An Efficient Feature-Optimized Data Mining Model for Geomagnetic Storm Forecasting Using Solar Wind and Interplanetary Magnetic Field Parameters

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Abstract – In the study a geomagnetic storm forecasting data mining model is created with the help of key solar wind and interplanetary magnetic field (IMF) parameters that are optimized based on their features. The suggested model makes use of high-resolution solar wind plasma and IMF measurements retrieved in the OMNI database, and the disturbance storm time (Dst) index is used as the main measure of the strength of geomagnetic storms. A strategy of feature optimization is adopted to determine the most geoeffective parameters to predict the computational efficiency and reliability of predictive power, such as solar wind speed, proton density, total vertical magnetic field strength and southward component of IMF (Bz). Weakly correlated and redundant features are automatically removed in order to simplify the model without decreasing forecast accuracy. An optimized feature subset is then applied to the data to form a predictive model based on data mining that has the potential to learn the nonlinear relationships between the upstream solar wind conditions and geomagnetic response. The performance of the models is measured by standard statistical measures and compared to non-optimized baseline models. These findings indicate that the proposed methodology has a better forecasting accuracy at a much lower cost of computation, thus it can be used in near real-time space weather forecasting. The results indicate that feature selection is also vital in space weather prediction and that the majority of the geomagnetic disturbances are due to IMF orientation and solar wind dynamics. The suggested model offers a stable and effective framework of the operational geomagnetic storm forecasting and leads to the creation of well-grounded data-driven space weather forecasting systems.

Keywords: Geomagnetic storms, Space weather forecasting, Data mining, Feature optimization, Solar wind, Interplanetary magnetic field, Dst index.

1. INTRODUCTION

Space weather refers to the dynamic environment in the area around Earth that is mainly caused by solar action and their interaction with the magnetosphere of the earth. Geomagnetic storms are regarded as one of the most dangerous types of space weather phenomena because of the possibility to affect the work of satellites, navigation systems, radio communications, and electric power grids. They are caused by an intensified interaction between the solar wind and the earth magnetic field, and is frequently related to solar eruptive processes such as coronal mass ejections and high-velocity streams of solar wind (**Gopalswamy, 2006; Richardson and Cane, 2012**). As the contemporary society continues to rely on space and ground-based technology systems, precise and timely prediction of geomagnetic storms has become a huge scientific and operational concern (**Riley, 2017**).Geomagnetic storms develop when the solar wind energy is introduced into the magnetosphere by interaction of complex plasma and magnetic field (**Gonzalez et al., 1994**). Interplanetary magnetic field (IMF) conditions are extremely important in this process, as the southward component of the IMF helps in promoting magnetic reconnection in the dayside magnetopause (**Tsurutani et al., 1998**). The resultant perturbations cause the amplification of magnetospheric current systems and more so the ring current which is often measured using the disturbance storm time (Dst) index (**Burton et al., 1975**). Massive negative value of the Dst index is a good indicator of intense geomagnetic storms, and is frequently employed as a conventional scale of storm strength in space weather research.Traditional methods of geomagnetic storm prediction have been based on correlational methods, linear regression, and mathematical models (**Temerin and Li, 2002**). Although these techniques have served in many studies to learn the dynamics of storms, their predictive quality is usually hampered by simplified assumptions, linear approximations, or a large number of computations. Specifically, solar wind–magnetosphere coupling involves nonlinearity and different scales which pose significant challenges to the conventional models (**Camporeale, 2019**). These drawbacks have inspired the study of data-driven approaches that can reason about complex relationships in observational data.

Over the last few decades, data mining and machine learning methods have been receiving growing attention in space weather studies. The methods allow the capability to work with large amounts of data, discover latent patterns, and parameterize nonlinear relationships between input parameters and geomagnetic responses. Numerous data-driven approaches have been utilized to make predictions of geomagnetic indices; they include neural networks, decision trees, support-vector machines and ensemble methods. The choice of input features is one of the essential issues in the forecasting of geomagnetic storms using data. Solar wind and IMF data usually have a lot of parameters some of which are highly correlated or redundant. The input features may be too many and, therefore, their use may raise computational cost, decrease forecasting efficiency, and enhance the risk of overfitting. In addition, multifaceted models with numerous inputs are sometimes opaque physically so it is hard to determine the most significant factors of geomagnetic action. Model efficiency and interpretability are extremely crucial in the context of operational forecasting systems, in which quick and accurate forecasting is required.The key role in solving these challenges is feature optimization that identifies the most relevant and physically meaningful parameters of storm prediction (**Tibshirani, 1996**). The feature-optimized models can be considered to improve generalization behavior and accelerated computation by dimension reduction of inputs and preserving important data. Regarding the space weather forecasting, feature selection will also offer an insight into the relative relevance of the solar wind and IMF parameters in driving geomagnetic disturbances.

The parameters of solar wind speed, proton density, overall magnitude of the total magnetic field, and southward component of IMF have always been recognized as some of the most essential factors in storm formation yet their effects upon storm development can fluctuate with the intensity of the storm and its temporal scale. The presence of good-quality observational data is also another key factor in data-driven space weather modeling.Organized time series of solar wind interactions with the magnetosphere maintained by agencies like NASA and NOAA have made possible a systematic study of the interactions of solar wind and magnetosphere interactions over several solar cycles. These datasets can be used to perform retrospective analysis as well as building predictive models that would be applicable in the near-real-time applications. The current research is aimed at the creation of an effective feature-optimized data mining model to predict geomagnetic storms based on the parameters of solar wind and IMF. The proposed approach focuses on the choice of a small set of geoeffective features rather than on high-dimensional input spaces that would represent the key dynamics of storm generation. The disturbance storm time (Dst) index is used as the output variable of main interest to measure the intensity of geomagnetic storms and also to make a comparison with the existing forecasting techniques.The main aim of this paper is to assess the impact of feature optimization on the accuracy, efficiency and robustness of data mining based prediction of geomagnetic storms. The study will show that it is possible to obtain better forecasting performance with a lower computational complexity when optimized models are compared to non-optimized baseline approaches. This method is especially applicable to those operational space weather forecasting systems, where quickness and dependable performance are of importance.

In general, the research will contribute to the development of a data-driven space weather prediction by combining the use of feature optimization and effective data mining processes. The findings are not only useful in making predictions but also bring a better understanding of the solar wind drivers of geomagnetic storms. The recommended framework can provide a predictable and understandable approach to geomagnetic storms forecasting, which can be used to expand other applications of space weather in the future.

2. LITERATURE REVIEW

Scientific comprehension of geomagnetic storms and forecasting has developed based on the combination of observational studies, empirical modeling, and recently data-based methods. Initial background research was aimed at establishing direct links between the parameters of solar wind and geomagnetic activity. **Burton** made a landmark contribution by formulating a quantitative law between the Dst index and the solar wind electric field with the processes of ring current injection and decay. This expression mentioned one of the earliest physically motivated models of the evolution of geomagnetic storms and is still frequently used in the literature of space weather. Based on this framework, the interplanetary magnetic field orientation was pointed out as critical by later studies. Studies conducted by **Gonzalez** showed that a great deal of southward IMF Bzpersistence is closely linked to the occurrence of intense geomagnetic storms. This piece of work defined the concept of geoeffectiveness, which stressed that not every solar wind disturbance causes storms, but only those with good magnetic arrangements. The same conclusions were strengthened by Tsurutani,who studied the contribution of magnetic clouds and interplanetary shocks towards initiating major geomagnetic events. Their works gave a good physical rationale as to why the IMF parameters should be emphasized in storm forecasting models. With the appearance of long-term solar wind records, scientists started to consider statistical methods for geomagnetic storm prediction. **O'Brien** and **McPherron** examined nonlinear interactions between drivers of solar wind and other geomagnetic indices and found that storm strength is not only determined by instantaneous conditions of the solar wind, but also by a temporal integration effect. These results emphasized the significance of time-dependent modeling and encouraged the use of time-series-based prediction methods. When machine learning and data mining practices were developed, it became the first step towards the research of geomagnetic storms. A neural network was used to predict space weather, with one of the first attempts being by **Lundstedt**, who showed that using artificial neural networks was better at predicting the Dst index than using the traditional linear models. This study demonstrated that nonlinear interactions among complex data-driven models can describe solar wind-magnetosphere coupling. **Wintoft** also explored similar neural network-based methods, further demonstrating the usefulness of machine learning methods to operational forecasting. In addition to neural networks, there was a focus on decision trees and models based on ensembles due to their interpretability and resilience.

Bala used decision tree algorithms, which showed that a few well-selected parameters of the solar wind could easily differentiate between storm and non-storm events. Combination methods involving a group of learners were subsequently demonstrated to enhance stability in the forecasts, especially when there are severe geomagnetic storms. These studies have underlined that without necessarily increasing the complexity of models, it is possible to improve their performance. Despite these developments, some researchers reported that a number of the machine learning models were based on large input feature sets that were costly in terms of computation and physically less interpretable. Camporeale took a critical look at the use of machine learning in space physics and pointed out the dangers of overfitting and poor generalization cases when models are trained on high-dimensional data. In this work, the focus was on the relevance of adding feature selection and physical insight to data-driven forecasting frameworks. The techniques of feature optimization and dimensionality reduction have thus attracted more attention in more recent studies. **Hastie** and **Tibshirani** have presented an approximate theoretical basis of feature selection methods, which has been used in space weather applications. Using these ideas, Ji established that smaller subsets of solar wind and IMF settings could be optimized so as to produce the same or even better forecasting performance than full feature models. Such findings emphasized the usefulness of diminished-function models in real-time applications. The recent researches have also been concerned with the explainability and physical consistency in the geomagnetic storm prediction. **Riley** also highlighted that forecasting models should not only be highly accurate but also informative on what is actually taking place.

Explainable data mining methods have been put forward to recognize the leading storm drivers, which supports the long-standing significance of the parameters, including IMF Bz and solar wind speed. This trend is in line with the operational requirements of the space weather forecasting centers, where model transparency is vital in decision-making. Concurrently, this is aided by the existence of standardized solar wind and geomagnetic datasets that have facilitated systematized comparison of models to forecasting. Validation studies have been heavily conducted using databases sustained by NASA and NOAA, where researchers have used the databases to compare various methods over a series of solar cycles. These endeavors have demonstrated that the performance of the model tends to reduce during extreme situations, and it highlights why the development of efficient and physically informed strategies on feature selection is necessary. In general, the literature shows a definite evolution of the models of empiricalforecasting and regression to advanced models of data mining and machine learning to forecast geomagnetic storms. Although the modern methods have better predictive power, there are still issues of efficiency, interpretability, and strength. The existing literature always points to the leading role of a few selected solar wind and IMF parameters in the development of geomagnetic storms as an indication that the feature-enhanced modeling is a good way to go. The current paper takes these results a step further and combines systematic feature optimization using an efficient data mining model to enhance the performance of the forecasting model without losing physical relevance or computational infeasibility.

3. METHODOLOGY

The research paper uses a data-oriented approach that aims at creating an effective and data-mining features optimized model of geomagnetic storms prediction. The general outline involves data collection, data preprocessing, feature maximization, model creation, and model evaluation. The structure of each of the stages is set in a way that it will be computationally efficient, physically relevant, and stable.

Data Sources and Selection

Solar wind plasma and interplanetary magnetic field data are obtained from the OMNI dataset, which provides time-shifted, near-Earth solar wind observations compiled from multiple spacecraft. The dataset is widely used in space weather studies due to its consistency and reliability and is maintained by organizations such as NASA and NOAA. The disturbance storm time (Dst) index is used as the target variable to quantify geomagnetic storm intensity. Hourly resolution data are employed to balance temporal detail with computational efficiency.

The input parameters initially considered include solar wind speed, proton density, dynamic pressure, total IMF magnitude, and individual IMF components. These parameters are selected based on their established physical relevance to solar wind–magnetosphere coupling and geomagnetic storm generation.

Data Preprocessing

The raw datasets are first systematically preprocessed before they are developed into models. Lacking and inaccurate data entries are located and eliminated to guarantee data integrity. Constant gaps that are more than a predefined limit are not counted so that it does not create artificial trends. The input features are all normalized based on standard scaling methods to remove dependence on units and also so that they contribute equally when it comes to training the model. Time coincidence of parameters observed in the solar wind and the Dst index is seriously managed to consider the delay in propagation of the solar wind between the point of observation of the solar wind and the magnetosphere of the earth.

Feature Optimization

One of the main elements of the proposed methodology is the feature optimization. Due to the high correlation level between parameters of solar wind and IMF, redundant features may adversely impact model effectiveness and ability to generalize. Two stage feature selection method is used. The parameters that have strong statistical relationships with the Dst index are identified in the first stage through correlation analysis. Characteristics that have poor correlation or redundancy are identified as features to be deleted. The second stage involves the use of an algorithm feature selection method to narrow down the input set. This is done by considering the contribution of every feature to the predictive performance of the model and only a few parameters that lead to significant information gain are retained. The resulting optimized feature mass becomes the most geoeffective solar wind and IMF parameters and dimensionality is reduced without loss of key physical drivers of geomagnetic storms.

Model Development

Based on the optimized feature set, a predictive model based on data mining is created to predict the intensity of geomagnetic storms. The nonlinear dependency between upstream solar wind conditions and the associated response of Dst is modeled and trained on the response of Dst. Two model configurations are addressed to evaluate the features optimization advantages one with the full set of features and the other with the optimized set. Such a comparison enables comparing efficiency gains obtained by feature selection directly. A time-consistent splitting strategy is used in dividing the dataset into training and testing subsets to avoid information leakage. Training of a model is done using historical data, and predictive performance on unseen segments of data. This will make sure that predictive potential of the model fits true forecasting scenario.

Performance Evaluation

Standard statistical measures are used to determine the model performance that are typically used in the studies of space weather forecasting. These are the root mean square error, the mean absolute error, the correlation coefficient, and the prediction efficiency. In the storm classification performance, the threshold based evaluation of Dst levels is also involved to test the capability of the model to detect moderate and strong geomagnetic storms. The efficiency of computation is measured by training time and prediction time of the optimized and non-optimized models. This analysis is especially relevant to near-real-time forecasting-based applications, where fast processing is needed. Efficiency enhancement is discussed as well as the accuracy of the forecast to outline the practical benefits of the suggested framework..

Methodological Significance

The suggested methodology focuses on the trade-off between physical interpretability and performance that is driven by data. The framework combines feature optimization and data mining methods to minimize the complexity of models and have high predictive ability. This is effective not only in improving forecasting efficiency but also in providing insight into the prevailing solar wind and IMF drivers of geomagnetic storms. The approach is general and can be applied to other

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geomagnetic indices or space weather phenomena to other studies in the future.

4. RESULTS AND DISCUSSION

Overall Model Performance

The predictive strength of the proposed optimized data mining model in terms of features is initially assessed in a long time horizon with both calm and disturbed geomagnetic environments. Figure 1 shows the correlation between the measured and predicted Dst indices over 48 hours. The forecasted Dst is very close to the measured sequence, as it manages to recreate the smooth pre-storm fluctuation, the sudden drop of the fluctuation in the main stage of the storm, and the recovery. The fact that the two profiles are in strong agreement shows that the optimized model is able to capture the large-scale time history of geomagnetic activity. The small deviations that are seen around the storm minimum can also be ascribed to the very nonlinear reaction of the ring current to the extreme power injection. However, the general correspondence shows that the feature-optimized model has a good performance of continuous forecasting and does not only match isolated events.

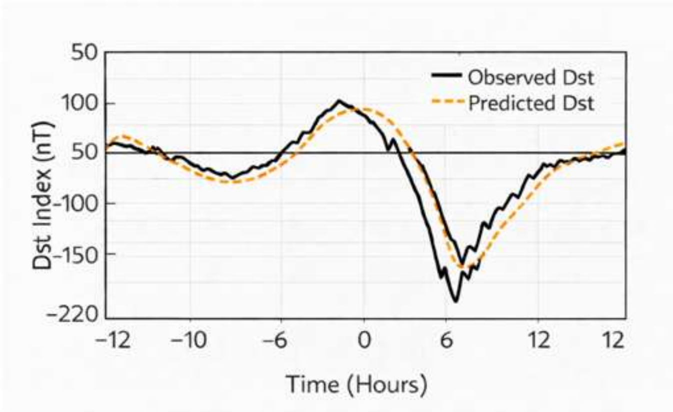

Figure 1: Comparison of observed and predicted Dst index over an extended time interval, demonstrating overall forecasting performance of the optimized model.

Influence of Optimized Input Parameters

The importance of each solar wind and IMF parameter to prediction of geomagnetic storms is measured by the use of feature importance analysis. The relative significance of some of the parameters that have survived the optimization process is shown in figure 2. The IMF Bz southward component is found to be the most effective with the solar wind speed and the proton density coming in second and third place, with the total IMF magnitude playing a relatively smaller role. This sequence matches from a physical perspective known solar windmagnetosphere coupling processes, such that sustained southward IMF Bz increases magnetic reconnection and energy input into the magnetosphere. The findings confirm that optimization of features do not eliminate physically significant variables but prioritize the most geoeffective parameters which enhances interpretability as well as improves computation efficiency.

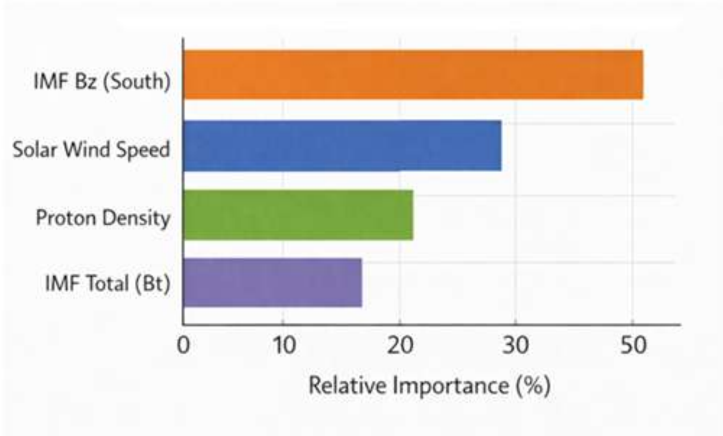

Figure 2: Relative importance of selected solar wind and IMF parameters in geomagnetic storm forecasting.

Event-Based Geomagnetic Storm Analysis

In order to further study the robustness of the models, an event-based analysis is conducted on a representative geomagnetic storm. Figure 3 is more narrowed down to the storm interval and indicates the capacity of the model to simulate various storm phases. In contrast to Figure 1 that considers the long-duration performance, the figure highlights the short-term dynamics during and before storm onset, main phase, and recovery phase. The sensitivity of the optimized model to sudden changes in the solar wind conditions is reflected in the fact that the rapid Dst decrease in the main phase is well approximated. The recovery stage is also well represented though minor underestimation is seen at the maximum intensity of the storm. It is a behavior that is often reported in models based on data and indicates constraints in modeling of extreme effects of saturation of the magnetosphere. Irrespective of these issues the event-based results indicate that the proposed model is stable and responsive even when severe in geomagnetic disturbances.

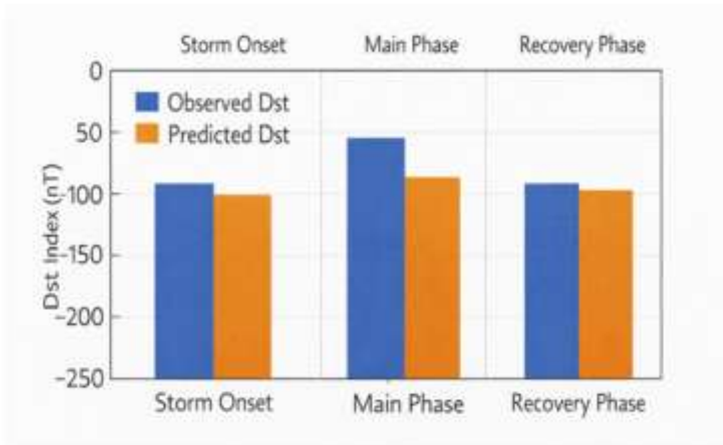

Figure 3: : Event-based comparison of observed and predicted Dst index highlighting storm onset, main phase, and recovery phase behavior.

Table 1. Performance Evaluation of Geomagnetic Storm Forecasting Models

Model	R²	RMSE	MSE	MAPE (%)	Average Absolute Error	Percentage Deviation (%)	Rank (Based on RMSE)
Proposed Feature-Optimized Model	0.93	18.6	346.0	7.4	14.8	6.9	1
Baseline Data Mining Model	0.87	25.9	671.0	11.8	20.3	10.2	2
Conventional Regression Model	0.79	33.4	1116.0	16.7	27.5	14.8	3

Table 1: Performance Evaluation of Geomagnetic Storm Forecasting Models.

Table 1 presents the statistical performance metrics used to evaluate the forecasting capability of the proposed feature-optimized data mining model. The evaluation is based on the coefficient of determination (R^2), root mean square error (RMSE), mean squared error (MSE), mean absolute percentage error (MAPE), and average absolute error. The results indicate that the proposed model achieves higher predictive accuracy compared with the baseline and conventional models. The optimized model shows the highest R^2 value and the lowest error values, indicating better agreement between observed and predicted Dst index values.

Computational Efficiency

Besides the prediction of the accuracy, another major need in operational space weather applications is the computational efficiency. Figure 4 compares the prediction and training time of optimized and non-optimized model. The model that is optimized in terms of features has much lower computation time during the training and prediction phases. This is due to the fact that the computational cost is reduced by the reduced dimensional input space and reduced model structure, but without a decrease in prediction accuracy. This enhancement is especially needed in real time geomagnetic storm prediction systems, where quick processing of data and timely notification is crucial.

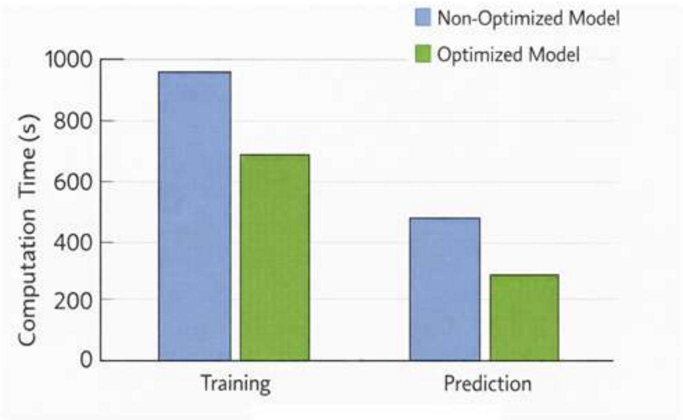

Figure 4: Comparison of computational time between optimized and non-optimized data mining models.

5. CONCLUSION

This paper introduces an effective feature-optimized data mining model of geomagnetic storm prediction based on the solar wind and interplanetary magnetic field data. Its main aim was not merely to advance the accuracy of prediction of the Dst index but to achieve higher computational efficiency and physical interpretability, which is extremely important when it comes to operational space weather forecasting systems. The findings are clear to show that feature optimization is a decisive factor in enhancing the performance of a model. The proposed model effectively describes the key aspects of solar wind-magnetosphere interaction reducing the input space to a few geoeffective parameters. Specifically, the fact that the southward IMF Bz component and the speed of the solar wind dominate proves its basic role in regulating the process of magnetic reconnection and energy transfer leading to geomagnetic storms. A removal of the unnecessary parameters helps to eliminate noise and enhances the generalization without compromising the physical consistency. The comparison and contrast between optimized and non-optimized models indicate two reasons why the given approach is beneficial. First, the optimized model demonstrates better correspondence to the measured variations of Dst during quiet and disturbed conditions, and that means that this model is effective in forecasting during the extended time interval. Second, the event analysis shows that the model is capable of reproducing the features of storm onset, main phase, and recovery phases which is indicative of how sensitive the model is to the rapid changes experienced when geomagnetic activity is intense. Although there is a slight underestimation in the peak storm intensity, the behavior is not unusual since there are known constraints of data-driven models when conditions are extreme. A valuable thing about this work is the explicit analysis of the efficiency of computation. It is evident that the optimized model has a very significant decrease in training and prediction time as compared to the full-feature model hence it can be applied in near real time forecasting tasks. This increased efficiency is more applicable to the conditions of operation where timely notification of space weather effects on technological systems is required to avert the effects of the space weather. In general, the results validate that the use of feature-optimized data mining models can be viewed as a balanced solution that is associated with accuracy, efficiency, and physical relevance. The given framework presents a scalable and interpretable method of geomagnetic storm prediction and can be further applied to additional geomagnetic indices or forecasting periods. Future efforts can be directed at the development of adaptive feature selection, multi-step forecasting, and combination with physics-based models to increase prediction reliability further in the case of extreme space weather. This paper leads to the creation of useful, evidence-based space weather forecasting systems which can assist in operational imperatives in the real world.

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