Probabilistic Predictions of Geomagnetic Field Perturbations and Using Explainability Methods to Uncover Drivers of the Localization Effect

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

Introduction

Rapid changes in the ground magnetic field **(dB/dt)** often exhibit large, highly **localized** spikes, showing substantial differences in measurements within small spatial areas which can be attributed to drivers originating in the ionosphere and magnetosphere [2]. **Region-to-Specific Difference (RSD)** [1] is a parameter that can be used to quantify this localization effect. Here we explore the use of a variety of data sources in making predictions of these phenomena, including data from the **Advanced Composition Explorer (ACE)** satellite, the **Two Wide-Angle Imaging Neutral-Atom Spectrometers (TWINS)**, and the **SuperMAG** network. We then use **SHapley Additive exPlanation (SHAP)** values to examine the driving features of these phenomena.

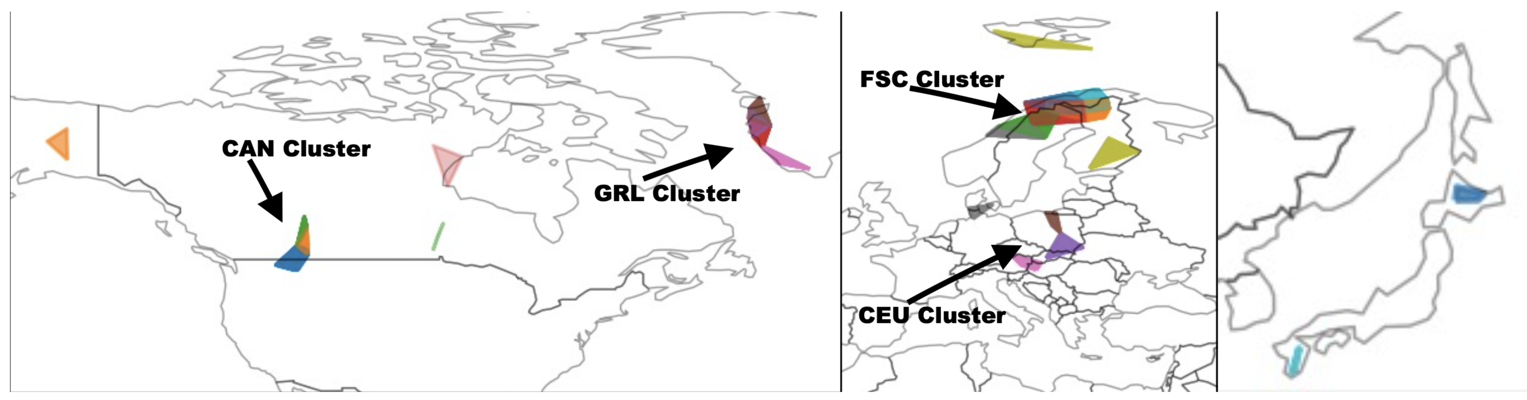

Figure 1. Regions identified for this work. Non-uniform distribution of magnetometers creates several clusters of overlapping regions.

Method

- Two **Convolutional Neural Networks (CNN)** were trained, one forecasting extreme threshold crossings of dB/dt (dB/dt model) and one forecasting times of extreme localization (RSD model).
- The model predicts a probability that the $(dB/dt)_{max}$ or RSD_{max} in the region will exceed the 99^{th} percentile.
- Several dimensionality reduction techniques were tested to process the TWINS ion temperature maps, of those a simple Maxpooling obtained the best performance.
- Sixty minutes of time history from the solar wind and magnetometer data were utilized in the model.
- Monte-Carlo Dropout was used to create an ensemble providing a mean (μ) and uncertainty (σ) as output.

Conclusions

- Both versions of the model show skill in their forecasting ability.
- Models for the regions in the High latitude bin performed the best, exemplifying the SW-M-I connection in this area.
- The addition of TWINS ion temperature maps do not appreciably improve the model's skill despite the model recognizing important features in the data.
- A small region near the typical auroral oval exists where the RSD models outperform the dB/dt models.
- SHAP calculations can allow us to examine input affects on the models.
- The logT parameter has a more suppressive affect during the test storm for the dB/dt model in some areas than the RSD model, contributing to the differences in model predictions.
- An asymmetry is present in the influence of B_x, with more negative input values showing a positive dawn-side bias. Additional parameter breakdowns can be found in the associated GitHub (See QR code).

Influence of Ion Temperature Maps

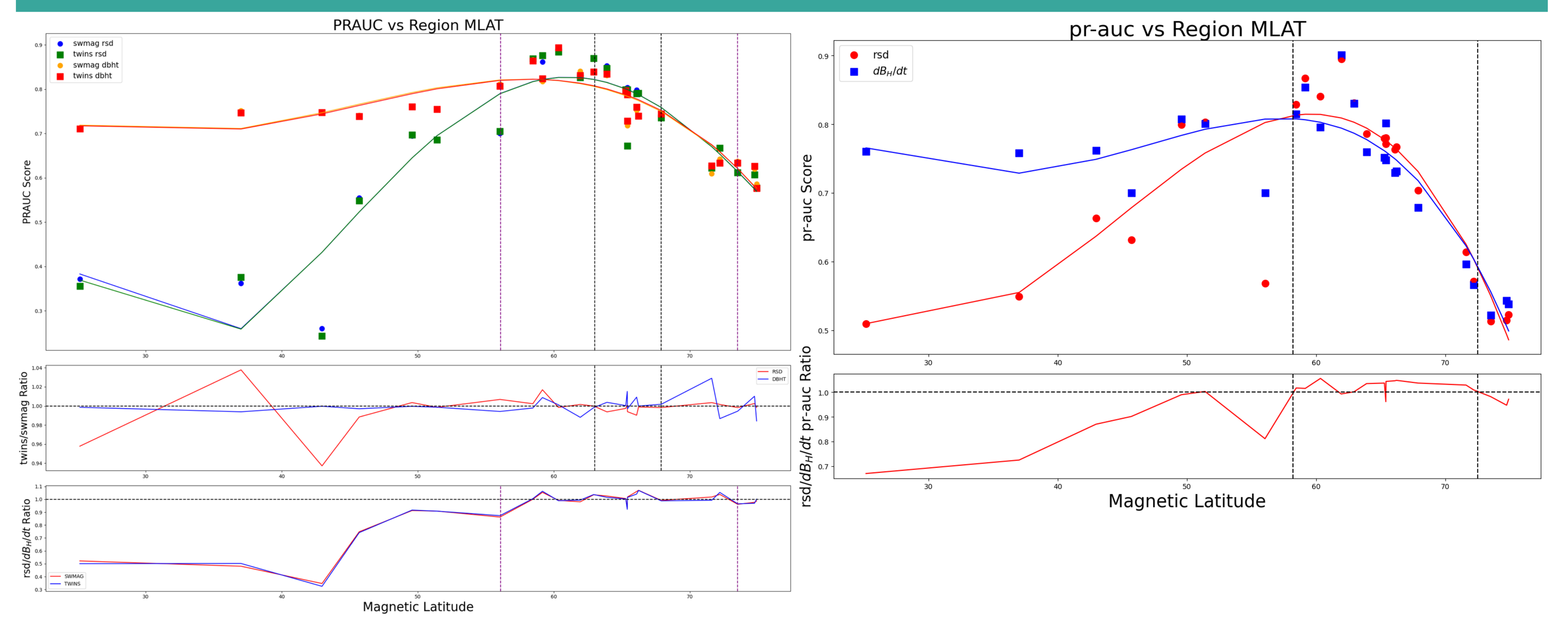

Figure 2. (Left) Area under the Precision-Recall Curve (pr-auc) for both model types for a model that incorporates the ion temperature maps (TWINS) and one that does not (SWMAG). Plotted as a function of the mean magnetic latitude of the regions created for this work. (Right) Pr-auc for the SWMAG models only after the dataset had been expanded once dropping the requirement of staying within the times with available ion temperature data.

SWMAG Model Predictions

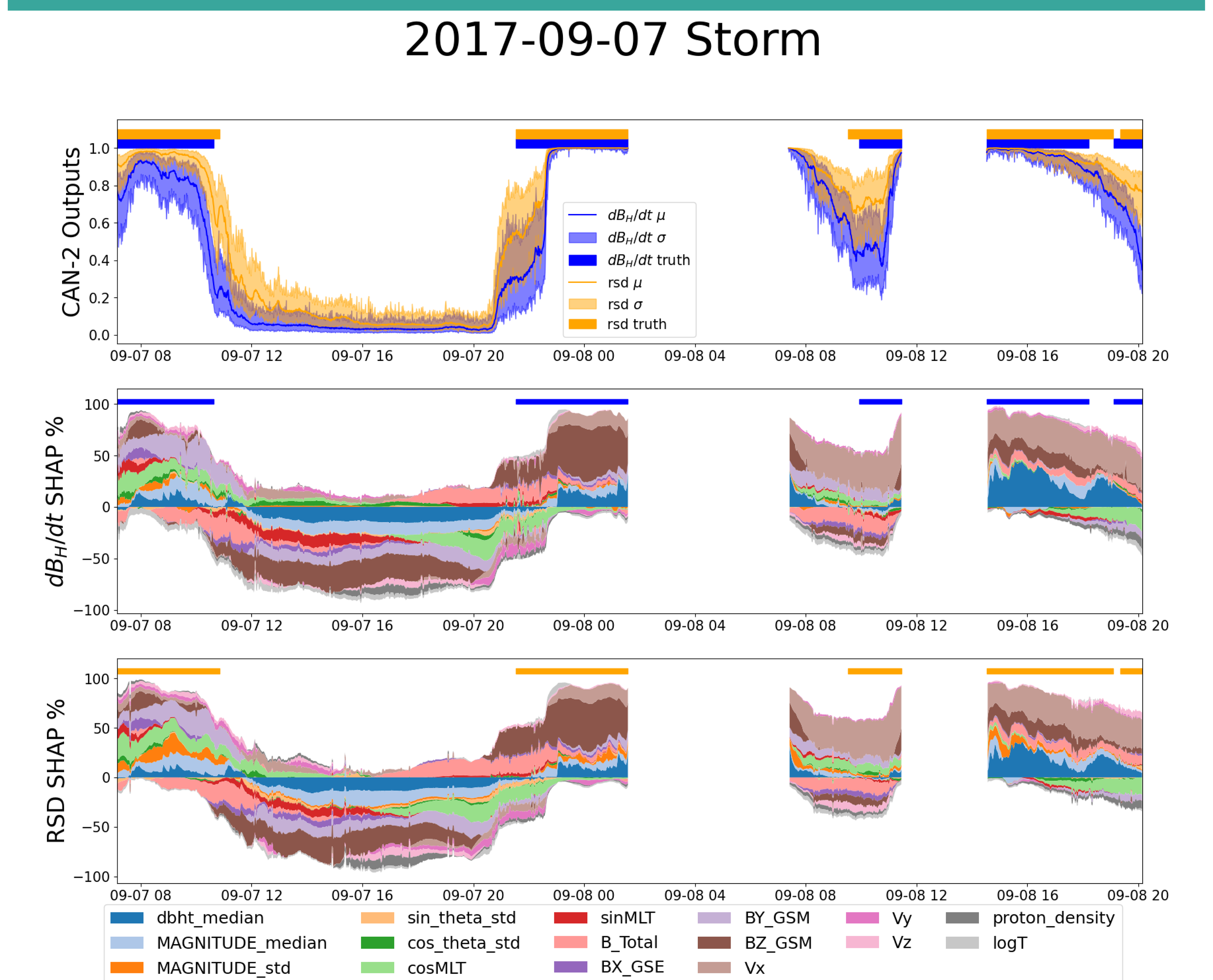

Figure 3. Top panel shows the model outputs for the CAN-2 region during the September 2017 Storm, where the blue line indicates the mean probabilities of the dB_H/dt model and the blue shaded area the uncertainty. Orange is the same for the RSD model. The colored bars at the top of the plot show the times where the ground truth crosses the threshold. The other two panels show the SHAP values for each model as a time series, with values above zero raising the model output probabilities and below zero lowering the model outputs. The model outputs show similar trends with the RSD model consistently outputting slightly higher mean values. Upon careful examination, we can see that this is at least partially due to a depressive effect of the LogT parameter on the dB_H/dt model.

References/Acknowledgements

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[1] A. P. Dimmock, L. Rosenqvist, D. T. Welling, A. Viljanen, I. Honkonen, R. J. Boynton, and E. Yordanova. On the Regional Variability of d B /d t and Its Significance to GIC. *Space Weather*, 18(8), Aug. 2020.

[2] C. M. Ngwira, D. Sibeck, M. V. D. Silveira, M. Georgiou, J. M. Weygand, Y. Nishimura, and D. Hampton. A Study of Intense Local d B /d t Variations During Two Geomagnetic Storms. *Space Weather*, 16(6):676–693, June 2018.

RSD Model DeepSHAP Contributions

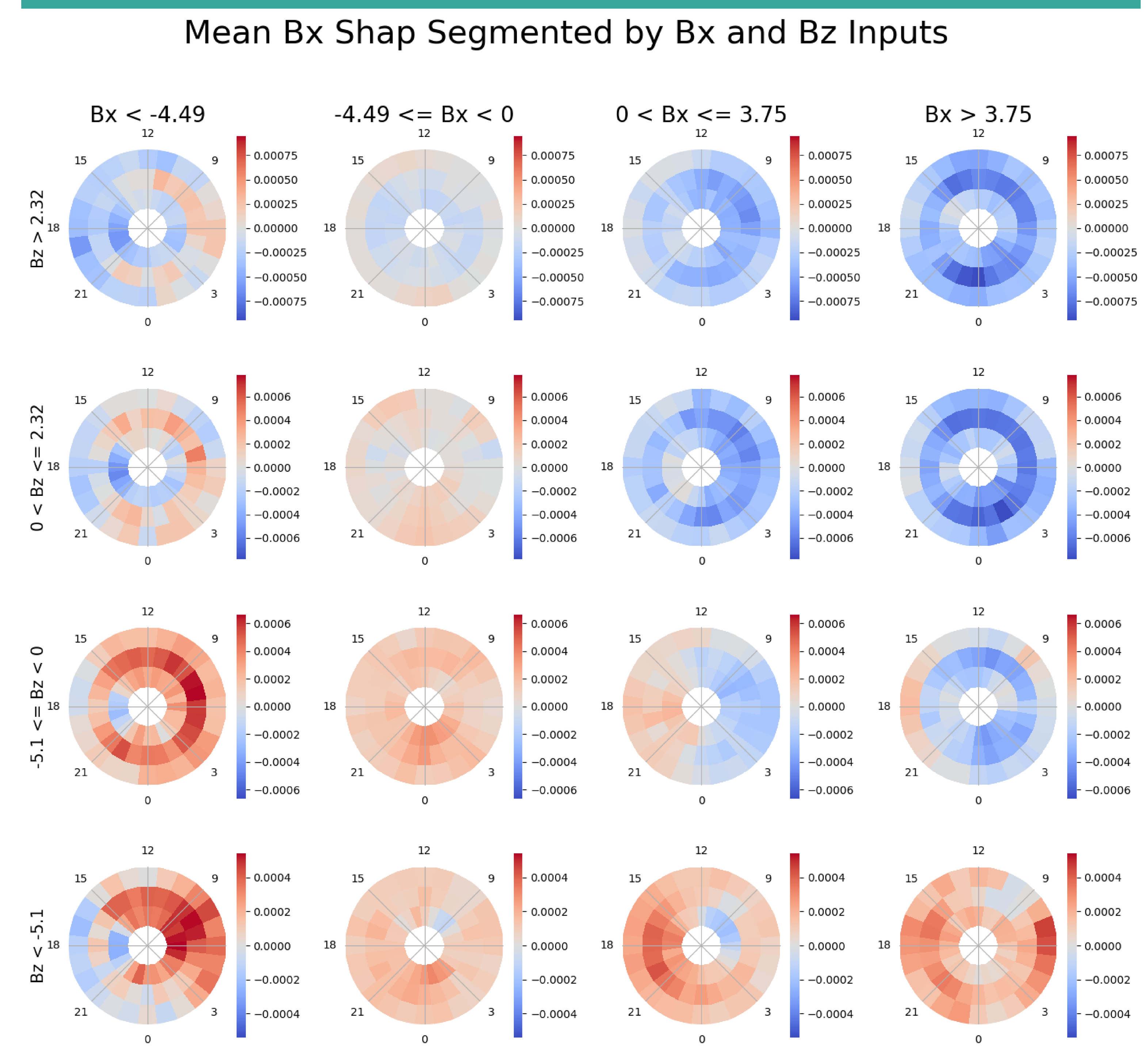

Figure 4. Median B_x SHAP values for the SWMAG RSD model broken down by input values of B_x and B_z. Input variables are sliced at 0 to show differences between positive and negative, as well as the 25th and 75th percentile values. Figures are broken down into three latitude bands: Mid lat (<55°), High lat (55°-68°) and Polar lat (>68°), and one hour MLT bands. Latitude bands increase towards the center of the circle, and 12 MLT is at the top of each plot. Red values are positive (push the model output higher) and blue are negative values which push the model outputs towards zero. There is an apparent dawn side positive bias for highly negative B_x which strengthens with increasingly negative B_z.

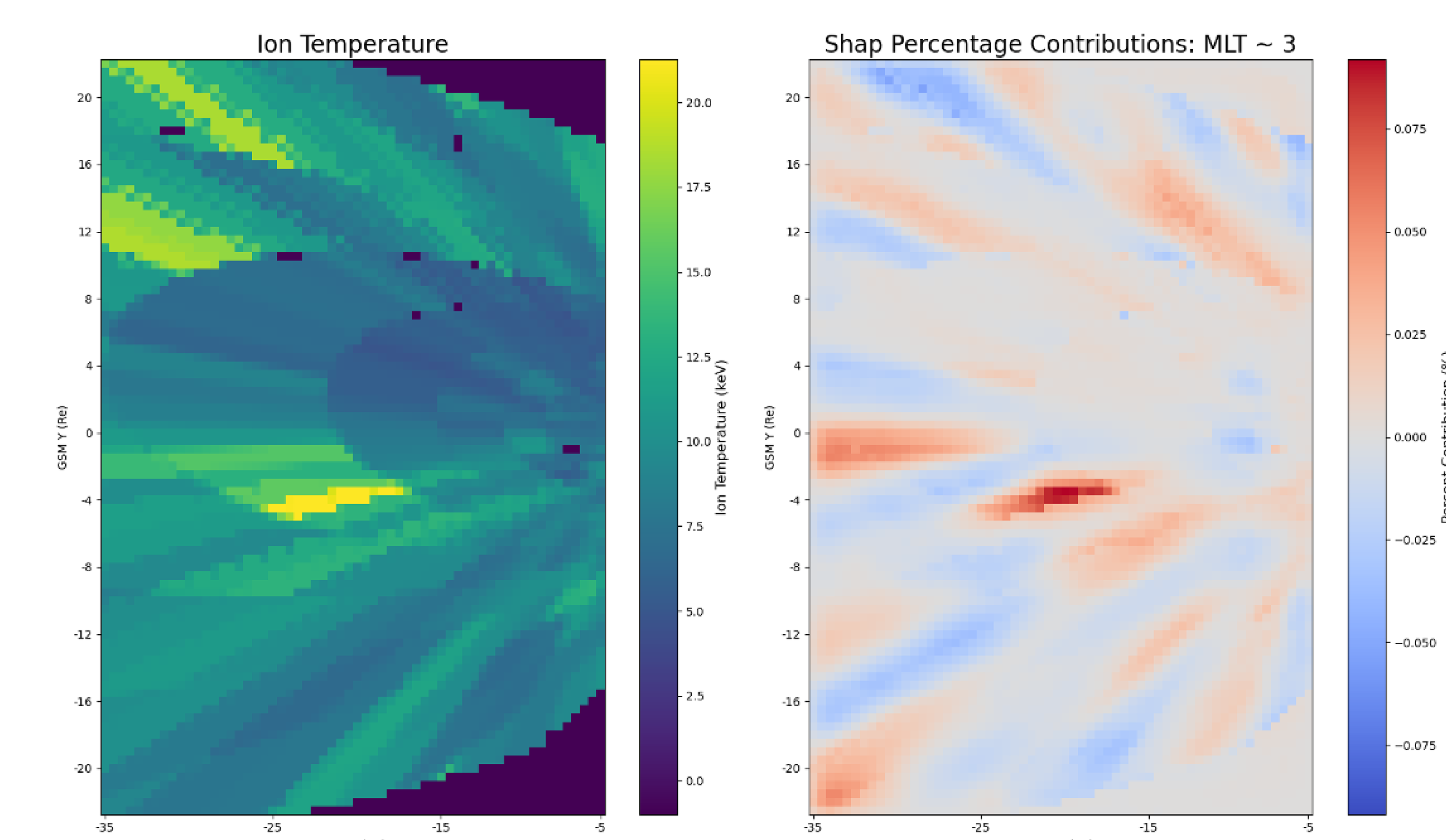

Figure 5. Example of the SHAP calculations done on one of the Ion Temperature Maps used as input. The left panel shows the ion temperature map (unscaled) and the right the contribution of the SHAP values for this map. These values are the percentage contribution and represent a small portion of the overall SHAP contributions, showing that while the model correctly identifies the high temperature flow near the center of the map, the overall influence is negligible.

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