# Forecasting Ground Magnetic Perturbations at High and Mid-Latitudes Using Deep Learning and Near Real-Time Solar Wind Data.

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UNIVERSIDAD DE SANTIAGO DE CHILE

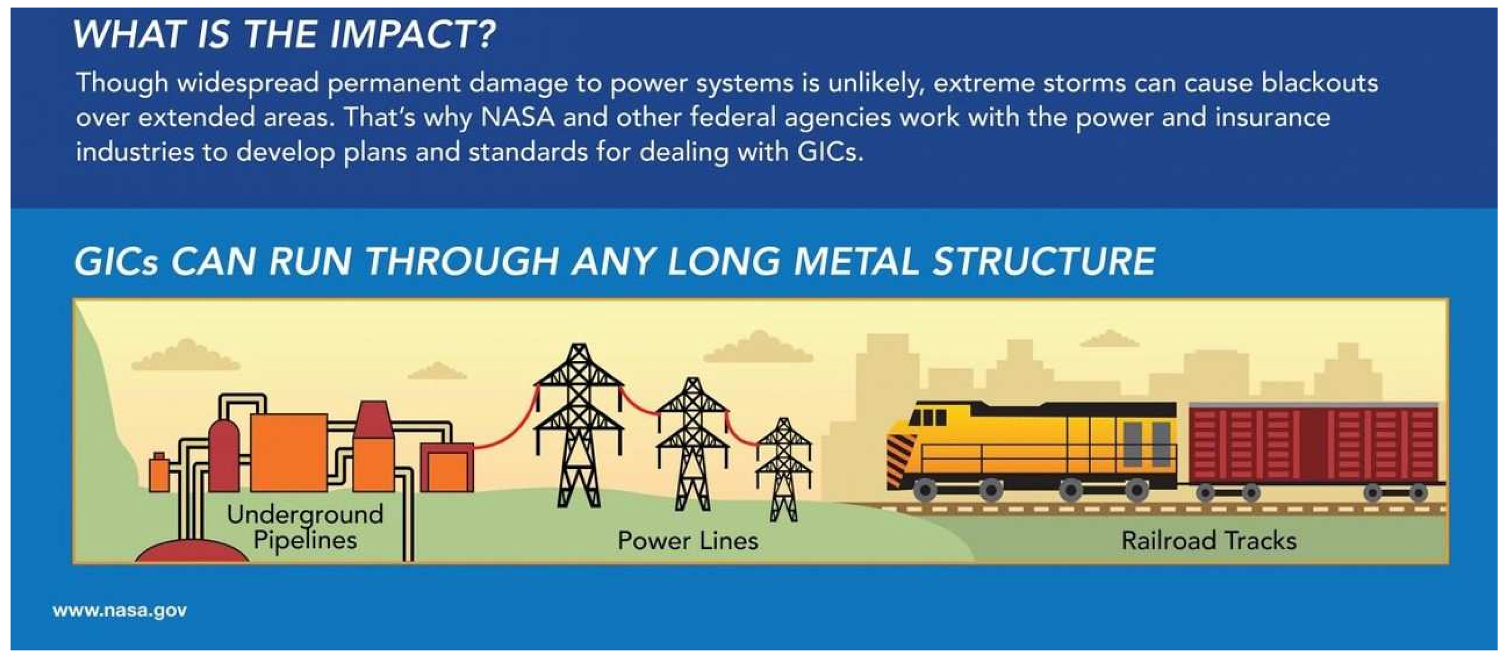
**AGU Fall Meeting, December 12-16 2022, Chicago, IL**

NG52A-0153

## Introduction and Motivation

Ground magnetic fluctuations can serve as proxy for geomagnetically induced current risk assessment. $dB_H/dt$ (horizontal component) has been a recurrent target for evaluation of models. The use of machine learning tools for $dB_H/dt$ forecast is supported by the availability of solar wind data and the advancement of the field. Several models have shown moderate degree of success in the past.

Here we build over previous works (Keesee et al., 2020; Pinto et al., 2022) to develop a deep learning model based on a feed-forward neural network to forecast 1-minute resolution $dB_H/dt$ data at different ground magnetometer stations using data from the solar wind monitor ACE. Validation of the model was done following the guidelines provided by the GEM challenge for ground magnetic field perturbations (Pulkkinen et al., 2013) but comparison are being done against a previous set of deep learning models developed using OMNI data on the same set of stations and storms (Pinto et al., 2022)



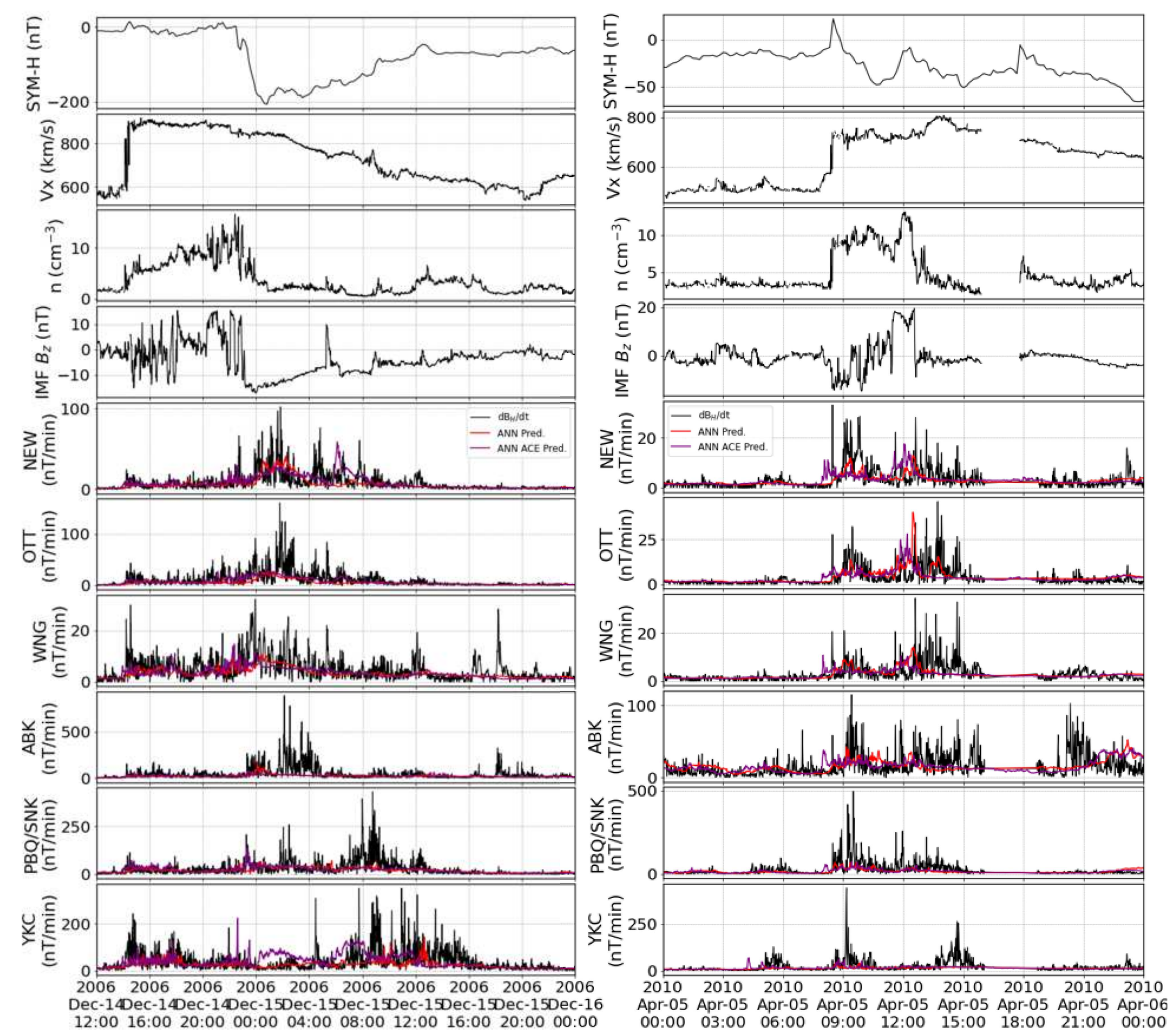

## Methodology

- Supermag data from stations NEW, OTT, WNG, ABK, YKC and PBQ between 1995-2019 was used to calculate the horizontal component of ground magnetic fluctuations which is the target variable to forecast

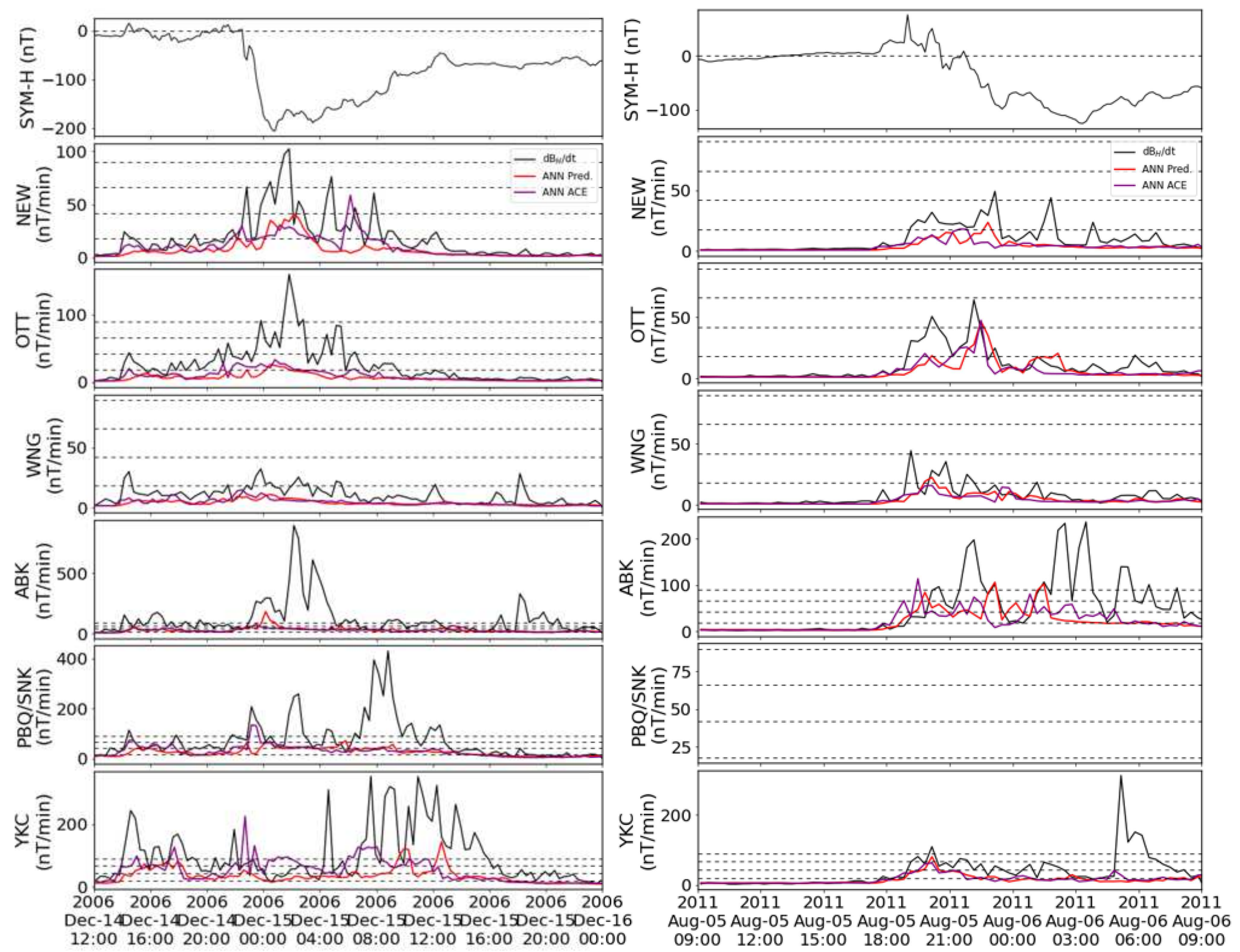
$$\frac{dB_H}{dt} = \sqrt{\frac{dB_E}{dt} + \frac{dB_N}{dt}}$$

- Solar wind parameters measured by ACE (1-min resolution) were used to build the feature vector. Only plasma parameters and IMF were used for the training (no geomagnetic indices or $dB_H/dt$ time-history were used).
- A simple Artificial Neural Network (ANN) was chosen as the model to forecast dBH/dt. Architecture consist of 4 hidden layers of 320-160-80-40 nodes, with a single dropout layer (0.1) in between layers 1 and 2. Model was implemented in Tensorflow.
- A time dependence of 60 minutes was built-in the feature vector for E, B, Bz, Vx, n and T. MLT and SZA from stations were also include as features. Further details can be found in Keesee et al., (2020). For training, we selected ?storm-time only? calculated using SYM-H $< -50$ nT
- The validation storms (6 storms, see Pulkkinen et al., (2013)) were removed from the training data. For the remaining dataset, a 70/30 split was performed for training/testing.
- After a model for each station was trained, a prediction on each storm was performed. Then, data was processed to obtain maximum values every 20 minutes and evaluation shifts to a classification problem of hits or misses against 4 different thresholds at 18, 42, 66 and 90 nT/min

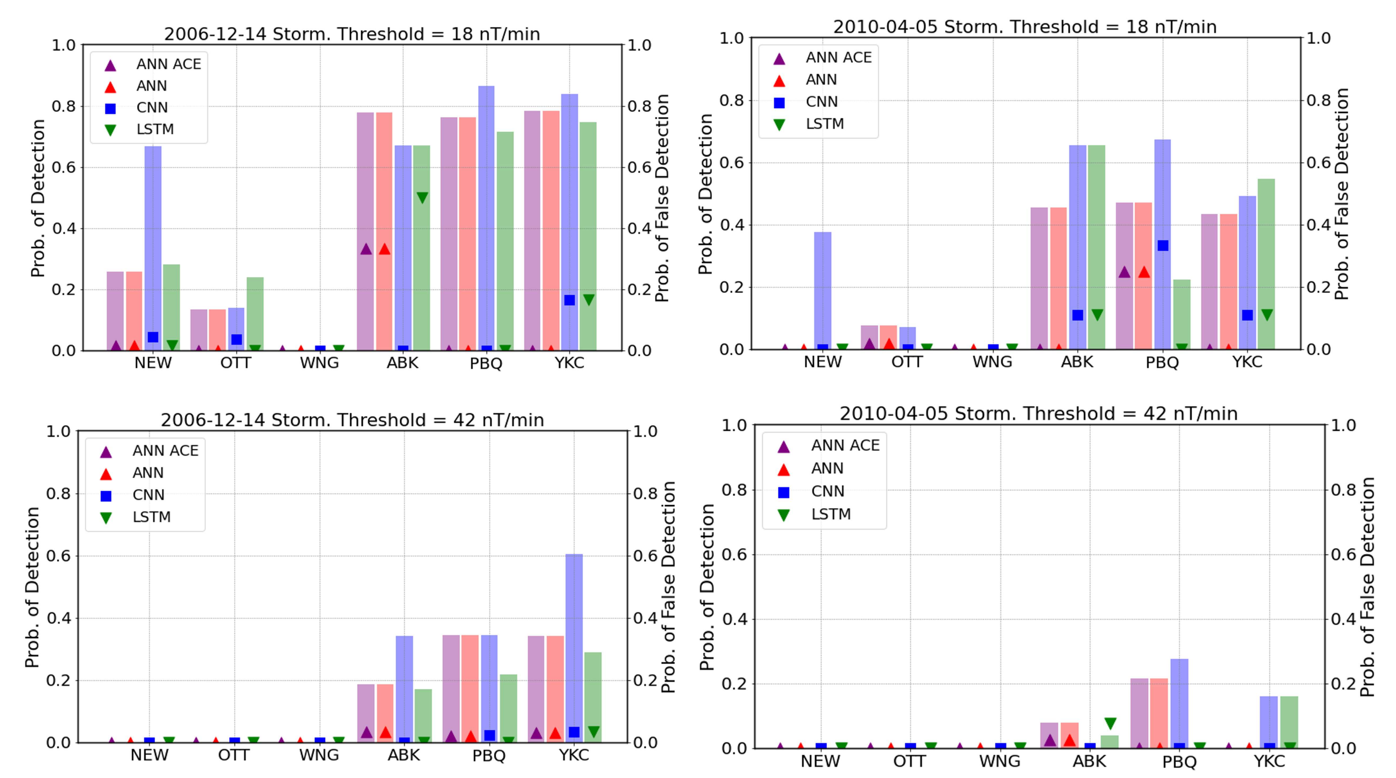
## December 2006 and April 2010 Storms



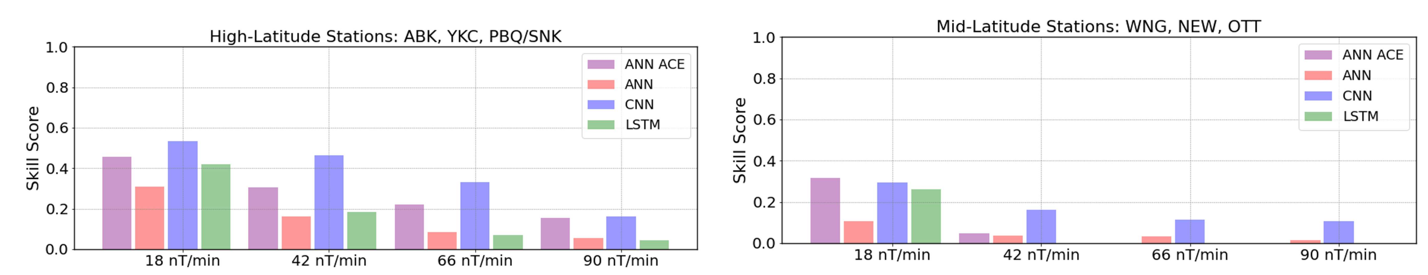

## Prediction for maximum every 20 minutes




## Metrics for Thresholds – 20 minute prediction




## Aggregated Heidke Skill Scores




## Summary and Conclusions

- Prediction of ground $dB_H/dt$ from data available in near real-time seems possible using artificial neural networks, in particular for mid and high-latitude stations
- Current model for 30-min forecast presents acceptable skills scores, performing better than our previous models trained using OMNI data
- Although the GEM Challenge scores are limited in scope, they provide a prior history of model performance and make our models comparable to previous attempts
- In the future, we plan to move towards near real-time data as it allows for fixed-time forecast. Additionally, it is crucial to train in near real-time for possible real-time applications.

### References:

- Pulkkinen, A., et al. (2013), Community-wide validation of geospace model ground magnetic field perturbation predictions to support model transition to operations, Space Weather, 11, 369?385, doi:10.1002/swe.20056.
- Keesee A.M., et al. (2020) Comparison of Deep Learning Techniques to Model Connections Between Solar Wind and Ground Magnetic Perturbations. Front. Astron. Space Sci. 7:550874. doi: 10.3389/fspas.2020.550874
- Pinto V. A. et al., (2022) Revisiting the Ground Magnetic Field Perturbations Challenge: A Machine Learning Perspective. Front. Astron. Space Sci. 9:869740. doi: 10.3389/fspas.2022.869740

Acknowledgments: This work has been funded by NSF EPSCoR Track II Award OIA-1920965 and ANID SIA SA772100112 project. We thank the Supermag project for the pre-processed baseline removed ground magnetometer data. Solar wind data was obtained from CDAWeb and ACE repository