Machine Learning Prediction of Rain-Induced Signal Loss for Resilient Satellite Communication in the Tropics

Olivia Ong Yi Hui[1], Mawarni Mohamed Yunus[2*], Mas Haslinda Mohamad[3], and Jafri Din[4]

[1,2]Centre of Technology for Disaster Risk Reduction, Faculty Technology dan Kejuruteraan Elektronik dan Computer, University Technical Malaysia Melaka, Jalan Hang Tuah Jaya, Durian Tunggal, Melaka, Malaysia

[3]Centre for Telecommunication Research and Innovation, Faculty Technology dan Kejuruteraan Elektronik dan Computer, University Technical Malaysia Melaka, Jalan Hang Tuah Jaya, Durian Tunggal, Melaka, Malaysia

[4]Wireless Communication Center, Faculty Kejuruteraan Electric, University Technology Malaysia, Sukadi, Johor Bahru, Malaysia

***Corresponding Author**

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ABSTRACT

Satellite communication is vital for global services such as internet access, weather forecasting, and military operations. However, systems operating above 10 GHz are highly affected by rain-induced signal loss, especially in tropical regions. This study introduces a machine learning-based approach to predict rain attenuation using linear regression, polynomial regression, and artificial neural networks (ANN). Rain attenuation data was generated using the Synthetic Storm Technique (SST) with rainfall measurements from 2019 to 2022 at University Technical Malaysia Melaka (UTeM). Model performance was evaluated against the ITU-R P.618-13 and the Simple Attenuation Model (SAM). The ANN model showed the highest accuracy, achieving an RMSE of 0.98 dB and R^2 of 0.93 at 0.1% and 0.01% exceedance probabilities. The results demonstrate the potential of machine learning to improve communication reliability and support climate-resilient infrastructure planning in high-rainfall regions.

Keywords: Rain fade, Satellite communication link, machine learning, ANN, regression

INTRODUCTION

Reliable communication infrastructure plays a critical role in ensuring digital inclusion, public safety, and socioeconomic development—especially in underserved and climate-vulnerable regions. In recent years, satellite communication has emerged as a key enabler of global connectivity, bridging digital divides in remote and rural communities. However, the effectiveness of satellite-based services in tropical regions is often compromised by intense rainfall, which causes signal degradation known as rain attenuation (Tirmizi et al., 2023). This issue is particularly urgent in equatorial regions, where heavy and frequent rains threaten the continuity of essential services such as telemedicine, disaster response, and distance education. Differences in raindrop size and intensity across regions greatly affect how much the signal weakens (Suhaimi et al., 2022; Yunus et al., 2021). When radio waves travel through rain, they are absorbed, scattered, and refracted (Liao et al., 2023). Additionally, rain and clouds can change the direction and polarization of the signal (Christofilakis et al., 2020), making it harder for the receiver to detect it accurately. These effects combined reduce the reliability of communication, especially during severe weather.

To mitigate these effects, accurate prediction models are essential for satellite communication systems (Samad et al., 2021). Conventional rain attenuation prediction models, including ITU-R, Moupfouma, and Crane Global, are often inadequate in tropical climates, as they fail to adapt to localized weather patterns and high rain intensities (Suhaimi et al., 2022; Alozie et al., 2022; Jong et al., 2018). The Synthetic Storm Technique (SST) offers improved simulation capabilities but still depends on empirical modelling (Jong et al., 2018). In contrast, machine learning (ML) offers a promising alternative by learning complex patterns from local meteorological data, enabling more accurate and adaptable predictions. Techniques including regression models, decision trees, neural networks, Long Short-Term Memory (LSTM) networks, and Gaussian Process Regression (GPR) have demonstrated superior predictive accuracy compared to traditional models (Samad & Choi, 2020; Xu et al., 2023; Kumar et al., 2022; Legesse et al., 2024; Yussuff et al., 2023; Jang et al., 2021; Ojo et al., 2022). ML models learn directly from historical data, reducing dependency on fixed assumptions, as shown by Samad and Choi (2020). Particularly, LSTM and deep learning approaches have yielded promising results in both microwave and millimeter-wave frequency bands (Xu et al., 2023; Kumar et al., 2022).

Despite growing interest in ML for signal loss prediction, most existing models are trained using data from temperate regions, limiting their effectiveness in the tropics (Yussuff et al., 2023). This presents a barrier to equitable access to resilient communication infrastructure. Addressing this gap is vital to ensuring that satellite connectivity remains reliable during extreme weather events, which are increasingly common due to climate change (Abolarinwa et al., 2024; Rao et al., 2021; Jang et al., 2021; Ojo et al., 2022).

This study aims to contribute to social resilience and digital equity by developing machine learning models trained on rain attenuation data derived from real rain rate measurements in Malaysia using the Synthetic Storm Technique. The assumption is that if machine learning models—when trained on SST-derived data—can closely match known reference models, it provides a strong indication of their effectiveness for use in tropical regions. Specifically, the study (1) simulates realistic rain attenuation using SST, (2) develops and evaluates ML models for prediction, and (3) examines model accuracy under intense rainfall. By offering a cost-effective, data-driven solution for rain fade prediction in tropical climates, this work supports the broader goal of strengthening communication systems that serve as lifelines during emergencies and gateways to opportunity in remote areas.

METHODOLOGY

Rainfall data for this study were collected from an Automatic Weather Station (AWS) installed on the rooftop of Block F at UTeM. The station records rainfall data at a one-second resolution, providing high temporal accuracy. The dataset spans four years, from 2019 to 2022. In this study, rain rate is used as the input parameter, while rain attenuation serves as the output parameter.

Since direct rain attenuation measurements are unavailable, the values were derived using the Synthetic Storm Technique (SST). Previous research by Jong et al. (2018) has validated SST-derived attenuation values, showing close agreement with actual measurements. Therefore, SST-derived rain attenuation at the Ku-band is assumed to represent actual attenuation in this study.

The SST estimates attenuation by convolving the time series of rain rate, $R(t)$, with a normalized specific attenuation function, $\gamma(R)$, to simulate the temporal dynamics of rain-induced signal fading. Specific attenuation is calculated using the power-law relation $\gamma = kR^\alpha$, where k and α are frequency- and polarization-dependent coefficients. Additionally, the SST considers storm characteristics such as velocity, vertical structure, and horizontal extent of rain cells. The full details of the SST computation are presented in our previous work (Yunus et al., 2021).

Rainfall data from 2019 to 2021 were used for model training, while the 2022 data were reserved for validation and testing. A scatter plot was initially used to examine the correlation between rain rate and rain attenuation. Outliers were identified by analysing the residuals, and a filtering approach was applied using +25 and –20 standard deviation thresholds to account for the skewed tails in the rain rate distribution. Approximately 0.7% of the dataset was removed, as illustrated in Figure 1.

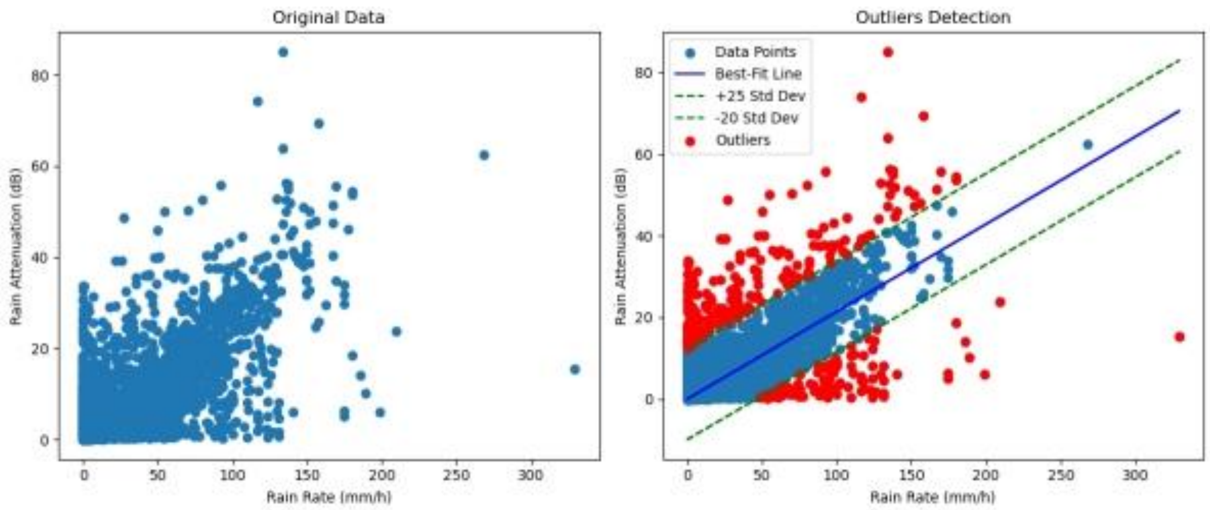

Figure 1. Outliers detection

Following outlier removal, the dataset was standardized to zero mean and unit variance. Outlier removal thresholds of +25 and –20 standard deviations were applied to account for the skewed distribution of rain rate data. Although aggressive, this method ensured training stability (Fan et al., 2021). Nevertheless, the exclusion of extreme events may limit the model's ability to predict rare but impactful attenuation cases.

The cleaned dataset was split into training and testing sets in an 80:20 ratios. Other split ratios (70:30 and 75:25) were also explored; however, the 80:20 split offered the best trade-off between training accuracy and generalization capability. Three machine learning algorithms were proposed to model rain attenuation: linear regression**,** polynomial regression, and an Artificial Neural Network (ANN)**.** Jupyter Lab was used as the development platform, and all models were implemented using Python.

For linear regression, the LinearRegression()command was employed. Polynomial regression was implemented by augmenting the input features with polynomial terms. For the ANN, the selected architecture was 1:5:1, consisting of one input layer, five hidden layers, and one output layer. Each of the hidden layers had 64 neurons, while the input layer had 128 neurons and the output layer had a single neuron as shown in Figure 2. This configuration was selected after extensive empirical testing across various architectures with 1 to 5 hidden layers and different neuron counts. Shallow networks with a single hidden layer showed underfitting, whereas deeper networks with excessive layers led to overfitting. The 1:5:1 structure was found to yield the most favorable balance between model complexity and predictive performance. Figure 3 illustrates how RMSE and R-squared (R^2) values varied across tested architectures, supporting the rationale for the final design.

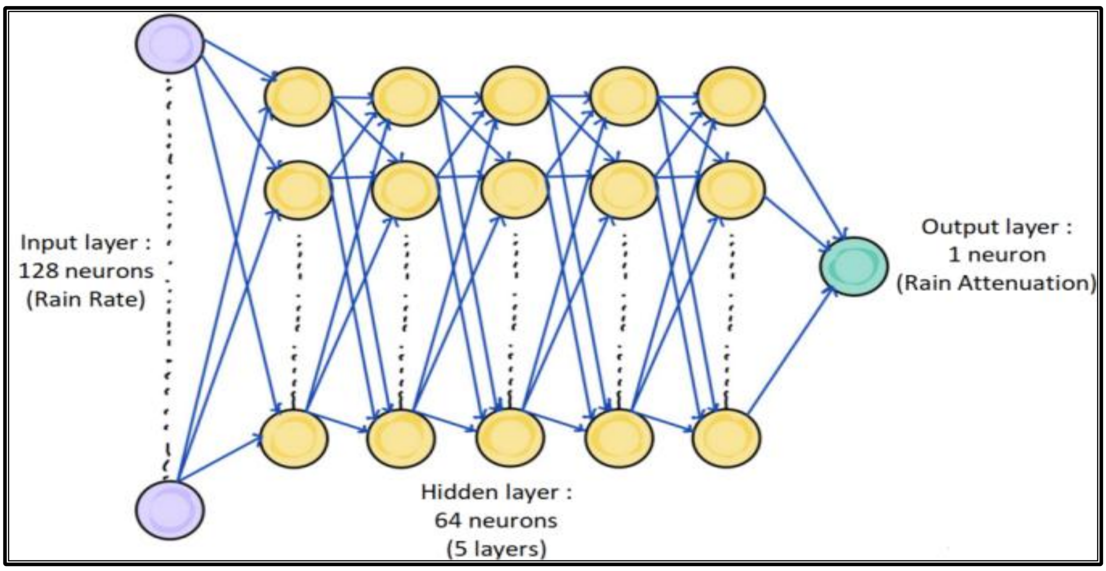

Figure 2. Layer structure of ANN algorithm

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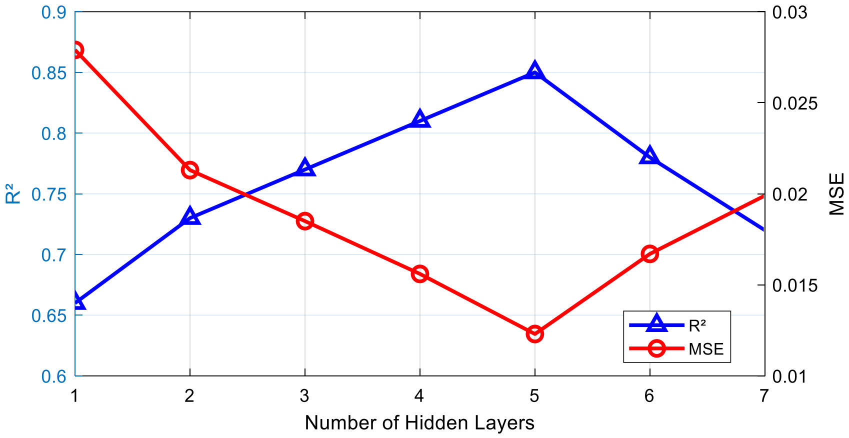


Figure 3. ANN architecture vs number of hidden layers

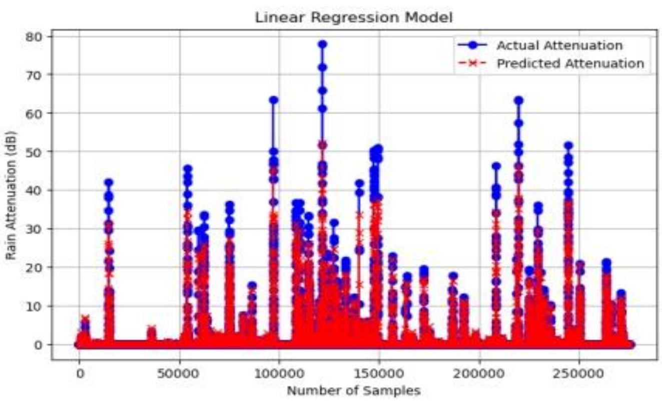
The ANN model utilized the Adaptive Moment Estimation (Adam) optimizer, which adaptively adjusts learning rates for each parameter to improve convergence. Key hyper parameters, including learning rate (0.01), number of epochs (1000), and batch size (600); were tuned using grid search to optimize model performance. The number of neurons in the hidden layers was also adjusted, though specific values were determined through experimentation. If initial results showed low accuracy during testing, hyper parameter tuning was repeated, and the model was retrained until satisfactory performance was achieved. EarlyStopping was applied with a patience of 10 epochs to prevent overfitting and enhance model generalization.

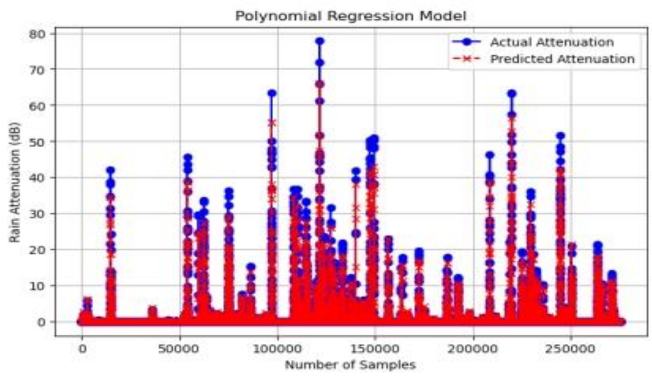
Once trained, the model was further validated using the 2022 rainfall data. To illustrate the probability of experiencing varying levels of signal degradation, Complementary Cumulative Distribution Functions (CCDF) were plotted. Finally, the performance of the proposed models was benchmarked against actual data and established models such as the ITU-R P.162-13 [19] and the Simple Attenuation Model (SAM)**.**

RESULTS AND DISCUSSION

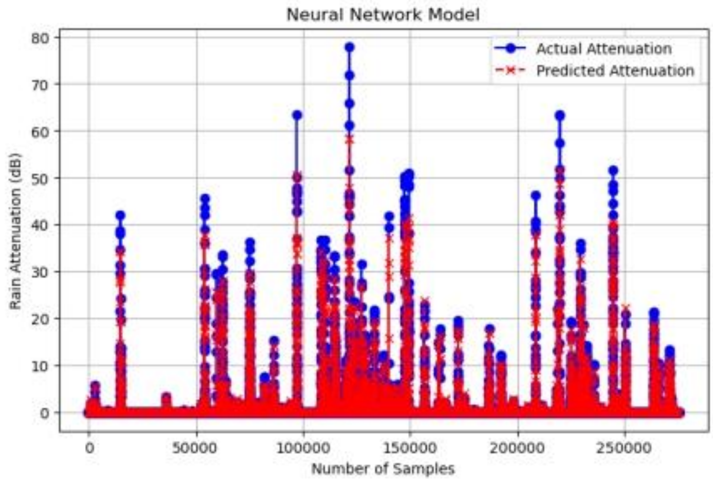
The performance of the models is assessed using the 2022 dataset after training, as shown in Figure 4. The time series plots reveal that all models tend to underestimate rain attenuation at higher rain rates, while predictions are more accurate at lower rain rates. This discrepancy occurs because most of the training data comprises lower rain rates and corresponding lower rain attenuation, leading to models that are well-calibrated for these conditions but struggle with higher rain rates. Consequently, while the models accurately predict lower rain attenuation, they face challenges in providing precise estimates for higher rain rates.

Table 1 depicts the performance of each machine learning model, evaluated using several metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). The ANN model exhibits the lowest error rates, with reduced MAE, MSE, and RMSE compared to the linear and polynomial models. Additionally, the ANN model achieves the highest R^2 value, demonstrating an accuracy of 84.76%.





(a) (b)



(c)

Figure 4. Comparison of the actual and predicted rain attenuation for (a) linear regression model, (b) polynomial regression model, (c) ANN model

Table 1. Performance comparison of the machine learning models

Performance Metrics	Linear	Polynomial	ANN
MAE	0.0196	0.0184	0.0168
MSE	0.0776	0.0751	0.0677
RMSE	0.2785	0.2740	0.2602
R^2	0.8304	0.8359	0.8476

According to Luini et al. (2020), a higher rain rate results in greater rain attenuation. This relationship is confirmed in Figure 5, which compares the proposed machine learning models with the actual data and the SAM model, plotting rain rate against rain attenuation. It is evident from the plot that as the rain rate increases, rain attenuation also rises. Both the proposed and existing models tend to underestimate rain attenuation, but the predictions from the polynomial and ANN models are closer to the actual rain attenuation compared to the SAM and linear models.

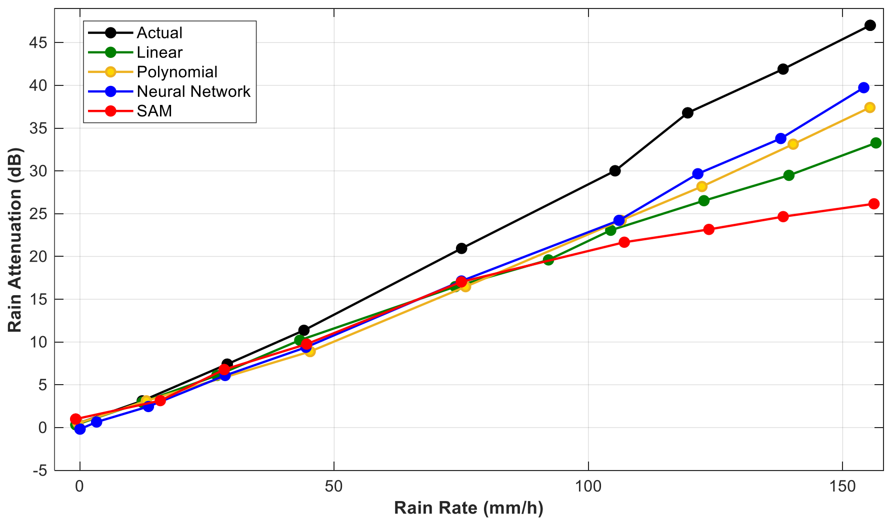


Figure 5. Comparison of the machine learning models with actual and SAM model in term of rain rate versus rain attenuation

Figure 6 illustrates the CCDF plot, which compares the proposed machine learning models with actual data and the ITU-R P618-13 and SAM models. The plot highlights the distribution of rain attenuation values based on the probability of exceeding those values. It shows that as the exceedance probability decreases, rain attenuation increases, indicating that higher attenuation values are less frequent but more severe when they do occur.

Among the models, the ANN model performs the best. For a 0.1%-time exceedance, it provides a value closest to the actual measurement of 8.21 dB, with a prediction of 7.45 dB. In contrast, the SAM and ITU-R models significantly underestimate the actual value, while the linear and polynomial models offer intermediate accuracy. For a 0.01%-time exceedance, the ANN model remains the most accurate, predicting 23.98 dB, which closely matches the actual value of 24.56 dB. The SAM model also underestimates the actual value but is closer than the ITU-R model, which significantly underestimates the actual data. This 0.01% exceedance level is particularly relevant for high-availability systems, as it corresponds to a 99.99% link availability target**.** Designing systems without accurately accounting for such rare but severe attenuation events may result in insufficient link margins**,** leading to QoS degradation or complete service outage during intense rainfall. Hence, the ANN model's ability to closely track actual attenuation at this threshold supports more reliable availability planning and robust satellite link design particularly in tropical regions.

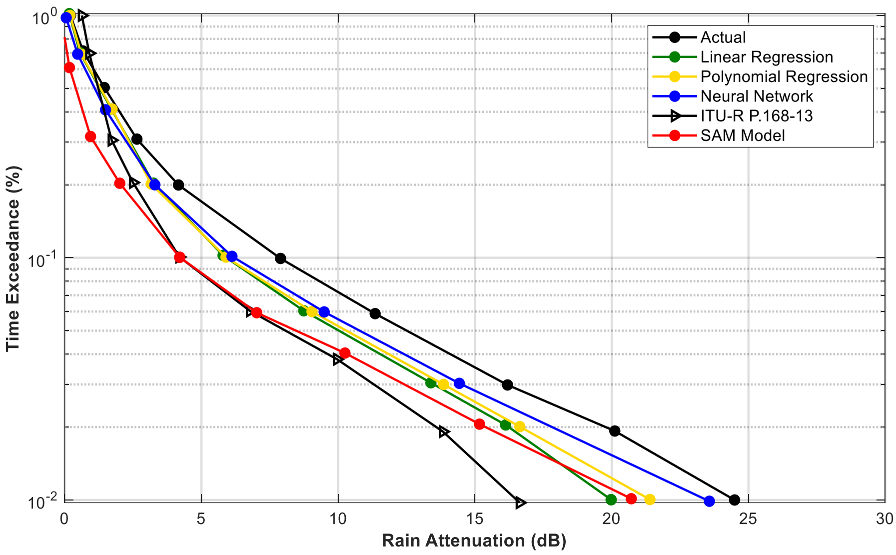


Figure 6. Comparison of the machine learning models with actual and SAM, ITU-R P.168-13 model in term of CCDF plot

The error between actual and predicted rain attenuation from the models is quantified using RMSE, as shown in Table 2. The results indicate that the ANN model achieves the lowest RMSE of 0.67 at both 0.1% and 0.01%-time exceedance, outperforming other models. This lower RMSE signifies that the ANN model provides the most accurate predictions of rain attenuation, with less deviation from the actual values compared to the SAM, ITU-R, linear, and polynomial models.

Table 2. RMSE comparison of the models with actual data

Time Exceedance (%)	**RMSE**				
	SAM	**ITU-R**	**Linear**	**Poly**	**ANN**
0.1	3.20	3.20	0.90	0.89	0.76
0.01	2.46	7.64	4.54	1.75	0.57

While this study is based on rainfall data from University Technical Malaysia Melaka (UTeM), it is important to acknowledge that the results may be region-specific due to local climatic characteristics. Nonetheless, the tropical nature of Malaysia shares several meteorological traits with other equatorial regions. Future work should validate the models using data from additional tropical countries to evaluate generalizability and enhance applicability across broader geographic zones.

CONCLUSION

This study demonstrates the effectiveness of machine learning models, especially Artificial Neural Networks (ANN), in predicting rain attenuation for satellite communication in tropical regions. The ANN model outperforms linear and polynomial regression by achieving lower error rates and higher prediction accuracy, particularly during heavy rainfall events. While all models tend to underestimate attenuation at very high rain rates, the ANN provides the most reliable estimates compared to conventional models such as the Simple Attenuation Model (SAM) and ITU-R P.618-13, especially at higher exceedance probabilities. These results underscore the potential of ANN-based prediction to enhance the reliability and resilience of satellite communication systems critical for connectivity in tropical areas. Improved prediction models contribute to more stable communication services, supporting social inclusion, emergency response, and economic development in regions vulnerable to severe weather. Future work should focus on refining ANN architectures and exploring diverse machine learning techniques to better manage extreme weather challenges.

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