ADAPTING STATE OF THE ART DATA ASSIMILATION APPROACHES FOR USE WITH THE MARS CLIMATE SOUNDER AND THE PLANETWRF MARTIAN GCM.

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Introduction: We shall present our approach and progress to date of our efforts to adapt state of the art data assimilation approaches within the terrestrial meteorological community for use with the infrared remote sensing dataset from the Mars Climate Sounder aboard the Mars Reconnaissance Orbiter and a general circulation model of the martian atmosphere, PlanetWRF.

Motivation: In order to address what the last decade of infrared remote sensing data has told us about the weather and climate of the martian atmosphere, one must inevitably interpret the data by way of data-derived products that link the measured radiances to the dynamic and thermodynamic state of the atmosphere. Such data-derived products are the solutions to inverse problems: a given atmospheric state will yield a unique radiance (the forward problem), but a given radiance could have come from a large family of possible atmospheric states. Formally, inverse problems yield a probability distribution over the family of possible states; in practice, one is often content with a single "best estimate" and perhaps its accompanying "error bars." While retrievals have been the popular data-derived products in the planetary sciences, the terrestrial meteorological community has gained much ground over the last decade by employing techniques of data assimilation to analyze radiances [1].

Ancillary information is required to close an inverse problem (*i.e.*, to disambiguate the family of possibilities that are consistent with the observations), and practitioners of data assimilation (DA) inevitably rely on numerical models for this information (*e.g.*, general circulation models (GCMs)). Data assimilation elicits maximal information content from available observations, and, by way of the physics encoded in the numerical model, spreads this information spatially, temporally, and across variables, thus allowing global extrapolation of limited and non-simultaneous observations. If the model is skillful, in the sense that it can reasonably represent and reproduce the mean climate of Mars, then a given, specific model integration can be corrected by the information spreading abilities of DA, and the resulting time sequence of "analysis" states are brought into agreement with the observations. These analysis states are complete, gridded estimates of all the fields one might wish to diagnose for scientific study of the martian atmosphere. Though a numerical model has been used to obtain these estimates, their fidelity rests in their simultaneous consistency with both the observations (to within their stated uncertainties) and the physics contained in the model. In this fashion, radiance observations can, say, be used to deduce the wind field.

There are several reasons why DA within the planetary sciences has lagged behind its use in terrestrial meteorology, most of which spawn from the sheer amount of effort required by the venture. One popular and valuable use of DA is for initializing weather forecasts, and this has spurred much development within the terrestrial community both in theory / algorithms and software infrastructure. Being a smaller community and lacking the forecasting motivation, planetary scientists have lagged behind: 1. Engineering-wise, in the terrestrial community, the software involved is typically written, managed, and supported by many-member teams. GCMs are complex endeavors in their own right, yet DA systems use them merely as one component, along with a forward operator to link them to the observations (*e.g.*, a radiative transfer model), observational quality control, and an actual algorithm to achieve the information spreading. 2. Theory-wise, particular flavors of DA should only be applied once the particular problem at hand is fairly well understood (*e.g.*, observational error characteristics, the atmosphere's relevant time and length scales, error growth characteristics, inherent biases), and many researchers in DA to date have not had interests in planetary problems. Nonetheless, a few efforts of planetary DA have been attempted [2,3,4], though only one, the UK effort, has reported any validated results [5]. That approach borrowed as directly as possible from an operational terrestrial DA scheme; however, the scheme that was chosen, the UK Met Office's Analysis Correction scheme [6], has since been replaced by a more "modern" scheme. Also, they chose to assimilate retrieved profiles (a data-derived product themselves) instead of directly handling radiances.

The state of the art has advanced, and, perhaps contrary to conventional expectations, DA has become in some ways more approachable to newcomers. A new class of DA approaches based on Monte Carlo approximations, "ensemble-based methods," has matured enough to be both appropriate for use in planetary problems and exploitably within the reach of planetary scientists. We have chosen to take advantage of this, and have begun adapting these methods for use with the data stream from the Mars Climate Sounder (MCS) aboard the Mars Reconnaissance Orbiter [7], along with a martian GCM that has been developed at Caltech, PlanetWRF [8].

Ensemble-Based DA: At the heart of being able to properly spread information throughout a system is the ability to accurately model the evolution of uncertainty (*i.e.*, covariance and / or correlations). Ensemble *forecasting* has been around in the terrestrial numerical weather prediction (NWP) community since at least the 1970s [9]. In ensemble forecasting, one makes many forecasts instead of a single one, and each forecast is begun from slightly different initial conditions, all in accordance with the presumed uncertainty. Then, as the forecasts evolve in time, one can estimate directly what features of a forecast are certain and uncertain (as gauged by the ensemble's relative agreement). This is a first step toward making true probabilistic forecasts (*e.g.*, 70% chance of rain). In the 1990s, researchers realized that this evolving uncertainty information is precisely what DA problems require for improved accuracy [10]. Hence, ensemble-based DA was born, and it has been improving rapidly since then.

One particularly satisfying aspect of ensemble-based DA is its inherent modularity. One needs to be able to run a numerical model many times, to link a model state to the available observations (via a forward operator), and to prescribe the observational uncertainties at hand. With these abilities in hand, the various components are rendered inputs to the main DA algorithm (either a "filter" or a "smoother"). Capitalizing on this ability, the National Center for Atmospheric Research (NCAR) has developed a framework within which one can essentially upload one's model of interest and one's dataset of interest, and be very close to being able to perform real DA. The framework is called DART, the Data Assimilation Research Testbed, and it is freely available on-line [11]. We have begun to take advantage of this rich software infrastructure, and are on our way toward performing state of the art DA in the martian atmosphere. An immediate benefit of the modularity of DART is that once we have a version working with MCS data, we can then swap in Thermal Emission Spectrometer (TES) data from the Mars Global Surveyor.

Planetary Nuances: Planetary DA problems pose several unique challenges that distinguish them from terrestrial applications. These challenges stem mainly from the fact that less is known about planetary atmospheres than earth's, and that planetary datasets are comprised solely of remote sensing data, whereas the terrestrial community has the benefit of many "direct" observations taken at surface stations around the globe and a highly organized radiosonde (weather balloon) network.

Care must be taken before performing DA, and one must have some intuition for how the system behaves, in particular how information and uncertainty propagate through the system. Earth's atmosphere has been well-studied, and we see that uncertainty grows in that system roughly in accordance with growth predicted by theories of deterministic chaos [12]. There is evidence that this paradigm does not necessarily hold throughout the year in the martian atmosphere [13], and this could have consequences when trying to blindly adapt terrestrial DA schemes to the martian atmosphere. Hence, much testing and tuning will inevitably need to be performed.

In regards to the remote sensing nature of planetary atmospheric datasets, at least two aspects of these datasets will need to be addressed: 1. Their coverage is much sparser than analogous datasets on earth, particularly when compared to the relevant atmospheric length and time scales; 2. Remote sensing data is by its very nature nonlinearly related to the atmospheric state (through radiative transfer models). *Ensemble-based DA is ideally suited to handle these idiosyncrasies.*

Regarding the first point above, there is evidence from the terrestrial community that as observations become sparser, the need for more accurately spreading information throughout the system becomes more crucial [14]. Ensemble-based methods provide precisely this ability by estimating uncertainty growth along with the evolution of the atmospheric state (*i.e.*, explicitly taking uncertainty's state-dependence into account). Regarding the second point above, many traditional DA approaches find their analysis states by gradient descent algorithms minimizing some specified cost-function (a sum of quadratic forms, essentially least squares). If one has a nonlinear forward operator (like a radiative transfer model), then in order to minimize a cost function containing this operator, one must be able to find gradients with respect to it – this requires the ability to code the operator's tangent linear and adjoint forms. While obtainable, there is typically great overhead in coding these, and the overhead is then sunk in a very specific operator (*i.e.*, if one updates one's radiative transfer operator or decides to use a different dataset, then these coding exercises must be repeated). Ensemble-based methods avoid this necessity because they do not operate by gradient descent minimization, rather they proceed by what might be considered a "direct solve" for a cost function's minimum.

Summary: In short, adapting state of the art terrestrial DA approaches for use with MCS data and the PlanetWRF GCM is not trivial. However, it has become a realistic venture due to the innovation of NCAR's DART framework. Once completed, the obtained time sequence of analysis model states will be an excellent product to probe and study what we have learned (and are still learning!) from the MCS data stream (and hopefully others).

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