TRAINING
COURSE

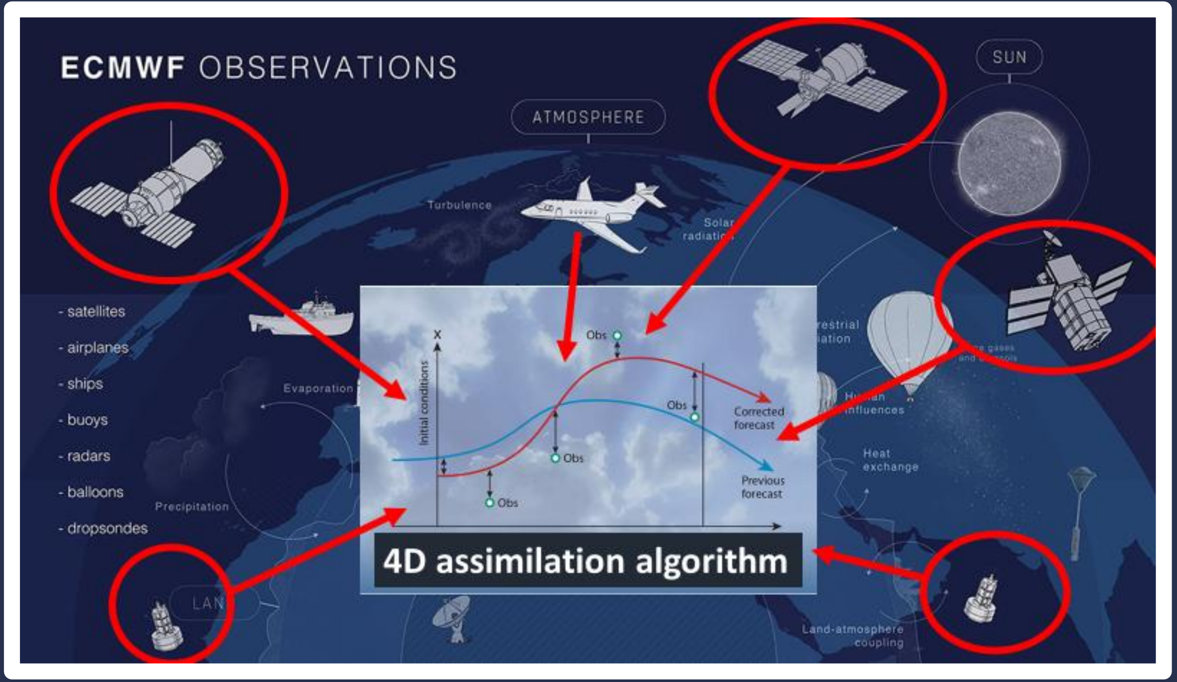
The assimilation of satellite radiance observations

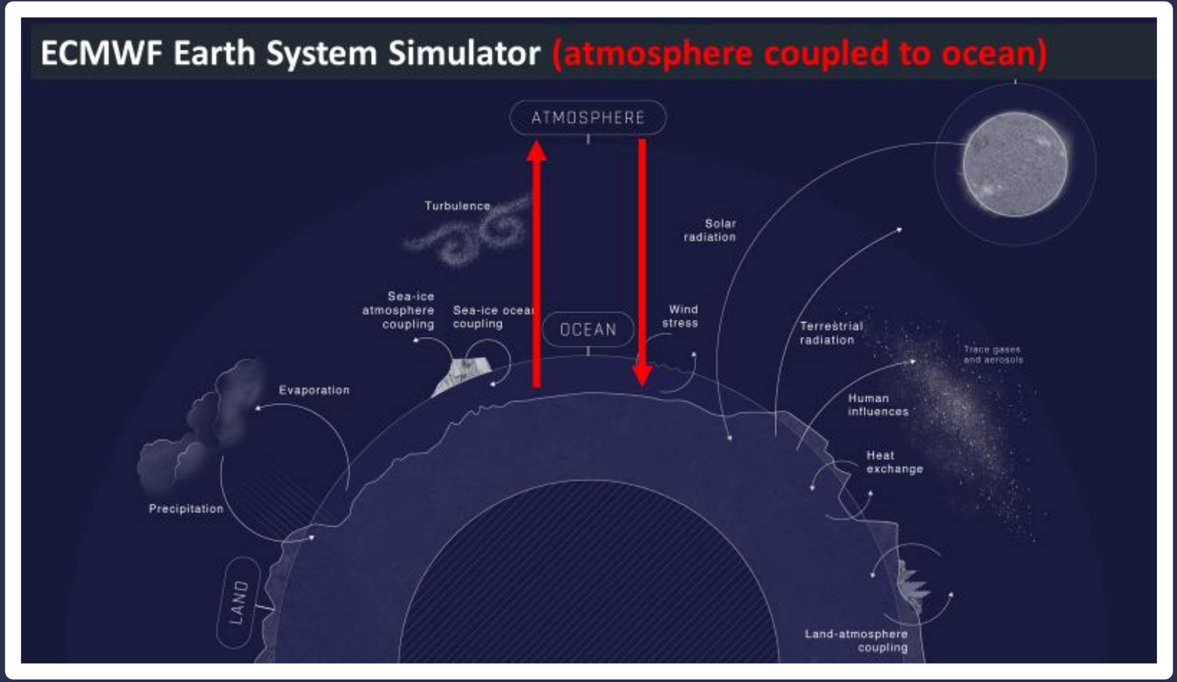
Tony McNally

Overview:

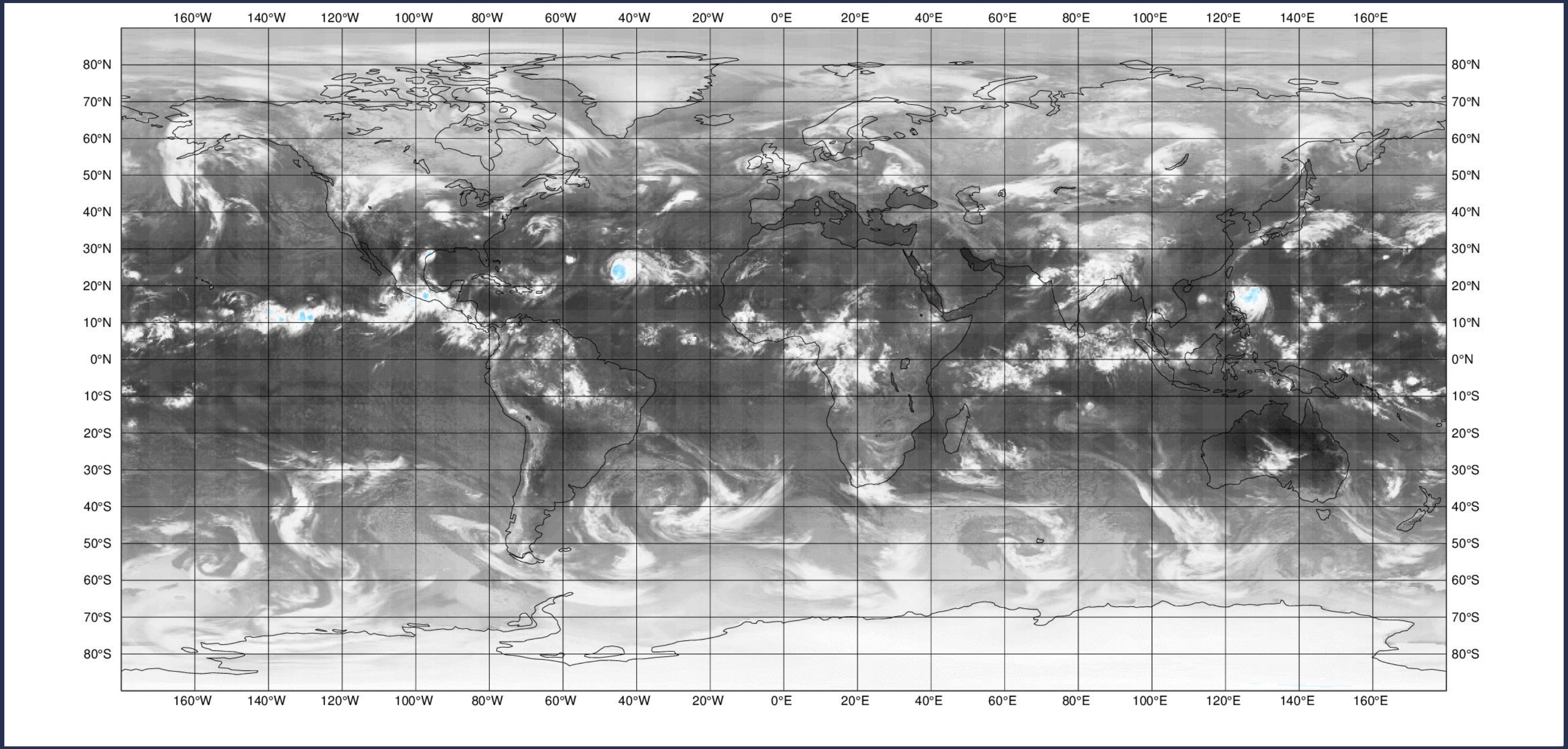
- Why do we need satellites ?
- What do we have and which are most important ?
- What is actually measured ?
- Key elements of satellite data assimilation

The Satellites and other observations provide **<u>initial conditions</u>** (what the atmosphere doing now) from which forecasts are launched

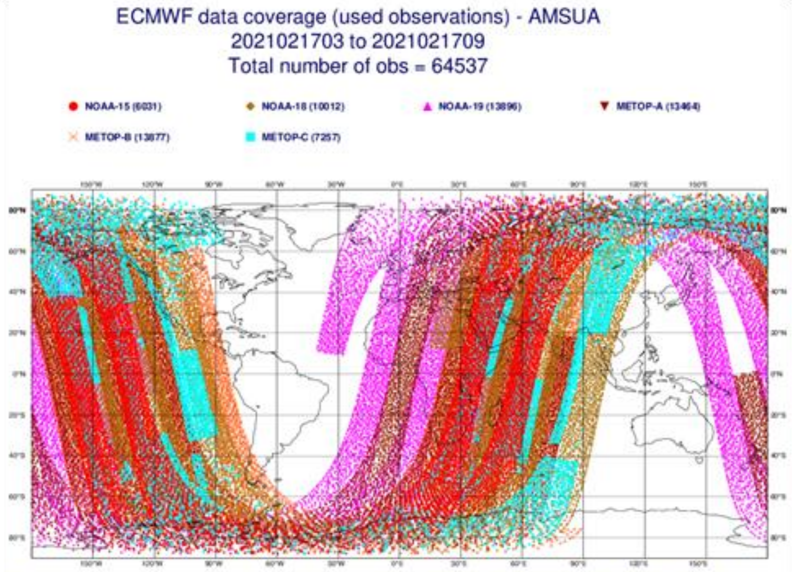


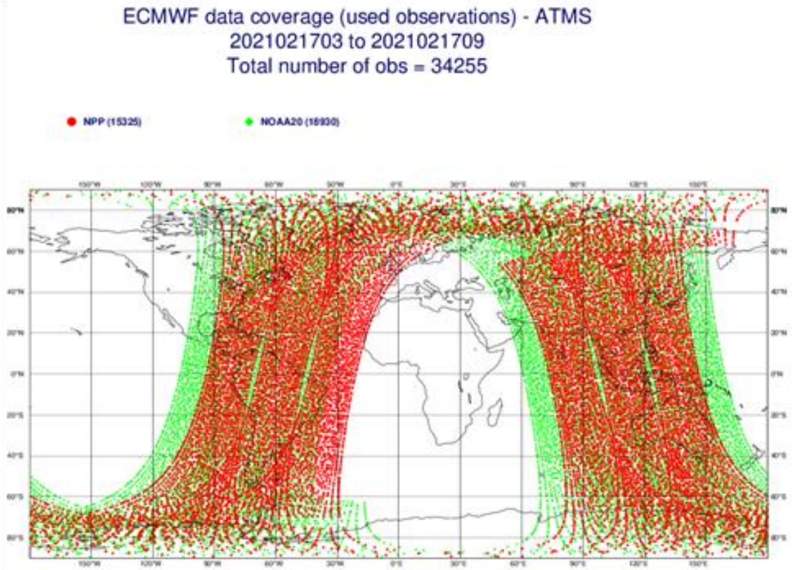


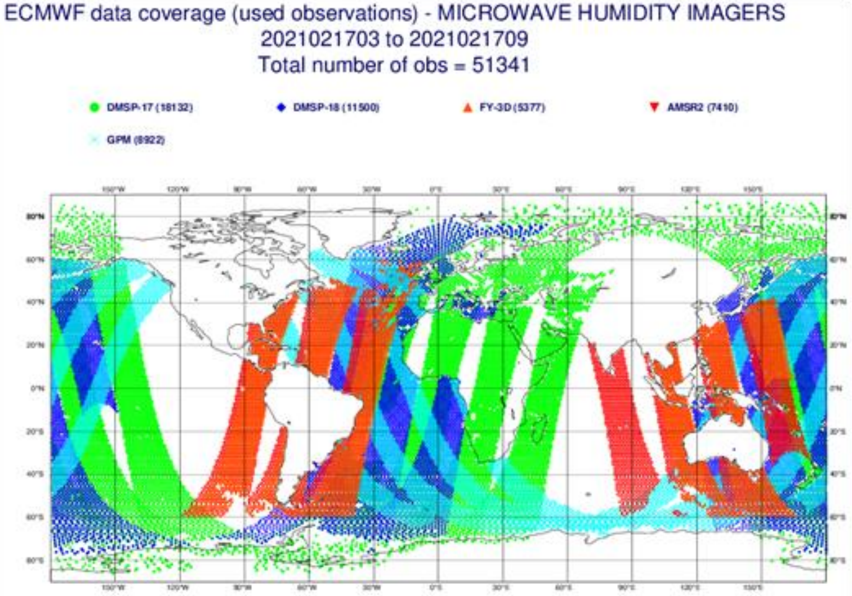
To forecast many days into the future, we need global initial conditions…and only satellites can provide this

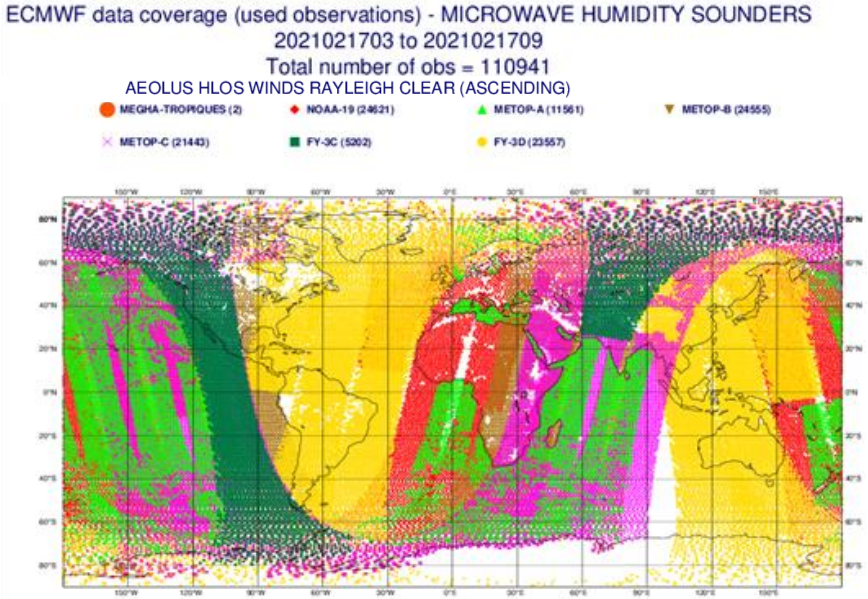


Passive microwave (LEO)

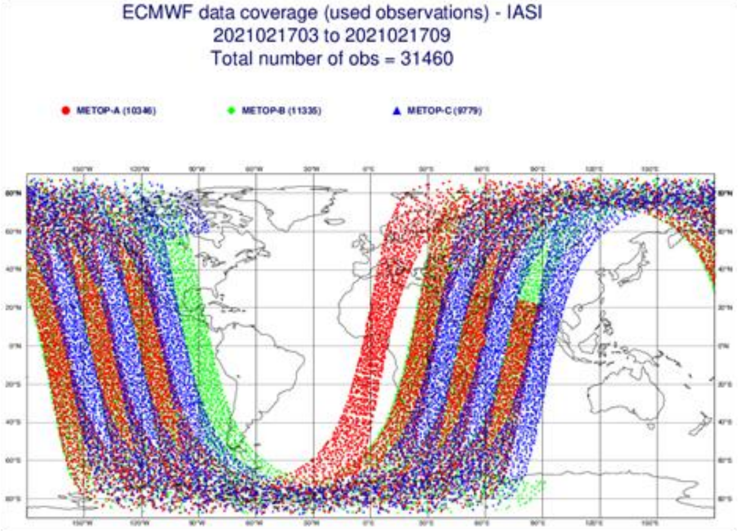


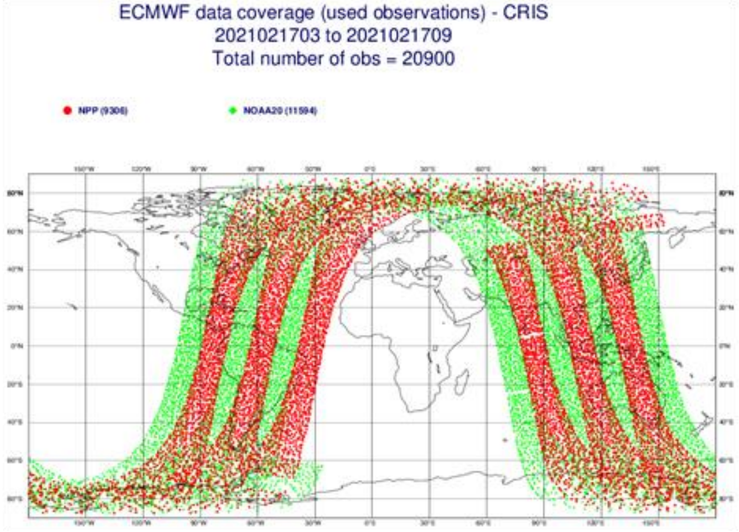


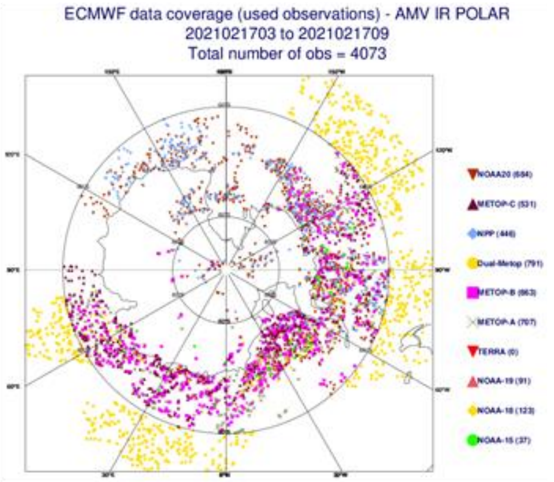


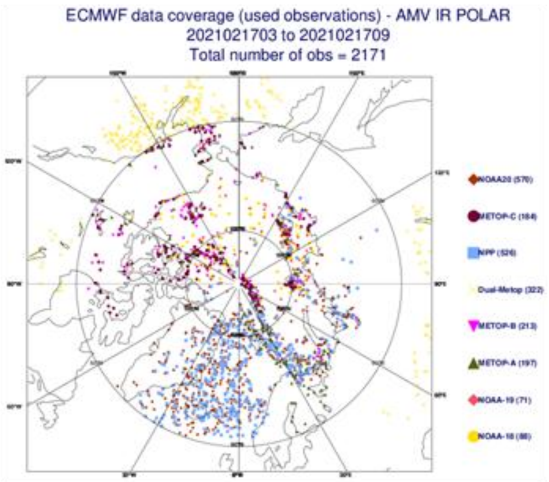


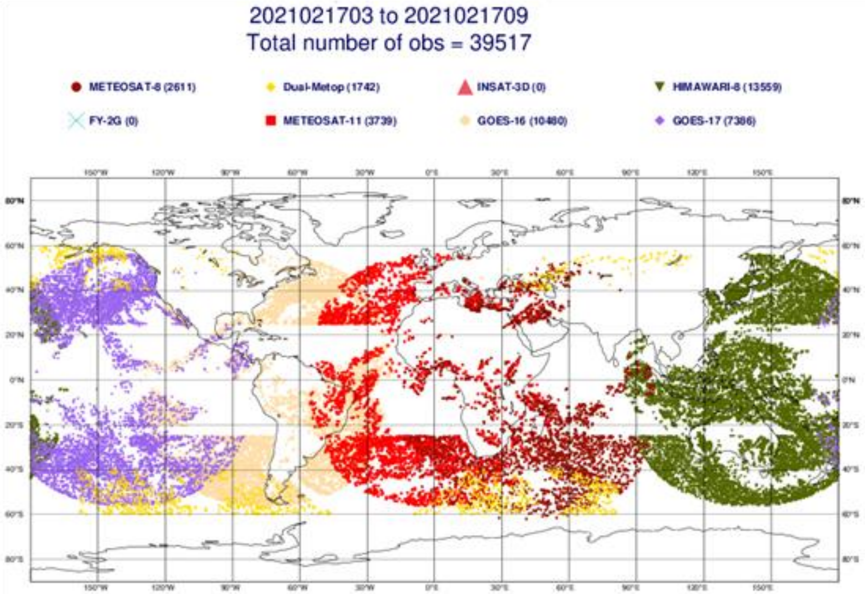
Passive infrared (LEO and GEO)



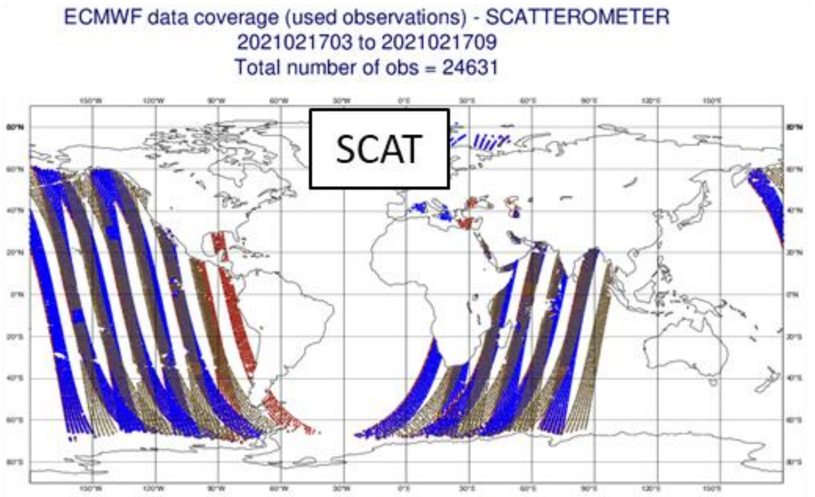


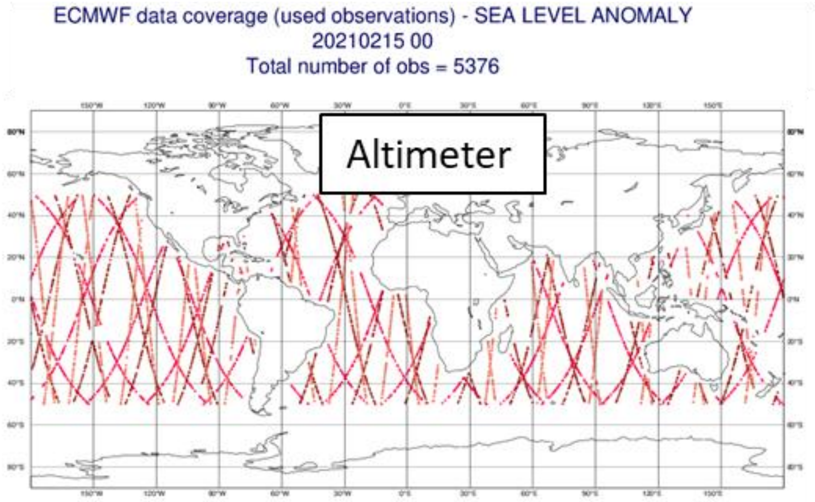


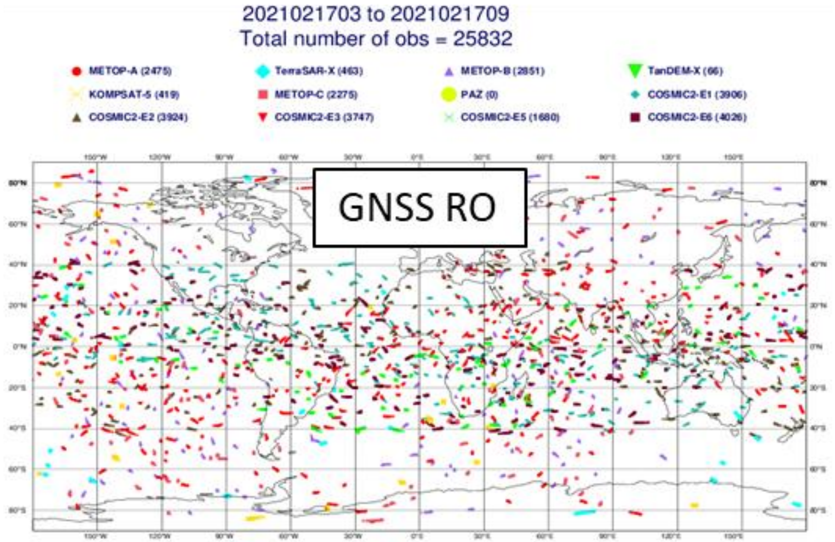


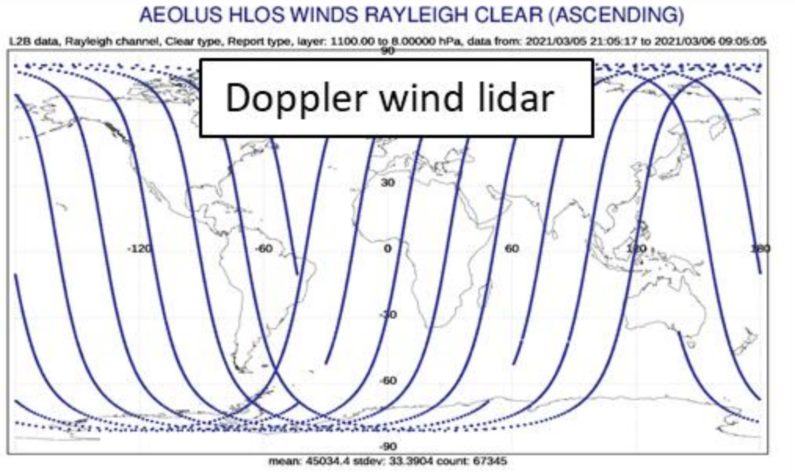


Active sensors









Can we quantify how important are satellites for NWP ?

…denial experiments…

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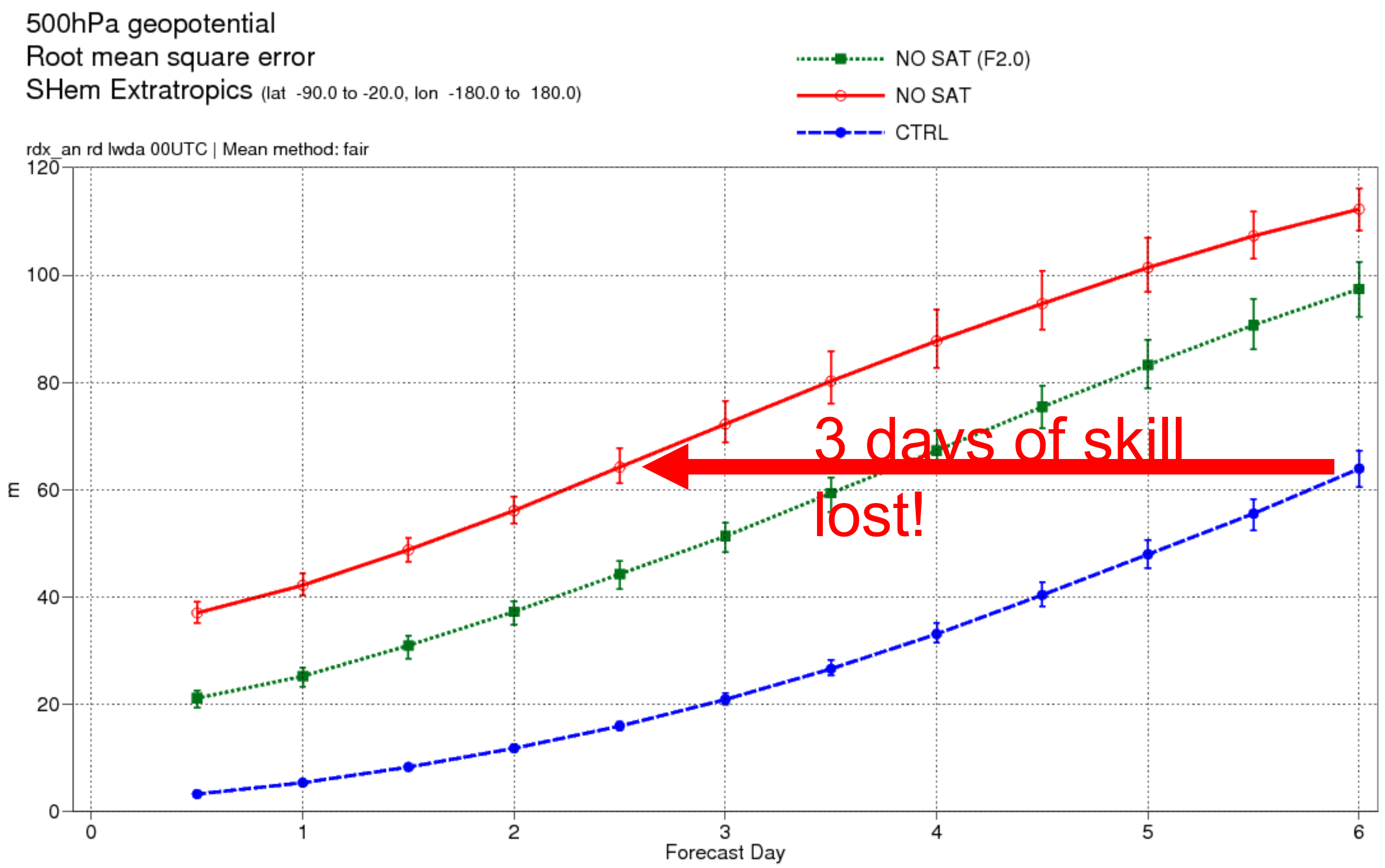


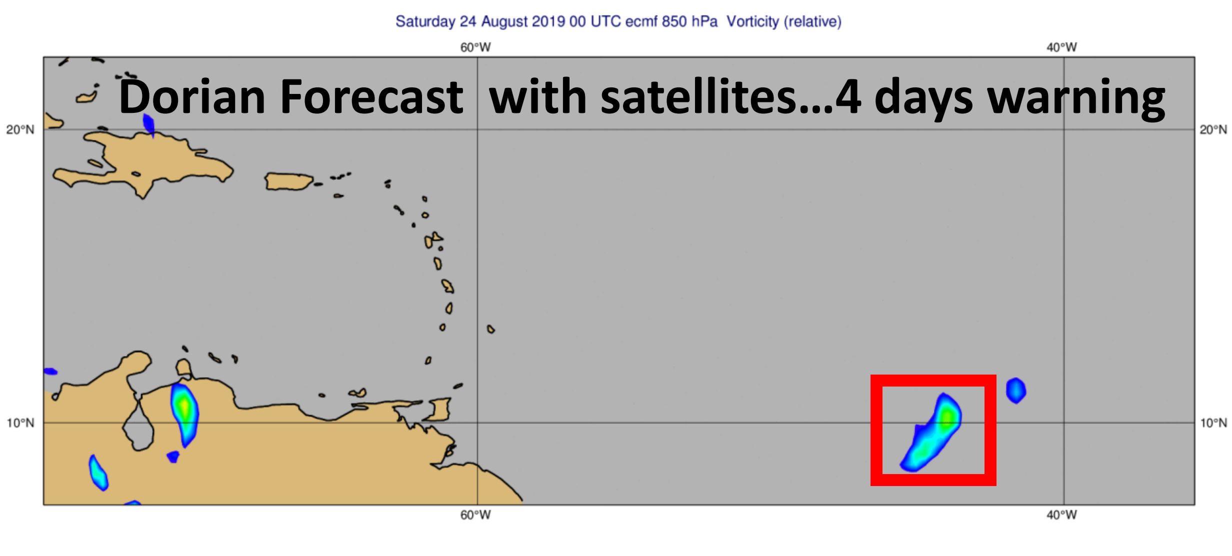
Dorian viewed from the Sentinel-3 satellite

Dorian viewed from the Sentinel-3 satellite

Dorian viewed from the Bahamas

Most deadly event in recent history is Nargis (2008) that claimed ~ 130,000 lives

Early identification of storm genesis with satellites saves many thousands of lives

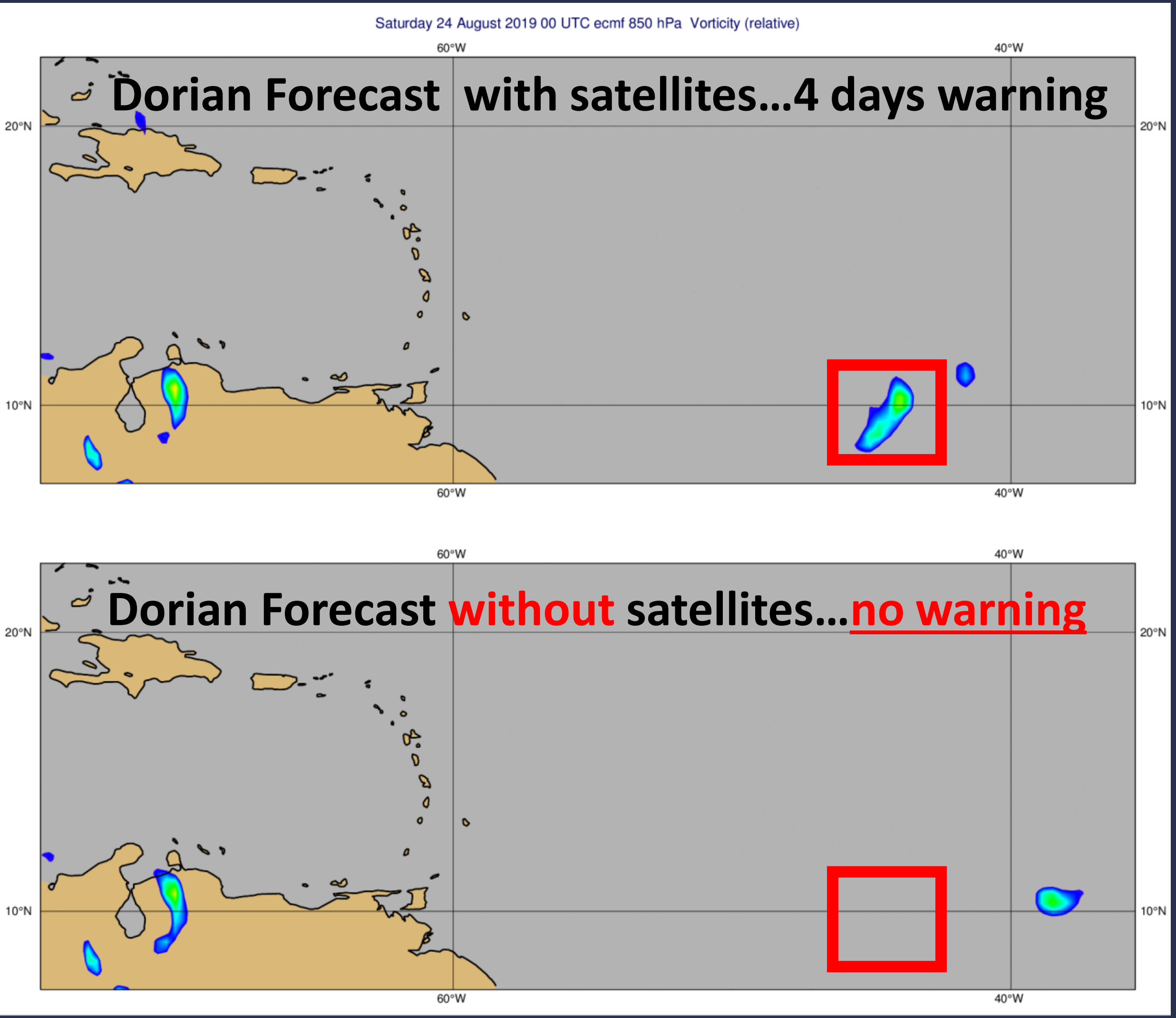


Key information

1. Ocean surface temperature
2. mid level humidity
3. wind sheer

Satellites provide this …

Without satellites we would often give no warning of severe weather!

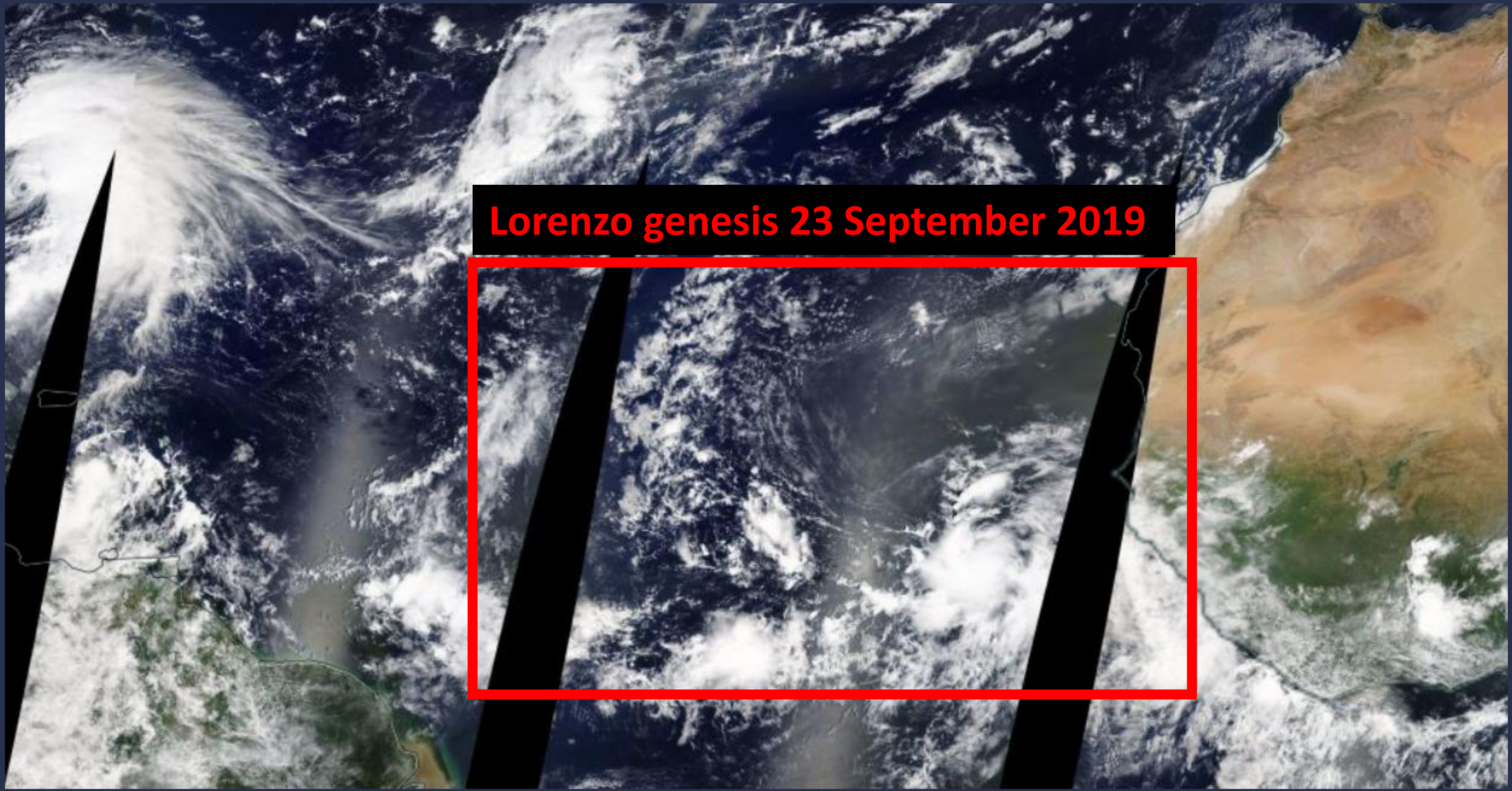


~~**Key observations**~~

1. ~~Ocean surface temperature~~
2. ~~mid level humidity~~
3. ~~wind sheer~~

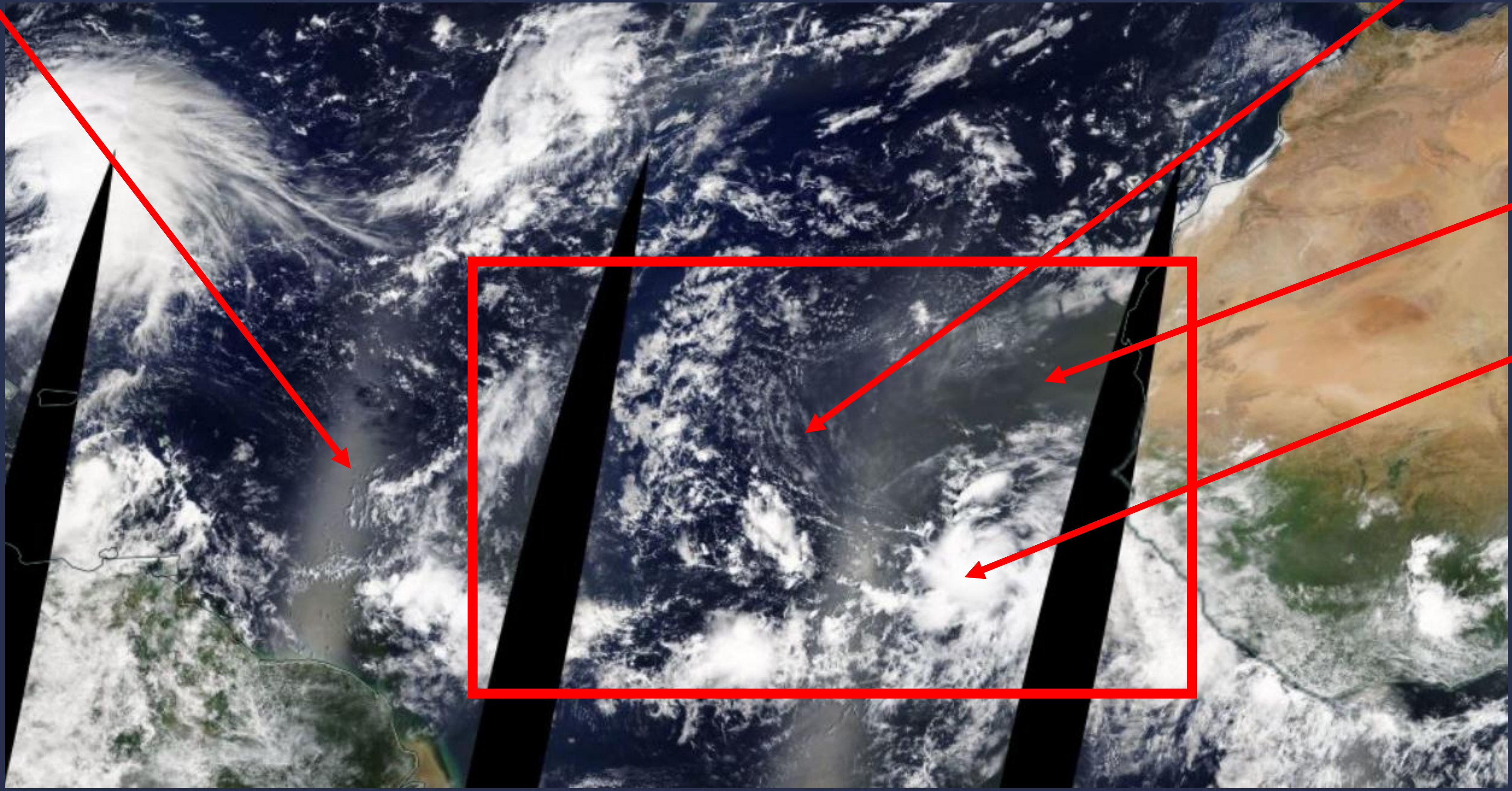
Early identification of storm genesis...Lorenzo

Key observations
- Ocean surface temperature ?
- mid level humidity ?
- wind sheer ?



Early identification of storm genesis…in a challenging environment

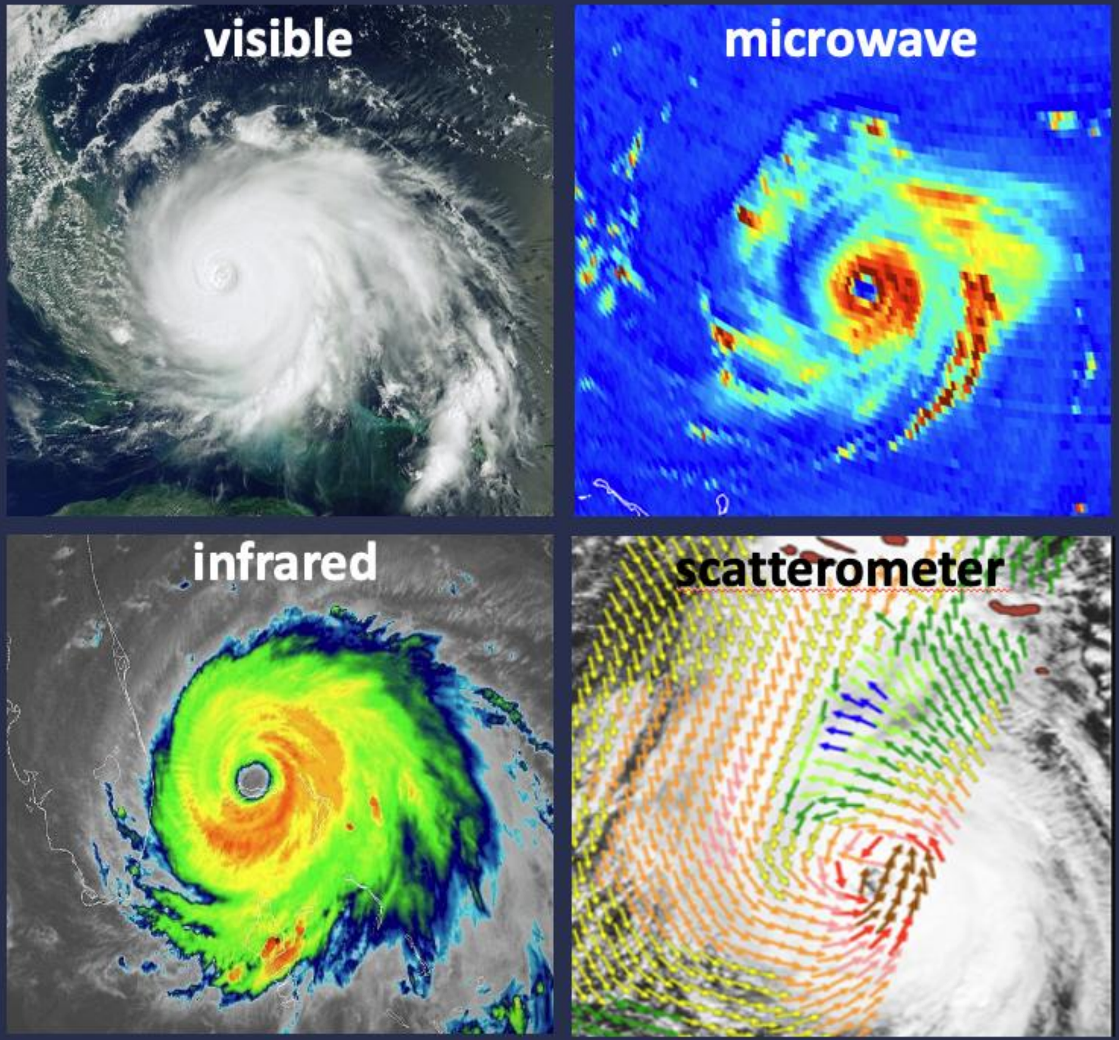
- Ocean surface temperature ?
- mid level humidity ?
- wind sheer ?



Satellite sensors operating at <u>different</u> <u>frequencies</u> are used to understand the full atmospheric state…

Cloud phase and motion (wind)

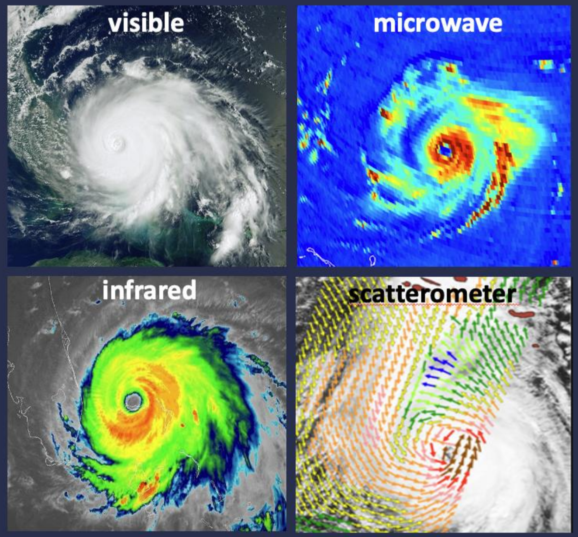
Water and rain content within clouds

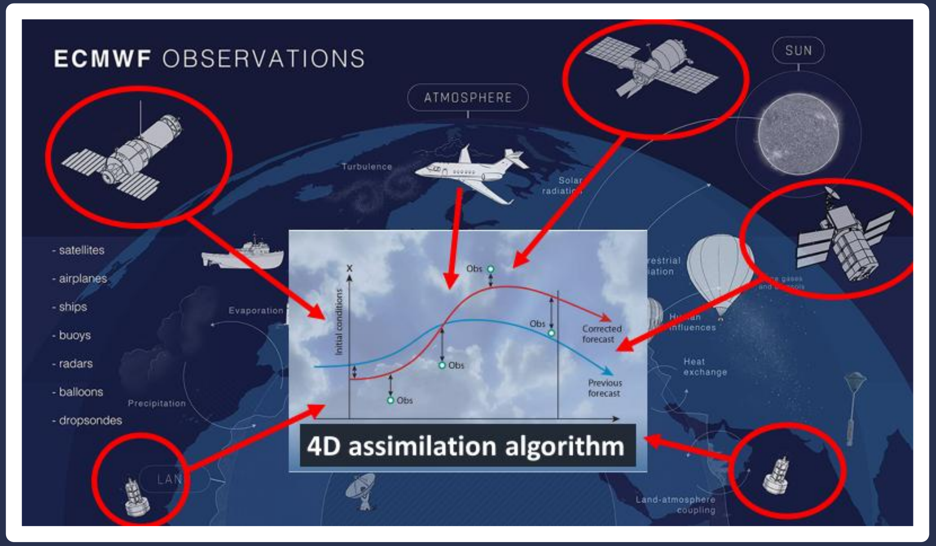


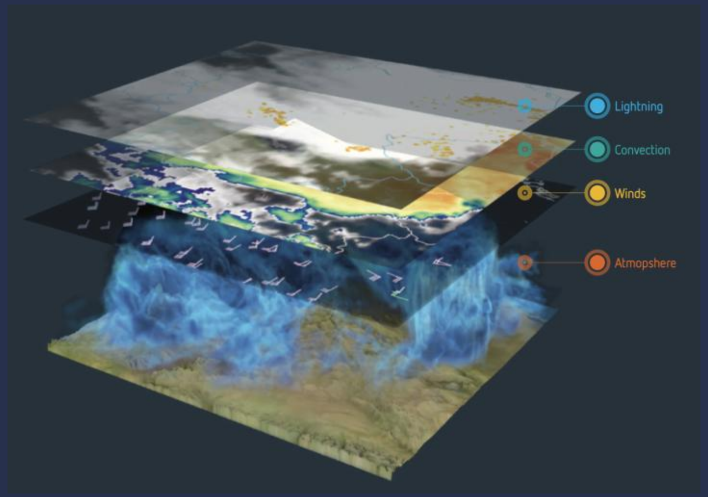
Temperature and height of clouds, humidity in clear sky

Penetrating the clouds to look at ocean roughness and land state

...But require highly sophisticated Data Assimilation Systems to combine these into a coherent 3D picture

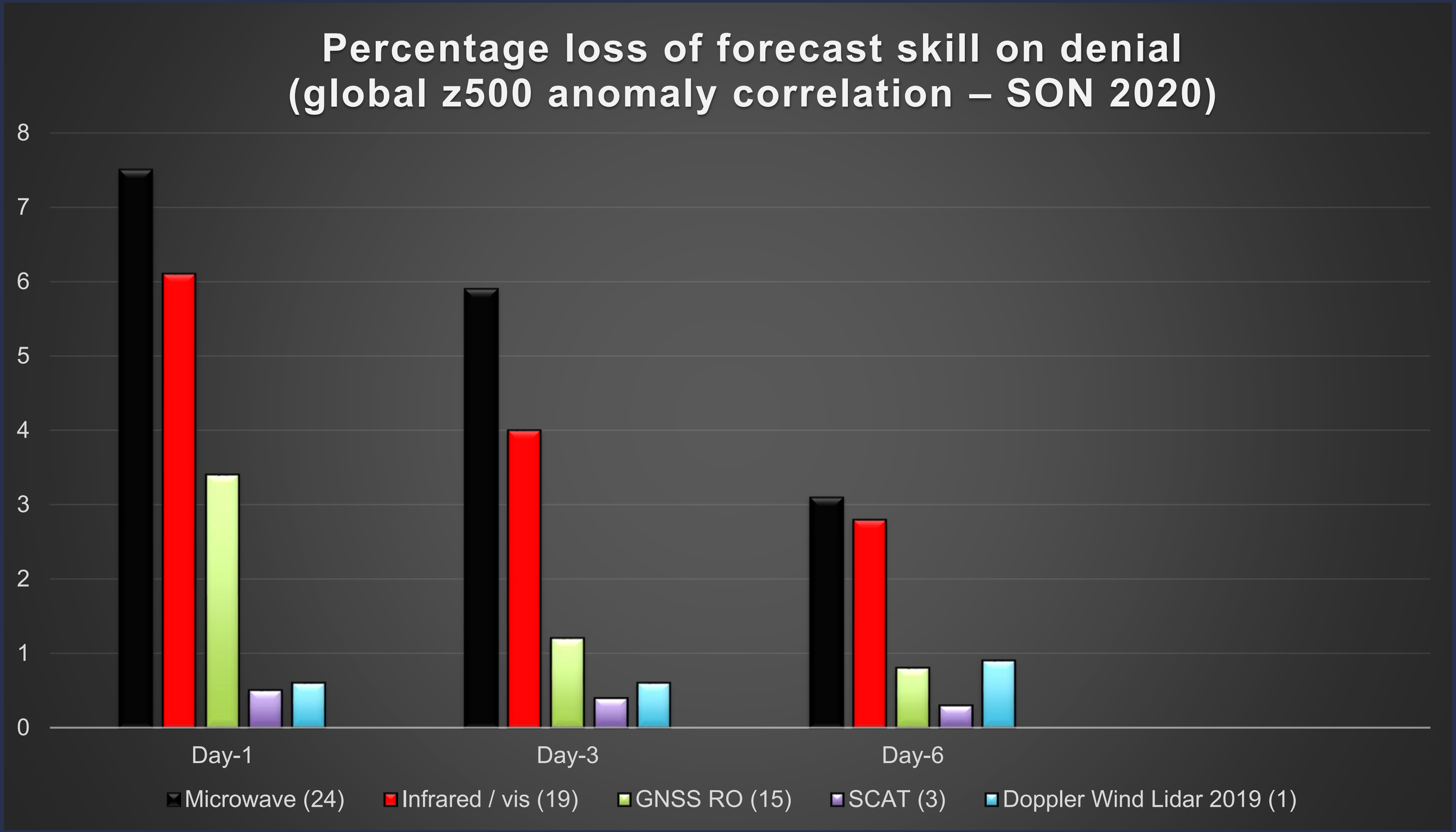






Which satellite observations are most important for NWP ?

Impact of different sensor technologies



Which satellite observations are most important for NWP ?

Sensor technology	Processing route
Passive microwave	L1 Radiances
Passive infrared	L1 Radiances / AMV
Radio occultation	Bending angles
SCAT / Altimeter	L2 wind / SLA / SWH
Doppler wind lidar	L2 LOS wind

Note that sensors available for NWP are **typically downward** looking instruments (**not limb viewing**)

What do passive microwave and infrared satellite instruments measure …?

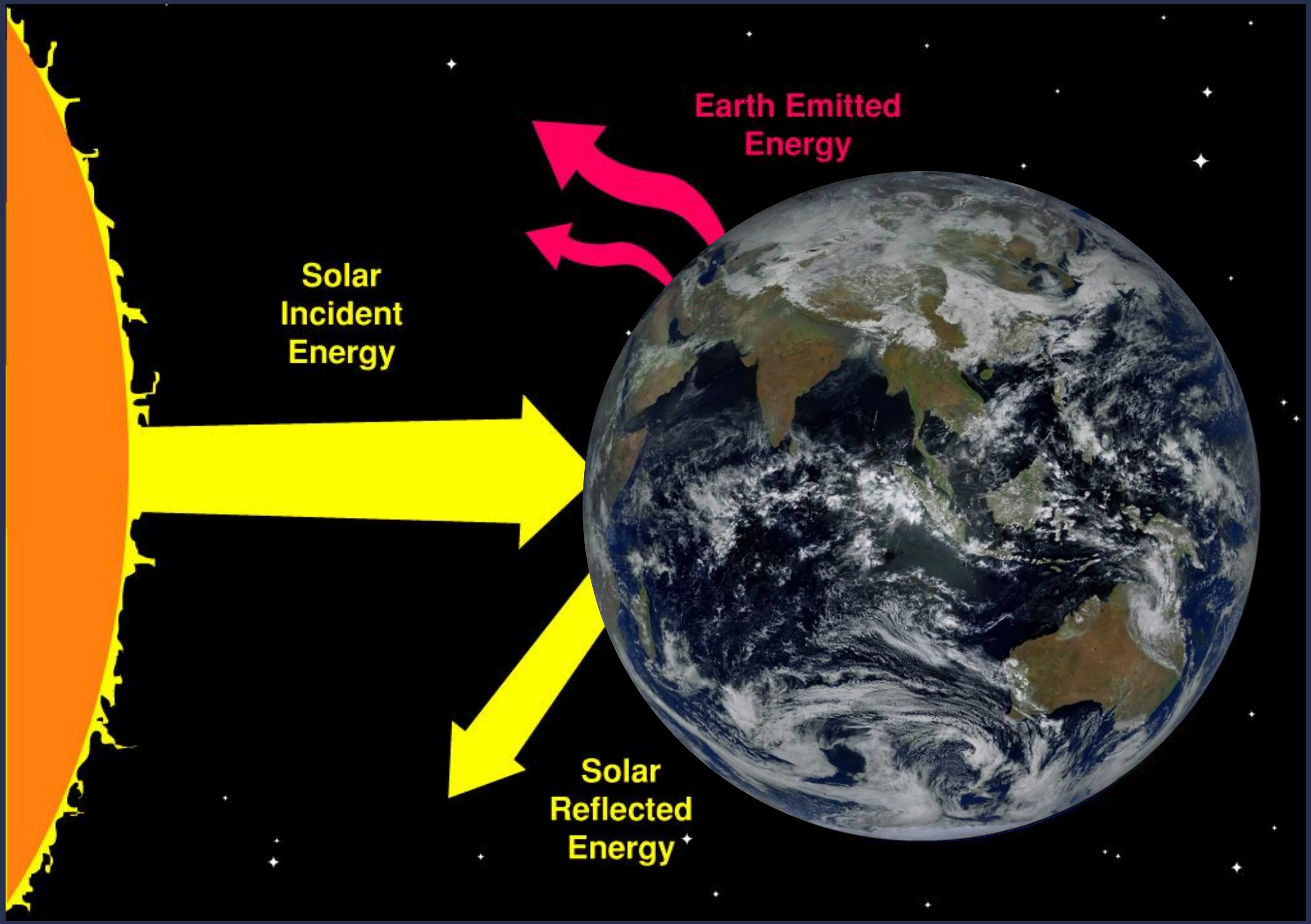
What do passive microwave and infrared satellite instruments measure …?

They DO NOT measure TEMPERATURE

They DO NOT measure HUMIDITY or OZONE

They DO NOT measure WIND

SATELLITES CAN ONLY MEASURE OUTGOING THERMAL RADIATION FROM THE ATMOSPHERE



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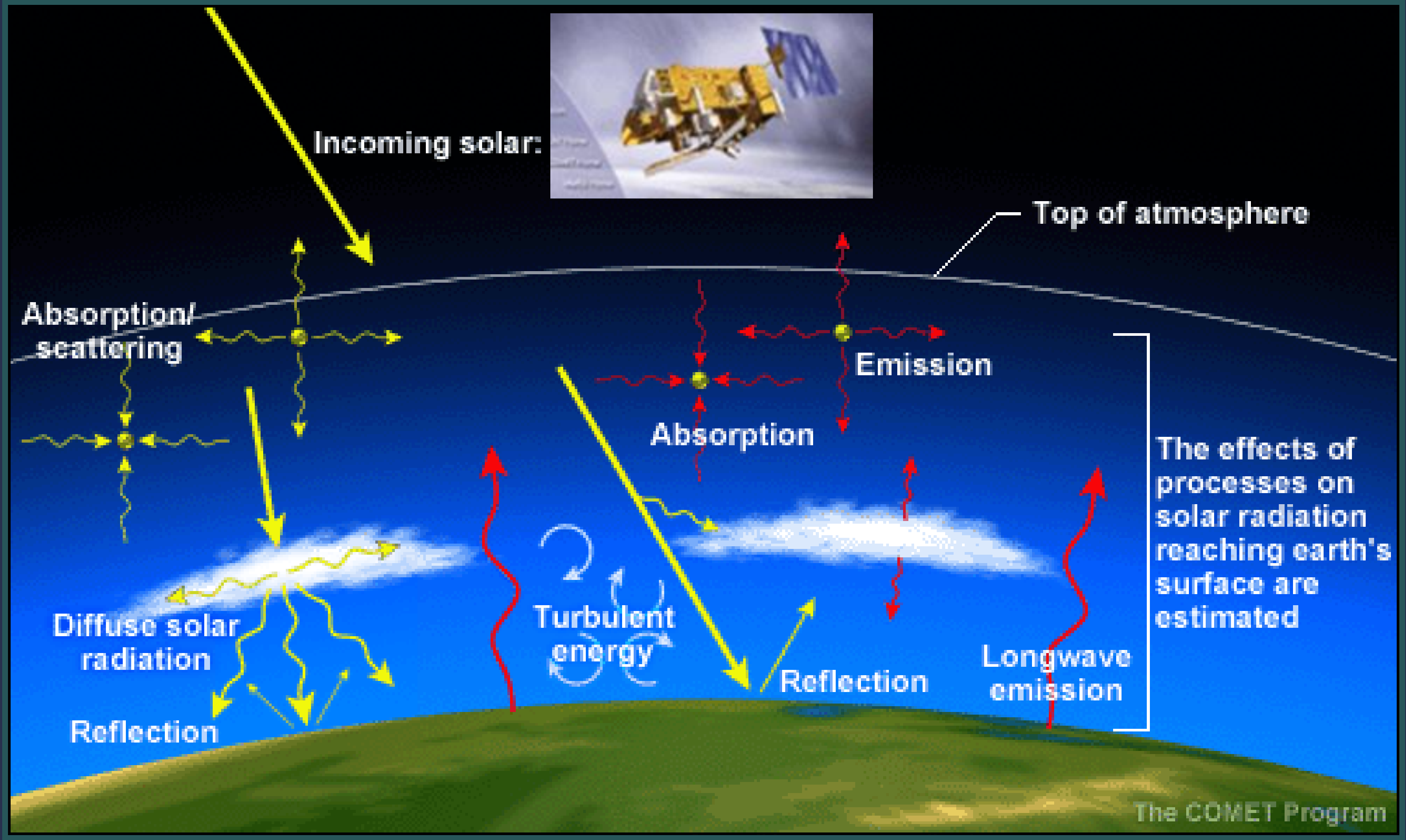


What do satellite instruments measure ?

Satellite instruments measure the radiation *L* that reaches the top of the atmosphere at given frequency *v* .

The measured radiance is related to geophysical atmospheric variables (T,Q,O_3, clouds etc…) by the

Radiative Transfer Equation

$$\overbrace{L(\nu)}^{\text{measured by the satellite}} = \overbrace{\int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz + \text{Surface emission} + \text{Surface reflection/ scattering} + \text{Cloud/rain contribution} + \ldots}^{\text{Our description of the atmosphere}}$$

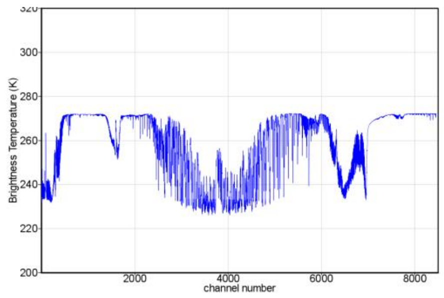
Planck source term* depending on temperature *T(z)* of the atmosphere

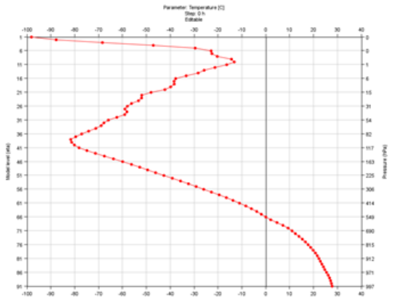
Transmittance / Absorption in the atmosphere

Other contributions to the measured radiances

The Radiative Transfer (RT) equation

$$\underbrace{L(\nu)}_{\text{measured by the satellite}} = \underbrace{\int_0^\infty B(\nu, T(z))\left[\frac{d\tau(\nu)}{dz}\right]dz + \text{Surface emission} + \text{Surface reflection/scattering} + \text{Cloud/rain contribution} + \ldots}_{\text{depends on the state of the atmosphere}}$$





The Radiative Transfer (RT) equation

"Forward problem"

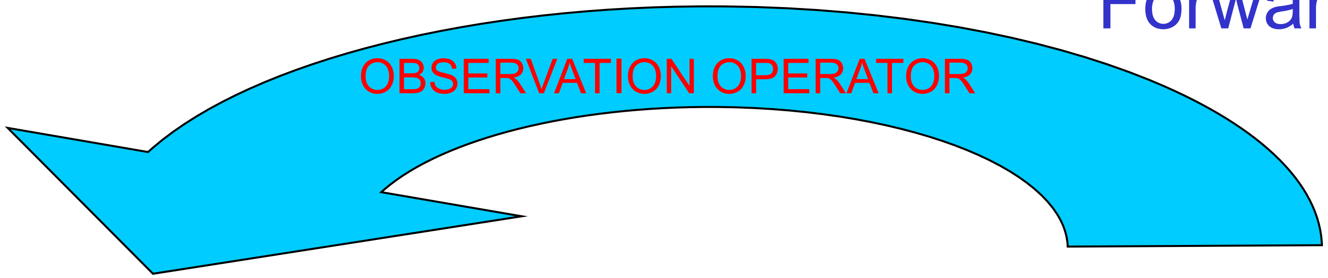
$$\overbrace{L(\nu)}^{\text{measured by the satellite}} = \overbrace{\int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz + \text{Surface emission} + \text{Surface reflection/ scattering} + \text{Cloud/rain contribution} + \ldots}^{\text{depends on the state of the atmosphere}}$$

…given the state of the atmosphere, what is the radiance…?

*i.e. we can **simulate** what radiation would reach the satellite from a particular atmosphere…*

The Radiative Transfer (RT) equation

“Forward problem”



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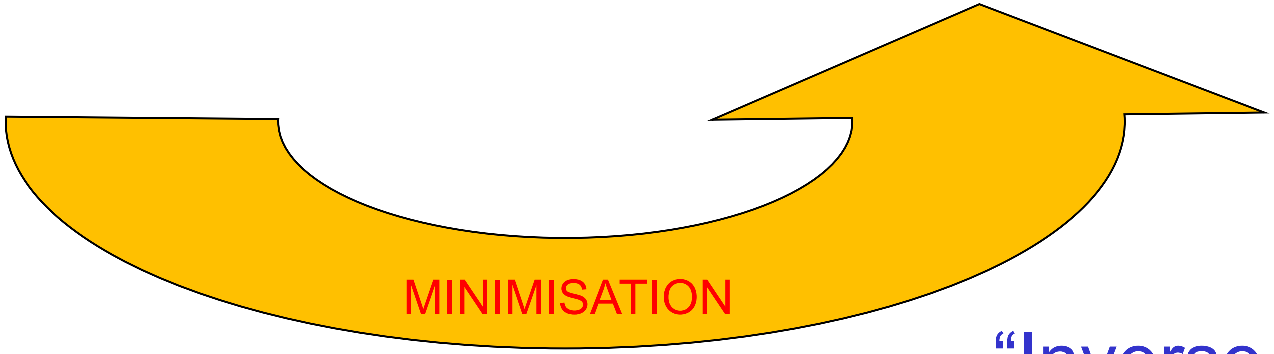


“Inverse problem”

…but first we have to simplify things a bit…

"Channel selection" …

…designing satellite instruments to measure atmospheric radiation at very specific frequencies (channels)

Measuring radiances in different frequencies (channels)

By deliberately selecting radiation at different frequencies or CHANNELS satellite instruments can provide information on specific geophysical variables for different regions of the atmosphere.

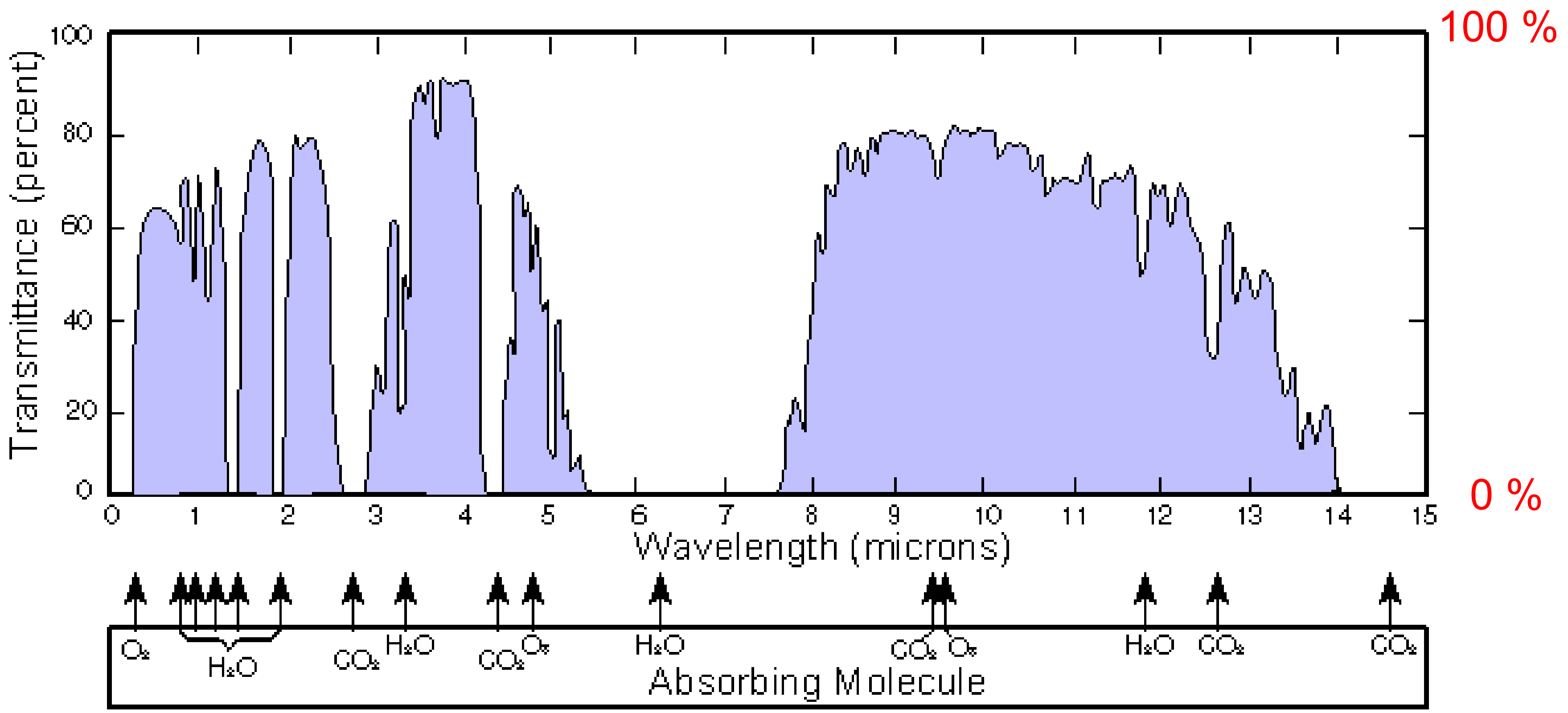
In general, the frequencies / channels used within NWP may be categorized as one of 2 different types …

1. atmospheric sounding channels
2. surface sensing channels

Note:

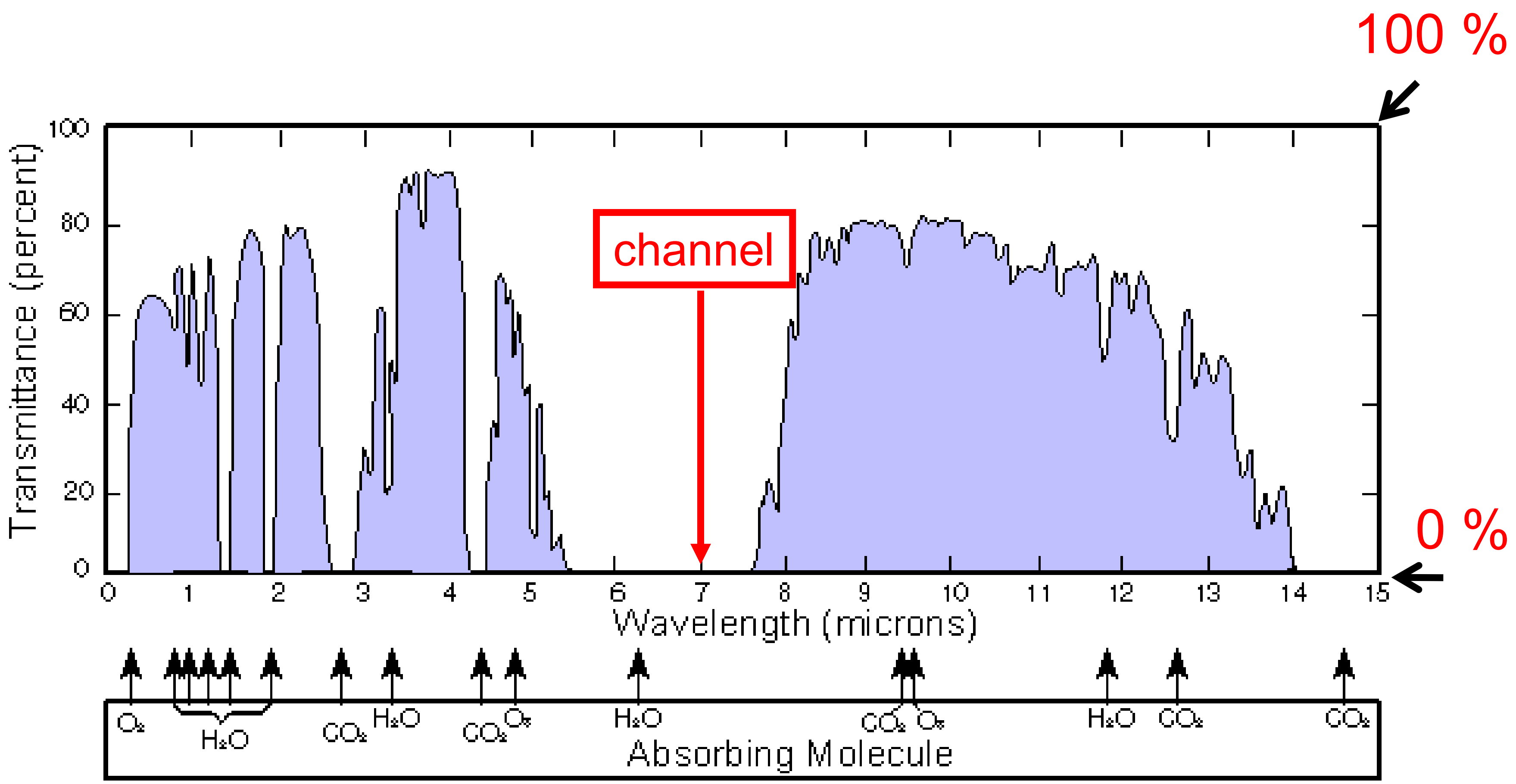
In practice (and often despite their name!) real satellite instruments have channels which are a combination of atmospheric sounding and surface sensing channels

Atmospheric transmission at different wavelengths

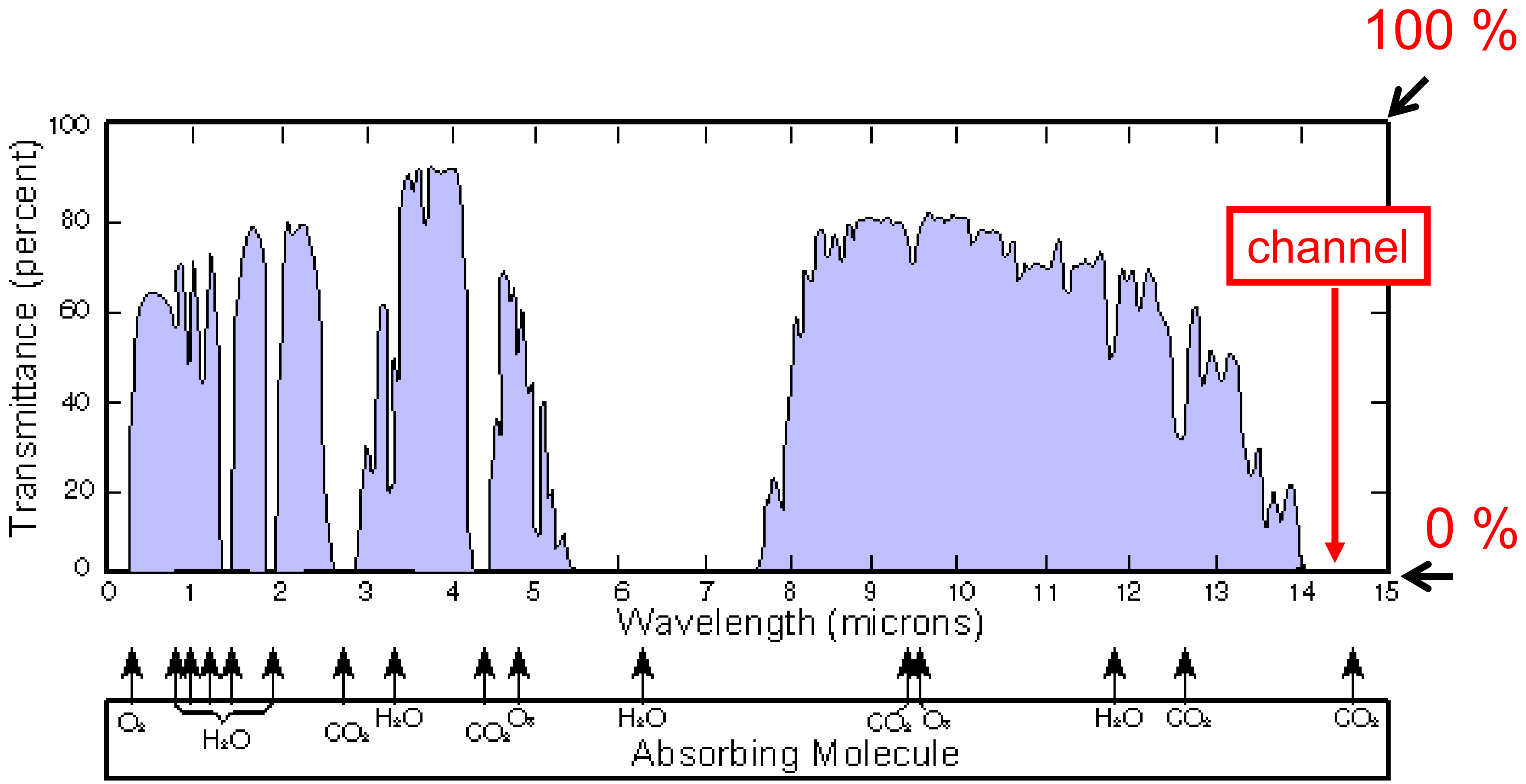


Atmospheric sounding channels…

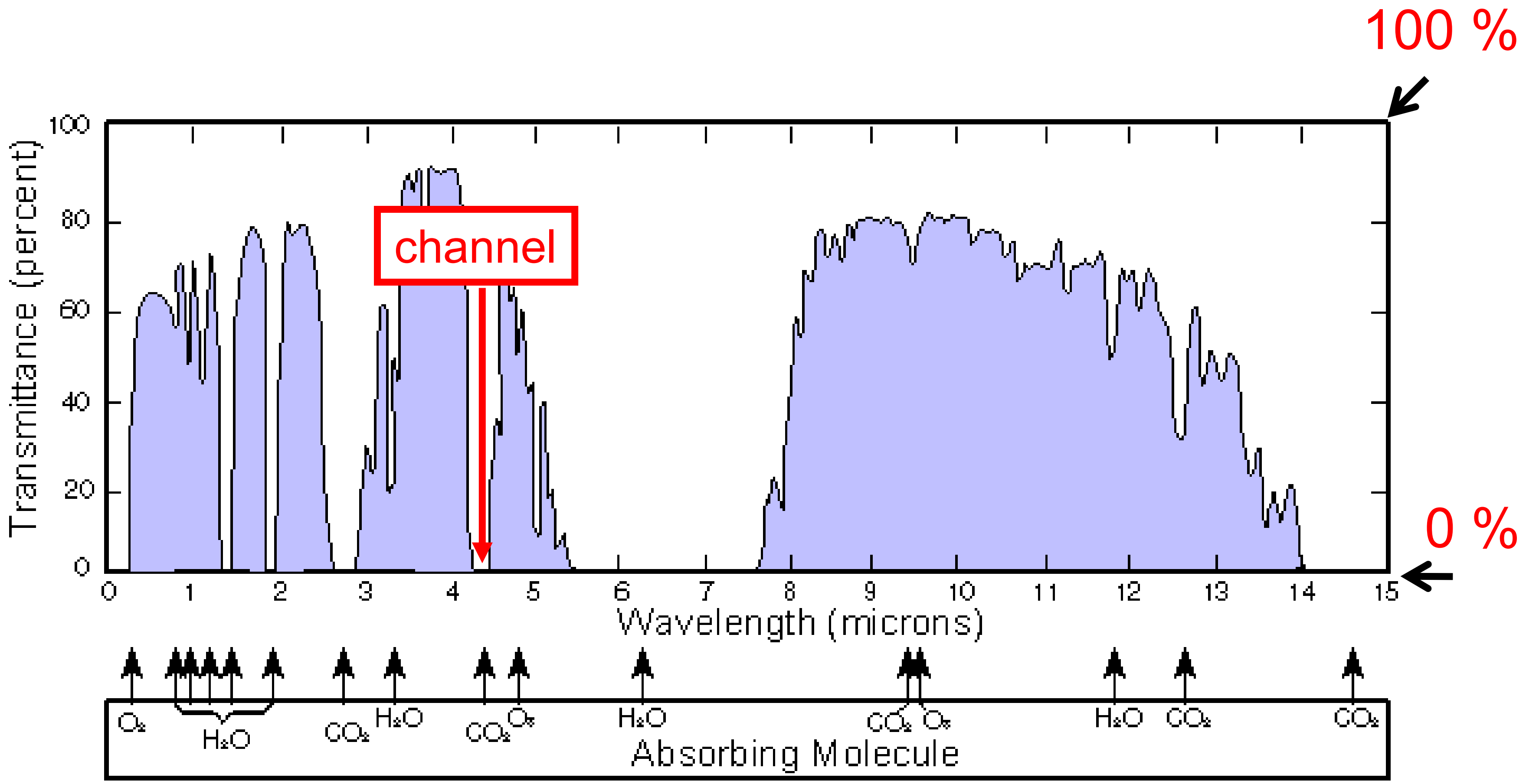
Atmospheric sounding channels…



Atmospheric sounding channels…



Atmospheric sounding channels…



Atmospheric sounding channels…

…selecting channels where there is no contribution from the surface….

$$L(\nu) = \int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz + \text{Surface emission} + \text{Surface reflection/ scattering} + \text{Cloud/rain contribution} + \ldots$$

Atmospheric sounding channels…

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Atmospheric sounding channels…

…if we additionally screen observations to remove measurements in cloudy or rain locations…

$$L(\nu) = \int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz + \cancel{\text{Surface emission}} + \cancel{\text{Surface reflection/scattering}} + \cancel{\text{Cloud/rain contribution}} + \ldots$$

We now have a much simpler forward …and inverse problem for the DA

Observation operator

$$\boxed{L(\nu)} = \boxed{\int_0^\infty B(\nu,T(z))\left[\frac{d\tau(\nu)}{dz}\right]dz} + \cancel{\text{Surface emission}} + \cancel{\text{Surface reflection/ scattering}} + \cancel{\text{Cloud/rain contribution}} + \ldots$$

minimisation

Screen data to remove clouds / rain

Atmospheric sounding channels…

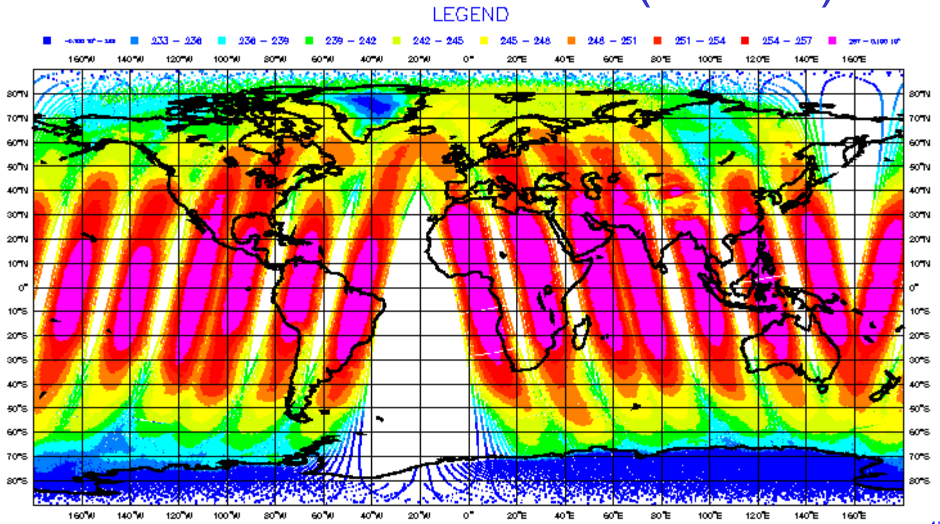
These channels are located in parts of the infra-red and microwave spectrum for which the main contribution to the measured radiance is from the atmosphere and can be written:

$$L(\nu) \approx \int_0^{\infty} B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz$$

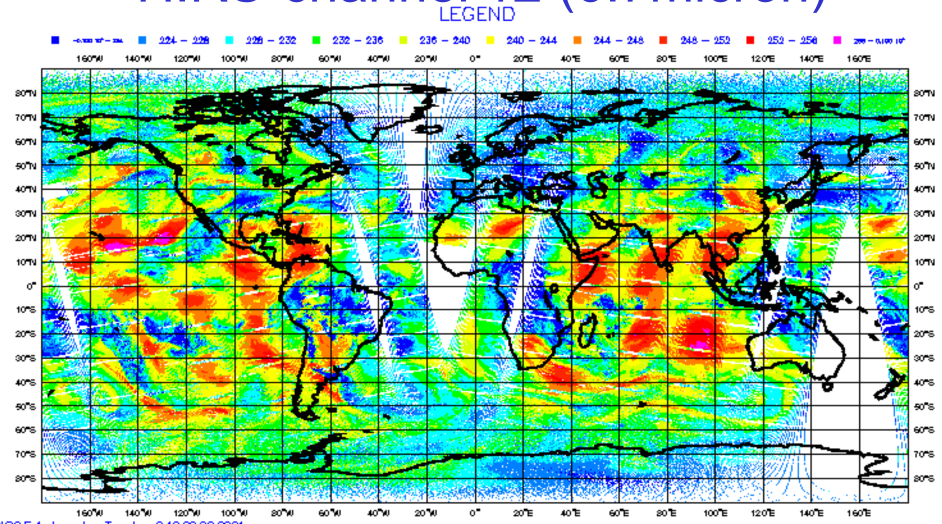
Where B=Planck function
t = transmittance
T(z) is the temperature
z is a height coordinate

That is they try to avoid frequencies for which surface radiation and cloud contributions are important. They are primarily used to obtain information about atmospheric temperature and humidity (or other constituents that influence the transmittance e.g. CO_2).

AMSUA-channel 5 (53GHz)

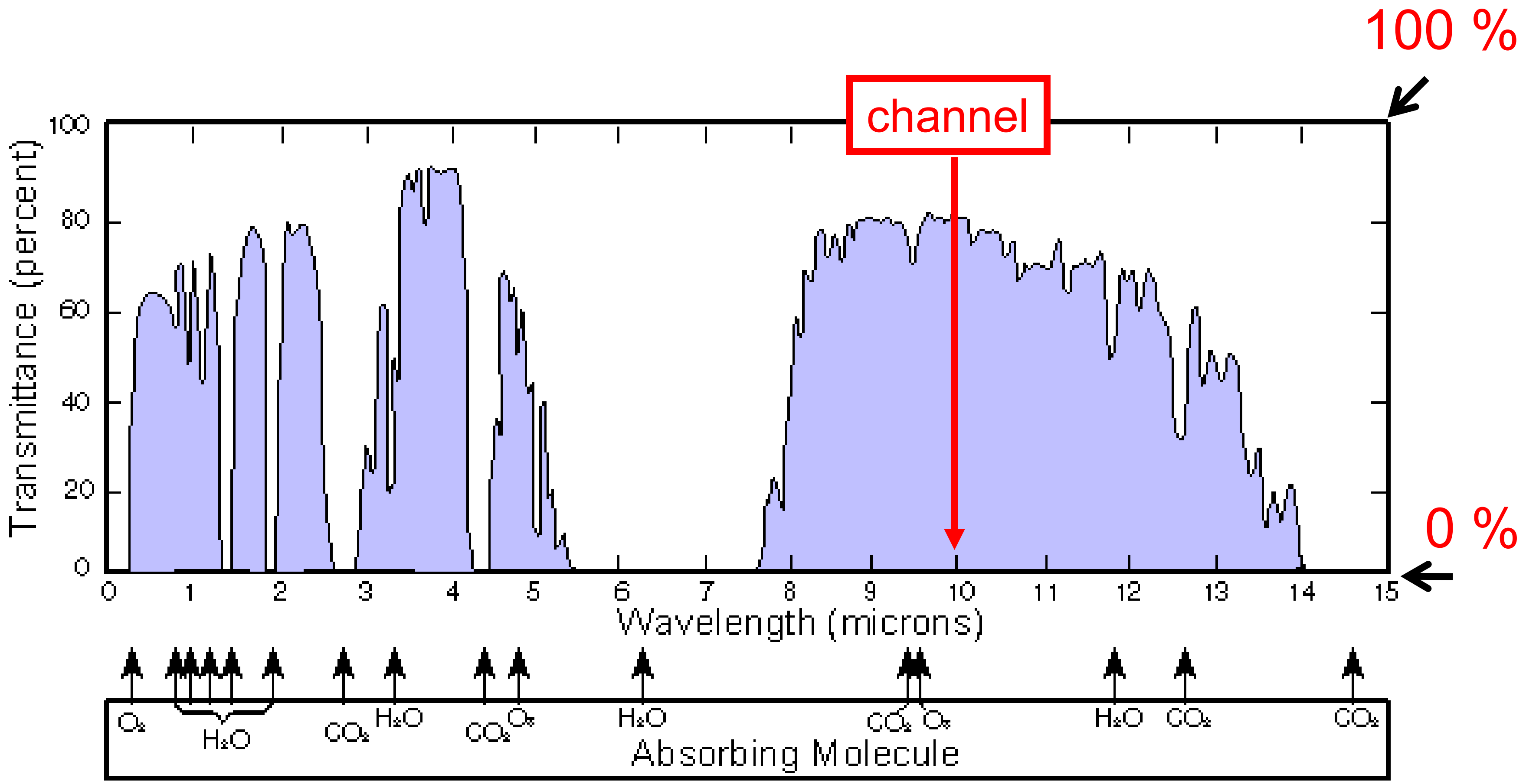


HIRS-channel 12 (6.7micron)

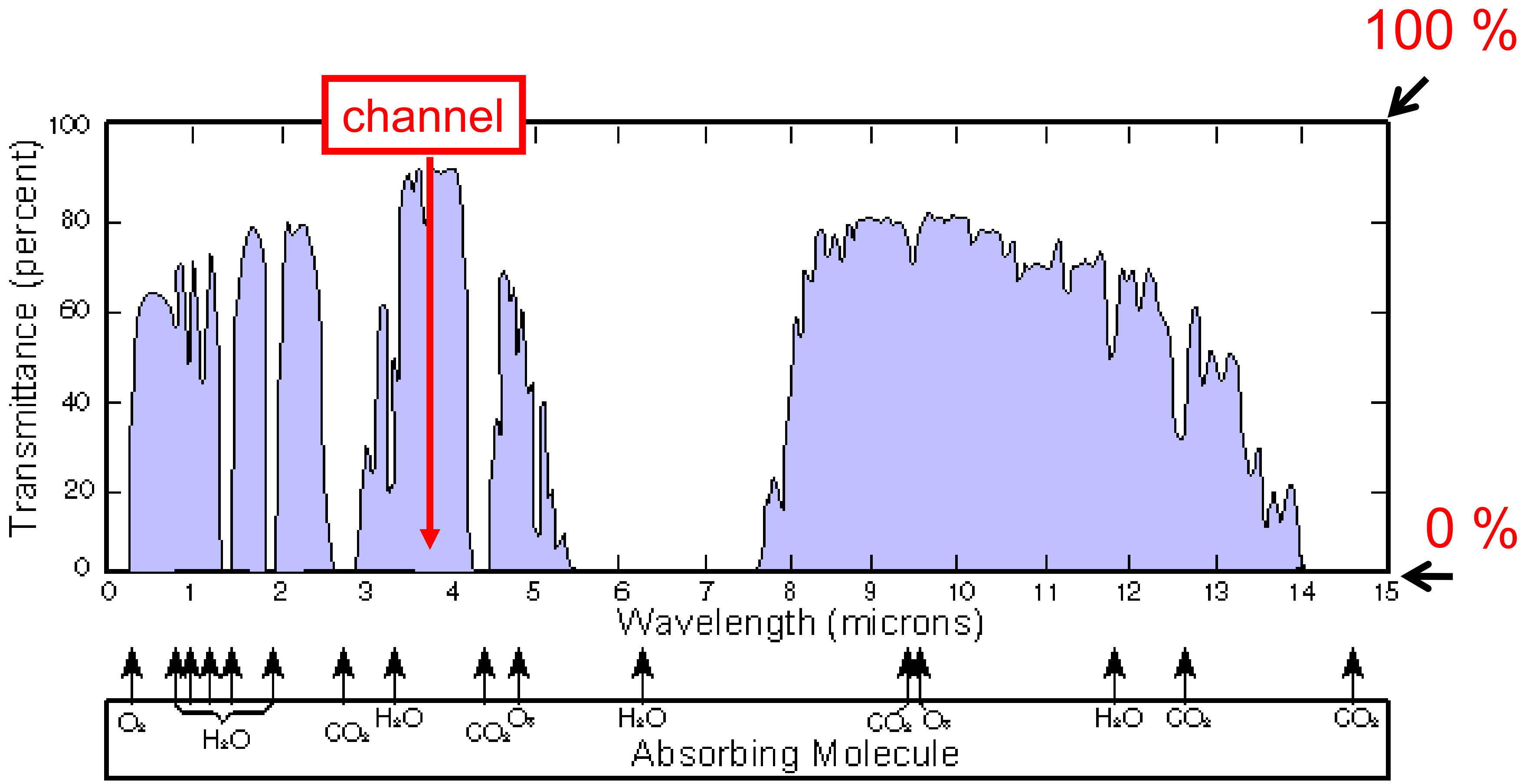


Surface sensing Channels…

Surface sensing Channels



Surface sensing Channels



Surface sensing Channels

…selecting channels where there is no interaction in the atmosphere….

$$L(\nu) = \int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz \; + \text{Surface emission} + \text{Surface reflection/scattering} + \text{Cloud/rain contribution} + \ldots$$

Surface sensing Channels

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IR ~ zero

Surface sensing Channels

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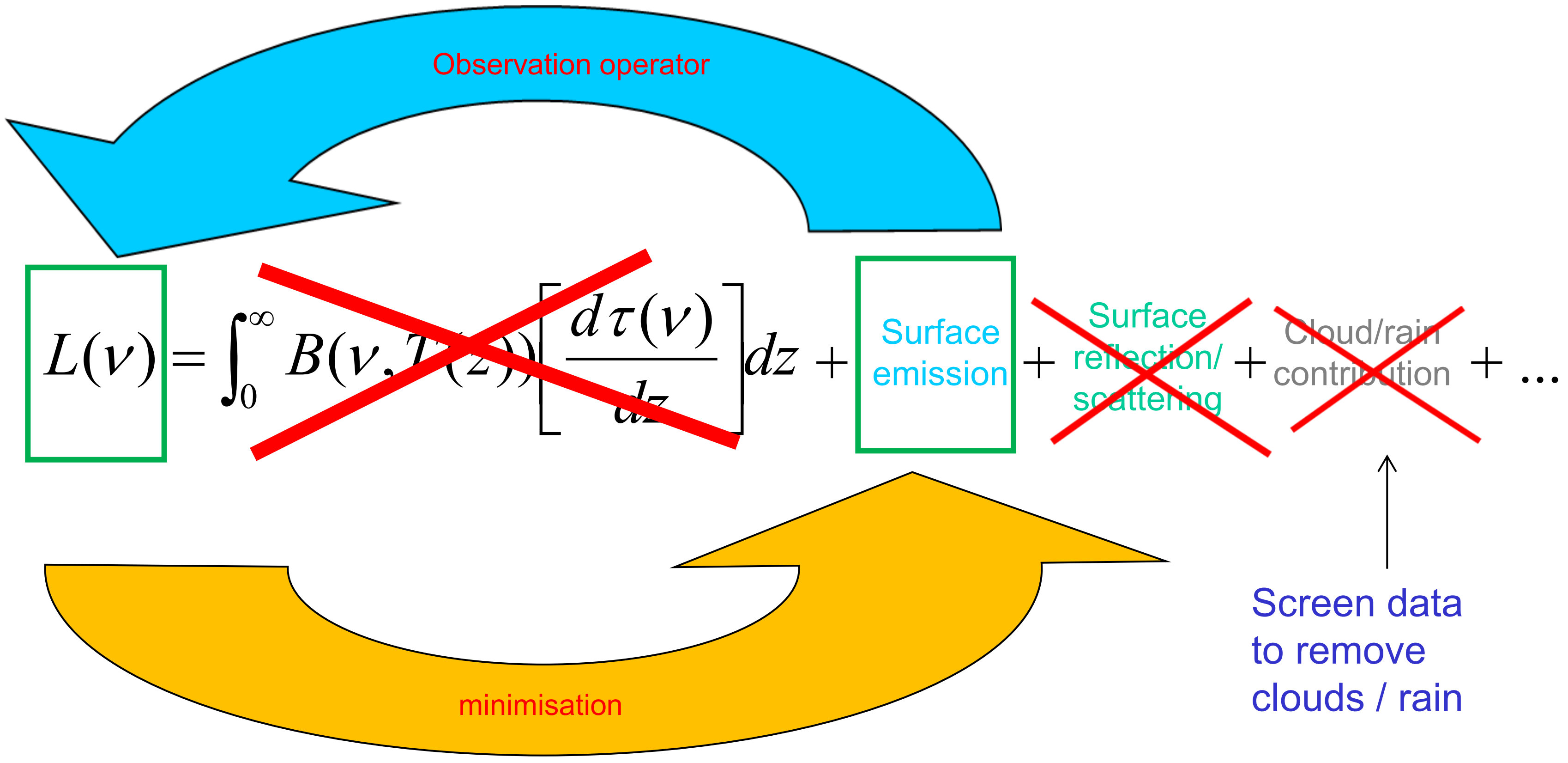
Screen data to remove clouds / rain

We now have a much simpler forward …and inverse problem for the DA



$$\boxed{L(\nu)} = \cancel{\int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz}\right] dz} + \boxed{\text{Surface emission}} + \cancel{\text{Surface reflection/ scattering}} + \cancel{\text{Cloud/rain contribution}} + \ldots$$

Surface sensing Channels

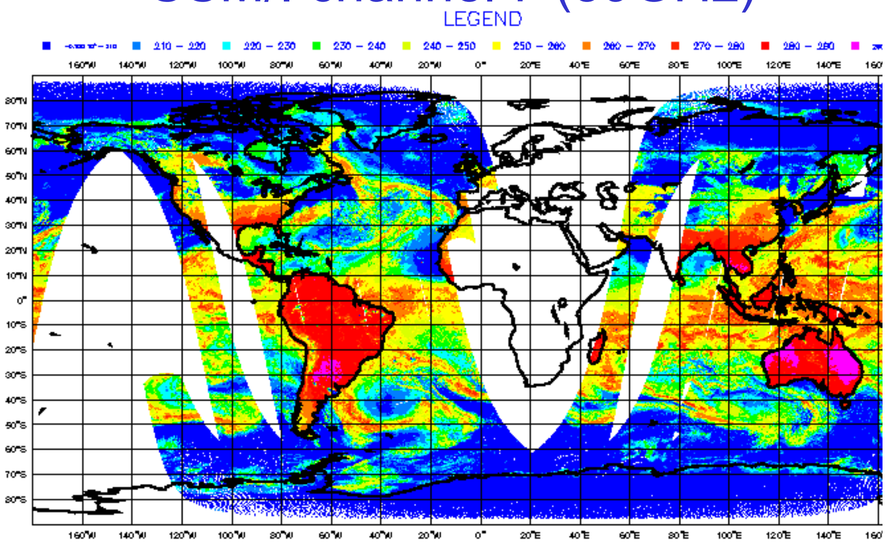
These are located in window regions of the infra-red and microwave spectrum at frequencies where there is very little interaction with the atmosphere and the primary contribution to the measured radiance is:

$$L(\nu) \approx B[\nu, T_{surf}]\varepsilon(u,v) \quad \text{(i.e. surface emission)}$$

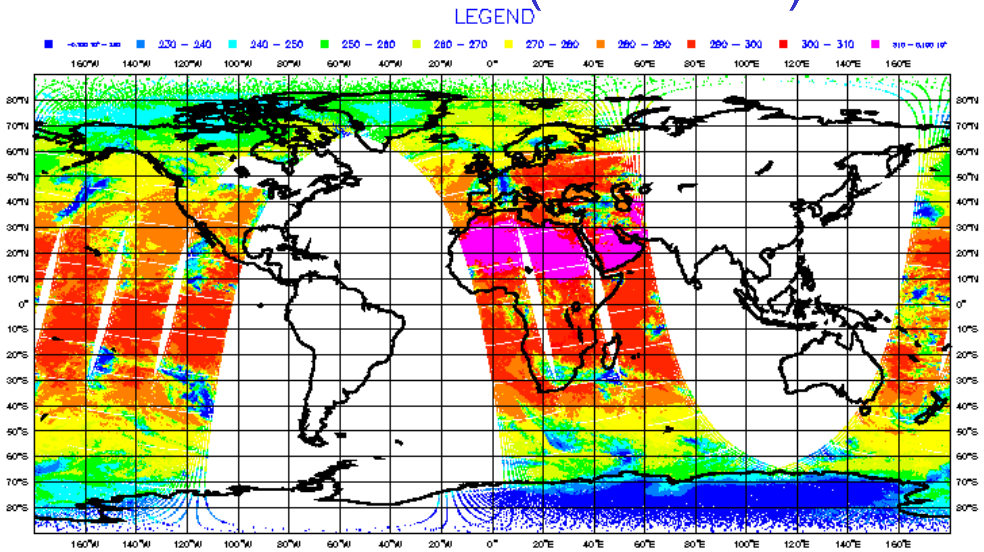
Where T_{surf} is the surface skin temperature and E the surface emissivity

These are primarily used to obtain information on the surface temperature and quantities that influence the surface emissivity such as wind (ocean) and vegetation (land). They can also be used to obtain information on clouds/rain and cloud movements (to provide wind information)

SSM/I channel 7 (89GHz)



HIRS channel 8 (11microns)



What type of channels are most important for NWP ?

Atmospheric temperature sounding…

Atmospheric temperature sounding – *weighting functions*

If radiation is selected in an atmospheric sounding channel for which

$$\boxed{L(\nu) = \int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz}$$

and we define a function $\quad H(z) = \left[\frac{d\tau}{dz} \right]$

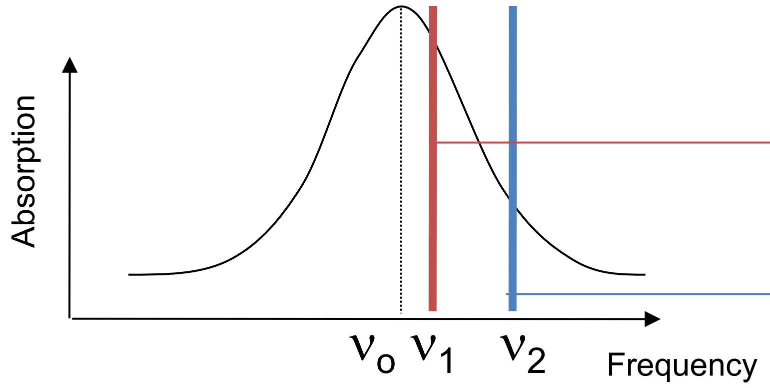
When the primary absorber is a well mixed gas (e.g. oxygen or CO_2) with known concentration it can be seen that the measured radiance is essentially a weighted average of the atmospheric temperature profile, or

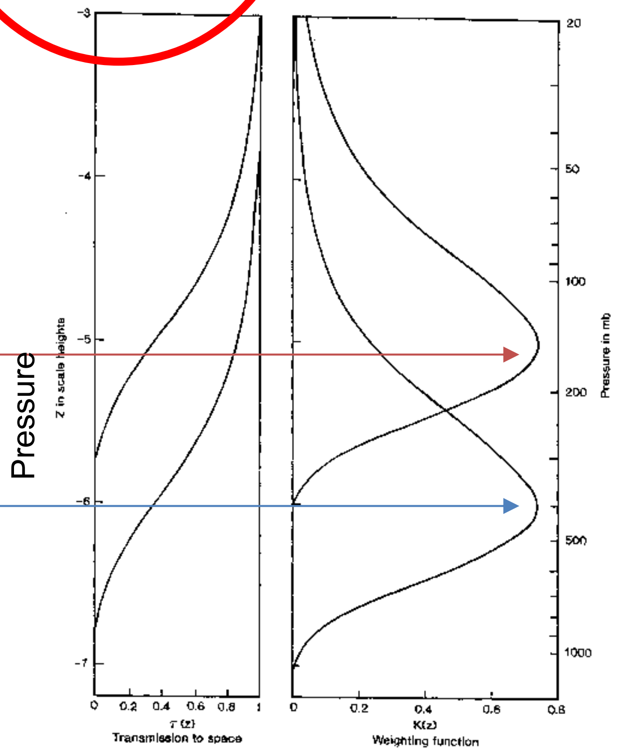
$$\boxed{L(\nu) = \int_0^\infty B(\nu, T(z))\; H(z)dz}$$

The function *H(z)* that defines this vertical average is known as a WEIGHTING FUNCTION

What do weighting functions look like ?

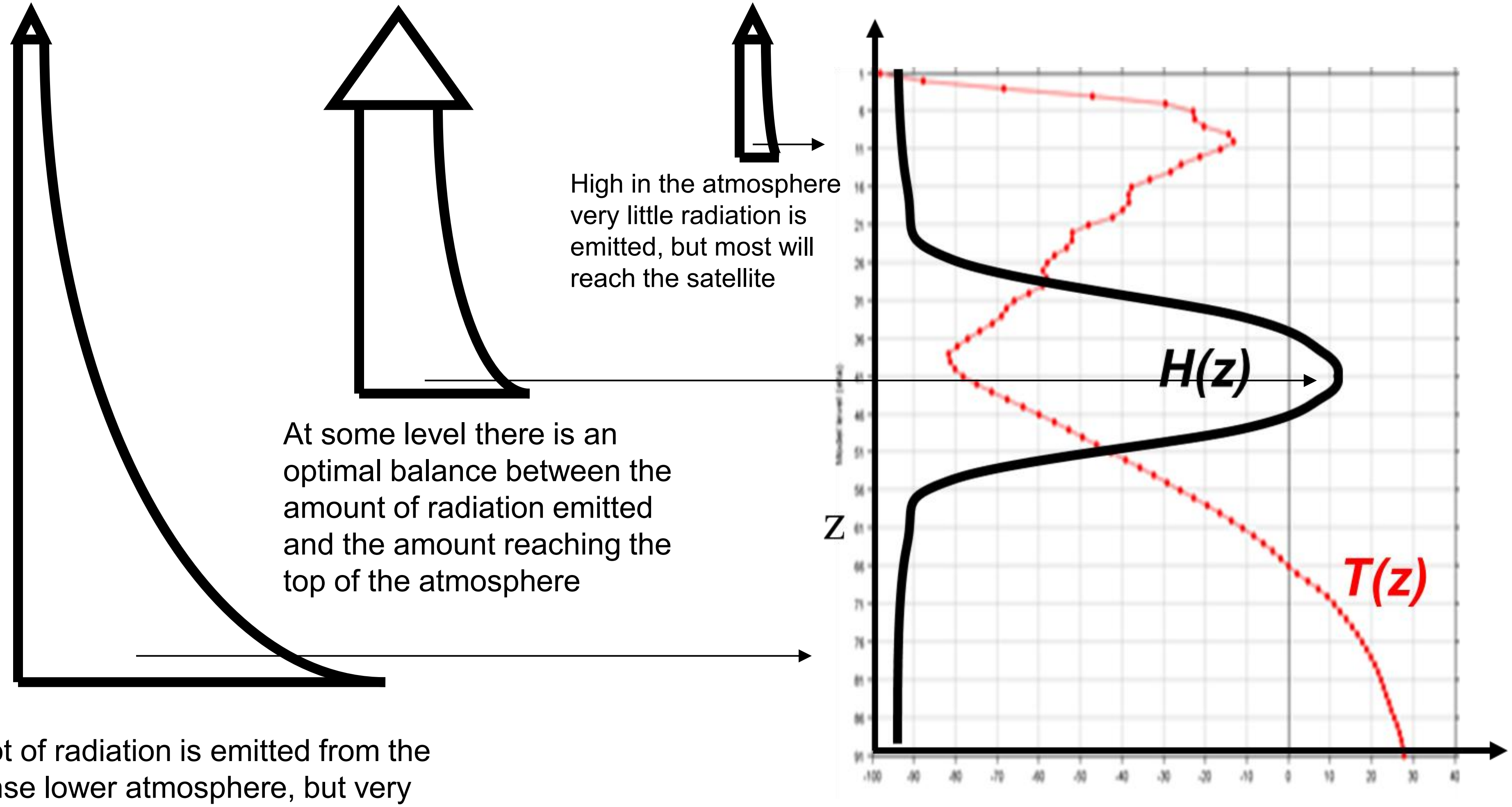
$$L(\nu)=\int_0^\infty B(\nu,T(z))\left[\frac{d\tau(\nu)}{dz}\right]dz$$





Transmission Weighting function

What do weighting functions look like ?

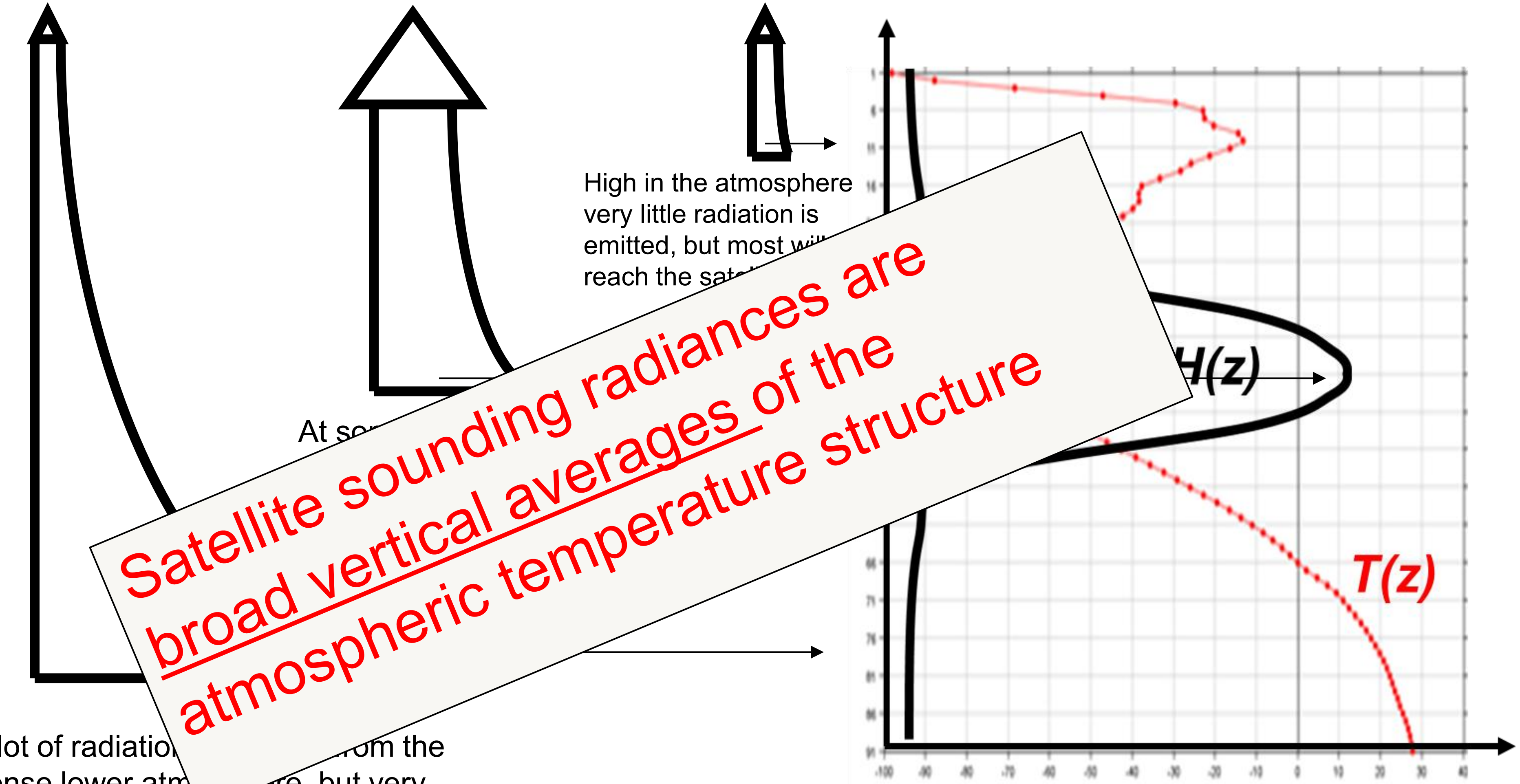


High in the atmosphere very little radiation is emitted, but most will reach the satellite

At some level there is an optimal balance between the amount of radiation emitted and the amount reaching the top of the atmosphere

A lot of radiation is emitted from the dense lower atmosphere, but very little survives to the top of the atmosphere due to absorption.

What do weighting functions look like ?



High in the atmosphere very little radiation is emitted, but most wi… reach the sat…

At so…

A lot of radiatio… …rom the dense lower atm… …ere, but very little survives to the top of the atmosphere due to absorption.

Satellite sounding radiances are <u>broad vertical averages</u> of the atmospheric temperature structure

What do weighting functions look like ?

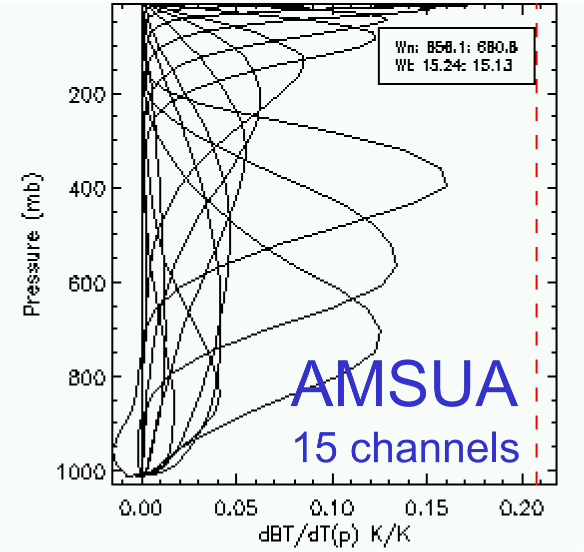
For any given channel the altitude at which the peak of the weighting function occurs depends on the strength of atmospheric absorption :

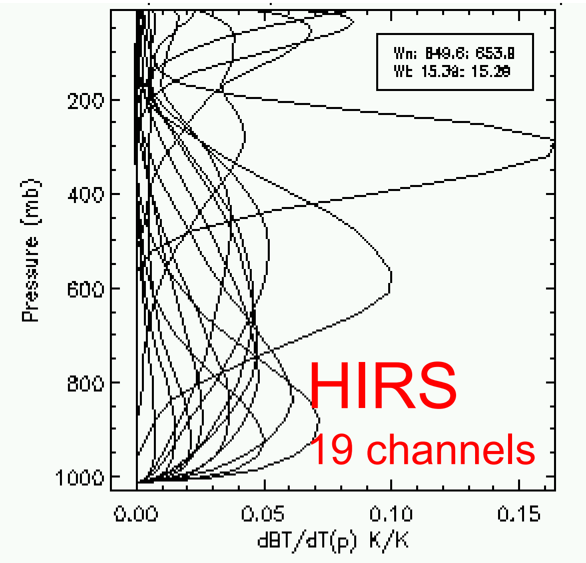
•Channels in parts of the spectrum where the absorption is strong (e.g. near the centre of CO2 or O2 lines) peak high in the atmosphere

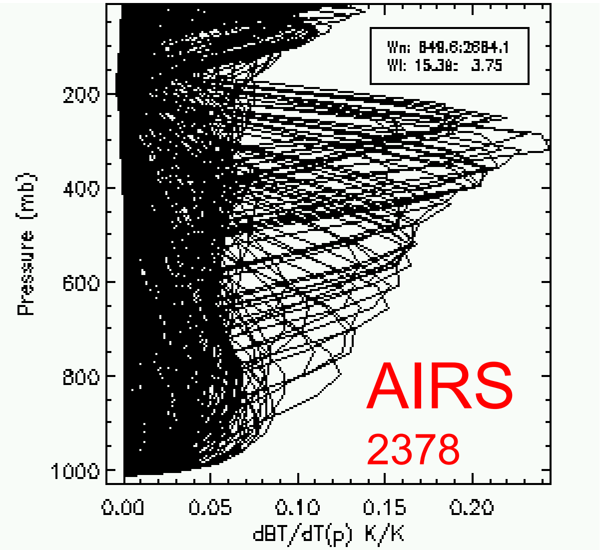
•Channels in parts of the spectrum where the absorption is weak (e.g. in the wings of CO_2 O_2 lines) peak low in the atmosphere

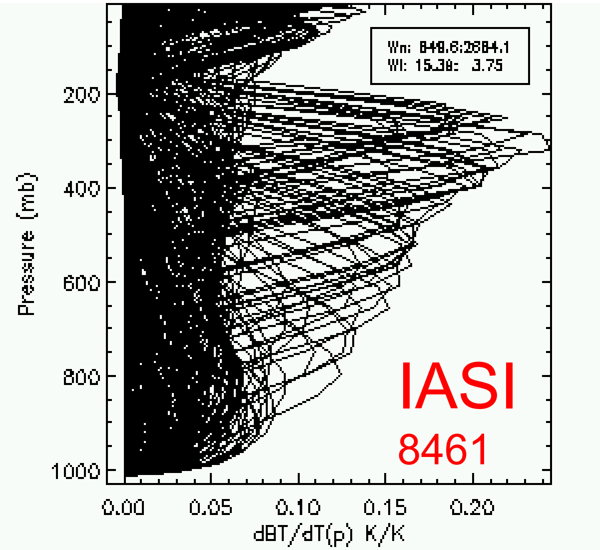
By building a satellite instrument that measures radiation in many different channels, all with varying absorption strengths we sample the atmospheric temperature profile at different altitudes (but of course not independently!)

What do <u>real</u> weighting functions look like ?



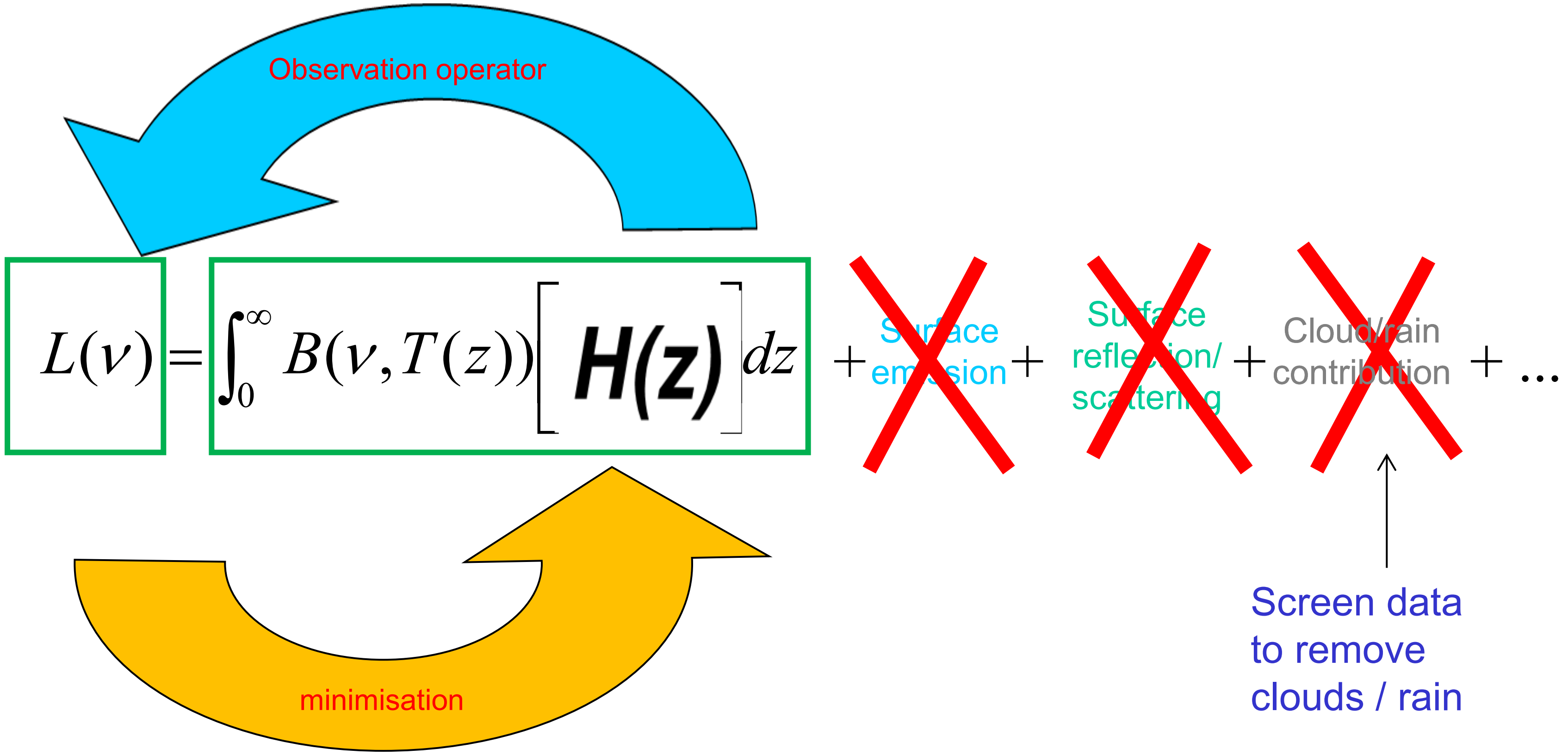




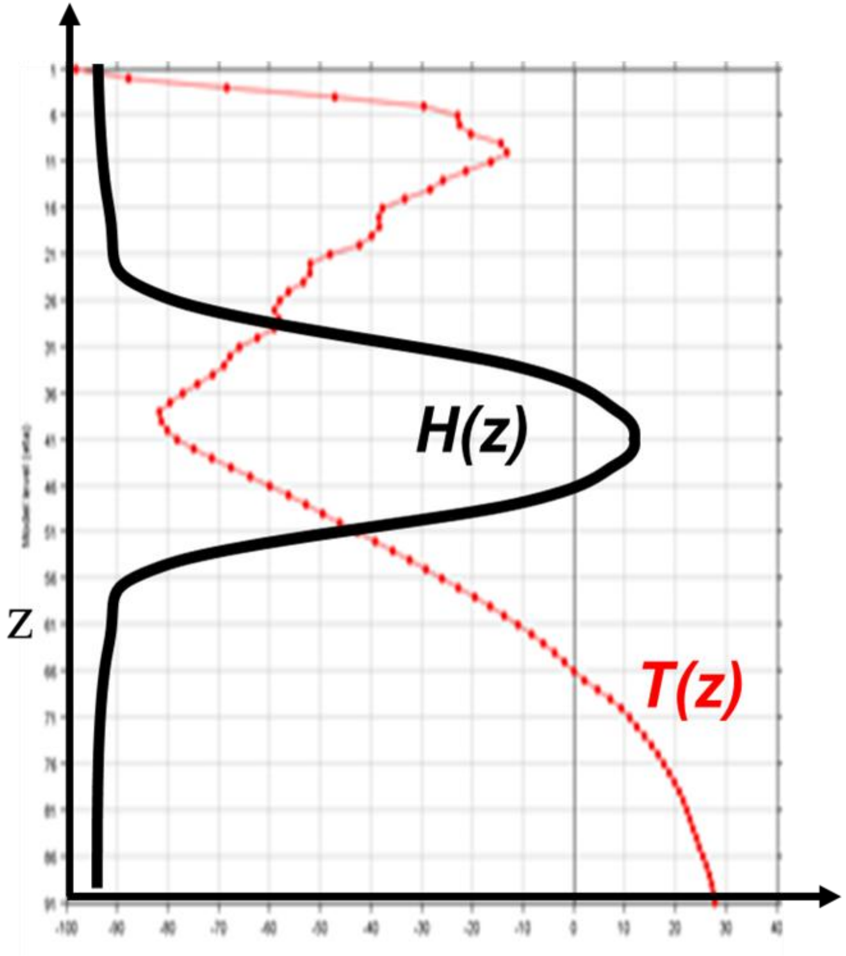


What are the implications of these broad weighting functions for Data Assimilation ?

The implications of broad weighting functions *H(z)*



The implications of broad weighting functions *H(z)*



In principle for a single channel an infinite number of different temperature profiles could produce exactly the same measured radiance…

The extraction of temperature information within the data assimilation for these observations is mathematically ill-posed

See paper by Rodgers 1976 Retrieval of atmospheric temperature and composition from remote measurements of thermal radiation. Rev. Geophys.Space. Phys. 14, 609-624

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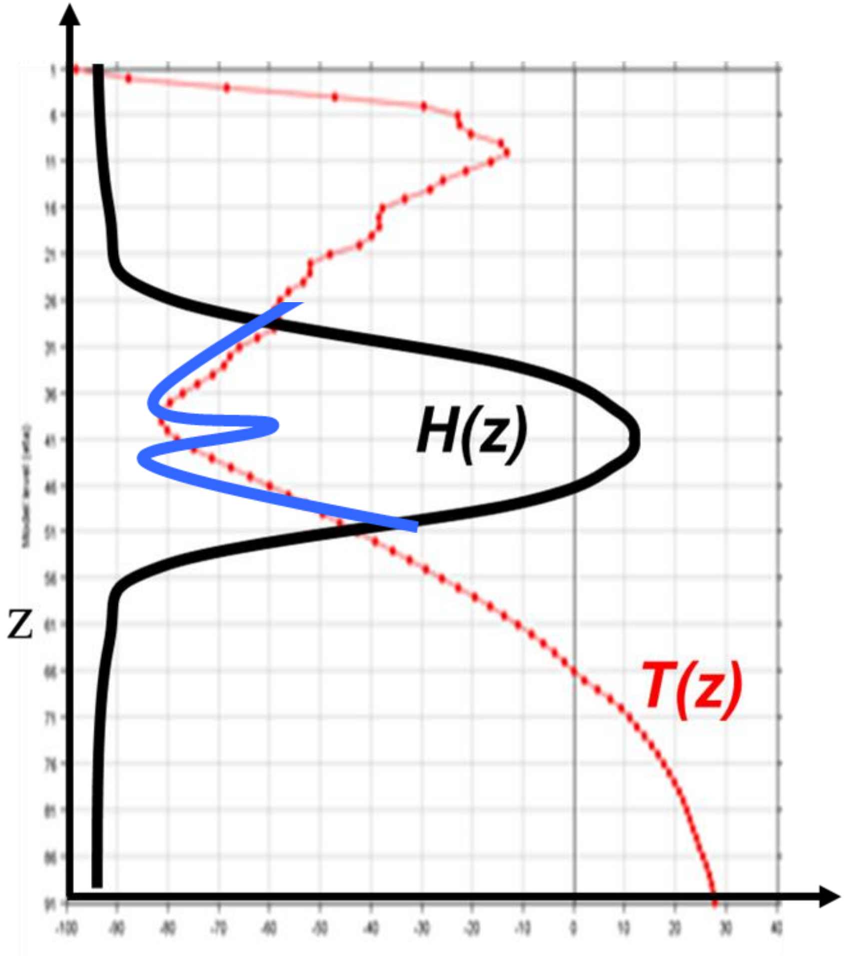

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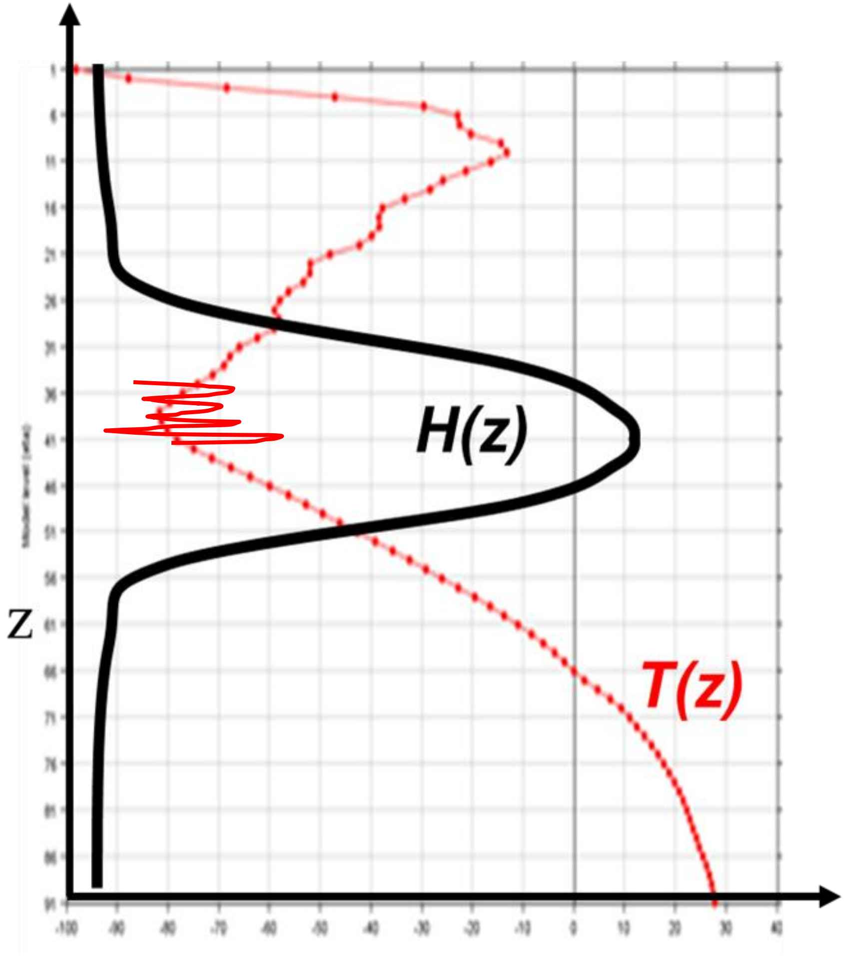
The implications of broad weighting functions *H(z)*



In principle for a single channel an infinite number of different temperature profiles could produce exactly the same measured radiance…

The extraction of temperature information within the data assimilation for these observations is mathematically ill-posed

But having lots of different channels improves resolution…see later lecture

See paper by Rodgers 1976 Retrieval of atmospheric temperature and composition from remote measurements of thermal radiation. Rev. Geophys.Space. Phys. 14, 609-624

What are the implications of these broad weighting functions for Data Assimilation …?

…there are some vertical scales we cannot measure…

…the assimilation of satellite radiance data relies heavily on prior or background information …

A QUICK REVIEW OF KEY CONCEPTS

•Satellite instruments measure **radiance** (not T,Q or wind)

• Downward looking satellite radiances are **broad vertical averages** of the temperature /humidity profile (defined by the weighting functions)

•The estimation of atmospheric temperature (or humidity) from the radiances is mathematically **ill- posed** and all DA algorithms rely heavily on background **prior information**

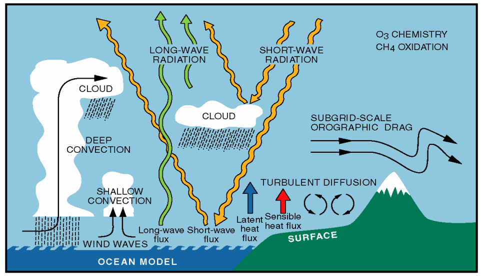
Basic principles of data assimilation

What is Data Assimilation ?

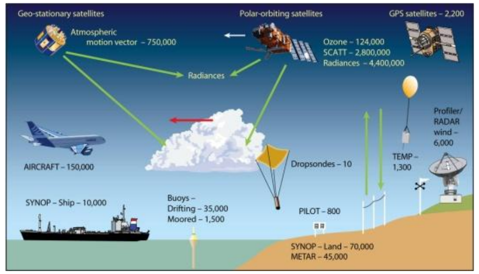
- Models give a complete description of the atmospheric, but **errors grow rapidly** in time
- Observations provide an **incomplete description** of the atmospheric state, but bring up to date information
- Data assimilation **combines** these two sources of information to produce an optimal (best) estimate of the atmospheric state
- This state (the *analysis*) is used as **initial conditions** for extended forecasts.

The assimilation system:

- Model



- Observations



- Assimilation algorithm

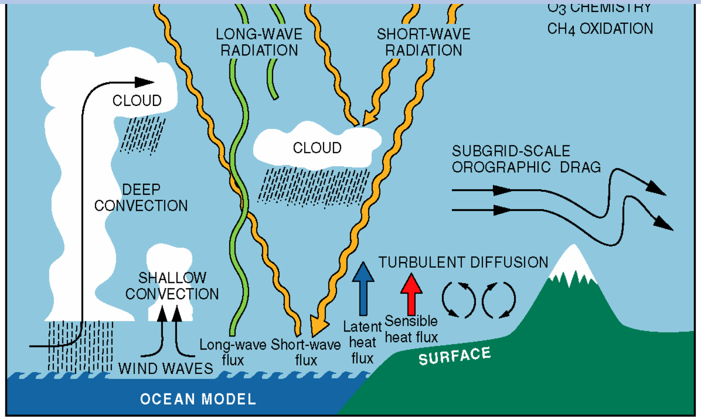
$$\boxed{\begin{aligned} J(x) = (x - x_b)^T \mathbf{B}^{-1}(x - x_b) + \\ (y - \mathrm{H}[x])^T \mathbf{R}^{-1}(y - \mathrm{H}[x]) \end{aligned}}$$

The forecast model

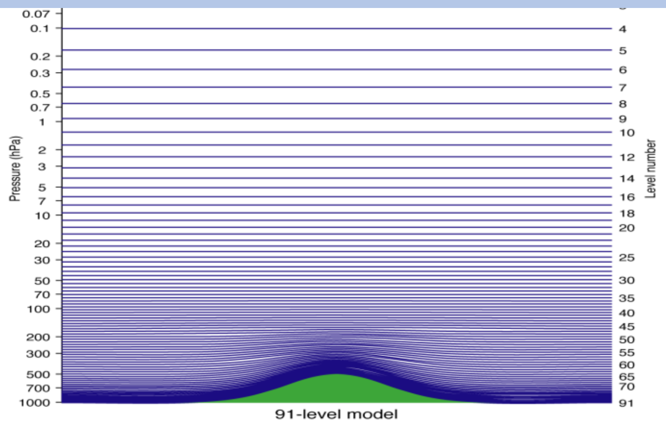
$$\boxed{X_{t=0}} \longrightarrow \boxed{X_{t=t}}$$

The forecast model

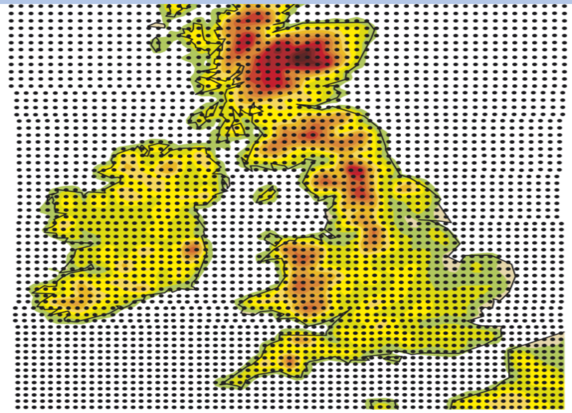
Physical and dynamical processes updated every 10 minutes



91 (**137**) vertical levels from the surface to 0.01hPa (approx: 80Km)

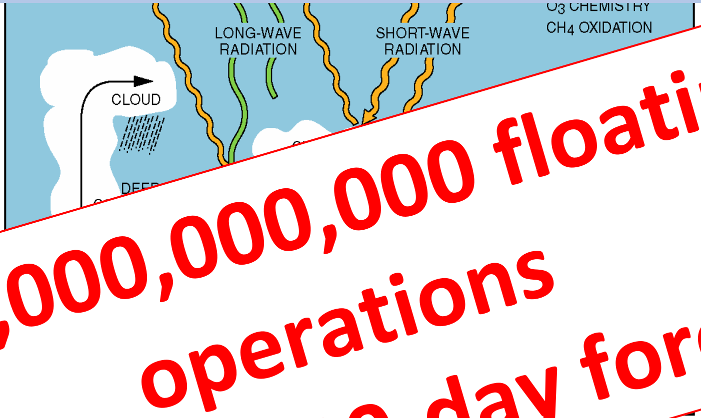


Global TCO1279 spectral resolution (9km grid point spacing)



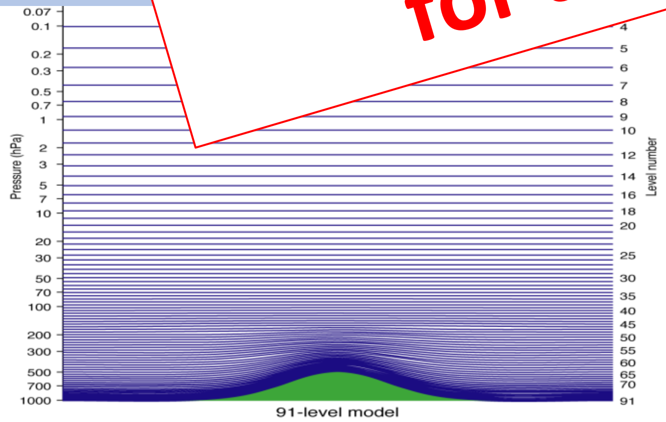
The forecast model

Physical and dynamical processes
updated every 10 minutes



6,300,000,000,000,000 floating point
operations
for a single 10-day forecast

91 (**137**) v
to 0.01hPa



Global TCO1279 spectral resolution
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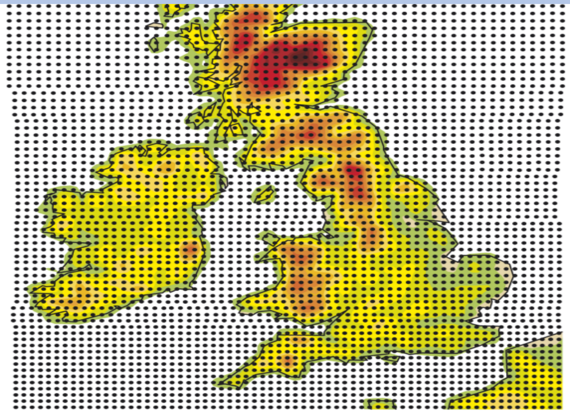
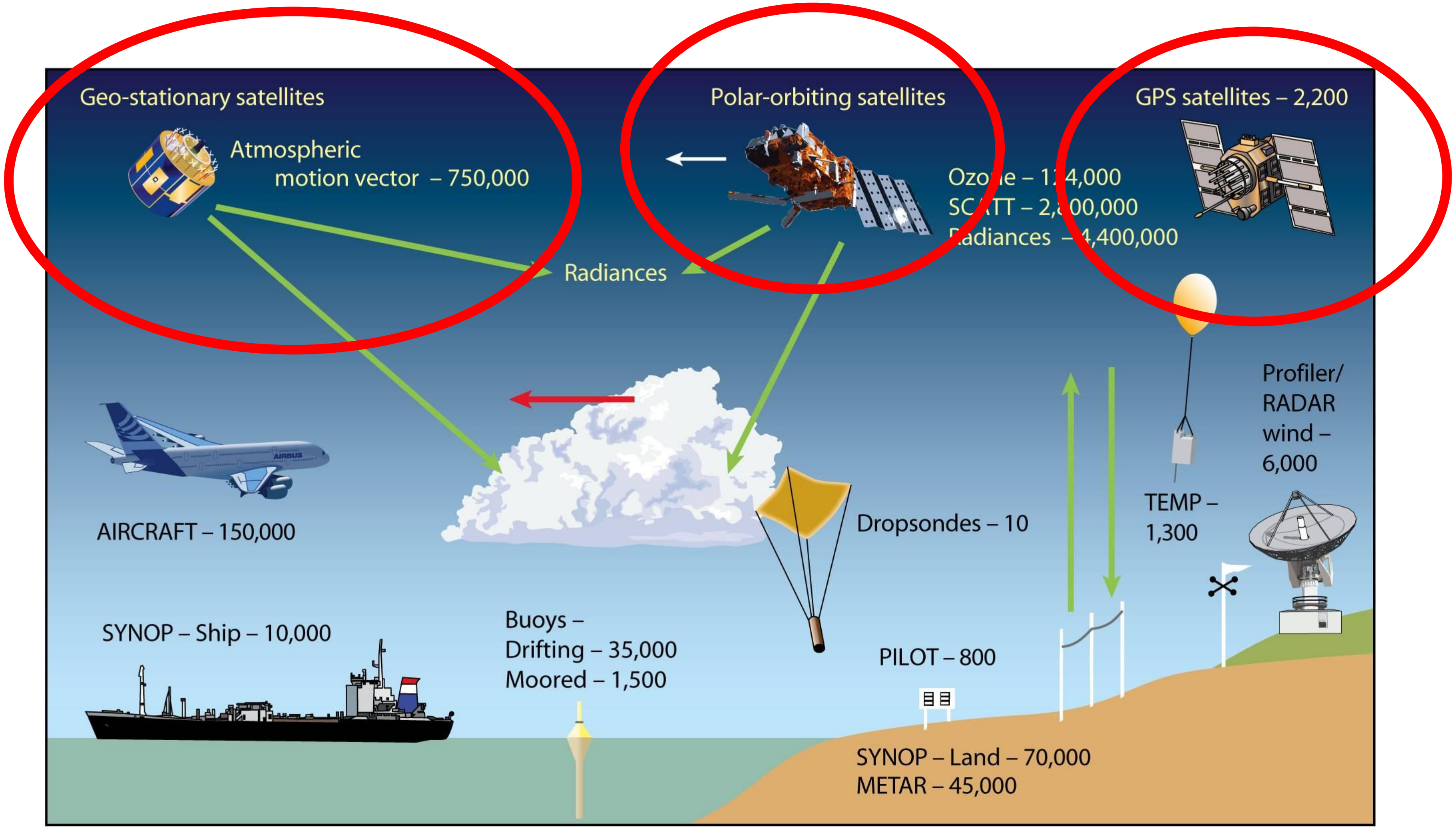


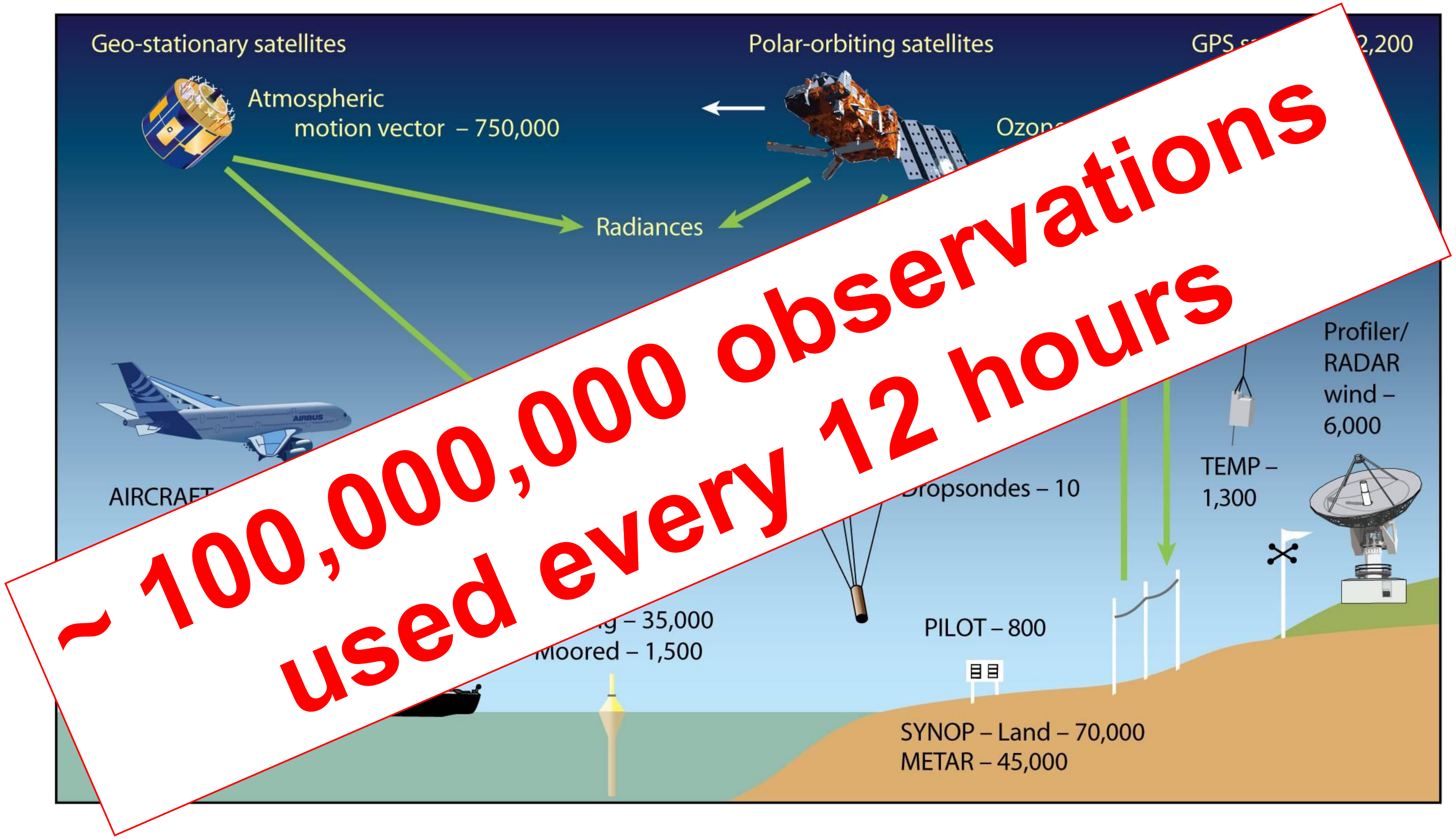
The Observations

$$\boxed{Y_{obs}}$$

Operational Global Observing Network



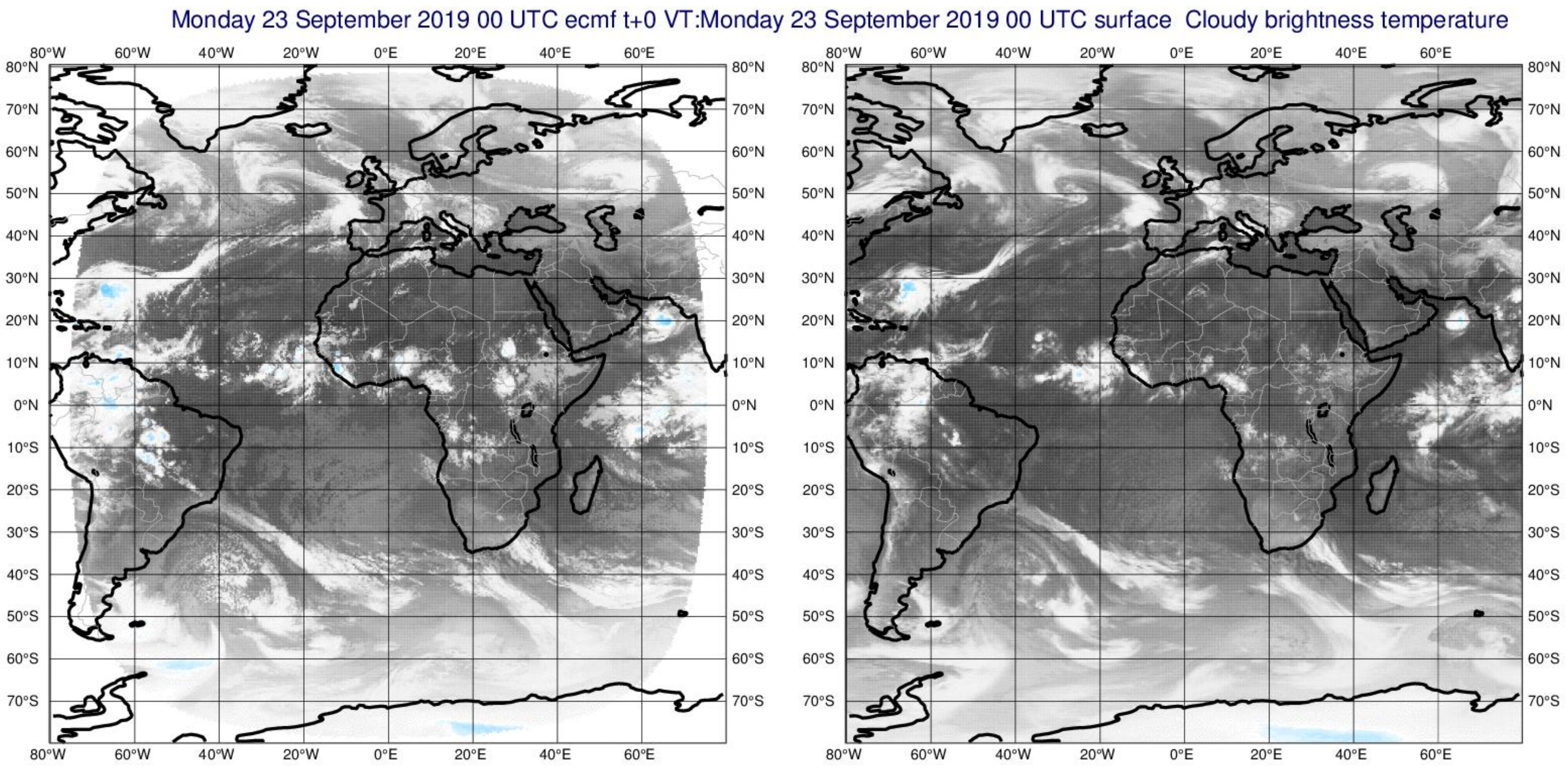
Operational Global Observing Network



The assimilation algorithm

Comparing OBS with model in OBS space

Observations from Meteosat-11 | Simulated by forecast model



Modern radiative transfer can simulate atmospheric radiation very accurately …so why do these diverge ?

Combining information

- At ECMWF we employ **variational data assimilation** methods
- These are based upon the **maximum likelihood combination** of observations and background information
- It can be shown that the most probable state of the atmosphere given a background $\mathbf{X}_b$ and some observations $\mathbf{Y}$ is that which minimises a **cost or penalty function J**
- The solution obtained is **optimal** in that it fits the prior (or background) information and measured radiances **respecting the uncertainty in both.**

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)

The cost function components (J_b)

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

Fit of the solution to the background estimate of the atmospheric state weighted inversely by the background error covariance **B**

The cost function components (J_o)

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

Fit of the solution to the observations weighted inversely by the measurement error covariance **R** (observation error + error in observation operator **H**)

…a helpful linear analogue …

It can be shown that the state that minimizes the cost function is equivalent to a linear **correction** of the background using the observations:

$$\underline{x_a} = \underline{x_b} + \underbrace{[\mathbf{HB}]^T[\mathbf{HBH}^T + \mathbf{R}]^{-1}(y - \mathbf{H}x_b)}_{\text{correction term}}$$

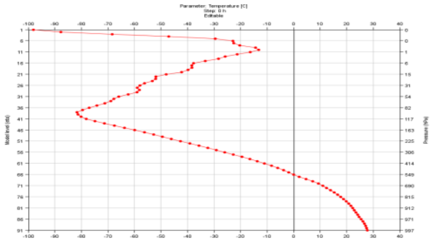
…and the **improvement** can be quantified in terms of the key parameters of the assimilation…(i.e. **B**, **R**, **H**)

$$S_a = B - \underbrace{[\mathbf{HB}]^T[\mathbf{HBH}^T + \mathbf{R}]^{-1}\, HB}_{\text{improvement term}}$$

Various implementations of the assimilation algorithm

- 1D-Var
- 3D-Var
- 4D-Var

One dimensional variational analysis (1D-Var)

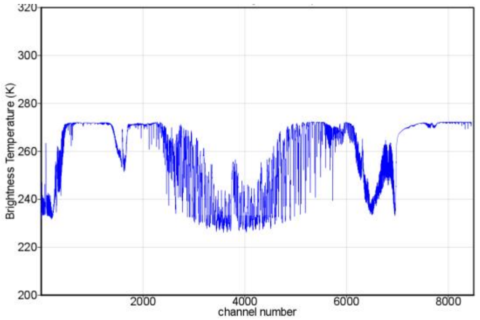


1D model state profile

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

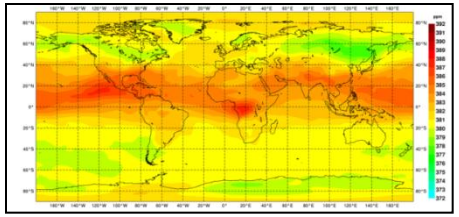
vector of measured radiances at one location

observation Operator = radiative transfer model



$$L(\nu) = \int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz$$

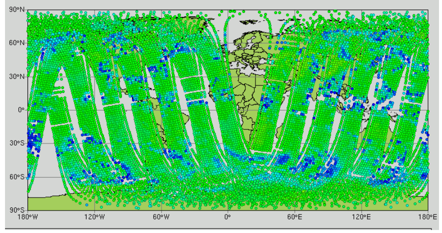
Three dimensional variational analysis (3D-Var)



3D model state

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

global vector of
measured radiances

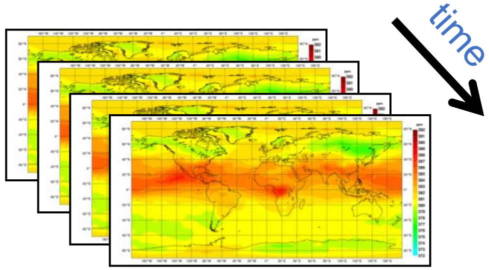


observation operator
= spatial interpolation +
radiative transfer model

$$L(\nu) = \int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz$$

Four dimensional variational analysis (4D-Var)

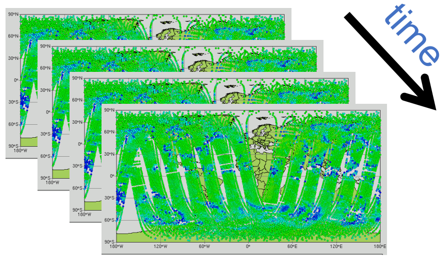
4D model state



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

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

global time windows of
measured radiances



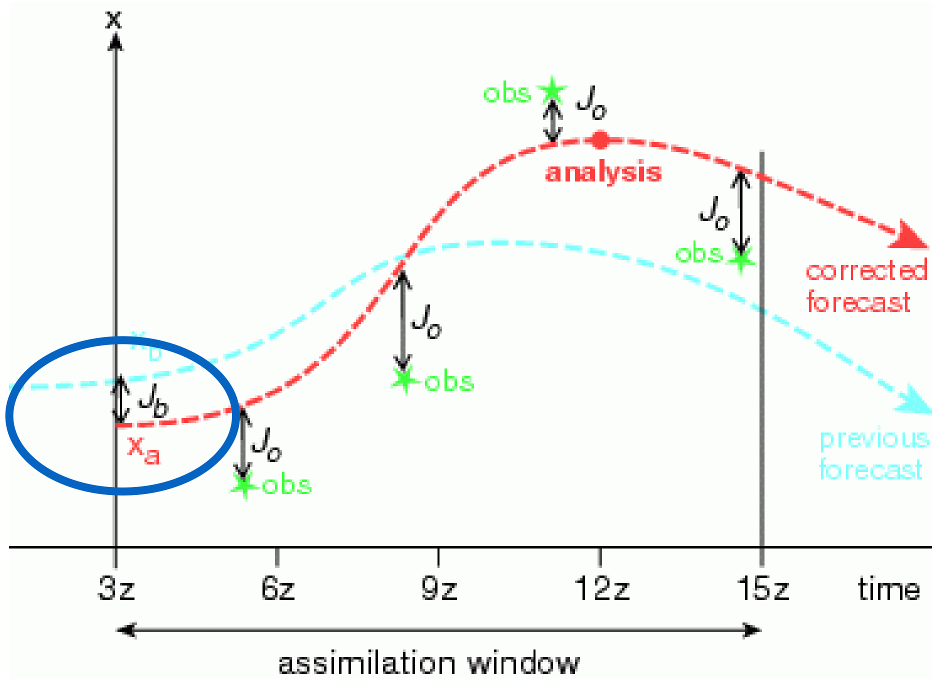
observation operator
= spatial interpolation + forecast model
radiative transfer model

$$L(\nu) = \int_0^\infty B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz$$

$$\boxed{X_{t=0}} \longrightarrow \boxed{X_{t=t}}$$

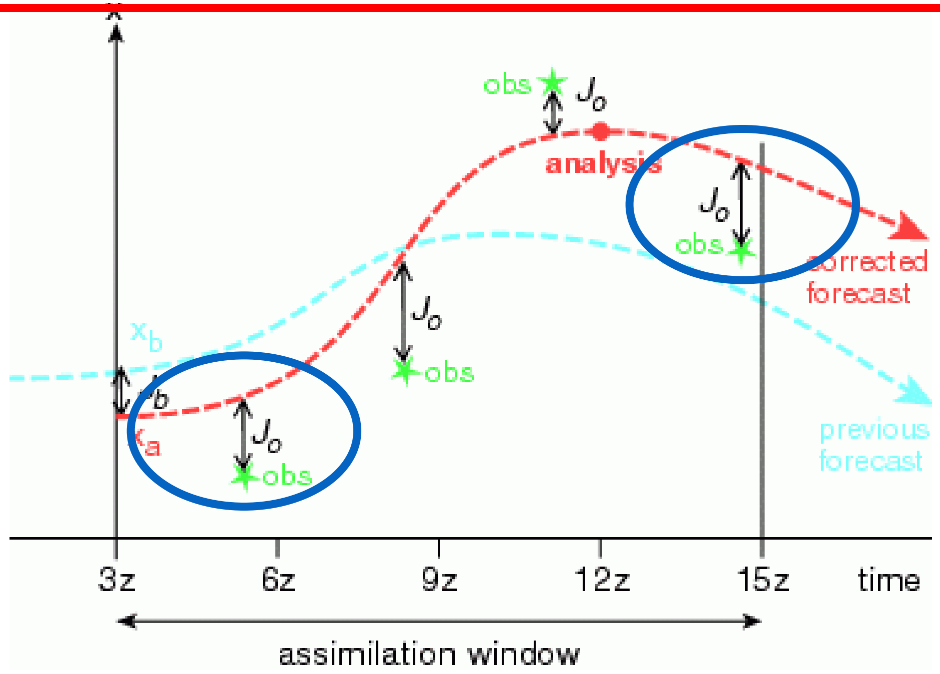
The 4D-Var Algorithm J_b

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



The 4D-Var Algorithm J_o

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



The key elements of a satellite data assimilation system

Key elements of a data assimilation system

- observation operator
- background errors
- observation errors
- bias correction
- data selection and quality control

Key elements of a data assimilation system

- observation operator
- background errors
- observation errors
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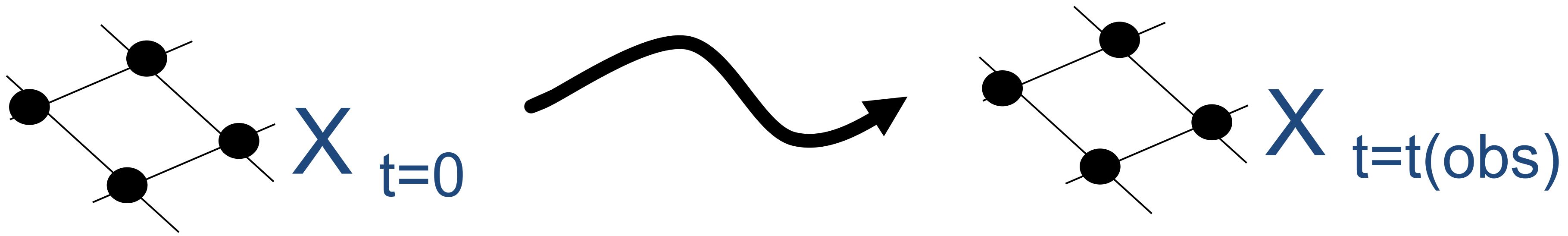
Observation operator

- The observation operator must map the model state at beginning of the assimilation window (t=0) to the observation time and location.
- In the **direct assimilation of radiance observations**, the observation operator must incorporate an additional step to compute radiances from the model state variables (radiative transfer model RTTOV).
- This means that radiance observations are significantly more computationally expensive than conventional observations (e.g. radiosonde temperature data)

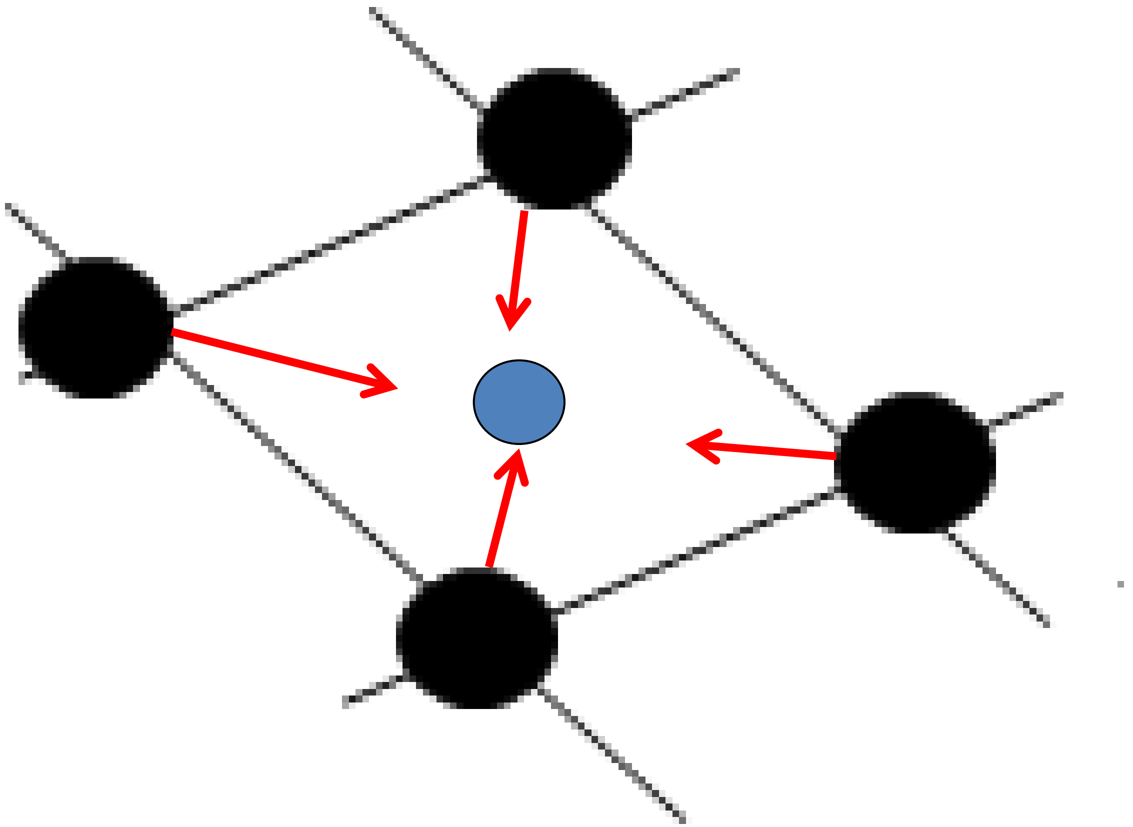
Observation operator

1) Time evolution of forecast model field to OBS time



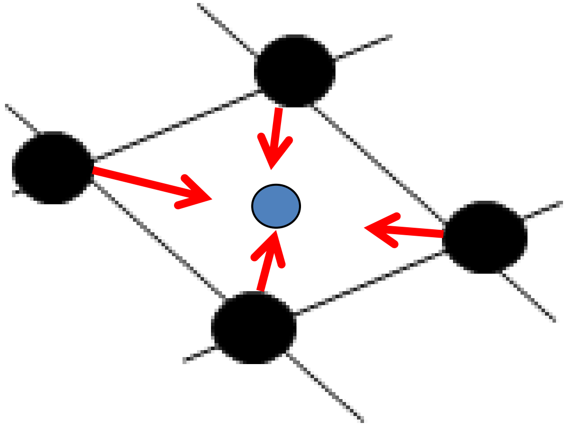
Observation operator

2) Spatial interpolation of model grid to OBS location

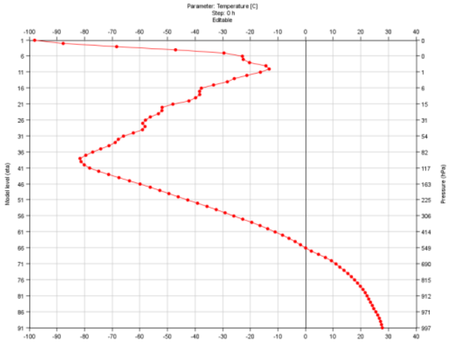


Observation operator

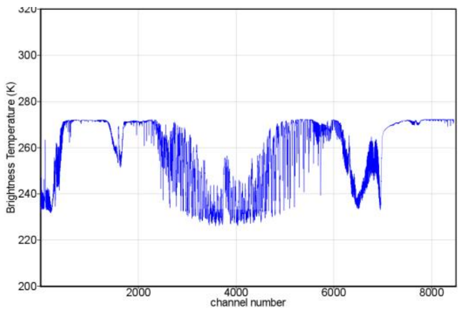
3) Radiative transfer calculation from model state at that location to radiances at that location



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



RTTOV



Key elements of a data assimilation system

- observation operator
- **background errors**
- observation errors
- bias correction
- data selection and quality control

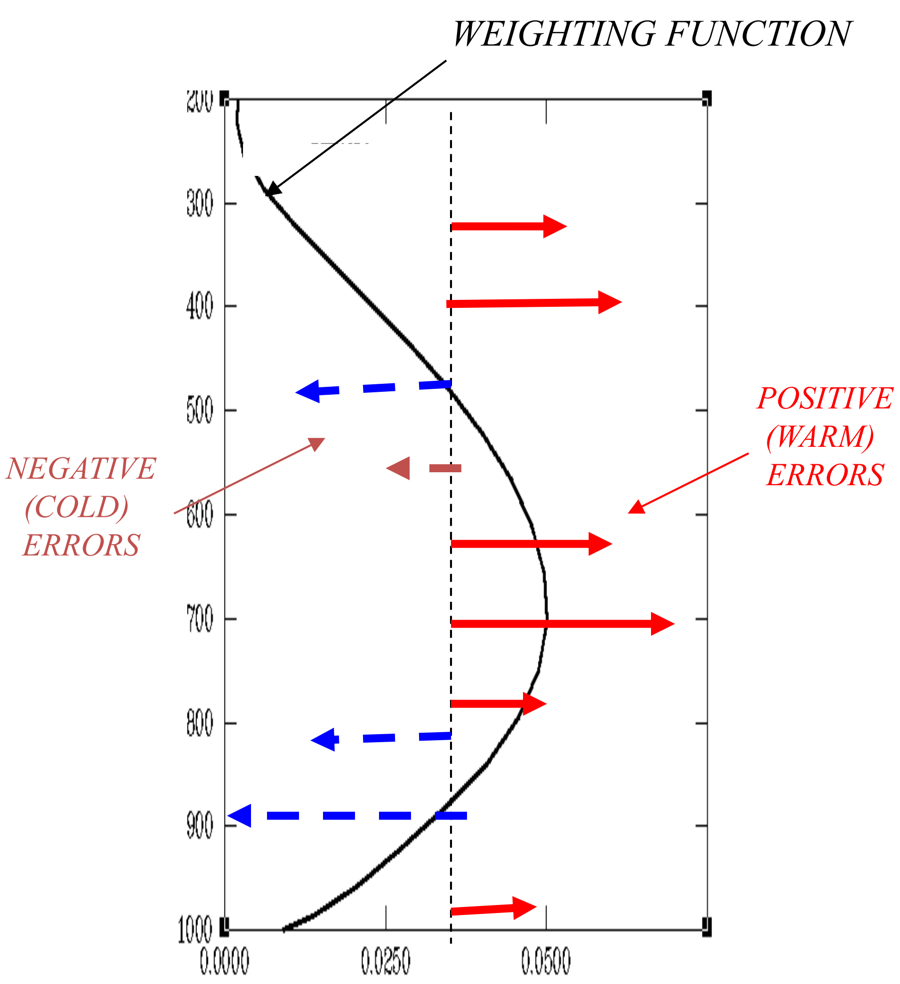
Background errors (and vertical resolution)

- The matrix B must accurately describe errors in the background estimate of the atmospheric state. It determines the weight given to the background information.

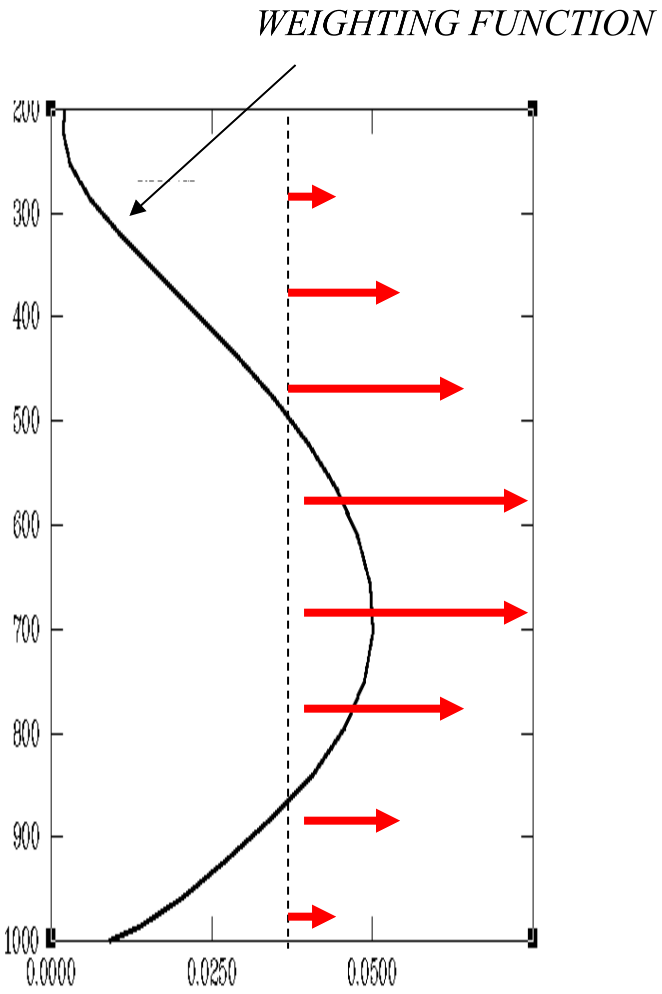
- A very important aspect for the assimilation of near-nadir viewing satellite radiances are the **vertical correlations** that describe how background errors are distributed in the vertical (sometimes called structure functions)

- These are important because satellite radiances have very **limited vertical resolution** (previous lecture)

Background errors (and vertical resolution)



"*Difficult*" to correct



"*Easy*" to correct

…a helpful linear analogue …

It can be shown that the state that minimizes the cost function is equivalent to a linear **correction** of the background using the observations:

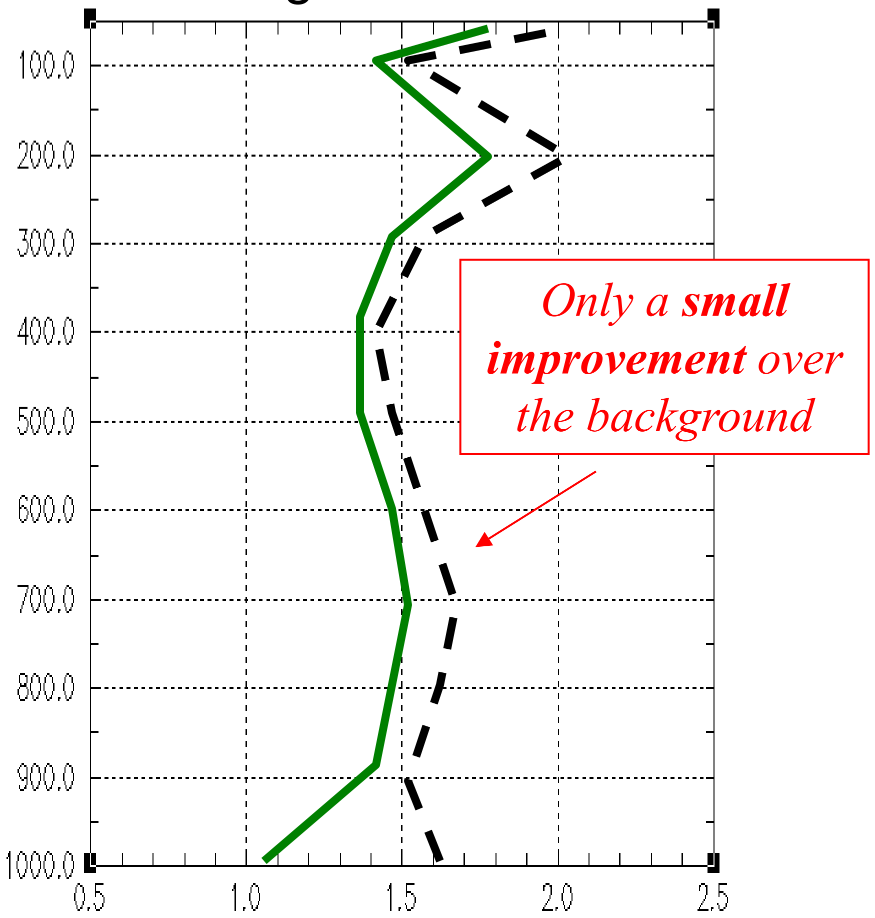
$$\underline{x_a} = \underline{x_b} + \underbrace{[\mathbf{HB}]^T[\mathbf{HBH}^T + \mathbf{R}]^{-1}(y - \mathbf{H}x_b)}_{\textbf{correction term}}$$

…and the **improvement** can be quantified in terms of the key parameters of the assimilation…(i.e. **B**, **R**, **H**)

$$\mathrm{S_a} = \mathrm{B} - \underbrace{[\mathbf{HB}]^T[\mathbf{HBH}^T + \mathbf{R}]^{-1}\,\mathrm{HB}}_{\textbf{improvement term}}$$

Background errors (and vertical resolution)

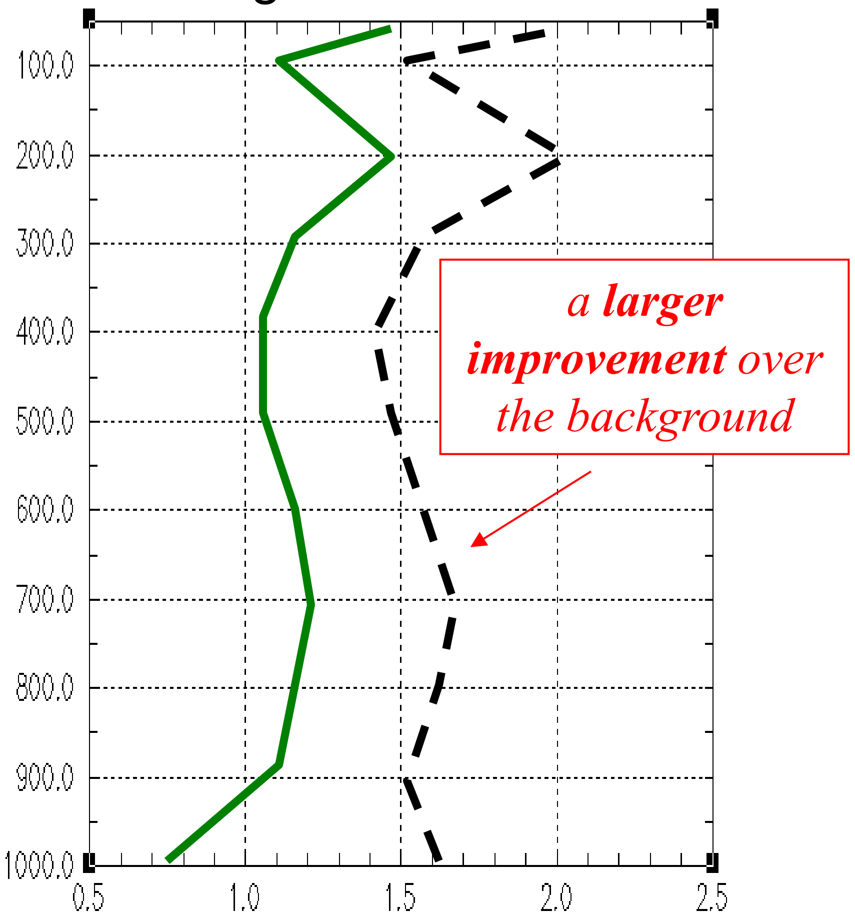
Sharp / anti-correlated background errors



Error standard deviation (K)

$\mathbf{S_a}$

Broad / deep correlated background error

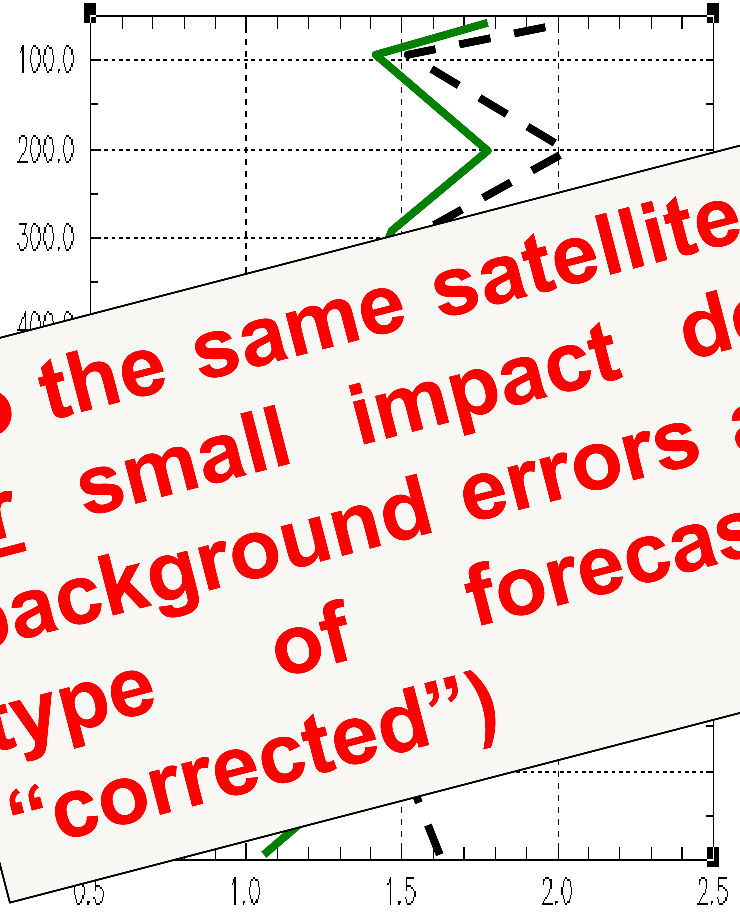


Error standard deviation (K)

$\mathbf{S_a}$

Background errors (and vertical resolution)

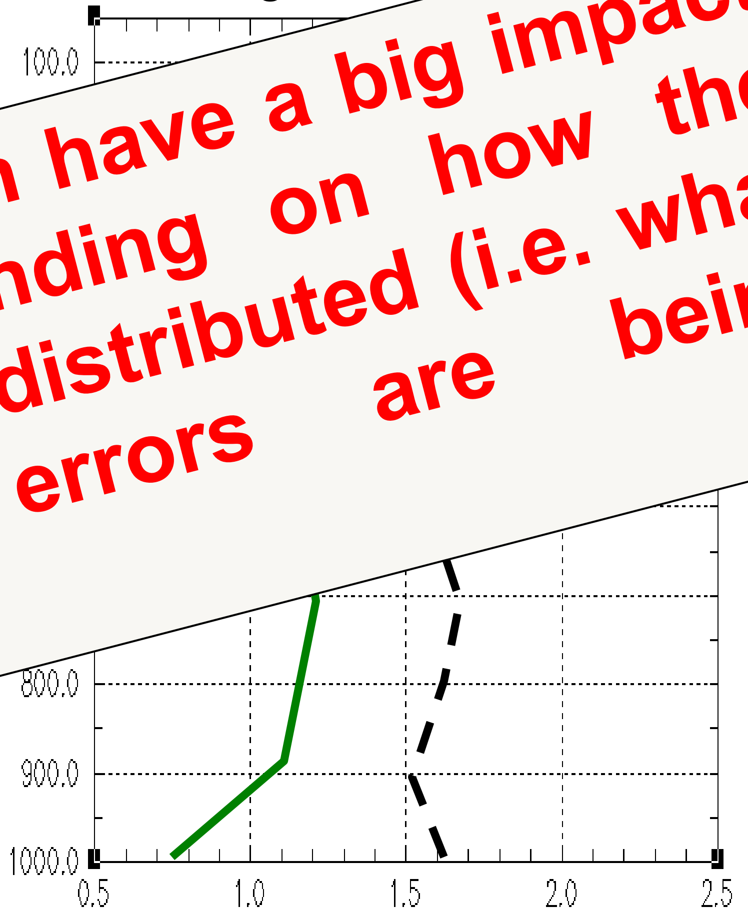
Sharp / anti-correlated background errors



Error standard deviation (K)

S_a

Broad / deep correlated background erro



Error standard deviation (K)

S_a

So the same satellite can have a big impact or small impact depending on how the background errors are distributed (i.e. what type of forecast errors are being "corrected")

Key elements of a data assimilation system

- observation operator
- background errors
- observation errors
- bias correction
- data selection and quality control

Observation errors:

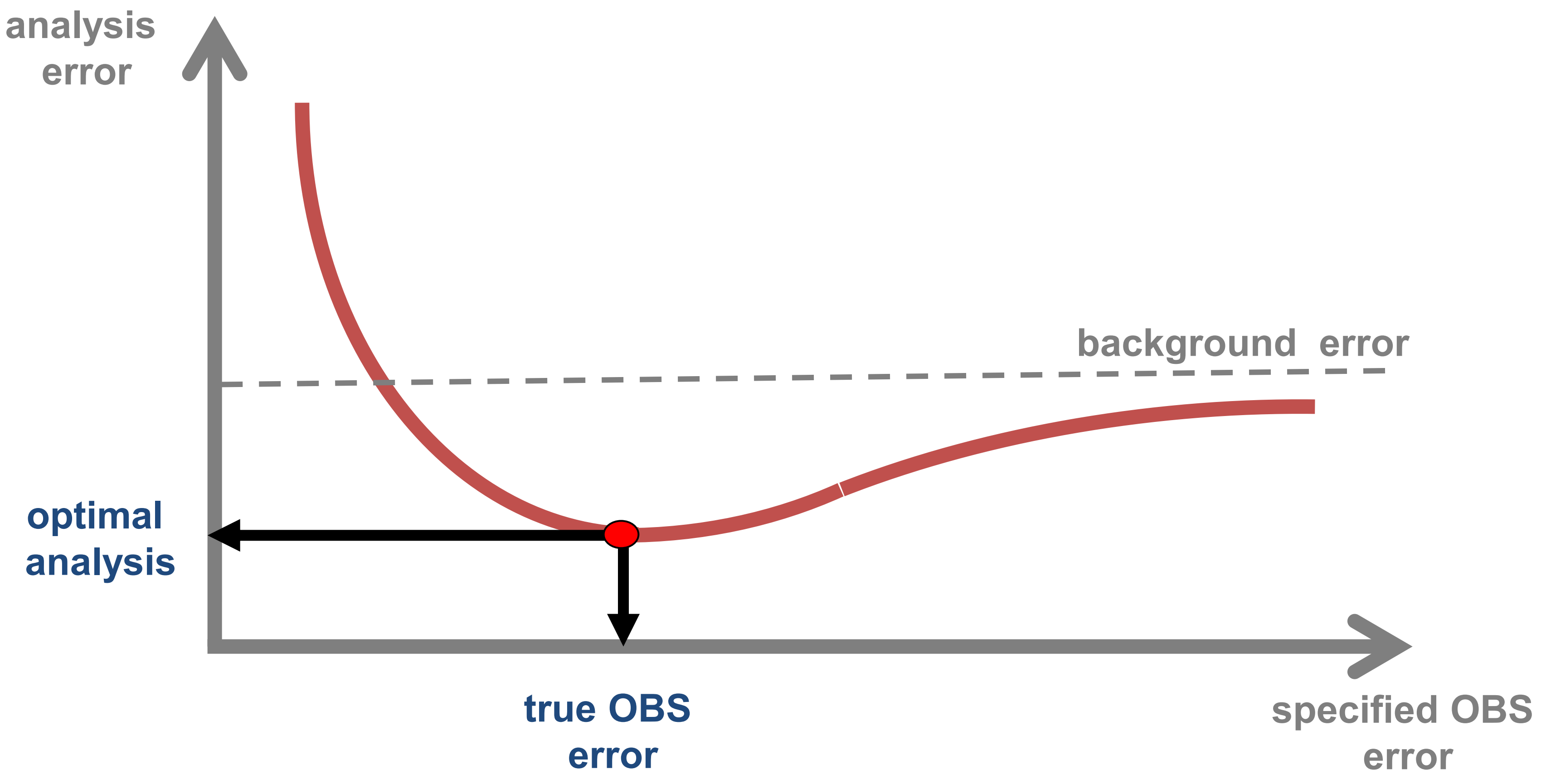
- These determine the weight we give to the radiance observations. The observation error must account for **instrument noise**, random uncertainties in the **observation operator** (e.g. RT model), errors in data **screening** (e.g. residual clouds) and errors of representativeness (e.g. scale mismatch).

- It is important to model both the magnitude of errors (diagonals of R) and **any inter-channel correlations**

- Wrongly specified observation errors can lead to an analysis with **larger errors than the background**!

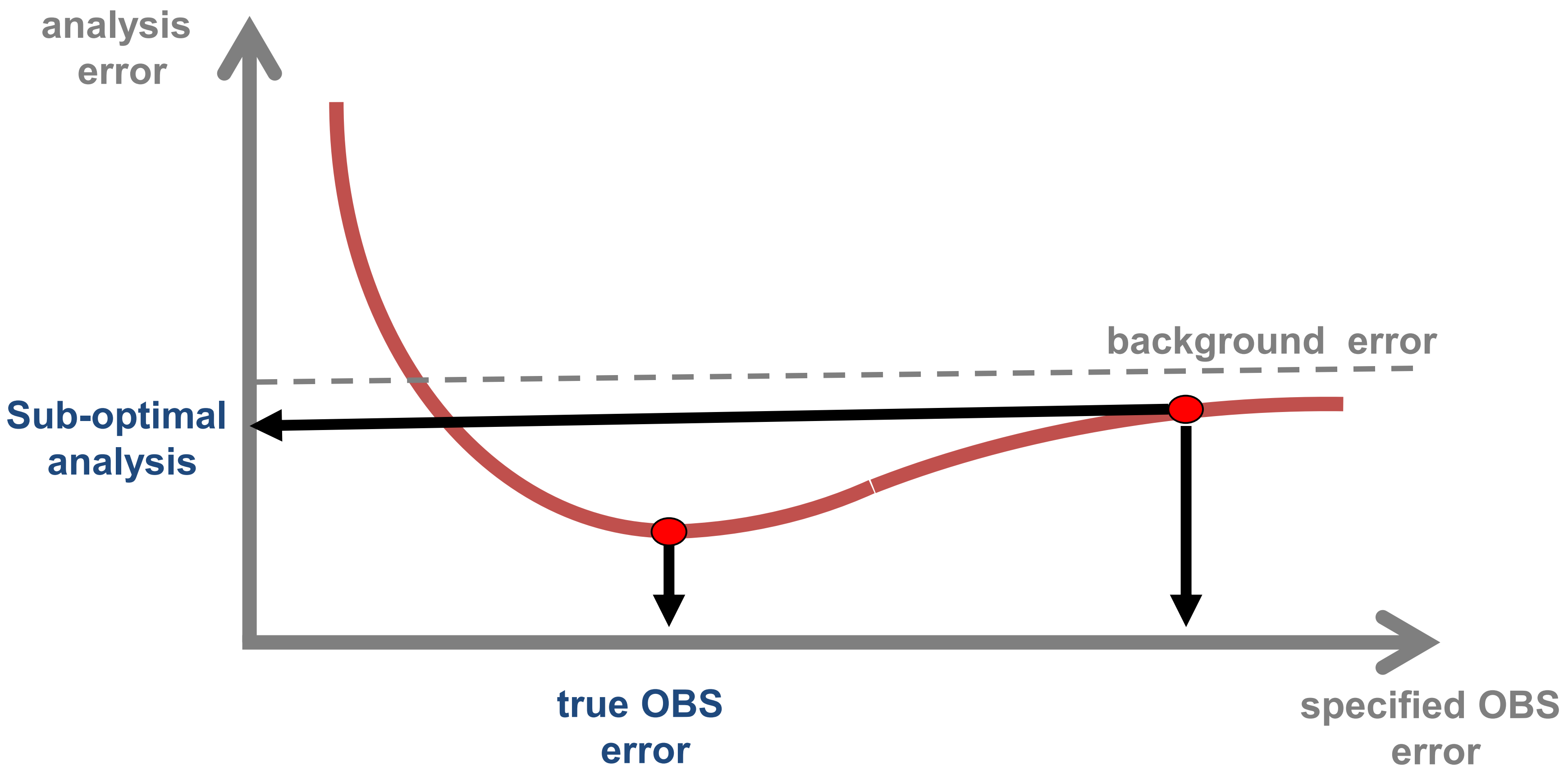
Observation errors:

- Specifying the correct observation error produces an optimal analysis with minimum error.



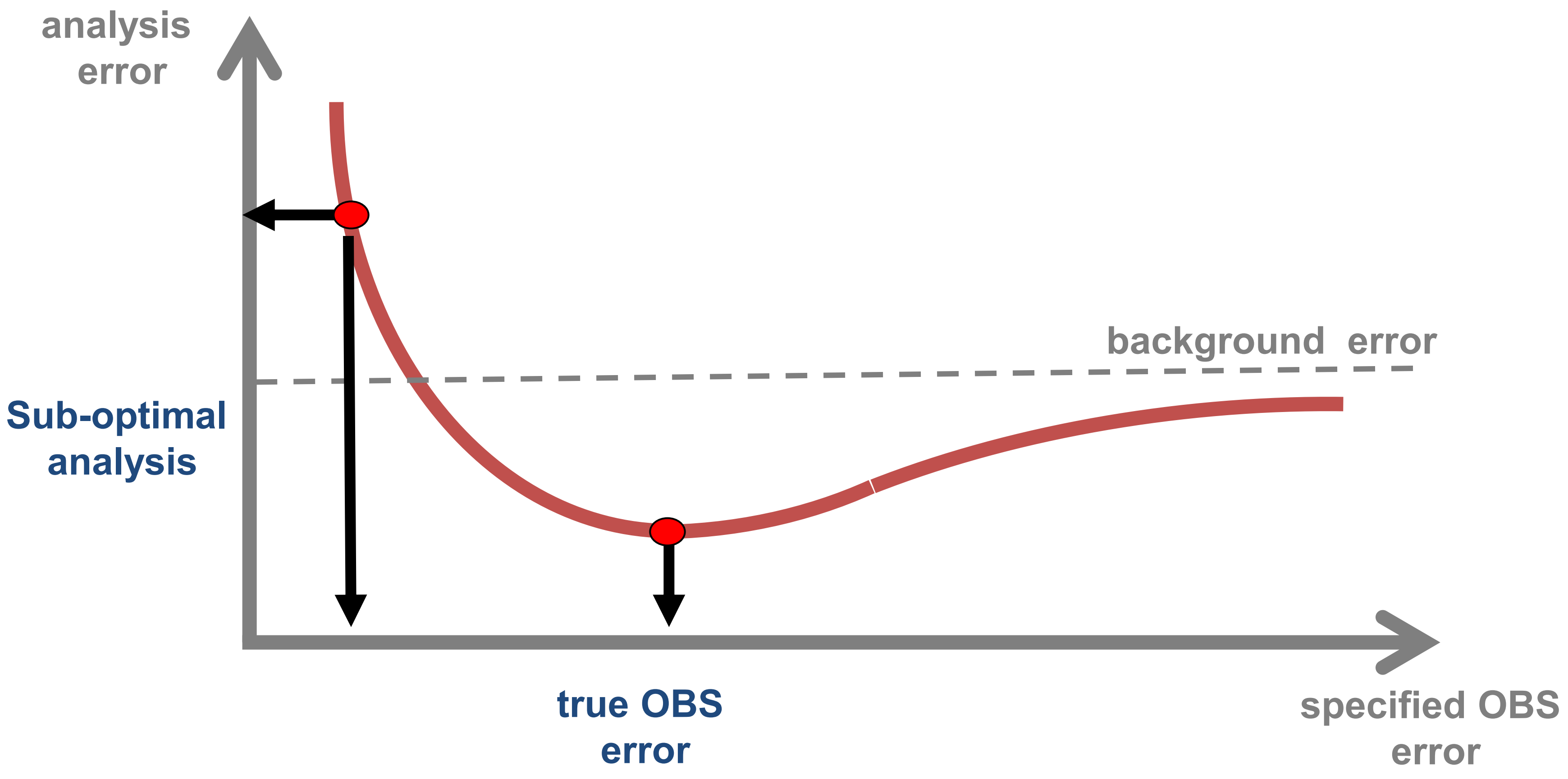
Observation errors:

- Over-estimating the OBS error degrades the analysis, but the result will not be worse than the background.



Observation errors:

- Under-estimating the OBS error degrades the analysis, and <u>**the result can be worse than the background**</u>!



Key elements of a data assimilation system

- observation operator
- background errors
- observation errors
- bias correction
- data selection and quality control

Bias correction:

Systematic errors must be removed otherwise biases will propagate in to the analysis (causing **global damage** in the case of satellites!). A bias in the radiances is defined as:

$$\textit{bias} = \textit{mean}\left[Y_{obs} - H(X_{true}) \right]$$

Sources of systematic error in radiance assimilation include:

- instrument error (scanning or calibration)
- radiative transfer error (spectroscopy or RT model)
- cloud / rain / aerosol screening errors

Key elements of a data assimilation system

- observation operator
- background errors
- observation errors
- bias correction
- data selection and quality control

Data selection and quality control (QC):

The primary purpose of this is to ensure that the observations entering the analysis are **consistent with the assumptions** in the observations error covariance (**R**) and the observation operator (**H**).

Primary examples include the following:

- Rejecting bad data with **gross error** (not described by **R**)
- Rejecting data affected by **clouds** if **H** is a clear sky RT
- Thinning data if no **correlation** is assumed (in **R**)
- Always **blacklisting** data where we do not trust our QC!

Data selection and quality control (QC):

Often checks are performed using the forecast background as a reference. That is an observations is rejected if the departure from the background exceeds a threshold T_{QC}:

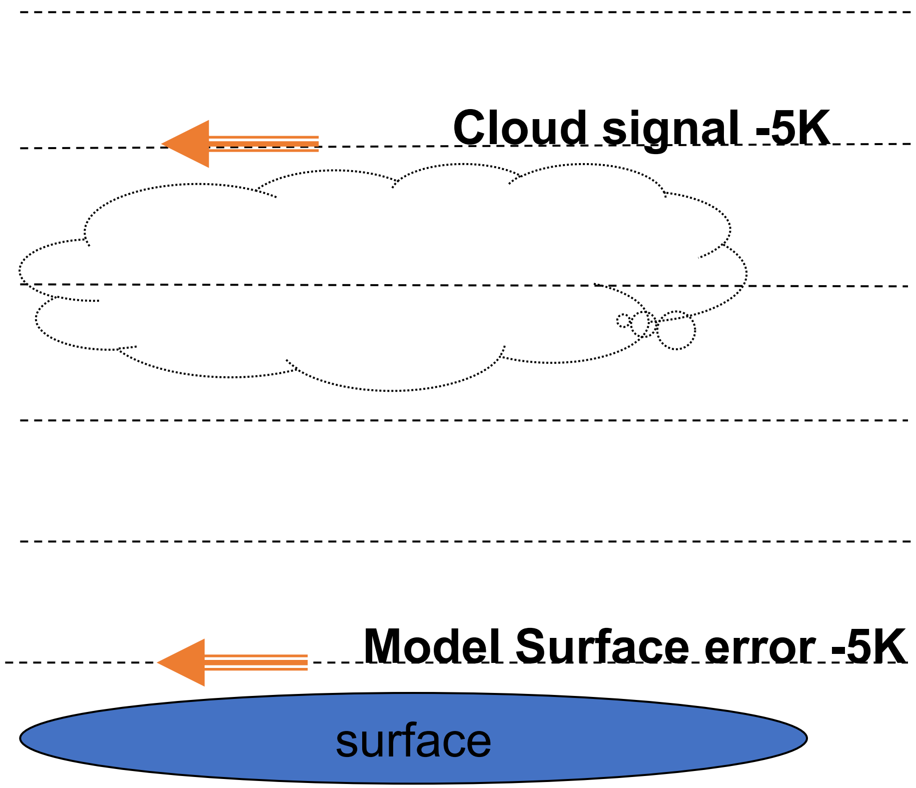
$$Y_{obs} - H(X_{true}) > T_{QC}$$

But sometimes large errors in the background can lead to:

- False rejection of a good observation
- Missed rejection of a bad observation

Data selection and quality control:

- Missed rejection of a **bad** observation



The radiance 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.

Thus our checking (against the background) sees no reason to reject the observation and is it **passed**!

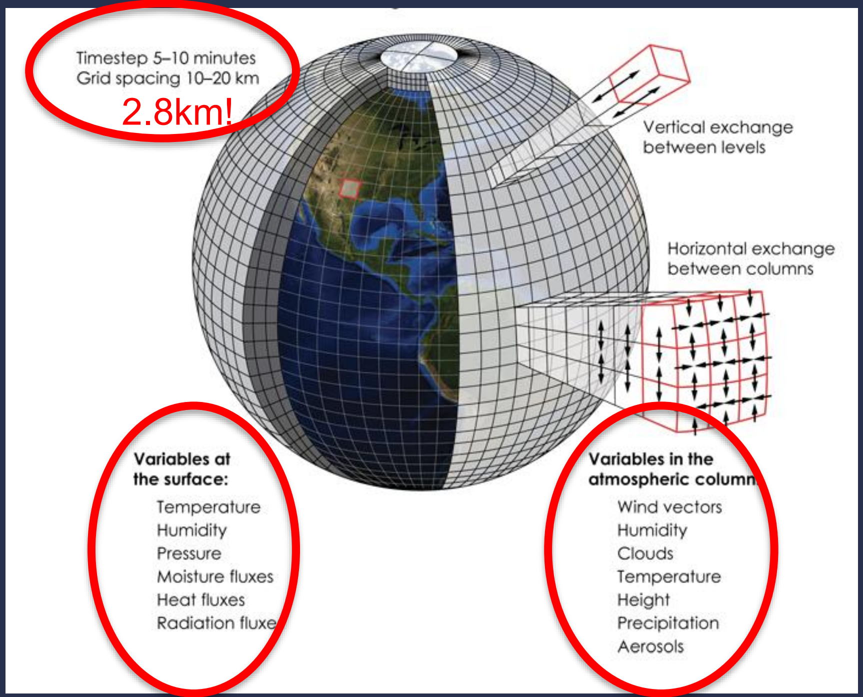
Summary

- observation operator
  (complex and expensive for radiances)
- background errors
  (important due to limited vertical resolution)
- observation errors
  (a challenge to specify correctly)
- bias correction
  (small, but global impact of bias)
- data selection and quality control
  (primarily data selection, few bad observations)

High-resolution and highly complex physics-based models present extreme challenges for DA

Observations are simply **insufficient** and generally of the **wrong variables** to provide initial conditions for NWP models of this resolution and complexity!

…so we are forced to blend observations with a background using DA….

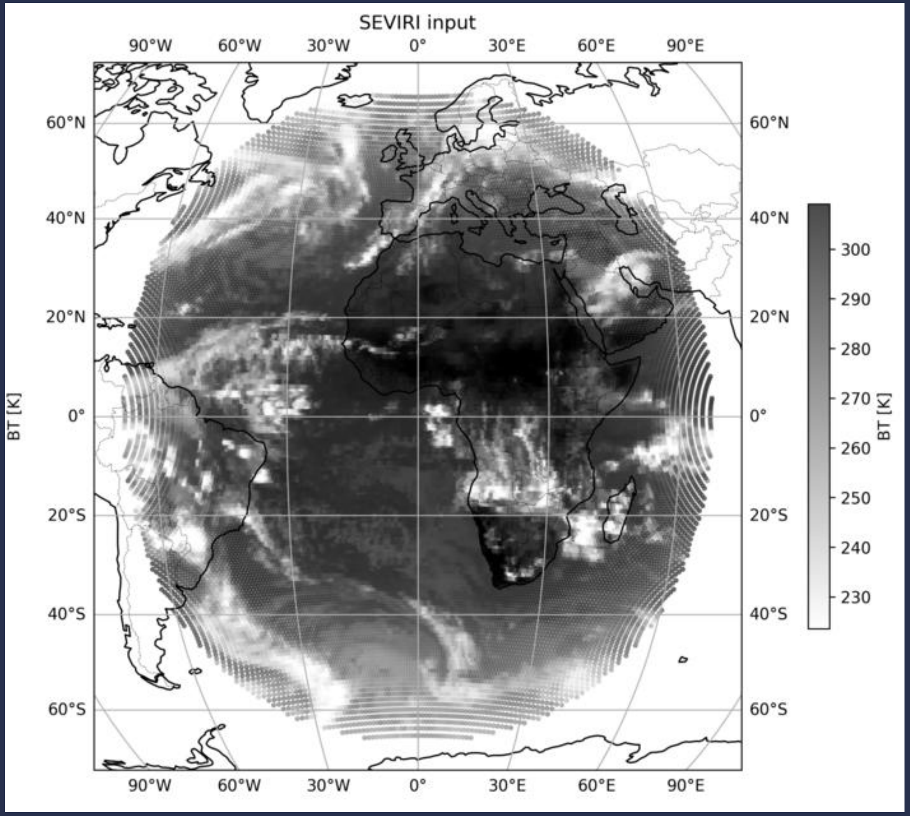


…requiring an exacting specification of poorly known error covariances (all huge multivariate tensors)

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_b) + \frac{1}{2}[\mathcal{H}(\mathbf{x})-\mathbf{y}]^T\mathbf{R}^{-1}[\mathcal{H}(\mathbf{x})-\mathbf{y}]$$

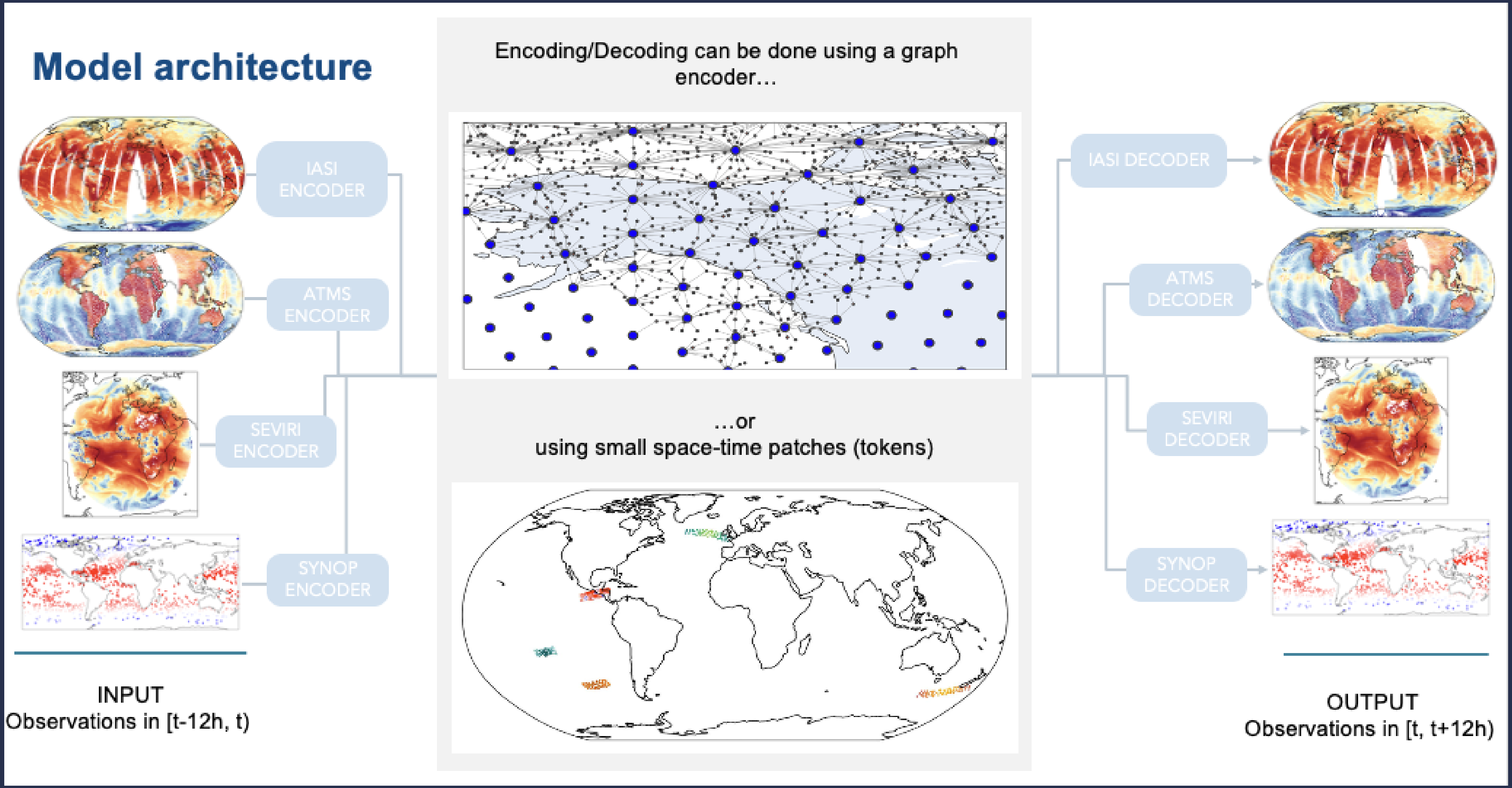
Accurate observation operators potentially limiting limiting the observations we can exploit…

Enhanced exploitation of satellite observations using Artificial Intelligence…Direct Observation Prediction



- We use historical observations to train a Neural Network (NN) to forecast <u>future</u> observations
- Include observations of the <u>full Earth system</u> (atmosphere, ocean, land) simultaneously
- Use <u>all</u> observations, without demanding a detailed physical model of the measurement
- Once trained, we initialize the model <u>directly</u> with the observations themselves, allowing <u>much faster</u> access to forecast warnings

Artificial Intelligence…Direct Observation Prediction (AI-DOP)



First medium-range forecasts made <u>directly</u> from observations:

AI-DOP model

Target real observations