

Aspects of data assimilation peculiar to space weather forecasting

George Siscoe¹ and Stanley C. Solomon²

Received 31 October 2005; revised 3 January 2006; accepted 4 January 2006; published 13 April 2006.

[1] Data assimilation in space weather forecasting is necessary but differs in important respects from terrestrial weather forecasting. These differences arise in part from the relative sparsity of data in space weather and from relatively direct driving of space weather phenomena. They present opportunities for space weather forecasting to add new data assimilation techniques to those developed in terrestrial weather forecasting.

Citation: Siscoe, G., and S. C. Solomon (2006), Aspects of data assimilation peculiar to space weather forecasting, *Space Weather*, 4, S04002, doi:10.1029/2005SW000205.

1. Data Assimilation in Meteorology

[2] "Data assimilation" refers to a technique that takes a set of numbers representing observations of some environmental variable and merges it in a special way with another set of numbers of the same variable computed by a model to obtain a new set of numbers of that variable that represents an optimal compromise between the observations and the model. Such techniques come in many forms depending on the sources of data and the model. This paper concerns peculiarities of space weather data sources and models that make data assimilation in space weather forecasting different in some respects than in terrestrial weather forecasting, which is not to deny that there are also important aspects in common. The peculiarities that differentiate, at least for the present, data assimilation in space weather forecasting from terrestrial weather forecasting are fairly obvious: data sparsity, directly driven dynamics versus instability driven, short timescales, and inherent limit on range of forecast set by unmeasurability of crucial parameters at the Sun compounded by intervening turbulence versus sensitivity to initial conditions. In some respects, space weather simulations have aspects in common with global ocean simulations—which are also data limited in the deep ocean—and with regional mesoscale tropospheric forecasts, which have short timescales and are strongly driven by their boundary conditions. These differences with global atmospheric models used in forecasting suggest that as we proceed to incorporate data assimilation in space weather forecast programs we might need to do more than import and modify techniques developed by meteorologists for

applications in meteorology. That is, besides borrowing techniques already developed elsewhere, we might also need to carry out research aimed at developing techniques suited specifically to the peculiarities unique to the space weather situation. Before considering these peculiarities, we take a quick look at the standard example of data assimilation as it has been developed for applications in meteorology [e.g., Kalnay, 2003].

[3] The daily weather forecast issued by the weather service owes its notable success in large part to data assimilation procedures that over many decades have evolved to a high level of sophistication. Here typically every six hours measurements of about ten different variables taken at 10^4 to 10^5 observing points from over the whole globe are quality checked, interpolated onto the more than 10^6 points of a three dimensional grid used by a numerical prediction program—few if any of which coincide with an observing point—and combined in a weighted average with values of the same variables predicted at each point by the program to produce an optimal set of values to initialize the next forecast run. What we have just described is a complicated operation but not necessarily a sophisticated one. The sophistication comes in optimizing the interpolation of the data onto the computation grid and in selecting the weights in the averages of measured and predicted quantities at each grid point—at some places and times observations can be trusted more than predictions and vice versa—to minimize expected errors in the prediction. Thus much work goes into estimating the errors in the observations and the predictions to determine optimal weights for each grid point. The procedure reaches its most sophisticated implementation when the estimated error in the prediction is updated at each forecast step by determining the time-varying, local sensitivity of the prediction to random perturbations of the model-generated inputs. Thus unstable conditions tend to decrease the weight of

¹Center for Space Physics, Boston University, Boston, Massachusetts, USA.

²High Altitude Observatory, National Center for Atmospheric Research, Boulder, Colorado, USA.

the prediction relative to the observations in regions of instability.

2. Meteorological Model Applied to Space Weather

[4] When meteorologists refer to data assimilation they are likely to have in mind something like the advanced version of it that they have developed for application in operational numerical weather prediction, as just described. Thus it is by comparison with this example that we wish to discuss the role of data assimilation in operational space weather forecasting. Also to maintain the analogy with the terrestrial case, which incorporates the whole globe in its computational grid, we will be concerned primarily with the corresponding “global” space weather system, that is, the Sun-to-Earth system. Of course, at the solar end of the system we must draw the line at some convenient place so as not to become involved with forecasting solar eruptive phenomena, at least for now. For the purpose of the present discussion therefore we consider the Sun to be an outer boundary on the prediction code at which values of quantities that the code needs at each grid point must be specified by measurements or by a separate model and not computed as part of the prediction code. Similarly at the terrestrial end of the space weather system we must put an inner boundary on the prediction code at some altitude in the atmosphere convenient for space weather applications at which values are prescribed on the computation grid from measurements or from another model. In this case there are codes that could in principle extend the computational grid into the lower atmosphere if such extension should ever be shown to have space weather relevance.

[5] In between the outer solar boundary and the inner terrestrial boundary a numerical code to predict space weather would have many grid points spread over the corona, the solar wind, the magnetosphere and the ionosphere/thermosphere. The question is to what extent can we think of data assimilation in this case as a process of periodically reinitializing the values on this array of grid points through a weighted combination of predicted values and measured quantities interpolated to the grid points? Such a procedure would represent a direct carryover of meteorological data assimilation to space weather. The assessment that we present here is that a direct carryover would work in some parts of the domain, but in other parts new techniques will probably need to be developed in the time period before sufficient data sources become available to carry out the procedure over the whole grid.

[6] Because we are focusing here on the whole Sun-to-Earth system and on forecasting as the aim of data assimilation, we intend this article to complement a differently focused series of pieces on data assimilation that *The CEDAR Post*—newsletter of NSF’s program to foster research in aeronomy—began publishing in its Spring 2005 issue. The focus of *The CEDAR Post* articles is more on regional applications of data assimilation in all aspects of

space physics and aeronomy (SPA). Given the conspicuous role that data assimilation plays in meteorology and oceanography, the series aims to further its application in SPA generally. One thing one learns from the series is that concepts and techniques like those developed for applications in meteorology and oceanography, when modified appropriately, have already led to tools of great utility in SPA. One example that stands out particularly is the assimilative mapping of ionospheric electrodynamics (AMIE) technique [Kamide *et al.*, 1981; Richmond and Kamide, 1988], which has become an indispensable tool in coordinated data analysis projects that involve the ionosphere. Although AMIE’s formalism comes from the literature on optimal estimation theory rather than the meteorological literature, it is very similar. Another pertinent example because of its intended application to space weather is the Global Assimilation of Ionospheric Measurements (GAIM) model which is being developed for operation at the U.S. Air Force Weather Agency in two versions, one by a consortium led by Utah State University [Schunk *et al.*, 2004, 2005; Scherliess *et al.*, 2004], the other by a consortium led jointly by the Jet Propulsion Laboratory and the University of Southern California [Hajj *et al.*, 2004; Wang *et al.*, 2004]. The USU version is currently being implemented at the Air Force Weather Agency. Whereas AMIE finds its main use in post hoc analyses of space weather events, GAIM is meant for operational space weather nowcasting and will be capable of forecasting when coupled to a code that forecasts its magnetospheric input parameters.

[7] AMIE and GAIM deal with the ionospheric piece of the Sun-Earth system. Their function is to make maps of ionospheric parameters at given times—snapshots of a changing scene—out of a combination of data and models. They are viable because there are enough data to feed them to produce synoptic maps with sufficient resolution and fidelity to be of value to a user community. AMIE can assimilate data from over 150 ground magnetometer stations, the SuperDARN radar network, and DMSP satellites to produce maps with a resolution of 1.67° in latitude and 10° in longitude with a 1 min time cadence. The USU-GAIM uses a network of 100 Digisondes, over 100 ground station GPS-TEC measurements, and other sources to produce 3 dimensional maps of ionospheric parameters with variable resolution depending on the area covered (local, regional, or global). These many hundreds of sources of information about ionospheric conditions set up the kind of comprehensive areal data coverage with which the standard data assimilation techniques of meteorology were designed to work. Thus AMIE and GAIM demonstrate that meteorological data assimilation techniques would carry over (in fact, are in effect being carried over) to the ionospheric part of a Sun-to-Earth space weather numerical prediction code.

3. Where the Meteorological Model Begins to Fail

[8] What about the magnetospheric part? Can the meteorological model of data assimilation be applied here?

We have in mind a magnetospheric prediction code like one of the several global MHD simulation codes that already exist or one with the addition of particle drift physics as in the Rice Convection Model. In this case the answer to the question is “probably not,” owing to undersampling of the magnetosphere. For example, one would need to resolve the plasma sheet with in situ measurements to reinitialize grid points in the plasma sheet, which at present cannot be done. If one were to combine data from existing geosynchronous satellites with those from some future magnetospheric constellation mission, it might be possible to implement a low-order form of the standard data assimilation procedure. In the meantime, innovation seems to be called for. Perhaps some hybrid scheme would work in which the ionospheric boundary condition is treated in a standard data assimilation manner that combines observations from a code like AMIE or GAIM with values predicted by the operational magnetospheric code, but grid points elsewhere in the magnetosphere would be reinitialized by a combination of predicted values and—instead of real-time data values—data values obtained from climatological models. By climatological models we mean global empirical models based on statistically combining observations made over time and space but binned to represent specific space weather conditions, for example, the Tsyganenko magnetic field models and the plasma sheet models of *Wing et al. [2003]*). The binned climatological models that are brought into the assimilation step of real-time operations must, of course, be appropriate to current weather conditions indicated, for example, by solar wind measurements (including IMF), geomagnetic disturbance indices, and as to the plasma sheet, perhaps also by geosynchronous measurements. Substorms, which are not well represented in climatological models, would cause a problem in this scheme, but the problem might be handled, for example, by reducing the relative weight of climatological values when a substorm materializes in the prediction code. In any case, the sparse data problem that applies to the magnetosphere illustrates the need to innovate outside of standard data assimilation techniques to optimize the use of data assimilation in an operational space weather prediction code.

[9] Why should we bother to carry the discussion beyond the magnetosphere? After all, today’s space weather user groups are interested in ground induced currents, ground magnetic disturbances, ionospheric disturbances, atmospheric drag, and the radiation environment of satellites, all of which occur within the magnetosphere. We ask the question rhetorically to point out another difference between terrestrial weather prediction and space weather prediction. Terrestrial weather is self-generated in the sense that the energy input from the Sun is constant but the atmospheric response to it is variable because of barotropic, baroclinic, and other instabilities. In contrast, space weather in the magnetosphere results mainly from variable solar wind conditions. Even the substorm—the magnetosphere’s prime candidate for a process resulting

from an inherent instability—is in most cases triggered by changes in solar wind conditions. This difference between the origins of terrestrial and magnetospheric weather means that whereas the dynamics that underlie terrestrial weather prediction is restricted to the atmosphere itself, the dynamics that underlie magnetospheric weather prediction must include the solar wind. To describe this fundamental distinction as it applies to geophysical systems, we suggest the terms *persistence* and *compliance*. Persistence means that a combination of the current state plus our knowledge of physics can adequately describe future states, regardless of how boundary conditions change. Compliance means that the system responds rapidly to changing boundary conditions. The terrestrial weather system is persistent; the magnetospheric, compliant. Data assimilation in persistent systems is confined to the system itself, whereas in compliant systems it must be extended to the external medium to which the system is compliant—the solar wind in this case.

[10] Data assimilation is more important in numerical modeling of persistent systems than in compliant systems. In fact, in nonperiodic systems like tropospheric weather, data assimilation is indispensable because such systems exhibit deterministic chaos. Without repeated assimilation steps, the predicted state would wander ever farther from the actual state. On the other hand, in numerical modeling of compliant systems, data assimilation is not as important, since compliant systems tend to be directly driven from boundary conditions. Their tight coupling to the boundary conditions holds the predicted state close to the actual state. As to the magnetosphere, our present understanding would suggest that, except for the expansion and recovery phases of substorms, solar wind boundary conditions are for the most part sufficient to characterize the state of magnetospheric weather.

[11] A further implication of the distinction between persistent and compliant systems is that the time into the future to which a forecast can be made in persistent systems depends on how well the data assimilation procedure and the prediction code can approach the inherent limit set by deterministic chaos. However, in compliant systems it is set by the predictability of the driving boundary conditions. This brings us to the solar wind and the role of data assimilation in numerical solar wind codes.

[12] Stand-alone magnetospheric and ionospheric codes of the type available to predict space weather are now driven by real-time data taken at the L1 point. This sets an upper limit on the forecast time of usually less than 1 hour, and part of this time must be used in the operational forecast procedure. We have here a practical difference between terrestrial and space weather forecasting—the very short time in the space weather case in which to prepare and release a forecast based on a numerical prediction code. The situation could improve markedly when the STEREO mission places an observing platform upstream from Earth in a corotational sense giving lead times from hours to days as the spacecraft recedes from

Earth. However, the improvement will be temporary since the correlation between conditions seen by the spacecraft and by Earth will degrade as they separate.

[13] To move permanently beyond the ~ 1 hour L1 forecast range, one needs a solar wind prediction code that can in principle extend the forecast range to roughly 2 to 4 days. Again we have in mind a physics-based, numerical prediction code. In situ data at a single L1 or even a STEREO observation site cannot be combined in a proper data assimilation step with predicted values from a solar wind code to reinitialize the values over the code's grid. However, it is precisely this kind of pan grid data assimilation that one needs if observed solar wind quantities are to be used to make an improvement in 2- to 4-day solar wind forecasts. How might this be done?

4. Space Weather Modifications of the Meteorological Model

[14] At present solar magnetograms are the primary sources of observational data used to drive solar wind codes [e.g., *Odstrcil et al.*, 2004, 2005]. These feed semiempirical algorithms that compute solar wind speed, density and temperature and IMF polarity at a spherical surface at a heliocentric distance beyond which the wind goes supersonic [Arge and Pizzo, 2000; Riley et al., 2001]. This allows the solar wind code to treat data input as a time variable boundary condition. Once values of the dependent variables have been specified on the inner boundary (and after a startup procedure to initialize its grid points), the code predicts the variables everywhere else for as long as it receives data at its boundary grid points. Efforts to improve agreement between predicted values and values observed at 1 AU focus on the algorithm that turns solar magnetograms into boundary conditions for the code. However, no data assimilation steps operate to nudge computed values toward observed values at grid points between the inner boundary and 1 AU. What solar wind observations are there between the inner boundary and 1 AU that could be so used?

[15] Interplanetary scintillation data (IPS) and Thompson scattering in the extended solar corona measured by coronagraphs on SOHO and SMIE are possible answers to the question. Use of these sources to drive a data assimilation scheme for a simple kinematic solar wind model has already been described by *Hick and Jackson* [2004]. In essence, one uses values of solar wind speed and density given by the model to predict the signals that these instruments should measure. Then one adjusts the code's boundary conditions to minimize the disagreement between predicted and observed signals. This technique could be applied as well to MHD solar wind codes. Then the data assimilation effort would determine the values on the boundary grid by optimally combining values given by the algorithm that turns solar magnetograms into boundary values and by the algorithm that adjusts boundary values to minimize the disagreement between predicted and observed IPS and coronagraph signals. This is a novel

space weather kind of data assimilation procedure which, to develop, would require a dedicated research effort.

[16] A final instance of data assimilation unique to the space weather situation deserves mention. As is well known, the single most important variable that determines magnetospheric weather (for example the value of the Ap index—a standard space weather product) is the north-south (z) component of the interplanetary magnetic field (IMF B_z). However, by current techniques, except for the magnetic field inside of a CME which can in principle be inferred from solar magnetograms [*Bothmer and Rust*, 1997], IMF B_z is unmeasurable as an input to a solar wind code. Moreover, turbulence in the solar wind causes IMF B_z to change sign on average every 10 min or so. Thus between the Sun and the Earth, IMF B_z typically changes sign every 1.6×10^{-3} AU on average, which is subgrid scale in any practicable solar wind code. This means that except for the large-scale regularities imposed on IMF B_z by the Parker spiral during equinoxes (the Russell-McPherron effect) and the magnetic field within an ICME which can hold its z orientation in transit [*Zhao and Hoeksema*, 1997], IMF B_z is inherently unpredictable. To address the problem that this condition poses to everyday space weather prediction, *McPherron and Siscoe* [2004] introduced the concept of climatological air mass analysis. The solar wind exhibits characteristic modes of behavior (fast streams, slow streams, CIRs, CMEs, etc.) which might be called solar wind air masses by analogy to atmospheric air masses in meteorology. The point is that if one can tell in advance what type of air mass the Earth will be in, one can predict in a statistical sense the climatological conditions that go along with such air masses, including the statistics of IMF B_z . The data assimilation implication here is that a solar wind code can predict 2 to 4 days in advance the type of solar wind air mass. Then an artificial IMF waveform can be generated from the statistical properties of the IMF appropriate to the predicted air mass. This artificial IMF combined with the solar wind parameters predicted from the solar wind code give boundary conditions that a magnetospheric or ionospheric code can use to generate ensemble examples of the type of space weather that will ensue when the predicted air mass arrives. These would then allow statistical forecasts to be made of space weather products such as the Ap index.

5. Parameter Space for Comparing Data Assimilation Requirements

[17] Figure 1 summarizes the points made in this discussion in the form of a plot that shows qualitatively the location of various weather domains relative to the availability of data (the ordinate) and the sensitivity to boundary conditions (the abscissa) for a presumed 24 hour weather forecast by a physics-based numerical prediction code. The troposphere is represented by the box in the upper left. The other boxes refer to space weather domains. Compared to these, the troposphere is highest in data availability and lowest in sensitivity to boundary

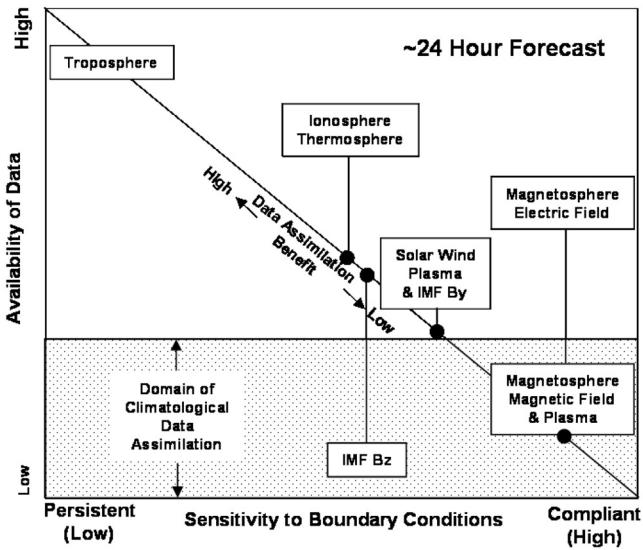


Figure 1. Approximate locations of various weather domains relative to data availability and sensitivity to boundary conditions as they apply to making 24 hour weather forecasts. The domains are also projected vertically onto the diagonal line, which qualitatively indicates the relative value of data assimilation in improving forecast skill.

conditions. Next down in data availability is the ionosphere/thermosphere box. Of the space weather domains, it is highest in data availability because of programs like AMIE and GAIM. On the abscissa, we put it in the middle between persistent and compliant since the thermosphere gives the domain 24 hour persistence but the ionosphere responds to magnetospheric inputs which are compliant. Under ionosphere/thermosphere in data availability comes magnetospheric electric field. It shares the data sources of AMIE and GAIM but lacks sources for field-aligned potential drops and induction electric fields. Being magnetospheric, it lies at the compliant end of the sensitivity axis. Under it comes solar wind plasma and IMF B_y , which has IPS and coronagraph measurements for solar wind data sources and solar magnetograms for sector polarity (IMF B_y)—fewer than AMIE and GAIM but still highly usable. We put it on the compliant side of the sensitivity axis because except for stream interactions and shock compression ahead of CMEs, boundary conditions govern most of solar wind dynamics. Under solar wind plasma comes the box for magnetospheric magnetic field and plasma. Here data availability is so low that the box lies in the domain of climatological models for the purpose of data assimilation. Being magnetospheric, it lies at the compliant end of the sensitivity axis. Finally at the bottom of the plot comes IMF B_z , for which except for the Russell-McPherron effect and ICMEs there are no data. It lies near the middle of the persistent/compliant axis since boundary conditions are needed to predict the solar wind air mass, but given this, the statistical properties are persistent.

[18] Most relevant to this discussion is the diagonal line labeled “Data Assimilation Benefit,” which attempts to indicate in a very qualitative way the benefit that incorporating some data assimilation scheme, presumably of the meteorological kind, would make in increasing forecast skill. The point it makes is simply this, the closer you are to the persistent end of the sensitivity axis the greater the benefit of data assimilation, and the closer you are to the compliant end, the less the benefit. For example, for a 24 hour forecast as illustrated here, there is virtually no persistence in magnetospheric quantities, so assimilating magnetospheric quantities into a magnetospheric code would not increase 24 hour forecast skill. For forecasts of less than 24 hours, all boxes shift to the left, and for a ~ 1 hour or less forecast magnetospheric data assimilation could increase forecast skill. However, for a 1 day forecast, all persistence in magnetospheric weather comes from the solar wind and the IMF sector structure. These can have autocorrelation timescales of the order of a day, which can give value to a persistence forecast of magnetospheric quantities. However, the real benefit of data assimilation in increasing skill in magnetospheric quantities lies in its application to the solar wind. Of course the case for the value of data assimilation in ionosphere/thermosphere forecasts has already been made, and its implementation is well underway.

6. Conclusions

[19] Space weather has peculiarities that call for developing new kinds of data assimilation procedures (in addition to importing already developed procedures) for the purpose of forecasting. One such peculiarity is data sparsity (magnetospheric plasma and magnetic field and IMF B_z), which might require climatological forms of data assimilation and so, in the case of IMF B_z , the development of the appropriate climatologies. Another peculiarity is a strong tendency of space weather domains to exhibit compliant dynamics. This emphasizes the importance of combining or coupling models so as to reduce the uncertainty associated with the future forcing by external boundary conditions. Future applications might entail a hybrid kind of data assimilation where the process of synthesizing measured values and predicted values in an optimal way takes place on boundary grid points, as in the magnetospheric electric field and the solar wind.

[20] **Acknowledgment.** This work was supported in part by the National Science Foundation under grant ATM-0220396 and by the CISM project, which is funded by the STC Program of the National Science Foundation under agreement ATM-0120950.

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G. Siscoe, Center for Space Physics, Boston University, 725 Commonwealth Avenue, Boston, MA 02215, USA. (siscoe@bu.edu)

S. C. Solomon, High Altitude Observatory, National Center for Atmospheric Research, 3080 Center Green, CG1-2132, Boulder, CO 80301, USA.