Contributions from the Solar Wind and Magnetospheric Processes to Localized Geomagnetic Disturbances

Raman Mukundan[1,2], Amy Keesee[1,2], José Marchezi[3], Mike Coughlan[4], Victor Pinto[5]

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[1]Department of Physics and Astronomy, University of New Hampshire
[2]Institute for the Study of Earth, Oceans, and Space, University of New Hampshire
[3]Space Weather Division, National Institute for Space Research, Brazil
[4]NASA GSFC, Greenbelt, Maryland
[5]Departamento de Física, Universidad de Santiago de Chile

MAGICIAN — Machine Learning Algorithms for Geomagnetically Induced Currents in Alaska and New Hampshire

Introduction

- The solar wind's interaction with the Earth's magnetic field can cause Geomagnetically Induced Currents (GICs), which are hazardous to power and communications infrastructure.
- Changes in the horizontal component of the ground magnetic field ($d\mathbf{B}_H$) or its time derivative are used as a proxy for GIC measurements.
- Our goal is to obtain a $d\mathbf{B}_H$ forecast at every point in a large region using the Spherical Elementary Current Systems interpolation technique.
- We used a neural network to model the physics that connects the solar wind and low Earth orbit environment to localized $d\mathbf{B}_H$ on the ground.
- We used Integrated Gradients to explain forecasts of $d\mathbf{B}_H$'s regional roughness, R_{ms}, in terms of its drivers.

Conclusions and Key Insights

- AMPERE features are overall more salient than OMNI features. The saliency ratio per feature is AMPERE/OMNI = 34, averaged across all storms in the test set
- Reconnection E-field ($||\mathbf{v} \times \mathbf{B}_z||$) is influential across many lookback times
- The model largely ignores the IMF besides the way it contributes to the reconnection E-field
- AMPERE measurements just south of a sharp magnetic field rotation are highly salient
  - These regions contribute to more localized disturbances

Acknowledgements and References

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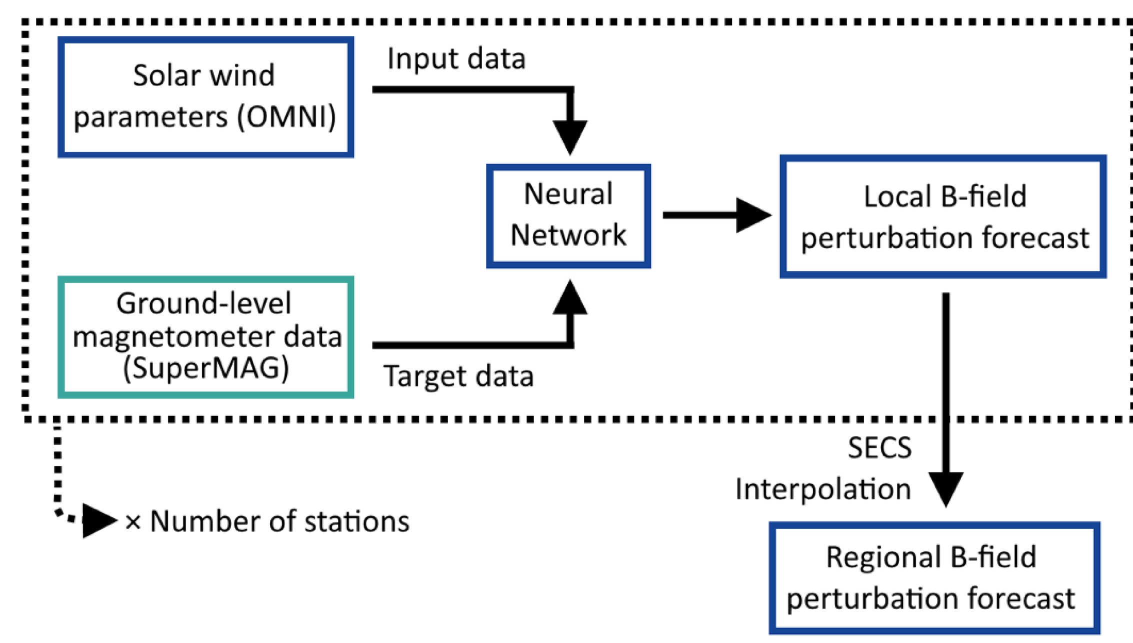
- OMNIWeb data from omniweb.gsfc.nasa.gov
- SuperMAG data from supermag.jhuapl.edu
- AMPERE data from ampere.jhuapl.edu

My website

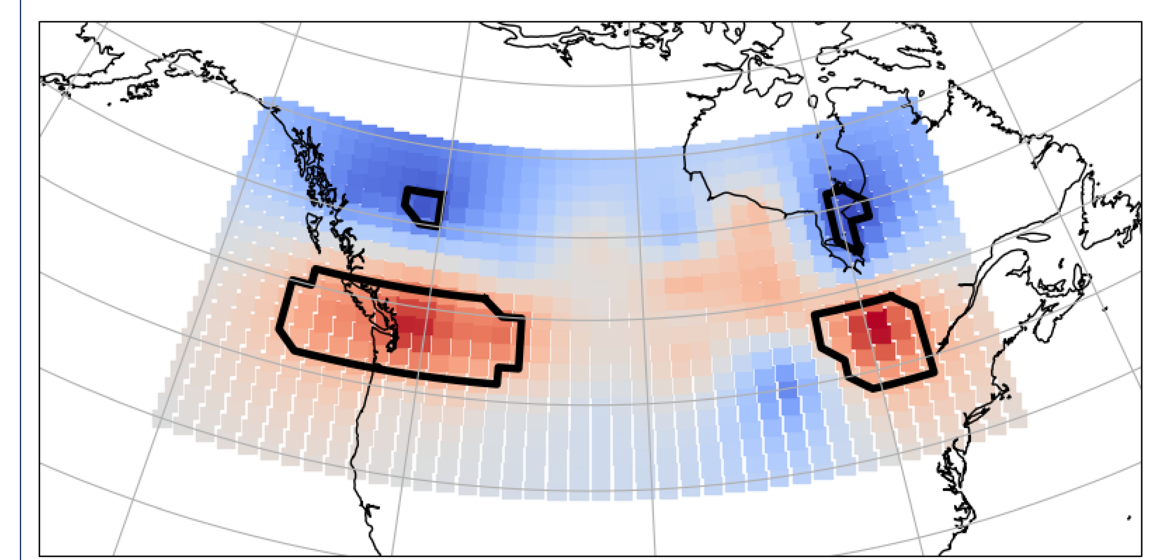
Read our related paper!

Magnetic Multi-Model Prediction



- Each of the 24 magnetometer stations has a convolutional neural network (CNN) trained to predict only that station's measurements using 60-minute time history. Spatial interpolation is performed afterward.

Spatial Interpolation as a Non-Learnable Layer

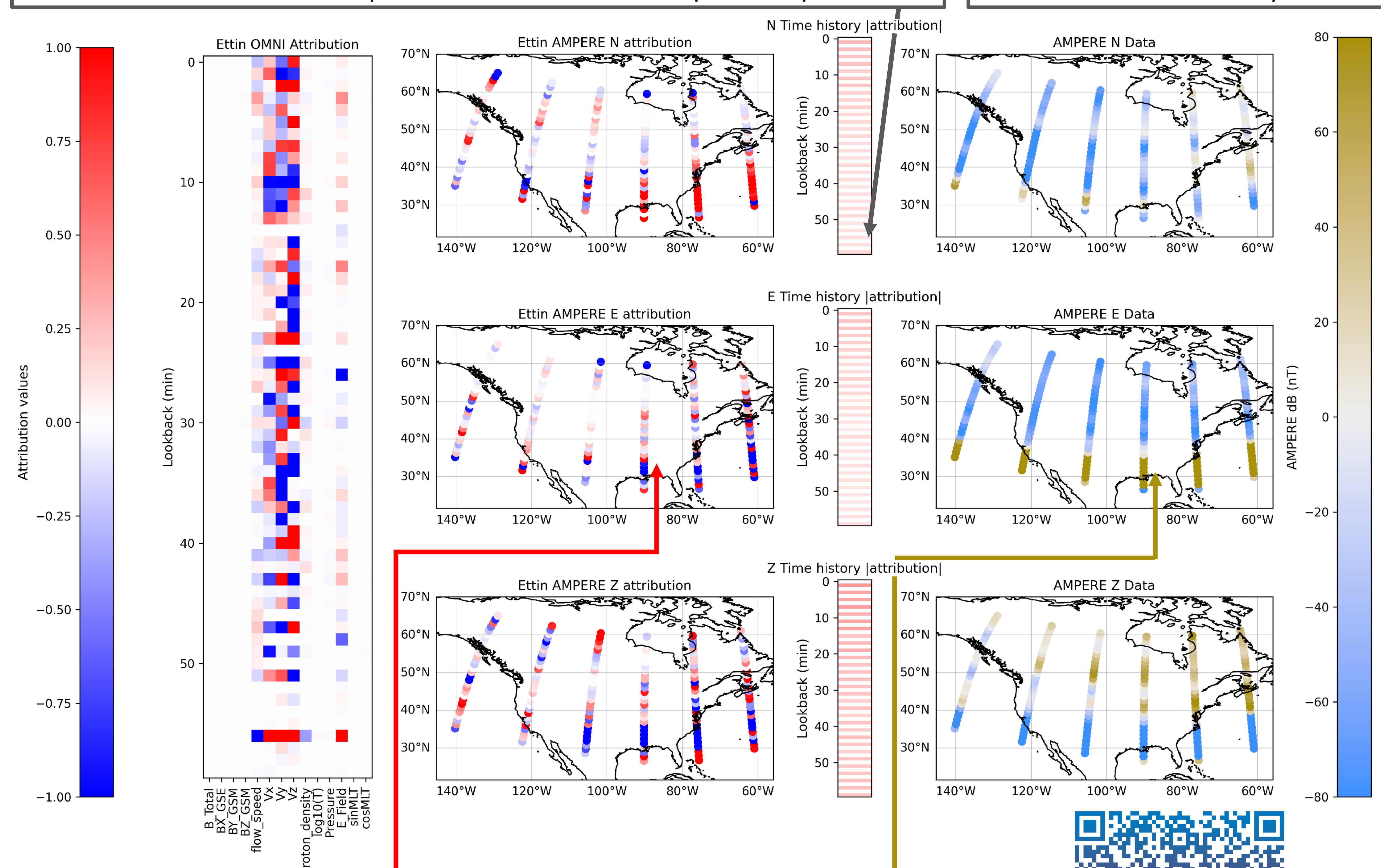


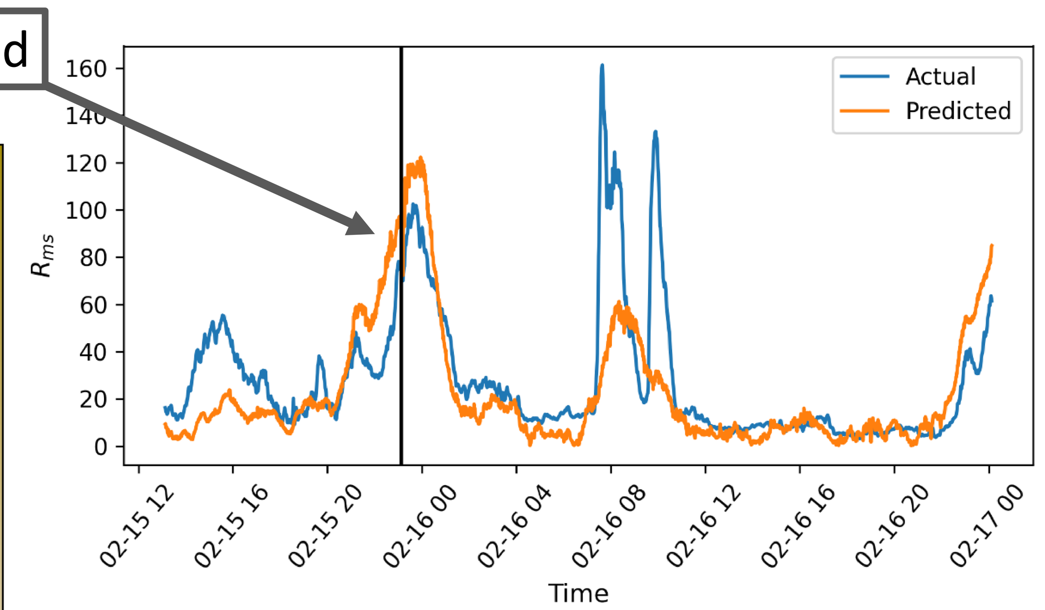
- The magnetometer forecast vector (CNN outputs) is used to fit a grid of Spherical Elementary Current Systems, representing ionospheric currents, to derive 1-minute cadence $d\mathbf{B}_H$ values during storm time in Solar Cycle 24 (2009-2019).
- An automated algorithm identifies localized geomagnetic disturbances (**black contours**) in the prediction.

Which Inputs Influence the Model's Prediction at any Given Moment?

AMPERE data further from the present is considered less important by the model

Ground-level B-field is very localized





The model thinks this region is very important...

...possibly because the region is directly south of an abrupt rotation in the magnetic field measured by AMPERE!

Attribution map movies

Integrated Gradients in 3 Easy Steps

1. For each input tensor, create a series of artificial inputs x_k' which lie along a path between that input x and the average inputs x_0'
2. Calculate $\partial F(x_k')/\partial x_k'$ for every feature in x_k' and every k
3. Take the mean of those gradients

Plotted are predictions for R_{ms}, the root mean square deviation of each $d\mathbf{B}_N$ map x_{ij} from its mean, μ.

$$R_{ms} = \left(\frac{1}{IJ} \sum_i^I \sum_j^J (x_{ij} - \mu)^2 \right)^{1/2}$$

R_{ms} is a measure of the roughness of a $d\mathbf{B}_N$ heatmap like the one above.

Red pixels mean those features contribute to increase the value of R_{ms}; blue pixels mean those features contribute to decrease that value.