

RESEARCH ARTICLE

AI-Driven Modeling of the S4 Index for UHF Satellite Communication

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ABSTRACT Ionospheric scintillation significantly affects satellite communication links, particularly in low-latitude regions such as Brazil. However, the lack of observational S4 data in the UHF band, mainly available from Global Navigation Satellite System (GNSS) receivers, limits advances in modeling and forecasting. This work proposes an artificial intelligence-driven approach based on a neural network trained to reproduce S4 data generated by the *Global Ionospheric Scintillation Model* (GISM), using a set of relevant environmental and geophysical input parameters. The objective is to emulate the short-term S4 behavior produced by GISM by using input variables such as signal frequency, geographic location, date, hour, Kp index, solar flux (F10.7), and sunspot number. The neural network was designed to learn the behavior of GISM and replicate its scintillation estimates through a computationally efficient methodology. The model was applied to three distinct regions of Brazil and across different phases of the solar cycle, capturing both spatial and temporal variability under scintillation conditions. As a practical application, a communication risk analysis was conducted for the *Perceive* CubeSat, considering the impact of ionospheric scintillation on UHF links. The results demonstrate the potential of neural networks as an efficient alternative tool for the rapid assessment of ionospheric effects in small satellite missions.

INDEX TERMS S4 index, ionospheric scintillation, satellite mission, artificial neural network.

I. INTRODUCTION

The space sector is experiencing a new era, characterized by the democratization of space access, cost reduction, and the development of small satellites, such as CubeSats. These standardized and modular devices enable low-cost missions in Low Earth Orbits (LEO), with applications in Earth observation, science, and communications [1]. The Very High Frequency (VHF) and Ultra High Frequency (UHF) bands, commonly used by CubeSats, offer robust propagation even under adverse conditions, although with low data rates. These characteristics make narrowband communications particularly attractive for remote areas, densely forested

environments, and critical applications such as defense and disaster management [2], [3], [4].

Narrowband systems present advantages such as low power consumption, wider coverage, reduced infrastructure requirements, and good signal penetration, making them suitable for the new paradigm of multilayer communication systems [5]. However, these frequencies, which include the signals in the Global Navigation Satellite Systems (GNSS), are more susceptible to ionospheric effects, such as ionospheric scintillation, a phenomenon that causes rapid fluctuations in signal amplitude and phase, especially in equatorial and polar regions [2], [6], [7], [8], [9].

The ionospheric scintillation results from the random fluctuations in the refractive index of the propagation medium. Such fluctuations are caused by electron density inhomogeneities in the ionosphere, which in equatorial

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and low-latitude regions are closely associated with the occurrence of equatorial plasma bubbles. These are sharp depletions in the electron density are observed in the post-sunset hours and can reach dimensions of several hundreds of kilometers. Instabilities processes responsible for the formation of plasma bubbles lead to irregularities in plasma density on various size scales within the bubbles [10]. The amplitude scintillation normally occurs when the Fresnel dimension of the propagation signal is of the order of the irregularities scales in the ionosphere [11].

The Rayleigh-Taylor mechanism is widely accepted as the mechanism responsible for the development of equatorial plasma bubbles. Throughout the years, good progress has been observed in understanding the underlying processes that control the climatological variability of plasma bubbles [12]. However, understanding their day-to-day variability is a challenging task that also poses a challenge for the prediction of ionospheric scintillation.

The ionospheric scintillation can lead to positioning errors on satellite navigation systems, which can lead to challenges for precision applications in agriculture, offshore operations, transportation, surveying and construction [13] and can contribute to satellite communication degradation and even outages [14], [15]. Given the impact ionospheric scintillation can have on different satellite communication applications, the development of methodologies to model/predict and mitigate such effect is of the most importance.

The effects of ionospheric scintillation tend to be overlooked or underestimated in performance analyzes and satellite communication link planning conducted by countries outside the region where ionospheric scintillation is expected to occur [16]. It should be noted that the main spacefaring nations are predominantly located outside the equatorial zone, between the 20° South and 20° North latitudes, which may contribute to the limited consideration of these phenomena in global studies.

The reliability of space missions depends on the proper allocation of link margin and understanding of propagation effects, which vary according to frequency, atmospheric conditions, and link geometry [17], [18]. Therefore, it becomes essential to characterize the climatology of the equatorial ionosphere and forecast ionospheric scintillation events to increase the reliability of satellite links, particularly in equatorial regions, especially for critical applications such as defense, public health, and disaster response.

The ionosphere in low-latitude regions, such as Brazil, exhibits high variability, influenced by phenomena like the Equatorial Ionization Anomaly (EIA) and the frequent occurrence of plasma bubbles, which significantly affect radio signal propagation [19]. These complexities highlight the need for advanced predictive tools capable of representing the nonlinear and dynamic nature of ionospheric disturbances. In this context, Artificial Intelligence (AI) techniques, especially those based on Total Electron Content (TEC) data obtained via GNSS, have proven effective in

improving the understanding and forecasting of ionospheric scintillation events [20].

Machine Learning (ML) algorithms have been widely applied to GNSS TEC data processing, allowing the identification of complex patterns, accurate forecasting, and classification of ionospheric disturbances. Supervised learning methods have proven effective for regression and classification tasks, while deep learning architectures enhance this capability by extracting features from large volumes of data [20].

Artificial Neural Networks (ANNs), in particular, have become effective alternatives to traditional ionospheric modeling methods [21]. Their ability to represent non-linear relationships makes them particularly suitable for describing the spatio-temporal variability of the F2 region of the ionosphere, influenced by factors such as solar photon flux, geomagnetic activity, and global thermospheric circulation [21], [22].

Several ionospheric scintillation models exist in the literature, typically using geophysical parameters such as latitude, longitude, station, and time [23]. Predicting scintillation remains challenging due to the spatio-temporal variability of the ionosphere [24]. ANNs are well suited for this task as they handle non-linear and noisy data, benefit from larger datasets and have shown competitive performance compared to Support Vector Machines (SVM), Radial Basis Function networks (RBF), and NARMAX models [21], [23], [25]. Therefore, their use in this study is justified by their flexibility, robustness, and alignment with recent space weather forecasting approaches [21], [26].

Building upon this, it is important to recognize that, while GNSS-based observations provide extensive measurements of scintillation in the L-band, direct measurements of scintillation effects in the UHF band are not publicly available. This limitation reinforces the importance of models capable of estimating UHF scintillation based on simulations or extrapolation from other frequency bands.

In this context, this study presents a neural network (NN) model designed as a surrogate for the GISM, emulating its S4 outputs under in-distribution conditions. The model provides a computationally efficient approximation of GISM behavior, reducing the reliance on time-consuming simulations while incorporating additional input variables beyond the standard GISM parameters. As a fast and lightweight surrogate, the NN offers rapid S4 estimates that can support large-scale analyses, sensitivity studies, and real-time scenario generation. Furthermore, it represents an initial step toward integrating AI-based modules within the GISM framework itself, potentially enhancing its flexibility for global applications, including low-latitude regions where empirical models such as NeQuick exhibit limitations. Rather than replacing observational validation or operational forecasting, this work provides an NN-based surrogate of the ITU-recommended GISM model, enabling accelerated simulations and improved support for satellite communication studies and mission planning.

Section II presents an overview of ionospheric disturbances affecting the UHF link, with emphasis on ionospheric scintillation modeled using GISM for three selected locations in the Brazilian equatorial region. Section III introduces the fundamentals of artificial neural networks and describes the proposed ANN model, including the network architecture, input variables, training methodology, and performance metrics. Section IV presents and discusses the results obtained from the developed models. Section V investigates the use of surrogate-based S4 estimates for communication reliability analysis in the CubeSat Perceive mission, including comparative data analysis. Finally, Section VI summarizes the main conclusions of the study.

II. IONOSPHERIC DISTURBANCES IN THE UHF LINK

Although ionospheric scintillation is commonly monitored using GNSS signals, particularly those from the Global Positioning System (GPS), which operates mainly in the L-band frequencies (e.g., 1575.42 MHz for L1 and 1227.60 MHz for L2), such data cannot be directly extrapolated to predict scintillation behavior in other frequency bands, such as the UHF band (300 MHz to 3 GHz). Despite some efforts to monitor scintillation at these frequencies, there is still no widely deployed operational network that is focused specifically on continuously measuring the S4 index in the UHF range, and the available data are not publicly accessible, which limits the use of direct observational information [27]. To overcome this limitation, this study uses simulated S4 values obtained through the GISM model, which employs space weather parameters and provides frequency-dependent scintillation estimates, including for the UHF band.

A. IONOSPHERIC SCINTILLATION

Ionospheric scintillation is a major disruption for signals below 3 GHz, though it can occasionally affect frequencies up to 10 GHz. It results from refractive index fluctuations caused by medium inhomogeneities, producing rapid amplitude and phase variations and altering signal coherence at the receiver [28]. In the equatorial region of the Americas, ionospheric scintillation commonly occurs after sunset, with increased activity around the equinoxes [10], [29].

The scintillation index S4 is a widely used parameter for characterizing ionospheric scintillation and is defined as shown in Equation (1), [28]:

$$S4 = \sqrt{\frac{\langle I^2 \rangle - \langle I \rangle^2}{\langle I \rangle^2}}, \quad (1)$$

where I denotes the signal intensity and $\langle \cdot \rangle$ represents the temporal average. Essentially, S4 is the normalized standard deviation of the signal intensity, providing a dimensionless measure of amplitude scintillation severity.

According to ITU-R P.531-15, scintillation is classified as weak when $S4 < 0.3$, moderate for $0.3 \leq S4 \leq 0.6$, and strong when $S4 > 0.6$. This categorization is widely

adopted in assessments of ionospheric impacts on satellite communications and GNSS performance [6].

B. DETERMINANT PARAMETERS OF IONOSPHERIC SCINTILLATION

In this study, an effort was made to consider the key space weather parameters associated with ionospheric scintillation. These include the solar flux index (F10.7), sunspot number, and the geomagnetic index Kp [25].

The F10.7 index represents the solar radio flux at a wavelength of 10.7 cm and serves as a key indicator of solar activity, which follows an approximately 11-year cycle. Intense ionospheric scintillations are typically observed during periods of high solar activity (solar maximum), while milder scintillations occur during solar minima [9], [25].

The maximum height and vertical drift velocity of the F2 layer are parameters that characterize the region of the ionosphere where scintillation is most intense. The sunspot number, associated with the Sun's magnetic field, indicates solar magnetic activity. A higher sunspot count is associated with stronger solar magnetic activity and more frequent solar flares and coronal mass ejections, which inject energy into the Earth's upper atmosphere. The Kp index quantifies Earth's geomagnetic activity by averaging the K index over 3-hour intervals throughout the day, distinguishing quiet days from those with geomagnetic disturbances and influencing scintillation intensity [25].

C. GLOBAL IONOSPHERIC SCINTILLATION MODEL

To evaluate the effects of scintillation on UHF satellite communication, the GISM model is adopted as the reference physical framework, and a computationally efficient surrogate model is developed to emulate its outputs. The GISM model, recommended by the International Telecommunication Union (ITU) to estimate scintillation intensity [28], provides the reference dataset used for training and validation of the proposed surrogate approach. GISM estimates the S4 index, the depth of fading of the amplitude, the phase of root mean square (rms) and the angular deviations along the signal paths, based on the positions of the satellite and ground station, time, date, and frequency. The ionospheric modeling in GISM is based on NeQuick 2, which computes the electron density at a given spatial point in the ionosphere [11]. The model is based on the multiple phase screen method. In its first stage, GISM computes the normalized standard deviations of intensity (S4) and phase (σ_ϕ) at ground level. Signal scintillations at the receiver are then estimated based on the specified receiver characteristics [8].

In this study, the locations of São Luís (2.5933° South, 44.2123° West), Natal (6.9917° South, 35.0265° West), and Boa Vista (2.8338° North, 60.6946° West) were selected (see Figure 1), all located within the EIA region. Natal lies on the southern crest of the EIA, while Boa Vista is situated on the northern crest. The years selected for this study were 2014 (solar maximum activity), 2016 (moderate solar activity), and 2018 (solar minimum activity). For each

year, March (autumnal equinox) and June (winter solstice) were chosen to capture seasonal variations. Additionally, the months with the highest annual F10.7 solar flux values were included to reflect periods of peak solar irradiance. These occurred on 4 January 2014 (253.3 s.f.u), 10 January 2016 (105.4 s.f.u), and 20 June 2018 (84.7 s.f.u). This selection enables the neural network to be tested across a broad spectrum of solar activity levels, enhancing its robustness and reliability in estimating ionospheric scintillation under diverse space weather scenarios, with simulations based on the commercially relevant frequency of 401.5 MHz.

The simulations were performed using the Global Ionospheric Scintillation Model (GISM), version 5.1, generating S4 ionospheric scintillation data for the selected regions with a temporal resolution of 10 minutes.

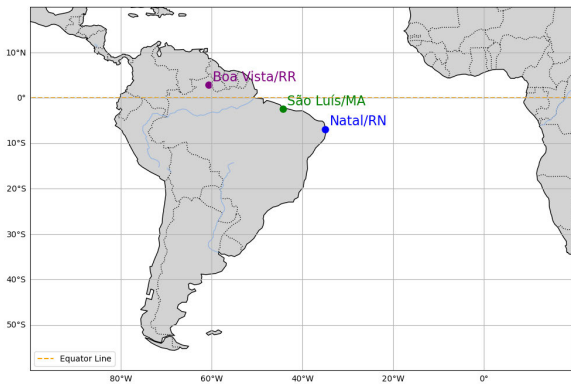


FIGURE 1. Locations of the city of Boa Vista, São Luís and Natal.

Figures 2, 3, and 4 illustrate the S4 index data obtained from GISM for São Luís/MA, Boa Vista/RR, and Natal/RN in 2014, 2016, and 2018, respectively, considering a commercially used frequency of 401.5 MHz.

On 4 January 2014, the highest annual F10.7 index was recorded for the year, reaching 253.3 s.f.u. As shown in Figure 2 (a), (b), and (c), the most intense S4 levels in January occurred between January 4 and 10 for the Boa Vista location, with a notably prolonged duration across all regions lasting until approximately 05:00 UTC. This extended period of scintillation activity is likely linked to the heightened solar activity on 4 January. This period corresponds to the solar maximum phase, and its effects on ionospheric scintillation can be observed by comparing Figures 2, 3, and 4, which show that higher S4 values tend to occur under stronger solar activity conditions.

Although the year 2018 was closer to the solar minimum, Figures 4 (a), (b), and (c) show that, in the month of March, all analyzed regions exhibited more frequent enhancements in the S4 index during the typical post-sunset hours when ionospheric irregularities tend to develop. Although the S4 values remained below 1.0, they were consistently elevated during these periods. This behavior may be associated with the intensification of electrodynamic processes in the equatorial ionosphere during the March equinox, which

favors the formation of plasma bubbles and instabilities that enhance scintillation effects, even under conditions of reduced overall solar activity.

III. ARTIFICIAL NEURAL NETWORKS IN SPACE WEATHER APPLICATIONS

A. ARTIFICIAL NEURAL NETWORKS FOR NONLINEAR MODELING

Artificial neural networks (ANN) emerged inspired by the way the human brain processes information in a nonlinear, parallel manner, distinct from digital computers. Their structure enables them to perform tasks such as pattern recognition and motor control with performance superior to that of many traditional computational systems [30].

An ANN is a massively parallel distributed processor composed of simple units, with an inherent capability to store experiential knowledge for subsequent use. The learning process is driven by algorithms that systematically adjust the synaptic weights of the network in order to achieve specific design objectives. This modification of weights is the classical method for the development of neural networks [30].

A neural network derives its computational power primarily from its massively parallel distributed architecture and, secondly, from its ability to learn and subsequently generalize. Generalization refers to the network's ability to produce appropriate responses to inputs that were not encountered during the training phase. These two information processing capabilities enable neural networks to find accurate approximate solutions to complex and large-scale problems that are intractable by conventional deterministic methods [30].

A neural network provides a robust framework for modeling complex nonlinear relationships by layering multiple elementary nonlinear functions. In its simplest form, an ANN receives a multidimensional input vector $\mathbf{x} = \{x_1, x_2, \dots, x_{N_i}\}$ of dimension N_i and produces a single scalar output y , using the following mapping [21]:

$$y(\mathbf{x}) = \sum_{i=1}^q w_i \sigma \left(\sum_{j=1}^{N_i} a_{ij} x_j + b_i \right), \quad (2)$$

where $\sigma(\cdot)$ is a continuous nonlinear function, known as the activation function. Modern neural networks typically employ the Rectified Linear Unit (ReLU) or its variants as the activation function. ReLU is defined as $\sigma(s) = \max(0, s)$.

In Equation (2), w_i and a_{ij} represent the weights, and b_i is the bias term. Together, w , a , and b are free parameters that must be optimized during the training process. A neural network structured as shown in Equation 2 is referred to as a single hidden-layer feedforward network [21].

In simple terms, the input vector $\mathbf{x}$ undergoes a linear transformation defined by the weights a and the biases b . The resulting vector is then passed through the activation function $\sigma(\cdot)$. This operation is repeated q times, each with distinct weights and biases, and the q outputs from $\sigma(\cdot)$ are finally

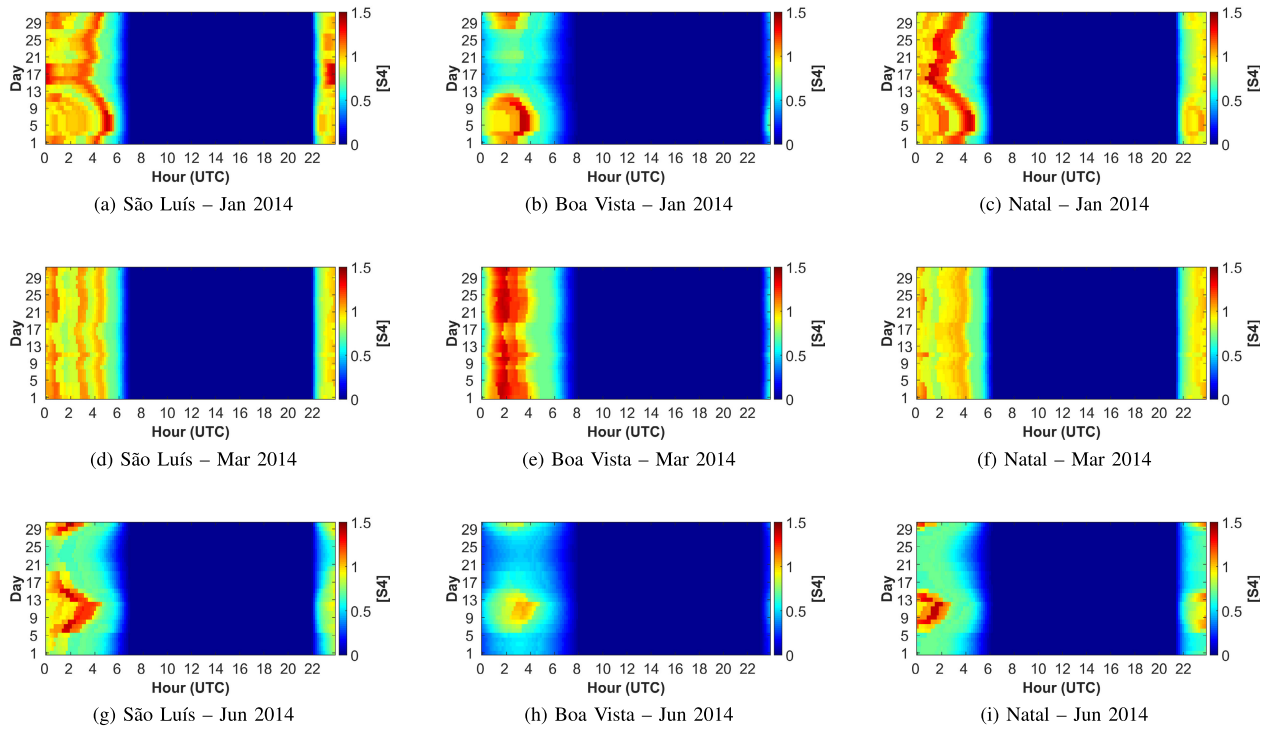


FIGURE 2. S4 scintillation index for São Luís, Boa Vista, and Natal during January, March and June 2014 (solar maximum activity) for a 401.5 MHz signal.

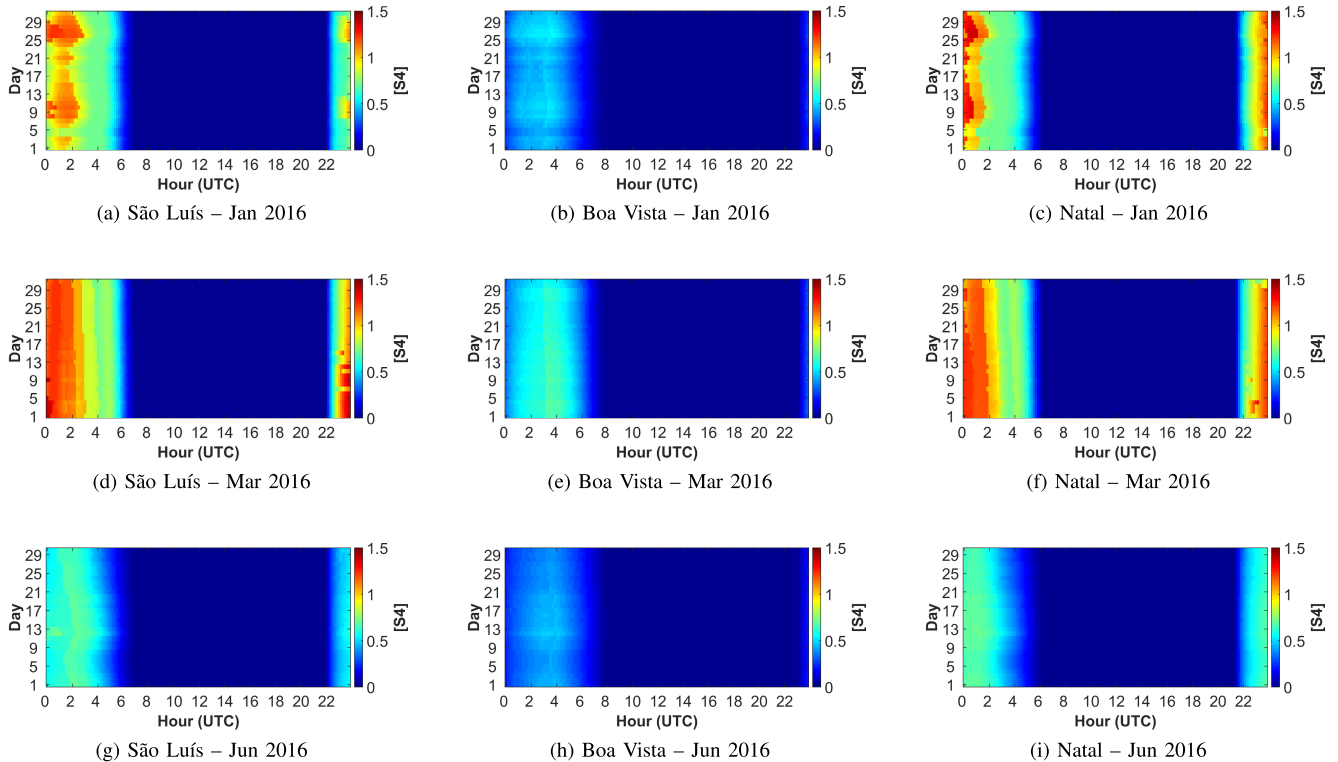


FIGURE 3. S4 scintillation index for São Luís, Boa Vista, and Natal during January, March and June 2016 (moderate solar activity) for a 401.5 MHz signal.

linearly combined using the weights w . The parameter q is known as the number of neurons in the hidden layer [21].

When multiple layers are stacked, forming a deep architecture, the resulting model is called a deep neural network. This

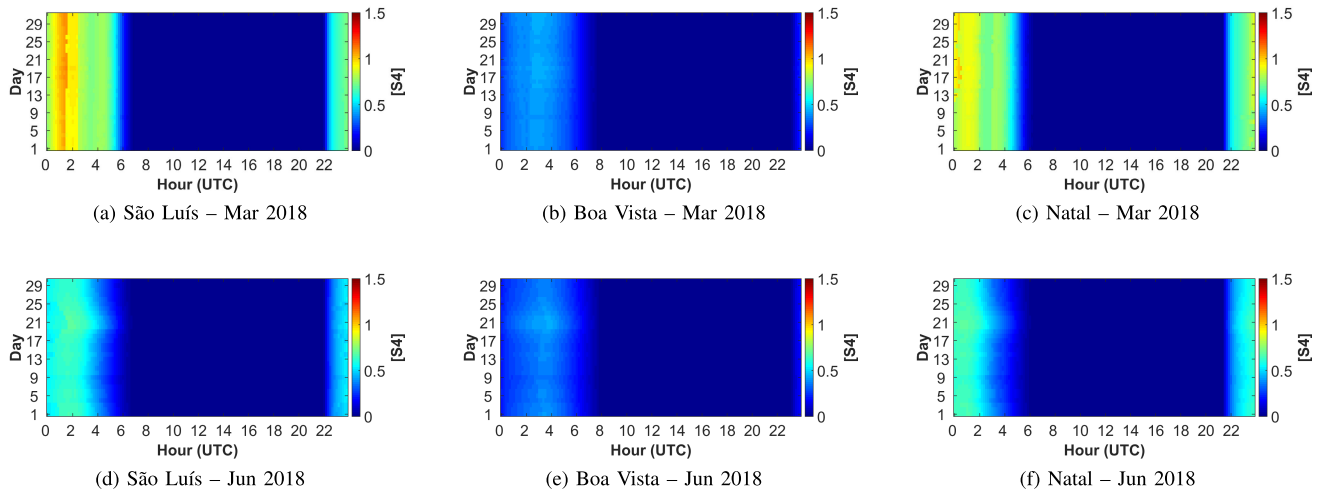


FIGURE 4. S4 scintillation index for São Luís, Boa Vista, and Natal during March and June 2018 (minimum solar activity) for a 401.5 MHz signal.

depth allows for greater representational capacity, enabling the network to approximate complex nonlinear functions. However, deeper models require more parameters and are more prone to overfitting [21].

B. DESIGN OF THE PROPOSED ANN MODEL

As illustrated in Figure 5, the neural network receives, at its input layer, ten variables that represent the model parameters. The input vector is processed by a stack of fully connected hidden layers with 256, 128, 64, 32, and 16 neurons, respectively, all using the Rectified Linear Unit (ReLU) activation function to enable the learning of nonlinear relationships among the variables. To mitigate overfitting, dropout layers with a rate of 0.20 are applied after the first two hidden layers. The output layer contains a single neuron with a linear activation function, which estimates the S4 index in the log-transformed space, $\log_{10}(S4 + 1)$. The inverse transformation is subsequently applied to recover the physical S4 values.

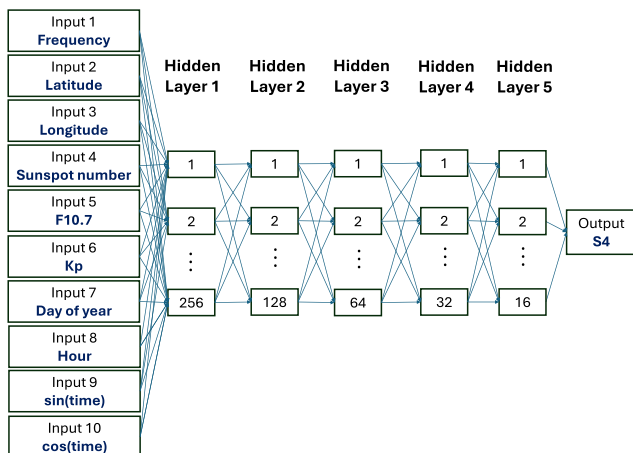


FIGURE 5. Schematic of the proposed neural network model.

As input for the neural network, the same variables used in the GSM model (Latitude, Longitude, F10.7, and Frequency) [31] were adopted, together with space weather parameters such as the Kp index and Sunspot Number. Temporal information (Date and Time) was represented using three features: Day of Year, Time in Seconds, and the periodic transformations $\sin(\text{time})$ and $\cos(\text{time})$, preserving the daily and yearly periodicity of the original model. Initially, the neural network was trained using S4 values generated by the GSM model for the specified periods and location.

The key parameters adopted in the neural network configuration and training process are summarized in Table 1.

TABLE 1. Summary of neural network configuration and training parameters.

Parameter	Value
Temporal resolution	10 min (144 samples/day)
Samples per month	4,320 per station-month
Data split	70/15/15 (train/val/test)
Target variable	S4 index
Preprocessing	Z-score normalization; cyclic time; $\log_{10}(S4 + 1)$
Model type	Fully connected NN
Hidden layers	[256, 128, 64, 32, 16] (ReLU)
Dropout	0.2 (first two layers)
Optimizer	Adam
Learning rate	0.001
Loss function	Huber
Batch size	32
Maximum epochs	300
Early stopping	Patience = 25
Random seeds	42, 7, 123, 2021, 999
Frequency	401.5 MHz (UHF)
Output variable	S4

Following the configuration summarized in Table 1, the dataset was divided according to the predefined geographic regions and time periods under analysis. Specifically, 70% of the data was used for training the neural network, 15% was reserved for validation during the hyperparameter tuning process, and the remaining 15% was employed

exclusively for testing. This partitioning strategy ensures that the model effectively captures the underlying patterns of the input data, while minimizing the risks of underfitting and overfitting. Moreover, it provides a fair and objective assessment of the model's estimation performance on unseen data corresponding to the selected regions and time intervals.

To evaluate the performance of the proposed neural network model, four commonly used statistical metrics were employed: Mean Absolute Error (MAE), Mean Squared Error (MSE), the Coefficient of Determination (R^2), and the Pearson Correlation Coefficient (r). These metrics provide a comprehensive assessment of the model's accuracy and generalization capability.

The MAE measures the average magnitude of the errors between estimated and actual values, regardless of their direction. It is defined as:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i|. \quad (3)$$

The MSE penalizes larger errors more heavily and is defined as:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2. \quad (4)$$

The Pearson Correlation Coefficient (r) quantifies the linear correlation between the estimated values and the observed values. It ranges from -1 to 1 , where values close to 1 indicate a strong positive linear relationship. It is defined as:

$$r = \frac{\sum_{i=1}^N (\hat{y}_i - \bar{\hat{y}})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (\hat{y}_i - \bar{\hat{y}})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}}. \quad (5)$$

The Coefficient of Determination (R^2) indicates the proportion of the variance in the observed data that is explained by the estimated values obtained from the model. In this work, R^2 is computed using the explained sum of squares (ESS) formulation, given by:

$$R^2 = \frac{\sum_{i=1}^N (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2}, \quad (6)$$

where N is the number of samples, y_i are the observed values, $\hat{y}_i$ are the estimated values, and $\bar{y}$ is the mean of the observed values. This formulation is equivalent to the more common definition based on the residual sum of squares (RSS), i.e., $R^2 = 1 - (SS_{\text{res}}/SS_{\text{tot}})$, assuming that the model includes an intercept term. These metrics were computed over the entire test dataset to quantitatively assess the estimation performance of the neural network.

IV. RESULTS AND ANALYSIS

A. BASELINE SAME-SITE PERFORMANCE EVALUATION

The results for the same-site analysis, summarized in Table 2 and illustrated in Figures 6, 7, and 8, were obtained for three representative Brazilian sites: São Luís, Natal, and Boa Vista.

These locations, situated in low-latitude and equatorial regions highly affected by scintillation, were strategically selected to test the model under challenging conditions. The outcomes indicate that the model achieves satisfactory accuracy at each site and demonstrates a consistent ability to generalize across different ionospheric scenarios. This reinforces the robustness and practical applicability of the neural network approach for space weather studies and satellite communication system planning.

TABLE 2. Comparative model performance metrics for São Luís/MA, Boa Vista/RR and Natal/RN.

Month	Year	Region	MSE	MAE	R^2	r
January	2014	São Luís	0.001	0.004	0.995	0.998
		Boa Vista	0.001	0.003	0.993	0.996
		Natal	0.001	0.003	0.996	0.998
	2016	São Luís	0.000	0.002	0.998	0.999
		Boa Vista	0.000	0.002	0.998	0.999
		Natal	0.001	0.003	0.995	0.998
	2018	São Luís	0.000	0.002	0.998	0.999
		Boa Vista	0.000	0.002	0.998	0.999
		Natal	0.001	0.003	0.997	0.998
March	2014	São Luís	0.000	0.002	0.998	0.999
		Boa Vista	0.000	0.002	0.998	0.999
		Natal	0.001	0.003	0.997	0.998
	2016	São Luís	0.001	0.004	0.997	0.999
		Boa Vista	0.000	0.002	0.998	0.999
		Natal	0.000	0.002	0.998	0.999
	2018	São Luís	0.000	0.002	0.998	0.999
		Boa Vista	0.000	0.002	0.996	0.999
		Natal	0.000	0.002	0.999	0.999
June	2014	São Luís	0.001	0.004	0.995	0.998
		Boa Vista	0.000	0.003	0.996	0.998
		Natal	0.001	0.002	0.994	0.997
	2016	São Luís	0.000	0.002	0.998	0.999
		Boa Vista	0.000	0.001	0.998	0.999
		Natal	0.000	0.002	0.998	0.999
	2018	São Luís	0.000	0.001	0.998	0.999
		Boa Vista	0.000	0.001	0.998	1.000
		Natal	0.000	0.002	0.999	1.000

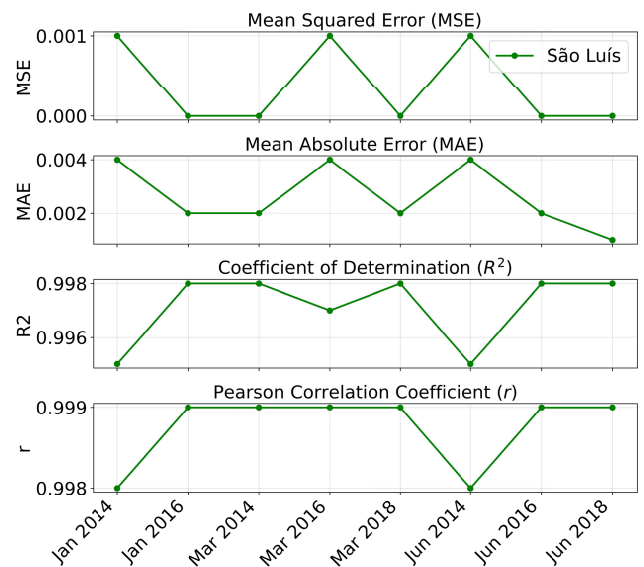


FIGURE 6. S4 estimation metrics (MAE, MSE, R^2 , r) at São Luís.

Figures 9, 10 and 11 present the temporal residuals of the S4 index (observed – estimated) for the years 2014, 2016, and

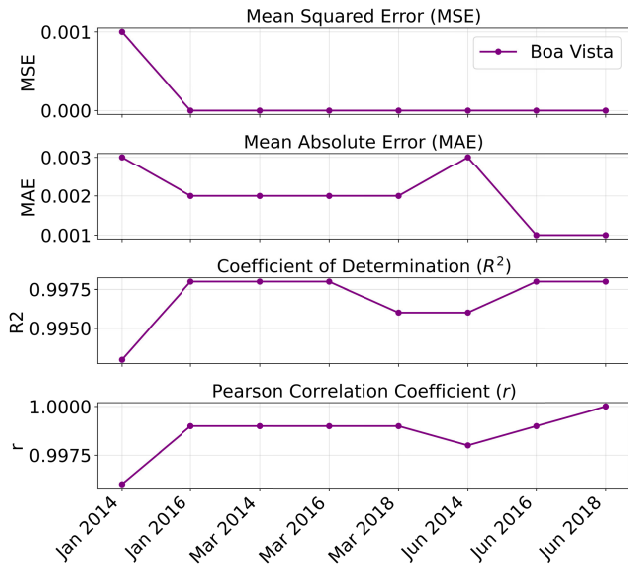


FIGURE 7. S4 estimation metrics (MAE, MSE, R^2 , r) at Boa Vista.

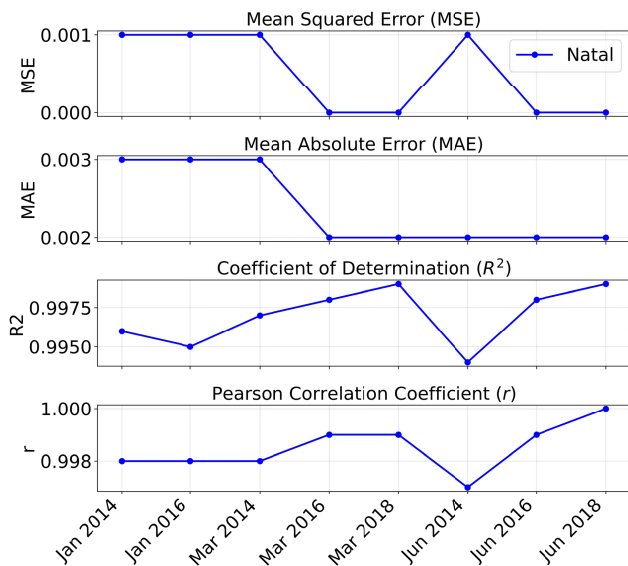


FIGURE 8. S4 estimation metrics (MAE, MSE, R^2 , r) at Natal.

2018, respectively. Each plot displays the residuals over time for the three analyzed regions: São Luís, Boa Vista, and Natal. The results demonstrate a strong agreement between the observed and estimated data, with most residuals fluctuating close to zero, indicating high model performance.

It is important to highlight that the network had a satisfactory performance even when analyzing three different regions of the EIA, across three different years with varying solar activity levels and over three different months. This demonstrates the robustness and generalizability of the model under diverse and challenging conditions.

In São Luís, the model presented excellent emulation performance throughout all evaluated periods, with very low

MSE and MAE values and R^2 consistently above 0.995 in 2014 and reaching 0.998 from 2016 onward. The high Pearson correlation coefficients ($r \geq 0.998$) indicate a very strong agreement between the ANN surrogate outputs and the S4 values simulated by GISM, particularly during the years 2016 and 2018.

In Natal, the results were similarly robust, with R^2 values between 0.994 and 0.999 and error metrics close to those obtained for São Luís. The best performance was observed in June 2016 and June 2018, when the model achieved $R^2 \approx 0.999$ and extremely low MSE and MAE values, confirming the stability of the model under different seasonal and ionospheric conditions.

In Boa Vista, the model also achieved high accuracy across all periods, with R^2 generally above 0.993 in 2014 and improving to 0.998 in 2016 and 2018. Pearson correlation coefficients remained close to or equal to $r = 0.999$ in most cases, particularly in June 2016 and June 2018, where performance reached its highest levels. These results indicate that, although Boa Vista exhibits stronger spatial variability compared to the other sites, the proposed ANN model was still able to accurately emulate the GISM outputs and maintain reliable surrogate performance across years and geophysical conditions.

To assess the robustness and generalization of the ANN model, additional experiments were conducted, including Leave-One-Site-Out (LOSO) and Leave-One-Year-Out (LOYO), as well as computational performance evaluation, ablation studies, and sensitivity to random seed initialization.

For clarity, the following subsections focus on a representative case for computational performance, ablation studies, and seed sensitivity: São Luís in January 2014, selected for being near the center of EIA and for corresponding to the solar maximum year among those analyzed (2014, 2016, and 2018). The results for the other regions and years were very similar, as expected, given that the same architecture and hyperparameter configuration tends to produce consistent behavior under different geophysical conditions, thus allowing a detailed evaluation of the model's performance under challenging yet representative conditions.

As a baseline comparison, a multivariate linear regression model was also evaluated for a representative case (São Luís, January 2014), using the same input variables and the same training and testing datasets adopted for the ANN. While the neural network achieved excellent performance for this case (MSE = 0.001, MAE = 0.004, $R^2 = 0.995$, and $r = 0.998$), the linear regression model showed significantly lower emulation capability, with $R^2 = 0.75$, MSE = 0.048, MAE = 0.163, and $r = 0.865$. This comparison highlights the importance of nonlinear modeling to adequately represent ionospheric scintillation behavior, particularly in the equatorial region.

B. CROSS-SITE GENERALIZATION (LOSO)

To evaluate the spatial generalization capability of the proposed ANN model, a LOSO validation strategy was

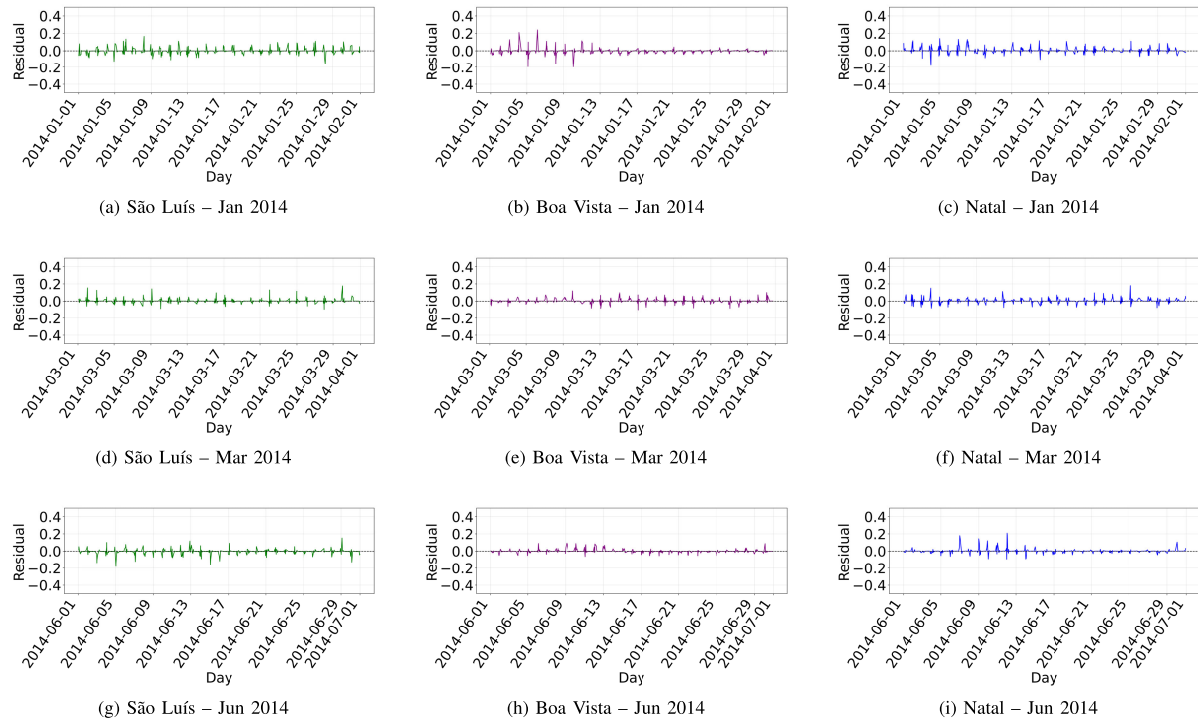


FIGURE 9. Temporal residuals of the S4 index (observed - estimated) for São Luís, Boa Vista and Natal during January, March and June 2014 (maximum solar).

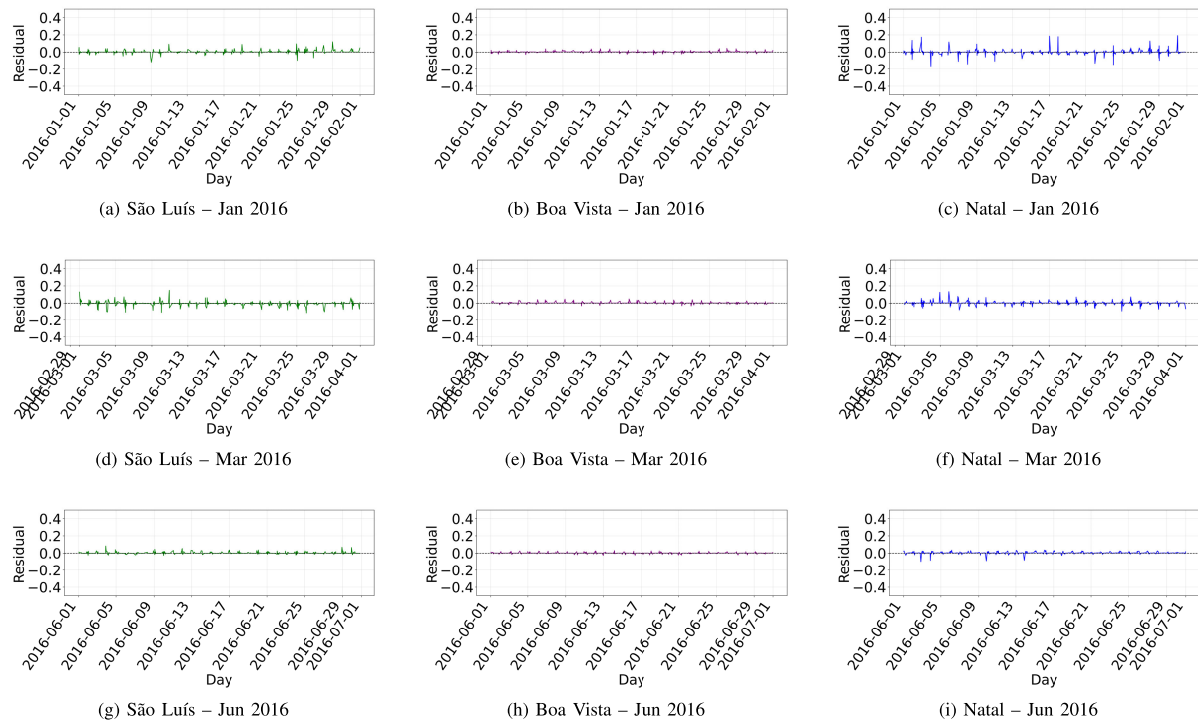


FIGURE 10. Temporal residuals of the S4 index (observed - estimated) for São Luís, Boa Vista and Natal during January, March and June 2016 (moderate solar).

applied. In this configuration, the model is trained using data from two locations and tested on the remaining site, which is fully excluded from the training stage.

This procedure allows assessing whether the model is able to generalize to geographic regions that were not observed during training, which is a relevant requirement for

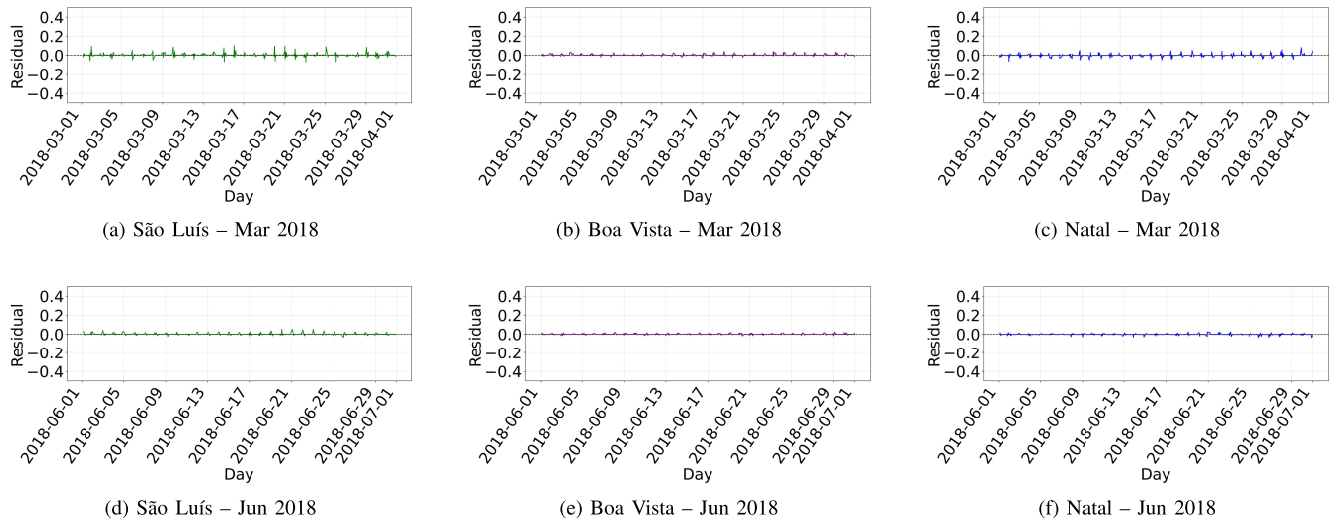


FIGURE 11. Temporal residuals of the S4 index (observed – estimated) for São Luís, Boa Vista and Natal during March and June 2018 (solar minimum).

potential operational use in areas with limited scintillation measurements.

The LOSO results in Table 3 assess the spatial transferability of the proposed ANN, by training the model on two locations and testing it on the remaining site. The model achieved good cross-site consistency for São Luís and Natal, with R^2 between 0.89 and 0.98 and Pearson correlation above 0.94. Performance degradation was observed when Boa Vista was used as the test site, particularly in March 2016 ($R^2 = 0.72$, $MAE = 0.0636$), indicating stronger site-specific variability and a distribution shift between the training and test domains. Even in these challenging scenarios, however, the correlation remained high ($r \geq 0.87$), suggesting that the learned physical relationships were preserved.

These results indicate that the model consistently reproduces the spatial behavior of the GISM across the analyzed regions. However, in areas where the GISM itself exhibits more complex scintillation dynamics, the network may require additional site-specific information to further reduce the emulation error with respect to the reference model.

TABLE 3. LOSO (Leave-One-Site-Out) cross-site generalization results using Artificial Neural Network (ANN).

Month	Year	Test Site	MSE	MAE	R^2	r
January	2014	São Luís	0.0220	0.0720	0.8890	0.9460
		Natal	0.0100	0.0520	0.9470	0.9750
		Boa Vista	0.0220	0.0800	0.8000	0.9420
March	2016	São Luís	0.0110	0.0510	0.9460	0.9850
		Natal	0.0050	0.0360	0.9740	0.9890
		Boa Vista	0.0150	0.0636	0.7214	0.8696
June	2018	São Luís	0.0020	0.0220	0.9650	0.9940
		Natal	0.0010	0.0170	0.9820	0.9920
		Boa Vista	0.0030	0.0320	0.8160	0.9650

C. TEMPORAL GENERALIZATION (LOYO)

In addition to spatial robustness, the temporal generalization of the model was assessed through a LOYO strategy. In this

approach, the model is evaluated on a year that is entirely excluded from the training dataset.

This validation setting tests the ability of the model to remain consistent across distinct solar and ionospheric conditions, which is essential for long-term surrogate reliability and for applications in operational monitoring environments.

Table 4 presents the LOYO results, where the model is trained on two years and tested on the remaining one. The ANN exhibited strong temporal robustness across all regions, with R^2 values ranging from 0.90 to 0.99 and Pearson correlation consistently above 0.98. The lowest performance occurred in Boa Vista during March ($R^2 = 0.90$, $MAE = 0.026$), whereas the highest stability was obtained in June, with $R^2 \approx 0.995$ and very low MAE ($6\text{--}8 \times 10^{-3}$) for all locations.

These results show that the network does not overfit to specific years and is able to capture persistent climatological patterns of equatorial ionospheric scintillation, reinforcing its suitability for operational scenarios in which unseen temporal conditions are expected.

TABLE 4. LOYO (Leave-One-Year-Out) temporal generalization results using Artificial Neural Network (ANN).

Site	Month	Test Year	MSE	MAE	R^2	r
São Luís	January	2016	0.013	0.048	0.906	0.982
	March	2018	0.010	0.045	0.921	0.988
	June	2018	0.000	0.008	0.996	0.998
Boa Vista	January	2016	0.001	0.016	0.975	0.998
	March	2018	0.002	0.026	0.900	0.997
	June	2018	0.000	0.006	0.995	0.999
Natal	January	2016	0.003	0.027	0.977	0.989
	March	2018	0.006	0.034	0.951	0.991
	June	2018	0.000	0.008	0.995	0.998

In general, the low error values and the high coefficients R^2 and r confirm that the neural network trained with GISM-simulated data is highly effective in *emulating* the

S4 index in the UHF band. This approach is especially valuable in offering greater flexibility for assessing the risks of communication degradation in satellite links affected by ionospheric scintillation. Additionally, it presents an innovative method that can be integrated into receivers and edge solutions, enabling continuous learning from data and adaptation across a wide range of frequencies.

The LOSO and LOYO evaluations, performed using blocked time partitions, demonstrate that the neural network captures with high fidelity both the spatial and temporal variability of ionospheric scintillation under different solar and geomagnetic conditions. In the LOSO experiments, the model maintains high skill across sites, with R^2 typically ranging from 0.89 to 0.98 and correlation coefficients $r > 0.94$. The largest performance deltas are observed for Boa Vista, where R^2 decreases by up to 15–20% in some months, reflecting the increased variability of scintillation near the magnetic equator rather than overfitting or temporal leakage.

The LOYO results further confirm temporal robustness, with $R^2 > 0.90$ across all regions and test years, and near-zero MSE values during June 2018. Slightly higher errors in January and March compared to June are consistent with known seasonal effects and enhanced geomagnetic coupling during equinoctial periods. These performance deltas across years remain modest, indicating stable generalization across different phases of solar activity.

This robustness, demonstrated in three distinct regions of the EIA, supports the applicability of the model for risk analysis and scenario-based assessments across diverse geospatial configurations. It is important to note that the GISM model, internationally recognized and recommended by the ITU as a reference for simulating ionospheric scintillation, served as the basis for training the neural network. By learning the complex behavior of GISM, the neural network provides a computationally efficient surrogate emulator capable of reproducing the essential characteristics of the reference model with comparable accuracy.

From a deployment perspective, these results suggest that the proposed surrogate model can be reliably applied under a wide range of solar and geomagnetic conditions. Nevertheless, region-specific fine-tuning or periodic retraining may further improve performance in equatorial regions or during periods of elevated solar activity. In this way, the neural network facilitates rapid estimation of the S4 index while expanding operational flexibility for near-real-time analysis, without the need for computationally intensive simulations for each new condition.

D. COMPARISON WITH ENSEMBLE-BASED MODELS

In order to provide a broader assessment of model performance and ensure that the observed generalization capability is not specific to neural network architectures, two additional machine learning approaches were evaluated: Random Forest (RF) [32] and Gradient Boosted Decision Trees (GBDT) [33].

These ensemble-based methods are widely used in regression problems due to their robustness to nonlinear relationships and reduced sensitivity to overfitting, making them suitable benchmarks for comparison with the proposed ANN model.

The same LOSO and LOYO validation strategies were applied to RF and GBDT, ensuring a fair and consistent comparison across all models. The corresponding results are presented in Tables 5–6 for LOSO and Tables 7–8 for LOYO.

TABLE 5. LOSO (Leave-One-Site-Out) cross-site generalization results using Random Forest (RF).

Month	Year	Test Site	MSE	MAE	R^2	r
January	2014	São Luís	0.0286	0.0859	0.8549	0.9271
		Natal	0.0287	0.0862	0.8535	0.9270
		Boa Vista	0.0760	0.1339	0.3116	0.8228
March	2016	São Luís	0.0151	0.0602	0.9254	0.9622
		Natal	0.0151	0.0603	0.9204	0.9621
		Boa Vista	0.1040	0.1650	-0.9296	0.8386
June	2018	São Luís	0.0068	0.0450	0.8729	0.9361
		Natal	0.0068	0.0450	0.8709	0.9361
		Boa Vista	0.0231	0.0813	-0.2245	0.8263

TABLE 6. LOSO (Leave-One-Site-Out) cross-site generalization results using Gradient Boosted Decision Trees (GBDT).

Month	Year	Test Site	MSE	MAE	R^2	r
January	2014	São Luís	0.0262	0.0868	0.8670	0.9325
		Natal	0.0219	0.0826	0.8881	0.9432
		Boa Vista	0.0674	0.1320	0.3891	0.8418
March	2016	São Luís	0.0186	0.0744	0.8685	0.9360
		Natal	0.0139	0.0577	0.9268	0.9650
		Boa Vista	0.1021	0.1659	-0.8943	0.8407
June	2018	São Luís	0.0066	0.0457	0.8754	0.9374
		Natal	0.0068	0.0463	0.8701	0.9357
		Boa Vista	0.0228	0.0823	-0.2102	0.8249

The LOSO results, presented in Tables 5 and 6, reveal significant limitations of the RF and GBDT models in terms of spatial generalization. Although these models achieve moderate to high correlation coefficients in some scenarios, a consistent degradation in performance is observed when compared to the ANN, particularly in terms of R^2 and MAE.

This limitation becomes especially evident in more challenging scenarios, such as at the Boa Vista site during March, where both models exhibit negative R^2 values, indicating a failure to generalize and performance worse than a simple mean predictor. This behavior highlights the difficulty of tree-based models in capturing the spatial complexity of ionospheric scintillation, particularly in equatorial regions.

In contrast, the ANN demonstrates greater robustness and stability, maintaining consistent performance even under conditions of increased variability. This superior performance suggests a stronger capability of the ANN to model the nonlinear relationships present in the GISM data, especially under more complex ionospheric conditions.

The LOYO (Leave-One-Year-Out) results, presented in Tables 7 and 8, indicate that RF and GBDT perform better

in temporal generalization than in spatial generalization. However, even in this more favorable scenario, the ANN continues to outperform both models, achieving lower errors and more consistent performance metrics.

TABLE 7. LOYO (Leave-One-Year-Out) temporal generalization results using Random Forest (RF).

Site	Month	Test Year	MSE	MAE	R^2	r
São Luís	January	2016	0.0238	0.0691	0.8313	0.9715
	March	2018	0.0108	0.0490	0.9183	0.9898
	June	2018	0.0002	0.0071	0.9954	0.9982
Boa Vista	January	2016	0.0035	0.0315	0.8882	0.9948
	March	2018	0.0057	0.0404	0.7634	0.9965
	June	2018	0.0001	0.0048	0.9944	0.9991
Natal	January	2016	0.0137	0.0527	0.9079	0.9717
	March	2018	0.0084	0.0472	0.9279	0.9929
	June	2018	0.0002	0.0068	0.9959	0.9990

TABLE 8. LOYO (Leave-One-Year-Out) temporal generalization results using Gradient Boosted Decision Trees (GBDT).

Site	Month	Test Year	MSE	MAE	R^2	r
São Luís	January	2016	0.0242	0.0781	0.8288	0.9680
	March	2018	0.0100	0.0492	0.9241	0.9892
	June	2018	0.0002	0.0082	0.9956	0.9979
Boa Vista	January	2016	0.0032	0.0320	0.8978	0.9930
	March	2018	0.0051	0.0000	0.7881	0.9967
	June	2018	0.0001	0.0054	0.9947	0.9989
Natal	January	2016	0.0174	0.0689	0.8834	0.9655
	March	2018	0.0083	0.0490	0.9283	0.9916
	June	2018	0.0002	0.0081	0.9964	0.9988

The comparison between LOSO and LOYO approaches highlights that spatial variability poses a significantly greater challenge than temporal variability for the evaluated models. This behavior is consistent with the highly localized nature of ionospheric scintillation, particularly in equatorial regions, where irregularities exhibit strong spatial dependence.

This performance gap among the models becomes even more evident in the heatmap representations shown in Figures 12 and 13. While the tables provide quantitative values, the heatmaps offer a clearer visualization of performance patterns, making the superiority of the ANN and the limitations of RF and GBDT immediately apparent, especially in the most complex scenarios.

Overall, the ANN consistently demonstrates superior performance, particularly in scenarios with higher variability, while RF and GBDT exhibit competitive results under more stable conditions.

These results further support the use of neural networks as effective surrogate models for ionospheric scintillation modeling, particularly in scenarios involving strong spatial and temporal variability.

E. COMPUTATIONAL PERFORMANCE AND EFFICIENCY

The computational performance comparison summarized in Table 9 refers to a representative benchmark conducted for the São Luís station (January 2014), comprising 4,464 samples

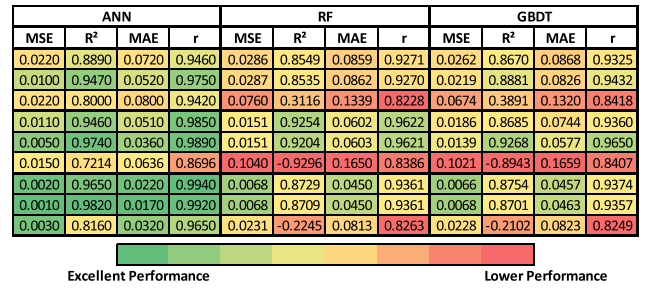


FIGURE 12. Heatmap representation of LOYO results comparing ANN, RF, and GBDT. The color scale highlights performance differences across sites and months, facilitating visual interpretation of spatial generalization. Higher R^2/r values and lower MSE/MAE values indicate better model performance, corresponding to the most favorable regions in the color scale, with warmer colors indicating better performance.

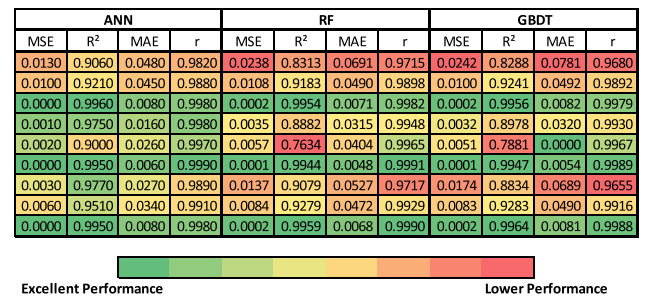


FIGURE 13. Heatmap representation of LOYO results comparing ANN, RF, and GBDT. The visualization emphasizes temporal generalization patterns and relative model performance across different years and regions. Higher R^2/r values and lower MSE/MAE values indicate better model performance, corresponding to the most favorable regions in the color scale, with warmer colors indicating better performance.

with 10-minute resolution. This controlled scenario was selected to enable a direct and reproducible comparison between the physical GISM model and the proposed ANN under identical conditions, while also corresponding to a region close to the center of the EIA and a period of high solar activity associated with the maximum of solar cycle 24.

For this representative case, the ANN exhibits a substantial reduction in execution time, with the wall-clock runtime decreasing from 1101.13 s (GISM) to 0.47 s. A corresponding increase in throughput is also observed, rising from 1.97 to 9518.57 samples/s, indicating a gain of several thousand times in computational efficiency per sample.

This performance evaluation considers exclusively the inference stage of the ANN, which was executed over the complete dataset (100% of the samples) after a warm-up phase, using a batch size of 64. Data preprocessing and network training times are not included, as the ANN is intended to operate as a surrogate model for repeated large-scale evaluations.

In contrast, the execution time reported for GISM corresponds to the full end-to-end simulation workflow, including model initialization, iterative physical computations, and input/output operations, for the entire period under analysis.

As GISM does not feature a separable inference stage, its reported runtime reflects the effective computational cost of operational use.

Although the benchmark is limited to a single station and a single month, the observed speedup is primarily driven by the architectural characteristics of the methods. ANN inference is dominated by fixed-cost matrix operations, which can be efficiently vectorized and parallelized, whereas GISM execution relies on iterative physical computations that scale with temporal resolution. Consequently, similar performance trends are expected when considering datasets involving multiple stations or longer time periods.

This computational advantage is accompanied by a higher memory demand. While GISM operates with an average memory usage of 66.47 MB (peak 77.54 MB), the ANN requires approximately 611.58 MB of memory, reflecting the storage of network parameters and the execution environment. Nevertheless, this memory footprint remains compatible with modern computing platforms.

Overall, the results indicate that the proposed ANN constitutes a computationally more efficient alternative to GISM in terms of processing time per sample, being particularly attractive for studies involving repeated evaluations over large datasets, while maintaining a well-characterized trade-off between speed and memory usage.

TABLE 9. Computational performance comparison for São Luís, January 2014.

Metric	GISM	ANN
Wall-clock time (s)	1101.13	0.47
Throughput (samples/s)	1.97	9518.57
Average memory (MB)	66.47	611.58
Peak memory (MB)	77.54	611.58

F. FEATURE ABLATION STUDY

This experiment investigates how each input variable contributes to the emulation capability of the ANN. By systematically removing one feature at a time and retraining the model, it is possible to identify which variables play a dominant role in reproducing the GISM-based S4 estimates and which ones have a secondary effect on the overall performance.

Table 10 presents the results of the feature ablation experiment, in which each input variable was removed individually to assess its contribution to the ANN performance. The largest degradation in accuracy occurs when the cyclic representation of local time ($\sin(\text{time})$ and $\cos(\text{time})$) is removed, leading to higher MSE values (between 1.41×10^{-3} and 1.73×10^{-3}) and a more pronounced reduction in the correlation coefficient r . This result indicates that the diurnal variability of scintillation, as represented in the GISM, is a dominant factor for reproducing the S4 index in the proposed model.

The removal of latitude and longitude also produces a noticeable decrease in performance, showing that the network effectively captures the spatial dependence of scintillation

structures, which is consistent with the regional behavior of the reference model. In contrast, omitting global geophysical indices (Sunspot number, Kp, and F10.7) produces a comparatively smaller impact on the metrics, suggesting that, in the analyzed scenario, spatial and diurnal variability play a stronger role than large-scale solar and geomagnetic variations.

TABLE 10. Feature ablation analysis for the representative case of São Luís, January 2014.

Removed feature	MSE	MAE	R^2	r
Frequency	0.0007970	0.0124	0.9959	0.9979
Latitude	0.0008838	0.0137	0.9955	0.9978
Longitude	0.0010923	0.0156	0.9944	0.9972
Sunspot number	0.0009243	0.0147	0.9953	0.9976
F10.7	0.0014503	0.0169	0.9926	0.9965
Kp	0.0009309	0.0140	0.9952	0.9976
Day of year	0.0008636	0.0143	0.9956	0.9978
Hour	0.0008214	0.0127	0.9958	0.9979
$\sin(\text{time})$	0.0014120	0.0196	0.9928	0.9965
$\cos(\text{time})$	0.0017282	0.0192	0.9912	0.9956

Overall, the results indicate that the ANN prioritizes high-resolution temporal and spatial information to reproduce the behavior of the GISM, while geophysical indices act mainly as complementary inputs that help to further reduce the emulation error.

G. SEED STABILITY AND ROBUSTNESS ANALYSIS

To assess whether the model performance depends on stochastic factors during training, an additional experiment was conducted to evaluate its sensitivity to random initialization. This analysis is important to verify the robustness of the learned representations and to ensure that the ANN does not rely on a particular optimization trajectory.

To quantify performance variability, we report the ANN metrics across five independent random seeds for the representative case of São Luís, January 2014. Table 11 presents the seed sensitivity analysis, in which the network was trained multiple times with different random initializations. The results show that the performance metrics remain highly consistent across seeds, with R^2 values between 0.9949 and 0.9963 and correlation coefficients r above 0.9974 in all cases. This indicates that the model exhibits strong training stability and is not significantly affected by stochastic weight initialization.

TABLE 11. Seed sensitivity analysis for the representative case of São Luís, January 2014.

Seed	MSE	MAE	R^2	r
42	0.000852	0.01350	0.99564	0.99785
7	0.000764	0.01597	0.99634	0.99823
123	0.000765	0.01387	0.99595	0.99820
2021	0.000829	0.01530	0.99568	0.99785
999	0.001060	0.01643	0.99488	0.99744

The results show mean $\pm$ standard deviation values of $\text{MSE} = 0.00085 \pm 0.00011$, $\text{MAE} = 0.0146 \pm 0.0013$,

$R^2 = 0.9957 \pm 0.0006$, and $r = 0.9979 \pm 0.0003$. These values indicate high robustness of the network with respect to random initialization.

Small variations in MSE and MAE are observed, particularly for seed 999, which yields a slightly higher emulation error. However, the magnitude of these differences is marginal and does not alter the global behavior of the model with respect to the GISM reference outputs. The results therefore suggest that the ANN converges to similar solutions across runs, and that ensemble effects from multiple seeds would provide only marginal additional gains in robustness.

In addition to performance stability, the variability across seeds was further exploited to quantify surrogate uncertainty. For each input sample, multiple S4 estimates were obtained using different random seeds. The mean (μ) and standard deviation (s) were computed across these runs. The nominal scenario corresponds to μ , while the pessimistic and optimistic scenarios were defined as $\mu + s$ and $\mu - s$, respectively. These scenarios were subsequently used to assess the impact of uncertainty on scintillation severity classification.

Fig. 14 presents the percentage distribution of S4 values according to the ITU classification thresholds (weak, moderate, and strong) for the three considered scenarios. While the nominal case indicates a balanced distribution of scintillation conditions, the pessimistic scenario significantly increases the proportion of strong scintillation events. Conversely, the optimistic scenario is dominated by weak conditions. This shift highlights the importance of incorporating uncertainty into the analysis, as it reveals a non-negligible probability of severe scintillation that would not be captured by a purely deterministic estimate.

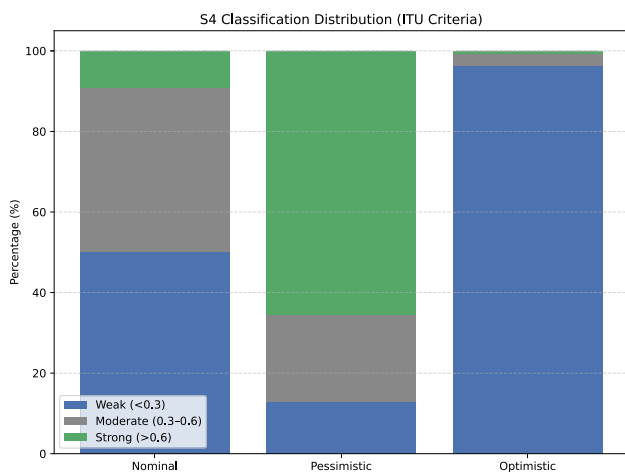


FIGURE 14. Percentage distribution of S4 values according to the ITU classification (weak, moderate, and strong) for the optimistic, nominal, and pessimistic scenarios derived from the ensemble-based uncertainty estimation.

H. OPERATIONAL DEPLOYMENT

Although the current study focuses on emulating the GISM simulations, several considerations are relevant for

potential operational deployment. The model could be retrained periodically, for example annually or semi-annually, to account for seasonal variations, solar cycle changes, or updates in the underlying simulation model. Drift detection could be implemented by monitoring the model's emulation error over time, triggering retraining or parameter adjustments when significant deviations are observed. Due to its low computational cost, the ANN model could also be deployed in an edge computing environment, enabling real-time processing close to the measurement stations or satellite payloads. While the current work does not incorporate real GNSS S4 measurements, given that GNSS S4 reflects scintillations observed at different radio frequencies (L-band) compared to the UHF S4 from GISM, leading to different temporal and spatial scales and distinct intensity characteristics, future studies could investigate correlations between these datasets and explore how GNSS observations might complement the ANN model.

V. USE OF SURROGATE-BASED S4 ESTIMATES FOR COMMUNICATION RELIABILITY IN THE PERCEIVE MISSION

As mentioned above, one of the main motivations of this work is to develop new methods and solutions to predict the impact of ionospheric scintillation on UHF satellite communication links. To illustrate this, a communication risk analysis is presented for the Perceive space mission using the proposed ANN model.

The Perceive mission is an integral component of the Perception System for strategic asset monitoring. The Perception System is an integrated architecture designed for large-scale, real-time environmental monitoring. It employs two satellite communication networks to collect data from ground-based sensor arrays, forming a relay network capable of ensuring continuous observation of strategic ecosystems. Communication between ground sensors and the satellite network follows a dual-link strategy: a high-data-rate link (HDL) is used to transmit large volumes of data from terrestrial sensors to the satellite, while a low-data-rate link (LDL), operated by the Perceive satellite network, enables telemetry, system health monitoring, and the exchange of mission-critical data. The HDL operates in high-frequency communication bands, which experience minimal attenuation due to ionospheric scintillation. In contrast, the LDL relies on two UHF band frequencies: 401.5 and 468.5 MHz, both of which are highly susceptible to ionospheric attenuation.

Based on the ionospheric scintillation index (S4) values estimated by the ANN surrogate model, an assessment is carried out regarding its applicability in estimating the communication success probability of the Perceive satellite. For this analysis, the same methodological procedure described in [34] and [35] was adopted, considering the worst-case scenario for the space-to-Earth link at 401.5 MHz, as presented below. Table 12 presents a selection of key parameters and values, obtained from the preliminary link budget analysis of

the Perceive CubeSat, which are considered the most relevant for the objectives of the present work.

TABLE 12. Selected parameters and values from the Perceive CubeSat preliminary link budget.

Parameter	Symbol / Unit	Value
Frequency	f (MHz)	401.5
Data Rate	R_b (bps)	9600
E_b/N_0	dB	19.93
E_b/N_0 (Required)	dB	10.00
Link Margin	dB	9.93

The communication success probability was calculated using the method described in [35], employing both the S4 values derived from the GISM model and those estimated by the neural network. The basic approach consists of empirically calculating the peak-to-peak signal intensity fluctuation P_{fluc} (dB) based on ITU-R Recommendation P.531-15, as given by the following equation below

$$P_{fluc} = 27.5 S_4^{1.26}. \quad (7)$$

Based on the level of peak-to-peak fluctuation of the signal associated with the observed S4 index, one can estimate the correspondent signal loss to be accounted in the link budget computation. The signal loss, L_p , associated with scintillation can be expressed as

$$L_p = \frac{1}{\sqrt{2}} P_{fluc}. \quad (8)$$

Based on the obtained value, the new link margin is estimated by accounting for the ionospheric loss caused by the occurrence of ionospheric scintillation. If the resulting value of the energy-per-bit to noise power spectral density ratio (E_b/N_0) exceeds the reference threshold, as required by the system design (Required E_b/N_0), transmission is considered feasible; otherwise, transmission is not recommended due to a high probability of communication failure [34], [35]. Finally, for the analyzed service region, communication success or failure is modeled as a Bernoulli random variable, with the corresponding expected value [35]. The overall procedure is summarized in the flowchart shown in Fig. 15.

Analyses of communication success probability were also performed for São Luís/MA, Boa Vista/RR, and Natal/RN, considering the years 2014, 2016, and 2018 across three representative months (January, March, and June), which match the scenarios used in neural network training.

The comparison of the communication risk analysis presented in Figures 16, 17, and 18, based on S4 index values obtained from the GISM model and the proposed neural network for the stations of São Luís, Boa Vista, and Natal, confirms a very strong agreement between the two approaches.

For São Luís, the results also show excellent consistency. GISM success probabilities range from 67.46% to 91.51%, while the neural network predicts values between 67.46% and 92.28%. The discrepancies remain below 0.9 percentage

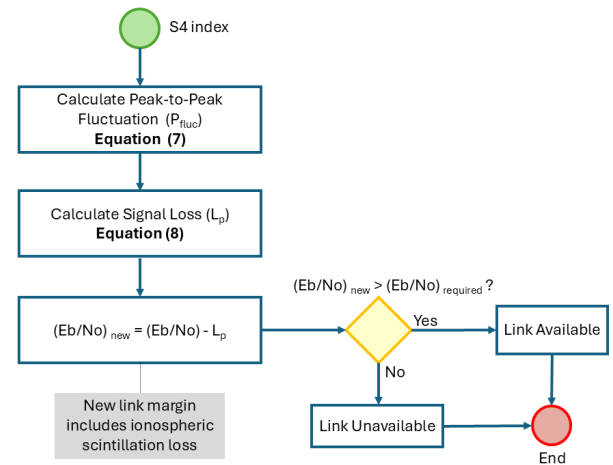


FIGURE 15. Flowchart of communication reliability analysis.

points, even during periods of increased scintillation activity, reinforcing the reliability of the proposed model.

In Boa Vista, the success probabilities derived from GISM range from 75.52% to 100.00%, while the neural network predictions span 75.67% to 100.00%. The differences between the two methods remain small across all analyzed periods, with discrepancies generally below 1.8 percentage points, indicating that the network accurately reproduces both moderate and high scintillation risk conditions.

For Natal, the agreement is similarly robust. The GISM-based success probabilities vary between 68.51% and 89.51%, whereas the predicted values range from 68.66% to 89.66%. The maximum absolute difference does not exceed 0.6 percentage points, demonstrating the network's ability to closely match the reference model across different years and seasonal conditions.

Overall, the results demonstrate that the neural network effectively reproduces the communication risk patterns obtained with GISM for all three stations, with only marginal deviations. This strong agreement supports the use of the proposed model as a fast and reliable surrogate for GISM in large-scale or near-real-time communication risk assessments.

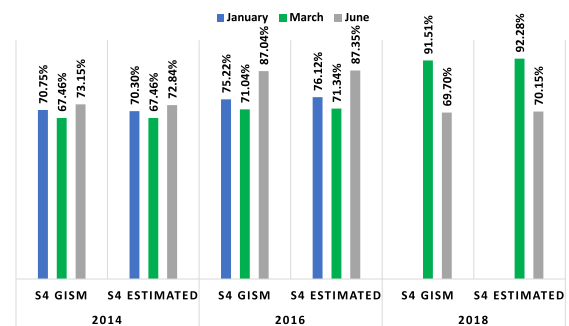


FIGURE 16. Comparison of the communication success probability for the Perceive satellite based on real S4 index values (GISM) and those estimated by the neural network for São Luís/MA.

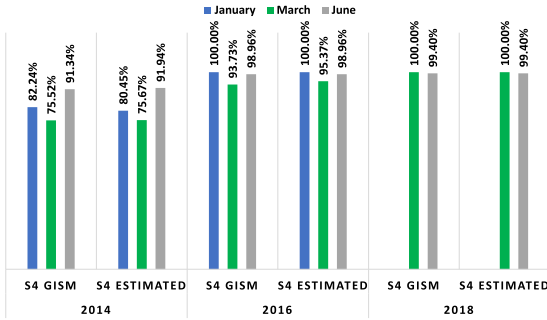


FIGURE 17. Comparison of the communication success probability for the Perceive satellite based on real S4 index values (GISM) and those estimated by the neural network for Boa Vista/RR.

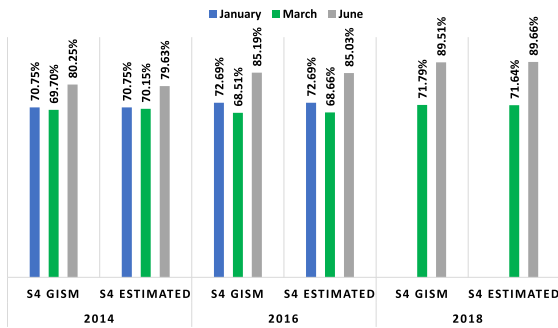


FIGURE 18. Comparison of the communication success probability for the Perceive satellite based on real S4 index values (GISM) and those estimated by the neural network for Natal/RN.

Fig. 19 presents the communication risk assessment derived from the S4 estimates under the optimistic, nominal, and pessimistic scenarios. These scenarios were constructed based on the variability of the neural network outputs, as previously described, and subsequently incorporated into the link performance evaluation.

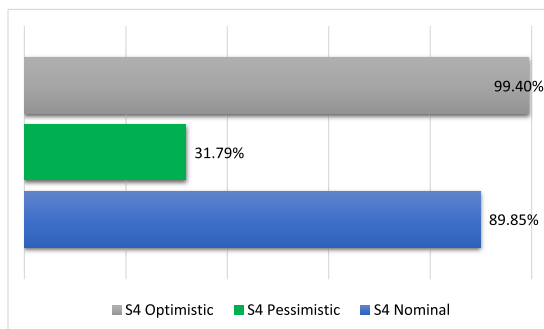


FIGURE 19. Communication success probability under optimistic, nominal, and pessimistic S4 scenarios.

The communication success probability was evaluated for the three considered scenarios. The optimistic scenario presented a success rate of approximately 99.40%, indicating that, under favorable ionospheric conditions, scintillation effects tend to have limited impact on communication performance. In the nominal scenario, the obtained success

probability was 89.85%, suggesting the presence of moderate degradation in link performance even under average conditions.

In the pessimistic scenario, the success probability was 31.79%, reflecting the influence of higher scintillation levels under adverse ionospheric conditions. This behavior is associated with the distribution of nominal S4 values, in which approximately 24.03% of the values fall within the interval between 0.4 and 0.6, corresponding to moderate scintillation conditions close to the strong scintillation threshold defined by the ITU ($S4 = 0.6$). Under these conditions, the consideration of variability ($\mu + s$) may result in the transition of part of these values into the strong scintillation range, increasing the occurrence of events classified in this category (Fig. 14) and contributing to the reduction in communication success probability observed in the pessimistic scenario (Fig. 19).

The inclusion of variability associated with S4 values allows a broader representation of possible operational conditions of the system, complementing analyses based exclusively on nominal values.

VI. CONCLUSION

This work proposed an artificial neural network approach to emulate the UHF ionospheric scintillation index (S4), aiming to support the planning and operation of satellite communication systems under adverse ionospheric conditions. The model was trained using data generated by the GISM model, incorporating relevant environmental and geophysical variables.

Performance evaluations were conducted for three ground stations located in equatorial and low-latitude regions in Brazil, covering different years, seasons, and levels of solar activity. In addition to conventional validation strategies, rigorous Leave-One-Station-Out (LOSO) and Leave-One-Year-Out (LOYO) cross-validation schemes were applied to assess the spatial and temporal generalization capability of the model. The results demonstrated consistent performance under both schemes, indicating that the neural network maintains high accuracy even when applied to unseen stations or years.

To ensure that the observed performance was not specific to neural network architectures, additional machine learning models, namely Random Forest (RF) and Gradient Boosted Decision Trees (GBDT), were also evaluated. While these ensemble-based methods demonstrated competitive performance, the neural network consistently achieved superior accuracy, confirming its suitability for capturing the complex nonlinear behavior of the GISM model.

Despite the diversity of ionospheric scenarios considered, the proposed model achieved high accuracy, with coefficients of determination (R^2) consistently above 0.993 and low error values, confirming its robustness and generalization capability. Additional ablation and seed sensitivity analyses further demonstrated the stability of the model with respect to stochastic training effects.

The variability across different random initializations was further exploited to quantify uncertainty in the S4 estimates. For each input sample, the mean and standard deviation across multiple runs were computed, enabling the construction of nominal, pessimistic, and optimistic scenarios. These scenarios revealed that even small variations in S4 may lead to significant changes in scintillation classification, particularly in the transition between moderate and strong conditions.

Since the neural network learns to reproduce the behavior of GISM, a model recommended by the ITU for ionospheric scintillation analysis, it can be interpreted as a computationally efficient surrogate emulator of the GISM model. In addition to the strong agreement with GISM outputs, a substantial reduction in computational cost was observed, with the neural network providing estimates with significantly higher throughput and lower memory requirements. This makes the approach particularly suitable for large-scale simulations and near-real-time applications.

Furthermore, the uncertainty-aware S4 scenarios were incorporated into a communication link analysis, allowing the evaluation of the impact of scintillation variability on communication performance. The results demonstrated that uncertainty can lead to non-negligible variations in link availability, reinforcing the importance of considering multiple scenarios in mission planning and risk assessment.

Therefore, the proposed methodology represents a practical and efficient alternative to direct GISM simulations, particularly in scenarios requiring rapid evaluation or when direct UHF scintillation measurements are not available. Future work includes validation using real GNSS-based scintillation measurements and the integration of this surrogate modeling framework into operational tools for CubeSat communication system design and analysis.

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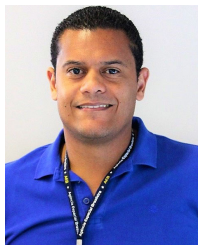
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