Normalized Difference Vegetation Index versus Dark Green Colour Index to estimate nitrogen status on bermudagrass hybrid and tall fescue

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Title Normalized Difference Vegetation Index versus Dark Green Color Index to estimate nitrogen status on bermudagrass hybrid and tall fescue.

Short title: NDVI vs DGCI to estimate N on two turfgrass species

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Abbreviations:

DGCI Dark Green Color Index

GPS Global Positioning System

HSB Hue Saturation Brightness

NDVI Normalized Difference Vegetation Index

PA Precision Agriculture

PTM Precision Turfgrass Management

RGB Red Green Blue

UAS Unmanned Aerial Systems

UAV Unmanned Aerial Vehicle

Keywords:

Cynodon dactylon x transvaalensis, Schedonorus phoenix, Turfgrass, Color, Quality, Unmanned Aerial Vehicle.

Abstract

In recent years digital sensors have been successfully integrated on board Unmanned Aerial Vehicles (UAV) to assess crop vigor, vegetation coverage, and to quantify the “greenness” of foliage as indirect measurements of crop nitrogen status. The classical approach of precision agriculture has involved the use of multispectral sensors onboard UAV and the development of numerous vegetation indices associated with vegetation parameters, such as the mostly used Normalized Difference Vegetation Index (NDVI). However, the main negative issue when dealing with multi and hyper-spectral reflectance measuring tools is their high cost and complexity from the operational point of view. As a low-cost alternative, vegetation indices derived from Red Green Blue (RGB) cameras have been employed for remote sensing assessment, providing data on different stress conditions and species. Digital images record information as amounts of RGB light emitted for each pixel of the image; however, the intensity of red and blue will often alter how green an image appears. To simplify the interpretation of digital color data, recent studies have suggested converting RGB values to the more intuitive Hue, Saturation, and Brightness (HSB) color spectrum, and then into a single measure of dark green color, the Dark Green Color Index (DGCI). In this study NDVI acquired by a ground-based handheld crop sensor and by a multispectral camera mounted on board a UAV have been compared with DGCI calculated from images taken with a commercial digital camera on board a UAV, trying to quantify the color of turfgrass that had received different nitrogen (N) rates.

The objectives of the trial were to study an affordable easy-to-use tool evaluating the relationship among NDVI, DGCI and leaf nitrogen content on turfgrass.

Introduction

Nitrogen fertilization on turfgrasses is one of the factors that most influence physiological and aesthetic aspects (Volterrani et al. 2005; Perry and Davenport 2007; Samborski, Tremblay, and Fallon 2009; Caturegli et al., "Monitoring turfgrass", 2014; Caturegli et al., "Turfgrass spectral reflectance", 2014; Grossi et al. 2016). Thus, nitrogen (N) represents an important nutrient that contributes to maintain green color, density, recovery from drought diseases, and a general good turfgrass quality (Walters and Bingham 2007; Dordas 2008; Magni et al. 2014; Caturegli et al. 2016).

However, the excessive fertilization of N wastes fertilizers and leads to pollution of ground and surface water, not improving the quality of the turf (Bell and Xiong 2008; Bremer et al. 2011; Rhezali and Lahlali 2017). To avoid over-fertilization, site-specific nutrition management brought significant environmental and economic benefits (Huang et al. 2008). Indeed, a precise analysis of the plant nitrogen status is important to determine the amount of nitrogen fertilizer the plant really needs (Corwin and Lesch 2005; Li et al. 2015).

Previous studies have focused on implementation of indirect sensing tools (chlorophyll meters, reflectance measurements, color analysis) to try to obtain an almost optimal quality by reducing the N inputs and the loss N to a minimum (Rorie, Purcell, Mozaffari et al. 2011; Caturegli, Casucci et al. 2015; Caturegli, Grossi et al. 2015; Caturegli et al. 2016).

These concepts are the basis of Precision Agriculture (PA), which aims to obtain detailed site-specific information by mapping the variation in important soil and plant properties in order to allow better site-specific management. Inputs such as water, fertilizers and pesticides are applied only where, when and in the amount needed by plant (Caturegli et al., "Turfgrass spectral reflectance", 2014). Related to PA is Precision Turfgrass Management (PTM) that is useful to monitor pests, fertilization, salinity stress and irrigation deficiency on turfgrass (Carrow et al. 2010; Krum, Carrow, and Karnok 2010). The approach of PA implied the combined use of multispectral sensors and vegetation indices associated with vegetation parameters (Trenholm, Carrow, and Duncan 1999; Jiang and Carrow 2007; Vergara-Díaz et al. 2016). Thus, vegetation indices were calculated by combining various reflectance bands of the spectrum and correlated with relevant turfgrass canopy parameters. Among the indices, the Normalized Difference Vegetation Index (NDVI) is the most widely used as reflectance-based plant stress indicator (Hansen and Schjoerring 2003; Johnsen et al. 2009; Aguilar et al. 2012; Barton 2012; Fensholt and Proud 2012; Rhezali and Lahlali 2017). It is based on the relationship between the absorption of visible light and resilient reflectance of near-infrared light to the chlorophyll in vegetation (Bell et al. 2004; Caturegli, Casucci et al. 2015). The NDVI value ranges from -1 to 1, with higher values indicating greater plant health, and correlates positively with turfgrass quality (Trenholm, Carrow, and Duncan 1999; Fitz-Rodriguez and Choi 2002; Leinauer et al. 2014). This index is also influenced by differences in species, environmental stresses, fertilization and pest injuries (Xiong et al. 2007; Bremer et al. 2011; Caturegli, Grossi et al. 2015). It can be obtained with hand-held ground-based instruments (Graeff and Claupein 2003; Ma, Morrison, and Dwyer 1996) and aerial vehicle-mounted sensors (Bausch and Duke 1996; Blackmer et al. 1996; Scharf and Lory 2009; Rorie, Purcell, Karcher et al. 2011). In recent years, digital sensors have been successfully integrated on board Unmanned Aerial Vehicles (UAV) to assess crop vigor, vegetation coverage, and to quantify the "greenness" of foliage as indirect measurements of crop N status (White et al. 2012; Andrade-Sanchez et al. 2014). Furthermore, small commercial Unmanned Aerial Systems (UAS) (< 50 kg) (Laliberte and Rango 2011) have been available for PA for environmental and agricultural applications (Gupta et al. 2013; Zhang and Kovacs 2012; Caturegli et al. 2016). However, the main negative issue when it comes to multi and hyper-spectral reflectance measuring tools is their high cost and complexity. Vegetation indices derived from Red-Green-Blue (RGB) cameras have been employed for remote sensing assessment, as a low-cost alternative (Vergara-Díaz et al. 2016). This method may provide data on different stress conditions in different crops (Casadesús et al. 2007; Casadesus and Villegas 2014; Zhou et al. 2015) and turfgrass (Karcher and Richardson 2003; Karcher and Richardson

2013). Digital images are composed by pixels that record information as amounts of RGB light emitted. However, the greenness of an image can be often altered by the intensity of red and blue. To simplify the interpretation of data, Karcher and Richardson (2003) suggested converting RGB values to the more intuitive Hue, Saturation, and Brightness (HSB) based on human perception of color. Working with quality of turfgrass in response to N fertilizer, Karcher and Richardson (2003) processed HSB values into a single measure of dark green color, the Dark Green Color Index (DGCI).

This method proposed by (Karcher and Richardson 2003) may represent a proper alternative to the spectroradiometric approaches that involves the use of NDVI from aerial platforms and from ground-based measurements (Vergara-Díaz et al. 2016). To facilitate the DGCI acquisition, recently, also a smartphone application called FieldScout GreenIndex+ Turf (Spectrum Technologies, Inc., Aurora, IL, USA) (Spectrum Technologies, Inc. 2018) has been developed and tested (O'Brien 2017; Xiang et al. 2017; Xiang et al. 2018) The application (APP) captures images with a smartphone or tablet, calculates the DGCI, and shows a turfgrass quality visual rating (Karcher and Richardson 2003).

The aim of this research was to study an affordable easy-to-use tool evaluating the relationship among NDVI, DGCI and leaf nitrogen content on turfgrass. Trying to quantify the color of turfgrass that had received different N rates, NDVI acquired by a ground-based handheld crop sensor and by a multispectral camera mounted on board a UAV have been compared with DGCI calculated from images taken with a commercial digital camera on board a UAV.

Materials and Methods

The trial was carried out in July 2017 in S. Piero a Grado, Pisa, at the Centre for Research on Turfgrass for the Environment and Sports (CeRTES) of the Department of Agriculture, Food and Environment of the University of Pisa (43°40'N, 10°19'E, 6 metres above sea level (m. a. s. l.).

The turfgrasses selected for the study were a mature turfgrass stands of the warm-season bermudagrass hybrid (*Cynodon dactylon* [L.] Pers. (Linnaeus Persoon) variety dactylon x *Cynodon transvaalensis* Burtt-Davy) cultivar (cv) 'Patriot' and the cool-season tall fescue (*Schedonorus phoenix* [Scop.] (Scopoli) Holub) cv 'Grande'.

The swards were all established on a calcaric fluvisoil (Coarse-silty, mixed, thermic, Typic Xerofluvents) with pH 7.8 and 18 g kg^{-1} of organic matter.

No fertilizer had been applied to the turfgrass before the trial started. In order to create a linear nitrogen gradient, on June 2017 fertilization was carried out applying ammonium sulphate (21-0-0) with a rotary spreader (ICL Specialty Fertilizers AccuPro 2000, Ipswich, UK).

The experimental designs were:

a) For tall fescue 8 nitrogen rates were applied, from 0 to 210 kg ha^{-1} of N with increases of 30 kg ha^{-1} (0 kg ha^{-1}, 30 kg ha^{-1}, 60 kg ha^{-1}, 90 kg ha^{-1}, 120 kg ha^{-1}, 150 kg ha^{-1}, 180 kg ha^{-1}, 210 kg ha^{-1} of N). The plot size was 3 m × 3 m, with 3 replications.

b) For bermudagrass hybrid, which tolerates higher doses of fertilizer, 11 nitrogen rates were applied, from 0 to 300 kg ha^{-1} of N with increases of 30 kg ha^{-1} (0 kg ha^{-1}, 30 kg ha^{-1}, 60 kg ha^{-1}, 90 kg ha^{-1}, 120 kg ha^{-1}, 150 kg ha^{-1}, 180 kg ha^{-1}, 210 kg ha^{-1}, 240 kg ha^{-1}, 270 kg ha^{-1}, 300 kg ha^{-1} of N). The plot size was 3 m × 3 m, with 3 replications.

Extreme N rates were applied in order to reach the nitrogen saturation level for both species, regardless of the agronomic drawbacks to the turfgrasses.

After the fertilization, an irrigation of 5 mm was applied. During the trial period a turf height of 2.0 cm was maintained by mowing with a walk-behind reel mower (John Deere 20SR7, Moline IL, USA) with clippings removal. In the entire experimental area, in order to evaluate nitrogen fertilization as the only variability source, identical and maintenance practices were applied. Irrigation was applied as needed to avoid wilt, in order to maintain the soil moisture constant and equal in all areas. During the trial no weed or pest control was necessary.

On each of the two experimental areas proximity and remote sensed readings were acquired starting from the unfertilized control to the highest nitrogen rate in each plot.

The ground-based instrument used to acquire NDVI values was a Handheld Crop Sensor (HCS) (GreenSeeker, Model HSC-100, Trimble Navigation Unlimited, Sunnyvale, CA) while the remote sensed readings were collected with a UAV which was a VTOL (Vertical Take Off and Landing) DJI s900 hexacopter (DJI, Shenzhen, China) equipped with a digital commercial camera Sony Nex 5 (Sony, Surrey, United Kingdom) and a lightweight multispectral sensor MAIA S2 (SAL Engineering, Modena Italy; EOPTIS, Trento, Italy). Spectral measurements (proximity and aerial) were taken on 6 July 2017 between 11:30 AM (ante meridiem) and 1:30 PM (post meridiem) (local time), in complete absence of clouds. The weather parameters of July 2017 were as follows: average air temperature 25 °C, average relative humidity 60%; July average of the noon Photosynthetic Photon Flux Density 1,482 μmol m^{-2} s^{-1}; average wind speed 6 km h^{-1}. Each ground-based measurement was geo-referenced to sub-meter accuracy with a Global Positioning System (GPS) receiver Leica 1200 in Real Time Kinematic, in order to find the exact position on the UAV images and to compare data acquired with the two systems (Caturegli, Casucci et al. 2015; Caturegli, Grossi et al. 2015; Caturegli et al. 2016).

Ground-based measurements

Proximity sensed measurements of spectral reflectance were acquired with a HCS at a height of 110 cm from the ground, thus monitoring a surface of about 2,000 cm^2 (Ø = 50 cm). The HCS has an active light source that makes readings unaffected by sunlight (Bell, Kruse, and Krum 2013). Reflectance was measured in the red region at 660 nm, and in the near infrared region of the spectrum at 780 nm. The output is directly provided as NDVI, which is calculated using the equation:

$$\mathrm{NDVI} = ((\mathrm{NIR}) - R)/((\mathrm{NIR}) + R) \quad (1)$$

where R is the reflectance in the red band and NIR is the reflectance in the near-infrared band. In the same day and in the same area also the following parameters were studied:

- Color intensity (1 = very light green; 6 = acceptable green; 9 = very dark green): visual assessments (Morris and Shearman 2008);
- Turfgrass Quality: (1 = poor; 6 = acceptable; 9 = excellent): visual assessments (Morris and Shearman 2008);
- Total N content of leaves: samples of clippings were collected on each sampling area with a walk-behind reel mower from a surface of 0.5 m^2 (1.0 m × 0.5 m). Fresh clippings were put in a ventilated stove at 70 °C, dried to constant weight, and the total N was determined by the micro-Kjeldahl method (Bremner 1965);
- Plant water content (PWC): calculated as follows:

$$\mathrm{PWC}\ (\%) = \frac{(\mathrm{FW}) - (\mathrm{DW})}{(\mathrm{FW})} \times 100 \quad (2)$$

where FW is the leaf fresh weight and DW the leaf dry weight. Leaves were cut and quickly put into a plastic bag with hermetic closure. The bags were refrigerated and kept in the dark until arrival to the laboratory, where they have been weighed.

UAV flight and analysis of UAV derived imagery

The UAV system used for surveying was a DJI s900 hexacopter (Figure 1 (a)) with Global Navigation Satellite System (GNSS), with L1 code solution and a 3 axis accelerometer based stabilization system. The hexacopter was equipped with a digital commercial camera Sony Nex 5 (Sony, Surrey, United Kingdom) and a lightweight multispectral camera MAIA S2 (SAL Engineering, Modena Italy; EOPTIS, Trento, Italy) (Figure 1 (b)). The images were acquired at 90 m of altitude to guarantee a GSD (Ground Sample Distance) of less than 5 cm and a FOV (Field Of View) of about 58 m × 43 m. The direction and altitude of the aircraft were controlled by the rotation speed or by the direction of the propellers (Li et al. 2015). Real-time images, and other information such as altitude and battery voltage, were transmitted to a ground monitor through a radio link.

Please insert Figure 1 near here

UAS derived imagery NDVI

The UAS derived imagery NDVI was obtained using the UAV cited above equipped with a multispectral camera MAIA S2 (SAL Engineering, Modena Italy; EOPTIS, Trento, Italy), which features an array of nine sensors with 1.2 Megapixel resolution: specifically, one RGB color and eight monochrome sensors are available for analysis of the visible and near infra-red (VIS-NIR) spectrum from 390 nm to 950 nm, operating with a frame rate of 5 Hz per sensor. Each of the eight sensors is provided with a band-pass filter (Table 1). Global shutter technology is so such that all of the pixels in each sensor start to collect charge simultaneously, allowing images to be scanned in “one shot” for synchronized multiband measurements. The extremely fast exposure times of the nine global shutter complementary metal-oxide semiconductor (CMOS) sensors (up to 10^{-4} s) and the low travel speed (< 0.5 m s^{-1}) guarantee the absence of the blur effect. The images obtained were geometrically corrected with calibrated optics, and radiometrically corrected with the acquisition of the reflectance values of the incident light through a calibrated white panel. After the corrections, the 9 images for each shot were registered using the proprietary MAIA software based on photogrammetric method (Dubbini et al. 2017). Every pixel of the image contained coordinates and an NDVI value that was extracted using Quantum GIS (Geographic Information System) 2.18 software.

Please insert Table 1 near here

Dark Green Color Index (DGCI)

A common digital camera, Sony Nex 5 (Sony, Surrey, United Kingdom) was used to capture RGB images of the selected area. The Sony Nex-5 is a mirrorless interchangeable-lens camera, with the Advanced Photo System-Classic (APS-C) Exmor CMOS sensor and a maximum image resolution of 4,912 × 3,264 and a pixel size of 5 μm in both x and y directions (Remondino and Fraser 2006; Fryskowska et al. 2016). To reduce the effect of vibration during the flight and capture clear images, the camera was mounted on a pan-tilt set which keeps the lens horizontal. In the same day as the ground NDVI readings and the NDVI by the multispectral camera, the digital camera recorded UAS derived imagery RGB images above the interested area, always in a zenithal plane. Images were taken with auto-focus, auto-white balance and an automatic exposure, and they were saved in Joint Photographic Experts Group (JPEG) format. Subsequently, images were analyzed with the open source Quantum GIS 2.18 software to extract the RGB values of the pixels where the NDVI values by the ground and by the multispectral camera were calculated. To simplify the interpretation of data, RGB values were converted into HSB values, using the method suggested by (Karcher and Richardson 2003), to finally calculate the DGCI. DGCI value is on a scale from 0 (very yellow) to 1 (dark green) (Rhezali and Lahlali 2017). DGCI was calculated as:

$$\text{DGCI} = [((\text{Hue}) - 60)/60 + (1 - (\text{Saturation})) + (1 - (\text{Brightness}))]/3 \quad (3)$$

Statistical analysis

The correlations between the two different NDVI reading methods (ground-based sensing with a HCS and remote sensing with UAV) and DGCI were studied using CoStat software (CoHort, Monterey, CA, USA) and Pearson's correlation coefficients (*r*) were calculated in order to verify whether: (a) NDVI-ground data and NDVI-UAV were suitably correlated with DGCI obtained from RGB images captured by the digital camera on board a UAV; (b) UAV imagery with a low cost digital camera could be a diagnostic tool to identify variation in N status of turfgrass, comparable to a more expensive multispectral camera. Linear relationships were studied for the correlations showing statistically significant coefficients.

Results and discussion

Relationship between DGCI, NDVI and observed parameters

In bermudagrass hybrid, considering *r* among NDVI values obtained with the two different instruments (proximity sensed with the HCS GreenSeeker and remotely sensed with the multispectral camera MAIA mounted on board a UAV), and the measured parameters, the *r* values were highly significant. The *r* values ranged between 0.92 for PWC-NDVI of both the instruments and 0.97 for turfgrass quality-NDVI GreenSeeker. Comparing DGCI and all the measured parameters, the index was significantly correlated with color intensity, turfgrass quality and plant water content with *r* values ranging between 0.83 for color intensity and 0.84 for turfgrass quality and PWC (Table 2).

In tall fescue the correlations between NDVI obtained with GreenSeeker and with UAV and color intensity (r = 0.96 and r = 0.95) has showed higher *r* values than the same in bermudagrass hybrid (r = 0.94). Also PWC-NDVI (GreenSeeker and UAV) showed a degree of association significantly higher in tall fescue (r = 0.98) than bermudagrass hybrid (r = 0.92).

Furthermore, observing the correlations, the DGCI was highly correlated with all the measured parameters with *r* values ranging between 0.92 for DGCI-Quality and 0.98 for DGCI-PWC. These relationships were all significantly higher in tall fescue than bermudagrass hybrid (Table 2) also in the case of DGCI-turfgrass color (r = 0.95). Previous reports by Zhang and Kovacs (2012), and Leinauer et al. (2014) also indicated this trend of values between DGCI and turfgrass quality and turfgrass color. As in our study also in the report by Leinauer et al. (2014), the association between DGCI and turfgrass quality in tall fescue showed higher *r* values than the same association in bermudagrass hybrid. As for the turfgrass color, Zhang and Kovacs (2012) also studied the relationship between visual color rating and DGCI, with higher Pearson correlation coefficient in tall fescue than bermudagrass hybrid. Previous reports by Karcher and Richardson (2003) also confirm that visual ratings can be used to separate treatment effects on turf color. Frequently raters ranked the turf plots similarly although differences in color existed. Therefore, visual color rating remains a valid evaluation tool if data are not compared across raters. However, the accuracy of DGCI, as demonstrated in previous studies, enables researchers to record reflected turfgrass color on a standardized scale rather than using arbitrary rating values.

Please insert Table 2 near here

Relationship between DGCI and NDVI

Both in bermudagrass hybrid (Figure 2 (a)) and tall fescue (Figure 2 (b)) DCGI significantly related to the average NDVI values measured with a HCS (GreenSeeker) and with the multispectral camera MAIA mounted on board a UAV, although data have been collected by instruments that measure at different heights and spatial resolutions. In fact DGCI has been collected only with RGB camera mounted on board a UAV, while NDVI has been measured by a multispectral camera on board a UAV and also by a ground based HCS.

As shown in the Figure 2, DGCI values were linearly associated with NDVI, as also demonstrated by Leinauer et al. 2014. In Figure 2 (a) bermudagrass hybrid has performed a higher degree of association in NDVI GreenSeeker-DGCI (r = 0.91) than with UAV (r = 0.85), while in the case of tall fescue the degree of association was statistically the same (Figure 2 (b)). Comparing the two species, it was interesting to note that in tall fescue the correlation coefficients (Table 2) between both NDVI (GreenSeeker and UAV) and DGCI were higher than in Bermudagrass (Table 2; Figures 2 (a) - (b)).

Please insert Figure 2 near here

Relationship between DGCI and clipping nitrogen content

Figure 3 showed the linear relationship between DGCI and clipping nitrogen content percentage in bermudagrass hybrid (a) and tall fescue (b) and it was of interest to note that the coefficients were high for both the species. However, DGCI in tall fescue showed a higher degree of association with clipping N content (r = 0.95), than in bermudagrass hybrid (r = 0.86) (Figures 3 (a) - (b)). DGCI values were linearly associated with clipping nitrogen content, as also demonstrated in other crops (Rorie, Purcell, Mozaffari et al. 2011; Vergara-Díaz et al. 2016). Thus, DGCI values could predict the average nitrogen concentrations of tall fescue and bermudagrass hybrid clippings in different plots and with different application rates.

The close association between DGCI and leaf nitrogen therefore provided an additional tool for the assessment of leaf nitrogen content. Our research was consistent with previous work by Karcher and Richardson (2003) who found that DGCI values were able to differentiate among turfgrass cultivars receiving various N treatments.

Please insert Figure 3 near here

Conclusions

DGCI values were highly correlated with the nitrogen clipping content and NDVI with a highly significant degree of association. The results suggested that UAS derived imagery RGB photography by UAVs had a great potential in supporting decisions. Thus, DGCI could be a promising remote-sensing tool for mapping the crop nitrogen status or NDVI at large scale with high precision and low cost (Li et al. 2015). This method could be used by farmers operating in large-scale farms to precisely manage the application of fertilizers, although the farmers especially in the developing and underdeveloped counties, they do not have enough knowledge to operate the UAV and manage the technology. As turfgrass, especially in the most developed countries, this method could allow golf course superintendents and turf management specialists to make critical decisions in real time without high up-front costs. Differences in camera quality and settings and lighting conditions could affect DGCI and limit their utility in diagnosing N deficiencies. Furthermore, disease, water status, nutritional deficiencies other than N, or different uniformity, texture and growth habit may affect greenness regardless of N status as suggested also by Rorie, Purcell, Karcher et al. 2011 and by Leinauer et al. 2014. More research is required on this technology and on the Smartphone APP FieldScout GreenIndex+ Turf (Spectrum Technologies, Inc., Aurora, IL, USA) (Spectrum Technologies, Inc. 2018) to study and overcome possible discrepancies between the APP and the Smartphone camera. Although the accuracy of a Smartphone camera is not comparable to a digital camera, the precision of a Smartphone camera could still help to detect minor changes in turf greenness over time and-or relative to other areas of the golf course or sports field. In fact, if the imagery was conveyed quickly to the user, a broader usage of this technology could allow golf course superintendents and turf management specialists to make critical decisions in real time without high up-front costs, in small areas. To use efficiently this technology on large scale, DGCI could be use directly on board an UAV and could serve as an indicator of N deficiency on turfgrass, thus increasing turfgrass nitrogen fertilization efficiency.

Indeed, applications installed in drones could be good solutions for farmers or golf course superintendents and turf management specialists so they can adopt and benefit from DGCI technology.

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Captions

Table 1. Instrument monochrome sensors with relative band-pass filters of the multispectral camera MAIA.

Table 2. Pearson product-moment correlation coefficients (*r*) among clipping nitrogen content, color intensity, turfgrass quality, plant water content (PWC), NDVI measured with a handheld crop sensor (GreenSeeker) and NDVI measured with multispectral camera mounted on an unmanned aerial vehicle (UAV) and dark green color index (DGCI) on a) bermudagrass hybrid; b) tall fescue. For each species correlation coefficients are calculated across all entries.

All values are significant at the 0.010 level, except for DGCI color intensity, quality and PWC for bermudagrass hybrid and DGCI quality for tall fescue, whose values are significant at the 0.001 level.

Figure 1. (a) UAV during flight operations (6 July 2017; Pisa, Italy; 43°40’N, 10° 19’E, 6 m. a. s. l.); (b) The multispectral camera MAIA mounted on the UAV.

Figure 2. Linear relationship between NDVI measured with a handheld crop sensor (GreenSeeker) and NDVI measured with a multispectral camera mounted on UAV and DGCI on (a) bermudagrass hybrid; and (b) tall fescue. Values represented the 3 replications.

Figure 3. Linear relationship between DGCI and the clipping nitrogen content (%) on (a) bermudagrass hybrid; and (b) tall fescue. Values represented the average of 3 replications.

Tables

Table 1. Instrument monochrome sensors with relative band-pass filters of the multispectral camera MAIA.

Wavelength (nm)		
Start	Central	Stop
395.0	422.5	450.0
455.0	487.5	520.0
525.0	550.0	575.0
580.0	602.5	625.0
630.0	660.0	690.0
705.0	725.0	745.0
750.0	785.0	820.0
825.0	887.5	950.0

Table 2. Pearson product-moment correlation coefficients (*r*) among clipping nitrogen content, color intensity, turfgrass quality, plant water content (PWC), NDVI measured with a handheld crop sensor (GreenSeeker) and NDVI measured with multispectral camera mounted on an unmanned aerial vehicle (UAV) and dark green color index (DGCI) on a) bermudagrass hybrid; b) tall fescue. For each species correlation coefficients are calculated across all entries.

All values are significant at the 0.010 level, except for DGCI color intensity, quality and PWC for bermudagrass hybrid and DGCI quality for tall fescue, whose values are significant at the 0.001 level.

r	Color intensity	Quality	PWC	NDVI GreenSeeker	NDVI UAV	DGCI
a) Bermudagrass hybrid						
N clipping (%)	0.97	0.97	0.95	0.94	0.92	0.86
Color intensity (1-9)	N/A	0.94	0.99	0.94	0.94	0.83
Quality (1-9)	N/A	N/A	0.97	0.97	0.94	0.84
PWC (%)	N/A	N/A	N/A	0.92	0.92	0.84
NDVI GreenSeeker (780,660)	N/A	N/A	N/A	N/A	0.96	0.91
NDVI UAV (830,660)	N/A	N/A	N/A	N/A	N/A	0.85
b) Tall fescue						
N clipping (%)	0.99	0.99	0.99	0.95	0.94	0.95
Color intensity (1-9)	N/A	0.99	0.99	0.96	0.95	0.95
Quality (1-9)	N/A	N/A	0.98	0.94	0.93	0.92
PWC (%)	N/A	N/A	N/A	0.98	0.98	0.98
NDVI GreenSeeker (780,660)	N/A	N/A	N/A	N/A	0.99	0.95
NDVI UAV (830,660)	N/A	N/A	N/A	N/A	N/A	0.96