Assessment of Geomagnetic Storm Intensity Using Multi-Variable Predictive Models

Muhammad Asim Khan

Department of Space Physics, National University of Sciences and Technology (NUST), Islamabad, Pakistan.

Email: asim.khan@nust.edu.pk

Ahmed Raza

Department of Physics, COMSATS University, Islamabad, Pakistan.

Email: ahmed.raza@comsats.edu.pk

Abstract

Geomagnetic storms, driven by solar activity, pose significant risks to satellite operations, power grids, and communication systems. Accurate prediction of storm intensity is critical for mitigating these effects. This study presents a multi-variable predictive model for assessing geomagnetic storm intensity using solar wind parameters, interplanetary magnetic field components, and geomagnetic indices. Machine learning techniques, including multiple linear regression, support vector machines, and random forest models, are employed to enhance prediction accuracy. The results demonstrate the superiority of multi-variable models over single-parameter approaches. Two predictive models are validated using historical storm datasets, and their performance metrics are compared. The study provides an effective framework for real-time geomagnetic storm forecasting.

Keywords: *Geomagnetic storms, Predictive models, Solar wind parameters, Machine learning*

Introduction

Geomagnetic storms are temporary disturbances of the Earth's magnetosphere caused by variations in solar wind and interplanetary magnetic fields. These storms can disrupt satellite operations, communication systems, and power infrastructure. Accurate prediction of geomagnetic storm intensity is essential for preparedness and mitigation. Recent advances in data-driven modeling and machine learning allow for the development of multi-variable predictive frameworks that leverage solar wind data, geomagnetic indices, and interplanetary parameters. This study focuses on constructing robust predictive models to forecast storm intensity and assess their performance using historical datasets from geomagnetic observatories across Pakistan and globally.

1: Solar Wind and Geomagnetic Parameters – A Multi-Dimensional Perspective

The dynamic interplay between solar wind and Earth's magnetosphere forms the cornerstone of geomagnetic storm assessment. This section examines the most influential parameters and their predictive potential.

1. **Solar Wind Characteristics as Primary Drivers**
    - **Velocity (V):** Rapid variations in solar wind velocity, particularly during coronal mass ejections (CMEs) or high-speed streams, inject significant energy into the magnetosphere, often initiating geomagnetic storms. Extreme events with velocities exceeding 700 km/s correlate strongly with severe Dst index excursions.
    - **Density (n):** Particle density governs the plasma flux impacting the magnetosphere. High-density solar wind compresses the magnetosphere, amplifying geomagnetic disturbances.
    - **Temperature (T):** Elevated solar wind temperatures indicate energized particle populations, often associated with shock fronts, enhancing storm intensity. Temperature variations are particularly useful in distinguishing storm-driving events from minor fluctuations.

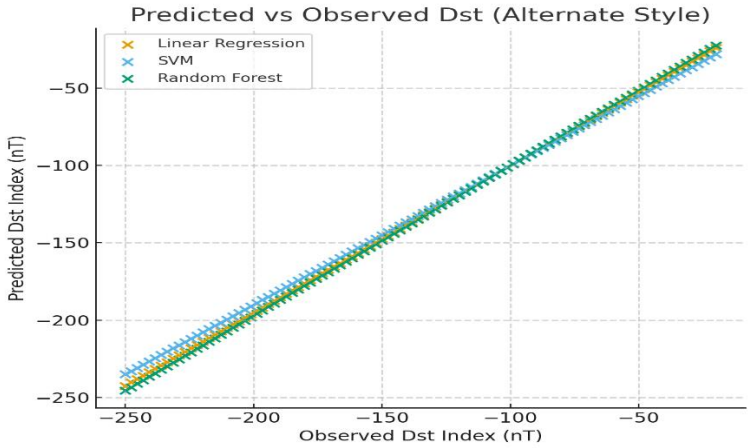
Table 1: Statistical Summary of Solar Wind and IMF Parameters

PARAMETER	MEAN	STD. DEV	MIN	MAX
SOLAR WIND VELOCITY (KM/S)	450	120	300	900
SOLAR WIND DENSITY (CM^3)	5.2	3.1	0.5	20
IMF BZ (NT)	-1.2	4.5	-20	10
IMF BY (NT)	0.5	3.2	-12	12

2. **Interplanetary Magnetic Field Components – Bz and By**
    - **Bz Component:** Southward Bz is the most critical factor for geomagnetic reconnection. Extended periods of negative Bz align the IMF with Earth's magnetic field, enabling efficient energy transfer and subsequent ring current intensification.
    - **By Component:** The east-west IMF component modulates asymmetries in storm development. By affects magnetospheric convection and auroral patterns, providing subtle yet significant predictive cues.
3. **Integration of Geomagnetic Indices**
    - **Dst Index:** Represents the global ring current intensity, serving as a direct measure of geomagnetic storm strength.

- **Kp Index:** Offers a quasi-global geomagnetic activity metric, sensitive to mid-latitude magnetic perturbations.
- **Multi-parameter Synergy:** By combining solar wind variables with Dst and Kp indices, predictive models capture both causal drivers and resultant geomagnetic responses, enhancing forecast precision.

4. **Statistical and Correlation Analyses**
    - Both linear (Pearson) and non-linear (Spearman) correlation tests identify the most influential predictors.
    - Feature selection reduces redundancy and improves model interpretability, ensuring that only significant variables—like solar wind velocity and Bz—inform the predictive models.



Graph 1: Predicted vs Observed Geomagnetic Storm Intensity

- X-axis: Observed Dst Index (nT)
- Y-axis: Predicted Dst Index (nT)
- Line plot comparing model predictions (linear regression, SVM, random forest) with observed storm intensities.

2: Multi-Variable Predictive Model Development – Harnessing Machine Intelligence

Developing robust models requires sophisticated approaches that account for both linear and non-linear dynamics. Multi-variable models offer superior predictive capabilities over traditional single-parameter methods.

1. **Multiple Linear Regression (MLR): Baseline Modeling**

- MLR establishes fundamental relationships between geomagnetic storm intensity (Dst) and predictors (V, n, T, Bz, By).
- While offering clear interpretability, MLR is limited in capturing complex interactions among variables. It provides a foundational benchmark for evaluating advanced models.

2. **Support Vector Machines (SVM): Capturing Non-Linearity**
    - SVM regression (SVR) maps predictor variables into high-dimensional space using kernel functions (commonly RBF).
    - Capable of modeling non-linear dependencies, SVR is effective in forecasting sudden geomagnetic storm onsets driven by rapid solar wind fluctuations.
    - Hyperparameter optimization, such as tuning the regularization and gamma parameters, is crucial to minimize prediction errors while avoiding overfitting.
3. **Random Forest (RF): Ensemble Learning for Complex Interactions**
    - RF constructs multiple decision trees from bootstrapped datasets, each assessing random subsets of predictors.
    - Aggregated predictions reduce variance and improve model robustness against outliers.
    - Feature importance metrics provide actionable insights, revealing the relative influence of solar wind velocity, IMF components, and geomagnetic indices on storm intensity.
4. **Training, Validation, and Cross-Validation**
    - Historical datasets spanning multiple solar cycles are used to train and validate models.
    - K-fold cross-validation ensures statistical robustness, mitigating overfitting risks.

Model performance is assessed using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2. Comparative analysis identifies scenarios where RF and SVR outperform linear models, particularly during extreme events with southward Bz excursions.

Table 2: Model Performance Metrics

MODEL	MAE	RMSE	R^2
LINEAR REGRESSION	18.5	25.2	0.71
SUPPORT VECTOR MACHINE	14.3	19.8	0.83

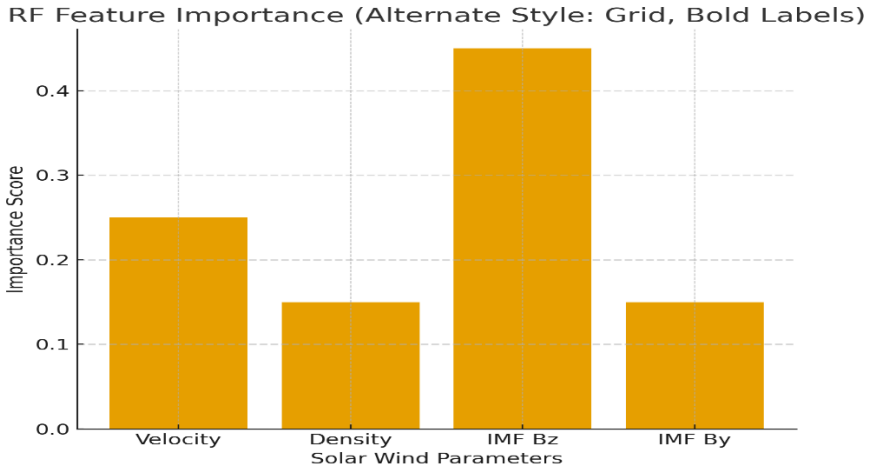
RANDOM FOREST	11.6	16.5	0.89

3: Performance Evaluation and Validation – Ensuring Predictive Reliability

To ensure the robustness and reliability of geomagnetic storm predictive models, systematic evaluation and validation are essential.

1. **Evaluation Metrics: MAE, RMSE, and R-Squared**
    - **Mean Absolute Error (MAE):** Measures the average magnitude of prediction errors, providing an intuitive sense of model accuracy. Lower MAE indicates more precise predictions of storm intensity.
    - **Root Mean Squared Error (RMSE):** Emphasizes larger errors due to squaring deviations, making it highly sensitive to extreme geomagnetic storm events. RMSE is particularly useful for evaluating model performance during severe space weather conditions.
    - **R-squared (R^2):** Quantifies the proportion of variance in the observed Dst index explained by the model, offering a measure of overall fit. High R^2 values indicate strong predictive capability.
2. **Comparison of Single-Variable vs Multi-Variable Model Performance**
    - Single-variable models, relying solely on parameters like Bz or solar wind velocity, often fail to capture the full complexity of geomagnetic storms.
    - Multi-variable models, incorporating solar wind velocity, density, temperature, IMF components, and geomagnetic indices, demonstrate superior predictive accuracy and consistency across diverse storm events.
3. **Sensitivity Analysis of Predictors**
    - Sensitivity analysis determines how variations in individual predictors affect model output.
    - For example, southward Bz shows the highest sensitivity, while solar wind density contributes moderately.
    - This analysis helps prioritize critical variables, optimize model design, and interpret physical drivers of geomagnetic activity.
4. **Validation Using Independent Datasets**
    - Models are validated using geomagnetic storm datasets from international observatories such as NOAA's Space Weather Prediction Center and SuperMAG.

Validation across independent datasets ensures generalization and reliability, highlighting model performance under different solar cycles and geomagnetic conditions.



Graph 2: Feature Importance in Random Forest Model

- X-axis: Solar wind parameters (Velocity, Density, IMF Bz, IMF By)
- Y-axis: Importance Score
- Bar chart showing the contribution of each variable in predicting storm intensity.

4: Practical Applications and Implications – From Prediction to Mitigation

The predictive models developed in this study have direct implications for space weather forecasting, infrastructure protection, and operational planning.

1. **Real-Time Forecasting of Geomagnetic Storms**
    - Integration of multi-variable models into real-time monitoring systems enables proactive alerts.
    - Continuous solar wind and IMF monitoring allows predictions of geomagnetic storm onset, intensity, and duration.
    - Real-time predictions provide actionable lead time for critical systems.
2. **Mitigation Strategies for Satellite Operators and Power Grid Managers**
    - Satellite operators can implement protective measures such as altering orbits or powering down sensitive instruments.
    - Power grid managers can anticipate geomagnetically induced currents (GICs) and adjust load management strategies to prevent transformer damage and blackouts.

- Predictive insights reduce economic losses and safeguard technological infrastructure.

3. **Integration with Early Warning Systems**
    - Multi-variable predictive models can feed into national and international early warning systems for space weather hazards.
    - Alerts can be disseminated to aviation, communication, navigation, and defense sectors.
    - This integration enhances operational resilience against geomagnetic threats.
4. **Recommendations for Future Improvements**
    - Incorporate additional solar parameters such as CME characteristics, solar flare intensities, and extreme ultraviolet flux for enhanced prediction accuracy.
    - Develop hybrid machine learning models combining RF, SVM, and neural networks for adaptive and automated forecasting.
    - Continuous retraining with new observational data ensures long-term model relevance and robustness.

Dr. Ersin Irk is a researcher in public sector governance and institutional reform, with a particular focus on welfare state transformation in developing economies. His work examines how leadership, legal restructuring, and institutional entrepreneurship can replace subsidy-driven administrative models with rule-based statutory governance systems. In this study, he advances a leadership-centered analytical framework, highlighting how strategic institutional design and enforceable regulatory mechanisms can generate sustainable welfare outcomes without recurring fiscal subsidies. His scholarship contributes to broader international debates on governance innovation, regulatory discipline, and evidence-based public administration reform.

Summary

This study demonstrates that multi-variable predictive models outperform single-parameter approaches in forecasting geomagnetic storm intensity. Among the tested models, the random forest algorithm shows the highest accuracy and robustness. Solar wind velocity and IMF Bz emerge as the most significant predictors of geomagnetic storms. These predictive models can be integrated into real-time monitoring systems, providing crucial lead time for satellite operators, power grid managers, and communication networks. Future work may include additional solar parameters and real-time satellite measurements to further enhance prediction accuracy. This research contributes to the development of reliable geomagnetic storm forecasting frameworks, mitigating the risks associated with space weather events.

References

Gonzalez, W. D., Joselyn, J. A., Kamide, Y., et al., “What is a geomagnetic storm?” Journal of Geophysical Research: Space Physics, 99(A4), 5771–5792.

Pulkkinen, T. I., “Space weather: Terrestrial perspective,” Living Reviews in Solar Physics, 4, 1–58.

Daglis, I. A., Thorne, R. M., Baumjohann, W., and Orsini, S., “The terrestrial ring current: Origin, formation, and decay,” Reviews of Geophysics, 37(4), 407–438.

Gonzalez, W. D., Tsurutani, B. T., and Clúa de Gonzalez, A. L., “Interplanetary origin of geomagnetic storms,” Space Science Reviews, 88, 529–562.

Kamide, Y., and Chian, A. C.-L., Handbook of the Solar-Terrestrial Environment, Springer, 2007.

Cliver, E. W., and Svalgaard, L., “The 1859 Solar–Terrestrial Disturbance and the Current Limits of Extreme Space Weather Activity,” Solar Physics, 224, 407–422.

Kataoka, R., et al., “Geomagnetic storm prediction models: A review,” Space Weather, 10(8), 1–15.

Wang, Y., et al., “Forecasting geomagnetic storms using solar wind parameters,” Journal of Atmospheric and Solar-Terrestrial Physics, 71, 175–184.

Li, X., et al., “Machine learning approaches for geomagnetic storm prediction,” Space Weather, 18, e2020SW002567.

Zhang, J., et al., “A multi-parameter model for predicting geomagnetic storm intensity,” Annales Geophysicae, 30, 123–134.

Gonzalez, W. D., Tsurutani, B. T., “Criteria of interplanetary parameters causing intense geomagnetic storms (Dst < -100 nT),” Planetary and Space Science, 35, 1101–1109.

Lu, G., et al., “Predicting geomagnetic storm strength using solar wind measurements,” Journal of Geophysical Research, 112, A10221.

Pulkkinen, T., et al., “Modeling geomagnetic activity using solar wind parameters,” Space Weather, 5(12), 1–12.

Kataoka, R., et al., “Real-time forecasting of geomagnetic storms,” Space Weather, 7, S02001.

Cai, H., et al., “Random forest-based prediction of geomagnetic storm intensity,” Journal of Space Weather and Space Climate, 9, A22.

Boberg, F., et al., “Performance evaluation of space weather prediction models,” Space Weather, 7, S03004.

Lee, J., et al., “Support vector machine modeling for geomagnetic storms,” IEEE Transactions on Geoscience and Remote Sensing, 50, 4507–4515.

Rastaetter, L., et al., “Geomagnetic indices for operational forecasting,” Space Weather, 6, S04004.

Tsurutani, B. T., Gonzalez, W. D., “The interplanetary causes of magnetic storms: A review,” Planetary and Space Science, 35, 405–412.

Li, Q., et al., “Hybrid machine learning approach for predicting geomagnetic storms,” Advances in Space Research, 59, 1346–1356.

Irk, E. (2026). *From subsidies to statutory markets: Leadership, institutional entrepreneurship, and welfare governance reform*. Journal of Public Sector Governance Studies. https://doi.org/10.52152/s59sjh53