Current Status and Future of Satellite Data Assimilation

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With input from:
Many others

Outline

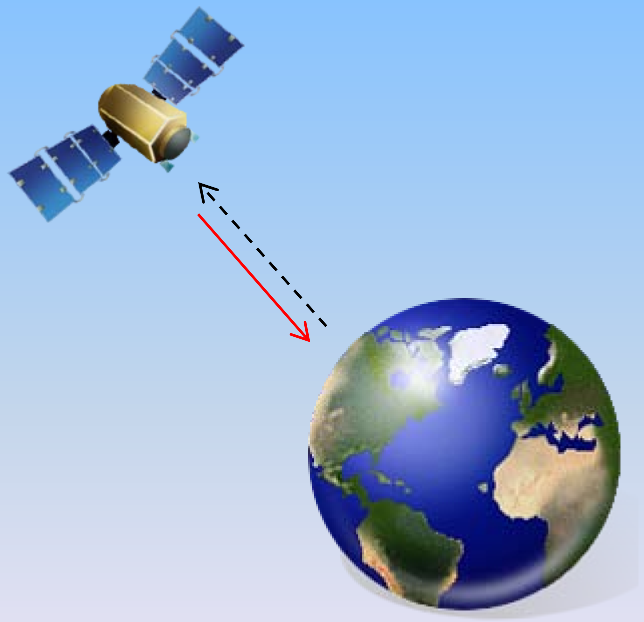
- What makes satellite data different?
- Different types of satellite data.
- Using satellite data.
  - Forward Model.
  - Bias correction.
  - Quality control.
  - Monitoring.
  - Thinning or superobbing.
  - Observation errors.
- Future of satellite data assimilation.

What Makes Satellite Data Different?

- Remote sensing (instrument is not at the location of what you are trying to measure).
- Observed variables are often not what you really want to measure.
- One instrument making many observations over different locations.
  - Satellite observations are large percentage of observing system (Radar obs only other comparable number).
- Cannot access instrument to make calibration measurements or to fix it.
- Asynoptic data.
- Instruments are very expensive.

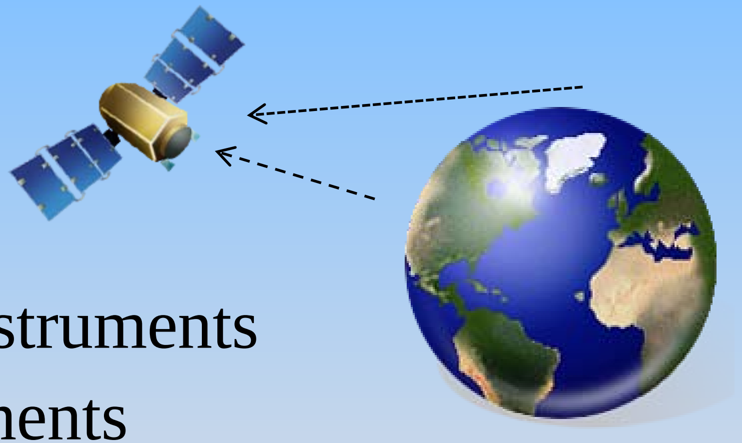
Different Types of Satellite Data

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



Different Types of Satellite Data

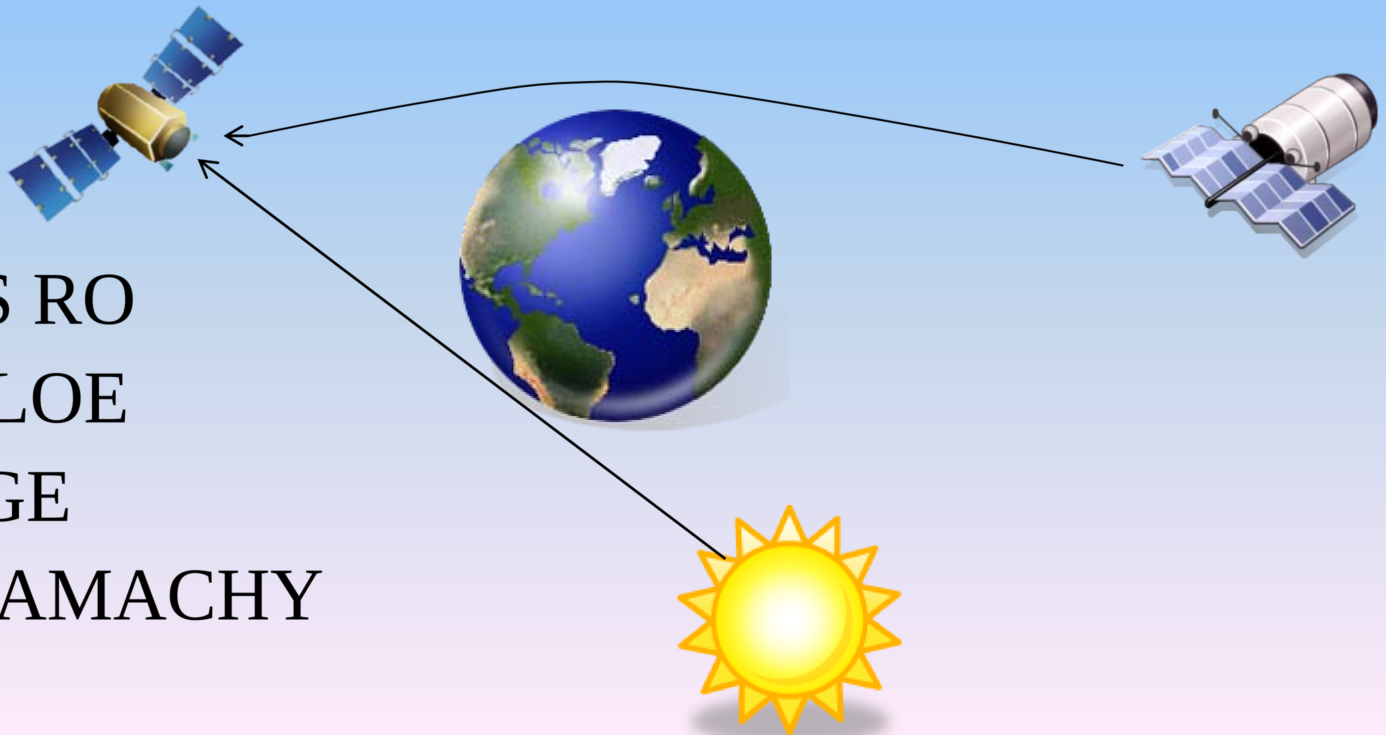
- Passive (receiving radiative signal from source)



  - Visible instruments
  - IR instruments
  - Microwave instruments
  - Limb vs Nadir sounding instruments

Different Types of Satellite Data

- Occultation (signal passing through atmosphere)



  - GPS RO
  - HALOE
  - SAGE
  - SCIAMACHY

Overall Comments

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

Atmospheric Analysis Problem

$$J = J_b + J_o + J_c$$

$$J = (x-x_b)^T B_x^{-1}(x-x_b) + (K(x)-O)^T(E+F)^{-1}(K(x)-O) + J_C$$

J = Fit to background + Fit to observations + constraints

x = Analysis
x_b = Background
B_x = Background error covariance
***K* = Forward model (nonlinear)**
O = Observations
E+F = R = Instrument error + Representativeness error
J_C = Constraint term

Forward Model

- K operator – transforms control variables (x) into simulated observation.
  - Can include forecast model (4-D).
  - For purposes of this talk K will only transform from usual meteorological variables to simulated observation.
- Different levels of complexity for different observations.
  - Retrieved Atmospheric Motion Winds – can be as simple as a 3-d interpolation.
  - GPS RO – simulation of Bending Angle or refractivity profile.
  - Radiances – radiative transfer model to simulate radiances or brightness temperatures.
- Approximations in forward model should not result in error larger than signal.

Satellite Data Forward Model

- Example – $K(x,z) \approx y$
  - y are radiance observations,
  - x are profiles of temperature, moisture and ozone,
  - *K* is the radiative transfer equation and ,
  - z are unknown parameters such as the surface emissivity (dependent on soil type, soil moisture, etc.), CO_2 profile, methane profile, etc.
- In general, *K* is not invertible – hence satellite agencies perform retrievals.
  - Physical retrievals – usually very similar to 1D variational problems .
    - 3-D/4-D analysis problem can be thought of as a 3-D/4-D retrieval
  - Statistical retrievals – given y predict x using regression.

Satellite Data Forward Model

- If unknowns in *K*(x,z) – either in formulation of *K* or in unknown variables (z) are too large, data cannot be reliably used and must be removed in quality control.
  - Examples:
    - Clouds.
    - Trace gases.
    - Aerosols.
  - As more relevant variables are properly added to analysis – impact of unknown variables reduced, more data can be used and generally data will be used better.
- Note that errors in formulation or unknown variables generally produce correlated errors. This can be a significant source of difficulty.

Satellite Data Forward Model

- Nonlinearity in K.
  - The K operator can be nonlinear (but discontinuous functions should be avoided).
    - Minimization algorithms can be written to handle nonlinear K operators, but can make minimization more complex and more expensive.
    - Nonlinearities generally slow convergence.
    - Many operational minimization algorithms, make implicit assumptions of nonlinearity which when violated can make convergence questionable (e.g. Inner and Outer iterations).

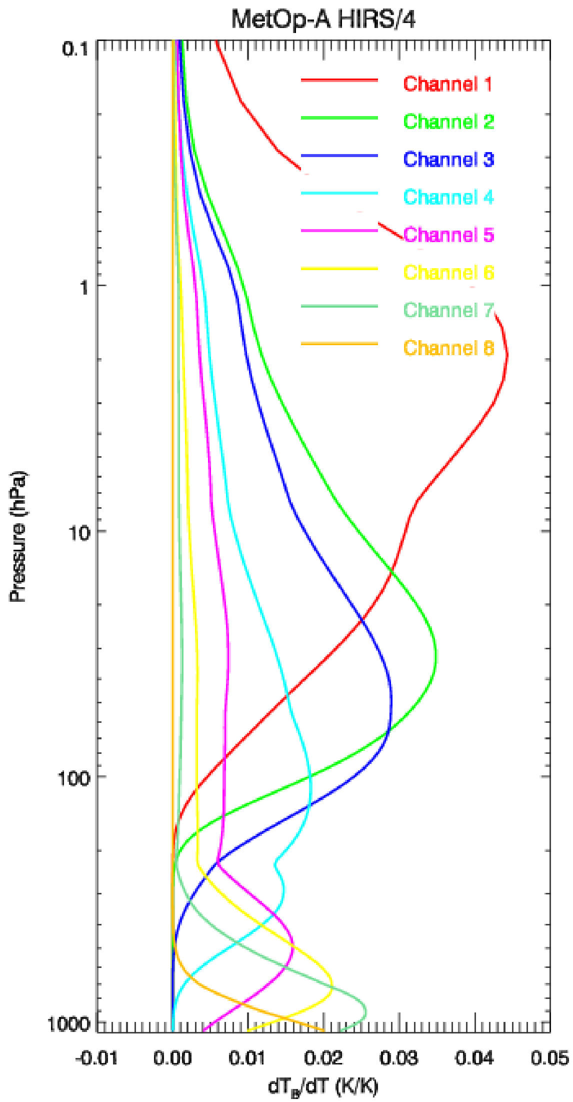
Satellite Radiance Observations

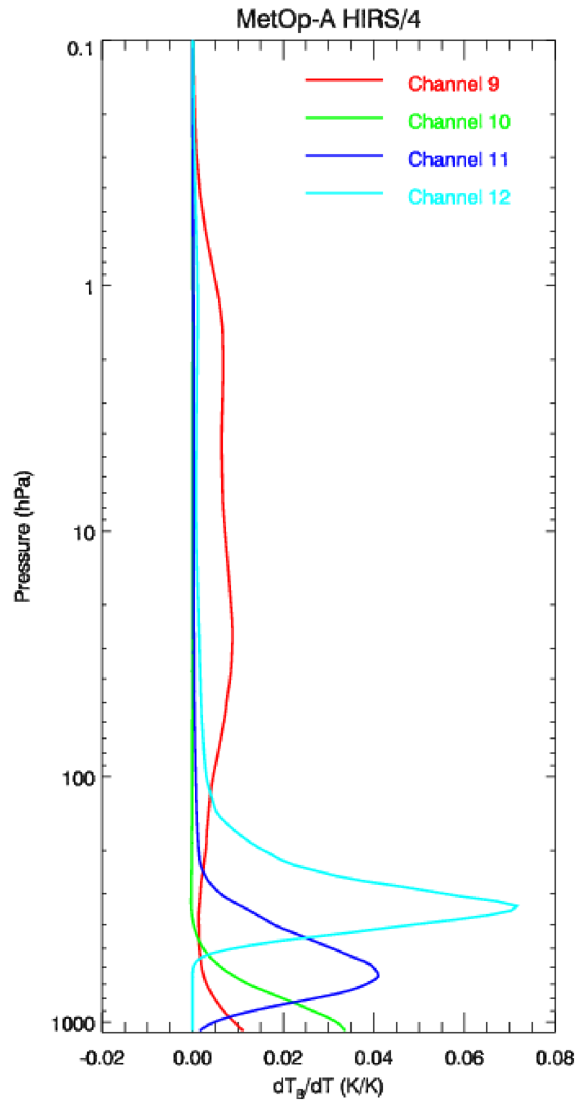
- Measures upwelling radiation at satellite.
- Measurement comes from deep layers.
  - IR not quite as deep as microwave.
  - New IR instruments (AIRS, IASI, GIFTS) narrower, but still quite deep layers - vertical resolution improvement created by using many channels.
  - Deep layers generally associated with large horizontal scale

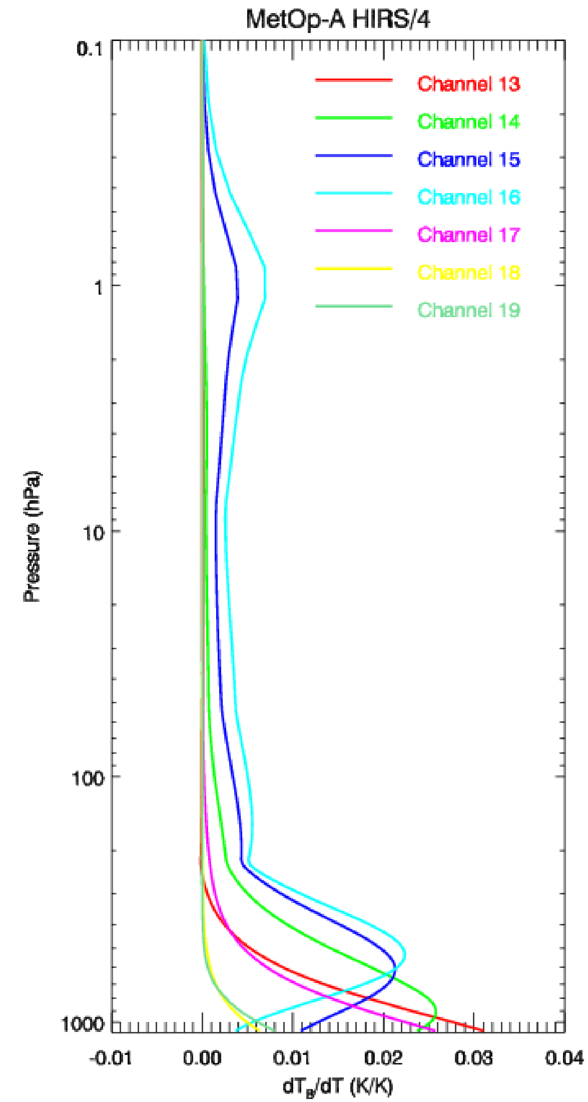
Forward Model for RT

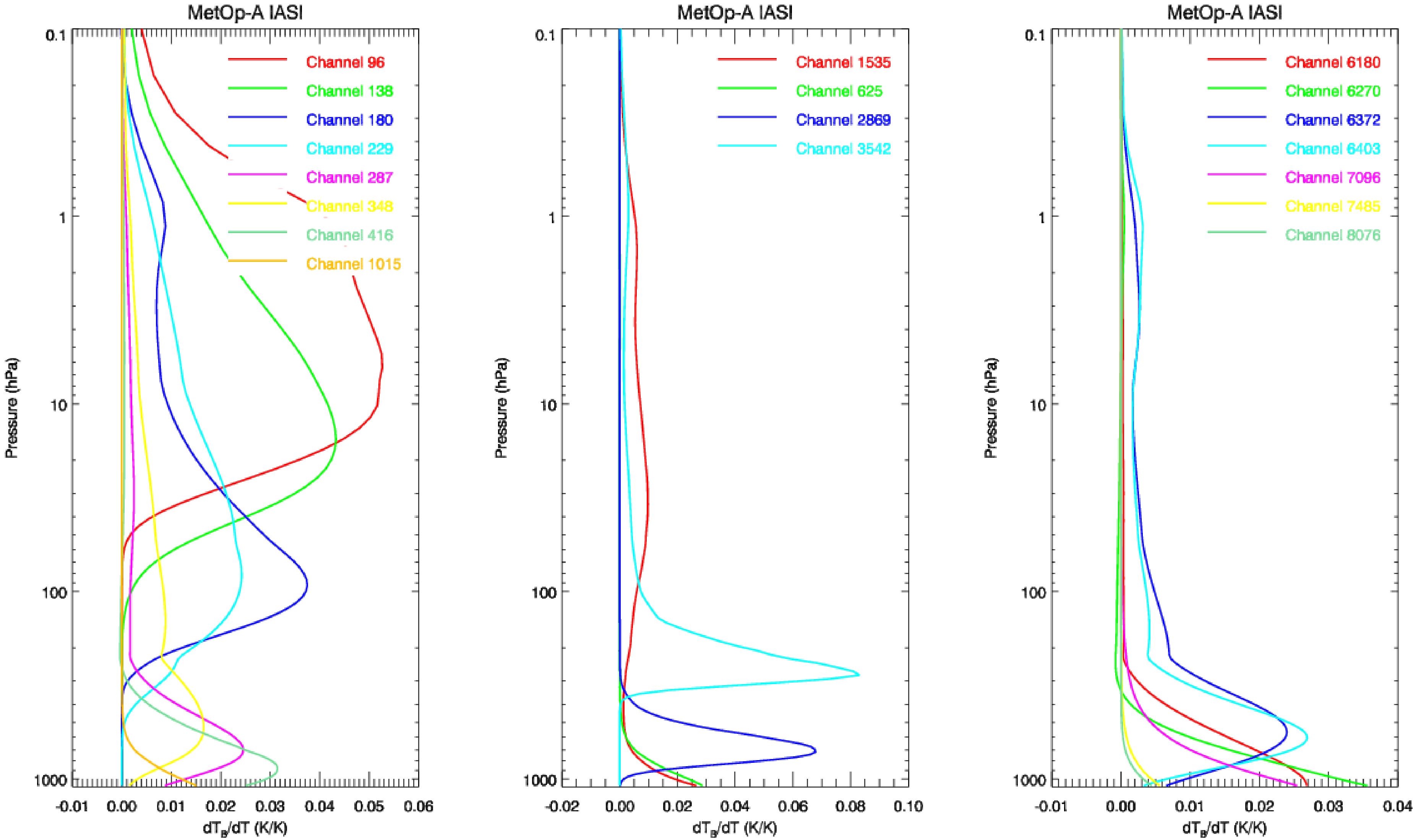
- Need fast forward models because of computational expense.
- RTTOV – CRTM two examples of fast forward models.
- From CRTM get both simulated radiance and Jacobians

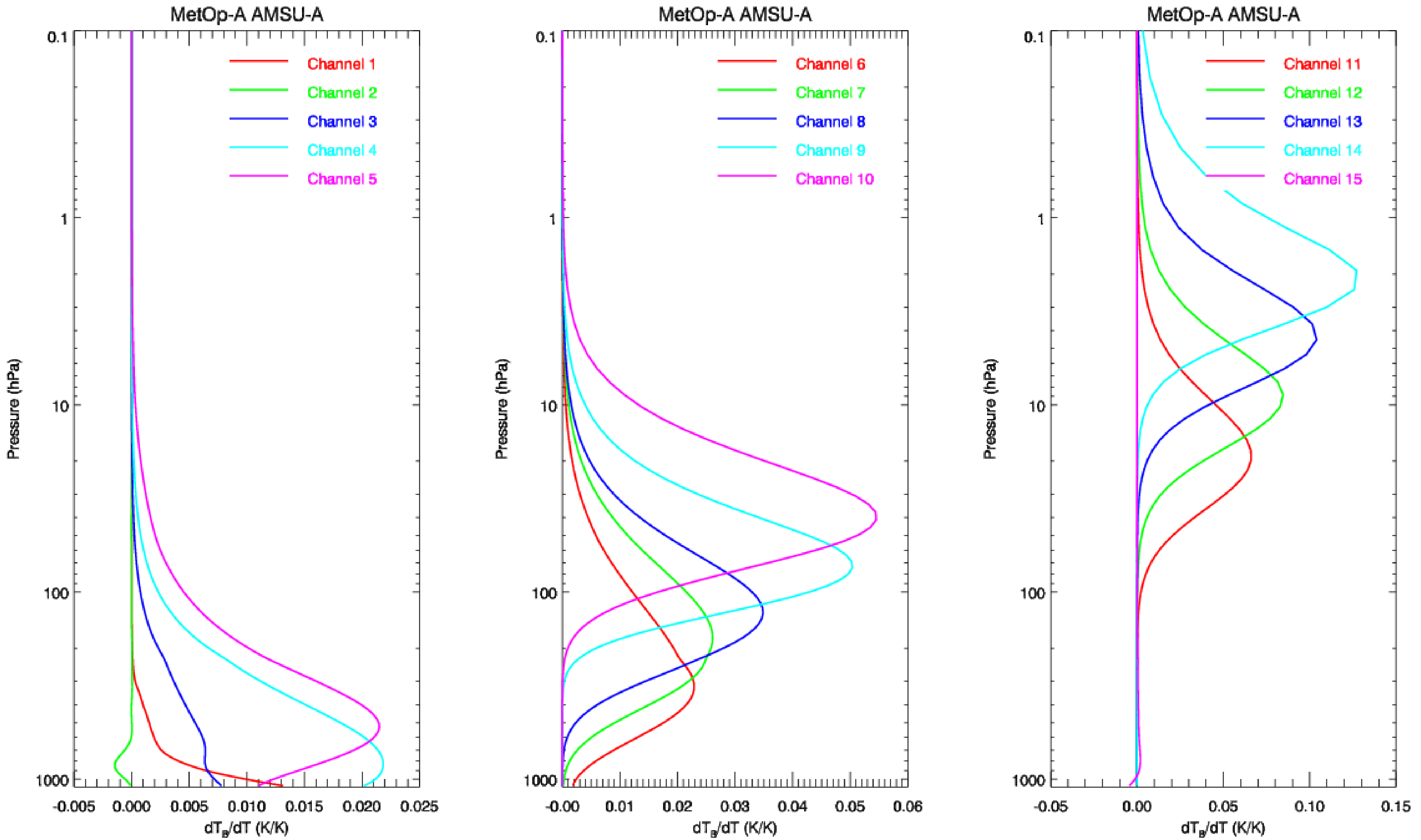
$$\frac{\partial R}{\partial T}, \frac{\partial R}{\partial q}, \frac{\partial R}{\partial T_s}, \frac{\partial R}{\partial O_3}, \ldots$$


MetOp-A HIRS/4
Channel 1
Channel 2
Channel 3
Channel 4
Channel 5
Channel 6
Channel 7
Channel 8
Pressure (hPa)
dT_B/dT (K/K)

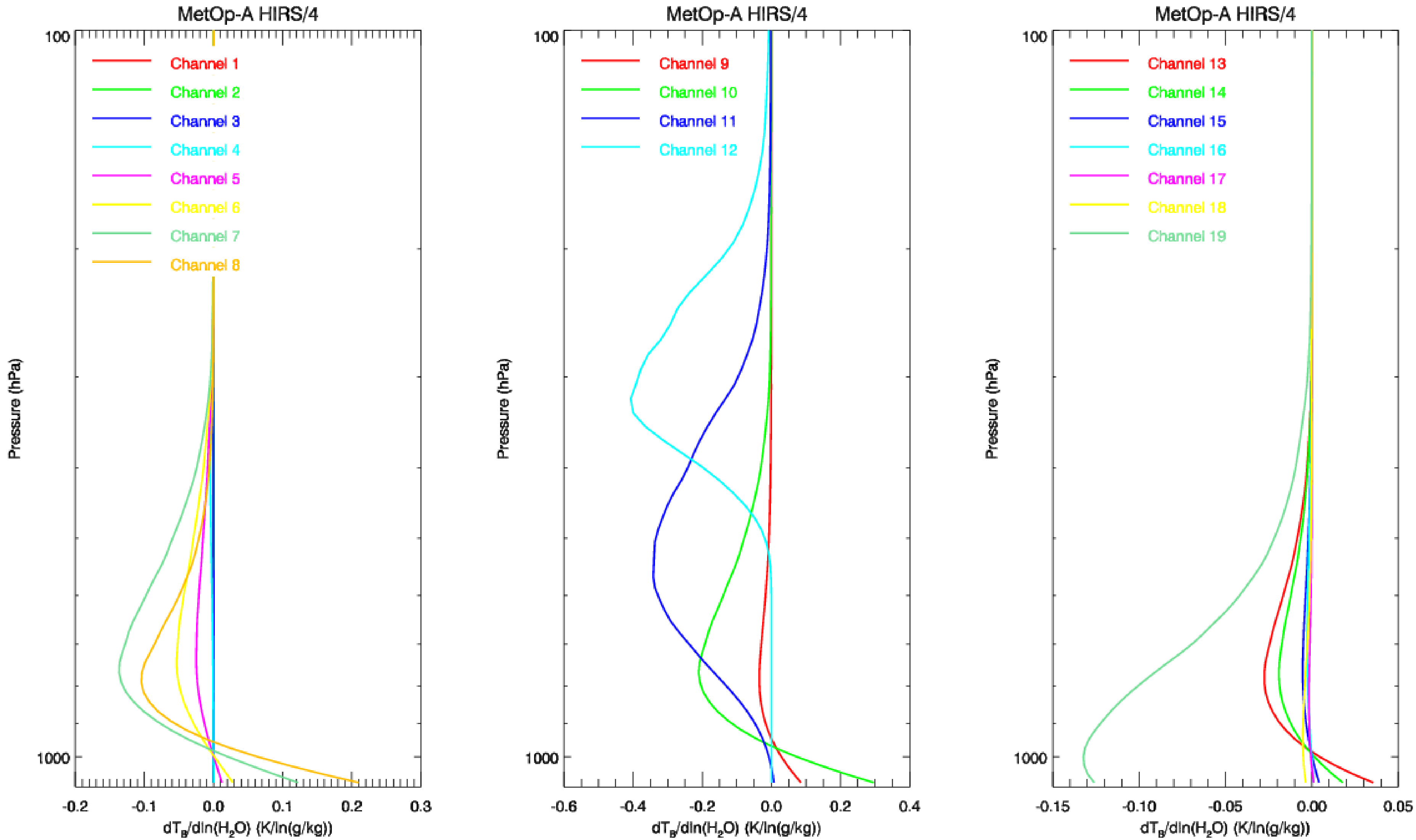

MetOp-A HIRS/4
Channel 9
Channel 10
Channel 11
Channel 12
Pressure (hPa)
dT_B/dT (K/K)

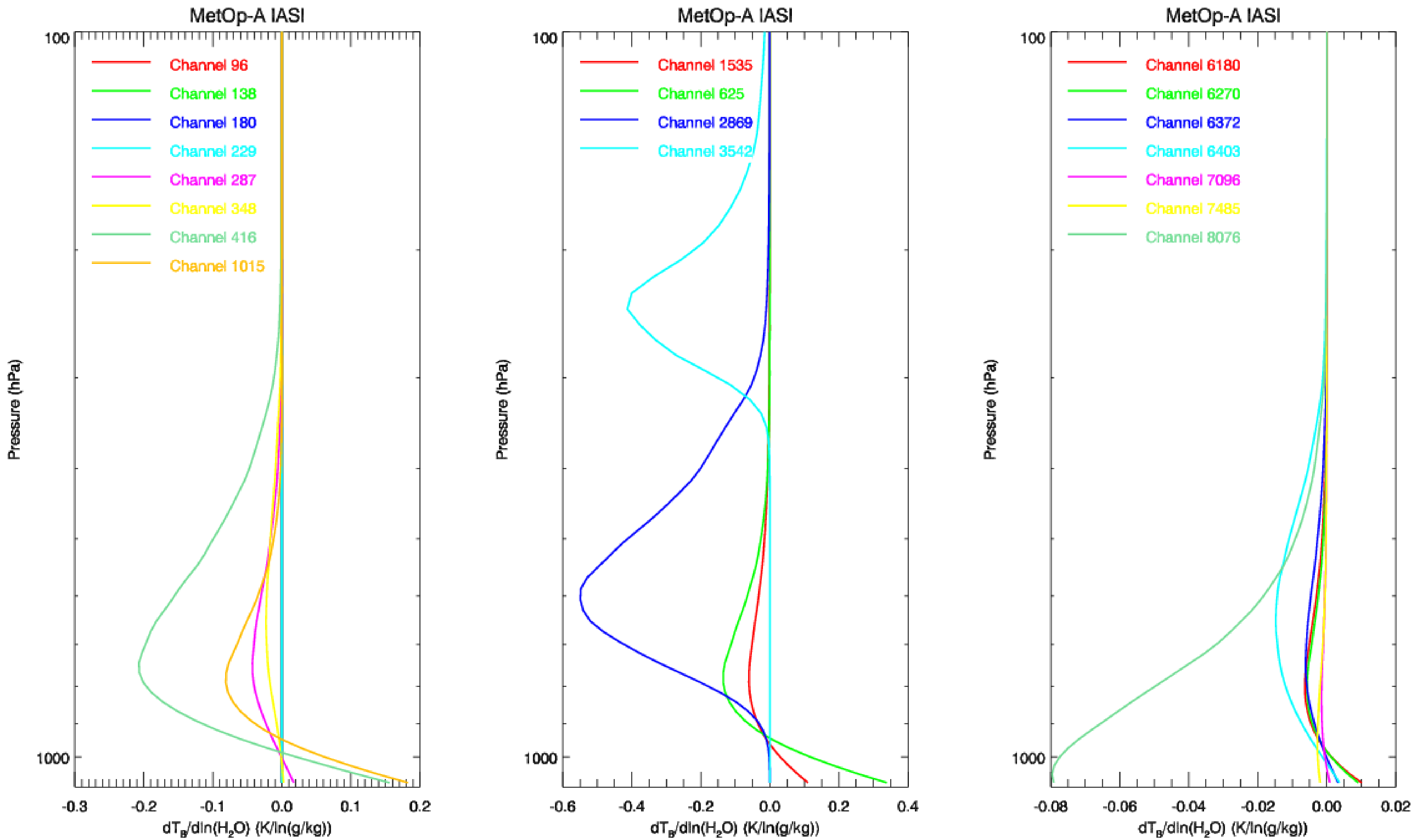

MetOp-A HIRS/4
Channel 13
Channel 14
Channel 15
Channel 16
Channel 17
Channel 18
Channel 19
Pressure (hPa)
dT_B/dT (K/K)

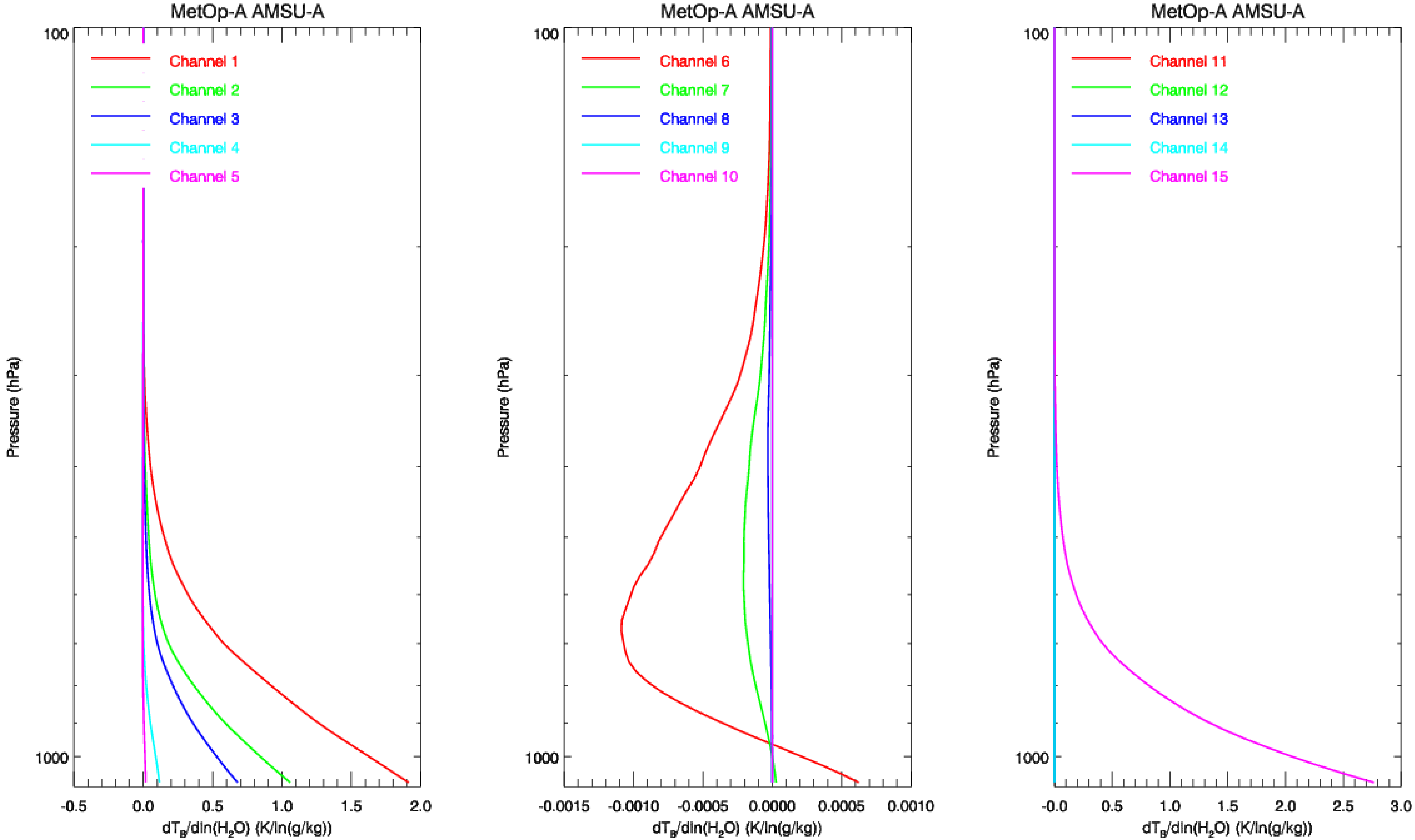

MetOp-A IASI
Channel 96
Channel 138
Channel 180
Channel 229
Channel 287
Channel 348
Channel 416
Channel 1015
Pressure (hPa)
dT$_B$/dT (K/K)
MetOp-A IASI
Channel 1535
Channel 625
Channel 2869
Channel 3542
Pressure (hPa)
dT$_B$/dT (K/K)
MetOp-A IASI
Channel 6180
Channel 6270
Channel 6372
Channel 6403
Channel 7096
Channel 7485
Channel 8076
Pressure (hPa)
dT$_B$/dT (K/K)

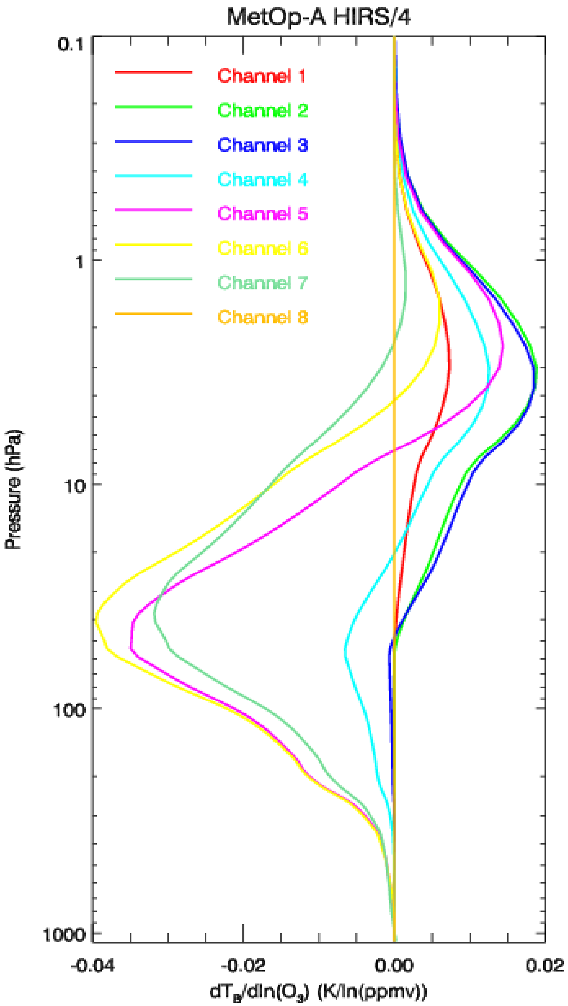


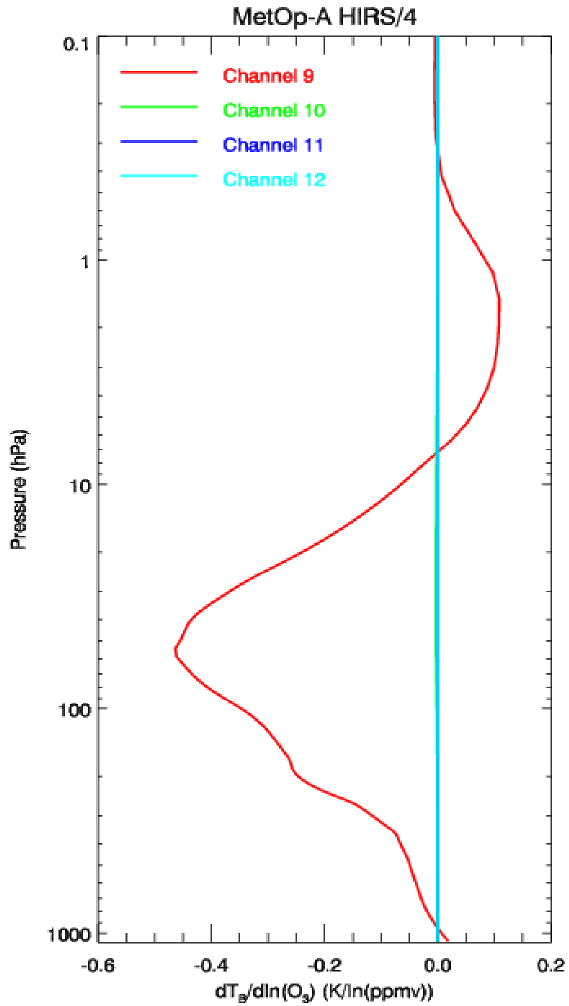
MetOp-A AMSU-A
Channel 1
Channel 2
Channel 3
Channel 4
Channel 5
Pressure (hPa)
dT_B/dT (K/K)
MetOp-A AMSU-A
Channel 6
Channel 7
Channel 8
Channel 9
Channel 10
Pressure (hPa)
dT_B/dT (K/K)
MetOp-A AMSU-A
Channel 11
Channel 12
Channel 13
Channel 14
Channel 15
Pressure (hPa)
dT_B/dT (K/K)

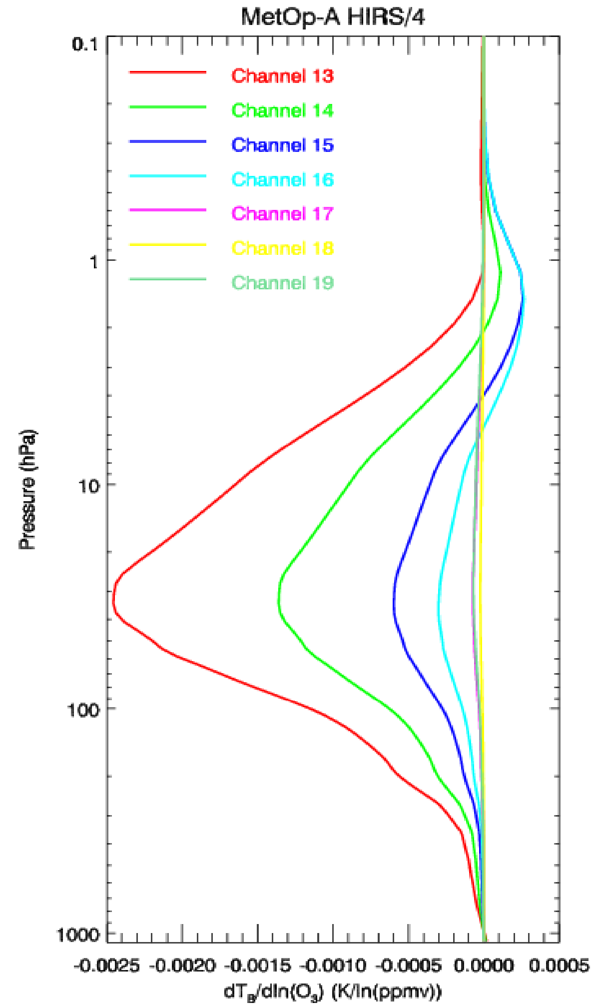

MetOp-A HIRS/4
Channel 1
Channel 2
Channel 3
Channel 4
Channel 5
Channel 6
Channel 7
Channel 8
Pressure (hPa)
100
1000
-0.2
-0.1
0.0
0.1
0.2
0.3
$dT_B/d\ln(H_2O)$ (K/ln(g/kg))
MetOp-A HIRS/4
Channel 9
Channel 10
Channel 11
Channel 12
Pressure (hPa)
100
1000
-0.6
-0.4
-0.2
0.0
0.2
0.4
$dT_B/d\ln(H_2O)$ (K/ln(g/kg))
MetOp-A HIRS/4
Channel 13
Channel 14
Channel 15
Channel 16
Channel 17
Channel 18
Channel 19
Pressure (hPa)
100
1000
-0.15
-0.10
-0.05
0.00
0.05
$dT_B/d\ln(H_2O)$ (K/ln(g/kg))


MetOp-A IASI
Channel 96
Channel 138
Channel 180
Channel 229
Channel 287
Channel 348
Channel 416
Channel 1015
Pressure (hPa)
100
1000
-0.3 -0.2 -0.1 0.0 0.1 0.2
dT_B/dln(H_2O) (K/ln(g/kg))
MetOp-A IASI
Channel 1535
Channel 625
Channel 2869
Channel 3542
Pressure (hPa)
100
1000
-0.6 -0.4 -0.2 0.0 0.2 0.4
dT_B/dln(H_2O) (K/ln(g/kg))
MetOp-A IASI
Channel 6180
Channel 6270
Channel 6372
Channel 6403
Channel 7096
Channel 7485
Channel 8076
Pressure (hPa)
100
1000
-0.08 -0.06 -0.04 -0.02 0.00 0.02
dT_B/dln(H_2O) (K/ln(g/kg))

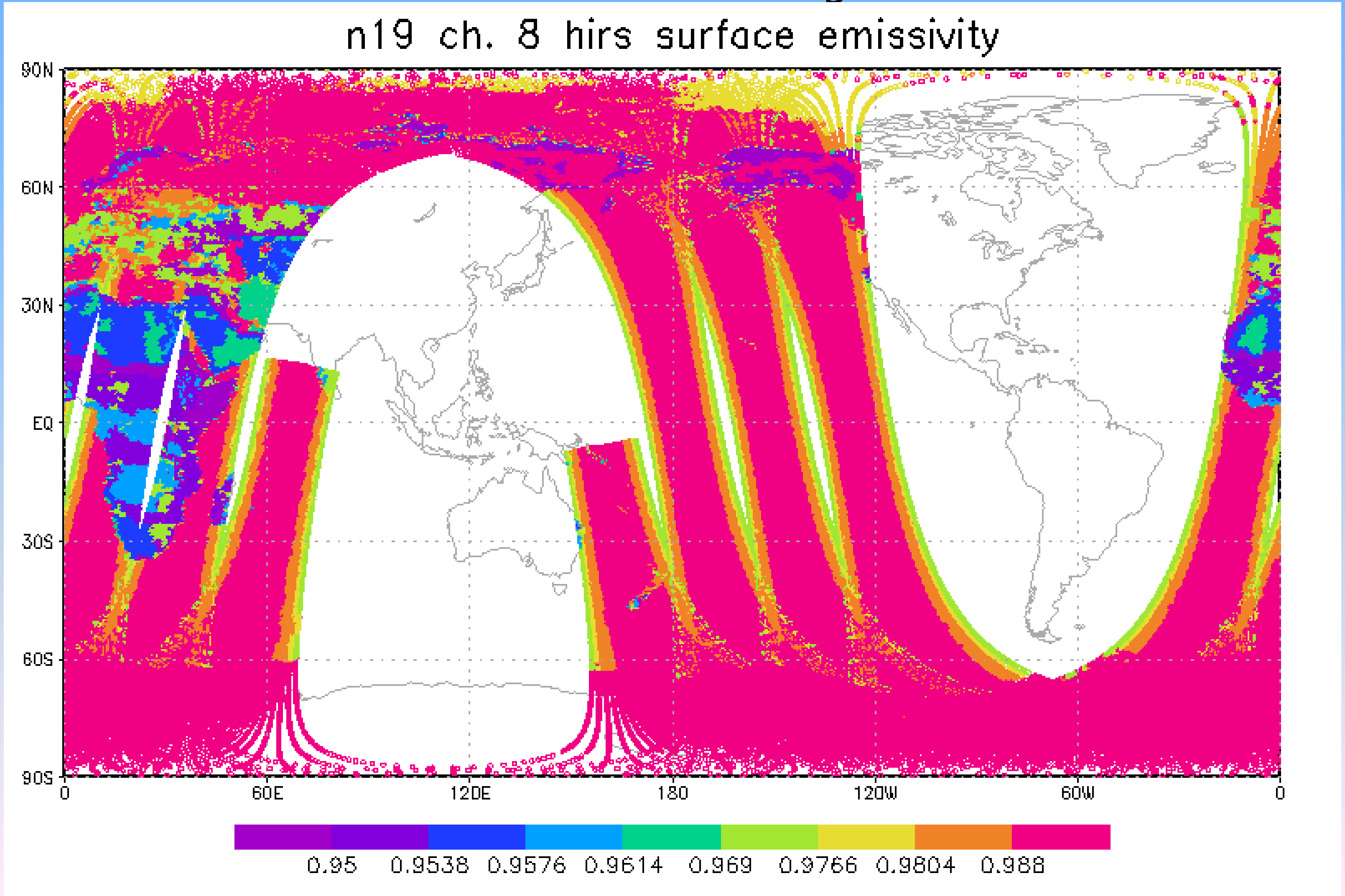

MetOp-A AMSU-A
Channel 1
Channel 2
Channel 3
Channel 4
Channel 5
Pressure (hPa)
100
1000
-0.5
0.0
0.5
1.0
1.5
2.0
$dT_B/d\ln(H_2O)$ (K/ln(g/kg))
MetOp-A AMSU-A
Channel 6
Channel 7
Channel 8
Channel 9
Channel 10
Pressure (hPa)
100
1000
-0.0015
-0.0010
-0.0005
0.0000
0.0005
0.0010
$dT_B/d\ln(H_2O)$ (K/ln(g/kg))
MetOp-A AMSU-A
Channel 11
Channel 12
Channel 13
Channel 14
Channel 15
Pressure (hPa)
100
1000
-0.0
0.5
1.0
1.5
2.0
2.5
3.0
$dT_B/d\ln(H_2O)$ (K/ln(g/kg))


MetOp-A HIRS/4
Channel 1
Channel 2
Channel 3
Channel 4
Channel 5
Channel 6
Channel 7
Channel 8
Pressure (hPa)
0.1
1
10
100
1000
-0.04
-0.02
0.00
0.02
dT$_B$/dln(O$_3$) (K/ln(ppmv))

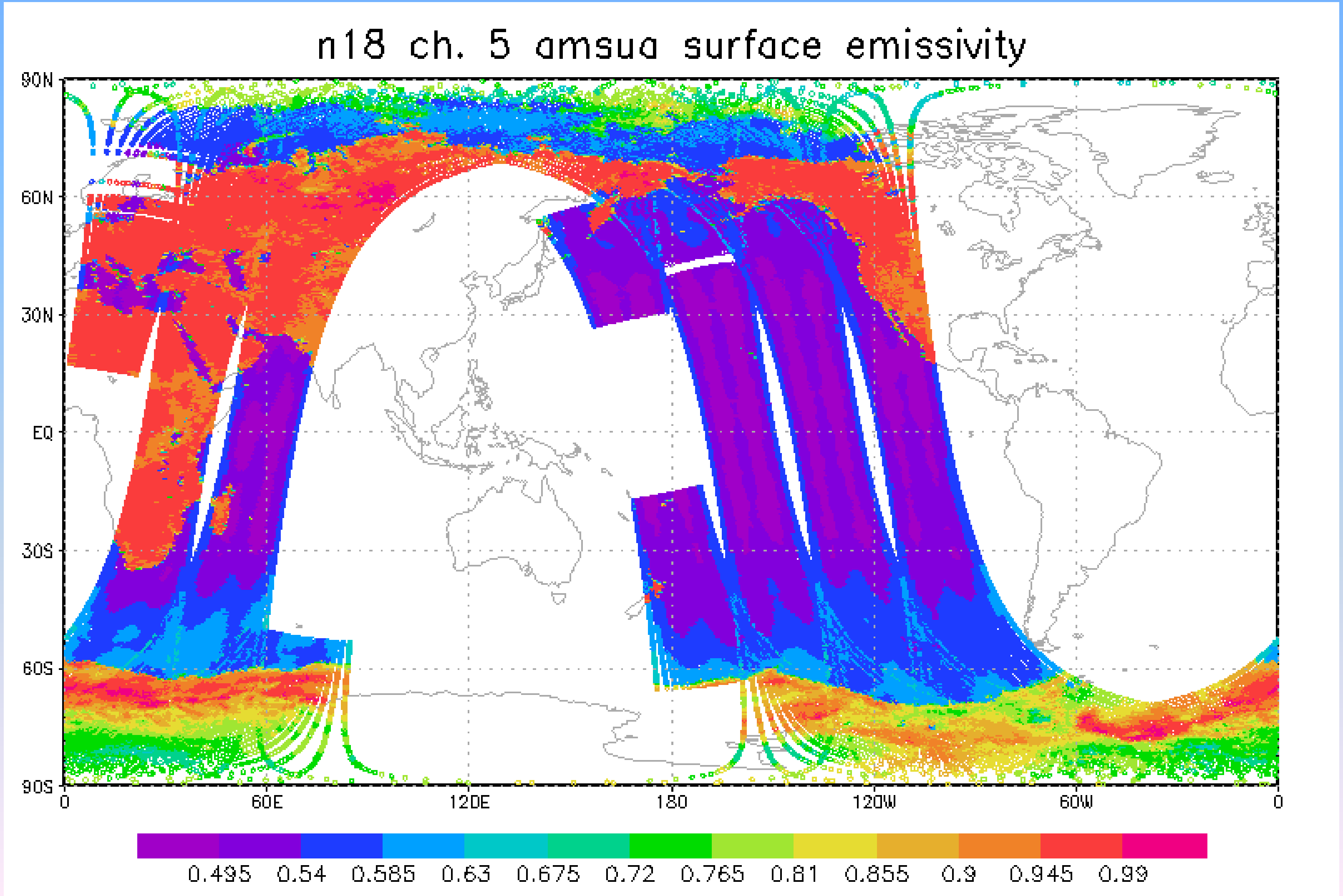

MetOp-A HIRS/4
Channel 9
Channel 10
Channel 11
Channel 12
Pressure (hPa)
0.1
1
10
100
1000
-0.6
-0.4
-0.2
0.0
0.2
dT$_B$/dln(O$_3$) (K/ln(ppmv))

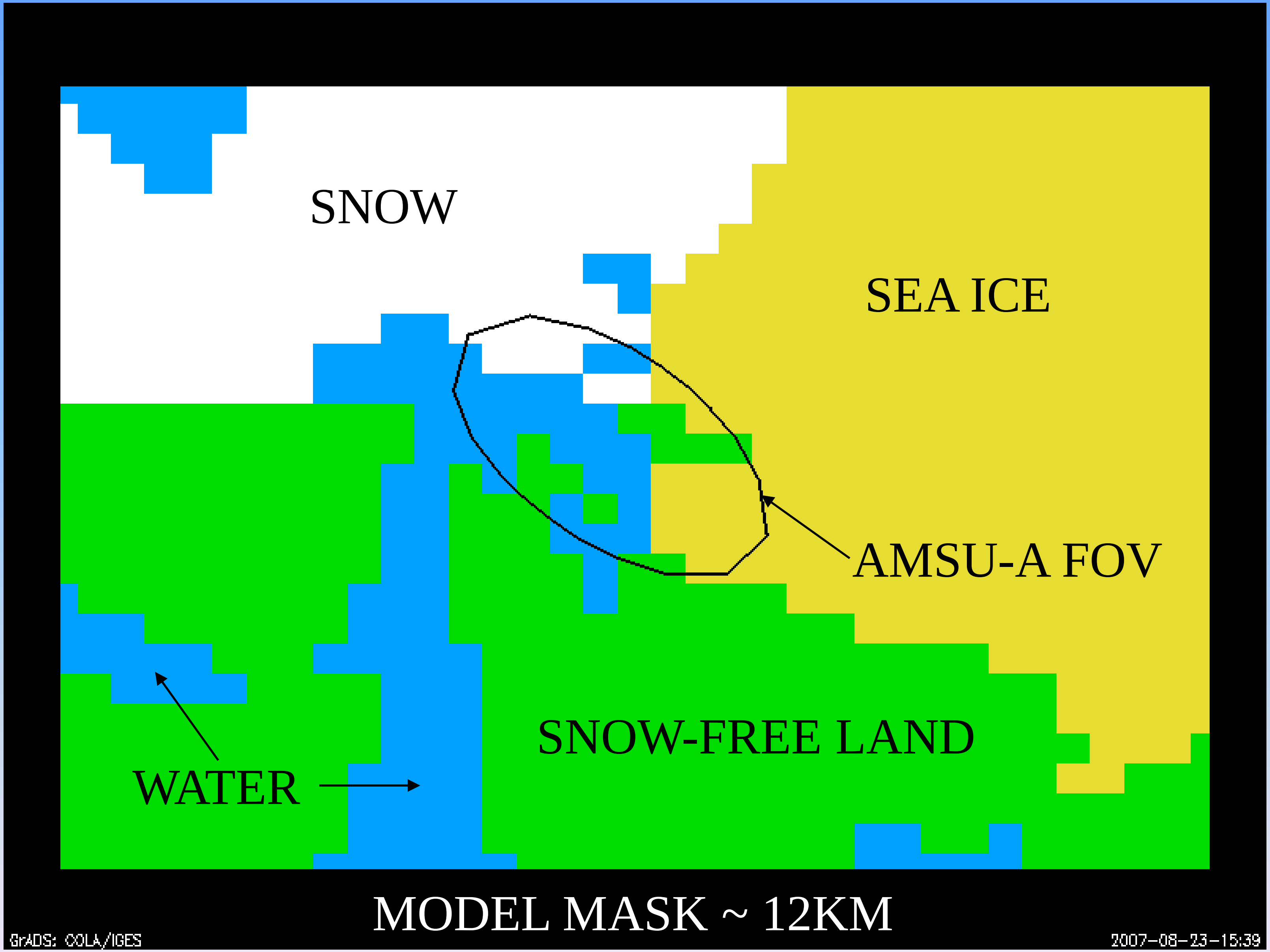

MetOp-A HIRS/4
Channel 13
Channel 14
Channel 15
Channel 16
Channel 17
Channel 18
Channel 19
Pressure (hPa)
0.1
1
10
100
1000
-0.0025
-0.0020
-0.0015
-0.0010
-0.0005
0.0000
0.0005
dT$_B$/dln(O$_3$) (K/ln(ppmv))

Surface Emissivity Infrared



Surface Emissivity Microwave

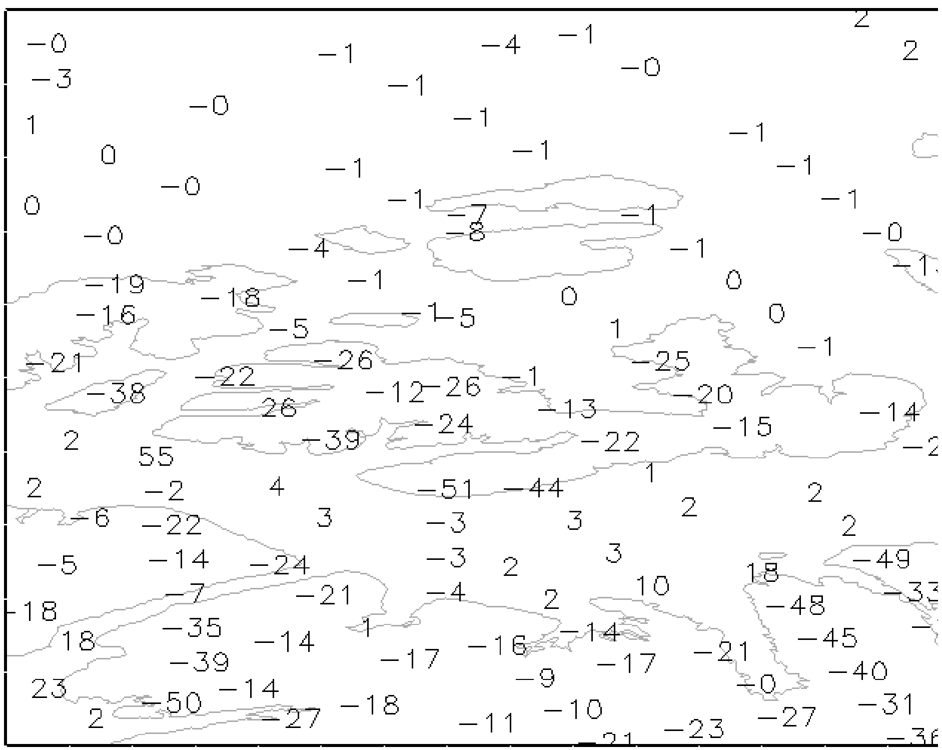



SNOW
SEA ICE
AMSU-A FOV
SNOW-FREE LAND
WATER
MODEL MASK ~ 12KM
GrADS: COLA/IGES
2007-08-23-15:39

IMPACT: ACCOUNTING FOR FOV

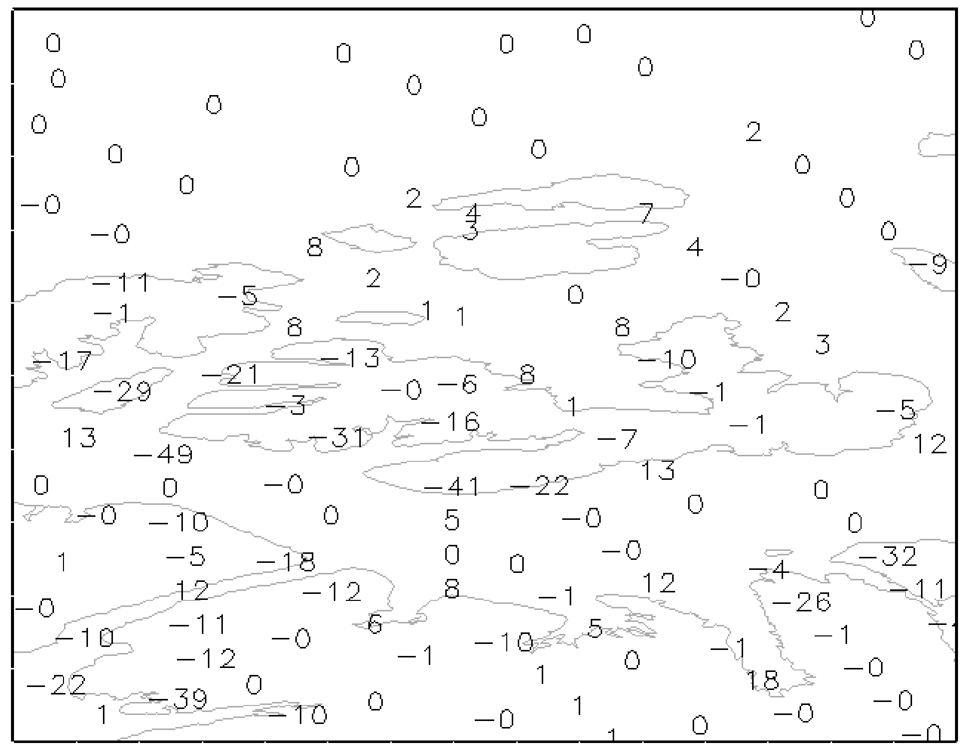
EX: NOAA-15 AMSU-A, CHANNEL 2

CONTROL:
OBS. MINUS GUESS T_b



NORTHERN CANADA

IMPACT: CHANGE IN
OBS. MINUS GUESS T_b

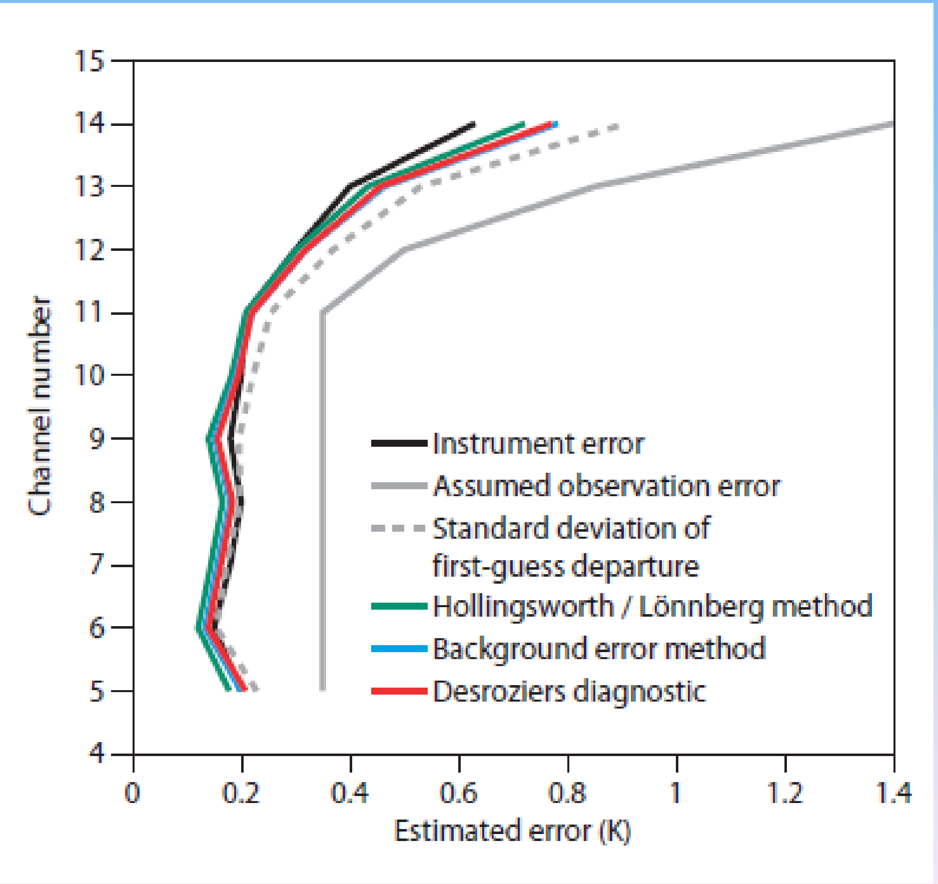


NEGATIVE IS IMPROVEMENT

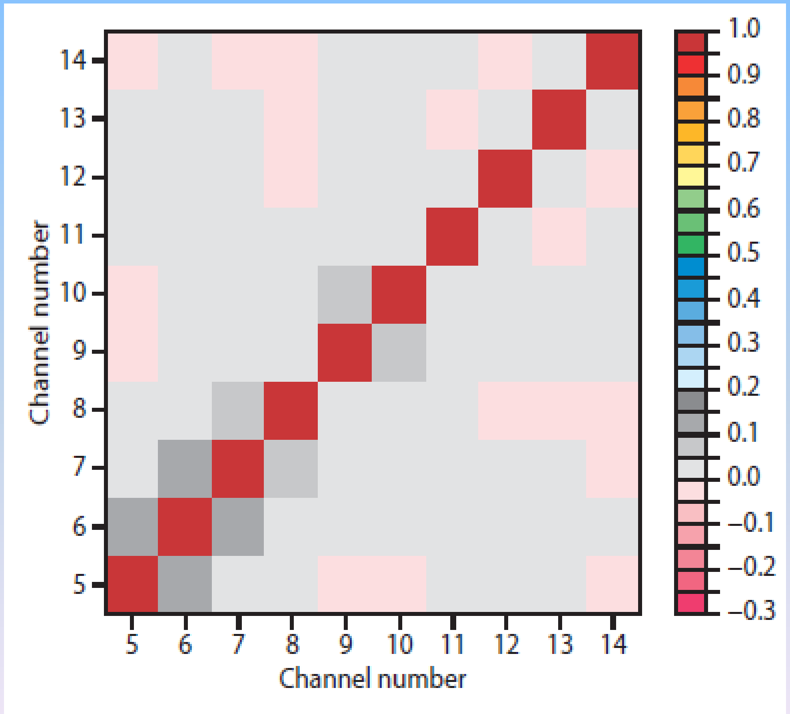
Observational Errors

- Observation errors specified based on instrument errors and statistics (see presentation by Desroziers).
- Generally for satellite data, variances are specified a bit large since the correlated errors (from RT/and instrument errors) are not well known.
- Following slides from Bormann, N., A. Collard, and P. Bauer, Observation errors and their error correlations for satellite radiances, ECMWF Newsletter No. 128, p17-22.

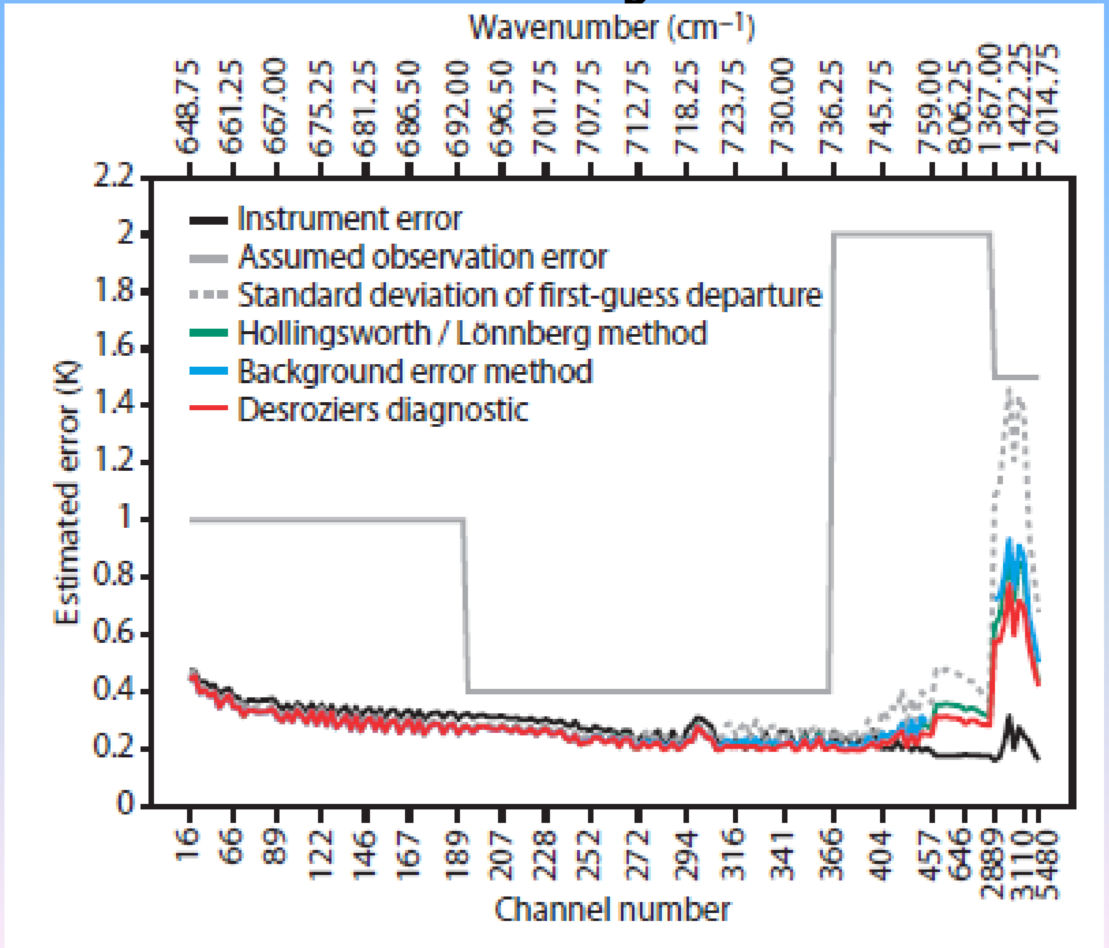
AMSU-A Observation Errors in ECMWF System



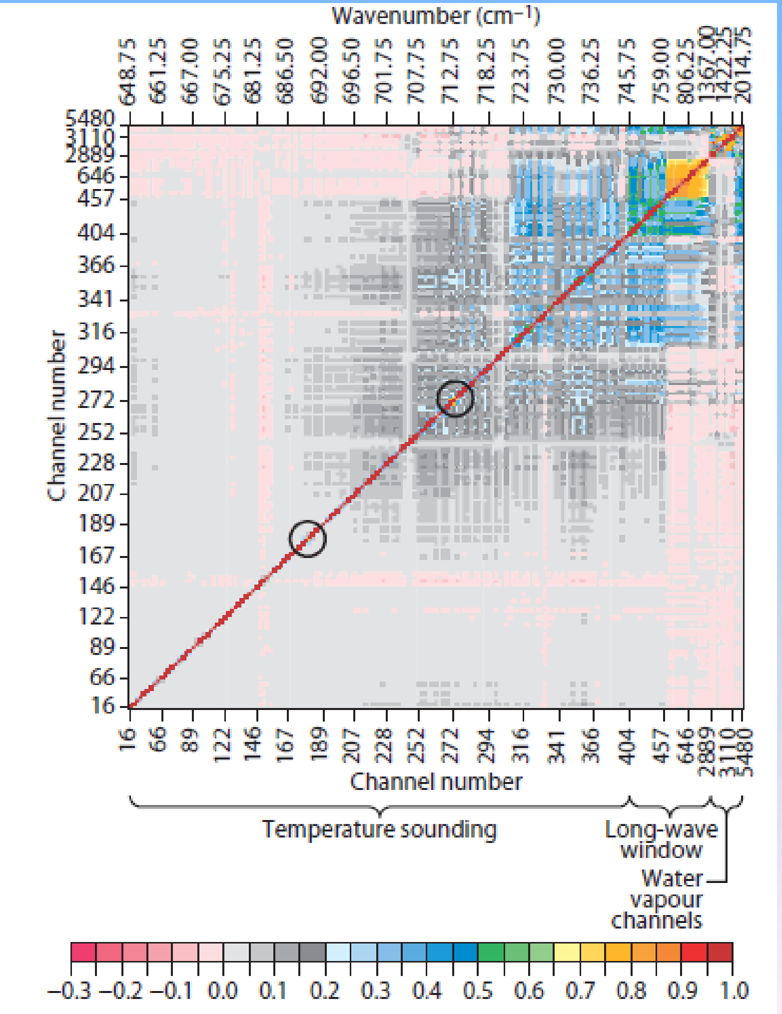
AMSU-A Inter-Channel Error Correlations



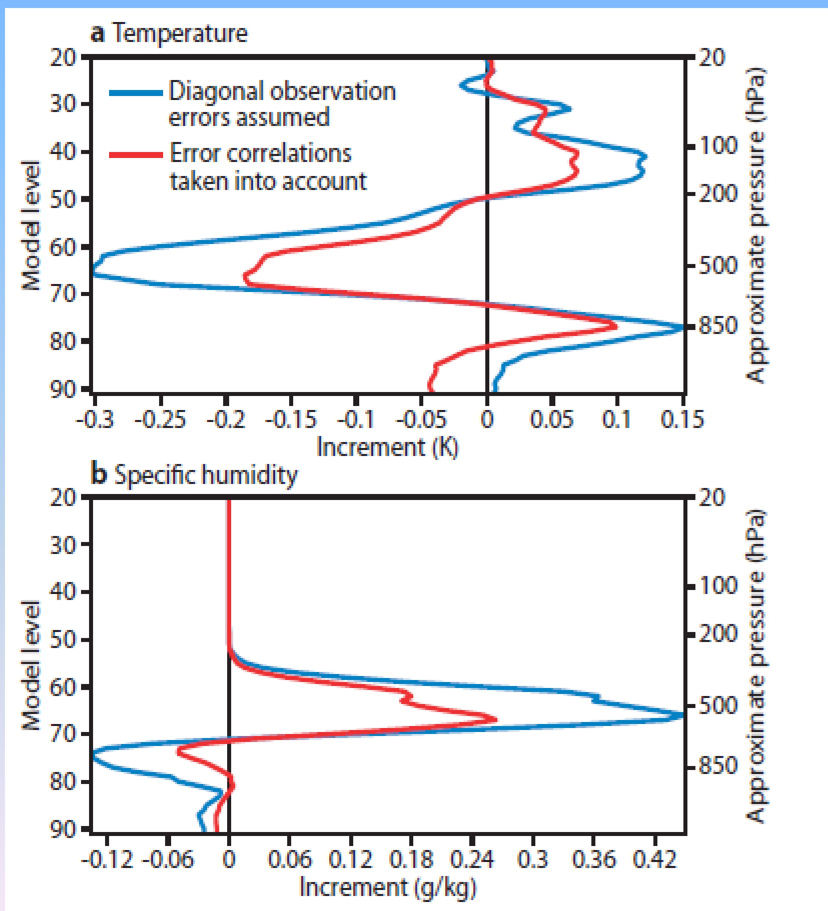
IASI Observation Errors in ECMWF System

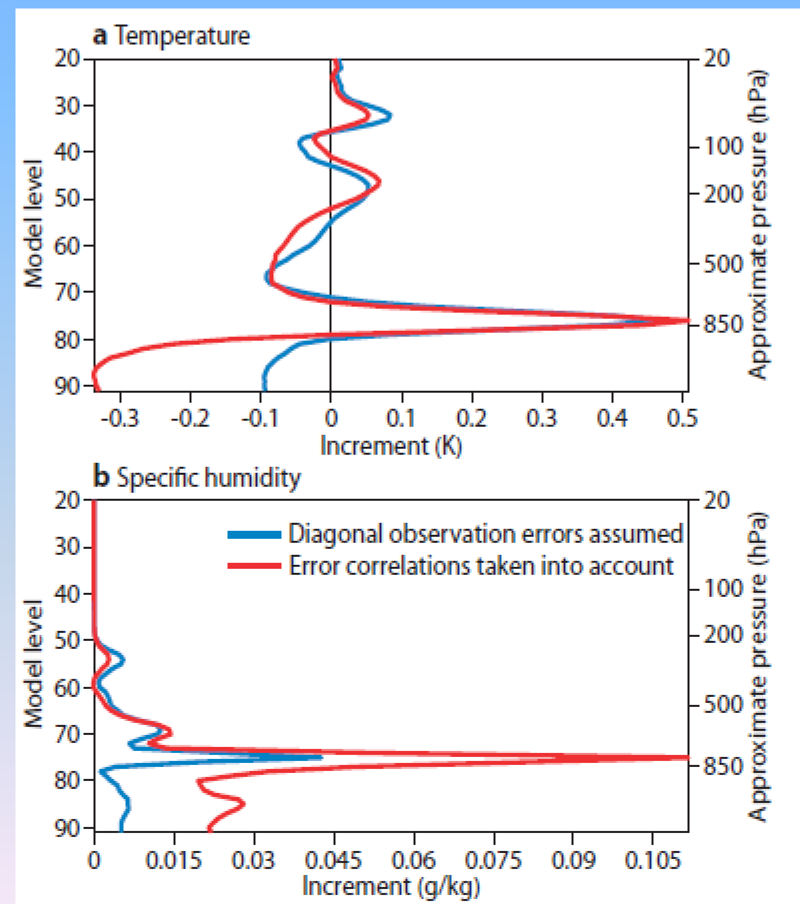


IASI Inter-Channel Correlations



Profile of Increments for 2 Different Radiance Cases





Bias Correction

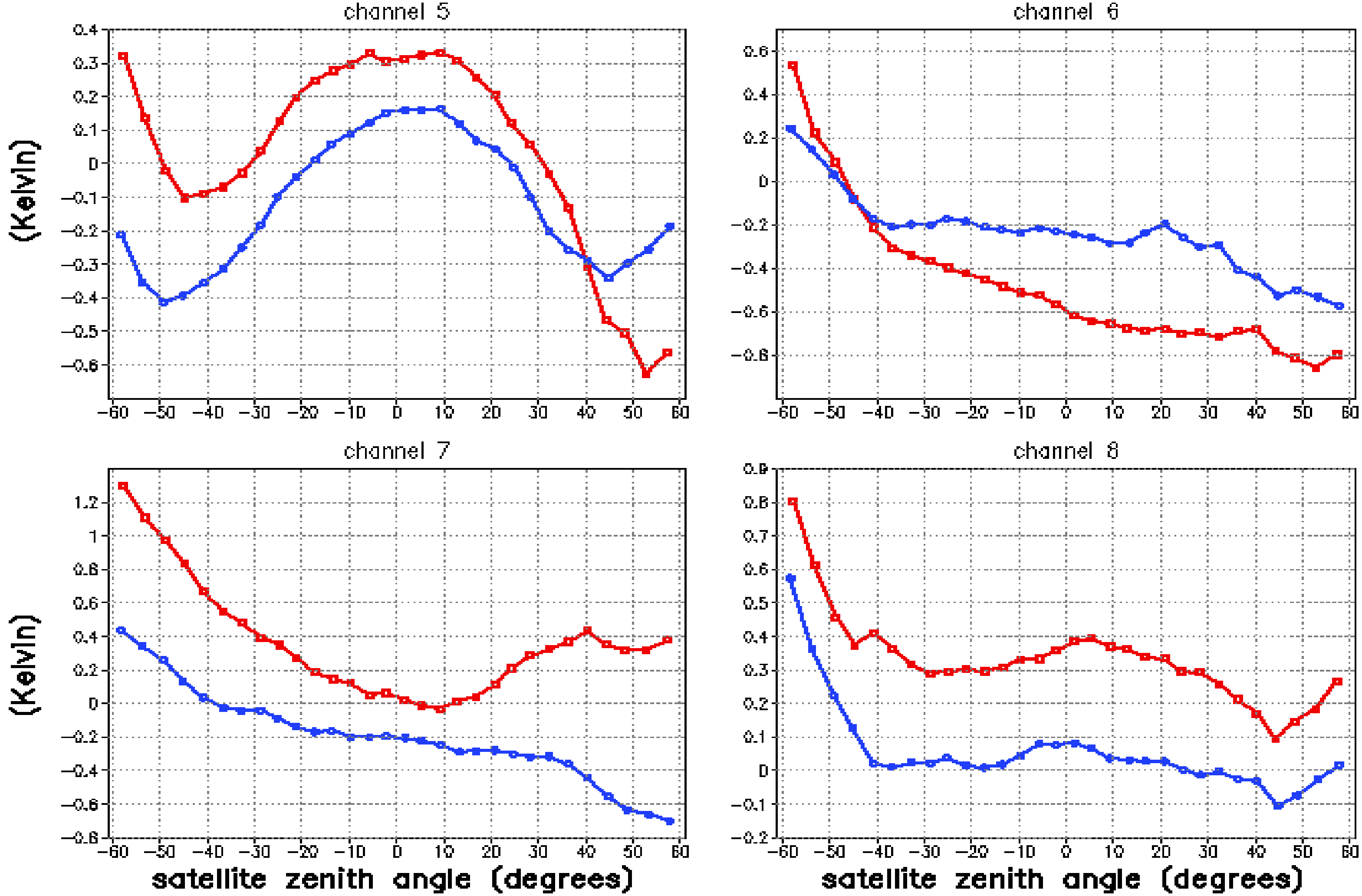
- The differences between simulated and observed observations can show significant biases.
- The source of the bias can come from:
  - Inadequacies in the characterization of the instruments.
  - Deficiencies in the forward models.
  - Errors in processing data.
  - Biases in the background.
- Except 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 currently uses a 2-step process for radiances (others centres are similar).
  - Angle correction (very slowly evolving – different correction for each scan position).
  - Air Mass correction (slowly evolving based on predictors).

platform: amsua
region : global
variable: observed−simulated (without bias correction) (K)
valid : 00Z20FEB2001 00Z22MAR2001

NOAA−15 (red)
NOAA−16 (blue)



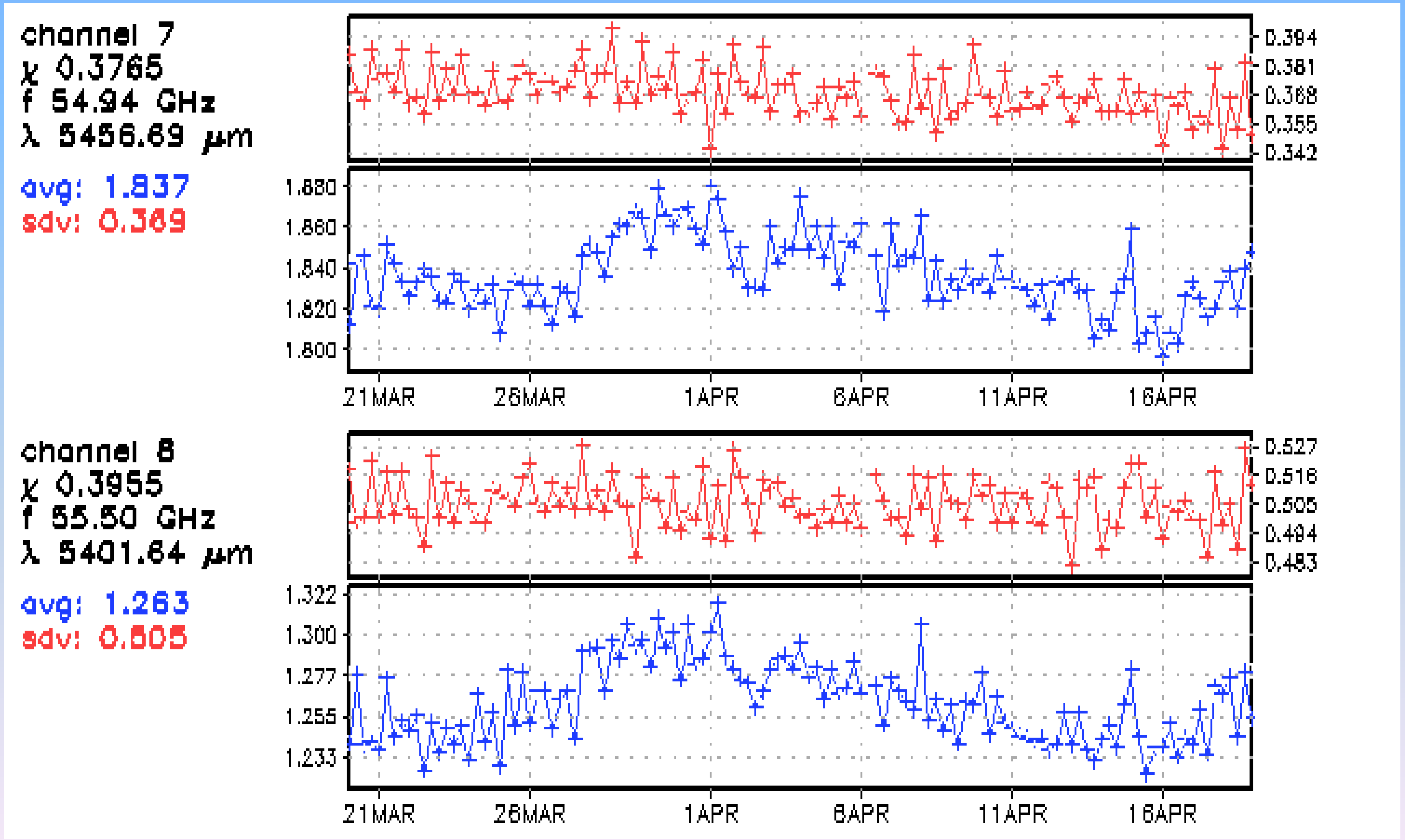
Satellite radiance observations Bias correction

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

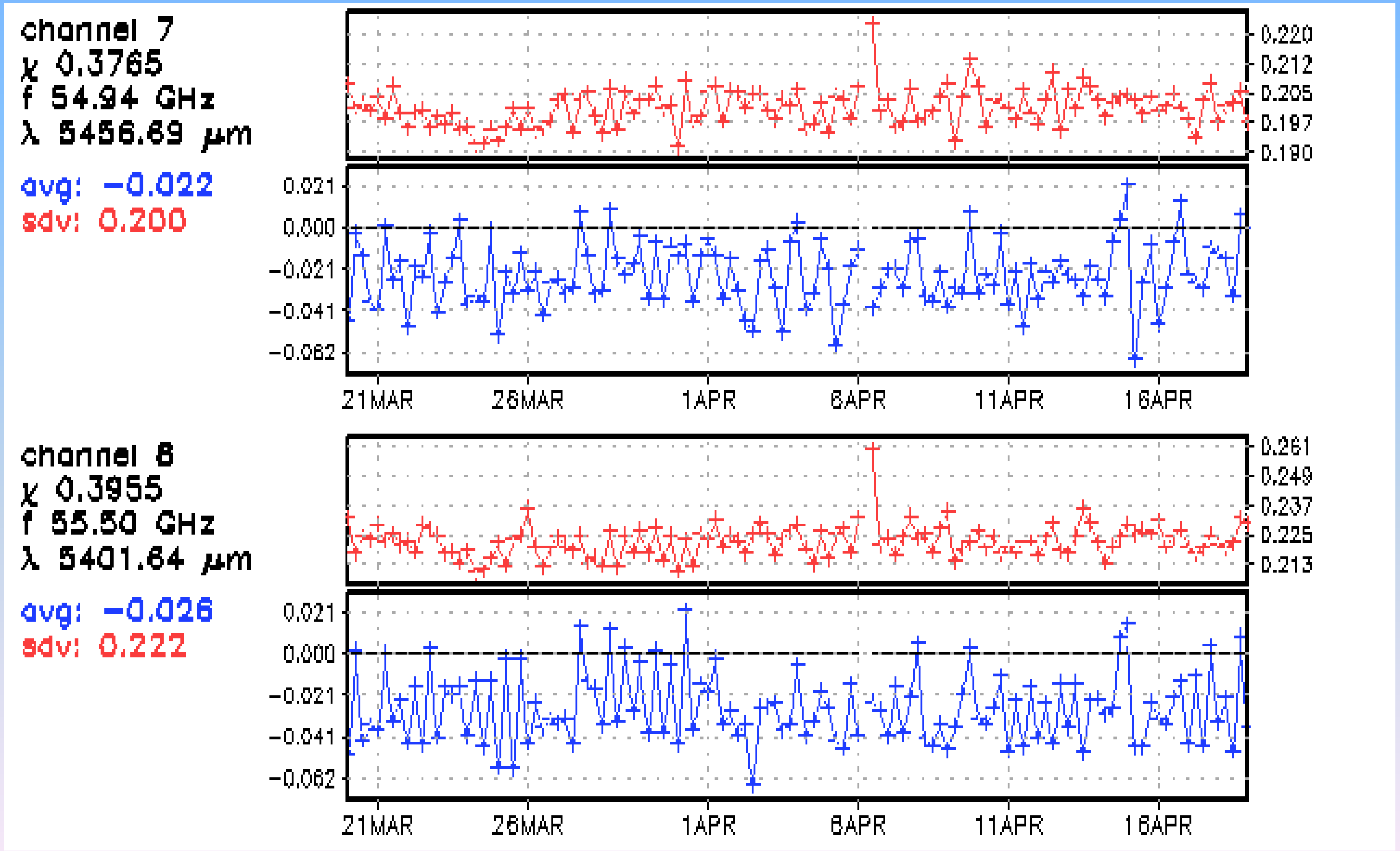
    where total bias correction = $\sum_{1}^{n_p} x_{n+i} p_i$

  - Predictors (p_i) for each channel
    - mean
    - path length (local zenith angle determined)
    - integrated lapse rate
    - (integrated lapse rate)^2
    - cloud liquid water

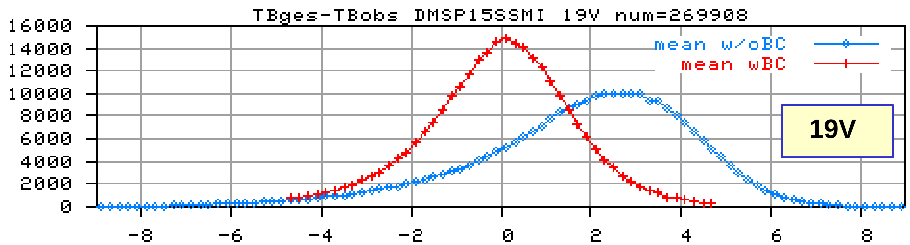
NOAA 18 AMSU-A
No Bias Correction

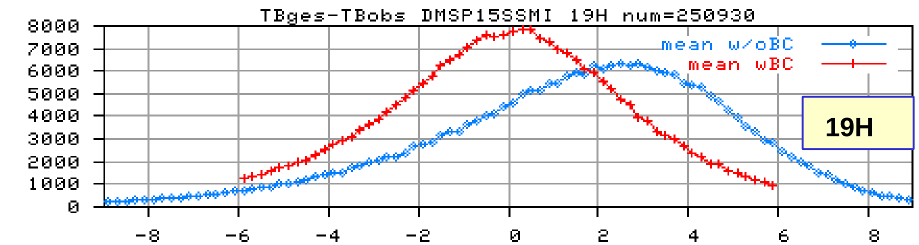


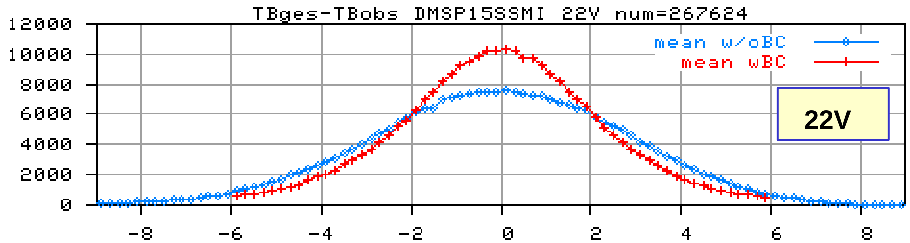
NOAA 18 AMSU-A
Bias Corrected

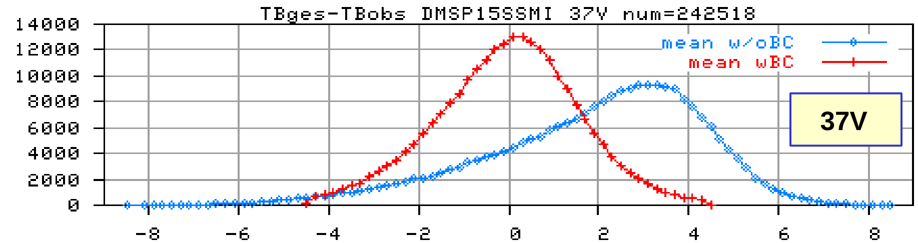


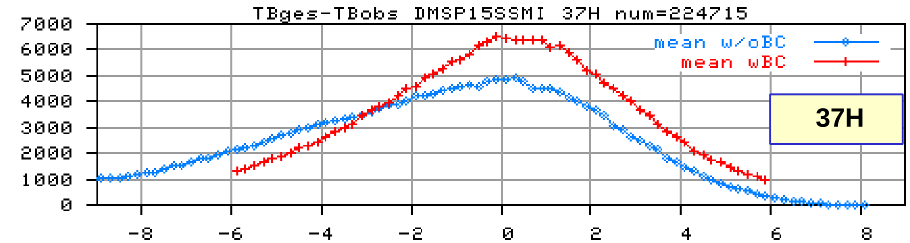
Observation - Background Histogram

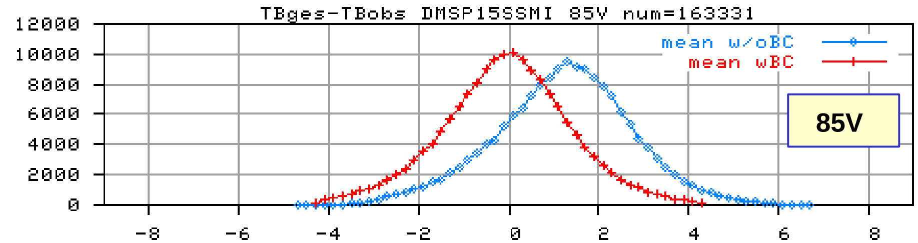


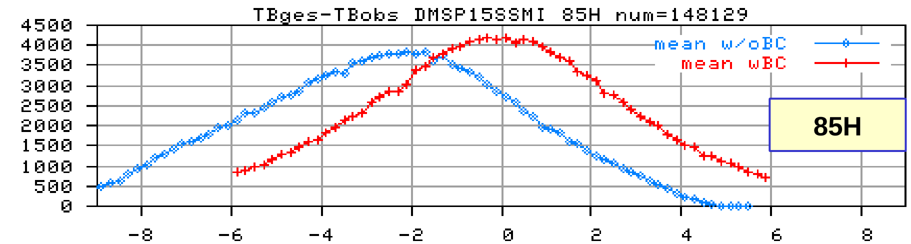












DMSP15 July2004 : 1month

before bias correction

after bias correction

gl use 2004070200-073118(63cases)

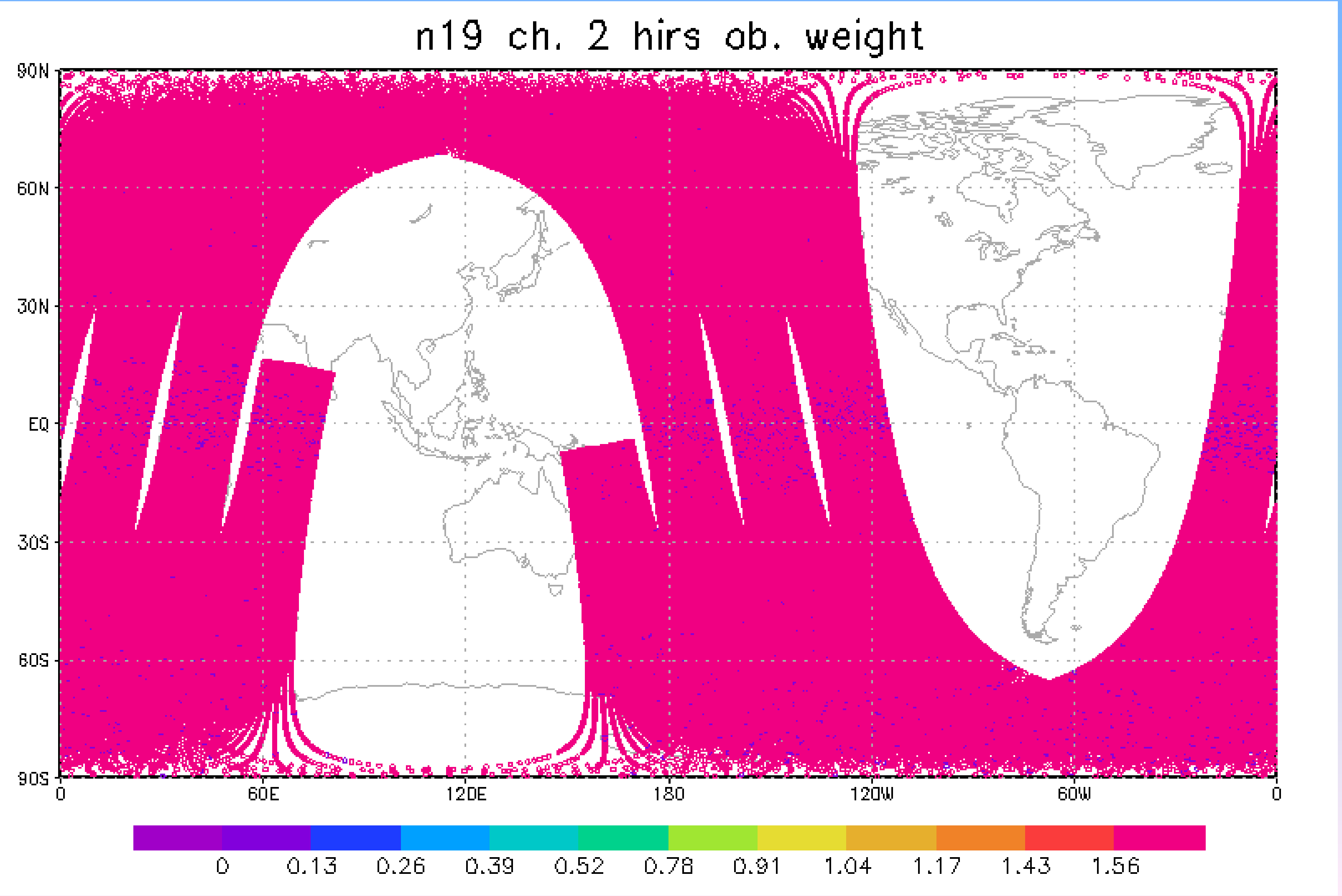
Quality Control Procedures

- 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).

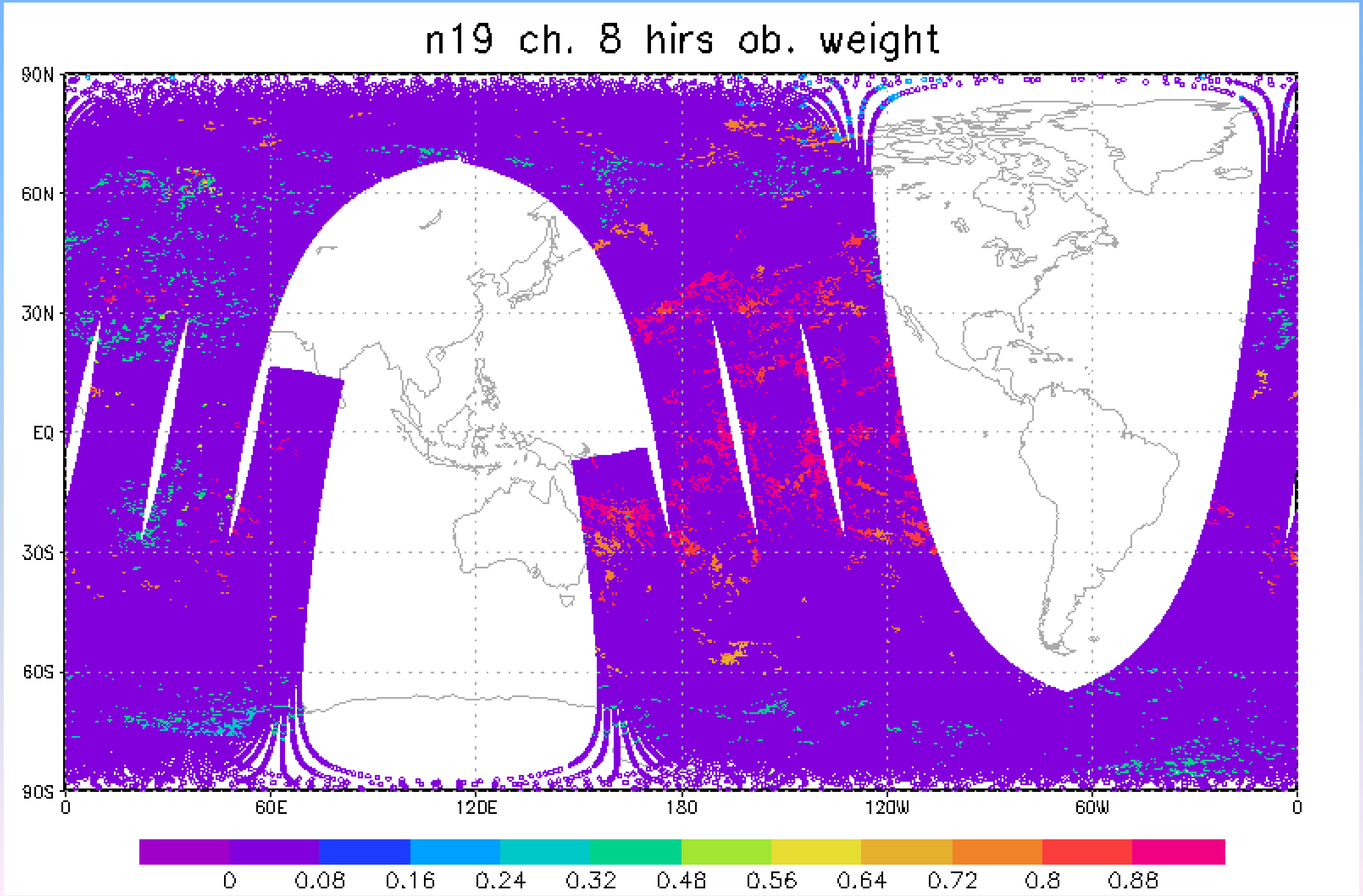
Quality Control Procedures

- 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.
- Surface emissivity and temperature characteristics not well known for land/snow/ice.
  - Also makes detection of clouds/precip. more difficult over these surfaces.
- Error distribution may be asymmetric due to clouds and processing errors.

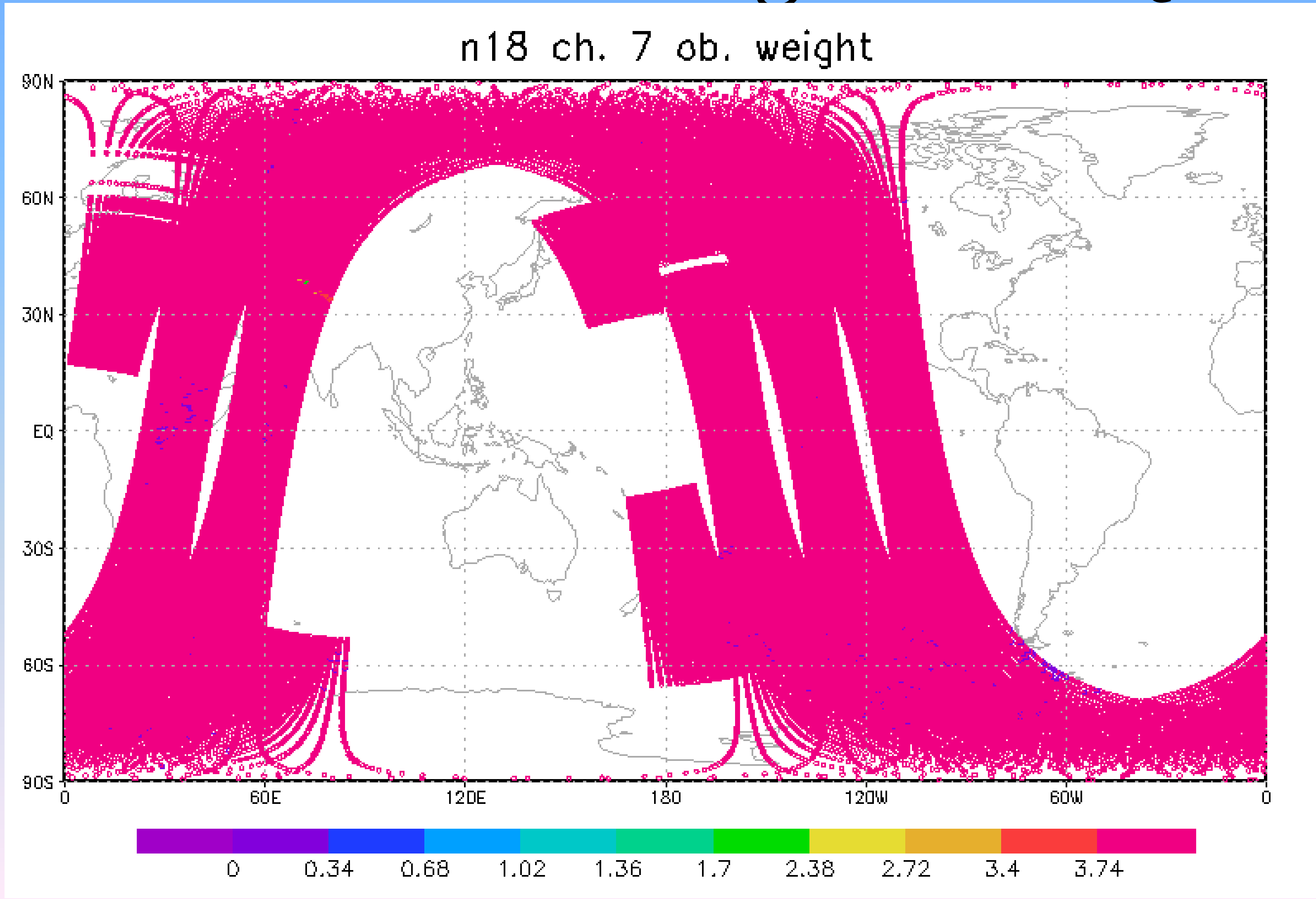
Observation Weight after QC



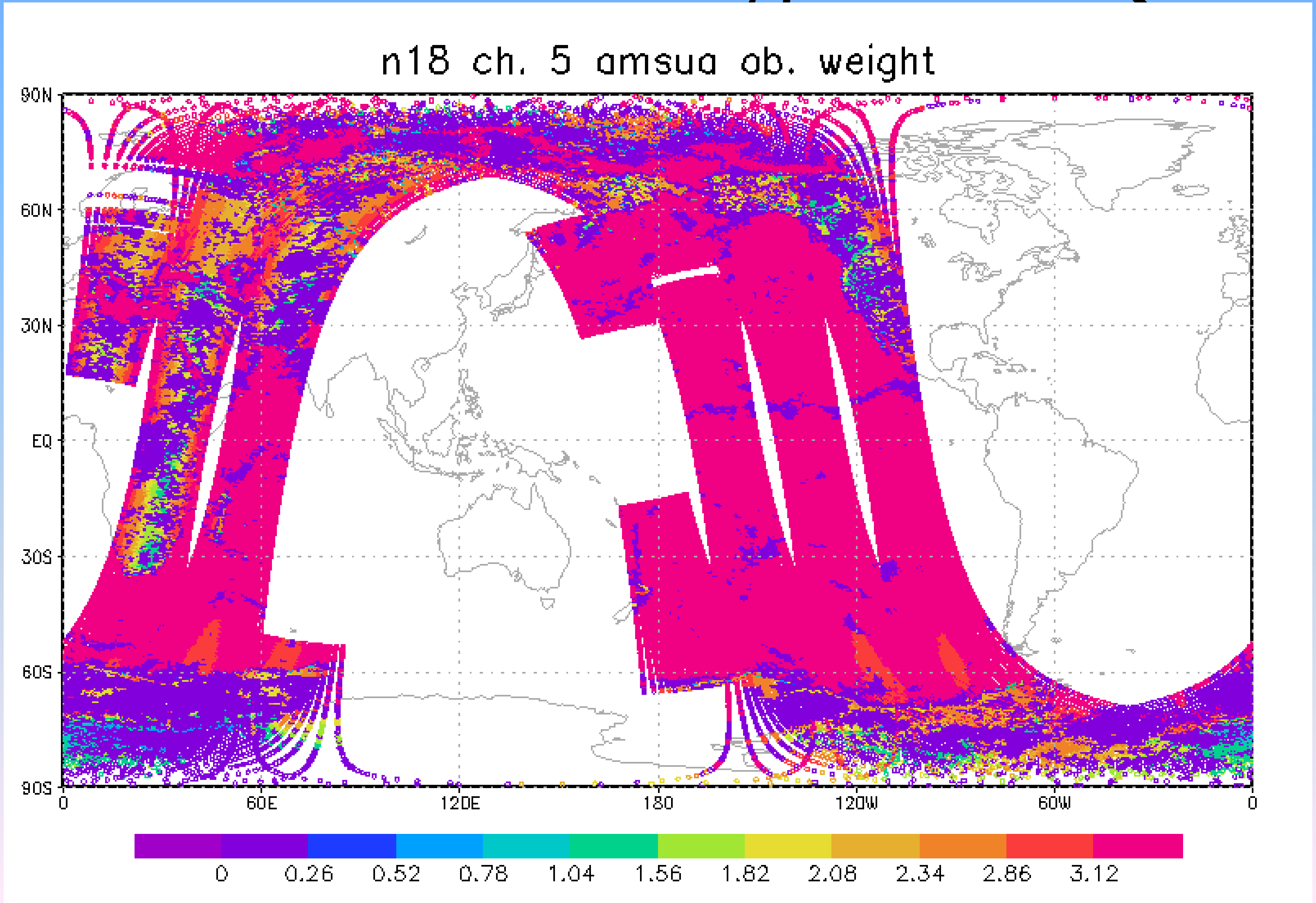
Observation Weight after QC



Observation Weight after QC



Observation Weight after QC

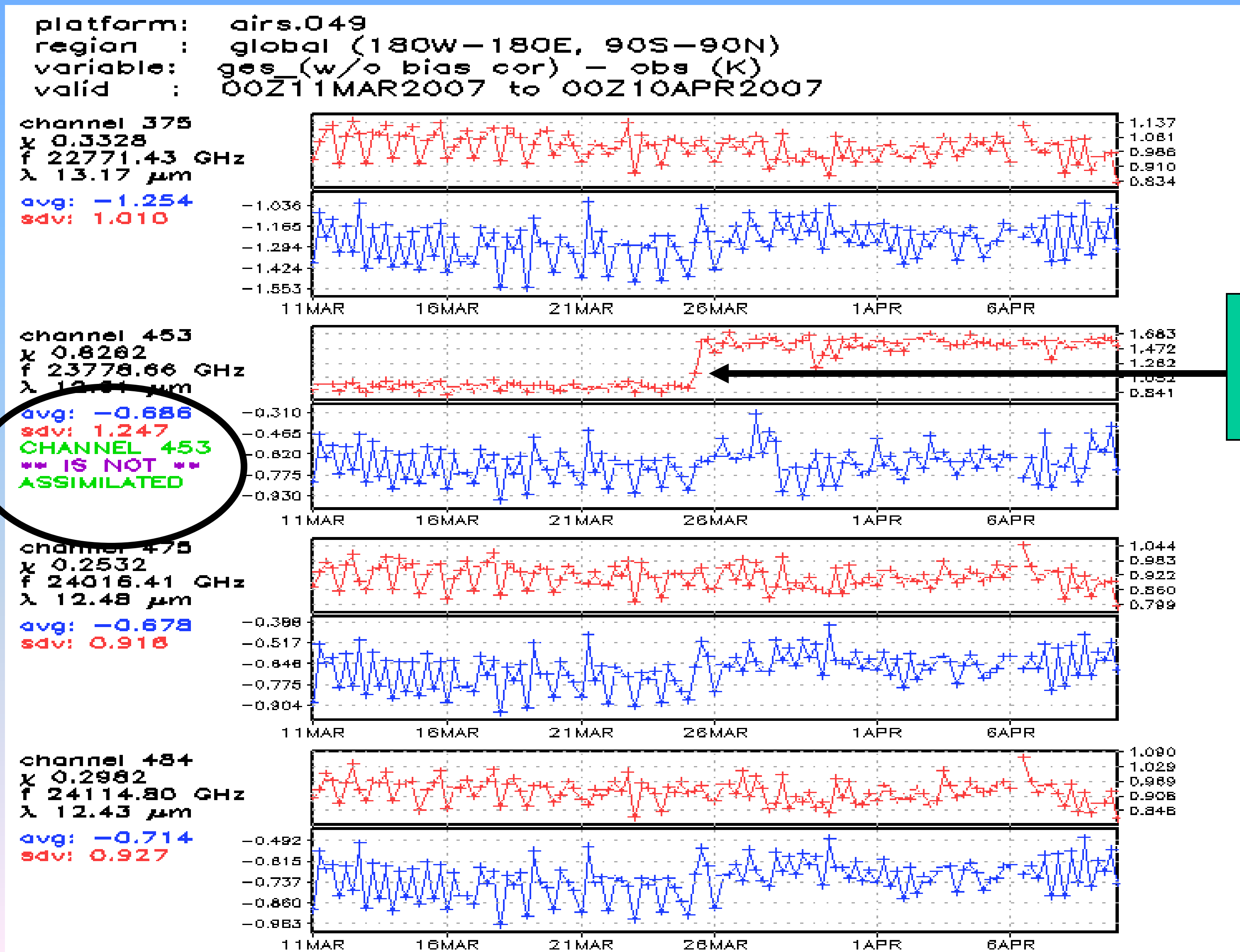


Data Monitoring

- It is essential to have good data monitoring.
- Usually the NWP centres 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.
- https://groups.ssec.wisc.edu/groups/itwg/nwp/monitoring

Quality Monitoring of Satellite Data

AIRS Channel 453 26 March 2007



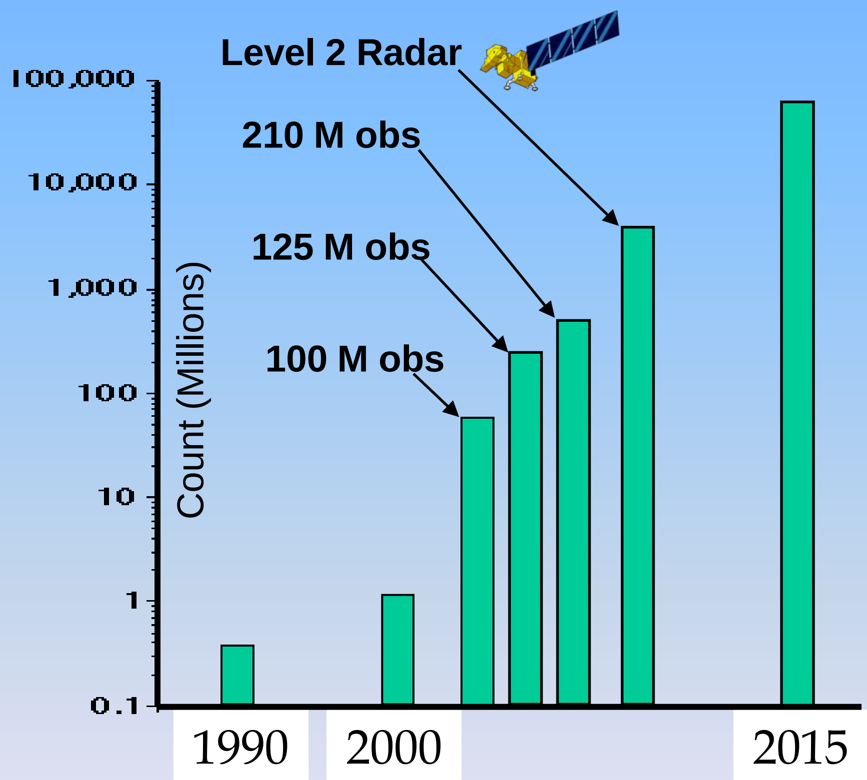
Increase in SD Fits to Guess

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.

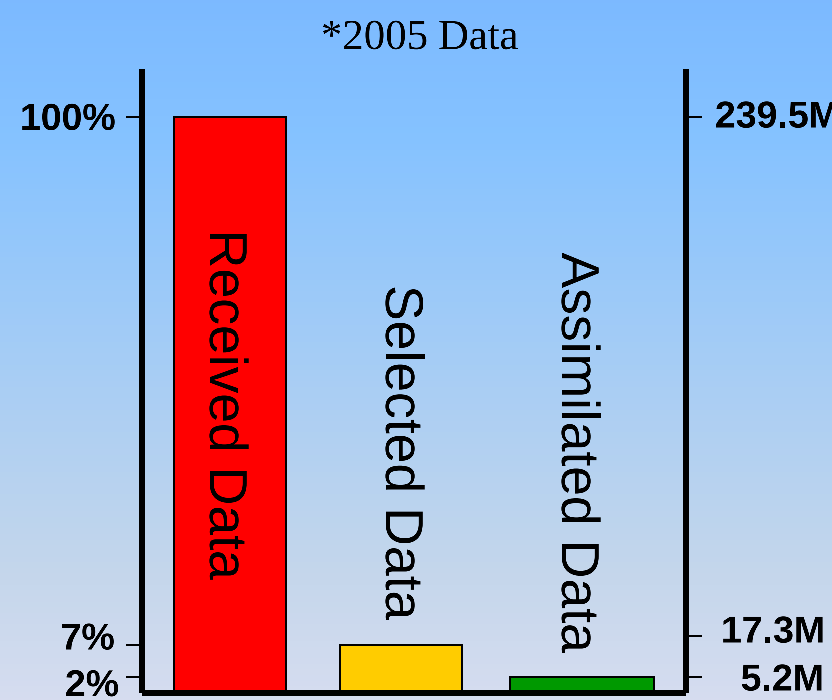
Satellite Data Ingest

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



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

"Mr Derber , may I go home? I can't assimilate any more data today."

Future of Satellite Data

- Assimilation of new variables.
  - Cloud and precipitation (Mahfouf presentation).
  - Trace gases and Aerosols (Simmons presentation).
  - Land Surface (de Rosnay presentation).
  - Ocean Assimilation (Haines and Moore presentations).
- Improving use of current data.
  - Skin temperature and Emissivity.
  - Observation geometry.
  - Cloud detection techniques.
  - Inclusion of Trace gas and aerosol information.
  - Moving the use of data towards what the instrument measures.
  - Improved thinning/superobbing techniques.
  - Improved/reduced bias correction – how to handle focal plane arrays?
- Keeping up with new instruments (more international).
  - GOES-15, NPP, GOES-R, FY– satellites, etc.
- Data Volume issues will continue!

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