Cloudy Radiance Data Assimilation

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Outline

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- Why are clouds difficult?
- Strategies for dealing with clouds
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  - Correcting for Clouds
  - Modeling Clouds
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  - Assimilate Cloud Information
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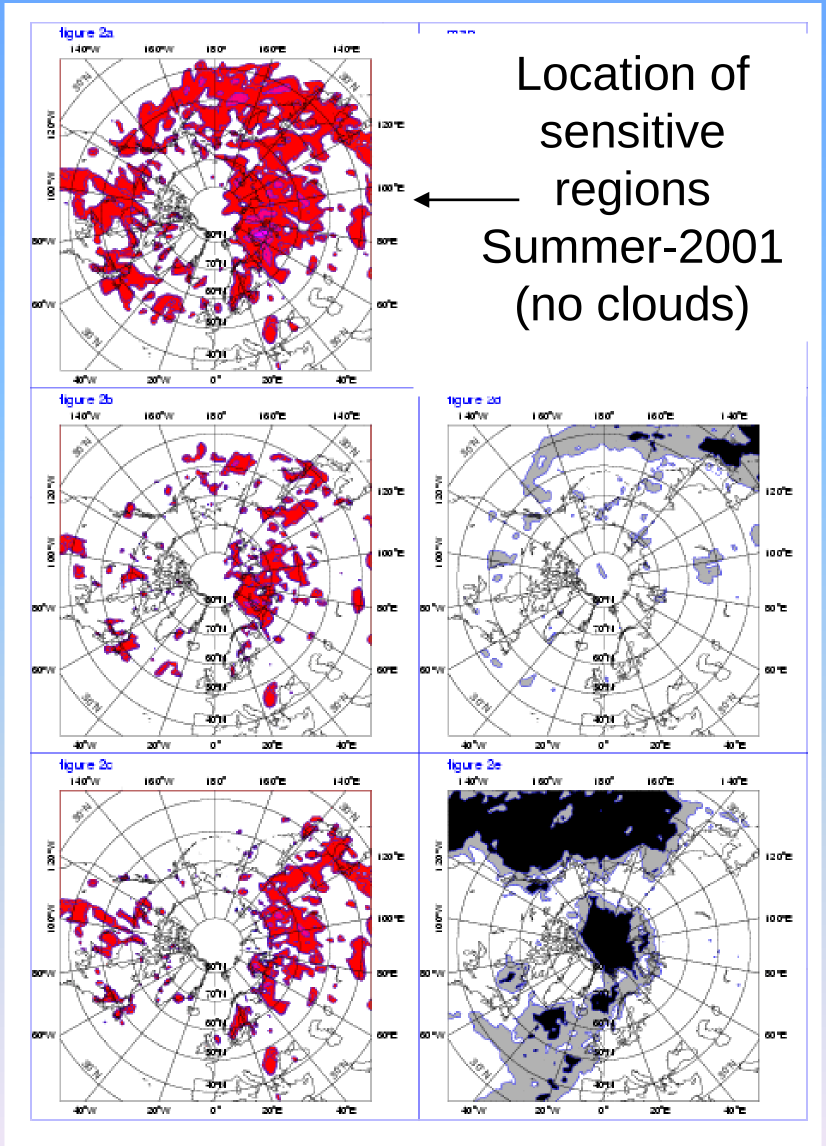
Why are clouds important?

- 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 meteorologically very important areas
- By selectively assimilating clear radiances we may be biasing the model (representivity issues).

Sensitive areas and cloud cover



sensitivity surviving high cloud cover

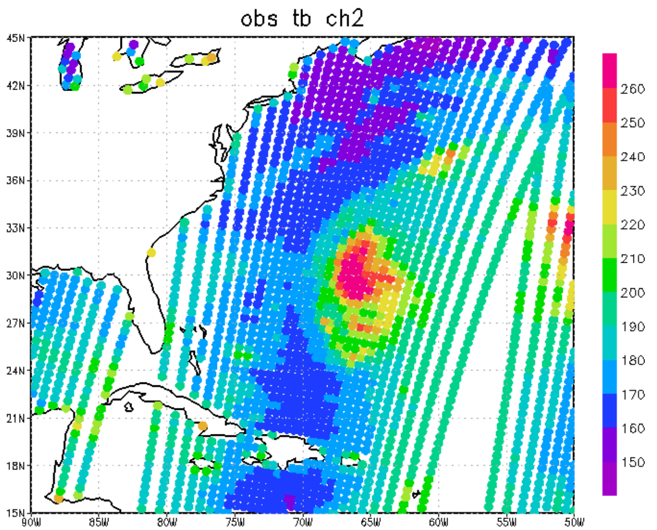
monthly mean high cloud cover

sensitivity surviving low cloud cover

monthly mean low cloud cover

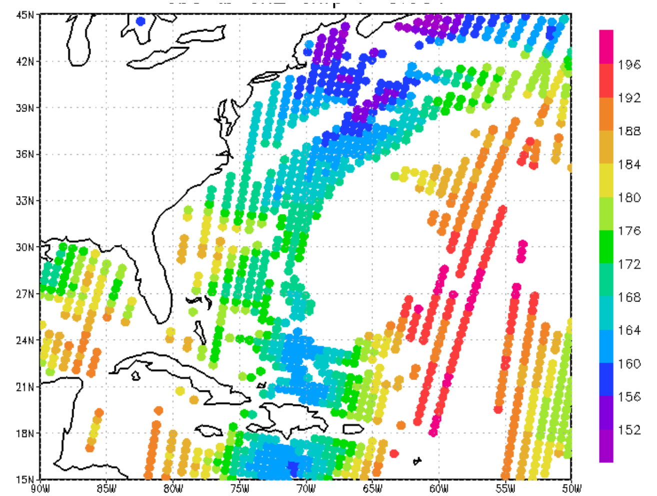
From *McNally (2002) QJRMS 128*

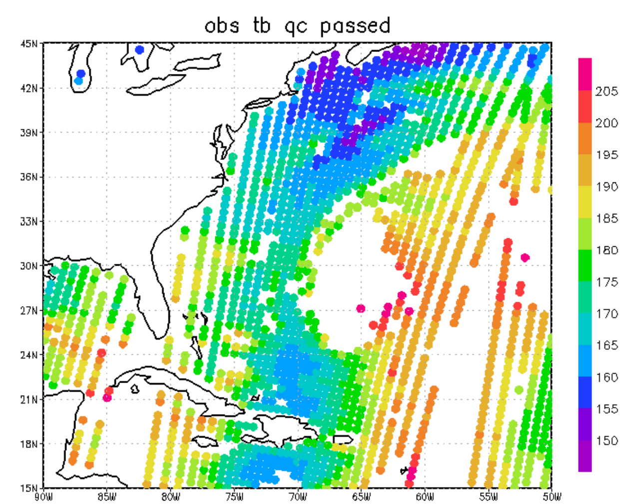
Microwave Obs of Hurricane Igor (9/19/2010)



All Obs

(cloud liquid water path < 0.001 kg/m^2)





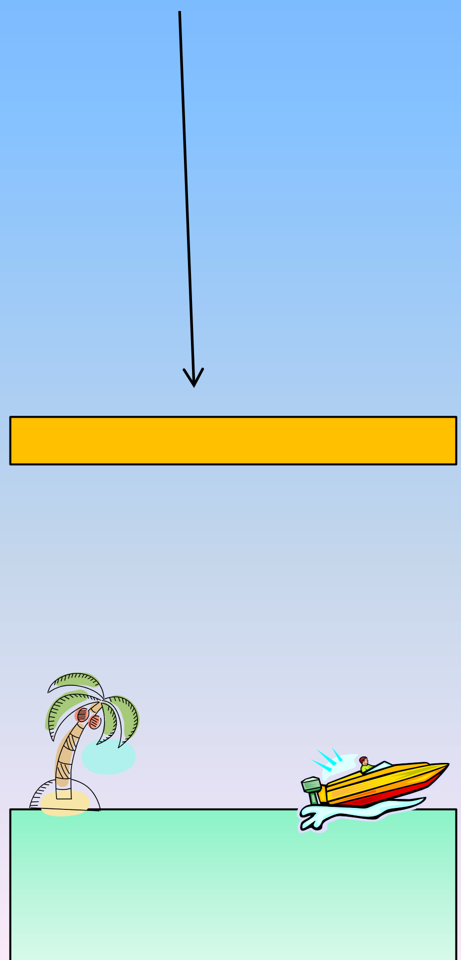
Passed QC in GSI

Cloud or precipitation indicates that some dynamically important weather is occurring. Subsequent forecasts are often sensitive to initial conditions in regions with cloud and precipitation.

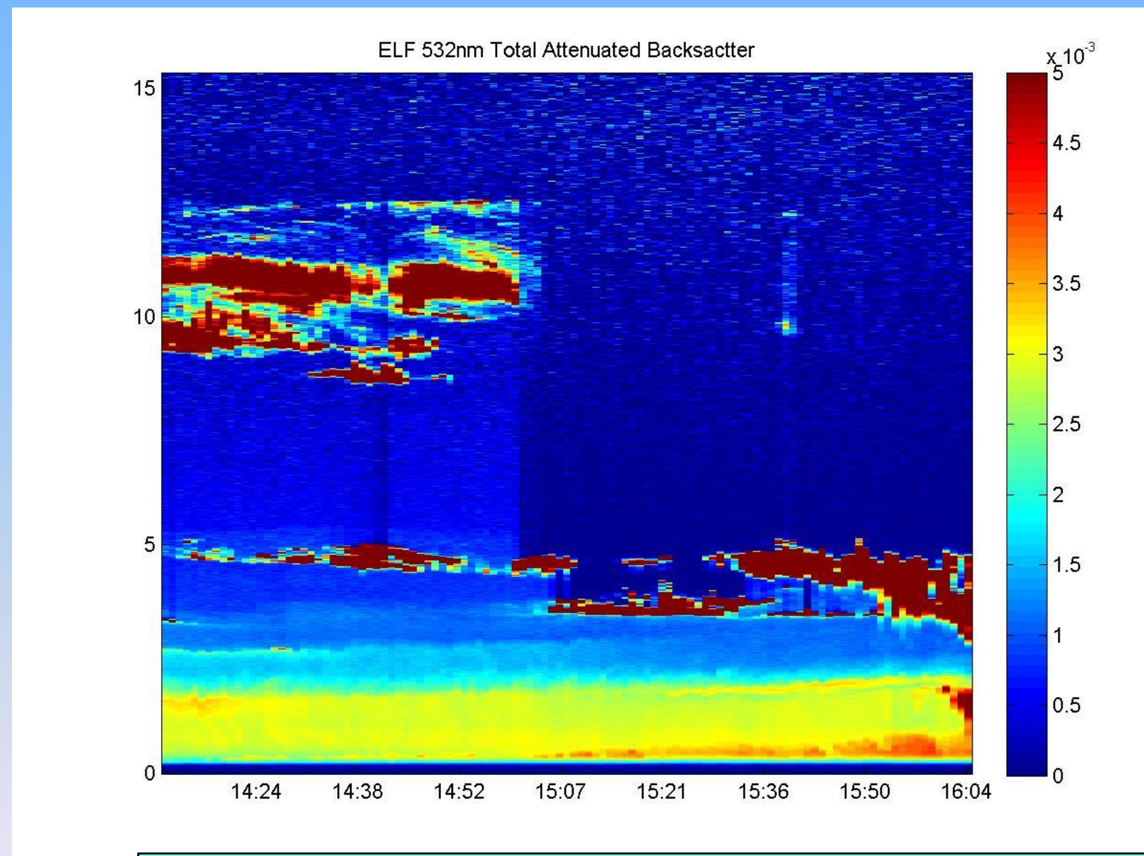
Why are clouds difficult?

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 absorption – and hence emission – which depends on phase (water or ice), crystal habit and particle size distribution
- Scattering from cloud and precipitation particles can be very significant – tends to lower the observed brightness temperature in the microwave.

Clouds can introduce non-linearities

- The radiative signal from clouds is often large and non-linear so the tangent-linear assumption used in variational data assimilation does 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.

Strategies for dealing with clouds

- Avoid them
  - Do not assimilate radiances that are affected by clouds
- Correct for them
  - Try to remove the cloud signal from the observations
- Model them
  - Infer cloud properties and account for them in the radiative transfer model, but do not assimilate.
  - The cloud properties are usually inferred by retrieving from the observations.
- Assimilate them
  - Either directly or through modification of the humidity fields.

Infrared Radiances

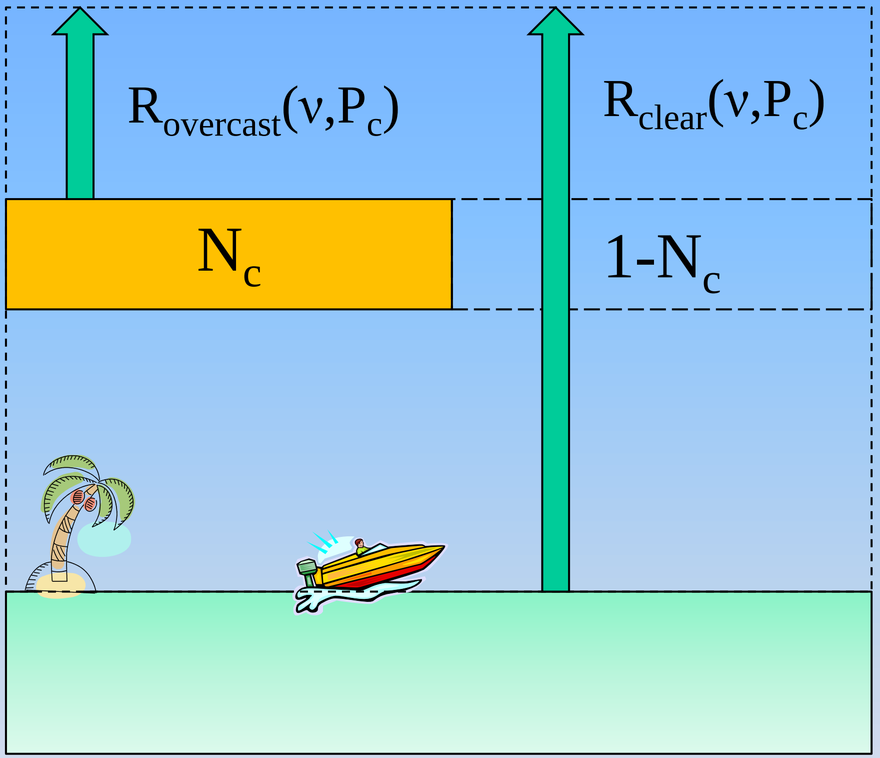
Infrared Radiances

Avoid the Clouds

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.
- $0 \leq N_c \leq 1$
- 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.



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

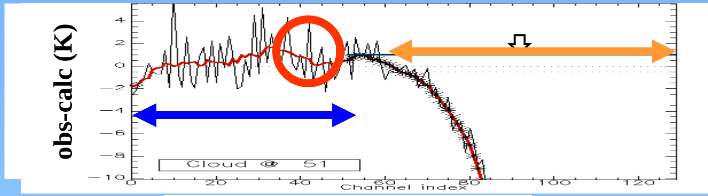
$$J(N_c,P_c) = \sum_{\nu} \left(\frac{R_{cld}(\nu,P_c) - R_{obs}(\nu)}{\sigma(\nu)} \right)^2$$

$\sigma(\nu)$ is the assumed observation error for channel ν

This calculation must be done in radiance, not brightness temperature space.

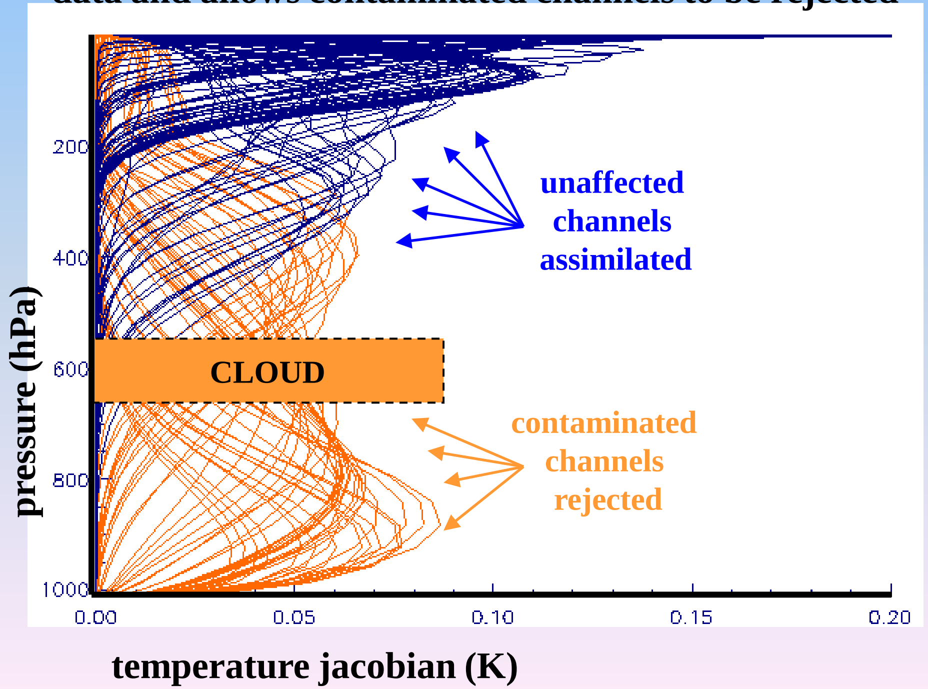
Cloud detection in the infrared - ECMWF Method

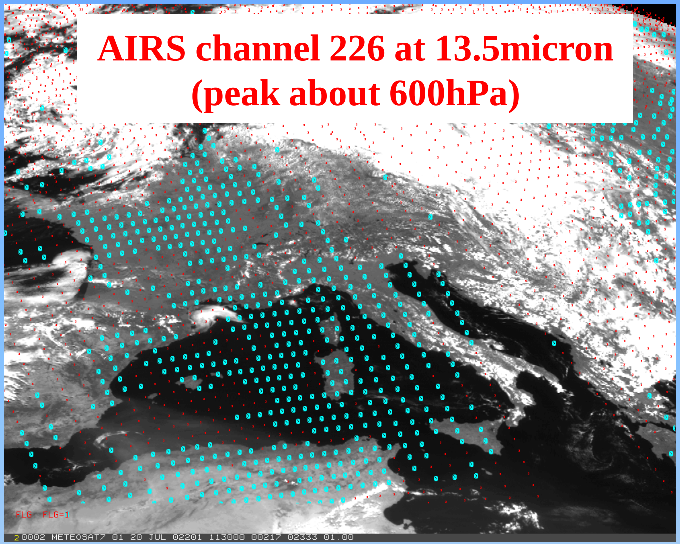
A non-linear pattern recognition algorithm is applied to departures of the observed radiance spectra from a computed clear-sky background spectra.

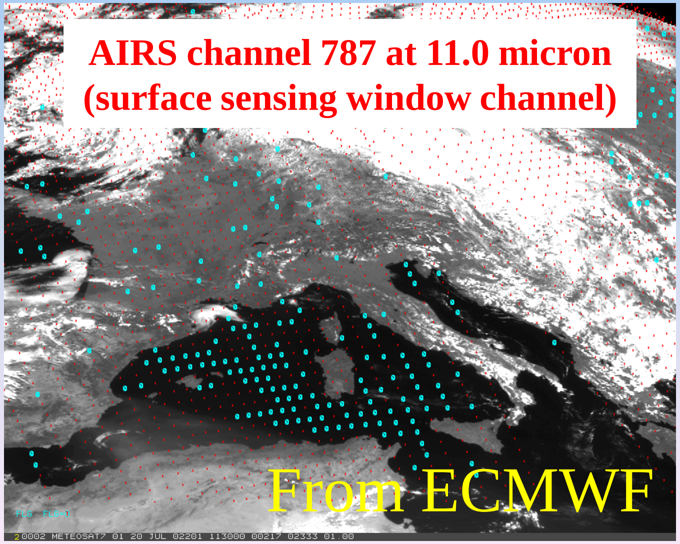


Vertically ranked channel index

This identifies the characteristic signal of cloud in the data and allows contaminated channels to be rejected

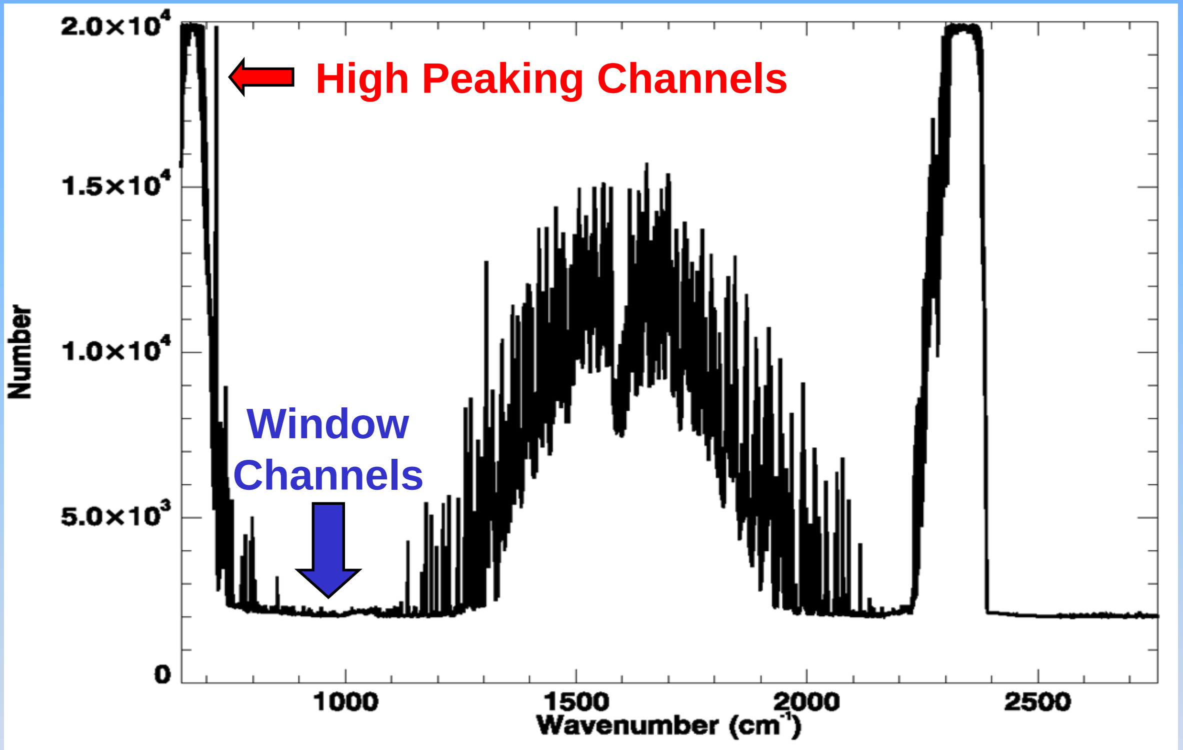






Number of Clear Channels in infrared spectrum

For low peaking channels in the infrared only 5-10% of fields of view are considered clear

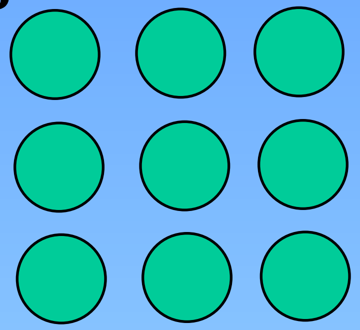


Not only are we throwing away useful information but by only considering clear observations in regions that are mostly cloudy we are introducing representivity errors.

Infrared Radiances

Correct for the clouds

Cloud Cleared Radiances



Cloud Cleared Radiances derive a single "clear" spectrum from an array of partially cloudy fields-of-view (9 in the case of AIRS)

Assumes the cloud height in each FOV is identical and only cloud fraction varies between the FOVs.

Needs a high-quality first guess (often an AMSU-A retrieval)

Can calculate a noise amplification factor which is the basis of the QC flag

Infrared Radiances

Model the Clouds

Inferring cloud properties from the observations

- Clouds properties are inferred from the observations, either via a 1DVar retrieval (and retrieving temperature, humidity etc simultaneously with clouds) or more simple least-squares methodology with fixed temperature and humidity from the background fields.
- Usually a grey cloud is assumed. The cloud may then be defined by cloud top pressure (CTP) and Cloud Fraction.
- The retrieved cloud may then be passed to the assimilation stage where is may either be treated as fixed or may be modified during the minimization as a “sink variable” – one that does not make up part of the analysis itself.
- At ECMWF, only completely overcast situations are considered.

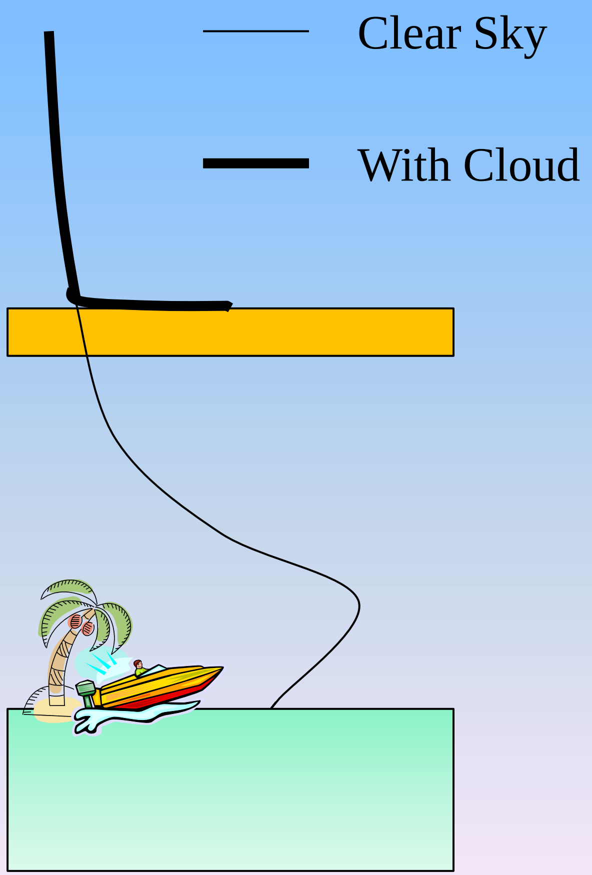
Form of Jacobians

The Jacobians of low-peaking channels (in clear sky) will all peak at the top of an opaque cloud.

So there is a lot of information about the cloud top temperature.

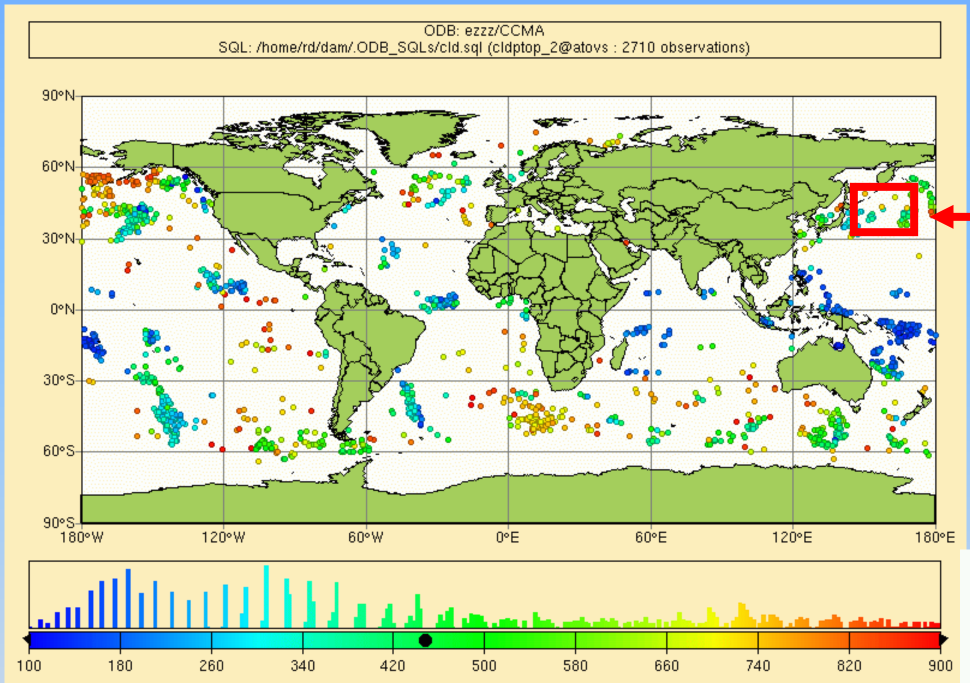
But to use this information we need to be able to infer exactly where the cloud top is.

Also if the cloud top height changes the Jacobian values near the cloud top will change rapidly – the problem is highly non-linear.



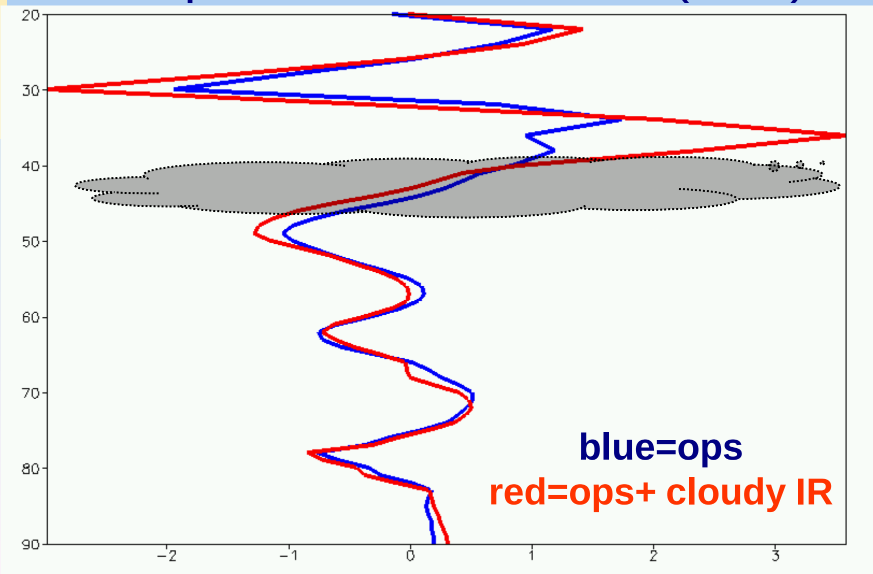
Temperature increments at the cloud top

Tony McNally



Cell of very high overcast clouds off the coast of PNG

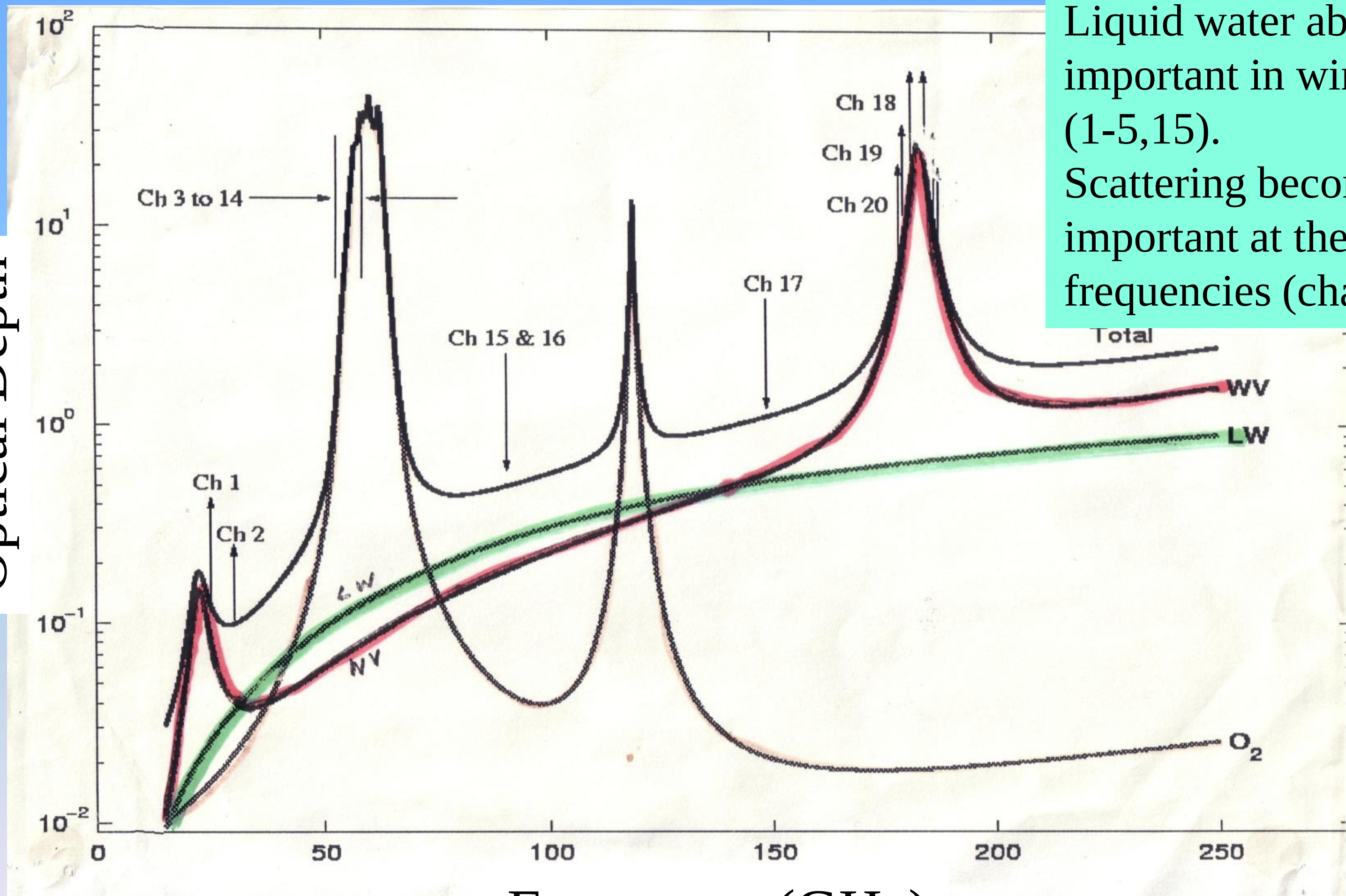
Temperature increments (IASI)



All channels collapse to near delta-functions at the cloud top giving very high vertical resolution temperature increments just above the diagnosed cloud

Microwave Radiances

Microwave Spectrum



Optical Depth

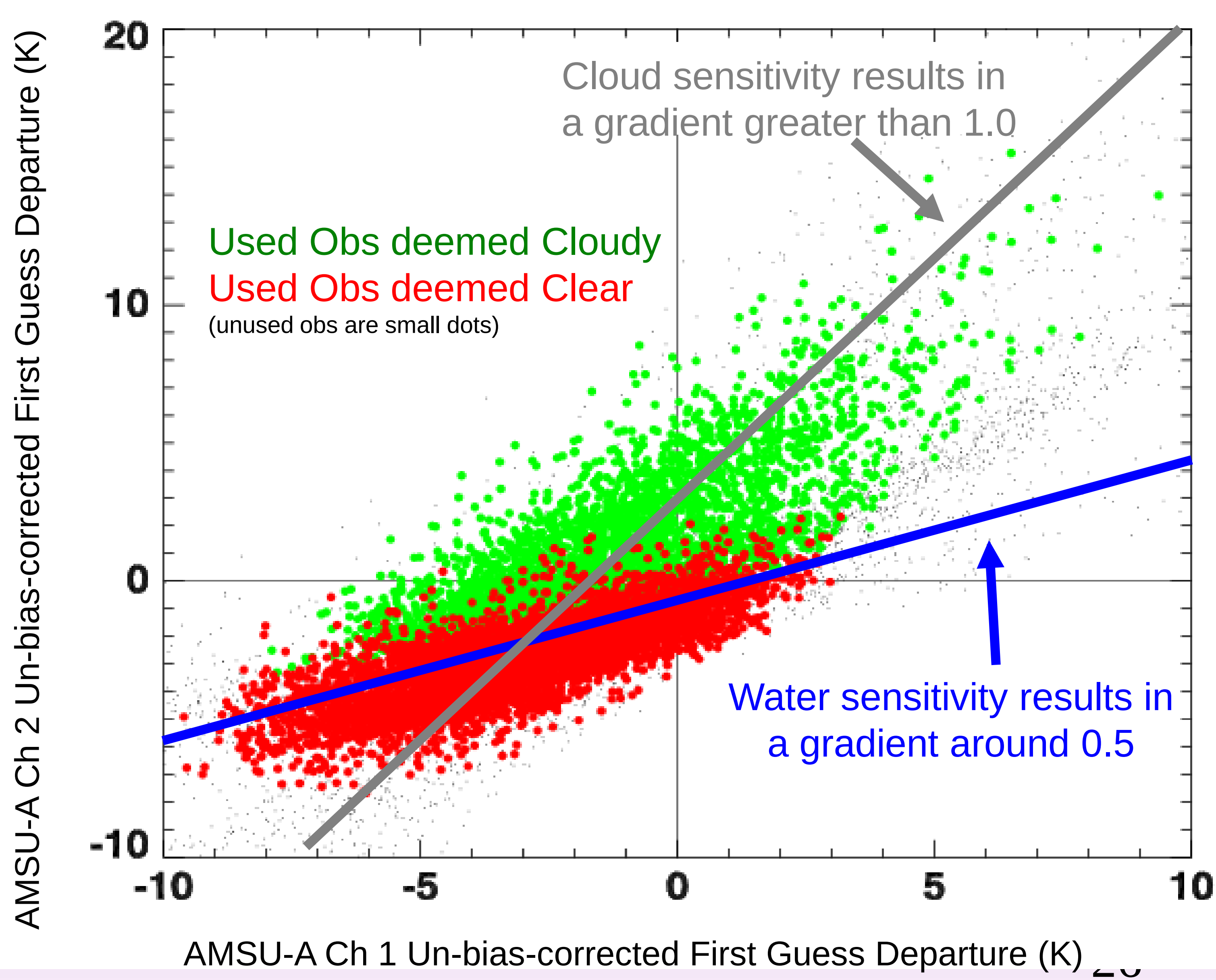
Frequency (GHz)

Liquid water absorption is important in window channels (1-5,15).
Scattering becomes more important at the higher frequencies (channels 15-20).

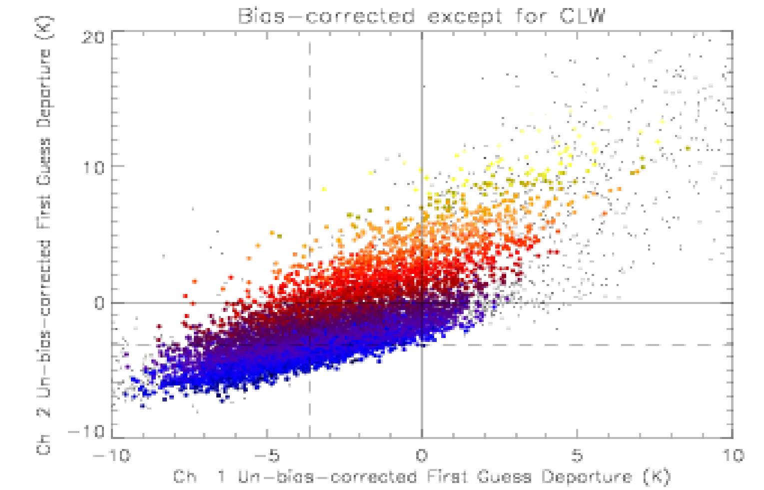
Microwave Radiances

Avoid and Mitigate for Clouds

Cloud detection in the microwave

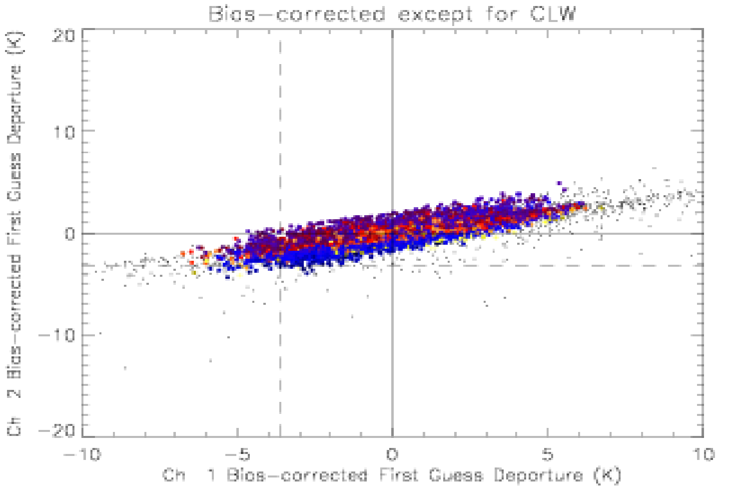


Using retrieved CLW in the GSI bias correction



Similar to previous slide – color-coded by retrieved CLW

After bias correction where CLW is a bias-correction predictor



Microwave Radiances

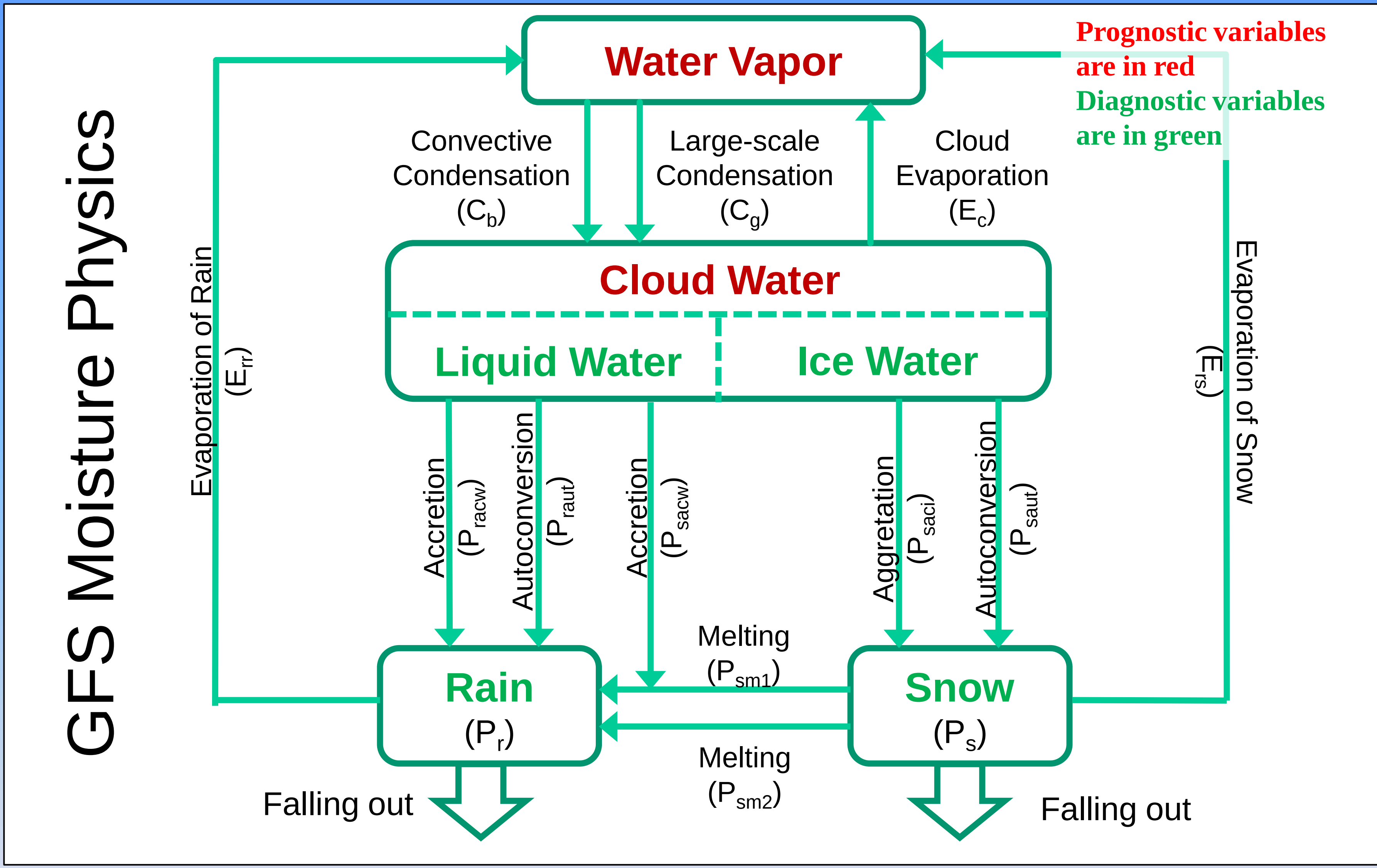
Assimilate cloud information

Cloudy Radiance Assimilation in the Microwave

- Balance
- Control variable
- Assignment of Observation Errors and Representivity
- Linearity

Balance

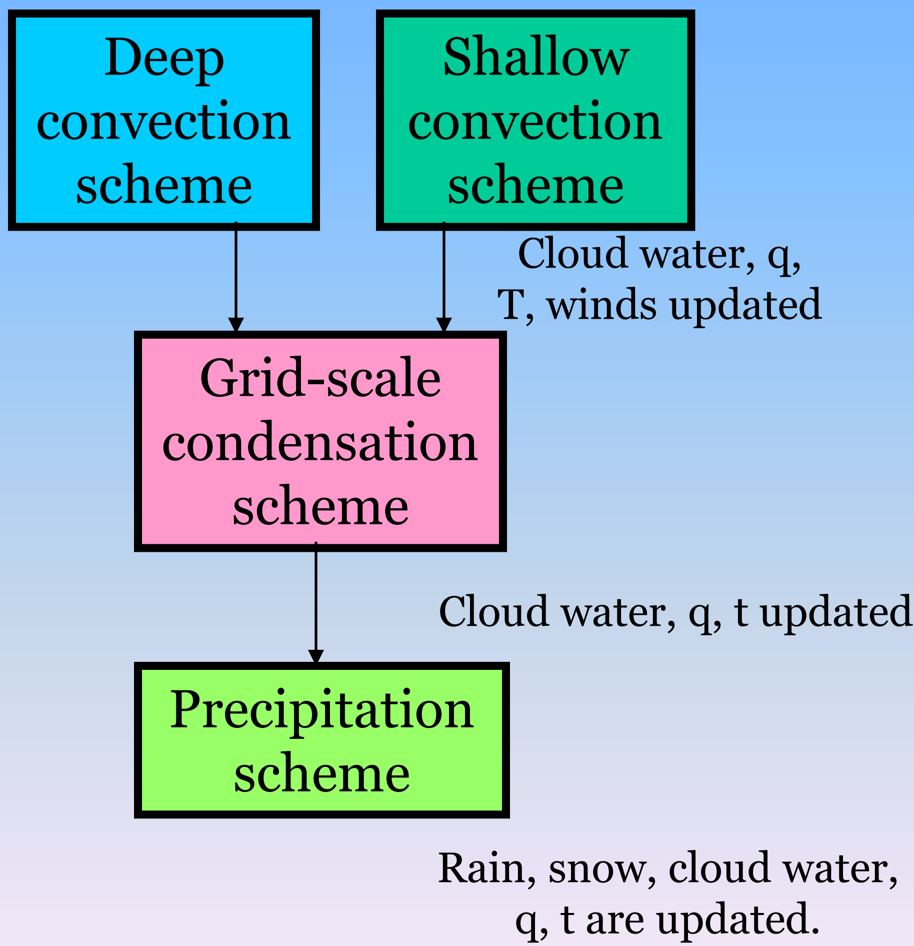
- We want to ensure during the minimization process that the temperature, humidity and cloud fields are consistent.
- We use the moisture physics package from the Global Forecasting System (GFS) to impose this constraint.



- The tangent-linear (TL) and adjoint (AD) of full GFS moisture physics are under development and validation.
- These linearized moisture physics are added in the minimization to ensure control variables are more physically related and balanced.

Moisture Physics Models

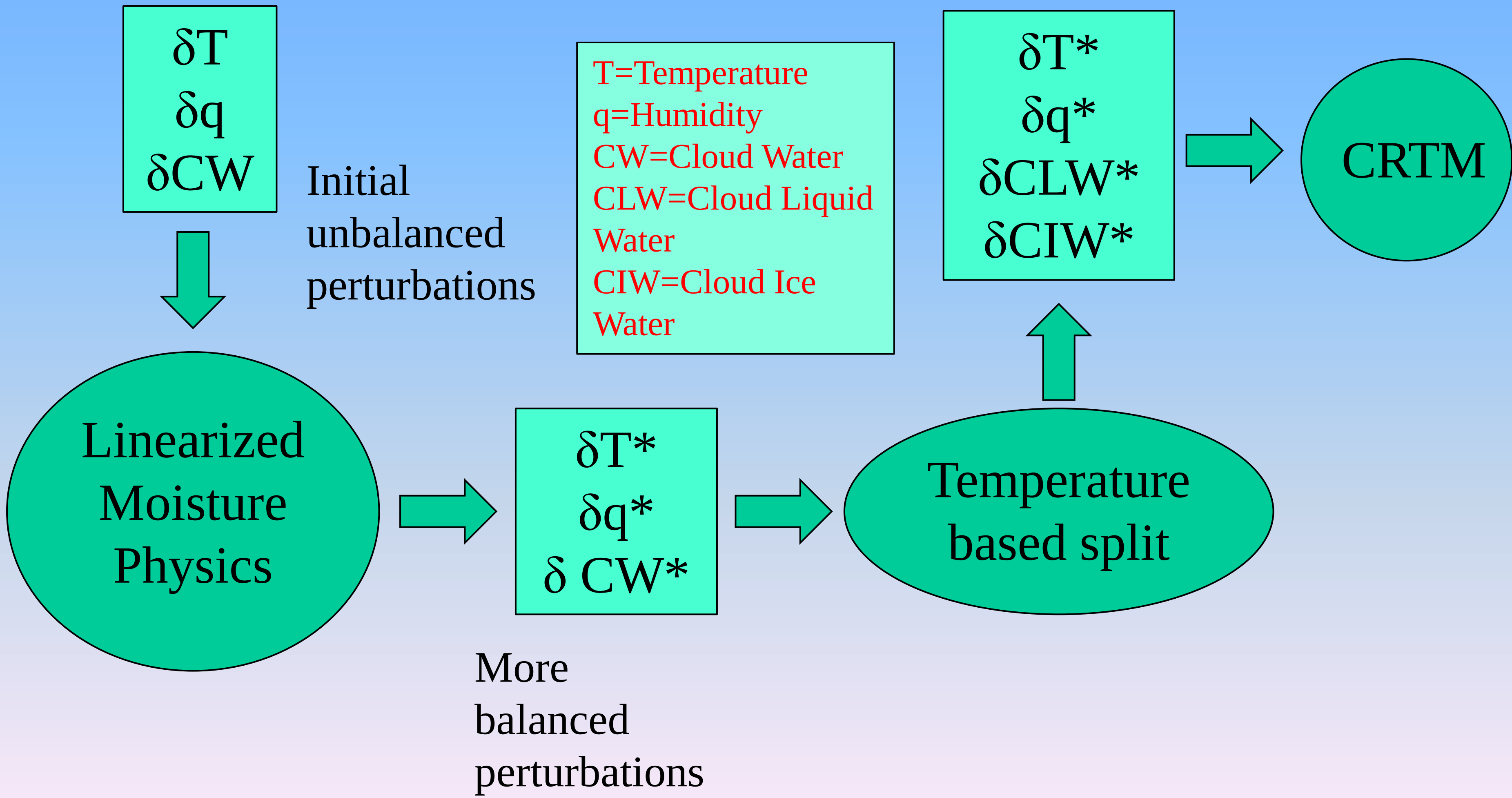
NCEP GFS moisture physics schemes



- **NCEP Global Forecast System(GFS) moisture physics schemes are composed of**
  (1) Simplified Arakawa-Schubert (SAS) convection scheme,
  (2) a shallow-convection scheme,
  (3) a grid-scale condensation scheme,
  and (4) a precipitation scheme.

- **The Tangent-linear and adjoint codes for (1), (3), and (4) have been developed and currently being tested in GSI for cloudy radiance data assimilation**.

Linearized Moisture Physics in the Inner Loop of the Minimization



Linearized Moisture Physics in the Inner Loop of the Minimization - Adjoint

$$\frac{\partial J}{\partial T*} \quad \frac{\partial J}{\partial q*} \quad \frac{\partial J}{\partial CW*}$$

Balanced gradients

J is the minimization cost function

$$\frac{\partial J}{\partial T*} \quad \frac{\partial J}{\partial q*} \quad \frac{\partial J}{\partial CLW*} \quad \frac{\partial J}{\partial CIW*}$$

CRTM K

Unbalanced gradients

Adjoint of Linearized Moisture Physics

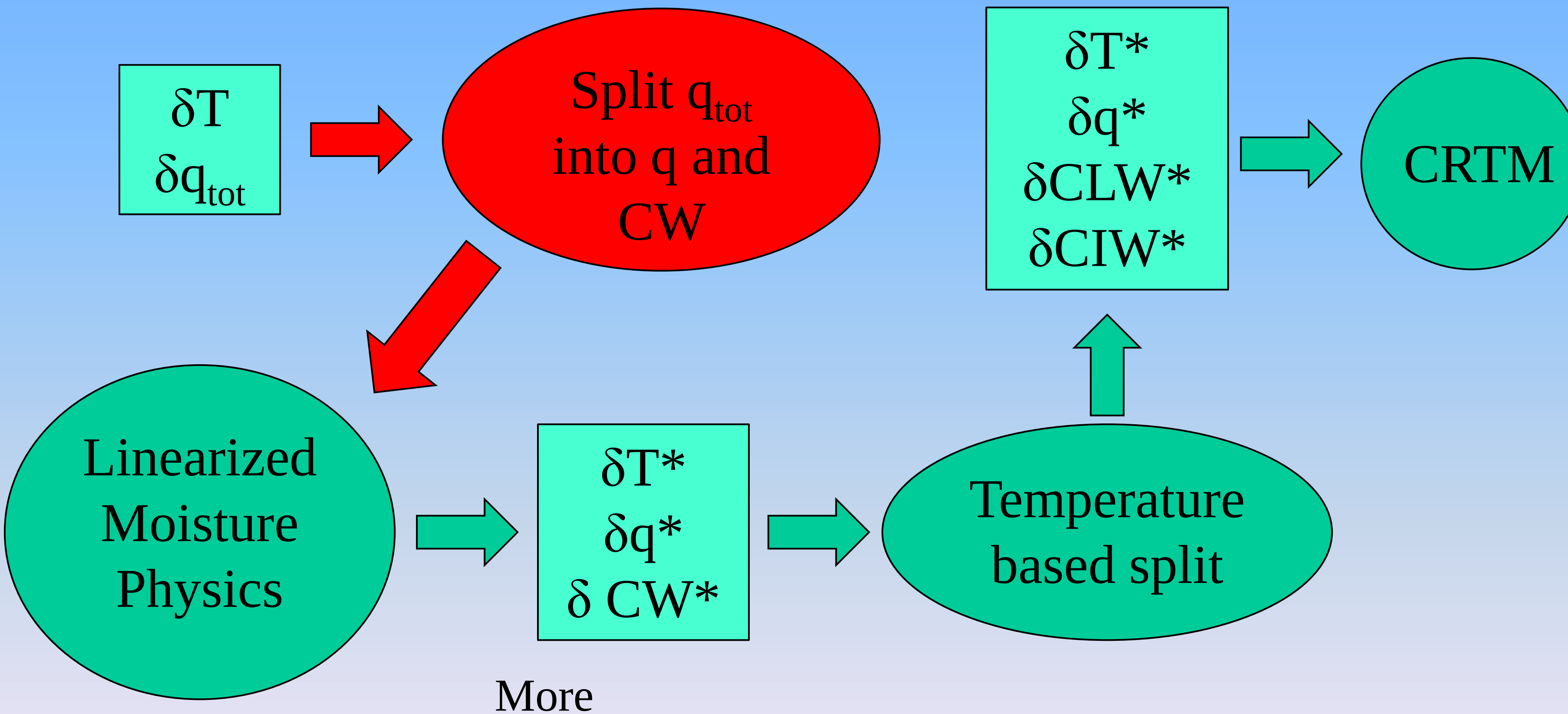
$$\frac{\partial J}{\partial T*} \quad \frac{\partial J}{\partial q*} \quad \frac{\partial J}{\partial CW*}$$

Sum CLW* and CIW* terms

Control Variable Choice

- Consider two possibilities for the cloudy control variables in the minimization:
  - A three variable approach: Cloud liquid water (CLW), Cloud Ice Water (CIW) and Water Vapor (q)
  - A single total water variable (qtot)
  - Of course, each of these will be a profile
- The difference is whether we use the background error covariance matrix to partition the increments or model physics
- The Gaussianity of the variables’ first-guess departure statistics will affect which is chosen.

Total Humidity requires an extra step before the moisture physics

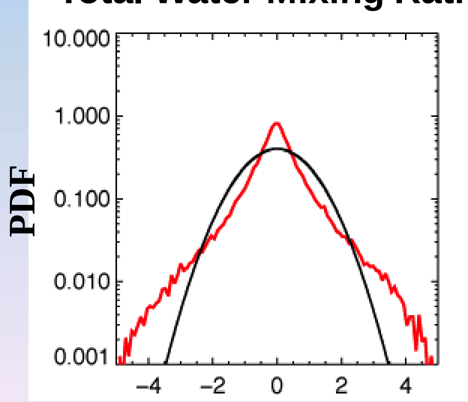


More balanced perturbations

Total Water as Moisture Control Variable

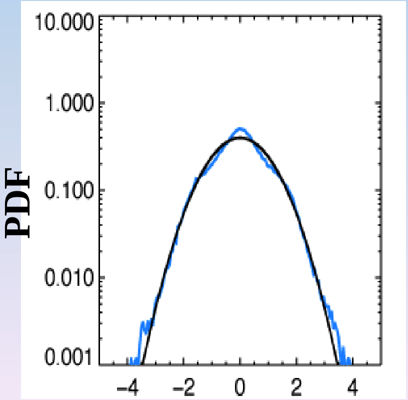
- Find a form of total water with its error distribution Gaussian (in practice, closer to Gaussian)
- The background errors are directly related to forecast differences in that if the forecast difference are Gaussian, so are the background errors (can be mathematically proven)
- 60 pairs of 24 and 48-hour forecasts from GFS were used to study the error distribution of total water (NMC method)

Total Water Mixing Ratio



$$\frac{\delta q_T}{\sigma}$$

Total Water Relative Humidity



$$\frac{\delta RH_T}{\sigma(RH^b)}$$

Total Water as Moisture Control Variable Pros and Cons

- Advantages
  - Reduce the dimension (computationally efficient)
  - Condensation/evaporation rapidly converts between humidity and cloud water, but total water is more constant in time (more linear)
  - Changes in total water is spatially more homogeneous than in cloud water (has a simpler error characteristic)
- Disadvantages
  - Need to separate total water increment into water vapor increment and cloud water increment in the minimization (prone to introduce biases)

* Currently, assuming total water has uniform distribution in a grid box

Assignment of observation errors

- The observation errors assigned when doing cloudy assimilation need to reflect:
  - Instrument error (generally a small contribution)
  - Forward model error (higher for cloudy radiances, even higher for ice clouds and precipitation where scattering is an issue)
  - Representivity error
- We define the observation error as a function of cloud amount.
  - Cloud may be derived from the model …
  - … or from the observations as with the cloud detection above

Observation errors

function of observed cloud or model cloud ??

Geer et al. (2010)

Obs: Cloudy sky
Model: Clear

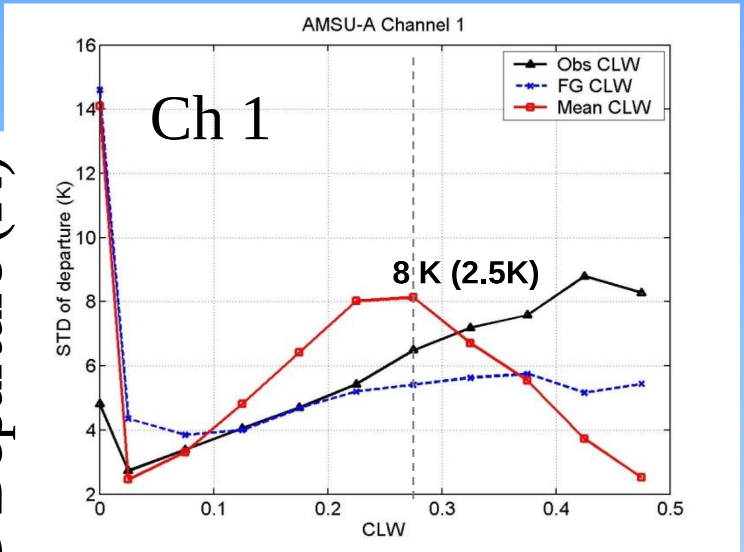
Obs: Clear sky
Model: Cloudy

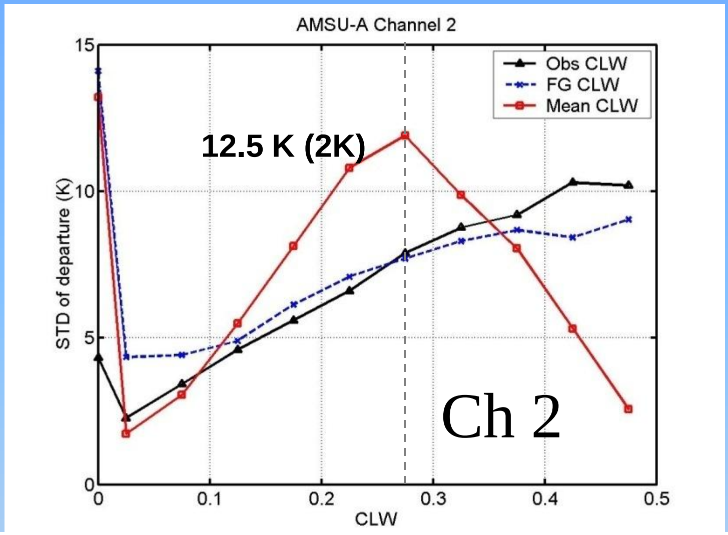
Obs error function of Obs cloud → Large obs error (Small weight) | Small obs error (Large weight) → Dry model atmosphere

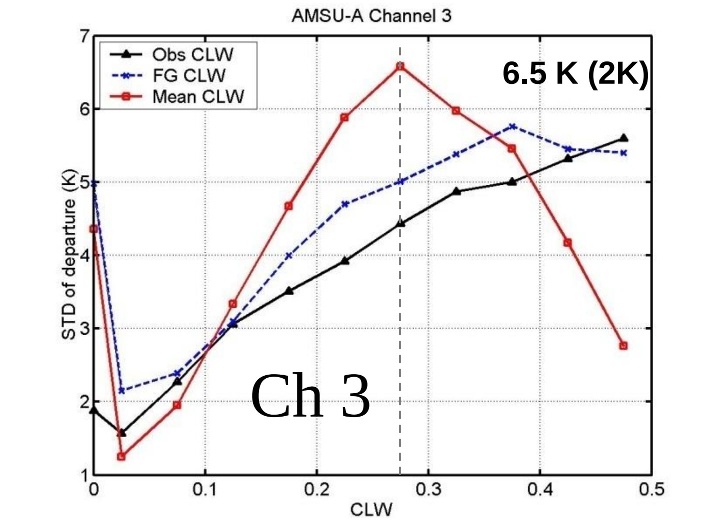
Obs error function of Model cloud → Small obs error (Large weight) | Large obs error (Small weight) → Moisten model atmosphere

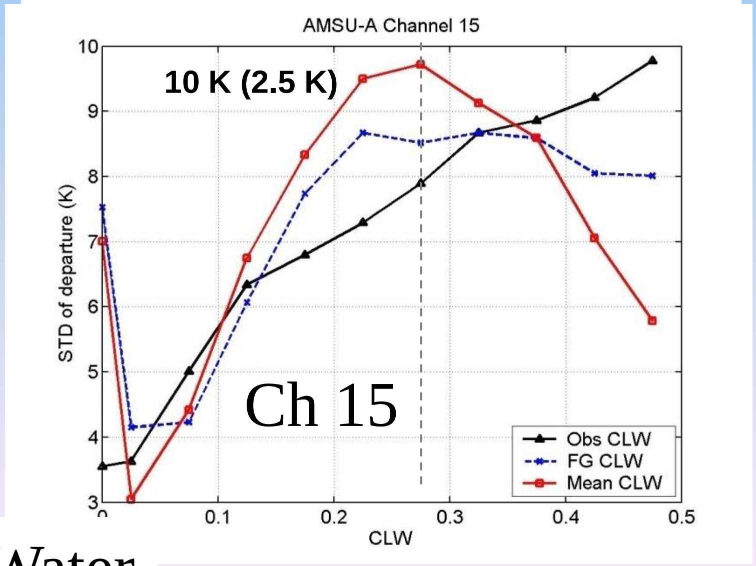
Standard deviation of AMSU-A Tb departure (clwp < 0.5 kg/m^2)

Std Dev of FG Departure (K)









Cloud Liquid Water

New Observation Errors
for clear and non-precipitating cloudy sky over the ocean

CLD = 0.5*(observation + model estimates for CLW)

A_i = clear sky error for each channel(i)

B_i = cloudy sky error for each channel(i)

If(CLD .lt. 0.05) then

$Obs\_error_i = A_i$

else if (CLD .ge. 0.05 .and. .lt. 0.275) then

$Obs\_error_i = A_i + (CLD-0.05)*(B_i-A_i)/(0.275-0.05)$

else

$Obs\_error_i = B_i$

endif

New Observation Errors
for clear and non-precipitating cloudy sky over the ocean

CLD = 0.5*(observation + model estimates for CLW)

A_i = clear sky error for each channel(i)

B_i = cloudy sky error for each channel(i)

In satinfo:

if(CLD ...

Obs_...

else if (C...

Obs_...

else

Obs_...

endif

!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	[illegible]	[illegible]	4.500	10.000	0.000
hirs3_n17	1	-1	[illegible]	[illegible]	4.500	10.000	0.000
hirs3_n17	2	-1	[illegible]	[illegible]	2.500	10.000	0.000
hirs3_n17	3	-1	[illegible]	[illegible]	2.500	10.000	0.000
hirs3_n17	4	-1	[illegible]	[illegible]	2.000	10.000	0.000
hirs3_n17	5	-1	0.360	0.000	2.000	10.000	0.000

A_i B_i

Linearity and Quality Control

- As with the infrared, there can be significant non-linearity when the brightness temperature departures are large.
- In the GSI we impose a quality control check where the retrieved cloud liquid water amount is less than 0.5 kg m^{-2}.

Summary

- Observations of clouds have until recently been under-used in operational data assimilation schemes.
- A number of strategies may be adopted to either allow assimilation of temperature/humidity in cloudy regions or to use the information about the clouds themselves.
- The main issues that need to be addressed when using cloudy radiances are non-linearity, representivity and internal consistency of the analysis.

Questions?

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