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Modeling Electron Density in the Topside of the Ionosphere using Machine Learning

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Abstract

Modeling the Earth's ionosphere is a critical component of forecasting space weather, which in turn impacts radio wave propagation, navigation and communication. This research focuses specifically on predicting the electron density in the topside of the ionosphere, using data collected 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 with two hidden layers was developed and trained on two solar cycles worth of data, including features such as time series F10.7, time series average interplanetary magnetic field (IMF), time series Kp, solar azimuth, and location to generate an electron density prediction. We tested the model on six years of subsequent data, and found a correlation coefficient of 0.73 for a nowcast of electron density. Figure 1 depicts the predicted electron densities along with the true densities measured by a DMSP satellite over a 5-hour period. Upcoming work includes improved testing performance via modified model inputs, tweaking the model architecture, and further rounds of hyperparameter searching. A forecast will then be computed by providing the nowcast model with forecasted global inputs (solar wind, IMF, geomagnetic indices) as part of a larger space weather forecasting effort currently underway. Therefore, we eventually hope to better forecast the electron density of the Earth's ionosphere and in turn better predict space weather, mitigating its negative effects. In addition, these accuracy of these results will be assessed with out-of-training DMSP satellite data alongside the International Reference Ionosphere (IRI).

1 Introduction

Space weather forecasting is of interest to both Earth and space scientists as well as government and industry due to the interaction of the sun with Earth's atmosphere and magnetic field, which can have potentially deleterious effects on Earth communication systems and power grids [1]. In this paper, we focus on ionospheric modeling as a critical component of such a forecasting system, and look to improve upon the current standard empirical physics-based model, the IRI [2]. Since many physics-based models often make simplifying assumptions which decouple the interactions between layers of the atmosphere/ionosphere, they are not as robust to sudden disturbances from high solar activity [3]. Unfortunately, this means the models do not perform well at the times we need accurate forecasts the most. Shim et. al. [4] compares electron density models using RMS error and prediction efficiency binned by latitude range and true density variability. The study found the IRI to perform better than other model types, including data assimilative models and purely physics-based models. However, the IRI does not perform well in predicting the electron density in the topside of the ionosphere, noted by both the developers of the IRI and validated by them and others via comparison of IRI model output to topside electron density data taken from in-situ SWARM, DMSP, and CHAMP measurements [5], [6], [7]. Therefore, development of a standalone topside ionospheric electron density model using the data that proves the IRI does not perform well in the topside would advance our overall ionospheric modeling capabilities. The DMSP alone has topside electron density data from 1988 to the present, making the modeling problem a strong candidate for the application of machine learning (ML) techniques. ML allows for model creation with fewer assumptions, since the coupling to other portions of the space weather system is empirically but very generally defined, and it is easier for a model to predict quiet times and storm times, and include nonlinear dependencies. Therefore, we developed a neural network that is trained on existing electron density data to create a model

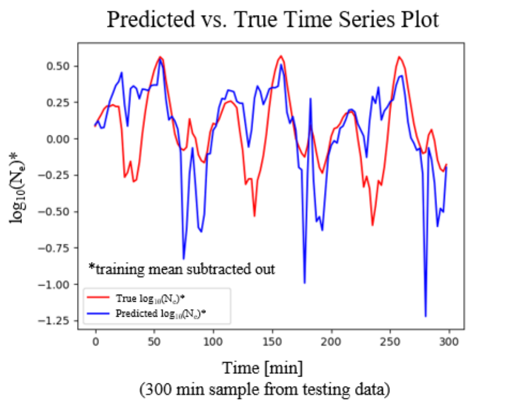

Figure 1. 5-hour sample of model nowcasts of $\log_{10}(N_e)$ compared to actual $\log_{10}(N_e)$ values reported by a DMSP satellite along its path. The training mean electron density was $10^{10.3}$ electrons/m^3.

that can nowcast the electron density at any location and time, given the values of global indices F10.7, average IMF, and Kp. In the paper, we outline the exact sources of data used, the model architecture selected, and the feature selection process, ending with a discussion of our results and future improvements.

2 DMSP Data Source and Cleanup

When applying a machine learning technique to create predictions, data quality and preparation are of the utmost importance. A model trained on poor data will not be a good predictor of future behavior of a system, even with a sophisticated architecture. We accessed the DMSP dataset via the CEDAR Madrigal Database. Although the DMSP has been running since 1982, the first 7 satellites did not record electron density data, so we restrict our focus to satellites 8 through 19 (a total of 12 satellites). As a result of this restriction, the earliest usable data are from 1988. After filtering out any DMSP data points where the recorded electron density was *NaN*, we examined the distribution of electron densities obtained. The distribution of electron densities

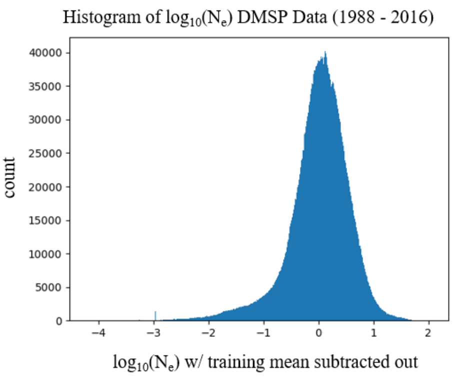

Figure 2. Histogram showing distribution of $\log_{10}(N_e)$ with mean value subtracted out.

sampled along satellite paths of the DMSP appears to be a normal distribution with a left tail skew as seen in Figure 2. Earlier satellites clipped high electron density values, while more recent satellites clipped lower electron density data in Figure 3. In order to improve the integrity of the model, we chose to limit our training and testing data electron densities to be between 10^7 and 10^{11} electrons/m^3. Given that there were 12 satellites polar orbiting the Earth for anywhere from 2-5 years each, it was unlikely that the data would favor any specific locations apart from the poles, however; we also verified that our expectation was met. Having more coverage in the polar region is advantageous since the electron density in that region is far more variable than in the mid-latitudes.

3 Model Architecture

When applying neural networks to a problem, there are many types of nets to choose from. While the problem can

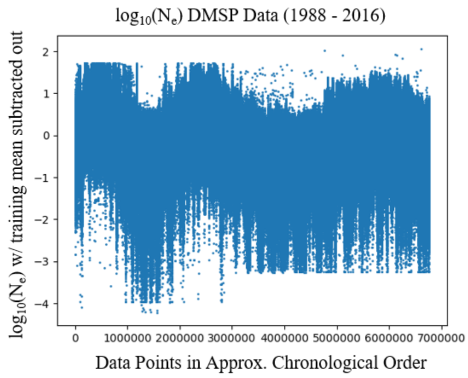

Figure 3. All $\log_{10}(N_e)$ data from DMSP satellites with mean value subtracted out. The mean $\log_{10}(N_e)$ was around 10, so the values that were kept for training lie between -3 and 1 on this graph.

be thought of as a forecasting problem, the data available make the problem non-traditional. Traditional forecasting problems are often best solved by using Recurrent Neural Networks (RNNs). Specifically, Long Short Term Memory (LSTM) networks are used to learn both long range and short range patterns, or contexts, that occur within a system [8]. However, these networks rely on perfect prior information of the quantity being predicted over the entire spatial model domain. For example, if an LSTM network were to be used to predict the electron density at all coordinates in the topside of the ionosphere, we would need access to the prior electron density at all of those coordinates over a variety of times, which we do not have, since the electron density at altitudes above 300 km require in-situ measurements. Instead, we have spatially sparsely sampled data from the DMSP satellites, which provide the electron density at a new location every second as the satellite orbits the Earth. Thus, for this forecasting model, we instead opted to use a fully connected neural network, using location features and global geomagnetic index values to provide the neural network with a sense of time, as suggested in [9], which focused on predicting global plasma density in the magnetosphere.

4 Feature Selection

Since a solar cycle is 11 years long, it is logical to pick a multiple of 11 years worth of data to train the neural network on so that it can learn some of the long range drivers of the electron density of the ionosphere. Therefore, the model was trained on data from 1988 to 2009 inclusive, a total of 22 years, while data from 2010 to 2016 was used for validation. Input features to the neural network include location (latitude, longitude, altitude, etc.), and global geomagnetic indices relating to different latitudes of the topside ionosphere, which is a critical design choice. At the poles, the ionosphere is impacted by the solar wind and the interplanetary magnetic field (IMF), and at mid-latitudes it is coupled to the magnetic field. Therefore, the best combination

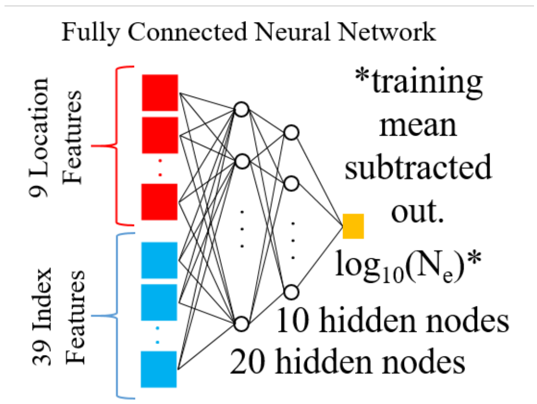

Figure 4. Model architecture used to predict ionospheric electron density. The nine location features are sin/cos of MLT, geographic latitude, sin/cos of geographic longitude, altitude, sin/cos of solar azimuth, and L shell. The prior index values used are daily F10.7 (7 days), 3 hour Kp (8 values), and hourly average IMF (24 hours).

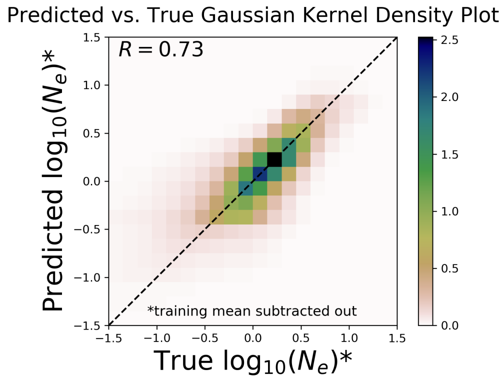

Figure 5. Gaussian Kernel Density plot comparing real electron densities from DMSP data and the electron densities predicted by the model. Higher values (darker blue color) indicate more points are in that box. Perfect prediction is given by the dotted line.

of global indices requires experimentation. The IMF directly impacts the magnetosphere and plasmasphere, which are coupled to the polar ionosphere. Kp, Sym-H, and DST all encode information about perturbations of the Earth's magnetic field and are thus likely to provide information about the mid-latitude ionosphere. F10.7 and sunspot number are indicators of the phase of the solar cycle. Past values of these indices are readily available through NASA's OMNIWeb Data Explorer. In order to pick the optimal set of features, the 9 location features referenced in Figure 4 were held constant, and 7 models were trained, each containing one of the index features mentioned earlier. Whichever index feature produced the best correlation coefficient on test set data was kept, and the next 6 possible models were trained. This process was stopped once the addition of a feature reduced the correlation coefficient in the testing data. After empirically testing multiple combinations of input features, we settled on using past values of IMF, Kp, and F10.7, which cover the polar region, the mid-latitude region, and the solar cycle respectively. These inputs were used in the model architecture in Figure 4.

5 Results

As noted in Feature Selection, we chose to train on two full solar cycles worth of data, or 22 years of data, and test the model on the next 6 years of data, all from DMSP satellites. Put another way, 80% of the data is used for training and 20% for testing. On the data held out for testing, the model predicts the electron density with an R score of 0.73 on testing data, as depicted by the Gaussian kernel density plot seen in Figure 5. Further analysis shows that the model performs better in the mid-latitude regions compared to the polar regions, see the Gaussian kernel density plots in Figure 6. The correlation is clear, but the model may be further refined, as discussed in Future Work.

6 Future Work

Improving the current nowcast ability may occur in a few ways. Some logical improvements to the model include further input parameter tuning. For example, the current model uses the average IMF, but to improve electron density prediction in the polar region, we can create a model with the z-component of the IMF as a separate feature. Another way to improve the polar region nowcasts would be to artificially increase the amount of input data that comes from the polar latitudes by inputting the same polar data point multiple times into the dataset. Finally, there may be too much time history of the indices, ultimately hurting model performance. For example, instead of using the last full day of average IMF, the last 12 or 6 hours might be enough to make a better test prediction. Increased model complexity often leads to overfitting to training data, so reducing the number of inputs to this model is an area of ongoing study. Eventually, forecasts of the input global indices will be used to convert the nowcast into a forecast. Since the current IRI model has difficulty modeling the topside of the ionosphere, the IRI may be augmented with the ML model developed and improved upon to advance ionospheric modeling and space weather prediction.

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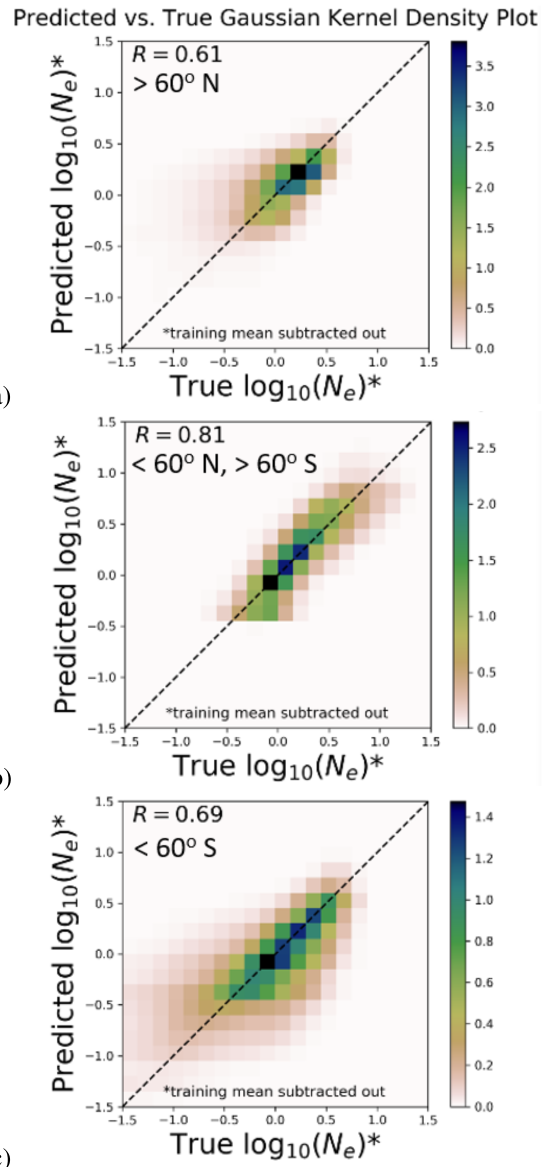

(a)

(b)

(c)

Figure 6. Gaussian Kernel Density plots comparing real electron densities from DMSP data and the electron densities predicted by the model, binned by latitude. (a) is latitudes greater than 60°N, (b) is latitudes between 60°N and 60°S, and (c) is latitudes less than 60°S. Higher values (darker blue color) on the graphs indicate more points are in that box. Perfect prediction is given by the dotted line.

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