

Roles of empirical modeling within CISM

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Abstract

Within the CISM project empirical models serve as baselines against which to monitor the increase in predictive skill of physics-based numerical codes as they advance. Empirical models also establish a suite of forecast models from which to evolve toward greater forecast accuracy by incorporating numerical codes as they advance enough to increase forecast skill. Establishing a suite of forecast models allows the CISM project to contribute results of use to operational space weather forecasting earlier than might otherwise be possible. Developing a suite of empirical models allows CISM to address issues of data ingestion early in the project under relatively simple conditions. Out of the data-ingestion effort has come a technique of probabilistic forecasts, which allows one to ingest information on IMF B_z from solar data instead of from measurements taken only at the Lagrangian L1 point. To implement the evolution from empirical to numerical forecast models, CISM has adopted a coupled two-line system of model development, a science-model line interacting with a forecast-model line.

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1. Roles of empirical models

The primary task of the Center for Integrated Space Weather Modeling (CISM) is to link together a suite of numerical codes that integrate the equations of Newton and Maxwell from the sun to the ionosphere. CISM's approach is to take advantage of research by groups working on the separate links of an unbroken chain of physics-based models that connects the sun with the ionosphere—corona, solar wind, magnetosphere, and ionosphere/thermosphere—and to focus on coupling these links while at the same time working to improve

them. The goal is to produce a single, integrated, physics-based numerical model of the solar–terrestrial system that does for space weather prediction what general circulation models of the atmosphere do for tropospheric prediction. They are the underlying, physics-based research codes on which operational prediction codes are based.

Why, then, is the CISM project also interested in a line of empirical models? There are four reasons. As it undertakes to develop a physics-based, end-to-end model, the CISM project needs empirical models to provide baseline predictions against which the skill of its physics-based models can be measured. Second, empirical models also serve as starting points from which the ability to predict space weather parameters can be improved by incorporating physics-based models as

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these reach a stage of development at which they give better predictions than the empirical model they replace. Third, as the previous statement implies, by initially adopting and tailoring a suite of empirical models, the CISM project may be able to produce something of value to operational forecasting (namely, one or more improved prediction algorithms of space weather parameters) earlier in its life. And fourth, linking together empirical models allows the CISM project to acquire experience in dealing with problems associated with model integration and data ingestion. The following sections elaborate on these four functions of empirical models.

2. Empirical models provide baseline predictions to measure skill

A project such as CISM to develop a set of linked, physics-based numerical codes capable of predicting environmental conditions at any place and time throughout the solar–terrestrial system obviously needs metrics to tell how well it is performing. To provide metrics, CISM has adopted an accepted method, which is to compare the prediction accuracy of the linked physics-based codes against the corresponding accuracy of existing data-based algorithms. One such metric that can then be generated is skill score defined by

$$\text{Skill score} = (1 - \text{MSE}/\text{MSE}_{\text{ref}}) \times 100,$$

where MSE is the mean-square error in the predictions of the physics-based codes and MSE_{ref} is the mean-square error in the predictions of the data-based algorithms, used as a reference. If the MSE of the physics-based codes is bigger than the MSE of the data-based algorithms the skill is negative, positive otherwise. As applied to CISM, the data-based algorithms used to make the reference predictions are the mentioned suite of CISM baseline empirical models.

The role of empirical models in providing baselines to evaluate the performance of CISM's physics-based models is the subject of Spence et al. (2004). Here we wish to focus on the general concept of a “baseline” model. The most important property of a baseline model is that it never changes. A baseline model must not improve over time, otherwise it could not serve as a baseline against which to measure the improvement of other models. If for some reason a baseline model is changed or replaced by another in the future, then the progress of improvement of skill of the physics-based models would need to be re-evaluated ab initio. As a corollary, a baseline model need not be the best among models available even at the time of its adoption, for, since it may not improve, other models should soon surpass it anyway. Other factors such as ease of use and guaranteed availability of data with which to run the

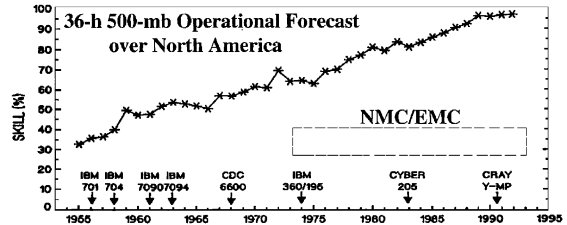


Fig. 1. Long-term record of skill in the 36-hour 500-mb operational forecast over North America from the Numerical Meteorological Center (now the Environmental Modeling Center). (From McPherson, 1994.)

model could be more important than being the most accurate of current models. Of course, a model chosen as a baseline should nonetheless be as good as possible within these considerations.

Fig. 1 illustrates why a baseline model must not change in time. It shows a plot that gives as a function of time the skill in the 36-hour forecast of the average height of the 500 mb surface over the US. The forecast in this case is based on operational, physics-based numerical codes used by the US Weather Service. The plot starts in 1955, when the Weather Service initiated operational numerical weather prediction. As measured by this metric the skill of numerical weather forecasting in 1955 was around 33%, which was about as good as was possible with traditional weather map analysis. The low skill level in 1955 implies that the average error that the numerical-based forecast made was about 88% of the average error that the reference algorithm made (climatology, say). By 1992 (when the plot ends) the average error in numerical-based forecast had dropped to about 14% of the average error in the forecast of the reference algorithm. Obviously by 1992 the success of the numerical algorithms had greatly diminished the value of the reference algorithm as a forecasting tool. By then the reference algorithm was good for little more than to serve as the standard against which improvement in numerical algorithms could be measured. But this was an immensely valuable function, because the reference algorithm's role as a fixed standard over 40 years had achieved an otherwise impossible result. Although it had sunk to minimal use as a contemporary forecast tool, the reference algorithm had allowed progress in forecast skill to be quantified.

The lesson to be learned from this is that when a data-based algorithm is chosen for use as a baseline algorithm for measuring skill, its use as a forecast algorithm per se becomes irrelevant. Its status in the world of algorithms has been elevated to a standard. It would instantly lose its elevated status should it become “improved” since the sine qua non of a standard is to be frozen in time.

The CISM project has chosen two suites of empirical algorithms to serve as baseline models. One suite is

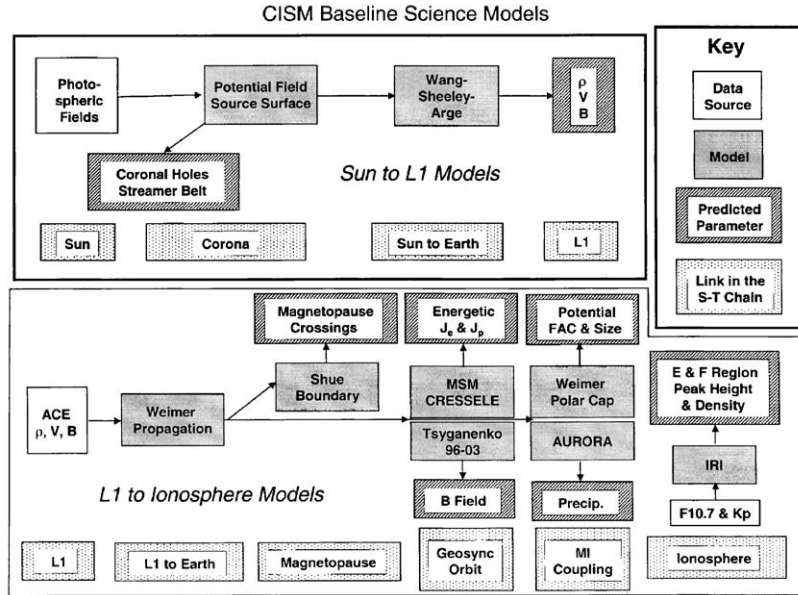


Fig. 2. The suite of CISM baseline science models together with their data sources and prediction parameters.

meant to monitor the performance of the physics-based codes as science tools, the other as forecast tools. We list the former in this section and the latter in Section 4 below. The suite of science baseline models, shown schematically in Fig. 2, begins at the sun with a coronal hole index in the form of the “Potential Field Source Surface Model” (PFSS), which was developed for use as input to the Wang–Sheeley model (Wang and Sheeley, 1992). Complementary to the coronal hole index is a white-light streamer belt index, also based on the PFSS. The PFSS predicts coronal hole boundaries from which one may infer the regions that should appear dark in SOHO ultraviolet images of the sun (coronal holes) and regions that should appear light in SOHO white light coronagraph images (streamer belts). The coronal hole and streamer belt indices serve as baseline models to evaluate the performance of CISM’s physics-based numerical code that treats the corona (Abbett et al., 2004) and use a different set of boundary conditions than PFSS to predict coronal structure.

The skill of the combined corona and solar wind codes (Odstroil et al., 2004) will be monitored by comparison against the Wang–Sheeley–Arge (WSA) model (Arge and Odstroil, 2004) using data at the L1 Lagrangian point. The WSA model currently predicts the speed of the solar wind and the polarity of the magnetic field. The intention is to augment it with simple additions that allow it also to predict (albeit crudely) the density of the solar wind and the strength of the magnetic field at 1AU. For example, solar wind density is statistically anticorrelated with solar wind

speed so that their product, which is the mass flux density, is approximately constant (Schwenn, 1990, p. 143).

The science baseline models omit a model to monitor the progress of the ability of CISM’s numerical codes to simulate transient events, among which are the particularly important coronal mass ejections (CMEs). Also omitted is a model to monitor the progress of the ability of CISM’s numerical codes to simulate solar energetic particle events (SEPs). These monitoring functions have instead been relegated to the forecast baseline models, described below. The choice of adding baseline CME and SEP models to the forecast set instead of the science set was made mainly because of the great relevance that CME and SEP predictions have to space weather forecasting. Obviously, however, regardless of which set they are in, they will play a dual role in base lining the science models and the forecast models.

Coming closer to Earth, the skill of the magnetospheric code (combined Lyon–Fedder–Mobary (LFM) and Rice Convection Model (RCM), see Toffoletto and Lyon, 2004) in predicting the location of the magnetopause (using an archival data base of magnetopause crossings) will be tested against the Shue et al. model (Shue et al., 1997, 1998). For this purpose, data taken by an L1 monitor (the Advanced Composition Explorer, ACE) will be propagated to Earth using the Weimer propagation model (Weimer et al., 2003). The Tsyganenko empirical magnetic field model (Tsyganenko, 1995) will serve as the standard against which to determine the skill of the combined LFM/RCM code

by comparing predictions against magnetic field measured by the GOES satellites at geosynchronous orbit. In the inner magnetosphere, the skill of the RCM code operating within the global LFM MHD code to predict ring current parameters will be measured by reference to the Magnetospheric Specification Model (MSM) operating in stand-alone mode. The forecast skill of CISM's physics-based electron radiation belt model (Baker et al., 2004) will be measured by comparing their predictions against those of an empirical model based on electron data taken by the CRESS satellite (CRESSELE, Hilmer, 1999). This comparison will use data from the GOES and LANL geosynchronous orbit satellites.

To measure how well the combined LFM/TING code (TING stands for Thermosphere–Ionosphere Nested Grid model; Wiltberger et al., 2004) simulates the coupling between the magnetosphere and the ionosphere, the CISM project will compute a skill score that uses empirically based Weimer models as baselines. The Weimer models predict the distribution of the polar cap potential and field-aligned currents and the shape and size of the polar cap boundary on the basis of solar wind and IMF measurements taken at L1 (Weimer, 1996, 2001). The skill of the part of the numerical code that predicts particle precipitation will be evaluated by comparing its predictions against those of an empirical code named Aurora based on a compilation of time-averaged auroral ion and electron data (Hilmer, 1999). The comparison will use data from DMSP satellites.

At the extreme, terrestrial end of the sun-to-earth chain of linked models we find the TING model predicting pure ionospheric parameters, the heights and densities at the peaks of the E and F regions. Skill in this case will be based on reference to the International Reference Ionosphere (IRI) using solar radio F10.7 intensity and the geomagnetic Kp index.

It will perhaps be useful to repeat here that the version of any model chosen as a CISM baseline will be regarded by the CISM project to be fixed in its algorithmic specification and to be frozen in time. This will be true even though outside its baseline use in CISM project each model has a life of its own and will continue to evolve. In its role as a CISM standard, each model can be used to monitor its own progress.

To sum up this section, the CISM project needs empirical models to serve as reference algorithms with which to monitor the progress of its end-to-end, physics-based chain of models. Any algorithm chosen for this purpose changes status from a living, evolvable operational algorithm, or pretensions thereto, to an unchanging, non-evolvable standard. A set of empirical models has been identified that cover key aspects of the solar–terrestrial environment at each major linking point in the chain.

To serve as static baseline models, fixed in time as described in this section, is one function of empirical

models within the CISM project. A different function, almost the opposite, is to evolve in time, as the next section describes.

3. Empirical models establish a substructure from which advanced forecast models can evolve

A major lesson that Fig. 1 can teach a fledgling environmental field such as space weather that aspires to match tropospheric meteorology in forecasting skill is that it is important to begin operational forecasting using physics-based numerical codes as quickly as possible. The advent of numerical weather prediction in 1955 allowed tropospheric weather prediction to advance much farther in the subsequent 40 years than it had in the preceding 100 years using techniques of weather map analysis. Over the 40 years covered in the plot, numerical weather prediction went from a skill of 33–98%, whereas skill based on traditional weather map analysis has changed hardly at all. But notice that progress was gradual. It is not the case that with the advent of physics-based numerical weather prediction forecasting skill shot up instantly. In 1955, the two modes of forecasting—weather map and numerical—were at about the same skill level. Increase in numerical forecasting skill accrued slowly through better representations of physical processes, more powerful and faster computers, and better data assimilation techniques. But improvement was driven by operational demand for greater forecast accuracy. Without continuous feedback between researcher/coder and forecaster, the researcher/coder would not know where to exert effort to achieve greatest operational effect. The two divisions of labor were tightly coupled. Without this tight coupling even the seemingly slow progress seen in the figure would not have occurred. To think of research/coders by themselves ending up with the highly evolved forecast codes of 1992 without feedback, and so without guidance or stimulus, is unreasonable.

CISM accepts the lesson that the earlier numerical codes are pressed into making operational forecasts the better. But faced with the reality that numerical space weather codes such as CISM's are too large to be imposed suddenly on the Space Environment Center with all the attendant startup and training overhead, CISM has adopted a hybrid strategy in which empirical models play a crucial role. The idea is to adopt a set of end-to-end (sun-to-earth) empirical forecast models that give operational, forecast parameters as output. This set of forecast models then leads two lives, one of which is to become frozen into an unchanging set of baseline models like those just described. But here their use is to monitor improvement in skill in predicting operational forecast parameters (rather than, as above, parameters that monitor the codes' skills in predicting parameters of

the solar–terrestrial medium of interest to scientists). The other life of the set of forecast models is to evolve by incorporating the outputs of the numerical codes, singly or in combination, as these improve enough with that, in place of one or more of the empirical codes that make up the forecast models, they increase forecasting skill. This selective, one-by-one way of bringing numerical codes into the forecast models when they increase skill in the overall forecast reduces demand on SEC resources for operational forecasting. The evolution of forecast models is discussed further in Section 5 below.

The purpose of this section has been to point out that Fig. 1 has an important lesson for space weather—initiate numerical forecasting ASAP—and to describe the strategy that the CISM project has adopted to evolve toward numerical forecasts from empirical models. The strategy outlined here puts operational space weather forecasting on the path toward achieving the benefit of numerical forecasting that Fig. 1 demonstrates. It has the additional benefit of providing a suite of forecast models that can be put into operation in the meantime, as the next section describes.

4. The CISM suite of forecast models

To define its suite of forecast models, the CISM project asked the agency in the United States National Oceanographic and Atmospheric Administration (NOAA) responsible for space weather warnings and forecasts, the Space Environment Center (SEC), and its Defense Department counterpart to provide a list of

their most used or important forecast parameters. With few exceptions, concerning mainly the thermosphere and the equatorial ionosphere, this list has become the suite of CISM baseline forecast models, which Fig. 3 displays together with the models’ data sources and forecast parameters.

The models fall into groups distinguished by their data sources: a CME prediction model, a solar energetic particle (SEP) prediction model, an ionosphere-state prediction model, and a set of models that predict various magnetic disturbances and the fluxes of relativistic electrons in the radiation belts and at geosynchronous orbit. The CME prediction model is based on the sun-to-earth propagation model of Gopalswamy et al. (2001) (based on halo CME speed data) as improved by Vrsnak and Gopalswamy (2002) and augmented by the addition of a climatological prediction of B_z orientation within the CME (Bothmer and Rust, 1997) and an empirical prediction of CME field strength (Owens and Cargill, 2002). The SEP prediction model, dubbed PROTONS in the figure, uses integrated soft X-ray flux of the initiating event (measured by GOES) together with the event location and radio sweep data to put the event into bins that contain predicted values of peak flux and rise times obtained statistically (Balch, 1999). The ionosphere state model is the International Reference Ionosphere (IRI).

As the bottom box in Fig. 3 shows, five models use solar wind data or IMF data or both as input. The input data are taken at L1 for short-term forecasts (< ~ 1 hour) or, for longer-term forecasts (> 1 day) are predicted by the WSA model using solar magnetograms as input. The WSA models therefore become both

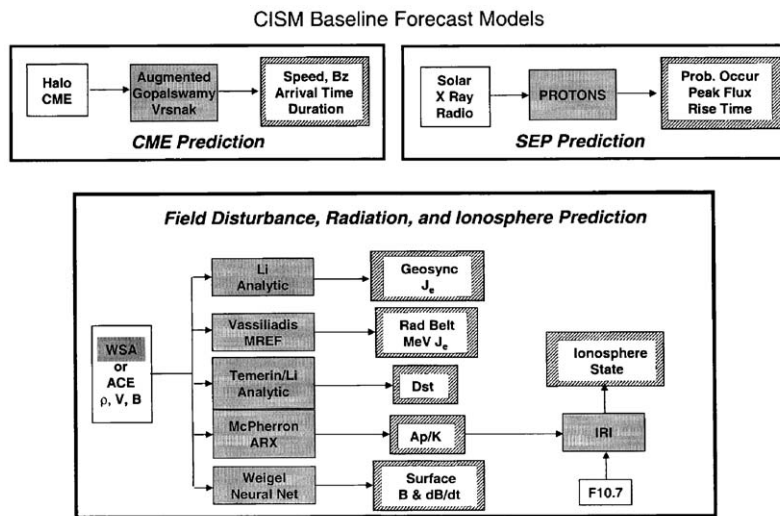


Fig. 3. The suite of CISM baseline forecast models together with their data sources and prediction parameters.

a science and a forecast model. At the top of this set of five models is the Li et al. radial diffusion model that predicts the flux of relativistic electrons at geosynchronous orbit up to two days in advance (Li et al., 2003). Below this is the Magnetosphere Relativistic Electron Forecast (MREF) model of Vassiliadis et al. based on the AutoRegressive Moving-Average (ARMA) technique (Vassiliadis et al., 2004). The MREF model predicts relativistic electron fluxes in the radiation belts in three regions beyond $L = 3$, also days in advance. Next comes the Temerin and Li (2002) model for short-term predictions of the Dst index based on an extension and refinement of the Burton equation (Burton et al., 1975). There follows an AutoRegressive exogenous (ARX) algorithm developed by McPherron (2004) to make 24-hour forecasts of the Ap and K indexes. The bottom of the five forecast models that use solar wind/IMF data as input is the Weigel model for short-term predictions of the perturbation magnetic field in the auroral zone and its time derivative (Weigel et al., 2003). The Weigel model is based on a probability distribution function derived from 2 years of auroral zone magnetometer data.

The nine models shown in Fig. 3, and possible later additions, have become CISM’s suite of baseline forecast models in the strict sense of the meaning of “baseline” discussed above in Section 2, namely, forever unchanging. The next section illustrates how the forecast models in their non-baseline role interact with CISM’s physics-based numerical codes to evolve toward the desired goal of an end-to-end numerical forecast model.

5. Interaction between CISM’s science and forecast models

As mentioned in Section 3, CISM’s strategy for evolving toward one or more physics-based, numerical forecast models is to run the forecast models with and without a numerical model serving as one of their components and comparing the skill relative to the baseline models of the two results. When a numerical model has improved enough that it raises the skill above that achieved without it, the time has come to incorporate it into the forecast model. In this way the numerical models can be brought incrementally, singly or in combination, into the links of an operating forecast chain.

To illustrate the strategy Fig. 4 depicts schematically a line of physics-based, numerical models labeled Science Models and a line labeled Forecast Models. The depiction is clearly schematic since, as Figs. 2 and 3 show, in neither case is there a single line. The simplified, two-line depiction nonetheless serves to illustrate the point of interest by focusing on just the solar wind link in the chain. In the initial forecast models, the semi-empirical WSA model will provide the sun-to-L1 or sun-to-magnetosphere values of solar wind and IMF parameters that, as seen in Fig. 3, drive a suite of models that forecast operational magnetospheric parameters. At some point in the development of the Science Models, the MAS-ENLIL code should begin to provide values of solar wind and IMF parameters that increase the skill of forecast models that use them over that obtained with WSA. Then the MAS-ENLIL code

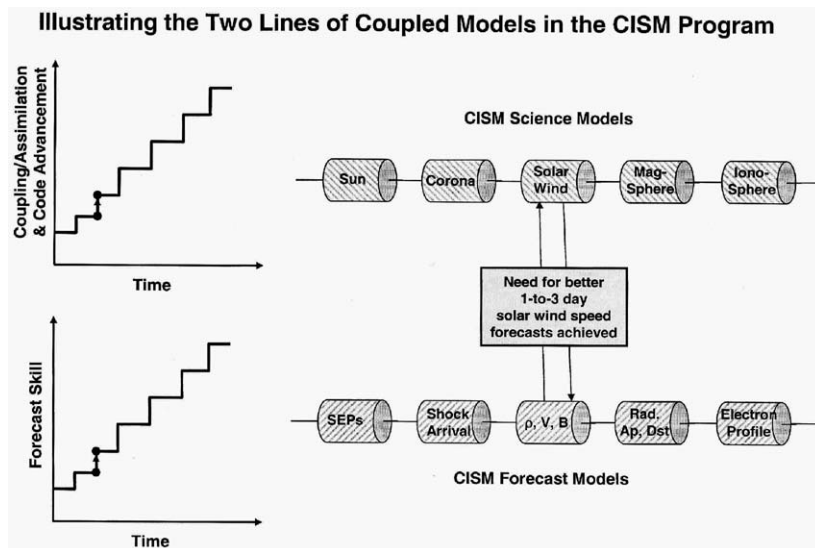


Fig. 4. A schematic to illustrate the two lines of models in the CISM project (a science line and a forecast line) and their interaction. The steps at the left of the figure suggest that incremental improvements in the science line result in corresponding improvements in the forecast line.

should replace the WSA model as the provider of solar wind and IMF parameters in the suite of forecast models. At this point the solar wind-IMF part of the forecast models will have arrived at the stage of numerical forecasting where the systematic, incremental increase in skill realizable in physics-based codes becomes possible, as suggested by the stepwise rise in skill on the left side of Fig. 4.

One can identify other replacements besides MAS-ENLIL replacing WSA that might be possible in the relatively near future. CME shock arrival time and strength and post-shock conditions are likely to be predicted better with physics-based, numerical codes than with semi-empirical models in the near future. Somewhat farther out in time the same might be hoped for solar energetic particles and radiation belt predictions, especially protons. It should be recognized, however, that some parameters of interest to forecasters, such as the non-physics-definable quantities A_p and K_p , are likely to remain better forecast by statistical models for a longer time.

One envisions, therefore, a protracted period during which physics-based, numerical codes operate in tandem with semi-empirical and statistical models to provide the full suite of parameters that space weather forecasters need. In other words, it may be necessary for a time to run an ensemble of model runs that includes pure empirical algorithms and empirical-numerical hybrid algorithms. For this reason at the same time that CISM works to incorporate physics-based, numerical codes into the chain of forecast models to the extent possible, it also intends to evolve a complementary suite of semi-empirical and statistical models as such. This effort includes developing new forecast products that might serve the space weather user community better than products now available. One such effort is the dB/dt algorithm shown at the bottom of the set of five models in Fig. 3. It responds to a call from the electrical power industry for a space weather product more tailored to their concerns than the K_p or A_p indices (Simpson, 2004).

Since it is intended that the forecast models will see operational service early in the life of the program, they will also be the first of CISM's models to grapple with issues of data ingestion. The next section illustrates the challenges in this many-faceted area by describing an aspect that is unique to the space weather field.

6. Empirical models address the L1 barrier

Forecast models that ingest solar wind and IMF data taken by L1 spacecraft such as ACE give about a one hour maximum warning in advance of a coming event. However, forecast models that ingest solar wind and IMF data from the WSA model, based on solar

magnetograms, can predict space weather conditions up to four days in advance. But the WSA model has a time resolution of about eight hours, which means that changes faster than this are not predictable. One quantity that changes faster than this is the north–south component of the interplanetary magnetic field, which is, of course, one of the most important space weather variables. It changes from northward to southward or vice versa once every 10 min on average (approximately), but with great variations. At any time between the sun and the earth there are typically 600 north–south flips of the IMF. Such changes are too rapid for any technique of ingestion of solar data to follow. Thus, except for large-scale structures such as IMF polarity sectors and CMEs where the IMF in the north–south direction can be ordered on longer scales (by the Russell–McPherron effect in the case of IMF polarity sectors), IMF B_z is normally unpredictable beyond the hour or so available from L1 data. Consequently forecast models that use IMF B_z as input are likewise limited to an approximately 1-hour forecast horizon.

To address the “L1 barrier” in IMF B_z ingestion, the empirical modeling group in the CISM project has adopted a concept of probabilistic forecasting based on an analogy to air-mass climatology in meteorology (McPherron and Siscoe, 2004). The idea is to divide the solar wind speed profile predicted by the WSA model into “air-mass” intervals during which IMF B_z has distinct probability distribution functions (pdfs). These pdfs can then be used in conjunction with the forecast models to derive corresponding pdfs for the forecast parameter, which allows the forecaster to make a probabilistic forecast for each time interval that has an identifiable pdf; for example: “There is a 50% probability that A_p will exceed 40 during the next 24 hours”. McPherron and Siscoe (2004) found that the interface between solar wind streams divides the solar wind into distinct air-mass intervals. At a practical level, marking off one-day time steps before and after the predicted passage of the stream interface provides intervals with distinct pdfs for the values of IMF B_z . One is able to break the L1 barrier in IMF B_z ingestion by going from deterministic to probabilistic forecasts.

At present probabilistic forecasting falls under the heading of new products under development. Eventually it should enter the forecast model chart (Fig. 3) as a model to be used in conjunction with WSA to cover the range one hour to three days continuously for most of the forecast models. Similarly the statistical methods used by Weigel and Baker (2003) will also be evaluated for their ability to provide longer lead time forecasts. This work showed that the probability of rapid fluctuations in the ground magnetic field can be characterized by a single heavy-tailed probability distribution function with a standard deviation that is strongly dependent on the solar wind velocity and local

time. Given a 3-hour lead time forecast of the solar wind velocity, the pdf can be used to estimate the likelihood of a rapid geomagnetic change as a function of local time in the next 1-hour interval.

7. Summary

Empirical models are essential complements to the development of physics-based, numerical models within the CISM project. They provide baseline models against which to quantify increase in skill as numerical models advance. They establish a substructure of forecast models from which to evolve incrementally in accuracy and scope by incorporating numerical models as they advance enough to increase forecast skill. To implement the evolution from empirical to numerical models, CISM has adopted a coupled two-line system of model development, a science-model line interacting with a forecast-model line. Empirical models allow the CISM project to impact the world of operational space weather forecasting earlier than would otherwise be possible by developing a line of forecast models, which has also forced an early effort on issues of data ingestion. Out of this has emerged the technique of probabilistic forecasts to overcome the L1 barrier to ingesting IMF B_z .

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