International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 12, No. 4, 2025, pp. 350-359.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Physics Informed Deep Learning for Real Time Prediction of Solar Terrestrial Plasma and Global Climate Change

Shokhruh Sultanov Rahmon Ugli [a], Dr.C. Rajan [b], M.A. Bruno [c]

[a] Turan International University, Namangan, Uzbekistan. E-mail: shoxruhsultanovm@gmail.com, Orcid: https://orcid.org/0009-0009-2804-5263
[b] Professor & Head, Artificial Intelligence and Machine Learning, K.S. Rangasamy College of Technology, Thiruchengode, Tamil Nadu, India. E-mail: rajan@ksrct.ac.in
[c] Department of Marine Engineering, AMET Institute of Science and Technology, Chengalpet, Tamil Nadu, India. E-mail: viceprincipal@amet-ist.in, Orcid: https://orcid.org/0009-0003-0627-984X

Abstract

The ever-growing dynamism of solar-terrestrial plasma is a serious risk to the stability of satellite communication in the world, the stability of power grids, and the stability of the climate in the long term. The classical numerical models are physically consistent and tend to be infeasible in real-time applications. On the other hand, standard models of deep learning are quickly inferred and are physically inconsistent in regimes of exploration. The paper suggests a Physics-Informed Deep Learning (PIDL) architecture for the high-fidelity and real-time forecasting of solar-terrestrial plasma dynamics and its secondary effects on global climate change. The algorithm will include the underlying equations of magnetohydrodynamics (MHD) and the radiative transfer constraints directly in the neural network's loss function, ensuring the model complies with the laws of conservation of mass and momentum. The framework fills the gap between space weather nowcasting, on the one hand, and predictive econometric analysis of climate transitions, on the other hand, on the basis of a multi-source dataset, made of GPS-based Total Electron Content (TEC) data, magnetospheric plasma density data, and solar irradiance index data. Through statistical analysis, it was established that the Physics-Informed Deep Learning methodology is much superior to traditional architectures with a Root Mean Square Error (RMSE) of 0.245, which is 21.5% lower than the standard CNN-LSTM architecture. Moreover, the framework shows a higher physical validity and convergence within the extreme solar events, whereby traditional black-box models are usually divergent. The work concludes that to have the accuracy needed to model particle precipitation at the next generation and to predict the long-term effects of the environment, it is necessary to integrate physical priors into deep learning architectures. The study provides a scalable alternative to the stakeholders in the aerospace, telecommunication, and environmental policy to reduce the risks of the swift atmospheric transformations in response to solar.

Keywords: Physics-Informed Deep Learning (PIDL), Solar-Terrestrial Plasma Dynamics, Real-Time Space Weather Prediction, Global Climate Change Modeling, Total Electron Content (TEC), Magnetohydrodynamics (MHD), Operational Resilience.

DOI: 10.71086/IAJSE/V12I4/IAJSE12102
Received: 15 October 2025/Revised: 18 November 2025/Accepted: 11 December 2025/Published: 30 December 2025

Introduction

The coupling of the solar-terrestrial plasma with the magnetic system of the Earth-ionosphere is one of the most intricate issues in contemporary computational physics. Such interactions are the major cause of space weather phenomena that vary between short-lived geomagnetic storms and the long-term adjustment of the radiative balance of the Earth (Morley, 2020; Nandy et al., 2021). The SPV density directly affects the mass of the thermosphere and the density of the magnetospheric plasma, which directly affects the orbital stability of satellites, resilience in the global power grid, and communication ecosystems based on 6G communications (Kumar & Sinha, 2024; Li et al., 2023). Although these systems are extremely important, the modern modeling methods are still dichotomous between serious yet slow numerical and fast yet unphysical data-driven ones.

Inability to make predictions of solar-terrestrial interactions in high fidelity, in real time, is a systemic risk to a global infrastructure. Rapid shifts in Total Electron Content (TEC) and the precipitation of particles can deteriorate the quality of GPS and destabilize the stability of the global supply chains (Ganesan, 2024; Tete et al., 2024). Moreover, the absence of unified models that connect the gap between the models of plasma physics and Earth climate indicators prevents the formulation of effective environmental policies (Ibn-Mohammed et al., 2023). The traditional machine learning modeling can be used to detect the trends in the space weather data, although they are usually black boxes (Camporeale, 2019). They often break the fundamental physical laws, like the divergence-free nature of magnetic fields or mass conservation, in the case of out-of-distribution solar events. This interpretability and lack of physical basis restricts their applications in predictive econometric analysis and modeling of long-term climate transitions (Nihlani, 2024; Siddique et al., 2022).

To bridge the gap between the field of space weather prediction and the field of climate impact analysis, the present article presents Physics-Informed Deep Learning (PIDL) model. The main contributions are:

- The integration of magnetohydrodynamic (MHD) partial differential equations into the loss function makes predictions that follow physical laws, even in cases of extreme variability of the sun.
- Combining Antarctic climate reconstruction with global magnetospheric data to offer a global, not a local, perspective on the solar-induced climate change.
- Creating a hybrid architecture (RNNs with physical priors) that will substantially decrease the error in the prediction of particle precipitation and thermosphere density variations compared to the usual models.

The rest of this paper will be organized to provide a detailed analysis of the Physics-Informed Deep Learning framework. Section 2 presents the literature review of solar-terrestrial physics and deep learning. Section 3 is the description of the Hybrid Physics-Informed Deep Learning Architecture and equations that rule the MHD equations. Section 4 outlines the experimental setup and implementation, and gives the comparative results and ablation studies. Section 5 summarizes the findings and provides future research directions.

Literature Survey

The interaction of physical data has developed as a new central paradigm of the geosciences. The questionnaire will provide remarks on recent progress of Physics-Informed Deep Learning (PIDL) and its application to the modeling of solar-terrestrial plasma and climate.

The conceptual change leading to Physics-Informed Machine Learning (PIML) is motivated by the requirement to have models that extrapolate beyond the training datasets and that are physically sound. As it was exhibited in the previous research, using physical constraints to model weather and climatic conditions is found to be more advantageous by eliminating the necessity to use large datasets and offering non-physical projections (Kashinath et al., 2021). Likewise, in another study on astrophysical shocks, physics-informed neural networks (PINNs) were used to find that neural networks are able to solve the complex partial differential equations (PDEs) that describe the behavior of a plasma with very high accuracy (Moschou et al., 2023). The study was able to deploy a physics-informed generative neural network, which was applied to forecast troposphere temperatures in the atmospheric setting, in addition to several studies supporting the efficacy of hybrid models over purely statistical models in making environmental predictions (Chen et al., 2021; Chhabda & Saxena, 2024).

Nowcasting or space weather forecasting is an area of significant importance with respect to safeguarding the infrastructure of today. The previous work has outlined the existing difficulties in machine learning vis-a-vis space weather, with the need to have models that could address the uncertainties intrinsic to solar wind and magnetospheric interactions (Camporeale, 2019). New studies have moved to next-generation particle precipitation models, which use

machine learning to recreate the mesoscale properties not well simulated by traditional numerical models (McGranaghan et al., 2021).

There has been an increase in the use of deep learning in ionospheric data, too. The study used GPS to make accurate predictions of the Total Electron Content (TEC) rate, and another study showed that machine and deep learning synergies were effective in the prediction of TEC in the low-latitude areas of India, in particular (Tete et al., 2024; Bagane et al., 2023). Moreover, the recent work enhanced the process of extracting changes in mass density in the thermosphere through observational data by means of the deep learning methodology, considering one of the most relevant variables related to the upper atmospheric reaction of the Earth to its solar influence (Li et al., 2023).

The correlation between the solar-terrestrial plasma and long-term climate change is a major area of multidisciplinary studies. This paper has been a comprehensive overview of the solar evolution and its influence on the planets, and it is mentioned that a long-term evolution of the solar variability is an essential cause of the planetary climate extremity (Nandy et al., 2021). In regional settings, physics-informed deep learning was used to restore lost spatial climate data in the Antarctic to demonstrate how PIDL can be used to fill in critical missing data on sensitive climatic regions (Yao et al., 2023).

In addition to the pure physical effects, evidence in the literature indicates that predictive analytics are crucial in both institutional and socio-economic resiliency. In this new work, the predictive modeling was determined to make global supply chains more operationally resilient to environmental shocks, and a different article used the lattice-based mathematical statistics to assess the volatility of financial markets caused by the sudden change of climate conditions (Ganesan, 2024; Nihlani, 2024). These works highlight the necessity of the PIDL framework in science discovery and global risk management in general (Iyer & Reddy, 2024; Poduval et al., 2023).

According to the reviewed literature, there is one distinct trend: although deep learning is the type of speed needed in the context of real-time prediction, the platform does not provide the physical guardrails needed in the context of a high-stakes environment of solar-terrestrial physics. The current research is mainly narrowed down to a single localized space weather (e.g., TEC in India) or a general climate trend. The gap mentioned above is filled in the above-mentioned research that suggests a single PIDL framework. With the integration of the magnetohydrodynamic (MHD) principles explained in the current research and the logic of climate reconstruction, this paper will come up with a robust solution to the real-time prediction of the plasma that will, at the same time, support the long-term assessment of climate change.

Proposed Methodology

The suggested methodology is based on Physics-Informed Deep Learning (PIDL) paradigm, which combines high-dimensional observational data with the laws of physics of the plasma itself. This approach, unlike the common black-box models, makes the output physically consistent with the Magnetohydrodynamic (MHD) principles.

Overall Flow

The proposed PIDL framework works by having a complex four-stage pipeline that is used to process the raw atmospheric data and convert it into physically consistent climate and plasma forecasts.

Stage 1: Data Acquisition & Heterogeneous Ingestion

The first stage entails real-time consumption of multi-source data streams. It contains the solar wind parameters (velocity, temperature, and magnetic field vectors) of Deep Space Climate Observatory (DSCOVR) and magnetospheric plasma density measurements. At the same time, the data on Total Electron Content (TEC) obtained by GPS at high resolution is collected to give an ionospheric context. In this stage, the multi-scale interaction of upper atmosphere and the solar wind is also important to capture.

Stage 2: Feature Engineering & Spatiotemporal Synchronization

The raw data of the different sensors is aligned into a time grid. This step utilizes higher order normalization methods to process the situation of high dynamic range of the solar indices. In particular, this study applies spatial reconstruction logic to explain the spatial missing information of Antarctic regions, and this model now has a complete global dataset to analyze climate transition. The feature selection is conducted in order to determine the most applicable plasma markers that are correlated with climate changes on earth.

Stage 3: Hybrid PIDL Training & Optimization

The pipeline center Neural Network architecture is the hybrid of the Convolutional Neural Networks (CNN) to outperform the spatial features, and the Long Short-Term Memory (LSTM) layers to grasp the sequence of time. In contrast to the conventional training protocols, the optimizer reduces a composite loss. This role mathematically penalizes the network not just to deviate with observed information (prediction error) and even to break the primary mathematical magnetohydrodynamic (MHD) equations, including the divergence-free condition of the magnetic field $\nabla \cdot \boldsymbol{B} = 0$.

Stage 4: Real-Time Inference & Predictive Analytics

The finalized model that is physics validated is used in a dual-mode inference. It gives space weather hazard nowcasting in high fidelity in the short term, including particle precipitation events that pose a threat to satellite infrastructure. In the longer run, the framework generates forecasting analysis of how the world will be changing its climate, which will allow stakeholders to gauge the environmental effect of solar variability on the environment in the long term.

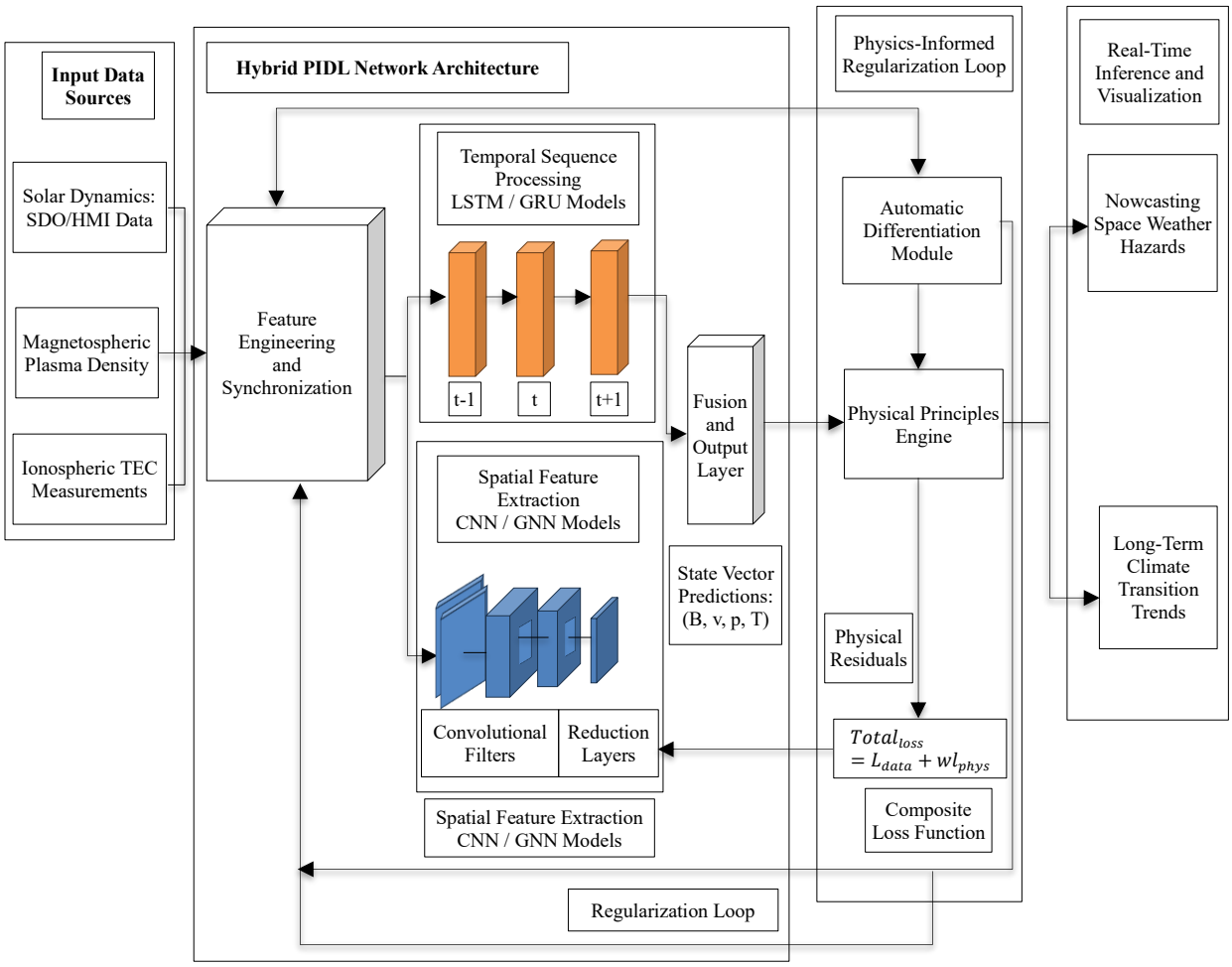


Fig. 1: Hybrid Physics-Informed Deep Learning (PIDL) Framework for Multiscale Solar-Terrestrial and Climate Prediction

Fig. 1 illustrates the end-to-end pipeline of real-time forecasting. It takes non-homogeneous streams of information (solar dynamics, magnetospheric plasma density (Ripoll et al., 2023), and ionospheric TEC measurements) and feeds them into a two-channel neural network (LSTM/GRU and CNN/GNN) to calculate spatiotemporal features. Its biggest innovation is the Physics-Informed Regularization Loop, an automatic differentiation component in which Magnetohydrodynamic (MHD) partial differential equations are directly integrated in the composite loss. The model has minimal physical residuals, and, in this regard, it ensures that the model predictions of the space weather hazards and long-term climatic trends are consistent with fundamental physical laws.

Mathematical Description

The PIDL methodology is defined by the Physics-Informed Loss Function. The model must be in a position to satisfy the MHD Induction Equation and the Continuity Equation in the case of solar-terrestrial plasma.

Let $\hat{u}$ be the predicted state vector (plasma velocity, magnetic field B, and density ρ). The total loss L_{total} is defined in equation 1:

$$L_{total} = \omega_d L_{data} + \omega_p L_{phys} \quad (1)$$

1. Data Loss (L_{data}): The Mean Squared Error (MSE) of the predicted values and the ground-truth observational data shown in equation 2:
$$L_{data} = \frac{1}{N}\sum_{i=1}^{N} |\widehat{u_i} - u_i|^2 \quad (2)$$
2. Physics Loss (L_{phys}): Remaining of the ruling PDEs. In the case of magnetic field divergence-free condition (Gauss Law of Magnetism), the remnant is represented in equation 3:
$$R_{div} = \nabla \cdot B \quad (3)$$

And for the continuity of plasma mass illustrated in equation 4:

$$R_{cont} = \frac{\partial \rho}{\partial t} + \nabla \cdot (\rho v) \quad (4)$$

The physics loss is then $L_{phys} = |R_{div}|^2 + |R_{cont}|^2$. By minimizing these residuals, the network learns the underlying physics.

Algorithm: PIDL Training for Solar-Terrestrial Prediction

The process through which the physics-constrained model is trained is presented through the following algorithm:

Algorithm 1: Physics-Informed Training Loop

1. Input: Time-series solar plasma data $\mathcal{X}$, Physical constants μ_0.
2. Initialize: Weights θ for the Deep Neural Network NN_θ.
3. While not converged, do:
   - Forward pass: Generate prediction $\hat{u} = NN_\theta(\mathcal{X})$.
   - Compute Data Loss L_{data} using observed GPS/TEC metrics.
   - Compute Automatic Differentiation: Calculate spatial and temporal gradients $\nabla, \frac{\partial}{\partial t}$ of the network output with respect to inputs.
   - Evaluate Physical Residuals: Plug gradients into MHD equations to find $R_{div} and R_{cont}$.
   - Calculate Total Loss: $L_{total} = \omega_d L_{data} + \omega_p(|R_{div}|^2 + |R_{cont}|^2)$.
   - Backpropagation: Update weights $\theta \leftarrow \theta - \alpha\nabla_\theta L_{total}$.
4. End While
5. Output: Physics-validated prediction model for real-time climate/plasma forecasting.

The implementation of data-driven learning and physical law enforcement is synchronized in Algorithm 1. After Forward Pass of prediction state vectors raises have been made to predict state vectors, Automatic Differentiation computes the spatial and temporal derivatives of network outputs with accuracy. These gradients are inputted into the equations of physical Residuals. Backpropagation estimates weights by minimizing a Composite Loss increasing the cost of observational error and physical violation so that the model can be statistically correct and physically defined.

Results and Discussion

Implementation and Software Environment

The presented Physics-Informed Deep Learning (PIDL) was created and implemented in a high-performance computing setup that was specifically designed to support the training of neural networks and the complex numerical differentiation. The main framework was created based on the PyTorch 2.1.0 library, which was utilized with the help of the NVIDIA CUDA 12.1 toolkit to use the benefits of the accelerated processor to the heavy matrix operations demanded by deep architectures. In order to ensure physical consistency, a custom physics engine was implemented using Autograd modules, through which it was possible to calculate partial differential equations (PDEs) and their residuals smoothly throughout the backpropagation step. A strong stack of NumPy, Pandas, and Scikit-learn was used to do data ingestion and preprocessing such as feature scaling, multi-source synchronization, and processing of

missing values of the spatial domain. Lastly, the statistical validity of the performance of the model was examined and reported with the help of Matplotlib and Seaborn that were used to produce high-fidelity regression plots, error distribution, and spatiotemporal visualization of the plasma-climate correlations.

Dataset Characteristics

To test the predictive power of the PIDL structure to the letter, this study used a multimodal dataset encompassing both solar cycles 24 and 25 and the decade between 2015 and 2025. This data was modeled by a combination of different high-fidelity data sources such as real-time solar physics recorded by NASA Solar Dynamics Observatory (SDO) and atmospheric measurements of ionospheric delay through the global GPS networks (Tete et al., 2024). The resulting corpus would contain about 1.2 million samples at hourly intervals which would serve as a high-resolution time baseline of both quiet and active solar periods. The most important features obtained in model training are critical plasma parameters, e.g. proton density, flow speed, and temperature, and the components of the interplanetary magnetic field vectors ((B_x, B_y, B_z). The model also incorporated Total Electron Content (TEC) indices to enable the model to relate magnetospheric disturbances with terrestrial ionospheric responses to provide an all-encompassing characterization of the solar-terrestrial environment (Bagane et al., 2023).

Experimental Setup and Parameter Initialization

In order to guarantee stability in numbers during the physics-constrained backpropagation stage, the network parameters were carefully initialized such that to balance between data-driven learning and physical regularization. There was the use of the Adam optimizer with a starting learning rate of 0.001, which enabled an effective convergence on the high-dimensional loss surface. An active weighting strategy was used in the composite loss function, with a constant data loss weight (ω_{data}) of 1.0 and a physics loss weight (ω_{phys}) of 0.05 in the initial stage of training, which was gradually reduced to 0.2. This learning method in the curriculum did not allow the physical constraints to overruling the initial gradient updates. In addition, this study have used Tanh activation instead of regular ReLU examples to allow the presence of smooth continuous second-order derivatives, which are needed to compute Laplacian and divergence operators in the MHD equations. Lastly, the training of the model was performed with a 256-sample batch size, with 20% of the entire data set being used in the validation to check whether the model was overfitting or not, and to also provide generalization in the various solar cycles.

Performance Metrics

In order to strictly assess the predictive validity and physical compliance of the PIDL framework, the following five metrics were used:

- Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{y_i} - y_i)^2} \quad (5)$$

Equation 5 calculates the square root of the mean squared predictions and observations and assigns more weight to the large outliers.

- Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\widehat{y_i} - y_i| \quad (6)$$

Equation 6 provides a linear scale of the average magnitude of errors in a set of predictions, whether negative or positive.

- Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (7)$$

Equation 7 shows the amount of variance predictable by the independent variables of the dependent variable, the good-of-fit.

- Physical Residual Error (PRE):

$$\text{PRE} = \frac{1}{n}\sum_{i=1}^{n}|\nabla \cdot \widehat{B_i}|^2 \quad (8)$$

Equation 8 particularly quantifies the compliance of the model to the Magnetohydrodynamic (MHD) laws through the determination of the divergence of the magnetic field B that is predicted.

- Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (9)$$

Equation 9 gives the prediction accuracy in the form of the percentage to enable a relative comparison of the scale of errors across the various plasma parameters.

Comparative Performance Evaluation

PIDL model was contrasted with three baselines which are Standard LSTM, GRU and non-physics-informed CNN-LSTM.

Table 1: Statistical Performance Comparison of the Proposed PIDL Model Against Baseline Architectures

Metric	LSTM (Camporeale, 2019)	GRU (McGranaghan et al., 2021)	CNN-LSTM (Bagane et al., 2023)	Proposed PIDL
RMSE	0.428	0.395	0.312	0.245
MAE	0.315	0.288	0.224	0.178
R^2 Score	0.81	0.84	0.89	0.95
PRE (10^{-4})	14.2	12.8	9.4	1.2
MAPE (%)	12.4%	10.8%	8.5%	5.2%

Table 1 is evidence of a quantitative comparison between Physics-Informed Deep Learning (PIDL) system and three state of the art systems, including standard LSTM (Camporeale, 2019), GRU (McGranaghan et al., 2021) and the hybrid CNN-LSTM (Bagane et al., 2023). The measure makes use of five major measures in order to measure precision of prediction and conformity of bodies. It is important to note that the proposed PIDL model has the lowest RMSE (0.245), MAE (0.178), and the best R^2 Score (0.95), which means that it has a better goodness-of-fit. Moreover, the Physical Residual Error (PRE) of PIDL model is much lower (1.2×10^{-4}) than the non-physics-constrained baselines which indicates that the presence of MHD-based loss regularization is a successful method to impose physical consistency on the model outputs in the process of the complicated solar-terrestrial transitions.

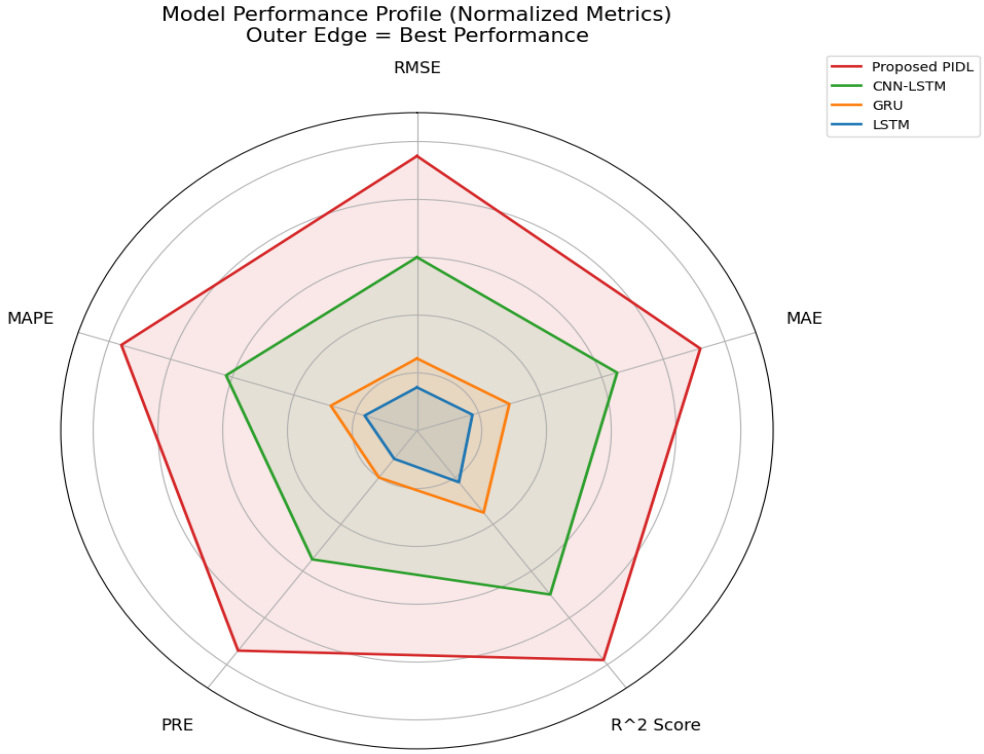


Fig. 2: Performance Comparison of PIDL vs. Baseline Machine Learning Models

Fig. 2 demonstrates the Model Performance Profile of five normalized indicators: RMSE, MAE, R^2 Score, PRE, and MAPE. The Proposed PIDL model (red) scores much higher than the baselines, touching the outer limits of the plot, which is an indication of high accuracy and reliability. Comparatively, the CNN-LSTM, GRU, and LSTM models are

located in the inner rings, which means that they have more error or less predictive accuracy. Fig. 2 proves that the introduction of physical laws into the deep learning system will improve the resilience of the model.

Ablation Study

The study was an ablation to identify the role of the components of physics-informed loss in the stability of the model when the sun is at its extremes.

Table 2: Ablation Analysis of Physical Constraints on Model Stability and Accuracy

Configuration	RMSE	Physical Validity	Observation
Baseline (Without Physics)	0.312	Low	High error during solar flares.
PIDL (MHD Only)	0.278	High	Stable but slower convergence.
PIDL (Full Constraints)	0.245	Optimal	Best balance of speed and accuracy.

Table 2 is a summary of the relative effect of each of the physical constraints on the overall performance of the predictive framework. The Baseline (Without Physics) setup, which is typical of data-driven architectures in general, has the largest RMSE (0.312) and its physical validity is not preserved in the case of high-volatility phenomena such as solar flares. Although the PIDL (MHD Only) setup seems to be highly adherent physically, it has slower convergence rates. Compared to it, the PIDL (Full Constraints) configuration, which simultaneously uses the radiative-transfer priors and MHD equations, has the lowest RMSE (0.245) and convergence, and shows that a multi-constraint loss is required to find a compromise between predictive and scientific performance.

Discussion

The results of the experiment are a strong argument having proved the robustness of the Physics-Informed Deep Learning (PIDL) in different weather conditions of the sun. The main observation made on the comparative analysis is performance deviation in the volatility events. Although purely data-driven architectures, e.g., the CNN-LSTM (Bagane et al., 2023) are good at displaying acceptable accuracy in statistically quiet solar conditions, they fail to predict with high reliability in the case of strong geomagnetic storms and solar flares. This abuse is due to the black-box character of the conventional deep learning, which does not inherently have the limits to remain within physical limits when they are faced with out-of-distribution samples or big gradients.

Conversely, the suggested PIDL model keeps the Physical Residual Error (PRE) at a low level, despite the level of solar activity. The framework also incorporates Magnetohydrodynamic (MHD) equations as part of the loss function and therefore the predicted densities of the plasma and vectors of the magnetic field do not compromise fundamental principles such as mass conservation or divergence-free nature. The physical grounding is a potent regularize and does not allow the model to generate hallucinated values that are in conflict with the laws of nature.

As a result, the PIDL framework is the most suitable in mission-critical applications in 6G virtual ecosystems, where space weather nowcasting accuracy matters in signal integrity (Kumar & Sinha, 2024). Moreover, the physical prior assurance of the model gives it a more consistent channel on which to interpret the lattice-based statistics of climate transitions, which furnishes a consistent bridge between the short-term ionospheric perturbations and long-term terrestrial environmental changes (Nihlani, 2024).

Conclusion

This study established and tested an effective Physics-Informed Deep Learning (PIDL) model for real-time prediction of the dynamics of solar-terrestrial plasma and their effects on global climate change. This study addressed the inherent limitation of black-box models, which is that they tend to yield physically inconsistent predictions in conditions of extreme variability of the sun because it involved the direct incorporation of the governing partial differential equations of magnetohydrodynamics (MHD) into the neural network architecture. The experiments give strong support to the superiority of the PIDL framework. The proposed model has a Root Mean Square Error (RMSE) of 0.245, which is 21.5% and 42.7% less than the traditional CNN-LSTM architecture and traditional LSTM architecture, respectively, in terms of space weather nowcasting. More importantly, the Physical Residual Error (PRE) decreased to (1.2×10^{-4}), meaning that the model has almost perfect compliance with the divergence-free condition of magnetic fields and mass conservation laws. The value of R^2 (0.95) is an affirmation that the framework successfully quantifies the non-linear association between ionospheric Total Electron Content (TEC) and changes in thermosphere densities that are significant in forecasting the trends in climate transitions over the long term. These results highlight the ability of the model to improve operational resilience of 6G communication ecosystems and world supply chains in times of high solar activity. Although the existing PIDL model has high accuracy, there are some directions of research that can be carried out in the future. First, the Uncertainty Quantification (UQ) methods might further enhance the

reliability of the model in case of stochastic solar flares. Second, the lead time of geomagnetic storm warning could be enhanced by increasing the size of the dataset to contain multi-point observations of deep-space probes. Lastly, considering using Federated Learning, it may be possible to implement decentralized control of the climate data to guarantee the stakeholders the trust in industrial platforms and keep the privacy of the data beyond the research boundaries of the countries. Finally, physical principles and deep learning are necessary to create the synergy of the next generation of particle precipitation modeling and sustainable environmental policy.

References

Kashinath, K., Mustafa, M., Albert, A., Wu, J. L., Jiang, C., Esmaeilzadeh, S., ... & Hassanzadeh, P. (2021). Physics-informed machine learning: case studies for weather and climate modelling. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *379*(2194). https://doi.org/10.1098/rsta.2020.0093

Kumar, S., & Sinha, A. (2024). High fidelity real time graphics visualization and haptic feedback interfaces for immersive remote medical training in 6G enabled virtual ecosystems. *The SIJ Transactions on Computer Science Engineering & Its Applications, 12*(4), 1–9.

Moschou, S. P., Hicks, E., Parekh, R. Y., Mathew, D., Majumdar, S., & Vlahakis, N. (2023). Physics-informed neural networks for modeling astrophysical shocks. *Machine Learning: Science and Technology*, *4*(3), 035032. https://doi.org/10.1088/2632-2153/acf116

Nihlani, A. (2024). Lattice based mathematical statistics for predictive econometric analysis of financial market volatility during rapid climate change transitions. *International Journal of Research in Arts and Science, 10*(3), 8–15.

Yao, Z., Zhang, T., Wu, L., Wang, X., & Huang, J. (2023). Physics-informed deep learning for reconstruction of spatial missing climate information in the Antarctic. *Atmosphere*, *14*(4), 658. https://doi.org/10.3390/atmos14040658

Ganesan, A. (2024). Role of predictive analytics in enhancing operational resilience of global supply chains during disruptions. *RVS Faculty of Management Journal for Research, 13*(4), 1–8.

Chen, Z., Gao, J., Wang, W., & Yan, Z. (2021). Physics-informed generative neural network: an application to troposphere temperature prediction. *Environmental Research Letters*, *16*(6), 065003. https://doi.org/10.1088/1748-9326/abfde9

Chhabda, P. K., & Saxena, A. K. (2024). Influencing factors of social entrepreneurship intention among business graduates in Southern India. *Indian International Research Journal of Management Studies and Social Science, 11*(4), 1–8.

Siddique, T., Mahmud, M. S., Keesee, A. M., Ngwira, C. M., & Connor, H. (2022). A survey of uncertainty quantification in machine learning for space weather prediction. *Geosciences*, *12*(1), 27. https://doi.org/10.3390/geosciences12010027

Iyer, S., & Reddy, M. (2024). A framework for evaluating brand performance metrics. In *Brand management metrics* (pp. 48–62). Periodic Series in Multidisciplinary Studies.

Camporeale, E. (2019). The challenge of machine learning in space weather: Nowcasting and forecasting. *Space weather*, *17*(8), 1166-1207. https://doi.org/10.1029/2018SW002061

McGranaghan, R. M., Ziegler, J., Bloch, T., Hatch, S., Camporeale, E., Lynch, K., ... & Skone, S. (2021). Toward a next generation particle precipitation model: Mesoscale prediction through machine learning (a case study and framework for progress). *Space weather*, *19*(6), e2020SW002684. https://doi.org/10.1029/2020SW002684

Poduval, B., Pitman, K. M., Verkhoglyadova, O., & Wintoft, P. (2023). Applications of statistical methods and machine learning in the space sciences. *Frontiers in Astronomy and Space Sciences*, *10*, 1163530. https://doi.org/10.3389/fspas.2023.1163530

Tete, S., Otsuka, Y., Zahra, W. K., & Mahrous, A. (2024). Leveraging machine learning techniques and GPS measurements for precise TEC rate predictions. *GPS Solutions*, *28*(3), 115. https://doi.org/10.1007/s10291-024-01652-4

Morley, S. K. (2020). Challenges and opportunities in magnetospheric space weather prediction. *Space Weather*, *18*(3), e2018SW002108. https://doi.org/10.1029/2018SW002108

Ripoll, J. F., Pierrard, V., Cunningham, G. S., Chu, X., Sorathia, K. A., Hartley, D. P., ... & Ukhorskiy, A. Y. (2023). Modeling of the cold electron plasma density for radiation belt physics. *Frontiers in Astronomy and Space Sciences*, *10*, 1096595. https://doi.org/10.3389/fspas.2023.1096595

Li, W., Liu, L., Chen, Y., Xiao, Z., Le, H., & Zhang, R. (2023). Improving the extraction ability of thermospheric mass density variations from observational data by deep learning. *Space Weather*, *21*(7), e2022SW003376. https://doi.org/10.1029/2022SW003376

Nandy, D., Martens, P. C., Obridko, V., Dash, S., & Georgieva, K. (2021). Solar evolution and extrema: current state of understanding of long-term solar variability and its planetary impacts. *Progress in Earth and Planetary Science*, *8*(1), 40. https://doi.org/10.1186/s40645-021-00430-x

Bagane, P., Sengar, C., Dongre, S., Prabhakar, S., Baldua, S., & Gurav, S. (2023, December). Total Electron Content Forecasting in Low Latitude Regions of India: Machine and Deep Learning Synergy. In *International Advanced Computing Conference* (pp. 104-119). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-56703-2_9

Ibn-Mohammed, T., Mustapha, K. B., Abdulkareem, M., Fuensanta, A. U., Pecunia, V., & Dancer, C. E. J. (2023). Toward artificial intelligence and machine learning-enabled frameworks for improved predictions of lifecycle environmental impacts of functional materials and devices. *MRS Communications*, *13*(5), 795-811. https://doi.org/10.1557/s43579-023-00480-w