A CLIMATE DATABASE FOR THE MARTIAN ATMOSPHERE

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Abstract

A new engineering model of the environment of Mars is outlined. The model is based on a database of statistics computed from a state-of-the-art Global Circulation Model of the martian atmosphere which represents our best knowledge of the atmosphere to date. A novel scheme for the representation of large scale variability in the engineering model, in terms of an optimal set of basis functions derived from the Global Circulation Model, is also outlined and shown to be an efficient and accurate method of representing correlated structures in vertical profiles.

1 Introduction

Engineers require information about planetary environments in order to design spacecraft which operate in those environments. They typically use 'Engineering Models' of planetary environments to provide such information. These models are an amalgamation of observational data and theoretical models combined to provide the best known state of the planetary environment within a useful operational structure.

In this paper we particularly focus on the environment of Mars which will undergo an intensive program of exploration by both remote sounding and *in situ* missions over the next decade. The widely used engineering model of mars, Mars Global Reference Atmosphere Model (Mars-GRAM) (Justus (1990)), combines the very sparse set of observations from the Mariner and Viking Missions. Dynamical balances (hydrostatic and thermal wind balance) are then invoked to produce pressure, density, wind speed and direction. Various important processes, such as the seasonal CO_2 cycle and the thermal tide, are either inferred from observations or theoretical models.

In recent years, Global Circulation Models (GCMs) of the martian atmosphere have improved greatly due to increased computer power and due both to large efforts by several modelling groups in the USA and Europe to improve the representation of physical processes that occur in the atmosphere (e.g. Haberle *et al.* (1993), Hourdin *et al.* (1993)). It is now believed that these GCMs currently represent the best knowledge of the atmosphere of Mars (see the accompanying paper by Hourdin *et al.* in this issue), as recognised with the award by the European Space Agency to LMD and Oxford to use an enhanced GCM to produce a much improved engineering model of Mars.

A full description of this new engineering model has and will be published in various papers elsewhere (e.g. Read *et al.* (1996)). However in this paper we give a brief description of the database of atmospheric statistics that will form the basis for the model and give a more detailed description of a novel representation of large scale variability in the model to be incorporated into the database.

2 The Database

We are currently using the Mars GCM to compile a database of statistics of the martian climate which will form the basis of the engineering model of Mars. The database will comprise longitude-latitude-height fields of temperature, pressure, density, wind speed and direction and turbulence intensity, as well as surface longitude-latitude fields of topographic height, CO_2 ice, emissivity, albedo and ground temperature. Mean fields will be stored 12 times a day and at 12 'seasons' or 'months' in order to accurately represent the diurnal and seasonal cycles. In addition standard deviations of selected variables will be included to give some indication of departures from the mean. Fields will be stored on a grid of 96 regularly space longitude points and 48 regularly spaced latitude points and on a grid of 25 irregularly spaced height points ranging from the surface to approximately 90km. As suspended dust is probably the most sensitive and unknown parameter in the martian atmosphere, various dust scenarios will be included in the database ranging from low dust, nearly clear conditions through the modest dust values observed by the Viking mission to global dust storm conditions.

Figure 1 shows two typical latitude height sec-

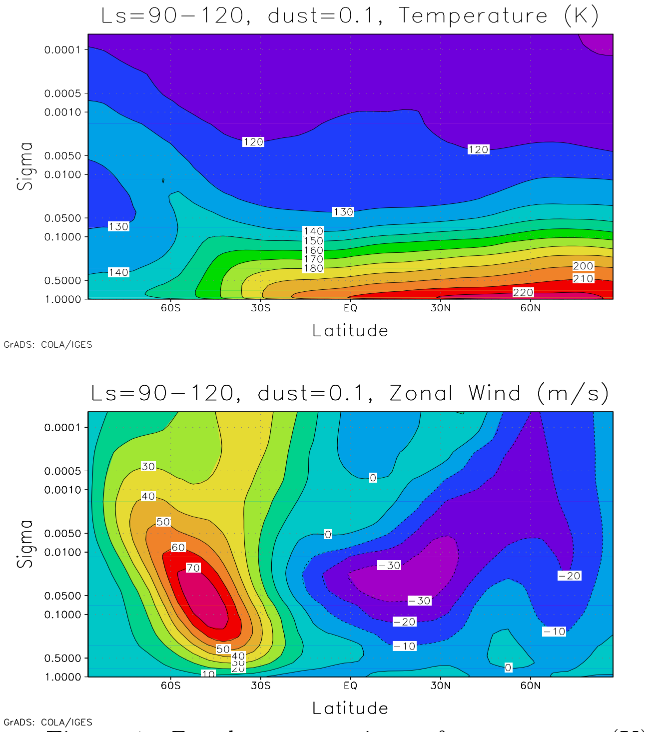

Figure 1: Zonal mean sections of temperature (K) and zonal wind (m/s) from a low dust simulation of the GCM. The vertical coordinate (sigma) is the ratio of the pressure to the surface pressure.

tions of zonally averaged temperature and zonal wind from a low dust simulation of the GCM. Circulation statistics such as these will form part of the database.

3 Representation of Variability

Mean fields are stored in the database once a season, a season being typically 50-70 days long. Although the main variability, which is due to the diurnal cycle, is captured by storing the fields 12 times a day there may still be significant variation about the mean due to, for example, motions of baroclinic weather systems. Figure 2 shows a selection of vertical profiles of temperature and normalised density taken at several times during one season at a particular point in the GCM, together with the mean profiles. We must in some way represent these profiles in the engineering model to capture the model variability.

A simple solution would be to run the GCM for the season in question and sample the profiles. However proves to be prohibitive as such an integration may take several hours or perhaps days even on the fastest of workstations. This would render the engineering model unusable in practical circumstances.

Various representations of variability have been used in other engineering models. Mars-GRAM (Justus (1990)) uses a relatively crude representation in

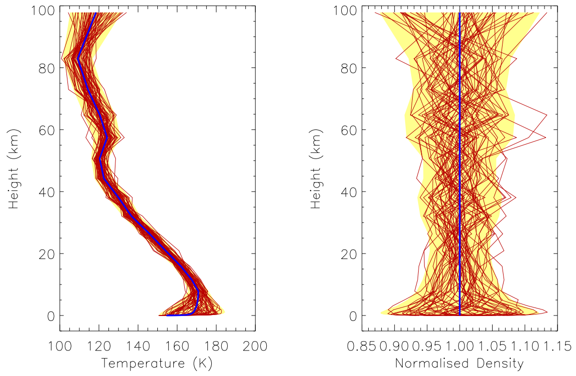

Figure 2: Profiles of temperature (left panel) and normalised density (right panel) from a single point in the GCM. The mean profile is in blue and the yellow shading indicates 2 standard deviations from this mean.

which a random white noise perturbation is added at each vertical level, e.g. if $D(z)$ is the simulated vertical profile of a meteorological variable then

$$D(z) = \overline{D}(z) + \sigma(z)q \qquad (1)$$

where $\overline{D}(z)$ is the mean, $\sigma(z)$ is a vertical profile of standard deviation and q is a Gaussian distributed random variable with zero mean and unit standard deviation. This results in very noisy profiles however and in particular the vertical derivatives of the meteorological fields are overestimated (e.g. unrealistic wind shears are produced).

GRAM-95 (the terrestrial global reference atmosphere model, Justus *et al.* (1995)) sought to overcome this problem by adding correlated noise in the vertical, e.g.

$$D(z) = \overline{D}(z) + \sigma(z)\mu(z) \qquad (2)$$

where

$$\mu(z) = r\mu(z-\Delta z) + (1-r^2)^{1/2}q \qquad (3)$$

and r is a correlation coefficient approximated by exponential decay on some empirically-derived length scale. Also GRAM-95 includes cross-correlations of variables from theoretical and empirical formulas to provide some consistency between simulated profiles of different variables.

4 A New Approach

We have chosen to represent large scale variability in the engineering model using a novel approach based on a technique that is widely used in meteorological data analysis as well as in other subject areas.

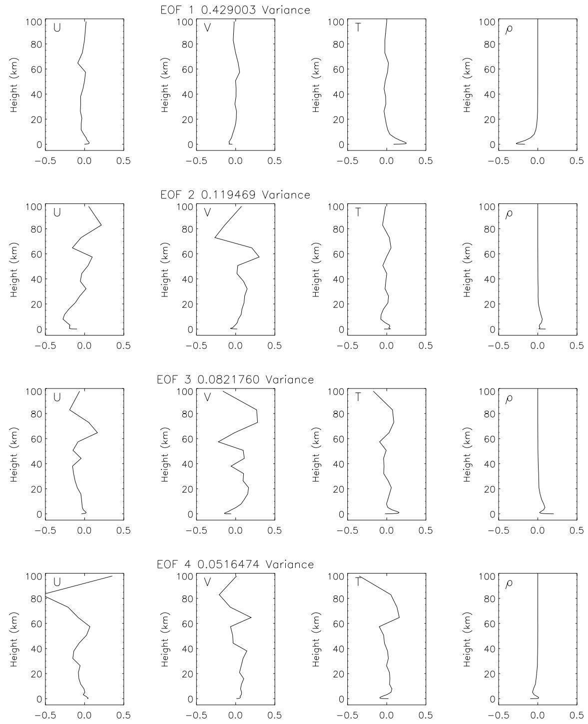

Figure 3: The top four multivariate EOFs calculated from the profiles shown in fig. 2. The fraction of variance 'explained' by the EOFs is also given.

We add a series of functions to the mean vertical profile,

$$D(z) \ = \overline{D}(z) \ + \ \sum_{n=1}^{N} \ p_i e_i(z) \qquad (4)$$

where the functions $\mathbf{e_i}$ are eigenvectors of the covariance matrix of the modelled profiles and p_i are the amplitudes of the functions. The eigenvectors $\mathbf{e_i}$ are often called Empirical Orthogonal Functions (EOFs) and the p_i are referred too as the Principal Components (PCs) (see e.g. Mo and Ghil (1987)). The $\mathbf{e_i}$ form an optimal linear basis such that the variance capture is high even when the truncation limit is low. In order to retain cross-correlations in altitude between different variables we combine all the variables together and form a set of multivariate functions. Mathematical details of the entire formulation are given in Appendix A.

Figure 3 shows the top four (i.e. maximum variance) EOFs calculated from the profiles shown in fig. 2. The function has been split into different variables (zonal wind, meridional wind, temperature and density) for display reasons. In this case the top six EOFs 'explain' ~75% of the profile variance.

The PCs i.e. the amplitudes of the EOFs are shown as a function of time in the GCM simulation in fig. 4. To perform a simulation of the profiles we must model these PCs in some way. A second order polynomial fit, to capture any seasonal trend, plus some white noise, to capture any oscillatory phenomena, seems to be an efficient model. One particular realisation of the PCs may be seen in fig. 5.

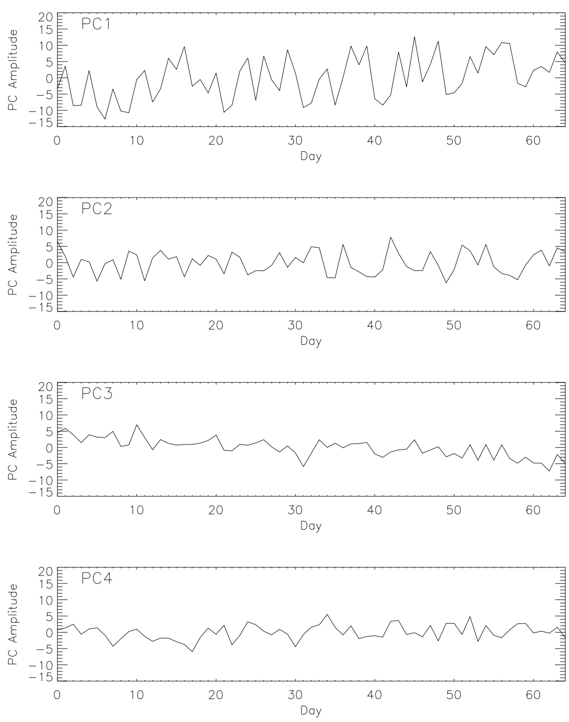

Figure 4: The principal components for the EOFs shown in fig. 3.

One we have the modelled PCs we can simulate the profiles by substituting them in equation (4). The resulting simulated profiles are shown in fig. 6 and are very similar to the original profiles shown in fig. 2.

5 Future Work

Although the use of a truncated set of EOFs provides a realistic way of representing variability, the truncation means that a small fraction of the variance is left unaccounted for (25% in this case). This variance comes from the higher order EOFs which are ignored. We must parameterise this variance in some way, perhaps using a simple noise model or maybe by re-scaling the PCs in order to capture all the variance.

Also, for the engineering model, we must add some estimation of small scale variability that is not modelled by the GCM. Such variability will come from turbulence in the boundary layer and in the free atmosphere and from sub-grid scale wave mo-

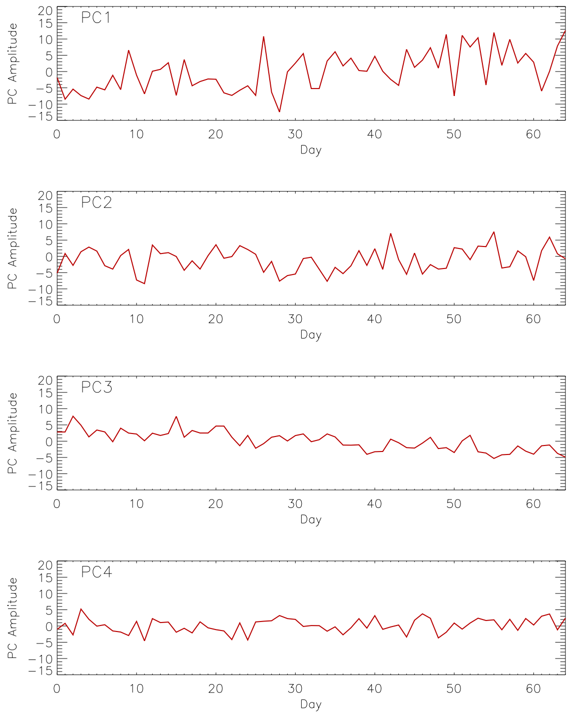

Figure 5: Principal components modelled using a second order polynomial fit plus noise.

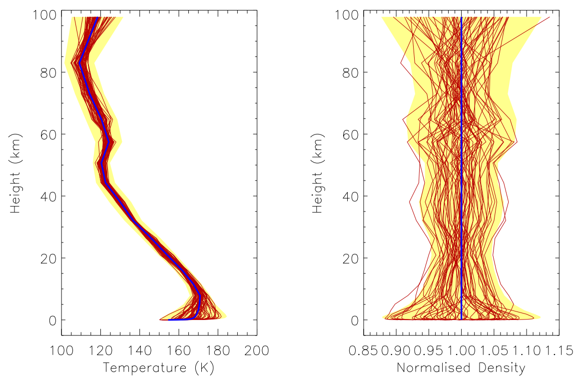

Figure 6: Simulated profiles corresponding to those shown in fig. 2.

tions such as gravity waves. For this type of variability we may draw on the GCM itself, which includes parameterisation schemes for such processes (e.g. Collins *et al.* (1996)) to constrain the distribution of turbulence intensity. Realisations along specific trajectories will use methods based on those used in GRAM-95.

6 Summary

We are currently engaged in a project to produce an engineering model of the atmosphere of Mars for use in spacecraft mission planning. The model will be based on a database of statistics compiled from a state-of-the-art Global Circulation Model of the martian atmosphere. The model has been extensively validated against observations and provides the best knowledge to date of the global atmospheric conditions on Mars (Hourdin *et al.* this issue).

A novel scheme for the representation of large scale variability in the engineering model has been developed and shown to be an effective means of representing variability with realistic vertical structures. The scheme uses a small set of functions based on an optimal basis derived from the GCM, combined with a simple model for the amplitudes of the functions. This scheme will be combined with more conventional models of small scale variability to produce realistic profiles of meteorological variables.

Acknowledgements

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Appendix A

Consider a time series of vertical profiles of $\mathbf{u}(p,t)$, $\mathbf{v}(p,t), \mathbf{T}(p,t), \rho(p,t)$ and surface pressure $p^*(t)$ at M times and at L levels. We form a time series of vectors $\mathbf{D}(\mathbf{t})$ where

$$\mathbf{D}(t) \;=\; (\hat{\mathbf{u}}(p,t), \hat{\mathbf{v}}(p,t), \hat{\mathbf{T}}(p,t), \hat{p^*}(t), \hat{\rho}(p,t)) \quad (5)$$

and the hat ˆ denotes a removal of the series mean and normalisation of variance operator e.g.

$$\overline{u} \;=\; \frac{1}{ML}\sum_{m=1}^{M}\sum_{l=1}^{L} u_{ml} \quad (6)$$

$$\hat{u}_{ml} \;=\; \frac{u_{ml}-\overline{u}}{\sqrt{\frac{1}{ML}\sum_{m=1}^{M}\sum_{l=1}^{L}(u_{ml}-\overline{u})^2}} \quad (7)$$

where the m denotes time and the l denotes vertical level. Hence the variance of the entire time series of $\mathbf{D}(t)$ is unity.

We then form the $(N \times N)$ covariance matrix, $\mathbf{C}$, such that

$$\mathbf{C} \;=\; \mathbf{D}\mathbf{D}^T \quad (8)$$

where $N = 4L+1$, $\mathbf{D}$ is the $(N \times M)$ matrix whose rows are the vectors $\mathbf{D}(t)$ and the superscript T indicates the transpose.

The matrix $\mathbf{C}$ is real symmetric and we can find the eigenvectors and eigenvalues and order them in decreasing eigenvalue magnitude. We note that if $\mathbf{E}_i$ is the i'th eigenvector then

$$|\mathbf{E}_i| \;=\; 1 \quad (9)$$

where $|\cdot|$ is the Euclidean Norm, and

$$\sum_{i=1}^{N}\lambda_i \;=\; 1 \quad (10)$$

where λ_i is the i'th eigenvalue.

The i'th principal component at time m, p_{mi} is defined as

$$p_{mi} \;=\; \sum_{n=1}^{N} D_{mn}E_{in} \;=\; \mathbf{D}\cdot\mathbf{E}_i \quad (11)$$

and we note the result

$$\frac{1}{MN}\sum_{m=1}^{M}(p_{mi})^2 \;=\; \lambda_i \quad (12)$$

Each principal component has M values but for the database we choose to model them as

$$\mathbf{q}_i \;=\; a_i \;+\; b_i\mathbf{x} \;+\; c_i\mathbf{x}^2 \;+\; \phi \quad (13)$$

where

$$\mathbf{x} \;=\; \frac{1}{M}(1,2,...,M) \quad (14)$$

and ϕ is a normally distributed random variable chosen so that

$$\frac{1}{MN}\sum_{m=1}^{M}(q_{mi})^2 \;=\; \lambda_i \quad (15)$$

i.e.

$$P(\phi) \;=\; \frac{\sigma}{\sqrt{2\pi}}\exp\left(\frac{-\phi^2}{2}\right) \quad (16)$$

where

$$\sigma \;=\; \sqrt{\frac{1}{M}\sum_{m=1}^{M}(q_{mi} \;-\; p_{mi})^2} \quad (17)$$