Developing near real-time ground magnetic field perturbations predictions with machine learning models

Victor A. Pinto[1], Amy M. Keesee[1], Michael Coughlan[1], Raman Mukundan[1], Jeremiah Johnson[2], Hyunju K. Connor[3]

[1]*Institute for the Study of Earth, Oceans and Space, University of New Hampshire, Durham, NH 03824*
[2]*Department of Applied Engineering & Sciences, University of New Hampshire Manchester, Manchester, NH*
[3]*Department of Physics, University of Alaska Fairbanks, Fairbanks, AK*

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Introduction

- Ground magnetic fluctuations can serve as proxy for geomagnetically induced currents risk assessment. dB_H/dt (horizontal component) has been a recurrent target for evaluation of models.
- Use of machine learning 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 developed 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., *under review*)
- Near real-time forecast is constructed using python Dash module in combination with the streaming of data provided by NOAA SPWC

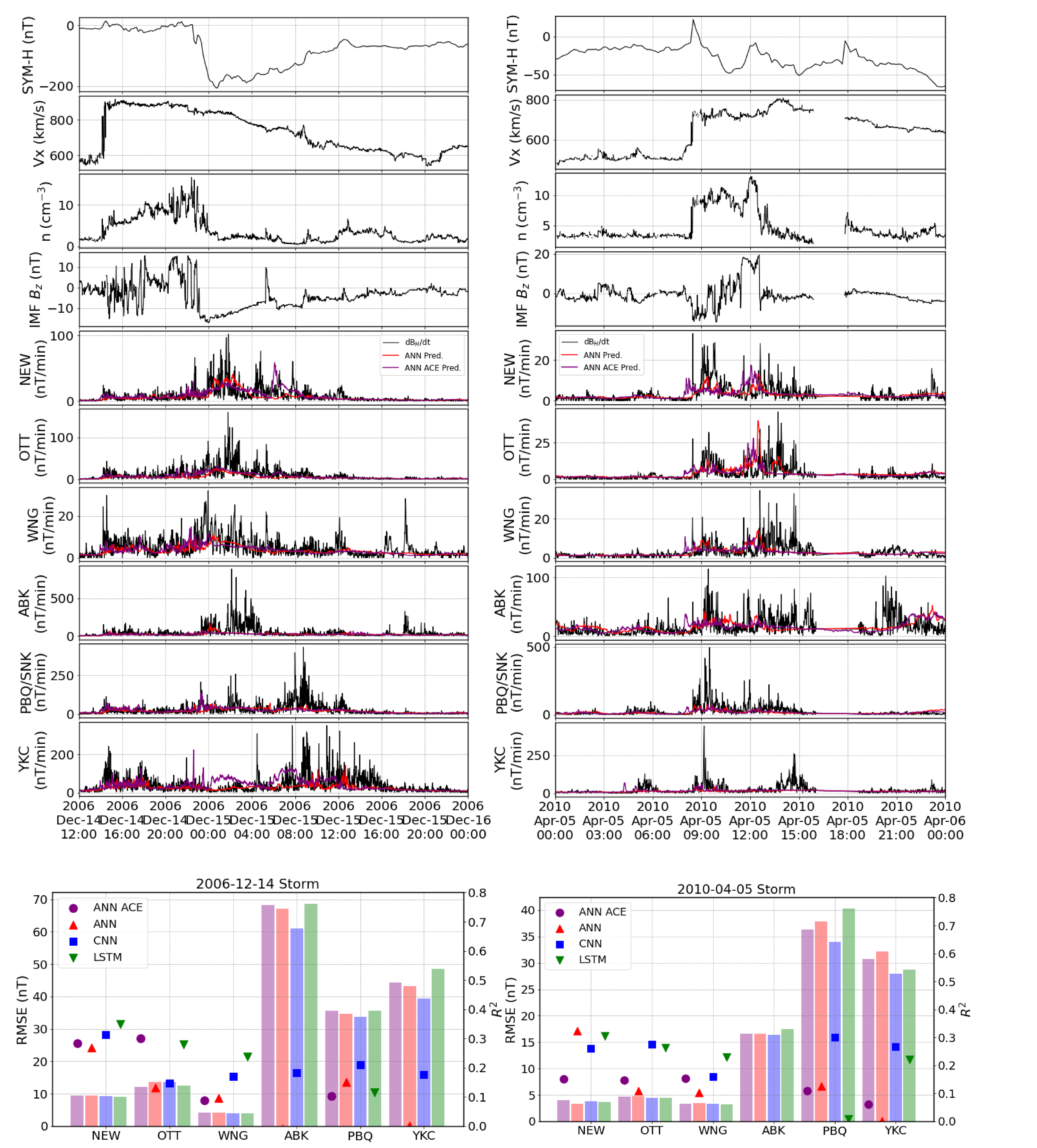
Methodology

- 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

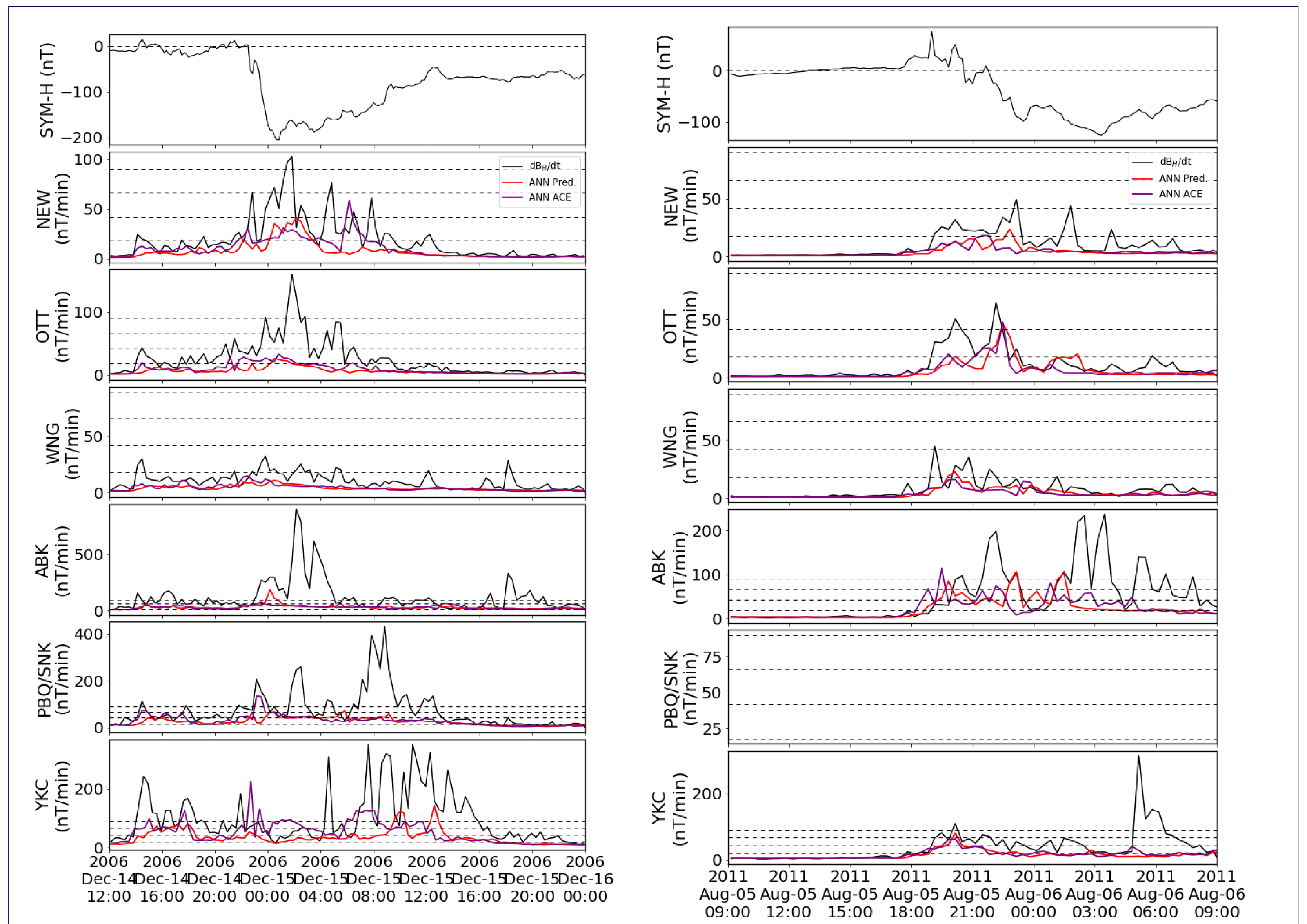
$$\frac{dB_H}{dt} = \sqrt{\frac{dB_E}{dt} + \frac{dB_N}{dt}}$$

- 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 dB_H/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
- Heidke Skill Score was used as the main metric of evaluation, with results calculated on each station and storm, and aggregating all storms and stations at high latitude and at mid latitude

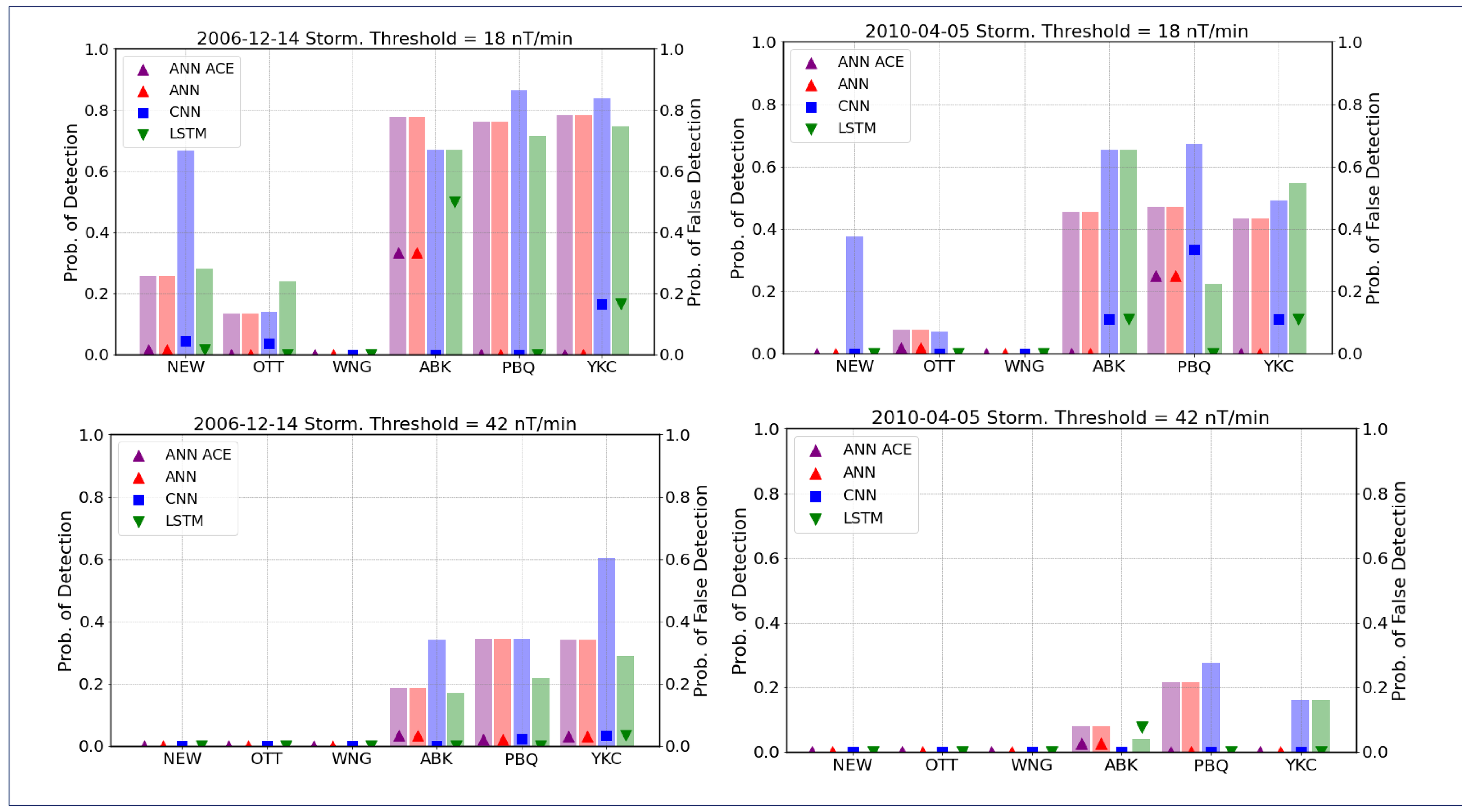
Results Evaluation – Dec 2006 and April 2010 Storms



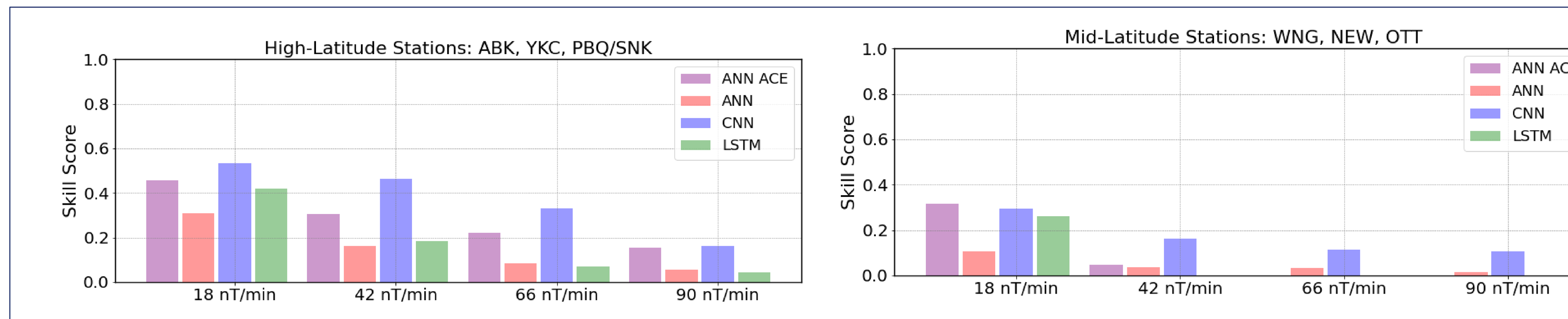
Results Evaluation – 20-minute windows



Results Evaluation – 20-minute windows



Aggregated results: HSS score



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
- Model is being deployed for real-time forecast using python Dash. Code will be available at the MAGICIAN Github repository https://github.com/UNH-GIC-EPSCoR-team/

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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., (under review) Revisiting the Ground Magnetic Field Perturbations Challenge: A Machine Learning Perspective. Submitted to Front. Astron. Space Sci.