Experimental Evaluation of Propagation Models for Precision Agriculture Wireless Links

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***Abstract*— This work analyzes signal propagation in Long Range (LoRa) wireless links for precision agriculture by comparing classical propagation models and models that account for vegetation attenuation against experimental measurements in three scenarios: short grass, maize crop, and palm plantation. Classical models include Log-distance, Close-In (CI), and Okumura-Hata, while vegetation attenuation models include ITU-R P.833, COST-235, FITU-R, LITU-R, and Chen-Kuo. This comparison provides site-specific evidence under the evaluated frequency and link conditions. CI yielded the lowest MAE in short grass and maize (3.81 and 3.14 dB, respectively), while COST-235 in-leaf yielded the lowest MAE for the palm dataset (9.50 dB).**

***Keywords*— LoRa, propagation modeling, path loss, vegetation.**

I. Introduction

Agriculture constitutes one of the main economic foundations in various regions of the world, particularly in Latin America. The incorporation of technologies associated with the Internet of Things (IoT) has driven the development of precision agriculture, enabling real-time monitoring of critical variables and resource optimization. However, the effective implementation of these solutions depends on reliable wireless communication systems capable of operating in open and highly variable environments, which represent challenging scenarios for signal propagation [1].

Low-power wireless technologies such as LoRaWAN, Zigbee, and Sigfox have been widely adopted for rural IoT applications [2], [3]. Among them, LoRaWAN has emerged as a key solution due to its long-range coverage, low power consumption, and low deployment cost, enabling smart agriculture monitoring applications [2], [4]. However, link performance strongly depends on propagation conditions in the environment [5]. In vegetated environments, electromagnetic wave propagation is affected by absorption, scattering, and blockage caused by foliage and terrain, making link behavior difficult to predict using conventional models. Moreover, variability introduced by factors such as operating frequency, link distance, and vegetation density leads to complex channel behavior, making propagation modeling necessary to characterize path loss and support reliable network design [2], [5], [6]. Although several models have been developed to represent this behavior [7], many were originally conceived for other environments, while vegetation-specific models are often based on empirical adjustments from particular scenarios, limiting their ability to represent the phenomenon in a general manner [8], [9].

Propagation models in vegetated environments include general and specific approaches to represent medium effects on the link. Base models such as log-distance, Close-In (CI), and Okumura-Hata are widely used due to their empirical calibration capability [1], [7]. Vegetation loss models including Weissberger, ITU-R P.833, COST-235, and variants FITU-R, LITU-R, and Chen-Kuo add foliage attenuation terms [6], [10]. These models combine baseline propagation with vegetation loss, but simplify the phenomenon and may reduce accuracy in complex environments [11]. In contrast, numerical methods such as the parabolic equation explicitly model environmental effects [12], [13]. However, their use in LoRa vegetated scenarios remains limited compared to empirical approaches. As a result, gaps still exist in understanding the behavior of these models in real scenarios where vegetation, terrain, and environmental factors interact in a complex manner.

Countries such as Colombia and Brazil share a strong agricultural tradition, with agriculture being one of the main economic pillars of both nations. Their tropical regions also present similar climatic and environmental conditions, where dense vegetation and crop structures can significantly affect wireless signal propagation. In this context, this work analyzes experimental measurements carried out in representative agricultural environments in Colombia and evaluates the performance of semi-empirical propagation models for the planning of LoRa-based agricultural IoT networks. Propagation is studied in three scenarios: short grass, maize, and oil palm. Based on the measurements obtained, classical propagation models are compared with vegetation attenuation models to assess how their performance varies according to the characteristics of each agricultural scenario.

II. Propagation Models in Vegetation Environments

In this section, the propagation models considered in this work are presented. These models were selected because they are commonly used in recent studies on wireless propagation in vegetated environments and provide different levels of empirical representation of path loss and vegetation-induced attenuation.

A. Log-distance Model

The classical log-distance model is adopted as a baseline propagation model, widely used to describe the logarithmic

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variation of path loss with distance [14], [15]. In this work, the formulation presented in [7] is followed, which uses the free-space loss at a 1 m reference distance and a path loss exponent to represent environmental attenuation.

B. Close-In (CI) Model

The Close-In (CI) model uses free-space path loss at a reference distance as a physical anchor while maintaining the log-distance structure [1]. The main difference is that the path loss exponent n is not assumed as a fixed value, but is estimated by fitting experimental data, allowing the model to adapt to the actual channel behavior. The free-space loss is expressed as:

$$FSPL(d_0) = 20\log_{10}(d_0) + 20\log_{10}(f) - 27.56 \quad (1)$$

where f is the frequency in MHz and $d_0 = 1$ m is the reference distance.

C. Okumura-Hata Base Model

The Okumura-Hata base model is adopted, widely used to estimate path loss as a function of distance, frequency, and transmitter and receiver antenna heights. In this work, the formulation presented in [7] is followed, including the correction factor associated with receiver antenna height for small and medium urban environments.

D. Weissberger Modified Exponential Decay Model (MED)

The Weissberger model was developed based on experimental data obtained in forest environments, being suitable for scenarios where propagation occurs through dense vegetation, with the antennas immersed within the vegetative medium.

The vegetation loss L_v is given by:

$$L_{v,\text{WEISS}} = 1.33 f^{0.284} d^{0.588}, \quad 14 < d \leq 400 \quad (2)$$

where f is the frequency in GHz and d is the vegetation depth in meters between transmitter and receiver [7].

E. ITU-R P.833 Early Vegetation Attenuation Model

The ITU-R model is widely used to predict attenuation as a function of signal frequency and vegetation depth. It is described by the following expression:

$$L_{v,\text{ITU}} = 0.2 f^{0.3} d^{0.6} \quad (3)$$

where f is the frequency in GHz and d is the vegetation depth in meters [7], [6].

F. COST 235 Model

The COST 235 model was developed from measurements under different vegetation conditions, considering distinct foliage states, and adjusted through regression to represent vegetation loss L_v:

$$L_{v,\text{COST}} = \begin{cases} 15.6 f^{-0.009} d^{0.26}, & \text{in-leaf} \\ 26.6 f^{-0.2} d^{0.5}, & \text{out-of-leaf} \end{cases} \quad (4)$$

In-leaf conditions refer to vegetation with leaves present and dense foliage, whereas out-of-leaf conditions represent sparse or leafless vegetation, where f is the frequency in MHz and d is the distance in meters [7], [6].

G. FITU-R Model

The FITU-R model (*Fitted ITU-R*) corresponds to an adjusted version of the ITU-R P.833 model, obtained from experimental data, allowing the representation of attenuation under different foliage conditions [6]. The vegetation loss is expressed as

$$L_{v,\text{FITU}} = \begin{cases} 0.39 f^{0.39} d^{0.25}, & \text{in-leaf} \\ 0.37 f^{0.18} d^{0.59}, & \text{out-of-leaf} \end{cases} \quad (5)$$

where f is the frequency in MHz and d is the distance in meters.

H. LITU-R Model

The LITU-R model (*Lateral ITU-R*) corresponds to an adaptation of the ITU-R P.833 model, oriented toward near-ground propagation scenarios [6]. The model expression is given by:

$$L_{v,\text{LITU}} = 0.48 f^{0.43} d^{0.13} \quad (6)$$

where f is the frequency in MHz and d is the distance in meters [11], [16].

I. Chen-Kuo Model

The Chen-Kuo model is an empirical model that estimates attenuation in vegetated environments considering the effect of wave polarization [7]. The vegetation loss is expressed as

$$L_{v,\text{ChenK}} = \begin{cases} (f \cdot 10^{-6} + 0.2)d + 5f \cdot 10^{-4} + 3, & \text{vertical} \\ (2f \cdot 10^{-7} + 0.2)d + 3f \cdot 10^{-5} + 2, & \text{horizontal} \end{cases} \quad (7)$$

where f is the frequency in MHz and d is the distance in meters.

III. Study Environments and Scenario Description

A. Short Grass Scenario

The first scenario corresponds to an open environment with low-height vegetation, mainly short grass uniformly distributed, with an approximate height of 3 cm, resulting in minimal interaction with the signal. Measurements were conducted in Cúcuta, Colombia [9], under near line-of-sight conditions due to the absence of significant obstacles. The system operated at 2.4 GHz with a transmission power of 7 dBm. Antennas with 10 dBi gain were placed at 1.5 m height in a symmetric configuration. Data were collected using a fixed receiver and a moving transmitter, allowing the characterization of signal variation with distance. The experimental setup is shown in Fig. 1.

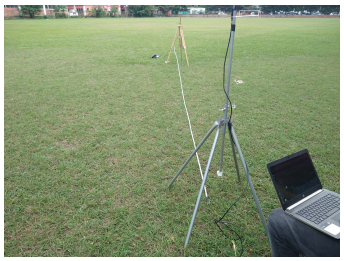


Fig. 1: Short grass scenario setup.

B. Maize Crop Scenario

The second scenario corresponds to an agricultural environment with intermediate vegetation density, represented by a maize crop in the growth stage. Measurements were conducted at the San Pablo experimental station in Chinácota, Norte de Santander, Colombia [17]. The plants have heights of approximately 0.5 m and stems around 2.5 cm in diameter. The row arrangement and spacing between 15 and 20 cm create a denser environment than the previous scenario. The system operated at 2.4 GHz with a transmission power of 17 dBm, using 10 dBi antennas placed at 0.5 m height within the vegetation, increasing interaction with the foliage.

C. Palm Plantation Scenario

The third scenario represents a dense and tall vegetation environment, corresponding to a mature palm plantation located in El Zulia, Norte de Santander, Colombia [13]. The palm trees reach heights between 10 and 15 m, creating a propagation environment dominated by vertical obstacles. This setup operates at 915 MHz with a transmission power of 14 dBm. Antennas with a gain of 5.8 dBi were installed at 1.5 m height, resulting in propagation mainly below the canopy. The scenario configuration is illustrated in Fig. 2. The measurements were analyzed in two distance ranges: 0–300 m and 400–700 m, with 100 m spacing in the latter.

IV. Results

The experimental data, originally measured as RSSI, were converted into *path loss* using link budget analysis. Fig. 3 shows the *path loss* versus distance for grass, maize, and palm



Fig. 2: Palm plantation scenario setup.

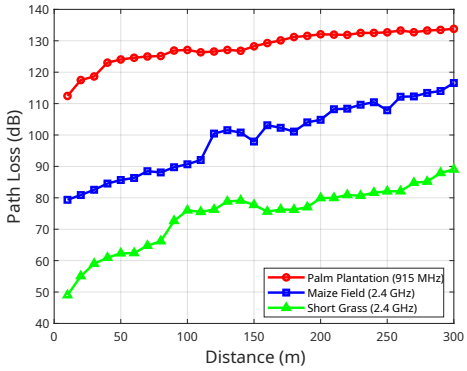


Fig. 3: Visual comparison of the measured *path loss* in the three study environments.

scenarios, highlighting increasing loss with distance and higher attenuation in denser vegetation.

The log-distance, CI, and Okumura-Hata models were used as an initial reference. Fig. 4 shows that they capture the increasing trend of *path loss* with distance, although discrepancies with the experimental data are observed, as reflected in Table I through the mean absolute error (MAE) and the root mean square error (RMSE).

CI yielded the lowest errors among the baseline models when compared with the experimental measurements, with MAE and RMSE values of 10.76 and 12.63 dB for palm, 3.14 and 3.94 dB for maize, and 3.81 and 4.44 dB for short grass, respectively. In contrast, the log-distance model exhibits larger discrepancies, underestimating in palm plantation with an MAE of 33.97 dB and overestimating in the other scenarios. Okumura-Hata shows partial improvements, for instance in short grass with an MAE of 8.91 dB, but still fails to accurately represent the observed behavior. Overall, while baseline models capture the general propagation trend, they present significant limitations in vegetated environments.

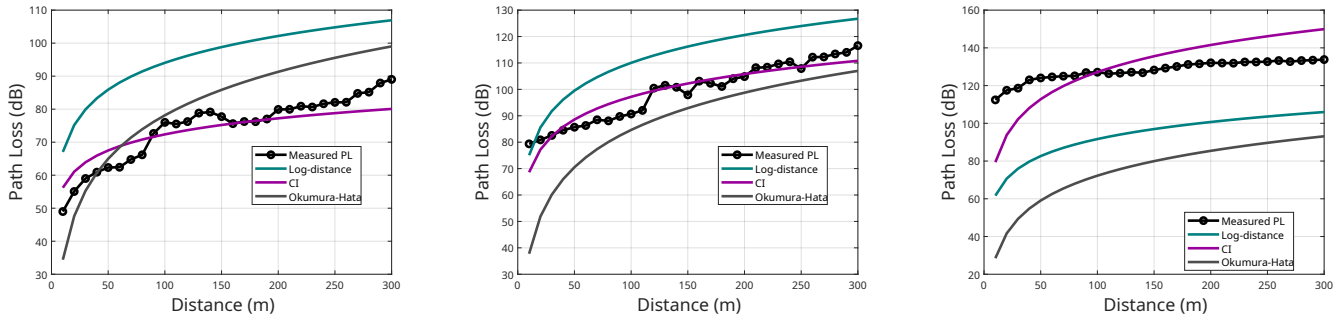
To model attenuation in vegetated environments, widely used empirical models such as Weissberger (MED), ITU-R P.833, COST-235, FITU-R, LITU-R, and Chen-Kuo were employed. These follow an additive approach, where the total loss is given by:

$$PL_{total} = FSPL + L_{vegetation} \tag{8}$$

where $FSPL$ represents free-space attenuation and $L_{vegetation}$ accounts for additional losses due to vegetation.

TABLE I: Errors of baseline models with respect to experimental data

Scenario	Model	MAE (dB)	RMSE (dB)
Short grass	Log-distance	21.73	21.85
	CI	**3.81**	**4.44**
	Okumura-Hata	8.91	9.85
Maize	Log-distance	13.91	14.38
	CI	**3.14**	**3.94**
	Okumura-Hata	10.83	13.33
Palm plantation	Log-distance	33.97	34.47
	CI	**10.76**	**12.63**
	Okumura-Hata	52.28	53.39



(a) Short grass (b) Maize field (c) Palm plantation

Fig. 4: Comparison between measured path loss and baseline propagation models for the three analyzed scenarios.

TABLE II: Errors of vegetation models with respect to experimental data

Model	**Short grass**		**Maize**		**Palm trees**	
	MAE(dB)	RMSE(dB)	MAE(dB)	RMSE(dB)	MAE(dB)	RMSE(dB)
MED	38.63	39.86	15.14	16.40	30.84	32.82
ITU-R P.833	47.73	49.56	23.88	25.98	24.40	28.01
COST-235 in-leaf	58.81	59.33	34.07	34.85	**9.50**	**12.45**
COST-235 out-of-leaf	73.42	76.03	48.78	52.09	33.59	38.53
FITU-R in-leaf	34.59	34.77	10.17	10.60	35.94	36.39
FITU-R out-of-leaf	35.19	36.20	11.86	12.83	31.21	33.11
LITU-R	**32.73**	**32.81**	**8.04**	**8.84**	37.89	38.09
Chen-Kuo vertical	42.73	45.38	19.49	22.58	22.55	27.98

Fig. 5 compares the measured *path loss* with the vegetation models across the three scenarios, while Table II summarizes the MAE and RMSE values.

For the short grass case, most vegetation models exhibit high deviations with respect to the measured behavior, reflecting the limited adaptation of their formulations to environments with low vegetation height and minimal obstruction. Models such as COST-235 in its out-of-foliage configuration reach an average absolute error close to 73.42 dB, while the ITU-R P.833 model presents deviations around 47.72 dB, evidencing a strong overestimation of path losses. This is due to the fact that these models assume dense vegetation structures and multiple scattering mechanisms that are not present in low-coverage environments, leading to an excessive prediction of attenuation. In contrast, LITU-R presents the best relative performance, with an average absolute error close to 32.72 dB, although still showing significant differences with respect to the measured values.

In the maize scenario, the propagation behavior becomes more structured due to the intermediate vegetation height and moderate density, which introduces a combination of partial shadowing, scattering, and attenuation caused by interaction with leaves and stems. In this case, LITU-R achieves the best agreement with the measurements, with an average absolute error close to 8.04 dB, followed by FITU-R, which maintains a performance around 10 dB. This indicates that models incorporating explicit vegetation loss mechanisms are better suited to represent this type of intermediate crop environment.

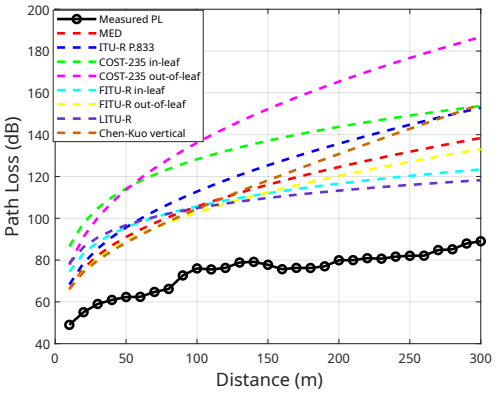
In the palm plantation scenario, the propagation environment is strongly influenced by tall and dense vegetation, which introduces multiple mechanisms of absorption, scattering, and progressive blockage along the radio link. Under these conditions, COST-235 in its in-foliage configuration presents one of the best agreements with the measurements, with an average absolute error close to 9.50 dB, followed by the Chen-Kuo vertical model with around 22.55 dB, indicating that models incorporating explicit vegetation interaction can partially represent the channel behavior, although with limitations in the three-dimensional structure of the environment.

The longer-distance palm plantation measurements were examined separately to determine whether the relative performance of the models changed with link range. The results, summarized in Table III, show that in this range the CI model loses representativeness, reaching an average absolute error of approximately 20.54 dB, while Log-distance, ITU-R P.833, and Okumura-Hata exhibit even larger deviations.

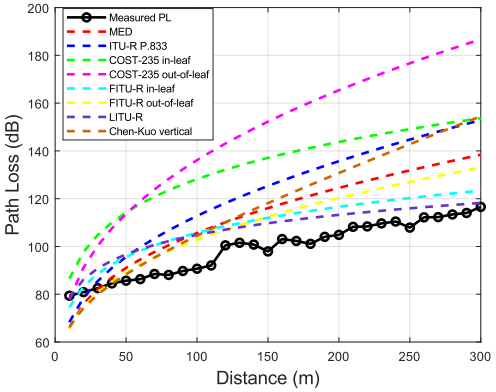
In contrast, the best performance is achieved by the MED

TABLE III: Error in 400–700 m Range for Palm.

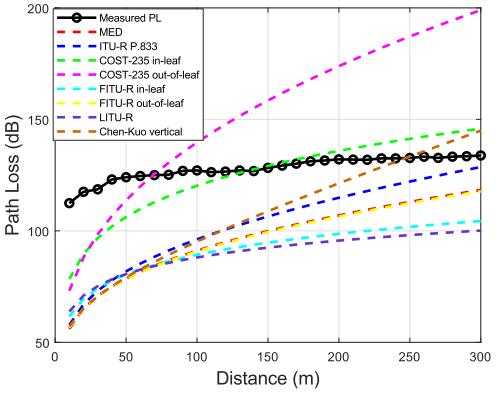
Model	**MAE (dB)**	**RMSE (dB)**
MED	**4.72**	**5.81**
ITU-R P.833	12.62	14.55
COST-235 (in-leaf)	20.15	20.36
COST-235 (out-leaf)	103.44	104.56
FITU-R (in-leaf)	28.34	28.35
FITU-R (out-leaf)	4.90	6.11
LITU-R	34.81	34.82
Chen-Kuo vertical	58.74	62.49
Log-distance	27.91	27.91
CI	20.54	20.59
Okumura-Hata	37.28	37.30



(a) Short grass



(b) Maize



(c) Palm plantations

Fig. 5: Comparison between measured *path loss* and vegetation models for the three analyzed scenarios.

model, with an error close to 4.7 dB, indicating that in this regime the cumulative effects of vegetation are more relevant than distance-based formulations.

V. Conclusions

The results show a strong influence of the environment on LoRa propagation, with clear differences between scenarios. The short grass case presents lower path losses, while maize and palm scenarios exhibit significant increases, reaching errors such as MAE = 10.76 dB / RMSE = 12.63 dB (CI in palm) and up to MAE = 52.28 dB (Okumura–Hata), highlighting the strong sensitivity of the channel to vegetation.

No single empirical model yielded the lowest error across all evaluated scenarios and distance ranges. COST-235 in-leaf had the lowest MAE for palm over 0–300 m (9.50 dB), while MED did so over 400–700 m (4.72 dB), closely followed by FITU-R out-of-leaf (4.90 dB). In maize, LITU-R had the lowest MAE among the vegetation models (8.04 dB). Thus, model performance depends on both the evaluated environment and link range.

Empirical models reproduce general propagation trends but remain limited in complex tropical environments, where vegetation structures introduce mechanisms not fully captured by simplified formulations. This motivates deterministic and other physics-based approaches to better represent absorption, scattering, and blockage.

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