Correlation of NDVI with RGB Data to Evaluate the Effects of Solar Exposure on Different Combinations of Ornamental Grass Used in Lawns

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Abstract. In the urban areas, the use of water to irrigate the green areas must be improved by the use of technology to reach water efficiency. Normalized Difference Vegetation Index (NDVI) is the most important indexes to evaluate the vegetation vigour, but the required equipment for its gathering have a high cost. In this paper, we present the use of NDVI and pictures taken with a regular camera to evaluate the status of two groups of plots under different solar exposure. Besides, we study the possibilities to correlate data obtained from regular pictures with NDVI, offering a low-cost option for monitoring plant status. From the 18 evaluated plots, which include 3 different grass combinations, the mean value of NDVI and one picture is taken. Then, we obtain the red, green, and blue histograms of each picture using Matlab software. The histograms were included in Statgraphics to search for correlations between histograms and Normalized Difference Vegetation Index of each plot. The highest correlation was found with the data of red histogram ($R^2 = 0.58$ and high significance level). Finally, the variance of both evaluated variables is analyzed, and we have determined that both variables are useful in determining the solar exposure of studied plots. Significance level was higher in NDVI than with data of the histogram, but both of them have a P-Value lower than 0.05 in the analysis of variance.

Keywords: GreenSeeker · Matlab · Camera · Solar radiation · Turf · NDVI · RGB

1 Introduction

In urban areas, water management is critical, especially given the future previsions of climate change. A reduction of 40% on the rainwater might be expected in the following

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50 years [1]. Thus, it is essential to maximize the efforts to reduce the water waste and enhance the efficiency in the water use. Several efforts are being made to reach water efficiency, in which the use of technology, are becoming priceless tools. The use of sensors for water distribution network [2] and the creation of systems to achieve water efficiency in water distribution network [3] are some examples.

However, there are several aspects in the urban areas linked to water use which must be addressed to attain true water efficiency. One of these aspects is the proper maintenance of green areas. Traditionally, the irrigation of green areas, mainly composed by grasses, is performed considering the climatic and agronomic parameters (such as temperature and expected evapotranspiration) [4]. Nonetheless, there are other parameters which can affect the water requirements of turf and have to be considered to program the irrigation. One of those parameters is the changes in solar radiation caused by the shade projected by buildings and trees or different orientation. Differences in solar radiation lead to different water need of the lawns.

With regards to the use of technology for plants monitoring and its irrigation needs, we can identify the Wireless Sensor Network (WSN) as one of the most useful solutions in agriculture. Precision Agriculture (PA) is mainly based on the use of sensors and remote sensing for archiving the sustainability of agriculture. In different papers, we can see the use of similar systems for Precision Gardening (PG). Although, the WSNs are very important in agriculture, in PG the remote sensing can have a better performance. In view of the periodicity of required mows to maintain the gardens, and the mowing equipment, remote sensing can be implemented in the lawnmowers.

In PA, the Normalized Difference Vegetation Index (NDVI) is one of the most used indexes for plant vigour monitoring. The regular cameras, or RGB cameras, can be an excellent alternative to estimate the greenness of plants. In previous papers, we have estimated the plant coverage in lawns by using RGB pictures and operating with their histograms [5]. Although the use of RGB images might not be as precise as NDVI to detect alterations of the health of plants (water stress, pests, diseases, etc.), they should be considered as a good alternative for daily monitoring. The RGB cameras are much cheaper than the equipment required for NDVI calculation. In addition, a microprocessor can be included to calculate the histograms and derived products.

In this paper, we present the use of NDVI and RGB histograms to detect changes in grass lawns when they have different sun exposure. A total of 18 plots have been analyzed, from which we can divide two subgroups. The first subgroup (plots 1 to 9) receive lower solar radiation than the second one (plots 12 to 18). Two technological solutions have been used to evaluate the changes between two subgroups of plots, the GreenSeeker, which measures the NDVI, and an RGB camera. From each picture, the red, green, and blue histograms are analyzed. Then, multivariate analyses to search correlations between the NDVI and the histogram of the 18 analyzed plots are carried out. From the regions of the histograms in which correlations are found are studied in detail. Finally, analysis of variance is performed to determine if there are differences between plots with different solar exposure in NDVI and RGB data.

The rest of the paper is structured as follows; Sect. 2 outlines the related work and highlight the differences between existing studies and the proposed analysis. The material and methods are defined in Sect. 3. Section 4 presents the results and discussion of the proposed analysis, including the statistical correlations and analyses of variance. Finally, the conclusions and future work are detailed in Sect. 5.

2 Related Work

In this section, we summarize the current solutions for monitoring plant status, focusing on the use of NDVI, other indexes and RGB images. In addition, a comparison between the proposed analysis and existing ones is presented.

The NDVI is widely used for plant monitoring, and several papers demonstrate its benefits. It can be measured in-situ with specialized equipment with remote sensing. Following we include a series of papers that have used the NDVI information for monitor plant status. First of all, the NDVI is highly used in PA, in [6] authors proposed the use of optical and analogue sensors for vineyard monitoring. They propose to change the remote sensing information by data gathered by proximal sensing technologies. Authors develop the idea of creating a mobile lab which includes GreenSeeker RT100, ultrasonic sensors to estimate canopy thickness, and DGPS receiver. Their results showed that NDVI data and ultrasonic lectures where highly correlated and NDVI was used to estimate the real vine phytosanitary status.

In [7], authors propose to obtain the NDVI data using an unmanned aerial vehicle in wheat agronomy and breeding trials. They use a multispectral camera in the unmanned aerial vehicle, and the handheld GreenSeeker to obtain data. Then, they correlate data of both methods and use the gathered information for phenotyping the crop. They were able to identify the d flowering time and maturity with the NDVI. Authors of [8] have exposed the use of NDVI with remote sensing to determine the drought. Their results point out that the NDVI is highly correlated with the standardized precipitation index. Finally, they show the use of NDVI to predict the yield.

The use of NDVI in rice was presented in [9]. The authors demonstrate the effectiveness of NDVI to estimate the yield of rice in dry and wet seasons. In the conclusions, authors indicate that the measurement of NDVI during the early reproductive stages is the measure with the highest correlation with yield in dry seasons. The use of NDVI in pastures has also been reported in [10]. In that paper, authors present the use of NDVI for rapid determination of evapotranspiration coefficient. The evapotranspiration coefficient is vital for irrigation management, and it is measured with vaporation chambers. Its correlation with the NDVI allows rapid estimation of the evapotranspiration to adjust the irrigation. The test performed in [10] were carried out with *Festuca arundinacea* during two consecutive growing seasons. Results showed a high correlation between NDVI and evapotranspiration coefficient of *F.arundinacea.*

Finally, the use of RGB data has also been presented for plant monitoring. We are going to detail some examples. In [11] authors propose the use of RGB data for Assessing Early Plant Vigor in Winter Wheat jointly with GreenSeeker and hyperspectral camera. Their results indicate that the RGB data can be used as a low-cost option in the very early growth stages. After this moment, the use of other methods is recommended. On the other hand, we also found the use of RGB data in lawns monitoring to assess the plant coverage using the data of green histogram [5].

After analyzing the related work, and as far as we know, no work has been published aimed to relate the RGB data and NDVI in grass crops. Besides, no publications focused on the effect of solar exposure on the NDVI have been found.

3 Materials and Methods

The description of used equipment to gather data from the plots, and software selected to analyze the data is shown. In addition, the plots, its composition, and differences are detailed in this section.

3.1 Equipment Used to Gather the Data

For data collection, two different devices have been used. On the one hand, for the RGB pictures acquisition, a reflex camera was used. On the other hand, specific equipment, the GreenSeeker [12], was used for the obtention of NDVI data of plots.

The camera selected for gathering the RGB pictures was the Canon EOS 77 [13]. Several parameters of the camera can be modified; the configuration of the camera can be seen in Table 1. The pictures were taken at a distance of 1.5 m from the soil. One picture is gathered for each plot, and we ensure that 100% of the picture contains the plot. To avoid including the variability of the edges of the plot, the borders are not included in the picture. Therefore, the picture contains the centre of each plot. The pictures were taken without flash in a day with no clouds.

With regard to the NDVI data, the GreenSeeker Handheld, see Fig. 1, has been used. This device is able to measure the NDVI of a surface (the plots) in dynamic mode, and after the measurement, the mean value is displayed in the screen. To obtain the mean value, the device was located at 1.5 m from the soil and moved along the plot to gather the NDVI of several points.

Table 1. Configuration of Canon EOS 77 Camera in the moment of taking the pictures.

Characteristics	Canon EOS 77
Size of the image	6000 × 4000 pixels
Horizontal and vertical resolution	72 ppp
Bit depth	24
F point	f/5
Focal distance	18 mm
Exposure time	1/160 s
ISO velocity	ISO - 100

Fig. 1. Device used to gather data from NDVI of each plot.

3.2 Software for Data Analysis

Once the data were gathered in the field, the pictures have to be processed to extract the histograms before obtaining any existent correlation between NDVI and RGB data or find variances between plots with high and low solar exposure. After processing the image, statistical analyses were done to find correlations.

To extract the histograms form the pictures, the Matlab software [14] was selected due to its high capacity and the option to implement it in the future in the Raspberry nodes. The code used to obtain the histograms, based on the code described in [5], is saved in a script. This code generates a series of matrixes and vectors that contain the information about the value of each pixel in RGB and the histograms themselves. The Red, Green and Blue files contain the value of each pixel for the specified colour, and the histograms are contained in files h_R, h_G, and h_B. The rest of the generated files are elements needed to calculate the histograms.

The other used software is a statistical tool which is used first to find correlations between NDVI and the histograms, and then to analyze the variance between plots with different solar exposure. The selected software was the Statgraphics Centurion XVI [15] due to its easy-to-use interface and its powerful capabilities. First of all, multivariate analysis to search for correlations is conducted. In this analysis, the data of NDVI and the number of pixels for each value of brightness for red, green, and blue histograms are included. The objective of this analysis is to find which region or regions of histogram have a high correlation with NDVI data. The second set of analyses was aimed to find the linear regression between the NDVI values and the part of the histogram, which has the greatest correlation. Finally, ANalysis Of VAriance (ANOVA) with NDVI and the data of histogram with better linear regression was performed to determine if evaluated factors are affected by the different solar exposure.

3.3 Plots Description

The studied area is composed of 18 small plots which contain different grass combinations. The plots are placed in the fields of Instituto Madrileño de Investigación y Desarrollo Rural, Agrario y Alimentario (IMIDRA) in the Finca el Encín (Alcalá de Henares). Half of these plots are located in an area with higher solar exposure; there is no shadow over those plots along the day. The rest of them are closer to the trees, which project a shade over the plots in the first hours of the morning.

The differences in solar exposure are the sole differentiating parameter. The soil characteristics, irrigation, and fertilization remain equal in both groups of plots since its seed. The plots were seed on 4th of Abril of 2019, and the pictures were taken after 204 days (25th of October of 2019).

All the included plots are formed by a combination of two grass species, a C3 and a C4 plant. More information about the aim of these combinations can be found in [16]. As a C3 plant, *Festuca arundinacea* is included in all the plots. Meanwhile, different C4 species are used (*Brachypodium distachyon*, *Zoysia japonica*, and *Cynodon dactylon*). Thus, we can find three grass combinations in the plots: *Festuca Arundinacea* with *Brachypodium distachyon* (F+B), *Festuca Arundinacea* with *Zoysia japonica* (F+Z), and *Festuca Arundinacea* with *Cynodon dactylon* (F+C). Each combination is repeated three times for each solar exposure regime (R1, R2 and R3). A picture of the location is depicted in Fig. 2. A scheme of the combinations and its location with regard to the path of the Sun can be seen in Fig. 3. The plots are located in a single row almost perpendicular to the path of the Sun and parallel to the road and the ornamental trees responsible for the shade projection.

Fig. 2. Picture of the studied area.

4 Results

The description of used equipment to gather data from the plots, and software selected to analyze the data is shown. In addition, the plots, its composition, and differences are detailed in this section.

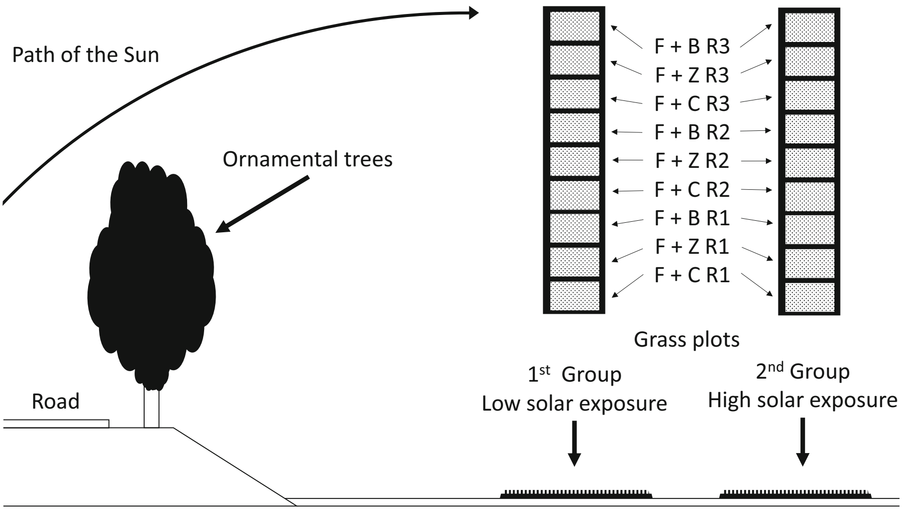

Fig. 3. Scheme of the plots, grass combinations and path of the Sun.

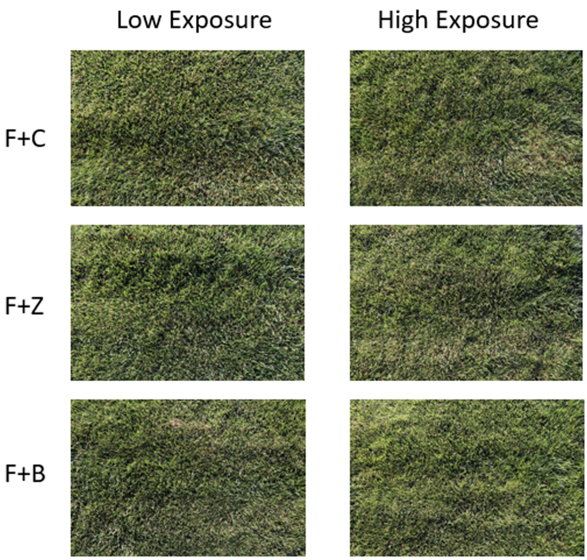

Fig. 4. Example of the taken pictures in the plots including the three grass combinations under high and low solar exposure

4.1 Histogram Analysis

Part of the taken pictures is shown in Fig. 4. We present the first replica of the three compositions with high and low solar exposure. It is important to note that no differences are observed in the pictures, or the plots can be identified to the bare eye.

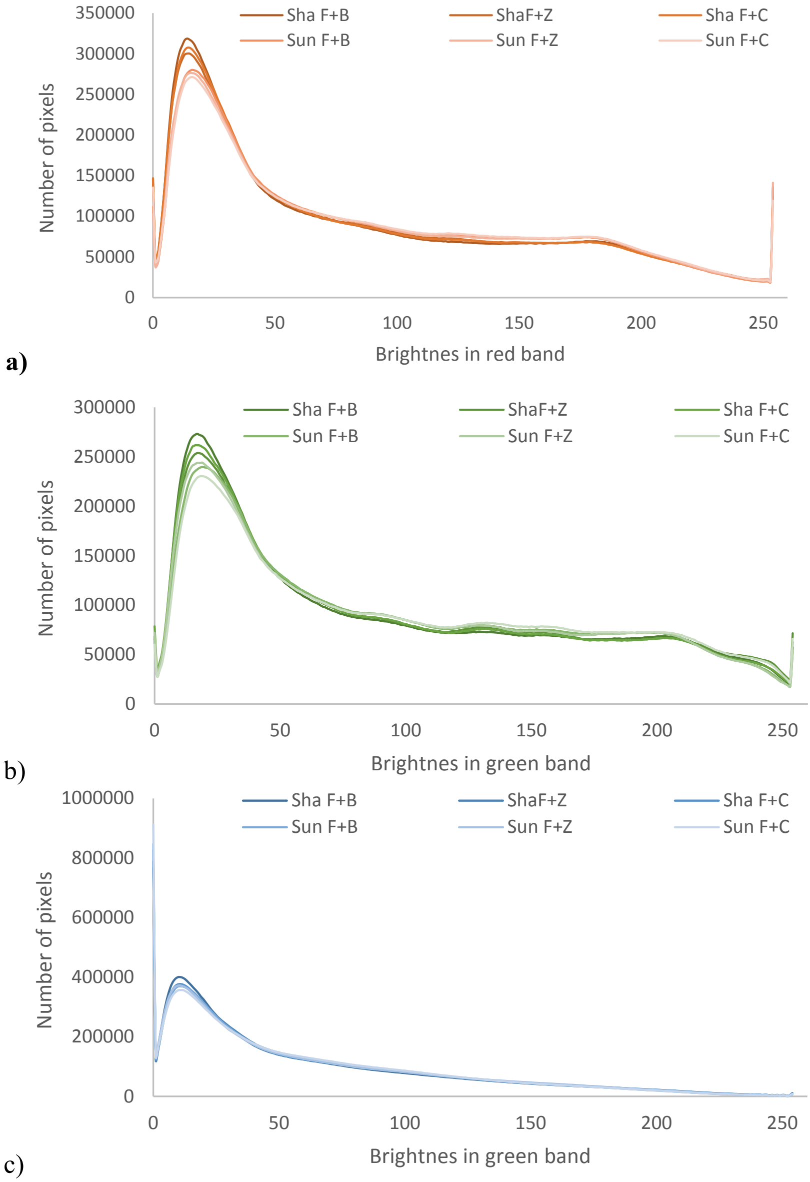

Fig. 5. Mean of red (a), green (b), and blue (c) histogram for each grass combination with high (Sun F+X) and low (Sha F+X) solar radiation exposure (Color figure online)

Next, we apply the code presented in Fig. 2 to extract the data for the histograms from each picture. The three histograms (red histogram a), green histogram b), and blue histogram c)) are displayed in Fig. 5. In the histograms, we have presented the mean values of the three repetitions for each grass combinations in the same solar exposure. They are identified as Sun or Sha according to the high and low solar exposure, respectively. Therefore, a total of 6 histograms are represented for each colour.

Concerning the red histogram, see Fig. 5a), it is possible to note that in the first region of the histogram (brightness values between 10 and 25) the plots with different solar exposure have different values. After this region, the data of plots remain similar until brightness value of 70. Then, the values of brightness are different for plots under high and low solar exposure until the brightness value of 180. Thus, we can identify two regions of the histogram in which the brightness values change with solar exposure.

With regards to the green histogram (Fig. 5b)), we can find similar results than in the red histogram. There is a region with low values of brightness (13 to 29) where the values of brightness are different for plots with different solar exposure.

In addition, we can identify another region (values of brightness from 150 to 200) with differences. Finally, for the blue histogram, see Fig. 5c), there is only one region where we can differentiate the plots (from 8 to 16) under high and low solar exposure.

4.2 Correlation Between NDVI and RGB Data

Following, we are going to present the results of analyses to found correlations between Normalized Difference Vegetation Index (NDVI) data and histograms. For these analyses, we include the mean value of NDVI for each plot obtained with the GreenSeeker as the first column of data in Statgraphics and the number of pixels for each value of brightness as the rest of the columns. Thus, for each analysis, we have included 257 values for each plot. The multivariate analysis search for correlations between each column of data. In this case, we only consider the correlations between first column (NDVI) and the rest (histogram). In general terms, we consider that there is a correlation between two variables when the P-value of the correlation is lower than 0.05. In our analyses, we focus on the correlations with P-values lower than 0.002. Table 2 outlines the results of these analyses. First, we indicate the number of cases with P-value < 0.002 (62 for red, 4 for green, and 7 for blue histograms). Then, we specify the values of the brightness of those cases, which represent two regions in red, one in green and blue histograms. Finally, we portray the case with the highest correlation and the P-Value for this case. For the red histogram, the value of brightness equal to 86 is the point with the most significant correlation. For green and blue histograms, the values of brightness are 24 and 13.

Once the specific value of brightness for each colour which is highly correlated with the NDVI data, we plot both variables (number of pixels with the selected value of brightness as a percentage and NDVI). The fact of using the percentage instead of as the summation of pixels allows us to apply our results (equations and models) for further analysis using other pictures with different size in the future. For the regressions, a lineal model and the method of least squares.

Figure 6a) presents the linear regression for NDVI and the percentage of pixels in the red histogram with brightness value equal to 86. The indicators of the goodness of this linear regression can be seen in Table 3. The regression model with data of red histograms is the one that has the better correlation in terms of R2, standard and absolute errors and P-Value of the variance analyses. The error and the P-Value are lower with data from the red histograms, and the R2 is higher than in the data of green and blue histograms. The obtained models have a negative correlation between variables.

The regression models for green histograms, in which the percentage of pixels with a brightness value equal to 24 is used, is presented in Fig. 6b). With these data, we have a positive correlation between NDVI and data from the histogram. With blue histogram, see Fig. 6c), we also found a positive correlation.

Table 2. Summary of multivariate analyses to search correlation between NDVI and RGB data from the histograms. For each colour cases (values of brightness) from 0 to 255 are included. Significance levels: ns, not significant; $*p < 0.05$; $**p < 0.01$ and $***p < 0.001$.

	Red	Green	Blue
Number of cases with P-value < 0.002	62	4	7
Cases (values of brightness)	9–22, 73–121	21–24	10–16
Case with the highest correlation	86	24	13
Level of significance	0.0001***	0.0012**	0.0001***

According to the results of the regressions, we can affirm that it is possible to interfere with the NDVI data from simple RGB picture. Hence, we have demonstrated that with equipment which has a lower cost than GreenSeeker, we can monitor the grass vigour.

4.3 Effectiveness of NDVI and RGB Data for Assessing Grass Status Concerning Different Solar Exposures

After analyzing the three obtained regression models, the one that relates the red histogram presents better results than green and blue histograms. Therefore, we are going to use this data for the last part of the paper in which we compare the results of both groups of plots to evaluate the suitability of NDVI and percentage of pixels with brightness values equal to 86 in the red histogram to differentiate the plots under high and low solar exposure. Thus we present the results of two Box-and-whisker diagram and two ANOVAs. From the diagram of Box-and-whisker we can affirm that the data of NDVI, see Fig. 6a) is more accurate to differentiate both group of plots than data from the red histogram, see Fig. 6b).

Nevertheless, to affirm if the variance between plots under high and low solar exposure is caused by the differences in solar exposure of just by the randomness of the data, the results of ANOVAs must be analyzed. The first ANOVA has been performed with the NDVI data of both groups of plots, identified as Low and High solar exposure. The results of ANOVA with NDVI data, see Table 4, indicate that this variable (NDVI) is suitable to differentiate both groups of plots and the observed differences on the NDVI data is caused by the different solar exposure of plots. The results for the ANOVA performed with the percentage of pixels from the red histogram is also significant. Nonetheless, the level of significance of the ANOVA performed with the red histogram (P-value of 0.0452) is lower than with the data of NDVI histogram (P-value of 0.0001). Thus, both

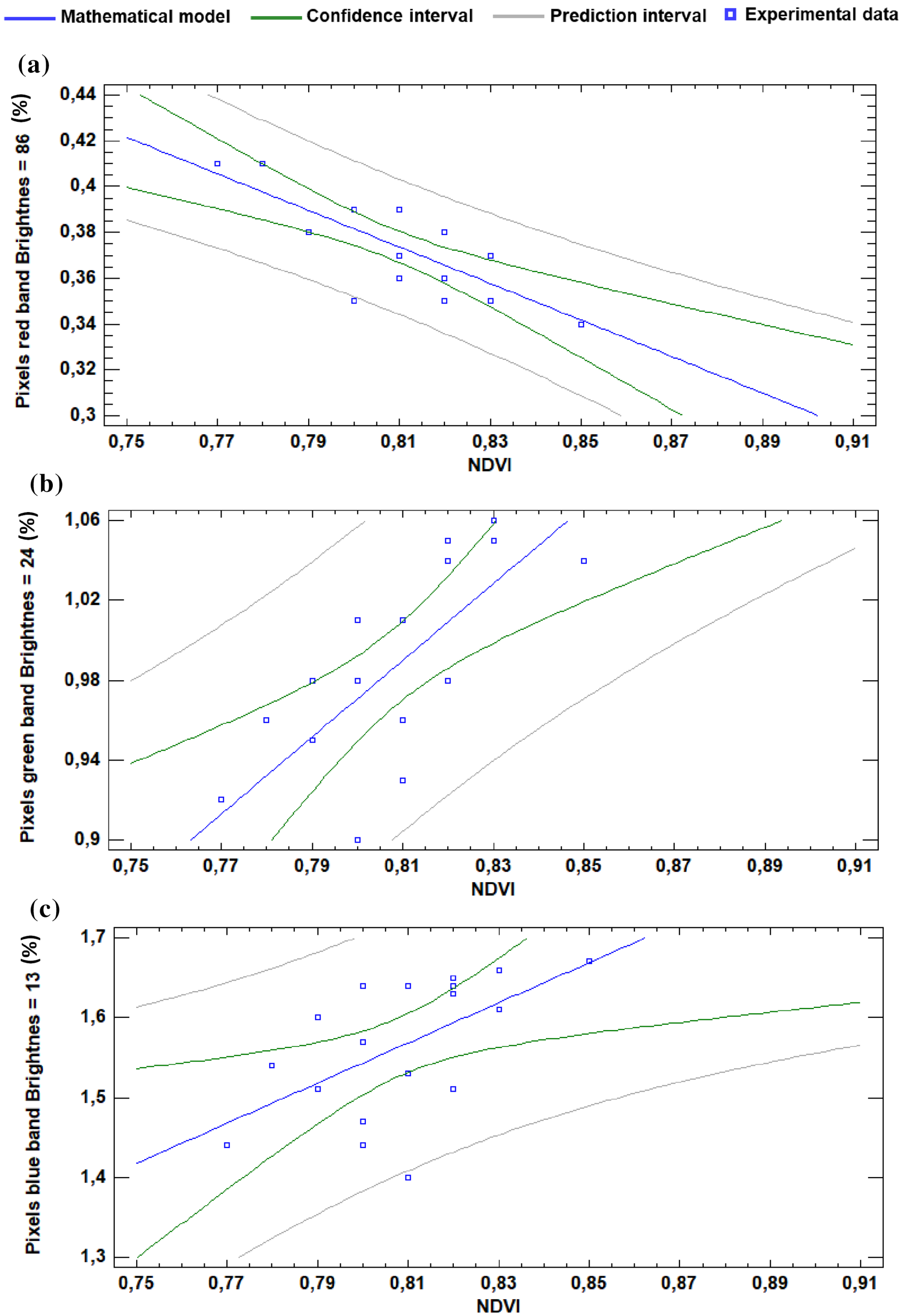

Fig. 6. Linear regression for selected data from red (a), green (b), and blue (c) histograms. (Color figure online)

Table 3. Summary linear regression, including the equations, R2, standard and absolute errors and P-value of the variance analyses for the linear regression. Significance levels: ns, not significant; *$p < 0.05$; **$p < 0.01$ and ***$p < 0.001$.

Colour	Equation	R2	Standard error	Absolute error	P-value
Red	Pixels (%) = 1,02 − 0,798 * NDVI	0.58	0,013	0,011	0,0002***
Green	Pixels (%) = −0,57 + 1,922 * NDVI	0.49	0,039	0,032	0,0012**
Blue	Pixels (%) = −0,47 + 2,514 * NDVI	0.32	0,073	0,057	0,0142**

variables can be used to identify the effects of solar exposure in our plots. Although the significance is higher for NDVI data, the lower cost of the RGB system can justify its use (Fig. 7).

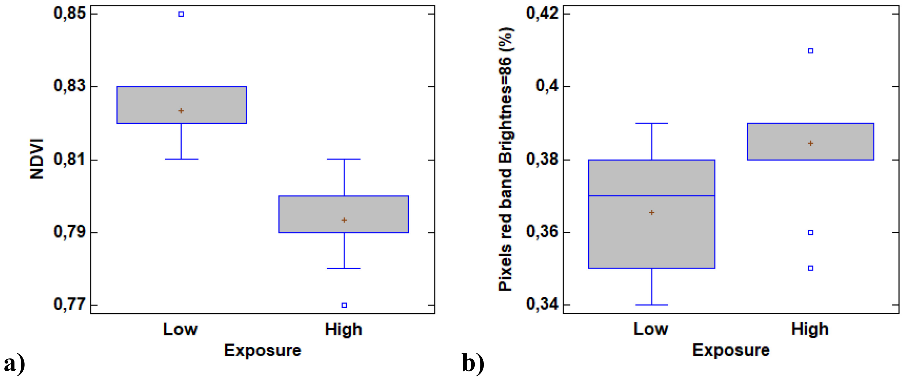

Fig. 7. Box-and-whisker diagram for NDVI (a) and Percentage of pixels red band brightness = 86 (b) for the two different groups of plots (high and low solar exposure) (Color figure online)

Table 4. Results of ANOVA for both monitoring methods and both groups of plots (high and low solar exposure). Significance levels: ns, not significant; *$p < 0.05$; **$p < 0.01$ and ***$p < 0.001$.

	NDVI	% of pixels red band brightness = 86
Solar exposure		
Low	0,793333[a]	0,365556[a]
High	0,823333[b]	0,384444[b]
Level of significance	0,0001***	0,0452*

The different letter succeeding the means are significantly different ($p < 0.05$) according to Tukey's honestly significant difference (HSD) test.

5 Conclusions

In this paper we have studied the relation between NDVI and RGB picture for 18 grass plots which are maintained under different solar exposure with the aim to find in the RGB data can be used to evaluate the plant vigour. The importance of using RGB is justified by the low cost of the systems to gather this type of data compared with the equipment required for NDVI data. It is important to note that the data included in these analyses correspond to different grass combinations, which implies a greater variability in the data.

The results of our analyses portray that there are correlations between some areas of the red, green, and blue histogram and the NDVI data. The highest correlation and the best lineal regression was found in the red histogram with the number of pixels which has brightness value equal to 86. It should be pointed out that although the variability between different grass combinations, the data of NDVI and a specific region of the red histogram can be used to differentiate the plots under low and high solar exposure.

In future work, we want to include data of other grass combinations, having variability in the C3 specie (including the specie *Poa pratensis*). Furthermore, we plan to implement the same analysis with pictures gathered with a drone and evaluate the suitability of the RGB histograms to monitor changes in plant vigour due to water scarcity and use a Raspberry as a node to process the data.

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