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Ask the Plants Directly: Understanding Plant Needs using Electrical Impedance Measurements

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Abstract

Food security is a major problem nowadays. Ensuring enough food for the entire human population is becoming harder due to climate change and world population growth. Smart agriculture is a promising solution: integrating sensors and data analysis in agriculture is leading to a reduction of food production waste and an increase in production yield. However, currently environmental monitoring is not sufficient since different plants may have disparate reactions even if their environmental conditions are similar. This paper shows a novel way of understanding plant status based on direct measurement of in-vivo stem electrical impedance. This was achieved with a system designed by the authors and validated by showing relations (correlation and Granger's causality) between stem electrical impedance and environment parameters. Validation was accomplished by monitoring and analyzing multiple plants at the same time. Statistical analysis showed a correlation of up to 95% between impedance and soil moisture, and that soil moisture variations caused variation in the impedance of the plants.

Keywords— Impedance measurements, in-vivo, sensor system, plant health

1 Introduction

The world's population is growing, and it is expected to reach over 10 billion this century, as stated by UN. Population Division (2019). Furthermore, arable lands on the planet are decreasing. Although this is mainly due to urbanization in some regions (such as northern Europe), this is not the case for warmer climate territories. As stated by the European Environment Agency (2020), by Burrell et al. (2020), and by Mahato (2014), the reduction of arable lands is primarily due to both climate change and land usage. Arable land reduction and world population growth are the two main factors causing the problem of food security. Producing enough food to feed the entire world population is becoming critical, and new approaches are needed to face this issue.

Smart agriculture can improve food production and, therefore, food security. Sensors and electronics are used to monitor and intervene in every aspect of the food chain, from crops to final consumers. Integrating sensor data with farmers' experience leads to increased production and reduced waste of resources: monitoring climate and crops condition enables the actuation of a precise watering strategy, reducing the use of pesticides (Berenstein and Edan 2017), and increasing crop yield. Currently, environmental parameters are widely inspected, and numerous examples are present in literature (Garlando et al. 2020a). Indirect measurement is the most adopted solution nowadays. Custom weather stations are present in literature, like the ones presented by Tenzin et al. (2017) and Kasama et al. (2019). Soil is another important category of parameters widely considered by the research community. Soil moisture, in particular, is a key factor in the wellness of plants. Different approaches to measuring soil moisture are available. Nakayama et al. (2008) inspected soil thermal conductivity and capacity while Daskalakis et al. (2014) detected soil moisture level with a receiving antenna which performed signal frequency modulation.

However, measuring environmental conditions is not enough to understand plant status. Therefore, another approach is to monitor plant parameters directly. For example, Ramos-Giraldo et al. (2020) measured water stress with a camera pointed at plants and not by inspecting the soil. Similarly, Palazzi et al. (2019) stated that comparing leaf temperature with that of air makes it possible to perform soil moisture measurements. Thus the sensor they developed is clipped on a leaf. It measures leaf and air temperature and sends valuable data to the farmer to understand when to irrigate the fields. These examples require expensive and special sensors, making this approach difficult to implement.

It has been discovered that valuable information regarding plant status can be derived inspecting plant electrical impedance. Garlando et al. (2020b) discovered that stem electrical impedance rises when the plant dries out and drops after it gets watered. It means that by evaluating in-vivo plant stem impedance over time, it is possible to understand when the plant needs to be watered. Therefore, focusing on electrical impedance measurements could pave the way to developing small, low-cost, smart devices specifically monitoring each plant in the target field. In-vivo plant electrical impedance analysis was also carried by Bar-On et al. (2021). They extracted a lumped element model to mimic the behavior of stem impedance with respect to the injected signal frequency. Their studies have been conducted on *Nicotiana Tabacum* plants. Although it represents a step forward in deepening the knowledge of stem electrical impedance behavior, at the moment, it has not been developed to provide high-level information in real-time. Borges et al. (2012) had also performed *Electrical Impedance Spectroscopy* and Kobata and Honda (2014) exploited *Finite Element Modeling* to solve partial differential equations and infer information about a plant's status. Similarly, Corono-Lopes et al. (2019) applied *Electrical Impedance Tomography* to the volume in proximity of plant roots to achieve pathogen detection. Differently from previous authors, Jinyang et al. (2016) implemented a technique to diagnose potassium stress. The technique relies on impedance spectroscopy of tomato plant leaves carried out in a wide range of frequencies. Analyzing their response with respect to frequency, they extract a model to detect the lack of potassium. Apart from Garlando et al. (2020b) who presented a first approach meant to be expanded further, these latter studies concerned with complex, time-consuming, and not real-time or in-vivo techniques.

Our approach was to monitor in-vivo plant stem impedance: impedance variations are then analyzed to assert their relation with external parameters. Our ultimate long-term goal is to remove all the environmental sensors and rely on direct measurement of plant parameters only, eventually placing the sensors directly on the plants themselves and leveraging the stem as the communication channel among them as done by Motto Ros et al. (2019).

Our experiments used a bench impedance analyzer and a dedicated sensor node to determine relationships among electrical impedance and environmental data. Sensors collected data regarding soil moisture level, air temperature and humidity, and ambient light intensity. At the same time, a multiplexer-based system (described in section 2) analyzed stem electrical impedance of multiple plants simultaneously. The sensor node improved a prototype presented by Bar-on et al. (2019b).

The paper is organized as follows. Section 2 describes the measuring system and how measurements were performed. Section 3 shows measurement results and the statistical analysis performed on data. Finally, conclusions are derived in section 4.

2 Materials and Methods

In this section, the different components of the presented system are depicted. The novel measuring system measures both environmental parameters and plants stem impedance. Furthermore, plants used in the experiments are also introduced.

2.1 Impedance measuring system

Impedance measurements were performed using a Keysight 4294A impedance analyzer. It is a bench instrument ranging from 40 Hz to 100 MHz used to acquire accurate impedance values in this stage of the analysis. A four-wire measuring system was adopted (Bar-on et al. 2019a) to increase accuracy and reduce error due to interconnections. Implementing the four-wire measuring system was possible thanks to the use of two *Kelvin*'s clips per plant and connecting instrument wires as reported by Janesch (2013). Each clip contains two of the four wires needed for this measurement methodology. In these devices, a force-and-sense pair is connected to a single clip (one per jaw). The same instrument was used to monitor multiple plants, thanks to a multiplexing system. Each channel of the impedance analyzer was connected to up to four plants thanks to commercial multiplexers. Multiplexers are based on relays: two relays connect both the signal and ground terminal of two BNCs. In this way, cables coming from the impedance analyzer are alternatively connected to up to four plants. The selected multiplexers have a serial interface that was used to control the relays and change the interconnections. A Raspberry Pi was used to send control commands to the multiplexers. The impedance analyzer was connected to a PC running a LabVIEW program that managed the measurement procedure and stores impedance spectra. The LabVIEW script was synchronized with the multiplexing control in order to sample the plants under test. Small stainless steel needles, 0.4 mm diameter, were inserted into each plant stem, as depicted in Figure 1. Needles were placed at a distance of 5 cm, with the bottom one placed 3 cm above the ground. Kelvin clips were used to connect the electrodes inserted in the plant stems to the instrument. Impedance measurements were triggered every 15 minutes, resulting in a sampling period of one hour for each plant.

2.2 Environment sensing node

A sensor node for the environmental parameters was also developed. It was used to monitor parameters surrounding the plant under test. In particular, the sensor node measured light intensity, ambient temperature, relative humidity, and soil moisture. Other essential soil parameters were not considered to reduce sensor

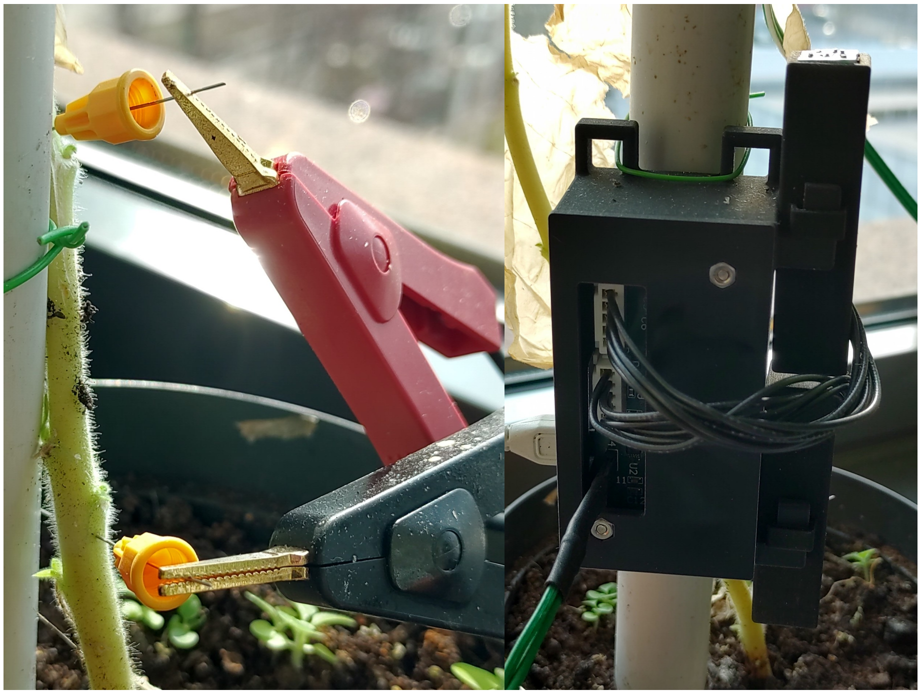

Figure 1: Pictures of the measuring system. Left: detailed view of the needles and kelvin clips used to measure impedance of the stem. Right: sensor case for environmental measurements. The central box contains the Raspberry Pi with the custom designed PCB. The two small boxes connected with the cables hold the temperature, humidity and light sensors. The green cable connects the Watermark sensor.

node cost and complexity. Moreover, soil moisture has been considered to be the leading parameter affecting stem impedance. It is probably the most analyzed soil parameter and one of the easiest ones to inspect. Nevertheless, not considering other soil parameters can be a system's limitation since some of them, such as soil salinity or nutrient concentration, may influence stem electrical impedance. A custom PCB to be placed on top of a Raspberry Pi ZERO W was developed. In this way, wireless communication was used to configure the nodes and acquire data. The PCB has two headers for I^2C connection to external sensors. Temperature, humidity, and light sensors were mounted on a small PCB connected to the central one. Two integrated circuits were used to monitor those parameters. The former is a Texas Instruments (TI) HDC2080, a digital sensor that embeds an ADC and can sample temperature and relative humidity. It has excellent accuracy and very low power consumption. The latter is a TI OPT3001, an ambient light sensor with automatic range detection and low power capabilities. Short wires were used to connect the two boards to the main system. Furthermore, it is possible to add other sensors in future applications using an empty header already available on the board.

A different approach was needed for the soil moisture sensor. An Irrometer Watermark sensor was used to measure soil water tension. It is a gypsum block, and its resistance changes depending on soil moisture level. The manufacturer provides a curve that relates resistance values to moisture ones. The soil moisture level is provided in kPa since it is derived from soil water potential. This is defined as the amount of energy required for a plant to perform work to extract moisture from the soil, and it is evaluated per unit of volume: thus soil moisture unit of measure turns out to be a pressure. Moisture values extracted by the sensor are negative since it performs differential measurements: the read gypsum's resistance is compared with a reference one assessed in an environment with known humidity conditions. In the sensor's datasheet, it is reported that moisture values below -200kPa must be discarded since they exceed the lowest value this sensor can accurately detect. The main issue with this sensor is that a DC current flowing inside its electrodes could damage the device. Therefore, a pseudo-AC circuit is suggested: a multiplexer rapidly connects and disconnects the sensor terminal to VDD and GND. However, this solution is needlessly complex for our case: it enables connecting multiple sensors to the same system, but only one was used in the actual sensor node. Therefore, another approach was adopted in order to reduce complexity and avoid sensor damage. The schematic of the designed circuitry is depicted in Figure 2.

The idea was to use a timer with the watermark sensor in the feedback loop. In this way, the resistance value of the sensor affects the frequency generated by the timer ensuring only AC in the sensor. Furthermore, a power switch, a SiP32432 from Vishay Siliconix, was used to reduce power consumption. When the *Sensor On* signal is "low", the power source is disconnected from the timer portion of the circuit. When it is "high", the timer is correctly powered, and it generates a frequency signal that the Raspberry processor can read.

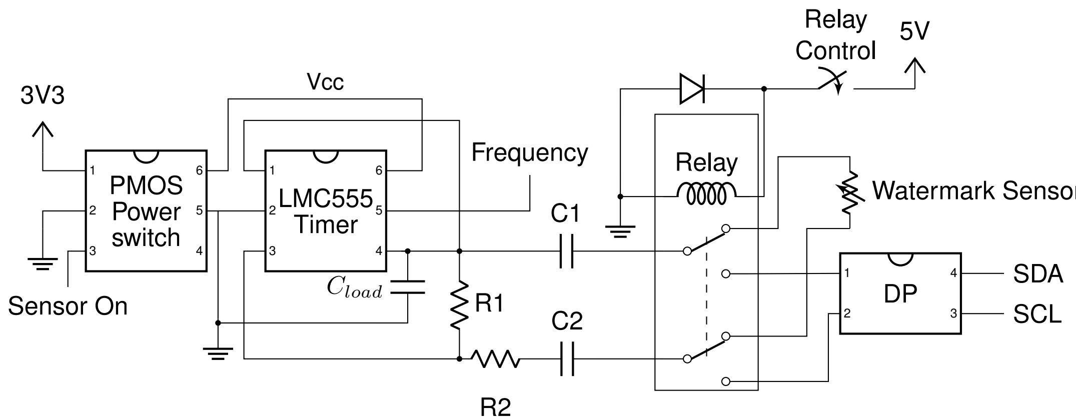

Figure 2: Schematic of the watermark sensor reading circuitry

A TI LMC555 timer was used in this case. *Pin 2* and *pin 6* of the timer were used to provide ground and power supply, respectively. *Pin 3* is the output of the timer: this signal is connected to the load capacitor C_{load} through the resistive network formed by R1, R2, and the watermark sensor. These two resistors were used to set minimum and maximum frequency: when the watermark sensor is disconnected or fully dry, R1 limits the current in the load and, therefore setting the minimum frequency. Similarly, when the watermark sensor is fully wet, and its resistance is almost zero, R2 can be considered in parallel with R1, thus setting the maximum frequency. The two capacitors, C1 and C2, are used to block the DC component flowing in the sensor in series with the sensor. Threshold (*Pin 1*) and trigger (*Pin 4*) pins are both connected to C_{load}. In this way, the timer works in direct feedback mode, where its output charges the capacitor, and the same value is used to trigger the polarity change in the timer. Finally, *Pin 5* is the discharge pin: it is an open collector output that changes the timer's output pin accordingly. The Raspberry sensed this signal to measure the generated frequency. Frequency range can be defined by selecting the values of the components. C_{load} was set to 0.1µF while R1 and R2 to 150kΩ and 390Ω respectively. A value of 4.7µF was selected for both C1 and C2. With those values, the generated frequency ranges from about 50Hz to 14.5kHz.

A relay was used to disconnect the watermark circuitry when it is not measured. A reed relay with a nominal coil voltage of 5 V was inserted in the circuitry. In this way, it was possible to activate the relay

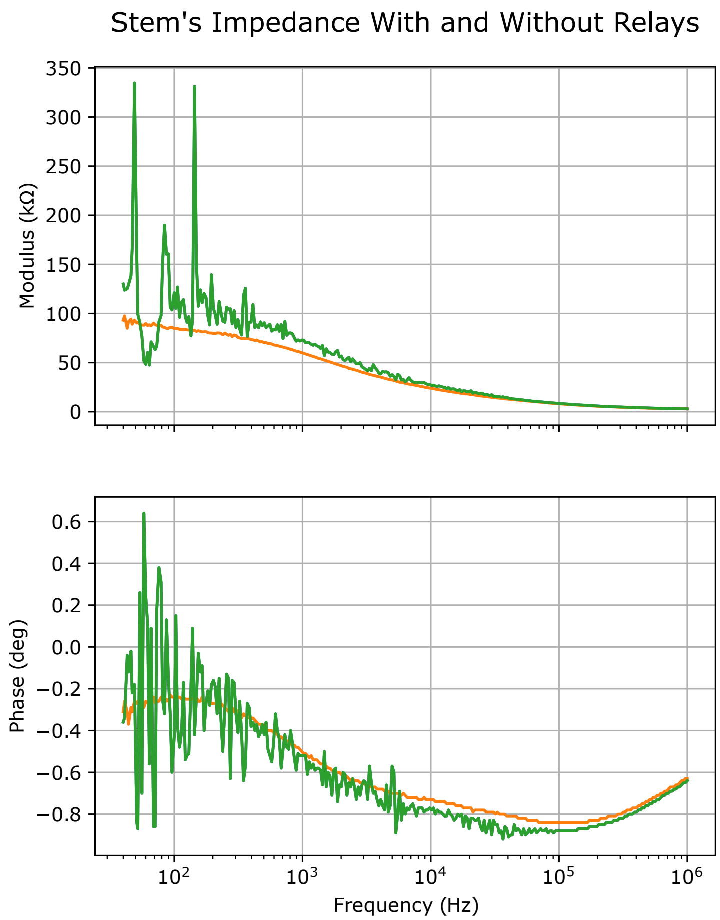

Figure 3: Impedance modulus and phase of the same plant when the watermark sensor is connected to the reading circuitry (green lines) and with the relay used to disconnect it (orange lines). The measurements were taken a few minutes away from each other in order to have similar conditions.

with the 5 V pin of the Raspberry Pi and a power switch controlled by an enabling signal. A reed relay was selected instead of a solid-state one to ensure galvanic isolation of the sensor when it is not needed. In this way, any potential noise injected by the reading circuitry is avoided. Furthermore, ground loops can be prevented thanks to this solution. This is not achievable with other kinds of switches. Moreover, an automatic calibration function was implemented. A digital potentiometer, AD5272 by Analog Devices, provides resistance values to the timer circuit. In particular, this potentiometer has a 1% tolerance on the selected resistance value. Therefore it is suitable for a calibration procedure. During the calibration, specific resistive values were selected. The Raspberry set the potentiometer values via I^2C communication and read the frequency generated by the timer. Acquired pairs are stored in memory, and when the watermark sensor is measured, the resistance is interpolated from calibration data. The entire procedure can be performed automatically, thanks to the adoption of a double SPDT (Single Pole Double Throw) relay. When it is not powered, the timer circuitry is connected to the potentiometer's wiper terminals. On the contrary, the timer is connected to the sensor when the current flows in the coil.

The described circuitry reduced the complexity of the sensor reading procedure: the program running on the Raspberry Pi counts the number of edges in a unit of time, evaluating the frequency. The manufacturer then provides a curve to relate resistance values to water tension (expressed in kPa). The relay adds complexity to the circuitry, but it solves other issues, i.e., the calibration curve from frequency to resistance and the direct path to ground when the sensor is inserted in the soil. Components tolerance could slightly modify the relation between sensor resistance and the measured frequency. Manual calibration was possible but not practical: the relay and the digital potentiometer automate the procedure. The other issue was even more severe: with the sensor inserted in the pot and the plant under measurements, a ground loop with the power source of the Raspberry Pi is formed. This last configuration was tested, and Figure 3 shows the obtained results. The design without the relay clearly presents noise in the impedance spectrum.

The final PCB was designed to match the Raspberry Pi ZERO W dimensions and stacked directly on top of it. Given the reduced components' cost, each plant is equipped with a dedicated board during the experiments. Figure 1 shows the resulting measurement node. Thanks to Raspberry Pi's wireless capability, it is possible to use a central computer to monitor each sensor node. The resulting wireless sensor network could be deployed inside laboratories or greenhouses, where a Wi-Fi network and power sources are available. A Python script with a graphical user interface reads the sensor data and stores them periodically. The script is used to configure time intervals among the measurements and also to perform sensor calibration.

2.3 Plants used in the tests

In the following, plants are numbered from one to five. Each one is a tobacco (Nicotiana tabacum) plant growing inside a single pot. This plant species was chosen because of its completely sequenced genome, and since its life-cycle is widely known. Moreover, it could adapt perfectly to climatic conditions present in the laboratory where the analyses were conducted. As described before, each plant was associated with one sensor node. Plants were tested for up to one month. Sometimes periods in which plants were analyzed did not overlap to investigate how plants reacts in different periods of the year. During the experiment, plants were not watered regularly. Water stress conditions were induced in plants, and watering events were performed when their conditions were critical. Plants' conditions criticality was asserted by merging information extracted by sensors and visual analysis (mainly leaves color and stem and leaves turgescence). Moreover, two of the five plants were analyzed during the same period and kept in close proximity. Thus they were exposed to the same environmental conditions, except for soil moisture. One was watered regularly (twice per week), while the other was kept under water stress and watered when its conditions were critical. This has been done as a first step to disentangle each environment parameter's contribution to stem impedance. Each plant was about 50 cm to 60 cm high.

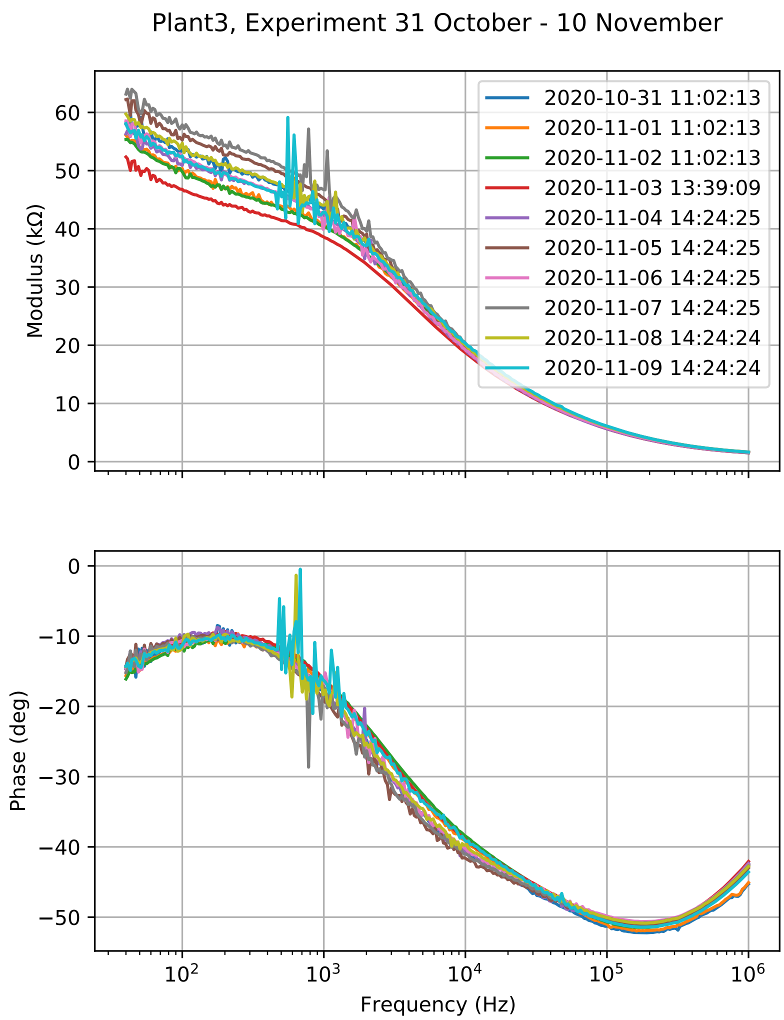

Figure 4: Example of impedance spectrum. Each color represents measurements in different days

3 Results and Discussion

Figure 4 shows the impedance spectrum of a single plant over ten days. Different spectra are superposed to show the whole range of frequencies in which analysis was performed. The picture highlights that below 100 Hz measurements are noisy. Moreover, as highlighted by Garlando et al. (2021), stem electrical impedance varies over time in response to environmental parameter variations. These variations are less marked in the high-frequency range. Therefore, 1 kHz to 10 kHz is a more suitable range for analysis. From now on, a specific frequency is selected. Impedance analysis was carried out for a period of up one month.

Analyses highlighted that environmental conditions may be optimal even if the plant is suffering. In fact, figure 5 shows both impedance analysis and environmental sensors data collected in a period where the plant dries. Although data collected by environmental sensors do not show any drastic change, Figure 5 shows the characteristic behavior that the stem impedance has when a plant is about to dry completely. Impedance modulus has, at first, a significant drop, and then it boosts sharply. In fact, after this steep increase, $|Z|$ is around 5 MΩ, so at least two orders of magnitude greater than before. Plots showing the impedance after *Jan.* 7^{th} are not reported since they are so higher than the previous one that it is impossible to find a suitable scale to show them clearly. In Figure 6 a picture taken on *Jan.* the 7^{th} of the same plant analyzed in figure 5 is shown. It is easily noticeable that it is completely dried. Figure 5 shows that environment parameters had not underwent any dramatic change. Thus, exclusively monitoring environment parameters may not be enough to understand plant's health status.

Our work dealt with the first steps toward understanding a plant's health status through its stem impedance analysis. As a first step, it was important to find the relation between impedance and environmental condition, trying to understand how the impedance changes in reaction to the other parameters. Moreover, it was expected that every plant not to react in the same way in terms of absolute values. Thus a relative and statistical approach is by sure needed.

Impedance measurement was carried out once per hour, and it was performed together with the evaluation of data collected by the environment sensor. As stated previously, soil moisture sensor is reliable only

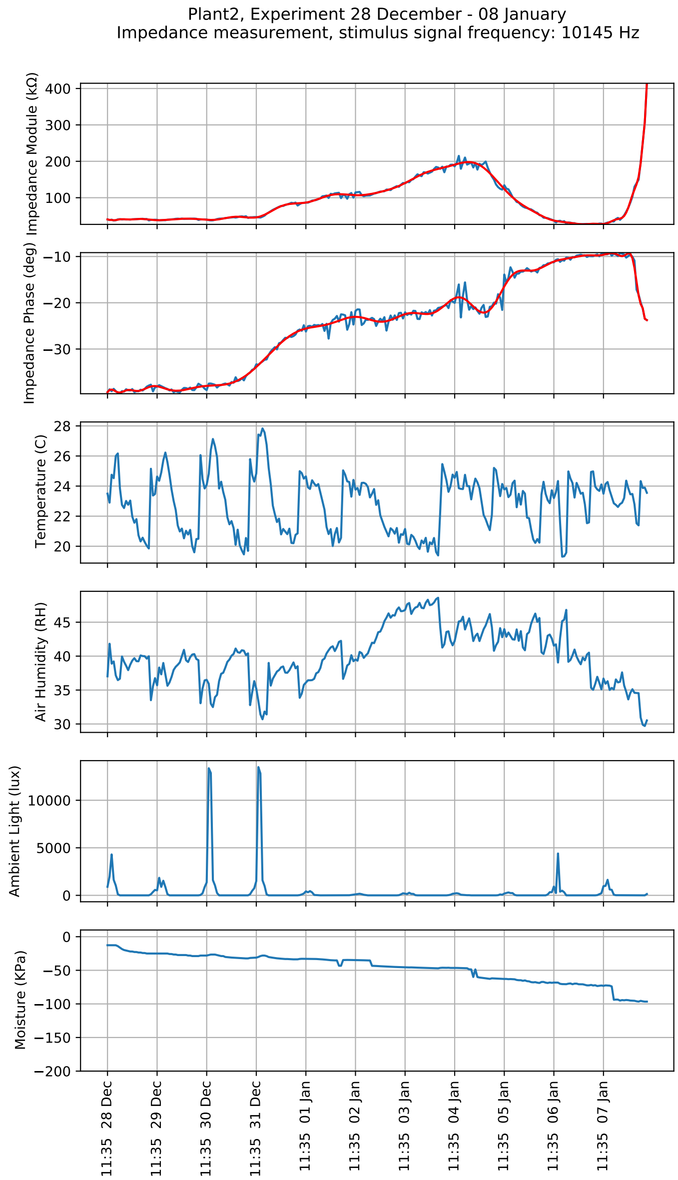

Figure 5: Plant stem's impedance modulus and phase presented with environment sensors data. These data have been collected right before the plant dies (see Figure 6). Red lines in the first two plots are 49^{th} degree polynomial fitting curves of impedance modulus and phase.

Figure 6: Picture taken with a camera depicting the critical condition of the plant despite optimal environmental conditions (see Figure 5).

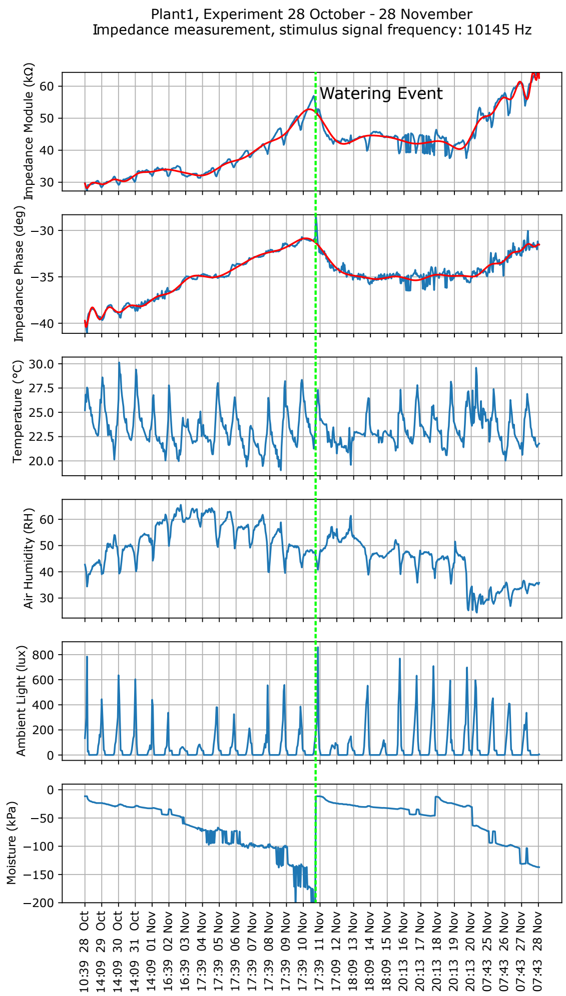

Figure 7: Stem impedance phase and modulus, ambient light, soil moisture, and air humidity evaluated for plant 1 between *Oct.* 28th and *Nov.* 28th. Red curves in the first two plots (modulus and phase) are 49th degree polynomial fitting curves, while the dashed vertical green line indicates the occurrence of a watering event.

down to −200 kPa. Thus, lower values were discarded and not reported in any of the plots. Ambient light, temperature, and relative humidity were also reported in the figure. The experiment was performed inside a laboratory. Therefore temperature is always above 20 ℃. Figure 5 shows a clear relationship between temperature and relative humidity. In Figure 7 data collected on plant 1 during the period *Oct.* 28th to *Nov.* 28th are reported.

At the beginning of the considered period, a watering event occurred. Soil moisture value was approximately equal to 0 kPa, so water concentration inside the soil was maximum. While soil moisture level was decreasing, both impedance modulus and phase increased their value. After the watering event (dashed green line in the figure), both modulus and phase presented a sharp drop followed by a period of stability. Phase and modulus started to increase again when soil moisture level crossed the value of approximately −50 kPa. This behavior suggested that there was a sort of cause-effect ratio linking soil moisture and impedance phase and modulus. In fact, fitting curves shown in Figures 7, 8, and 9 have a flexion in correspondence of every watering event. It is easily noticeable that, before every dashed green line, they increase and, after, decrease. This behavior is repeatedly noticeable in Figure 9 where two watering events occurred. The first one was performed when the soil was not completely dry, causing a modulus and phase drop less steep than the second one.

Plant stem impedance modulus and phase show ripples both in their increasing and decreasing slopes. Ripples repeat daily. It can be noticed that they appear when ambient light shows its peaks, thus when the plant gets illuminated by the sun. This behavior suggested that the amount of light impinging on the plant affects stem impedance. However, light, temperature, and humidity show very similar trends, and it is not clear which is the reason behind daily impedance changes. Further analysis of ratios linking these quantities will be carried out in the following section, where correlation and causality relations will be evaluated. Results reported in Figure 7 were not recorded for one plant only. Figures 8, and 9 demonstrate that similar conclusions can be done for all plants and for different periods of time.

In particular, Figure 8 shows data of a different plant over twenty days. Soil moisture's curve shows

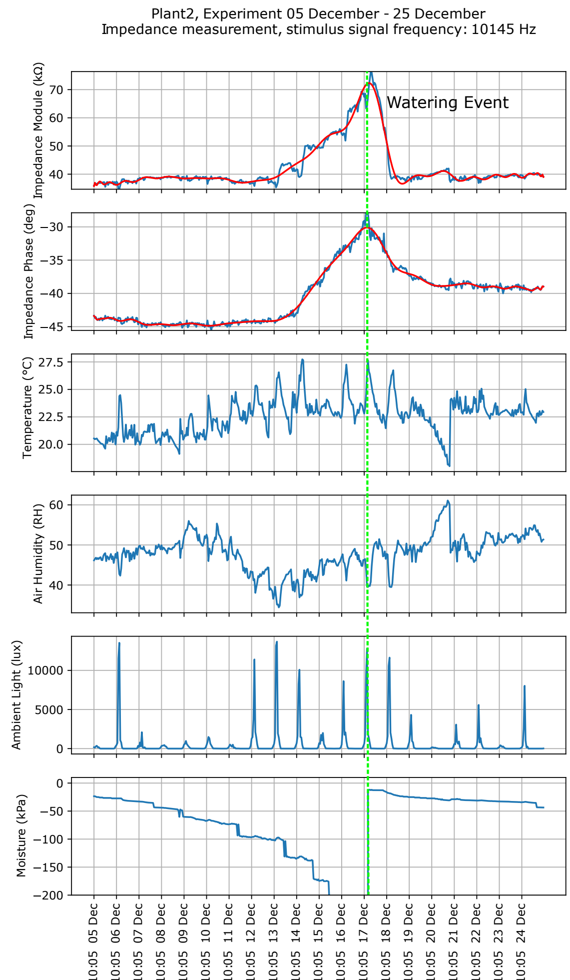

Figure 8: Impedance modulus and phase, and environment data collected during the period *Dec.* 5th to *Dec.* 25th for plant 2. Every impedance analysis was carried out at the frequency of 10 kHz. Soil moisture values lower than -200 kPa should not be considered and therefore not shown here. Red curves in the first two plots (modulus and phase) are 49th degree polynomial fitting curves, while the dashed vertical green line indicates the occurrence of a watering event.

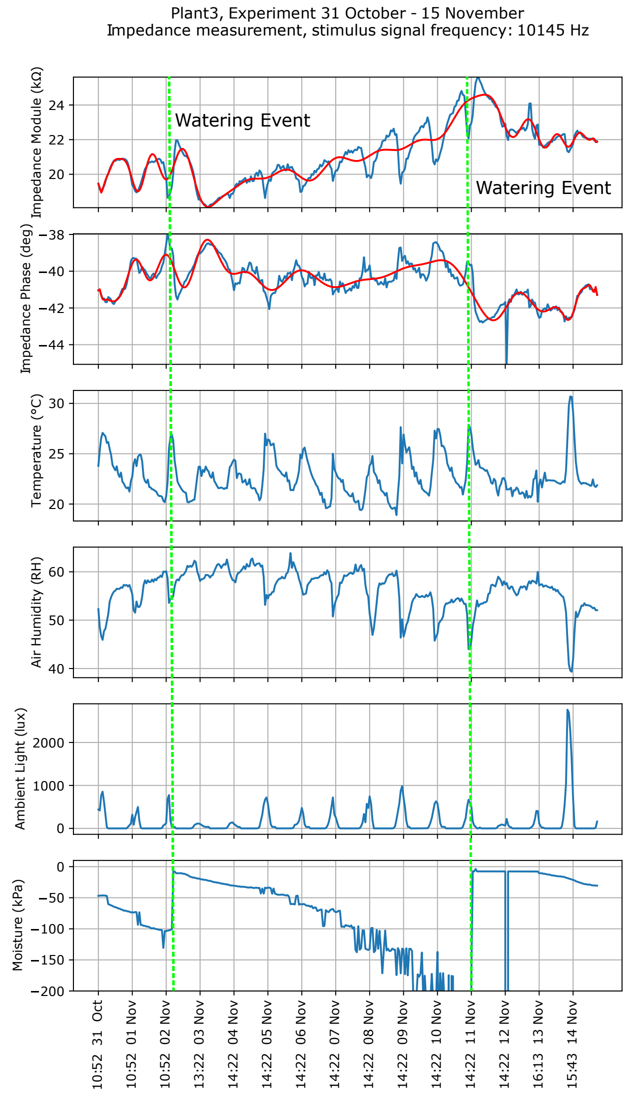

Figure 9: Impedance modulus and phase, and environment data collected during the period *Oct.* 31th to *Nov.* 15th for plant 3. Every impedance analysis was carried out at the frequency of 10 kHz. Soil moisture values lower than −200 kPa should not be considered and therefore not shown here. Red curves in the first two plots (modulus and phase) are 49th degree polynomial fitting curves, while the dashed vertical green lines indicate the occurrence of watering events.

that the plant was not watered until December, the 18th. Both impedance modulus and phase show similar behavior as in the previous case. However, in this case, daily ripples are less marked. Figure 9 on the contrary, shows clearly daily variations, but the trend due to soil drying is less evident.

Graphs reported in Figures 7,8, and 9 seem to indicate that soil moisture plays the most important role in determining stem impedance modulus and phase trend. In fact, after watering events, they rapidly decrease. Therefore, two more plants were tested to confirm our hypotheses. One of them (plant 5) was watered frequently (twice per week) to keep its soil moisture level high and (almost) constant. The second one (plant 4) was subjected to water stress and watered exclusively when the soil was dry. Analysis was carried out exactly in the same period of April 2021 for both of them. As stated in section 2.3, they were kept in the same room and close to each other to have similar environmental conditions. In Figures 10 and 11 stems impedance and environment data are reported. As expected, Figure 10 shows that stem impedance modulus overall behavior increased before the watering event, while it steeply decreased afterward, showing the same behavior seen in Figures 7, 8, and 9. In contrast, stem impedance reported in Figure 11 does not show a clear overall trend. Impedance's changes are only due to the already mentioned daily ripples, and they are milder than plant 4's ones. Same conclusions could not be drawn for stems impedance phase. In fact, in Figure 10, it rises after the watering event. Thus, it is in contrast with the trend shown in Figures 7, 8, and 9.

To better understand how stem electrical impedance is affected by variations in the environment surrounding the plant, statistical tests exploited by Garlando et al. (2020b) were performed on both data coming from environment sensors and impedance analyses. At first, the correlation matrix was computed to understand how quantities are correlated with each other. Each matrix row and column is associated with a physical quantity, and each value indicates the correlation between the two corresponding quantities; matrices are symmetrical. Correlation values are adimensional real numbers in the range $[-1, 1]$ where -1 corresponds to the highest level of anticorrelation and $+1$ to the highest correlation; if (nearly) 0, then the two quantities are not (significantly) related. A positive correlation implies that, statistically, two quantities increase (or decrease) simultaneously. A negative one implies that they, statistically, have opposite behavior. Therefore

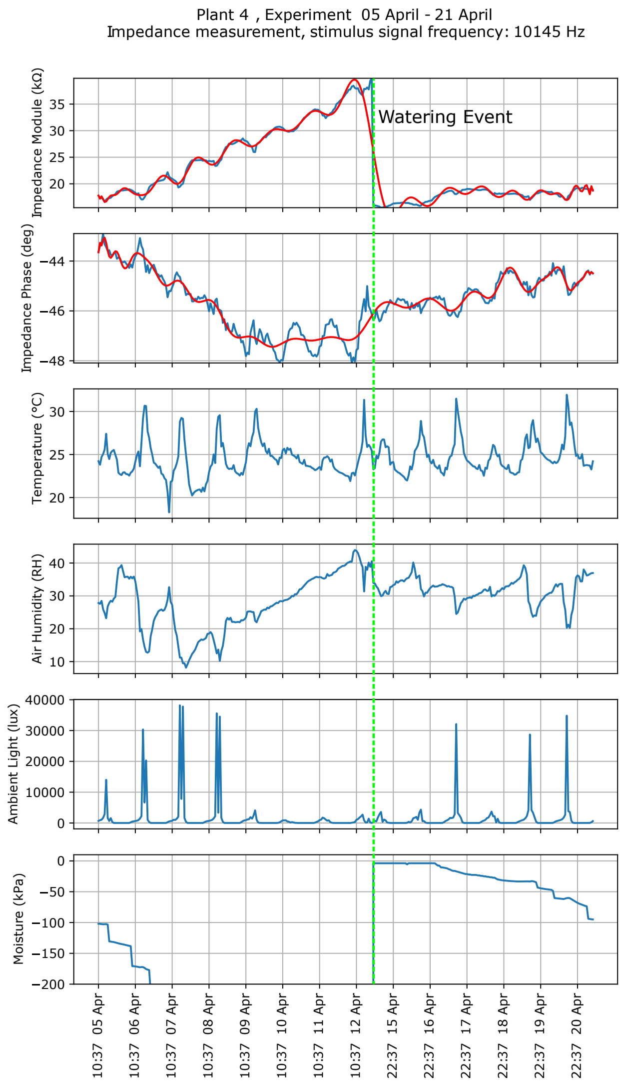

Figure 10: Impedance modulus and phase, and environment data collected during the period *Apr.* 5th to *Apr.* 21st for plant 4. Every impedance analysis was carried out at the frequency of 10 kHz. Soil moisture values lower than −200 kPa should not be considered and therefore not shown here. Red curves in the first two plots (modulus and phase) are 49th degree polynomial fitting curves, while the dashed vertical green lines indicate the occurrence of a watering events.

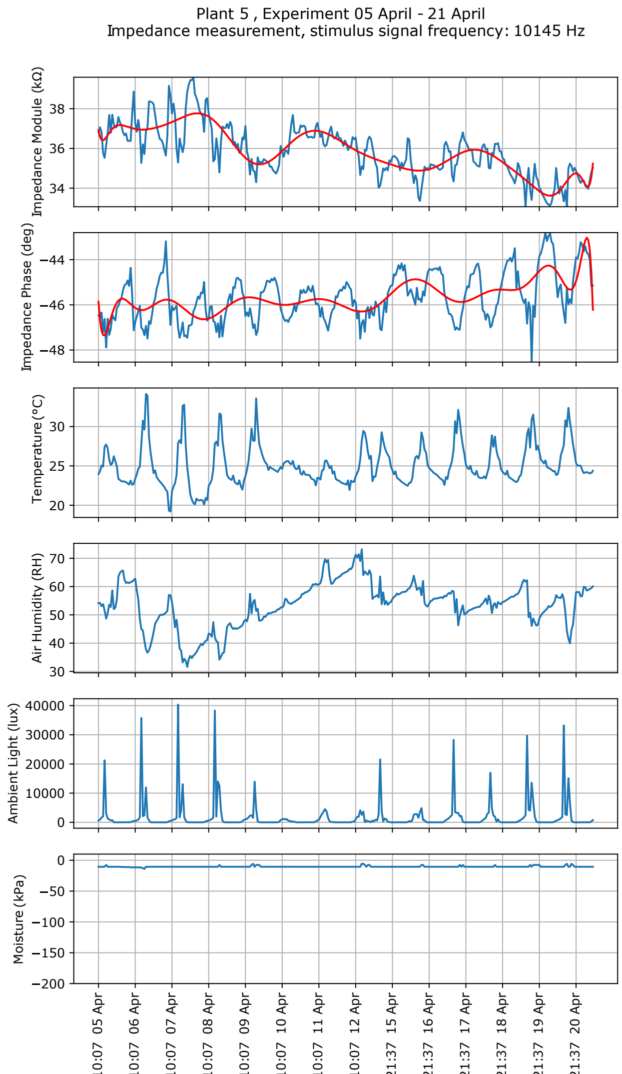

Figure 11: Impedance modulus and phase, and environment data collected during the period *Apr.* 5th to *Apr.* 21st for plant 5. Every impedance analysis has been carried out at the frequency of 10 kHz. Red curves in the first two plots (modulus and phase) are 49th degree polynomial fitting curves.

when one rises the other decreases and viceversa. Unfortunately, correlation does not imply causality. Thus, to verify if a cause-effect ratio exists between two quantities, *Granger*'s causality tests (Granger (1969)) were performed, and related matrices were evaluated. This test indicates how valuable data relative to one of the two quantities are to foresee the other's following values. If the test is successful, it is said that a quantity *"Granger causes"* the other one. Data must be stationary to perform these statistical tests. Therefore, each set of data (time series) used for the analysis underwent a stationary test. The first difference was applied if it was not stationary, with each sample substituted by the difference with the previous one. The resulting data were then tested again to avoid misleading results. Another essential parameter to be considered is the lag parameter. It represents how many of the previous samples of one series are used to predict the new values of the tested one. In this preliminary analysis, different lag values, ranging from one to eight, were tested, the value resulting in the minimum matrix coefficient selected. In particular, in the results presented here, a lag value equal to four was always chosen. Analyzed quantities are associated with rows and columns of *Granger*'s matrices, and the corresponding element indicates how significant the data for one quantity is in predicting another one. A quantity is said to *Granger cause* the other one, with a 95% of confidence, if the related matrix's element is lower than 0.05. If it is higher than the threshold, the test fails. The matrices are not symmetrical: if a cause-effect relation holds, column quantity causes variations in the row's one, not vice-versa. Figures showing correlation and *Granger*'s matrices relative to plants 1,2, and 3 are reported in the *Supplementary Material.*

Since this work aims to understand how the environment affects plant impedance behavior, the attention will be focused on the correlation between stem impedance and environmental parameters. As expected, in each correlation matrix, soil moisture is negatively correlated to stem impedance modulus. Water and sap's flows inside the stem highly impact the impedance: under water stress, there is a flow reduction in the stem, causing impedance modulus to increase.

Impedance phase, on the contrary, showed different behavior in experiments. It is highly correlated with impedance modulus, but there is a positive correlation in some cases (plants 1 and 2) and negative in

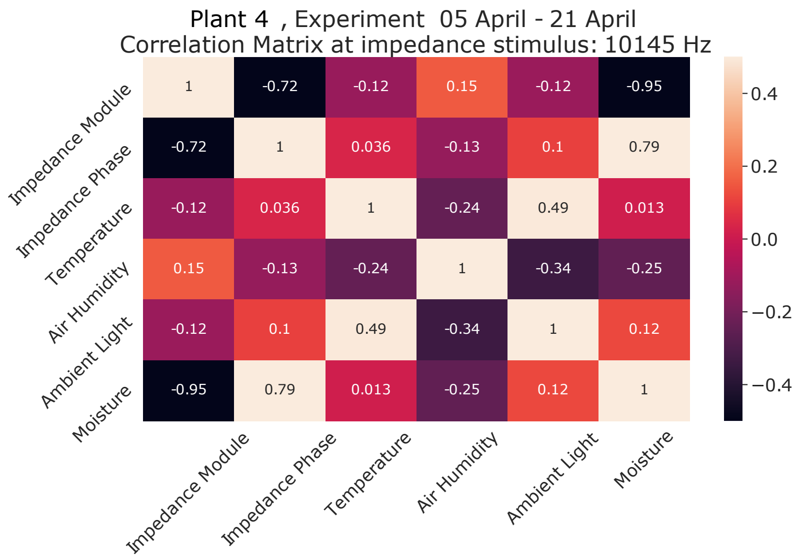

Figure 12: Correlation matrix evaluated for environmental and impedance data of plant 4 taken during the period 5/4/2021-21/4/2021.

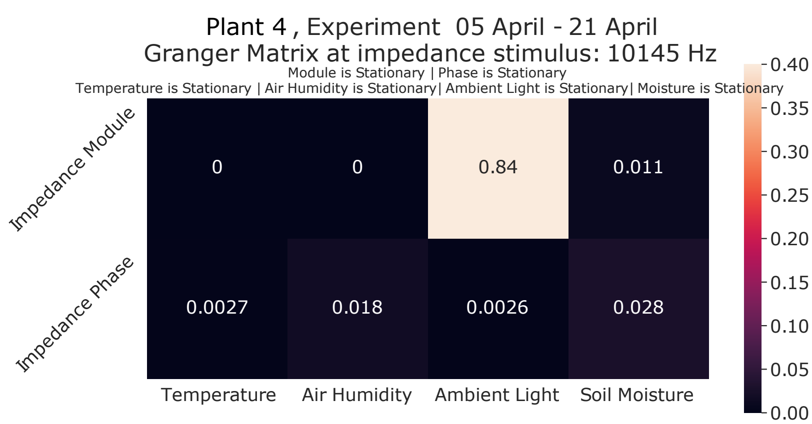

Figure 13: *Granger*'s matrix evaluated for environmental and impedance data of plant 4 taken during the period 5/4/2021-21/4/2021.

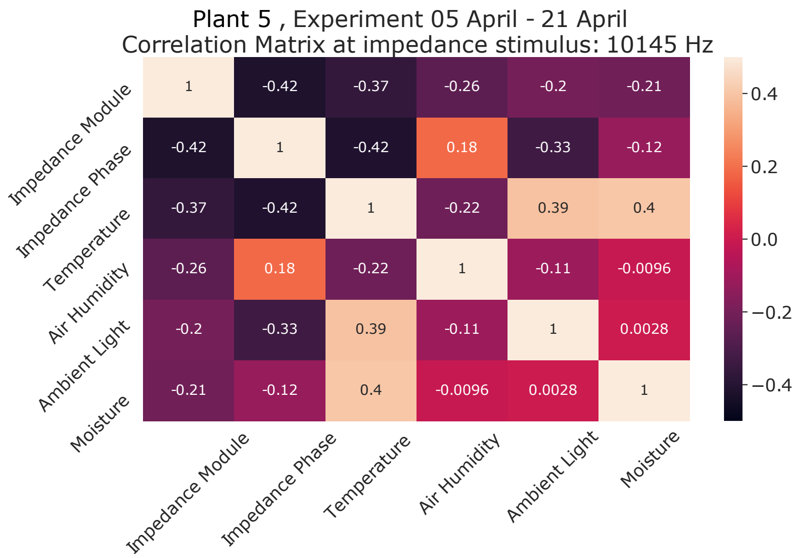

Figure 14: Correlation matrix evaluated for environmental and impedance data of plant 5 taken during the period 5/4/2021-21/4/2021.

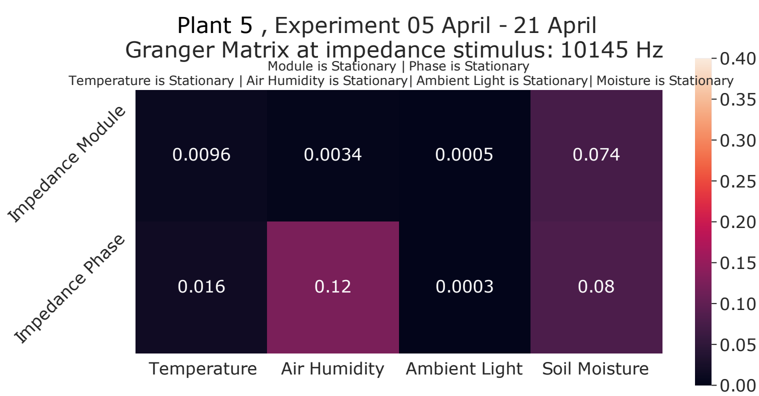

Figure 15: *Granger*'s matrix evaluated for environmental and impedance data of plant 5 taken during the period 5/4/2021-21/4/2021.

others (plants 3, 4, and 5). Therefore, correlation between impedance and soil moisture was not common among all the plants involved in the tests. Correlation between impedance and environmental parameters was different in every experiment. Furthermore, the laboratory where experiments took place was not a controlled environment: sunlight entering from windows caused an increase in temperature and a drop in ambient humidity. This relation is visible in the correlation matrices, where values relative to these quantities are similar in all experiments. However, the impact of temperature, light, and humidity is visible in the daily trend of impedance modulus and phase (Garlando et al. 2021).

As mentioned before, *Granger*'s causality test was performed on every data set. Matrices relative to plant 1,2, and 3 are reported in the *Supplementary Material*. This analysis showed inconsistent results. For example, plant 1 showed that all parameters, except soil moisture, are causing impedance modulus, while all environmental parameters affect the impedance phase. Differently, from plant 2, it seems that all values are causing both impedance modulus and phase. Thus, it is impossible to prove a causality relation among different quantities valid for all plants and experiments. For this reason, the experiment involving plants 4 and 5 was performed to better understand how soil moisture affects stem electrical impedance. As already mentioned, plant 5 was watered regularly, and it was analyzed together with plant 4 (subject to water stress), used as a counter-check. As it can be seen in Figures 10 and 11, data acquired from environment sensors are very similar. Only the air humidity show the same trend but in a different range: this may be due to more intense evaporation, since soil moisture of plant 5 was overall significantly higher and kept almost constant.

Correlation between measured environmental parameters (plant 4 and 5) are reported in Table 1: with the exception of ambient light whose sensor is significantly sensitive to its positioning with respect to the specific plant, correlation values are nearly two order of magnitude greater than the soil moisture one. These results confirm that the only significant difference between the environmental conditions of plant 4 and 5 is the soil moisture.

Focusing on the correlation between electrical impedance and environmental conditions, and in particular, on the first column of Figures 12 and 14, it is clear that in plant 5 impedance modulus is much less related

Table 1: Plant 4 and 5 environmental parameters correlation coefficients

	Ambient Light	*Air Humidity*	*Temperature*	*Soil Moisture*
Correlation	0,25	0,95	0,93	-0,016

Each value represents the correlation of the same quantity relative to the two plants.

to the soil moisture with respect to what happened for plant 4. The correlation coefficient equals -0.97 (very strong negative correlation) for plant 4, while it is -0.21 for plant 5 (mild anticorrelation). Conversely, the other environment parameters (temperature, air humidity, and ambient light) show a stronger correlation with stem impedance in plant 5. The comparison of impedance modulus variations between plants 4 and 5 and the experimental setup (plant 5 regularly watered and plant 4 subject to water stress) and correlation matrices results further reinforced the hypothesis that soil moisture can mostly affect stem impedance. As expected *Granger's* matrices for plant 4 and 5 (Figures 13 and 15) show that for the latter soil moisture is no more useful to foresee stem impedance values since, for plant 5, the coefficient is higher than 0.05. It leads to the conclusion that relevant changes in soil moisture cause significant changes in the stem impedance. However, otherwise, all the other environmental factors should be taken into account more thoroughly.

4 Conclusion

In this paper, a new sensor node to monitor different environmental parameters was presented. The node is small, cheap and exploits wireless communication. Given its properties, it was possible to use a node for each plant, placed directly close to it. Multiple nodes were used in a wireless sensor network to automatically monitor the environment, and a remote PC was used to collect all the data. Furthermore, a multiplexing circuit was used to measure the impedance of up to four plants simultaneously. This system was used to perform experiments to demonstrate the relations among impedance modulus, phase and plant status. The relation between environmental conditions and plant status was derived from electrical impedance variations. Various examples of water stress conditions were presented, together with the effects of temperature and light intensity on impedance spectra. Furthermore, statistical analysis was performed on data acquired during experiments: correlation among the different quantities is described, showing promising results. Indeed correlation values as high as 95% were found among impedance and soil moisture. However, since correlation does not imply causality, the *"Granger causality"* was tested. These analyses proved that soil moisture statistically caused variations in the impedance of the plants. Nevertheless, soil moisture seems to be the parameter that most affected both phase and modulus trends as shown in graphs 7, 8, 10 which show environmental parameter data together with stem impedance. For these reasons, further analyses carried out in controlled environments are needed to disentangle each environmental parameter's contribution to stem impedance behavior over time. Moreover, since the amount of collected data will continue to grow, machine learning algorithms will be implemented to better interpret them. This goal will be pursued in future works.

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