AI-Driven S4 Index Forecasting for Ionospheric Scintillation Impact Analysis in Satellite Missions

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Abstract: This work proposes a finite impulse response (FIR) artificial neural network to predict ionospheric scintillation levels (S4 index) based on data from the Global Ionospheric Scintillation Model (GISM). Given the stochastic nature of ionospheric irregularities, traditional models rely on statistical parameters, such as power spectral densities and structure functions. However, despite these efforts, their forecasting capabilities are still considerably limited. The proposed model uses input features including signal frequency, particularly in the UHF band, which is commonly used by CubeSats, geographic coordinates, date, time, Kp index, sunspot number, and F10.7 solar flux to perform short-term predictions. The results demonstrate the potential of AI-driven methods to improve scintillation forecast precision and reduce computational costs, while offering a versatile tool that can be applied to a wide range of applications, from real-time risk assessment in small satellite communications to broader uses in space weather monitoring and system planning.

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1 Introduction

Small satellites are spacecraft developed with relatively low production costs, offering capabilities that go beyond educational applications, encompassing a wide range of services and various types of space missions. Within this category, CubeSats stand out as an accessible and efficient platform, especially for academic institutions engaged in space research and technological development.

The frequency bands commonly used for CubeSat communications are typically allocated within the Very High Frequency (VHF) and Ultra High Frequency (UHF) ranges [1]. Different frequency bands are suitable for different weather conditions, service categories, and user types. The bandwidth available in the VHF and UHF bands is relatively narrow, allowing for the transmission of small data sets, which typically include satellite payload information, along with telemetry and command data.

Lower frequency bands, typically ranging from 300 MHz to 4 GHz, offer several advantages over higher frequency bands, including improved signal penetration through buildings and vegetation, as well as reduced attenuation under adverse weather conditions [2]. Despite their advantages in the aforementioned scenarios, narrowband satellite communications are limited by their low data transfer rates, primarily due to the restricted bandwidth available. Additionally, trans-ionospheric signals transmitted within these frequency bands are more susceptible to ionospheric effects, which can further degrade communication quality [3].

Among the primary effects in the ionospheric layer, scintillation is recognized as the leading cause of disturbances along transionospheric propagation paths for frequencies below 3 GHz, though it can occasionally occur at frequencies up to 10 GHz [4]. Ionospheric plasma irregularities, associated to, for example, plasma bubbles, induce rapid and random fluctuations in the refractive index, causing modulation of the amplitude and phase of trans-ionospheric signals. This phenomenon, known as ionospheric scintillation, significantly disrupts signals, especially those below 3 GHz [4].

Given the complexity and variability of ionospheric behavior in low-latitude regions such as Brazil, where phenomena such as the Equatorial Ionization Anomaly (EIA) and the frequent emergence of plasma bubbles significantly impact radio signal propagation [5], the need for advanced analytical tools becomes evident. These challenges underscore the importance of robust predictive techniques capable of capturing the non-linear and dynamic nature of ionospheric disturbances. In this context, Artificial Intelligence (AI) methods, particularly those applied to Total Electron Content (TEC) data derived from the Global Navigation Satellite System (GNSS), have emerged as powerful tools for improving the understanding and forecasting of ionospheric scintillation events [6].

Machine learning (ML) algorithms have been extensively employed in the processing of GNSS TEC data for ionospheric research. These algorithms are capable of identifying complex patterns, performing accurate predictions, and classifying ionospheric disturbances, thereby improving the understanding of space weather dynamics. Supervised learning models, trained on labeled datasets, are particularly effective for classification and regression tasks. Deep learning, a specialized branch of ML, leverages multi-layered neural architectures to extract features from large and complex datasets. This approach has demonstrated significant effectiveness in ionospheric applications, especially in analyzing large-scale GNSS TEC datasets and capturing subtle and intricate ionospheric variations [6].

The neural network (NN) technique has been widely employed as an alternative to classical methods for addressing ionospheric prediction problems. Its application is primarily motivated by the ability of neural networks to handle complex nonlinear behavior, which makes them particularly suitable for modeling the dynamic and nonlinear processes, both spatial and temporal, associated with the F2 region of the ionosphere. These processes are driven by various factors, including solar photon flux, geomagnetic activity, and global thermospheric circulation [7].

This work proposes the use of a neural network as a predictive tool to model the effects of ionospheric scintillation. The ability to forecast this phenomenon with greater accuracy can not only support advanced research in space weather and contribute to the improvement of ionospheric models, but also offer practical solutions to operational challenges. Potential applications include estimating the probability of success in satellite-to-ground communication links, mitigating failures in GNSS systems, planning space missions, and enhancing the reliability of communication and navigation systems affected by ionospheric variability.

2 Methodology

For this study, the city of São Luís (2.6° S, 44.3° W), located in the state of Maranhão (MA), in northeastern Brazil, was selected. This region was chosen due to its location within the EIA, where ionospheric effects are more intense and frequent. Fig. 1 illustrates the geographical location of São Luís/MA.

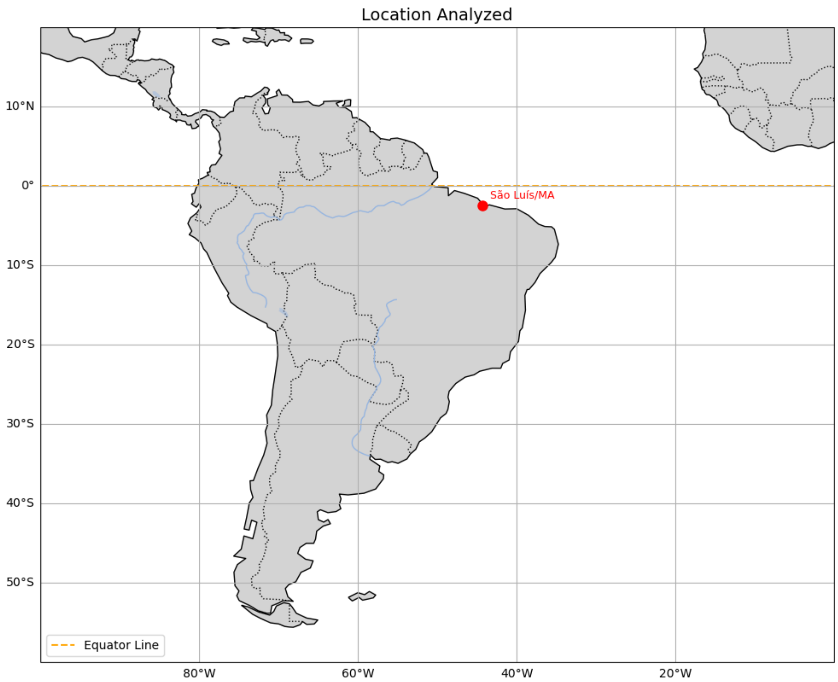

Figure 1.: Location of the city of São Luís/MA.

The selected years for this study were 2014 (Solar Maximum), 2016 (Moderate Solar Activity), and 2018 (Solar Minimum). For these years, the months chosen were March (Autumnal Equinox) and June (Winter Solstice). These periods have been selected to investigate the impact of solar activity variability on the prediction. Accordingly, for each year, months corresponding to the annual maximum values of the solar flux at 10.7 cm (F10.7 index) were also selected. In 2014 and 2016, the annual F10.7 maxima occurred on January 4, 2014, and January 10, 2016 with values of 253.3 s.f.u and 105.4 s.f.u, respectively. In 2018, the annual peak occurred on June 20, within the month of the winter solstice, with a value of 84.7 s.f.u. These different scenarios of solar activity are important to ensure that the neural network remains adaptable, accurate, and effective in predicting ionospheric scintillation under a wide range of space weather conditions, which is essential for practical modeling and forecasting applications.

A commonly used parameter for monitoring ionospheric scintillation is the scintillation index S_4, which is defined according to Eq. 1 [4].

$$S_4 = \sqrt{\frac{\langle I^2 \rangle - \langle I \rangle^2}{\langle I \rangle^2}}, \tag{1}$$

where I represents the signal intensity and $\langle\rangle$ denotes the temporal average. In other words, the S_4 index is the standard deviation of the signal intensity normalized by its mean, computed over a specified time interval. It is a dimensionless quantity that provides a direct measure of the severity of amplitude scintillation.

According to ITU-R P.531-15, scintillation intensity can be categorized as weak when $S_4 < 0.3$, moderate for $0.3 \leq S_4 \leq 0.6$, and strong when $S_4 > 0.6$. This classification is widely adopted in studies involving ionospheric effects on satellite communication systems and GNSS performance.

To investigate the effects of scintillation on UHF satellite communication systems, we have utilized the Global Ionospheric Scintillation Model (GISM), which is the model recommended by the International Telecommunication Union (ITU) for predicting ionospheric scintillation intensity. This model has been validated in numerous studies and is well-suited for estimating scintillation levels in both navigation and telecommunications applications [3].

For the region of São Luís/MA (SALU), ionospheric scintillation data (S4 index) were generated using the GISM model, considering the selected periods and a temporal resolution of 10 minutes. Fig. 2

presents an example of the simulated S4 values used as the neural network output for January 2014, serving as an illustration of the behavior of ionospheric scintillation during the month.

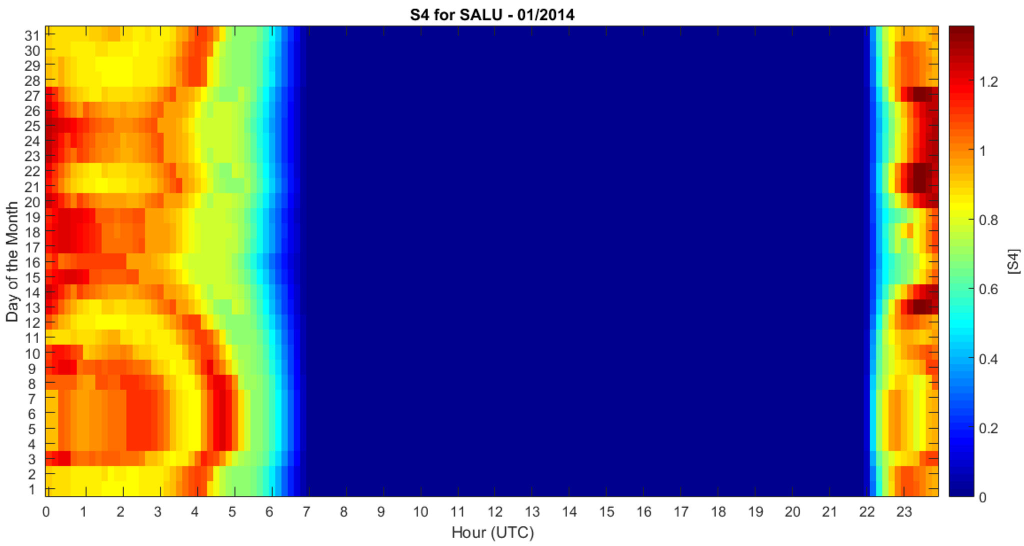

Figure 2.: S4 values obtained from the GISM for the month of January 2014.

As input for the neural network, the same variables used in the GISM model were adopted (Date, Time, F10.7, Frequency, Latitude, and Longitude) [8], combined with other space weather parameters such as the Kp index and Sunspot Number.

As shown in Fig. 3, the input layer of the neural network processes eight input variables corresponding to the model's parameters. This layer is followed by three densely connected hidden layers with 64, 32, and 16 neurons, respectively. The output layer consists of a single neuron responsible for estimating the ionospheric scintillation index (S4). The hidden layers use the Rectified Linear Unit (ReLU) activation function, while the output layer employs a linear activation function, appropriate for regression tasks.

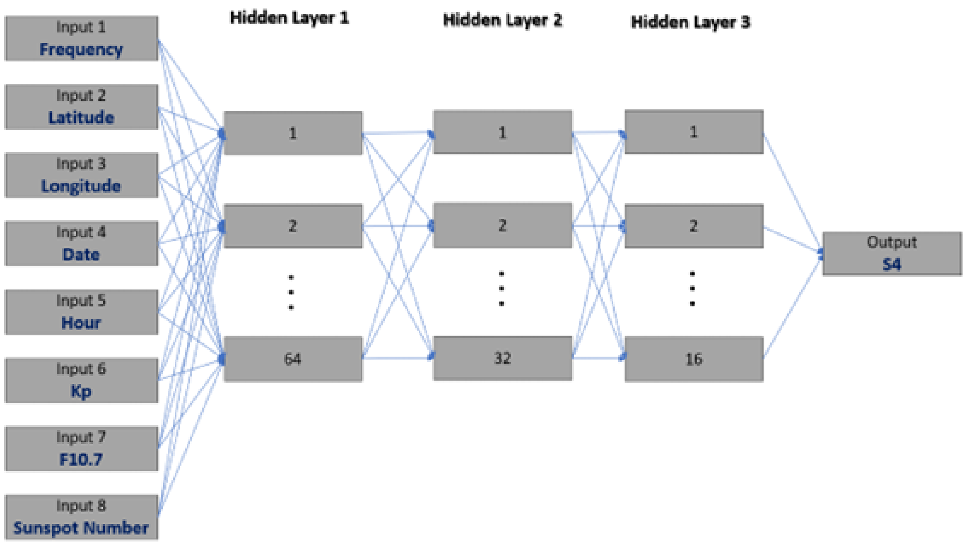

Figure 3.: The architecture of the proposed neural network model for S4 prediction.

The dataset was partitioned into three distinct subsets: 70% was allocated for training the neural network, 15% was reserved for validation during the hyperparameter tuning process, and the remaining 15% was used exclusively for testing. This division aims to ensure that the model effectively learns the underlying patterns within the data, while avoiding both under-fitting and over-fitting. In addition, it enables an objective and unbiased evaluation of the predictive performance of the model on previously unseen data.

3 Results and Discussion

As expected, Fig. 2 demonstrates that ionospheric scintillation is predominantly a nighttime phenomenon. This behavior is associated with the formation of plasma density irregularities in the ionosphere after sunset, particularly in regions near the magnetic equator, such as São Luís/MA.

On January 4, 2014, the highest annual F10.7 index value was recorded, reaching 253.3. As illustrated in Fig. 2, the most intense S4 levels in January were observed between January 4 and 10, with a notably prolonged duration extending until approximately 05:00 UTC. This extended duration may be attributed to the increased solar activity on January 4.

The neural network developed in this study demonstrated consistent performance in estimating the ionospheric scintillation index (S4), evaluated using statistical metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Pearson Correlation Coefficient (r), applied to the test set across all scenarios. As shown in Table 1, all scenarios yielded strong statistical indicators, with the R^2 remaining above 0.98 and the r exceeding 0.99 in nearly all cases, confirming a very strong linear relationship between predicted and observed values. Similarly, the MSE and MAE values remained low across all scenarios, indicating that the differences between predicted and actual S4 values were minimal, and that the model was able to maintain low prediction error even under varying ionospheric conditions.

Table 1.: Model performance metrics for different months and years.

Month	Year	MSE	MAE	R^2	r
January	2014	0.003	0.019	0.984	0.992
	2016	0.005	0.008	0.996	0.998
March	2014	0.001	0.011	0.994	0.997
	2016	0.002	0.016	0.990	0.995
	2018	0.000	0.006	0.998	0.999
June	2014	0.001	0.012	0.991	0.996
	2016	0.000	0.010	0.993	0.997
	2018	0.000	0.007	0.996	0.998

The Fig. 4 presents the temporal comparison between the S4 values simulated by the GISM model and the values predicted by the proposed neural network for the São Luís/MA region during the month of January 2014. Strong agreement is observed between the time series profiles, and the neural network accurately captures both the amplitude and frequency of the daily S4 fluctuations.

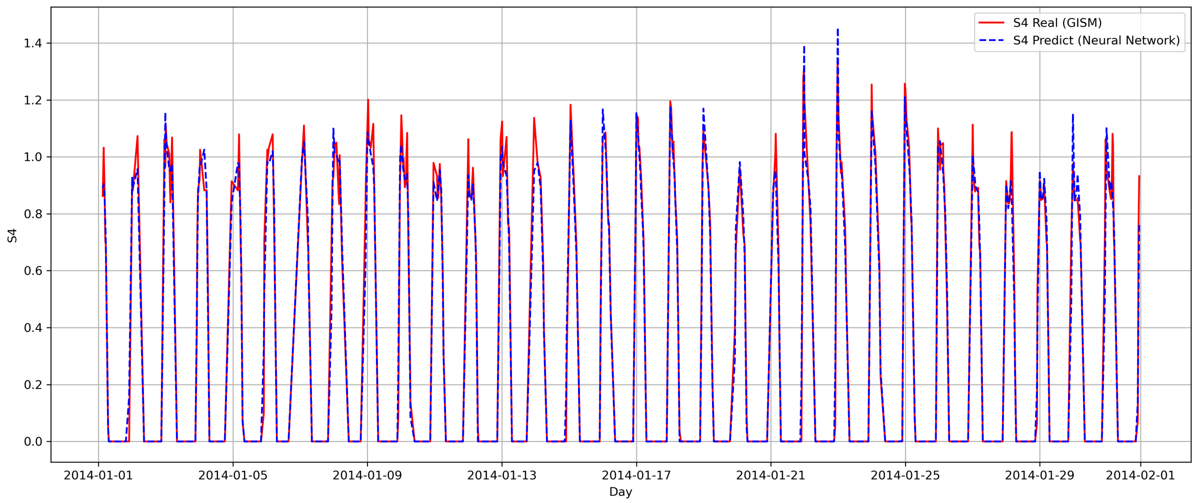

Figure 4.: Comparison between Real S4 (GISM) and Predicted S4 (Neural Network).

Fig. 5 shows the histogram of residuals, calculated as the difference between the real (GISM) and predicted values. The distribution is approximately symmetric and centered around zero, with most errors concentrated around -0.02 e +0.02. This concentration indicates low residual dispersion and reinforces the accuracy of the model. The presence of few extreme errors suggests robustness in the generalization of the model to the analyzed period.

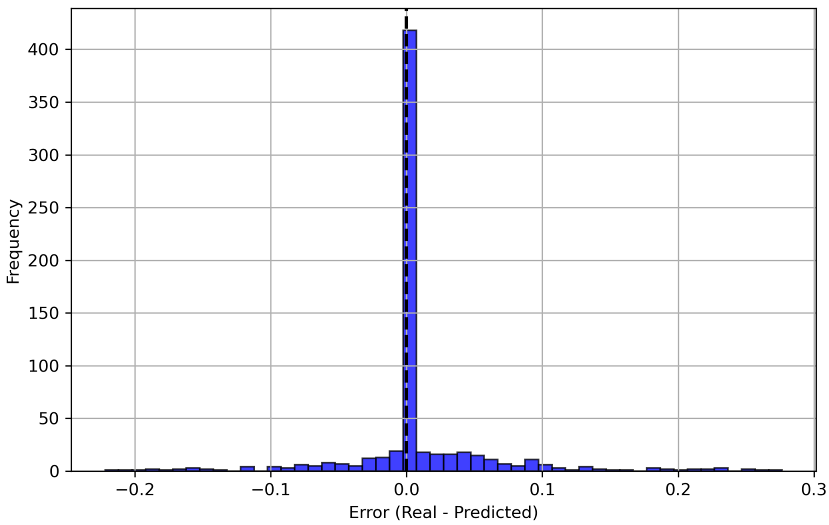

Figure 5.: Residuals histogram for the month of january 2014.

4 Conclusions

This work illustrated the feasibility of using an AI-driven artificial neural network to predict the ionospheric scintillation index (S4) based on environmental and geomagnetic variables, using data simulated by the GISM model. The neural network was trained and validated with data from the São Luís/MA region, an equatorial area known for strong scintillation activity, during January 2014. The results showed excellent model performance, with a high correlation between the predicted and simulated values, and low residual errors concentrated near zero.

The temporal comparison showed that the model accurately predicted the daily scintillation peaks, respecting the typical variation of the phenomenon in the equatorial regions. Furthermore, the residual histogram revealed a symmetric and centered distribution, indicating stability and generalization capability of the network for the analyzed period.

This performance highlights the potential of the neural network as a complementary tool in link planning for space missions, especially in applications requiring agility and lower computational cost, such as near-real-time assessments or large-scale simulations.

4.1 Fundings

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4.2 Acknowledgements

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