Characterizing Particle Dynamics from a Data-Driven Model of the Inner Magnetospheric Electric Field

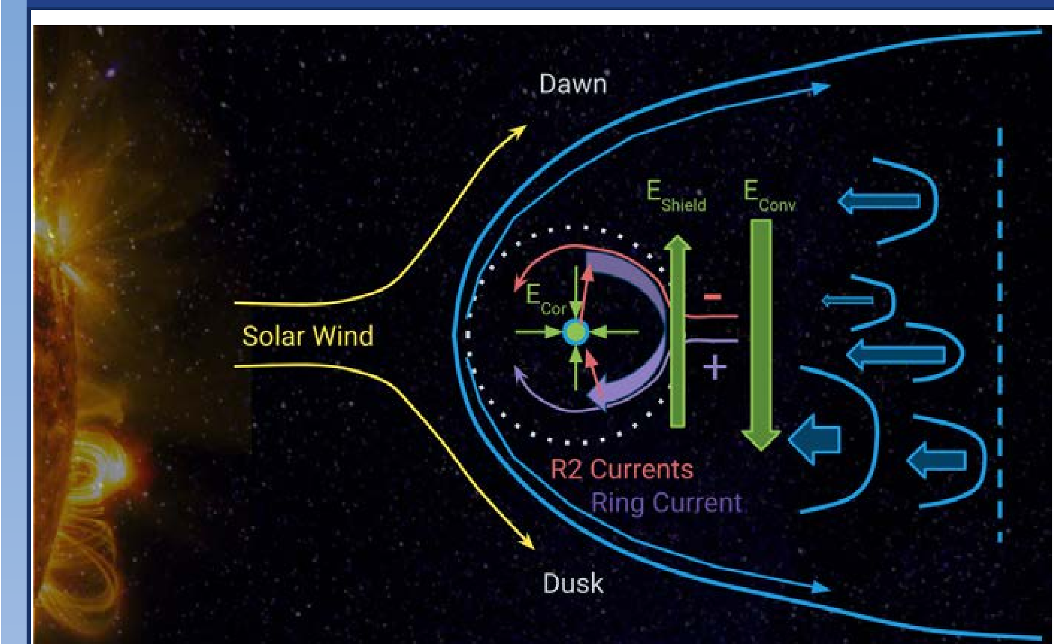
Brianna Isola[1], Izzak Boucher[1], Matthew R. Argall[1], Roy B. Torbert[1,2]

1. University of New Hampshire 2. Southwest Research Institute, San Antonio, TX

ABSTRACT

We report the progress of the **Machine learning Empirical Electric Potential (MEEP) Model** derived from a neural-network data-driven inner-magnetospheric electric field (IMEF) model with the aim to advance the state of physics-based modeling of the magnetosphere through improved accuracy and predictive capabilities. We use electric field data from the Electron Drift Instrument (EDI) onboard the Magnetospheric Multiscale (MMS) mission and characterize it by both upstream IMF conditions and geomagnetic indices. To create the model, EDI measurements are binned by spacecraft position and activity level to obtain the average. Model is trained on a 3-layer neural network that uses the time history of location data and geomagnetic indices. To characterize IMEF particle dynamics, particle tracing is implemented for select geomagnetically quiet and active periods. We additionally provide a comparative analysis of particle tracing and injection events against other models such as the Weimer and Volland-Stern.

THE MAGNETOPSHERIC ELECTRIC FIELD



- The solar wind drives global energy circulation within the magnetosphere (Dungey, 1961) which generates global convective electric fields (EF) that helps transport plasma toward Earth where the gradient and curvature of magnetic field lines result in charge-dependent drifts
- The convective electric fields gradually build up the ring current and establish the Region 2 (R2) current system that connects the inner magnetosphere to the ionosphere.

BACKGROUND & MOTIVATION

We are in development of a **dynamic, neural-network driven inner magnetospheric electric field model** with the **aim to advance the state of physics-based modeling of the magnetosphere through improved accuracy and predictive capabilities**.

- The behavior of the inner-magnetosphere is an important link in the chain of energy transfer within the total solar-terrestrial system.
- Machine learning as a geospatial modeling tool has already been used with remarkable success reconstructing the evolution of magnetospheric plasmas[1]
- This model will extend on the foundation of the UNH-IMEF model, which presented enhanced performance overall when compared to other models, but still did not reproduce all characteristics of the data[2,3]

The goal of this project is to study the energy transfer in the solar-terrestrial system caused by the inner magnetospheric electric field by using a global, data-driven model of the IMEF

[1] Bortnik, J. et al. (2016). https://doi.org/10.1002/2015JA021733.
[2] Matsui, H. et al. (2008). https://doi.org/10.5194/angeo-26-2887-2008 .
[3] Jordanova, V. K. et al. (2009).https://doi.org/10.1016/j.jastp.2009.08.043.

ELECTROMAGNETIC MODEL INPUTS

Base inputs for current particle tracing simulation.

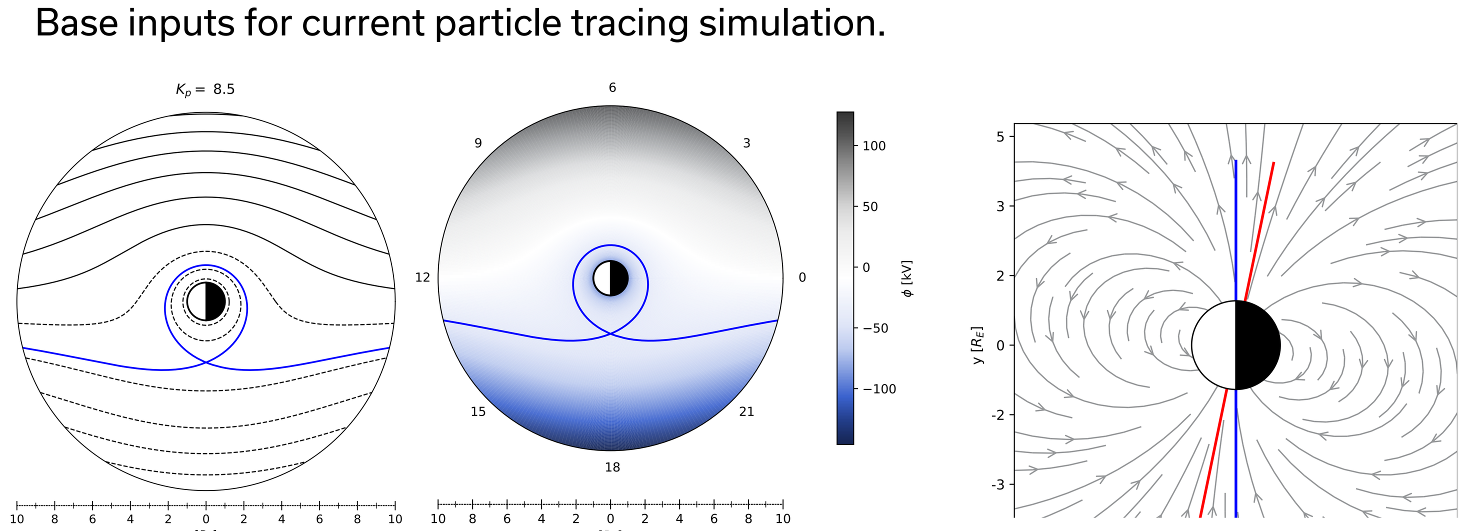


Fig. 1: (LEFT) Volland-Stern potential contours and color map for k_p = 8.5. Blue line indicates last closed equipotential (for the E in LCE); (RIGHT) Simplified dipole field of Earth

DATA DRIVEN MODEL

NEURAL NETWORK

To determine the electric field around Earth at any time, we trained a **3-layer neural network**, using a method similar to (Bortnik et al. 2016), that uses location data and 5 hours of geomagnetic index data to predict the electric field.

Electric potential training data approximated through solving the **inverse problem**:

- EDI data cleaned and binned by radial distance from the Earth (L) and angle (MLT)
- Equation inverted by defining a loss function and determining minimum value
- Geomagnetic index (e.g. Dst, Kp index) and/or solar wind driver used to crudely determine good indicators of activity in inner-magnetosphere

Creation of electric field map uses Field Line Mapping and follows two-step process:

1) Obtain E-field measurements in the orbital plane over aprox. 7 years from the MMS EDI Data

2) Map the E-field to all points along the magnetic field

Assume magnetic field lines are equipotentials such that potential (*V=ExB*) is constant

Observations

- Convection field (Ey) increases for higher Kp
- Potentially see shielding in Ey at L < 5 for Kp=[6,9] and MLT=[18, 7] (this is contrary to the CRRES and THEMIS studies)
- Ex and Ez can be as large as Ey
- This is the first study of Ez defining a loss function and determining minimum value along field lines

MODEL RESULTS

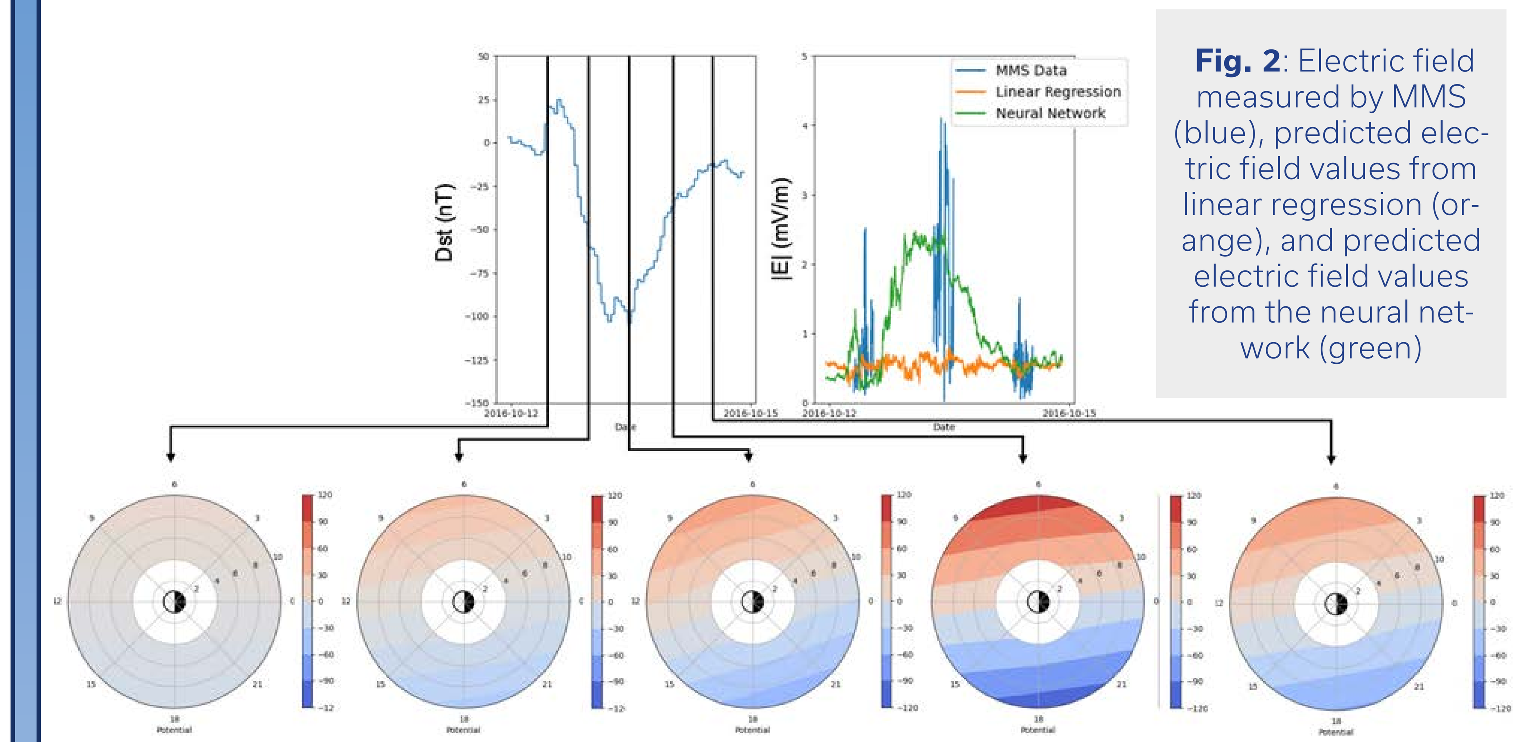


Fig. 2: Electric field measured by MMS (blue), predicted electric field values from linear regression (orange), and predicted electric field values from the neural network (green)

Potential maps resulting from the inversion of the reconstructed global electric field in the inner magnetosphere at 12 hr intervals

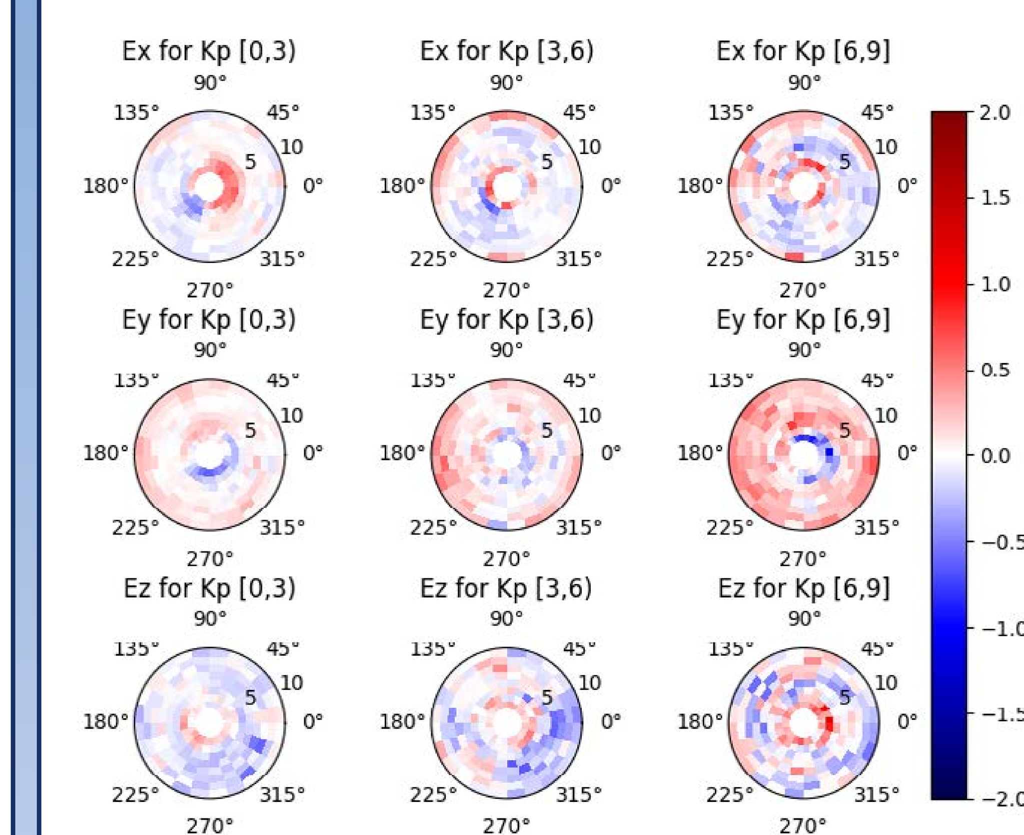


Fig. 3 (LEFT): Number of EDI measurements in each 1 MLT x 1 RE bin in the region 3 < R < 10 RE from 2015-2022.

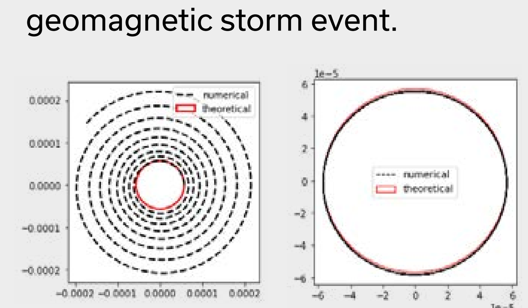
CHARGED PARTICLE MOTION

The motion of a particle with mass *m* and charge *q* is defined by the Newton-Lorentz Force (Relativistic Lorentz):

$$\frac{\mathrm{d}(\gamma m \mathbf{v})}{\mathrm{d}t} = q\mathbf{E}(\mathbf{r}) + q\mathbf{v} \times \mathbf{B}(\mathbf{r})$$

Determining the evolution of particle position over time by solving the **Boris Particle Pusher**

- Chosen due to its speed, efficiency, and notable volume-preserving properties[6]; similar methods, such as forward difference, can artificially inflate the energy.
- Particles traced backward in time give initial velocity and position provided by MMS data of geomagnetic storm event.



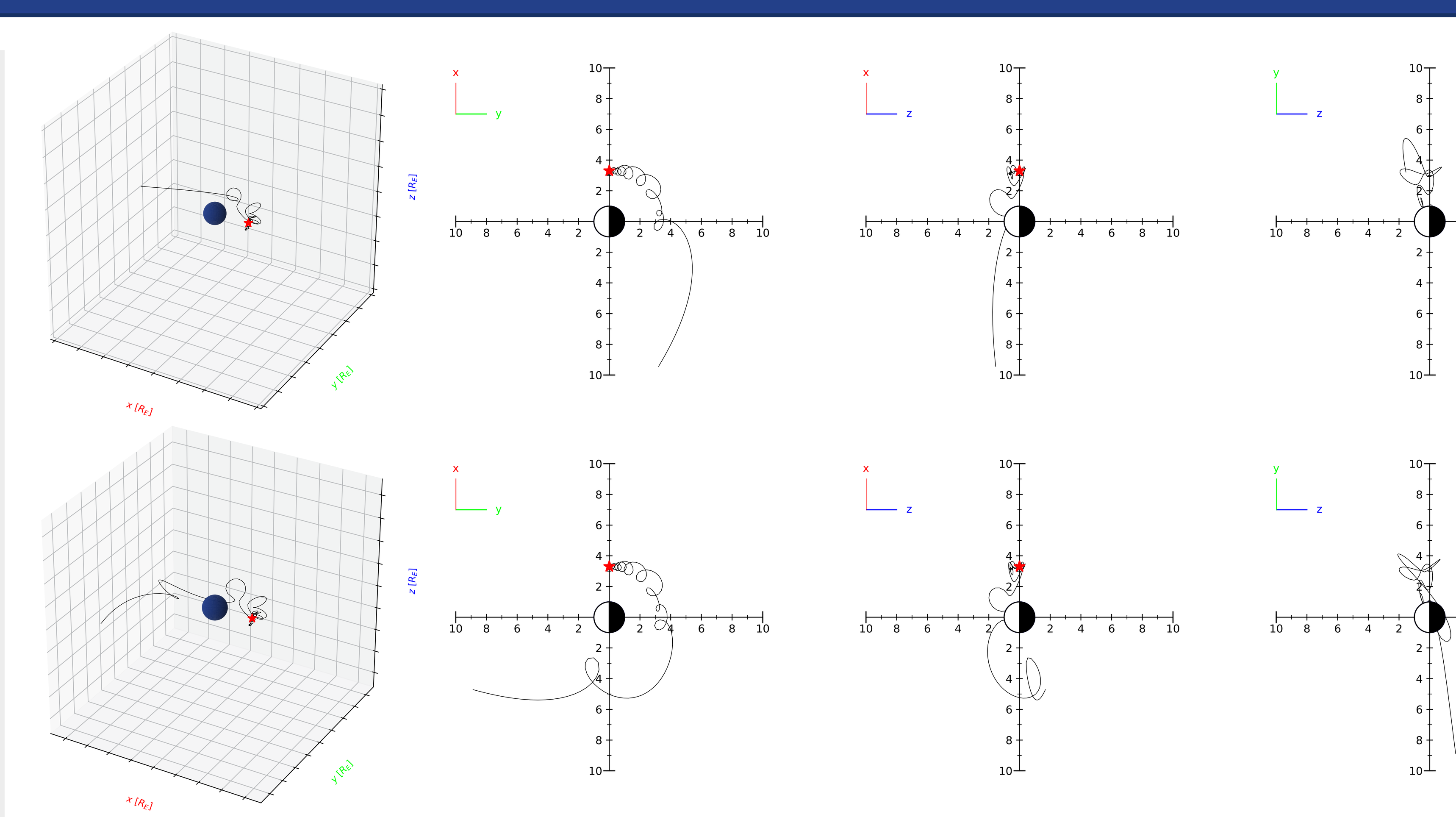


Fig. 4: Backwards tracing results in 3D isometric view and 2D profile views for k_p = 8.5 with energy E = 50 kev (top) and 40 keV (bottom)

MODEL DATA: MMS

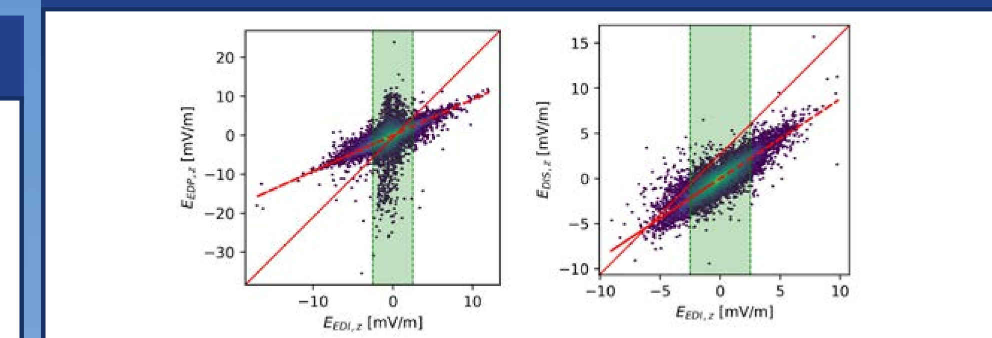


Fig. 5: Comparison of electric field values to EDI values for the EDI and DIS MMS instruments from 2015-2020. Data measured on MMS-1. Plotted datapoints are grouped by hexagonal bins, or "hexbins," such that each hexbin denotes the log number of points, log(N), in it.

EDI E-Field data agrees more with DIS than EDP

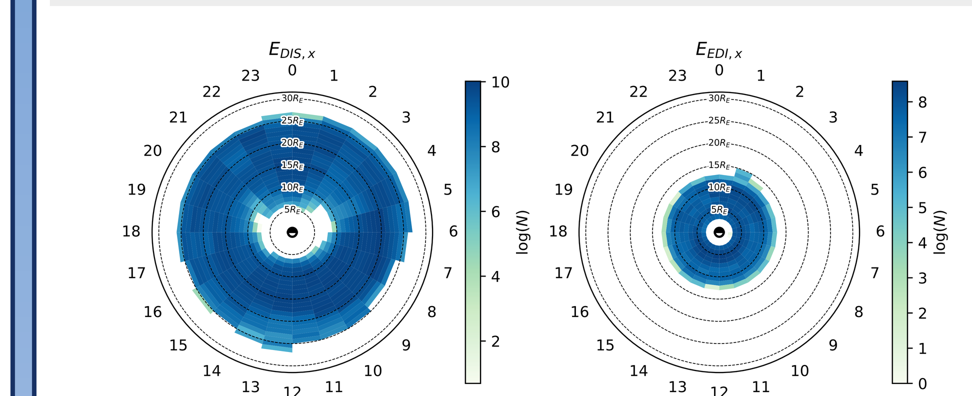


Fig. 6: Coverage comparison of the DIS (LEFT) and EDI (RIGHT) MMS instruments. Plot is colored by log(*N*) number of data points.

EDI and DIS have complementary spatial coverage, especially in the critical flow breaking region

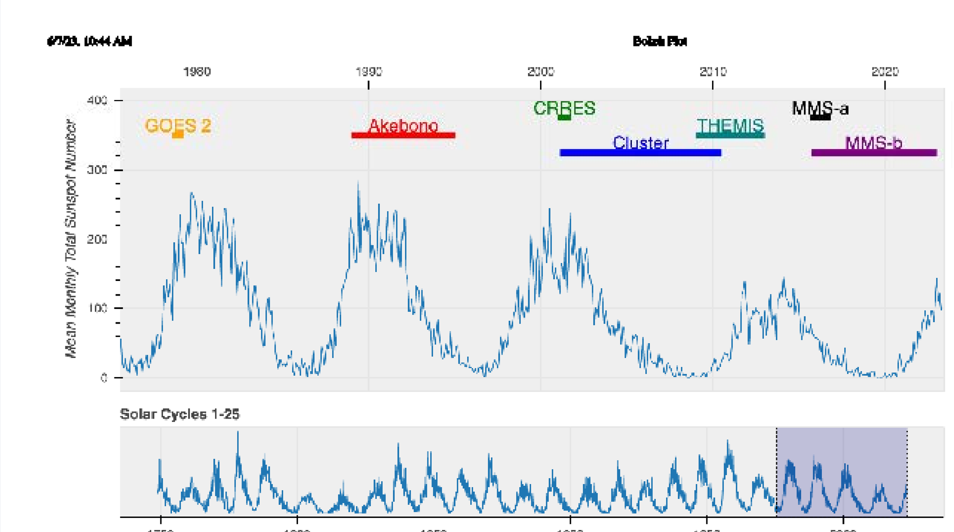


Fig. 7: Plot of large-scale statistical studies of the IMEF are scattered over the last 5 solar cycles. GOES 2, Cluster, and MMS have an EDI instrument, where MMS is also entering a new solar maximum in solar cycle 25

FUTURE WORK

1) Write-in other comparative electromagnetic models for model validation, such as the Weimer 96 and UNH-IMEF electric field models, and the IGRF and **Tsyganenko** magnetic field models.

2) Compare tracing results to developed model for different periods of geomagnetic storms (e.g. 27-30 May 2017, 25-30 Aug. 2018.)

Acknowledgments: This work is supported by NASA MMS Early Career Grant #80NSSC20K1802, the New Hampshire Space Grant Fellowship, and NASA subcontract #NNG04EB99C.

Contact: brianna.isola@unh.edu