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New Technologies for Evaluating Putting Green Surface Characteristics

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New Technologies for Evaluating Putting Green Surface Characteristics

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ABSTRACT

Golf course putting greens require a high level of inputs predicated on timely, well-informed decisions. Putting green quality is ultimately defined by performance of the turfgrass, and this performance encompasses both *(i)* the health and vitality of the turfgrass plants, and *(ii)* the ability of the turfgrass to exist as a playing surface, as it interacts with the golf ball. For golf course superintendents, accurately and efficiently assessing moisture levels and nutrient status are critical for guiding maintenance practices. This research sought to examine new ways for measuring each of these parameters, and compared them to ground-truth data and/or industry standard methodology/devices. Putting green moisture levels are typically measured as volumetric water content (θ) using portable time domain reflectometry (TDR) meters; in this research a common TDR meter (FieldScout TDR300, Spectrum Technologies Inc.) was fit with spacer-blocks, so that new measurement depths closer to the putting surface (1.2 and 2.5 cm depth) could be obtained. For nutrient status (as well as overall turf health), green color is often used as a general (and subjective) assessment; in this research, a new smartphone app (GreenIndex+ Turf, Spectrum Technologies) utilizing the dark green color index (DGCI) was compared to (i) visual color ratings, as well as (ii) standard research methodology using digital image analysis (DIA). The modified TDR 300 produced significant ($P < 0.0001$) linear prediction equations for 1.2 and 2.5 cm depths. The DGCI from the GreenIndex+ Turf app lacked the consistency of standardized DIA. Based on these results, simple modifications to an existing TDR300 meter can provide additional moisture information very close to the putting surface. For DIA, further research and refinements are necessary to improve ambient light adjustments, in order to produce reliable data across a range of different lighting conditions.

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I. Introduction

Turfgrass research and management rely on technology. Specialized tools capable of providing precise, reliable, and objective measurements play an important role in evaluating turfgrass characteristics and aiding in management decisions. For many golf course superintendents and turfgrass researchers, the ability to perform these measurements depends upon a tool's portability, its investment costs (both money and time), as well as the accuracy and applicability of the information it generates. Adaptations of existing technologies have the potential to reduce investment costs while increasing information available to turfgrass professionals. Specifically, methods and technologies which have been demonstrated to be reliable may be modified and or applied in novel ways at reduced costs to developers and end users. Potential benefits may be found by: *(i)* expanding the scope of measurements that can be collected; *(ii)* improving the efficiency of the measurement taking process (and increasing the number of measurements collected); *(iii)* introducing greater objectivity into data collected.

Two primary challenges facing turfgrass researchers and golf course superintendents involve *(i)* managing moisture levels of putting green turf, and *(ii)* obtaining timely, objective visual assessments for turfgrass color. This research focused on two particular technologies relating to those challenges: *(i)* time domain reflectometry (TDR) for measuring moisture content near the putting green surface (the uppermost 1.2 cm and 2.5 cm of the putting green), and *(ii)* a recently released smartphone app for quantifying turfgrass color by utilizing dark green color index (DGCI) obtained through digital image analysis (DIA).

STUDY 1 - Measuring putting green surface moisture with time domain reflectometry

Managing sand-based putting greens requires appropriate and continual balancing of the dual (and often competing) interests of maintaining adequate moisture in the rootzone for plant health, while preserving firmness of the putting surface in order to optimize playability. Examining the effects moisture levels have on the relationship between playability and plant health requires the ability to repeatedly and reliably measure volumetric water content (θ) over a range of maintenance practices as well as environmental conditions. Time domain reflectometry has become a preferred technology among golf course superintendents for measuring θ due to its non-destructive nature, its portability, and relative affordability (Moeller, 2012). However, while portable TDR devices have been able to provide valuable measurements of θ throughout the rootzone, they are limited in their ability to rapidly estimate moisture levels exclusively within the uppermost regions of the putting green profile, very near the actual playing surface. Currently sampling depths of portable TDR devices include 3.8 to 20 (Spectrum Technologies Inc., 2011; Campbell Scientific Inc., 2010), and measurements reflect the entire length of the TDR rods.

While moisture levels near the putting green surface influence playability (such as slower green speeds and softer surfaces more susceptible to damage), factors attributing to higher moisture content within this portion of the green may involve multiple aspects of putting green management practices. Measuring θ within the uppermost region of putting green profile has implications for playability, irrigation scheduling, cultural management practices relating to thatch, wetting agent applications, and potential disease development; however, current practical methodology to attain such information is lacking. Alternative methods for measuring moisture near the surface involve either destructive gravimetric determination of water content by means of removing turf samples from the green; or stationary devices inserted horizontally into a single location within the putting green (where they remain). However, adapting a currently available portable TDR device and expanding its effective measurement range to include surface levels of putting greens offers potential for incorporating new data into evaluations of putting green moisture, its impact on playability, and how it is affected by various maintenance practices.

This research involved modifying the penetrating depth of a commonly used portable TDR meter and developing empirically derived equations so that θ within 1.2 cm and 2.5 cm of a putting green's surface could be accurately predicted.

General principles of TDR

Time Domain Reflectometry has become an accepted technology for accurately estimating water content of a soil by measuring its dielectric permittivity, based on the relationship between a material's permittivity and its water content (Robinson et al., 2003). TDR devices accomplish this by generating an electromagnetic wave, transmitting it along a waveguide (*i.e.* stainless-steel rods) inserted into the soil, and measuring the time required for that wave signal to travel a known distance and return (Noborio, 2001; Robinson et al., 2003).

$$\boldsymbol{t = \frac{2LK^{0.5}}{c}} \qquad \textbf{[1]}$$

$$\kappa = \boldsymbol{\left(\frac{ct}{2L}\right)^{2}} \qquad \textbf{[2]}$$

Equation [1] from Fellner-Feldegg, 1969 calculates the round-trip travel time of the wave *t*, using: the length *L* of the TDR probe (m); the dielectric constant κ; the velocity of electromagnetic waves in free space *c* (m s^{-1}) (3 x 10^{8}); (Noborio, 2001). Equation [2] rearranges the original equation to calculate for the dielectric constant κ (Noborio, 2001). The fact that water has a much larger dielectric constant relative to the other soil components (air, soil-solids) allows TDR devices to utilize κ values for further determining the volumetric water content of a sampled soil (Noborio, 2001; Spectrum Technologies Inc., 2011).

Work by Topp et al. (1980) presented an empirically determined equation relating known volumetric water content (θ) to dielectric constant (κ). Equation [3] comes from the practical application of this work, where typically, the dielectric constant (κ) is measured and used to determine an unknown θ.

$$\boldsymbol{\theta} = -\mathbf{5.3} \text{ x } \mathbf{10^{-2}} + \mathbf{2.92} \text{ x } \mathbf{10^{-2}}\kappa - \mathbf{5.5} \text{ x } \mathbf{10^{-4}}\kappa^{\mathbf{2}} + \mathbf{4.3} \text{ x } \mathbf{10^{-6}}\kappa^{\mathbf{3}} \qquad \textbf{[3]}$$

While the Topp et al. equation [3] has been confirmed by subsequent research and applied to many different situations, alternative calibrations, including linear equations, have also been developed to describe the relationship between κ and θ (Noborio, 2001).

Advantages of TDR over alternative methods

General advantages of TDR compared to direct soil moisture measurements include: portability, efficiency, minimal soil disturbance, ability to operate (in many situations) without soil specific calibrations (Munoz-Carpena, 2004); all while maintaining accuracy and consistency. Direct methods for measuring water content (thermo-gravimetric and thermo-volumetric) are accepted to be the most accurate, however the destructive nature and amount of time required for that type of sampling (Munoz-Carpena, 2004; Noborio, 2001) make them particularly undesirable for use on a golf course putting green or even in turfgrass research plots. The ability for TDR to be adapted and applied in new ways has contributed to its interest throughout soil physics (Robinson et al., 2003). Within the overarching principles of TDR technology research has also used frequency domain analysis to model TDR waveforms, and the performance of specific devices in an effort to characterize electromagnetic wave properties and distinguish higher frequency (and typically more expensive) TDR devices from lower frequency water content reflectometers (Heimovaara, 1994; Kargas et al., 2013). The potential for new and evolving applications, along with current levels of use among researchers and golf course superintendents suggest that TDR will continue to be a utilized technology for the foreseeable future, and justify it as an appropriate technology for this research.

Current applications and importance

Objectively quantifying and communicating moisture levels is fundamental for managing putting greens; particularly in establishing, monitoring, and refining irrigation schedules (Gatlin, 2011). Portable TDR meters and in particular, the FieldScout TDR300 moisture meter (Item# 6430FS, Spectrum Technologies, Aurora, IL), have been identified by golf course superintendents as a valued and trusted tool for aiding in moisture management decisions (Gatlin, 2011). Without such instruments, evaluation of soil moisture becomes a much more subjective "art" (Moeller, 2012) described by increasingly ambiguous language (Gatlin, 2011). The benefits of providing rapid, accurate readings, as well as being portable, versatile, and affordable, have all contributed to TDR300's popularity within the golf industry (Moeller, 2012). That same ability to precisely and repeatedly quantify soil moisture levels validate the TDR300's usefulness to turfgrass researchers. Currently, with 3.8 cm as the minimum rod length, and because the meter measures along the entire length of the rods, information generated by portable TDR meters describes moisture content of the putting green rootzone extending beyond that of the actual playing surface. While the TDR300 is one of the most popular models, and the particular device used in this research, other portable TDR devices are subject to similar limitations.

Limitations

Portable TDR instruments' ability to make shallow measurements is limited by a necessary minimum length of the rods required to produce accurate, reliable measurements (Robinson, 2003). The measurements obtained from a TDR300 represent the entire length of the rods, and the minimum rod length currently manufactured for the TDR300 is 3.8 cm (Spectrum Technologies Inc., 2011). Other commercially available TDR meters popular among golf course superintendents (Moeller, 2012) have minimum rod lengths of 12 cm (Hydrosense II, Campbell Scientific, Logan, UT). The inability to measure how θ specifically relates to the putting green surface is a result of this limitation.

While moisture of the putting surface is of general interest to many golf course superintendents and turfgrass researchers, one specific application involves the effects wetting agent products have on moisture distribution of putting greens (Karcher et al., 2008). Previous research has found that on average, the closer to the surface TDR measurements were taken, the less uniform the moisture distribution became, however 7.2 cm was the minimum sampling depth available for that study (Karcher et al., 2008). There have also been anecdotal claims from golf course superintendents of excess moisture retention at the putting green surface brought on by particular wetting agent products, resulting in softer, slower greens that were more susceptible to damage and disease (Karcher personal communication, 2013). Measuring θ closer to the putting green surface would allow for more precise, objective evaluation regarding the interaction of applied wetting agents and surface level moisture – affecting both playability and plant health. Using alternative TDR devices (Toro Turfgard, UgMo) (Moeller, 2012), which can be inserted into the putting green relinquish the benefits of portability and efficiency offered by devices such as the TDR300. By using a device such as the TDR300, the benefits of rapidly obtaining surface moisture measurements at multiple locations, across multiple putting greens, may extend beyond simply wetting agent behavior, and may also elucidate the relationship between surface moisture and playability. This relationship is derived from multiple factors involvingcultural practices for managing thatch, irrigation scheduling, and the effects of weather/environmental conditions.

Overcoming the aforementioned limitations may be accomplished by reducing the penetrating depth (rather than the overall length) of the 3.8 cm rods. Such modifications would preserve the accuracy associated with necessary minimum TDR rod length, and allow a portable TDR meter to measure θ very near the actual putting surface. This may be achieved by physically blocking the 3.8 cm TDR rods from fully entering into the putting green. It is important that such adaptations be consistent, repeatable, and free from the influence of water; and that they not damage the waveguides (rods) or interfere with the electromagnetic signal in any way.

It is important to recognize that blocking a portion of the TDR rods alters the actual sampling depth, so that internal calculations used by the TDR300 to produce θ are no longer applicable and a new equation (accounting for travel time through the blocked and exposed portions of the rods) is required. One feature of the TDR300 making it particularly well suited for this research is that in addition to θ, it is capable of recording and displaying the raw travel time of the electromagnetic wave along the wave guides. The TDR300 manual outlines a soil-specific calibration procedure using regression analysis, where the raw travel time of the wave (in microseconds) is plotted against an independent θ calculation of an extracted sample, determined through differences in weight (Spectrum Technologies Inc., 2011). This procedure was the basis for Study 1, whereby empirically derived equations were developed for TDR300 fit with a “spacer-block” at reduced penetrating depths of 1.2 and 2.5 cm.

STUDY 2 - Evaluating turfgrass color with smartphone digital image analysis

Turfgrass color plays an important role in its aesthetic value, as well as acting as an indicator for its nutrient and water status (Beard, 1973). In addition to management decisions involving fertility and water, the degree to which turfgrasses fulfill their intended purpose include color evaluations made by the human eye (Karcher and Richardson, 2013). Furthermore, turfgrass quality relies on a composite of individual attributes including: uniformity, shoot density, leaf texture, growth habit, smoothness, and color (Beard and Beard, 2005). Yet, as with other visual assessments, color evaluations are influenced by the (i) individual making the evaluations, and (ii) the lighting conditions under which the turfgrass is observed (Horst et al. 1984; Karcher and Richardson, 2003)

Visually rating turfgrass is a longstanding part of turfgrass research (Krans and Morris, 2007). Typically, a 1-9 scale is used by trained turfgrass evaluators to rate the observed value of a particular parameter of interest (with 1 = worst/lowest representation, and 9 = best possible/optimum value). However, visual ratings are subject to variability even among experienced evaluators, as well as inconsistencies within evaluation techniques (Horst et al., 1984); this may be attributed largely to the inherent subjectivity of the process (Karcher and Richardson, 2013). Additionally, it may arise from the fact that standardized protocols behind visual quality ratings are not consistently defined throughout the literature (Krans and Morris, 2007). In the research by Horst et al.(1984), ambiguity within the definitions of assessed variables was identified as a source of observed inconsistencies. It was further concluded that having evaluators rely instead on more objective, quantifiable dimensions (with specific reference points) would be beneficial. Yet, visual ratings remain a widely used practice in turfgrass research, due in large part to their ability to quickly (and without the need for highly specialized equipment) generate data on characteristics of interest – such as turfgrass color and quality (Karcher and Richardson, 2013). Comparing visual ratings data from different evaluators, across time and/or location must accept such limitations.

The National Turfgrass Evaluation Program (NTEP) is an example of turfgrass research where aesthetic information across various regions and geographic locations is often desired. In these trials, one individual cannot rate all turfgrass plots involved, and the subjectivity of different evaluators can affect comparisons of the data (Horst et al., 1984). Similar issues apply to data collected over time, when multiple individuals preform visual ratings. Furthermore, because turfgrass color assessments may be influenced by the ambient lighting conditions present at the time, temporal limitations may not be exclusive to multiple individuals. Practically speaking, such limitations may be understood in the context of golf course maintenance, where color is often used as an indicator of moisture stress on sand-based putting greens, and multiple individuals are responsible for monitoring greens throughout the day, interpreting such information, and making watering decisions. The inherent subjectivity of the visual ratings process supports the notion that turfgrass research and management can benefit from greater use of objective evaluation tools for describing visual characteristics (Karcher and Richardson, 2013).

A more comprehensive evaluation of turfgrass visual characteristics, specifically color, should seek to balance human eye interpretations with objective, quantitative data. The advent of digital photography and image analysis technology has contributed to incorporating such sought-after objectivity into turfgrass visual assessments. Digital Image Analysis (DIA) using digital photography and image analysis software has been applied in a variety of ways as an objective evaluation tool (Karcher and Richardson, 2013). One of the most appreciated benefits of DIA is the way in which digital images of turfgrass plots can be compared to visual color ratings by precisely converting the specific pixel color information into dark green color index (DCGI) values (Karcher and Richardson, 2013). While additional parameters of interest (such as % green cover) may also be evaluated through DIA, however the research in Study 2 focused strictly on turfgrass color.

Digital image analysis has provided an objective way of measuring turfgrass color, however such methods require a high quality digital camera, specialized software, and due to the effects of ambient lighting (so that turf images to be compared across time or location), the use of a standardized artificial lighting source (Karcher and Richardson, 2013). Reducing costs associated with specialized DIA equipment, as well as minimizing the time required to obtain and process images are two potential areas for improving traditional DIA methodology in order to make it more feasible beyond research settings. Ultimately, a process which efficiently provides objective DGCI measurements collected through DIA is desirable for both turfgrass research and maintenance.

This research evaluated a recently developed product from Spectrum Technologies Inc., the GreenIndex+ Turf App, which utilizes the DCGI as the basis for generating its own turfgrass color ratings on a 1-9 scale. Specifically, this research focused on methods for evaluating turfgrass color and compared the GreenIndex+ Turf app to *(i)* visual ratings, and *(ii)* traditional DIA methodology involving the use of a standardized light source and image analysis software.

General principles of DIA and DGCI

There are three fundamental parts to DIA of turfgrass: *(i)* acquiring quality images, *(ii)* selecting portions of the image to measure, and *(iii)* quantifying particular parameter(s) of interest located within that selection (Karcher and Richardson, 2013).

There are many choices available when selecting a digital camera for DIA. The number of picture elements (pixels), and consequently the amount of information contained within an image, is determined by the resolution, and turfgrass parameters measured by DIA do not necessarily require high resolution cameras (1 megapixel = 1 million pixels) (Karcher and Richardson, 2013). Digital cameras currently built into smartphones/mobile devices may be considered adequate for meeting necessary resolution requirements. Depending on particular parameters of interest being evaluated, image quality may benefit from cameras with options for manual shutter speed, aperture, ISO, and white balance; however, all digital cameras can produce images of turfgrass suitable for DIA (Karcher and Richardson, 2013).

Images acquired for DIA, particularly for turfgrass color, are affected by ambient lighting conditions (Ikemura, 2003). Using an enclosed lighting source to standardize the lighting for all digital images collected is an accepted practice in turfgrass color evaluations. Standard lighting conditions, as well as consistent camera settings are necessary to compare turfgrass color data acquired at different times and/or locations (Karcher and Richardson, 2013).

Color information for each pixel within a digital image is described by red, green, and blue (RGB) light intensities, as well as spatial (X, Y) coordinates for that pixel's location within the image (Karcher and Richardson, 2013). Amounts of RGB light for each pixel range from 0 (absent) to 255 (maximum intensity) and the combination of these three values convey the overall color for the pixel (Karcher and Richardson, 2013). Translating the RGB color numbers into a scale more representative of how the human eye perceives color (hue, saturation, brightness HSB) is important for further analysis and application of information captured in digital images (Karcher and Richardson, 2013). Applying those three fundamental parts of the overall DIA process specifically to turfgrass color becomes: *(i)* acquiring quality digital images, *(ii)* obtaining average numbers of RGB pixels within an image, and *(iii)* translating RGB values into HSB (Karcher and Richardson, 2013).

The hue of a color can be described on a continuous 360 degree circular scale, where the angle of an observed color corresponds within established benchmarks of 0° = red, 60° = yellow, 120° = green, 180° = cyan, 240° = blue, 300° = magenta (Adobe Systems, 2002). Hue values may be calculated from RGB values using the appropriate formula from Karcher and Richardson (2003):

$$\textbf{If } \mathbf{max_{R,G,B} = R, 60 \times [(G - B)/(max_{R,G,B} - min_{R,G,B})]} \qquad \textbf{[4]}$$

$$\textbf{If } \mathbf{max_{R,G,B} = G, 60 \times \{2 + [(B - R)/(max_{R,G,B} - min_{R,G,B})]\}} \qquad \textbf{[5]}$$

$$\textbf{If } \mathbf{max_{R,G,B} = B, 60 \times \{4 + [(R - G)/(max_{R,G,B} - min_{R,G,B})]\}} \qquad \textbf{[6]}$$

Saturation is a measurement of a color’s purity, ranging from 0% (gray) to 100% (fully saturated) (Adobe Systems, 2002). Using RGB values, Karcher and Richardson (2003) determined saturation as:

$$\mathbf{(max_{R,G,B} - min_{R,G,B})/max_{R,G,B}} \qquad \textbf{[7]}$$

The brightness value also uses a 0% (black) to 100% (white) scale to expresses a color’s relative lightness/darkness (Adobe Systems, 2002), and is obtained from the RGB values simply as the $max_{R,G,B}$ (Karcher and Richardson, 2003).

Bringing the three parameters of the HSB values into a single numerical value (DGCI), allows for more direct comparisons of digital images to visual color ratings (Karcher and

Richardson, 2003). The following equation from Karcher and Richardson (2003) is used to convert HSB values to DGCI:

$$\mathbf{DGCI = [(H\text{-}60)/60 + (1\text{-}S) + (1\text{-}B)]/3} \qquad \textbf{[8]}$$

The DGCI values will range from 0-1, with darker green color increasing as the value approaches 1.

Advantages of DIA over alternative methods of measuring turfgrass color

In general, the primary benefit of existing DIA methodology is the introduction of increased objectivity into evaluations of multiple visual characteristics. The precision, consistency, versatilityof the technique (virtually no limitations with respect to turfgrass species or time of day), and longevity (creating images which can be preserved for future viewing/comparisons) may all be considered strengths of traditional DIA. Advantages DIA has over visual ratings are: the removal of human subjectivity from the data collected; the fact that trained evaluators are not required to produce data (*i.e.* less experienced personnel can produce a large number of digital images for analysis; and when images are saved, then visual plot conditions are historically archived as well (Karcher and Richardson, 2013).

Alternative methods for objectively measuring turfgrass color include measuring reflectance (Birth and McVey, 1968), chlorophyll, or amino acid analysis (Johnson, 1974; Nelson and Sosulski, 1984) – which all require relatively expensive equipment and laboratory analysis of samples to produce values (Karcher and Richardson, 2003; Karcher and Richardson, 2013). Species and cultivar differences must also be accounted for when comparing chlorophyll and amino acid data (Johnson, 1974; Nelson and Sosulski, 1984). Digital image analysis and DGCI have demonstrated an ability to detect significant differences in color with respect to turfgrass species, cultivar, and nitrogen fertility treatments (Karcher and Richardson, 2003; Karcher and Richardson, 2013). Providing objective measurements without expensive equipment or laboratory analysis is an advantage DIA maintains over alternative color assessment methods. Compared to other research techniques, the relative accessibility of DIA offers potential application beyond research settings, and into turfgrass management situations.

Standardized color charts have also been used for evaluating turfgrass color (Beard, 1973) however, the resulting qualitative descriptions are not amenable traditional statistical analysis (Karcher, 2003; Karcher and Richardson, 2013). The numerical values obtained through DIA can be subjected to further statistical analysis and would be considered an advantage over standardized color charts.

Colorimeters have been used in turfgrass research to quantify color of creeping bentgrass cultivars (Landschoot and Mancino, 2000), as well as measure color variability across seasons (Kimura et al., 1989), cultivars, and genetic lines (Thorogood et al., 1993). However, the relatively small ($\leq$ 20 cm^2) sampling area is a disadvantage for their ability to represent variability within typical turfgrass field plots (Karcher and Richardson, 2013). The ability of DIA to evaluate larger, more representative turfgrass areas is another advantage of the process.

Additional technologies such as normalized difference vegetation indices (NDVI), which measure photosynthetically active tissue in a plant canopy (Mangiafico and Guillard, 2007) provide values which have been correlated to turf color, but do not directly measure turfgrass color (Karcher and Richardson, 2013). By contrast, the DGCI value is calculated directly from color measurements for HSB values. The advantage for DIA is that it does not require specialized equipment such as light emitters or filters as are needed to accommodate NDVI measurements (Karcher and Richardson, 2013; Spectrum Technologies Inc., 2013).

Current applications and importance

Because turfgrass color is a prominent component in turf quality and is often used as an overall indicator of plant health relating to water and nutrient levels (Beard,1973) there are many applied situations where DCGI utilized through DIA may be a measurement of interest. The DGCI has been used in research involving nitrogen sources and rates on warm-season zoysiagrass (*Zoysia japonica* Steud.) fairway and (cool-season) creeping bentrgrass (*Agrostis stolinifera* L.) putting green turf (Karcher and Richardson, 2003). Additional putting green research with creeping bentgrass and annual bluegrass (*Poa annua* L.) also involved measuring DGCI based on different nitrogen forms and rates (Schlossberg and Schmidt, 2007). Overseeding research by Richardson et al. (2007) observed significant differences in DGCI among different species of cool-season grasses. Other research involving DGCI included salt stress on annual bluegrass (Dai et al., 2009), establishment of perennial ryegrass (*Lolium perenne*) on different growing medium (Stehouwer et al., 2010), and also with turf colorant products applied to dormant bermudagrass (*Cynodon dactylon x C. transvaalensis*) and semi-dormant zoysiagrass (*Zoysia matrella*) putting greens (Briscoe et al., 2010). Given such diverse and extensive application of DGCI within turfgrass research, this index of quantifying turfgrass color was an appropriate selection for this research – which involved varying nitrogen fertility rates on creeping bentgrass putting greens.

Limitations

While traditional DIA is an accepted method for turfgrass research, its application to turfgrass management, apart from research, has been limited. This may be attributed to costs associated with necessary equipment (digital camera and image analysis software), the inconvenience of using an enclosed light box system, as well as the time required to complete color evaluations of turfgrass plots. Even within research settings, the time involved to complete the process may be considered a limitation, as it affects efficiency and impacts the total number of data points available. Increasing turfgrass images to be analyzed – both in quantity and area offer potential benefits to turfgrass researchers. Development of a color evaluation process that balances the practical benefits of visual ratings (low overhead cost, minimal equipment requirements, and quick results) with the consistent objectivity of DIA has potential for widespread application. Making the objectivity of DIA more readily available for turfgrass color evaluations is the foundation for Study 2. The FieldScout GreenIndex + Turf app seeks to address some of these specific issues, however, research is needed to compare its method for quantifying turfgrass color to published, accepted DIA methodology.

FieldScout GreenIndex+ Turf App

Seeking to build upon advantages of traditional DIA methods, while simultaneously addressing perceived limitations, the GreenIndex+ Turf app employs the DGCI for measuring turfgrass color without the use of a standardized light source, expensive camera equipment, or specialized software, and it generates a rapid in-field assessment of turfgrass color, which is translated to a 1-9 visual rating scale (Spectrum Technologies Inc., 2013). The app is designed for use through an iPhone, iPod Touch, or iPad, and is described as an "*accurate, low-cost method*" for turf management through DIA (Spectrum Technologies Inc., 2013). The GreenIndex+ Turf app acquires images using the built in digital camera in the devices mentioned above. The device's touch screen allows the operator to select portions of the turf within the image to be evaluated, and the app calculates turfgrass color within selected portions of the image (Spectrum, GreenIndex+, 2013). The app utilizes the DGCI formula (Eq. 8) for quantifying turfgrass color; DGCI values are also converted to a traditional 1-9 visual rating. Individual users can adjust visual ratings calculated by the app to match their own 1-9 visual rating, and all DGCI values of subsequent images will be converted to 1-9 values based on the DGCI values corresponding to maximum and minimum visual ratings assigned by that evaluator (Spectrum Technologies Inc., 2013.

Where traditional DIA methodology sought to eliminate the effects of ambient lighting, the GreenIndex+ Turf app seeks an alternative process to account for ambient lighting and adjust accordingly when calculating DGCI of the turf. This process does not require an artificial light source and enclosure when acquiring images. Based on a process developed from research quantifying greenness and nitrogen content of corn leaves, the GreenIndex+ Turf app instead incorporates the use of a target board with reference color standards (green and yellow) into each image (Rorie et al., 2011). After an image has been captured, the user identifies three regions within the image: (i) the turf area to be evaluated, (ii) the green portion of the target board, and (iii) the yellow portion of the target board. The app compares observed values for the green and yellow sections of the target board to known values for each of the sections to determine the ambient lighting effect on color in that image.

As different species of turfgrasses have their own natural color range, the GreenIndex+ Turf app is designed to accommodate multiple turfgrass species (Spectrum, GreenIndex+, 2013). By using the previously described procedure for customizing the DGCI correlation to a 1-9 scale and saving it as a specific species, the same relationship between visual ratings and DGCI may be used repeatedly over time and location when rating a particular turfgrass species or variety. The GreenIndex+ Turf app also allows for averaging DGCI values of multiple images in order to create more representative ratings of larger turf areas. Other features include: the capability to log HSB values (in addition to DGCI); comparing indices of collected data between two separate turf areas; the ability to save images; and data sharing via email. While these features have potential application for end users, this research in study 2 focused exclusively on DGCI values calculated by the app, and comparing those to (i) DGCI from published DIA methods, and (ii) visual ratings.

OBJECTIVES

The overall objective of this research was to determine the suitability of various technologies for evaluating putting green surface characteristics of moisture and color. Specifically, the objective of Study 1 using the FieldScout TDR300 was to predict θ within the uppermost 1.2 and 2.5 cm of sand-based putting greens using TDR. It was hypothesized that the relationship between travel time of the TDR meter wave and θ could be observed with spacer-blocks on the TDR300 rods.

The objective of Study 2 using the GreenIndex+ Turf app was to compare DGCI values from the GreenIndex+ Turf app to i) DGCI determined through published DIA methods, and also to ii) visual ratings for turfgrass color. It was hypothesized that color board adjustment process of the GreenIndex+ app could predict turfgrass DGCI without the need for an enclosed light box.

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II. Measuring Surface Moisture in Sand-Based Putting Greens using Time Domain Reflectometry

ABSTRACT

The health and performance of sand-based putting greens depends upon adequate moisture in the rootzone concurrent with firmness of the putting surface. Assessing moisture throughout the profile is critical in balancing plant health with playability, and while time domain reflectometry (TDR) is an accepted technology for quantifying volumetric water content (θ) in putting green rootzones, current portable TDR meters are unable to isolate and describe moisture near the putting surface (< 3.8 cm). The objective of this research was to predict θ within the uppermost 1.2 and 2.5 cm of sand-based putting greens using TDR, depths that were one-third and two-thirds the current minimum rod length for portable TDR meters. Spacer-blocks were constructed to reduce measurement depth of a TDR300 (Spectrum Technologies Inc.) from 3.8 to 1.2 and 2.5 cm. Samples were extracted from creeping bentgrass (*Agrostis stolonifera* L.) and ultradwarf bermudagrass [*Cynodon dactylon* (L.) Pers. *x C. transvaalensis* Burtt Davy] putting greens to create a range of θ. All TDR readings were taken in microseconds (μs) and actual θ was determined by weight. At both depths, significant linear prediction models were produced relating TDR microsecond readings to θ. For θ observed under field conditions, slope and intercept coefficients at 1.2 cm were 0.00242 and – 4.768, and, at 2.5 cm, were 0.00134 and – 2.649, respectively. These new θ measurement depths enhance the ability to evaluate surface conditions, refine maintenance practices, and improve both management and research of sand-based putting greens.

Abbreviations: DI, deionized; EC, electrical conductivity; LDS, localized dry spot; LOI, loss on ignition; OM, organic matter; TDR, time domain reflectometry; θ, volumetric water content; 95% CL, ninety-five percent confidence limits; USGA, United States Golf Association.

Managing sand-based putting greens requires maintaining adequate moisture within the rootzone while maximizing firmness of the putting surface. Design features of sand-based putting greens which promote drainage, in order to optimize moisture at the putting surface (USGA Green Section Staff, 2004), also create management challenges due to limited water holding capacity of the rootzone. Accurately monitoring moisture distribution throughout the profile is critical in achieving an appropriate balance of plant health and playability (Moeller, 2012). Precise, objective information about putting green moisture conditions, as they change in response to weather, irrigation, and other turfgrass management practices, should include not only the rootzone, but putting surface as well.

Time Domain Reflectometry (TDR) has become an accepted technology for accurately estimating water content of a soil by measuring its dielectric permittivity, due to the relationship between a material's permittivity and its water content (Robinson et al., 2003). Measurement devices based on TDR principles accomplish this by generating an electromagnetic wave, transmitting it along a waveguide inserted into the soil, and measuring the time required for that wave signal to travel a known distance and return (Noborio, 2001; Robinson et al., 2003). The work of Topp et al. (1980) produced empirically derived equations relating volumetric water content (θ) to relative permittivity. Since Topp's seminal work, additional calibrations have been developed through extensive research (Noborio, 2001; Robinson et al., 2003). Electromagnetic properties and behavior of TDR devices continue to garner research interest within laboratory settings (Heimovaara, 1994; Kargas et al., 2013), and at the same time, there is also a place for practical, applied adaptations of this technology that are accessible and beneficial to end users. For end users such as golf course superintendents, comparisons of waveform characteristics and/or frequencies may not necessarily be applicable to their daily decision making. For the daily challenges they face, increasing the amount of available information provided by a currently owned TDR device may have more tangible and practical benefits.

Portable TDR meters have become prevalent within the golf industry for objectively measuring θ at various depths within sand-based putting greens (Moeller, 2012). The rapid, non-destructive nature of the measurements, along with portability, versatility (the ability to measure at various depths), and affordability, are preferred features of TDR meters among golf course superintendents (Moeller, 2012). Measurement depth is determined by the length of the waveguides (stainless steel rods) attached to the meter and inserted into the rootzone, and while multiple options are available for portable TDR meters, 3.8 cm is the current minimum rod length. Measurements are based on the round-trip travel time of the TDR wave, along the full length of the rods. Obtaining TDR measurements closer to the putting surface has potential to provide unique moisture information, with implications for both playability and maintenance practices.

The limited water holding capacity of sand-based putting greens can be magnified by the development of localized dry spot (LDS), whereby organic compounds coat the sand particles in the rootzone, leading to hydrophobic conditions and further reduction of available water to turfgrass roots (Gaussoin et al., 2013). Soil surfactants, commonly referred to as wetting agents, are used by golf course superintendents to treat symptoms of LDS. While the benefits of wetting agent applications have been shown to alleviate hydrophobicity in sand-based putting greens (Karnok and Tucker, 2001; Lyons et al., 2009), there are also perceptions among superintendents that certain wetting agents lead to greater moisture being held at the putting surface, compared to other products – which move water deeper into the profile (Karnok and Tucker, 2009). Further claims have been made by superintendents describing “excessive” moisture retention at the putting surface as an unintended consequence of regular wetting agent applications (D. Karcher, personal communication, 2013). Excessive surface moisture negatively impacts both plant health and playability, and can lead to softer, slower putting surfaces that are more susceptible to damage and disease. A method for measuring moisture near the putting surface would offer superintendents and turfgrass researchers the ability to investigate such claims involving wetting agents, as well as an opportunity to evaluate the impact of other maintenance practices and weather conditions on moisture levels affecting health and quality of the playing surface.

Portable TDR measurements at the putting surface are limited by a necessary minimum rod length required to reliably produce accurate measurements; as the rod length decreases, the travel time of the wave approaches the same order of magnitude as the measurement error (D.Kieffer, email correspondence, January 2015). However, adapting a TDR meter (equip with 3.8 cm rods), by physically blocking the penetrating depth of the rods (rather than reducing their overall length) would bring the measurement range closer to the putting surface, while preserving the necessary minimum length. This technique effectively creates shallower sampling depths for current portable meters. It is acknowledged that moisture measurements have been attainable at such shallow depths through the installation of horizontally-oriented rods within putting green rootzones, yet the stationary nature of such devices greatly limits the putting surface area over which information can be collected. Rapidly obtaining numerous TDR measurements throughout the uppermost regions of sand-based putting greens offers potential for enhanced understanding of interactions between weather effects, maintenance practices, and playing conditions.

The objective of this research was to predict θ within the uppermost 1.2 and 2.5 cm of sand-based rootzone using TDR. It was hypothesized that the relationship between raw travel time of the TDR wave and θ could be observed with spacer-blocks fit onto the TDR300's 3.8 cm rods. By controlling the penetrating depth of the TDR rods, taking all readings in microseconds (µs), and independently calculating the θ within the measurement depth, models for relating modified TDR readings in µs to θ at each depth were developed.

MATERIALS AND METHODS

For this research, the FieldScout TDR300 Soil Moisture Meter (Item #6430FS, Spectrum Technologies, Aurora, IL) was used for all TDR measurements. The TDR300 was fit with standard 3.8 cm rods and *Turf* rod length was selected. In 2013, firmware version 6.2 was used, and in 2014, firmware was updated to version 6.9. While the *Standard VWC Mode* for the TDR300 uses built-in equations to calculate and display an estimated θ percentage, for this research the meter was set to *Period Mode* so that the raw travel time of the electromagnetic wave could be reported in µs.

Reduced measurement depths of 1.2 and 2.5 cm were achieved by constructing spacer-blocks, that were attached to 3.8 cm rods, so that only the corresponding length at the terminal end of the rods were exposed and inserted into the putting green (Figure 1). Primary considerations in selecting materials used for spacer-block construction were that they would not alter or affect the TDR electromagnetic signal being transmitted, and that they were inherently durable, water-resistant, and capable of fitting tightly around the rods. Materials were also selected that would be readily available, affordable, and practical for end users. Interlocking foam mats (Cha Yay Sponge Enterprises Co., Ltd., Chang Hau, Taiwan) measuring 12 mm in thickness were the principal material used in construction of the spacer-blocks. Cut sections of the foam mat (7.6 x 2.6 cm) were wrapped with two layers of a weather resistant tape (Gorilla

Tape, Gorilla Glue Company, Cincinnati, OH) to prevent any moisture absorption by the foam material itself. For the 2.5 cm depth, a single cut piece of the foam mat was used. For measurements at the 1.2 cm depth, two cut pieces of the mat were stacked prior to being wrapped with all-weather tape. In each of the spacer-blocks, two, 3.2 mm diameter holes were drilled corresponding to the exact location and spacing of the rods on the TDR300. The overall goal of the spacer-block construction was to create a reliably consistent medium through which the transmitted wave would repeatedly travel (unaffected) at the same velocity, resulting in measured differences of the *Period Mode* readings attributable only to the moisture content encountered by the exposed terminal ends of the rods. Preventing the formation of air pockets surrounding the rods, as well as preventing moisture absorption by the block materials themselves, were essential objectives in the construction of the spacer-blocks.

Sand-Based Putting Green Samples

All putting green samples were extracted from research greens located at the University of Arkansas Agricultural Research and Extension Center in Fayetteville, AR. The greens were constructed according to United States Golf Association (USGA) recommendations (United States Golf Association Green Section Staff, 2004) and maintained under typical putting green management practices (3.2 mm height of cut). In 2013, all samples were from an 11-yr-old creeping bentgrass (*Agrostis stolonifera* L. cv. Penn G2) green. In 2014, samples were collected across several putting greens that varied in turfgrass age, cultivar, and species to represent sand-based putting greens with a range of surface characteristics. In 2014, samples from the same ‘Penn G2’ block represented a mature, established creeping bentgrass putting green. Additional samples of ‘Tyee’ creeping bentgrass, renovated and seeded in April 2013, represented a younger putting green with less time to accumulate thatch and organic matter near the surface. Samples from a warm-season ultradwarf bermudagrass [*Cynodon dactylon* (L.) Pers. *x C. transvaalensis* Burtt Davy] putting green cv. TifEagle were also included. The *Soil Specific Calibration* procedure described in TDR300 manual (Spectrum Technologies Inc., 2011) was the basis for sampling methods used in this research. The notable adjustment to the Spectrum procedure was that in 2013 and 2014 all samples were removed from the field and taken into the laboratory prior to saturation and data collection.

Samples (10.8 cm diameter) were extracted from the greens using a standard size cup-cutter (Item# RP1001, R&R Products Inc., Tucson, AZ), then cut to a uniform depth of 6.5 cm. All samples were saturated in deionized (DI) water for 16 h, removed and air dried (22℃) for varying time intervals (0 to 145 h) in an effort to create a diverse range of moisture contents. For each sample, the TDR300, fit with spacer-blocks, was inserted and a *Period Mode* reading was made. The sample was then immediately cut to the corresponding depth of the TDR measurement, and the fresh weight (to the nearest 0.1 g) was recorded. Based on the description by the manufacturer (Spectrum Technologies Inc., 2011), it was assumed that TDR measurements corresponded to rod length, and did measure θ depths in the soil beyond the end of the rod tips. Diameter and thickness measurements for each sample were confirmed and recorded at this time as well. Samples were further dried at 105°C for 24 h and reweighed to obtain an oven-dry weight. Differences between fresh and oven-dry weights, along with sample volume were used to calculate θ (v/v) for each sample as described in Eq. [1]

$$\boldsymbol{\theta = (M_{wet} - M_{dry}) / (\rho_w \times V_{tot})} \qquad \textbf{[1]}$$

where M_{wet} is the mass of the fresh sample (g); M_{dry} is the mass of oven-dry sample (g); ρ_w is the density of water (1 g/cm^3); and the V_{tot} is the total sample volume (cm^3) (Black, 1965).

Two-Point Calibration Procedure

In addition to data from extracted samples, for each measurement depth, a second model was created using a two-point calibration procedure. Beginning with firmware version 6.5, a calibration feature became available for TDR300 meters (Spectrum Technologies Inc., 2011). By selecting *Calibration Mode* and then taking two readings – first in air, then with rods fully submerged in DI water, meters could be standardized, for interchangeable use; this procedure could be performed with all standard TDR300 rod lengths available from the manufacturer (Spectrum, 2011). However, this built-in calibration procedure was unsuccessful when spacer-blocks were fit onto 3.8 cm rods. For this research, the TDR300 was set to *Period Mode* and a two-point calibration was carried out similar to the *Soil Specific Calibration* procedure previously described on extracted putting green samples. All TDR300 readings (in air and DI water) were taken with spacer-blocks on. For each measurement depth, three readings per substance were averaged to create a single μs value for both air and DI water. Values of 0 and 1 were used as θ for readings taken in air and DI water, respectively. For readings in DI water, the bottom of the spacer-block was brought to the surface of the water so that only the exposed 1.2 or 2.5 cm portions of the TDR rods were submerged. Based on these two endpoints, linear models were developed for each new measurement depth, that could be compared to empirically derived versions.

2015 Field Samples

In 2015, additional in situ sampling was performed on previously described putting greens to evaluate laboratory derived models under field conditions. In addition to the TDR300, θ measurements were made with a TH300 moisture probe (Dynamax Inc., Houston, TX), fitted with its own spacer-blocks, constructed from the same materials as those for the TDR300, creating corresponding 1.2 and 2.5 cm depths. Within each putting green site, plots were established (0.9 x 0.9 m), and were individually irrigated (by hand). Similar to extracted samples, the goal was to create a diverse range of θ across the plots. A single moisture meter measurement was made within each plot (using one device, at one depth). The measured area was immediately extracted, cut (to depth), and weighed. Previously described drying procedures were carried out to provide ground truth θ, to which moisture meter readings were compared. This field sampling procedure was repeated for both moisture meters, at each depth.

Statistical Analysis

Prediction models for 1.2 and 2.5 cm depths were developed from regression analysis performed using SAS PROC REG (SAS 9.4, SAS Institute Inc., Cary, NC), where TDR300 *Period Mode* readings (µs) were used to predict θ. An overall model was developed for each depth based on all putting green samples. Model fit and parameter estimates of regression coefficients were assessed based on p-value ($\alpha \leq 0.05$). Individual models and tests for significant differences among β coefficients were performed on specific sample groups within *(i)* putting green age and *(ii)* turfgrass variety (and species) using SAS PROC GLM, and were evaluated based on p-value ($\alpha \leq 0.05$). Comparisons of two-point calibration models to empirically derived equations used tests for significant differences of regression coefficients ($\alpha \leq$ 0.05) as well as 95% confidence limits (95% CL) of predicted θ values.

RESULTS & DISCUSSION

Sand-Based Putting Green Samples

In 2013, significant linear prediction models ($p < 0.0001$) relating TDR300 µs readings to ground-truth θ resulted from sample data at both the 1.2 and 2.5 cm depths. At the 1.2 cm depth, the initial 2013 model contained a slope of 0.00233, an intercept of -4.551, with an r^2 value of 0.89 (Table 1). For 1.2 cm samples *Period Mode* readings ranged from 1970 to 2320 µs, and ground-truth θ (determined by weight) ranged from 0.001 to 0.809 $m^3\ m^{-3}$. At the 2.5 cm depth, the 2013 prediction model had a slope of 0.00139, an intercept of -2.720, and an r^2 value of 0.98 (Table 1). For 2.5 cm samples, *Period Mode* readings ranged from 1990 to 2460 µs, and ground-truth θ ranged from 0.023 to 0.698 $m^3\ m^{-3}$. These results indicated that the TDR300 fit with spacer-blocks was *(i)* capable of detecting θ differences within the uppermost 1.2 and 2.5 cm of sand-based putting green samples, and that *(ii)* θ could be estimated by a linear prediction equation using the meter's *Period Mode* value (µs).

While maximum values for θ at each sampled depth exceeded 0.50 ($m^3\ m^{-3}$), these large values may be attributed to the physical characteristics of the samples themselves. In an effort to measure moisture as it would exist (and affect playability) at the putting surface, all above ground plant tissue remained intact, so that TDR readings and weights were recorded on samples comprised of actively growing plant tissue and rootzone constituents. At these reduced measurement depths, the relative proportion of plant tissue (included in θ calculations) contributed to the amount of water lost during the drying process. As a result, these θ values described not only the volume of water present within the pore space of the growing medium, but rather a more comprehensive account of overall moisture present near the putting surface. The organic matter (OM) content of each sample was determined through a standard procedure for evaluating putting green rootzone materials (Anonymous, 1993), using the loss on ignition

(LOI) method (Norman, 1965). Organic matter ranged from 0.051 to 0.156 kg kg^{-1} for 1.2 cm samples, and from 0.058 to 0.097 kg kg^{-1} for 2.5 cm samples. The prevalence of plant tissue and accumulated OM within these measurement depths, supported the decision that extracted samples be expanded (from the original set of exclusively ‘Penn G2’) to include putting greens of different turfgrass ages, varieties, and species, in order to sufficiently evaluate prediction models across a range of surface characteristics. The range of OM present, and corresponding r^2 values, indicated regression models developed in this research could be considered robust and applicable to different putting green situations.

In 2014, significant linear prediction models at both 1.2 and 2.5 cm depths resulted from samples comprised of different turfgrass ages, varieties, and species. For both depths, slope and intercept coefficients were significantly different from 0. At the 1.2 cm depth, the 2014 model had a slope of 0.00240 and an intercept of -4.723, with an r^2 value of 0.92 (Table 1). At the 2.5 cm depth, the 2014 model had a slope of 0.00118 and an intercept of -2.313 with an r^2 value of 0.95 (Table 1). At both depths, average OM was greatest among warm-season ‘TifEagle’ samples and least among the recently renovated ‘Tyee’ samples. Across all samples, OM ranged from 0.041 to 0.201 kg kg^{-1} at the 1.2 cm depth; and ranged from 0.023 to 0.163 kg kg^{-1} at the 2.5 cm depth.

Combining all 2013 and 2014 data, significant linear prediction models relating TDR300 μs readings to θ were produced from both 1.2 and 2.5 cm samples. Individual slope and intercept coefficients at both depths were all significantly different than 0. The overall model at the 1.2 cm depth was based on 80 samples and had a slope of 0.00234, an intercept of -4.584, with an r^2 value of 0.90 (Table 1). *Period Mode* readings of the 1.2 cm samples ranged from 1960 to 2350 μs, and calculated θ (including green, above ground plant tissue) ranged from 0.002 to 0.887 m^3

m^{-3}. At the 2.5 cm depth, the overall model was based on 56 samples and contained a slope of 0.00122, an intercept of -2.372, and had an r^2 value of 0.94 (Table 1). For 2.5 cm samples *Period Mode* readings ranged from 1970 to 2610 µs and calculated θ ranged from 0.001 to 0.715 m^3 m^{-3}. Both depths exhibited overlap of β coefficients across age, species, and variety (Figs. 2 & 3).

Further analyses of the individual sample groups used to construct the overall models determined no differences among regression coefficients based on *(i)* putting green age or *(ii)* turfgrass variety (and species). For putting green age, all samples were divided into two groups: *new* (‘Tyee’), and *established* (‘Penn G2’ and ‘TifEagle’), with data from each group fit independently. Within each depth, comparison of the slopes failed to reject the null hypothesis (H_o: $\beta_1 = \beta_2$) and concluded no differences between new and established models based on p-values of 0.3881 at the 1.2 cm depth and 0.1225 for 2.5 cm samples. For turfgrass variety (which included multiple species), samples were classified into one of three groups: ‘Tyee’, ‘Penn G2’, and ‘TifEagle’; each fit with its own linear model. Comparison of slope estimates again failed to reject H_o and concluded no differences among varieties/species, based on p-values 0.5162 at 1.2 cm and 0.1581 at 2.5 cm. These results supported the r^2 values associated with combined regression models using all 2013-14 samples, and further indicated the capability of a single linear model at each depth to predict moisture content across sand-based putting greens of different variety, age, and species (Table 1).

Assessing adequacy of the fitted models as θ for both depths exceeded 0.6 (m^3 m^{-3}) identified an expanded horizontal distribution of data points above this threshold (Figs. 4 and 5). At the 1.2 cm depth, this was indicated by increased variability on either side of the linear model; while at the 2.5 cm depth, a plateau was observed within plotted data. In terms of subject matter implications, as previously discussed, recognition of the relative amounts of actively growing plant tissue within the samples, coupled with the reliability of the gravimetric sampling procedures (Muñoz-Carpena, 2004) used in θ determination provided a reasonable explanation and confidence to the accuracy of θ values exceeding 0.5 $m^3\ m^{-3}$. Yet from a statistical standpoint, it was necessary to address correlation structure, increased residuals, and potential influential observations at $\theta > 0.6\ m^3\ m^{-3}$ to justify selection of a linear model for the data. For both 1.2 and 2.5 cm depths, regression analysis of all samples below 0.6 $m^3\ m^{-3}$ resulted in significant linear models ($p < 0.0001$), with r^2 values of 0.91 and 0.94 respectively (Figs. 4 and 5). However, for samples with $\theta \geq 0.6\ m^3\ m^{-3}$, TDR300 *Period Mode* readings were no longer a significant predictor of θ. Regression analysis for 1.2 and 2.5 cm samples with $\theta \geq 0.6\ m^3\ m^{-3}$ resulted in linear prediction models that were nonsignificant based on p-values of 0.3959 and 0.4543, respectively. For the overall model at the 1.2 cm depth, there were seven observations with studentized residuals outside the range of $\pm$ 2, all having $\theta > 0.6\ m^3\ m^{-3}$ (Figure 6). At the 2.5 cm depth, there were two such observations, which were also the only observations with a Cook's D statistic > *4/n*, indicating their potential to act as influential observations on the model. These results indicated limitations of linear prediction models under extremely wet conditions. Furthermore, while alternative models, such as a linear plateau model, may have provided an opportunity for incorporating these large θ data points, because θ exceeded the max θ observed in the field, there were no practical reasons supporting their inclusion in prediction models.

Examining the methodology used in this research, extracting putting green samples first and subsequently saturating within the laboratory allowed for more rapid processing of TDR measurements and weights. However, increased variability and leveling-off of data for samples having $\theta \geq 0.6\ m^3\ m^{-3}$ may have reflected artificially high moisture contents not typically present within a USGA sand-based rootzone. Consequently, there was a need to investigate whether such measurements actually contributed to the development of a model intended for practical application.

Furthermore, attempts to incorporate such values could lead to overfitting of the data with higher order polynomial equations. For the sand-based putting greens used in this research, θ of 0.6 $m^3 m^{-3}$ was determined to be an appropriate threshold based on 2015 field samples that produced maximum θ of 0.59 $m^3 m^{-3}$ at 1.2 cm and 0.57 $m^3 m^{-3}$ at 2.5 cm. By imposing appropriate boundaries on data used in model development, linear prediction coefficients could be refined to represent the range of θ actually observed in sand-based putting greens under field conditions, and avoid undue influence from extreme θ values only detected in extracted samples, within the laboratory. Further justification for refining linear prediction models was based on Appendix 1 in the TDR300 manual. In its *Standard VWC Mode*, the TDR300 does not display 100% with rods fully submerged in DI water, as the meter's built-in equations were developed to be, "most accurate in the volumetric water contents typically found in mineral soils" (Spectrum Technologies Inc., 2011). Refining the overall 1.2 and 2.5 cm models to include only θ observed under field conditions did adjust slope and intercept coefficients from the overall model (Table 1). These refined models were based on 56 samples at the 1.2 cm depth and 43 samples at the 2.5 cm depth (Figures 4 and 5). For both depths, refined models increased the proportion of studentized residuals within the $\pm$ 2 range to 0.93 for 1.2 cm and 0.95 for 2.5 cm (Figure 6). These adjustments also aligned the fitted model more closely to data points with $\theta \leq 0.1$ $m^3 m^{-3}$, a moisture range critical in management of sand-based putting greens. By controlling samples used in constructing the fitted models to correspond with the field conditions observed at this research site, the applicable range of θ predictions should be limited to < 0.6 $m^3 m^{-3}$. Application of the refined models resulting in predicted θ beyond this specified range should be considered extrapolation.

Two-Point Calibration Procedure

Linear prediction models for 1.2 and 2.5 cm depths relating TDR300 µs values to θ determined by weight were developed from *Period Mode* readings taken in air and DI water. At the 1.2 cm depth, *Period Mode* readings of 1953 and 2397 µs were used for air and DI water respectively, resulting in a slope of 0.00225 and an intercept of -4.399 (Table 1). At the 2.5 cm depth, *Period Mode* readings of 1957 and 2743 µs used for air and DI water, respectively, resulted in a linear model with a slope of 0.00127 and an intercept of -2.490 (Table 1). Comparison of regression coefficients concluded no differences between slopes based on p-values of 0.3981 at 1.2 cm, and 0.4545 at 2.5 cm. Both slope and intercept coefficients for the two-point calibration equations (at each depth) fell within the 95% CI for the parameter estimates of the refined linear models (Figs. 7 and 8). At 1.2 cm, for *Period Mode* readings < 2050 µs the two-point calibration model fell outside of the 95% CL of predicted θ (Figure 7). At 2.5 cm, the two-point calibration model again produced θ values that were greater than the refined empirical model, yet remained within 95% CL for predicted θ (Figure 8). Predicted values from two-point calibration models produced residuals similar to overall models (Figs. 9 and 10). These results indicated that linear prediction models created from only two *Period Mode* readings (air and DI water) presented a simplified method of developing equations for estimating θ of sand-based putting greens, with regression coefficients not significantly different from empirical models. However, refined empirical models demonstrated improved residuals among samples with the lowest observed surface moisture contents – a preferred attribute of championship putting greens.

Further assessments of model adequacy focused on the tendency of two-point calibration models to overpredict θ towards the lower end of the observed range. Residuals between ground-truth θ determined by weight and θ predicted by each of the three models were plotted against the ground-truth θ of the sample (Figures 9 and 10). For 1.2 cm samples with the lowest θ (< 0.2 $m^3\ m^{-3}$), the refined model (Fig. 9) produced estimates of actual θ with the lowest residual in 25 of the 28 samples. At that same depth, for θ of 0.2 through 0.6 $m^3\ m^{-3}$, the overall model (Table 1) produced estimates with the lowest residuals in 18 of 28 samples (Figure 9). At 2.5 cm, for θ < 0.3 $m^3\ m^{-3}$, the refined model (Table 1) provided the best estimates of θ, producing the lowest residuals in 17 of the 20 samples (Figure 10). At 2.5 cm, from 0.3 to 0.6 $m^3\ m^{-3}$, the overall model (Fig. 10) produced the least residual for the majority of the samples (14 out of 23). All of these results indicated that, while regression coefficients of two-point calibration equations did not differ from empirically derived models, under field conditions observed in this research, empirical models provided better estimates of θ in 47 out of 56 samples at the 1.2 cm depth and 40 out of 43 samples at the 2.5 cm depth. These results reinforced the rationale for refining empirical models, and that, by eliminating samples > 0.6 $m^3\ m^{-3}$, more precise estimates of θ were obtained for the lower-end range of moisture contents, prevalent in the management of sand-based putting greens. These results further indicated that the best estimations of θ for a given depth may be obtained through use of multiple regression models, depending on the θ range being evaluated. For end users, it is the *Period Mode* reading, rather than the θ that would be available for defining such ranges. At each depth, the θ identified as thresholds for model selection were converted to μs using both the refined model and the overall model (Table 1);

those two values were averaged to create a single *Period Mode* value for determining which linear prediction model to use. At 1.2 cm, θ of 0.2 m^3m^{-3} corresponded to 2048 µs, and at 2.5 cm θ of 0.3 m^3m^{-3} corresponded to 2196 µs.

The *Period Mode* readings taken in air as a part of the two-point calibration procedure also supported the assertion that materials used in the construction of the spacer-blocks were appropriate selections and did not interfere with the transmitted wave signal. For the TDR300 meter used in this research, *Period Mode* readings taken in air using the 3.8 cm rods without spacer-blocks ranged from 1950 to 1960 µs, with an average value of 1952 µs. The same range was observed for readings taken in air during the two-point calibration, using both spacer blocks. For future research, such a evaluations may be useful in providing initial information on potential modifications to measurement depths and spacer-block construction materials different from those used in this research.

2015 Field Samples

Regression models of TDR300 measurements on subsequently extracted putting green samples at 1.2 and 2.5 cm depths produced r^2 values of 0.92 and 0.94, respectively (Figs. 11 and 12). A larger difference in slopes between laboratory and field samples was observed at the 1.2 cm depth, compared to 2.5 cm (Table 1). Differences between field sample θ and predicted θ of laboratory and two-point calibration models was greatest for 1.2 cm samples at the largest observed θ (Fig. 11). Differences in this region of the data may have been due to: the method of saturation (from the bottom up in the laboratory, contrasted with from the top down in the field), combined with additional time involved in extracting samples in the field – which may have allowed for the movement of water that was encountered by TDR waves, beyond the section ultimately cut and weighed. It was hypothesized that the use of irrigation water in the field, contrasted to DI water used in the laboratory, could have potentially played a role in observed differences, as TDR has been used for measuring electrical conductivity (EC), in addition to soil moisture (Noborio, 2001), and research has suggested sensitivity of the TDR300 to EC at levels less than what is listed by the manufacturer (Kargas et al., 2013). However, further investigation is needed to fully compare laboratory and field sampling. Overall, the large r^2 values, similar to those in laboratory samples, were observed with in situ sampling. Differences in predicted θ between the various models at $\theta \geq 0.4$ would not necessarily be within a critical range for managing plant health in sand-based putting greens, and may not represent desired moisture levels for optimizing playability.

When fit with the spacer blocks, the TH300 displayed the words *Under Range* rather than numeric θ values for 15 of the 64 total readings. In this research, TH300 measurements ranged from 0.0 to 13.6 %VWC across both depths. Using the available θ measurements from the TH300 as predictors of ground-truth θ, at 1.2 and 2.5 cm, extracted samples produced r^2 values of 0.83 and 0.86, respectively (Fig. 13). These results supported the selection of TDR300 as the primary moisture meter used in this research, which focused on modified, shallow measurement depths.

Research by Kargas et al. (2013) noted that the specific frequency of the electromagnetic wave used by the TDR300 was not listed by the manufacturer, and further commented that the TDR300 exhibited attributes of a (lower frequency) water content reflectometer, more than a time domain reflectometry device. Concerns with signal attenuation are generally associated with lower frequencies, while higher frequency time domain reflectometry devices are associated with greater costs. The relative affordability of the TDR300 and its current prevalence within the golf industry aligned with the practical, end-user applications that were a specific aim of this research. Future comparisons with devices, such as the TH300, may benefit from examining waveform characteristics rather than in situ measurements, as measured in engineering (rather than horticultural) settings.

Summary & Conclusions

Information on the moisture content of sand-based putting greens can be acquired at shallow depths, close to the putting surface, using the methodology described in this research. The TDR300 moisture meter is capable of detecting θ differences at reduced measurement depths of 1.2 and 2.5 cm through the use of simple spacer-blocks. The portable nature of this device allows for θ near the putting surface to be measured similar to other depths throughout the rootzone, greatly expanding the number of sampling locations over which data may be collected for both turfgrass management and research. While the meter's *Standard VWC Mode* can display relative differences in θ at these reduced depths using built-in equations, more precise estimates of actual θ can be obtained through empirically derived linear prediction models. The resulting values will facilitate more comprehensive and consistent discussion of putting green moisture impacting both plant health and playability.

Regression coefficients in these developed models demonstrated the ability to quantify θ across sand-based putting greens of various ages, varieties, and species. Constructing prediction models using only samples within the range of θ observed under field conditions improved precision of estimates as θ approached zero. At each measurement depth, a combination of linear models was ultimately best for reducing residuals within the range of θ values measured under field conditions. Specific model selection, dictated by the range of *Period Mode* readings, minimized residuals of predicted θ. Based on the results of this research, at the 1.2 cm depth, for *Period Mode* readings of 1960 to 2048 μs the refined model, using based on samples with θ < 0.6 m^3 m^{-3} was the best candidate model; and, for readings > 2048 μs, the overall model using all 2013-14 samples produced the best estimates of θ. At the 2.5 cm depth, for *Period Mode* readings ranging from 1970 to 2196 μs the refined version of the model was the best for reducing residuals; while for readings > 2196 μs the overall 2013-14 combined model consistently minimized residuals. For both depths, 0.6 m^3m^{-3} was an appropriate upper limit for prediction models based on θ measured in sand-based putting greens under field conditions. This research further concluded that, while a two-point calibration may serve as a simplified alternative to sample extraction and weighing procedures for approximating coefficients of empirical models at measurement depths between 1.2 and 3.8 cm, overestimating θ as values approach zero remains a concern. Appropriate application of multiple linear models per measurement depth can be achieved through relatively simple programing steps within a data management spreadsheet.

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CAPTIONS

Fig. 1. a: FieldScout TDR300 using *Turf* rods for standard 3.8 cm measurement depth. **b:** FieldScout TDR300 using *Turf* rods fit with spacer-block to achieve 2.5 cm measurement depth. **c:** FieldScout TDR300 using *Turf* rods fit with spacer-block to achieve 1.2 cm measurement depth.

Fig. 2. Ninety-five percent confidence limits (95% CL) for regression coefficients of linear prediction models relating TDR300 *Period mode* readings in microseconds (μs) to volumetric water content (θ) at the 1.2 cm depth. Black bar denotes slope estimate for each model.

Fig. 3. Ninety-five percent confidence limits (95% CL) for regression coefficients of linear prediction models relating TDR300 *Period mode* readings in microseconds (μs) to volumetric water content (θ) at the 2.5 cm depth. Black bar denotes slope estimate for each model.

Fig. 4. All 2013 and 2014 data relating TDR300 *Period* Mode readings in microseconds (μs) to volumetric water content (θ) $m^3\ m^{-3}$ at the 1.2 cm depth. The maximum θ measured under field conditions was 0.6 $m^3\ m^{-3}$. Fitted regression model from samples less than 0.6 $m^3\ m^{-3}$ was compared to the overall model based on all 1.2 cm samples.

Fig. 5. All 2013 and 2014 data relating TDR300 Period Mode readings in microseconds (μs) to volumetric water content (θ) at the 2.5 cm depth. The maximum θ measured under field conditions was 0.6 $m^3\ m^{-3}$. Fitted regression model from samples less than 0.6 $m^3\ m^{-3}$ was compared to the overall model based on all 2.5 cm samples.

Fig. 6. Studentized residuals from overall prediction models using all 2013 and 2014 samples plotted against volumetric water content (θ) determined by weight. Maximum θ observed under field conditions was 0.6 $m^3\ m^{-3}$.

Fig. 7. At the 1.2 cm depth, the refined fitted model based on samples <0.6 m^3m^{-3}, with corresponding 95% confidence intervals and prediction intervals, was compared to the two-point calibration model based on readings in air and deionized water.

Fig. 8. At the 2.5 cm depth, the refined fitted model based on samples <0.6 m^3m^{-3}, with corresponding 95% confidence intervals and prediction intervals, was compared to the two-point calibration model based on readings in air and deionized water.

Fig. 9. Differences between actual volumetric water content (θ) and predicted θ based on TDR300 *Period Mode* readings for three different linear models, at the 1.2 cm depth. The maximum θ observed under field conditions for this research was 0.6 $m^3\ m^{-3}$.

Fig. 10. Differences between actual volumetric water content (θ) and predicted θ based on TDR300 *Period Mode* readings for three different linear models, at the 2.5 cm depth. The maximum θ observed under field conditions for this research was 0.6 $m^3\ m^{-3}$.

Fig. 11. Comparison of models from (previously) extracted samples, and two-point calibration, to in situ sampling using TDR300 at 1.2 cm depth.

Fig. 12. Comparison of models from (previously) extracted samples, and two-point calibration, to in situ sampling using TDR300 at 2.5 cm depth.

Fig. 13. Linear regression of (modified) TH300 moisture meter readings to gravimetrically determined volumetric water content (θ) of (subsequently) extracted putting green samples at 1.2 and 2.5 cm depths.

Table 1. Summary of linear regression models for using TDR300 *Period Mode* readings in microseconds (μs) to estimate volumetric war content (θ) at 1.2 and 2.5 cm depth, using spacer-blocks.

Table 1.

Linear regression models for estimating θ at 1.2 and 2.5 cm using TDR300 with spacer-blocks

Depth (cm)	Model	P-value	r^2	β_1	β_0
1.2	**2013 Initial ‘Penn G2’ samples (only)**	<0.0001	0.89	0.00233	-4.551
	2014 All varieties (‘Penn G2’, ‘Tyee’, ‘Tifeagle’)	<0.0001	0.92	0.00240	-4.723
	2013-14 All samples combined	<0.0001	0.90	0.00234	-4.584
	Refined model (all 2013-14 samples with θ < 0.6 m^3 m^{-3})	< 0.0001	0.91	0.00242	-4.768
	Two-point calibration model (air/DI water)	<0.0001	1	0.00225	-4.399
	2015 Field Samples	<0.0001	0.92	0.0017	-3.270
2.5	**2013 Initial ‘Penn G2’ samples (only)**	<0.0001	0.98	0.00139	-2.720
	2014 All varieties (‘Penn G2’, ‘Tyee’, ‘Tifeagle’)	<0.0001	0.95	0.00118	-2.313
	2013-14 All samples combined	<0.0001	0.94	0.00122	-2.372
	Refined model (all 2013-14 samples with θ < 0.6 m^3 m^{-3})	< 0.0001	0.94	0.00134	-2.649
	Two-point calibration model (air/DI water)	<0.0001	1	0.00127	-2.490
	2015 Field Samples	<0.0001	0.94	0.0011	-2.103

Fig. 1. a: FieldScout TDR300 using Turf rods for standard 3.8 cm measurement depth. **b:** FieldScout TDR300 using Turf rods fit with spacer-block to achieve 2.5 cm measurement depth. **c:** FieldScout TDR300 using Turf rods fit with spacer-block to achieve 1.2 cm measurement depth.

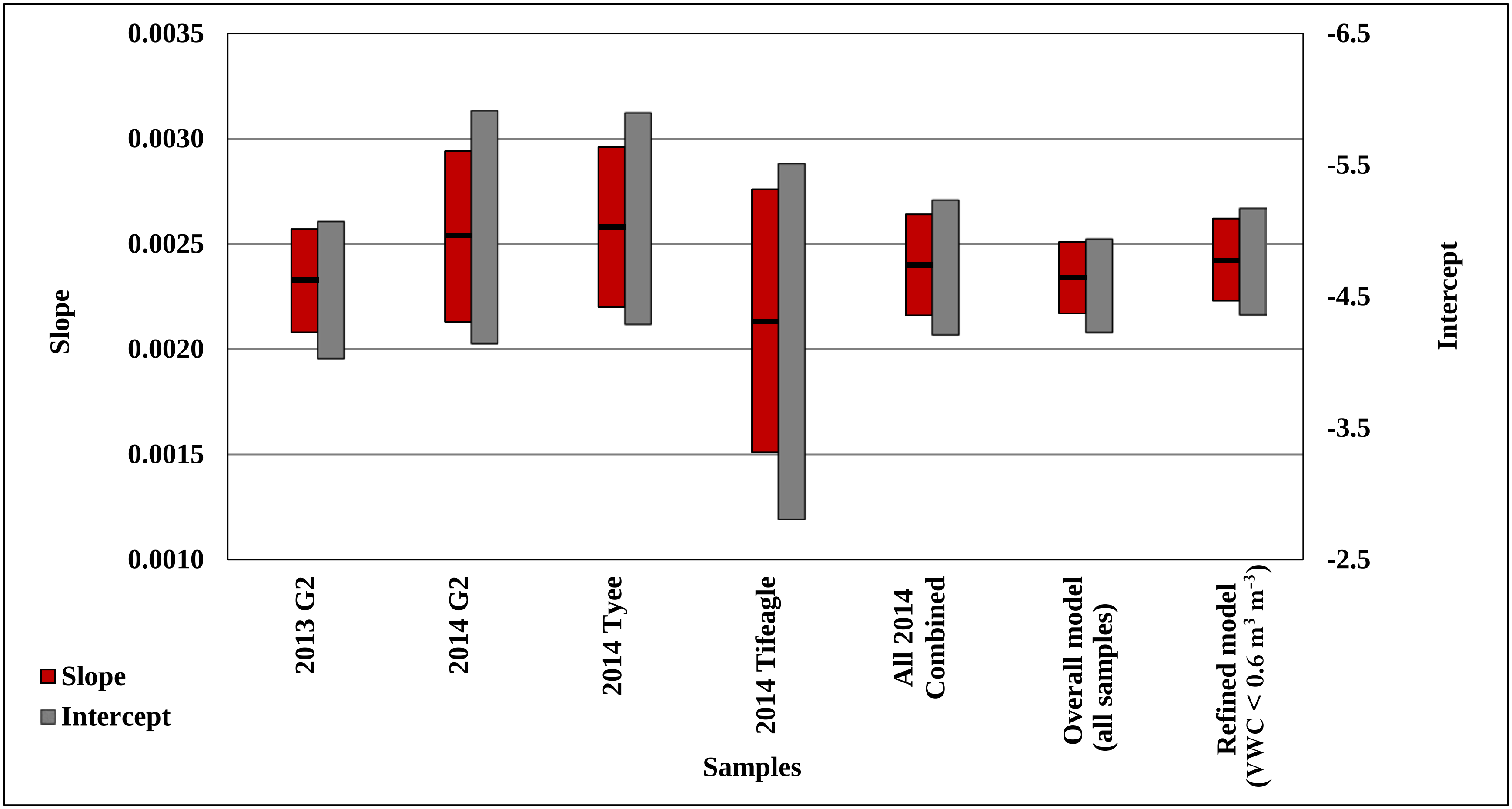

Fig. 2. Ninety-five percent confidence limits (95% CL) for regression coefficients of linear prediction models relating TDR300 Period mode readings in microseconds (μs) to volumetric water content (θ) at the 1.2 cm depth. Black bar denotes slope estimate for each model.

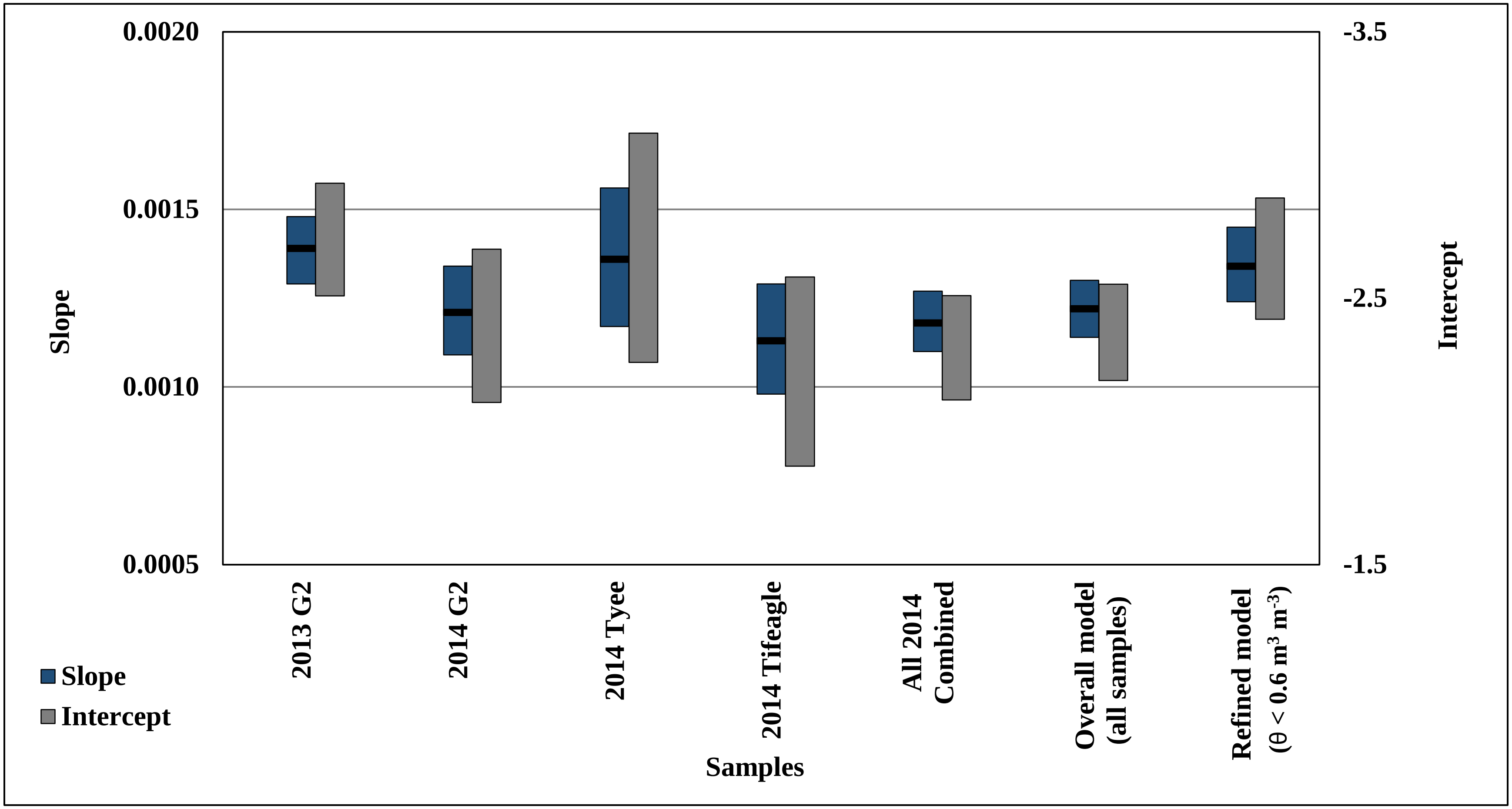

Fig. 3. Ninety-five percent confidence limits (95% CL) for regression coefficients of linear prediction models relating TDR300 Period mode readings in microseconds (μs) to volumetric water content (θ) at the 2.5 cm depth. Black bar denotes slope estimate for each model.

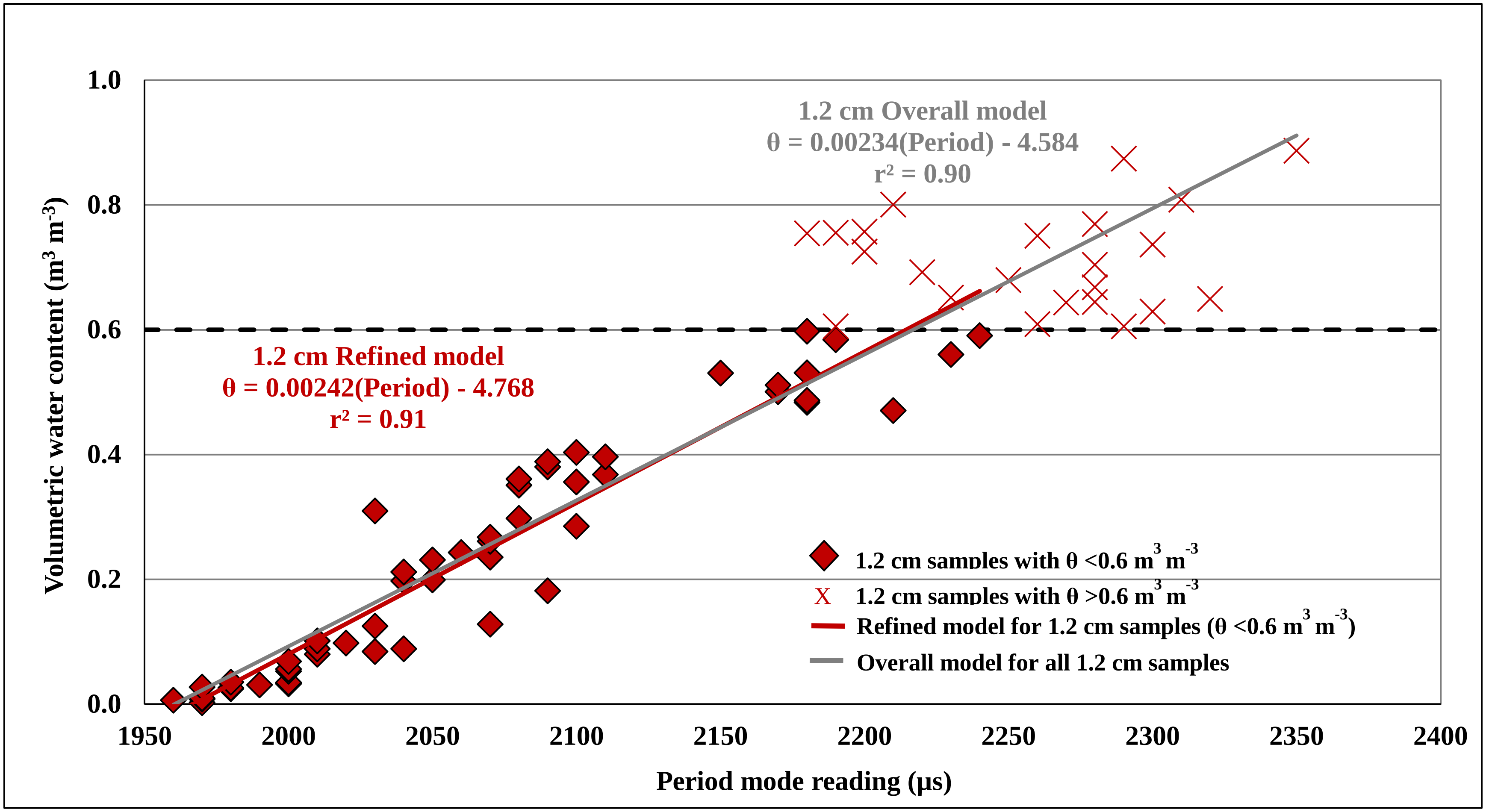

Fig. 4. All 2013 and 2014 data relating TDR300 Period mode readings in microseconds (µs) to volumetric water content (θ) $m^3\ m^{-3}$ at the 1.2 cm depth. The maximum θ measured under field conditions was 0.6 $m^3\ m^{-3}$. Fitted regression model from samples less than 0.6 $m^3\ m^{-3}$ was compared to the overall model based on all 1.2 cm samples.

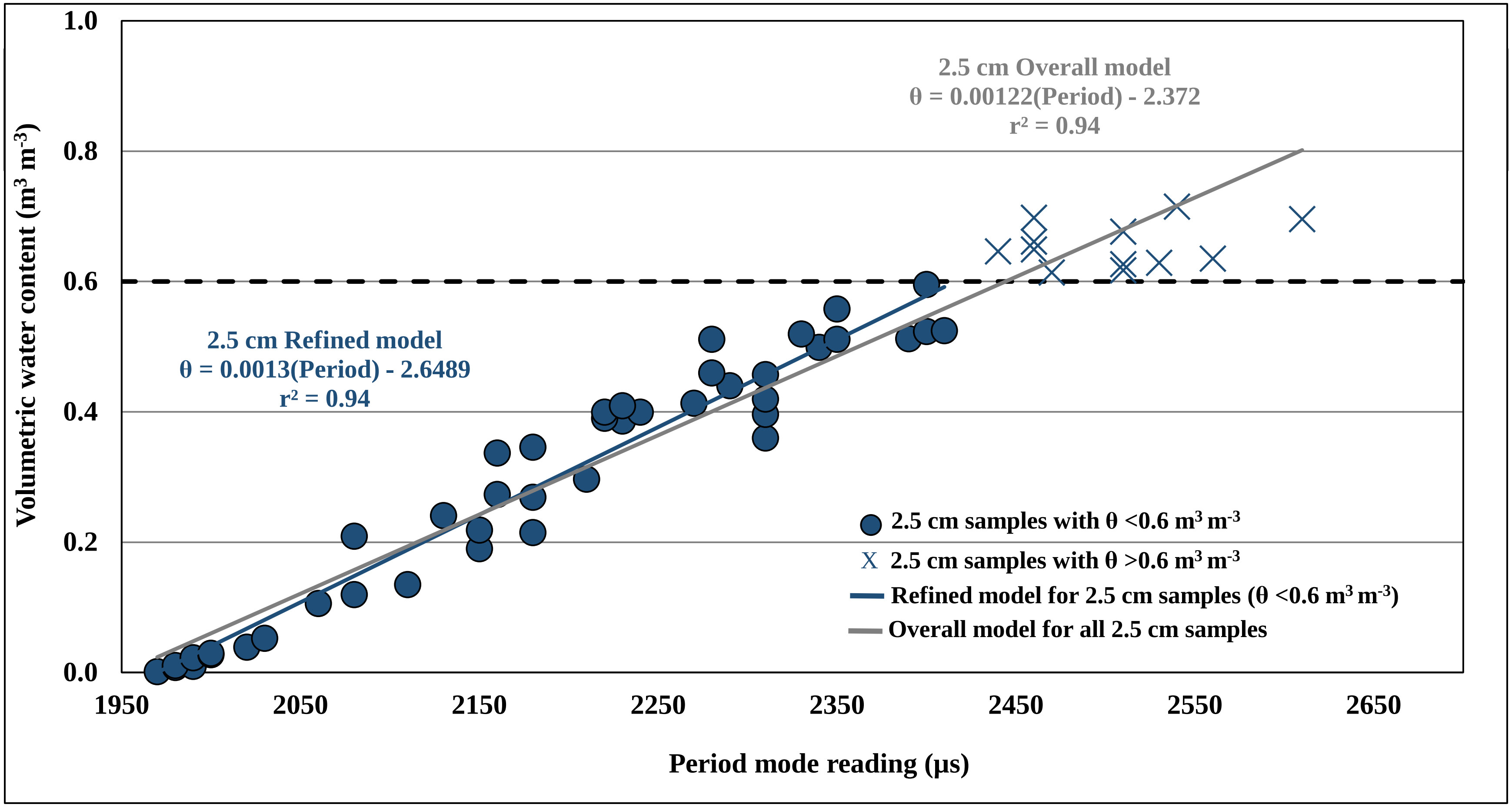

Fig. 5. All 2013 and 2014 data relating TDR300 Period mode readings in microseconds (µs) to volumetric water content (θ) at the 2.5 cm depth. The maximum θ measured under field conditions was 0.6 m^3 m^{-3}. Fitted regression model from samples less than 0.6 m^3 m^{-3} as compared to the overall model based on all 2.5 cm samples.

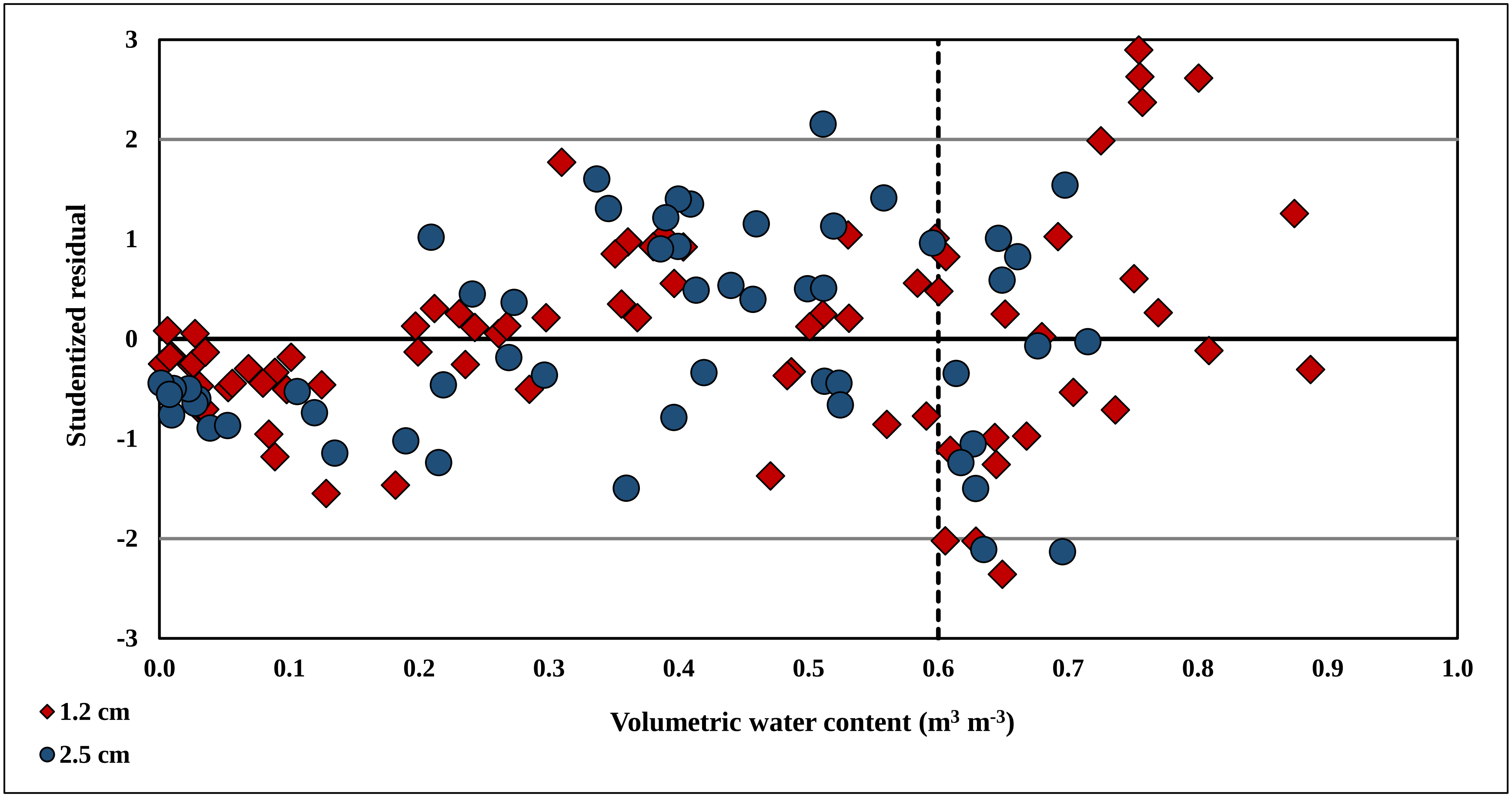

Fig. 6. Studentized residuals from overall prediction models using all 2013 and 2014 samples plotted against volumetric water content (θ) determined by weight. Maximum θ observed under field conditions was 0.6 m^3 m^{-3}.

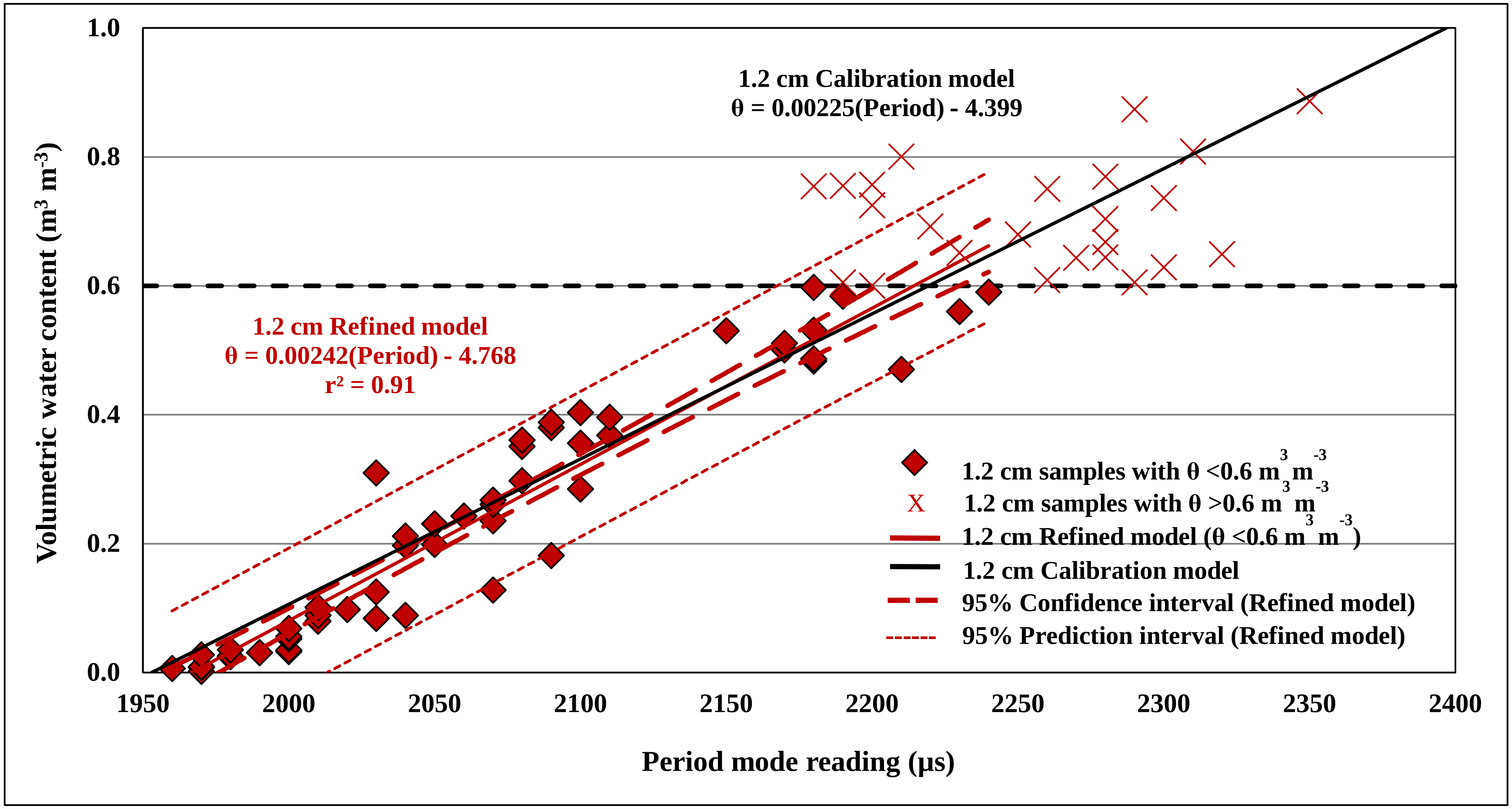

Fig. 7. At the 1.2 cm depth, the refined fitted model based on samples <0.6 $m^3 m^{-3}$, with corresponding 95% confidence intervals and prediction intervals, was compared to the two-point calibration model based on readings in air and deionized water.

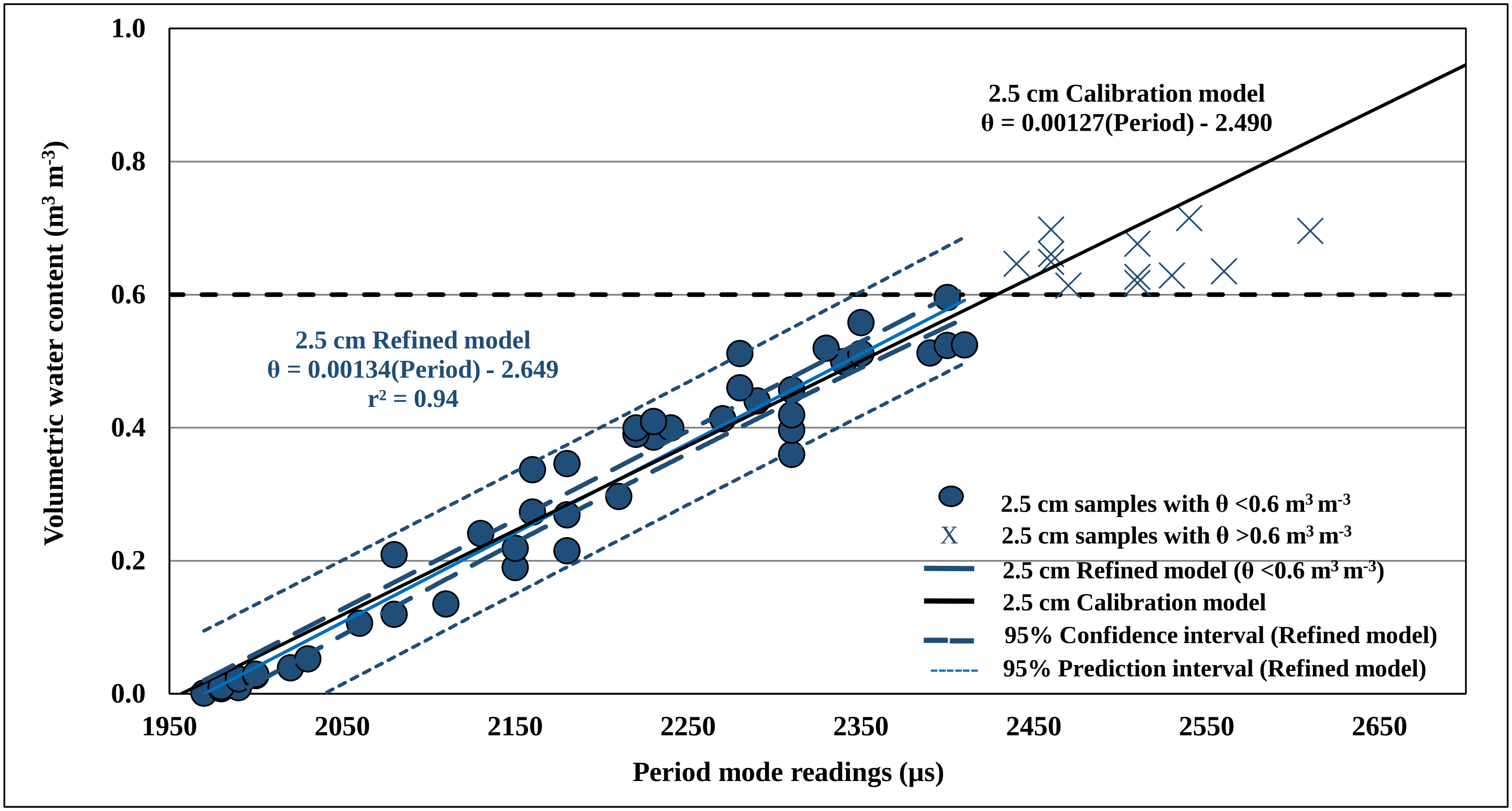

Fig. 8. At the 2.5 cm depth, the refined fitted model based on samples <0.6 m3m-3, with corresponding 95% confidence intervals and prediction intervals, was compared to the two-point calibration model based on readings in air and deionized water.

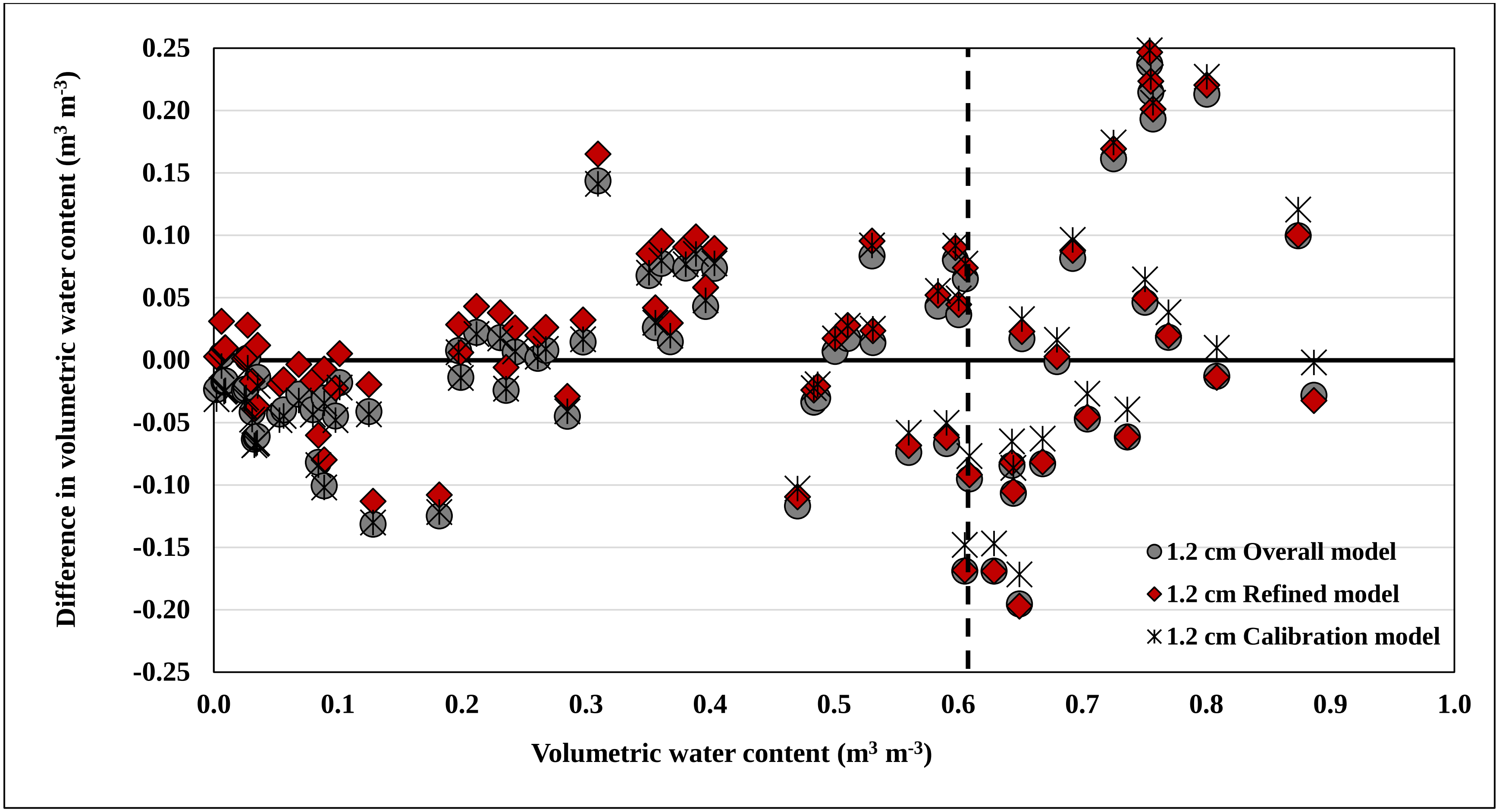

Fig. 9. Differences between actual volumetric water content (θ) and predicted θ based on TDR300 Period Mode readings for three different linear models at the 1.2 cm depth. The maximum θ observed under field conditions was 0.6 $m^3\ m^{-3}$.

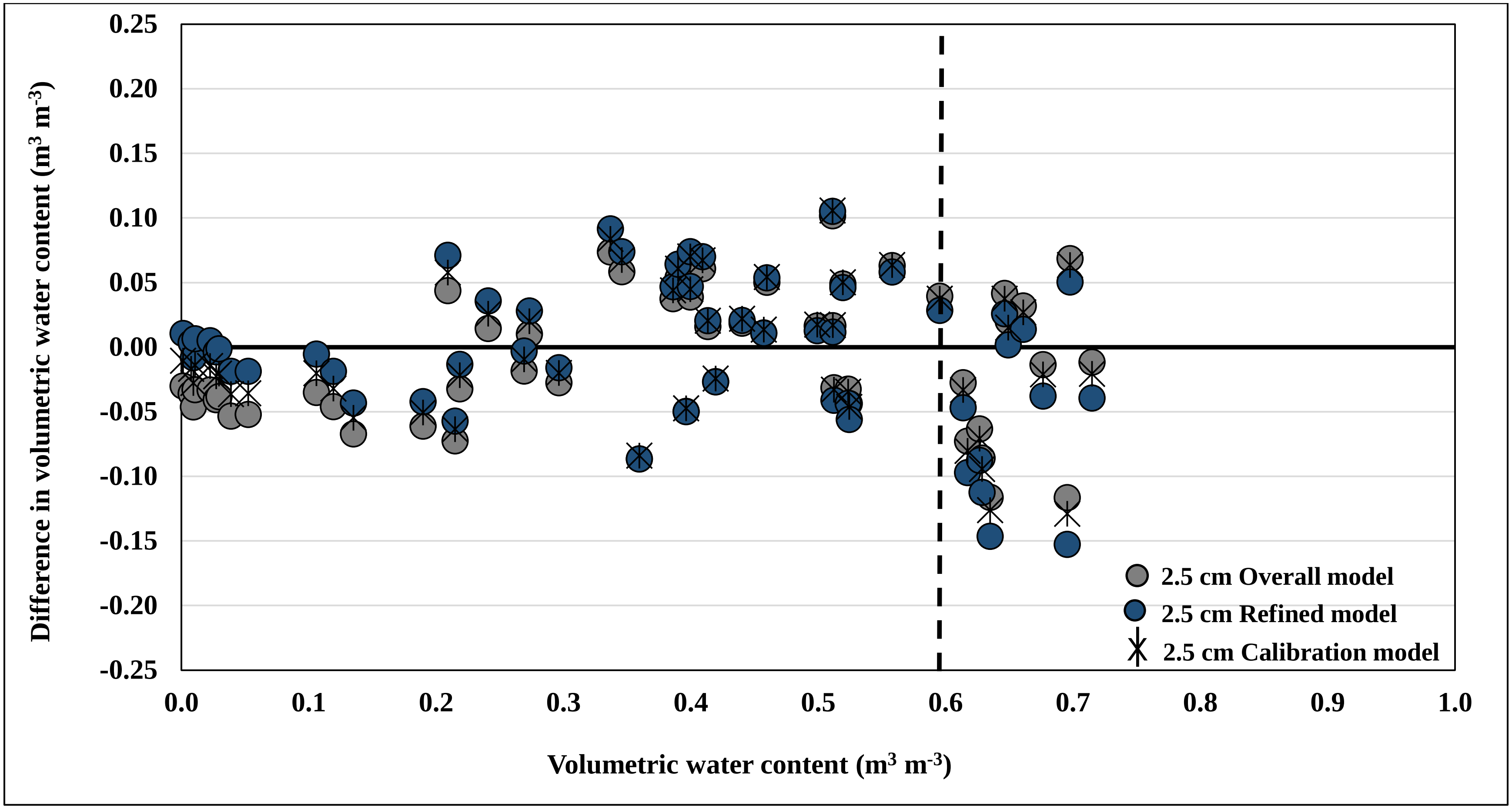

Fig. 10. Differences between actual volumetric water content (θ) and predicted θ based on TDR300 Period Mode readings for three different linear models, at the 2.5 cm depth. The maximum θ observed under field conditions was 0.6 m^3 m^{-3}.

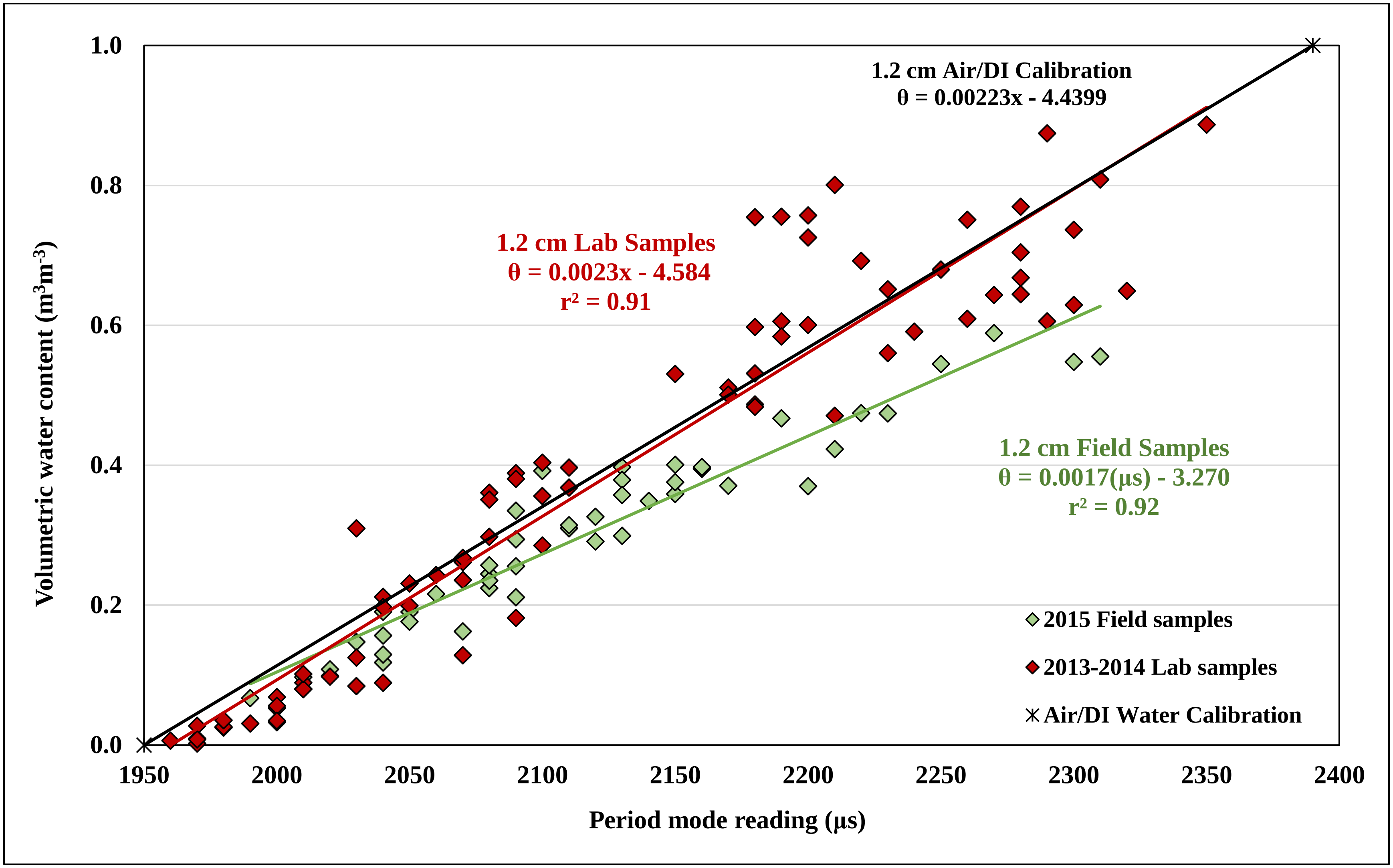

Fig. 11. Comparison of models from (previously) extracted samples, and two-point calibration, to in situ sampling using TDR300 at 1.2 cm depth.

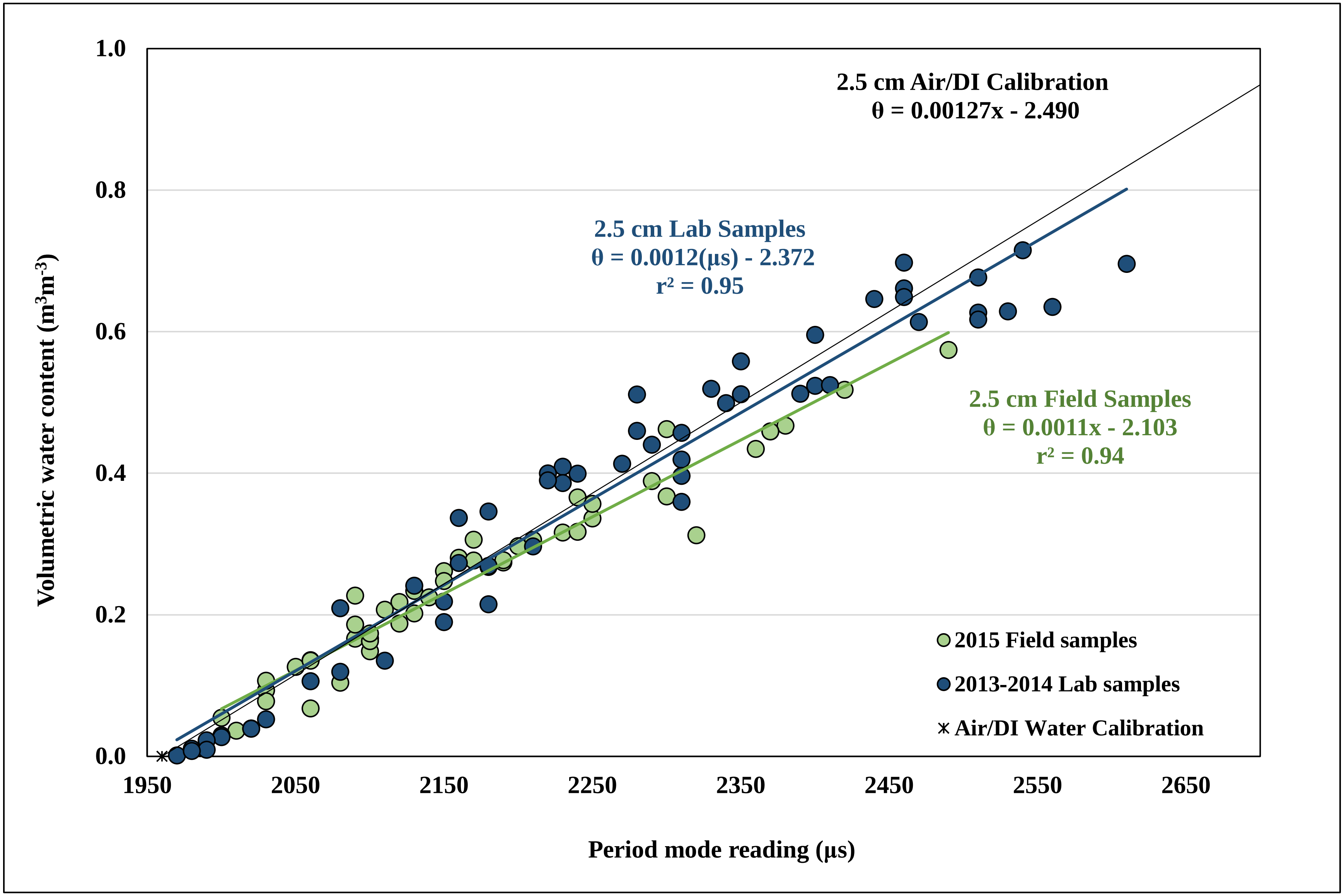

Fig. 12. Comparison of models from (previously) extracted samples, and two-point calibration, to in situ sampling using TDR300 at 2.5 cm depth.

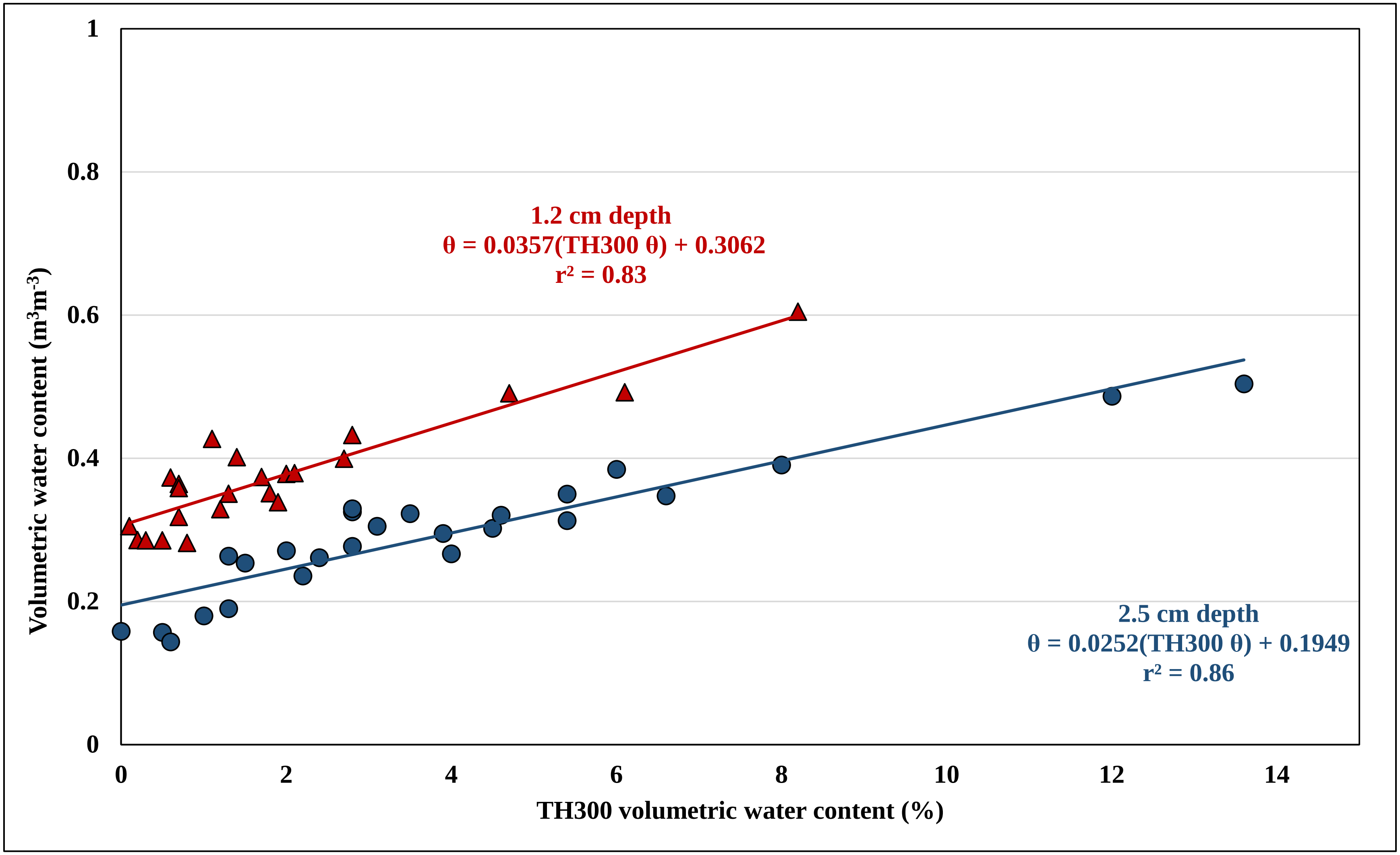

Fig. 13. Linear regression of (modified) TH300 moisture meter readings to gravimetrically determined volumetric water content (θ) of (subsequently) extracted putting green samples at 1.2 and 2.5 cm depths.

III. Evaluating Turfgrass Color in Sand-Based Putting Greens through Digital Image Analysis using the GreenIndex+ Turf app

ABSTRACT

Turfgrass color is an important component of overall turf quality, and visual assessments of turfgrass color can be valuable indicators of plant health. While visually rating turf color using a 1-9 scale is a longstanding practice in turfgrass research, visual evaluations are an inherently subjective process, that encounter both temporal and spatial limitations due to effects of ambient lighting. Digital image analysis (DIA) based on the dark green color index (DGCI) is a more objective method for quantifying turfgrass color; however, a digital camera, standardized lighting source, and image analysis software are required. The GreenIndex+ Turf app (Spectrum Technologies Inc.) calculates DGCI in the field while accounting for ambient lighting conditions. The GreenIndex+ Turf app utilizes the built-in digital camera of a smartphone, along with reference color standards of a target board, without the need for artificial lighting or additional image analysis software. The objective of this research was to compare the GreenIndex+ Turf app to traditional DIA methods for measuring turfgrass color. In 2014, various nitrogen fertility treatments were used to create a range of turfgrass color on a creeping bentgrass (*Agrostis stolonifera* L.) putting green. Plots were evaluated 10 times over nine weeks using both methods. Regression analysis produced a linear prediction equation relating DGCI values from the GreenIndex+ Turf app to those obtained from traditional DIA methods with an average slope and intercept of 0.452 and 0.424, respectively. In 2015, ambient lighting conditions were measured throughout image collection as plots were evaluated eight times over a 16-hour period. Comparisons using the 2014 equation achieved maximum r^2 (0.75) within ambient light range of 7 to 24 μmol m^{-2} s^{-1}. Further comparisons using additional parameters for ambient light

adjustments have potential for improving correlation of this app to accepted research methodology.

Abbreviations: DGCI, dark green color index; DIA, digital image analysis; HSB, hue, saturation, brightness; JPEG, Joint Photographic Experts Group; NTEP, National Turfgrass Evaluation Program; RGB, red, green, blue; NDVI, normalized difference vegetative index; σ, standard deviation; VR, visual ratings; VWC, volumetric water content; 95% CL, ninety-five percent confidence limits

Color evaluations play a fundamental role in turfgrass management. Turfgrass color is an important component of overall turf quality, as well as a valuable indicator of plant health pertaining to nutrient and water status (Beard, 1973). Furthermore, performance of turfgrasses towards their intended purpose often involve an aesthetic component encompassing color (Karcher and Richardson, 2013). While visually rating turf color using a 1-9 scale is a longstanding practice in turfgrass research, even among experienced raters, visual evaluations are an inherently subjective process, which encounter both temporal and spatial limitations due to effects of ambient lighting (Horst et al., 1984; Ikemura, 2003; Krans and Morris, 2007). Minimizing subjectivity, along with variability due to ambient light, are critical in producing reliable data for color assessments. Efficiently creating consistent, objective data for turfgrass color has broad application in turfgrass selection, management, and research.

Digital image analysis (DIA) is an accepted method for measuring and comparing turfgrass color across time and location through the use of standardized artificial lighting conditions to improve objectivity and consistency (Karcher and Richardson, 2003). Digital photography and image analysis software are used to measure values of color contained within the pixels of collected images. Published methods for DIA involve using a portable enclosure with a self-contained lighting system (light box) to eliminate the effects of ambient light and create a consistent environment under which digital images are captured for analysis (Fig. 1). A digital camera mounted to the light box acquires the images using fixed settings (Karcher and Richardson, 2013). Within each image, color information for each pixel is described by red, green, and blue (RGB) light intensities (Karcher and Richardson, 2003). Image analysis software can be utilized to quantify RGB within the image. Translating RGB color information into a scale more representative of how the human eye perceives color is important for further analysis and application; digital image analysis involves converting RGB to hue, saturation, brightness (HSB) (Karcher and Richardson, 2013). Bringing the three parameters of the HSB values into a single numeric value allows for more direct comparisons of digital images to visual color ratings (Karcher and Richardson, 2003). The following equation, published by Karcher and Richardson (2003), is used to convert HSB to a single dark green color index (DGCI) value:

$$\mathbf{DGCI = [(H - 60)/60 + (1 - S) + (1 - B)]/3} \qquad \mathbf{[1]}$$

DGCI values range from 0-1, with dark green color increasing as the value approaches 1. Utilizing the DGCI scale also quantifies turfgrass color as a continuous random variable (rather than discrete) for the purposes of statistical analysis (Karcher and Richardson, 2003). Yet, while DIA and the DGCI offer considerable improvements towards objectivity, consistency, and comparison, incorporating such methodology into management decisions remains challenging. Ultimately, the necessity for, and costs associated with, specialized equipment and software, as well as time required to collect and process images, limits DIA application beyond research settings.

The prevalence of smartphones (and tablets) with advancing quality of built-in digital cameras and processing capabilities offer potential for expanding the application of DIA. By consolidating both image acquisition and analysis into a single device capable of rapidly producing DGCI values in the field, turfgrass management decisions may benefit from the increased objectivity, consistency, and precision DIA has provided to color evaluations performed in research settings. While the smartphone itself may contain the necessary camera and computing components to efficiently produce DGCI values, in the absence of an enclosed light box, the process of image collection, and the way in which ambient light is accounted for are critical in achieving consistency across time and location. Management decisions pertaining to sand-based golf course putting greens could benefit from such information. High levels of monitoring and maintenance, coupled with the ephemeral nature of moisture and nutrients within the rootzone create situations where golf course superintendents supplement regularly scheduled management practices based on visual assessments, often involving color. Because putting greens exist in separate physical locations throughout the golf course and are often collectively managed by different personnel within a maintenance staff, operating with consistent turfgrass color data could aid superintendents in making timely and site-specific management decisions.

Previous research on corn (*Zea mays* L.) quantifying leaf "greenness" using DIA showed that the inclusion of calibration discs within digital images taken under ambient light conditions improved the precision of DGCI (Rorie et al., 2011). Calibration discs used by Rorie et al. (2011) consisted of green and yellow sections that functioned as calibration standards. By comparing known DGCI values of these sections with the observed DGCI of each section within each image, slope and intercept values could be calculated. Through linear regression, these slope and intercept values could be used to apply appropriate adjustments (due to the effects of ambient light) to corn leaves within the same images (Rorie et al., 2011). Methodology used in that research has been incorporated into a smartphone app from Spectrum Technologies, the GreenIndex+ Turf app. While this app calculates turgrass HSB and DGCI using the same algorithms as published DIA methods, the distinction the app makes by compensating for ambient light (rather than eliminating it) during image collection needs to be compared to published research methods.

The objective of this research was to compare the GreenIndex+ Turf app to *(i)* research DIA methods and *(ii)* visual ratings, for evaluating turfgrass color. Digital images of sand-based putting green plots ranging in green color were collected under different ambient lighting conditions, and DGCI values were calculated using each method. It was hypothesized that calibration disc adjustment process of the GreenIndex+ app could predict turfgrass DGCI without the need for an enclosed light box.

MATERIALS & METHODS

The GreenIndex+ Turf app (v. 2.0) and target board from Spectrum Technologies (Item#2910TA and 2910T, Spectrum Technologies Inc., Aurora, IL) were used to evaluate turfgrass color. In 2014, the GreenIndex+ Turf app was utilized through an Apple iPod touch (model A1367, Apple Inc., Cupertino, CA) (Fig. 2). The iPod touch was a 16 GB (4th generation, 2012) model equipped with 0.7 megapixel built-in digital camera. All 2014 GreenIndex+ Turf images were captured from a height of approximately 130 cm and were Joint Photographic Experts Group (JPEG) images with overall dimensions of 720 x 960 pixels. In 2015, the GreenIndex+ Turf app was utilized through an Apple iPhone 5 (model A1428, Apple Inc., Cupertino, CA) with built-in 8 megapixel iSight camera producing 3264 x 2448 pixel JPEG images (Fig. 2). The decision to change from the iPod touch to the iPhone 5 in 2015 was based on practical considerations for evaluating the GreenIndex+ app on the most representative, contemporary smartphone device available at the time. A portable iPhone stand was constructed so that all 2015 GreenIndex+ Turf app images were taken from a height of 128.5 cm, with fixed positioning of the target board within each image. In accordance with the GreenIndex+ Turf manual, white balance was locked prior to each set of images collected, and image processing was carried out to obtain DGCI values (Spectrum Technologies Inc., 2013). Calibration standards on the target board consisted of a green section (14.6 by 22.9 cm) with HSB of

91/38/42, and a yellow section (14.6 by 16.5 cm) with HSB of 66/88/100. Resulting DGCI values for the standards were 0.572 for green and 0.073 for yellow.

Digital Image Analysis Methods and Equipment

Images using standard, published DIA methods were acquired with a Canon Powershot G1X digital camera (Canon USA Inc., Melville, NY) and portable enclosed light box (NexGen Turf LLC, Albany, OR) (Fig. 1). The Powershot G1X was a 14.3 megapixel camera, set to ISO 200, with a shutter speed of 1/5 s, aperture of f/4.0, and focal length of 23 mm. White balance was manually set according to manufacturer instructions (Canon U.S.A. Inc., 2012) under illuminated conditions within the light box. All DIA images were captured from a height of 55 cm; turfgrass area within each image measured 37 by 50 cm. All images were 1200 x 1600 pixel JPEG files. The light box used four TCP 9W compact fluorescent light bulbs (TCP, Inc., Item#4890965, Aurora, OH), and was powered by Duracell Powerpack Pro 600 battery pack (Product number DR600PWR, Battery-Biz Inc., Camarillo, CA). Images were downloaded to a personal computer and subsequent color analysis was performed using SigmaScan Pro 5 (Systat Software, Chicago, IL). Threshold settings for analysis macro (Turf Analysis 1-4) had hue range of 35-160 and saturation range of 0-100 (Karcher and Richardson, 2005). Microsoft Excel (Microsoft Corporation, 2013) was used to automate calculations of DGCI according to Eq. [1].

Experimental Area & Evaluations

All research was conducted at the University of Arkansas Agricultural Research and Extension Center in Fayetteville, AR on a creeping bentgrass (*Agrostis stolonifera* L.) sand-based putting green built to USGA specifications (United States Golf Association Green Section Staff, 2004). Five nitrogen fertility rates (0, 0.5, 1.2, 2.4, and 4.9 g N m^{-2}) were applied every 28 days with a CO_2 backpack sprayer in the effort to create a range of green color. Consistent with these objectives, in 2015, based on observations from fertility applications as a part of putting green maintenance, the 4.9 g N m^{-2} rate was replaced by 2.4 g N m^{-2} + $FeSO_4$ (0.24 g Fe m^{-2}). Plots were arranged in a randomized complete block design with four replications of each fertility treatment. Research plots were mowed six times per week at a height of 3.2 mm, and aside from fertility treatments, were uniformly maintained under typical management practices. In 2014, fertility treatments were applied on 8 Aug., 5 Sept., and 3 Oct. (following DIA and VR on 10/03). In 2015, fertility treatments were applied on 29 July.

In 2014, 0.9 x 0.9 m plots of 'Tyee' creeping bentgrass were evaluated 10 times over 9 weeks from 11 Aug. through 14 Oct. to observe the relationship in color assessments made on a recurring basis. On each evaluation date, three sets of color data were obtained for each plot. Visual ratings from a single rater were made using 1-9 scale (1 = brown or dead turf, 6 = minimally acceptable, 9 = optimum dark green turf). GreenIndex+ Turf app and target board were used to calculate DGCI of the plot from a single image. Digital image analysis using an enclosed light box was carried out, collecting a single image per plot from which DGCI was calculated (Karcher and Richardson, 2013). Hue, saturation, brightness values associated with each image were automatically recorded as a part of both DIA processes.

In 2015, 1.8 x 1.2 m plots of 'Penn G2' creeping bentgrass were evaluated eight times within a 16-hour period to observe the effects of different ambient light levels on the relationship between DGCI values calculated by the GreenIndex+ Turf app and light box DIA. Solar irradiance values were obtained from an onsite weather station. To ensure that the same physical location within each plot was evaluated for each set of images, markers were inserted into the putting green corresponding to the corners of the light box. An additional marker was used to position the iPhone stand, so that turf selected for GreenIndex+ Turf app analysis was centered within the overall dimensions of the light box. Prior to initial set of images, dew was removed by rolling plots using a walking greensmower (Toro Greensmaster Flex 2100, The Toro Company) with blades disengaged.

Statistical Analyses

Regression analysis was performed using SAS PROC REG (SAS 9.4, SAS Institute Inc., Cary, NC) comparing DGCI values *(i)* between the two different DIA methods, and *(ii)* to visual ratings. Within each plot, mean DGCI, 95% confidence limits (95% CL), and standard deviation (σ) were calculated for each of the two DIA methods. Analysis of variance (ANOVA) for significant differences between DIA methods was performed using SAS PROC TTEST and PROC ANOVA; significant differences in DGCI data were based on p value (α=0.05).

RESULTS & DISCUSSION

2014 Comparison of DGCI values

In 2014, the GreenIndex+ Turf app, utilized through the iPod touch, produced DGCI values that were correlated with, but not equivalent to, DGCI values from published research methods using Sigma Scan (Fig. 3). A significant linear relationship using DGCI for the GreenIndex app as a predictor of light box DGCI was observed for all evaluation dates (Table 1). Across all 2014 data, DGCI values from GreenIndex+ app were less than the corresponding Sigma Scan values, with the exception of a single plot on the final evaluation date (Fig. 3). Throughout 2014, GreenIndex+ DGCI ranged from 0.328 to 0.742, while Sigma Scan DGCI ranged from 0.574 to 0.729 (Fig. 3). For each of the 20 plots individually, mean DGCI values from the GreenIndex+ app was outside 95% CL of Sigma Scan DGCI (Table 2). These differences, along with the larger range of values reported by the GreenIndex+ app (despite using the same published algorithm to calculate DGCI), indicated that the ambient lighting conditions still influenced app DGCI in a manner not completely accounted for by the target board correction process. The observed consistency of light box DGCI values relative to GreenIndex+ app DGCI (Fig. 3) suggested that comparison of GreenIndex+ DGCI values over time may be misleading. Furthermore, the significant differences in DGCI values within individual plots quantified what was observed in plotted data that direct comparisons of DGCI values across methods were not suitable for research purposes.

While DGCI values of the two methods differed, there was an observed linear relationship of the data within each evaluation date (Fig. 4). Regression analysis using GreenIndex+ DGCI as a predictor of Sigma Scan DGCI resulted in significant linear models ($p < 0.0001$), with significant p values for all parameter estimates and r^2 values of the models ranged from 0.73 to 0.94 (Table 1). These results indicated that, for a given date, under ambient lighting conditions, relative differences in turfgrass color detected by the app were correlated to published research methods. However, a single linear model combining all 2014 data, while having significant p values for model, slope, and intercept, resulted in a considerably lower r^2 value (0.23) compared to models based on a single evaluation date (Table 1). These differences in r^2 values indicated: *(i)* the app's target board was capable of adjusting for ambient lighting conditions within a given image collection event, however *(ii)* this process was limited in its ability to standardize those adjustments across multiple dates. The greater r^2 values for a given date suggested that relative differences in green color were detected by the app, however, the system of quantifying relative differences did not hold true across all dates. Ultimately, while linear regression models were useful for relating app DGCI values to what may be considered ground-truth values from published research methods, for practical purposes, turfgrass managers would not need to convert the DGCI of the app to that of a light box. Linear models were useful for comparative purposes in this research to relate the app's process of adjusting for ambient lighting to that of an enclosed light box. Because light box methodology completely eliminates the effects of ambient lighting, the GreenIndex+ app needs to demonstrate that the DGCI values it produces are also independent of variable lighting conditions. These linear models provided a basis for interpreting DGCI values of the two methods; however, patterns in the relationship between the two sets of DGCI values warranted further examination.

Temporal patterns were observed for GreenIndex+ data in 2014. Noticeable fluctuations in app DGCI values for consecutive evaluation dates were observed across all fertility treatments and replications (Fig. 3). This pattern consisted of comparatively low DGCI (25 Aug., 12 Sept., and 3 Oct.), followed by DGCI values ranking among the largest observed for a given plot (4 Sept., 19 Sept., and 14 Oct.). Such trends were not reflected in DIA of images obtained within the light box, and because they were observed in control plots, fertility applications/response did not provide an adequate explanation for DGCI fluctuations (Fig. 3). These patterns raised questions regarding the specific lighting conditions for each date, and how light levels potentially contributed to such fluctuations. Solar radiation data were obtained based on the time stamp of the images, and average solar irradiance was calculated for the period of GreenIndex+ image collection.

Comparing the consecutive dates in question, the initial dates (with lower app DGCI) corresponded to considerably lower solar irradiance, while the subsequent dates corresponded to irradiance values up to five times greater during periods of image collection (Figs. 5, 6, 7).

Patterns in GreenIndex+ DGCI values may be explained in terms of solar radiation differences among dates (Fig. 3). However, it should be noted that the correlation between GreenIndex+ and Sigma Scan DGCI (specifically r^2 values) did not necessarily exhibit similar patterns due to differences in solar radiation (Table 1). The previously discussed dates of 25 Aug. and 4 Sept. were the minimum and maximum solar irradiance values, yet r^2 values for these dates were 0.87 and 0.88, respectively (Table 1). Additionally, the maximum r^2 values corresponded to 14 Oct. and 12 Sept. (0.94, and 0.92, respectively), yet solar radiation values for these dates varied considerably, ranking second largest and second smallest, respectively (Table 1). Based on these inconsistencies between irradiance, r^2, and DGCI differences, identifying optimum light levels for consistent GreenIndex+ data collection was not achieved. These results indicated that, while solar irradiance during image collection did affect the specific DGCI values produced by the GreenIndex+ app, the app's ability to detect relative differences in turfgrass color was less impacted by disparities in ambient lighting. Furthermore, users should not necessarily be concerned about overall light quantity affecting the app's ability to process images and generate comparisons within a given set of images. However, when comparing DGCI values over multiple sets of images, across time or location, the effects of different solar radiation levels need to be considered. Ultimately, the temporal variability of GreenIndex+ DGCI raised questions about the ability of a target board to consistently standardize DGCI values processed under a broad range of ambient lighting conditions, in a manner comparable to an enclosed light box system.

In 2014, across evaluation dates for each of the 20 plots, GreenIndex+ DGCI displayed greater variability than Sigma Scan (Fig. 8). While slight variations in DGCI over the course of nine weeks were expected, utilization of DGCI values for research objectives or management decisions inevitably depend upon comparisons made over time. Ensuring that changes in DGCI reflect differences in turfgrass physiology (and not lighting conditions) is imperative for meaningful application of such data. For each of the 20 plots, σ of GreenIndex+ DGCI was greater than that of the enclosed light box system (Table 2). Standard deviations differed ($p<0.05$) between the two DIA methods. Averaged across all plots, σ of the GreenIndex+ app was 0.053, while Sigma Scan σ was 0.025. Comparing DGCI values within each plot, tests for equality of variance ($\alpha = 0.05$) indicated unequal variance between the two methods in 11 of the 20 plots (Table 2). Collectively, these results indicated that over multiple weeks, variability of the GreenIndex+ app was significantly different from published research methods. Furthermore, comparisons of app DGCI values over time were more likely to report differences which may not be attributable to the turf itself. Such inherit variability in DGCI values presents challenges for consistently and reliably interpreting app data and incorporating it into management decisions.

2014 Comparisons with Visual Ratings

In 2014, linear regression of visual ratings to DGCI values observed similar r^2 values among the two DIA methods (Fig. 9). Linear models were developed for each date with GreenIndex+ app r^2 values ranging from 0.67 to 0.92 ($\bar{x}$ = 0.78), and light box DIA using Sigma Scan ranging from 0.64 to 0.89 ($\bar{x}$ = 0.80) (Fig. 9). On five of the 10 dates in 2014, GreenIndex+ data produced greater r^2 values than Sigma Scan DGCI (Fig. 9). When all 2014 data were combined, the overall model for the GreenIndex+ app had an r^2 value of 0.52, and for Sigma Scan DGCI, r^2 was 050. For all dates, GreenIndex+ slope values were greater than those of Sigma Scan in both magnitude and variability, ranging from 0.042 to 0.086 ($\bar{x}$ = 0.059), compared to 0.022 to 0.038 ($\bar{x}$ = 0.029) for Sigma Scan (Fig. 9). Plotted data revealed a general trend towards convergence of DGCI values at the upper end of the visual rating scale, with greatest divergence occurring in the lowest rated plots (Fig. 9). These results supported previous findings in this research, that the GreenIndex+ app could detect relative differences in green color similar to published research methodology; furthermore, the relative differences detected by the app were correlated with human eye perceptions of turfgrass color, similar to published methods.

For this research, ratings from a single experienced rater represented human eye perception of turfgrass color. It is acknowledged that additional sets of visual ratings may aid in development of more robust comparisons. Maintaining consistency of rater(s) throughout all evaluations was a priority in this study, as to not confound DGCI comparisons with documented inconsistencies associated with multiple raters (Horst et al., 1984; Karcher and Richardson, 2003; Krans and Morris, 2007). For the 2014 evaluations, for logistical reasons, the effort to maintain consistency over nine weeks resulted in a single set of ratings, from a single rater. While these methods were considered reasonable for an initial comparison of the app's DGCI values to human eye perceptions of turfgrass color, the benefits of multiple raters (Karcher and Richardson, 2003) should be incorporated into future research.

2015 Comparison of DGCI values

On 15 Aug. 2015, DIA was carried out eight separate times between 5:53 and 20:55 CDT using both the GreenIndex+ app and published research methods (Fig. 10). During the initial and final image sets, solar irradiance of 0 W m^{-2} affected data collection by the GreenIndex+ app (Fig. 11). Under these lighting conditions, for image set 1, only Sigma Scan DGCI from light box images were generated; for image set 8, GreenIndex+ processing was made possible only through use of the iPhone 5 camera flash. Intuitively, such image collection procedures would not facilitate appropriate DIA; however, given the objectives of this research, image sets 1 and 8 provided necessary context regarding the limitations involved with a comprehensive comparison of these two DIA methods under the broadest range of lighting conditions possible. Additionally, these sets validated the consistency of published research methodology used in DGCI comparisons. Regression of DGCI values from image set 8 was performed strictly for comparative reference. Analysis of variance and other subsequently discussed comparisons for 2015 data were based only on image sets 2-7.

In 2015, the GreenIndex+ app utilized through the iPhone 5 produced DGCI values that were greater than those from Sigma Scan DIA, for all plots, across all sets of paired images (Fig. 12). GreenIndex+ DGCI ranged from 0.506 to 0.843, and Sigma Scan from 0.376 to 0.433 (Fig. 13). Compared to 2014, these ranges represented an increase in both minimum and maximum DGCI for GreenIndex+ app, while simultaneously corresponding to a decrease in both minimum and maximum DGCI for Sigma Scan values; the overall effect being an inverted relationship of DGCI values compared to 2014 (Fig. 12). While such a change was unexpected, subsequent investigation supported the validity of these results. The shift in Sigma Scan DGCI most likely involved a combination of factors. It could be partially attributed to cultivar differences (‘Tyee’ in 2014, and ‘Penn G2’ in 2015). Genetic color differences have been detected with the light box system since its inception (Karcher and Richardson, 2003), and concurrent DIA on bentgrass putting green cultivars as part of the National Turfgrass Evaluation Program (NTEP) observed DGCI ranges of 0.27 across cultivars (unpublished data). In addition to cultivar differences, fertility applications may have played a role in DGCI differences. Within this research, there were fewer fertility treatments applied in 2015 than 2014 (three applications during 2014 evaluations, compared to a single application prior to 2015 data collection). Based on these factors, along with the documented consistency of published DIA methods (Karcher and Richardson, 2013), it was reasonable to consider 2015 Sigma Scan DGCI values as ground truth data for turfgrass color.

A smartphone camera effect was also investigated as a potential factor affecting the upward shift in GreenIndex+ DGCI. While specific smartphone evaluations were beyond the scope of this research, a simple comparison of the devices used was conducted as a follow-up to 2015 results. The decision to change devices was justified by the statement in the GreenIndex+ manual that both iPod and iPhone were listed as suitable options for utilizing the app, and no discussion on device variability pertaining to DGCI was included (Spectrum Technologies Inc., 2013). GreenIndex+ DGCI values from each device were modeled as predictors of Sigma Scan DGCI, and it was shown that the iPod touch DGCI was consistently greater than corresponding iPhone 5 values (Fig. 14). When iPod DGCI was used as a predictor of iPhone DGCI, the resulting slope was 0.282, and the r^2 value was 0.56. Based on this comparison, there was no evidence to indicate that changing to the iPhone 5 caused the observed upward shift in app DGCI. This iPod/iPhone comparison was for the expressed purpose of interpreting data from the specific devices used in this research and these results were not intended to provide definitive conclusions regarding device effects on the performance of the GreenIndex+ app.

While the relative position of GreenIndex+ DGCI had changed, with respect to Sigma Scan values, similar patterns in the differences between values of the two methods were observed (Figs. 3 & 12). The general trend was that the greatest differences between DGCI values of the two methods were observed in image sets 3 and 6, while differences were noticeably reduced for image sets 4, 5, and 7 (Fig. 12). Overall, these results indicated that the lighting conditions under which GreenIndex+ images were collected affected the specific DGCI values produced by the app.

Regression analysis was conducted by fitting linear models to each individual set of images (Fig. 15). GreenIndex+ app DGCI was used as a predictor of Sigma Scan DGCI, resulting in significant p values for model, slope and intercept, while r^2 values ranged from 0.60 to 0.75 (Table 3). As with 2014 data, r^2 values did not follow the pattern of differences in DGCI values (Table 3), and attempts to fit an overall model to all 2015 data resulted in considerably lower r^2 (0.41) than models for individual image sets (Fig 15). These results supported 2014 findings, that the GreenIndex+ app could detect relative changes in turfgrass color under a range of lighting conditions; however, the relationship between DGCI values could not be adequately characterized by a single linear model. These results suggested that the app may be best used when solar radiation < 100 W m^{-2} (but > 0 W m^{-2}), as these image sets provided best correlation to light box DGCI. Further evaluations are needed to confirm these findings and develop definitive recommendations.

These models, and corresponding r^2 values, were based on simple linear regression of DGCI data only. The decision was made not to include additional solar radiation terms in a multiple regression model (at this time) so that the GreenIndex+ app, as used according to manufacturer's recommendations, could be compared to light box DIA and DGCI. (Subsequent efforts to develop multiple regression models from GreenIndex+ app data were carried out, and those results are discussed in the next section.) Inconsistencies observed throughout the day in DGCI differences, and r^2 values, limited the ability to quantify the effects of ambient lighting on the target board process using only app DGCI.

Comparing the consistency of the two DIA methods over a 16-hour period, DGCI values obtained under standardized lighting conditions displayed considerably less variability then those acquired under ambient lighting conditions (Fig. 16). As in 2014, σ of the GreenIndex+ DGCI was greater than that of Sigma Scan for each of the 20 individual plots (Table 4). As with 2014 results, in 2015, standard deviations differed ($p<0.05$) between the two DIA methods. Averaged across all plots, app σ was 0.083, compared to 0.005 for light box DIA (Table 4). For the DGCI values recorded throughout the day, within each plot, tests for equality of variance indicated unequal variance between the two DIA methods for all plots (Table 4). These results supported the variability observed in 2014, and indicated that comparing DGCI values of images collected with the GreenIndex+ app at different times, under different lighting conditions, was not equivalent to comparisons using published DIA methods. The consistency of light box DGCI indicated that turfgrass color was not changing throughout the day to the extent reported by the GreenIndex+ app. Given the observed range of solar irradiance for 2015 image sets, it was reasonable to conclude that the significantly greater variability in app DGCI was due to ambient lighting conditions. This variability further indicated that the target board was not capable of fully compensating for the lighting conditions present in this research. Essentially GreenIndex+ app DGCI values were actually comprised of two parts: *(i)* a turfgrass component, and *(ii)* an ambient light component; and meaningful comparisons of the portion attributed to turfgrass were not possible without quantifying the portion attributed to ambient lighting.

Additional Regression Models

Based on the observed effects of ambient lighting on both magnitude and correlation of DGCI values in this research, an additional question of interest developed: Could DGCI models be improved with the addition of a solar radiation term? The GreenIndex+ app's process of locking the white balance and referencing color standards had demonstrated *(i)* correlations with published DIA methods, and *(ii)* an ability for detecting relative differences in turfgrass color within a given set of images. However, variability between image sets acquired on different dates, or at different times of day, suggested a need to further standardize smartphone DIA and the DGCI values it produced. Instead of using GreenIndex+ DGCI as the sole predictor of light box DGCI, various candidate models were evaluated that incorporated solar irradiance and other information from the GreenIndex+ app's log file. The GreenIndex+ app's log contained raw (unadjusted) HSB of the turf, from which a raw DGCI value could be calculated. The raw HSB, raw DGCI, and solar irradiance were evaluated as additional/alternative predictors of Sigma Scan DGCI. These terms, along with, the original predictor (GreenIndex+ app DGCI), were included in a stepwise regression process based on p-value of β coefficients.

Solar irradiance and raw DGCI were identified as potential predictors for an expanded DGCI model (Fig. 17). The inclusion of a solar irradiance term in the model resulted in raw DGCI, rather than the corrected app DGCI, being selected. The model using raw DGCI and solar irradiance resulted in significant p-values and improved r^2 values, for five of the six image sets (Fig. 17). Image Set 4 was the notable exception, where p-value for the expanded model was 0.07, and r^2 values were greatly reduced (Fig. 17). Overall, these results indicated that directly incorporating solar irradiance into a model may help correlate smartphone images, collected under ambient lighting conditions, to DGCI of published research methods, using a light box.

Image Set 4 corresponded with the maximum observed ambient light (934 W m^{-2}); all other images sets resulting in significant p-values and improved r^2 values occurred at solar irradiance < 850 Wm^{-2} (Fig. 17). Future research may seek to examine not just light quantity, but angle of incoming light, and relative camera angle for capturing images. It should be noted that for image set 4, the original (corrected) app DGCI was determined to be the best predictor of light box DIA. These results indicated that the app's standard target board adjustments performed well under bright conditions. However, as light levels decreased, throughout the majority of the lighting present in this research, alternative options of correcting for ambient light improved the correlation of DGCI values to published research methods within individual image sets.

These additional models represent a starting point for future research and are not intended to be interpreted as a current alternative to the target board process. Based on the variability of app DGCI throughout this research, further understanding of how to best compensate for ambient lighting conditions, at different light thresholds, may be useful for improving consistency of smartphone DGCI.

For this research, solar irradiance values were obtained from an onsite weather station. Coordinating GreenIndex+ image processing with smartphone apps that utilize the device itself as a light meter could conceivably provide more instantaneous, precise ambient light measurements for each individual image. Overall, these results further illustrated the substantial effects of ambient light on DIA, and the difficulty of applying a single model (or process) to account for the broad range of lighting conditions observed within a single day. Given the variability observed with the target board/color standard method of accounting for ambient lighting in smartphone DIA, these results suggest that direct quantification of ambient lighting may be capable of contributing to improved consistency to smartphone DIA. Additional research is needed to determine the best method of incorporating such information and for the development of potential models.

Summary & Conclusions

For the purposes of quantifying turfgrass color through DIA, the GreenIndex+ Turf app provided less consistency than published DIA methods. Within a given set of images, the app's process of referencing color standards on a target board under ambient light produced DGCI values highly correlated to images from an enclosed, standardized lighting environment. The GreenIndex+ app offered simplified image acquisition and processing features, along with the ability to detect relative differences in turfgrass color. However, when tracking DGCI values over time, the convenience of this process may become a liability. Comparing DGCI values across multiple image collection events, the greater variability of app data compared to light box methodology, raised serious questions about interpreting the data. While the target board provided a reference for comparing turfgrass color under ambient lighting conditions, the adjustments it generated were not capable of consistently accounting for differences in ambient lighting observed in this research. Compared to light box DIA, the specific DGCI values from the GreenIndex+ app still exhibited the effects of the light under which images were collected.

It should be expected that smartphone devices capable of rapidly generating data within the field will continue to be sought after by turfgrass managers and researchers alike. For turfgrass research or intensively managed turfgrass situations, DGCI values need to be comparable over time. While the GreenIndex+ app has demonstrated an ability to detect relative differences in turfgrass color, the mechanism of adjusting for ambient lighting may benefit from incorporating additional light data. Directly quantifying ambient lighting conditions in order to improve the mechanism of adjustment and achieve consistency comparable to published research methodology warrants further research. Replacement of the target board with direct light measurements made by the smartphone device would only add to the convenience of the app, and possibly the correlation to DGCI of published research methods as well. Ultimately, the convenience of data acquisition has to be balanced by the accuracy of the measurements. The consistency demonstrated by published DIA methods, which completely eliminate ambient light, demands that smartphone DIA methodology fully account for the effects of variable ambient lighting, in order to be considered a comparable research alternative.

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CAPTIONS

Table 1. Parameter estimates, r^2, and P values for 2014 linear models relating dark green color index (DGCI) of the GreenIndex+ Turf app to DGCI from published digital image analysis (DIA) methods using Sigma Scan; average solar irradiance and range of observed DGCI for each date, are also included.

Table 2. Individual plot comparisons of dark green color index (DGCI) means, with 95% confidence limits (CL), and standard deviation (σ) for all 2014 data.

Table 3. Parameter estimates, r^2, and p values for 2015 linear models relating dark green color index (DGCI) of the GreenIndex+ Turf app to DGCI from published digital image analysis (DIA) methods using Sigma Scan; average solar irradiance and range of observed DGCI values for each Image Set, are also included.

Table 4. Individual plot comparisons of dark green color index (DGCI) mean, with 95% confidence limits (CL), and standard deviation (σ) for all 2015 data.

Fig. 1. (a) Portable enclosed light box and camera used for published research methods of digital image analysis (DIA). **(b)** View of standardized lighting conditions inside light box, looking upward from turfgrass perspective. **(c)** Image produced for color analysis by DIA using enclosed light box.

Fig. 2. (a) Smartphone devices and target board used in GreenIndex+Turf app data collection; iPod touch (left) used in 2014 and iPhone 5 (right) used in 2015. Grey section of target board used to lock white balance of smartphone camera; green and yellow sections used as reference standards for adjusting images based on ambient light conditions. **(b)** “Process” screen of GreenIndex+ Turf app.

Fig. 3. Dark green color index (DGCI) values obtained in 2014 using: *(ii)* the GreenIndex+ Turf app, and *(ii)* published research methods involving light box digital image analysis and Sigma Scan.

Fig. 4. Values for dark green color index (DGCI), with fitted regression models for 2014 evaluation dates.

Fig. 5. Comparison of GreenIndex+ Turf app images and corresponding solar irradiance values for Aug. 25 and Sept. 4, 2014.

Fig. 6. Comparison of GreenIndex+ Turf app images and corresponding solar irradiance values for Sept. 12 and Sept. 19, 2014.

Fig. 7. Comparison of GreenIndex+ Turf app images and corresponding solar irradiance values for Oct. 3 and Oct. 14, 2014.

Fig. 8. Comparison of variability in dark green color index (DGCI) values observed within each plot throughout 2014.

Fig. 9. Linear regression relating turfgrass visual ratings to dark green color index (DGCI) values for 2014 data.

Fig. 10. Observed solar irradiance (W m^{-2}) during data collection on 15 Aug. 2015. GreenIndex+ Turf app was unable to process images under ambient lighting conditions of Image set 1.

Fig. 11 Images from 15 Aug. 2015 when solar irradiance was 0 W m^{-2}. **(a)** Ambient lighting conditions of experimental area during collection of image set 1. **(b)** GreenIndex+ Turf app image processing screen during image set 1. **(c)** Light box image from set 1 with greatest dark green color index (DGCI). **(d)** GreenIndex+ Turf app image of corresponding plot from final image set (8) using iPhone camera flash. **(e)** Light box image of corresponding plot from final image set (8).

Fig. 12. Dark green color index (DGCI) values obtained in 2015 using: *(ii)* the GreenIndex+ Turf app, and *(ii)* published research methods involving light box digital image analysis and Sigma Scan.

Fig. 13. Light box images of plots with minimum and maximum dark green color index (DGCI) values observed in 2014 and 2015. Plots with min. and max. DGIC according to Sigma Scan (**a, b, c, d**) on the left; plots with min. and max. DGIC according to GreenIndex+ Turf app (**e, f, g, h**) on the right.

Fig. 14. Comparison of dark green color index (DGCI) values produced by GreenIndex+ Turf app using iPod touch and iPhone 5.

Fig. 15. Values for dark green color index (DGCI), with fitted regression models for 2015 image sets using GreenIndex+ Turf app and light box digital image analysis with Sigma Scan processing.

Fig. 16. Comparison of variability in dark green color index (DGCI) values observed within each plot throughout 15 Aug. 2015.

Fig. 17. Comparison of 2015 linear models for predicting dark green color index (DGCI) of published research methods using Sigma Scan. App DGCI only models based on standard protocol of GreenIndex+ app; alternative model constructed using solar irradiance measurements and raw DGCI based on hue, saturation, and brightness in the app's log file.

Table 1. Parameter estimates, r^2, and P-values for 2014 linear models relating dark green color index (DGCI) of the GreenIndex+ Turf app to DGCI from published digital image analysis (DIA) methods using Sigma Scan; average solar irradiance and range of observed DGCI for each date, are also included.

Table 1.

2014 Linear regression models for dark green color index values

						Sigma Scan DGCI		GreenIndex+ Turf DGCI	
Date	**Slope**	**Intercept**	**r^2**	**P-value (model)**	**Avg. solar radiation* (W m^{-2})**	**min.**	**max.**	**min.**	**max.**
11 Aug.	0.476	0.428	0.81	<0.0001	330	0.637	0.729	0.430	0.626
15 Aug.	0.398	0.454	0.92	<0.0001	552	0.614	0.698	0.413	0.629
25 Aug.	0.473	0.466	0.87	<0.0001	178	0.637	0.717	0.359	0.543
4 Sept.	0.520	0.352	0.88	<0.0001	948	0.602	0.661	0.489	0.604
8 Sept.	0.382	0.446	0.73	<0.0001	472	0.597	0.668	0.421	0.572
12 Sept.	0.382	0.459	0.92	<0.0001	316	0.582	0.673	0.331	0.576
19 Sept.	0.458	0.388	0.73	<0.0001	863	0.591	0.675	0.465	0.620
26 Sept.	0.497	0.354	0.87	<0.0001	825	0.574	0.654	0.452	0.603
3 Oct.	0.473	0.477	0.90	<0.0001	353	0.625	0.718	0.328	0.511
14 Oct.	0.456	0.417	0.94	<0.0001	878	0.595	0.727	0.427	0.742
All 2014 combined	0.233	0.534	0.23	<0.0001		0.574	0.729	0.328	0.742

*Avg. Solar radiation for the time of GreenIndex+ Turf app image collection

Table 2. Individual plot comparisons of dark green color index (DGCI) means, with 95% confidence limits (CL), and standard deviation (σ) for all 2014 data.

Table 2.

2014 Comparison of dark green color index values and variability

		Sigma Scan DGCI				GreenIndex+ Turf app DGIC				
Fertility ($g\ N\ m^{-2}$)	**Plot**	**Mean**	**95% CL**		**σ**	**Mean**	**95% CL**		**σ**	**P-value**
0.0	**3**	0.623	0.607	0.639	0.023	0.423	0.380	0.466	0.061	0.0076
	9	0.636	0.620	0.652	0.022	0.463	0.424	0.502	0.055	0.0114
	11	0.607	0.591	0.624	0.023	0.426	0.386	0.465	0.055	0.0171
	17	0.611	0.595	0.628	0.023	0.430	0.397	0.464	0.047	0.0500*
0.5	**4**	0.634	0.619	0.649	0.021	0.448	0.400	0.496	0.067	0.0023
	7	0.652	0.634	0.670	0.025	0.494	0.462	0.527	0.045	0.0991*
	12	0.610	0.595	0.624	0.020	0.436	0.400	0.472	0.050	0.0112
	19	0.636	0.618	0.654	0.025	0.467	0.435	0.498	0.044	0.1077*
1.2	**2**	0.650	0.630	0.669	0.028	0.485	0.447	0.523	0.531	0.0629*
	10	0.656	0.639	0.673	0.024	0.503	0.469	0.538	0.049	0.0432
	14	0.633	0.617	0.649	0.022	0.467	0.429	0.505	0.053	0.0147
	16	0.635	0.618	0.651	0.023	0.483	0.450	0.516	0.046	0.0515*
2.4	**5**	0.682	0.663	0.701	0.026	0.546	0.506	0.585	0.056	0.0364
	8	0.684	0.664	0.704	0.028	0.575	0.536	0.614	0.054	0.0579*
	13	0.666	0.649	0.683	0.024	0.542	0.503	0.580	0.054	0.0224
	18	0.663	0.641	0.685	0.031	0.533	0.493	0.574	0.057	0.0897*
4.9	**1**	0.686	0.664	0.708	0.031	0.565	0.520	0.610	0.063	0.0463
	6	0.688	0.668	0.708	0.028	0.578	0.548	0.607	0.041	0.2634*
	15	0.680	0.660	0.700	0.028	0.558	0.526	0.590	0.045	0.1716*
	20	0.678	0.657	0.700	0.030	0.583	0.533	0.682	0.070	0.0186

*Equality of variance test indicated DIA methods were not significantly different

Table 3. Parameter estimates, r^2, and p-values for 2015 linear models relating dark green color index (DGCI) of the GreenIndex+ Turf app to DGCI from published digital image analysis (DIA) methods using Sigma Scan; average solar irradiance and range of observed DGCI values for each Image Set, are also included.

Table 3.

2015 Linear regression models for dark green color index values

						Sigma Scan DGCI		GreenIndex+ Turf DGCI	
Image set	**Slope**	**Intercept**	**r^2**	**P-value (model)**	**Avg. solar radiation ($W\ m^{-2}$)**	**min.**	**max.**	**min.**	**max.**
2	0.295	0.213	0.75	<0.0001	10	0.381	0.433	0.598	0.732
3	0.155	0.290	0.60	<0.0001	422	0.383	0.426	0.638	0.843
4	0.230	0.263	0.68	<0.0001	934	0.377	0.415	0.517	0.658
5	0.186	0.284	0.69	<0.0001	843	0.382	0.411	0.522	0.663
6	0.188	0.267	0.73	<0.0001	515	0.381	0.416	0.612	0.778
7	0.258	0.251	0.73	<0.0001	82	0.379	0.413	0.506	0.633
8	0.222	0.224	0.35	<0.0001	0	0.376	0.418	0.689	0.800
Image sets 2-7 combined	0.097	0.335	0.41			0.377	0.433	0.506	0.843

Table 4. Individual plot comparisons of dark green color index (DGCI) mean, with 95% confidence limits (CL), and standard deviation (σ) for all 2015 data.

Table 4.

2015 Comparison of dark green color index values and variability

		Sigma Scan DGCI				**GreenIndex+ Turf app DGIC**				
Fertility ($g\ N\ m^{-2}$)	**Plot**	**Mean DGCI**	**95% CL**		**σ**	**Mean DGCI**	**95% CL**		**σ**	**P-value***
0.0	**2**	0.388	0.382	0.394	0.007	0.601	0.516	0.686	0.092	<0.0001
	7	0.386	0.383	0.389	0.004	0.607	0.540	0.675	0.073	<0.0001
	11	0.385	0.379	0.391	0.007	0.605	0.532	0.677	0.078	<0.0001
	20	0.394	0.391	0.396	0.003	0.624	0.543	0.706	0.088	<0.0001
0.5	**5**	0.390	0.389	0.391	0.001	0.607	0.534	0.681	0.080	<0.0001
	8	0.400	0.395	0.406	0.006	0.650	0.581	0.719	0.075	<0.0001
	12	0.386	0.383	0.390	0.004	0.598	0.536	0.660	0.067	<0.0001
	17	0.380	0.378	0.383	0.003	0.616	0.532	0.699	0.090	<0.0001
1.2	**1**	0.400	0.394	0.407	0.007	0.635	0.551	0.719	0.091	<0.0001
	9	0.387	0.384	0.390	0.003	0.619	0.543	0.695	0.082	<0.0001
	13	0.389	0.383	0.394	0.006	0.635	0.552	0.718	0.090	<0.0001
	18	0.390	0.385	0.395	0.006	0.635	0.559	0.710	0.082	<0.0001
2.4	**4**	0.401	0.395	0.407	0.007	0.654	0.575	0.731	0.084	<0.0001
	10	0.395	0.390	0.400	0.006	0.647	0.571	0.724	0.083	<0.0001
	15	0.391	0.385	0.395	0.005	0.639	0.556	0.722	0.090	<0.0001
	16	0.405	0.400	0.410	0.006	0.668	0.590	0.747	0.085	<0.0001
2.4 + Fe	**3**	0.419	0.412	0.426	0.008	0.712	0.645	0.778	0.07	<0.0001
	6	0.408	0.402	0.414	0.007	0.684	0.613	0.760	0.080	<0.0001
	14	0.410	0.404	0.415	0.006	0.715	0.622	0.808	0.100	<0.0001
	19	0.409	0.406	0.412	0.003	0.696	0.624	0.767	0.077	<0.0001

*P-values associated with equality of variance test

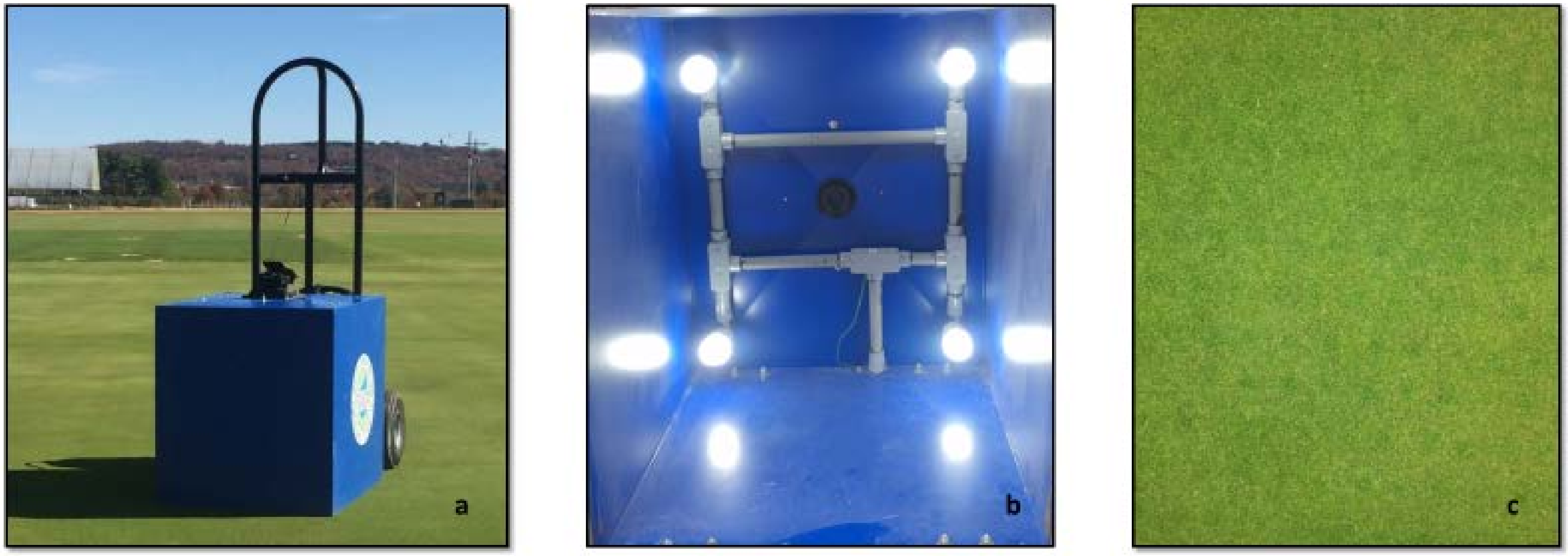
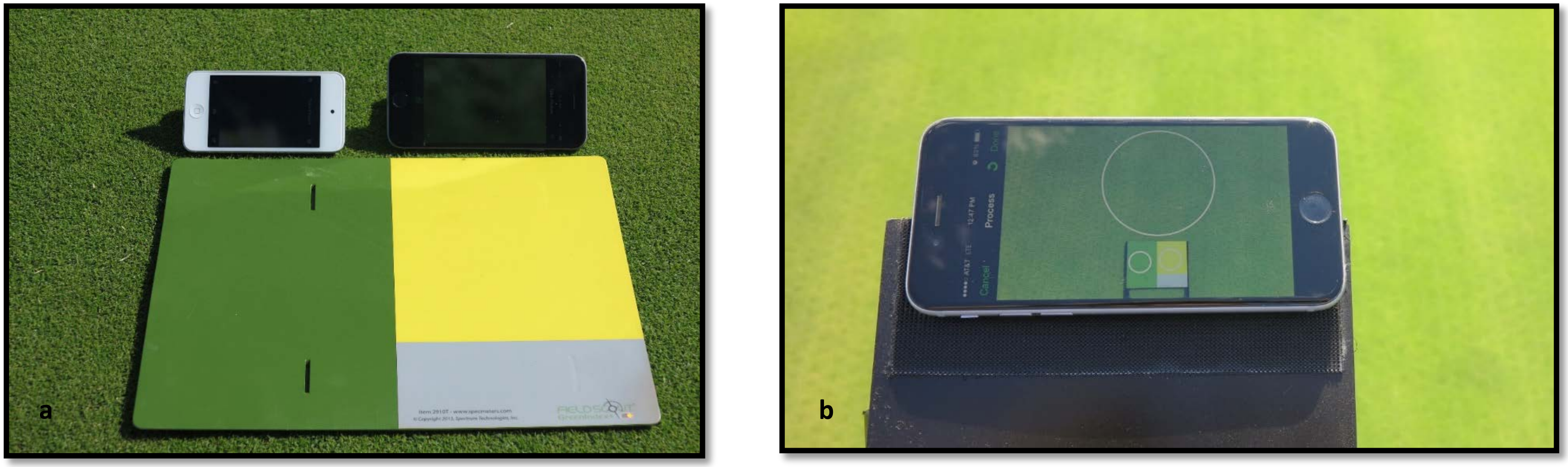


Fig. 1. (a) Portable enclosed light box and camera used for published research methods of digital image analysis (DIA). **(b)** View of standardized lighting conditions inside light box, looking upward from turfgrass perspective. **(c)** Image produced for color analysis by DIA using enclosed light box.



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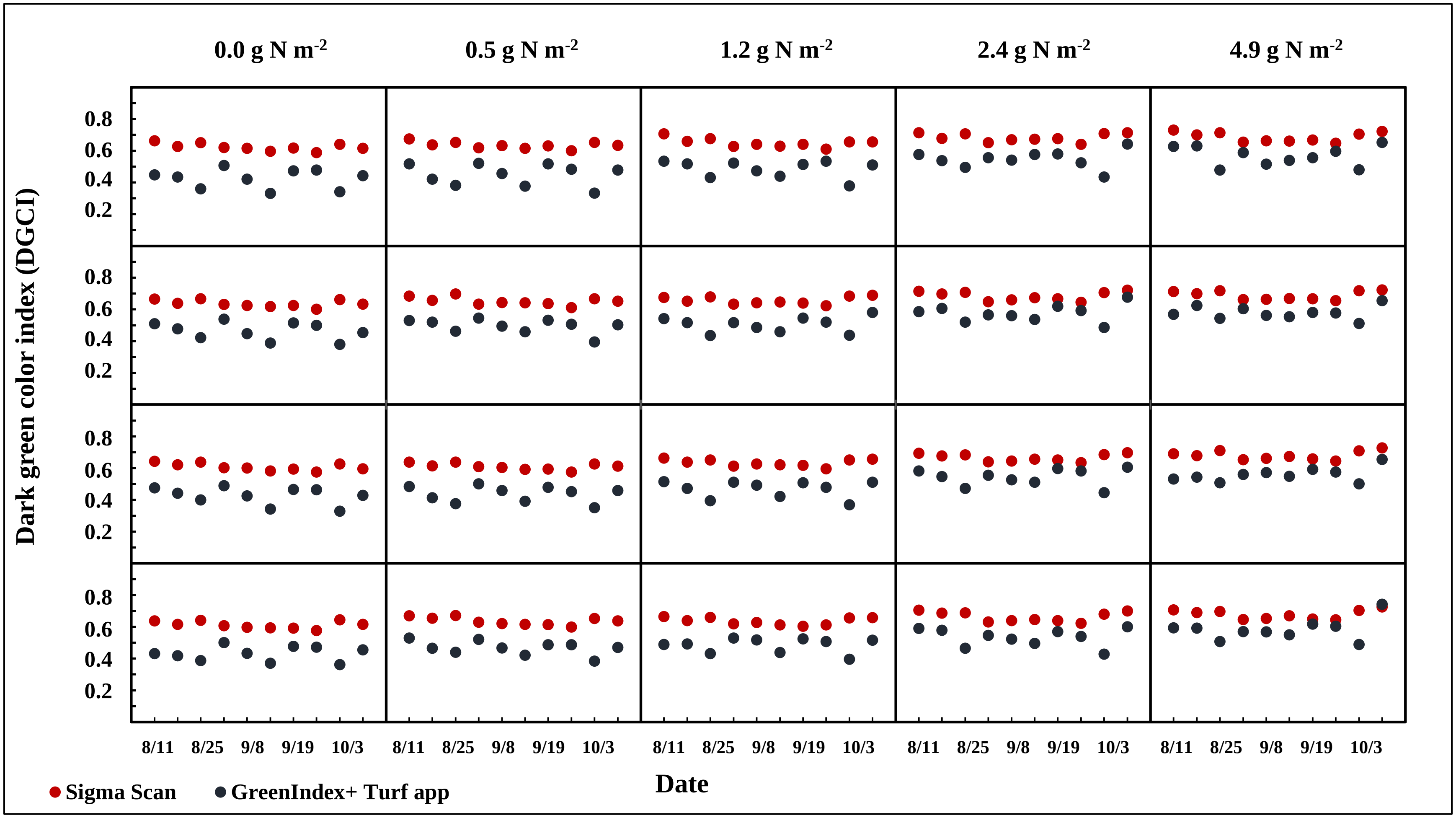


Fig. 3. Dark green color index (DGCI) values obtained in 2014 using: *(ii)* the GreenIndex+ Turf app, and *(ii)* published research methods involving light box digital image analysis and Sigma Scan.

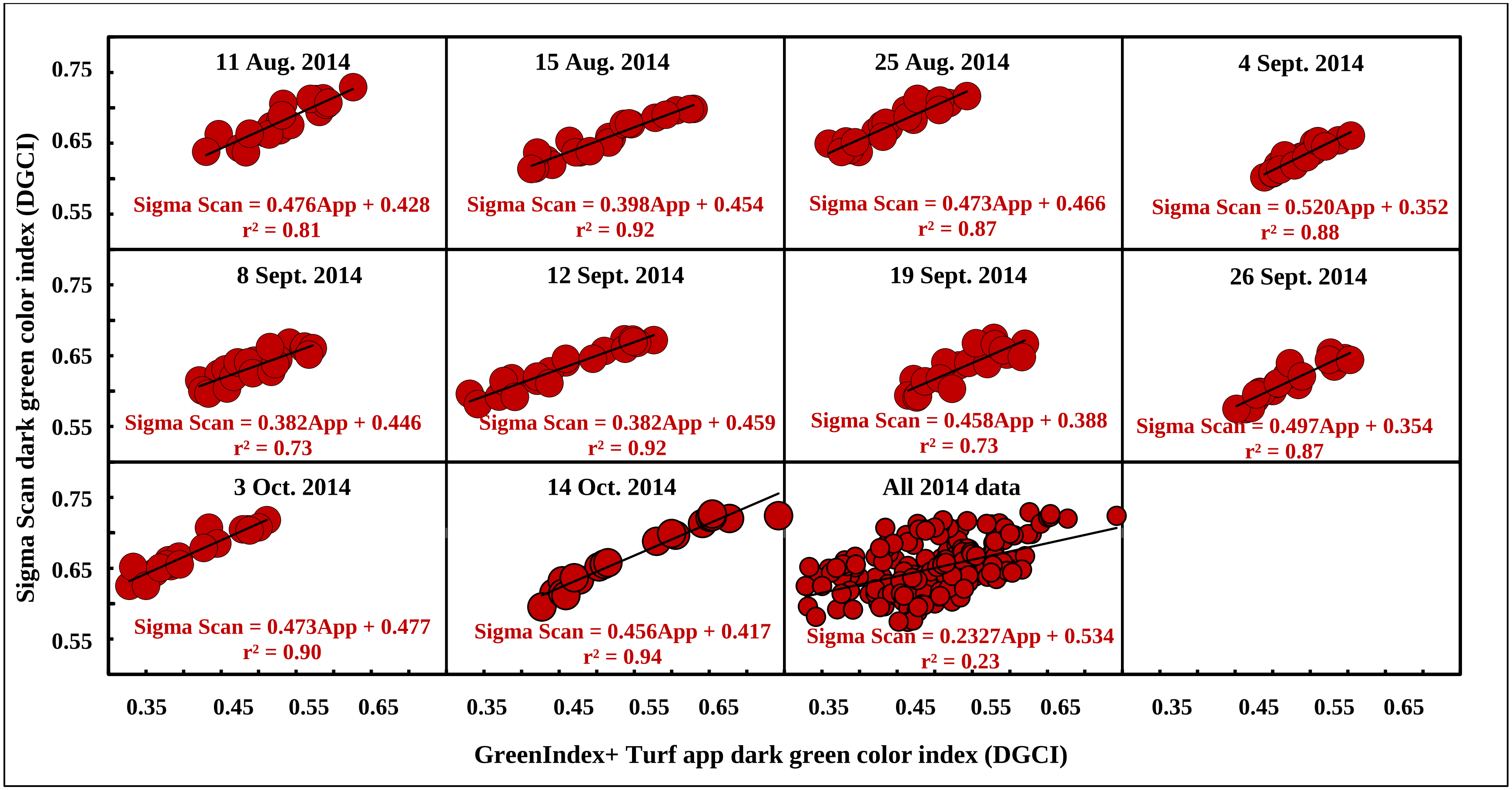


Fig. 4. Values for dark green color index (DGCI), with fitted regression models for 2014 evaluation dates.

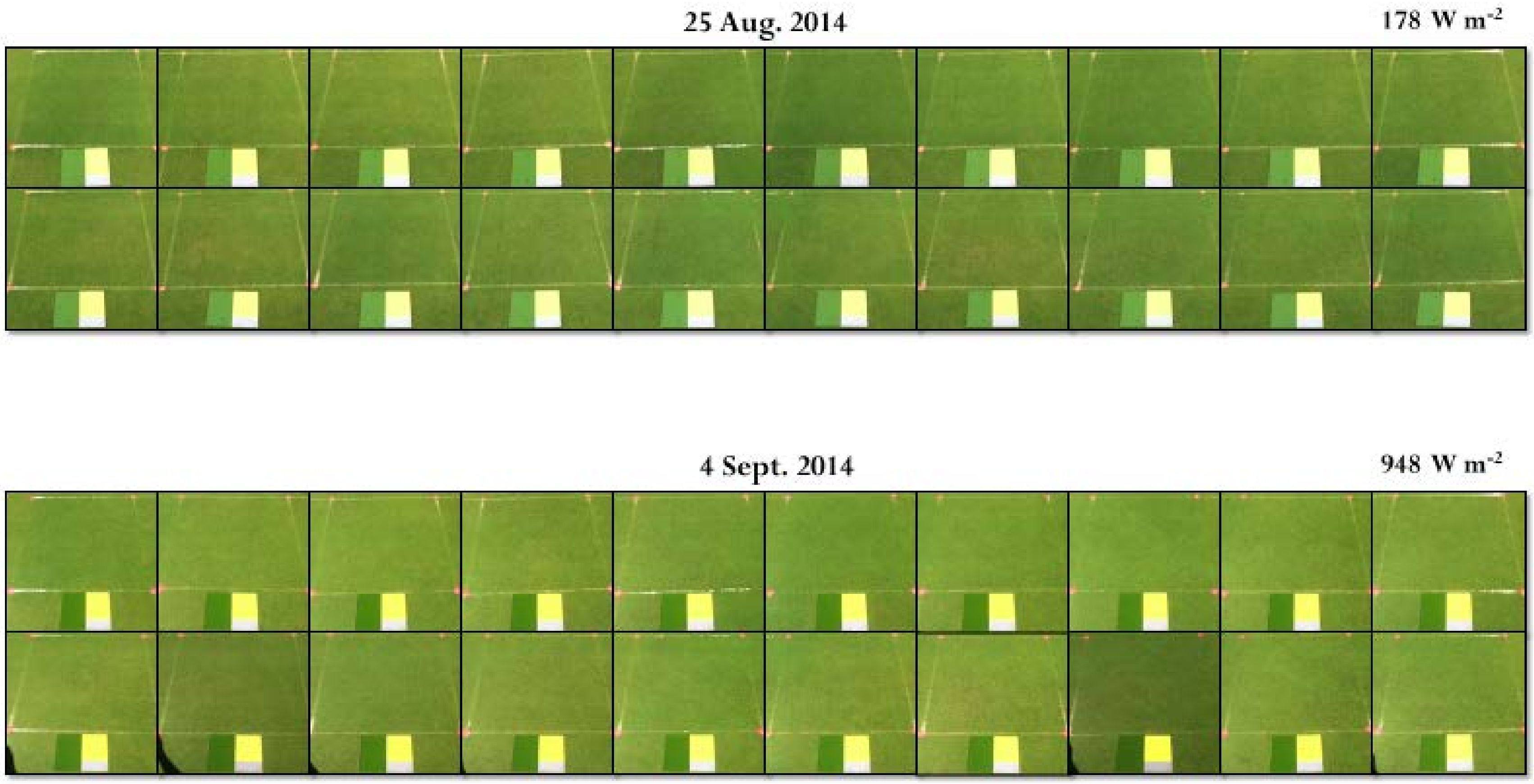


Fig. 5. Comparison of GreenIndex+ Turf app images and corresponding solar irradiance values for Aug. 25 and Sept. 4, 2014.

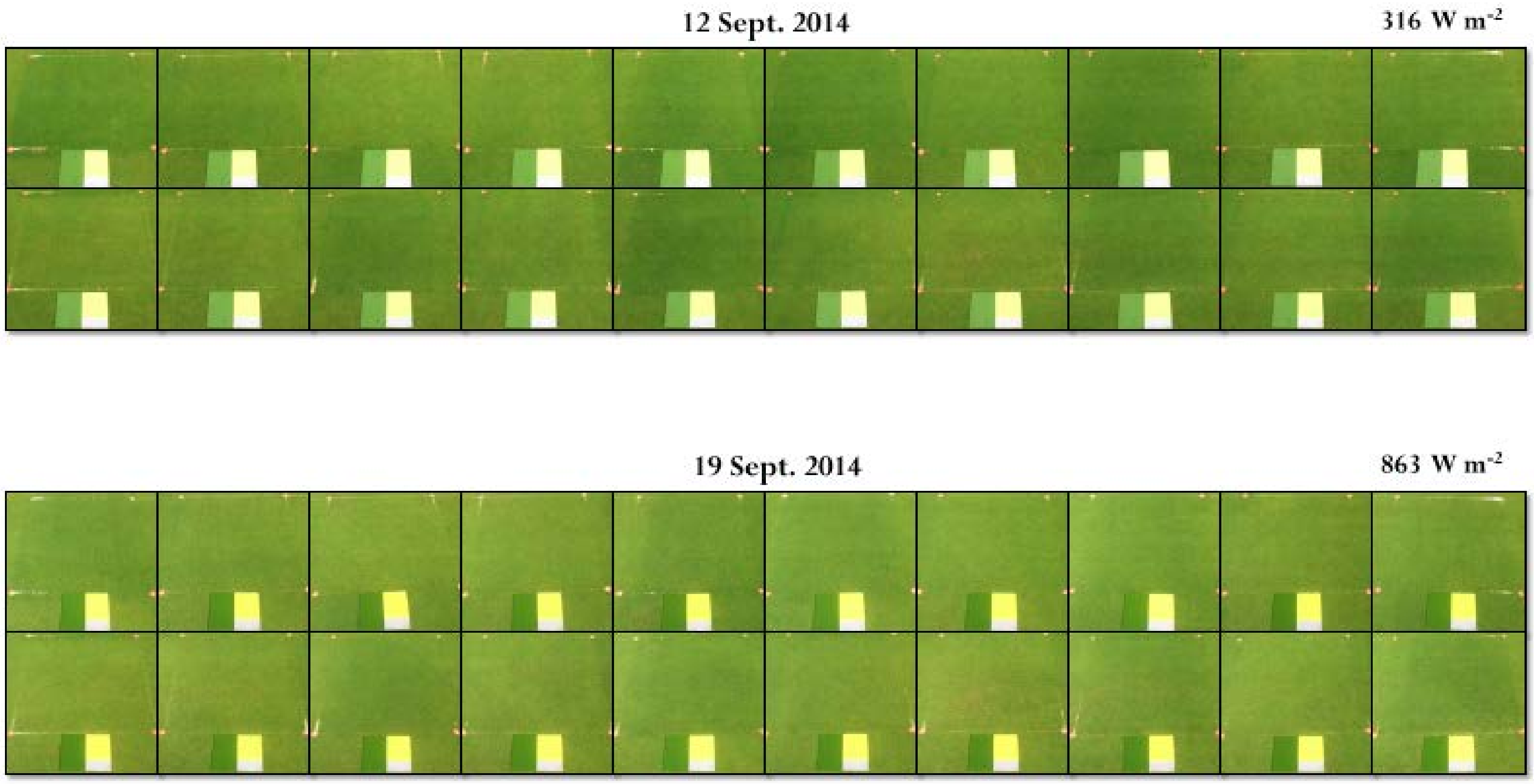


Fig. 6. Comparison of GreenIndex+ Turf app images and corresponding solar irradiance values for Sept. 12 and Sept. 19, 2014.

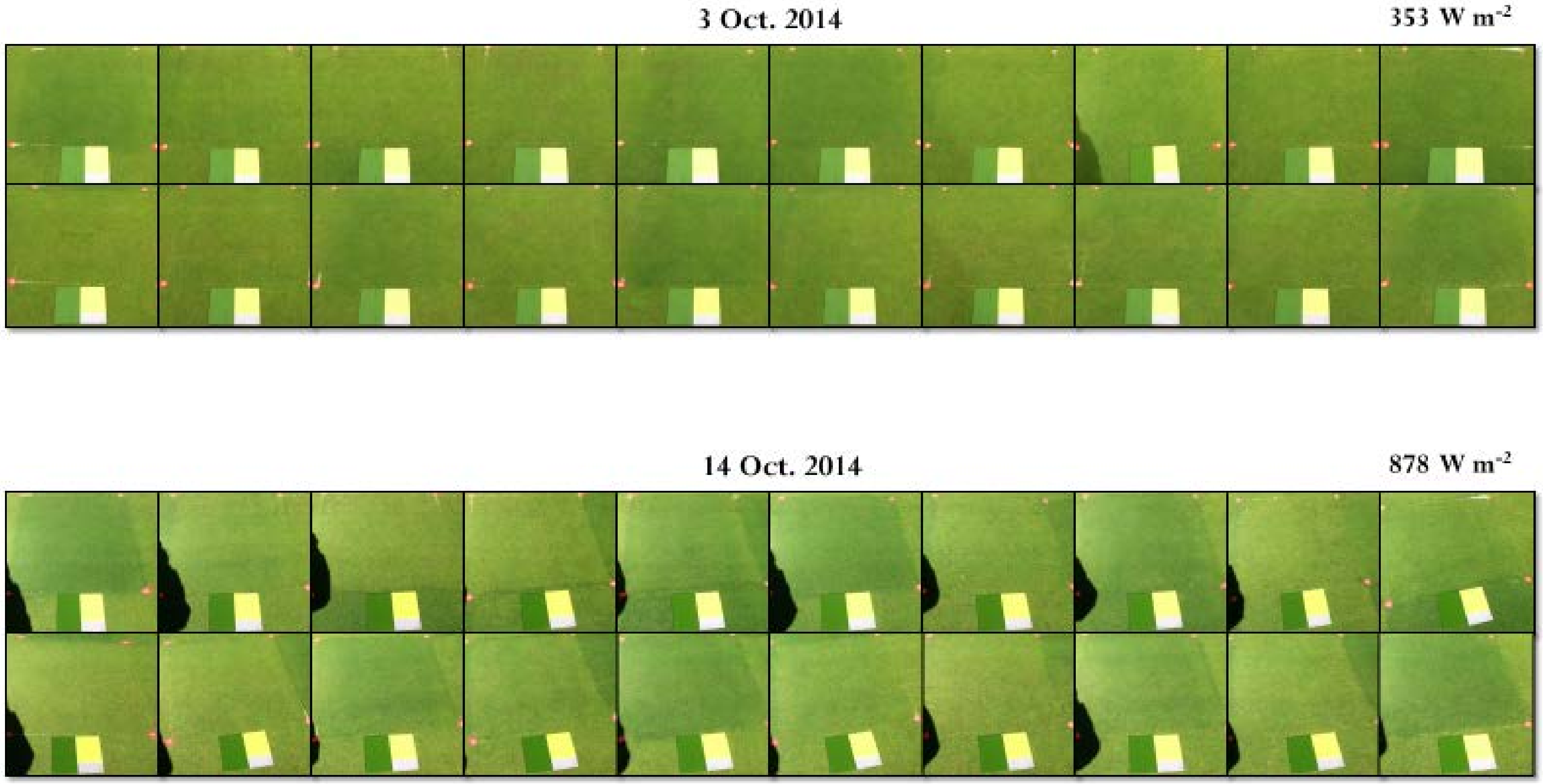


Fig. 7. Comparison of GreenIndex+ Turf app images and corresponding solar irradiance values for Oct. 3 and Oct. 14, 2014.

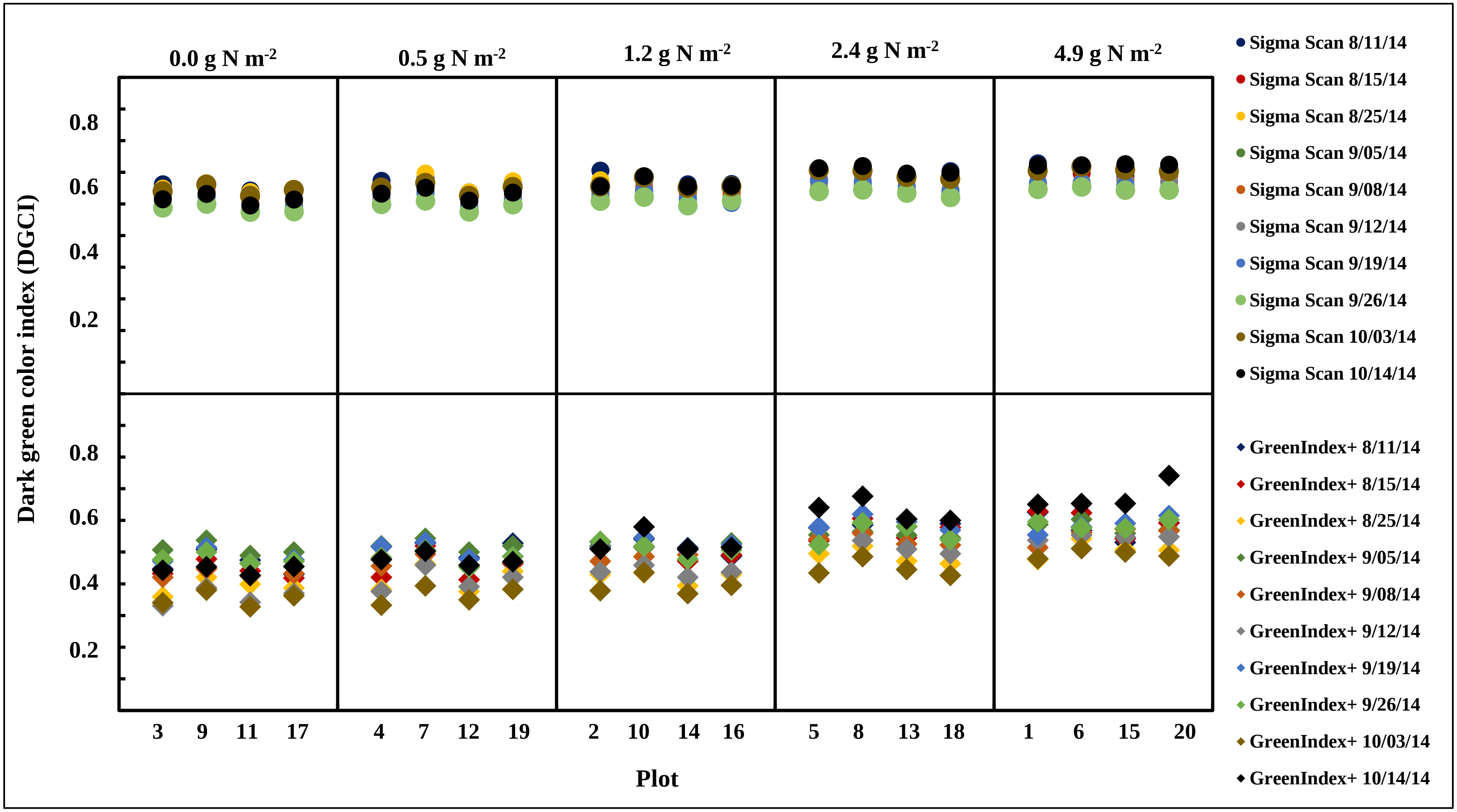


Fig. 8. Comparison of variability in dark green color index (DGCI) values observed within each plot throughout 2014.

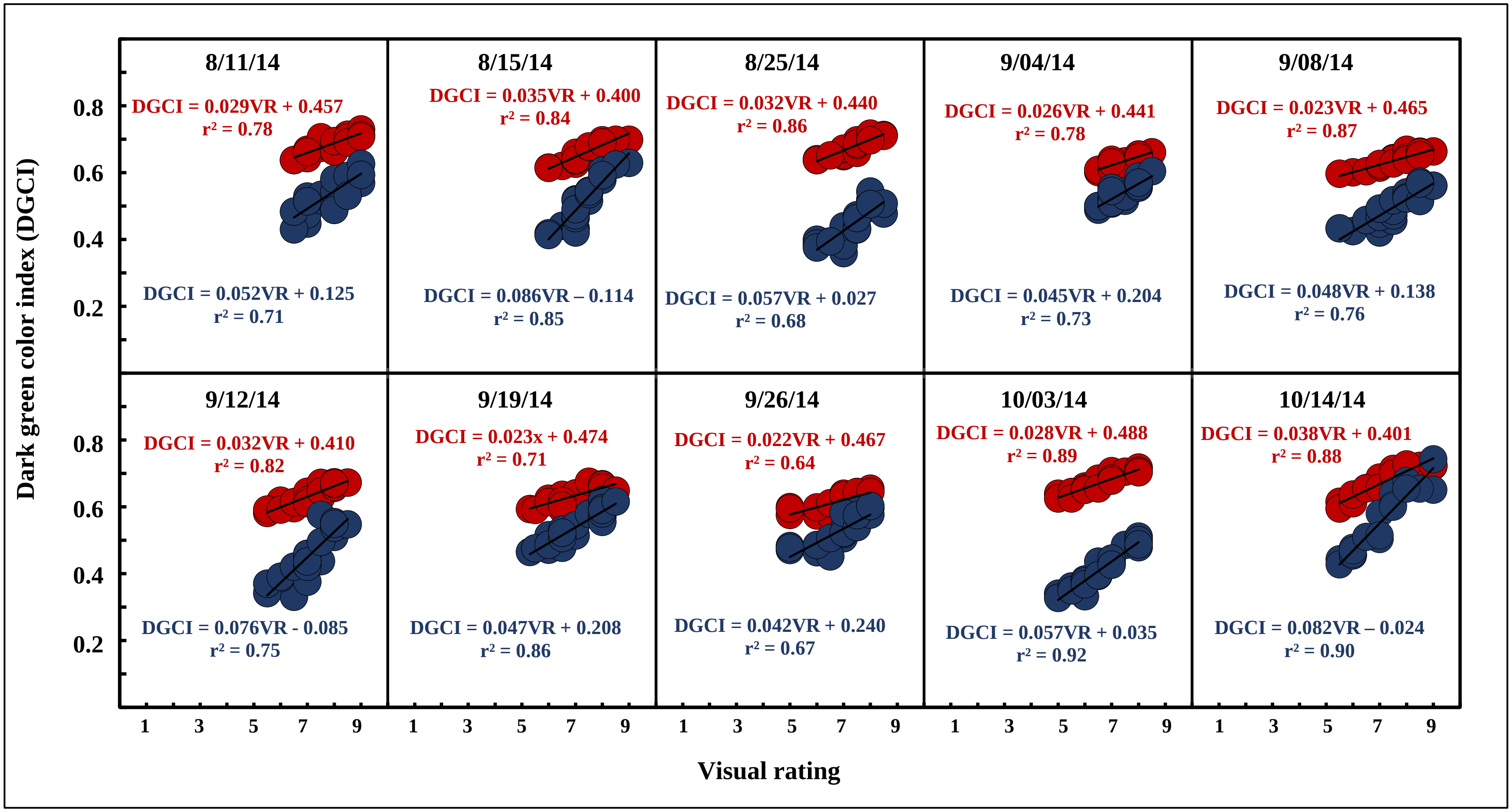


Fig. 9. Linear regression relating turfgrass visual ratings to dark green color index (DGCI) values for 2014 data.

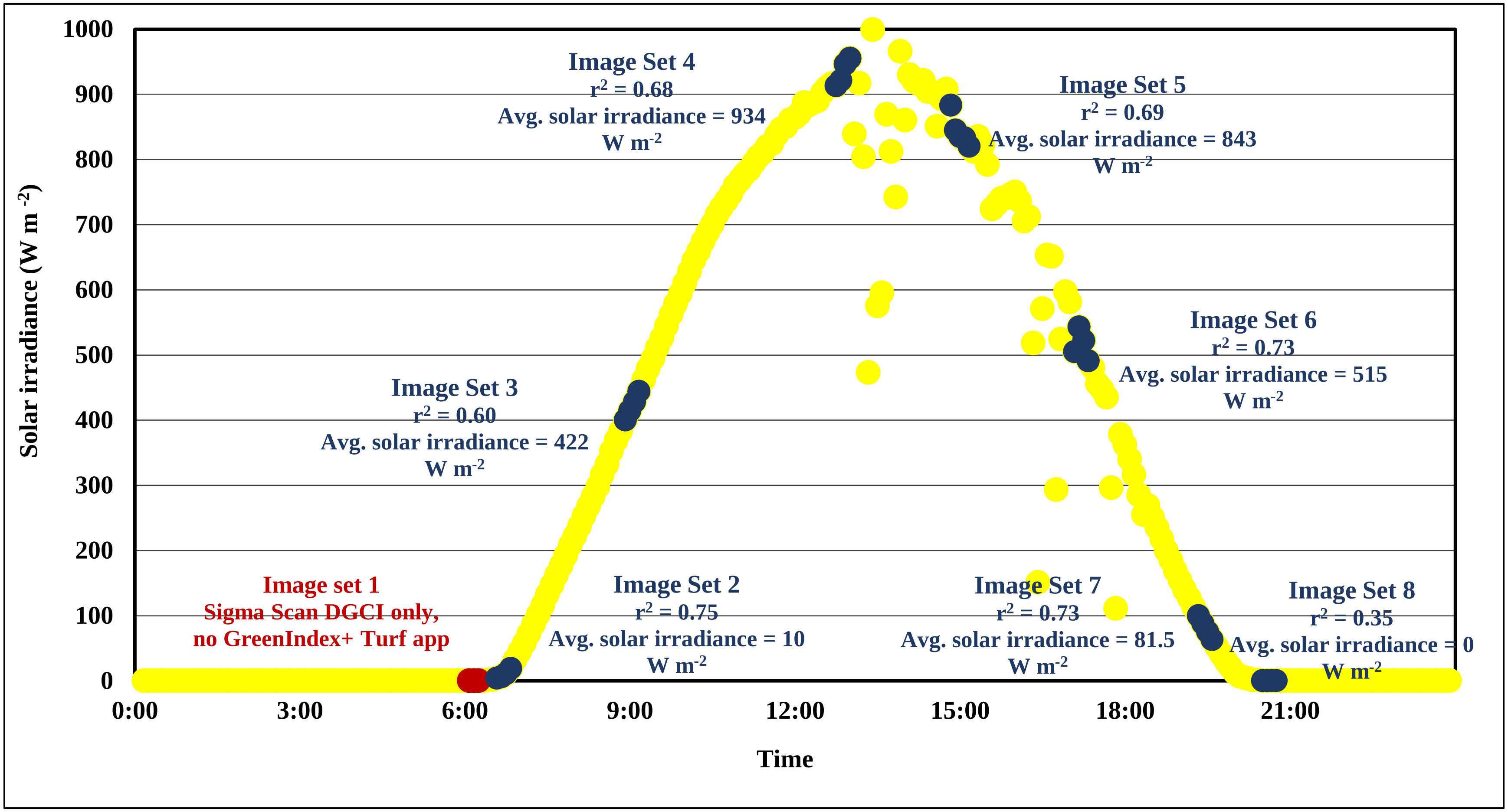


Fig. 10. Observed solar irradiance (W m^{-2}) during data collection on 15 Aug. 2015. GreenIndex+ Turf app was unable to process images under ambient lighting conditions of image set 1.

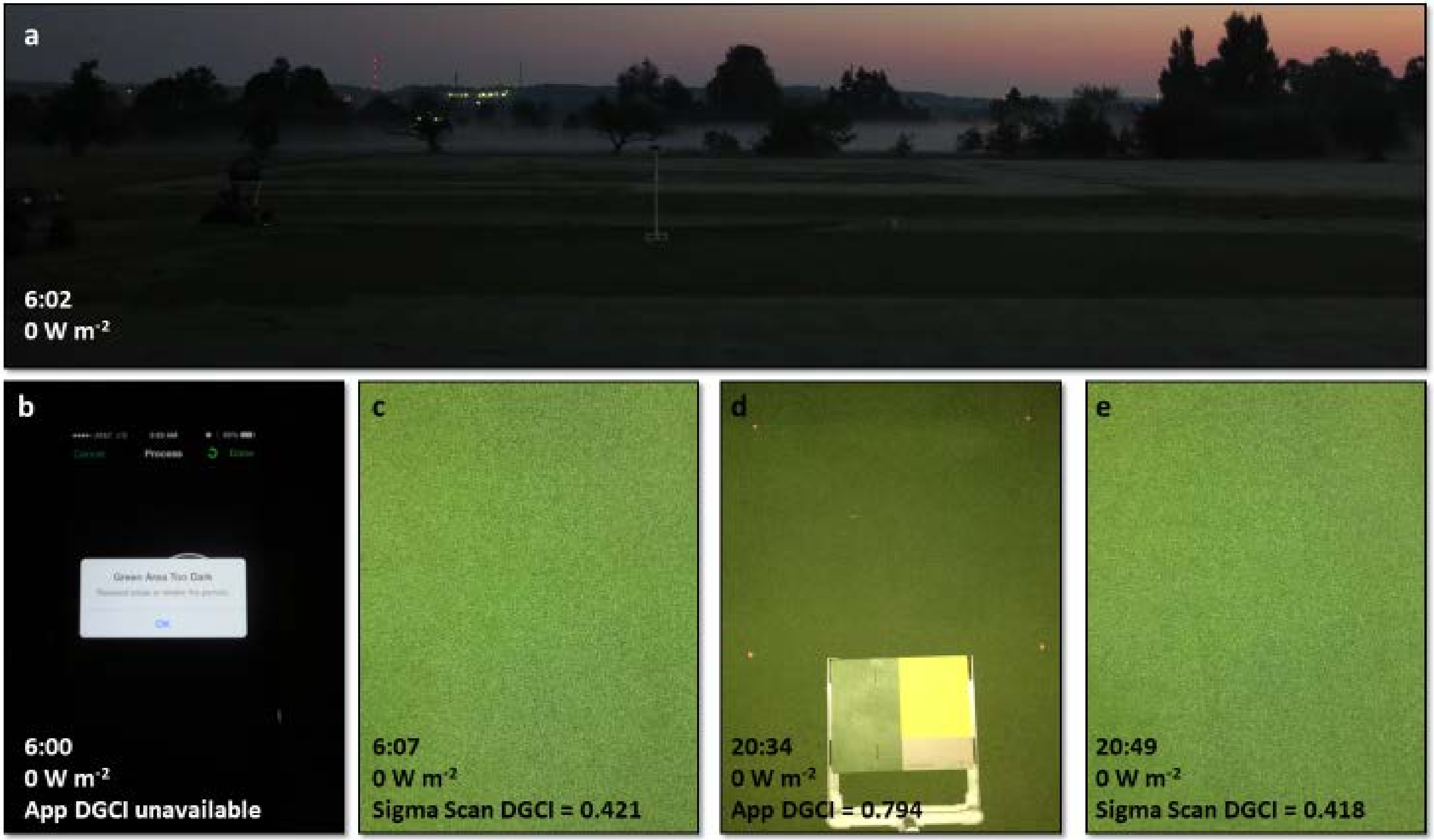
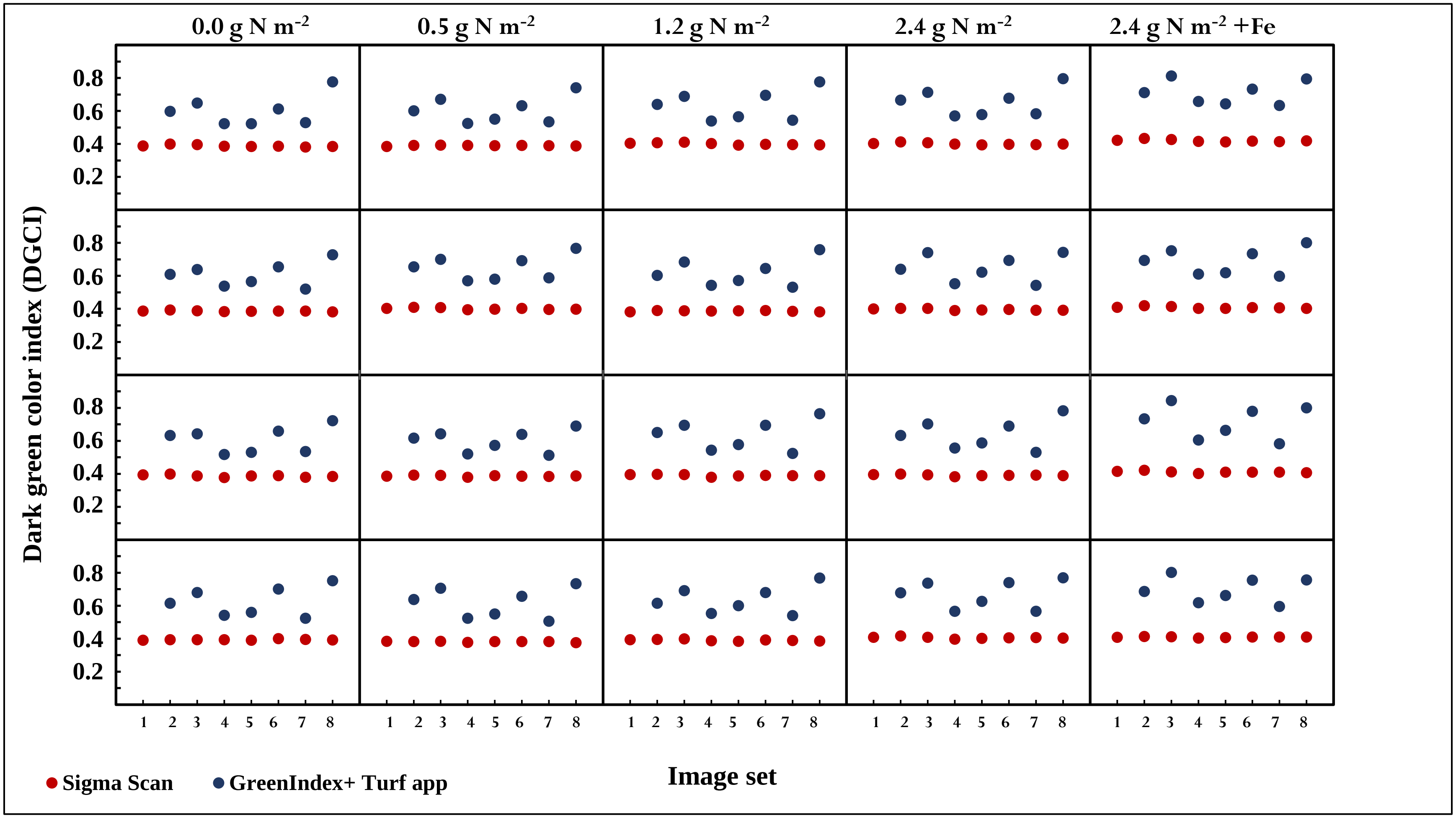


Fig. 11 Images from 15 Aug. 2015 when solar irradiance was 0 W m^{-2}. **(a)** Ambient lighting conditions of experimental area during collection of image set 1. **(b)** GreenIndex+ Turf app image processing screen during image set 1. **(c)** Light box image from set 1 with greatest dark green color index (DGCI). **(d)** GreenIndex+ Turf app image of corresponding plot from final image set (8) using iPhone camera flash. **(e)** Light box image of corresponding plot from final image set (8).



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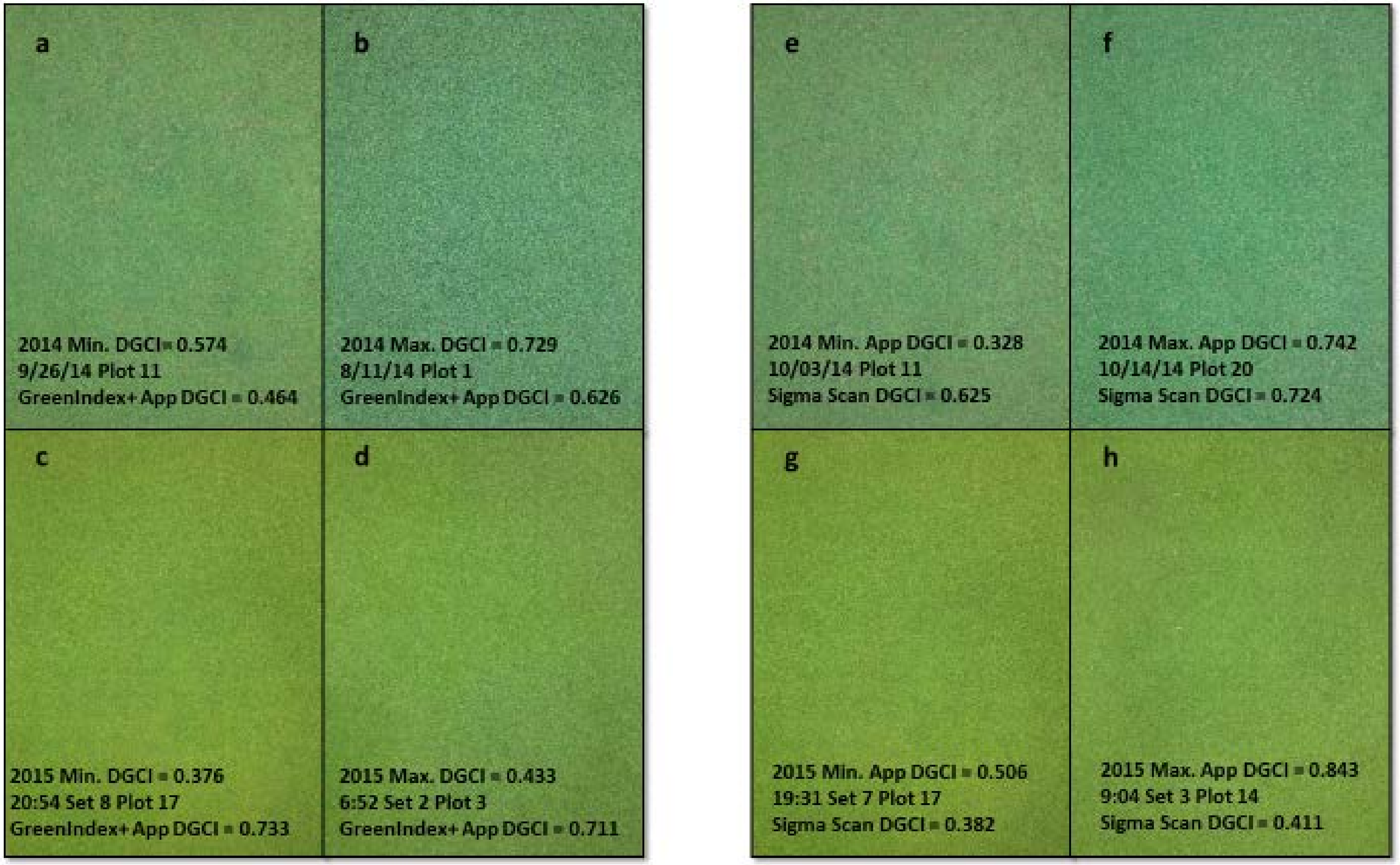

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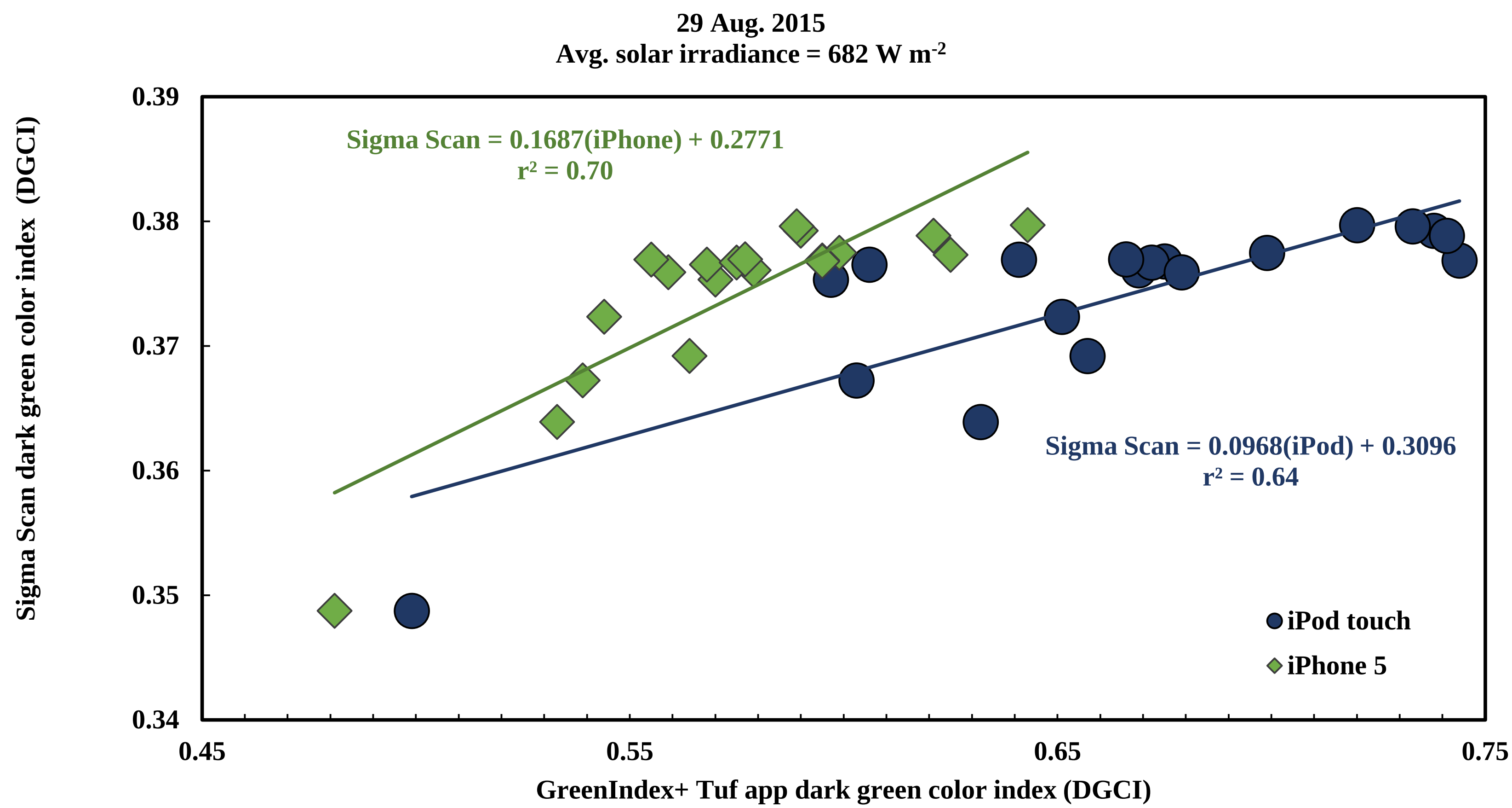

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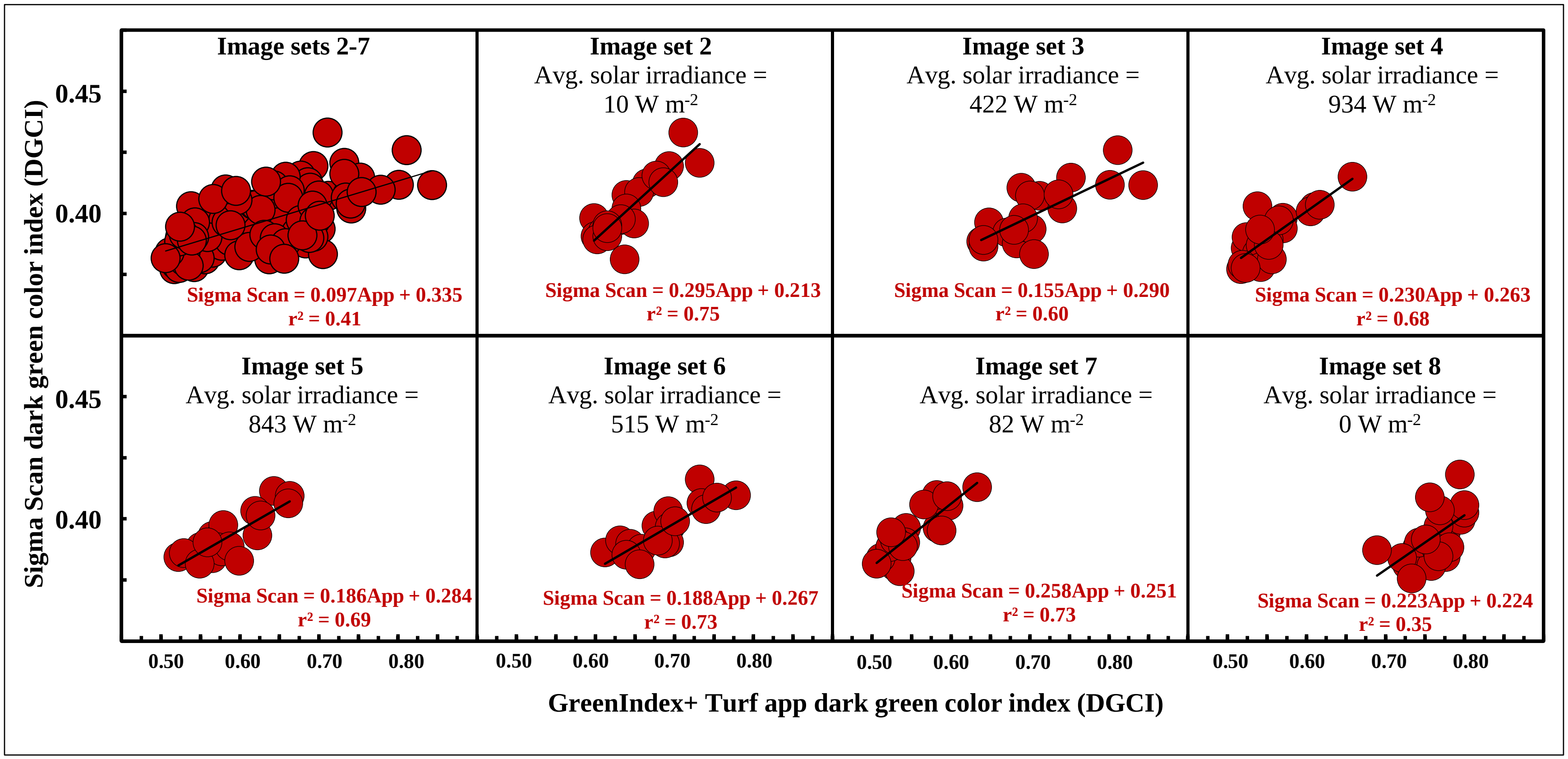


Fig. 15. Values for dark green color index (DGCI), with fitted regression models for 2015 image sets using GreenIndex+ Turf app and light box digital image analysis with Sigma Scan processing.

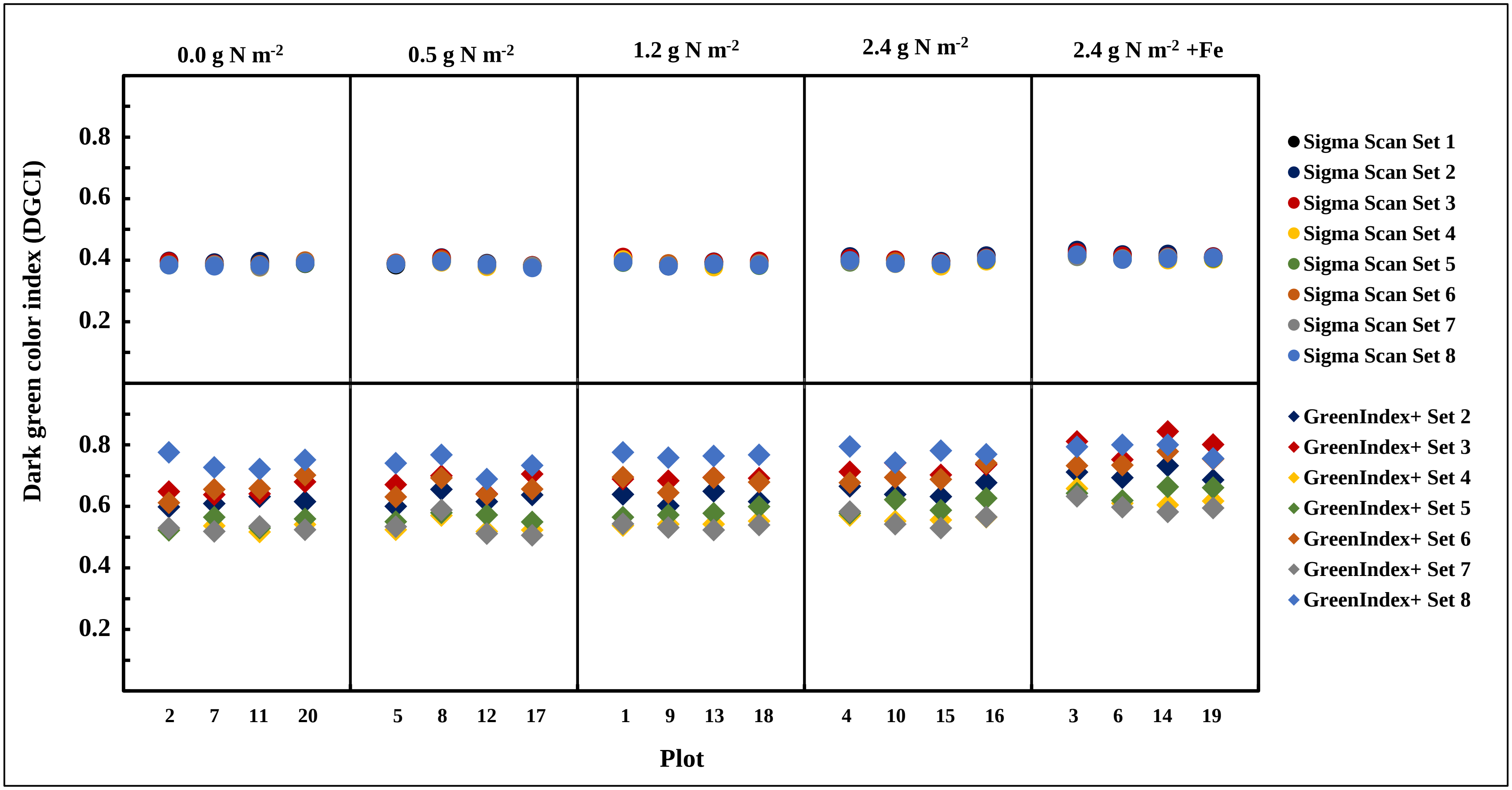
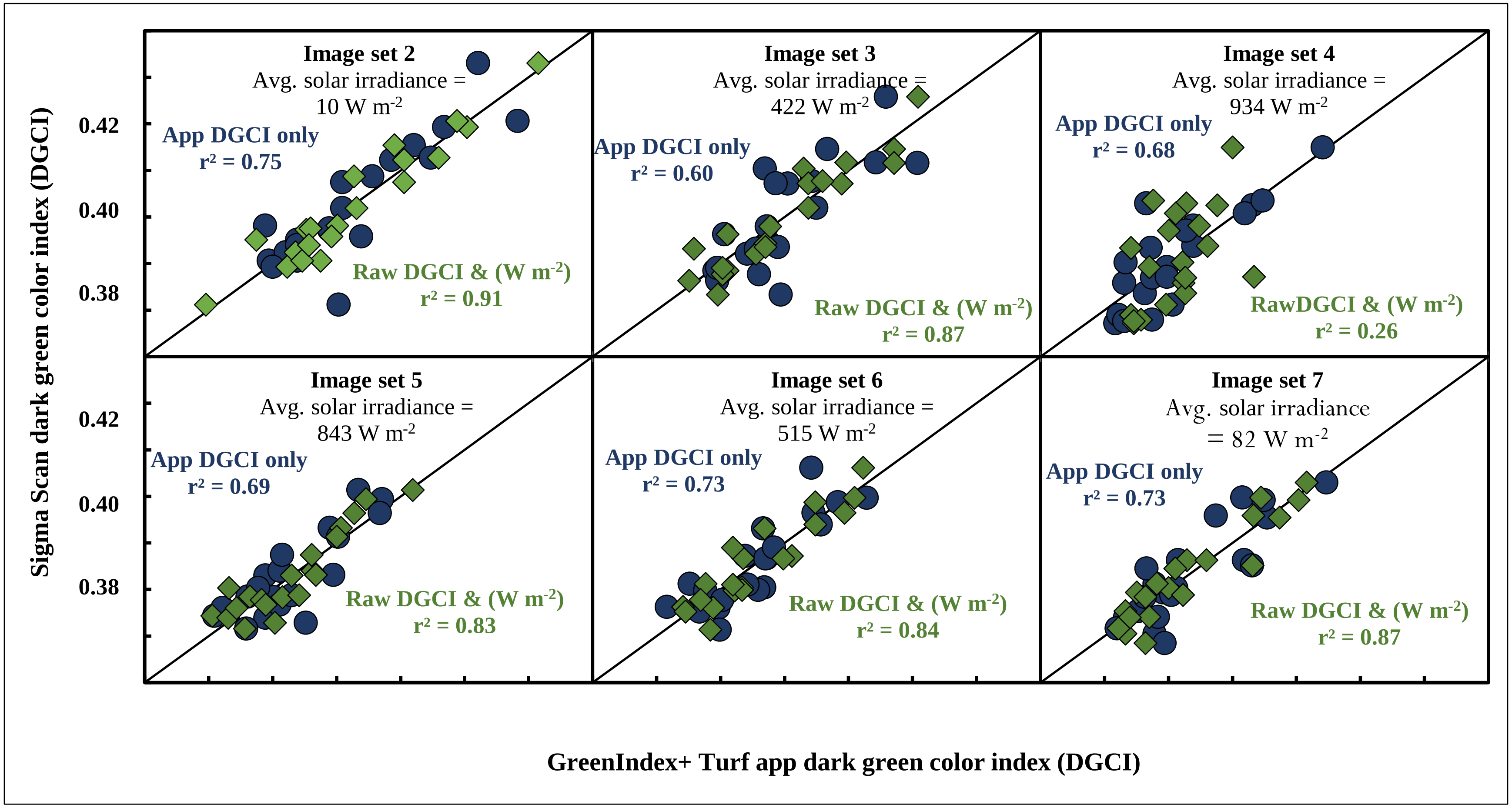


Fig. 16. Comparison of variability in dark green color index (DGCI) values observed within each plot throughout 15 Aug. 2015.



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V. Conclusions

The benefits of any new technology are intertwined with an appropriate understanding of the accompanying limitations. For intensively managed turfgrass situations, such as putting greens, as novel measurements continue to emerge and evolve, it is important for superintendents to have clarity regarding the precision and consistency associated with such measurements. It is important that advantages of new technologies, such as increased affordability, efficiency, and quantity of data, are not allowed to overshadow the ultimate goal of providing accurate, reliable data that reflect conditions of the putting surface in meaningful ways, capable of contributing to enhanced management.

Modifying a TDR300 moisture meter to measure at shallower depths produced a strong overall correlation with ground-truth θ. This simple adaptation did not alter the inherent characteristics of the TDR measurement process, and offered an opportunity to supplement current 3.8 cm θ measurement depths on sand-based putting greens. Interpretations of θ from the empirical models developed in this research should consider the relative influence of moisture within above-ground plant tissue, especially when comparing to θ values calculated internally by the TDR meter (at deeper depths).

Dark green color index values from smartphone images taken under ambient lighting conditions exhibited greater variability than DGCI produced within an enclosed light box. While DGCI from the GreenIndex+ Turf App was capable of detecting relative differences in turfgrass color within a given date, comparing DGCI values from the app across date and time lacked the precision of research methodology. Further correction for the variability of ambient light is needed in order to create greater temporal stability with the measurement process. Color standards (provided by the manufacturer) have potential to be a part of that correction, but at this time, do not appear to provide enough consistency when calculating DGCI values under different light levels.