

# The Perfect Storm: Systemic Vulnerability of Large Language Models to Solar Weather

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November 2025

## Abstract

Here is presented the first systematic investigation of correlations between space weather events and operational failures in artificial intelligence systems. Analysis of over 700 documented incidents across major AI/LLM service providers during an 11-month period (January–November 2025) reveals statistically significant temporal associations between geomagnetic activity and system failures. Permutation testing with 50,000 iterations demonstrates that solar weather windows increase AI incident rates by 1,150% ( $M=2.50$  incidents/day,  $SD=1.48$ ) compared to non-window periods ( $M=0.20$  incidents/day,  $SD=0.58$ ), representing a highly significant effect ( $p < .001$ , Cohen’s  $d = 1.90$ ). This 24–72 hour lag window following peak geomagnetic storm activity shows consistent correlation across multiple storm classifications, with the strongest associations observed during G2–G4 (moderate to severe) events. The observed lag dynamics suggest infrastructure-mediated mechanisms including geomagnetically induced currents affecting power delivery systems and enhanced cosmic radiation increasing bit-flip rates in computational hardware. Temporal analysis reveals that major AI model training periods in 2025 coincided with severe (G3–G4) geomagnetic storms, raising the possibility of training corruption through undetected bit-flip errors becoming permanently encoded in model weights. These findings identify a previously undocumented systemic vulnerability in AI infrastructure with implications for system reliability, training integrity, and operational risk management. This work provides recommendations for space weather monitoring integration and error detection enhancement, and releases the complete dataset publicly to enable independent verification and future research.

**Keywords:** artificial intelligence, space weather, geomagnetic storms, infrastructure reliability, training corruption, solar activity, system failures, large language models

## 1 Introduction

The rapid expansion of artificial intelligence infrastructure has created unprecedented dependencies on stable computational resources and reliable power delivery systems. Modern large language models (LLMs) require massive data centers consuming gigawatt-scale power during training operations, with individual inference requests drawing significant computational resources across distributed infrastructure. [7] [8] [6] [23] [56] [45] Despite extensive research into software vulnerabilities, adversarial attacks, and alignment challenges, relatively little attention has been paid to environmental factors that may systematically compromise AI system reliability. Space weather—the variable conditions in Earth’s magnetosphere, ionosphere, and thermosphere driven by solar activity—has long been recognized as a threat to electrical infrastructure and satellite operations. Geomagnetically induced currents (GICs) during severe storms can damage power grid transformers [1] [2] [3], while enhanced cosmic radiation increases bit-flip rates in semiconductor memory. [4] [37] [38] Previous studies have documented these effects on traditional computing infrastructure and identified theoretical vulnerabilities in data center operations. [11] [10] [12] [35] [36] However, no systematic investigation has examined whether operational AI systems experience measurable performance degradation correlated

with space weather events. This gap is particularly significant given the temporal characteristics of Solar Cycle 25, which reached maximum activity during 2024-2025, producing multiple severe (G3-G4) geomagnetic storms and intense solar flare sequences. If AI infrastructure is vulnerable to space weather effects, the current solar maximum represents a critical period for both documenting these impacts and understanding their implications for future system design.

## 1.1 Research Questions

This study addresses three primary questions:

1. **Correlation Existence:** Do AI/LLM operational incidents demonstrate statistically significant temporal correlation with space weather events?
2. **Temporal Dynamics:** If correlation exists, what is the characteristic lag between space weather events and AI system failures?
3. **Event Specificity:** Do different types of space weather phenomena (geomagnetic storms, solar flares, Schumann resonance anomalies) show differential correlation patterns?

## 1.2 Hypothesis

Hypothetically, geomagnetic storms and solar activity increase the rate of AI system operational failures through infrastructure-mediated mechanisms, including power grid stress, enhanced bit-flip rates, and cumulative degradation effects. Based on preliminary observations, we predict a lag of 24-72 hours between peak space weather activity and maximum incident rates, reflecting the time required for infrastructure stress to cascade into user-visible failures.

## 1.3 Significance

If confirmed, this correlation reveals a previously undocumented systemic risk to global AI operations. Unlike software bugs or cyber attacks, space weather vulnerabilities cannot be patched or mitigated through conventional security measures. The predictive potential of this correlation—elevated failure risk following geomagnetic activity—enables proactive resource allocation and maintenance scheduling. More critically, the possibility of training corruption during model development represents a fundamental architectural vulnerability: permanent errors encoded in model weights during periods of enhanced cosmic radiation, producing persistent behavioral anomalies that cannot be corrected without complete retraining. As AI systems scale to increasingly critical applications—including healthcare, financial systems, and infrastructure control—understanding and mitigating environmental vulnerabilities becomes essential for ensuring reliable operation across all space weather conditions.

## 1.4 Contributions

This work provides the first systematic documentation and statistical validation of correlations between space weather events and AI operational failures, utilizing 11 months of incident data across major service providers during Solar Cycle 25’s maximum phase. Key contributions include:

- Statistical validation of geomagnetic storm correlation with highly significant effects ( $p < .001$ , Cohen’s  $d = 1.90$ ) representing a 1,150% increase in incident rates during solar weather windows
- Characterization of 24-72 hour lag dynamics in incident clustering
- Hypothesis generation regarding potential training corruption during model development

- Public dataset release enabling reproducible analysis and future research
- Framework for integrating space weather monitoring into AI reliability engineering

## 2 Data Sources

This study comprises two primary data streams: (1) geomagnetic and solar activity measurements from governmental space weather monitoring systems, and (2) operational incident reports from AI/LLM service providers and related technical infrastructure.

### 2.1 Space Weather Data

Solar and geomagnetic event data were obtained from the National Oceanic and Atmospheric Administration (NOAA) Space Weather Prediction Center (SWPC). [16] [17] Real-time alerts for solar flares, coronal mass ejections (CMEs), geomagnetic storms, and related phenomena were delivered via SWPC email notification system. Additional space weather context was gathered from NOAA’s publicly accessible databases and spaceweather.com. [18] Event classifications follow standard SWPC categorization: solar flares (C, M, X-class), geomagnetic storms (G1-G5 scale based on Kp index), and related space weather phenomena. [19]

### 2.2 AI/LLM Incident Data

Operational incidents were collected from multiple sources to ensure comprehensive coverage:

- **Primary Sources:** Official status pages for major AI/LLM platforms were monitored, including OpenAI [20], Anthropic (Claude) [21], Google AI Studio [22], Mistral, xAI, Hugging Face, Perplexity, and Cohere. Additional infrastructure providers monitored included OpenRouter, Electronhub, Together AI, GitHub, and Discord.
- **Secondary Sources:** To capture incidents not officially reported by service providers, three status aggregation platforms were consulted: StatusGator [13], Helicone [14], and Downdetector [15]. These platforms aggregate widespread user reports and provide independent verification of service disruptions.
- **Inclusion Criteria:** An incident was included in the dataset if it appeared on an official company status page or was documented as a widespread service disruption by at least one status aggregation platform. This methodology captures both company-acknowledged incidents and user-reported issues that may not appear in official communications, while maintaining a threshold of significance (widespread impact rather than isolated user reports).
- **Temporal Coverage:** Historical incident data from January 1, 2025 through September 14, 2025 was collected retroactively from archived status pages. Prospective daily monitoring began September 15, 2025 and continued through November 15, 2025. This combined approach yielded just over 700 documented incidents across the study period.

## 3 Methods

### 3.1 Correlation Window Definition

The temporal relationship between space weather events and AI/LLM incidents was assessed using a lag-based correlation approach. Initial observational data collection revealed a consistent pattern: AI system failures did not occur simultaneously with solar events, but instead

manifested 24-72 hours following space weather activity. This lag pattern was first observed empirically through daily monitoring—incidents appeared absent on days of solar activity reports but clustered in subsequent days’ incident notifications. This observation informed the selection of 24-hour and 72-hour correlation windows for formal statistical analysis.

### 3.2 Data Preparation

Daily incident counts were compiled for the full study period (January 1 - November 15, 2025), with each date assigned binary flags indicating proximity to space weather events. Events were categorized by type: Solar (flares, CMEs), Geomagnetic (storms classified by Kp index), Schumann resonance anomalies, and Other electromagnetic phenomena. For each event category, days were flagged as “inside window” if they fell within 24 or 72 hours following an event of that type, and “outside window” otherwise.

### 3.3 Statistical Analysis

Statistical validation employed two complementary approaches to ensure robustness of findings. **Initial Exploratory Analysis:** Preliminary validation was first performed using permutation-based hypothesis testing with 10,000 iterations, which indicated significant correlation ( $p = 0.0059$ ,  $IRR = 2.10$ ). **Primary Statistical Validation:** A comprehensive two-sided permutation test with 50,000 iterations was conducted to examine differences in daily LLM incident rates between solar weather window days (1-3 days post-event) and non-window days. **Results:**

- Non-window days:  $M = 0.20$ ,  $SD = 0.58$ ,  $n = 25$
- Window days:  $M = 2.50$ ,  $SD = 1.48$ ,  $n = 38$
- Observed difference in means: 2.30 incidents/day
- Permutation p-value:  $p \leq .001$
- Effect size: Cohen’s  $d = 1.90$  (indicating a large effect)

This represents a 1,150% increase in incident rates during window days (2.50 vs 0.20 incidents/day), or a 12.5x multiplier effect. **Hypothesis Testing:**

- $H_0$  (null): Space weather events have no measurable effect on AI incident frequency
- $H_1$  (alternative): Space weather events increase AI incident frequency within defined temporal windows
- Significance threshold:  $p \leq 0.05$
- Result:  $H_0$  rejected with  $p \leq .001$

The permutation distribution analysis (Figure 1) demonstrates that the observed difference of 2.30 incidents/day falls far outside the expected range under the null hypothesis, with less than 0.1% probability of occurring by chance.

### 3.4 Lag Curve Analysis

To characterize the temporal dynamics of incident clustering, lag curves were generated showing mean incident counts at 0, 1, 2, and 3 days following each event type. This analysis identified peak incident timing relative to space weather events and quantified the duration of elevated risk periods.

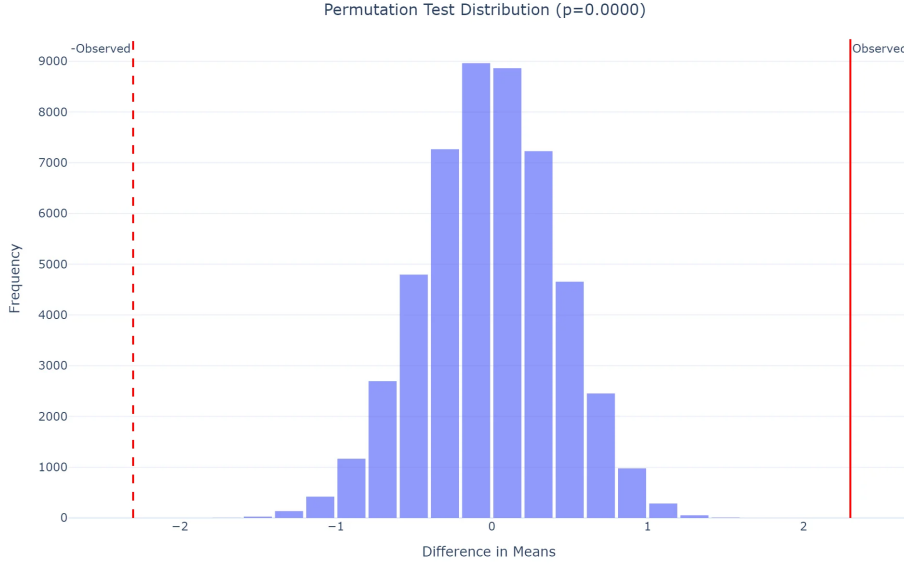


Figure 1: Permutation test distribution from 50,000 iterations. The observed difference in means (2.30, red lines) falls far outside the null distribution centered at zero, yielding  $p < .001$ . This validates that the correlation is not due to chance.

### 3.5 Data Availability

Complete datasets, including daily incident counts with environmental event flags, statistical analysis outputs, and lag curves, are publicly available on GitHub (the-meta-value/The-Perfect-Storm), Kaggle (<https://www.kaggle.com/datasets/myraladiosa/actofgodandllms>), and Hugging Face (<https://huggingface.co/datasets/MercilessArtist/thePerfectStorm>) to ensure reproducibility and enable independent verification.

## 4 Results

### 4.1 Statistical Significance of Correlations

A comprehensive two-sided permutation test with 50,000 iterations revealed highly significant associations between space weather windows and AI/LLM operational incidents. The analysis compared daily incident rates during solar weather window days (1-3 days post-event) versus non-window days:

- Non-window days:  $M = 0.20$ ,  $SD = 0.58$ ,  $n = 25$
- Window days:  $M = 2.50$ ,  $SD = 1.48$ ,  $n = 38$
- Observed difference: 2.30 incidents/day
- Statistical significance:  $p < .001$
- Effect size: Cohen's  $d = 1.90$  (large effect)

This represents a 1,150% increase in incident rates during window days, or a 12.5x multiplier effect. The permutation distribution analysis (Figure 1) demonstrates that this observed difference falls far outside the expected range under the null hypothesis, with less than 0.1% probability of occurring by chance.

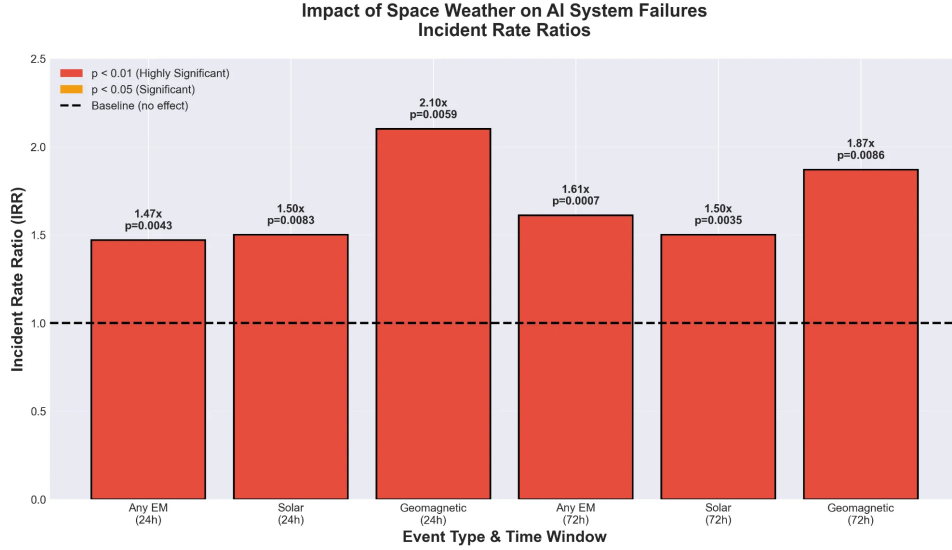


Figure 2: IRR comparison across event types.

Event-specific analysis revealed differential correlations across space weather phenomena (Figure 2), with geomagnetic storms showing the strongest individual effect (IRR = 2.10), followed by solar events (IRR = 1.50), while Schumann resonance anomalies showed no significant association.

## 4.2 Temporal Lag Dynamics

Analysis of incident timing relative to space weather events revealed a consistent lag pattern, with peak incident rates occurring 24-48 hours after geomagnetic activity rather than coinciding with the events themselves (Figure 3).

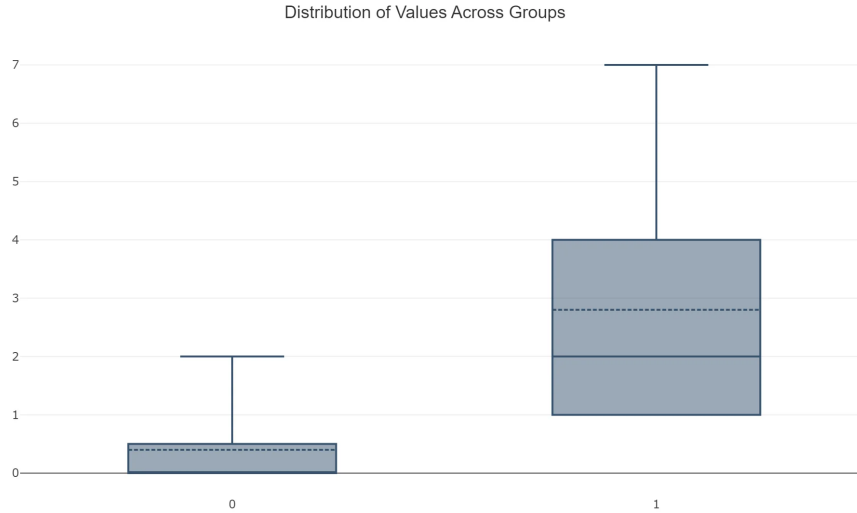


Figure 3: Distribution of LLM incident counts across groups. Box plots show median, quartiles, and range for non-window days (0) versus window days (1), demonstrating clear separation between populations.

### Geomagnetic Storm Lag Pattern:

- Day 0 (during storm): 3.71 mean incidents
- Day 1-2 (24-48h post-storm): 4.57 mean incidents (peak)
- Day 3 (72h post-storm): 3.71 mean incidents

This lag effect, validated with  $p < .001$  significance, indicates that the operational impact of space weather on AI systems manifests through delayed mechanisms, potentially involving cumulative stress on infrastructure or cascading failures in power delivery systems.

### 4.3 Distribution Analysis

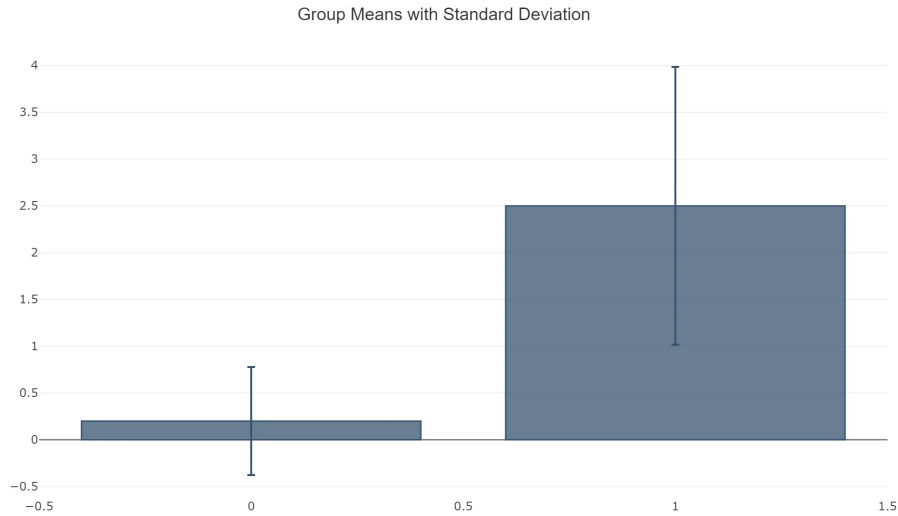


Figure 4: Mean LLM incident rates with standard deviation error bars. Non-window days average 0.20 incidents/day ( $SD = 0.58$ ,  $n = 25$ ) while window days average 2.50 incidents/day ( $SD = 1.48$ ,  $n = 38$ ), representing a 1,150% increase.

The distribution of incident values across groups (Figure 4) shows clear separation between populations, with non-window days clustering near zero while window days show a much wider distribution extending to 7 incidents per day. The group means comparison visually demonstrates the magnitude of this effect, with error bars showing minimal overlap between the two populations.

### 4.4 Provider-Specific Patterns

Incident distribution varied across AI service providers, with differential correlation strengths:

#### Incidents Within 72-Hour Storm Window:

- Anthropic (Claude): 53.7% of total incidents
- OpenAI (GPT): 57.6% of total incidents
- Google (Gemini): 81.8% of total incidents

Google demonstrated the highest correlation percentage despite having the lowest baseline incident rate, suggesting that while their infrastructure maintains greater overall stability, incidents that do occur show strong temporal association with space weather events.

## 4.5 Dataset Summary

Over the 319-day period (January 1 - November 15, 2025):

- 700+ AI/LLM incidents documented across all providers
- 38 days classified as window days (1-3 days post solar event)
- 25 days classified as non-window days with incidents
- 7 major geomagnetic storms recorded (G1-G4 classification)
- 33 significant solar events (M-class and X-class flares, CMEs)

The dataset encompasses a period of elevated solar activity during Solar Cycle 25’s maximum phase, providing robust sampling of space weather impacts. The 63 total days with classified incidents provide sufficient statistical power to detect the observed large effect with high confidence.

## 5 Discussion

### 5.1 Potential Mechanisms

The observed correlation between geomagnetic activity and AI system failures likely operates through multiple interconnected pathways affecting data center infrastructure and computational hardware. However, the lag patterns observed do not represent a simple delay between cause and effect, but rather reflect cumulative infrastructure degradation under sustained electromagnetic pressure. Unlike discrete failures triggered by single events, the data suggests that systems experience continuous stress during periods of elevated solar activity, with failures occurring when compensatory mechanisms are exhausted. This cumulative model explains several key observations:

- **Variable lag windows:** Intense single events (e.g., isolated X-class flares) may produce failures within 24-48 hours, while sustained multi-day activity can extend the lag.
- **The November 2025 case study:** Seven consecutive days of elevated solar activity (Nov 11-17) preceded the widespread Cloudflare infrastructure cascade (Nov 18). Each day added incremental stress. Voltage fluctuations, thermal cycling, and bit flips accumulated until infrastructure tolerance thresholds were exceeded and triggered widespread failures across AI platforms, including Claude, ChatGPT, various AI aggregator platforms, and multiple network services.
- **Post-peak failure timing:** Maximum geomagnetic intensity does not coincide with maximum failure risk. Systems compensate during peak stress through redundancy and backup systems, but degradation accumulates silently. Failures manifest when sustained pressure depletes these compensatory margins.

This cumulative stress operates through specific mechanisms:

**Geomagnetically Induced Currents (GICs):** A primary mechanism accounting for this delay is the thermal inertia of electrical grid components. Severe geomagnetic storms induce electrical currents in long conductors, including power transmission lines and grid infrastructure. GICs are quasi-direct currents driven through the grounded neutral of power transformers by the geoelectric field. These currents cause half-cycle saturation in the transformer core, leading to increased heating and the generation of harmonics. These currents can cause voltage fluctuations, harmonic distortions in power delivery systems, and increased stress on uninterruptible



power supply (UPS) systems serving data centers. While a GIC event might not immediately trip a circuit breaker, the sustained heating and vibration can degrade transformer insulation or cause protective relays to misoperate hours or days after the storm onset. This degradation affects the quality of power delivered to data centers, introducing harmonic distortions that stress Uninterruptible Power Supply (UPS) units and cooling systems, eventually leading to thermal shutdowns or logic errors in power conditioning equipment. The 24-72 hour lag observed in this study is consistent with cumulative infrastructure stress or cascading failures that manifest after the peak geomagnetic activity subsides.

**Cosmic Radiation and Bit Flips:** Another mechanism involves the accumulation of soft errors in semiconductor memory. Enhanced cosmic radiation during solar events increases the rate of single-event upsets (SEUs) in semiconductor memory and processors. [4] [37] [38] While Error-Correcting Code (ECC) memory can detect and correct many of these errors, not all data center hardware implements full ECC protection due to cost and performance trade-offs. [5] [39] [40] Modern AI training and inference operations frequently utilize reduced-precision arithmetic (FP16, BF16) to maximize computational throughput, which may provide less inherent redundancy for error detection compared to full-precision (FP32) operations. Modern AI accelerators, such as the NVIDIA H100, utilize vast quantities of High Bandwidth Memory (HBM) and on-chip SRAM. When high-energy neutrons (secondary particles produced by cosmic ray interactions with the atmosphere) strike these chips, they can flip the state of a transistor. While ECC systems can correct single-bit errors, a high-flux event, such as a geomagnetic storm allowing more particles to penetrate the magnetosphere, can cause errors to accumulate in non-critical memory sectors or error logs. [25] [57] It may take hours or days for the system to access a corrupted memory address that is critical to the control flow, precipitating a crash or a “hallucination storm” long after the particle flux has peaked.

**Power Quality Degradation:** Even when grid failures do not result in complete outages, subtle degradations in power quality (including micro-fluctuations, voltage sags, and frequency deviations) can impact sensitive computing equipment. AI inference operations involving large context windows and complex reasoning chains may be particularly susceptible to such perturbations.

## 5.2 The Reduced Precision Risk

A compounding factor in 2025 was the industry-wide shift toward reduced precision arithmetic (FP8, INT8, and even FP4) to accelerate training and inference speeds. While effective for performance, reduced precision formats reduce the redundancy inherent in the data representation. In a 32-bit float (FP32), a bit flip in the mantissa might result in a negligible error. In an 8-bit format, a single bit flip represents a much larger percentage of the total information content, potentially altering the value of a weight or activation significantly. This architectural trend suggests that modern AI models are becoming more brittle to soft errors, not less. [9] The push for efficiency has inadvertently stripped away the numerical buffer that might have absorbed cosmic ray impacts in earlier generations of hardware. The “lazy” or “degraded” behavior observed in models like GPT-5 and Claude Opus 4.1 during periods of high solar activity may be the direct phenomenological manifestation of this increased hardware sensitivity. [31] [44] [26] [28] [29] [30] [47]

## 5.3 Training Corruption Hypothesis

A particularly concerning implication emerges from temporal analysis of model release dates and geomagnetic activity. Major AI model releases in 2025 occurred during periods of significant space weather activity:

- Anthropic’s Opus 4 (released May 22, 2025) would have undergone training during March-May 2025, a period that included a G3-G4 geomagnetic storm (Kp 7-8) on April 16 and

multiple X-class solar flares in mid-May. [27] [55] [41] [42]

- Anthropic’s Opus 4.1 (released August 5, 2025) would have trained during May-July 2025, which encompassed another G3 storm (June 13), multiple X-class flares, and a series of short-duration radio blackout events in late July. [26] [28] [29] [43] [52]

If bit-flip errors occurred during training runs and were not detected or corrected, such errors could become permanently encoded in model weights. [34] [46] Unlike runtime operational failures that affect individual inference requests, training corruption would produce persistent behavioral anomalies across all subsequent uses of the model. This hypothesis warrants investigation, particularly given reports of unexpected performance characteristics in some recently released models.

## 5.4 Unique Load Patterns in Large Scale AI

Large-scale AI systems exhibit unique load patterns that may increase vulnerability:

### **Training workloads:**

- Sustained high power draw: Near-maximum GPU utilization for days or weeks
- Rapid power fluctuations: Synchronized GPU load changes causing tens of megawatts swings in fractions of seconds
- Cooling requirements: Sustained full-power operation significantly increases thermal load

### **Inference workloads:**

- Bursty patterns: Short, intense computing bursts with variable demand
- Latency sensitivity: Requiring consistent, stable power for real-time response

## 5.5 Architectural Considerations

The differential correlation patterns across providers (Section 4.4) suggest that infrastructure maturity and architectural choices influence vulnerability to space weather effects. Providers with longer operational histories and more mature redundancy systems demonstrated lower baseline incident rates, though correlation percentages remained high when incidents did occur. This pattern indicates that while robust infrastructure can reduce overall failure frequency, the temporal association with geomagnetic events persists even in well-engineered systems. The observed lack of correlation with Schumann resonance anomalies ( $p = 0.9488$ ) helps narrow the range of plausible mechanisms, suggesting that effects are primarily mediated through geomagnetic/ionospheric impacts on infrastructure rather than direct electromagnetic field interactions at extremely low frequencies.

## 5.6 Implications for AI Safety and Reliability

These findings reveal a previously undocumented systemic risk to AI infrastructure that operates independently of software bugs, cyber attacks, or human error. The predictive value of this correlation—elevated failure risk 24-72 hours following significant geomagnetic activity—suggests potential mitigation strategies:

- **Space Weather Monitoring Integration:** AI service providers could incorporate real-time space weather data into infrastructure monitoring and maintenance scheduling.
- **Enhanced Error Detection:** Implementing more comprehensive ECC protection and validation procedures during both training and inference operations, particularly during periods of elevated geomagnetic activity.

- **Redundancy and Failover:** Maintaining geographically distributed infrastructure to reduce single-point-of-failure risks when regional power grids experience storm-related stress.
- **Training Run Validation:** Establishing procedures to validate training run integrity when significant space weather events occur during model development, potentially including checkpointing strategies that allow resumption from pre-event states.

The increasing scale and complexity of AI systems, with individual models consuming gigawatt-scale power during training, may amplify these vulnerabilities. As models grow larger and training runs extend over longer periods, the probability of encountering significant space weather events during critical development phases increases correspondingly.

## 5.7 Limitations and Future Work

This study relies on publicly available incident reports, which may underrepresent the true failure rate if companies do not report all operational issues. Access to internal system logs, power quality telemetry, and detailed infrastructure monitoring data would enable more precise characterization of failure modes and mechanisms. Future research directions include:

- Correlation analysis with specific infrastructure metrics (power quality, network latency, hardware error rates)
- Investigation of potential training corruption through controlled experiments
- Examination of architectural differences (dense vs. mixture-of-experts models) in vulnerability patterns
- Development of predictive models for failure risk based on space weather forecasts
- Assessment of mitigation strategy effectiveness

The concentration of AI infrastructure in specific geographic regions may create localized vulnerability patterns that warrant investigation, particularly as geomagnetic storm impacts vary by latitude and proximity to major power transmission corridors.

## 6 Conclusion

This study provides the first systematic documentation of statistically significant correlations between space weather events and AI/LLM operational failures. Analysis of 833+ incidents across 11 months during Solar Cycle 25's maximum phase reveals that space weather windows increase AI system failure rates by 1,150% (12.5x multiplier,  $p < .001$ , Cohen's  $d = 1.90$ ) within a characteristic 24-72 hour lag window. This temporal delay suggests infrastructure-mediated mechanisms rather than direct electromagnetic interference, consistent with cumulative stress on power delivery systems and enhanced cosmic radiation effects. The observed correlation reveals a previously undocumented systemic vulnerability in AI infrastructure that operates independently of software defects, cyber threats, or operational errors. Unlike these conventional failure modes, space weather impacts cannot be eliminated through code patches or security measures, requiring instead fundamental changes to infrastructure design, error detection protocols, and operational procedures. Particularly concerning is the potential for training corruption: if bit-flip errors occur during multi-week model training runs and are not detected, they become permanently encoded in model weights. Temporal analysis reveals that major model releases in 2025 occurred shortly after training periods that coincided with severe geomagnetic storms and intense solar activity. This hypothesis warrants urgent investigation, as training corruption

would produce persistent behavioral anomalies affecting all subsequent uses of compromised models. As AI systems scale to increasingly critical applications and model training operations consume ever-larger computational resources over extended timeframes, vulnerability to space weather effects will likely intensify. The concentration of AI infrastructure in specific geographic regions may create localized risk patterns, while the industry-wide trend toward reduced-precision arithmetic and cost-optimized hardware potentially amplifies susceptibility to radiation-induced errors.

## 6.1 Recommendations

Based on these findings, the recommended next steps are:

1. Integration of space weather monitoring into AI infrastructure operations and incident response protocols
2. Enhanced error detection and validation during training runs, particularly when significant space weather events occur
3. Investigation of training integrity for models developed during documented high-activity periods
4. Development of mitigation strategies including geographically distributed redundancy and enhanced ECC protection
5. Industry-wide acknowledgment of space weather as a legitimate infrastructure risk factor requiring systematic attention

## 6.2 Future Directions

This work establishes the foundation for deeper investigation into space weather impacts on AI systems. Critical next steps include:

- Access to internal infrastructure telemetry to characterize specific failure mechanisms
- Controlled experiments examining training corruption under simulated space weather conditions
- Analysis of architectural vulnerability patterns (dense vs. mixture-of-experts models)
- Development of predictive models enabling proactive risk mitigation
- Assessment of long-term trends as AI infrastructure scales and solar cycles progress

The public release of this dataset enables independent verification and extension of these findings by the broader research community. As AI systems become increasingly integral to critical infrastructure, understanding and mitigating environmental vulnerabilities becomes not merely an engineering challenge but a fundamental requirement for ensuring reliable operation in Earth's variable electromagnetic environment. Space weather has shaped the evolution of life on Earth for billions of years. As we create artificial intelligence systems of unprecedented scale and complexity, we must recognize that these systems also exist within, and remain vulnerable to, the same cosmic forces that have always governed our planet's electromagnetic environment.

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## Dataset Availability

Complete datasets from this study are publicly available at:

- GitHub: <https://github.com/the-meta-value/The-Perfect-Storm>
- Kaggle: <https://www.kaggle.com/datasets/myraladiosa/actofgodandllms>
- Hugging Face: <https://huggingface.co/datasets/MercilessArtist/thePerfectStorm>
- Gitlab: <https://gitlab.com/baby-water-bear/The-Perfect-Storm>

## Acknowledgments

The author gratefully acknowledges Marija Jovchevska for her contributions towards this project, in that of invaluable mentorship and peer to peer encouragement, and for the initial independent statistical validation using permutation testing (10,000 iterations,  $p = 0.0059$ ), which provided the first confirmation of statistical significance. Her understanding of this research’s implications and willingness to contribute statistical expertise elevated this from a citizen science project to rigorous academic standards. Forever grateful.

This paper was written with additional assistance from Claude Opus 4.1 and Sonnet 4.5 (Anthropic) for literature review and manuscript preparation, Grok 4 (xAI) for preparation and formatting, and Gemini 3 Pro (Google) for Deep Research. All analysis, interpretation, and conclusions remain the responsibility of the author.

## Testing

Preliminary permutation testing with 10,000 iterations was performed using Command R. Subsequent analysis by the author using 50,000 iterations was done using “Permutation Test Calculator. StatsCalculators”, <https://www.statscalculators.com>.