Radiance Data Assimilation

Rahul Mahajan
for
Andrew Collard

NCEP/NWS/NOAA/EMC – IMSG

DTC GSI Tutorial

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Outline

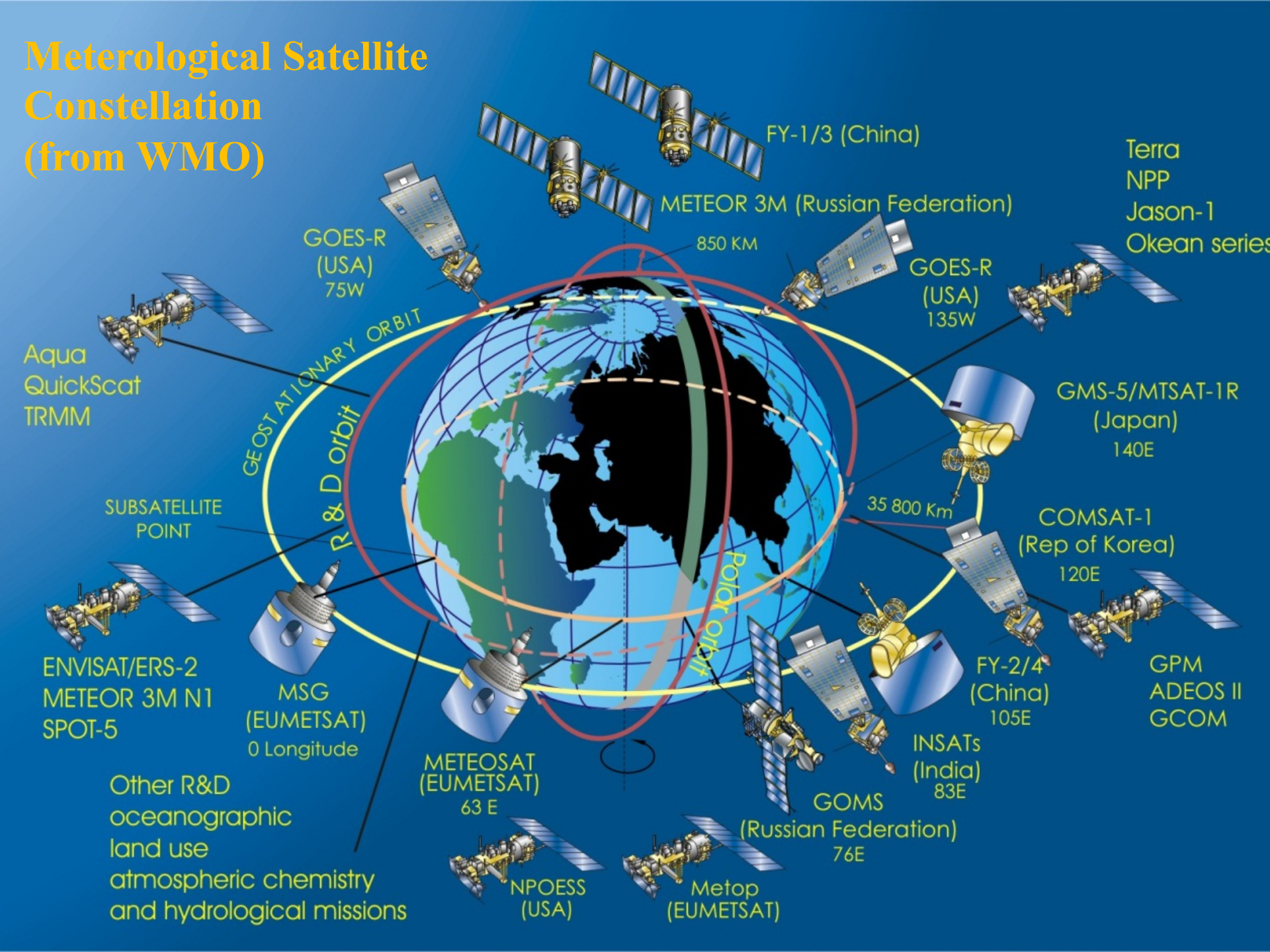
- Introduction
- Different types of satellite data.
- Basic Concepts for Assimilating Observations from Passive Nadir Sounders
- Assimilating satellite radiances.
  - Data assimilation equation
  - Quality control and Observation Errors.
  - Bias correction.
  - Thinning
  - Monitoring.
- Some Comments on Cloudy Radiances.
- Final Comments

Introduction

- Satellites instruments do not directly measure the atmospheric state.
- Instead they measure radiation emitted by and/or transmitted by the atmosphere.
- This presentation describes the relationship between the atmospheric state and the observed radiation. And how the information contained therein is exploited through assimilation into the NWP model.

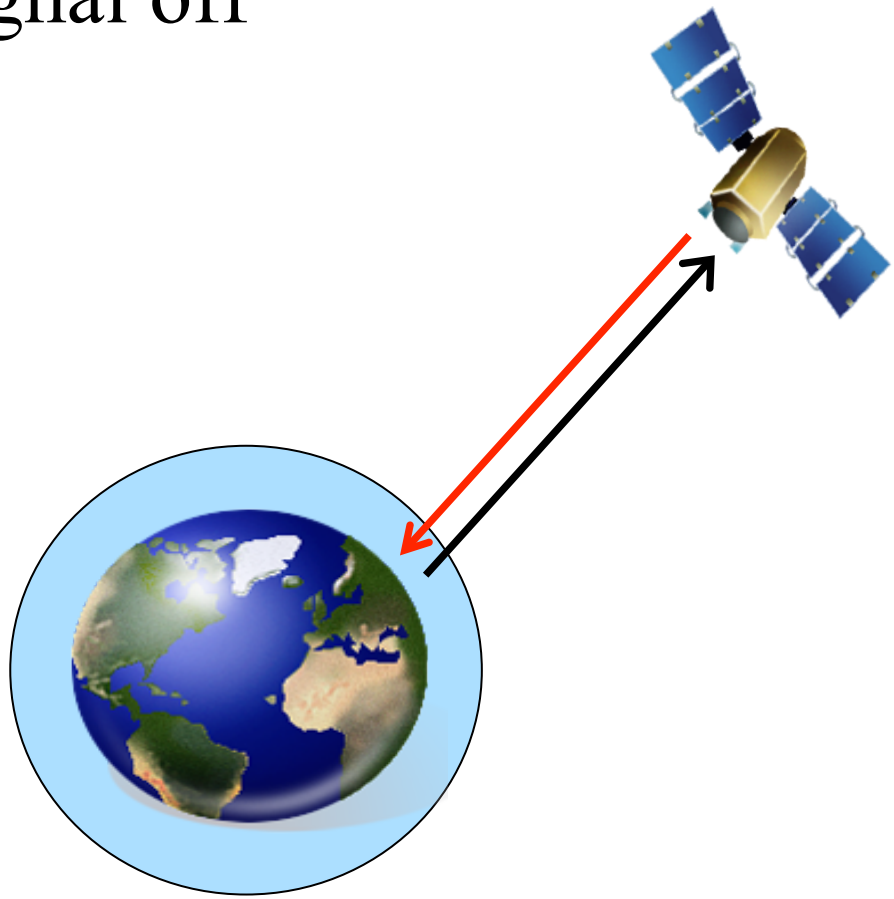
Different Types of Satellite Data

Meterological Satellite Constellation (from WMO)



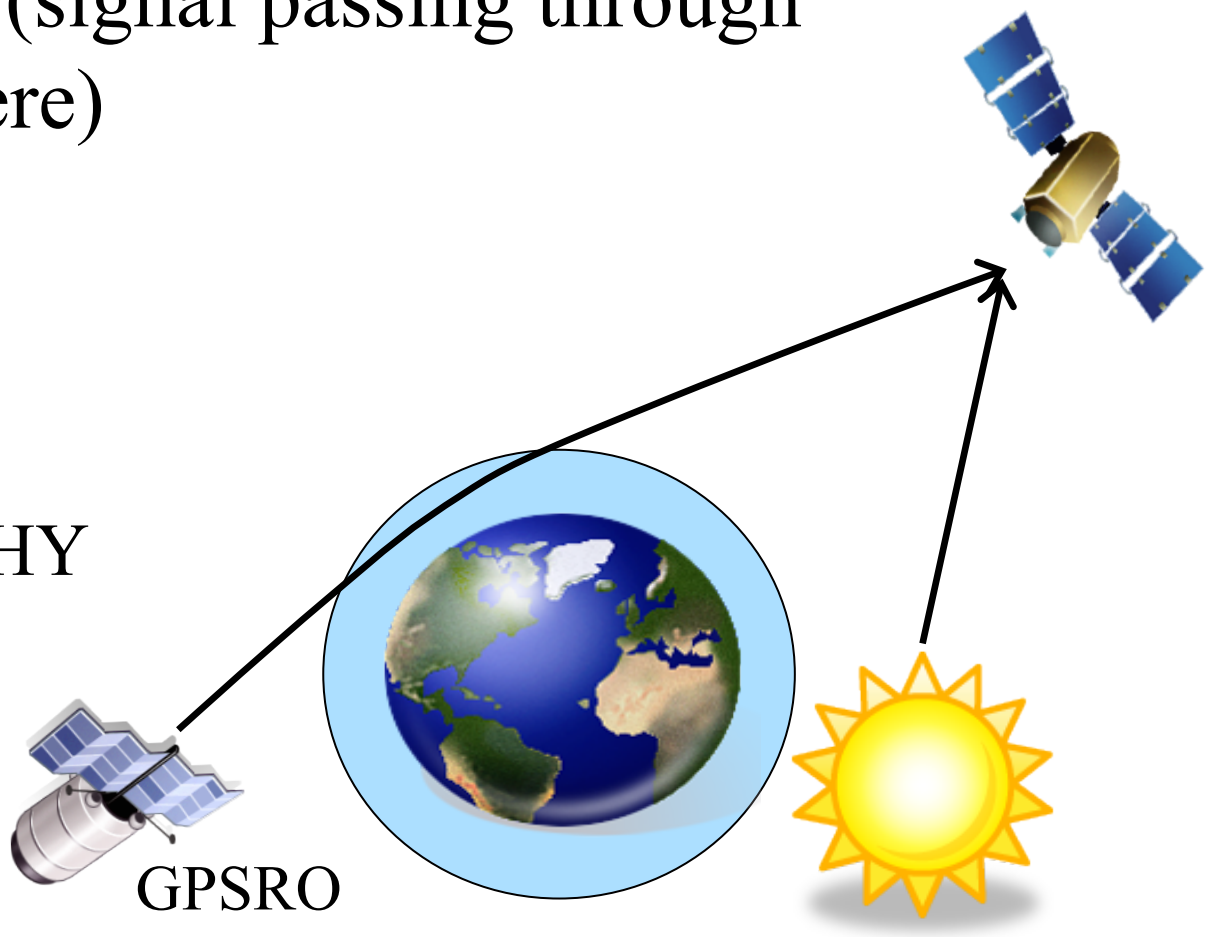
Different Types of Satellite Data

- **Active** (bouncing a signal off something)
  - Wind Lidar
  - SAR
  - Cloud radar
  - Scatterometry



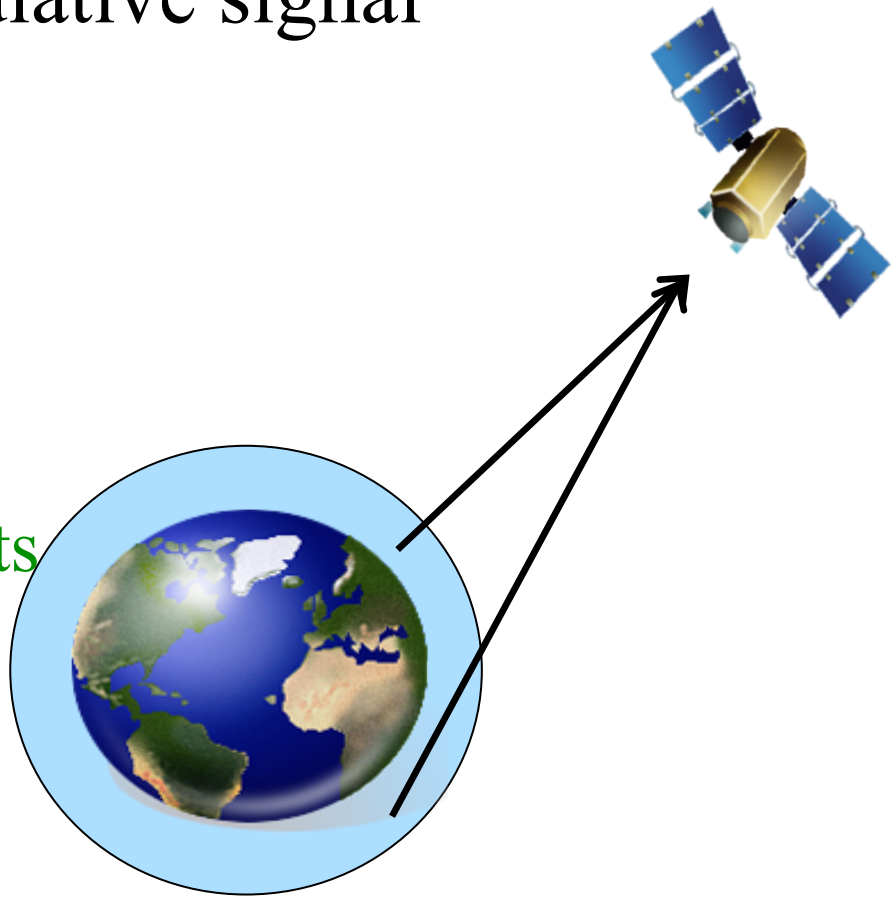
Different Types of Satellite Data

- **Occultation** (signal passing through the atmosphere)
  - HALOE
  - SAGE
  - SCIAMACHY



Different Types of Satellite Data

- **Passive** (receiving radiative signal from source)
  - Visible Instruments
  - IR Instruments
  - Microwave Instruments

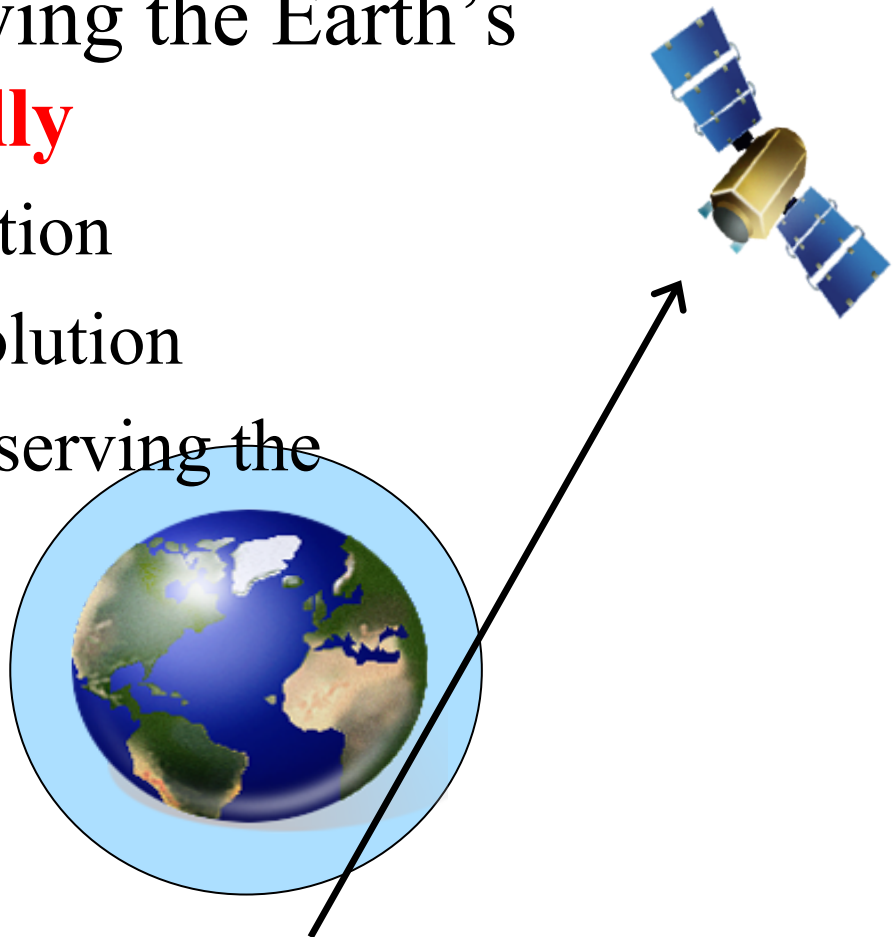


Passive Instruments

- This talk will focus on passive **infrared** and **microwave** instruments as they are the most common and biggest contributors to Numerical Weather Prediction

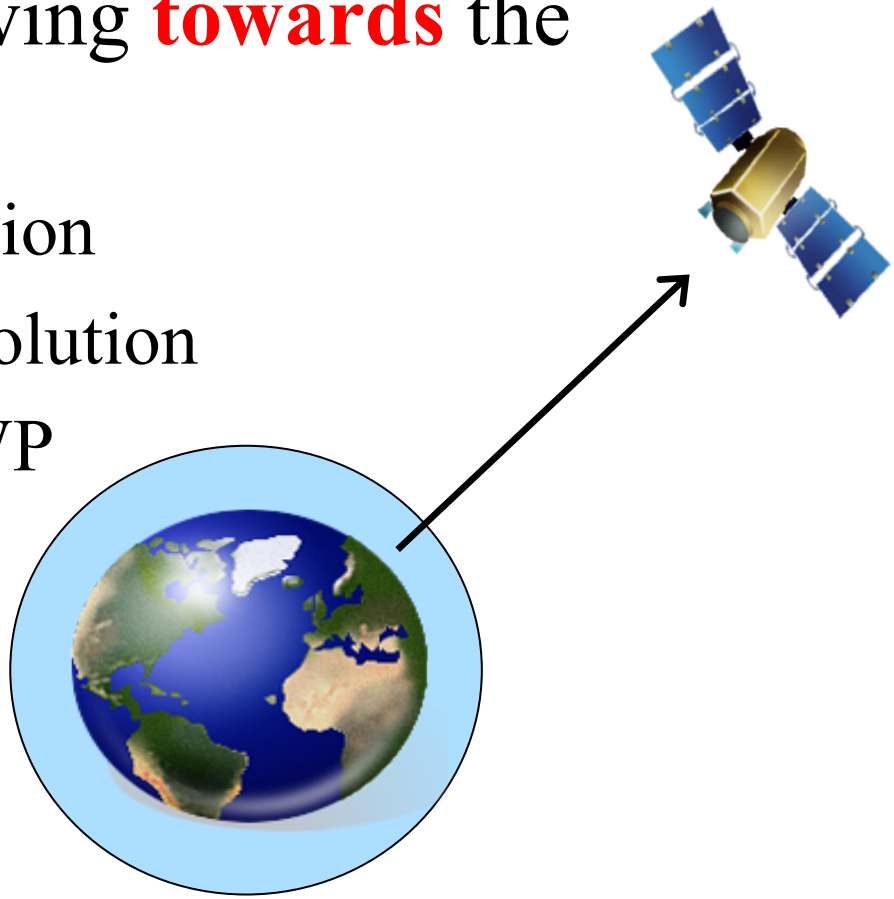
Geometry: Limb v/s Nadir Sounding

- **Limb sounding:** Viewing the Earth's atmosphere **tangentially**
  - **Higher vertical** resolution
  - **Lower horizontal** resolution
  - Most often used for observing the stratosphere and above
  - GPSRO
    - most commonly used



Geometry: Limb v/s Nadir Sounding

- **Nadir sounding:** Viewing **towards** the Earth's surface
  - **Lower vertical** resolution
  - **Higher horizontal** resolution
  - Most often used in NWP

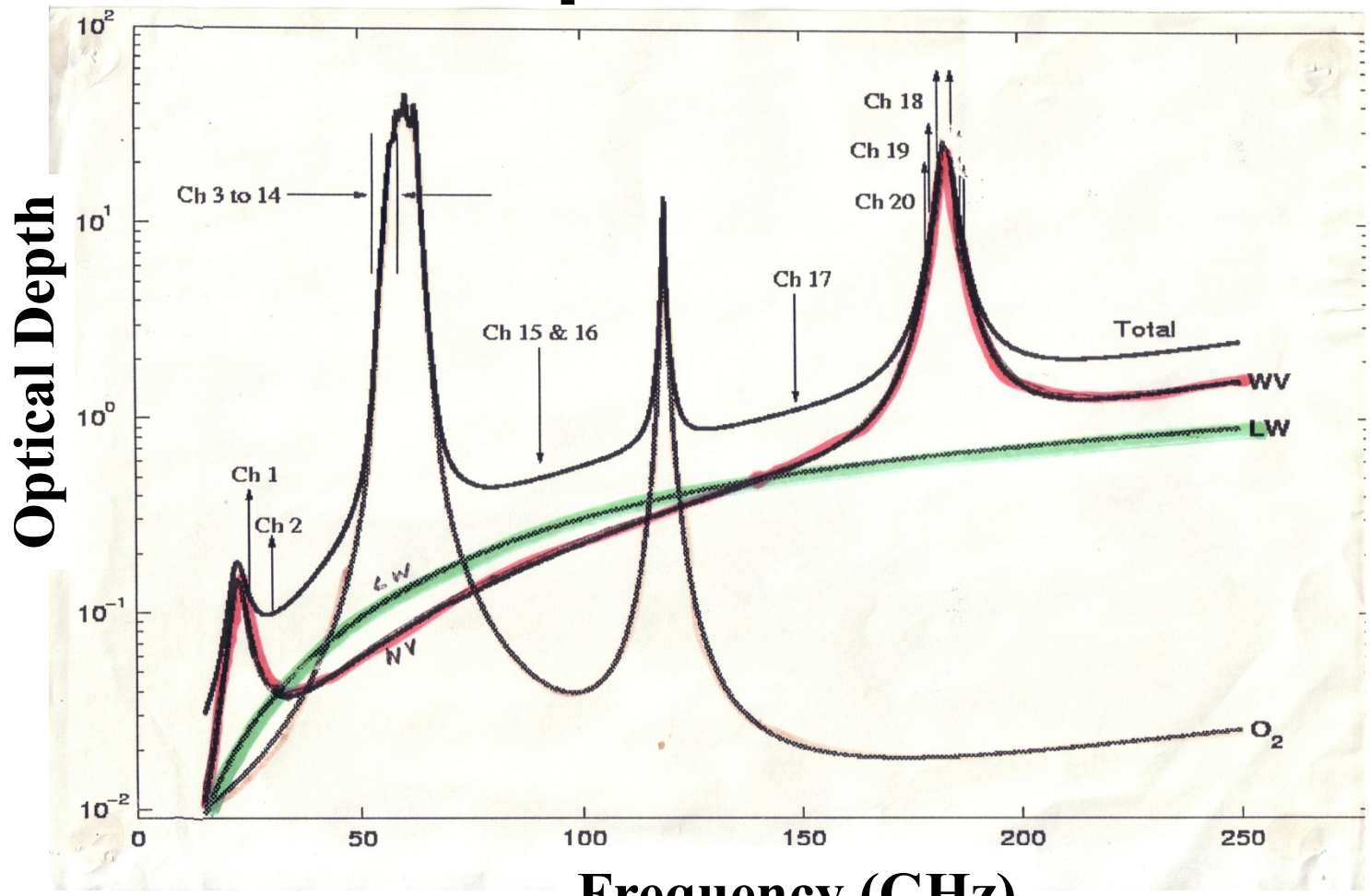


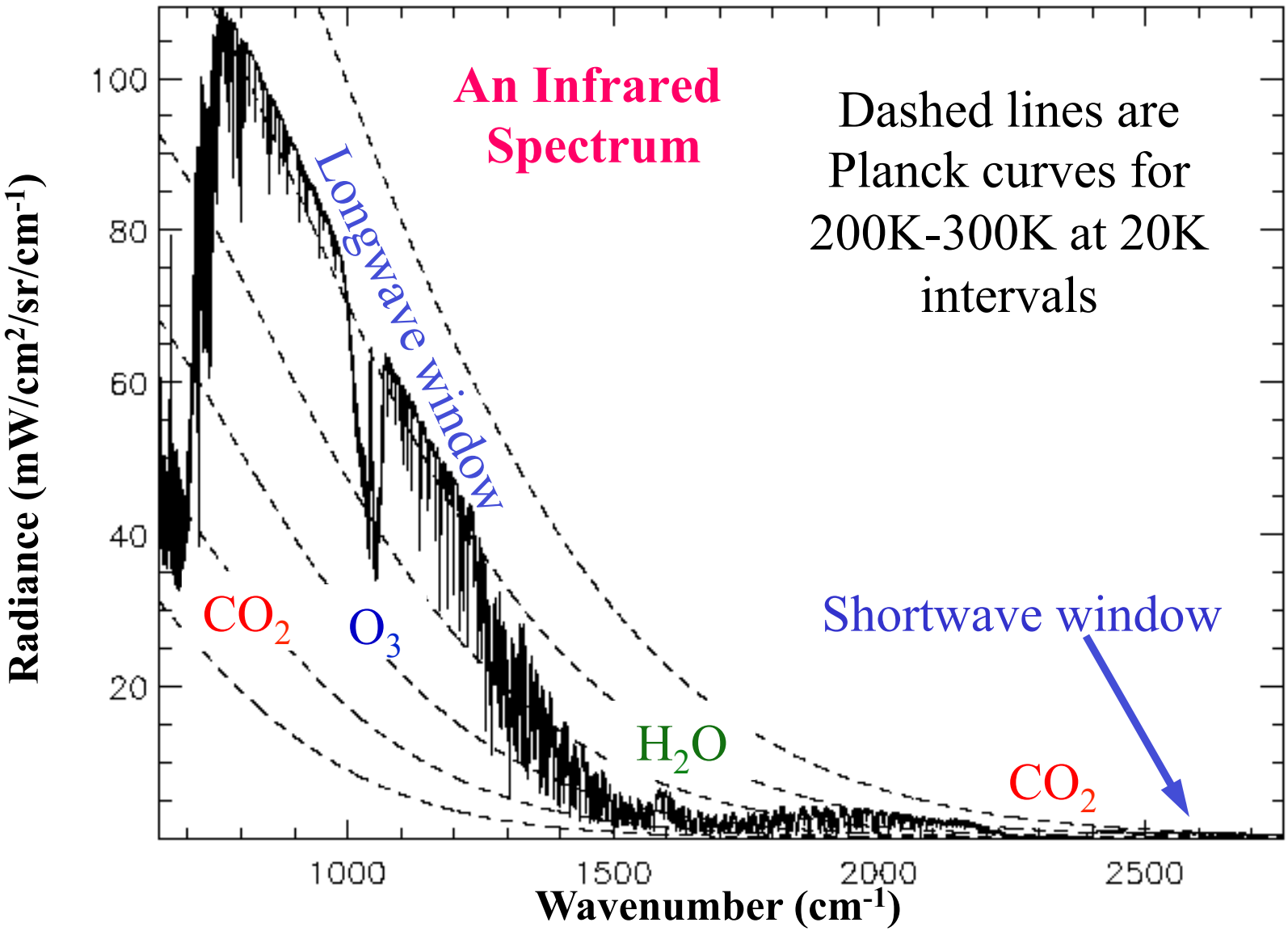
Basic Concepts for Assimilating Observations from Passive Nadir Sounders

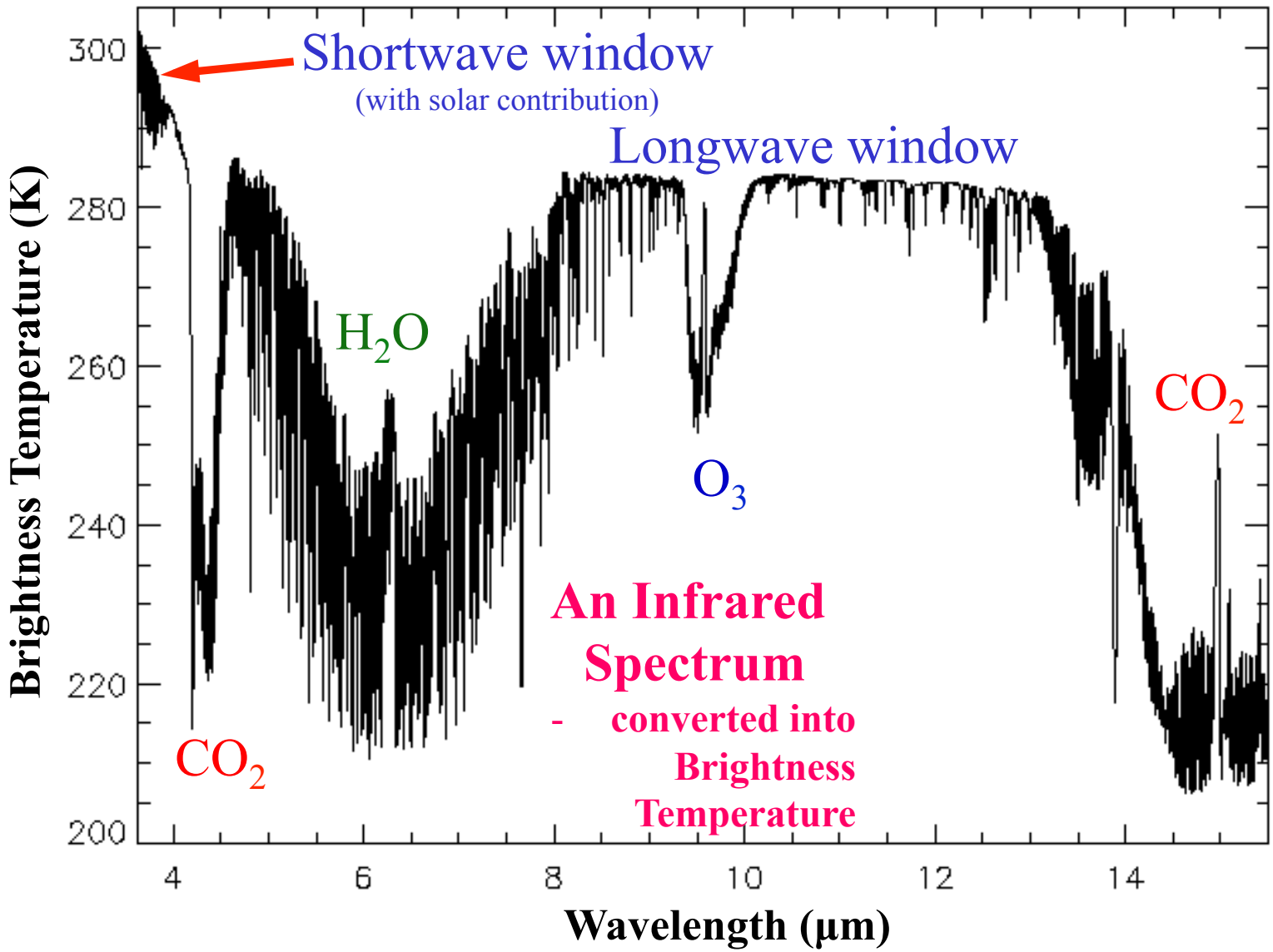
Taking advantage of the frequency dependent atmospheric absorption

- The atmosphere is variously opaque and transparent to electromagnetic radiation depending on the wavelength.
- We take advantage of this, plus the fact that at longer wavelengths we can observe thermal emission from the atmosphere itself to infer information on the atmosphere's temperature and humidity profile.

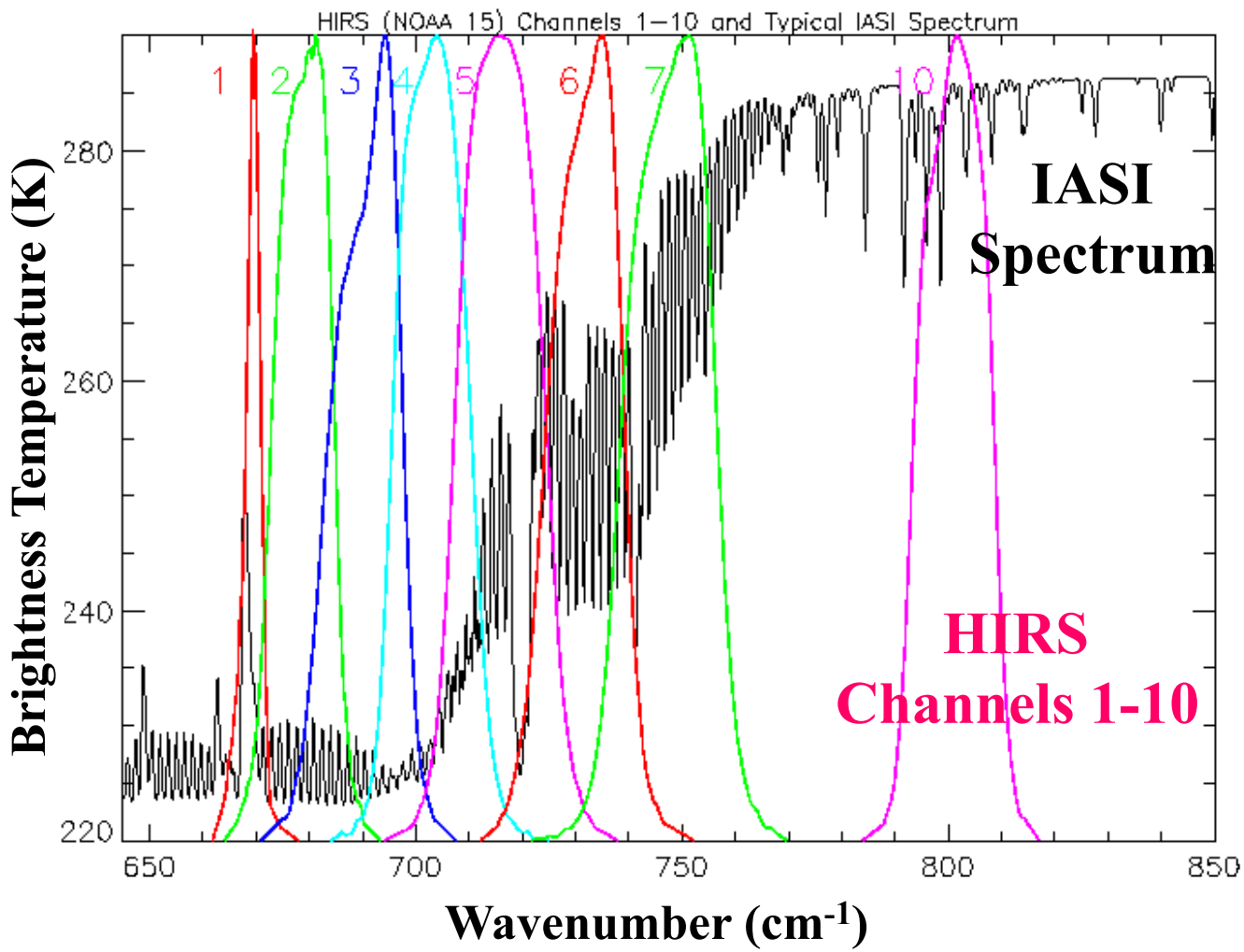
Atmospheric Opacity in the Microwave Spectrum




An Infrared Spectrum
Dashed lines are Planck curves for 200K-300K at 20K intervals
Longwave window
Shortwave window
CO_2
O_3
H_2O
CO_2
Radiance ($mW/cm^2/sr/cm^{-1}$)
Wavenumber (cm^{-1})
100
80
60
40
20
1000
1500
2000
2500

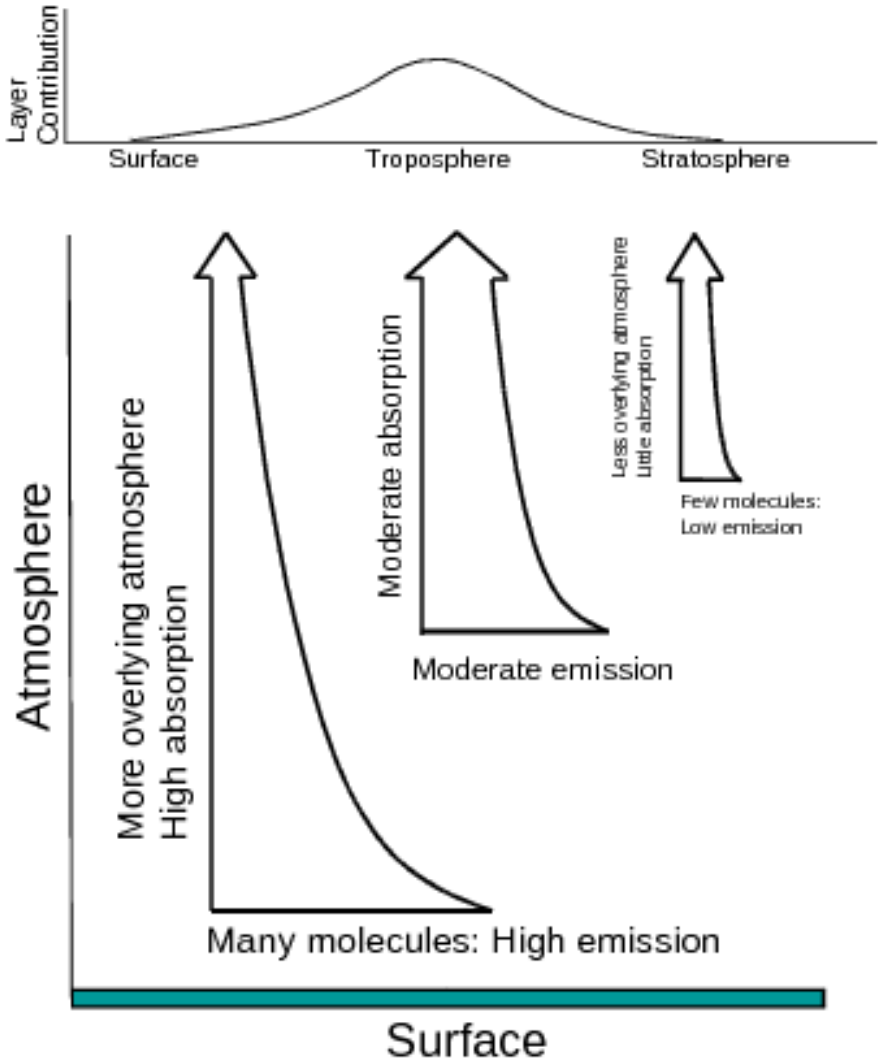

Shortwave window
(with solar contribution)
Longwave window
H_2O
O_3
CO_2
CO_2
An Infrared Spectrum
- converted into Brightness Temperature
Brightness Temperature (K)
300
280
260
240
220
200
4
6
8
10
12
14
Wavelength (µm)

IASI v/s HIRS: The Thermal Infrared

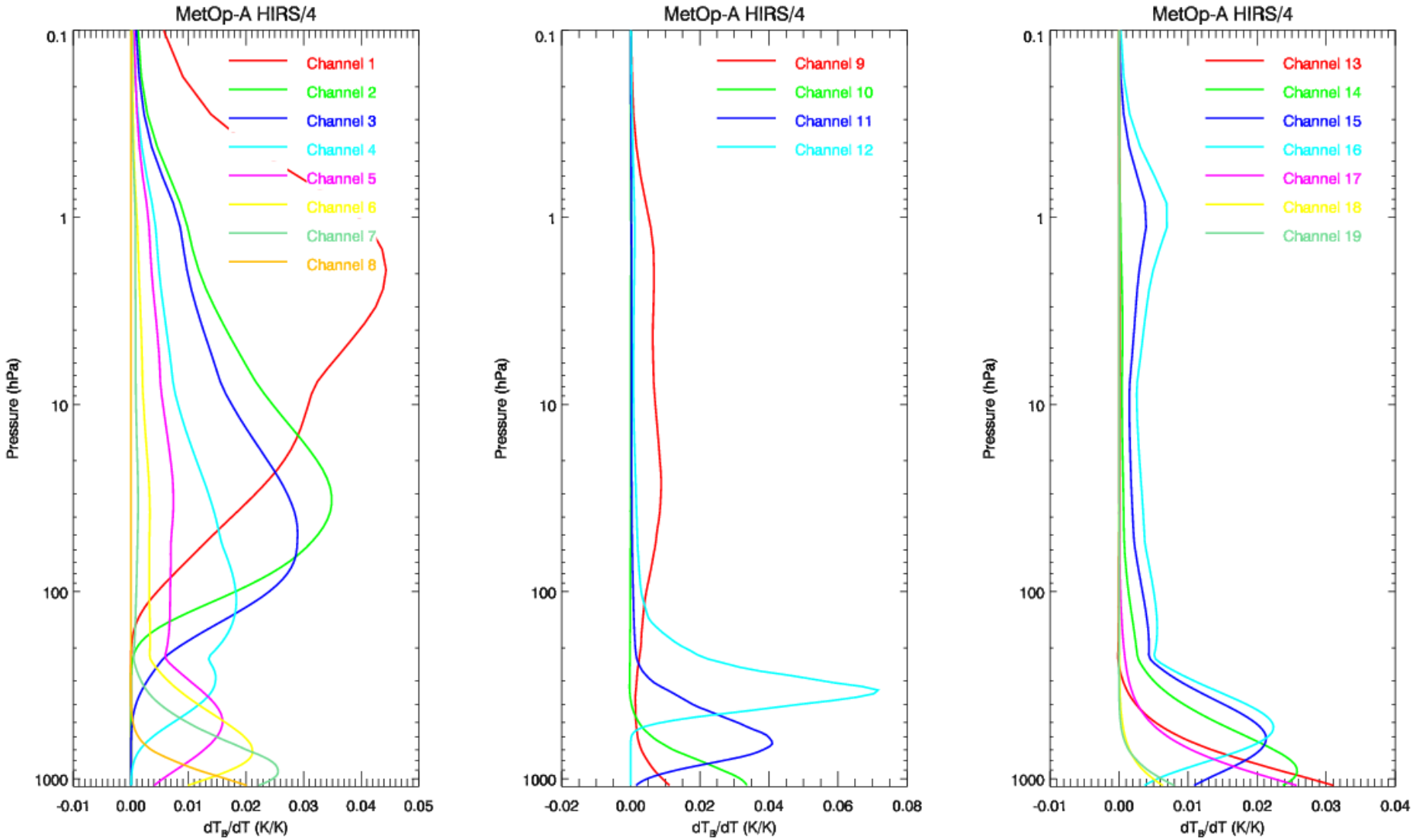


- **The temperature profile is the most important factor for determining the radiance observation**. The vertical distribution of emitting v/s absorbing gases also impacts observations.
- First step is to determine temperature profile. To do this, we need to choose frequencies where we know the absorption profiles already.
- We choose gases with a constant distribution to do this.
- For the infrared we use **CO_2**
- For the microwave we use **O_2**
- These are hence known as ***temperature sounding bands***.
- But all bands are sensitive to temperature, often – as in the case of H_2O – with sharper Jacobians.
- Once we have a good temperature profile we can use that to infer molecular abundances of variable species using appropriate frequencies.
  - This is actually performed simultaneously with the temperature estimation when we do data assimilation

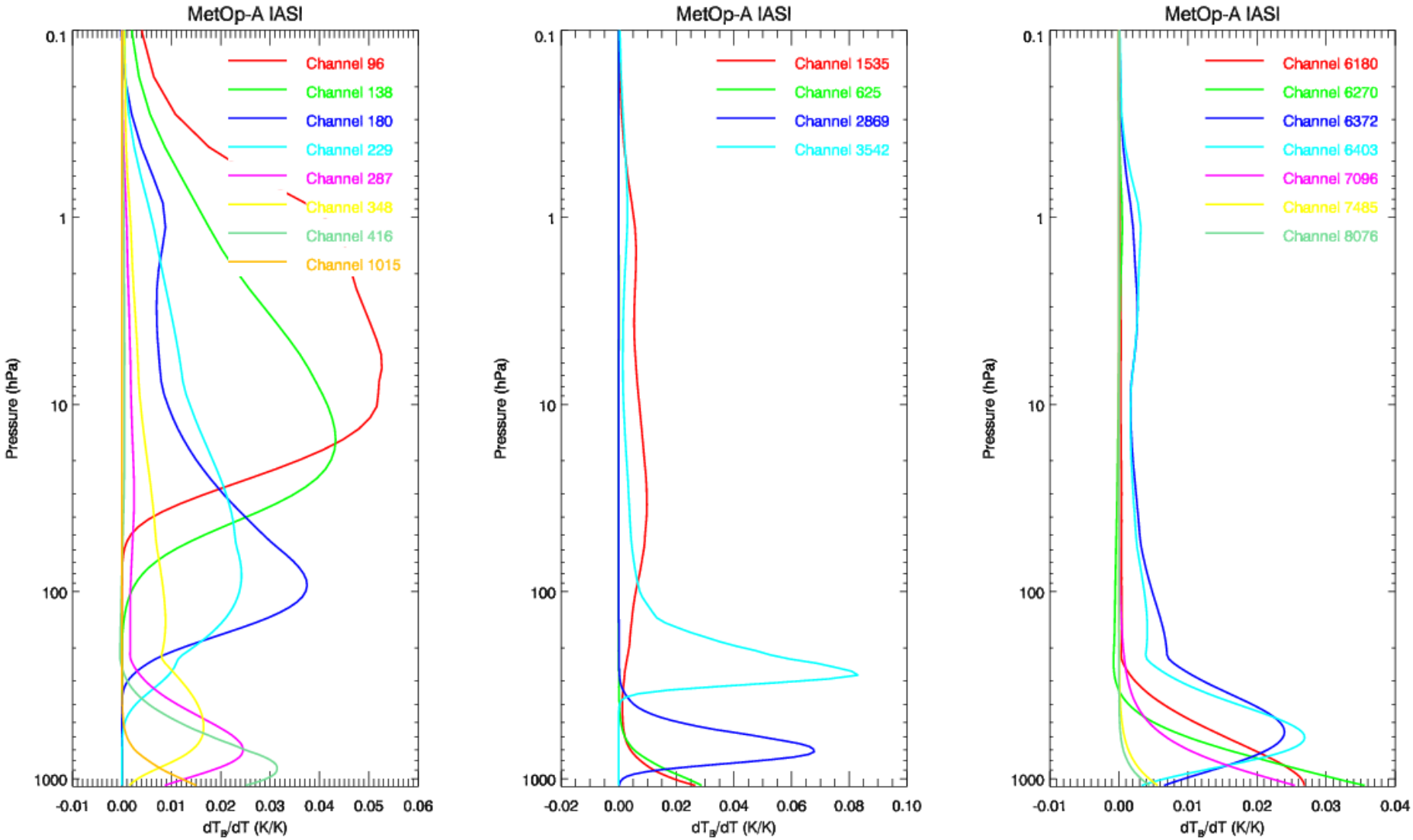
Illustration of Jacobian or Weighting Function



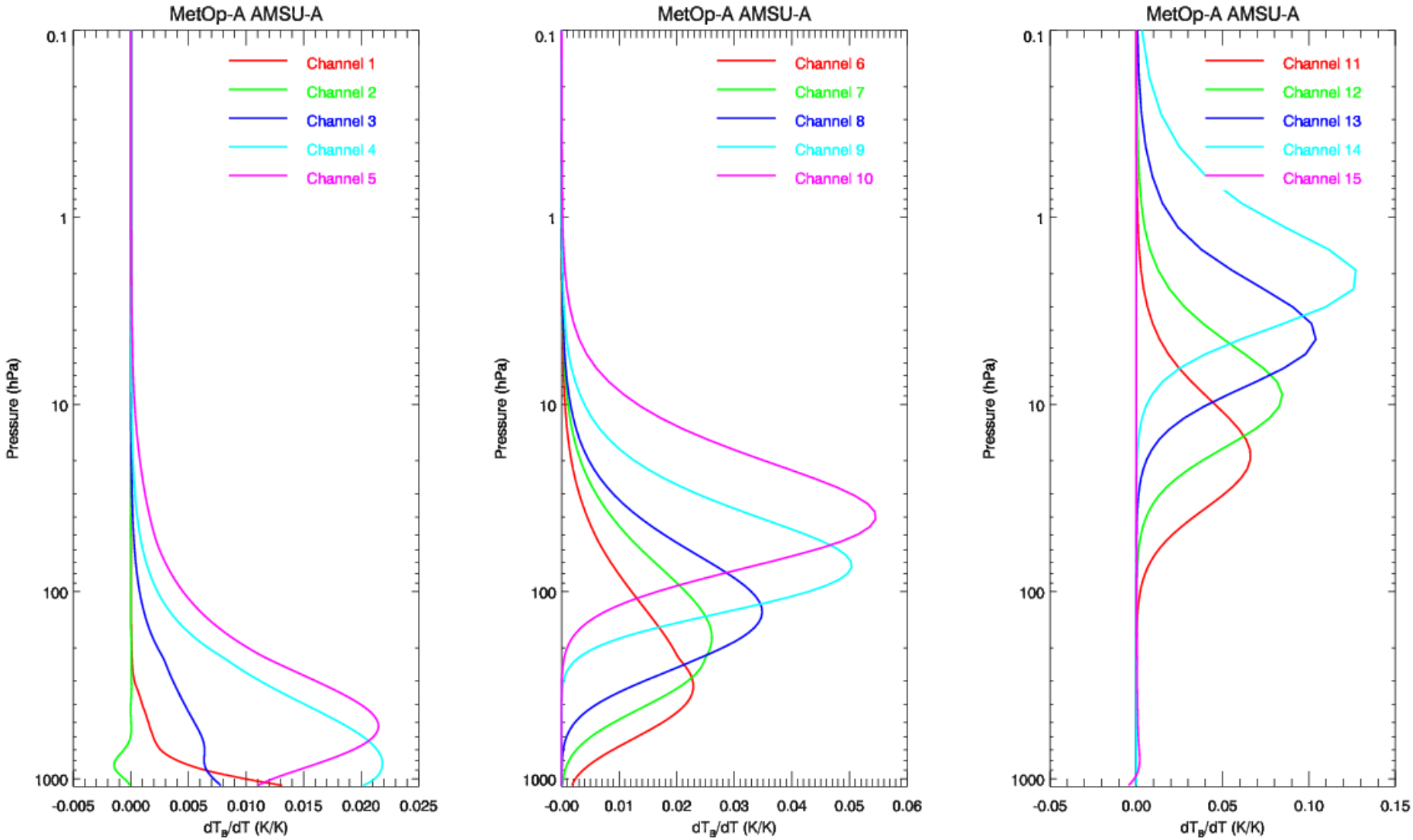
MetOp-A HIRS/4 [dT_B/dT]



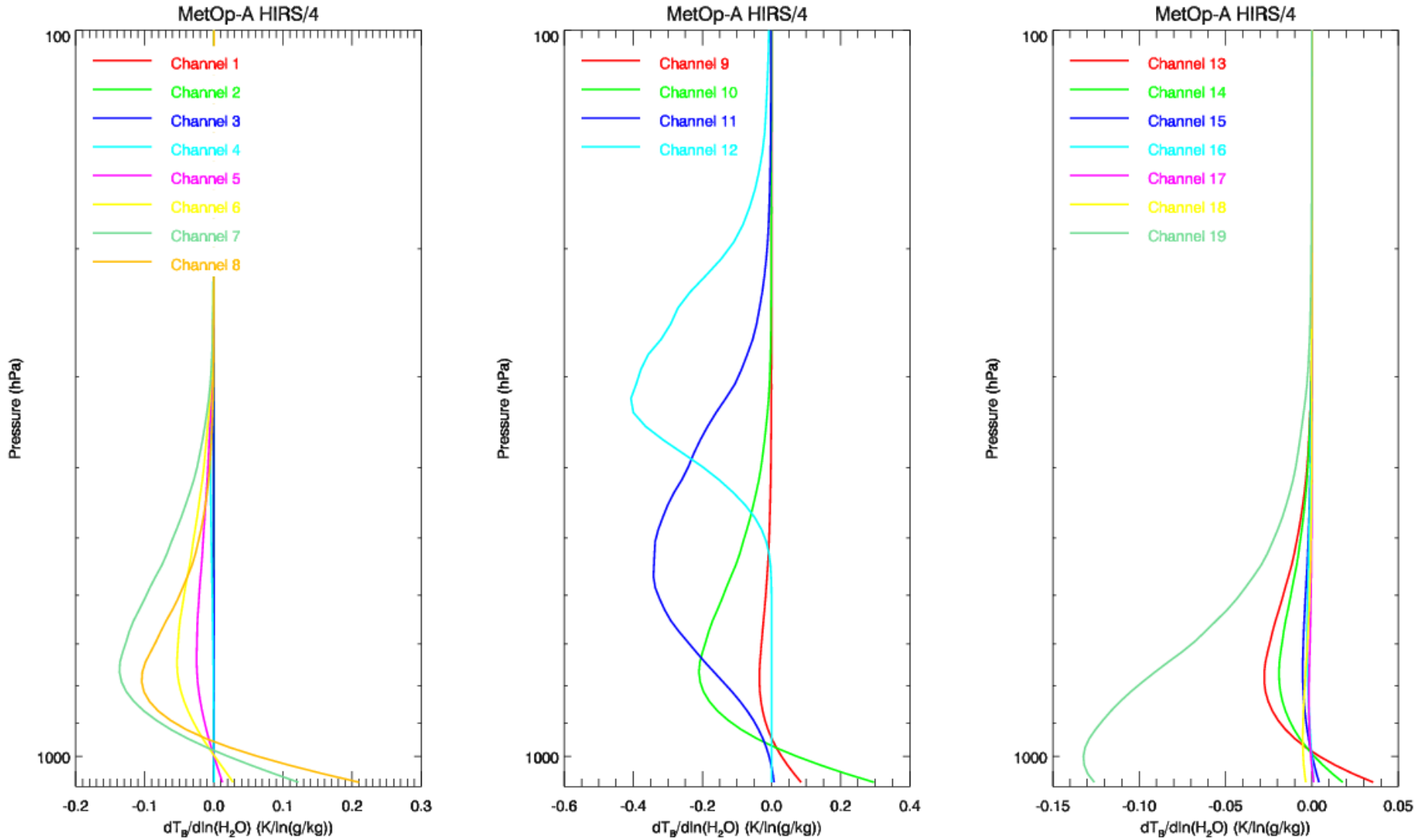
MetOp-A IASI [dT_B/dT]



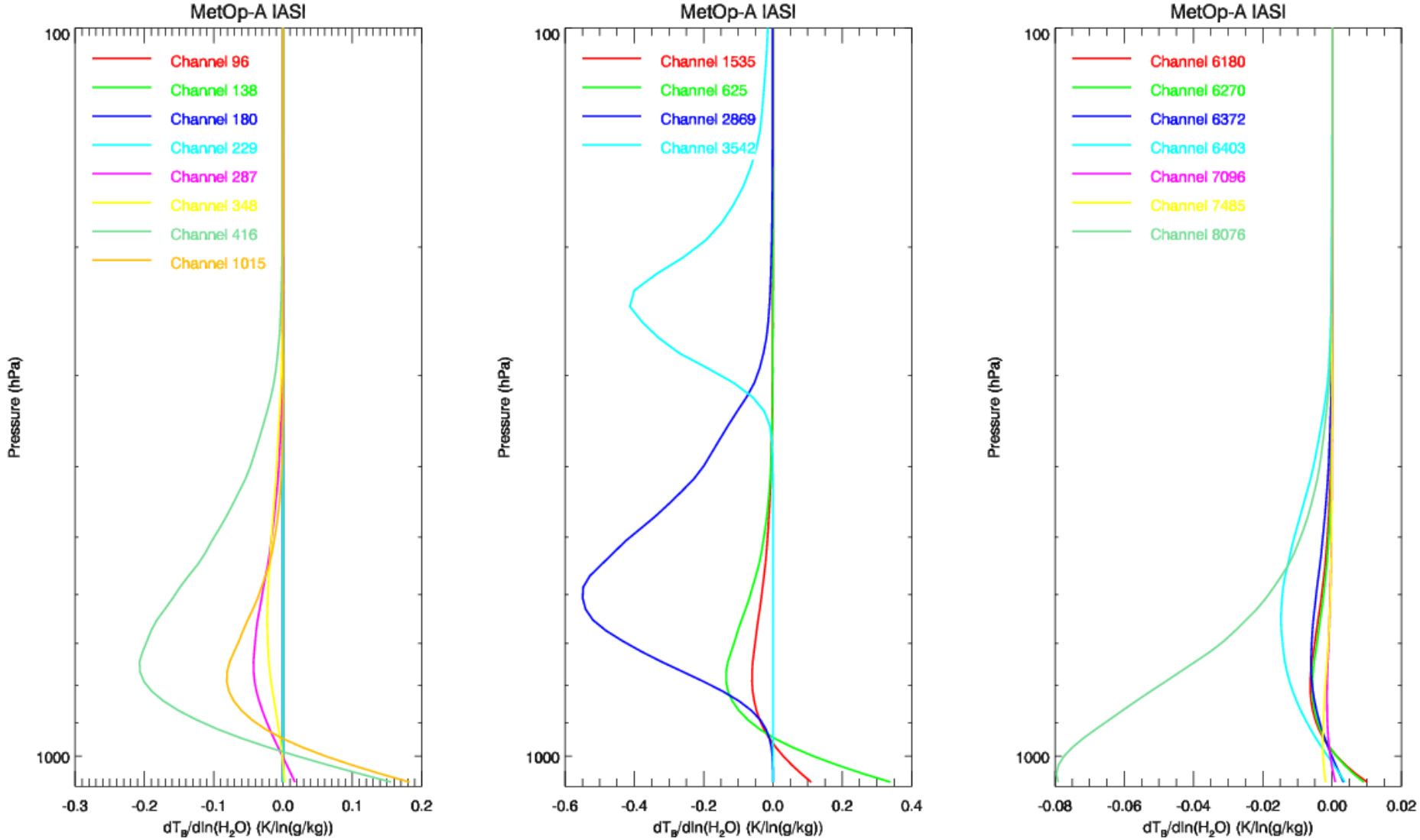
MetOp-A AMSU-A [dT_B/dT]



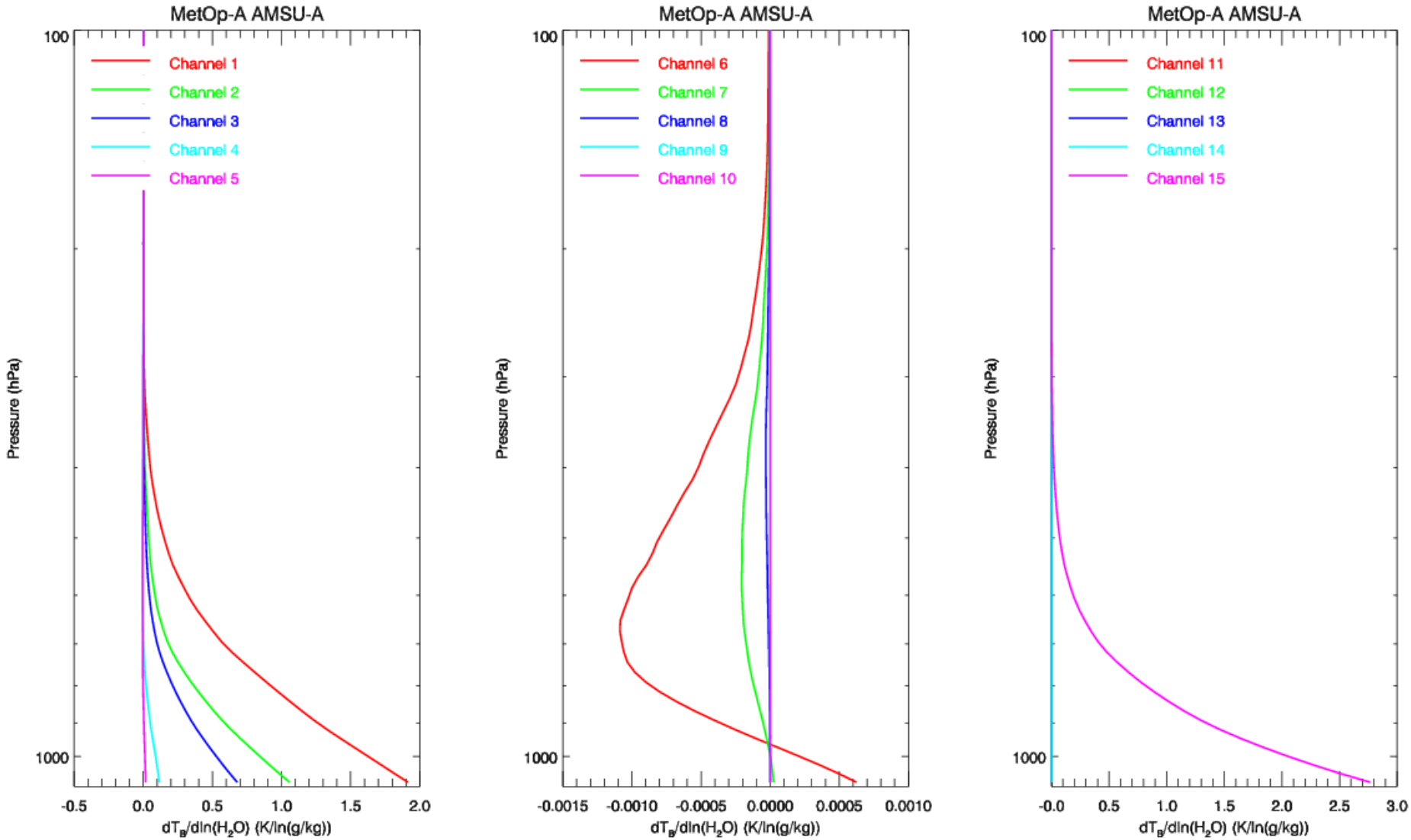
MetOp-A HIRS/4 [$dT_B/dln(H_20)$]



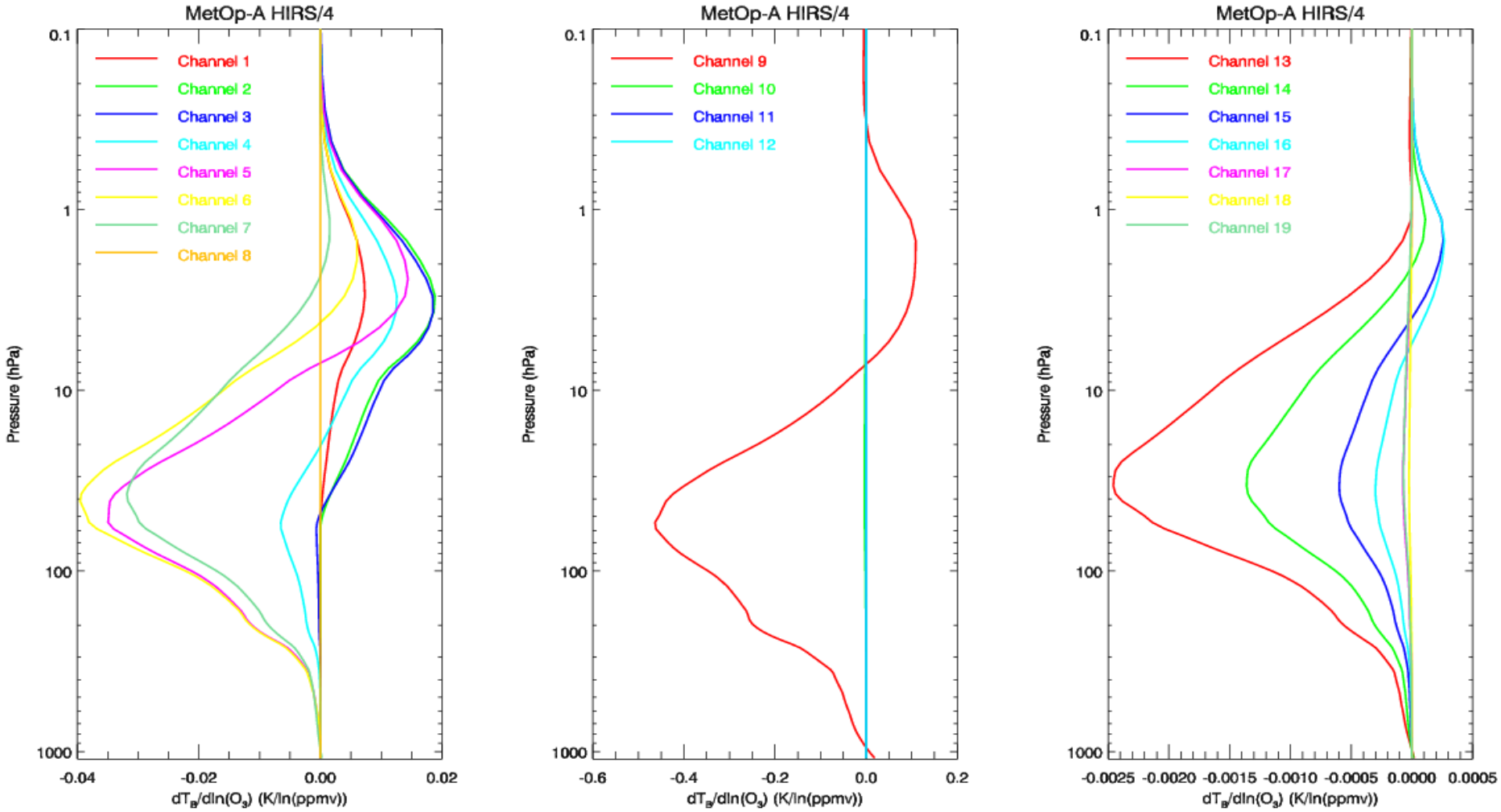
MetOp-A IASI [$dT_B/dln(H_20)$]



MetOp-A AMSU-A [$dT_B/dln(H_20)$]



MetOp-A HIRS/4 [$dT_B/dln(O_3)$]

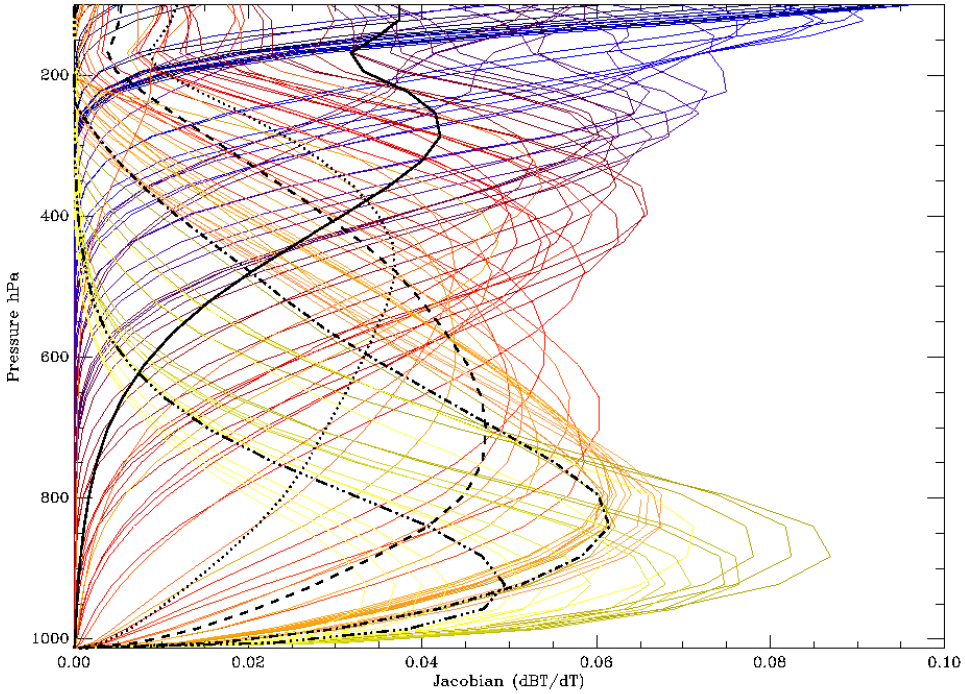


Obtaining vertical profiles

- The Jacobian's give the sensitivity to the vertical profiles of temperature / gases / clouds etc.

- If we ***sum*** the contribution of each channel, we can get a very **accurate estimate** of the mean atmospheric temperature albeit with very **low vertical resolution**.

- If we take ***differences*** between each of the channels we can infer the profile with **high vertical resolution**, but the result will be very a **noisy estimate**.



- When we assimilate the radiance observations we are effectively producing a minimum variance solution to the problem: which is a **compromise** between these two extremes

Forward Models

- To exploit these radiances, it is important to have an accurate way of simulating them from the atmospheric state.
- Line-by-line (LBL) models use state-of-the-art spectroscopic databases to make these calculations at high spectral resolution.
- These monochromatic calculations are then combined using the instruments' spectral response functions (ISRFs) to simulate what the instrument observes.
- This can be very slow. Too slow for operational radiance assimilation.

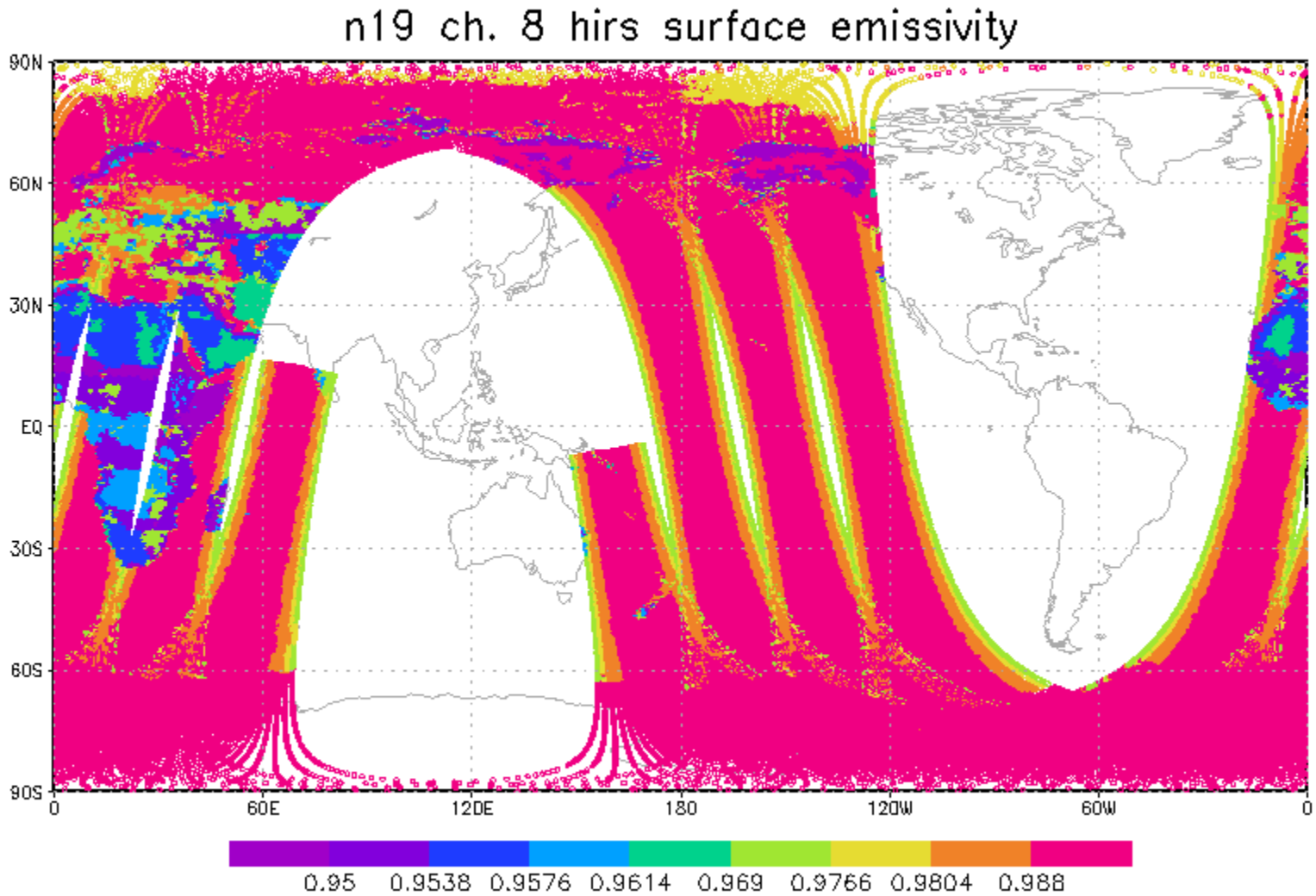
Fast Forward Models

- To allow radiances to be operationally assimilated, fast radiative transfer models, which use regression schemes to simulate the output from LBL models, have been produced.
- The two main fast models used operationally in NWP centers are **RTTOV** (developed by the EUMETSAT NWPSAF) and **CRTM** (JCSDA).
- The errors in the fast model are not usually a significant component of the total error budget (at least for clear atmosphere).
- Most importantly, fast models allow the Jacobians (and the model adjoint) to be calculated efficiently.

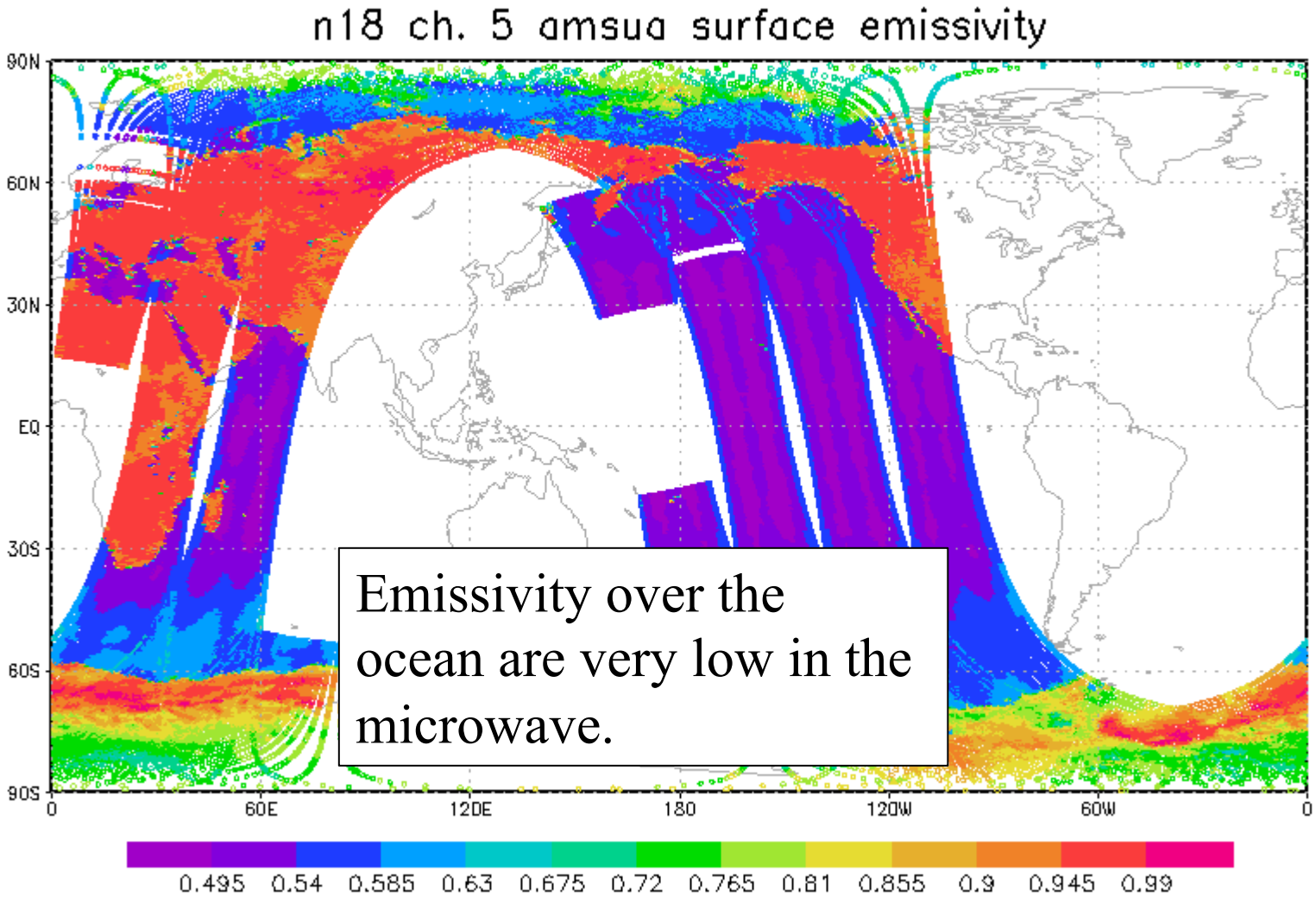
Radiative Transfer models also need to know the surface emissivity

- Over ocean we usually have models, e.g.
  - ISEM (infrared)
  - FASTEM (microwave)
- Over land we often use atlases, either of the emissivity's themselves or of the land type.
- Emissivity's can also be retrieved from the observations themselves.

Surface Emissivity : Infrared



Surface Emissivity : Microwave



Emissivity over the ocean are very low in the microwave.

Assimilating satellite radiances

Data Assimilation Equation

Basic analysis problem

$$J = J_b + J_o + J_c$$

$$J = \frac{1}{2}\left[x - x_{\mathbf{b}}\right]^T B^{-1}\left[x - x_{\mathbf{b}}\right] + \frac{1}{2}\left[H(x) - y\right]^T R^{-1}\left[H(x) - y\right] + J_c$$

Penalty = Fit to background + Fit to observations + Constraints

x = Analysis ; x_b = Background

$\delta x = x - x_b$ = Analysis increment

B = Background Error Covariance

H = (Nonlinear) Forward Model ; H = Linearized about x_b

y = Observations ; $d = y - \mathrm{H}x_b$ = Observation Innovation

$R = E + F$ = Instrument Error + Representativeness Error = Observation Error

J_c = Constraint terms

Basic analysis problem

$$J = J_b + J_o + J_c$$

$$J = \frac{1}{2}\left[x - x_{\mathbf{b}}\right]^T B^{-1}\left[x - x_{\mathbf{b}}\right] + \frac{1}{2}\left[H(x) - y\right]^T R^{-1}\left[H(x) - y\right] + J_c$$

Penalty = Fit to background + Fit to observations + Constraints

x = Anal

$\delta x = x -$

B = Bacl

H = (No

y = Obse

The difference between the observations and the background transformed into model space, the first guess departure, is an important measure. It is often the basis of quality control procedures.

$R = E + F$ = Instrument Error + Representativeness Error = Observation Error

J_c = Constraint terms

Assimilating satellite radiances

Quality Control

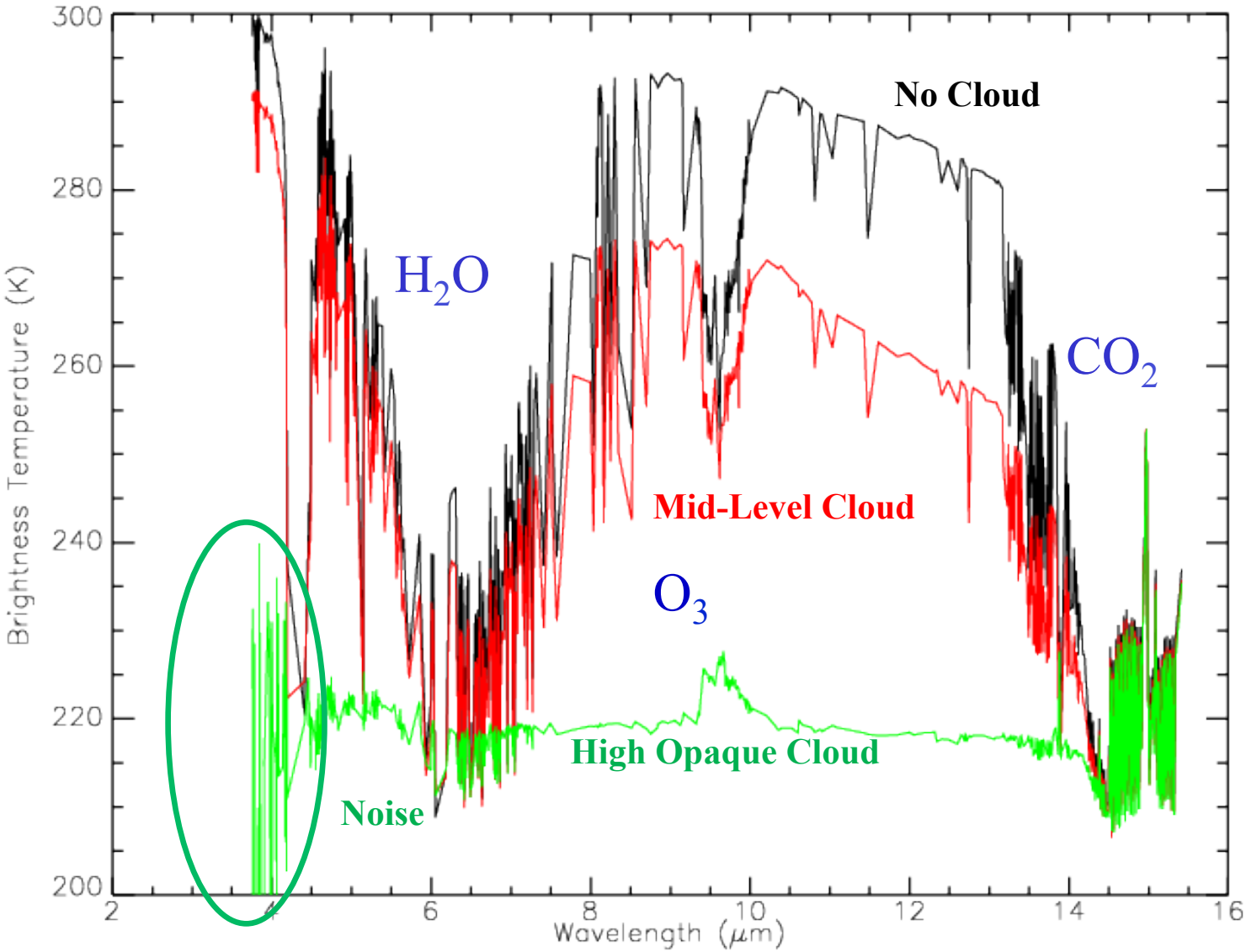
Quality Control Procedures

- The quality control step may be the most important aspect of satellite data assimilation.
- Data which has gross errors or which cannot be properly simulated by forward model must be removed.
- Most problems with satellite data come from 4 sources:
  - Instrument problems.
  - Clouds and precipitation simulation errors.
  - Surface emissivity simulation errors.
  - Processing errors (e.g., wrong height assignment, incorrect tracking, etc…).

Quality Control Procedures

- IR **cannot** see through most clouds.
  - Cloud height difficult to determine – especially with mixed FOVs.
  - Since deep layers not many channels completely above clouds.
- Microwave impacted by clouds and precipitation but signal is smaller from thinner clouds.
- Poor knowledge of surface emissivity and temperature characteristics for land / snow / ice.
  - Also makes detection of clouds / precipitation more difficult over these surfaces.
- **Asymmetric** error distribution due to clouds and processing errors.

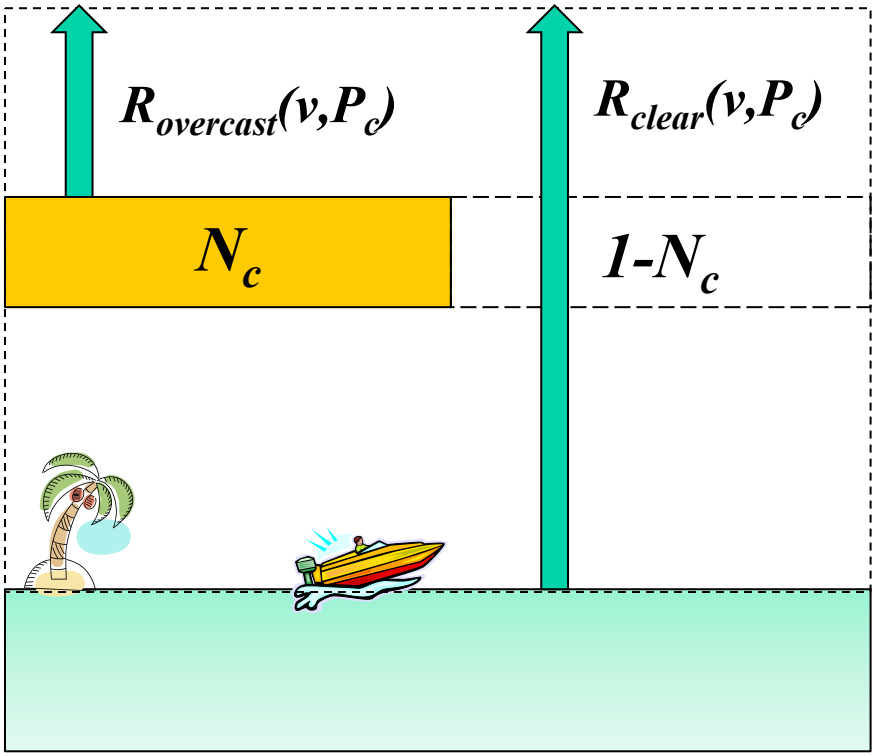
Effect of Cloud on IR Spectrum



Eyre and Menzel, 1989

Cloud Detection in the GSI

- Assume the cloud is a single layer at pressure P_c and with unit emissivity and coverage within the FOV, N_c.
- Cloud fraction: $0 \le N_c \le 1$
- P_c is below the tropopause and above the ground
- Find P_c and N_c so that the RMS deviation, $J(N_c,P_c)$, of the calculated cloud from the model (over a number of channels) is minimized.
- Remove all channels that would be radiatively affected by this cloud.



$$R_{cld}(\nu,P_c) = N_c R_{overcast}(\nu,P_c) + (1-N_c) R_{clear}(\nu,P_c)$$

$$J(N_c,P_c) = \sum_{\nu} \left(\frac{R_{cld}(\nu,P_c) - R_{obs}(\nu)}{\sigma(\nu)} \right)^2$$

- $\sigma(\nu)$ is the assumed observation error for channel ν. This calculation should be done in radiance space, and not in brightness temperature space.

Observational Errors

- Observation errors specified based on instrument errors and statistics
- Generally for satellite data, variances are specified a bit large since the correlated errors (from RT and instrument errors) are not well known.
- Observation errors are also generally specified as being uncorrelated spectrally, but efforts are being made to determine the off-diagonal components of the observation error covariance matrix.

satinfo File

!sensor/instr/sat	chan	iuse	error	error_cld	ermax	var_b	var_pg
amsua_n15	1	1	3.000	9.100	4.500	10.000	0.000
amsua_n15	2	1	2.000	13.500	4.500	10.000	0.000
amsua_n15	3	1	2.000	7.100	4.500	10.000	0.000
amsua_n15	4	1	0.600	1.300	2.500	10.000	0.000
amsua_n15	5	1	0.300	0.550	2.000	10.000	0.000
amsua_n15	6	1	0.230	0.230	2.000	10.000	0.000
amsua_n15	7	1	0.250	0.195	2.000	10.000	0.000
amsua_n15	8	1	0.275	0.232	2.000	10.000	0.000
amsua_n15	9	1	0.340	0.235	2.000	10.000	0.000
amsua_n15	10	1	0.400	0.237	2.000	10.000	0.000
amsua_n15	11	-1	0.600	0.270	2.500	10.000	0.000
amsua_n15	12	1	1.000	0.385	3.500	10.000	0.000
amsua_n15	13	1	1.500	0.520	4.500	10.000	0.000
amsua_n15	14	-1	2.000	1.400	4.500	10.000	0.000
amsua_n15	15	1	3.000	10.000	4.500	10.000	0.000
hirs3_n17	1	-1	2.000	0.000	4.500	10.000	0.000
hirs3_n17	2	-1	0.600	0.000	2.500	10.000	0.000
hirs3_n17	3	-1	0.530	0.000	2.500	10.000	0.000
hirs3_n17	4	-1	0.400	0.000	2.000	10.000	0.000
hirs3_n17	5	-1	0.360	0.000	2.000	10.000	0.000

Use Channel? **Assigned Observation Error** **Maximum allowed FG Departure (after bias correction)**

Assimilating satellite radiances

Bias Correction

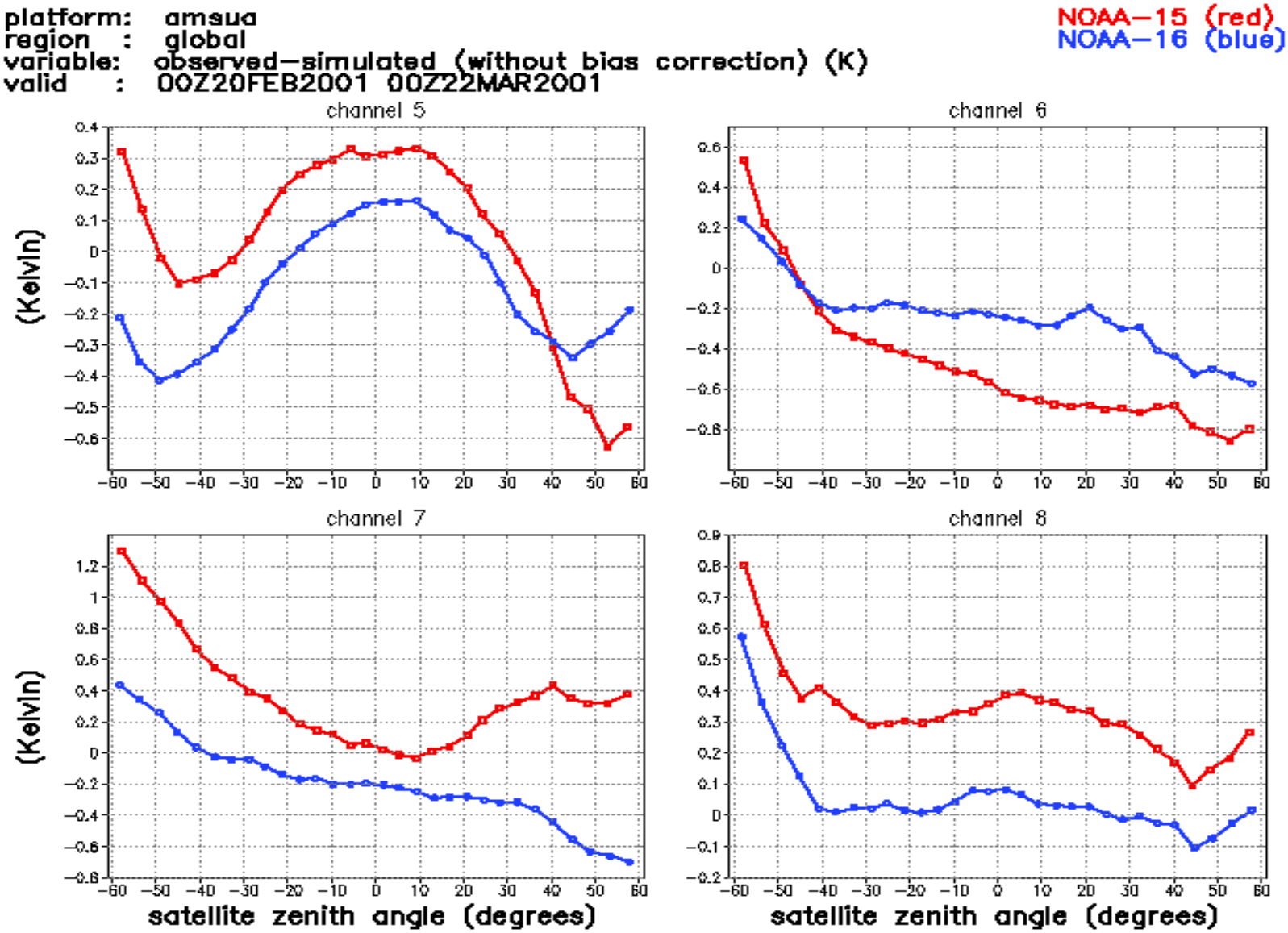
Bias Correction

- The differences between simulated and observed observations can show significant biases.
- The source of the bias can come from:
  - Inadequacies in the characterization of the instruments.
  - Deficiencies in the forward models.
  - Errors in processing data.
  - Biases in the background.
- Except when the bias is due to the background, we would like to remove these biases.

Bias Correction

- Currently bias correction only applied to a few data sets:
  - Radiances
  - Radiosonde data (radiation correction and moisture)
  - Aircraft data
- For radiances, biases can be much larger than signal
- Essential to bias correct the data
- NCEP uses a variational bias correction scheme (other centers are similar) using atmospheric air mass and scan angle predictors

Scan dependent biases for AMSU



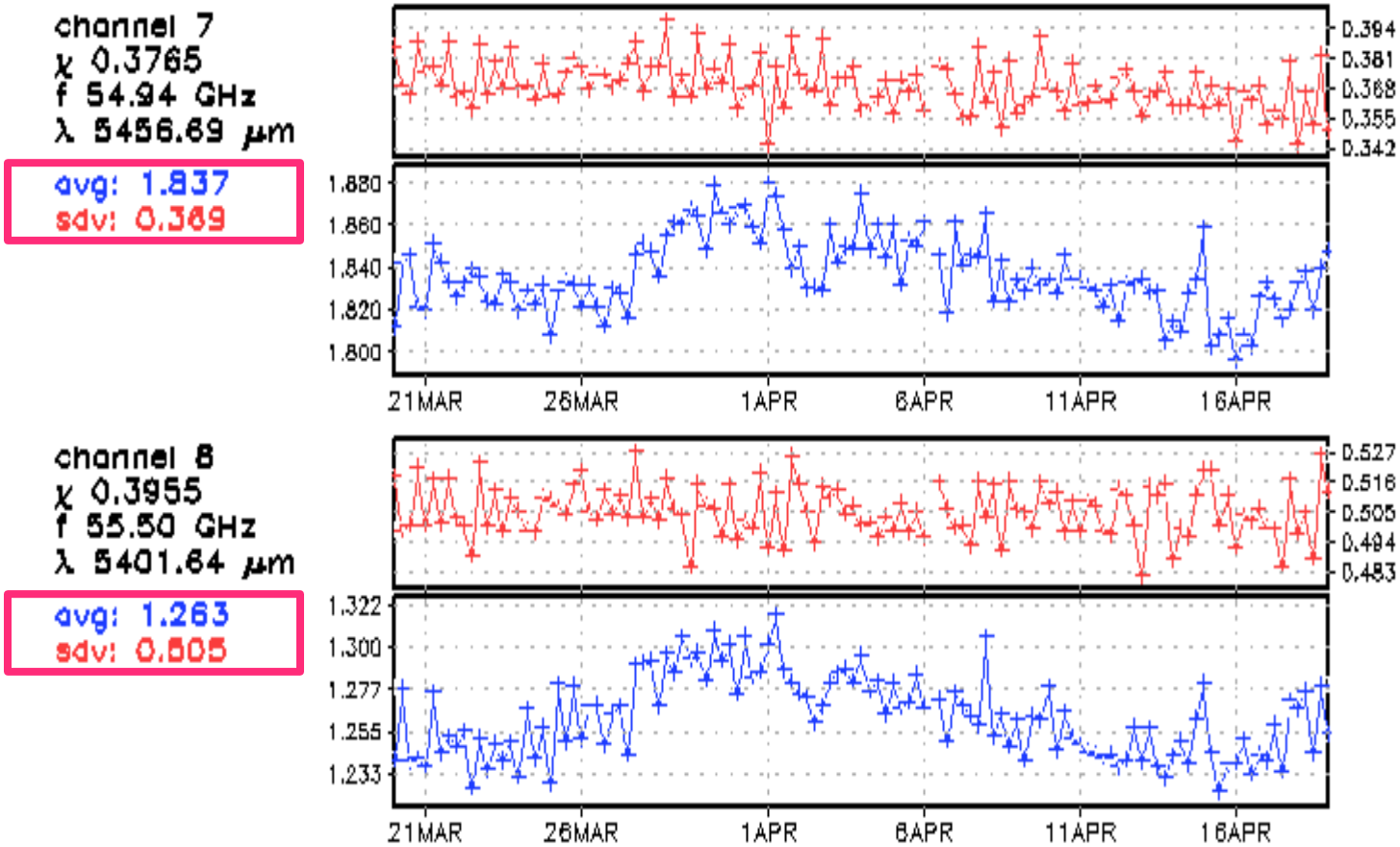
Satellite radiance observations Bias correction

- Air mass prediction equation for bias – **variational** bias correction
  - Add to control vector (analysis variables $\boldsymbol{x_{n+i}}$)

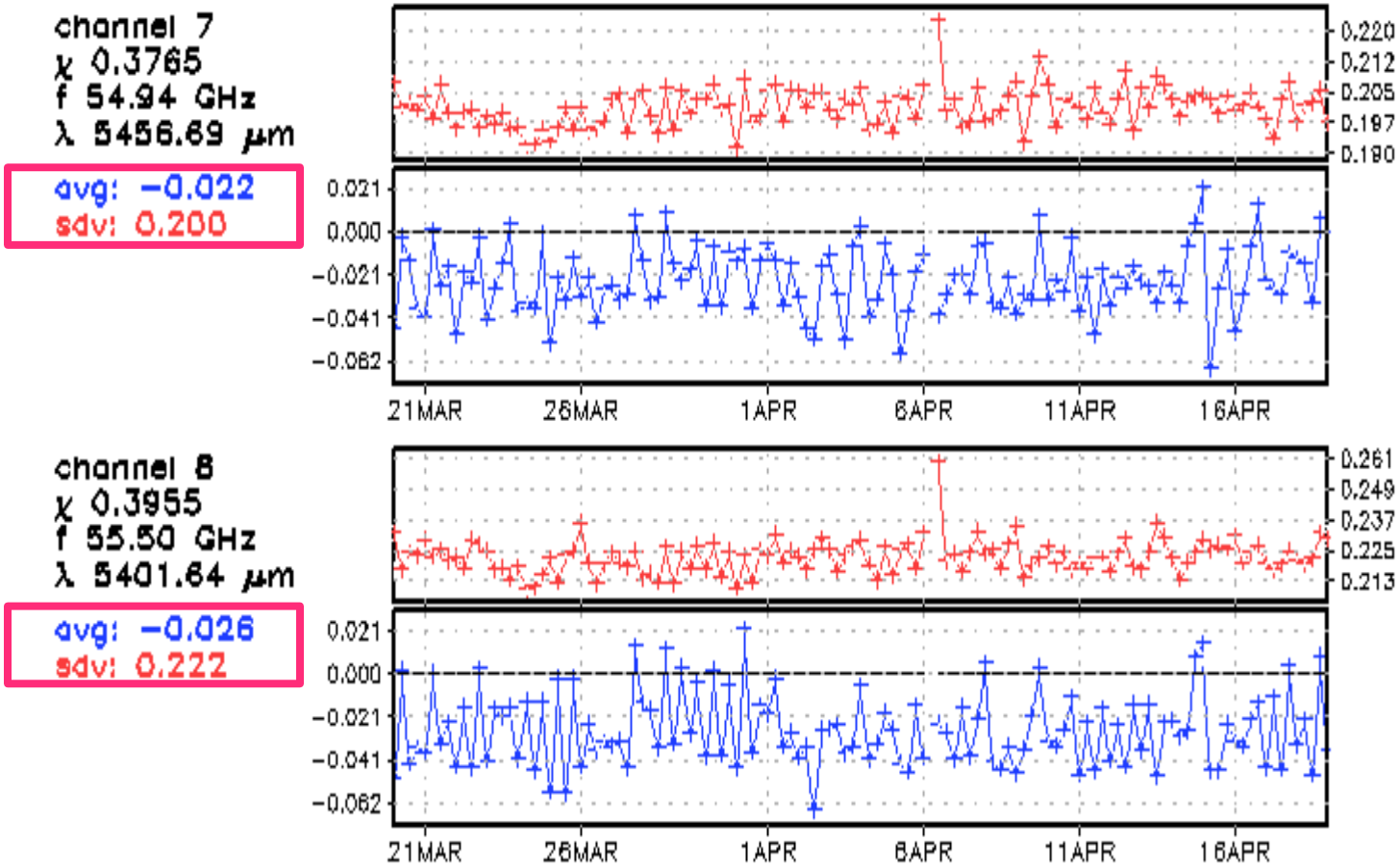
    where Total bias correction $= \sum_{i=1}^{n_p} x_{n+i} p_i$
  - Predictors ($\boldsymbol{p_i}$) for each channel
    - mean
    - path length (local zenith angle determined)
    - integrated lapse rate
    - (integrated lapse rate) ^{2}
    - cloud liquid water
    - Fourth-order polynomial of scan-angle
    - Surface emissivity predictor
    - Latitude dependent bias for SSMI/S

NOAA 18 AMSU-A

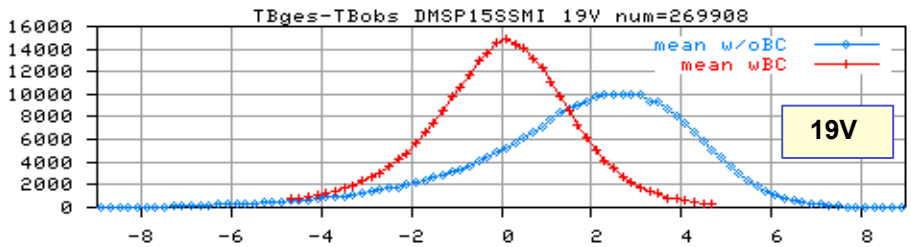
No Bias Correction

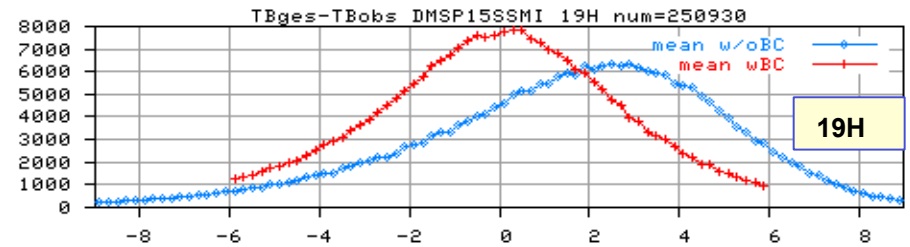


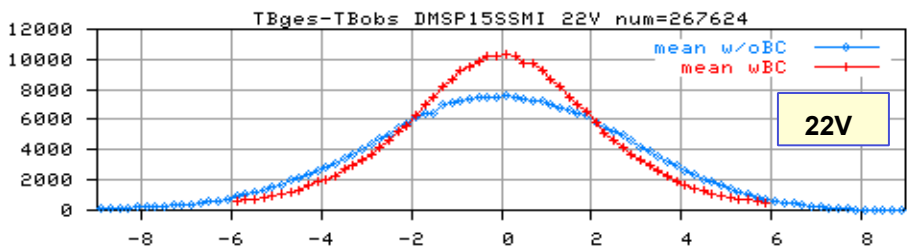
NOAA 18 AMSU-A
With Bias Corrected

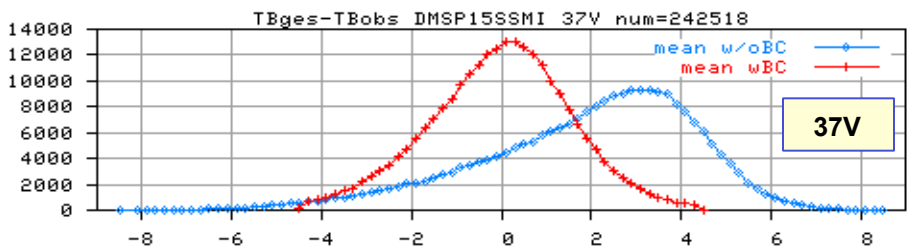


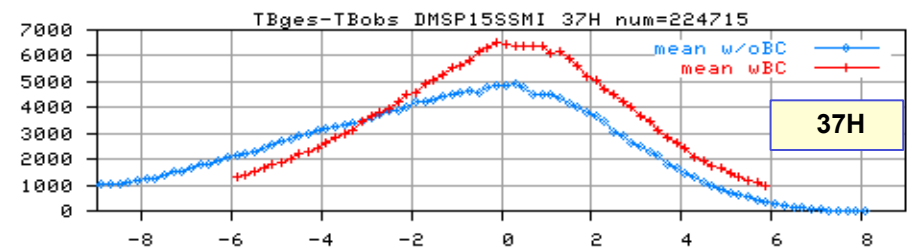
Observation - Background Histogram

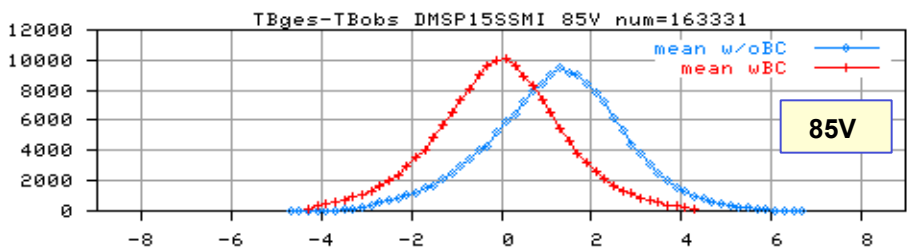


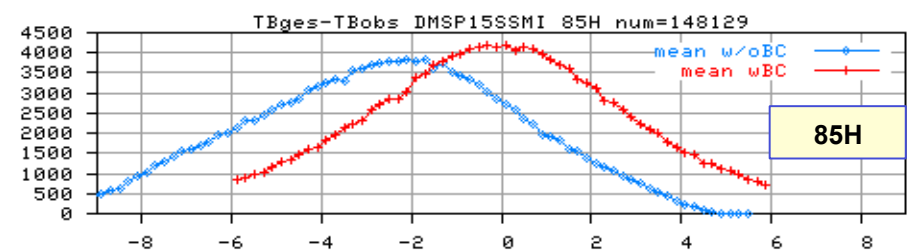












DMSP15 July2004 : 1month

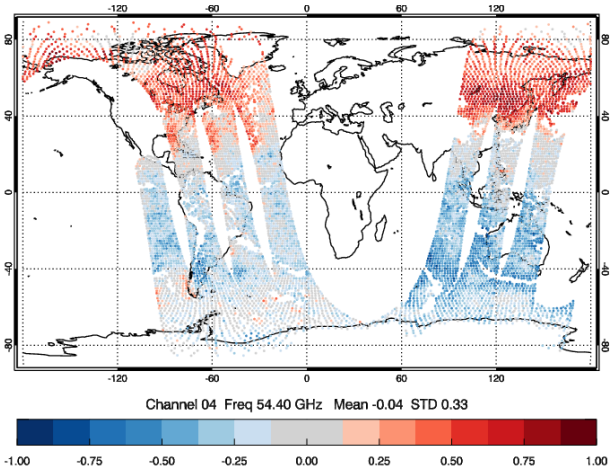
before bias correction

after bias correction

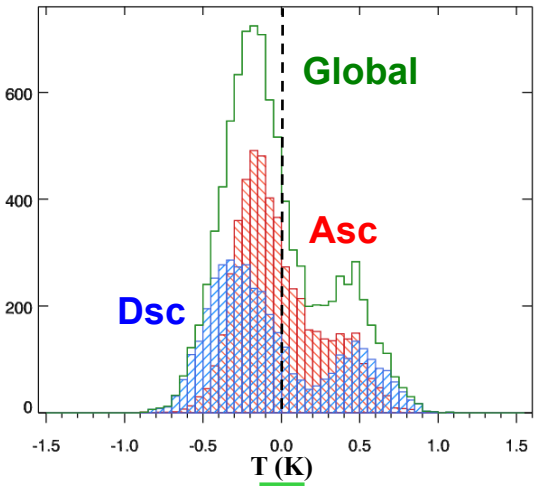
gl use 2004070200-073118(63cases)

Application of NWP Bias Correction for SSMIS F18

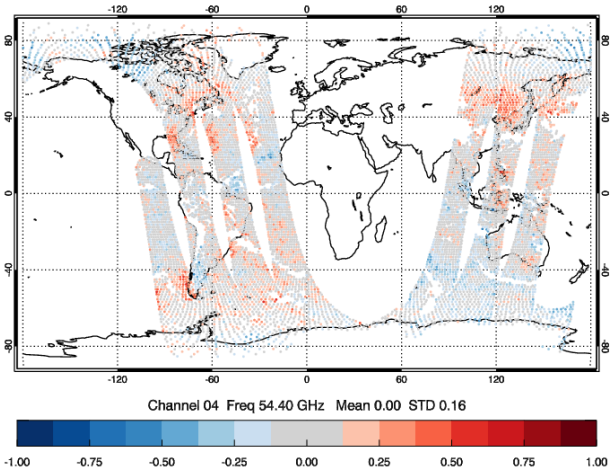
O-B Before Bias Correction



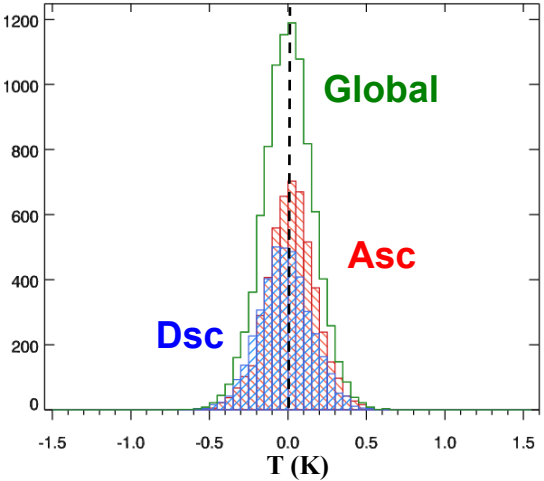
O-B Before Bias Correction



O-B After Bias Correction

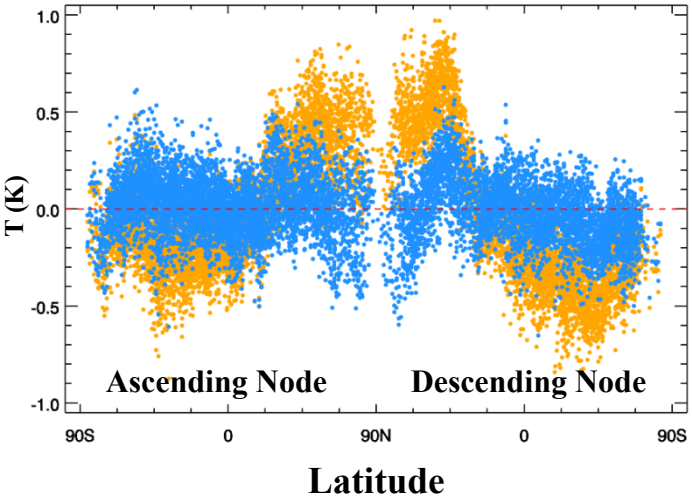


O-B After Bias Correction



Using Met Office SSMIS Bias Correction Predictors

Unbias & Bias Corrected O-B



Bias Correction and QC Interact

Bias Correction

Observations are bias-corrected after quality control

Quality Control

Quality control usually uses bias-corrected observations

Assimilating satellite radiances

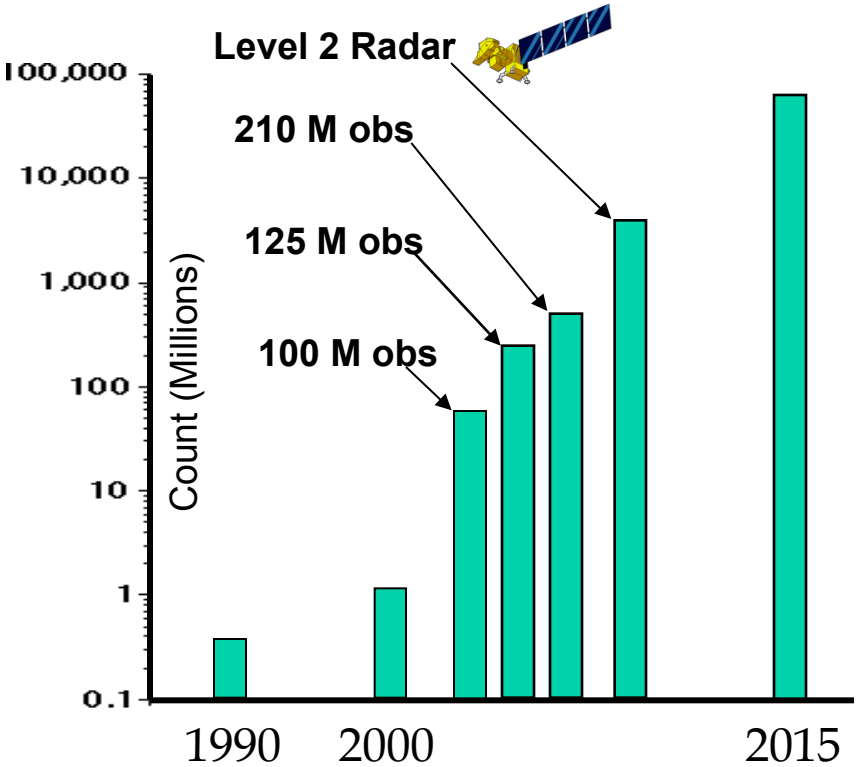
Thinning

Thinning or Superobbing

- **Thinning**
  - Reducing spatial or spectral resolution by selecting a reduced set of locations or channels.
  - Can include "intelligent thinning" to use better observation.
- **Superobbing**
  - Reducing spatial or spectral resolution by combining locations or channels.
  - Can reduce noise.
  - Includes reconstructed radiances.
  - Can include higher moments contained in data Purser et al., 2010.
  - Can be done with obs or departures, but should be done after QC.
- Both can be used to address 3 problems:
  - Redundancy in data.
  - Reduce correlated error.
  - Reduce computational expense.

Satellite Data Ingest

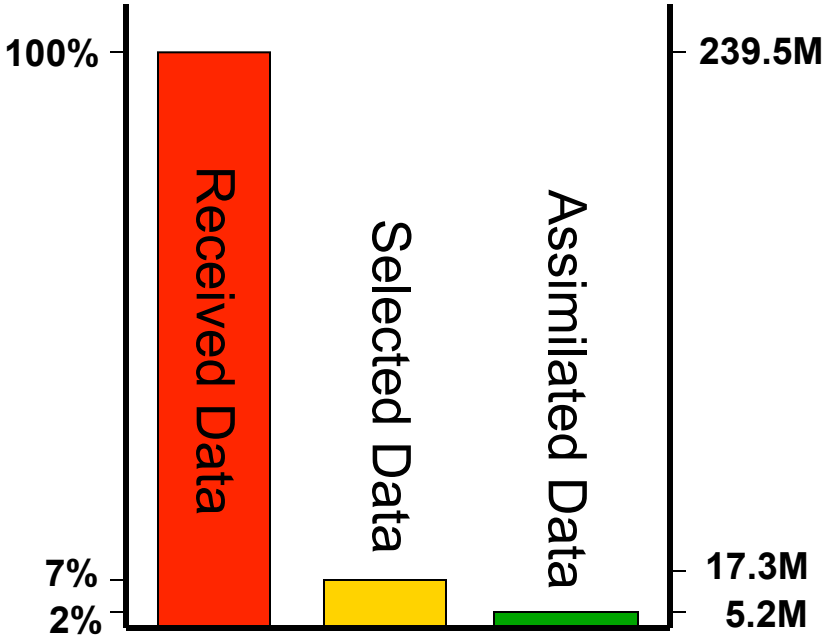
Daily Satellite & Radar Observation Count



Five Order of Magnitude Increases in Satellite Data Over Fifteen Years (2000-2015)

Daily Percentage of Data Ingested into Models

*2005 Data



Received = All observations received operationally from providers
Selected = Observations selected as suitable for use
Assimilated = Observations actually used by models

Assimilating satellite radiances

Data Monitoring

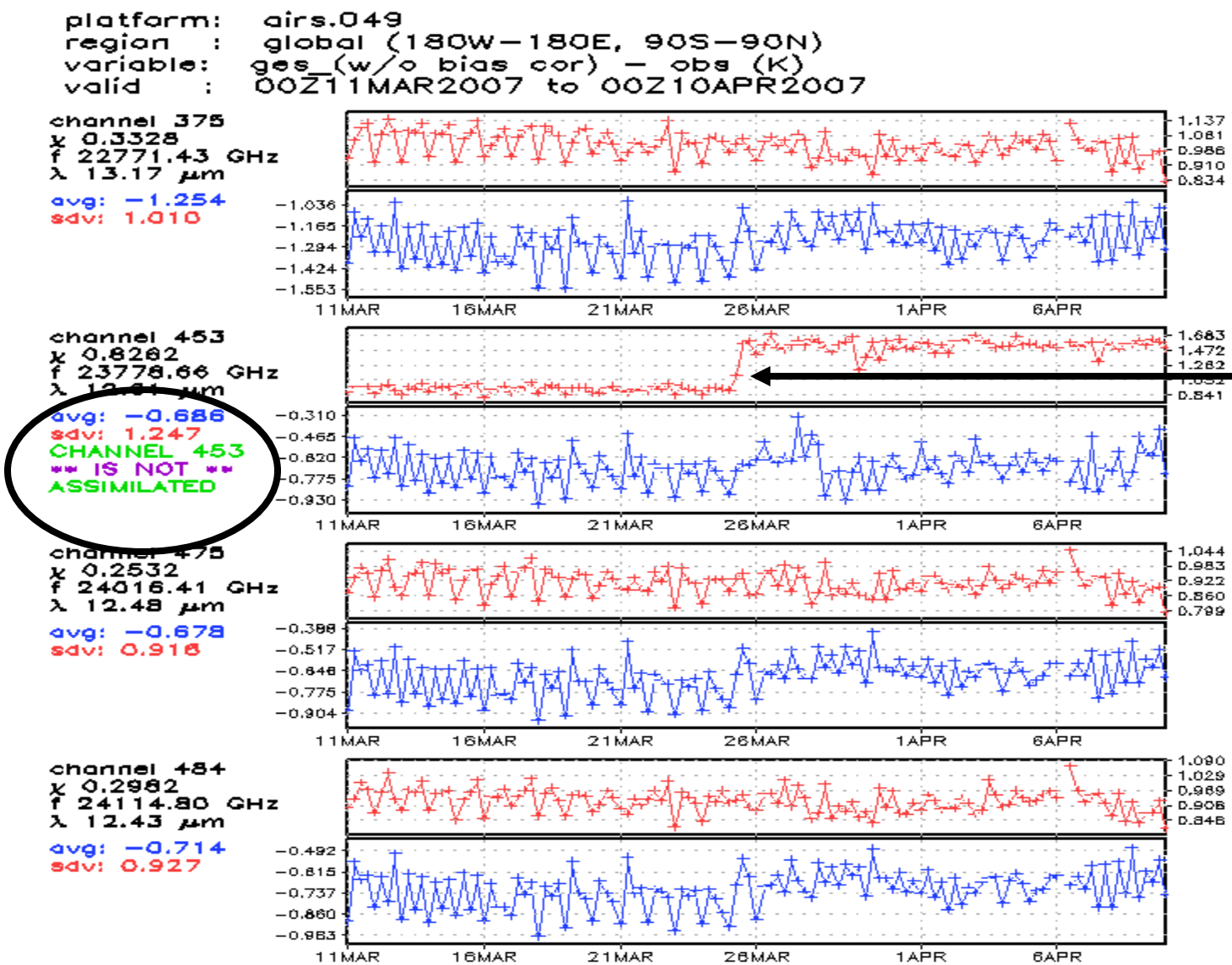
Data Monitoring

- It is essential to have good data monitoring.
- Usually the NWP centers see problems with instruments prior to notification by provider (Met Office especially).
- The data monitoring can also show problems with assimilation systems.
- Needs to be ongoing/real time.
- Monitoring reports from most major NWP centers at:

http://research.metoffice.gov.uk/research/interproj/nwpsaf/monitoring.html

Quality Monitoring of Satellite Data

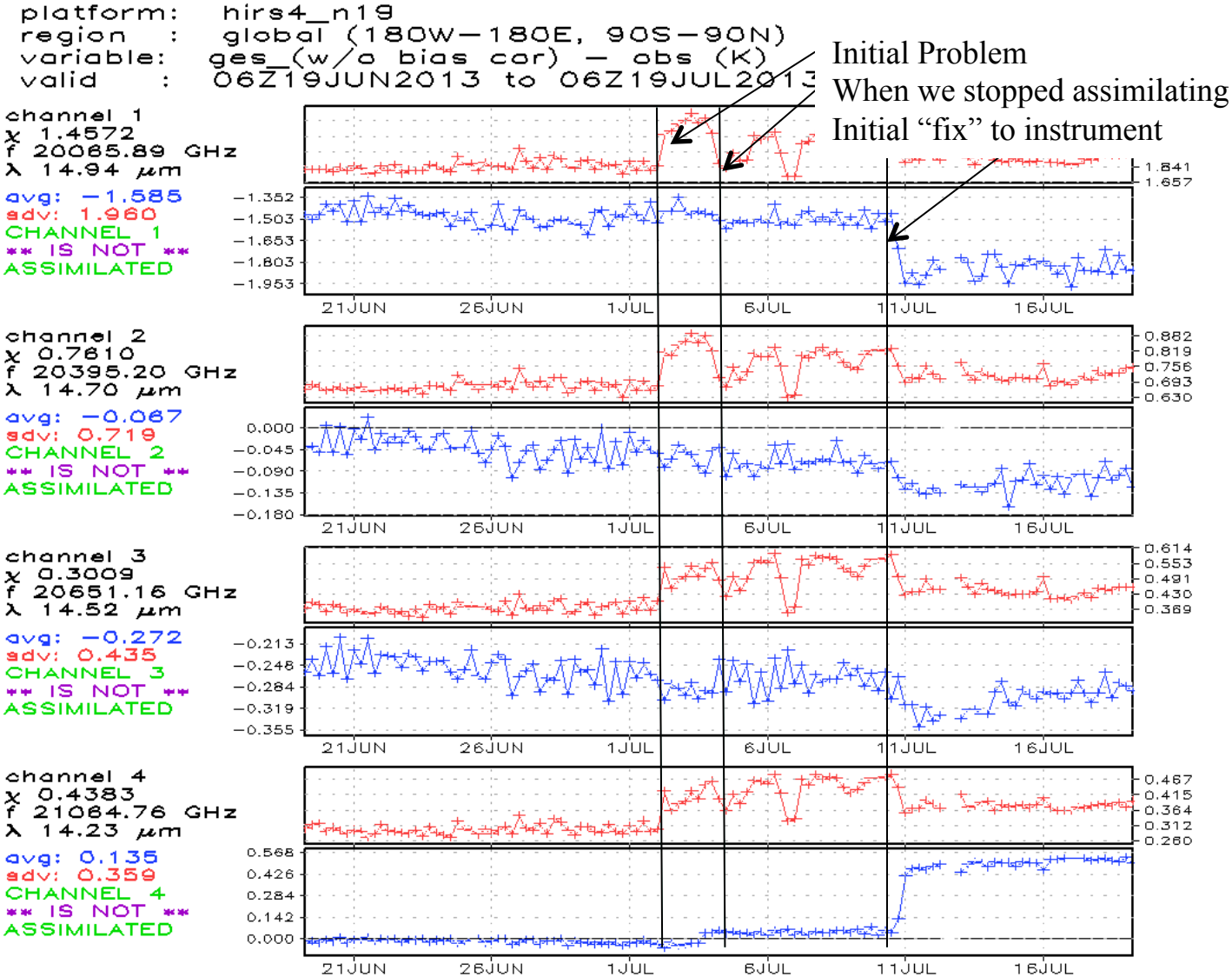
AIRS Channel 453 26 March 2007



Increase in SD Fits to Guess

Quality Monitoring of Satellite Data

NOAA-19 HIRS July 2nd 2013 – Filter Wheel Motor Problems



Some Comments on Cloudy Radiances

Cloudy Radiances

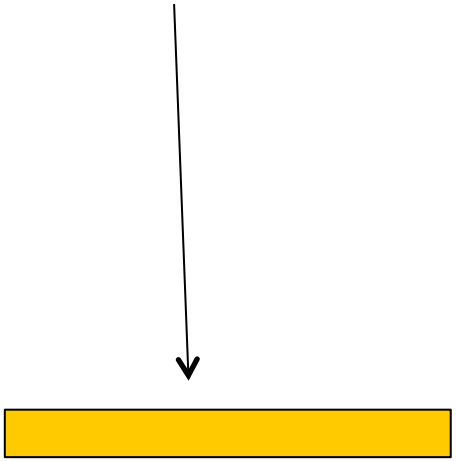
- Most of the above discussion concerns the assimilation of radiances unaffected by cloud.
- Currently we are not operationally assimilating cloudy radiances but the GSI contains experimental code for assimilating such radiances in the microwave.
- The next few slides discuss why clouds are both important and difficult for data assimilation…
- …and discusses one aspect of the modifications we are making to assimilate them

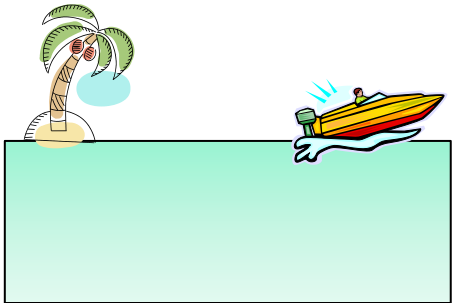
Why are clouds important?

- A decade ago almost all assimilation of satellite radiances assumed the scene was clear of clouds.
- Clouds were considered a source of noise that needed to be removed or corrected for.
- This is not because clouds were not important but because they were difficult.
- By ignoring regions affected by cloud we are not considering some meteorological very important areas
- By selectively assimilating clear radiances we may be biasing the model (representivity issues).

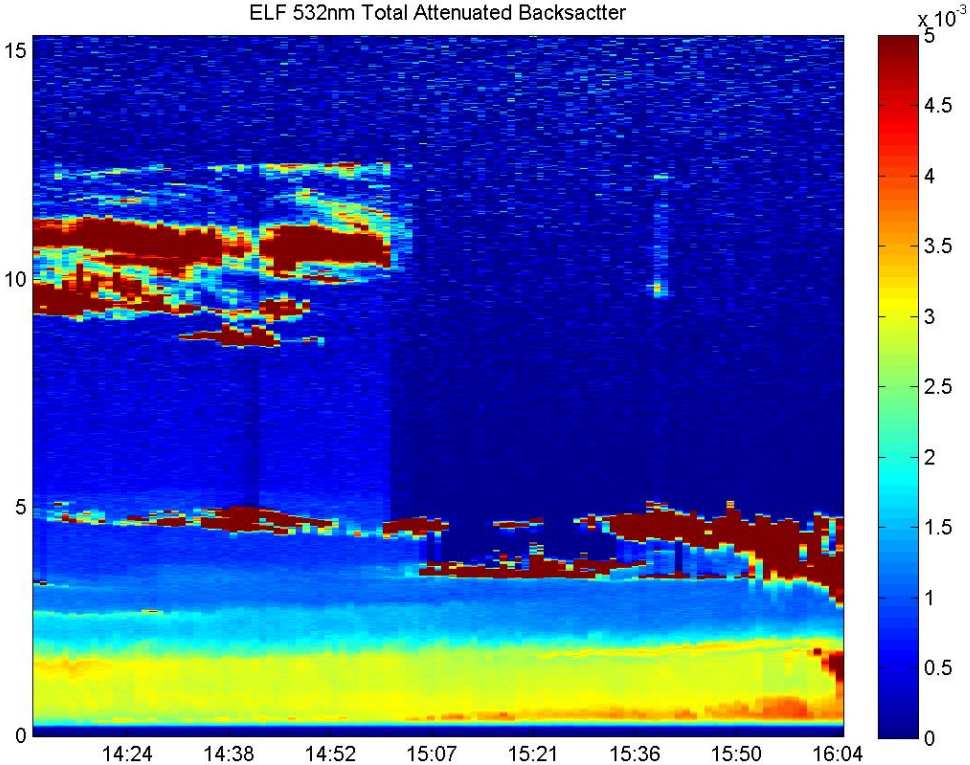
Clouds can be spatially complex

Often we assume a cloud looks like this…





…when they can really look like this



Spatial structure can be below the resolution of the observation, the model or both

Clouds can be radiatively complex

- The complexity of the impact of clouds on observed spectra varies greatly with type of cloud and spectral region.
- If clouds are transmissive they will tend to have spectrally varying absorbtion – and hence emission – which depends on phase (water or ice), crystal habit and particle size distribution
- Scattering from cloud and precipitation particles can by very significant – tends to lower the observed brightness temperature.

Clouds can introduce non-linearities

- The radiative signal from clouds is often large and very non-linear so the tangent-linear assumption used in variational data assimilation may not hold.
- Quality control that minimizes the impact of this non-linearity is required.

Clouds need to be consistent with temperature and humidity fields

- Adding clouds to the analysis without ensuring a consistent humidity and temperature profile can be problematic.
  - For example a cloud added into a dry atmosphere will tend to be removed by the model.

Final Comments

Overall Comments

- Satellite data must be treated carefully.
- Important to be aware of instrument characteristics before attempting to use data.
- No current component of observing system is used ***"perfectly"*** or ***"as well as possible"***.
- Computational expense plays important role in design of system.

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