Satellite Observations

of

Greenhouse Gases

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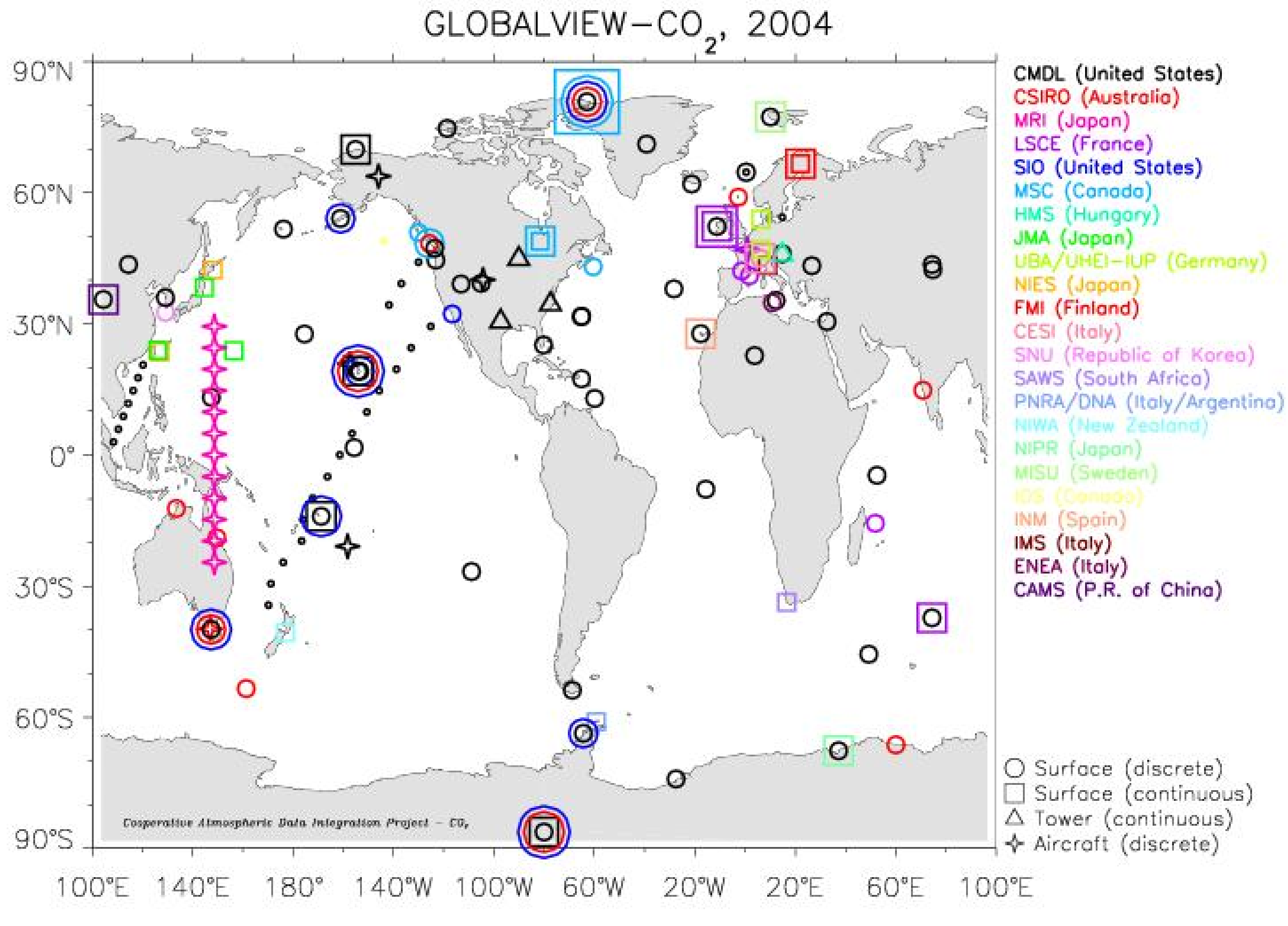
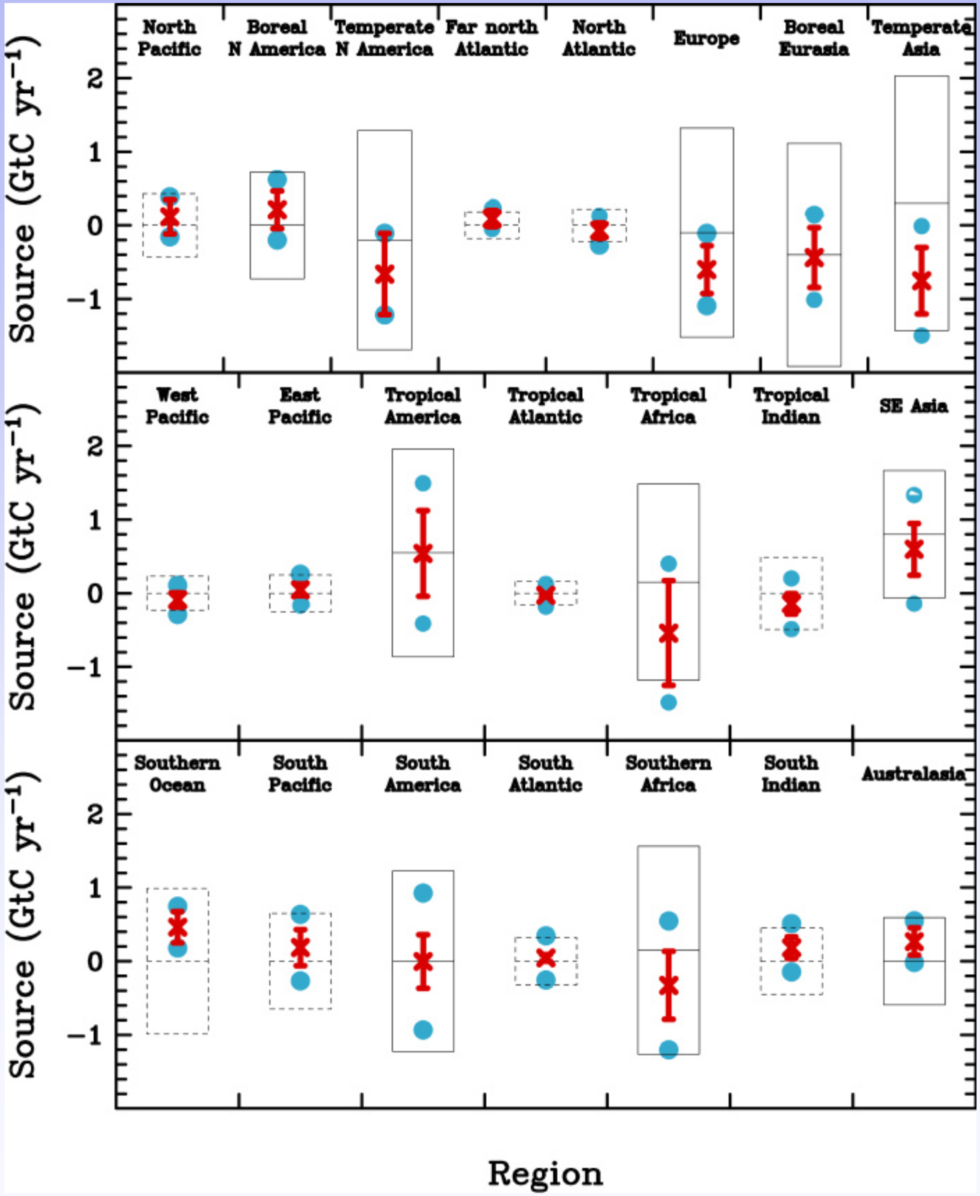
Outline

- Introduction
- Data assimilation vs. retrievals
- 4D-Var data assimilation
- Observations
- Forecast model
- Background constraint
- Examples

In-situ Observations



Synthesis inversion

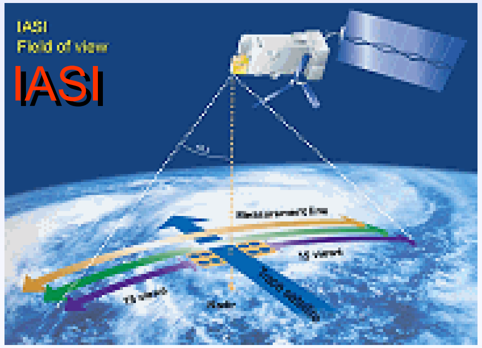


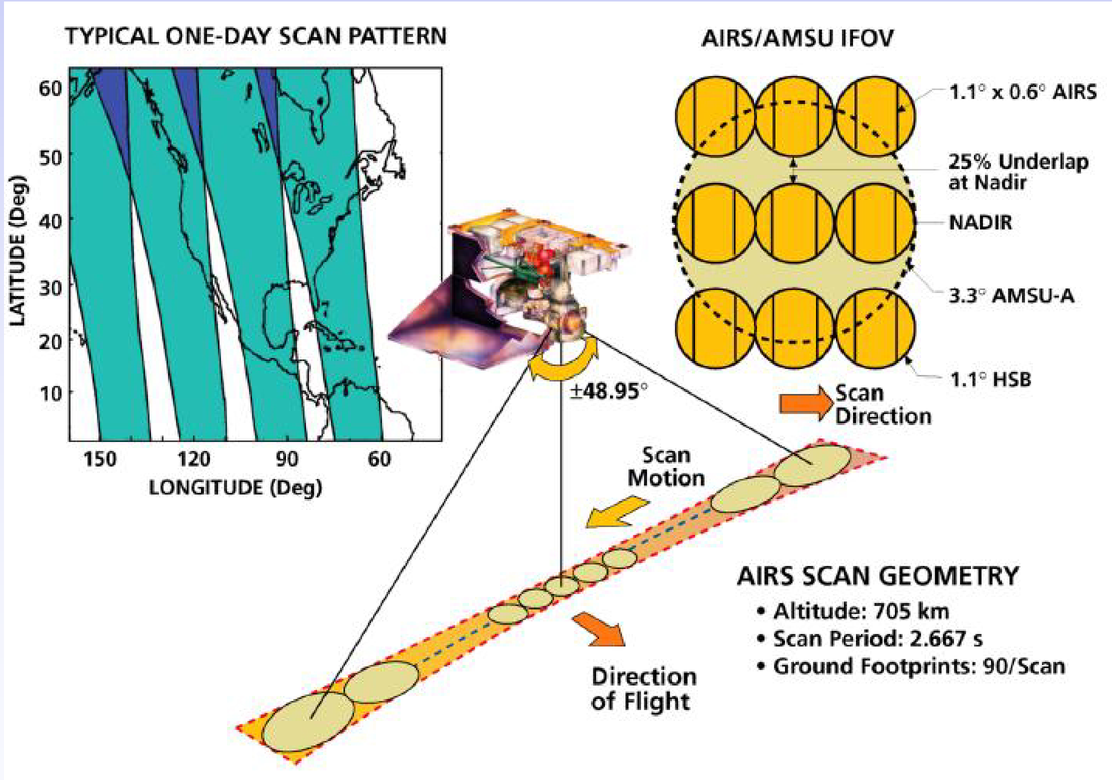
- Red 'x' indicates mean flux across 15 models
- Blue circles indicate mean a posteriori uncertainty ('within' model error)
- Red error bars indicate model spread ('between' model error)
- 'Within' model uncertainty larger than 'between' model uncertainty for most regions

- Current inversion system is data limited!

From Gurney et al. (2002)

Satellite Observations





Data assimilation vs. stand-alone retrieval

Data Assimilation

✓ Various sources of atmospheric observations are used to estimate atmospheric state in consistent way.

✓ Spatial and temporal interpolation of information is done with atmospheric transport model.

✘ Attribution of random and systematic errors is complicated.

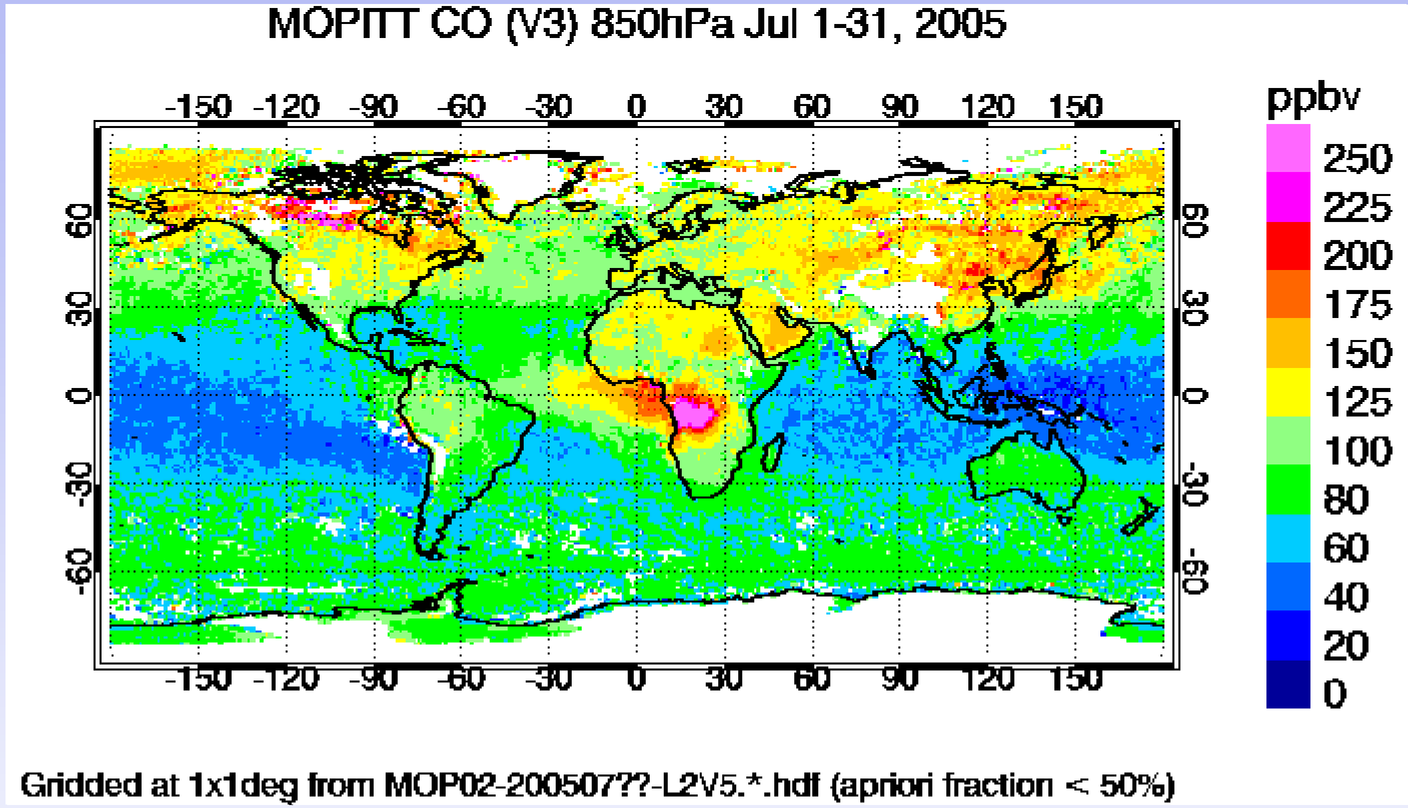
Stand-alone Retrieval

✘ Individual retrievals need to be gridded and averaged to produce 3-dimensional fields.

✘ Only observations from single satellite platform are used to estimate atmospheric state.

✓ Attribution of random and systematic error less complicated.

Retrieval example



The MOPITT stand-alone algorithm retrieves CO, T_s, and ε using proper first guess estimates and NCEP reanalysis profiles for T and q.

Satellite data assimilated operationally at ECMWF

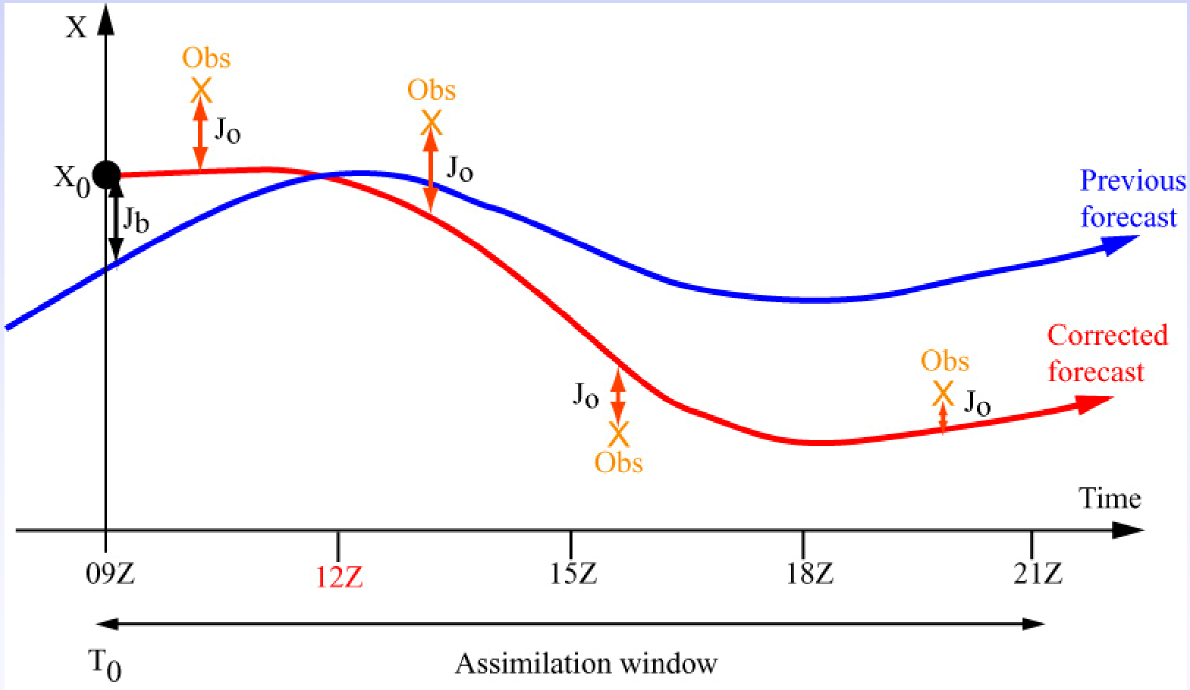
27 different satellite sources!
Coming soon: NOAA-18, SSMIS, radio occultation (GPS),...

- 3xAMSU-A (NOAA-15/16 + AQUA)
- 2xAMSU-B (NOAA-16/17)
- 3 SSMI (F-13/14/15) in clear and rainy conditions
- 1xHIRS (NOAA-17)
- AIRS (AQUA)
- Radiances from 5 GEOS (Met-5, Met-8, GOES-9/10/12)
- Winds from 4 GEOS (Met-5/8 GOES-10/12) and MODIS/TERRA+AQUA
- Scat winds from QuikSCAT and ERS-2 (Atlantic)
- Wave height from ENVISAT RA2 + ERS-2 SAR
- Ozone from SBUV (NOAA 16) and SCIAMACHY (ENVISAT)

4D-Var Data Assimilation

4-dimensional variational data assimilation is in principle a least-squares fit in 4 dimensions between the predicted state of the atmosphere and the observations.

The adjustment to the predicted state is made at time T_o, which ensures that the analysis state (4-dimensional) is a model trajectory.



4D-Var Data Assimilation

Minimize the incremental 4-dimensional cost function:

$$\delta \mathbf{x}_0 = \mathbf{x}_0 - \mathbf{x}^b$$

$$\delta \mathbf{x}(t_i) = \mathbf{M}(\delta \mathbf{x}_0)$$

$$\mathbf{d}_i = \mathbf{y}_i^o - H_i(M_i(\mathbf{x}^b))$$

$$J(\delta \mathbf{x}_0) = \underbrace{J_b}_{\text{Background term}} + \underbrace{J_o}_{\text{Observation term}}$$

$$= \delta \mathbf{x}_0^{\mathrm{T}} \mathbf{B}^{-1} \delta \mathbf{x}_0 + \sum_{i=0}^{n} \left(\mathbf{H}_i \delta \mathbf{x}(t_i) - \mathbf{d}_i \right)^{\mathrm{T}} \mathbf{R}_i^{-1} \left(\mathbf{H}_i \delta \mathbf{x}(t_i) - \mathbf{d}_i \right)$$

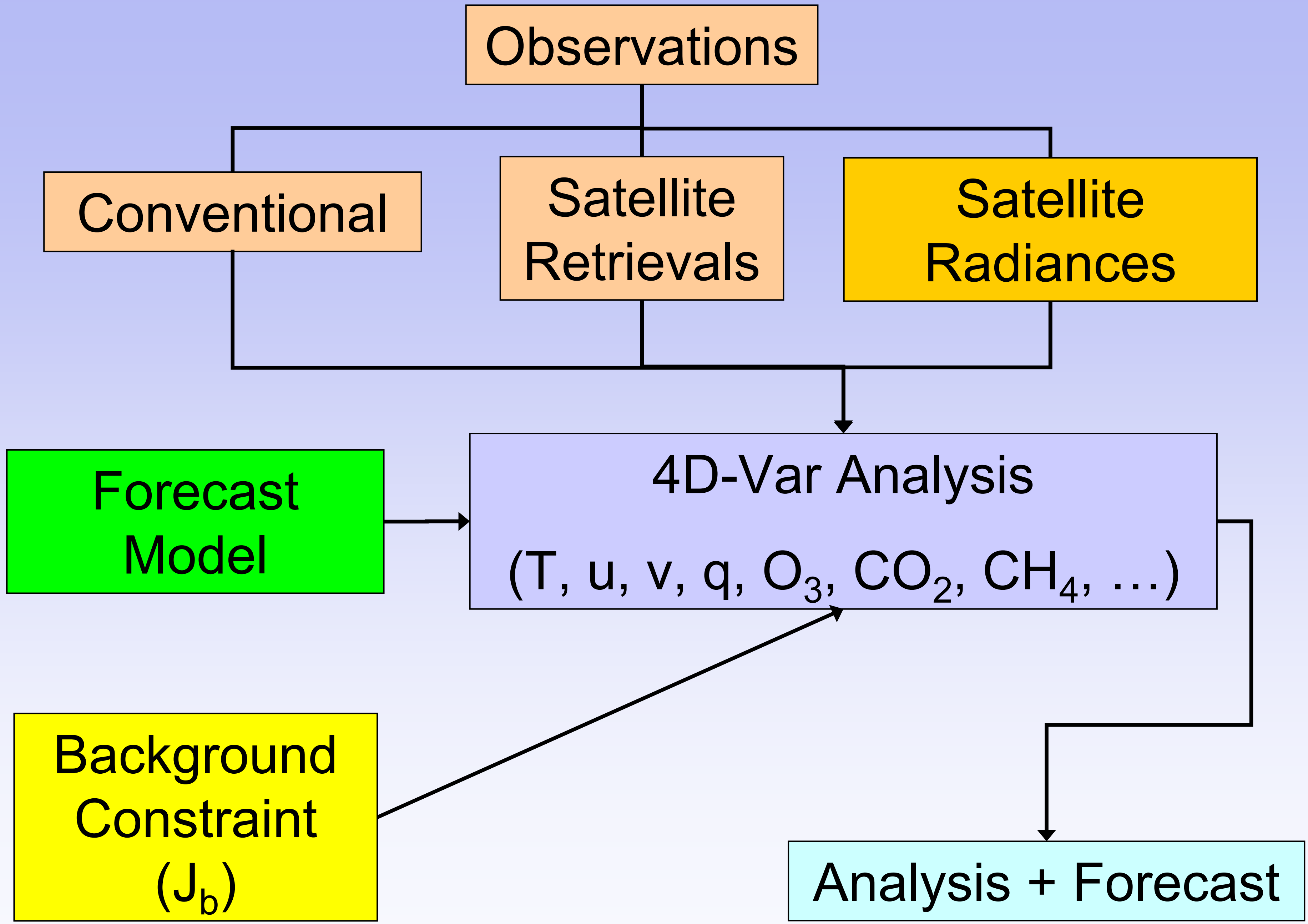
State vector increments

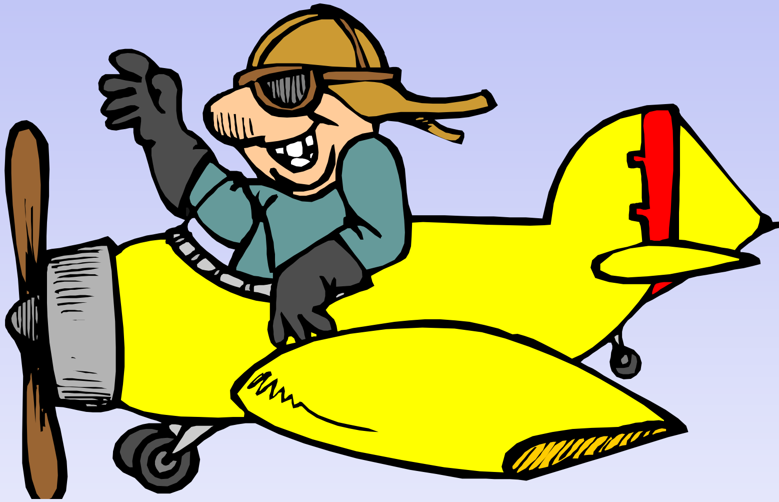
Background covariance matrix

Linearised observation operator

Observation covariance matrix

Observation departures


Observations
Conventional
Satellite Retrievals
Satellite Radiances
Forecast Model
4D-Var Analysis
(T, u, v, q, O_3, CO_2, CH_4, …)
Background Constraint (J_b)
Analysis + Forecast



Observations

CO_2 Observations

Satellite observations:

- AIRS
- IASI

Infrared; Lots of data, bu
sensitive to middle- and u

- Sciamachy

Near infrared; large foot

- OCO
- GOSAT

Near infrared; only over s
to lower troposphere

In-situ observations:

- airborne flasks
- surface flasks

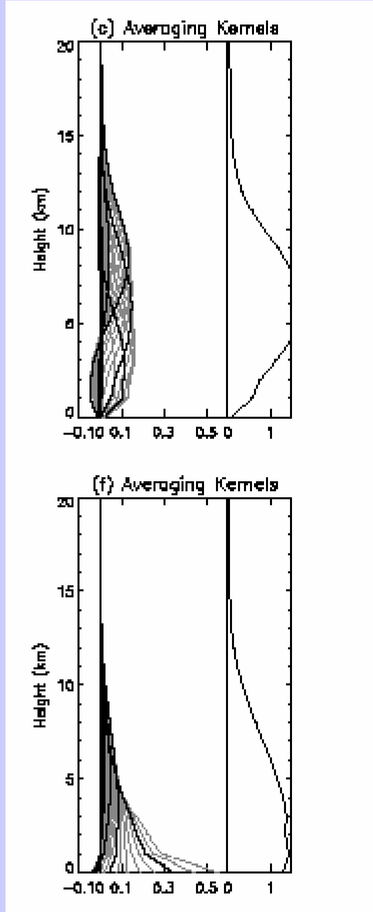
Very accurate, but
real time

Focus is currently on satellite observa
and global availability. They are also a
operational NWP system. In-situ data

Satellite sensitivity to CO_2

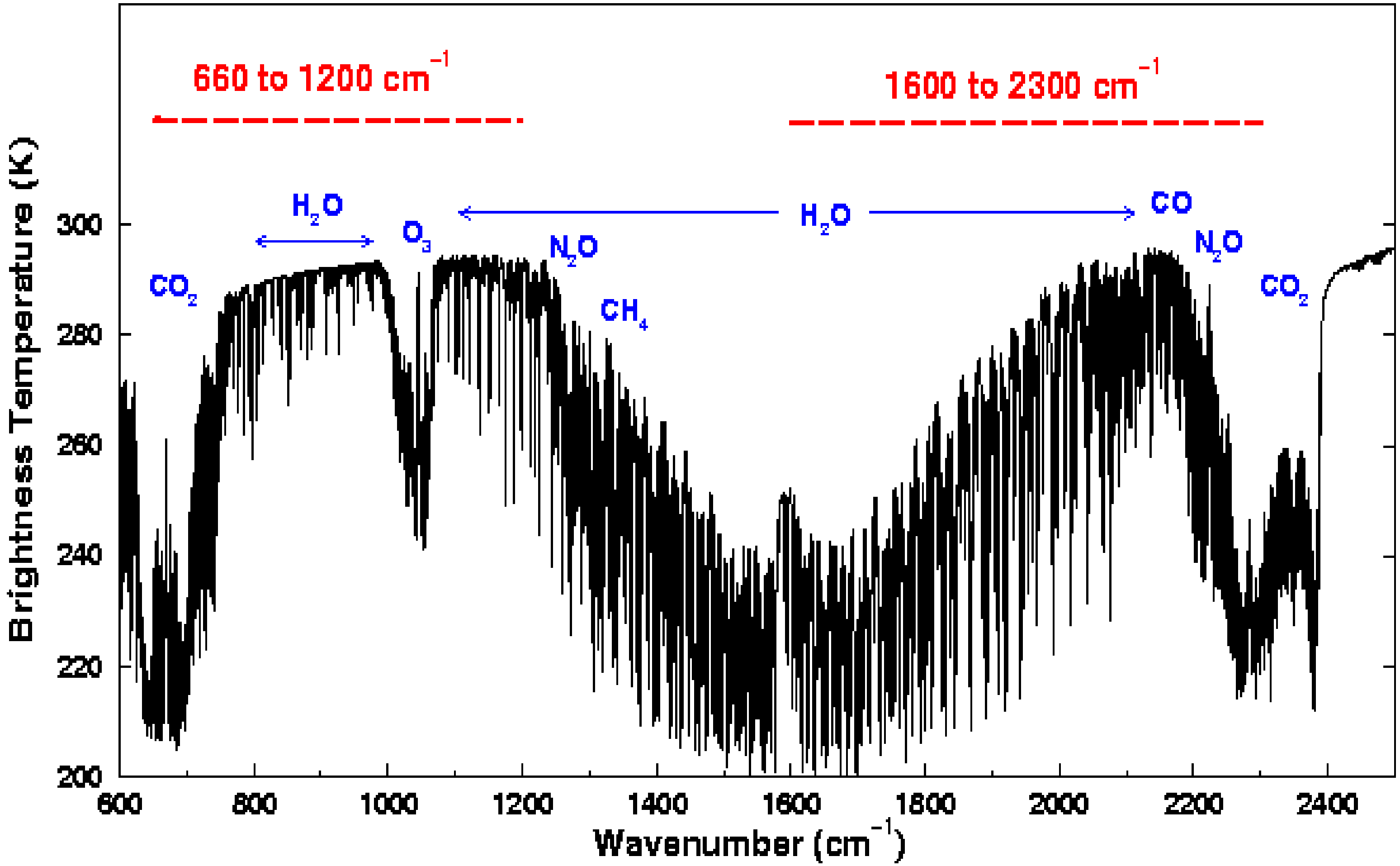
IR

NIR



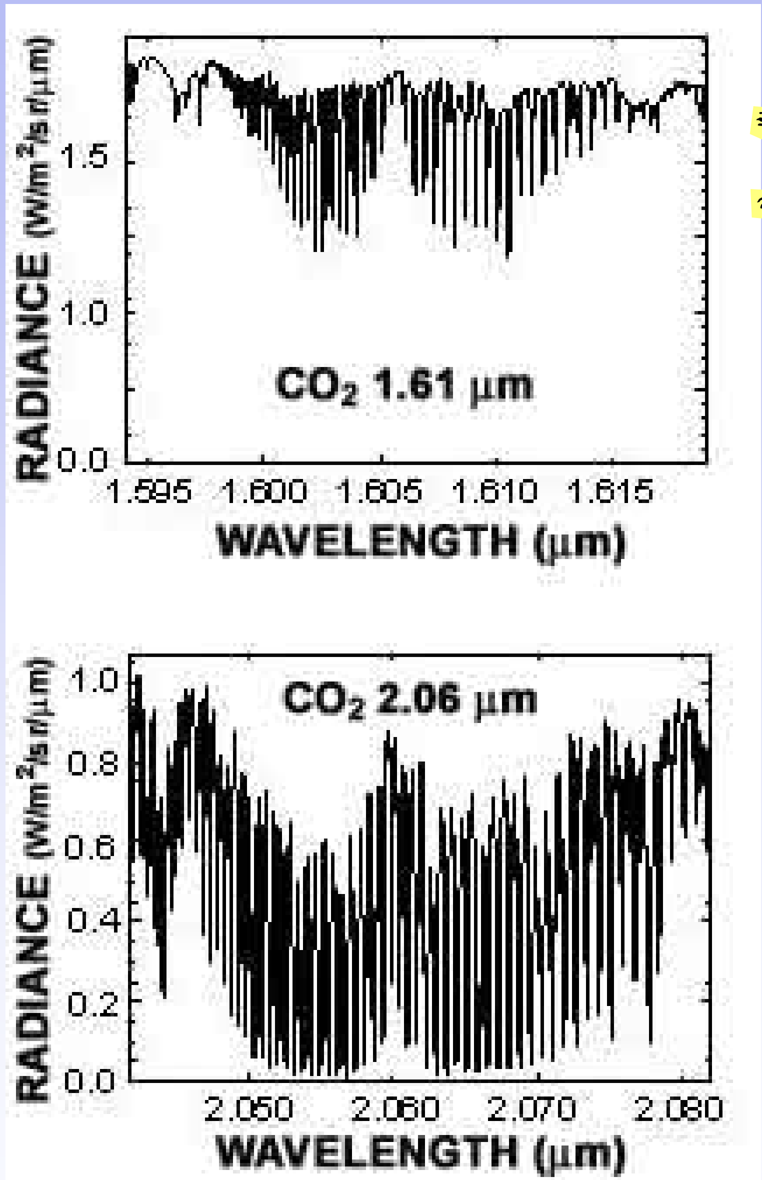
Christi and Stephens, 2004

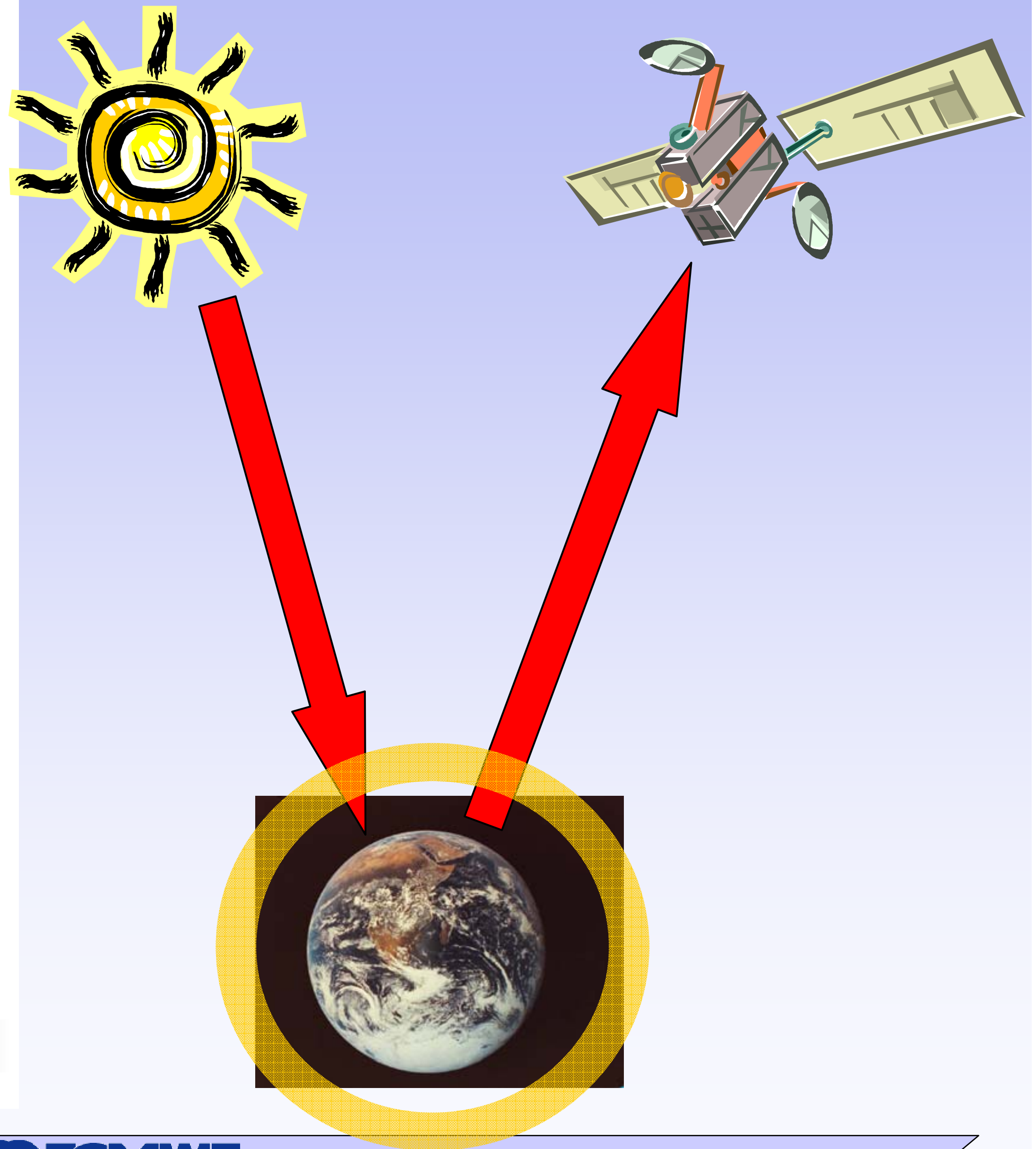
Observations - Infrared



$$\text{Radiance} = \mathcal{F}\,(\,T, CO_2, H_2O, O_3, CO, CH_4, N_2O\,)$$

Observations – Near Infrared





Data limitations

• Emission based instruments (AIRS, IASI) have low sensitivity to the lower troposphere. They also can only observe the atmosphere above clouds.

• Reflection based instruments (Scia, OCO, GOSAT) are sensitive to the whole column, but suffer from aerosol scattering and cloud scattering and absorption.

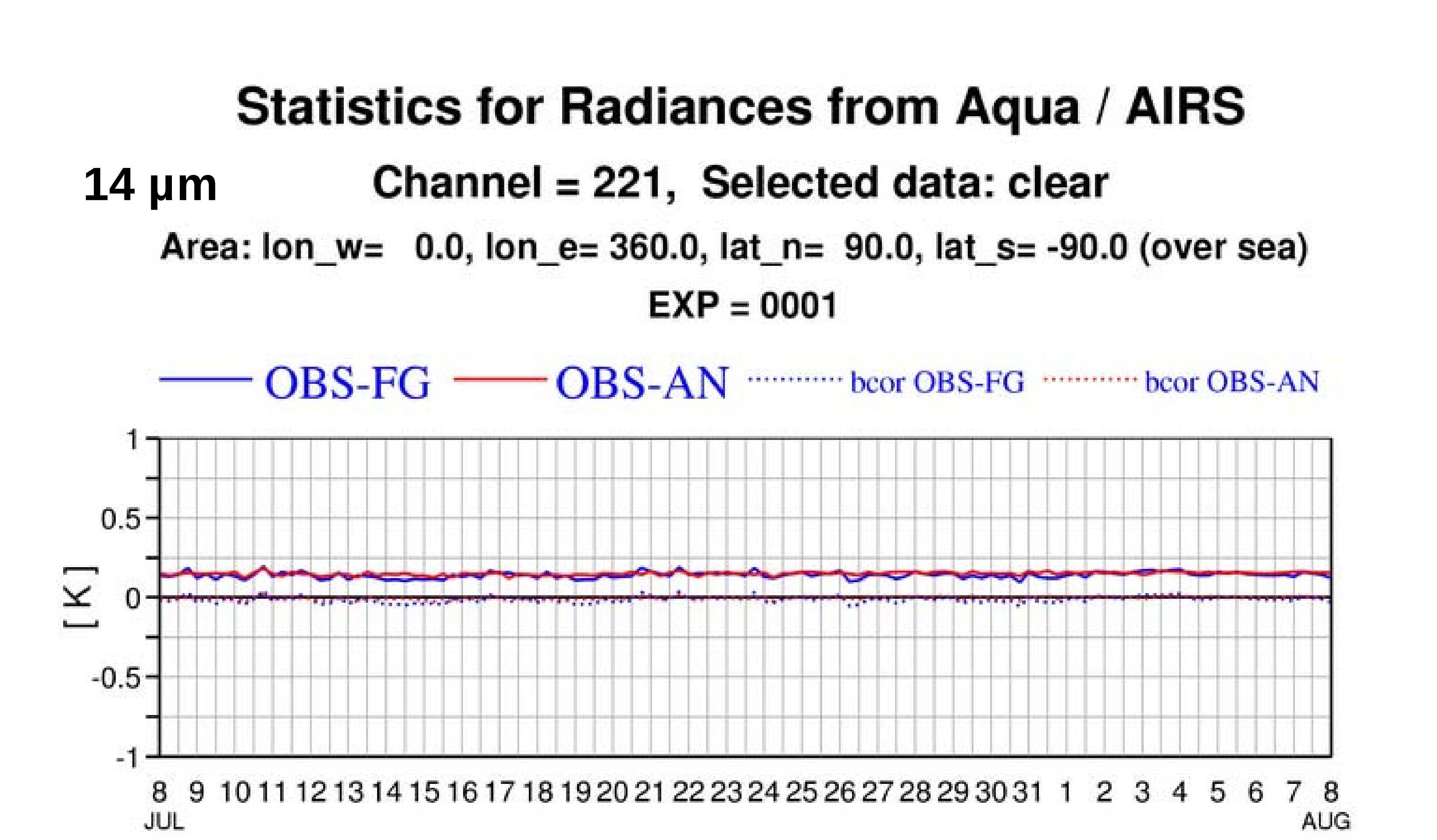
• First dedicated CO_2 satellite instruments, making use of near-infrared technique, will not be launched before end of 2007 with an expected lifetime of 2 years.

• Validation data for satellite estimates is very limited.

Bias correction

- 4D-Var data assimilation is based on the general assumption that errors are random. Therefore, any significant systematic errors in the observations and/or the radiative transfer model need to be corrected before proper assimilation can be done.
- Model bias should be corrected as well, but is difficult to estimate. There is currently no model bias correction at ECMWF, but research is being done on this issue.
- Model bias might end up in the observation bias correction, because there is no straightforward method to distinguish between model bias and observation bias.
- Therefore, any bias correction method is in theory capable of removing some of the CO_2 (CO, CH_4, N_2O) signal!! Slow variations in time or global means could be incorrectly seen as model bias!!!

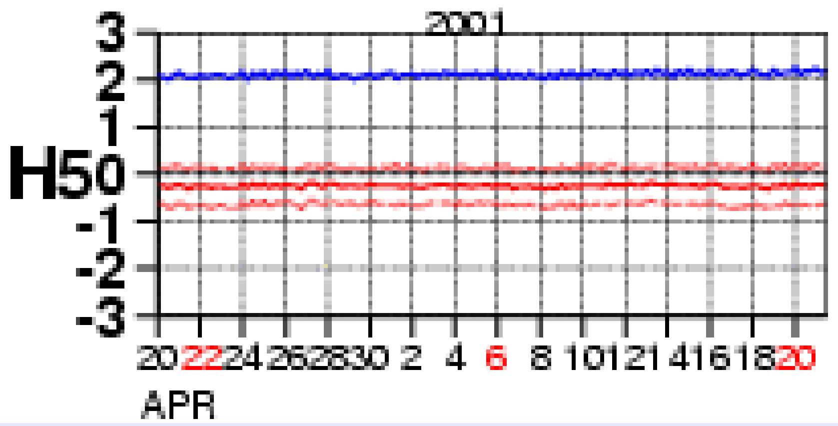
Monitoring



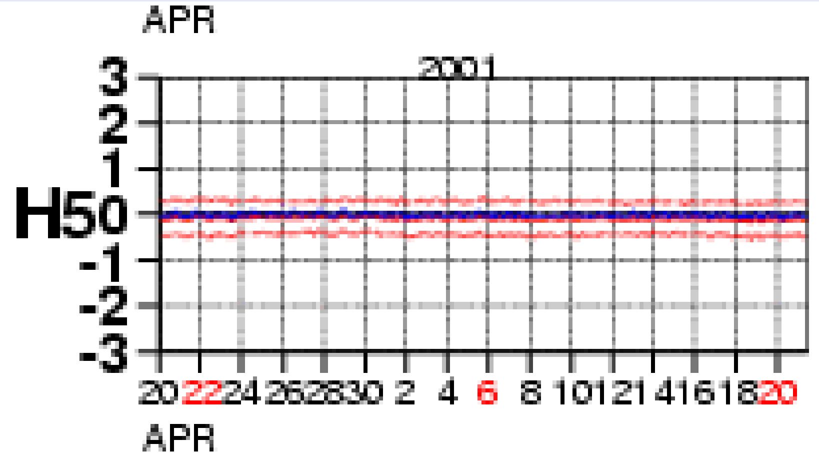
Observed radiances are being monitored against clear model radiances. Biases can be detected and corrected.

Example of bias correction

Systematic errors in observations are usually identified by monitoring against the forecasted background in the vicinity of constraining radiosonde data.



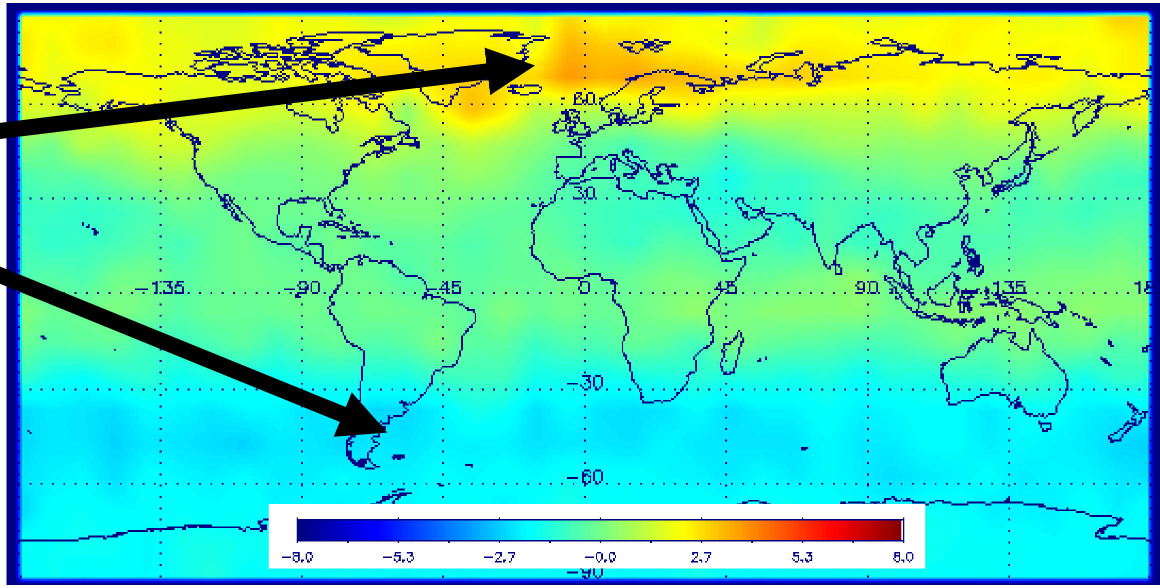
HIRS channel 5 (peaking around 600hPa on NOAA-14 satellite has +2.0K radiance bias against model



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

Biases in Upper Stratospheric Channels

Systematic errors in the model upper stratospheric temperatures give apparent air-mass dependent biases



Seasonal dependence of bias (K)

Dec 2004 **date** **June 2004**

AIRS channel 75
(stratopause/mesosphere)

Bias correction methods

- **Flat bias**

  One single global mean bias correction value.

- **Air-mass dependent bias**

  Regression against model thicknesses (1000 – 300 hPa and 200 – 50 hPa), column water vapour, and surface skin temperature to account for air-mass dependency of biases.

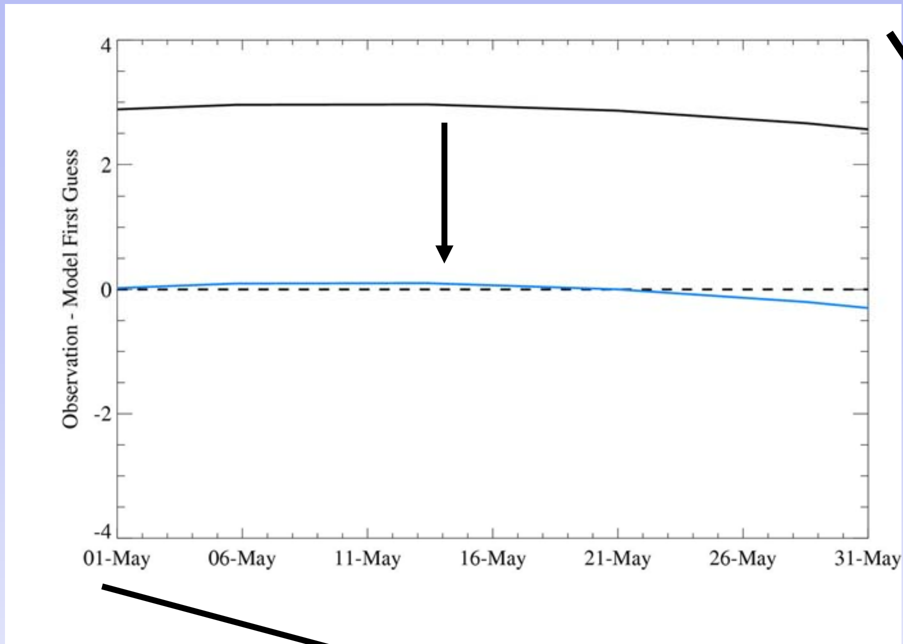
- **Gamma-correction**

  Combination of flat bias and gamma correction of radiative transfer. It tries to correct for errors in the RT by multiplying the optical depth with a correction factor.

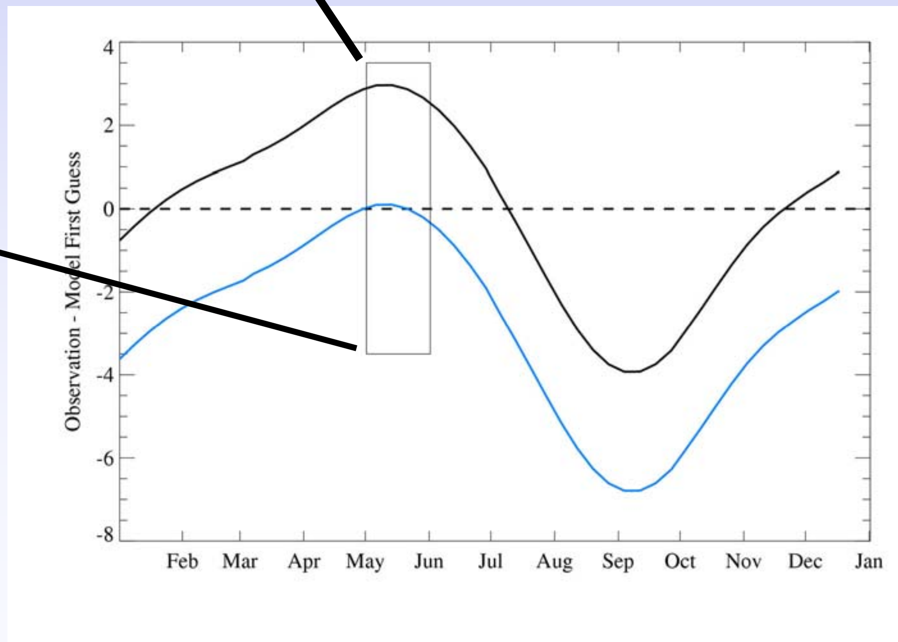
- **Internal bias variable**

  Any of the above bias correction methods can be built into the assimilation system as a slow-moving state variable.

Potential problems with slow-moving signals

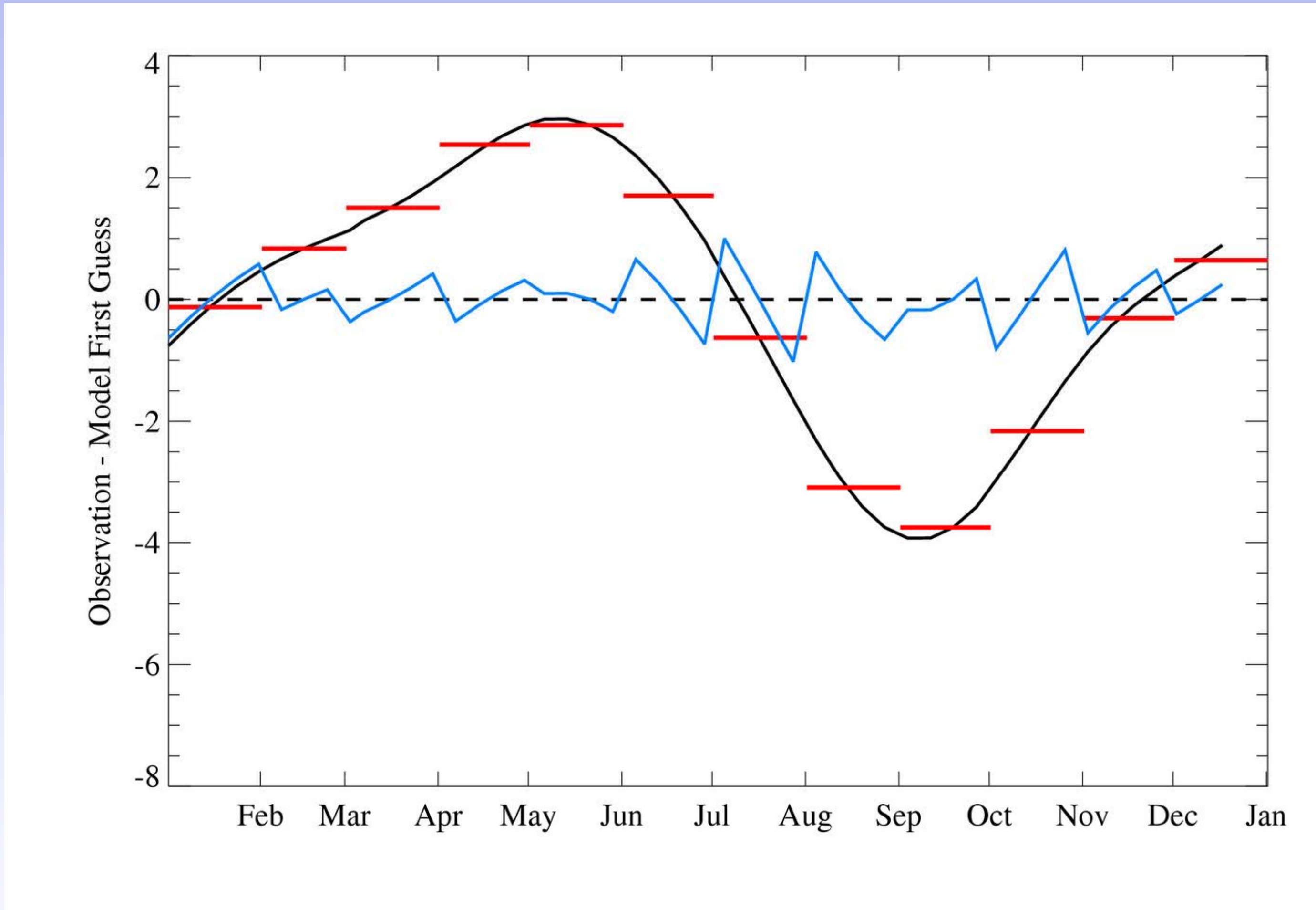


After a month of monitoring a relatively constant bias is observed and then corrected.

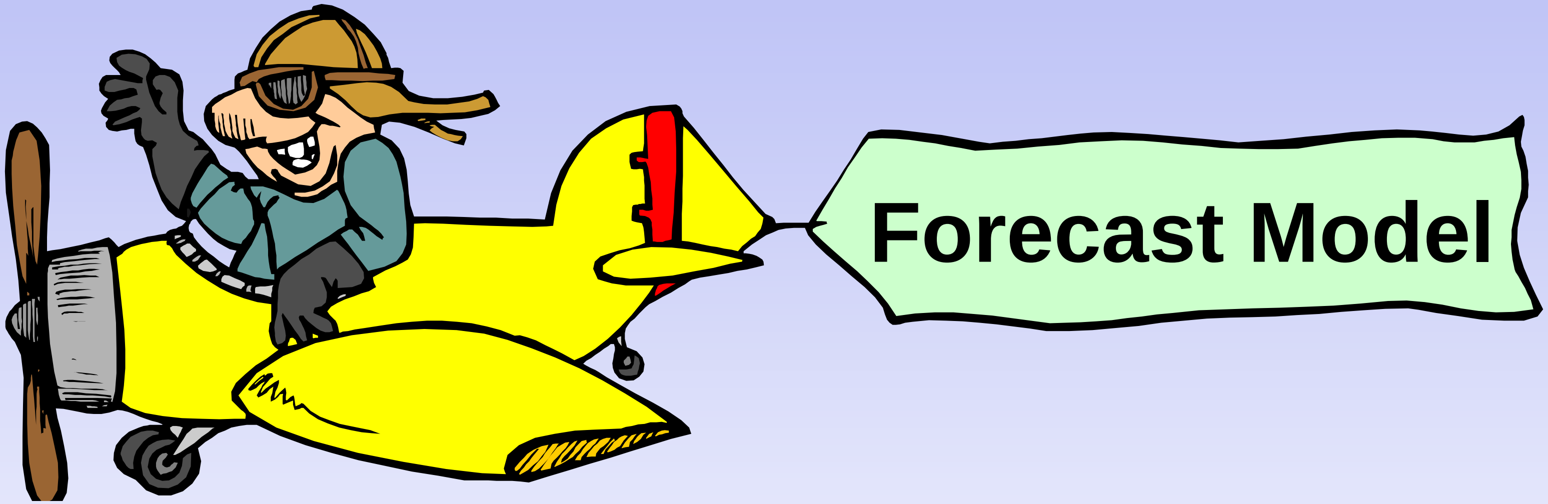


Greenhouse gas signals are much smaller than temperature signals. An apparently constant bias in a 1 month time series is in reality part of a seasonal cycle.

Potential problems with slow-moving signals



With an adaptive bias correction (e.g., a new flat bias each month) the small signal is removed from the observations.


Forecast Model

Forecast model

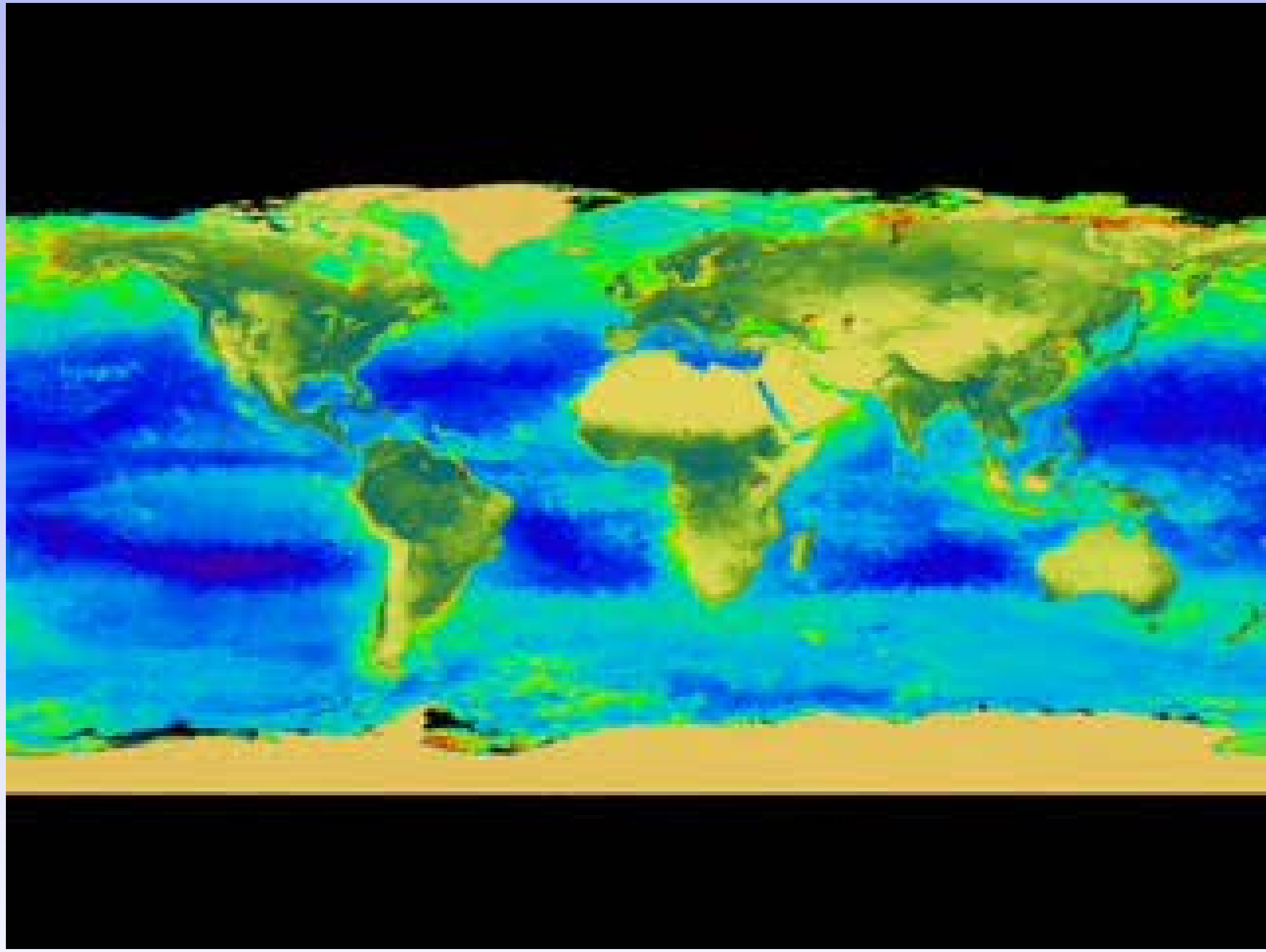
- The forecast model is used to predict the atmospheric state at the observation locations and times starting from the initial state.
- It therefore needs to include the proper dynamics and physics to be able to fit the observations within the specified error margins.
- For greenhouse gases this means that advection, vertical diffusion, convection, and surface fluxes are needed with sufficient accuracy for a 12 hour forecast.

Forecast model

The forecast model for the greenhouse gas assimilation will most likely be run at resolution T159 (1.125° by 1.125°) with 60 levels. The transport is based on the following:

- Semi-Lagrangian advection (not fully mass conservative)
- Implicit K-diffusion formulation for the vertical diffusion
- Fully-implicit 1st order conservative mass flux advection for the convection
- Radiation: 6 band SW scheme and the AER LW code

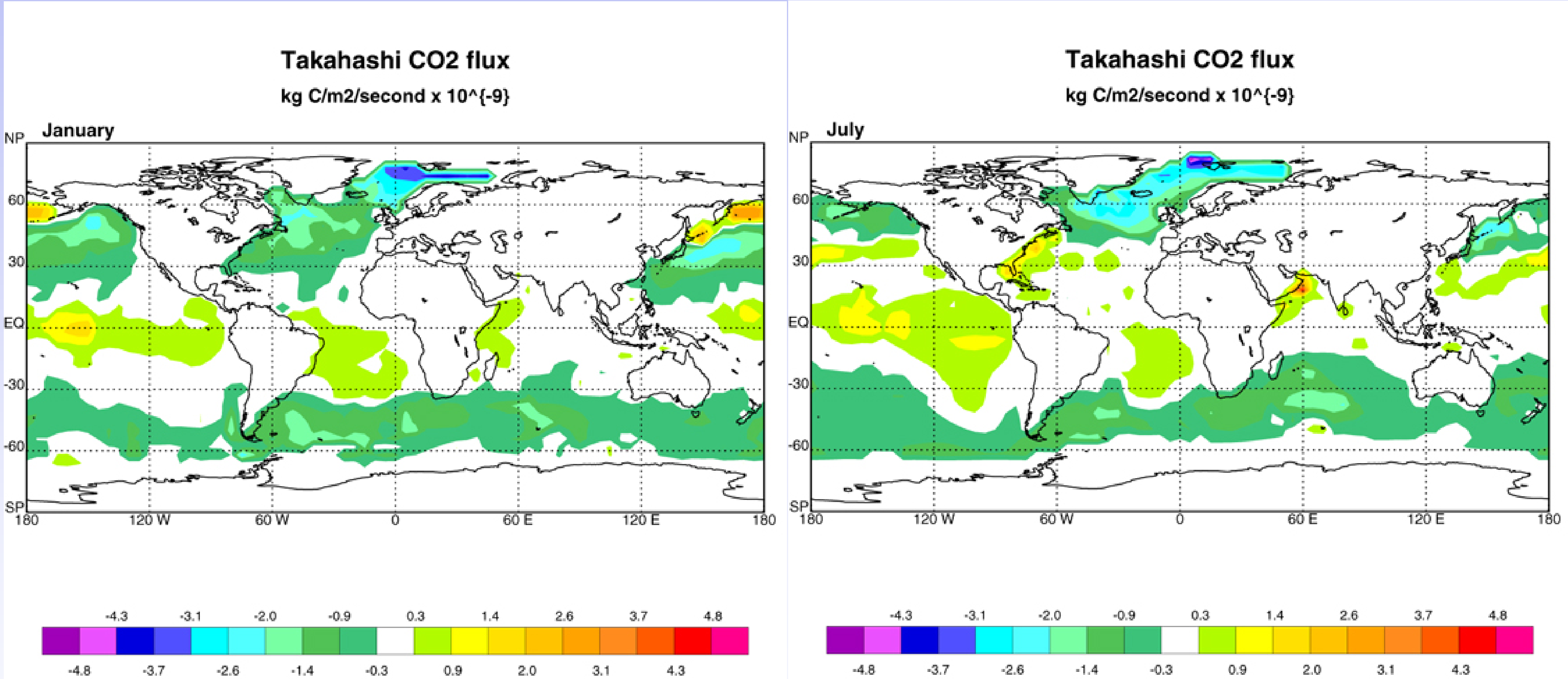
Land and ocean biosphere from space



Seawiffs observations provide a nice view of the temporal and spatial variability of the biosphere. This has then to be captured in climatological surface fluxes.

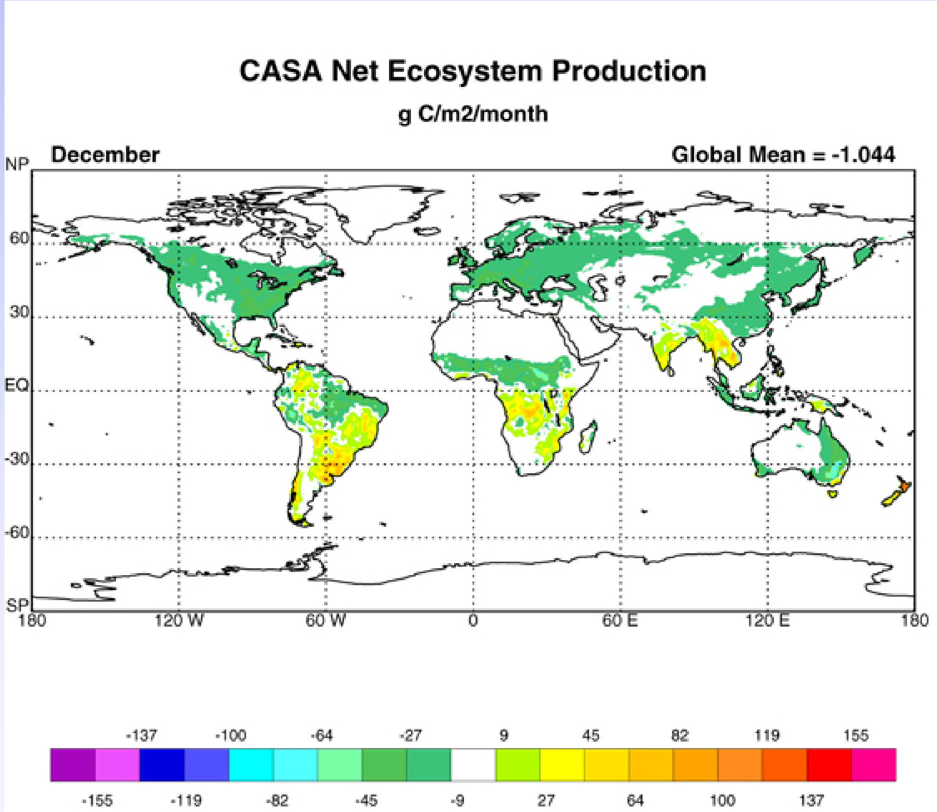
CO_2 surface fluxes - climatology

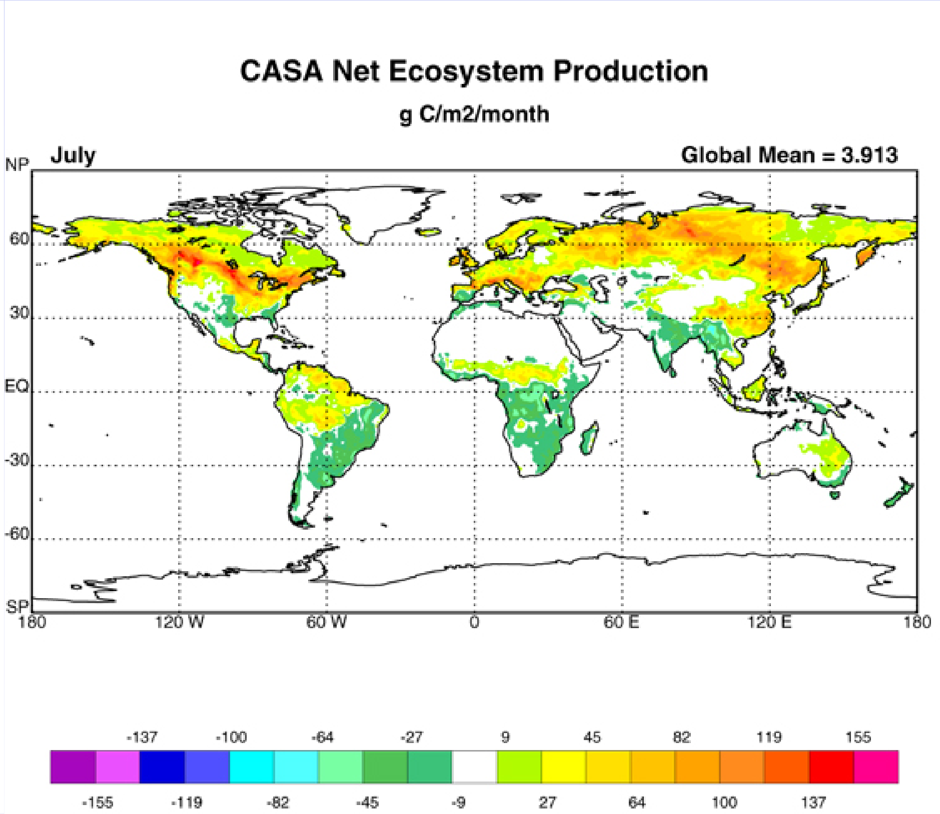
Ocean



CO_2 surface fluxes - climatology

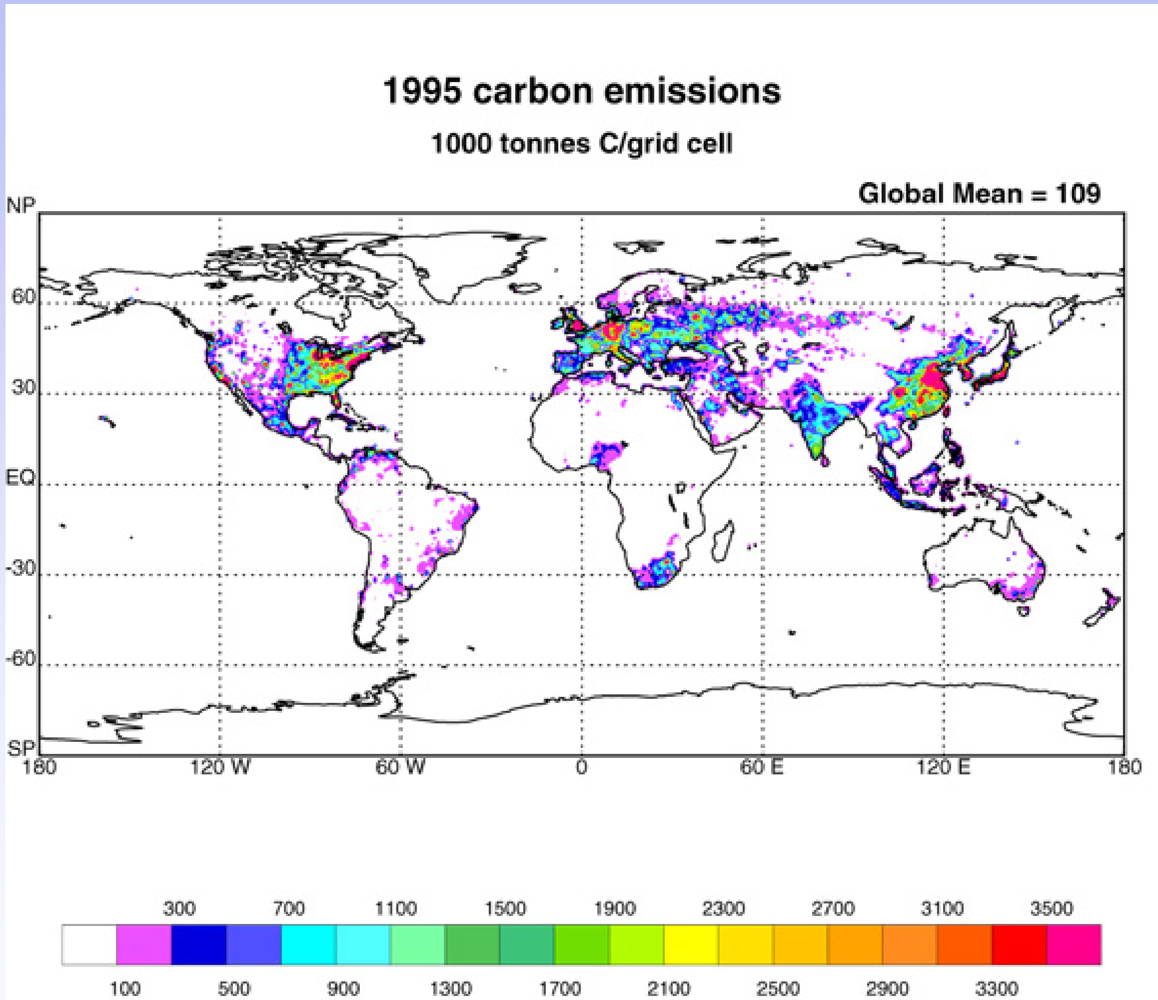
Natural Biosphere



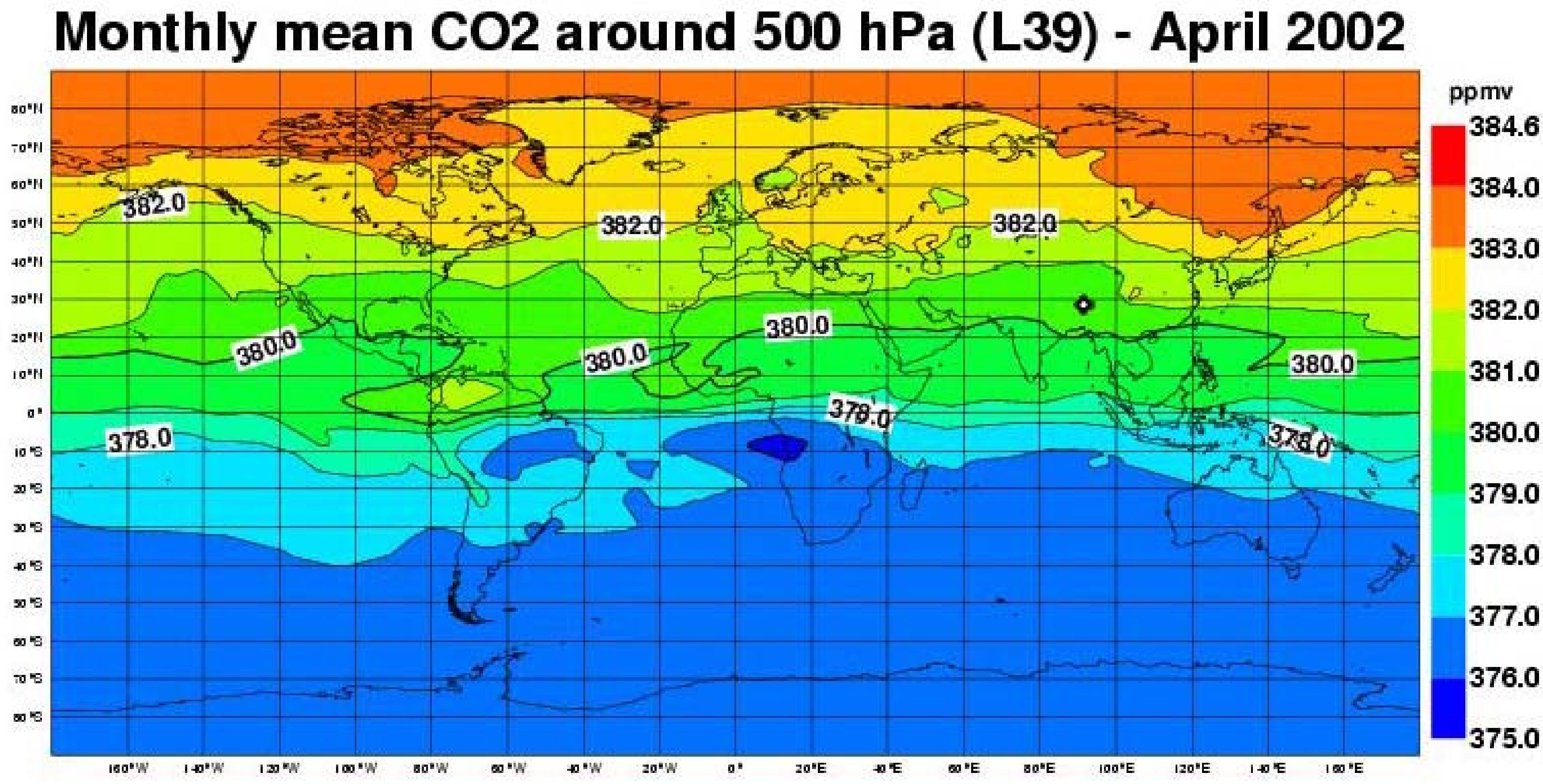


CO_2 surface fluxes - climatology

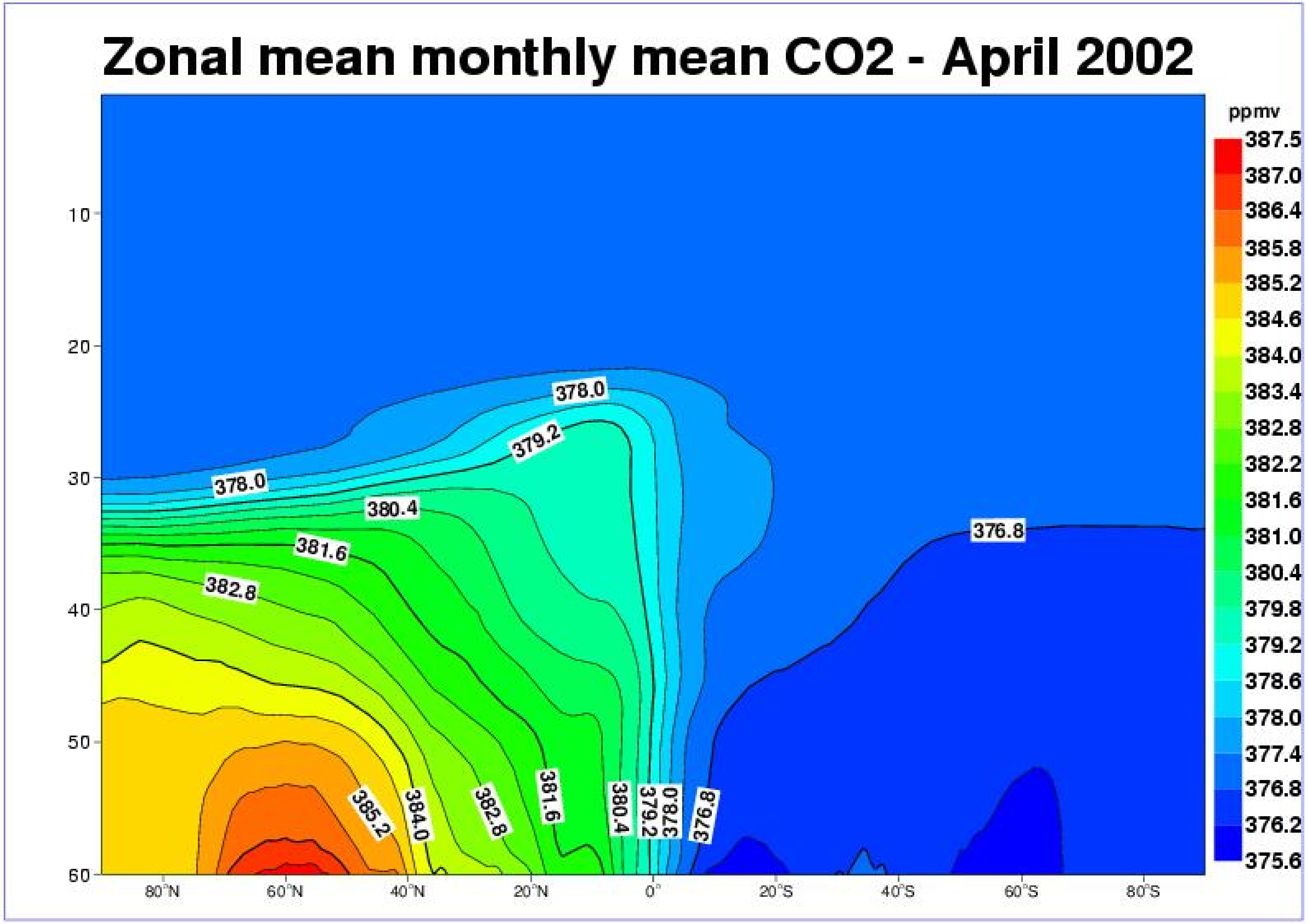
Anthropogenic

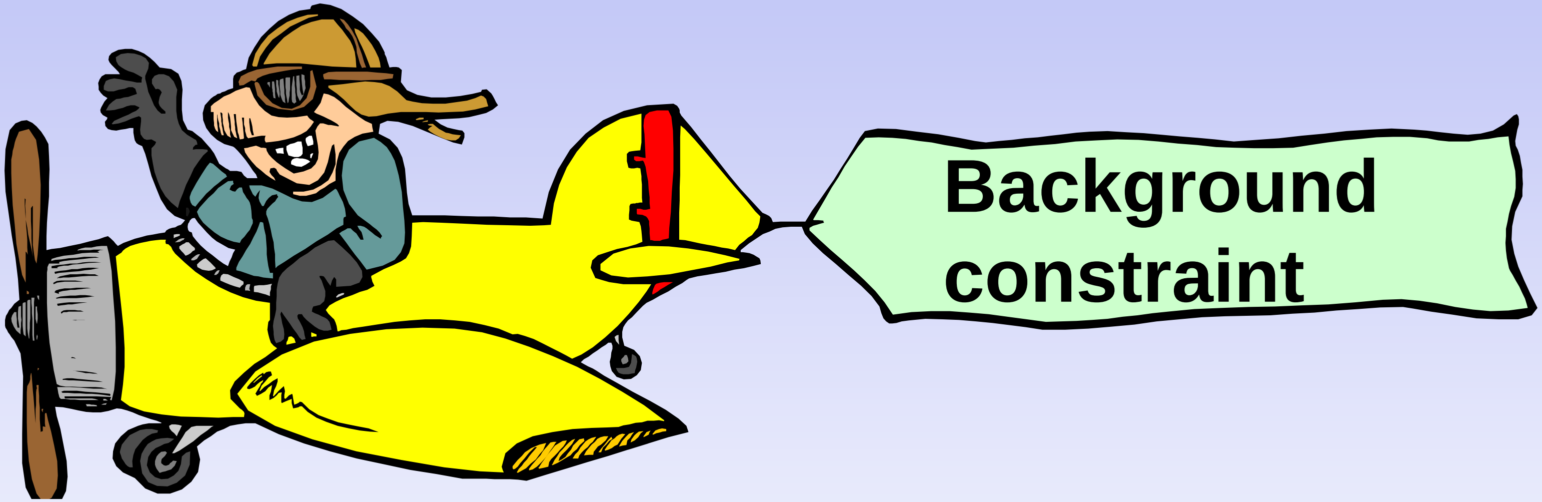


Tracer Transport



Tracer transport




Background
constraint

Background constraint

Background term

Observation term

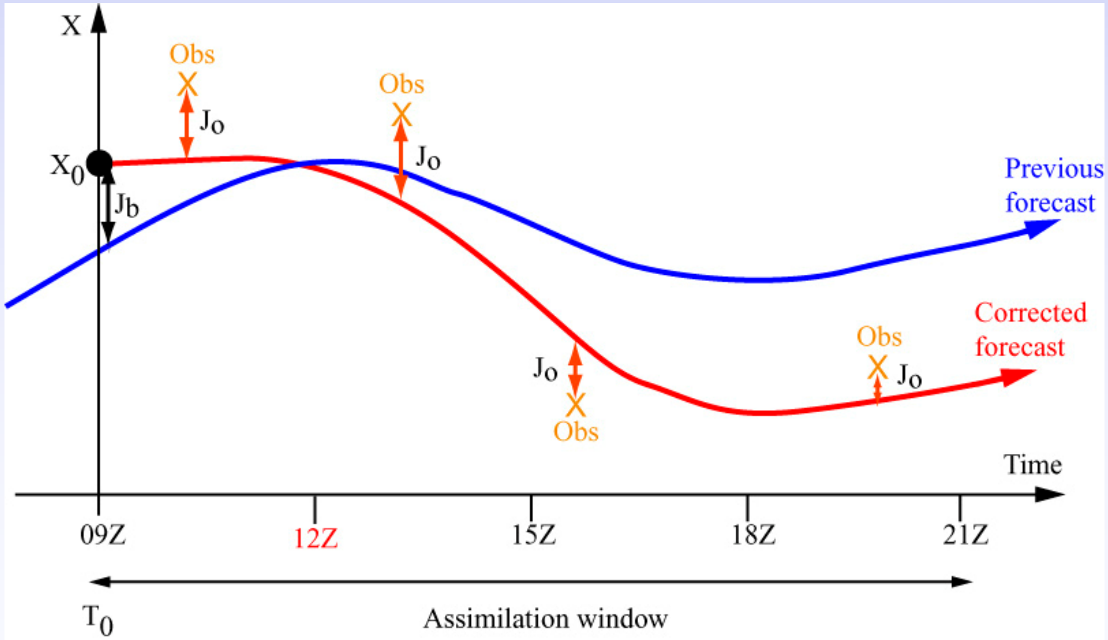
$$\delta\mathbf{x}_0 = \mathbf{x}_0 - \mathbf{x}^b$$

$$\delta\mathbf{x}(t_i) = \mathbf{M}(\delta\mathbf{x}_0)$$

$$\mathbf{d}_i = \mathbf{y}_i^o - H_i(\mathbf{x}^b(t_i))$$

$$J(\delta\mathbf{x}) = J_b + J_o$$

$$= \delta\mathbf{x}_0^{\mathrm{T}}\mathbf{B}^{-1}\delta\mathbf{x}_0 + \sum_{i=0}^{n}\left(\mathbf{H}_i\delta\mathbf{x}(t_i) - \mathbf{d}_i\right)^{\mathrm{T}}\mathbf{R}_i^{-1}\left(\mathbf{H}_i\delta\mathbf{x}(t_i) - \mathbf{d}_i\right)$$



Background constraint

The role of the background error covariance matrix B is to:

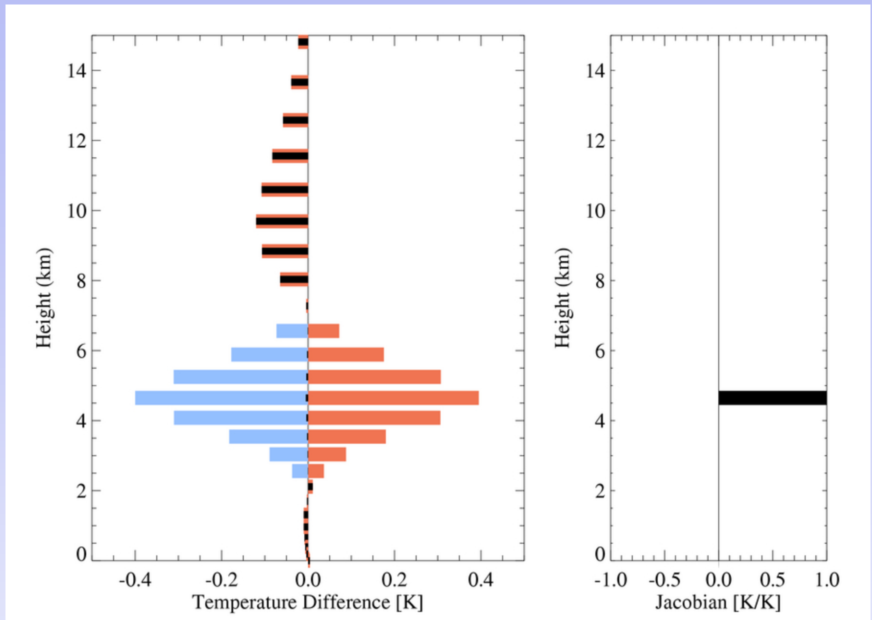
- provide statistically consistent increments at the neighbouring gridpoints and levels of the model

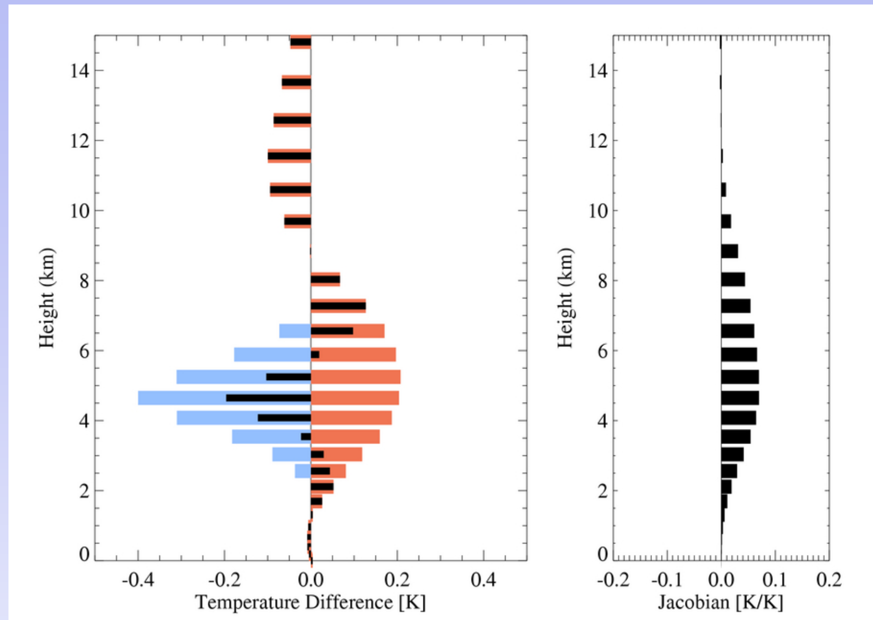
Two problems:

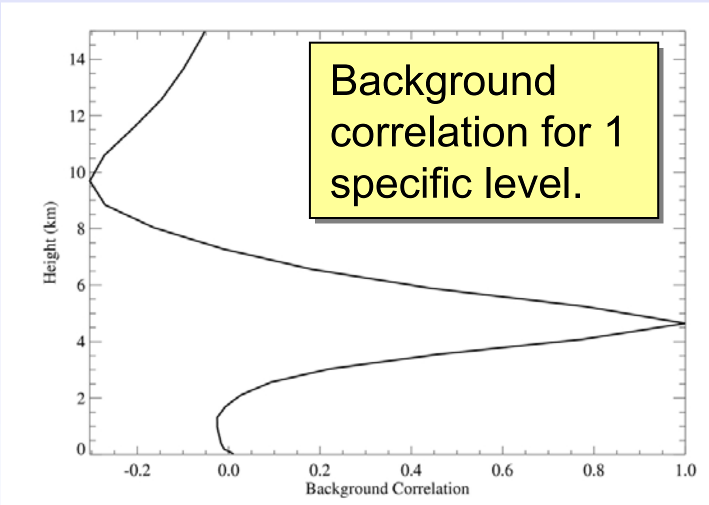
- We want to describe the statistics of the errors in the background, but we don't know what the true state is
- The B matrix is enormous (~$10^7 \times 10^7$), so we are forced to simplify it.

Differences between 48 and 24 forecast (NMC method, Parrish and Derber, 1992) or an analysis-ensemble method (Fisher, 2004) are usually used to estimate the background error covariance matrix.

Example of background constraint





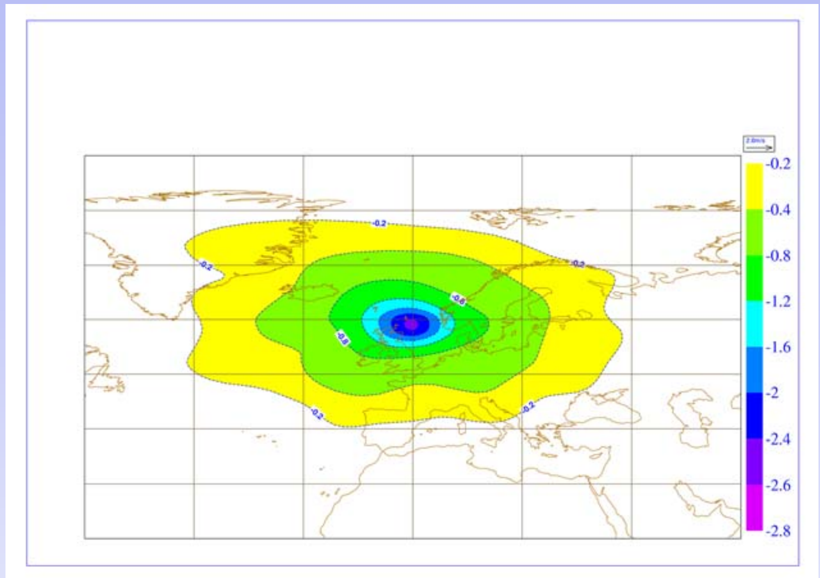


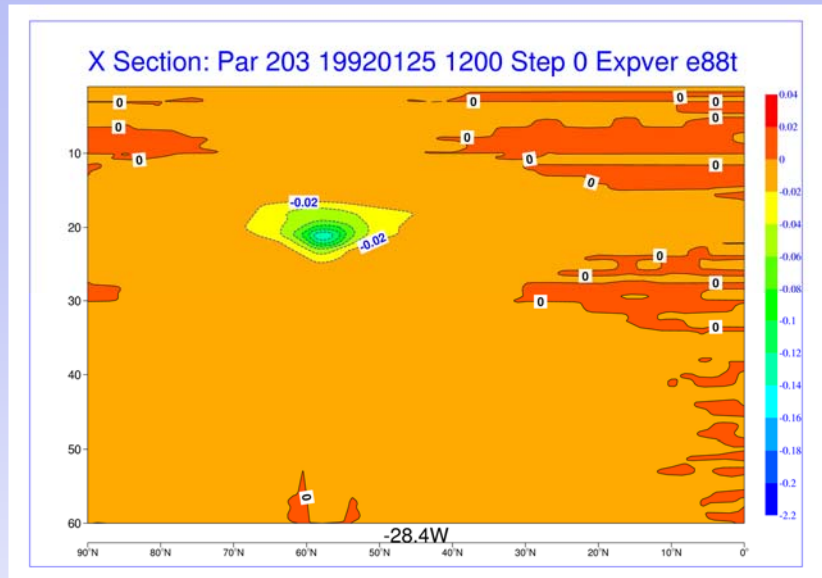
Background departures

Increments

Analysis departures

Background constraint

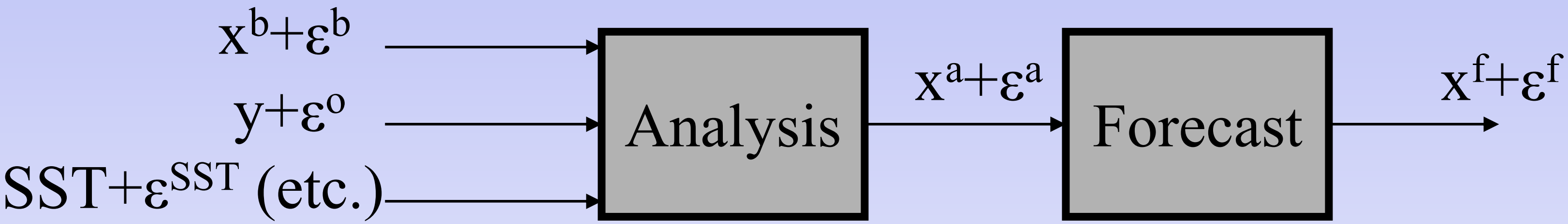




An observation departure is spread out both in the horizontal and the vertical by means of the background covariance structures.

Operational Estimation of Background Error Statistics

- Perturb all the inputs to the analysis/forecast system with random perturbations, drawn from the relevant distributions:



- The result will be a perturbed analysis and forecast, with perturbations characteristic of analysis and forecast error.
- The perturbed forecast may be used as the background for the next (perturbed) cycle.
- After a few cycles, the system will have forgotten the original initial background perturbations.
- This ultimately provides statistics representing the background error.

Problems with greenhouse gas variables

- We don’t have a proper analysis to start from.
- Current satellite observations constrain globally a limited vertical part of the atmosphere.
- Current surface and flight profiling observations are only available at a small number of locations.
- This means that we obtain a reasonable estimate of the forecast error, but a very limited estimate of the analysis error. Both are important for the background error.

Possible Solution?

Specify a background covariance model with a few unknown parameters.

$$\mathbf{B} = \begin{bmatrix} \theta_1^2 & 0.5 \cdot \theta_1 \theta_2 \\ 0.5 \cdot \theta_1 \theta_2 & \theta_2^2 \end{bmatrix}$$

Minimize the following cost function with respect to the unknown covariance model parameters using a representative set of observations:

$$L_\theta = \frac{1}{2} \ln \left| \mathbf{HBH}^{\mathrm{T}} + \mathbf{R} \right| + \frac{1}{2} \left(\mathbf{y} - \mathbf{H}\mathbf{x}_{\mathrm{b}} \right)^{\mathrm{T}} \left(\mathbf{HBH}^{\mathrm{T}} + \mathbf{R} \right)^{-1} \left(\mathbf{y} - \mathbf{H}\mathbf{x}_{\mathrm{b}} \right)$$

This can be done either formally or by using a Monte Carlo set-up.

Example

$$L_\theta = \frac{1}{2}\ln\left|\mathbf{HBH}^\mathrm{T} + \mathbf{R}\right| + \frac{1}{2}\left(\mathbf{y} - \mathbf{Hx}_\mathrm{b}\right)^\mathrm{T}\left(\mathbf{HBH}^\mathrm{T} + \mathbf{R}\right)^{-1}\left(\mathbf{y} - \mathbf{Hx}_\mathrm{b}\right)$$

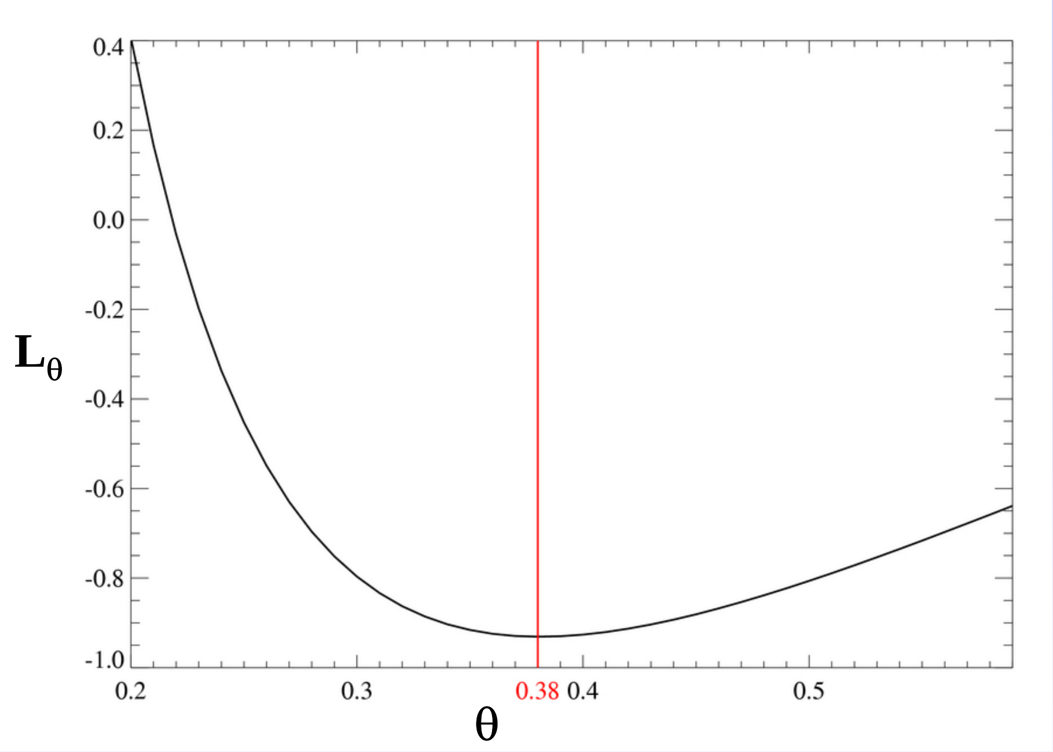
$$\mathbf{B} = \begin{bmatrix} \theta^2 & 0 \\ 0 & \theta^2 \end{bmatrix}$$

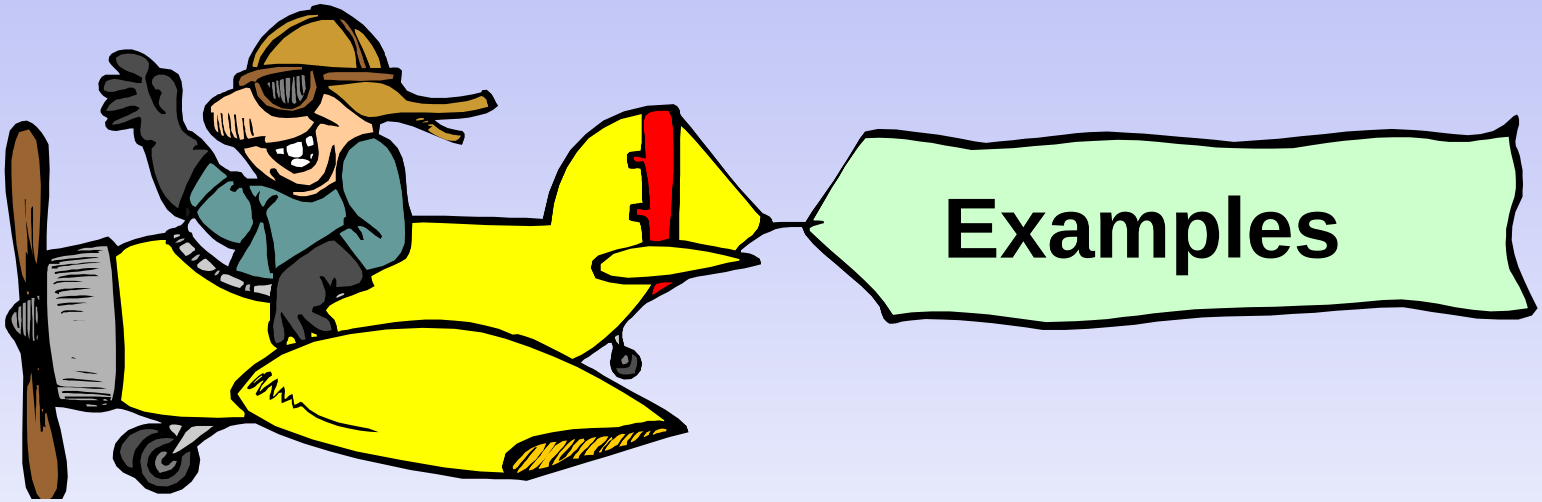
$$\mathbf{H} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\mathbf{R} = \begin{bmatrix} 0.1^2 & 0 \\ 0 & 0.1^2 \end{bmatrix}$$

$$\mathbf{x}_\mathrm{b} = [2.5, 2.8]$$

$$\mathbf{y} = [2.0, 3.0]$$

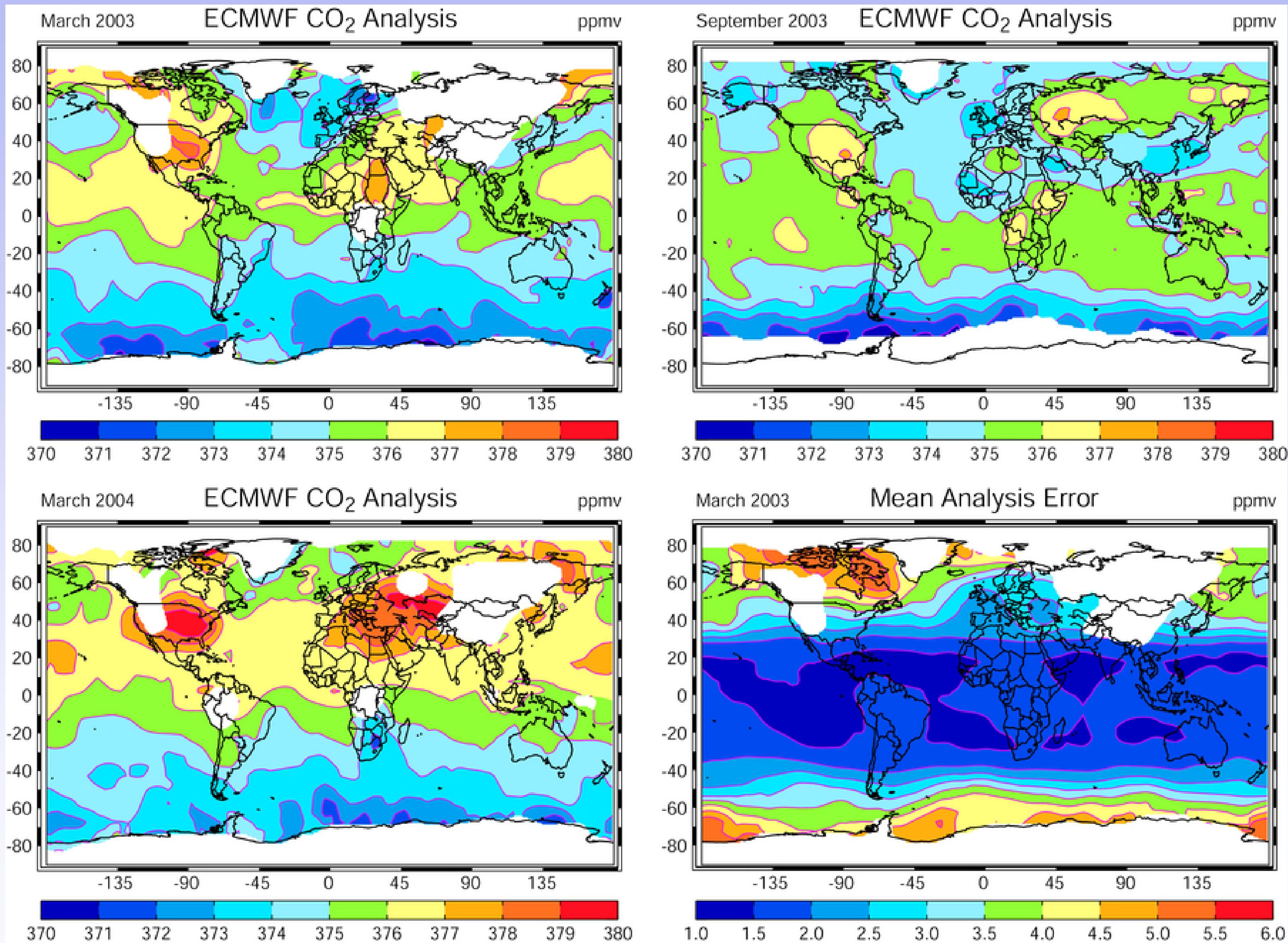



Examples

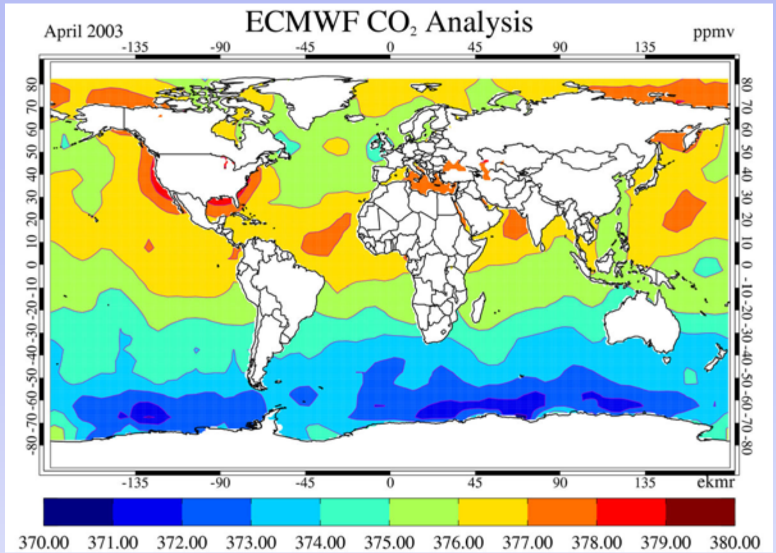
Example 1: CO_2 column estimates

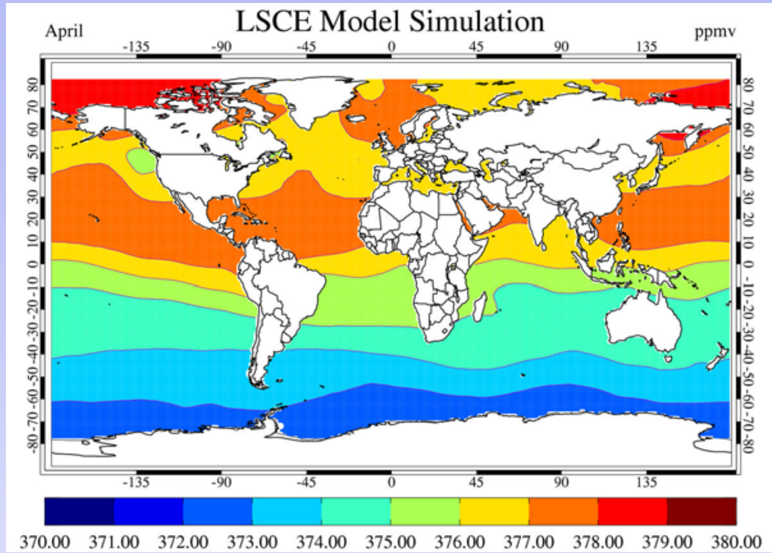
- CO_2 has already been implemented as a so-called 'column' variable within the 4D-Var data assimilation system.
- This means that CO_2 is not a model variable and is therefore not moved around by the model transport.
- For each AIRS observation location a CO_2 variable is added to the control (minimisation) vector. The CO_2 estimates therefore make full use of the 4D-Var fields of temperature, specific humidity and ozone.
- The CO_2 variable itself is limited to a column-averaged tropospheric mixing ratio with fixed profile shape, but a variable tropopause.
- A background of 376 ppmv is used with a background error of 30 ppmv.
- 18 channels in the long-wave CO_2 band are used

Example 1: CO_2 column estimates



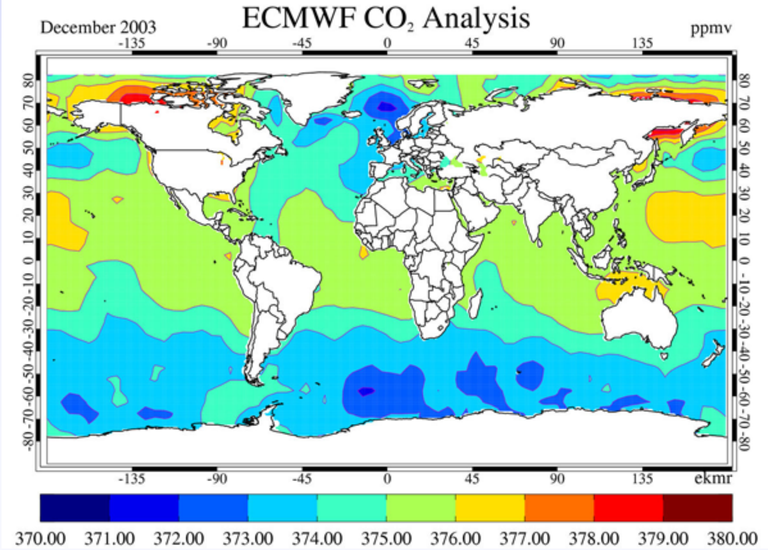
Example 1: CO_2 column estimates

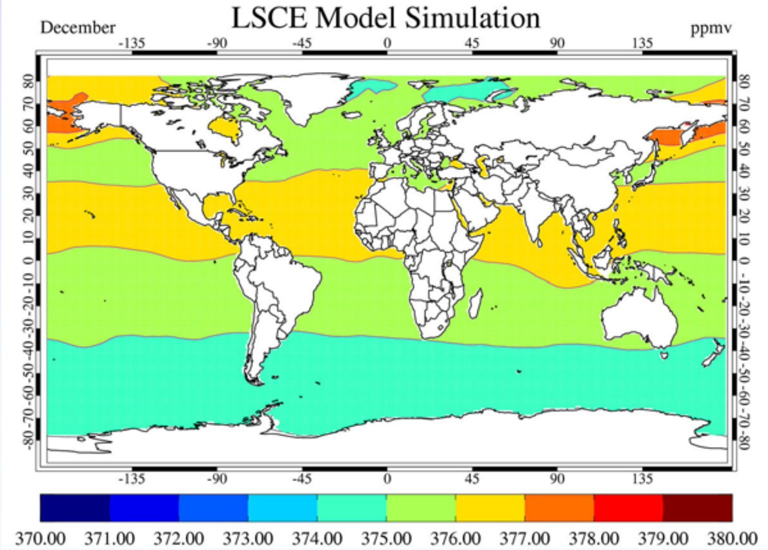




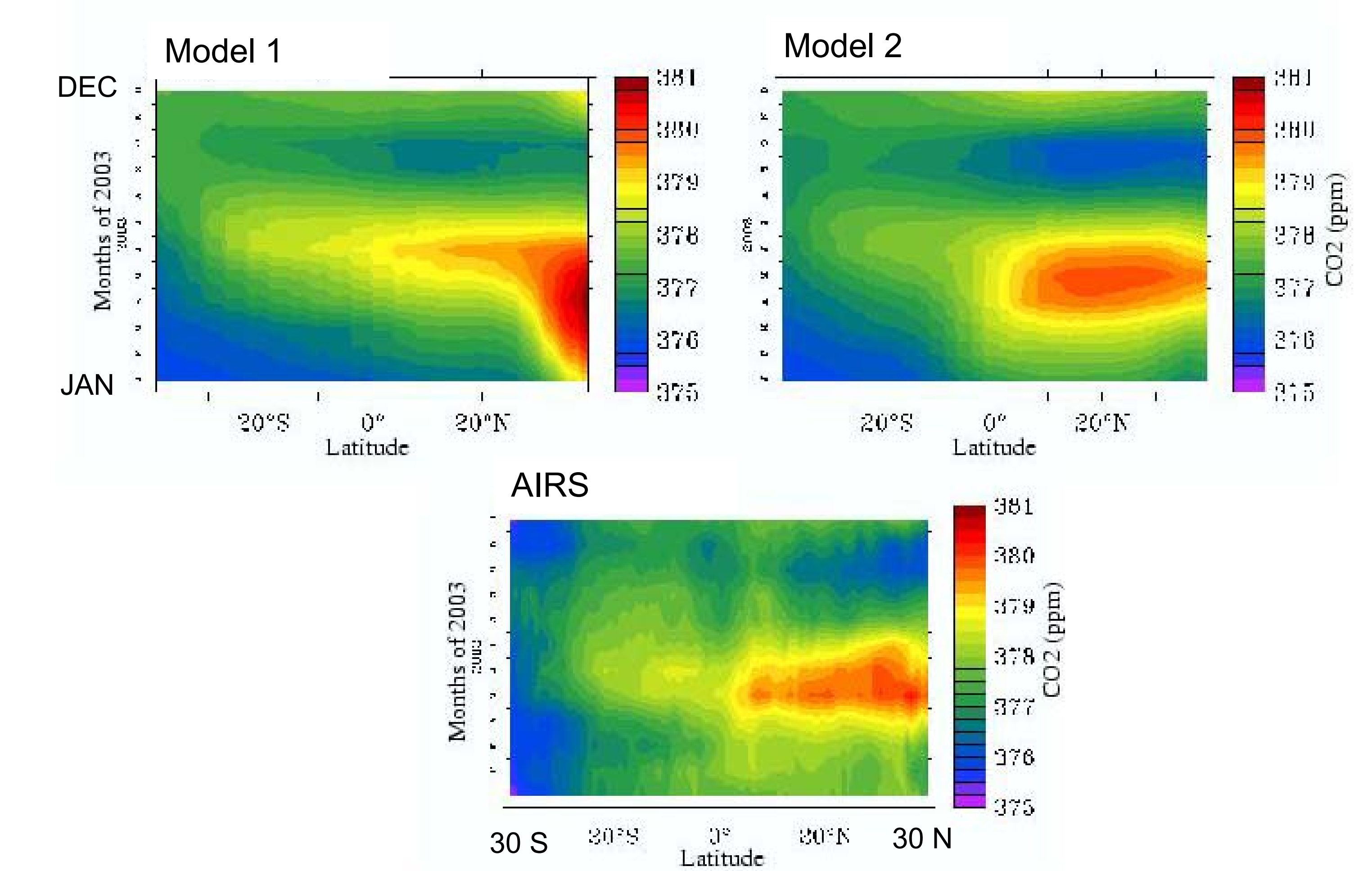
ECMWF estimates

LSCE CO_2 simulation



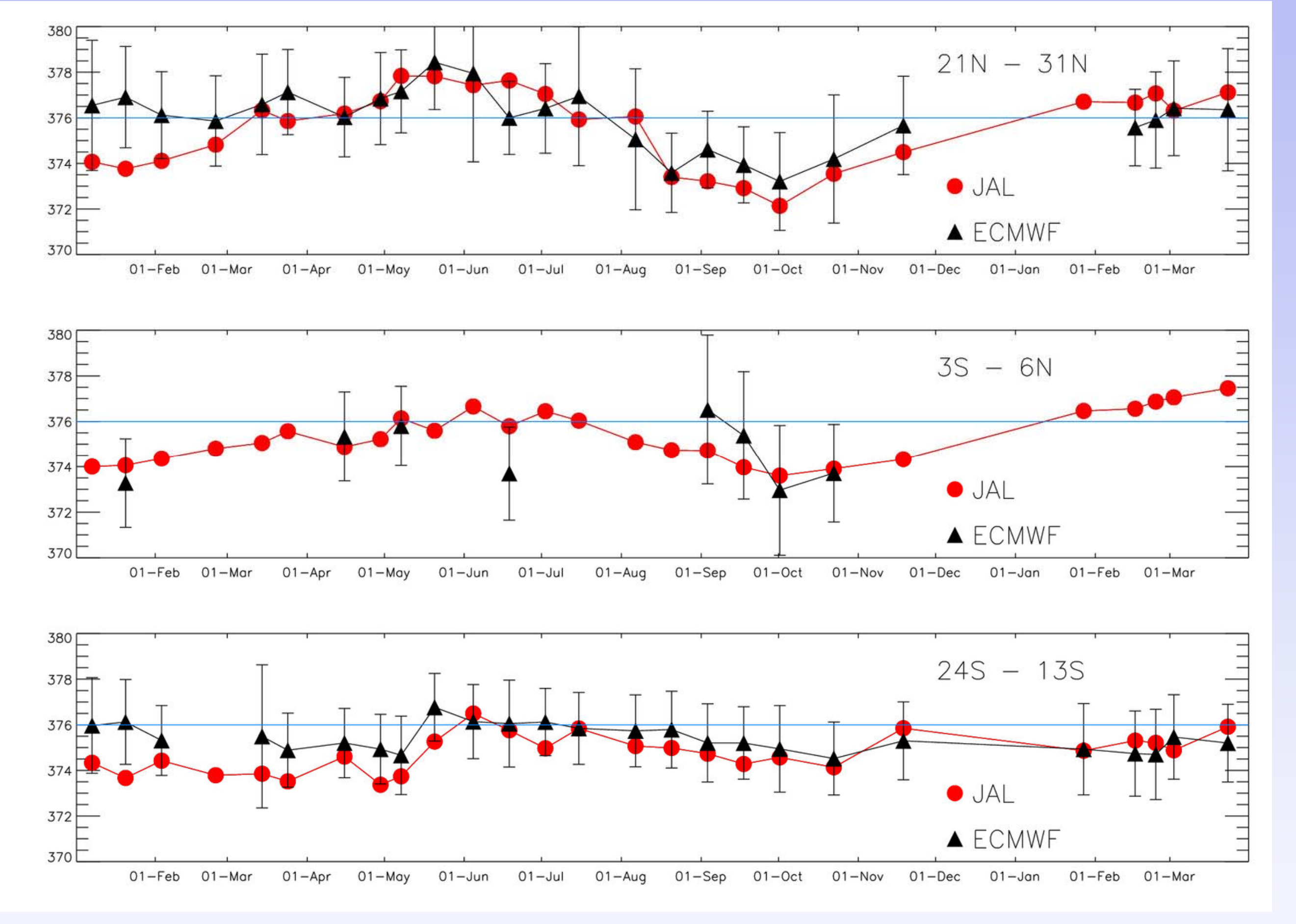


Example 1: CO_2 column estimates



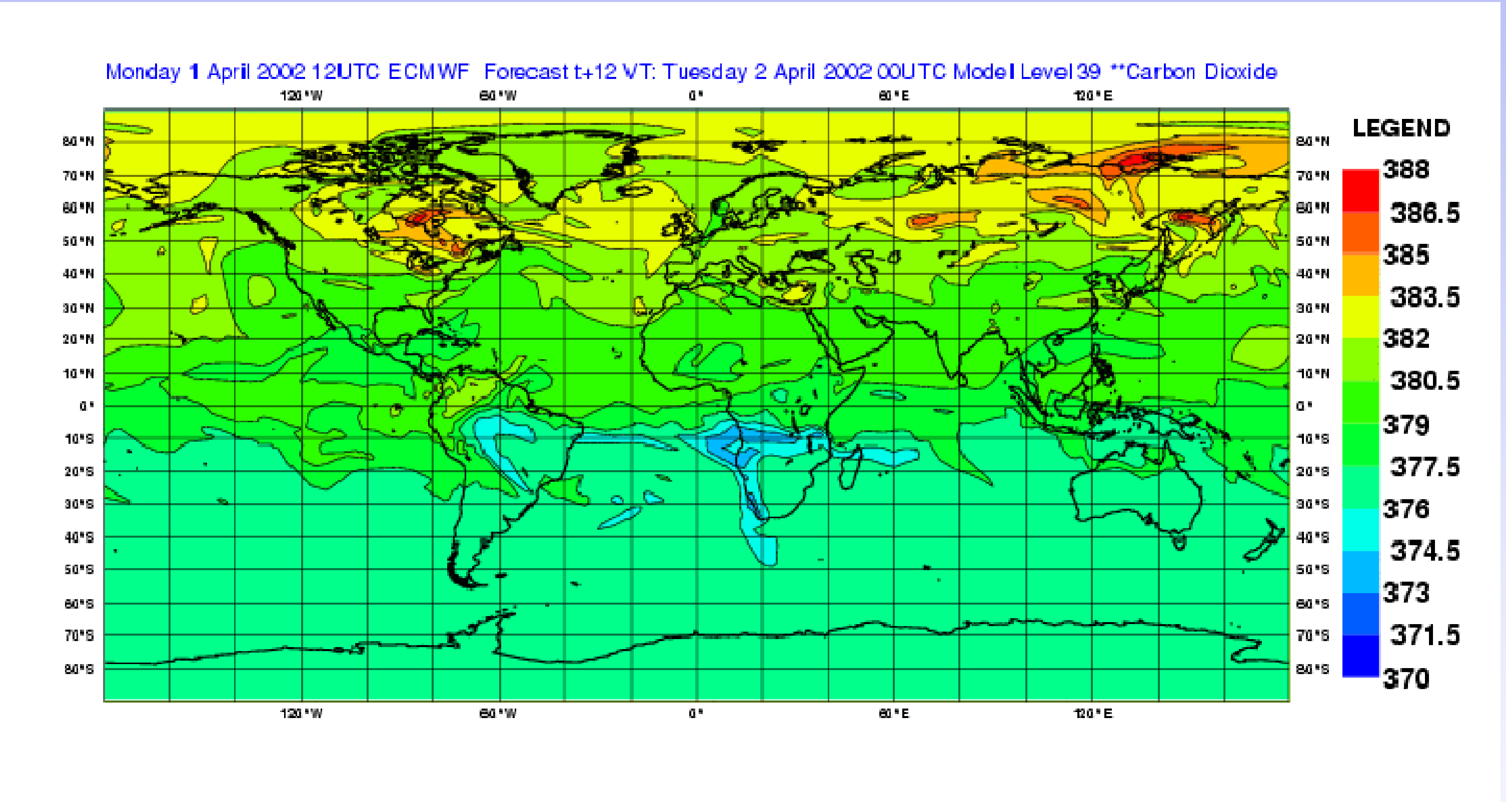
Satellite CO_2 estimates can already be used to learn more about differences between transport models!

Example 2: Validation



Flight data kindly provided by H. Matsueda, MRI/JMA

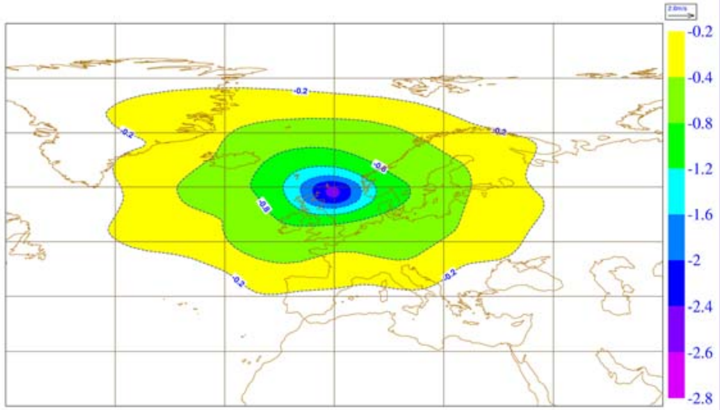
Example 3: CO_2 tracer transport



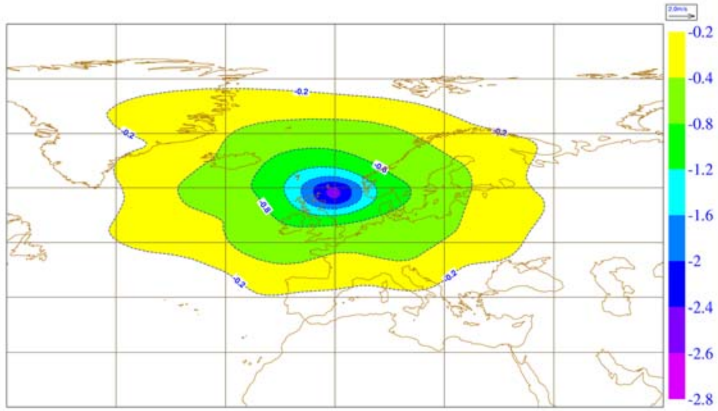
1 April – 30 August simulation for 500 hPa from ECMWF CO_2 forecast model.

Example 4: Tracer constraint on winds

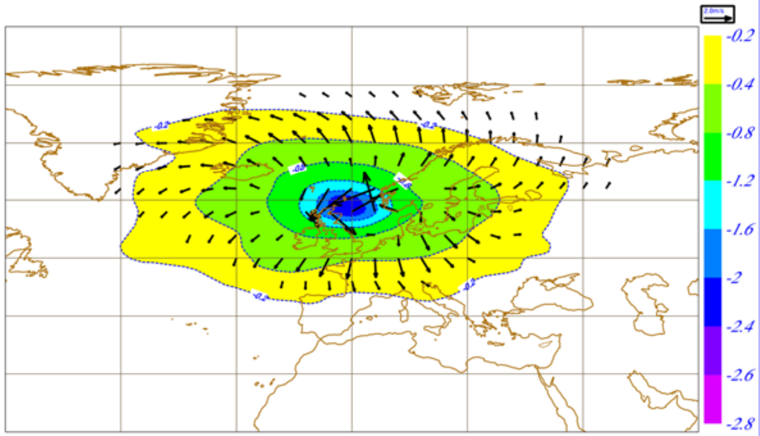
3D Var • 1 obs



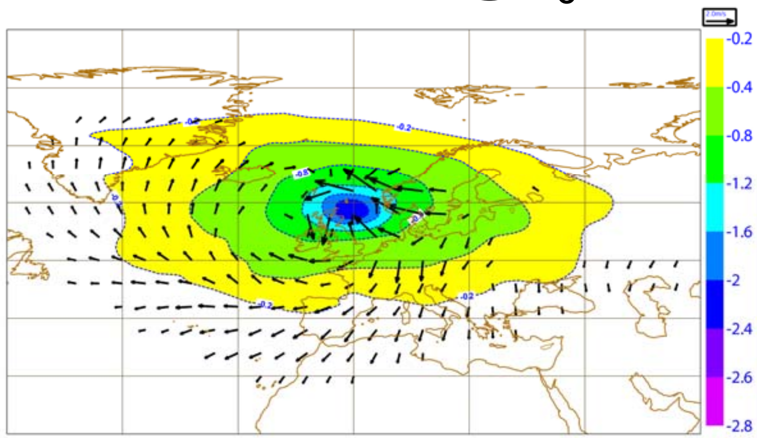
4D Var • 1 obs @ t_0



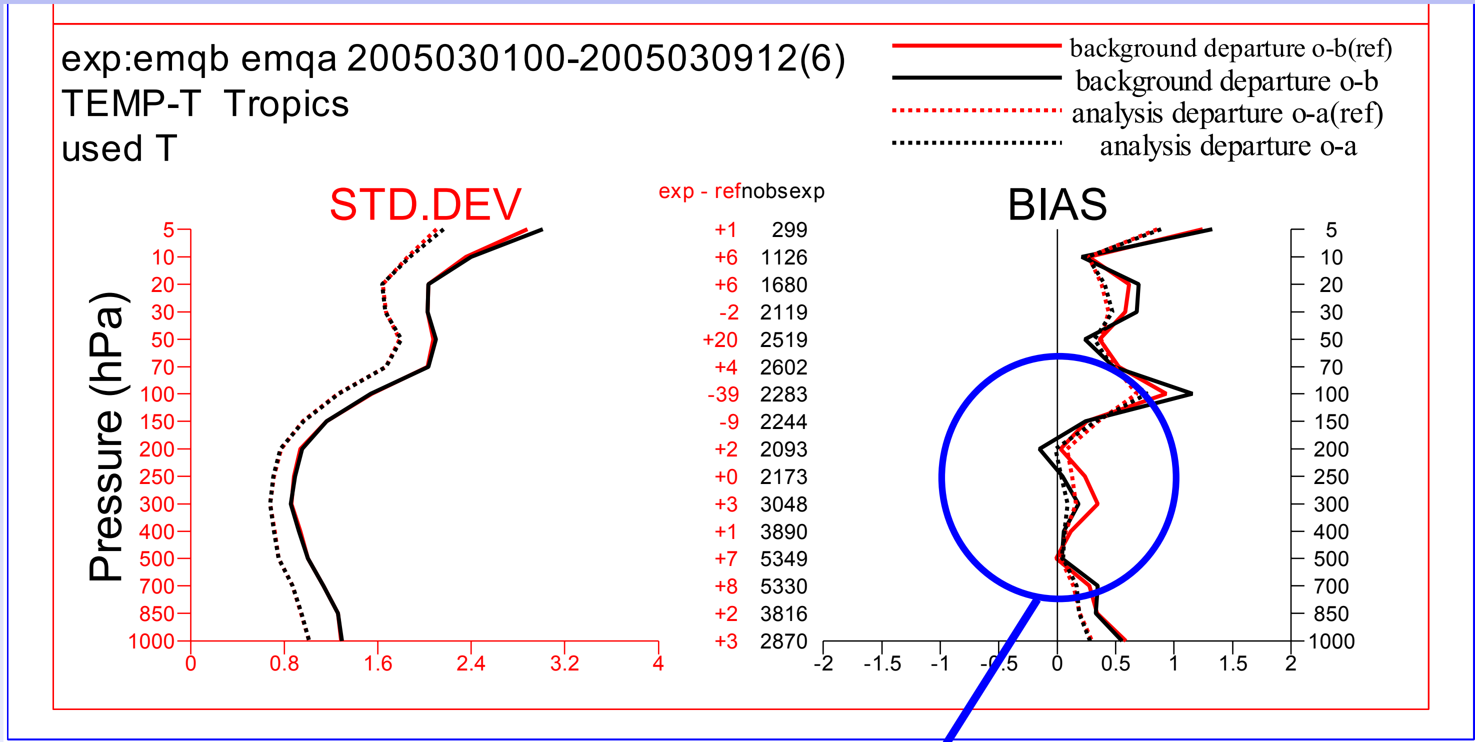
4D Var • 1 obs @ t_0+3



4D Var • 1 obs @ t_0+6



Example 5: Impact of CO_2 on Temperature Analysis



Including CO_2 in the analysis results in an improved fit to the radiosonde temperature profiles in the vertical range where AIRS is sensitive to CO_2.

Conclusions

- Challenging and exciting advance in data assimilation
- Possible because of intensive collaboration between ECMWF and various research institutes
- Aim is to build an operational system by 2009 to monitor the atmospheric greenhouse gases
- The 4D atmospheric fields will then hopefully contribute to a better quantification and understanding of the carbon surface fluxes.