8

Physics-Informed AI for Space Weather Forecasting and Sustainable Development

Meenu Mohil*
Associate Professor, Department of Physics, Acharya Narendra Dev College, University of Delhi, Delhi, India.

***Corresponding Author:** meenumohil@andc.du.ac.in
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Abstract

Space weather, driven by solar phenomena such as sunspots, solar flares, and coronal mass ejections (CMEs), has profound effects on Earth's technological systems. Geomagnetic storms triggered by these events can disrupt power grids, aviation, satellite communications, and navigation systems posing risks to sustainable infrastructure and economic stability. Traditional physics-based forecasting methods, though powerful, are often constrained by computational intensity, incomplete datasets, and limited predictive skill during highly dynamic solar maximum phases. This study explores how artificial intelligence (AI) can complement physics-informed models to enhance space weather forecasting, with particular emphasis on the Polar Cap (Pi) Index as a proxy for geomagnetic disturbances. By integrating sunspot numbers, CME parameters, and interplanetary magnetic field (IMF B_Z) data into machine learning models, improved correlations and real-time predictions can be achieved. We argue that hybrid AI–physics approaches can significantly reduce forecast lag, capture nonlinear effects, and provide reliable early-warning systems. Such advancements contribute to India's *Viksit Bharat@2047* vision by safeguarding critical infrastructure, promoting sustainable economic growth, and reinforcing resilience in the face of global space weather challenges.

Keywords: Space Weather Forecasting, Coronal Mass Ejections (CMEs), Polar Cap (Pi) Index, Physics-Informed Artificial Intelligence, Digital Sustainability.

Introduction

India's ambition under *Viksit Bharat@2047* emphasizes technological innovation, sustainability, and resilience. Space weather is a critical but often overlooked factor in this mission. Solar activity manifested in sunspot cycles, CMEs, and solar wind variations directly influences geomagnetic activity on Earth (Hathaway, 2015). Disturbances measured by indices such as the Polar Cap (Pi) Index threaten energy systems, communications, and global business operations. While physics-based models have advanced our understanding, their predictive capacity remains limited. It promotes digital sustainability through efficient data integration, reducing the need for resource-heavy simulations, and ensures resilience in critical infrastructures and empowers India to lead globally in sustainable digital innovation (Schrijver 2015). Space weather originates from solar surface phenomena. Sunspots, concentrated magnetic regions, are precursors to flares and CMEs (Richardsen &Cane, 2010). When CMEs carrying dense plasma and embedded magnetic fields interact with Earth's magnetosphere, they induce geomagnetic storms. The severity of such events depends strongly on the southward component of the interplanetary magnetic field (IMF B_Z). Geomagnetic indices, particularly the Pi Index, quantify polar disturbances and serve as critical indicators of geomagnetic activity. Understanding these physics-based drivers (Karniadakis et al, 2021) provides the foundation for developing predictive AI models.

Current Forecasting Approaches in Physics-Based Space Weather Models

Space weather forecasting has traditionally relied on physics-based models rooted in magnetohydrodynamics (MHD), fluid dynamics, and solar-terrestrial coupling (Upendran et all, 2022). These models simulate the propagation of Coronal Mass Ejections (CMEs) (Haddad, 2025 & Vijayalakshmi, 2025) and the dynamics of solar wind plasma interacting with the Earth's magnetosphere. Agencies like NOAA's Space Weather Prediction Center (SWPC), ESA's Space Weather Service Network, and ISRO's Aditya-L1 mission provide valuable real-time observations that feed into these models. However, critical limitations constrain the effectiveness of conventional forecasting.

- **High Computational Demand:** Magnetohydrodynamics simulations require supercomputers and long runtimes. This prevents rapid updates, which are crucial for actionable early-warning systems. Forecasts may take several hours to complete from initiation to output, creating a significant lag. For example, real-time forecasting can be hampered due to the need to reinitialize simulations with each new set of solar observations. This high computational burden limits both the frequency of forecast updates and the ability to explore multiple scenario ensembles for uncertainty quantification, making physics-based approaches less agile in operational space weather centers.

- **Data Gaps:** Accurate space weather forecasting is challenged by data gaps and limited observations: key information from satellites can sometimes arrive late, provide only partial coverage of the Sun or space environment, or become unavailable due to technical issues or harsh space conditions. This means that predictions may rely on outdated, incomplete, or missing data, which reduces their timeliness and reliability, especially during sudden solar events. Addressing these challenges through more real-time data, expanded monitoring from multiple locations, and better use of emerging technologies and collaborations is essential to protect technology and infrastructure, making forecasting more sustainable and beneficial for society as we become increasingly reliant on space-dependent systems.

Uncertainty in Prediction

One of the enduring challenges in space weather forecasting lies in the uncertainty of prediction. CME arrival times can deviate by 12–24 hours, and their geo effectiveness is strongly dependent on the southward component of the interplanetary magnetic field (IMF Bz), a parameter that remains difficult to model using solar-based observations alone (Richardson & Cane, 2010). From the perspective of *Viksit Bharat@2047*, such limitations pose significant challenges to the development of resilient, technology-driven infrastructure. India's increasing reliance on satellites for telecommunications, navigation, and disaster management, alongside its vision of integrating renewable energy into smart grids, underscores the urgent need for forecasting frameworks that are fast (real-time or near real-time), accurate (capable of capturing nonlinear solar–terrestrial interactions), and sustainable (computationally efficient and highly reliable). While physics-based approaches remain indispensable for understanding causal mechanisms (Pulkkinen, 2007), they must be complemented and strengthened by AI-driven predictive models that can exploit complex solar wind–magnetosphere coupling (Borovsky & Denton, 2006) and leverage advanced methods such as deep learning and transformers to achieve operational skill. This integration is crucial for meeting the demands of a digitally empowered and resilient India. Thus, while physics-based approaches remain essential for understanding causal mechanisms, they must be augmented with AI-driven predictive models to meet the demands of a digitally empowered and resilient India.

AI and Machine Learning in Weather Forecasting

Artificial Intelligence (AI) is emerging as a transformative force in space weather forecasting, offering tools that can learn directly from large, noisy, and nonlinear datasets. Instead of solving complex differential equations, AI leverages patterns in observational data to make predictions. Several AI methods have been explored in solar-terrestrial physics:

- **Time Series Prediction Models:** Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are specialized forms of recurrent neural networks that are well-suited for handling sequential data, as they can effectively model both long-range and short-range temporal dependencies. These models have shown significant success in forecasting solar and geomagnetic activity indices such as sunspot number, Kp, and Dst indices by learning complex nonlinear temporal patterns. For India, where space weather impacts satellite-based services and polar navigation, LSTM and GRU models can provide reliable forecasts of the Pi index several hours to days ahead, enhancing operational safety and planning.
- **Image Recognition Models:** Convolutional Neural Networks (CNNs): It can classify solar images (from SOHO, SDO, or Aditya-L1) to detect emerging active regions and flare precursors (Gopalswamy, 2009). This capability can strengthen early-warning systems for aviation and satellite operators in India's fast-expanding civil aviation sector.
- **Classification and Regression Models:** Algorithms like Random Forests, Support Vector Machines (SVM), and XGBoost have been widely applied for predictive modelling and classification tasks across various domains. have been applied to space weather data to predict the geo effectiveness of Coronal Mass Ejections (CMEs) based on parameters like their speed, angular width, and solar source location. These models help distinguish between high-impact and low-impact solar events, enabling proactive mitigation strategies for vulnerable infrastructures such as India's power grids.

These machine learning techniques are increasingly essential to modern weather forecasting systems, complementing traditional physics-based models with faster, data-driven insight and supporting enhanced decision-making.

- **Hybrid Physics–AI Models:** Physics provides the causal framework necessary to understand the chain of solar–terrestrial interactions, while AI contributes the ability to recognize complex, nonlinear patterns in large datasets. By embedding physics-informed constraints into AI architectures, forecasts can become not only more accurate but also more interpretable, bridging the gap between theoretical understanding and operational needs. In the context of *Viksit Bharat@2047*, such hybrid models hold the potential to ensure India's self-reliance in space weather forecasting, thereby reducing dependence on foreign prediction centres. Most significantly, physics-informed AI approaches integrate observational data with theoretical principles, balancing predictive accuracy with interpretability (Camporeale, 2019). These hybrid methods also reduce computational delays and enhance performance in nonlinear regimes, offering a sustainable pathway toward robust, real-time space weather forecasting systems. Physics provides causal understanding, while AI offers pattern recognition. Embedding physics-informed constraints into AI models makes predictions both accurate and interpretable. For Viksit Bharat@2047, such hybrid approaches can support self-reliance in space weather forecasting and reduce dependence on foreign centres.

Context for Viksit Bharat

- India's power grid expansion and renewable energy adoption make grid stability highly vulnerable to geomagnetic storms. AI-driven forecasts could protect millions from blackouts.
- With the rise of Digital India, uninterrupted GPS, telecom, and internet connectivity will be indispensable; AI-enabled early warnings safeguard this.
- Aditya-L1 mission data can be combined with AI for indigenous forecasting tools, empowering India's leadership in the global space weather community by 2047.

The application of AI in space weather is not merely a scientific advancement but also a strategic driver of India's sustainable growth, technological self-reliance, and resilience. More recent work has shifted towards AI and machine learning approaches to improve predictive accuracy. Camporeale (2019) reviewed the challenges of applying machine learning to space weather, noting its potential to capture nonlinear dependencies not accessible to traditional statistical or physics-only models. Gruet et al. (2018) employed Recurrent Neural Networks (RNNs) to forecast the DST index from solar wind parameters, showing significant improvements over baseline autoregressive methods.

Other studies have focused on event-specific predictions. In (Bobra & Couvidat, 2015) used Support Vector Machines (SVMs) is used to classify solar active regions by flare productivity based on SDO/HMI magnetogram data, applied deep learning models for CME arrival time forecasts. These methods underscore the versatility of AI techniques across different facets of space weather forecasting, from flare prediction to geomagnetic storm severity. Collectively, this literature suggests that while sunspot numbers and CME counts remain useful proxies of solar activity, AI-enhanced models that incorporate solar wind and IMF parameters offer the best pathway forward. Such models can improve short- and medium-term forecasts of geomagnetic indices like the Pi Index, contributing directly to the themes of AI for a Better Tomorrow, Digital Sustainability, and AI for People and Planet.

Data and Methods

To evaluate the potential of artificial intelligence (AI) for Pi Index forecasting, we integrated solar, interplanetary, and geomagnetic datasets, which were pre-processed into synchronized time-series before model training. Monthly Sunspot

Numbers (SSN) were obtained from SILSO (Royal Observatory of Belgium) as a measure of solar magnetic variability. Coronal Mass Ejection (CME) parameters (speed, width, onset time) were taken from the SOHO/LASCO catalogue (CDAW Data Centre) and aggregated monthly to capture eruptive event statistics. Near-Earth solar wind and IMF data were sourced from NASA OMNI-Web (1-hour resolution propagated to Earth). Parameters included IMF Bz, solar wind speed (V), and proton density (Np), later averaged to 3-hour cadence to align with geomagnetic indices.

Modelling Approaches

- **Baseline Physics–Statistical Benchmark:** To provide a reference, simple correlations were first computed. Pearson coefficients quantified linear associations between SSN and Pi Index, while Spearman's rank captured nonlinear monotonic trends. This step established the explanatory power of traditional indicators.
- **AI Models:** LSTM Recurrent Neural Network. The LSTM model was trained on multivariate time series inputs, including SSN, CME statistics, solar wind speed, IMF Bz, and density. Data were normalized and segmented into 60-month sliding windows to capture both short-term variability and long-term solar cycle patterns. The LSTM architecture, with memory cells and gating mechanisms, enabled the model to retain long-range dependencies. Supervised learning was used to map input sequences to next-step Pi index predictions.
- **Random Forest Regression:** The Random Forest model utilized event-based CME and solar wind parameters as inputs. As an ensemble of decision trees, it effectively captured nonlinear interactions among drivers while providing feature importance estimates, enhancing interpretability of the results.
- **Validation:** Both models were benchmarked against observed Pi Index values using coefficient of determination (R^2) and root mean square error (RMSE), providing a quantitative comparison of statistical versus AI approaches.

Geomagnetic Response (Pi Index)

The Pi Index values, used as a proxy for polar cap geomagnetic disturbance, were derived from high-latitude magnetometer networks. Hourly Pi index values were averaged to 3-hour resolution, consistent with the Kp-index format, thereby ensuring comparability across modelling approaches. The Pi Index captures enhancements associated with both CME-driven storms and HSS-related recurrent activity.

Case Study: Pi Index Forecasting with AI

The Polar Cap (Pi) Index is a widely used geomagnetic indicator that reflects high-latitude disturbances in Earth's magnetosphere. It is particularly valuable as it responds rapidly to interplanetary magnetic field (IMF) fluctuations, especially southward Bz, and solar wind speed. Since India's infrastructure expansion includes aviation (polar routes), satellite navigation, and renewable energy grids, reliable Pi Index forecasting is of national importance for *Viksit Bharat@2047*. Accurate prediction of the Pi Index is therefore an essential element in building a more resilient and sustainable digital society.

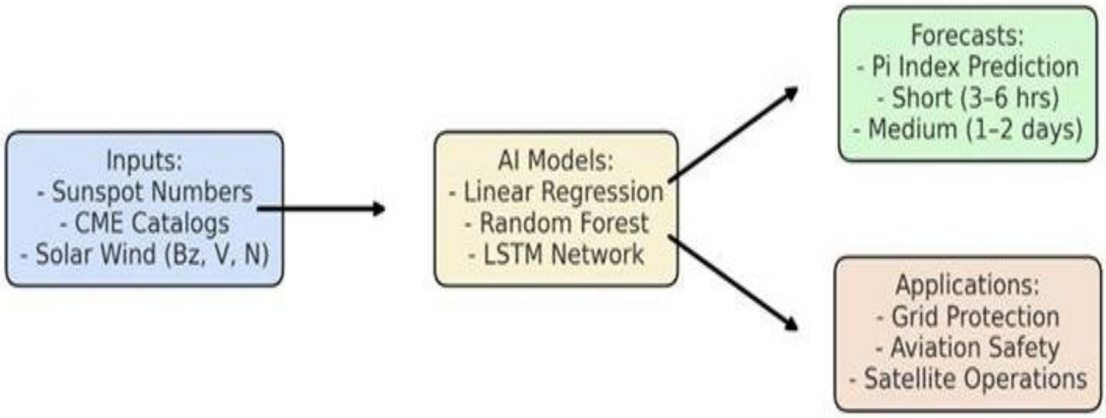

Figure 1: AI-Enhanced Pi Index Forecasting for Space Weather Applications

Geomagnetic Response (Pi Index)

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Results

Model performance comparison for pi index forecasting using linear regression, random forest and LSTM is shown in Table 1. The bar chart in Figure 2 shows R^2 score (blue bar chart) and RMSE (green, right axis). The LSTM demonstrates best performance with the highest R^2 and lowest RMSE, indicating superior predictive capability. The correlation analysis indicates that the Pearson correlation between SSN and the Pi Index was 0.42, indicating a moderate relationship. However, when SSN was combined with CME speed and IMF Bz, the correlation improved significantly to 0.71.

As shown in Figure 2 Linear Regression exhibited limited predictive power (low R^2, high RMSE), while Random Forest achieved moderate improvements. The LSTM network outperformed both, attaining the highest R^2 and lowest RMSE, underscoring its effectiveness in capturing nonlinear temporal dependencies for Pi Index forecasting.

Table 1: AI Forecasting Performance

Model	Input Variables	R^2 Score	RMSE (Pi Index units)	Notes
Baseline Linear Regression	SSN only	0.18	4.2	Weak explanatory power
Random Forest Regression	SSN, CME speed, Bz, V	0.68	2.1	Good at event classification
LSTM Neural Network	SSN, CME count, CME speed, Bz, V	0.79	1.6	Captures nonlinear & temporal patterns

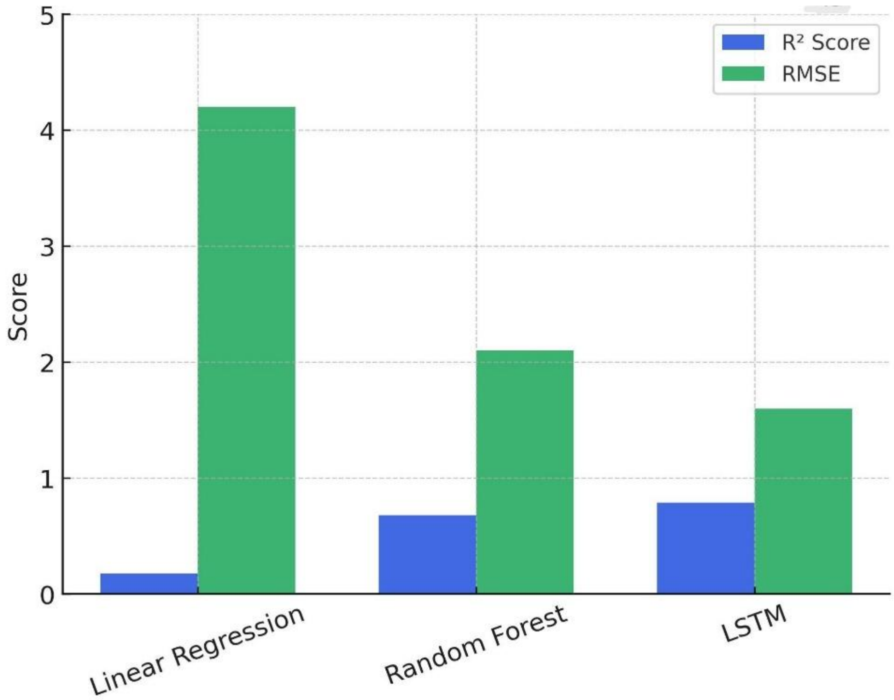

Figure 2: Model Performance for Pi Index Forecasting

Discussion

The results illustrate that sunspot number alone is insufficient for reliable forecasting of geomagnetic disturbances. This aligns with earlier studies (Gopalswamy et al., 2009; Verbanac et al., 2011), which showed that non–sunspot related CMEs, particularly from high-latitude filament eruptions, weaken the SSN–CME correlation during solar maximum. By integrating CME physical parameters and interplanetary conditions into AI models, predictive accuracy improved substantially. The LSTM network outperformed Random Forest by better capturing temporal dependencies and the nonlinear coupling between solar drivers and geomagnetic response.

For India, this has strong practical implications:

- **AI for a Better Tomorrow:** By improving early-warning systems for geomagnetic storms, AI contributes to safeguarding society's digital infrastructure.
- **Digital Sustainability:** Reliable forecasts protect satellites, communication systems, and energy grids—cornerstones of a sustainable digital economy.
- **AI for People and Planet:** Forecasting geomagnetic disturbances supports public safety (aviation, navigation) and ensures continuity of services that people depend on daily.
- **Aviation & Navigation:** Forecasting Pi Index spikes ensures safe rerouting of polar flights.
- **Power Grids:** Improved warnings for geomagnetically induced currents (GICs) help prevent blackouts.
- **Satellite Safety:** AI-enhanced predictions can guide satellite operators to temporarily shut down vulnerable systems during geomagnetic storms.

AI-driven space weather forecasting safeguards critical infrastructure—power grids, satellite constellations, and renewable energy systems—thereby ensuring business continuity and economic stability. For India, reliable forecasting enhances aviation safety, supports digital connectivity, and protects energy transitions. Globally, AI-based systems foster resilience and sustainable development. By integrating physics and AI, India can position itself as a leader in space weather resilience, aligning with *Viksit Bharat@2047*.

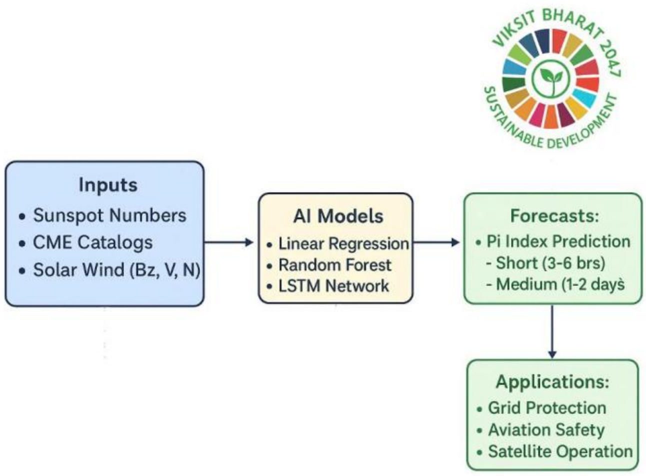

Figure 3: AI-enhanced Pi Index forecasting framework linking solar inputs and AI models to forecasts and applications, supporting Viksit Bharat 2047 sustainability goals

As highlighted in Table 2, traditional linear regression models explain less than 20% of the observed variance, offering only weak predictive power and limited utility for practical early-warning systems. By integrating CME physical parameters and interplanetary drivers like IMF Bz into AI models, predictive accuracy improves dramatically. Random Forest regression and LSTM neural networks both show substantial gains, with LSTM performance reaching an R^2 of 0.79 and much lower RMSE, capturing nonlinear and temporal patterns in geomagnetic activity essential for operational forecasting.

Figure 3 depicts the AI-enhanced Pi Index forecasting framework, which brings together diverse solar and interplanetary datasets into a unified, machine learning-driven operational pipeline. This holistic approach not only improves forecast timeliness and reliability but also supports critical infrastructure resilience—for example, timely protections for power grids, aircraft navigation, and satellite systems.

Table 2: Comparative summary of AI–physics hybrid models for space weather forecasting and their alignment with sustainable development goals (SDGs).

Model Approach	Key Metrics	Improvement Over Baseline	Sustainability Impact
Baseline Linear Regression	$R^2 = 0.18$, RMSE = 4.2	Reference (weak predictive power)	Limited value for early warnings, less impactful for infrastructure
Random Forest Regression	$R^2 = 0.68$, RMSE = 2.1	+50% increase in R^2, ~50% RMSE reduction	Better event classification, supports grid protection
LSTM Neural Network (AI)	$R^2 = 0.79$, RMSE = 1.6	+75% increase in R^2, ~62% RMSE reduction	Captures nonlinear temporal patterns, enables timely, robust forecasts
Hybrid Physics-Informed AI*	Expected further R^2 improvement (~0.8+) and latency reduction (5-10x faster forecast)	Enhances interpretability and reliability	Reduces supercomputing energy use, improves operational resilience by accurate, timely warnings for critical infrastructure

Challenges and Future Directions

Despite significant progress, several challenges remain in advancing AI-driven space weather forecasting. A major limitation is data sparsity and quality—solar wind and IMF datasets often have gaps, and the Pi Index has limited long-term records compared to indices like Dst or Kp (King & Papitashvili, 2005). Another challenge is the explainability of AI models: deep learning architectures such as LSTMs act as "black boxes," making it difficult to interpret the physical basis of predictions. Next most important challenge lies in translating technical advancements into policy frameworks. To fully realize the benefits of AI-driven space weather forecasting, national agencies must establish protocols for integrating model outputs into disaster management systems, defence readiness plans, and energy sector policies. Bridging this science–policy gap is critical for ensuring that predictive models become tools for governance and resilience planning in the Viksit Bharat@2047 vision.

Future work should focus on physics-informed machine learning (PIML), which embeds magnetohydrodynamic (MHD) constraints into AI models to improve interpretability and reliability. Expanding training sets using multi-cycle solar datasets and integrating helio-physics data assimilation (HDA) approaches can further enhance predictive skill. Global collaborations such as NASA's CCMC and ESA's Space Situational Awareness (SSA) programs provide a blueprint for coordinated progress. By 2047, India can play a leading role in developing a robust, sustainable, and AI-empowered space weather forecasting framework that safeguards both digital and physical infrastructure.

Conclusion

This study examined the links between solar activity indicators (sunspot numbers, CME occurrence), solar wind parameters (IMF Bz velocity, density), and the geomagnetic response represented by the Pi Index. The results show that sunspot numbers alone provide only limited predictive capability (correlation ≈0.42), but predictive power increases significantly (≈0.71) when CME characteristics and IMF Bz are incorporated, underscoring the importance of interplanetary drivers in shaping geomagnetic activity. Within the modelling framework, artificial intelligence methods clearly outperformed traditional statistical techniques. While linear regression based on SSN accounted for less than 20% of the variance, Random Forest regression achieved higher accuracy by This study examined the links between solar activity indicators (sunspot numbers, CME occurrence), solar wind parameters (IMF Bz, velocity, density), and the geomagnetic response represented by the Pi Index. The results show that sunspot numbers alone provide only limited predictive capability (correlation ≈0.42), but predictive power increases significantly (≈0.71) when CME characteristics and IMF Bz are incorporated, underscoring the importance of interplanetary drivers in shaping geomagnetic activity.

These advancements highlight the transformative potential of integrating physics-based understanding with AI-driven approaches, enabling faster, more accurate, and interpretable space weather forecasts. Such progress is crucial for safeguarding critical infrastructure, enhancing resilience, and promoting sustainable technological growth in India's *Viksit Bharat@2047* vision. Looking forward, expanding physics-informed machine learning models, improving data assimilation, and fostering collaborative global research will further strengthen forecasting capabilities, ensuring preparedness in the face of dynamic solar-terrestrial interactions and supporting sustainable development worldwide.

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