Near-Ground IEEE 802.11 b/g/n Coverage Design for Precision Agriculture

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Abstract—**Due to the broad range of options that wireless systems offer; Wi-Fi products are increasingly being used in agriculture environments to improve farming practices and better control the output of the production. However, the foliage has proven to harm radio-frequency propagation as well as decreasing the coverage area of Wireless Sensor Networks (WSNs). Therefore, near-ground channel characterization can help in avoiding high antennas and vegetation. Nevertheless, theoretical models tend to fail forecasting near-ground path losses. A comprehensive analysis of the influence of rural environments can help obtain better near-ground WSN performance and coverage in precision agriculture. Hence, this paper aims at determining how field components such as, soil, grass, and trunks affect radio-links in near-ground scenarios. To do this, we measure the Received Signal Strength (RSSI), the Signal to Interference Ratio (SIR) and the Round-Trip Time (RTT) of a Wireless Local Area Network (WLAN) at different distances and compare the results with 6 prediction models: the Free-Space Propagation Model, the Two-Ray Ground Reflection Model, the One-Slope Log-Normal Model, the Two-Slope Log-Normal Model, the Okumura-Hata Model, and the Walfisch-Ikegami Model. The experiment was carried out by collecting experimental data at four different locations, i.e., an orange tree plantation with mature trees, an orange tree plantation with young trees, a persimmon field, and a field without vegetation, to compare and contrast the influence of field components on signal losses.**

Keywords—Wireless Coverage; IEEE 802.11; Precision agriculture; Propagation Losses; Propagation Model.

I. INTRODUCTION

This paper is an extended version of the paper presented by M. Botella-Campos et al. in [1].

Smart Farming (SF) emphasizes the use of Information and Communication Technologies (ICTs) to leverage the farm management cycle. Improving the production capacity does not only enhance business efficiency. It also allows to increase production and reduce the environmental impact. Since the world population is expected to reach 9.8 billion by 2050, human societies are facing the challenge of providing nourishment and livelihoods, while addressing the effects of climate change [2]. Smart farming applies measures that are ecologically meaningful and site-specific, focusing on implementing auto-piloted harvesters and other farm machinery [3].

The Internet of Things (IoT) and Cloud Computing are expected to move forward in farming management development by introducing these technologies into machinery and production systems [4]. The gathered information will then be sent via different technologies such as, IEEE 802.11 standards, Bluetooth, Zigbee, LoRa, 6LoWPAN, 3G, 4G, etc., depending on the amount of data to be transmitted [5]. Although IoT systems usually deal with small amounts of data to be transmitted through short distances, in some cases it could be required to send higher amounts of data and include images to monitor the status of the plants. The two main storage systems used to save the gathered information from the sensors are traditional databases or clouds. The most used databases are MySQL and SQL, while the ThingSpeak platform is the most used in cloud systems [5].

Wireless Sensor Networks (WSNs) are needed to monitor environmental conditions and provide decision-making information and are composed of a group of spatially dispersed sensors to monitor and record environmental conditions such as, humidity, temperature, soil moisture, etc. WSNs are made up of four parts: a wireless sensor node, a gateway node, a wireless communication network, and a server [6]. Nowadays, sensor nodes have evolved to be small devices with sensing, communication, and computing devices. However, each node can only monitor a specific part of the field. Thus, the coverage area is a key problem since all nodes among a WSN must be autonomous to cooperatively pass data through the network to a main location. Moreover, its topology can vary enormously depending on the field.

Many WSN applications generally use IEEE 802.11 g/n standard because it allows distances up to approximately 300 meters in outdoor environments (when there is free space between devices) [7]. This allows a maximum raw data throughput of 54 Mbps or 600 Mbps, depending on the standard used. Likewise, the radio-frequency band can vary from 2.4 GHz to 5 GHz using Modulation Code Keying (CCK), Direct-sequence Spread Spectrum (DSSS) or Orthogonal Frequency-Division Multiplexing (OFDM) modulation schemes. Moreover, the use of this standard will reduce the cost of the deployment of the nodes as well as other time-consuming actions when processing the data.

In 2019, Bacco et al. [8] conducted a survey on SF research activities to state the achieved results and current investigations within EU territory. In this study, challenges impeding the adoption of recent technologies and techniques were highlighted. Although the current use of sensor nodes and analytic techniques is boosting Decision Support Systems (DSSs) in farms, the lack of diffusion programs is preventing areas affected by the digital divide from incorporating ICTs. Nevertheless, technology is expected to have an increasing role in agriculture so that operations, such as, planting and harvesting, may be automatized. Moreover, the availability of real-time data will allow finer control of pesticides and other chemicals. However, none of this will be possible without supporting policies to address poor telecommunication infrastructures and reduced digital skills.

As for Precision Agriculture (PA), Lindblom et al. [9] conducted a review on agricultural DSSs within the frame of the ongoing Swedish project. This project intends to identify the scientific disciplines and other competences that need to work together in developing technology for agricultural DSS. Therefore, the discussion is focused on the importance of considering in-land processes to design suitable WSNs. However, the lack of active participation in agricultural research and development processes is preventing the development of new practices and behaviours for more sustainable farming.

The effect of vegetation on radio-wave signals can be of great deal when designing such networks. Many studies have strived to evaluate and characterise land components that may affect signal strength. Still, the lack of experimental data has prevented scientists from developing generalized procedures to assess the foliage effect on attenuation. The International Telecommunication Union (ITU) recommends a series of propagation models depending not only on frequency ranges but also different link geometries and vegetation types [10]. Nonetheless, relying on prediction models in near-ground scenarios may lead on over or underestimating the networking capacities of terrestrial systems.

This paper aims to study near-ground wireless coverage in rural environments to ease multi-hop routing design. To this end, the Received Signal Strength Indicator (RSSI), the Signal to Interference Ratio (SIR), and the Round-Trip Time (RTT) of a wireless signal were measured at two orange fields, a persimmon field, and a land with no vegetation. This study attempts to determine how near-ground radio-links are affected by field components such as, grass, soil, and trunks, and examine how accurate path loss estimation models are in this type of scenarios. In all cases, we used an access point and a laptop to take measurements at different distances, 30 cm above the ground at 2.437 GHz.

The rest of this paper is structured as follows. Section II presents some related work. In Section III, several well-known propagation models are explained. The methodology and materials used in the experiment are presented in Section IV. In Section V, the experimental results are analysed. A comparison with previous works discussed in Section VI. Finally, the main conclusions and future work are exposed in Section VII.

II. RELATED WORK

Few technical works characterize near-ground radio-frequency propagation. In this section, some of the related works are discussed.

In [11], Torabi et al. proposed a near-ground prediction model to facilitate accurate WSN simulations using the principles of the Fresnel zones. In this study, the effects of antenna height, frequency, polarization, and electrical and geometrical properties of the terrain were studied. The accuracy of the proposed model was verified by comparing the theoretical results with near-ground measurements carried out in outdoor open areas at 300 MHz and 868 MHz. The results of this study showed that antenna height was by far the most influential parameter on network connectivity. Moreover, the wireless connection was proven to be sensitive to the reflection coefficient in near-ground situations.

In 2014, Yildiz et al. [12] investigated the impact of path loss models on near-ground WSN lifetime. In this study, researchers performed a comparative analysis on the effects of path loss models and proposed a novel Mixed Integer Program (MIP) to maximize WSN lifetime. By designing an effective energy dissipation system, and using empirically validated characteristics of Mica2 motes, this investigation managed to characterize the parameter space through numerical evaluations of the MIP model at four different frequencies: 315 MHz, 433MHz, and 868/916 MHz. The analysis of the results demonstrated that theoretical models, such as, the Free-Space Model and the Two-Ray Model, can lead to overestimations on WSN lifetime and should be avoided in such scenarios.

Tang et al. [13] studied a near-ground WSN at 470 MHz in four different scenarios to obtain the corresponding path loss models. To do this, measurements were taken on a flat concrete road, flat grass and two derived scenarios placing the transmitter directly on the ground. Three different antenna heights were used: 5 cm, 50 cm and, 1 m, and the RSSI was measured every meter at a distance up to 10 m, every 2 m at a distance of up to 20 m and every 5 meters at a distance of up to 50 m. The results showed that when antenna height is lower than 50 cm, prediction models tend to inaccurately forecast path loss and thus, network connectivity.

Klaina et al. [14] performed a narrowband characterization of near-ground channels for WSNs at 5G-IoT bands. In this study, RSSI signal was measured at two different heights: 0.2 and 0.4 m, to test the effects of ground coverings in path loss for three frequency ranges: 868 MHz, 2.4 GHz, and 5.8 GHz. To fit the signal strength decay caused by agriculture fields, an experimental measurement campaign was carried in agriculture fields with three types of ground: soil, short and tall grass. The path loss was estimated with a proposed narrowband radio channel model: the three-slope log-distance model. The analysis of the results demonstrated that the difference between the Free-Space model and the measured path loss is reduced with the increase in frequency. Moreover, lowering antenna heights increased attenuation.

In 2017, Klaina et al. [15] presented a narrowband radio channel model operating under near-ground conditions. To do this, a WSN based on ZigBee was designed to analyse the effects caused by soil and grass fields. In this case, radio communications were made at 868 MHz, 2.5 GHz, and 5.8 GHz. In order to estimate signal quality, RSSI was measured and compared to path loss. Finally, they concluded that the ground has no effects on RF propagation except in the cases where antenna heights were 40 cm or less. However, signal levels decreased in the presence of grass fields and soil.

Masadan et al. [16] studied the foliage effect in terms of attenuation and its contribution to the pathloss and link budget estimations. In this study, researchers quantified the path loss through 5 tree types in Malaysia for different path crossings (trunk, tree-top and branches) at 915 MHz. The analysis of the results showed that the RSSI values obtained in Line of Sight (LOS) scenarios were lower than expected due to tropical climate environment, as well as the size of the trees and density of the crowns. As for Non-Line of Sight (NLOS) scenarios, the obstructions caused diffractions, scattering of energy, and reflections that lead to larger attenuations.

In [17], Wang et al. depicted a statistical model for near-ground channels based on experimental data collected through three different scenarios at 2.4 GHz. The main objective of this study was to develop a WSN to collect data in military explosive research. To do this, sensor nodes with a 3 cm antenna height were fixed to the ground to resist damages from detonations. Different propagation models were applied to predict path loss and compare the results with the performance of the obtained model. The main conclusion of this research was that antenna height determines the breakpoint distance of the nodes.

In 2011, Lloret et al. [18] presented a WSN that uses image processing to detect bad leaves in vineyards and sends an alarm to the farmer. In this case, wireless communications are made through IEEE 802.11 a/b/g/n standard to allow long-distance connections. Although the proposed system does not identify the cause of the deficiency, it detects bad leaves and notifies it to the farmer who can then decide what actions need to be taken. This solution provides a cost-effective sensor based on IP routers that have been adapted to fulfil this purpose. The designed WSN takes into account both sensing and radio coverage areas to allow low bandwidth consumption and higher scalability. The system to detect bad leaves goes through a 5-stage process before the node decides whether an alarm needs to be sent.

In 2015, Szajna et al. [19] characterized path loss and near-ground channels at 2.45 GHz on forested areas covered by snow. This study aimed to investigate the impact of antenna height and distance between nodes on path loss and special correlation. To do this, measurements were carried out in two different scenarios: a multi-purpose sports facility and a forested area covered by 15 cm of snow. In this case, antenna heights varied from 0 to 130.8 cm and the distance between the nodes varied in steps of 15.24 m and up to 79.2 m. The analysis of the results showed that reducing antenna heights increased path loss and reduced spatial correlation.

Luciani et al. [20] described a study done on near-ground node range at different heights in Wi-Fi crowded environments. The designed WSN used IEEE 802.15.4 standard to avoid direct Wi-Fi interference. Signal quality and range were determined by collecting RSSI data of three nodes at increasing node separation distance until signal loss. To perform the tests, measures were taken at three different heights: 15 cm, 30 cm, and 100 cm, at three different scenarios. The results of this experiment showed that prediction models failed to accurately forecast path loss. Moreover, ground-loss proved to be a major issue that determines node range and thus, must be taken into account when designing WSNs.

Sangodoyin et al. [21] presented a near-ground channel model to achieve precision ranging and localization of ultrawideband (UWB) propagation channels. This experiment was performed using a self-built channel sounder with an arbitrary waveform generator and a high-bandwidth sampling oscilloscope. In this case, antenna heights ranged from 10 cm up to 2 m above ground to determine its effects on signal strength. The results showed that the distance-dependent path loss was highly dependent on antenna heights. Moreover, under near-ground situations, frequency-dependent path loss exponent and shadowing variance increased.

Though many of these studies have attempted to characterize near-ground wireless systems in rural environments, the wide range of parameters to take into account, together with the randomness introduced by foliage and its different geometries in fields, have prevented researchers from stablishing a generalized procedure to assess the design and planning of WSN.

For these reasons, in this work we present a site-specific study to guarantee the performance of near-ground radio-links in fruit plantations. To do this, measurements of RSSI, SIR, and RTT were collected at two orange tree plantations with different tree sizes, as well as a persimmon plantation and a land with no vegetation, to stablish the accuracy of six prediction models and test how distinct vegetation environments affect radio-links.

III. PROPAGATION MODELS

In this section, several propagation models are presented to predict the average signal strength drop and assess the level of accuracy that can be achieved in near-ground WSN scenarios. Thus, this section is divided into six different subsections.

A. Free-Space Model

The Free-space propagation model is the simplest way to calculate radio-signals propagation. From [12], we can extract the Free-Space propagation model based on Friis Transmission Formula. This equation is usually used when there are no obstacles in the LOS, and it is given by equation (1).

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2} \tag{1}$$

where:

P_t: transmitter power, in watts.

G_t: transmitter antenna gain.

G_r: receiver antenna gain.

λ: wavelength.

d: distance, in meters, between transmitter and receiver.

However, it is possible to calculate the losses between a transmitter and a receiver in terms of the frequency with equation (2).

$$FSPL\,(dB) = 20\log\left(\frac{4\pi\, d\, f}{c}\right) - G_T - G_R \qquad (2)$$

where:

d: distance, in meters, between transmitter and receiver.

f: frequency in Hz.

c: speed of light in the vacuum (meters per second).

G_T: transmitter antenna gain, in dBi.

G_R: receiver antenna gain, in dBi.

B. Two-Ray Ground Reflection Model

The Two-Ray Ground Reflection Model predicts path losses between a Tx and a Rx when they are both in line-of-sight but have different antenna heights. This way, the received signal has two components: the line-of-sight component and the multipath component which is given by ground reflected waves. From [12], the given equation for the Two-Ray Model can be expressed by equation (3).

$$P_r = P_t G_t G_r \frac{{h_t}^2 {h_r}^2}{d^4} \qquad (3)$$

where:

P_t: transmitter power, in watts.

G_t: transmitter antenna gain.

G_r: receiver antenna gain.

h_t: transmitter antenna height, in meters.

h_r: receiver antenna height, in meters.

d: distance, in meters, between transmitter and receiver.

Nevertheless, from the work in [13], we can tell that when radio-waves propagate near-ground in line-of-sight conditions, the path loss can be described by the plane-earth path loss formula, given by equation (4).

$$PL(dB) = 40\log(d) - 20\log(h_r) - 20\log(h_t) \qquad (4)$$

where:

d: distance, in meters, between transmitter and receiver.

h_t: transmitter antenna height, in meters.

h_r: receiver antenna height, in meters.

C. One-Slope Log-Normal Model

The log-distance path loss model is a statistical model that takes into consideration object blockage, environmental clutter, and other changes to predict path loss. From [12], the log-normal model can be described by equation (5).

$$PL\,(d) = PL(d_0) + 10n\log\left(\frac{d}{d_0}\right) + X_\sigma \qquad (5)$$

where:

PL (d): path loss at distance d, in dB.

PL (d_0): path loss, in dB, at reference distance of 1 meter (FSPL at 1 meter).

n: path loss factor (n = 2).

X_σ: zero mean Gaussian distributed variable with standard deviation σ.

σ: linear regression of measured data.

However, from reference [22] we can express One-Slope Log-Normal Model by equation (6).

$$PL\,(d) = FSPL(f, 1\,m) + 10n\log\left(\frac{d}{1\,m}\right) \qquad (6)$$

where:

PL (d): path loss at distance d, in dB.

FSPL (f, 1 m): free space path loss, in dB, at a reference distance of 1 meter.

n: path loss factor (n = 2).

d: distance, in meters, between transmitter and receiver.

D. Two-Slope Log-Normal Model

Although the Two-Slope Model is not often utilized in near-ground propagation scenarios, experimental studies on WSNs have shown that its use may result on better representations of the collected data [12]. From [20], this path loss estimation model can be expressed by equation (7).

$$PL(d_i) = \begin{cases} L_0 + 10\, n_1\, \log_{10}\left(\dfrac{d_i}{d_0}\right) & d_i \le d_b \\ L_{b+1} + 10\, n_2\, \log_{10}\left(\dfrac{d_i}{d_{b+1}}\right) & d_i > d_b \end{cases} \qquad (7)$$

where:

PL (di): path loss at di distance (in meters), in dB.

db: breakpoint distance, in meters.

L_0, L_{b+1}: path losses before and after the breakpoint, respectively.

n_1, n_2: path loss factor (n = 2).

The breakpoint distance indicates a change rate of the path loss and can be calculated by equation (8) in LOS conditions [17].

$$d_b = \frac{4h_t h_r}{\lambda} \tag{8}$$

In this case, the estimated breakpoint distance for the given dataset was 8.64 meters.

E. Okumura-Hata Model

The Okumura-Hata path loss estimation model is an empirical formulation typically used for the frequency range of 150 MHz to 1500 MHz. However, this radio propagation model identifies the signal attenuation caused by reflections, diffractions, and the scattering of energy [16]. From [23], the Okumura-Hata path loss can be calculated by equation (9).

$$L_b = 69.55 + 26.16\log(f) - 13.82\log(h_b) - a(h_m) + [44.9 - 6.55\log(h_b)]\log(d) + C \tag{9}$$

where:

f: frequency, in MHz.

h_b, h_m: Tx and Rx antenna heights in meters, respectively.

d: distance between transceiver and receiver, in kilometres.

The function a(hm) is dependent on the environment. In the case of rural areas, this correction factor corresponds to the same as in urban areas [23] and is described by equation (10).

$$a(h_m) = (1.1\log(f) - 0.7)h_m - (1.56\log(f) - 0.8) \tag{10}$$

As for the factor C, equation (11) formulates its value for rural areas [23].

$$C = -4.78[\log(f)]^2 + 18.33\log(f) - 40.98 \tag{11}$$

F. Walfisch-Ikegami Model

This empirical model is considered to have a high accuracy in urban environments when the distance between the Tx and the Rx is relatively small [23-24]. In LOS scenarios, the Walfisch-Ikegami estimation model can be described by equation (12).

$$L_{LOS}(dB) = 42.6 + 26\log(d) + 20\log(f) \tag{12}$$

where:

d: distance between Tx and Rx in the range of 20 m to 5000 m, in kilometres.

f: frequency in MHz (800-2000 MHz).

Other studies have determined that, when antenna heights are lower than 50 cm, the One-Slope Model tends to estimate path losses better than other models [13]. However, other researchers state that the use of these theoretical models can lead to overestimations of the networking capacities and should be avoided [12]. In the following sections, we will compare these six models with collected data to evaluate their performance and verify their accuracy in near-ground scenarios.

IV. Scenario Description and Tools Used

This section describes the devices used to perform the experiments, as well as the setup. Therefore, this section is segmented in four different subdivisions.

A. Place of measurement

In order to evaluate the path loss caused by vegetation in near-ground radio-wave signals, we sought out different plantations with no walls: an orange tree plantation of mature trees, an orange tree plantation of young trees, and a persimmon plantation of mature trees. Furthermore, we collected data at a land with no vegetation in order to compare and contrast the attenuation introduced by field components.

B. Hardware used

To perform this experiment, we used Linksys WRT320N-EZ router as a Tx configured to work at 2.437 GHz (channel 6) with IEEE 802.11 b/g/n standard [25]. This router has three internal antennas with 1.5 dBi of antenna gain and an RF power of 17 dBm. The Rx was ASUS Gaming Notebook GL753V, which has a 2.8 GHz Intel Core i7-7700 HQ processor, 16 GB of memory. Wireless connections are made with Intel Dual Band Wireless Wifi Bluetooth Card 7265NGW that uses the IEEE 802.11 ac standard and has two antennas of 5 dBi of gain.

C. Software used

The measurements were made using the software Vistumbler [26] to scan the wireless network and measure both the SIR and the RSSI. As for the latency of the connection, it was measured by sending a ping signal through MS-DOS commands to the gateway.

D. Set-up of the experiment

Both Tx and Rx were positioned along the same line, 30 cm above the floor to measure the SIR and the RSSI. The evaluation of the path loss of RF signals was made by taking measurements in four different scenarios.

- Scenario 1: Measurements were made on a field with no vegetation, collecting data every meter 30 cm above the ground.
- Scenario 2: Measurements were made at an orange tree plantation with mature trees, with data being collected every meter 30 cm above the ground.
- Scenario 3: Measurements were made at an orange tree plantation of young trees (3-year-old), with data being collected every 2 meters, 30 cm above the ground.
- Scenario 4: Measurements were made at a persimmon plantation, with data being collected every 2.5 meters, 30 cm above the ground.

Fig. 1 illustrates the set-up of the experiment and the vegetation geometry of Scenario 2. In order to be able to perform comparisons of the signal strength, measurements were made at the same distances in Scenario 1. Fig. 2 shows the set-up in Scenario 2. Fig. 3 exemplifies the geometry of Scenario 3 and the established set up. In Fig. 4 Scenario 3 is displayed. As it can be seen, the size of the trees is relatively small. As for Scenario 4, its geometry and set up are illustrated in Fig. 5. Fig. 6 shows the persimmon trees of Scenario 4. The noise floor in all cases was -80 dBm. Additionally, measurements were taken three times at each point.

V. EXPERIMENTAL RESULTS

In this section, the accuracy of the chosen prediction models will be verified by comparing them to near-ground measurements. First, the measured data will be examined and then prediction models will be discussed and compared with collated data.

Fig. 7 shows the RSSI levels measured in the chosen scenarios at 2.437 GHz. As the figure shows, the RSSI from Scenario 2 fluctuates much more than the one from Scenario 1. This can be due to the random distribution of vegetation, as well as the presence of trunks. Moreover, the absorption of energy in Scenario 2 may be caused by the presence of grass. In the case of Scenario 3, the RSSI signal is quite stable up until 31 meters and does not reach levels lower than -80 dBm for the first 37 meters. This can be due to the cleanliness of this land as well as the low height of these trees. As this figure shows, the coverage area of Scenario 3 is larger than in Scenario 2. Finally, the signal levels of Scenario 4 are lower than in Scenario 2, which means that persimmon trees have a greater effect on the strength of the signal than mature orange trees. However, the RSSI signal does not exceed the established noise floor up until 23.5 meters, which is the same that happened in Scenario 2.

Fig. 8 shows the SIR measured in all four scenarios. In this case, we can observe that mature orange trees from Scenario 2 do not introduce interferences up until 15 meters. However, the collected SIR data shows that mature orange trees have little effect on the quality of the signal. In Scenario 3, the interferences appear after 11 meters and its SIR levels fluctuate much more than in Scenario 2 after 19 meters and surpass the 60% after 23.5 meters. This can be caused by the reflections on the ground, as well as the short height of the trees. As for Scenario 4, interferences appear after 6 meters. This may be due to the geometry of the land shown in Figure 5. As the figure shows, the SIR levels rapidly drop. Though the signal levels do not fluctuate as much as in the rest of scenarios, its levels exceed 60% after 23.5 meters, which is the same that happened in Scenario 3, and errors may appear depending on the modulation used.

Fig. 9 shows the RTT measured during the experiment. In this case, the time delays vary far more in Scenario 2 than in Scenario 1. In the case of Scenario 3, time delays are generally lower than in Scenario 2, although the measured RSSI in Scenario 3 is higher than in Scenario 2. As for Scenario 4, persimmon trees seem to have a greater effect on time delays even though RSSI levels are higher than in Scenario 3.

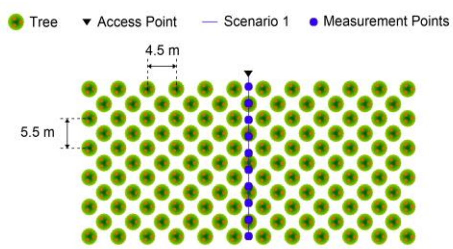

Figure 1. Vegetation geometry and measurement points of Scenario 2.

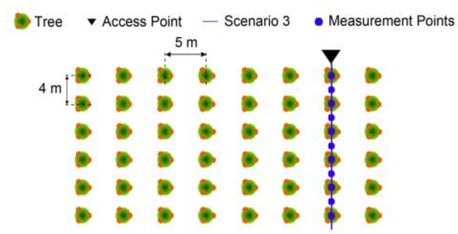

Figure 2. Vegetation geometry and measurement points of Scenario 3.

Figure 3. Scenario 2.

Figure 4. Scenario 3.

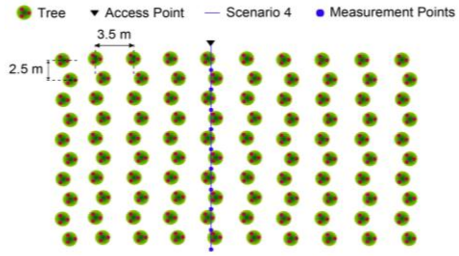

Figure 5. Vegetation geometry and measurement points of Scenario 4.

Figure 6. Scenario 4.

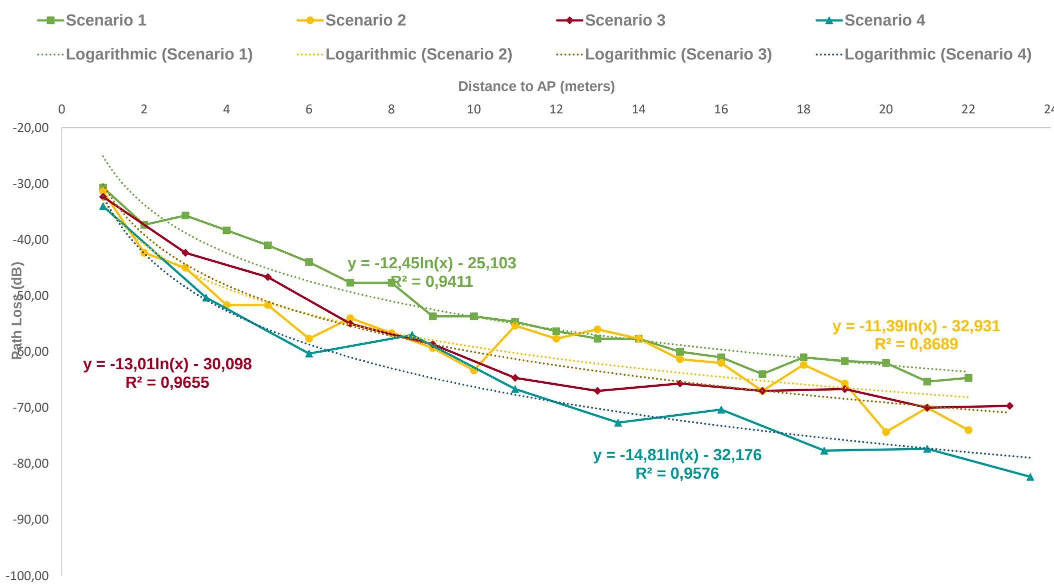

Figure 7. Measured Received Signal Strength Indicator.

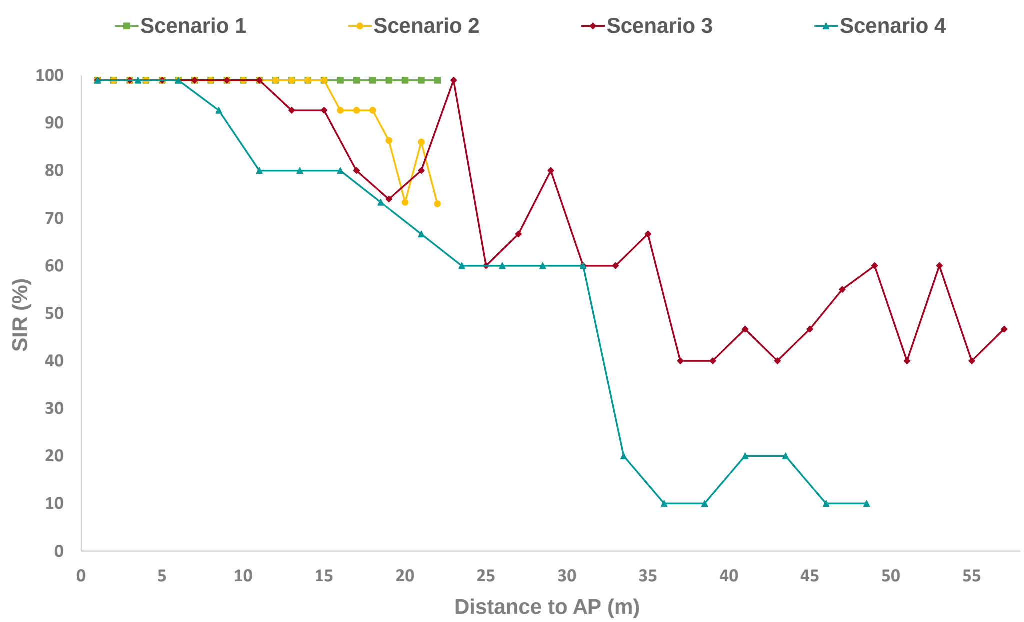

Figure 8. Measured Signal to Interference Ratio.

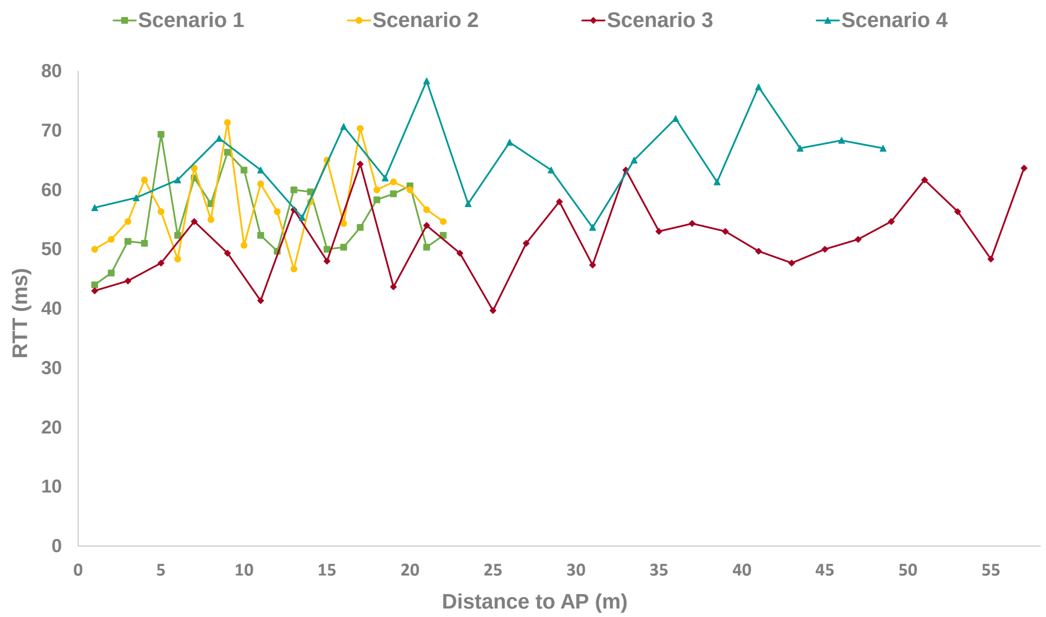

Figure 9. Measured Round Trip Time.

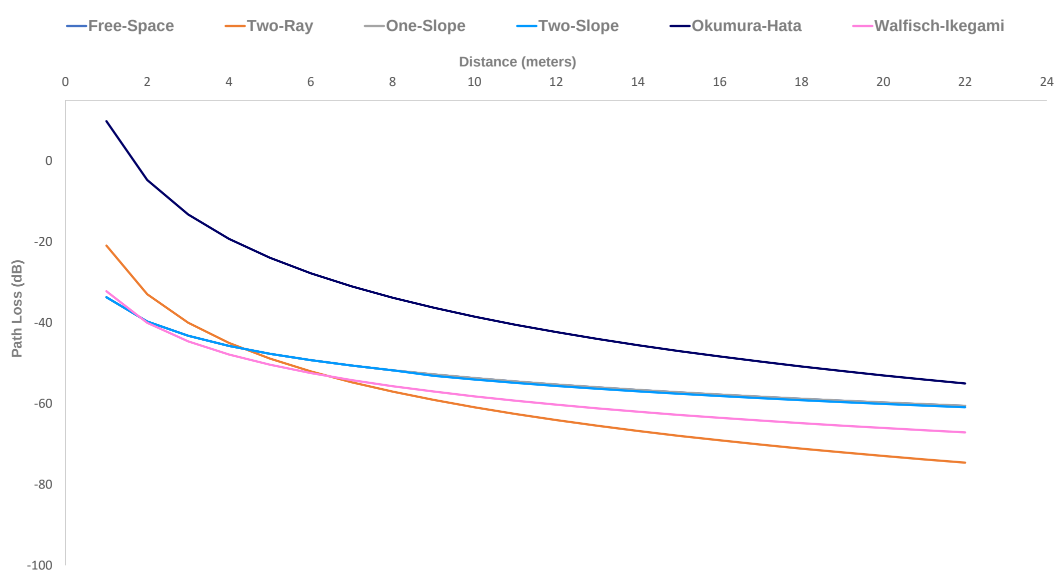

Figure 10a. Comparison of path loss models.

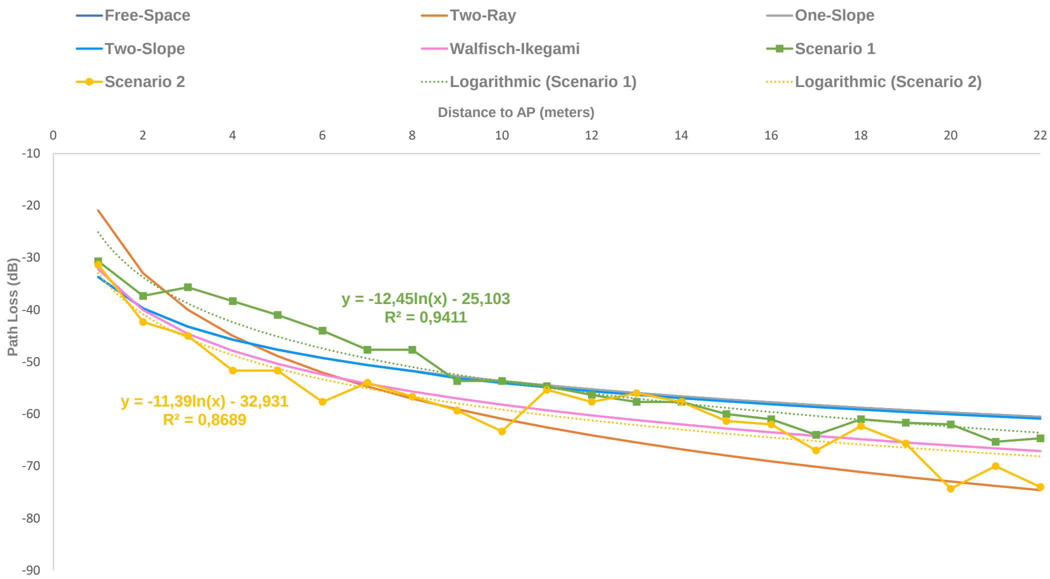

Figure 10b. Comparison of path loss models with collated data from Scenario 1 and Scenario 2.

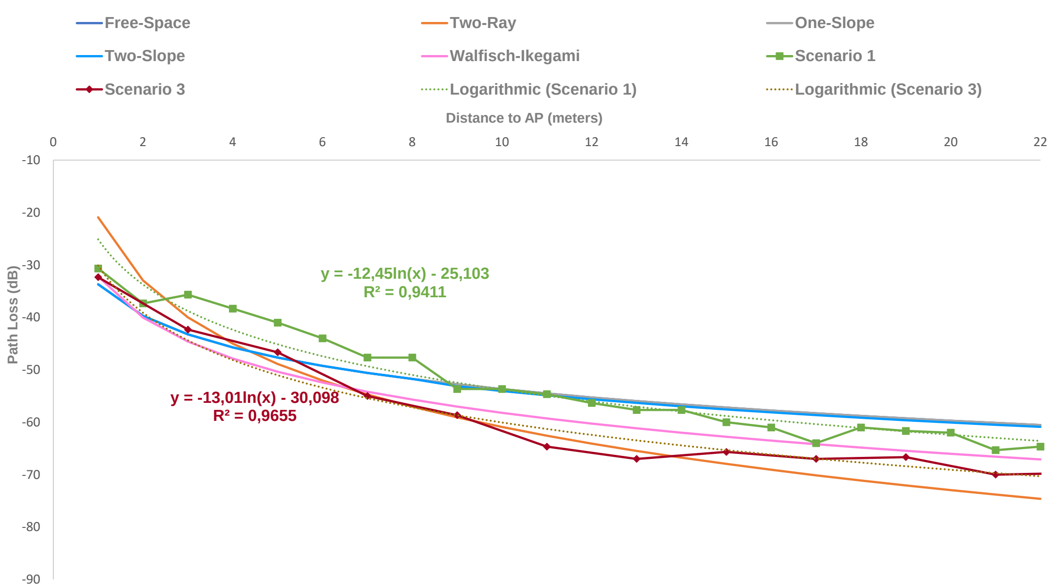

Figure 10c. Comparison of path loss models with collated data from Scenario 1 and Scenario 3.

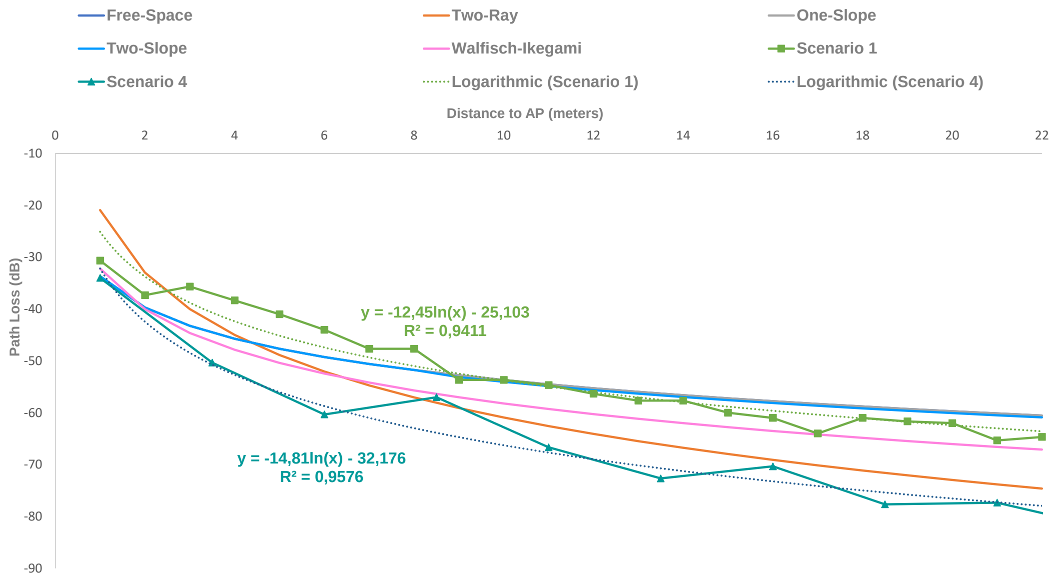

Figure 10d. Comparison of path loss models with collated data from Scenario 1 and Scenario 4.

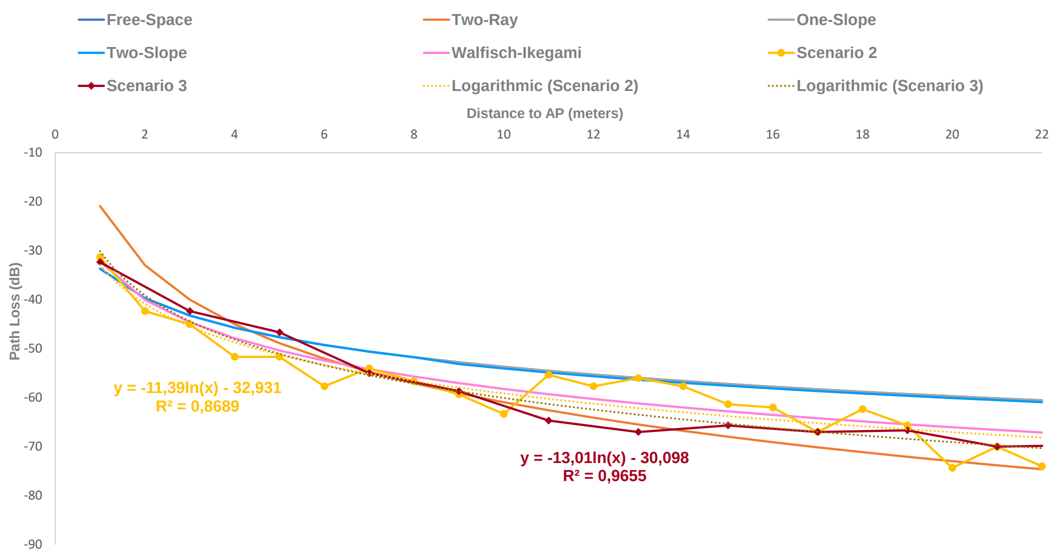

Figure 10e. Comparison of path loss models with collated data from Scenario 2 and Scenario 3.

Figure 10f. Comparison of path loss models with collated data from Scenario 2 and Scenario 4.

Finally, we compared the selected prediction models by plotting them in Fig. 10a. In this figure, Two-Slope Model overlaps both Free-Space Model and One-Slope Model. Attending to the collected data curves from Fig. 7, the path loss is higher in all three scenarios with vegetation than in Scenario 1, which proves that vegetation does in fact introduce attenuations on wireless signal. As Fig. 10a shows, the Okumura-Hata Model failed to predict the attenuation correctly and will be taken out from the graphs for a more fluent reading.

Fig. 10b shows the collected data from Scenario 1 and Scenario 2, together with the selected prediction models. In this case, the Walfisch-Ikegami prediction model is the only path loss model that accurately predicts attenuation for Scenario 1. Furthermore, the collected data from Scenario 1 shows a greater path loss than one the predicted by the Free-Space Model and the Log-Normal Shadowing Models.

In Fig. 10c, the collected data from Scenario 1 and Scenario 3 were plotted, as well as the beforementioned prediction models. However, none of the selected models succeeded foreseeing attenuation for Scenario 3. In this case, the plotted data of this scenario shows a higher attenuation than Walfisch-Ikegami Model, but lower than the path loss predicted by the Two-Ray Model.

In Fig. 10d, the collected data from Scenario 1 and Scenario 4 was plotted together with prediction models. As for the previous case, none of the selected path loss models managed to predict attenuation correctly. Persimmon trees seem to introduce much more losses than what prediction models estimated.

Fig. 10e illustrates the collected data from Scenario 2 and Scenario 3 along with the propagation models. When comparing the trendline of the path losses from both scenarios, one can clearly see that young orange trees introduce higher attenuations on the radio-wave signal than mature orange trees. The reason for this is that, although young orange trees have lighter foliage, the treetop is in line with both the Tx and the Rx. As for the previous cases, none of the selected propagation models managed to forecast path losses, which highlights the need of finding ways to predict attenuation.

Finally, Fig. 10f shows the collected data from Scenario 2 and Scenario 4 together with the selected prediction models. Although none of the selected prediction models managed to predict attenuation, it can be highlighted that the attenuation introduced by persimmon trees is much higher than the one introduced by mature orange trees.

VI. COMPARISON WITH PREVIOUS WORKS

In this section, we will discuss previous studies that have attempted to characterize near-ground wireless communications in rural environments in order to establish how frequency ranges and different testbeds may influence the results.

A comparative of similar studies is presented in TABLE I. The research in [11] demonstrated that wireless connections were fairly sensitive to the reflection coefficient in near-ground situations, achieving 101 dB of attenuation in over 14 meters. Moreover, the study performed in [12] verified that theoretical propagation models fail to characterize near-ground wireless communications. In this case, path loss reached 102 dB of attenuation in a radio network of 175 m. In [13], a near-ground WSN with a transmitter placed directly on the ground was presented, showing that prediction models fail to accurately forecast path loss when antenna heights are lower than 50 cm, although in this case, path loss surpassed 100 dB after almost 200 meters. Furthermore, the studies carried in [14-15] to design a WSN based on ZigBee under near-ground conditions showed that grass fields and soil affect signal strength, but still reached 120 meters of distance to the access point with good coverage. In [16], Okumura-Hata, Log-Normal Shadowing and foliage models were used as a reference to test their performance when comparing the predicted attenuation in tropical environments. However, none of these models managed to accurately predict path loss in tropical environments, which demonstrates the importance of characterizing foliage attenuation in different environments. In this case, path loss exceeded 100 dB after 13 meters. The statistical model described in [17] demonstrated that antenna height determines coverage area and that propagation models fail to accurately forecast path loss. However, path loss only surpassed 100 dB after 100 m. In [18], the presented solution did manage to detect bad leaves. However, in this case, vegetation loss was not introduced into the power balance formula and no information was given about the amount of attenuation. The study performed in [19] concluded that reducing antenna heights increased path loss, though this investigation was carried out in forested areas covered by snow where attenuation reached 96 dB after almost 40 m. Moreover, the study depicted in [20] demonstrated that ground-loss is a major issue when determining node range. Nevertheless, this experiment was performed in Wi-Fi crowded environments and after 30 m attenuation reached 100 dBm. The experiment performed in [21] to characterize near-ground UWB propagation channels showed that the node range is highly dependent on antenna heights and only reached 75 dB after 200 meters.

As it can be seen on TABLE I, our work expands the knowledge on this area by including the most common prediction models used in near-ground scenarios, and other propagation models that identify reflections, diffractions, and scattering. Furthermore, we attempted at testing these prediction models by measuring at different heights than the ones employed in other existing works.

TABLE I. COMPARATIVE OF TESTBEDS OF STUDIES ON THE EFFECTS OF VEGETATION ON NEAR-GROUND WIRELESS SIGNALS

Authors	Year	Frequency	Tx height	Rx height	Models					Path Loss
					Free-Space	*Two-Ray*	*One-Slope*	*Two-Slope*	*Others*	
Torabi et al. [11]	2015	300 MHz, 868 MHz	13 cm, 0.87 m, 1.15 m, 1.55 m, 2 m	0.4 – 1.8 m	-	YES	-	-	-	32 - 101 dB
Yildiz et al. [12]	2014	315 MHz, 433 MHz, 868/916 MHz	< λ	< λ	YES	YES	YES	YES	-	31 – 102 dB
Tang et al. [13]	2019	470 MHz	5 cm, 50 cm, 1 m	5 cm, 50 cm, 1 m	YES	YES	YES	YES	Walfisch-Ikegami	57 – 115 dB
Klaina et al. [14]	2018	868 MHz, 2.4 GHz, 5.8 GHz	0.2 m, 0.4 m	0.2m, 0.4 m	YES	-	-	-	Three-Slope Log-Normal	0 – 37 dB
Klaina et al. [15]	2017	868 MHz, 2.5 GHz, 5.8 GHz	20 cm, 40 cm	20 cm, 40 cm	YES	-	-	-	-	31 – 90 dBm
Masadan et al. [16]	2019	915 MHz	0.65 - 4.5 m	0.19-1.4 m	YES	-	YES	YES	Okumura-Hata	83 – 104 dB
Wang et al. [17]	2012	2.4 GHz	3 cm, 1 m	1 m, 2 m	YES	YES	YES	YES	-	40 – 109 dB
Lloret et al. [18]	2011	2.44 GHz	6 m	6 m	YES	-	-	-	-	-
Szajna et al. [19]	2015	2.45 GHz	0 cm, 86.4 cm, 130.8 cm	0 cm, 86.4 cm, 130.8 cm	-	-	-	YES	-	60 – 96 dB
Luciani et al. [20]	2013	2.48 GHz	15 cm, 30 cm, 100 cm	15 cm, 30 cm, 100 cm	-	YES	-	-	-	60 – 100 dBm
Sangodoyin et al. [21]	2016	3–10 GHz	10 cm, 20 cm, 50 cm, 200 cm	10 cm, 20 cm, 50 cm, 200 cm	-	-	-	-	Distance & Frequency Dependent Pathloss Models	20 – 75 dB
Our proposal	2020	2.4 GHz	30 cm	30 cm	YES	YES	YES	YES	Okumura-Hata Walfisch-Ikegami	31 - 82 dB

VII. Conclusion and Future Work

In this paper, we attempted to determine how near-ground radio-waves are affected by field components such as, grass, soil, and trunks. To this end, we performed an experiment at four different scenarios: a land with no vegetation, an orange tree plantation with mature trees, an orange tree plantation with young trees, and a persimmon field, where measurements were taken 30 cm above the ground.

In this case study, we analysed the signal quality by measuring the RSSI, the SIR and the RTT of a wireless signal and compared the collated data with six different path loss prediction models. The results showed that, in near-ground scenarios, the RSSI tends to fluctuate much more in the presence of vegetation. In other terms, the geometry of the trees and the presence of grass produce a scattering of energy and a higher number of reflections and refractions. However, the interference was only noticeable at the persimmon field, where noise was introduced from 6 meters. As for the selected prediction models, Walfisch-Ikegami Model managed to accurately predict attenuation for Scenario 1. However, none of the presented path loss models managed to accurately forecast path loss for Scenario 3 and Scenario 4, and Okamura-Hata Model failed capturing the effect of vegetation.

As future work, we would like to include in the experimental test different types of plantations and agriculture environments, such as, vineyards [18]. Moreover, it would be interesting to test other propagation models to verify their accuracy in near-ground scenarios. Another important point for future researches would be introducing simulation models to effectively design and plan wireless networks in near-ground scenarios with vegetation. Additionally, it could be interesting to perform these practical experiments with other technologies such as, LoRa [27], Zigbee and Sigfox which are currently being used in farming activities and compare them with the results of IEEE 802.11 standard.

Acknowledgment

This work has been partially supported by European Union through the ERANETMED (Euromediterranean Cooperation through ERANET joint activities and beyond) project ERANETMED3-227 SMARTWATIR, by the “Ministerio de Ciencia, Innovación y Universidades” through the “Ayudas para la adquisición de equipamiento científico-técnico, Subprograma estatal de infraestructuras de investigación y equipamiento científico-técnico (plan Estatal I+D+i 2017-2020)” (project EQC2018-004988-P), by the Universidad de Granada through the "Programa de Proyectos de Investigación Precompetitivos para Jóvenes Investigadores. Modalidad A jóvenes Doctores” of "Plan Propio de Investigación y Transferencia 2019" (PPJIA2019.10) and by the Campus de Excelencia Internacional Global del Mar (CEI·Mar) through the "Ayudas Proyectos Jóvenes Investigadores CEI·Mar 2019" (Project CEIJ-020) and by the "Ministerio de Economía y Competitividad" in the "Programa Estatal de Fomento de la Investigación Científica y Técnica de Excelencia, Subprograma Estatal de Generación de Conocimiento" within the project under Grant TIN2017-84802-C2-1-P.

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