Atmospheric data assimilation at the Met Office

Stephen English

JCSDA summer school Tuesday 14 July 2009

Contents

This presentation covers the following:

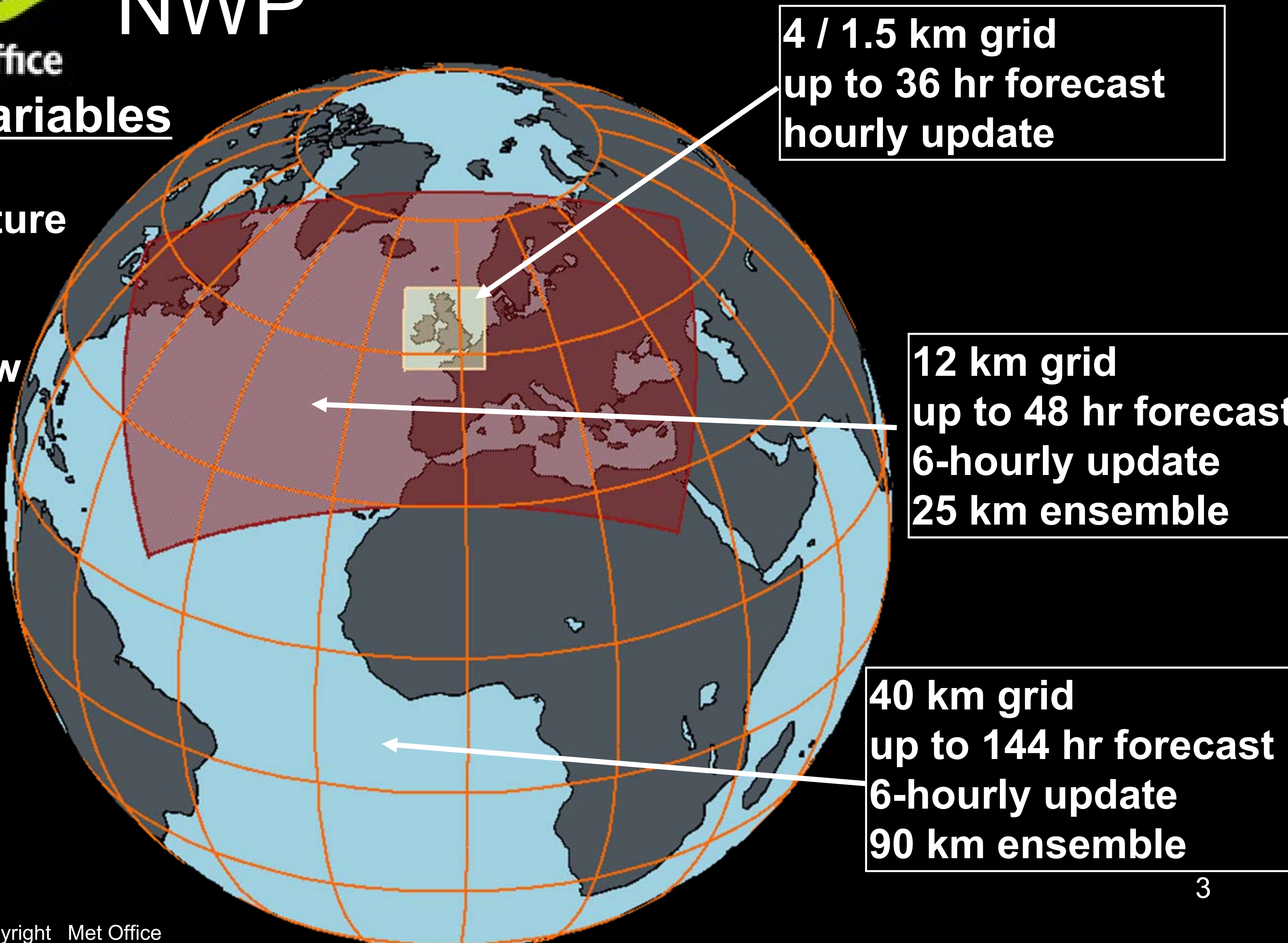
- The Met Office NWP systems
- Observations used in the Met Office 4D-var
- Basic concepts of data assimilation (relevant to Met Office system)
- Relative value of observations in Met Office system and how do we measure this
- Recent improvements
- Plans for the future

Numerical weather prediction, NWP

Met Office

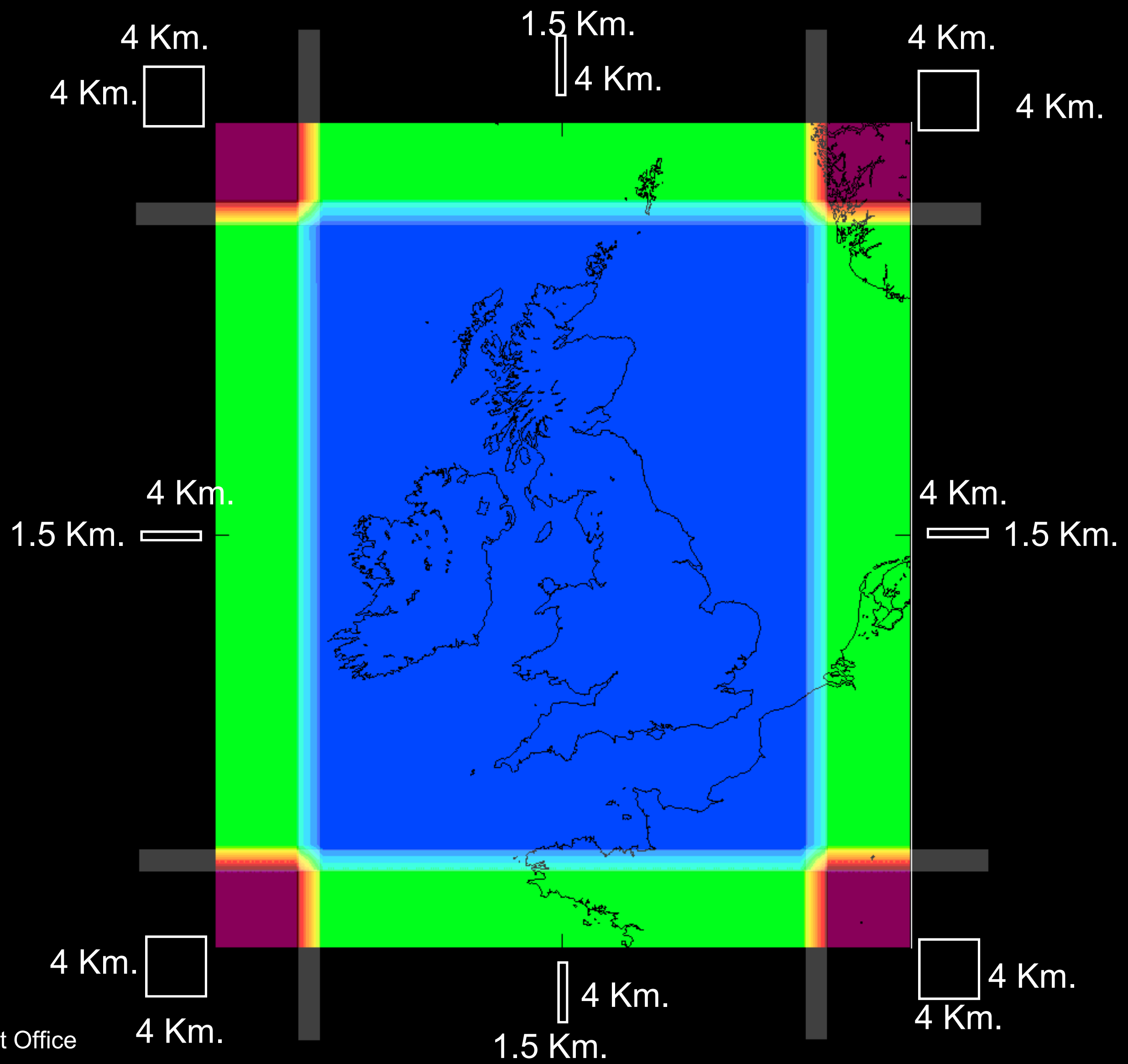
Main Variables

wind
temperature
humidity
cloud
rain/snow
visibility
surface



Model domain

From J. Borneman

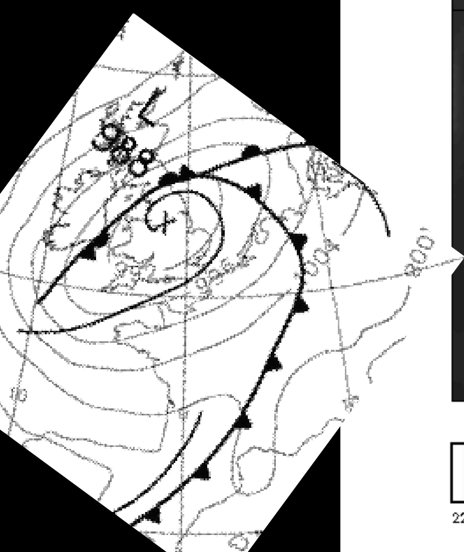


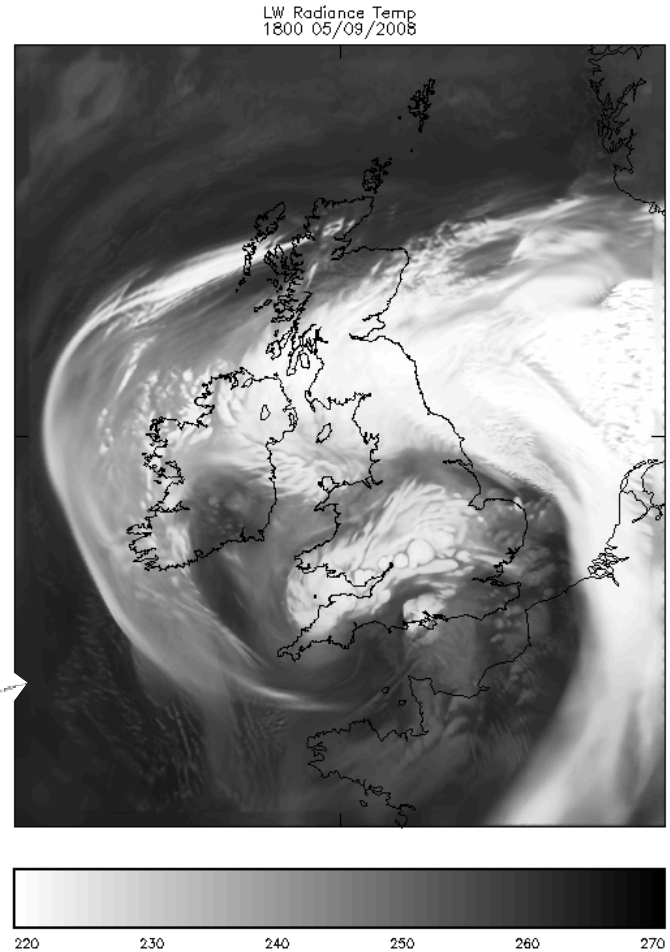
Convective scale model

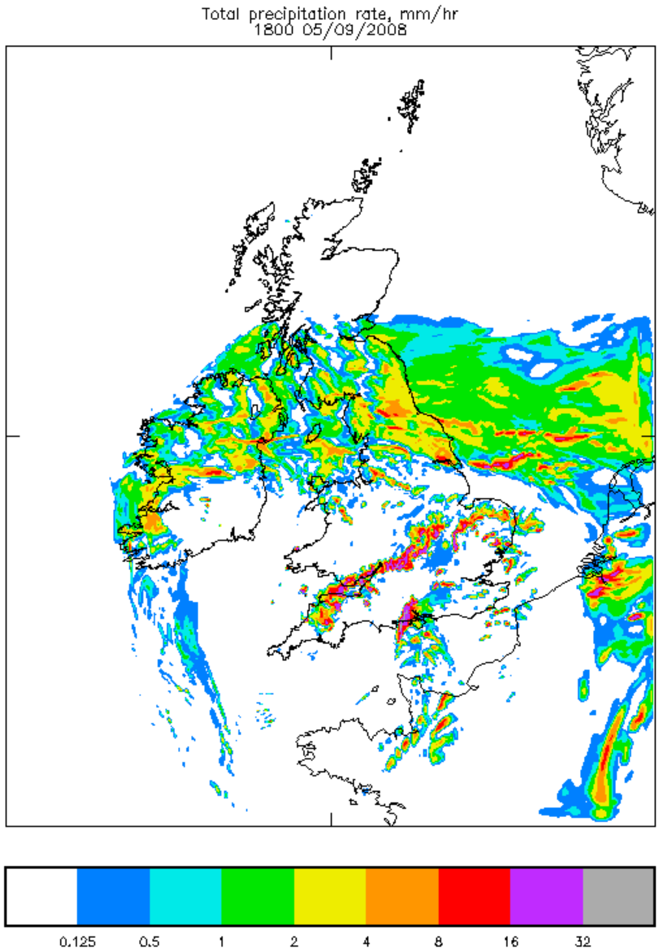
- Inner area 1.5 Km gridlength
- Inner area size:
  - 622 gridboxes E-W
  - 810 gridboxes N-S
- Full area size:
  - 744 gridboxes E-W
  - 928 N-W
- Nested in NAE (12 Km gridlength)
- LBC update frequency: 30 min.
- Model top: 40000 m.
- 70 vertical levels.
- Timestep: 50 sec.
- Forecast length: 24 hours

The ‘Morpeth Flood’, 06/09/2008

1.5 km L70
Prototype UKV
From
15 UTC 05/09
12 km

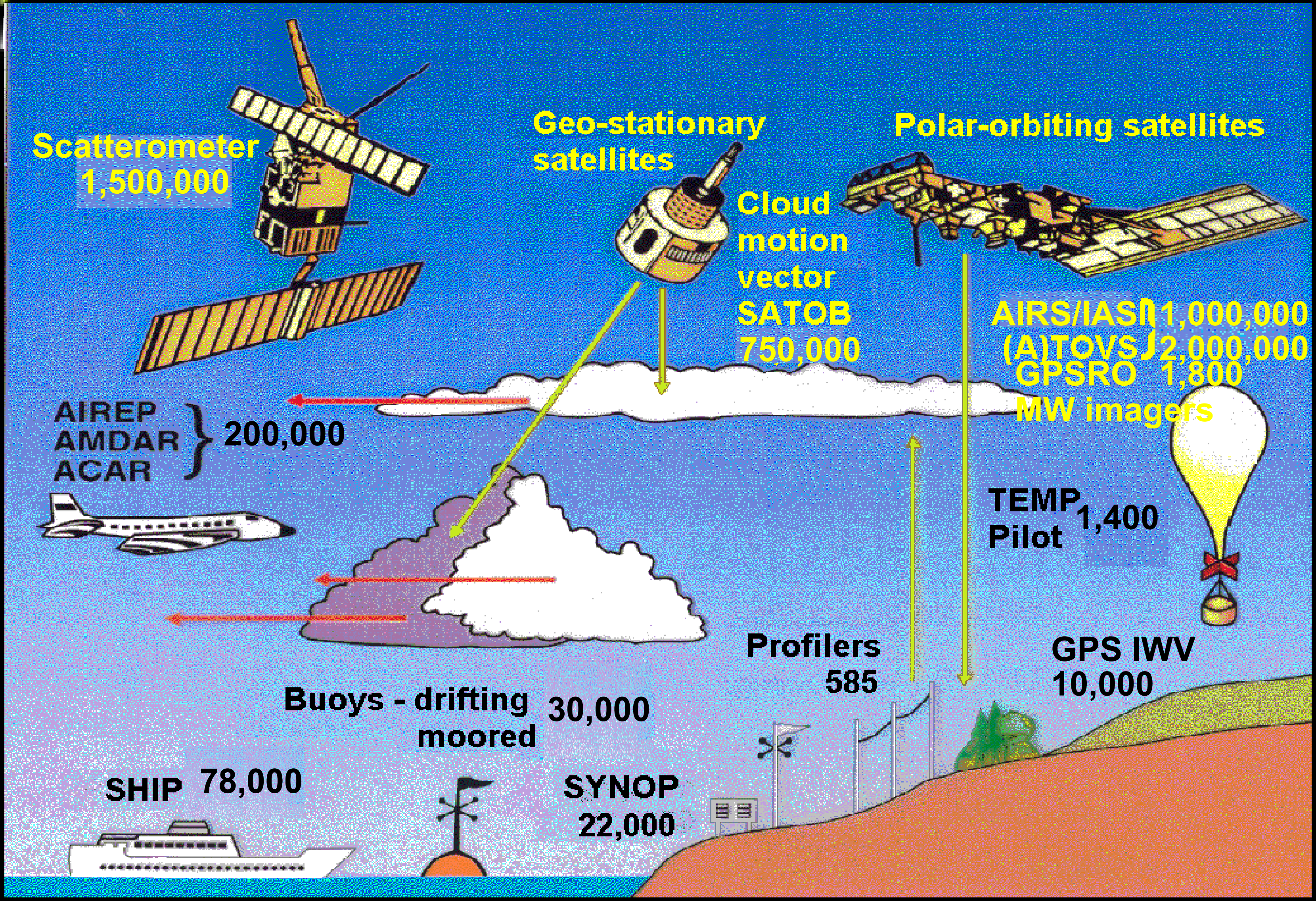


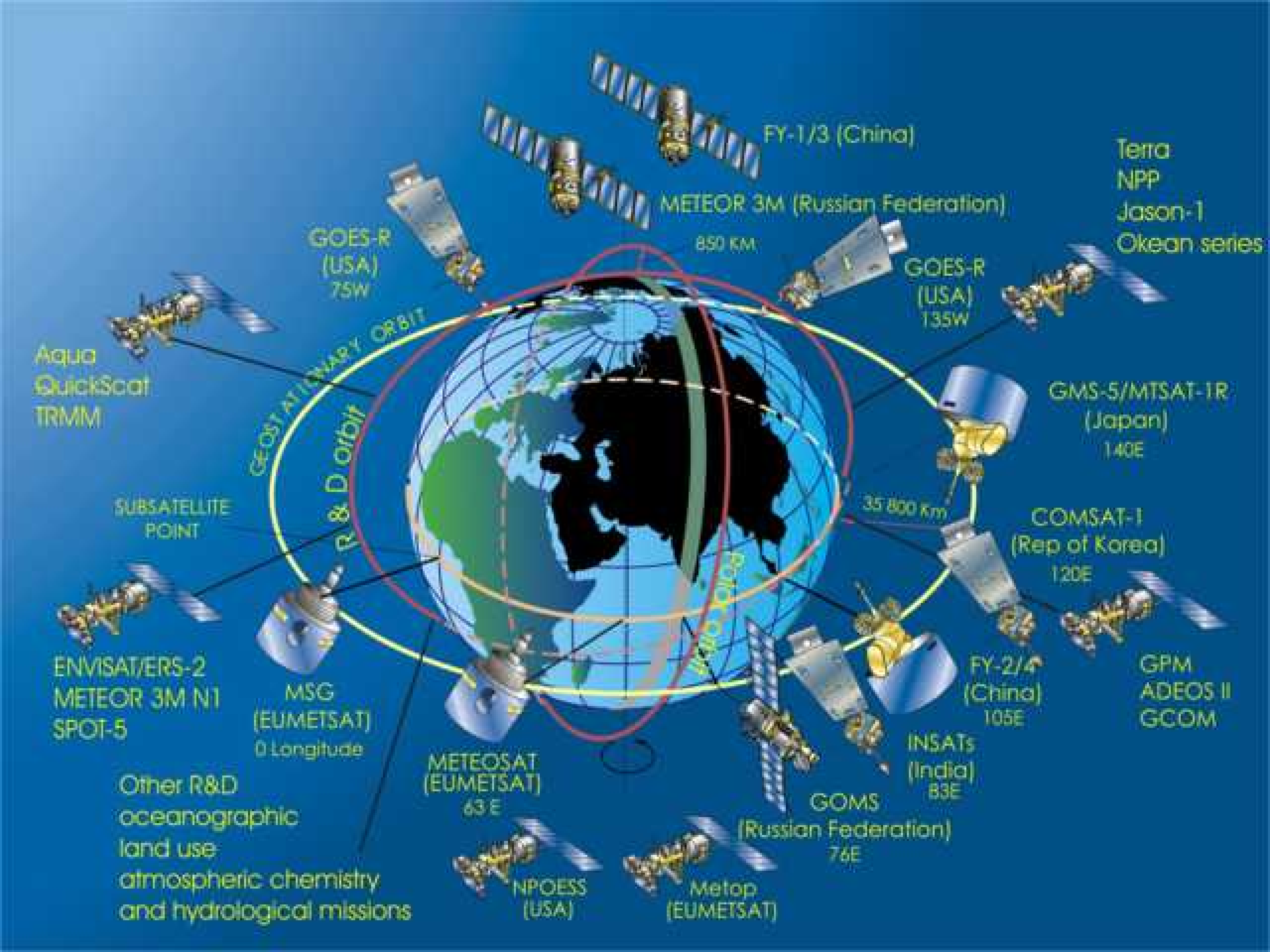




0600 UTC

Global Observing System

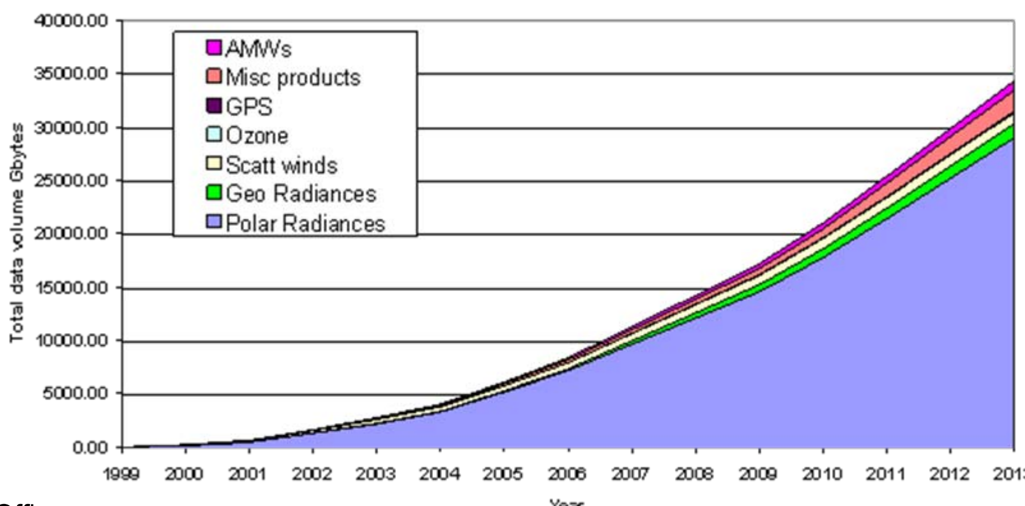



FY-1/3 (China)
Terra
NPP
Jason-1
Okean series
METEOR 3M (Russian Federation)
850 KM
GOES-R
(USA)
75W
GOES-R
(USA)
135W
Aqua
QuickScat
TRMM
GEOSTATIONARY ORBIT
R & D orbit
GMS-5/MTSAT-1R
(Japan)
140E
35 800 Km
SUBSATELLITE
POINT
COMSAT-1
(Rep of Korea)
120E
ENVISAT/ERS-2
METEOR 3M N1
SPOT-5
MSG
(EUMETSAT)
0 Longitude
FY-2/4
(China)
105E
GPM
ADEOS II
GCOM
INSATs
(India)
83E
METEOSAT
(EUMETSAT)
63 E
GOMS
(Russian Federation)
76E
Other R&D
oceanographic
land use
atmospheric chemistry
and hydrological missions
NPOESS
(USA)
Metop
(EUMETSAT)

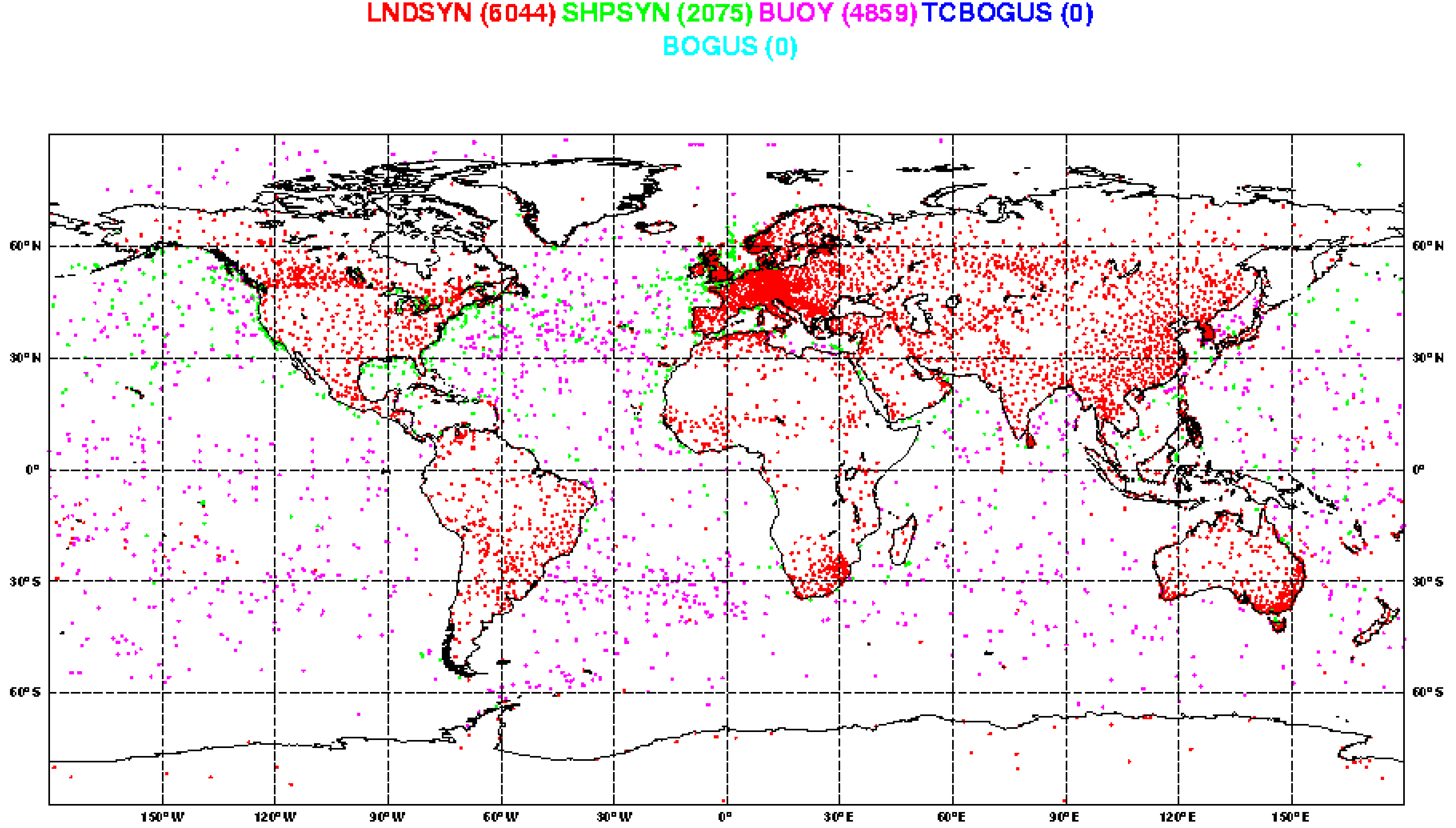
Growth of the GOS

	> 10 years ago	Now or soon (METOP, POESS, DMSP, Research)
Mass	2 HIRS, 2 MSU	3 HIRS 6 AMSU-A 2 SSMIS 2 AIRS/IASI 9 GPSRO
Wind	Some Geo AMVs	5 Geo AMVs 6 AMVs
Humidity	2 HIRS	3 HIRS 6 AMSU-B + MHS 5 SSMIS + SSM/I + AMSR-E + TMI 2 AIRS/IASI Many Ground based GPS
Cloud and rain, snow	2 AVHRR 2 SSM/I	5 SSMIS + SSM/I + AMSR-E + TMI 4 AVHRR 1 SEVIRI plus other Geo imagers
Surface (sea ice, SST, Surface wind, snow, vegetation)	1 ERS Scat, 2 AVHRR	4 Scat-like (QuikScat, ERS, ASCAT, WindSat) 5 SSMIS + SSM/I + AMSR-E + TMI 4 AVHRR 1 SEVIRI plus other Geo imagers 1 L-band SMOS (9/9/09) (plus other L-band missions).

Figure 6: Projected growth in data volumes for various types of data assumes combined obs/mergeback and obs research files archived indefinitely



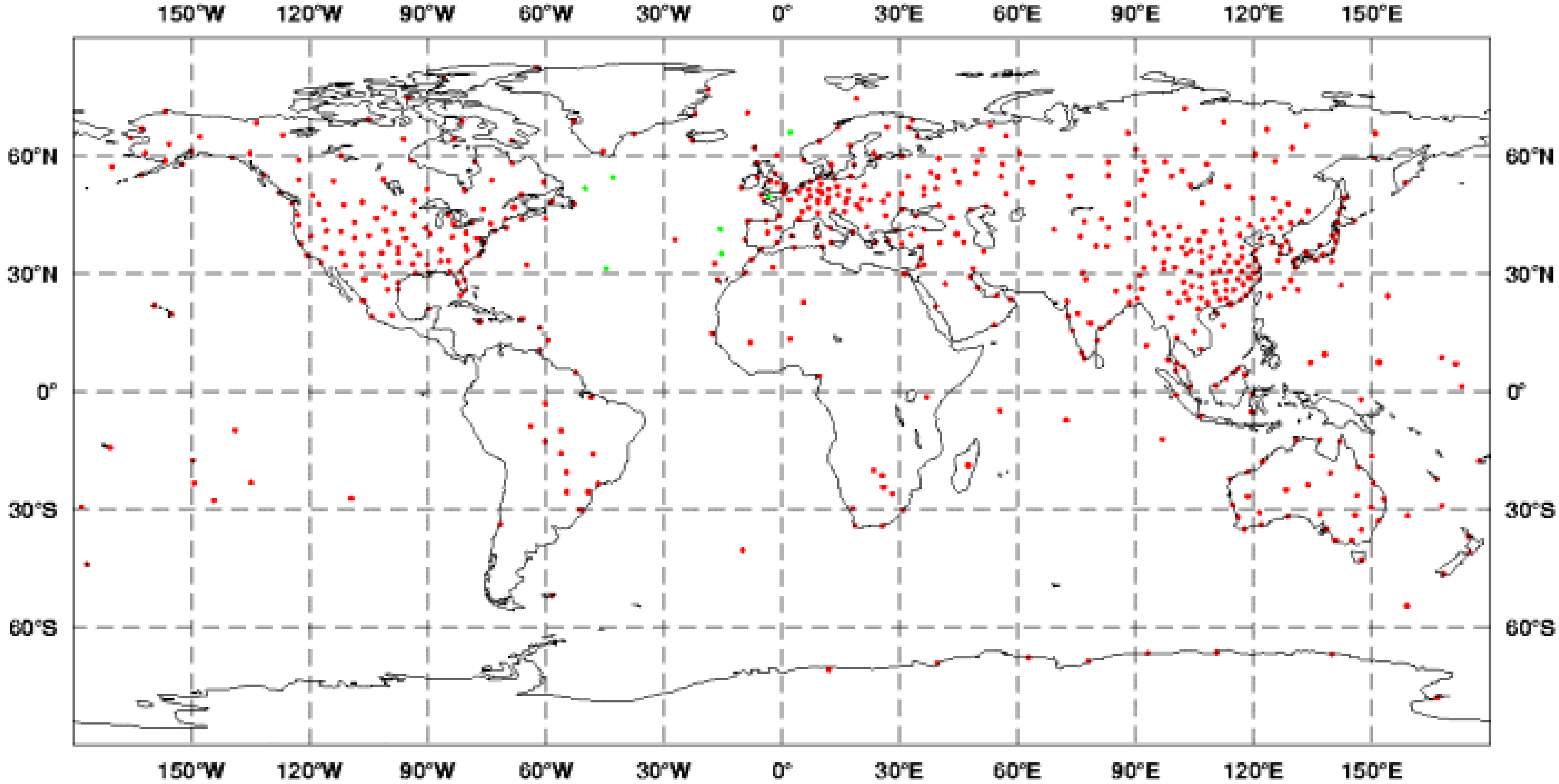
Data Coverage: Surface (20/6/2007, 12 UTC, qu12)
Total number of observations assimilated: 12978



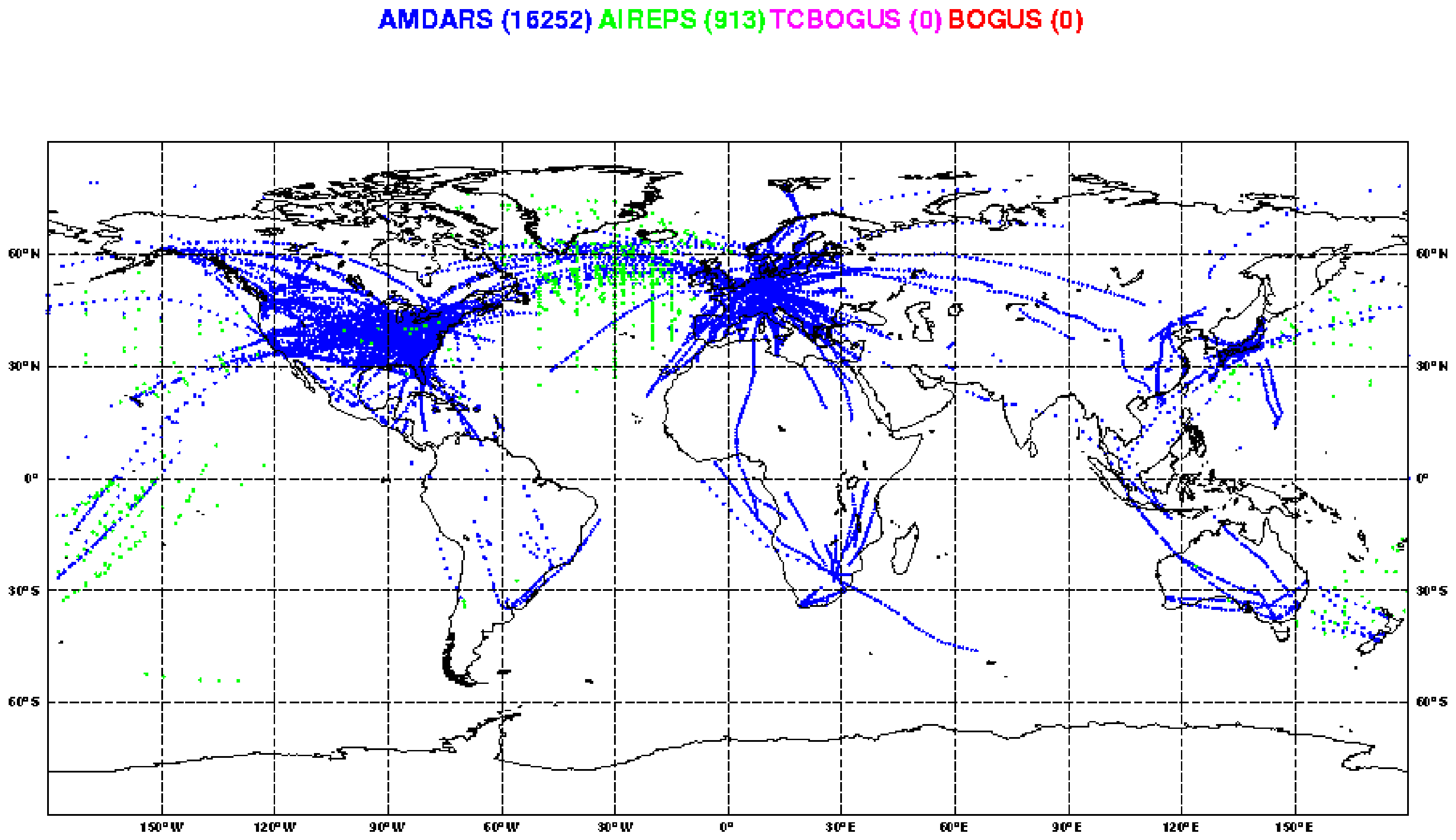
Data Coverage: Sonde (26/9/2001, 0 UTC, qg00)
Total number of observations assimilated: 562

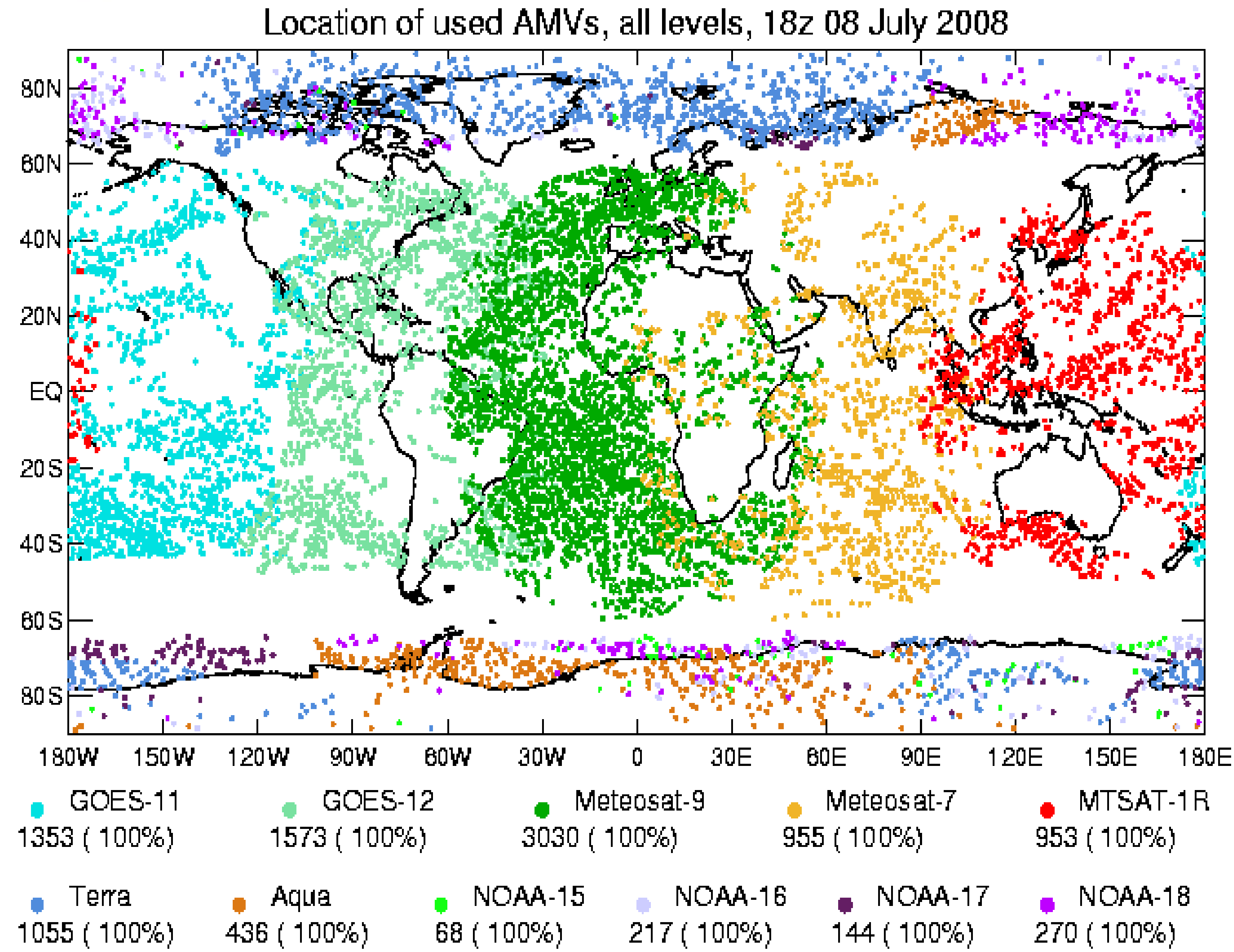
Met Office

TEMP LAND (555) TEMP SHIP (7) TEMP MOBILE (0)



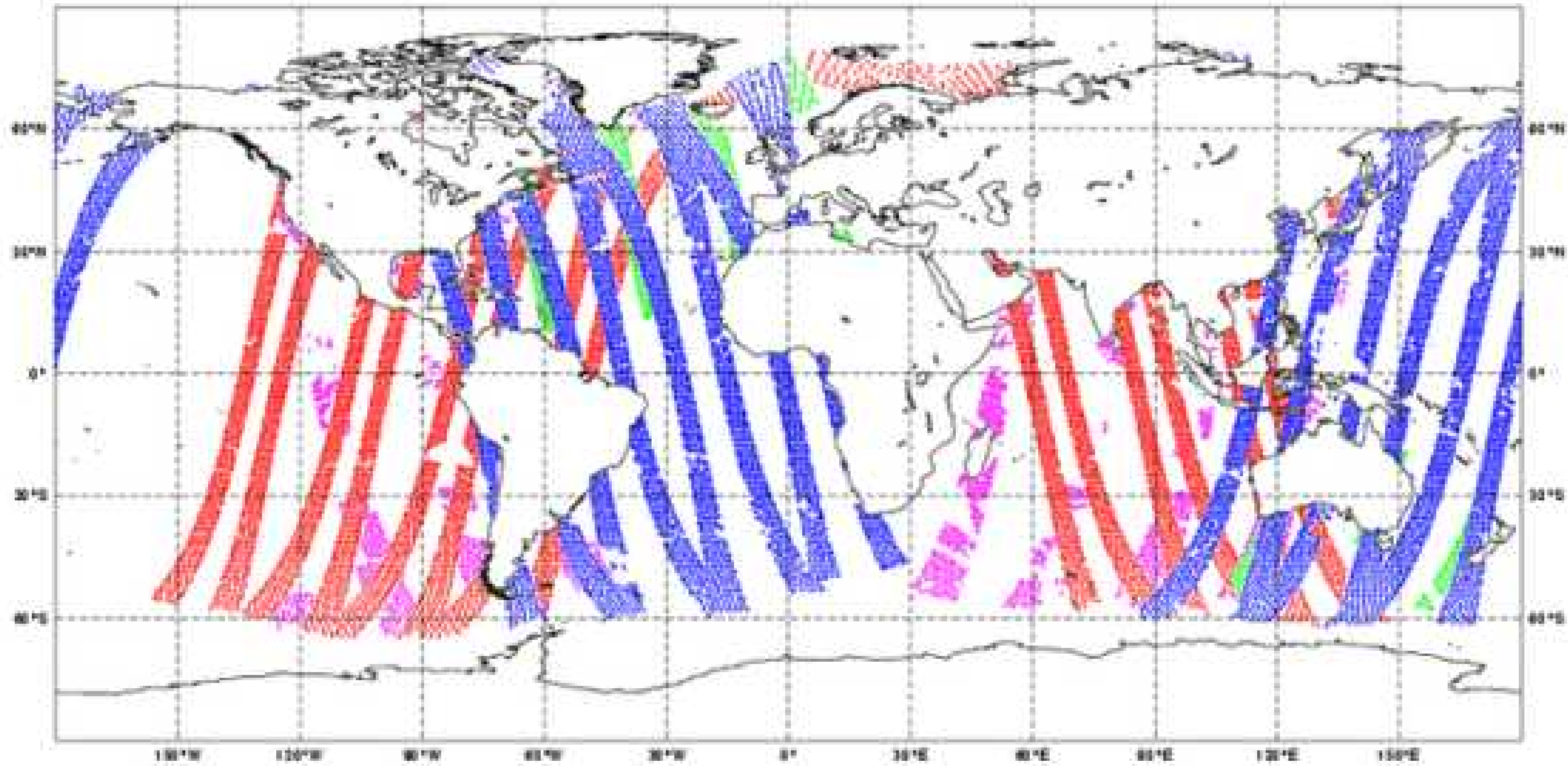
Data Coverage: Aircraft (20/6/2007, 12 UTC, qu12)
Total number of observations assimilated: 17165




Location of used AMVs, all levels, 18z 08 July 2008
80N
60N
40N
20N
EQ
20S
40S
60S
80S
180W
150W
120W
90W
60W
30W
0
30E
60E
90E
120E
150E
180E
GOES-11
1353 (100%)
GOES-12
1573 (100%)
Meteosat-9
3030 (100%)
Meteosat-7
955 (100%)
MTSAT-1R
953 (100%)
Terra
1055 (100%)
Aqua
436 (100%)
NOAA-15
68 (100%)
NOAA-16
217 (100%)
NOAA-17
144 (100%)
NOAA-18
270 (100%)

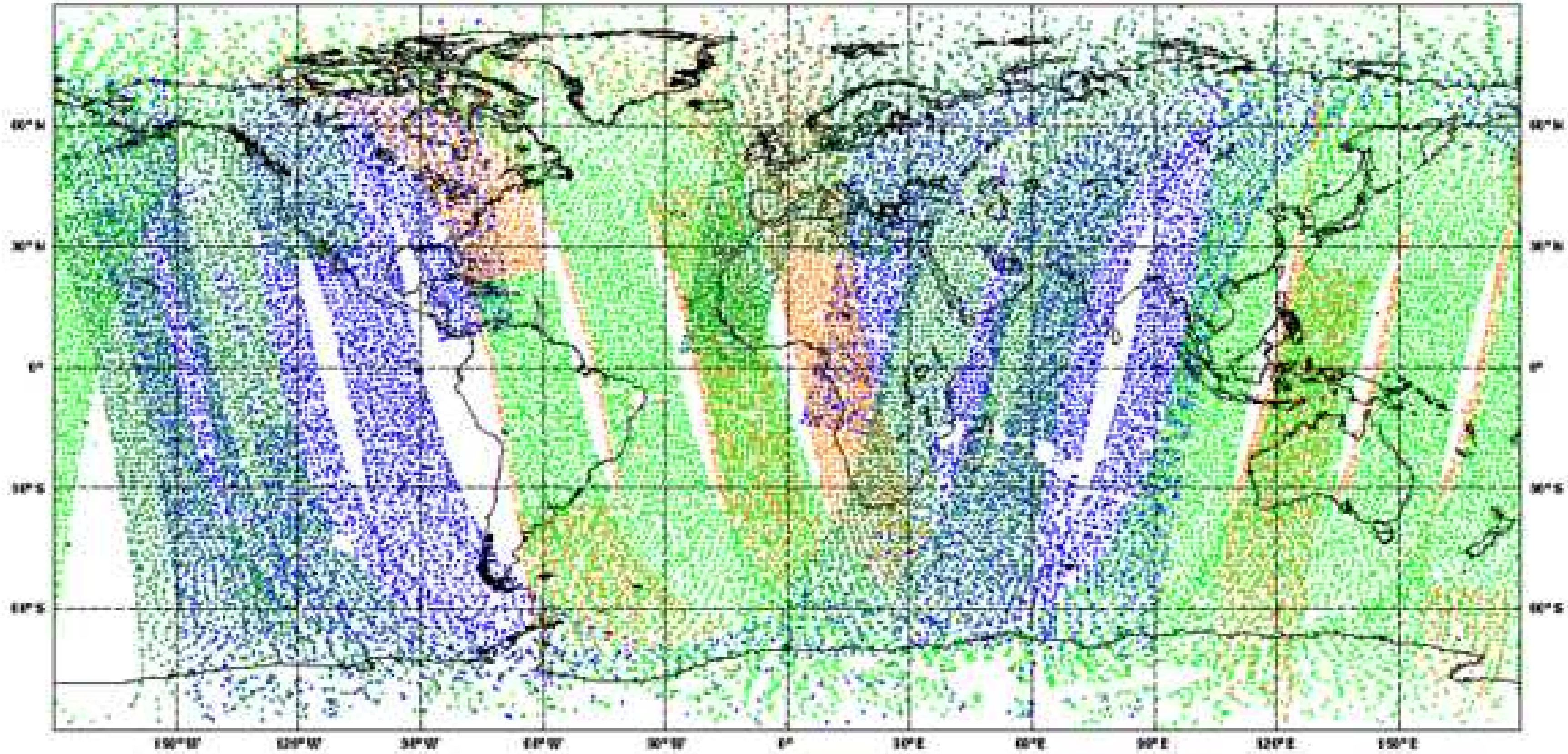
Data Coverage: Scatwind (18/6/2009, 0 UTC, qu00)
Total number of observations assimilated: 17121

Seawinds (6343) ERS (448) ASCAT (9071) WindSat (1259)



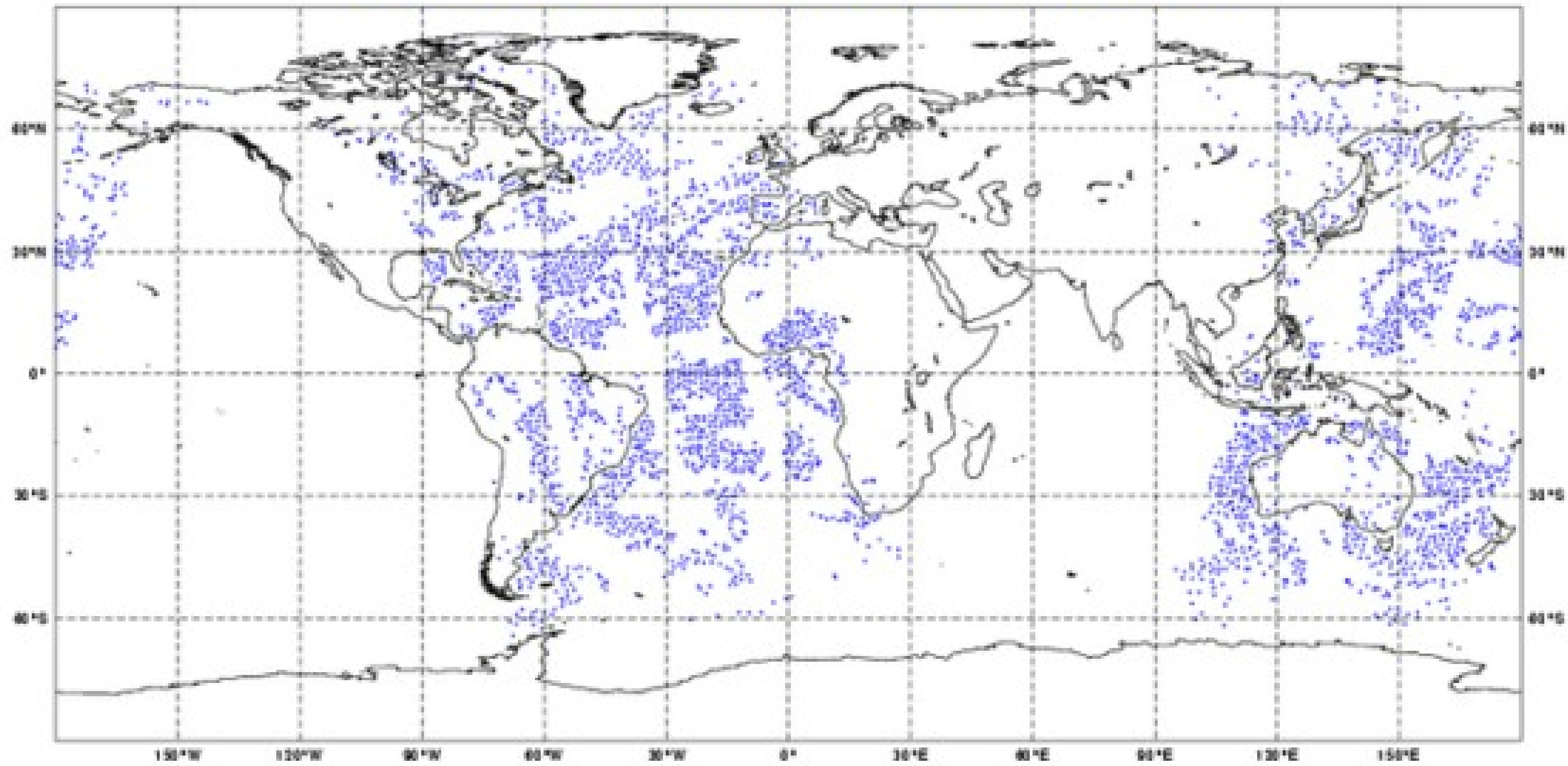
Data Coverage: SatRad ATOVS (21/6/2007, 0 UTC, qu00)
Total number of observations assimilated: 32210

11006 METOP-A
7676 NOAA-18
9024 NOAA-16
4504 NOAA-17

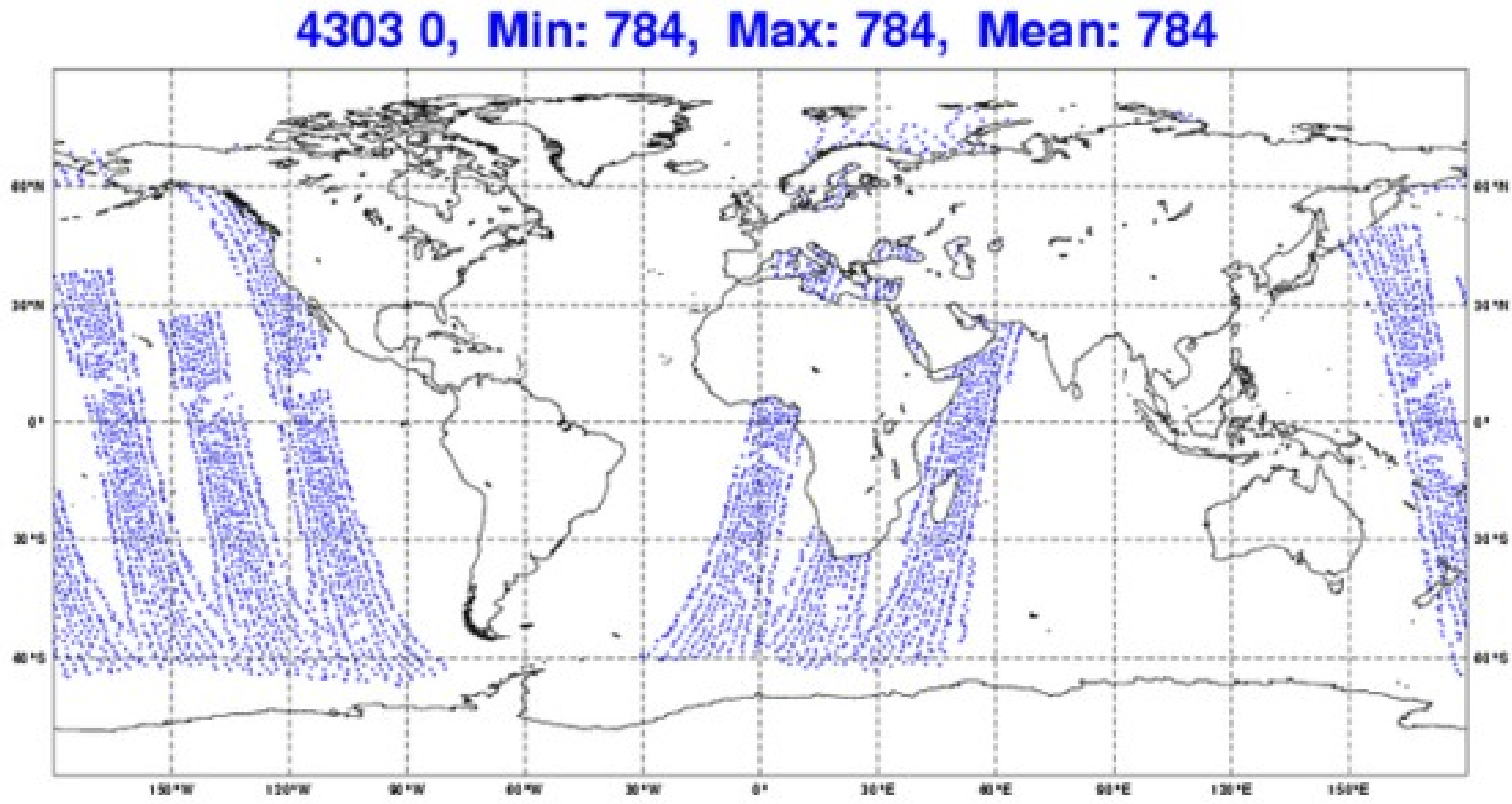


Data Coverage: IASI (18/6/2009, 0 UTC, qu00)
Total number of observations assimilated: 2948

2948 obs, Min: 4, Max: 4, Mean: 4

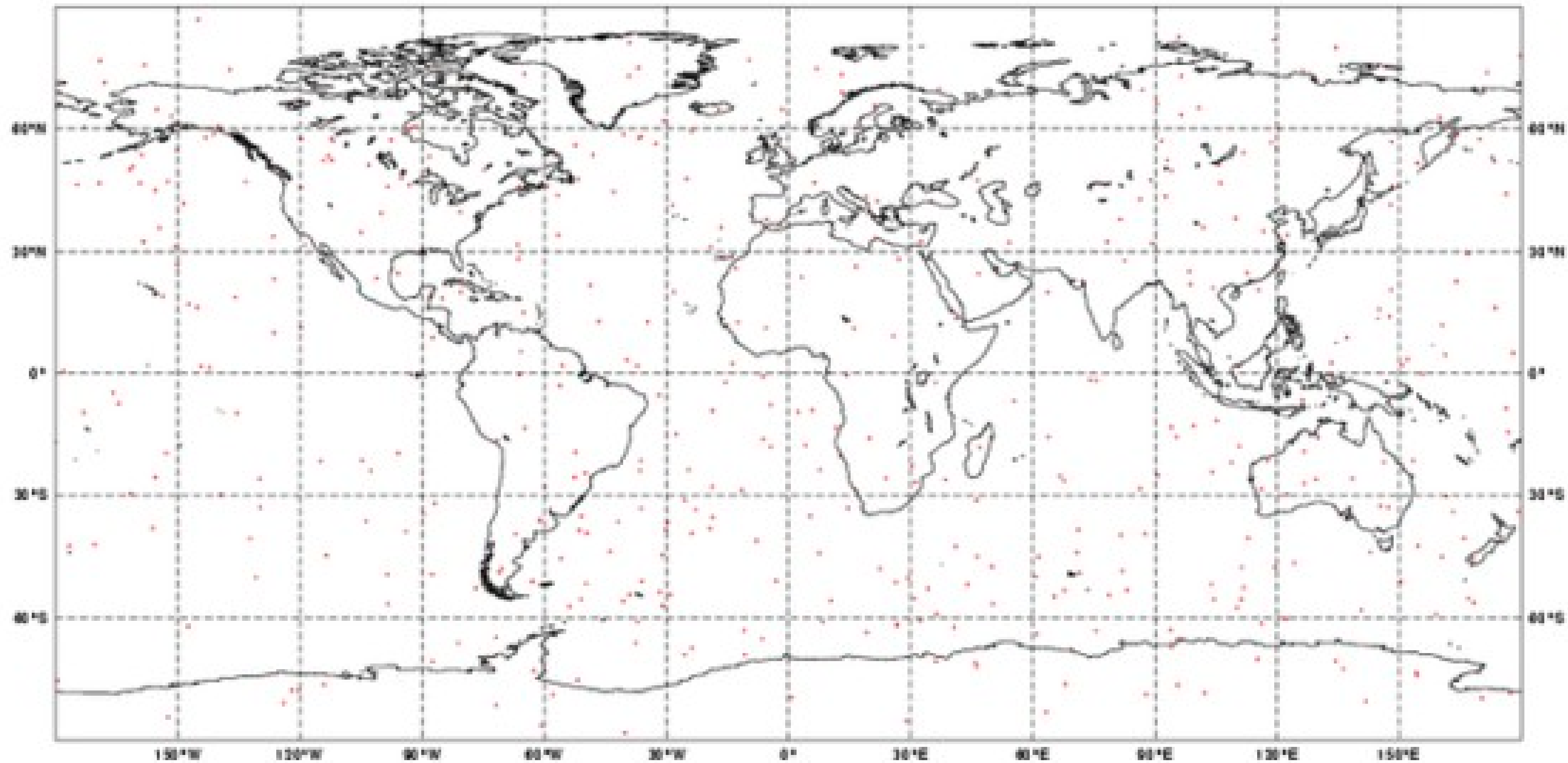


Data Coverage: AIRS (18/6/2009, 0 UTC, qu00)
Total number of observations assimilated: 4303



Data Coverage: GPSRO (18/6/2009, 0 UTC, qu00)
Total number of observations assimilated: 449

GPSRO (449)



Basic concepts of data assimilation

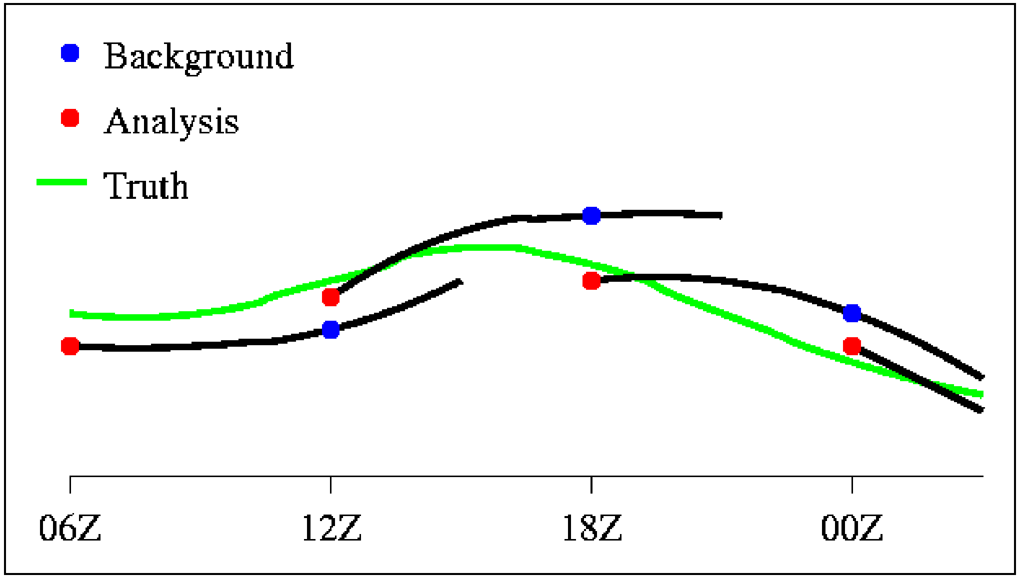
What is data assimilation?

- To do a forecast, we need to know what the atmosphere is like now
- Estimates of the atmospheric state are called **analyses.**
- Sources of information:
  - Observations
  - NWP model
  - Physical laws / dynamical knowledge (geostrophy, hydrostatic balance, etc.)
  - Error characteristics (observations and model)

From R. Renshaw

Combining obs and models

- The best and most powerful analysis systems are obtained by incorporating numerical models into analysis algorithms.
- The model encapsulates our understanding of the physical laws, and can be used to propagate observational information forwards in time.
- Typically, an *intermittent* data assimilation cycle is used:



Combining information: Bayes' Theorem

- The basic problem in data assimilation is to combine different sources of information (…close to optimally if possible!).
- *Bayes' Theorem* states how our (prior) statistical knowledge of something is updated in the light of new information:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$P(A)$: Prior probability of event A (knowing nothing about event B)

$P(A|B)$: Posterior probability of event A, given that event B is known to have occurred

NASTY FEVER

0.1% of the population are infected.
The Nasty Test is positive for 99% of those that have it
and for 1% of those that don't.

Event A: You have Nasty Fever

Event B: You test positive

- Bayes theorem: P[A|B] = P[B|A].P[A]/P[B]
- We know that P[A] = 0.001, P[B|A] = 0.99
- Clearly P[B] = P[B|A].P[A] + P[B|not A].P[not A]
- And P[B|not A] = 1 – P[B|A] = 0.01, P[not A] = 0.999
- P[A|B] = P[B|A].P[A] / (P[B|A].P[A] + P[B|not A].P[not A]

= 0.09

… 91% chance you're ok (99.9% before the test!).

4D-var

Variational data assimilation

Define events:

- O — observations $\mathbf{y}$
- B — model background $\mathbf{x_b}$ through assimilation "window"
- A — analysis $\mathbf{x_a}$ best represents the atmosphere

$$P(A|O \text{ and } B) = \frac{P(O|A).P(B|A).P(A)}{P(O).P(B)}$$

To find most likely analysis given O and B,

calculate $\mathbf{x_a}$ to maximise probability

Gaussian assumption…

P(O|A) P(B|A) P(A)

Exp(-Jo) Exp(-Jb) Exp(-Jc)

Most likely analysis **x** minimises J(**x**) = Jo + Jb + Jc

Jo =	$[H(\mathbf{x}) - \mathbf{y}]^T \mathbf{R}^{-1} [H(\mathbf{x}) - \mathbf{y}]$	fit to obs	[ob space]
Jb =	$[\mathbf{x} - \mathbf{x}_b]^T \mathbf{B}^{-1} [\mathbf{x} - \mathbf{x}_b]$	fit to background	[model space]
Jc =		balance constraint…	

Background error covariance matrix B

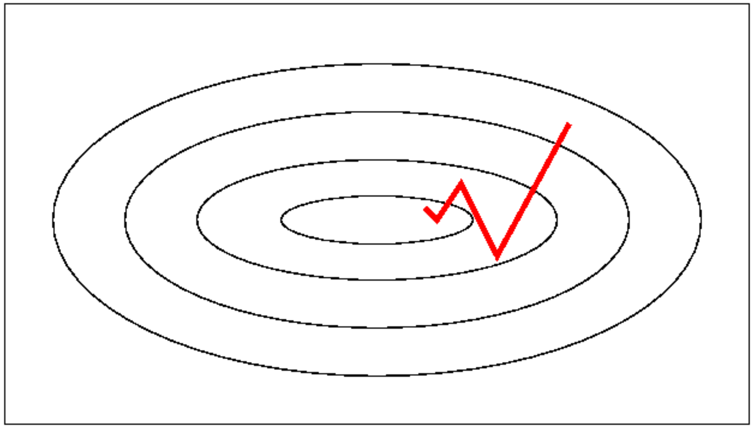
Observation operator H: model space -> ob space

Finding the best analysis **x**

Minimise J(x)

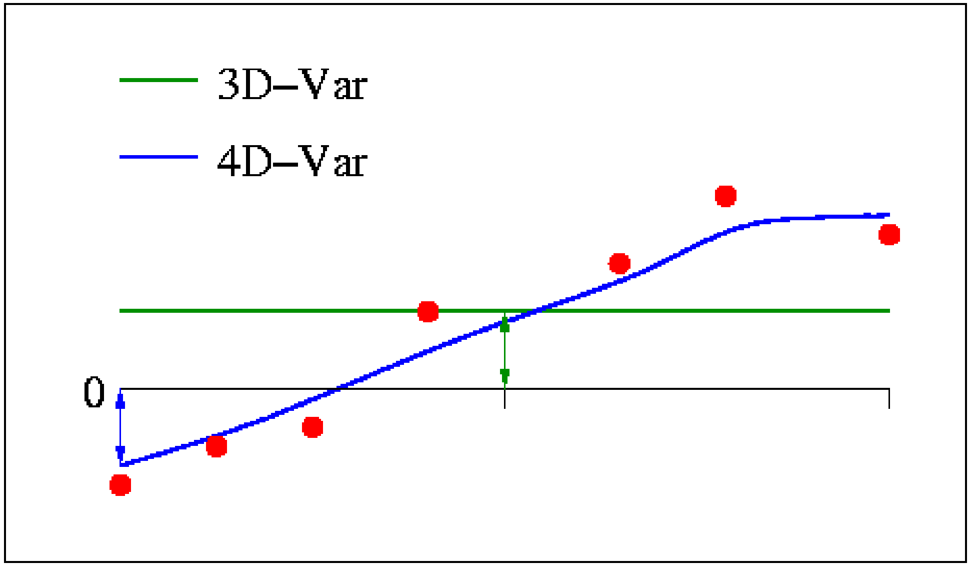
$\Rightarrow$ Solve $$\frac{\partial J}{\partial x} = 0$$

Use iterative descent algorithm



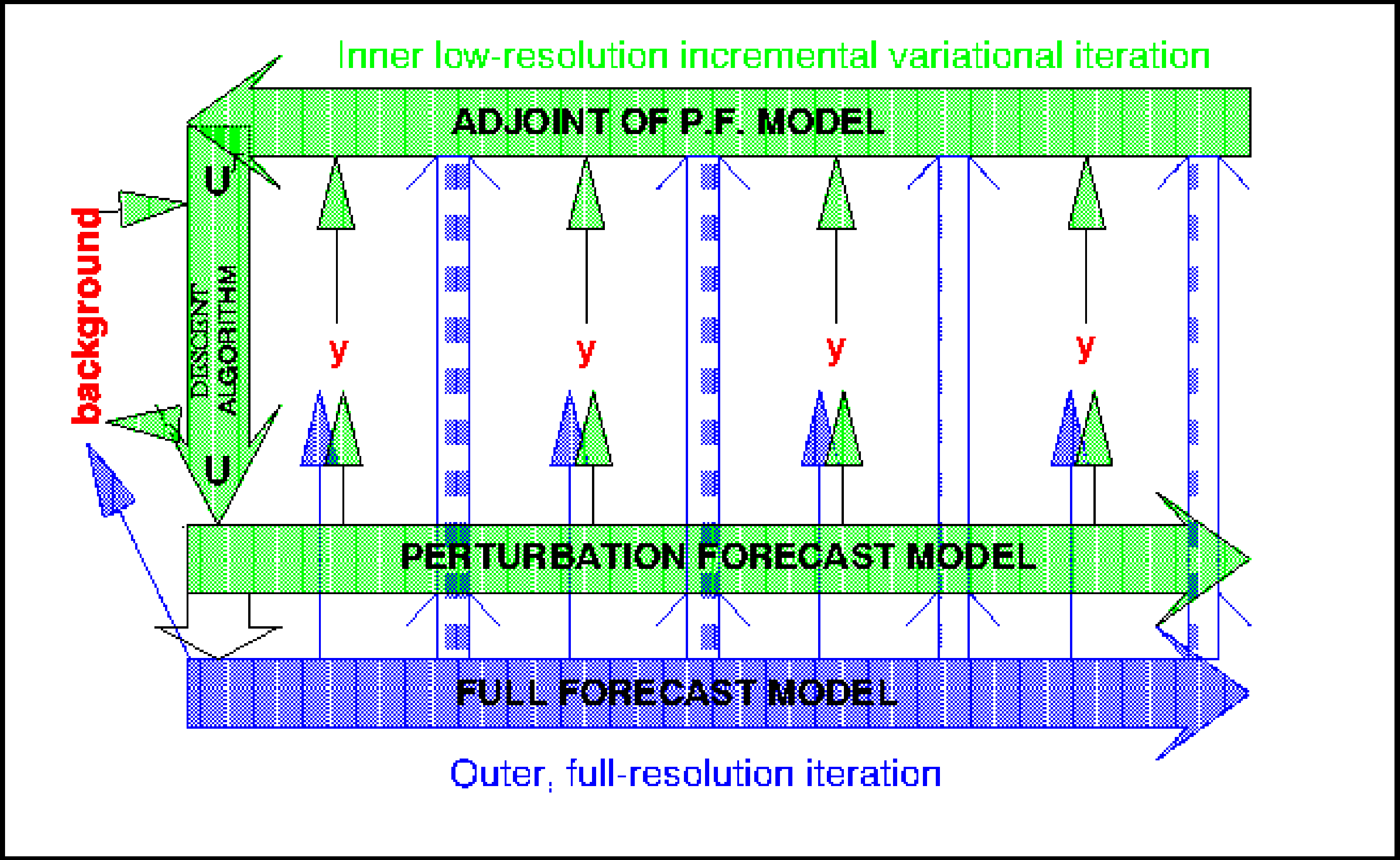
Incremental 4D-Var

- In 4D-Var, the observation operator includes model forecasts to the observation times:



- Forecasts are performed with a simplified linear `**Perturbation Forecast**' (**PF**) model.

Incremental 4D-Var



Elements of the problem

- 4D-var state vector, v
- Model for evolving increments, M
- Variable transforms and incrementing operators, U
- Observation operator, H
- Background error covariance, B
- Observation error covariance, R
- Observation selection, y

The state vector, v, at the Met Office and PF model variables

Full model (x)

- Many prognostic and diagnostic variables

Perturbation Forecast model increment variables (**w**)

- 3D wind components: u´, v´, w´
- Potential temperature: θ´
- Moist density: ρ´
- Pressure: p´
- Specific humidity: q´
- Cloud variables: c´

4D-var state vector increment variables (**v**)

- Velocity potential: χ´
- Stream function: ψ´
- The unbalanced part of the pressure: p´
- Total moisture: q´

U transform operators, incrementing operators

- w´=**U**.v´

Model prediction of obs - "Outer-loop"

The steps in calculating y are:

Forecast $$x_t^g = M_t^{UM}(x^g).$$

Horizontal interpolation $$c_x = H_h(x_t^g).$$

Model prediction of obs - "Inner-loop"

Transform $$w' = U v.$$

Forecast $$w'_t = M_t^{PF} w'.$$

Horizontal interpolation $$c_{w'} = H_h w'_t.$$

Incrementing operator + $$c_x^+ = c_x + H_v c_{w'}.$$

Obs operator + $$y = H_{ob}(c_x^+).$$

Hv incrementing operator is not always straightforward, Cw' total moisture, Cx specific humidity, cloud variables, rainfall etc.

How accurate a PF model do we need?

As long as incremental 4DVAR converges, PF model only determines weighting of increments in spreading to other times & variables.

- It is necessary that increments “go in the right direction” to affect full UM’s behaviour in the desired way. So test using

$$PF(x_a-x_b)=UM(x_a)-UM(x_b)$$

- Difficult for some processes e.g. convection

What processes do we need to include?

- *One approach is to try to linearise everything in the full model, and only approximate if forced to.*
- Surface drag necessary for stability
- Resolved precipitation improves frontal dynamics
- Convective precipitation needed for tropics but difficult!
- Cloud has the most abundant observations – currently under-used!
- Cloud-radiation interactions have significant effect on surface – important & many obs.

How do we handle cloud?

- We have a single moisture variable, q´.
- What action do we want to have on temperature and humidity if we add or remove cloud due to observations:
  - Spreading of increments
  - “no cloud” information e.g. above cloud top
  - Cloud has an on/off nature which is difficult

Observation operator H

4D-Var is an *“inverse variational problem”*

- we don’t interpolate obs to model but vary model to fit obs

H(**x**) includes:

- Interpolating model **x** to observation locations and heights
- Change of variable (e.g. potential temperature -> temperature
  or calculate satellite radiances)
- Most important for radiance observations – more this afternoon!
- (Linear forecast model to evolve the increment in **x** forward in time to the time of the observation “perturbation forecast model”.)

Background Error Matrix **B**

- model state vector **x** is 10^7 elements
- **B** is 10^7 x 10^7 - too big to store
- **B** describes the error **variance** for each model variable, and the **correlations** between errors in different model variables
- Jb = $[\,\mathbf{x} - \mathbf{xb}\,]^T \; B^{-1} \; [\,\mathbf{x} - \mathbf{xb}\,]$

  has to be calculated with simplifying approximations

  - transform to independent variables
  - treat horizontal/vertical separately

Observation error: R

- Can be very complex for satellite observations.
- To be discussed this afternoon.
- Issues include:
  - Variability e.g. sonde type, clouds
  - Correlated errors, esp. in satellite data
  - Are errors Gaussian?
  - Non-linearity errors
  - Errors of representivity

Observation selection

The background is information rich for many variables, especially large scale mass fields.

→ One "bad" ob can degrade a forecast significantly.

Errors include:

- instrument error, poor calibration (drifting buoys susceptible)
- errors in reported position (e.g. ships near the date line)
- format errors (transposed digits, "." in wrong place)
- **Errors or neglected terms in H operator**

Observations: Quality Control

Checks for:

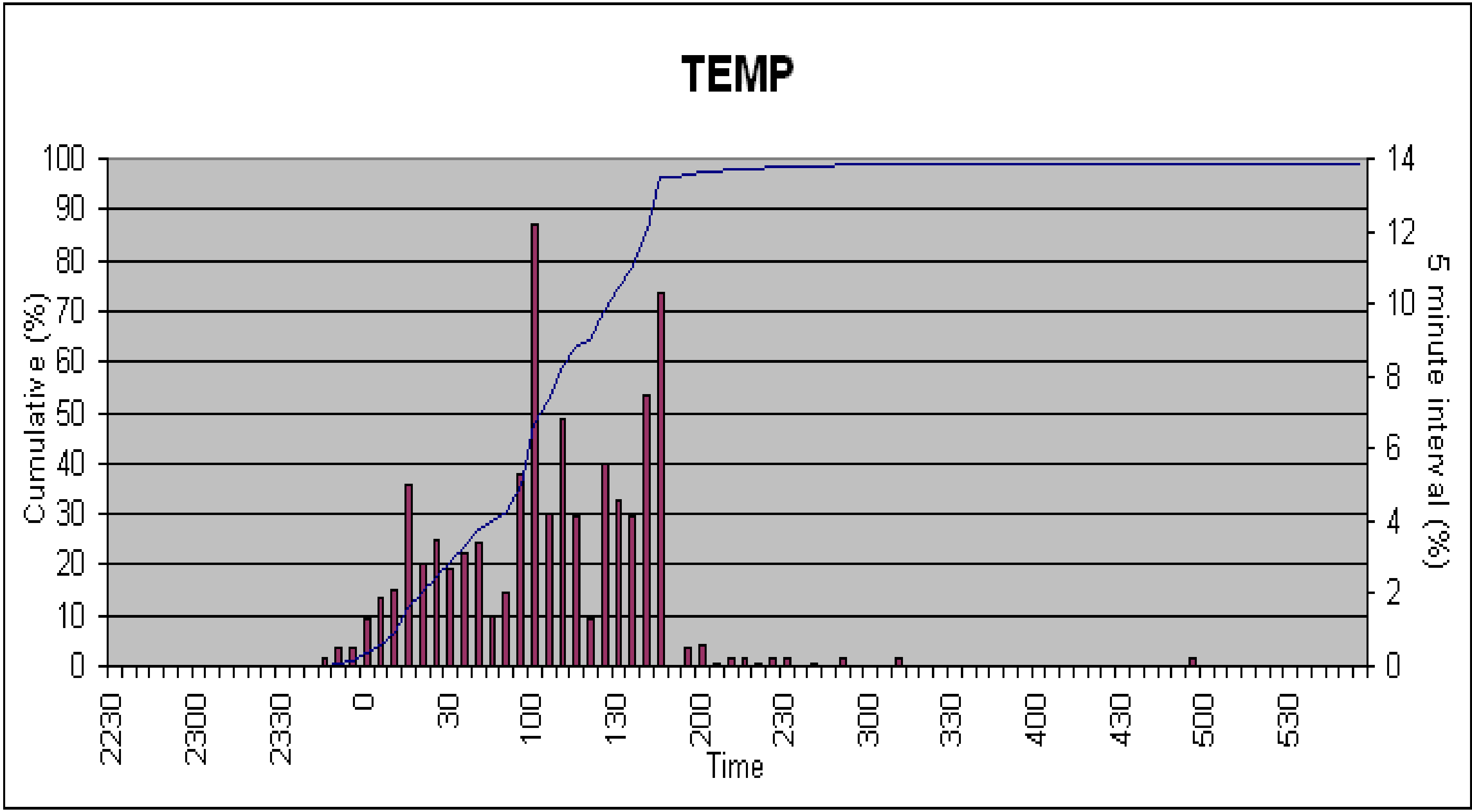
- Physically plausible
- Position (e.g. ships over land)
- Track (movement since last report)
- Buddy checking (against neighbours)
- Model background O-B comparison
- Rejection lists from regular monitoring (O-B, O-A)

Observation Volumes in 6 hours (20 Oct 2008)

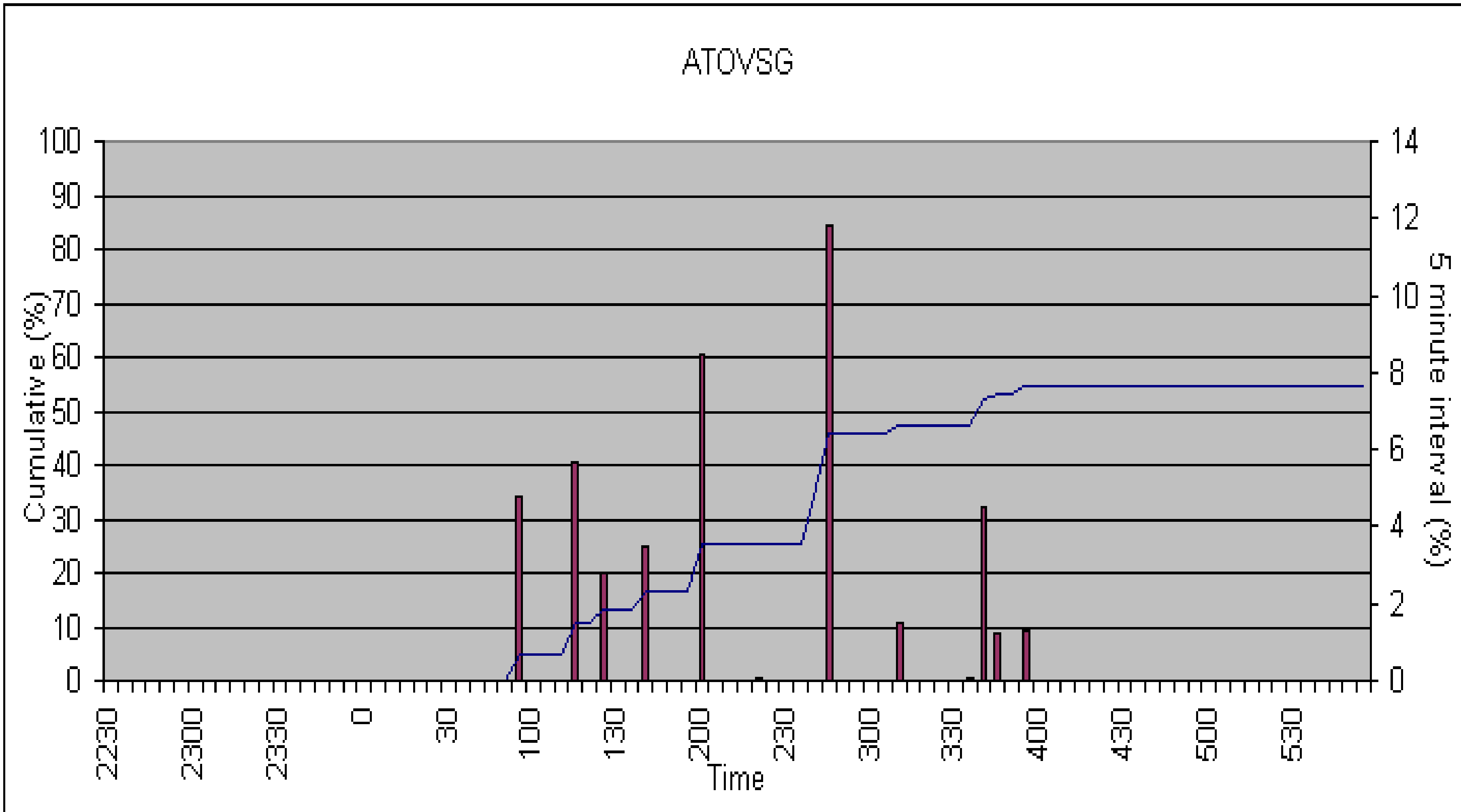
Increased resolution=>Increased Obs usage

Category	Count	% used	Category	Count	% used
TEMPs	637	99%	Satwinds: JMA	26103	**4%**
PILOTs	307	99%	Satwinds: NESDIS	142478	**3%**
Wind Profiler	1355	39%	Satwinds: EUMETSAT	220957	**1%**
Land Synops	16551	99%	Scatwinds: Seawinds	436566	**1%**
Ships	3034	84%	Scatwinds: ERS	27075	**2%**
Buoys	8727	63%	Scatwinds: ASCAT	241626	**4%**
Amdars	64147	23%	SSMI/S	532140	**1%**
Aireps	7144	12%	SSMI	698048	**1%**
GPS-RO	776	99%	ATOVS	1127224	**3%**
			AIRS	75824	**6%**
			IASI	80280	**3%**

Observations: Timeliness



Observations: Timeliness



Observations: Timeliness

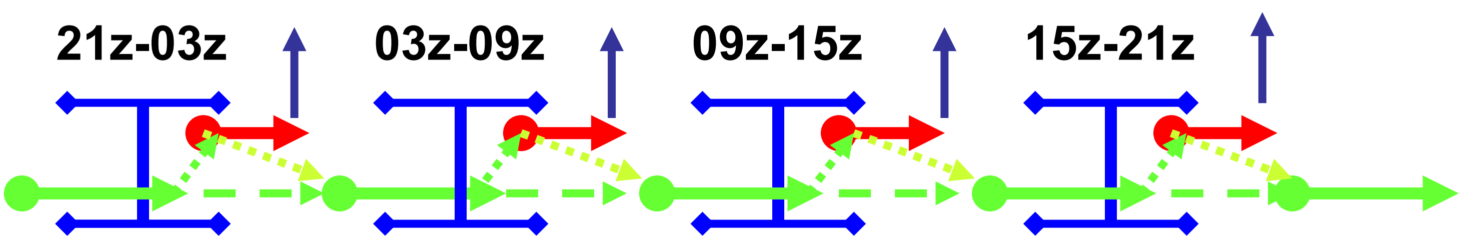
Compromise solution:

- Early cut-off 4D-var (~2-3h) (*main runs*)

  - to provide forecast to 2 or 6 days

- Late cut off 4D-var (~7h) (*upgrade runs*)

  - to provide new background for 4D-var



Observations: Summary

- Need sophisticated quality control
  - Especially for satellite data (more this afternoon!)
- Trade-off between forecast timeliness and quality – update cycle obvious solution.
- Number of observation types increasing and improving all the time…..
  - Most need significant effort for H, observation selection and quality control
  - “business as usual” overheads very large

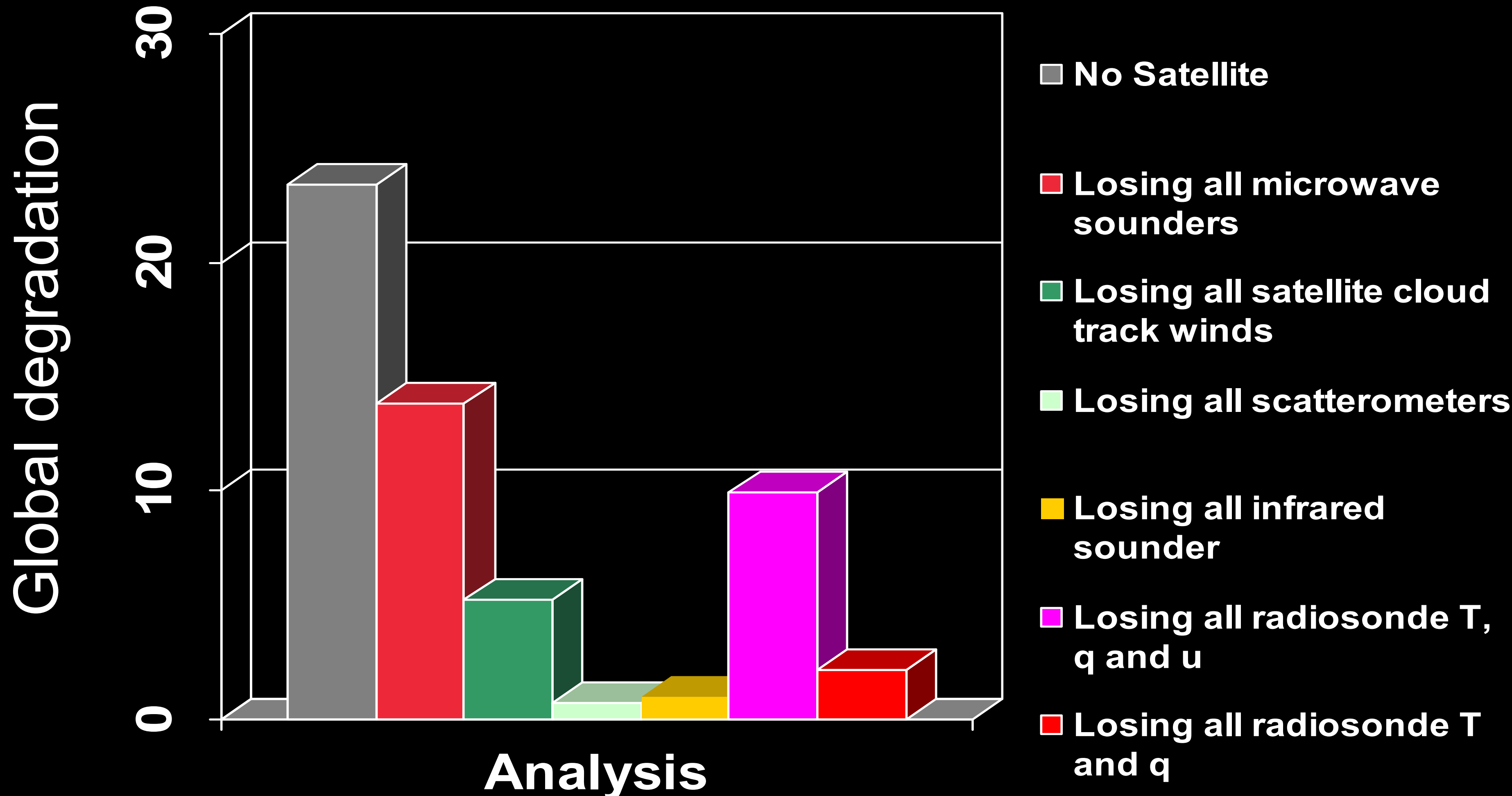
Relative value of observations in Met Office system and how do we measure this

Results from Global Data Denial Experiments

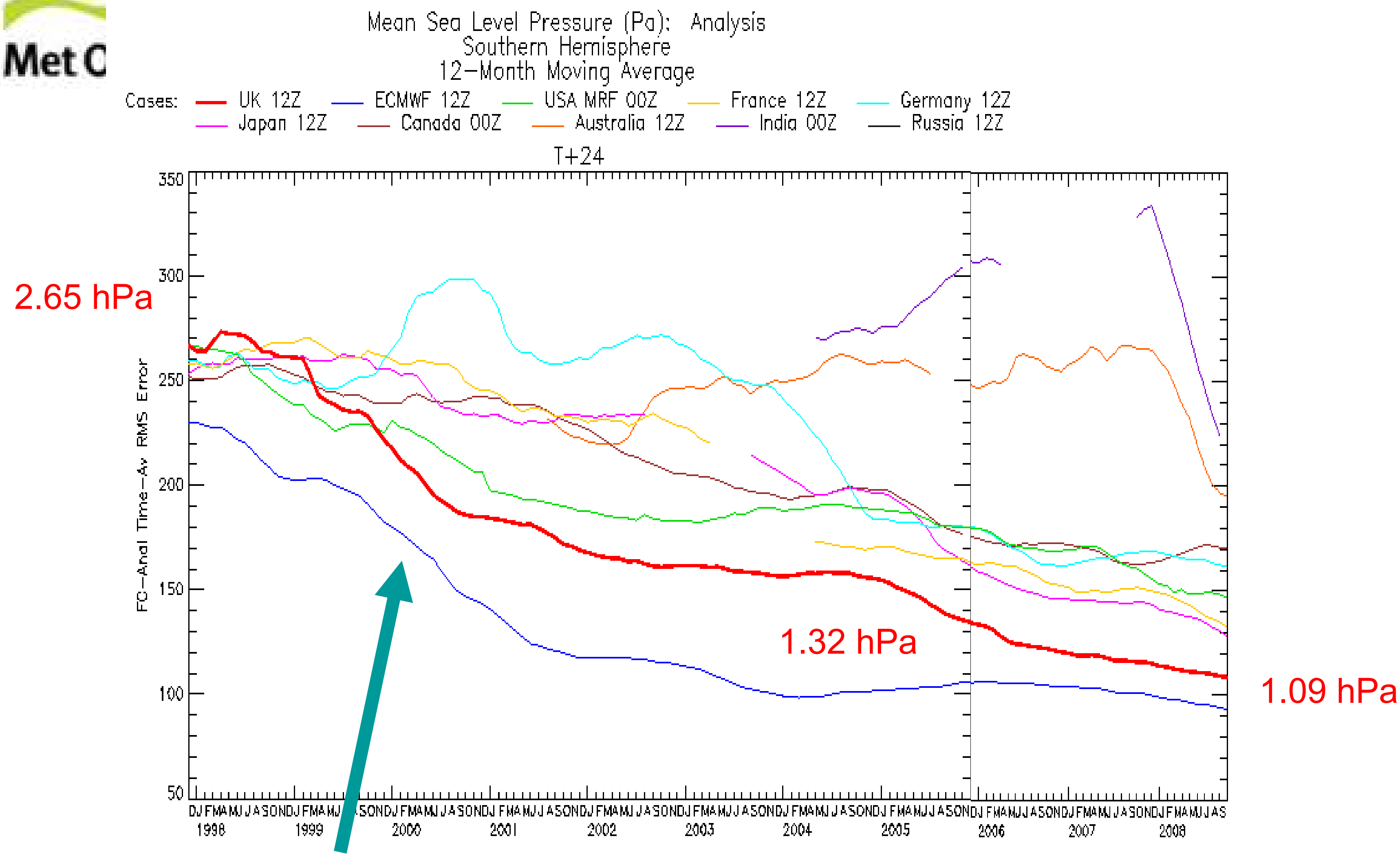
- All data have a positive impact.
- Satellite data are very important in the SH and increasingly important in the NH
- Satellite radiances (polar orbiters) have a bigger impact than AMVs (geostationary)
- Radiosonde winds are the most important 'in-situ' data source
- Surface data have a large impact on short range MSLP forecasts largely due to a problem with biases in the system.

[Richard Dumelow]

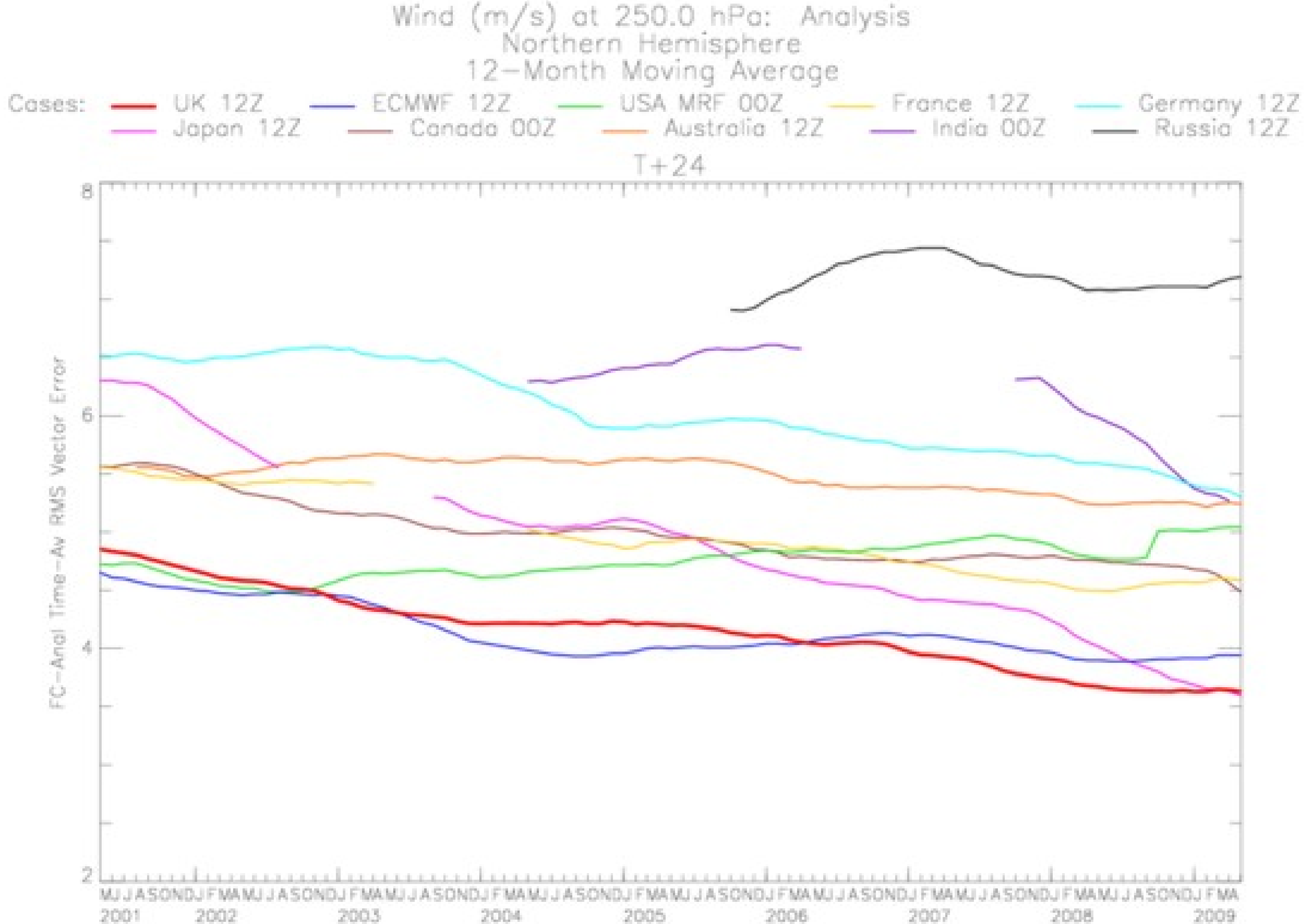
Comparison of impact of observing sounding data



12 month rolling average score



Arrival of microwave obs (AMSU) 1999-2001 still contributed to a period of rapid improvement.


Wind (m/s) at 250.0 hPa: Analysis
Northern Hemisphere
12-Month Moving Average
Cases:
UK 12Z
ECMWF 12Z
USA MRF 00Z
France 12Z
Germany 12Z
Japan 12Z
Canada 00Z
Australia 12Z
India 00Z
Russia 12Z
T+24
FC-Anal Time-Av RMS Vector Error
8
6
4
2
2001
2002
2003
2004
2005
2006
2007
2008
2009

Recent or forthcoming improvements

- 4D-var Inner loop resolution – currently N108 model is N320.
- Multiple outer loop – considered to be very important for observations with highly non-linear observation operators (e.g. clouds).
- Covariance statistics – but only tuning: is this real improvement? Or do we need to improve the covariance model?
- Variational bias correction – might make life easier, not necessarily better?

A few key points to remember….

- 4D-var is conceptually simple but practical problems mean there are real differences between different centres.
- Centres using 4D-var have best overall performance.
- Satellite observations are most important, but we are increasingly robust to loss of any one type due to skill of 4D-var and increasing number of observation types.
- Convective scale models (~1.5 km or better) pose new challenges and much more attention must be paid to observations of cloud and over land (….more this afternoon!).
- See you later

Thank you for listening for so long and please ask questions!

Assimilation of satellite radiances

Stephen English

JCSDA summer school Tuesday 14 July 2009

Contents

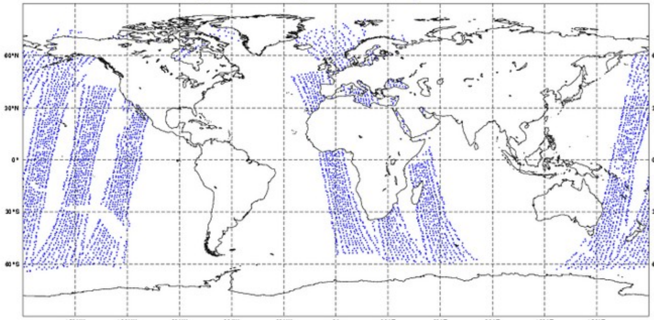
This presentation covers the following:

Types of satellite data used in NWP models

- Infrared and microwave sounder radiances

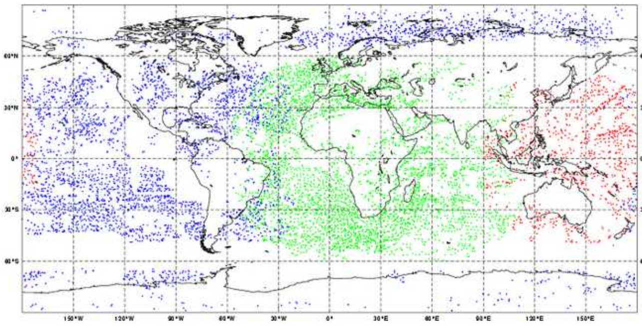
⇨ Temperature, water vapour and ozone profiles

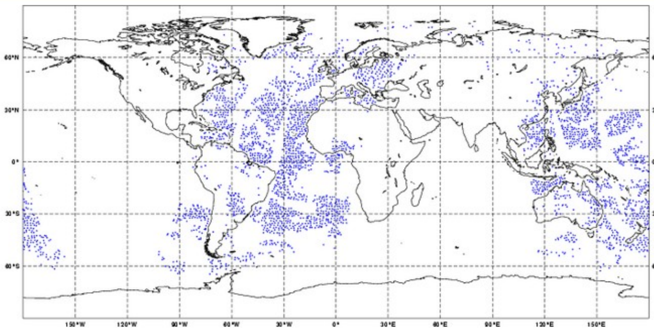
- Atmospheric motion vectors ⇨ tropospheric winds
- Ambiguous scatterometer winds ⇨ marine wind vectors
- GPS-RO bending angle ⇨ stratospheric temperature
- Visible and infrared imagery ⇨ clouds, surface temperature, surface vegetation etc.
- Microwave imagery ⇨ precipitation, cloud water, water vapour and winds over ocean
- Radar altimetry ⇨ wave height, sea level



AIRS ~4,500

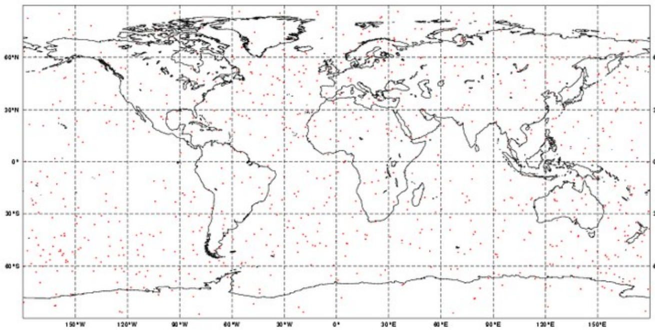
AMVs ~9,000

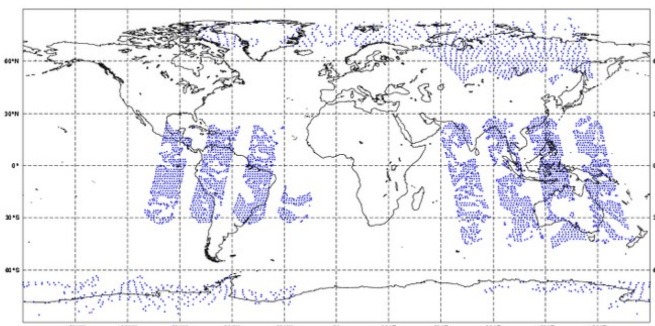




IASI ~3,000

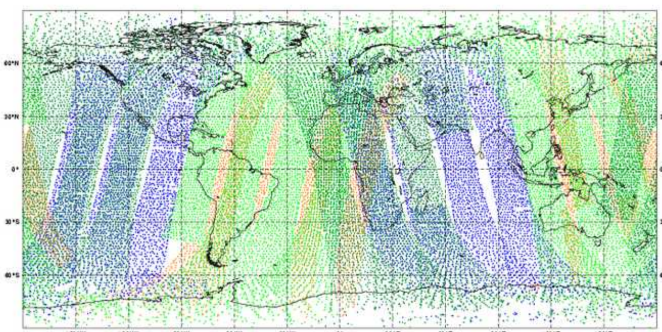
GPSRO ~800

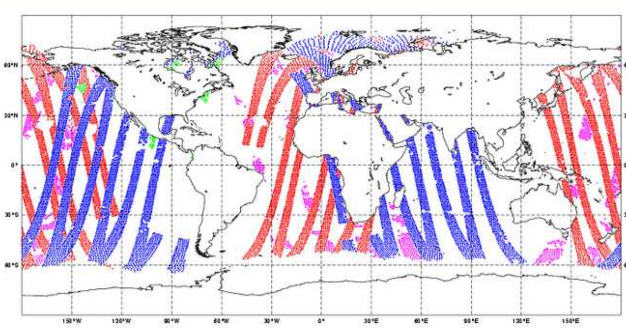




SSMIS ~4,500

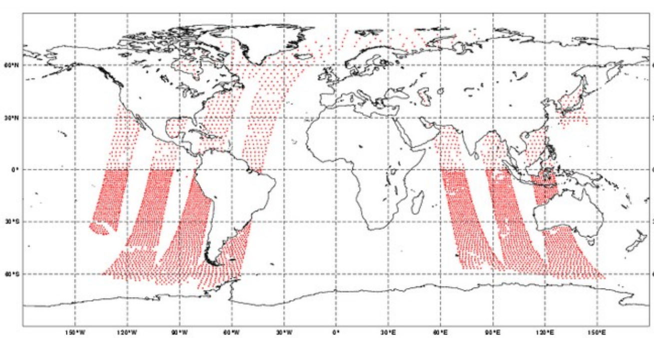
ATOVS ~36,000



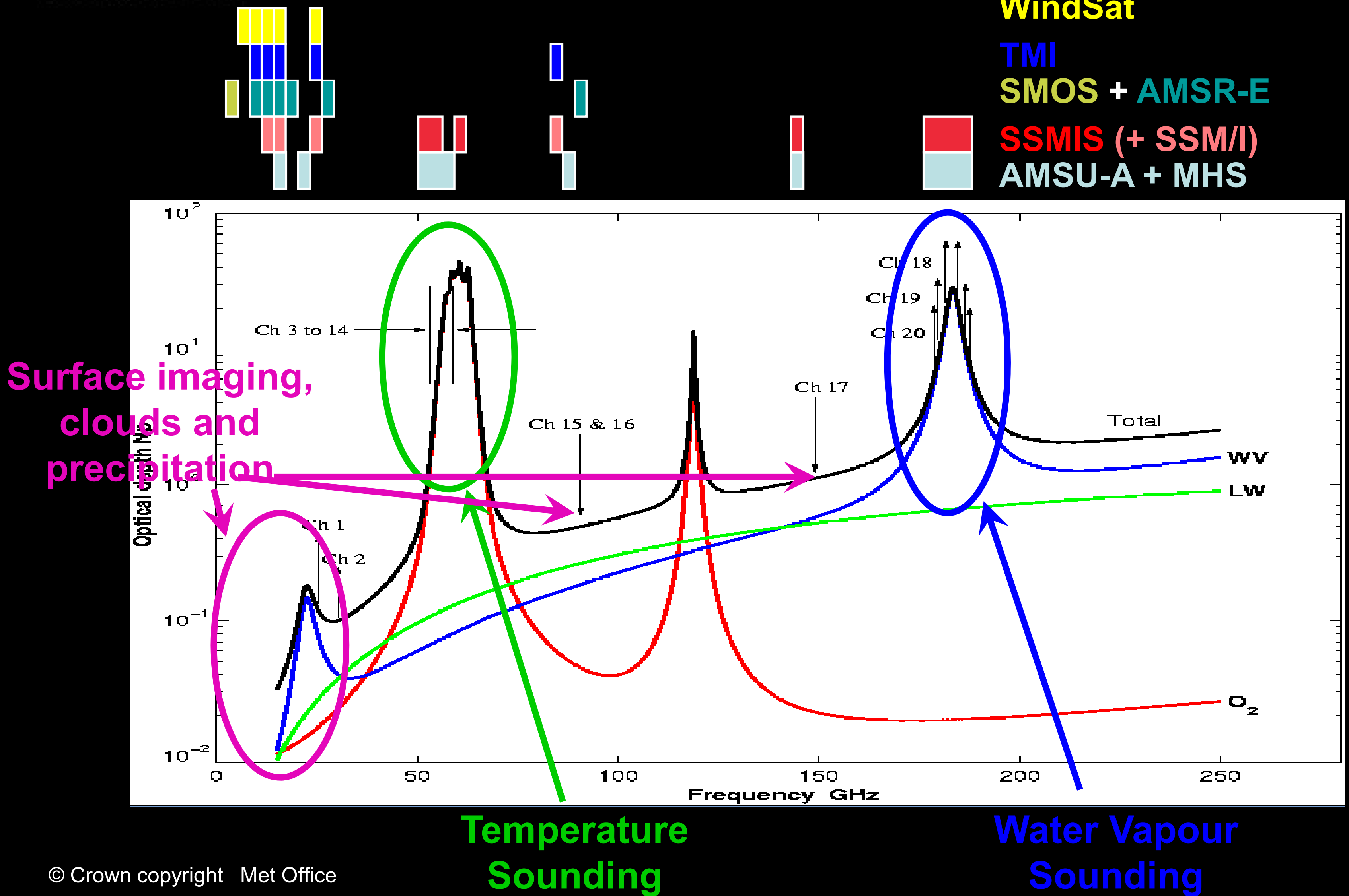


Scat ~16,500

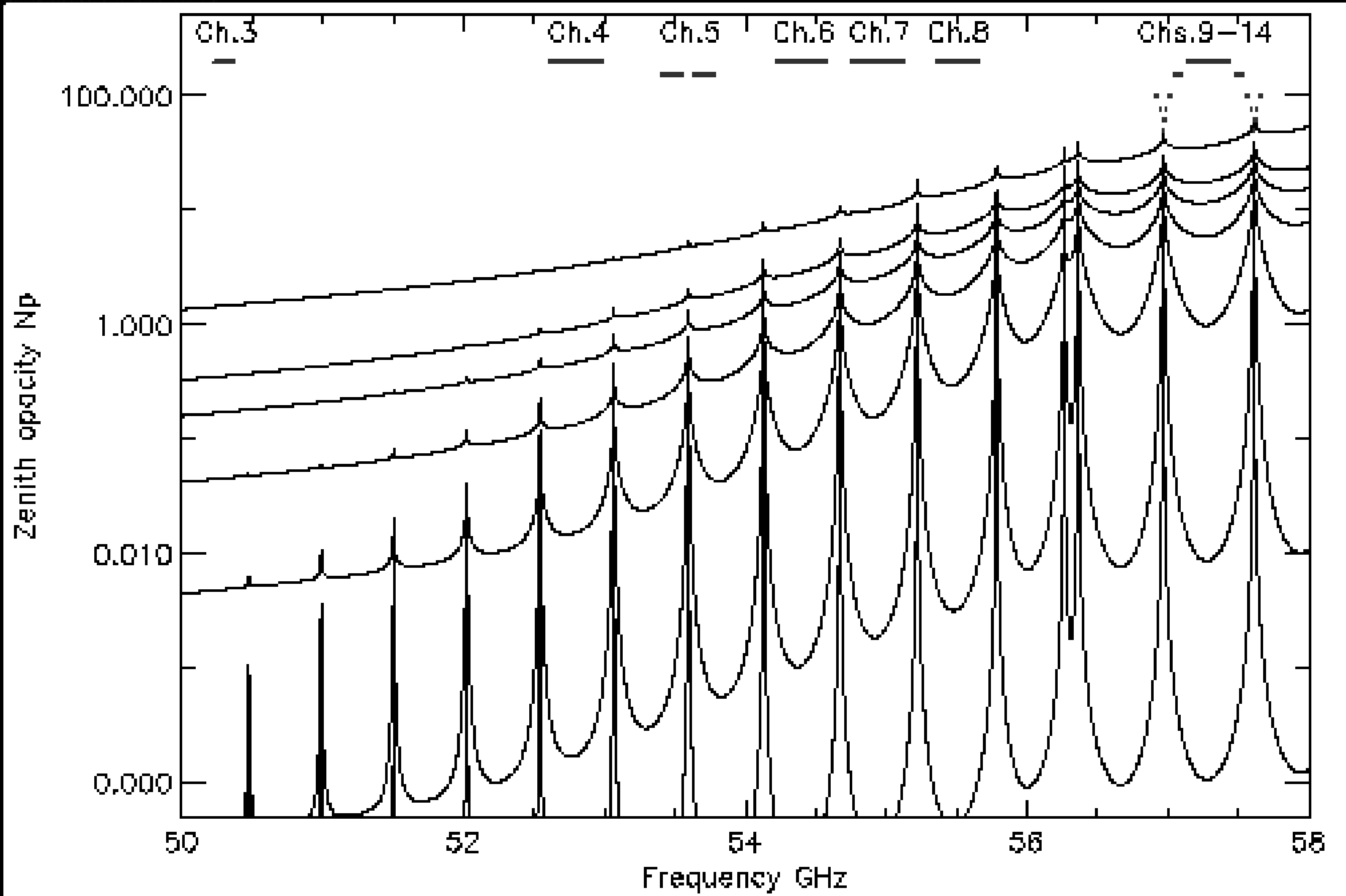
SSM/I ~4,500



Microwave spectrum

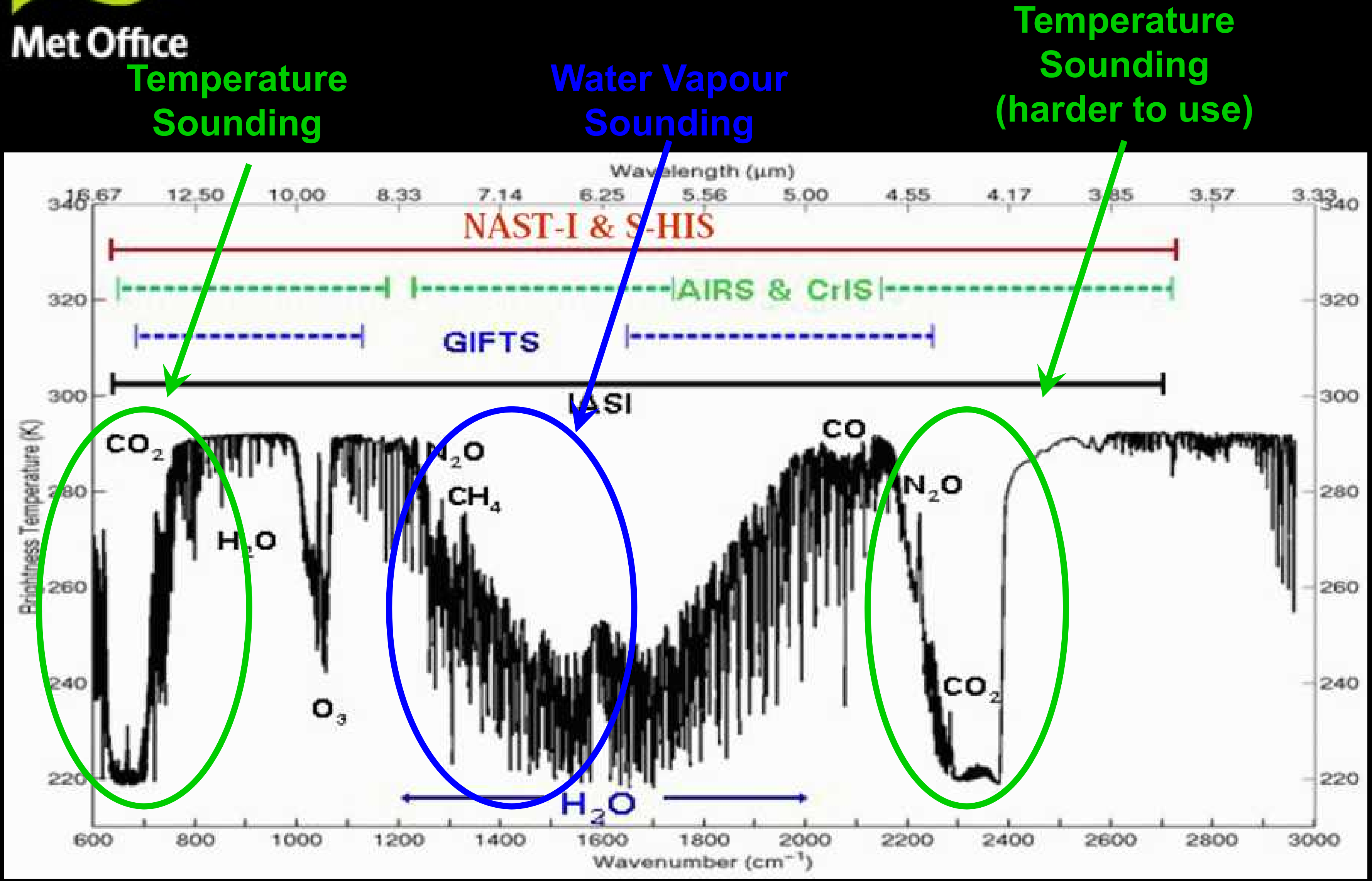


50-58 GHz oxygen spectrum



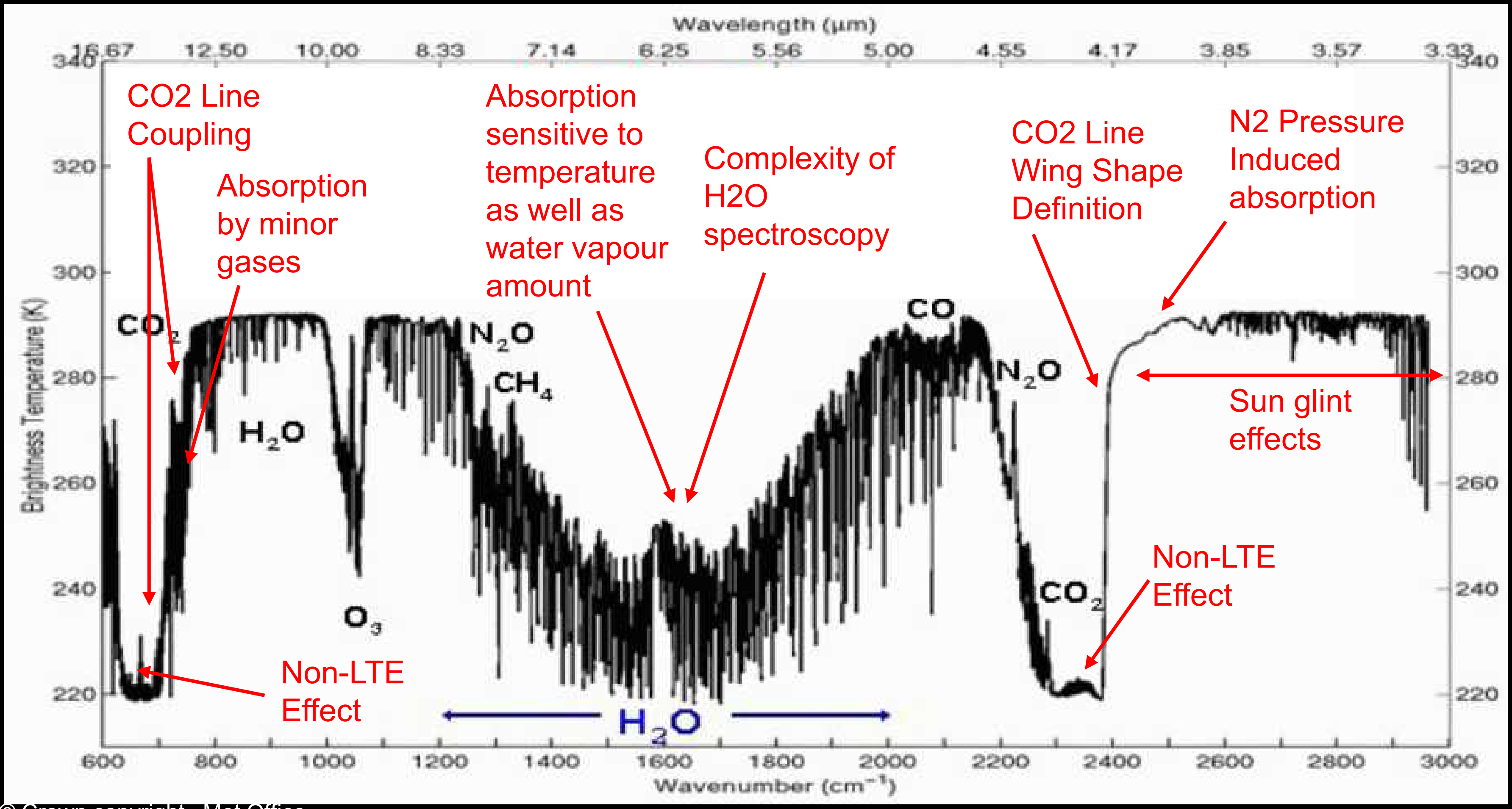
Altitudes
1000,
850,
700,
250,
100,
10,
0.1 hPa

The Infrared Spectrum

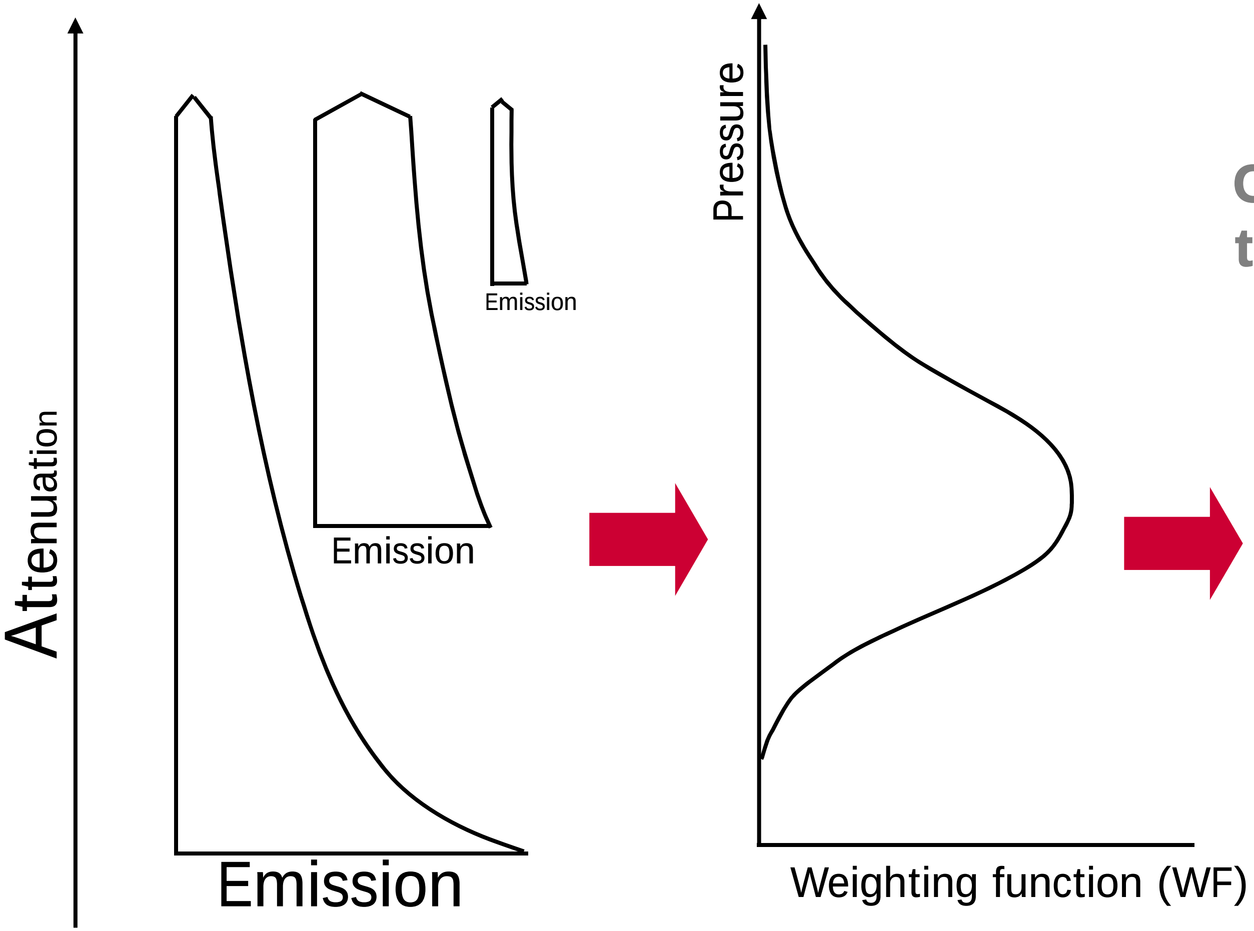


IR Radiative Transfer

The radiative transfer is affected by a multitude of factors, which may affect our ability to use parts of the spectrum. For example:



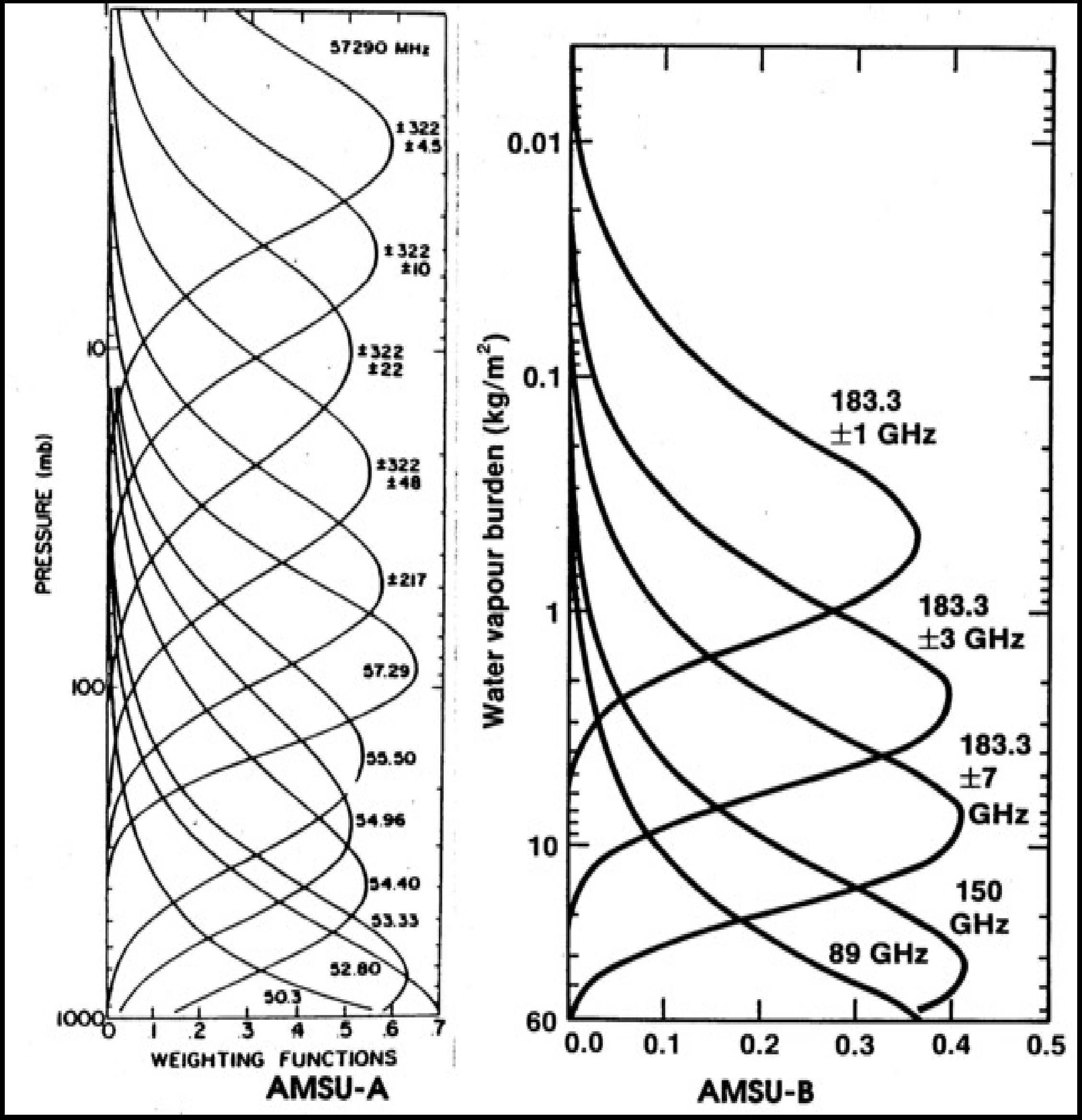
Weighting functions



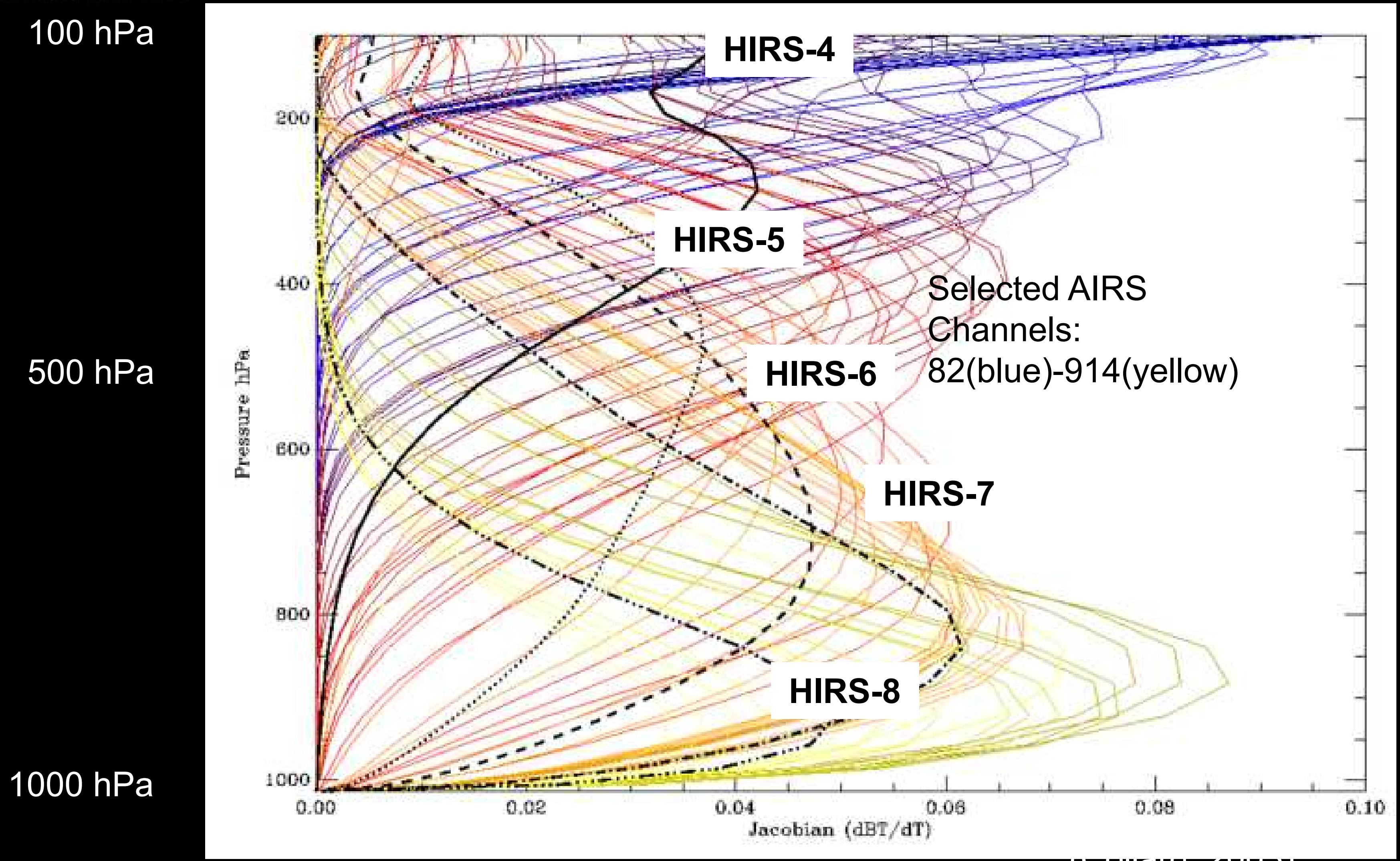
Observed brightness temperature (TB)

$$= \int_{\text{Surface}}^{\text{Space}} WF(p).T(p)\,dp$$

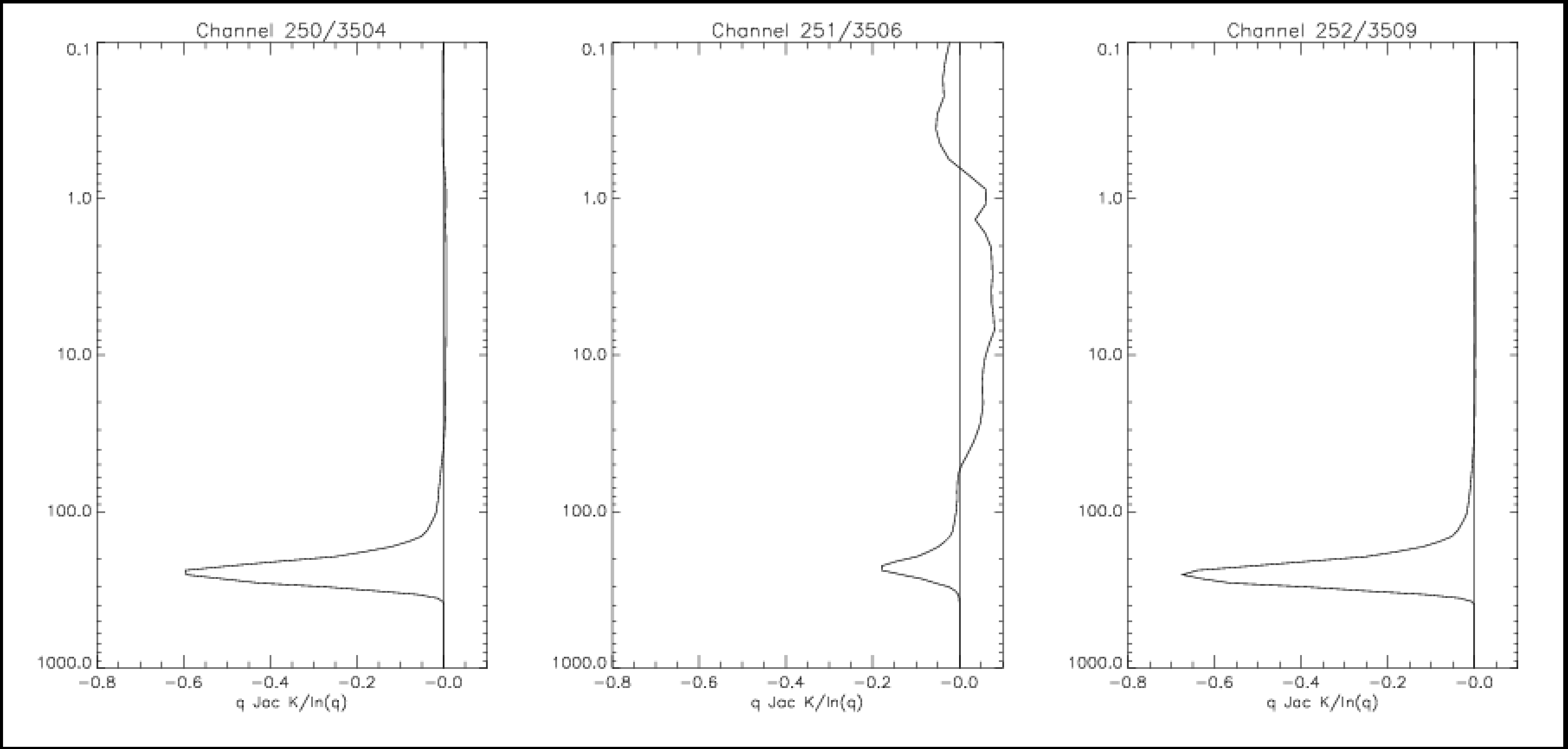
AMSU weighting functions



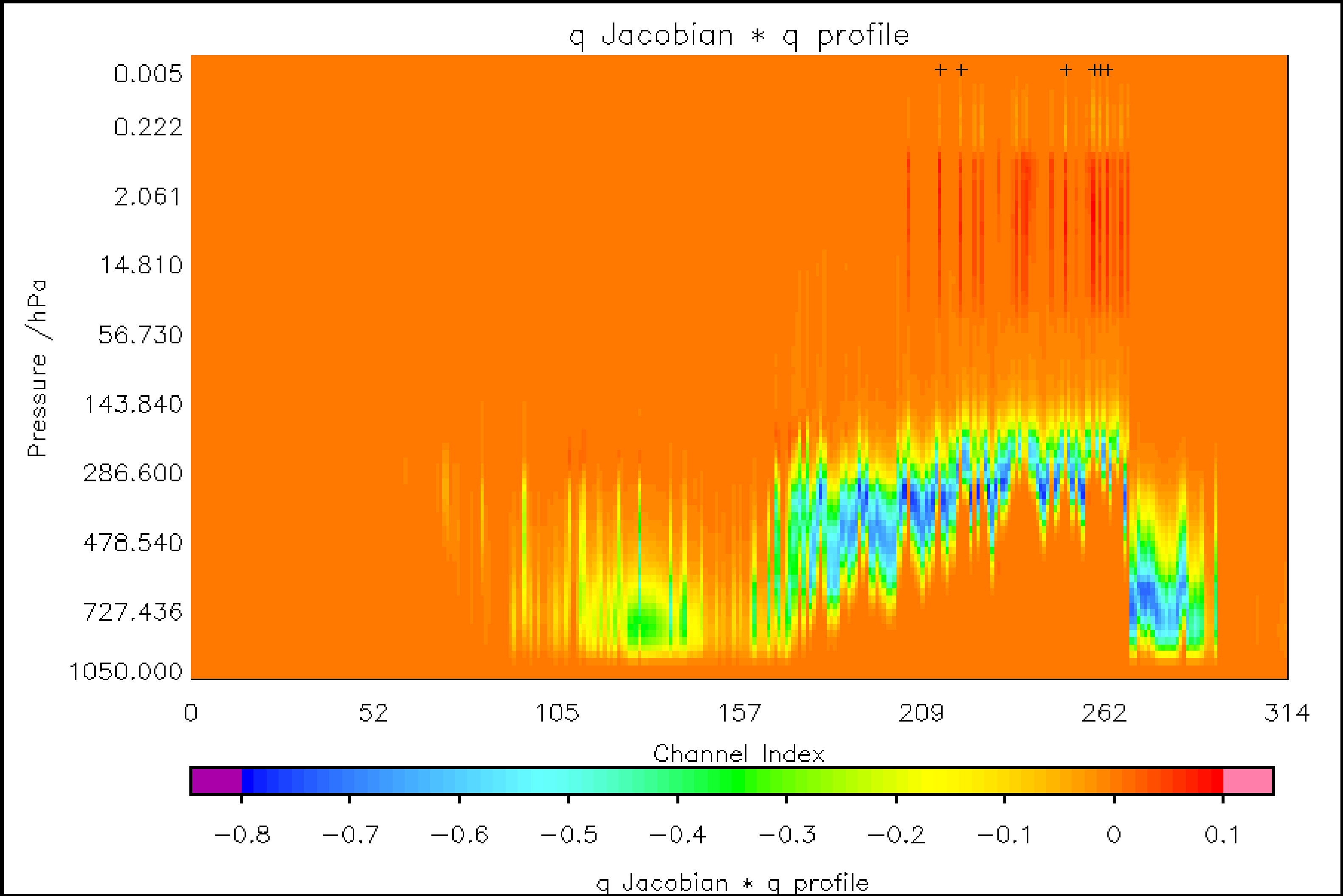
AIRS vs HIRS Jacobians
in the 15μm CO_2 band



High-peaking WV channel

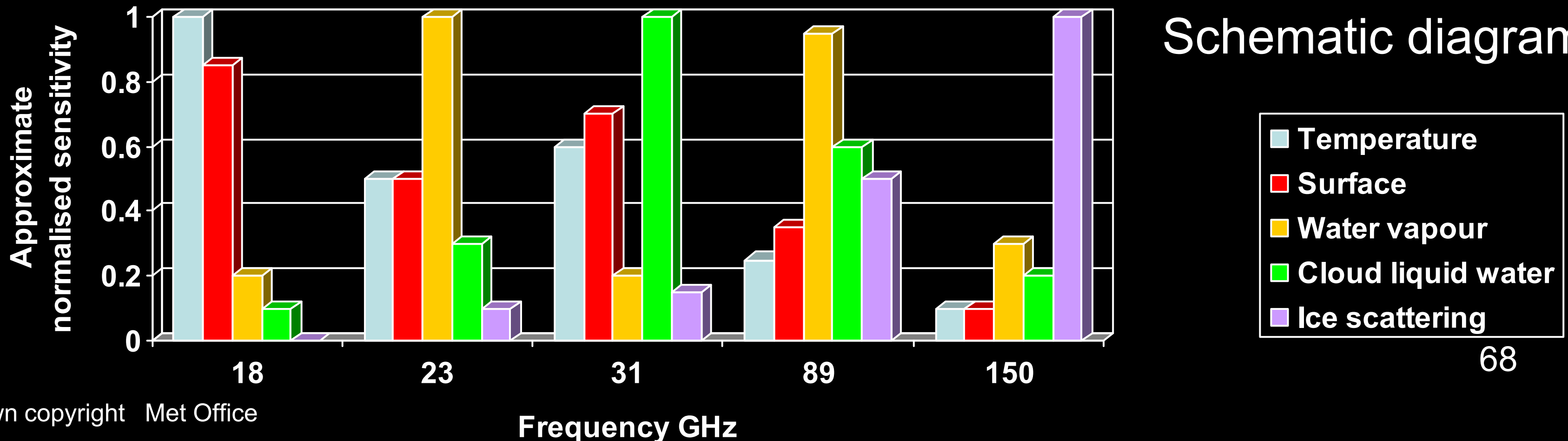


Water Vapour Jacobian



MW imager channels

- Five measurements: 18.7, 23.8, 31, 89, 150 GHz
- Five unknowns to solve for:
  - Surface temperature
  - Surface properties (which affect emission & reflection)
  - Total column water vapour
  - Total column cloud liquid water
  - Ice scattering (depends on ice microphysics)

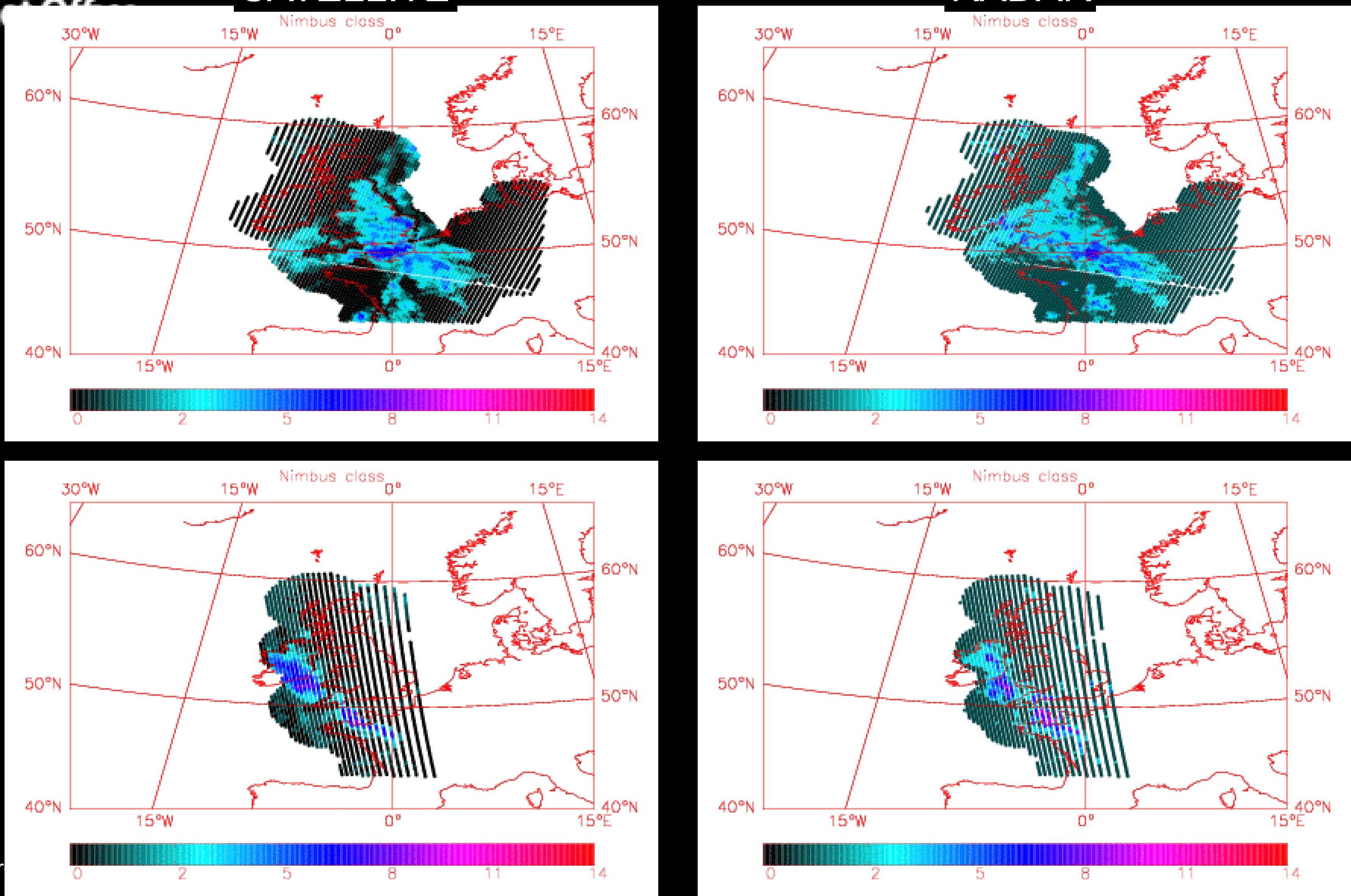


Schematic diagram

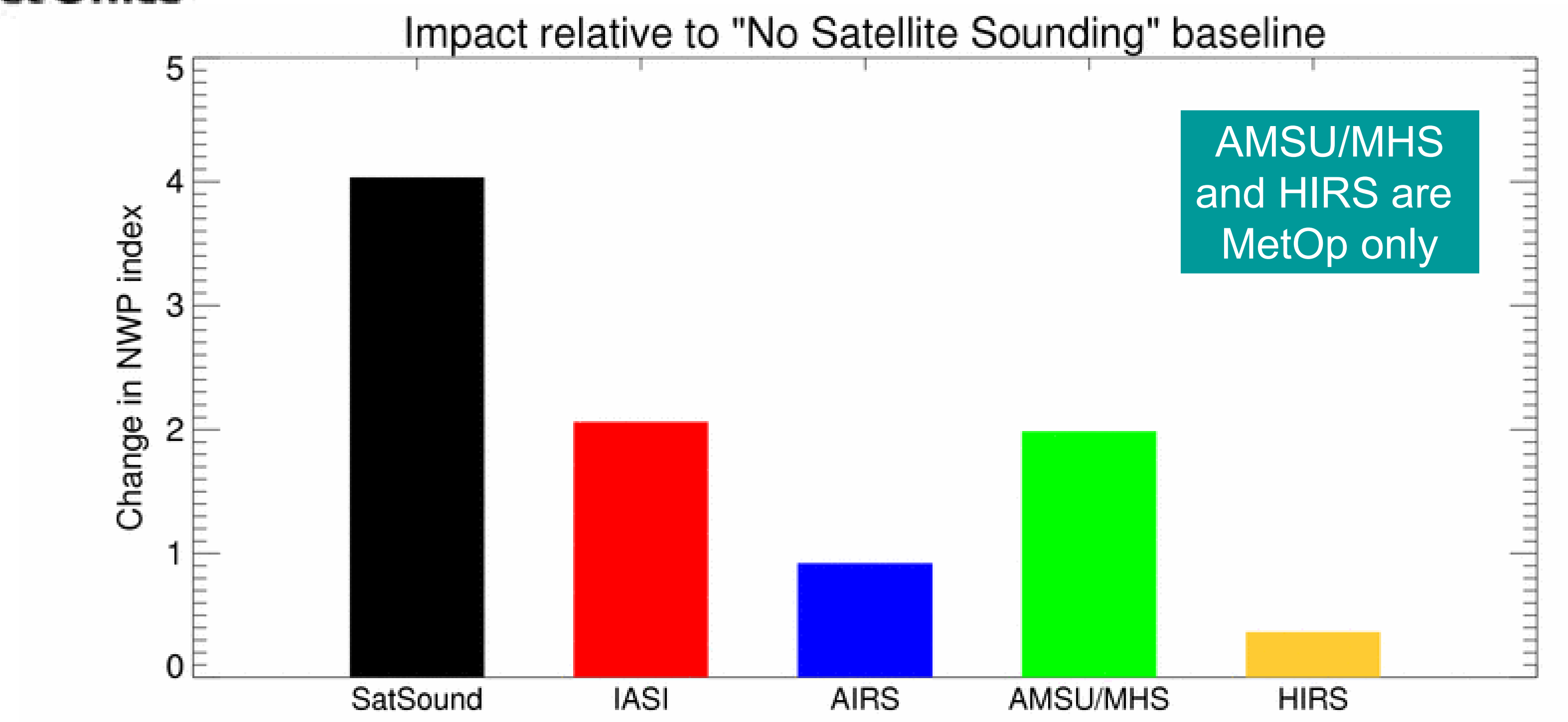
MW imager precipitation

From Una Lean

SATELLITE RADAR

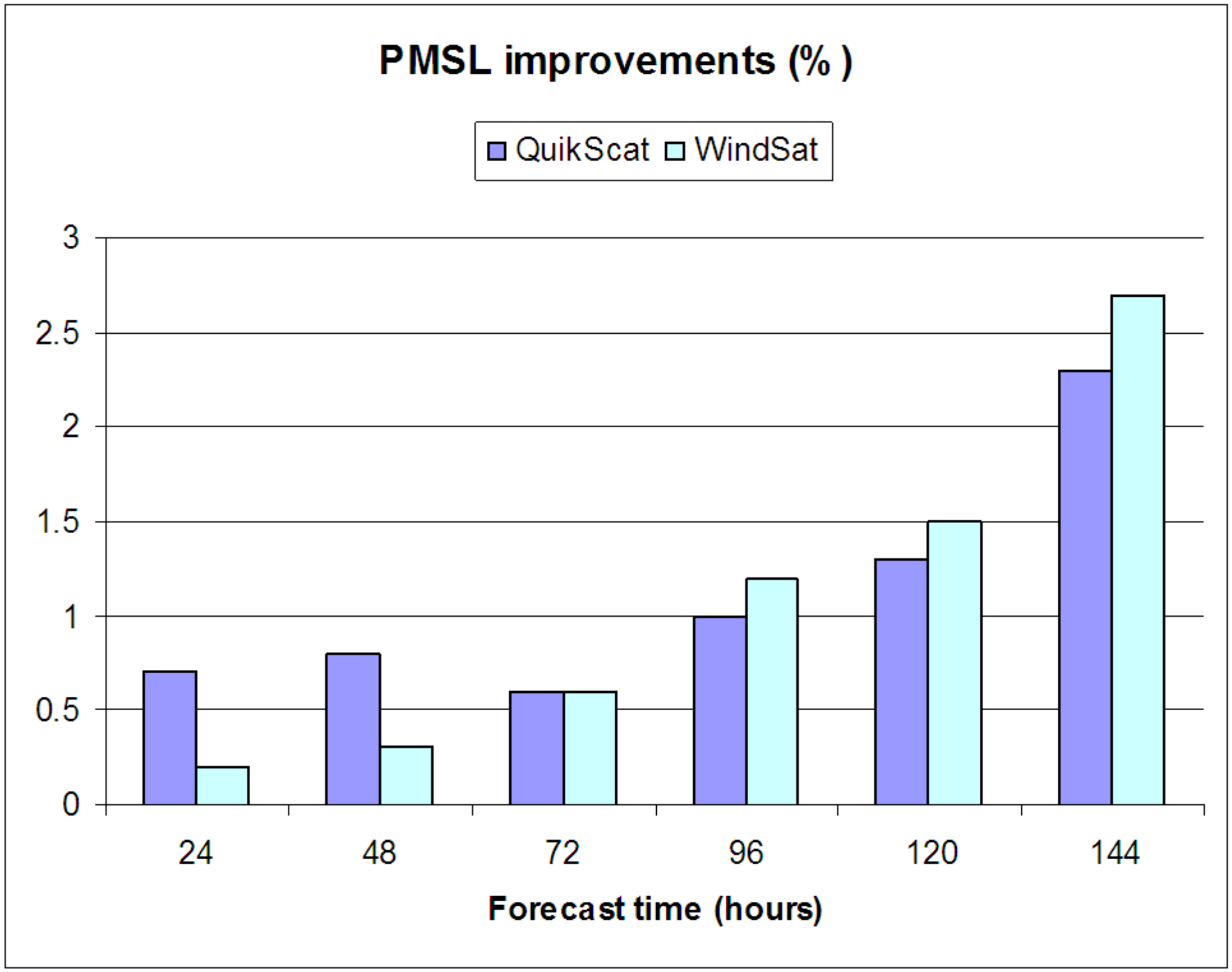


Impacts of radiance observations
Verified against observations

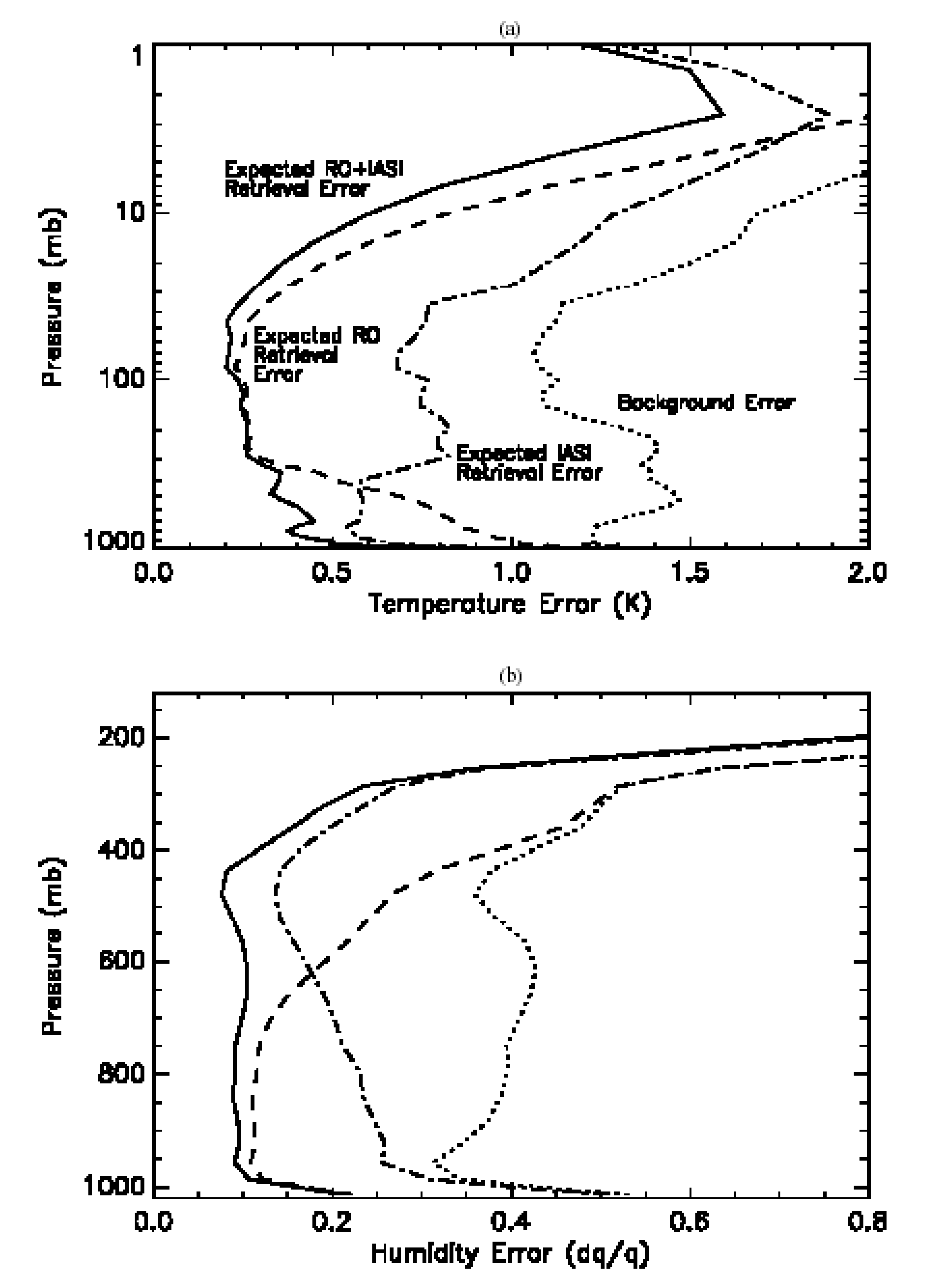


- **IASI impact very similar to one AMSU/MHS**
  - **Compare more channels with coverage in cloudy areas**
- **AIRS impact about half of IASI (agrees with other trials)**
  - **Probably due to observation weighting**
  - **Cloudy AIRS trial brings impact up to similar level as IASI or AMSU**

WindSat v QuikScat Impacts



Scatterometer gives good improvement to forecast in short range. Windsat loses sensitivity for winds below 5 m/s.



- Taken from *Collard and Healy (2003), QJRMS 129.*

- GPS-RO and IASI offer complimentary information, IASI most important at altitudes with p > 300 hPa, GPS-RO most important at higher altitudes.

- Sean Healy's trials of GPS-RO confirm impact around tropopause height and above, even based on very small number of soundings from CHAMP.

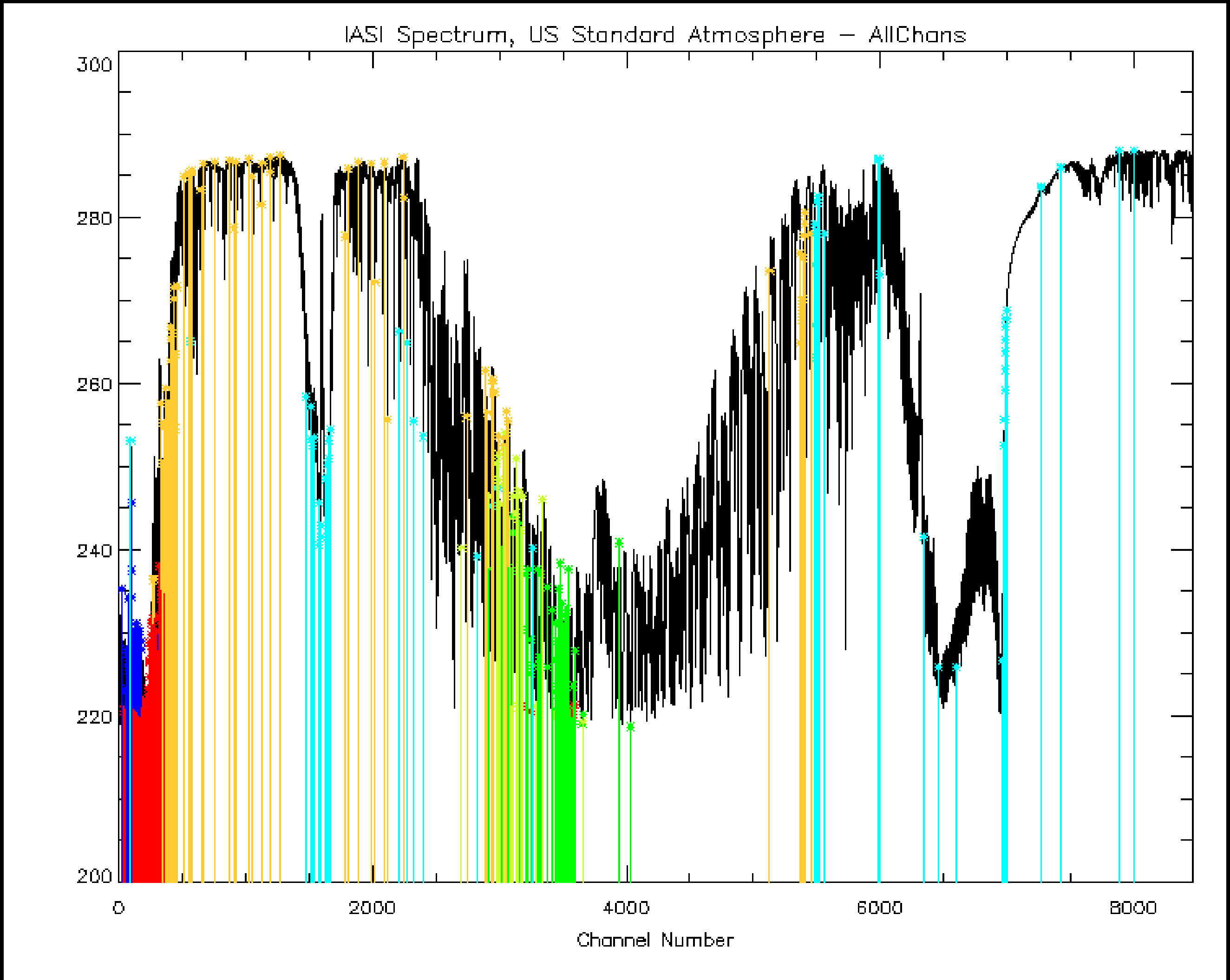
Approaches to assimilating satellite observations

- Why don’t we just assimilate all the raw radiances?
- Bias correction
  - What is truth?
- Quality control
- Clouds and surfaces

Obs selection AMSU MHS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Sea SI > T																				
Sea IWC > T																				
Sea LWC > T2																				
Sea LWC > T1																				?
Sea IR cloud > T																				
Sea no cloud																				
Land SI > T																				
Land AMSU O-B Ch.4 > T																		?		
Land IR cloud > T					?														?	?
Land no cloud																				

Obs selection IASI



Red – Used (Sea/Land, Clear/MWcloud)

Yellow – Used (Sea/Clear only)

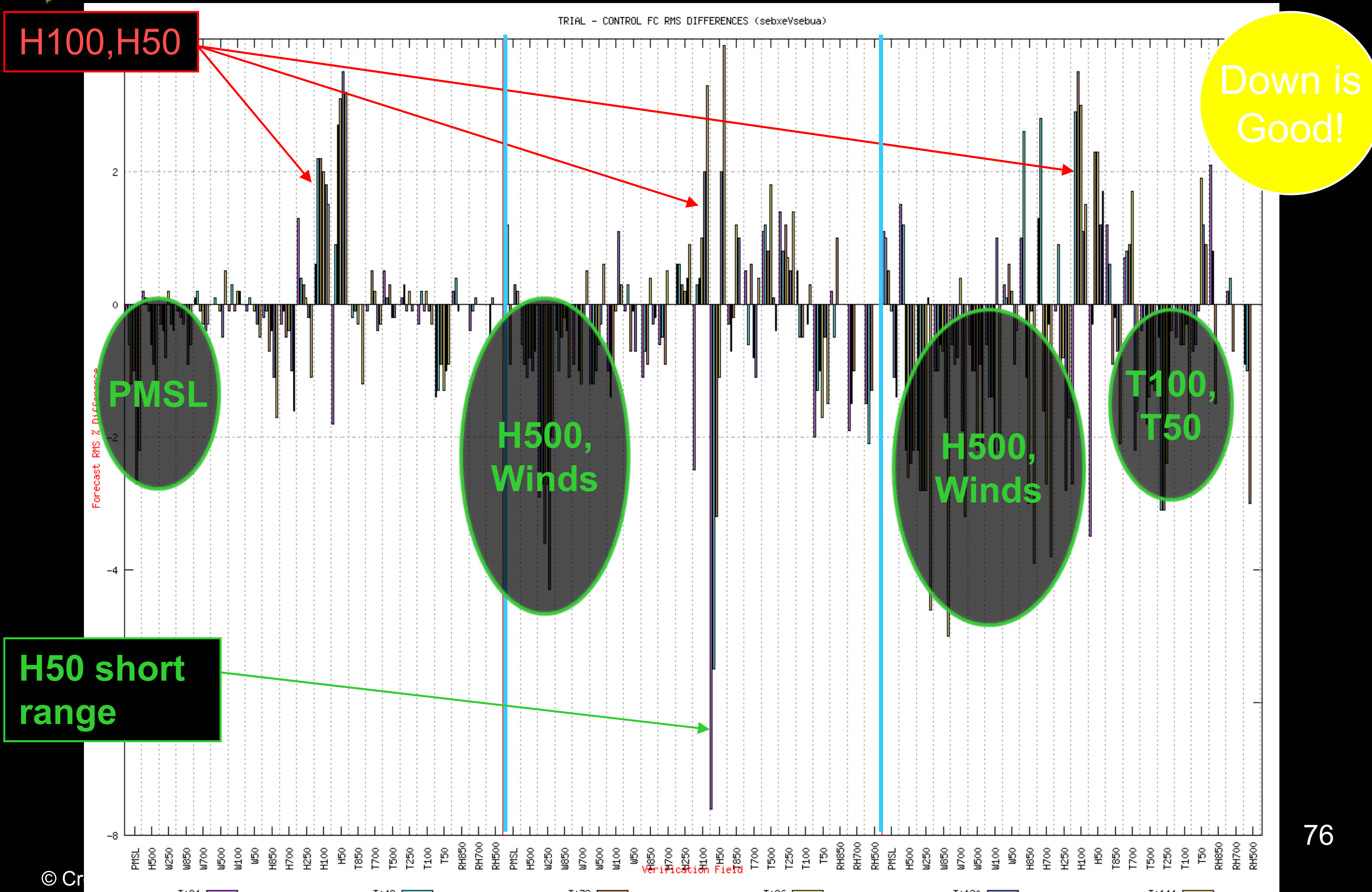
Blue – Used (1D-Var preprocessor only)

Cyan – Rejected

Green / Lime – Rejected water vapour channels

IASI

Change in rms forecast error v Obs



© Cr

Efficient representation of the information in the spectrum

- Principal components and reconstructed radiances
- Slides courtesy of Andrew Collard

Spectral data compression and de-noising

Leading eigenvectors (200,say) of covariance of spectra from (large) training set

Mean spectrum

$$\mathbf{p} = \mathbf{V}^{\mathrm{T}}(\mathbf{y} - \overline{\mathbf{y}})$$

Original Spectrum

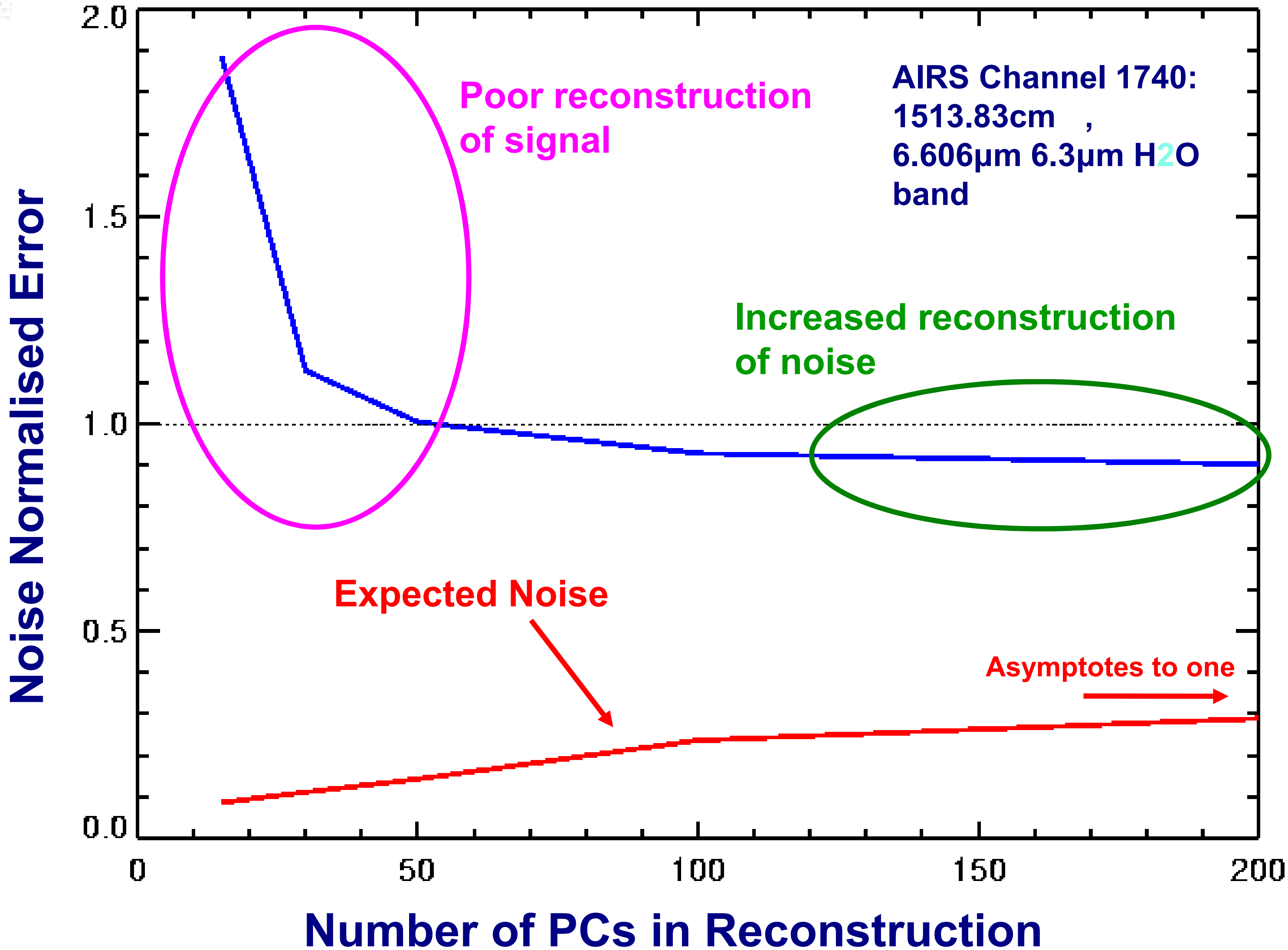
Reconstructed spectrum

$$\mathbf{y}_{\mathbf{R}} = \overline{\mathbf{y}} + \mathbf{V}\mathbf{p}$$

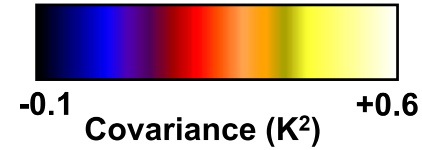
N.B. This is usually performed in noise-normalised radiance space

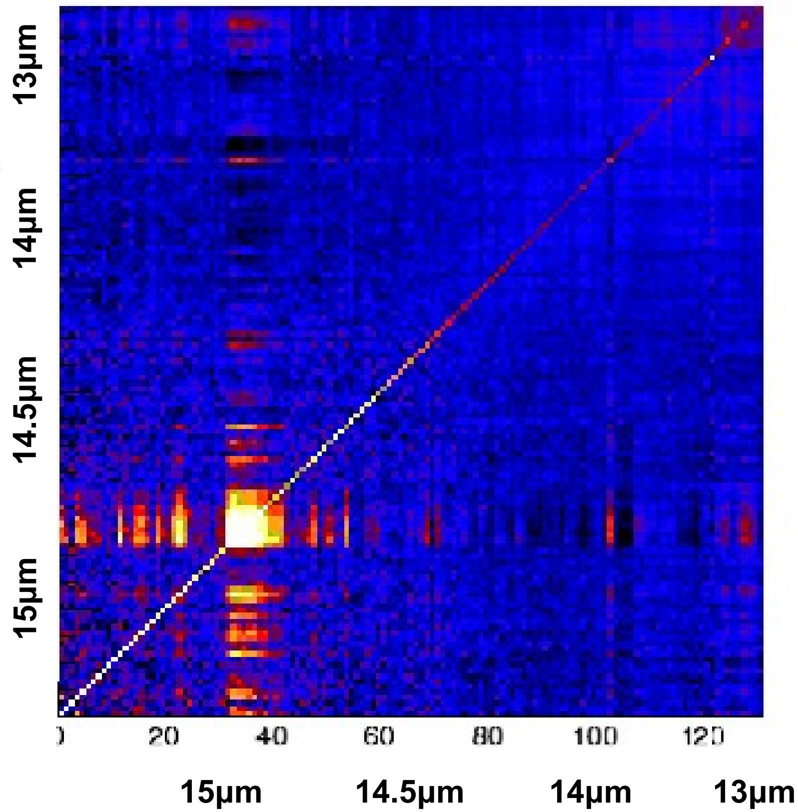
Each reconstructed channel is a linear combination of all the original channels and the data is significantly de-noised.

Reconstruction Errors



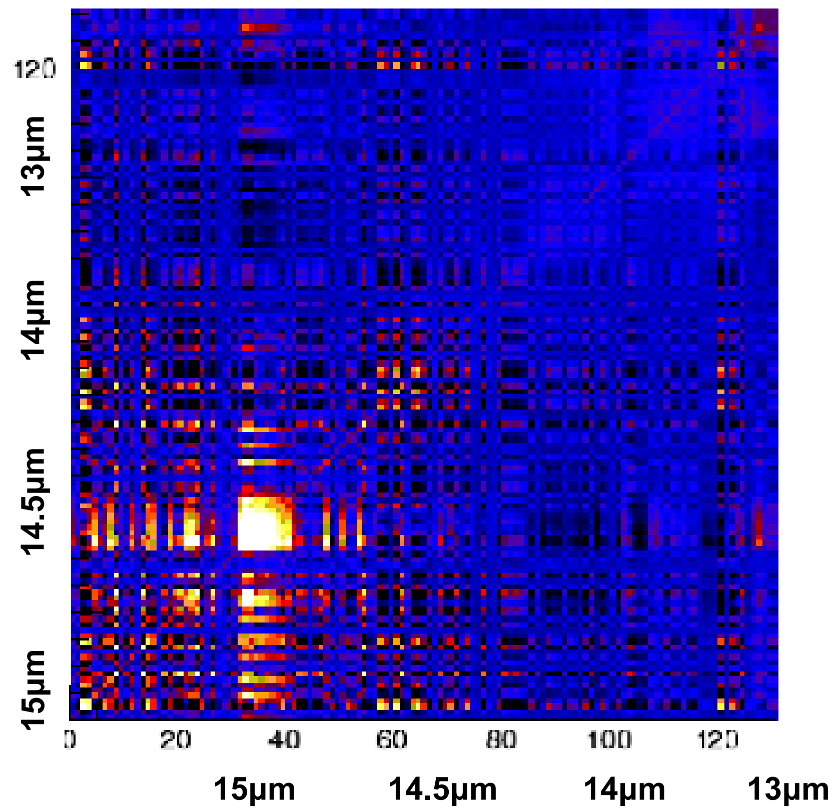
A look at Reconstructed Radiances' Errors





Original Radiances

Instrument noise is dominant and diagonal.
Correlated noise is from background error

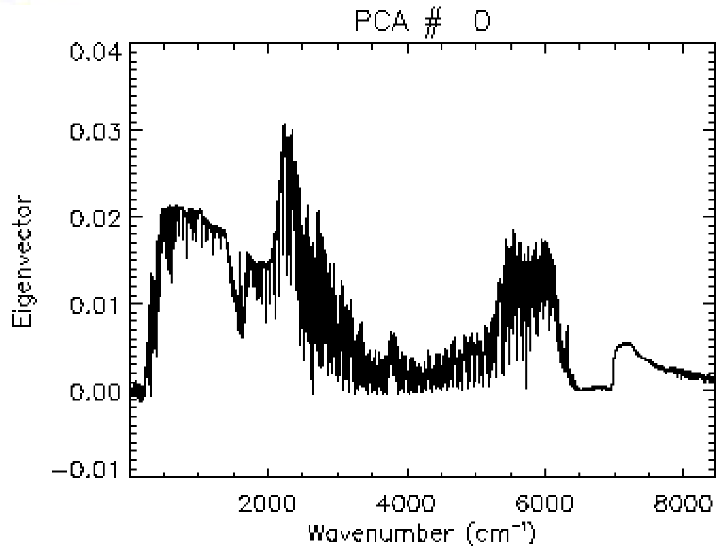


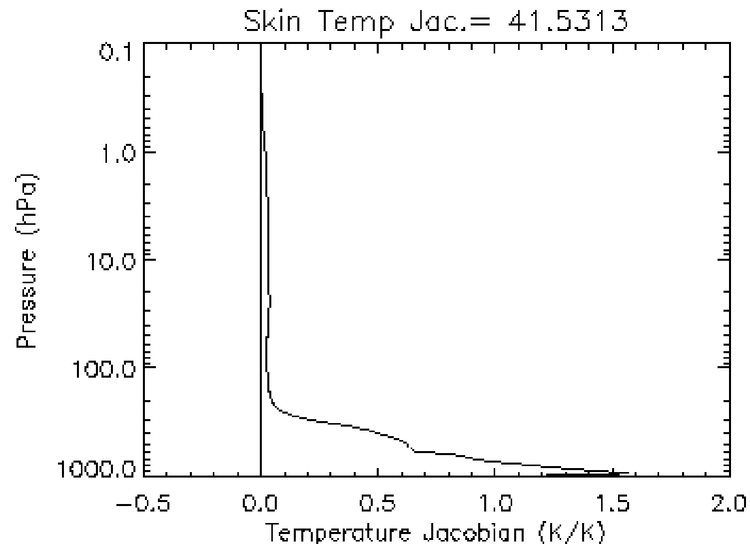
Reconstructed Radiances

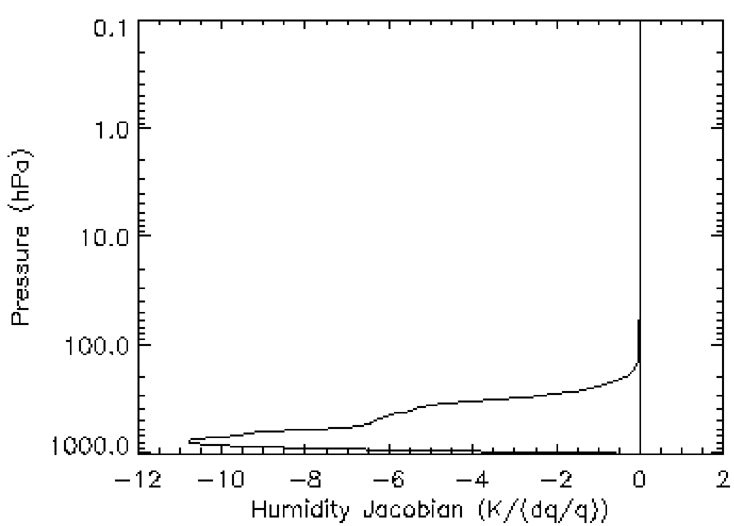
Instrument noise is reduced but the errors have become correlated.

Covariances of y-H(x_b) for clear observations in 15µm CO_2 band

Jacobians of PCs (1)





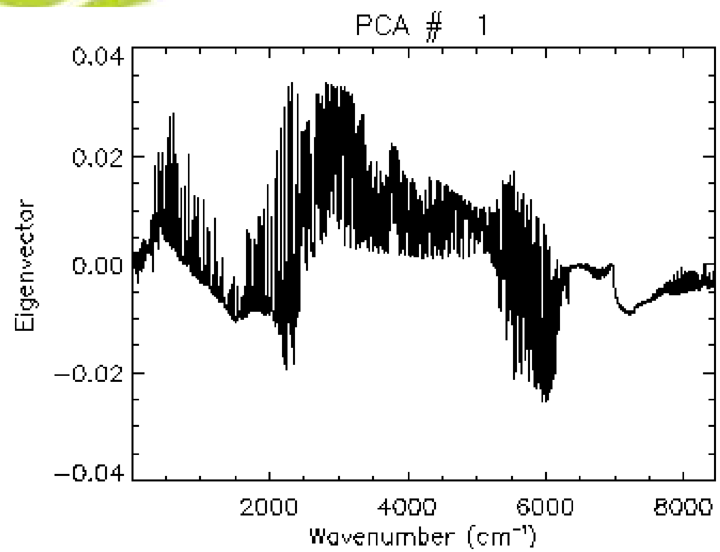


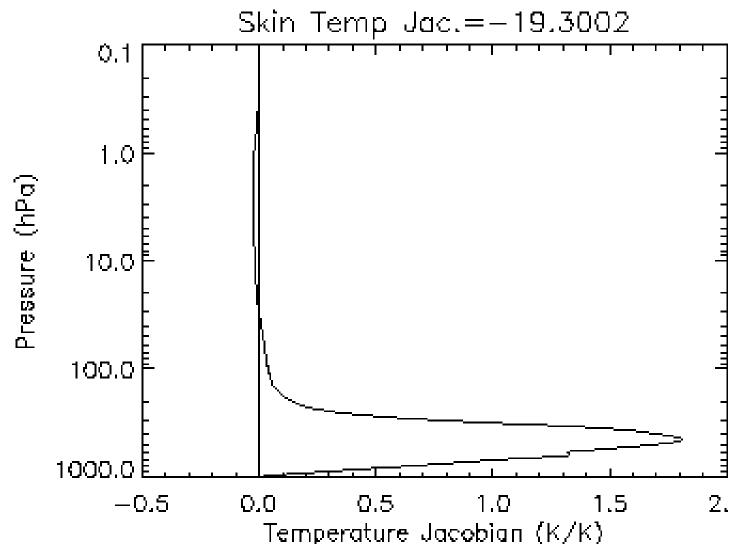
Spectrum of Principal Component #1

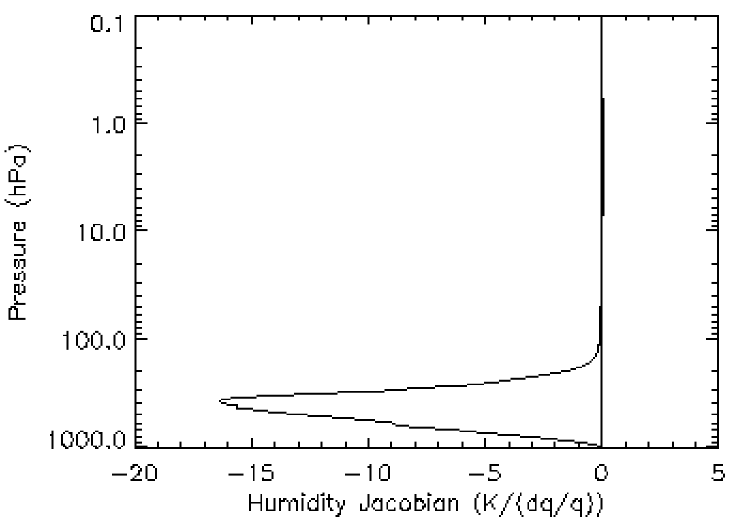
Temperature Jacobian

Humidity Jacobian

Jacobians of PCs (2)





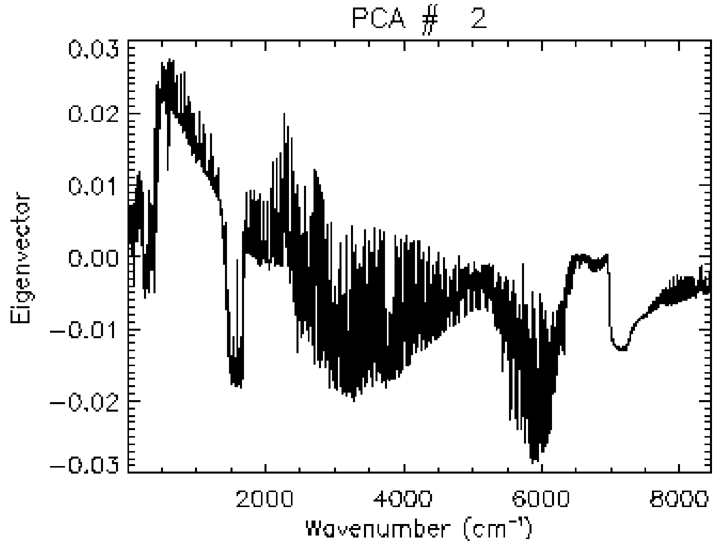


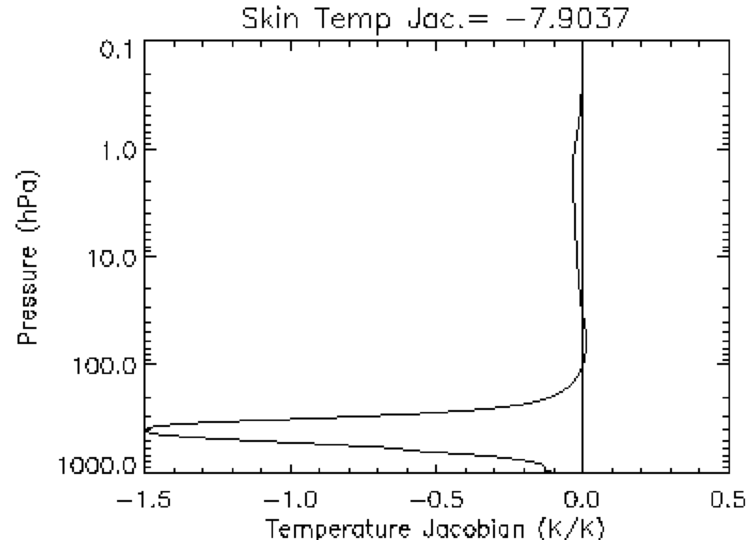
Spectrum of Principal Component #2

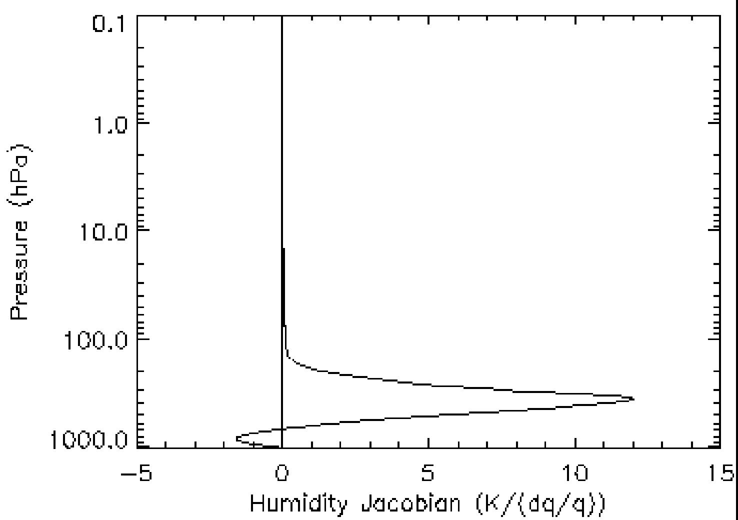
Temperature Jacobian

Humidity Jacobian

Jacobians of PCs (3)





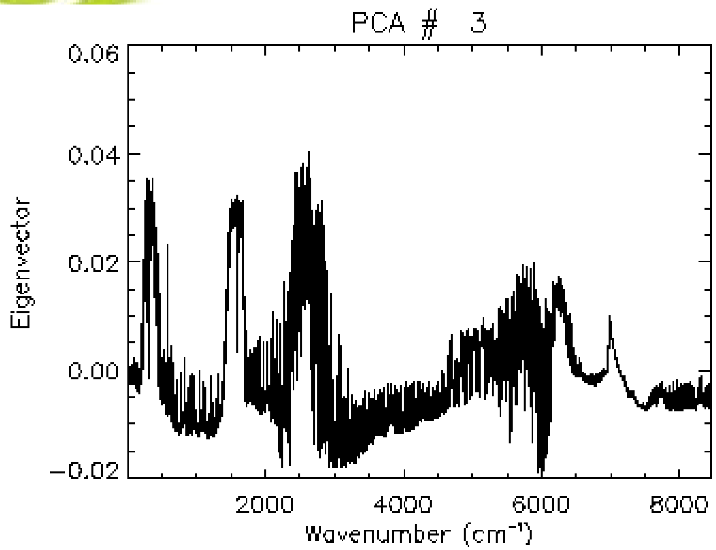


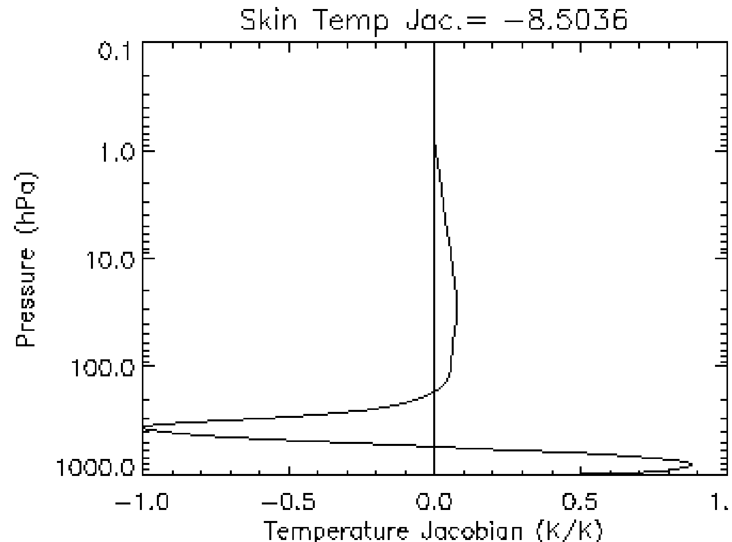
Spectrum of Principal Component #3

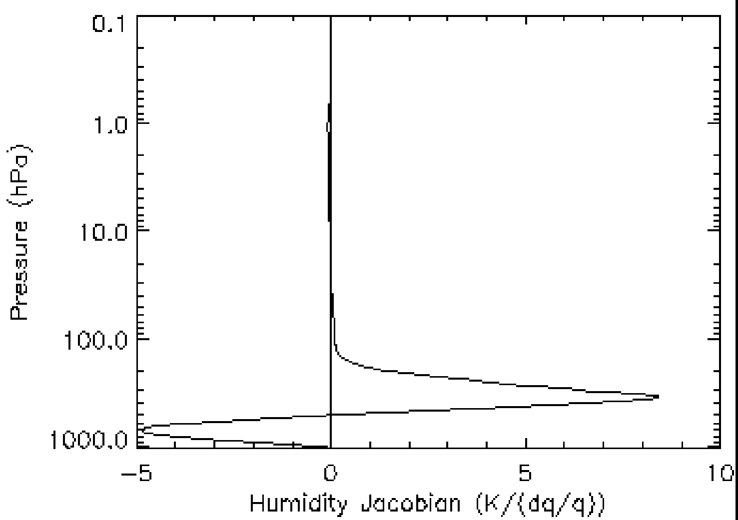
Temperature Jacobian

Humidity Jacobian

Jacobians of PCs (4)





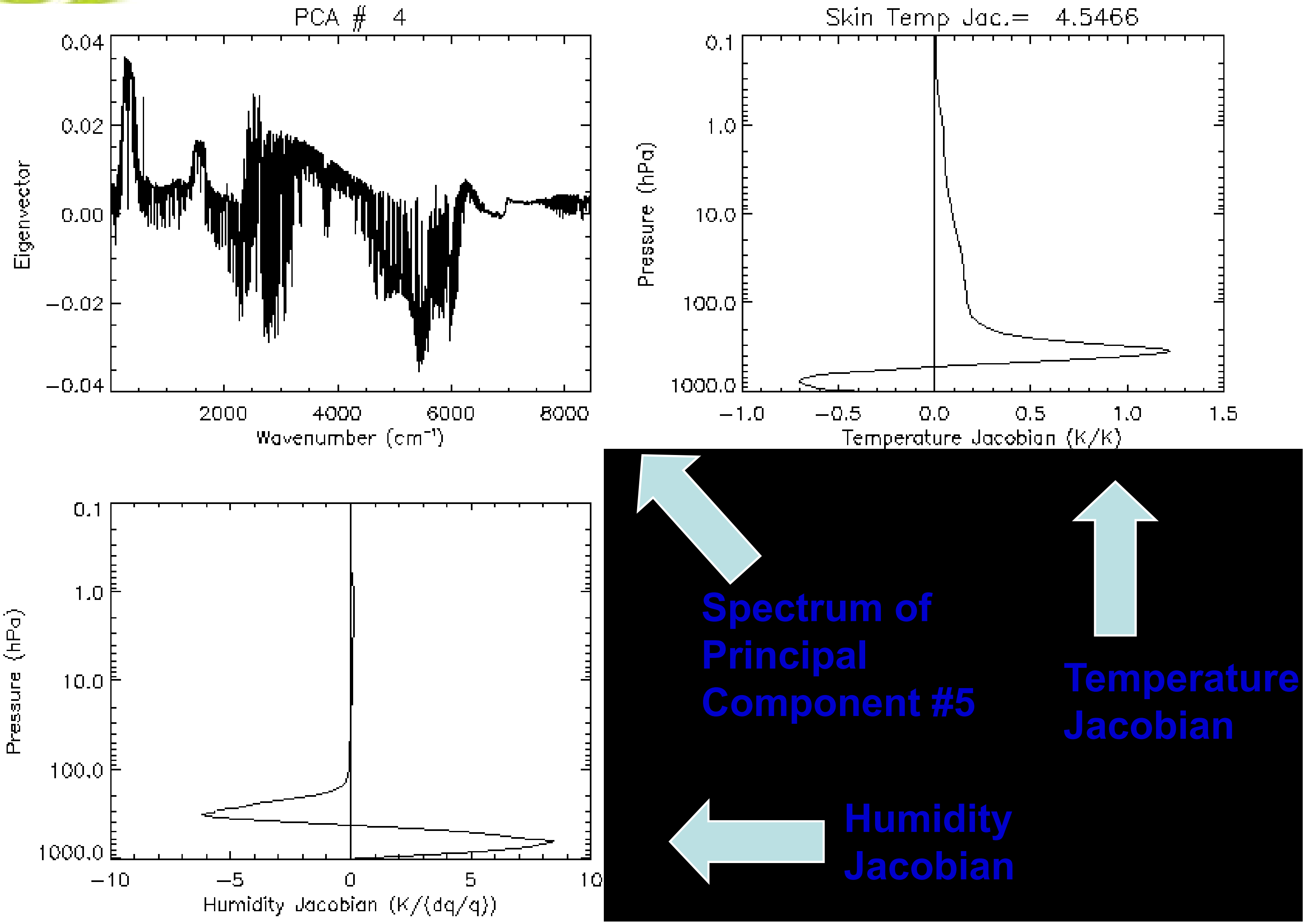


Spectrum of Principal Component #4

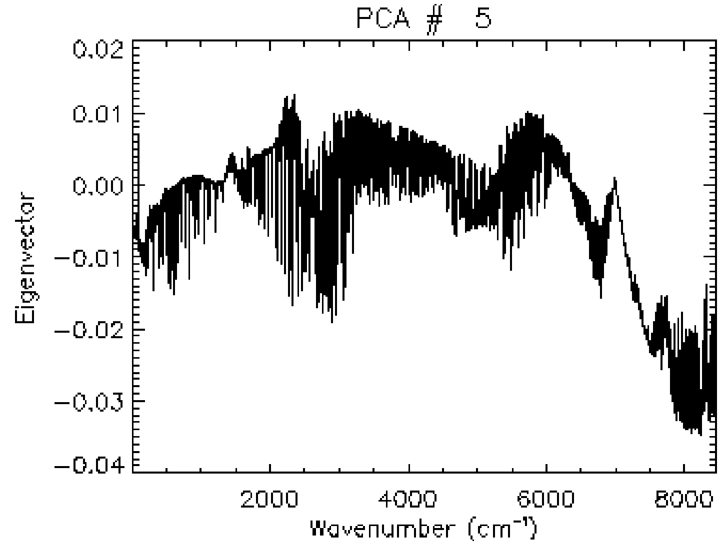
Temperature Jacobian

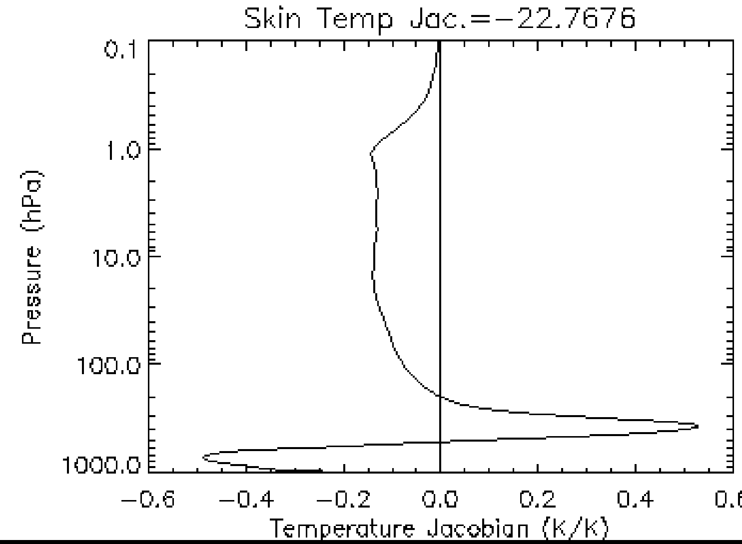
Humidity Jacobian

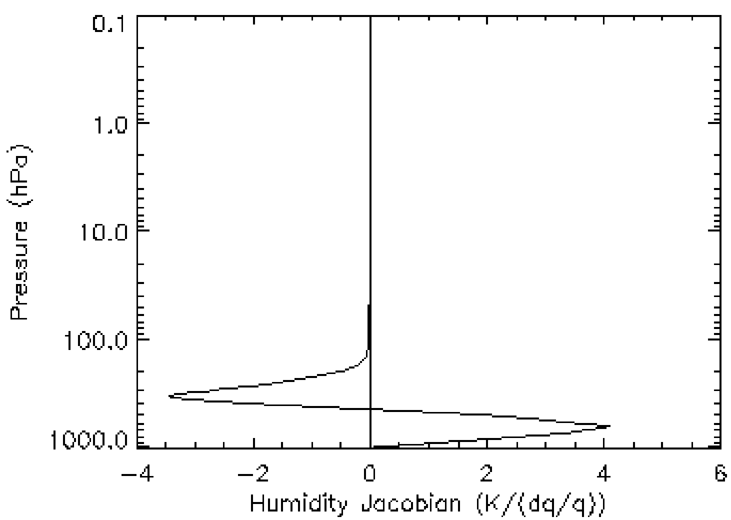
Jacobians of PCs (5)

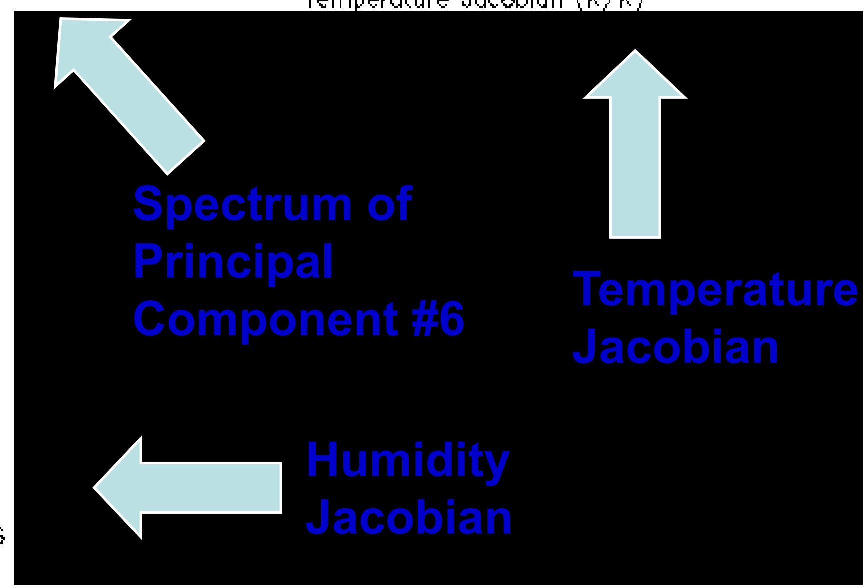


Jacobians of PCs (6)

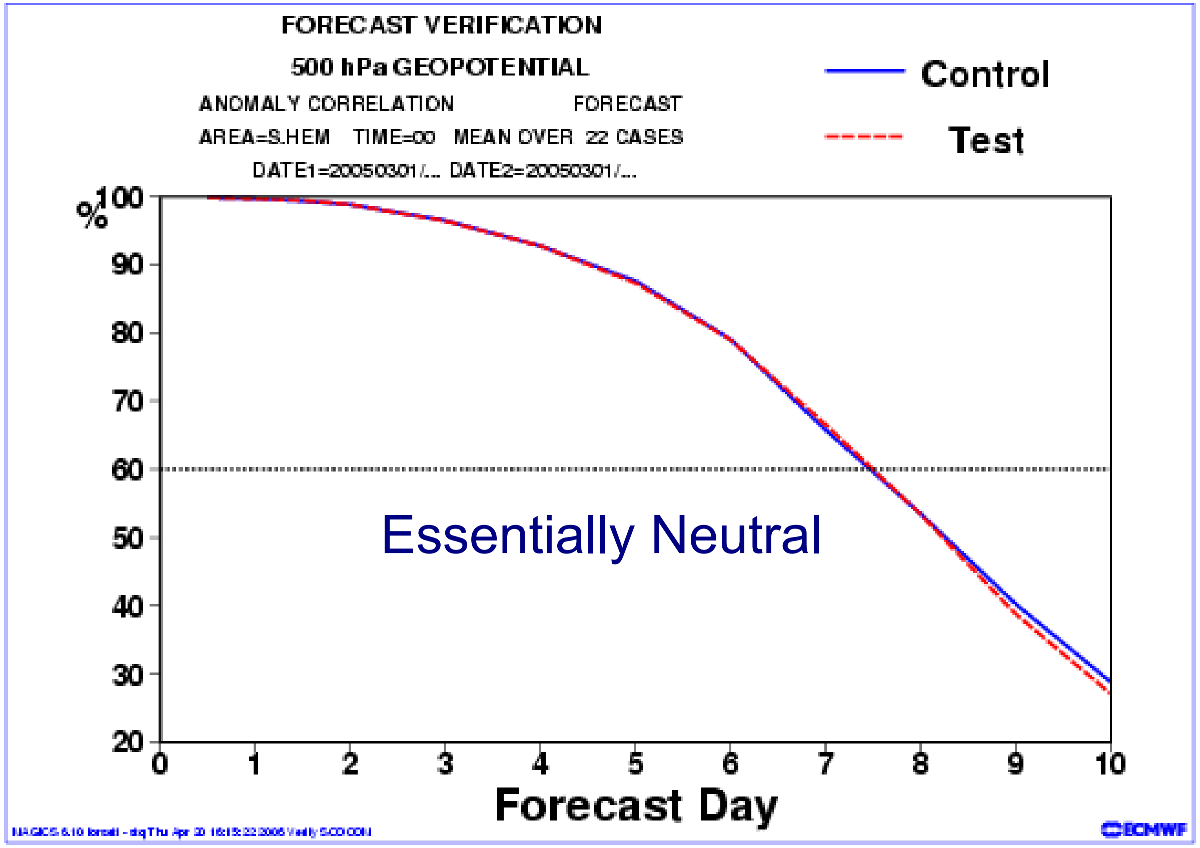








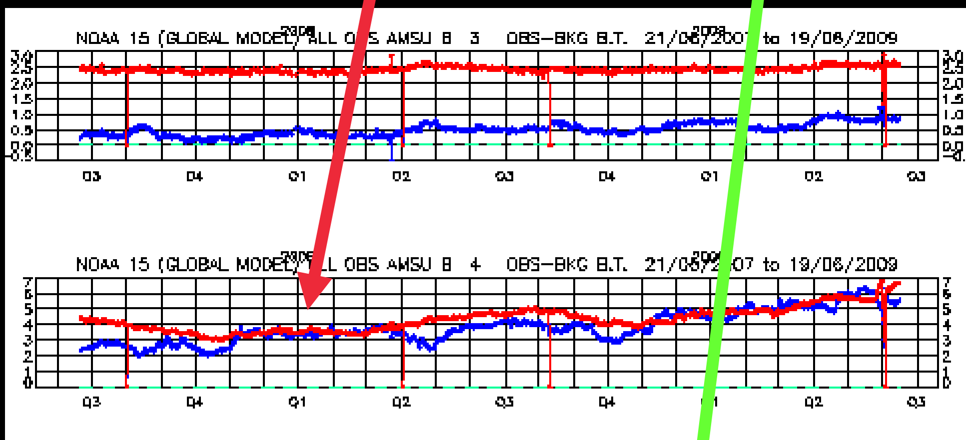
Forecast Impact of Reconstructed Radiances (ECMWF)

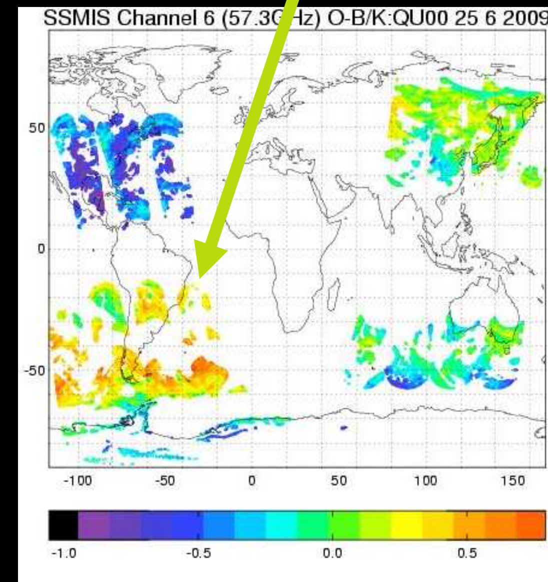


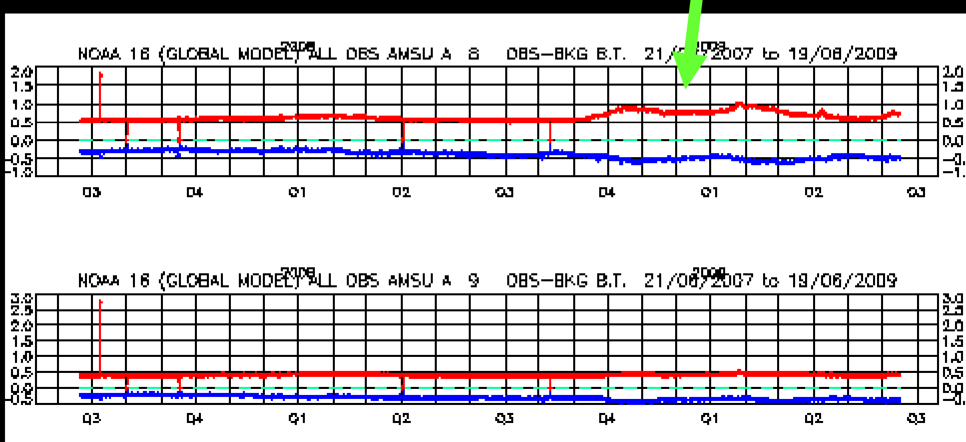
Why bias correct?

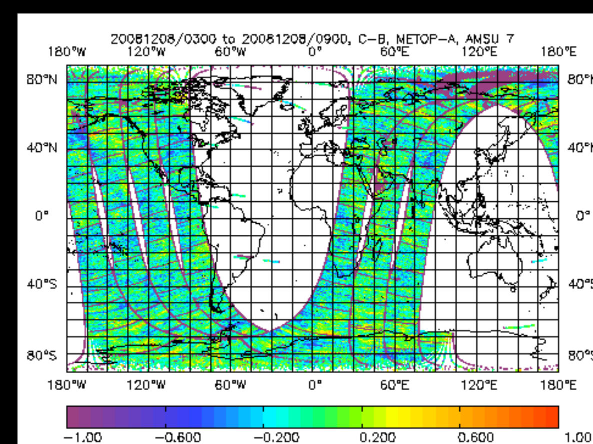
SSMIS biases

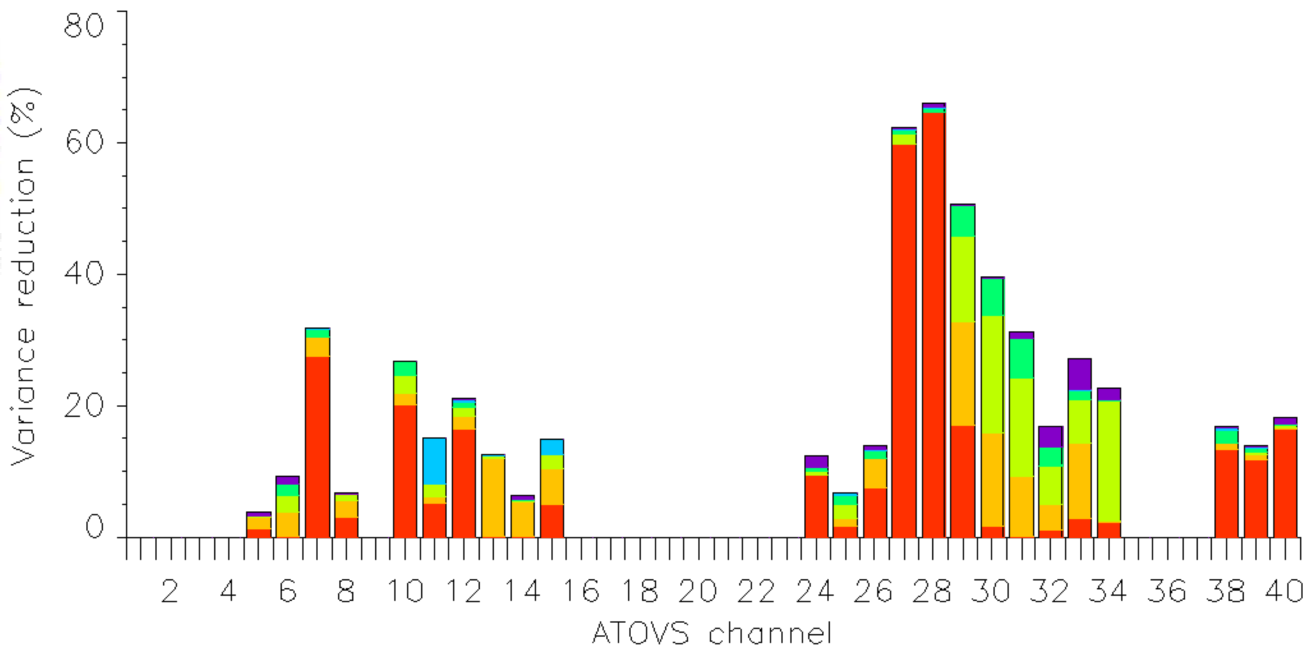
N15 AMSU-B Ch.4, N16 AMSU-A Ch.6



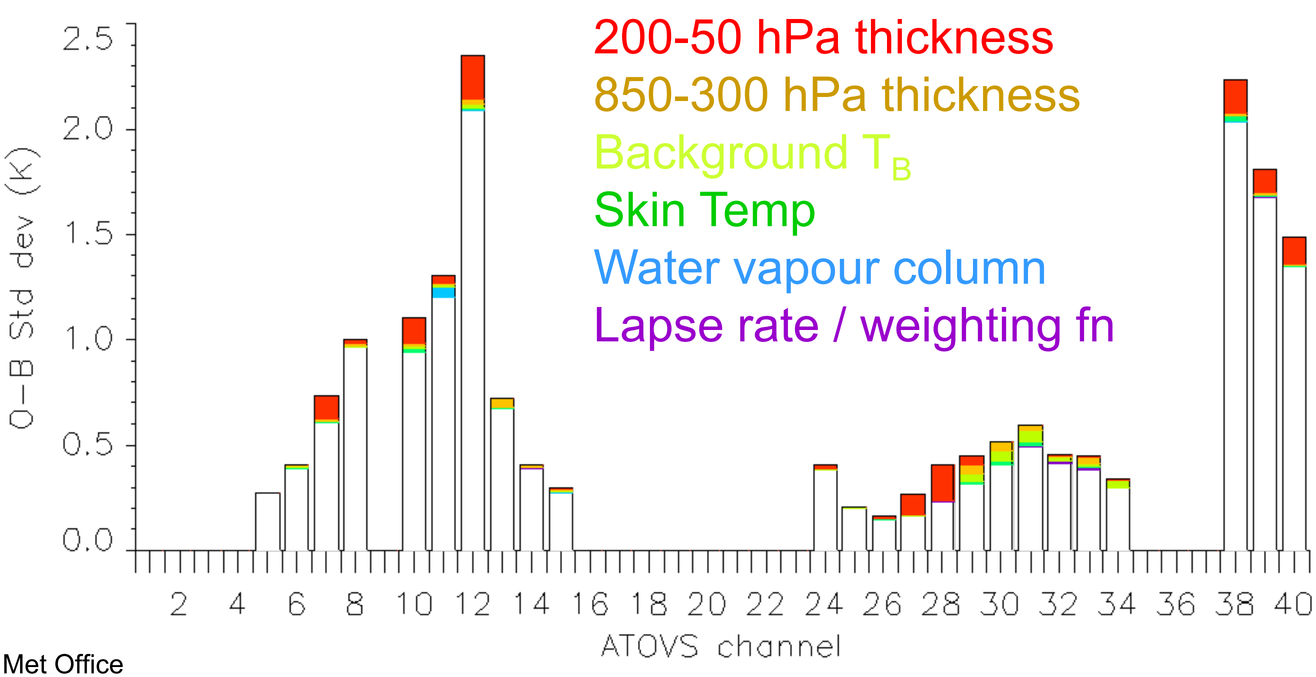








80
60
40
20
0
Variance reduction (%)
2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40
ATOVS channel

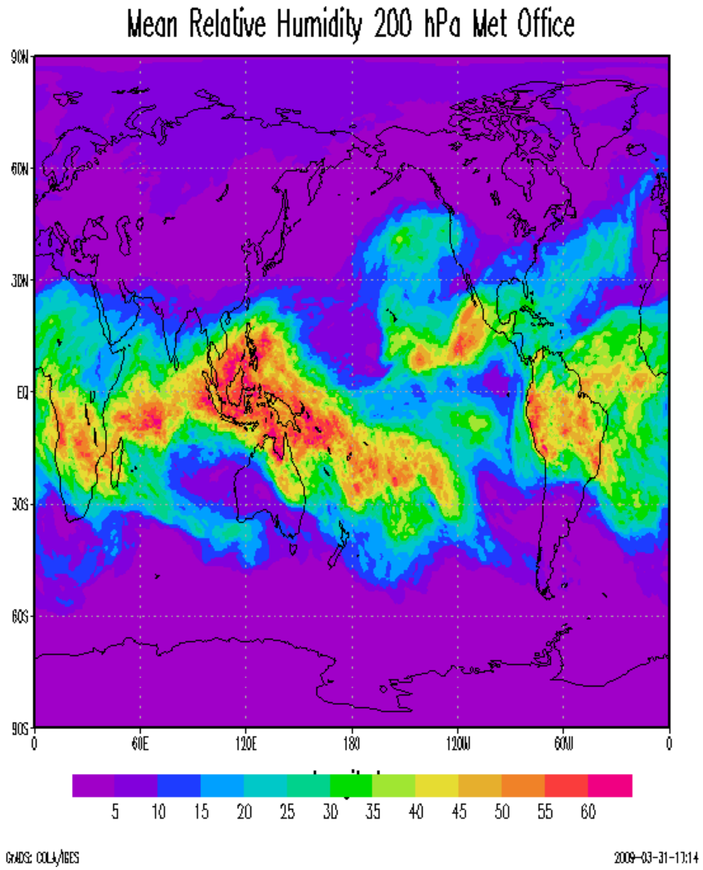


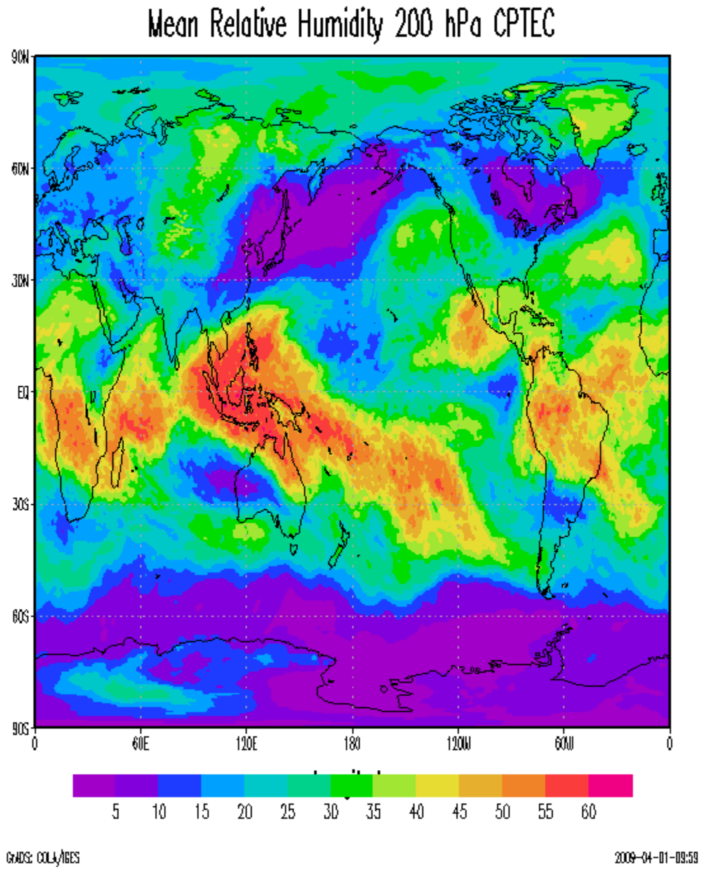
2.5
2.0
1.5
1.0
0.5
0.0
O−B Std dev (K)
2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40
ATOVS channel
200-50 hPa thickness
850-300 hPa thickness
Background T_B
Skin Temp
Water vapour column
Lapse rate / weighting fn

But….

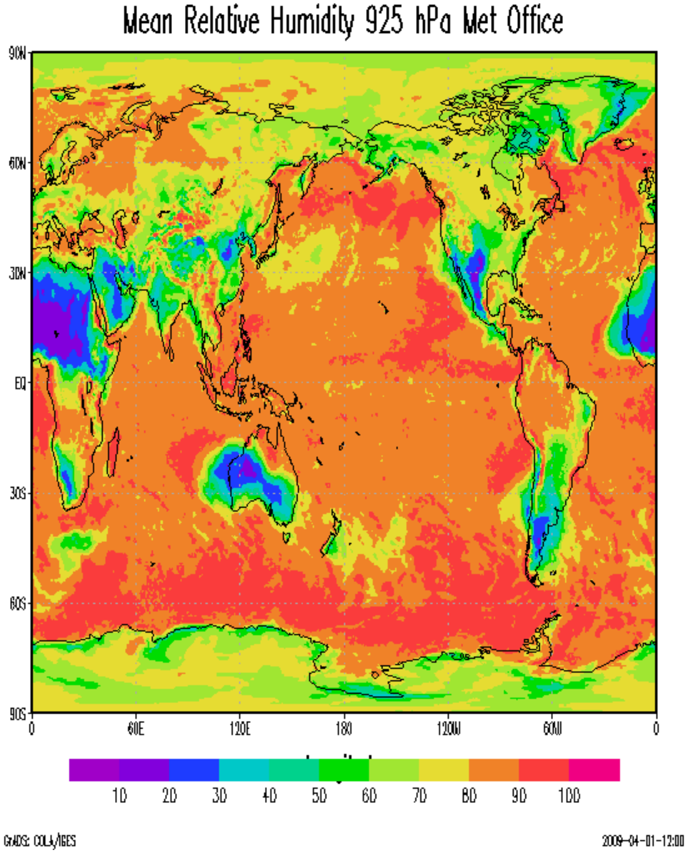
- What is truth?
- What if the model is biased?
- What if other observations are biased?
- What about radiative transfer model biases?
- What should the error model look like?
- Should we bias correct against background or analysis?
- Should we apply a static bias correction or update regularly, adaptively?

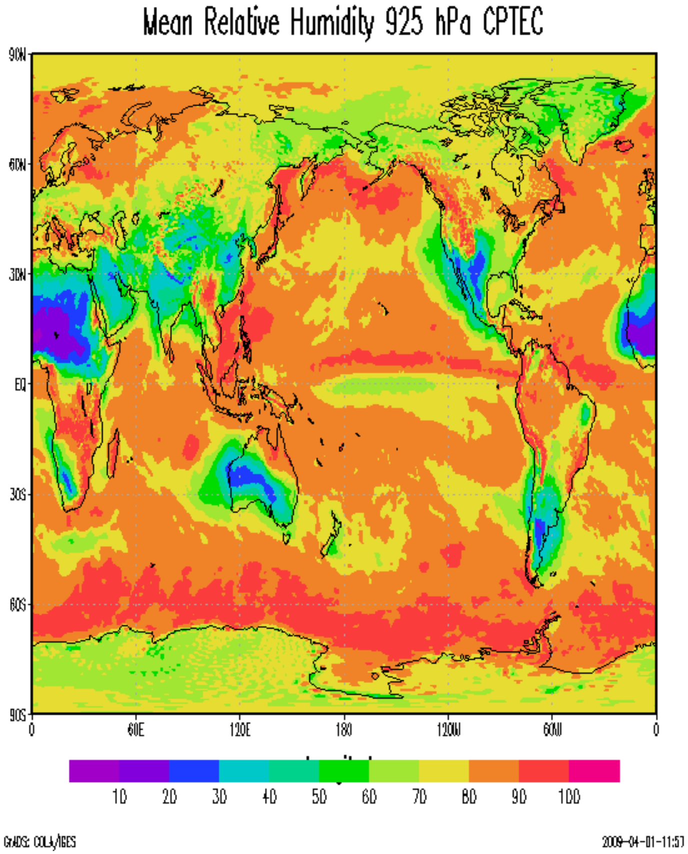
e.g. Met Office dry bias at 200 hPa January 2009





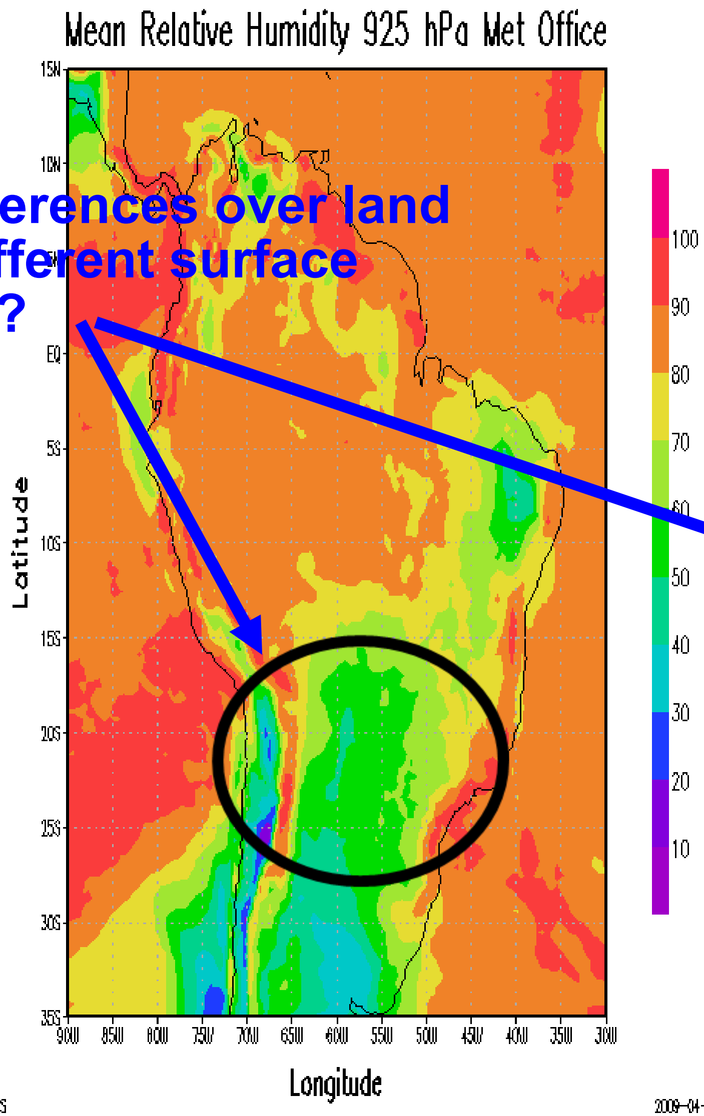
925 hPa: CPTEC-Met Office differences January 2009

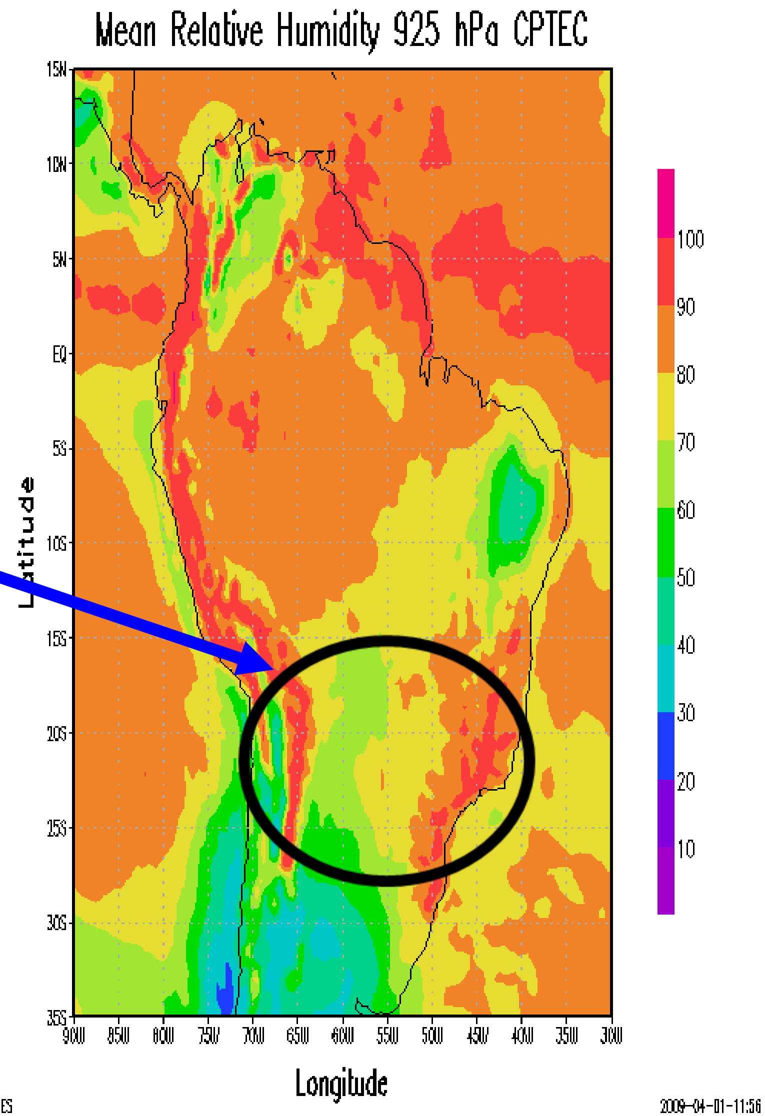




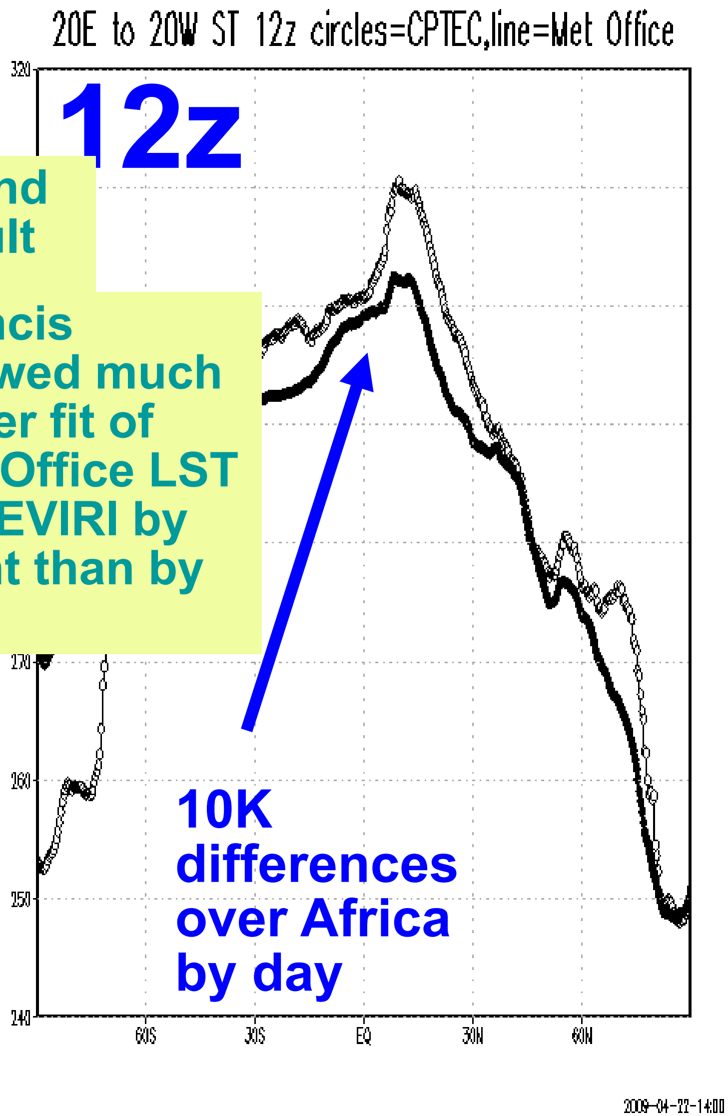
Humidity differences: compare CPTEC and Met Office global models

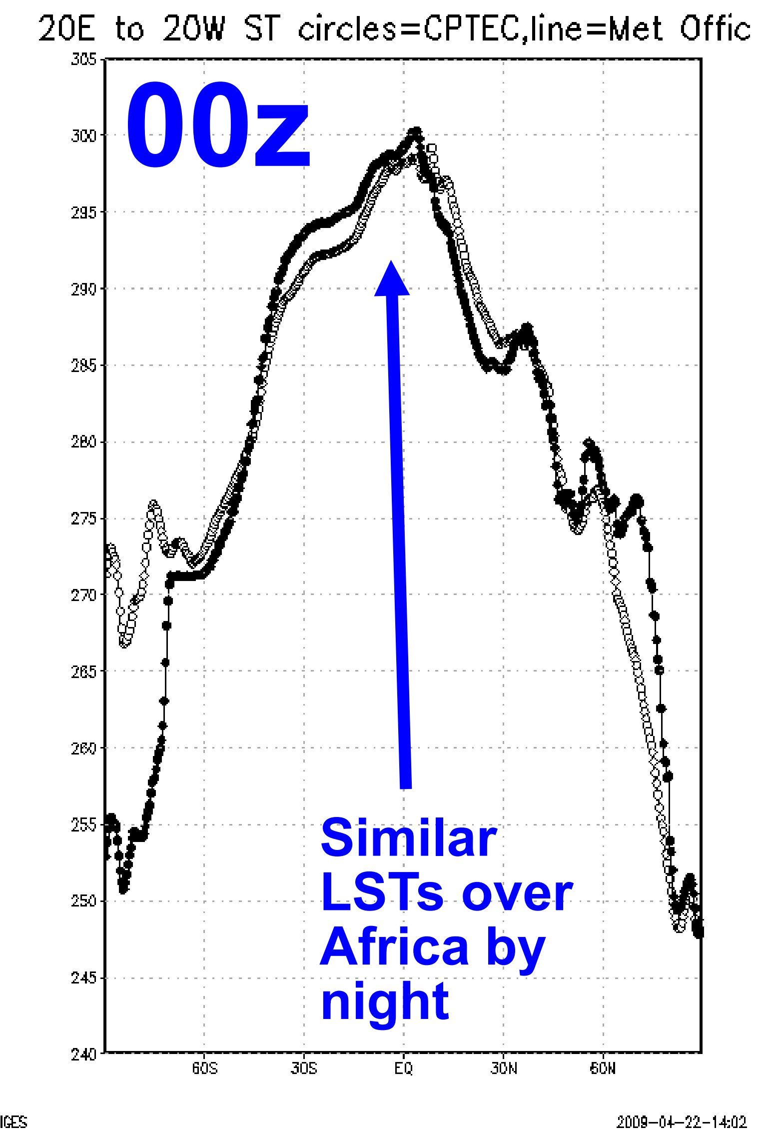
Huge differences over land due to different surface schemes?





Land Surface Temperature comparison: 20E to 20W

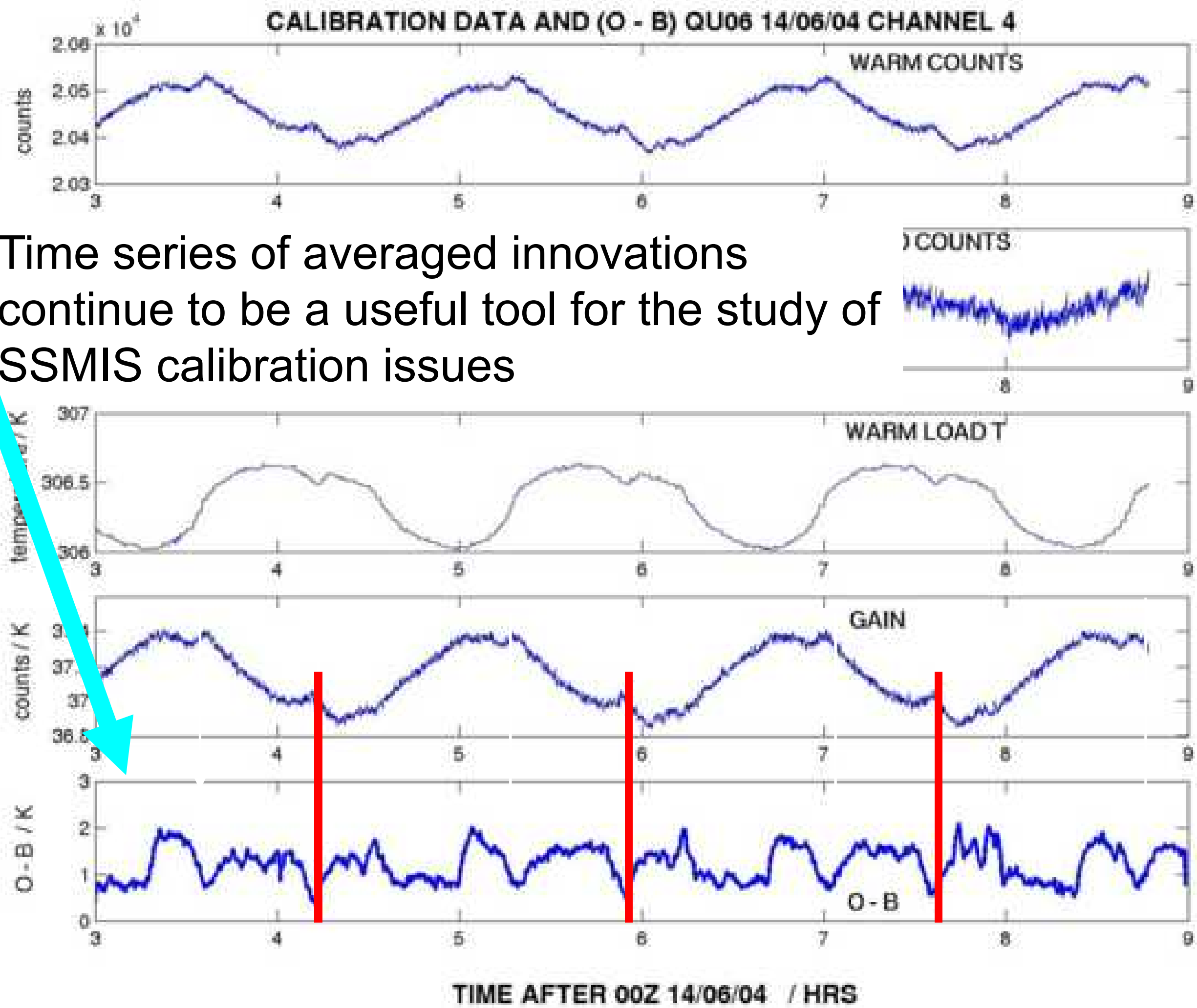




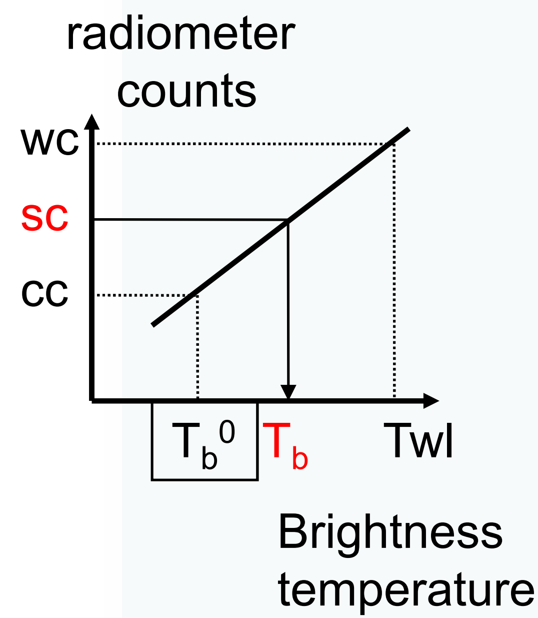
Ruston found similar result between ECMWF, Met Office and NRL.

Francis showed much better fit of Met Office LST to SEVIRI by night than by day.

Instrumental Biases: warm load solar intrusions



Time series of averaged innovations continue to be a useful tool for the study of SSMIS calibration issues



H and R for radiance assimilation

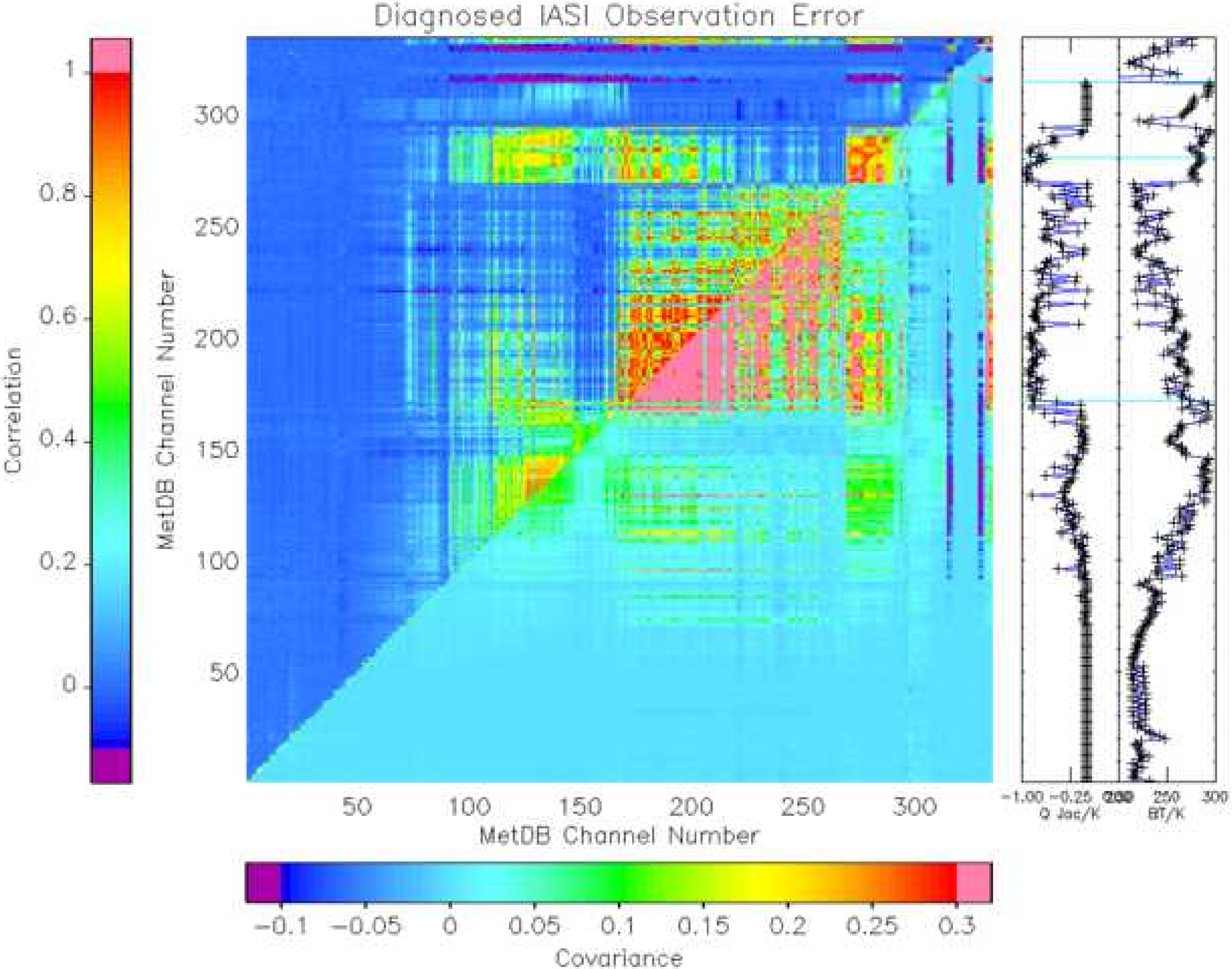
- Recall this morning's presentation
- $Jo = [H(\mathbf{x}) - \mathbf{y}]^T \mathbf{R}^{-1} [H(\mathbf{x}) - \mathbf{y}]$
- For radiances H and R are not well known
- H needs a radiative transfer model
- R = O + F + N + Z
  - O = Obs error - sometimes O is well known
  - F = Forward model error – aspects are known
  - N = Non-linearity error – situation dependent
  - Z = Representivity error – often not well known

Met Office

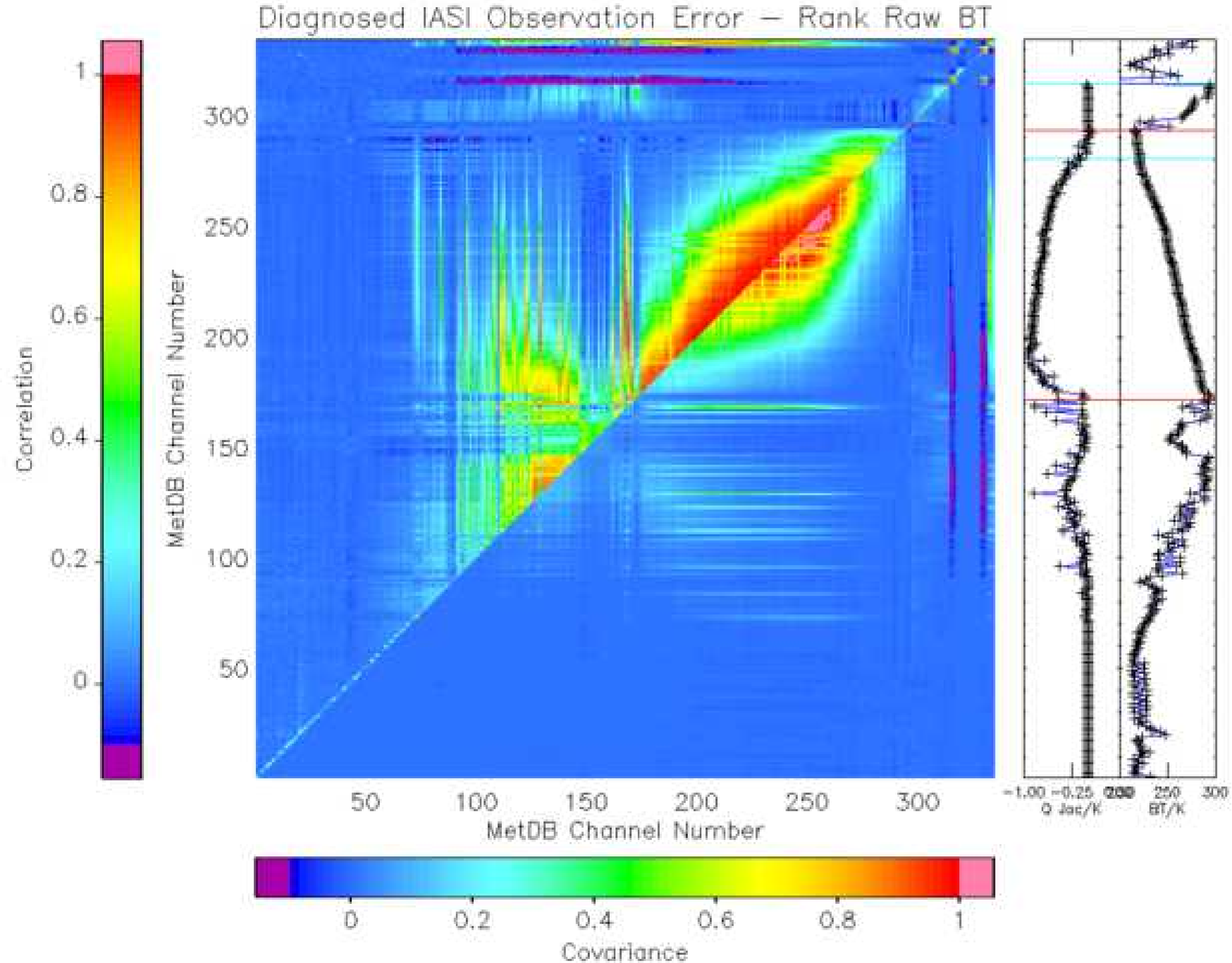
What does R look like?

- Normally R is assumed to be diagonal!
- But how bad an assumption is this?

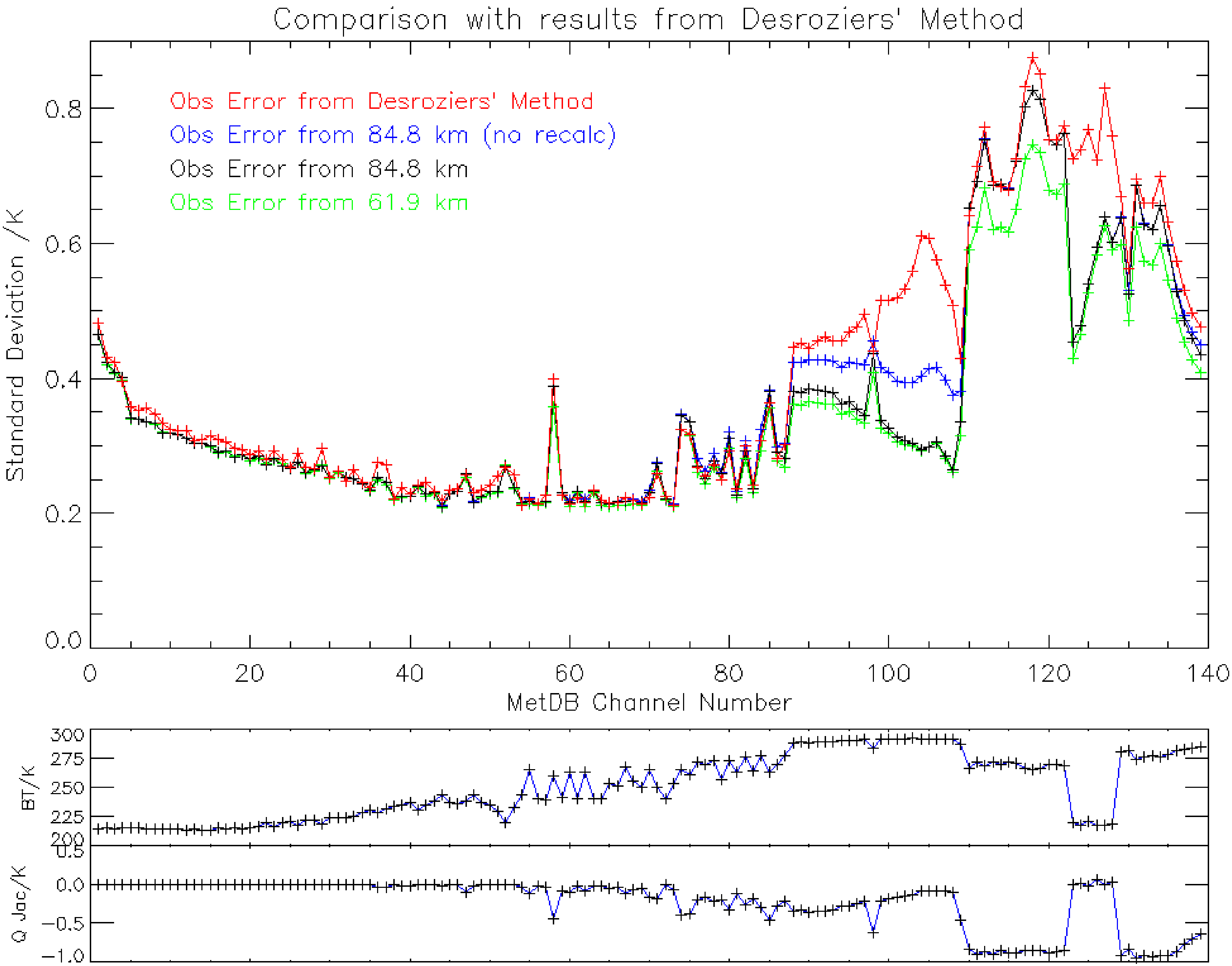
- Methods exist for estimating error covariance from innovations:
  - Hollingsworth-Lonberg: spatial separation
  - Dezroziers: correlation of O-B and O-A



Diagnosed IASI Observation Error
Correlation
1
0.8
0.6
0.4
0.2
0
MetDB Channel Number
300
250
200
150
100
50
50
100
150
200
250
300
MetDB Channel Number
Q Jac/K
BT/K
-0.1
-0.05
0
0.05
0.1
0.15
0.2
0.25
0.3
Covariance



Diagnosed IASI Observation Error - Rank Raw BT
Correlation
1
0.8
0.6
0.4
0.2
0
MetDB Channel Number
300
250
200
150
100
50
50
100
150
200
250
300
MetDB Channel Number
-1.00 -0.25
Q Jac/K
250
300
BT/K
0
0.2
0.4
0.6
0.8
1
Covariance



Comparison with results from Desroziers' Method
Obs Error from Desroziers' Method
Obs Error from 84.8 km (no recalc)
Obs Error from 84.8 km
Obs Error from 61.9 km
Standard Deviation /K
0.0
0.2
0.4
0.6
0.8
0
20
40
60
80
100
120
140
MetDB Channel Number
BT/K
200
225
250
275
300
Q Jac/K
−1.0
−0.5
0.0
0.5

Radiative transfer models

Fast models for assimilation

- RTTOV (NWPSAF) and CRTM (JCSDA)
- Fast approximations errors ~ < 0.2 K
- These models are becoming complex and increasingly difficult to use…..end of the general purpose fast model?

But spectroscopic, scattering and reflection parameters can lead to much larger forward model errors.

What is RTTOV?

Met Office

Estimate of atmospheric state and surface parameters for observation point X

View angle + sun angles

RT model for required sensor

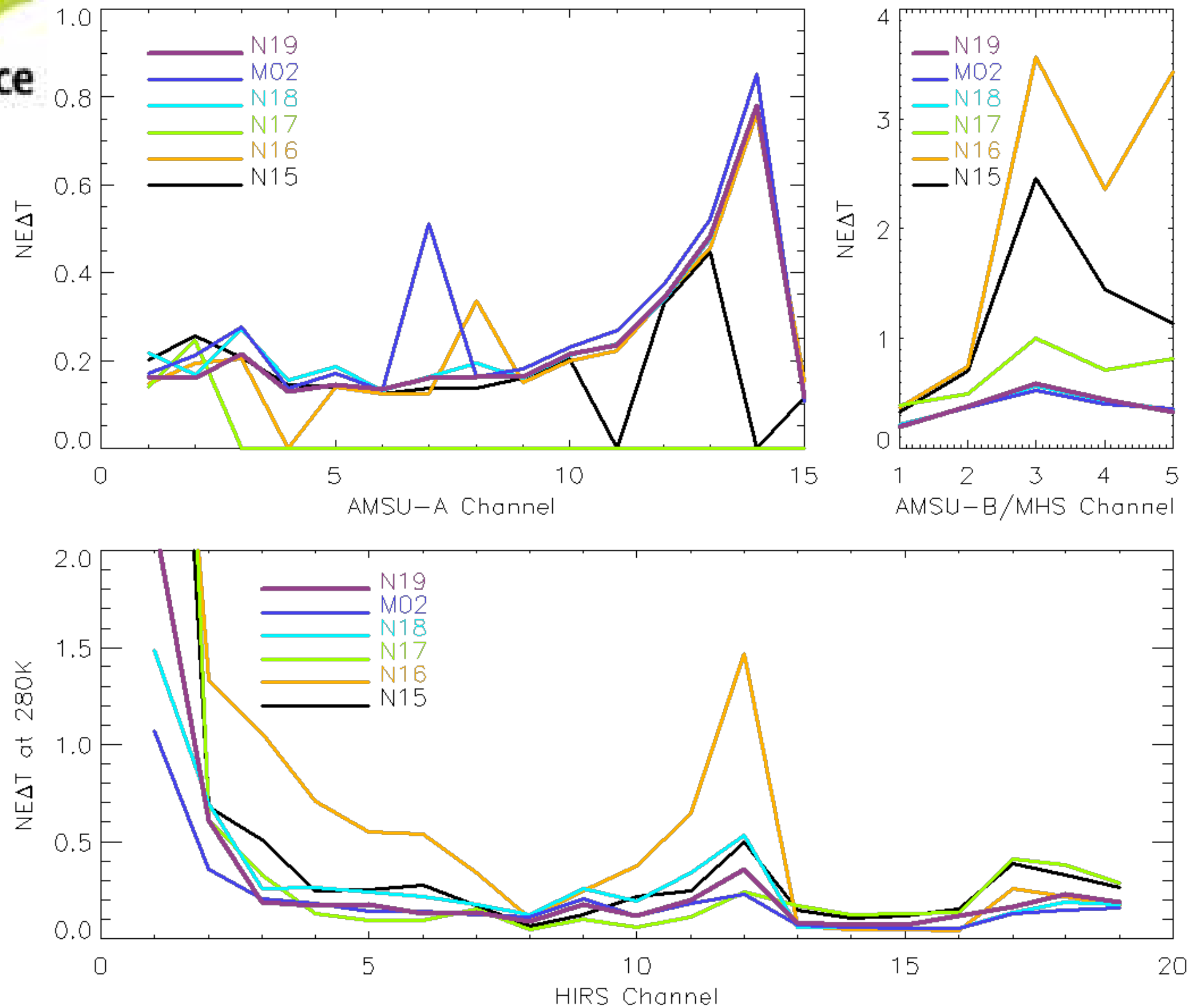
Time ~ 1ms for 20 chans

Radiances for required satellite channels $y=H(X)$
and optionally jacobians $H \equiv \frac{\partial y_i}{\partial X_j}$
as TL, AD, or K

Future?

- Assessing a new instrument e.g. NOAA-19 AMSU-A+MHS
- Hyperspectral sounding in Geo orbit
- NPOESS and post-EPS
- Convective scale NWP

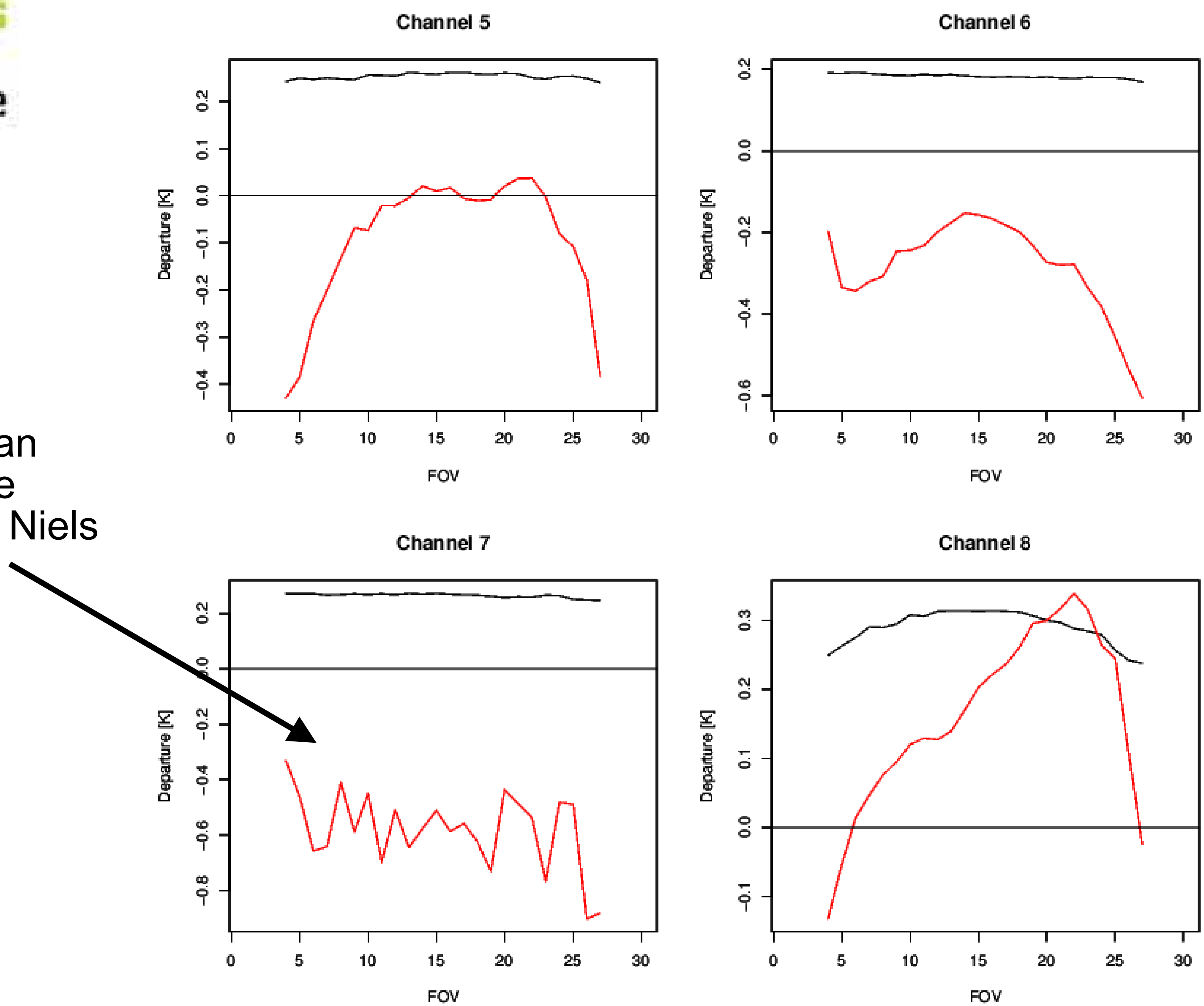
NEΔTs (07/04/2009)



Problem with AMSU channel 7 ?

O-B plots:

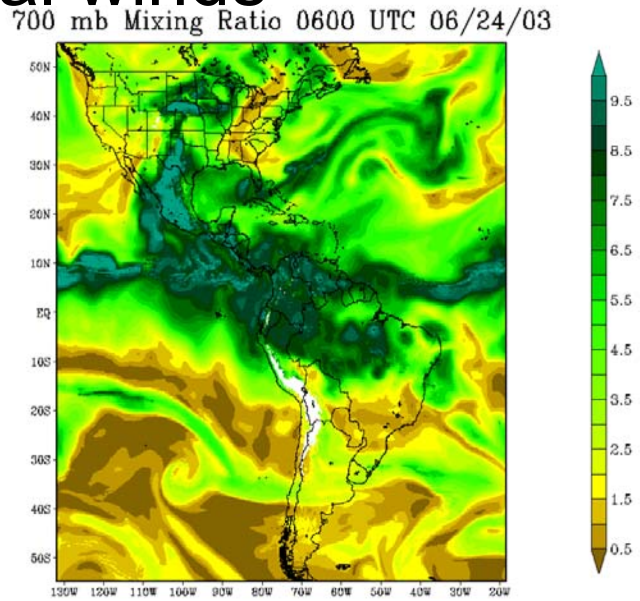
Unusual scan dependence reported by Niels Bormann

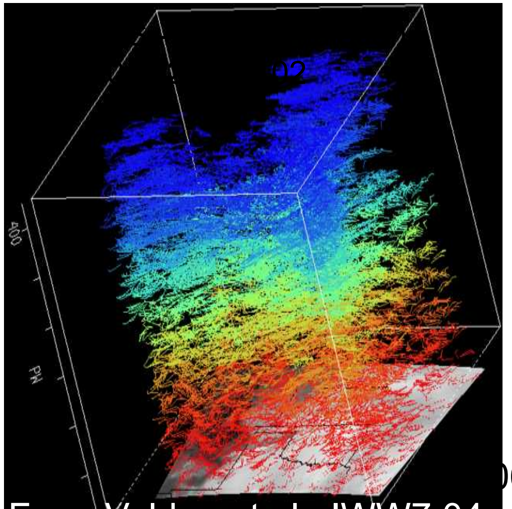


Other wind observations for the future
MTG IRS hyperspectral winds

Timescale: 2015-2020

- Advanced IR sounders on future geostationary platforms will have more and sharper weighting functions
- Can use the sounder data to derive high vertical resolution moisture analyses in clear sky areas.
- Wind profiles can be derived by applying AMV tracking techniques to sequences of moisture analyses on different levels.
- Resulting winds should have more reliable heights





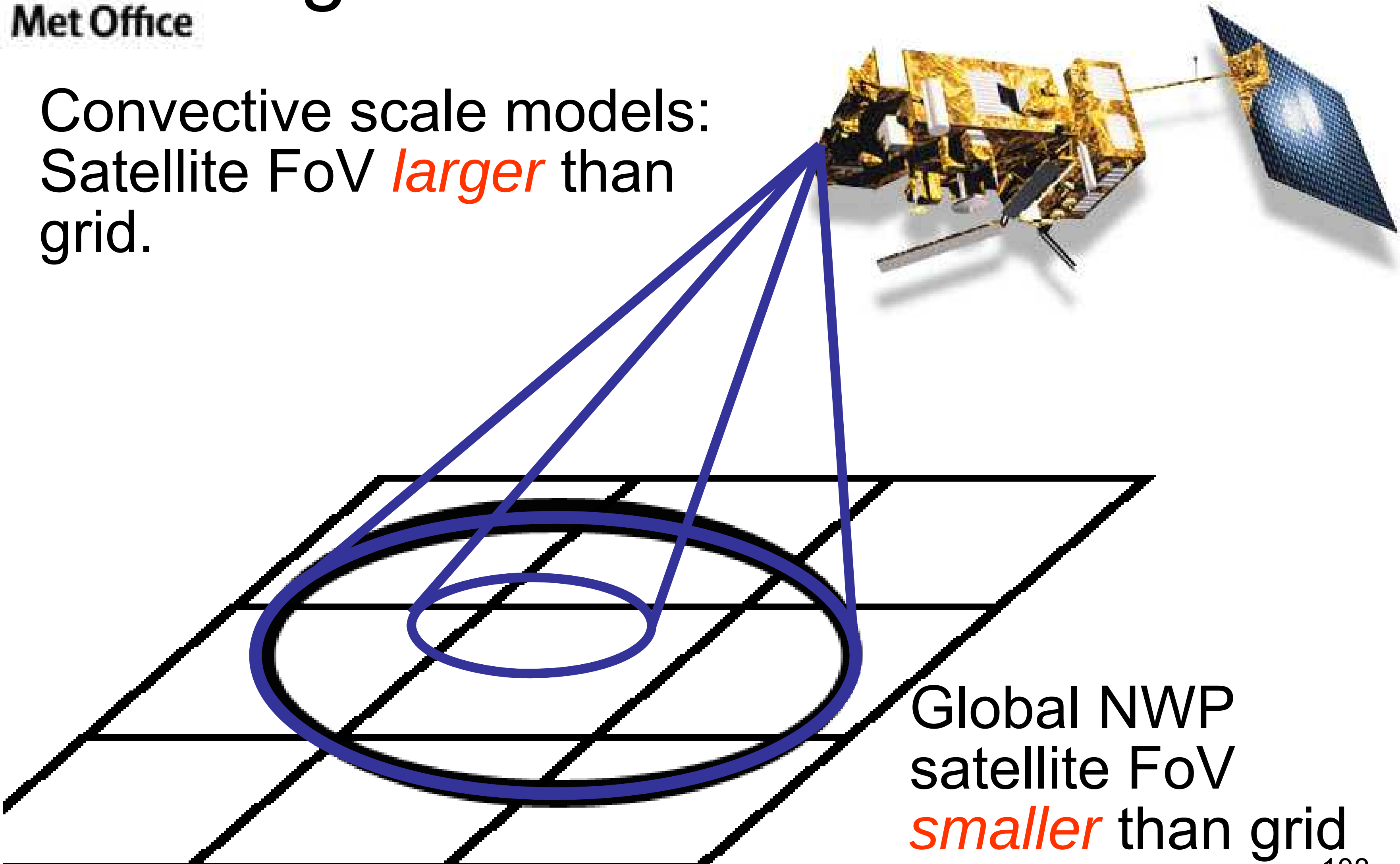
From Velden et al., IWW7 04

Post-EPS – generic missions and their heritage

1. High-resolution infra-red sounding	IASI		11. Dual view radiometry	AATSR
2. Microwave sounding	AMSU ATMS		12. Altimetry	S-3 + Jason
3. Scatterometry	ASCAT		13. Cloud and precipitation profiling radar	TRMM/PR EarthCare
4. VIS/IR imaging	AVHRR MODIS		14. Microwave imaging – cloud	
5. Microwave imaging – precipitation	SSM/I TMI		15. Radiant energy radiometry	ERB CERES
6. Microwave imaging – ocean and land	AMSR		16. Total solar irradiance monitoring	TSIM
7. Radio occultation	COSMIC		17. Ocean colour imaging	MERIS SeaWIFS
8. Nadir-viewing UV/VIS/NIR sounding	GOME		18. Aerosol profiling lidar	
9. Multi-viewing, -channel, -polarisation imaging	POLDER		*+ 3 others not studied at Phase 0*	
10. Doppler wind lidar	ADM			

Assimilating satellite data in high resolution NWP models

Convective scale models: Satellite FoV *larger* than grid.

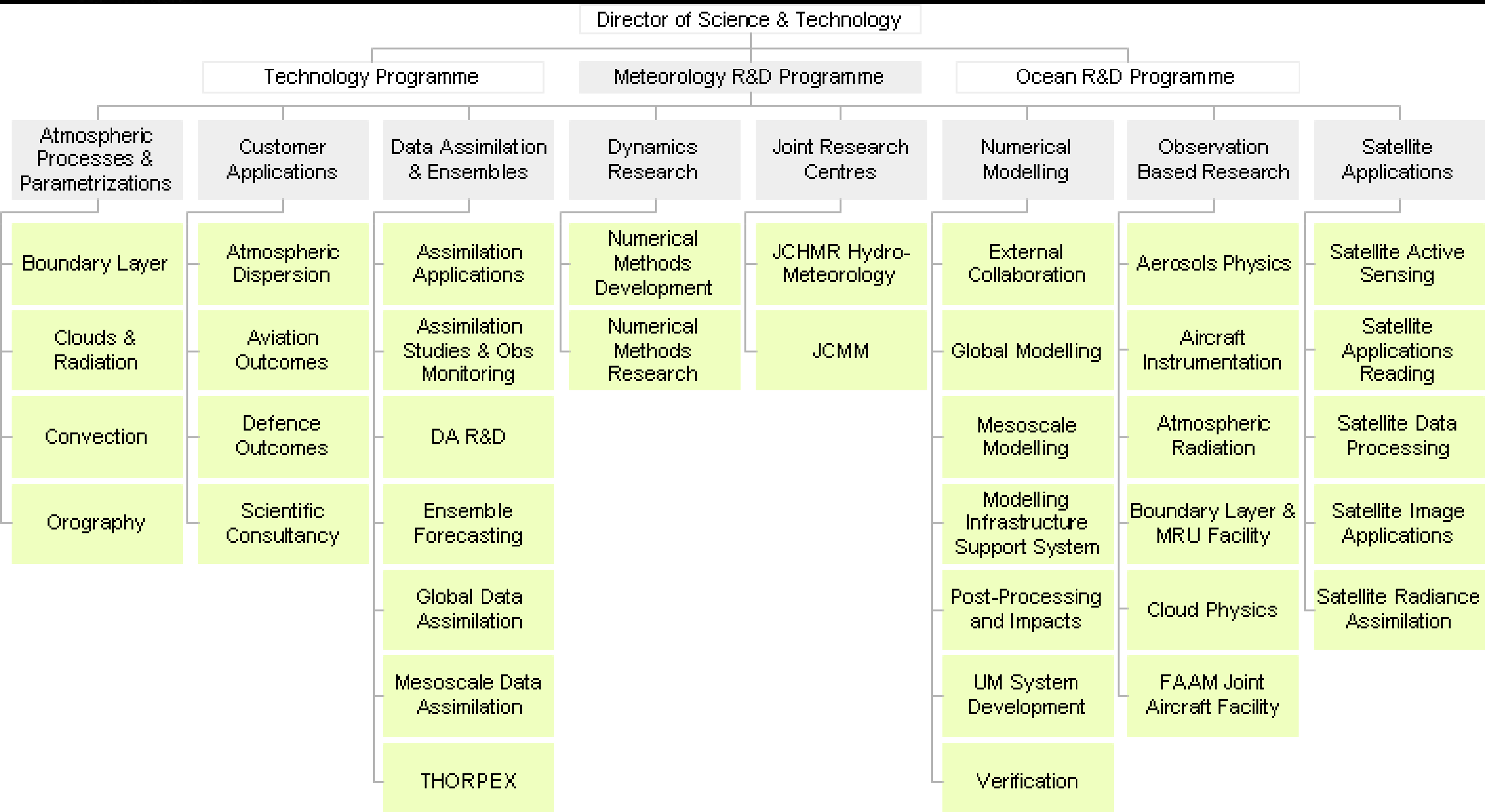


Global NWP satellite FoV *smaller* than grid

Questions and answers

O Met Office

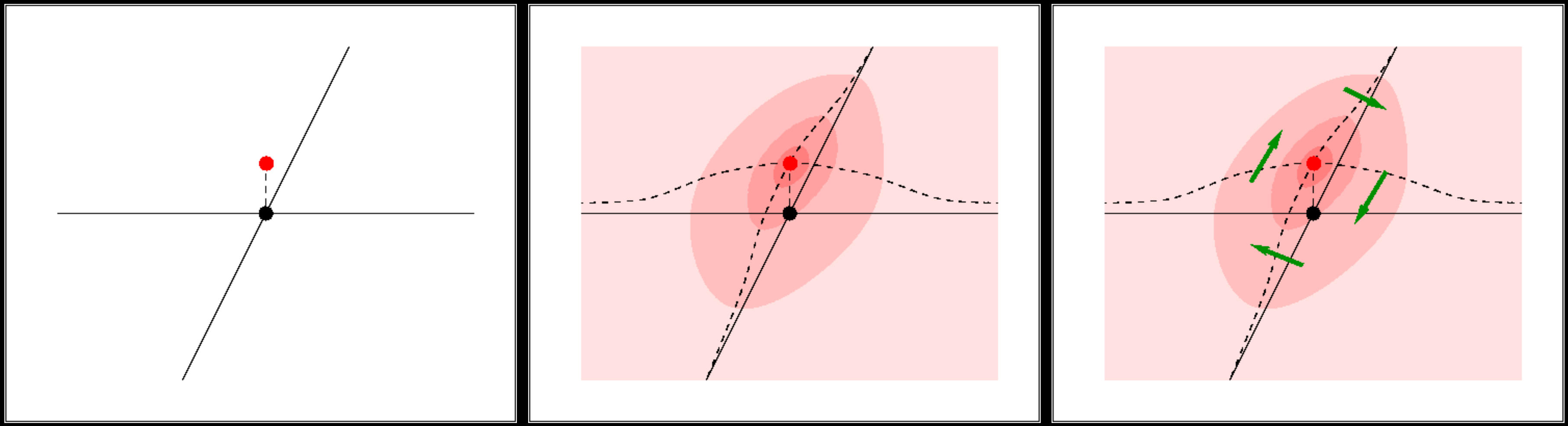
- National Meteological Service of the UK
- Owned by the Ministry of Defence but self financing “trading fund”
- Located in Exeter, UK.
- 1700 people, 200 in NWP, 30 in satellite work, 40 in DA.
- Computer: IBM Power-6



Director of Science & Technology
Technology Programme
Meteorology R&D Programme
Ocean R&D Programme
Atmospheric Processes & Parametrizations
Boundary Layer
Clouds & Radiation
Convection
Orography
Customer Applications
Atmospheric Dispersion
Aviation Outcomes
Defence Outcomes
Scientific Consultancy
Data Assimilation & Ensembles
Assimilation Applications
Assimilation Studies & Obs Monitoring
DA R&D
Ensemble Forecasting
Global Data Assimilation
Mesoscale Data Assimilation
THORPEX
Dynamics Research
Numerical Methods Development
Numerical Methods Research
Joint Research Centres
JCHMR Hydro-Meteorology
JCMM
Numerical Modelling
External Collaboration
Global Modelling
Mesoscale Modelling
Modelling Infrastructure Support System
Post-Processing and Impacts
UM System Development
Verification
Observation Based Research
Aerosols Physics
Aircraft Instrumentation
Atmospheric Radiation
Boundary Layer & MRU Facility
Cloud Physics
FAAM Joint Aircraft Facility
Satellite Applications
Satellite Active Sensing
Satellite Applications Reading
Satellite Data Processing
Satellite Image Applications
Satellite Radiance Assimilation

Background Error Matrix **B**

B describes how information from observations should be spread:



Incorporating better approximations of the `true' background error covariance matrix is perhaps THE most important theoretical challenge in data assimilation.