

# Atmospheric Data Assimilation

Thomas Navarro (LMD)

with F. Forget, E. Millour

and University of Maryland (S. Greybush<sup>1</sup>, T. Miyoshi<sup>2</sup>, E. Kalnay)

1 : Now at Penn State University

2 : Now at Riken Institute (Japan)

ACS Team Meeting, October 14<sup>th</sup> 2013

# Assimilation of LMD Mars Global Climate Model (GCM)

- What is data assimilation ?
- Science goals and roadmap
- Assimilation of ACS meteorological data

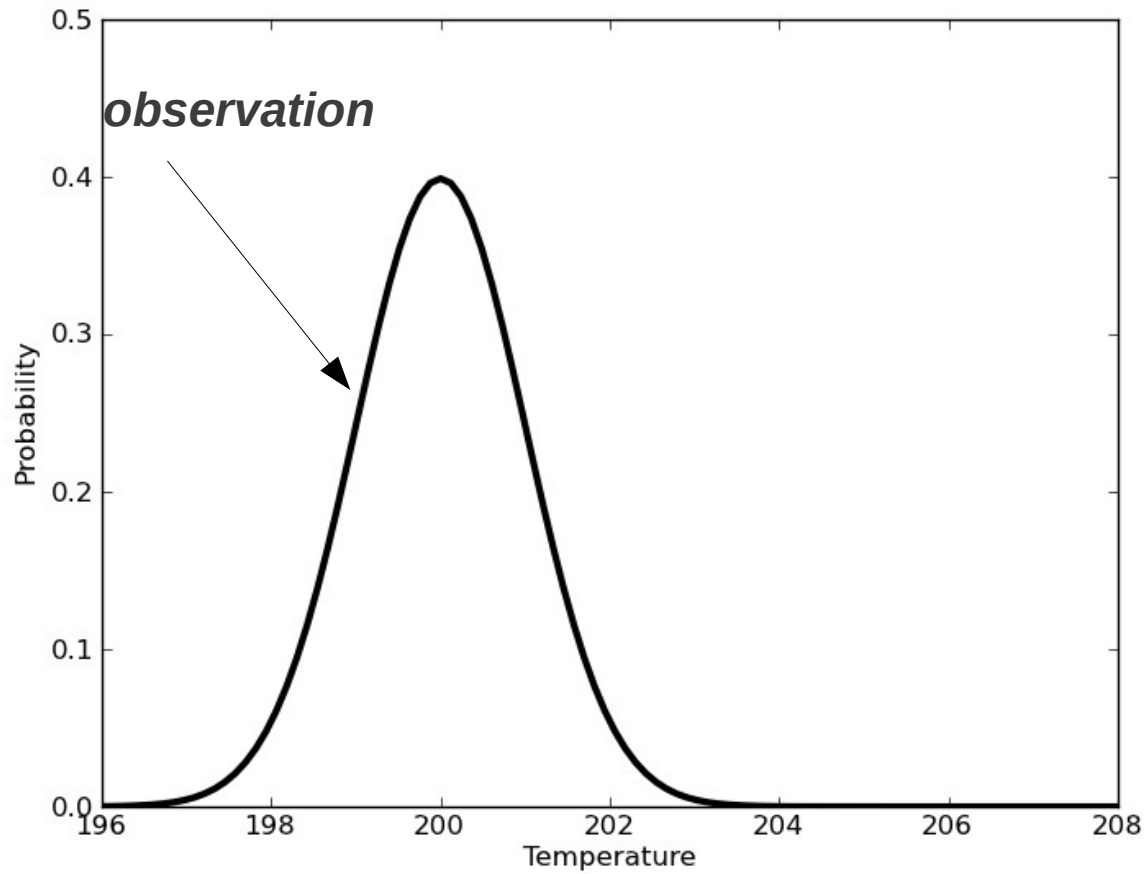
# What is data assimilation ?

- « *Using **all the available information** to determine as accurately as possible the state of the **atmospheric flow.*** »  
(O.Talagrand)
- **Optimal interpolation** of observations, taking into account their **errors**, with the help of a **model**.

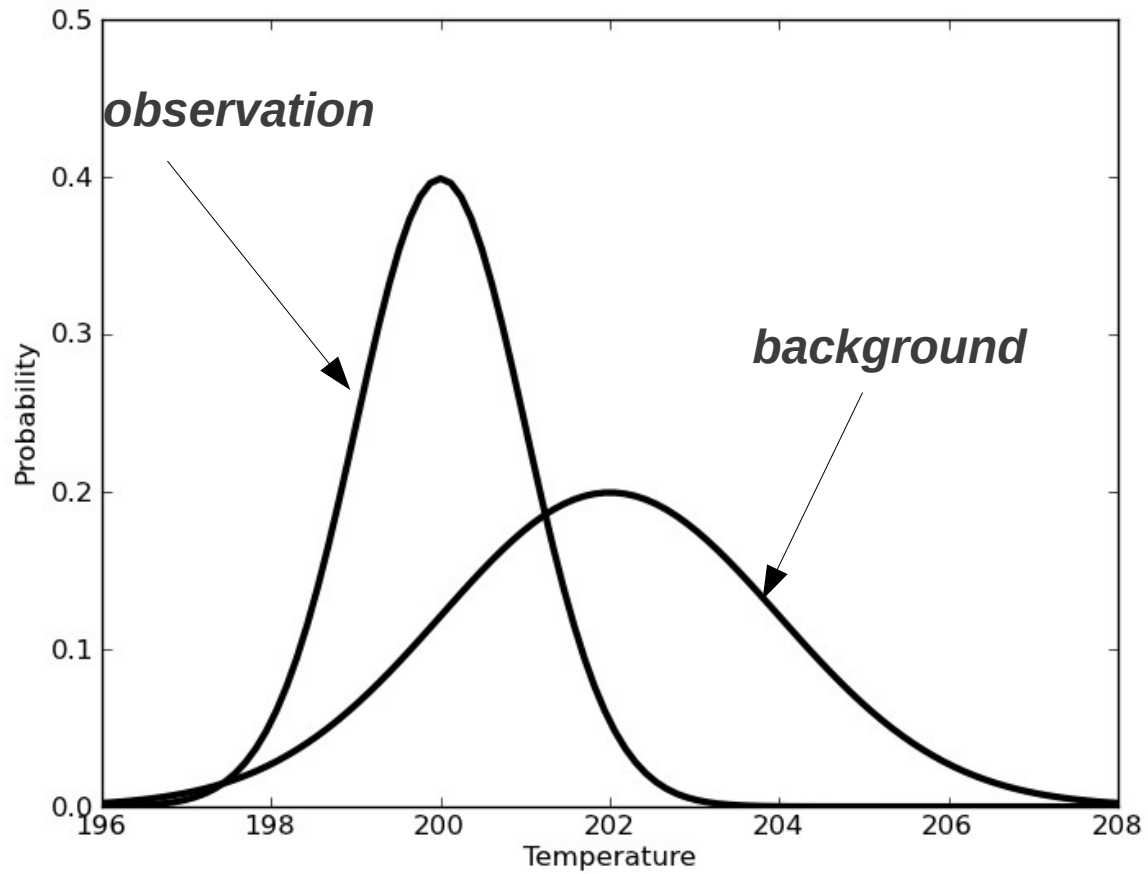
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- **Optimal interpolation** of observations, taking into account their **errors**, with the help of a **model**.
- Usually, **more confidence in observations vs. more data points in a model.**
- Two advanced techniques for chaotic systems: ensemble methods or variational methods

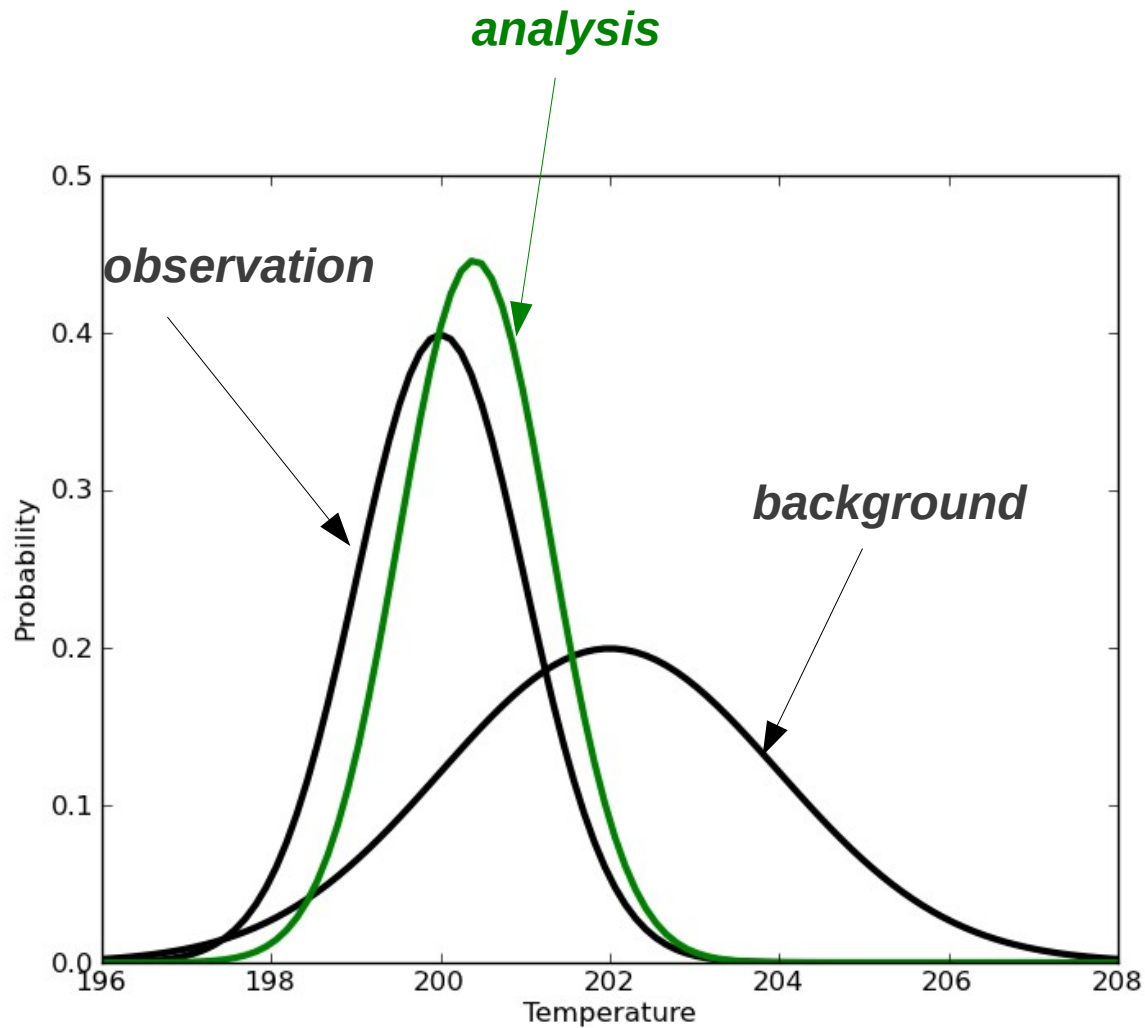
# Simple exemple



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$$T_a = T_b + k(T_o - T_b)$$

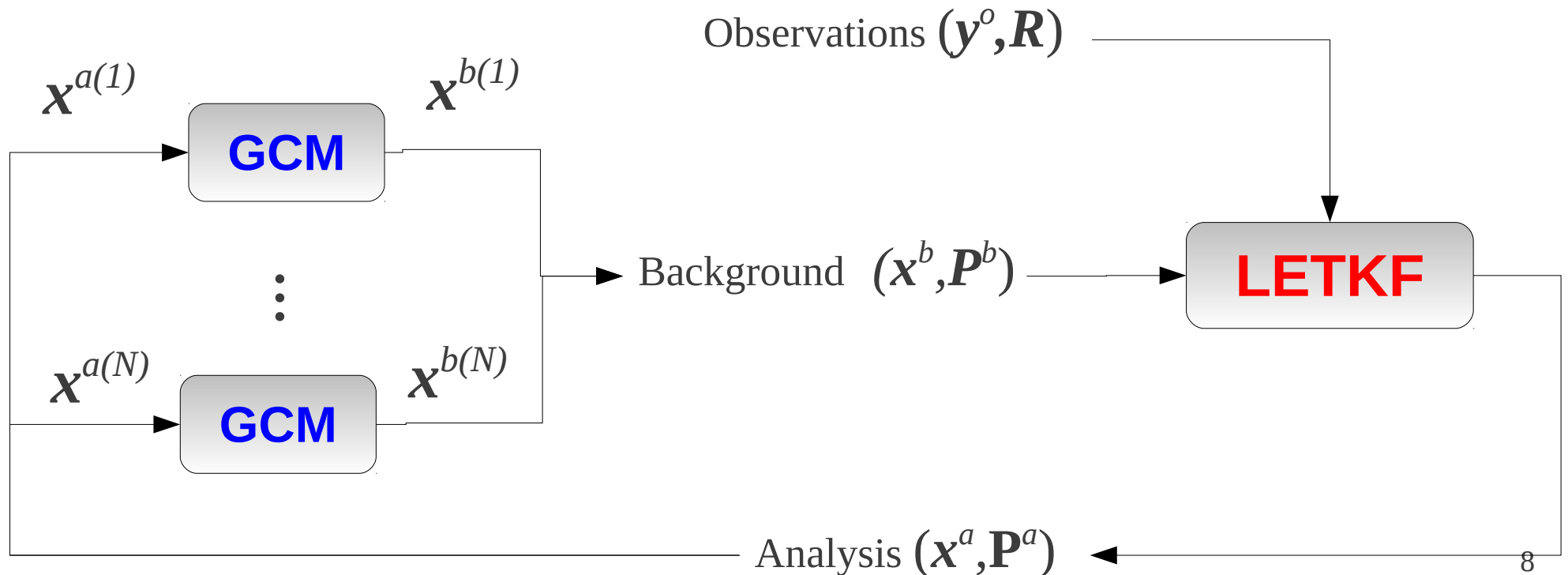
$$\text{with } k = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2}$$

$$\frac{1}{\sigma_a^2} = \frac{1}{\sigma_b^2} + \frac{1}{\sigma_o^2}$$

# Atmospheric assimilation

- $\mathbf{x}$  atmospheric state vector
- $\mathbf{y}^o$  vector of observations
- $\mathbf{P}$  atmospheric covariance matrix
- $\mathbf{R}$  error covariance matrix of observations

Typical numbers :  
~ 20 members  
State vector size :  $10^5$   
Cycle length : 6 hours  
Spin-up : ~ 5 days





# What is LETKF ?

*LETKF* is developed at University of Maryland. It is used today with numerous geophysical models.

## Local

Only observations within a certain distance are considered.

## Ensemble

An *ensemble* of GCM forecasts is used to estimate the mean state and its covariance.

## Transform

Square-root filter

## Kalman Filter

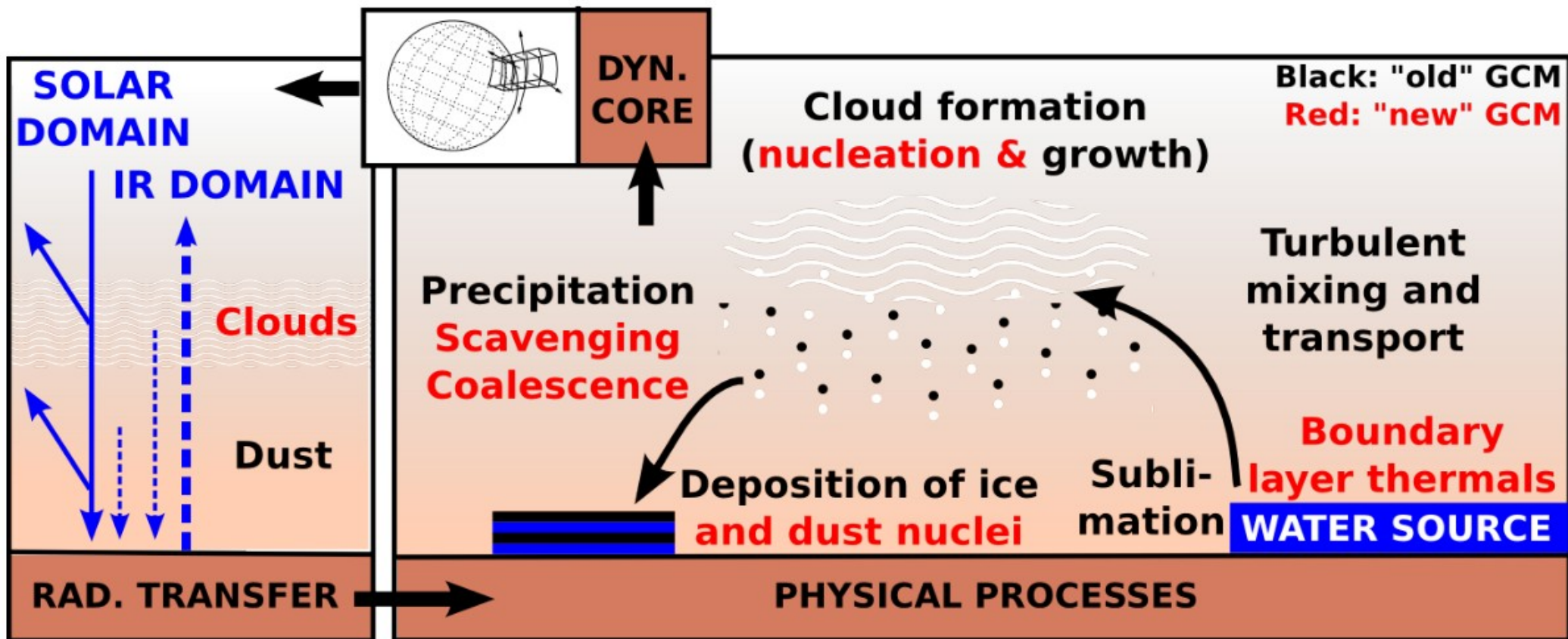
A filter uses past information to update the present state

A Kalman filter estimates both the state and its uncertainty (via its covariance)

# LMD Mars Global Climate Model

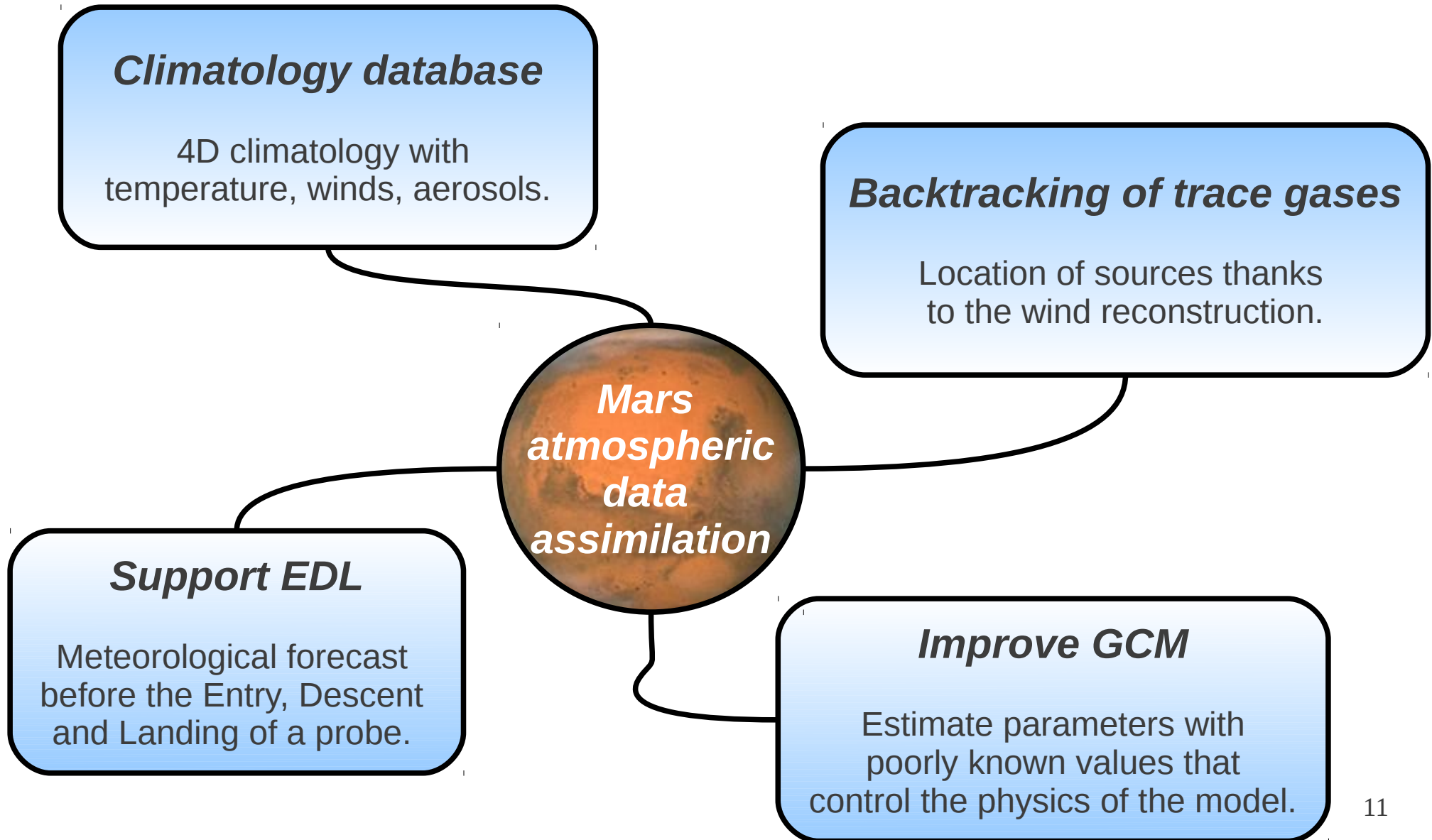
A complete model including dust, water, clouds and CO2 cycle.

Also : Photochemistry model, extension to the thermosphere

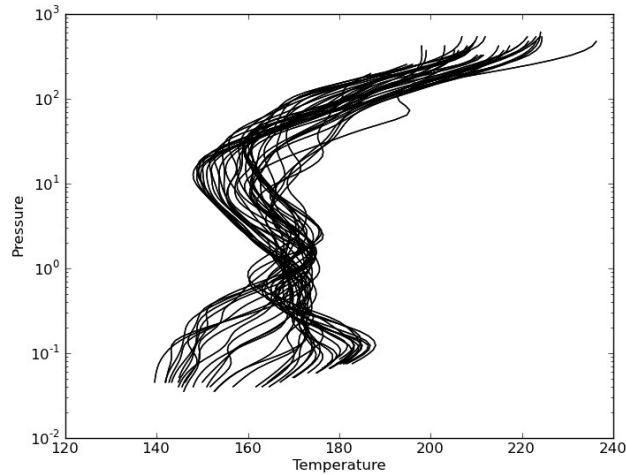


Courtesy of J.-B. Madeleine

# LMD Science goals

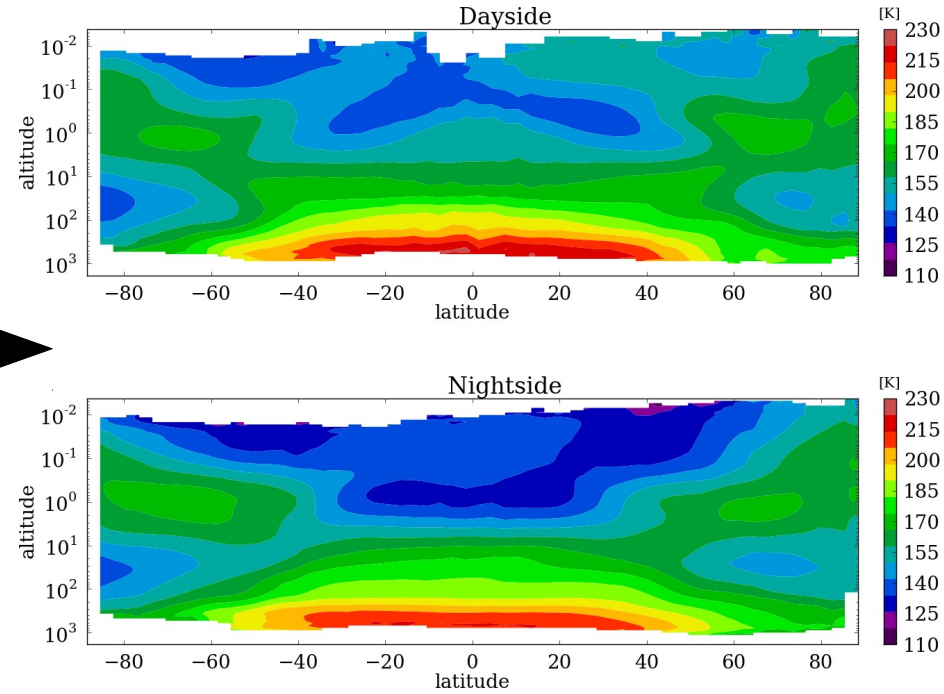


# Sun-synchronous orbit (MRO)



*Vertical profiles*

Straightforward



**TWO LOCAL HOURS** Climatology



# TGO local time

[MARS] ExoMars/TGO

Orbit - Ground track

Recurrence = [12;+02;227] 2818

>>>> Time span shown: 4438.6 min = 3.00 sols

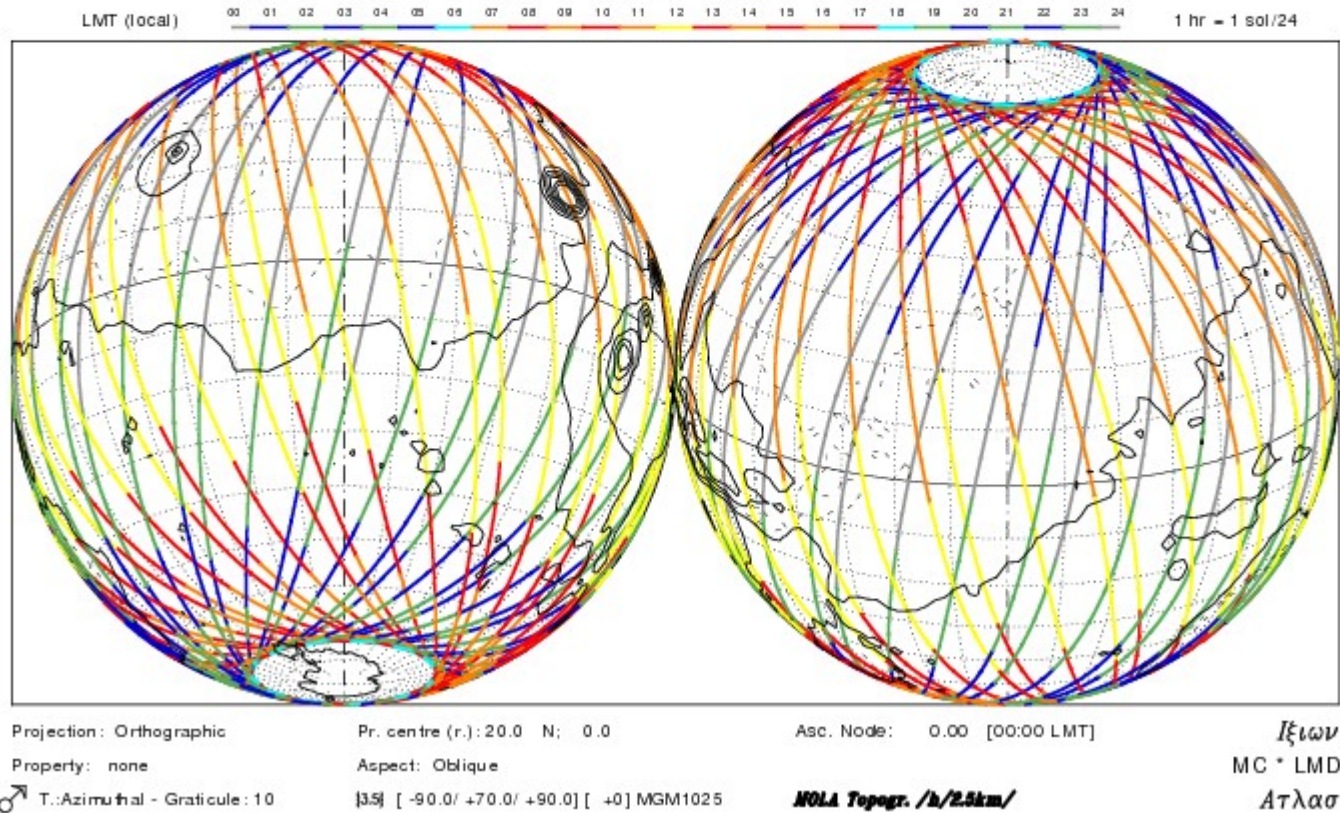
Altitude = 391.1 km

a = 3788.060 km

Inclination = 74.04

Period = 118.17 min \* rev/sol = 12.52

Equat. orbital shift = 1720.9 km ( 29.0 deg)



*Ixion software:*

<http://climserv.ipsl.polytechnique.fr/ixion.html>

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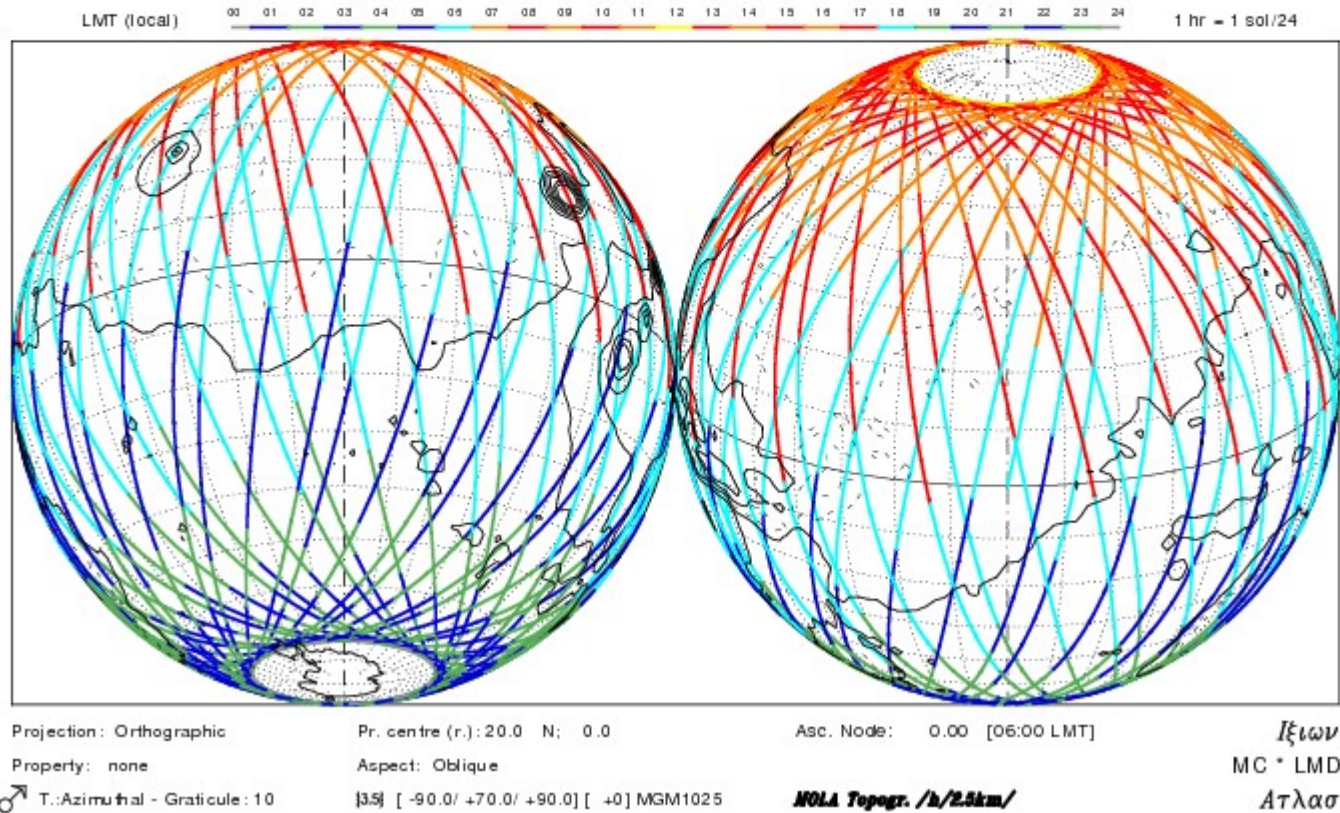
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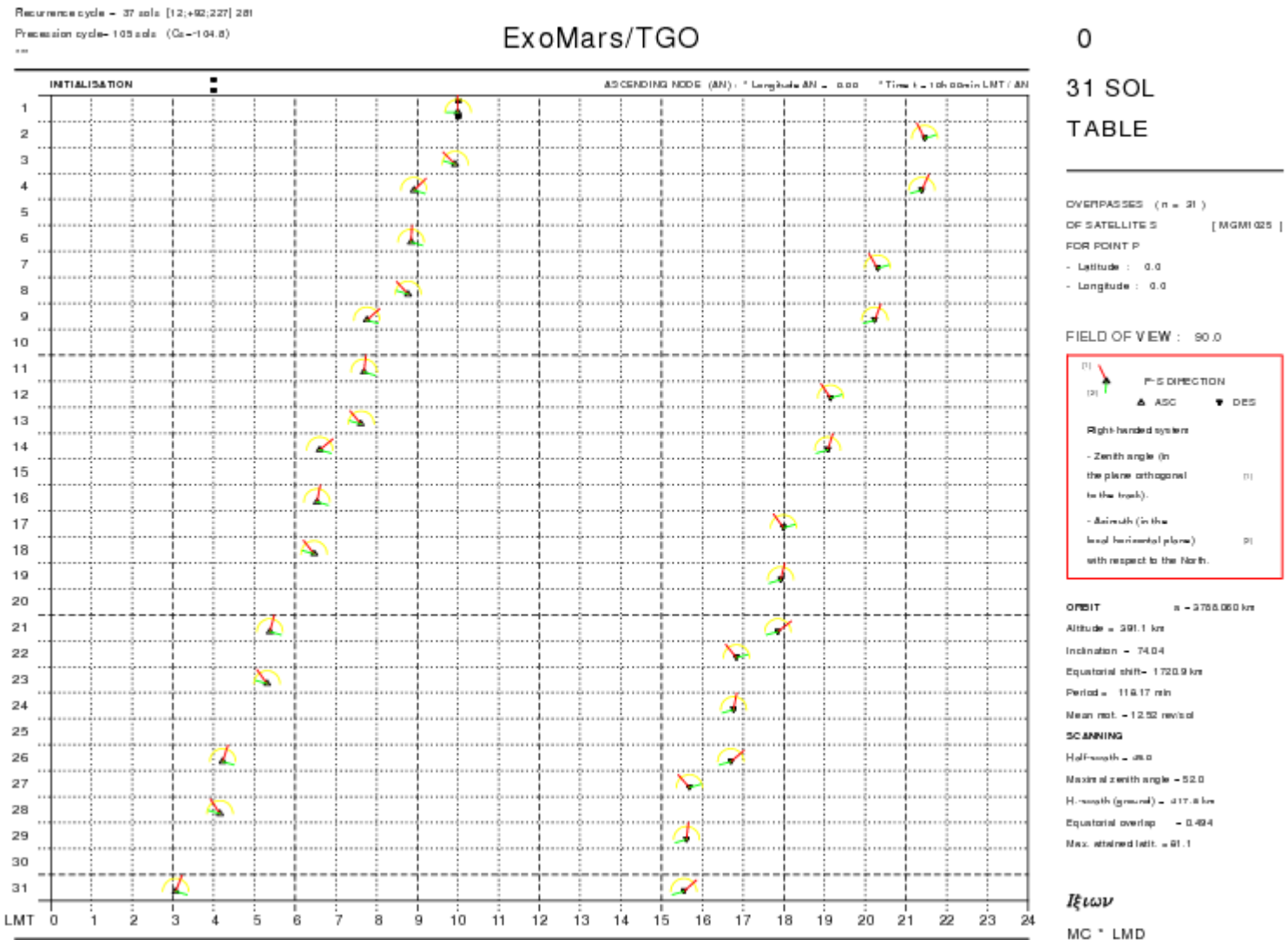
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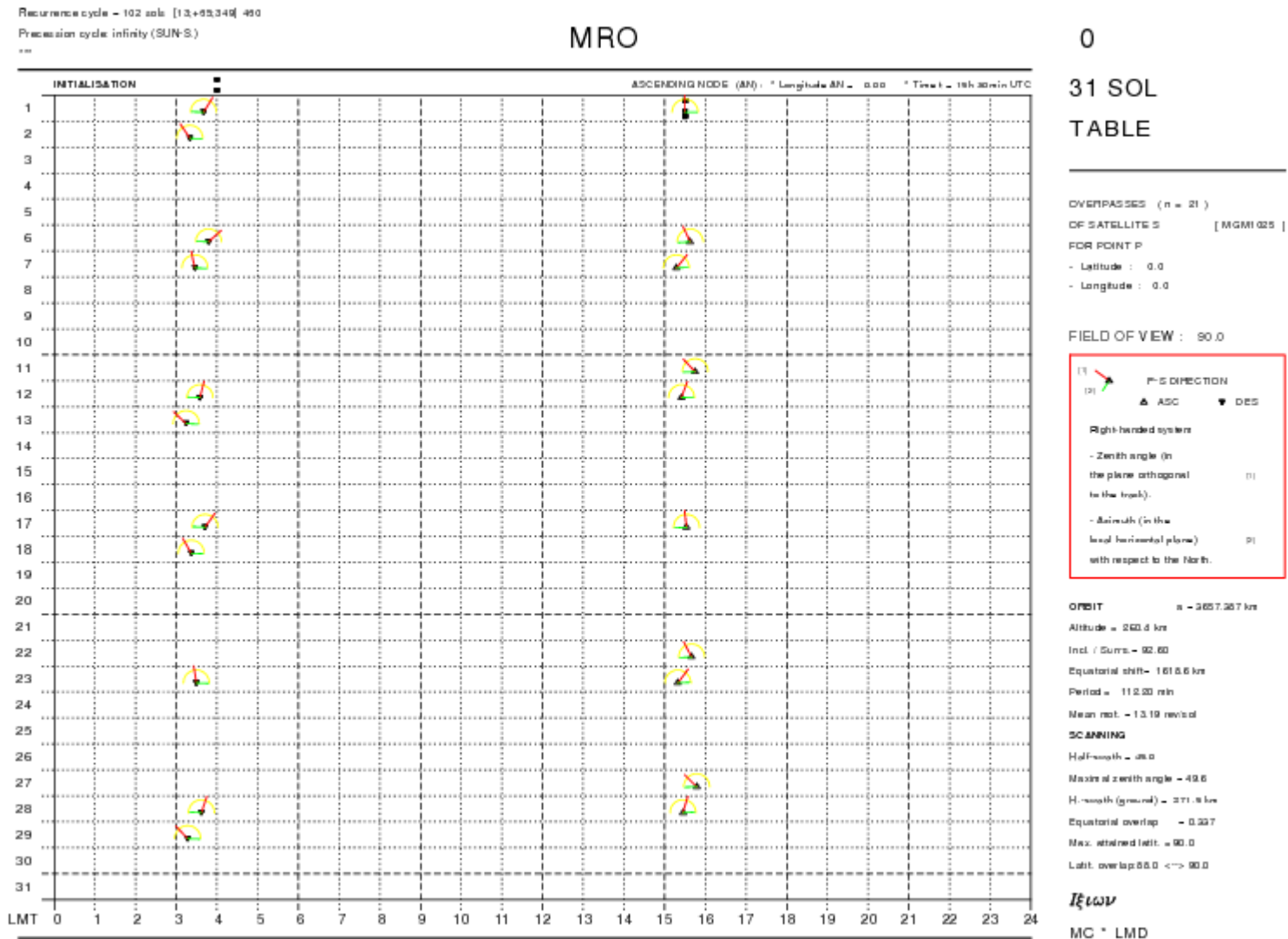
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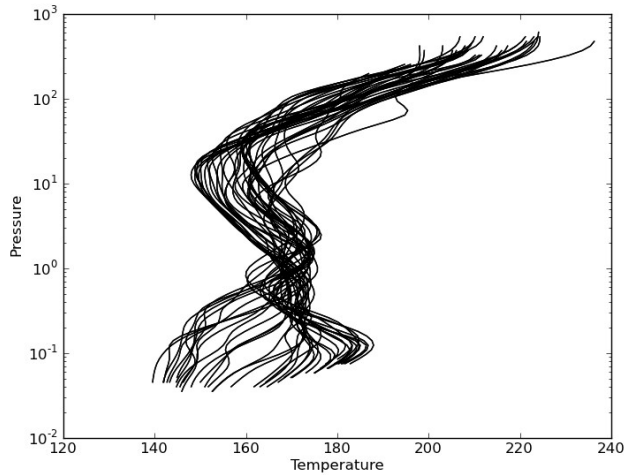


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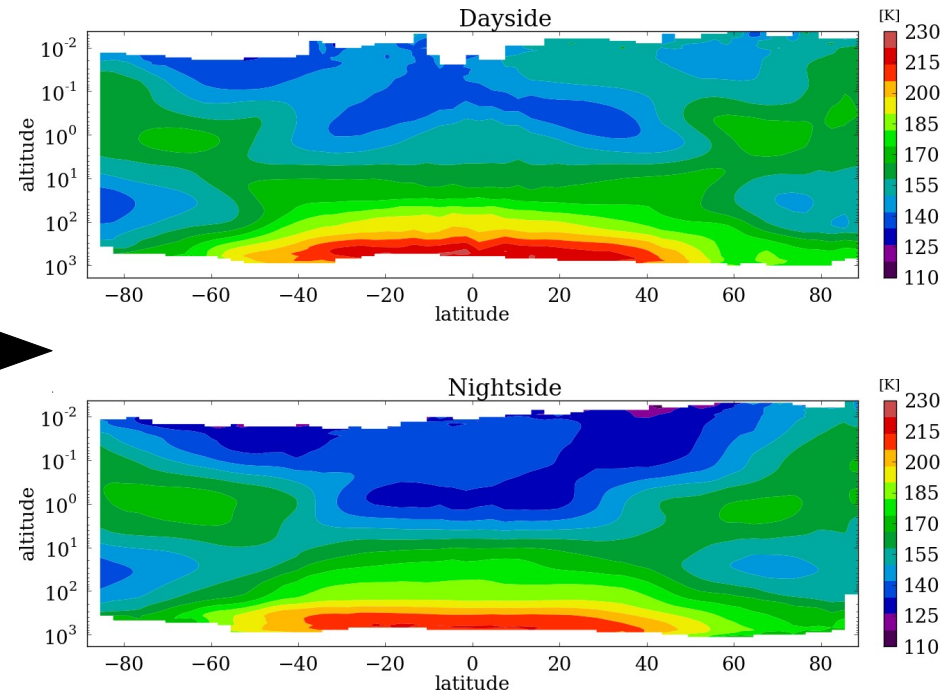


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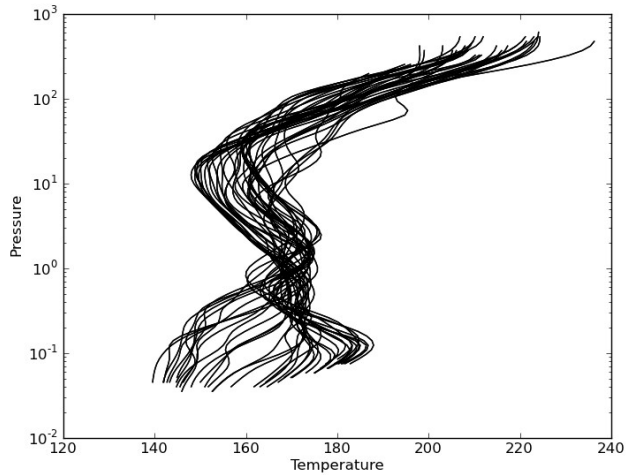
*Vertical profiles*

Straightforward



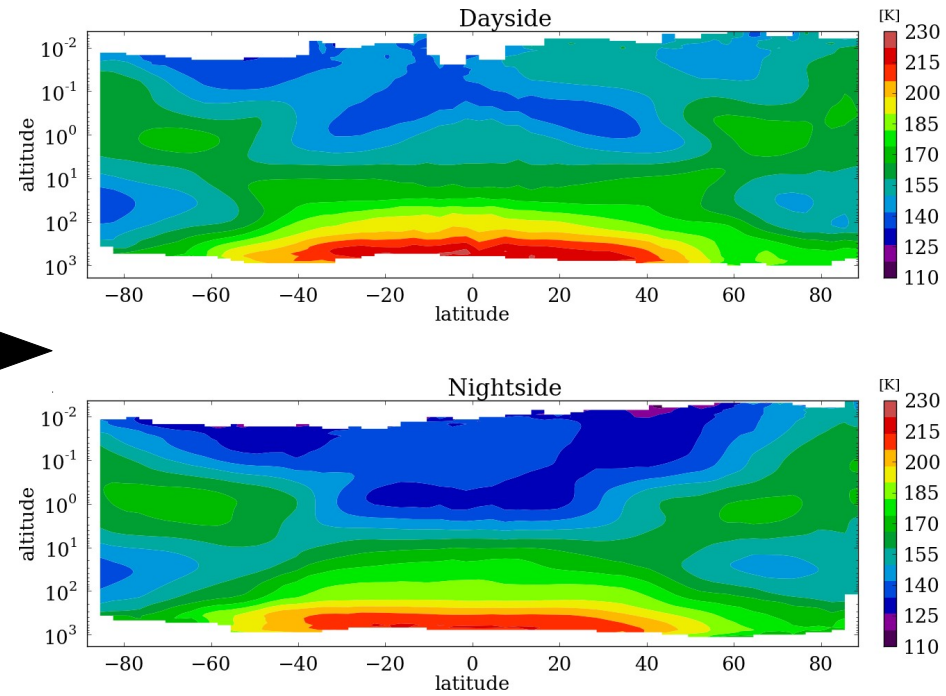
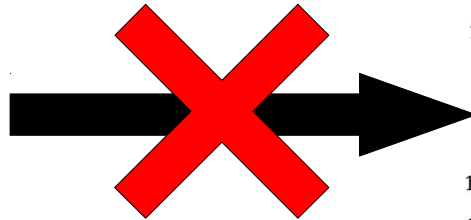
**TWO LOCAL HOURS** Climatology

# Not sun-synchronous (TGO)

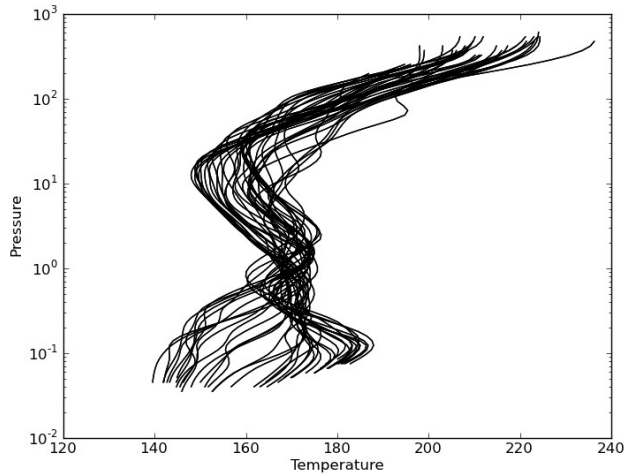


*Vertical profiles*

Not adapted

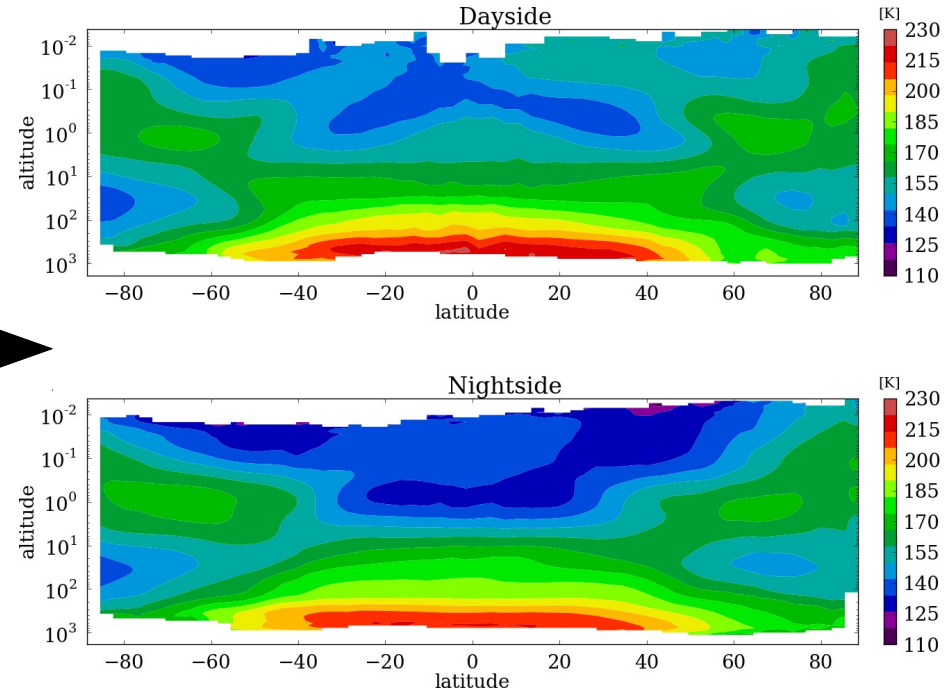
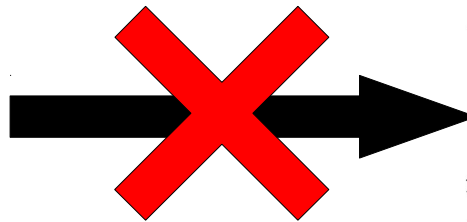


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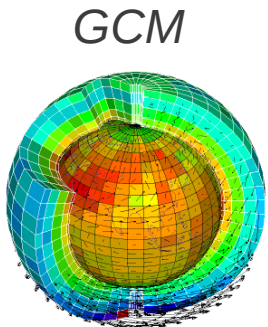


*Vertical profiles*

Not adapted



**GLOBAL 4D** *Climatology*



Data Assimilation

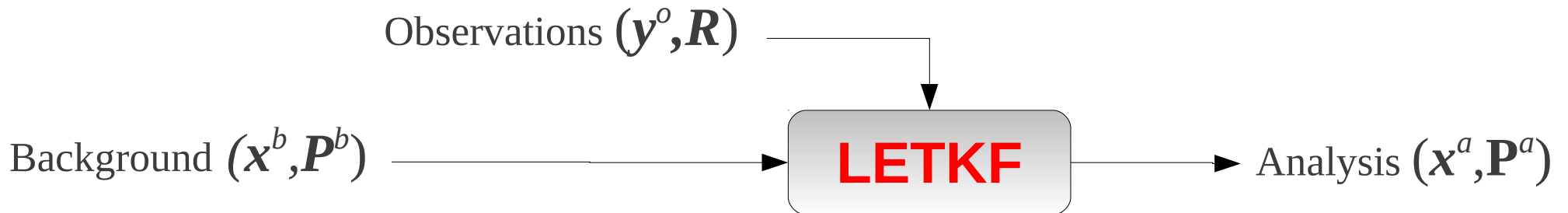
# *Near-Real Time* « Analysis »

- Winds reconstruction for **retro-transport** of observed trace gases
- Profiles of temperature, density, dust, etc ... at night/day interface for **solar occultations**

# Roadmap

- Coupling of LMD Mars GCM with University of Maryland's LETKF
- Assimilation of MCS and PFS temperatures
  - Validation by radio-occultations
- Assimilation of MCS dust and ice profiles
- Assimilation of MCS/PFS radiances ?
  - Preparation of near real-time assimilation of ACS data
    - temperature, dust, water ice from TIRVIM
    - water vapor, water ice (?), dust (??) from NIR

# How can we use observations ?

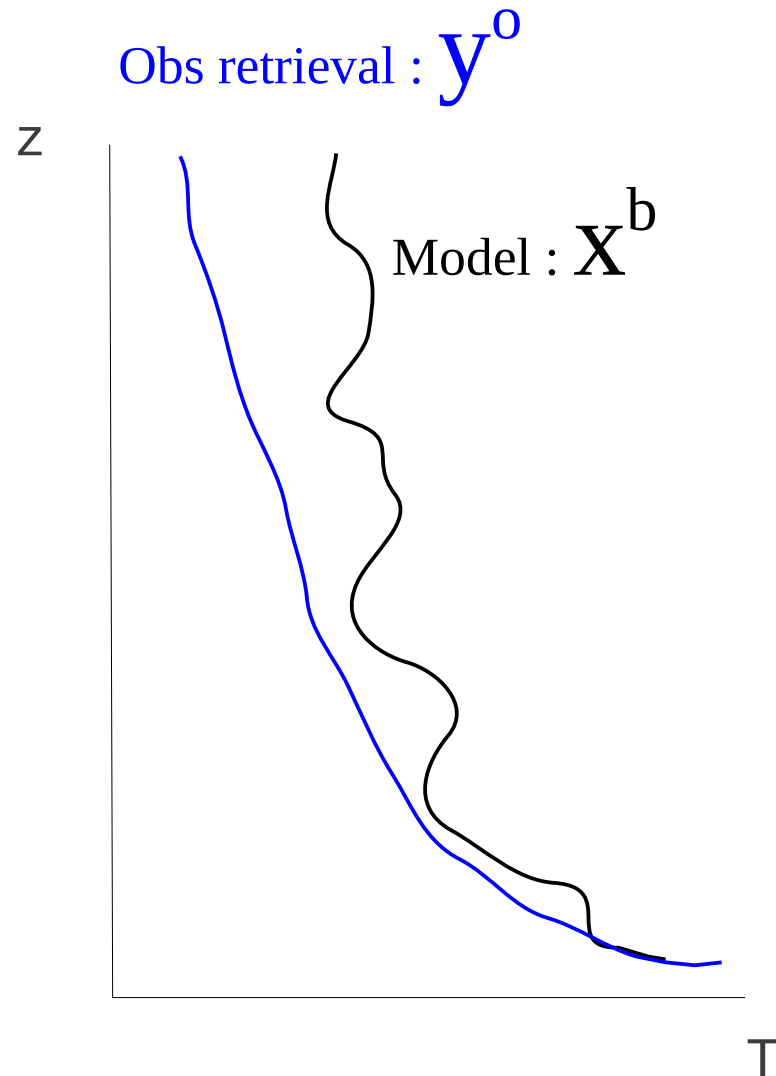


- We need to compare the same quantities

$$\mathbf{y}^b = H(\mathbf{x}^b)$$

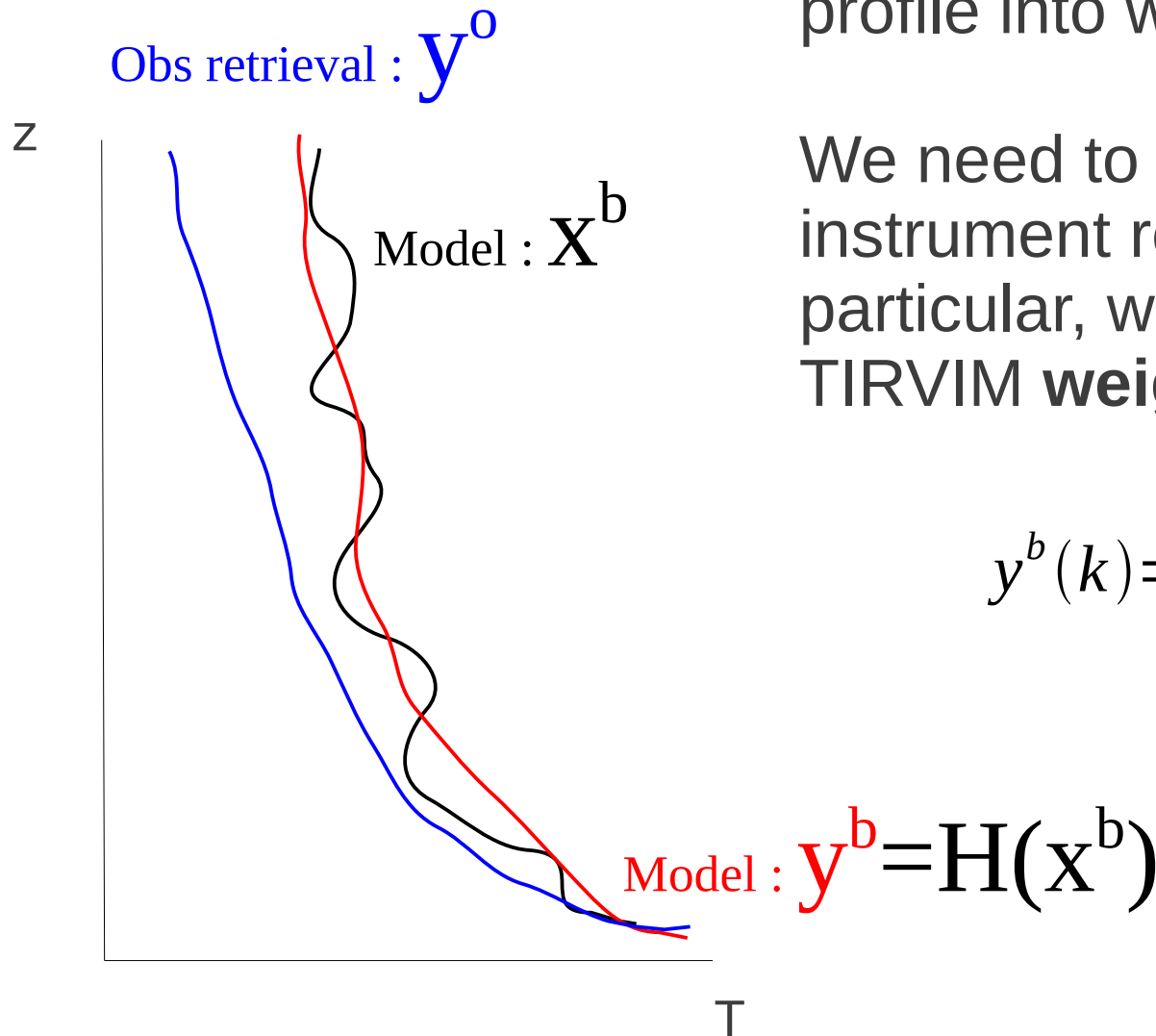
- Two possibilities for vector of observations  $\mathbf{y}^o$ 
  - 1) Atmospheric retrievals
  - 2) Instrument radiances

# 1) Atmospheric retrievals



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H transforms a GCM « real » profile into what ACS would see.

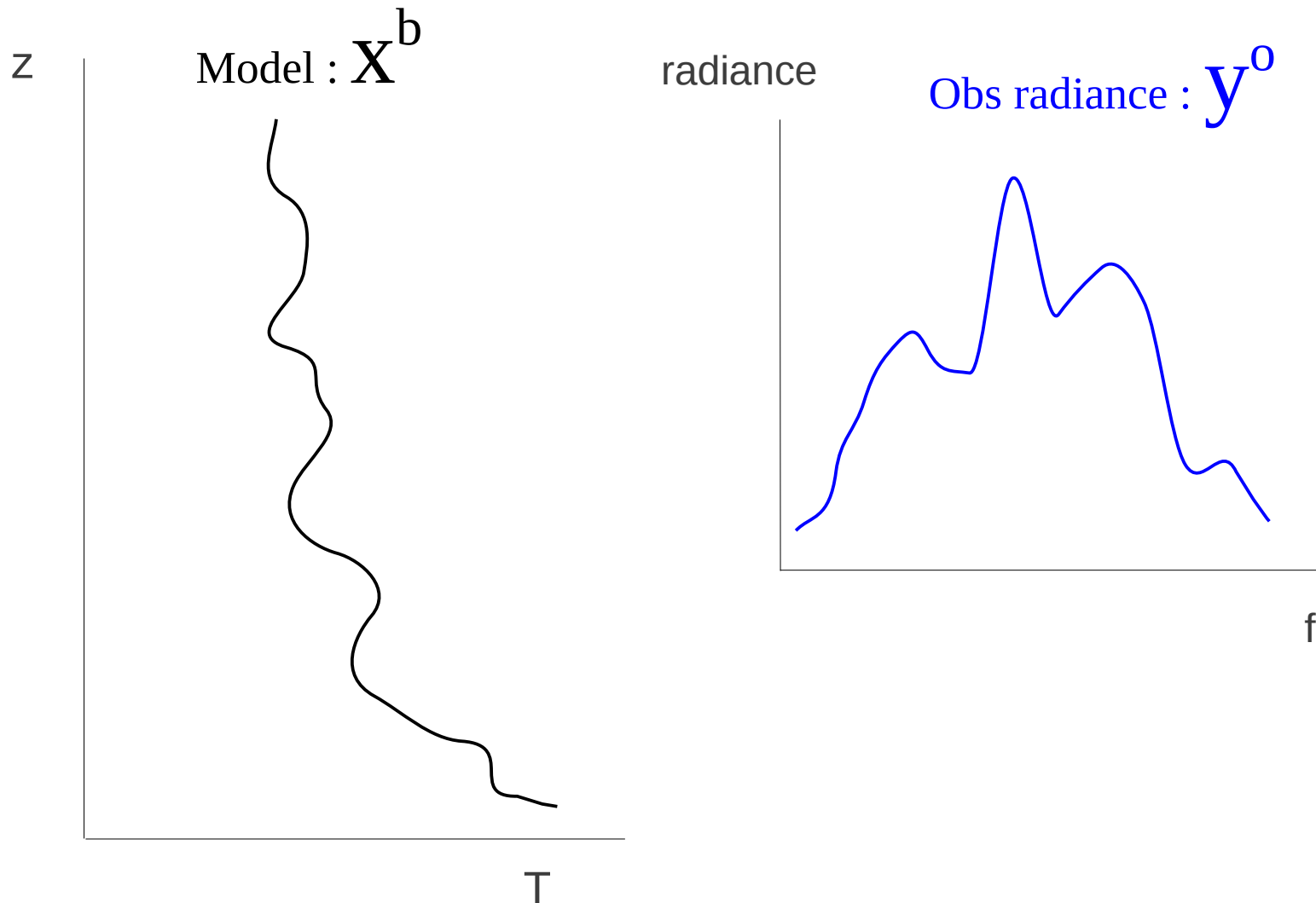


We need to simulate the instrument response, and in particular, we need to use the **TIRVIM weight functions** :

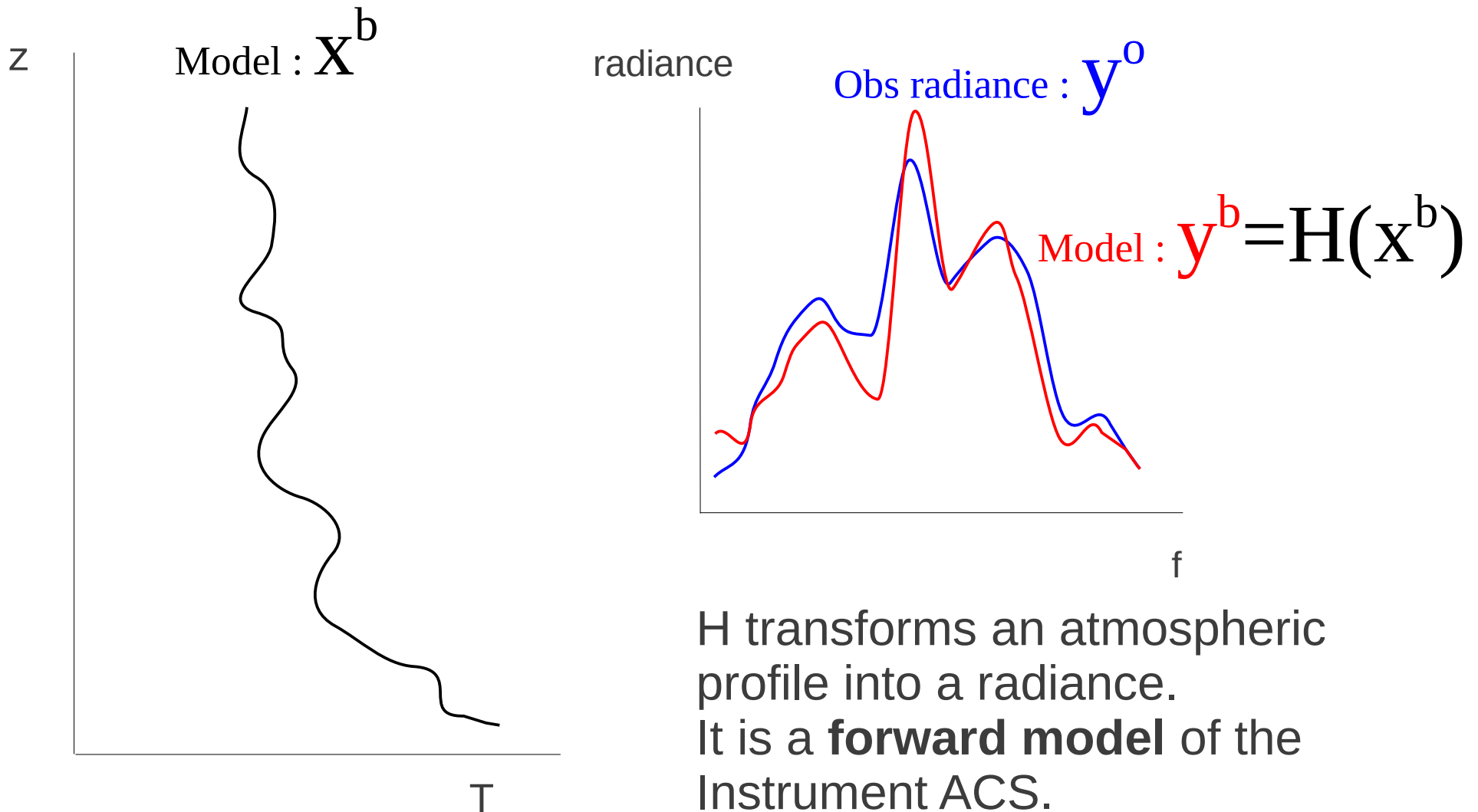
$$y^b(k) = \sum_i w_i(x^b)$$



## 2) Instrument radiances



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# Radiance vs Retrievals assimilation

- **Retrievals**

- Easier to implement, because the observational operator  $H$  **does not require a forward model.**

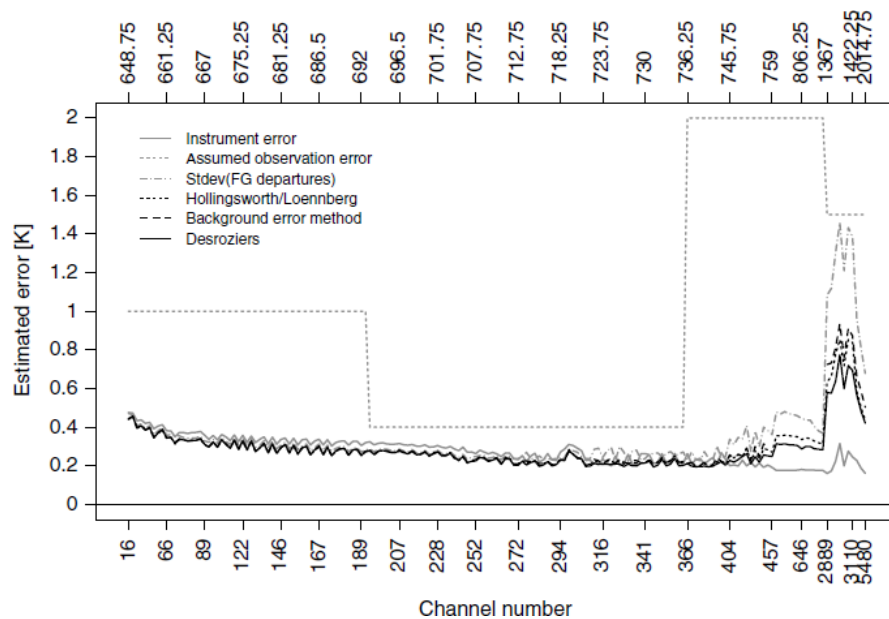
- **Radiance**

- Better performance, because there is **no vertical correlation** and a **better error constraint.**

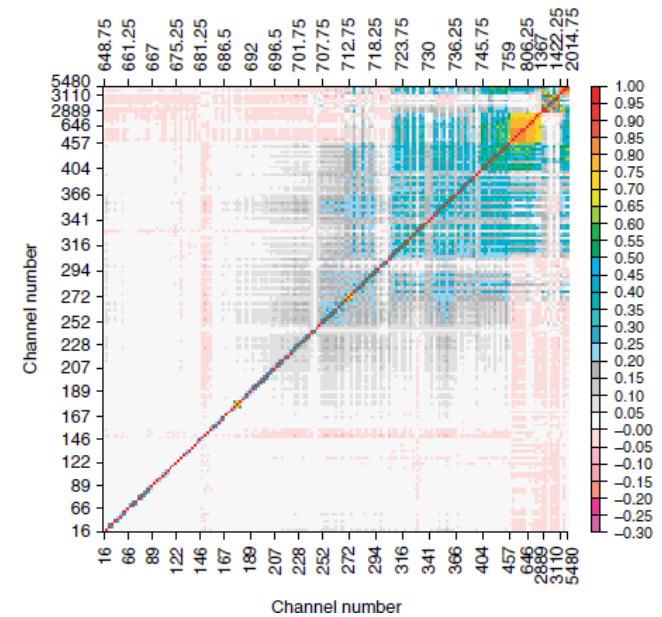
*Experience for Earth shows that radiance assimilation greatly improve results. Experience on Mars shows it is very difficult [Lee et al, 2011].  
We will do it for dust & ice first, then possibly temperature.*

# Observation errors

One can estimate **observations errors** and **correlations** using the statistics of the innovation vector ( $y^o - y^b$ )



Estimation of Observation error of IASI channels  
*Bormann et al, 2010*



Estimation of IASI channel correlation matrix  
*Bormann et al, 2010*

# Conclusion : for a successful data assimilation...

## 1 A good model for the atmosphere

- **Modeling of aerosols is critical** for temperature and global circulation!
  - Dust lifting and transport
  - Water ice clouds

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## 2 A good data assimilation technique

- A team dedicated to LETKF, large community in data assimilation, long experience for the Earth ...
- ... but **Mars is not the Earth!**
  - Local analysis?
  - Mars atmospheric flow is less chaotic : not enough variability, but evolution of dust & ice induce a specific « Martian variability »

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## 3 A good instrument with well specified observation errors

- The orbit is awesome for assimilation
- Possibility to estimate errors
- **A forward model would improve the analysis**

**→ We look forward to a close collaboration  
with the ACS instrument team**