Thermal Imaging Detects Early Drought Stress in Turfgrass Utilizing Small Unmanned Aircraft Systems

Mu Hong,* Dale J. Bremer, and Deon van der Merwe

ABSTRACT

Recent advances in aerial platforms and thermal imaging provide opportunities to improve water management in turfgrass, but research on this topic is limited. Our objectives were to: (i) evaluate the ability of canopy temperature ($T_c$) imaging from small unmanned aircraft systems (sUAS) to detect drought stress early in turfgrass; (ii) compare early drought-stress detection ability of $T_c$ measurements with that of sUAS-mounted and handheld optical sensors; and (iii) evaluate thermal data’s relationship to spectral reflectance from sUAS-mounted and handheld sensors, soil volumetric water content (VWC), soil temperature, turfgrass visual quality (VQ), and percentage green cover (PGC). The study was conducted during summer 2017 on creeping bentgrass (Agrostis stolonifera L.) irrigated with 15 to 100% evapotranspiration (ET) replacements to impose a gradient of drought stress. Airborne spectral reflectance measurements included three bands (near infrared [NIR, 680–780 nm], green and blue bands [overlapped, 400–580 nm]) and eight derived vegetation indices. Results indicated $T_c$ measurements via the sUAS detected rises of $T_c$ in 15 and 30% compared with 100% ET plots, corresponding with declines in VWC, before drought stress became visible. This was comparable to the best spectral parameters on companion flights, and $T_c$ was closely correlated with spectral data from sUAS-mounted ($|r| = 0.52–0.69$) and handheld sensors ($|r| = 0.75–0.82$). Thermal data were more strongly correlated with turfgrass VQ ($r = -0.60$ to $-0.77$) and PGC ($r = -0.58$ to $-0.78$) than with VWC ($r = -0.43$ to $-0.63$) and soil temperature ($|r| = 0.27–0.41$).

Abbreviations: AGL, above ground level; B, blue band; ET, reference evapotranspiration; FOV, field of view; G, green band; NDRE, normalized difference red edge index of RapidScan; NDVI, normalized difference vegetation index; NDVIF, NDVI of FieldScout; NDVIR, NDVI of RapidScan; NIR, near infrared band; NIRG, near infrared band of RapidScan; PGC, percentage green cover; RedR, red band of RapidScan; sUAS, small unmanned aircraft systems; $T_a$, air temperature; $T_c$, canopy temperature; $T_{soil}$, soil temperature; VI, vegetation index; VQ, turfgrass visual quality; VWC, soil volumetric water content.

There are an estimated 13 to 20 million ha of turfgrass in the United States, including on roadsides, residences, golf courses, sports facilities, campuses, etc. (Milesi et al., 2005). Besides aesthetic and recreational benefits to the community, turfgrass also improves the environment, for example by mitigating heat buildup, stabilizing soil and dust, sequestering C in the soil, and reducing glare, noise, and air pollution (Beard, 1973). Water is increasingly a limited resource; therefore, it is increasingly important to conserve water through wise irrigation management in turfgrass.

Recent advances in aerial remote sensing platforms, specifically small unmanned aircraft system (sUAS) technology, and remote sensing instrumentation provide a potentially efficient method for early detection of drought stress and conserving water in turfgrass management (Hong et al., 2019). The advantages of applying the sUAS include flexibility and increasingly user-friendly operational requirements, decreasing costs, improved reliability and safety, and excellent performance for high-quality data acquisition in low altitude environments, compared with expensive and time-flexible satellite data (Pajares, 2015).

Other researchers have modeled soil moisture with canopy spectral reflectance on creeping bentgrass (Agrostis stolonifera L.) and perennial ryegrass (Lolium perenne L.) (Dettman-Kruse et al., 2008). Under drought stress, turfgrass visual quality decreases, mainly because soil moisture becomes limited. However, due to variability in drought resistance among turfgrass species and cultivars, and because other environmental factors besides soil moisture (e.g., soil...
type, climate) affect turf performance in response to drought stress, relationships between turfgrass visual performance and declines in soil moisture may vary. This could result in inaccurate timing of irrigation for the prevention of visible drought-stress symptoms. Therefore, site-specific remote sensing measurements that predict declines in turfgrass visual performance due to early drought stress may provide for a more accurate and timely irrigation schedule.

Canopy temperature ($T_c$) is an important component of the turfgrass physiology and environment. As water stress occurs, transpiration and its cooling effects are reduced by stomatal closure, which results in an increase in $T_c$ (Blonquist et al., 2009; Peterson et al., 2017). Canopy temperature and canopy–air temperature difference ($T_c - T_a$) is useful for assessing plant water stress and stomatal regulation in turfgrass (Martin et al., 1994; Blonquist et al., 2009; Ballester et al., 2017; Peterson et al., 2017). More recently, thermal infrared sensors have been incorporated with the sUAS for research over agricultural crops, vineyards, and orchards (Berni et al., 2009; Zarco-Tejada et al., 2012, 2013; Ballester et al., 2017).

Companies have promoted and turfgrass managers have begun using thermal imaging on turfgrass, such as golf courses. Surprisingly, little research has investigated the utility of measuring $T_c$ via sUAS for turfgrass management, not to mention the relationships between $T_c$ and spectral reflectance or vegetation indices (VI's), in response to plant stresses (Fenstermaker-Shaulis et al., 1997; Taghvaeian et al., 2013; Van der Merwe et al., 2017).

Taghvaeian et al. (2013) found evapotranspiration estimates of turfgrasses to be similar between a Grass Water Stress Index (crop water stress index for turfgrass using a handheld thermometer) and METRIC (a surface energy balance model using a handheld multispectral radiometer) under varying irrigation treatments. Therefore, there might be relationships between spectral reflectance and canopy temperature of turfgrass under drought stress.

In the current study, we acquired a whole-season profile of $T_c$ in response to drought stress in turfgrass using thermal infrared imaging via sUAS platforms, which provided a wide range of data for evaluation. Our objectives were to: (i) evaluate the ability of thermal infrared imaging via sUAS platforms to detect drought stress early in turfgrass; (ii) compare the early drought-stress detection ability of thermal imaging with that of spectral reflectance data obtained concurrently from sUAS-mounted and handheld optical sensors; and (iii) evaluate relationships between thermal imaging data and spectral reflectance of other canopy and soil variables.

**METHODS AND MATERIALS**

The research was conducted under an automatic rainout shelter at the Rocky Ford Turfgrass Research Center near Manhattan, KS (39°13′53″ N, 96°34′51″ W). The rainout shelter covered the whole study area (about 66 m²) when precipitation reached 0.25 mm and retracted an hour after rainfall ceased. The soil was a Chase silty clay loam (fine, smectitic, mesic Aquert Argudollis).

From 7 June to 31 August 2017, irrigation treatments were applied to ‘Declaration’ creeping bentgrass in 24 plots (1.7 x 1.5 m each) arranged in a randomized complete block design. Irrigation amounts were calculated from daily reference evapotranspiration ($E_T$, hereafter referred to as ET) using on-site weather data (http://mesonet.k-state.edu) and the American Society of Civil Engineers (ASCE) standardized reference ET equation (Walter et al., 2001). Six deficit-irrigation treatments were included to induce a gradient of drought stress symptoms within each of the four blocks: 15, 30, 50, 65, 80, and 100% ET replacement. Irrigation was applied three times per week by hand with a wand attached to a meter (Model 03N31, GPI) and hose. The rainout shelter malfunctioned on 5 August, permitting 19 mm of precipitation.

**Maintenance**

Creeping bentgrass was initially seeded at 48.8 kg ha⁻¹ on 18 Sept. 2014, and reestablished by verticutting, seeding at 40 kg ha⁻¹, and topdressing on 22 Sept. 2016. The creeping bentgrass was aerified on 5 June 2017. Plots were not cultivated during the dry-down periods to avoid damage to the turfgrass canopy during drought stress. In 2017, plots were aerifed to promote growth 4 d before the dry down began. This slightly disrupted the turf canopy during the first week of measurements, but those effects diminished rapidly thereafter. Plots were mowed three times a week at 15.9 mm and clippings were removed. Turfgrass was fertilized with 48.9 kg N ha⁻¹ in May 2015, on 22 Sept. 2016, on 20 Apr. and 12 May 2017; 38.7 kg P ha⁻¹ on 22 Sept. 2016 and 3.1 kg P ha⁻¹ on 12 May 2017; and 73.1 kg K ha⁻¹ on 22 Sept. 2016 and 40.6 kg K ha⁻¹ on 12 May 2017.

For preventative insect control, chlororantraniliprole [3-bromo-N-[(4-chloro-2-methyl-6-[(methy lamino)carbonyl]phenyl]-1-(3-chloro-2-pyridinyl)-1H-pyrazole-5-carboxamide] (Accelepryn, Syngenta Crop Protection) was applied at 0.26 kg a.i. ha⁻¹ on 26 May 2017. For preventative weed control, dithiopyr [SS-dimethyl 2-(difluoromethyl)-4- (2-methylpropyl)-6-(trifluoromethyl)-3,5-pyridinedicarboxylate] (Dimension, Dow AgroSciences) at 0.56 kg a.i. ha⁻¹ and a mixture of [(+)-(R)-2-(2-methyl-4-chlorophenoyl)propionic acid, 2,4-dichlorophenoxyacetic acid, and 3,6-dichloro-o-anisic acid (Trimec bentgrass formula, PBI Gordon Corporation) at 0.76 kg a.i. ha⁻¹ was applied in mid-April over 2015–2017. For preventative control of dollar spot (caused by Sclerotinia homoeocarpa F. T. Bennett) and other diseases in 2017, triticonazole [(RS)-(E)-5-(4-chlorobenzylidene)-2,2-dimethyl-1-(1H-1,2,4-triazol-1-ylmethyl)cyclopentanolo] (Triton FLO, Bayer Environmental Science) and chlorothalonil (2,4,5,6-tetrachlorobenzene-1,3-dicarboxitrile) (Docket WS, Syngenta) was applied at 1.1 kg a.i. ha⁻¹ on 28 May and 6.9 kg a.i. ha⁻¹ on 23 June, respectively.

**Data Collection**

All measurements were taken weekly (weather permitting) on cloud-free days with wind speed below 24 km h⁻¹ and within 2.5 h of local solar noon. On each measurement day, a thermal camera (FLIR VUE PRO R 336), mounted on an IRIS+ (3D Robotics) flown at 25 m above ground level (AGL), was used to attain $T_c$ from 15 June to 31 August. The camera has a 35° FOV (field of view) and a 9-mm focal length with 4.7-cm ground resolution, as calculated from Mission Planner (v.1.3.56, ArduPilot). One thermal image containing the whole study area was selected for each measurement date. Average canopy temperatures were retrieved from the center 60% of each plot from the thermal images using the FLIR tool (5.13), which also produced color-enhanced thermal maps. Average 5-min air temperatures at 2 m above ground level during the $T_c$-data acquisition period were obtained from the on-site weather station and used to calculate rough estimates of $T_c - T_a$ for each plot. Although irrigation treatments began on 7 June, airborne canopy temperature measurements were not acquired until 15 June due to technical issues.

A series of ultra-high spatial resolution images (<1-cm ground resolution) were also collected on each measurement date with a Canon PowerShot S100 camera modified by Llewellyn Data...
The camera sensor was equipped with filters blocking visible red light (580–680 nm) and near infrared band (NIR) above 780 nm while allowing visible blue (B) and green bands (G) (overlapped, 400–580 nm), and the transition of visible red edge to NIR band (680–780 nm), to pass to the sensor. The camera was mounted on a hexacopter (S800 EVO, DJI) flown 25 m AGL to achieve image overlap of at least 75%. The camera was set to manual mode with autofocus and ISO at 100, and the exposure level was set to be two stops below the standard while facing straight down toward the turfgrass surface by adjusting shutter speed with F-stop being fixed (f/2.2). The resulting JPEG images were stitched into averaged orthomosaics using Agisoft Photoscan Professional (version 1.3.4 build 5067).

Treatment effects were analyzed from the orthomosaics using AgVISR (v. 2.1.6, AgVISR Services). The three individual band spectral reflectances contained in the extracted squares and eight vegetation indices (calculated from the three bands) were evaluated for their ability to detect drought stress. According to AgVISR, the eight vegetation indices included NDVI Enhanced1 ([NIR + G – 2B]/[NIR + G + 2B]), NDVI Enhanced2 ([NIR + G – B]/[NIR + G + B]), NDVI Enhanced3 ([NIR – G – B]/[NIR + G + B]), Blue NDVI ([NIR – B]/[NIR + B]), Green NDVI ([NIR – G]/[NIR + G]), GreenBlue ([G – B]/[G + B]), NIR Blueratio (NIR – B), NIR Green Diff ([NIR – G – B]/[NIR – G + B]). The absolute scales of NDVI from sUAS in the study may not be comparable to the traditional scale because calibration plates were not used, but it did not affect the ability to detect comparative differences among treatments. Additional details about NDVI scales, as well as about image processing to develop the VIs, can be found in the companion study (Hong et al., 2019).

Turfgrass performance was evaluated by visual quality ratings (VQ) and percentage green cover (PGC). Two personnel evaluated the VQ of turfgrass to reduce individual biases on a numeric scale from 1 to 9 (1 = dead or dormant turf; 9 = uniform, green and dense turf; and 6 = minimally acceptable turf for use in golf course fairways) according to color, texture, density, and uniformity (Morrison and Shearman, 1999; Bell et al., 2002). Images were collected for PGC analysis using the method of Karcher and Richardson (2005) (SigmaScan Pro v. 5.0, SPSS Science Marketing Dep.). Images were taken for each plot with a Nikon D5000 digital camera (f-stop of 5.6, 1/125 s exposure time, and 800 ISO speed; Nikon) using a lighted camera box (51 × 61 × 56 cm).

Additional measurements included soil volumetric water content (VWC), soil temperature, and NDVI by two handheld optical sensors. The VWC was measured with time domain reflectometry (TDR; FieldScout TDR 300 Soil Moisture Meter, Spectrum Technologies) at a 0- to 7.6-cm depth in two random locations within each plot. Soil temperature was measured with digital soil thermometers (DT310LAB Lab Digital Stem Thermometer, General Tools & Instruments), with one reading per plot at a 7.6-cm depth. One of the handheld measurements of NDVI was obtained with a passive optical sensor (FieldScout CM1000 NDVI meter [FS], Spectrum Technologies) in three random locations within each plot. It sensed ambient light spectral reflectance peaking at wavelengths of 660 and 840 nm for computing NDVI (hereafter labeled NDVI_s) to denote FieldScout. Each reading was collected at approximately 0.9 m AGL with a conical FOV of approximately 6.5 cm diameter on the ground. Another NDVI measurements were obtained with a handheld active remote sensor (RapidScan CS-45 [RS], Holland Scientific), which measured self-generated light spectral reflectance peaking at narrow bands of 670 nm (red, Red_s), 730 nm (red edge), and 780 nm (near infrared, NIR_s) (bandwidths are proprietary), which allows for computing NDVI ([NIR_s – Red_s]/[NIR_s + Red_s]), hereafter labeled NDVI_RS to denote RapidScan as well as normalized difference red edge index (NDRRED = [NIR_s – red edge]/[NIR_s + red edge]). Averages of each measurement was obtained by scanning about 80% of each plot at approximately 0.9 m AGL.

**Statistical Analysis**

Analysis of irrigation main effects on all variables was conducted in PROC GLIMMIX (SAS 9.4, SAS Institute) with irrigation being a fixed effect by each measurement date (Fisher’s LSD, P < 0.05). Pearson’s correlations among variables were conducted by PROC CORR of SAS (T statistic of r, P < 0.05).

Linear relationships were analyzed between Tc and VQ and PGC, grouped by irrigation treatments. Analysis of variance F-test (P < 0.05) and adjusted r² were calculated in PROC REG of SAS. A significant relationship between PGC and Tc was detected among 15 to 50% ET irrigated plots, for which a sigmoid model developed by Karcher et al. (2008) was adopted to fit the data. The parameters of this model, slope and Tc where PGC equals 50%, were determined by Solver Parameter in Microsoft Excel (16.0.11001.20070) when the coefficient of determination (r²) was the maximum.

**RESULTS AND DISCUSSION**

**Irrigation Main Effect on Canopy Temperature and Turf Visual Performance**

As mentioned earlier, Tc from the sUAS was not measured until 1 wk after irrigation treatments began (15 June). By then, Tc was already greater in 15 and 30% than in 100% ET plots, and remained so throughout the study (Table 1). Greater Tc in 15 and 30% ET plots throughout the study was likely an ability of Tc to detect lower VWC in less-irrigated plots (Dettman-Kruse et al., 2008). Because turfgrass fully covered the soil throughout the study, higher Tc in less-irrigated plots was likely caused by reductions in canopy ET as the soils dried, which reduced evaporative cooling compared with higher irrigated treatments (Blonquist et al., 2009; Peterson et al., 2017). Color-enhanced thermal images of creeping bentgrass revealed negligible differences in Tc among treatment plots early in the study, but striking differences by the study’s end (Fig. 1).

Early in the study, Tc increased in drier plots before drought stress became evident in VQ or PGC. For example, on 15 June there were no differences in VQ among treatments, and PGC remained similar between the wettest (100% ET) and driest (15% ET) plots despite lower VWC and higher Tc in 15 and 30% than 100% ET plots (Table 1). In addition, there were no significant correlations between irrigation level and VQ or PGC. On 15 June (Table 2). Five days later (20 June) there were still no differences in VQ among treatments, nor significant correlations between irrigation level and VQ or PGC, although PGC was less in 15% ET plots than in all other irrigation treatments. Decreases in VQ were not observed in 15 and 30% ET plots until 1 July, which was 16 d after Tc increased in those treatments. By 1 July, 3 wk into the dry down, PGC had also decreased in 30% compared with higher ET treatments, and VQ and PGC also became correlated with irrigation levels.
Table 1. Irrigation main effect by date on canopy temperature ($T_c$), visual quality (VQ), percentage green cover (PGC), and volumetric water content (VWC) in Declaration creeping bentgrass in 2017 ($P < 0.05$).

<table>
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<th>15 June</th>
<th>20 June</th>
<th>1 July</th>
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<th>25 July</th>
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<th>31 Aug.</th>
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<td>31.8A</td>
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† Percentage of reference evapotranspiration replacement.
‡ Airborne canopy temperature was not available on 7 June.

Fig. 1. Color-enhanced thermal image of plots on 15 June (A) and 31 August (B). Percentages denote fractions of reference evapotranspiration replacement.
The lack of correlation between irrigation treatment and VQ or PGC during the first 2 wk of the study (i.e., through 20 June; Table 2) was likely because of the slower response of VQ and PGC to drought stress than \( T_c \), as discussed above. The decrease in PGC in 15% ET plots compared with the other treatments by 2 wk into the study (20 June) indicated PGC was more sensitive to early drought stress than VQ, although VQ could vary with different evaluators. Regardless, \( T_c \) was even more sensitive than PGC in detecting early drought stress, based on VWC patterns. For example, VWC was lower in 30% than 100% ET plots on 15 June, which was detected by \( T_c \) but not PGC (Table 1). Interestingly, \( T_c \) was similar among the highest three irrigation treatments (i.e., 65–100% ET) throughout the study.

Correlations between irrigation level and VWC were consistently strong (\( r > 0.80, P < 0.05 \)) during the dry down (Table 2). This, along with clear patterns of decreasing VWC with irrigation treatment level during the dry down (Table 1), indicated that a strong gradient of drought stress was achieved across the treatments. Not surprisingly, \( T_c \) was inversely correlated with irrigation level throughout the study, with correlation coefficients (\( r \)) ranging from –0.65 to –0.82. The strongest correlation with \( T_c \) was on the final day of the study, when differences among irrigation treatments were the greatest.

<table>
<thead>
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<th>15 June</th>
<th>20 June</th>
<th>1 July</th>
<th>10 July</th>
<th>25 July</th>
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<th>31 Aug.</th>
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<td>NS</td>
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<tr>
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<td>Red edge</td>
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<td>–0.82</td>
<td>–0.81</td>
<td>–0.76</td>
</tr>
</tbody>
</table>

† Correlations were not significant at \( P < 0.05 \) probability level.
‡ NIR, near infrared spectral reflectance, peaks within 680–780 nm.
§ GreenBlue = (Green – Blue)/(Green + Blue).
¶ NDVI Enhanced1 = (NIR + Green – 2Blue)/(NIR + Green + 2Blue).
# NDVI Enhanced2 = (NIR + Green – Blue)/(NIR + Green + Blue).
†† NDVI Enhanced3 = (NIR – Green – Blue)/(NIR + Green + Blue).
# Blue NDVI = (NIR – Blue)/(NIR + Blue).
 §§ Green NDVI = (NIR – Green)/(NIR + Green).
¶¶ NIR Blue ratio = NIR – Blue.
## NIR Green Diff = (NIR – Green – Blue)/(NIR – Green + Blue).
††† NDVI_1+ = (NIR_r – red)/(NIR_r + red); 660 (red) and 840 (NIR_r) nm.
§§ NDVI_2+ = (NIR_r – Red_r)/(NIR_r + Red_r); NIR_r peaks at 780 nm. Red_r, peaks at 670 nm.
¶¶ NDRE_1+ = (NIR_r – Red edge)/(NIR_r + Red edge). Red edge, peaks at 730 nm.
The data presented above clearly indicated that $T_e$ detected drought stress before drought stress symptoms appeared. However, the window of time between the initial rise in $T_e$ and the onset of visible drought symptoms (i.e., in VQ or PGC) is less certain. For example, drought symptoms may have appeared in 30 and 15% treatments before 1 July (Table 1), but it would not have been observed by VQ, because VQ was not evaluated on days before sUAS flights. Therefore, it is unlikely that $T_e$ detected drought stress a full 16 d before symptoms became visible in VQ (i.e., from 15 June to 1 July). Additional research is needed to refine the time between initial drought stress detection by sUAS thermal imaging and the appearance of drought stress symptoms.

Comparisons of Drought-Stress Detection Ability between Canopy Temperature and Spectral Reflectance Data from Suas-Mounted and Handheld Optical Sensors

One week into the study (15 June), before any differences in VQ emerged, early drought stress was detected in less-irrigated treatments by $T_e$, NIR, and five VIs from sUAS measurements, and NDVI$_{1s}$ and Red$_{1s}$ from the handheld active but not the handheld passive optical sensor (NDVI$_{1p}$) (Table 3). Moreover, $T_e$, NIR, and GreenBlue VI from the sUAS were more sensitive at detecting early drought stress in the lower irrigation levels than the other spectral reflectance measurements from the sUAS and the handheld active optical sensor. Specifically, $T_e$, NIR, and GreenBlue VI all differentiated 100% from 15 and 30% ET plots, whereas the other measurements by the sUAS and the handheld active optical sensor only detected drought stress in 15% ET plots compared with the 100% ET (Table 3). This observation is supported by stronger correlations between $T_e$, NIR, and the GreenBlue VI and irrigation levels than nearly all of the other VIs and reflectance bands (Table 2, 15 June). Thus, the ability of $T_e$ to detect early drought stress is comparable to the best spectral parameters (i.e., NIR and GreenBlue VI) on a companion flight. Hong et al. (2019) conducted research over 3 yr on these same plots and reported NIR and GreenBlue VI were consistently more sensitive to detecting early drought stress than the other spectral reflectance parameters obtained from sUAS-based and handheld sensors.

Researchers of other plant systems have reported that using $T_e$ to detect plant water stress is better than other parameters, including spectral reflectance measurements. For example, in almond, lemon, and peach trees, airborne $T_e$ was more sensitive to water stress than stem water potential, stomatal conductance, and VIs acquired by the same sUAS (Ballester et al., 2017). Thermal infrared imaging on orange trees from an sUAS showed that $T_e$ had a stronger relationship with stomatal conductance than did spectral reflectance and fluorescence indices conducted with hyperspectral radiance imaging, when xylem water potential ranged from −0.5 to −2 MPa (Zarco-Tejada et al., 2012). The thermal images were single snapshots by the FLIR camera mounted on an sUAS (Fig. 1). In contrast, spectral reflectance measurements required the stitching together of multiple images to produce orthomosaics, meaning more data collection and processing, as well as software costs. Furthermore, VIs or reflectance bands (e.g., NIR) derived from single photos with the modified digital camera were not able to differentiate treatment differences across the study area (data not shown). Therefore, thermal imaging may require fewer aerial measurements than spectral reflectance imaging over the same area. However, more thermal image collection may still be necessary for reducing errors, especially when short focal length lenses are used, the surface is rough, or the solar angle away from zenith is large (Van der Merwe et al., 2017).

Correlations between Aerial Thermal Data, Aerial and Ground-Based Spectral Reflectance Data, and Ground-Based Canopy and Soil Measurements

Same-day measurements of $T_e$ and spectral reflectance obtained aerially, spectral reflectance obtained by handheld optical devices,
and of VQ, PGC, VWC, and $T_{\text{air}}$ provided a unique opportunity to examine correlations between $T_{c}$ and the other measurements. Although $T_{c}$ provides a relative estimate of plant stress among irrigation levels, $T_{c} - T_{a}$ was also examined because it adjusts for differences in meteorological conditions that affected $T_{a}$ on a given day (Martin et al., 1994). Presumably, greater differences between $T_{c}$ and $T_{a}$ indicate greater drought stress relative to $T_{c} - T_{a}$ of well-watered plants (100% ET plots).

Over the entire study, thermal data ($T_{c}$ and $T_{c} - T_{a}$) were better correlated with PGC and VQ than with VWC or $T_{\text{air}}$ (Table 4). This indicated that under varying drought conditions, thermal data were more directly associated with the turfgrass canopy properties than with soil properties. The reason is that $T_{c}$, which is a direct measure of the surface temperature of turfgrass covering the plots, increases as transpiration decreases in response to drying soils in less-irrigated plots (Peterson et al., 2017). Strong correlations between $T_{c}$ and canopy properties were a result of wide ranges in $T_{c}$ and VQ and PGC across the season in lower irrigation treatments (15–50%) (Fig. 2 and 3). Correlations between $T_{c}$ and canopy properties were not significant in 65, 80, and 100% ET plots, probably because transpiration in each of those treatments remained relatively stable throughout the season and extraneous factors may contribute to VQ and PGC more.

A sigmoid curve was fitted in the relationship between PGC and $T_{c}$ among 15 to 50% ET irrigated plots (Fig. 4). The PGC declined relatively slowly when drought stress started to develop, as indicated by relatively low $T_{c}$. Then $T_{c}$ increased dramatically with decreasing PGC, and finally began to level out. This is supported by the relatively slow decline in turfgrass VQ during early drought stress development that allowed for early detections with remote sensing, as discussed in previous sections (Table 1). Interestingly, similar sigmoidal relationships were reported between PGC and the number of days after irrigation withheld in a turfgrass dry down study (Karcher et al., 2008).

Canopy temperature was also significantly correlated with VWC and $T_{\text{air}}$, but the relationships were weaker than with VQ and PGC, as discussed above (Table 4). The correlation of $T_{c}$ with VWC was stronger than with $T_{\text{air}}$ probably because of the strong impact of irrigation treatments on VWC (Tables 1 and 2). In contrast with VWC, the effects of irrigation level on $T_{\text{air}}$ in less-irrigated plots did not appear until later in the experiment (Table 1, 1 July), and even then, the correlations were weaker throughout the study (Table 2). Although $T_{\text{air}}$ typically increases as the soil dries, other factors such as shading by the turfgrass canopy may confound relationships between $T_{\text{air}}$ and $T_{c}$ (Bremer and Ham, 1999; Bremer et al., 2001).

Overall, thermal data were significantly correlated with spectral reflectance data obtained by sUAS and handheld sensors (with the exception of green reflectance from the sUAS) measured across the irrigation gradients ($|r| = 0.52–0.82$ for $T_{c}$ and $|r| = 0.20–0.68$ for $T_{c} - T_{a}$, Table 4). Correlations of thermal data with spectral parameters obtained with handheld optical sensors ($|r| = 0.59–0.82$) were slightly higher than spectral parameters obtained with the sUAS ($|r| = 0.20–0.69$). This may have been an artifact of different reflectance signal processing between the camera sensor and the handheld optical sensors, as well as different VIs and reflectance bands that were used in these sensors. Also, spectral reflectance data from the sUAS were derived from narrow bands, whereas handheld optical measurements were from narrow bands.

### Table 4. Pearson correlation coefficients ($r$) of canopy temperature ($T_{c}$) and canopy–air temperature difference ($T_{c} - T_{a}$) with volumetric water content (VWC), visual quality (VQ), percentage green cover (PGC), soil temperature ($T_{\text{air}}$), spectral reflectance data acquired from small unmanned aerial system (sUAS), and handheld optical sensors (FieldScout, FS; and Rapid-Scan, RS), on Declaration creeping bentgrass ($P < 0.05$).

<table>
<thead>
<tr>
<th>Variable</th>
<th>$T_{c}$</th>
<th>$T_{c} - T_{a}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ground-based measurements</strong></td>
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<td></td>
</tr>
<tr>
<td>VWC</td>
<td>-0.63</td>
<td>-0.43</td>
</tr>
<tr>
<td>VQ</td>
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<td>-0.60</td>
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<td>PGC</td>
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<td>-0.58</td>
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<td>$T_{\text{air}}$</td>
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<tr>
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<td></td>
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<td>sUAS-based</td>
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<tr>
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<tr>
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<td>GreenBlue§</td>
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<td>-0.66</td>
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<tr>
<td>NDVI Enhanced2¶</td>
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<tr>
<td>Red edge</td>
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</table>

† Correlation was not significantly different at $P < 0.05$ probability level.
‡ NIR, near infrared spectral reflectance, peaks within 680 to 780 nm.
§ GreenBlue = ($\text{NIR} - \text{Green})/\text{Green} + \text{Blue}$.
¶ NDVI Enhanced1 = ($\text{NIR} + \text{Green} - 2\text{Blue})/(\text{NIR} + \text{Green} + 2\text{Blue})
# NDVI Enhanced2 = ($\text{NIR} + \text{Green} - \text{Blue})/(\text{NIR} + \text{Green} + \text{Blue})
†† NDVI Enhanced3 = ($\text{NIR} - \text{Green} - \text{Blue})/(\text{NIR} + \text{Green} + \text{Blue})
∥ Blue NDVI = ($\text{NIR} - \text{Blue})/(\text{NIR} + \text{Blue})
§§ Green NDVI = ($\text{NIR} - \text{Green})/(\text{NIR} + \text{Green})
¶¶ NIR Blueration = NIR – Blue.
#### NIR Green Diff = ($\text{NIR} - \text{Green} - \text{Blue})/(\text{NIR} - \text{Green} + \text{Blue})$
††† NDVI Enh = (NIR$_{\text{enh}}$ – red)/(NIR$_{\text{enh}}$ + red); 660 (red) and 840 (NIR$_{\text{enh}}$) nm.
‡‡‡ NDVI Enh$_{\text{enh}}$ = (NIR$_{\text{enh}}$ – R)/(NIR$_{\text{enh}}$ + R). NIR$_{\text{enh}}$ peaks at 780 nm. Red, peaks at 670 nm.
†††† NDRE Enh = (NIR$_{\text{enh}}$ – Red edge)/(NIR$_{\text{enh}}$ + Red edge). Red edge, peaks at 730 nm.

Interestingly, most VIs were better correlated with $T_{c}$ than $T_{c} - T_{a}$. This may be explained by slight differences in the time between measurements of $T_{c}$ and $T_{c} - T_{a}$. Specifically, $T_{c}$ was measured aerially from the sUAS and $T_{a}$ was obtained from a weather station within 50 m from the study area. Although every effort was made to match the time of $T_{c}$ measurements with $T_{a}$, they were likely separated by several minutes, which probably affected the accuracy the $T_{c} - T_{a}$ estimates. However, it is notable that compared with sUAS data, $T_{c} - T_{a}$ was significantly and best correlated with NIR.
and the GreenBlue VI (Table 4), which were also the best at predicting early drought stress (Table 3) (Hong et al., 2019). It may indicate these spectral parameters NIR and GreenBlue VI were more sensitive to initial increases in turfgrass $T_c$ relative to $T_a$ in response to early drought stress.

**CONCLUSIONS**

In this study, $T_c$ acquired by the sUAS predicted drought stress before symptoms were evident in either VQ or PGC. The ability of $T_c$ to predict drought stress was also comparable to the best spectral parameters acquired by sUAS on companion flights (i.e., NIR and GreenBlue VI), and slightly better than with spectral data obtained from handheld sensors. Better drought-prediction ability combined with faster and more affordable data collection using sUAS indicates significant potential for sUAS-based compared with ground-based drought stress monitoring methods. Further investigation is needed to refine the time between initial rises in $T_c$ and the onset of visible drought stress symptoms. Additional research is also needed using thermal and spectral reflectance imaging via sUAS on different turfgrass species and cultivars in different locations.

**ACKNOWLEDGMENTS**

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**REFERENCES**


