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

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

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

4  
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16

17 **Abbreviations:**

18 DGCI Dark Green Color Index

19 GPS Global Positioning System

20 HSB Hue Saturation Brightness

21 NDVI Normalized Difference Vegetation Index

22 PA Precision Agriculture

23 PTM Precision Turfgrass Management

24 RGB Red Green Blue

25 UAS Unmanned Aerial Systems

26 UAV Unmanned Aerial Vehicle

27 **Keywords:**

28 *Cynodon dactylon x transvaalensis*, *Schedonorus phoenix*, Turfgrass, Color, Quality, Unmanned

29 Aerial Vehicle.

30

## 31 **Abstract**

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

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

52

## 53 **Introduction**

54 Nitrogen fertilization on turfgrasses is one of the factors that most influence physiological and  
55 aesthetic aspects (Volterrani et al. 2005; Perry and Davenport 2007; Samborski, Tremblay, and  
56 Fallon 2009; Caturegli et al., “Monitoring turfgrass”, 2014; Caturegli et al., “Turfgrass spectral  
57 reflectance”, 2014; Grossi et al. 2016). Thus, nitrogen (N) represents an important nutrient that  
58 contributes to maintain green color, density, recovery from drought diseases, and a general good  
59 turfgrass quality (Walters and Bingham 2007; Dordas 2008; Magni et al. 2014; Caturegli et al.  
60 2016).

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

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

71 These concepts are the basis of Precision Agriculture (PA), which aims to obtain detailed site-  
72 specific information by mapping the variation in important soil and plant properties in order to  
73 allow better site-specific management. Inputs such as water, fertilizers and pesticides are applied  
74 only where, when and in the amount needed by plant (Caturegli et al., “Turfgrass spectral  
75 reflectance”, 2014). Related to PA is Precision Turfgrass Management (PTM) that is useful to  
76 monitor pests, fertilization, salinity stress and irrigation deficiency on turfgrass (Carrow et al. 2010;  
77 Krum, Carrow, and Karnok 2010). The approach of PA implied the combined use of multispectral

78 sensors and vegetation indices associated with vegetation parameters (Trenholm, Carrow, and  
79 Duncan 1999; Jiang and Carrow 2007; Vergara-Díaz et al. 2016). Thus, vegetation indices were  
80 calculated by combining various reflectance bands of the spectrum and correlated with relevant  
81 turfgrass canopy parameters. Among the indices, the Normalized Difference Vegetation Index  
82 (NDVI) is the most widely used as reflectance-based plant stress indicator (Hansen and Schjoerring  
83 2003; Johnsen et al. 2009; Aguilar et al. 2012; Barton 2012; Fensholt and Proud 2012; Rhezali and  
84 Lahlali 2017). It is based on the relationship between the absorption of visible light and resilient  
85 reflectance of near-infrared light to the chlorophyll in vegetation (Bell et al. 2004; Caturegli,  
86 Casucci et al. 2015). The NDVI value ranges from -1 to 1, with higher values indicating greater  
87 plant health, and correlates positively with turfgrass quality (Trenholm, Carrow, and Duncan 1999;  
88 Fitz-Rodriguez and Choi 2002; Leinauer et al. 2014). This index is also influenced by differences in  
89 species, environmental stresses, fertilization and pest injuries (Xiong et al. 2007; Bremer et al.  
90 2011; Caturegli, Grossi et al. 2015). It can be obtained with hand-held ground-based instruments  
91 (Graeff and Claupein 2003; Ma, Morrison, and Dwyer 1996) and aerial vehicle-mounted sensors  
92 (Bausch and Duke 1996; Blackmer et al. 1996; Scharf and Lory 2009; Rorie, Purcell, Karcher et al.  
93 2011). In recent years, digital sensors have been successfully integrated on board Unmanned Aerial  
94 Vehicles (UAV) to assess crop vigor, vegetation coverage, and to quantify the “greenness” of  
95 foliage as indirect measurements of crop N status (White et al. 2012; Andrade-Sanchez et al. 2014).  
96 Furthermore, small commercial Unmanned Aerial Systems (UAS) (< 50 kg) (Laliberte and Rango  
97 2011) have been available for PA for environmental and agricultural applications (Gupta et al.  
98 2013; Zhang and Kovacs 2012; Caturegli et al. 2016). However, the main negative issue when it  
99 comes to multi and hyper-spectral reflectance measuring tools is their high cost and complexity.  
100 Vegetation indices derived from Red-Green-Blue (RGB) cameras have been employed for remote  
101 sensing assessment, as a low-cost alternative (Vergara-Díaz et al. 2016). This method may provide  
102 data on different stress conditions in different crops (Casadesús et al. 2007; Casadesus and Villegas  
103 2014; Zhou et al. 2015) and turfgrass (Karcher and Richardson 2003; Karcher and Richardson

104 2013). Digital images are composed by pixels that record information as amounts of RGB light  
105 emitted. However, the greenness of an image can be often altered by the intensity of red and blue.  
106 To simplify the interpretation of data, Karcher and Richardson (2003) suggested converting RGB  
107 values to the more intuitive Hue, Saturation, and Brightness (HSB) based on human perception of  
108 color. Working with quality of turfgrass in response to N fertilizer, Karcher and Richardson (2003)  
109 processed HSB values into a single measure of dark green color, the Dark Green Color Index  
110 (DGCI).

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

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

124

## 125 **Materials and Methods**

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

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

133 The swards were all established on a calcareous fluvisoil (Coarse-silty, mixed, thermic, Typic  
134 Xerofluvents) with pH 7.8 and 18 g kg<sup>-1</sup> of organic matter.

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

138 The experimental designs were:

139 a) For tall fescue 8 nitrogen rates were applied, from 0 to 210 kg ha<sup>-1</sup> of N with increases of 30 kg  
140 ha<sup>-1</sup> (0 kg ha<sup>-1</sup>, 30 kg ha<sup>-1</sup>, 60 kg ha<sup>-1</sup>, 90 kg ha<sup>-1</sup>, 120 kg ha<sup>-1</sup>, 150 kg ha<sup>-1</sup>, 180 kg ha<sup>-1</sup>, 210 kg ha<sup>-1</sup>  
141 of N). The plot size was 3 m × 3 m, with 3 replications.

142 b) For bermudagrass hybrid, which tolerates higher doses of fertilizer, 11 nitrogen rates were  
143 applied, from 0 to 300 kg ha<sup>-1</sup> of N with increases of 30 kg ha<sup>-1</sup> (0 kg ha<sup>-1</sup>, 30 kg ha<sup>-1</sup>, 60 kg ha<sup>-1</sup>,  
144 90 kg ha<sup>-1</sup>, 120 kg ha<sup>-1</sup>, 150 kg ha<sup>-1</sup>, 180 kg ha<sup>-1</sup>, 210 kg ha<sup>-1</sup>, 240 kg ha<sup>-1</sup>, 270 kg ha<sup>-1</sup>, 300 kg ha<sup>-1</sup>  
145 of N). The plot size was 3 m × 3 m, with 3 replications.

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

148 After the fertilization, an irrigation of 5 mm was applied. During the trial period a turf height of 2.0  
149 cm was maintained by mowing with a walk-behind reel mower (John Deere 20SR7, Moline IL,



150 USA) with clippings removal. In the entire experimental area, in order to evaluate nitrogen  
151 fertilization as the only variability source, identical and maintenance practices were applied.  
152 Irrigation was applied as needed to avoid wilt, in order to maintain the soil moisture constant and  
153 equal in all areas. During the trial no weed or pest control was necessary.

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

156 The ground-based instrument used to acquire NDVI values was a Handheld Crop Sensor (HCS)  
157 (GreenSeeker, Model HSC-100, Trimble Navigation Unlimited, Sunnyvale, CA) while the remote  
158 sensed readings were collected with a UAV which was a VTOL (Vertical Take Off and Landing)  
159 DJI s900 hexacopter (DJI, Shenzhen, China) equipped with a digital commercial camera Sony Nex  
160 5 (Sony, Surrey, United Kingdom) and a lightweight multispectral sensor MAIA S2 (SAL  
161 Engineering, Modena Italy; EOPTIS, Trento, Italy). Spectral measurements (proximity and aerial)  
162 were taken on 6 July 2017 between 11:30 AM (ante meridiem) and 1:30 PM (post meridiem) (local  
163 time), in complete absence of clouds. The weather parameters of July 2017 were as follows:  
164 average air temperature 25 °C, average relative humidity 60%; July average of the noon  
165 Photosynthetic Photon Flux Density 1,482  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ; average wind speed 6 km h<sup>-1</sup>. Each ground-  
166 based measurement was geo-referenced to sub-meter accuracy with a Global Positioning System  
167 (GPS) receiver Leica 1200 in Real Time Kinematic, in order to find the exact position on the UAV  
168 images and to compare data acquired with the two systems (Caturegli, Casucci et al. 2015;  
169 Caturegli, Grossi et al. 2015; Caturegli et al. 2016).

## 170 **Ground-based measurements**

171 Proximity sensed measurements of spectral reflectance were acquired with a HCS at a height  
172 of 110 cm from the ground, thus monitoring a surface of about 2,000 cm<sup>2</sup> ( $\varnothing = 50$  cm). The HCS  
173 has an active light source that makes readings unaffected by sunlight (Bell, Kruse, and Krum 2013).  
174 Reflectance was measured in the red region at 660 nm, and in the near infrared region of the

175 spectrum at 780 nm. The output is directly provided as NDVI, which is calculated using the  
176 equation:

$$177 \quad \text{NDVI} = ((\text{NIR}) - R) / ((\text{NIR}) + R) \quad (1)$$

178 where  $R$  is the reflectance in the red band and NIR is the reflectance in the near-infrared band.

179 In the same day and in the same area also the following parameters were studied:

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

$$189 \quad \text{PWC (\%)} = \frac{190 \quad (\text{FW}) - (\text{DW})}{(\text{FW})} \times 100 \quad (2)$$

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

## 194 **UAV flight and analysis of UAV derived imagery**

195 The UAV system used for surveying was a DJI s900 hexacopter (Figure 1 (a)) with Global  
196 Navigation Satellite System (GNSS), with L1 code solution and a 3 axis accelerometer based  
197 stabilization system. The hexacopter was equipped with a digital commercial camera Sony Nex 5  
198 (Sony, Surrey, United Kingdom) and a lightweight multispectral camera MAIA S2 (SAL  
199 Engineering, Modena Italy; EOPTIS, Trento, Italy) (Figure 1 (b)). The images were acquired at 90

200 m of altitude to guarantee a GSD (Ground Sample Distance) of less than 5 cm and a FOV (Field Of  
201 View) of about 58 m × 43 m. The direction and altitude of the aircraft were controlled by the  
202 rotation speed or by the direction of the propellers (Li et al. 2015). Real-time images, and other  
203 information such as altitude and battery voltage, were transmitted to a ground monitor through a  
204 radio link.

205 **Please insert Figure 1 near here**

206

## 207 **UAS derived imagery NDVI**

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

224 **Please insert Table 1 near here**

225

## 226 **Dark Green Color Index (DGCI)**

227 A common digital camera, Sony Nex 5 (Sony, Surrey, United Kingdom) was used to capture  
228 RGB images of the selected area. The Sony Nex-5 is a mirrorless interchangeable-lens camera, with  
229 the Advanced Photo System-Classic (APS-C) Exmor CMOS sensor and a maximum image  
230 resolution of  $4,912 \times 3,264$  and a pixel size of  $5 \mu\text{m}$  in both x and y directions (Remondino and  
231 Fraser 2006; Fryskowska et al. 2016). To reduce the effect of vibration during the flight and capture

232 clear images, the camera was mounted on a pan-tilt set which keeps the lens horizontal. In the same  
233 day as the ground NDVI readings and the NDVI by the multispectral camera, the digital camera  
234 recorded UAS derived imagery RGB images above the interested area, always in a zenithal plane.  
235 Images were taken with auto-focus, auto-white balance and an automatic exposure, and they were  
236 saved in Joint Photographic Experts Group (JPEG) format. Subsequently, images were analyzed  
237 with the open source Quantum GIS 2.18 software to extract the RGB values of the pixels where the  
238 NDVI values by the ground and by the multispectral camera were calculated. To simplify the  
239 interpretation of data, RGB values were converted into HSB values, using the method suggested by  
240 (Karcher and Richardson 2003), to finally calculate the DGCI. DGCI value is on a scale from 0  
241 (very yellow) to 1 (dark green) (Rhezali and Lahlali 2017). DGCI was calculated as:

$$242 \quad \text{DGCI} = [((\text{Hue}) - 60)/60 + (1 - (\text{Saturation})) + (1 - (\text{Brightness}))]/3 \quad (3)$$

243

## 244 **Statistical analysis**

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

## 253 **Results and discussion**

### 254 **Relationship between DGCI, NDVI and observed parameters**

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

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

267 Furthermore, observing the correlations, the DGCI was highly correlated with all the measured  
268 parameters with  $r$  values ranging between 0.92 for DGCI-Quality and 0.98 for DGCI-PWC. These  
269 relationships were all significantly higher in tall fescue than bermudagrass hybrid (Table 2) also in  
270 the case of DGCI-turfgrass color ( $r = 0.95$ ). Previous reports by Zhang and Kovacs (2012), and  
271 Leinauer et al. (2014) also indicated this trend of values between DGCI and turfgrass quality and  
272 turfgrass color. As in our study also in the report by Leinauer et al. (2014), the association between  
273 DGCI and turfgrass quality in tall fescue showed higher  $r$  values than the same association in  
274 bermudagrass hybrid. As for the turfgrass color, Zhang and Kovacs (2012) also studied the  
275 relationship between visual color rating and DGCI, with higher Pearson correlation coefficient in  
276 tall fescue than bermudagrass hybrid. Previous reports by Karcher and Richardson (2003) also

277 confirm that visual ratings can be used to separate treatment effects on turf color. Frequently raters  
278 ranked the turf plots similarly although differences in color existed. Therefore, visual color rating  
279 remains a valid evaluation tool if data are not compared across raters. However, the accuracy of  
280 DGCI, as demonstrated in previous studies, enables researchers to record reflected turfgrass color  
281 on a standardized scale rather than using arbitrary rating values.

282 **Please insert Table 2 near here**

283

## 284 **Relationship between DGCI and NDVI**

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

291 As shown in the Figure 2, DGCI values were linearly associated with NDVI, as also demonstrated  
292 by Leinauer et al. 2014. In Figure 2 (a) bermudagrass hybrid has performed a higher degree of  
293 association in NDVI GreenSeeker-DGCI ( $r = 0.91$ ) than with UAV ( $r = 0.85$ ), while in the case of  
294 tall fescue the degree of association was statistically the same (Figure 2 (b)). Comparing the two  
295 species, it was interesting to note that in tall fescue the correlation coefficients (Table 2) between  
296 both NDVI (GreenSeeker and UAV) and DGCI were higher than in Bermudagrass (Table 2; Figures  
297 2 (a) - (b)).

298

299 **Please insert Figure 2 near here**

300

301



## 302 **Relationship between DGCI and clipping nitrogen content**

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

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

315

316 **Please insert Figure 3 near here**

317

318

## 319 **Conclusions**

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

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

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354

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522

523 **Captions**

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

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

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

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

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

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

541

542

543 **Tables**

544 **Table 1.** Instrument monochrome sensors with relative band-pass filters of the multispectral camera  
 545 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

546

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

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

<i>r</i>	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

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556