# Multi-Sensor Data Fusion and Artificial Neural Network to Estimate the Velocity of Sportive Turfgrass in Putting Green Areas

Lorena Parra[1, 2], Pedro V. Mauri[1], Jaime Lloret[2], Salima Yousfi[1] and José F. Marín[3]
[1]Instituto Madrileño de Investigación y Desarrollo Rural, Agrario y Alimentario (IMIDRA), Finca "El Encin", A-2, Km 38, 2, 28800 Alcalá de Henares, Madrid, Spain
[2] Instituto de Investigación para la Gestión Integrada de Zonas Costeras Universitat Politècnica de València, Valencia, Spain
[3] Area verde MG Projects SL. C/ Oña, 43 28933 Madrid, Spain
Email: pedro.mauri@madrid.org, loparbo@doctor.upv.es, jlloret@dcom.upv.es, salima.yousfi@madrid.org, jmarin@areaverde.es

***Abstract*—Although the use of sensors is extended in the environmental monitoring, there are some variables which cannot be directly measured and must be estimated. The velocity of sportive turfgrass is one of them. In this paper, we attempt to estimate the velocity in two putting greens of a golf course, before and after a maintenance action, by the measurement of agronomic variables with digital devices. We measure the soil moisture and temperature, the canopy temperature and the Normalised Difference Vegetation Index. The measurements are performed during five months in two putting greens of *Agrostis stolonifera*. The results indicated that the monitoring of a single agronomic parameter is not useful to evaluate the recovery of the putting green. The agronomic variables showed a total recovery 22 after the maintenance action. Meanwhile, the data of velocity indicates that full recovery was not achieved after 124 days. Finally, we use the agronomic variables to estimate the velocity. A multiple regression model was defined with Normalised Difference Vegetation Index, soil moisture, and soil temperature. Then, those variables are included in an artificial neural network model to generate graphics, which can be used by greenkeepers to estimate the velocity. The model archived 70% of correctly classified cases. Graphics of classification to be used by the greenkeepers, which include the estimated velocity based on soil moisture and Normalised Difference Vegetation Index, for four different temperatures are generated.**

***Keywords-velocity of the putting greens; soil moisture; soil temperature; Normalized Difference Vegetation Index; turfgrass***

## I. INTRODUCTION

In the last decades, the use of sensing devices for environmental monitoring has become more and more popular. One of the areas in which the use of sensors has arisen more useful is the motorisation of crops. The use of Wireless Sensor Networks (WSN) in agriculture, as part of precision agriculture systems, provides higher sustainability and profitability of the activity. The sensors can be used to monitor the soil, the plants or the water as it was said in a survey about the Internet of Things (IoT) for agriculture [1]. The same systems can be applied for turfgrass monitoring in gardens or sportive areas such as golf courses, Football or Rugby camps.

Nonetheless, in many cases, there are variables which cannot be easily measured with the current sensors or digital devices. Some examples are the sportive parameters of turfgrass such as velocity, firmness or traction. Nowadays, for the measurement of the aforementioned variables, analogic devices must be used, which require from the human action and cannot be connected with a WSN of an IoT system. Even though autonomous digital devices cannot measure those parameters, there exist the possibility to estimate them upon other parameters. It is usual to combine different easy-to-measure parameters to estimate another parameter, which is not possible to measure it directly. This technique is known as multi-sensor data fusion, and we can find several examples of its applications for agriculture such as phenotyping [2], or estimating the evapotranspiration [3].

In some cases, a simple linear regression model can be used to estimate the seek parameters. Nonetheless, occasionally the use of artificial intelligence (AI) systems must attain better results. In [4], authors proposed the use of soil temperature, moisture and pH values to estimate farmland soil carbon sink factors using multi-sensor data fusion and artificial neural network (ANN). Therefore, we can affirm that these techniques have been already used to estimate parameters in agriculture.

Though, none of these techniques or methods has been used in sportive grass management. Unlike other examples found in agriculture, the use of estimating parameters in sportive turfgrass has a low direct impact on the sustainability of the activity. Nonetheless, the estimation of parameters such as velocity, firmness or traction of grass has an impact on the quality of the game of the users. Apart from the assumption that not all the greenkeepers have the devices or the time to monitor the status of the turfgrass, the measurement of velocity is one of the most tedious actions. It is generally measured only before a tournament. Besides this, the velocity is an excellent indicator of putting green status. The velocity might be controlled by changing some of the management variables. Some of the maintenance actions, such as aeration, have a dramatic effect on the velocity causing an abrupt reduction.

The aim of the paper is to evaluate if the data gathered from digital sensing devices can be used to estimate the green velocity to monitor its recovery after aeration. The objective is to reduce the time required in the regular field monitoring in the golf courses. To have enough data to test the effectiveness of the results of ANN, we gathered measures before and after the maintenance action during several months. Data is analysed to determine which parameter or parameters can be used to estimate green velocity. We want to confirm two hypotheses, the first one if a single variable can

 ISBN: 978-1-61208-820-4 

be used to estimate the putting green recovery as it can be done with the velocity. The second one is to determine if Multi-sensor data fusion and ANN can be used to estimate the velocity.

The remainder of this paper is structured as follows. Section 2 outlines the related work in the field of turfgrass monitoring. The test bench is described in Section 3. Section 4 presented our results and their applicability. Finally, the conclusions are summarised in Section 5.

## II. Related Work

In this section, we described the existing efforts in turfgrass monitoring and multi-sensor data fusion with AI in agriculture.

Although the interest in turfgrass monitoring is lower than in other farming systems, we can found several examples. Marin et al. [5] proposed the use of remote sensing to evaluate the turfgrass coverage by analysing the histograms of gathered images. They work oriented to ornamental lawns rather than sportive grasses. Parra et al. presented a new methodology for the identification of the weed plant in sportive turfgrass [6]. The authors use remote sensing images and image processing techniques based on edge detection to detect weed plants.

Straw et al. measured multiple parameters in natural turfgrass sports fields to identify short-term spatiotemporal relationship [7]. The authors gather data about soil and plant variables finding some interesting correlations, for example, between Normalized Difference Vegetation Index (NDVI) and surface hardness. Nonetheless, in this paper, no sportive variables are measured, estimated or correlated. More examples of the multi-sensor approach are found for grasslands. In [8], Ouyang et al. analysed vegetation dynamics by utilising the standardised NDVI data gathered with different remote sensing sources. By combining NDVI values, they were able to estimate the biomass. A parallel proposal was presented by Reddersen et al. [9]. In this case, the authors select and extensively managed grassland and several measures are gathered in the experimental area. The measured parameters included Leaf area index, ultrasonic sward height, and 12 vegetation indices to estimate the biomass for different species. The combination of different measured variables offers reasonable estimations of plant biomass. The objective in [8] and [9] was somehow similar to our aim, determine the value of a parameter which is hard to measure (the biomass) with other easy-to-measure variables (NDVI).

Focusing on our objective, the estimation of velocity in the putting green, no one paper has been found that details the existence of a relation of agronomic variables and velocity. The only paper where the velocity of the putting green was measured we found is [10]. In [10], Rana and Askew evaluate the if *Poa pratensis* (one of the species that composes the green) has an effect on ball rolling behaviour. To do so, they measure the rolling behaviour in the putting gree, using a high-speed camera. Their results indicate that no effect was found on ball velocity regardless of tested surface (different grass species). Nonetheless, we are going to analyse more parameters to find a correlation between surface and velocity.

We can affirm that currently there is no one technique which can be used to measure in-situ the green velocity, which can be integrated into IoT systems. Furthermore, no one authors have presented the possibility to estimate the velocity basing on multi-sensor data fusion with or without AI system.

## III. Test Bench

In this section, the description of the studied area, the measured parameters and used equipment are detailed.

### A. Description of the studied area

The studied area is two greens, green two and green 17, of the "Encin Golf Course" located at the region of Madrid (Spain). The greens are the part of the golf course in which the velocity becomes critical; therefore, it is essential to measure this parameter. Although many greens might have a low or null slope in the studied greens, we can identify areas with certain slopes as can be seen in Figure 1.

The green is composed of *Agrostis stolonifera* T1 and presents a small incidence of *Poa annua* as an undesired plant. The greens are mowed, as average, three times per week. The height of the grass in the green area is between 3 and 4mm. The greens are irrigated every day after sunrise according to the recommendations of the Food and Agriculture Organization. In each one of the greens, we have identified three areas to be measured.

After starting the measurements, a maintenance action, green aeration, was carried out. Among the existing techniques for improving the green aeration, we have applied the half-inch-diameter hollow tines. It was done from 23$^{rd}$ to 29$^{th}$ of March. The first measurement was carried out the 24$^{th}$ of February of 2020 with the green in normal status. In the 2$^{nd}$ of April, the greens were monitored after the maintenance actions. After this date, the greens are monitored once or twice per month according to the time disposal and the restrictions due to the COVID. A total of 8 records have been performed, finishing the experiment on 31$^{st}$ of July of 2020. Table 1 details the days in which the greens are monitored and the label that we are going to use for each day. The label indicates the time pass after the maintenance action.

### B. Measured parameters

We measure a total of four agronomic parameters (two forms the soil and two from the vegetation) using digital devices, and the green velocity as a sportive parameter. The monitored parameters are the soil moisture (SM), soil temperature (ST), canopy temperature (CT), and NDVI.

Figure 1. Image of Green 2 took on 1/07/2020

TABLE I. SUMMARY OF MEASUREMENTS

| Nº of measurement | Day | Label | Description |
|---|---|---|---|
| 1 | 24/02/2020 | -1 | Before the maintenance action |
| 2 | 02/04/2020 | 0 | Just after the maintenance action |
| 3 | 20/04/2020 | 1 | After the maintenance action |
| 4 | 19/05/2020 | 2 | |
| 5 | 02/06/2020 | 3 | |
| 6 | 16/06/2020 | 4 | |
| 7 | 17/07/2020 | 5 | |
| 8 | 31/07/2020 | 6 | |

The soil moisture is measured with the TDR 350 FieldScout [11] at 5cm. In each point, we gather three measurements and only the mean value is used in this paper. The TDR was configured according to the instructions, and the selected soil type was set on the sand. The soil temperature is also measured with the TDR at 5cm. Again, three records are done in each one of the measured points.

The CT is measured using an infrared thermometer. We have used the Fluke 561 [12]. Three records are performed in each one of the monitored areas, and again, the mean value is used. For the NDVI measurement, we have used the Handheld Crop Sensor GreenSeeker [13]. Since this device allows to perform a scan of the measured area, and the mean value is automatically calculated, we used this option. Both devices are considered as remote sensing devices and have been used at 1m above the soil.

Finally, to measure the green velocity, we have used a stimpmeter. The stimpmeter is a tool designed by the United States Golf Association in 1930 used to measure the velocity of a golf ball in the green area. This measurement is performed manually using the stimpmeter and three golf balls. Although this is the official process to obtain the velocity of the green and it is used in before the most important championships, the process is tedious and might be affected by the person who is performing the measures.

## IV. RESULTS

In this section, we present our results. First, the evolution of monitored parameters after the aeration is displayed. Then, the existing correlations and the use of ANN are analysed.

### A. Evolution of sensed variables

In order to verify one of our main hypothesis, we are going to present the recorded values of all monitored parameters (including the measured with digital devices and with stimpmeter).

First, we present the measured values of soil measurements. Figure 2 a) and b) represent the mean and the Fisher Least significant difference (LSD) intervals of measured soil moisture and soil temperature for the studied period. Regarding the soil moisture, Figure 2 a), the detected change is a constant increase of soil moisture, unless in data gathered in the second measurement after the maintenance. This increase is explained by a modification in irrigation due to the increase in the temperature, which must be compensated by a higher amount of applied irrigation. Apparently, no relation between the green recovery and the soil moisture can be detected. Concerning the soil temperature, Figure 2 b), again the general trend is due to the changes in environmental conditions. Nonetheless, we can identify that just after the aeration of the green (measure 0) the temperature of soil increases. This fact is caused by the change of surface during the aeration action, when part of the surface, previously covered by grass, changes to sand. Since the sand has different thermic properties than the green plants, the value of soil temperature increases. After 22 days (measure 1), the soil temperature lowers again and present similar values than before the maintenance action. Therefore, we can affirm that in terms of soil temperature, the disturbance caused by the aeration of the greens is recovered after 22 days.

Following, we are going to detail the results of monitored vegetation variables, see Figure 3 a) and b). The results of CT, Figure 3 a) are similar to the results of soil temperature. Although the values are a bit lower due to the capability of reducing the temperature of healthy plants, the observed trend is the same. There is an increase of CT just after the maintenance action due to the introduced modification in the surface. The increase of CT is corrected in the next measure (Measure 1).

Concerning the NDVI, Figure 3 b), the measured NDVI just after the maintenance was much lower than the NDVI before the maintenance. Again, this alteration is corrected after 22 days. Thus we can affirm that considering the agronomic variables, the disturbance of the aeration of greens is recovered in less than 22 days. Finally, we analyse the evolution of green velocity in Figure 4.

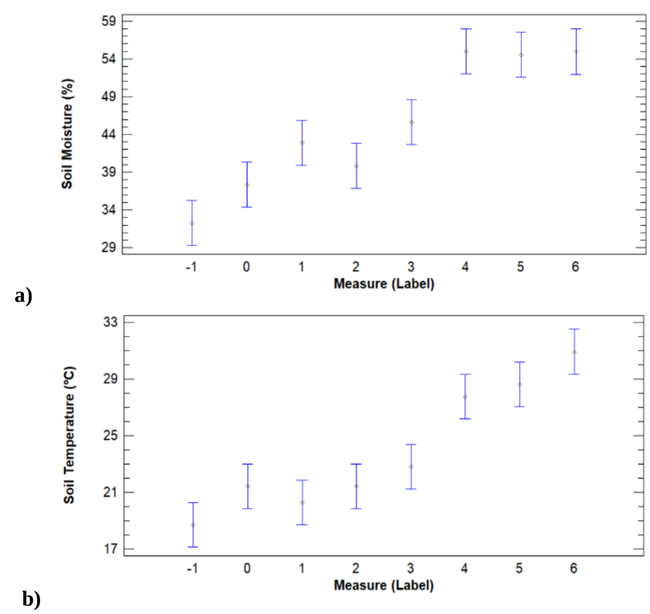


Figure 2. Evolution on measured soil variables as mean value and Fisher LSD intervals

This is the variable that truly indicates us the recovery of the green after the aeration. We can identify that although there is a recovery in measures 1 and 2, the green is not entirely recovered after measure 6 (31/07/2020). We must clarify that the velocities of 7 feet are appropriate for playing. Even so, we cannot consider that green is recovered until the measured velocity is equal to the velocity measured in measure -1 (before the action).

Thus, we can affirm that the simple measure of agronomic variables cannot inform us about the recovery of the green after maintenance action, at least in the case of aeration. According to the measured agronomic variables, we will establish the recovery of the green in Measure 1, 22 days after the aeration. On the other hand, attending to the green velocity, the recovery of green will be reached in Measure 6, 124 days after the aeration. Therefore we need to discard our first hypothesis.

## *B. Using agronomic variables to predict the green velocity*

Our second hypothesis is that the combination of two or more agronomic values can be used to predict the green velocity, allowing the evaluation of the recovery. In order to evaluate this option, different tools are proposed. First, a multiple regression, including agronomic variables as independent variables and the velocity as dependent variables, is presented.

Following, and with the purpose of developing a graphics useful for greenkeepers, the application of the ANN is proposed. Despite there are other AI more powerful than ANN, such as Support Vector Machine (SVM), we focus on ANN as the first step of applying AI to gathered data. Other authors compared the performance of SVM with ANN of biological data and SVM showed slightly better accuracy, 80% for ANN and 85% for SVM[14].

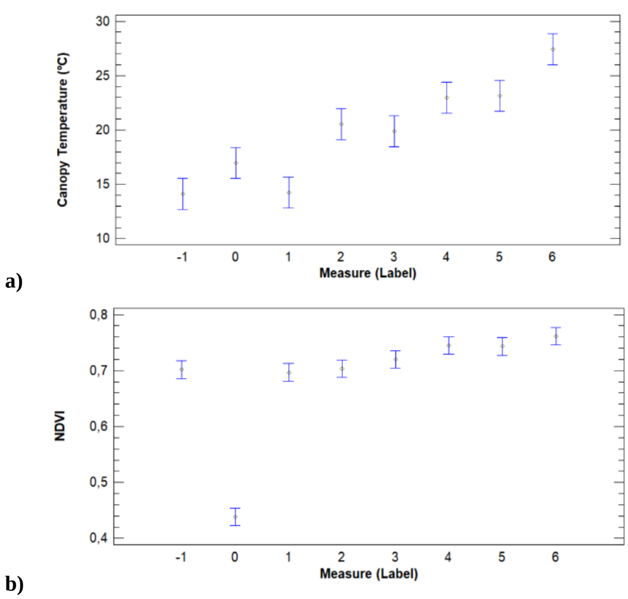


Figure 3. Evolution on measured vegetation variables as mean value and Fisher LSD intervals

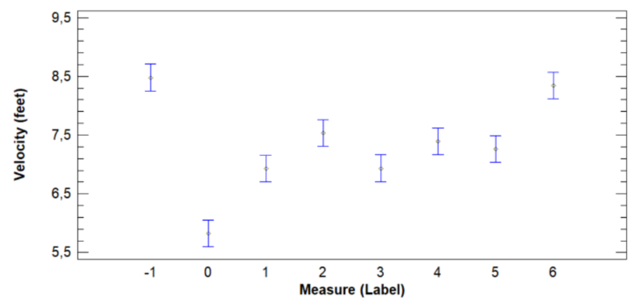


Figure 4. Evolution on measured velocity as mean value and Fisher LSD intervals

Concerning the multiple regression, a first attempt is performed including all the variables and selecting the ordinary minimum squares as adjusting procedure. The generated model has an $R^2$ of 0.63. Nonetheless, the results of statistical software pointed out that some of the CTs might be extracted to simplify the model. After extract this value from the model, the $R^2$ has not changed; its value is 0.63. In Figure 5, we can compare the observed value of velocity and the predicted value according to the generated model. We can identify that the lower errors are linked to values of velocity between 6.7 and 7.8 feet. The proposed mathematical model is presented in (1).

$$V\ (feet) = 3.296 \times SM\ (\%) + 7.059 \times NDVI + 0.115 \times ST\ (ºC) \quad (1)$$

where:

V is the velocity of the green
SM is the soil moisture
ST is the soil temperature

Although the proposed model confirms our hypothesis, the combination of three agronomic variables can be used to estimate the green recovery or velocity, and one more step must be carried out. Besides the application of proposed above model can be useful and its accuracy indicated by the R2, it is almost useless for the daily monitoring activities. Considering the different tasks of greenkeepers if we expect that the proposed model is adopted we need to avoid the use of equations and present the results in a more easy-to-apply and straightforward way. Therefore, and with the aim of generating a series of graphics, an ANN model is created. It will be easier for the greenkeepers to use the classification graphics of the ANN than the application of (1).

The proposed ANN has three input neurons (soil moisture, soil temperature and NDVI), two hidden layers, and six output neurons. In order to simplify our variables, the velocity was included without decimals in the model. The velocity values go from 5 to 10 feet. The rest of the variables are maintained as they are. The probability was set as proportional to the observed and the cost of error equal to all groups. Finally, the sphere of influence was determined by jackknifing.

From the total of 48 observations, most of the cases have a measured velocity of 7 and 8 feet, with 25 and 15 observations. The optimised value of jackknifing during the training was set on 0.073. The results of the proposed ANN pointed out that 70.83% of cases were classified correctly. The percentage of correct classification is shown in Table 2.

According to our results, we can affirm that as found in the regression, the highest error are linked to the most extreme velocities (5, 9 and 10 feet with 0% of correct classified cases). The best accuracy, 88% of correct classified cased, is related to the central velocity, 7 feet. Now, we compare the results of ANN with the regression model. Even that we use the discrete values of velocity values in the regression, the R2 of the newly generated model is 0.60. Thus, we can affirm that ANN not only offers a more straightforward way to use their results for greenkeepers, the classification graphics but also offers the best accuracy compared with regression models.

Finally, we present in Figure 6, the summary of classification graphics obtained. Since in our model, we have three variables we include as x and y-axis the SM and NDVI, and four different graphics are presented for four different ST.

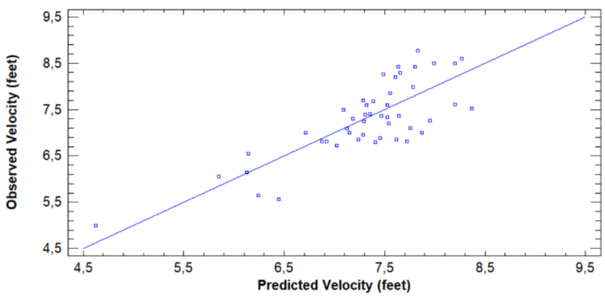


Figure 5. Observed vs predicted values of velocity with the proposed mathematical model

The objective is that those graphics can be easily used by the greenkeepers to estimate the velocity of their greens in the daily monitoring. Figure 6 a) shows the estimated velocity for a soil temperature of 10ºC. We can identify that the higher the NDVI, the faster the velocity. Meanwhile, the soil moisture has the opposite effect, the higher the soil moisture, the slower the green velocity. The same trend is found in Figure 6 b) for 20 ºC, Figure 6 c) for 30ºC and Figure 6 d) for 40ºC. For scenarios with 10ºC, the maximum expected velocity will be 8 feet. The predicted velocities increase with the temperature, and for scenarios with 30 ºC or more, velocities of 10 feet can be expected.

TABLE II. SUMMARY OF CLASSIFIED CASES

| Velocity (feet) | Number of observations | Correct classified percentage |
|---|---|---|
| 5 | 1 | 0,0 |
| 6 | 4 | 50,0 |
| 7 | 25 | 88,0 |
| 8 | 15 | 66,6667 |
| 9 | 2 | 0,0 |
| 10 | 1 | 0,0 |
| Total | 48 | 70,8333 |

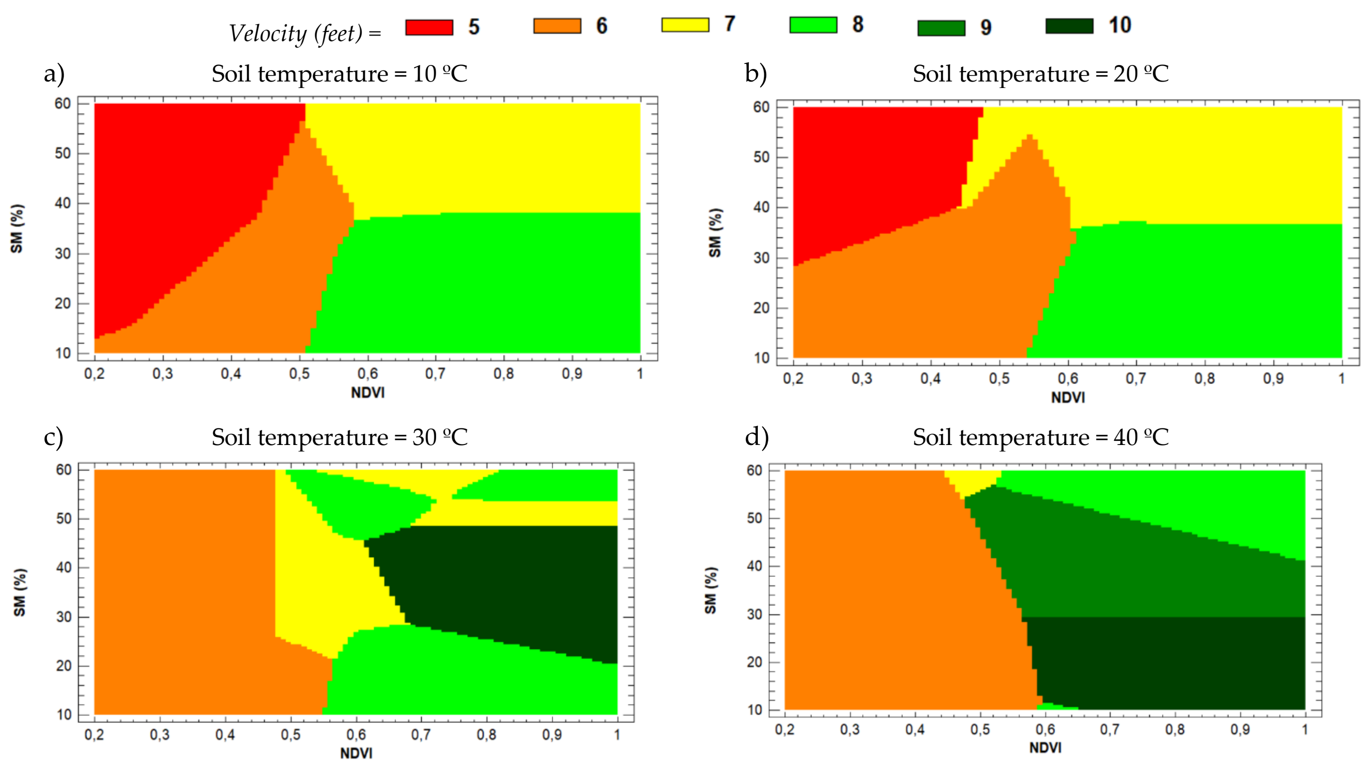


Figure 6. Classification results of ANN applied to gathered data to estimate the velocity from SM, NDVI and ST.

It must be noted that, although the data included in this ANN model is limited, include just one type of grass coverage, and it is affected by the maintenance action, the results are promising. The main limitation of this study is the fact that most of our measured have a similar velocity, between 7 and 8, see Table 2. It is necessary to increase the measuring time to obtained more data under different circumstances.

In addition, results are aligned with the empirical experience of greenkeepers. The knowledge of greenkeepers indicates that the greens are faster when they are dry. Those dry conditions correspond to low soil moisture. Therefore, we have demonstrated that although in previous papers authors have pointed out that no relation was found between ball velocity and surface [10] there is a correlation between soil conditions (NDVI, SM, and ST) and ball velocity. These papers follow the ideas developed in [8] and [9], to estimate parameters, which are hard to measure from NDVI.

## V. Conclusion

In this paper, we have dealt with the use of sensing devices to monitor the changes in the velocity in two greens of *Agrostis stolonifera*. The objective is to obtain a way of using the data of the employed digital devices to estimate the velocity, which measurements are a tedious and time-consuming practice.

Our study is performed before, during and after a maintenance action that produces a decrease in the velocity. The results indicated that the measurement and analysis of a single variable are not enough to characterise the velocity of the green. Nonetheless, the combination of soil moisture, soil temperature and NDVI can be used to estimate the velocity. This was demonstrated with a multiple regression model and with the ANN model. The proposed ANN model offers a series of graphics, which can be used by the greenkeepers to estimate the velocity in the daily routine.

The future work will be focused on extending the amount of data from the greens performing more measurements and including more variables. Furthermore, the comparison of our results with other AI techniques will be considered, as well as validate and test the obtained machine learning model with new data. In addition, we will start to monitor greens composed of other grass species and greens with a higher percentage of *Poa annua*. This must be considered since other species have different colourations and might affect to the NDVI measures.

## Acknowledgment

This work has been partially funded by AREA VERDE-MG projects, Projects GO-PDR18-XEROCESPED funded, by the European Agricultural Fund for Rural Development (EAFRD) and IMIDRA, and by Conselleria de Educación, Cultura y Deporte with the Subvenciones para la contratación de personal investigador en fase postdoctoral, grant number APOSTD/2019/04.

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 ISBN: 978-1-61208-820-4 