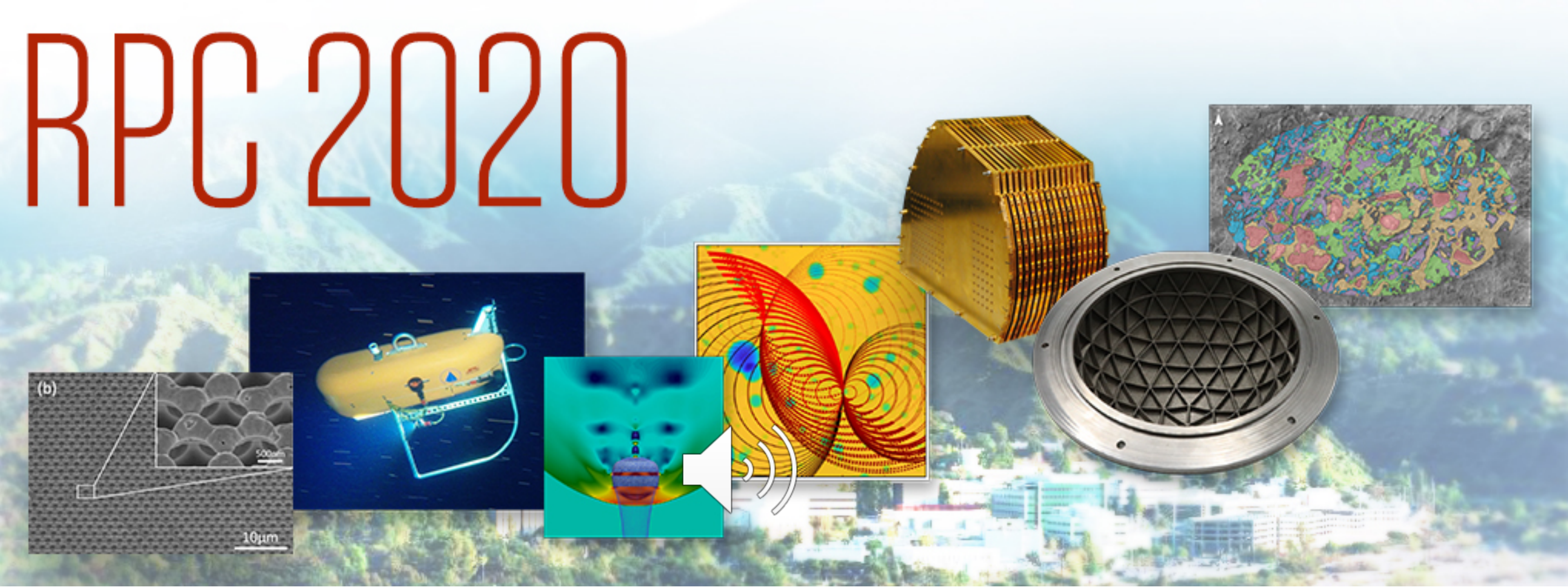

Virtual Research Presentation Conference

Revealing Drivers of Global Ionospheric Map Using Information Theory

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Program: Innovative Spontaneous Concepts

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Tutorial Introduction

Abstract

The terrestrial ionosphere, located between about 60km and 1000km altitudes, is a layer of the atmosphere where free electrons and ions are abundant. These electrons cause delays of radio signals transmitting through the ionosphere, impacting the performance of space-bourn technological systems. The abundancy of ionospheric electrons can be represented by total electron content (TEC), which is provided by Global Ionospheric Map (GIM), a routine data product by 335G to support Deep Space Network (DSN), several JPL missions as well as scientific research. The TEC is spatially and temporally variable and is subjected to external drivers: space weather conditions and lower atmospheric forcing. For the first time, this investigation quantified contributions of individual external drivers to the GIM variability by applying modern machine learning methods to decades' worth of GIM products, providing insights of the GIM predictability.

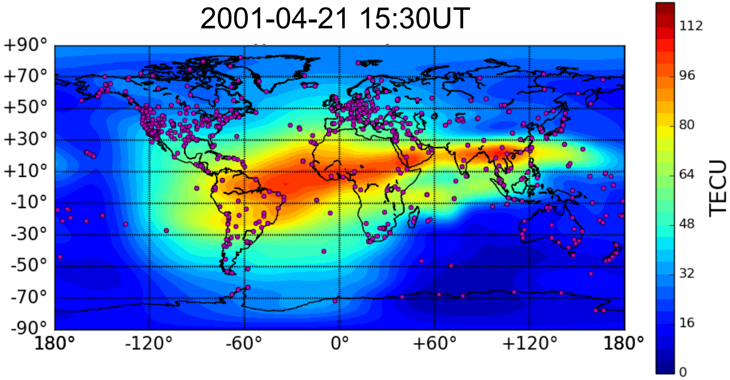

Figure 1. An example TEC map from GIM. The unit of TEC is TECU, and 1 TECU = 10^{16}electrons/m^2.

Problem Description

- **Context**

  While the GIM has been routinely used to provide mission support, a systematic and quantitative study of how GIM-provided TEC maps vary under different external driving conditions has never been carried out, partially due to the large data volume. Modern machine learning techniques, in particular information theory, offer a great tool to analyze the GIM and gain insight into its variability.

- **Advancement Over Current State-of-the-Art**

  This work is a pioneer effort to quantitatively estimate relative contributions from various external drivers to the ionospheric state, which is not well understood to date.

- **Relevance to NASA and JPL**

  The work aligned well with strategic goals of the Interplanetary Network Directorate by establishing the foundation for improving the ionospheric calibration for the DSN. The results will guide our daily ionospheric calibration for the DSN and the validation of our GIM products for many years to come. Our identification of key external drivers for GIM can serve as the basis for the development and input specification of a predictive GIM in the future, which will eventually provide more accurate short-term GIM forecast products to better support DSN and JPL missions.

Methodology

- **Methodology Description**
  - Transfer entropy -- a measure of information transfer from one system to another.

    For two time-series X(t) and Y(t), the Transfer Entropy from X to Y with delay time τ can be expressed by

$$TE_{X\to Y}(\tau) = \sum_{bins} P\big(Y(t+\tau), Y(t), X(t)\big) log_2 \left(\frac{P(Y(t+\tau)|(Y(t), X(t)))}{P(Y(t+\tau)|Y(t))}\right)$$

    Physical meaning: the amount of information contained in the present of X and in the future of Y but not in the present of Y.
  - Developed software to compute transfer entropy from external driver parameters to the GIM parameters for 2000 – 2017.
  - GIM parameters: extracted time series of TEC global minimum, TEC global median, local time and latitude at TEC global maximum, and Global Electron Content (GEC) from 15-minute instantaneous TEC maps
  - Space weather drivers: daily F10.7 index as a proxy for solar irradiance (ftp://ftp.ngdc.noaa.gov), OMNI solar wind data (https://spdf.gsfc.nasa.gov)
  - Lower atmospheric drivers: total column ozone, total precipitable water vapor, low-latitude zonal mean tropopause temperature, convective precipitation data from MERRA-2 (Modern-Era Retrospective analysis for Research and Applications) (https://disc.gsfc.nasa.gov/)
- **Innovation and Advancement**

  This is the first time that transfer entropy has been applied to quantify external drivers for the GIM.

Results

- **Accomplishments**
  - We have applied information theory, in particular transfer entropy, to quantify the relative importance of external drivers for the GIM.
  - On a daily basis, solar irradiance is the most important space weather driver to the ionospheric TEC.
  - For the solar wind parameters, solar wind speed, interplanetary magnetic field magnitude, and solar wind density are the most important parameters in terms of the amount of information transferred to the ionospheric TEC.
  - Lower atmospheric forcing can have a comparable or even larger information transfer to the ionospheric TEC than the space weather drivers for time scales beyond five days.

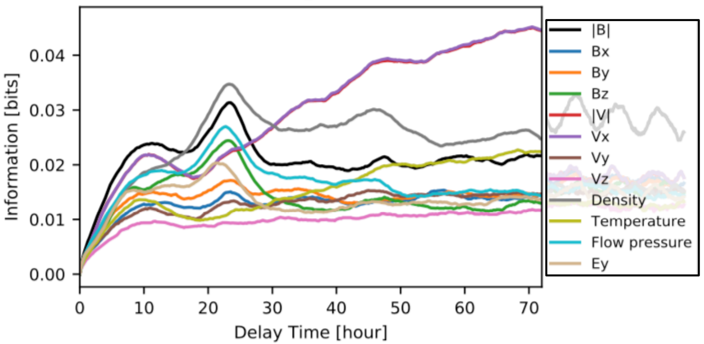

Figure 2. Transfer entropy from solar wind parameters to GIM TEC global median.

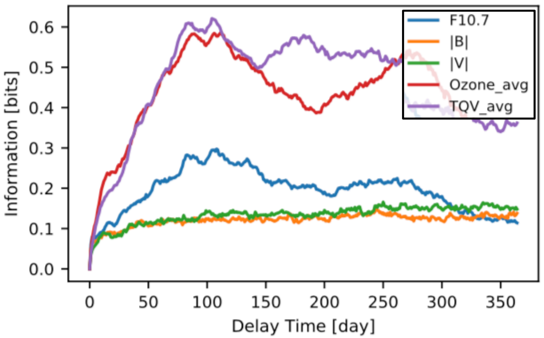

Figure 3. Transfer entropy from selected space weather and lower atmospheric driver parameters to GIM GEC.

Results

- **Significance**
  - For the first time, we identified key external drivers for the GIM on various time scales, which significantly improved our understanding of the behavior of the GIM under various driving conditions.
  - For the first time, we quantified the relative contributions from space weather and lower atmospheric drivers to the ionosphere. Our results imply the importance of lower atmosphere-ionosphere coupling in determining the long-term ionospheric variability, which is not well understood. The research can potentially drive mission concepts investigating the connection between atmospheric tides and ionospheric signal not only for the Earth but also for planets like Venus.

- **Next steps**
  - Develop the software to compute the significance of the transfer entropy.
  - Quantify the importance of external drivers for GIM during various solar cycles and under different geomagnetic activity levels.
  - Investigate the possibility of building a predictive GIM given key external drivers using machine learning methods.

Publications and References

Publication

Xing Meng and Olga Verkhoglyadova, “Revealing External Drivers of Global Ionospheric Map Using Information Theory”, presented at *workshop on machine Learning, data Mining and data Assimilation in Geospace (LMAG2020)*, online, 21 – 24 September 2020.

References

[1] Schreiber T (2000) Measuring information transfer. Physical Review Letters, 85, 461–464.
[2] Ronald Gelaro, et al., (2017) The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), J. Clim., doi: 10.1175/JCLI-D-16-0758.1
[3] Materassi M, Wernik A, Yordanova E (2007) Determining the verse of magnetic turbulent cascades in the Earth's magnetospheric cusp via transfer entropy analysis: preliminary results. Nonlinear Processes in Geophysics, 14, 153–161.
[4] De Michelis, P.; Consolini, G.; Materassi, M.; Tozzi, R. An information theory approach to the storm-substorm relationship. J. Geophys. Res. 2011, 116, A08225.
[5] Wing, S.; Johnson, J.R.; Camporeale, E.; Reeves, G.D. Information theoretical approach to discovering solar wind drivers of the outer radiation belt. J. Geophys. Res. 2016, 121, 9378–9399.
[6] Stumpo, M.; Consolini, G.; Alberti, T.; Quattrociocchi, V. Measuring Information Coupling between the Solar Wind and the Magnetosphere–Ionosphere System. Entropy 2020, 22, 276.
[7] Afraimovich, E. L., E. I. Astafyeva, and I. V. Zhivetiev (2006a), Solar activity and global electron content, Geophys. Earth Sci., 409A(6), 921–924.
[8] Perreault, W. K., and S-I. Akasofu (1978), A study of geomagnetic storms, Geophys. J. R. Astron. Soc., 54, 547.
[9] Kan, J. R., and L. C. Lee (1979), Energy coupling and the solar wind dynamo, Geophys. Res. Lett., 6, 577.
[10] Newell, P. T., T. Sotirelis, K. Liou, C.-I. Meng, and F. J. Rich (2007), A nearly universal solar wind-magnetosphere coupling function inferred from 10 magnetospheric state variables, J. Geophys. Res., 112, A01206
[11] Borovsky, J. E. (2014), Canonical correla- tion analysis of the combined solar wind and geomagnetic index data sets, J. Geophys. Res. Space Physics, 119, 5364–5381.

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