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Assimilation of temperatures and column dust opacities measured by ExoMars TGO-ACS-TIRVIM during the MY34 Global Dust Storm

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15 Key Points:

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We assimilate temperature and dust observations from ExoMars TGO-ACS-TIRVIM during the MY34 global dust storm. The analysis verifies well against independent Mars Climate Sounder temperature and dust profiles, and Curiosity pressure measurements. At the peak of the global dust storm the winds strengthen, the diurnal tide mi-grates poleward, and the semi-diurnal tide strengthens.

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22 Abstract

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We assimilate atmospheric temperature profiles and column dust optical depth obser-23 vations from the ExoMars Trace Gas Orbiter Atmospheric Chemistry Suite thermal in-24 frared channel (TIRVIM) into the LMD Mars Global Climate Model. The assimilation 25 period is Mars Year 34 $L_s = 182.3 - 211.4^{\circ}$, covering the onset and peak of the 2018 26 global dust storm. We assimilated observations using the Local Ensemble Transform Kalman 27 Filter with 36 ensemble members and adaptive inflation; our nominal configuration as-28 similated TIRVIM temperature profiles to update temperature and dust profiles, followed 29 by dust column optical depths to update the total column dust abundance. The obser-30 vation operator for temperature used the averaging kernels and prior profile from the TIRVIM 31 retrievals. 32

We verified our analyses against in-sample TIRVIM observations and independent 33 Mars Climate Sounder (MCS) temperature and dust density-scaled opacity profiles. When 34 dust observations were assimilated, the root-mean-square temperature error verified against 35 MCS fell by 50% during the onset period of the storm, compared with assimilating tem-36 perature alone. At the peak of the storm the analysis reproduced the location and mag-37 nitude of the peak in the nighttime MCS dust distribution, along with the surface pres-38 sure diurnal cycle measured by Curiosity with a bias of less than 10 Pa. The analysis 39 winds showed that, at the peak of the storm, the meridional circulation strengthened, 40 a 125 m s^{-1} asymmetry developed in the midlatitude zonal jets, the diurnal tide weak-41 ened near the equator and strengthened to 10-15 K at midlatitudes, and the semi-diurnal 42 tide strengthened almost everywhere, particularly in the equatorial lower atmosphere. 43

44 **P**

Plain Language Summary

The ExoMars Trace Gas Orbiter (TGO) has been in a low orbit around Mars since early 2018. Halfway through 2018 (Mars Year 34) a large amount of dust was lifted from Mars' surface into the lower atmosphere. This dust eventually obscured most of the planet, called a global dust storm. These storms have a large effect on the temperature and weather in Mars' atmosphere.

⁵⁰ In this study we have used observations from TGO's thermal infrared instrument ⁵¹ TIRVIM. This measures how much light comes from the Martian atmosphere and sur-⁵² face at wavelengths where heat is emitted; these measurements can be used to work out

the atmospheric temperature and how much dust it contains. We combined these observations with a numerical model of Mars' climate in a way that takes into account how uncertain we are about the atmospheric properties measured by TIRVIM and the climate predicted by the model.

We compared our results with separate temperature and dust observations made by the Mars Climate Sounder instrument on board another Mars orbiting satellite, Mars Reconnaissance Orbiter. We also studied how the atmospheric wind, the day-night cycle, and the surface pressure all changed while the dust storm was raging.

61 **1** Introduction

The ExoMars Trace Gas Orbiter (TGO) reached its final orbit around Mars in April 62 2018. It carries the Atmospheric Chemistry Suite (ACS), which comprises three infrared 63 spectrometers covering different wavelength ranges (Korablev et al., 2018). The thermal 64 infrared spectrometer TIRVIM continuously monitors the atmospheric column in nadir, 65 while the near- and mid-infrared channels NIR and MIR (and occasionally TIRVIM) per-66 form solar occultation measurements when the spacecraft-Mars-Sun geometry permits. 67 TGO's orbit made ACS-TIRVIM's (TIRVIM hereafter) observations of Mars unique at 68 the time among existing Mars spacecraft, because it systematically measures the atmo-69 spheric structure over all local times of day. Nearly all spacecraft that have orbited Mars 70 since Mars Global Surveyor at the start of the modern era have taken observations at 71 two fixed local times of day separated by 12 hours (Mars Express has an orbit that means 72 it does take observations at varying local times of day (Giuranna et al., 2021), but not 73 systematically, and since May 2021 the Emirates Mars Mission has observed Mars from 74 high orbit with full local time coverage (Amiri et al., 2022)). TGO takes about 55 sols 75 to cycle through the full 24 hours of sub-spacecraft local times, which is close to the op-76 timal repeat period to sample the diurnal cycle (Capderou & Forget, 2004). 77

TIRVIM took observations at Mars from March 2018, shortly before TGO reached its final orbit, until the end of 2019, when its cryocooler failed, rendering it impossible to cool the instrument to the required temperature to make thermal infrared measurements. At the start of this ~20-month period, about halfway through Mars Year (MY) 34, a Global Dust Storm (GDS) took place. This started around $L_s = 186^{\circ}$ in Acidalia, reached a peak in visible dust optical depth between $L_s = 200-205^{\circ}$, and faded away

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⁸⁴ by about $L_s = 300^{\circ}$ (Kass et al., 2019; Montabone et al., 2020; Kleinböhl et al., 2020). ⁸⁵ The storm was severe enough to end the solar-powered Opportunity rover's 15-year mis-⁸⁶ sion. The start of the TIRVIM dataset covers the onset and peak of this GDS; fortuitously, ⁸⁷ as these events happen in only about one Mars year out of three (Kahre et al., 2017).

Over the last 20–25 years, scientists have studied Mars using data assimilation, which 88 combines observations with our best scientific understanding encoded within numerical 89 simulations (Kalnay, 2003). A variety of methods have been used, with most work us-90 ing Analysis Correction (AC) (Lorenc et al., 1991; Lewis & Read, 1995; Lewis et al., 2007; 91 Steele, Lewis, & Patel, 2014) or the Ensemble Kalman Filter (Evensen, 2003; M. J. Hoff-92 man et al., 2010; Greybush et al., 2012; Navarro et al., 2014). These have assimilated 93 various observations, primarily atmospheric temperature profiles, but also dust column optical depths (Lewis & Barker, 2005; Montabone et al., 2014; Ruan et al., 2021), dust 95 profiles (Navarro et al., 2017; Ruan et al., 2021), and column abundances of water ice 96 (Steele, Lewis, & Patel, 2014), water vapour (Steele, Lewis, Patel, Montmessin, et al., 97 2014), ozone (Holmes et al., 2018), and carbon monoxide (Holmes et al., 2019). The pri-98 mary assimilated quantity is temperature, because it is readily available from thermal 99 infrared measurements from multiple spacecraft, changes in other atmospheric quanti-100 ties such as pressure and winds are related to changes in temperature via known phys-101 ical laws, and while wind observations are a vital part of Earth data assimilation (Hersbach 102 et al., 2019), they are not available for Mars. 103

Most relevant to the current work, Navarro et al. (2014, 2017) built a data assim-104 ilation scheme for Mars' atmosphere using the Local Ensemble Transform Kalman Fil-105 ter (LETKF) (Hunt et al., 2007) and the Laboratoire de Météorologie Dynamique Mars 106 Global Climate Model (LMD Mars GCM) (Forget et al., 1999; Pottier et al., 2017), as-107 similating observations from the Mars Climate Sounder (MCS) instrument on board NASA's 108 Mars Reconnaissance Orbiter (MRO). MCS retrieval products include temperature, dust, 109 and water ice profiles taken from a Sun-synchronous polar orbit at ~ 3 AM / 3 PM lo-110 cal mean solar time (Kleinböhl et al., 2009). 111

In this paper we report on assimilation of observations from the early part of the ExoMars TGO ACS-TIRVIM observation period, covering the onset and peak of the MY34 GDS. We make two methodological improvements to the existing scheme documented by Navarro et al. (2017). First, we improve the way temperature forecasts are compared

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with observations by using the averaging kernel matrix and prior from the TIRVIM tem-116 perature retrievals. This is the correct way to compare forecast with observations when 117 assimilating retrieval products (R. N. Hoffman, 2011). Second, the scheme can now as-118 similate column dust optical depths (CDOD); previous work with this particular scheme 119 did not assimilate CDOD because such data are not available from MCS (while dust pro-120 files are available, they do not reach the ground, and published MCS CDODs interpo-121 late the dust profiles to the ground in the lowest part of the atmosphere, typically the 122 lowest 10 km). We describe both of these improvements in detail in Sect. 3. 123

The aims of this paper are as follows. First, to demonstrate assimilation of obser-124 vations from TIRVIM on board ExoMars TGO. Second, to validate the assimilation against 125 independent datasets such as MCS temperatures and dust opacities, and surface pres-126 sure measurements from the Curiosity rover. Finally, to investigate the dynamics of Mars' 127 atmosphere during the MY34 GDS, particularly those properties that cannot be mea-128 sured directly but which can be retrieved by the assimilation process, such as wind. Sec-129 tion 2 describes the TIRVIM observations, and in Section 3 we describe the model, as-130 similation scheme, and observation operator. Section 4 describes sensitivity tests done 131 to optimise the assimilation parameters. Section 5 describes the main results of the pa-132 per, and in Section 6 we conclude. 133

¹³⁴ 2 Observations

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TIRVIM is a thermal infrared spectrometer that observes Mars at wavelengths be-135 tween 1.7–17 μm (590–5900 cm⁻¹) (Korablev et al., 2018). It was designed to be con-136 tinuously operating during TGO's mission (although in practice this was not possible 137 due to the limited lifetime of the instrument's cryocooler). TIRVIM measures radiance 138 spectra in nadir, from which have been retrieved atmospheric temperature profiles, sur-139 face temperatures, dust column optical depths (at 1090 $\rm cm^{-1}$) and water ice column op-140 tical depths (at 820 cm⁻¹). These retrievals are fully described by Guerlet et al. (2022). 141 In this paper we focus on atmospheric temperature and column dust optical depth ob-142 servations only. TIRVIM operated from MY34 $L_s = 142.79^{\circ}$ (13 March 2018) until MY35 143 $L_s = 115.16^{\circ}$ (2 December 2019), when its cryocooler failed. 144

¹⁴⁵ TIRVIM takes observations at all local times over a 55-sol period. TGO's inclina-¹⁴⁶ tion is 74°, so there are no nadir observations poleward of this latitude in either hemi-

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Figure 1. Temperature uncertainty in the TIRVIM dataset between MY34 $L_s = 182.288 - 211.388^{\circ}$ as a function of $\sigma = p/p_{surf}$. The right y-axis is pseudo-altitude $z = -H \ln \sigma$, assuming a scale height of H = 8.5 km, as per the Mars standard atmosphere from the surface to 85 km altitude in Table 4.7 of M. D. Smith et al. (2017) (an underestimate in the lower atmosphere and an overestimate in the middle atmosphere, but it is sufficiently accurate for plotting). We use H = 8.5 km for all pseudo-altitudes in this paper. The solid line is the mean, dashed lines are mean +/- 1 standard deviation, and the dotted lines show the minimum and maximum.

sphere. The temperature profiles have a maximum sensitivity between 5 and 50 km above 147 the ground, and a vertical resolution of about 10 km (Guerlet et al., 2022). The instru-148 ment is only sensitive to the true atmospheric temperatures at altitudes of 3–55 km, based 149 on retrieval averaging kernel statistics (see Section 3.3). From the trace of the averag-150 ing kernel matrix, the number of degrees of freedom in each temperature retrieval is 3.3 151 \pm 0.2. The measurement uncertainty, shown in Fig. 1, is a function of altitude. It is typ-152 ically 2–4 K over most of the altitude range, increasing at the top and the bottom of the 153 profile. Column dust optical depths typically have an uncertainty of 0.06–0.20 (the 25– 154 75% range over the assimilated observations, with mean 0.16). 155

In this paper we assimilate observations from just before the onset of the MY34 global dust storm to just after its peak, from $L_s = 182.288-211.388^\circ$. Figure 2 shows the data availability and distribution in latitude and local time for this period. These specific start and end points were chosen because there are long gaps in the data imme-

diately before and afterwards. There are 312,741 temperature profiles and 214,806 col-168 umn dust retrievals during this period. There is a gap in the data between $L_s = 191.567 -$ 169 194.420°), with significantly higher observation density afterwards. The local time of day 170 for the majority of observations moves backwards over time; almost all 24 hours of lo-171 cal time are sampled during this period. Exceptions are the northern hemisphere around 172 4 AM, and the southern hemisphere around 4 PM. A significant fraction of TIRVIM ob-173 servations have missing values for CDOD, as it cannot be retrieved in conditions when 174 the temperature contrast between surface and lower atmosphere is low, which typically 175 occurs near dawn and dusk in non-stormy conditions (see Guerlet et al. (2022)). Most 176 of the missing dust retrievals are poleward of 60° , where almost all dust retrievals are 177 removed. 178

$\mathbf{187}$ **3** Methods

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3.1 Model

The LMD Mars GCM solves the hydrostatic primitive equations on a rotating sphere 189 alongside parametrizations of many physical processes relevant to Mars (Forget et al., 190 1999). Most pertinent to the current work is the treatment of dust, which is transported 191 by the model in a two-moment scheme which separately transports a mass mixing ra-192 tio and the number of dust particles within each grid cell (Madeleine et al., 2011). By 193 transporting these two quantities separately one can deduce the dust particle size dis-194 tribution by assuming a log-normal particle size distribution. The LMD Mars GCM has 195 been validated against many observational data sets since the Viking landers in the 1970s 196 (Forget et al., 1999). 197

We run the model at the standard climate model resolution of 64×48 points in 198 longitude and latitude, corresponding to $5.625^{\circ} \times 3.75^{\circ}$ horizontal resolution. The ver-199 tical grid is stretched so there are more points near the ground; we use 32 hybrid (sigma-200 pressure) levels with the lowest level about 4 m above the ground, and the highest level 201 at about 100 km altitude, depending on local conditions. The model's dynamical time 202 step δt is 1/960 of a sol (~94.5 s), and the physical parametrisations are called every 10 203 dynamical timesteps (i.e. every physics timestep, 1/96 of a sol, or four times per Mar-204 tian hour). Supporting Text S1 describes the time axis used in the GCM and how it re-205 lates to observation times. 206

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(a) vs MY34 L_s and latitude.

(b) vs local true solar time and latitude.





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Figure 2. Number of TIRVIM temperature profiles (left) and column dust optical depth retrievals (right) as a function of MY34 L_s , latitude, and local true solar time during the period assimilated in this work. (a) vs MY34 L_s and latitude; (b) vs local true solar time and latitude; (c) vs MY34 L_s and local true solar time. Observations are counted in bins with width 5.0° in latitude, 0.5 hours in local time, and 0.5° in L_s ; bins with no observations are white. The upper *x*-axis shows the equivalent model sol numbers; see Supporting Text S1 for details.

Dust sediments and can fall out of the bottom of the model onto the surface. When 207 run without assimilation, dust column abundances in the GCM are forced by rescaling 208 at each physics timestep to a global "dust scenario" map based on observed dust opac-209 ities, with gaps filled in by kriging (Montabone et al., 2015, 2020). The GCM also lifts 210 dust from the surface at a constant rate, to preserve the dust particle size distribution 211 by seeding the atmosphere with larger particles, which preferentially sediment out. Wa-212 ter is transported by the model (Pottier et al., 2017), and can condense into water ice 213 clouds, whose particles have an effective radius that varies with local conditions, and which 214 are treated as radiatively active. Dust acts as a source of cloud condensation nuclei, and 215 precipitating water ice can remove dust from the atmosphere by scavenging. 216

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3.2 Assimilation Scheme

Assimilation is based on the LETKF, which is a standard method for ensemble data assimilation (Evensen, 2003; Hunt et al., 2007). Full details of the LETKF itself as applied in this context are described in Navarro et al. (2014) and Navarro et al. (2017); here we give a summary and focus on the changes to the scheme since Navarro et al. (2017).

Before starting the assimilation we spin up an ensemble of N GCM simulations. 222 This ensemble is used as the forecast for the first assimilation step. Its ensemble mean 223 $\overline{\mathbf{x}}^{b}$ is used as the *background* atmospheric state in the assimilation, and the purpose of 224 the ensemble is to estimate the uncertainty in the background state. We use the spread 225 of values to set the background error covariance matrix **B** in the assimilation. For the 226 spin up stage in this case we ran an ensemble of GCM simulations starting at MY34 sol 227 318 ($L_s = 150.2^{\circ}$), i.e. about 30 L_s before the start of the assimilation period. This 228 gave the ensemble members enough time to spin up to an equilibrium state individually, 229 and to spread out over the model state space such that the standard deviation of the en-230 semble at each point quantified the uncertainty in the background state. As dust is the 231 major unknown in Mars' atmosphere, and the atmospheric state is so sensitive to it, to 232 span the range of possibilities we ran each spin-up simulation with a different globally-233 fixed visible CDOD, log-uniformly distributed between 0.05 and 1.5. This spans the typ-234 ical range of realistic dust column optical depths in non-GDS years (Montabone et al., 235 2015).236

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The assimilation step computes an *analysis* ensemble $\mathbf{x}^{a,i}$, $i = 1 \dots N$, at the anal-237 ysis time t_a . Most of the results are presented using the mean of this ensemble, which 238 we shall simply refer to as the *analysis*. The assimilation uses the forecast ensemble as 239 the background state $\mathbf{x}^{\mathrm{b},i}$, and observations \mathbf{y}_{o} within an assimilation window stretch-240 ing from $t_a - t_b$ to $t_a + t_f$, where t_b is the window length backwards in time and t_f is 241 the window length forward in time. To ensure each observation is used in exactly one 242 assimilation step, $t_b = t_f = \Delta t/2$, where Δt is the assimilation cycle length, the time 243 between consecutive assimilation steps. Adaptive covariance inflation is applied to the 244 background ensemble. The observation operator $H(\dots)$ is applied to the background en-245 semble, to interpolate the forecasts in space and time to the observation points, and to 246 ensure that the forecast and observations are subsequently compared as if TIRVIM were 247 observing the background state; Sect. 3.3 provides full details. 248

To perform the assimilation, at each model grid point we identify observations within $L_{\rm eh} = 900$ km horizontally (along a great circle), and within $L_{\rm ev} = 0.2\sqrt{6}$ vertically in log(p), a process called localisation (Hamill et al., 2001), which significantly speeds up the calculation and also reduces the effects of random noise in the observations acting over large distances. The measurement uncertainty for each observation is modified according to its horizontal (d_h) and vertical distance (d_v) from the grid point, where d_v is measured in log p. For observation l, this modified observational uncertainty is

$$\sigma_l^{\rm o} = \sigma^{\rm o} \exp\left(\frac{d_h^2}{2L_{\rm ih}^2}\right) \exp\left(\frac{d_v^2}{2L_{\rm iv}^2}\right) \tag{1}$$

where σ^{o} is the unmodified observational uncertainty, $L_{\rm ih} = 600$ km is the internal horizontal localisation length, and $L_{\rm iv} = 0.2$ is the internal vertical localisation length.

The Local Ensemble Transform Kalman Filter equation for the analysis mean $\bar{\mathbf{x}}^{a}$ is (Hunt et al., 2007; Navarro et al., 2017)

$$\bar{\mathbf{x}}^{\mathrm{a}} = \bar{\mathbf{x}}^{\mathrm{b}} + \mathbf{X}^{\mathrm{b}} \tilde{\mathbf{P}}^{\mathrm{a}} (\mathbf{Y}^{\mathrm{b}})^{\top} \mathbf{R}^{-1} (\mathbf{y}^{\mathrm{o}} - H(\bar{\mathbf{x}}^{\mathrm{b}}))$$
(2)

where $\bar{\mathbf{x}}^{b}$ is the background mean, \mathbf{X}^{b} is the matrix whose columns are individual forecast ensemble members minus the ensemble mean, in model space, \mathbf{Y}^{b} is the matrix whose columns are individual forecast ensemble members mapped to the observation points mi²⁶³ nus the ensemble mean, in observation space, **R** is the matrix of observation uncertain-²⁶⁴ ties (diagonal) modified by the localisation weights above, $\mathbf{y}^{o} - H(\bar{\mathbf{x}}^{b})$ is the difference ²⁶⁵ between the observations, in observation space, called the "innovation", and

$$\tilde{\mathbf{P}}^{\mathrm{a}} = \left[(N-1)\mathbf{I} + (\mathbf{Y}^{\mathrm{b}})^{\top} \mathbf{R}^{-1} \mathbf{Y}^{\mathrm{b}} \right]^{-1}$$
(3)

is a normalization factor. The terms before the innovation are essentially the ratio of the
 background error covariance to the sum of the background and observational error co-

variances, but for vectors of background forecasts and observations.

Equation 2 can be written as

$$\bar{\mathbf{x}}^{\mathrm{a}} = \bar{\mathbf{x}}^{\mathrm{b}} + \mathbf{X}^{\mathrm{b}} \mathbf{w}^{\mathrm{a}} \tag{4}$$

where \mathbf{w}^{a} is a matrix of weights assigned to each ensemble member based on the differ-270 ences between the forecast and observations, the observational error covariance, and the 271 background error covariance. We are not restricted to using \mathbf{w}^{a} to update solely the quan-272 tity that is observed; \mathbf{w}^{a} can be used to update any prognostic variable. This is only phys-273 ically sensible where there are correlations between changes in the observed quantity and 274 changes in the other prognostic variable. This can be justified by noting that some quan-275 tities are related by known physical laws; for example the atmospheric temperature and 276 wind structure are related, as are the atmospheric temperature and surface pressure. This 277 assimilation of such *indirectly observed* variables is discussed by Navarro et al. (2017) in 278 detail. 279

In this work we use atmospheric temperature observations to update the GCM atmospheric temperature field (temperature updates temperature, TuT). We then use \mathbf{w}^{a} computed for temperature to update the zonal and meridional velocities (TuW) and the surface pressure (TuPs, using \mathbf{w}^{a} at the lowest model grid level).

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In most configurations (see below) we also use temperature to update the dust mass mixing ratio (TuD). Navarro et al. (2014) showed that Mars' observed detached dust layers (Heavens et al., 2011) are reproduced by the assimilation when TuD is employed, as dust modifies the temperature field. TuD is applied only where the correspondence between changes in dust and changes in temperature are strong, i.e. where the shortwave

heating rate is above 0.2 K hr^{-1} and the total insolation is above 100 W m^{-2} (this is 289 essentially a condition on time of day and latitude as a function of time of year). It is 290 also constrained to occur only above pseudo-altitude ~ 11 km, because the correspon-291 dence between dust and heating is based on MCS observations, which have systematic 292 biases close to the ground (Navarro et al., 2014). Whenever the dust mass mixing ra-293 tio (MMR) is updated by the assimilation the dust number is also updated, so that any 294 new dust has a particle size distribution with fixed dust effective radius; this radius is 295 a free parameter of the assimilation scheme. 296

- In the forecast step we step forward the GCM in time, starting from the analysis ensemble, from analysis time t_a up to $t_a + \Delta t + t_f$, which is the next analysis time plus the window length forward in time. The cycle then begins anew at the new analysis time $t_a + \Delta t$. During the forecast step the GCM runs freely with no constraints on the dust field. In the assimilation experiments the only processes that can add or remove dust from the atmosphere are the assimilation step and sedimentation onto the surface.
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3.3 Observation Operator Using Averaging Kernels

The comparison between forecast and observations $\mathbf{y}^{o} - H(\mathbf{x}^{b})$ is a crucial part 304 of the data assimilation process. This comparison must compare like-with-like to min-305 imise representation errors and ensure that forecast errors are calculated accurately. The 306 observation operator must not only interpolate the forecast to the observation locations, 307 but also reproduce what TIRVIM would observe if it were to observe the forecast atmo-308 sphere. When retrievals are used, the correct way to do this is to use the same averag-309 ing kernels and prior profile that were used in the retrieval (Rodgers & Connor, 2003; 310 R. N. Hoffman, 2011). 311

We have improved on earlier versions of this assimilation scheme by basing the observation operator for atmospheric temperature on the TIRVIM retrieval averaging kernels. Earlier work using this scheme by Navarro et al. (2017) had no vertical smoothing in the observation operator. This was (reasonably well) justified as they assimilated limb observations from MCS, which have a vertical resolution of about 5 km (Kleinböhl et al., 2009), similar to the model's vertical resolution throughout most of the atmosphere. Nadir measurements have a coarser vertical resolution, so some smoothing of the forecast profile is required. We believe this is the first time averaging kernels have been applied directly in Mars data assimilation.

Before the averaging kernels are applied, we interpolate from the forecast grid to each observation location linearly in longitude, latitude, and time, and then vertically to the observed σ coordinates, linearly in log σ .

The averaging kernels quantify the relative contributions to each point in a retrieved profile from the true and prior atmospheric states at each altitude. The vertical width of the averaging kernel sets the true vertical resolution of the instrument. The retrieval \mathbf{y}^{o} is related to the true atmospheric state $\hat{\mathbf{x}}$ and the prior profile \mathbf{x}^{p} by the averaging kernels **A** (Rodgers & Connor, 2003) such that

$$\mathbf{y}^{\mathrm{o}} = \mathbf{x}^{\mathrm{p}} + \mathbf{A}(\hat{\mathbf{x}} - \mathbf{x}^{\mathrm{p}}) \tag{5}$$

A perfect retrieval has $\mathbf{A} = \mathbf{I}$, in which case $\mathbf{y}^{o} = \hat{\mathbf{x}}$, with no prior information retained. A retrieval that contains no information from the true atmospheric state has $\mathbf{A} = \mathbf{0}$, in which case $\mathbf{y}^{o} = \mathbf{x}^{p}$. Real instruments are somewhere in between, and \mathbf{A} is a strong function of altitude.

To assimilate a retrieval, the observation operator $H(\mathbf{x}^{b})$ is a slightly modified form of Eq. 5:

$$H(\mathbf{x}^{\mathrm{b}}) = \mathbf{x}^{\mathrm{p}} + \mathbf{A}(\mathbf{x}^{\mathrm{b}} - \mathbf{x}^{\mathrm{p}})$$
(6)

where \mathbf{x}^{b} is the background profile interpolated to the retrieved profile levels. The result is a "retrieved forecast", i.e. what a retrieval of a hypothetical TIRVIM spectrum would look like if it observed the forecast atmosphere.

Figure 3 shows two examples of this observation operator applied to a real forecast of TIRVIM retrievals. Figure 3a is a "good" case near the top of the range of retrieval degrees of freedom (3.97), and Fig. 3b is a "bad" case at the low end of the range (2.62). As TIRVIM is a nadir sounder, the averaging kernels (second column) are quite broad, and the "retrieved forecast" ensemble and ensemble mean are smoother than the raw forecast ensemble and ensemble mean.

(b) $L_s = 208.84^\circ$, longitude 108.94°W, latitude 40.82°N, LTST 15.87.

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The retrieved temperature profile and the retrieval prior converge at the top of the 360 profiles, indicating that almost all the information in the retrieval comes from the prior 361 there, and so we should avoid assimilating this part of the profile. After the observation 362 operator is applied to the forecast ensemble (Eq. 6), at the top of profile the ensemble 363 collapses onto the retrieval prior, so differences between the forecast and retrieved tem-364 perature profiles are artificially small in this region (note also the change in ensemble 365 spread in the 4th column of Fig. 3 before and after Eq. 6 is applied). Conversely, lower 366 in the profiles, most or all of the spread in the forecast ensemble is preserved by the ob-367 servation operator, hence in this region the difference between the forecast temperature 368 profile and the retrieved temperature profile is real, and so we should include such ob-369 servations in the assimilation. 370

To distinguish between these two cases, and quantify how much information comes 371 from the prior and the true atmospheric state, we use the sum over the averaging ker-372 nels at each level (Fig. 3, 3rd column). Where the averaging kernel sum is near zero, all 373 the information in the retrieval comes from the prior. Where the averaging kernel sum 374 is close to one (e.g. at 10 Pa), almost all the information in the retrieval comes from the 375 observed radiances. Therefore a suitable way to distinguish between these two cases is 376 to impose a filter on the averaging kernel sum at each level of the temperature profile, 377 and only assimilate observations whose averaging kernel sum falls within a particular range. 378 This ensures that observations which are assimilated contain as much information from 379 the observed radiances as possible, and as little information from the retrieval prior. The 380 grey band in the 3rd column of Fig. 3 identifies the levels that would be retained if a fil-381 ter of 0.75–1.25 were applied. The main practical difference between the two cases in Figs 3a 382 and 3b is that the vertical range of retained observations extends higher in the atmo-383 sphere when the retrieval degrees of freedom are higher. 384

Figure 4 shows averaging kernel sum statistics for TIRVIM temperature retrievals between MY34 sols 376–424. Between 5–40 km a large majority of the profiles have averaging kernel sums close to one, and even between 1–50 km in many cases. Figure 4c shows how much of the dataset remains when various filters are applied. Between 10– 30 km almost all observations are kept, whatever the condition. The largest differences are between 40–60 km, where imposing strict limits of 0.85–1.15 removes at least 50% of the observations, and also in a narrow band of altitudes around 5–10 km. If the fil-

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Figure 4. Averaging kernel sum statistics for TIRVIM temperature retrievals between MY34 $L_s = 182.288 - 211.388^\circ$, as a function of pseudo-altitude. (a) Sum over averaging kernels. The black dotted lines are the minimum and maximum, the solid line is the median, the dashed lines are the 25th and 75th percentiles, and the vertical grey lines indicate 0 (all weight on the prior) and 1 (all weight on the measured radiances). (b) Standard deviation of averaging kernel sums. (c) Percentage of observations kept when an averaging kernel sum filter is applied.

- ter is relaxed slightly to 0.75–1.25, then most of the observations that were rejected for the strict limits are included.
- 402

3.4 Column Dust Optical Depth Assimilation

The second major update to our scheme is to assimilate column dust optical depths 403 (denoted CuD, i.e column-updates-dust). Column dust optical depths have been assim-404 ilated by others previously (Lewis & Barker, 2005; Montabone et al., 2014; Ruan et al., 405 2021), but were not used by Navarro et al. (2014, 2017) in previous work with this scheme. 406 They used MCS observations, and MCS is a limb scanner that does not measure CDOD 407 directly as it rarely sounds the dust profile all the way to the ground. TIRVIM dust re-408 trievals do have to make some assumptions about the vertical dust distribution, which 409 is a limitation of TIRVIM data, but as a nadir instrument it does view the full atmo-410 spheric column. 411

Guerlet et al. (2022) assume dust is well-mixed in the lowest two scale heights and that its mixing ratio decreases linearly with $\log(p)$ above. A quality flag is assigned to each CDOD observation, related to the sensitivity of the radiance to changes in dust load.

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Above warm surfaces, dust retrievals are quite reliable, but above colder surfaces, there can be systematic biases and non-unique solutions depending on the assumed dust vertical distribution. Only retrievals with a good quality flag are assimilated; this excludes about a third of the CDOD retrievals (Fig. 2).

We forecast the column dust optical depth at the TIRVIM frequency of 1090 cm⁻¹ using the forecast dust mass mixing ratio profile. For each available column dust observation we interpolate the forecast dust MMR field to the observation longitude, latitude, and time. We then integrate the total dust column opacity in the vertical based on Eq. 1 of Madeleine et al. (2011):

$$\tau_{\rm dust} = \sum_{k=1}^{K} \frac{3}{4} \frac{Q_{\rm ref} q_k}{\rho_p r_{\rm eff} g} \Delta p_k \tag{7}$$

where τ_{dust} is the column dust optical depth; K is the total number of model levels; $Q_{\text{ref}} =$ 424 1.53112 is the effective dust extinction coefficient at the TIRVIM wavelength, that ac-425 counts for integration over a dust particle size distribution with dust effective radius $r_{\rm eff}$ 426 1.5 μ m and effective variance $\nu_{\text{eff}} = 0.3$; q_k is the dust mass mixing ratio at level k; $\rho_p =$ 427 2500 kg m⁻³ is the dust density; and Δp_k is the pressure thickness of model level k. We 428 made some of the same assumptions as in the retrieval, such as using the same fixed $Q_{\rm ref}$ 429 and $r_{\rm eff}$, but in the GCM $r_{\rm eff}$ is a function of location, and the GCM does not assume 430 any particular vertical dust distribution, so these restrictions could be relaxed in future. 431

Once CDOD is forecast at each observation location, observations are assimilated into the GCM CDOD field using the LETKF in the same way as for atmospheric temperature (Eq. 2), except vertical weighting is not required. As CDOD is not a prognostic variable in the LMD Mars GCM, once we have the CDOD analysis we adjust the dust MMR profile so that its column dust optical depth is the same as the CDOD analysis. As CDOD varies linearly with dust MMR this is a simple linear rescaling of the atmospheric dust profile. The dust number is also updated, as described at the end of Sect. 3.2.

We ran two versions of the dust assimilation. In the first case (CuD) we just used the column dust optical depth observation to update the dust column abundance. In this case we might expect the vertical dust distribution not to reflect the real vertical dust distribution, as the model does not generate detached dust layers spontaneously. We try to avoid this problem with our second version (TuD-CuD), which combines the direct

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assimilation of CDOD with an indirect update of the dust profile using temperature (TuD). 444 First we perform the TuD step, and then assimilate CDOD. The TuD step should pro-445 duce a more accurate vertical dust distribution than the model alone, and the column 446 dust assimilation constrains the total amount of dust in each column using real obser-447 vations. The order of operations is important here: TuD must be done first and CuD 448 second, because otherwise the total amount of dust in the column will not be the amount 449 that is assimilated from observations; if we assimilate CDOD first there is no guaran-450 tee that the TuD step will conserve the total amount of dust in the column. This is sim-451 ilar to Ruan et al. (2021), who assimilated MCS dust profiles alongside TES and THEMIS 452 dust column abundances, but note we do not assimilate the dust vertical distribution di-453 rectly, but only infer it from changes in temperature. 454

455 4 Sensitivity Analysis

The assimilation scheme has several tuneable parameters. To optimise the temper-456 ature assimilation we performed sensitivity tests running short assimilations during the 457 onset of the MY34 GDS (i.e. the period during which the dust concentrations are chang-458 ing most rapidly). We varied four parameters, and ran an assimilation for each combi-459 nation of values, 72 in total. We varied the number of ensemble members N (18, 36, and 460 72), the length of the assimilation cycle Δt (2, 3, 6, and 12 hours), the threshold on the 461 averaging kernel sum filter (0.50-1.50, 0.75-1.25, and 0.85-1.15), and the effective ra-462 dius of new dust added to the model $r_{\rm eff}$ (1.0 μ m and 1.5 μ m). 463

The goal of the ensemble is to sample the range of uncertainties in the forecast model. 464 However, the ensemble is finite, and the mean and covariance of a finite ensemble will 465 differ from the mean and covariance of an infinitely large ensemble. If an infinitely-large 466 ensemble spanning all possible atmospheric states has mean \bar{x} and variance σ^2 , then an 467 ensemble of size N will have an expected error in the ensemble mean of σ/\sqrt{N} , and an 468 expected error in the ensemble variance of $\sigma^2 \sqrt{2/(N-1)}$ (Ahn & Fessler, 2003). Hence 469 if the ensemble is too small then outlying values and noise will have a disproportionately 470 large influence on the ensemble mean and variance, so we expect the assimilation to be 471 more accurate for larger ensembles. This is an important part of the rationale for using 472 localization in LETKF assimilation (Hamill et al., 2001). Conversely, larger ensembles 473 consume more resources, and we might expect the forecast step to be more unstable, as 474 the simulations span a larger (and hence more extreme) range of atmospheric states. 475

(a) Verification against TIRVIM at 10–30 km pseudo-z, coloured by cycle length.

(b) Verification against MCS at 10-100 Pa, coloured by new dust effective radius.

Figure 5. Time series showing RMS error for short test assimilations verified against (a)
TIRVIM temperature observations at 10–30 km pseudo-altitude, and (b) MCS temperature observations at 10-100 Pa. In (a) the lines are colour-coded by the length of the assimilation cycle,
and in (b) they are colour-coded by the dust effective radius used for new dust. The different
lines for a given colour correspond to variations in the other three parameters.

There is a trade-off when choosing the assimilation cycle length between the fore-482 cast length and the number of grid points that are updated during each cycle. When the 483 cycle is short, the model has less time to diverge from reality. For Mars the forecast er-484 ror can saturate in 3-6 hours (Navarro et al. (2017), Fig. 2). But when the analysis cy-485 cle is longer a larger fraction of the model grid points are updated during each analy-486 sis. This is particularly important for assimilation of tracer quantities such as dust, be-487 cause the only way that new dust is added to the model state is during the assimilation 488 step. 489

Figure 4c shows different averaging kernel sum filter limits. The very narrow range (0.85–1.15) excludes many observations near 10 km and 40 km pseudo-altitude, the moderate range (0.75–1.25) encompasses those observations, and the wide range (0.5–1.5) includes a lot of observations, but some will have 50% of their information content from the prior profile.

The dust effective radius r_{eff} for new dust added to the analysis state is tested for 1.0 μ m, because Navarro et al. (2017) use this value, and 1.5 μ m, because the dust retrievals we assimilate use that value (Guerlet et al., 2022). Dust with smaller radius takes longer to sediment and fall out onto the surface.

We ran each test assimilation from sols 397–407 ($L_s = 194.8 - 200.9^{\circ}$), using the 499 TuTD configuration (i.e. no CDOD assimilation), and we compared the results with TIRVIM 500 and MCS temperature profiles. We interpolated the analysis in time and space to the 501 TIRVIM (on σ levels) and MCS (on pressure levels) observations. To compare with TIRVIM 502 we applied the averaging kernel operator and the averaging kernel sum filter. We did not 503 apply any vertical smoothing before making the comparison with MCS observations, as 504 the vertical resolution of those observations is comparable with the grid level spacing. 505 We then computed the bias and the root-mean squared error (RMSE) over various pseudo-506 altitude ranges for TIRVIM (0-10, 10-30, and 30-50 km) and various pressure ranges 507 for MCS (100–1000, 10–100, 1–10, 0.1–1, and 0.01–0.1 Pa). Time series for each of the 508 72 test assimilations are shown in Fig. 5. Because we ran every possible combination of 509 parameters, we were also able to plot individual comparisons between cases varying just 510 one parameter with all others held constant. These are shown in Fig. 6. In both figures 511 we only show select cases where there were significant differences (gauged by eye) be-512 tween parameter values. 513

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514	The clearest difference is between the assimilation cycle lengths. Over altitude ranges
515	where TIRVIM is sensitive (i.e. up to 50 km), the shorter the cycle the better the match
516	to observations. Figure 5a shows a representative set of RMSE time series, and Fig. $6b$
517	shows scatter plots, both verifying against TIRVIM. This trend remains when compared
518	against MCS, although it is not as strong. A clearer trend when verifying against MCS
519	is that $r_{\rm eff} = 1.0~\mu{\rm m}$ for new dust is generally better than 1.5 $\mu{\rm m},$ particularly for 1–
520	100 Pa (i.e. where the TIRVIM observations are), as illustrated in Figs 5b and 6d.

The ensemble size makes a smaller difference, but overall both N = 36 and N =72 produce lower RMSE than N = 18 (Figure 6a). The differences between the averaging kernel sum filters are smaller still (Fig. 6c); 0.50–1.50 clearly performs the worst, but there is no visible difference between 0.75–1.25 and 0.85–1.15.

The only parameter that had any effect on the practical aspects of running the as-534 similation was the ensemble size. The clock time to assimilate 1 sol of data was strongly 535 correlated with ensemble size, with N = 72 taking 38–58 min (5–95th percentiles over 536 all N = 72 cases) while N = 36 took 25–39 min and N = 18 took 22–34 min. The 537 forecast step run time depends on the maximum time for any one ensemble member to 538 finish, so the more ensemble members there are, the longer this is. The number of times 539 individual forecast members became unstable was significant only for N = 72 (1.2–13.6 540 times per sol, compared with 0.1-1.2 for N = 36). We had planned to run a series of 541 tests with N = 108, but chose not to do so as a result. 542

In conclusion, $r_{\rm eff} = 1.0 \ \mu {\rm m}$ for new dust was generally better than 1.5 $\mu {\rm m}$. An 543 averaging kernel sum filter of 0.75–1.25 was better than 0.5–1.5 in most cases, and marginally 544 better than 0.85–1.15 in some cases. As it allows more observations to be assimilated 545 over a wider range of altitudes, we chose the more inclusive 0.75-1.25 condition. An en-546 semble size of N = 36 was better than N = 18 in most cases. N = 36 and N = 72547 were very similar, but N = 72 required lots of manual restarts and had more model in-548 stability in the forecast step, so we chose N = 36 ensemble members. Finally, a 2-hour 549 cycle length was better than 6- and 12-hours in most cases. It was also better than 3 hours 550 in some cases, when compared with TIRVIM observations, but 2- and 3-hour cycles were 551 generally similar. As a 2-hour cycle provides higher time resolution in the final data prod-552 uct, we chose $\Delta t = 2$ hrs. 553

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(c) Varying averaging kernel sum filter, verifying against MCS at 10–100 Pa.

(d) Varying new dust effective radius $r_{\rm eff},$ verifying against MCS at 1–10 Pa.

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526 Figure 6. Scatter plots showing temperature RMS error comparisons between 10-sol test assimilations, varying one parameter at a time. Each dot corresponds to a single analysis. Filled 527 and line contours indicate point density, and individual points are outliers. Equality is the diag-528 onal grey line, and all axes are in K (note not all go to zero). In (a) ensemble size N is varied, 529 verifying against TIRVIM at 30–50 km; (b) varies the assimilation cycle length Δt , verifying 530 against TIRVIM at 10-30 km; (c) varies the averaging kernel sum filter range, verifying against 531 MCS at 10-100 Pa; and (d) varies the effective radius for new dust $r_{\rm eff}$, verifying against MCS at 532 1-10 Pa.

554 5 Results

We ran three versions of the assimilation between sols 376–424 of MY34, encom-555 passing the onset and peak of the Global Dust Storm. These were TuTD (temperature 556 updates temperature and dust profile), TuT-CuD (temperature updates temperature, 557 and then column dust updates the dust column and hence the dust profile), and TuTD-558 CuD (temperature updates temperature and dust profile, and then column dust updates 559 the dust column and hence the dust profile). The assimilation period splits nicely into 560 three distinct segments: before the storm (sols 376–385, $L_s = 182.3 - 187.6^{\circ}$); during 561 the onset of the storm (sols 385–410, $L_s = 187.6 - 202.7^{\circ}$); and at the peak of the storm 562 (sols 410–424, $L_s = 202.7 - 211.4^{\circ}$). 563

In assimilation experiments it is usual to compare the analysis with a free running 564 model as a control. Alongside the three assimilations we ran a "GCM ensemble" of GCM 565 simulations without assimilation, where the dust column abundances are constrained to 566 match the MY34 dust scenario (Montabone et al., 2015, 2020). This is not a true free-567 running model, but it is the standard configuration for this GCM; if the LMD Mars GCM 568 is run without such constraints then dust will sediment out and the model will crash af-569 ter O(10 sols) as the lack of airborne dust leads to extremely low atmospheric temper-570 atures. When the GCM is run with a dust scenario, dust is added and removed from the 571 atmosphere by rescaling to the column abundances, by dust lifting from the surface (which 572 occurs at a constant rate), and by sedimentation onto the surface. The results below use 573 the mean of this ensemble when referring to the "GCM ensemble". 574

One additional complication is that the dust scenario used in the GCM ensemble 575 is based on MCS observations. So when our analyses are verified against MCS observa-576 tions and the assimilation's performance compared against the GCM ensemble, the com-577 parison between the GCM ensemble and MCS observations is more like an "in-sample 578 comparison", while the comparison between the analyses and MCS observations is a com-579 pletely independent verification. When we assimilate column dust optical depths directly, 580 the comparison between our analyses and the GCM ensemble is a fairer comparison than 581 when they are not assimilated. 582

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5.1 In-sample Verification against TIRVIM Observations

We computed the forecast and analysis bias and RMSE with respect to the TIRVIM observations that were assimilated, as described in Sect. 4, and over the same vertical ranges. We also computed CDOD at 1090 cm⁻¹ from the forecasts and analysis using Eq. 7, and verified them against TIRVIM CDOD observations (i.e. with fixed $Q_{\rm ref}$ and $r_{\rm eff}$).

Figure 7 shows the temperature bias and RMSE, and Fig. 8 shows the CDOD bias 596 and RMSE. In both fields the analysis RMSE is typically 50% of the forecast RMSE, and 597 the analysis bias is close to zero, showing that the assimilation reduces the error by adding 598 observational information to the system. The temperature RMSE is close to the observed 599 uncertainty (Fig. 1). There is no systematic bias in the analyses at any altitude. The 600 forecasts typically have a cool bias below 10 km altitude, and between 30–50 km in the 601 TuTD case there is a cool bias while in the other two cases there is a warm bias from 602 about sol 398 onwards. The GCM ensemble is generally biased cool before the dust storm 603 begins, and once the dust storm begins it is biased warm at 0-10 km and cold at 30-50 604 km. There is a gap in the data between sols 391.7126–396.4636, after which the forecast 605 RMSE is temporarily high, but returns to an equilibrium after about 1 sol (note this also 606 quantifies the convergence time for the assimilation). 607

For the CDOD observations, when dust is assimilated the error reduction by the 608 assimilation is about 50% before the GDS begins, and 20-40% once the GDS has begun. 609 In the TuTD case (where no dust observations are assimilated, so this is an out-of-sample 610 verification), the error reduction is close to zero, except at the peak of the storm. There 611 is a significant negative bias in the TuTD case (i.e. significantly less dust in the anal-612 ysis than in the TIRVIM observations). When dust is assimilated directly the analysis 613 error is significantly less, leaving a small negative bias of about 0.1–0.2 in each case. This 614 is comparable with the typical uncertainty in the CDOD measurements (mean 0.16 over 615 this study period) The GCM ensemble has a strong positive bias (about 1.0) compared 616 with the TIRVIM CDOD observations at the peak of the storm. 617

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Figure 7. In-sample verification against TIRVIM temperature profiles. The left column shows 591 the bias (analysis/forecast - observations) and the right column shows the RMS error. Data 592 are split by pseudo-altitude: (a) 30-50 km; (b) 10-30 km; and (c) 0-10 km. Solid lines show 593 the analysis mean, and dashed lines show the forecast mean. TuTD is blue, TuT-CuD is green, 594 TuTD-CuD is red, and the GCM ensemble is grey. Data are averaged over 0.5-sol bins. 595

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Figure 8. As Fig. 7, but showing in-sample verification against TIRVIM extinction column
 dust optical depths.

5.2 Out-of-sample Verification against MCS Observations

We verified the analysis and forecast means against MCS temperature observations as described in Sect. 4. We also computed the dust density-scaled opacity (DSO) in extinction at 21.6 μ m (Eq. 7 from Madeleine et al. (2011)):

$$\tau_{\rm DSO} = \frac{3}{4} \frac{Q_{\rm ref}(r_{\rm eff})q}{\rho_{\rm dust} r_{\rm eff}} \tag{8}$$

where in this case both $r_{\rm eff}$ and $Q_{\rm ref}$ take the local dust effective radius into account.

Figures 9 and 10 show bias and RMSE time series for temperature and dust DSO, over pressure ranges where the assimilated TIRVIM observations typically lie. These results are clearly poorer than the in-sample verification against TIRVIM observations, but that is not surprising. However, it is important to identify and understand the degree to which they are poorer.

The GCM ensemble, which is constrained by CDOD derived from MCS dust opacities, has a bias and RMSE that falls within the range of values from the three cases assimilating TIRVIM observations. This is encouraging because it implies that, while the absolute errors are larger than when compared with TIRVIM observations, the out-ofsample comparison is comparable with what is effectively an in-sample comparison between the GCM ensemble and MCS observations.

Before the storm there is little difference between the bias and RMSE in the three cases where TIRVIM observations are assimilated. Lower in the atmosphere than 100 Pa, the temperature analysis (as well as the GCM ensemble) has a cold bias of 2–8 K

Figure 9. Independent verification against MCS temperature profiles. The left column shows the bias (analysis/forecast – observations) and the right column shows the RMSE. Data are split by pressure ranges: (a) 1-10 Pa; (b) 10-100 Pa; and (c) 100-1000 Pa. Solid lines show analysis means, and the dashed line shows the mean of the GCM ensemble. TuTD is blue, TuT-CuD is green, TuTD-CuD is red, and the GCM ensemble is grey. Data are averaged over 0.5-sol bins.

in all cases; we note that when dust observations are assimilated this bias is closer to zero.
Higher in the atmosphere than 100 Pa, the TuTD case has a cold bias during the onset
of the storm, while the TuT-CuD and TuTD-CuD cases have a warm bias during that
period, with the three cases converging at the peak of the storm. Similarly, during the
onset of the storm the RMSE in the TuTD case is significantly poorer than in the two
other assimilation cases, showing that it is crucial to assimilate some information about
dust when it is changing quickly.

There is significantly lower dust DSO during the onset of the storm in the TuTD 658 case than in the MCS observations, at all pressure ranges shown (Fig. 10). For TuT-CuD 659 and TuTD-CuD there is, on average, a higher dust DSO than in the MCS observations 660 during the onset of the storm, and by the peak of the storm the bias is close to zero be-661 tween 10-100 Pa and positive in the other two ranges. The GCM ensemble overestimates 662 the amount of dust below the 100 Pa pressure level, and underestimates it above. At all 663 altitudes the RMSE increases from a low level before the onset of the storm, and increases 664 thereafter. As for temperature, we note that the RMSE in the three analyses is compa-665 rable with the RMSE in the GCM ensemble. 666

The amount of dust in the atmosphere is considerably more when dust observa-667 tions are assimilated, and so the heating effect of more dust helps to explain why, on av-668 erage, the cases assimilating dust are warmer than the TuTD case. At the peak of the 669 dust storm the analysis temperature bias in all three cases between 10-100 Pa is close 670 to zero, while the GCM ensemble has a cold bias. This is possibly because the GCM en-671 semble does not exhibit detached dust layers, with its dust distribution monotonically 672 decreasing upwards, so the dust is more concentrated at the surface, heating the low-673 est atmospheric layers and cooling the higher layers, compared with when dust is assim-674 ilated. This is analysed further in the next section. 675

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5.3 Temperature and Dust Structure during the Onset of the MY34 GDS

We now compare the atmospheric temperature and dust structure between the analyses, the GCM ensemble, and MCS observations. Figures 11 and 12 show Hovmöller diagrams for temperature and dust DSO at 21.6 μ m, at 30 Pa (where MCS dust concentrations are highest during the storm). These cover all latitudes starting before the storm and ending just after its peak. Figure 13 shows vertical cross-sections of temperature at

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Figure 10. As Fig. 9, but showing independent verification against MCS extinction dust
 density-scaled opacity profiles.

⁶⁸² 3 PM and 3 AM local mean solar time (chosen because that is the observation time for
⁶⁸³ MCS), and Fig. 14 shows the same for dust density-scaled opacity.

There is significant heating associated with the global dust storm, with equatorial 684 temperatures rising from 180 K to 225 K over this period (Fig. 11). Assimilating dust 685 observations significantly improves the temperature analysis with respect to the inde-686 pendent MCS observations. When no dust observations are assimilated (Fig. 11a) the 687 temperature change due to the storm over this L_s range is somewhat slower than observed 688 by MCS (although 225 K is reached by the end). But when column dust optical depths 689 are assimilated (Fig. 11 b-c) the change in temperature better matches the MCS obser-690 vations. Other details also match better, such as the hemispheric asymmetry at the peak 691 of the storm. The differences between the case with and without the TuD step are small, 692 but TuTD-CuD gives marginally better results, particularly for sols 391–396 (Fig. 11 c). 693

The GCM ensemble captures the minimum at the equator around sol 395 better than the analyses, but overall the analyses match the MCS observations better. The former underestimates the atmospheric temperature at most latitudes, and does not fully reproduce the observed hemispheric asymmetry at the peak of the storm.

The temperature results at 3 AM are similar, although the differences between the GCM ensemble and the analyses are smaller. Hovmöller diagrams for 3 AM are shown in Supporting Fig. S1.

The differences in dust DSO between the various configurations (Fig. 12) are larger than for temperature. MCS observations show a peak in the dust DSO around 60×10^{-4} m² kg⁻¹. The GCM ensemble (Fig. 12d), whose column abundance is constrained by MCS observations, matches the dust DSO reasonably well, at least in terms of its evolution during the onset of the storm up to the peak, although the distribution is more strongly concentrated at the equator than for the MCS observations.

The three analyses each contain overall less dust than do the MCS observations. The largest difference is between TuTD and the other two cases. For TuTD (Fig. 12a), dust opacity increases slowly during the onset of the storm, and only begins to change rapidly close to its peak. The other two cases (Figs 12 b-c) follow the increase in dust during the onset of the storm better, although neither reach the peak opacity measured by MCS at this pressure by the peak of the storm. None of the three analyses reproduce

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(d) GCM ensemble.

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Figure 12. As Fig. 11 but showing Hovmöller diagrams for dust density-scaled opacity at 21.6 709 μm at 30 Pa. Line contours are every $10\times 10^{-4}~m^2~kg^{-1}.$ 710

the short-lived peak at the equator between sols 389–393, but we note this partially coincides with a gap in the TIRVIM data. Nevertheless, it is clearly better to have assimilated the dust information directly, both in terms of the temperature analysis and the
dust analysis.

The equivalent plots at 3 AM, shown in Supporting Fig. S2, show a more favourable comparison between the TuT-CuD / TuTD-CuD analyses and MCS observations. Both reach the peak dust opacity seen in MCS observations by the peak of the storm (which we note the GCM ensemble does not do at 3 AM). They also reasonably reproduce the growth in dust concentration from sol 397 onwards. Kleinböhl et al. (2020) discuss the significant diurnal variations of temperature and dust opacity in the MCS observations during the dust storm in some detail.

Figures 13 and 14 show vertical cross-sections of the temperature and dust densityscaled opacity before and at the peak of the global dust storm. These figures show how well the analysis reproduces the vertical structure, compared with the GCM ensemble and MCS observed profiles. In these figures and hereafter we only use our "best case" assimilation TuTD-CuD, alongside the GCM ensemble.

Both the temperature and dust opacity increase significantly during the storm, dur-748 ing daytime and nighttime. Unfortunately it is not possible to compare directly with day-749 time MCS observations at the peak of the storm near the surface, as the high dust con-750 centration prevents a reliable retrieval of both temperature and dust (Fig. 13b, right). 751 Before the storm, both the analysis and the GCM ensemble match the MCS observa-752 tions well during nighttime. During the daytime the temperatures below 100 Pa are gen-753 erally lower than the MCS observations. This may be because at low altitudes during 754 daytime the MCS observations are biased warm compared with TIRVIM due to a lack 755 of retrievals in cloudy regions; see Guerlet et al. (2022), Fig. 19. The analysis and GCM 756 ensemble both have a temperature maximum of 250–260 K close to the surface during 757 the daytime at the peak of the storm. The maximum MCS temperature is at about 100 758 Pa, and appears to be a local maximum. In northern midlatitudes the observed profiles 759 do reach the ground, and the analysis reasonably reproduces the observed meridional tem-760 perature gradient from about 30° poleward (Fig. 13b). Both the analysis and the GCM 761 ensemble are cooler than MCS at its maximum temperature point around 100 Pa, 30– 762 50° S, with the analysis about 10-20 K cooler, and the GCM ensemble about 5-10 K cooler 763

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(b) 3 PM LMST, at the peak of the storm (sols 416–420).

(c) 3 AM LMST, before the storm (sols 380–384).

(d) 3 AM LMST, at the peak of the storm (sols 416–420).

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than observed. Both the analysis and the GCM ensemble reproduce the tongue of warm
air in the middle atmosphere at northern hemisphere midlatitudes, which appears at the
peak of the storm.

At 3 AM the analysis and GCM ensemble reproduce the MCS observations bet-767 ter at the peak of the storm than during the daytime (Fig. 13d). The analysis reproduces 768 the local temperature maximum around 100 Pa that appears in the MCS observations 769 better than does the GCM ensemble. The analysis also better reproduces the meridional 770 temperature variation below 10 Pa. The analysis and GCM ensemble have quite differ-771 ent temperature structures near the top of the domain near the equator, with the local 772 temperature minimum in the GCM ensemble being about a decade in pressure below where 773 it is in the analysis. However, the MCS observations do not allow us to distinguish be-774 tween these two, as the observations cease just above 0.1 Pa, but there does not appear 775 to be an obvious temperature minimum as the GCM ensemble predicts. Note also that 776 the assimilated TIRVIM observations typically go up to about 1 Pa, so above this any 777 differences are due to the GCM's response to assimilated data rather than being con-778 strained directly by observations. 779

As in the Hovmöller diagrams, there is a larger difference between the analysis and 784 the GCM ensemble in the dust opacity cross-sections (Fig. 14) than in temperature (Fig. 13). 785 Before the storm, the amount of dust peaks around 5×10^{-4} m² kg⁻¹ in the analysis and 786 10×10^{-4} m² kg⁻¹ in the GCM ensemble, with little diurnal variation (Fig. 14 a, c). The 787 MCS observations peak at about 5×10^{-4} m² kg⁻¹, but the main difference is that the 788 dust is more vertically extended in the observations, with a clear "detached dust layer" 789 peak near the equator during the night-time around 100 Pa of about 5×10^{-4} m² kg⁻¹. 790 which is not visible in either the analysis or the GCM ensemble. 791

At the peak of the storm there are larger differences between daytime (Fig. 14b) 792 and nighttime (Fig. 14d), as well as between the analysis, GCM ensemble, and MCS ob-793 servations (Fig. 14, different columns). In general, the GCM ensemble contains signif-794 icantly more dust than either the analysis or the MCS observations. The peak in the GCM 795 ensemble is close to the ground in the southern hemisphere, about 90×10^{-4} m² kg⁻¹ at 796 both 3 PM and 3 AM, while the MCS observations peak at about 30 Pa, with maxima 797 around 60×10^{-4} m² kg⁻¹ at 3 PM and a concentrated peak of 50×10^{-4} m² kg⁻¹ at 3 798 AM. 799

(b) 3 PM LMST, at the peak of the storm (sols 416–420).

(c) 3 AM LMST, before the storm (sols 380–384).

(d) 3 AM LMST, at the peak of the storm (sols 416–420).

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Figure 14. As Fig. 13, but showing dust density-scaled opacity at 21.6 μ m at 3 PM and 3 AM local mean solar time. Line contours are spaced every 10^{-4} m² kg⁻¹ from $1-4 \times 10^{-4}$ m² kg⁻¹, and then every 5×10^{-4} m² kg⁻¹ thereafter.

The analysis reproduces the vertical and latitudinal distribution of dust opacities 800 significantly better than does the GCM ensemble. In particular, it very clearly contains 801 a detached dust layer at both 3 PM and 3 AM, with a broad peak between 10–100 Pa, 802 as seen in the MCS observations, while the GCM ensemble peaks near the surface (al-803 though note not exactly at the surface). The peak dust DSO in the analysis is about 40×10^{-4} 804 $m^2 kg^{-1}$ at both 3 PM and 3 AM. During the daytime this is an underestimate, as the 805 dust opacity peak in the MCS observations is above $50 \times 10^{-4} \text{ m}^2 \text{ kg}^{-1}$ between 60°S and 806 20°N. During nighttime the MCS observations peak at 50×10^{-4} m² kg⁻¹ near the equa-807 tor. However, there is significantly less dust than during the daytime, with the opacity 808 above $40 \times 10^{-4} \text{ m}^2 \text{ kg}^{-1}$ between 20°S and 20°N. This distribution is matched well by 809 the analysis dust opacity at this time, which is above $40 \times 10^{-4} \text{ m}^2 \text{ kg}^{-1}$ between 20°S 810 and the equator. 811

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5.4 Wind Structure Retrieved by Assimilation

Having demonstrated that our reanalysis state fits the independent MCS observations reasonably well, we now turn to wind, a quantity that is not observed but which is retrieved by the assimilation. This is one of the main strengths of the data assimilation process.

Figures 15 and 16 show the meridional mass stream function and zonal velocity at 823 3 PM and 3 AM local mean solar time averaged over two time periods before the storm 824 and at its peak. Before the storm, the daytime overturning circulation (Fig. 15 a-b) shows 825 a Hadley cell covering the whole of each hemisphere. There is a weak counter-rotating 826 cell higher than 10 Pa, which only appears in the GCM ensemble. The study period is 827 close to the autumnal equinox, so the Hadley cell is approximately symmetric about the 828 equator. During nighttime (Fig. 15 c-d) the overturning circulation is reversed, with the 829 descending branch of the main overturning cell at the equator, with a weaker thermally 830 direct cell between 1–10 Pa. The meridional overturning circulation is generally weaker 831 in the analysis than in the GCM ensemble. 832

The overturning circulation strengthens during the daytime as the storm progresses, and extends higher into the atmosphere, significantly strengthening the overturning circulation aloft. The thermally-indirect cell present in the GCM ensemble disappears, leaving a single Hadley cell spanning the whole model domain from the surface to 100 km

-37-

(a) 3 PM LMST, before the storm (sols 380–384).

(b) 3 PM LMST, at the peak of the storm (sols 416–420).

(c) 3 AM LMST, before the storm (sols 380–384).

(d) 3 AM LMST, at the peak of the storm (sols 416–420).

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Figure 15. As Fig. 13, but showing the meridional mass streamfunction at 3 PM and 3 AM local mean solar time. The right hand column shows the difference between the analysis and GCM ensemble (analysis — GCM). In the left two columns brown is clockwise motion and blue is anticlockwise motion. In the right column red means more clockwise, and blue means more

pseudo-altitude. Close to the surface, the southern hemisphere cell extends about 40°
into the northern hemisphere. At nighttime the circulation changes considerably. The
symmetric Hadley cells are severely disrupted, and a cross-equatorial cell develops which
covers most latitudes with a weak Hadley circulation in the northern polar region.

The zonal velocity response to the storm (Fig. 16) is noticeably asymmetric about 844 the equator, both during daytime and nighttime. Like the meridional overturning cir-845 culation, this change is more profound during nighttime. Before the storm there are pro-846 grade jets in both hemispheres with a retrograde jet above 1 Pa at low latitudes, and 847 these jets are slightly weaker at 3 AM. By the peak of the storm, the equatorial retro-848 grade jet and the prograde northern hemisphere jet increase in speed by about 25 m s^{-1} 849 and 75 m s⁻¹ respectively, while the southern hemisphere prograde jet remains approx-850 imately the same speed but its vertical extent shrinks, becoming a more focused jet around 851 75° S / 10 Pa. During nighttime, the northern prograde jet strengthens by about 50 m 852 s^{-1} , but the southern prograde jet weakens significantly by about 75 m s^{-1} , almost dis-853 appearing. At the peak of the storm, the two prograde jets differ in speed by 125 m s^{-1} . 854 The strong strengthening of the northern hemisphere jet at both 3 PM and 3 AM is con-855 sistent with the steepening of the latitudinal temperature gradient near 60°N at the peak 856 of the storm (Fig. 13 b-d), via thermal wind balance. A similar argument explains the 857 weakening of the southern prograde jet: the temperature contours are flattened in the 858 southern hemisphere around 10 Pa (Fig. 13 a-b) 859

⁸⁶⁰ Differences between the analysis and the GCM ensemble are relatively small com-⁸⁶¹ pared with the magnitude of the jets, with typical differences up to $\pm 25 \text{ m s}^{-1}$ over most ⁸⁶² of the domain. The analysis winds are typically more eastward at lower latitudes than ⁸⁶³ the GCM ensemble, in particular above 10 Pa, and they are typically more westward at ⁸⁶⁴ higher latitudes.

865

5.5 Diurnal Cycle and Thermal Tides

One of the reasons for the design of the ExoMars TGO orbit is that it samples the Martian atmosphere at different local times of day. In this section we present how this affects the analysis, and analyse how the diurnal cycle changes during the global dust storm. Assimilation constrains the atmosphere at particular local times, and then the forecast model transfers that information to other local times during model integration,

-39-

(a) 3 PM LMST, before the storm (sols 380–384).

(b) 3 PM LMST, at the peak of the storm (sols 416-420).

(c) 3 AM LMST, before the storm (sols 380–384).

(d) 3 AM LMST, at the peak of the storm (sols 416–420)

-40-

Figure 16. As Fig. 15, but showing the zonal velocity at 3 PM and 3 AM local mean solar time. Line contours are spaced every 25 m s⁻¹.

841

further constraining the atmospheric structure at local times that were not observed. For sols 380–384 the bulk of the TIRVIM observations are at 1–2 AM / PM, and for sols 416– 420 they are at 5–6 AM / PM (Fig. 2c). First we look at the diurnal cycle in two different ways (Figs 17–18) and then analyse the migrating Sun-synchronous tide modes (Figs 19–20). Note that where MCS observations are not part of the analysis, we do our computations in LTST, as that is more dynamically relevant than LMST, and it is the local time used in the GCM.

Figure 17 shows the temperature diurnal cycle averaged over two different latitude bands before and at the peak of the global dust storm. We interpolated the analysis and the GCM ensemble to fixed pressure levels, and then interpolated to each local time in 1-hour steps. We then averaged the temperature at each pressure and local time over latitude and sol ranges. This was done at $60-65^{\circ}$ S (to match Fig. 4.13 of M. D. Smith et al. (2017)), and over a latitude band at the equator.

There is a significant difference between the diurnal cycle before and at the peak of the storm. At 60–65° S (Fig. 17 a-b) the range of temperatures at all altitudes significantly increases with the peak to peak diurnal variability increasing from about 10 K at 30 Pa before the storm to about 60 K at the peak of the storm. In the middle atmosphere (0.1-1 Pa), the 12-hour oscillation is overwhelmed by a 24-hour oscillation that peaks between 3-6 AM.

The main difference between the analysis and GCM ensemble is in the lower atmosphere temperature maximum around 6 PM. In the analysis this is concentrated in the local time direction between 6-8 PM, and is extended in the pressure direction up to about 10 Pa. In the GCM ensemble the peak is concentrated closer to the ground, up to about 100 Pa, but spans a longer range of local times. The peak during the night time in the lower atmosphere is quite similar in the analysis and the GCM ensemble.

At the equator (Fig. 17 c-d) we also see the 12-hour oscillation in the upper part of the domain weaken. In the analysis the peak around 12 PM between 0.1–1 Pa almost completely disappears during the peak of the storm, while in the GCM ensemble it is still distinguishable. Lower in the atmosphere the 12-hour oscillation is strengthened both in the the analysis and the GCM ensemble at the peak of the storm, and the 24-hour oscillation is less clear, although in the analysis the 12-hour oscillation is dominant while in the GCM ensemble the 24-hour oscillation is dominant.

-41-

(b) GCM ensemble averaged over 60–65°S.

(c) TuTD-CuD analysis averaged over 10°S–10°N.

(d) GCM ensemble averaged over 10°S–10°N.

(b) GCM ensemble.

(c) MCS observations.

Figure 18. Difference between 3 PM and 3 AM temperatures (local mean solar time) for (a) TuTD-CuD analysis; (b) GCM ensemble; and (c) MCS observations (using observations between LMST 2-4 AM/PM). The left column shows sols 380–384, before the storm, and the right column shows sols 416–420, at the peak of the storm. Brown is missing data (either below the surface, or not observed). Numbers above and below the colour bars indicate the minimum and maximum values for sols 416–420. Line contours are at 5 K intervals.

We can compare diurnal variations in our analysis against independent MCS ob-917 servations by measuring the temperature differences between 3 PM and 3 AM. This com-918 parison can only be made between those two local times, but it is one aspect of the di-919 urnal cycle that can be compared directly with observations. This is shown in Fig. 18. 920 Both the analysis and the GCM ensemble reproduce most basic aspects of the MCS ob-921 servations, both before the storm and at its peak. Differences between 3 PM and 3 AM 922 temperatures are generally smaller in the analysis compared with the MCS observations. 923 The GCM ensemble matches the MCS observations reasonably well before the storm, 924 while at the peak of the storm it tends to overestimate differences in the upper atmo-925 sphere and underestimate them in the lower atmosphere. The general position of the peaks 926 and troughs in the MCS observations are reproduced well by both the analysis and the 927 GCM ensemble. 928

At the peak of the storm the quadrupole structure disappears and is replaced at 929 mid-to-high latitudes by a strong positive anomaly in the lower atmosphere and a strong 930 negative anomaly in the middle atmosphere. Near the equator the temperature differ-931 ence is small in the lower atmosphere and increases significantly in the middle atmosphere. 932 In most areas the analysis is closer than the GCM ensemble to the MCS observations. 033 In the northern hemisphere the analysis better matches the anomaly magnitudes and ver-934 tical structure. In the equatorial region the positive anomaly in the GCM ensemble is 935 more compact than in the MCS observations. Because the MCS observations don't reach 936 the ground, we cannot tell whether the analysis or GCM ensemble better matches re-937 ality near the ground in the southern hemisphere. 938

Figures 19 and 20 show the amplitude and phase of the westward-propagating Sun-939 synchronous migrating diurnal and semi-diurnal tides, respectively, before and at the peak 940 of the storm. We interpolated the analysis and the GCM ensemble temperature fields 941 to a fixed set of pressure coordinates. At each pressure and latitude point this gave tem-942 perature as a function of longitude and absolute time (over the 4-sol periods we have used 943 throughout), which we then decomposed into its Fourier modes to give a two-dimensional 944 spectrum as a function of longitudinal wavenumber and frequency. We then extracted 945 the amplitude and phase of the period-(1 sol), wavenumber-(-1) mode, which is the westward-946 propagating Sun-synchronous migrating diurnal tide S_1 ; and the period-(0.5 sol), wavenumber-947 (-2) mode, which is the equivalent semi-diurnal tide mode S_2 . The phase is expressed 948 in terms of hours (0-24 for the diurnal tide, 0-12 for the semi-diurnal tide). 949

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(a) TuTD-CuD analysis.

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Figure 19. Amplitude and phase of the sun-synchronous migrating diurnal tide S_1 . (a) TuTD-CuD analysis; (b) GCM ensemble. The left column is for sols 380–384, and the right column is for sols 416–420. Filled colour contours show the phase (scaled to local true solar time between 0–24 hours), and line contours show the amplitude (spaced at 1 K intervals).

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Before the storm the the spatial patterns of the diurnal tide (Fig. 19) are similar 955 to those in Fig. 18. The phase data exhibit a quadrupole structure before the storm, and 956 at the peak of the storm the vast majority of the power in the diurnal tide is at mid- and 957 high latitudes, with a weaker diurnal tide at the equator. This is consistent with what 958 we showed in Fig. 17. Before the storm, the diurnal tide has a maximum amplitude near 959 the equator of about 5 K in the analysis and 10 K in the GCM ensemble (note that Fig. 18 960 shows the difference between two local times separated by 12 hours, not a wave ampli-961 tude). This difference suggests that the amplitude of the diurnal tide is overestimated 962 in the GCM ensemble. 963

At the peak of the storm the diurnal tide amplitudes in the GCM ensemble and 964 analysis are closer, although near the equator the analysis is again weaker than the GCM 965 ensemble, particularly at high altitudes. The analysis peaks at about 6 K right at the 966 top of the domain, while the GCM ensemble peaks at 8K around 0.1 Pa. At mid and 967 high latitudes, however, the analysis and the GCM ensemble agree within about 1 K. 968 One difference between the analysis and the GCM ensemble at the peak of the storm is 969 the phase of the diurnal tide near the equator below 1 Pa. In the analysis this phase is 970 3-9 hours, whereas in the GCM ensemble it is 9–24 hours, a significant phase shift. 971

Before the storm the amplitude of the semi-diurnal tide (Fig. 20) is small in the 976 lower atmosphere, increasing to about 4 K in the upper parts of the domain. The am-977 plitude is largely independent of latitude in the analysis, but there is a slightly larger am-978 plitude and one peak in each hemisphere around 50° N/S in the GCM ensemble. We may 979 compare these figures before the storm directly with equivalent figures in Kleinböhl et 980 al. (2013). Before the storm the general pattern is similar except for the phase near the 981 equator. The phase generally increases downwards, starting around 0 hours at the top 982 of the domain, and reaching 6 hours around 1 Pa. In Kleinböhl et al. (2013) this is only 983 a weak function of latitude, but in our analysis (Fig. 20a, left) the phase of the semi-diurnal 984 tide is 0–3 hours throughout most of the column, while in the GCM ensemble it displays 985 the full range of phases, but goes though 6 hours much higher in the atmosphere than 986 at higher latitudes. 987

At the peak of the storm the amplitude of the semi-diurnal tide increases at all altitude and latitudes, particularly near the surface, which increases in the analysis from less than 1 K to about 4 K. In the upper part of the domain the amplitude increases from

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Figure 20. Same as Fig. 19, but showing the amplitude and phase of the sun-synchronous migrating semi-diurnal tide S_2 . In this case the filled colour contours show the phase scaled to local true solar time between 0–12 hours.

 $_{991}$ 4 K to about 7 K at 0.1 Pa around 60° N. Again the amplitudes in the analysis are generally smaller than in the GCM ensemble, but not by much.

993

5.6 Verification against Independent Surface Pressure Observations from Curiosity-REMS

The final verification of our analysis is to compare surface pressures with high time 995 cadence measurements taken by the Mars Science Laboratory (MSL) Curiosity rover Rover 996 Environmental Monitoring Station (REMS). We interpolated the analysis surface pres-997 sure field from the GCM grid to Curiosity's longitude and latitude before the storm (sols 998 380-384) and at the peak of the storm (sols 416-420). We then corrected the surface pres-999 sure to account for the difference in surface elevation between the GCM grid and Cu-1000 riosity. We used Mars Orbital Laser Altimeter (MOLA) data with 32 points per degree 1001 (D. E. Smith et al., 2001) to obtain the altitude of the Curiosity rover, interpolating the 1002 MOLA surface elevation to Curiosity's location at each time it made a pressure measure-1003 ment during these two periods. We corrected the analysis surface pressure assuming hy-1004 drostatic balance and a pressure scale height based on the temperature at 1 km pseudo-1005 altitude (Spiga et al., 2007). The correction factor is 1006

$$p_{\text{corrected}} = p_{\text{original}} \exp\left(-\frac{z_{\text{Curiosity}} - z_{GCM}}{H}\right) \tag{9}$$

where H = RT/g is the scale height. Because Curiosity is deep within Gale Crater, which is not resolved by the LMD Mars GCM, the typical change in elevation from the GCM grid to Curiosity's location was an enormous -2,720 m, typically +160 Pa.

There are uncertainties associated with the finite resolution of the MOLA grid (about 2 km), and we also assume that errors due to using Curiosity's location in the rover landing frame of reference (which is inclined to the direction of gravity by about 3°) are small. However, our estimated uncertainty due to these assumptions is smaller than the uncertainty in the pressure measurements themselves (5.8 Pa).

Figure 21 shows surface pressure time series and diurnal cycles at the Curiosity rover location over two 4-sol periods before and at the peak of the storm, for the GCM ensemble and our best-case assimilation (TuTD-CuD). Both the analysis and the GCM ensemble generally fit the measured Curiosity observations well. For the analysis, the match

Surface pressure time series and diurnal cycle at the Curiosity rover location. The 1016 1017 left column shows the GCM ensemble, and the right column shows assimilation TuTD-CuD. In each case the red line shows the Curiosity data, and the black line shows the analysis or GCM 1018 ensemble. (a-b) are before the storm, sols 380–384, and (c-d) are at the peak of the storm, sols 1019 416–420. (a) and (c) show surface pressure time series, corrected for the difference in surface 1020 elevation between the GCM grid and the rover location on the surface, but otherwise unmodified. 1021 (b) and (d) show the same data binned into 30-minute local true solar time bins, where the mean 1022 in each bin is the thick line, and the shaded region shows +/- the standard deviation. Before bin-1023 -49ning the data the diurnal mean pressure was removed from the time series using a 1-sol moving 1024 average. The mean and RMS surface pressure error (analysis/GCM - Curiosity) are listed above 1025 each time series. 1026

1015

to the time series at the peak of the storm is particularly good, falling within the Curiosity measurement uncertainty. Given that we are down-sampling a climate resolution model (which does not resolve Gale Crater) with grid boxes approximately 300×200 km to a single location within the crater, and then correcting the surface pressure for a difference in surface elevation close to 3 km, a mean error close to 10 Pa is remarkable.

The surface pressure rises during the storm by about 50 Pa, and the diurnal mode 1036 becomes stronger, with the peak-to-peak diurnal variation increasing from 80 Pa to 120 1037 Pa. The analysis is closer to the Curiosity observations than the GCM ensemble, reflect-1038 ing the additional constraints on surface pressure from the assimilated temperatures. The 1039 analysis is better both in its absolute match to the Curiosity time series, and in how well 1040 the diurnal cycle is reproduced, both before and at the peak of the storm. The GCM en-1041 semble overestimates the absolute pressure, and overestimates the peak-to-peak diurnal 1042 variability, compared with the analysis and the Curiosity measurements. This is reflected 1043 in the mean and RMS errors, which are significantly smaller for the analysis than for the 1044 GCM ensemble: about 50% before the storm and about 70% at the peak of the storm. 1045 Only between 2–7 AM does the analysis poorly track the diurnal surface pressure cy-1046 cle at the Curiosity location at the peak of the storm, where it overestimates the obser-1047 vations. The same is seen in the GCM ensemble, although the error is larger. This is most 1048 likely due to mesoscale meteorology specific to Gale Crater, which is not accounted for 1049 in the model (see e.g. Rafkin et al. (2017) for a review). Our analysis' good agreement 1050 with observations, despite the difficulties associated with interpolating into a crater, is 1051 encouraging for possible future assimilation of surface pressure observations. 1052

As the analysis verifies well against Curiosity observations, Fig. 22 shows surface 1063 pressure diurnal cycles at several other locations; we may reasonably believe the anal-1064 ysis reproduces the surface pressure diurnal cycle there. These points of interest are: the 1065 final location of the Opportunity rover (which succumbed to dust loading during the study 1066 period); the landing sites for Perseverance and Insight, both currently operational; the 1067 Viking 2 landing site, chosen as it is one of the locations used to tune the pressure cy-1068 cle in the LMD Mars GCM; Acidalia, where flushing dust storms often originate, and 1069 within the northern hemisphere baroclinic zone; Hellas, where global dust events have 1070 originated (Mulholland et al., 2013), and the location of the highest surface pressures 1071 on Mars; and Tharsis, the location of the lowest surface pressures on Mars. 1072

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Surface pressure diurnal cycles at several locations during assimilation TuTD-Figure 22. 1054 CuD. Red lines are from the period before the storm (sols 380–384) and black lines are from the 1055 peak of the storm (sols 416–420). The diurnal cycle plots are otherwise the same as in Fig. 21. 1056 The mean pressure over each 4-sol period is given in each legend. The locations are (a) Oppor-1057 tunity final location; (b) Perseverance landing site; (c) Insight landing site; (d) Viking 2 landing 1058 site (these locations were all obtained using NASA GISS' Mars24 software); (e) Acidalia; (f) 1059 Hellas; and (g) Tharsis. (h) shows these seven locations with an additional X at the Curiosity 1060 -51landing site, for reference [137.44°E, 4.59°S]; topography is from MOLA (D. E. Smith et al., 1061 2001). 1062

In all cases the surface pressure increases from before the storm to the peak of the storm, ranging from about +20 Pa in Hellas to about +80 Pa at the Viking 2 landing site. The magnitude of the diurnal mode also increases at the peak of the storm, and at most locations the magnitude of the semi-diurnal mode also increases. The day-to-day variability (quantified by the width of the shaded region accompanying each line) is noticeably higher in the analysis than in the GCM ensemble (an equivalent figure to Fig. 22 for the GCM ensemble is included as Supporting Fig. S3).

The mid-afternoon low at each location is typically weaker in the analysis than in 1080 the GCM ensemble, as it was at the Curiosity location, and the mean pressure differ-1081 ence between the analysis and the GCM ensemble is typically 5–15 Pa. One exception 1082 is Acidalia (Fig. 22e), where the analysis pressure is about 30 Pa higher than the GCM 1083 ensemble, and the diurnal cycle is qualitatively different. The diurnal mode is relatively 1084 weak compared with other locations, about 20 Pa peak-to-peak before the storm, and 1085 40 Pa at the peak of the storm, and the phase of the diurnal pressure mode is shifted 1086 in the analysis by about 3–6 hours relative to the GCM ensemble. Figure 23 shows the 1087 pressure time series in both cases for the whole assimilation period. In the GCM ensem-1088 ble the baroclinic waves are clear, with a period of about 10 sols. In the analysis, how-1089 ever, while some signatures of the baroclinic wave remain (peaks at sols 390 and 405, for 1090 example), there are shorter-period oscillations that do not appear in the GCM ensem-1091 ble. Variability on diurnal timescales is also noisier, better reflecting real conditions; we 1092 saw this in the Curiosity dataset, where the day-to-day variability in the analysis diur-1093 nal cycle (Fig. 21d, right) is similar to the day-to-day variability in the Curiosity obser-1094 vations. 1095

1100

6 Summary and Conclusion

In this paper we have assimilated observations from ACS-TIRVIM, the thermal in-1101 frared spectrometer on board ExoMars Trace Gas Orbiter, into the LMD Mars Global 1102 Climate Model during the onset and peak of the MY34 global dust storm. We assim-1103 ilated both temperature profiles and dust column optical depth measurements using the 1104 LETKF in three configurations, with our nominal case TuTD-CuD assimilating temper-1105 ature profiles to update temperature and dust profiles, followed by column dust optical 1106 depths to update the total dust column abundance. We ran an ensemble of GCM sim-1107 ulations alongside the assimilations, constrained by MY34 MCS dust observations. Our 1108

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(a) TuTD-CuD analysis.

Figure 23. Surface pressure time series in Acidalia $[30^{\circ}W, 60^{\circ}N]$ throughout the full assimilation period for (a) analysis TuTD-CuD and (b) the GCM ensemble. Black shows the instantaneous surface pressure (every two hours) and red shows a running diurnal mean. Note the different y-axis scales.

other improvement over previous work was to compare forecast with observations using the retrieval averaging kernels. This allowed a like-by-like comparison to be made between forecast and observation, and by application of a filter to the sum over the averaging kernels at each vertical level, we ensured that information assimilated from the retrievals was strongly weighted towards information from the real atmospheric state rather than the retrieval prior. This is important for assimilating such temperature profiles derived from nadir-viewing geometry, which have rather coarse vertical resolution.

Our nominal assimilation verified well against in-sample observations from TIRVIM, and was at least as good as the GCM ensemble when verified against independent MCS observations. This was encouraging because the GCM ensemble was itself constrained by dust opacities measured by MCS. There was a significant reduction in RMS error when verifying temperatures against MCS once we assimilated column dust optical depth observations.

The atmospheric temperature structure at 30 Pa followed the MCS observations 1122 closely in our TuTD-CuD case, and was noticeably closer to the MCS values than the 1123 GCM ensemble (Fig. 11 c-e). While the 3PM analysis dust density-scaled opacity did 1124 not reach the maximum observed by MCS at the peak of the storm, there was partic-1125 ularly good correspondence with MCS at 3AM. The analysis reproduced detached dust 1126 layers, while the GCM ensemble did not, and the latter also overestimated the dust DSO 1127 at the storm's peak (Fig. 14). The assimilation retrieved the (unobserved) atmospheric 1128 wind structure before and during the storm, which showed that the meridional overturn-1129 ing circulation significantly strengthened during the storm (Fig. 15), as well as the de-1130 velopment of a 125 m s⁻¹ asymmetry in the midlatitude jets between the two hemispheres 1131 (Fig. 16). 1132

Assimilating observations over a range of local times gives us confidence in our results related to the diurnal cycle. The diurnal tide strengthened considerably at midlatitudes during the global dust storm, at the expense of the diurnal tide near the equator (Fig. 19), and the semi-diurnal tide increased in strength everywhere, particularly in the lower atmosphere (Figs 17c, 20). The diurnal cycle was also verified against independent Curiosity-REMS surface pressure measurements. Despite the large difference in surface elevation between the GCM topography and the rover, the analysis surface

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pressures at the peak of the storm accurately reproduced the diurnal cycle measured byCuriosity (Fig. 21).

Assimilation during the onset of a Mars global dust storm is a particularly hard 1142 stress test of our assimilation scheme, so it is encouraging that we are able to reproduce 1143 many features of independent observational datasets. But one shortcoming of the assim-1144 ilation has been made particularly clear when the total amount of dust in the atmosphere 1145 changes quickly over time. There is a lag in changes to the global amount of dust (and 1146 hence the onset of the global dust storm) by 6–8 sols (Fig. 12c). This is also present in 1147 temperature, but it is only 1–2 sols in that case. We expect this is because not all model 1148 grid points are updated during each assimilation cycle. If only a small fraction of grid 1149 points are updated at any one time, trends in the total amount of dust and heat in the 1150 analysis will lag behind such trends in the real atmosphere, because in reality the dust 1151 and heat content change at both unobserved and observed locations at the same time. 1152 This is a fundamental limitation in the observations, particularly when assimilating data 1153 from a single polar-orbiting satellite where the number of model grid columns updated 1154 in a single 2-hour assimilation cycle is typically 20–30% of the total. 1155

This could be overcome in a number of ways. First, by simultaneously assimilat-1156 ing more observations at different locations, such as by assimilating MCS in addition to 1157 ACS observations. Second, by increasing the length of the assimilation window to include 1158 more observations, but this increases the forecast time. Third, by assimilating single ob-1159 servations multiple times, as in Analysis Correction (Lorenc et al., 1991). Fourth, one 1160 could use a longer assimilation window for dust than for temperature. Finally, one could 1161 update non-observed locations in some ad hoc way, for example by assuming that dust 1162 lingers in place over some timescale, or by assuming some spatial distribution of dust link-1163 ing observed locations. This is already done in a sophisticated way for the GCM dust 1164 scenarios, which are complete maps but which use incomplete observations with gaps filled 1165 in by kriging (Montabone et al., 2015). Only the first of these options avoids some ad 1166 hoc intervention or a substantial change to the assimilation method, so the next step will 1167 be to focus on joint assimilation of multiple instruments' observations. 1168

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1181 Data Availability Statement

The processed TIRVIM data and retrievals used in this paper are available in NetCDF 1182 format on the Institut Pierre Simon Laplace (IPSL) data server, see: 1183 https://doi.org/10.14768/ab765eba-0c1d-47b6-97d6-6390c63f0197. The authors acknowl-1184 edge Sandrine Guerlet and the ACS/TGO team for supplying the data and the data cen-1185 ter ESPRI/IPSL for their help in accessing the data. The observations use version 7 of 1186 the retrieval algorithm, and version 4 of the IKI calibration algorithm. Mars Climate Sounder 1187 observations are available on the NASA Planetary Data System Atmospheres node at 1188 https://pds-atmospheres.nmsu.edu/data_and_services/atmospheres_data/MARS/ 1189 mars_reconnaissance_orbiter.html. Mars Science Laboratory Curiosity rover Rover En-1190 vironmental Monitoring Station observations are available on the NASA Planetary Data 1191 System Atmospheres node at https://atmos.nmsu.edu/data_and_services/atmospheres_data/ 1192 MARS/curiosity/rems.html. MOLA topography data are available on the NASA Plan-1193 etary Data System Geosciences node at https://pds-geosciences.wustl.edu/missions/mgs/megdr.html. 1194 The LMD Mars GCM is available from http://www-mars.lmd.jussieu.fr/; we used GCM 1195 subversion revision r2533. The assimilation uses letkfmars git revision 1196 f28935f6472a280394a98ac64f99213d1cbb2e01. Mars24 is available from NASA GISS at 1197 https://www.giss.nasa.gov/tools/mars24/. The data produced by our assimilation will 1198 be deposited after review using Zenodo or an equivalent repository. 1199

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1200 References

- Ahn, S., & Fessler, J. A. (2003). Standard Errors of Mean, Variance, and Standard
 Deviation Estimators (Technical Report 413 No. 48109-2122). Comm. and
 Sign. Proc. Lab., Dept. of EECS, Univ. of Michigan, Ann Arbor, MI.
- Amiri, S., Brain, D., Sharaf, O., Withnell, P., McGrath, M., Alloghani, M., ...
 Yousuf, M. (2022). The Emirates Mars Mission. Space Science Reviews, 218,
 4. doi: 10.1007/s11214-021-00868-x
- Capderou, M., & Forget, F. (2004). Optimal orbits for Mars atmosphere remote
 sensing. *Planetary and Space Science*, 52, 789–798. doi: 10.1016/j.pss.2004.03
 .006
- Evensen, G. (2003). The Ensemble Kalman Filter: Theoretical formulation and practical implementation. *Ocean Dynamics*, 53(4), 343–367. doi: 10.1007/ s10236-003-0036-9
- Forget, F., Hourdin, F., Fournier, R., Hourdin, C., Talagrand, O., Collins, M., ...
- Huot, J.-P. (1999). Improved general circulation models of the Martian atmosphere from the surface to above 80 km. *Journal of Geophysical Research*, 104 (E10), 24155–24175. doi: 10.1029/1999JE001025
- Giuranna, M., Wolkenberg, P., Grassi, D., Aronica, A., Aoki, S., Scaccabarozzi, D., ... Formisano, V. (2021). The current weather and climate of Mars: 12 years of atmospheric monitoring by the Planetary Fourier Spectrometer on Mars Express. *Icarus*, 353, 113406. doi: 10.1016/j.icarus.2019.113406
- Greybush, S. J., Wilson, R. J., Hoffman, R. N., Hoffman, M. J., Miyoshi, T., Ide, K.,
 Kalnay, E. (2012). Ensemble Kalman filter data assimilation of Thermal
 Emission Spectrometer temperature retrievals into a Mars GCM. Journal of
 Geophysical Research, 117(11), E11008. doi: 10.1029/2012JE004097
- Guerlet, S., Ignatiev, N., Forget, F., Fouchet, T., Vlasov, P., Bergeron, G., ... Korablev, O. (2022). Thermal Structure and Aerosols in Mars' Atmosphere From TIRVIM/ACS Onboard the ExoMars Trace Gas Orbiter: Validation
- 1228 of the Retrieval Algorithm. Journal of Geophysical Research Planets, 127, 1229 e2021JE007062. doi: 10.1029/2021JE007062
- Hamill, T. M., Whitaker, J. S., & Snyder, C. (2001). Distance-Dependent Filtering of Background Error Covariance Estimates in an Ensemble Kalman
 Filter. Monthly Weather Review, 129(11), 2776–2790. doi: 10.1175/

1233	1520-0493(2001)129(2776:DDFOBE)2.0.CO;2
1234	Heavens, N. G., Richardson, M. I., Kleinböhl, A., Kass, D. M., McCleese, D. J.,
1235	Abdou, W., Wolkenberg, P. M. (2011). Vertical distribution of dust in
1236	the Martian atmosphere during northern spring and summer: High-altitude
1237	tropical dust maximum at northern summer solstice. Journal of Geophysical
1238	Research, $116(1)$, E01007. doi: 10.1029/2010JE003692
1239	Hersbach, H., Bell, B., Berrisford, P., Horányi, A., Sabater, J. M., Nicolas, J.,
1240	Dee, D. (2019). Global reanalysis: Goodbye ERA-Interim, hello ERA5.
1241	ECMWF Newsletter, 159, 17–24. doi: 10.21957/vf291hehd7
1242	Hoffman, M. J., Greybush, S. J., Wilson, R. J., Gyarmati, G., Hoffman, R. N.,
1243	Kalnay, E., Szunyogh, I. (2010). An Ensemble Kalman Filter Data Assim-
1244	ilation System for the Martian Atmosphere: Implementation and Simulation
1245	Experiments. Icarus, 209(2), 470–481. doi: 10.1016/j.icarus.2010.03.034
1246	Hoffman, R. N. (2011). A retrieval strategy for interactive ensemble data assimila-
1247	tion. arXiv, 1009.1561.
1248	Holmes, J. A., Lewis, S. R., Patel, M. R., & Lefèvre, F. (2018). A reanalysis of
1249	ozone on Mars from assimilation of SPICAM observations. $\ Icarus,\ 302,\ 308-$
1250	318. doi: 10.1016/j.icarus.2017.11.026
1251	Holmes, J. A., Lewis, S. R., Patel, M. R., & Smith, M. D. (2019). Global analy-
1252	sis and forecasts of carbon monoxide on Mars. <i>Icarus</i> , 328, 232–245. doi: 10
1253	.1016/j.icarus.2019.03.016
1254	Hunt, B. R., Kostelich, E. J., & Szunyogh, I. (2007). Efficient data assimilation for
1255	spatiotemporal chaos: A local ensemble transform Kalman filter. $Physica D$,
1256	230(1-2), 112–126. doi: 10.1016/j.physd.2006.11.008
1257	Kahre, M. A., Murphy, J. R., Newman, C. E., Wilson, R. J., Cantor, B. A., Lem-
1258	mon, M. T., & Wolff, M. J. (2017). The Mars Dust Cycle. In The Atmosphere
1259	and Climate of Mars (pp. 295–337). Cambridge University Press.
1260	Kalnay, E. (2003). Atmospheric Modeling, Data Assimilation and Predictability.
1261	Cambridge University Press.
1262	Kass, D. M., Schofield, J. T., Kleinböhl, A., McCleese, D. J., Heavens, N. G.,
1263	Shirley, J. H., & Steele, L. J. (2019). Mars Climate Sounder Observa-
1264	tion of Mars' 2018 Global Dust Storm. Geophysical Research Letters, 46,
1265	e2019GL083931. doi: $10.1029/2019GL083931$

1266	Kleinböhl, A., Schofield, J. T., Kass, D. M., Abdou, W. A., Backus, C. R., Sen, B.,
1267	McCleese, D. J. (2009). Mars Climate Sounder limb profile retrieval of
1268	atmospheric temperature, pressure, and dust and water ice opacity. $Journal \ of$
1269	Geophysical Research, 114(10), E10006. doi: 10.1029/2009JE003358
1270	Kleinböhl, A., Spiga, A., Kass, D. M., Shirley, J. H., Millour, E., Montabone, L.,
1271	& Forget, F. (2020). Diurnal Variations of Dust During the 2018 Global
1272	Dust Storm Observed by the Mars Climate Sounder. Journal of Geophysical
1273	Research - $Planets,125,e2019JE006115.$ doi: 10.1029/2019JE006115
1274	Kleinböhl, A., Wilson, R. J., Kass, D., Schofield, J. T., & McCleese, D. J. (2013).
1275	The semidiurnal tide in the middle atmosphere of Mars. $Geophysical Research$
1276	Letters, 40 , 1952–1959. doi: 10.1002/grl.50497
1277	Korablev, O., Montmessin, F., Trokhimovskiy, A., Fedorova, A. A., Shakun, A. V.,
1278	Grigoriev, A. V., Zorzano, M. P. (2018). The Atmospheric Chemistry Suite
1279	(ACS) of Three Spectrometers for the ExoMars 2016 Trace Gas Orbiter. Space
1280	Science Reviews, 214(1), 7. doi: 10.1007/s11214-017-0437-6
1281	Lewis, S. R., & Barker, P. R. (2005). Atmospheric tides in a Mars general circula-
1282	tion model with data assimilation. Advances in Space Research, $36(11)$, 2162–
1283	2168. doi: 10.1016/j.asr.2005.05.122
1284	Lewis, S. R., & Read, P. L. (1995). An operational data assimilation scheme for the
1285	Martian atmosphere. Advances in Space Research, $16(6)$, 9–13. doi: 10.1016/
1286	0273-1177(95)00244-9
1287	Lewis, S. R., Read, P. L., Conrath, B. J., Pearl, J. C., & Smith, M. D. (2007).
1288	Assimilation of thermal emission spectrometer atmospheric data during the
1289	Mars Global Surveyor aerobraking period. $Icarus$, 192 (August), $327-347$. doi:
1290	10.1016/j.icarus.2007.08.009
1291	Lorenc, A. C., Bell, R. S., & Macpherson, B. (1991). The Meteorological Office anal-
1292	ysis correction data assimilation scheme. Quarterly Journal of the Royal Mete-
1293	orological Society, 117(497), 59–89. doi: 10.1002/qj.49711749704
1294	Madeleine, JB., Forget, F., Millour, E., Montabone, L., & Wolff, M. J. (2011).
1295	Revisiting the radiative impact of dust on Mars using the LMD Global
1296	Climate Model. Journal of Geophysical Research, 116(11), E11010. doi:
1297	10.1029/2011JE003855
1298	Montabone, L., Forget, F., Millour, E., Wilson, R. J., Lewis, S. R., Cantor, B.,

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1299	Wolff, M. J. (2015). Eight-year climatology of dust optical depth on Mars.
1300	Icarus, 251, 65–95. doi: 10.1016/j.icarus.2014.12.034
1301	Montabone, L., Marsh, K., Lewis, S. R., Read, P. L., Smith, M. D., Holmes, J.,
1302	Pamment, A. (2014). The Mars Analysis Correction Data Assimilation
1303	(MACDA) Dataset V1.0. Geoscience Data Journal, 1(2), 129–139. doi:
1304	$10.1002/{ m gdj}3.13$
1305	Montabone, L., Spiga, A., Kass, D. M., Kleinböhl, A., Forget, F., & Millour,
1306	E. (2020). Martian Year 34 Column Dust Climatology from Mars Cli-
1307	mate Sounder Observations: Reconstructed Maps and Model Simulations.
1308	Journal of Geophysical Research - Planets, 125, e2019JE006111. doi:
1309	10.1029/2019JE006111
1310	Mulholland, D. P., Read, P. L., & Lewis, S. R. (2013). Simulating the interan-
1311	nual variability of major dust storms on Mars using variable lifting thresholds.
1312	Icarus, 223(1), 344–358. doi: 10.1016/j.icarus.2012.12.003
1313	Navarro, T., Forget, F., Millour, E., & Greybush, S. J. (2014). Detection of de-
1314	tached dust layers in the Martian atmosphere from their thermal signature
1315	using assimilation. Geophysical Research Letters, $41(19)$, 6620–6626. doi:
1316	10.1002/2014GL061377
1317	Navarro, T., Forget, F., Millour, E., Greybush, S. J., Kalnay, E., & Miyoshi, T.
1318	(2017). The challenge of atmospheric data assimilation on Mars. Earth and
1319	Space Science, $4, 690-722$. doi: 10.1002/2017EA000274
1320	Pottier, A., Forget, F., Montmessin, F., Navarro, T., Spiga, A., Millour, E.,
1321	Madeleine, JB. (2017). Unraveling the martian water cycle with
1322	high-resolution global climate simulations. <i>Icarus</i> , 291, 82–106. doi:
1323	10.1016/j.icarus.2017.02.016
1324	Rafkin, S. C. R., Spiga, A., & Michaels, T. I. (2017). Mesoscale Meteorology. In The
1325	Atmosphere and Climate of Mars (pp. 203–228). Cambridge University Press.
1326	Rodgers, C. D., & Connor, B. J. (2003). Intercomparison of remote sounding in-
1327	struments. Journal of Geophysical Research, 108(D3), 4116. doi: 10.1029/
1328	2002JD002299
1329	Ruan, T., Young, R. M. B., Lewis, S. R., Montabone, L., Valeanu, A., & Read,
1330	P. L. (2021). Assimilation of Both Column- and Layer-Integrated Dust Opac-
1331	ity Observations in the Martian Atmosphere. Earth and Space Science, 8,

1332	e2021EA001869. doi: $10.1029/2021EA001869$
1333	Smith, D. E., Zuber, M. T., Frey, H. V., Garvin, J. B., Head, J. W., Muhleman,
1334	D. O., Sun, X. (2001). Mars Orbiter Laser Altimeter: Experiment sum-
1335	mary after the first year of global mapping of Mars. Journal of Geophysical
1336	Research, $106(E10)$, 23689–23722. doi: 10.1029/2000JE001364
1337	Smith, M. D., Bougher, S. W., Encrenaz, T., Forget, F., & Kleinböhl, A. (2017).
1338	Thermal Structure and Composition. In The Atmosphere and Climate of Mars
1339	(pp. 42–75). Cambridge University Press.
1340	Spiga, A., Forget, F., Dolla, B., Vinatier, S., Melchiorri, R., Drossart, P.,
1341	Gondet, B. (2007). Remote sensing of surface pressure on Mars with the
1342	Mars Express/OMEGA spectrometer: 2. Meteorological maps. Journal of
1343	Geophysical Research: Planets, 112(E8), E08S16. doi: 10.1029/2006JE002870
1344	Steele, L. J., Lewis, S. R., & Patel, M. R. (2014). The radiative impact of water ice
1345	clouds from a reanalysis of Mars Climate Sounder data. $Geophysical Research$
1346	Letters, $41(13)$, 4471–4478. doi: 10.1002/2014GL060235
1347	Steele, L. J., Lewis, S. R., Patel, M. R., Montmessin, F., Forget, F., & Smith,
1348	M. D. (2014). The seasonal cycle of water vapour on Mars from assimi-
1349	lation of Thermal Emission Spectrometer data. <i>Icarus</i> , 237, 97–115. doi:
1349	lation of Thermal Emission Spectrometer data. Icarus, 237, 97–115. doi:

1350 10.1016/j.icarus.2014.04.017