Bias estimation and correction for satellite data assimilation

Tony McNally

ECMWF

T.Auligne, D.Dee, G.Kelly, R.Engelen, A. Dethof, G. Van der Grijn …

Outline of presentation

Three basic questions ….

•What biases do we observe with satellite data

•Where do the biases come from

•How do we correct for biases

What biases do we observe with satellite data

Radiance monitoring

For many years NWP centres have monitored satellite radiance observations for **systematic** departures (or biases) relative to the Assimilation system.

In general the radiances are compared to equivalent values computed from the NWP short-range forecast (or background) and/or analysis estimates of the atmospheric state using a radiative transfer (RT) model.

$$\boxed{\textit{mean}\ [\,\underbrace{Y_{obs}}_{\text{Observed radiance}} - \underbrace{H}_{\text{RT model}}(\underbrace{X_b}_{\text{Background Atmospheric state}})\,]}$$

What do these biases look like ?

a) Time varying (e.g. diurnal or seasonal)

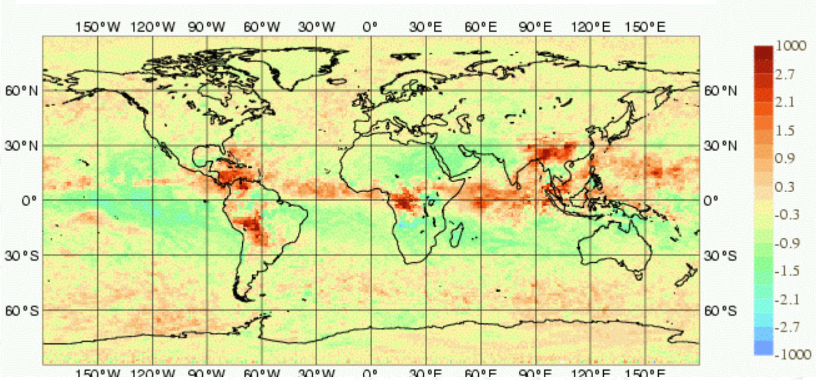
b) Geographically varying or air-mass (inc. underlying surface) dependent

c) Varying with the scan position of the satellite instrument

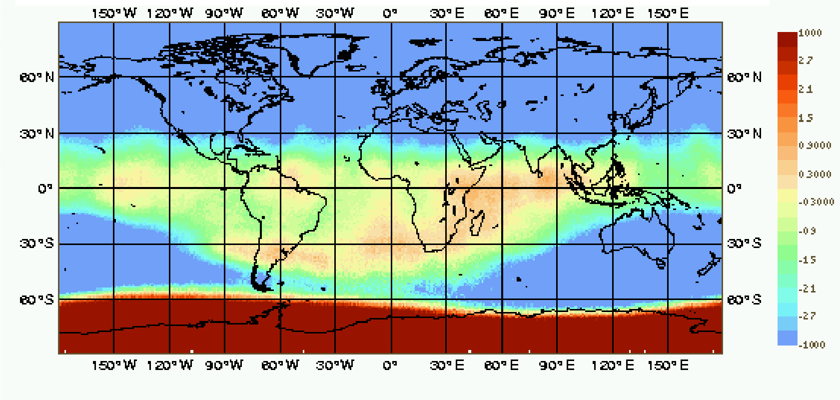
d) Varying with position of the satellite around its orbit

Examples of air-mass dependent biases

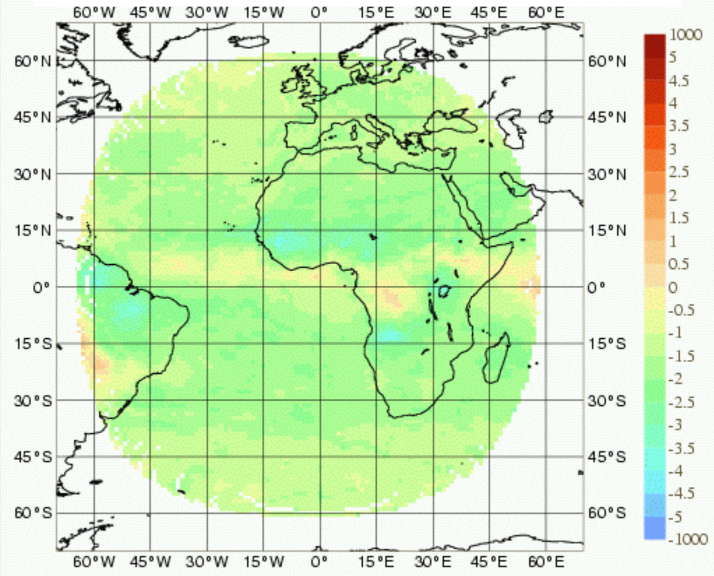
HIRS-12 water vapour



AMSUA-14 temperature

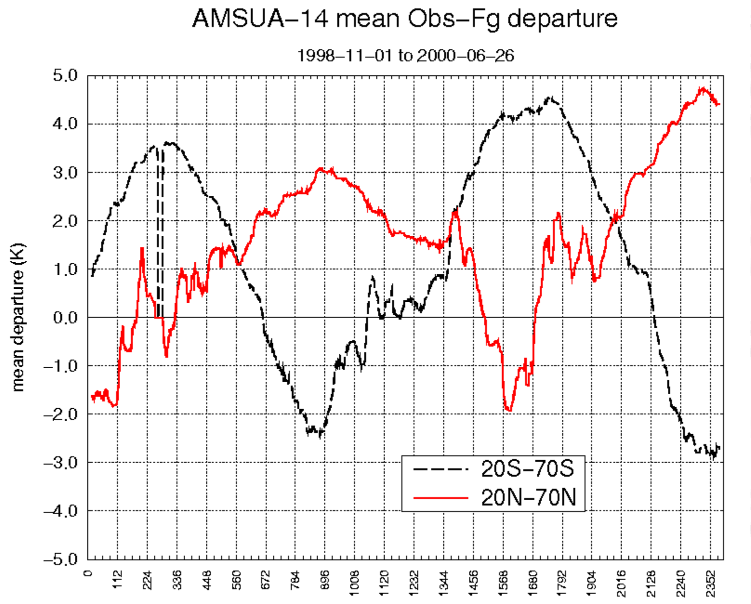


MET-8 water vapour

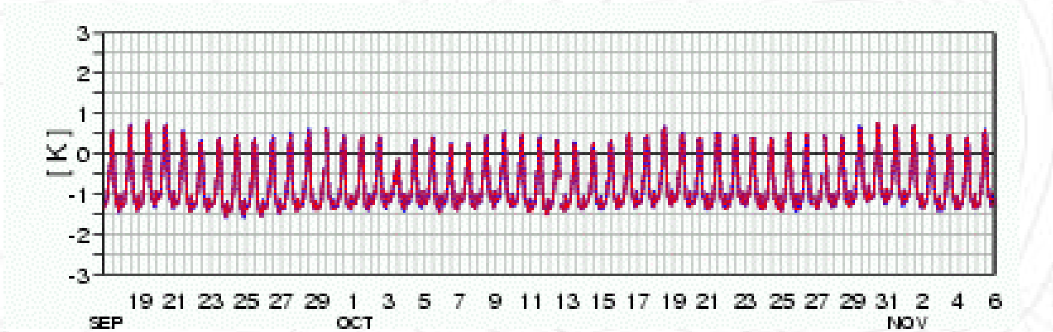


Examples of time dependent biases

Seasonal departure variations in a two year time series of AMSUA-14 radiance departures (sensitive to temperature near the stratopause) averaged over the N and S polar regions

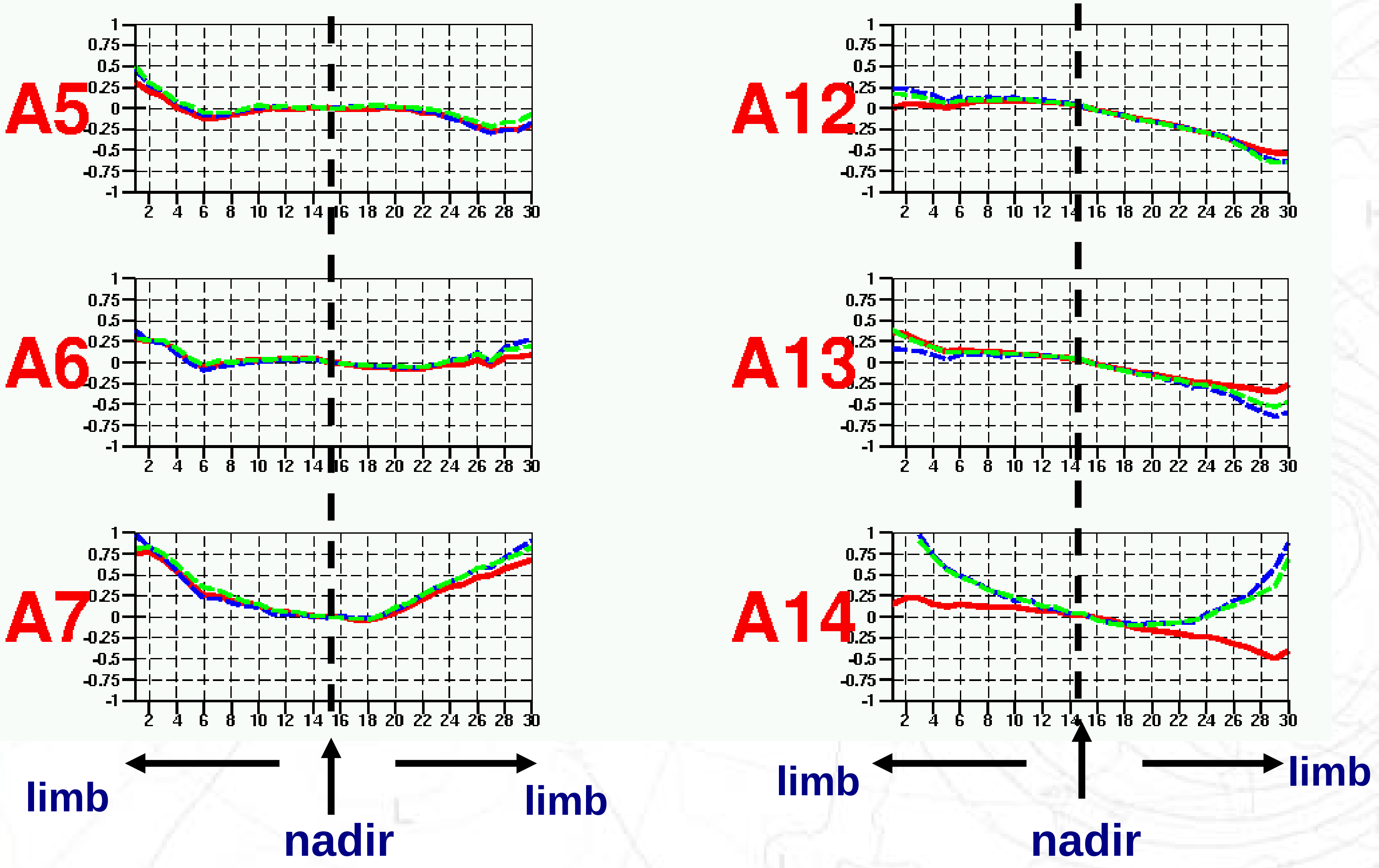


Diurnal departure variations in a time series for MET-8 window channel sensitive to surface skin temperature



Examples of scan dependent biases

NOAA-18 AMSUA temperature sounding channels



Where do these biases come from ?

Where do these biases come from ?

- **Satellite instrument**

  (calibration / charaterization / environmental effects)

- **Radiative transfer (RT) model**

  (physics / specroscopy / non-modelled processes)

- **Pre-processing of observations**

  (cloud-precipitation detection / level-2 process)

- **NWP model ***

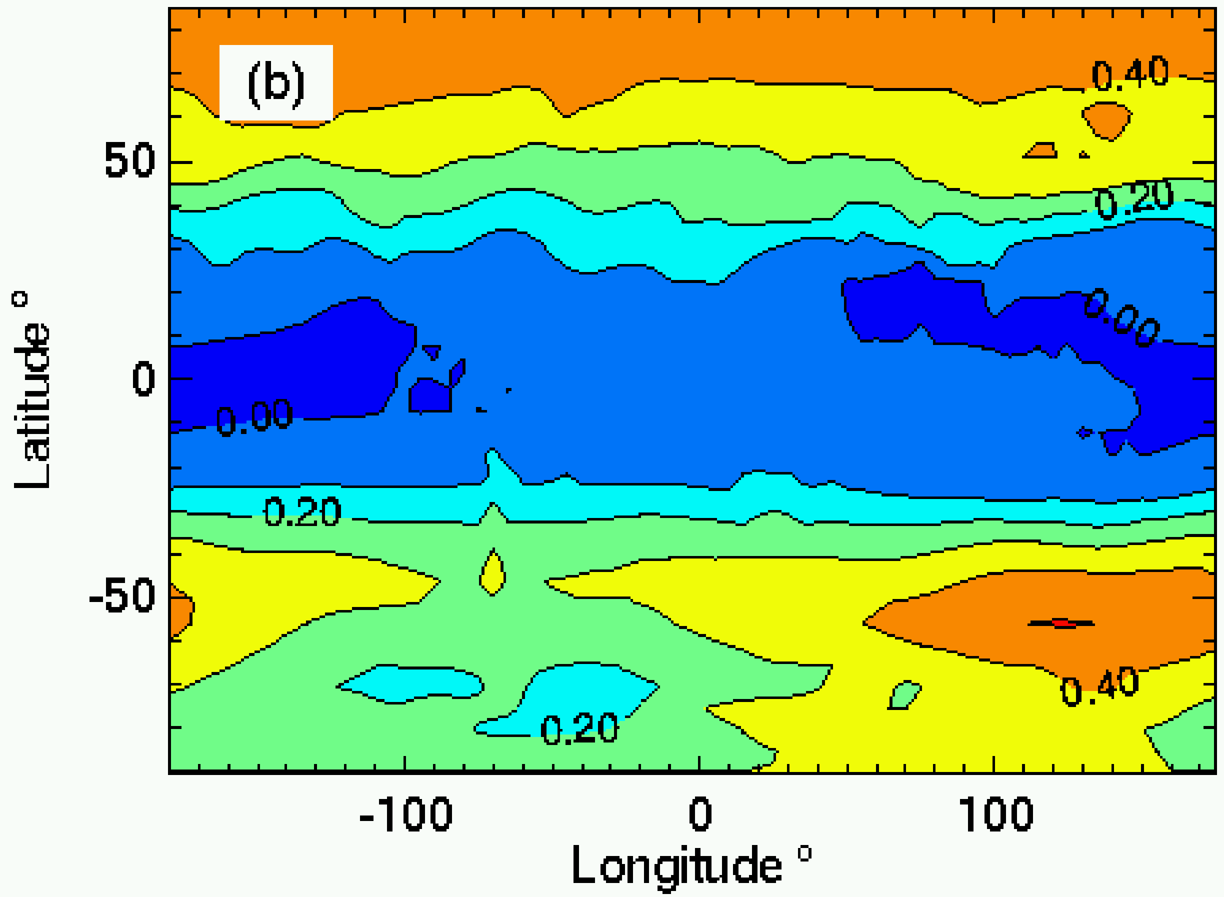
  (systematic errors in the background state)

What do we expect biases to look like ?

	Time varying	Air-mass dependent	Scan dependent	Orbit dependent
Instrument calibration	Yes	No (hot surfaces)	Yes	Yes
RT model	No	**Yes**	Yes	Yes
NWP model	Yes	Yes	**Yes**	No
Observation preprocessing	No	Yes	Yes	No

RT model error giving air-mass bias

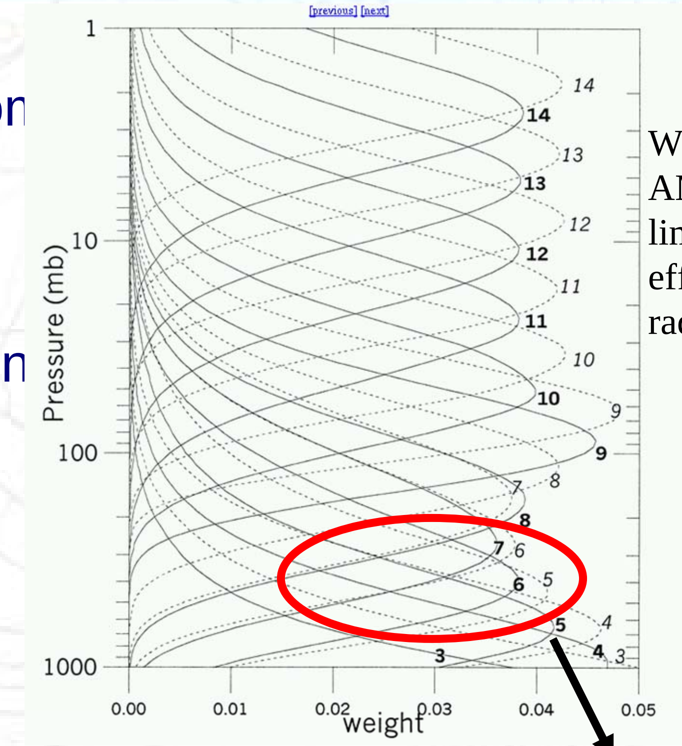
Even a simple RT error (e.g. constant 5% error in the atmospheric absorption) maps into an air-mass dependent bias via variations in the atmospheric lapse rate.



Radiance error (K) due to a 5% error in AMSUA channel 8

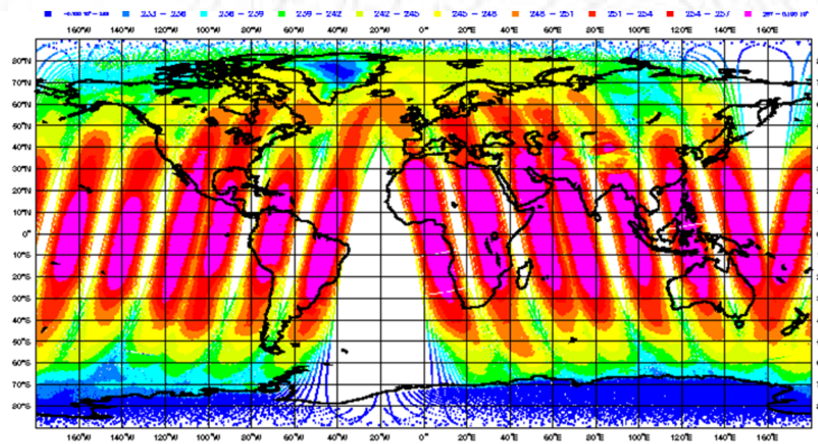
NWP error giving apparent scan dependent bias

As a satellite scans away from nadir the atmospheric path increases and there is more absorption. This effectively causes the weighting function to move up in the atmosphere.



Weighting functions for AMSUA at nadir and limb producing a limb effect in the observed radiances

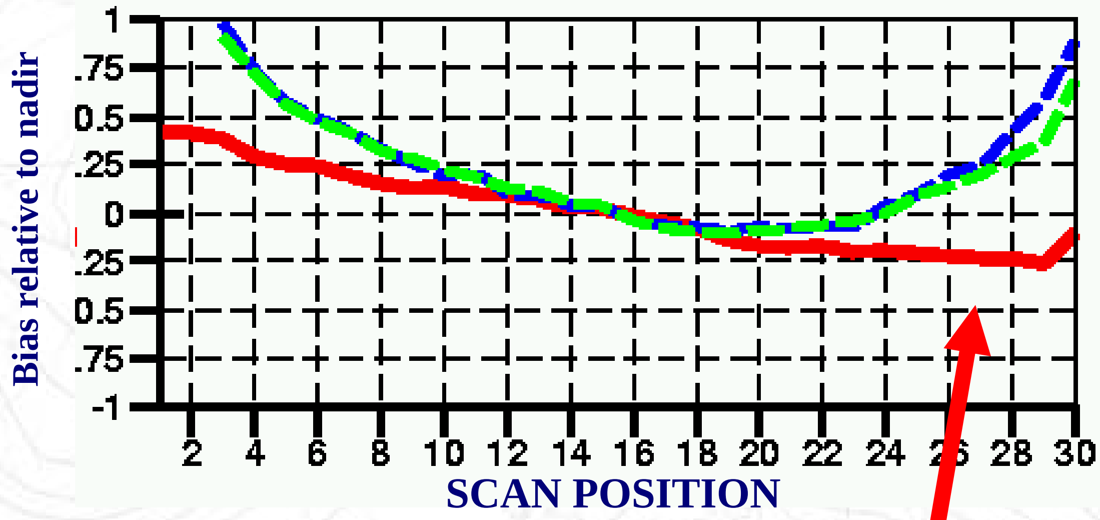
This causes a corresponding increase (or decrease) in the observed radiance depending on the atmospheric lapse rate. This is the well known **limb effect**.

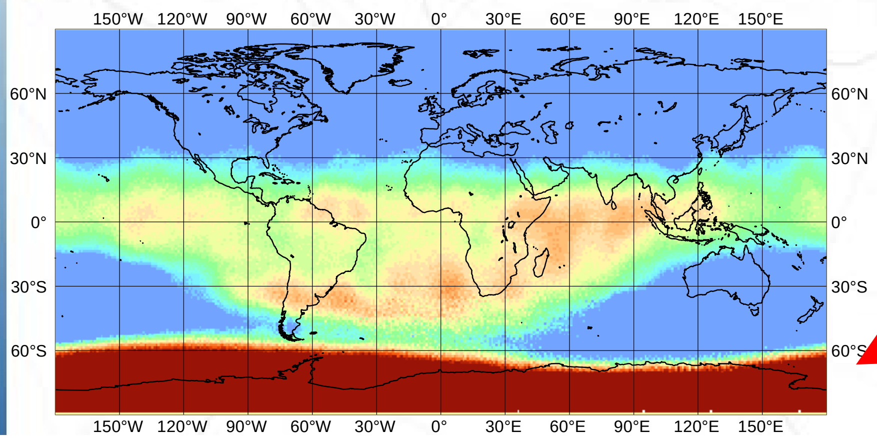


NWP error giving apparent scan dependent bias

When we compute radiances from the NWP model, if we have a systematic error in the atmospheric lapse rate (e.g. polar night stratosphere) we will systematically compute the **wrong limb effect**. This will give rise to a **scan dependent bias** between the NWP model and observations

AMSUA channel 14





Asymmetric scan dependent bias associated with large systematic lapse rate error in the polar night

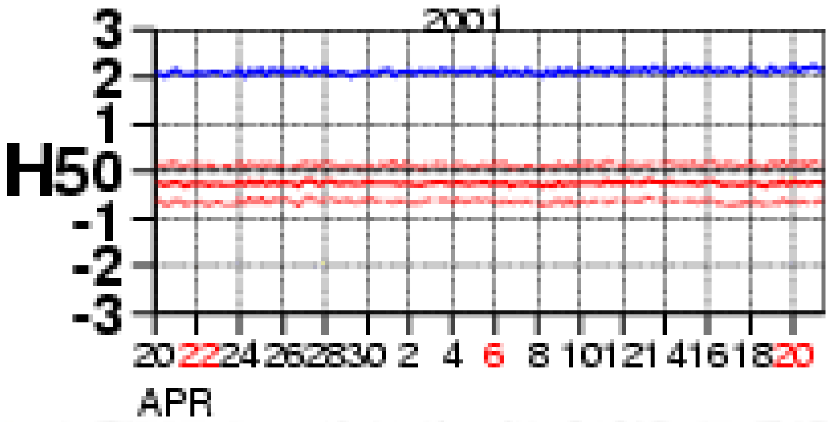
Identifying / separating sources of bias

In general the biases we observe in our radiance monitoring will be a mixture of many different sources of systematic error. However, there are ways to attempt to separate some of the contributions:

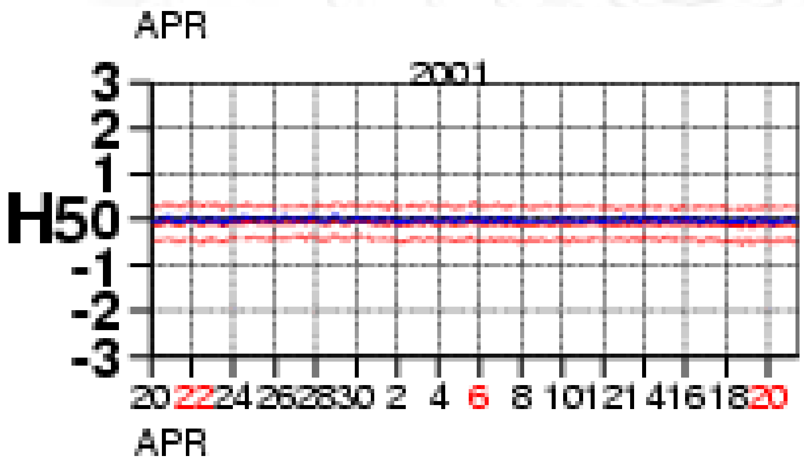
- **Cross validation** (other satellites or convetional data)
- **Time series analysis** (surface temperature / seasonal model error)
- **Monitor using campaign data** (limited) and not (O-B)
- **Prior knowledge** (correlation with know bias / spectral signature)

Un-ambiguous instrument problem

…sometimes it’s easy …



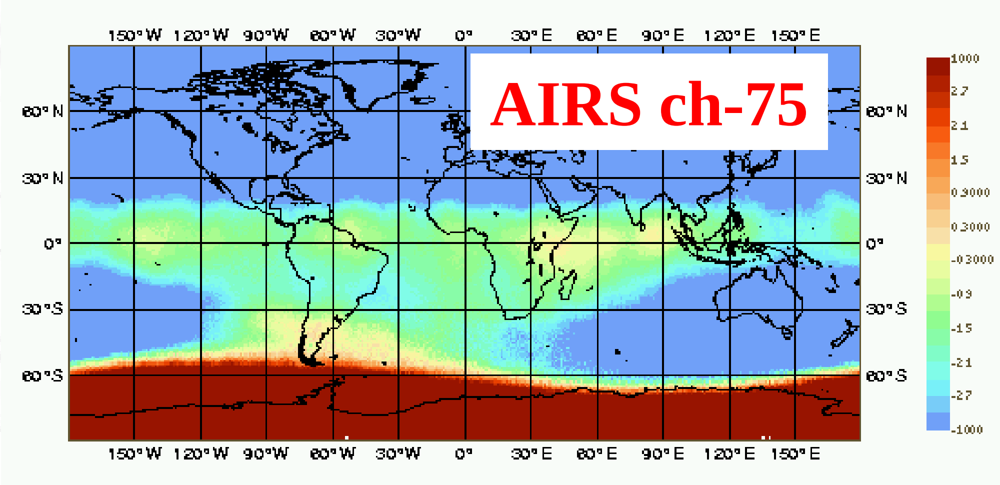
HIRS channel 5 (peaking around 600hPa on NOAA-14 satellite has +2.0K radiance bias against model

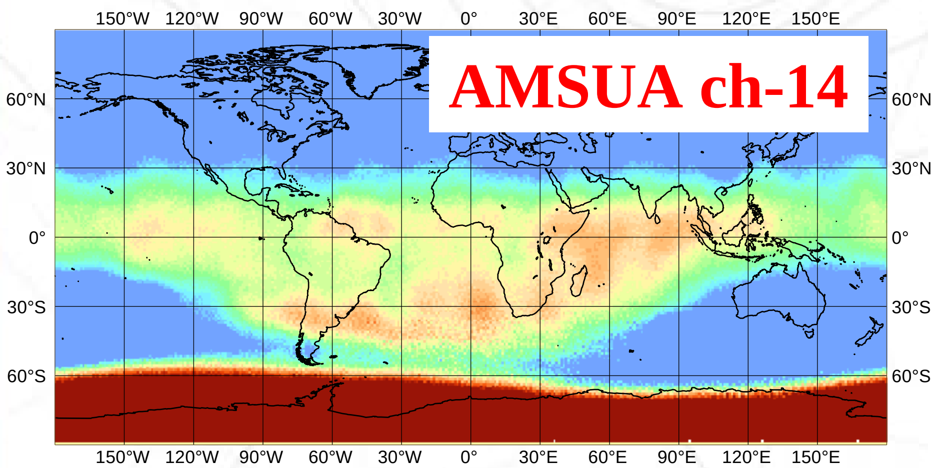


HIRS channel 5 (peaking around 600hPa on NOAA-16 satellite has no radiance bias against model.

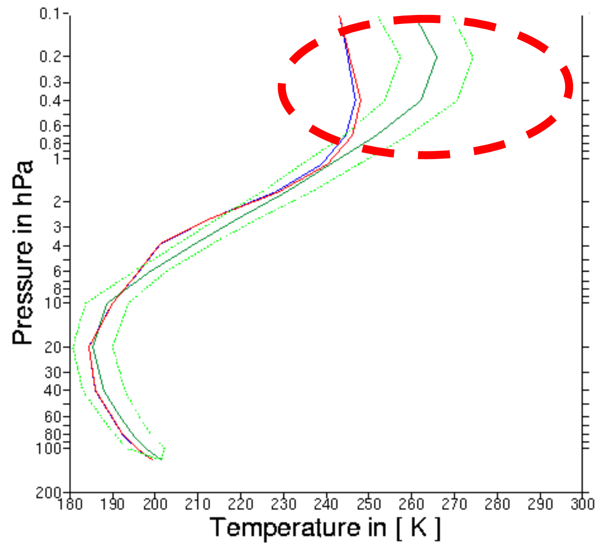
Un-ambiguous NWP model bias

A number of independent sensors confirm the existence of a significant cold bias in the NWP model for the polar night stratosphere



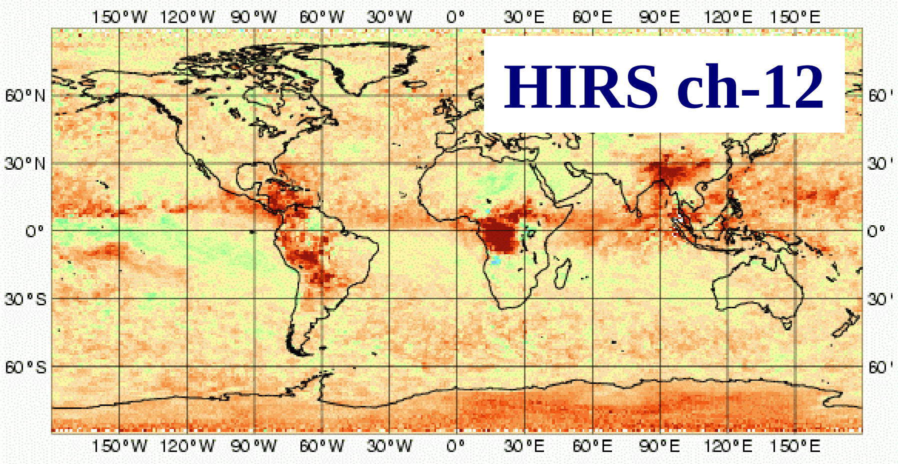


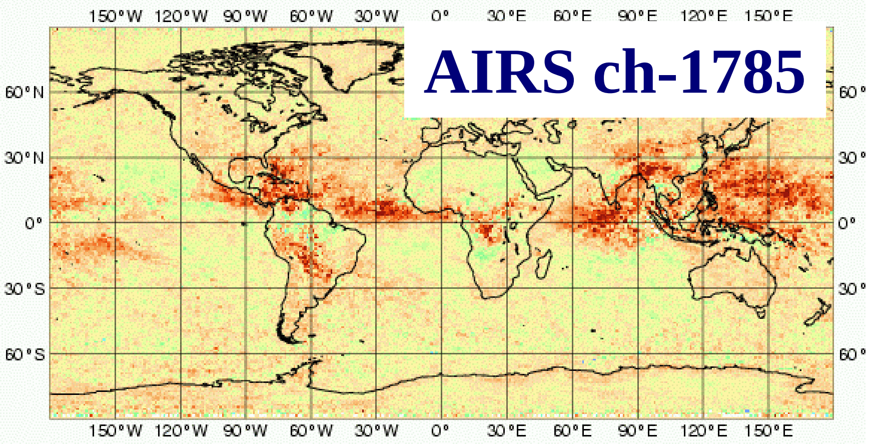
MIPAS retrievals

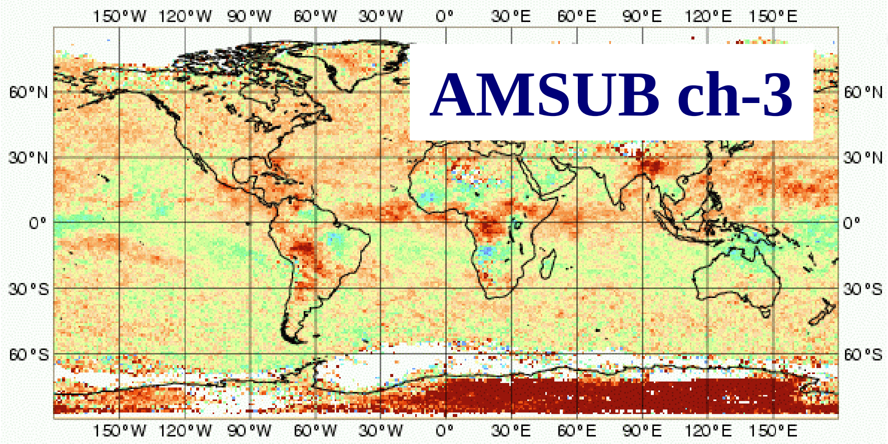


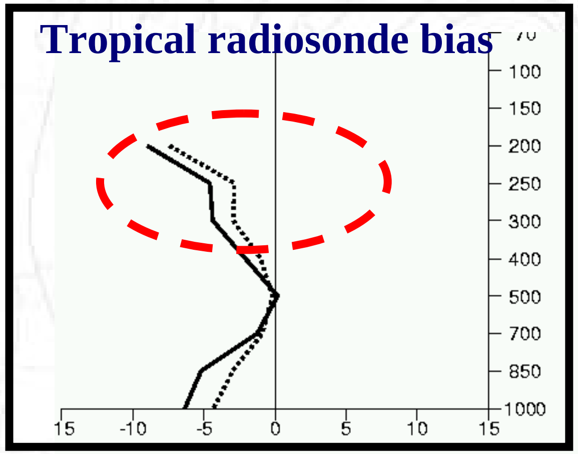
Un-ambiguous NWP model error

A number of independent sensors and radio-sonde observations confirm the existence of a moist bias in the upper tropospheric humidity of the NWP model









Do we care about separating biases ?

1) Yes, because we wish to understand the origin of the bias and ideally correct instrument / RT / NWP model at source.

2) Yes, because *in principle* we **do not** wish to apply a correction to unbiased satellite data if it is the NWP model which is biased. Doing so is likely to …

   a) **re-enforce the model bias** and degrade the analysis fit to other observations

   b) Produce a **biased analysis** (bad for re-analysis / climate applications)

What should we do with systematic NWP error ?

If we don't wish to correct for NWP error …

1) Use the observed departures to tune NWP model parameters
   - soil resistance / Rayleigh friction / radiation

2) Explicitly treat the model systematic error in the assimilation
   - add forcing tendencies to the control vector in 4DVAR

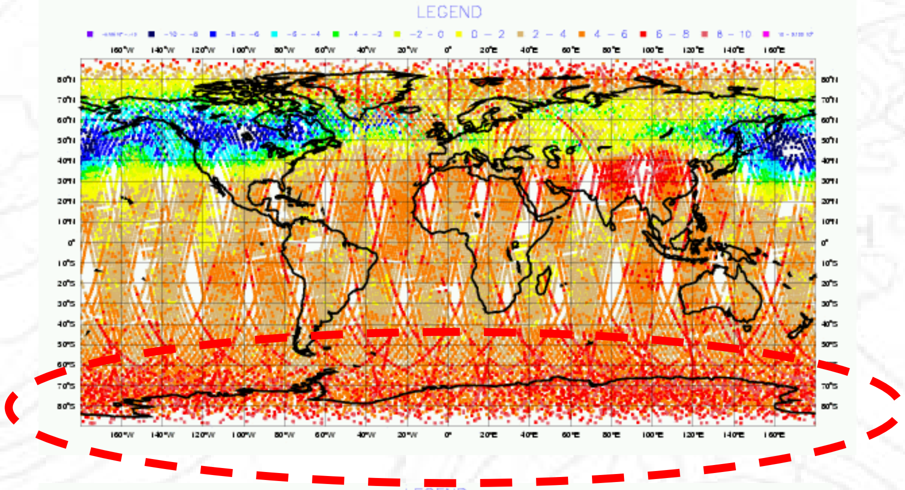
3) Force the good data into the biased NWP model.
   - assimilate uncorrected data

But analysis schemes are not designed to do (3) and we may have problems with inappropriate Jb statistics / undesirable oscillations / spin –up-down etc..

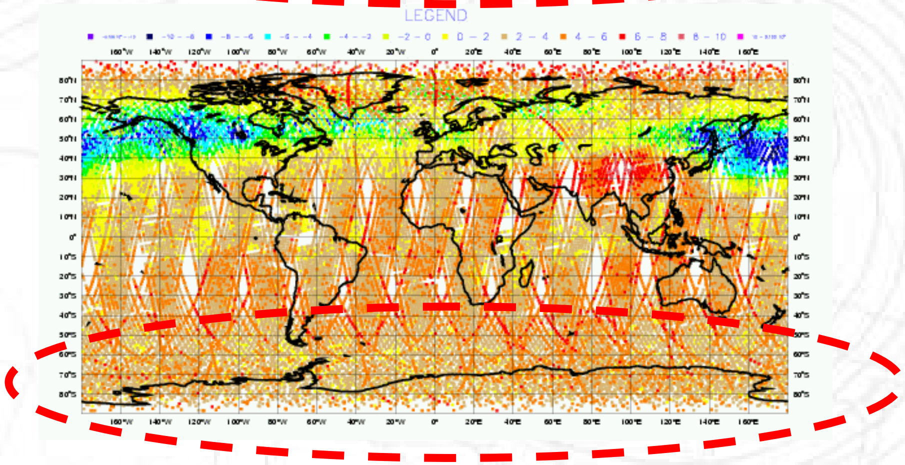
1) Tune NWP model parameters to observations

Some of the temperature biases in the stratosphere have been reduced by tuning parameters such as Rayleigh friction

Mean AMSUA ch-14 radiance departures with OLD Rayleigh friction



Mean AMSUA ch-14 radiance departures with NEW Rayleigh friction

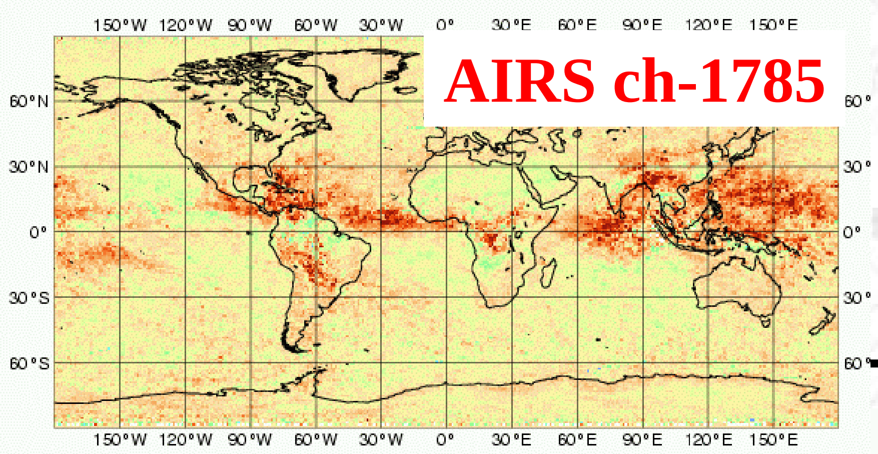


2) Account for NWP model error explicitly in the assimilation

See presentation by Yannick Tremolet

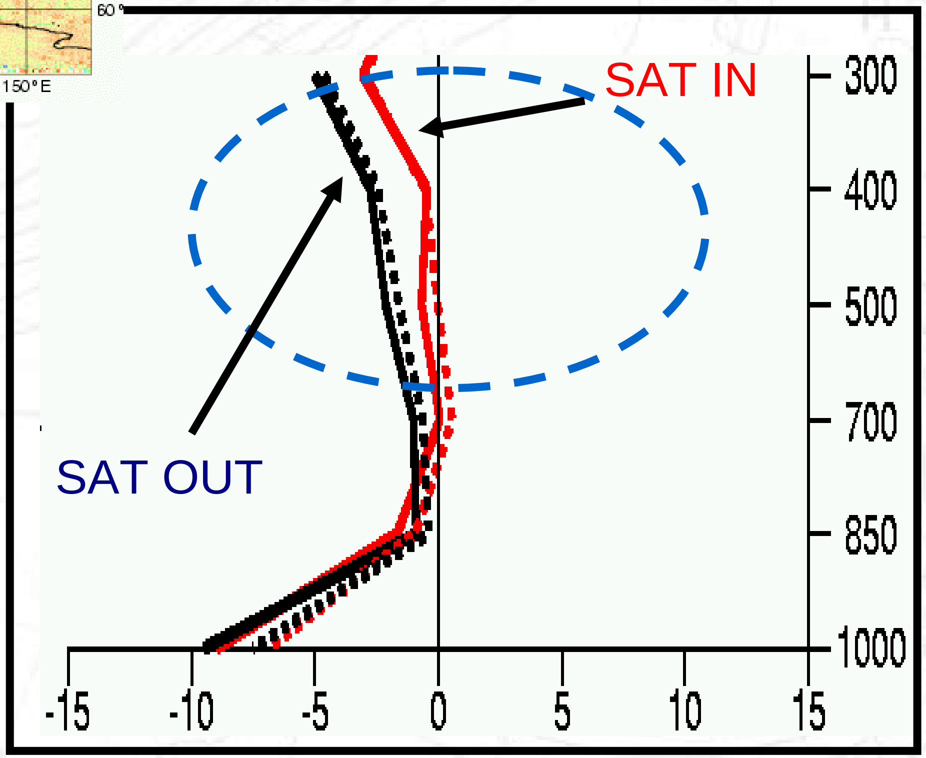
3) Forcing good data into a biased NWP model

… good example…

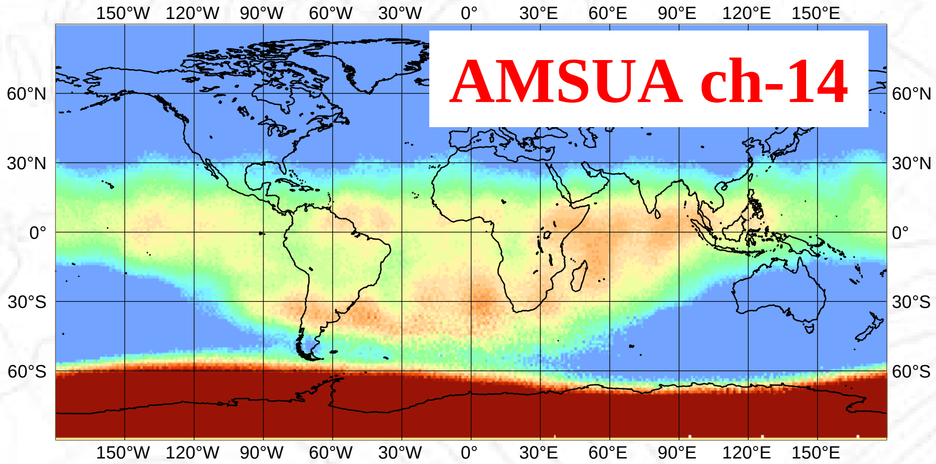


IR and MW radiance suggest the NWP model has a dry bias in the upper tropospheric humidity

Forcing these data in improves the fit of the analysis and short range forecast background to radio-sonde humidty data

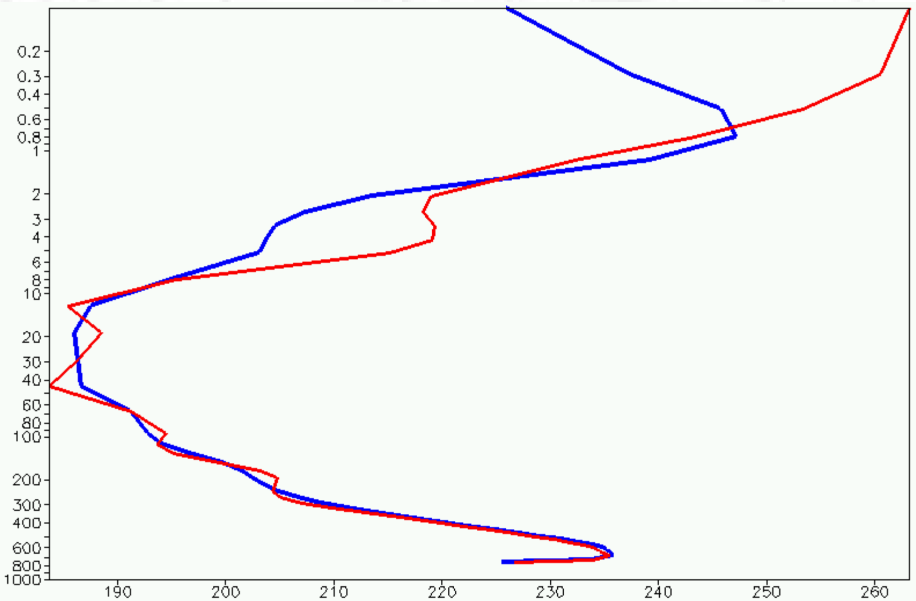


Forcing good data into a biased NWP model
… a bad example …



AIRS and AMSUA suggest a cold bias in the NWP model in the stratospheric polar night

Forcing these data in improves the NWP model top, but causes significant spurious oscillations in the temperature profile below



How do we correct for biases ?

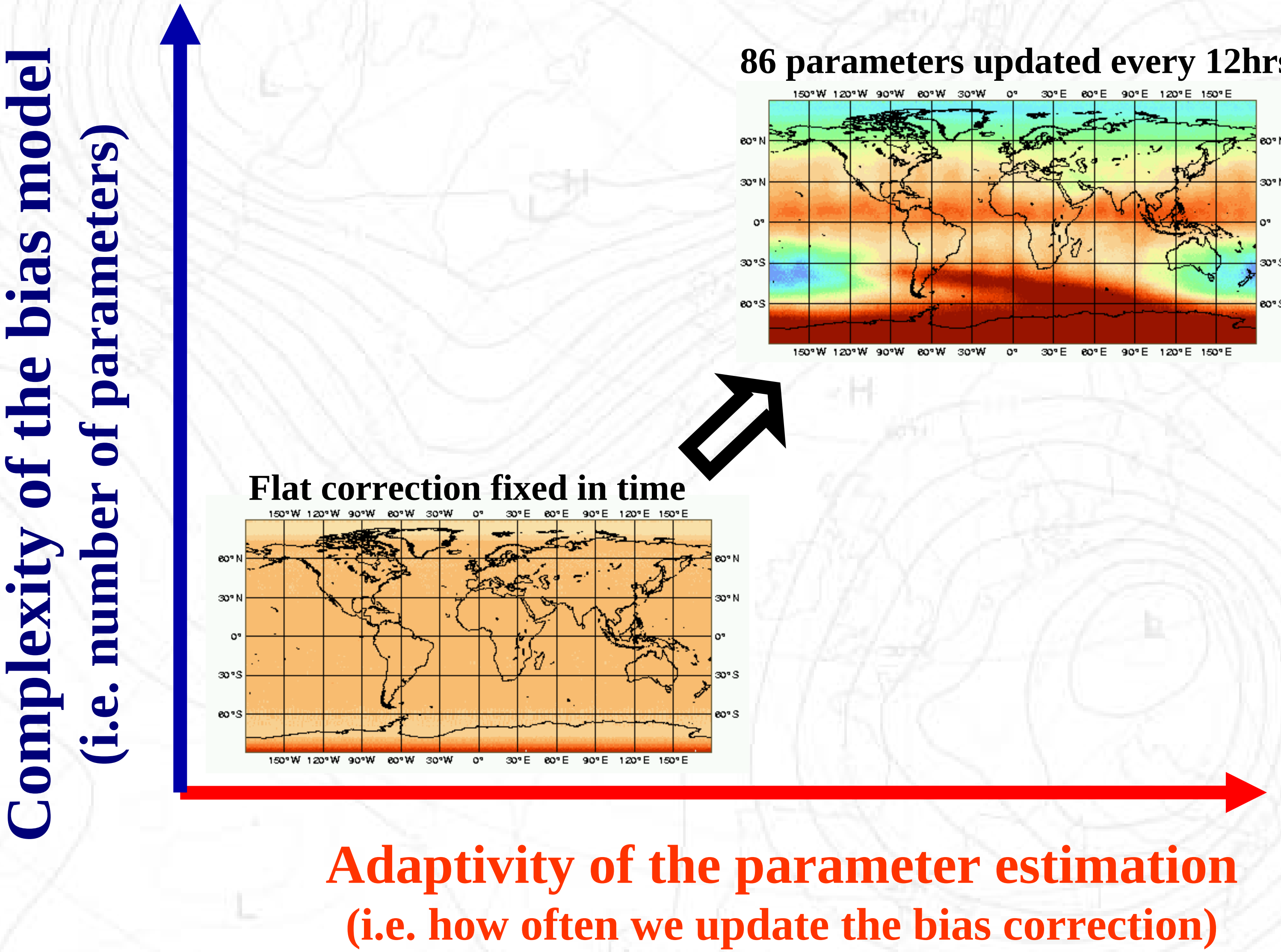
(and potential problems!)

Options for bias correction

- Static with very simple bias model
- Adaptive (offline) with simple bias model
- Adaptive (inline) with simple bias model
- Static with complex bias model
- Adaptive (offline) with complex bias model
- Adaptive (inline) with complex bias model

Power = adaptivity x complexity

Complexity of the bias correction



Our choice may depend on …

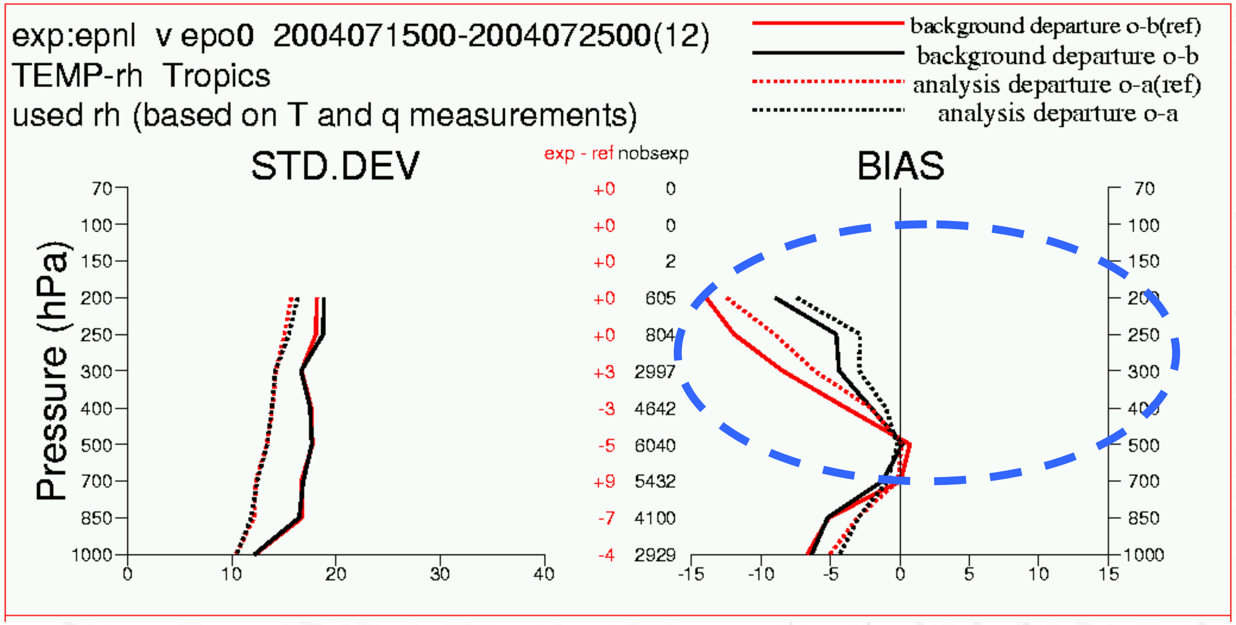
- The expected nature (e.g. time and spatial variability) of the biases we wish to correct

- If we are concerned with not correcting for NWP model error

- Logistical considerations such as how many instruments we have in the assimilation system (and how many people to monitor them)

Dangers of a powerful correction

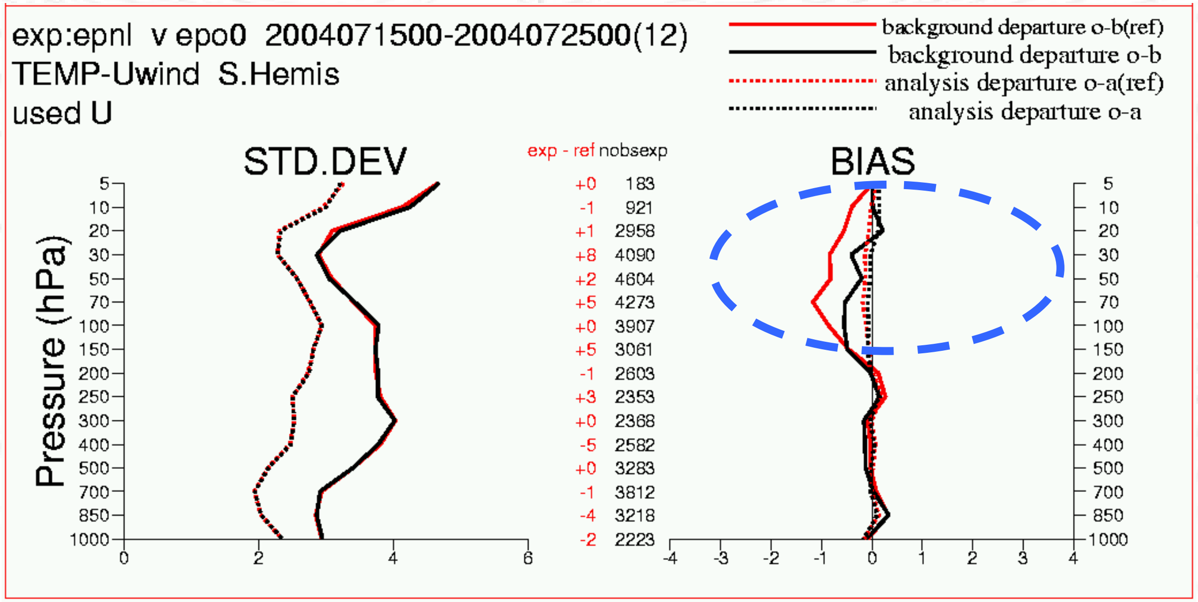
Too simple a correction may not follow all the variations in bias, but a too complex / adaptive model may remove useful information from the data and degrade the assimilation system



The bias corrected satellite data produce a analysis similar to a NO-SAT system !

… another example …

A large scale correction of satellite temperature data has caused a strengthening of the N – S thermal gradient and degraded the U-component of wind.



The bias corrected satellite data produce a analysis similar to a NO-SAT system !

Constraining bias correction schemes

- Other (**uncorrected** observations e.g. RS)
- Choice of bias model (e.g. gamma)
- Time inertia of adaptivity
- Spectral filtering penalty function terms

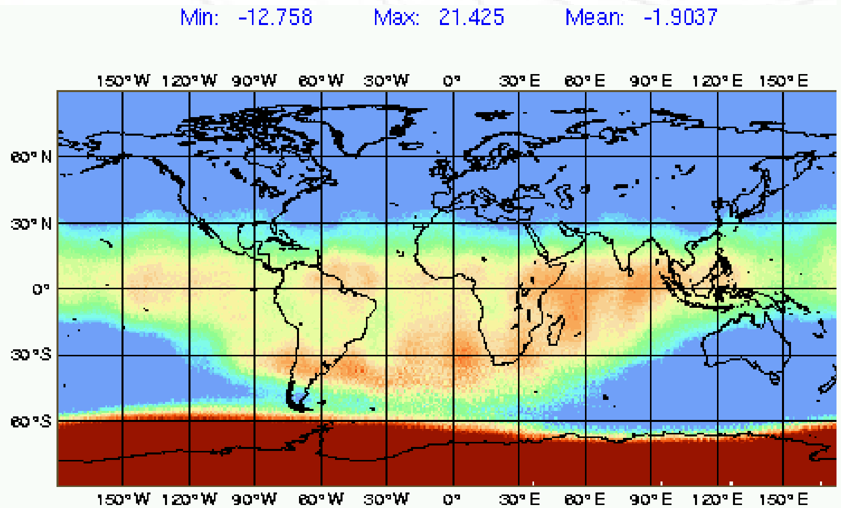
See presentation by T. Auligne

Active vs Passive monitoring

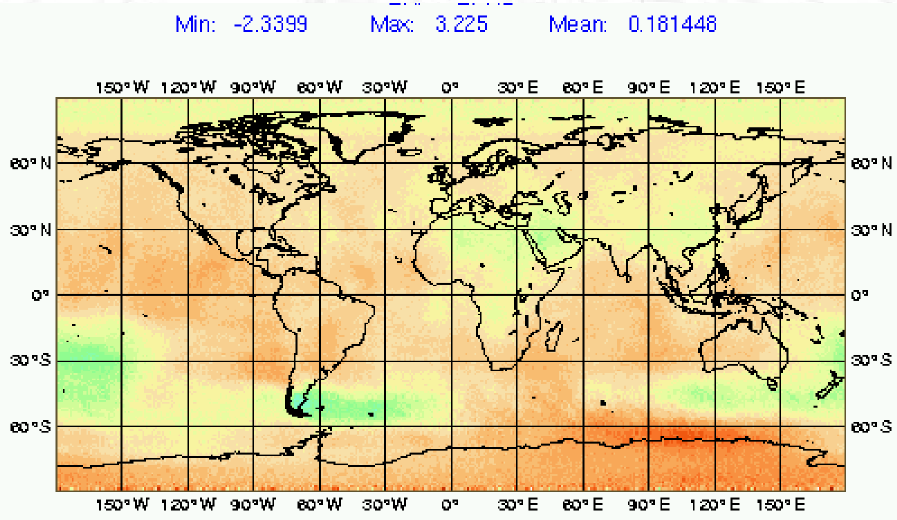
Care must be taken in the way bias corrections are computed. Establishing the bias correction for a channel that is passively monitored may give a very different result compared to when the channel is actively assimilated.

The latter will only reflect the proportion or component of the bias that cannot be assimilated with mean (temperature) increments

AMSUA-14 against NOSAT



AMSUA-14 against FULL-SAT



Sharing bias corrections …

… as a consequence …

We **cannot** use bias corrections estimated in one NWP system for another system. The bias correction from an active channel is just the residual that cannot be assimilated.

Corrections may reflect significant NWP model error, not common to the 2 different systems.

Interaction of QC and bias correction

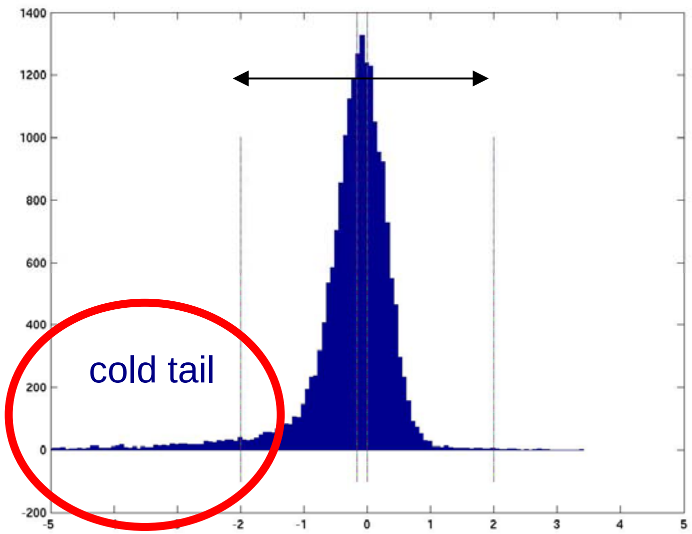
- Before estimating the bias of a population we may wish / need to apply QC to remove either bad data or data affected by a phenomena not explicitly treated by our forward operator

- But if the QC is based upon (O-B) departures, the choice of QC threshold will affect the estimated bias

- If the process is adaptive, the estimated bias will in turn affect the QC of the next step and so on …

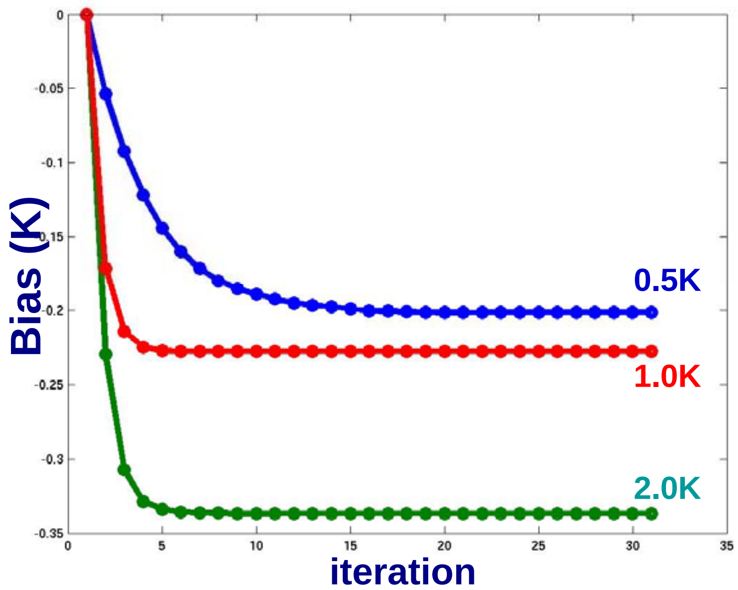
- The most extreme example of this is the estimation of biases for IR data affected by clouds.

Adaptive bias correction and QC



A typical distribution of (Obs-Calc) departures has a cold / warm tail due to residual cloud contamination. A boxcar QC window is often applied to remove the tail before estimating the bias.

However, successive applications of this (as in adaptive bias correction leads to a “dragging” of the mean by the cold tail. The speed and size of the drag depends on the number of iterations and the size of the boxcar window QC. To combat this we are evaluating use of the MODE for bias estimation as opposed to the mean.



Summary

•The biases observed when we compare satellite observations with the NWP model can be highly variable with space / time and instrument view.

•The sources of these biases are numerous (including the NWP model) and are generally not easy to separate.

•Great care must be taken in the treatment of biases as they can have large scale significant impacts upon the quality of the NWP system.

End