A Chapter In
Space Weather: Physics and Effects
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Forecasting Space Weather

Abstract.

Forecasting space weather effects presents the ultimate challenge to a space physics model. Not only should physical constraints be satisfied, but also practical issues such as timeliness, accuracy, and reliability should be addressed. We give a tutorial review of model types, and compare their relative strengths. The basics of data assimilation and Kalman filtering are presented. We intersperse brief descriptions of case studies and cite examples to illustrate the concepts discussed. Summarizing, we conclude with the relevant current developments and future outlook.

1. Introduction

Space weather forecasting is the specification of the future state of a space environment. Forecasting is one of the most challenging hypothesis-testing methods since, in addition to formulating and implementing a test of a model or theory, it is burdened with the practical complications of issuing a predictive statement in advance of an event. A related concept is nowcasting, the specification of the present state of the environment. In the preceding chapters we have seen that space weather comprises a broad collection of electrodynamic and plasma physical phenomena. Typically these phenomena are classified in terms of the spatial regions where they take place as solar-heliospheric, magnetospheric, ionospheric, and non-plasma (neutral). The technology assets affected by space weather are located within Earth's magnetosphere (satellites, re-entry vehicles, and space stations), less on the ground (electric power grids, pipeline systems, communication networks, etc.), and a much smaller number in extraterrestrial space (exploration spacecraft, and lunar and planetary bases). Other classifications are frequently used as well. For instance, we can distinguish the phenomena based on their physical causes. Thus as discussed in Chapters 12 and 13, space radiation is divided into cosmic rays, solar energetic particles, radiation-belt ions and electrons, etc. Because of the diversity, each space weather environment constitutes a separate challenge in terms of data collection, real-time monitoring, model and theory development, and validation and verification. As a result, space weather models available at the time of writing are at very different evolution stages.

Instead of the diversity, in this chapter we focus chiefly on the underlying theoretical and modeling issues. Space weather phenomena can be understood and predicted in the context of information dynamics and, much more specifically, plasma physics and electrodynamics. The former approach is the basis of empirical modeling; the latter, of physical modeling. As observations of a space weather environment become more comprehensive, practitioners typically are able to identify a growing number of dynamical and physical features, which are included in next-generation models. As a result, forecasts become increasingly accurate.

At the end of the chapter we will give a summary of several current forecasting efforts and the future outlook. It is important to put these developments in a historical context, because although space weather is a fast-developing field, it follows the same path as older disciplines have, namely meteorology and oceanography. Indeed, space forecasting efforts began in the mid 1960s, but growth was slow until 1995 when a national space weather plan was formally established in the US and then in several European and Asian countries [Behnke and Tascione, 1995; Behnke et al., 1997]. Today space forecast centers have been put in place by government, academic, and private-industry sponsors (Fig. 1). Currently space weather forecasting capabilities are comparable to the tropospheric weather science in the late 1960s, but evolve at a much faster pace.

Input-output modeling

Space weather systems are open, i.e. they exchange mass, momentum, and energy with one or more neighboring plasmas. Therefore plasma physical "box models" need to have time-dependent inputs such as electric and magnetic fields, injected beams, and inflowing plasmas in order to be developed as realistic space weather tools. The open-system property introduces the notion of stability under perturbations and susceptibility, response time and amplitude, conditions of transmission and amplification, etc.

The main direction of the transfer of information is heliocentric. However there are many different pathways for these quantities to be transmitted. Propagation speeds differ greatly among different environments and even within the same environment. For instance in the interplanetary medium there are orders of magnitude of differences in speed between electromagnetic radiation, energetic particles, waves, and flows. Thus a model needs to keep track very different time histories for each type of interplanetary input.

Generally measurements made close to the solar or interplanetary source of space weather events have a higher significance than those made closer to Earth, since the former allow for a greater lead time in its prediction. On the other hand, information about the initial solar or interplanetary perturbations becomes distorted and eventually unreliable as they travel through different environments. The effective distortion can be measured with correlation or structure functions, as we shall see in Sections 2 and 5 below.

Empirical and physical models: tracking information vs. energy

The interaction of space weather systems can be effectively described in two different ways. First, it can be viewed as an exchange of information. For instance, changes of interplanetary magnetic field (IMF) B_z polarity do not involve significant energy changes per se; e.g., they may reflect the passage of a convected structure, or simply the presence of turbulence. However, in the context of the interaction with Earth's magnetosphere, a Southward turn of the IMF at the L_1 point means that magnetic reconnection will commence on the dayside equatorial region 30-60 minutes later. Thus the IMF B_z amplitude can be part of a magnetospheric model, which does not account for the energy balance. Representing space environment interactions in terms of information dynamics leads to the development of empirical models.

Empirical models are typically the first to be developed for a given space weather environment. Examples include nonlinear regressions and superposed epoch analyses, and more generally averages of a field or other variable conditioned on measurement location and/or activity level. Widely used cases include semiempirical models of the solar wind expansion [Wang and Sheeley, 1990], and the magnetospheric magnetic [Mead and Fairfield, 1975; Tsyganenko, 1987, 1995, 2002a, b] and electric field [Volland and Stern; Weimer, 1996, 2001].

Time-dependent models define the state of the system in terms of relevant physical or proxy variables. For instance, in order to describe the essential, large-scale dynamics of the dynamic terrestrial magnetosphere, one can use the state vector:

$$\mathbf{x}(t) = \left(\Phi_{lobe}, E_{tail}, I_{tail}, E_{iono}, I_{iono}\right) \tag{1}$$

whose components represent two repositories of energy (Φ: lobe flux; E_{tail}: cross-tail electric field) and two sinks (E_{tail}, I_{tail}: plasma sheet; E_{iono}, I_{iono}: ionosphere). Proxies for these variables can be used (the PC index for the lobe flux; the AE index for the ionospheric current) and the observed dynamics are fit to differential or time-difference equations [for an example see Horton and Doxas, 1996; 1998]. The model is driven by a time-dependent solar wind input. Alternatively, models are first developed from observed proxies, and then their dynamics are interpreted physically [Vassiliadis et al., 1995].

Second, space weather events can be described as the transport of physical quantities, such as energy, momentum, mass, helicity, etc. Physical models are based on an electrodynamic, MHD, or kinetic description. MHD models include descriptions of the corona and solar wind [Linker et al., 1999; Odstrcil and Pizzo, 1999], as well as Earth's magnetosphere [Fedder and Lyon, 1995; Gombosi et al., 1998; Lyon et al., 2004]. Kinetic models have been developed for the ring current [Fok et al., 1995; Kozyra, Jordanova, Liemohn, etc] and the electron radiation belts [Boscher, 1996; Bourdarie, etc.].

Realistic models contain elements of both the information-based and the physics-based approach. The development of empirical models, for instance, is guided by knowledge of the plasma physics of the system to determine variables of interest (such as moments of the plasma distributions; or relevant components of the IMF). And physics-based models regularly rely on empirical fits to data to represent external, nonlinear, or subgrid processes.

Forecast performances of empirical and physical models vary widely. Empirical models are trained to reproduce a small set of variables and are not constrained by conservation laws as physical models are. For these reasons empirical models tend to be faster and more accurate than physical ones in predicting the set of variables they are trained on. On the other hand, physical models provide predictions on a broad set of variables. In addition, they can predict events whose amplitude is outside the training domain (given the correct physics is included in the model), whereas empirical models simply extrapolate from the domain that they are trained on. Generally, empirical models are often "rigid" in the sense that they are limited by the spatial, temporal, and energy resolution of the measured data, and cannot be easily generalized to produce additional physical quantities of the same or a similar space environment.

Climatology and dynamics

Some of the most efficient models are obtained by averaging a representative number of past measurements of the system's activity. Examples include the average sunspot variation over a solar cycle, obtained from measurements over several recent cycles; or the corresponding A_p geomagnetic index variation over the same time scale. Such models of the historically average activity are called climatological.

Dynamical terms are important corrections to the baseline model provided by climatology. The zeroth-order dynamical term is the persistence term, representing the system's inertia. If the climatology model has the form of a linear regression, $x(t) = a \cdot u(t) + b$ with u(t) being an external driver, including a persistence term takes the form:

$$x_{t+1} = \alpha x_t + (1-\alpha)(au_{t+1} + b) \tag{2}$$

where the value of α is chosen to balance the persistence over the new information. If the time step is small compared to the time scales of physical processes, Eq. (2) can be rewritten as a differential equation. In Section 4 we will discuss more sophisticated methods for assimilating recent observations.

2. Predictive model development: ring current dynamics and the D_{st} index.

In this and the next two sections we will use the D_{st} geomagnetic index as an example for modeling and forecasting a space weather environment. We have chosen D_{st} because its time variations can be well captured by relatively simple dynamical models whose physical interpretation is straightforward. The index is designed to represent of the magnetic effects of the ring current and is defined as a weighted average of the horizontal perturbation's North-South component, measured at four mid-latitude locations. The ring current is the dominant (but not only[1]) contributor to the magnetic activity.

Southward turns of the IMF are followed by intensifications of the ring current. Relevant to D_{st} dynamics is the East-West rectified component of the interplanetary electric field, $\left(\mathbf{V}_{SW} \times \mathbf{B}\right)_y = V_{SW} B_{South}$, where V_{SW} is the radial component of the solar wind velocity and B_{South} is the rectified IMF B_z component (i.e., it is 0 when B_z is positive and $-B_z$ when B_z is negative). GSE coordinates are used. Applied to the magnetotail, the field leads to enhanced plasma sheet convection earthward into the inner magnetosphere and thereby to an increase in the ring current's ion population. As a starting point in modeling D_{st}, one can consider a linear regression between the two variables:

$$D_{st}\left(t\right) = a + b \cdot V_{SW}\left(t\right) B_{South}\left(t\right) \tag{3}$$

where time is measured in hours, and therefore the variations in the solar wind driver and the resulting plasma sheet convection can be considered as instantaneous. The regression is a simple climatology model.

However, Eq. (3) is a static equation, and therefore does not account for the D_{st} time variations during magnetic storms. For instance, when $V_{SW}B_{South}$ goes to zero, D_{st} decreases approximately exponentially as ring current ions are lost through magnetopause exits, Coulomb collisions, charge exchange, and wave-particle interactions. To a large extent, this dynamics is captured by balancing the driving term with a loss term and adding a persistence term. The result is a first-order differential equation [Burton et al., 1975]:

$$\frac{dD_{st}\left(t\right)}{dt} = bV_{SW}\left(t\right) B_{South}\left(t\right) - \frac{D_{st}\left(t\right)}{\tau} \tag{4}$$

where $bV_{SW}\left(t\right) B_{South}\left(t\right)$ represents the injection rate of ions into the ring current. The decay time τ represents the effects of the loss processes mentioned. The [Burton et al., 1975] model is a simple, yet effective model of the D_{st} time variations with terms motivated by observed effects. A comparison of the model with the observed D_{st} is shown in Fig. 2.

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[1] Several other currents contribute to the measured D_{st} index. The effects of the most important one, the magnetopause current which responds to high interplanetary pressure, is removed from D_{st} [Burton et al., 1975]. We will not discuss the distinction further, and assume that effects due to other currents are negligible.

In order to measure the degree of success in reproducing the observed variation, the time series of the model-predicted index, $\hat{D}_{st}(t)$, is compared to observations, $D_{st}(t)$. Section 5 goes over several techniques and related issues. Here we mention a standard technique, namely the correlation coefficient:

$$C^{(\hat{D}_{st},D_{st})} = \frac{1}{T}\frac{1}{\sigma_{\hat{D}_{st}}\sigma_{D_{st}}}\int_0^T \left(\hat{D}_{st}(t)-\bar{\hat{D}}_{st}\right)\left(D_{st}(t)-\bar{D}_{st}\right)dt \qquad (5)$$

where $\bar{X}$ and σ_X are the average and standard deviation of variable X, respectively. The correlation (5) takes values in the range 50-60% therefore the variance of the D_{st} measurements explained by model (4) is 25-36%.

3. Enhancing the model

Having the preceding example as a baseline model, we now consider additional complexities.

3a. Time dependence

A different way to generalize the regression (3), in order to improve on both the forecast accuracy and the physics represented, is to include a longer history of the recent solar wind input rather than a single term. Starting from (3) we write the current state of the system in terms of the history of the solar wind input:

$$D_{st}(t) = \int_0^\infty H(\tau) V_{SW}(t-\tau) B_{South}(t-\tau) d\tau \qquad (6)$$

The coupling between D_{st} and $V_{SW}B_{South}$ is now represented by the impulse response function $H(\tau)$, which contains all the information needed to represent the linear dynamics of D_{st}. The type of model (6) is known as the finite impulse response (FIR) model and has found many applications in geomagnetic studies since the 1980s [Clauer, 1986]. A fundamental property of (6) is that if the solar wind input is an impulse (similar to a delta function) the estimated geomagnetic amplitude is $D_{st}(t) = H(t)$.

Obtaining the impulse response function is straightforward when an analytical model, such as Eq. (4), is available. In that case $H(\tau)$ is derived via a Laplace transform. Typically, however, the dynamics is unknown and the response function needs to be solved for directly from experimental time series data. For a time series of length N, Eq. (6) is written

$$D_{st}(t) = \sum_{i=0}^{T} H(i\Delta t) V_{SW}(t-i\Delta t) B_{South}(t-i\Delta t) \qquad (7)$$

where we keep track of the solar wind history up to a time T, and Δt is the time resolution [Iyemori et al., 1979]. Inverting (7) as a multi-linear regression gives

$$H = \left[\mathbf{VB}_s \mathbf{VB}_s^T\right]^{-1} \left[\mathbf{D}_{st} \mathbf{VB}_s^T\right] \qquad (8)$$

where $\mathbf{D}_{st}$ is a N-dimensional column vector (the D_{st} time series) and $V_{SW}B_{South}$ is a NxT matrix obtained from the corresponding $V_{SW}B_{South}$ measurements. Here the superscript T denotes the transpose.

FIR models have been useful in analysis of geomagnetic and particle-flux time variations. FIR models have been developed for various geomagnetic indices and solar wind/IMF inputs [Bargatze et al., 1985; Clauer, 1986; Trattner and Rucker, 1989] and the relativistic electron flux at geosynchronous orbit [Nagai, 1988; Baker et al., 1990] and other altitudes [Vassiliadis et al., 2002]. The Baker et al. model is used at NOAA/SEC as a forecasting tool (http://www.sec.noaa.gov/refm/ doc/REFMDoc.html).

3b. Input Selection

The significance of input-output modeling for space weather systems has already been mentioned. It is important to include all physically relevant, independent input variables. The most relevant solar and interplanetary inputs include the IMF B_z, the radial speed and density of the solar wind plasma, UV radiation, and energetic particle fluxes. They drive very different types of coupling between the interplanetary medium and the terrestrial domain (magnetosphere and ionosphere): magnetic reconnection, viscous interaction, and electrodynamic coupling, among others.

Solar and interplanetary activity is highly correlated especially during the development and propagation of structures. Therefore few variables can be considered as mutually independent. Magnetic field components, plasma flows, and energetic particle fluxes follow characteristic time variations in the formation and propagation of geoeffective structures such as interplanetary shocks, coronal mass ejections, and high-speed streams.

We can assess the geoeffectiveness of a solar/interplanetary input, or of a given type of structure, by means of a metric such as the correlation coefficient (5). Additional metrics are discussed in Section 5. It is instructive to compare geoeffectiveness across different inputs to determine the most important ones. In fact scalings of the geoeffectiveness function can be used to identify the dominant physical processes in a given system. Fig. 3 shows a comparison of 17 solar, interplanetary, and magnetospheric parameters of interest for electron radiation belt models. The geoeffectiveness of the parameters, expressed in the correlation coefficient between model predictions and observations of the electron flux, is plotted as a function of L shell. Parameters are grouped according to the geoeffectiveness profiles, which seem to indicate three different types of coupling: hydrodynamic (incl. viscous) interactions, magnetic reconnection and resulting geomagnetic activity, and loss-enhancing or driver-mitigating processes. Thus validating a model's forecasts can be useful in identifying physical mechanisms in observational datasets [Vassiliadis et al., 2005].Finally, structure identification is possible from the observed time series of fields, flows, or fluxes. A method based on superposed epoch analysis has given the average time profile of a high-speed stream in velocity, field, and other variables [McPherron and Siscoe, 2004]. That time profile has then been used as a template to compare experimental data with and identify stream signatures in them.

3c. Feedback and Nonlinearity.

These two properties are distinct, but are closely related and in practice they often occur together. While feedback is generally associated with instabilities and the linear regime, nonlinearities are related to the saturation of instabilities. Nontrivial nonlinearities presuppose a form of dynamics and feedback.

Feedback. In space plasmas, positive feedback mechanisms include the development of plasma instabilities. If the feedback between subsystems can be described by linear differential equations (i.e., the system is in the linear regime), the energy in the unstable mode increases exponentially. Negative feedback represents damping and loss processes as in Eq. (4) for the ring current.

The evolution of D_{st} may depend on higher-order terms than in (4). In discrete-time such a model is written:

$$D_{st}(t) = \sum_{i=0}^{m} a_i D_{st,i}(t - i\Delta t) + b \cdot V_{SW}(t) B_{South}(t) \tag{9}$$

Nonlinearity.

There are countless ways to introduce nonlinearities. A small number of them are discussed below. In all cases, nonlinearity can be viewed as the breaking of a symmetry, namely the invariance of the dynamics for different levels of activity. Typically this breaking occurs for extreme (much higher or lower than average) levels of activity.

Coupling coefficients are functions of the input. In those cases where the system is driven by an external source, a direct way to make the model dynamics nonlinear is to parametrize the dynamics in terms of the input level.

For instance, in a nonlinear version of the D_{st} model (4), the loss rate τ has been modeled as a function of solar wind input $V_{SW}B_{South}$ [O'Brien and McPherron, 2000]. The coefficients b and τ are obtained by fitting to historical data of D_{st} and $V_{SW}B_{South}$.

In a modern and flexible methodology, one approximates the form of the nonlinearity by a neural network or other iterative approach. A simple network, such as a multilayer perceptron, has a hierarchical input-output structure where the outputs of layer n are the inputs to layer n+1. The inputs of the first layer are the inputs to the system (in this case $V_{SW}B_{South}(t)$ and lags thereof) and the output of the last layer is the system output (in this case, the geomagnetic activity at time t, $D_{st}(t)$) [Wu and Lundstedt, 1996]. The i-th element (neuron) of the n-th layer is determined as follows:

$$x_i^{(n+1)} = g\left(\sum_j w_{ij}^{(n+1)} x_j^{(n)} - \mu_i^{(n+1)}\right) \tag{10}$$

where the activation function g(.) maps the weighted sum of the layer inputs to the output, $x_i^{(n+1)}$. The function g(.) is nonlinear, such as the hyperbolic tangent and more generally a radial basis function. In order to calculate the activation functions for a given network architecture, one uses iterative methods such as backpropagation [Hertz et al., 1991] rather than the simple regression used to solve (7).

Local phase-space dynamics. So far we have discussed "global" methods because the same functional form applies to the entire phase space. Sparse measurements and, more generally, nonuniform coverage of the phase space can hamper the effectiveness of these methods. Neural networks with two or more layers can reproduce any smooth function, but the number of data needed rises rapidly with nonlinear features. Under those conditions it is more useful to develop local models, or “maps”, for individual neighborhoods of the phase space and then combine them in an “atlas” model. A local-linear model has the form similar to (9)

$$D_{st}(t) = \sum_{i=0}^{m} a_i^{(NN)} D_{st,i}(t - i\Delta t) + b \cdot VB_s(t) \tag{11}$$

but here the coefficients $a_i^{(NN)}$ are determined from a small subset of D_{st} measurements, which have the same recent history as the current state whose future we want to predict, rather than the entire dataset [Vassiliadis et al., 1999]. The number NN of the historic measurements used in each incarnation of (11) represents the degree of nonlinearity in the local model: if it goes to infinity (or the size of the entire database), we recover the linear model (9). Comparisons between local models and linear or nonlinear FIR models of the type (7) show that the former are much more accurate [Vassiliadis et al., 1995].

Modeling subsystems. A third way to introduce nonlinear couplings is by identifying physical subsystems, model each one individually, and then synthesize the individual forecasts to estimate the activity of the entire system.

The D_{st} index, for instance, is determined by the symmetric ring-current time variations, but also those of the asymmetric ring current, and the magnetopause and tail currents (including the substorm current wedge). In the Burton et al. [1975] model for D_{st} (4), the model of the ring current magnetic signature was built from separate fits to the data for active ($V_{SW} B_{South} \neq 0$) and quiet conditions. The geomagnetic effect of the magnetopause current was modeled separately. In a more comprehensive treatment, the geomagnetic effects of five currents contributing to the index were modeled separately based on driving by the solar wind and IMF [Temerin and Li, 2001] using intrinsic growth and decay times with models that resemble Eq. (4). In that model, the estimated D_{st} activity was the sum total of the geomagnetic effects of all these currents, but one can envision similar models with strong coupling between subsystems.

3d. Higher dimensions.

While indices of activity, when accurately calculated, are invaluable for space weather since they describe succinctly the global or regional level of activity, users are typically interested in local forecasts. Therefore field models have been developed from either empirical or, primarily, physical models.

Parametrization by spatial scales.A linear FIR model of the log-flux (logarithm of the flux) j_e which is parametrized by L shell has the form:

$$j_e(t; L = \text{const.}) = \int_0^{\infty} H(\tau; L = \text{const.}) V_{sw}(t - \tau)\, d\tau \tag{12}$$

Note that the log-flux and the impulse response function are parametrized by L. In addition, the response lag takes both negative and positive values. Negative lags are acausal and indicate the flux increases are due to other interplanetary (e.g., IMF), or internal (e.g., ionospheric) activity than V_{SW}. If that activity is uncorrelated with V_{SW}, the impulse response is zero for $\tau<0$; otherwise peaks at negative lags will indicate where the correlation of the other activity is highest and can be used to identify the source of the activity.

The response $H(\tau;L)$ has three prominent peaks: two positive, P_0 and P_1, and one negative, V_1 (Fig. 4), Peak P_1 occurs in the region L=4-7.5 including the geosynchronous orbit. The flux in P_1 responds coherently to solar wind velocity increases such as those in high-speed streams. Peak P_0, on the other hand, occurs at L=3-4. The flux corresponds to increases in V_{sw}, but also to increases of IMF B_z, which produces dayside reconnection, followed by enhanced convection and rapid injections deeper in the magnetosphere than P_1. This response is excited by the passage of CMEs (including magnetic clouds and other ejecta) rather than high-speed streams. Therefore the peaks represent two different modes of response of the inner magnetosphere [Vassiliadis et al., 2003]. The negative peak, V_1, occurs in the same spatial region as P_1, but earlier in time. It corresponds to the quasiadiabatic diffusion and loss brought about by the variation of the ring current close to L=5.5.

The response of the flux as a function of L shell thus shows a complex dynamics, which characterizes the radiation belts. In addition to the solar wind velocity, other interplanetary and magnetospheric variables are important in determining the radiation belt electron flux [Vassiliadis et al., 2005].

Convection-diffusion models.

A recent quasi-empirical diffusion model of the electron flux [Li et al., 2001] has its starting point at the diffusion and loss of the electron phase space density:

$$\frac{\partial f_e(t;L)}{\partial t} = L^2 \frac{\partial}{\partial L}\left(\frac{D_{LL}}{L^2}\frac{\partial f_e}{\partial L}\right) - \frac{f_e}{\tau_{loss}} \tag{13}$$

The phase space density is defined in terms of the observed flux J as $f = J/p^2$, where p is the relativistic momentum of the particles. Diffusion occurs as electrons interact with low-frequency waves whose power is significant in the region close to and below geosynchronous orbit. Importantly, parameters D_{LL} and τ_{loss} are functions of time-dependent solar wind velocity and IMF B_z as well as of other interplanetary inputs [Li et al., 2001]. An example of the model's prediction capability is shown in Fig. 5. Eq. (13) represents the daily flux at geosynchronous orbit at high fidelity and has been placed on line (http://lasp.colorado.edu/space_weather/xlf3/xlf3.html).

A complementary approach is to investigate the effects of a specific interplanetary parameter on the energetic electron flux at different altitudes. Probably the single most significant interplanetary parameter for electron flux levels is the solar wind bulk speed V_{SW}. Its increases are typically followed by increases in the relativistic electron flux at geosynchronous orbit, as a simple correlation shows [Paulikas and

Blake, 1979]. The relation between geosynchronous flux and interplanetary velocity was refined more by Baker et al. [1990] who used a linear filter (6) approach to show that the response lagged by 2-3 days on average which is the time it takes for ULF waves to develop [Rostoker et al., 1998] and electron diffusion to occur [Li et al., 2001] as seen above. However, diffusion alone does not explain the flux variability at other L shells.

MHD and kinetic models.

Brief description of SW efforts with MHD codes, primarily heliospheric.

RAM ring-current model. <u>Fig. 6.</u> Comparisons with observations and other D_{st} models.

4. Data assimilation

Since the mid-1990s real-time space environment data became publicly available through the Internet and World Wide Web[2]. This availability enabled and justified the development of models that could ingest and use the measurements to improve forecast quality. Data assimilation is the inclusion of measurements into models with the aim of improving forecast quality. **The Kalman Filter.**

Implementing data assimilation includes choosing a method for locally correcting the forecast using actual measurements. One of the best available mechanisms for integrating measurements in the estimation of a system's state is the Kalman filter. We will discuss only the discrete Kalman Filter, which is shown to be the optimal state estimator for systems with linear dynamics [Welch and Bishop, 2001]. Its extension to nonlinear systems, or Extended Kalman Filter [Welch and Bishop, 2001; Rigler, 2004; others, is quite analogous in structure, but much more complex and beyond the scope of this review.

We consider a system with a state space structure:

$$\begin{aligned} x_k &= Ax_{k-1} + Bu_{k+1} + w_{k-1} \\ y_k &= Hx_k + v_k \end{aligned} \tag{14}$$

where A is the system dynamics and B is the coupling to an external source u_k. Except for the noise term w_{k-1}, the top equation of (14) is completely analogous to (4). The state x_k cannot be observed directly, but measurements y_k are obtained, possibly in real-time, from it through a known measurement function H. Our estimate of the state is $\hat{x}_k$ so the estimate error is $e_k = \hat{x}_k - x_k$. The noise terms for the system dynamics, w_k, and for the observation, u_k, are normally distributed with zero mean and covariances Q and R, respectively.

The question is, how we can improve our estimate $\hat{x}_k$ of the space environment state using the available measurements y_k. A specific way to state this is to find a scheme that reduces the uncertainty in $\hat{x}_k$, expressed as the error covariance

$$P_k = E\left[e_k e_k^T \right]$$

The Kalman filter is an optimal solver for this problem.

The filter equation is the correction to the state estimate

$$\hat{x}_k \leftarrow \hat{x}_k + K\left(y_k - H\hat{x}_k^- \right) \tag{15}$$

[2] In actuality, it takes about 10-20 minutes for raw measurements to be processed and publicly available on a World Wide Web or FTP interface. This is a small delay compared to substorm time scales (1-4 hours), or storm time scales (tens of hours-days).

where the state estimate is adjusted by the difference between the actual measurement y_k and the prediction $H\hat{x}_k$. The difference is modulated by the Kalman gain, K.

By minimizing the error covariance P_k we derive the gain:

$$K_k = \frac{P_k H^T}{H P_k H^T + R}$$

The estimate state and its covariance can then be written using (15):

$$\begin{aligned} \hat{x}_k &= A\hat{x}_{k-1} + Bu_k + K_k \left(y_k - H\hat{x}_k^- \right) \\ P_k &= \left(1 - K_k H\right)\left(A P_{k-1} A^T + Q \right) \end{aligned}$$

Parameter Estimation in a Radiation-belt Model

The ideas of the Kalman filter can be adapted to a wide variety of space weather environments and applications. As we saw, a key space weather region is the inner magnetosphere and more specifically the electron radiation belts. Real-time measurements from geostationary satellites are readily available. A preliminary study showed the potential of these measurements for data assimilation [Moorer and Baker, 2001].

Rigler [2004] examined the variability of the radiation belt state and explored ways to describe it in a Kalman Filter formalism. In that application the system state was defined as the response to an input. Therefore obtaining the state is tantamount to parameter estimation. Rigler [2004] rewrote Eq. (12) as

$$j_{e,t} = \hat{\mathbf{H}}_t \cdot \mathbf{V}_{SW,t}$$

where $j_{e,t}$ is the electron log-flux at time t, produced by the solar wind-magnetosphere coupling $\hat{\mathbf{H}}_t$ (a vector; the hat indicates that it is estimated rather than observed) convolved with the velocity $\mathbf{V}_{SW,t}$. The Kalman filter equations are:

$$\begin{aligned} K_t &= \frac{P_t \mathbf{V}_{SW,t}^T}{\mathbf{V}_{SW,t} P_t \mathbf{V}_{SW,t}^T + R} \\ \hat{\mathbf{H}}_{t+1} &= \hat{\mathbf{H}}_t + K_t \left(j_{e,t} - \hat{\mathbf{H}}_t \mathbf{V}_{SW,t} \right) \\ P_t &= \left(1 - K_t \mathbf{V}_{SW,t}\right)\left(P_{t-1} + Q \right) \end{aligned} \tag{16}$$

Rigler [2004] showed that the model $\hat{\mathbf{H}}_t$ estimated from Eq. (16) differs substantially from the average (least-squares) FIR model $\mathbf{H}$ of Eq. (12). Differences exist both for high-activity intervals (passages of high-speed streams, CMEs, etc.) and for quiescent intervals (e.g., prolonged Northward B_z). At the same time, the time-dependent model gives substantially lower errors for the 1-step-ahead forecasts (Fig. 7). The reduction of errors is expected since the model flexibly adapts to changing solar wind conditions; however, the amount of error reduction is highly significant.

Ionospheric Data Assimilation

Summary of Assimilative Method for Ionospheric Electrodynamics (AMIE) [Kamide et al., 1981; Richmond et al., 1988]

5. Testing and Validation

***Topics:

- Metrics. Correlation, prediction efficiency, prediction error, skill score. Fig. 8. Validation and verification.***

6. Summary and Outlook

While the diversity of space weather environments is high, we have explored several common themes above, which are essential in developing forecasts. Modeling has to take into account that these environments are open systems exchanging mass, momentum, and energy with their environment. Representing all physically relevant, independent inputs correctly is necessary for capturing the complete variability of the system. The actual development of accurate and reliable forecast models relies on physical laws as well as more general information-theoretic principles. Physical and empirical models are parts of the process of describing a space weather environment, as the example of D_{st} prediction has shown.

Forecast providers.

Today's space weather forecasts are provided by government, academic, and private sources. The distribution of providers affects the establishment of forecast standards, protocols, and the overall efficiency of the information transfer.

Historically, national and continental agencies have provided the most comprehensive nowcast and forecast suites. These include NOAA's Space Environment Center, ESA's Space Weather Services, Japan's Space Environment Information Service, and Australia's IPS Solar and Space Services among others. China's National Space Administration has evolving plans for space weather monitoring. More specialized providers, almost exclusively of nowcasts, are Los Alamos National Laboratories geosynchronous energetic particle data, NASA centers (e.g., Marshall SFC's Polar/UVI near-real-time data and images, and the Space Weather Bureau; JPL's Ionospheric and Atmospheric Remote Sensing), NCAR/HAO, and UCAR (e.g., the Space Physics and Aeronomy Research Collaboratory).

Academic providers offer more specialized nowcasts and forecasts. They include University of Michigan, Iowa, Alaska, Rice University, NJIT, etc. Several private companies have entered the field ranging from Lockheed-Martin's laboratories and APL, to small entities such as Solar-Terrestrial Dispatch and Space Environment Technologies.

As demand for space weather forecasts changes only slowly, the current distribution of providers will remain the same with minor changes in forecast standardization.

Future spacecraft missions

***Is this section part of this chapter or a separate one? If so, it should discuss the impact of the missions to forecast timeliness and accuracy, as well as validation and verification. To be written up.

Section should include:

- LWS: SDO, RBSP, etc.
- STEREO

- Etc.***

Closing remarks

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Figure Captions

1. Space weather forecast centers issue forecasts on all space weather environments. Here the NOAA/SEC forecast center is shown. The photograph was taken in 2004.

2. D_{st} index prediction from upstream solar wind measured spacecraft ISEE-3 [after Lindsay et al., 1995]. The model, summarized in Eq. (4) in the text, has been described in detail by Burton et al. [1975].

3. Solar, interplanetary, and magnetospheric variable classification of their impact on electron flux using an empirical model and the correlation function. An FIR model driven with each variable produces a forecast electron flux. The correlation function (5) for observed and predicted electron flux at shell L is plotted as a function of L. Correlation curves are grouped in 3 different categories, each plotted in a different panel.

4. a. Impulse response of energetic electron flux j_e, at geosynchronous orbit (L=6.6) and energies larger than 1 MeV as measured by LANL spacecraft, to the upstream solar wind plasma velocity V_{SW} [Baker et al., 1990]. b. As above, but for all L in the range 1-10 and E=2-6 MeV as measured by SAMPEX to V_{SW} [Vassiliadis et al., 2002].

5. A forecast of the relativistic electron flux at geosynchronous orbit based on the diffusion model of Li et al. [2001]. Solar wind parameters and the D_{st} index are displayed at the top panels.

6. The equatorial cross-section of the energetic electron flux in the inner magnetosphere as predicted by the Fok et al. [2001] convection-diffusion code, implemented in a collaboration with the University of Alaska/GI and Johns Hopkins University/APL.

7. Assimilation of SAMPEX/PET 2-6 MeV daily electron flux via an Extended Kalman Filter. The flux is shown as a function of time and L shell. The first panel displays the original (uncorrected) FIR model output; the second, the Kalman-filter version; and the third, the SAMPEX observations. Note the improvement in next-day forecast accuracy as quantified by the prediction efficiency [after Rigler, 2004].

8. Model optimization using the normalized prediction error for AL geomagnetic index data. Left panel: actual data; right panel: synthetic data from the Klimas et al. [1994] model. The error is plotted versus the number of neighbors (NN) representing nonlinearity; and the model order [after Vassiliadis et al., 1995].

Tables

Table 1

Priority* Guidance Based on Customer Need				
Priority	Model	Customer Examples	Impact Area	Lead Time
1	Solar energetic particle forecast	Commercial Airlines HF Communication Satellite Launch Manned Space Flight	Solar energetic particles	5 - 12 hours 12 hours 5 days
2	Regional geomagnetic activity forecast and nowcast	Electric Power Commercial Airlines HF Communication	Geomagnetic Activity	Different actions are taken for different lead times and skills
2	Relativistic electron forecast for International Space Station	Manned Space Flight	Radiation belt electrons	5 days
3	Ap prediction	Various military and civilian users	Geomagnetic Activity	1-3 days, 7 days, and 27 days
3	Ionospheric disturbance forecast and nowcast	Navigation (GPS) Exploration/surveying	Ionospheric scintillation	1 day
4	Dst prediction	Various military and civilian users	Geomagnetic Activity	Storm onset, strength, time of maximum and time to recover

Caption: High-priority forecast and nowcast models for NOAA/SEC (2003) based on customer need. The enumeration is simply indicative and does not completely prioritize a type of model relative to others. Priorities vary with factors such as readiness, accuracy, lead time. Different aspects of each model or model area could have different priorities. Examples of forecast users are given [Courtesy T. Onsager].