Exploring the Weather on Mars by Data Assimilation: An Overview

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Contributors

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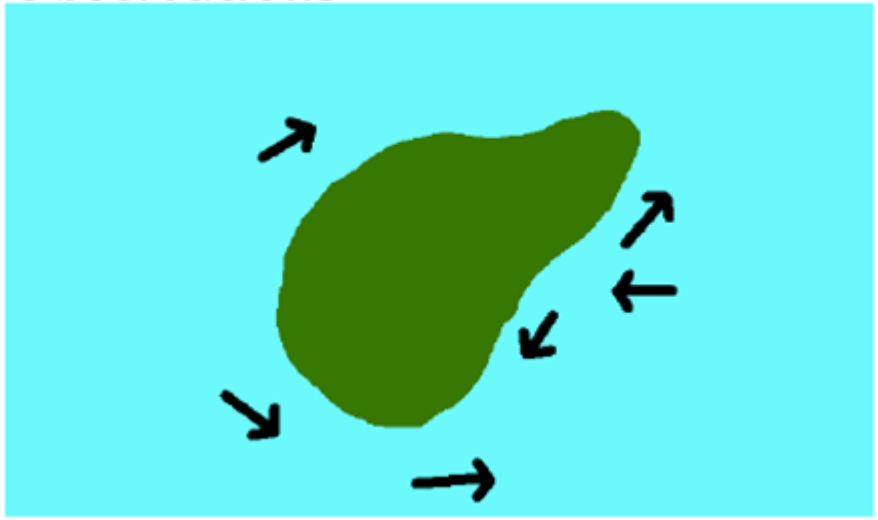
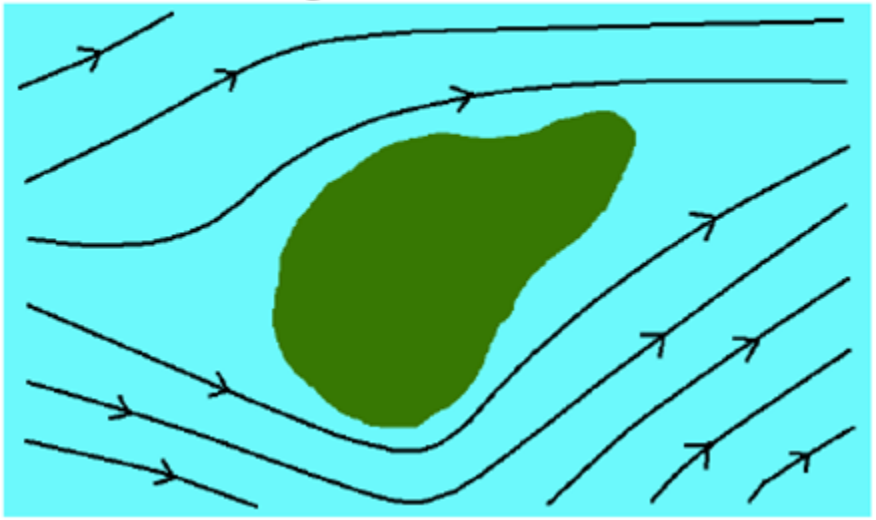
CPS workshop -4th February 2013

Basic principle

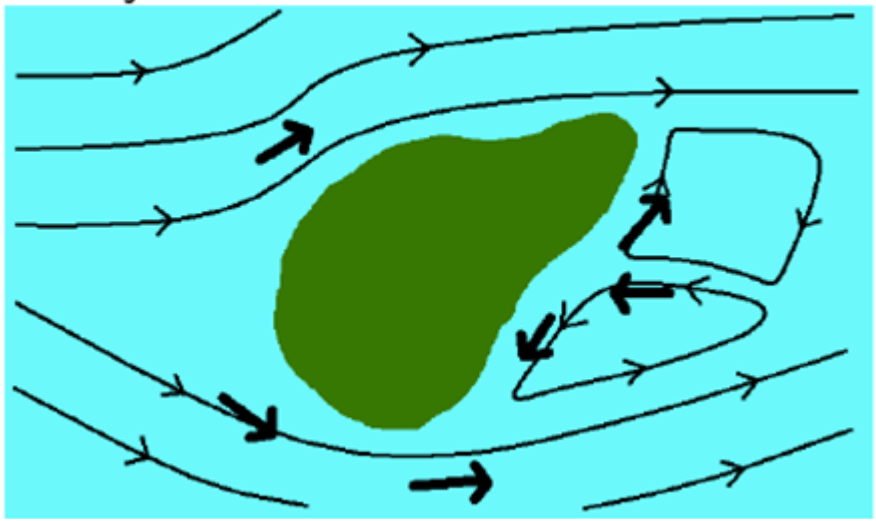
Observations



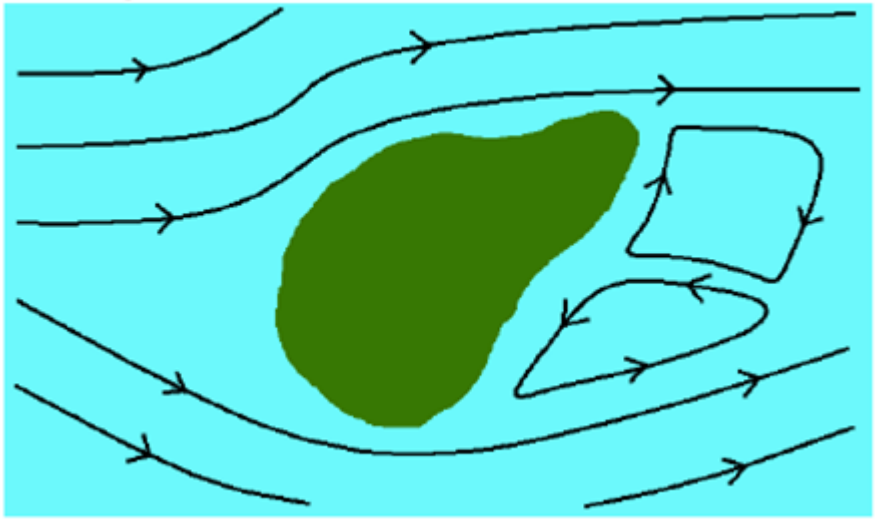
Free-running model



Analysis with observations



Analysis



Courtesy of R. Young, Univ. of Oxford

Objectives

Data Assimilation aims to:

- Produce a **regular, physically consistent, four dimensional** representation of the state of a system
  - from a **heterogeneous** array of in situ and remote instruments which sample **imperfectly** and **irregularly** in space and time
  - e.g. to initialize a model prediction/forecast
- Enable **reconstruction of state variables** that are not measured directly
  - Accessing data-sparse areas
- Identify and characterize systematic **model errors and biases**
  - from statistics of misfit to measurements

Strategies

DA has its origin in:

- **(Least square) curve fitting**
  - Given a "model" $y = M(x;a,b) := ax + b$ and observations (x_i, y_i), $i = 1,\ldots,M$, the optimal estimate of model parameters a, b is provided by minimizing: $\mathrm{J} = \sum_i (y_i - (ax_i + b))^2$
- **Bayes' theorem**
  - Given inexact and incomplete observations **y** and a deterministic model **M** connecting **x** and **y**, the probability of state **x**, given **y** and **M** is:

$$\mathrm{prob}(\mathbf{x}\,|\,\mathbf{y},\mathbf{M}) = \frac{\mathrm{prob}(\mathbf{y}\,|\,\mathbf{x},\mathbf{M})\,\mathrm{prob}(\mathbf{x}\,|\,\mathbf{M})}{\mathrm{prob}(\mathbf{y}\,|\,\mathbf{M})}$$

Posterior | Prior | Support of y to x

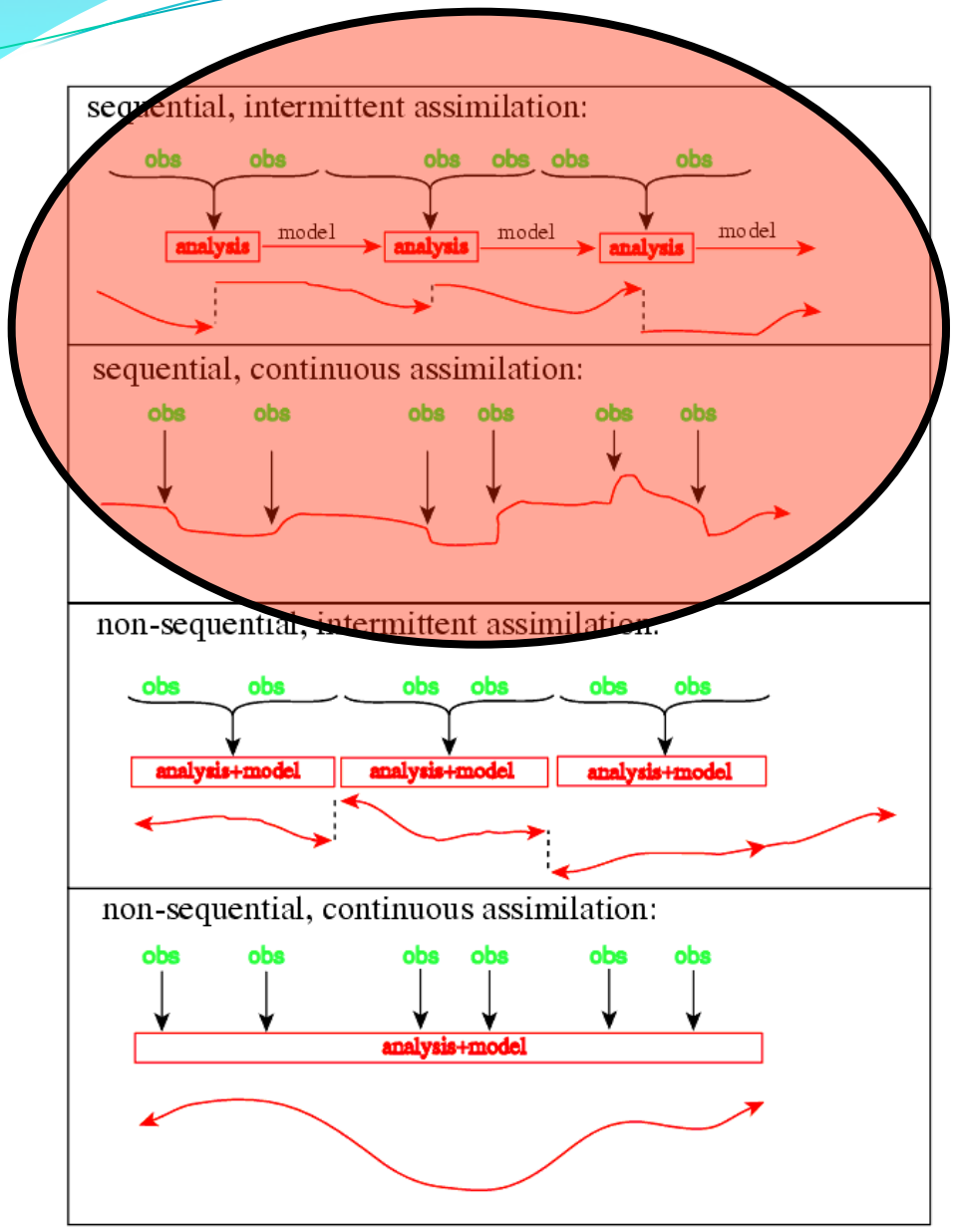
  - The optimal estimate of state **x** is provided by maximizing prob

Strategies

Several Categories of DA Strategies:

- **Sequential** (or "real time")
  - Treats measurements in chronological order or from the past & present only
- **Non-sequential**
  - Can use measurements from both past, present and future
- **Intermittent**
  - Produce analysis at coarsely discrete intervals
- **Continuous**
  - Assimilates measurements when they become available

Strategies



real time assimilation

complexity

non-linear methods

(4D-Var or) 4D-PSAS with model error

EKF

intermittent 4D-Var or 4D-PSAS

3D-Var or 3D-PSAS

Optimal Interpolation (OI)

Cressman Successive Corrections nudging

Interpolation of observations

Strategies

DA general strategy:

- General form of sequential estimator: $\mathbf{x}_a = \mathbf{x}_b + \mathbf{W}(\mathbf{y} - \mathbf{H}[\mathbf{x}_b])$
  - $\mathbf{x}_a$ - Analysis
  - $\mathbf{x}_b$ - Background or *a priori* (e.g. earlier model prediction)
  - $\mathbf{y}$ - Observations
  - $\mathbf{W}$ - Matrix of weights
  - $\mathbf{H}$ - Observation operator
- Other useful quantities
  - $\mathbf{x}_t$ – True state
  - $\mathbf{B}$ – Covariance of background errors $(\mathbf{x}_b - \mathbf{x}_t)$
  - $\mathbf{R}$ – Covariance of observation errors $(\mathbf{y} - \mathbf{H}[\mathbf{x}_t])$
  - $\mathbf{A}$ – Covariance of analysis errors $(\mathbf{x}_a - \mathbf{x}_t)$

Strategies

DA general strategy:

- The "Best Linear Unbiased Estimator" (BLUE) analysis (or "optimal interpolation" analysis) is the state $\mathbf{x}_a$ which minimizes the cost function:

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

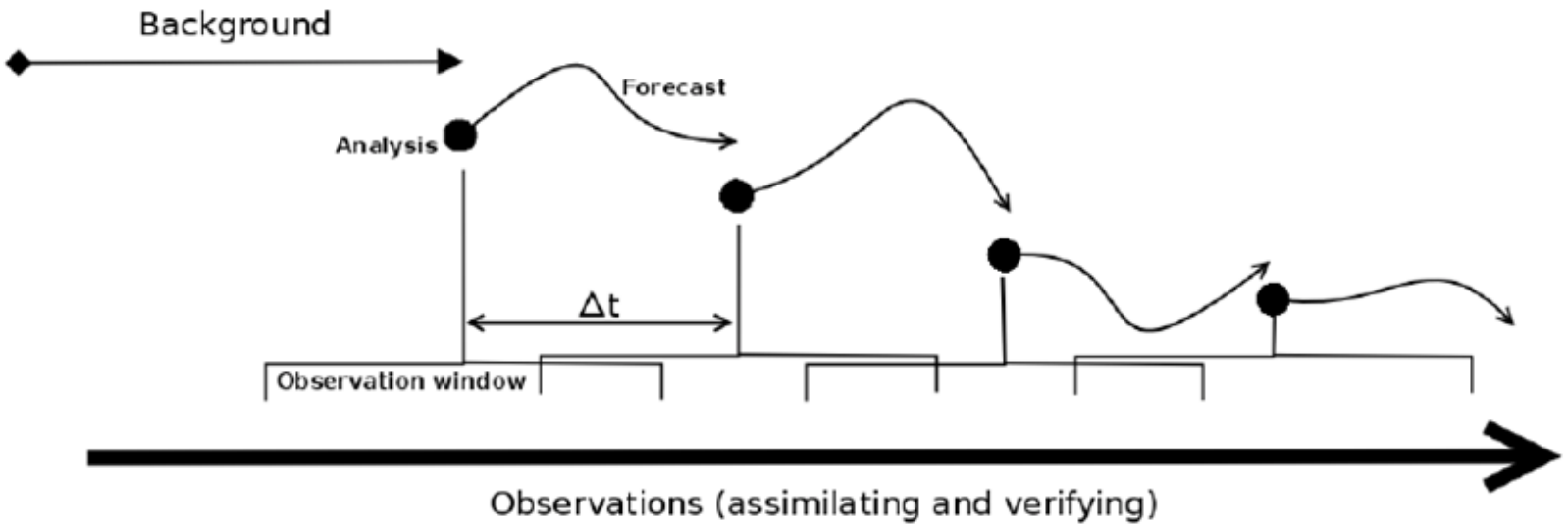
- If background and observation errors are Gaussian, then $\mathbf{x}_a$ is a "maximum likelihood estimator".
- Different sequential schemes compute/approximate covariances and PDFs in distinctive ways:
  - **Ensemble Kalman Filter** – Estimates covariances by a Monte Carlo ensemble of perturbed model simulations
  - **3D-Var** – Avoids computing weights by iteratively minimising $J(\mathbf{x})$ *(at fixed time)*: $\nabla J(\mathbf{x}) = 2\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) - 2\mathbf{H}^T \mathbf{R}^{-1}(\mathbf{y} - \mathbf{H}[\mathbf{x}])$
  - **4D-Var** – Iteratively minimises $J(\mathbf{x})$ evaluated over a finite time interval

Analysis Correction

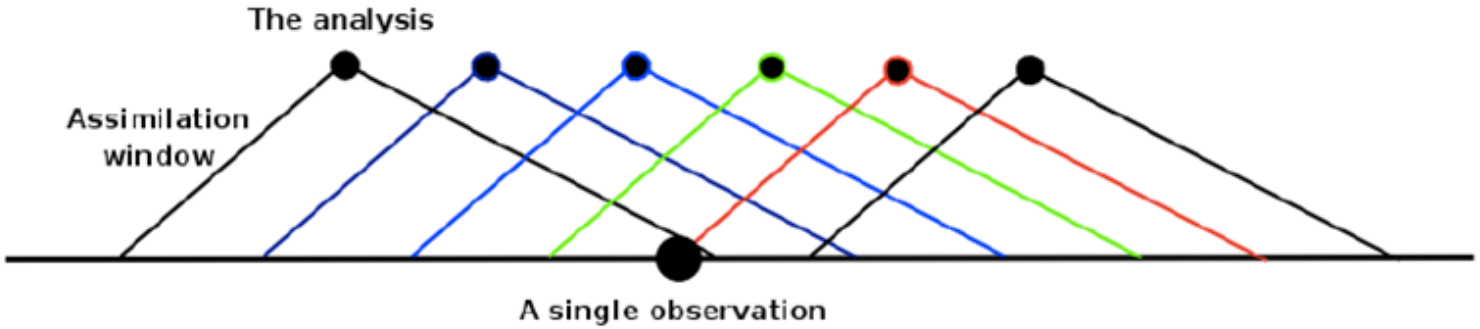
- A pragmatic approach to data assimilation, used by the UK Met Office (1988-1999) and developed by Lorenc et al., 1991.
- Take first guess ('background') field: $\mathbf{x}[0]=\mathbf{x}_b$ & observations $\mathbf{y}[0]=\mathbf{y}_o$
- Use iterations $$\mathbf{x}(n+1) = \mathbf{x}(n) + \mathbf{W}\tilde{\mathbf{Q}}[\mathbf{y}(n) - \mathbf{H}[\mathbf{x}(n)]]$$
  - $\mathbf{W}$ – Matrix of weights (assumed diagonal) based on distance between model points and observations
  - $\tilde{\mathbf{Q}}$ – Normalisation, based on observation density & error statistics
  - $\mathbf{x}(n) \rightarrow \mathbf{x}_a$ (BLUE) as $n \rightarrow \infty$

Analysis Correction

The analysis cycle



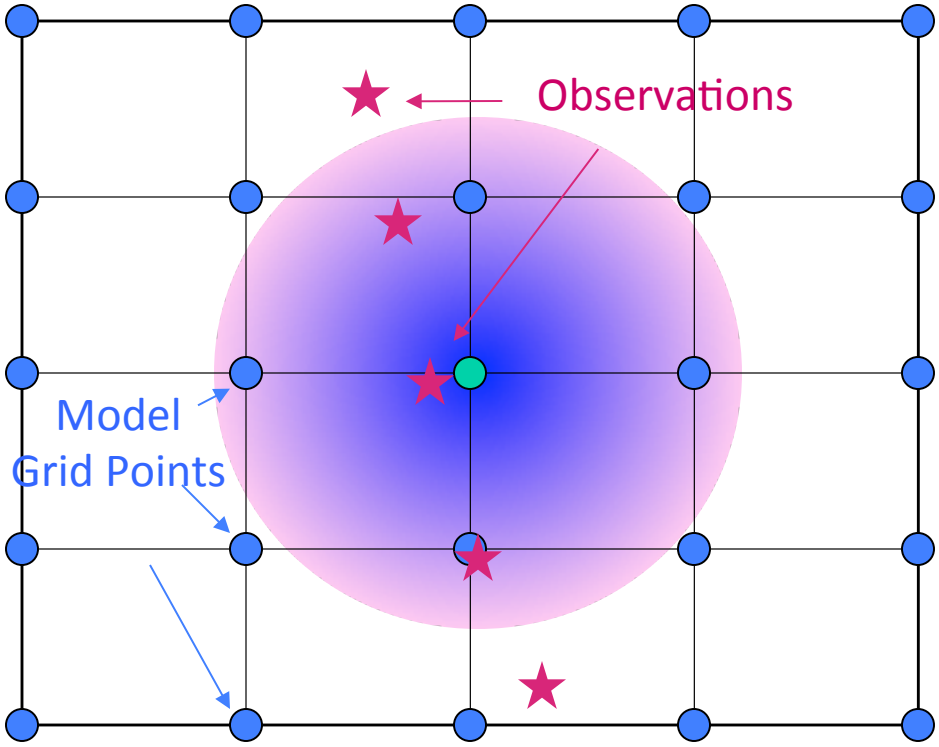
Repeated insertion



Courtesy of R. Young, Univ. of Oxford

Analysis Correction

Goal: find analysis ($\mathbf{x}_a$) at each model grid point



- Analysis at a given grid point: background at that point ($\mathbf{x}_b$) plus a weighted sum (W) of observation increments ($\mathbf{y}$-$\mathbf{H}[\mathbf{x}_b]$) within a localization radius.
- Analysis increment at a given grid point is based on only one realization.
- Background, or forecast, errors are usually deterined a priori and might or might not evolve with the flow.

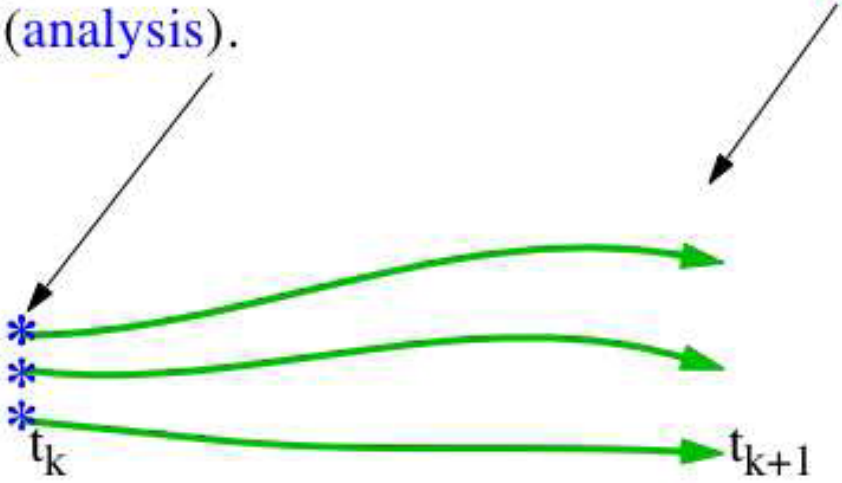
Ensemble Kalman Filter

How an Ensemble Filter Works for Geophysical Data Assimilation

1. Use model to advance ensemble (3 members here) to time at which next observation becomes available.

Ensemble state estimate after using previous observation (analysis).

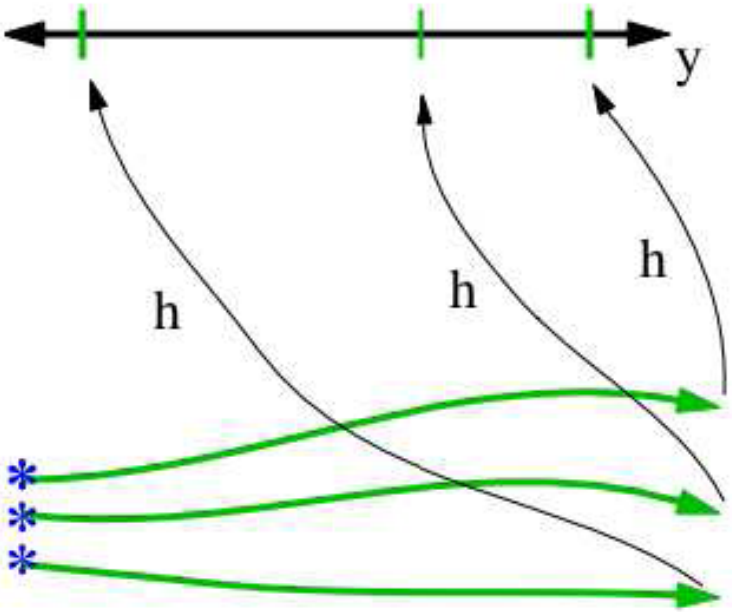
Ensemble state at time of next observation (prior).



Ensemble Kalman Filter

How an Ensemble Filter Works for Geophysical Data Assimilation

2. Get prior ensemble sample of observation, y=h(x), by applying forward operator h to each ensemble member.

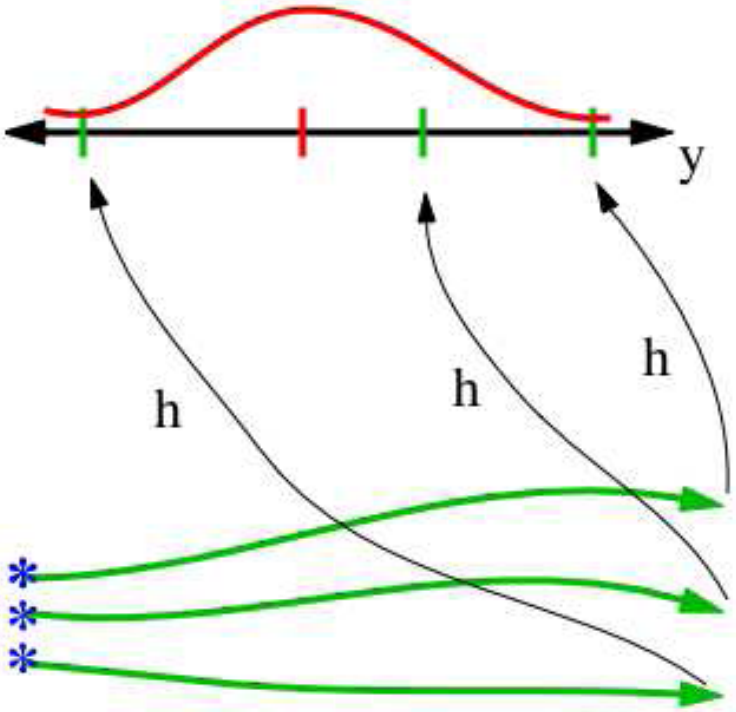


Theory: observations from instruments with uncorrelated errors can be done sequentially.

Ensemble Kalman Filter

How an Ensemble Filter Works for Geophysical Data Assimilation

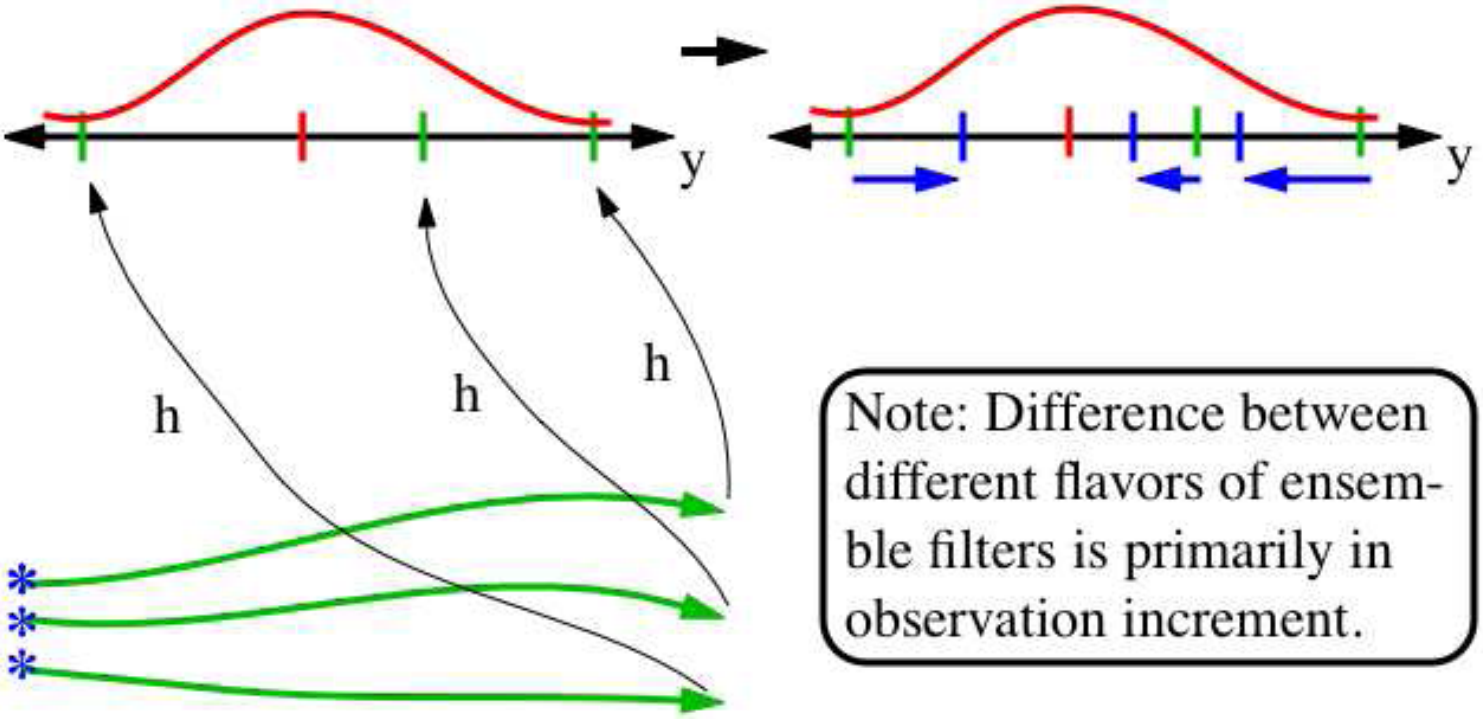
3. Get observed value and observational error distribution from observing system.



Ensemble Kalman Filter

How an Ensemble Filter Works for Geophysical Data Assimilation

4. Find increment for each prior observation ensemble
(this is a scalar problem for uncorrelated observation errors).

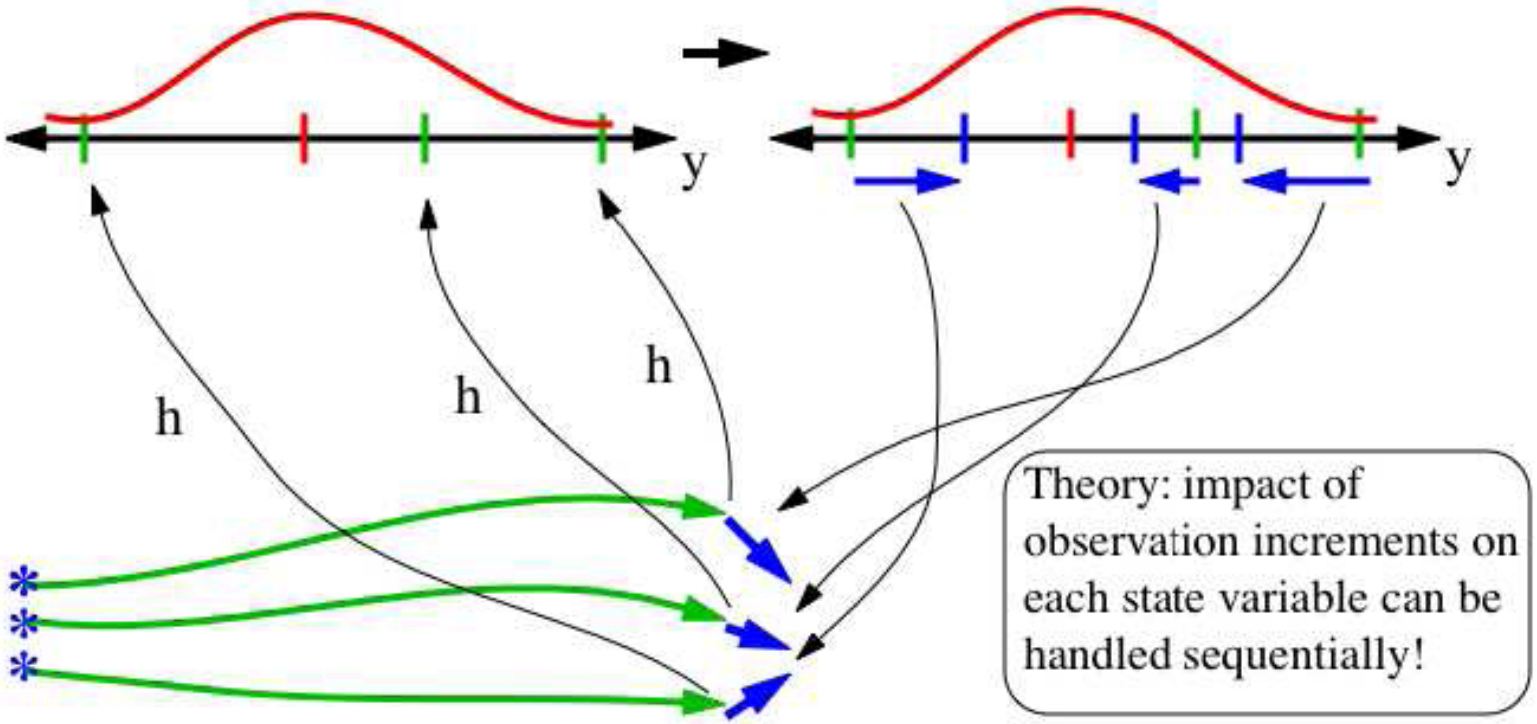


Note: Difference between different flavors of ensemble filters is primarily in observation increment.

Ensemble Kalman Filter

How an Ensemble Filter Works for Geophysical Data Assimilation

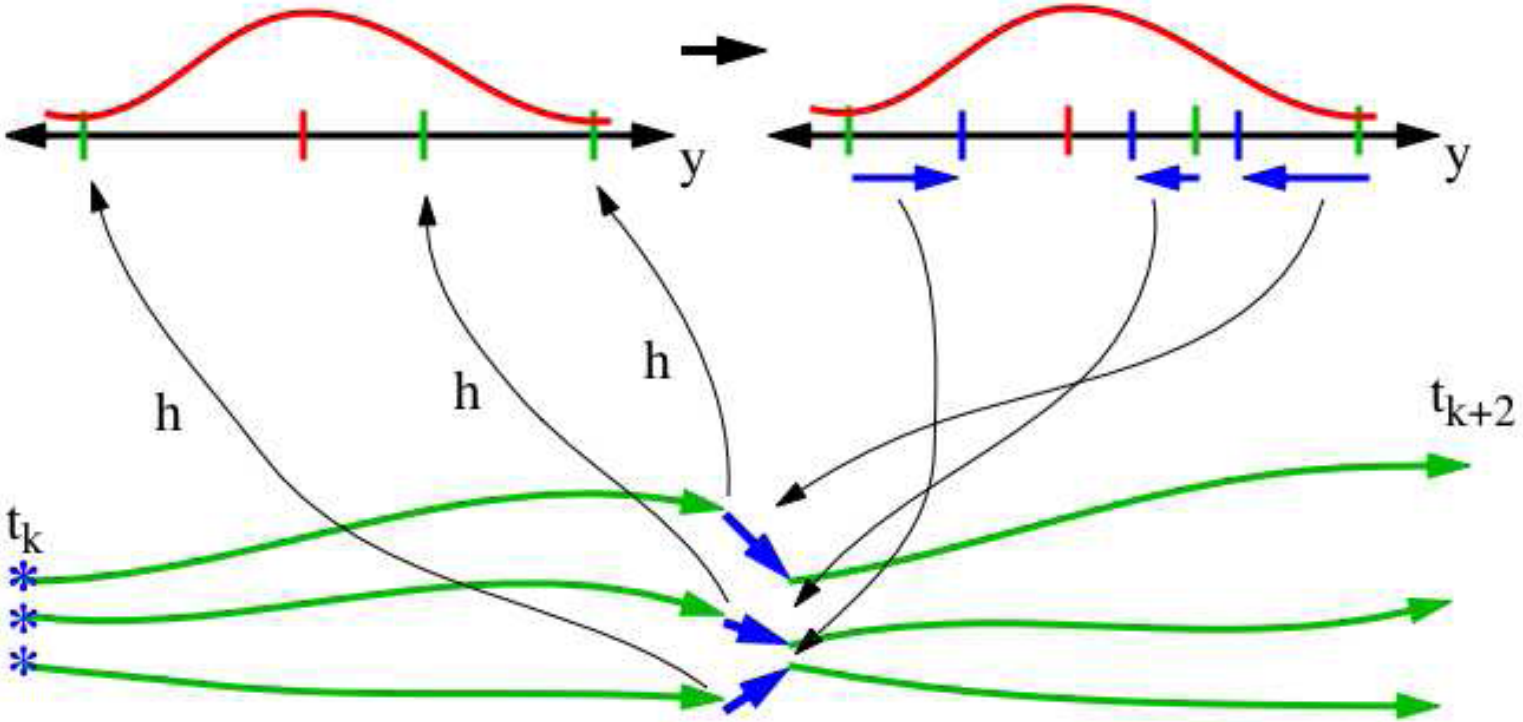
5. Use ensemble samples of y and each state variable to linearly regress observation increments onto state variable increments.



Ensemble Kalman Filter

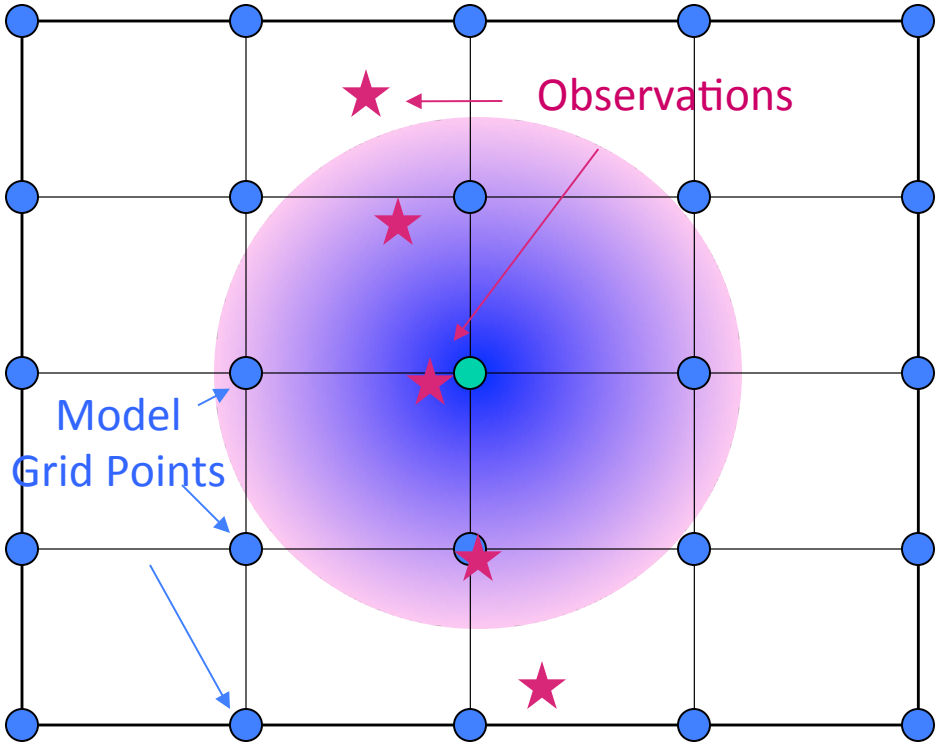
How an Ensemble Filter Works for Geophysical Data Assimilation

6. When all ensemble members for each state variable are updated, have a new analysis. Integrate to time of next observation...



Ensemble Kalman Filter

Goal: find analysis ($\mathbf{x}_a$) at each model grid point



- Analysis at a given grid point: background at that point ($\mathbf{x}_b$) plus a weighted sum (W) of observation increments ($\mathbf{y}$-$\mathbf{H}[\mathbf{x}_b]$) within a localization radius.
- Analysis increment at a given grid point is a local linear combination of ensemble perturbations.
- Background, or forecast, errors are described by an ensemble of MGCM states , and evolve with the flow (an important advantage of ensemble data assimilation methods).

DA for Mars (so far…)

Data Assimilation for Mars is a worldwide effort:

Strategy	Group	DA Scheme	GCM Model	State/Main purpose
Analysis Correction	Oxford University and The Open University (UK)	AC (Lorenc et al. 1991)	LMD-UK MGCM (Spectral)	TES and MCS Reanalyses
Ensemble Kalman filter	University of Maryland (MA, USA)	LETKF (Hunt et al. 2007)	GFDL (Spectral)	TES Reanalysis / OSSE
	Ashima Research (CA, USA)	DART (Anderson @ NCAR)	MarsWARF (Finite Differences)	Initial TES Reanalysis / model bias study
	LMD (Paris, France)	LETKF (Hunt et al. 2007)	LMD MGCM (Finite Differences)	In preparation/Quasi real time Exomars TGO assimilation

UK Mars DA

UK "Mars Analysis Correction Data Assimilation" (MACDA)

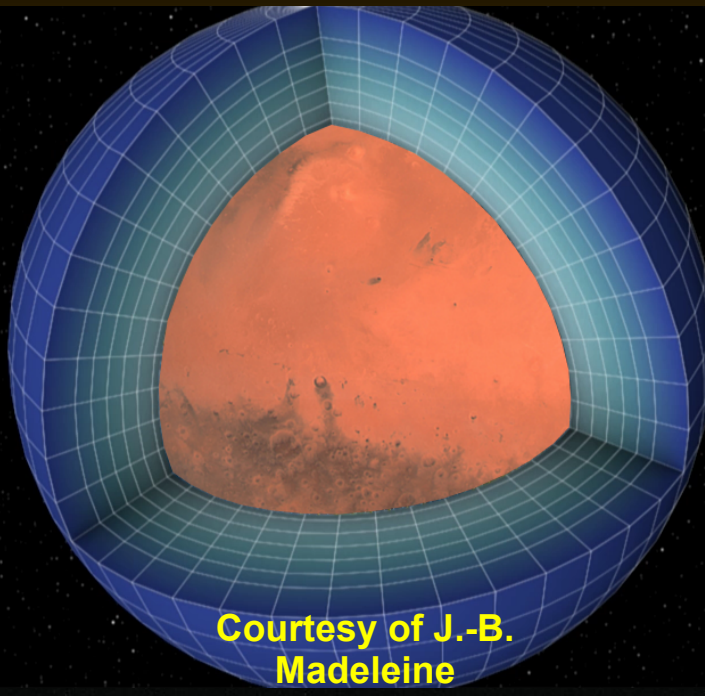
Model: LMD-UK Mars General Circulation Model

Observations (so far):
Temperature,
Dust Optical Depth
***Water vapour**
***Water ice**

*In progress

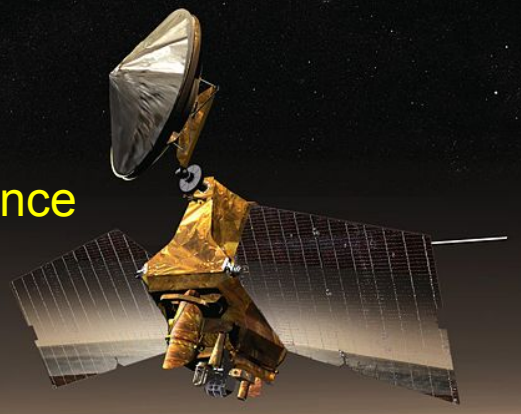
Assimilation Scheme:
Analysis Correction (Lorenc et al., 1991)

Mars Global Surveyor



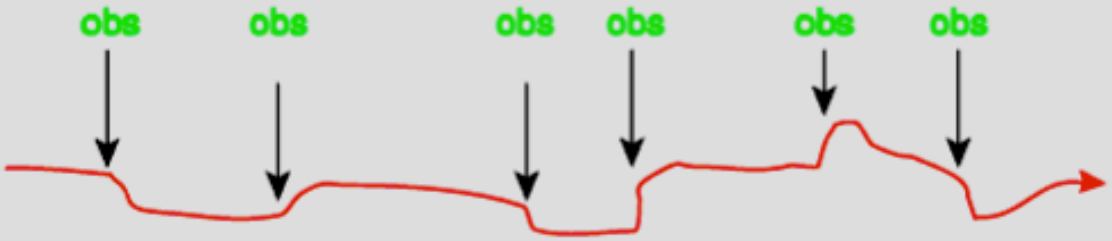
Courtesy of J.-B. Madeleine

Mars Reconnaissance Orbiter



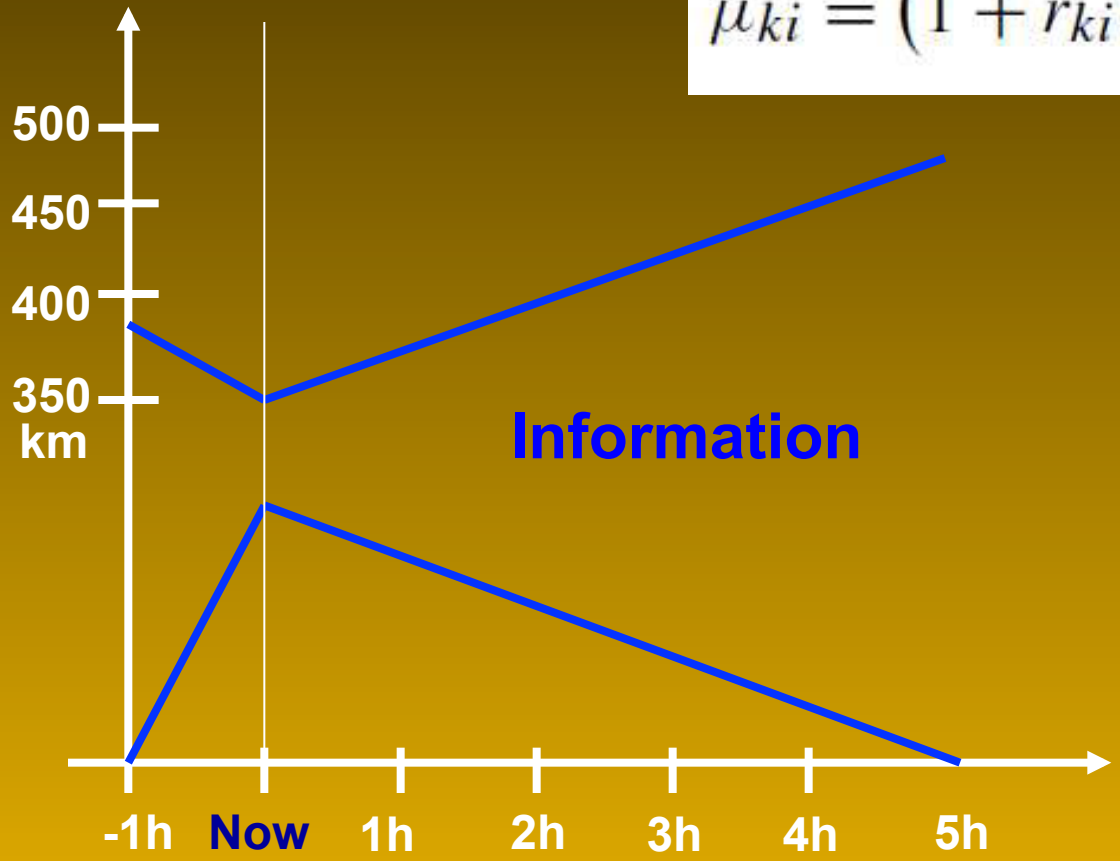
UK Mars DA

sequential, continuous assimilation:



$$\Delta x_k = \lambda \sum_i \mu_{ki} \tilde{Q}_i R_i^2(\delta t_i) C_i ,$$

$$\mu_{ki} = \left(1 + r_{ki}/S_i(\delta t_i)\right) \exp\left(-r_{ki}/S_i(\delta t_i)\right)$$



Horizontal Correlation Scale

Time Factor

UK Mars DA: A bit of history

- **First attempts:**

  Lewis & Read (1995), Lewis et al. (1996, 1997)

- **First development of AC scheme for Mars:**

  Lewis et al. (2007)

- **Implementation and validation of TES assimilation:**

  Montabone et al. (2006)

- **Science based on TES assimilation:**

  Variability of dust storms: Montabone et al. (2005)

  Thermal tides: Lewis & Barker (2005)

  Weather at Beagle 2 atmospheric entry: Montabone et al. (2006)

  Radiative effects of tropical clouds: Wilson et al. (2008)

  2001 planet encircling dust storm: Martinez-Alvarado et al. (2009)

  Atmospheric predictability: Rogberg et al.(2010)

UK Mars DA: Present studies

- **Science based on TES assimilation:**

  Solstitial pause in baroclinic wave activity: Lewis et al.

  Boundary layer studies: Lewis et al.

  Super-rotating equatorial jets: Ruan et al.

  Non-local effects of dust storms: Montabone et al.

  Dynamics and variability of polar vortices: Montabone et al.

- **Science based on TES and MCS assimilation:**

  Dust cycle and variability of dust storms: Ruan et al.

  Water ice clouds: Lee et al.

- **Science based on assimilation of future observations:**

  Ozone photochemistry: Holmes et al.

UK Mars DA: TES 3-year reanalysis

British Atmospheric Data Centre
NATIONAL CENTRE FOR ATMOSPHERIC SCIENCE
NATURAL ENVIRONMENT RESEARCH COUNCIL

***M*ars**
***A*nalysis**
***C*orrection**
***D*ata**
***A*ssimilation**

(so far, for MGS/TES)

PUBLICLY AVAILABLE ONLINE

Search for "MACDA" at **http://badc.nerc.ac.uk/search/**

LMD-UK Mars GCM

Dynamical Core:

(Semi-) spectral
(adapted from University of Reading,
Hoskins et al. 1974, and ECMWF improvements)

Physical Parameterizations:

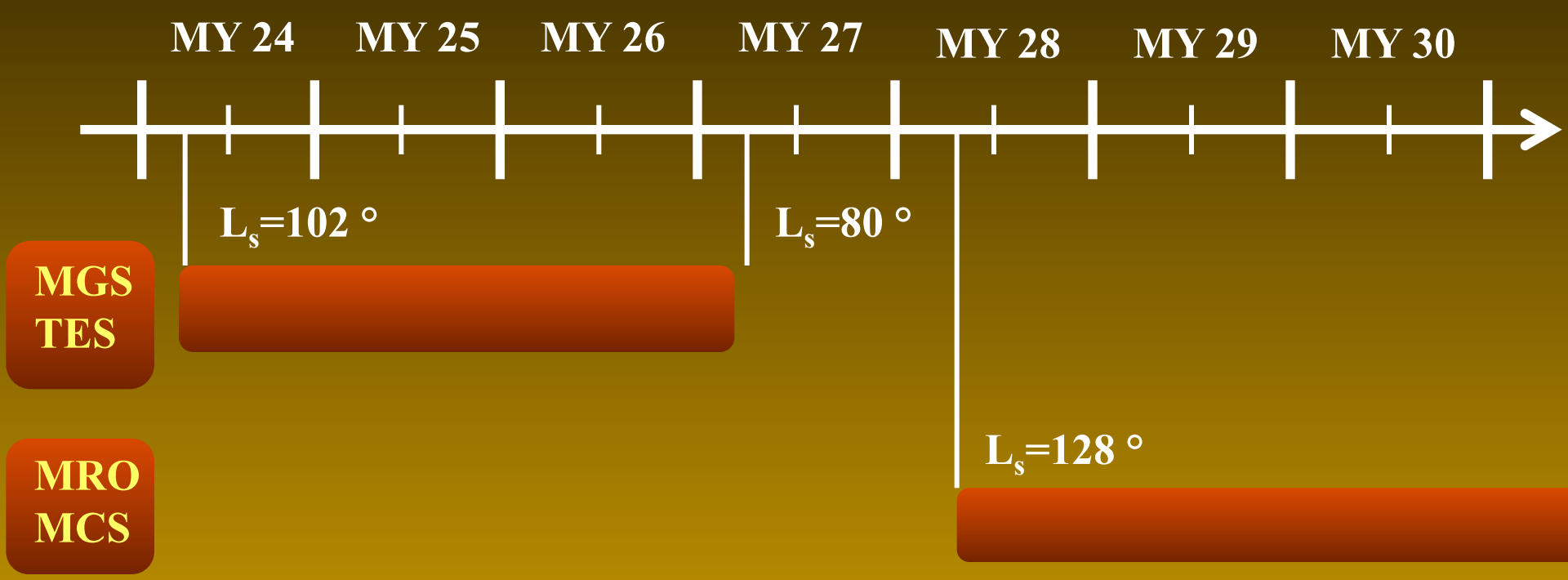
LMD / University of Oxford / The Open University /
Istituto de Astrofisica de Andalusia

Typical resolutions:

5°x5° degrees in horizontal (down to ~1°x1° degrees)
25 layers in vertical (σ-coordinates) or more (up to 200)

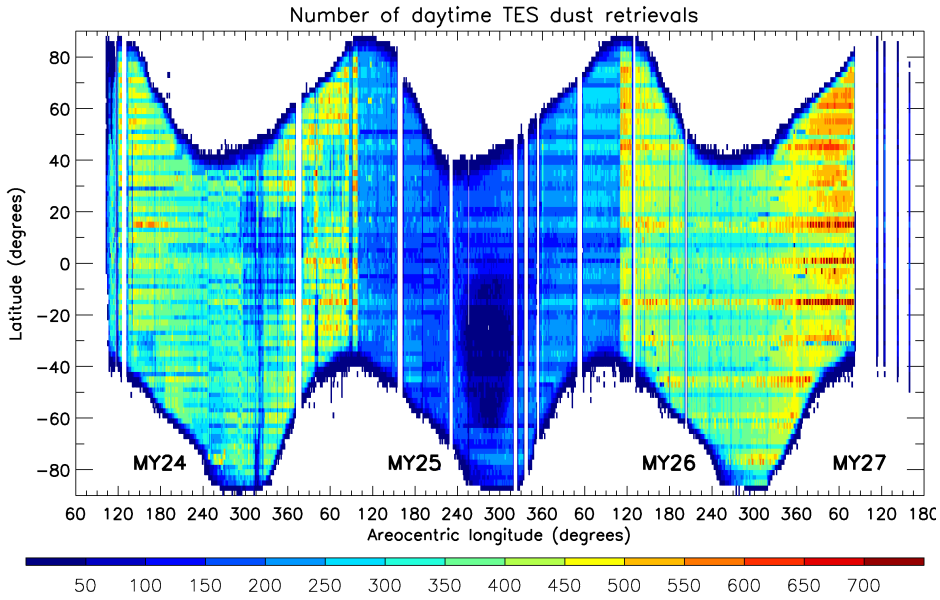
Observations

Spacecrafts, Instruments and Availability



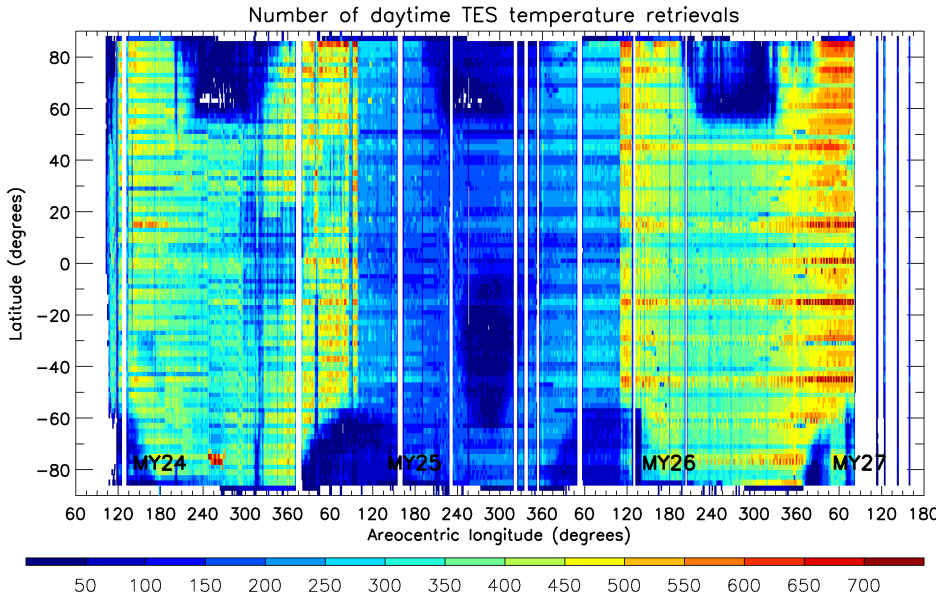
Observations: MGS/TES

Dust Retrievals (☼)



MY24 | MY25 | MY26 | MY27

Temp. Retrievals (☼)



MY24 | MY25 | MY26 | MY27

Mars Global Surveyor

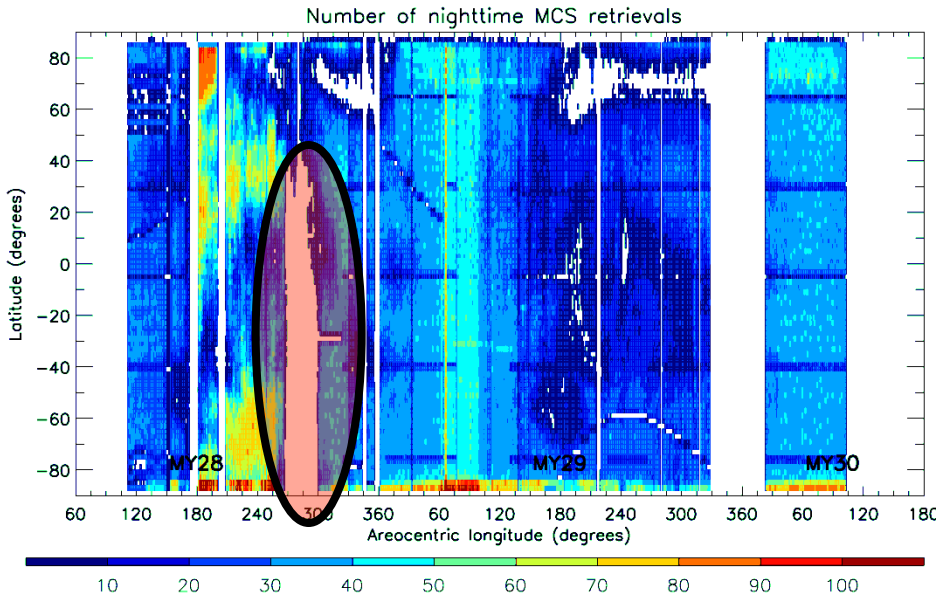
Thermal Emission Spectrometer

- **Nadir Temperature profiles (below ~ 40 km)**
- **Total dust optical depth**
- *** Water vapour**
- *** Water ice**

*** In progress**

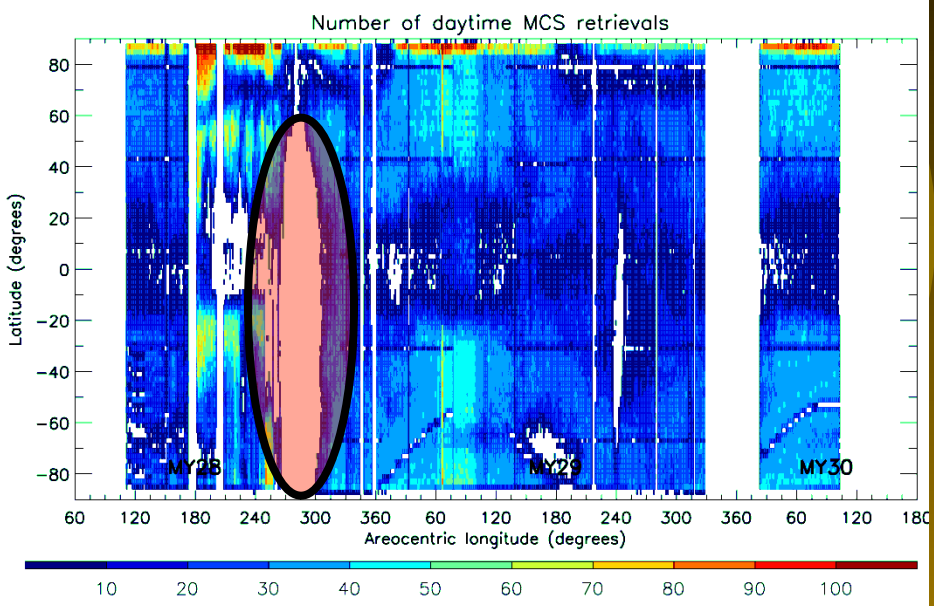
Observations: MRO/MCS

Retrievals (☾)



MY28 | MY29 | MY30

Retrievals (☼)



MY28 | MY29 | MY30

Mars Reconnaissance Orbiter

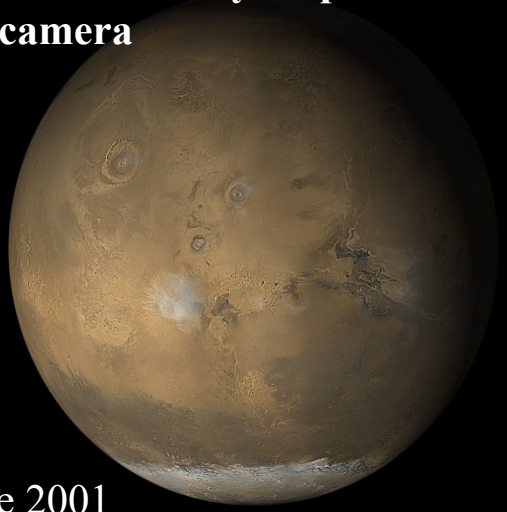
Mars Climate Sounder

- **Limb Temperature profiles (below ~ 80 km)**
- **Column integrated dust optical depth**
- *** Limb dust optical depth profiles**

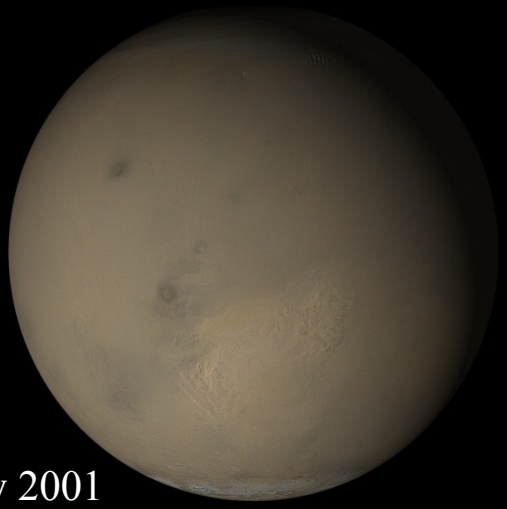
*** In progress**

Selection of past results

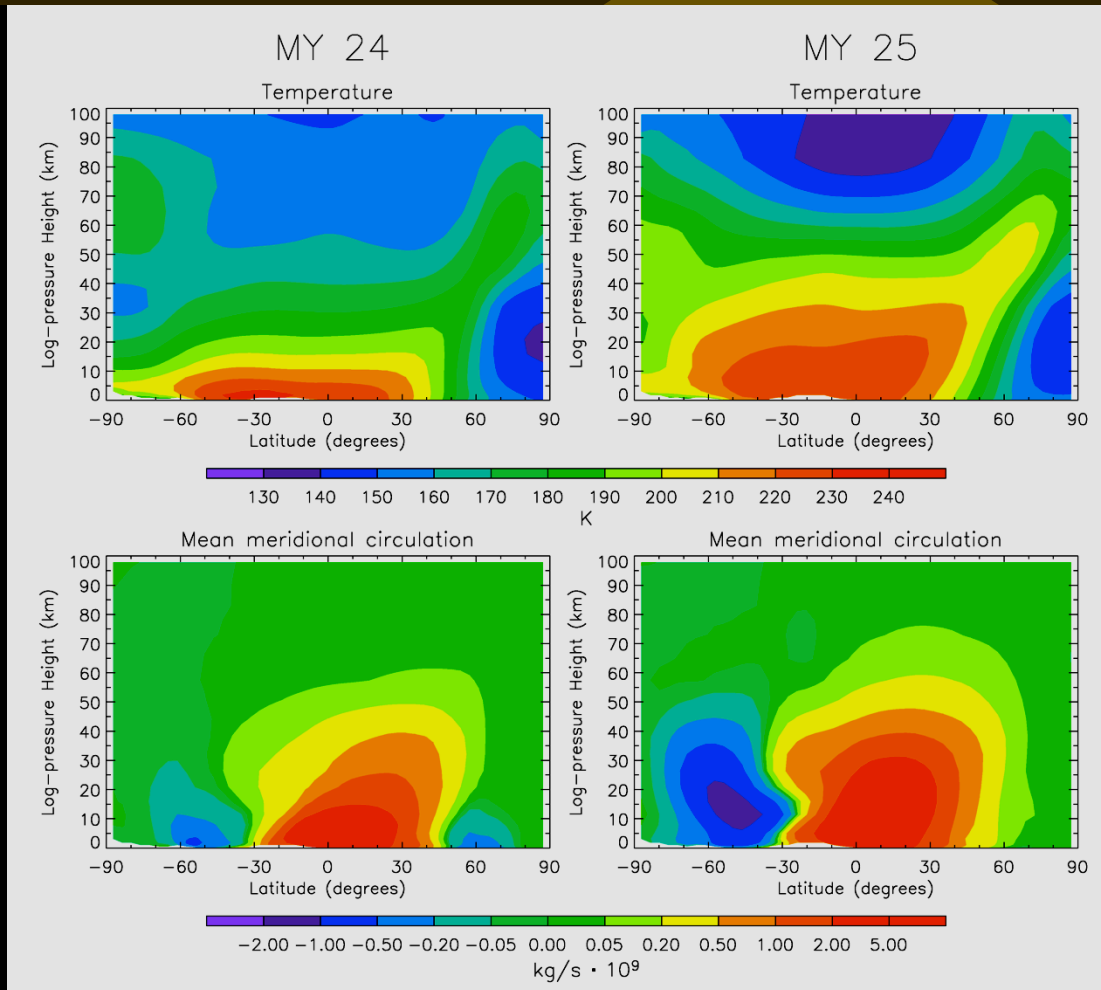
Mars Global Surveyor spacecraft MOC camera



20 June 2001



31 July 2001

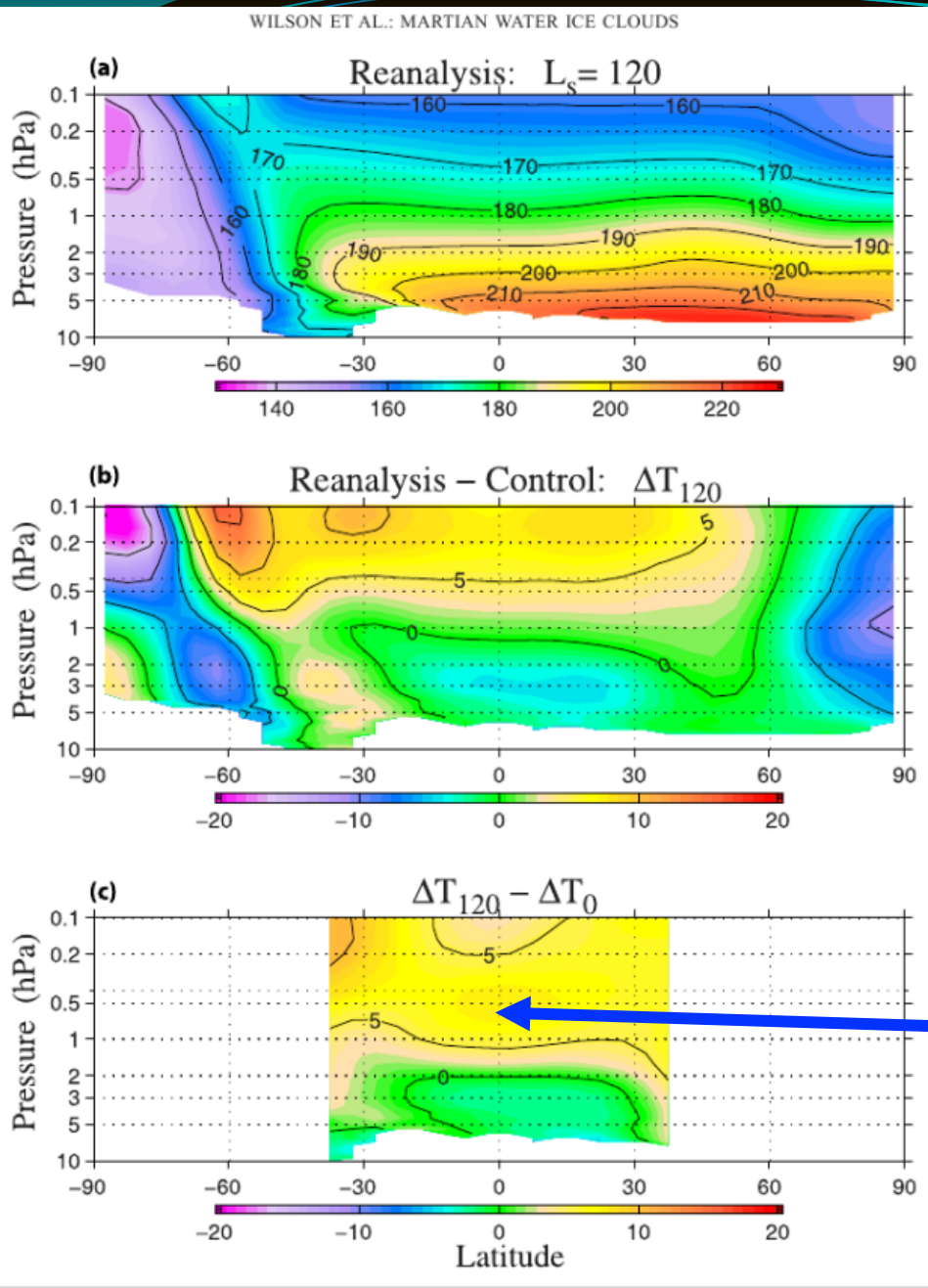


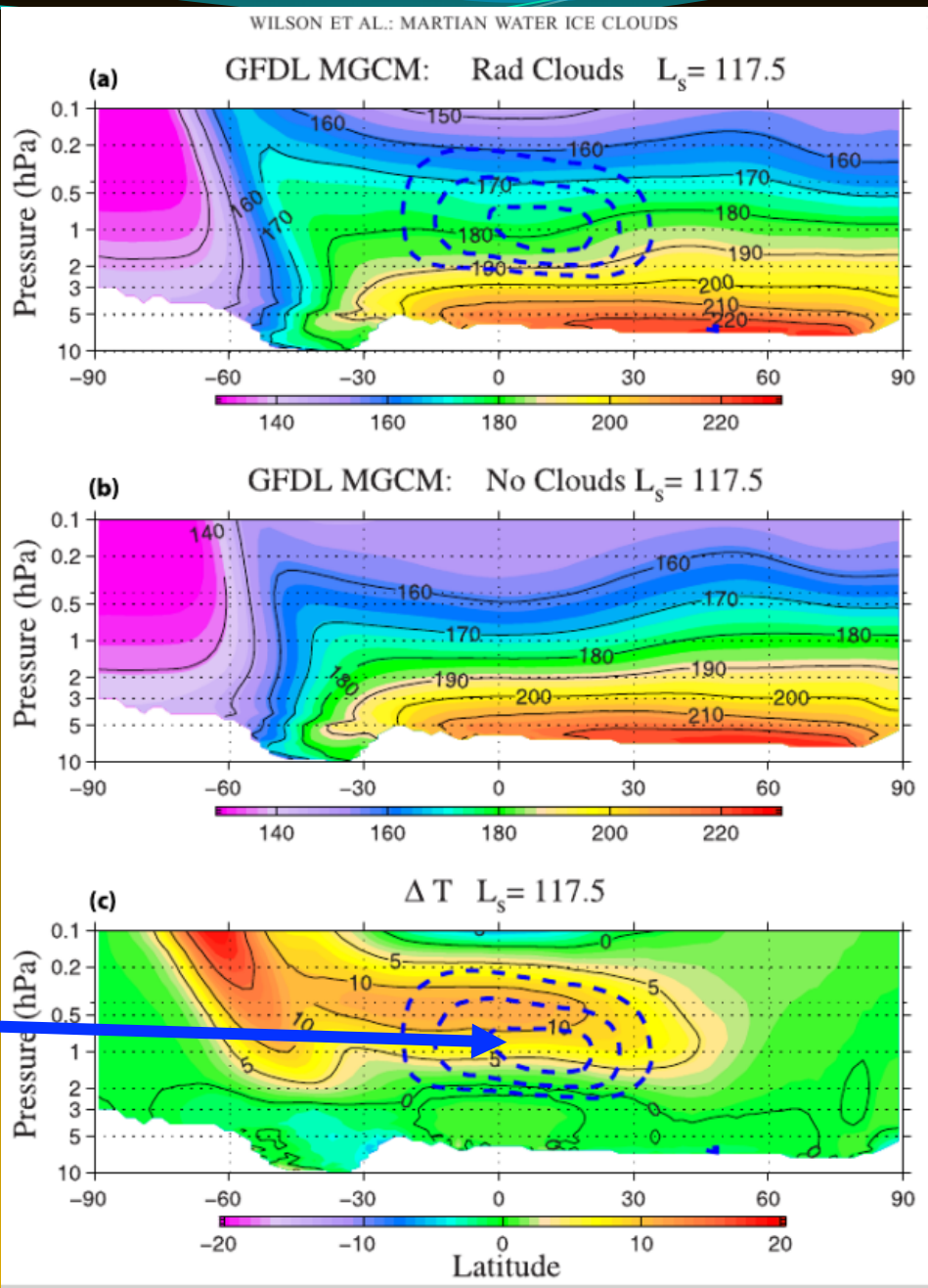
Averages over L_s =195°–225°

Montabone et al., 2006

Selection of past results

Wilson et al., 2008

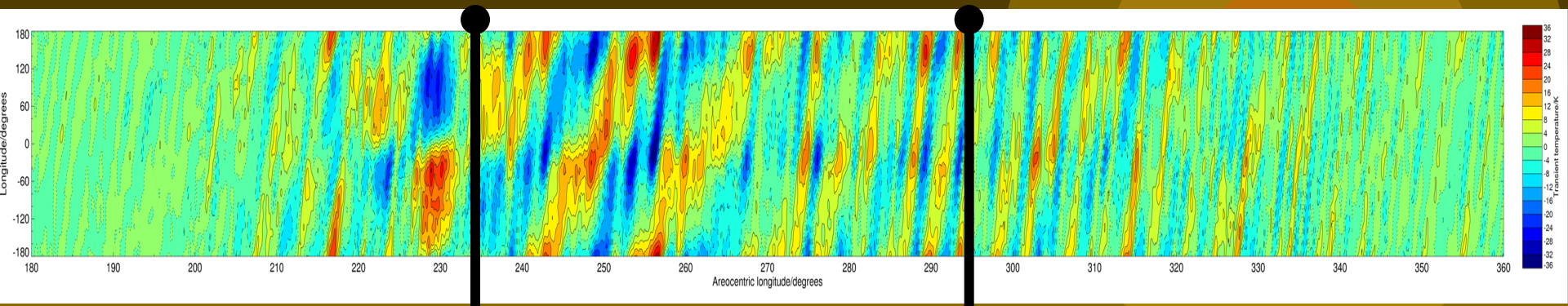




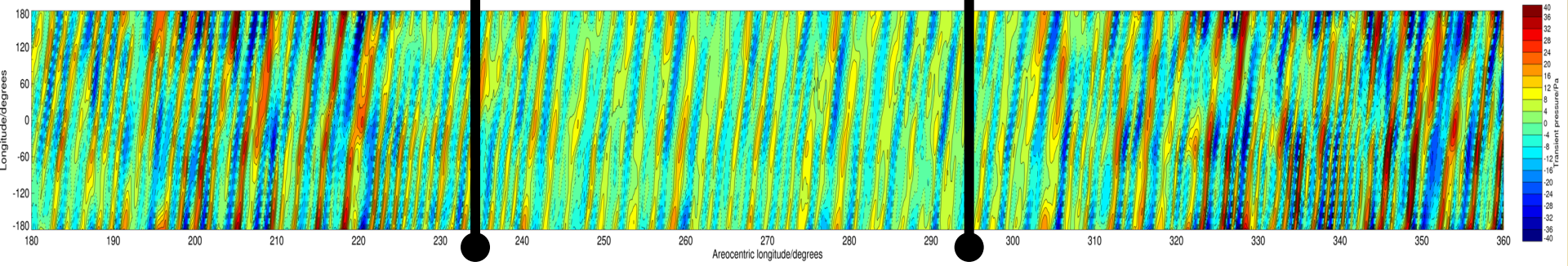
Selection of present results

Solstitial pause in baroclinic wave activity

62.5°N, MY24



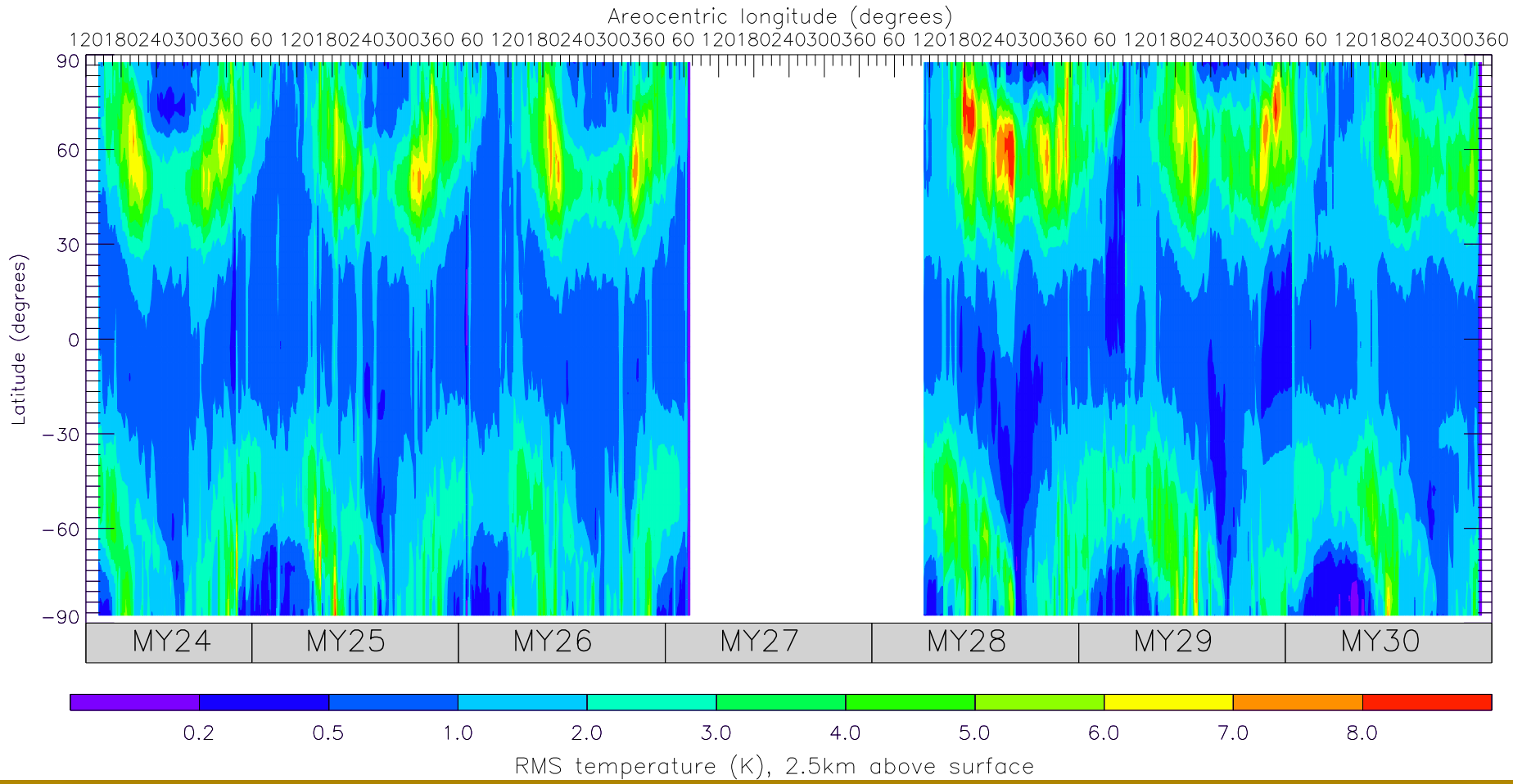
Transient Temperature at 50 Pa, ~25 Km (TES data assimilation)



Transient Surface Pressure (TES data assimilation)

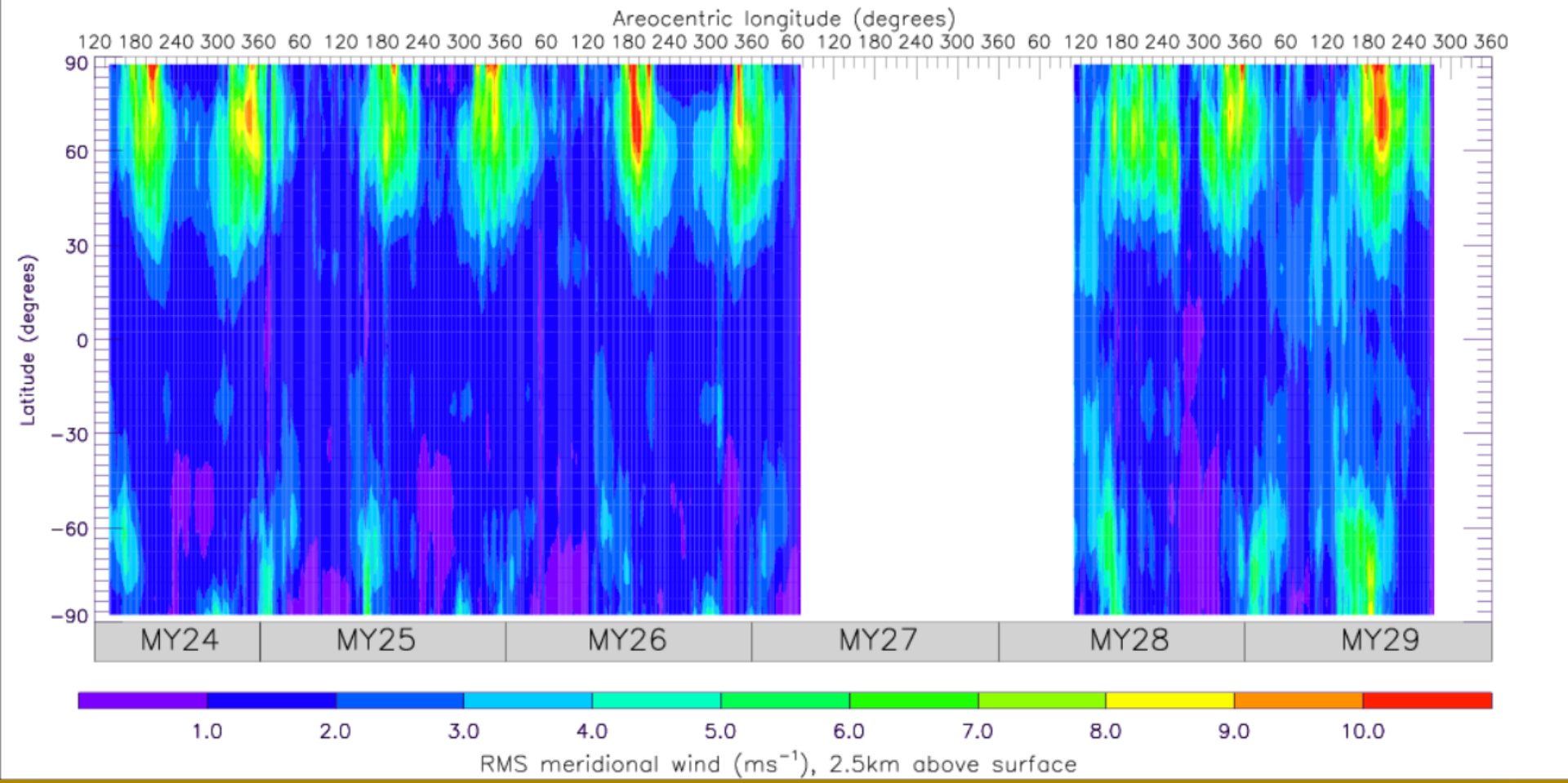
Lewis et al., in preparation

Selection of present results



RMS Temperature (TES data assimilation) **(2.5 km altitude)**

Selection of present results



RMS Meridional Wind (TES data assimilation) **(2.5 km altitude)**

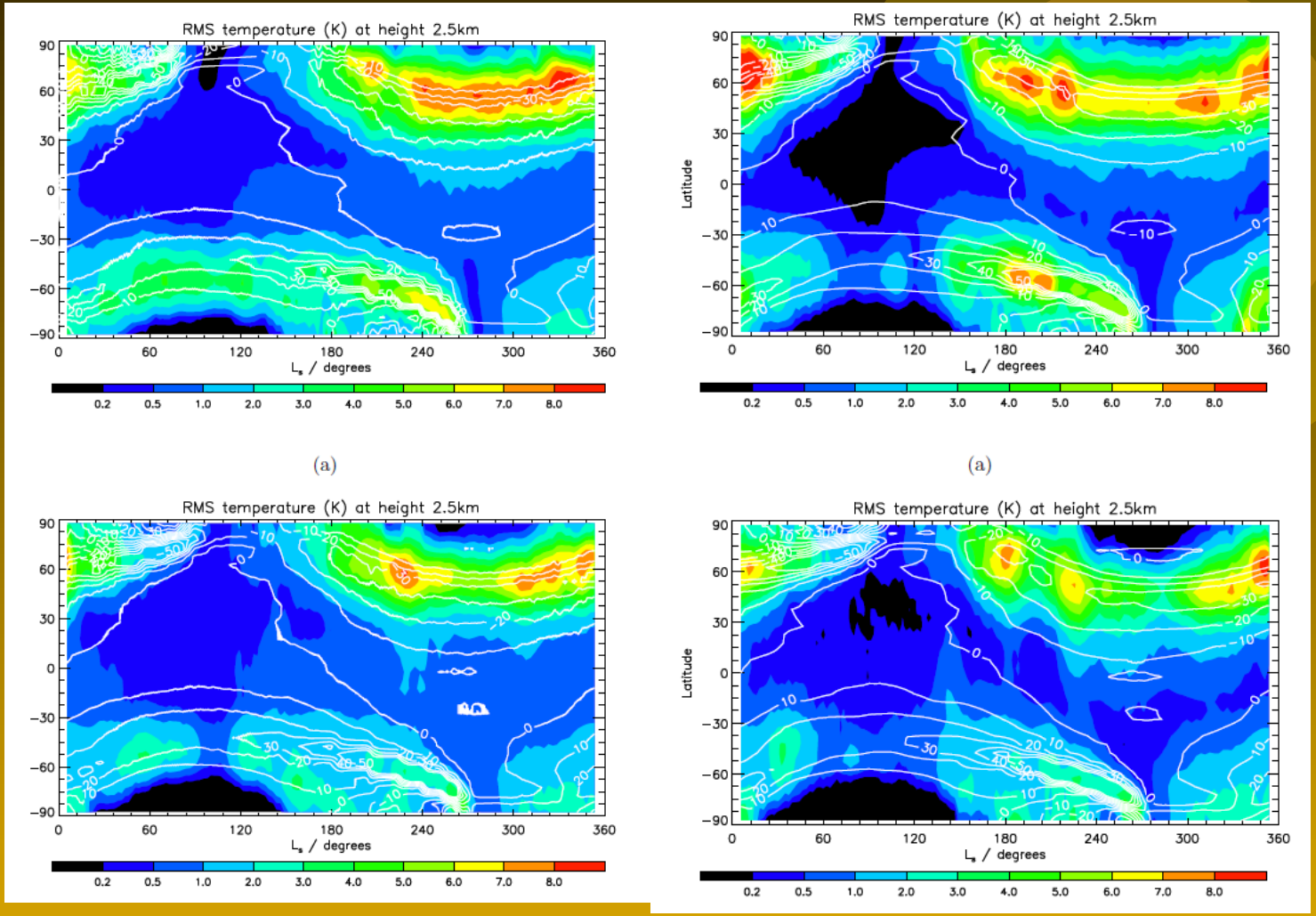
Theoretical confirmation of solsticial pause :
Near-surface baroclinic waves activity in LMD/UK GCM

(RMS of Temperature at 2.5 km)

Non active clouds | **Active clouds**

tau = 0.2

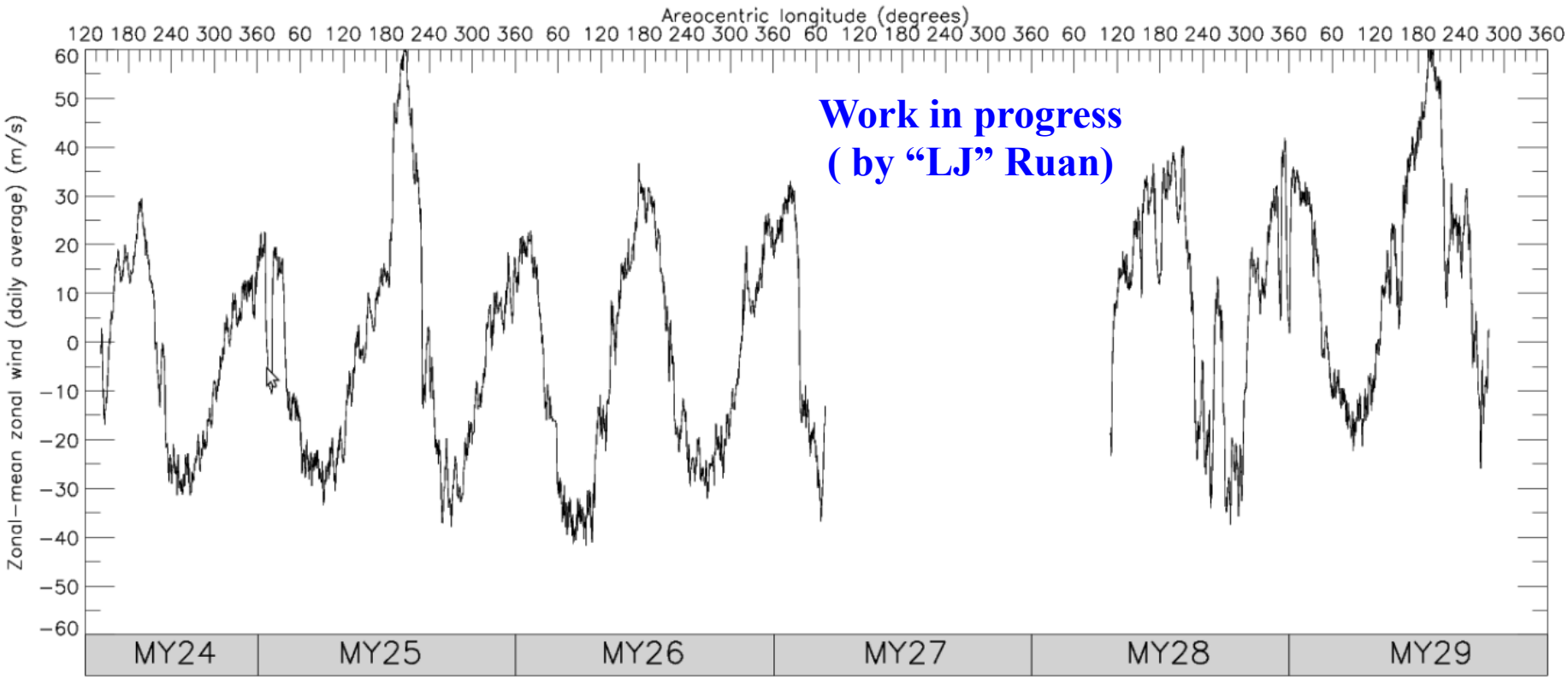
MY 24 Scenario



Mulholland et al., in preparation

Work inspired by results in Kuroda et al. , 2008

Selection of present results

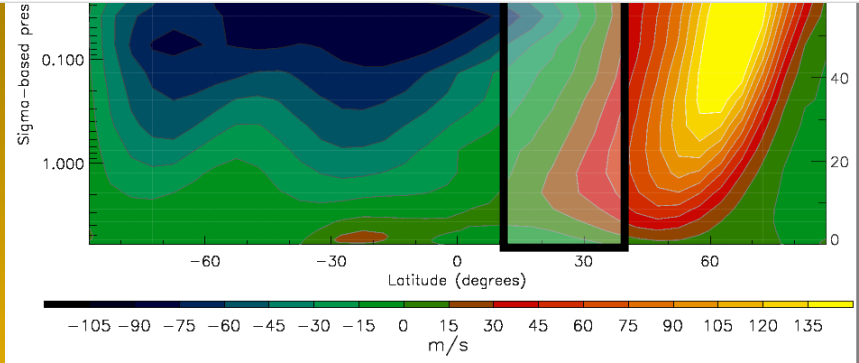


Time series at ~55 km altitude (~0.04 mbar)

Zonal wind

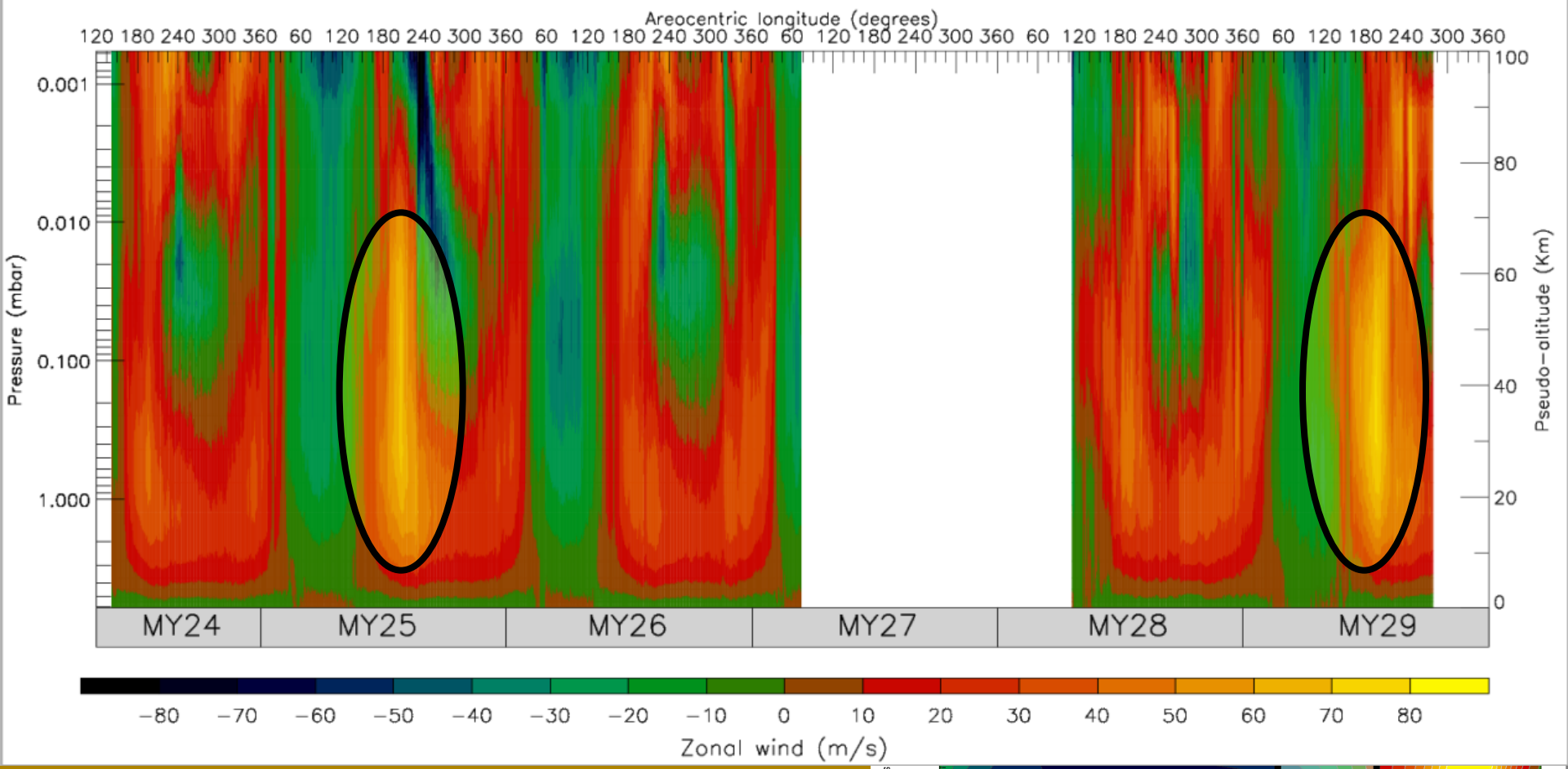
(semi-annual oscillation)

Zonal mean, daily averages



Work inspired by results in Lewis & Read, 2003

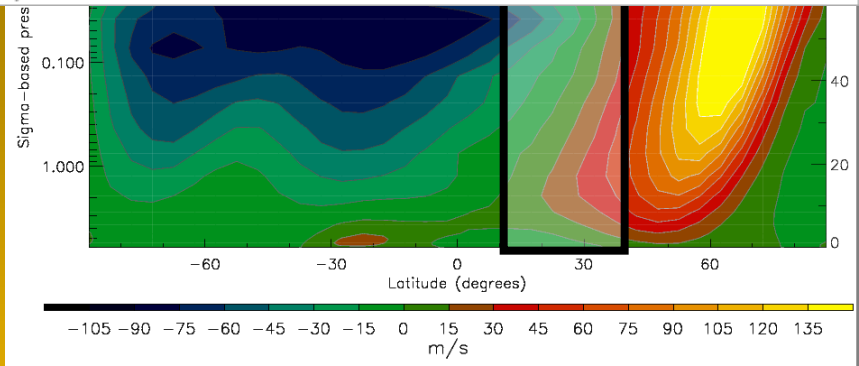
Selection of present results



Zonal wind

(Westerly equatorial jet)

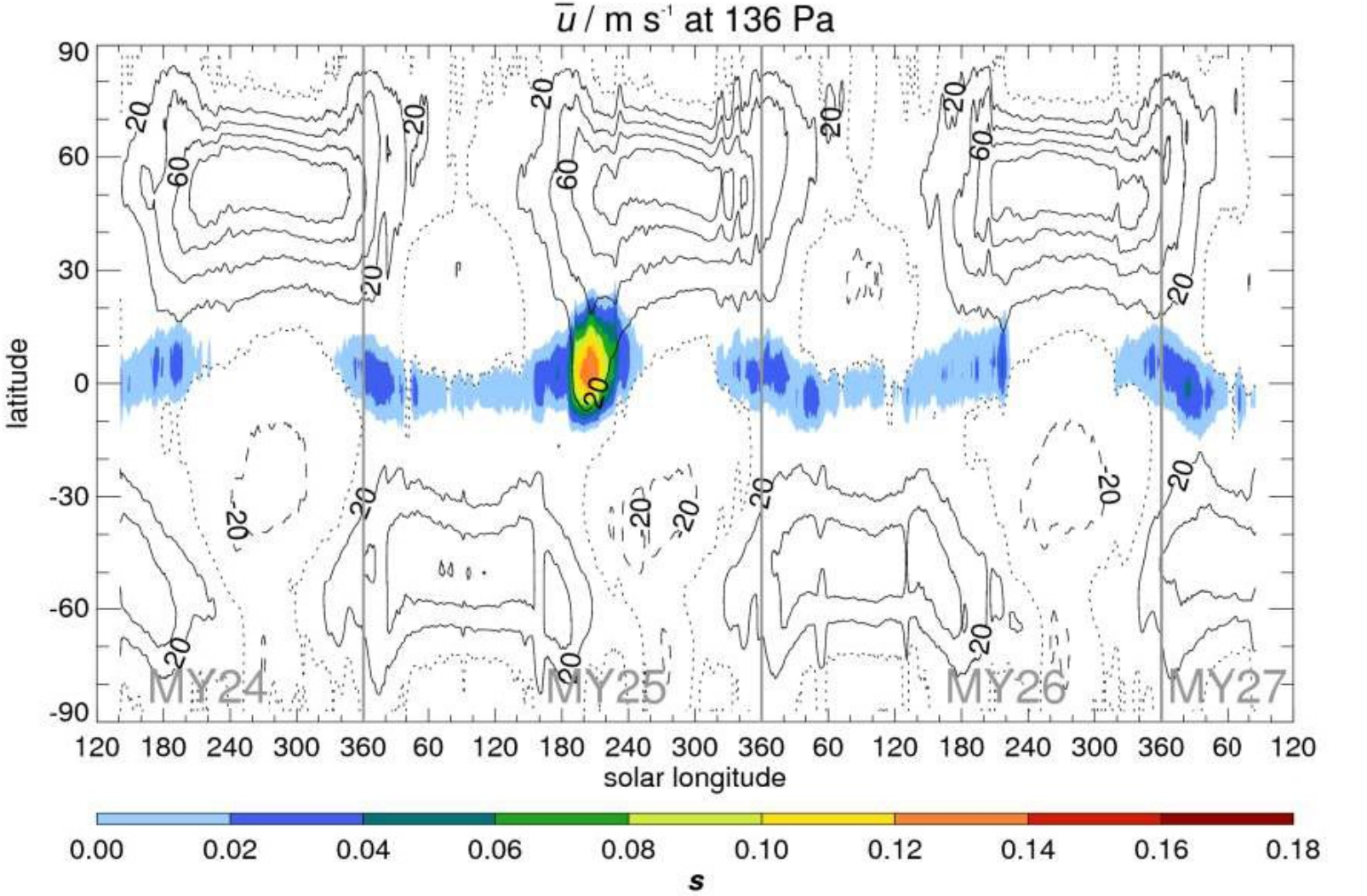
Zonal mean, daily averages



Selection of present results

Local super-rotation index: Mars

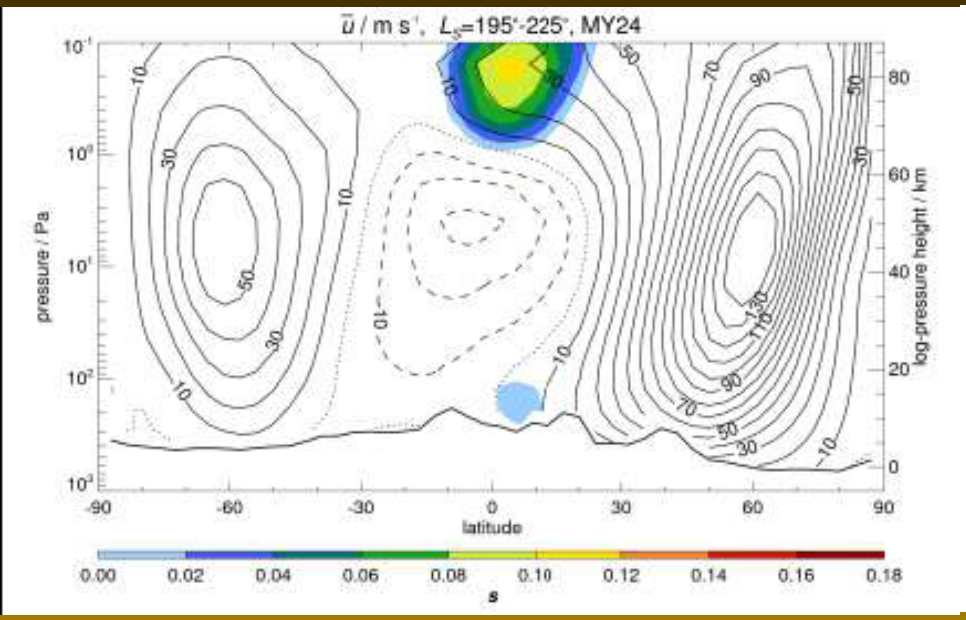
$$s = \frac{L_{atm}}{L_{rest}} - 1 > 0$$

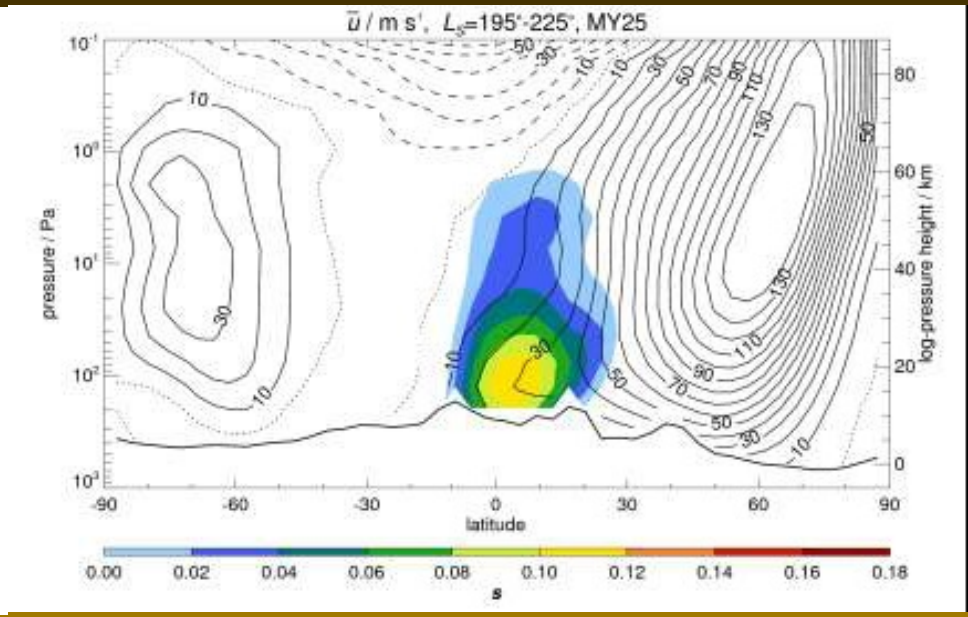


Selection of present results

Local super-rotation index: Mars

$$s = \frac{L_{atm}}{L_{rest}} - 1 > 0$$



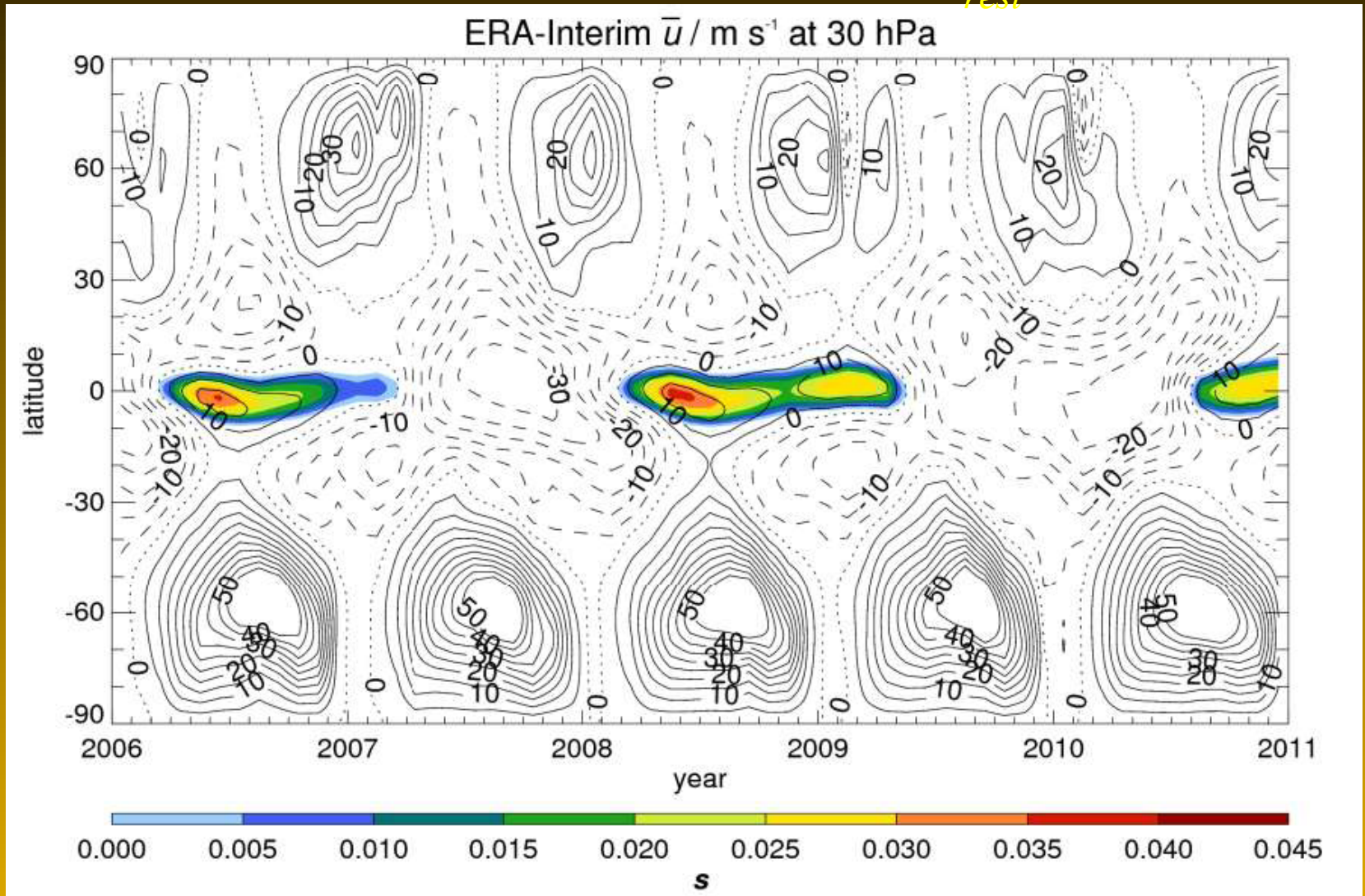


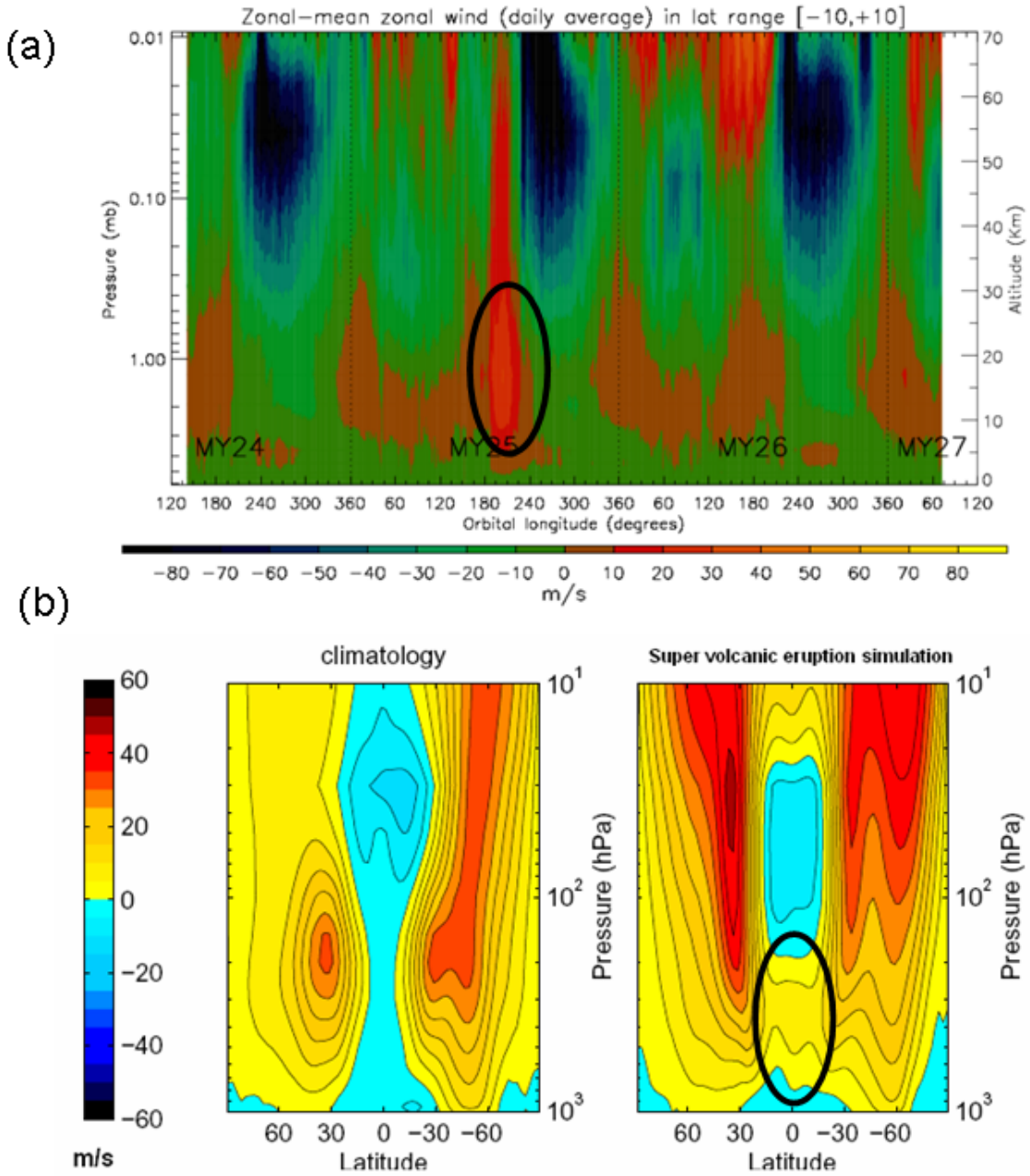
Autumn (L_S = 195°—225°) in MY24 and MY25

Selection of present results

Local super-rotation index: Earth

$$s = \frac{L_{atm}}{L_{rest}} - 1 > 0$$





Mars

(Past) Earth

B. Harris (Ph.D. thesis, 2009)

“Nothing is Perfect,

Nothing is Finished,

Nothing Lasts.”

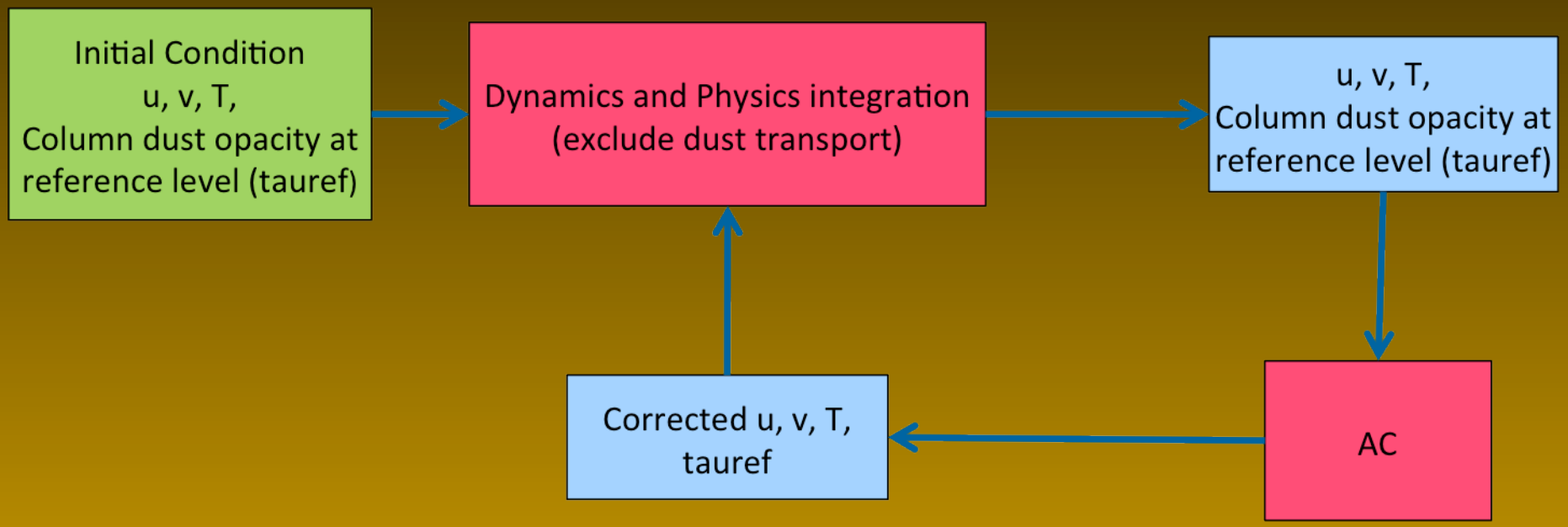
(“Wabi-Sabi” aesthetic)

Everything Evolves!

(…after Darwin)

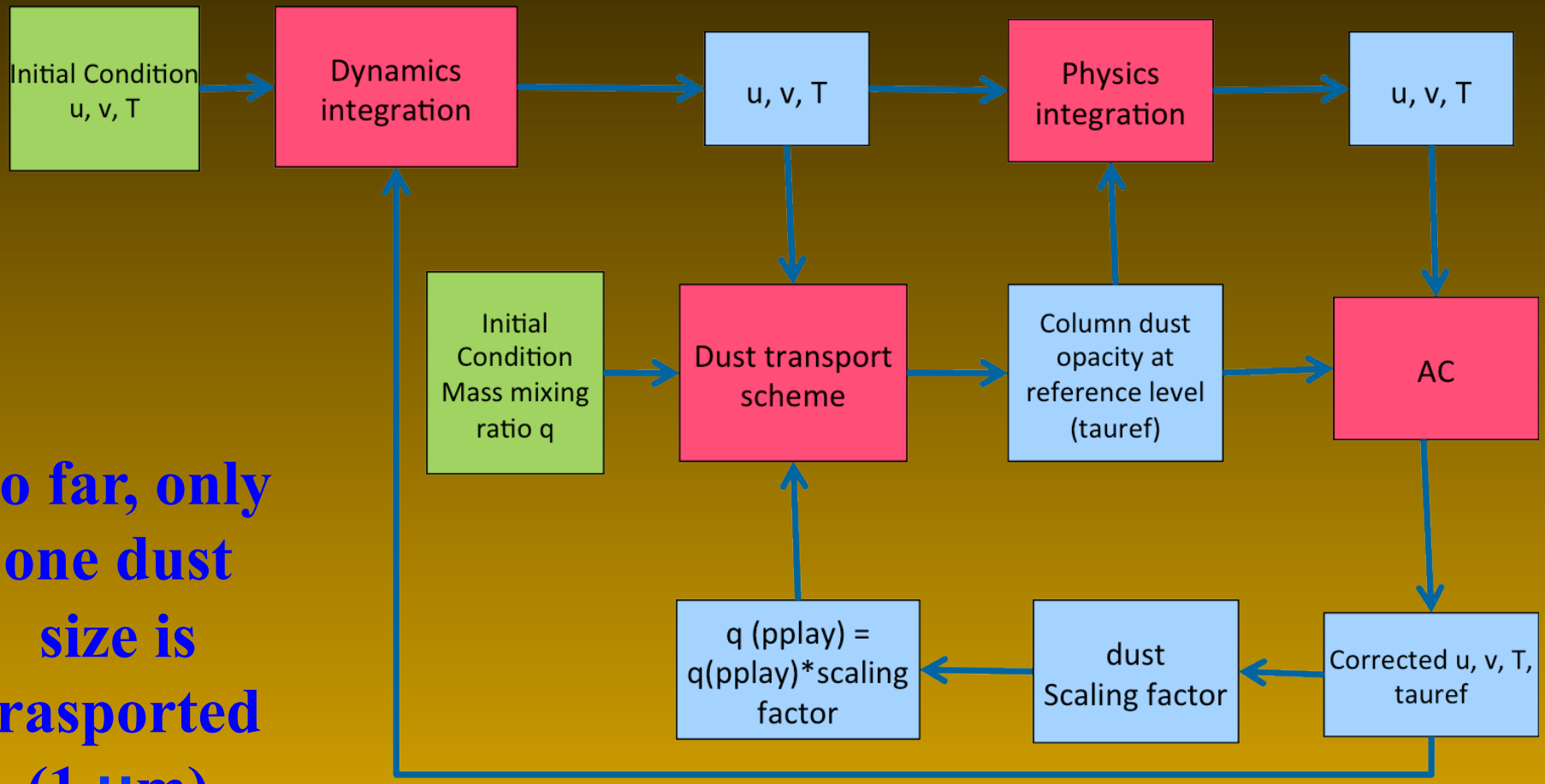
Dust assimilation

Old scheme (dust is not transported)



Dust assimilation

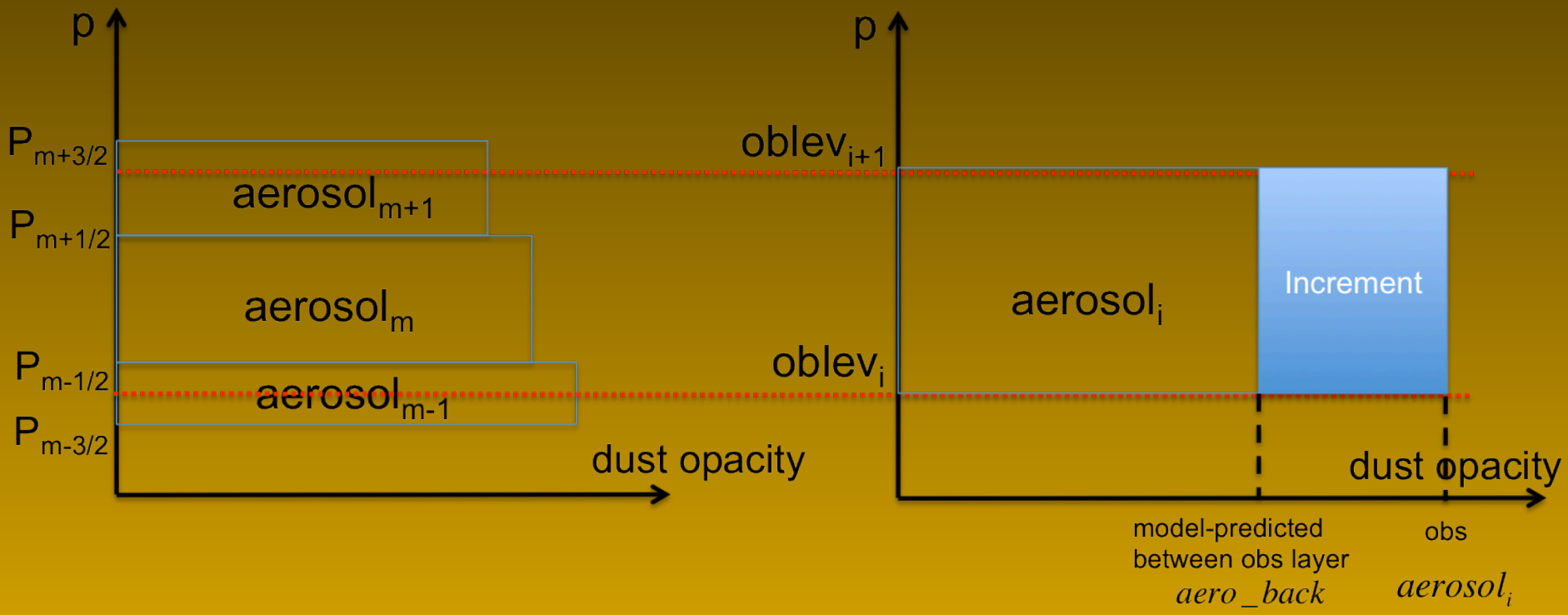
New "2D" scheme (dust is transported, column opacity is assimilated)



So far, only one dust size is trasported (1 μm)

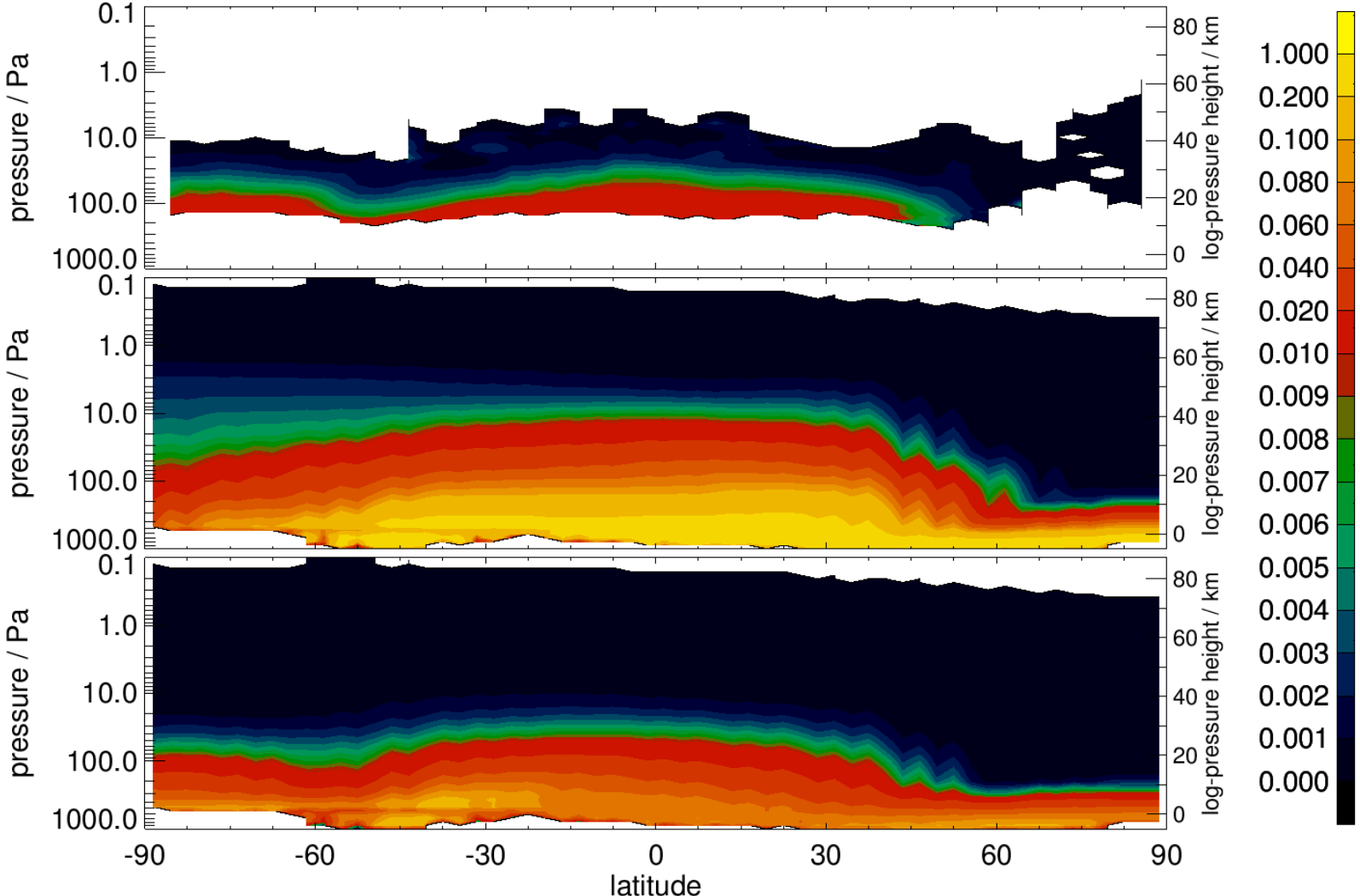
Dust assimilation

New "3D" scheme (dust is transported, full dust opacity profile is assimilated)



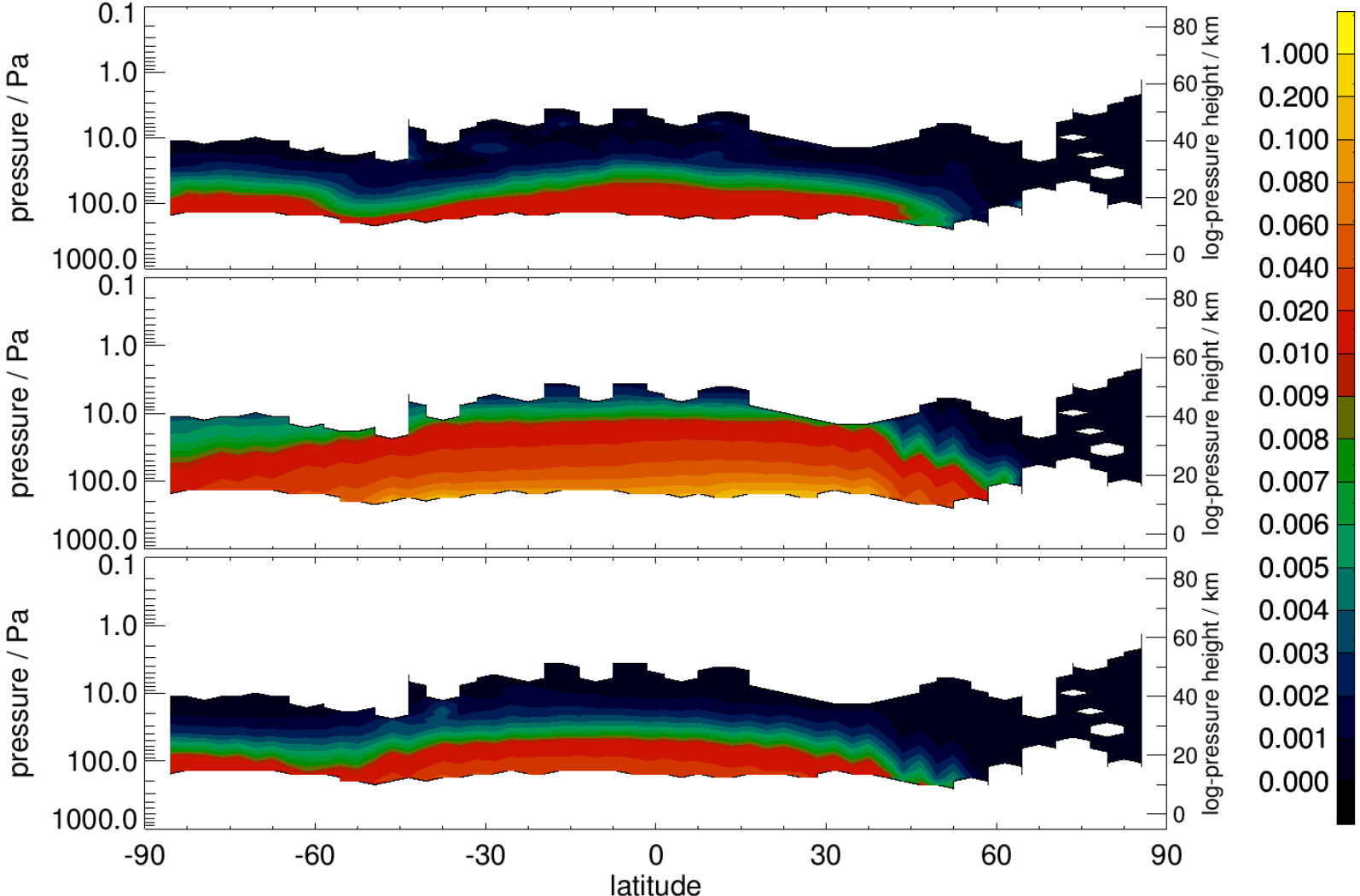
Dust assimilation

MCS temperature + dust opacity profile assimilation, MY 28, Ls=262.5° (Northern winter), nighttime



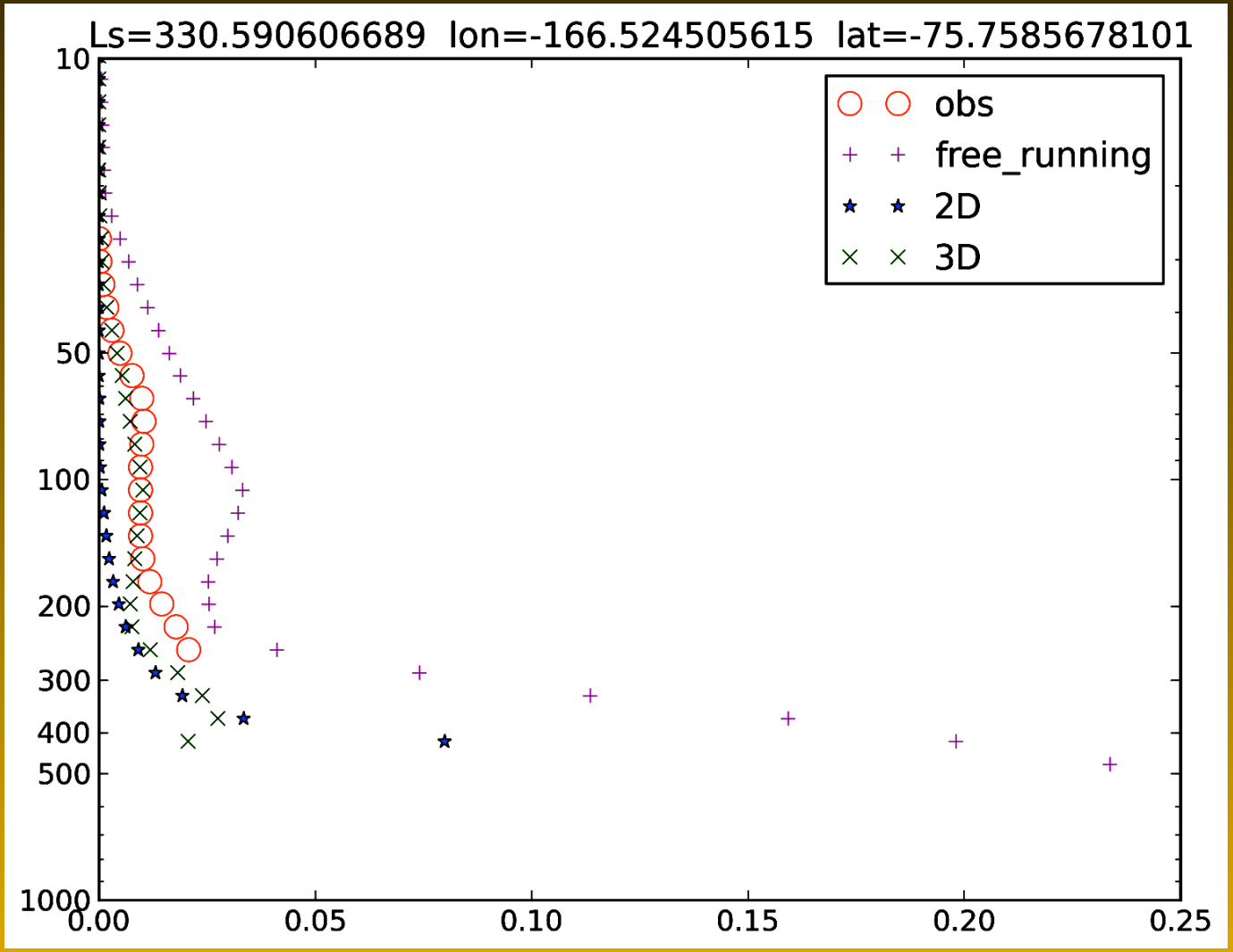
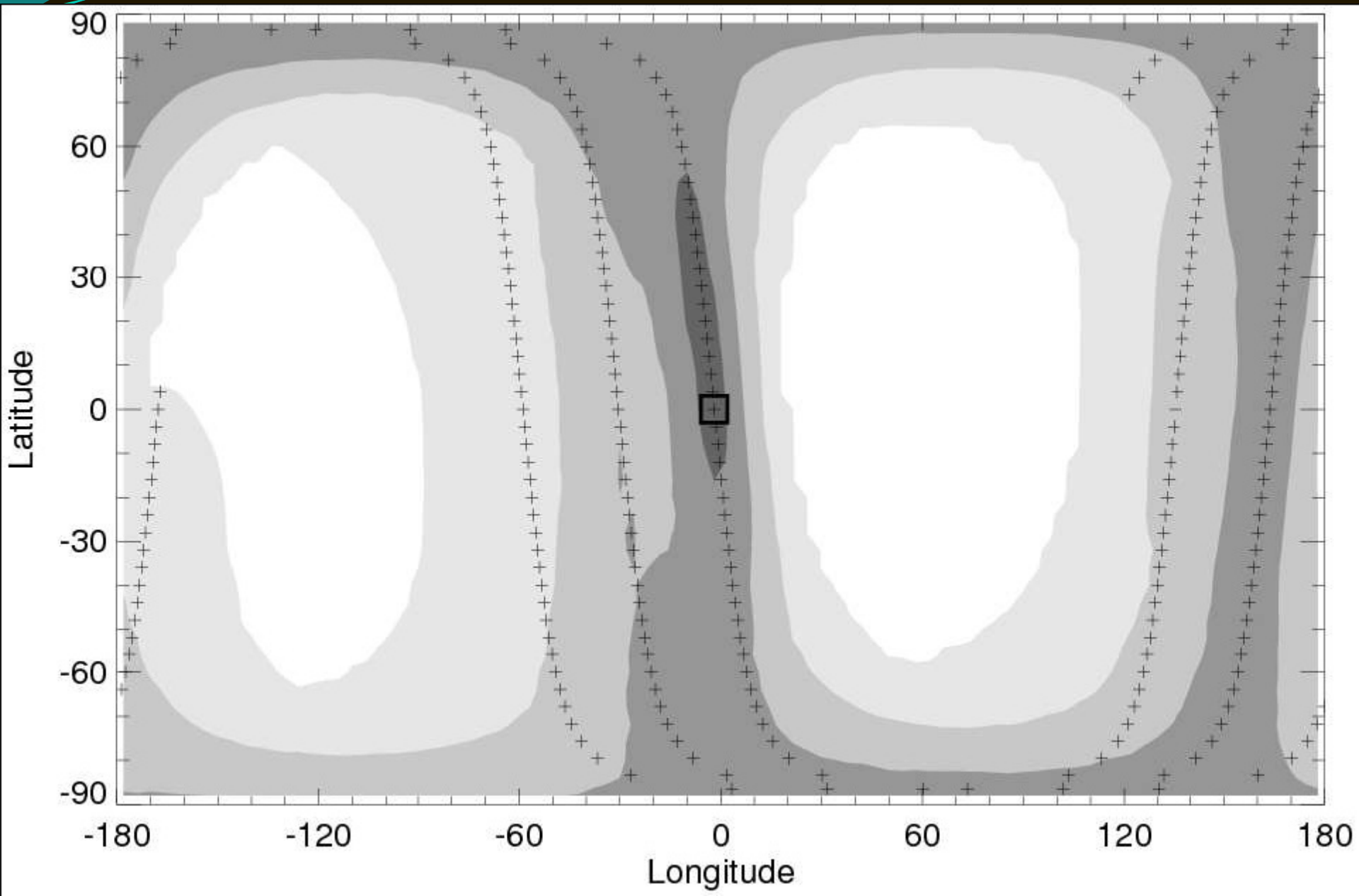
Dust assimilation

MCS temperature + dust opacity profile assimilation, MY 28, Ls=262.5° (Northern winter)



Dust assimilation

MCS temperature + dust opacity assimilation, MY 28, Ls=330.5° (Northern winter)



UK AC assimilation: Data impact