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Quantifying Contributions of External Drivers to the Global Ionospheric State

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Abstract To advance our understanding of the global response of the ionospheric total electron content (TEC) to various external drivers, we apply entropy-based information theory to quantify contributions of solar, interplanetary, and lower atmospheric drivers to the global ionospheric state described by the Global Ionospheric Map (GIM). By computing normalized transfer entropy on 18 years of GIM TEC, F10.7, solar wind, and lower atmospheric data, we obtain the predictive information transfer from the present drivers to the global ionospheric state at various future times. We find that the solar extreme ultraviolet (EUV) irradiance dominates the information transfer within 3 days into the future, while the lower atmospheric migrating tidal sources dominate beyond 3 days into the future. The maximum information transfer from individual drivers reveals the maximum contributions from the drivers to the global ionospheric state. Among all drivers considered, the lower atmospheric migrating tidal sources contribute most. The solar EUV irradiance and tropospheric deep convection are secondary drivers with comparable contributions at about half of the contribution from migrating tidal sources. The interplanetary driving contributes the least to the global ionospheric state during both geomagnetic storm and quiet time, even though the contribution from the interplanetary magnetic field can enhance four to six times during geomagnetic storm time than quiet time.

Plain Language Summary The terrestrial ionosphere, located between about 60 and 1,000 km altitudes, is a layer of the atmosphere where free electrons and ions are abundant. The electrons cause delays of radio signals transmitting through the ionosphere, impacting the performance of space-bourn technological systems. The abundance of ionospheric electrons is spatially and temporally varying and subjected to external driving from the Sun and the lower atmosphere. For the first time, we quantify the contributions of individual external drivers to the height-integrated ionospheric electron density using information theory, a modern machine learning technique. Our results reveal the dominant and persistent role of lower atmospheric tides in driving the ionospheric electron density beyond 3 days into the future.

1. Introduction

The terrestrial ionosphere is subjected to continuous driving from space weather and the lower atmosphere on various temporal and spatial scales. Space weather, originated from the solar activity, drives the ionosphere mainly via the solar extreme ultraviolet (EUV) and X-ray irradiance, as well as the solar wind arriving at the Earth that causes geomagnetic activities (Kutiev et al., 2013; Mendillo, 2006). The lower atmosphere, hereby referring to the troposphere, stratosphere, and lower mesosphere reside below the ionosphere, impacts the ionosphere through upward propagating waves such as planetary waves, tidal waves, gravity waves, and acoustic waves and via electrical and electromagnetic processes (Laštovička, 2006; Liu, 2016). Several studies have distinguished contributions from different external drivers to the global ionospheric variability. For example, the lower atmospheric forcing is found to contribute about 15%–35% to the variability of the ionospheric F2-layer electron density peak in observational studies (Forbes et al., 2000; Rishbeth & Mendillo, 2001). Moreover, a recent modeling study (Fang et al., 2018) reveals that the geomagnetic activity is the dominant driver of the relative variabilities of total electron content (TEC), while the contributions from the solar activity and lower atmosphere perturbations are less.

Despite of the significant advances in quantifying drivers of the ionospheric variability, the amount of contributions from different external drivers to the ionospheric state is not well understood, especially from the ionospheric forecast perspective (Heelis & Maute, 2020). Unlike the ionospheric variability, often represented by standard deviations of ionospheric variables, the ionospheric state is described by ionospheric
variables themselves, which are directly solved for and output by predictive ionospheric models. The concept of the ionospheric forecast can be encapsulated as “given the present ionospheric state and external driver conditions, what is the ionospheric state in the future?” A successful forecast of the future ionospheric state depends on the knowledge of the present ionospheric state, external drivers, and internal dynamics, which correspond to initial conditions, boundary conditions, and governing equations respectively in first-principles ionospheric models. In particular, a systematic and quantitative understanding of various external driver contributions to the global ionospheric state is essential to ionospheric forecast, yet this knowledge is lacking.

For the first time, we apply transfer entropy, an information theoretical approach, to quantify external driver contributions to the global ionospheric state. Transfer entropy (Schreiber, 2000) has been demonstrated as a powerful technique to uncover the directional information transfer between two physical quantities. Successful applications of transfer entropy to space physics research have brought new insight and discoveries for traditional problems (De Michelis et al., 2011; Johnson et al., 2018; Materassi et al., 2007; Stumpo et al., 2020; Wing et al., 2016, 2018; Wing & Johnson, 2019). In this study, we consider the global ionosphere as a closed system driven by solar, interplanetary, and lower atmospheric conditions. We neglect magnetospheric inputs to the ionosphere based on the assumption that any magnetospheric processes impacting the ionosphere are ultimately driven by interplanetary conditions. The magnetosphere-ionosphere coupling is thus taken as part of “internal dynamics”. Using transfer entropy, we investigate the predictive information transfer from the solar, interplanetary, and lower atmospheric data to the TEC data for 18 years. We obtain percentage contributions from individual drivers to the global ionospheric state over contributions from all drivers plus internal dynamics. The outcome of the study improves the understanding of ionospheric responses to external driving and offers new perspectives for the ionospheric forecast by answering the open question: to what extent each driver determines the future global ionospheric state?

The following content of the paper is divided into three parts. Section 2 describes the transfer entropy formulation specialized for this study and data sets used. Section 3 presents results on the information transfer from external drivers to the global ionospheric state. Section 4 concludes the study.

2. Methodology

2.1. Transfer Entropy

Transfer Entropy, introduced by Schreiber (2000) and rooted in information theory, is a quantitative measure of the directional information transfer between two time-dependent processes. Given two processes $X$ and $Y$ that evolve in time $t$, the transfer entropy (TE) from $X$ to $Y$ can be expressed by a general form (Bennett et al., 2019; Bossomaier et al., 2016):

$$\text{TE}_{X \rightarrow Y, \text{general}} = I(Y_t; X_t^{(k,\tau)}|Y_t^{(l,\omega)})$$  \hspace{1cm} (1)

where $I(Y_t; X_t^{(k,\tau)}|Y_t^{(l,\omega)})$ is the conditional mutual information (Wyner, 1978) measuring the shared information between $Y$ and $X$, and $X_t^{(k,\tau)}$ that is, not contained in $Y_t^{(l,\omega)}$. $X_t^{(k,\tau)}$ and $Y_t^{(l,\omega)}$ are the past histories of the source $X$ and the target $Y$, specifically, $X_t^{(k,\tau)} = (X_{t-\tau}, X_{t-\tau-1}, \ldots, X_{t-k-1})$ and $Y_t^{(l,\omega)} = (Y_{t-\omega}, Y_{t-\omega-1}, \ldots, Y_{t-l-1})$. $k$ is the source history length, while $l$ is the target history length. $\tau$ and $\omega$ are the time lags for the source and target, respectively. The choices for the history lengths and time lags depend on applications, leading to slightly different formulations of transfer entropy.

In this work, we take the history lengths $k = l = 0$ for simplicity and the time lags $\tau = 0$. We also substitute $t$ with $t + \tau$ for a more natural interpretation from the perspective of prediction. The resulting transfer entropy formulation with discretized distributions for $X$ and $Y$ becomes

$$\text{TE}_{X \rightarrow Y} = I(Y_{t+\tau}; X_t|Y_t) = \sum_{a,b,c} p(Y_{t+\tau} = a|X_t = b, Y_t = c) \log_2 \frac{p(Y_{t+\tau} = a|X_t = b, Y_t = c)}{p(Y_{t+\tau} = a|Y_t = c)}$$  \hspace{1cm} (2)

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where H represents the entropy in information theory and \( p() \) is the probability. Here we have taken the base 2 logarithm, which gives the unit of entropy, conditional mutual information, and transfer entropy as bits. Other values for the base can be used, leading to different units (Schreiber, 2000). \( \Sigma \) is for all value combinations of \((Y_{x+i}, X, Y)\). The specific formulation of transfer entropy given by Equation 2 is also used in a number of studies (Bhaskar et al., 2017; De Michelis et al., 2011; Das Sharma et al., 2012; Johnson et al., 2018; Materassi et al., 2007; Stumpo et al., 2020; Wing et al., 2016).

The transfer entropy given by Equation 2 quantifies the amount of information transferred from the current X to the future Y at \( r \) time later. The transfer entropy is positive when there is information transfer from X to Y. A larger transfer entropy corresponds to more information transfer. Theoretically, \( \text{TE}_{X \rightarrow Y} = 0 \) when the information transfer is absent. However, the transfer entropy has intrinsic bias caused by the finite number of data points and binning method (Gencaga et al., 2015) for calculating the probabilities. Therefore, in practice \( \text{TE}_{X \rightarrow Y} > 0 \) even if there is no information transfer from X to Y (Bossmo et al., 2016). To characterize the statistical significance of transfer entropy values and to compare transfer entropy values obtained for different source-target pairs, we use the normalized transfer entropy (NTE) (Gourevitch & Eggermont, 2007) instead:

\[
\text{NTE}_{X \rightarrow Y} = \frac{\text{TE}_{X \rightarrow Y} - \text{TE}_{X^S \rightarrow Y}}{H(Y_{r+\tau}|Y)}
\]

where

\[
H(Y_{r+\tau}|Y) = -\sum_{a,c} p(Y_{r+\tau} = a,Y = c) \log_2 p(Y_{r+\tau} = a|Y = c)
\]

In Equation 3, \( \text{TE}_{X^S \rightarrow Y} \) is the mean of \( \text{TE}_{X^S \rightarrow Y} \) calculated from a set of surrogate source \( X^S \) and the target Y. The set of \( X^S \) is constructed to remove any potential information transfer to Y while maintaining the statistical properties of X. In this study, we randomly shuffle the order of the original X values for a certain number of times to obtain the set of \( X^S \). The denominator \( H(Y_{r+\tau}|Y) \) is the maximum possible value of \( \text{TE}_{X \rightarrow Y} \) and quantifies the information in \( Y_{r+\tau} \) not found in its history Y. This information is composed of the information transferred from all external drivers to Y and the information generated from intrinsic uncertainties, that is, internal dynamics of Y. NTE\( \text{TE}_{X \rightarrow Y} \) is dimensionless and always less than or equal to 1. A positive NTE\( \text{TE}_{X \rightarrow Y} \) indicates a statistically significant ratio of information transfer from X to Y over the information transferred from all external drivers plus any internal dynamics of Y (Lizier et al., 2010). To evaluate the uncertainty of NTE\( \text{TE}_{X \rightarrow Y} \), we compute

\[
\text{bounds}(\text{NTE}_{X \rightarrow Y}) = \frac{\text{TE}_{X \rightarrow Y} - (\text{TE}_{X^S \rightarrow Y} \pm 3\sigma(\text{TE}_{X^S \rightarrow Y}))}{H(Y_{r+\tau}|Y)}
\]

where \( \sigma(\text{TE}_{X^S \rightarrow Y}) \) is the standard deviation of the transfer entropy values from the set of surrogate source \( X^S \) to target Y. Equation 5 gives the lower and upper bounds of NTE\( \text{TE}_{X \rightarrow Y} \) based on 3-σ spread of \( \text{TE}_{X^S \rightarrow Y} \). We refer the difference between the lower and upper bounds of NTE\( \text{TE}_{X \rightarrow Y} \) as the 3-σ uncertainty of NTE\( \text{TE}_{X \rightarrow Y} \) in Section 3.

The information transfer revealed by transfer entropy is a different concept from the physical causality (Pearl, 2000) that identifies “to what extent the change in the state of the source modifies the state of the target” (Bossmo et al., 2016; Lizier & Prokopenko, 2010). Instead, transfer entropy is closely related to, sometimes equivalent to, the Wiener-Granger causality (Granger, 1969; Wiener, 1956) that identifies “to what extent knowing the state of the source helps predict the state of the target” (Barnett, 2009; Barnett & Bossmo, 2012). Therefore, the transfer entropy specialized for our study, expressed by Equation 2, indicates “given the current Y, to what extent knowing the current X helps predict the future Y at \( r \) time later?” This resonates with the concept of the forecast, in particular, ionospheric forecast in our study. Furthermore, the relation between transfer entropy and physical causality is not fully understood. Research efforts (Parrondo et al., 2015; Prokopenko et al., 2013; Spinney et al., 2016; Toyabem et al., 2010) have discovered the relevance between entropy-based information and thermodynamic quantities for specific micro-scale systems, yet the physical interpretation of information and transfer entropy remains incomplete, especially for macro-scale systems like the ionosphere. As a result, we do not attempt to connect the information transfer calculated in our study with any physical processes. Instead, we use transfer entropy as a tool to find out
the influence of external drivers on the global ionospheric state for applications to ionospheric forecasting. Note that the term “external driver” here refers to the source $X$ that transfers predictive information to the target $Y$ and does not necessarily indicate a physical causal relationship between $X$ and $Y$. Nevertheless, external drivers investigated in our study, including solar, interplanetary, and lower atmospheric drivers, are known to have physical causality relationships with the global ionospheric state.

In this study, we focus on the normalized transfer entropy described by Equation 3, which characterizes the external driver contribution by a ratio or percentage. The normalized transfer entropy values from different pairs of the external driver and global ionospheric state variables can be inter-compared. By examining the normalized transfer entropy as a function of the time lag $\tau$, one can evaluate the impact of the present source $X$ on the target $Y$ at various future time $\tau$. We introduce “information coupling time” from $X$ to $Y$ as the $\tau$ at which the normalized transfer entropy maximizes. The information coupling time indicates how far into the future the present source $X$ has the largest influence on the target $Y$, and thus offers insight on the history of external driving to consider for forecasting the global ionospheric state. We emphasize that the information coupling time is not the time taken for the information to transfer from $X$ to $Y$. Moreover, the information coupling time is conceptually different from the physical coupling time, that is, the time taken for the ionosphere to respond to external driving through certain physical processes (Afraimovich et al., 2008; Jacobi et al., 2016; Khan & Cowley, 1999; Mannucci et al., 2008; Pedatella & Forbes, 2010; Rishbeth et al., 1985; Schmölter et al., 2020), though the two coupling time values could be close as reported in Section 3.

### 2.2. Description of Data Sets

We utilize ionospheric, solar, interplanetary, and lower atmospheric data sets to extract multiple time series representing the global ionospheric state and the external driver conditions from 2000 to 2017.

We represent the global ionospheric state by global median TEC, global maximum TEC, and global electron content (GEC) extracted from the Jet Propulsion Laboratory (JPL) Global Ionosphere Map (GIM) (Mannucci et al., 1998). GIM is gridded TEC data obtained by spatially interpolating and temporally Kalman filtering Global Navigation Satellite System derived TEC measurements at ground receivers distributed worldwide. While the JPL GIM can provide TEC maps at various temporal and spatial resolutions, for this study we use the finest-resolution GIM product: TEC maps with a spatial resolution of $1^\circ \times 1^\circ$ and a temporal resolution of 15 min (https://sideshow.jpl.nasa.gov/pub/ions_daily/gim_for_research/jpli/). An example TEC map at a geomagnetic quiet time and locations of ground receivers, from which measurements were taken to generate the map, is displayed in Figure 1. For each TEC map during 2000–2017, we extract three variables: global median TEC, global maximum TEC, and GEC, which is the global sum of the TEC for each grid cell multiplied by the area of the grid cell (Afraimovich et al., 2006, 2008). The unit of GEC is
GECU and 1 GECU = 10^{22} \text{ electrons. For each of the three TEC variables, we compute daily averages and hourly averages to obtain a daily and an hourly time series, both spanning from 2000 to 2017. Histograms of the daily average data are shown in Figure 2. These histograms indicate probability distributions of the TEC variables, which are fundamental quantities required for the calculation of conditional probabilities in Equations 2 and 4.}

We represent the solar and interplanetary drivers by the F10.7 index and solar wind conditions at 1AU, respectively. The daily F10.7, or the F10.7 cm solar radio flux, is a widely used proxy for solar EUV irradiance (Tapping, 2013). We construct a daily F10.7 time series for 2000–2017 (ftp://ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/KP_AP/). For the solar wind, we obtain OMNI hourly-averaged data (https://spdf.gsfc.nasa.gov/pub/data/omni/), including the interplanetary magnetic field (IMF) magnitude and $B_z$, solar wind speed, density, and temperature, for 2000–2017. Daily averaged solar wind time series is then calculated.

For lower atmospheric forcing, we focus on upward-propagating wave driving, which is considered to be more important than electrical and electromagnetic forcing (Laštovička, 2006). The lower atmospheric waves of importance to the ionosphere have a variety of spatial and temporal scales and arise from various sources (Liu, 2016). We investigate two important lower atmospheric wave sources: solar radiative heating and tropospheric deep convection. These two types of wave sources cover the primary sources for atmospheric tides, which not only impact all ionospheric layers globally but also are the dominant lower atmospheric forcing mechanism included in current state-of-the-art global ionospheric models (Chen et al., 2013; Liu, 2014). In the lower atmosphere, solar radiation is primarily absorbed by ozone in the ultraviolet (UV) wavelengths and by water and water vapor in the infrared (IR) wavelengths. The resulting solar radiative heating is the primary source for migrating thermal tides (Hagan et al., 2001). We represent the strength of the solar radiative heating by the global average of total column ozone (TCO) and the global average of total precipitable water vapor (TPW) from Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) (Gelaro et al., 2017), an observational data assimilation model describing the state of the atmosphere from the surface to about 70–80 km altitude. Tropospheric deep convection is a source for migrating and non-migrating thermal tides (Hagan & Forbes, 2002; Linzden, 1977). In addition, tropospheric deep convection can excite other planetary-scale waves, gravity waves, and acoustic waves (Liu, 2016). We represent the strength of the tropospheric deep convection by the global average of convective precipitation from MERRA-2. We extract both daily averaged and hourly-averaged time series for each of the global average TCO, TPW, and convective precipitation for 2000–2017. For simplicity, we will omit the phrase “global average” when referring to the three lower atmospheric variables hereafter.
3. Results

We consider each driver variable as the source \( X \) and each TEC variable as the target \( Y \). For every source-target pair, we divide the source and target data into bins of equal lengths (examples shown in Figure 2) to calculate the required conditional probabilities. The surrogate source data \( S_X \) is constructed by randomly shuffling the source time series for 100 times. The normalized transfer entropy from \( X \) to \( Y \) and its uncertainty bounds are then computed according to Equations 3 and 5, respectively.

Figure 3 displays the normalized transfer entropy for the daily average data from 2000 to 2017. In panels (a), (c) and (e), the normalized transfer entropy is shown as a function of the time lag \( \tau \). Different colors represent different driver variables. The shaded area around each line marks the 3-\( \sigma \) uncertainty of the normalized transfer entropy from the 100 randomly permuted driver time series to the TEC time series. Observing panels (a), (c), and (e), for any TEC variable, the normalized transfer entropy (a) varies with different driver variables, indicating various amount of contributions from different drivers to the future of the TEC variable, and (b) varies with \( \tau \), indicating varying influence of a driver variable on the TEC variable at different future time. For \( \tau < 3 \) days, the information transfer from driver variables to TEC variables is dominated by the F10.7, while for larger \( \tau \), the information transfer is dominated by the TCO and TPW. Hence, given all driver variables and TEC variables at the present time, the F10.7 contributes most to the TEC variables. 

![Normalized Transfer Entropy from External Drivers to TEC Variables for 2000 - 2017](image-url)
days for all TEC variables. For the global median TEC, this first peak is the most significant peak of the normalized transfer entropy from the F10.7, indicating an information coupling time of 2 days from the F10.7 to the global median TEC. Interestingly, the two-day information coupling time falls into the 1–3 days of time delay for the TEC to respond to the F10.7 revealed by previous studies (Afraimovich et al., Jakowski et al., Min et al., 2008; Jakowski et al., 2002; Min et al., 2009). For the global maximum TEC and GEC, the maximum normalized transfer entropy from the F10.7 occurs around \( \tau = 108 \) days, and thus it takes four solar rotation periods for the information transfer from the F10.7 to maximize. The information transfer from the TCO and TPW peaks between \( \tau = 80 \) and \( \tau = 120 \) days mostly, implying a 3- to 4-months information coupling time from the lower atmospheric migrating tidal sources to the TEC variables. The 3–4 months of information coupling time does not contradict the propagation time of migrating tides from the lower atmosphere to the ionosphere, which is on a time scale of days. This is because (a) the 3–4 months of information coupling time is for TCO and TPW, representations of migrating tidal sources, rather than for the migrating tides themselves and (b) the 3–4 months refer to the time required for the information transfer from TCO and TPW to maximize, which does not mean that the information transfer takes 3–4 months. In fact, the normalized transfer entropy values from TCO and TPW are positive at time lags of a few days and more (panels (a), (c), and (e)), indicating the present migrating tidal sources influence the TEC variables starting a few days into the future. Such influence persists for months and reaches the maximum at 3–4 months. The information transfer from the solar wind variables, in particular, the IMF magnitude and solar wind density, peaks at \( \tau = 1 \) day then quickly drop to values close to zero at larger \( \tau \), indicating that the solar wind impacts the TEC variables only a few days into the future. The information transfer from the convective precipitation peaks at around \( \tau = 185 \) days for all TEC variables, which is the longest information coupling time among all driver variables considered.

The maximum normalized transfer entropy values during \( \tau = 0 \) to \( \tau = 210 \) days are shown in Figures 3b, 3d, and 3f. These maximum values represent the maximum ratio or percentage of contributions from drivers to the future global ionospheric state over contributions from all external drivers (included and not included in this study) plus internal ionospheric dynamics, according to the definition of the normalized transfer entropy in Equation 3. As an example, the F10.7 contributes at most 6% to the global median TEC, 10% to the global maximum TEC, and 7% to the GEC. Averaging the maximum contributions from a given driver variable to all three TEC variables, the largest contributions come from the TCO and TPW, with 17% and 18% respectively, followed by the F10.7 and the convective precipitation with 8% contribution each, and then the solar wind variables, with 1%–3% contributions. The result reveals the dominant role of migrating tidal sources as well as the secondary and similar roles of the solar EUV irradiance and tropospheric deep convection for determining the future global ionospheric state. The sum of percentage contributions from all driver variables analyzed in this study is about 60%. Since the driver variables are not fully independent of each other, such as the intercorrelations between the solar wind variables (Borovsky, 2018), the total contribution from the drivers considered in the study may be far less than 60%. This indicates that external drivers not analyzed in the study plus internal ionospheric dynamics contribute at least 40% to the future global ionospheric state. Here the internal ionospheric dynamics refers to complex physical and chemical processes in the ionosphere and in particular includes magnetosphere-ionosphere coupling.

To investigate the contributions of interplanetary and lower atmospheric driving to the global ionospheric state on time scales shorter than one day, we calculate the normalized transfer entropy for the hourly averaged data. Geomagnetic quiet and storm time intervals are analyzed separately to account for possibly different contributions from interplanetary driving of different strengths. We identify all geomagnetic storms with the minimum Dst \( \leq -30 \) nT during 2000–2017. The start time of a storm interval is defined as 12 h before the first time Dst drops to be equal to or lower than \( -30 \) nT. The end time of a storm interval is defined as the last time Dst remains equal to or lower than \( -30 \) nT. Using the above definitions for storm start and end times, we find 1,152 storm intervals, each lasting 35 h on average. We define geomagnetic quiet time as the non-storm time interval with Dst > \( -15 \) nT that lasts for 12 h at least. With the criterion, we identify 1,491 quiet time intervals, each lasting 56 h on average. We then calculate the normalized transfer entropy for the driver data and TEC data that fall into the quiet and storm intervals separately.
Displayed in Figure 4, normalized transfer entropy values are very different for the quiet time and storm time. During the quiet time, the TCO and TPW are the two prevailing driver variables in terms of the amount of information transfer to all three TEC variables. The normalized transfer entropy from the solar wind variables is merely above zero for all \( \tau \). During the storm time, distinctive peaks in normalized transfer entropy from the solar wind variables are present, reaching or exceeding the normalized transfer entropy values from the TCO and TPW at the same \( \tau \). For the global median TEC, the information transfer from the IMF \( B_z \), IMF magnitude, solar wind density, and solar wind speed peaks at \( \tau = 14, 15, 24, 36 \) hours, respectively. For the global maximum TEC, only the information transfer from the IMF \( B_z \) exhibits a distinctive peak at \( \tau = 18 \) hours. For the GEC, the information transfer from the IMF \( B_z \) and IMF magnitude peaks at \( \tau = 17 \) and 24h, respectively. On average, IMF \( B_z \) has the shortest information coupling time of about 16h to the global ionospheric state, followed by the IMF magnitude (20h), solar wind density (24h), and solar wind speed (36h). Therefore, the present IMF \( B_z \) has the largest influence on the global ionospheric state about 16 hours into the future, while the present solar wind speed has the largest influence on the global ionospheric state about 36h into the future. This indicates that the present interplanetary conditions impact the global ionospheric state most within the next 16h and 36h. Moreover, the maximum information transfer from the solar wind variables are all less than 5\% even during the storm time. The low percentages may be attributed to the fact that the storm time includes all geomagnetic storms with the minimum \( Dst \leq -30nT \). It is highly possible that the solar wind contributes more during stronger storms.
The different amount of information transfer during quiet versus storm times is more clearly visualized in Figure 5, which shows the normalized transfer entropy averaged for $\tau \leq 24$ hours for each driver-TEC variable pair. The normalized transfer entropy is shown in percentage for simplicity. Two major features can be identified. First, lower atmospheric driver contributions remain approximately unchanged for quiet and storm times, while interplanetary driver contributions are significantly enhanced during the storm time than the quiet time. The largest increase is found for IMF $B_z$. Quantitatively, the contribution of IMF $B_z$ during the storm time is 4–6 times of its contribution during the quiet time. Second, comparing the contributions from different driver variables, the TCO and TPW have comparable contributions and dominate among all driver variables during the quiet time. Even during the storm time when the solar wind contributions increase, the TCO remains the most important driver variable. The average contribution from the solar wind variables to the TEC variables is about 10%–30% of the average contribution from the TCO and TPW for the quiet time, and the percentages increase to 30%–90% for the storm time. Furthermore, the contribution from the convective precipitation is about 30%–50% of the average contribution from the TCO and TPW during both quiet and storm times, which agrees with the result obtained with the daily resolution data.

**Figure 5.** Normalized transfer entropy averaged for $\tau \leq 24$ hours from driver variables to the global median total electron content (TEC) (a), global maximum TEC (b), global electron content (c) and for quiet and storm times separately. The average normalized transfer entropy values are presented on the vertical bars. The black vertical lines on top of the bars represent the 3-$\sigma$ spread.
4. Conclusions

This work is the first systematic quantification of the contributions from the solar, interplanetary, and lower atmospheric drivers to the global ionospheric state using transfer entropy. We compute the normalized transfer entropy to obtain the relative amount of information transfer from external drivers to the global ionospheric state, which characterizes the percentage contributions from individual driver variables to the global ionospheric state out of the contributions from all drivers plus internal ionospheric dynamics. The result quantifies the extent of each driver variable in determining the future global ionospheric state and leads to a driver importance ranking: the TCO and TPW representing the primary sources of lower atmospheric migrating tides are the most important drivers with 17% and 18% contributions respectively; the F10.7, a proxy for the solar EUV irradiance, and convective precipitation representing tropospheric deep convection that can generate tides and other atmospheric waves to drive the ionosphere are the secondary drivers with comparable contributions of 8%; the solar wind variables have the least contributions of less than 5% even during geomagnetic storm time. The ranking is based on the maximum information transfer from individual driver variables to the global ionospheric state over a range of time lags. The time lag at the maximum information transfer is defined as the information coupling time, which varies for different driver variables. For the information coupling time, the IMF $B_z$ is the shortest, about 16 hours, followed by the other solar wind variables ($36 \leq \text{hours}$), F10.7 (2–108 days), TCO and TPW (3–4 months), and convective precipitation (6 months).

The driver importance ranking and the information coupling time should be interpreted within the framework of ionospheric forecast: given prior knowledge of the present global ionospheric state and the present external driver conditions, the driver importance ranking corresponds to the ranking of the maximum impacts of present external drivers on future global ionospheric state, while the information coupling time indicates how far into the future the maximum impacts of present external drivers occur. Moreover, the impacts of the external drivers vary with different future times. Even though the lower atmospheric migrating tidal sources are top ranked in terms of the maximum impacts, their impacts are not prominent until after a few days into the future. In fact, within 3 days into the future, solar EUV irradiance is the dominant driver. This is because of the dominant role of F10.7 in information transfer to the TEC variables at time lags of less than 3 days as shown in Figure 3. In a typical ionospheric forecast with a lead time of a few days, solar EUV irradiance is the most important driver to consider. In such forecast, the impacts of the migrating tidal sources and convective precipitation mostly enter via the present global ionospheric state, that is, the initial condition. Essentially, the initial global ionospheric state has already been modified by the migrating tidal sources and convective precipitation from the past. Therefore, using realistic initial ionospheric conditions with migrating tidal source impacts already taken into account is important for forecasting the global ionospheric state a few days ahead. This is consistent with the importance of ionospheric preconditioning from lower atmospheric forcing identified in earlier research (Hagan et al., 2015; Mannucci et al., 2016). Our results also imply the long-lasting impact of migrating tidal sources on the ionosphere. While migrating tides propagate from the lower atmosphere to the ionosphere in days, migrating tidal sources in the troposphere and stratosphere could influence the global ionosphere state for months. For future work, we will seek to better understand the information coupling time by exploring more parameter space in the transfer entropy formula, including the history lengths and different time lags for the driver variables and TEC variables. Other lower atmospheric waves and wave sources not included in this study could be addressed as well, for example, lunar tides, interacting planetary waves and gravity waves, storm tracks, jet streams, and frontal systems. In addition, further analysis can be carried out to identify and quantify major drivers of the ionospheric state at various local times, longitudes, and latitudes.

Data Availability Statement

The JPL GIM data are available at https://sideshow.jpl.nasa.gov/pub/iono_daily/gim_for_research/jpli/. The data used to produce the figures in the paper are available at https://doi.org/10.48577/jpl.U1JB40.
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