# **AI-Based Ionospheric Scintillation Impact Prediction**

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## **OVERVIEW**

We built lonospheric Scintillation Impact Prediction AI (ISIP.AI), a novel tool that leverages machine learning (ML) to enhance the accuracy of nowcasting and forecasting ionospheric scintillation at L-band frequencies in the lowlatitude ionosphere. ISIP.AI utilizes observations of ionospheric irregularities and scintillation along satellite-tosatellite links to predict scintillation for space-to-ground links. ISIP.AI attempts to estimate the maximum amplitude scintillation (S4) over specified timespans or at each minute.



station link.

## LISN GROUND STATION DATA

This effort utilizes satellite radio occultation (RO) observations as well as ground-based observations from the Low-latitude Ionospheric Sensor Network (LISN). We processed all available LISN data from three ground stations in the year 2022. LISN measures S4 and TEC along established GNSS links at a one-minute cadence.





## **RADIO OCCULTATION** DATA



Our RO data is provided by the COSMIC-2 (C2) mission, consisting of 6 satellites in LEO. The C2 satellites measure total electron content (TEC) and S4 along RO links established with GNSS satellites. We downloaded and processed over 200 days of C2 link data within the year 2022, comprising 38,541,467 minutes worth of link data, retained at a one second cadence. We compiled this dataset into a collection of graphs for every minute. A typical minute will have around 120 active RO links.

Figure 4: Visualization of RO observation geometry over 15 minutes.

## MODEL SELECTION STRATEGY

## We explored three classical ML models and two DL-based models

- Decision Tree
- Random Forest
- XGBoost
- Graph Neural Network (GNN)
- **1D-Convolutional Neural** Network (CNN)

We use a suite of regression-based metrics to assess our models (R2, MAE, MSE and RMSE) to identify the best model architectures. Our model selection strategy includes exploration of the optimal data formats and structures. We tested models that estimate S4 at a one-minute cadence, and the max S4 over a 15-minute window. We additionally experimented with graphbased methods in which the global graph of C2 links is retained, and with the selection of the nearest *n* C2 links to a particular LISN station.

input\_7 input: [(None, 18, 900)] inputLayer output: [(None, 18, 900)] 
 conv1d\_16
 input:
 (None, 18, 900)

 Conv1D
 output:
 (None, 180, 179)

 max\_pooling1d\_14
 input:
 (None, 180, 179)

 MaxPooling1D
 output:
 (None, 180, 89)
conv1d\_17 input: (None, 180, 89) Conv1D output: (None, 81, 17) 
 conv1d\_18
 input:
 (None, 81, 8

 Conv1D
 output:
 (None, 45, 2)
dropout\_6 input: (None, 45, 2) Dropout output: (None, 45, 2)



applied to each RO link.

Acknowledgements: The Phase I and II SBIR program was performed under NASA topic S14.01-1662 (Space Weather Research-to-Operations-to-Research (R2O2R) Technology Development and Commercial Applications), contract 80NSSC23PB356



link geometry





The Wide Band MODel (WBMOD) is an established climatological software tool that can be used to estimate the scintillation parameters S4 and sigma phi along with their errors. The WBMOD is based on extensive datasets covering both the equatorial region and high latitudes. We compare our GNN model results with WBMOD evaluated at the three LISN ground stations, over a 10-day period of high scintillation in 2022. Note that while our model had better testing metrics when compared on the entire sample set, the WBMOD outperformed our model on the subset of samples who's true S4 was larger than 0.2.

<b>GNN Model Error</b>	MSE	RMSE	MAE	$R^2$
Train	0.00203	0.0451	0.0253	0.2362
Test	0.00143	0.0379	0.0227	0.2899
Table 1: Graph Neural Network evaluation metrics.				
<b>GNN Model Error When</b>	MCE	DMCE		D2
True S4 ≥ 0.2		RIVISE		Γ
Train	0.04978	0.2231	0.1931	-3.3071
Test	0.04903	0.2214	0.1885	-2.9410
Table 2: Graph Neural Network evaluation metrics on samples with high S4.				
WBMOD Error	MSE	RMSE	MAE	$R^2$
Full Set	0.00627	0.0792	0.0656	-1.6617
True S4 ≥ 0.2	0.0392	0.1981	0.1589	-2.7506
Table 3: The WBMOD evaluation metrics.				

## CHALLENGES AND FUTURE IMPROVEMENTS

Scintillation impact is a local phenomena requiring a large volume of measurements to accurately estimate; we plan to incorporate more data sources as model inputs. The occurrence of S4 large enough to cause scintillation is rare, causing severe class imbalance and biased ML models.



**RESULTS - COMPARED WITH WBMOD**