Variation in Spectral Reflectance of Turf Type Bermudagrass Genotypes

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Abstract

Green plants absorb a photosynthetically active radiation (PAR) spectral region and use it as a source of energy in photosynthesis. High throughput phenotyping of the green vegetation using proximal sensors has become an important tool to quantify the biophysical characteristics of the turfgrass. A total of 50 hybrid bermudagrass (*Cynodon dactylon* x *C. transvaalensis*) accessions were grown in the greenhouse from stolon cuttings in 36 well flats and arranged in three replicates each with 12 plugs. RapidScan CS-45, a height independent active crop canopy sensor that measures crop reflectance at 670 nm, 730 nm, and 780 nm was used to collect spectral data. Six indexes related to canopy photosynthetic area and chlorophyll content were calculated. Significant variation was observed among the genotypes in all the indexes. The correlation and selection indexes analyses using the indexes as selection differentials identified superior genotypes and validated the practical application of the technique in the turf aesthetic value assessment.

Background

Considerable genetic variability exists among bermudagrass germplasm for turf characteristics. However, conventional selection technique based on visual evaluation can be slow and inefficient and the precise variations of genotypes often remain concealed. Phenomics has shown to greatly aid in identifying genotypes carrying superior traits, increasing selection efficiency, and shortening the time period for cultivar development (Lobos and Hancock, 2015).

High throughput phenotyping using remote and proximal sensing techniques are increasingly used to capture agronomic and physiological traits associated with adaptation, yield potential, and stress tolerance traits in plants (Cabrera-Bosquet et al., 2012).

Spectral reflectance of plants is closely associated with absorption at certain wavelengths across the electromagnetic spectrum that are linked to specific characteristics or plant conditions (Lobos and Hancock, 2015). Hence, selection based on spectral indexes in plant breeding is expected to improve genetic gains for different important traits.

This experiment was conducted under controlled environments to measure the genetic variation of 50 bermudagrass genotypes using RapidScan CS-45, a height independent active crop canopy sensor that measures canopy reflectance at 670 nm, 730 nm, and 780 nm.

To identify superior genotypes, multi-trait selection differential based on six different indexes that were calculated to measure canopy photosynthetic area and chlorophyll content.

Materials and Methods

Fifty turf type bermudagrass genotypes developed at Oklahoma State University were grown from stolon cuttings in 36 well flats in the greenhouse at USDA-ARS, U. S. Arid-Land Agricultural Research Center. The flats were arranged in three replicates of 12 plugs each.

Canopy reflectance measurements were collected using a Crop Circle RapidScan CS-45 (Holland Scientific, Lincoln, NE, USA). Spectral reflectance data at 670 nm, 730 nm, and 780 nm bands were recorded and six indexes were calculated (Table 1).

Correlation among the indexes and multi-trait genotype-ideotype distance index (MGIDI) (Olivoto and Nardino, 2021) analyses were conducted to identify superior genotypes.

Table 1: The formulae and references of different spectral reflectance indices used in these study.

Spectral reflectance indices	Formula	References
Normalized difference vegetation index (NDVI)	(R780 - R670)/(R780 + R670)	Raun et al., 2001
Normalized difference red edge index (NDRE)	(R780 - R730)/(R780 + R730)	Gitelson & Merzlyak, 1994
Normalized difference vegetation index-Red-Red edge (NDRRE)	(R730 - R670)/(R730 + R670)	Gitelson, et al., 2002
Canopy chlorophyll content index (CCCI)	NDRE/NDVIR	Long et al., 2009
The MERIS terrestrial chlorophyll index (MTCI)	(R780 - R730)/(R730 - R670)	Dash and Curran, 2004
The chlorophyll index using red edge (CIRE)	(R780/R730) -1	Gitelson et al., 2005

Results

Indexes density heatmap showed MTCI has wide range, while NDRE and CCCI have narrow range than others (Fig. 1). Statistically, highly significant differences were observed among the genotypes for all the indexes.

Performance analytics revealed high similarity between NDRE & CIRE (Fig. 2). NDVI was also highly correlated with NDRRE, NDRE and CIRE. NDRE is also highly correlated with NDRRE.

Similarly, MTCI and CCCI are highly correlated, while both were weakly or negatively correlated with the rest of the indexes used in this study.

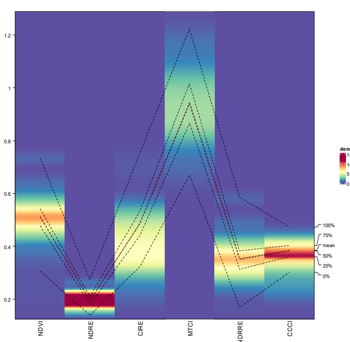

Figure 1: Density heatmap of the indexes used to evaluate 50 turf type bermudagrass genotypes.

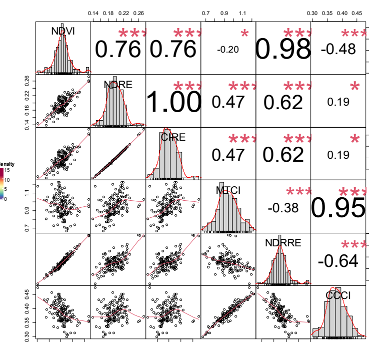

Figure 2: Scatter plots, frequency distributions, and relationships among the six indexes used to evaluate 50 turf type bermudagrass genotypes for genetic variation based on canopy reflectance at different wavelengths.

Principal component analysis using MGIDI revealed two factors accounting for a total of 99.8% (PC1=67.3% and PC2 =32.5%) of the variations among the genotypes.

Factor analysis using indexes as selection differentials selected OSU2102, OSU2120, OSU2053, OSU2108, OSU2039, OSU2123, OSU2075, OSU2015, OSU2118, and OSU2124 as superior over the others (Fig. 3A).

Factors analysis to the MGIDI indicated that factor 1 contributed more towards the selection of OSU2102 (Fig. 3B). Factor 2 (MTCI and CCCI) contributed mainly for the selection of OSU2053 and OSU2075. Both factors contributed towards the selection of OSU2039, OSU2015, and OSU2118.

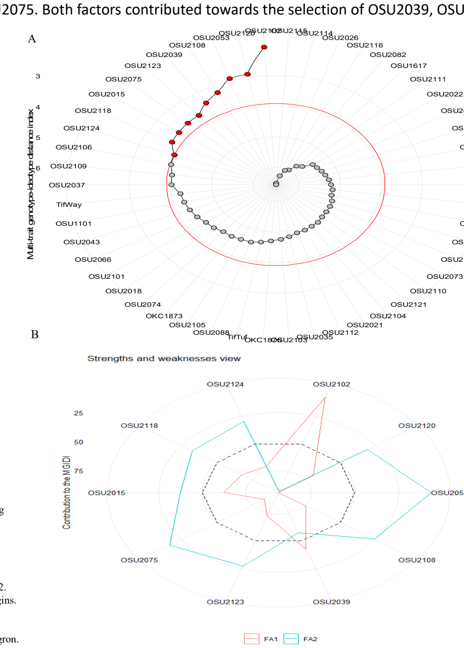

Fig. 3: Genotype rankings for MGIDI. The selected genotypes based on this index are shown in red (A) and the strengths and weaknesses view of the selected genotypes (B).

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