GRAS SAF ACTIVITIES IN SUPPORT OF CLIMATE DATA GENERATION

Hans Gleisner

Danish Meteorological Institute (DMI), Denmark

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2. Climate data processing and climate data
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EUMETSAT’s GRAS Satellite Application Facility

The GRAS SAF is one of EUMETSAT’s *Satellite Application Facilities* – distributed network of center’s to process and distribute satellite data to the user community.

- 4 partners in the GRAS SAF: DMI, MetO, ECMWF, IEEC.
- Operational facility for generating and delivering GRAS/MetOp data in NRT (3 hours) and Offline (30 days).
- Current phase (2007-2012) has been focused on NRT data to NWP applications.
- Next phase (2012-2017) will have an equal focus on the generation of climate data.
- Continued developments of the software (*ROPP*) provided by the GRAS SAF for handling RO data (forward modelling, assimilation, 1DVar retrievals, etc.).

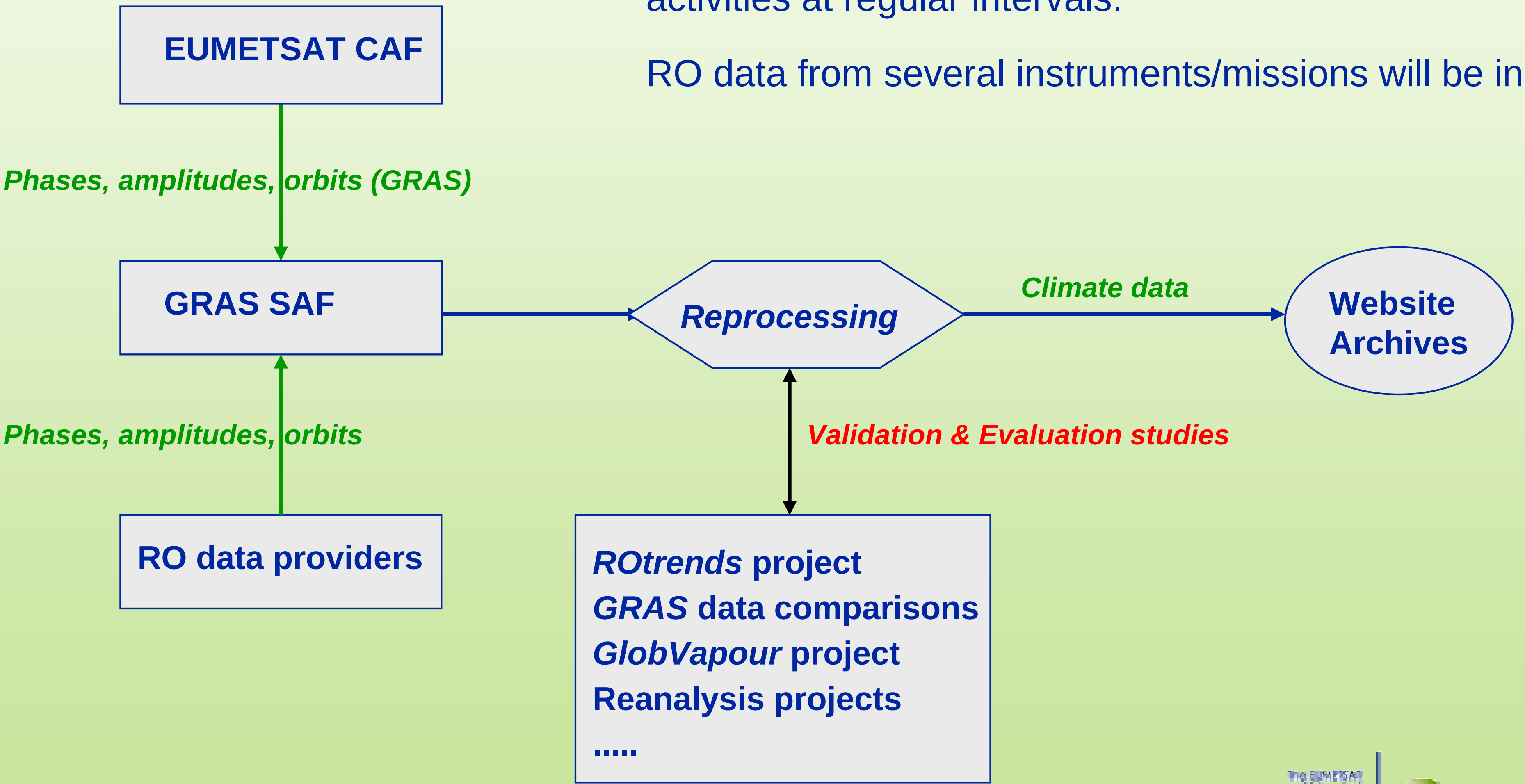
EUMETSAT's GRAS Satellite Application Facility

- Main responsibility of the GRAS SAF is to provide data from GRAS onboard the series of MetOp satellites and follow-on missions (post-EPS will most likely include an RO instrument).
- GRAS SAF will also generate climate data from CHAMP and COSMIC.
- Developing capabilities to process data from other missions as well.
- GRAS/MetOp climate data will be generated on a monthly basis from the Offline data.
- GRAS/MetOp, CHAMP, and COSMIC climate data will be generated in committed *reprocessing* projects. Potentially also data from other missions – depending on GRAS SAF resources.
- Climate data includes both atmospheric profiles of "climate quality" and globally gridded data sets.

GRAS SAF climate data generation
– through reprocessing –

RO climate data will be generated through *reprocessing* activities at regular intervals.

RO data from several instruments/missions will be included.



GRAS SAF climate data generation

– processing chain –

OCC / ROPP codes

Level 1a
PHASES, AMPLITUDES,
ORBIT INFORMATION

FILTERING FOR NOISE REDUCTION
QUALITY CHECK
COORDINATE TRANSFORMATION
GEOMETRICAL OPTICS ROUTINE
WAVE OPTICS ROUTINE (CT2)

Level 1b
BENDING ANGLES (L1,L2)

IONOSPHERIC CORRECTION

BENDING ANGLES (LC)

STATISTICAL OPTIMIZATION
ABEL TRANSFORM

Level 2a
REFRACTIVITY

1D-VARIATIONAL RETRIEVAL

Level 2b
TEMPERATURE
SPECIFIC HUMIDITY
GEOPOTENTIAL HEIGHT

QUALITY CONTROL
GRIDDING & AVERAGING
SAMPLING ERROR ESTIMATION

“Level 3” – grids & averages
BENDING ANGLE
REFRACTIVITY
TEMPERATURE
SPECIFIC HUMIDITY
GEOPOTENTIAL HEIGHT

GRAS SAF climate data products

Climate data product	2D zonal grid: [1] climate + errors	Time resolution	Spatial [2] resolution	*Formats, graphical*	*Formats, numerical*
Bending angle	yes	Monthly	5 deg latitude	PNG, JPG	ASCII, netCDF
Refractivity	yes	Monthly	5 deg latitude	PNG, JPG	ASCII, netCDF
Temperature	yes	Monthly	5 deg latitude	PNG, JPG	ASCII, netCDF
Specific humidity	yes	Monthly	5 deg latitude	PNG, JPG	ASCII, netCDF
Geopotential height	yes	Monthly	5 deg latitude	PNG, JPG	ASCII, netCDF

[1] A latitude-height grid where the height can be expressed in MSL altitude, geopotential height, or ”pressure height”.

[2] The height resolution of the grid will be 200 meter – on the same order as the height resolution of the profiles.

Gridded data will be generated separately for each mission, as well as combined.

Weighted averaging in latitude grid boxes

Area-weighted grid-box mean:

$$\bar{X} = \frac{1}{A}\int X(\varphi,\lambda)\,dA$$

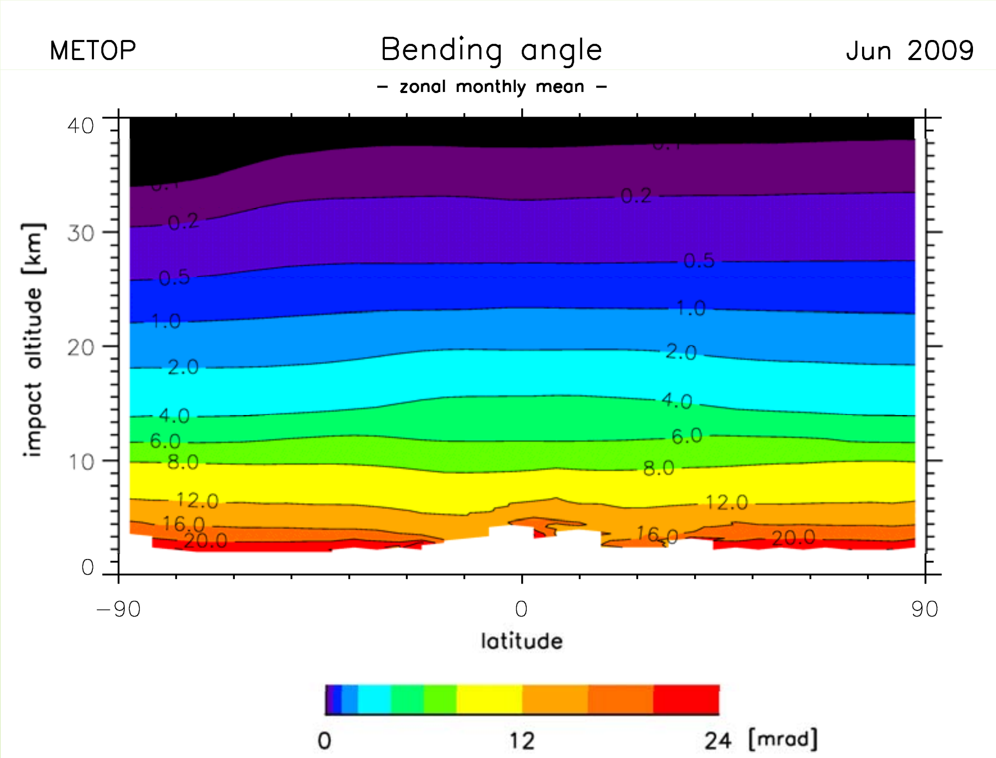
To achieve a correctly area-weighted mean *within 5-degree latitude grid boxes*, we have adopted the strategy of sub-dividing grid boxes into smaller regions and then weight the regional means by the respective area.

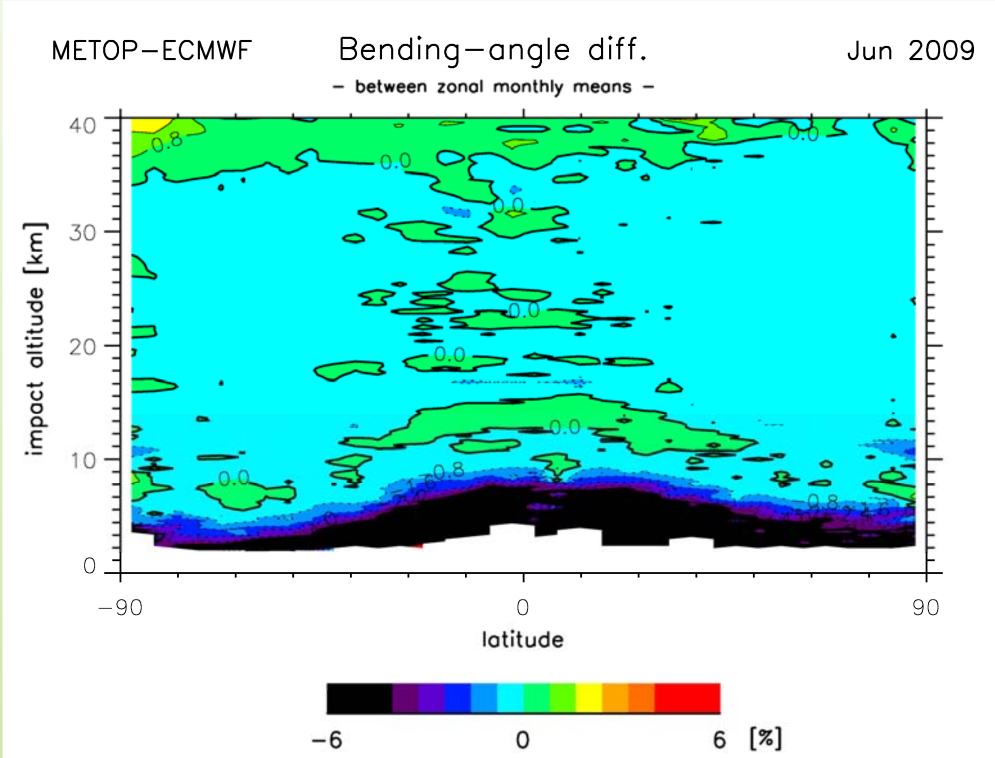
$$\bar{X}' = \frac{1}{A}\sum_{s=1}^{2}\bar{X}_s A_s = \frac{1}{A}\sum_{s=1}^{2}\left[\frac{1}{M_s}\sum_{j=1}^{M_s} X_{s,j}\right]A_s$$

The choice of weighting strategy depends on *the latitudinal distribution of observations across the grid box*.

GRAS SAF climate data

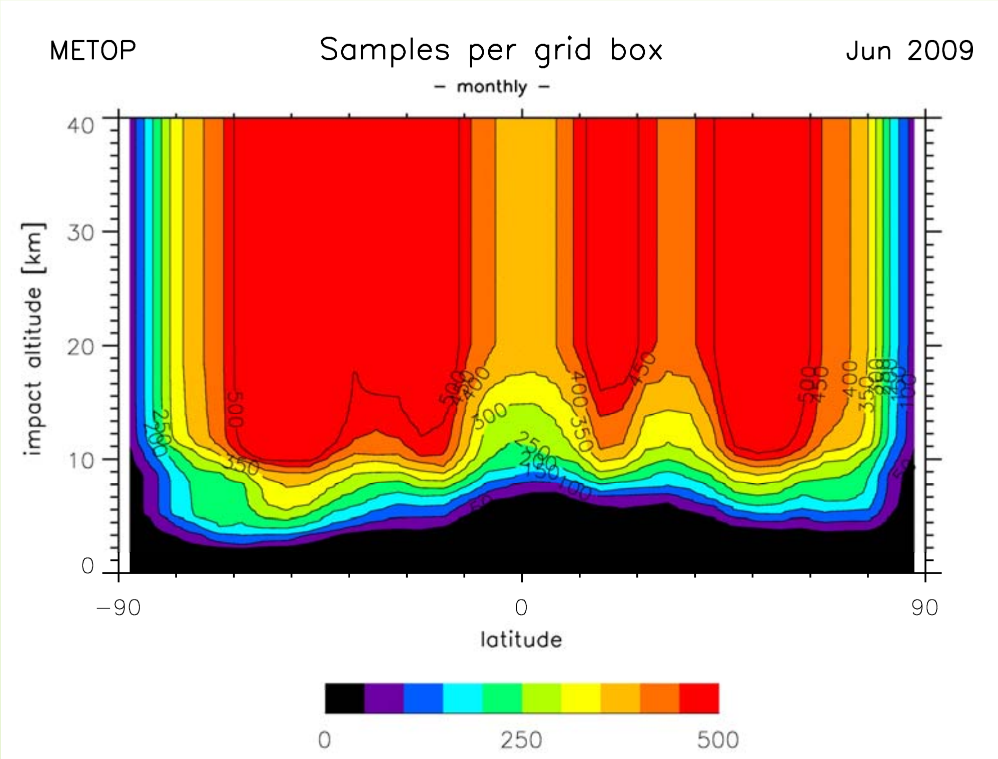
– bending angle –

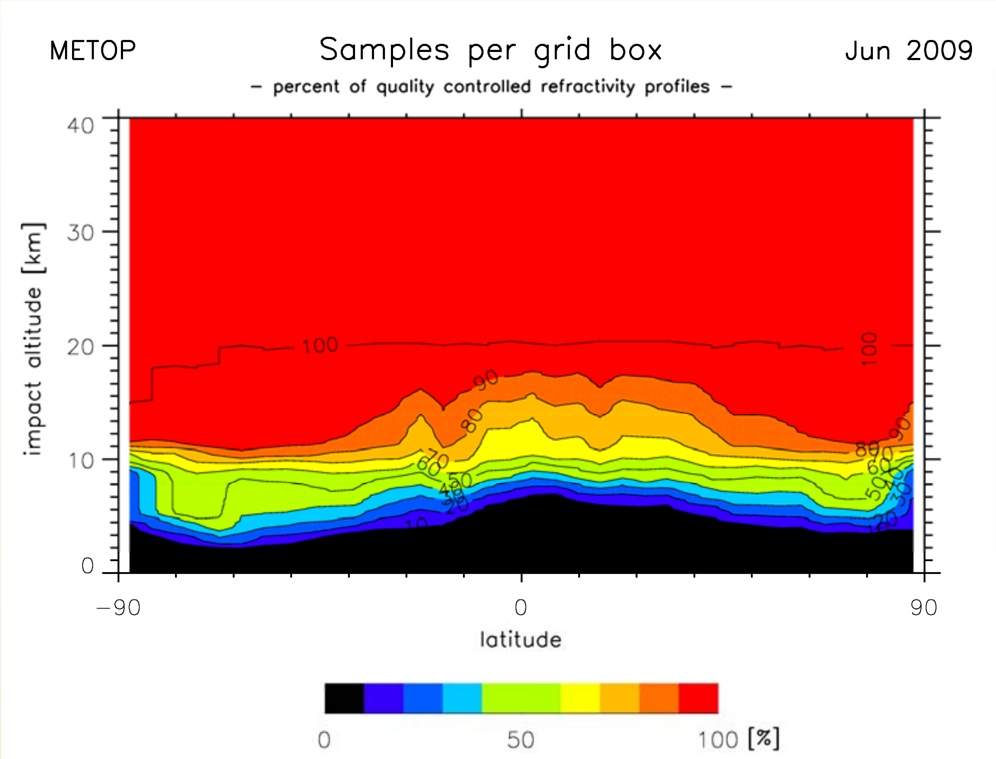




GRAS SAF climate data

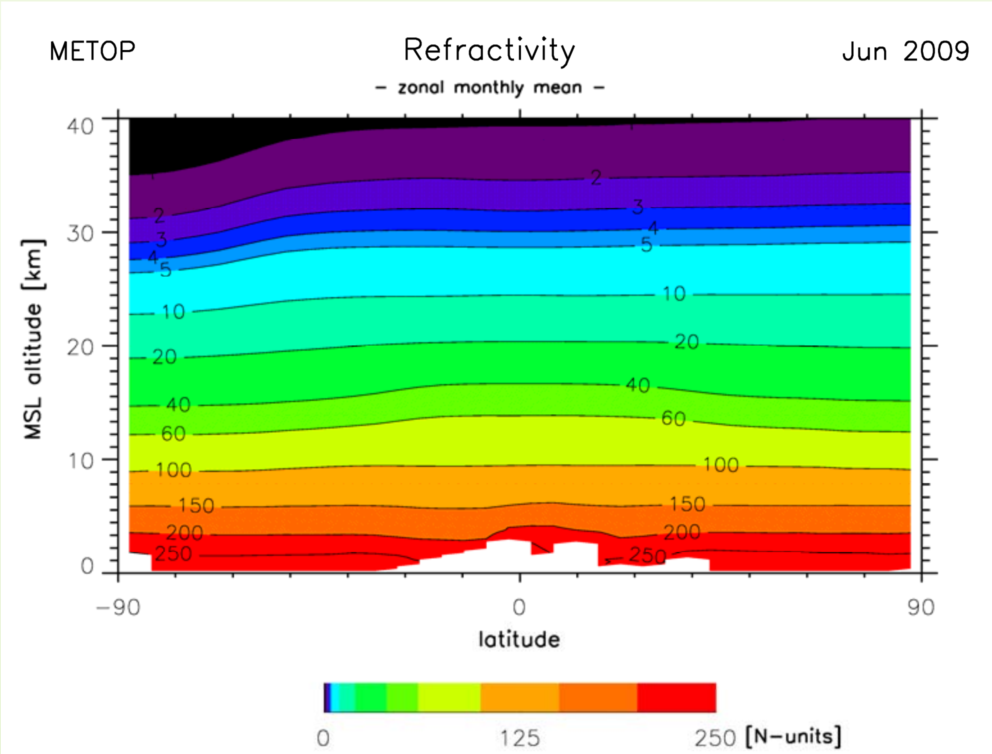
– bending angle –

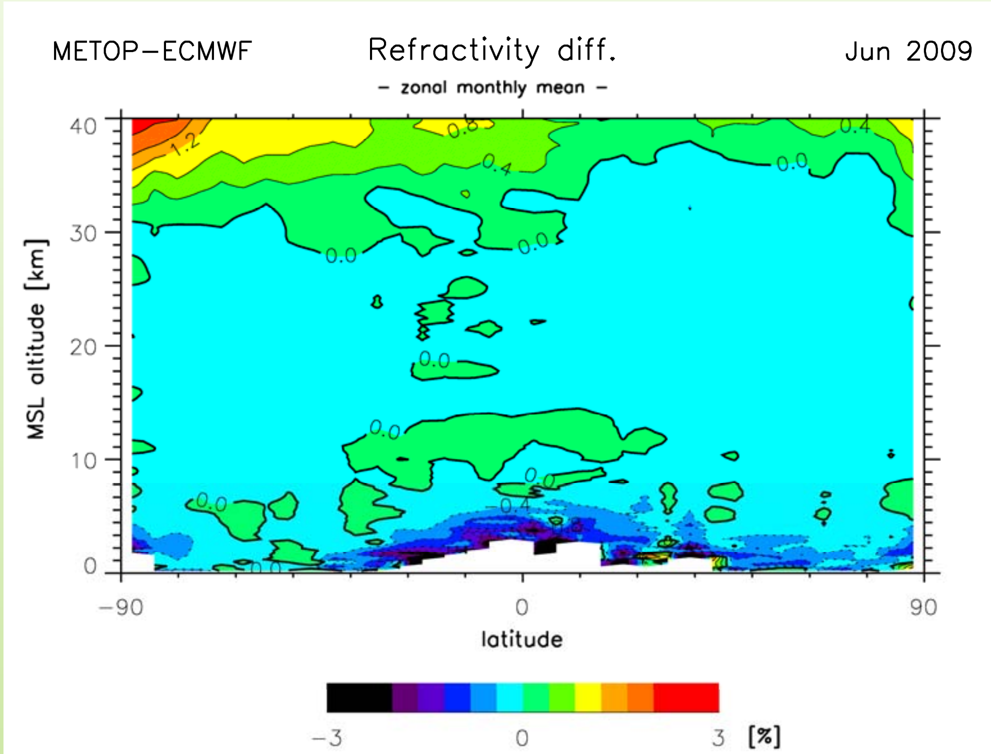




GRAS SAF climate data

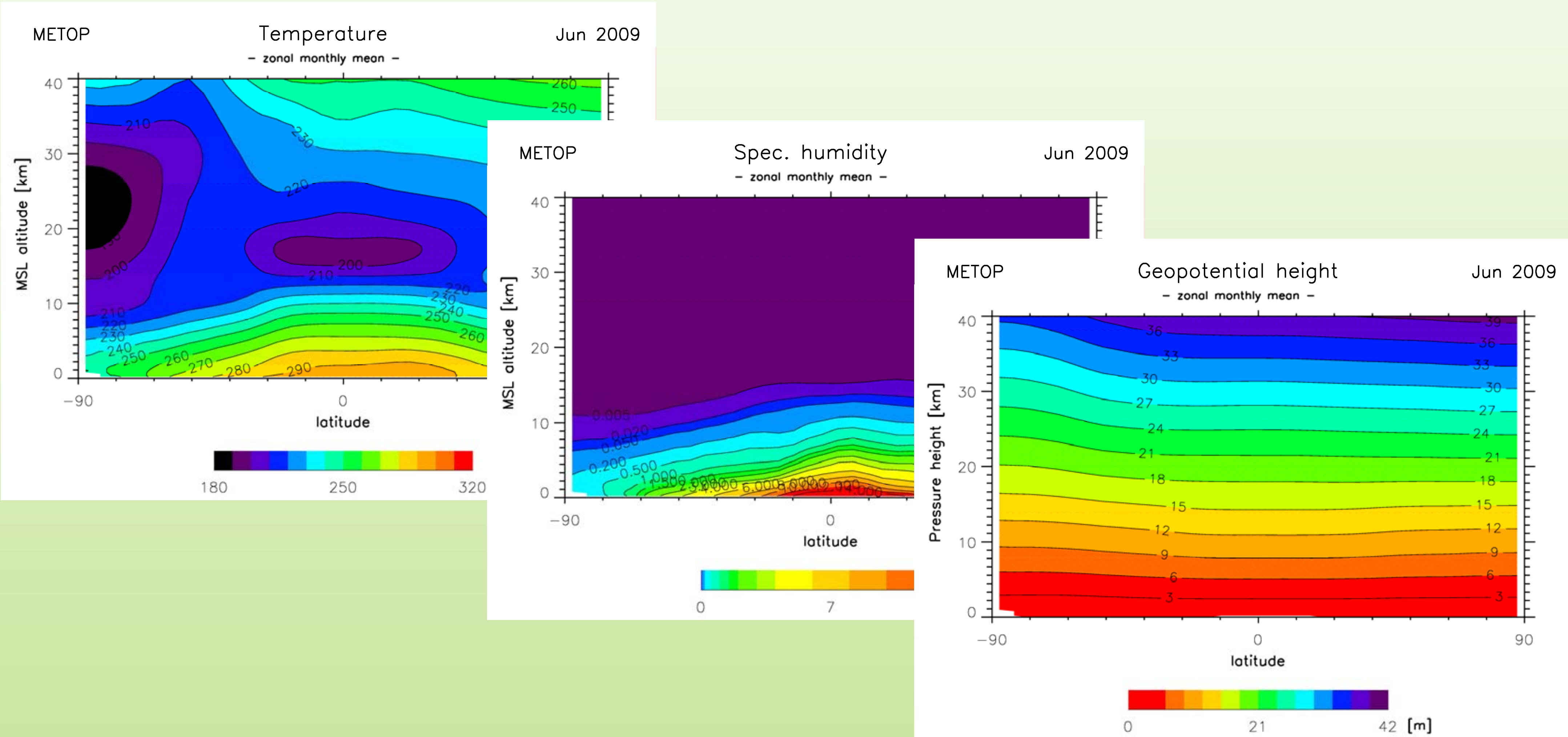
– refractivity –





GRAS SAF climate data

– 1D-Var products –

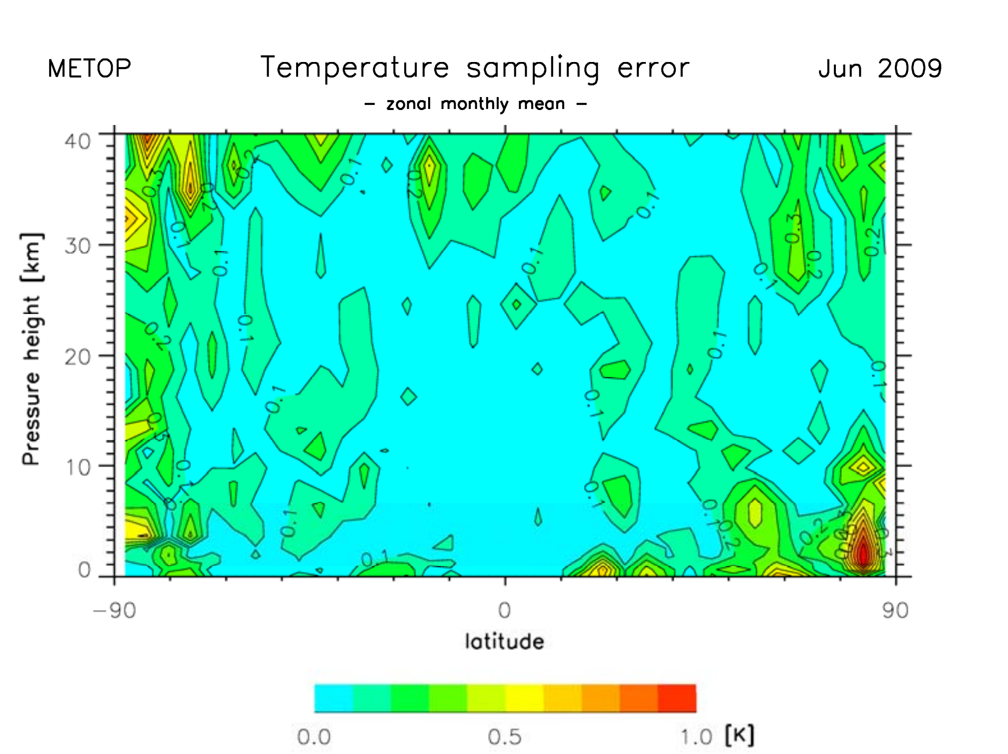


GRAS SAF

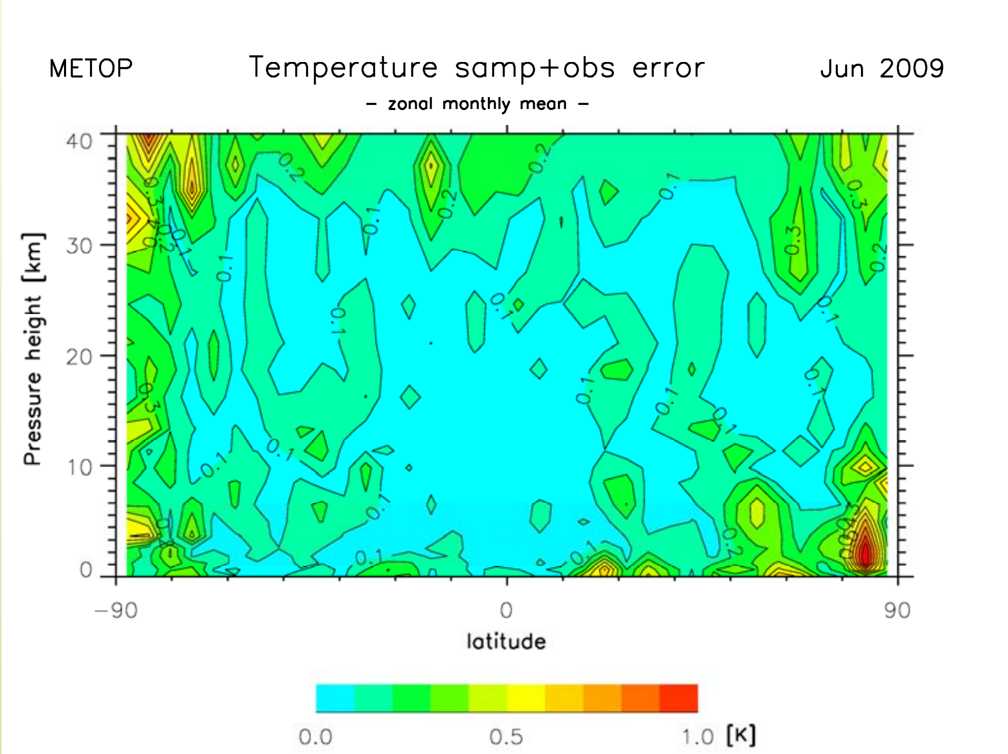
GRAS SAF climate data

– error estimates –

Sampling errors



Sampling + observational errors



The sampling errors are estimated by sampling a model at the nominal time and locations of the observations. The model resolution should be similar to the horizontal resolution of the observations.

GRAS SAF climate data

– monitoring –

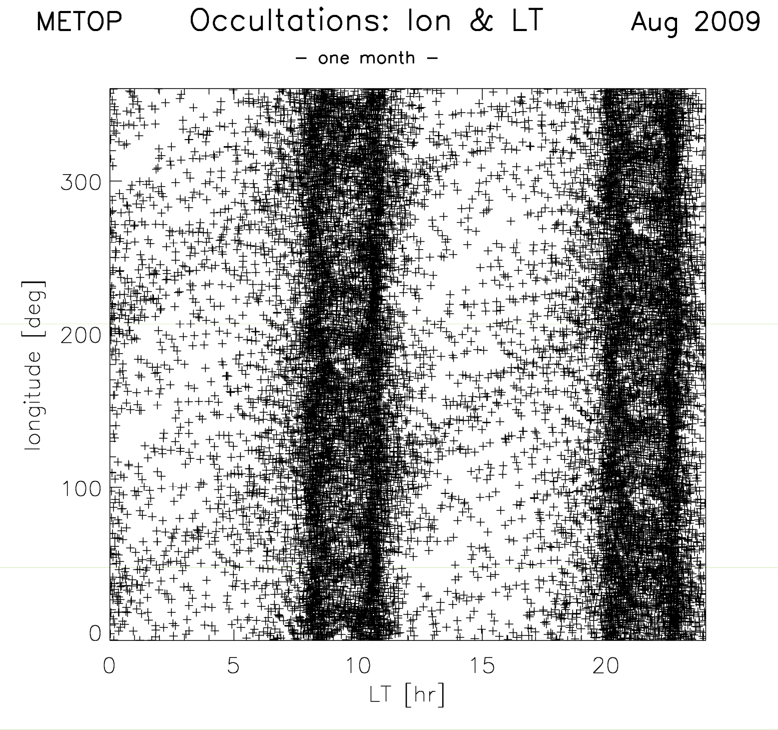
Climate records obtained from RO data are affected by:

- observational errors: - propagated from errors in phase observations
  - for climate data, biases are more serious than random errors
  - time variation in random errors may potentially cause trends in climate data
- sampling errors, biases, & drifts in time
- inversion errors: effects of algorithmic choices, different QC procedures, etc.

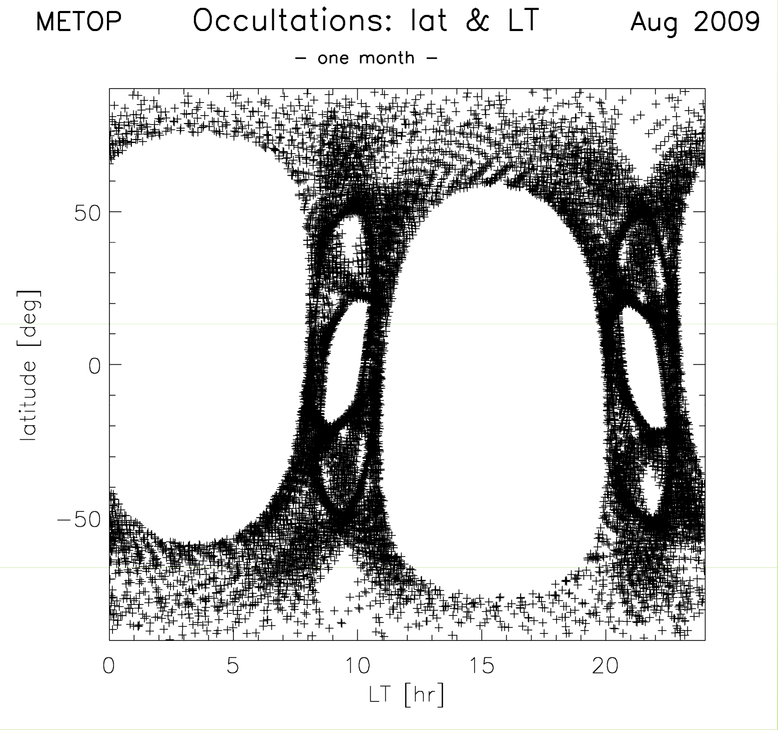
GRAS SAF climate data

– sampling –

Longitude vs. local time



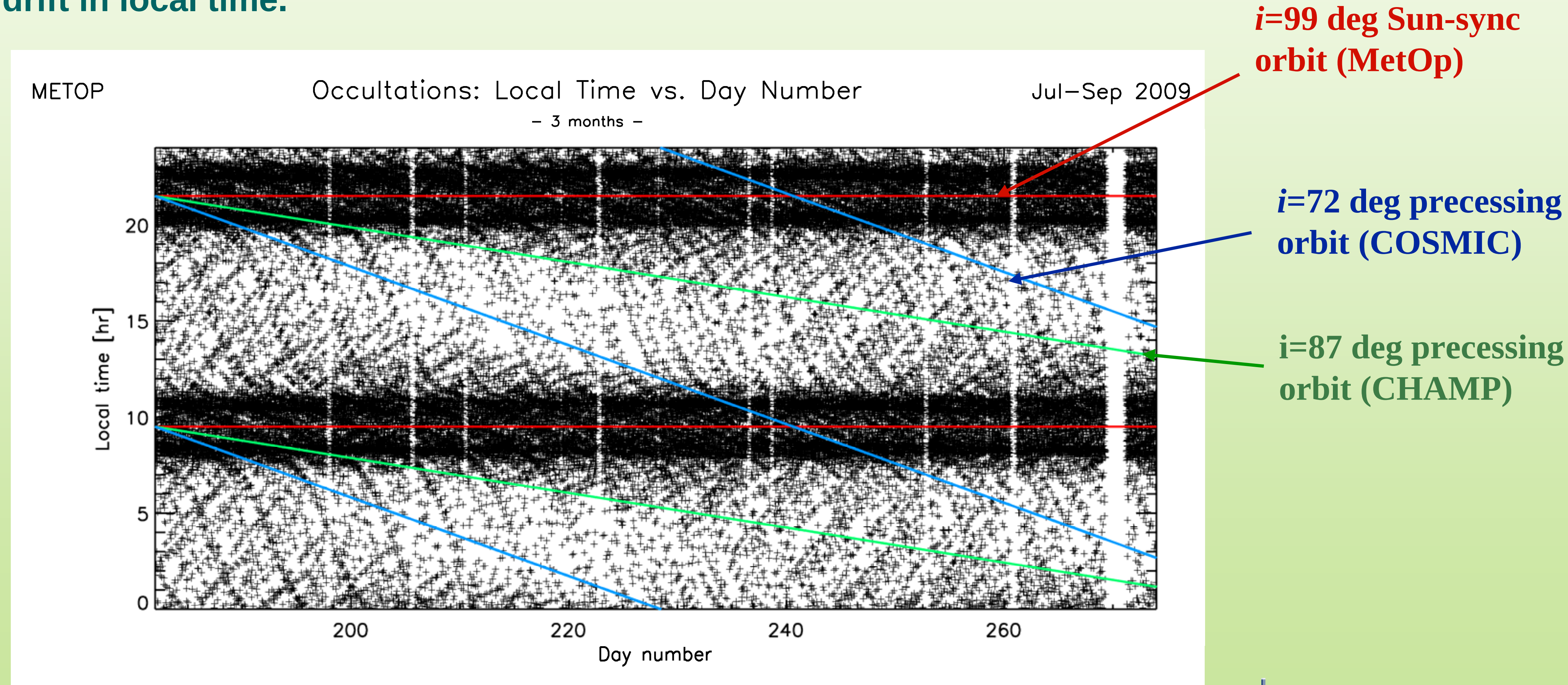
Latitude vs. local time



GRAS SAF climate data

– sampling –

MetOp is in a Sun-synchronous orbit, whereas CHAMP and COSMIC slowly drift in local time.

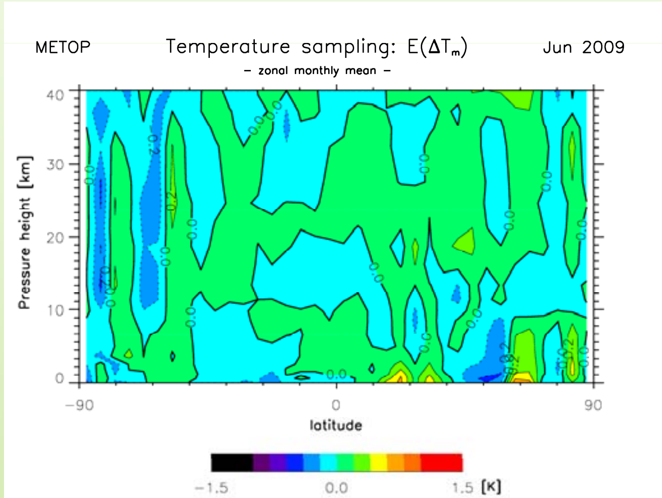


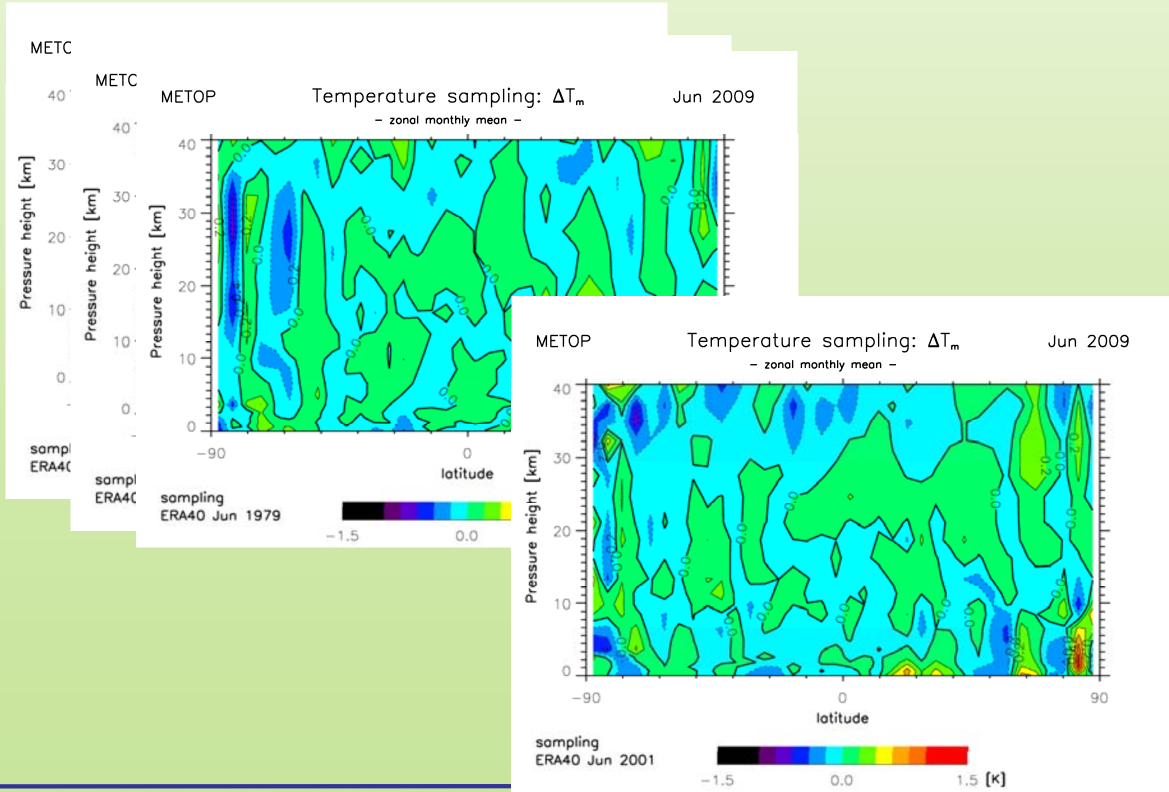
GRAS SAF climate data

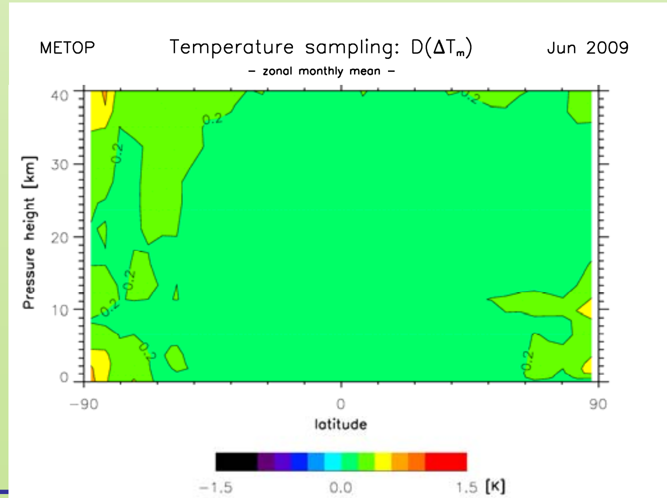
– monitoring of errors –

For a certain distribution of observations, the sampling error has a random and a systematic component. These are due to (a) undersampling of the synoptic variability, and (b) under-sampling of the underlying climatology and of diurnal/semi-diurnal cycles.

We get 25 error fields from sampling 25 model fields. The mean of these error fields gives the systematic component, and the standard deviation describes the random component.





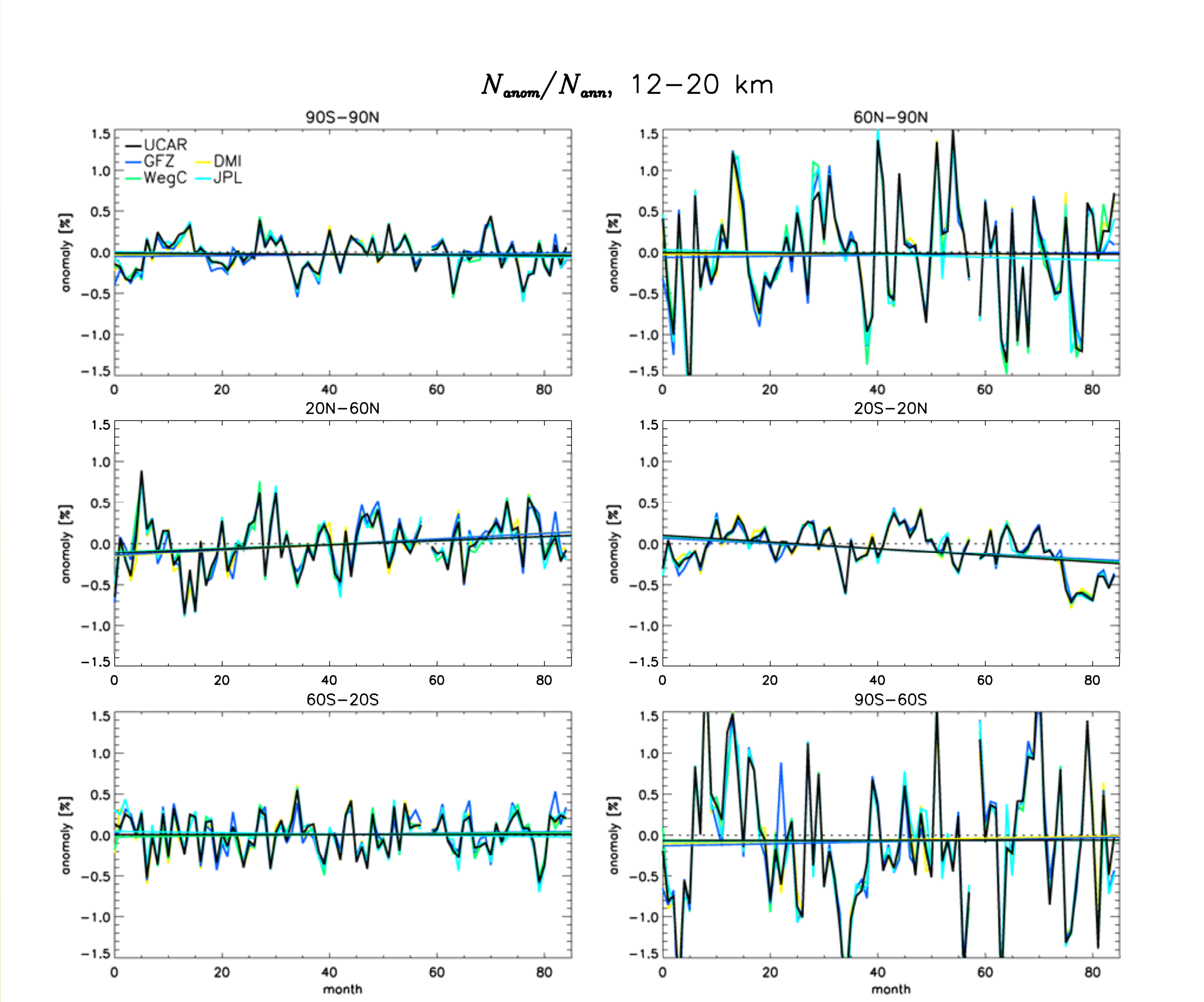


GRAS SAF climate data

– structural uncertainties –

From the *ROtrends* project.

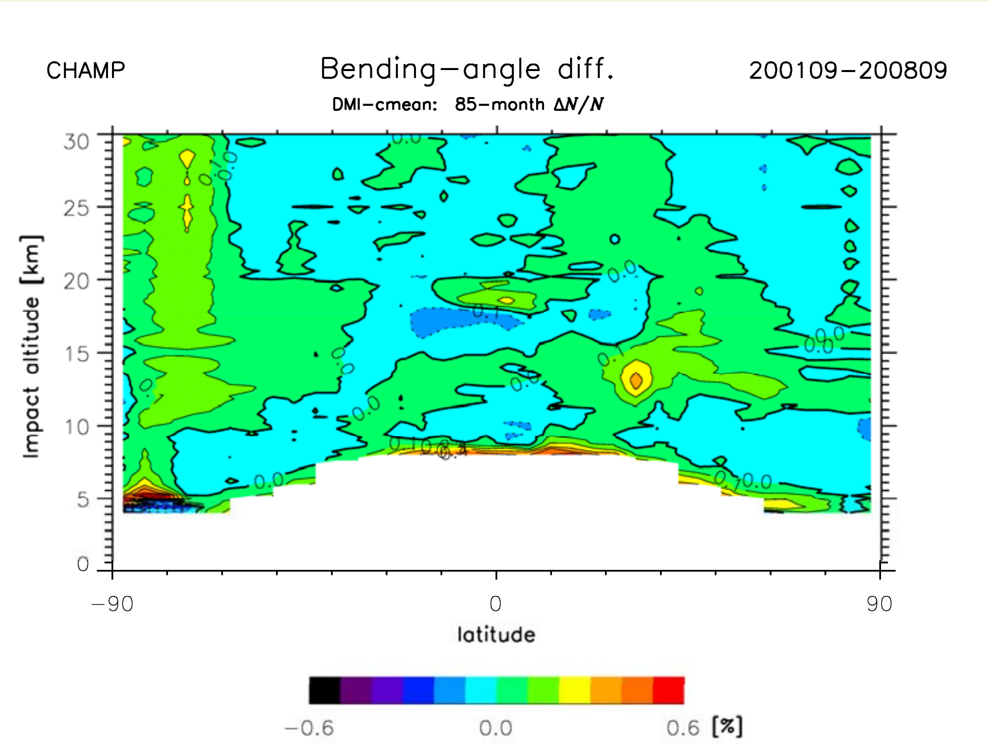
Ben Ho *et al* [2009] + DMI data

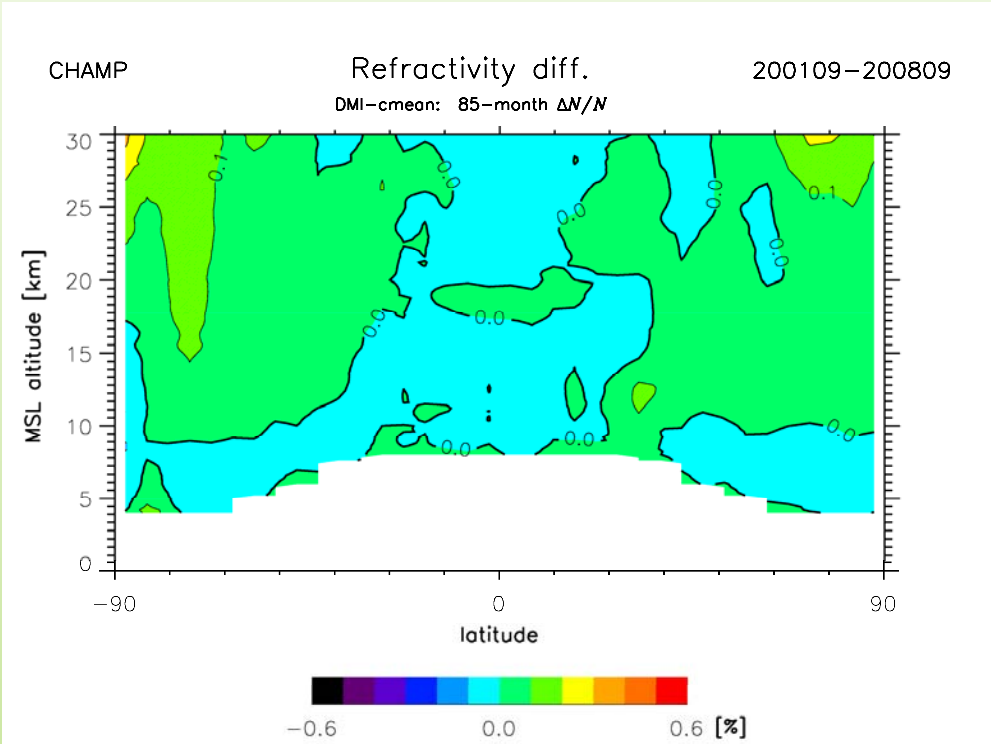


GRAS SAF climate data

– structural uncertainties –

DMI vs. mean of 6 centers (from the *ROtrends* project).





GRAS SAF climate data products

STOP

GRAS SAF climate data processing

– ionospheric correction & statistical optimization –

Removing the influence of the ionosphere + smoothing and extending to infinity.

Linear kombination of L1 & L2:

$$\alpha_{LC} = \frac{f_1^2 \alpha_1 + f_2^2 \alpha_2}{f_1^2 + f_2^2}$$

Optimal linear combination:

$$\alpha_N = \alpha_{BG} + \frac{\sigma^S}{\sigma^S + \sigma^N} \left(\alpha_{LC} - \alpha_{BG} \right)$$

We use the method devised by Gorbunov [2002] with the background taken from MSIS.

MSIS is searched for a BA profile that best fits the observations after 2-parameter fit of logarithmic BA to a smoothed version of the observed BA. The search is global.

BACK

GRAS SAF climate data products

– 1DVar retrieval –

Input: $N_{obs}, \{p, T, q, p_{sfc}, z_{sfc}\}_{bgr}$ + error covariances for background, observations, and forward model

Minimize: $$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x} - \mathbf{x}^{\mathrm{b}})^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^{\mathrm{b}}) + \frac{1}{2}(\mathbf{y}^{\mathrm{o}} - \mathbf{H}(\mathbf{x}))^{\mathrm{T}}\mathbf{O}^{-1}(\mathbf{y}^{\mathrm{o}} - \mathbf{H}(\mathbf{x}))$$

We obtain the state vector *x* that provides an optimal compromise between observation and background to within the errors.

Which background should be used for climate reprocessing? ECMWF 6-hr forecasts, ERA reanalysis, climatological model?

Requirements: **- the same RO observation should not have influenced the background**
- the model should be the same over the climate data set time span

BACK

The EUMETSAT Network of Satellite Application Facilities | GRAS SAF GRAS Meteorology

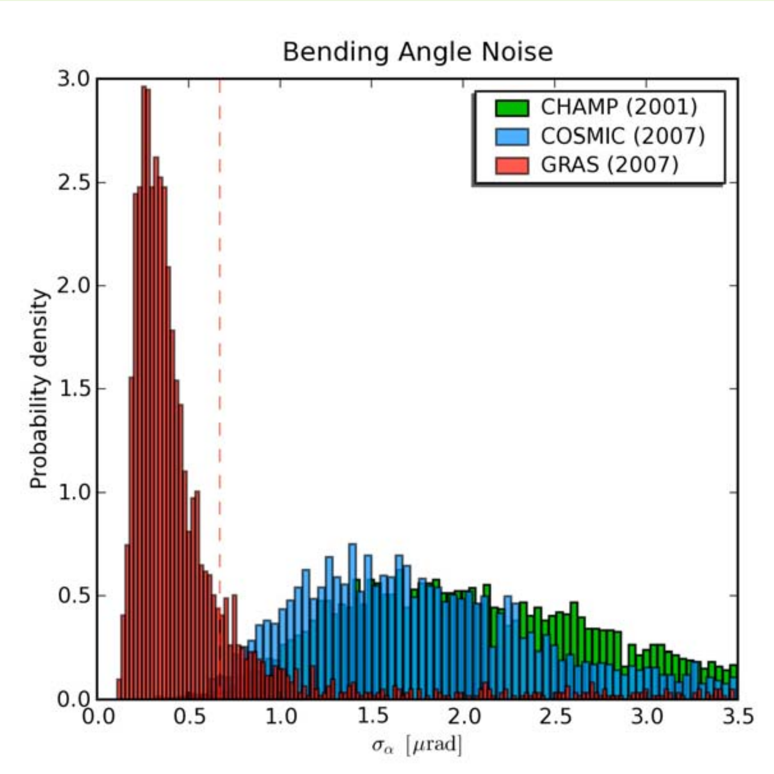
GRAS SAF climate data products

STOP

GRAS SAF climate data

– monitoring of errors –

Observational errors



From *Marquardt et al.*, presentation at the COSMIC User Workshop, 2007.

Weighting methods

Equal weighting

$$\overline{X}' = \frac{1}{M}\sum_{j=1}^{M} X_j$$

Cosine weighting

$$\overline{X}' = \frac{1}{\sum_{j=1}^{M}\cos(\varphi_j)}\sum_{j=1}^{M} X_j \cos(\varphi_j)$$

Sub-gridding

$$\overline{X}' = \frac{1}{A}\sum_{s=1}^{2} \overline{X}_s A_s = \frac{1}{A}\sum_{s=1}^{2}\left[\frac{1}{M_s}\sum_{j=1}^{M_s} X_{s,j}\right] A_s$$