Towards assimilation of ExoMars TGO ACS observations into the LMD Mars GCM

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Challenges for Mars ensemble data assimilation $_{\rm OOOOO}$

ACS assimilation

LMD data assimilation scheme for Mars

LMD Mars General Circulation Model

LETKF: Local Ensemble Transform Kalman Filter. Ensemble of 16 members estimates background mean $\bar{\mathbf{x}}^{b}$ and error covariance **P**.

Covariance inflation:

P increased by adaptive scalar factor based on comparison of forecast errors with error covariances $\langle \mathbf{dd}^{\mathsf{T}} \rangle = \mathbf{HPH}^{\mathsf{T}} + \mathbf{R}$ (Miyoshi, 2011)

[Navarro, 2016]



Some unobserved variables updated assuming same covariances and using known correlations (e.g. SW heating \sim dust)

Always: $T \rightarrow T$ $T \rightarrow p_s, u, v$

 $egin{aligned} & ext{Optional:} \ & \mathcal{T}, \ & q_{ ext{dust}}
ightarrow & q_{ ext{dust}} \ & q_{ ext{ice}}
ightarrow & q_{ ext{ice}}, \ & q_{ ext{vap}} \end{aligned}$

 $\begin{array}{c} \mathsf{Current:} \\ \mathcal{T} \to \mathcal{T}, q_{\mathrm{dust}} \\ \mathsf{No} \ q_{\mathrm{ice}}, \ q_{\mathrm{vap}_{\supset Q, \mathbb{C}}} \end{array}$

Challenges for Mars ensemble data assimilation $_{\rm OOOOO}$

ACS assimilation

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Temperature assimilation

Zonal mean temperature vs. MCS observations, MY29 $L_s = 165 - 170$



Assimilation reduces distance between model temperatures and observations, particularly in lower atmosphere.

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ACS assimilation

Effect of assimilation cycle length on temperature





Challenges for Mars ensemble data assimilation $\bullet \circ \circ \circ \circ$

ACS assimilation

Challenges for Mars ensemble-based data assimilation

Ensemble, observations diverge Dust / water ice hard to assimilate with as ensemble converges (unlike Earth) temperature: all are inter-dependent



Ensemble, observations diverge quickly once assimilation stops



 \rightarrow Observed q_{dust} , q_{ice} can easily fall outside ensemble when obs or whole ensemble = 0. \rightarrow Ensemble aerosol uncertainty distributions are non-Gaussian.

→ Observed dust structures may not be reproducible by model, so forecast step removes them.



 \rightarrow Water ice needs model-consistent dust concentration as condensation nuclei, otherwise forecast step will adjust one or the other. \rightarrow Direction of causality connecting changes in water ice and temperature is ambiguous.

Observations always at same local time of day (until TGO): 3h, 15h



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Challenges for Mars ensemble data assimilation

ACS assimilation

What is un-Earthlike — (1) Covariance inflation

Reminder (Miyoshi, 2011): Multiply background error variance at observations by α_i $\langle \mathbf{dd}^{\mathsf{T}} \rangle = \alpha_i \mathbf{HPH}^{\mathsf{T}} + \mathbf{R}$ where $\mathbf{d} = \mathbf{y} - H(\mathbf{x}^{\mathsf{b}})$. KF updates α_i .



Inflation parameter is $\gg 1$. Will occur when ensemble SD is underestimated, but also when bias \gg observational error. The second

Challenges for Mars ensemble data assimilation $\circ \circ \circ \circ \circ$

ACS assimilation

What is un-Earthlike — (2) Chaos and bias

Mars' atmosphere is not always chaotic

Many observations fall outside ensemble



 ${\sim}35\%$ observations outside

Bias $+0.4\sigma$, spread 0.5σ [Hamill, 2001]

On Mars, model-obs distance can become dominated by model error. Ensemble shrinks over time at certain times of year. Can't be alleviated by chaos expanding ensemble to fill state space.

Breeding vector growth rates

Month	Time of year	Mean daily growth rate
1	Northern mid-spring	-0.0197
2		-0.0495
3		-0.00308
4	Northern mid-summer	-0.0307
5		-0.0494
6		-0.0363
7	Northern mid-autumn	-0.0376
8		0.130
9		0.262
10	Northern mid-winter	0.330
11		0.126
12		0.140

[Newman et al., 2004] Always +ve for Earth

Correction steps in ensemble data assimilation

- E.g. Earth atmosphere/oceans, oil industry reservoir modelling
 - (1) Estimate, remove bias (forecast mean observations \neq 0)
 - (2) Correct for model errors (additional matrix "big **Q**" in background error covariance)
 - (3) Covariance inflation

Bias correction (method from Dee & Da Silva, 1998):

- "Forecast bias" = "Non-zero mean forecast error"
- If forecast is biased, assigning more weight to observations will reduce bias, but analysis will be noisier.
- Unbiased Kalman filter:

$$\mathbf{\tilde{x}}^{\mathrm{a}} = \mathbf{\tilde{x}}^{\mathrm{b}} + \mathsf{K}(\mathbf{\tilde{y}}^{\mathrm{o}} - \mathcal{H}[\mathbf{\tilde{x}}^{\mathrm{b}}]) \qquad \mathsf{K} = \mathsf{PH}^{\mathsf{T}}[\mathsf{HPH}^{\mathsf{T}} + \mathsf{R}]^{-1}$$

• Where unbiased quantities are

$$\boldsymbol{\tilde{x}}^{a} = \boldsymbol{x}^{a} - \boldsymbol{b}^{a} \qquad \boldsymbol{\tilde{y}}^{o} = \boldsymbol{y}^{o} - \boldsymbol{b}^{o} \qquad \boldsymbol{\tilde{x}}^{b} = \boldsymbol{x}^{b} - \boldsymbol{b}^{b}$$

• Plug these in and, assuming observation operator is linear:

 $\mathbf{x}^{\mathbf{a}} = \mathbf{x}^{\mathbf{b}} + \mathbf{K}[\mathbf{y}^{\mathbf{o}} - \mathbf{H}\mathbf{x}^{\mathbf{b}}] \qquad \mathbf{b}^{\mathbf{a}} = \mathbf{b}^{\mathbf{b}} + \mathbf{K}[\mathbf{b}^{\mathbf{o}} - \mathbf{H}\mathbf{b}^{\mathbf{b}}]$

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Accounting for model error

Additive inflation ("big Q")

- Parametrizes model errors by adding random perturbations with a certain covariance structure to each ensemble member.
- $\mathbf{x}_{k}^{f} = \mathbf{x}_{\rho(k)}^{f} + r\mathbf{q}_{k}$ with $\mathbf{\bar{q}}_{k} = 0$, r constant tuneable parameter.
- Background error covariance increases by $\mathbf{Q} = r^2 \langle \mathbf{q}_k \mathbf{q}_k^T \rangle$ but in a physically sensible way.
- Li+ (2009) [Earth atmosphere]: \mathbf{q}_k are randomly selected 6h tendencies in NCEP reanalyses (i.e. the selection is random, not the field). Geostrophically balanced.
- Lang+ (2017) [Solar wind]: "**Q** ... contains the relevant MHD balances to perturb the ensemble with a model error term"

Parameter ensemble

 Simplest form: Assign different values of unknown parameters to different ensemble members (e.g. Greybush et al. 2012 for dust opacities)

Challenges for Mars ensemble data assimilation

ACS assimilation

ESA/Roscosmos ExoMars Trace Gas Orbiter

Main goal: To search for rarified gases such as methane







Inserted into Mars orbit 19 October 2016. Reached final orbit 7 April 2018.

Instruments:

ACS (3 infrared spectrometers), CASSIS (stereo visible imaging camera), FREND (neutron detector — subsurface), NOMAD (3 infrared/UV spectrometers)

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Towards assimilation of ACS data

Thermal infrared channel (TIRVIM). Retrievals at LMD by Sandrine.

Initially: Atmospheric temperature profiles

Potentially: Surface temperatures, column dust opacity, column ice opacity

Local times vs MCS:

MCS/PFS local times

ACS local times at 45°N / 0°E



Observation operator for TIRVIM $(x^{a} = x^{b} + K(y^{o} - H[x^{b}]))$

What would a retrieval (of e.g. T) look like if TIRVIM observed the background x^b?

- $\bullet\,$ This is the correct comparison with retrieved observations $\boldsymbol{y}^{o}.$
- Earlier work with MCS used (naïve, but simpler) linear interpolation to observation points.
- [Alternative assimilate radiances directly]

Correct form is observation- and instrument-specific. Our TIRVIM assimilation scheme uses two steps:

- Interpolate background to retrieval position and pressures, as before (linear in \mathbf{x} , t)
- Use averaging kernels to retrieve what ACS would see:

$$\hat{\boldsymbol{\mathsf{x}}} = \boldsymbol{\mathsf{x}}^{\mathrm{p}} + \boldsymbol{\mathsf{A}}(\boldsymbol{\mathsf{x}}^{\mathrm{b}} - \boldsymbol{\mathsf{x}}^{\mathrm{p}})$$

(Rodgers & Connor, 2003) Prior \mathbf{x}^{p} and averaging kernels \mathbf{A} are the same as for retrieval used to create observations \mathbf{y}^{o} .

Current goals

Improving assimilation scheme

- Work out what's going on with aerosols
- Explicit correction of forecast biases
- Ensemble of poorly constrained parameters

Assimilating ACS observations

- Start working with calibrated observations
- Set up pipeline to assimilate as new retrievals come in
- \bullet Add $\mathcal{T}_{\rm surf},$ dust and ice column-integrated quantities to assimilation
- Co-assimilation of ACS and MCS observations
- See EPSC in September for progress...!

Talking points

Mars atmosphere fundamentally different from Earth's (sometimes non-chaotic)

Ensemble schemes can struggle with this

Help and ideas are available from other fields, where non-chaotic systems are more common

These three correction steps are well-established in more fully-developed ensemble data assimilation:

- (1) Estimate and remove bias
- (2) Correct for model errors ("big \mathbf{Q} ")
- (3) Covariance inflation