

INVESTIGATION OF THE CONNECTION BETWEEN THE SPACE WEATHER AND EARTH ATMOSPHERIC INSTABILITIES USING AI

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Abstract. The study of space weather, particularly its influence on Earth's atmospheric dynamics, has gained attention due to its potential impact on various technological systems, communication networks, and even global climate. Recent advancements in Artificial Intelligence (AI) have opened new pathways to investigate and understand the connections between space weather phenomena and atmospheric instabilities on Earth. This paper explores the application of AI models, particularly machine learning (ML) techniques, to examine the interplay between space weather events – such as solar flares, geomagnetic storms, and cosmic rays – and atmospheric disturbances like thunderstorms, turbulence, and jet stream anomalies. By analyzing large datasets from both space weather satellites and ground-based atmospheric sensors, AI-driven algorithms aim to identify correlations and predict how space weather can trigger or exacerbate atmospheric instability.

Key Words: Climate change, solar wind – magnetic field interaction, artificial intelligence.

Introduction

Space weather refers to the changing conditions in space driven primarily by solar activity, including solar flares, CMEs, high-speed solar wind streams, and variations in the interplanetary magnetic field (IMF). When these disturbances interact with Earth's magnetosphere and ionosphere, they can trigger geomagnetic storms, ionospheric scintillations, and even influence tropospheric circulation patterns.

Understanding the connection between solar space weather and Earth's atmospheric instabilities is a complex problem due to: the multi-scale nature of interactions, the nonlinear coupling between solar drivers and atmospheric responses, and the rarity of extreme events such as Carrington-class storms.

Traditional models based on magnetohydrodynamics (MHD) and atmospheric circulation provide insights but are limited in forecasting skill. AI and machine learning (ML) offer complementary capabilities: the ability to process massive datasets, identify hidden structures, and improve predictive power.

Prikryl et al. [2], for example, found a connection between SW activity and extratropical cyclones in the northern hemisphere. They hypothesized that high-speed SWs generate atmospheric gravity waves that can reach the troposphere, transferring energy from the aurora region to the troposphere, initiating convection and altering the distribution of clouds and precipitation. Earlier, Elsner and Jagger [3] found a similar connection between intense tropical cyclones occurred during stronger solar activity, finding that their results were in accordance with the heat-engine theory of hurricanes: an active sun warms the lower stratosphere and upper troposphere due to the ozone's absorption of UV radiation, which reduces the temperature difference between the surface and the top of hurricanes.

More recently, working on even smaller timescales, Todorović and Vujović [4] researched the link between geomagnetic activity and the passage of atmospheric cold fronts. They proposed a mechanism for which when less solar UV radiation reaches the stratosphere, less ozone is created, less warming happens in the stratosphere, and the temperature gradient is weaker, ultimately leading to a weakening of the stratospheric jet stream.

Earth's atmosphere and its ionized part, the ionosphere, are influenced by several processes of external origin, i.e., solar and magnetospheric processes [5]. Solar electromagnetic radiation and solar wind (SW) particle flux deeply affect the circumterrestrial environment. In particular, solar wind energy is transmitted to the different layers of the atmosphere through magnetospheric processes. For example, energetic particle precipitation at auroral latitudes from the radiation belts and magnetic Field-Aligned Currents closing in the high-latitude ionosphere are very important in producing changes in the structure of the atmosphere. The electron precipitation during magnetospheric storms and substorms plays a role, by ionization, in the atmospheric chemical composition and conductivity variations.

This study aims to investigate the potential links between space weather events and atmospheric instabilities using AI-based models. By leveraging deep learning algorithms and advanced statistical techniques, we seek to identify patterns, causal relationships, and predictive indicators that could improve our understanding of how space-originated disturbances affect atmospheric behavior [1]. The ultimate goal is to enhance predictive meteorological models and contribute to a more resilient understanding of Earth's coupled space-atmosphere system. Research in recent decades has particularly focused on finding links between the changing activity of the sun and processes in Earth's atmosphere lasting not less than several days or years. Only relatively recently have scientists put efforts into understanding how geomagnetic activity can affect the weather over timescales of less than a week. Most of them suggested that there is an important downward impact from the SW to the middle and then lower atmosphere that influences weather development.

Study area, material and methods

In this study, using monthly resolution data to understand more broadly the conditions that lead to geomagnetic storms is analysed. By incorporating the interplanetary magnetic field and other heliophysical variables like solar wind speed and interplanetary magnetic field the effect of the latter with geomagnetic field fluctuations is revealed.

The data used in this study are from the OMNI2 dataset, which is available in the <https://omniweb.gsfc.nasa.gov/> directory of the NASA OMNIWEB website. These data comprise hourly mean values of the interplanetary magnetic field (IMF), solar wind plasma parameters, and various geomagnetic and solar activity indices, as well as energetic proton fluxes [1].

OMNI2 was developed at the NSSDC (National Space Science Data and Services Center) in 2003 as an evolution of the OMNI data set, initially created in the mid-1970s. These data are collected from various NASA space missions, including: IMP 1, 3, 4, 5, 6, 7, 8 these space probes [6], also known as Explorers, have contributed significantly to the collection of data on the interplanetary environment near Earth orbit; WIND [7], is a space mission equipped with a magnetometer, has provided detailed measurements of the solar wind and the interplanetary magnetic field; ACE (Advanced Composition Explorer) [8] which is a space probe that has collected precise measurements of solar wind and energetic particles from its orbit around the L1 Lagrange point; and Geotail [9], a joint mission between JAXA (Japan Aerospace Exploration Agency) and NASA; among others.

Also, data from the Dusheti Observatory is used to study the properties of global geomagnetic storms as measured in the territory of Georgia. This analysis is crucial due to the impacts of the storms on technology and human activities, for example causing power outages and disturbing communication, making it important to understand their local effects [10], whose extent in Georgia is currently unknown.

The Dusheti geomagnetic data have been used only in a very limited number of studies [11, 12], and are therefore currently strongly under-exploited. Being the only geomagnetic 159 field measurement station in Georgia, this database represents a unique, precious asset 160 for the study of geomagnetism and space weather in the Caucasus area. This study focuses on data collected from January to August, 2024. We will use measurements of the horizontal component of the geomagnetic field, H , with 1-minute resolution, allowing for a detailed temporal analysis and still ensuring sufficient coverage. A few data gaps, which amounted to roughly 0.7% of the entire geomagnetic data, were filled using linear interpolation. The data used in this study are available in a Zenodo repository 1 [11]. As an initial assessment of data quality, we compare the Dusheti measurements of H with the SYM- H index obtained from OMNIWeb. The comparison shows excellent agreement between the two measurements, visually validating the accuracy of the Dusheti Observatory data. This enables further analysis of Dusheti Observatory measurements of the geomagnetic field perturba-

tions. During storm commencements (SCs), abrupt increases in the geomagnetic field H component are systematically recorded by magnetometers worldwide, with amplitudes as large as 69.2 nT being well documented for the May 2024 storm [14]. The Dusheti Observatory measurements showed a similar increase, with the H component reaching -307 nT.

The approach involves robust statistical models, including multiple linear and nonlinear regressions and machine learning models, to capture the non-linear dynamics between the number of Geomagnetic storms and predictor variables. This offers a more comprehensive understanding of the factors influencing them and enhances predictive accuracy beyond traditional correlational analyses.

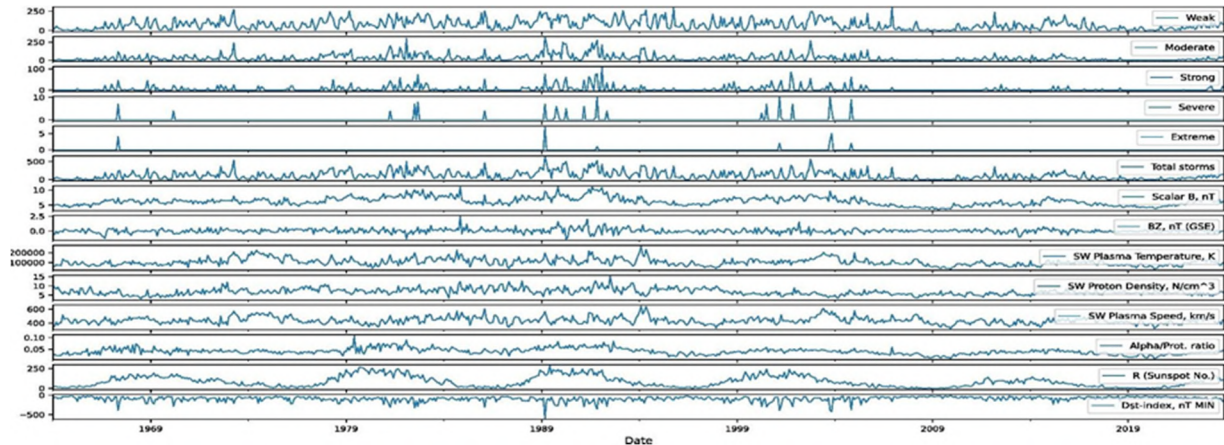


Fig. 1. Temporal distribution and evolution of geomagnetic storms.

Fig. 1. shows the temporal distribution and evolution of geomagnetic storms according to Dst index, for cycles 20 to 25 (still in progress) from the data collected and processed. Additionally, the temporal distribution of the heliospheric dynamics supporting variables is shown. The figure shows a clear correlative trend between the number of geomagnetic storms and some solar indices, particularly sunspots and interplanetary magnetic fields.

In order to detail a methodology, HSIC-Lasso nonlinear regression analysis is used to detect nonlinear Granger-causal relationships from solar-wind and interplanetary magnetic field (IMF) variables onto geomagnetic indices (e.g., Dst, SYM-H, AE, Kp). The results are results with linear Granger causality and information-theoretic methods (transfer entropy / conditional mutual information), validated via permutation tests and storm case studies, and assess robustness across solar-cycle phases.

Geomagnetic indices respond nonlinearly to drivers such as IMF Bz, solar wind speed/density and dynamic pressure; linear Granger tests miss nonlinear couplings. HSIC (Hilbert–Schmidt Independence Criterion) measures nonlinear dependence in RKHS; HSIC-Lasso blends HSIC dependency scoring with Lasso-style sparse selection, making it suitable to discover a sparse set of nonlinear predictors from many lagged candidate variables.

Fig. 2. shows which lagged solar wind features (like Bz lag 5 or V lag 10) are most strongly selected as causal predictors of the geomagnetic index (Dst).

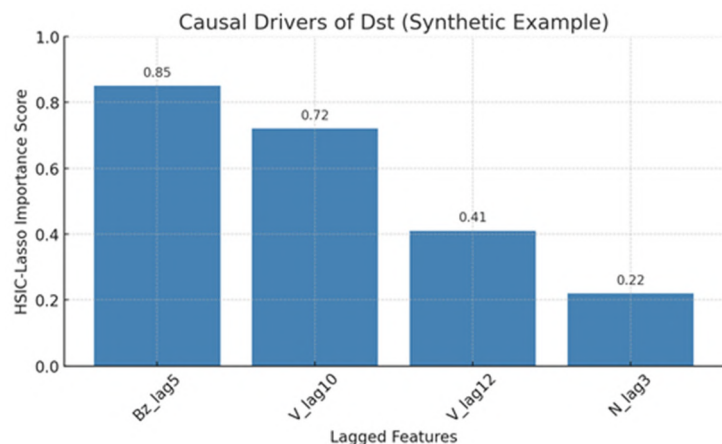


Fig. 2. the HSIC-Lasso causal importance plot.

Conclusion

The study of solar wind–geomagnetic interactions remains a central challenge in space weather research, as nonlinear coupling processes govern how interplanetary conditions drive magnetospheric and ionospheric responses. Traditional approaches such as linear Granger causality provide valuable insights into time-lagged dependencies, but they often fail to capture the nonlinear and high-dimensional nature of solar wind–magnetosphere coupling.

In this work, the integration of HSIC-Lasso with causality analysis demonstrates a powerful framework for identifying the most relevant solar wind drivers of geomagnetic activity. By combining nonlinear dependence measures with sparse feature selection, HSIC-Lasso is capable of isolating meaningful lagged predictors – such as southward IMF Bz and solar wind speed at 20–60 minute delays – while suppressing spurious correlations. This ability to extract causal structures directly from complex, multivariate time series offers a more physically consistent representation of the solar wind–geomagnetic system compared with purely linear methods.

The results underscore that nonlinear causality models are better suited than linear Granger causality for space weather studies, particularly during intense geomagnetic storms where interactions are highly nonlinear. Moreover, this methodology provides a foundation for operational forecasting systems, in which causal drivers identified by HSIC-Lasso can be integrated into hybrid AI models for real-time storm prediction.

Future work should extend this framework to include multi-scale analysis (e.g., wavelet-based decomposition), cross-index coupling (Dst, SYM-H, AE, Kp), and validation across multiple storm events to test robustness. In addition, integrating this causality-based feature selection with deep learning architectures could further enhance both interpretability and predictive performance.

In summary, HSIC-Lasso–based Granger causality analysis offers a promising pathway to uncovering the nonlinear causal mechanisms that connect solar wind dynamics to Earth’s magnetospheric response, strengthening both scientific understanding and the practical forecasting of space weather hazards.

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