Evaluation of Trimble Hand Held Crop Sensor and Greenseeker™ Sensors At Different Heights and for Various Crops

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ABSTRACT

Sensors that estimate normalized difference vegetative index (NDVI) can increase nitrogen use efficiency and help meet the expected increased food demand; however, current devices are cost prohibitive to small farming operations. The objectives of this study were to determine the relationship of GreenSeeker™ (GS) sensor and HandHeld Crop Sensor (HHCS), manufactured by Trimble, when used to collect NDVI data at different heights, by different operators, in several crops; and to determine the reliability of the less-costly HHCS to accurately collect NDVI data. Tests were conducted in Stillwater, Oklahoma, in the fall of 2012. Both sensors were operated by two operators at 60 and 100 cm above the bare soil or crop canopy. Regression, correlation, and analysis of variance, were performed in SAS. Correlation coefficient (R^2) between HHCS and GS readings averaged 0.95, indicating a strong correlation between sensor readings. There was no significant effect of operator, heigth, or their interactions; however, although readings between sensors were highly correlated, they were significantly different. Mean NDVI colleted via GS averaged 0.43 as compared to 0.39 via HHCS, with a root mean square error (RMSE) of 0.049 across all 1200 collected values, witha trend of slight underestimation of NDVI values by the HHCS. Results indicates that NDVI readings are independent of operator or height collected, and despite the high correlation between

NDVI readings obtained via GS and the new HHCS, the latter yields slighly lower NDVI values than the former.

Abbreviations: GS, GreenSeeker^{TM} sensor; HHCS, HandHeld Crop Sensor; NDVI, Normalized Difference Vegetative Index; RMSE, Root Mean Square Error.

Keywords: NDVI, HandHeld Crop Sensor, GreenSeeker^{TM}, nitrogen, precision agriculture

INTRODUCTION

Food production will have to be increased anywhere from 70 to 100% by 2050 in order to meet the demand caused by a 35% increase in world population with higher diet and consumption patterns from current population (Bruinsma, 2009; Rosegrant et al., 2009; UNFPA, 2010). The increase in food production can occur either by achieving better yields in the current productive areas or increasing the area cultivated to agronomic crops (Licker et al., 2010; van Wart et al., 2013). Although only half of the worldwide area suitable for agriculture is currently being cultivated, the remaining area is characterized by tropical rainforests, and cleaning and cultivating these areas can have tremendous social, economic, and ecological impacts (Ramankutty et al., 2002). Thus, increase in food by enhancing the efficiency of already cultivated area is crucial.

The agricultural input that resulted in greater increase in crop productivity throughout the years is nitrogen (N) fertilizer (Johnston et al. (2000). Without the application of N fertilizer, maize production could drop by 41% and sorghum production by 19% (Smith et al. (1990). However, environmental concerns from over-application of N fertilizer are major as “dead-zones” can be formed due to eutrophication of lakes and oceans, and therefore many researchers have focused on minimizing environmental problems caused by fertilizer waste (Loehr, 1974; Sharpe et al., 1988; Edwards and Daniel, 1992). Given the importance of N fertilizer to increase crop productivity and also the environmental concerns from its over-application, management practices that optimize the use of N, increasing its use efficiency and decreasing its losses, are warranted.

Filella et al. (1995) proposed the use of remote sensing to determine the N status of crops, and thus improving the accuracy of fertilizer N. Work by Kanke et al. (2012), listed benefits of using the optical sensor system in agriculture, reaffirming that the development of this technology can be very useful in detecting plant N status and making fertilizer recommendations. Optical sensors work based on emissions of beam of light that can be absorbed or reflected, depending on the characteristics of the material that is illuminated (Kenyon, 2008). Both the morphology and physical characteristics of plants, such as area of leaves, will influence the absorption or reflectance of the light beam (Araus et al., 2001). The greatest advantage of the use of light is that its behavior can provide information that can be used to estimate a number of parameters (Araus et al., 2001), such as biomass, photosynthetic area, amount of active radiation (PAR) absorbed and photosynthetic potential (Reynolds et al., 2001), and thus, result in better N recommendations.

Increased nitrogen use efficiency by the use of spectral radiance, including Normalized Difference Vegetative Index (NDVI), has been widely reported in the literature (Li et al., 2009; Raun et al., 2005; Stone et al., 1996; Zillman et al., 2006). However, the cost of adoption of this technology due to sensor costs renders it unfeasible in most farm operations in the developing world, and also in many farms across the United States (Crain et al., 2012). Therefore, if a low-cost affordable sensor can be used to predict spectral radiance values with high reliability, this could increase nitrogen use efficiency and food production in both developed and developing world, helping to meet food demand by 2050.

The objectives of this study were: a) to determine the relationship between GreenSeeker^{TM} (GS), a reliable source for NDVI measurements, and the HandHeld Crop Sensor (HHCS), a more affordable NDVI sensor, when used to collect NDVI data at different heights by different operators for bermuadgrass (Cynodon dactylon L), winter wheat (Triticum aestivum L.), and Canola (Brassica sp); and b) to determine the reliability of the GS and HHCS sensors over a wide range of NDVI values.

MATERIAL AND METHODS

This study was conducted during the fall semester of 2012 at the Oklahoma State University Agronomy Farm (36°07' N, 97°05' W) and EFAW Research Station (36°08' N, 97°05' W), both located in Stillwater, Oklahoma. Predominant soil series where the readings were taken were Norge loam (fine-silty, mixed, active, thermic Udic Paleustolls) at the Agronomy Farm in Stillwater, and Easpur loam (fine-loamy, mixed, superactive, thermic Fluventic Haplustolls) at EFAW Research Station.

Normalized Difference Vegetation Index (NDVI) was developed based on the concept of multiple absorption and reflection (Rouse et al., (1973)). Its formula can be defined as the difference between the reflectance in the near infrared and visible red divided by sum of both (Eq. 1):

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \qquad [1]$$

The GS sensor, an optical sensor designed to measure NDVI, was developed by Oklahoma State University and marketed commercially by N-Tech Industries (Ukiah, CA). Crain et al. (2012) provided a thorough description of the GS sensor. This sensor has its own light source (active sensor), which allows measurements to be taken during the day or night, nullifying the effects of atmospheric interference. It works in red (660 ±10nm) and near infrared (780 ± 15nm) wavelengths and can easily collect more than ten readings per second which are stored in a handheld PC unit (Crain et al., 2012). Since it has all readings recorded, it can be used to evaluate homogeneity of the area with the coefficient of variation among readings (CV) (Arnall et al., 2006). When the GS sensor is held between 60 and 100 centimeters of height above the crop, its operating area is 1 x 60 cm (Crain et al., 2012). The limitations of the GS sensor are its size, weight, and price, as the box and fittings weigh over 5 kg and its price is estimated at approximately US$ 4,000, rendering it unavailable to most of small operation farms.

Recently a pocket version of the GS sensor has been developed by Trimble's Agriculture Division. The HandHeld Crop Sensor (HHCS) follows the same principle of the GS, instantly calculating NDVI from the crop below the sensor (Crain et al., 2012). However, the wavelengths measured are sligthly different: the range of HHCS is 657 (± 20mn) for red light and 771 (±25 mn) for near infrared. Also, this sensor collects 1 reading per second and the average of that sample is displayed for ten seconds after the trigger is released, and no information can be stored. Unlike the GS, the HHCS has a circular measurement area, so when operated at 60 cm aboce crop canopy the area which is measured is approximately 200 cm^2. Its greatest advantages are its small size, light weight and ease of use, and lower cost. The HHCS became commercially available in August 2012 and its price the United States is estimated at US$ 495, which makes it affordable for small farms in both developing and developed countries.

Readings of NDVI were collected with the GS and the HHCS from one hundred randomly selected areas encompassing approximately three square feet each, in fields planted to winter canola (*Brassica spp.*), winter wheat (*Triticum aestivum L.*), or Bermuda grass (*Cynodon dactylon L.*). Furthermore, readings were taken from bare soil or wheat residue, resulting in a dataset with NDVI values ranging from 0.1 to 0.95. Crop type, stage of crop development, bare soil, or wheat residue were not treated as variables in this study as we were interested in the correlations of the NDVI values regardless of cover type. Readings were taken first using the GS sensor, followed by the HHCS at the same point in space.

In order to compare the measurements of NDVI via GS to measurements via HHCS, three NDVI readings were taken at 60 and three at 100 cm above soil level in each one of the 100 randomly selected areas using both sensors, by two different operators. This accounted for a total of 2400 readings, or 1200 paired readings. Data was carefully analyzed for outliers, which were considered first quartile minus 1.5 x interquartile range for the lower fence of data; or third quartile plus 1.5 x interquartile range. Furthermore, if there was any discrepancy in data from one out of the three reps (i.e. GS values of 0.21, 0.23, 0.85), the pair related to the discrepant values was discarted.

In order to evaluate the relationship between the values obtained by HHCS and the GS sensor, data were submitted to statistical analyses using SAS 9.3 (SAS Institute, Cary, NC, 2001). Pearson's correlation coefficient (r), coefficient of determination (R^2), and root mean square error (RMSE), were generated. Analysis of variance was performed using the PROC GLM procedure and significance of the variables or their interactions was tested at $\alpha = 0.05$.

RESULTS

Values of NDVI obtained via HHCS were highly correlated to readings obtained via GS, regardless if the analysis was done separating data by operator, height of instrument above soil, both, or pulled across the whole dataset (Table 1). The correlation analysis resulted in R^2 values ranging from 0.88 to 0.98, indicating that the variation in NDVI values collected via HHCS were well explained by variation in NDVI values collected via GS. When analyzed separately by height and operator, the R^2 between the NDVI values measured with the GS and the HHCS ranged among 0.88 and 0.97 (Table 1). Correlation coefficients ranged between 0.89 and 0.97 when comparing solely the performance of the operators independent of height, results similar to the ones obtained by Crain et al. (2012). Furthermore, the relationship between NDVI values obtained via the same sensor at different heights was also strong. Determination coefficients higher than 0.96 indicates that NDVI values collected at 60 cm are strongly correlated with the values collected at 100 cm. Consequently, the operator can choose to collect readings at 60 or 100 cm above the canopy without significant difference between the NDVI values. Despite the high correlations obtained, the estimated intercept of the regressions derived from such analyses were often different from zero, and their slopes different from 1 (Table 1). This indicates that the actual NDVI values collected via GS and HHCS may be different, and that the fashion to which they respond to change in vegetation coverage also differs.

The regression resultant from the whole dataset, encompassing different operators, heights, and ground covers, resulted in and r^2 of 0.95; an intercept of -0.04 which was significantly different from zero; and a slope of 1.017, which was significantly higher than one (Figure 1). Coefficient of determination of 0.95 reveals the strength of the correlation between the readings made by HHCS and GS sensors, independent of operator or the height of collection. Intercept lower than zero, however, indicates that values of NDVI collected via HHCS were lower than the ones collected via GS at low NDVI values, and the slope greater than one implies that this difference between readings decreases as NDVI values increases. Indeed, it becomes clear when analyzing Figure 1 that the regression line lays below the 1:1 line, confirming that the HHCS results in lower NDVI readings than does the GS sensor.

The analysis of variance established that there was no significant effect of height, operator, or their interactions (Table 2). Means of NDVI obtained at different heights or by different operators were grouped together due to the lack of significance between them. However, sensor proved to be a significant effect on the model, confirming the trend observed in the regression analysis (Table 2).

Values of NDVI obtained across the whole dataset ranged from 0.13 to 0.74 via GS sensor, and from 0.07 to 0.72 with the HHCS (Figure 2). Mean NDVI achieved with the GS sensor was 0.43, as compared to 0.39 averaged by the HHCS. This difference is statistically significant and HHCS proved to underestimate NDVI when compared to the GS sensor. This difference between sensors resulted in a root mean square error of 0.05 pulled across the whole dataset. The calculated RMSE for values below or equal 0.42 (median of the collected NDVI) represents 19% of the below-median mean, while for values higher than the median the RMSE represented around 9% of this mean. These results indicate that for low NDVI values the HHCS presented a higher percent error than it did for higher NDVI values.

DISCUSSION

The analysis of this robust dataset makes clear that the NDVI readings collected by HHCS are strong correlated to NDVI values collected via the tradition GS sensor. However, despite the straight correlation between sensors, the values resultant from the HHCS are significantly lower than the ones resulting from the GS sensor. In order to avoid this limitation in the newer, more affordable sensor, either a calibration must be performed or the final user needs to be aware of the intrinsic difference between readings.

An average RMSE of 0.05 with consistent lower values read by the HHCS as compared to the GS sensor indicates that the different bands being read by both sensors results in lower NDVI values read by the HHCS. This is an important focus for further calibration of the HHCS. Furthermore, the slope of 1.017 on the regression in Fig. 1 suggests that the average difference between the both sensors is greater at low NDVI values, and is closer to the 1:1 line at greater NDVIs. This indicates that the calibration must be focused on the low range of NDVI values

The interference of height and the operator were analyzed and verified that neither one affects the results. Thus, any operator can choose any of both height (60 or 100 cm above soil) to take readings that there is no significant difference in the final readings. Attention has been given especially for angle to the ground to which the sensors are being held, as it interferes how the beam is receipted by the sensor.

The GS sensor has been widely used to monitor crop growth and development (Arnall et al., 2006; Raun et al., 2001; Raun et al., 2005). Therefore, due to the strong relationship inherent between the readings of HHCS and GS, with average r^2 of 0.95, we here state that both sensors have lush performance to monitored crop growth. It is important, however, that the end user have in mind that the HHCS results in lower NDVI readings than the ones resultant from the GS sensor. Therefore, the use of NDVI values derived from HHCS in equations to predict yield potential (Prasad et al., 2007; Raun et al., 2001) or its use in other empirical equations derived from NDVI values collected with the GS sensor may be compromised. As empirical equations not always can be extrapolated to situations other than the ones they were derived from, a new set of empirical equations should be developed for the HHCS not to lead to wrong analyses and conclusions.

CONCLUSIONS

Height at which the measurement is taken above ground or the operator presented no significant effect on NDVI values, indicating that either 60 or 100 cm above ground could be used when using either sensor.

Values of NDVI derived from the HHCS presented a very high correlation with values read with the GS sensor. This indicates that both sensors can be used to monitor crop growth. However, with a RMSE of 0.05, NDVI values collected by HandHeld Crop Sensor presented slightly lower values than those collected with the GreenSeeker™, which leads to the conclusions 1) the HHCS must be calibrated to achieve higher readings, similar to the ones performed by the GS; and 2) when using the HHCS as it is now, values of NDVI derived from the readings can be used to monitor crop growth, but should not be used in the empirical equations derived from previous work performed with the GS sensor, such as yield potential estimation.

The HandHeld Crop Sensor has the advantages of being lightweight and easier to operate, and it is also cheaper than the GreenSeeker™. All these attributes facilitate data collection and also make it more attractive for its low cost. Therefore, if the intuit of the NDVI measurements is to reflect crop growth, it can be of great value. However, based on its current calibration the NDVI data collected with the HHCS should not be used as a substitute for data collected with the GS.

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Table 1

Regression analysis between Normalized Difference Vegetative Index values collected via HandHeld Crop Sensor and GreenSeeker™ testing that intercept = 0 and slope = 1. A: readings collected 60 cm above soil by operator 1; B: readings collected 100 cm above soil by operator 1; C: readings collected 60 cm above soil by operator 2; D: readings collected 100 cm above soil by operator 2; E: readings collected 60 cm above soil via GreenSeeker™ comparing operator 1 x operator 2; F: readings collected 100 cm above canopy via HandHeld Crop Sensor comparing operator 1 x 2; G: readings collected via GreenSeeker™ at 60 and 100 centimeters above canopy performed by operator 1; H: readings collected via HandHeld Crop Sensor at 60 and 100 cm above canopy performed by operator 2. I: Correlation between all data collected within the experiment using the HS and the GS sensors.

Analysis	n	Test variable	Estimate	r^2	Pr > |t|	Lower 95% confidence limit	Upper 95% confidence limit
A	300	Intercept=0	-0.058	0.943	0.000	0.000	-0.072
		Slope=1	1.047		0.000	0.000	1.018
B	300	Intercept=0	-0.040	0.966	0.000	-0.050	-0.030
		Slope=1	1.007		0.000	0.986	1.029
C	300	Intercept=0	-0.007	0.911	0.386	-0.023	0.009
		Slope=1	0.969		0.000	0.934	1.003
D	300	Intercept=0	-0.016	0.884	0.084	-0.034	0.002
		Slope=1	0.965		0.000	0.925	1.005
E	300	Intercept=0	0.006	0.893	0.524	-0.012	0.023
		Slope=1	0.970		0.000	0.931	1.008
F	300	Intercept=0	0.012	0.975	0.002	0.004	0.020
		Slope=1	0.980		0.000	0.962	0.998
G	300	Intercept=0	-0.039	0.957	0.000	-0.051	-0.027
		Slope=1	1.063		0.000	1.038	1.089
H	300	Intercept=0	-0.037	0.977	0.000	-0.045	-0.028
		Slope=1	1.049		0.000	1.031	1.068
I	1193	Intercept=0	-0.039	0.953	0.000	-0.044	-0.033
		Slope=1	1.017		0.000	1.004	1.030

Table 2
Analysis of variance evaluating sensors, heigth of collection, repetition, operator, and thei interactions, Stillwater, Oklahoma, 2012.

Source	DF	Type III SS	Mean Square	F Value	Pr>F
Rep	2	0.00223	0.00111	0.04	0.97
Height	1	0.07220	0.07220	2.30	0.13
Sensor	1	0.55464	0.55464	17.66	<0.0001
Operator	1	0.00004	0.00004	0.00	0.97
Height * Sensor	1	0.00491	0.00491	0.16	0.69
Height * Operator	1	0.00016	0.00016	0.01	0.94
Sensor * Operator	1	0.02798	0.02798	0.89	0.35
Height * Sensor * Operator	1	0.00651	0.00651	0.21	0.65
Source of Variation		Means	n	Duncan Grouping	
Height	60	0.414	1197	a	
	100	0.403	1196	a	
Sensor	GS	0.424	1193	a	
	HHCS	0.393	1200	b	
Operator	1	0.409	1194	a	
	2	0.408	1199	a	

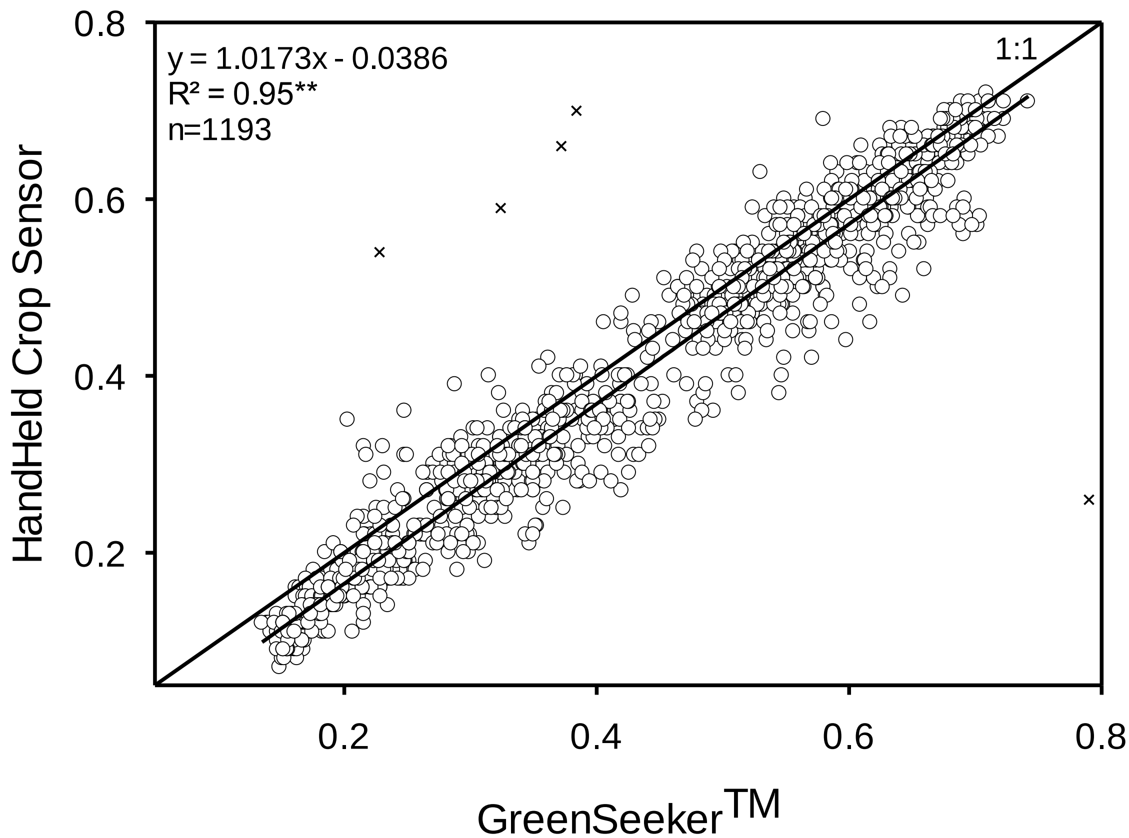

Figure 1. Regression between Normalized Difference Vegetation Index collected via GreenSeeker™ and HandHeld Crop Sensor pooled across the whole dataset. Edge-to-edge line indicates 1:1; line across the sampled points indicates regression line; x symbols are outliers ignored in the analysis.

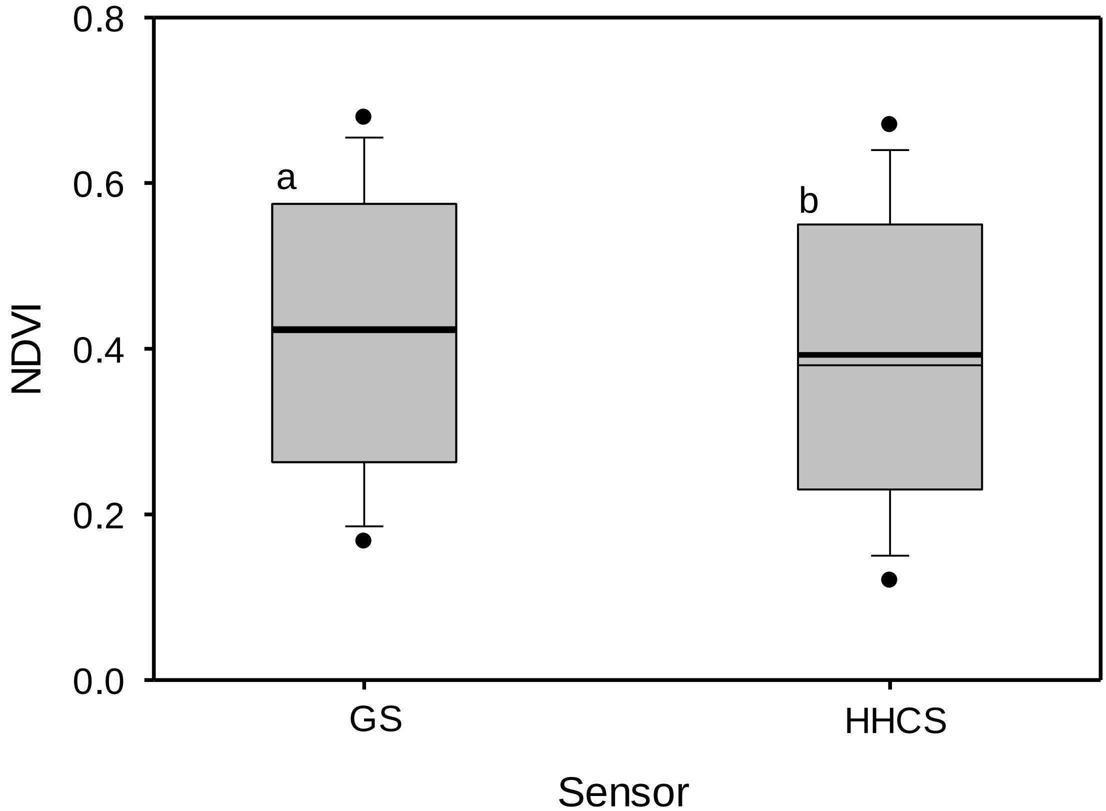

Figure 2. Normalized Vegetative Development Index as measured via GreenSeeker™ sensor (GS) and Hand Held Crop Sensor (HHCS) across the complete dataset. Whiskers indicate the 5th and 95th percentiles. From bottom to top, the three lines in each box represent the first quartile, median, and third quartile. The heavy black lines represent the mean, and different letters indicate statistical differences at $\alpha = 0.05$ (Duncan grouping).