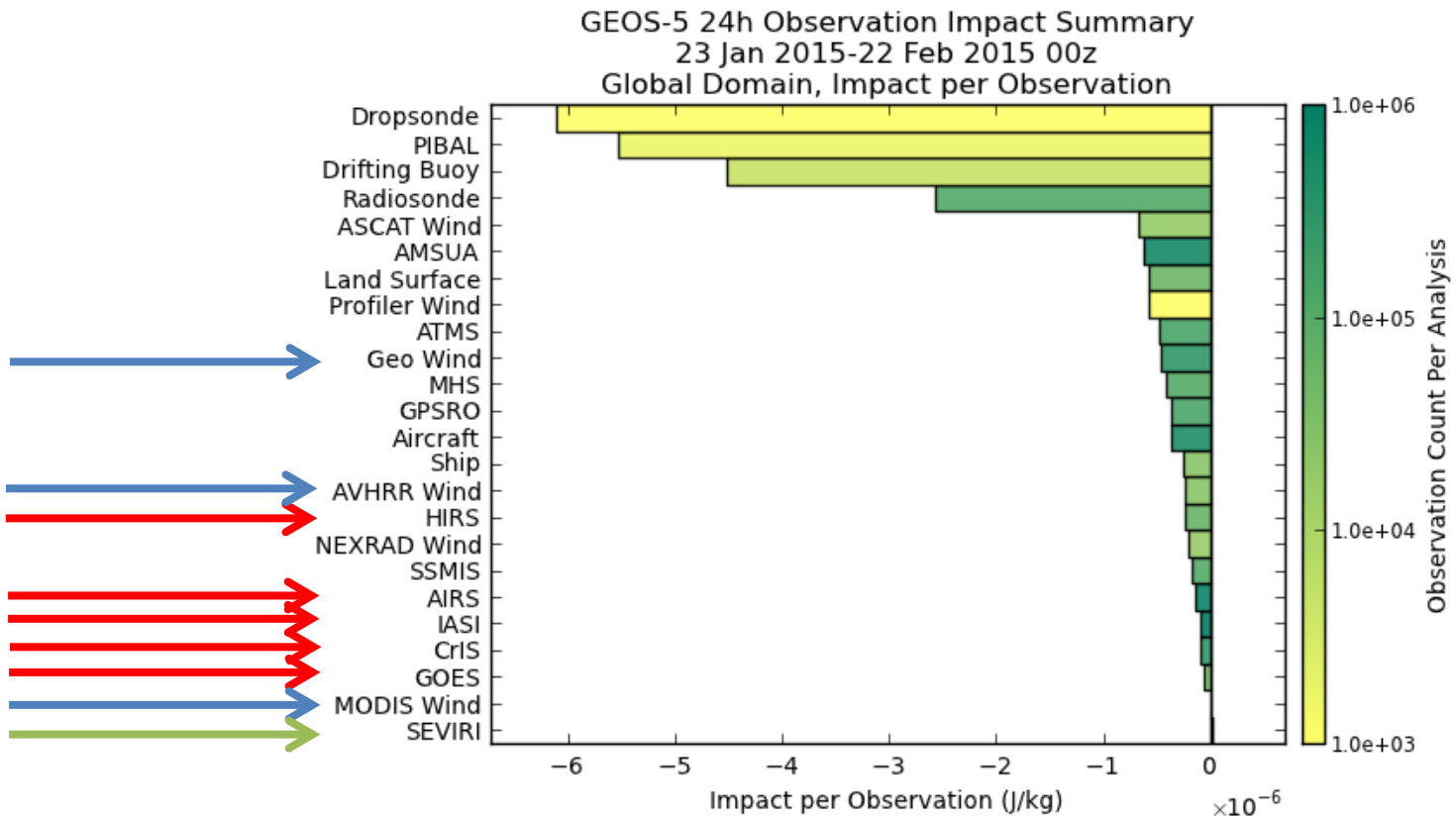
- In terms of trade-offs, imagers sacrifice spectral and radiometric resolution for spatial and temporal resolution
  - In terms of NWP, biggest contribution is atmospheric motion vectors (AMVs)
- Sounders do the opposite, as spectral and radiometric resolution can be equated to vertical resolution
  - Pre-Modern era: Vertical Temperature Profile Radiometer (VTPR), NOAA-2 through NOAA-5 (1972-1979)
    - 8 Channels
  - Modern era: High-resolution InfraRed Sounder/2-4 (HIRS), TIROS-N, NOAA-6 through NOAA-19, Metop-A/B
    - ~20 channels
  - EOS period, onward: Atmospheric InfraRed Sounder (AIRS, on Aqua), Infrared Atmospheric Sounding Inferferometer (IASI, on Metop-A/B/C), Cross-Track Infrared Sounder (CrIS, on NPP & JPSS)
    - O(1000-10000) channels

How IR Observations Contribute



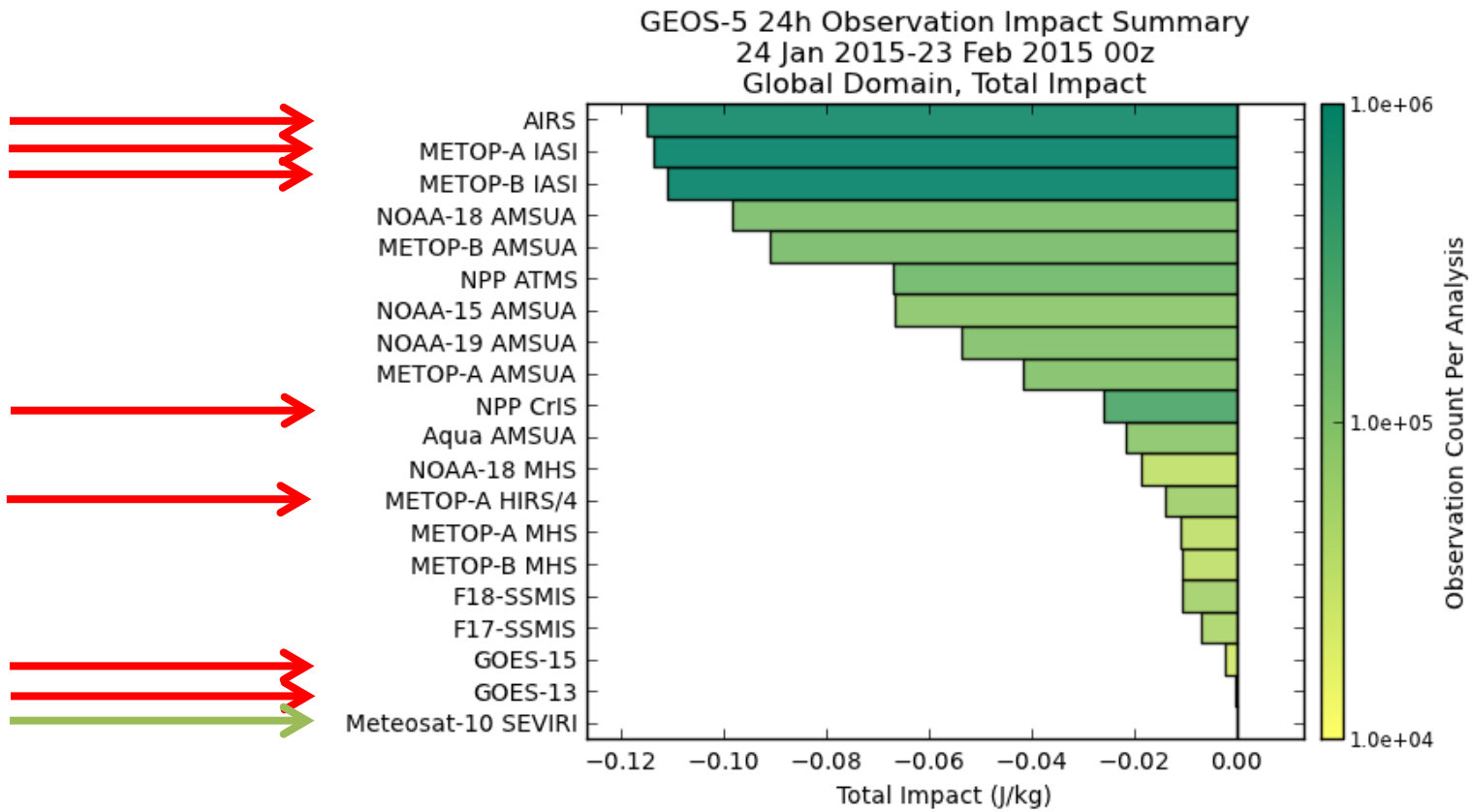
Observation impacts, also known as Forecast Sensitivity to Observations, are a projection of 24 hours forecast error into observations space

How IR Observations Contribute



Normalizing by the number of observations, it is seen that the infrared observations drop to the bottom.

How IR Observations Contribute



Per instrument, the modern infrared sounders are near, or exceed, the microwave sounders in total impact.

Infrared Observation Impact

As seen, IR observations make up ~65% of the current global observing system

But only a small portion of the total number of observations available are utilized:

- Spectral Thinning
  - AIRS: 281 of 2378 channels are available, 124 active (5.2% of total)
  - IASI: 616 of 8461, 137 active (1.6%)
  - CrIS: 399 of 1305, 81 active (6.2%)
- Spatial Thinning
  - 1 spectra per instrument for every 145x145 km thinning mesh (observation footprint size is ~15km) (~1.5% of the previous percentages)
- Quality Control
  - Via traditional means, infrared observations sensitive to clouds are discarded via quality control (~25% of the previous 1.5%)

Infrared Observation Impact

So based on real numbers:

- AIRS: 0.04% of all observations are assimilated
- IASI: 0.04%
- CrIS: 0.19%

So while the instruments provide as much bang as any other satellite instrument type out there, why can we only use such small percentages of the data?

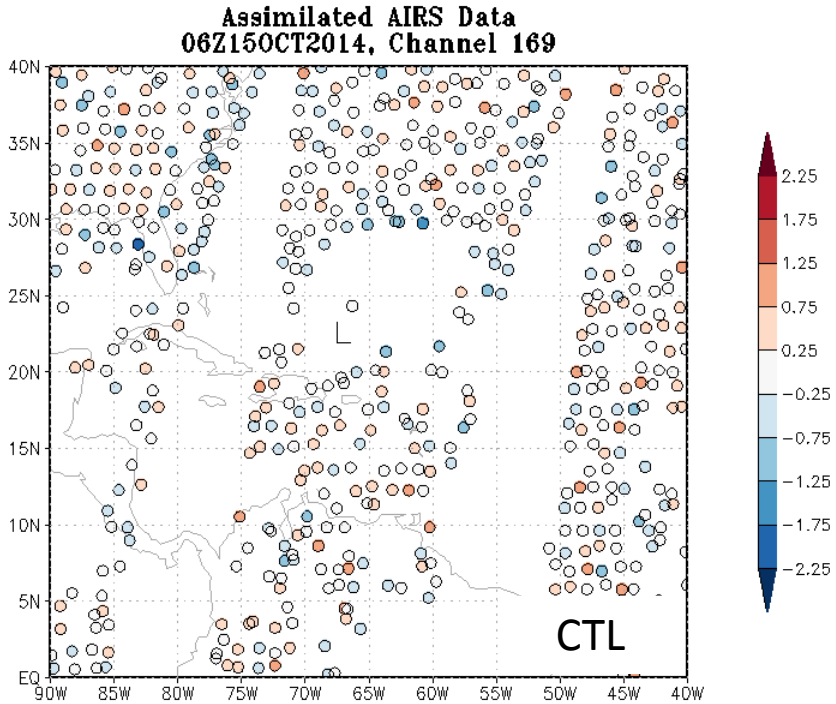
Data Thinning

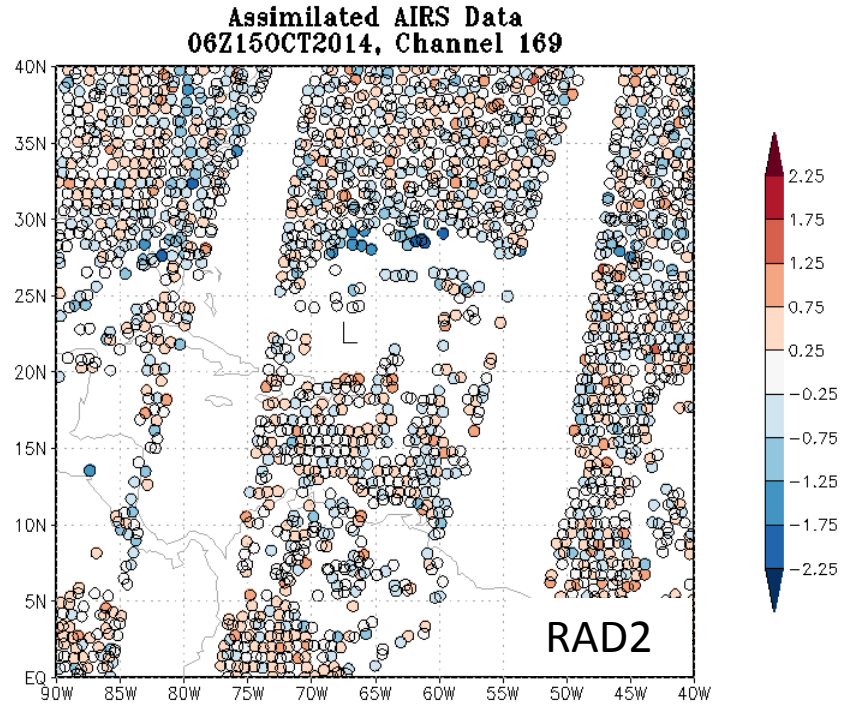
Data is thinned spatially to compensate for horizontal correlations in representativeness

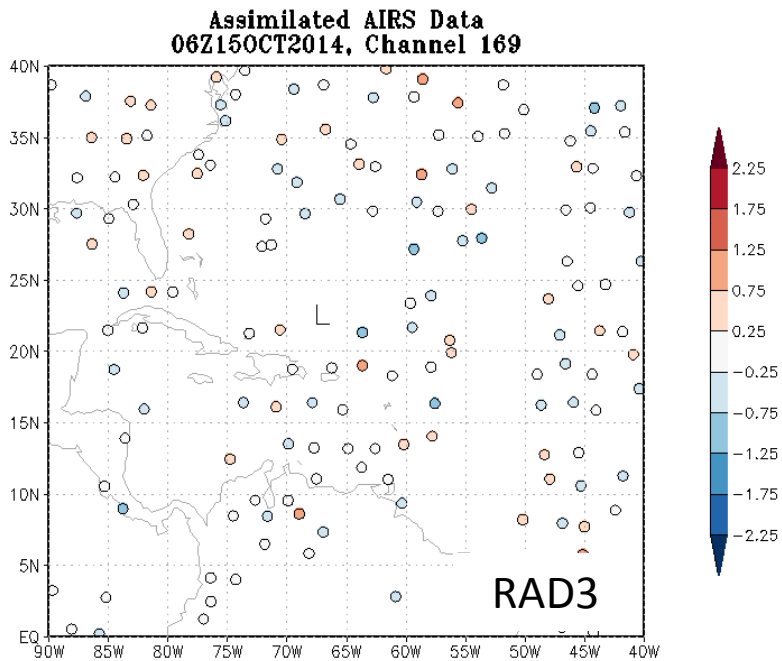
- Even as model grid spacing approaches and exceeds observation resolution, the models are not resolving meteorological features at the resolution of grid spacing
- Too many small-scale features will cause gravity waves that are numerical, non-physical in nature

Data is generally thinned in the infrared to get the most cloud-free observations

- In the infrared, this is generally the spectrum with the warmest observations in the 11 µm window
- Are there situations where less thinning would be desirable?





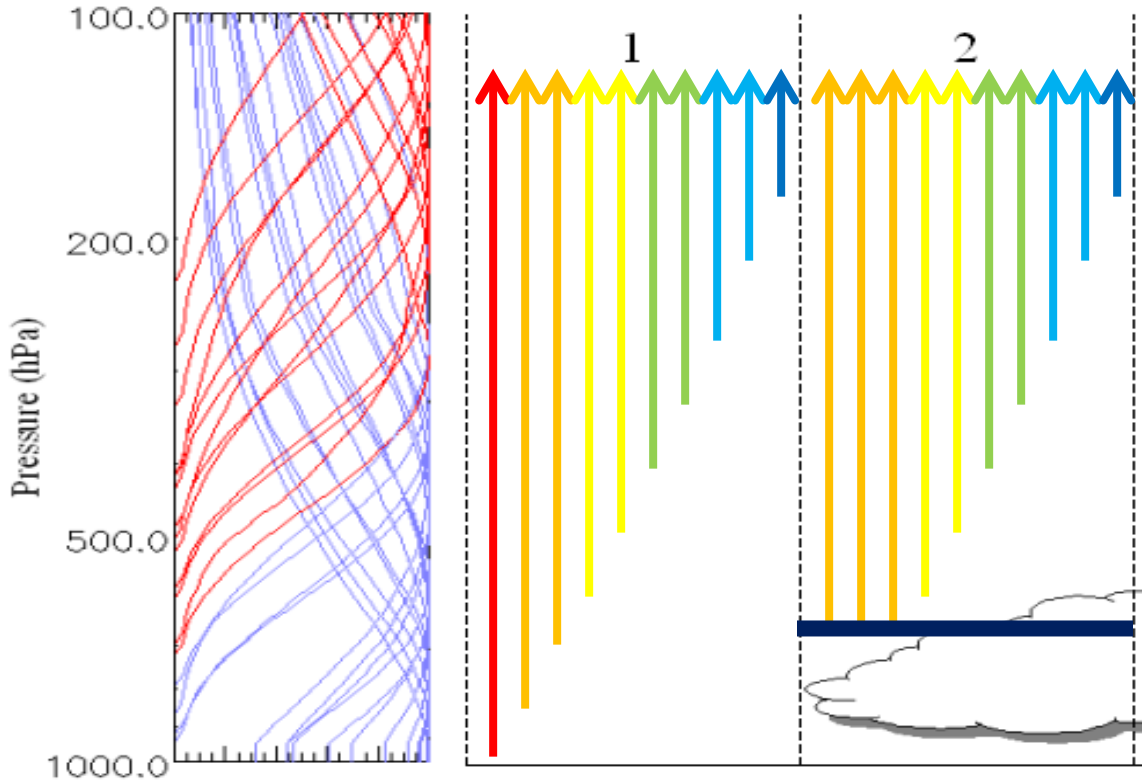


In the presence of Hurricane Gonzalo (L), more observations in the hurricane can be seen by reduced thinning (Top Right) versus the control (Top Left). For comparison, the equivalent increased thinning (bottom) is shown

O. Reale, E. McGrath-Spangler

Clouds and the Infrared

Currently in the GSI, which is the data assimilation algorithm used at GMAO, NCEP, and many other locations through the US, radiative transfer only treats radiances as clear-sky observations



Only those obs that are insensitive to clouds are assimilated

- Cloud-free spectra
- Individual channels that are insensitive to the cloud surface

Retrieved Cloud Height

How are Clouds Handled in GSI

Cloud screening is a two-step process

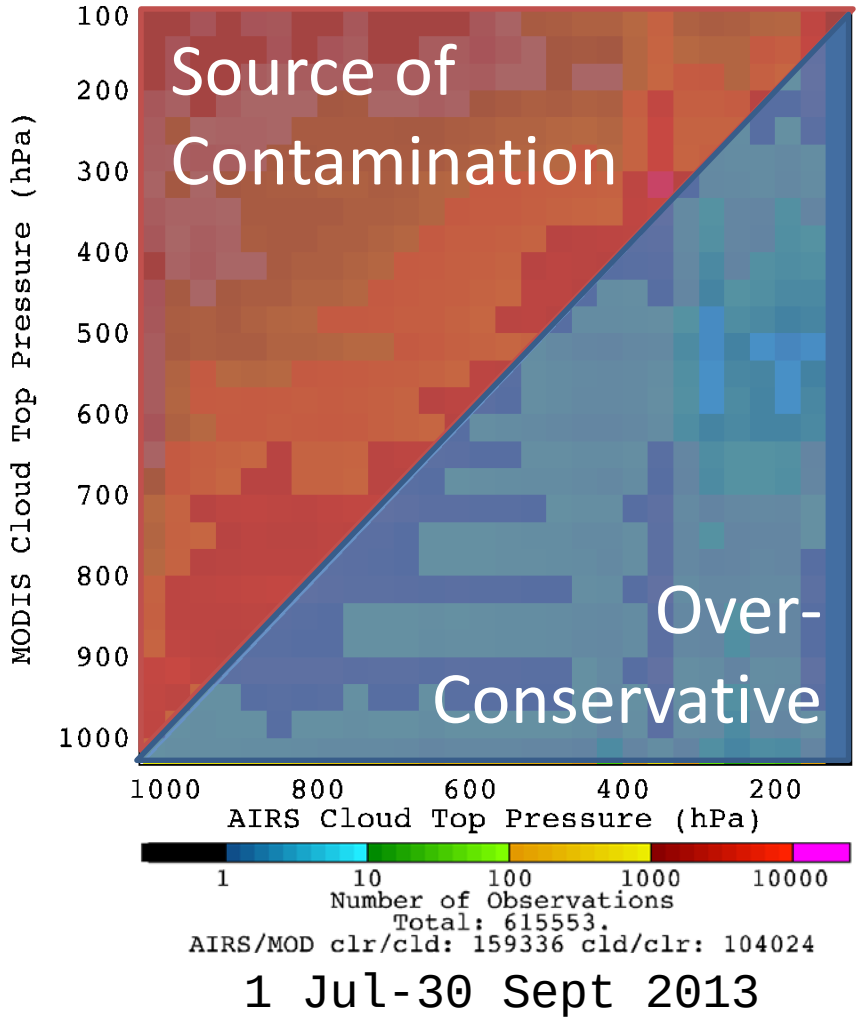
1. Retrieve a cloud height
   - This is done via a minimum residual method (Eyre and Menzel 1989)
2. Compare cloud height against transmittance profile
   - If layer-to-top of atmosphere transmittance of a channel at the retrieved cloud height is greater than 2% reject the channel

For channels most-sensitive to the surface, this rejects ~80% of these data.

Assumptions in this method are fundamental sources of error:

- Single layer clouds; Infinitesimally thin, black clouds; treated as fractionally gray
- Background biases can propagate into the retrieval
  - Both with respect to variational bias correction and uncorrected observation departures

AIRS CTP vs. MODIS High CTP



Comparing:

- AIRS Cld Top Pressure (CTP)
  - ~15 km
- MODIS MYD06 CTP
  - 5 km, coincident 3x3
  - highest CTP reported

Considering observations as function of cloud fraction shows biases in confident (opaque) and uncertain (variant) areas of cloudiness

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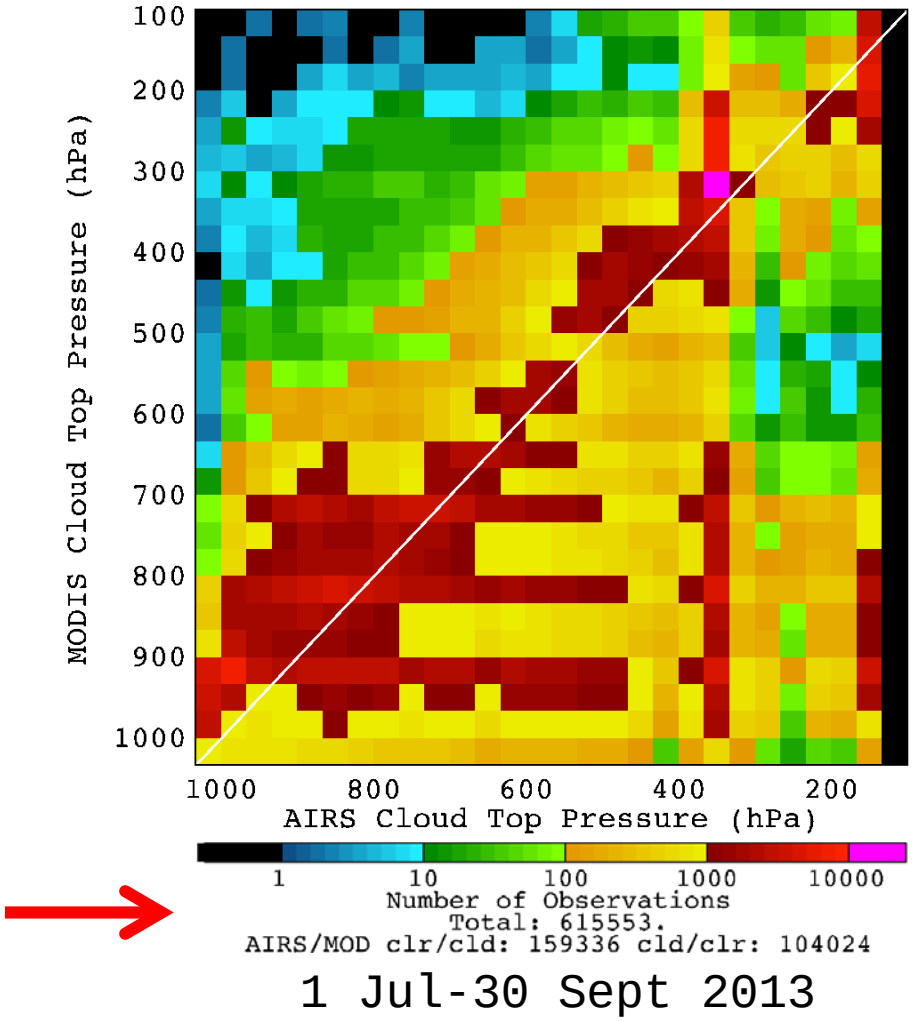

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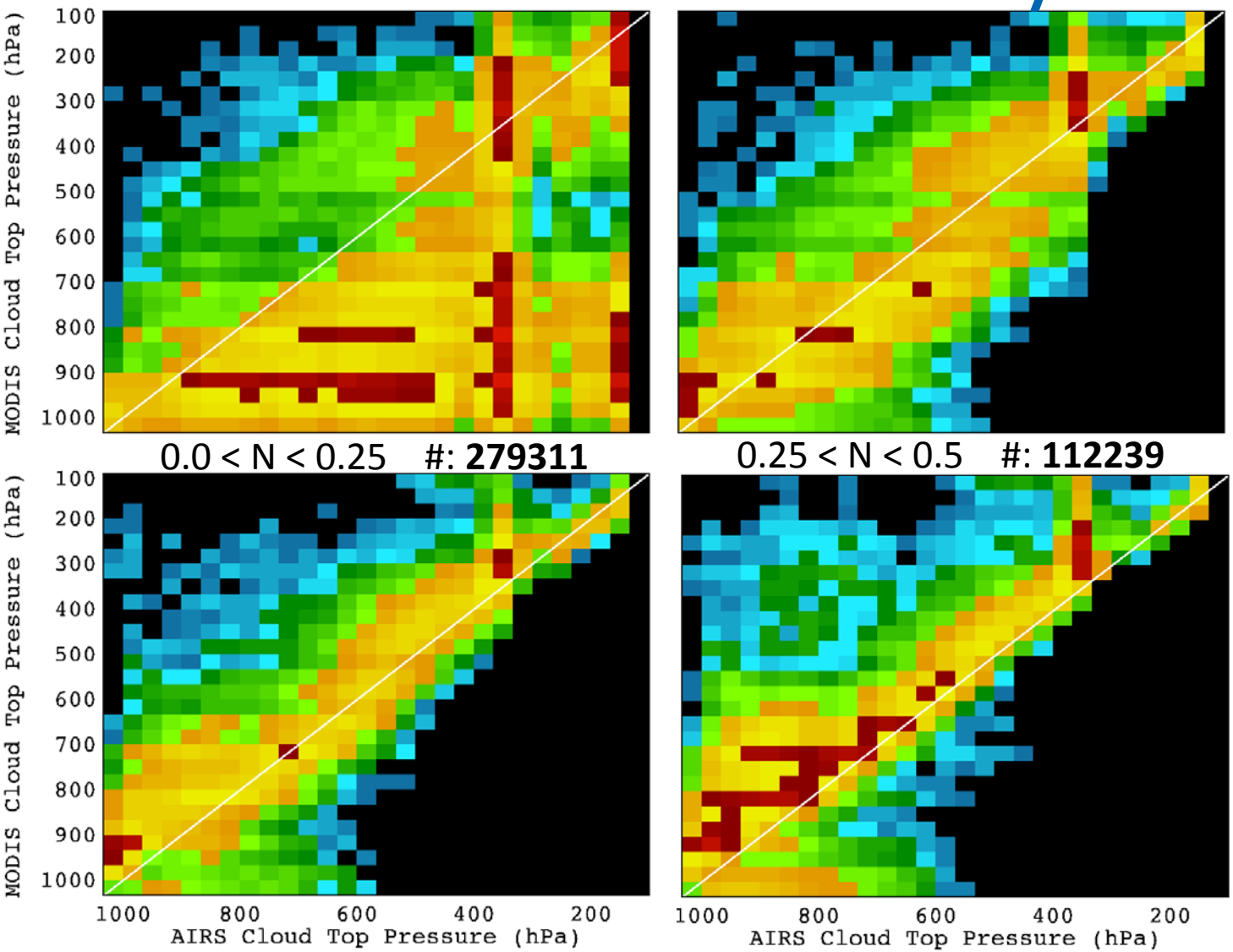
AIRS v. MODIS CTP by Fraction



0.0 < N < 0.25 #: **279311**

0.25 < N < 0.5 #: **112239**

0.5 < N < 0.75 #: **85490**

0.75 < N < 1.0 #: **138513**

MODIS CTP uncertain > 700 hPa and in low fraction

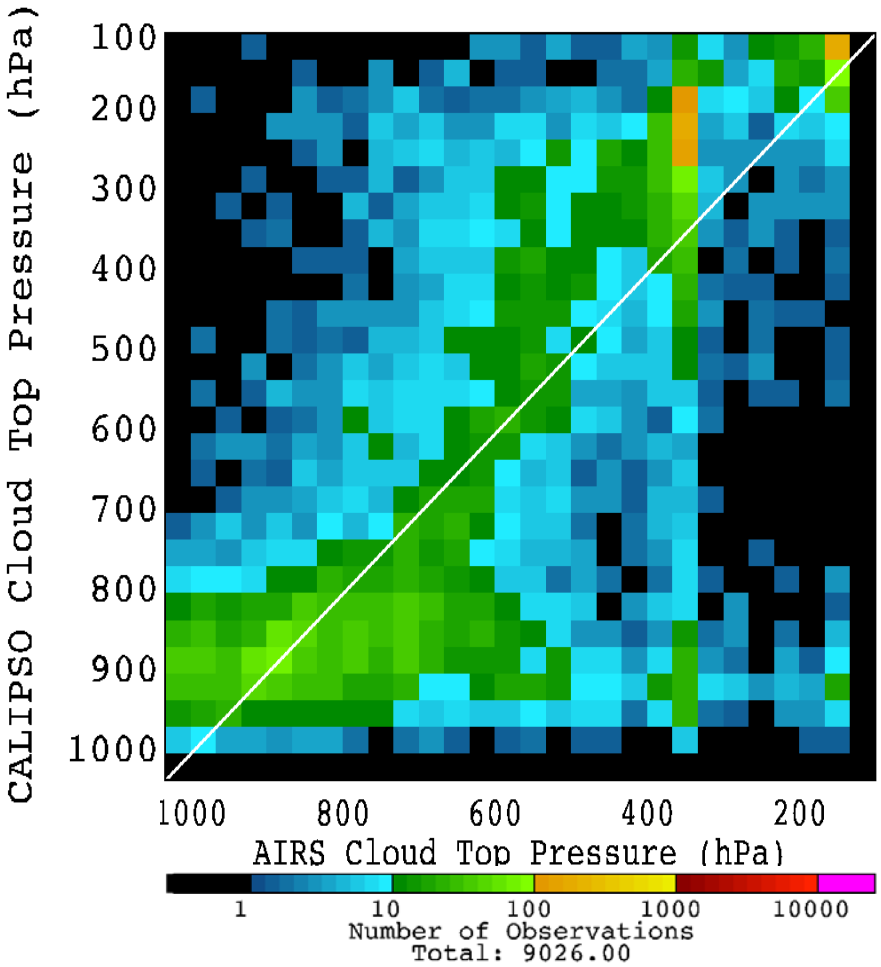
Conservative in areas of low fraction

Apparent bias in areas of high fraction

More low fraction observations by design

Global Modeling and Assimilation Office
Goddard Space Flight Center
National Aeronautics and Space Administration

AIRS CTP vs. CALIPSO Highest CTP



1 Jul 2013 – 28 Feb 2014

- Compared against L2 CALIPSO-CALIOP determined CTP (1 km, V3-30)
- Similar trends, but reduction in lower-troposphere contamination (600-800 hPa)
- Includes poles, but separation was considered
  - No distinct polar signals
- Likely sampling issues (spatial and temporal)

Forecast Impact of Cloud Contamination

The misassessment of cloud height can result in the cloud signals being erroneously projected on the mass (T & q) fields

- This analysis error will then translate into a forecast error

To quantify this source of error:

- **Observation Departures (bias corrected)**
  - Observed minus Forecasted Brightness Temperature (O-F)
- **Adjoint-Based Observation Impacts**
  - A 24 hour forecast error projected onto the observations of its initial analysis using the adjoints of the forecast model and assimilation system
  - The measure is a moist energy norm (u, v, T, p_s , q_v → J/kg)
  - This method is run routinely in GMAO ops at 0000 UTC
  - **A negative value equates a reduction in error, so NEGATIVE = GOOD**

Adjoint Method for Computing Observation Impact

The adjoint of a data assimilation system allows accurate and efficient estimation of the impacts of **all observations simultaneously** on analyses and short-range forecasts

Forward Data Assimilation-Forecast Procedure:

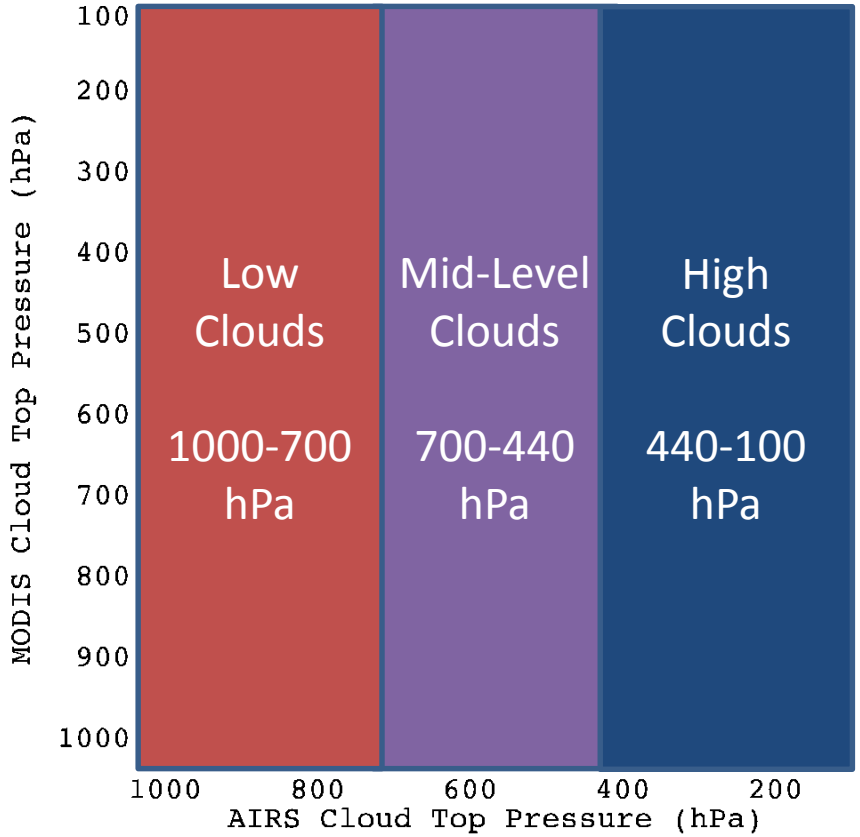
Input: Observations and Background → **Analysis System** → Forecast Initial State → **Forecast Model** → **Output:** Forecast

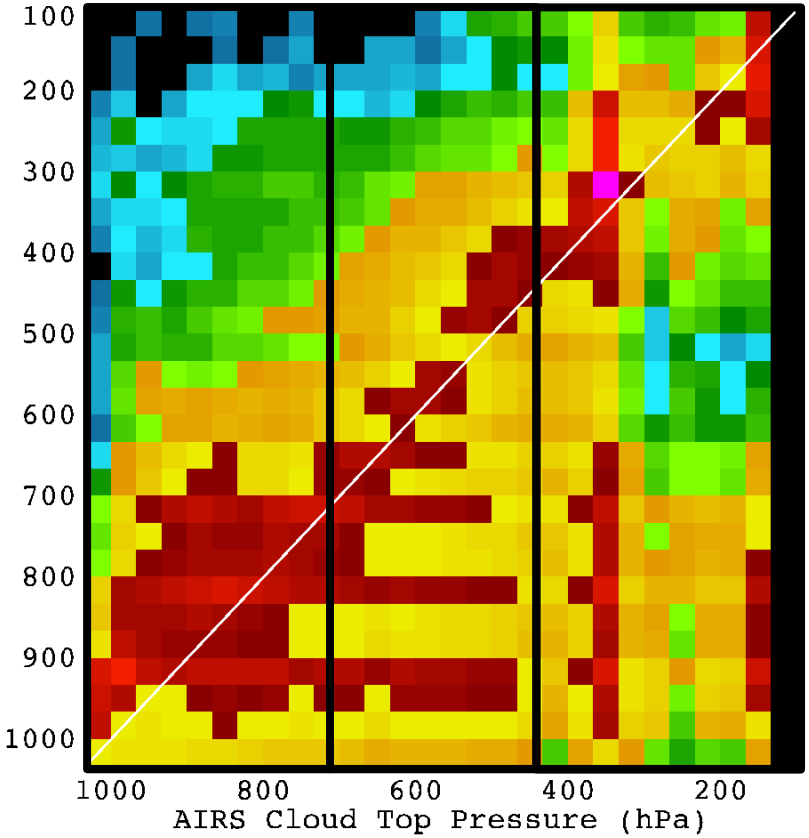
Adjoint Data Assimilation-Forecast Procedure:

Input: Forecast → **Adjoint Forecast Model** → Forecast Sensitivity to Initial State → **Adjoint Analysis System** → **Output:** Forecast Sensitivity to Observations

Observation Impact

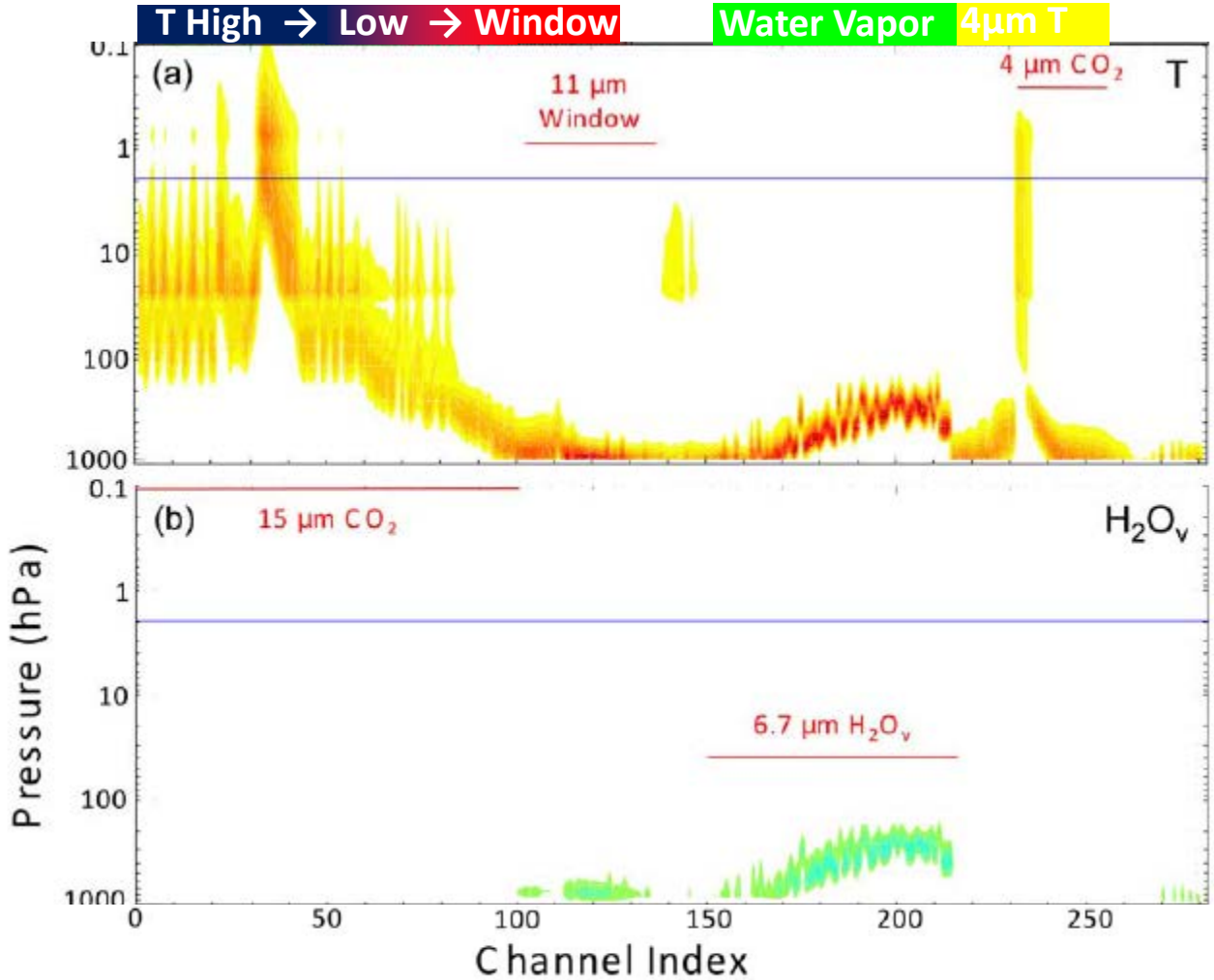
AIRS CTP vs. MODIS High CTP





Clouds classified into (roughly) ISSCP height classifications as a function of AIRS Cloud Top Pressure

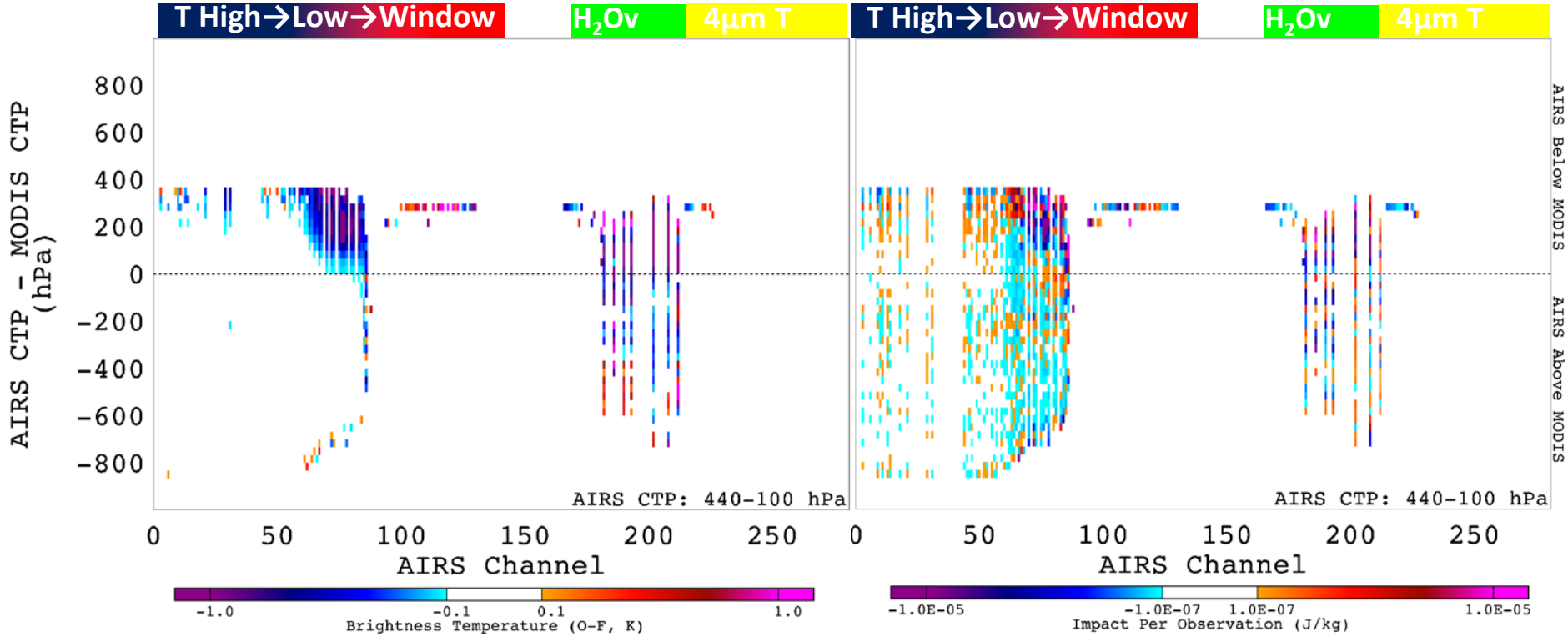
Channel Sensitivity



AIRS Jacobians for temperature and water vapor

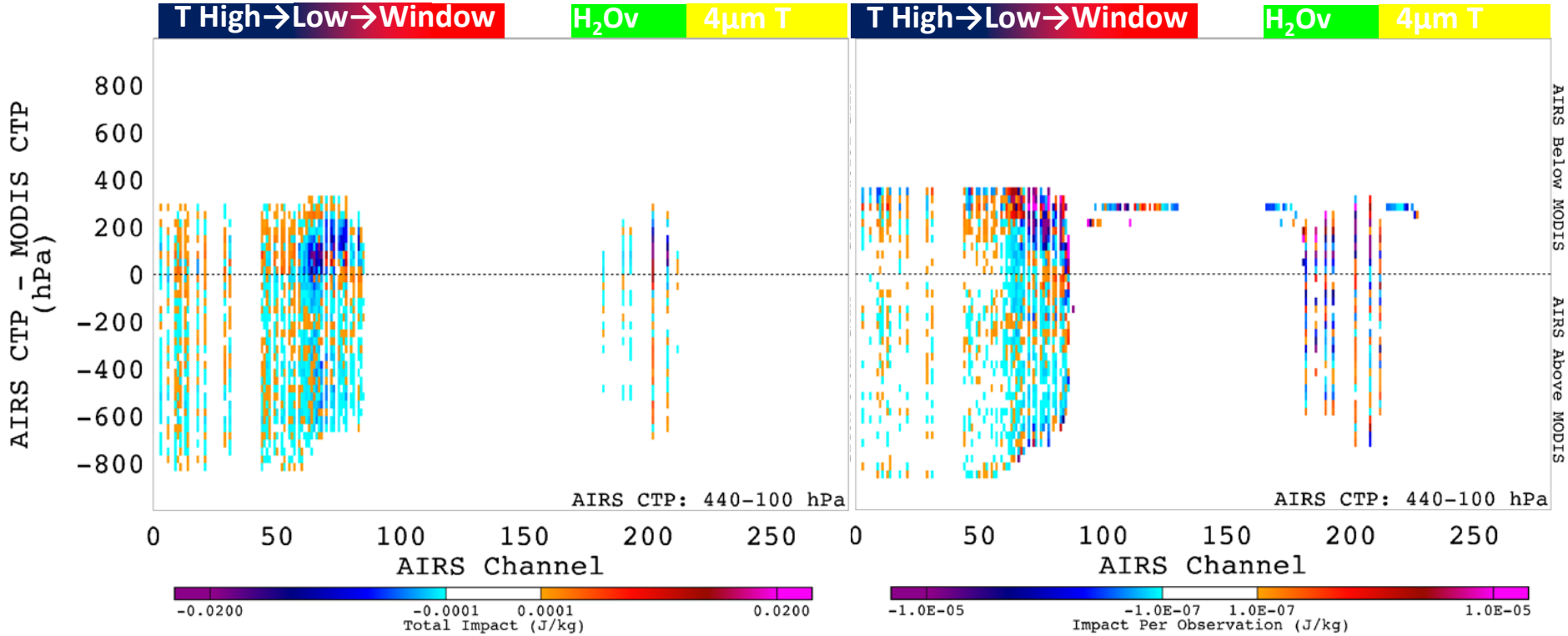
The top color bar will serve as reference for the remaining plots

Observation Impact – High Clouds



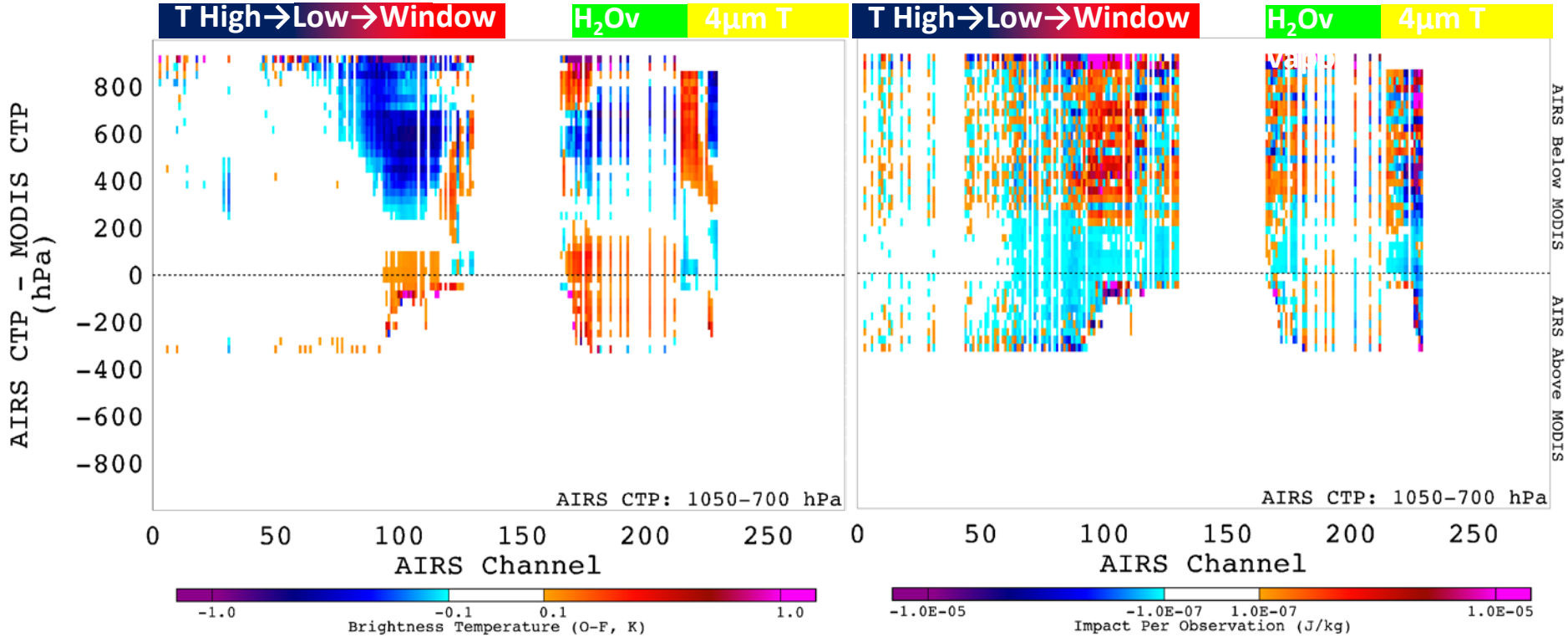
- Negative O-F signal apparent where MODIS/AIRS disagree most towards contamination
- Small count relative to total, but show inconsistent impact per observation in this region

Observation Impact – High Clouds



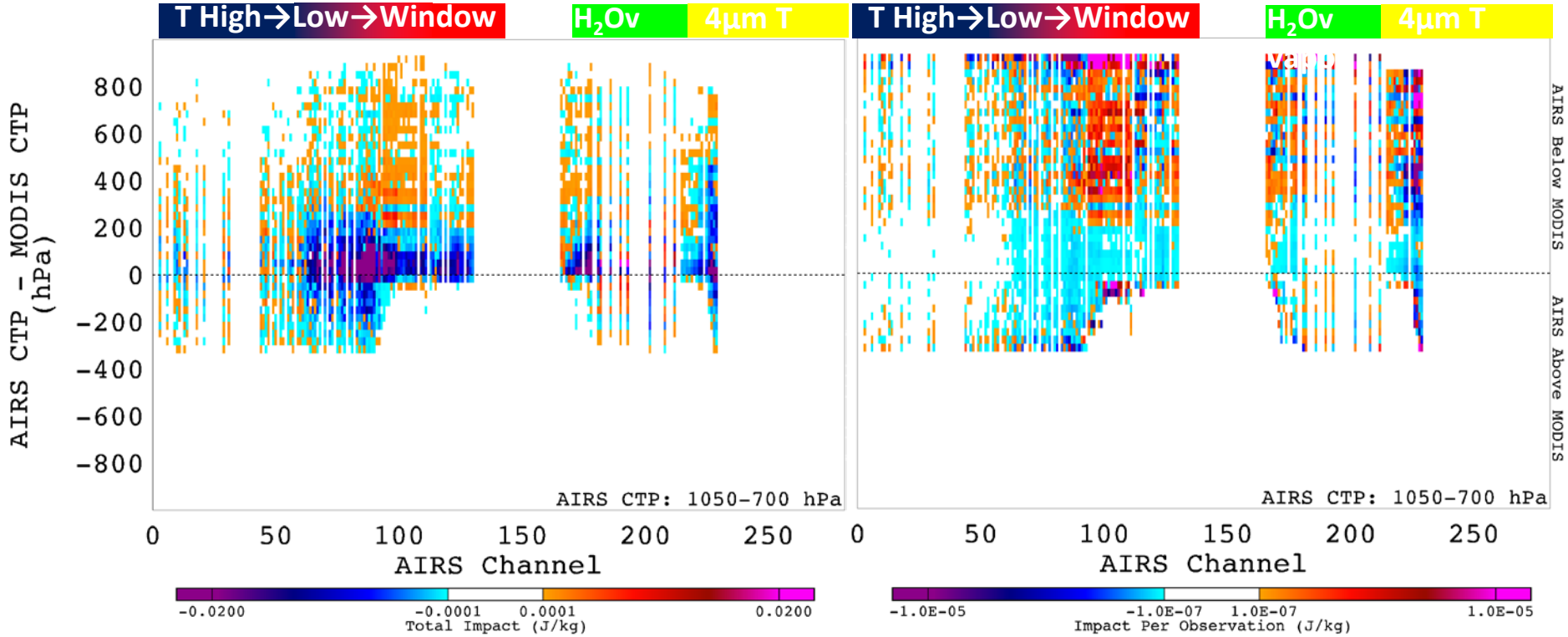
- High clouds show that even w/ an AIRS low bias (vertically), impact is generally show observations reduce error
- Channels less effected by these high clouds (< 50) show more neutral impact – effect of the metric

Observation Impact – Low Clouds



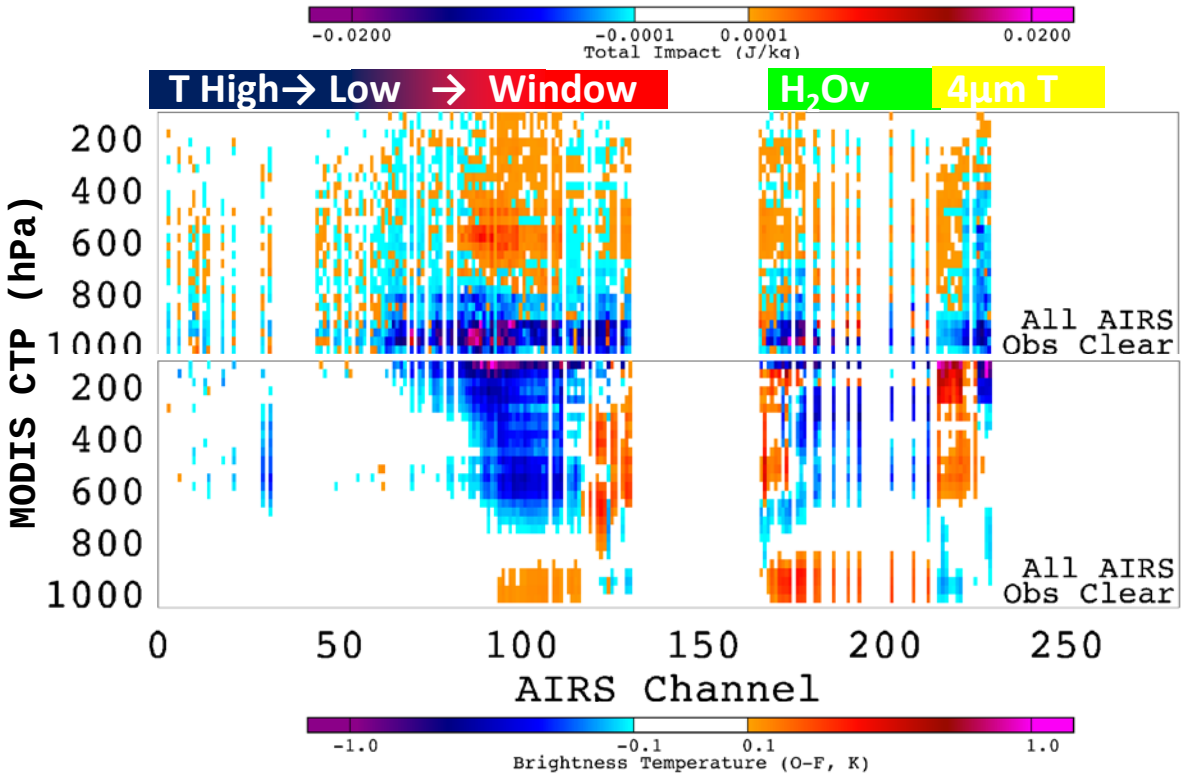
- Cloud signal again apparent
- Positive O-F bias in areas of agreement – potentially a feedback of cloud contamination having an effect on bias correction
- Impact per observation strongly negative in areas of cloud contamination

Observation Impact – Low Clouds



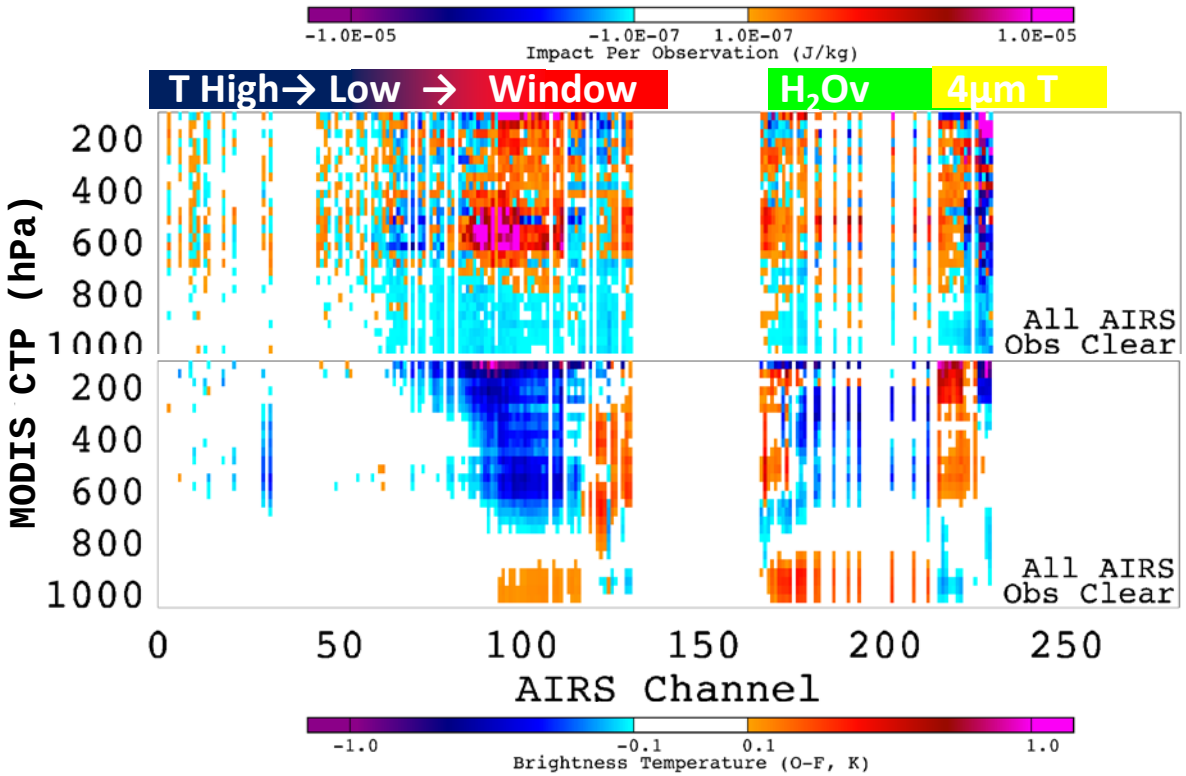
- Misrepresentation of low clouds relative to MODIS show clear increase in error for channels sensitive to low clouds
- There is a real chance that thin cirrus over small clouds can be a source of error
- Magnitude of total degradation due to clouds becomes much more significant w.r.t. overall positive impact

AIRS 'Clear'/MODIS Cloudy Observations



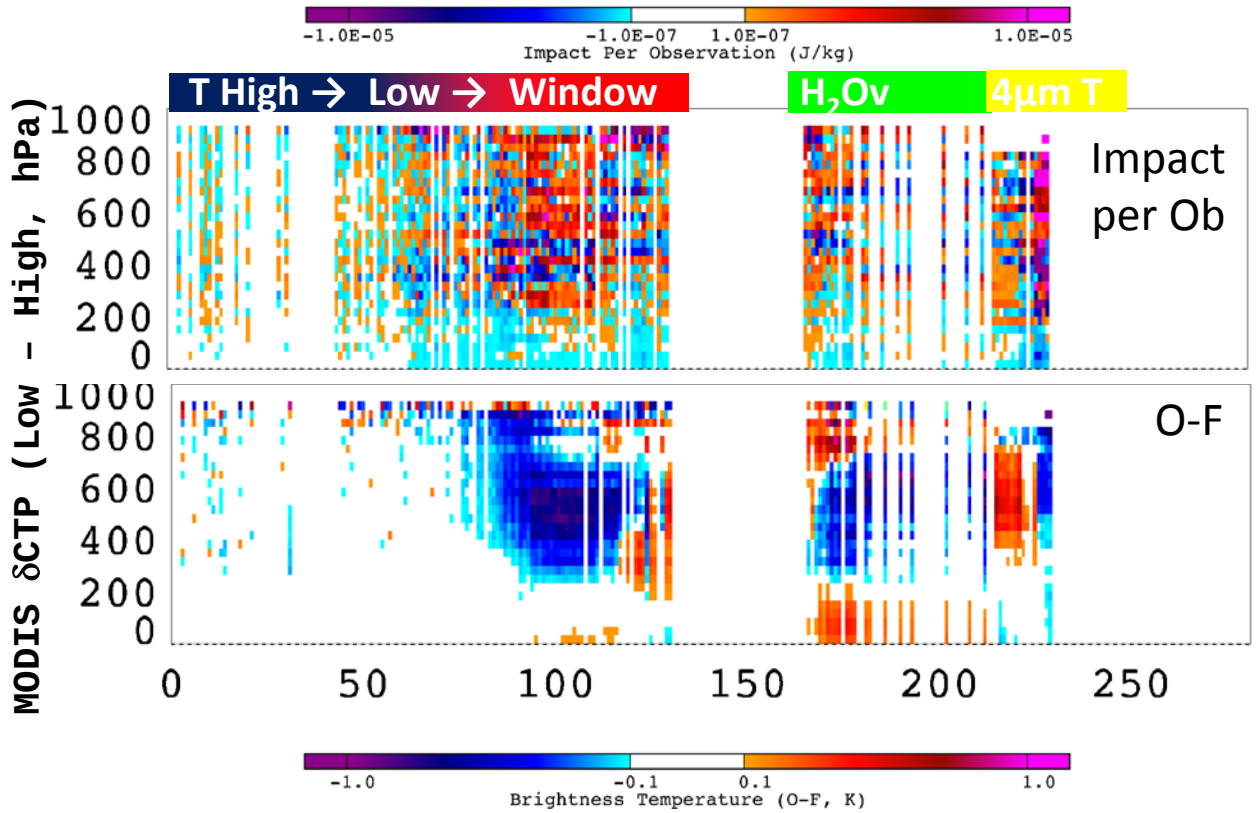
- Cloud signal again apparent, and largest magnitude of total degradation
- Warm O-F signal near sfc again

AIRS 'Clear'/MODIS Cloudy Observations



- Per observation, the degradation is again apparent

Heterogeneity in AIRS Observations



- Observations with notable subscale variability generally degrade, and have a negative O-F signal.
- This is using MODIS, which has many of the same limitations as AIRS.

Clouds in the Infrared

To further exploit infrared data, the next step is to include some characterization of clouds in the analysis

Approaches for all-sky situations in the microwave are having some success, but the nonlinearities of clouds in the infrared make it more difficult

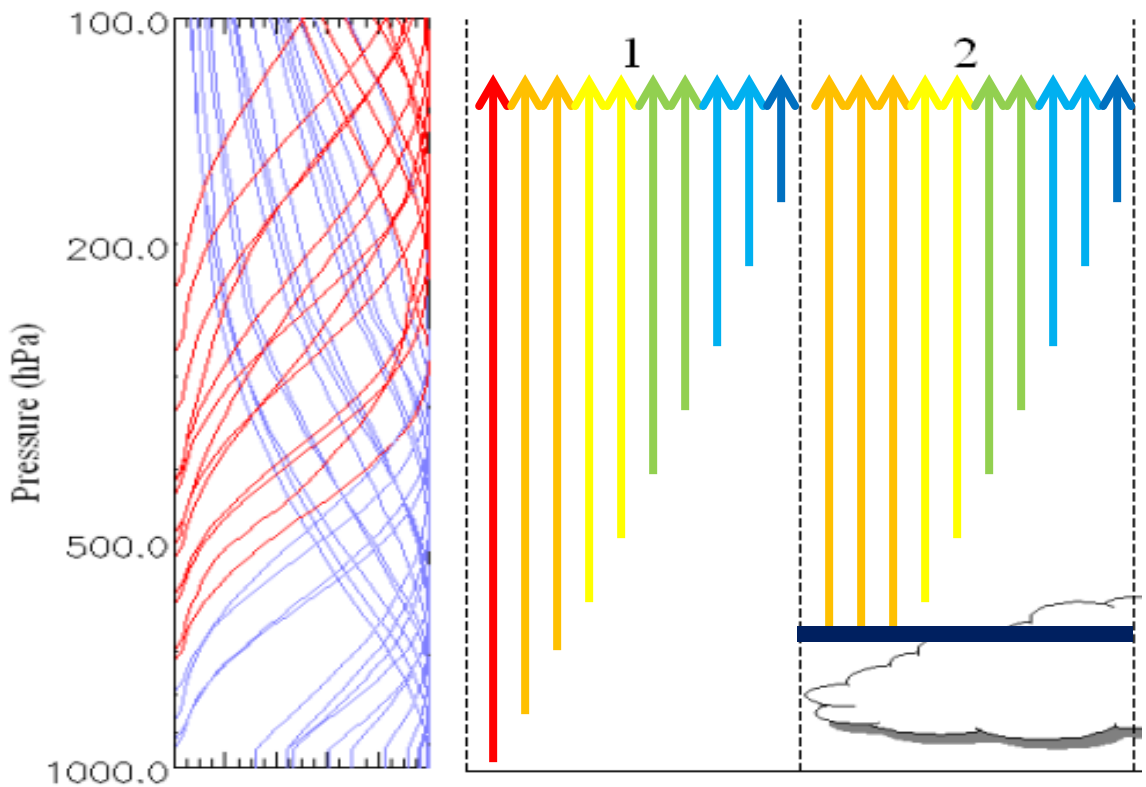
Instead of attempting all-sky, initial approaches are focusing on the cloudiest observations

Clear IR Measurement =

Surface + Σ(Atmospheric Layers)

Cloudy IR Measurement =

Cloud Top + Σ(Atmospheric Layers above cloud)



Retrieved Cloud Height

Clouds in the Infrared

In the cloud height retrieval, a cloud fraction, N, is also solved

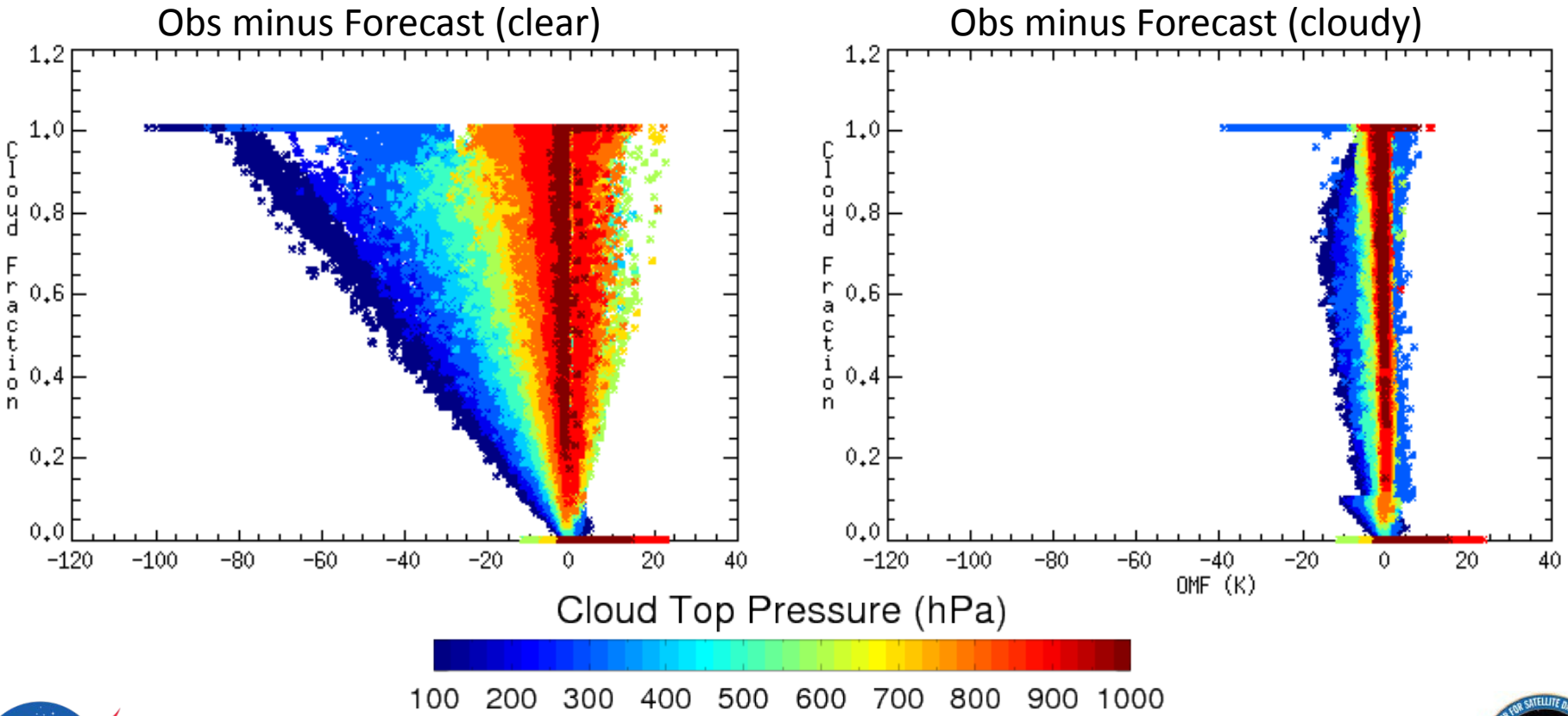
Under the graybody assumption, the partially cloudy observation can then be considered for a single, fractional cloud as:

Partially Cloudy IR Measurement =
*N * Cloudy IR Measurement +*
*(1 – N) * Clear IR Measurement*

In the GSI, we can then restructure the H operator to include the Cloud Height and Cloud fraction to allow for a partially cloudy forward operator (and also partially cloudy Jacobians)

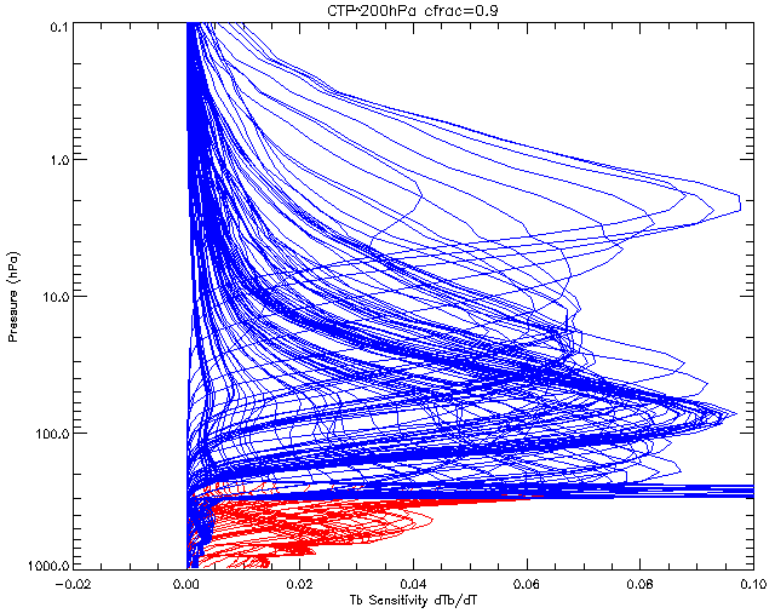
Considering the O-Fs versus cloud fraction, it is seen that the O-Fs are closer, but the cold bias is, as expected, amplified for higher (colder) clouds

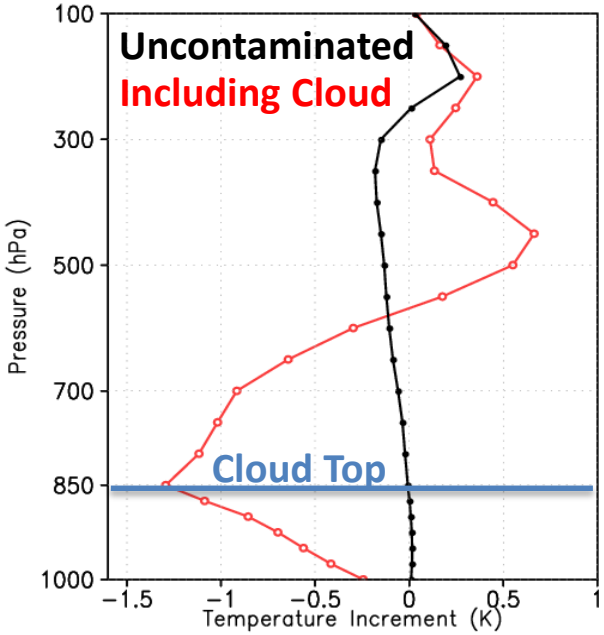
The accuracy of the calculated cloudy radiance is fundamentally dependent on **the accurate retrieval of cloud height and fraction**



Cloudy Infrared Radiance Assimilation

- Jacobians are adjusted to move sensitivity from below cloud to cloud surface
- Single footprint assimilation shows that the system is drawing to the retrieved cloud top
  - Magnitude is inflated due to low observation errors.
- Error in CTP will result in an erroneous O-F, which then can negatively impact the analysis
- To compensate, CTP is allowed to vary in the minimization as a control variable





Observation-Centered Control Variables

Current GSI implementations consider control variable only in terms of grids (2D & 3D) and channel-by-channel bias predictors

Bias prediction coefficients are of the dimension [number of predictors, number of channels]

- each satellite channel on each instrument has its own set of predictors (i.e. MetOp_AMSU-A channel 8 will have the same set of five coefficients across every footprint globally

Observation-Centered control variables

- consider a control variable at a footprint location over all channels measured at that point
- Dimension dynamic -> any number of observation-centered control variables can be appended to the control vector

Observation-Centered Control Variables

Once developed, the functionality was expanded to CTP

- Cloud Fraction still considered constant and set as the retrieved value

Jacobians

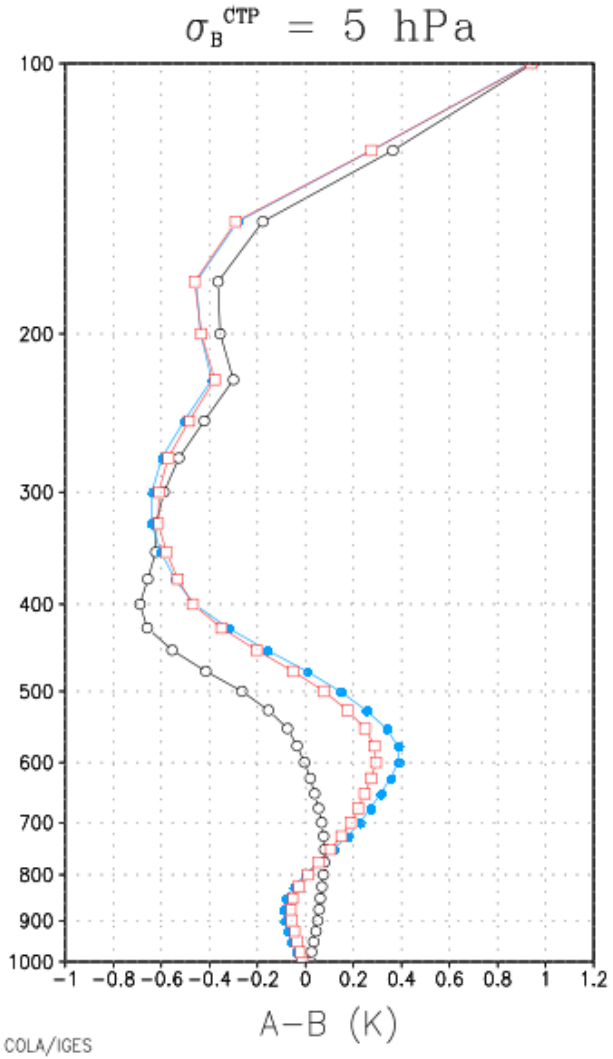
- In addition to modified $\partial T_B/\partial T(p)$, $\partial T_B/\partial q_v(p)$, etc., the minimization now incorporates the CTP Jacobian, $\partial T_B/\partial p_{cld}$.
- $\partial T_B/\partial p_{cld}$ can be directly differentiated from the radiative transfer equation (i.e. the appendix of Li et al. 2001)

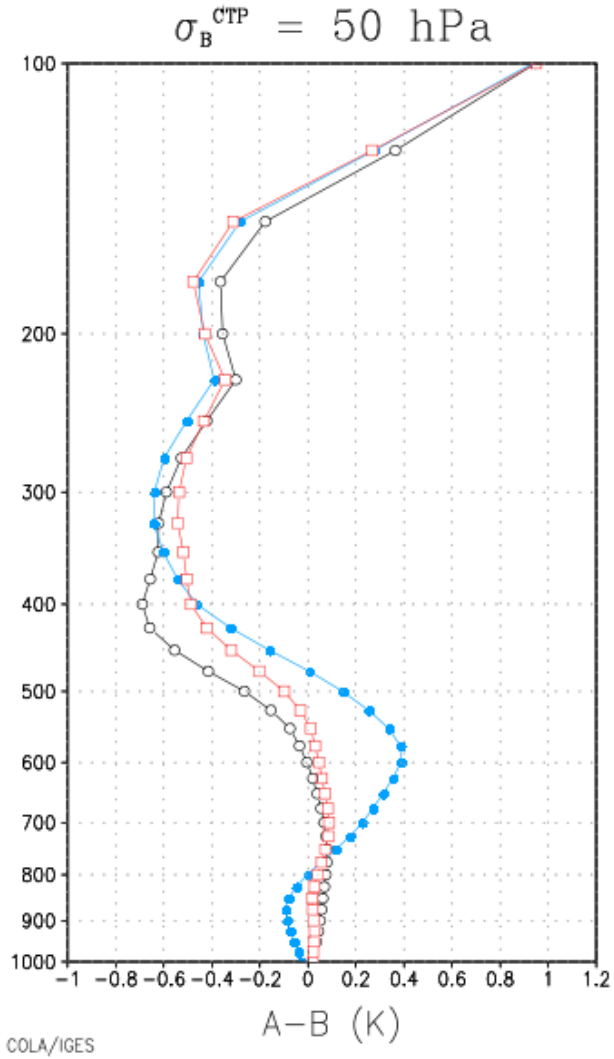
Background error for CTP

Background error for CTP

- Background error for CTP (σ_B^{CTP}) was considered first in a single-footprint case:
  - Initial CTP – 624 hPa
  - Initial N – 0.968
- Consider behavior of two values of σ_B^{CTP} compared to clear-sky observations only and a static CTP (no variational CTP)
  - σ_B^{CTP} = 50 hPa and 5 hPa

Background error for CTP





Clear

Cloudy Static CTP

Cloudy varCTP

Background error for CTP

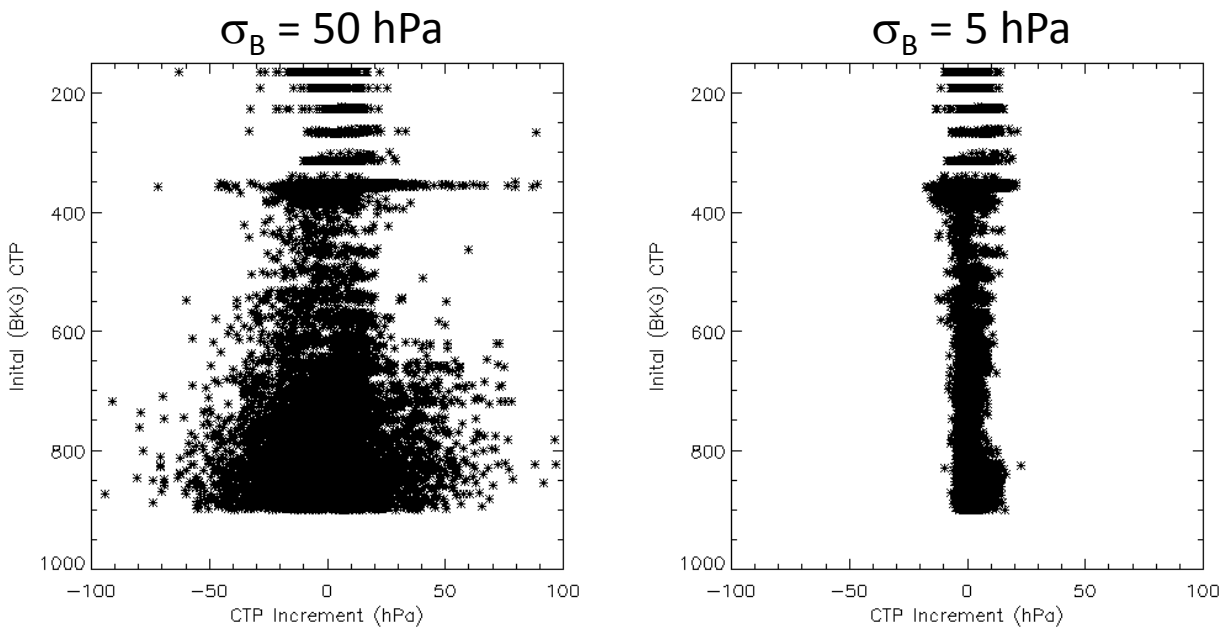
Variational CTP acts as a "sink", as a function of σ_B^{CTP}

- As the bkg error is increases, the cloud signal is absorbed into the CTP variable
- the solution approaches clear-only result
- As bkg error is decreased, result approaches static CTP
  - Expected as CTP is tightly constrained to retrieved guess

This is only for a single footprint. How does the analysis respond to a full suite of observations

- Since only CTP is varying, only consider cloudy IR if 1.0 $\geq$ N $\geq$ 0.9 -> higher confidence in cloud height for opaque clouds

CTP Increments

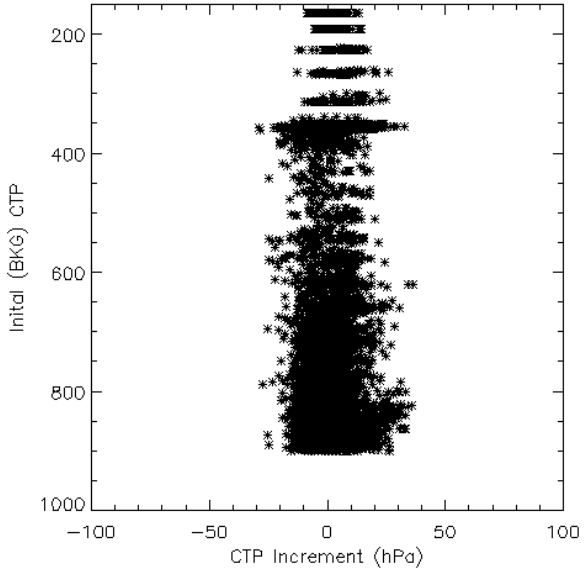


On a full analysis, large CTP background error values had a negative impact on the convergence of the minimization

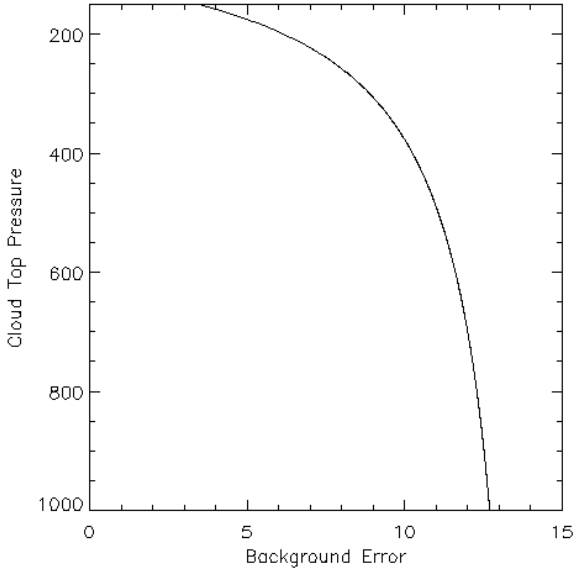
- Consistent with Tony McNally's effort @ ECMWF

CTP Increments

$\sigma_B = f(CP)$



Error Model



One potential issue involved with this is the use of a single σ_B value

- In this study, the real sensitivity we are adding is the temperature of the cloud top
- The $\partial T/\partial p_c$ @ 250 hPa very different than $\partial T/\partial p_{cld}$ at 850 hPa

Advancing the Assimilation Methodology

Cloud-affected infrared radiances are considered as a second stream of data

- Each AIRS, CrIS, and IASI footprint is considered twice – once for clear-sky assimilation and once for cloudy assimilation

Data in the GSI is thinned to a 145 km thinning grid

- Data selection on this grid is key to increasing yields
- For clear-sky assimilation, many tests are performed to get the clearest footprint available
- For cloudy assimilation, the "cloudiest" footprint is desired – but what does that mean?

It is noted here that "selected" means data that gets past thinning. Data that is "used" is actively assimilated. *Selected data can still be excluded by quality control*

Data Thinning and Selection

For AIRS and CrIS, the coldest footprint, as determined by a 11 µm window brightness temperature, is selected

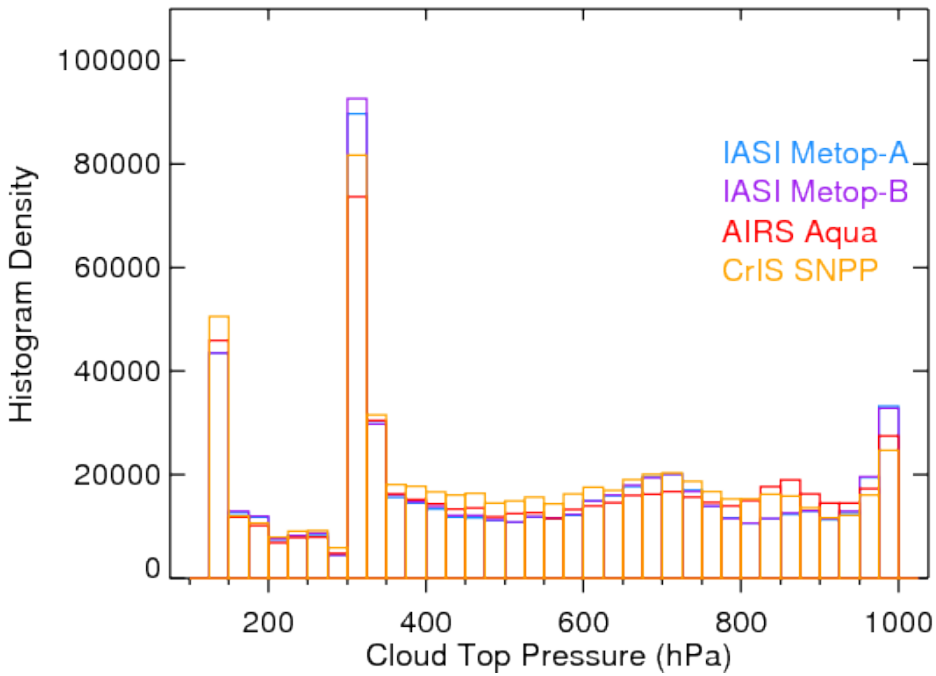
- This skews selection to heterogeneous scenes, as a flat cloud will be warmer than a flat cloud that is under thin cirrus

The IASI data streams (BUFR) include AVHRR cloud information

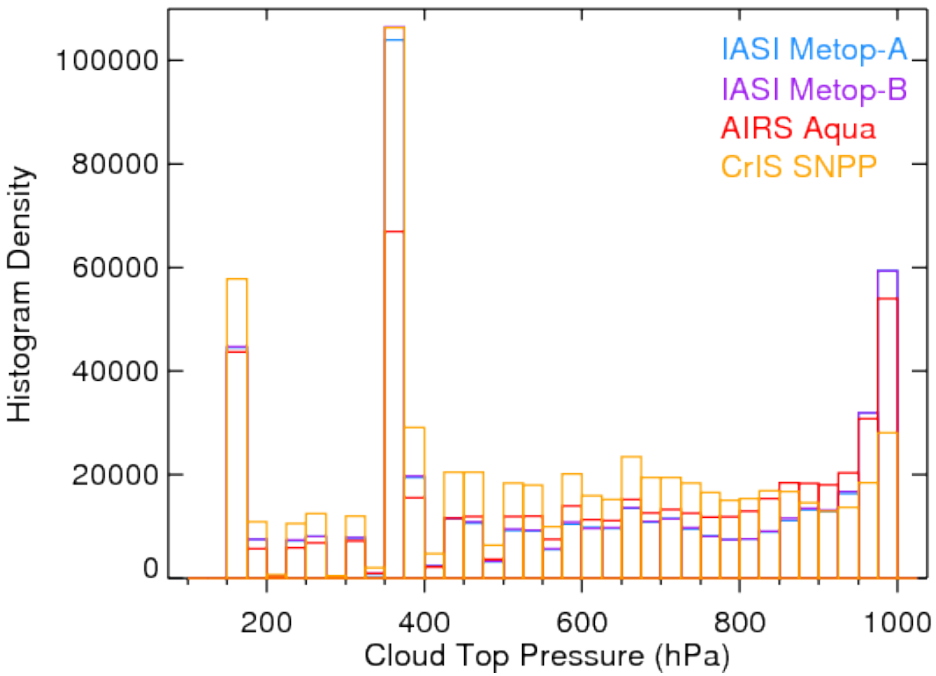
- The number of cloud levels, determined by a clustering algorithm, and their fractional coverage is reported
- Clear-sky data thinning uses this data to avoid clouds
- Now, the cloudy radiance assimilation can use this to increase the likelihood of selecting homogeneous cloud scenes
  - Simply exclude all observations that have more than two cloud clusters
  - This would make sense for clear observations as well

Selected Data

All Selected Data – Cloudy Stream



All Selected Data – Clear Stream

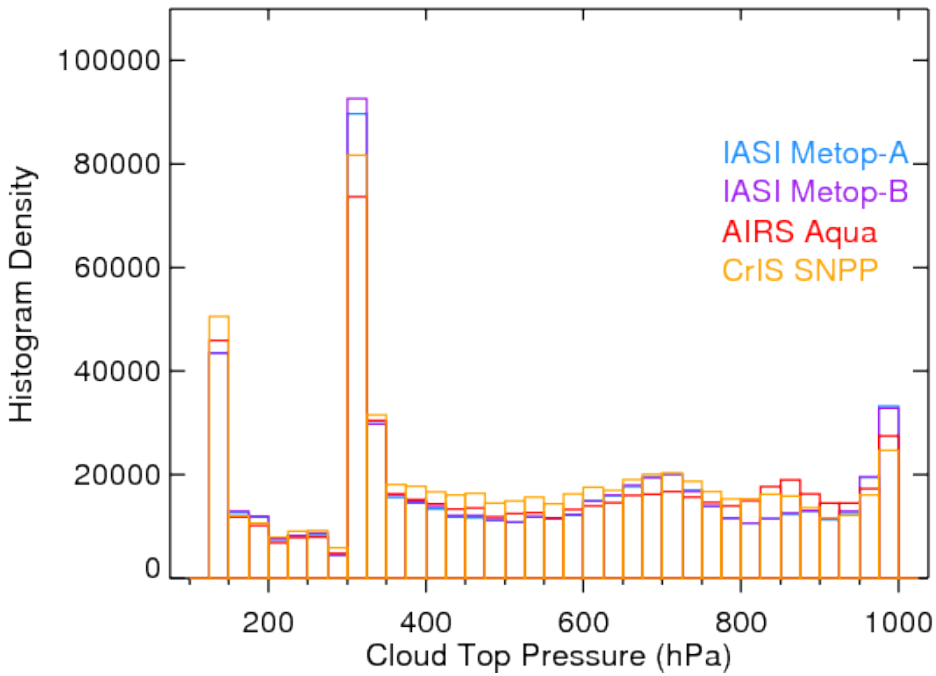


By design, the distributions are shifted towards higher cloud retrievals for all four instruments

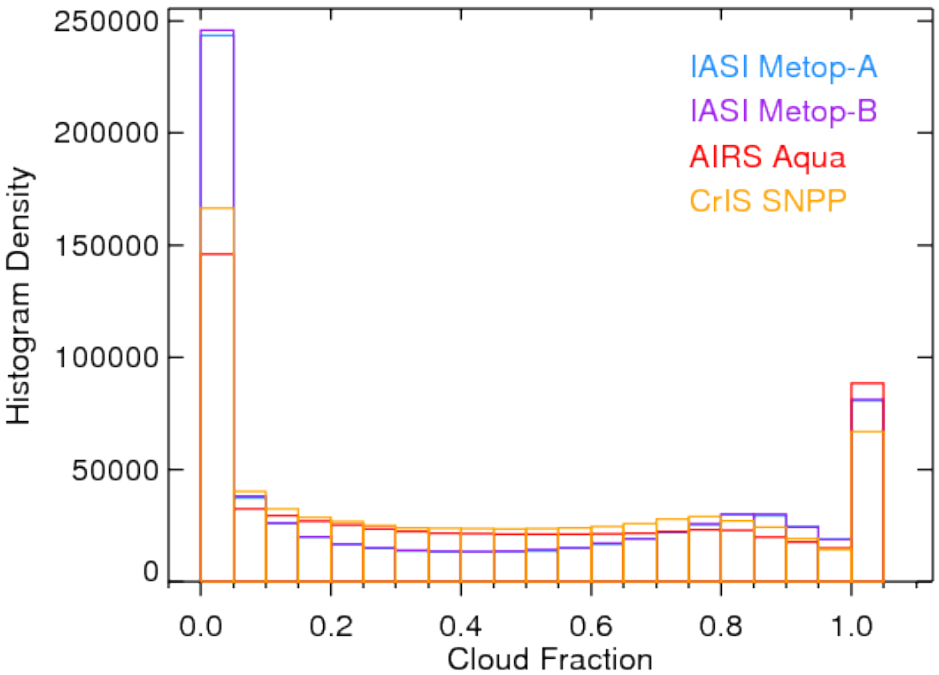
- In cloudy situations, AIRS and CrIS behave more like each other than the IASI instruments
- The comparison of cloud fractions for the two streams is not shown, but are consistent in that cloud fraction increases in the cloudy stream

Selected Data

All Selected Data – Cloudy Stream



All Selected Data – Cloudy Stream

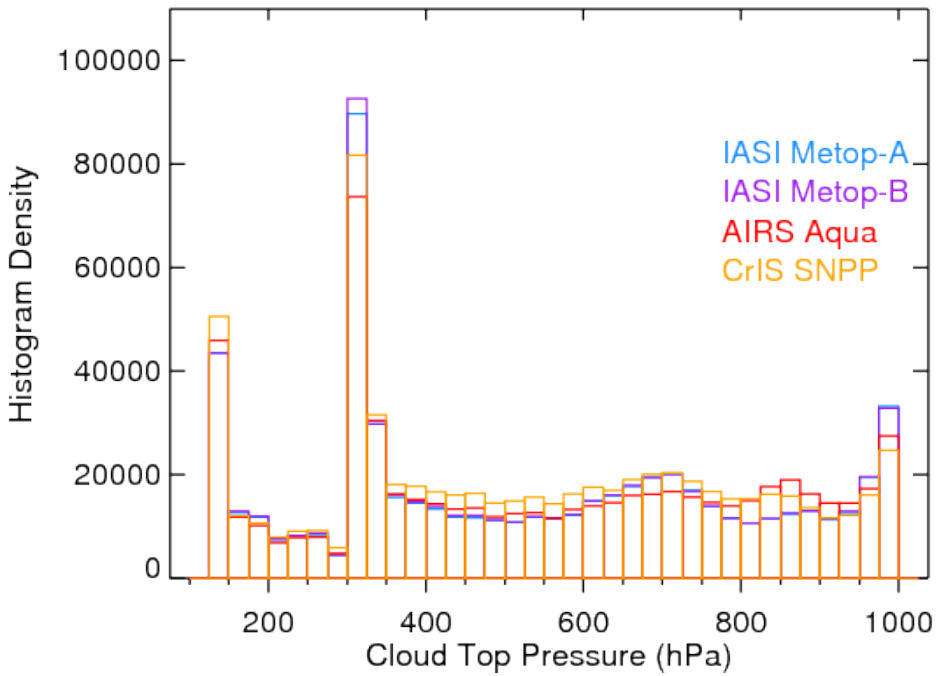


In cloudy selection, IASI is shifted towards opaque, which CrIS and AIRS both are more flat across all fractions

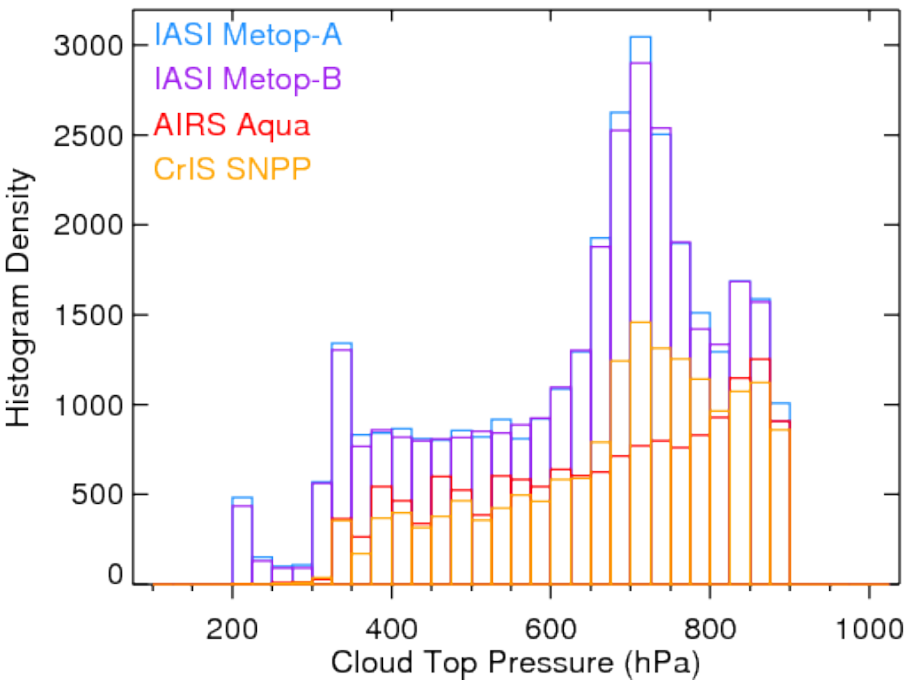
- Though non-physical, cloud fractions greater than 1.0 can be retrieved, though they cannot be assimilated
- In this approach, opaque observations are considered ideal, so skewing the distribution towards opaque is ideal

Selected Data and Used Data

All Selected Data – Cloudy Stream



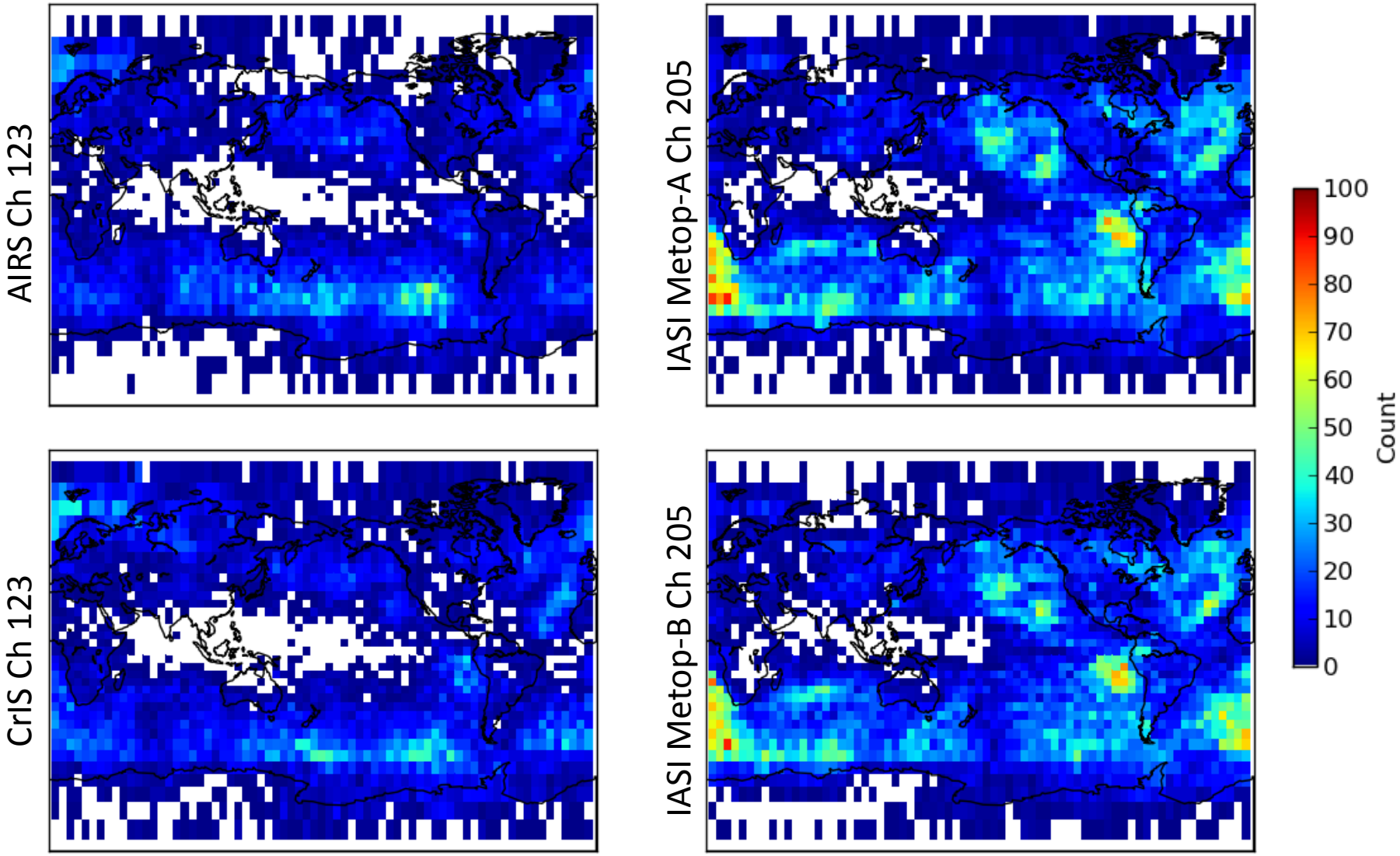
All Selected Data – Cloudy Stream



Once considering only those that fall within certain thresholds of cloud fraction (0.9 – 1.0) and cloud height (200-900 hPa), observation only a small fraction of observations considered are retained

- The increase generally ranges an increase of 4-8% of total radiances, but these percentages can mean different (i.e. no WV channels in cloudy)

Spatial Distribution of Assimilated Data

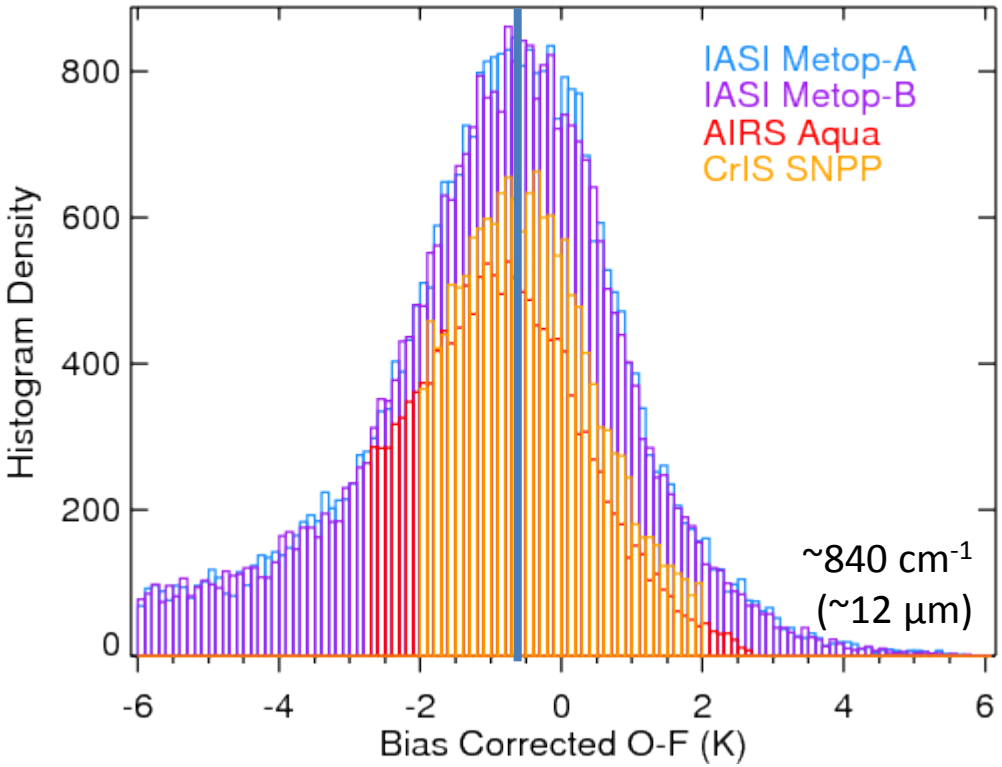


O-F Distribution

Clearly skewed distribution across all instruments
- Cloud Heights skewed high
- Better gross checks needed to eliminate long tail

Shift in mode of AIRS vs other instruments

The yield of IASI is still larger, near the mode, but the tails are larger
- Improvement near the mode shows potential benefit of cluster analysis
- The overall increase in yield is also do to more loose gross checks



Future Work and Conclusions

The minimum-residual cloud height retrieval seems to be a fundemental limitation of all infrared assimilation

- Letting clouds into clear radiance assimilation
- Height characterization alone note enough information for cloudy assimilation
- Validation shows that the retrieval is flawed

Clustering algorithms to CrIS, AIRS may be useful

- Develop a preprocessor? Need to colocate a lot of observations from MODIS, VIIRS
- CrIS will eventually get cloud height and fraction information in BUFR stream, but that may not be enough for heterogeneity

The first step is to evaluate gross checks – displacement of mode and mean will affect bias correction