The detection and assimilation of cloud-affected infrared satellite radiances

ECMWF/EUMETSAT NWP-SAF Satellite Data Assimilation Training Course

11-15 March 2024

Tony McNally, Reima Eresmaa, **Chris Burrows**

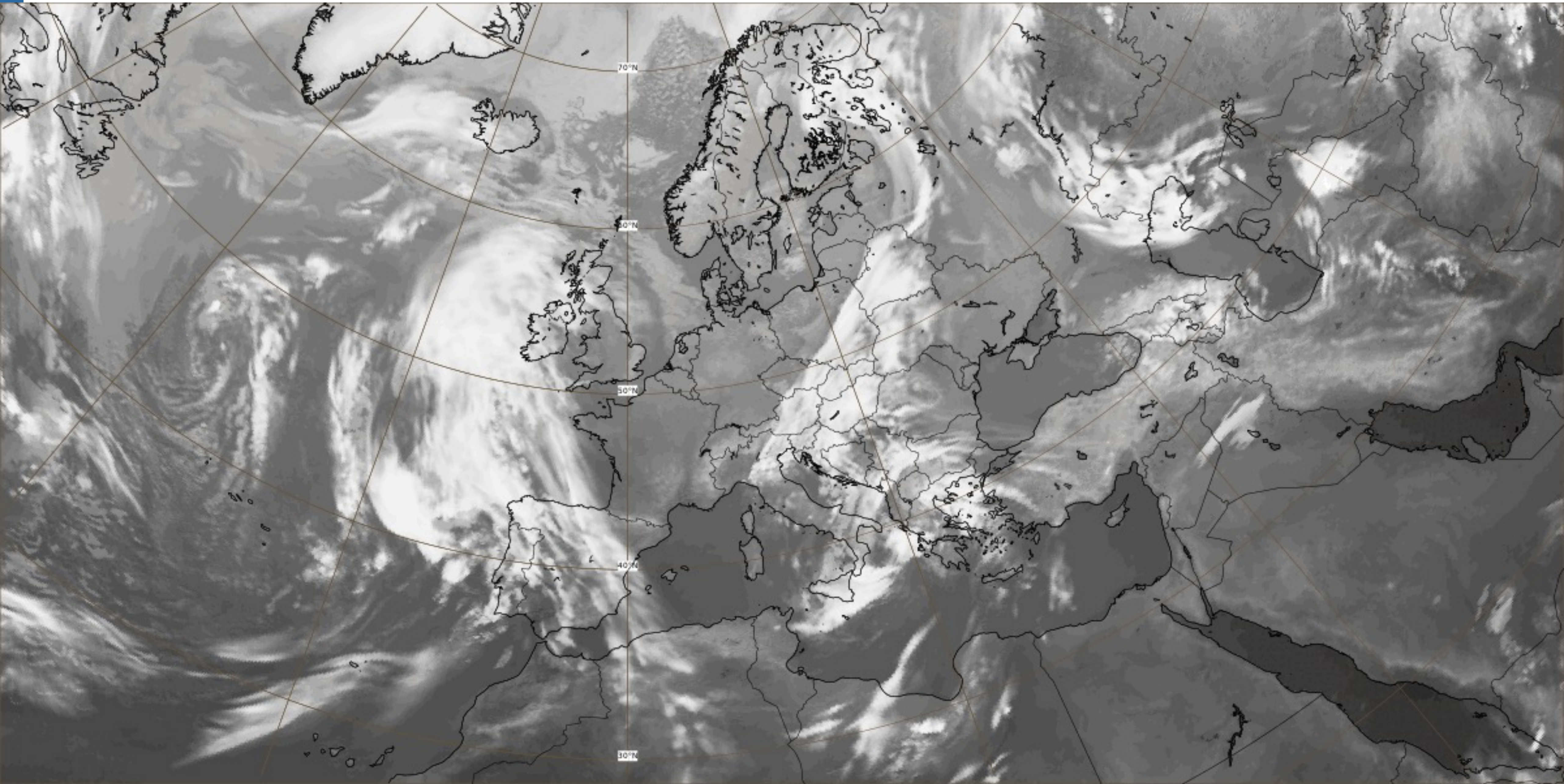
chris.burrows@ecmwf.int

Outline

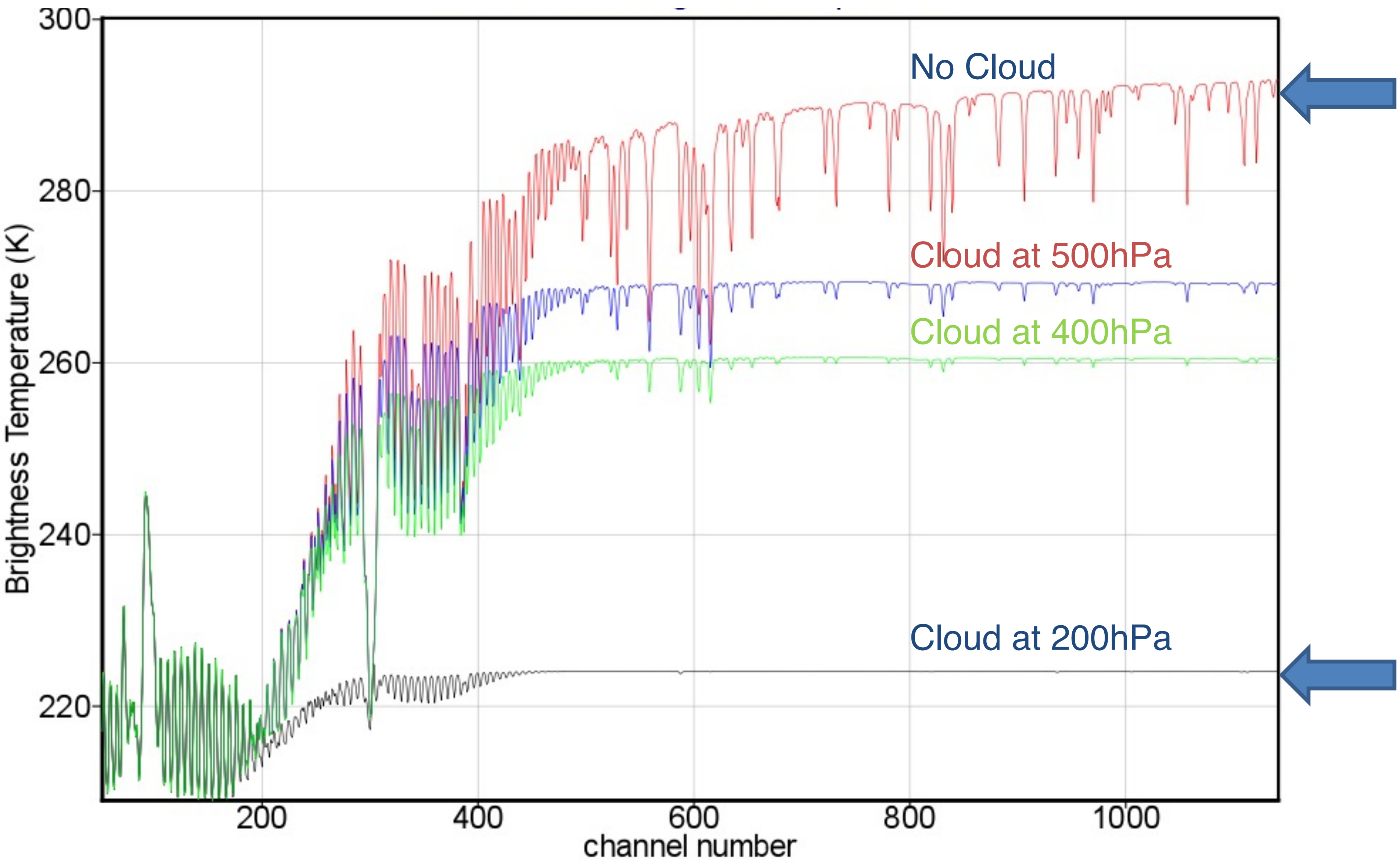
- **The effect of cloud on infrared radiances**
- **Cloud detection/rejection methods:**
  - simple departure checks
  - co-located imager information
  - pattern recognition
  - hybrid approach
  - machine learning
- **“All-sky” infrared assimilation:**
  - simplified approach
  - recent progress

ECMWF

The detection and assimilation of clouds in IR radiances



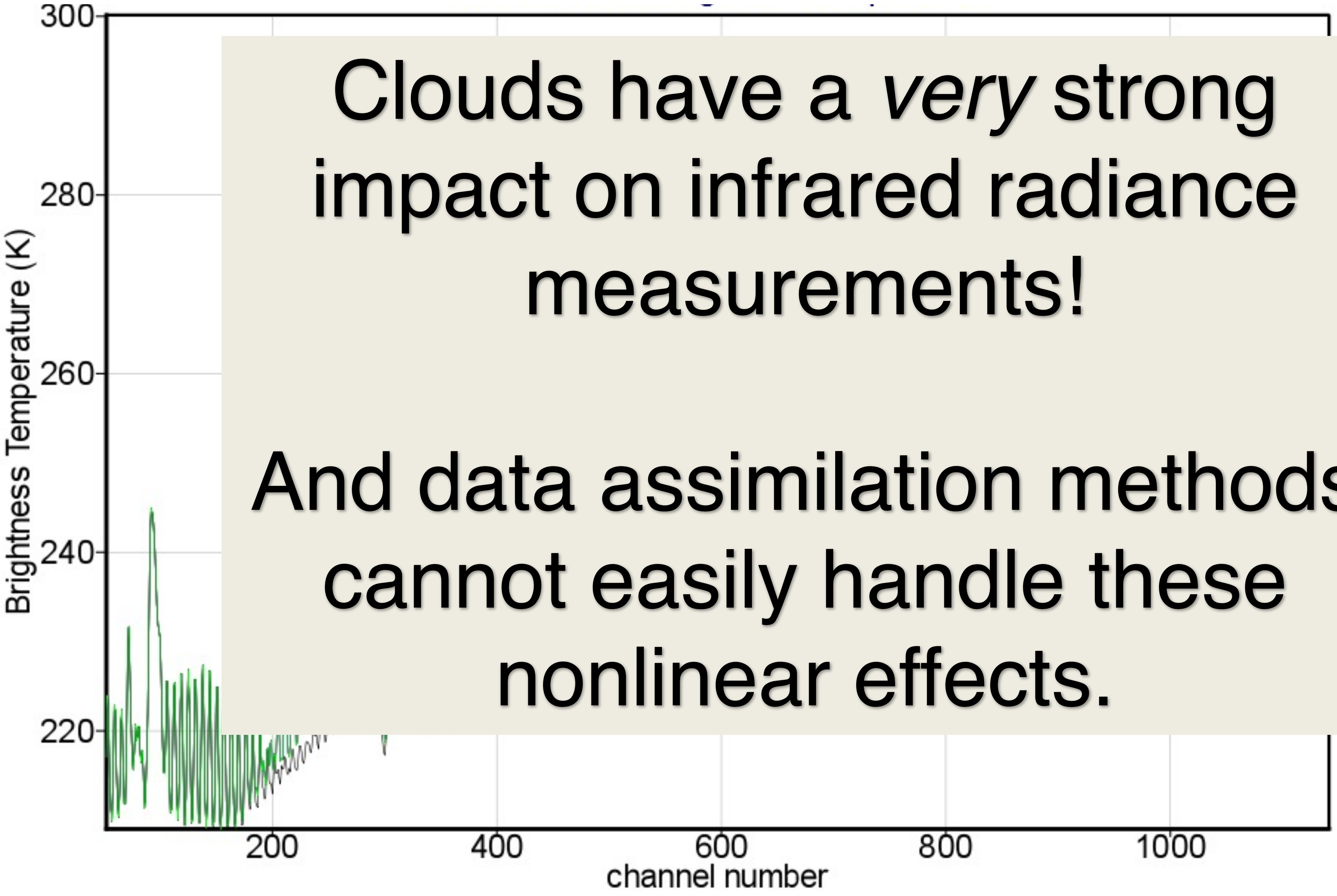
IR spectra with (and without) clouds



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!

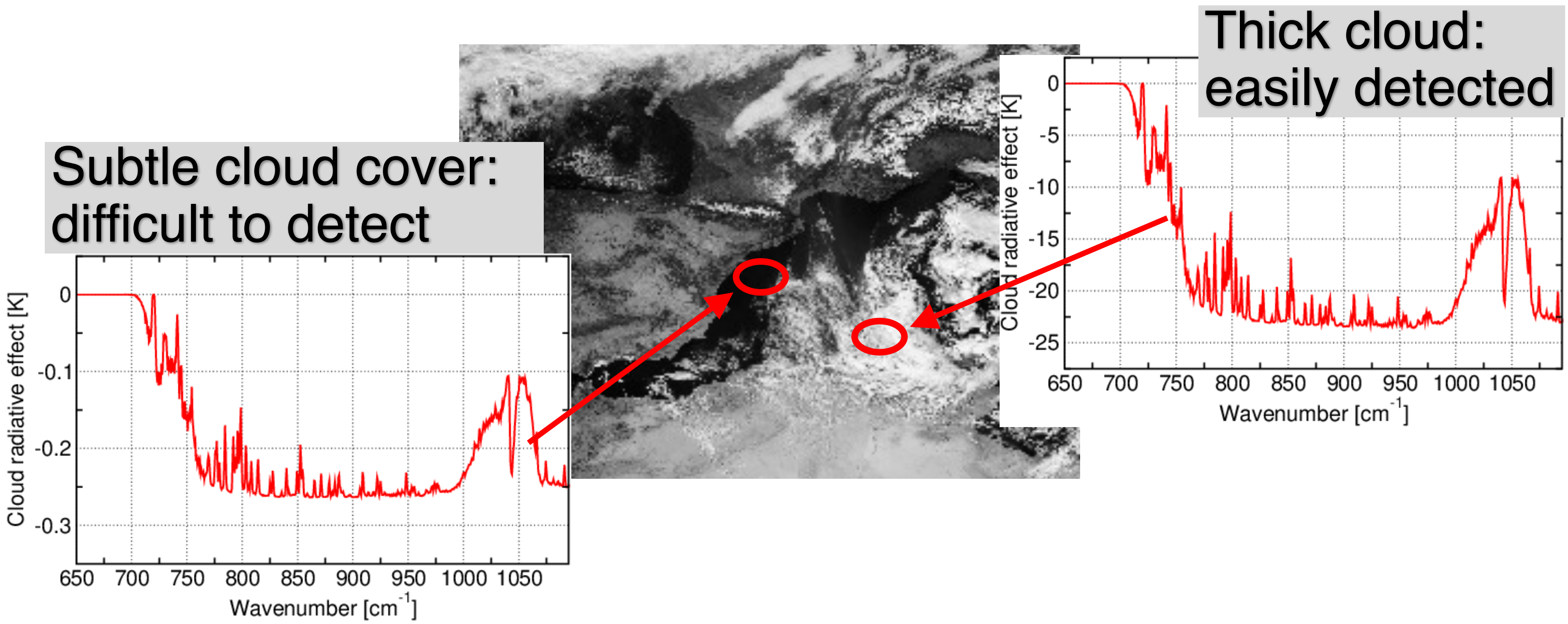
Big question: How should we handle clouds when assimilating infrared radiance observations??

- **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!

ECMWF

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

Simple

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

Complex

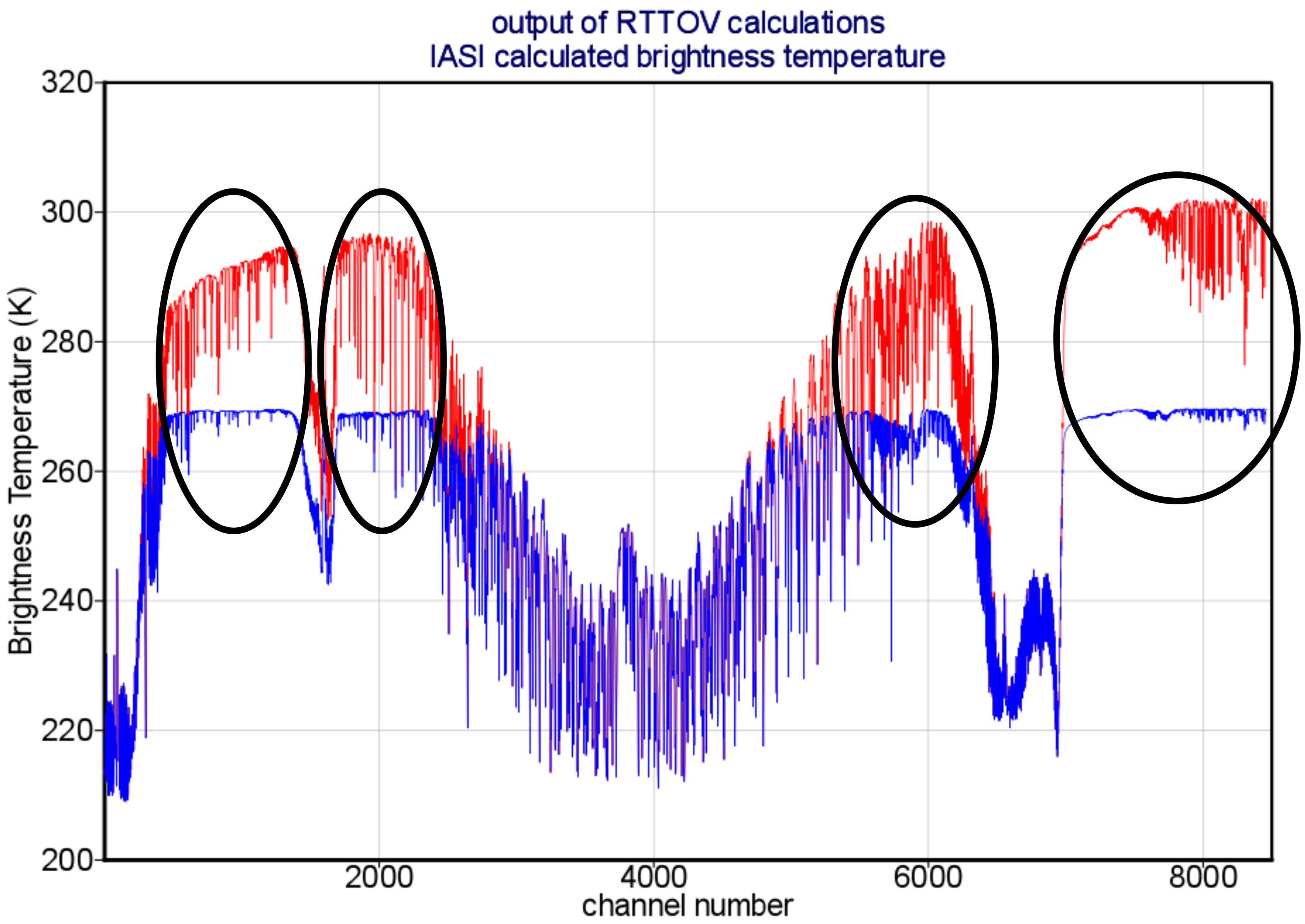
Cloud detection methods

Simple

Complex

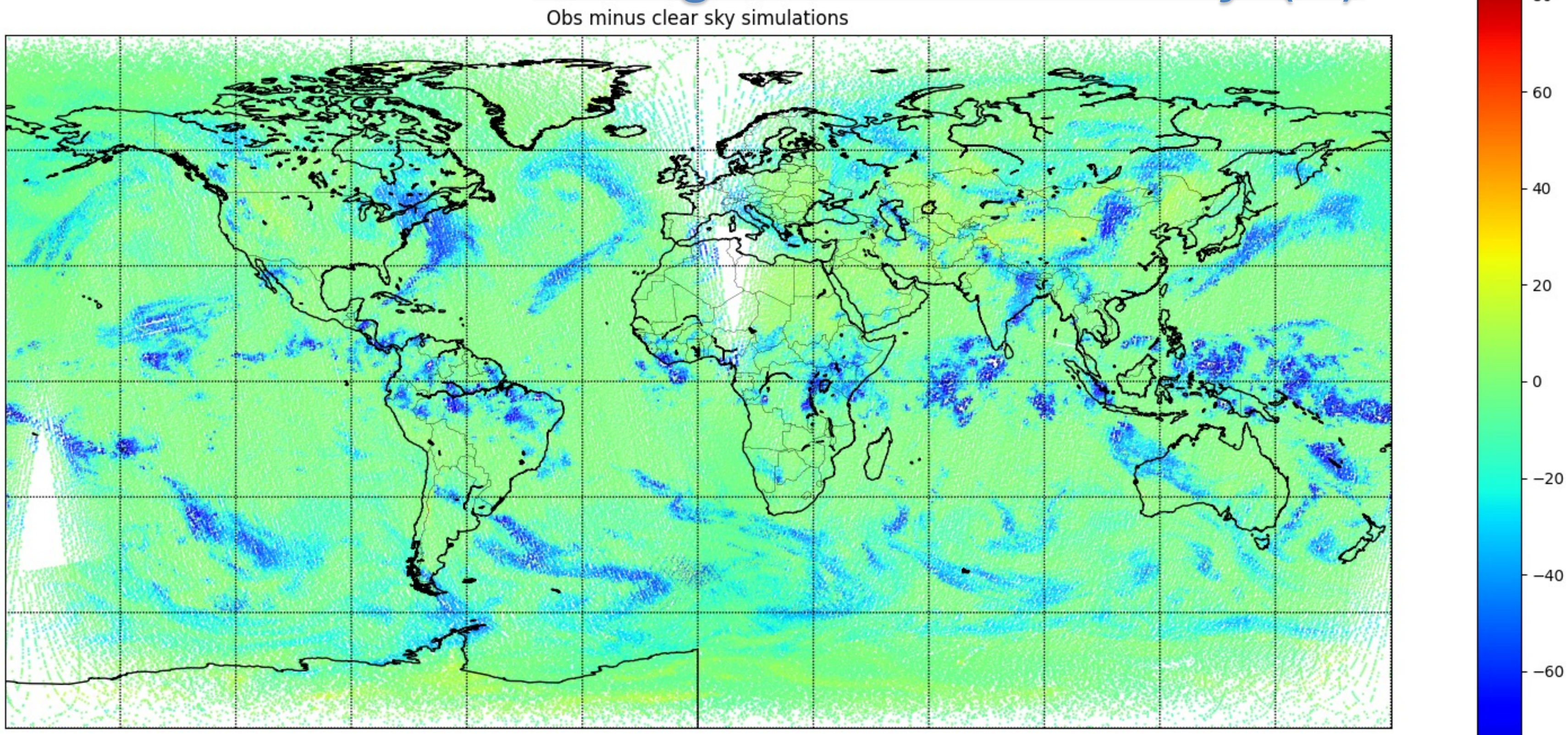
- Window channel departure (O-B) checks
- Co-located imager checks
- Pattern recognition algorithms
- Hybrid systems

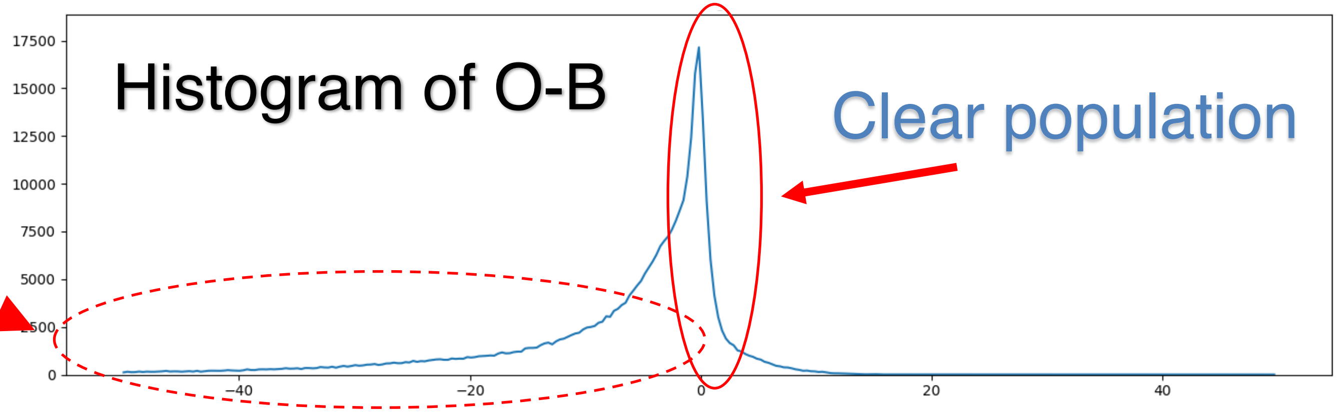
Window channels have the highest sensitivity to cloud



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)





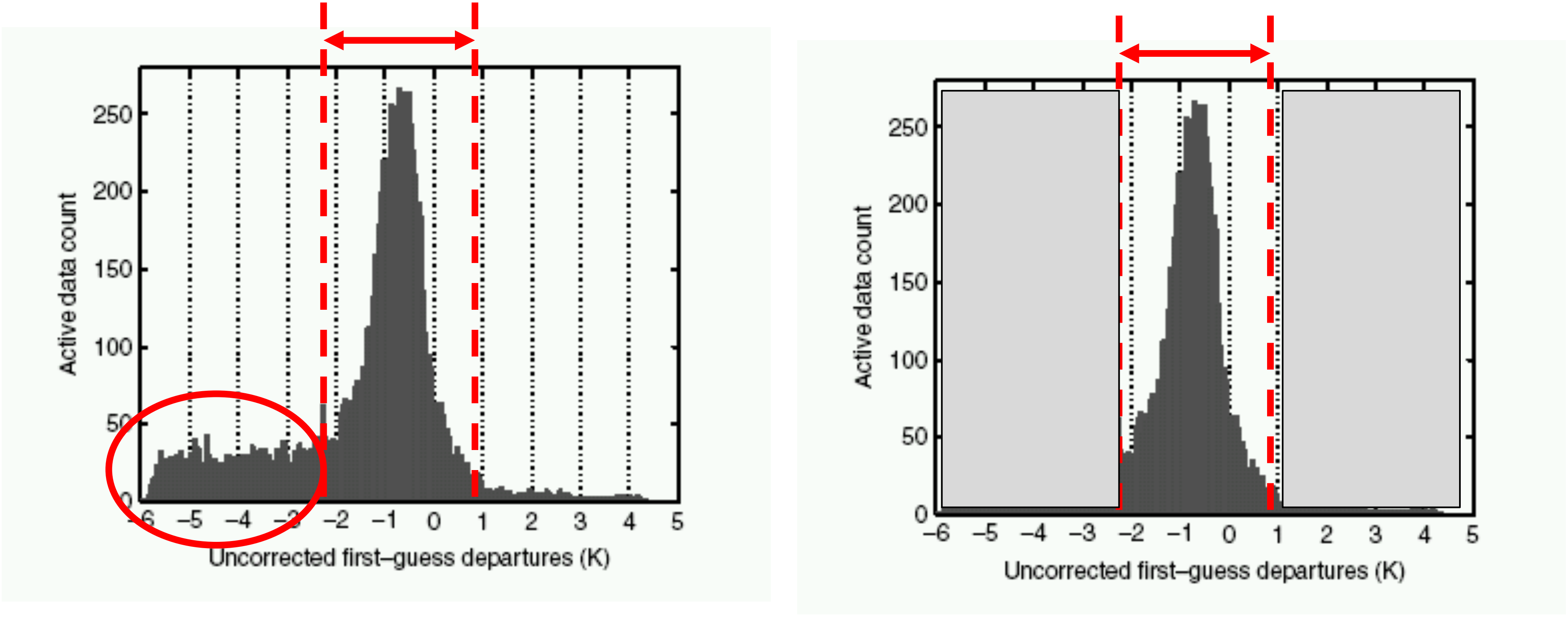
Cold departures indicating cloud contamination in obs. The "**cold tail**".

ECMWF

Simple window channel departure check

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

RT operator

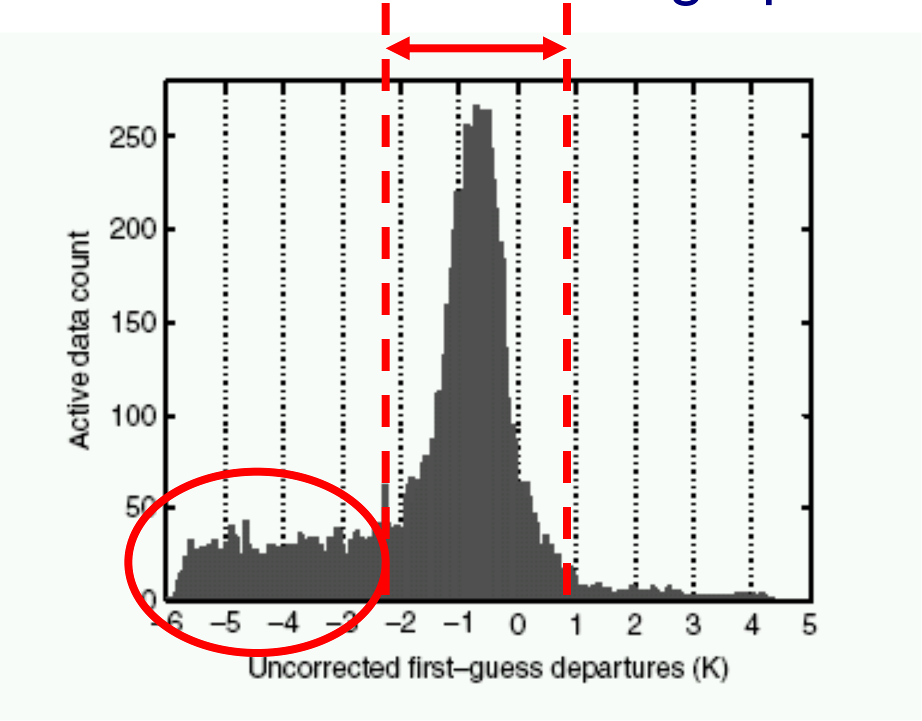


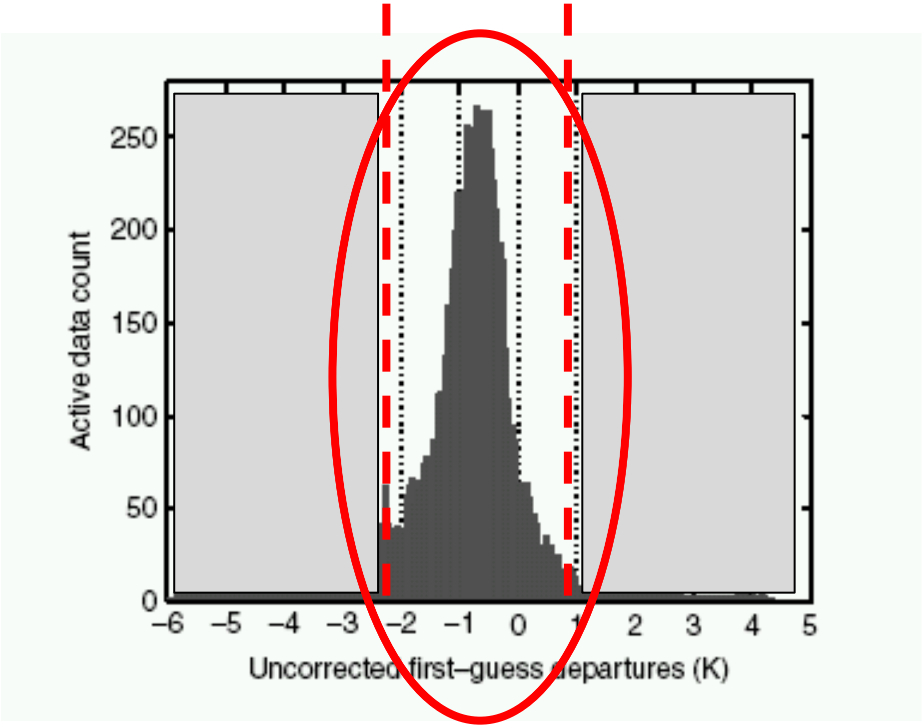
ECMWF

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.





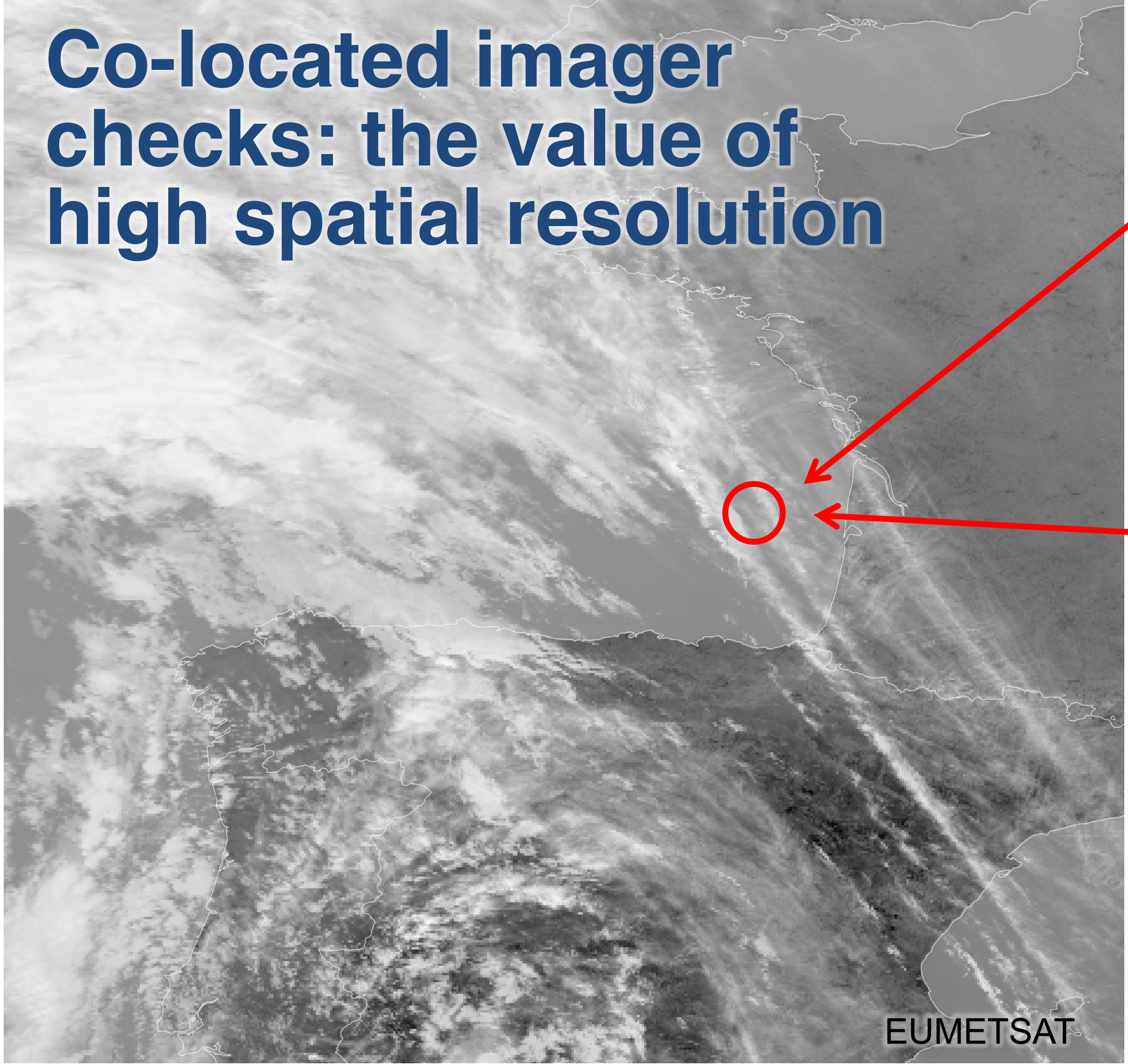
Cloud detection methods

Simple

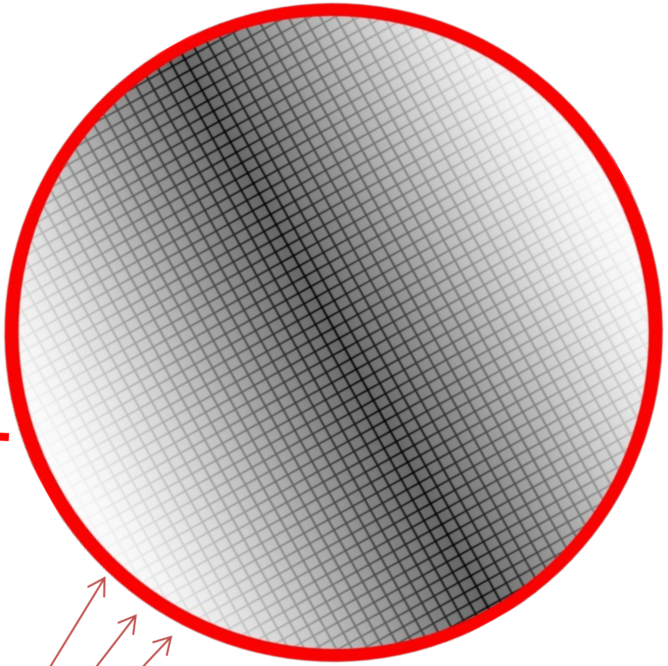
Complex

- 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

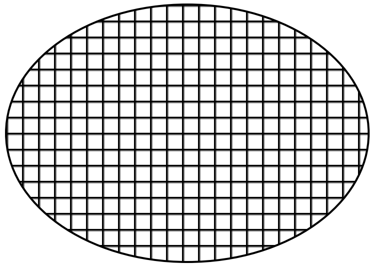


IASI (or CrIS) field of view ~10 km

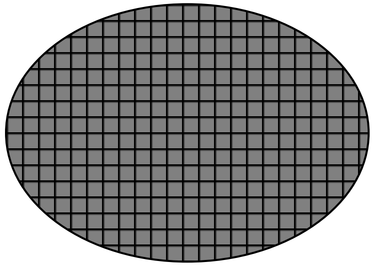


AVHRR (or VIIRS) imager pixels ~1 km

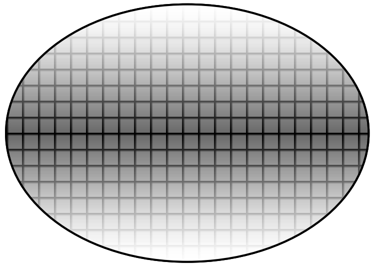
We can evaluate the mean and variance of Tb imager values inside the sounder field of view



Homogenous cloudy
(low mean Tb, low variance)

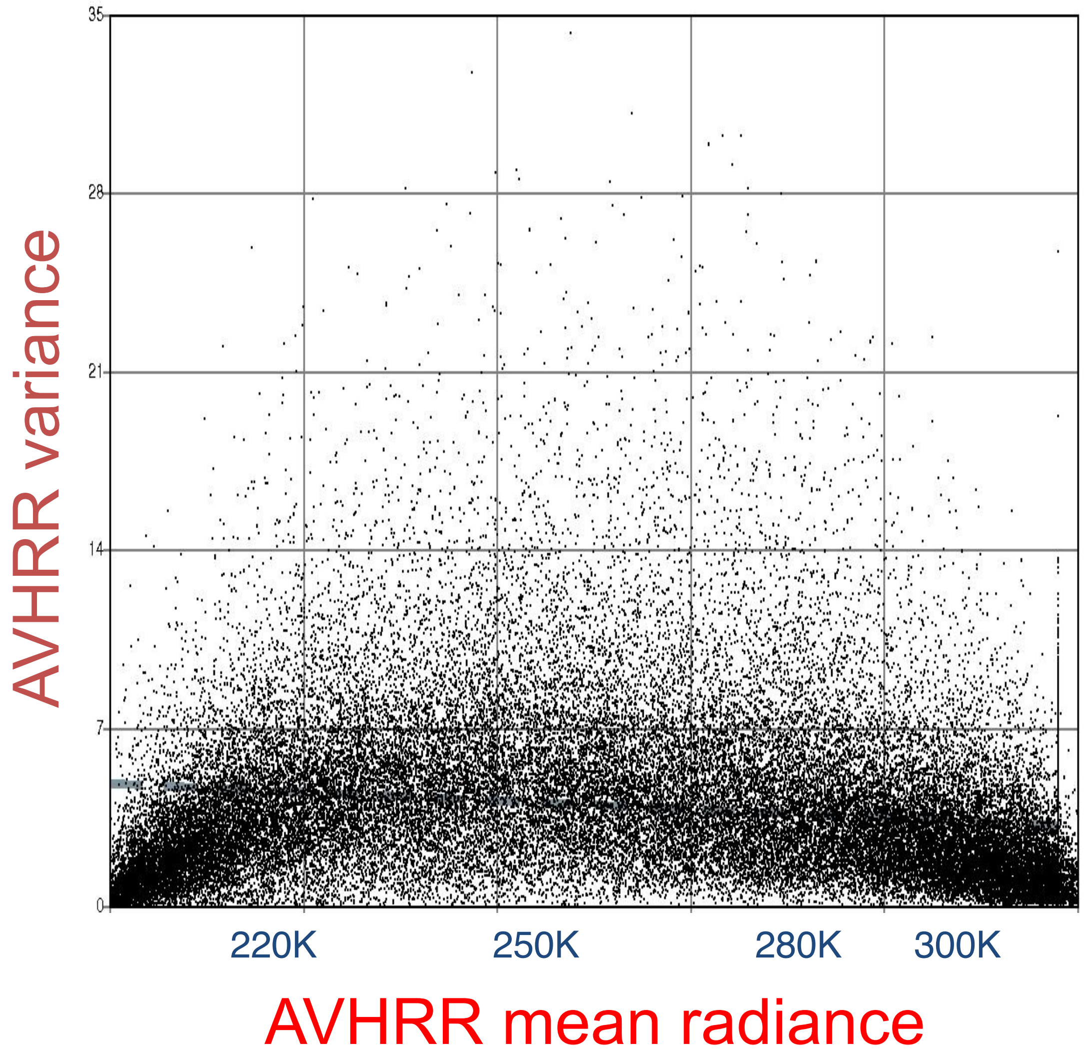


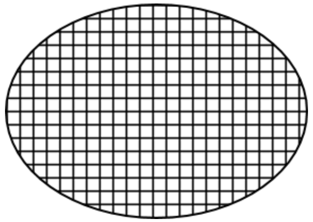
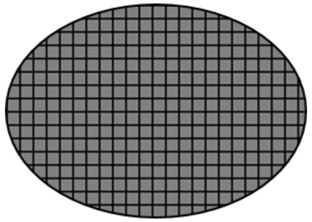
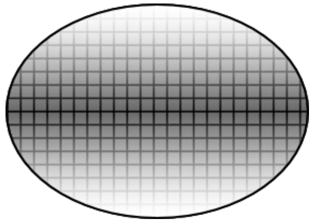
Homogenous clear
(high mean, low variance)

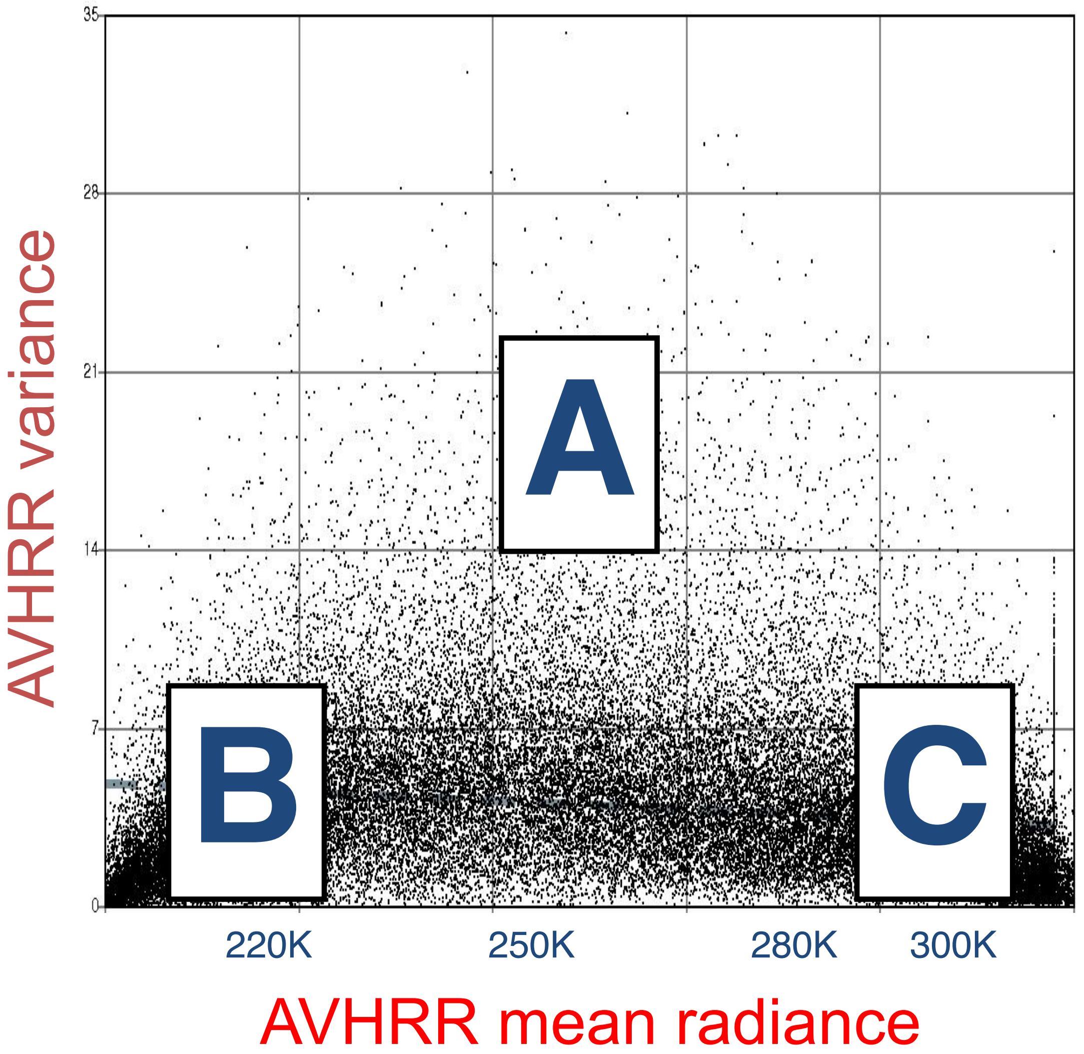


Mixed cloud scene
(any mean, high variance)

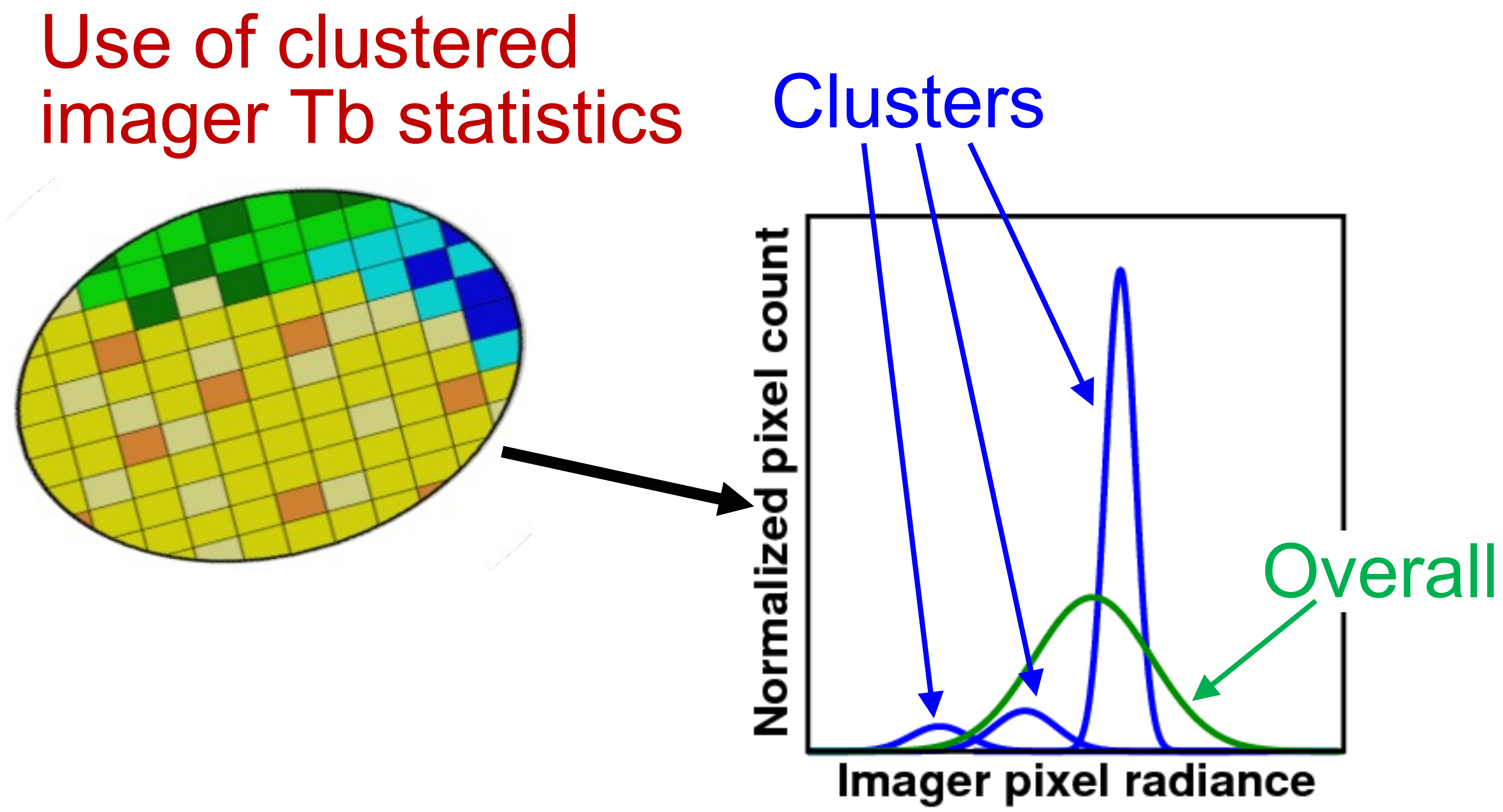
Scatter plot of variance of AVHRR imager pixels within the IASI footprint versus mean brightness temperature



Where would , , and  be in this scatter plot ?

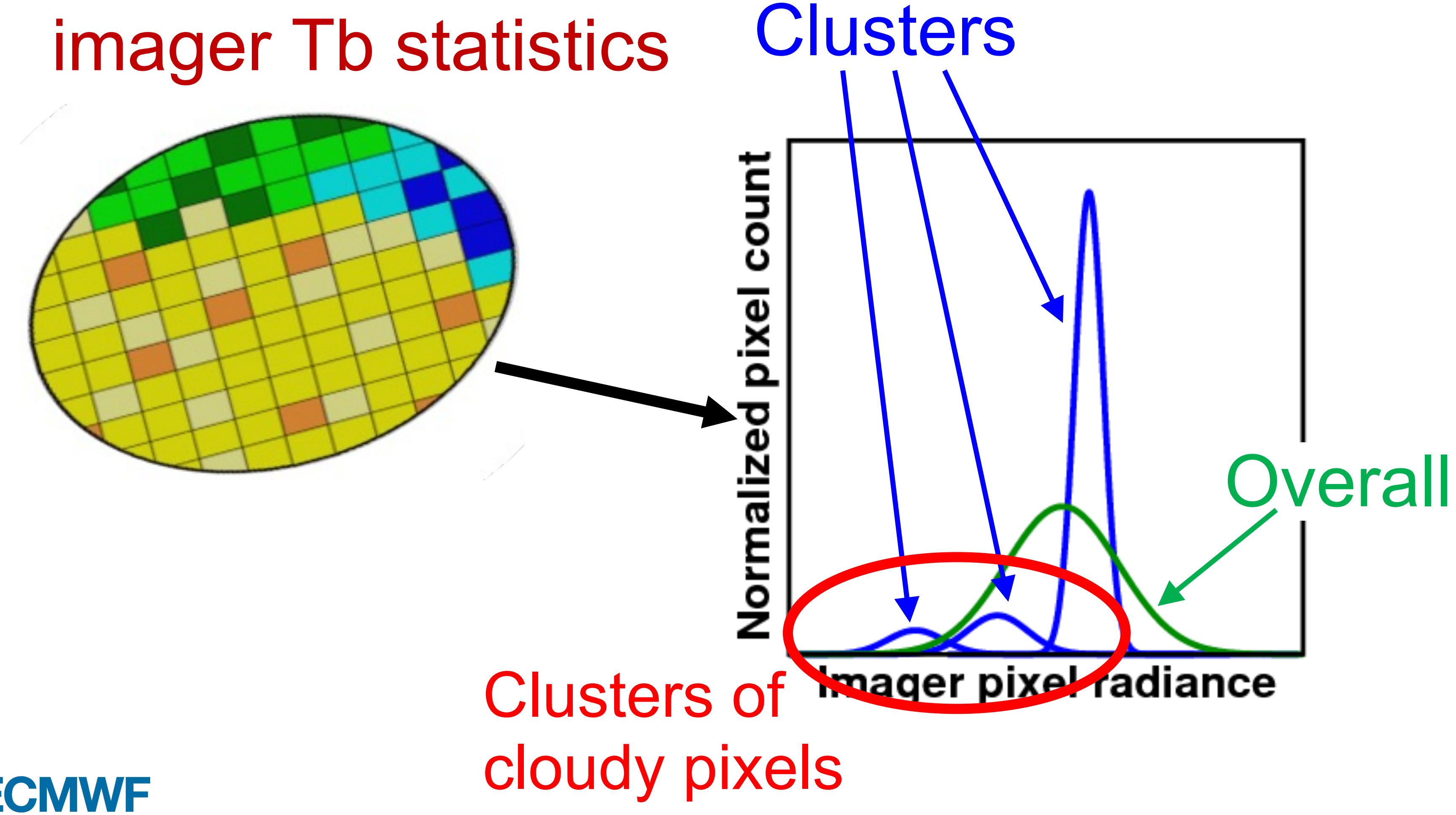


More sophisticated: image *clustering*



More sophisticated: image *clustering*

Use of clustered
imager Tb statistics



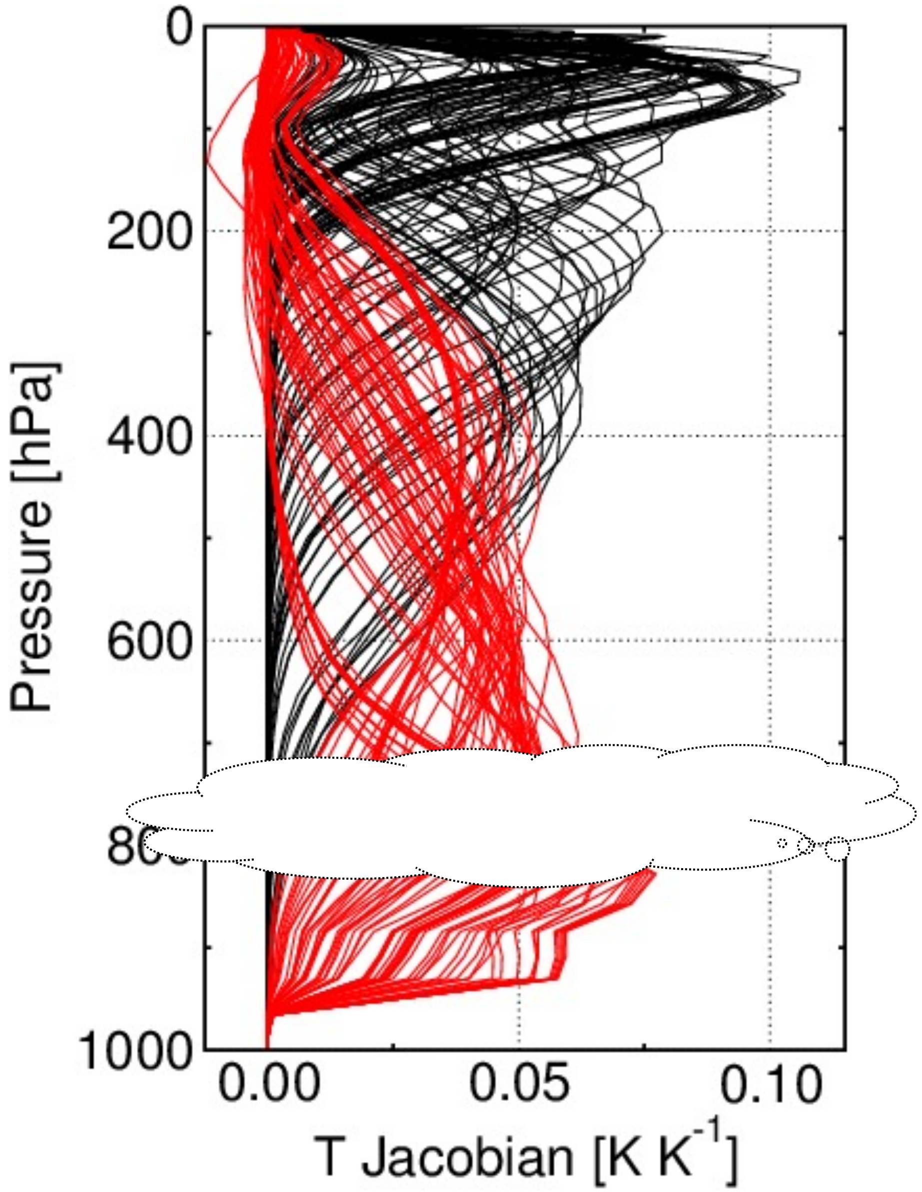
Cloud detection methods

Simple

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

Complex

Pattern recognition algorithms

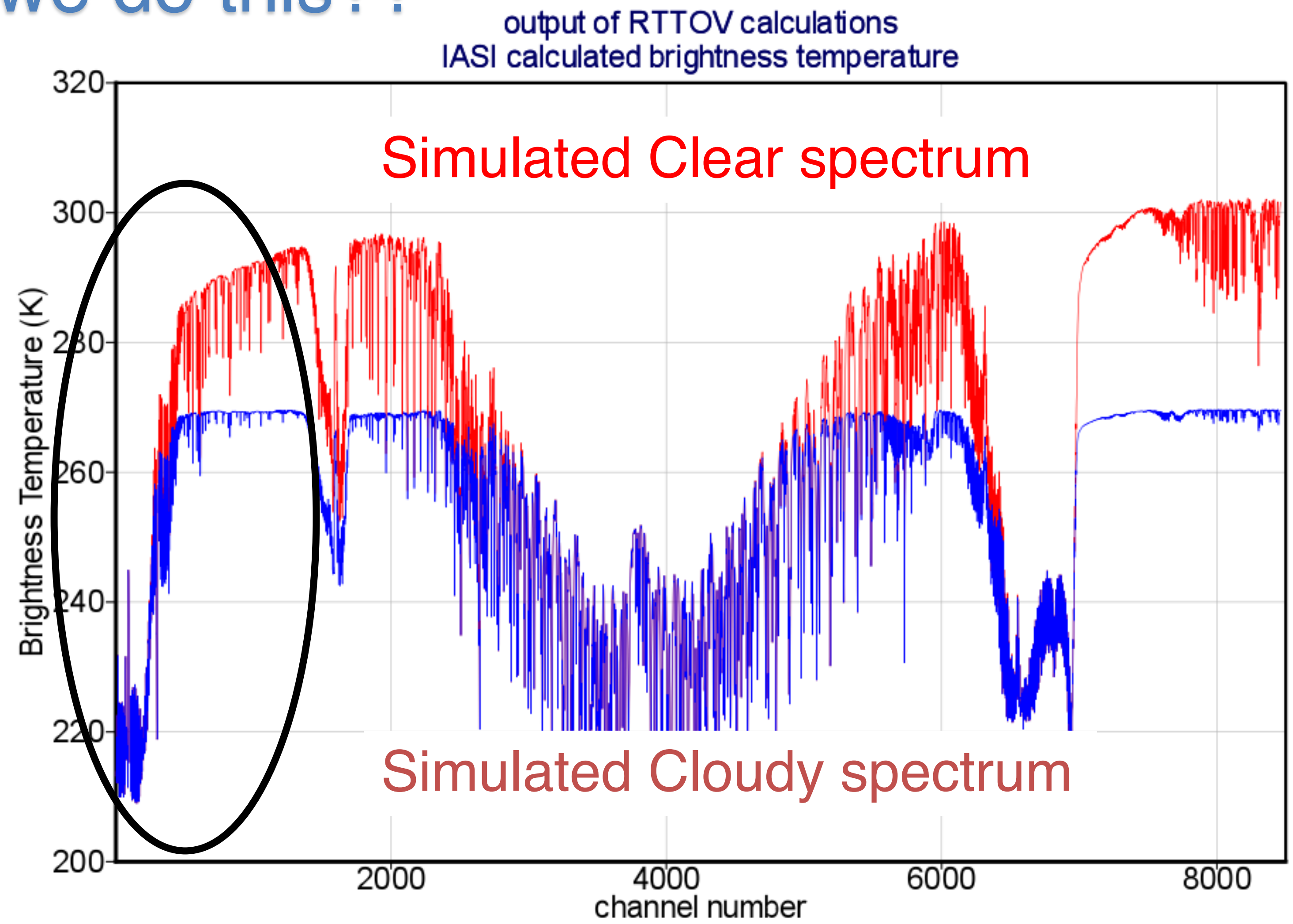


If channels are sensitive only to the atmosphere above a cloud (**black** lines), we would like to keep this data.

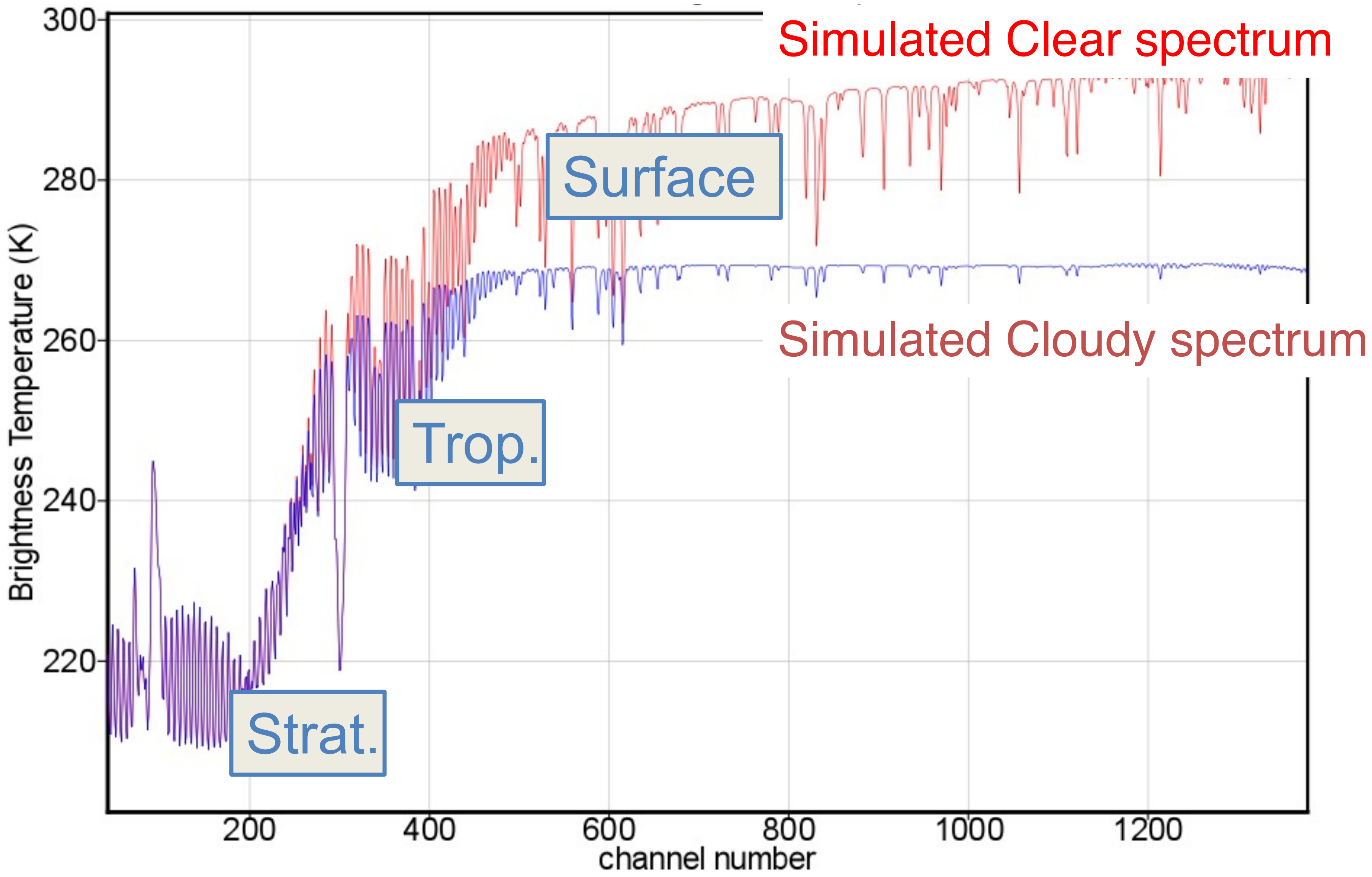
So here, we only reject cloud-contaminated channels (**red** lines), and keep the rest!

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

How do we do this??

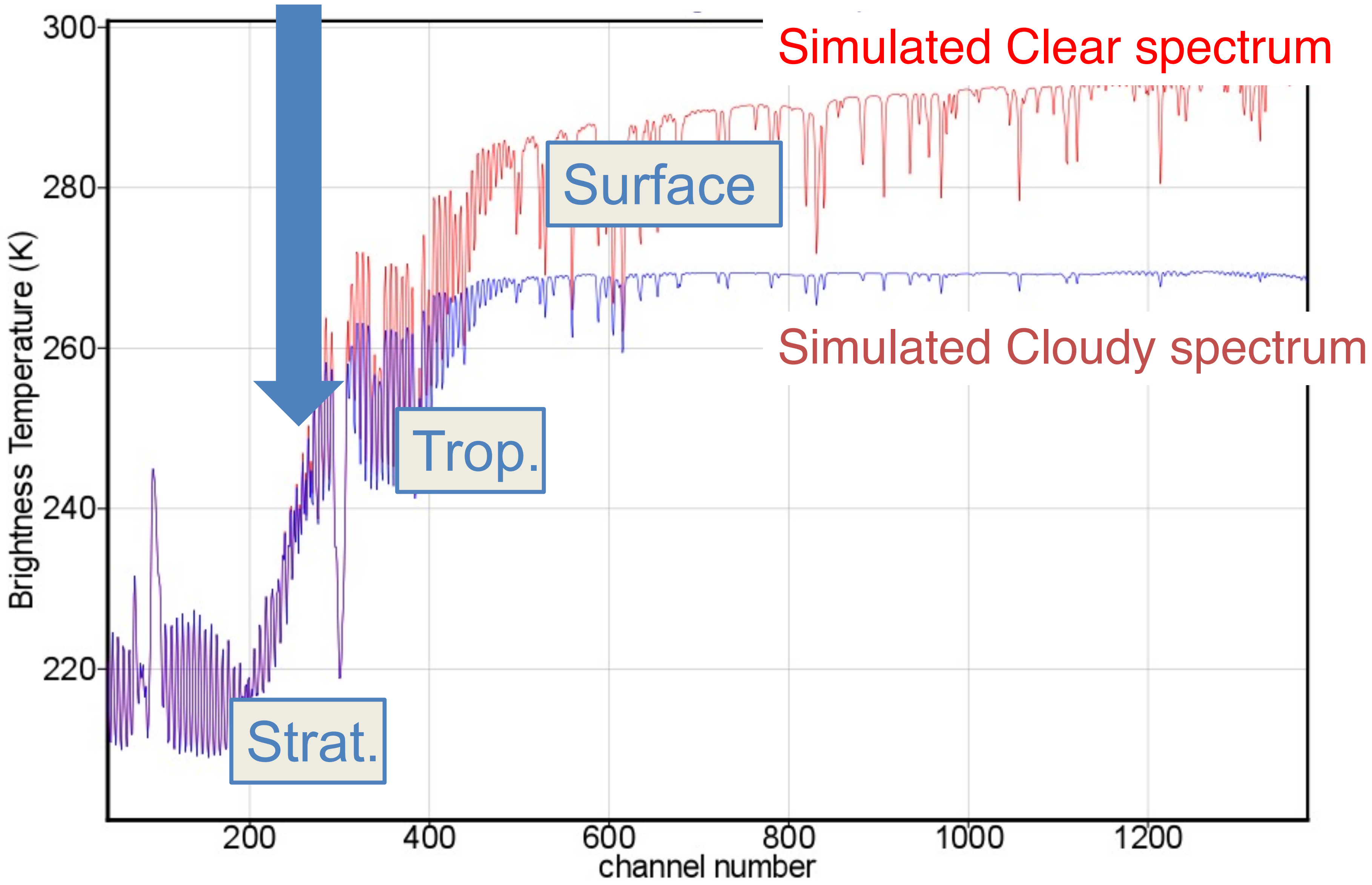


Let's zoom into the long-wave part of the spectrum which has good vertical resolution



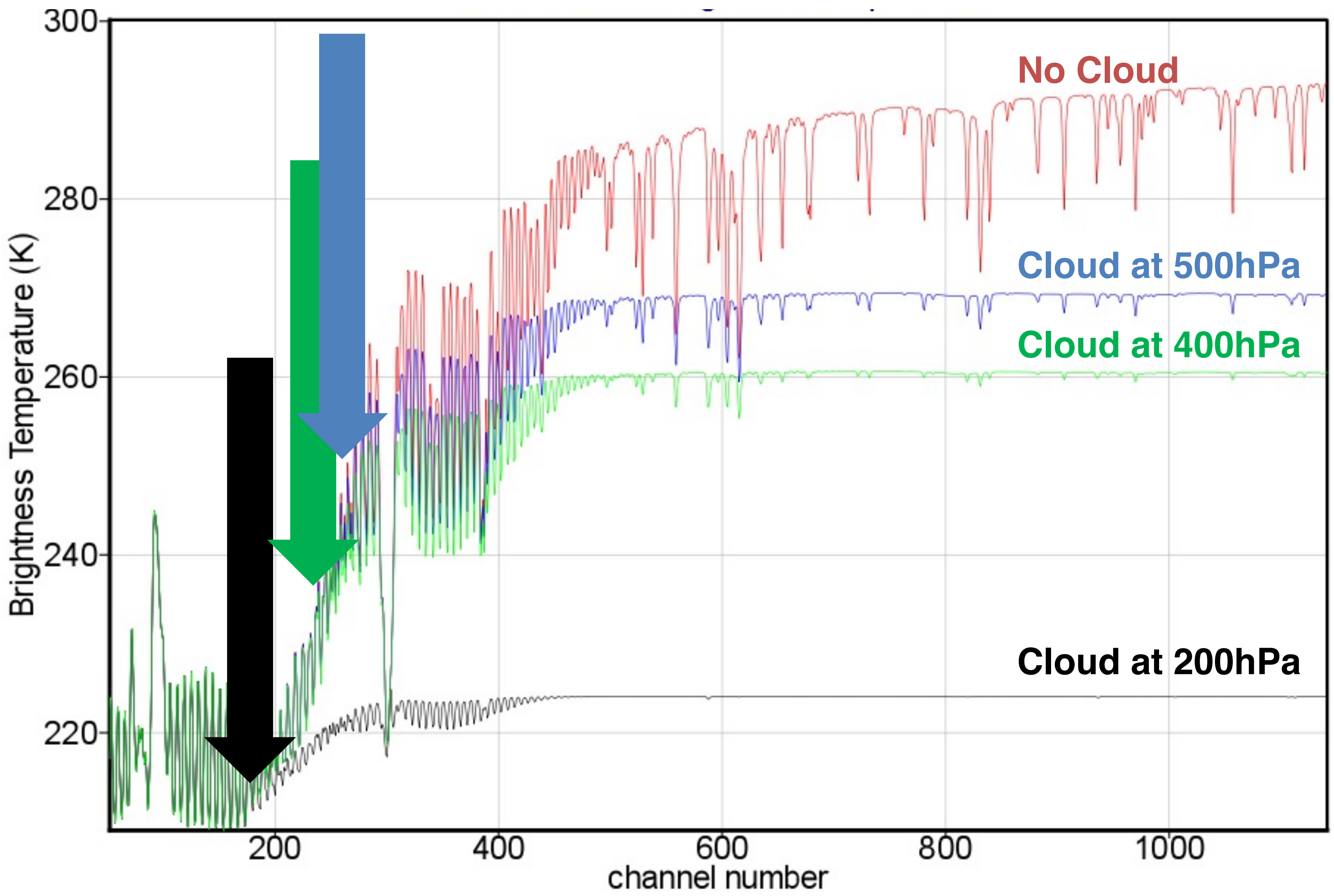
Simulated Clear spectrum
Simulated Cloudy spectrum
Surface
Trop.
Strat.
Brightness Temperature (K)
channel number
300
280
260
240
220
200
400
600
800
1000
1200

Break point

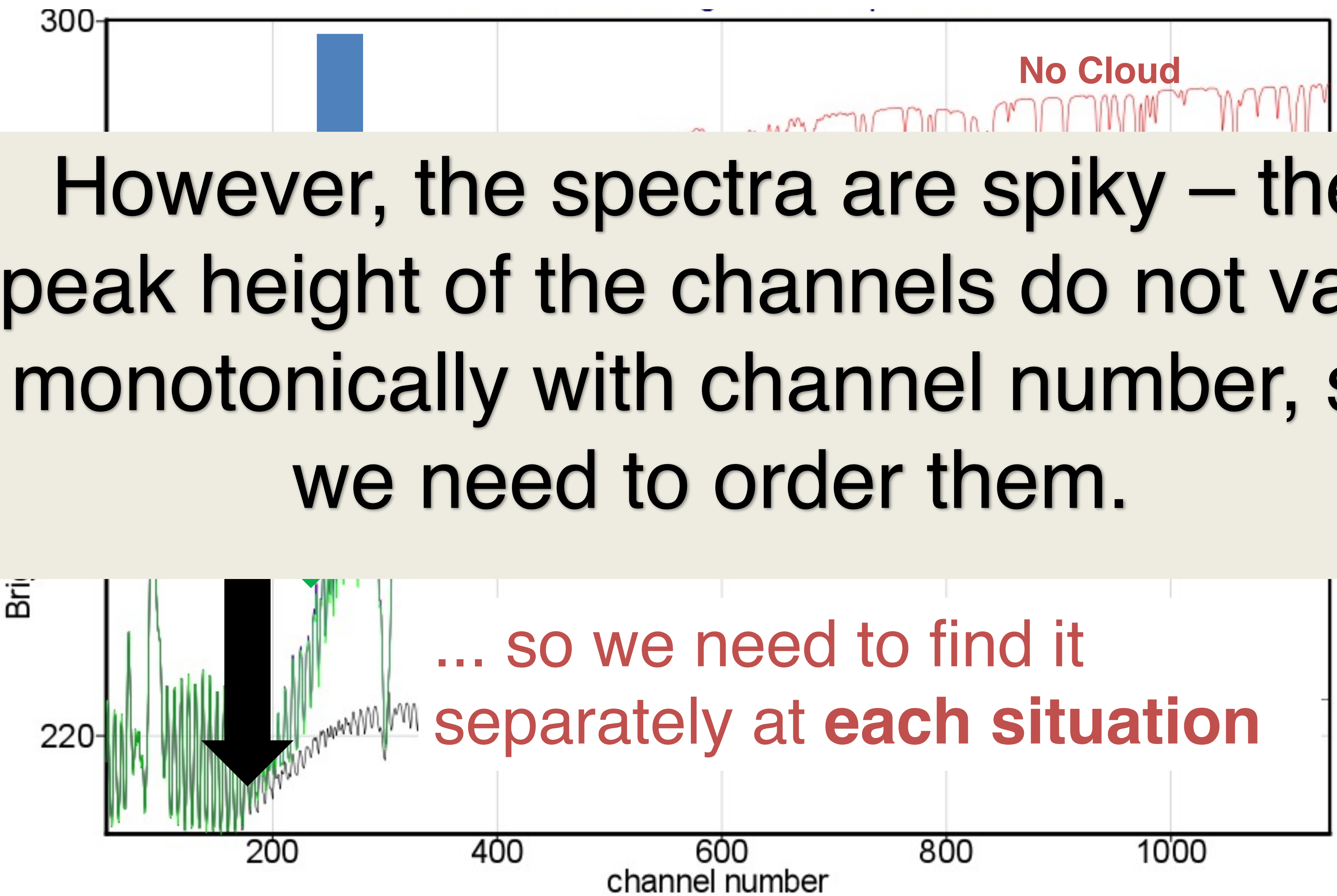


Simulated Clear spectrum
Simulated Cloudy spectrum
Surface
Trop.
Strat.
Brightness Temperature (K)
channel number
300
280
260
240
220
200
400
600
800
1000
1200

Break point depends on cloud height …



Break point depends on cloud height …

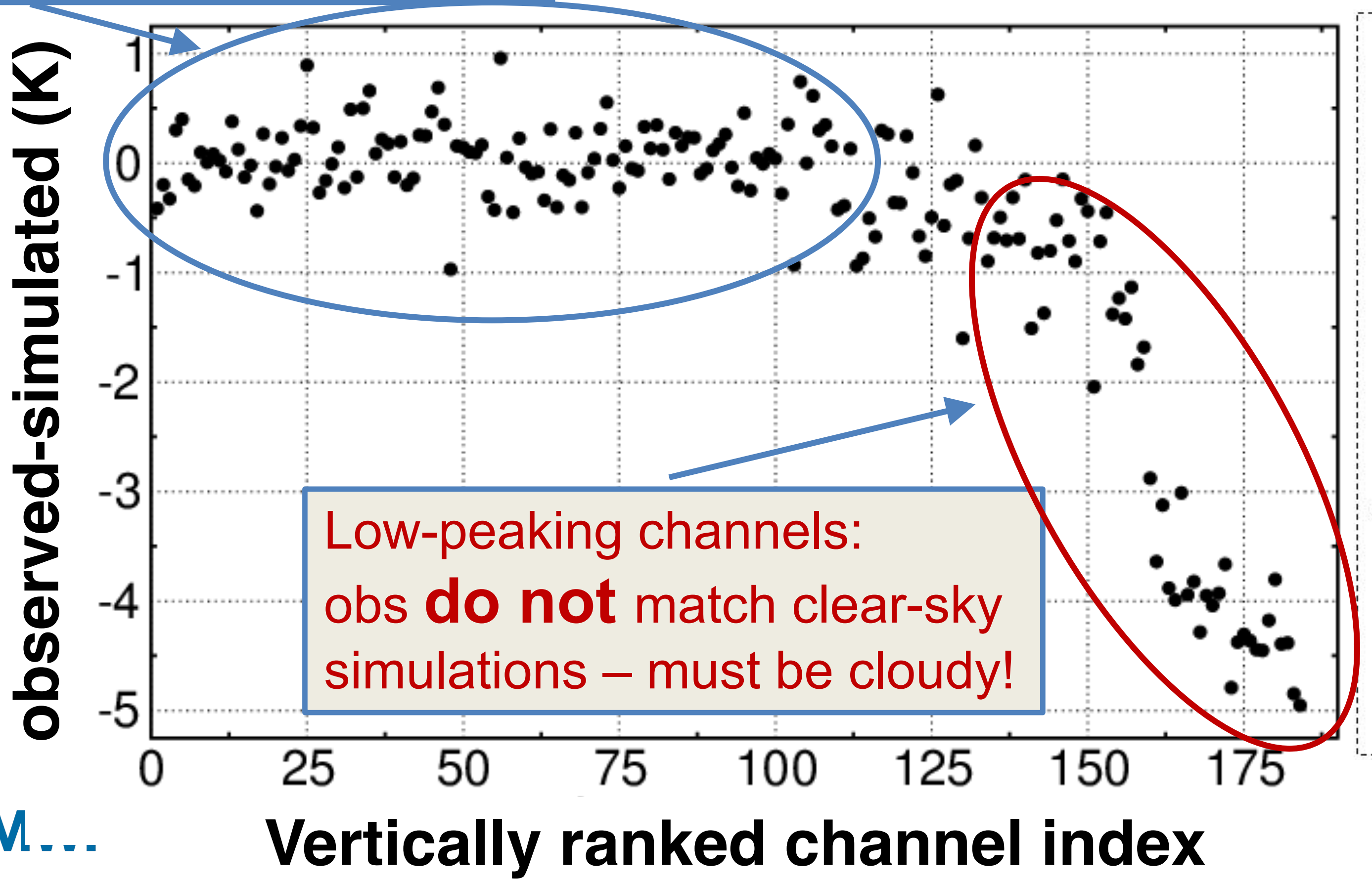


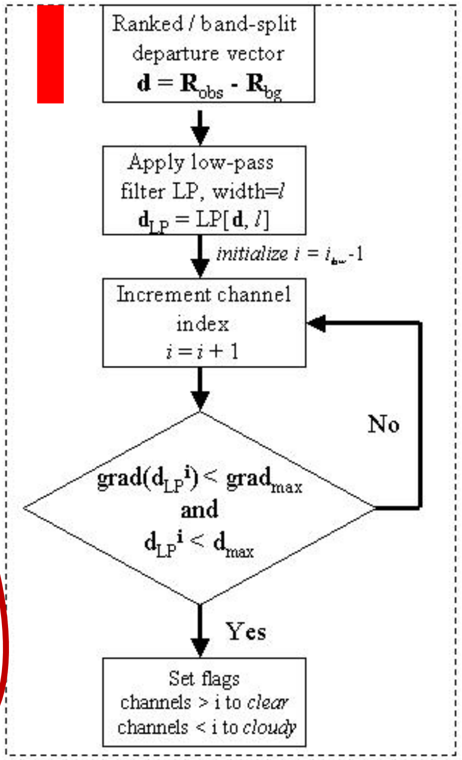
However, the spectra are spiky – the peak height of the channels do not vary monotonically with channel number, so we need to order them.

... so we need to find it separately at **each situation**

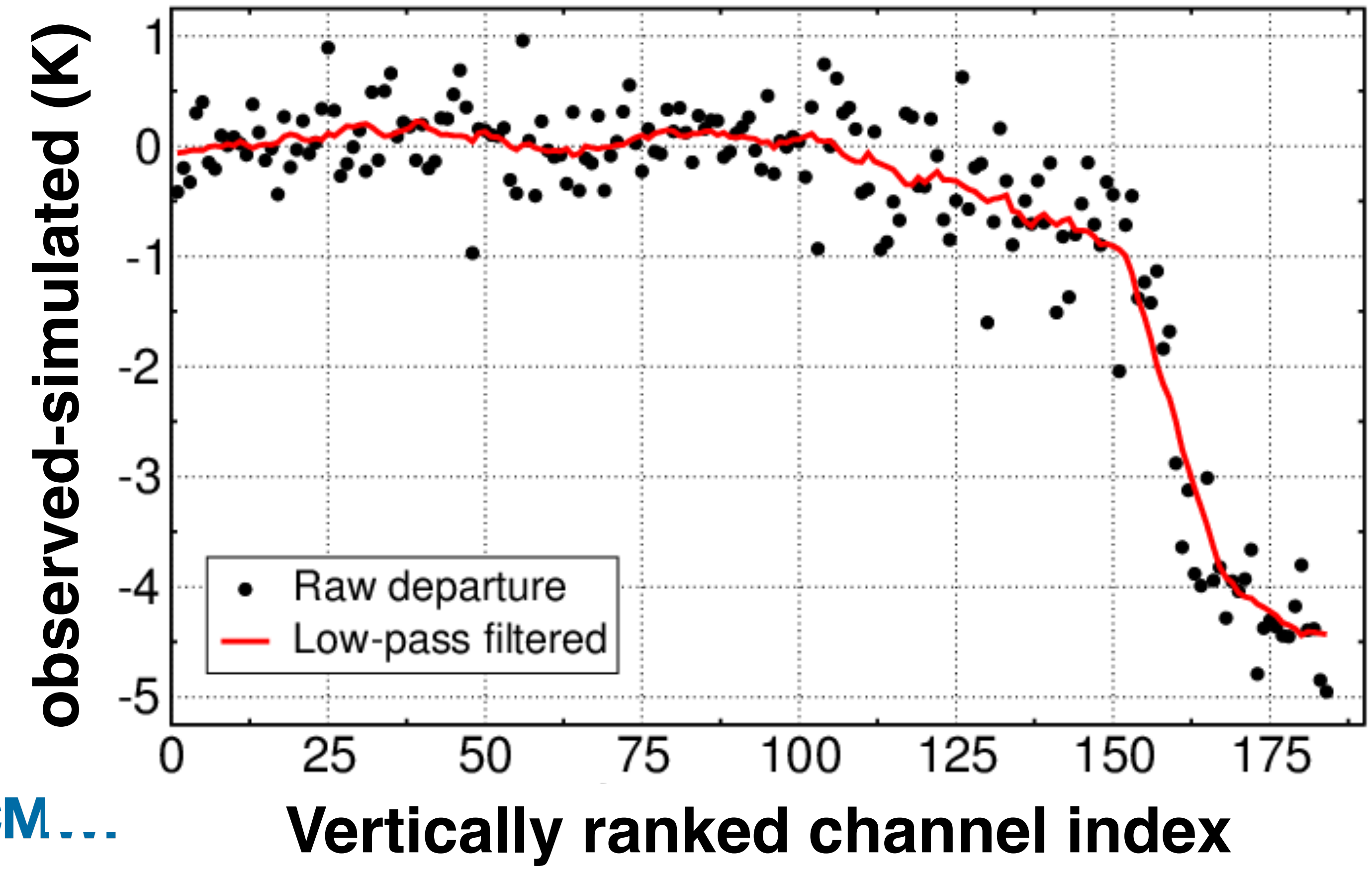
- First we compute the observations minus (clear-sky) simulations.
- Then re-order (rank) the channels according to their height of cloud sensitivity.

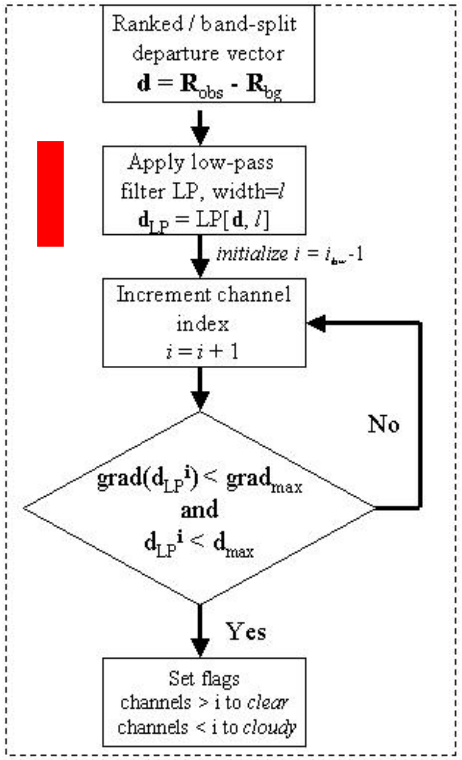
High-peaking channels:
obs match clear-sky simulations.



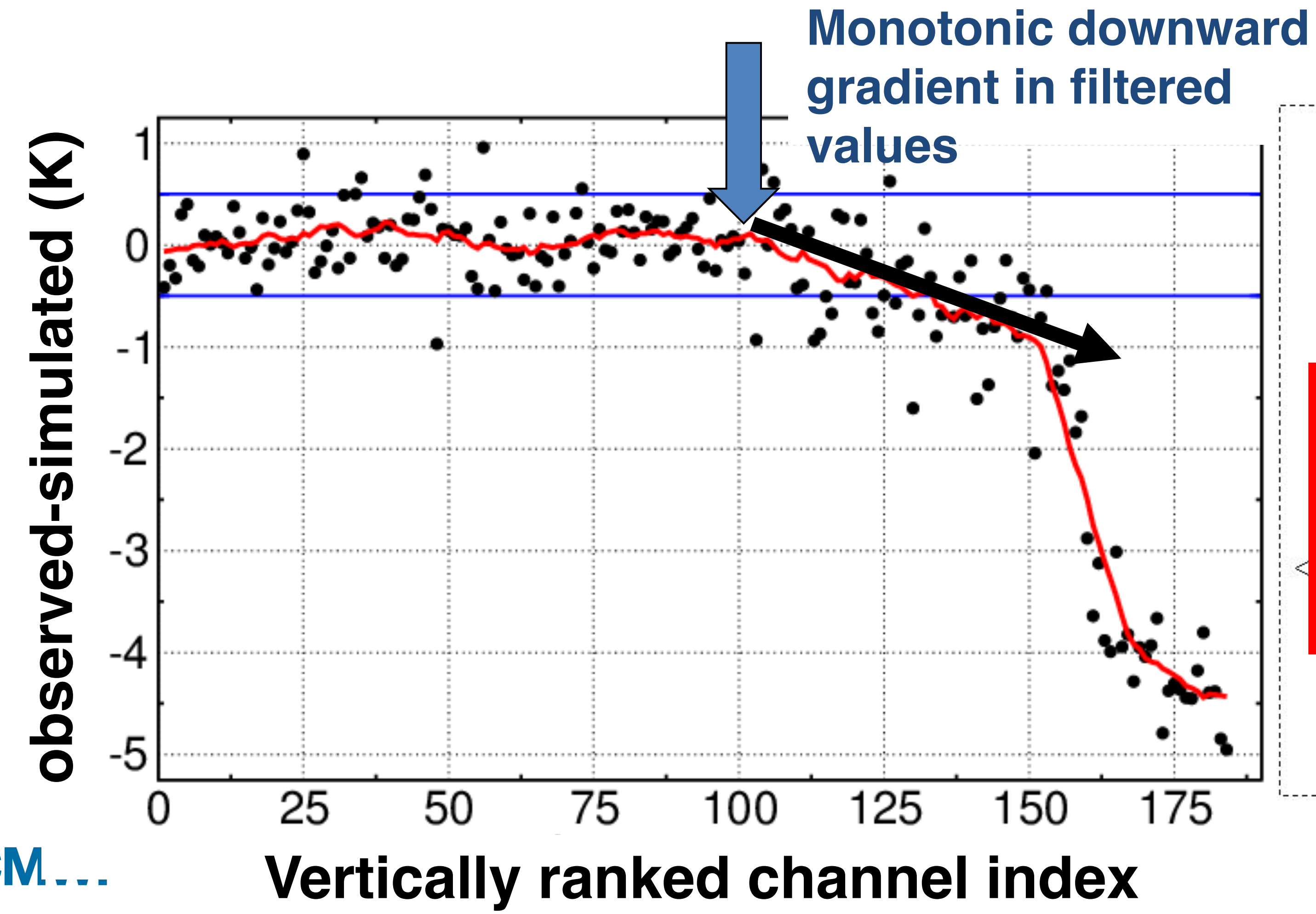


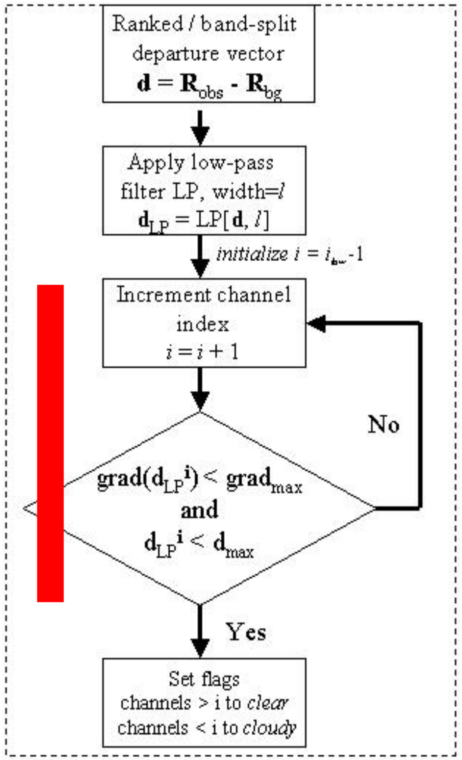
… then we apply a low-pass filter to reduce the effect of noise …





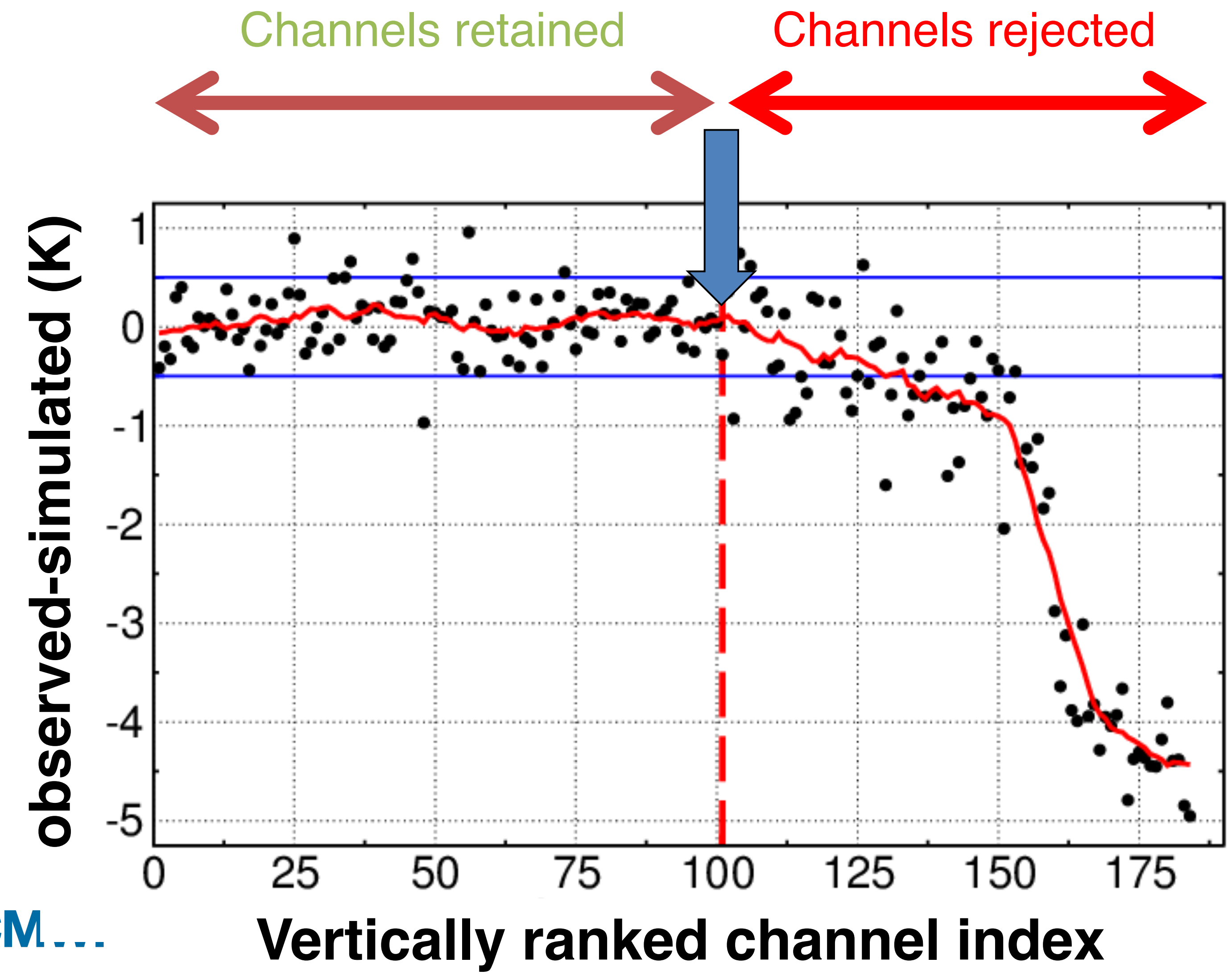
… then we find the break point according to some determined thresholds ...

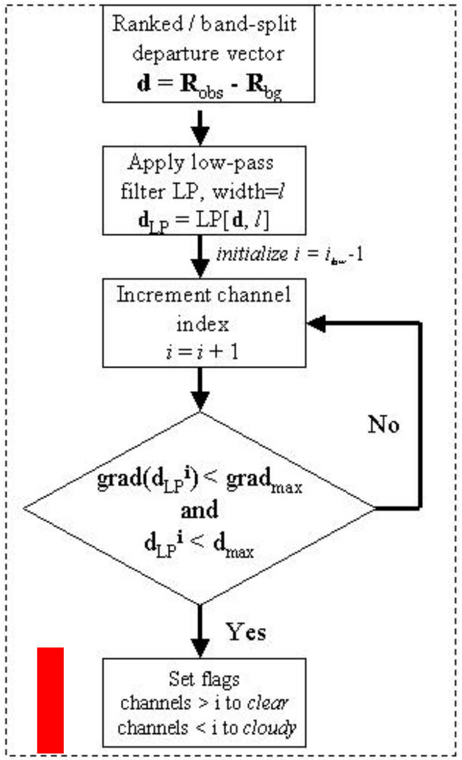


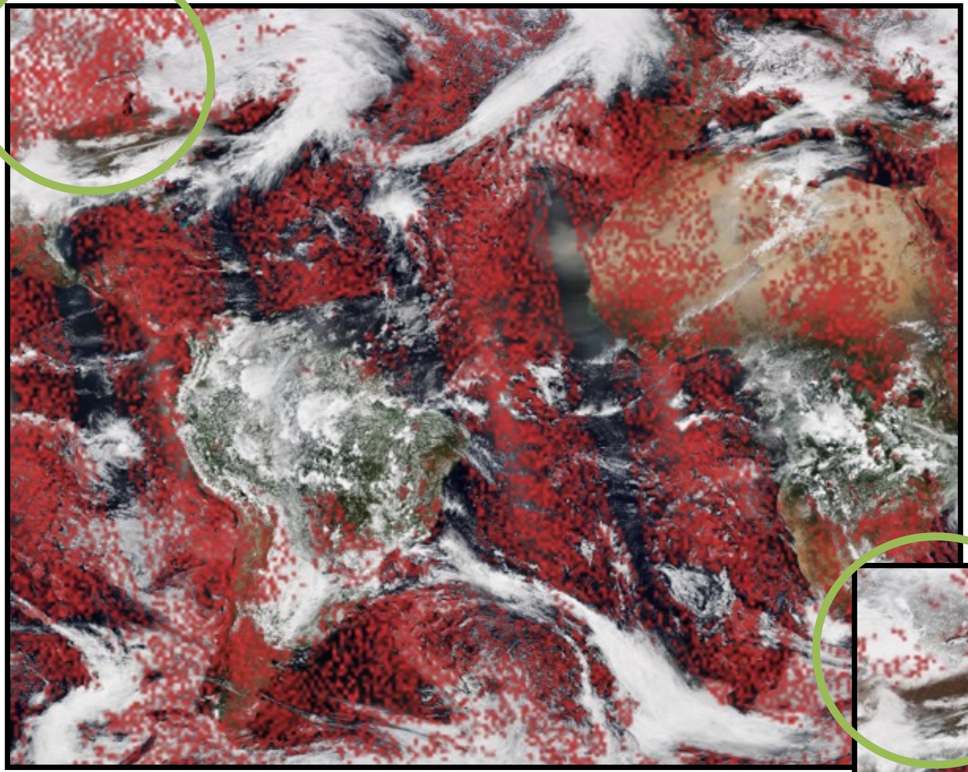


ECM...

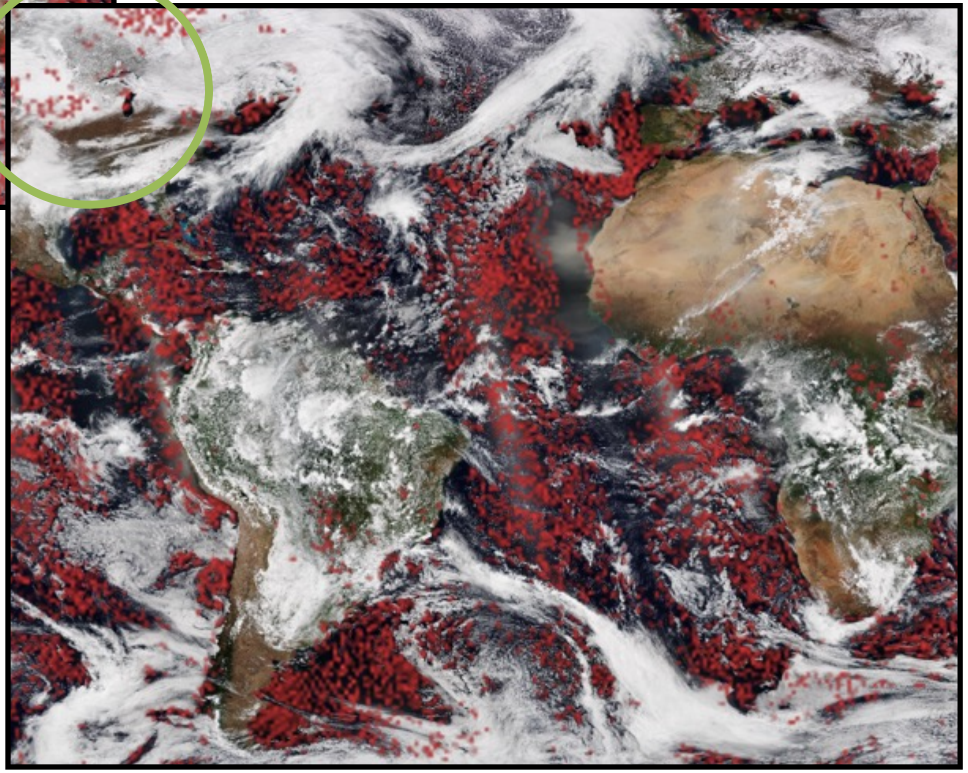
… and finally we set flags to indicate cloud-affected channels







CrIS channel at 14.2 μm
(peak pressure 350 hPa)



CrIS channel at 13.6 μm
(peak pressure 600 hPa)

Cloud detection methods

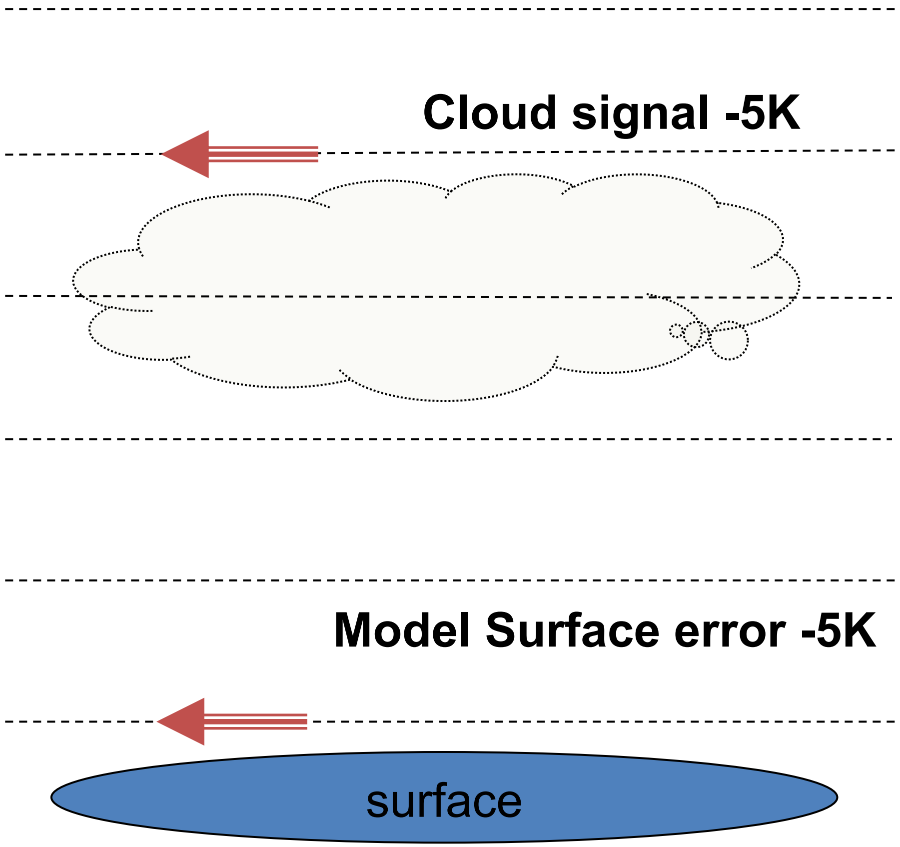
Simple

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

Complex

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	$\Delta T_b = -5$ K	$\Delta T_b = -10$ K
	0 K	$\Delta T_b = 0$ K	$\Delta T_b = -5$ K
	-5 K	$\Delta T_b = 5$ K	$\Delta T_b = 0$ K

Missed cloud

False alarm

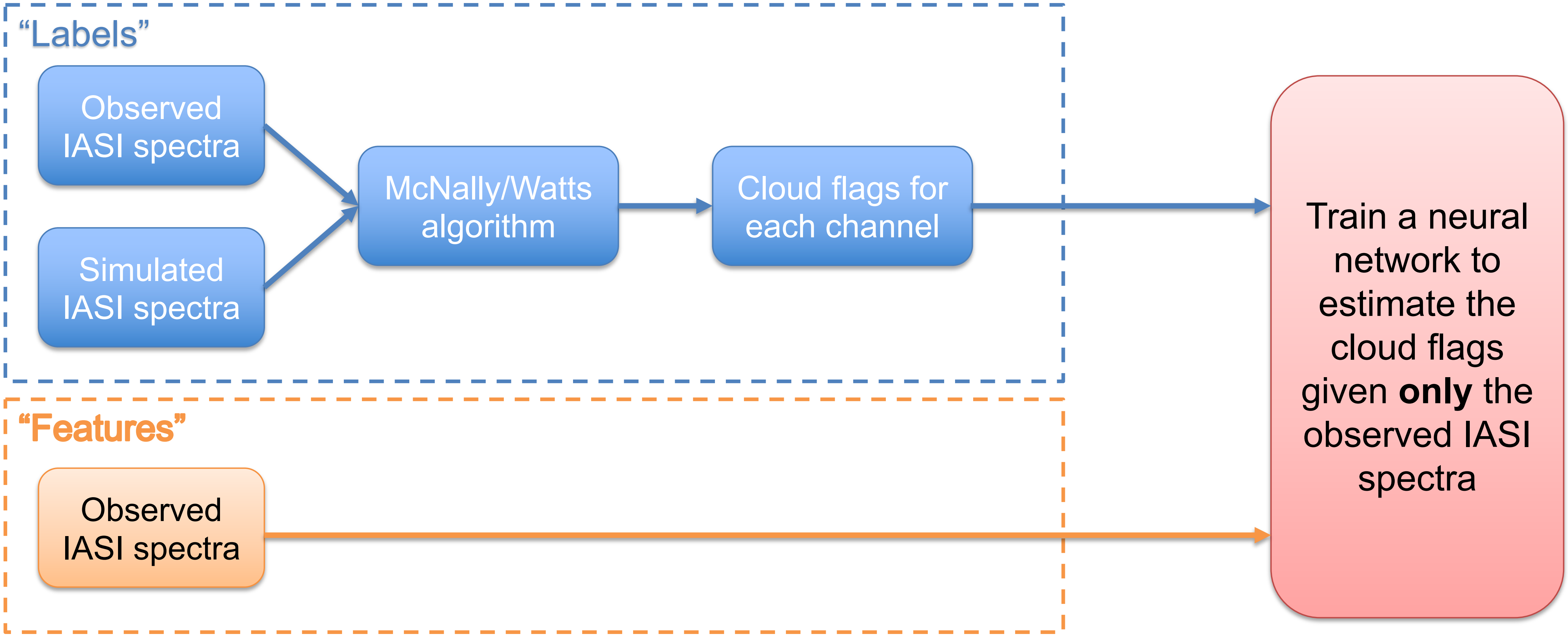
The ECMWF implementation is a **hybrid** scheme that combines the use of co-located imager data with departure-based pattern recognition.

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?

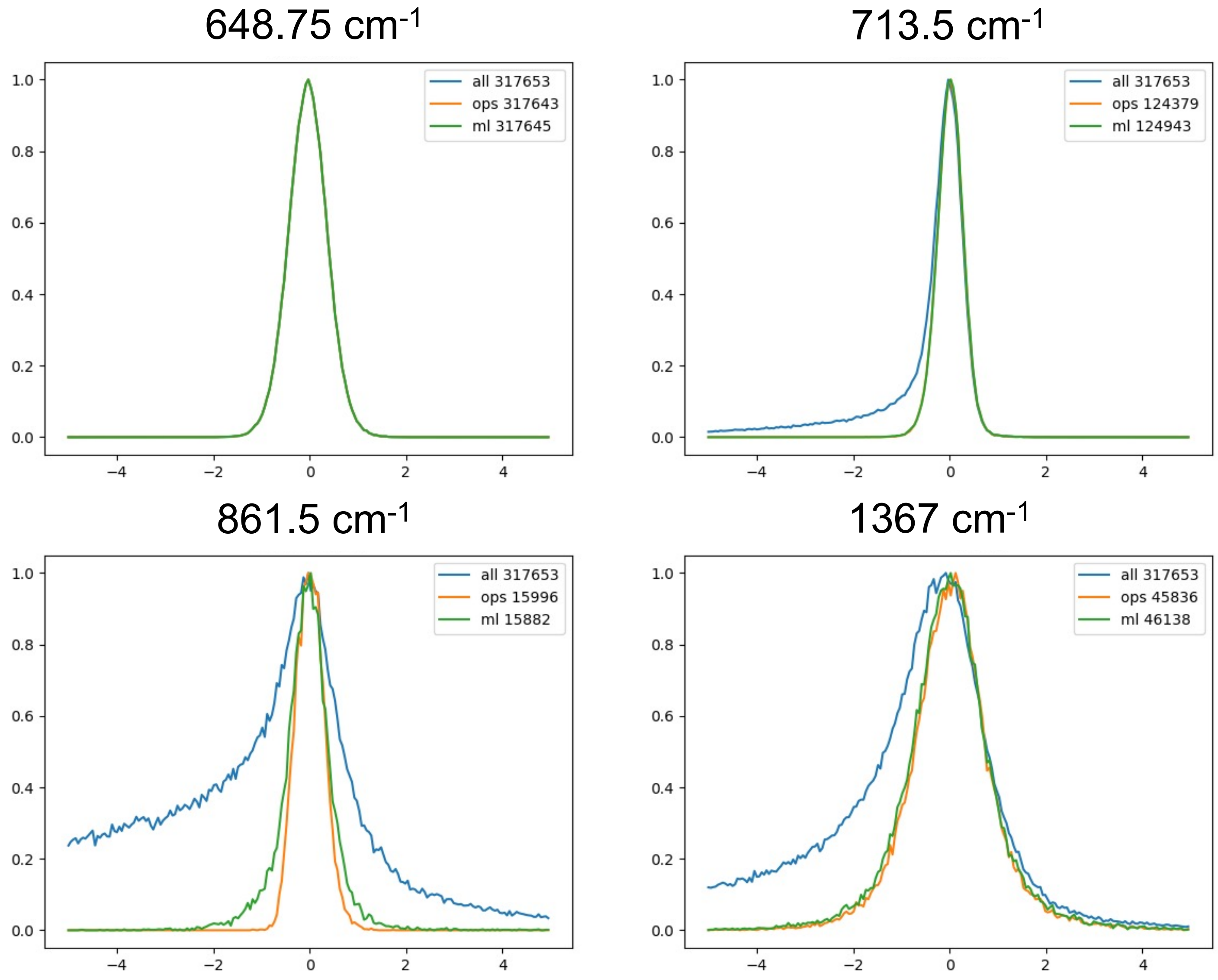
Approach – train a NN to replicate the flags from the **ECMWF hybrid** cloud detection scheme, but using **only** observed IASI values as inputs



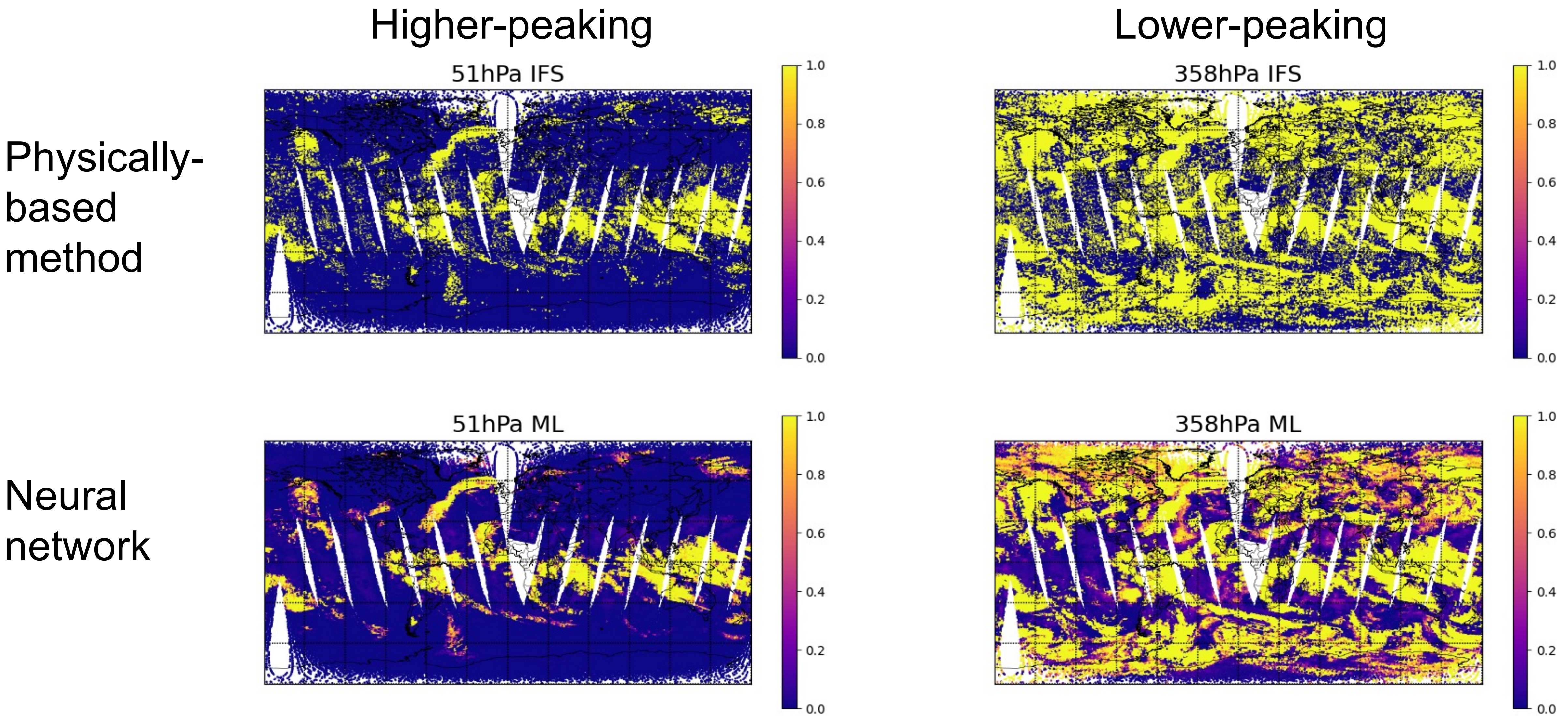
McNally A, Watts P. 2003. A cloud detection algorithm for high-spectral-resolution infrared sounders. Q. J. R. Meteorol. Soc. 129: 3411– 3423, doi: 10.1256/qj.02.208

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.



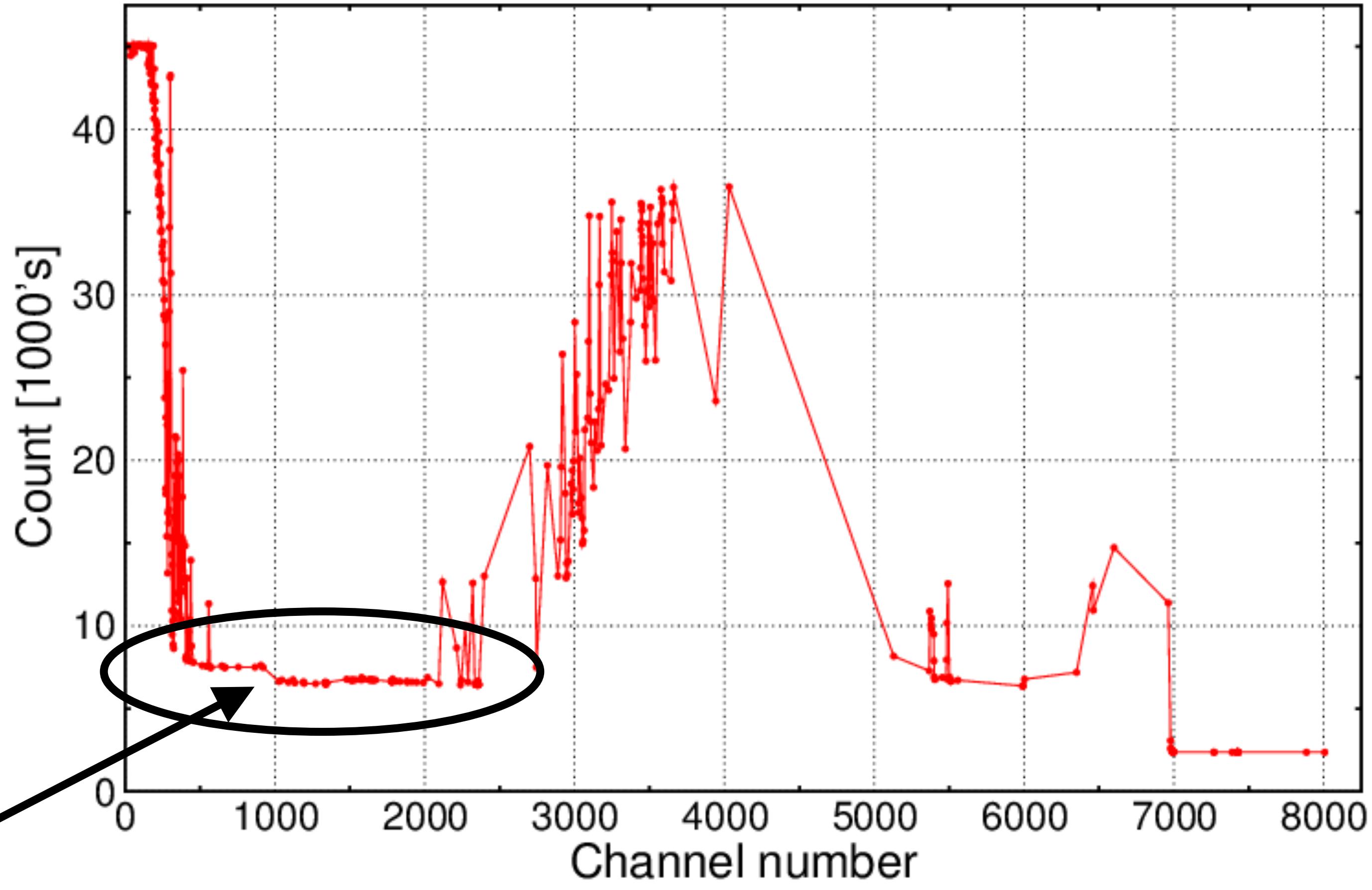
Initial fit looks fairly good, even with a limited training set
Yellow is cloudy, blue is clear



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(x)

model state

background error covariance

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

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)

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

The cost function J(x)

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

$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) +$$

$$(y - \mathrm{H}[x])^T \mathbf{R}^{-1} (y - \mathrm{H}[x])$$

The cost function J(x)

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

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

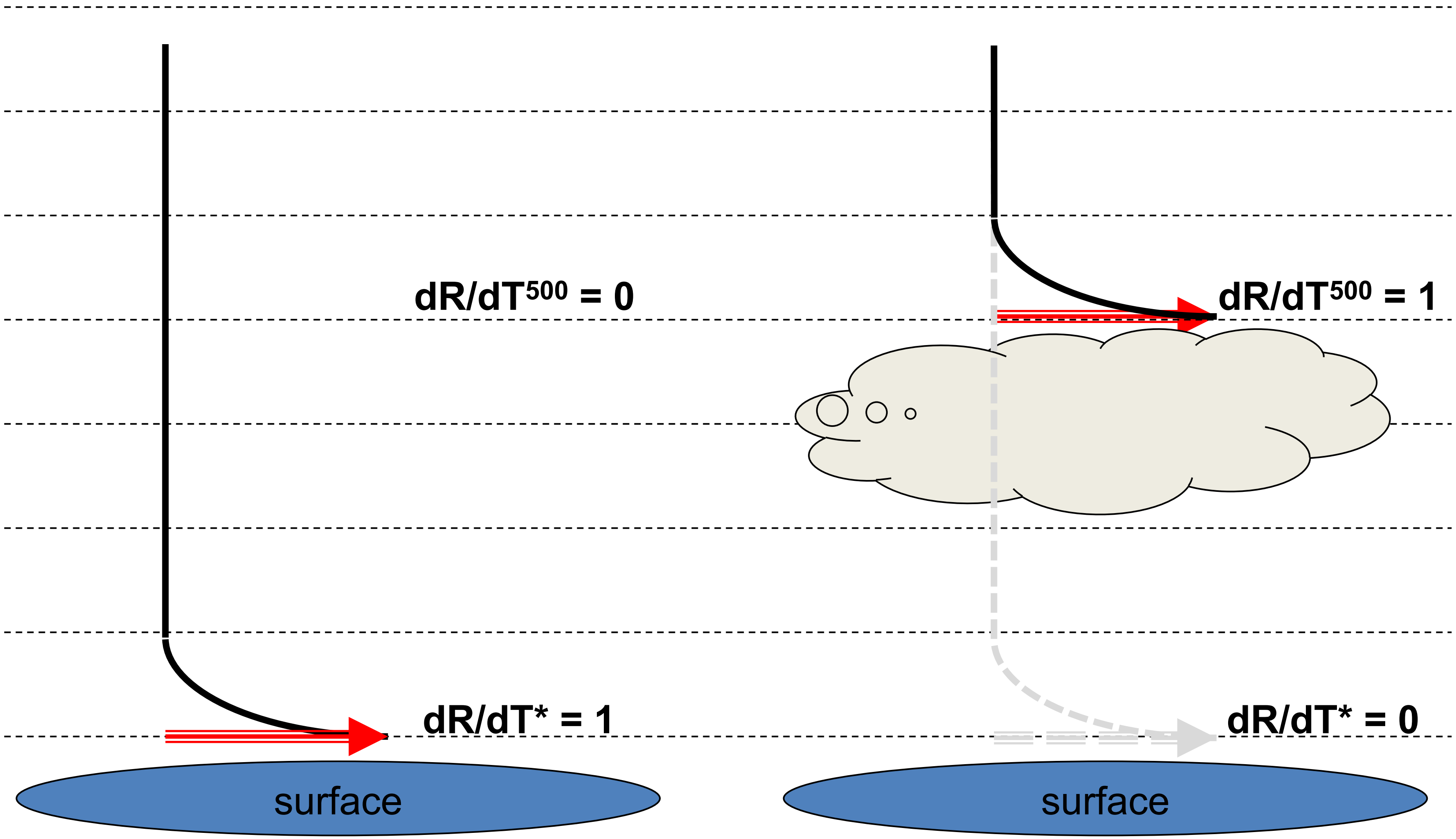
Note!

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.

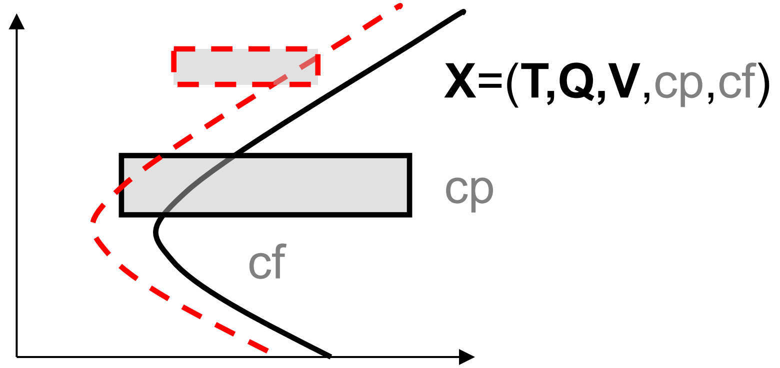
Weighting Functions in clear and cloudy sky



Two approaches to assimilate cloud- affected infrared radiances

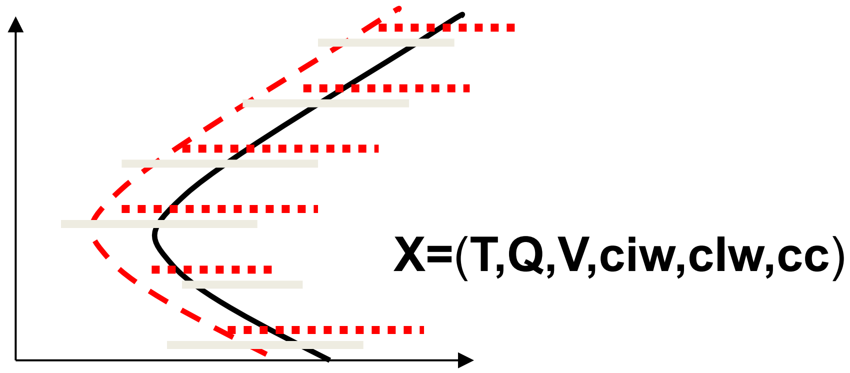
Simplified system:

- 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



ECMWF

Simplified system

model state has only one *extra* variable = cloud top height

$$J(x) = (x - x_b)^T \mathbf{B}^{-1}(x - x_b) +$$

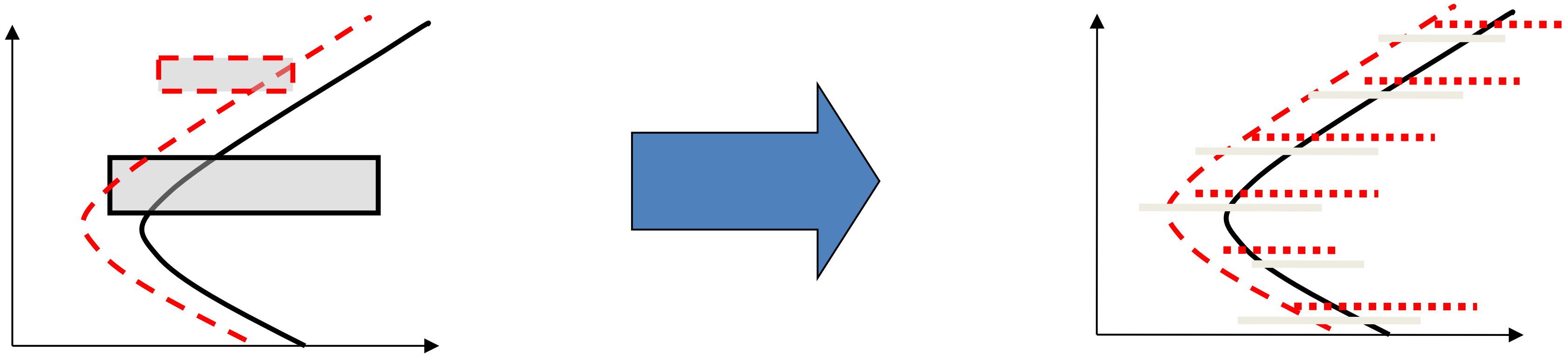
$$(y - \mathrm{H}[x])^T \mathbf{R}^{-1}(y - \mathrm{H}[x])$$

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.

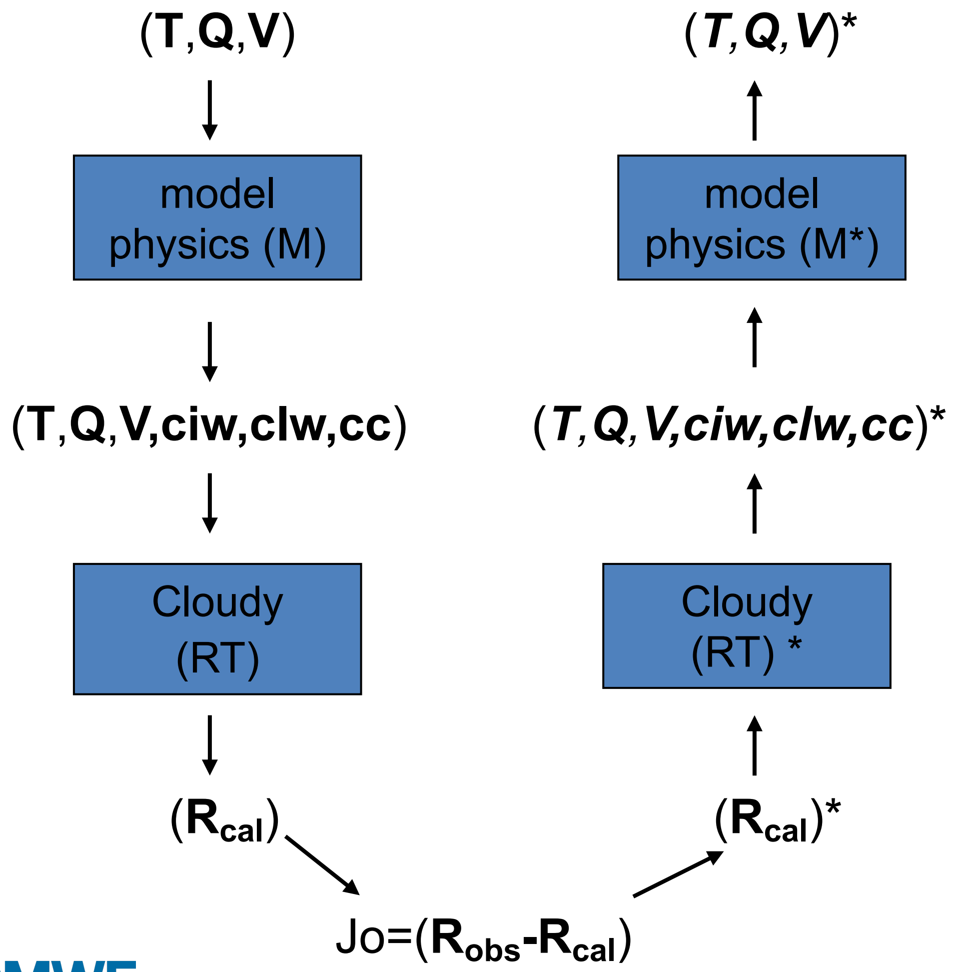
ECMWF

*See McNally (2009) QJRMS **135**, 1214-1229 for more details…*

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 (Jo)

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

ECMWF

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.

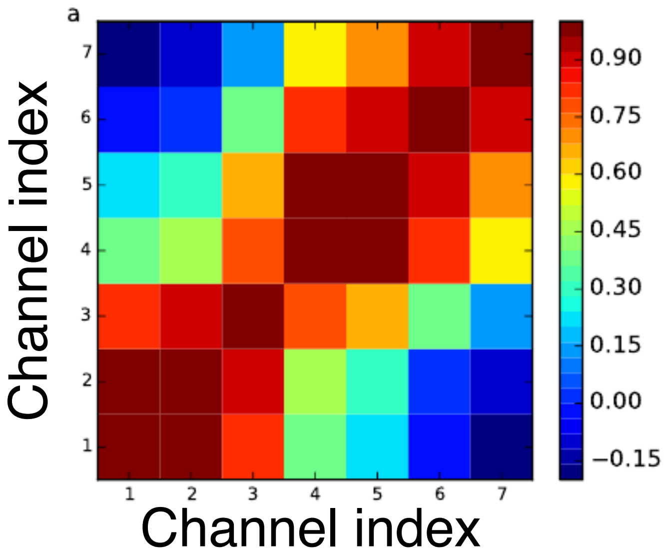
Recent review on all-sky IR progress: https://doi.org/10.1007/s00376-021-1088-9

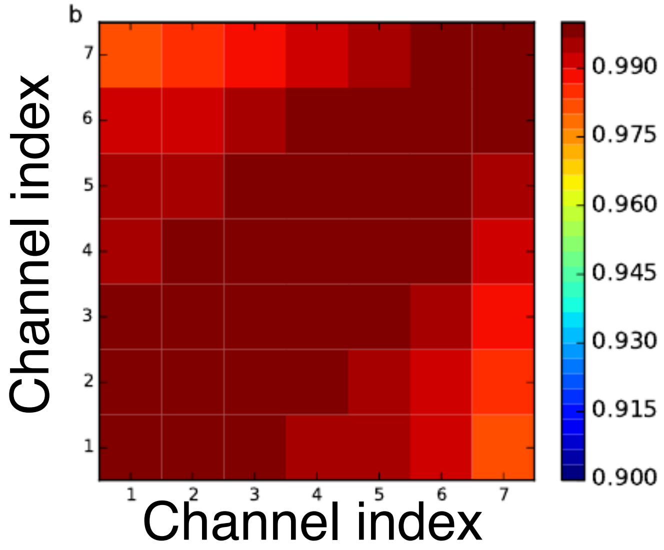
Questions ?

ECMWF

Situation-dependent observation error model

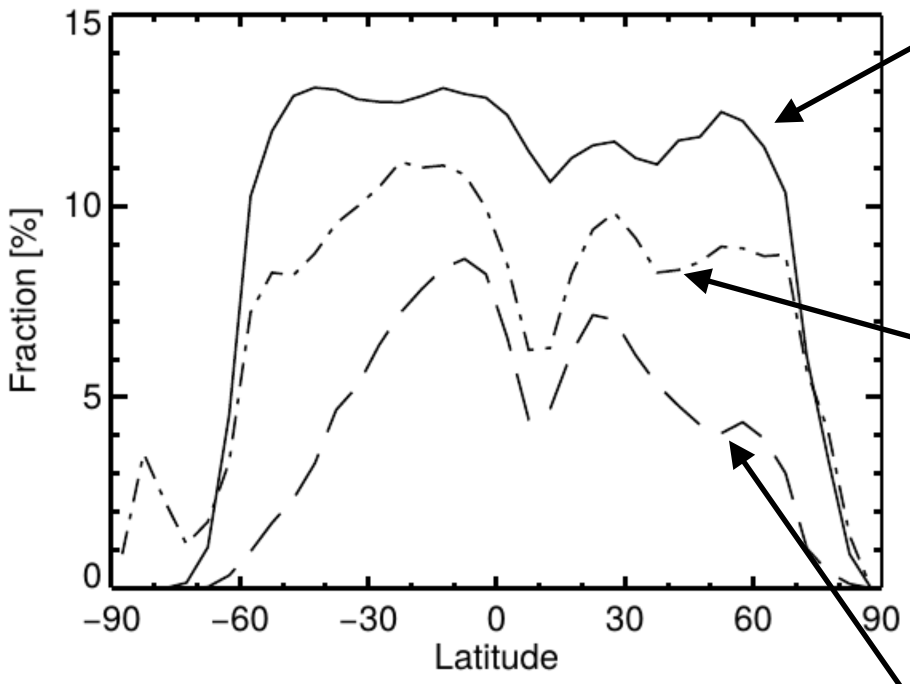
Observation error correlation in clear-sky conditions





Observation error correlation in fully cloudy conditions

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



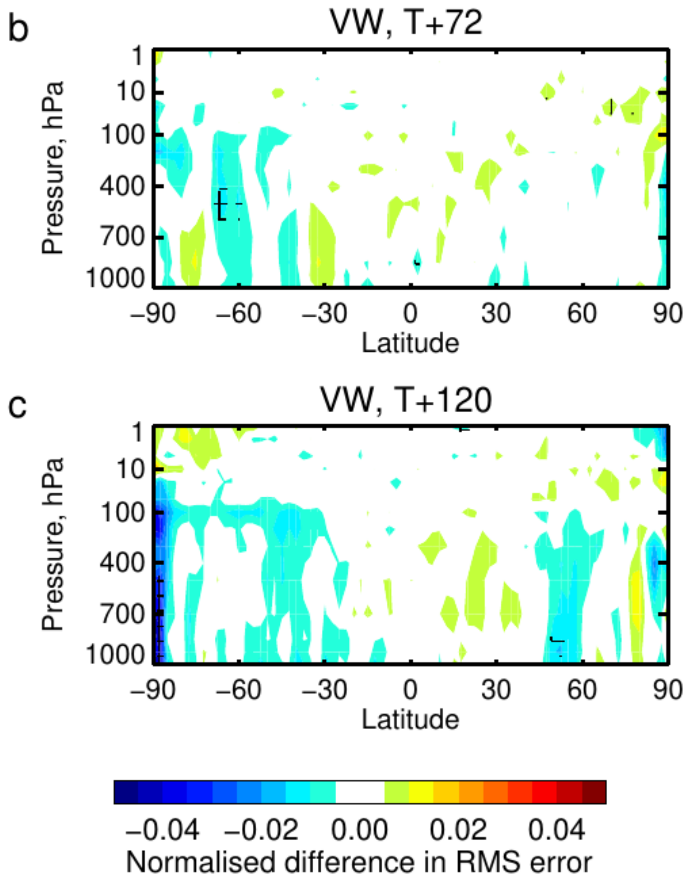
Any WV channel, using clear and cloudy data

High-peaking channel, using clear data only

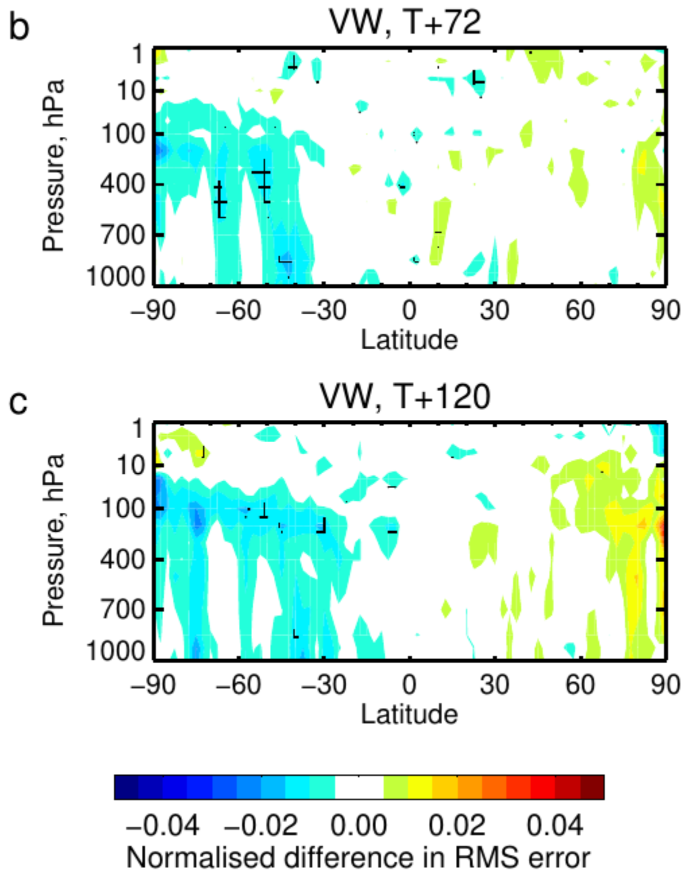
Low-peaking channel, using clear data only

The two systems produce comparable forecast impacts

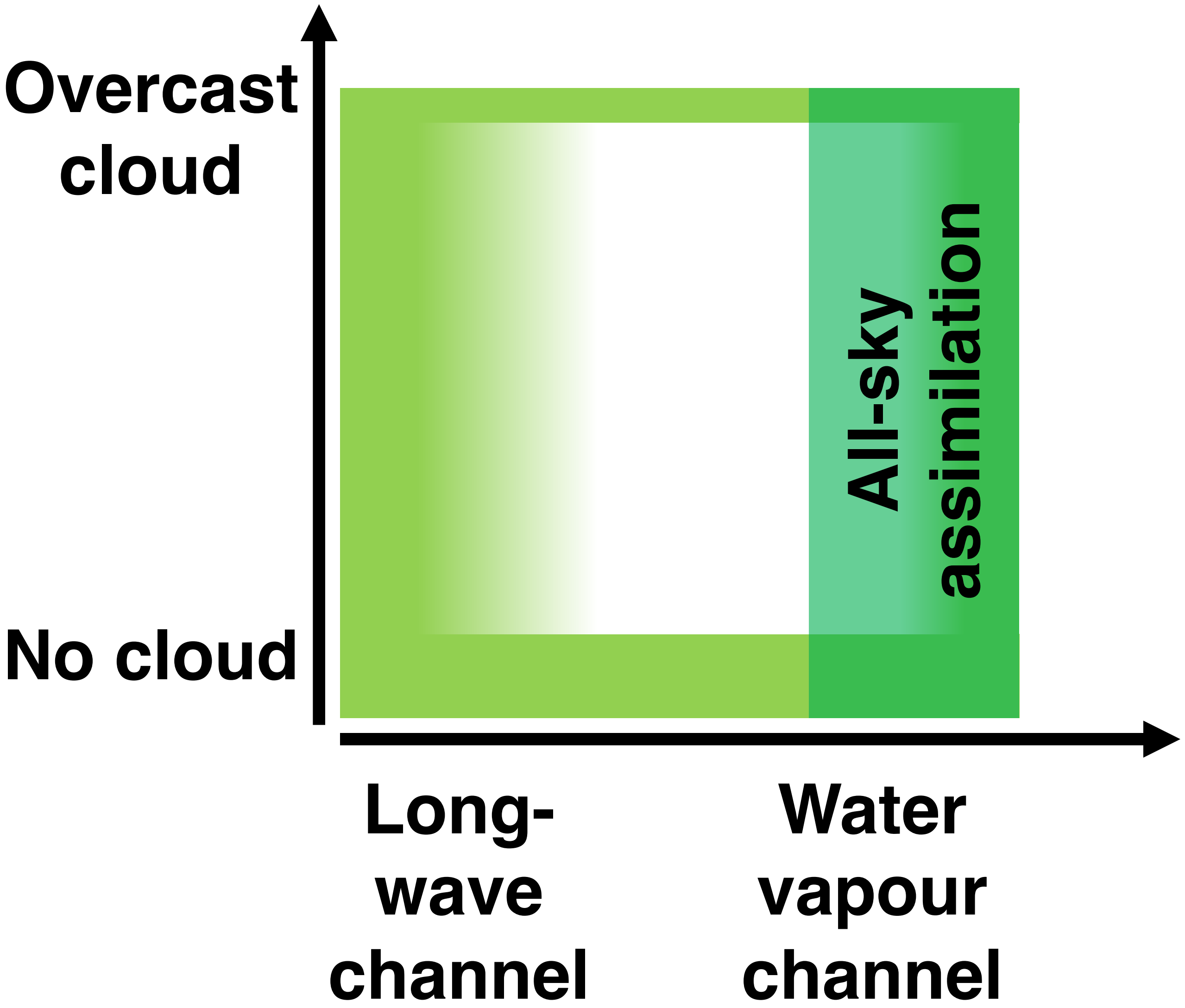
Adding seven humidity-sensitive IASI channels when clear



Adding seven humidity-sensitive IASI channels when clear or cloudy



Summary


Overcast cloud
No cloud
All-sky assimilation
Long-wave channel
Water vapour channel

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

Using departures only

Using imager only

	Clear	Cloudy	Total
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*