Contents

1 Proposal Summary

Objectives: The primary objective of the proposed work is to derive the most robust and accurate prediction of the interplanetary magnetic field, nominally at least 24 hours in advance. Additionally, our approach will also provide estimates of solar wind speed, density, and temperature.
Methodology: Our approach is unique in that it focuses not primarily on understanding the physical processes that modulate the interplanetary magnetic field (although we anticipate that this will occur as an inevitable byproduct of the work), but with the single-minded objective of providing the most robust estimation of the interplanetary magnetic field, primarily at 1 AU. To achieve this, we will assemble a comprehensive range of viable techniques for predicting the interplanetary magnetic field, applying rigorous statistical methodologies to discriminate between, and combine them as appropriate. These include, but are not necessarily limited to: persistence (which provides the base prediction that any approach must exceed); historical pattern matching (using k-nearest neighbor, Euclidean distance, and dynamic time warping); neural networks; empirically based CME models (e.g., spheromak-cone model); and first-principle, physics-based models. *A priori*, we do not know which technique(s) will be superior; notably, though, we will pursue those that add the most value to the prediction, which may lead us in directions that we had not fully anticipated. Moreover, we will employ several data mining techniques (e.g., classification, clustering, frequent patterns discovery) to better understand the data-stream. Our team was carefully chosen to encapsulate the wide range of data collection, analysis, and both statistical and physics-based modeling expertise necessary to achieve our goals. Additionally, our team includes members from the operations arena. We will also derive metrics for each of the in-situ measurements being predicted. We will quantify when, where, and to what extent they agree with the observations. Moreover, we will provide robust statistical measures of the uncertainty in the prediction. By so doing, we will provide necessary targets that other contemporaneous, or subsequent investigations must improve upon.
Proposed Contributions to the Focus Team Effort: Our proposed effort seeks to address all goals of this Focused Science Topic. Specifically, we will be able to provide estimates of the three components of the interplanetary magnetic field at least 24 hours in advance (and even up to 4-5 days within commensurately larger uncertainties). Additionally, the approach will allow us to provide predictions at other locations such as Mercury (Messenger) and Jupiter (Juno) and elsewhere (Solar Orbiter, Solar Probe+). Finally, our methodology lends itself to prediction of the remaining plasma parameters, including solar wind speed, density, and temperature.
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2 Science, Technical Aspects, and Management

2.1 Scientific Background

2.1.1 Introduction

In this proposal, we outline a program to derive the most robust and accurate prediction of the z-component of the interplanetary magnetic field (IMF B_z) with up to 24 hours advance warning. In essence, we aim to build up a prediction of IMF B_z by combining several distinct elements that arise on different temporal and spatial scales: slowly-evolving stream structure; rapidly-changing large scale perturbations from (interplanetary) coronal mass ejections ((I)CMEs); and high-frequency fluctuations from waves and turbulence. To achieve this, we will combine a diverse set of potential predictive techniques, ranging from statistical models to first principles algorithms, incorporating both remote solar and *in situ* observations. To quantify our success, we will develop a set of metrics that will reliably track our progress during the course of the investigation.

Conceptually, it is illuminating to consider the various processes that contribute to a non-zero z-component of the IMF. The large-scale quiescent heliospheric magnetic field has no net B_z. Waves and turbulence can be superposed on top of this large-scale picture (e.g. Horbury & Balogh, 2001), but, in and of themselves, they do not actively drive substantial space weather. From a geoeffective viewpoint, large solar eruptions generating coherent flux rope structures that propagate relatively undisturbed to 1 AU represent the major source, particularly if the axis of the flux rope lies in, or near to, the ecliptic plane. In addition, fast CMEs drive fast-mode shocks ahead of them that compress the IMF, amplifying the wave/turbulent fluctuations. Furthermore, draping of the large-scale field around the ejecta can result in large, sustained values of B_z (Gosling & McComas, 1987). Finally, it is worth noting that it is the z-component of the IMF in Geocentric Solar Magnetospheric (GSM) coordinates that is relevant for most space weather applications. The semiannual variation in geomagnetic activity due to this so-called "Russell-McPherron" effect (Russell & McPherron, 1973) is easily accounted for.

Since the previous Focused Science Topic (FST) on this subject in 2007, models have improved, both remote and *in situ* observations have expanded, and our understanding of both the eruption process and evolution of CMEs through the solar wind is better. In spite of many advances, it is not clear that any of them have improved our predictive capabilities: Predicting IMF B_z with any reliability, during disturbed time periods is a challenging and perhaps under-appreciated endeavor. Yet it is precisely during these geoeffective intervals where our predictions must be the most accurate and thus should have the highest priority.

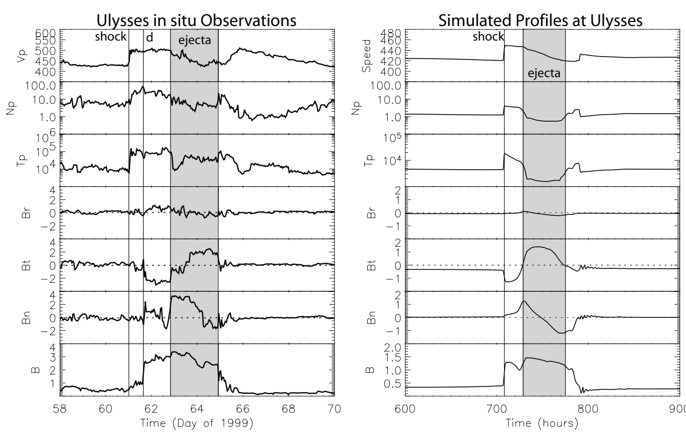

Figure 1: *Comparison of (a) observed plasma and magnetic field parameters with (b) simulated parameters for an ICME observed by the Ulysses spacecraft at 5 AU and 22°S heliographic latitude. Adapted from Riley et al. (2003).*

It is important to distinguish between studies that aim to understand the magnetic-field properties of particular events retrospectively from those that attempt to predict them in advance. Consider, for example, the comparison shown in Figure 1. This could be interpreted as a validation that global MHD models are capable of reproducing the essential features of ICMEs. If so, it might further be inferred that such models should be a useful predictive tool. While we do not dispute

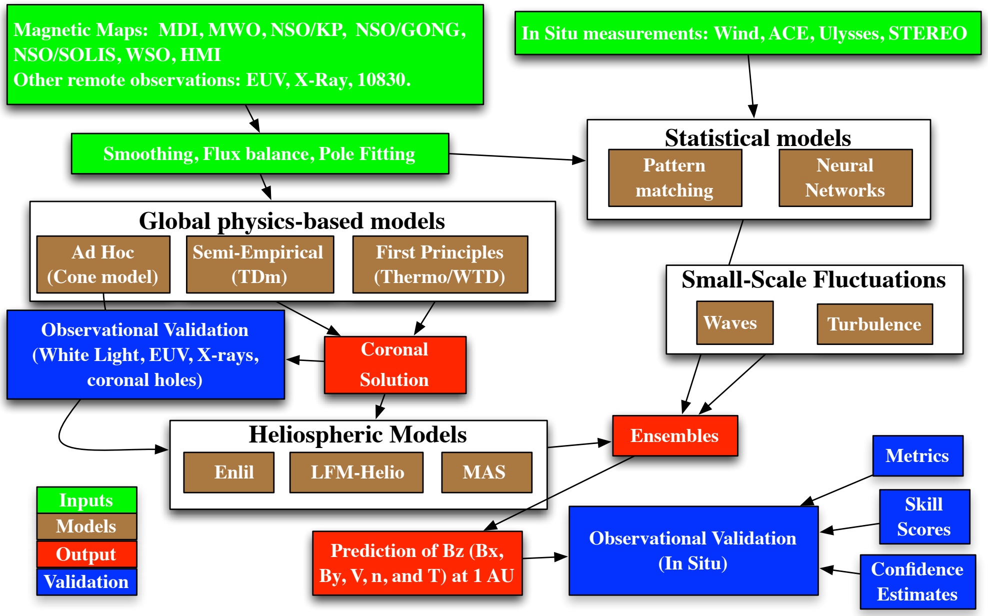

Figure 2: *Main elements of our proposed B_z Forecasting Framework (BFF). Extensive use will be made of both remote solar observations and in situ measurements (green), a range of physics-based and statistical models (brown), and use of model output (red) for validation and prediction (blue). See text for more details.*

that this will ultimately transpire, we caution that such comparisons necessarily amplify the positive aspects of the comparison and, inadvertently, convey the sense that the model is more accurate and robust than it really is. To emphasize this point, consider that this event was chosen because: (1) it was extremely simple; and (2) it matched the model results. The serendipity of identifying such a simple event for which one of our limited number of simulations matched well cannot be overstated. In contrast, if we are seeking to predict an event, we do not have the luxury of hindsight to choose the model result that most matches the observations.

2.1.2 The Current "State of the Art"

Currently, although a number of ideas and models have been proposed, there are no reliable predictions for IMF B_z. Perhaps the most defensible model at present is that of "persistence," that is, the value of B_z in the next hour, day, or even week is its current value. On average this value will be zero. During the passage of large, coherent magnetic clouds (MCs), on the other hand, it may have a sustained value that is substantially different from zero. Previous studies that have assessed our ability to predict the bulk solar wind speed (an undoubtedly easier quantity to forecast than B_z) have revealed that models are only modestly, if at all, better than persistence (e.g. Norquist & Meeks, 2010). Additionally, we can define "recurrence" as a prediction based on observed values 27 days ago (Owens et al., 2013). Yet, such predictions are likely to be valid only under "all quiet" or "all clear" conditions, which makes the most sense for parameters that have systematic variations during quiescent conditions, such as speed, density, and temperature, and even the radial and azimuthal components of the IMF. The periods of most interest, however, when B_z deviates from zero for substantial periods of time, occur during the passage of a fast CME.

2.1.3 Overview of Proposed Effort

Two quite diverse avenues can be pursued to substantially improve our forecasting ability. First, using a combination of observations and models we can physically propagate what we observe at the Sun to the vicinity of the Earth. We will outline a broad array of observational signatures and spectrum of models that can help us accomplish this. Second, statistically extrapolating what we observe in the vicinity of the Earth (and near the Sun) forward in time we can predict how B_z will change over the next 12-24 hours. The first approach will lead to predictions that can be made days in advance of the observations but, as we will discuss, is fraught with uncertainty. The second approach, while limited to near-term predictions will likely provide more accurate forecasts at least initially. The combination of the two, we believe, will also be synergistic: The statistical modeling (or data mining) approach may unveil new relationships that indicate physical processes that have, thus far, been ignored by the physics-based models. Similarly, the physics-based models may offer guidance as to which parameters to data-mine and correlate. Our proposed investigation will create the necessary infrastructure to develop both paths, quantitatively estimating their accuracy and providing key confidence intervals. Additionally, by employing simple ensemble techniques, we can combine the various approaches yielding an optimized forecasting scheme that can incorporate new approaches as they are uncovered.

Figure 2 summarizes the essential components of our proposed effort, which we call the B_z Forecasting Framework (BFF, because we hope it will be!). Each of these modules will be described in more detail in the sections that follow. Here, we make several remarks. First, the overall framework is the most important aspect, not any specific model. Our team will develop a toolkit that can be accessed and used by all team members initially, and later, the community-at-large, allowing them to objectively test various approaches. Second, our approach is comprehensive. We cannot predict which path will provide the optimum prediction. Indeed it is likely to be a composite of approaches which, when appropriately combined, will lead to the best forecasts. Moreover, different techniques will likely mature and/or supersede others either during, or after the lifetime of this study. Third, the package we propose to develop will be based on standard, open source programming practices. This will allow a greater number of people to contribute to it and extend its life beyond the confines of a four-year program.

2.2 Scientific Objectives

The primary scientific objective of this investigation is to develop, apply, and test a comprehensive suite of prediction algorithms, including new ones conceived of during the course of the investigation, to provide the most reliable and robust prediction of IMF B_z. We will also compute the other magnetic field components (B_x and B_y) as well as the bulk solar wind speed, density, and plasma temperature. To accomplish this goal requires that we:

1. Develop an easy-to-use framework for testing B_z prediction algorithms;
2. Develop a rigorous set of metrics with associated skill scores that include estimates of uncertainty;
3. Develop benchmark datasets (same data sources, sets, and sampling techniques);
4. Test the currently most promising statistical and numerical modeling techniques;
5. Develop a prioritized set of new predictive techniques; and
6. Provide the completed framework as an open source resource to the scientific community.

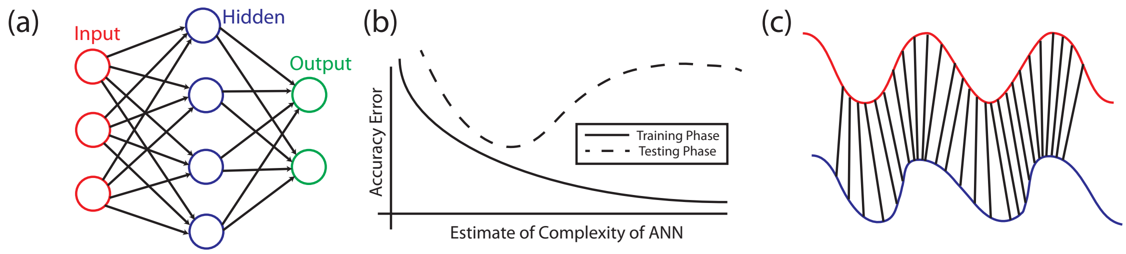

Figure 3: *(a) Illustration of a three-layer neural network. (b) Schematic of accuracy error when the ANN is overfit (solid line) or not (dashed). The "estimate of complexity" could be the number of iterations, neurons, or hidden layers. (c) Illustration of dynamic time warping for B_z time series.*

2.3 Perceived Impact of the Proposed Work

The proposed data analysis and modeling techniques, together with the application of metrics and skill scores represent a comprehensive and unique approach to solving a specific applied problem. If successful, our work will substantially advance our ability to forecast potentially geoeffective conditions 24 hours (and, in principle, up to four days) in advance. At the very least, we will be able to accurately quantify the current state of predictive capabilities, discriminate between approaches that are likely to be successful from those that are not, and provide a framework that future investigations can incorporate.

2.4 Technical Approach and Methodology

2.4.1 Introduction

We propose to apply a range of statistical and physics-based modeling techniques to uncover the optimum combination of approaches that can provide the most accurate prediction of B_z.

2.4.2 Statistical Models for Predicting B_z

Over the last decade or so, data mining and knowledge discovery approaches to revealing and predicting a range of phenomena within datasets have blossomed (Han et al., 2006; Pang-Ning et al., 2006). Moreover, a variety of publicly available and scientifically vetted toolkits have been developed for applying these techniques relatively easily (e.g., Weka, DBMiner, Rapidminer, Rattle, MCL++). These machine learning approaches have not yet been widely embraced in the solar/heliophysics community. In part, this may be due to their limited ability to make accurate predictions as well as the hurdle of understanding new concepts. However, a more likely explanation is that, for the most part, such techniques do not directly address the question of *why* particular relationships exist.

2.4.2.1 Artificial Neural Networks: Artificial Neural networks (ANNs) are models inspired by neurons in the brain. Conceptually, ANNs consists of three layers: an input layer, one or more "hidden" layers, and an output layer. Figure 3(a) illustrates the connectivity of nodes (i.e., "neurons") between these layers. Biological connections between neurons have been simulated in ANNs using links between the neurons (i.e., graph nodes) that have adaptive weights, and an activation function that can cause the neuron to fire with a value dependent on the type of function and the neuron's activation threshold. Intuitively, ANNs (particularly the multi-layer feed-forward techniques) can be thought of as a nonlinear generalization of a linear filter. ANNs have found modest success in the prediction of geomagnetic indices based on solar wind parameters (Lundstedt, 1996). Of more relevance, Wintoft & Lundstedt (1999) attempted to predict the daily solar wind speed at 1 AU using a neural network based on flux tube expansion factor (computed from a potential field source surface (PFSS) model). They were able to obtain correlation coefficients as high as 0.57 for monthly averages, which dropped to 0.38 for daily averages. These disappointing results are likely more due to the inputs rather than the technique, as Riley & Luhmann (2012) and Riley & Linker (2014) have shown that expansion factor alone is a relatively poor predictor of solar wind speed, the distance from the coronal hole boundary providing much higher correlations (~ 0.75). Liu et al. (2011) applied a particular type of ANN technique, known as support vector regression (SVR) to forecast solar wind velocity. They were able to predict speeds with an accuracy of over 90%; however, this was limited to a 3-hour prediction, and did not perform well during CME intervals.

Qahwaji et al. (2008) applied ANN (the Cascade Correlation Neural Network algorithm) as well as Support Vector Machines (SVM) techniques to predict CMEs based on the properties of flares (intensity, duration, duration of decline/growth). While promising, the approach suffers from several issues, including false positives, the use of only M/X-class flares, and the neglect of erupting filaments/prominences.

The most common error in using ANNs is a lack of respect for the complexity of the models they are capable of generating (whilst still being only visible as a "black box" to the user). To understand this more clearly, consider the analogy of the curve-fitting problem: Intuitively, we invoke "Occam's razor", that is, the principle of parsimony, and choose the lowest-order polynomial that still fits our data. The main challenge is that the nonlinear models that the ANN built to reflect our data are so complex that they must be treated as a "black box." This often leads to the creation of ANNs that show excellent results during the training phase (interpolation), but which perform poorly when applied to the prediction of future, or unseen data (extrapolation). The greater the number of hidden layers, or even nodes in the ANN, the higher the risk. This problem is well known in fields outside Solar Physics (Astion et al., 1993; Alman & Ningfang, 2002; Tetko et al., 1995), leading researchers to validate the quality of their ANN using the entire error of the training charts and not simply a single error measure (Figure 3(b)). In our investigation, we will monitor our ANNs for such errors and minimize their impact.

2.4.2.2 Pattern Matching Approaches: A precursor to the pattern matching approaches that we plan to incorporate into our analysis was developed by Chen et al. (1996). Their insight relied on identification of well-defined and coherent MC structures. They suggested, and presented examples whereby certain classes of long-duration events could be identified at 1 AU by *in-situ* spacecraft relatively early through the rotation of the large-scale magnetic field and the trailing portion (up to 80%) could be predicted by extrapolating a sinusoidal pattern forward in time. Particularly for flux ropes whose axes are located in the ecliptic plane and points along the azimuth direction, the variation in B_z approximates a $\pm$sine function. If the helicity of the event is such that a northward excursion of B_z occurs first, a reliable prediction of both the timing and magnitude of the all-important southward excursion can be made. Although this may appear to limit the applicability of this technique to a certain class of events, it is precisely this signature that results in the largest geomagnetic consequences. We will develop several refinements to this basic idea, including flux-rope fits to real-time data and machine learning concepts, such as pattern recognition.

Figure 4 illustrates how simple pattern matching techniques can be employed to predict, at least near term, the evolution of B_z, particularly when there are coherent variations, such as during the passage of a MC. The prediction was made by taking the previous 24 hours of B_z data from a point shortly after a large ICME was detected by Wind and sliding this window along the entire time series back to 1975, computing the Euclidean distance (essentially an estimate of χ^2). We then chose the best 20 matches and used the data during the following 24 hours of each match as a prediction for the current time. These are shown by the grey traces in Figure 4. The ensemble average of these traces is shown in red and compared with the actual data (thick black line). No attempt was made to "tune" or tweak this comparison, yet the correlation was ~ 0.8. We believe it demonstrates that these techniques, and important refinements to them may be a useful addition to our prediction tool chest. Our illustration here has been limited to a simple one-to-one mapping of the profiles. Given the variability in scale size of transient phenomena, we anticipate incorporating dynamic time warping (DTW, Figure 3(c)) to uncover similarities in time series where the structures are either moving at different speeds, have expanded in a non-linear way (Keogh & Pazzani, 1998; Ding et al., 2008; Keogh et al., 2001, 2004), or have substantially different spatial/temporal scales (Moldwin et al., 2000).

To the extent possible, we will also extend this pattern matching to incorporate feature recognition at the solar source of the CMEs. In fact, solar feature detection in SDO observations has already yielded some surprises, challenging previously established "rules of thumb." Martens et al. (2014), for example showed that the hemispheric chirality preference for filaments, established by Pevtsov et al. (2003), appears to disappear during parts of the decline of cycle 23 and is less well established during the onset of cycle 24. To the extent that filaments and sigmoids can be used as proxy indicators of ICME properties, and particularly for any inference on flux rope axis orientation, these quantitative trends can be incorporated into a comprehensive model.

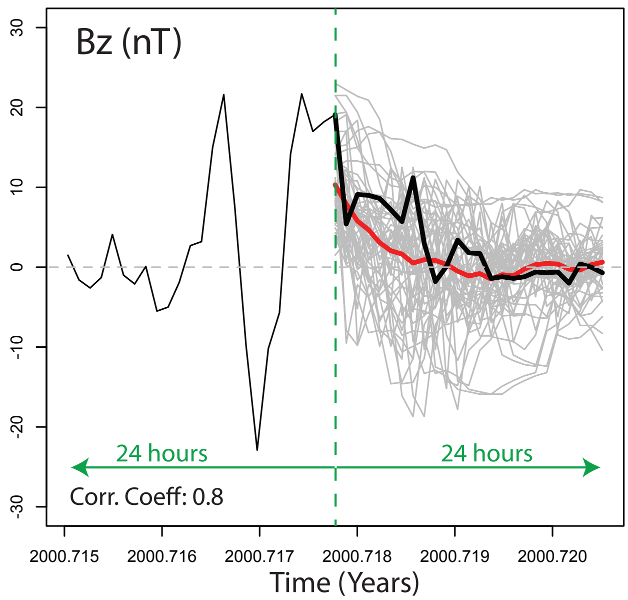

Figure 4: *Example of pattern matching through in-situ measurements, predicting B_z for next 24 hours: Predictions based on the top-20 patterns identified from the Euclidean distance, together with the actual data (black) and the ensemble average prediction (red), based on these realizations (CC ~ 0.8).*

2.4.3 Empirically-based Models of ICMEs

We can group event-based models under the monikers "empirically-based" and "physics-based" models in order to distinguish them from the statistical models described above, while recognizing that they encompass a wide range of overlapping concepts and techniques. Thus, these classifications are, at best, intended to be a helpful guide. Indeed, during our proposed effort, we envisage even more complex combinations of the basic approaches described below.

2.4.3.1 Feature Tracking Approaches: Tracking features through various remote solar and *in-situ* measurements, although simple, can be a powerful way to infer a variety of properties of a CME as it passes through the observing window. DeForest et al. (2013) outlined a comprehensive analysis of the December 12, 2008 CME from its origin in the low corona through its interception with near-Earth spacecraft. While the study identified the origin of various features of the ICME, from a predictive standpoint, it also illustrated the unique capabilities of heliographic imagers to provide real-time global information on the structure as it propagates from the Sun to 1 AU. With a goal of providing 24-hour predictions, these observations can provide either direct information that can be incorporated into a prediction of plasma conditions that will occur at 1 AU, or, as constraints to global MHD models, which themselves may contain the important magnetic field information. At the least, such observations can provide key timing information for both the CME-driven shock, the following sheath region, and the flux rope/ejecta itself.

2.4.3.2 Transit Time Approaches: A number of techniques have been developed to compute the arrival time of interplanetary (IP) shocks, which, while not providing information on B_z directly, alerts the prediction algorithm that sheath region and possibly a subsequent MC will be encountered. The Shock Time Of Arrival (STOA) model (Dryer & Smart, 1984), for example, relies on the time, location, drift speed, and duration of radio burst measurements. Kadinsky-Cade et al. (1998) used IMP-8 and Wind data to evaluate this model during the interval 1991-1997 and found that the average deviation between the predicted and actual arrival of the shock was ± 36 hours. Riley & McComas (2009) developed a set of fluid conservations to infer near-Sun properties of CMEs from their in-situ measurements, which was validated against other techniques, and could be adapted to estimate the transit time for ICMEs. Other approaches relying on white-light observations and effective acceleration profiles (Gopalswamy et al., 2001) and low-frequency radio measurements (Reiner et al., 2007) have also been proposed. Gopalswamy et al. (2005) estimated typical errors of ~ 10.7 hours in the predicted arrival time of the shock.

Vandegriff et al. (2005) described a technique for predicting the arrival time of interplanetary shocks at Earth based on energetic particle signatures observed at 1 AU prior to the shock's arrival. They found that the predicted arrival time of the shock was accurate to within 8.9 hours 24 hours in advance and 4.6 hours when the shock was 12 hours from the spacecraft. Although these uncertainties are not obviously better than NOAA's Space Weather Prediction Center (SWPC) estimate of median errors of ± 6 hours based on a prediction made several days in advance, they offer a unique extra piece of information – that the event has generated a shock that will intercept Earth, a result that cone-model-based predictions sometimes miss. Moreover, in principle, analysis of the energetic particle signatures can provide insight into the strength of the following shock, which in turn, provides albeit indirect information about the properties of the driver ejecta.

2.4.3.3 Relating Solar Signatures to 1 AU Measurements: Numerous attempts have been made to relate magnetic structures observed in connection with a solar eruption and the subsequent properties of the magnetic flux rope observed at 1 AU. These have met with mixed success. In an early study, Hoeksema & Zhao (1992) correlated the source regions of five strong $-B_z$ events observed at 1AU, inferring that the computed field orientation at the point in the corona where the acceleration of the ejecta ceased matched with *in-situ* measurements. Bothmer & Schwenn (1998) found a good correlation between MCs and large quiescent filament disappearances. Specifically, the magnetic orientation of the prominence axis, the polarity of the overlying field lines, and the helicity pattern of the filaments "agreed well" with the properties of the MCs. In another study, Leamon et al. (2004) related the magnetic properties of MCs to their associated active region sources. In particular, they looked at the helicity, finding that the twist within the cloud was typically an order of magnitude greater from the twist measured in the active region. More recently, Yurchyshyn (2008) found strong correlations between: (1) the direction of the axial field in EIT arcades and elongations in halo CMEs; and (2) the tilt of the coronal neutral line and the axis of MCs. They speculated that in some cases, the MC axis tended to align with the heliospheric current sheet. CMEs often rotate through substantial angles as they propagate through the corona (e.g. Török & Kliem, 2005), for reasons that have not yet been well established.

The relationship between solar and *in-situ* signatures can be probed and quantitatively described using the approaches outlined here. The handedness of an active region, and hence the orientation of the MC axis, for example, can be inferred from localized MHD calculations driven by vector

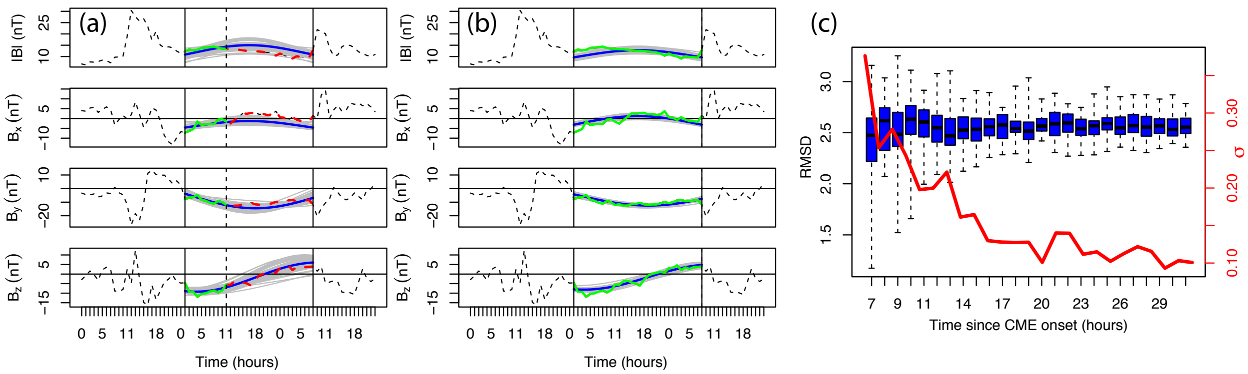

Figure 5: *(a) Hourly-averaged magnetic field magnitude and three components during a MC observed at Earth (Wind) on April 18, 2002. The 50 realizations shown (grey curves) were fit using MCMC to only the solid green curves, the dashed red line indicating 'future' data that had not yet been observed. (b) As (a) but the entire interval (solid green line) was used to fit to the flux rope model. The two vertical lines in (a) and (b) mark the MC boundaries. (c) "Whisker plot" showing; (blue boxes) the reduction in uncertainty (RMSD) in the fit; and (red curve) the standard deviation of the ensembles, as more data points are observed.*

magnetograms. Moreover, the global location and hence orientation of the HCS can be determined from global MHD simulations. While qualitative inferences of the degree of match may not be sufficient to provide a quantitative prediction scheme, the results suggest that a statistically-based approach, such as described in Section 2.4.2.2, which incorporates all of the potentially relevant features, may yield a predictive capability.

2.4.3.4 Flux Rope Fitting Predictions: Force-free (e.g. Russell et al., 1990; Lepping et al., 1990) and non-force-free (e.g. Mulligan & Russell, 2001; Riley et al., 2004; Owens et al., 2006; Reinard et al., 2010) fitting models have been used successfully for many years to reconstruct the basic properties of flux ropes as they pass over the spacecraft. However, a novel, and as yet unexplored application is to use these fits as a predictive tool, in some sense, a refinement of the Chen et al. (1996) idea (Section 2.4.2.2).

Figure 5 illustrates how such an approach might reasonably provide a prediction of all three components of the field, as well as its magnitude up to 24 hours in advance. We fitted the April 18, 2002 MC using a cylinder flux-rope model as described by Marubashi et al. (2007) with six parameters: intensity and radius of the MC, latitude and longitude of the cylinder axis, impact parameter (distance from the cylinder axis to the spacecraft trajectory), and handedness of the magnetic field helicity. The joint posterior distribution for the model parameters was determined using a Metropolis-Hastings Markov Chain Monte-Carlo (MCMC) procedure (Riley et al., 2013a). At each step in the chain, a new set of parameters was sampled from a uniform distribution and used to calculate a model profile for the magnetic field. The root mean square deviation between the calculated and observed field was then used in a standard rejection method to determine if the move should be accepted or rejected. For each case we simulated 50 MCMC chains with 5×10^7 steps. Figure 5(a) shows 50 realizations (grey) when only 30% of the data are used to fit the MC. The scatter in these profiles gives a measure of the uncertainty in the ensemble average. Figure 5(b) shows the fit when all data points are used. The final panel (c) demonstrates how the uncertainty in the estimate decreases as more data points are added to the model fit, providing a quantitative estimate of the error.

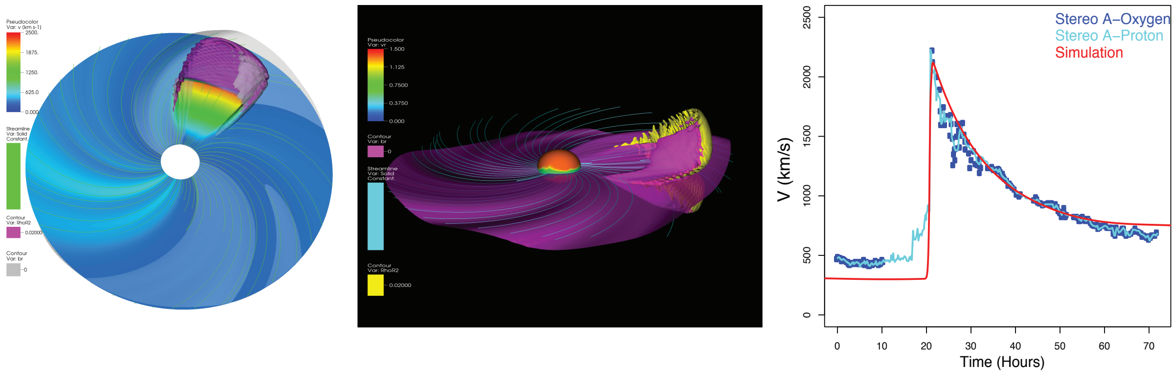

Figure 6: *(a) and (b): Two 3-D views of ICME as it approaches 1 AU. The legends to the left of each panel indicate what parameters are being displayed. A selection of interplanetary magnetic field lines are also shown. (c): Comparison of a hypothetical observer at 1 AU with STEREO A velocity measurements. This ICME was launched with an initial speed of 2500 km/s, consistent with remote solar observations.*

2.4.3.5 Cone-Model ICMEs: A subset of PSI's modeling suite, CORHEL, consists of the WSA-Enlil model, with a cone-model CME generator, which recently became the National Weather Service's first space weather model, running real-time at NOAA/SWPC (Farrell, 2011; Pizzo et al., 2011). We have developed a similarly capable version of the cone model (Riley et al., 2014) using a recently developed massively parallel interplanetary version of our global MHD algorithm (Lionello et al., 2013). Several approaches exist for deriving the initial parameters to drive the simulation (Zhao et al., 2002; Pizzo & Biesecker, 2004; de Koning & Pizzo, 2011), but for all, CMEs are treated as purely plasma ejecta, specifying the location of 'launch' (on a sphere of height $21.5R_S$), direction, speed, density, and duration (or width). The lack of magnetic structure within the ejecta precludes it from giving meaningful predictions of the flux rope field. It can, however, provide information on the field in the sheath region, which, at least for fast events, is draped over the ejecta. We have also begun investigating techniques for incorporating magnetic fields within the ejecta. One promising idea was motivated by more theoretical results from modified Titov-Demoulin (TDm) simulation results (see Section 2.4.4.1), suggesting that substantial reconnection could occur under a flux rope leading to a spheromak-like structure. Although we found that the *in-situ* profiles from such an event can mimic the observed rotations within observed ejecta, it remains to be seen whether this can lead to a robust estimate of flux rope fields. An alternative idea, which would allow one to retain the simplicity of the cone-model approach would be to "kinematically" incorporate, say, a force-free type flux rope close to the Sun (e.g. Owens et al., 2006), using the evolving velocity field to distort the flux rope as it is propagated through the inner heliosphere (Riley & Crooker, 2004). This would require knowledge of the orientation of the flux rope axis, which could be inferred from several remote solar observations, although not without substantial caveats.

Krall & Cyr (2006) developed a simple technique for parameterizing a three-dimensional flux rope based on white-light observations. The synthetic images produced capture many of the features observed in the eruption of simple limb events, and, although they did not develop it, in principle, the technique can be used to estimate the orientation of the flux-rope axis. This, however, would require observations at quadrature to predict B_z at Earth. As with many of these techniques, the concept is simple, its implementation is straightforward, but its ability to predict B_z has not been ascertained. Thus, it represents an ideal candidate for testing.

2.4.3.6 Predicting B_z within Sheath Regions of ICMEs: Echer et al. (2008) estimated that the sheath regions of ICMEs are responsible for $\sim 25\%$ of all intense ($Dst < -100$nT) geomagnetic storms. Thus, an accurate estimate of these intervals alone is an important component of any prediction scheme. We envisage at least two processes that could contribute to producing a non-zero B_z within sheath regions. The first, as already noted, is due to the process of draping. As ambient solar wind is swept up, field lines are caught up and dragged through the solar wind by the ejecta. A second, and more subtle effect, however, concerns the effects of the shock itself. It is well known, based on the Rankine-Hugoniot (RH) relations, that the magnetic field changes direction across a shock (e.g. Priest, 1982). Specifically, the magnitude of the tangential (relative to the shock normal) component is not conserved. Across a fast-mode shock this translates into a compression, with the resulting effect that the magnetic field vector is deflected away from the shock normal. Thus, with prior knowledge of the likely properties of the shock as it passes Earth, the amplification of the tangential component can be estimated and converted into a B_z component (Horbury, Personal Communication, 2014). In principle, this effect should already be directly included within global cone-model simulations such as Enlil. However, this information can also be derived independently from Heliospheric Imager observations when available, which will provide estimates of the shock/sheath orientation and strength, coupled with more reliable estimates of the modeled ambient solar wind at Earth. Moreover, global MHD models of CME ejecta themselves are not capable of reproducing the small-scale (but large amplitude) fluctuations produced by waves and turbulence, opening up the possibility of using the RH approach to estimate the amplification of this contribution to B_z.

2.4.4 Physics-based Models of ICMEs

The modeling group at PSI has developed state-of-the-art global models of CME initiation and evolution for many years (e.g. Linker & Mikić, 1995; Linker et al., 1996, 2001; Riley et al., 2003; Linker et al., 2003; Riley et al., 2007; Riley et al., 2008; Riley et al., 2008). However, they are – at least at present – time consuming; both in terms of computer time and personnel. Thus, we developed an interim solution that bridges the gap between "empirically-based" models and these "first principles" models. The current version of this practical CME generator relies on a modified description of the Titov-Démoulin flux rope model (TDm). The essential difference between these types of models and either empirically-based models or statistical models is that we anticipate deriving a greater physical understanding of the processes that give rise either to the eruption and/or evolutionary properties of CMEs and their interplanetary counterparts. For this specific investigation, however, this promised understanding is of value only if it allows for a better prediction. We further anticipate that, at least initially, these types of models will not provide forecasts that are as accurate as the simpler approaches. However, it is likely that this will change in the foreseeable future. Moreover, by including them at the outset, we provide quantitative skill scores that these or any comparable model must exceed to be considered better from a predictive standpoint.

2.4.4.1 Pre-Existing Flux Rope Eruptions: The TDm model is an analytic model of a force-free coronal flux rope embedded within the solar corona. The eruption can be initiated by either allowing the initially out-of-equilibrium flux rope to erupt, or by first establishing an equilibrium for the flux rope, then introducing a perturbation (such as canceling flows near the polarity inversion line), which then produces an eruption. We believe it is possible to use available observations to constrain the initial characteristics of the flux rope (location, orientation, axial field strength), providing the key ingredients for a predictive type of model, in much the same way that cone-model simulations are routinely driven by parameters derived from white-light observations (Odstrcil & Pizzo, 2009).

2.4.4.2 "First Principles" Models of CMEs: Our group at PSI has, and continues to investigate fundamental issues related to the initiation and evolution of CMEs in the corona and solar wind (e.g. Mikić et al., 2013) and to improve the physics describing the origin of the slow and fast components of the solar wind through the incorporation of waves and turbulence (Lionello et al., 2014). These types of simulations are extremely time consuming and could not, at least currently, be incorporated into a predictive scheme for forecasting B_z. However, we recognize that as these models improve and more computational resources are provided for their use, it may become feasible for them to find a place within the forecasting framework.

2.4.4.3 "Hybrid" Schemes: An intriguing idea we will pursue is to couple the predictions from different types of statistical, empirical, and physics-based CME models. For example, one could combine either coronagraph or HI observations with magnetic field observations of the flux rope observed by Messenger at Mercury. Although this would only work under certain conditions and geometries, it could provide a unique prediction of what the combined magnetic/plasma structure of the CME was near to the Sun, but sufficiently far that it could be evolved either kinematically (e.g. Riley & Crooker, 2004) or using a (magneto)hydrodynamic algorithm. Alternatively, one could use the cone model, which has arguably the best capabilities of propagating the ejecta and associated shock to 1 AU, to specify the large scale non-magnetic properties of the event at 1 AU. Into this, the magnetic field from a force-free, TDm, or even first-principles model could be embedded; the rationale being that the cone-model reproduces the most accurate dynamical evolution of the ejecta, including non-linear deformations and event timings, but the magnetic model captures the structure of the field. Finally, we can combine disparate approaches. Bieber et al. (2013), for example, described a technique for inferring B_z from neutron monitor data, based on the idea that cosmic rays hitting the Earth have already passed through and interacted with the IMF upstream of the Earth. They found that the correlation between the predicted and measured B_z for 161 ICMEs ranged from $\sim 85\%$ to $\sim 60\%$ for predictions 1-3 hours into the future.

2.4.5 The Ambient Solar Wind

While prediction of the ambient solar wind in the absence of any transient phenomena is likely not a high priority from the perspective of geoeffective consequences (although all-clear forecasts are important), the role of the quiet-time solar wind is crucial in the evolution and hence prediction of large excursions in B_z produced by ICMEs. Fast CMEs, in particular, are more significantly distorted and decelerated when slow and dense ambient wind lies ahead (Riley et al., 2003). Moreover, the properties of the wind into which the CME propagates will be modified by its passage: Large-scale deflections across the CME-driven shock will alter the perpendicular components of the IMF. Additionally, the presence of large-amplitude Alfvén waves in fast solar wind will result in the large and temporally compressed B_z fluctuations. Thus, the prediction of the ambient solar wind is a key component of any B_z prediction scheme.

We have developed robust and relatively accurate models of the ambient solar wind over the last decade, making direct comparisons with observations (Riley et al., 2001, 2002, 2003; Riley, 2007b, 2010; Riley et al., 2010, 2011, 2012; Riley et al., 2012b). We have found that the modeled results are capable of reproducing *in-situ* measurements with a typical correlation coefficient of 0.75 (Riley & Linker, 2014), during relatively stable conditions (declining phase and solar minimum) and in the absence of obvious transient activity (Riley & Linker, 2014). These models, however, are demonstrably quite sensitive to the input magnetograms (Riley, 2007a; Riley et al., 2012; Riley et al., 2013b). To substantially improve our predictions, requires a thorough analysis of these inputs, which should include the best reconstruction of polar fields and, optimally, incorporate temporal evolution. As part of other funded studies, we are investigating which approaches most accurately reproduce *in-situ* measurements.

2.4.5.1 Persistence and Probabilistic Forecasts: Although our goal will be to provide real-time, event-driven predictions, at a minimum, we can use combinations of persistence and probabilistic forecasts to make crude estimates for B_z in the absence of any other reliable information. This could form the basis for the reference model from which skill scores are computed (Owens et al., 2013). As discussed above, persistence refers to the assumption that the Sun now is exactly as it was one hour, say, earlier. If valid, we can use those data to predict the next one, six, or 24 hours, obviously with increasing uncertainties. Similarly, recurrence relies on predictions based on solar conditions measured 27 days earlier. Probabilistic forecasting summarizes what is known about likely future events by assigning a probability to a range of outcomes. This may offer some value during intervals surrounding stream interfaces (McPherron & Siscoe, 2004). Such techniques were employed in terrestrial meteorology prior to the development of sophisticated global circulation models. Since it is not yet clear whether space meteorology has yet crossed the threshold whereby models outperform these statistical approaches, it seems prudent to include them in our arsenal.

2.4.5.2 Waves and Turbulence: Our discussion so far has focused on the large-scale variations in the IMF. However, a substantial amount of power is contained within higher frequency waves and turbulence. From a prediction point of view, these are the most challenging to attempt to forecast. Fortunately, from a geoeffective standpoint, their phase information is not as important as their statistical properties (Merkin et al., 2007). Thus, we can superpose a contribution from waves and turbulence, based on properties of the predicted large-scale field at that time which contains contributions up to the highest frequencies, and which is statistically indistinguishable from observations. The properties of the turbulent solar wind are well established both as a function of solar wind (e.g., slow/fast) and phase of the solar cycle (Bruno & Carbone, 2013). This idea is similar to the technique of "downscaling" used in terrestrial climate modeling, and which has been successfully tested by Owens et al. (2014) in constructing appropriate inputs to drive ensemble magnetospheric forecast models.

2.4.6 Relevant Data

Our proposed work will rely on the full range of datasets produced by NASA missions. Time series data of the IMF field vectors will of course be indispensable, as well as speed, density, and temperature to validate model predictions. Additionally, remote sensing white light images will drive cone-model simulations and provide key clues about the three-dimensional structure of the ejecta, including, possibly, the orientation of the flux-rope axis. Heliospheric Imager data from STEREO will provide important information on the propagation and evolution of some ICMEs. EIT and X-ray images will provide feedback on the quality of global model solutions and may provide "actionable" information for making predictions. Sigmoid structures, dimming regions, flares, and EIT waves, for example, can be used to provide timing information during an eruption, and may, in principle, lead to a prediction scheme based on recognized patterns of features. Photospheric magnetic field measurements, while providing a direct measurement of the parameter we are hoping to estimate at 1 AU, undergo significant transformation before reaching the Earth. The properties and evolution of such measurements, however, are crucial for advancing our predictive capabilities, including better boundary conditions for the physics-based models, but also as input into the statistical approaches, such as feature tracking and recognition.

We will also leverage the work by the Solar Physics/Computer Science team at Montana State

University (currently in transit to Georgia State University), who have developed a feature recognition algorithm for SDO observations (Martens et al., 2012; Banda & Angryk, 2009; Banda et al., 2013b,a; Schuh et al., 2014), incorporating it with previously revealed associations, such as the presence of dimming regions being a threshold requirement for the production of fast (> 800 km/s) CMEs (Reinard & Biesecker, 2009). Various combinations of different structures/phenomena can be incorporated into the pipeline we are proposing and tested for efficacy.

2.4.7 Ensemble Modeling

A crucial advance that propelled terrestrial modelers forward was the development of ensemble modeling techniques, some of which will be implemented in our proposed investigation. Ensemble forecasting is defined as a method of prediction that relies on the use of a representative sample of possible future states to derive a prediction. One of the appealing aspects of such an approach is that it offers a rigorous method for computing confidence bounds of the solution by estimating the uncertainty in the ensemble (Wilks, 2006). Moreover, the mean of the ensemble of forecasts is, or should be more accurate than the forecast from any individual member; the reason being that the random, or unpredictable regions of the forecast tend to cancel one another, while the aspects of the forecast that the majority of the models agree on are not removed (Warner, 2010).

Ensemble modeling techniques have only recently and tentatively been applied to the heliophysics environment (e.g. Riley et al., 2012a; Riley et al., 2013; Pizzo, 2014). However, they have been developed, tested, and rigorously applied within the terrestrial weather community for more than a decade, thus, providing a wealth of resources that can be adapted to space weather phenomena (Figure 7). As an illustration, we can define the following ensemble model for B_z: $\hat{B}_z(t) = \sum_{i=1}^{K} \omega_i B_z(t)$, where ω_i are the model weights and $\sum_{i=1}^{K} \omega_i = 1$ (Wichard & Ogorzalek, 2004). Intuitively, this emphasizes that those predictions that produce robust and reliable forecasts will also be associated with large weights.

2.4.8 Metrics, Probabilities, Skill Scores, and Confidence Intervals

Model validation refers to the task of identifying the strengths and weaknesses of a model through detailed comparisons of model output with observations. Similarly, metrics are used to measure the long-term trends in model improvement. Whereas model validation involves a comprehensive comparison of all available data, metrics target a small set of specific benchmarks.

Focusing initially on B_z, the forecast error is the difference between the actual measured value of B_z ($B_{z,t}$) and the forecast ($\hat{B}_{z,t}$): $E_t = B_{z,t} - \hat{B}_{z,t}$. From this, we can develop a number of measures of the aggregate error, which describe the accuracy of the prediction over some interval $t = 1, N$. These include the mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute deviation (MAD), percent mean absolute deviation (PMAD), mean squared error (MSE), and root mean squared error (RMSE). The MSE, for example, is given by:

$$MSE = \frac{\sum_{t=1}^{N} E_t^2}{N} \quad (1)$$

Additionally, the forecast skill score (SS) is defined by:

$$SS = 1 - \frac{MSE_{forecast}}{MSE_{ref}} \quad (2)$$

where MSE_{ref} is the mean square error calculated from some standard, reference model, typically the simplest and least accurate in the suite. Thus, SS serves as a measure of how well (or poorly)

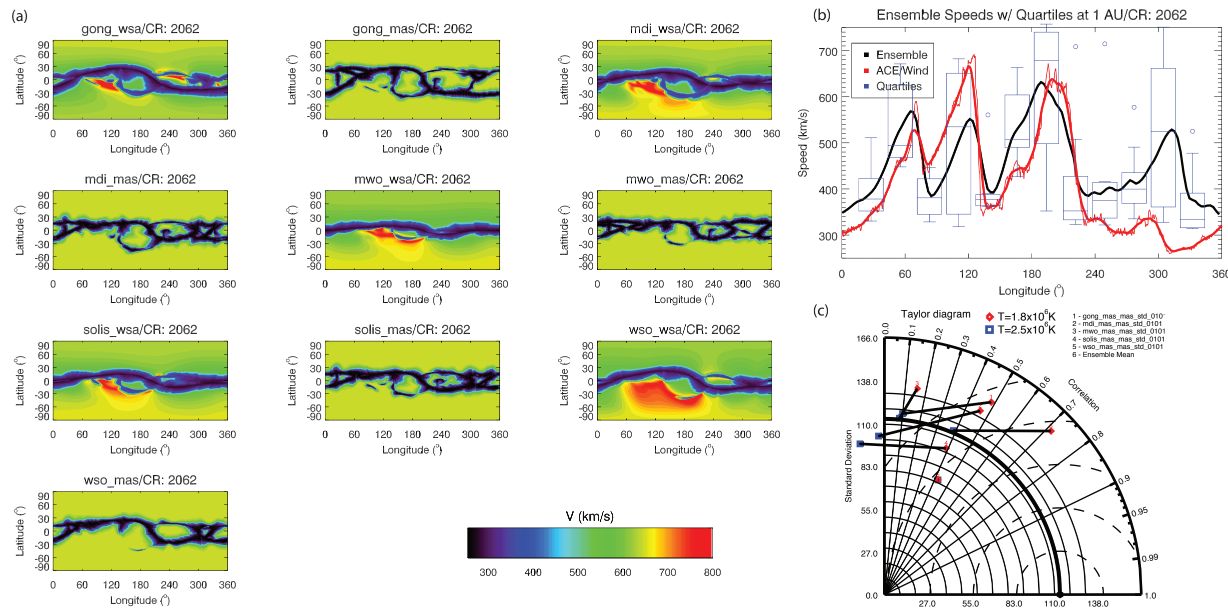

Figure 7: *(a) A subset of model realizations computed for CR 2062. (b) 'Whisker" plot of model realizations from (a) at 1AU: Black line is the ensemble solution; red are in-situ measurements; and boxes with "whiskers" summarize the variability of the realizations. (c) A "Taylor diagram" for summarizing the performance of model runs. See Taylor (2001) for further details. The blue squares mark the new locations of the solutions when the base temperature is raised from* $1.8 \times 10^6 K$ *to* $2.5 \times 10^6 K$*. Adapted from Riley et al. (2013).*

model refinements perform.

We will initially define a number of metrics to track our progress. These will not be limited to just predicting B_z, but also related quantities that are relevant. For example, we will employ both MSE estimates, as well as event-based tests, such as the arrival time of sector boundary crossings, and CME-driven shocks. From these analyses, it is straightforward to define "skill scores," which track the improvements in the model over time.

Confidence intervals (CIs) are used to indicate the reliability of an estimate. They are a measure of our confidence with a particular prediction, or alternatively the likely uncertainty, typically given at the 95% level. Thus, in addition to estimating retrospectively how well our predictions performed, we will also provide prospective confidence intervals for all predictions made. CIs can be constructed in a number of ways. We could, for example, combine the output from different models (both statistical and mathematical) to derive an estimate of the CI. Not surprisingly, the confidence in a predicted time series of B_z would decline as the prediction stretched farther into the future. Importantly, they would provide a direct and quantitative indication of the quality of the prediction to the user.

Thus far, we have assumed a goal of predicting B_z as a function of time. It is likely, however, that at least for some users, a forecast probability would be more appropriate. For event predictions, such as the time of arrival of a shock, a high-speed stream, or a sector boundary crossing, this can be phrased simply by the probability that the event will, or will not occur within the next 24 hours, say. We might generalize this concept for B_z by estimating the probability that B_z exceeds some negative threshold, say, -20nT for some period of time, say, six hours, again within the next 24 hours, say. These values would be situation-dependent: Different customers would likely have different requirements for the forecast probability to be useful to them. 'All clear' forecasts based on the absence of such events would also likely have value to a wide range of users.

2.5 Proposed Contributions to the Focus Team Effort

NASA's Living With a Star program (LWS) seeks to "improve our understanding of how and why the Sun varies, how the Earth and solar system respond, and how the variability and response affects humanity in space and on Earth." More generally, NASA's Heliophysics Research Program aims to "Understand the fundamental physical processes of the space environment from the Sun to Earth,..." and to "enabl[e] the capability to predict the extreme and dynamic conditions in Space." Our objectives directly address these goals by investigating the properties of CMEs, whose impact with the Earth's magnetosphere can cause a range of adverse effects, and providing the most robust and accurate forecasts of B_z. Dr. Macneice at NASA's CCMC has expressed a keen interest in the objectives and deliverables proposed here, and our team includes three members of NOAA's SWPC.

2.5.1 Relevance to the scientific objectives of the Focused Topic

Our proposed investigation directly addresses all objectives of the focused topic. Specifically, we will provide a continuous estimate of B_z (as well as B_x, B_y, bulk solar wind speed, density, and temperature) primarily in the vicinity of Earth, but also at other strategically important locations, such as at Mercury and, in principle, along the orbits of Solar Orbiter, Solar Probe Plus, Sunjammer, and even upstream of Jupiter in support of the Juno mission.

2.5.2 Contributions to the Focused Science Team's effort

The team we have assembled combines all the skills necessary to meet the objectives of this FST. We are observers, modelers, theorists, and operators. We have expertise in the analysis of remote solar observations (white-light and HI, EUV, X-ray, and photospheric magnetic field observations) and *in-situ* measurements. We represent the key developers of relevant models from simple *ad hoc* techniques to state-of-the-art global, time-dependent MHD simulations. We are a cross-disciplinary team, including experts from the fields of computer science, magnetospheric physics, solar, and heliospheric physics.

2.5.3 Metrics and milestones for determining success of proposed research

Our goal is to produce a framework that is available to the scientific community by the end of the project. In Section 2.6 we summarize the main milestones we will achieve. Our metrics for success will literally be the metrics defined to quantitatively assess our ability to predict B_z. We believe that to claim to be able to make an accurate real-time, continuous prediction of B_z on the timescale of four years is probably unrealistic. We do, however, believe that we can objectively quantify our initial abilities and track the progress during the course of the investigation. Based on the further development of the promising ideas presented here, we are confident that our forecasting abilities will improve substantially during the project.

2.6 Outline of the General Plan of Work

This proposal is for four years. Our principal goals are to: (1) define a set of robust metrics for quantitatively, reliably, and efficiently assessing a range of prediction techniques for estimating IMF B_z at 1 AU up to 24 hours in advance; and (2) develop techniques for predicting B_z – both in the short and long term – that have the most likelihood of success.

- First Year

- Develop a B_z Forecasting Framework (BFF) that can be downloaded and installed by all team members. We will use a combination of shell scripts, Fortran, C/++, and R/Python served from an Subversion (SVN) repository, providing a platform-agnostic toolkit;
- Populate the BFF with a limited subset of the predictive algorithms outlined above. These will be prioritized based on several factors, including likelihood of success and ease of implementation;
- Assemble the necessary datasets as well as any relevant meta-datasets for driving, testing, and validating the BFF. Some will be stored directly in the SVN repository while others will be either disseminated from PSI or from their original source location;
- Complete initial set of validation studies, computing relevant metrics and skill scores. Focus initially on predicting ambient solar wind and simple CME events;
- Identify data sources and generate Benchmark Data Sets that can be used for creation and evaluation of our future models.

- Second Year
  - Incorporate more models into the BFF;
  - Incorporate dynamic time warping into time series pattern recognition technique;
  - Compare various physics-based model predictions for a set of ICMEs that cover the range of observed events;
  - Write set of papers documenting the BFF as well as the initial results from its application and present results at scientific meetings.
- Third Year
  - Develop a statistical model (e.g.,ANN) that incorporates automatically recognized solar features (dimmings, sigmoids, flares, etc);
  - Initiate contact with NASA (CCMC) and NOAA (SWPC) and discuss possible avenues for delivering and/or operationalizing the BFF;
  - Perform parametric studies of all models and combinations thereof to optimize the predictive capability of the BFF;
  - Revise and refine validation studies, computing a comprehensive set of skill scores and model uncertainties for all model combinations. Publish results in peer-reviewed journal and present current status at selection of meetings and/or workshops.
- Fourth Year
  - Investigate efficacy of running first principle models for specific events as a predictive model;
  - Complete development of BFF, including full documentation, and make available to scientific community;
  - Deliver the BFF to NASA/CCMC and/or NOAA/SWPC;
  - Write final set of peer-reviewed manuscripts comprehensively describing the BFF and the various modules developed for it. Attend a selection of scientific meetings to promote the use and availability of the BFF.

Although our proposed work appears ambitious, it is necessary if we are to make meaningful advances in our ability to predict B_z. Our team has developed, or is developing most of the models we are proposing to test in this effort. Thus, the emphasis is more on development of the framework to quantitatively test them as well as the insight on how best to combine them to improve our predictive capabilities.

2.7 Management Plan

The investigation outlined here requires a well-directed and coordinated management plan. In addition to the intrinsic value brought by individual team members, we believe that a key factor in our success lies in the members' abilities to think outside of their specific areas of expertise. It is crucial that we meet on a regular basis to develop and test new ideas and report back on progress made. We propose to hold biweekly web based meetings (using Citrix's GoToMeeting) as well as two in-person meetings per year, one in Southern California and the other in Boulder, Colorado or Atlanta, Georgia. We believe that through these largely conceptualizing interactions, our team of experts will be able to formulate novel and related ideas that can then be tested within the BFF. Each team member is fully aware and has agreed to the specific and focused goal of the proposed work and will devote their resources as necessary to achieving them.

Pete Riley (PI) will manage, and be responsible for the completion of the proposed research. He will work with Co-I's Roberto Lionello, Piet Martens, Rafal Angryk, Chris Russell, Roger Ulrich, Vic Pizzo, Curt de Koning, Alysha Reinard, Todd Hoeksema, and Yang Liu, and collaborators Jon Linker, Tim Horbury and Matt Owens, to undertake the tasks outlined here. Dr. Lionello, together with Dr. Riley and a junior scientist, will be primarily responsible for any necessary developments of PSI's numerical codes, including the cone-model, TDm, and first-principles approaches. Dr. Martens will provide expertise in the interpretation of the solar signatures of transient activity. He also directs a complementary SDO data mining and pattern recognition program, the results of which will be of considerable value to our proposed work. Dr. Angryk is a computer scientist with significant experience in pattern recognition, data mining, and general machine learning techniques. He will direct a full-time graduate student in developing and testing the statistical modeling portion of our investigation. Drs. Martens and Angryk have a decade-long collaboration record on data-driven analyses of solar activity (SOHO, TRACE, and SDO) and the creation of statistical models. Dr. Russell will provide expertise in the interpretation of *in situ* measurements. He will guide a post-doc in implementing some of the modeling and data-fitting techniques outlined here, particularly, involving (non) force-free fits to MCs. Dr. Ulrich will provide expertise in the interpretation of photospheric magnetic fields and direct a post-doc on various aspects of the proposed work, who will develop time-dependent, differentially rotated maps for improving our ambient solar wind solutions use the maps to generate PFSS and MHD solutions. Dr. Pizzo will provide his modeling expertise (MHD models and 3-D reconstructions of CMEs observed by STEREO) at no cost as well as the interpretation of global remote solar observations and *in situ* measurements. Dr. de Koning will run NOAA's CME Analysis Tool (CAT). He will also assist in the development and incorporation of techniques into the BFF. Dr. Reinhard will assist in the assembly of the relevant datasets for assessing the various prediction tools under development. She will also use the tools developed and compute the relevant metrics from which skill scores can be computed. Drs. Hoeksema and Liu will contribute special data products from HMI and MDI, including daily-update synchronic maps and vector magnetic field data for synoptic and region-specific computations, as well as time-evolved synchronic maps of the global magnetic field using both line-of-sight and vector magnetic data. Dr. Jon Linker, will provide input at no cost through a complementary project supported through AFOSR, which shares several objectives with the proposed investigation. This project will be carried out in collaboration with Drs. Horbury and Owens at Imperial College and the University of Reading, respectively, who will provide expertise and insight during the planning stages of the investigation as well as interpretation of the results. This will complement projects they are currently managing at their institutions. Finally, at PSI we currently support undergraduate interns on a variety of computer- and science-related projects, and we will include them in portions of this investigation, as appropriate.

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A Facilities and Equipment

At Predictive Science Incorporated (PSI), San Diego, California, we maintain a set of Macintosh workstations that are more than adequate for meeting the data-processing, storage, and analysis requirements of the proposed investigation. Any necessary large-scale computations of CME initiation and evolution will be performed on massively parallel computers at NASA (Pleiades) and NSF (Stampede) through other contracts, for which we currently maintain, and envisage receiving further allocations sufficient to perform the proposed work. We maintain a Subversion (SVN) repository for all of team-oriented code development projects (e.g., CORHEL) and will develop a complete SVN package to serve the algorithms and data for the proposed work. This will be used by all team members and, in due course, opened up to the scientific community. We will develop and continue to update a team web page for this investigation, communicating our results and providing access to project-developed packages. Finally, we continue to maintain a set of modeling web pages (e.g., www.predsci.com/hmi/home.php), which will incorporate elements of the proposed investigation.

B Curriculum Vitae

C Current and Pending Support

D Budget Justification

Narrative and Details

Direct Labor Summary

Travel

Other Direct Costs

Indirect Rates

Detailed Yearly Budgets