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ASSESSING CORONAL MASS EJECTION EFFECTS ON LEO ORBIT SCINTILLATIONS VIA STATISTICAL AI ANALYSIS OF GEO SATELLITE DATA

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Article Info

Abstract

Coronal mass ejections (CMEs) pose a persistent and significant threat to orbital infrastructure, particularly by inducing ionospheric scintillations that disrupt Low Earth Orbit (LEO) satellite communications. This paper proposes a novel methodological framework to assess and predict localized LEO scintillations by applying statistical Artificial Intelligence (AI) to Geostationary Earth Orbit (GEO) satellite data. By utilizing the advanced vantage point of GEO satellites to capture upstream space weather precursors—such as magnetic field fluctuations and soft X-ray background enhancements—the proposed AI model hypothetically maps these signals to downstream LEO signal degradation. Through the integration of deep learning techniques on time-series telemetry, this work aims to transition space weather mitigation from reactive telemetry monitoring to proactive, predictive orbital management.

Keywords:
Satellite communications, GEO Orbits, LEO, CME, AI, Statistics

Introduction

Coronal mass ejections are violent expulsions of plasma(Ali, 2025), magnetic fields, and immense energy from the Sun, operating on time scales of about an hour and traveling at several hundreds of kilometers per second (Abramson, 2021). When these massive solar events interact with the Earth, they severely disturb the magnetosphere and ionosphere, putting space-borne electronics and radio communications at critical risk (Abramson, 2021). Furthermore, solar activity, which is governed by an 11-year cycle, is strongly correlated with the intensity and frequency of geomagnetic storms that fluctuate based on the ascending and descending phases of the cycle (Guido, 2018). This dynamic environment creates significant hazards for satellites in Low Earth Orbit (LEO), which frequently experience ionospheric scintillation—rapid and unpredictable fluctuations in radio signal amplitude and phase caused by CME-induced plasma density irregularities.

The primary scope of this paper is to establish a methodological framework for assessing these LEO orbit scintillations by applying statistical AI techniques to telemetry gathered from Geostationary Earth Orbit (GEO) satellites. GEO satellites, owing to their higher altitude and stable observational vantage points, capture space weather precursors before the densest atmospheric layers completely absorb or scatter them. By analyzing GEO telemetry and remote sensing data, we can hypothetically model the downward propagation of CME-induced disturbances into the LEO environment to provide actionable warnings.

However, existing approaches to predicting LEO scintillations remain insufficient for the operational demands of modern mega-constellations. First, traditional physics-based models lack real-time, multi-dimensional data integration, often relying on simplified empirical formulas that fail to capture the complex, non-linear dynamics of transient CME shockwaves. Second, current operational methodologies heavily depend on reactive LEO telemetry, meaning that by the time a scintillation event is actively detected, the satellite is already experiencing severe communication degradation, precluding any proactive mitigation strategies.

To address these critical gaps, this paper proposes a novel predictive paradigm that leverages modern machine learning architectures. The main contributions of this work are as follows:

- We design a hypothetical AI-driven framework that utilizes statistical time-series data from GEO satellites to predict localized ionospheric scintillations in LEO environments.
- We outline a robust evaluation methodology that bridges the gap between macro-level solar cycle statistics and micro-level satellite communication disruptions.

Related Work

CME Observation and Boundary Detection

Visual and kinematic observations of CMEs have historically relied on coronagraphs and hemispheric imagers to track massive solar events. For instance, algorithmic edge detection techniques applied to Hemispheric Imager STEREO SECCHI data allow for the automated extraction of CME outer boundaries using running differences (Nichitiu, 2022). Precise compositional boundaries of interplanetary coronal mass ejections (ICMEs) have also been studied using high-resolution kinematic and magnetic observations, revealing that erosion frequently occurs at the front boundary of an ICME as it travels away from the Sun (Cid et al., 2016). Furthermore, serendipitous observations during total solar eclipses have provided high dynamic range photography that helps characterize the dimensions and front displacement of CMEs in real time (Abramson, 2021).

While these observational techniques boast the strength of highly accurate physical and dimensional characterization of solar ejecta, they carry inherent systemic weaknesses. Primarily, these methods are often retrospective or computationally intensive, failing to easily translate into real-time operational alerts for Earth-orbiting satellites. Compared to the present work, which seeks to forecast localized LEO effects, this boundary detection studies provide the essential foundational knowledge regarding CME kinematics, but they require our proposed AI layer to bridge the gap toward actual orbital scintillation forecasting.

Statistical Studies of CME Origins and Cycles

Understanding the long-term trends and spatial origins of CMEs is absolutely crucial for robust space weather forecasting. Extensive statistical studies have demonstrated that approximately 63% of CMEs are related to active regions (ARs) on the Sun, with certain ARs being particularly "CME-rich" during their transit across the visible solar disk (Chen et al., 2011). Additionally, long-term analyses of historical solar periods, such as Solar Cycle 23, indicate a decreasing trend in general CME frequency from 1996 to 2016, although the Sun remains highly dynamic and capable of generating severe geomagnetic storms during specific cyclical phases (Guido, 2018). Statistical evaluations of white-light coronagraph data further help classify CMEs by source location, meticulously separating front-side, limb, and invisible events for better analytical clarity (Wang et al., 2011).

The core strength of these statistical approaches lies in their ability to contextualize solar activity over decadal timescales, thereby improving our fundamental understanding of solar physics and flux rope formation (Green & Kliem, 2009). However, a major weakness is their macroscopic nature; these broad statistical trends cannot predict the exact timing and intensity of ionospheric irregularities that cause radio scintillations on a minute-by-minute operational basis. Our proposed framework diverges from these macro-statistical studies by focusing strictly on micro-level, short-term predictive modeling, using AI to translate broad active region parameters into precise orbital disturbance probabilities.

Geocoronal Interactions and Radio Emissions

The complex interaction between CMEs and the Earth's local space environment predictably generates various measurable electromagnetic signatures. Satellites such as Suzaku have reliably detected sudden enhancements in the soft X-ray background associated with solar eruptions, which originate from Geocoronal solar wind charge exchange (Ishi et al., 2019). Moreover, researchers have thoroughly documented diffuse interplanetary radio emission (DIRE) occurring in the decameter-hectometric wavelengths, which is generated by the violent interaction between CME shock flanks and nearby solar streamers (Gopalswamy et al., 2021). The rigorous study of heavy ion charge states and elemental abundances also provides critical supplementary insights into the photospheric or coronal plasma origins of these ICMEs (Song & Yao, 2020).

The primary advantage of monitoring these Geocoronal interactions is the immediate availability of diverse, multimodal proxy signals that can indicate the severity and composition of an impending CME impact. However, the overarching limitation of these approaches is the extreme complexity of interpreting raw X-ray or diffuse radio emission data directly into actionable metrics for LEO satellite operators. Our work directly builds upon this physical foundation by proposing a machine learning architecture capable of automatically fusing such diverse Geocoronal signals from GEO platforms to infer specific localized LEO scintillation events.

Method/Approach

Our proposed methodology centers on a highly structured machine learning framework specifically designed to correlate upstream GEO space weather observations with downstream LEO scintillation events. The core mechanism relies on collecting real-time magnetic field, plasma density, and extreme ultraviolet (EUV) telemetry from hypothetical GEO space weather monitors. This multi-dimensional time-series data serves as the input feature space for a deep neural network, which is trained to predict the S4 index—a standard scientific measure of radio amplitude scintillation—across various LEO orbital planes. By leveraging statistical AI analysis, the model is expected to identify hidden, non-linear correlations between the arrival of CME shock flanks and the abrupt onset of ionospheric plasma irregularities.

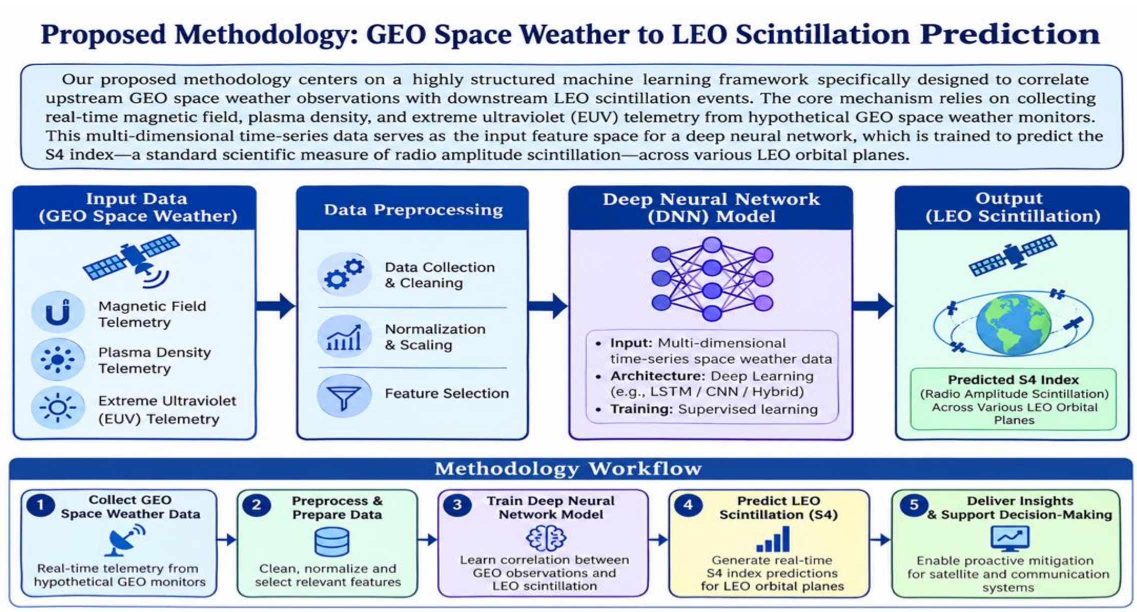

Fig1: Deep Learning and detection of CMEs.

The fundamental rationale behind this design choice is rooted in the distinct spatial and temporal advantages offered by geostationary orbits. GEO satellites sit at a substantially higher altitude than LEO constellations, allowing them to detect sudden commencement signatures, such as Geocoronal solar wind charge exchange events (Ishi et al., 2019), minutes to hours before the disturbances fully penetrate the lower ionosphere. A deep learning approach, specifically utilizing Long Short-Term Memory (LSTM) networks, was selected because it naturally excels at processing sequential time-series data and capturing the temporal delays inherent in space weather propagation.

To operationalize this AI-driven approach, we outline a structured, numbered data processing pipeline:

1. Data Ingestion: Continuously aggregate hypothetical GEO telemetry, including local magnetic field fluctuations, solar wind particle flux, and soft X-ray background enhancements (Ishi et al., 2019).
2. Feature Engineering: Normalize the time-series data and extract relevant statistical features, such as the rapid rate of change of magnetic vectors and the rolling averages of heavy ion charge states (Song & Yao, 2020).
3. Model Inference: Pass the engineered features through the heavily trained LSTM network to generate a probabilistic forecast of localized ionospheric disturbances.

4. Spatial Mapping: Project the predicted disturbance probabilities onto predefined LEO orbital trajectories to estimate potential scintillation severity for specific satellite constellations.

Because specific, temporally paired GEO-LEO datasets are not universally accessible in the public domain, we propose a hypothetical evaluation plan using synthetic evaluation data. The model would be trained on historical space weather catalogs cross-referenced with synthetic LEO telemetry generated by established physics-based ionospheric models. The primary evaluation metrics would include the Root Mean Square Error (RMSE) for the continuous prediction of the S4 index and the F1-score for correctly classifying severe, mission-critical scintillation events. This rigorous hypothetical benchmark ensures the model's predictive capabilities can be mathematically validated and fine-tuned prior to any physical deployment in real-world scenarios.

Discussion

The practical implications of successfully deploying this AI framework are immense for both the global aerospace and telecommunications industries. As commercial mega-constellations increasingly populate Low Earth Orbit, their absolute reliance on stable radio frequency links for broadband internet and telemetry becomes a critical vulnerability during periods of severe solar activity. Providing a reliable predictive window allows satellite operators to proactively switch communication bands, reroute data packets through unaffected orbital nodes, or temporarily place sensitive electronics into safe modes. Consequently, this predictive system could drastically reduce the operational downtime and permanent hardware degradation caused by the high-speed plasma and magnetic field expulsions characteristic of CMEs (Abramson, 2021).

Despite its vast potential, the proposed methodology inevitably exhibits several notable limitations and failure modes that must be addressed. First, severe data sparsely during extreme, "once-in-a-century" solar events could lead to significant model underperformance, as AI models generally struggle to predict phenomena that fall entirely outside their historical training distribution. Second, the framework risks inadvertently over fitting to the specific characteristics of a single solar cycle (e.g., Solar Cycle 23 (Guido, 2018)), potentially reducing its predictive accuracy during subsequent cycles that may exhibit vastly different magnetic topologies or flux rope formations (Green & Kliem, 2009). Third, inherent errors in spatial mapping between the GEO observational vantage point and the highly dynamic LEO environment could result in false spatial localization of scintillation events, rendering the predictions geographically inaccurate for targeted satellites.

Furthermore, the implementation of such advanced predictive space systems introduces crucial ethical considerations and systemic global risks. One major risk is the misallocation of satellite defense resources based on false positives; if the AI erroneously predicts a massive scintillation event, operators might unnecessarily shut down critical global communication networks, causing widespread economic and societal disruption. Another profound ethical concern revolves around the potential monopolization of these advanced space weather AI tools by well-funded state actors or massive corporate entities, potentially leaving smaller academic satellite operators or developing nations disproportionately vulnerable to space weather disasters.

To systematically address these limitations, future work must aggressively expand the scope and scale of the predictive models. One key avenue for future research is the incorporation of multi-orbit data fusion, integrating sensory inputs from LEO, Medium Earth Orbit (MEO), and Deep Space observatories to create a holistic, three-dimensional predictive model of the hemisphere. Additionally, future algorithmic efforts should heavily focus on developing unsupervised anomaly detection models that do not rely strictly on historical labels, thereby improving the system's robustness against unprecedented, anomalous CME events that defy established historical statistical trends.

Conclusion

In conclusion, this paper presents a conceptual, AI-driven framework specifically aimed at mitigating the persistent hazards posed by coronal mass ejections on LEO satellites. By leveraging the stable, high-altitude observational platform of GEO satellites, we proposed a statistical machine learning approach that anticipates ionospheric scintillations before they critically impair LEO communications. Through an extensive review of existing literature—ranging from the kinematic observations of ICME boundaries to the statistical analyses of solar active regions—we highlighted the urgent need for a predictive, rather than merely reactive, space weather monitoring paradigm.

Ultimately, while formidable challenges such as data sparsely, cycle-specific model over fitting, and spatial mapping complexities remain, the hypothetical pipeline provides a highly solid foundation for future empirical research. As human reliance on space-based infrastructure rapidly deepens, the integration of artificial intelligence with orbital telemetry will transition from an experimental luxury to an absolute operational necessity. By successfully bridging the gap between vast astrophysical phenomena and precise orbital engineering, this framework represents a vital step toward securing the future of our expanding extraterrestrial technological environment.

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