Interpretable Probabilistic Forecasting of Ground Magnetic Perturbation Spikes at Mid-Latitude Stations

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

Introduction

- The interaction between the solar wind and the Magnetosphere can produce **Geomagnetically Induced Currents (GICs)** on the ground, which can cause power outages and damage to crucial infrastructure.
- Direct prediction of dB/dt consistently proves difficult. Probabilistic predictions of dB/dt exceeding a threshold can offer a way to determine the risk of GICs without having to capture the exact geomagnetic fluctuations.
- Here, a **Convolutional Neural Network (CNN)** utilized 30 minutes of time history to determine if the dB/dt value would go above the 99^{th} percentile threshold, between 30 and 60 minutes into the future at eight ground magnetometer stations.
- The **localization effect of dB/dt** presents an issue for forecasting models that are heavily dependant on data from solar wind monitors.
- Including ground magnetometer data raises concerns about the models becoming no more useful than persistence models [1].

Method

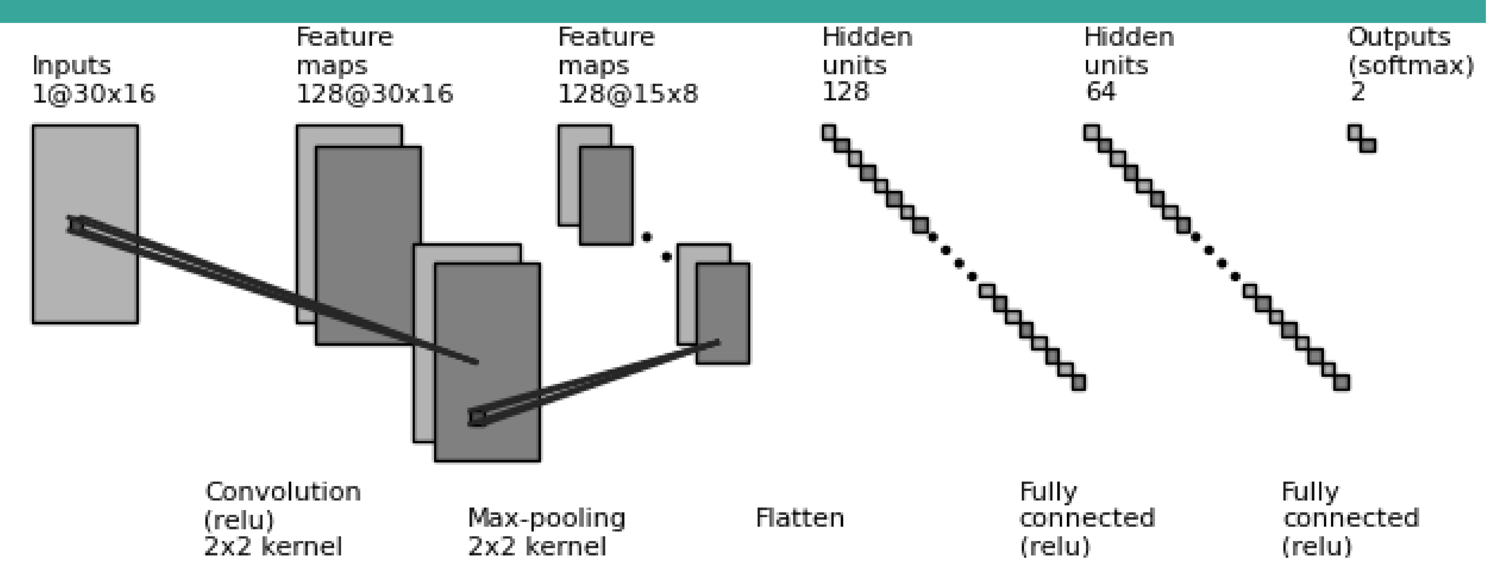

Figure 1. The models consists of 1 CNN layer with 'RELU' activation, a MaxPooling layer, a Flatten layer and two Dense layers with Dropout in between. The output layer is a Dense layer with softmax activation.

- The model was trained exclusively on storm time data.
- The input features included solar wind data from the **ACE** satellite; AE Index from **OMNI**; ground magnetometer data from the **SuperMAG** network.
- 100 models were trained for each station using a bootstrapping method which allows us to evaluate the uncertainty of the ensemble.

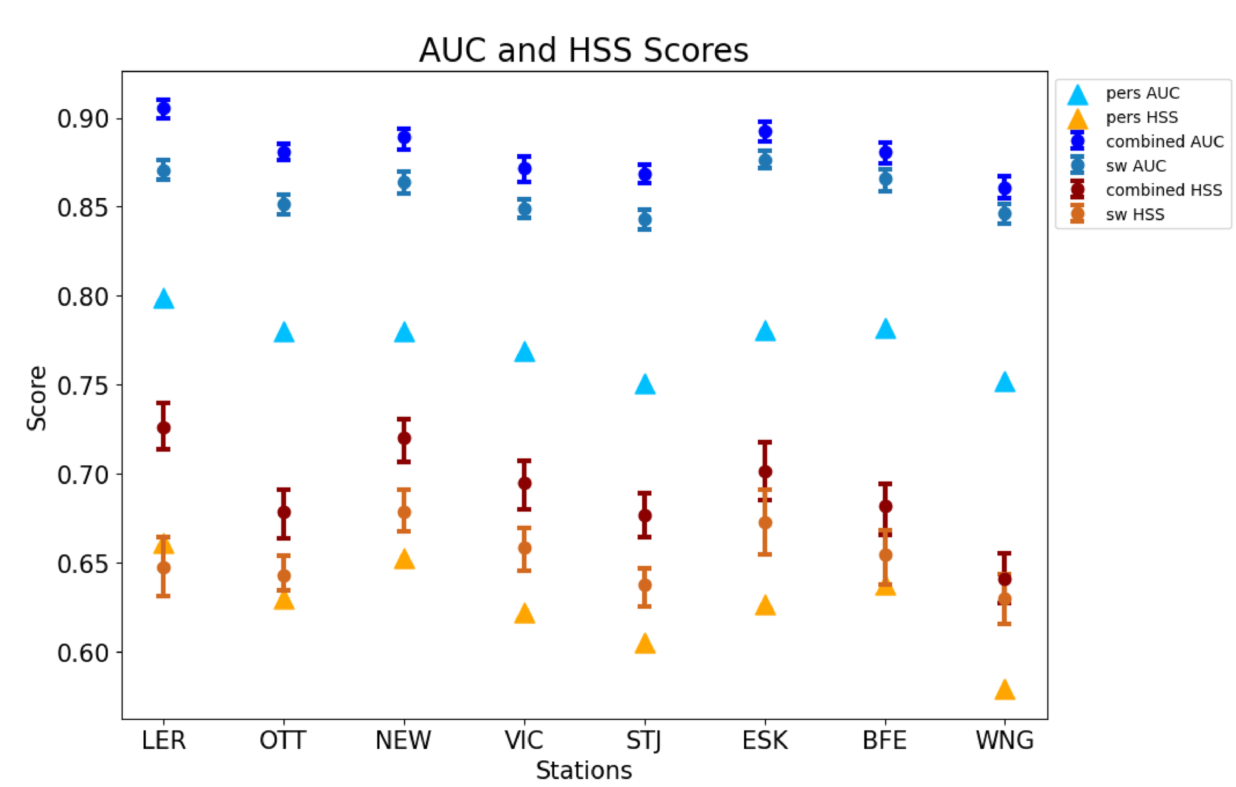

Figure 2. Area Under the Precision-Recall Curve (AUC) and HSS scores calculated across all tested storms. Stations are sorted in descending order of average magnetic latitude over the training period.

Model Predictions

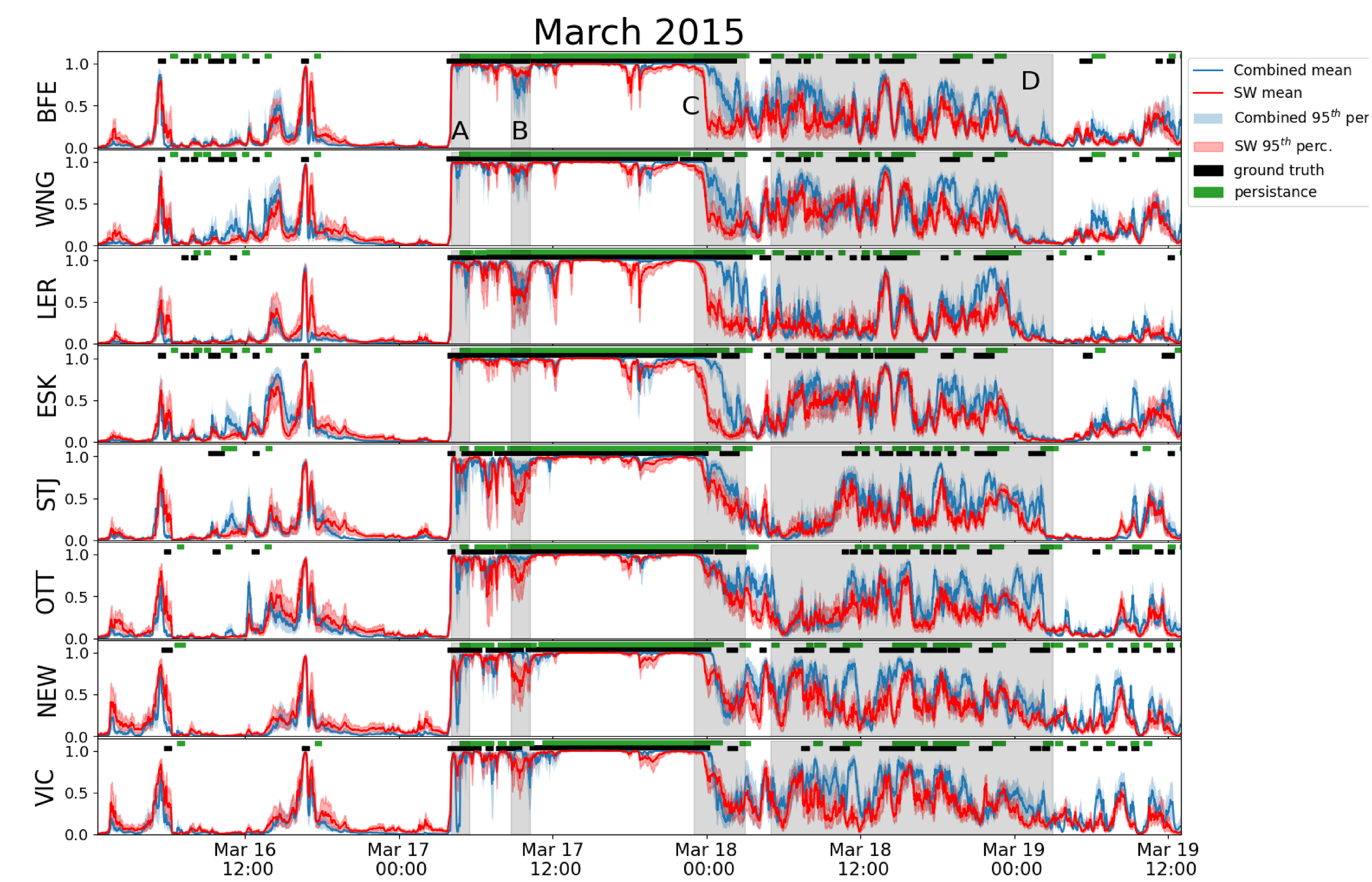

Figure 3. Model outputs for March 2015 storm. The grey shading highlights periods of interest.

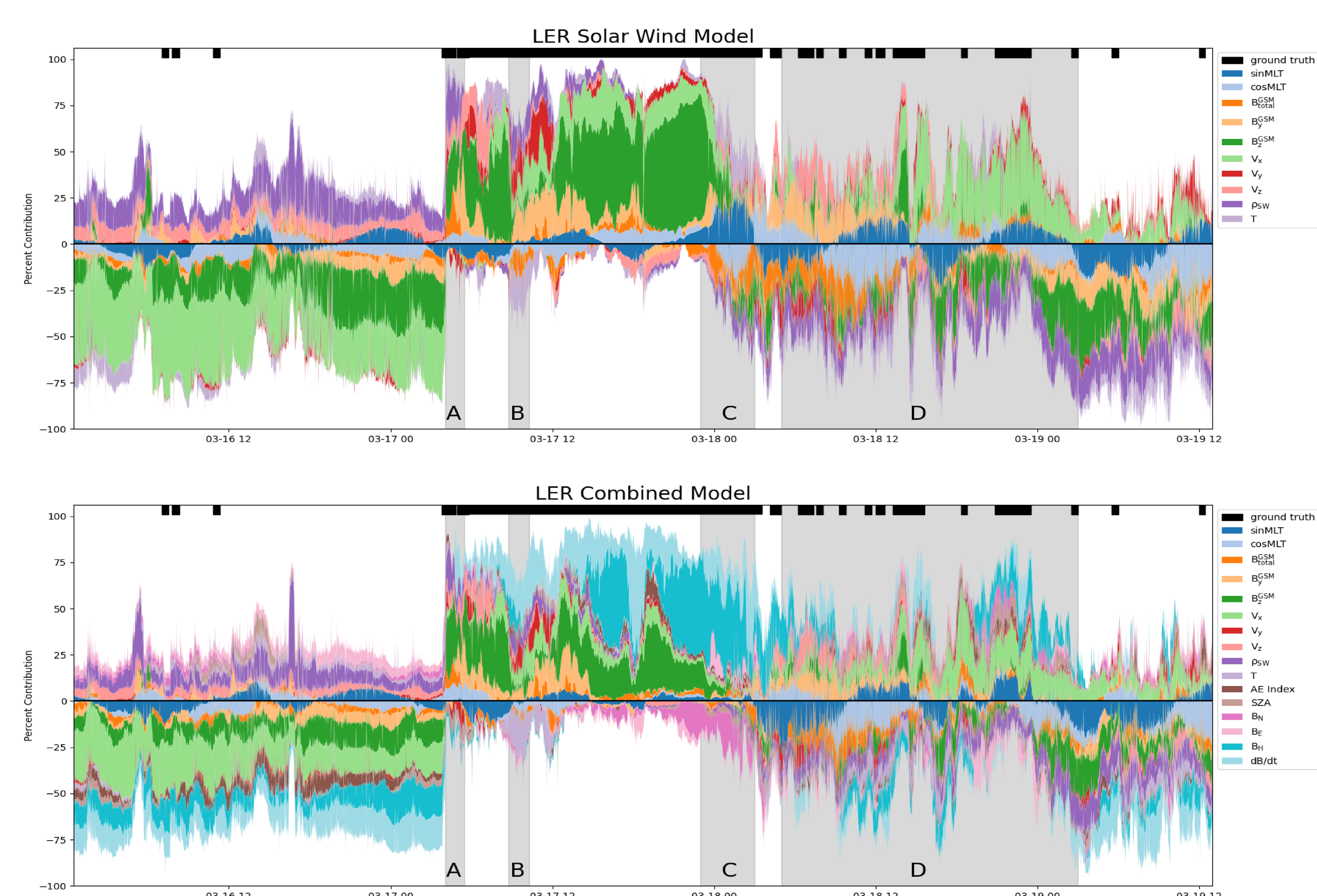

Figure 4. LER model percentage contributions of each parameter's SHAP values. Positive percentage contributions influence the model's output to be closer to one and negative percent contributions push the model output to be closer to zero. Grey blocks indicate areas of interest corresponding to those in Figure 3.

References/Acknowledgements

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Figure 1 generated by adapting the code from https://github.com/gwding/draw_convnet.

Section does not contain all references used for this work. For full list of references see GitHub repository.

[1] A. W. Smith, C. Forsyth, I. J. Rae, T. M. Garton, T. Bloch, C. M. Jackman, and M. Bakrania. Forecasting the Probability of Large Rates of Change of the Geomagnetic Field in the UK: Timescales, Horizons, and Thresholds.

SHAP Contributions vs. Parameter Values

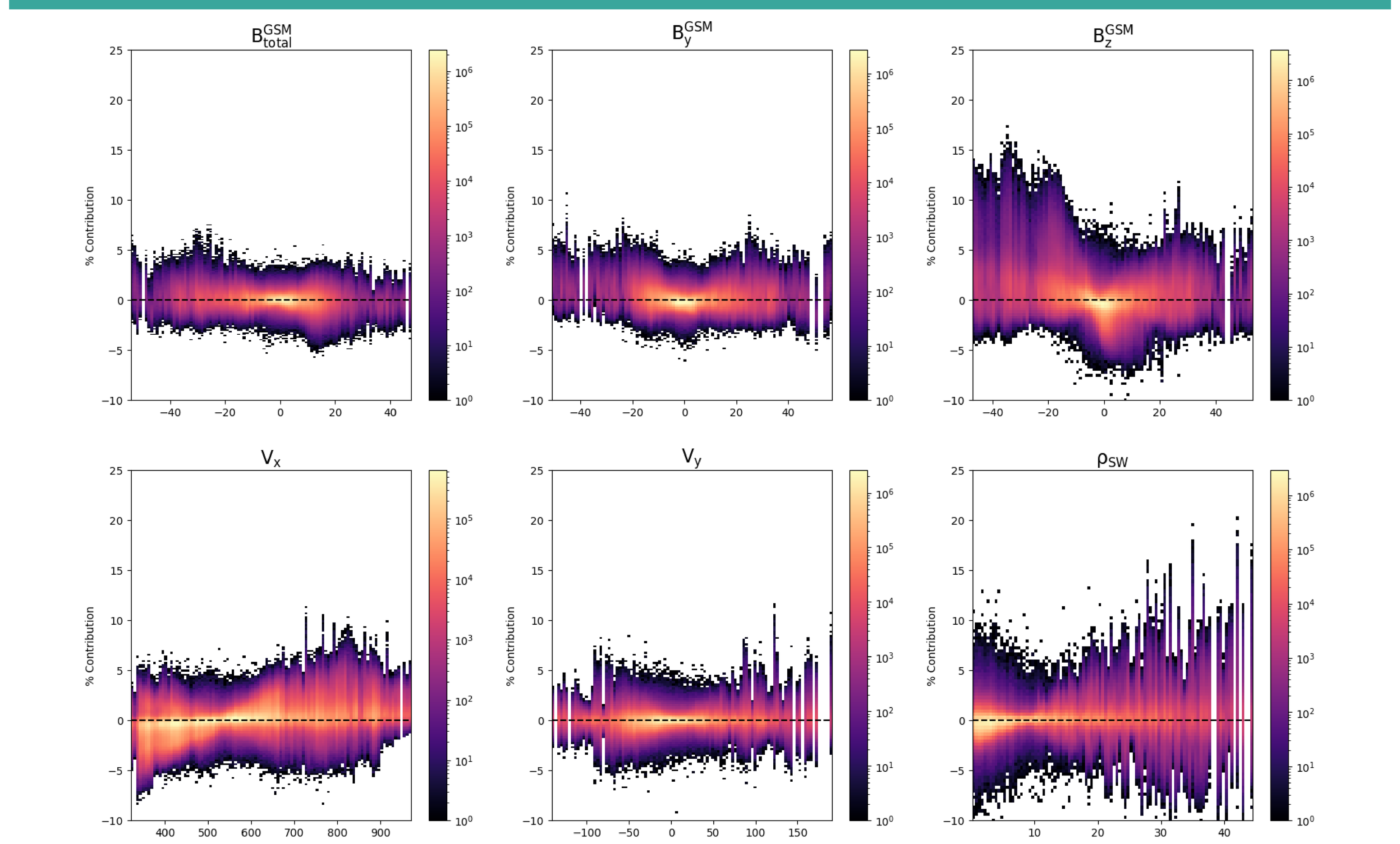

Figure 5. Histograms of percent contribution as a function of input parameter value for a subset of Solar Wind Model inputs. Color bar indicates histogram count.

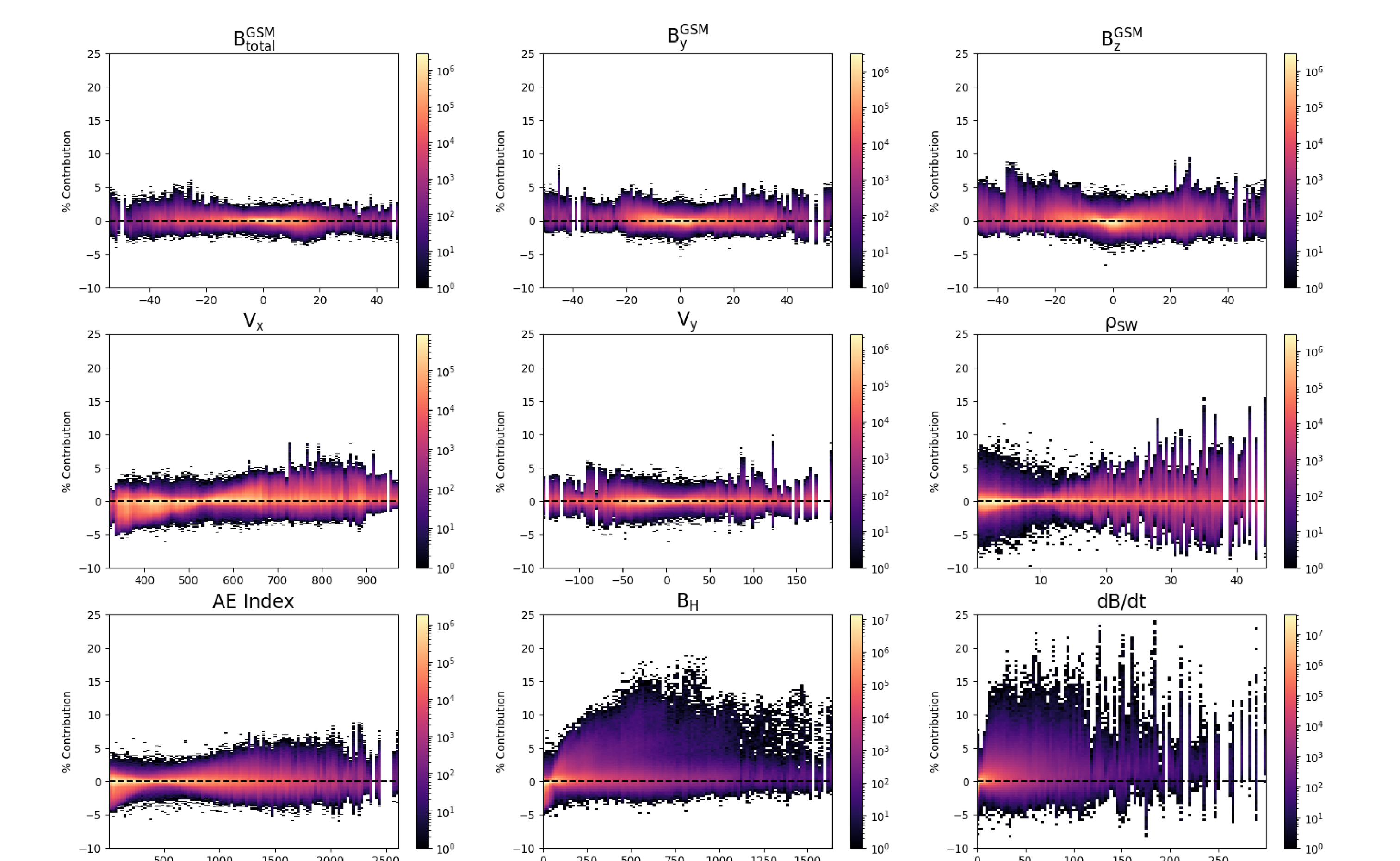

Figure 6. Histograms of percent contribution as a function of input parameter value for a subset of Combined Model inputs. Top two rows represent the same parameters as those in Figure 5. Bottom row contains a subset of parameters not present in the Solar Wind model.

Conclusions and GitHub Link

- Models are able to make different predictions at stations near one another when there are differences in the dB/dt profile.
- Combined models outperform solar wind only models.
- The lower bound of 95^{th} percentiles for all stations are above persistence models for the AUC scores, and mostly above persistence for the HSS.
- SHAP values show models adhering to our current understanding of the solar wind - magnetosphere system.

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