EXPLORING CAUSAL RELATIONSHIPS IN SPACE WEATHER USING INFORMATION THEORETIC APPROACHES: A CASE STUDY OF GEOMAGNETICALLY INDUCED CURRENTS

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Abstract:

This paper investigates the complex causal pathways within the Sun-Earth system by applying information-theoretic frameworks to space weather dynamics. Traditional correlation-based analyses often fail to capture the nonlinearities and time-lagged dependencies inherent in solar-terrestrial interactions. To address this, we employ Conditional Mutual Information (CMI) and Transfer Entropy (TE) to quantify the directed information flow from the interplanetary medium to Earth's surface. The study specifically focuses on the drivers of Geomagnetically Induced Currents (GICs), analysing the causal influence of key solar wind parameters, including the interplanetary magnetic field (IMF) components and solar wind parameters (e.g. velocity, density and pressure). By utilising these model-independent measures, we distinguish between mere statistical associations and true physical causality. Our results aim to rank the predictive importance of various interplanetary drivers. This approach provides a rigorous methodology for improving the predictive modelling of GICs, ultimately enhancing the resilience of critical electrical infrastructure against extreme space weather events.

Keywords:

Causal relation; Space weather; Information theoretic methods; Geomagetically induced currents (GICs)

1. Introduction

The increasing reliance of model life on modern complex, interconnected technological systems has heightened our vulnerability to the dynamic environment of near-Earth space. Space weather, driven primarily by the sun's relentless emission of magnetised plasma, represents a significant natural hazard. Among the most concerning consequences of extreme space weather events are Geomagnetically Induced Currents (GICs) [1]. These currents, induced in long-distance grounded conductive networks such as power grids and pipelines, can lead to transformer saturation, equipment damage, and widespread blackouts. As our infrastructure becomes more integrated, understanding the precise causal mechanisms that bridge the gap between the interplanetary medium and terrestrial GICs is no longer just a scientific pursuit, but a socio-economic necessity.

The chain of events leading to GIC formation begins in the solar atmosphere. The solar wind, a stream of charged particles, carries the interplanetary magnetic field (IMF) across the heliosphere to interact with Earth's magnetosphere. This interaction is highly dynamic and governed by complex physical processes, most notably magnetic reconnection. When the IMF possesses a strong southward component, it can effectively merge with Earth's geomagnetic field lines, allowing for a massive transfer of energy and momentum into the magnetospheric system. This energy is subsequently dissipated through various channels, including the intensification of ionospheric currents, which create rapidly varying magnetic fields (*dB/dt*) at the Earth's surface. According to Faraday's law of induction, these fluctuating fields drive the electric fields responsible for GICs.

Historically, the relationship between solar wind drivers and geomagnetic activity has been analysed using linear correlation and spectral analysis. While these methods have provided foundational insights, they possess inherent limitations. The solar wind-magnetosphere-ionosphere (SW-M-I) system [2] is fundamentally nonlinear, non-stationary, and characterised by feedback loops and varying time delays. Traditional Pearson correlation coefficients, for instance, only capture linear associations and can be misled by indirect dependencies or "common driver" effects. To truly understand the physics of the system, we must move beyond simple association toward a framework of directed information flow and causality.

This paper adopts Information Theoretic (IT) approaches to deconstruct the causal architecture of space weather. Information theory, originally developed for communication systems, provides a powerful toolkit for analysing complex systems without requiring a prescribed physical model. Central to this study are the concepts of Conditional Mutual Information (CMI) and Transfer Entropy (TE) [3],[4]. Unlike standard mutual information, which measures the shared information between two variables, CMI allows us to evaluate the relationship between a driver (e.g., solar wind velocity, V_{sw}) and an effect (GICs) while accounting for the influence of a third "nuisance" variable. This is critical for isolating the unique contribution of specific solar wind parameters.

Furthermore, Transfer Entropy offers a non-parametric way to detect the directed dynamic coupling between time series. By measuring how much the uncertainty in the future state of GICs is reduced by knowing the past states of the solar wind, beyond what is already known from the GIC history itself, we can rigorously establish a causal arrow of time. This methodology is particularly adept at identifying the characteristic lag times between interplanetary perturbations and ground-level responses, providing a clearer picture of the "system memory."

The specific objective of this paper is to apply these IT measures to a high-resolution dataset of solar wind conditions, including IMF components (B_x, B_y and B_z), solar wind parameters (e.g. speed, density and pressure), and correlate them with observed GIC signatures. By doing so, we aim to rank the various interplanetary drivers by their causal strength and determine how these relationships shift during different geomagnetic conditions. Through this information-theoretic lens, we seek to provide a more robust foundation for GIC forecasting and a deeper understanding of the energy pathways that define our space environment.

2. Related work

The study of GICs is critical for safeguarding global power grids from space weather hazards. Recently, the application of Information Theoretic (IT) methods, specifically Conditional Mutual Information (CMI) and Transfer Entropy (TE), has emerged as a powerful framework for deciphering the complex, non-linear causalities between solar wind drivers and ground-level electromagnetic responses.

The shift toward IT methods is driven by the need to understand the directional coupling in solar-terrestrial physics. Research in [5] utilised Transfer Entropy (TE) to establish the asymmetric nature of energy transfer from the solar wind to the coupled magnetospheric-ionospheric system. In [6], a multivariate TE methods was proposed to explore common solar wind drivers behind magnetic storm–magnetospheric substorm dependency.

Furthering this causal investigation, the work in [7] applied TE and CMI to detect causal delays from solar wind parameters to geomagnetic indices such AE and SYM-H indices. This is complemented by the work in [8] used CMI as a measure of causality to investigate the possible coupling direction and pattern of interactions among different electron fluxes of different energies and various solar wind variables and geomagnetic activity indices.

In terms of isolating specific drivers, Wing et al. [9] used CMI used conditional mutual information to untangle and isolate the effect of individual solar wind and magnetospheric drivers of the radiation belt electrons. In [10] TE was utilised to study the relativistic electron (E > 2MeV) fluxes data, and found that the AE index and solar wind velocity were the dominant driving parameters for relativistic electrons flux at GEO orbit.

For geomagnetically induced current (GIC) studies, research directly examining the application of CMI and TE remains notably scarce. Limited research to date has explored the direct application of CMI and TE within GIC analysis is briefed below. The work in [11] provides a broader perspective of recent advances in space weather modelling including GIC generation mechanisms using data-driven information flow. Collectively, these studies indicate that information metrics including CMI and TE provide a robust basis for the next generation of space weather modelling, moving beyond black-box machine learning toward physically interpretable forecasting. In [12], a block entropy method was employed to analyse GIC activity at mid-latitude European observatories during the March 2015 and May 2024 storms. GIC indices were higher in May 2024, indicating greater risk. SYM-H and GIC entropy decreased during both storms, reflecting a shift from lower to higher system organisation.

The work presented here seeks to bridge the gap between the growing need to characterise causal relationships between GICs and key space-weather drivers and the limited methodologies available, ultimately enabling more robust modelling and forecasting of GIC activity.

3. Methodology

This section provides brief descriptions of the two information theoretic methods: conditional mutual information (CMI) and transfer entropy (TE).

3.1 Conditional mutual information

Conditional Mutual Information (CMI) [13] is a powerful metric for causality testing because it quantifies the directed information flow between variables while controlling for third-party influences. In terms of Shannon entropy, CMI is mathematically defined as:

$$I(X;Y|Z) = H(X|Z) - H(X|Y,Z) \quad (1)$$

or alternatively it can be written as the difference between two conditional entropies as:

$$I(X;Y|Z) = H(X,Z) + H(Y,Z) - H(X,Y,Z) - H(Z) \quad (2)$$

where $H(X|Z)$ is the uncertainty in X given Z, and $H(X|Y,Z)$ is the uncertainty in X given both Y and Z. The CMI $I(X:Y|Z)$ is the Kullback-Leibler (KL) divergence between the joint conditional probability $P(X,Y|Z)$ and the product of their marginal conditionals $P(X|Z)P(Y|Z)$. In the KL sense, CMI may be formulated as:

$$I(X;Y\,|\,Z)=\sum_{z\in Z}p(z)\sum_{y\in Y}\sum_{x\in X}p(x,y\,|\,z)\log\left(\frac{p(x,y\,|\,z)}{p(x\,|\,z)\,p(y\,|\,z)}\right) \quad (3)$$

CMI measures the expected reduction in uncertainty about random variable *X* provided by variable *Y*, given that variable *Z* is already known. It quantifies the remaining dependence between two variables *X* and *Y* when conditioned on a third variable *Z*, acting as a crucial tool for analysing causality and conditional independence. Unlike standard Mutual Information (MI), which is symmetric, CMI can identify if a random variable *X* provides unique information about the future of another random variable *Y* that is not already contained in *Y*'s own past.

CMI has the following properties:

- **Non-negativity:** $I(X:Y|Z) \geq 0$.
- **Zero CMI**: $I(X:Y|Z) = 0$ if and only if *X* and *Y* are conditionally independent given *Z*.
- **Sign-independent**: $I(X;Y|Z)$ can be greater than, less than, or equal to $I(X;Y)$.
- **Non-monotony:** Unlike standard mutual information, conditioning can either increase or decrease the dependence between two variables.

3.2 Transfer entropy

Transfer entropy (TE) [14] is an information-theoretic measure that quantifies the directed (asymmetric) information flow from a source process X to a destination process Y. It measures the reduction in uncertainty about the future state of gained by knowing the past states of X, over and above the information already provided by the past states of itself. TE is widely used to analyze causality in nonlinear dynamical systems. TE can be defined as:

$$TE_{X\to Y}=H(Y^{F[t+1:t+s]}\,|\,Y^{P[t-\delta:t]})-H(Y^{F[t+1:t+s]}\,|\,Y^{P[t-\delta:t]},X^{P[t-\tau:t]}) \quad (4)$$

where Y^F represents a future state of the destination process, e.g., $y_{t+1},\ldots,y_{t+s}$; Y^P represents past states of the destination process, e.g., y_t, $y_{t-1},\ldots, y_{t-\delta}$; X^P represents past states of the source process, e.g., x_t, $x_{t-1},\ldots, x_{t-\tau}$; $H(B|A)$ represents Shannon entropy.

Using probability thoery, TE can be written as:

$$TE_{X\to Y}=\sum p(y_{t+1},y^P,x^P)\log\frac{p(y_{t+1}\,|\,y^P,x^P)}{p(y_{t+1}\,|\,y^P)} \quad (5)$$

For a simple Markov process of order 1, where only the immediate past state is considered, (5) can be simplified to:

$$TE_{X\to Y}=\sum p(y_{t+1},y_t,x_t)\log\frac{p(y_{t+1}\,|\,y_t,x_t)}{p(y_{t+1}\,|\,y_t)} \quad (6)$$

Three key interpretations of TE are as follows:

- If $TE_{X\to Y} = 0$, then the source *X* does not provide any new information about the future of destination variable *Y* that is not already present in *Y*'s past. Therefore, *X* does not drive *Y*.
- If $TE_{X\to Y} > 0$, then information is flowing from *X* to *Y*.
- The net flow, defined by the difference $TE_{X\to Y} - TE_{Y\to X}$, can be used to determine the dominant direction of coupling.

4. Causal relationships in space weather

This section provides an illustration of the application of CMI and TE in exploring causal relationships in space weather. Due to space limit, the focus is mainly on geomagnetically induced currents (GICs).

4.1 Problem, variables and data

While a strong negative southward component ($B_z < 0$) of the interplanetary magnetic field (IMF) creates the necessary conditions for a storm, the largest GIC-driving disturbances arise from the rapid, turbulent variations in the solar wind pressure and magnetic field, rather than just the orientation of the field itself. This present study focuses on nine IMF and solar wind variables, which are listed in Table I.

During 10-12 May 2024, NOAA Active Region 13664 triggered a large geomagnetic storm, which was referred to as the *Gannon* or *Mother's Day Storm*, was the most one that has ever occurred in over 20 years [15],[16].

The GIC data used were recorded by scientists in the Laboratorio Nacional de Clima Espacial (LANCE), Mexico, (https://doi.org/10.17605/OSF.IO/AV9HT) [16]. A 5-minute interval dataset (consisting of 1152 samples) was derived from their original 1-minute interval dataset of the period 10-13 May 2024 containing 5760 samples in total. The corresponding 5-minute interval data of the same period for all the variables listed in Table 1 were obtained from (https://omniweb.gsfc.nasa.gov/form/omni_min_def.html).

4.2 Experimental settings and evaluation metric

To facilitate the comparison of correlation strength between the GIC data and the data of all the different variables, we preprocessed all the data as follows:

$$x_{\text{new}} = = \frac{x_{\text{raw}} - x_{\text{raw,average}}}{\max\left(|x_{\text{raw}}|\right)} \tag{7}$$

The values of all the original variables fall into the range $[-1,1]$ through the transform (7). Such a transform and other commonly used linear transforms do not change the values of the associated CMI and TE values.

TABLE 1. Potential drivers of GICs considered in this study

Variable	Description
B_x, B_y, B_z in GSE	Interplanetary magnetic field (IMF) in Geocentric Solar Magnetospheric components, unit: nT
B_y, B_z in GSM	IMF Geocentric Solar Ecliptic coordinates, unit: nT
V_{sw}	Magnitude of solar wind speed, unit: km/s
V_x, V_y, V_z	Solar wind velocity in x, y, and z coordinates, Unit: km/s

We propose to use the following metric, referred to as *Relative Increase in Information* (RII), to measure the information flow strength from one variable X to another variable Y:

$$RII_{X\to Y} = \frac{\Delta_{X\to Y} - \Delta_{Y\to X}}{\varepsilon + \max(0, \Delta_{Y\to X})} \tag{8}$$

where Δ represents either CMI (conditional mutual information) or TE (transfer entropy), ε is a small positive number (e.g. between 0.001 and 0.01) to avoid drawing misleading conclusion when both $\Delta_{X\to Y}$ and $\Delta_{Y\to X}$ are very small (e.g. $\leq$ 0.01).

4.3 Results

The two information theoretic methods, CMI and TE, were applied to the 5-minute interval data involving 9 potential drivers of the GIC. Results are shown in Figures 1-9, where:

- Top left panel displays the raw values of a driver.
- Middle left panel displays the raw values of the GIC.
- Bottom left panel displays the normalised values of the driver and GIC.
- Top right panel displays the CMI values from the driver to GIC and GIC to the driver, respectively.
- Middle right panel displays the TE values from the driver to GIC and GIC to the driver, respectively.
- Bottom right panel displays the RII metric, defined in (8), related to CMI and TE values displayed in the top and middle right panels. *Solid blue line*: the metric $\text{RII}(\text{TE})_{\text{driver}\to\text{GIC}}$; *dashed blue line*: the average of the relevant 30 RII values. *Solid purple line*: $\text{RIII}(\text{CMI})_{\text{Driver}\to\text{GIC}}$; *dashed purple line*: the average of the relevant 30 RII values.

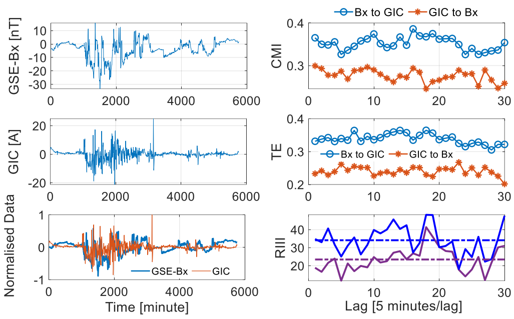

FIGURE 1. Causal relationship between B_x and GIC.

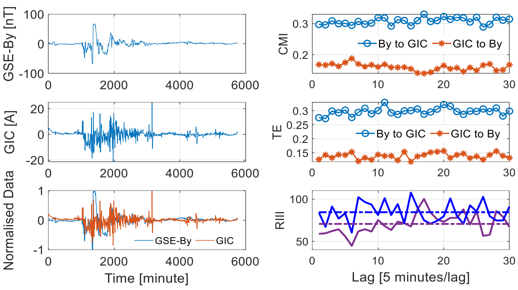

FIGURE 2. Causal relationship between GSE-B_y and GIC.

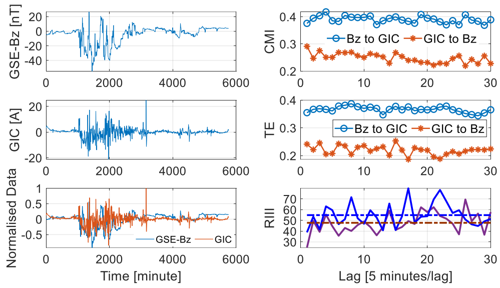

FIGURE 3. Causal relationship between GSE-B_z and GIC.

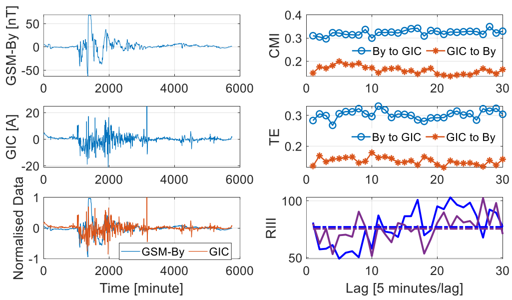

FIGURE 4. The causal relationship between GSM-B_y and GIC.

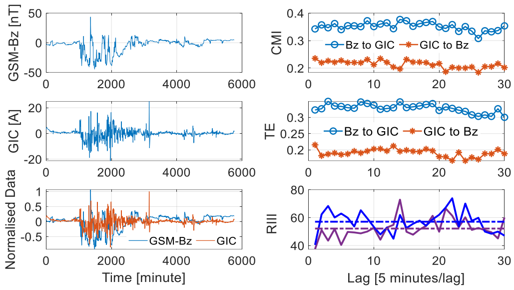

FIGURE 5. Causal relationship between GSM-B_z and GIC.

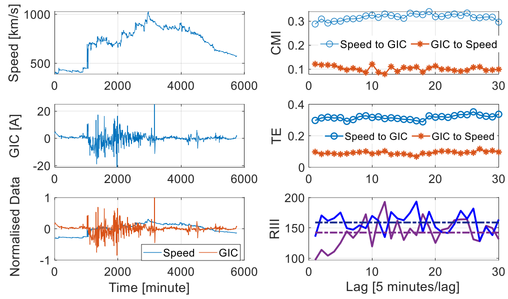

FIGURE 6. The causal relationship between solar wind speed V_{sw} and GIC.

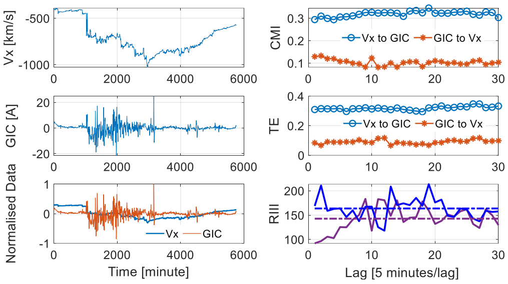

FIGURE 7. Causal relationship between V_x and GIC.

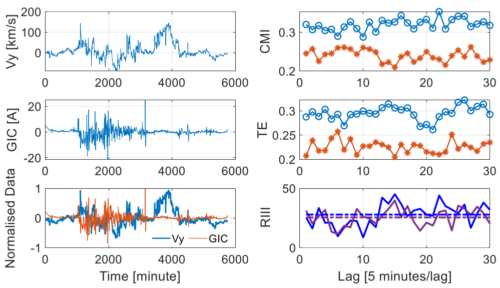

FIGURE 8. Causal relationship between V_y and GIC.

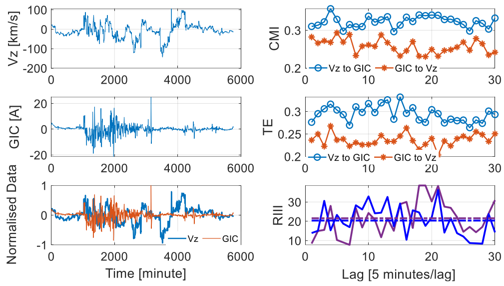

Figure 9. The causal relationship between V_z and GIC.

4.4 Observations and findings

From the results presented in the previous section, we can obtain the following observations and findings:

- The two variables that show the strongest strength in driving GIC are solar wind speed (V_{sw}) and solar wind velocity in x-coordinate (V_x). The relative increase in conditional mutual information and transfer entropy is around 150%.
- The weakest variable in driving GIC is solar wind velocity in z-coordinate (V_z), with the relative increase in conditional mutual information and transfer entropy being around 20%.

The rank of the nine variables, in order of their overall strength in driving GIC, measured by the values of the relative increase in conditional information (mutual information and transfer entropy), is shown in TABLE 2.

TABLE 2. The rank of the nice variable strength in driving GIC during the Gannon (or Mother's Day) storm

Variable	**Strength**
V_{sw}	150%
V_x	150%
GSM-B_y	80%
GSE-B_y	75%
GSM-B_z	55%
GSE-B_z	50%
B_x	30%
B_y	25%
B_z	20%

5. Conclusions

The two information theoretic methods, conditional mutual information (CMI) and transfer entropy (TE), have been applied to detect, evaluate and analyse the potential drivers of geomagnetically induced currents (GICs), which is a highly important and yet challenging problem in space weather. The novel research findings of this work is of high significance and very useful for developing powerful data-driven models for better predicting GIC behaviour to mitigate or prevent disastrous consequences caused by extreme GIC events. Further investigations will be conducted in the following two directions in future: 1) To carry out experiments using data with different time resolutions, recorded in different regions and countries; 2) To develop new methods that accurately estimate the characteristic response patterns (e.g. response time) of GICs to most important drivers; and 3) To make use the causal relationship information to develop more powerful predictive models.

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