# Testing and Validation of Monitoring Technologies to Assess the Performance and Genotyping of *Poa pratensis* (C3) Mixed with Other Grass Species (C4)

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***Abstract*—Precision agriculture is vital to ensure the sustainability of farming systems. Nonetheless, the selection of parameters to be monitored can be a difficult decision, especially when the required equipment has a high cost. In this paper, we analyze the usability of five variables, including soil moisture, canopy temperature and three vegetation indexes, in turfgrass composed of different species. Our objectives are, on the one hand, determine which parameter or parameters are more specific for determining the species which compose the turfgrass. On the other hand, we expect to find correlations between variables in order to reduce the evaluated parameters in the turfgrass monitoring. Our results indicated that only the vegetation indexes are useful for genotyping, to determine the species that compose the turfgrass. From the vegetation indexes, the green area was the one which offers the best results. On the other hand, correlations were found between soil moisture and canopy temperature, and between the different vegetation indexes. Thus, we can affirm that it is possible to reduce the measured variables in turfgrass monitoring. The most significant advantage is the possibility of avoiding the monitoring of a vegetation index, for which the calculation requires a specific device with higher cost.**

***Keywords-precision agriculture; soil moisture; canopy temperature; vegetation indexes; correlations; experimental plots.***

## I. INTRODUCTION

Precision Agriculture (PA) is becoming more and more popular in the last years due to its benefits for farmers [1]. The use of technology for crops monitoring, such as Wireless Sensor Networks (WSN) or Internet of Things (IoT) leads the farming activity to a higher degree of sustainability and profitability. Even so, the selection of the needs of our systems in terms of required data, data periodicity or monitored variables can be confusing. In the PA, several aspects can be monitored, such as soil, water, and plants. In a recent work [2], an evaluation of included parameters in PA concludes that most of the IoT-based smart irrigation systems are focused on monitoring the soil, and few of them monitored the plants.

The fact of measuring basically a single, or a limited number of parameters might be problematic. This is because the characteristics of soil such as Soil Moisture (SM), chiefly if it is measured in a unique location and close to the surface, can suffer abrupt changes. As the measurement of isolated parameters might drive the system into wrong actions, it is essential to combine several parameters in order to take the correct action. Nonetheless, it prompts us to another problem, the proper selection of parameters to be monitored. It is essential to monitor plant and soil parameters, given the fact that plant parameters are more stable in time than soil parameters [3]. Different parameters offer us different sort of information, which can be useful in order to take the most appropriate measure, i.e. when to irrigate, the required amount of water, required fertilizer, identification of plant diseases.

The dilemma of using different types of devices and techniques when we are monitoring the performance of crops (or gardens) is the high cost of some devices and the required time to gather data manually. In addition, the data processing and analyses may require more time than the value of obtained information if we include several parameters. Therefore, it is necessary to evaluate, test, and validate the real value of the information provided by different commonly used devices in the monitoring of plants, soils, and agriculture. This evaluation is critical to allow us to minimize the number of monitored parameters without reducing the conclusions based on the gathered information and the value of gathered data.

One of the activities which clearly demonstrate the possible benefits of reducing the number of monitored variables is public gardening. In gardening, we have one of the highest requirements of water and PA must help to reduce the irrigation [4] and evaluate the performance of different species to find a combination that requires less irrigation [5].

The aim of this paper is to evaluate, test, and validate which of the monitored parameters in experimental plots of turfgrass offers more valuable information. The objective of monitoring those parameters is two-fold. First, we use the monitored parameters to evaluate the performance of 4 grass combinations, including C3 and C4 plants (different in the water management). Furthermore, we expect to use gathered data to identify the grass combination, also known as genotyping. Therefore, we are going to gather data of 5 variables, including three vegetation indexes, the Canopy Temperature (CT), and the SM. With these data, a series of statistical analyses will be performed to try to evaluate the performance of each grass combination and to genotype the combinations. In addition, we also expect to find a correlation between different pairs of variables in order to reduce the number of parameters that must be monitored in the future.

The remainder of this paper is structured as follows. The presentation and analysis of the related work are presented in Section 2. Section 3 describes the materials and methods that have been used for this experiment. The results are detailed and discussed in Section 4. Finally, Section 5 outlines the main conclusions of this work.

## II. RELATED WORK

In this section, we describe several papers which analyze the correlation of parameters monitored in PA and the use of parameters for genotyping and monitoring crops and gardens.

First of all, the different vegetation indexes and their use are described. We have selected three vegetation indexes which are the most used vegetation indexes is the Normalized Difference Vegetation Index (NDVI). The NDVI is widely used for monitoring plant vigour in different crops. In a previous work, Marin et al. [5] have used the NDVI compared with RGB information, Green Area (GA) and the Greener Area (GGA), to compare the performance of grass combinations. They conclude that NDVI, GA and GGA can be used in the grass as an indicator of biomass and to estimate the resistance of the plant combinations to water restriction. However, the NDVI, GA, and GGA are not only used for grass monitoring but also crop assessment. In particular, its use is extended in cereal crops [6]-[8]. In [6], Fernandez-Gallego et al. used the aforementioned indexes for grain yield estimation in wheat as a low-cost option, compared with other existing methods. They conclude that the change in canopy colour from green to yellow is the most useful indicator for grain yield estimation. Yousfi et al. in [7] used NDVI, GA, Canopy Temperature Depression, and Stable Carbon Isotope Composition to determine the wheat grain yield under different irrigation and fertigation conditions. Their results pointed out the relevance of different indexes to estimate wheat harvest. In addition, the GA and the Stable Carbon Isotope Composition were the unique methods that offer a correlation with harvest in all the evaluated scenarios. In [8], Buchaillot et al. performed a similar study, including a Soil Plant Analysis Development (SPAD) sensor in maize fields. For the calculation of indexes, images captured with a drone and with a regular camera were used and correlated. Their results highlight the relevance of the evaluated indexes and the SPAD in grain yield estimation. It is important to note that, although some indexes might be attained with remote sensing, some of the included parameters cannot be measured with existing sensors. Therefore, the correlation or estimation of variables is crucial to reduce the number of sensors and simplify the infrastructure of WSN or IoT systems.

Another vital parameter, which is not monitored in most of the IoT proposals for irrigation is the CT [2]. The CT has a high relevance when drought-tolerant crop cultivars and the irrigation are being monitored. In [9], Zhang et al. gather data of the CT jointly with RGB and thermal images with a drone to evaluate the water stress of the crops. Their results indicate the importance of combining the CT with other technologies as the image gathered with the drone for a proper assessment of maize in water stress conditions. The use of CT for irrigation is discussed by Kumar et al. in [10]. In their experiments, the authors kept wheat plants under different degrees of water stress, CT and SM were monitored. Their results clearly indicate that using both variables in an algorithm for triggering irrigation events save up to 20% of water for irrigation. The CT measurement can be easily included in IoT systems or WSN with thermal cameras or infrared thermometers.

The measurement of CT in turfgrass is less standard but we can find some examples where the CT is monitored. In [11], Culpepper et al. developed an experiment combining different types of grasses and exposing them to different irrigation levels. The CT was useful to identify the plants kept with or without irrigation, but only in specific periods of the experiment. Meanwhile, the NDVI was not useful for differentiating the two scenarios. Another example can be found in Hong et al. [12]. The authors maintain *Agrostis stolonifera* under different regimes (100 to 15% of evapotranspiration) and images were captured using a thermal camera mounted over a drone. The CT has a high correlation with the irrigation regimes (-0.65 to 0.82) in different moments. Nevertheless, in general terms, other variables such as NDVI presented higher correlations.

As far as we know, the use and evaluation of NDVI, GA, GGA, CT, and SM to assess water stress or its correlation is not performed with *Poa pratensis* mixed with other C3. It is essential to evaluate if a reduction in the monitored parameters can be applied, to simplify the required sensor in the future deployment of WSN and IoT systems.

## III. MATERIAL AND METHODS

In this section, the equipment and process used to gather the data, software employed to analyze it, and the details of the mixed plant species are portrayed.

### A. Experimental plots

A total of 3 grass combinations, which include C3 and C4 species, have been tested in the research facilities of IMIDRA during 8 months. The mixtures of C3 and C4 grasses are kept in experimental plots of 4.5m$^2$ (1m per 3.5m). As a C3 grass, the Poa pratensis represents 75% of the planted seeds. As a C4 (25% of the plot) we include three different species combined individually with the C4 (*Cynodon dactylon (PC)*, *Buchloe dactyloides (PB)*, and *Zoysia japonica (PZ)*). Each one of the selected combinations is repeated six times in individual plots. In addition, the most used grasses combination in ornamental gardening is tested to serve as a control. This *Control* is composed of *Festuca arundinacea* (70%), Lolium perenne (15%), and *Poa pratensis* (15%).

Thus, a total of 22 plots are included in the experiment. All the plots have the same environmental conditions of soil and irrigation. The irrigation was automatically calculated by the Rain Bird [13]. In Figure 1, we can see a representation of the 3 combinations. The presence of pluviometers used to check the uniformity of irrigation can be seen in some of the plots.

Figure 1. Experimental plots from up to down Control, *Poa pratensis* mixed with *Cynodon dactylon*, *Zoysia japonica*, and *Buchloe dactyloides.*

### B. Data gathering

During the experimental period, which had a duration of 6 weeks, data was gathered in each plot one per week, from October to November. The data gathered include different types of variables related to the soil (soil moisture) and plant (canopy temperature and vegetation indexes).

To gather these data, different devices have been used. For the SM, the Time-Domain Reflectometry (TDR) 350 FieldScout was selected [14]. One measure is taken in each plot. Regarding the CT, a Fluke 561 was used [15]. This device allows us to collect the mean temperature of each plot.

Finally, for the lectures of the electromagnetic spectrum of the plant to regions are considered, the visible and the infrared. Two instruments were used, the first of them was a SONY DSC-W120, selected to obtain pictures of each plot. With this camera, we gather information about the visible spectrum. Meanwhile, the Handheld Crop Sensor GreenSeeker [16] was used to measure the information related to the red and infrared region. The GreenSeeker allows us having a mean value of the NDVI of the entire plot. The information gathered with the camera and the GreenSeeker were obtained, placing both instruments at 1.5m from the soil.

### C. Data processing

Once the data were gathered, different processes are carried out. The first of them was to analyze the images with specific software, the BreedPix. It is open-source software, mainly used for cereal crops. With this software, we can obtain information about the GA and GGA contained in the picture. The GA contains the portion of the picture with pixels from yellow to bluish-green. On the other hand, the GGA excludes the yellowish-green tones.

Thus, for each plot, we have five variables (soil moisture (SM), canopy temperature (CT), NDVI, GA, and GGA). The variables were included in statistical software to analyze the relationship between variables and to analyze the performance of different grass species. The used software for data processing was the Statgraphics Centurion. Two different statistical tests were carried out. First, the ANalysis Of Variance (ANOVA) is performed to compare the mean and variances of included variables for each grass combination. To determine the existence of similitudes or differences between the evaluated grass combinations, the Tukey Honestly Significant Difference (HSD) was selected. Finally, bivariate correlations for each pair of variables are performed.

## IV. RESULTS

In this section, we present our results and discuss their importance. First, the identification of differences between different plots is detailed. Finally, the correlation between the analyzed parameters is described.

### A. Testing the benefits of sensing devices to evaluate the performance of different grass combinations

Considering that in each plot we obtain an individual measure of each one of the evaluated parameters and we have 22 plots monitored during six weeks, a total of 132 observations were carried out for each variable, which is considered a significant amount of data. It is important to note that at plain sight, it is not easy to differentiate between combination. Only experts are capable of identifying the differences in their leaves.

Before performing the ANOVA to evaluate if the user devices can be useful to differentiate between different combinations (genotyping), it is essential to confirm that data follows a normal distribution. It is a prerequisite for the ANOVA. In Table 1, we have included the skewness and kurtosis if obtained indexes are between ±2 we can use the ANOVA tests. Data included in Table 1 indicates that SM, CT, and GA follow normal distributions and ANOVA tests can be performed. Nonetheless, the variables NDVI and GGA do not follow a normal distribution; thus, alternative tests must be performed. In this case, the test median of Mood will substitute to the ANOVA, and the Kruskal-Wallis will be used to estimate the different groups. The results of variance analyses are summarized in Table 2.

TABLE I. SUMMARY SKEWNESS AND KURTOSIS OF DATA.

| | Skewness | | | | | Kurtosis | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **SM** | **CT** | **NDVI** | **GA** | **GGA** | **SM** | **CT** | **NDVI** | **GA** | **GGA** |
| **Control** | 0.686056 | 0.904177 | -0.8997 | 0.138911 | 0.929755 | -0.56894 | -0.187175 | -0.9178 | -1.28267 | -0.76948 |
| **PC** | 0.325911 | 1.36113 | -1.7536 | -0.14744 | 1.29273 | -0.60346 | 0.335747 | -0.7891 | -1.09587 | -0.94227 |
| **PB** | 1.4669 | 1.31779 | -2.460 | -0.43471 | 2.36019 | -0.37907 | 0.00324324 | 0.9359 | -0.32923 | 0.109402 |
| **PZ** | 1.07606 | 1.55038 | -2.1278 | 0.999044 | 1.52993 | -0.54186 | 0.0515326 | 0.4999 | -0.89322 | -0.67507 |
| **Normal Distribution** | Yes | Yes | No | Yes | No | | | | | |

TABLE II. SUMMARY OF ANOVA AND KRUSKAL-WALLIS. SIGNIFICANCE LEVELS: NS, NOT SIGNIFICANT; * P < 0.05; ** P < 0.01 AND *** P < 0.001. THE DIFFERENT LETTER SUCCEEDING THE MEANS ARE SIGNIFICANTLY DIFFERENT (P < 0.05) ACCORDING TO TUKEY'S HONESTLY SIGNIFICANT DIFFERENCE (HSD) TEST.

| | **SM** | **CT** | **NDVI** | **GA** | **GGA** |
|---|---|---|---|---|---|
| **Control** | 35.2583 $^{a}$ | 14.6125 $^{a}$ | 0.76 $^{a}$ | 0.67875 $^{b}$ | 0.35 $^{a}$ |
| **PC** | 35.5 $^{a}$ | 14.8417 $^{a}$ | 0.745 $^{a}$ | 0.61805 $^{a}$ | 0.295 $^{a}$ |
| **PB** | 34.3944 $^{a}$ | 14.6056 $^{a}$ | 0.79 $^{b}$ | 0.77944 $^{c}$ | 0.48 $^{b}$ |
| **PZ** | 36.3722 $^{a}$ | 14.4694 $^{a}$ | 0.77 $^{b}$ | 0.76472 $^{c}$ | 0.425 $^{b}$ |
| **Level of significance** | 0.8727 $^{ns}$ | 0.9579 $^{ns}$ | 0.0005*** | 0.0000*** | 0.0000*** |

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According to the data presented in Table 2, we can affirm that SM and CT have no variation, which means that those parameters cannot be used to identify the different combinations. Thus, SM and CT are variables which are not useful for genotyping. In addition, those variables are profoundly affected by environmental conditions and can experience huge variations along the day.

On the other hand, the variables that consider the electromagnetic spectrum of the plants (visible and infrared) are offering more remarkable information. We need to remark that this data is more stable in the time, there is no variation along the day and it is not quickly affected by the environmental parameters such as solar radiation, wind, or rain among others.

With the data of NDVI, it is possible to identify two groups of genotypes. The first group includes the mixture of C3 species (Control) and the Poa with Cynodon. Meanwhile, the mixtures of Poa with Zoysia and Buchloe have different values and belong to a separate group. Therefore, information of NDVI is not suitable to identify the presence of C4 species in all cases. The highest NDVI values are linked to the second group (PZ and PB).

With regard to the information from the visible spectrum, different results were obtained with GA and GGA. In both cases, the results of the tests have pointed out that there are differences in the observed grass species since the p-values are lower than 0.05. The GGA index can identify differences in two groups of plots. The Control and te PC mixtures form the groups on the one hand, and PB and PZ on the other hand. These results are coupled with the outcome obtained with the NDVI.

On the contrary, the results obtained with GA data are more specific than with GGA and NDVI. Again, the ANOVA indicate with a p-value lower than 0.05 that there are differences statistically significant among the different grass combinations tested. In this case, the multiple range test indicates that it is possible to identify three different groups. PC mixture is included in the first group. The second group is composed solely by the Control grass combination. Finally, PZ and PB are the mixtures identified as the third group. The different groups and distribution of data can be seen in the Box diagram of Figure 2. In this graphic, the mean, median outliers and other relevant information are summarized. Figure 2 presents clearly the similarity in the data of PB and PZ, which cannot be differentiated with GA data.

Thus, the data of GA offers better results than the other variables. It is important to note that with NDVI and GGA data we have worked with non-parametric statistical tests due to the distribution of the data, and those tests tend to be less powerful to identify differences than parametric tests. To obtain better results with GGA and NDVI, we would need a larger amount of data. Therefore, it is possible that GGA and NDVI can be used in the future with similar accuracy than GA if the amount of data increase.

### B. *Correlation between evaluated variables*

The seek of correlations between data, we aim to find the relation between variables in order to reduce the number of controlled variables in experimental plots. The fact of gathering data from several variables implies an elevated time consumption in the plots using diverse types of equipment. In addition, some of the used equipment (particularly the GreenSeeker) have a high cost and having the opportunity of using another tool, as the digital pictures, to estimate the value of NDVI is vital to save costs.

Thus, we are going to focus the correlation between variables in trying to obtain an equation that allows us to obtain or predict the value of NDVI based on the information obtained from the digital pictures. In addition, we will seek to have a correlation between SM and CT, since the measurement of the CT is much faster, and the required equipment is cheaper than the required for SM measuring.

To explore the existing correlation in the gathered data, and to attend to the non-normal distribution of some variables, Spearman correlation is selected. Although it is less powerful than the Pearson correlation, the existence of variables without normal distribution force us to use this test. The first outcome of the correlation test is the correlation graphic, in which the X-Y distributions of each pair of variables, also known as Dispersion Matrix, can be seen in Figure 3 a). Therefore, we can have in a simple graphic the tend of data of all the included variables in the test. According to the results of presented in Figure 3, we can identify at plain sight that some of the variables are highly correlated.

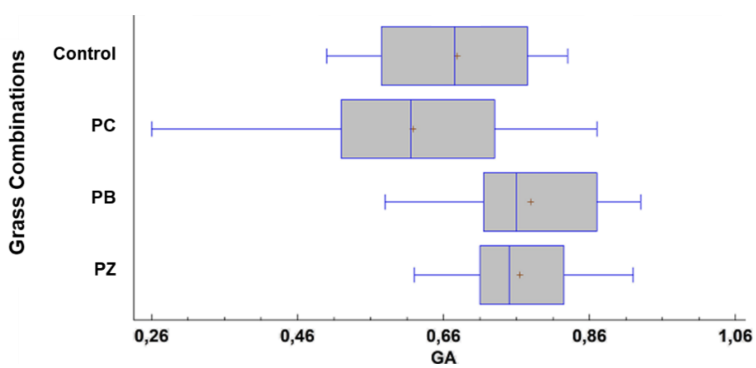


Figure 2. Box Diagram with GA data for the different grass combinations where the different distribution of data can be identified.

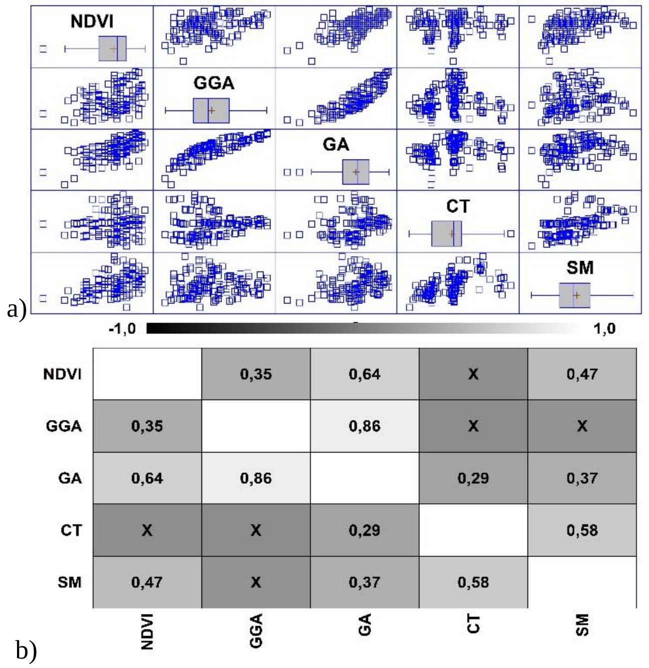


Figure 3. Correlation between different variables, a) Dispersion Matrix, b) Spearman Correlation Graphic (where X means that their correlation is not statistically significant, and the numbers indicate the strength of correlations from -1 to +1).

Meanwhile, in Figure 3 b) we depict the strength of correlations between each pair of variables. The values close to +1 indicate a strong and positive correlation, while values close to -1 indicate a strong negative correlation. The strongest correlations for the variables of plant aspect, or electromagnetic spectrum, are found for GA with GGA (0.86), and GA with NDVI (0.64). The correlation between GGA and NDVI is much lower. On the other hand, regarding the plant-soil interaction, a correlation was found between SM and CT (0.58). Last but not least, another interesting correlation between SM and NDVI was also found; however, the strength of this correlation is lower than 0.50 (0.47).

Considering the results of the correlation test, we are going to focus on the relation between GA and GGA, GA and NDVI and TC and SM. The objective, as described before, is to reduce the number of required measures and required equipment for grass monitoring. The relation between variables GA and GGA can be explained with a linear model, in which given a certain value of GA it is possible to estimate the GGA for the picture. The proposed mathematical model is described in (1). It is important to note that this model is developed for the different combinations of *Poa pratensis* with other C4 species and include the Control mixture. The proposed model is characterized by a correlation coefficient of 0.83 and an R2 of 70% and can be seen in Figure 4. Although there are other models which can explain with higher accuracy the relation between both variables (R2 of 76%), we have selected the linear model due to its higher simplicity and lower complexion in the calculation.

Concerning the relation between variables GA and NDVI, again a linear model, in which given a specific value of GA, it is possible to estimate the NDVI, is presented. Equation (2) described the linear mathematical model that related both variables. In this case, among all the evaluated mathematical models, the linear regression was the one that offered higher accuracy. The proposed model is characterized by a correlation coefficient of 0.65 and an R2 of 43% and can be seen in Figure 5. The equation of the proposed model is detailed in (2).

Finally, the correlation found between SM and CT is displayed. In this case and given the low accuracy of the linear model, we have selected the "S-Curve" model. The S-Curve model, which can be seen in Figure 6 has a correlation coefficient of -0.57 and an R2 of 33.25. The equation that follows the model is depicted in (3).

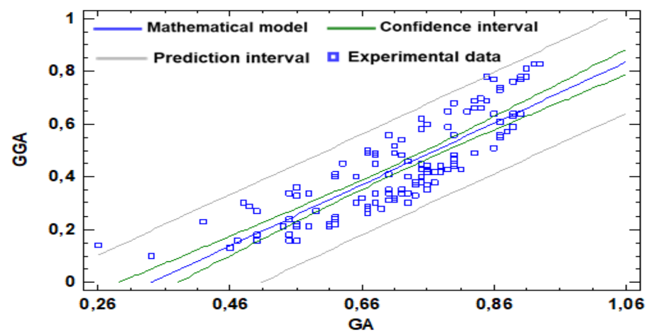


Figure 4. Simple regression between GA and GGA with a lineal mathematic model

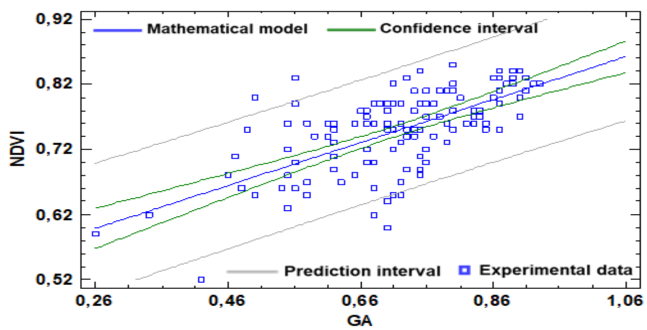


Figure 5. Simple regression between GA and NDVI with a lineal mathematic model

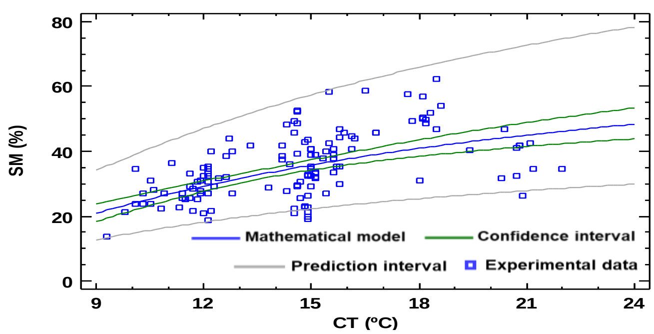


Figure 6. Simple regression between CT and SM with an S-Curve mathematic model

$$GGA = 1.16152*GA - 0.395785 \quad (1)$$

$$NDVI = 0.513359 + 0.329084*GA \quad (2)$$
$$SM (\%) = \exp(4.38257 – 12.0825/CT (ºC)) \quad (3)$$

The obtained results will allow the attainment of two objectives. First, we verify a methodology to identify the species that compose a lawn of *Poa pratensis* with other grasses. Secondly, we present the correlation of variables that will allow a reduction in the number of monitored parameters in future experiments in which WSN and IoT are deployed. We can use only one type of camera to monitor the GA and estimate the GGA and NDVI from (1) and (2). Furthermore, we will avoid the need of CT measurement by estimating this value from the SM data. Thus, we will have the deployed sensor underground instead than at certain height, as need for CT measurement. This will facilitate the integration of IoT systems with the daily activities carried out in lawns such mowing or irrigating, which can be problematic with sensor deployed over the ground.

It is important to note that the obtained results are only based on data from *Poa pratensis* and more data must be gathered to extrapolate our results to general turfgrass assessment.

## V. CONCLUSION

The fact of using several devices for monitoring agriculture, or gardening, is widely discussed in this paper. The tradeoff between the relevance of gathered information and required time and costs to obtain this data is presented. To solve this problem, we have evaluated the existing correlation between different variables. Furthermore, the effectiveness of each studied parameter for monitoring grass performance and genotyping different species is presented.

In this paper, five different variables monitored in precision agriculture are evaluated for genotyping, and the existing correlation between variables is explored. Our results point out that the variable which offers better results for genotyping different grass combinations, including C3 and C4 plants, is the GA index. Other evaluated indexes such as GGA and NDVI offered promising results, but more data is required to evaluate their capabilities. With regards to existing correlations, we found a correlation between CT and SM, GA and NDVI, and GA and GAA. From those correlations, the most interesting one is the possibility of estimating the SM based on the CT.

In future work, we are going to include the measure of the temperature of the soil surface, with no coverage, in our datasets in order to obtain a more accurate estimation of SM from the data of CT and soil temperature and the estimation of coverage based on [17]. On the other hand, for the genotyping, we will include data of other grass mixtures to determine if GA by itself can identify more genotypes.

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