Broadband Spectral Reflectance Models of Turfgrass Species and Cultivars to Drought Stress

Yiwei Jiang and Robert N. Carrow*

ABSTRACT

The objective of this study was to assess canopy broadband spectral reflectance for turfgrasses under drought stress. Optimum turf quality (TQ) and leaf firing (LF) models were developed and compared based on two, three, and five wavelength bands. Sods of bermudagrass (*Cynodon dactylon* L. × *C. transvaalensis* Burtt-Davy), seashore paspalum (*Paspalum vaginatum* Swartz), zoysiagrass (*Zoysia japonica* Steud.), and St. Augustinegrass [*Stenotaphrum secundatum* (Walt.) Kuntze], and seeded tall fescue (*Festuca arundinacea* Schreb.) were used in this study with three cultivars each of bermudagrass, seashore paspalum, and tall fescue. Traditional vegetation indices (VIs) based on two bands within 660 to 950 nm were not as sensitive as three to five broadband models using a wider band range of 660 to 1480 nm. Optimum models were cultivar specific models, even within a species. The broadband wavelength at R900 and R1200 should be considered in drought sensitive spectral models since they were most often observed and exhibited high partial R^2 values. These results suggest that mobile broadband spectral devices to map turfgrass responses to drought stress would benefit by the availability of three to five broadbands that could be user selected for optimum, cultivar specific models.

Y. Jiang, Dep. of Agronomy, Purdue Univ., West Lafayette, IN 47907-2054; R.N. Carrow, Dep. of Crop and Soil Sciences, Georgia Experiment Station, Univ. of Georgia, Griffin, GA 30223-1797. Received 6 Oct. 2006. *Corresponding author (rcarrow@uga.edu).

Abbreviations: B, bermudagrass; IR/R, reflectance in the near-infrared radiation divided by reflectance in the red range; LAI, leaf area index; LF, leaf firing; NDVI, normalized difference vegetation index; NIR, near-infrared; SA, St. Augustinegrass; SP, seashore paspalum; TF, tall fescue; TQ, turf quality; VI, vegetation index; ZZ, zoysiagrass.

Precision turfgrass management must deal with obtaining information relative to the inherent spatial and temporal variability on a site for improved efficiency in management. Site-specific management requires specific information on the site characteristics. Vehicle-mounted spectral sensing devices are commercially available that have been used on turfgrass situations or may be adapted to provide field mapping of turfgrass characteristics (Hansen and Jørgensen, 2001; Bell et al., 2002; Reusch et al., 2002; GreenSeeker, 2006). Field-based spectral mapping must rely on spectral models predictive of specific turfgrass characteristics for either real-time use such as in variable-rate applications or for incorporation into global positioning system or geographic information system maps that are then used for management decisions. Spectral reflectance response models based on one or two broadbands have been reported for turfgrass characteristics such as turfgrass quality, color, degree of cover, drought stress, wear, and diseases (Nutter et al., 1993; Fenstermaker-Shaulis et al., 1997; Trenholm et al., 1999, 2000; Bell et al., 2002).

Spectral relationships to specific plant parameters or responses may involve individual hyperspectral or broadbands, ratios as indices, normalized indices, derivatives, or regression equations

Published in Crop Sci. 47:xx–xx (2007).
doi: 10.2135/cropsci2006.09.0617

677 S. Segoe Rd., Madison, WI 53711 USA

(Broge and Leblanc, 2001; Thenkabail et al., 2000; Poss et al., 2006). Numerous vegetative indices (VIs) based on use of two wavelength bands have been reported in the literature using various hyperspectral (<4 nm band width) or broadband (10–50 nm width) wavelength bands (Poss et al., 2006). When hyperspectral bands or broadbands are used for calculation of VIs based on two wavelength bands or when more than two bands are used to develop multiple regression models that relate to a plant parameter such as leaf area index (LAI) or biomass, these spectral models have been found to be species or possibly genotype specific on other crops. Thenkabail et al. (2000) demonstrated that 12 common spectral band regions provided the optimum relationships for crop biophysical characteristics across five crops. These spectral regions exhibit commonality across plants because of their relationships to specific physical and physiological plant properties (Knipling, 1970), However, when optimum models were developed using one to four wavelength variables, the models differed for crop (Thenkabail et al., 2000). They noted the same general spectral bands are involved in VIs or regression models for all plants, but species may differ in reflectance response at certain wavelengths within a general band region and, thereby, result in different best model among species. Additionally, spectral reflectance data have also been used to discriminate between species by using the same multiple wavelengths in regression models, but identifying different spectral responses among species (Clark et al., 2005). Major et al. (2003) noted that cellulose, lignin, and protein absorption in the near-infrared (NIR) region could result in significant differences among species and perhaps genotypes.

Hansen and Jørgensen (2001) and Reusch et al.(2002) described field-mapping equipment capable of using up to five user-selected wavelength bands. Flexibility in band selection (wavelength bands used and number of bands) could be important if the optimum bands differed with species and genotype; using more than two bands would allow for potentially more accurate models. Recently, best models were reported using hyperspectral bands for turfgrass drought stress that were based on using more than two wavelength bands at the species level (Hutto et al., 2006) and among species and cultivars (Jiang and Carrow, 2005). Leaf firing and turfgrass quality relationships to spectral responses were somewhat stronger when more than two bands were used, which supports the results of Thenkabail et al. (2000) for other crops and plant parameter relationships where inclusion of more bands improved the model. Additionally, the specific bands exhibiting best correlations have been found to vary with species (Trenholm et al., 2000; broadband data, two species) or species and genotype (Jiang and Carrow, 2005; hyperspectral band data).

Due to the potential for more accurate or flexible field spectral mapping models using two or more user-selected bands and the possibility for optimum models to be inter- or intraspecific rather than a uniform model for all grasses, the objective of this study was to assess canopy broadband spectral reflectance models (two, three, and five broadband models) for turf quality (TQ) and leaf firing (LF) responses to drought stress across turfgrass species and within species. Species included bermudagrass (*Cynodon dactylon* L. × *C. transvaalensis* Burtt-Davy), seashore paspalum (*Paspalum vaginatum* Swartz), zoysiagrass (*Zoysia japonica* Steud.), and St. Augustinegrass [*Stenotaphrum secundatum* (Walt.) Kuntze], which are commonly used warm-season turfgrasses, and tall fescue (*Festuca arundinacea* Schreb.) a cool-season turfgrass that can grow in the upper to midsouthern climates of the USA.

MATERIALS AND METHODS

Plant Materials

Sods were collected from mature field plots on 24 Apr. 2001 at the Griffin Campus of the University of Georgia including bermudagrass (B; ‘TifSport’, ‘TifEagle’, ‘Tifway’), seashore paspalum (SP; ‘Sea Isle 1’, ‘Sea Isle 2000’, ‘Temple’), zoysiagrass (ZZ; ‘Meyer’), and St. Augustinegrass (SA; ‘Palmetto’), and seeded tall fescue (TF; ‘Plantation’, ‘Greystone’, ‘TULSA II’). All soil was removed from sods and grasses were grown in barrels filled with Profile (Profile Products LLC, Buffalo Grove, IL), a calcined illite clay and amorphous silica material, to provide a uniform root zone media based on the work of van Bavel et al. (1978). For seeded grasses, the quantity of seed was 10 g per barrel. Barrels were 0.65-m diameter by 0.90-m depth with surface area of 0.24 m^2 with a volume of 206 L and with holes in the bottom for drainage. All grasses were mowed twice weekly using a hand clipper at 2.54 cm (B, ZZ, SP) or 5.08 cm (SA, TF) with clippings removed. Granular fertilizer (N–P–K) applied to the barrels (in terms of kg N ha^{-1}) was 97.6 N on 2 April (6–2–0), 48.8 N on 28 April (15–5–15), 24.4 N on 9 May (15–5–15), 24.4 N on 16 May (15–5–15), 48.8 N on 25 May (6–2–0), and 24.4 N on 31 May (13–0–13). Irrigation was applied as necessary to maintain healthy turfgrass and in sufficient volume to allow drainage.

Drought Stress and Spectral Reflectance

Drought stress was initiated after bringing all containers to well-watered conditions and then withholding water during dry-down periods. A sensor-controlled, removable rainout shelter facility (12.8 by 30.5 m) was used to maintain dry-down conditions. The rainout shelter was placed in its original position and was able to move automatically to cover all barrels when it rained and to move back after raining. The study consisted of three dry-downs with each period from 11 to 15 d. After each dry-down, TQ was allowed to fully recover to a nonstress level before the next dry-down started. The dry-down periods were 10–25 July, 20–31 Aug., and 10–21 Sept. 2001. The duration of each dry-down was determined by how rapidly TQ declined in response to drought stress, which allowed a range of drought stress symptoms occurring among different grasses for collection of TQ, LF, and canopy spectral reflectance data with all grasses exhibiting LF of at least >10% at the end of each dry-down. Data for each grass for drought stress responses in terms of TQ and LF are presented by Jiang and Carrow (2005), with LF at the end of dry-downs ranging from 12.3% (Temple SP) to 55.2% (Tulsa II TF).

Spectral responses were related to TQ and LF as the plant parameters. Turf quality was rated visually based on color, shoot density, and uniformity, where 1 = brown, dead turf and 9 = ideal dark-green color, density, and uniformity for the species. Leaf firing refers to leaf chlorosis starting at leaf tips and margins. Initial injury is a yellowing but often progresses into a tan or brown color with death of the tan or brown areas. Leaf firing rating was based on percentage of leaves exhibiting the above symptoms (Carrow and Duncan, 2003).

Canopy spectral reflectance was collected with a CropScan Multispectral Radiometer (CROPSCAN, Inc., Rochester, MN.). This broadband spectral device determined reflectance in a 10 to 15 nm band width centered around 660, 710, 760, 810, 900, 950, 1200, and 1480 nm with matched upward and downward sensor arrays to minimize solar radiation effects with the incident radiation used as a baseline for the reflected radiation in the same band. The 950-, 1200-, and 1480-nm bands were chosen since they represent water bands. The radiometer was held at a height of 1 m above canopy and measured about a 0.12-m^2 area inside barrel. The reflectance readings were taken at 1300 h to minimize background noise. All measurements were taken daily during each dry-down period. The following indices related to canopy status were developed based on reflectance:

- Normalized difference vegetation index 1 (NDVI1) = (R760 − R710)/(R760 + R710) (modified from Gamon and Surfus, 1999)
- Normalized difference vegetation index 2 (NDVI2) = (R950 − R660)/(R950 + R660) (modified from Trenholm et al., 1999)
- Stress index 1 = R710/R760
- Stress index 2 = R710/R810 (modified, Trenholm et al., 1999)
- Leaf area index (reflectance in the near-infrared radiation divided by reflectance in the red range [IR/R]) = R950/R660 (modified from Trenholm et al., 1999)
- Water band index = R700/R950 (modified from Penuelas et al., 1997)

Experiment Design and Data Analysis

The experiment was a randomized complete block design with repeated dry-down cycles. A total of 11 grasses (five species and selected cultivars or ecotypes for some species) was used with each individual grass replicated three times (three barrels) within each single dry-down. Correlation coefficients (*r*), coefficient of determination (R^2), and general linear model procedures were determined using Statistical Analysis System (SAS Institute, 1987) to develop the relationship between canopy characteristics and reflectance and models for TQ against reflectance. The optimum models were then summarized for each individual grass, each species, and all grasses combined. The partial coefficient of determination (R^2) for individual wavelength bands exhibited in the model was analyzed to determine relative importance of a given band in a model.

Data of TQ, LF, and canopy spectral reflectance within each treatment day were averaged for a single grass (cultivar) across the three replicates, and the averaged data were combined across three dry-downs and used for statistical analysis and model development for each individual grass. For the general model of each species, data from individual grass within the species were combined. Data from all species were combined to generate a model over all 11 grasses. Spectral data collected on low incident radiation days (<300 W/m^2) were not included in the analysis due to limited reliability of crop reflectance and instrument limitations under low radiation.

RESULTS

All grasses exhibited a substantial decline in TQ and increased LF under the three drought stress periods with considerable differences among grasses. The detailed results of TQ and LF for each grass under drought stress have been described (Jiang and Carrow, 2005). Differences in TQ (6.8–4.9 with 9.0 ideal) and LF (12.3–55.2%) for all grasses under drought stress provided a range of responses for broadband spectral reflectance relationships with these plant responses.

Vegetation Indices

In assessment of two broadband, wavelength VIs for correlation with TQ and LF, only four grasses exhibited a significant VI for TQ and none for LF (Table 1). The best VI differed for all four grasses which included three species with Stress 2 (TifSport B, $r = -0.56$), IR/R (Sea Isle 1 SP, $r = 0.65$), NDVI1 (Temple SP, $r = 0.62$), and Stress 1 (Palmetto SA, $r = 0.46$). Broadband wavelengths represented in the significant VI relationships for TQ were R710 and R810 nm (Stress 2), R60 and R950 nm (IR/R), and R710 and R760 nm (Stress 1 and NDVI1).

Table 1. Strongest correlation between turf quality and leaf firing indices and vegetation index (VI) of 11 grasses under drought stress.

Grass†	Turf quality		Leaf firing	
	Indices‡	*r*	Indices‡	*r*
'TifSport' B	Stress 2	−0.56*	Stress 2	0.36
'TifEagle' B	Stress 1	−0.41	IR/R	−0.43
'Tifway' B	Stress 2	−0.42	Stress 2	0.16
'Sea Isle 1' SP	Stress 2	−0.30	Stress 2	0.14
'Sea Isle 2000' SP	IR/R	0.65**	IR/R	−0.41
'Temple' SP	NDVI1	0.62**	NDVI1	−0.16
'Plantation' TF	NDVI1	0.37	NDVI2	0.11
'Greystone' TF	Stress 2	−0.26	Stress 2	0.43
'Tulsa II' TF	NDVI1	0.42	Stress 2	0.31
'Meyer' ZZ	NDVI1	0.35	NDVI1	0.38
'Palmetto' SA	Stress 1	0.46*	Stress 1	−0.31

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

†B, bermudagrass; SP, seashore paspalum; TF, tall fescue; ZZ, zoysiagrass; SA, St. Augustinegrass.

‡IR/R, reflectance in the near-infrared radiation divided by reflectance in the red range; NDVI, normalized difference vegetation index. NDVI1 = (R760 − R710)/(R760 + R710); NDVI2 = (R950 − R660)/(R950 + R660); Stress index 1 = R710/R760; Stress index 2 = R710/R810; Leaf area index (IR/R) = R950/R660; Water band index = R700/R950.

Three Broadband Wavelength Models

Using three broadband wavelengths from the eight spectral bands that were measured, optimum models were developed for TQ and spectral reflectance relationships for each grass (Table 2). Significant models for all grasses were developed with a range of R^2 from 0.40 to 0.74. Each model was unique for the specific grass (cultivar) and the broadband wavelength combinations within the models varied with grass (Table 2).

Based on partial coefficient of determination, the most significant bands for TQ spectral relationships were R1200 (five grasses); R710 (four grasses); and R810, R900, and R1480 (two grasses each) (Table 3). No spectral region was present in all cultivar models for bermudagrass and seashore paspalum. In contrast, R1200 was significant and present in all tall fescue cultivar models. For the bands exhibiting significant partial R^2 values, no particular band had higher values compared to the other bands across all grasses. Most cultivars demonstrated at least two significant spectral regions within their model with the exceptions being the seashore paspalums, Greystone TF, and Palmetto SA, all with only one significant band.

Significant optimum three broadband wavelength models for LF and spectral reflectance were observed for each grass except Temple SP. (Table 4). The range of significant R^2 values was 0.38 to 0.76. Spectral regions observed for LF spectral reflectance relationships with a significant partial coefficient of determination included: R1200 (five grasses); R900 and R950 (four grasses each); R810 (three grasses); and R660 and R1480 (one grass each) (Table 5). The highest R^2 values were noted in the R950, R900, and R1250 bands. As was noted for the TQ models, the R1200 band was evident in all tall fescue cultivars for LF models. No other species had the same band in each cultivar model.

Table 2. The optimum three-wavelength model for turf quality (TQ) and coefficient of determination (R^2) under drought stress for each grass.

Grass†	Model‡	(R^2)
'TifSport' B	TQ = 6.361 – 0.137 R710 + 0.036 R810 + 0.063 R1480	0.66***
'TifEagle' B	TQ = 4.094 + 0.312 R660 – 0.478 R710 + 0.139 R950	0.74***
'Tifway' B	TQ = 5.164 – 0.124 R710 + 0.055 R900 + 0.071 R1480	0.59**
'Sea Isle 1' SP	TQ = 3.273 + 0.163 R950 – 0.117 R1200 + 0.04 R1480	0.44*
'Sea Isle 2000' SP	TQ = 6.371 – 0.198 R710 + 0.063 R950 + 0.049 R1480	0.57**
'Temple' SP	TQ = 6.998 – 0.216 R710 + 0.07 R760 + 0.029 R1480	0.40*
'Plantation' TF	TQ = 6.448 + 0.175 R710 + 0.23 R810 – 0.323 R1200	0.63**
'Greystone' TF	TQ = 5.81 – 0.105 R760 + 0.226 R810 – 0.14 R1200	0.51**
'Tulsa II' TF	TQ = 3.83 + 0.076 R810 + 0.078 R900 – 0.12 R1200	0.58**
'Meyer' ZZ	TQ = 3.092 – 0.29 R810 + 0.201 R950 + 0.196 R1200	0.63**
'Palmetto' SA	TQ = 3.554 – 0.233 R710 + 0.101 R900 + 0.154 R1480	0.60**

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

***Significant at 0.001 probability level.

†B, bermudagrass; SP, seashore paspalum; TF, tall fescue; ZZ, zoysiagrass; SA, St. Augustinegrass.

‡R, reflectance at specified wavelength (e.g., R710 means reflectance at 710 nm).

Table 3. Partial coefficient of determination (R^2) in the three-wavelength turf quality model for each grass.

Grass†	R660‡	R710	R760	R810	R900	R950	R1200	R1480
'TifSport' B	–	0.24**	–	0.36**	–	–	–	0.06
'TifEagle' B	0.08	0.26**	–	–	–	0.41**	–	–
'Tifway' B	–	0.02	–	–	0.40**	–	–	0.17*
'Sea Isle 1' SP	–	–	–	–	–	0.19	0.21*	0.04
'Sea Isle 2000' SP	–	0.37**	–	–	–	0.10	–	0.09
'Temple' SP	–	0.31*	0.05	–	–	–	–	0.04
'Plantation' TF	–	0.15*	–	0.19	–	–	0.30*	–
'Greystone' TF	–	–	0.03	0.11	–	–	0.37**	–
'Tulsa II' TF	–	–	–	0.03	0.35**	–	0.20*	–
'Meyer' ZZ	–	–	–	0.21*	–	0.23*	0.19*	–
'Palmetto' SA	–	0.13	–	–	0.17	–	–	0.30**

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

†B, bermudagrass; SP, seashore paspalum; TF, tall fescue; ZZ, zoysiagrass; SA, St. Augustinegrass.

‡R, reflectance at specified wavelength (e.g., R660 means reflectance at 660 nm).

Five Band Wavelength Models

Use of five broadbands resulted in significant, optimum regression models for each grass when relating TQ to spectral reflectance (Table 6). For bermudagrass, seashore paspalum, and tall fescue, a combined model was developed across all cultivars of the species (Table 6). The resulting model was significant for each of these three species, but with a lower R^2 than expressed for individual cultivar models within the species. The range of R^2 across all grasses was 0.47 to 0.78. Partial coefficient of determination analysis revealed that R710 and R900 bands were involved in models of four grasses each, with R1480 and R1200 in three grass models, while all other bands were in one or two grass models (Table 7). The highest partial R^2 values generally occurred within the R900 band.

Significant LF spectral reflectance models using five wavelength bands were observed for six grasses with a range of R^2 for significant models of 0.54 to 0.83 (Table 8). When cultivars were combined within a species, a significant species model resulted even when some cultivars within the species did not exhibit a significant model. Bands that were in the most individual grass models were R1200 (five grasses) and R950 (four grasses) with the highest partial R^2 values evident at R950 (Table 9).

DISCUSSION

Spectral mapping of drought stress on turfgrasses would be beneficial for identifying spatial and temporal variation relative to drought stress and other stresses that may influence spectral reflectance. This information could be used to make irrigation system adjustments in either design for more uniform application or scheduling for site-specific irrigation needs. Development of drought sensitive spectral models that have a strong relationship with TQ or LF is necessary to obtain useful information. Three issues in broadband model development for drought stress on turfgrasses are (i) the influence of the number of bands included in the model on model strength, (ii) which bands are appropriate to obtain the optimum model, and (iii) whether models differ at the inter- or intraspecific level.

The most common spectral models for relating to plant characteristics are VIs. Common characteristics of VIs are (i) whether broadband or narrow band-based, they are almost always based on two spectral bands, and (ii) they use bands between 430 and 1100 nm (Poss et al., 2006). Normalized difference vegetation index, determined by broadband spectral reflectance under stresses other than drought, is a commonly used indicator for green biomass, leaf area, and stress status in plants (Daughtry et al., 1992; Gamon et al., 1995; Penuelas et al., 1997) and was found correlated to TQ and turf color under various nondrought stresses (Trenholm et al., 1999; Bell et al., 2002; Jiang et al., 2003) or biomass (Fenstermaker-Shaulis et al., 1997). The VI IR/R, associated with shoot biomass, and the Stress 1 and 2 VIs have also been related to TQ (Daughtry et al., 1992; Trenholm et al., 1999, 2000).

The broadband-based VIs used in our drought stress study demonstrated a significant relationship with TQ for only four grasses and no relationship with LF (Table 1). The best VI for the four grasses differed with each grass. The most common broadband involved was R710 in three of the VIs. Broadband spectral reflectance data and turfgrass TQ or LF as affected by drought as the specific stress are limited. On drought stressed tall fescue, Fenstermaker-Shaulis et al. (1997) observed significant relationships for broadband-based NDVI (R600–650; R800–890) versus biomass (r = 0.55), canopy temperature (r = 0.54), and tissue moisture content (r = 0.90). Hutto et al. (2006:1566) on drought-stressed bentgrass (*Agrostis stolonifera* L.) reported that "broadband widths or vegetative indices were not successful in differentiating between stresses." Our results and the above reports suggest that broadband VIs based on two bands may be better for some species or cultivars than for others for estimating TQ and drought stress relationships; when LF is the plant parameter of interest, VIs may be less accurate than for TQ; the best VI to use may be dependent on the cultivar; and there is no consistent drought-sensitive VI, but that the R710 band may be useful, which is a red-edge band sensitive to vegetation stress and a band region common in optimum hyperspectral models of many plants (Thenkabail et al., 2004).

As the number of broadband wavelengths increased from two, three, and five bands (with the three and five band models developed by regression) the number of significant models for TQ out of the 11 grasses increased from 4, 11, and 11, respectively (Table 1, 2, and 6). Likewise, the R^2 or partial R^2 value increased for all grasses, as the number of broadband wavelengths in the model increased, except Temple SP

Table 4. The optimum three-wavelength band model for leaf firing (LF) and coefficient of determination (R^2) under drought stress for each grass.

Grass†	Model‡	(R^2)
'TifSport' B	LF = 24.805 + 2.413 R710 – 0.827 R1200 – 1.141 R1480	0.40*
'TifEagle' B	LF = 76.787 – 7.734 R660 + 11.842 R710 – 3.303 R950	0.76***
'Tifway' B	LF = 39.314 + 1.318 R760 – 1.678 R950 – 0.728 R1480	0.38*
'Sea Isle 1' SP	LF = 84.993 – 2.824 R950 + 1.950 R1200 – 1.863 R1480	0.45*
'Sea Isle 2000' SP	LF = 56.102 + 2.41 R710 – 1.286 R900 – 1.412 R1480	0.40*
'Temple' SP	LF = 14.03 + 0.287 R810 + 0.429 R900 – 0.935 R950	0.16
'Plantation' TF	LF = 11.828 – 3.973 R660 – 5.353 R810 – 7.229R1200	0.64**
'Greystone' TF	LF = 79.885 – 4.139 R810 – 1.000 R900 + 4.628 R1200	0.65**
'Tulsa' II TF	LF = 41.175 – 5.061 R810 + 5.844 R1200 – 1.896 R1480	0.59**
'Meyer' ZZ	LF = 104.11 + 6.842 R810 – 5.071 R950 – 4.298 R1200	0.74***
'Palmetto' SA	LF = 65.826 + 3.325 R710 – 1.577 R900 – 2.311R1480	0.60**
Overall	LF = 31.730 + 2.360 R710 – 6.146 R810 + 4.978 R900	0.64*

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

***Significant at 0.001 probability level.

†B, bermudagrass; SP, seashore paspalum; TF, tall fescue; ZZ, zoysiagrass; SA, St. Augustinegrass.

‡R, reflectance at specified wavelength (e.g., R710 means reflectance at 710 nm).

Table 5. Partial coefficient of determination (R^2) in the three-wavelength leaf firing model for each grass.

Grass†	R660‡	R710	R760	R810	R900	R950	R1200	R1480
'TifSport' B	–	0.08	–	–	–	–	0.28*	0.04
'TifEagle' B	0.15*	0.10	–	–	–	0.51**	–	–
'Tifway' B	–	–	0.06	–	–	0.26*	–	0.07
'Sea Isle 1' SP	–	–	–	–	–	0.25*	0.13	0.07
'Sea Isle 2000' SP	–	0.04	–	–	0.26*	–	–	0.10
'Temple' SP	–	–	–	0.01	0.01	0.14	–	–
'Plantation' TF	0.07	–	–	0.13*	–	–	0.44**	–
'Greystone' TF	–	–	–	0.13*	0.36**	–	0.17*	–
'Tulsa II' TF	–	–	–	0.07	–	–	0.42**	0.11
'Meyer' ZZ	–	–	–	0.15*	–	0.46**	0.13*	–
'Palmetto' SA	–	0.09	–	–	0.25*	–	–	0.27**

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

†B, bermudagrass; SP, seashore paspalum; TF, tall fescue; ZZ, zoysiagrass; SA, St. Augustinegrass.

‡R, reflectance at specified wavelength (e.g., R660 means reflectance at 660 nm).

Table 6. Optimum five-wavelength model for turf quality (TQ) and coefficient of determination (R^2) under drought stress for each species and cultivars or ecotypes within species.

Grass	Model†	R^2
Bermudagrass	TQ = 5.431 + 0.299 R660 – 0.461 R710 + 0.044 R760 + 0.054 R900 + 0.067 R1200	0.57***
‘TifSport’	TQ = 6.324 + 0.199 R660 – 0.368 R710 + 0.061R760 + 0.012 R900 + 0.077 R1200	0.72**
‘TifEagle’	TQ = 4.05 + 0.399 R660 – 0.557 R710 + 0.049 R760 + 0.089 R900 + 0.058 R1200	0.78***
‘Tifway’	TQ = 5.56 + 0.274 R660 – 0.435 R710 + 0.035 R760 + 0.059 R900 + 0.074 R1200	0.67**
Seashore paspalum	TQ = 6.075 – 0.222 R710 + 0.102 R760 + 0.028 R950 – 0.054 R1200 + 0.051R1480	0.33***
‘Sea Isle 1’	TQ = 2.302 – 0.184 R710 + 0.247 R760 + 0.118 R950 – 0.246 R1200 + 0.107 R1480	0.56*
‘Sea Isle 2000’	TQ = 5.917 – 0.193 R710 + 0.08 R760 + 0.048 R950 – 0.066 R1200 + 0.078 R1480	0.63*
‘Temple’	TQ = 6.769 – 0.26 R710 + 0.142 R760 + 0.002 R950 – 0.063 R1200 + 0.056 R1480	0.47*
Tall fescue	TQ = 5.806 + 0.166 R710 – 0.211 R760 + 0.322 R810 + 0.054 R900 – 0.269 R1200	0.56***
‘Plantation’	TQ = 5.689 + 0.19 R710 + 0.027 R760 + 0.157 R810 + 0.038 R900 – 0.294 R1200	0.68**
‘Greystone’	TQ = 3.992 + 0.26 R710 – 0.66 R760 + 0.547 R810 + 0.205 R900 – 0.254 R1200	0.78**
‘Tulsa’ II	TQ = 6.255 + 0.151 R710 – 0.347 R760 + 0.423 R810 + 0.040 R900 – 0.24 R1200	0.61*
‘Meyer’ ZZ‡	TQ = 3.704 + 0.303 R660 – 0.352 R710 – 0.24 R810 + 0.198 R950 + 0.189 R1200	0.70**
‘Palmetto’ SA§	TQ = 3.895 – 0.28 R710 + 0.103 R810 + 0.075 R900 – 0.096 R1200 + 0.148 R1480	0.71**

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

***Significant at 0.001 probability level.

†R, reflectance at specified wavelength (e.g., R660 means reflectance at 660 nm).

‡ZZ, zoysiagrass.

§SA, St. Augustinegrass.

Table 7. Partial coefficient of determination (R^2) in the five-wavelength turf quality model for each species and within species.

Grass	R660†	R710	R760	R810	R900	R950	R1200	R1480
Bermuda	0.11***	0.04	0.07**	–	0.21***	–	–	0.15***
‘TifSport’	0.04	0.27**	0.31*	–	0.01	–	–	0.09
‘TifEagle’	0.09*	0.08	0.03	–	0.47**	–	–	0.12*
‘Tifway’	0.06	0.02	0.03	–	0.40**	–	–	0.17*
Seashore paspalum	–	0.24***	0.01	–	–	0.04	0.03	0.02
‘Sea Isle 1’	–	0.03	0.09	–	–	0.19	0.21*	0.04
‘Sea Isle 2000’	–	0.37**	0.04	–	–	0.10	0.02	0.09
‘Temple’	–	0.24*	0.05	–	–	0.07	0.07	0.04
Tall fescue	–	0.03	0.03	0.20***	0.19***	–	0.11**	–
‘Plantation’	–	0.05	0.26**	0.03	0.32*	–	0.02	–
‘Greystone’	–	0.14*	0.06	0.03	0.35**	–	0.20*	–
‘Tulsa II’	–	0.07	0.13	0.12	0.12	–	0.17	–
‘Meyer’ ZZ‡	0.04	0.03	–	0.21*	–	0.23*	0.19*	–
‘Palmetto’ SA§	–	0.13	–	0.05	0.17	–	0.07	0.30**

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

***Significant at 0.001 probability level.

†R, reflectance at specified wavelength (e.g., R660 means reflectance at 660 nm).

‡ZZ, zoysiagrass

§SA, St. Augustinegrass.

where NDVI1 had the highest R^2. For TQ spectral relationships of grasses under drought stress, each grass had a unique optimum model for the two (VIs), three, and five broadband wavelength models (Tables 1, 2, and 6).

For LF and spectral relationships of grasses exposed to drought stress, the number of significant models observed as the number of broadband wavelengths increased was two bands (0), three bands (10), and five bands (6). While inclusion of five bands resulted in only six significant models, four of these grasses showed a substantial increase in partial R^2 compared to the three band model (Tables 1, 4, 8). The lower sensitivity of spectral models in relationship with LF versus TQ may be due to the observation that as drought was imposed, TQ was affected earlier in the dry-down than LF.

This research demonstrated that for TQ and LF broadband spectral models in response to drought stress, a stronger model generally resulted by inclusion of more wavelength bands and the optimum model was specific to the grass. Our findings were in agreement with Thenkabail et al. (2000) for five crop species where the biophysical characteristics measured were wet biomass, LAI, plant height, and yield. They reported that models differed with crop and that the four band models performed marginally better than two band models. In a later study, Thenkabail et al. (2004) reported that five bands accounted for a high percentage of the variability in models to separate species and separation accuracies of greater that 90% occurred when using 13 to 22 bands. The wavelength bands in their study were normally about 10 nm in width since they included several adjacent hyperspectral bands. Bell et al. (2002) and Trenholm et al.(2000), using a C_3 and C_4 grass species, found that the R^2 for NDVI versus turf color, percentage of plant cover, or TQ varied considerably with species.

Table 8. Optimum five-wavelength band models for leaf firing (LF) and coefficient of determination (R^2) under drought stress for each species and cultivars/ecotypes within species.

Grass	Model†	R^2
Bermudagrass	LF = 34.998 – 11.094 R660 + 14.413 R710 – 0.596 R760 – 2.053 R950 – 0.958R1480	0.52***
'TifSport'	LF = 22.523 – 10.207 R660 + 13.401 R710 – 1.332 R760 – 0.901 R950 – 1.504 R1480	0.52
'TifEagle'	LF = 79.441 – 6.808 R660 + 10.892 R710 + 0.709 R760 – 3.720 R950 – 0.567 R1480	0.78***
'Tifway'	LF = 29.478 – 5.780 R660 + 7.295 R710 + 0.577 R760 – 1.886 R950 – 1.003 R1480	0.47
Seashore paspalum	LF = 32.805 – 3.065 R660 + 4.827 R710 – 1.605 R950 + 0.401R1200 – 0.904 R1480	0.20*
'Sea Isle 1'	LF = 82.981 – 0.46 R660 + 0.692 R710 – 2.841 R950 + 1.960 R1200 – 1.867 R1480	0.41
'Sea Isle 2000'	LF = 49.373 – 4.916 R660 + 7.37 R710 – 2.924 R950 + 1.187 R1200 – 1.495 R1480	0.54*
'Temple'	LF = 18.429 – 0.167 R660 + 0.735 R710 – 0.598 R950 + 0.250 R1200 – 0.580 R1480	0.19
Tall fescue	LF = 26.645 – 3.681 R660 + 4.516 R760 – 8.082 R810 – 0.889 R900 + 6.611 R1200	0.60***
'Plantation'	LF = 17.736 – 4.70 R660 + 1.299 R760 – 5.572 R810 – 0.709 R900 + 7.013 R1200	0.65*
'Greystone'	LF = 72.759 – 5.989 R660 + 13.809 R760 – 13.781 R810 – 4.038 R900 + 7.082 R1200	0.83***
'Tulsa II'	LF = 27.011 – 1.732 R660 + 5.394 R760 – 8.079 R810 – 0.455 R900 + 4.823 R1200	0.54
'Meyer' ZZ‡	LF = 91.069 – 6.734 R660 + 7.442 R710 + 5.772 R810 – 5.007 R950 – 3.999 R1200	0.80***
'Palmetto' SA§	LF = 68.446 + 3.499 R710 – 0.287 R810 – 1.976 R900 + 0.685 R950 – 2.547 R1480	0.61*

*Significant at 0.05 probability level.

***Significant at 0.001 probability level.

†R, reflectance at specified wavelength (e.g., R660 means reflectance at 660 nm).

‡ZZ, zoysiagrass

§SA, St. Augustinegrass.

While Hutto et al. (2006) did not find any significant broadband spectral relationships of turfgrass to drought stress, they were able when using hyperspectral reflectance data in a discriminate analysis approach to identify stressed areas at >98% of the time by using 14 wavebands between 861 and 887 nm or 33 bands between 719 and 799 nm. Jiang and Carrow (2005) focused on hyperspectral approaches, in a companion paper to this one, and obtained significant spectral reflectance models for TQ on seven out of 11 grasses (R^2 range of 0.32–0.70) and for LF on eight grasses (R^2 range of 0.27–0.71). The models differed with cultivar and included two to three narrow band wavelengths selected from the 10 wavelengths between 400 and 1100 nm with the best correlations of reflectance to TQ or LF.

Table 9. Partial coefficient of determination (R^2) in the five-wavelength leaf firing model for each species and within species.

Grass	R660†	R710	R760	R810	R900	R950	R1200	R1480
Bermuda	0.24***	0.07*	0.01	–	–	0.17**	–	0.04
'TifSport'	0.08	0.10	0.23*	–	–	0.03	–	0.07
'TifEagle'	0.09*	0.29**	0.01	–	–	0.38**	–	0.01
'Tifway'	0.08	0.10	0.01	–	–	0.26*	–	0.03
Seashore paspalum	0.02	0.04	–	–	–	0.09*	0.01	0.04
'Sea Isle 1'	0.0002	0.001	–	–	–	0.22*	0.12	0.07
'Sea Isle 2000'	0.05	0.04	–	–	–	0.19	0.19*	0.06
'Temple'	0.0002	0.02	–	–	–	0.14	0.01	0.02
Tall fescue	0.04	–	0.03	0.29***	0.15**	–	0.10*	–
'Plantation'	0.10*	–	0.002	0.30***	0.01	–	0.24**	–
'Greystone'	0.13**	–	0.04	0.13*	0.36**	–	0.17*	–
'Tulsa II'	0.01	–	0.03	0.06	0.02	–	0.42**	–
'Meyer' ZZ‡	0.04	0.01	–	0.24*	–	0.38**	0.13*	–
'Palmetto' SA§	–	0.09	–	0.05	0.20*	0.01	–	0.26**

*Significant at 0.05 probability level.

**Significant at 0.01 probability level.

***Significant at 0.001 probability level.

†R, reflectance at specified wavelength (e.g., R660 means reflectance at 660 nm).

‡ZZ, zoysiagrass.

§SA, St. Augustinegrass.

The VIs we used were based on broadband wavelengths between R660 to R950 nm, which is within the spectral range of R430 to R1100 nm used for the various VIs published in the literature (Poss et al., 2006). The three and five band regression models for TQ and LF, however, included all broadbands from R660 to R950 plus the two water bands of R1200 and R1440 nm. Based on the three and five band models for TQ spectral relationships, the most prevalent bands in the models were the water band at R1200 nm and the R900-nm band (Table 3 and 7). Broadband wavelengths most common in the LF spectral models using three or five bands were R1200, R900, and R950 nm, where R950 nm is another water band sensitive to tissue moisture content (Tables 5 and 9) (Thenkabail et al., 2000). Other studies also found that reflectance at the 950- to 970-nm region were an indicator of plant water status (Penuelas et al., 1993). Thenkabail et al. (2000, 2004) noted that the 915-nm band was one of the bands often observed in optimal hyperspectral models and represents the NIR reflectance peak that is sensitive to total chlorophyll, biomass, LAI, and protein. The R900 band range was not included in the bands used by Trenholm et al. (1999, 2000) or in other turfgrass studies involving broadband reflectance (Fenstermaker-Shaulis et al., 1997; Bell et al., 2002). Further investigation of this band in VIs or multiple regression models for relationship to drought stress or other turfgrass parameters may be worthwhile.

This research indicates that broadband-based spectral data can be used to monitor TQ and LF plant responses to increasing drought stress, but (i) traditional VIs based on two bands within 660 to 950 nm may not be as sensitive as three to five band models using a wider band range of 660 to 1480 nm, (ii) cultivar specific models, even within a species, should be considered to obtain highest sensitivity, and (iii) the bands at R900 and R1200 should be considered in drought-sensitive spectral models. Additionally, mobile broadband spectral devices to map turfgrass responses to drought stress would benefit by the availability of three to five broadbands that could be user selected for optimum, cultivar specific models. To develop the optimum band combination, a site could be mapped using all sensors and then the optimum model determined based on multiple regression methods.

Acknowledgments

Funding for this research from The Toro Company is gratefully acknowledged.

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