

# 274. On the causal inference in magnetosphere / solar wind system during geomagnetic storms.

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## Abstract

The Sun, a vital source of light and energy, poses potential hazards through solar storms, particularly during active solar phases occurring every eleven years. These storms can disrupt power grids, radio networks, and satellites if directed toward Earth. In these cases geomagnetic storms can occur. Since these events are typically monitored through the SYM-H geomagnetic index, a comprehensive understanding and accurate modeling of the SYM-H index's dynamics features are essential for investigating about geomagnetic storms. This work aims to study the causal relations between magnetospheric dynamics and external drivers, using a bivariate time series causality analysis, which let us to estimate the normalized information transfer between the variables of the system. Preliminary results show important qualitatively agreements with [1] which used linear correlation analysis.

## Research objectives

- Objective:** investigate the causal relations between magnetospheric dynamics and external drivers during geomagnetic storms

## Introduction

Solar storms are emissions of energy and charged particles from the Sun, such as *Coronal Mass Ejection* (CME), and can affect Earth's magnetic field, if directed toward Earth. The magnetosphere can usually shield Earth from solar storms, but sometimes, they can cause saturation of transformers, blackout of power systems, disturbances of international communications, damage satellites and be responsible for exposing astronauts to abnormal levels of radiation [2].

The energy transferred from a solar storm to Earth's magnetic field is primarily determined by the relative orientation of the interplanetary magnetic field within the CME, the source of the geomagnetic storms [3]. If the magnetic field has a southward component for enough time, the interplanetary plasma can penetrate the magnetosphere, intensifying its current systems. This intensification, particularly of the ring current circulating in the magnetospheric equatorial plane, triggers geomagnetic storms. These events are typically monitored through the SYM-H geomagnetic index [4, 5]. Therefore, a comprehensive understanding and accurate modeling of the SYM-H index's dynamic features are essential for investigating about geomagnetic storms.

This work aims to study the causal relations between magnetospheric dynamics and external drivers, using a bivariate time series causality analysis, which let us to reconstruct the causal graph of the system, following the methodology outlined by [6]. This method takes as input a linear 2D continuous-time stochastic system for a bivariate time series and provides an estimation of the asymmetric information transfer between the system's components. As defined by [6], these values are normalized and subjected to statistical significance testing.

This work focuses on finding the most relevant solar wind / magnetosphere coupling functions [1] in terms of the normalized information transfer with respect to SYM-H. In detail, in order to study the response time of the magnetosphere to external solar wind drivers, here it is used a delayed version of the net normalized information flow.

## Data and Methods

### Data

In this study we use solar wind time series from Advanced Composition Explorer (ACE) spacecraft and geomagnetic time series of the low-latitude, retrieved at OMNI website, during periods of 36 geomagnetic storms occurred between 1998 and 2018:

- Magnetic field measurements are in GSM reference frame with a temporal resolution of 16 s (ACE).
- Solar wind speed, also in GSM, and proton density with a temporal resolution of 64 s (ACE).
- Geomagnetic index SYM-H with a temporal resolution of 1 min (OMNIWeb).

In the Figure 1, we focus on the north-south component ( $B_z$ ) of the magnetic field, the solar wind speed, the proton density and the SYM-H index, during a strong geomagnetic storm ( $K_p, max = 7+$ ).

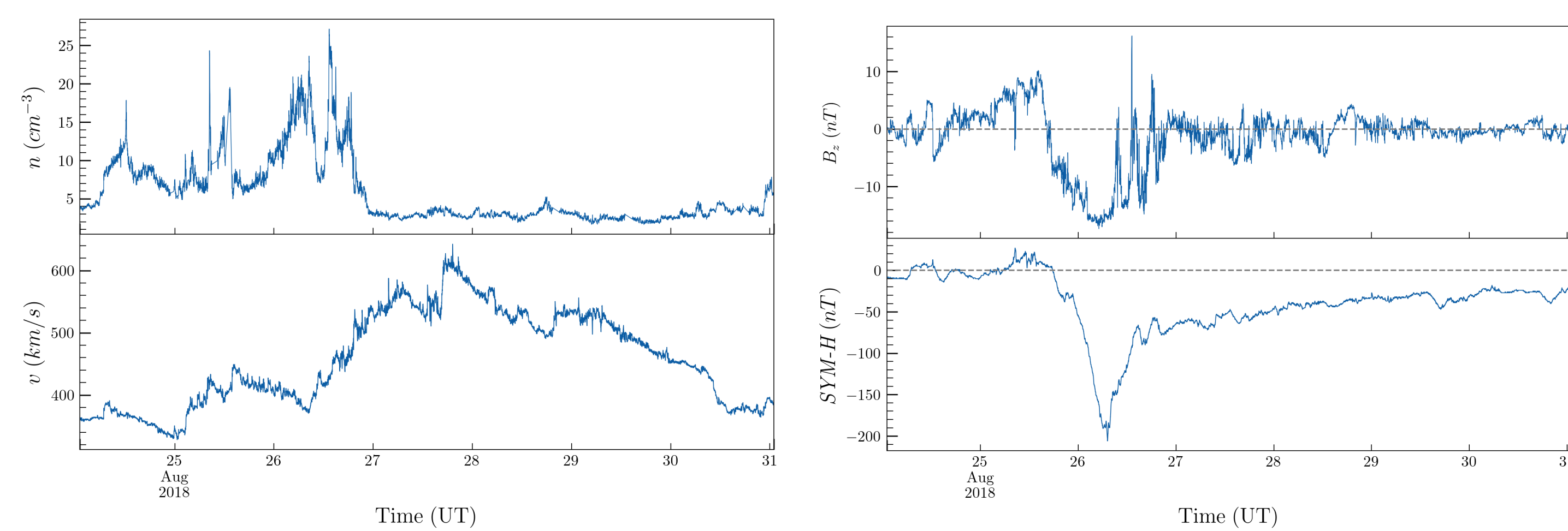


Figure 1. The solar wind speed,  $v$ , and the proton density,  $n$  (on the left). The north-south component,  $B_z$ , and the SYM-H index, for a selected period relative to a geomagnetic storm (on the right).

Following the procedure of [7] the magnetic field and the plasma data are time-shifted from ACE position (L1) to the nose of the bow shock to focus on the response of the magnetosphere to the solar wind, and finally resampled at 1 min.

### Methods

Consider a linear 2D continuous-time stochastic system for  $\mathbf{X} = (X_1, X_2)$ :

$$d\mathbf{X} = \mathbf{f} + \mathbf{A}\mathbf{X}dt + \mathbf{B}d\mathbf{W}, \quad (1)$$

where  $\mathbf{f} = (f_1, f_2)$  is a constant vector,  $\mathbf{A} = (a_{ij})$  and  $\mathbf{B} = (b_{ij})$  (matrix of perturbation amplitudes) are constant matrices, and  $\mathbf{W}$  a vector of standard Wiener process. The assumptions are:

- $\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ , with  $\boldsymbol{\mu} = (\mu_1, \mu_2)^T$  and  $\boldsymbol{\Sigma} = (\sigma_{ij})$  being the mean vector and covariance matrix, respectively;
- data is stationary and equal-distanced with time stepsize  $\Delta t$ ;
- $N$  is large with respect to  $\Delta t$ ;
- $b_{ij} = 0$  if  $i \neq j$ ;
- $\mathbf{f} = \mathbf{f} + \mathbf{A}\mathbf{X}$  and  $\mathbf{B}$  are differentiable.

Let the transition pdf be  $\rho(\mathbf{X}_{n+1} | \mathbf{X}_n; \boldsymbol{\theta})$ , where  $\boldsymbol{\theta}$  stands for the vector of parameters to be estimated, so, the log likelihood is

$$\ell_N(\boldsymbol{\theta}) \simeq \sum_{n=1}^N \log \rho(\mathbf{X}_{n+1} | \mathbf{X}_n; \boldsymbol{\theta}). \quad (2)$$

Maximizing  $\ell_N$  leads to the maximum-likelihood estimators (mle), which led to the estimator of the information flow, for example from  $X_2$  to  $X_1$ :

$$T_{2 \rightarrow 1} = \frac{1}{\det \mathbf{C}} \cdot \sum_{j=1}^2 \Delta_{2j} C_{j,1} \cdot \frac{C_{12}}{C_{11}}, \quad (3)$$

where  $C_{ij}$  and  $C_{i,j}$  are the sample covariances, and  $\Delta_{ij}$  are the cofactors of the matrix  $\mathbf{C} = (C_{ij})$ .

The normalization of (3), following [6], is given by

$$\mathcal{T}_{2 \rightarrow 1} = \frac{T_{2 \rightarrow 1}}{Z_1} \in [-1, 1], \quad (4)$$

where

$$Z_1 = |a_{11}| + |T_{2 \rightarrow 1}| + \frac{1}{2} \frac{b_{11}^2}{|C_{11}|}.$$

The first term represents the contribution of itself, the second part are the information to flows  $X_1$  and the last term is the effect of the noise.

## Results and discussion

We start the causal analysis by computing all the solar wind/magnetosphere coupling functions reported in [1], as listed in Table 1.

For each coupling function  $Q(t)$ , we considered a time-shifted version, i.e.,  $Q(t + \tau)$ , with  $\tau \in [1, 200]$  min. We then defined  $X(t) = \text{SYM-H}(t)$  (response) and  $Y(t) = Q(t + \tau)$  (driver), and computed the *delayed normalized net information flow*  $\Delta \mathcal{T}_{Y \leftrightarrow X}(\tau) = |\mathcal{T}_{Y \rightarrow X}(\tau)| - |\mathcal{T}_{X \rightarrow Y}(\tau)|$ . This analysis was conducted for each storm, after which the results were averaged, and the standard deviation of the mean was considered as error. Figure 2 presents the results associated with each of the coupling functions considered. Table 2 ranks the coupling functions with respect to the higher values of  $(\Delta \mathcal{T}_{Y \leftrightarrow X}(\tau^*))$ , where  $\tau^* = \text{argmax}_{\tau} (\Delta \mathcal{T}_{Y \leftrightarrow X}(\tau))$ .

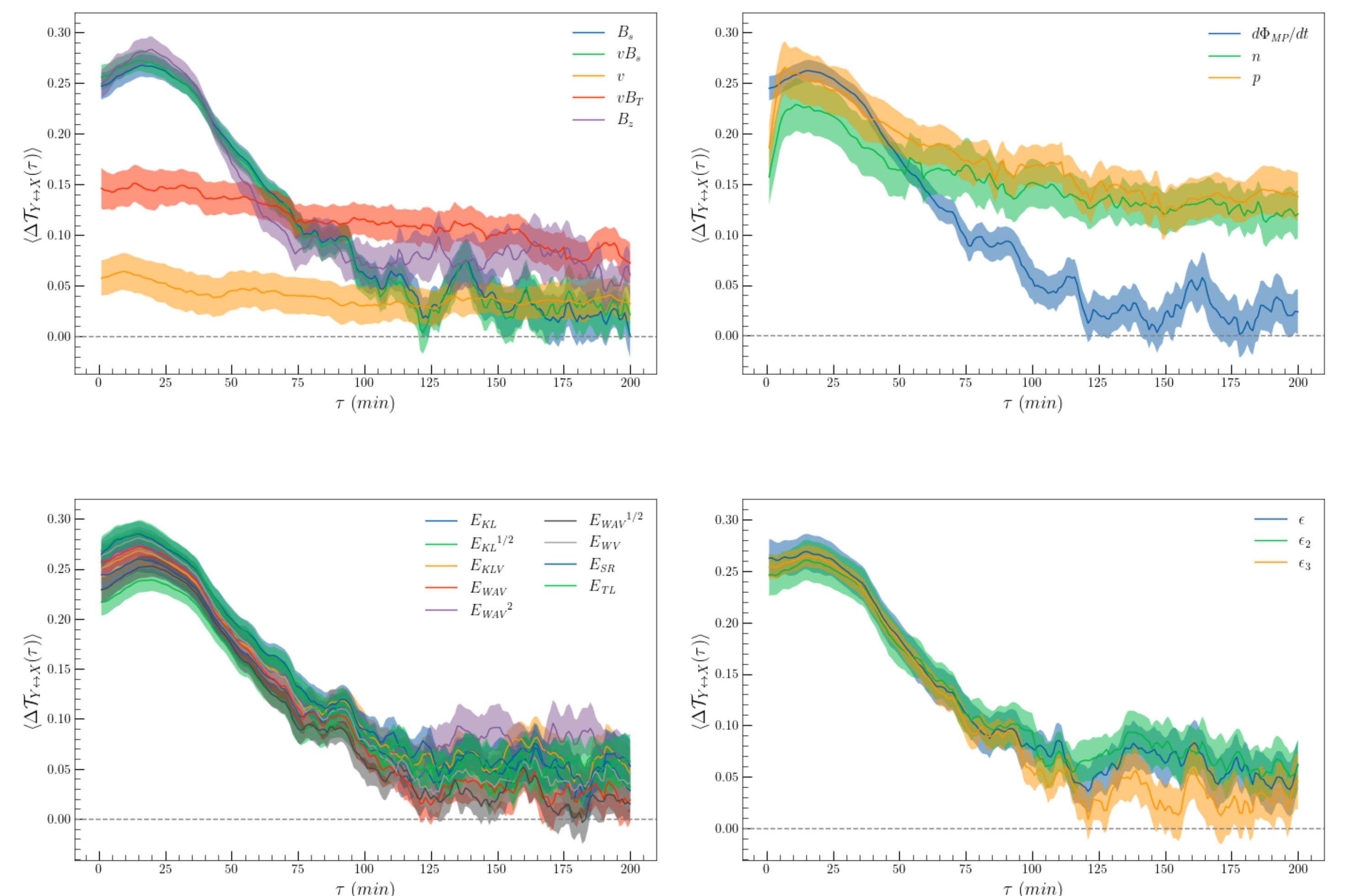


Figure 2. Mean normalized net information flow  $\langle \Delta \mathcal{T}_{Y \leftrightarrow X}(\tau) \rangle$  between  $Q(t + \tau)$  and SYM-H as a function of  $\tau$ , for all the coupling function considered (solid line) together with its standard deviation (shaded area).

Our analysis reveals that the functional form of the electric field emerges as the optimal choice. This finding aligns qualitatively with the results presented by [1], which is a reasonable outcome given our use of a linear model (1) in conjunction with linear correlations of [1]. The observed discrepancies may be attributed to the use of different datasets compared to those used by [1]. Notably, our dataset boasts a higher resolution (1 min) as opposed to [1]'s 1-hour resolution.

These findings set the stages for future work in modeling the magnetosphere's response to the solar wind, for example, using differential equations.

Name	$Q(t)$
$B_z$	$B_z$
Velocity	$v$
Density	$n$
$p$	$nv^2/2$
$B_s$	$B_z (B_z < 0)$ $0 (B_z \geq 0)$
Half-wave rectifier	$v B_s$
$\epsilon$	$v B^2 \sin^4(\theta_c/2)$
$\epsilon_2$	$v B_T^2 \sin^4(\theta_c/2)$
$\epsilon_3$	$v B \sin^4(\theta_c/2)$
Solar wind E-field	$v B_T$
$E_{KL}$	$v B \sin^2(\theta_c/2)$
$E_{KL}^{1/2}$	$[v B_T \sin^2(\theta_c/2)]^{1/2}$
$E_{KLV}$	$v^{1/3} B_T \sin^2(\theta_c/2) p^{1/6}$
$E_{WAV}$	$v B_T \sin^4(\theta_c/2)$
$E_{WAV}^2$	$[v B_T \sin^4(\theta_c/2)]^2$
$E_{WAV}^{1/2}$	$[v B_T \sin^4(\theta_c/2)]^{1/2}$
$E_{WV}$	$v^{4/3} B_T \sin^4(\theta_c/2) p^{1/6}$
$E_{SR}$	$v B_T \sin^4(\theta_c/2) p^{1/2}$
$E_{TL}$	$n^{1/2} v^2 B_T \sin^6(\theta_c/2)$
$d\Phi_{MP}/dt$	$v^{4/3} B_T^{2/3} \sin^{8/3}(\theta_c/2)$

Table 1. Solar wind-magnetosphere coupling functions taken from [1].

$Q(t)$	$\langle \Delta \mathcal{T}_{Y \leftrightarrow X}(\tau^*) \rangle$	$\tau^*$ (min)
$E_{TL}$	$0.286 \pm 0.012$	16
$E_{SR}$	$0.285 \pm 0.013$	15
$B_z$	$0.283 \pm 0.013$	20
$E_{WV}$	$0.281 \pm 0.011$	15
$E_{WAV}^2$	$0.276 \pm 0.013$	15
$v B_s$	$0.273 \pm 0.011$	16
$E_{WAV}$	$0.272 \pm 0.011$	15
$\epsilon$	$0.269 \pm 0.017$	15
$E_{KLV}$	$0.268 \pm 0.014$	15
$B_s$	$0.268 \pm 0.011$	16
$p$	$0.266 \pm 0.026$	7
$\epsilon_3$	$0.264 \pm 0.010$	15
$d\Phi_{MP}/dt$	$0.262 \pm 0.011$	15
$\epsilon_2$	$0.260 \pm 0.020$	15
$E_{KL}$	$0.260 \pm 0.013$	15
$E_{WAV}^{1/2}$	$0.252 \pm 0.010$	20
$E_{KL}^{1/2}$	$0.239 \pm 0.011$	20
$n$	$0.229 \pm 0.026$	11
$v B_T$	$0.151 \pm 0.018$	14
$v$	$0.064 \pm 0.018$	9

Table 2. Solar wind-magnetosphere coupling functions taken from [1].

## Conclusions

This study analyzed causal relations between magnetospheric dynamics and solar wind drivers during geomagnetic storms using high-resolution data. Key findings include:

- Electric field-related coupling functions ( $E_{TL}$ ,  $E_{SR}$ ) exhibit the highest normalized information transfer, highlighting their significant role in geomagnetic storms.
- Results align with previous studies (e.g., Newell et al., 2007), validating our methodology.

Future work will focus on extending this analysis to differential equations to model the magnetosphere's response to solar wind.

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