Near-Ground Wireless Coverage Design in Rural Environments

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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 when forecasting near-ground path losses. This paper aims at determining how the 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 the results are compared with 3 prediction models: the Free-Space Propagation Model, Two-Ray Ground Reflection Model and, One-Slope Log-Normal Model. The experiment was carried out by collecting experimental data at two different locations, i.e., an orange tree plantation and a field without vegetation, taking measurements every meter. A comprehensive analysis of the influence of rural environments can help to obtain better near-ground WSN performance and coverage in precision agriculture.**

Keywords—Wireless network coverage; IEEE 802.11; Precision agriculture; Propagation Losses; Free-Space Propagation Model; Two-Ray Ground Reflection Model, One-Slope Log-Normal Model.

I. INTRODUCTION

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 but increases production and reduces the environmental impact. Since the United Nations expects the world population 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 [1]. As it is, smart farming applies measures ecologically meaningful and site-specific, focusing on implementing auto-piloted harvesters and other farm machinery to achieve the smartest treatment [2].

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 [3]. 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 and the distance [4]. Nevertheless, IoT systems usually deal with small amounts of data to be transmitted through short distances. 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 [4].

Wireless Sensor Networks (WSNs) are needed to monitor environmental conditions and provide decision-making information. This type of networks is 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 [5]. With the evolution of microelectronic technology, 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.

Whatever WSN application may be, IEEE 802.11 g/n standard is generally used in WSN because it allows distances up to approximately 300 meters in outdoor environments (when there is free space between devices) [5]. 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.

In 2019, Bacco et al. [7] conducted a survey on SF research activities to state the achieved results and current investigations within EU territory. As a result, 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 these will be possible without supporting policies to address poor telecommunication infrastructures and reduced digital skills.

As for Precision Agriculture (PA), Lindblom et al. [8] 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

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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.

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 an orange field. This study aims to determine how near-ground radio-links are affected by field components such as grass, soil, trunks, etc. In this experiment, measurements were made at two different scenarios: one without vegetation and one at an orange tree plantation. In both cases, we used an access point and a laptop to take measurements at different distances, 30 cm above the ground.

The rest of this paper is structured as follows. Section II presents some related works. In Section III, the most popular 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. Finally, the main conclusions and future work are exposed in Section VI.

II. RELATED WORKS

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

In 2011, Lloret et al. [9] 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 [10], 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 were fixed on the ground and had an antenna height of 3 cm 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.

Luciani et al. [11] 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.

In 2015, Szajna et al. [12] 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.

In [13], 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. 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 fairly sensitive to the reflection coefficient in near-ground situations.

Sangodoyin et al. [14] 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.

In 2017, Klaina et al. [15] presented a narrowband radio channel model operating under near-ground conditions [15]. 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, 2.4 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.

Tang et al. [16] 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 m 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.

After analysing previous works, we can conclude that near-ground wireless systems are difficult to characterize. In [9], the presented solution did manage to detect bad leaves. However, in this case, vegetation loss was not introduced into the power balance formula. The statistical model described in [10] demonstrated that antenna height determines coverage area and that propagation models fail to accurately forecast path loss. Moreover, the study depicted in [11] demonstrated that ground-loss is a major issue when determining node range. Nevertheless, this experiment was performed in Wi-Fi crowded environments. The study performed in [12] concluded that reducing antenna heights increased path loss, though this investigation was carried out in forested areas covered by snow. The research in [13] demonstrated that wireless connections were fairly sensitive to the reflection coefficient in near-ground situations. The experiment performed in [14] to characterize near-ground UWB propagation channels showed that the node range is highly dependent on antenna heights. Furthermore, the study carried in [15] to design a WSN based on ZigBee under near-ground conditions showed that grass fields and soil affect signal strength. Finally, in [16], a near-ground WSN where a transmitter was placed directly on the ground was presented, showing that prediction models fail to forecast path loss when antenna heights are lower than 50 cm.

For the reasons stated above, in this work, we present a site-specific study to guarantee the performance of near-ground radio-links in orange tree plantations.

III. ANALYTICAL STUDY

In this section, three 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 three different subsections.

A. *Free-Space Model*

The Free-space propagation model is the simplest way to calculate radio-signals propagation. From [17], 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 line-of-sight, 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 (Tx) and a receiver (Rx) in terms of the frequency with equation (2).

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

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 [17], the given equation for the Two-Ray Model can be expressed by equation (3).

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

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 [16], 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).

$$PL(dB) = 40\log(d) - 20\log(h_r) - 20\log(h_t) \tag{4}$$

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 [17], the log-normal model can be described by equation (5).

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

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 [18] 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.

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 [16]. However, other researches state that the use of these theoretical models can lead to overestimations of the networking capacities and should be avoided [17]. In the following sections, we will compare these three models with collated 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 in near-ground radio wave signals, we sought out an orange tree plantation with an area of 1.775 m^2, with a length and a width of 71 m by 25 m, with no walls.

B. Hardware used

To perform this experiment, we used Linksys WRT320N-EZ router as a Tx configured to work at 2.4GHz with IEEE 802.11 b/g/n standard [19]. 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 [20] 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 two different scenarios.

- Scenario 1: Measurements were made at an orange tree plantation, with data being collected every meter 30 cm above the ground.
- Scenario 2: Measurements were made on a field with no vegetation, collecting data every meter 30 cm above the ground.

Fig. 1 illustrates the set-up of the experiment at the orange tree plantation. In order to be able to perform comparisons of the signal strength, measurements were made at the same distances in both scenarios. Fig. 2 shows the set-up in Scenario 1. The noise floor in both cases was 80 dBm. 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 to collated data.

Fig. 3 shows the RSSI levels measured in the chosen scenarios. The RSSI from Scenario 1 fluctuates much more than the one from Scenario 2. This can be due to the random distribution of vegetation, as well as the presence of trunks. Moreover, the absorption of energy in Scenario 1 may be caused by the presence of grass.

Fig. 4 shows the SIR measured in both scenarios. It can be inferred that the presence of vegetation has little effect on the quality of the signal, though the reflection on the ground may cause errors depending on the modulation used.

Fig. 5 shows the RTT measured during the experiment. In this case, the time delays vary far more in Scenario 1 than in Scenario 2. This agrees with the observed fluctuations of RSSI in Scenario 1.

In Fig. 6, One-Slope Model was plotted as a function of the logarithm of the distance, in meters. The accuracy of this model was validated by performing its trend line and the related R-squared value. As Fig. 6 shows, the trend line that best fits the plotted data has a linear tendency and an R-squared value of 1.

Finally, we compared the selected prediction models by plotting them together with the collected data from both scenarios in Fig. 7. In this figure, One-Slope Model overlaps Free-Space Model. Attending to the collected data curves, the path loss is higher in Scenario 1. However, the Two-ray Model failed to predict the attenuation correctly. Furthermore, the collected data from Scenario 2 shows a greater path loss than one the predicted by the Free-Space Model and the One-Slope Model.

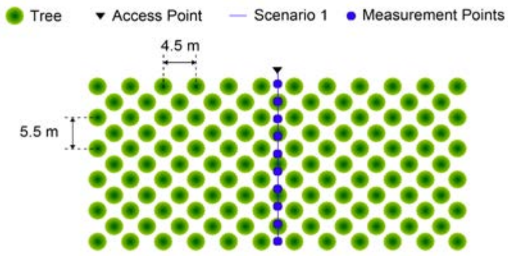

Figure 1. Vegetation geometry and measurement points.

Figure 2. Measurement scenario.

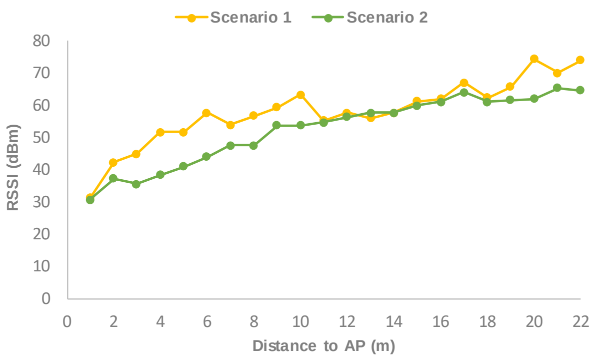

Figure 3. Measured Received Signal Strength Indicator.

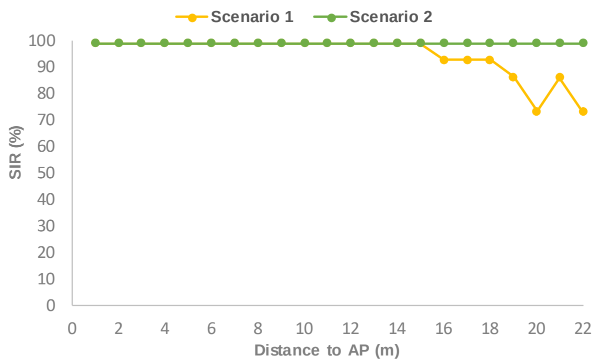

Figure 4. Measured Signal to Interference Ratio.

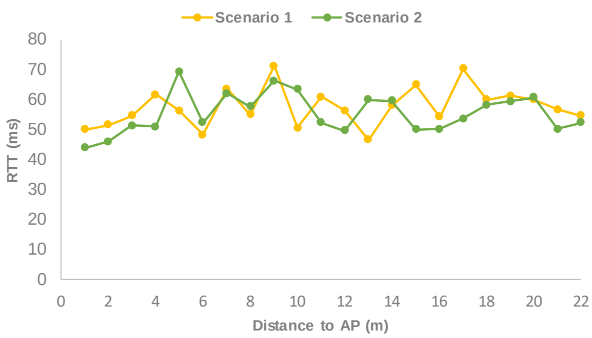

Figure 5. Measured Round Trip Time.

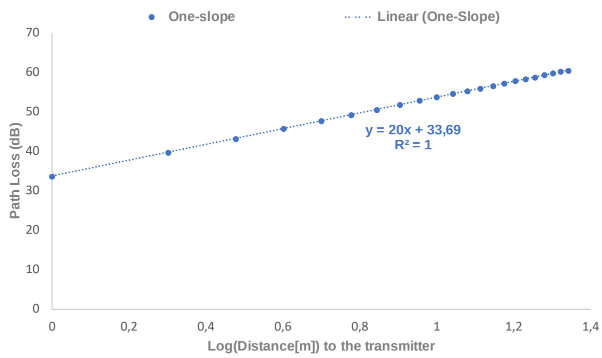

Figure 6. Log-normal Path Loss Model (One-Slope).

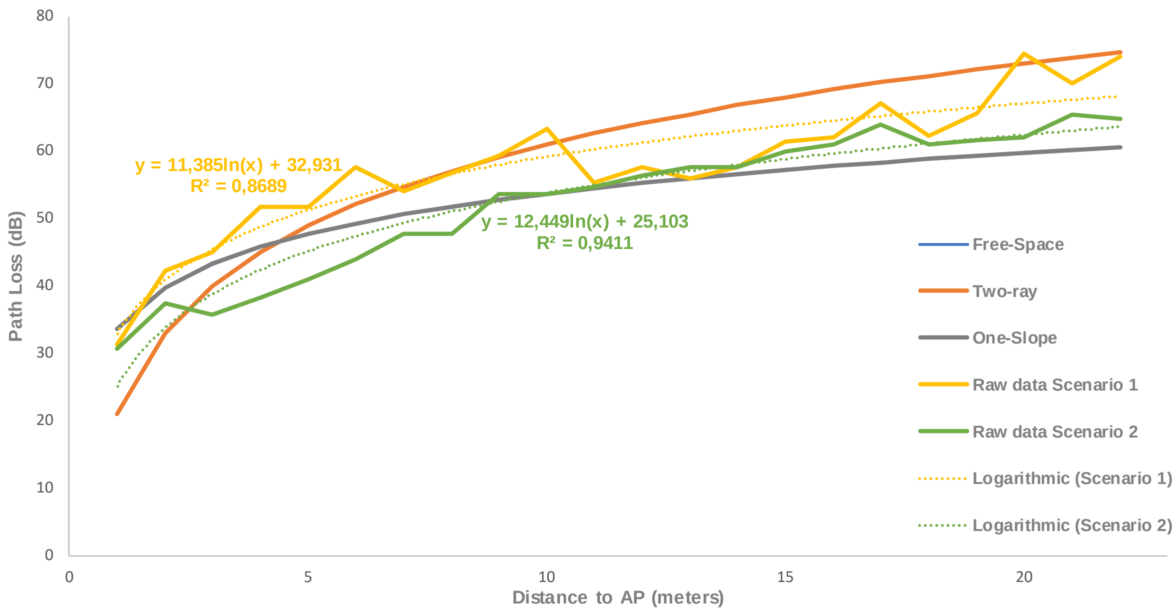

Figure 7. Comparison of path loss models with measured data from Scenario 1 and Scenario 2.

VI. 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 two different scenarios: one with vegetation and one without vegetation, 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 three 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 (Scenario 1). In other terms, the geometry of the trees and the presence of grass produced a scattering of energy, as well as a higher number of reflections and refractions. However, the interference was only noticeable from 15 m. As for the selected prediction models, none of them managed to accurately forecast the path loss, though Free-Space Model and One-Slope Model were close to the measured RSSI of Scenario 2.

As future work, we would like to include in the experimental test different types of plantations agriculture environments such as vineyard [9]. Additionally, it could be interesting to perform these practical experiments with other technologies such as LoRa [21], Zigbee and Sigfox which are currently being used in farming activities and compare them with the results of IEEE 802.11 standard.

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