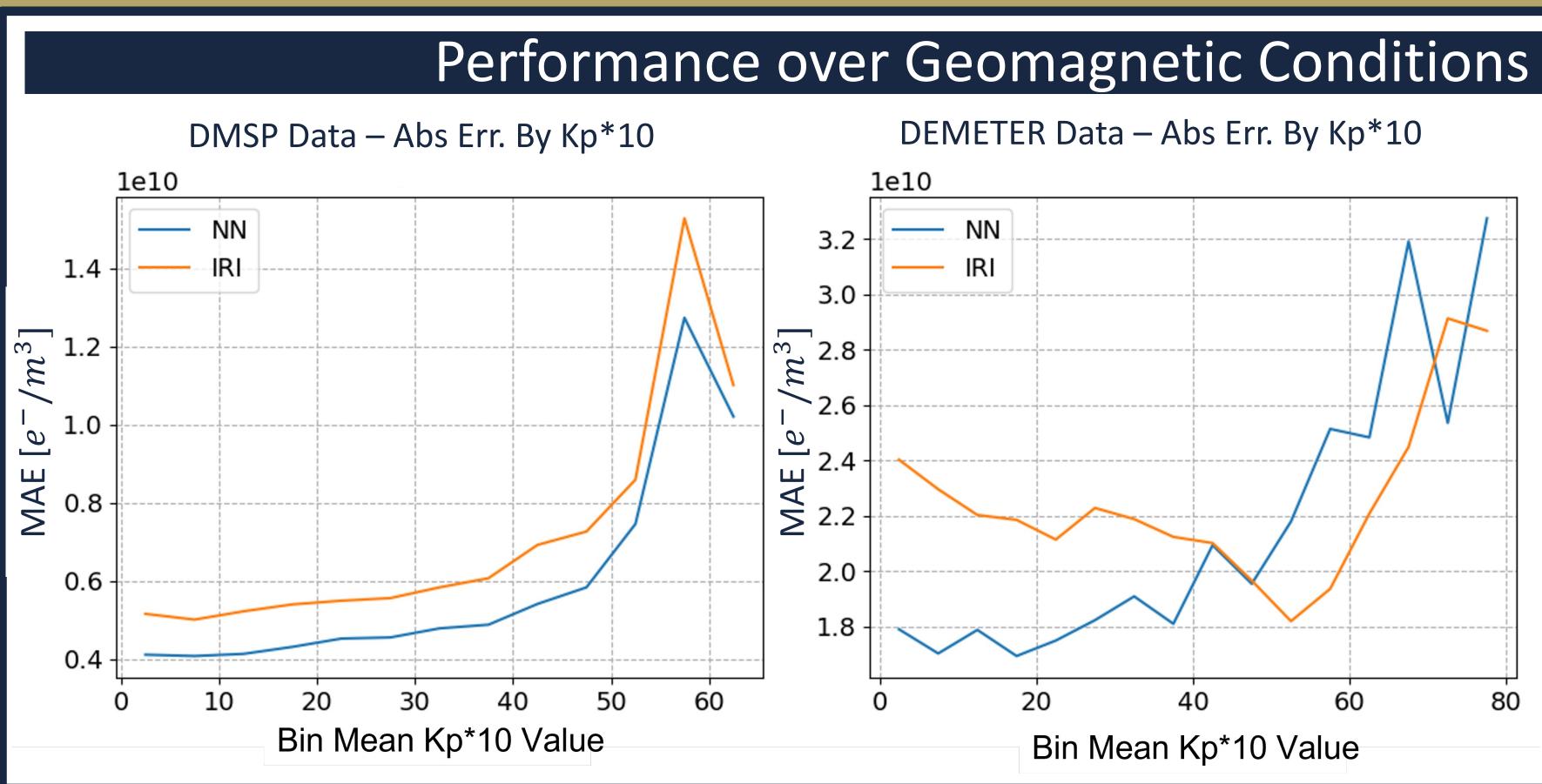


Abstract

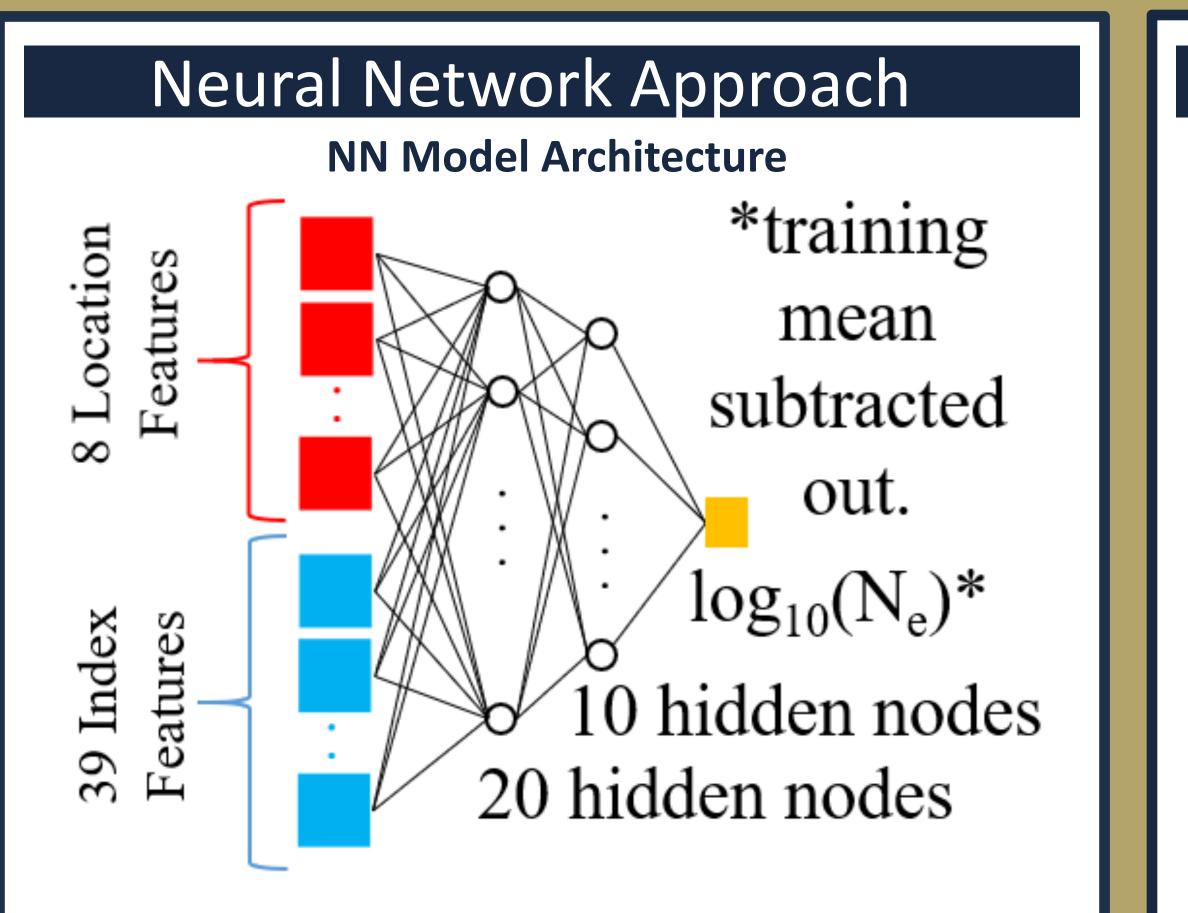
Modeling the Earth's ionosphere is a critical component of forecasting space weather, which impacts radio wave propagation, navigation, and communication. This research focuses on predicting the electron density in the topside of the ionosphere using data from the Defense Meteorological Satellite Program (DMSP), a collection of 19 satellites that have been polar orbiting the Earth for various lengths of times, fully covering 1982 to the present. An artificial neural network (NN) was developed and trained on two solar cycles worth of data from DMSP (113 satellite-years), along with global indices such as F10.7, interplanetary magnetic field (IMF), and Kp to generate an electron density prediction. Here, we present the latest iteration of this model and its performance on out-of-sample DMSP data and DEMETER satellite data, as well as comparison of our model to the International Reference Ionosphere (IRI).

Motivation

The IRI provides an empirical model of electron density over altitudes spanning 80-2000 km. However, the IRI struggles to predict the electron density in the topside of the ionosphere and does not use DMSP satellite data to create its topside model. Therefore, we posit that using an NN trained on DMSP data can create a stronger model of the topside ionosphere.



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(sin/cos), Magnetic **8 Location Features: MLT** Latitude, Geographic Latitude, Longitude (sin/cos), Altitude, Solar Zenith Angle

39 Index Features: Past values of IMF (24), Kp (8), and F10.7 (7), which cover the polar region, the midlatitude region, and the solar cycle, respectively.

NN Training

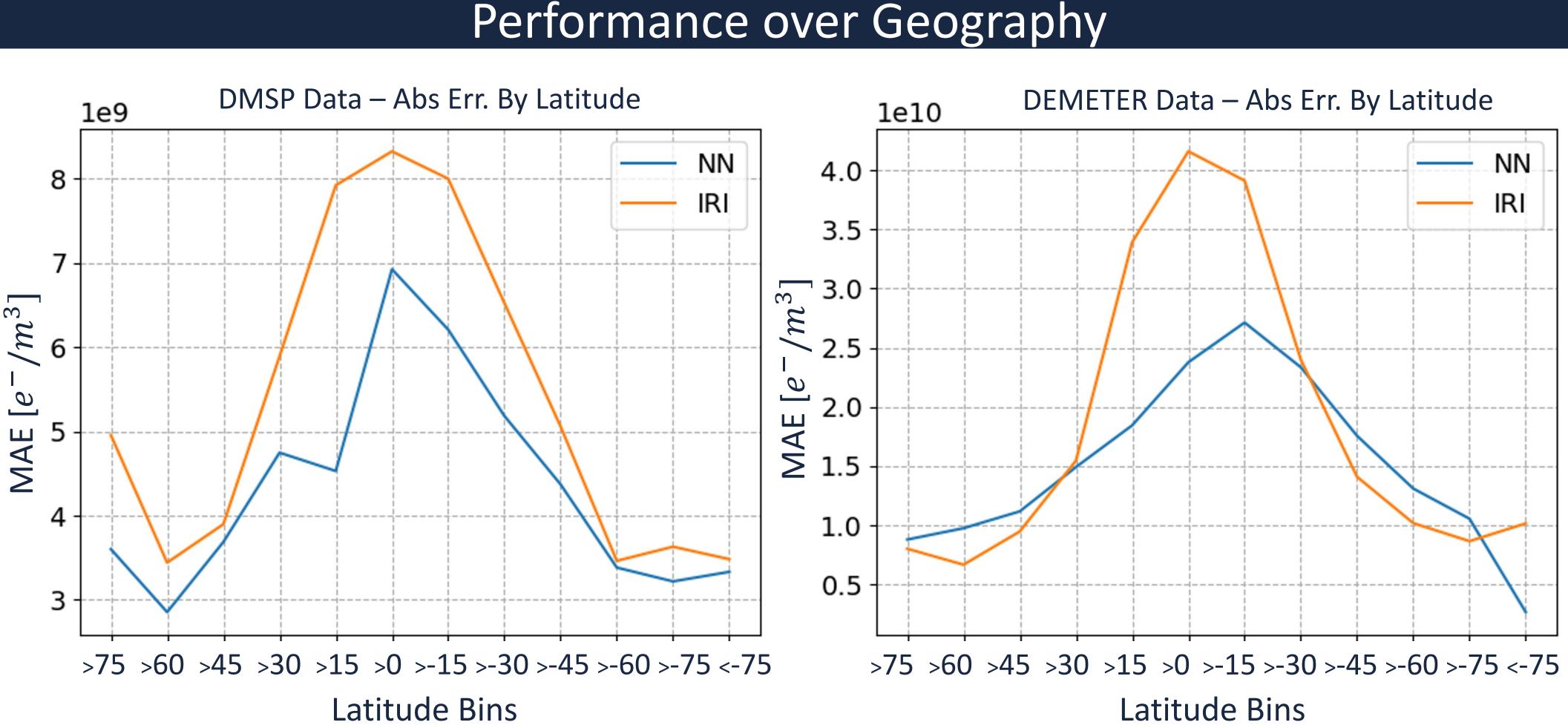
- DMSP Data Partitioning: Training 1988 2011, *Validation* 2012 – 2016, *Testing* 2017 – 2019
- Loss Function: Mean Square Error
- **Optimizer: Root Mean Square**
- Stopping: training complete when performance on the validation set stopped improving, with a patience of 15 epochs.

High Kp = disturbed geomagnetic conditions

Left: MAE of NN (blue) and IRI (orange) on DMSP testing data.

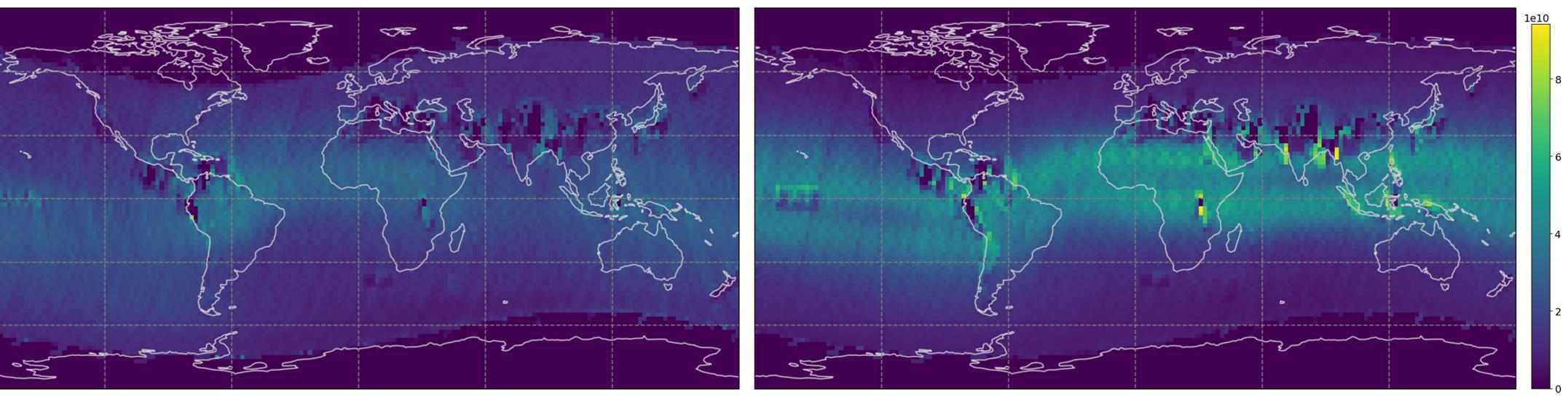
Right: MAE of NN and IRI on DEMETER data.

Comparison of NN (left) and IRI (right) mean absolute error on DEMETER Data. The NN performs better at making topside electron density predictions about the magnetic equator even when trained on a different altitude range than the test data, while the IRI consistently overestimates the electron density.



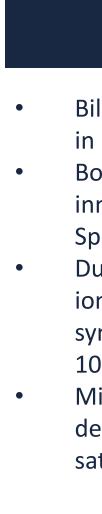
Above Left: MAE of NN (blue) and IRI (orange) on DMSP testing data. Above Right: MAE of NN and IRI on DEMETER data. DMSP satellites orbit at 850 km, DEMETER satellite orbited at 700 km in the data used here.

NN Absolute Error on DEMETER Data



Conclusions

The topside ionosphere is difficult to model, as IRI performance at high altitudes suggests DMSP provides a wealth of in-situ satellite data from the topside ionosphere, making this problem well suited to an ML solution The NN outperforms the IRI in calm geomagnetic conditions and around the magnetic equator Data augmentation will be implemented to improve performance of the NN in storms





IRI Absolute Error on DEMETER Data

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This work is supported by DARPA (D19AC00009) to Georgia Tech.

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