Forecasting of Extreme Ground Magnetic Field Fluctuations at Mid-Latitudes using Machine Learning

Mike Coughlan [1] Amy Keesee [1, 2] Victor Pinto [3] Raman Mukundan [1]
Jose Paulo Marchezi [2] Jeremiah Johnson [4] Hyunju Connor [5] Don Hampton [6]

[1]University of New Hampshire - Department of Physics & Astronomy [2]University of New Hampshire - Institute for Earth, Oceans & Space
[3]Departamento de Fisica, Universidad de Santiago de Chile [4]University of New Hampshire - Department of Electrical and Computer Engineering
[5]NASA Goddard Space Flight Center [6]University of Alaska Fairbanks - Geophysical Institute

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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

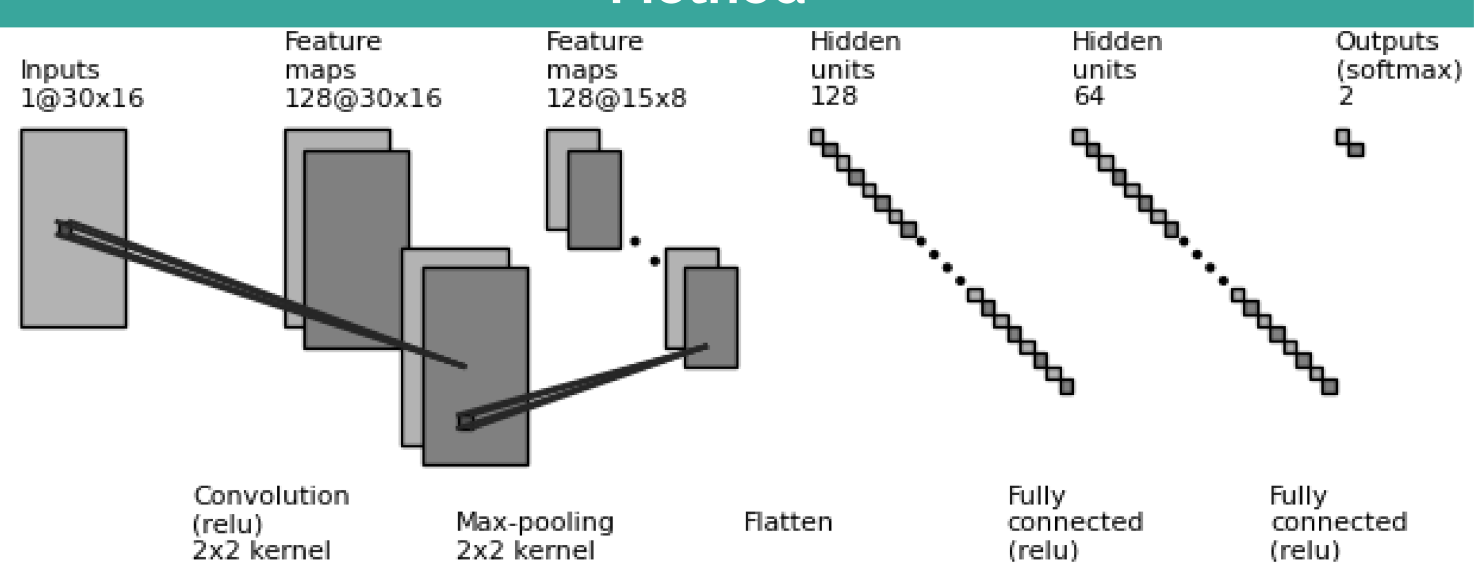

Figure 1. The models consists of 1 CNN layer with 'RELU' activation, a MaxPooling layer, a Flatten layer and two Dense layers with Dropout in between. The output layer is a Dense layer with softmax activation.

- The model was trained exclusively on storm time data as defined by adding ±12 hours to SYM-H minimums of less than -50 nT.
- The input features included solar wind speed (Vx, Vy, Vz), IMF GSM (BT, By, Bz), proton density, and temperature from the **ACE** satellite; AE INDEX and Solar Zenith Angle from the **OMNI** database; and horizontal magnetic field (N,E), dB/dt, and ground magnetometer sin(MLT) and cos(MLT) from the **SuperMAG** network.
- 100 models were trained for each station using a bootstrapping method which allows us to evaluate the uncertainty of the combined models.

Table 1. Ground magnetometer stations used in this study, 99^{th} percentile dB/dt.

Station	Threshold (nT/min)
BFE	6.801
WNG	5.587
LER	8.052
EKS	6.520
STJ	4.940
OTT	7.145
NEW	6.648
VIC	5.456

Table 2. Storms used for testing the models and min SYM-H values (subset from [2]).

Storm Start	SYM-H min (nT)
2001-03-29 10:00	-437
2001-08-29 22:00	-46
2005-05-13 22:00	-305
2005-08-30 08:00	-119
2006-12-13 10:00	-211
2010-04-03 22:00	-90
2011-08-04 07:00	-126
2015-03-16 00:00	-234

Model Predictions

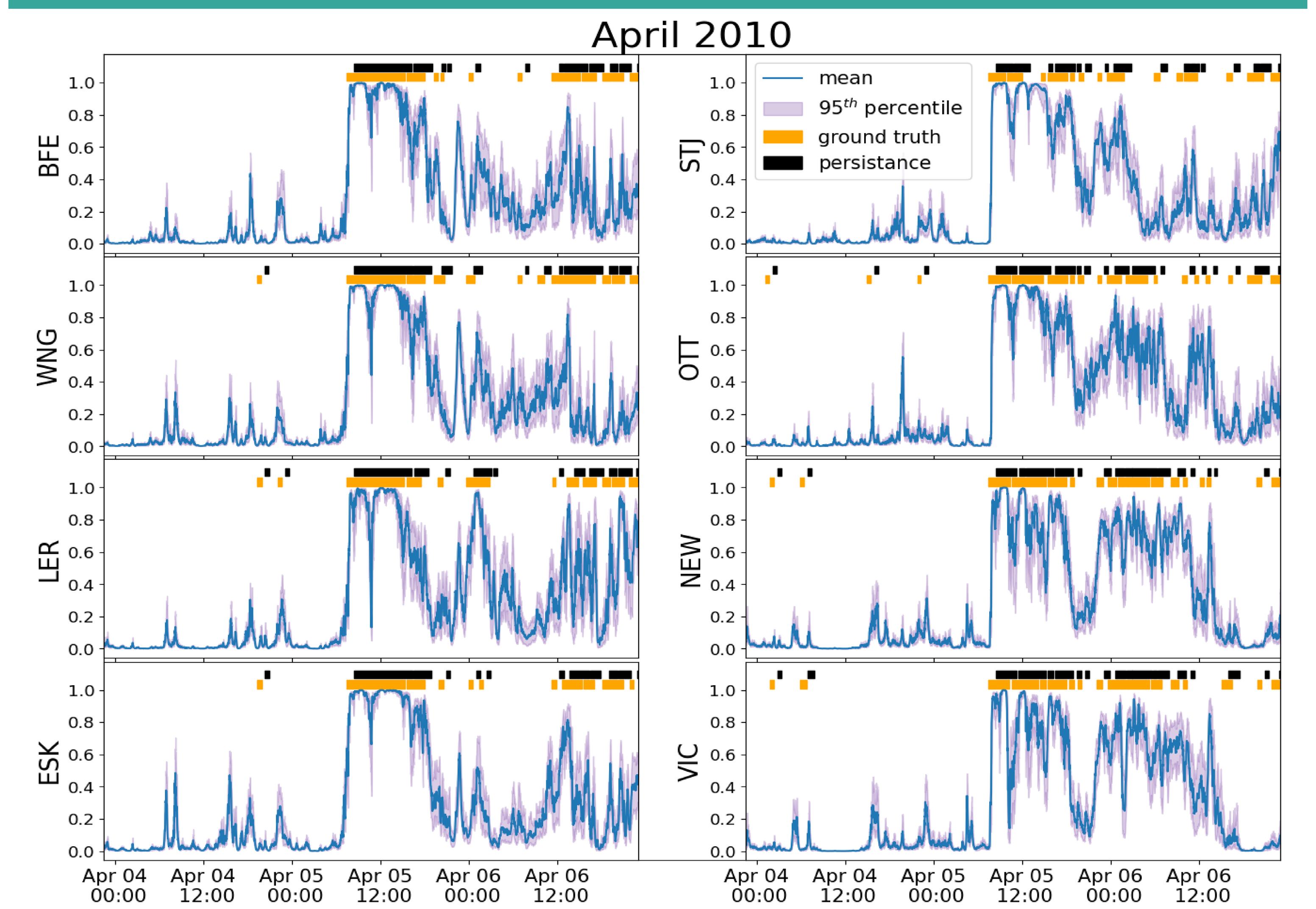

Figure 2. April 05, 2010 storm. Dark blue line: mean model output, light purple shading: 95^{th} percentile, orange bar: indicates positive class in the real data, black line: persistence model.

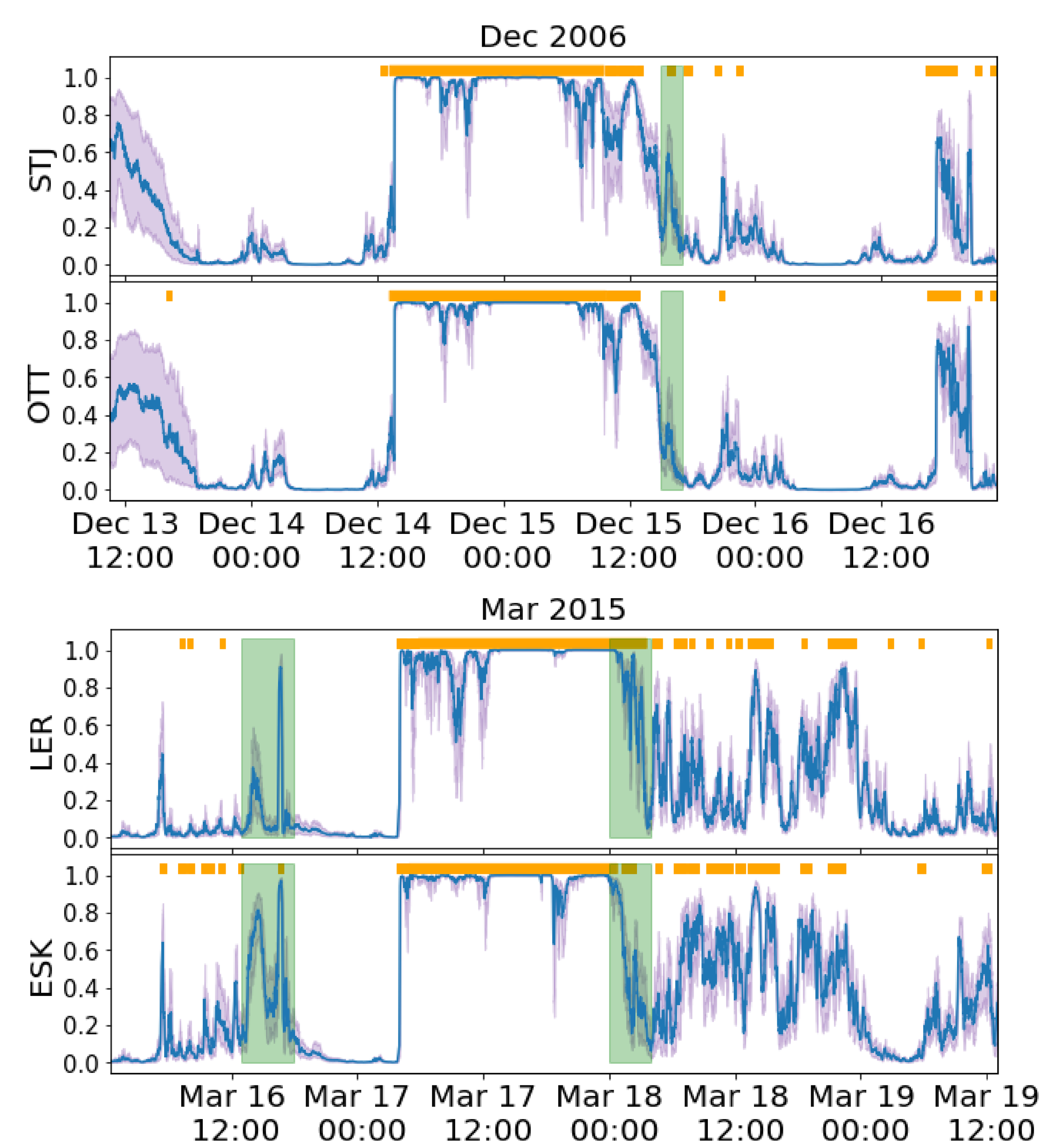

Figure 3. **(Top)** Green shading: STJ models with higher spike in probabilities during a threshold crossing at STJ and not OTT. **(Bottom)** First green shading: solar wind causing spike in all probabilities, second shading: LER models output elevated probs during higher spikes in dB/dt.

References/Acknowledgements

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

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

[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. *Space Weather*, 19(9), Sept. 2021.

[2] D. T. Welling, C. M. Ngwira, H. Opgenoorth, J. D. Haiducek, N. P. Savani, S. K. Morley, C. Cid, R. Weigel, J. M. Weygand, J. R. Woodroffe, H. Singer, L. Rosenqvist, and M. Liemohn. Recommendations for Next-Generation Ground Magnetic Perturbation Validation. *Space Weather*, 16(12):1912–1920, Dec. 2018.

Discussion

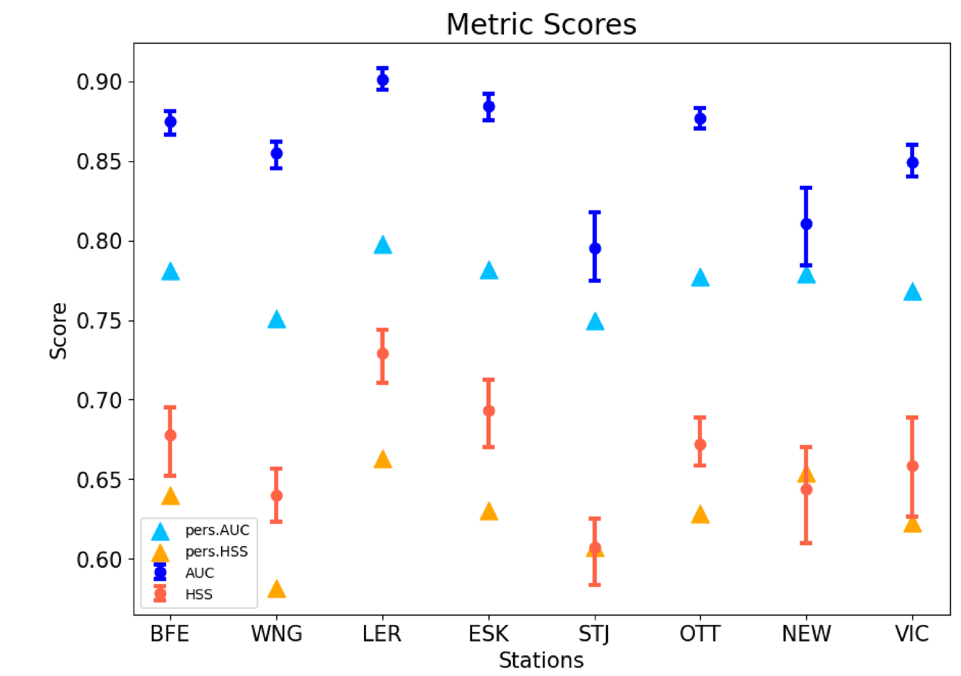

Figure 4. Area Under the Precision-Recall curve and Heidke Skill Scores. The bounds indicate the 95^{th} percentile and the points indicate the median result of the 100 models.

- When comparing stations in close geographic proximity, lower dB/dt values correlate with wider uncertainty bands.
- **AUC scores range from 0.77 to 0.91**, exceeding random model predictions.
- **HSS range from 0.58 to 0.74**, again above random model scores.
- The NEW and STJ station HSS is hampered by its ability to make predictions with missing data creating additional false positives.

Conclusions

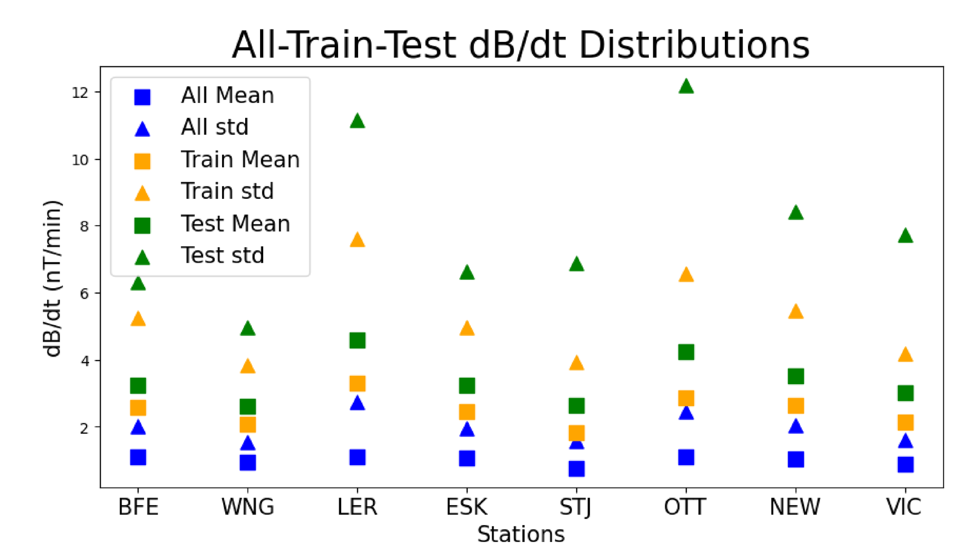

Figure 5. Mean (circle) and standard deviation (triangle) of dB/dt for all data between 1998-2017 (blue), the data used for training (orange), and the testing data (green).

- Models are able to make different predictions at stations near one another when there are differences in the dB/dt profile.
- Differences in the predictions are seen in elevated probabilities at the station with the larger dB/dt spike, while the station with the smaller spike has smaller probabilities.
- 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.

Other MAGICIAN Presentations and GitHub Link

Amy Keesee (NG46A-01, ED45B-03), **Victor Pinto** (NG52A-0153), **Raman Mukundan** (SM32C-1738), **Jose Marchezi** (SM22E-1955), **Jeremiah Johnson** (NG45A-03), **Declan Baker** (NG52A-0174), **Talha Siddique** (SM32C-1734) **Charles Smith** (ED41E-02), **Hyunju Connor** (SM12B-08), **Dogacan Ozturk** (ED45C-0619, SA12A-04), **Sai Gowtam Valluri** (SA25B-1923), **Matthew Blandin** (SA45C-2182), **Gabrielle Nowak** (SM52C-1425), **Chigomezyo Ngwira** (SM35B-1756), **Austin Cohen** (SH55B-07), **Charles Owolabi** (SA45C-2178)

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michael.coughlan@unh.edu