

# Machine Learning for Ionospheric Extrapolation and Forecasting in a Data-Model Fusion Approach

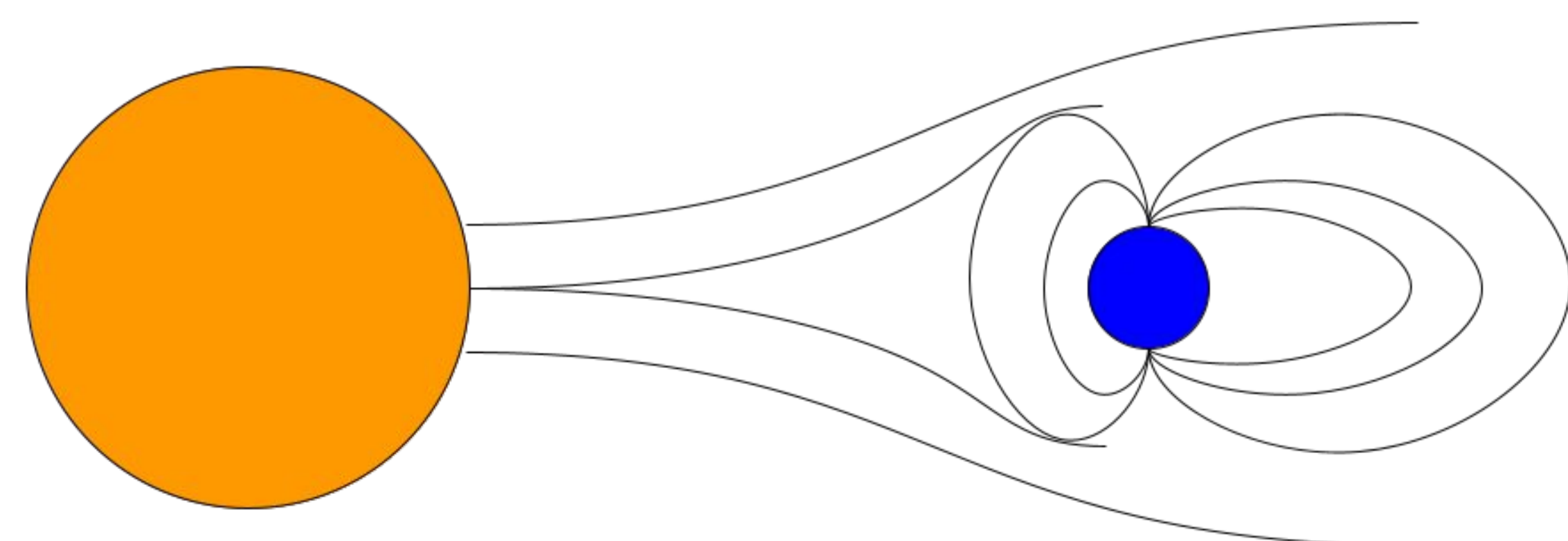
## Abstract

Ionospheric properties are key in space weather monitoring. Of particular note is the electron density as a function of altitude, which helps infer the impacts of space weather. There exist different ionospheric prediction approaches, such as physics-based modelling like SAMI3, as well as empirically supported models. The physics-based models require a lot of computational power and often cannot be expanded with arbitrary additional parameters. Despite this, the quality of results from physics-based models is still desirable. We have trained neural networks using the outputs of SAMI3 in addition to other inputs to demonstrate forecasting ability without the need for a heavy computational model. Additionally, the machine learning approach is tending towards extension with the integration of external observational data sets, which leads to data-model fusion.

Various neural networks approaches have been designed to forecast electron density using interplanetary magnetic field (IMF) parameters alongside SAMI3 outputs. Most recently, the networks have been adjusted to perform spatial extrapolation in addition to the forecasting to allow for input of observed ionospheric conditions and expected spatial and temporal propagation of those conditions.

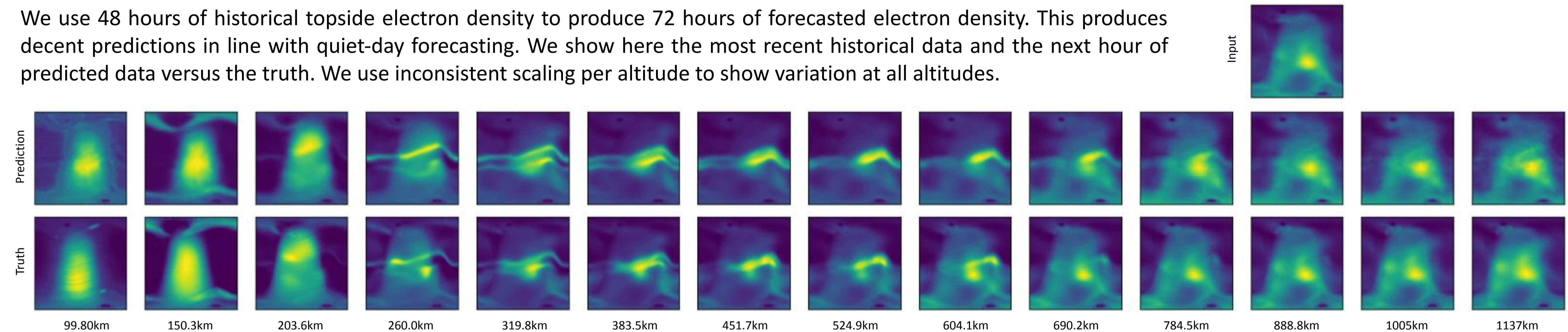
## Background and Motivation

- The ionosphere is influenced by space weather, such as by magnetic reconnection with solar and terrestrial magnetic fields; see below graphic.
  - Space weather and the ionosphere impact wireless communications and power grids.
- A data-model fusion of observations and physics-based modelling would be desirable to produce reliable, empirically-supported ionospheric predictions.
  - We are working to produce such forecasts by training a neural network on synthetic ionosphere data and using an extrapolating network to link areas of empirical modelling [2] with global simulation.
  - The synthetic dataset we use is generated by SAMI3. This is a physics-based model that uses 10.7cm wavelength solar noise (f10.7) and geomagnetic indices (specifically Kp and Ap) as major inputs [1].



## Extrapolation Network

We use 48 hours of historical topside electron density to produce 72 hours of forecasted electron density. This produces decent predictions in line with quiet-day forecasting. We show here the most recent historical data and the next hour of predicted data versus the truth. We use inconsistent scaling per altitude to show variation at all altitudes.



## Results

- Previous work showed correlation of interplanetary magnetic field (IMF) parameters with ionospheric measurements.
- Building upon this, various network structures were developed to produce accurate electron density forecasting that captures diurnal variation.
  - Such neural networks demonstrated that spatial and temporal trends within synthetic data can be captured using convolution and LSTMs.
- To consider the global scale of electron density, a 3D encoder structure (with associated decoder) was used to reduce the memory usage of the large 3D data into a smaller 1D space. This allowed for faster neural network training once the encoder was sufficiently trained.
  - Such an encoding approach is able to accurately represent the majority of the global electron density profile.
- To take advantage of the low dimensional representation, we have created an extrapolating network that takes an input of topside electron density and predicts the electron density in a large range of altitudes. A result from this may be seen in the above figure.

## Next Steps

- The extrapolation network performs well, as seen in the above figure, but performs similarly to a simple network with only time of year and averaged f10.7 values. This is because the synthetic training data consists mainly of quiet-day information, so any anomalies or other unusual occurrences are not represented.
  - We aim to supplement the synthetic training data with such unusual or different non-quiet-day information to allow for a model to generalize to such activity.
  - If generalization is successful, such a model should outperform a simple climatological model that only uses a few simple parameters, as such unusual activity could be captured in the topside altitude information.
- Current work is being performed on predicting with the difference between current and 24-hour ago data (thus removing the easily predictable diurnal variation).
- After completing training and adjustment of an extrapolation network that performs well, input data will be supplemented with topside predictions of another model [2] that is trained on observations.
  - Such a model (trained on observations) cannot be made for the entire ionosphere as only a few altitudes (i.e., those where satellites are) have or can have measurements of electron density. Thus we aim to use those measurements where possible and extrapolate using physics where observations are lacking.

## Summary

- Various networks have been constructed to perform prediction of electron density. These are able to capture the diurnal variation of electron density.
- An extrapolation-based model has been created that aims to fuse empirical models with physics-based models. This is currently a work-in-progress, but it is able to capture the same diurnal variation as other models.

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## References and Contact

[1] J. Huba and J. Krall, "Modeling the plasmasphere with SAMI3," Geophysical Research Letters, vol. 40, pp. 6–10, 1 2013.

[2] S. Dutta and M. B. Cohen, "Modeling Electron Density in the Topside of the Ionosphere using Machine Learning," 2021 XXXIVth General Assembly and Scientific Symposium of the International Union of Radio Science (URSI GASS), 2021, pp. 1-4, doi: 10.23919/URSIGASS51995.2021.9560493.

Email: [lsmith377@gatech.edu](mailto:lsmith377@gatech.edu)