DATA ASSIMILATION: THE IMPORTANCE OF ATMOSPHERIC FORCINGS

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Introduction: Data assimilation is a technique widely used in geosciences, especially meteorology and weather forecast. It enables to optimally reconstruct a best estimate of the atmospheric state by combining instrumental observations and theoretical information provided by a numerical model. In Earth atmosphere science, it is systematically used to provide climatologies derived from space-based observations.

The very first Martian data assimilation project was carried out by [1], who applied the Analysis Correction Scheme to their Mars Global Climate Model (MGCM).

More recently, ensemble methods have been used for Martian data assimilation. The Local Ensemble Transform Kalman Filter (LETKF) [2] has been coupled to the GFDL MGCM [3] and used with observations from the Thermal Emission Spectrometer (TES) [4]. The Data Assimilation Research Testbed (DART) has been used to apply an ensemble Kalman filter to the MarsWRF GCM with TES radiance data [5]. The purpose of this work is to develop a data assimilation chain by coupling the Laboratoire de Météorologie Dynamique (LMD) MGCM with the LETKF assimilation framework.

Motivation: There are various possibilities and applications presented for data assimilation. In this specific case, the reasons to develop such an assimilation are numerous:

- The reconstruction of atmospheric fields is *per se* a strong motivation. It provides a best estimate of the known atmosphere and could be seen as a useful tool for atmospheric science community.
- Data assimilation could help to characterize the local conditions for landers and rovers on the Martian ground on a daily basis.
- One of the main objectives of the Trace Gas Orbiter (TGO), that will be launched in 2016, is to detect the presence and origin of trace gas in the Martian atmosphere. A data assimilation chain using data from the Atmospheric Chemistry Suite (ACS) on board TGO can be used to backtrack winds to locate the sources of such trace gases.
- Another asset of data assimilation is the possibility to point out disagreements between model and observations. It is a very powerful tool to estimate MGCM parameters or characterize instrumental errors.

Atmospheric Model: The model used in this data assimilation scheme is the MGCM developed at LMD [6]. It includes a semi-interactive dust scheme guided by dust scenarios, a thermal plume model [7], a water cycle that includes radiatively active water ice clouds [8] with interaction between dust and clouds and a photochemical model [9].

Data Assimilation Scheme: The principle of data assimilation is to successively alternate two steps: analysis and forecast (figure 1). In the analysis step, an *a priori* estimate of the system state, called the background, is used to obtain a new estimate, called the analysis, by being combined to observations. The forecast, or propagation step, consists of applying the numerical model to the analysis to get a new background after time integration (of typically 6 hours).

The assimilation scheme used is LETKF, which consists of an approximation of the Kalman Filter. It uses an ensemble, that is to say a set of a large enough number of forecast members that samples the variability of the system. The analysis step then consists of applying the filter to the background ensemble to create a new ensemble, the analysis. Observations are localized, that is to say their influence is limited and weighted in space within an arbitrary range.

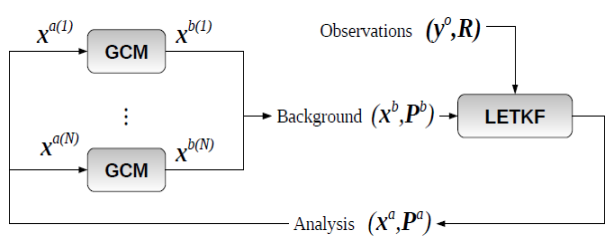

Figure 1: *Simple schematics of an ensemble data assimilation framework. The atmospheric state vector* $\mathbf{x}$*, made of atmospheric variables of the GCM, has a covariance matrix* $\mathbf{P}$ *constructed from an ensemble of N simulations, and is compared to the vector of observations* $\mathbf{y^o}$*, with specified error matrix* $\mathbf{R}$*.*

Development strategies: The development of a data assimilation chain is strongly incremental. After the validation of the assimilation with synthetic observations derived from the model itself, the assimilation of temperature from the Mars Climate Sounder (MCS) on board Mars Reconnaissance Orbiter has been initiated. We plan to also assimilate data from

the Planetary Fourier Spectrometer (PFS) on board Mars Express, thus taking advantage of the combination of the different local times between PFS and MCS measurements. The next goal is to directly assimilate dust and ice from MCS data.

Beyond this preparatory assimilation, the goal is to prepare the real-time assimilation of data from ACS on board TGO whose orbital insertion is expected in the second half of 2016. Ultimately, the direct assimilation of ACS radiances instead of temperatures will be attempted with the help of a direct model.

Forcings and predicatiblity: When compared to Earth, the specifities of the Martian atmosphere (low atmospheric density, water in trace quantities, absence of oceans) give Mars a very predictible weather. For a large portion of the year, instabilities in the Martian atmosphere do not grow [10,11]. On the contrary, this situation never occurs on Earth, where the atmosphere is intrinsically more chaotic. Paradoxically, this makes assimilation of Martian data more difficult in a certain sense, because the main source of disagreement between model and observations are biases (whether these are model or observational biases), rather than flow instabilities [12].

In order to tackle this issue, the approach in this work is to use observations to get an estimate of the strong forcings of the Martian atmosphere, rather than just the atmospheric flow, which is totally dominated by forcings on short timescales. These forcings are:

- Dust loading of the atmosphere, which controls most of its thermal structure, through dust radiative effects.

- Water ice clouds, whose radiative effects are known to be possibly as significant as the ones of dust, depending on the time of the year [8].

- Surface temperature, controlled by the thermal properties of the ground, that can influence the atmospheric temperatures in the first kilometers above the surface.

By taking advantage of the ensemble approach, one can make parameters and forcings vary within the ensemble of atmospheric states, and construct correlations between observed variables and such parameters. This is the asset of an Ensemble Kalman Filter over an efficient but simpler technique like nudging.

So far, the assimilation of MCS temperature profiles has revealed how critical it is to estimate the dust vertical distribution in order to improve the forecast on temperature (figure 2). This compensates the current inability of MGCMs to reproduce dust detached layers observed by MCS [13].

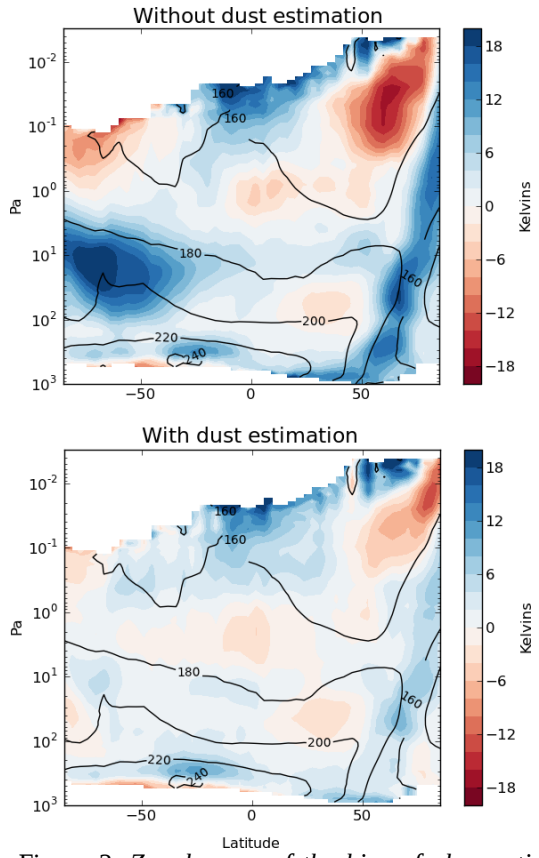

Figure 2: *Zonal mean of the bias of observations minus forecast of dayside temperatures, for the period Ls=310°-315°, MY29. Top: The MGCM uses a guiding scenario for dust opacity. A regional dust storm in the southern hemisphere causes the strong cold bias observed in the southern latitudes. Bottom: the dust is updated in the analysis thanks to its correlation with temperature, and freely evolves in the MGCM, without any guiding scenario. The forecast is clearly improved at 10 Pa, where the dust storm occurs.*

References:

[1] Lewis, S. R. and Read, P. L. (1995) *ASR*, *16*, 9–13. [2] Hunt, B. R., Kostelich E. J. and Szuniogh, I. (2006) *Elsevier Physica D*, *230*, 112-126. [3] Hoffman, M. J., et al. (2010) *Icarus*, *209*, 470-481. [4] Greybush, S. J. et al. (2012) *JGR*, *117*. [5] Lee C., et al. (2011) *JGR*, *116*. [6] Forget, F. et al. (1999) *JGR*, *104*, 24165-24175. [7] Colaitis, A. et al. (2013) *JGR*, *118*, 1468-1487. [8] Madeleine, J.-B. et al. (2012) *GRL*, *39*. [9] Lefèvre, F. et al. (2004) *JGR*, *109*. [10] Newman, C. E. et al. (2004) *QJRMS*, *130*, 2971-2989. [11] Greybush, S. J. et al. (2013) *QJRMS*, *139*, 639-653. [12] Rogberg, P. et al. (2010) *QJRMS*, *136*, 1614-1635. [13] McCleese, D. J. et al. (2010) *JGR*, *115*.