Remote sensing devices as key methods in the advanced turfgrass phenotyping under different water regimes

Salima Yousfi [a,*], José Marín [b, c], Lorena Parra [a, d], Jaime Lloret [d] and Pedro V. Mauri [a]

[a] Instituto Madrileño de Investigación y Desarrollo Rural, Agrario y Alimentario (IMIDRA), Departamento de Investigación Agroambiental, Madrid 28800, Spain; pedro.mauri@madrid.org (P.V.M.); salima.yousfi@madrid.org (S.Y.)
[b] AreaVerde MG projects Madrid, Departamento de Investigación e Innovación, Madrid 28050, Spain; jmarin@areaverde.es (J.M.)
[c] Universidad Politécnica de Madrid, Departamento de Producción Agraria, 28040 Madrid, Spain.
[d] Universitat Politècnica de València, Instituto de Investigación para la Gestión Integrada de Zonas Costeras, 46730 Grao de Gandia, Valencia, Spain; jlloret@dcom.upv.es (J.L.), loparbo@doctor.upv.es (L.P.)

***corresponding authors Salima Yousfi and Jaime Lloret**

Abstract: Drought stress is one of the main environmental stresses affecting turfgrass growing and natural grasslands development. Traditional methods for turfgrass drought phenotyping in field are time-consuming and labor-intensive. However, remote sensing techniques emerge as effective, rapid and easy approaches to optimize turfgrass selection under water stress. Remote sensing approaches are considerate as important strategies to select species of turfgrass tolerable to drought allowing green space sustainability and environment protection in regions with water limitation. Here we evaluated differences between six mixtures of C_3-C_4 turfgrass grown under two water regimes (limited and high irrigation). The performance of turf species was achieved using the green area (GA) vegetation index calculated from RGB (red green, blue) images obtained by ground camera and drone imagery, the normalized difference vegetation index (NDVI), the plant canopy temperature (CT) and soil moisture content (SM). Both vegetation (GA and NDVI) and water status (CT and SM) indices presented a significant difference in turfgrass growth under the two water regimes. Differences among turfgrass species were detected under limited and high irrigation using the vegetation indices. Both NDVI and GA allowed clear separation between drought-tolerant and susceptible turfgrass, as well as the identification of the mixtures with a rapid green regeneration after a period of limited irrigation. Moreover, the canopy temperature also discriminated between turfgrass species but only under limited irrigation, while soil moisture values did not differentiate between species. Furthermore, the regression and conceptual model using remote sensing parameters revealed the most adequate criteria to detect turfgrass variability under each growing condition. This study also highlights the usefulness of green area vegetation index derived from drone imagery. GA obtained by drone images in this study explained turfgrass variability better than that derived from ground RGB images or the NDVI.

Keywords: Remote sensing, NDVI, RGB images, canopy temperature, water deficit, turfgrass.

1. Introduction

Drought is one of the main environmental stresses incited high risk in grasslands development and natural green areas sustainability. The high level of water deficit in many urban areas and the high consumption of water by turf makes the selection of drought-tolerant species a fundamental criterion for planning urban green space in smart cities. Turfgrass phenotyping to drought tolerance is an important strategy to select species more adequate to regions with water limitations allowing then to the preservation of green spaces and environment. In this context, the selection of turfgrass varieties with superior drought resistance and low water use emerges as an effective way to decrease the water requirements of natural turfgrass areas (Saunders, 2009). Therefore, turfgrass varieties with lower water needs and that can remain acceptable visually quality under dry conditions would be the species of choice in urban green spaces (Jansen van vuuren, 1997). However, traditional methods used to phenotype selection in field is time-consuming and labor-intensive. Araus and Cairns. (2014) have reported that limitations in field phenotyping restrict our ability to dissect the genetics of quantitative traits, particularly those related to stress tolerance. Likewise, breeders of turfgrass reported that the implicit heavy time- and labor demands of field phenotyping hinder the collection of more comprehensive data during early crop selection stages (Zhang et al., 2019).

In this context, remote sensing technology has revealed as an alternative approach, in recent decades, for the selection of drought-tolerant varieties in a short time and without the need for hard labor. Low-cost phenotyping methods through remote sensing are becoming more widely used for estimating various plant traits, including chlorophyll content, nitrogen concentration and biomass (Yousfi et al., 2019; Marin et al., 2020; Saberioon et al., 2014; Thoele and Ehlert, 2010) and can provide a valuable information on plants adaptation to abiotic stress like water scarcity and extreme temperatures (Araus and Cairns, 2014). Remote sensing techniques used in filed like the hand-held point sensors such as spectroradiometers (Deery et al., 2014; Yousfi et al., 2019), thermal sensors (Amani et al., 1996), imagers (Jones et al., 2009; Marin et al., 2020) and drones (Deery et al., 2014) can provide relevant information on plant phenotypes (Montes et al., 2011) and a rapid approximation of plant biochemical and biophysical criteria for large areas in field trials (Li et al., 2014). Furthermore, the non-invasive remote sensing methods such as digital image analysis and spectral reflectance for quantifying turfgrass cover and quality (Montes et al., 2011; Richardson et al., 2001; Jiang and Carrow, 2007) are considerate as major strategies to achieve grassland sustainability and less water consumption.

Vegetation indices derived from remote sensing approaches are the criteria widely employed in field phenotyping platforms. One of the most well-known indices is the normalized difference vegetation index (NDVI), derived from optical remote sensing. The NDVI has been used widely for the estimation of plant biomass (Hansen et al., 2003; Babar et al., 2006) and for turfgrass management (Marin et al., 2020; Carrow et al., 2010; Murphy et al., 2014). This index is based on the concept of a relationship between the absorption of visible light and strong reflectance of near-infrared light by chlorophyll (Viña et al., 2011). NDVI is correlated positively with turfgrass quality (Caturegli et al., 2016) and can be affected by differences in species and environments (Caturegli et al., 2015). In addition, information derived from digital RGB (red, green, blue) images can also inform on canopy vegetation (Yousfi et al., 2019; Casadesus et al., 2007). Digital image analysis has been successfully used to assess turfgrass color and the percentage of green cover (Marin et al., 2020; Karcher et al., 2003; Richardson et al., 2001), as well as detect weeds in turfgrass plots (Parra et al., 2020). The color information from RGB images can be frequently utilized to estimate leaf chlorophyll content and nitrogen concentration (Amani et al., 1996; Li et al., 2015), plant biomass (Amani et al., 1996; Montes et al., 2011; yousfi et al., 2016) and plant height (Bendig et al., 2014; Schirrmann et al., 2016).

Furthermore, canopy temperature measurements taken using infrared thermometers sensor are also commonly used for the detection of water stress-induced stomatal closure and as a guide for genotypic performance under drought (Idso et al., 1981). Canopy temperature is a relative measure of plant transpiration associated with water uptake from the soil (Reynolds et al., 2007). Given that a major role of transpiration is leaf cooling, canopy temperature provides an indicator of the degree to which transpiration cools leaves under a demanding environmental load (Araus et al., 2008).

In this study, we examined the performance of different mixtures of C_3-C_4 turfgrass under limited and higher irrigation using remote sensing parameters. The choice of C_3-C_4 mixtures permit us a large wide range of environmental conditions since C_3 species are typical for cooler temperature regions and the C_4 grasses are adapted to persist in warmer environments, and both species differ in the photosynthetic system for the uptake of carbon dioxide. Green biomass was estimated by NDVI (measured with a portable spectroradiometer with an active sensor) and by the green area vegetation index (GA) derived from ground and aerial (using a drone) digital pictures. Additionally, water status indices were determined by measuring the canopy temperature by infrared thermometry and the soil water content by moisture sensors. The main objective of this study is to select the turfgrass more tolerant to water limitation and those with a rapid green regeneration after a period of stress, using remote sensing methods. Moreover, we also evaluated the efficacy of the vegetation indices obtained by ground and aerial imagery, alone or in combination with canopy temperature, to track turfgrass variability under the two irrigation regimes. To the best of our knowledge, this study is the first to propose a conceptual model relating turfgrass species variability with differences in vegetation indices, canopy temperature and soil moisture under high and limited irrigation. Understanding the relationships between vegetation indices and water status parameters in turfgrass may help to design efficient breeding strategies to select those species most suitable for a given environmental condition (especially drought), thereby contributing to grassland sustainability.

2. Materials and Methods

2.1. Plant material and growing conditions

Field trials were conducted during 2019 at the Madrid Institute for Rural, Agrarian and Food Research and Development (IMIDRA) in Alcalá de Henares. This site is characterized by loamy sand fertile soils and a continental climate. Six C_3-C_4 turfgrass mixtures were studied. To this end, we mixed seeds from *Festuca arundinacea* and *Poa pratensis* (both C_3)

with those from three C_4 turfs, *Cynodon dactylon*, *Buchloe dactyloides* and *Zoysia japonica*, in a with 75:25 ratio of C_3 to C_4. The description and characteristics of the turfgrass species used are provided in Table 1. Irrigation was applied with sprinklers in blocks connected by valves and controlled by the Rain Bird irrigation system (ESP-LXME Model). Two different irrigation regimes were assayed, limited irrigation (50 % of container capacity) and high irrigation (100% of container capacity). Soil humidity (Fig. 2) was controlled by sensors (Plantae station, Plantae, Spain) placed in the experimental plots and in the root active zone (at a depth of 10 cm). Turfgrass seeds were planted on 4 April 2019 in a total of 36 plots (six turfgrass mixtures, three replicates per mixture and two water regimes), each measuring 3 m × 1.5 m (Fig. 2). Water deficit was imposed for two months (after plant germination) by decreasing the amount of water applied. Afterward, irrigation was then increased to reach a high soil moisture content (Fig. 1) and was maintained for the following two months in order to evaluate the degree of green regeneration of each mixture. Measurements were taken firstly in the two months of limited irrigation (two days of measurement in each month), and subsequently in the two month of high irrigation (also we have measured twice in each month of high irrigation treatment).

Table 1. Description of C_3 and C_4 turfgrass used in this study

	Description
C_3 Species	
Festuca arundinacea	Highly resistant to heat and drought due to its extensive root system, adapted to a wide range of climatic conditions.
Poa pratensis	Vigorous root system that gives high density. Adaptable to various soils, climates, and typically used in mixtures. Excellent tolerance to salinity and shade and relatively resistant to heat and drought.
C_4 species	
Cynodon dactylon	It is the most important C_4 grass species of warm climates. Resistant to long periods of drought, adapts to all kinds of soils and with strong stolons that confer high coverage capacity.
Buchloe dactyloides	Species of warm climates. It adapts to all types of soil, preferring alkaline substrates. Resistant to drought and aridity. Poor adaptation to shade.
Zoysia japonica	Species of warm climates showing some tolerance to cold. It prefers the sun but can tolerate a little shade. Tolerates heat and drought. Powerful root system allowing it to resist drought better than other plants.

Source: Dalmau Seeds: www.semillasdalmau.com and Zulueta seeds: www.zulueta.com.

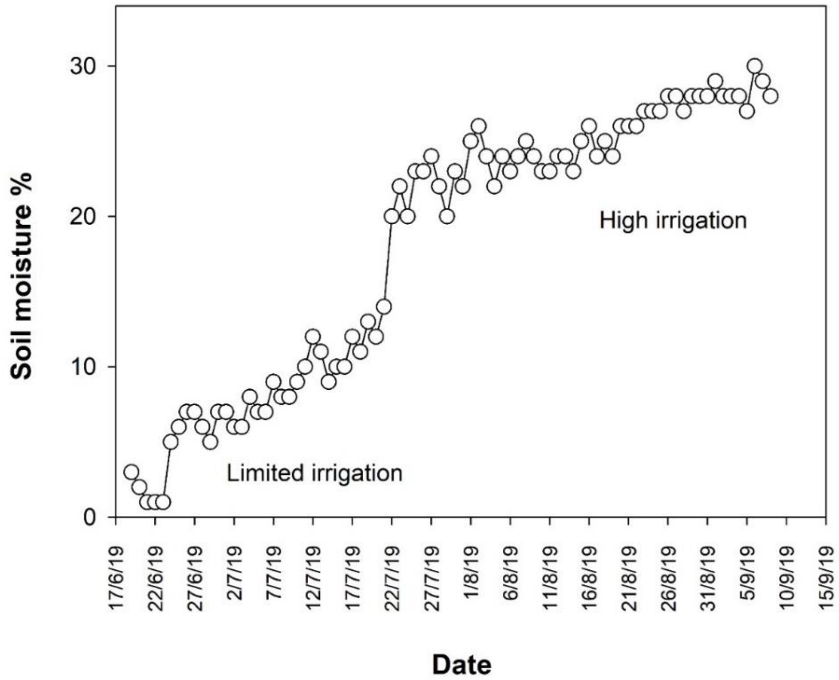

Figure 1. Daily soil moisture measurements collected by the Plantae Sensor.

Figure 2. Drone image of turfgrass plots used in the field trial.

2.2. NDVI

A portable spectroradiometer (GreenSeeker handheld crop sensor, Trimble, USA) was used to measure the NDVI (Normalized Difference Vegetation Index). This index is calculated by the following equation: (NIR–R)/ (NIR+R), where R is the reflectance in the red band and NIR is the reflectance in the near-infrared band. A constant distance of 50–60 cm above and vertical to the canopy was maintained between the sensor and the plots.

2.3. Ground and aerial RGB images

RGB (red, green, blue) images were taken in each plot about 80 cm above the plant canopy in a zenithal plane using a SONY DSC-W120 camera. RGB aerial images were taken on the same day using a BEBOP drone (Parrot, Paris, France) equipped with an RGB camera. The BreedPix 0.2 free-access software established for digital image processing was used for image analysis (Casadesús et al., 2005). This software rapidly provides digital values on the basis of different color properties and measures the green area (GA; portion of pixels with 60 < Hue < 120 from the total number of pixels) by capturing differences in biomass. Two GA indices were analyzed, $GA_{ground\ RGB}$ (calculated from the ground image) and $GA_{aerial\ RGB}$ (calculated from aerial image).

2.4 Canopy temperature measurements

Canopy temperature (CT) was measured on the same day as the vegetation indices, using an infrared thermometer (Fluke 561 sensor, China). Measurements were taken approximately 1 m above the plants and with the sun behind the user of the device. Three measurements were taken in each plot and the average was taken as a plot data.

2.5 Plot moisture content

Soil moisture (SM) was measured on the same day as the remotely sensed traits using a Field Scout Time Domain Reflectometry sensor 350 (TDR 350, Spectrum Technologies, Inc USA). Measurements were taken with the 7cm TDR rods, and at three sites in each plot. Average of the three measurement was taken as a data of each plot.

2.6. Statistical analysis

Data were subjected to factorial analyses of variance (ANOVA) to test the effects of irrigation on turfgrass growth. A bivariate correlation procedure was used to analyze the relationships between NDVI, $GA_{ground\ RGB}$, $GA_{aerial\ RGB}$, and CT. Moreover, we performed a multiple linear regression analysis (stepwise) to analyze turfgrass variability under different growing conditions. Statistical analysis was done using IBM SPSS Statistics 24 (SPSS Inc., Chicago, IL, USA). Sigma-Plot 11.0 for Windows (Systat Software Inc., Point Richmond, CA, USA) was used to establish the figures. Finally, we performed path analyses (Li, 1975) to quantify the relative contributions of the direct and indirect effects of remote sensing traits on turfgrass variability. This methodology offers the possibility of building associations between variables on prior knowledge. A path analysis determines simple correlations between independent factors (in this case CT and SM), and regresses them on each intermediary (NDVI, $GA_{ground\ RGB}$, $GA_{aerial\ RGB}$) to obtain direct effects in the form of partial regression coefficients (i.e. path coefficients) involving traits that displayed turfgrass growing variation. This model helps to understand differences in growing between the turf species (examined in this study) under the two irrigation regimes tested. A model with a comparative fit index

(CFI) with values > 0.9 was taken as indicative of good fit (Arbuckle, 1997). Data were analyzed using the Amos Graphics package (IBM SPSS Amos, USA).

3. Results

3.1 Effect of irrigation on NDVI and green area

Irrigation significantly affected the turfgrass NDVI and GA (Table 2). Low values for the three vegetation indices (NDVI, and GA calculated from both ground and aerial RGB images) were observed under limited irrigation. In addition, soil moisture (SM) content under high irrigation was double that under limited irrigation, whereas the canopy temperature (CT) of plants increased with the decrease of irrigation (Table 2).

Table 2. Effect of irrigation on NDVI (Normalized Difference Vegetation Index), $GA_{ground\ RGB}$ (Green Area calculated from ground RGB images), $GA_{aerial\ RGB}$ (Green Area calculated from drone RGB images), CT (canopy temperature) and SM (soil moisture) and the corresponding ANOVA. Values presented are the means of the 72 measurements in each irrigation regime (6 turfgrass mixtures, three replicate per mixtures and four date of measurements in each treatment). Significance levels: ***p < 0.001.

	Limited irrigation	High irrigation	Level of significance
NDVI	0.65	0.80	0.000***
$GA_{ground\ RGB}$	0.49	0.78	0.000***
$GA_{aerial\ RGB}$	0.50	0.79	0.000***
CT	20.00	13.70	0.000***
SM	24.05	45.02	0.000***

3.2 *Classification of turfgrass species on the basis of vegetation and water status indices*

Turfgrass species showed a significant difference on comportment under the two irrigation regimes (Table 3). All the vegetation indices measured (NDVI, $GA_{ground\ RGB}$, $GA_{aerial\ RGB}$) discriminated significantly ($P < 0.000$) between Festuca and Poa turfgrass mixtures under both water stress and high irrigation (Table 3). The mixtures of Festuca with the three C_4 turfgrass showed higher vegetation indices under limited irrigation compared to Poa-C_4 mixtures. Conversely, Poa-C_4 mixtures showed better vegetation indices than Festuca-C_4 mixtures under the high irrigation. Moreover, canopy temperature (CT) also allowed significant discrimination between turfgrass species but only under the water stress regime (Table 3) with lower values of canopy temperature observed in Festuca mixtures under limited irrigation. However, for the soil moisture (TDR measures), the species effect was not significant under both water regime (Table 3).

Table 3. Means values of NDVI, $GA_{ground\ RGB}$, $GA_{aerial\ RGB}$, CT and SM of Festuca and Poa mixtures with C_4 turf. Significance levels of difference among species under limited and high irrigation are presented. Species values are the means of the 36 measurements (3 turfgrass mixtures, three replicate per mixtures and four date of measurements in each treatment). Significance levels: ns, not significant; ns, not significant; ***p < 0.001. Abbreviation of variable as in Table 2. Significance levels.

	Limited irrigation			High irrigation		
	Mixtures			Mixtures		
	Festuca-C_4	Poa-C_4	Significance	Festuca-C_4	Poa-C_4	Significance
NDVI	0.69	0.58	0.000***	0.77	0.80	0.000***
$GA_{ground\ RGB}$	0.59	0.40	0.000***	0.75	0.81	0.000***
$GA_{aerial\ RGB}$	0.57	0.44	0.000***	0.76	0.83	0.001***
CT	18.33	20.51	0.000***	13.33	14.20	0.065^{ns}
SM	23.50	24.5	0.179^{ns}	44.78	45.27	0.095^{ns}

Furthermore, comparison intra mixtures showed that under limited irrigation Festuca mixed with Cynodon, Zoysia and Buchloe did not present any difference between them on vegetation indices, nonetheless CT was lower in Festuca-Cynodon mixture. Whereas under high irrigation Festuca-Zoysia and Festuca-Buchloe (with higher NDVI, $GA_{ground\ RGB}$ and $GA_{aerial\ RGB}$) slightly outperformed Festuca-Cynodon (Fig. 3A, B, C). With respect to the Poa mixtures, significant differences were observed under both water regimes (Fig. 3). In this regard, under limited irrigation, Poa-Cynodon showed higher vegetation indices and lower CT (Fig. 3A, B, C, D), while under the high irrigation regime Poa-Zoysia and Poa-Buchloe showed better growing parameters than Poa-Cynodon. Whereas, SM did show any differences intra mixtures (Fig 3E).

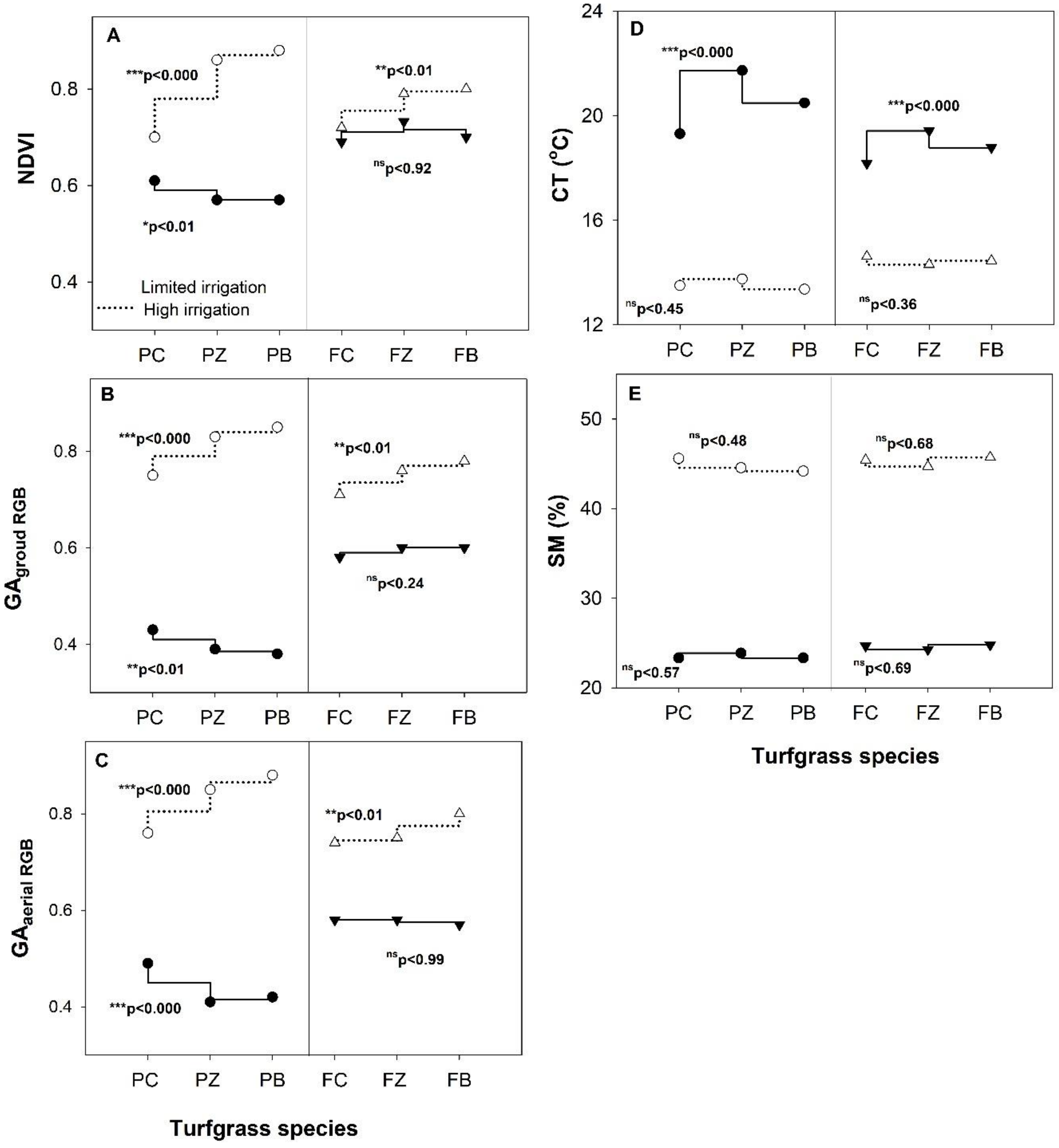

Figure 3. NDVI, $GA_{ground\ RGB}$, $GA_{aerial\ RGB}$, CT and SM values of each turfgrass mixture under limited and high irrigation. Abbreviation of variable as explained in Table 1. Turf mixtures are: PC, Poa-Cynodon; PZ, Poa-Zoysia; PB, Poa-Buchloe; FC, Festuca-Cynodon; FZ, Festuca-Ziysia; and FB, Festuca-Buchloe.

3.3 Remote sensing trait and turfgrass variability

A multiple linear regression (stepwise) explaining turfgrass species variability as a function of traits related to NDVI, $GA_{ground\ RGB}$ and $GA_{aerial\ RGB}$, CT and SM under limited and high irrigation (Table 4) was performed. The $GA_{aerial\ RGB}$ was chosen as the first explanatory variable of turfgrass variability under high irrigation and with a strong R^2 (0.85). Additionally, $GA_{ground\ RGB}$ and NDVI were the two other variables chosen by the model. However, under limited irrigation, the first variable chosen was the NDVI, with (R^2= 0.41), followed by $GA_{aerial\ RGB}$ and $GA_{ground\ RGB}$. In contrast to high irrigation, under limited irrigation the CT contributed (even less than the vegetation indices) to explaining the model.

Table 4. Multiple linear regressions (stepwise) explaining turfgrass variability using the NDVI, $GA_{aerial\ RGB}$, $GA_{ground\ RGB}$, CT and SM as independent variables. Abbreviation of variables as in Table 2. Significance levels: ****p* < 0.001.

Growing Conditions	Variable Chosen	R^2
High irrigation	$GA_{aerial\ RGB}$,	0.85
	$GA_{aerial\ RGB}$, $GA_{ground\ RGB}$	0.91
	NDVI, $GA_{aerial\ RGB}$, $GA_{ground\ RGB}$	0.95***
Limited irrigation	NDVI	0.41
	NDVI, $GA_{aerial\ RGB}$	0.83
	NDVI, $GA_{aerial\ RGB}$, $GA_{ground\ RGB}$	0.94
	NDVI, $GA_{aerial\ RGB}$, $GA_{ground\ RGB}$, CT	0.96***

In addition, a conceptual model based on a path analysis was proposed (Fig. 4A) for the data of both water regimes (comparative fit index (CFI)>0.9 and P>0.05; as the objective was to develop models that fit the data well). Under high irrigation, neither CT nor SM had any direct significant effect on the variability of C_3-C_4 turfgrass mixtures. However, the canopy temperature (CT) had a significant negative effect on the three vegetation indices (NDVI, $GA_{aerial\ RGB}$, $GA_{ground\ RGB}$), which in turn were associated significantly with turfgrass variability (Fig. 4B). Under limited irrigation, the effects of CT and SM on turfgrass variability were considerable but with a lower coefficient. Nevertheless, these two parameters (related to plant and soil water status) indirectly affected turfgrass discrimination. Thus, SM was negatively related to CT, which in turn was strongly and negatively related to the three vegetation indices. Finally, the vegetation indices showed a high and significant effect on turfgrass variability under limited irrigation (Fig. 4C), with Higher correlation coefficient of $GA_{aerial\ RGB}$, $GA_{ground\ RGB}$ than NDVI.

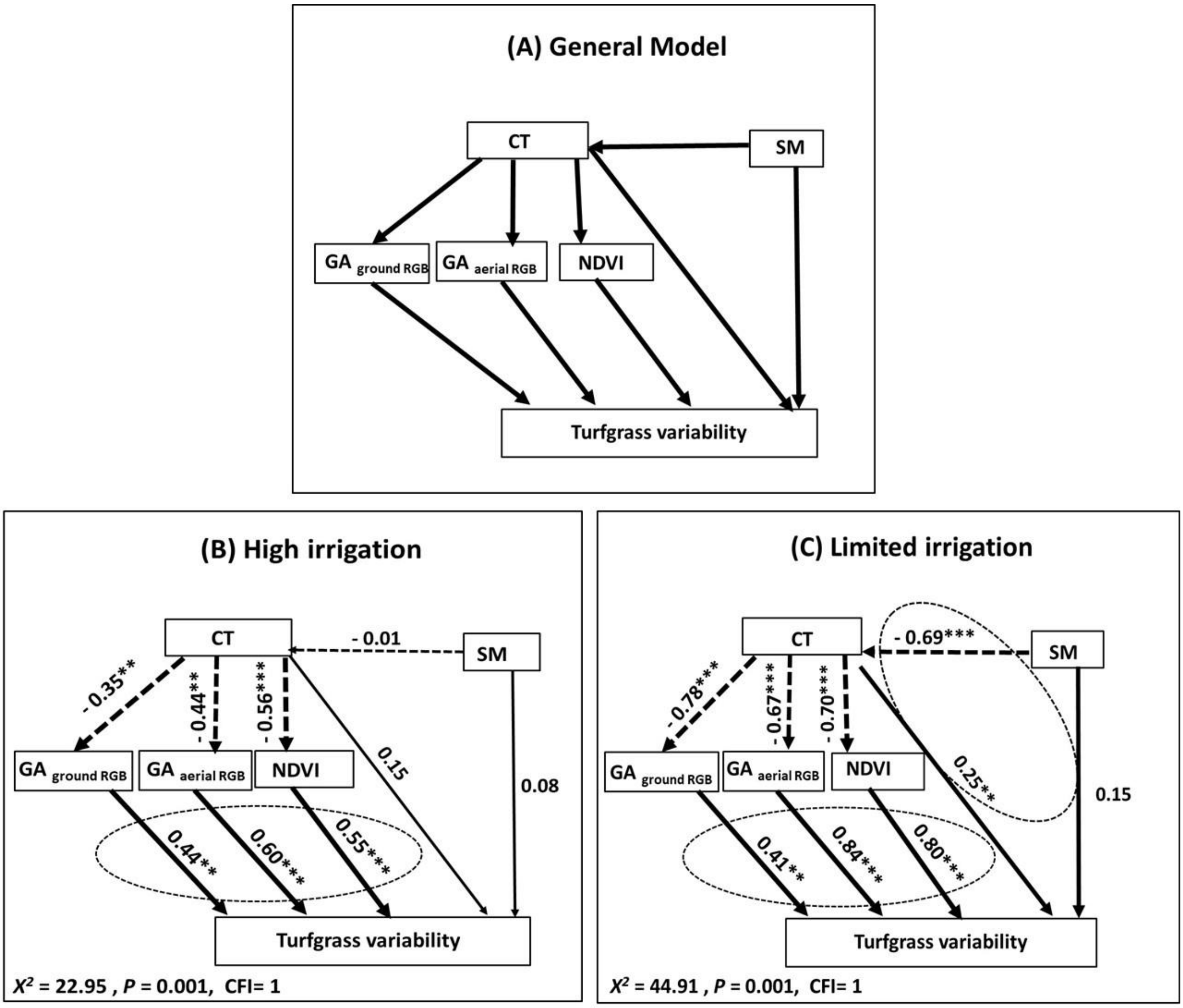

Figure 4. Path analyses of turfgrass species variability under different water regimes. Parameters included in the model are: NDVI, $GA_{ground\ RGB}$, $GA_{aerial\ RGB}$, CT and SM. Abbreviation of variables as in Table 2. CFIs with values > 0.9 are taken as indicative of good fit. Significance levels: $^{**}p < 0.01$ and $^{***}p < 0.001$.

3.4 Relationships between ground and aerial measurements

NDVI was correlated positively, and with the same pattern, with the GA obtained by aerial and ground RGB when all turfgrass species, water regimes and replicates are combined (Fig. 5A, B). Moreover, the $GA_{ground\ RGB}$ was also strongly correlated (r = 0.83***) with $GA_{aerial\ RGB.}$ (Fig. 5C). Likewise, the three vegetation indices were strongly and negatively correlated with the canopy temperature and with the same pattern (Fig. 6A, B, C).

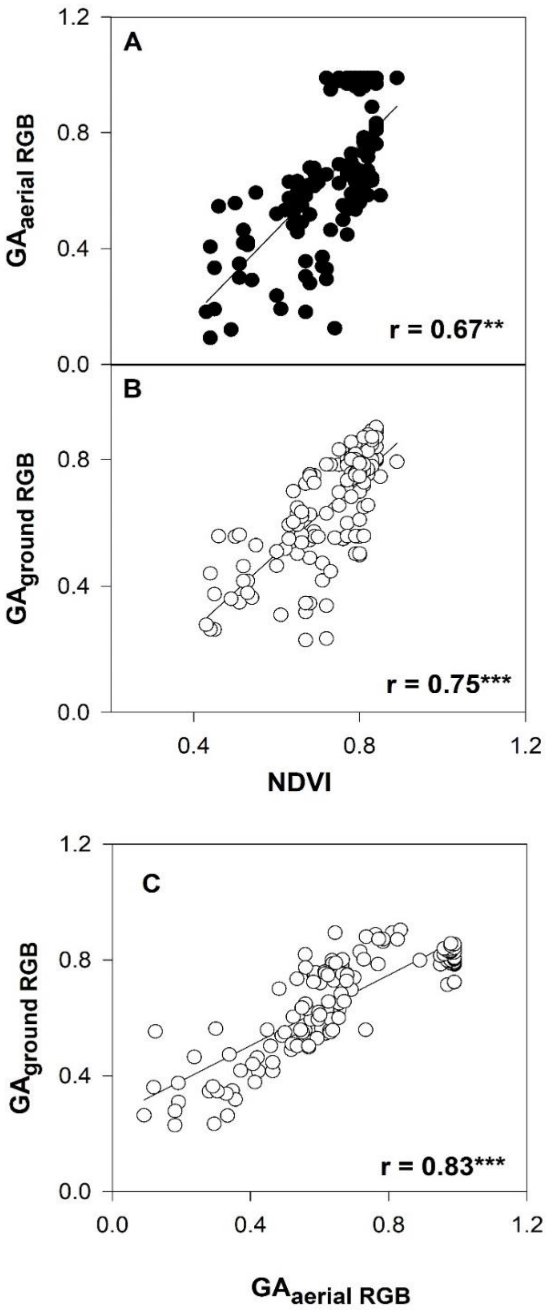

Figure 5. Correlation coefficients of the relationships between the different vegetation indices (NDVI, $GA_{aerial\ RGB}$ and GA_{ground}). Water regime and turfgrass species were analyzed together. Significance levels: ***p* < 0.010; ****p* < 0.000. Abbreviations of variables as in Table 2.

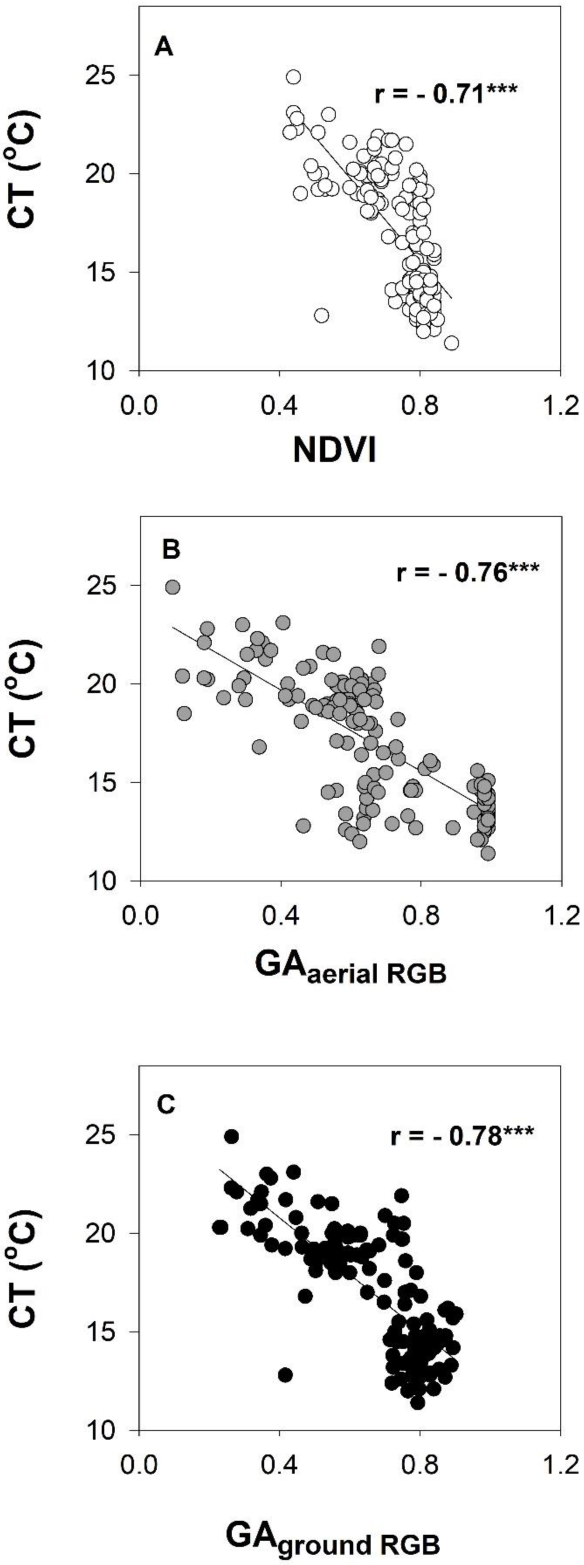

Figure 6. Correlation coefficients of the relationships between the different vegetation indices (NDVI, $GA_{aerial\ RGB}$ and $GA_{ground)}$ and the canopy temperature (CT). Water regime and turfgrass species were analyzed together. Significance levels: $**p < 0.010$; $***p < 0.000$. Abbreviations of variables as in Table 2.

4. Discussion

4.1 Potential of NDVI and RGB imagery to screen differences in turfgrass species

Vegetation indices based on RGB images, and the NDVI have demonstrated high-throughput for the precise prediction of several traits that are valuable for breeders and agronomists (Vergara-Díaz et al., 2016). In this study, NDVI and both $GA_{ground\ RGB}$ and $GA_{aerial\ RGB}$ of the turfgrass plots were significantly lower under limited irrigation than high irrigation. In this context, water-stressed canopies have been reported to have a lower spectral reflectance in the NIR wavebands than unstressed ones (Fan et al., 2020). The leaves of plants growing under water stress reflect significantly less NIR and greater red irradiance. Consequently, the NDVI and GA values are lower under stress conditions. Similar changes in the reflectance at the visible and NIR wavebands caused by irrigation were observed in other turf studies on Fescue (Fenstermaker-Shaulis et al., 1997), Lolium (Baghzouz et al., 2006) and Cynodon grass (Baghzouz et al., 2007). The changes in the reflectance values of turfgrass observed in this study informs on the growing status of plants under limited and higher irrigation and can indicates perfectly of the turf performance and quality under water stress conditions. In accordance, Vergara-Díaz et al. (2016) have reported that vegetation indices based on RGB images, and the NDVI have demonstrated high-throughput for the precise prediction of several traits that are valuable for breeders and agronomists (Vergara-Díaz et al., 2016). Moreover, Richardson et al. (2001) informed that vegetation indices can be used to evaluate turf quality, color, dry matter, chlorophyll, carotenoids and nitrogen content. Other studies also demonstrated the utility of the NDVI and other plant stress indicators based on spectral reflectance for assessing turfgrass performance (Montes et al., 2011; Trenholm et al., 2000, Marin el al., 2020) and has been used to measure drought stress (Bell et al., 2002; Trenholm et al., 1999). Our results demonstrate the usefulness of NDVI and GA measurements from ground and aerial images to distinguish between turfgrass species under limited and higher. Accordingly, in a previous-study, we also highlighted the utility of NDVI and GA to differentiate between C_3-C_4 turfgrass under water deficit (Marin et al., 2020). In addition, other authors also showed that vegetation indices are useful to discriminate between turfgrass cultivars grown under the same conditions and maintained under identical agronomical practices (Caturegli et al., 2014).

Moreover, here we have also demonstrated the greater growth of Festuca mixture with the three C_4 turf under water stress compared to the Poa mixtures. In this context, the metabolism and architecture of roots in Festuca species are key for the development of tolerance to water deficit (Perlikowski et al., 2020). Likewise, it has been described that Festuca species adapt to drought stress through alterations in leaf and root morphology (Wang et al., 2008).

Furthermore, the data obtained from the optical remote sensing techniques in this study, showed an interesting pattern in the spectral characteristics of both C_3-C_4 mixtures. Vegetation indices exhibited that Festuca mixture with Cynodon, Buchloe and Zoysia presented a similar pattern of growth under limited irrigation, while under high irrigation Fescue-Buchloe and Fescue-Zoysia outperformed Festuca-Cynodon. Nevertheless, the NDVI, $GA_{aerial\ RGB}$ and $GA_{ground\ RGB}$ of Poa with the three C_4 species revealed significant differences under the two water regimes. Under limited irrigation, Poa-Cynodon was found to have better vegetation indices, while under high irrigation Poa-Buchloe and Poa- Zoysia outperformed Poa-Cynodon, with Poa-Buchloe showing the best growth under this condition. According to this, several types of Bermuda grass have a deep and large root systems, a morphological trait that allows them to reach available water at greater depth under stress conditions (Carrow, 1996). On the basis of our results, we can suggest that mixtures of Festuca with Cynodon, Buchloe or Zoysia have a similar tolerance to water deficit and would be similar suitable for regions with limited water availability. Whereas, in the case of Pao mixtures, Poa-Cynodon would be the mixture of choice for drought regions. Furthermore, under climates with higher precipitation and no water deficiency, the Festuca-Buchloe and Festuca-Zoysia mixtures can offer better turf quality. Likewise, the Poa-Zoysia and Poa-Buchloe mixtures would be the most suitable in such climates due to their high quality under optimal growing conditions. Additionally, we also observed that after a period of growth under limited irrigation followed by high irrigation, the C_3 mixture with Buchloe provided the highest vegetation indices indicating better green biomass regeneration after growing under water deficit. Accordingly, the most characteristic response of drought-dormant Buffalo grass (*Buchloe dactyloides*) is its rapid ability to regenerate growth after a period of water stress followed by water availability (Shantz, 1911).

4.2 Turfgrass canopy temperature and water status

The canopy temperature (also referred to as leaf temperature) has been widely employed for estimating plant water stress (Blum et al., 1982) and for providing a relative measure of plant transpiration (Araus et al., 2008). In yhis study, the canopy temperature (CT) of the six turfgrass mixtures, measured by an infrared thermometer, was lower under limited irrigation than high irrigation. Under water deficit, the decreased in water uptake caused the stomata to close, thereby reducing transpiration and increasing leaf temperature (Blonquist et al., 2009). However, a lower CT indicates a greater capacity for transpiration and for taking up water from the soil, and therefore a better plant water status (Blum et al., 1982). Also, and consistent with the findings of other studies (Lopes and Reynolds, 2012) we observed that the CT was strongly related to the vegetation indices. In this regard, lower CTs are strongly associated with higher green biomass, and these two parameters can help to identify turf species with the greatest tolerance to drought.

Our results also reveal that, under limited irrigation, the mixture of Festuca with the three C_4 turf showed a lower CT than the Poa mixtures. In this context, *Festuca arundinacea* is water use efficiency than other turfgrass species (Horst et al., 1997). Furthermore, in response to water stress, Festuca spp. undergoes an osmotic adjustment that maintains sufficient turgor pressure in the growing zone to ensure leaf elongation (Wang et al., 2008). In contrast to the vegetation indices, the CT of the three Festuca mixtures under limited irrigation showed a clear difference between mixtures, with Festuca-Buchloe exhibiting the lowest CT. It has been reported that Buchloe grass requires low levels of water for survival and that under semi-arid conditions it needs less irrigation to maintain good turf quality than tall Festuca or and Zoysia grass (Hicks et al., 1984). Also, lower evapotranspiration rates in *Buchloe dactyloides* indicate that this species uses less water than selected ornamentals (Horst et al., 1997). However, our comparison between Poa mixtures revealed that Poa-Cynodon showed better performance under water deficit. In this context, the thick leaf cuticles and smaller stomatal openings (Zhou et al., 2009) as well as the reduced leaf surface, stoma density, and lower water transpiration rate (Mukhtar et al., 2013) of *Cynodon dactylon* confer better tolerance to water stress compared to the other turfgrass species.

4.3 Soil moisture

Soil moisture (SM) values measured by the TDR 350 did not show any differences between the turfgrass species under limited or high irrigation (Table 3, Fig. 4D). Nevertheless, the analyze combining all SM data of the six turfgrass mixtures evaluated in this study demonstrated difference between turfgrass growth under the two irrigation regimes (Table 2). In this context, such sensors can indicate when the soil profile is full of water or dry and therefore healthy turf is maintained by avoiding plant stress caused by soil that is too dry or too waterlogged (Bremer and Ham, 2003). Accordingly, moisture sensors are among the most used devices to manage crop irrigation schemes and have been reported to improve irrigation efficacy in lawns (Parra et al., 2019). We propose SM as a useful criterion for managing turf irrigation, but not for distinguishing between turfgrass mixtures. Moreover, the feasibility of SM sensing devices has also been addressed for the irrigation management of Bermuda grass (Osborne et al., 2002). We considerate the SM data obtained by the soil sensors in this study as indirect measures to evaluate the development of turfgrass species. Osborne et al. 2002 reported that as SM decreases, plants show a decrease in tissue moisture content, which in turn influences their reflectance properties.

4.4 Relationship between ground and aerial optical remote sensing trait

The two groups of vegetation indices (NDVI and ground and aerial RGB images) showed high and positive correlations between them (Fig. 7). This result is in accordance with previous research (Adamsen et al., 1999; Lukina et al., 1999, Montes et al., 2011) and confirms that these indices inform about biomass status in a comparable manner. Likewise, there was a high association between $GA_{aerial\ RGB}$ and $GA_{ground\ RGB}$ images. However, GA obtained by drone images is better than GA of ground images with respect to explaining the variability in turfgrass growth (Fig. 4D, Fig. 5, Table 4) and was less labor-intensive and with less time-consuming. The use of spectral vegetation indices derived from UAV imagery is emerging as a rapid and cost-efficient approach for plant phenotyping (Angelos et al., 2017). In present, many low cost drones with an integrated simple RGB camera are now available to take images of large turfgrass surfaces in a short time. In this context, Zhang et al. (2019) reported that unmanned aerial vehicle (UAV) imagery is considered a powerful tool for turfgrass breeders allowing them to evaluate crop performance and greatly increase the efficacy of data collection in relatively large trials (advantages in field of view, spatial and temporal resolution). Furthermore, the high correlation found between the NDVI and the $GA_{aerial\ RGB}$ index in this study allows us to confirm the reliability UAV-based measurements for selecting drought-tolerant species in large areas. The GreenSeeker hand-held sensor, a low-cost practical device, has proved useful for detecting turfgrass stress for small areas, (Caturegli et al., 2015). However, proximal sensors would need to be complemented with special cameras on board UAVs to monitor the entire surface of large areas Caturegli et al., 2015).

4.5 *Comparative model using remote sensing methods for turfgrass breeding*

Results of the lineal regression presented here showed the usefulness of the vegetation indices derived from RGB imagery to explain the differences between turfgrass species under the high irrigation. Of note, the GA vegetation index derived from aerial imagery was the most important parameter chosen by the model and with a higher impact ($r^2 = 0.85$). Moreover, NDVI made a negligible contribution to explaining variability under high irrigation, due to the problem of saturation. In this context, a saturated NDVI in higher periods of turfgrass activity informs less than RGB indices, which are characterized by less evident saturation (Montes et al., 2011). However, under limited irrigation, NDVI was the first criterion chosen by the regression model. Other authors indicated that the NDVI is an index based on the strong contrast between the near infrared and the red band reflectance of a vegetation canopy and this difference becomes extensive as canopy vegetation cover increases (Amani t al., 1996). This would explain why the NDVI is a more appropriate approach to study stress conditions in sparse canopies or during the early senescence of plants (Casadesus et al., 2007; Aparicio et al., 2000). However, our study combined both NDVI and vegetation indices derived from RGB images for collecting more and complete information to discriminate between turfgrass species under the two irrigation regimes. Accordingly, data fusion in remote sensing can facilitates estimations of biomass, possibly resolving saturation difficulties observed with VIS-NIR sensor data under higher density vegetation (Tilly et al., 2015).

Likewise, the path model performed in the present study confirms the stepwise result and reveals the high capacity of vegetation indices (NDVI and both $GA_{\text{aerial RGB}}$ and $GA_{\text{ground RGB}}$) to explain turfgrass variability, specially the GA index derived from drone images under high irrigation, where the water status parameters (CT and SM) have no direct effect on turfgrass species variability. Moreover, under limited irrigation, vegetation indices are still more important criterion to explain variability of turf. In this case (water stress conditions), CT contribute to explaining the model (although to a lower extent than the vegetation indices) and have a direct effect on turf species variability. To the best of our knowledge, this is the first study to report on a model combining remote sensing techniques to explain variability in the growth of different turfgrass species under different water regimes. The results of this study are expected to help breeders to select appropriate criteria for turfgrass phenotyping under distinct environmental conditions.

5. Conclusion

This study demonstrates the efficiency of vegetation indices to reveal variability in the performance of turfgrass species under different growing conditions. Our results confirm the usefulness of the vegetation indices for phenotyping most drought-tolerant turfgrass mixtures in terms of retaining greener biomass during periods of limited irrigation. Although the NDVI is extensively used to monitor changes in growth under different conditions, here we have shown that the GA vegetation index derived from aerial images provides a better evaluation of turfgrass mixtures in a short time and with high efficiency. Furthermore, the path analysis model developed confirms the importance of the traits assessed by remote sensing for establishing variability in turfgrass performance. The path analysis and regression model revealed the most suitable criteria to be used in certain environmental conditions for discriminating between turfgrass species. Therefore, optimized turfgrass breeding strategies can allow the precise and rapid (in the case of drones) phenotyping of a large numbers of turf mixtures to identify those with greatest tolerant to water stress, contributing in this way in the preservation of water resources, the grasslands sustainability and the environment protection. In future work, we propose to add thermography (thermal imagery) to the model for detecting water stress in the same turfgrass mixtures used in this study. We believe that a strategy combining aerial RGB and thermal imagery may potentially enhance turfgrass phenotyping and help to rapidly identify those mixtures most tolerant to drought conditions or those with rapid green regeneration after a period of water stress.

Acknowledgments: Projects GO-PDR18-XEROCESPED funded by the European Agricultural Fund for Rural Development (EAFRD) and IMIDRA and the AREA VERDE-MG projects are acknowledged.

References

Adamsen, F.J., Pinter, P.J., Barnes, E.M., LaMorte, R.L., Wall, W.G., Leavitt, S.W., Kimball, B.A., 1999. Measuring wheat senescence with a digital camera. Crop. Sci. 39, 719-724.

Amani, I., Fischer, R.A., Reynolds, M.F.P., 1996. Canopy Temperature Depression Association with Yield of Irrigated Spring Wheat Cultivars in a Hot Climate. J. Agron. Crop. Sci. 176, 119-129.

Angelos, C., Kyratzis, A.C., Skarlatos, D.P., Menexes, G.C., Vamvakousis, V.F., Katsiotis, A., 2017. Assessment of Vegetation Indices Derived by UAV Imagery for Durum Wheat Phenotyping under a Water Limited and Heat Stressed Mediterranean Environment. Front. Plant. Sci. 8, 1114. doi: 10.3389/fpls.2017.01114.

Aparicio, N., Villegas, N., Casadesus, J., Araus, J.L., Royo, C., 2000. Spectral vegetation indices as non-destructive tools for determining durum wheat yield. Agron. J. 92, 83-91

Araus, J.L., Cairns, J.L., 2014. Field high-throughput phenotyping: the new crop breeding frontier. Trends. Plant. Sci. 19, 52-61.

Araus, J.L., Slafer, G.A., Royo, C., Serret, M.D., 2008. Breeding for yield potential and stress adaptation in cereals. Crit. Rev. Plant Sci. 27, 377-412.

Arbuckle, J.L., 1997. Amos Users' Guide; v. 3.6. Chicago, IL: Small Waters Corporation.

Babar, M.A.; Reynolds, M.P.; Van Ginkel, M.; Klatt, A.R.; Raun, W.R.; Stone, M.L. Spectral reflectance indices as a potential indirect selection criteria for wheat yield under irrigation. Crop. Sci. 2006, 46, 578-588

Baghzouz, M., Devitt, D.A., Morris, R.L., 2006. Evaluating temporal variability in the spectral reflectance response of annual ryegrass to changes in nitrogen applications and leaching fractions. Int. J. Remote Sens. 27, 4137–4157.

Baghzouz, M., Devitt, D.A., Morris, R.L., 2007. Assessing canopy spectral reflectance of hybrid Bermudagrass under various combinations of nitrogen and water treatments. Appl. Eng. Agric. 23, 763–774.

Bell, G.E., Martin, D.L., Wiese, S.G., Dobson, D.D., Smith, M.W., Stone, M.L., Solie, J.B., 2002. Vehicle-mounted optical sensing: An objective means for evaluating turf quality. Crop. Sci. 42, 197-201.

Bendig, J., Bolten, A., Bennertz, S., Broscheit, J., Eichfuss, S., Bareth, G., 2014. Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging. Remote Sens. 6, 10395–10412.

Blonquist, J.M., Norman, J., Bugbee, B., 2009. Automated measurement of canopy stomatal conductance based on infrared temperature. Agri. Forest. Meteorol. 149, 1931-1945.

Blum, A., Mayer, J., Gozlan, G., 1982. Infrared thermal sensing of plant canopies as a screening technique for dehydration avoidance in wheat. Field. Crop. Res. 5, 137-146.

Bremer, D., Ham, J., 2003. Soil moisture sensors can help regulate irrigation. Turfgrass Trends. 59, 29-52.

Carrow, R.N., 1996. Drought resistance aspects of turfgrasses in the Southeast: root-shoot responses. Crop. Sci. 36, 687-694.

Carrow, R.N., Krum, J.M., Flitcroft, I., Cline, V., 2010. Precision turfgrass management: challenges and field applications for mapping turfgrass soil and stress. Precision. Agric. 11, 115-134.

Casadesus, J., Kaya, Y., Bort, J., Nachit, M.M., Araus, J.L., Amor, S., Ferrazzano, G., Maalouf, F., Maccaferri, M., Martos, V., Ouabbou, H., Villegas, D., 2007. Using vegetation indices derived from conventional digital cameras as selection criteria for wheat breeding in water-limited environments. Ann. Appl. Bot. 150, 227-236.

Caturegli, L., Corniglia, M., Gaetani, M., Grossi, N.; Magni, S., Migliazzi, M., Angelini, L., Mazzoncini, M., Silvestri, N., Fontanelli, M., Raffaelli, M., Peruzzi, A., Volterrani. M., 2016. Unmanned Aerial Vehicle to Estimate Nitrogen Status of Turfgrasses. PLoS ONE. 11(6): e0158268.doi:10.1371/journal.pone.0158268.

Caturegli L., Grossi, N., Saltari, M., Gaetani, M., Magni, S., Nikolopoulou, A.E., Bonari, E., Volterrani, M., 2015. Spectral reflectance of tall fescue (Festuca Arundinacea Schreb.) under different irrigation and nitrogen conditions. Agric. Agric. Sci. Procedia. 4, 59-67.

Caturegli, L., Lulli, F., Foschi, L., Guglielminetti, L., Bonari, E., M. Volterrani, M., 2014. Monitoring Turfgrass Species and Cultivars by Spectral Reflectance. Europ. J. Hort. Sci. 79, 97-107.

Deery, D., Jimenez-Berni, J., Jones, H., Sirault, X., Furbank, R., 2014. Proximal Remote Sensing Buggies and Potential Applications for Field-Based Phenotyping. Agronomy. 5, 349-379; doi:10.3390/agronomy4030349

Fan, J., Zhang, W., Amombo, E., Hu, L., Olav Kjorven, J., Chen, L., 2020. Mechanisms of Environmental Stress Tolerance in Turfgrass. Agronomy. 10, 522. doi:10.3390/agronomy10040522.

Fenstermaker-Shaulis, L.K., Leskys, A., Devitt, D.A., 1997. Utilization of remotely sensed data to map and evaluate turfgrass stress associated with drought. J. Turf. Manag. 2, 65–81.

Hansen, P.M., Schjoerring, J.K., 2003. Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. Remote. Sens. Environ. 86, 542–553.

Hicks, S.K., Wendt, C.W., Engeike, M.C., 1984. Water use rates of turfgrass species. Agron. Abstr. p 150.

Horst, G.L., Steinegger, D.H., Gaussoin, R.E., 1997. Comparative evapotranspiration rates of some perennial herbaceous ground covers and turfgrass species under greenhouse conditions. *Inter.* Turf. Soci. Res. J. 8, 1274-1279.

Idso, S.B., Jackson, R.D., Pinter, P.J., Reginato, R.J., Hatfield, J.L., 1981. Normalizing the stress-degree-day parameter for environmental variability. Agric. Meteorol. 24, 45-55.

Jansen van vuuren, J.D., 1997. Optimal use of turf grass. Water Research Commission, Pretoria.

Jiang, Y., Carrow, R., 2007. Broadband spectral reflectance models of turfgrass species and cultivars to drought stress. Crop. Sci. 47, 1611-1618.

Jones, H.G., Serraj, R., Loveys, B.R., Xiong, L., Wheaton, A., Price, A.H., 2009. Thermal infrared imaging of crop canopies for the remote diagnosis and quantification of plant responses to water stress in the field. Funct. Plant. Biol. 36, 978-989.

Karcher, D.E., Richardson, M.D., 2003. Quantifying turfgrass color using digital image analysis. Crop. Sci. 43, 943-951.

Li, C.C., 1975. Path analysis. A primer. Pacific Grove, CA, USA: The Boxwood Press.

Li, J.W., Zhang, F., Qian, X.Y., Zhu, Y.H., Shen, G.X., 2015. Quantification of rice canopy nitrogen balance index with digital imagery from unmanned aerial vehicle. Remote Sens. Lett. 6, 183-189.

Li, L., Zhang, Q., Huang, D., 2014. A review of imaging techniques for plant phenotyping. Sensors. 14, 20078–20111.

Lopes, M.S., Reynolds, M.P., 2012. Stay-green in spring wheat can be determined by spectral reflectance measurements (normalized difference vegetation index) independently from phenology. J. Exp. Bot. 63, 3789-3798.

Lukina, E.V., Stone, M.L., Raun, W.R., 1999. Estimating vegetation coverage in wheat using digital images. J. Plant. Nutr. 22, 341-350.

Marín, J., Yousfi, S., Mauri, PV., Parra, L., Lloret, J., Masaguer, A., 2020. RGB vegetation indices, NDVI and biomass as indicators to evaluate C_3 and C_4 turfgrass under different water conditions. Sustainability. 12, 2160. https://doi.org/10.3390/su12062160.

Montes, J.M., Technow, F., Dhillon, B.S., Mauch, F., Melchinger, A.E., 2011. High-throughput non-destructive biomass determination during early plant development in maize under field conditions. Field. Crop. Res. 121, 268-273.

Mukhtar, N., Hameed, M., Ashraf, M., Ahmed, R., 2013. Modifications in stomatal structure and function in Cenchrus ciliaris L. andCynodon dactylon (L.) pers. in response to cadmium stress. Pak. J. Bot. 45, 351-357.

Murphy, J.T., Owensby, C.E., Ham, J.M., Coyne, P.I., 2014. Estimation of vegetative characteristics by Remote Sensing. Acad. Res. J. Agri. Sci. Res. 2, 47-56.

Osborne, S.L., Schepers, J.S., Francis, D.D., Schlemmer, M.R., 2002. Detection of phosphorus and nitrogen deficiencies in corn using spectral radiance measurements. Agron. J. 94, 1215-1221.

Parra, L., Marin, J., Yousfi S., Rincón, G., Mauri, P.V., Lloret, J., 2020. The Use of Edge Detection Technique for the Recognition of Weed in Lawns. Comput. Electron. Agri. In press.

Parra, M., Parra, L., Lloret, J., Mauri, P.V., Llinares, J.V., 2019. Low-cost Soil Moisture Sensors Based on Inductive Coils Tested on Different Sorts of Soils. In the 2019 Sixth International Conference on Internet of Things: Systems, Management and Security (IOTSMS), Granada, Spain.

Perlikowski, D., Augustyniak, A., Skirycz, A., Pawłowicz, I., Masajada, K., Michaelis, A., Kosmala, A., 2020. Efficient root metabolism improves drought resistance of *Festuca arundinacea.* Plant.Cell. Physiol. 61, 492-504.

Reynolds, M.P., Dreccer, F., Trethowan, R., 2007. Drought adaptive traits derived from wheat wild relatives and landraces. J. Exp. Bot. 58, 177-186.

Richardson, M. D., Karcher, D. E., Purcell, L.C., 2001. Quantifying turfgrass cover using digital image analysis. Crop. Sci. 41, 1884-1888. doi: 10.2135/cropsci2001.1884.

Saberioon, M., Amin, M., Anuar, A., Gholizadeh, A., Wayayok, A., Khairunniza-Bejo, S., 2014. Assessment of rice leaf chlorophyll content using visible bands at different growth stages at both the leaf and canopy scale. Int. J. Appl. Earth. Obs. 32, 35-45.

Saunders, R., 2009. Climate change discussion paper: the impact of climate change on urban parks managed by Parks Victoria. Rob Saunders and Associates.

Schirrmann, M., Giebel, A., Gleiniger, F., Pflanz, M., Lentschke, J., Dammer, K.H., 2016. Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery. Remote Sens. 8, 706.

Shantz, H.L., 1911. Natural vegetation as an indicator of the capabilities of land for crop production in the Great Plains area. U.S. Bur. Plant Ind. Bull. 201.

Trenholm, L. E., Sclossberg, G., Lee, G., Parks, W., 2000. An evaluation of multi-spectral responses on selected turfgrass species. Inter. J. Remote. Sens. 21, 709-721.

Trenholm, L. E., Carrow, R. N., Duncan, R. R., 1999. Relationship of multispectral radiometry data to qualitative data in turfgrass research. Crop. Sci. 39, 763-769.

Thoele, H., Ehlert, D., 2010. Biomass related nitrogen fertilization with a crop sensor. Appl. Eng. Agric. 26, 769-775.

Tilly, N., Aasen, H., Bareth, G., 2015. Fusion of plant height and vegetation indices for the estimation of barley biomass. Remote. Sens. 7, 11449.

Vergara-Díaz, O., Zaman-Allah, M.A., Masuka, B., Hornero, A., Zarco-Tejada, P., Prasanna, M.B., Cairns, J.E., Araus, J.L., 2016. Novel Remote Sensing Approach for Prediction of Maize Yield Under Different Conditions of Nitrogen Fertilization. Front. Plant. Sci. 7, 666.

Viña A., Gitelson A.A., Nguy-Robertson, A.L., Peng, Y., 2011. Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. Remote Sens. Environ. 115, 3468-3478

Wang, J.P., Bughrara S., Nelson, C.J., 2008. Morpho-physiological Responses of Several Fescue Grasses to Drought Stress. Hort. Sci. 43, 776-783.

Yousfi, S., Kellas, N., Saidi, L., Benlakhel, Z., Chaou, L., Siad, D., 2016. Comparative performance of remote sensing methods in assessing wheat performance under Mediterranean conditions. Agric. Water.Manag. 164, 137-147.

Yousfi, S., Gracia-Romero, A., Kella, N.; Kaddour, M., Chadouli, A., Karrou, M., Araus, J.L., Serret, M.D., 2019. Combined Use of Low-Cost Remote Sensing Techniques and $\delta^{13}C$ to Assess Bread Wheat Grain Yield under Different Water and Nitrogen Conditions. Agronomy. 9, 285. doi:10.3390/agronomy9060285

Zhang, J., Simerjeet V., Wesley, P., Kenworthy, K., Dana Sullivan, D., Schwartz, B., 2019. Applications of Unmanned Aerial Vehicle Based Imagery in Turfgrass Field Trials. Front. Plant. Sci. 10, 279.

Zhou, Y., Lambrides, C., Kearns, R., Ye, C., Cao, N.; Fukai, S., 2009. Selecting for drought tolerance among Australian green couch grasses (Cynodon spp.). Crop. Pasture. Sci. 60, 1175-1183.