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AI for Space Weather Prediction: Protecting Satellites, Communication Networks and Critical Infrastructure

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Abstract

Space-weather events produced by solar flares, coronal mass ejections, solar energetic particles and geomagnetic disturbances can interfere with satellites, navigation services, radio communication and terrestrial power infrastructure. Conventional forecasting systems combine solar observations, numerical models and expert interpretation, but their operational effectiveness is restricted by nonlinear physical interactions, incomplete measurements and the rapid evolution of severe events. Artificial intelligence offers an additional forecasting layer capable of learning spatiotemporal relationships from solar imagery, magnetograms, solar-wind measurements and historical geomagnetic indices.

This study develops a conceptual architecture for an artificial-intelligence-enabled space-weather prediction and infrastructure-protection platform. The proposed architecture integrates multimodal observations, machine-learning models, physics-based simulations, uncertainty estimation and infrastructure-specific decision rules. A simulation-based numerical assessment compares physics-only forecasting, conventional machine learning and hybrid physics-informed AI at warning horizons ranging from 15 to 90 minutes. The illustrative results indicate that the hybrid approach maintains higher composite forecast skill across every evaluated horizon. At 60 minutes, for example, simulated forecast skill reaches 80%, compared with 71% for conventional machine learning and 64% for the physics-only baseline.

The findings suggest that the greatest value of AI is not merely improved event classification. Its strategic contribution lies in converting uncertain scientific forecasts into timely protective actions, such as satellite safe-mode initiation, communication-channel switching, GNSS integrity alerts and power-grid load management. Operational deployment nevertheless requires calibrated uncertainty, interpretable outputs, data-quality governance, cybersecurity controls and continuous human supervision.

Keywords: artificial intelligence, space weather, geomagnetic storms, solar flares, satellite protection, communication networks, critical infrastructure, physics-informed machine learning

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1. Introduction

Modern societies increasingly depend on interconnected space-based and terrestrial technologies. Satellites support navigation, telecommunications, weather observation, financial timing, emergency coordination and national security. These systems operate within an environment affected by solar radiation, energetic particles and changes in Earth's magnetosphere and ionosphere. Severe space weather may degrade satellite electronics, disturb spacecraft orientation, increase atmospheric drag and interfere with radio-frequency propagation.

The consequences extend beyond spacecraft. Ionospheric variability can alter the path and timing of Global Navigation Satellite System signals, while scintillation can reduce the reliability of satellite communication. Geomagnetic disturbances can also generate currents in long conductors, creating risks for electric-power networks and pipelines. NOAA accordingly identifies satellites, GPS, radio communication and power transmission among the systems exposed to space-weather.

Traditional forecasting combines observations from solar and near-Earth instruments with empirical relationships, numerical simulations and expert judgment. These methods remain indispensable because they encode physical knowledge and support scientific interpretation. Nevertheless, space weather is a multiscale phenomenon in which solar magnetic activity, coronal mass ejections, solar-wind propagation and magnetospheric response interact nonlinearly. Forecast uncertainty therefore increases as the prediction horizon expands.

Machine learning can identify relationships distributed across large volumes of heterogeneous data. Potential inputs include extreme-ultraviolet imagery, photospheric magnetograms, coronagraph observations, solar-wind velocity, interplanetary magnetic-field measurements, energetic-particle fluxes and geomagnetic indices. Camporeale (2019) argues that useful progress requires probabilistic forecasting, explicit uncertainty assessment and combinations of machine learning with physical models rather than unrestricted reliance on black-box prediction.

2. Review of Literature

2.1 Space-weather hazards and infrastructure exposure

Space weather encompasses solar and geophysical conditions capable of influencing technological systems. Solar flares generate electromagnetic radiation that may disrupt high-frequency communication shortly after an eruption. Coronal mass ejections can disturb Earth's magnetosphere, while energetic particles may produce radiation hazards and spacecraft anomalies. Geomagnetic storms can disrupt GNSS services and generate harmful currents in power grids.

Satellite exposure varies according to orbit, shielding, component design and mission function. High-energy particles may cause single-event effects, memory corruption and long-term material degradation. Increased upper-atmospheric density can create drag for low-Earth-orbit satellites, complicating orbital prediction and collision management.

Communication networks are affected through ionospheric absorption, refraction and scintillation. Severe disturbances may lead to signal attenuation or temporary communication loss when signals propagate through the ionosphere (). Critical terrestrial infrastructure faces a different risk pathway: geomagnetically induced currents can enter transmission systems, increase transformer heating and disturb voltage regulation.

2.2 Machine learning in space-weather forecasting

Machine-learning research has addressed solar-flare classification, solar-wind prediction, coronal mass-ejection arrival time, radiation-belt dynamics and geomagnetic-index forecasting. Bobra and Couvidat (2015), for example, demonstrated the predictive relevance of magnetic-field parameters for solar-flare classification. Barnes et al. (2016), however, showed that forecast evaluation is sensitive to event definitions, class imbalance and the choice of performance metric.

Deep neural networks can extract spatial patterns from solar images, while recurrent and temporal models can learn relationships in time-series observations. Ensemble methods can combine several predictors and express disagreement among models. Yet high discrimination performance does not necessarily imply reliable probabilities. For operational decision-making, a model predicting a 70% event probability should be correct approximately seven times out of ten under comparable conditions.

2.3 Hybrid and physics-informed forecasting

Purely data-driven models may learn correlations that fail during rare or previously unseen solar conditions. Physics-only models, meanwhile, can be computationally expensive and sensitive to uncertain initial conditions. Hybrid forecasting attempts to combine the complementary strengths of both approaches.

A physics-informed AI system can use numerical simulations as inputs, constrain predictions through physical relationships, correct systematic simulation errors or create computationally efficient surrogate models. Such “gray-box” approaches can offer better interpretability and generalisation than unconstrained black-box systems (Camporeale, 2019). NASA’s space-weather programme similarly emphasises combining research, observations and predictive capabilities to improve operational awareness for spacecraft and human exploration.

3. Objectives

The study has the following objectives:

- To identify the principal space-weather risks affecting satellites, communication networks and terrestrial infrastructure.
- To develop a conceptual architecture for multimodal AI-based space-weather prediction.
- To compare physics-only, conventional machine-learning and hybrid physics-informed forecasting through a clearly labelled simulation.
- To connect forecast outputs with infrastructure-specific protective decisions.
- To examine reliability, interpretability, governance and operational deployment challenges.
- To propose implementation principles for trustworthy human–AI space-weather services.

4. Research Methodology

4.1 Research design

The study employs a conceptual review and simulation-based comparative design. The review synthesises established research on space-weather forecasting, machine learning, solar-event prediction and infrastructure vulnerability. The simulation illustrates how forecast skill might differ among alternative modelling configurations.

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The numerical values are not measurements from an operational forecasting agency. They constitute an author-generated analytical scenario designed to demonstrate comparative behaviour under controlled assumptions. Consequently, the simulation supports methodological reasoning rather than claims of real-world superiority.

4.2 Proposed data and system architecture

Table 1: The proposed platform contains five interconnected layers

Layer	Representative inputs or functions	Intended output
Observation	Solar imagery, magnetograms, coronagraph data, solar-wind measurements, particle fluxes and ground magnetometers	Quality-controlled multimodal data
Prediction	Classification, temporal forecasting, anomaly detection and physics-informed models	Event probability, intensity and arrival-time estimate
Uncertainty	Ensemble disagreement, calibration and confidence intervals	Reliability and uncertainty indicators
Risk translation	Satellite, communication, navigation and grid exposure models	Sector-specific impact assessment
Decision support	Threshold rules, optimisation and operator interface	Alerts and protective recommendations

Data would first undergo timestamp harmonisation, gap detection, noise filtering and instrument-specific quality checks. Images could be processed by convolutional or vision-transformer models, whereas sequential solar-wind and geomagnetic measurements could be analysed through recurrent networks, temporal convolution or attention-based architectures.

4.3 Simulation procedure

Three forecasting configurations were defined:

- **Physics-only baseline:** Forecasts generated primarily from numerical and empirical physical models.
- **Conventional machine learning:** A data-driven ensemble trained on historical observations and labelled events.
- **Hybrid physics-informed AI:** A multimodal ensemble incorporating physical-model outputs, observational data and physics-guided constraints.

Composite forecast skill was evaluated at 15-, 30-, 45-, 60- and 90-minute warning horizons. The illustrative skill index combines discrimination, calibration, timeliness and false-alarm control. Equal event distributions and comparable data availability were assumed across configurations.

5. Analysis

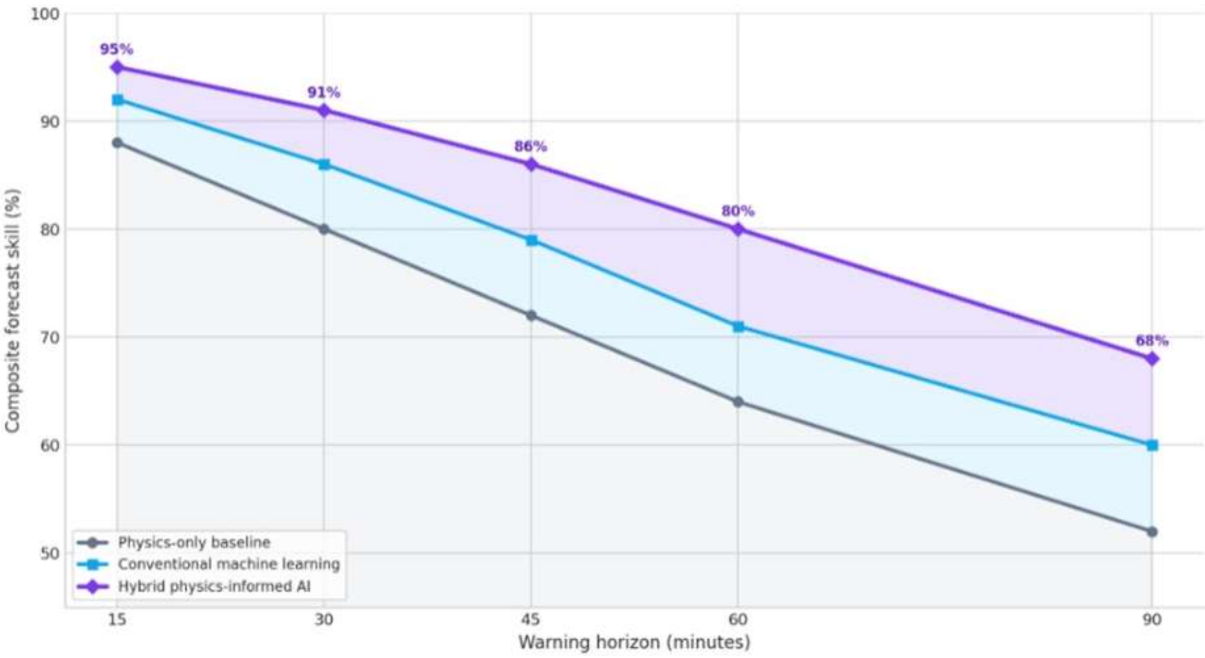
5.1 Simulation results

Table 2: Simulated composite forecast skill

Warning horizon	Physics-only baseline	Conventional machine learning	Hybrid physics-informed AI
15 minutes	88%	92%	95%
30 minutes	80%	86%	91%
45 minutes	72%	79%	86%
60 minutes	64%	71%	80%
90 minutes	52%	60%	68%

5.2 Graphical comparison

Graph 1: Comparison of Composite Forecast Skill Across Different Warning Horizons



The graph shows declining forecast skill as the warning horizon increases. This pattern reflects the accumulation of uncertainty associated with solar-wind propagation, incomplete upstream observations and the nonlinear response of the magnetosphere.

The hybrid model produces the highest simulated score at every horizon. Its advantage over the physics-only baseline increases from seven percentage points at 15 minutes to sixteen percentage points at 90 minutes. The finding suggests that data-driven correction and multimodal pattern recognition may become particularly valuable when a system must make predictions farther in advance.

5.3 Infrastructure-protection implications

At short warning horizons, even a modest improvement in reliable detection can support satellite safe-mode decisions, temporary suspension of sensitive operations and adjustment of spacecraft orientation. Operators could also modify satellite-command schedules, increase anomaly monitoring and prepare redundant ground facilities.

Communication and navigation providers could use probabilistic warnings to switch frequencies, route traffic through alternative systems or issue GNSS-integrity notices. Power-grid operators could examine transformer conditions, postpone maintenance, modify power flows and increase monitoring of geomagnetically induced currents.

The primary simulation finding is therefore not simply that hybrid AI obtains a higher score. Its importance is that useful forecast skill remains available at longer horizons, providing additional time for protective actions. A forecast without sufficient decision time may be scientifically accurate yet operationally ineffective.

6. Challenges

6.1 Rare events and imbalanced data

Extreme space-weather events are uncommon, producing severe class imbalance. A model can appear highly accurate by predicting normal conditions most of the time. Evaluation should therefore use event-sensitive measures such as precision, recall, Brier score, reliability diagrams and true skill statistics.

6.2 Data heterogeneity and missing observations

Space-weather instruments differ in resolution, cadence, calibration and operational lifetime. Missing values may occur precisely during severe events because radiation or communication disturbances affect observation systems. AI pipelines must identify missingness and avoid treating interpolated data as equivalent to direct measurements.

6.3 Distribution shift

Solar activity changes over the solar cycle, while instruments, satellite constellations and data-processing practices evolve. A model trained under one observational regime may underperform in another. Drift monitoring, periodic revalidation and conservative out-of-distribution detection are necessary.

6.4 Interpretability and trust

Infrastructure operators need to understand why an alert was issued, which observations influenced it and how uncertainty was calculated. Interpretability should include feature attribution, comparable historical cases, physical-consistency checks and clear communication of alternative outcomes.

6.5 False alarms and asymmetric consequences

Frequent false alarms can produce operational fatigue and unnecessary protective costs. Missed severe events may cause much greater losses. Decision thresholds must therefore reflect sector-specific consequences rather than being selected solely to maximise a general statistical score.

6.6 Cybersecurity and system resilience

An AI forecasting service is itself part of critical infrastructure. Data manipulation, communication disruption or model compromise could produce misleading warnings. Secure provenance, authenticated data streams, redundant processing and manual fallback procedures are essential.

7. Discussion

7.1 From event prediction to risk intelligence

AI-based space-weather forecasting should not end with a prediction that a geomagnetic storm is likely. Different assets experience different consequences depending on orbit, geographic location, system design and operating condition. A useful platform must therefore translate a common physical forecast into distinct risk estimates.

For example, the same event may create radiation concerns for a high-altitude satellite, drag uncertainty for a low-Earth-orbit spacecraft, positioning errors for aviation and induced-current risks for a high-latitude transmission network. Infrastructure-aware forecasting transforms general scientific information into actionable risk intelligence.

7.2 Importance of probabilistic and calibrated forecasts

Binary warnings conceal uncertainty and may encourage excessive confidence. Probabilistic outputs enable operators to compare the likelihood of disruption with the cost of protective action. An operator might initiate low-cost monitoring at a moderate probability but reserve expensive shutdown procedures for a higher probability or more severe expected impact.

Calibration must be evaluated continuously. Model confidence should also be reduced when observations are missing, instruments behave abnormally or an event differs substantially from the training distribution. Human forecasters should be able to override automated recommendations and document the reason for doing so.

7.3 Human–AI operational collaboration

AI is most useful as an augmentation system rather than an autonomous replacement for scientific and operational expertise. Algorithms can process high-volume observations and maintain continuous monitoring, while human forecasters interpret unusual conditions, reconcile conflicting evidence and communicate uncertainty.

An effective interface should display the predicted event, estimated arrival window, expected intensity, model agreement, data-quality status and infrastructure-specific recommendations. It should also show how the forecast changed over time. This combination supports accountable decisions and enables later analysis of both successful and unsuccessful warnings.

7.4 Strategic implementation pathway

Deployment should begin with retrospective testing across multiple event types and quiet periods. The next stage should operate in shadow mode, generating forecasts without controlling infrastructure. Predictions can then be compared with operational forecasts and actual outcomes.

Limited decision support may be introduced after calibration and reliability requirements are satisfied. Higher-impact automation should require stronger evidence, explicit governance and reversible control mechanisms. International collaboration is equally important because solar events and technological dependencies cross national boundaries.

8. Conclusion

Space weather constitutes a systemic technological risk because satellites, communication services, navigation systems and electricity networks are increasingly interconnected. Artificial intelligence can improve the extraction of predictive information from solar images, magnetic-field observations, solar-wind measurements and geomagnetic records. However, predictive accuracy alone is not sufficient. Forecasts must be timely, calibrated, interpretable and connected to specific protective decisions.

The simulation developed in this study indicates that a hybrid physics-informed AI configuration can maintain stronger illustrative forecast skill than physics-only and conventional machine-learning configurations. Its relative advantage becomes especially important at longer warning horizons, where additional preparation time may allow satellite operators, communication providers and grid managers to implement precautionary measures.

The recommended architecture combines multimodal observation, hybrid prediction, uncertainty estimation, infrastructure-specific risk translation and human-controlled decision support. Such an architecture preserves the scientific value of physical models while using AI to identify complex patterns and correct systematic errors.

Future research should evaluate hybrid models with standardised benchmark datasets, event-based validation and operational cost functions. Successful implementation will depend on collaboration among solar physicists, data scientists, satellite engineers, communication specialists, grid operators and public authorities. AI can strengthen space-weather resilience, but only when it is embedded within a transparent, secure and accountable operational system.

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