

The detection and assimilation of cloud-affected infrared satellite radiances

ECMWF/EUMETSAT NWP-SAF Satellite Data Assimilation
Training Course

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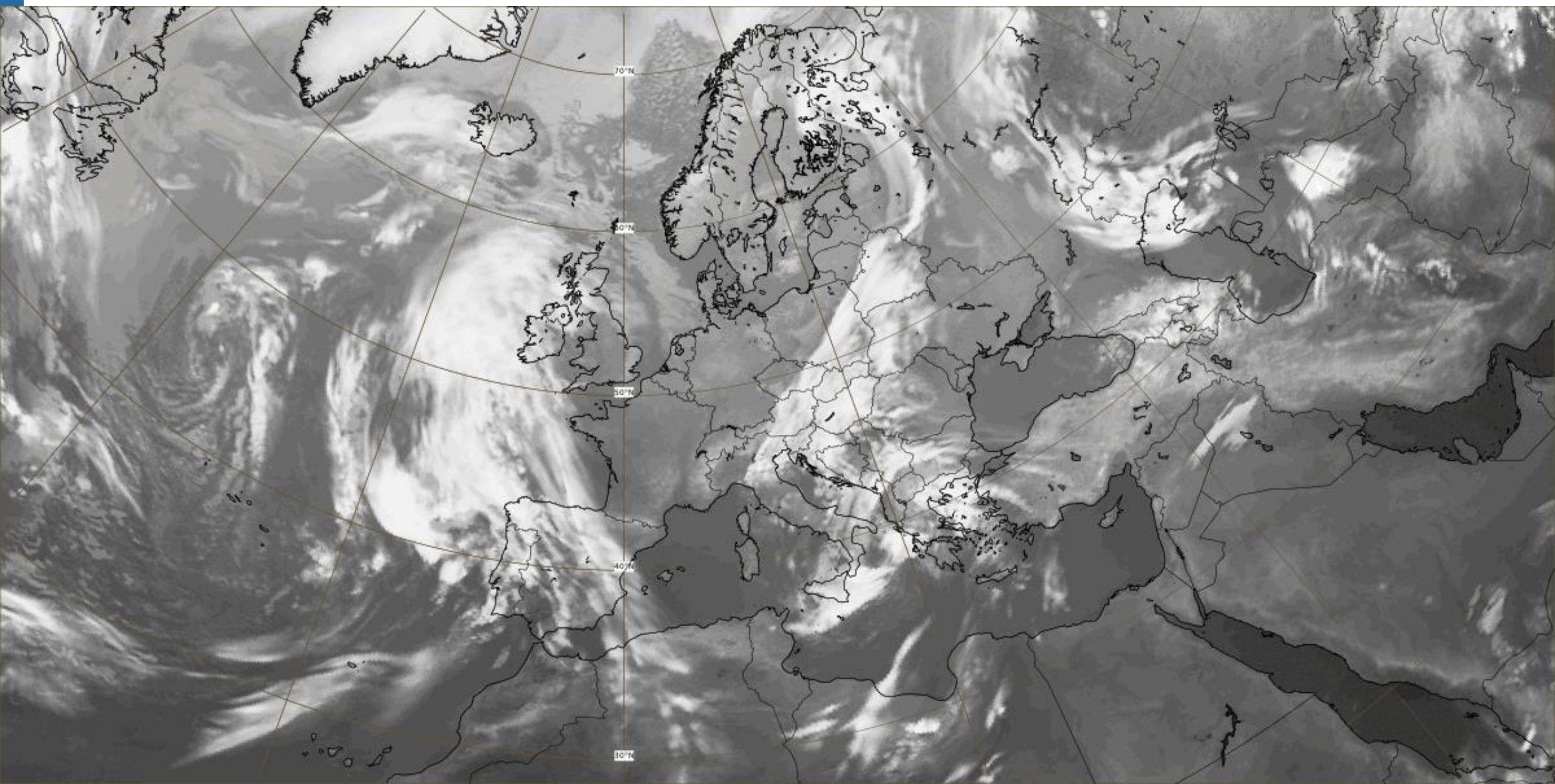
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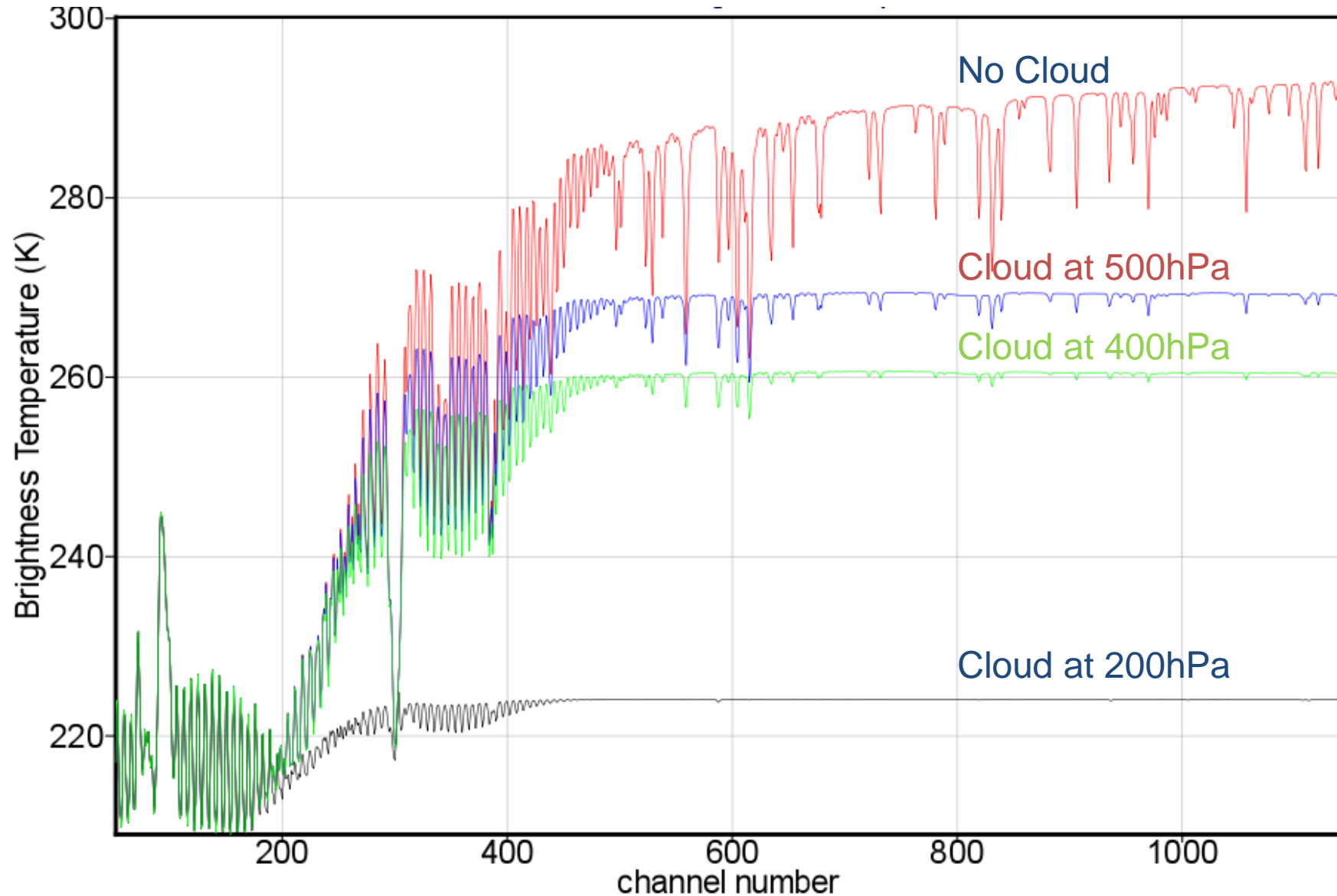
Outline

- **The effect of cloud on infrared radiances**
- **Cloud detection/rejection methods:**
 - simple departure checks
 - co-located imager information
 - pattern recognition
 - hybrid approach
 - machine learning
- **“All-sky” infrared assimilation:**
 - simplified approach
 - recent progress

The detection and assimilation of clouds in IR radiances



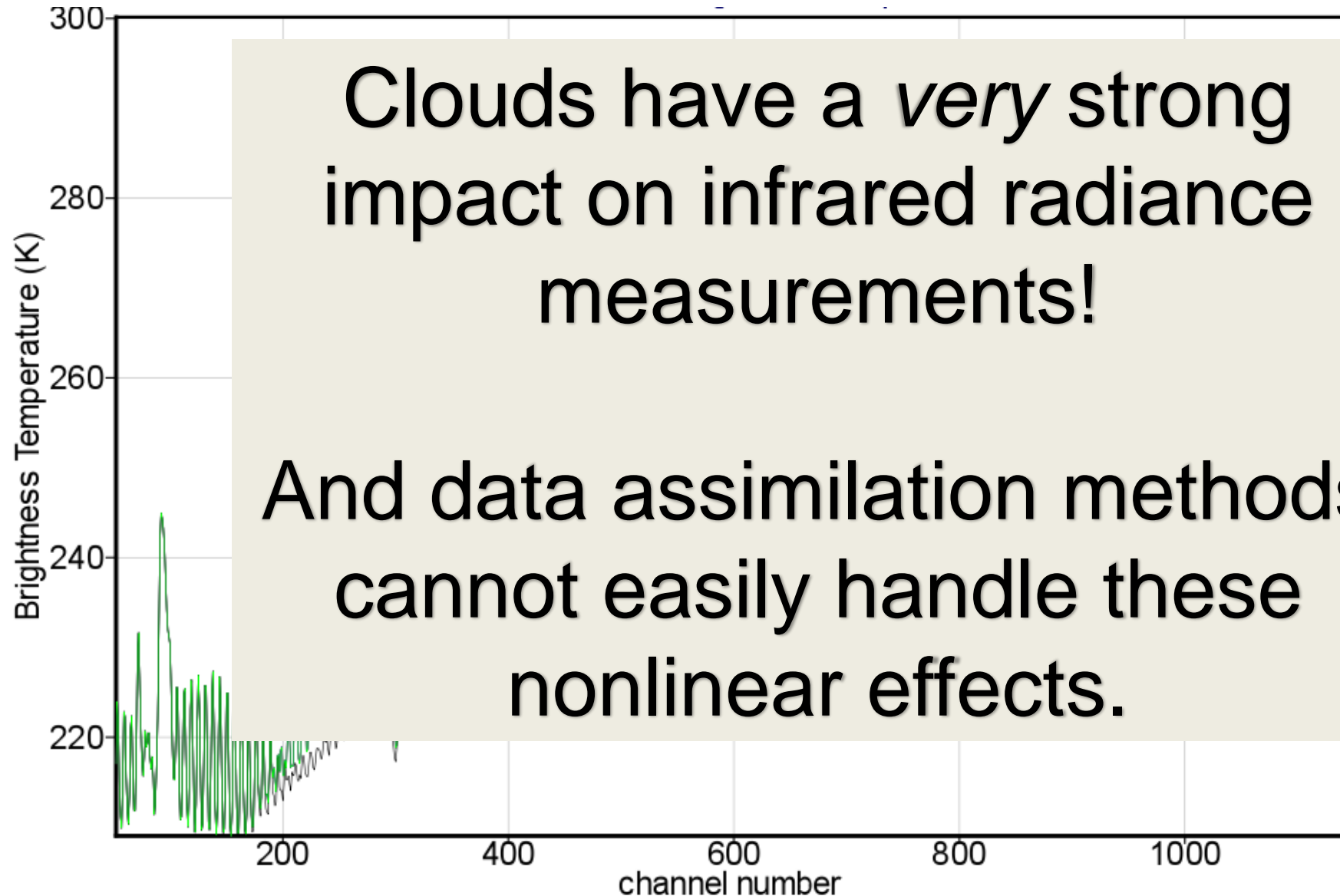
IR spectra with (and without) clouds



Channels sensitive to the surface in clear scenes.

Same channels are strongly sensitive to cold high clouds!

IR spectra with (and without) clouds



Clouds have a *very* strong impact on infrared radiance measurements!

And data assimilation methods cannot easily handle these nonlinear effects.

Channels sensitive to the surface in clear scenes.

Same channels are strongly sensitive to cold high clouds!

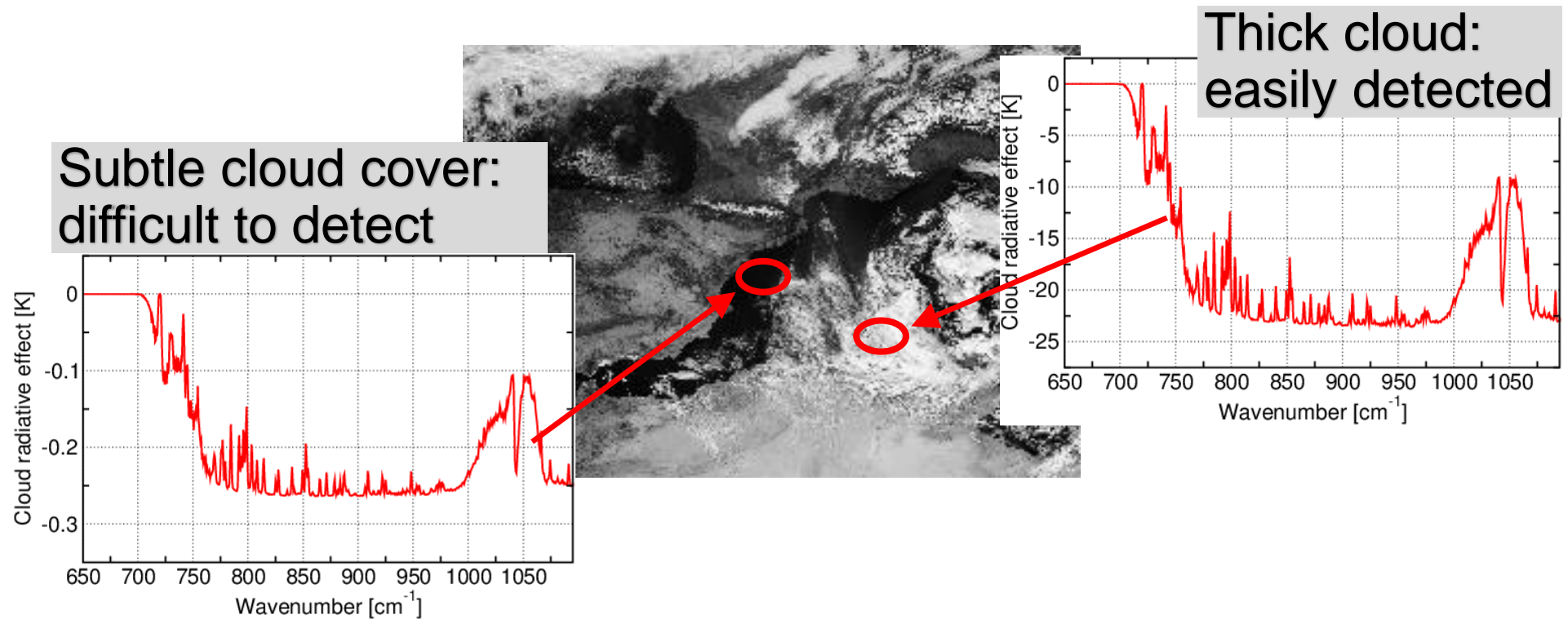
Big question: How should we handle clouds when assimilating infrared radiance observations??

- **Option 1:** **detect and reject** cloud-contaminated observations.
- **Option 2:** **Explicitly estimate** cloud parameters from the radiances within the data assimilation (T, Q, O₃ etc)

Big question: How should we handle clouds when assimilating infrared radiance observations??

- **Option 1:** **detect and reject** cloud-contaminated observations.
- **Option 2:** Explicitly estimate cloud parameters from the radiances within the data assimilation (T, Q, O₃ etc)

It is not trivial to get the cloud detection right in some IR sounder footprints



There is a “grey zone” where radiative effect of cloud is comparable with meteorological signals we’re looking for. Care is needed here, or the analysis can be degraded!

Note!

For this section, most simulated observations use cloud-free model information.

So, cloudy scenes in the observations will (in general) look colder than the model equivalents.

Cloud detection methods



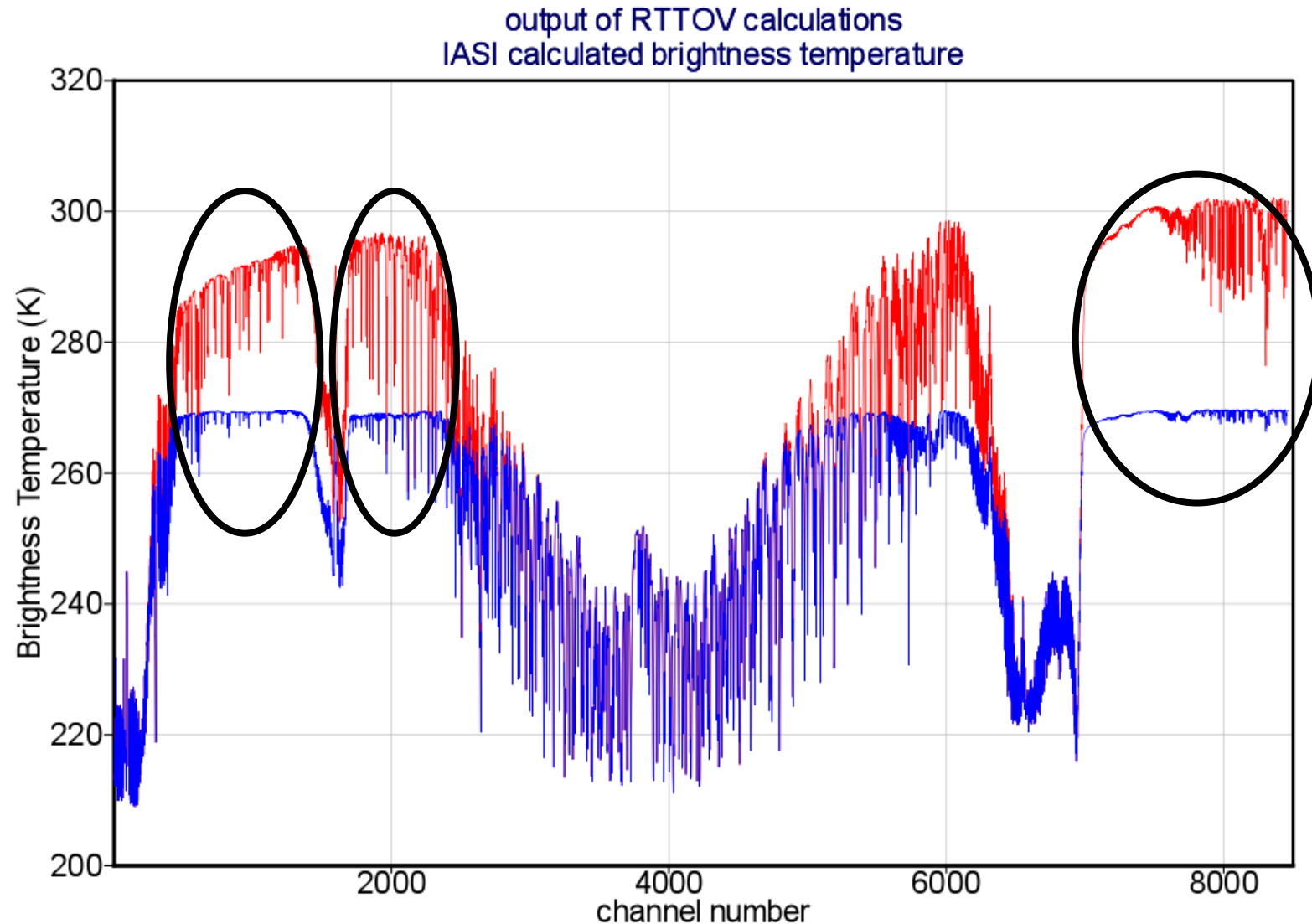
- Window channel departure (O-B) checks
- Co-located imager checks
- Pattern recognition algorithms
- Hybrid systems

Cloud detection methods



- Window channel departure (O-B) checks
- Co-located imager checks
- Pattern recognition algorithms
- Hybrid systems

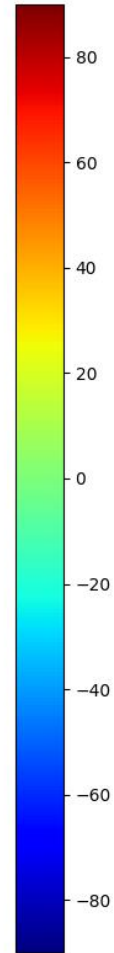
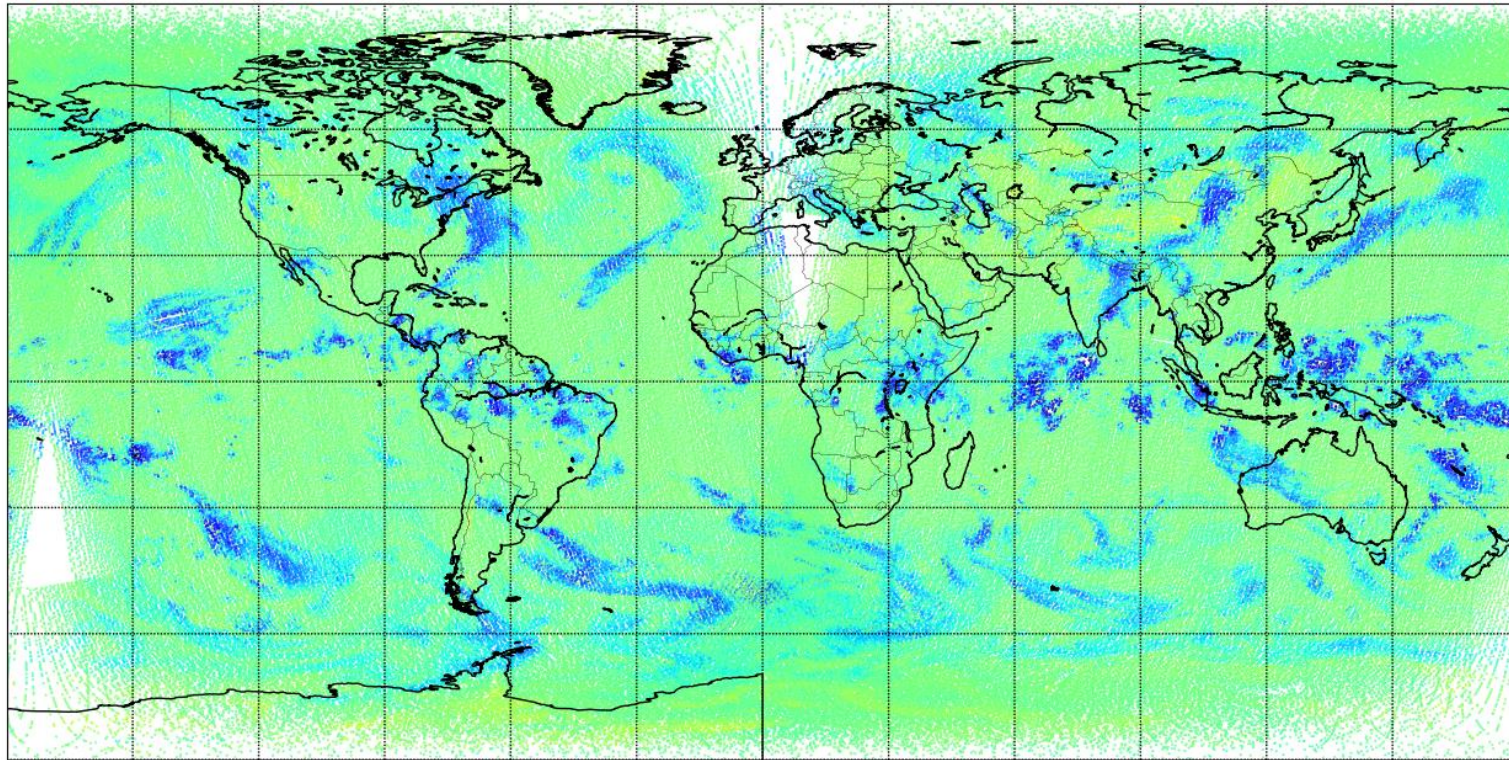
Window channels have the highest sensitivity to cloud



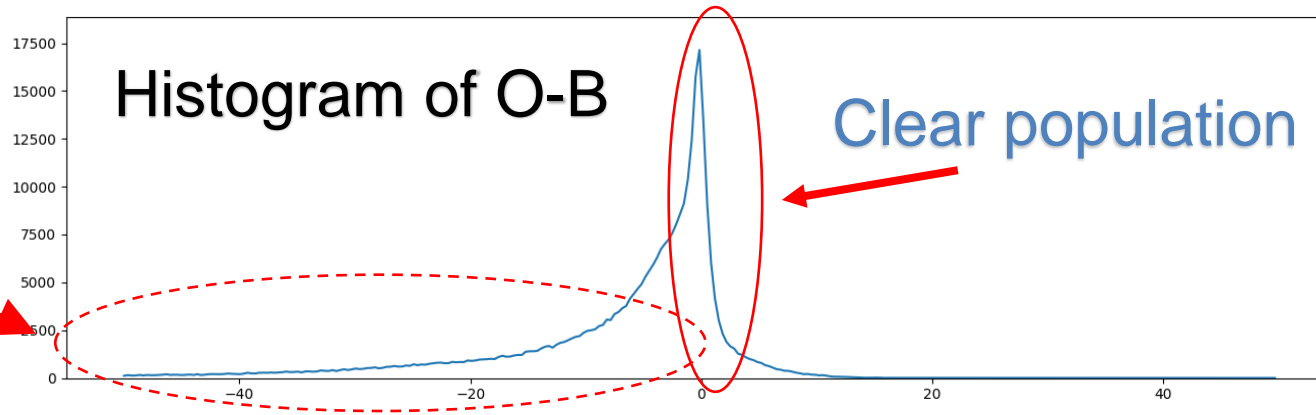
This is the classic spectral signature of the presence of cloud.

Observed radiance at 11 μm minus radiance calculated from background in *clear sky* (K)

Obs minus clear sky simulations



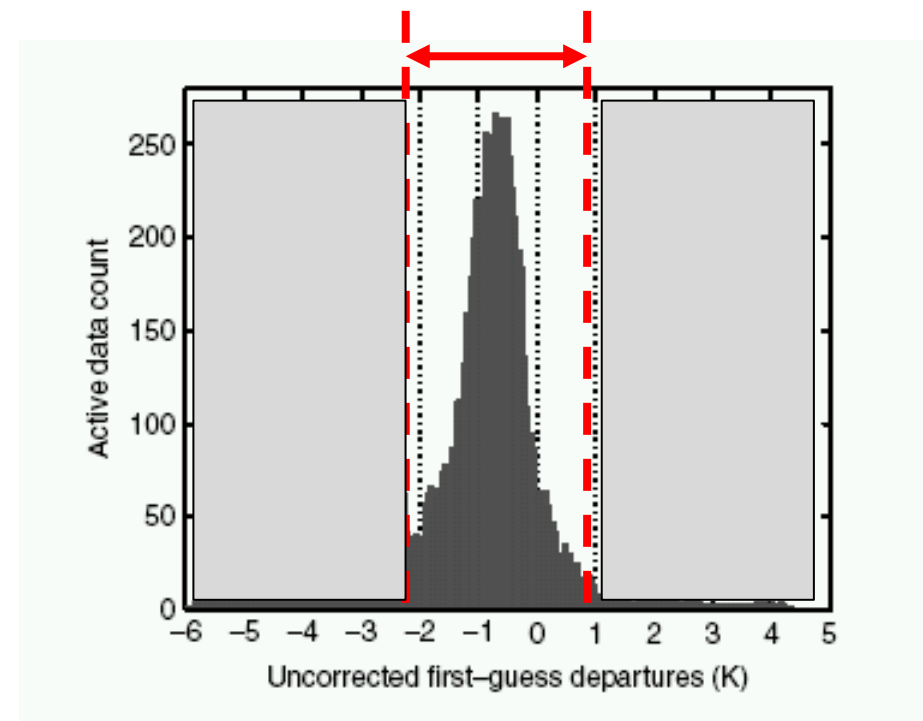
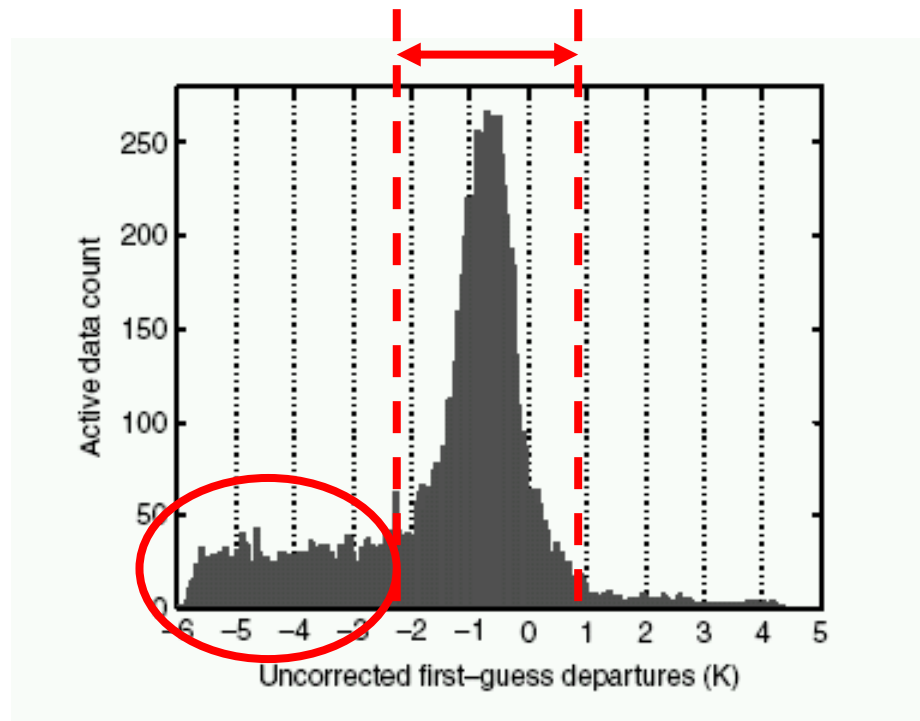
Cold departures indicating cloud contamination in obs. The “cold tail”.



Simple window channel departure check

$$\Delta BT_{thresh1} < (y_{obs} - H(x_{clear})) < \Delta BT_{thresh2}$$

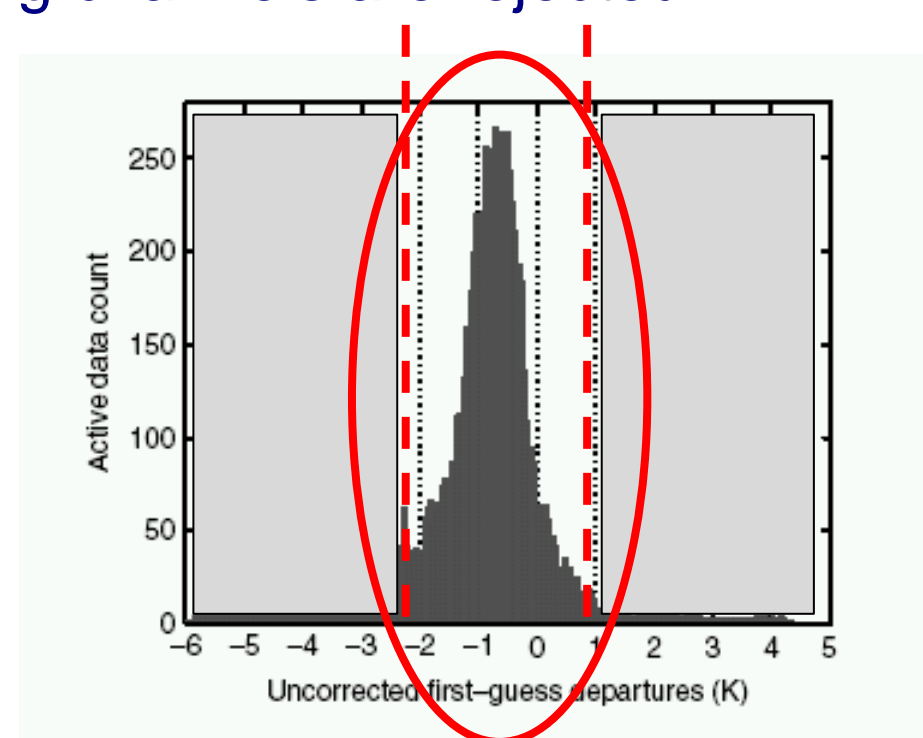
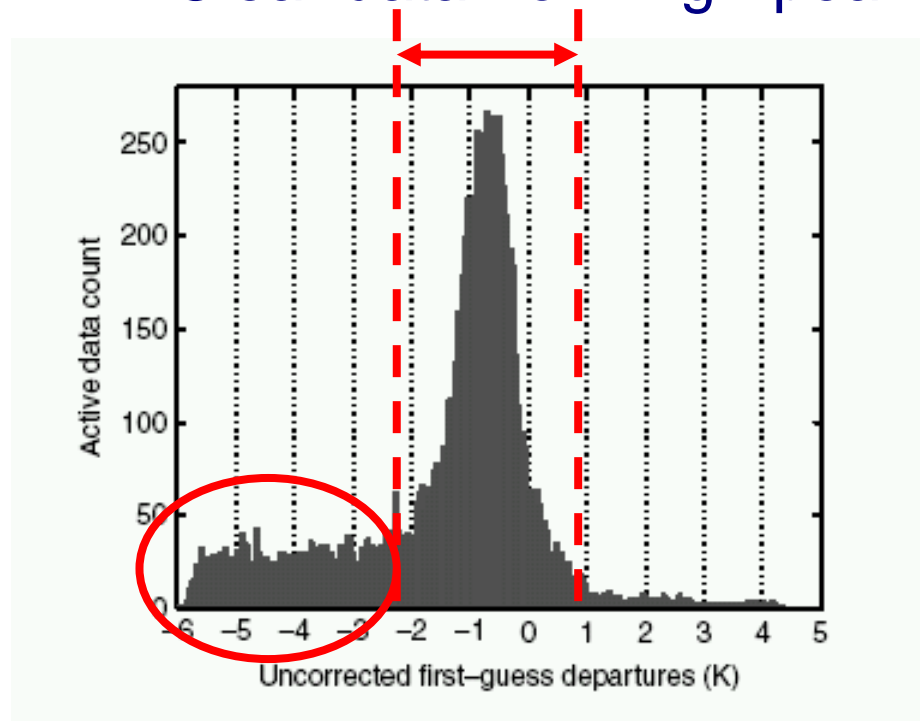
RT operator



Simple window channel departure check

Removes most cloud-affected obs. However.....

- Some cloud contamination remains in the “**grey zone**”.
- The resulting histogram is very **non-Gaussian**.
- Clear data from high-peaking channels are rejected.

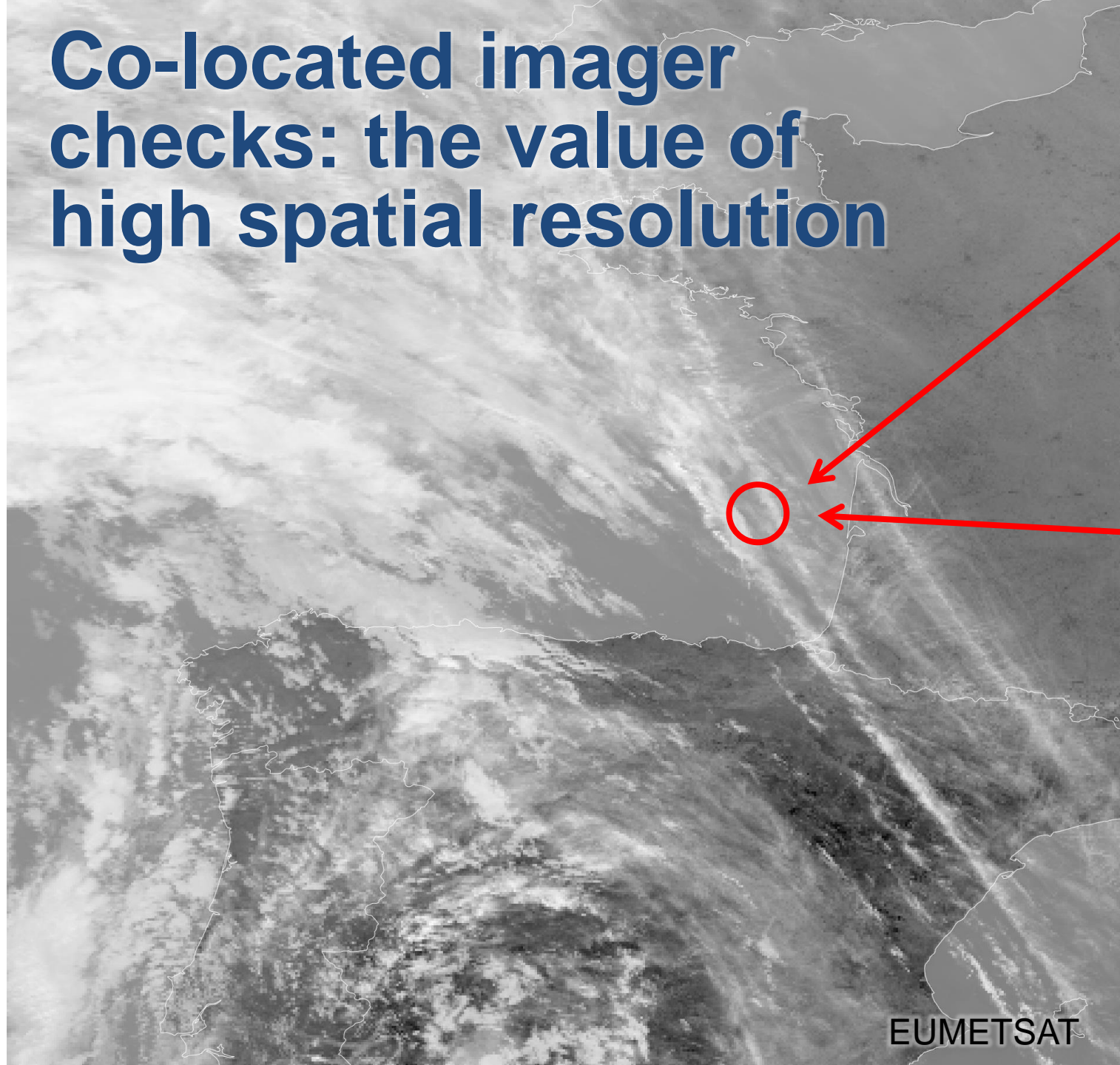


Cloud detection methods

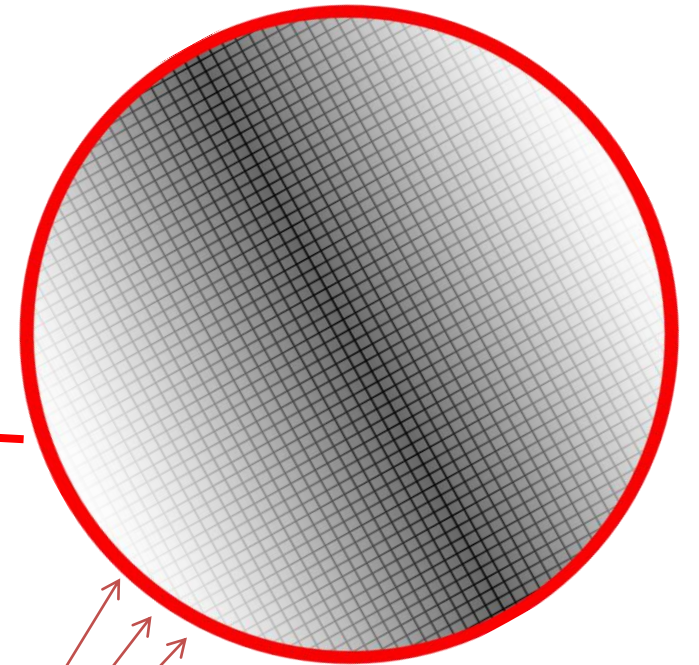


- Window channel departure (O-B) checks
- **Co-located imager checks**
- Pattern recognition algorithms
- Hybrid systems

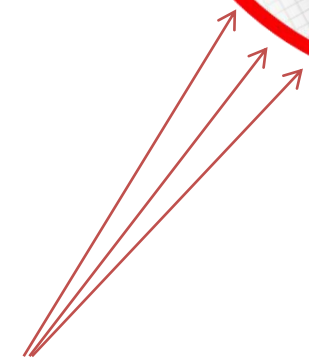
Co-located imager checks: the value of high spatial resolution



IASI (or CrIS) field of view ~10 km

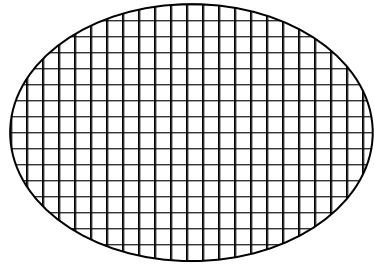


AVHRR (or VIIRS) imager pixels ~1 km

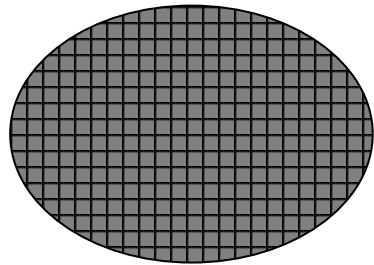


EUMETSAT

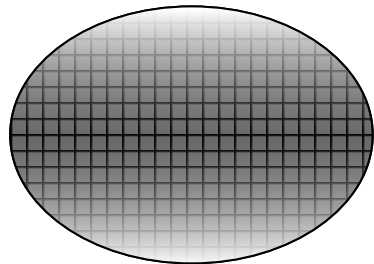
We can evaluate the mean and variance of Tb imager values inside the sounder field of view



Homogenous cloudy
(low mean Tb, low variance)

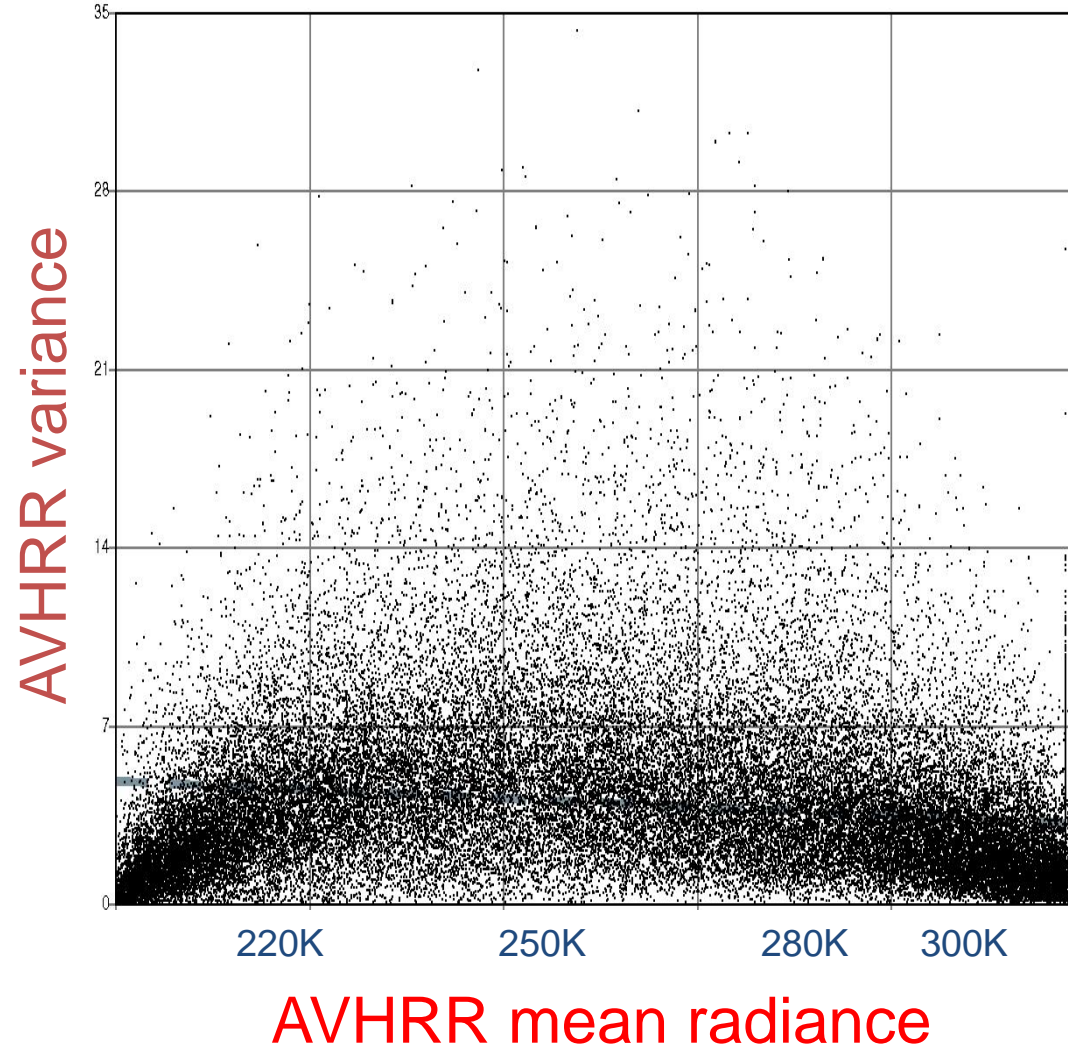


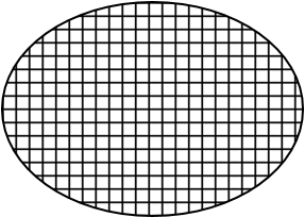
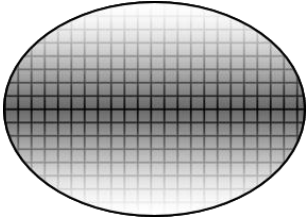
Homogenous clear
(high mean, low variance)

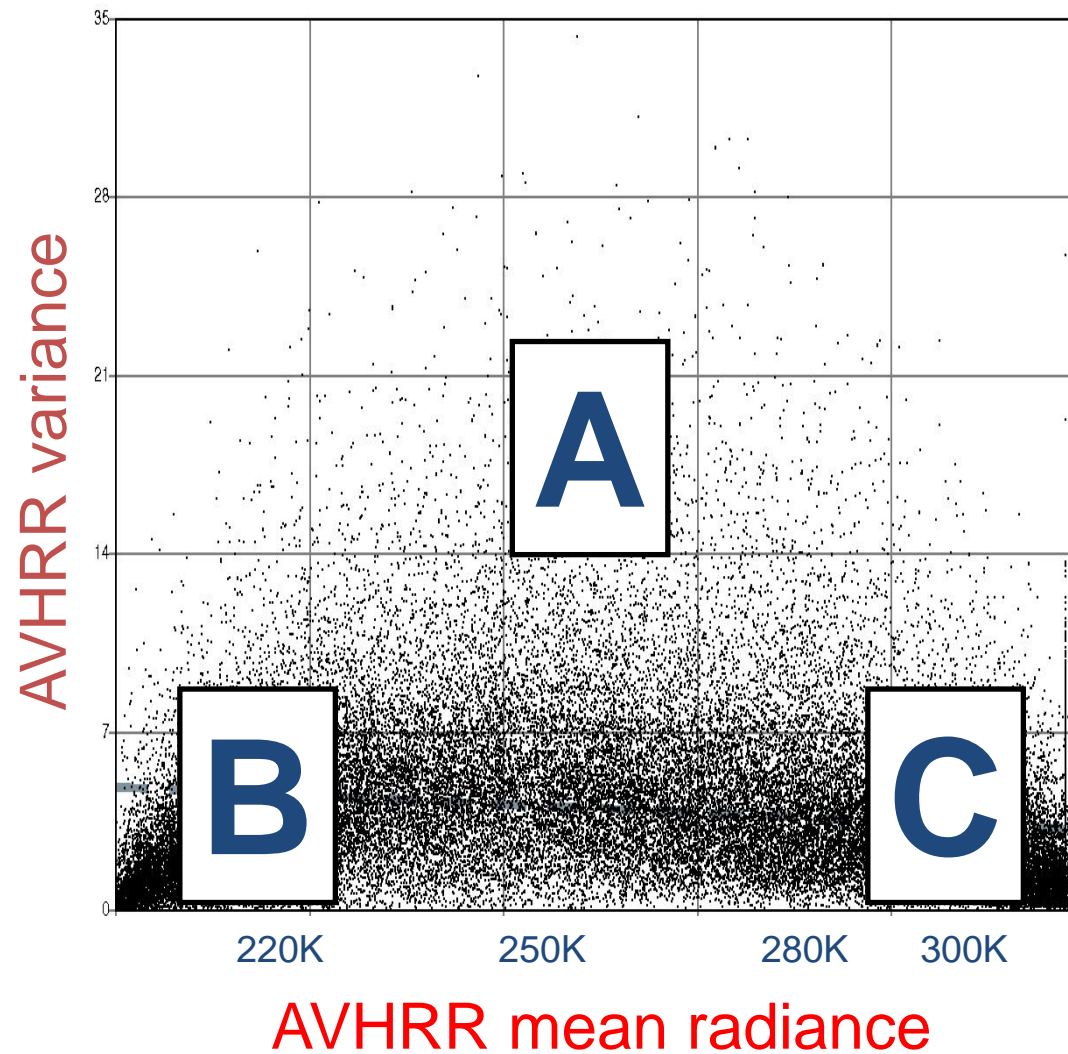


Mixed cloud scene
(any mean, high variance)

Scatter plot of variance of AVHRR imager pixels within the IASI footprint versus mean brightness temperature

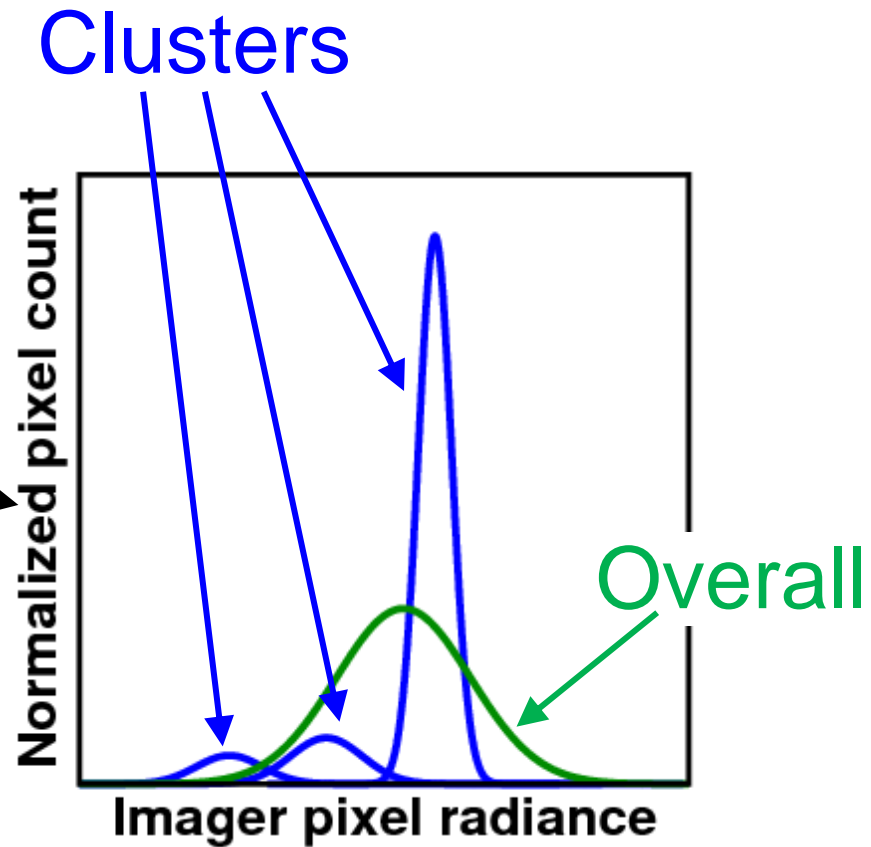
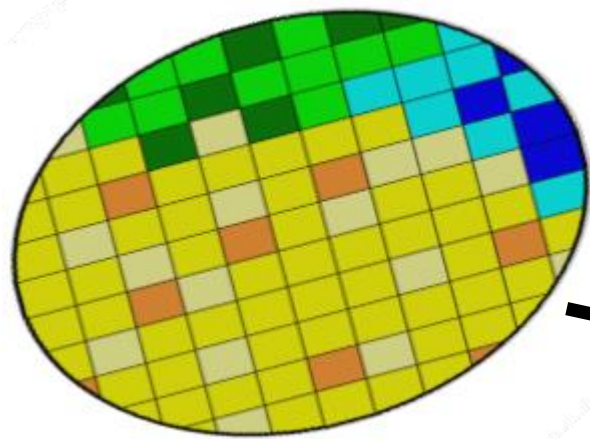


Where would , , and  be in this scatter plot ?



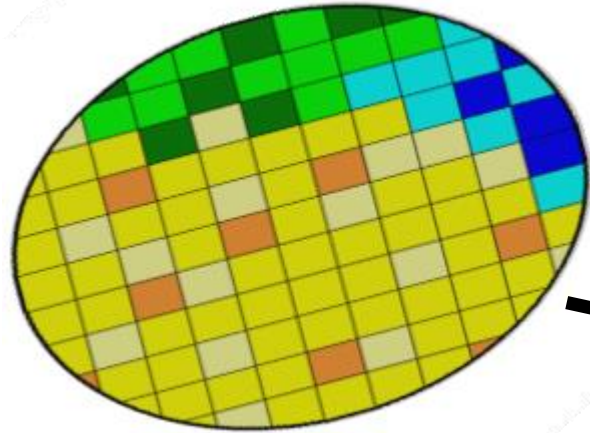
More sophisticated: image *clustering*

Use of clustered imager Tb statistics

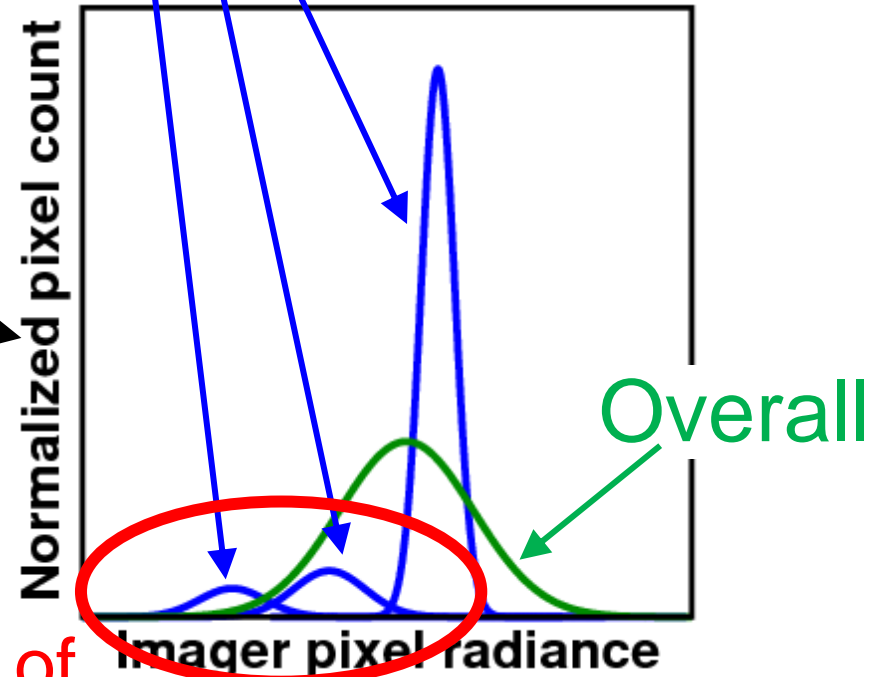


More sophisticated: image *clustering*

Use of clustered imager Tb statistics



Clusters



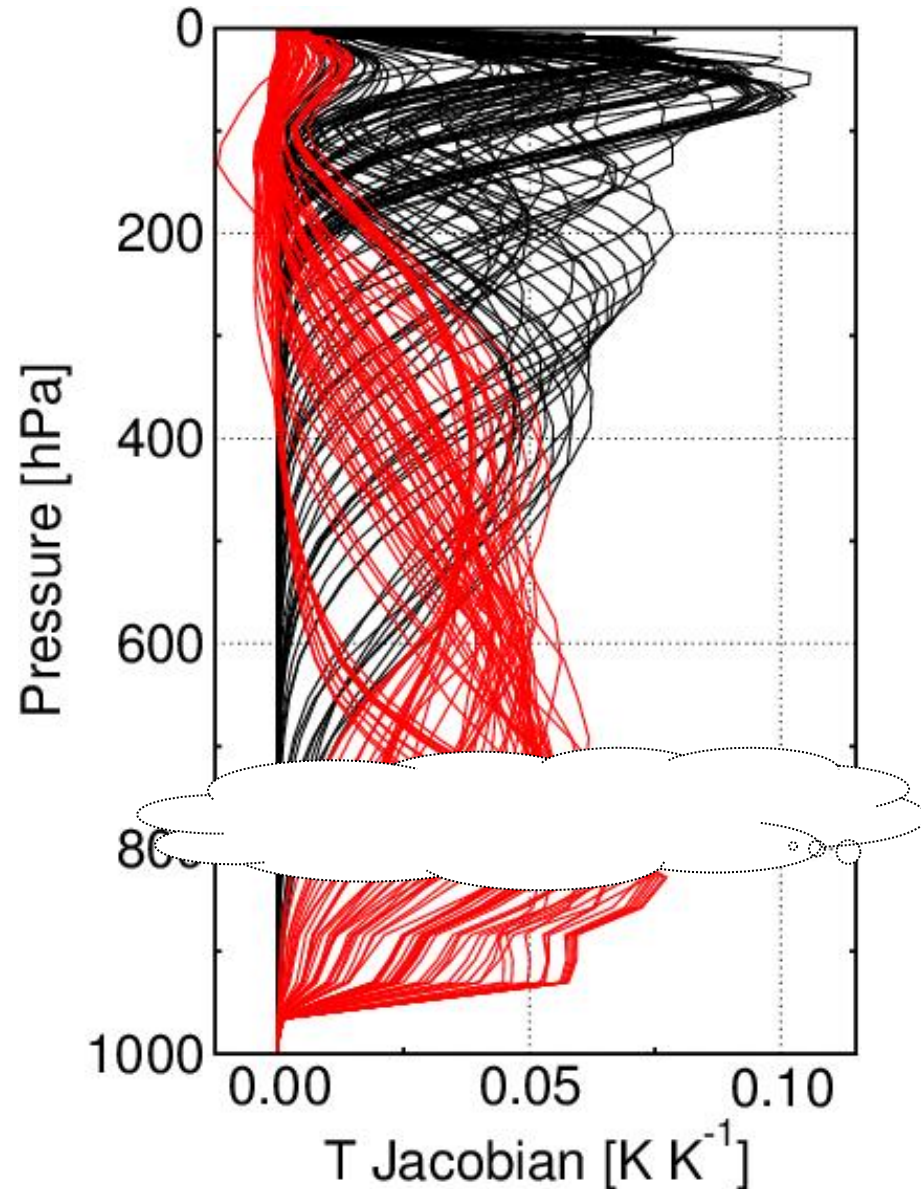
Clusters of cloudy pixels

Cloud detection methods



- Window channel departure (O-B) checks
- Co-located imager checks
- **Pattern recognition algorithms**
- Hybrid systems

Pattern recognition algorithms



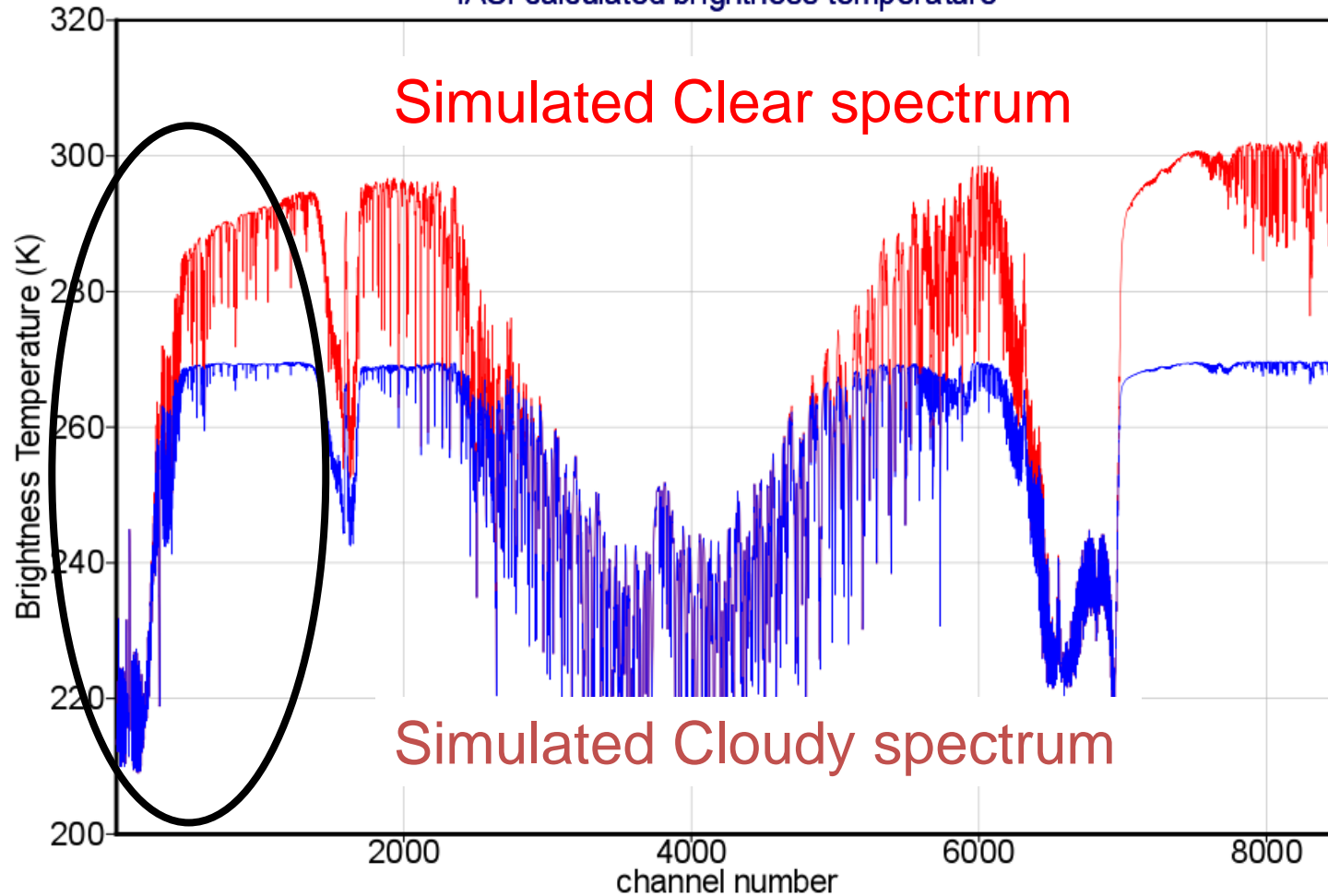
If channels are sensitive only to the atmosphere above a cloud (**black** lines), we would like to keep this data.

So here, we only reject cloud-contaminated channels (**red** lines), and keep the rest!

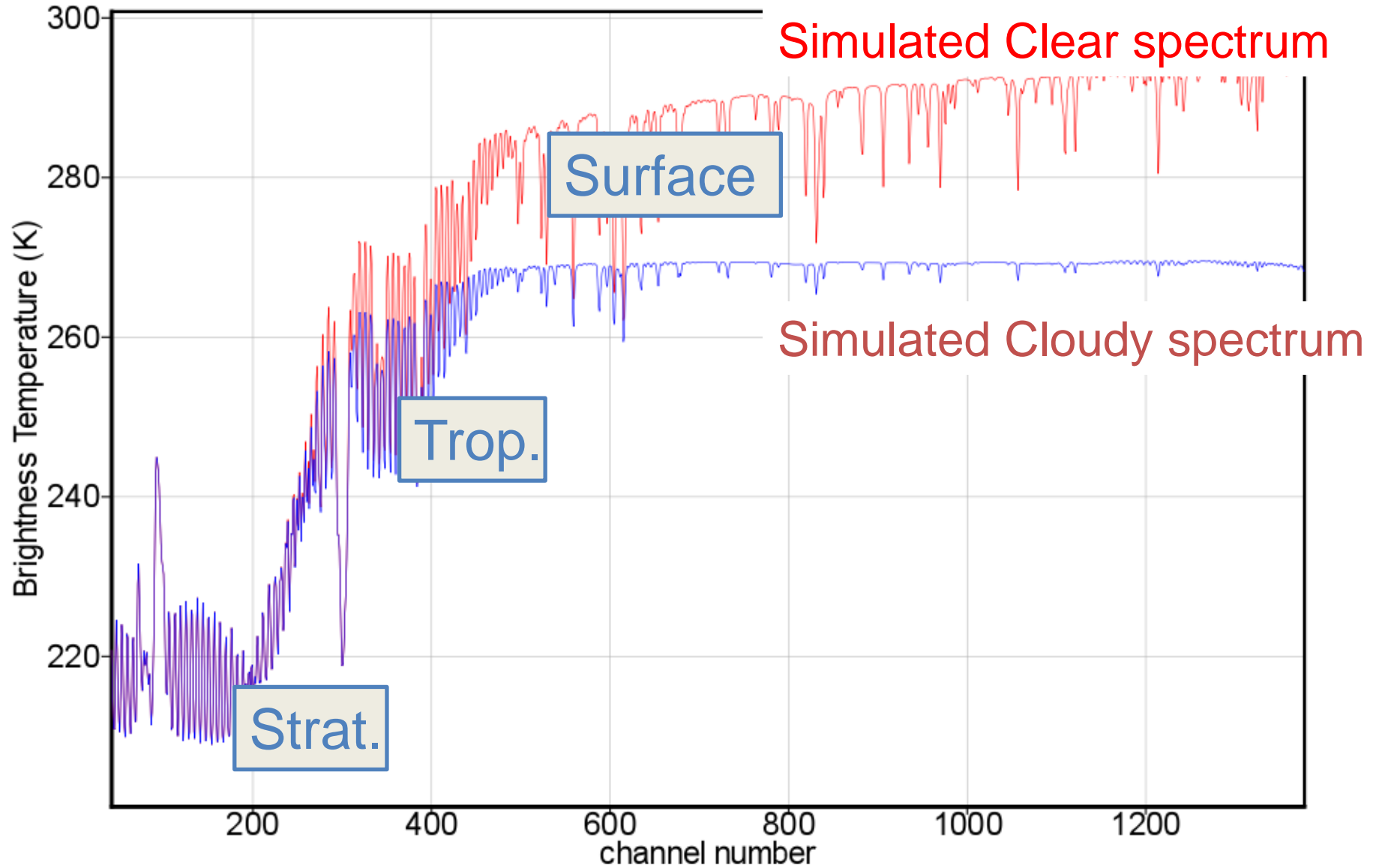
McNally & Watts 2003, <https://doi.org/10.1256/qj.02.208>

How do we do this??

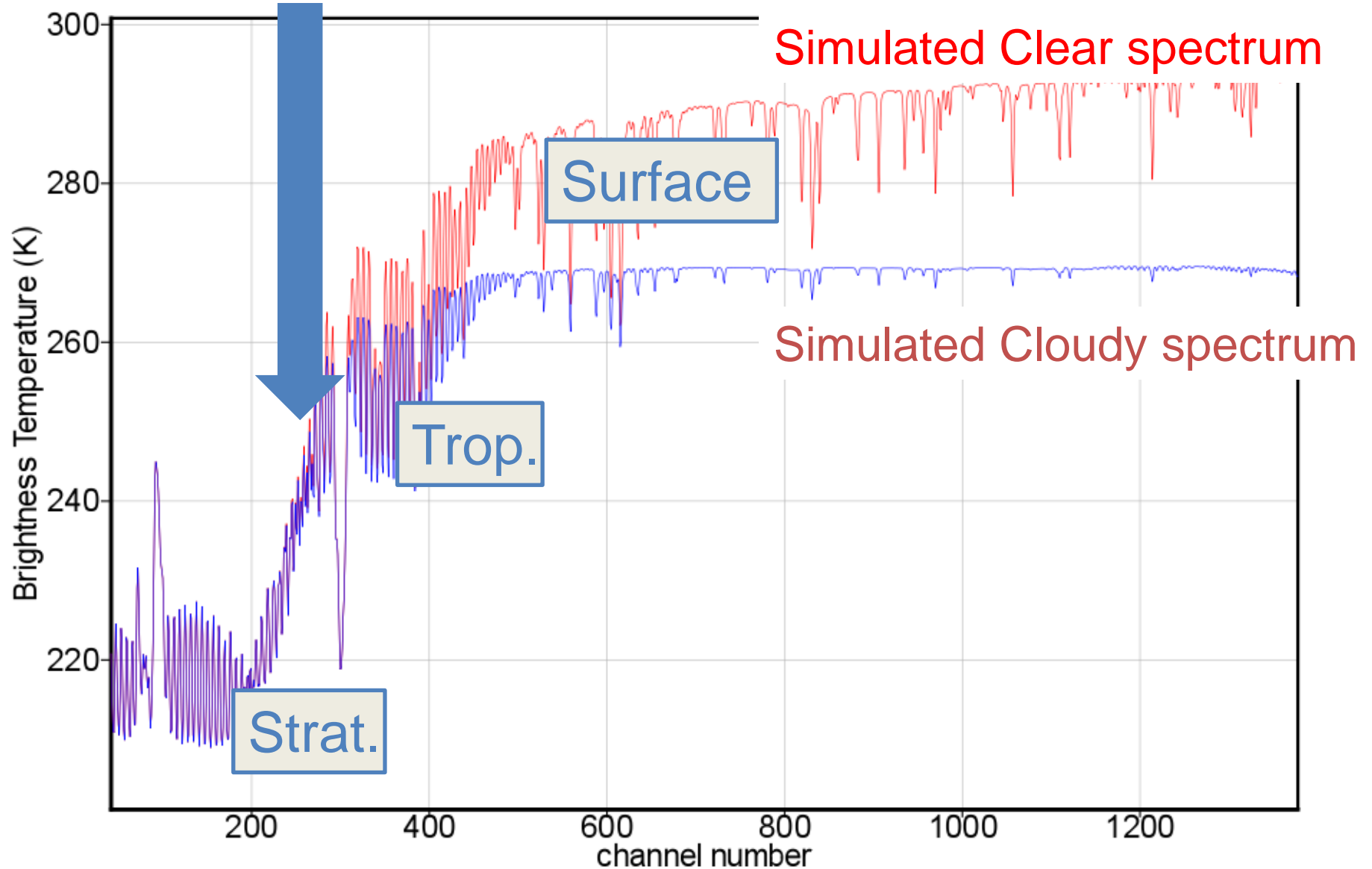
output of RTTOV calculations
IASI calculated brightness temperature



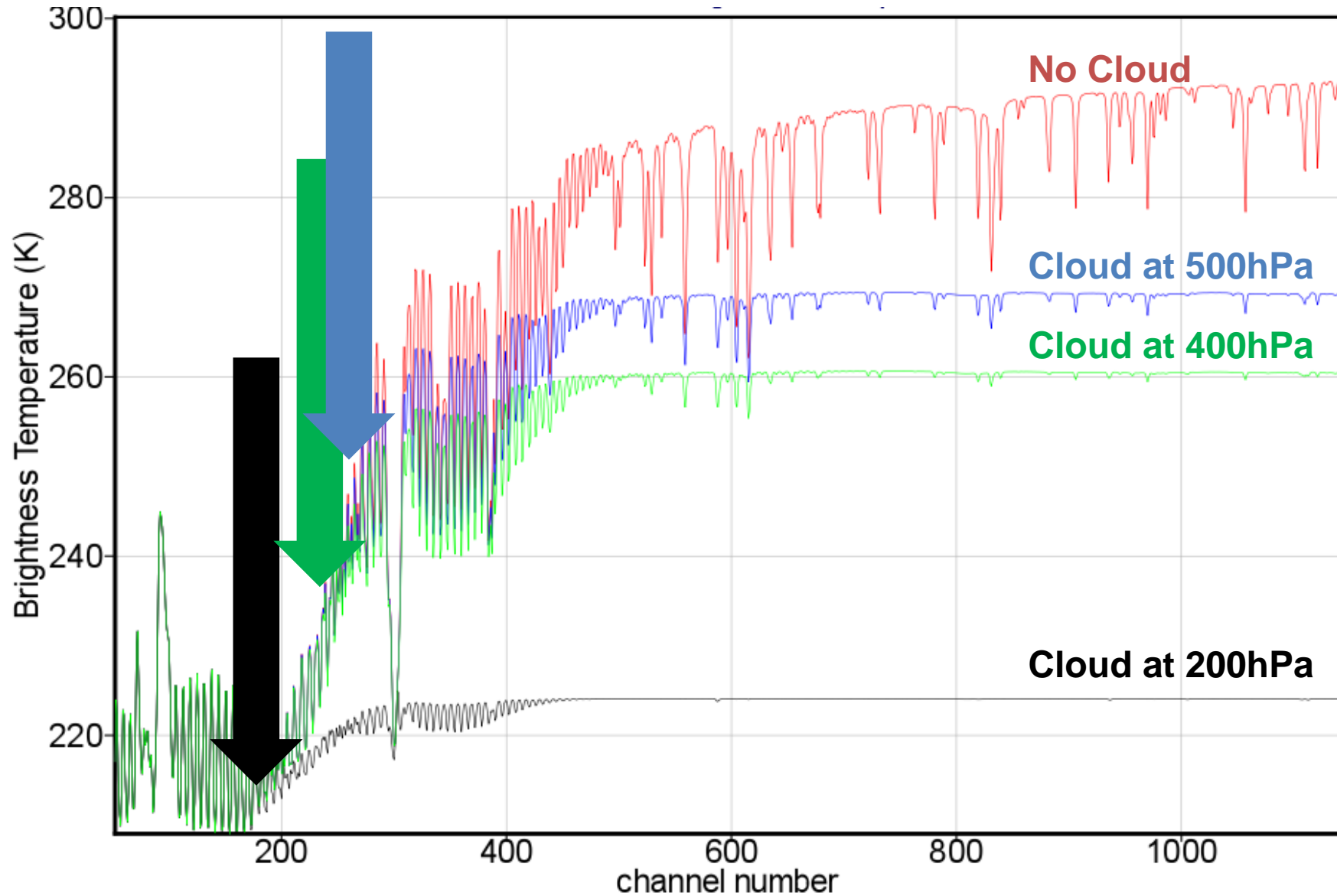
Let's zoom into the long-wave part of the spectrum which has good vertical resolution



Break point



Break point depends on cloud height ...



Break point depends on cloud height ...

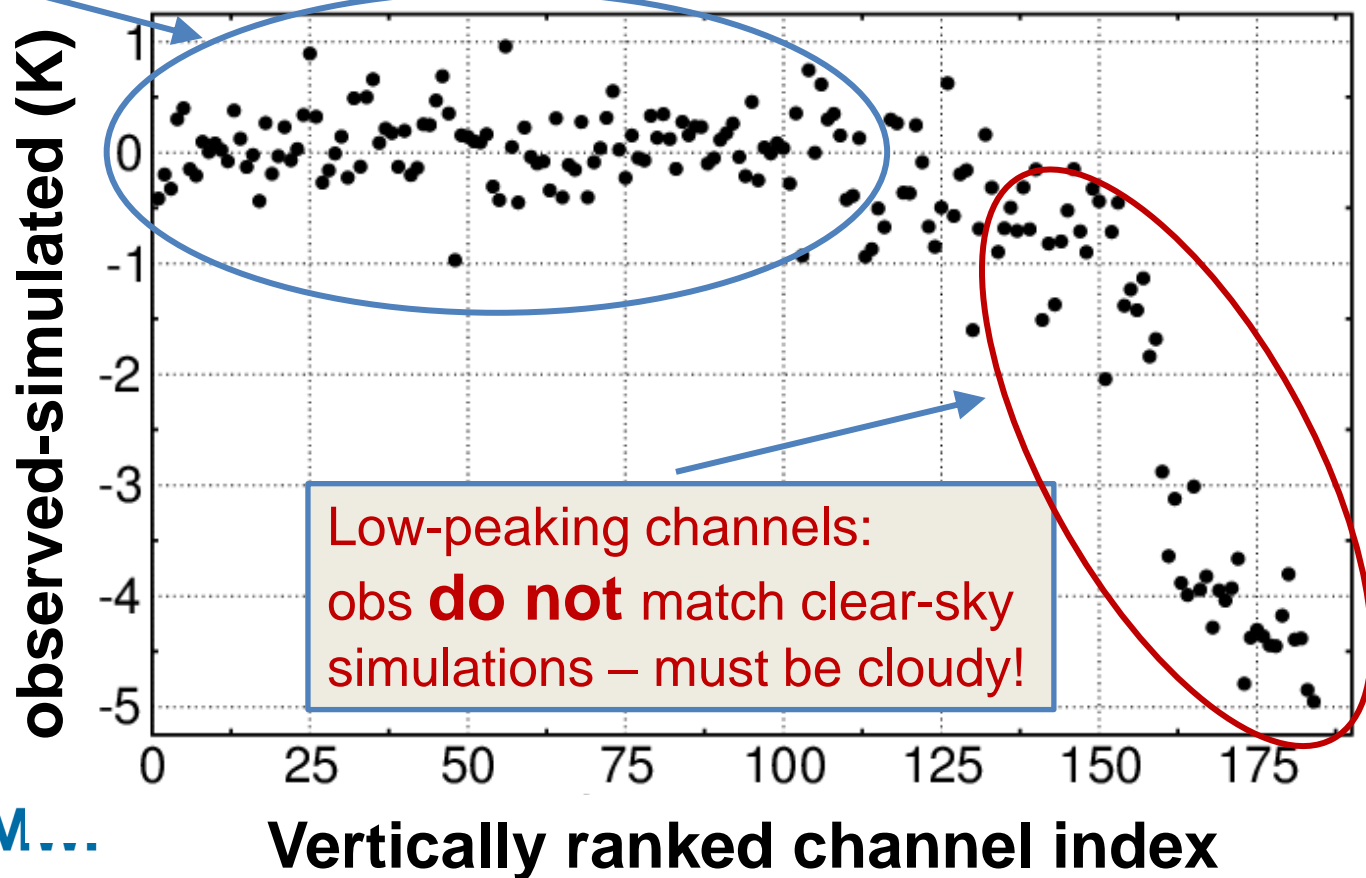


However, the spectra are spiky – the peak height of the channels do not vary monotonically with channel number, so we need to order them.

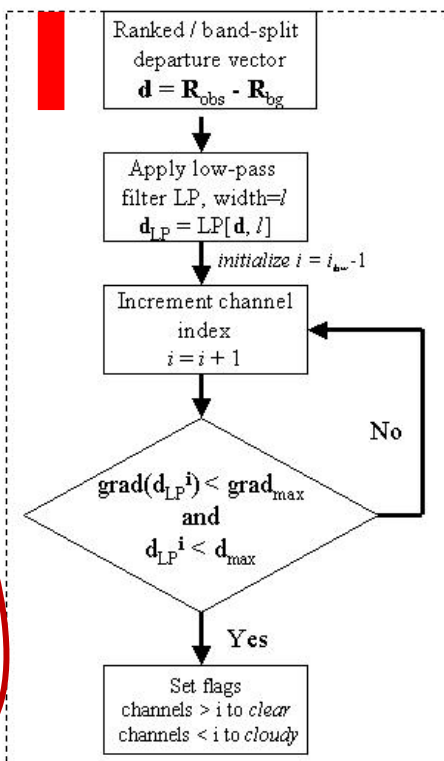


- First we compute the observations minus (clear-sky) simulations.
- Then re-order (rank) the channels according to their height of cloud sensitivity.

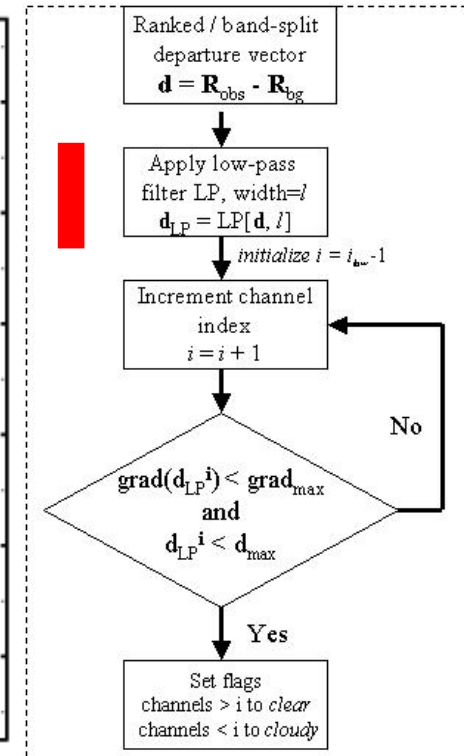
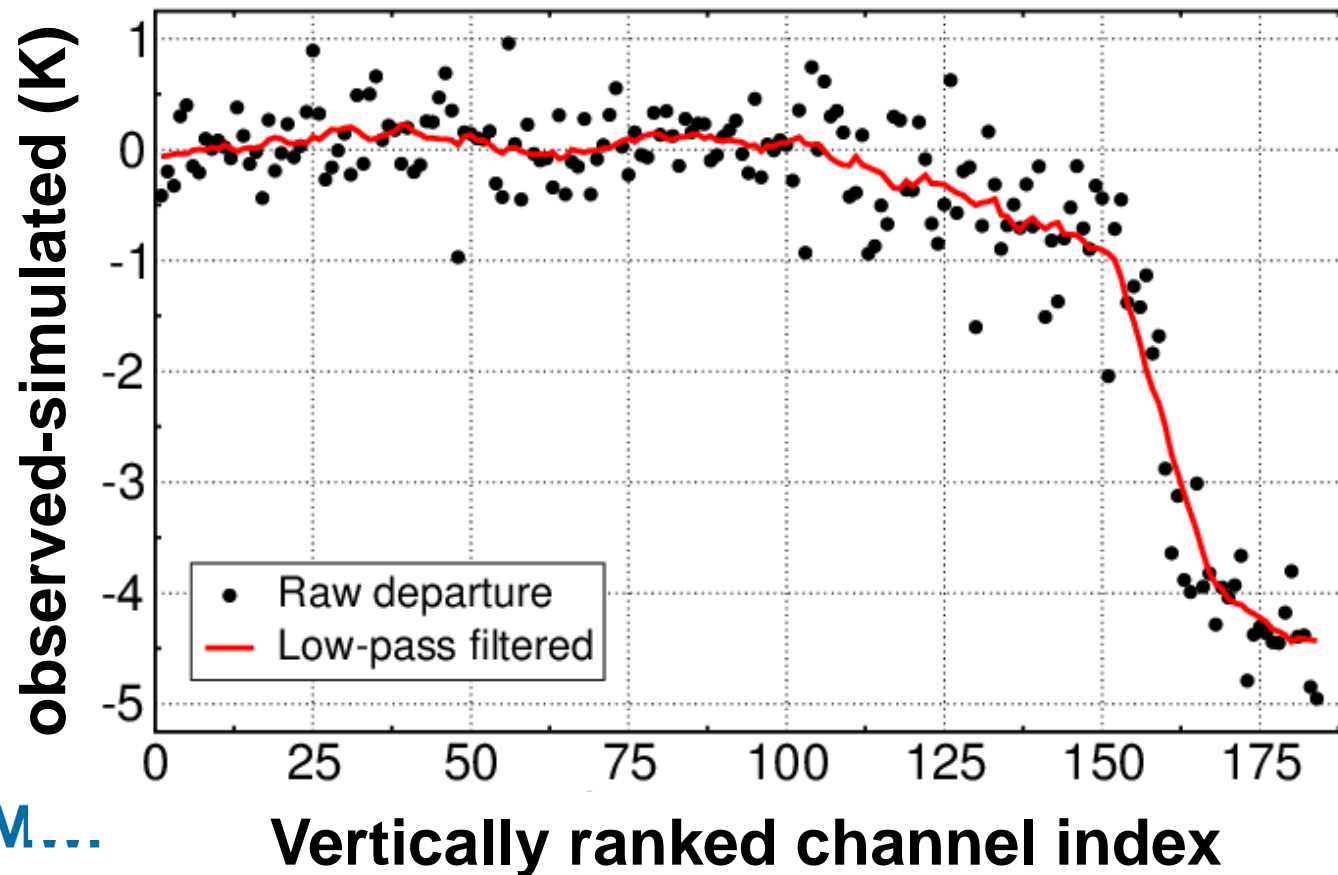
High-peaking channels:
obs match clear-sky simulations.



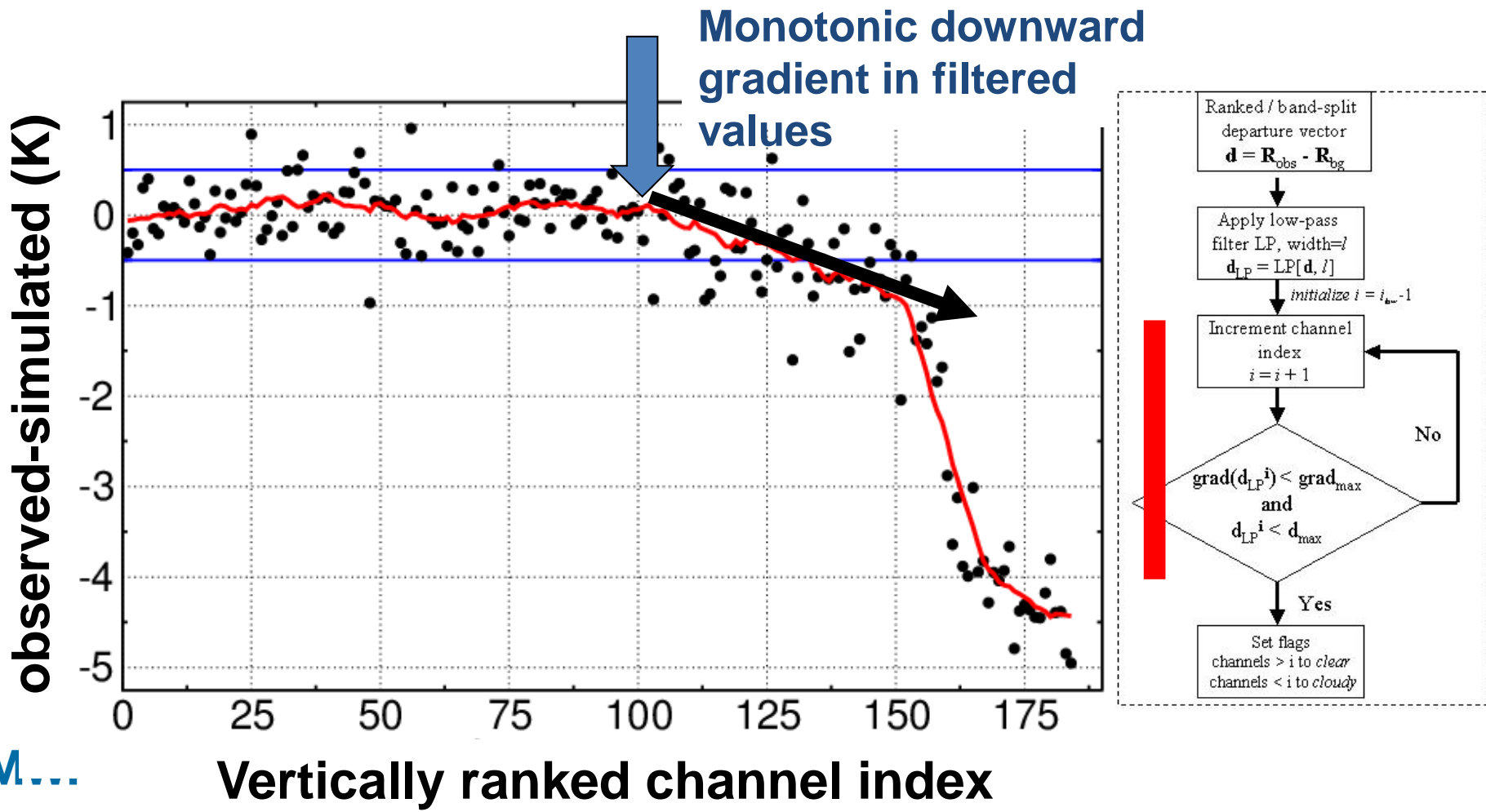
Low-peaking channels:
obs **do not** match clear-sky
simulations – must be cloudy!



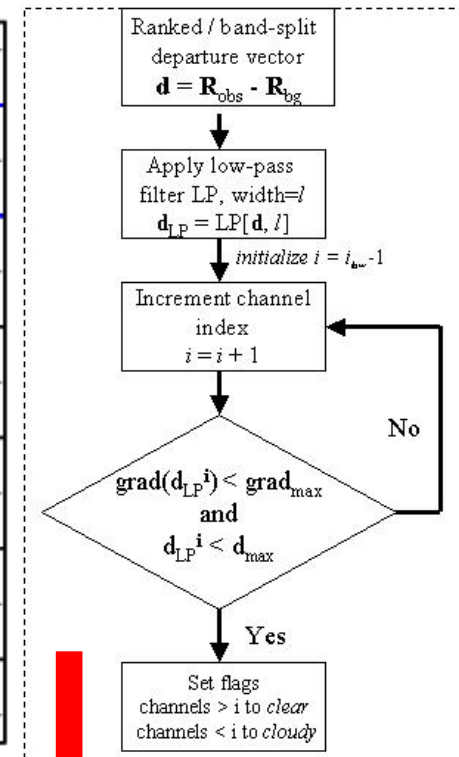
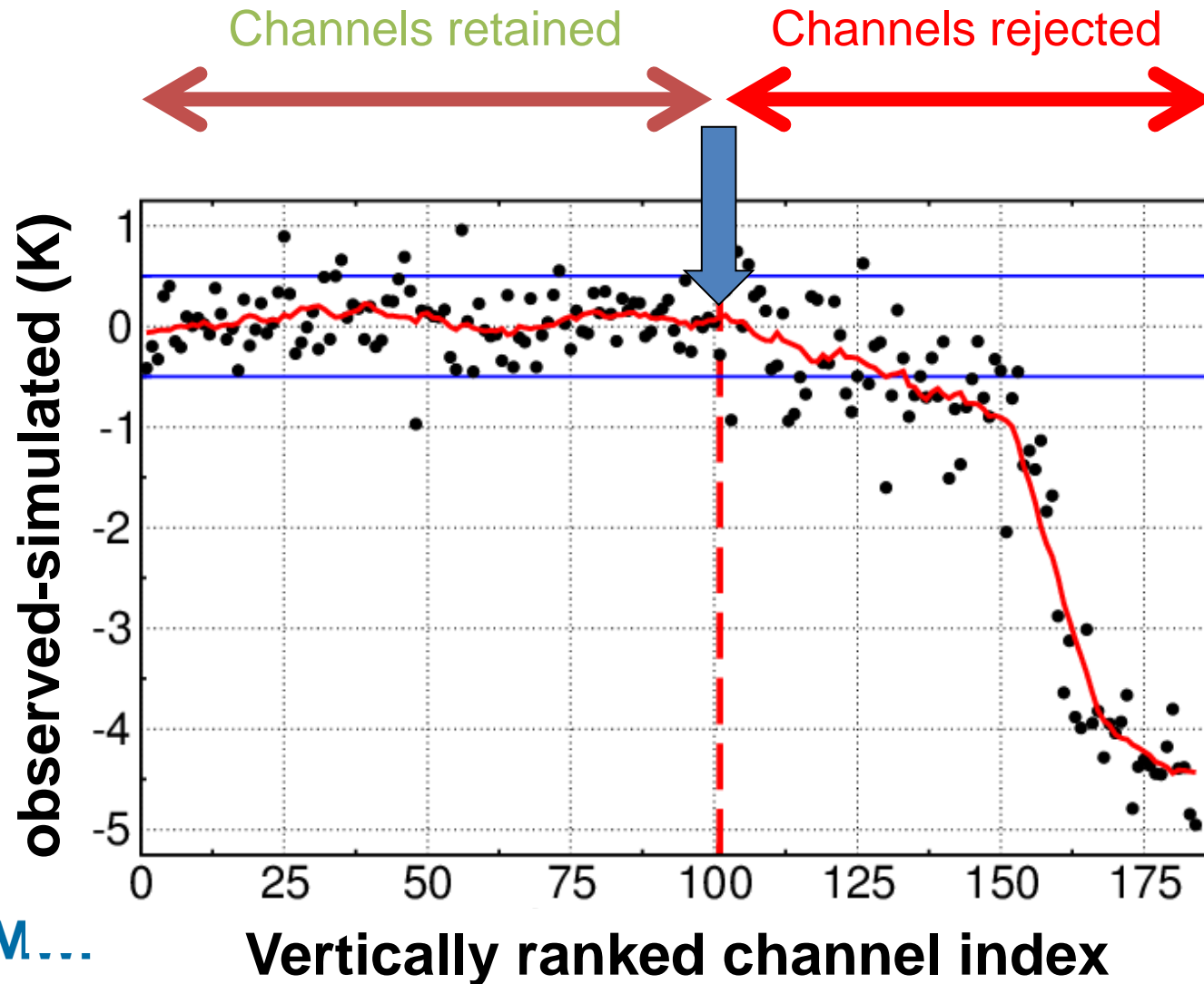
... then we apply a low-pass filter to reduce the effect of noise ...

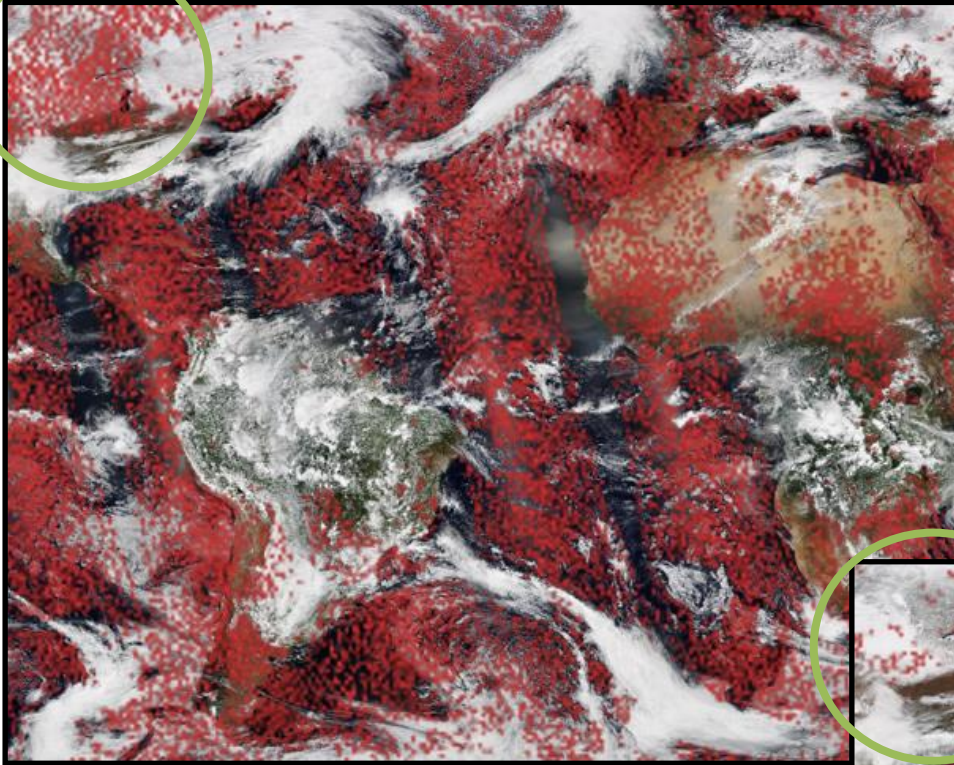


... then we find the break point according to some determined thresholds ...

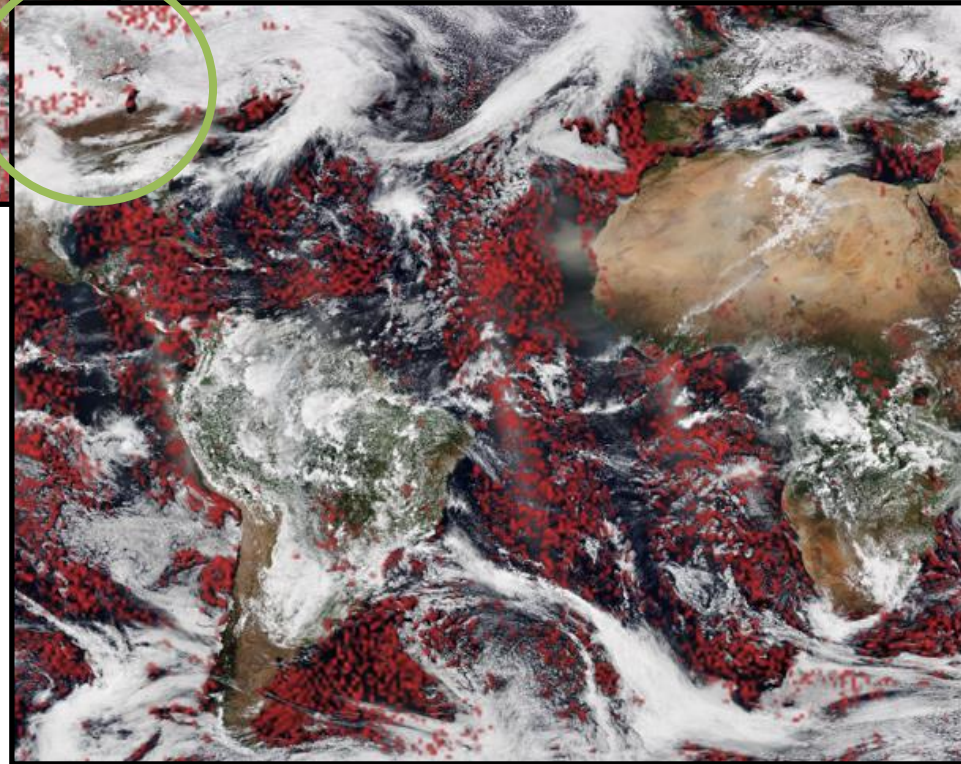


... and finally we set flags to indicate cloud-affected channels





CrIS channel at 14.2 μm
(peak pressure 350 hPa)



CrIS channel at 13.6 μm
(peak pressure 600 hPa)

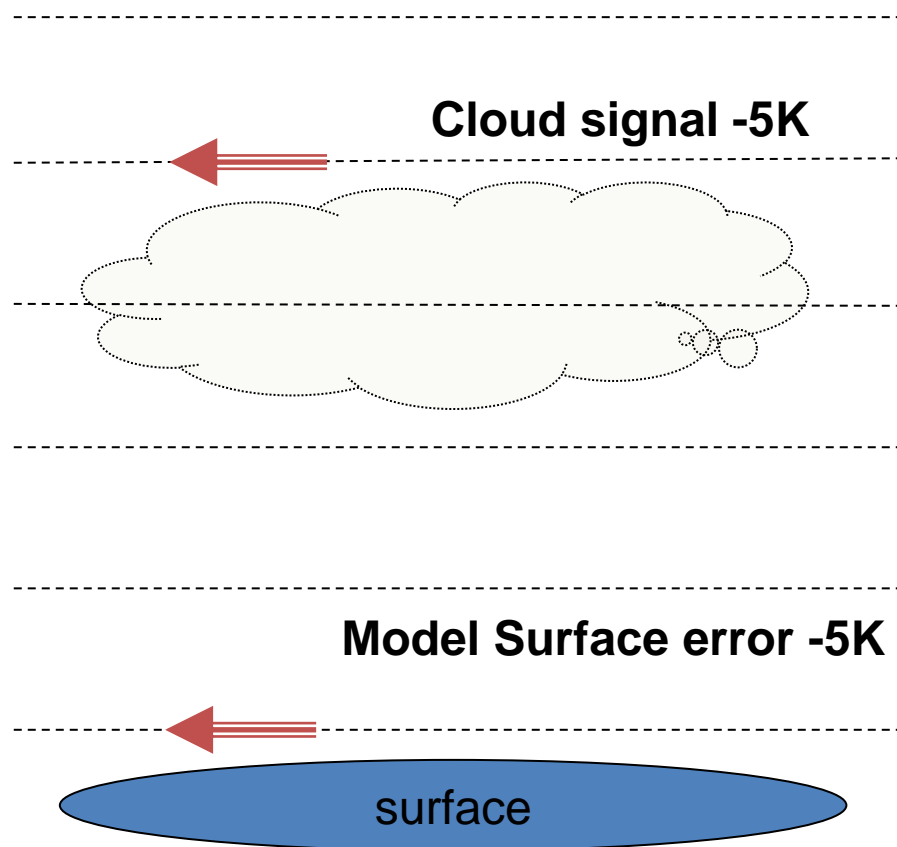
Cloud detection methods



- Window channel departure (O-B) checks
- Co-located imager checks
- Pattern recognition algorithms
- Hybrid systems

Difficult scenes

Consider this plausible situation when trying to assimilate a surface-sensitive infrared channel.



The **radiances** are contaminated by cloud (**cold 5K**) compared to the clear sky value.

But our **computation** of the clear sky value from the background is also **cold by 5K** due to an error in the surface skin temperature.

→ Checking against the background provides no reason to reject the observation and it is **passed as clear!**

Cloud detection can fail in the presence of background error!

		Cloud effect	
		0 K	-5 K
Background error	5 K	$\Delta T_b = -5 \text{ K}$	$\Delta T_b = -10 \text{ K}$
	0 K	$\Delta T_b = 0 \text{ K}$	$\Delta T_b = -5 \text{ K}$
	-5 K	$\Delta T_b = 5 \text{ K}$	$\Delta T_b = 0 \text{ K}$

False alarm (pointing to the cell where background error is 5 K and cloud effect is 0 K)

Missed cloud (pointing to the cell where background error is -5 K and cloud effect is -5 K)

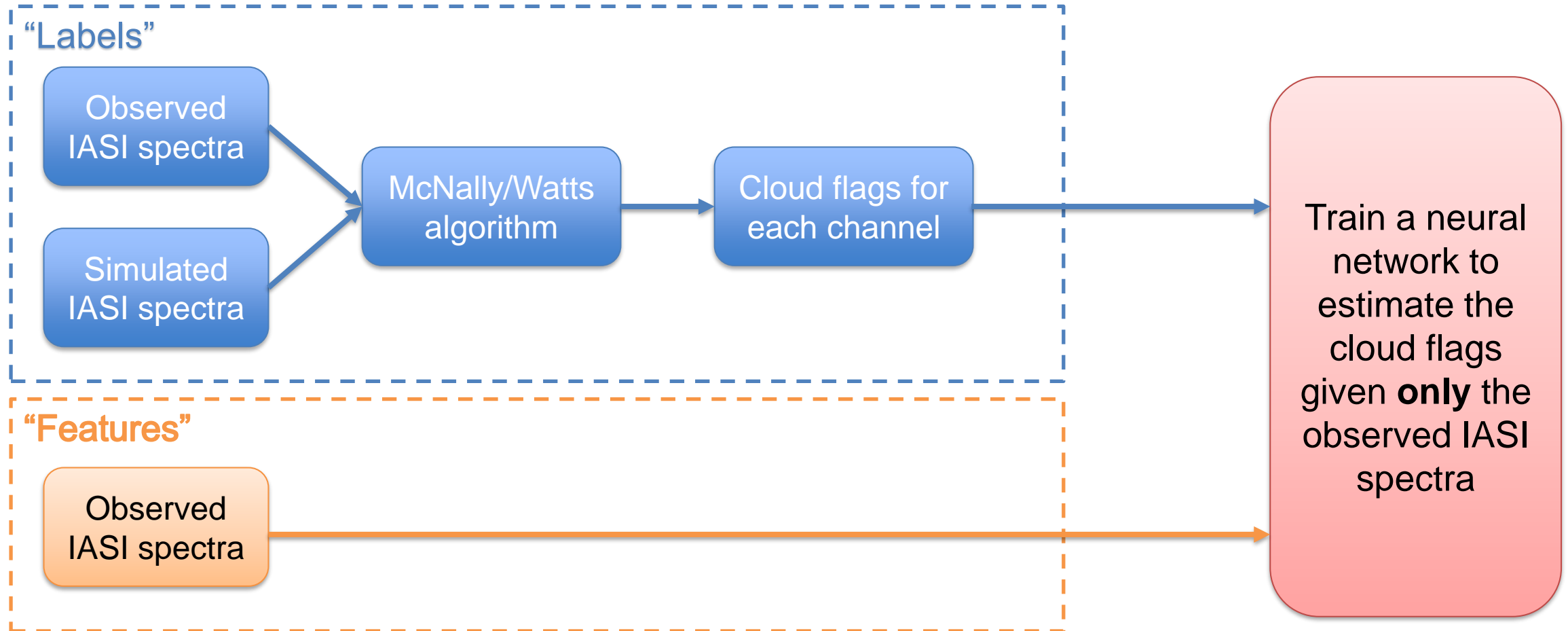
The ECMWF implementation is a **hybrid** scheme that combines the use of co-located imager data with departure-based pattern recognition.

This is complementary and helps to prevent the misidentification of cloud.

See Eresmaa (2014) QJRMS 140, 2342-2352 for details

Can machine learning help us?

Approach – train a NN to replicate the flags from the **ECMWF hybrid** cloud detection scheme, but using **only** observed IASI values as inputs

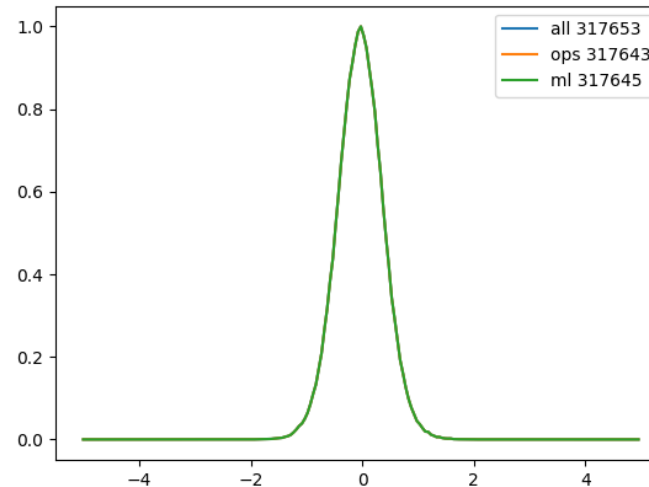


McNally A, Watts P. 2003. A cloud detection algorithm for high-spectral-resolution infrared sounders. Q. J. R. Meteorol. Soc. 129: 3411– 3423, doi: 10.1256/qj.02.208

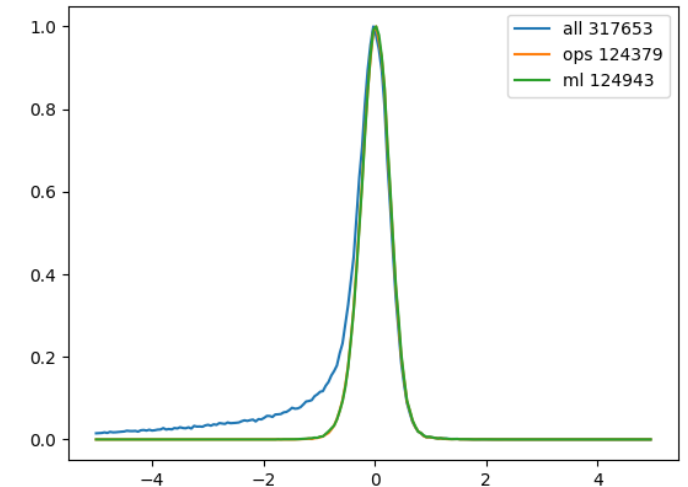
Histograms of observations minus simulations for a few channels

- The 'all' (blue) line shows both clear and cloudy obs (note the **cold tails**).
- The 'ops' (orange) line shows the cloud-free sample using the operational cloud detection scheme.
- The 'ml' (green) line shows the cloud-free sample from the neural network.
- **We want machine-learning statistics, 'ml' (green) to match the operational statistics, 'ops' (orange).**
- Generally, the agreement is very good and importantly, the cold tails are mostly removed.
- The window channel (861.5 cm⁻¹) shows the worst agreement, with significant broadening.

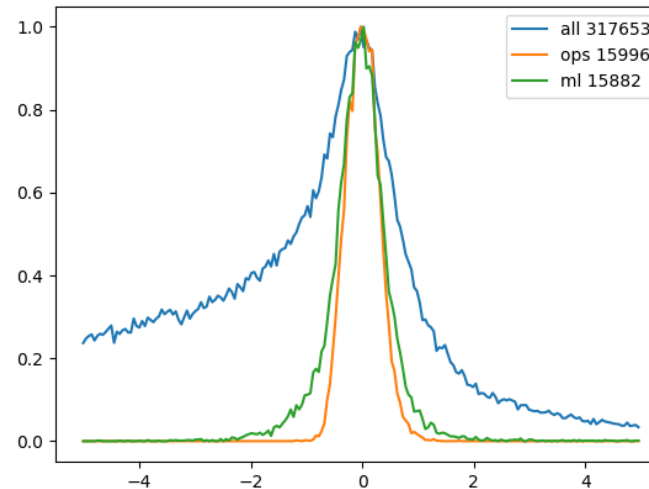
648.75 cm⁻¹



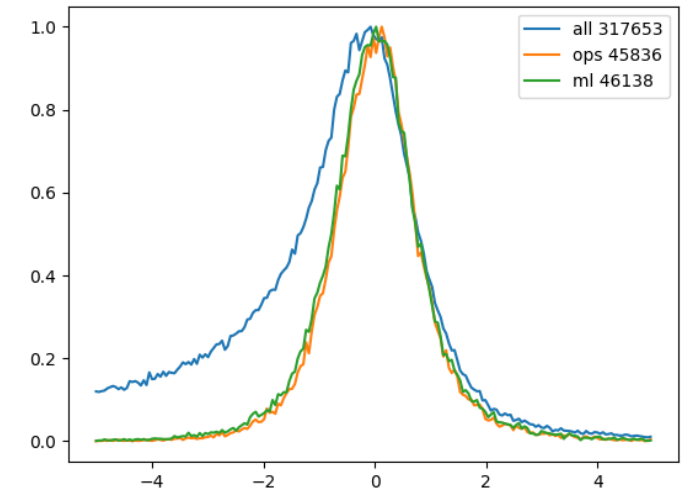
713.5 cm⁻¹



861.5 cm⁻¹



1367 cm⁻¹

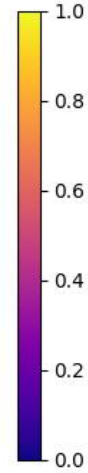
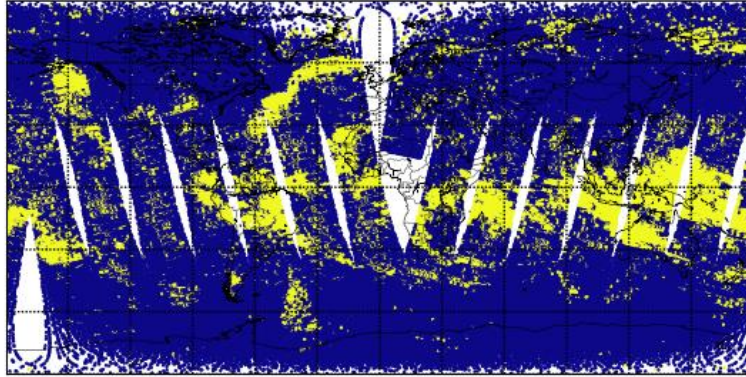


Initial fit looks fairly good, even with a limited training set

Yellow is cloudy, blue is clear

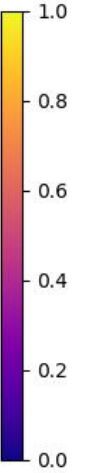
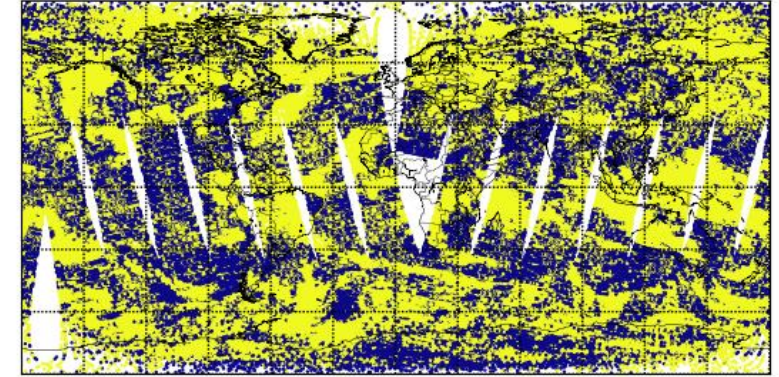
Higher-peaking

51hPa IFS



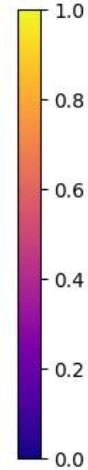
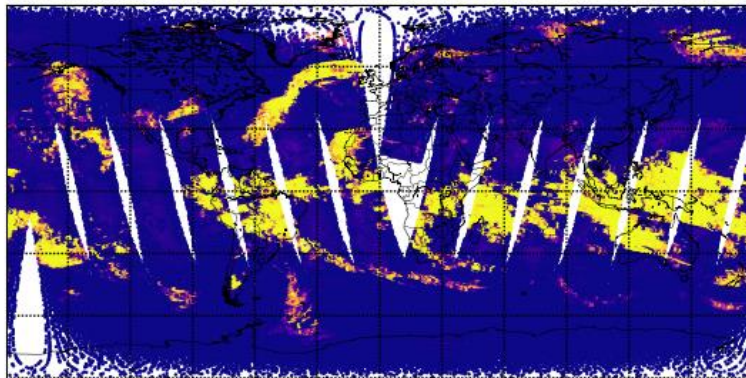
Lower-peaking

358hPa IFS

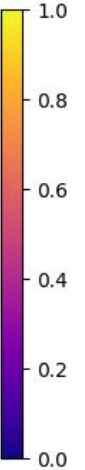
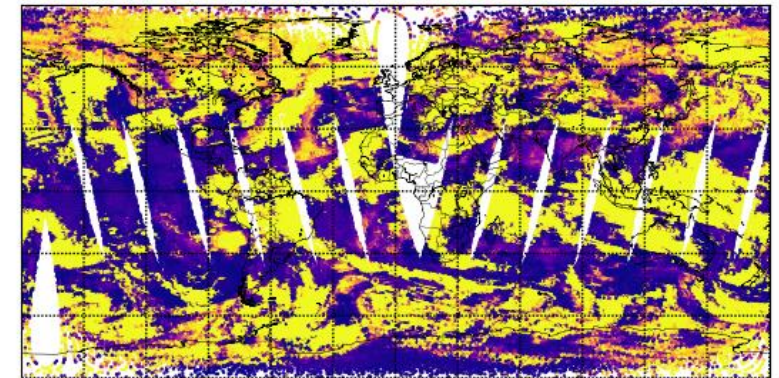


Physically-based method

51hPa ML



358hPa ML

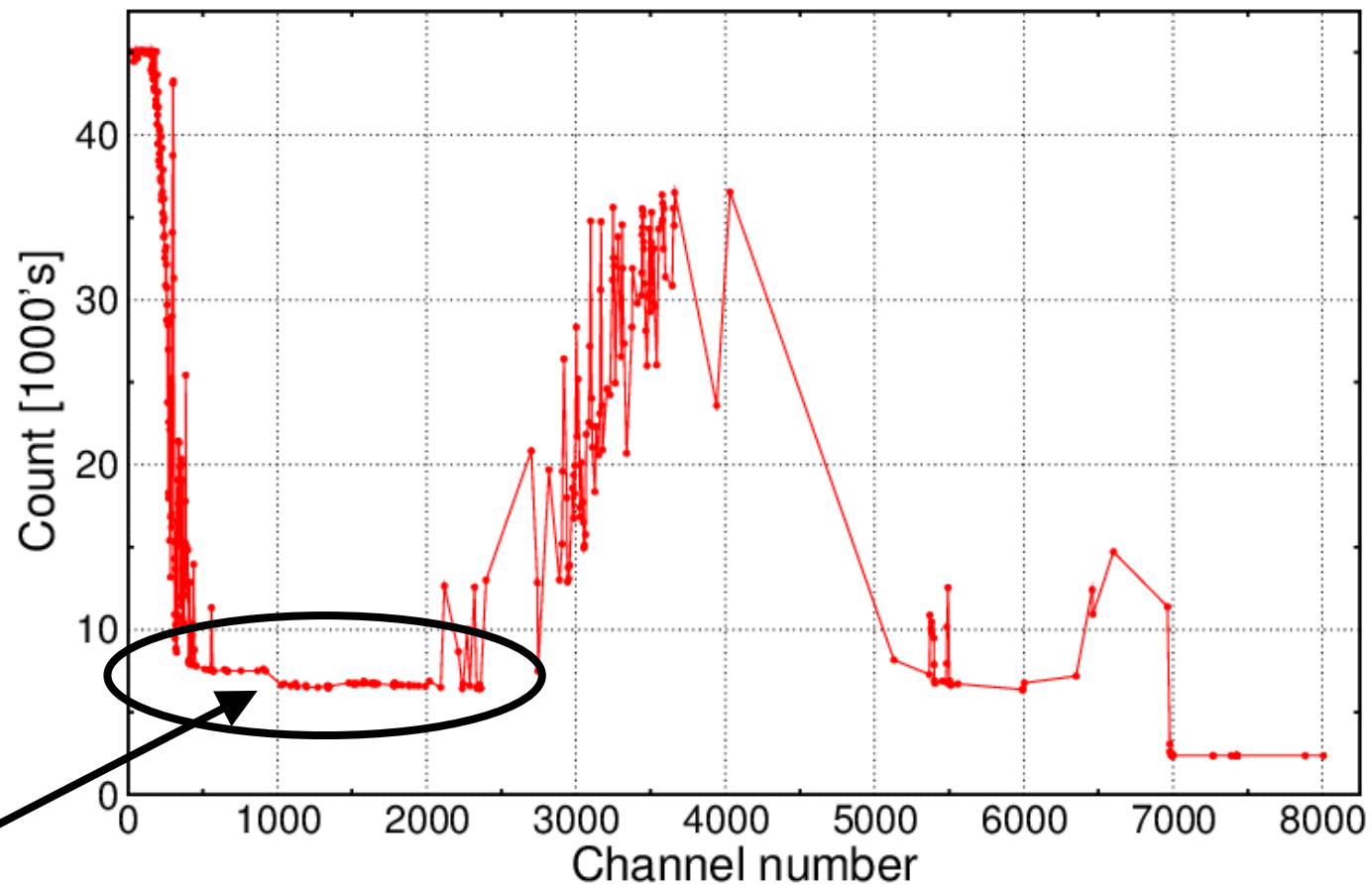


Neural network

Big question: How should we handle clouds when assimilating infrared radiance observations??

- **Option 1:** detect and reject cloud-contaminated observations.
- **Option 2:** **Explicitly estimate** cloud parameters from the radiances within the data assimilation (T, Q, O₃ etc)

This “**all-sky**” approach will allow us to use more data!



Window channels get used less than 20% of the time due to cloud-detection

“All-sky” assimilation: the cost function $J(\mathbf{x})$

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

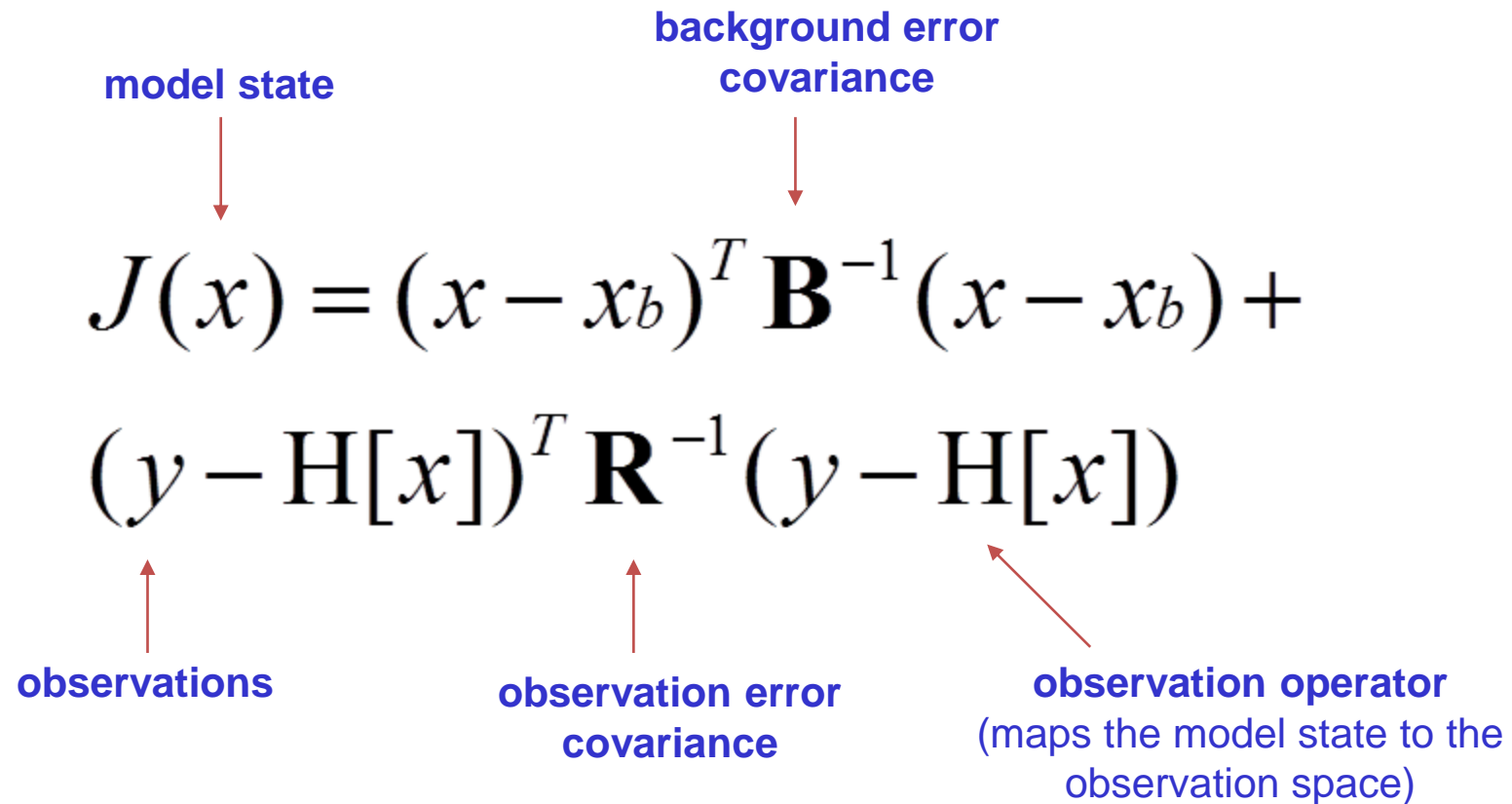
model state

background error covariance

observations

observation error covariance

observation operator
(maps the model state to the observation space)



If we wish to assimilate cloudy radiance observations

The cost function $J(x)$

model state must include clouds (clw,cic,cf)

$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) + (y - H[x])^T \mathbf{R}^{-1} (y - H[x])$$

The cost function $J(x)$

Background error covariance **must include clouds (clw,cic,cf)**



$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) + (y - H[x])^T \mathbf{R}^{-1} (y - H[x])$$

The cost function $J(x)$

$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) + (y - H[x])^T \mathbf{R}^{-1} (y - H[x])$$



Observation operator (RT and Model) **must include clouds (clw,cic,cf)**

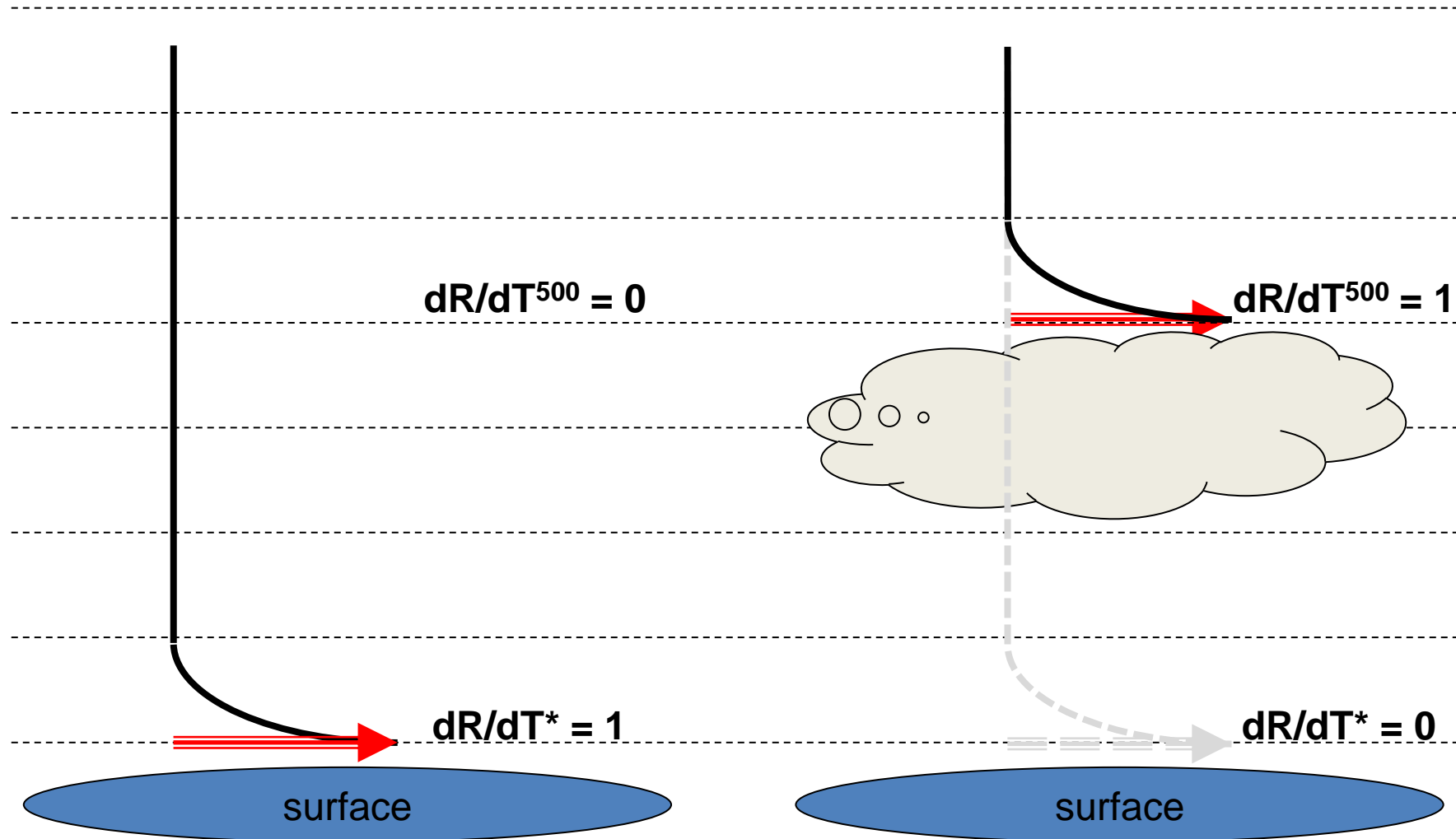
Note!

Unlike the first section, we are now simulating **cloud-affected** radiances.

Potential difficulties in practice

- The cloud uncertainty in radiance terms may be several orders of magnitude larger than the T and Q signal (i.e. 10s of kelvin compared to 0.1s of kelvin).
- Background errors may be difficult to quantify and model for cloud parameters.
- Conflict between having enough cloud variables for an accurate RT calculation while limiting the number of cloud variables to those that can be uniquely estimated in the analysis from the observations.
- The radiance response to cloud changes is highly non-linear.

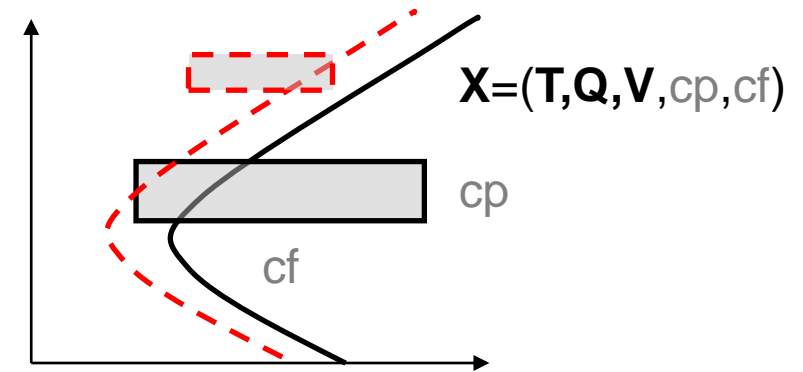
Weighting Functions in clear and cloudy sky



Two approaches to assimilate cloud- affected infrared radiances

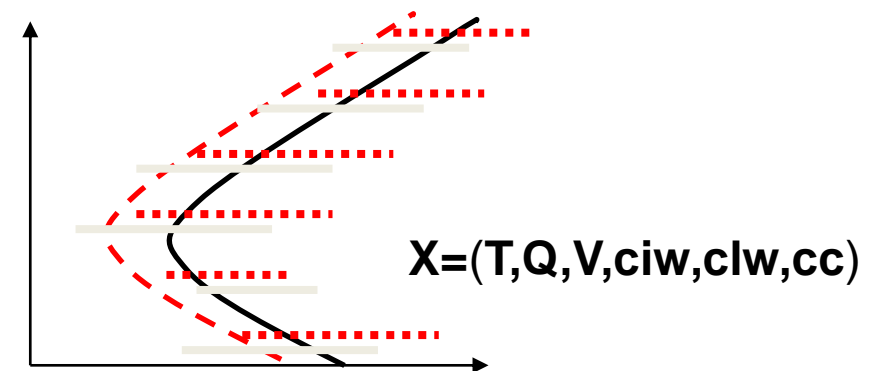
Simplified system:

- 2-parameter cloud representation
- Currently only **fully overcast** scenes are assimilated this way
- No background cloud information taken from the NWP model
- No interaction with NWP model via physics
- The retrieved cloud information is discarded



Advanced system:

- Cloud variables on model levels
- Aim to assimilate all cloud conditions
- Background cloud information is taken from the NWP model
- Back interaction with NWP model via physics



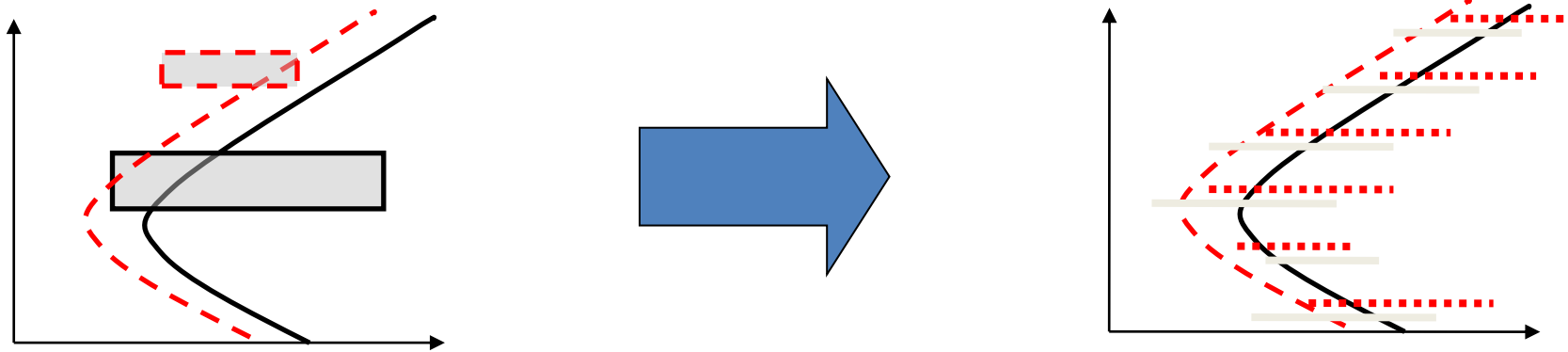
Simplified system

model state has only one extra variable = cloud top height

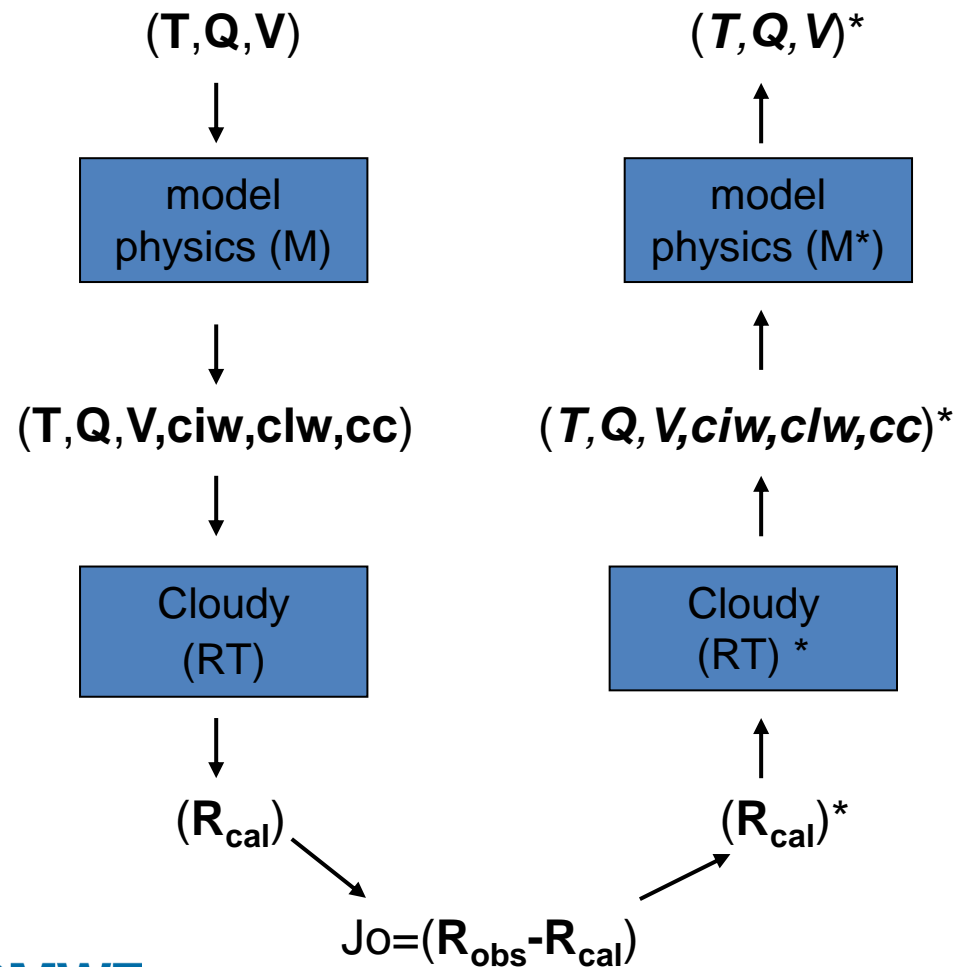
$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) + (y - H[x])^T \mathbf{R}^{-1} (y - H[x])$$

The additional cloud parameter is known as a “**sink**” variable. It is used in order to allow the assimilation of overcast radiances, but its retrieved cloud variables are not used by the model.

Towards an Advanced Cloudy IR Radiance Assimilation (“all sky” IR)



Towards an *Advanced* Cloudy IR Radiance Assimilation



We simulate cloudy radiances R_{cal} via a **chain of forward operators** (M,RT).

We compute the fit of the analysis to the observations (J_0)

We minimize J_0 by perturbing the analysis variables according to gradients from a **chain of adjoint operators** (RT*,M*)

Recent progress:

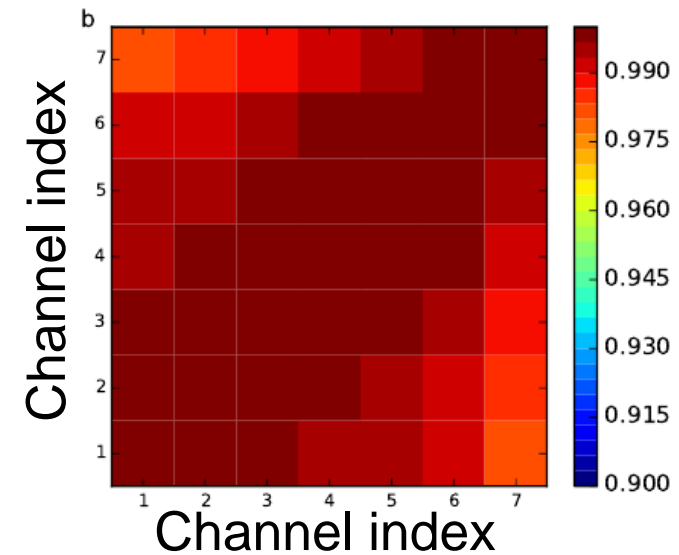
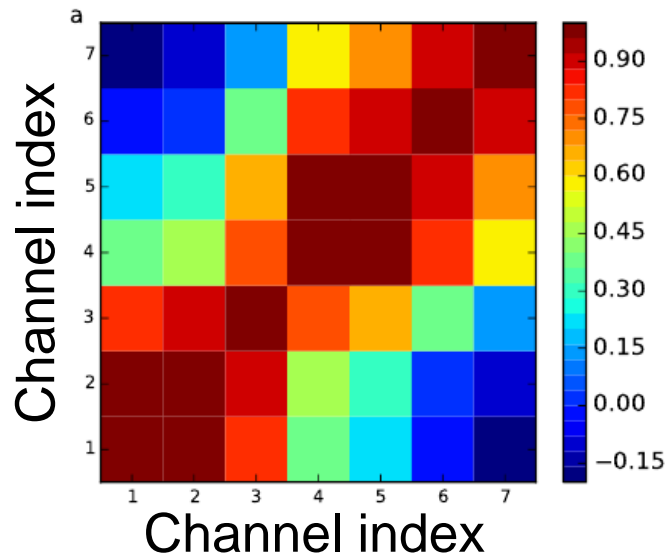
- Improved cloudy background via increased NWP resolution and sophisticated physical modelling of clouds.
 - Accounting for scattering effects in radiative transfer calculation.
 - Representation of ice cloud optical properties.
 - Efficient modelling of overlapping cloud layers.
 - Situation-dependent observation error specification.
- Promising results from the use of *humidity-sensitive* IR radiances in the microwave “**all-sky**” framework.

Recent review on all-sky IR progress: <https://doi.org/10.1007/s00376-021-1088-9>

Questions ?

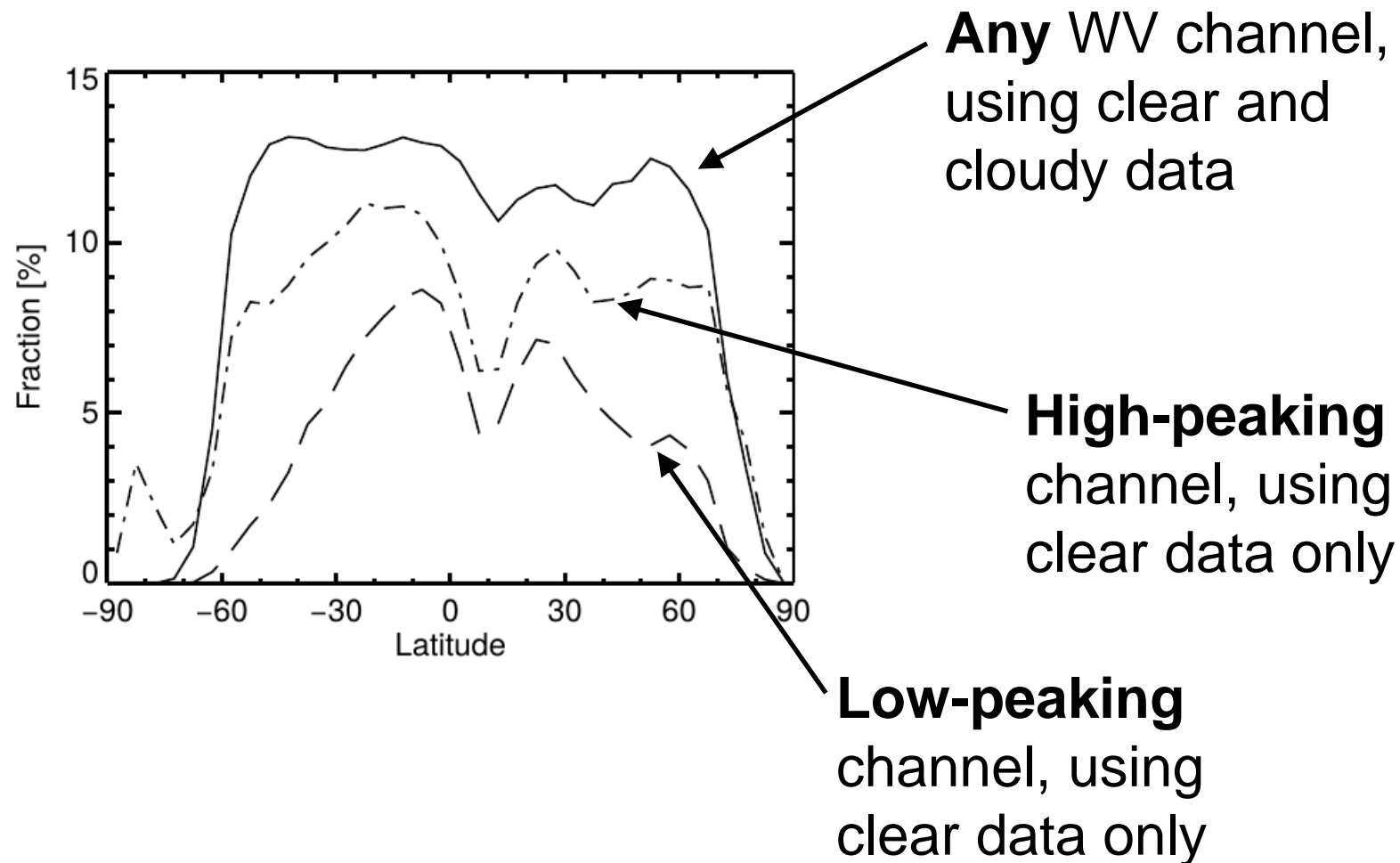
Situation-dependent observation error model

Observation error correlation in clear-sky conditions



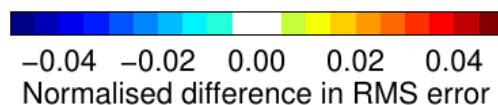
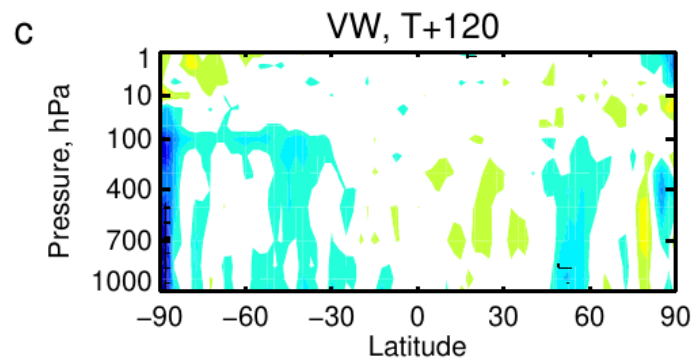
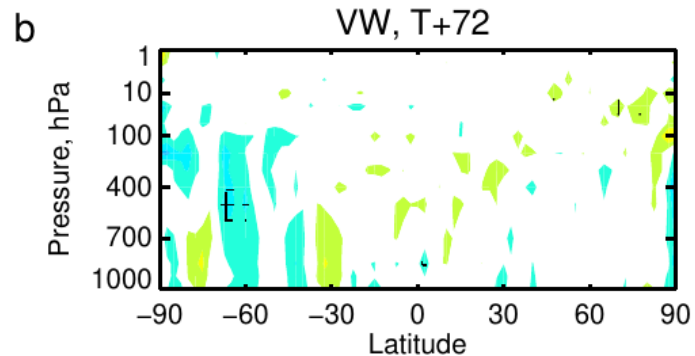
Observation error correlation in fully cloudy conditions

Active data count in “*clear-sky*” vs “*all-sky*” use of IR radiances

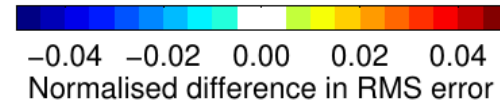
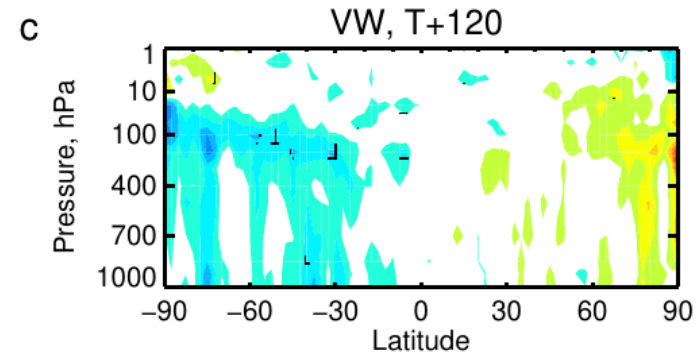
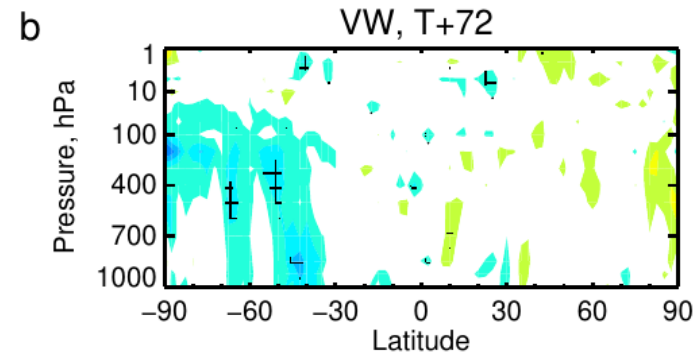


The two systems produce comparable forecast impacts

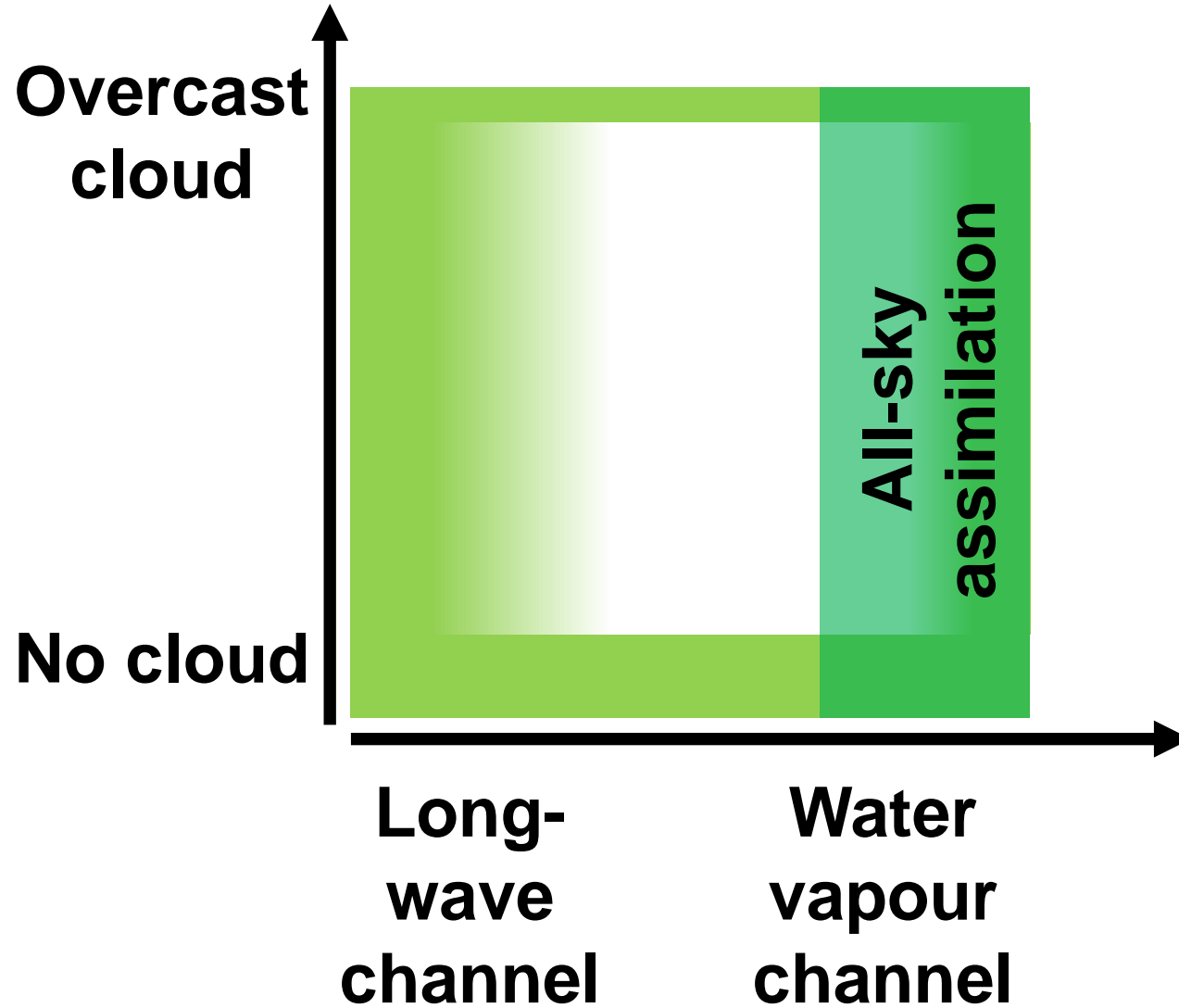
Adding seven humidity-sensitive IASI channels when clear



Adding seven humidity-sensitive IASI channels when clear or cloudy



Summary



The ECMWF implementation is a hybrid scheme that combines the use of co-located imager data with departure-based pattern recognition

Using departures only

		Clear	Cloudy	Total
Using imager only	Clear	5.2%	3.4%	8.6%
	Cloudy	5.5%	85.9%	91.4%
	Total	10.7%	89.3%	100.0%

See Eresmaa (2014) QJRMS **140**, 2342-2352 for details