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Active Optical Sensors in Irrigated Durum Wheat: Nitrogen and Water Effects

Kevin F. Bronson,* Jeffrey W. White, Matthew M. Conley, Doug J. Hunsaker, Kelly R. Thorp, Andrew N. French, Bruce E. Mackey, and Kyle H. Holland

ABSTRACT

Interest in active optical sensors (AOS) for guiding N fertilizer management of crops like wheat (*Triticum aestivum* L.) has grown rapidly since their introduction in the mid-1990s. Recently, AOS have been used to assess water status of crops in addition to plant N status. Specific vegetation indices (VIs) might assess N stress while minimizing effects of water stress. A 2-yr study (2013–2014) was conducted on a Casa Grande sandy loam soil in Maricopa, AZ, with durum wheat (*T. durum* Desf) under an overhead sprinkler system. Uniquely, this study had 10 unrandomized levels of irrigation and five rates of N fertilizer. The objectives were to compare 12 VIs for their ability to distinguish irrigation and N fertilizer effects and to determine how well the VIs estimated biomass, plant N, grain yield, grain N, and yellow berry (opaque starchy grain). Two Crop Circle 470 AOS were passed at a fixed height, 1 m above the tallest plants in the field, every 7 to 10 d during the growing season. The normalize difference vegetation indices (NDVIs) showed highly significant response to N rate in three of four growth-stage-years, but significant water and small N effects at Zadoks 32 (early stem elongation) in 2014. The canopy chlorophyll content index (CCCI), DATT (Datt, 1999), and Meris terrestrial chlorophyll index (MTCI) were the most consistent VIs in distinguishing N rates, with minimal water effects. No VIs detected water stress with minimal N effect as well as the infrared thermometer (IRT) measurements of canopy temperature did.

Core Ideas

- Interest in the use of active optical sensors for guiding N fertilizer management of crops like wheat has grown rapidly since the mid-1990s. Recently, active optical sensors have been used to assess water status of crops in addition to plant N status.
- We conducted a 2-yr study on a Casa Grande sandy loam soil in Maricopa, AZ, with durum wheat under an overhead sprinkler system. Uniquely, this study had 10 unrandomized levels of irrigation and five rates of N fertilizer.
- The objectives were to compare 12 vegetation indices for their ability to distinguish irrigation and N fertilizer rates and to determine how well the vegetation indices estimated biomass, plant N, grain yield, grain N, and yellow berry.
- The canopy chlorophyll content index, Datt, and Meris terrestrial chlorophyll index were the most consistent vegetation indices in responding well to N, with minimal water effects. No vegetation indices detected water stress with minimal N effect as well as canopy temperature measured with infrared thermometers.

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Grain yields of irrigated durum wheat in Arizona consistently average over 7 Mg ha^{-1}, twice the national average (USDA-NAAS, 2016). Similar systems for bread wheat, which CIMMYT classifies as mega-environment 1 (Hodson and White, 2007), are among the most productive wheat systems globally. Nitrogen management is critical in high-yielding wheat systems. For durum wheat in Arizona, prices received by growers are reduced if grain protein is less than 23 g N kg^{-1} (Blandino et al., 2015; Liang et al., 2014). Nitrogen fertilizer recommendations for durum wheat in Arizona currently target 33 to 37 kg N applications per 1000 kg grain for protein ranges from 19 to 22 g N kg^{-1} (Ottman and Thompson, 2006). However, there are currently no adjustments to N fertilizer recommendations based on crop water status. Nitrogen credits for pre-plant soil test NO_3 and irrigation water NO_3 can be subtracted from these N requirements. In addition to soil test NO_3, stem NO_3 testing is recommended (Ottman and Thompson, 2006), but is time-consuming and precludes rapid in-field management. Canopy reflectance measurements from hand-held or ground-based multispectral sensors have potential to assess in-season biomass and N status and therefore guide in-season N fertilizer applications in wheat (Raun et al., 2002; Mullen et al., 2003; Li et al., 2009). Crop reflectance has also been used to guide late-season N management for wheat grain protein levels (Wright et al., 2004). Canopy multispectral reflectance data are typically used to calculate a VI such as the normalized difference vegetation index (NDVI). Tucker (1979) proposed NDVI as

K.F. Bronson, U.S. Arid Land Agricultural Research Center, 21881 North Cardon Lane, Maricopa, AZ 85138; J.W. White, ALARC, USDA-ARS, 21881 N Cardon Lane, Maricopa, AZ 85138; M.M. Conley, D.J. Hunsaker, K.R. Thorp, U.S. Arid Land Agricultural Research Center, 21881 North Cardon Lane, Maricopa, AZ 85138; A.N. French, USDA-ARS, U.S. Arid Land Agricultural Research Center, 21881 N. Cardon Lane, Maricopa, AZ 85138; B.E. Mackey, USDA-ARS Western Regional Research Center Ringgold standard institution, 800 Buchanan Street, Albany, CA 94710; K.H. Holland, Holland Scientific, Inc., 6001 S. 58th St., Lincoln, NE 68516. *Corresponding author (Kevin.Bronson@ars.usda.gov).

Abbreviations: AOS, active optical sensor; CCCI, canopy chlorophyll content index; CI, chlorophyll index using amber; CIRE, chlorophyll index vegetation index; DATT, Datt, 1999; ET, evapotranspiration; FOV, field of view; IRT, infrared thermometer; MTCI, Meris terrestrial chlorophyll index; NDARE, normalized difference vegetation index-amber-red edge; NDRE, normalized difference red edge index; NDRRE, normalized difference vegetation index-red-red edge; NDVIA, normalized difference vegetation index amber; NDVIG; normalized difference vegetation index green; NDVIR, normalized difference vegetation index red; PRI, physiological reflectance index.

$(R_{NIR} - R_{red})/(R_{NIR}+R_{red})$, where R_{NIR} and R_{red} are reflectances in the near infrared (NIR) and red regions, respectively.

Highly productive wheat systems increasingly face challenges to jointly optimize water and N management when supplies of both inputs are constrained by availability, high costs, and concerns over adverse environmental impacts. Many VIs do not discriminate well between effects of water and N deficits. Canopy temperature is effective for water management, but adoption as a management tool appears to have been limited by the costs of sensors and the complexity of correcting sensor data for large, dynamic effects of wind, radiation, and humidity. Identifying VIs that independently diagnose water and N status might enable joint management of irrigation and N inputs.

In addition to guiding N fertilizer management, VIs, such as NDVI, have been tested extensively for managing irrigation in wheat (Hunsaker et al., 2005a; Er-Raki et al., 2007) and cotton (*Gossypium hirsutum* L.) (Hunsaker et al., 2005b). Specifically these studies used NDVI to estimate crop coefficients and/or to estimate ET (Hunsaker et al., 2005a; Hunsaker et al., 2005b; Glenn et al., 2011). Several studies have used VIs from canopy reflectance to assess both N management and irrigation effects in corn (Clay et al., 2006; Shiratsuchi et al., 2011) and in wheat (Fitzgerald et al., 2006; Cabrera-Bosquet et al., 2011; Clay et al., 2012; Tilling et al., 2007). In irrigated corn in Nebraska, Shiratsuchi et al. (2011) compared six VIs using the active sensors Crop Circles ACS 210 and ACS 470 for their ability to distinguish N from water stress. They reported that the DATT and Meris terrestrial chlorophyll index (MTCI) were the most sensitive VIs to N with minimal influence of water. Nitrogen by water field studies are lacking for high protein durum wheat with active optical sensors, and for large number of irrigation levels.

"Active" optical sensors for measuring canopy reflectance (Holland et al., 2004; Solari et al., 2008; Fitzgerald et al., 2010; Erdle et al., 2011) employ on-board polychromatic light sources, and are therefore less sensitive to time of day effects and cloudiness compared to passive sensors (de Souza et al., 2010). Typically, red reflectance has been used as a reference waveband in the NDVI calculation, but now there is growing interest in the use of "amber" wavebands at 590 nm (Holland et al., 2004; Solari et al., 2008). Amber (590 nm) or green (550 nm) reflectance has been selected to minimize the saturation observed at high leaf are indices and N rates when using the traditional red NDVI (Gitelson et al., 1996). Although several studies compared green/amber and red NDVIs from different sensor types (Hong et al., 2007; Shaver et al., 2010; Bronson et al., 2011), comparisons with the same sensor type are rare (Shiratsuchi et al., 2011). Another strategy researchers have employed to address the problem of the saturation of NDVI with dense, high N canopies is to calculate the normalized difference red edge index (NDRE). Rouse et al. (1974) proposed NDRE as $(R_{NIR} - R_{red\ edge})/(R_{NIR}+R_{red\ edge})$, where R_{NIR} and $R_{red\ edge}$ are at 760 and 720 nm, respectively. The NDRE index and canopy chlorophyll content index (CCCI, simple version calculated as NDRE/NDVI) are less well-studied in the literature than the NDVI, but their use in agricultural research is increasing (Barnes et al., 2000; Long et al., 2009; Shiratsuchi et al., 2011). Considering previous related work, there is a need for a systematic evaluation of a large number of VIs, calculated from more than two or three wavebands to assess N status of irrigated wheat at a large range of water regimes.

Infrared thermometry of canopy temperature has long been utilized as a plant water metric, and as a tool in irrigation management of wheat (Jackson et al., 1977; Idso et al., 1977). Although the main interest of this study is the use of VIs to assess plant N and water status, infrared thermometer (IRT) measurements of canopy temperature provide a valuable comparison reference for water and heat stress.

There were several hypotheses in this study. Vegetation indices may differentially detect N fertilizer rate and irrigation levels. Additionally, it was hypothesized that VIs using amber may be more sensitive to N than VIs using red visible bands, and that VIs that employ a red-edge band may be more sensitive to N or water stress than NDVI.

The objectives of this study were to:

1. Determine the effect of N fertilizer rate and irrigation level on 12 VIs calculated from weekly canopy reflectance from an AOS and on canopy temperature with mixed models and with partial correlation.
2. Assess with stepwise regression which plant variable each of the 12 VIs is the most sensitive to: in season biomass or plant N concentration.
3. Correlate in-season biomass, plant N concentration, grain yield, grain N, and percent yellow berry with the 12 VIs and with canopy temperature.

MATERIALS AND METHODS

The study was performed for two growing seasons, 2012–2013 and 2013–2014, at the Maricopa Agricultural Center (33.0675° N, 111.9715° W, 358 m above sea level) of the University of Arizona in Maricopa, AZ (Mon et al., 2016). Average annual rainfall is 170 mm, and the site is classified as a hot desert climate (Köppen climate classification). The soil is a Casa Grande sandy loam (fine-loamy, mixed, superactive, hyperthermic Typic Natrargid, USDA-NRCS, 2017). Initial 1 M KCl-extractable soil profile (0–1.2 m) NO_3–N was 32 kg N ha^{-1}. The experiment was conducted under one span (55 m long) of a two-span end-feed linear-move overhead sprinkler irrigation system (Valmont Industries, Inc., Valmont, NE; mention of commercial products does not imply endorsement or recommendation but is solely for reader convenience). The sprinklers were 1 m above the ground, and sprinkler spacing was 1.5 m. The study consisted of five rates of N fertilizer and 10 rates of irrigations (Mon et al., 2016). Durum wheat cultivar Orita was planted at 150 kg seed ha^{-1} in 18-cm rows in early December of each year.

Irrigation was scheduled according to estimated daily evapotranspiration (ET_c), calculated by the FAO-56 dual crop coefficient procedures (Allen et al., 1998). The field was uniformly irrigated from planting to mid-January each year, keeping soil water depletion <45%. Then an irrigation gradient of 10 unrandomized sections (Fig. 1), was applied by varying the nozzle size in a gradient pattern across 50 m of the 55-m linear span (Mon et al., 2016). Sections were 4.6-m-wide and were irrigated by three sprinkler nozzles of the same size. The 10 nozzle flow outputs ranged from 2.4 to 13.8 L min^{-1}. In each 4.6 m wide irrigation plot, the center 2.5 m was the prescribed rate and

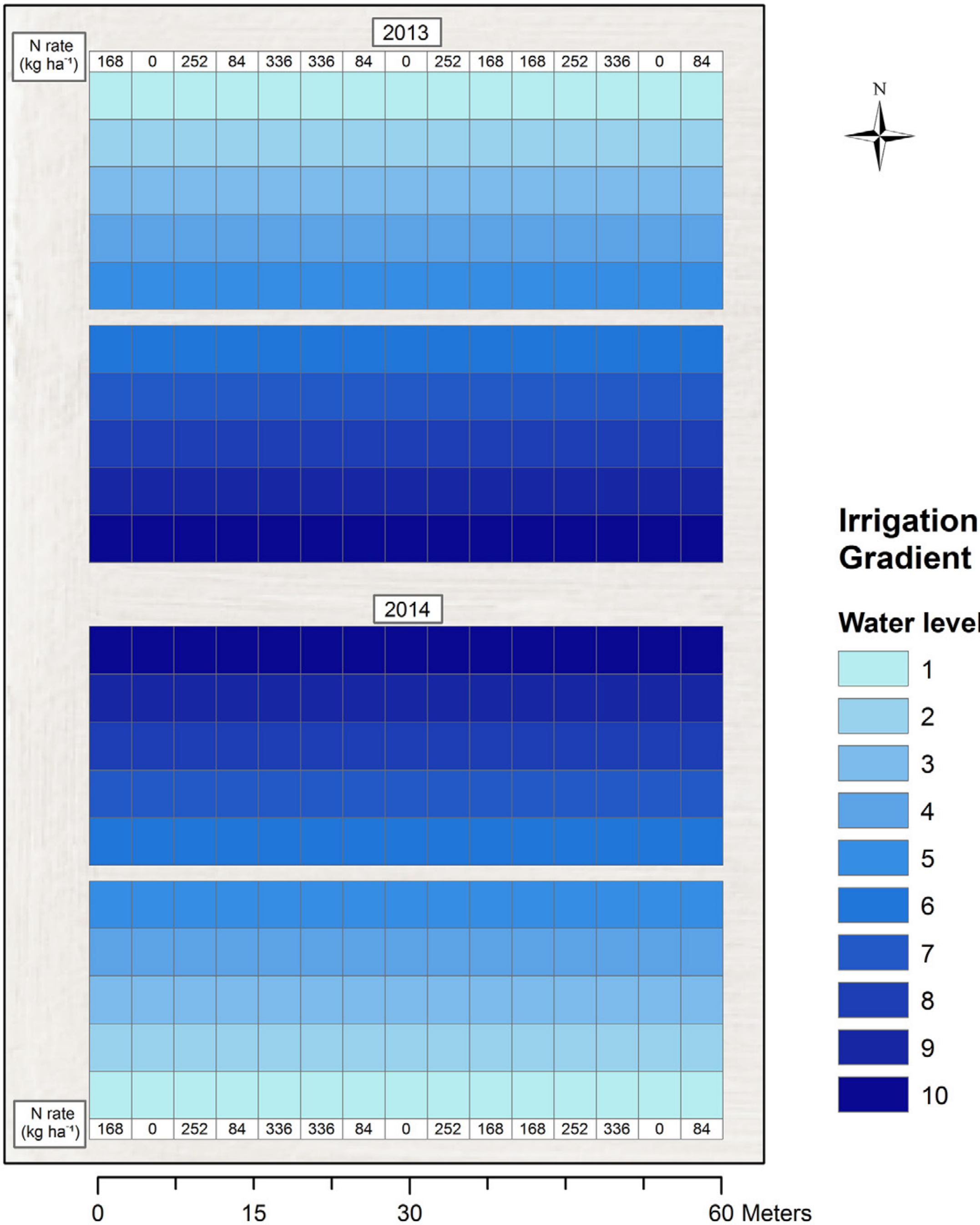

Fig. 1. Water and N plot layout for durum wheat overhead sprinkler study, Maricopa, AZ, 2013, 2014.

the 1.05 m ends were a blend of water from the adjacent plot. The base (1.0) irrigation level was applied in section 8 (Fig. 1), where soil water depletion was maintained <45% with the aid of soil water balance calculations. Irrigation levels varied from 0.35 irrigation fraction in water level 1 to 1.14 in water level 10. The study was conducted in the North span of the two-span overhead irrigation system in 2013, with the irrigation gradient decreasing from South to North. In 2014 the study was moved to the South span and the irrigation gradient direction was reversed, decreasing from North to South (Fig. 1). Soil texture (sampled in every subplot) was very uniform in our fields, with CVs of sand and clay content ranging from 8 to 20%, which may have been an issue if soil texture gradients were present in the direction of the irrigation gradients. As is frequently the case for large-scale irrigation studies, in this study irrigation levels were replicated three times, but they were not randomized (Hanks et al., 1980; Johnson et al., 1983), due to the limitation of having only one irrigation span available to us.

A total of 15 main plots were laid out perpendicular to the irrigation system in three randomized complete blocks with five N treatments (Fig. 1). Plot size was 50 by 4 m (length by width). Nitrogen fertilizer rates were 0, 84, 168, 252, and 336 kg N ha^{-1} using liquid urea ammonium nitrate (320 g N kg^{-1}) and was applied using a high clearance vehicle equipped with a Raven SCS 440 controller, Raven flow meter, GPS, and butterfly valve (Raven Industries, Sioux Falls, SD). Eight drop lines were fitted with spray nozzles every 30 cm. The highest N rate imposed was purposely chosen to exceed the University of Arizona's N recommendation of 168 and 280 kg N ha^{-1} for durum wheat for Trix clay loam (fine-loamy, mixed, superactive, calcareous, hyperthermic Typic Torrifluvent, USDA-NRCS, 2017) and Casa Grande sandy loam soils, respectively (Doerge et al., 1991). The total amount of N fertilizer for each treatment was equally split for three applications and applied at Zadoks stages 30, 32, and 39 (Zadoks et al., 1974). Every fertilizer application was followed immediately by an irrigation.

Plant samples were taken at Zadoks stages 32 (early stem elongation, second node visible), 39 (late stem elongation, flag leaf visible), and 75 (ripening, medium milk) for plant biomass and total N uptake from the five odd numbered irrigation subplots (i.e., 1, 3, 5, 7, 9) per N treatment. Zadoks 75 was considered the stage of maximum biomass accumulation and N uptake (Malhi et al., 2006). Two rows of plants, along 0.5 m row length were cut at the ground from each N subplot, and oven-dried at 65°C for 72 h.

Grain yield was harvested at grain maturity (Zadoks 92) from the undisturbed areas on the western half of the 4-m-wide N plots in May of each year. In 2013, plots were harvested with a Hege 180 plot combine (Wintersteiger AG, Ried im Innkreis, Austria) fitted with a 1.98-m cutter bar. In 2014, plots were harvested with a Model 8 Massey Ferguson combine (Massey Ferguson, Duluth, GA) fitted with a 1.52-m cutter bar. Grain from each plot was collected in bags and immediately weighed. Subsamples of grain were weighed and oven-dried at 65°C for 72 h, and then re-weighed to determine moisture content. Dried plant and grain samples were ground to 0.5 mm and analyzed for N analysis with a Leco-Truspec CN analyzer (Leco Corp., St. Joseph, MI). Grain yield, N uptake and N use efficiency inour study, as affected by the 10 rates of irrigation and the five rates of N are discussed in detail in a companion paper (Mon et al., 2016).

Canopy reflectance was measured every 7 to 10 d using two AOS, the Crop Circle ACS-470 sensors (Holland Scientific Inc., Lincoln, NE), starting after 1 January. Sensors were deployed on a four-wheel proxial sensing cart called PSCM1 (White and Conley, 2013), with the sensor height at 1 m above the tallest plants. The two sensors were mounted in-line with the detectors sets of each sensor 30 cm apart. The Crop Circle ACS-470 sensor field of view (FOV) is 30° ′ 14°. Data acquisition rate was 5 Hz, and one pass per plot was made traveling 0.4 to 0.7 m s^{-1}. The first Crop Circle sensor utilized interference filters of 800 nm (20 nm bandwidth), 590 nm (10 nm bandwidth), and 670 nm (10 nm bandwidth). The second sensor had filters of 780 nm (20 nm bandwidth), 530 nm (10 nm bandwidth), and 730 nm (10 nm bandwidth). One hour before the proximal sensing runs, both AOSs were calibrated to zero (blocked) and 1.0 fraction reflectance (to a small internal white panel) for each filter with a FieldCAL SC-1 (Holland Scientific Inc., Lincoln, NE). Crop Circle data were logged using a single Holland Scientific GeoSCOUT GLS-420 data logger. A Hemisphere (Hemisphere GPS, Calgary, AB, Canada) Crescent A100 GPS receiver provided submeter accurate differential geopositioning system information.

Formulas for the 12 VIs tested are shown in Table 1. There was some concern about potential problems with calculating VIs with reflectance data from both AOS, in terms of filters or sensor bias. Therefore checks were conducted where filters were swapped between the two sensors and after re-calibrating scanned reflection panels. Results were consistent after switching filters between sensors. The three NDVIs were also calculated normalized difference vegetation index amber (NDVIA), normalized difference vegetation index red (NDVIR), and normalized difference vegetation index green (NDVIG) by substituting R_{800} with R_{780}. The magnitude of these NDVIs with R_{780} were about 5% less than with R_{800} (R_{780} averaged 90% of R_{800}). However, results of the data analysis (described below) were identical, so therefore results for VIs using R_{780} are not presented.

A 28° full angle FOV Apogee IRR-P (SI-131) IRT was also deployed on the PSCM1, mounted level to the ground at AOS height with a sensor facing nadir (White and Conley, 2013). Air temperature was measured near the IRT using a Type T (copper-constantan, 43 μV °C^{-1}) shaded thermocouple junction. Temperature and GPS data were logged with a CR3000 data logger at 5 Hz (Campbell Scientific, Logan, UT). Radiometric temperatures were analyzed as canopy/air temperature differences (T_C–T_A) (Idso et al., 1977; Jackson et al., 1977). Canopy temperature data expressed as Tc–Ta were used because this reflects the surface energy balance, transpiration, and the leaf temperatures, which are affected by stomatal regulation (Jackson et al., 1977; Idso et al., 1977).

Table 1. Twelve vegetation indices used in water by N durum wheat field study, Maricopa, AZ, 2013–2014.

Vegetation index	Wavebands and calculation	Reference
Normalized difference vegetation index-red (NDVIR)	$(R_{800}- R_{670})/(R_{800} + R_{670})$†	Tucker, 1979
Normalized difference vegetation index-amber (NDVIA)	$(R_{800}- R_{590})/(R_{800} + R_{590})$	Holland et al., 2004; Solari et al. 2008
Normalized difference vegetation index-green (NDVIG)	$(R_{800}- R_{530})/(R_{800} + R_{530})$	Gitelson et al. 1996
Chlorophyll index (CI)	$(R_{800})/(R_{590}) - 1$	Gitelson et al., 2005; Shiratsuchi et al., 2011
Physiological reflectance index (PRI)	$(R_{590}- R_{530})/(R_{590} + R_{530})$	Peñuelas et al., 1994
Normalized difference vegetation index-red-red edge (NDRRE)	$(R_{730}-- R_{670})/(R_{730} + R_{670})$	Gitelson et al., 2002
Normalized difference vegetation index-amber-red edge (NDARE)	$(R_{730}- R_{590})/(R_{730} + R_{590})$	Modified from Gitelson et al., 2002
Normalized difference red edge index (NDRE)	$(R_{800}- R_{730})/(R_{800} + R_{730})$	Gitelson and Merzlyak 1994
Canopy chlorophyll content index (CCCI)	(NDRE)/(NDVI-Red)	Barnes et al., 2000, Cammarano et al., 2011
DATT	$(R_{800}v\ R_{730})/(R_{800}- R_{670})$	Datt, 1999
Meris terrestrial chlorophyll index (MTCI)	$(R_{800}-R_{730})/(R_{730}-R_{670})$	Dash and Curran, 2004
Chlorophyll index vegetation index (CIRE)	$(R_{800})/(R_{730}) - 1$	Gitelson et al., 2005

† R_{800} is reflectance (fraction of active light source) at 800 nm, R_{670}, is reflectance at 670 nm etc.

Canopy temperature data from the CR3000 data logger were merged with the Crop Circle data using PROC MERGE in SAS by "UTC_TIME" (SAS Institute, 2013). Data files were then assigned to subplots using "Geoprocessing/Intersect" procedures in ArcMap 10 (ESRI, 2015). The effects of N fertilizer rate, irrigation level, and their interaction on the 12 VIs, Tc–Ta, plant biomass, plant N, and total N uptake were determined at Zadoks 32, and 39 using the PROC MIXED procedure (SAS Institute, 2013), with a repeated measures option for irrigation level. Fernandez (1991) and Piepho et al. (2004) recommended an analysis of variance with repeated measures to account for the correlations arising from serial ordering of a treatment like line-source irrigation that is not randomized. Fernandez (1991) used PROC GLM in SAS, but the PROC MIXED framework was used by Piepho et al. (2004) and in the example of SAS/STAT User's Guide (SAS Institute, 2016), which uses the Hanks et al. (1980) original line-source irrigation data. The replications are not independent using the line-source irrigation systems and thus are considered repeated measures. PROC MIXED overcomes the unrandomized replicate issue by providing the option of incorporating a covariance structure among the repeated measures that results in appropriate adjustments to the error terms and their associated degrees of freedom. (Littell et al., 1996).

Replicate and replicate × N rate were considered random effects. Nitrogen rate, irrigation level, and N × irrigation were considered fixed effects. We employed the PDIFF option in the mixed procedure, which is for pairwise *t* tests of means, useful when main or interaction effects are significant. Irrigation levels will be referred to as "water" for the rest of the paper.

Second, the 12 VIs, Tc–Ta, plant biomass, plant N, and total N uptake at Zadoks 32 and 39 were partially correlated with water level, controlling for N rate, and partially correlated with N rate, controlling for water level. This was done with PROC CORR and a "partial statement". Third, a step-wise regression (addition method) of the 12 VIs (dependent variables, one at a time) was performed, vs. plant biomass, and plant N at Zadoks 32 and 39 using PROC REG. Finally, simple correlations were calculated of the 12 VIs, and Tc–Ta at all dates with final biomass, total N uptake, grain yield, grain N and percent yellow berry using PROC CORR.

RESULTS

Wheat biomass responded positively to irrigation level at Zadoks 32 and 39 in both years of the study (Table 2). Response of biomass to N, on the other hand, was not yet evident at Zadoks 32 in either year, and remained absent at Zadoks 39 in 2014. Plant N concentration showed strong N fertilizer rate effects at both growth stages in both years (Table 2). Total N uptake at Zadoks 32 and 39 responded positively to both N and water (irrigation) in all four growth stage–year combinations. Nitrogen × water interactions in three plant measures were most apparent at Zadoks 39 in 2014 (Table 2).

In both years, NDVIA, NDVIR, and NDVIG exhibited strong N and water effects at Zadoks 32 and 39 (*F* tests in Table 2, Fig. 2). Nitrogen × water interactions were significant only at Zadoks 39 in 2013 and 2014 (Table 2). The partial correlation coefficients for the three NDVIs were larger for N than for water at both growth stages in 2013, but at Zadoks 32 in 2014, water effects were larger (Table 2). The partial correlation coefficients for N with NDVIA and NDVIG were in all cases slightly larger than for NDVIR.

The chlorophyll index using amber (CI) showed significant N rate and water effects that were similar to the three NDVIs in both years (Table 2). The NIR and amber wavebands in the CI are the same as in NDVIA, so the sensitivity to N and water was similar. Partial correlation with N for the physiological reflectance index (PRI) was weaker at Zadoks 32 than the NDVIs in both years (Table 2). The sign of the partial correlations to N and water were mostly negative with PRI. The trend of PRI vs. N rate was far less pronounced than with NDVIs (Fig. 2).

Among VIs that employed red edge reflectance, partial correlation showed that NDRE was more sensitive to N than CCCI in both growth stages in 2013 (Table 2). Notably, in both growth stages in 2014, CCCI showed highly significant partial correlation with N (r = 0.80–0.86), with no significant partial correlation with water. The DATT (Fig. 2) and MTCI, on the other hand, showed significant partial correlation with N in 2013, with no correlation to water (Table 2). In 2014, DATT and MTCI had larger partial correlation coefficients with N than water. Figure 2a and 2b show this differential N and water trend for DATT that the other three VIs in the figure do not exhibit. At Zadoks 32, DATT had no N × water interaction, and very little water effect (Fig. 2a and 2b). Significant DATT water trend is noted at the two highest N rates at Zadoks 39 (Fig. 2a and 2b), determined by pairwise *t* tests which reflects the significant N × water interaction in the mixed model analysis (Table 2). The chlorophyll index vegetation index (CIRE) *F* tests for water and for N were similar to that of CI for all growth stage-year combinations.

Canopy temperature showed strong significant negative partial correlation with water (r = −0.76 to −0.90), with no significant partial correlation (r are ns to −0.35) with N in 2014 (Table 2). The partial correlation of canopy temperature with N in 2013 was substantially less than with the VIs. As discussed in Mon et al. (2016), canopy temperature was depressed with N fertilizer, but these effects were small compared to the large canopy cooling effect of irrigation rate.

Stepwise regression of the VIs vs. plant N and biomass showed higher R^2 values at Zadoks 39 compared to Zadoks 32 in both years (Table 3). The NDVIA estimated plant N before biomass in all growth–stage–year combinations. The NDVIR, on the other hand, estimated biomass before plant N in three of four of six growth-stage-years. Plant N was related well at Zadoks 32 and 39 in 2013 and at Zadoks 39 in 2014, with DATT and MTCI, that is, R^2s > 0.70. The NDRE and CCCI gave good correlations with plant N in several cases, but did not show greater R^2s than NDVIs or DATT and MTCI.

Simple correlation among the 12 VIs, grain yield, and plant measures are shown in Table 4. The NDVIs showed high correlation with grain yield in three of four growth stage–year combinations, that is, r > 0.78. The NDARE and NDREE estimated grain yield as well as the three NDVIs. The NDRE, CCCI, PRI, CI, and CIRE generally correlated very highly with grain yield as well in all combinations but Zadoks 32 in 2013. Correlations with grain N were highest with CCCI in two of four growth stage–year combinations, with r > 0.64. The DATT and MTCI had consistent high correlations with

Table 2. *F* tests for repeated measures proc mixed model, and partial correlation coefficients (corr coeff) of water and N effects for 12 vegetation indices of durum wheat, Maricopa, AZ, 2013–2014.

VIs†	Nitrogen *F* test	Water *F* test	W×N *F* test	N corr coeff	W corr coeff	Nitrogen *F* test	Water *F* test	W×N *F* test	N corr coeff	W corr coeff
	2013									
	Zadoks 32					Zadoks 39				
NDVIA	51**	9.6**	ns‡	0.89**	0.36**	131**	142**	5.4**	0.90**	0.77**
NDVIR	49**	14**	ns	0.85**	ns	112**	138**	3.8**	0.89**	0.76**
NDVIG	70**	15**	ns	0.90**	0.56**	140**	129**	4.7**	0.96**	0.77**
CI	48**	10**	ns	0.89**	0.35**	115**	94**	9.3**	0.87**	0.77**
PRI	12**	23**	ns	–0.66**	0.47**	116**	138**	10**	–0.87**	–0.76**
NDARE	33**	10**	ns	0.83**	0.49**	122**	123**	6.0**	0.89**	0.80**
NDRRE	30**	14**	ns	0.75**	ns	94**	143**	5.6**	0.88**	0.80**
NDRE	77**	8.3**	ns	0.91**	ns	162**	133**	10.3**	0.91**	0.74**
CCCI	56**	7.5**	ns	0.83**	–0.26*	30**	19**	14**	0.62**	–0.54**
DATT	67**	5.2**	ns	0.91**	ns	149**	24**	20**	0.90**	ns
MTCI	73**	5.3**	ns	0.91**	ns	112**	36**	21**	0.88**	ns
CIRE	74**	7.8**	ns	0.92**	ns	140**	135**	11**	0.91*	0.74**
Tc–Ta	7.1**	8.1**	ns	–0.50**	–0.50**	5**	84**	ns	–0.35**	–0.90**
Plant measures										
Biomass	ns	3.3*	ns	ns	–0.29*	6.3*	11**	ns	0.59**	ns
N concentration	39**	3.5*	ns	0.81**	ns	83**	8.1**	6.1**	0.94**	ns
Total N uptake	5.6*	3.6*	ns	0.66**	ns	26**	9.9**	3.4**	0.86**	ns
	2014									
NDVIA	7.7**	72**	ns	0.64**	0.89**	135**	129**	2.8*	0.80**	0.83**
NDVIR	6.1**	59**	ns	0.60**	0.90**	118**	166**	2.6*	0.79**	0.84**
NDVIG	8.1**	62**	ns	0.64**	0.90**	150**	138**	2.7*	0.82**	0.79**
CI	11**	85**	1.9*	0.74**	0.91**	96**	132**	8.9	0.84**	0.86**
PRI	5.1*	59**	ns	–0.44**	–0.85**	71**	80**	3.6*	–0.72**	-0.84**
NDARE	4.9*	98**	ns	0.58**	0.92**	124**	166**	4.6**	0.80**	0.87**
NDRRE	4.2**	38**	ns	0.53**	0.92**	106**	278**	5.5**	0.81**	0.88**
NDRE	14**	68**	ns	0.73**	0.87**	127**	145**	4.5**	0.84**	0.81**
CCCI	17.5**	ns	ns	0.80**	ns	45**	3.5*	5.0**	0.86**	ns
DATT	89**	5.8**	1.6*	0.82**	0.60**	107**	24**	6.1**	0.87**	0.59**
MTCI	86**	8.2**	1.6*	0.83**	0.65**	102**	28**	6.4**	0.88**	0.65**
CIRE	15**	71**	ns	0.74**	0.88*	98**	142**	7.2**	0.84**	0.84**
Tc–Ta	ns	60**	ns	ns	–0.76**	6.1**	57**	ns	ns	–0.90**
Plant measures										
Biomass	ns	4.2**	ns	0.48**	0.29*	ns	8.2**	2.0*	0.39**	0.44**
N concentration	8.0**	6.6**	ns	0.71**	0.49**	137**	5.5**	6.0**	0.91**	ns
Total N uptake	10**	8.9*	ns	0.68**	0.44**	34**	8.5**	3.4**	0.84**	0.47**

* Significant at the α < 0.05 level.

** Significant at the α < 0.01 level.

† VIs, vegetation indices; NDVIA, normalized difference vegetation index amber; NDVIR, normalized difference vegetation index red; NDVIG, normalized difference vegetation index green; CI, chlorophyll index using amber; PRI, physiological reflectance index; NDARE normalized difference vegetation index-amber-red edge; NDRRE, normalized difference vegetation index-red-red edge; NDRE, normalized difference red edge index; CCCI, canopy chlorophyll content index; DATT, Datt, 1999; MTCI, Meris terrestrial chlorophyll index; CIRE, chlorophyll index vegetation index.

‡ ns is not significant at α = 0.05.

grain N as well. At Zadoks 32 in 2013, correlation between grain N and NDRE, DATT, MTCI, and CIRE was 0.84 to 0.85. Yellow berry vs. VI correlations followed a similar trend as with grain N, with a negative sign. The CCCI, DATT, and MTCI had high negative correlations with yellow berry all four growth stage–site-years (Table 4). Correlations between final biomass and the NDVIs was high, that is, >0.81 in all combinations but Zadoks 32 in 2013. Biomass correlations with other VIs such as CI, CIRE, and PRI followed a similar pattern. Negative correlations between canopy temperature and grain yield or biomass were as high as the best performing VIs at Zadoks 39 in both years. At Zadoks 32 in 2013, the correlation between canopy temperature and grain yield was –0.65, while the second highest correlation was with NDVIG at 0.49.

DISCUSSION

Three-D surface response of NDVIA to water and N shows that the trends are smooth and consistent (Fig. 2a and 2b). The water-N response surface of CCCI is not nearly as smooth as NDVIA or DATT (Fig. 2a and 2b). The DATT had a larger,

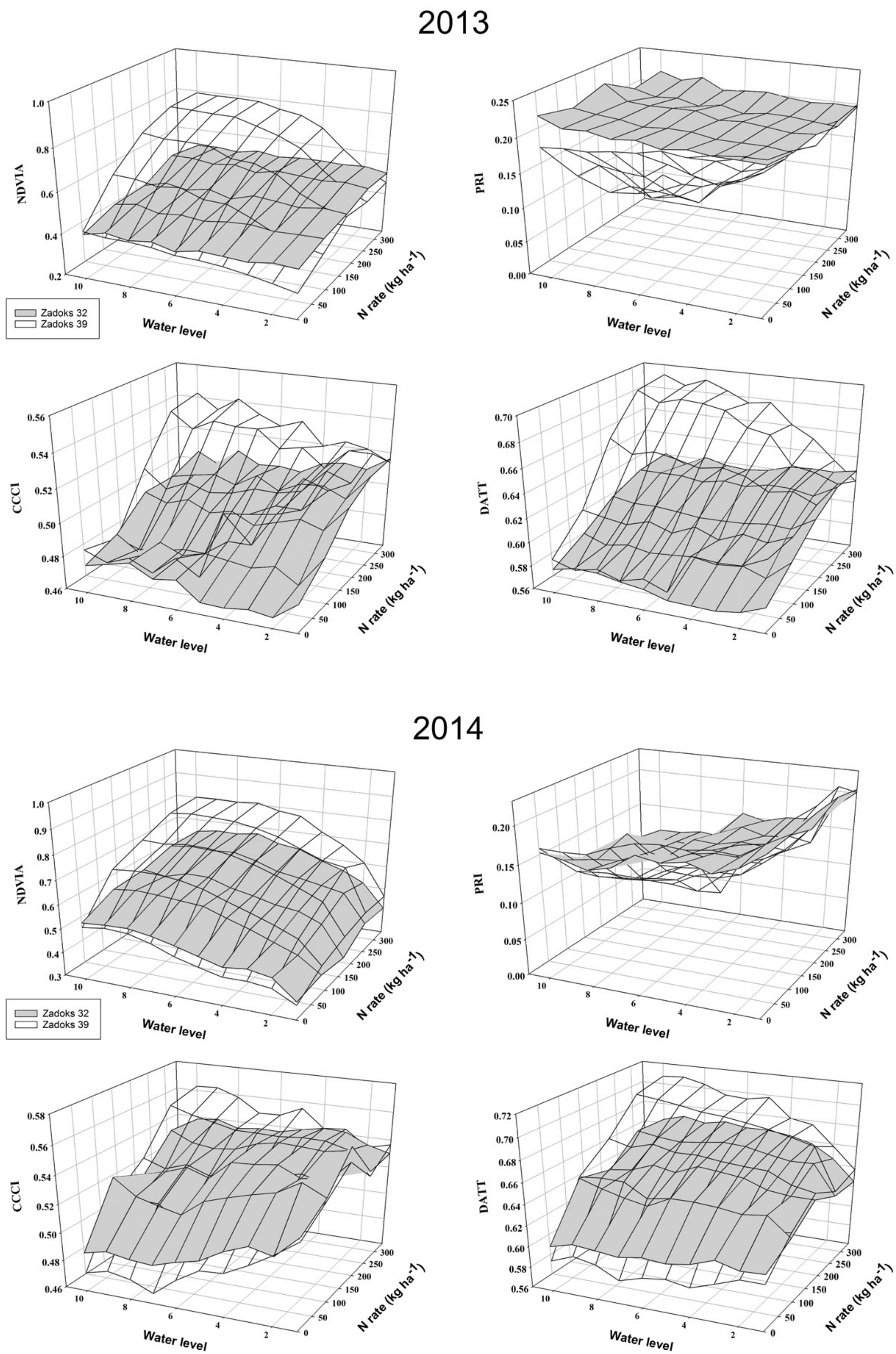

Fig. 2. Vegetation indices normalized difference vegetation index amber (NDVIA), physiological reflectance index (PRI), canopy chlorophyll content index (CCCI), and DATT at Zadoks 32 and 39 as affected by five N fertilizer rates and 10 overhead sprinkler irrigation levels, Maricopa, AZ, 2013, 2014.

Table 3. Partial R^2s and F tests for stepwise regression of 12 vegetation indices (dependent variables) of durum wheat vs. biomass and plant N concentration (independent variables) using proc reg, Maricopa, AZ, 2013–2014.

VIs†	Independent variable entered	Partial R^2	Model R^2	$C(p)$ ‡	F value	Independent variable entered	Partial R^2	Model R^2	$C(p)$	F value
					2013					
		Zadoks 32					Zadoks 39			
NDVIA	Plant N	0.61	0.61	2.2	115**	Plant N	0.53	0.53	28.7	81**
						Biomass	0.13	0.66	3.0	28**
NDVIR	Plant N	0.54	0.54	4.3	85**	Biomass	0.50	0.50	28	73**
	Biomass	0.02	0.56	3.0	ns§	Plant N	0.14	0.64	3.0	27**
NDVIG	Plant N	0.57	0.57	1.6	97**	Plant N	0.54	0.54	27.9	87**
						Biomass	0.12	0.66	3.0	27**
CI	Plant N	0.59	0.59	2.4	104**	Plant N	0.54	0.54	13.4	85**
						Biomass	0.07	0.61	3.0	12**
PRI	Plant N	0.34	0.34	3.5	38**	Plant N	0.50	0.50	21.2	72**
	Biomass	0.02	0.36	3.0	ns	Biomass	0.11	0.61	3.0	20**
NDARE	Plant N	0.46	0.46	1.4	63**	Plant N	0.50	0.50	20.9	72**
						Biomass	0.11	0.61	3.0	20**
NDRRE	Plant N	0.35	0.35	4.1	39**	Plant N	0.47	0.47	22.5	65**
	Biomass	0.03	0.38	3.0	ns	Biomass	0.12	0.59	3.0	22**
NDRE	Plant N	0.69	0.69	3.5	162**	Plant N	0.58	0.58	30.4	103**
	Biomass	0.01	0.70	3.0	ns	Biomass	0.12	0.70	3.0	29*
CCCI	Plant N	0.65	0.65	1.0	133**	Plant N	0.34	0.34	2.5	37**
DATT	Plant N	0.73	0.73	1.3	202**	Plant N	0.73	0.73	14.5	197**
						Biomass	0.04	0.77	3.0	14**
MTCI	Plant N	0.73	0.73	1.2	196**	Plant N	0.71	0.71	13.3	183**
						Biomass	0.04	0.75	3.0	12**
CIRE	Plant N	0.68	0.68	3.4	156*	Plant N	0.59	0.59	24.0	104**
	Biomass	0.01	0.69	3.0	ns	Biomass	0.10	0.69	3.0	23**
Tc–Ta	Plant N	0.10	0.10	1.7	8.3**					
					2014					
NDVIA	Plant N	0.25	0.25	20.9	24**	Plant N	0.34	0.34	36.7	38**
	Biomass	0.16	0.41	3.0	20**	Biomass	0.20	0.54	3.0	32**
NDVIR	Biomass	0.24	0.24	19.1	23**	Biomass	0.33	0.33	32.0	36**
	Plant N	0.15	0.39	3.0	18**	Plant N	0.20	0.53	3.0	31**
NDVIG	Plant N	0.25	0.25	22.0	24**	Plant N	0.37	0.37	33.7	43**
	Biomass	0.17	0.42	3.0	21**	Biomass	0.20	0.57	3.0	33**
CI	Plant N	0.28	0.28	19.8	28**	Plant N	0.45	0.45	24.9	60**
	Biomass	0.15	0.15	3.0	19**	Biomass	0.14	0.59	3.0	24**
PRI	Plant N	0.22	0.22	14.1	20**	Biomass	0.31	0.31	23.9	33**
	Biomass	0.12	0.34	3.0	13**	Plant N	0.17	0.48	3.0	23**
NDARE	Plant N	0.21	0.21	17.2	19**	Plant N	0.32	0.32	26.9	35**
	Biomass	0.12	0.35	3.0	16**	Biomass	0.18	0.50	3.0	26**
NDRRE	Biomass	0.23	0.23	15.4	22**	Plant N	0.35	0.35	28.9	35**
	Plant N	0.13	0.36	3.0	14**	Biomass	0.19	0.51	3.0	28**
NDRE	Plant N	0.30	0.30	25.2	31**	Plant N	0.44	0.44	38.4	59
	Biomass	0.18	0.48	3.0	24**	Biomass	0.19	0.63	3.0	37
CCCI	Plant N	0.10	0.10	1.8	8.0**	Plant N	0.64	0.64	3.7	132**
						Biomass	0.01	0.65	3.0	ns
DATT	Plant N	0.36	0.36	5.7	42**	Plant N	0.67	0.67	35.7	147**
	Biomass	0.04	0.40	3.0	4.7*	Biomass	0.11	0.78	3.0	35**

Continued next page

Table 3 (continued).

VIs†	Independent variable entered	Partial R^2	Model R^2	$C(p)$ ‡	F value	Independent variable entered	Partial R^2	Model R^2	$C(p)$	F value
MTCI	Plant N	0.38	0.38	7.5	45**	Plant N	0.68	0.68	36.3	153**
	Biomass	0.05	0.43	3.0	6.5*	Biomass	0.11	0.79	3.0	35**
CIRE	Biomass	0.31	0.31	24.8	33**	Biomass	0.48	0.48	36.4	67**
	Plant N	0.17	0.48	3.0	24**	Plant N	0.17	0.65	3.0	35**
Tc–Ta	Biomass	0.20	0.20	13.6	18**	Biomass	0.21	0.21	2.2	20**
	Plant N	0.12	0.32	3.0	13**					

* Significant at the $\alpha < 0.05$ level.

** Significant at the $\alpha < 0.01$ level.

† VIs, vegetation indices; NDVIA, normalized difference vegetation index amber; NDVIR, normalized difference vegetation index red; NDVIG, normalized difference vegetation index green; CI, chlorophyll index using amber; PRI, physiological reflectance index; NDARE normalized difference vegetation index-amber-red edge; NDRRE, normalized difference vegetation index-red-red edge; NDRE, normalized difference red edge index; CCCI, canopy chlorophyll content index; DATT, Datt, 1999; MTCI, Meris terrestrial chlorophyll index; CIRE, chlorophyll index vegetation index.

‡ $C(p)$ is Mallow's Cp statistic, smaller value is better fit.

§ ns is not significant at $\alpha = 0.05$.

Table 4. Simple correlation of 12 vegetation indices of durum wheat with grain N, yellow berry and grain yield, using PROC CORR, Maricopa, AZ, 2013–2014.

VIs†	Grain yield	Grain N	Yellow berry	Total biomass	Total N uptake	Grain yield	Grain N	Yellow berry	Total biomass	Total N uptake
					2013					
			Zadoks 32					Zadoks 39		
NDVIA	0.37**	0.78**	–0.76**	0.50**	0.77**	0.85**	0.51**	–0.52**	0.82**	0.88**
NDVIR	0.35**	0.75**	–0.73**	0.49**	0.75**	0.85**	0.50**	–0.50**	0.82**	0.86**
NDVIG	0.49**	0.74**	–0.67**	0.58**	0.81**	0.84**	0.52**	–0.53**	0.81**	0.88**
CI	0.36**	0.78**	–0.75**	0.49**	0.77**	0.86**	0.48**	–0.51**	0.78**	0.87**
PRI	0.21*	–0.65**	0.60**	ns‡**	–0.31**	–0.87**	–0.46**	0.49**	–0.83**	–0.88**
NDARE	0.39**	0.68**	–0.67**	0.57**	0.77**	0.88**	0.45**	–0.47**	0.83**	0.87**
NDRRE	0.35**	0.64**	–0.63**	0.53**	0.70**	0.88**	0.45**	–0.47**	0.83**	0.86**
NDRE	0.35**	0.84**	–0.80**	0.39**	0.73**	0.82**	0.56**	–0.57**	0.79**	0.89**
CCCI	0.19*	0.78**	–0.71**	ns	0.50**	ns	0.64**	–0.66**	ns	0.39**
DATT	0.22*	0.84**	–0.78**	0.27*	0.63**	0.63**	0.70**	–0.72**	0.57**	0.85**
MTCI	0.26*	0.85**	–0.78**	0.21*	0.65**	0.65**	0.68**	–0.70**	0.59**	0.85**
CIRE	0.33**	0.84**	–0.80**	0.39**	0.73**	0.83**	0.55**	–0.57**	0.78**	0.89**
Tc–Ta	–0.65**	–0.26*	0.21**	–0.58**	–0.55**	–0.82**	ns	ns	–0.78**	–0.51**
					2014					
NDVIA	0.78**	ns	–0.22*	0.82**	0.68**	0.84**	0.39**	–0.52**	0.82**	0.82**
NDVIR	0.76**	ns	–0.20*	0.81**	0.65**	0.84**	0.37**	–0.50**	0.83**	0.80**
NDVIG	0.78**	ns	–0.22*	0.82**	0.67**	0.84**	0.42**	–0.55**	0.81**	0.81**
CI	0.82**	ns	–0.41**	0.85**	0.75**	0.87**	0.39**	0.68**	0.81**	0.85**
PRI	–0.73**	ns	0.22**	–0.80**	–0.70**	–0.86**	–0.28**	0.43**	–0.85**	–0.81**
NDARE	0.76**	ns	ns	0.84**	0.65**	0.87**	0.32**	–0.47**	0.85**	0.85**
NDRRE	0.75**	ns	ns	0.82**	0.63**	0.87**	0.32**	–0.47**	0.86**	0.86**
NDRE	0.82**	0.25*	–0.36**	0.81**	0.74**	0.84**	0.48**	–0.60**	0.79**	0.86**
CCCI	0.27*	0.67**	–0.70*	ns	0.38**	0.51**	0.77**	–0.79**	0.21*	0.67**
DATT	0.70**	0.64**	–0.72**	0.51**	0.79**	0.74**	0.68**	–0.77**	0.59**	0.86**
MTCI	0.72**	0.62**	–0.70**	0.55**	0.81**	0.75**	0.66**	–0.73**	0.55**	0.81**
CIRE	0.75**	0.27*	–0.38**	0.82**	0.77**	0.68**	0.47**	–0.59**	0.87**	0.87**
Tc–Ta	–0.58**	0.18*	ns	–0.71**	–0.43**	–0.85**	ns	ns	–0.86**	–0.56**

* Significant at the $\alpha < 0.05$ level.

** Significant at the $\alpha < 0.01$ level.

† VIs, vegetation indices; NDVIA, normalized difference vegetation index amber; NDVIR, normalized difference vegetation index red; NDVIG, normalized difference vegetation index green; CI, chlorophyll index using amber; PRI, physiological reflectance index; NDARE normalized difference vegetation index-amber-red edge; NDRRE, normalized difference vegetation index-red-red edge; NDRE, normalized difference red edge index; CCCI, canopy chlorophyll content index; DATT, Datt, 1999; MTCI, Meris terrestrial chlorophyll index; CIRE, chlorophyll index vegetation index.

‡ ns is not significant at $\alpha = 0.05$.

smoother, and more consistent N trend than CCCI, and less effect of water than NDVIA. The DATT and MTCI, similar to the Shiratsuchi et al. (2011) irrigated corn (*Zea mays* L.) study, out-performed the NDVIs in being able to distinguish N rates while being relatively less sensitive to water. The strong N sensitivity, with weaker influence of water that CCCI showed in this study was similar to the report for broccoli (*Brassica oleracea*), in a similar water × N sprinkler study in Maricopa, AZ (El-Shikha et al., 2007). These VIs, however, did respond strongly to water at the two highest N rates at Zadoks 39, as shown for DATT in Fig. 2. This N × water interaction was significant for all VIs at Zadoks 39 (Table 2), but the fact that partial correlation does not pick this up is a major disadvantage of that procedure. On the other hand, the economic optimum N rate for grain yield in this study was 200 and 136 kg N ha^{-1} in 2013, and 2014, respectively, rates at which VIs like DATT were still less sensitive to water (Mon et al., 2016). Given that CCCI, DATT, and MTCI were the VIs with the most consistent ability to distinguish N rates across both years with minimal water effects, these VIs could be the subject of further N management studies with variable water regimes.

Another goal of the study was to identify VIs that were strongly sensitive to water, but not to N. No VIs did this as consistently as canopy temperature (Table 2). At Zadoks 39 in 2013, no VIs showed high water–low N partial correlation, but canopy temperature did. However, at Zadoks 32 in 2014, the three NDVIs, CI, PRI, NDARE, NDRRE, NDRE, and CIRE all showed larger partial correlation with water than with N. The mixed model analysis shows that for biomass, plant N and total N uptake, the effects of water and N were similar to the other data sets. Stepwise regression results for Zadoks 32 in 2014, however do show much lower R^2s than the other three growth stage–years (Table 3). In the warmer-than-average 2014 season (Mon et al., 2016), canopy temperature showed very high negative partial correlation to water, −0.76 and −0.90 at Zadoks 32 and 39, respectively, with no N effect. Suárez et al. (2008) reported that in olive orchard (*Olea* spp.) in Spain, PRI was highly correlated with canopy temperature.

In many cases, VIs had significant water or N effects, but biomass was not affected by N or water. Nitrogen concentration of wheat and total N uptake consistently showed N and water effects. The size of the plant sample was small compared to the area the active sensors scanned. The stepwise regression results in Table 3 clearly demonstrate the importance of plant N concentration in what the VIs are detecting, especially if biomass is not affected by N. Vegetation indices, however, were not consistent in whether plant N or biomass entered the stepwise regression models first. In terms of evaluating the VIs ability to detect N more than water, or water more than N, it is important to consider in this study that between growth stages, the N effect became stronger.

In terms of VIs ability to estimate plant N, the best performing VIs were NDVIA, DATT, and MTCI. The NDRE and CCCI showed high correlation with plant N in several cases, but these were not as consistent. This is contrast to the reports of Tilling et al. (2007) who reported that NDRE and CCCI had notably greater correlations with plant N than NDVI. The slight improvement of estimating plant N with NDVIA compared to NDVIR was previously reported in cotton by Bronson et al. (2011).

With respect to simple correlations, the NDVIs consistently showed high correlation with grain yield, with the exception of Zadoks 32 in 2013 (Table 4). All of the other VIs consistently correlated with grain yield, with the exception of CCCI, DATT, and MTCI. Correlations were high but negative between grain yield and PRI. The trade-off observed that CCCI, DATT, and MTCI were the best at distinguishing N rates with minimal water effects, but their correlation with grain yield was poor, was not expected. Interestingly, CCCI correlated better with grain N than with grain yield. Studies using VIs other than NDVI to estimate wheat grain N are rare (Hansen et al., 2002; Wang et al., 2004). Wright et al. (2004) reported that NDVIG correlated better than NDVIR with wheat grain protein, similar to our study.

CONCLUSION

In short, the NDVIs were consistently strong indicators of N and water effects, and in many cases showed modest distinction between the two factors. The VIs that were the most effective in exhibiting N effects with minimal water effects were CCCI, DATT, and MTCI. These three VIs also showed good potential in estimating grain N. None of the VIs were as effective as canopy temperature in detecting water effects with minimal N effects. Nitrogen and irrigation management in durum wheat could be improved with combined monitoring of N status-indicating VIs, such as CCCI, DATT, or MTCI, and of water status via canopy temperature.

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