

# **Remote sensing of moisture and nutrient stress in turfgrass systems**

by

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## ABSTRACT

Management of irrigation and fertility on a golf course or other large turfgrass area requires a significant amount of time scouting for and identifying problem areas to maintain optimum turfgrass quality. Once a problem is found, it is often necessary to collect plant and/or soil samples for laboratory analysis for an accurate diagnosis. Submitting samples for a laboratory analysis is very expensive and lag time before receiving results is often longer than most turfgrass managers are willing to wait. During the past two decades, research in agronomic crops has shown that optical remote sensing techniques can quickly and reliably identify stressed plants through use of various calculations based on reflectance data collected from a crop canopy. The overall objective of this research was to evaluate a remote sensing system for use in predicting the moisture and nutritional status of turfgrass plants.

The first study's objective was to evaluate the relationship between remotely sensed reflectance data collected from a turfgrass canopy and the associated phosphorus content of the tissue. The treatments consisted of four P rates (0, 0.5, 1.0, and 1.5 g m<sup>-2</sup>) applied as a foliar application. Phosphorus deficiency symptoms decreased and biomass production increased at P rates above 1.0 g m<sup>-2</sup> with a single application, while no increase in soil-P was observed. Reflectance measurements were taken in increments from 400 to 1050 nm and correlated with plant tissue P concentration, chlorophyll content, plant biomass and visual quality. Stepwise regression identified a model utilizing reflectance in the blue, yellow, orange, and red regions of the spectrum that explained 73% of the variability in plant tissue P concentration for all sampling dates in 2002 and 2003. Few correlations were found between vegetative indices such as the normalized difference vegetation index (NDVI) and plant response. Results indicate that P deficiencies of creeping bentgrass can be detected through the use of remote sensing. Phosphorus deficiencies were corrected with a single foliar application of P at rates above 1.5 g m<sup>-2</sup>.

The objective of the second study was to determine if a remote sensing system can be used to accurately predict nitrogen (N) content of turfgrass tissue through the use of reflectance data collected from the canopy. Using partial least-squares regression our results indicate a weak relationship between the actual and predicted values for turfgrass quality, biomass production, and chlorophyll content. However, a strong relationship was observed between actual and predicted values for N concentration of the plant tissue during 2002 and 2003 ( $r^2 = 0.90$  and  $0.74$  respectively).

The objective of the third study was to determine if there was a relationship between remotely sensed data collected from the turfgrass canopy and the associated soil moisture content as determined by time domain reflectometry (TDR). There was no correlation ( $r = -0.20$ ) between visual drought stress ratings and the associated soil moisture content for samples collected one day before the onset of visible drought stress on the perennial ryegrass fairways. However, a weak negative correlation was observed when drought stress symptoms were visible on some of the plots ( $r = -0.52$ ). In comparison, there was a weak correlation between the visual drought stress ratings and the soil moisture content for data collected from the creeping bentgrass green height study at both one day before, and on the day of drought stress symptom onset ( $r = -0.60$  and  $-0.52$ , respectively).

## **CHAPTER 1. GENERAL INTRODUCTION**

### **Introduction**

Remote sensing has been defined as a mix of art and science through which we obtain information from an object without physical contact with the object. Initial work on remote sensing systems began in agriculture during the 1980's to estimate the growth, yield, and stresses of crops. For the past two decades research has continued to improve the crop forecasting models used in assessing plant health. Most of the work currently being done has been focused on prediction of crop nutrient status based on remote sensing data (Bausch and Duke, 1996; Blackmer et al., 1996; Bronson et al., 2003; Osborne et al., 2002). More recently there has been an increased interest in using the remote sensing tools developed in agriculture for management of turfgrass systems.

Turfgrass managers continually monitor their fertilization and irrigation programs to ensure optimal appearance while minimizing losses to the environment and maximizing profit. Characterizing the spatial variability of nutrient and moisture status across a golf course or large sports facility requires careful observation and collection of many soil and tissue samples. Optical remote sensing techniques have been shown to be valuable tools in quickly and reliably identifying stressed plants through the use of various calculations based on reflectance data collected from the crop canopy. A few remote sensing studies have been conducted with turfgrass to evaluate its use in improving production quality and reducing economic inputs. Trenholm et al. (1999) investigated the use of a remote sensing system for evaluating turfgrass quality as it was influenced by wear. They reported that remote sensing data could be used to reliably evaluate turfgrass quality, thus offering an alternative to the subjective visual quality ratings that have become the cornerstone of turfgrass research.

## **Dissertation Organization**

This dissertation consists of a review of the literature and three manuscripts prepared for partial fulfillment of the requirements for the degree, Doctor of Philosophy. The author of the dissertation is Jason K. Kruse. Dr. Nick E. Christians and Dr. Michael H. Chaplin served as co-major professors and offered many constructive suggestions for the design of the experiments. The first chapter serves as a detailed literature review on the evolution of remote sensing as it relates to turfgrass management. There is an emphasis placed on the use of remote sensing systems in evaluating the nutritional status and moisture stress status of crops, including turfgrass. The second chapter is a manuscript submitted to the *International Turfgrass Society Research Journal* that reports on the use of a remote sensing system in the detection of phosphorus deficiencies in creeping bentgrass (*Agrostis stolonifera* L.) growing on a calcareous-sand based green. The third chapter is a manuscript to be submitted to *Crop Sci.* that reports on the use of a remote sensing system to evaluate and predict the N concentration of creeping bentgrass tissue. The fourth chapter is a manuscript to be submitted to *Applied Turfgrass Science* that reports on the relationship between remotely sensed reflectance data and the associated soil moisture status of turfgrass plants. Chapter five consists of the general conclusions for the studies included in the dissertation.

## **Literature Review**

**Remote Sensing.** Remote sensing is defined simply as obtaining information about an object by a device that is not in contact with the object (Lillesand and Kiefer, 1987). One of the first indications we had linking reflectance characteristics to specific wavelengths of light was reported by Gausman et al. (1973). Thomas and Gausman (1977) found that chlorophyll was the most important factor affecting leaf reflectance. The regression coefficients relating leaf reflectance to the chlorophyll concentration in leaves were greatest for the green (550 nm) wavelength, followed by the red (670 nm) wavelength and least for the blue (450 nm) wavelength. Results from a nitrogen deficiency study on sweet peppers

(*Capsicum annum* L.) by Thomas and Oerther (1972) showed that leaf reflectance in the visible spectrum increased as N-deficiency symptoms became more pronounced. They also noted that limiting N reduced the chlorophyll concentration. Maximum reflectance occurred at 550 nm and maximum absorption occurred at 670 nm. Similar results were reported by McMurtrey et al. (1994) and Blackmer et al. (1994) in corn (*Zea mays* L.) grown under varying N rates. Recognizing the problems with using reflectance at individual wavelengths in an attempt to characterize the status of a plant, researchers began investigating the use of two or more wavebands in combination, also known as vegetative indices (Walburg et al., 1982). The near infrared/red (NIR/R) vegetative indices are reported to enhance differences in canopy reflectance and reduce reflectance variability. Realizing that the spectral reflectance properties were dominated by changes in chlorophyll concentrations in the leaves, handheld chlorophyll meters were developed that measured transmittance of light through leaves at about 650 and 940 nm (Blackmer et al., 1996). These meters are able to identify N deficiencies because a N deficiency reduces the chlorophyll content of the leaves, which in turn results in an increased amount of light transmitted through the leaf. Chlorophyll meters have been used with varying success (Blackmer and Schepers, 1995; Piekielek and Fox, 1992; Wood et al., 1992) with the best results obtained when comparing readings to an in-field reference with no nutrient deficiencies.

**Nitrogen Deficiencies.** Handheld chlorophyll meters have been used to rapidly assess plant nitrogen status in agronomic crops (Piekielek and Fox, 1992; Schepers et al., 1996; Wood et al., 1992) by measuring optical density at two wavelengths and converting to a value that has been positively correlated with chlorophyll and nitrogen. Rodriguez and Miller (2000) reported that handheld chlorophyll meter readings are correlated with chlorophyll and nitrogen concentrations of greenhouse grown St. Augustinegrass [*Stenotaphrum secundatum* (Walt.) Kuntze]. While handheld chlorophyll meters are an attractive option for monitoring turfgrass health, they are limited in the amount of spectral

information collected from the turfgrass canopy since they collect reflectance values at a limited number of wavelengths and in some cases may only be able to collect data from a single leaf blade.

An alternative to chlorophyll meters is to measure light reflected from the turfgrass canopy with a multispectral radiometer. A major advantage of canopy analysis is that a single measure of reflected radiation can characterize the N status of many plants within a selected area. Multispectral radiometry assesses reflectance of light at various wavelengths where the percentage of light not reflected is either absorbed by the plant or transmitted to the soil surface.

Leaf reflectance in the visible (VIS) portion of the spectrum (400-700 nm) is relatively low due to increased absorption by chlorophyll and is correlated ( $r^2 > 0.97$ ) with concentration of leaf pigments (Gitelson and Merzlyak, 1994; Horler et al., 1983). As plants become stressed, they exhibit decreased reflectance in the near-infrared (NIR) spectral region due to decreased cell layers and increased reflectance in the red spectral region due to decreased chlorophyll content (Guyot, 1990). NIR reflectance spectroscopy is a rapid analytical method for measuring the chemical composition of materials. Covalent bonds between atoms such as C, N, H, and O absorb energy in the infrared region and have vibrational frequencies and overtones that are detectable in the NIR region (700-2500 nm) (Malley, et al., 2000; Gillon et al., 1999). Monitoring these changes in spectral reflectance may reliably indicate changes in plant growth or physiological status (Carter, 1993; Carter and Miller, 1994). The normalized difference vegetation index (NDVI) has been widely used for remote sensing of vegetation for nearly three decades (Rouse et al., 1974). This index has been used in many different ways, including estimation of crop yields and end-of-season above-ground dry biomass (Tucker et al., 1986). Several studies have been conducted to investigate the use of NDVI in identifying turfgrass plants exhibiting signs of stress (Fenstermaker-Shaulis et al., 1997; Trenholm et al., 1999). Despite the growing interest in

using remote sensing to manage turfgrass system, spectral analysis has not yet received widespread acceptance by turfgrass managers. One reason for this may be that after more than two decades of research in the field of agronomy, we cannot yet make a quantitative, or even qualitative translations from the raw spectral data without first calibrating some sort of empirical model (Richardson et al., 2004). Given the successful use of NIR spectroscopy in predicting biochemical composition of samples, it follows that the VIS/NIR spectra could potentially provide information about the chemical composition of samples as if we were to perform a full set of plant analysis techniques in a laboratory (Richardson et al., 2004).

**Phosphorus Deficiencies.** Remote sensing has received increased interest as a non-destructive tool for determining the nutrient status of growing crops due to the time and expense involved with traditional soil and plant analysis. While there have been numerous studies reported investigating the relationship between remote sensing data and the nitrogen status of plants, there is little available regarding the use of spectral radiance measurements in determining the phosphorus status of plants. Milton et al. (1991) reported that P-deficient soybean [*Glycine max* (L.) Merr.] plants grown in hydroponic solutions had higher reflectance in the green and yellow portions of the spectrum. Plants exhibiting P-deficiencies are characterized by purple discoloration in the leaf margins due to increased anthocyanin production (Marchner, 1995; Trull et al., 1997). Anthocyanin absorbs energy in the green region while reflecting in the red and blue regions of the spectrum (Salisbury and Ross, 1978). Osborne et al. (2002) reported that prediction of plant P in corn (*Zea mays* L.) was possible early in the growing season using reflectance in the blue (440 and 445 nm) and in the near infrared (NIR) (730 and 930 nm) regions of the spectrum.

Many of the golf greens in the Midwest built to United States Golf Association (USGA) specifications were constructed with sands that are high in calcium carbonate. In addition, many turfgrass managers are encouraged to apply supplemental calcium to their greens to “improve turfgrass health” after years of withholding P applications to limit annual

bluegrass (*Poa annua* L.) infestations. The alkaline pH of calcareous soils can render P and several micronutrients unavailable for plant uptake (Carrow et al., 2001). As a result, P deficiencies in turfgrass systems will become more common thus requiring an efficient means of identifying those areas requiring P fertilization.

### **Crop Growth**

Relationships with crop growth and yield have also been determined from spectral data. Asrar et al. (1994) reported that the normalized difference vegetation index (NDVI), defined as the NIR minus VIS reflectance divided by NIR plus the VIS reflectance, correlated well ( $r^2 = 0.97$ ) with absorbed photosynthetically active radiation (APAR) in wheat (*Triticum aestivum* L.). Using this relationship they were also able to determine the leaf area index (LAI). Similar results have been reported for the relationship between NDVI and APAR by Gallo et al. (1985) and Goward and Huemmrich (1992). Trenholm et al. (1999b) used multispectral radiometry to correlate vegetative reflectance with qualitative data (color, density, and uniformity) and to discriminate between wear-treated cultivars of seashore paspalum (*Paspalum vaginatum* Sw.) and bermudagrass (*Cynodon dactylon* (L.) Pers.). Trenholm et al. (2000) investigated multispectral responses on C3 (creeping bentgrass) and C4 (bermudagrass) grass species, showing that bermudagrass had higher reflectance in the visible range, while bentgrass had higher reflectance in the near-infrared range. In addition, they were able to detect differences in chlorophyll content as a result of N and herbicide applications.

### **Moisture Stress**

Few studies have been reported in the literature on the use of remote sensing to detect turfgrass moisture stress (Nutter et al., 1991; Horst et al., 1991; Jones et al., 1992; Kenna, 1995; and Fenstermaker-Shaulis et al., 1997). The majority of remote sensing literature has focused on detection of growth responses and plant stress in agricultural crops (Deering et al., 1975; Eckardt et al., 1982; Aase et al., 1986; Asrar et al., 1985; Kleman and Fagerlund,

1987; Wanjura and Hatfield, 1987) turf chlorophyll content (Howell, 1999), and turf injury and quality (Trenholm et al., 1999; Bell et al., 2000). Results of these studies indicate that remote sensing can be used to successfully detect plant stress. The use of remotely sensed data may prove to be a valuable tool in the modification of traditional irrigation and fertility programs to reduce inputs and improve environmental quality.

Water is one of the most important resources one must have to grow a high quality stand of turfgrass. Proper soil moisture is essential to maintaining the quality and playability of turfgrass areas. While the rainfall in many parts of the United States is ample, it is not evenly distributed, thus requiring the use of irrigations to prevent drought stress on turfgrass areas. Rising demand for available water resources has resulted in significant increases in the cost of the water. Golf courses on average have over 90 acres of irrigated turf. In arid regions it is common for courses to apply up to one million gallons of water each night. Increased use of irrigation and concern regarding environmental contamination over the past decade has increased the focus of turfgrass managers on utilizing the limited natural resources available to them efficiently while reducing negative environmental impacts. Irrigation management techniques vary greatly and include soil-, meteorological-, and plant-based techniques. In all cases, an effort is made to estimate the amount of water lost from the plant-soil system that needs to be replaced by irrigation to prevent drought stress. These measurements are very time-consuming and require numerous observations to fully characterize a golf course or athletic field complex. However, it is difficult for turfgrass managers to appreciate the impact a change in management can have on water use and turf response on the macro scale. As a result, changes are often made to large areas of the irrigation system to account for localized problems. When using irrigation systems complete with valve-in-head control, it is possible for site-specific modifications to the irrigation system to be made by the turfgrass manager. Because of the limitations in the above mentioned methods for scheduling irrigation events, it would be beneficial to develop a

remote sensing system that could detect water stress early and trigger the irrigation before turfgrass quality is negatively affected. Moran et al. (1989) investigated the use of remote sensing systems to identify the effect of water stress on canopy reflectance in alfalfa (*Medicago sativa* L.) and determined that water stress resulted in reduced reflectance in the near infrared (NIR) and red wavebands when compared to unstressed canopies. There are limitations to the use of traditional remote sensing systems like aerial or satellite photography in turfgrass systems is the presence of shade that is commonly cast across the areas of interest. To address this many systems include some means of compensating for ambient light levels to reduce variability and increase the reliability of canopy reflectance measurements. The utilization of remotely sensed data is a powerful quantitative tool that can aid in the development of management practices that save water while maintaining high turfgrass quality (Jackson et al., 1983; Cibula et al., 1992; and Kenna 1995). Utilization of conservation techniques that minimize the amount of water that is being wasted during turfgrass irrigation can generate significant financial savings for facilities that rely heavily on irrigation (Devitt et al., 1992).

### **Statistical Analysis**

Research often involves the use of controllable variables (factors) to explain or predict other variables (responses). For instance, we may be interested in the influence of N concentration on the biomass production of a particular turfgrass. When these factors are few in number, not highly collinear, and have a well understood relationship to the responses, multiple linear regression (MLR) can be a good way to turn data into useable information (Tobias, 1997). However, in the case of remote sensing, the factors used are the measurements from the spectrum that can number in the hundreds or thousands and are likely to be highly collinear. When using MLR in cases such as this, it is easy to produce a model that fits the data from the sample set perfectly while having little use in predicting result from new samples (Tobias, 1997). When this occurs, the model is said to be “over-fitting” the

data set. Over-fitting occurs when there are many factors but only a small number of the factors account for most of the variation in the response. Partial least-squares (PLS) is a method developed for constructing predictive models when there are a large number of highly collinear factors (Tobias, 1997). During the calculation of PLS, the X- and Y-scores are chosen so that the relationship between successive pairs of scores are as strong as possible. The PLS factors are computed as linear combinations of spectral amplitudes and the responses are predicted linearly based on these extracted factors. As a result, a PLS regression is not based on a single or even a few frequencies as would be the case with MLR or stepwise regression (Tobias, 1997).

Ideally the use of a remote sensing in turfgrass systems will predict nutrient and moisture deficiencies early enough to allow for site-specific correction of the deficiency prior to the decline in turfgrass health and the associated visual symptoms. Accurate prediction of nutrient and moisture deficiencies through the use of spectral reflectance requires the use of a statistical method that considers the number of variables involved and tests for multicollinearity. Traditional multiple-regression techniques do not compensate for collinearity and can increase the risk of overfitting if the reflectance at each wavelength is considered as an explanatory (*X*) variable (Helland, 1988). Partial least-squares (PLS) regression can be used to develop predictive models in cases where the number of factors exceeds sample numbers and are highly collinear (Tobias, 1997). In contrast to traditional multiple-regression techniques that only consider the influence of the independent variables, PLS regression utilizes the influence of both the independent and dependent variables in the formation of the factors (Garthwaite, 1994; Tobias, 1997).

The specific objectives of this research were (i) to determine if reflectance data may accurately be used to determine the phosphorus status of creeping bentgrass growing on a calcareous-sand based green, (ii) to determine if reflectance data may be used to accurately predict the nitrogen concentration of creeping bentgrass tissue and (iii) to determine if

reflectance data can be used to accurately predict soil moisture status prior to the onset of visual drought stress symptoms.

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## CHAPTER 2. REMOTE SENSING OF PHOSPHORUS DEFICIENCIES IN CREEPING BENTGRASS (*Agrostis stolonifera* L.)

A paper submitted to the *International Turfgrass Society Research Journal*

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### Abstract

Managing the fertility of turfgrasses growing in sand-based rootzones can offer many challenges due to the low nutrient-holding capacity of sand. Calcareous sands, which are widely used in construction of putting greens, can increase the problems with nutrient deficiencies, particularly P. The objectives of this study were to investigate the response of creeping bentgrass (*Agrostis stolonifera* L.) exhibiting visual phosphorous (P) deficiencies to applied P, and to determine the relationship between P deficiencies and canopy reflectance within the 400 to 1050 nm range in order to identify reflectance wavelengths and/or combinations of wavelengths that are sensitive to plant tissue P concentration in creeping bentgrass. The experiment was a randomized complete block design with three replications established on creeping bentgrass putting green built to USGA specifications with calcareous sand. The treatments consisted of four P rates (0, 0.5, 1.0, and 1.5 g m<sup>-2</sup>) applied as a foliar application. Phosphorus deficiency symptoms decreased and biomass production increased at P rates above 1.0 g m<sup>-2</sup> with a single application, while no increase in soil-P was observed. Spectral radiance measurements were taken in increments from 400 to 1050 nm and correlated with plant tissue P concentration, chlorophyll content, plant biomass and visual quality. Stepwise regression identified a model utilizing reflectance in the blue, yellow, orange, and red regions of the spectrum that explained 73% of the variability in plant tissue P concentration for all sampling dates in 2002 and 2003. Results indicate that remote sensing

of P status in creeping bentgrass is feasible using narrow-waveband reflectance measurements in the blue, green, and NIR regions of the spectrum.

### **Introduction**

Remote sensing has received increased interest as a non-destructive tool for determining the nutrient status of growing crops due to the time and expense involved with traditional soil and plant analysis. Remote sensing is defined as obtaining information from an object, area, or phenomenon by a device that is not in physical contact with the object, area, or phenomenon (Lillesand and Kiefer, 1987). While there have been numerous studies reported investigating the relationship between remote sensing data and the nitrogen status of plants, there is little available regarding the use of spectral radiance measurements in determining the phosphorus status of plants. Milton et al. (1991) reported that P-deficient soybean [*Glycine max* (L.) Merr.] plants grown in hydroponic solutions had higher reflectance in the green and yellow portions of the spectrum. Plants exhibiting P-deficiencies are characterized by purple discoloration in the leaf margins due to increased anthocyanin production (Marchner, 1995; Trull et al., 1997). Anthocyanin absorbs energy in the green region while reflecting in the red and blue regions of the spectrum (Salisbury and Ross, 1978). Osborne et al. (2002) reported that prediction of plant P in corn (*Zea mays* L.) was possible early in the growing season using reflectance in the blue (440 and 445 nm) and in the near infrared (NIR) (730 and 930 nm) regions of the spectrum.

Many of the golf greens in the Midwest built to United States Golf Association (USGA) specifications were constructed with sands that are high in calcium carbonate. In addition, many turfgrass managers are encouraged to apply supplemental calcium to their greens to “improve turfgrass health” after years of withholding P applications to limit annual bluegrass (*Poa annua* L.) infestations. The alkaline pH of calcareous soils can render P and several micronutrients unavailable for plant uptake (Carrow et al., 2001).

Few studies on response of creeping bentgrass (*Agrostis stolonifera* L.) to P applications grown on calcareous sand media have been reported. Christians et al. (1979) found no significant relationship between P application and turfgrass clippings, roots, or visual quality when grown in a sand media that contained 12 mg kg<sup>-1</sup> Bray-1 extractable P. Waddington et al. (1978) reported that P applications had limited influence on the clipping yields of creeping bentgrass grown on a sandy loam-silty clay loam soil that contained 12 mg kg<sup>-1</sup> Bray-1 extractable P on the no-P plots. However, Fry et al. (1989) reported significant P effects on turfgrass quality when grown on calcareous sands when extractable P was < 5 mg kg<sup>-1</sup>. Johnson et al. (2003) reported significant response by creeping bentgrass grown on calcareous sand to P fertilizer treatments when soil test levels for P were below 3 mg kg<sup>-1</sup> and tissue P concentrations were below 4 g kg<sup>-1</sup>.

There has been limited research investigating the potential of using remote sensing techniques to detect P and other nutrient deficiencies in turfgrass systems. Milton et al. (1991) reported that soybean [*Glycine max* (L.) Merr.] plants grown in hydroponic solutions at three P concentrations and measured weekly change in leaf spectral reflectance. Their results showed that P-deficient plants had a higher reflectance in the green and yellow portions of the spectrum and did not exhibit the normal shift of the red edge. Osborne et al. (2002) identified the blue portion of the visible spectrum (400 to 500 nm) as being important in predicting plant tissue P concentration. Anthocyanin was reported to absorb strongly in the green portion of the spectrum (500 to 600 nm) while reflecting light in the blue and red (600 to 700 nm) portions of the spectrum (Salisbury and Ross, 1978).

The normalized difference vegetation index (NDVI) has been widely used for remote sensing of vegetation for nearly three decades. This index has been used in many different ways, including estimation of crop yields and end-of-season above-ground dry biomass (Tucker et al., 1986). The vegetative indices  $R_{780}/R_{600}$  (IR/R) and  $R_{695}/R_{760}$  (FR/IR) have been reported to be sensitive to biological and herbicide stresses in a wide variety of species

(Carter, 1994; Carter and Miller, 1994; Trenholm et al., 1999). This sensitivity is largely attributed to the “blue-shift” from red to infrared light in the reflectance spectrum as chlorophyll concentration in plant tissue changes in response to stress (Carter et al., 1996; Cibula and Carter, 1992; Horler et al., 1983).

The objectives of this experiment were to determine the effects of foliar P applications on the soil P, tissue P, chlorophyll content, and visual quality of creeping bentgrass growing in a P deficient calcareous sand, and to determine wavelengths associated with P deficiencies of creeping bentgrass by remote sensing.

### **Materials and Methods**

The field experiment was conducted at the Iowa State University Horticulture Research Station on a creeping bentgrass putting green with an 80% sand 20% peat moss media constructed according to United States Golf Association specifications (USGA, 1993). Plots were  $1.52 \times 1.52$  m in size and arranged in a randomized complete block design with three replications per treatment. The Bray-1 extractable soil-P level prior to initiation of the study was  $3.0 \text{ mg kg}^{-1}$ . This level was well below the critical extractable P concentration of  $5.0 \text{ mg kg}^{-1}$  (Fry et al., 1989; Guillard and Dest, 2003). The  $\text{NH}_4\text{OAc}$  extractable K level of the soil was  $23 \text{ mg kg}^{-1}$  and the pH was 8.0.

Four phosphorus fertilizer treatments were applied at 0, 0.5, 1.0, and  $1.5 \text{ g}\cdot\text{m}^{-2}$  as phosphoric acid with a  $\text{CO}_2$  sprayer. Spray volume was 283 mL and spray pressure was 207 kPa. Treatments were applied once on 9 July 2002 and repeated once on 9 July 2003. No applications of N or P were applied to the plots during the study period. Plots were mowed four times a week at a height of 3.8 mm, removing clippings after each mowing. Irrigation was applied as needed to maintain turfgrass quality.

### **Biological Measurements**

Plots were evaluated for P deficiency based on color where 9 equaled dark green grass (no deficiency symptoms) and 1 equaled dark purple coloration (severe P deficiency).

Samples for nutrient analysis and dry biomass were collected by removing clippings from a 1.14 m<sup>2</sup> area in conjunction with collection of reflectance data. One gram of fresh tissue from each plot was analyzed for total chlorophyll content according to the method of Arnon (1949) as modified by Bruinsma (1961). The remaining plant tissue was oven-dried at 60° C for four days and weighed to determine biomass production. Samples were analyzed for phosphorous concentration through inductively coupled argon plasma spectroscopy (ICAP). Total N concentration was determined by using a LECO FP-2000 nitrogen/protein analyzer (LECO Corporation, St. Joseph, MI)

### **Reflectance Measurements**

Remotely sensed data was collected with a field portable fiber-optic spectrometer fitted with 30 degree field of view optics (Model S2000, Ocean Optics, Inc., Winter Park, FL). To reduce variability due to cloud cover and solar zenith angle, the tip of the fiber-optic cable was mounted inside a rectangular plastic hood that extended down to the turf canopy to block ambient light. Auxiliary lighting was provided by two 12 V halogen lights with an irradiance of 2250  $\mu\text{mol m}^{-2} \text{s}^{-1}$ . Radiance values were expressed as percent spectral reflectance after standardization with a white standard. The spectrometer has a nominal spectral range from 200 to 1200 nm with approximately 0.3-nm nominal band width. Thus, for each measurement the spectrometer program automatically collects 2500 data points covering the 200 to 1200 nm spectral range. A linear interpolation routine was used to estimate values at 1-nm interval prior to calculation of indices from the reflectance data. Eight scans were averaged for every measurement and approximately 10 measurements were collected from random locations and averaged for each plot. Recalibration of the instrument with the white standard was conducted immediately before collecting measurements from each replication. Canopy reflectance was measured on days with minimal cloud cover between 1100 and 1400 h central standard time (CST) to minimize variance that may be caused by diurnal and environmental conditions.

The following growth and stress indices were evaluated for their relationship to plant chlorophyll content, turfgrass quality, and phosphorus concentration.

1. Normalized Difference Vegetation Index (NDVI) growth indice computed as

$$R_{800} - R_{600} / R_{800} + R_{600}$$

2. Infrared/Red (IR/R) stress index computed as  $R_{780} / R_{600}$
3. Far Red/Infrared (FR/IR) stress index computed as  $R_{695} / R_{760}$

The normalized difference vegetation index (NDVI) has been widely used for remote sensing of vegetation for nearly three decades (Rouse et al., 1974). This index has been used in many different ways, including estimation of crop yields and end-of-season above-ground dry biomass (Tucker et al., 1986).

### **Statistical Analysis**

Regression analysis was used to test linear relationships between vegetative indices and tissue nutrient concentrations. The general linear models (GLM) procedure and the Fisher's least significant difference (LSD) option of Statistical Analysis Software (SAS, 1999) were used to determine differences in tissue nutrient concentration for each study. Stepwise regression was performed, using the REG procedure in SAS (SAS, 1999), on all data to develop multiple regression equations for predicting tissue P concentration. The PROC CORR procedure (SAS, 1999) was used to investigate relationships between the vegetative indices and tissue chlorophyll content, turfgrass quality, and biomass production.

## **Results and Discussion**

### **Plant Response to P Application**

Before application of phosphorus treatments, the creeping bentgrass leaves were dark green with the characteristic purple discoloration associated with P deficiency symptoms. Plots receiving P at 0.0 and 0.5 g m<sup>-2</sup> y<sup>-1</sup> had significantly reduced quality and exhibited the

characteristic purple leaf coloration as indicated by the P deficiency ratings (Table 1). These results are similar to those of Johnson et al. (2003) who reported poor quality in plots receiving  $0.55 \text{ g P m}^{-2} \text{ y}^{-1}$ . In comparison, Christians et al. (1981) did not report any significant quality response to P applications for creeping bentgrass growing on calcareous sand greens. However, the Bray-1 extractable P concentrations were  $12 \text{ mg kg}^{-1}$ , above the critical value of  $5.0 \text{ mg kg}^{-1}$  previously mentioned. The Bray-1 extractable P level for this study was below the critical value and was approximately  $3.0 \text{ mg kg}^{-1}$  for all treatment rates (Table 2). This work indicates that P deficiencies in creeping bentgrass on calcareous sand greens can be corrected through a foliar application of P at a rate of  $1.5 \text{ g m}^{-2} \text{ y}^{-1}$  as phosphoric acid. In addition, the improvement in turf quality lasted 8 weeks before a noticeable increase in visible P deficiency symptoms occurred, indicating that frequent applications should not be necessary to correct P deficiencies.

An increase in biomass production (Table 1) and tissue P concentration (Table 2) occurred with increasing P rate while a decrease in total chlorophyll content with increasing P rate was observed in 2002 and 2003 (Table 1). We believe this may be the result of a dilution effect caused by the increased biomass production with increased P rate in 2002 (Table 1). A similar relationship to chlorophyll content was found by Christians (1979) in Kentucky bluegrass (*Poa pratensis*) where chlorophyll content decreased with increasing P application under conditions of sufficient N. Foliar application of P to the creeping bentgrass plots had no significant effect on the P levels in the sand media at either sampling date in 2002 or 2003 (Table 2).

### **Reflectance Data**

Reflectance wavelengths used for predicting plant tissue P concentration were in the blue (480 nm) and the yellow, orange and red (565, 595, and 650 nm) of the spectrum for all sampling dates in 2002 and 2003 with an  $R^2 = 0.73$  (Table 3). These regions correspond with the spectral characteristics of anthocyanin (Salsbury and Ross, 1978) which increase in

concentration in the leaf tissue under conditions of P stress (Marchner, 1995; Trull et al., 1997). Similar regions of the spectrum were used in predicting the P deficiency ratings ( $R^2 = 0.66$ ), chlorophyll content ( $R^2 = 0.47$ ) (Table 3). Reflectance in the green (510 and 535 nm), red (635 nm) and NIR (735 nm) were significant in predicting the biomass production ( $R^2 = 0.46$ ) (Table 3). According to Lillesand and Kiefer (1987), reflectance in the near-infrared (NIR) (700 to 900 nm) region of the spectrum is primarily related to the internal structure of the plant leaves. Jacob and Lawlor (1991) found that the initial effect of P stress on corn, wheat, and sunflower was an increase in the number of smaller cells per unit of leaf area compared to nonstressed plants. This helps explain why reflectance in the NIR region of the spectrum was important in predicting plant tissue P concentration at two of the three sampling dates in our study.

The NDVI has been reported to be sensitive to changes in turfgrass biomass production (Sembiring et al., 1998; Trenholm et al., 1999) and turfgrass quality (Trenholm et al., 1999). However, NDVI was correlated with turfgrass P deficiency ratings and biomass production at only the 20 Sep. 2002 sampling date (Table 4). In addition, NDVI was correlated with chlorophyll content at the 28 Jul. 2002 sampling date (Table 4). A relationship was also observed between the IR/R and FR/IR vegetative indices and turfgrass quality at the 20 Sep. 2002 sampling date (Table 4). No other correlations were observed between the vegetative indices and turfgrass quality, chlorophyll content, or biomass production (Table 4). It is speculated that the dark green and purple colorations associated with the P deficiency symptoms limit the usefulness of the above mentioned vegetative indices under conditions of P stress for predicting turfgrass quality, chlorophyll content, or biomass production due to the various changes in cell structure and content that result from P deficiencies (Marchner, 1995; Trull et al., 1997).

### **Conclusions**

Foliar applications of P result in a rapid disappearance of P-deficiency symptoms and a corresponding increase in tissue P concentration and biomass production of creeping bentgrass established in calcareous sand based putting greens. The positive effects of foliar P application were observed for several weeks while no changes in soil-P concentration occurred. This study indicates that spectral reflectance data may be used for successful estimation of P concentration in creeping bentgrass. The best estimations of tissue P were achieved using reflectance in the blue, yellow, orange, and red regions of the spectrum. In addition, this study indicates that the physiological changes that result from plants growing in P-deficient conditions may reduce the sensitivity of vegetative indices in predicting turfgrass quality, chlorophyll content, and biomass. Additional research is needed to determine the ability of remote sensing to identify plant responses to specific nutrient deficiencies under various growing conditions. The ability of a remote sensing system to distinguish between different stress responses will improve the value of remote sensing as a decision making tool for turfgrass managers.

### **Acknowledgments**

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Table 1. Phosphorus treatment effects on visual quality, chlorophyll content, and biomass production. Treatments were applied to a stand of creeping bentgrass (*Agrostis stolonifera* L.) established on a green built according to United States Golf Association (USGA) standards that had an initial available P level of 3 mg kg<sup>-1</sup>.

Phosphorus rate	Visual quality†			Chlorophyll content			Biomass production		
	21 Aug. 2002	20 Sep. 2002	28 Jul. 2003	21 Aug. 2002	20 Sep. 2002	28 Jul. 2003	21 Aug. 2002	20 Sep. 2002	28 Jul. 2003
g m <sup>-2</sup>				-----mg g <sup>-1</sup> -----			-----g m <sup>-2</sup> d <sup>-1</sup> -----		
0.0	4.0	4.00	3.7	1.22	1.21	1.37	1.54	1.60	1.42
0.5	4.7	4.67	5.0	1.16	1.03	1.33	1.65	1.59	1.47
1.0	5.7	5.00	5.0	1.11	0.96	1.24	1.83	1.56	1.50
1.5	5.7	5.33	6.0	1.01	0.98	1.21	2.04	1.41	1.52
LSD <sub>0.05</sub> ‡	0.99	ns	0.58	0.09	0.33	0.29	0.35	0.59	0.07

† Plots were evaluated for P deficiency based on color where 1 equaled dark purple coloration (severe P deficiency) and 9 equaled dark green grass (no deficiency symptoms).

‡ Fisher's LSD,  $P < 0.05$

Table 2. Phosphorus treatment effects on tissue phosphorus concentration and soil phosphorus content. Treatments were applied to a stand of creeping bentgrass (*Agrostis stolonifera* L.) established on a green built according to United States Golf Association (USGA) standards that had an initial available P level of 3 mg kg<sup>-1</sup>.

Phosphorus rate	Tissue phosphorus			Soil phosphorus (Bray-1)	
	21 Aug. 2002	20 Sept. 2002	28 Jul. 2003	21 Aug. 2002	28 Jul. 2003
g m <sup>-2</sup>	-----g kg <sup>-1</sup> -----			-----mg kg <sup>-1</sup> -----	
0.0	181.4	159.81	195.6	3.0	3.2
0.5	199.5	182.1	235.1	3.0	2.8
1.0	215.2	202.2	263.3	3.2	2.7
1.5	291.9	244.9	285.7	3.2	2.8
LSD <sub>0.05</sub> †	39.4	17.2	21.3	ns	ns

† ns Nonsignificant

‡ Fisher's LSD,  $P < 0.05$

Table 3. Regression equations by sampling date for predicting tissue P concentration, P deficiency ratings, chlorophyll content, and biomass from spectral radiance data collected during 2002 and 2003 from creeping bentgrass (*Agrostis stolonifera* L.) growing on a green constructed with calcareous sand. Phosphorus treatments were applied at 0.0, 0.5, 1.0, and 1.5 g m<sup>-2</sup>. (n = 36)

Plant Response	Prediction Equation	R <sup>2</sup>
P concentration, g kg <sup>-1</sup>	$y = -0.56 - R_{470}(0.43)^\dagger + R_{565}(0.31) + R_{595}(0.57) - R_{650}(0.47)$	0.73
P Deficiency Ratings <sup>‡</sup>	$y = 3.18 - R_{500}(1.04) + R_{565}(0.98) - R_{660}(1.04) + R_{665}(0.70)$	0.66
Chlorophyll Content	$y = 0.74 - R_{440}(0.07) + R_{485}(0.16)$	0.47
Biomass Production	$y = 2.15 - R_{510}(0.28) + R_{535}(0.25) - R_{635}(0.31) - R_{735}(0.07)$	0.46

<sup>†</sup>  $R_x$  is the reflectance value at the  $x$  wavelength

<sup>‡</sup> Plots were evaluated for P deficiency based on color where 9 equaled dark green grass (no deficiency symptoms) and 1 equaled dark purple coloration (severe P deficiency).

Table 4. Pearson correlation coefficients for reflectance indices vs. P deficiency rating, chlorophyll content and biomass of creeping bentgrass (*Agrostis stolonifera* L.) growing on a USGA sand based green (n=12).

	NDVI†	IR/R‡	FR/IR§
8 Aug. 2002			
P Deficiency Rating	ns	ns	ns
Chlorophyll Content	ns	ns	ns
Biomass	ns	ns	ns
20 Sep. 2002			
P Deficiency Rating	0.68*	-0.73**	0.64*
Chlorophyll Content	ns	ns	ns
Biomass	0.60*	ns	ns
28 Jul. 2003			
P Deficiency Rating	ns	ns	ns
Chlorophyll Content	0.64*	ns	ns
Biomass	ns	ns	ns

ns, \*, \*\*, \*\*\* Nonsignificant or significant at  $P < 0.05$ , 0.01, or 0.001, respectively.

† Normalized Difference Vegetation Index (NDVI) =  $(R_{800} - R_{600}) / (R_{800} + R_{600})$ .

‡ Infrared/Red (IR/R) =  $R_{780} / R_{600}$ .

§ Far Red/Infrared (FR/IR) =  $R_{695} / R_{760}$

### **CHAPTER 3. REMOTE SENSING OF NITROGEN STRESS IN CREEPING BENTGRASS (*Agrostis stolonifera* L.)**

A paper to be submitted to *Crop Sci.*

Jason K. Kruse, Nick E. Christians, and Michael H. Chaplin

#### **Abstract**

Development of a remote sensing system that can reliably identify nutrient deficiencies may reduce time spent sampling turfgrass areas and allow for site-specific applications of fertilizers. The objective of this research is to evaluate the use of a ground-based remote sensing system to predict the nitrogen (N) status of grass plants. The study consisted of three N treatments arranged in a randomized complete block design. Spectral radiance measurements were obtained from plots using a fiber optic spectrometer to calculate vegetative indices. Data were evaluated to identify a model to predict the N status of creeping bentgrass (*Agrostis stolonifera* L. 'Penncross'). Partial least-squares (PLS) regression analysis indicated a strong relationship between the actual and predicted N concentration of creeping bentgrass plant tissue during 2002 and 2003. In comparison to other spectral analysis methods such as NDVI, PLS was able to accurately predict the N concentration of the tissue throughout the growing season while NDVI is only reliable for comparison between measurements collected on the same sampling date. With further research and development it may be possible to produce reliable maps of the N status of a turfgrass system for use in site-specific management.

## Introduction

Traditional soil and plant tissue sampling methods are time and labor intensive because they require collection of several samples from representative areas to adequately characterize the variability found on turfgrass sites. In addition, turfgrass quality may decline because of nutrient deficiencies in the interim between sampling and the availability of sample results. Therefore, many turfgrass managers make scheduled applications of N to prevent nutrient deficiencies and resulting variability in color and quality. Unnecessary applications of N may result in nutrient runoff and contamination of groundwater. Development of a remote sensing system coupled with mapping software to monitor the nutrient status of turfgrass areas may allow for site-specific applications of fertilizer only to areas that require supplemental nutrition.

Handheld chlorophyll meters have been used to rapidly assess plant nitrogen status in agronomic crops (Piekielek and Fox, 1992; Schepers et al., 1996; Wood et al., 1992) by measuring optical density at two wavelengths and converting to a value that has been positively correlated with chlorophyll and nitrogen. Rodriguez and Miller (2000) reported that handheld chlorophyll meter readings are correlated with chlorophyll and nitrogen concentrations of greenhouse grown St. Augustinegrass [*Stenotaphrum secundatum* (Walt.) Kuntze]. While handheld chlorophyll meters are an attractive option for monitoring turfgrass health, they are limited in the amount of spectral information collected from the turfgrass canopy since they collect reflectance values at a limited number of wavelengths.

An alternative to chlorophyll meters is to measure light reflected from the turfgrass canopy with a multispectral radiometer. A major advantage of canopy analysis is that a single measure of reflected radiation can characterize the N status of many plants within a selected area. Multispectral radiometry assesses reflectance of light at various wavelengths where the percentage of light not reflected is either absorbed by the plant or transmitted to the soil surface.

Leaf reflectance in the visible portion of the spectrum (400-700 nm) is relatively low due to increased absorption by chlorophyll and is correlated ( $r^2 > 0.97$ ) with concentration of leaf pigments (Gitelson and Merzlyak, 1994; Horler et al., 1983). As plants become stressed, they exhibit decreased reflectance in the near-infrared (NIR) spectral region due to decreased cell layers and increased reflectance in the red spectral region due to decreased chlorophyll content (Guyot, 1990). Near-infrared reflectance spectroscopy is a rapid analytical method for measuring the chemical composition of materials. Covalent bonds between atoms such as C, N, H, and O absorb energy in the infrared region and have vibrational frequencies and overtones that are detectable in the near-infrared region (400-2500 nm) (Malley, et al., 2000; Gillon et al., 1999). Monitoring these changes in spectral reflectance may reliably indicate changes in plant growth or physiological status (Carter, 1993; Carter and Miller, 1994). The normalized difference vegetation index (NDVI) has been widely used for remote sensing of vegetation for nearly three decades (Rouse et al., 1974). This index has been used in many different ways, including estimation of crop yields and end-of-season above-ground dry biomass (Tucker et al., 1986). Several studies have been conducted to investigate the use of NDVI in identifying turfgrass plants exhibiting signs of stress (Fenstermaker-Shaulis et al., 1997; Trenholm et al., 1999). Despite the growing interest in using remote sensing to manage turfgrass system, spectral analysis has not yet received widespread acceptance by turfgrass managers. One reason for this may be that after more than two decades of research in the field of agronomy, we cannot yet make a quantitative, or even qualitative translations from the raw spectral data without first calibrating some sort of empirical model (Richardson et al., 2004). Given the successful use of NIR spectroscopy in predicting biochemical composition of samples, it follows that the VIS/NIR spectra could potentially provide information about the chemical composition of samples as if we were to perform a full set of laboratory analysis (Richardson et al., 2004).

Research often involves the use of controllable variables (factors) to explain or predict other variables (responses). For instance, we may be interested in the influence of N concentration on the biomass production of a particular turfgrass. When these factors are few in number, not highly collinear, and have a well understood relationship to the responses, multiple linear regression (MLR) can be a good way to turn data into useable information (Tobias, 1997). However, in the case of remote sensing, the factors used are the measurements from the spectrum that can number in the hundreds or thousands and are likely to be highly collinear. When using MLR in cases such as this, it is easy to produce a model that fits the data perfectly from the sample set perfectly while having little use in predicting result from new samples (Tobias, 1997). When this occurs, the model is said to be “over-fitting” the data set. Over-fitting occurs when there are many factors but only a small number of the factors account for most of the variation in the response.

Partial least-squares (PLS) is a method developed for constructing predictive models when there are a large number of highly collinear factors (Tobias, 1997). During the calculation of PLS, the X- and Y-scores are chosen so that the relationship between successive pairs of scores are as strong as possible. The PLS factors are computed as linear combinations of spectral amplitudes and the responses are predicted linearly based on these extracted factors. As a result, a PLS regression is not based on a single or even a few frequencies as would be the case with MLR or stepwise regression (Tobias, 1997). In comparison, the factors used in the PLS regression are computed as linear combinations of the spectral amplitudes, and the response variable are predicted based on these linear extractions (Tobias, 1997). Instead of being based on a small group of frequencies as would be the case in using MLR, the PLS regression is based on all of the input factors.

Ideally, the use of a remote sensing in turfgrass systems will predict nutritional deficiencies early enough to allow for site-specific fertilization prior to the decline in turfgrass health and the associated visual symptoms. Accurate prediction of nutrient

deficiencies through the use of spectral reflectance requires the use of a statistical method that considers the number of variables involved and tests for multicollinearity. Traditional multiple-regression techniques do not compensate for collinearity and can increase the risk of overfitting if the reflectance at each wavelength is considered as an explanatory ( $X$ ) variable (Helland, 1988). Partial least-squares (PLS) regression can be used to develop predictive models in cases where the number of factors exceeds sample numbers and are highly collinear (Tobias, 1997). In contrast to traditional multiple-regression techniques that only consider the influence of the independent variables, PLS regression utilizes the influence of both the independent and dependent variables in the formation of the factors (Garthwaite, 1994; Tobias, 1997).

The specific objectives of this research were (i) to determine if reflectance data may accurately be used to determine plant nutrient status, (ii) to investigate the relationship between multispectral reflectance data, nitrogen status, chlorophyll content, and turfgrass quality, and (iii) compare partial least-squares (PLS) regression to normalized difference vegetation index (NDVI) for prediction of tissue N concentration.

## **Materials and Methods**

### **Experimental Setup**

A two-year field experiment was conducted at the Iowa State University Horticulture research station on a creeping bentgrass (*Agrostis stolonifera* L. ‘Penncross’) putting green constructed according to United States Golf Association specifications (USGA, 1993) to determine the correlation between nitrogen concentration of plant tissue and remotely sensed multispectral scanner data. Plots were  $1.52 \times 1.52$  m in size and arranged in a randomized complete block design with four replications per treatment.

Three nitrogen fertilizer treatments were applied at 0, 12.2, and 24.4  $\text{Kg}\cdot\text{ha}^{-1}$  fourteen times on a 15-day interval as urea in solution with a  $\text{CO}_2$  sprayer. Spray volume was 283 mL and spray pressure was 207 kPa. In addition to N, all plots received uniform phosphorus at

2.44 kg·ha<sup>-1</sup> 15 d<sup>-1</sup> as phosphoric acid and potassium at 5.0 kg·ha<sup>-1</sup> 15 d<sup>-1</sup> as potassium chloride.

Treatments were applied from 25 March 2002 to 8 October 2002 and from 9 June 2003 to 23 Sep. on a 15 day interval. Plots were mowed four times a week at a height of 3.8 mm, removing clippings after each mowing. Irrigation was applied as needed to maintain optimum turfgrass quality.

### **Biological Parameters**

Plots were evaluated for visual quality based on color, shoot density, and uniformity of stand, where 1 equaled no live grass and 9 equaled dark-green, dense, uniform grass. Samples collected for nutrient analysis and dry biomass were collected by removing clippings from a 1.74 m<sup>2</sup> area in conjunction with collection of reflectance data. One gram of fresh tissue from each plot was analyzed for total chlorophyll content according to the method of Arnon (1949) as modified by Bruinsma (1961). The remaining plant tissue was oven-dried at 60° C for four days and weighed to determine biomass production. Samples were analyzed for phosphorus, potassium, and micronutrient concentration through inductively coupled argon plasma spectroscopy (ICAP). Total N concentration was determined by using a LECO FP-2000 nitrogen/protein analyzer (LECO Corporation, St. Joseph, MI)

### **Reflectance Measurements**

Remotely sensed data was collected with a field portable fiber optic spectrometer fitted with 30 degree field of view optics (Model S2000, Ocean Optics, Inc., Winter Park, FL) on a 30-day interval corresponding with the collection of biological parameter data. To reduce variability due to cloud cover and solar zenith angle, the tip of the fiber was mounted inside a rectangular plastic hood that extended down to the turf canopy. Auxiliary lighting was provided by two 12 V halogen lights with an irradiance of 2250 μmol m<sup>-2</sup> s<sup>-1</sup>. Radiance values were expressed as percent spectral reflectance after standardization with a white

standard. The spectrometer has a nominal spectral range from 200 to 1200 nm with approximately 0.3-nm nominal band width. Thus, for each measurement the spectrometer program automatically collects 2500 data points covering the entire spectral range. A linear interpolation routine was used to estimate values at 1-nm interval prior to calculation of indices from the reflectance data. Eight scans were averaged for every measurement and approximately 10 measurements were collected and averaged for each plot. Recalibration of the instrument with the white standard was conducted immediately before collecting measurements from each replication. Canopy reflectance was measured on days with minimal cloud cover between 1100 and 1400 h central standard time (CST).

The NDVI was calculated by taking the reflectance in the near-infrared (NIR) minus visible reflectance divided by NIR plus the visible reflectance ( $R_{800} - R_{600}/R_{800} + R_{600}$ ) where  $R_x$  is the reflectance value at the  $x$  wavelength.

### **Statistical Analysis**

An analysis of variance (ANOVA) was performed to test N effect on leaf N, chlorophyll content, biomass production, and visual quality using PROC ANOVA in SAS (SAS Inst., 1999). Prediction equations for tissue nitrogen concentration were developed by regressing field data against derived spectra. The procedure for spectral calibration was partial least squares (PLS) regression as performed by SAS (SAS Inst., 1999). Equations were validated through single sample cross-validation. For the cross-validation, ten percent of the sample was left out for prediction at a time and the number of factors that minimized the predicted residual sum of squares (PRESS) was chosen (see Fig. 1 for graphical illustration). This process was repeated so that every observation was used exactly once for cross-validation.

### **Results and Discussion**

A weak relationship was observed between actual biomass production and the predicted biomass production as calculated through partial least-squares regression (Table 1).

This is likely due to a reduction in turfgrass growth during the summer months without a corresponding change in spectral properties. Previous research by Osborne et al. (2002) has shown that the spectral properties of plants are influenced primarily by the biochemical content and moisture status of the plant tissue. We theorize that the changes in spectral properties resulting from increased heat and/or drought stress made it more difficult to observe a relationship between spectral reflectance and actual biomass production in our results. Osborne et al., 2002 reported that the relationship between reflectance data and nitrogen concentration of corn (*Zea mays* L.) changed when subjected to moisture stress.

Nitrogen treatments applied to the bentgrass turf induced a broad variation in leaf N concentration during 2002 and 2003 (Table 2). The treatments succeeded in establishing tissue concentrations that ranged from low to sufficient according to the sufficiency values reported by Jones et al. (1991). Figure 2 illustrates the mean reflectance spectra curves of creeping bentgrass tissue for each N rate at the 22 July 2002 sampling date. Minimum reflectance in the blue (400 – 500 nm) and red (650 – 690 nm) regions is characteristic of maximum light absorption by chlorophyll. The broad peak centering at 550 nm in the green region (500 – 600 nm) is indicative of the minimal chlorophyll absorption. Bentgrass tissue receiving no N (0 kg ha<sup>-1</sup> N) showed a greater increase in reflectance near 550 nm compared to the other N rates, agreeing with the findings reported by Buscaglia and Varco (2002) and Fridgen and Varco (2004) from research conducted on cotton. Similar results were observed at all sampling dates in 2002 and 2003.

Analysis of the reflectance data by PLS regression yielded a model that could reliably predict the N concentration of creeping bentgrass tissue during 2002 and 2003 (Fig. 3). The results for the PLS regression in 2003 indicate a slightly weaker relationship between the actual and predicted N concentration in the tissue (Table 2, Fig 3). This may be explained by reduced uniformity in plot quality that resulted from localized dry spots that were present in several of the plots for a limited amount of time in 2003. Regressing tissue N concentration

against the normalized difference vegetation index (NDVI) as calculated from the reflectance data in 2002 yielded a very weak relationship (Fig. 4). In nearly every case in which NDVI had been reported previously to be related to plant stress or nutrient status the calculations were based on measurements that were collected during a limited portion of the growing season (Fenstermaker-Shaulis et al., 1997; Trenholm et al., 1999). The strength of a remote sensing system will be judged by its reliability throughout the growing season. Basing management decisions on NDVI would require recalibration of the model for each sampling date to ensure reliable results. In comparison, PLS regression yielded a strong relationship between the actual and predicted N concentration across all dates in 2002 and 2003, indicating the potential benefit in using it to develop models for future remote sensing systems.

Results of PLS regression did not indicate a relationship between the actual and the predicted chlorophyll concentration in the plant tissue through the use of reflectance data in 2002 or 2003 (Table 1). The initial concern upon observing these results was that there would be no relationship between the N and chlorophyll concentrations in the plant tissue. Regression analysis indicate a significant positive relationship exists between N and chlorophyll ( $r^2 = 0.87$ ) (data not shown). We hypothesize the severe N deficiency in the plant tissue dominated the characteristics of the reflectance values, thus masking the influence of the chlorophyll present in the leaf tissue. While it was not addressed in this study, it is possible that a handheld chlorophyll meter may be better able to predict the chlorophyll concentration in the tissue due to the limited number of wavelengths used in the calculation. However, this information would be of little value since chlorosis can be caused be any number of biotic and abiotic stresses on a plant.

The results from this study indicate the potential for using partial least-squares regression in the development of models for predicting the N status of creeping bentgrass. In comparison to other spectral analysis methods such as NDVI, PLS was able to accurately

predict the N concentration of the tissue throughout the growing season while NDVI is only reliable for comparison between measurements collected on the same sampling date. This is an important finding as it indicates that the resulting PLS model can be used reliably regardless of the sampling date. With further research on creeping bentgrass and other species it may be possible to base fertilizer applications on the results from spectral analysis of the turf canopy without calibration with samples analyzed by traditional lab analysis. When coupled with a global positioning system (GPS) it will be possible to develop surface maps tracking the N status of the turfgrass site that can then be used to make variable-rate fertilizer applications to those areas in need.

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Table 1. Partial Least Squares regression statistics for estimation of Nitrogen concentration, chlorophyll concentration, biomass production, and visual quality in creeping bentgrass.

Calibration	No. of factors†	$r^2$	SECV‡	$n$
<u>2002</u>				
Nitrogen ( $\text{g kg}^{-1}$ )	7	0.90	0.22	60
Biomass production ( $\text{g m}^2 \text{d}^{-1}$ )	5	0.48	0.13	60
Chlorophyll content ( $\mu\text{g g}^{-1}$ )	6	0.16	0.05	60
Visual quality	3	0.66	0.12	60
<u>2003</u>				
Nitrogen ( $\text{g kg}^{-1}$ )	4	0.74	0.25	48
Biomass production ( $\text{g m}^2 \text{d}^{-1}$ )	3	0.47	0.14	48
Chlorophyll content ( $\mu\text{g g}^{-1}$ )	2	0.03	0.05	48
Visual quality	2	0.51	0.16	48

† The number of factors necessary to achieve a minimum global standard error of prediction for the final partial least-squares regression model.

‡ Standard error of cross validation (the average difference between the actual values and predicted values of samples not used to develop the equation).

Table 2. Influence of N rate on N concentration of creeping bentgrass tissue during 2002 and 2003. Values are means of four experimental units.

N rate (kg·ha <sup>-1</sup> )	22 July 2002	22 Sep. 2002	28 July 2003	25 Sep. 2003
	<i>Nitrogen concentration (g kg<sup>-1</sup>)</i>			
0.0	40.1c†	30.8c	41.2b	32.0c
12.2	42.2b	36.4b	44.5b	37.5b
24.4	45.0a	42.0a	49.2a	41.1a

† Treatment means within a column followed by the same lower case letter are not significantly different at  $P \leq 0.05$  according to Fisher's least significant difference test.

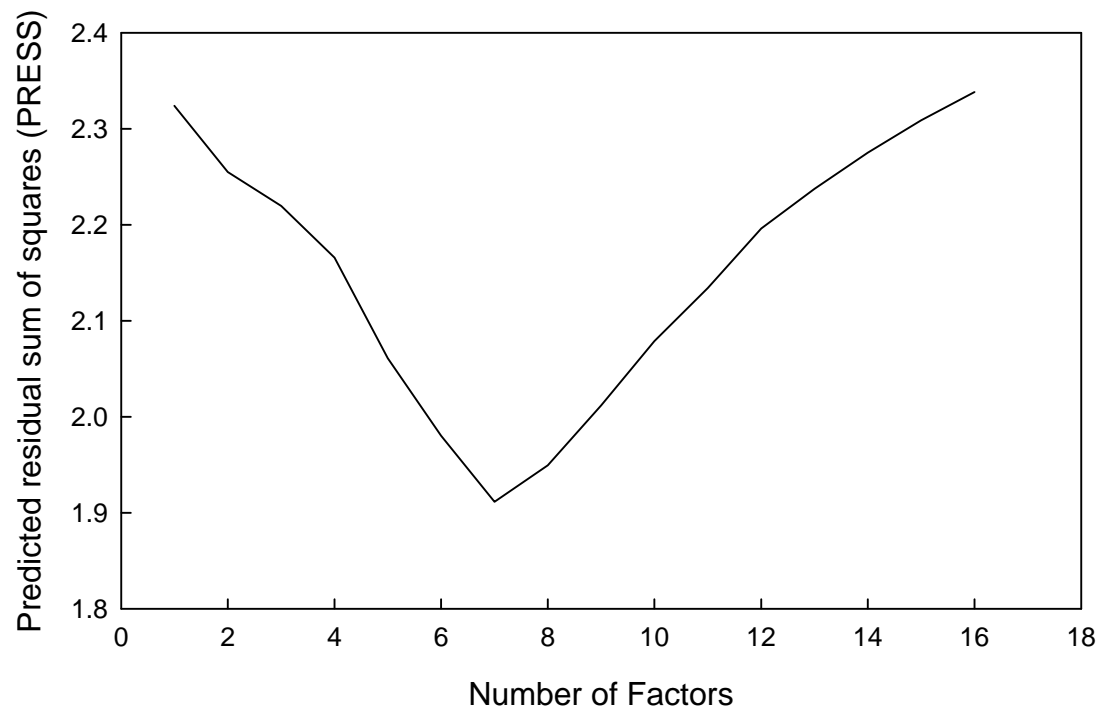


Fig. 1. Graphical illustration of the predicted residual sum of squares vs. the number of factors in the partial least-squares regression model.

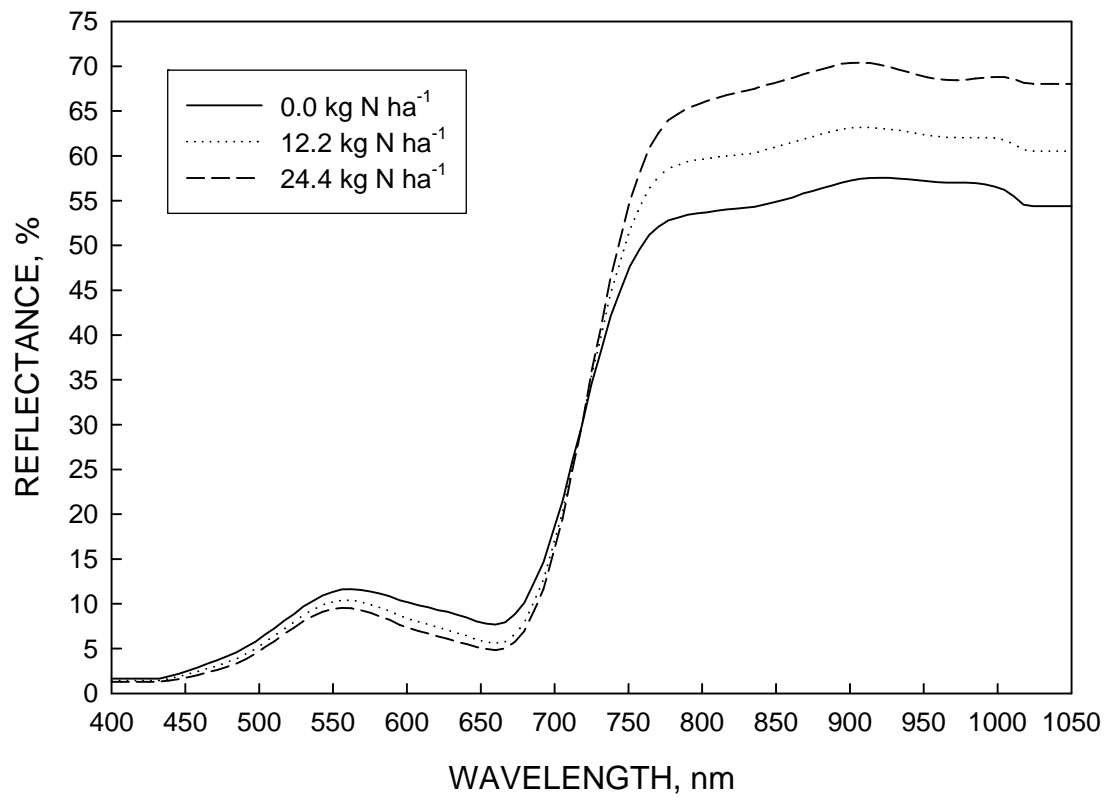


Fig. 2. Reflectance spectra of the three N treatments. Similar trends were observed for all sampling dates in 2002 and 2003.

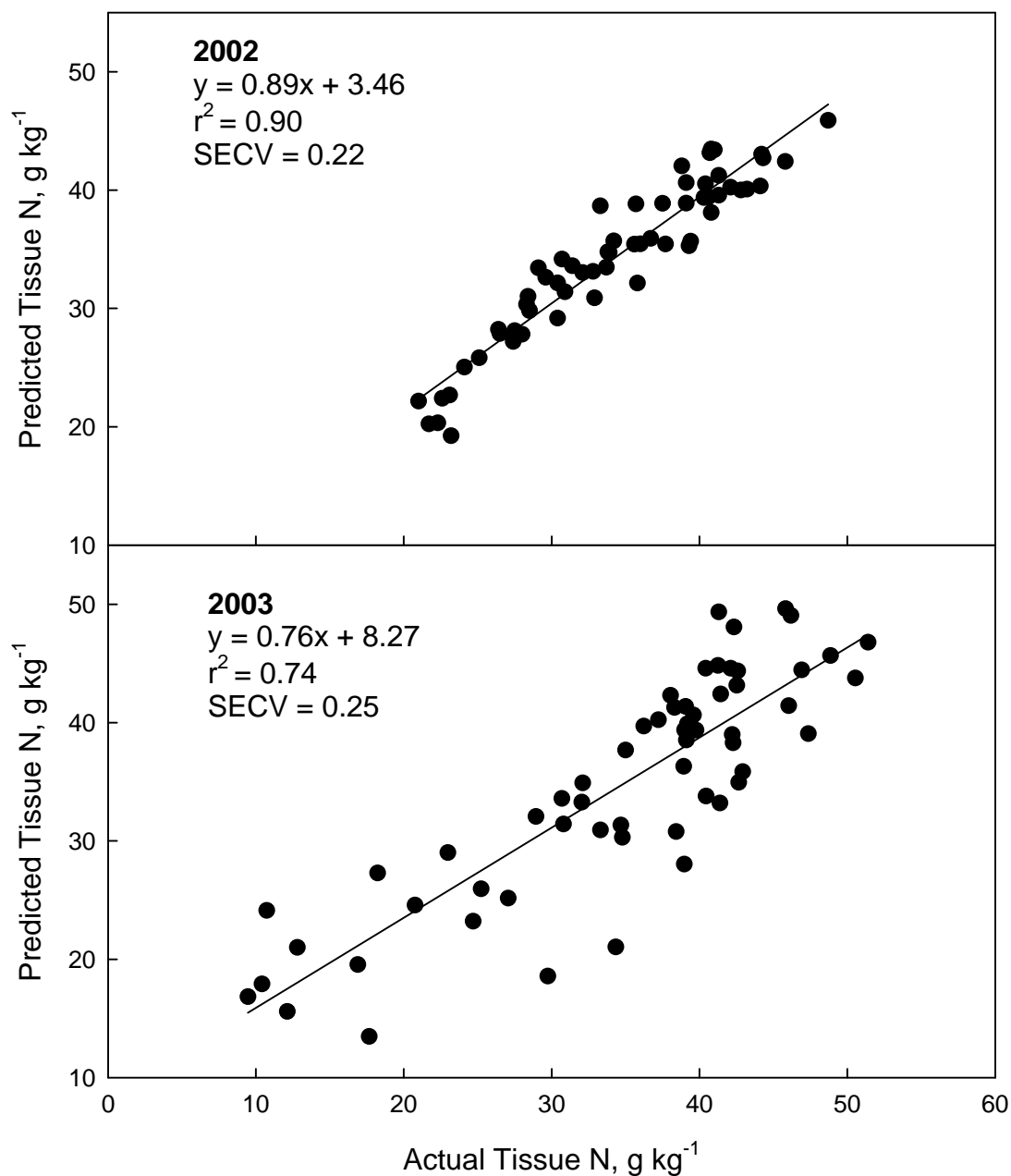


Fig. 3. Predicted vs. actual tissue N concentration for data collected in 2002 and 2003. Predicted tissue N concentration was calculated through the use of partial least-squares regression analysis of reflectance data collected from the plots.

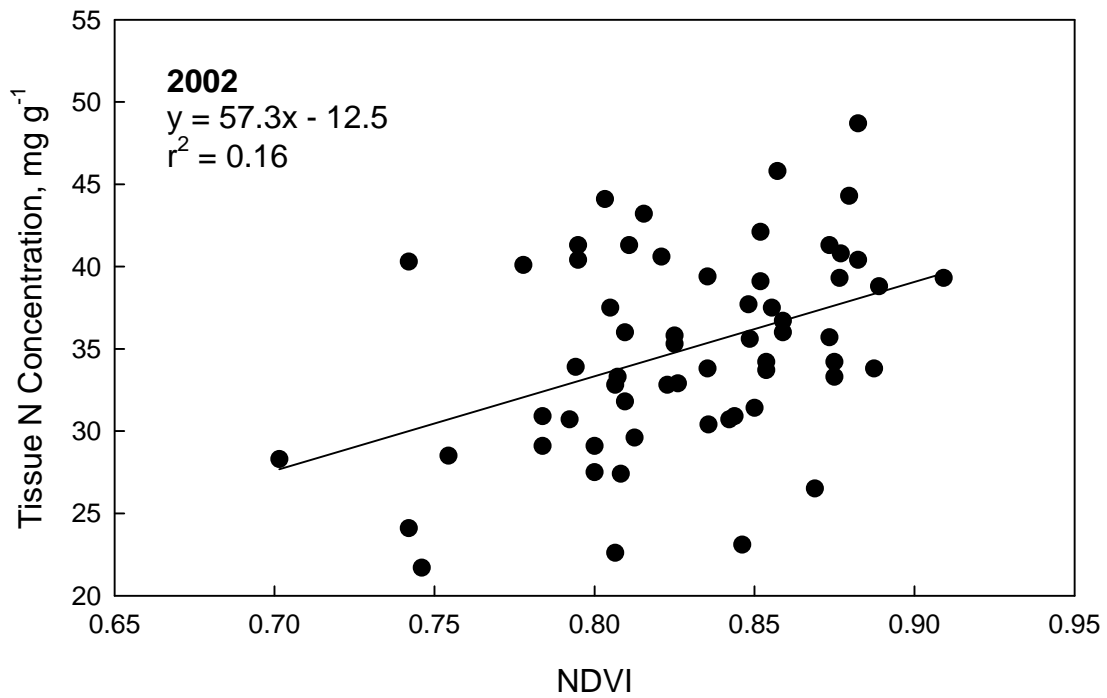


Fig. 4. Relationship between normalized difference vegetation index (NDVI) as calculated from spectral reflectance data collected in 2002 and the associated tissue N concentration as determined by laboratory analysis.

## CHAPTER 4. REMOTE SENSING OF MOISTURE STRESS ON PERENNIAL RYEGRASS (*Lolium perenne* L.) FAIRWAYS

A paper to be submitted to *Applied Turfgrass Science*

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### Abstract

Management of irrigation systems on turfgrass areas to maximize water use efficiency and reduce problems associated with over-watering requires repeated observations and manipulation of irrigation settings. Development of a remote sensing system that can reliably identify moisture stress may reduce time spent monitoring turfgrass areas and allow for site-specific applications of irrigation. The objective of this research is to evaluate the use of ground-based remote sensing systems to predict the moisture status of grass plants. Two studies were conducted, one at fairway height and one at greens height. Volumetric soil moisture at a 5 cm depth was collected by time domain reflectometry. Spectral radiance measurements were obtained from the plots using a fiber optic spectrometer to calculate vegetative indices. Partial least-squares (PLS) regression was used to predict the volumetric soil water content of perennial ryegrass (*Lolium perenne* L.) at fairway height and creeping bentgrass (*Agrostis stolonifera* L.) at greens height. Results indicate that PLS regression can reliably predict the soil moisture status of perennial ryegrass fairways one day prior to onset of drought stress symptoms. While the trends were the same, results were not as strong for samples collected from the creeping bentgrass green height study. Through continued research, the identification of a remote sensing model that can accurately predict the moisture status of turfgrass plants will make it possible to apply irrigation on a site-specific basis that may improve efficiency and reduce water use.

## Introduction

Proper soil moisture is essential to maintaining the quality and playability of turfgrass areas. While the rainfall in many parts of the United States is ample, it is not evenly distributed, thus requiring the use of irrigations to prevent drought stress on turfgrass areas. Rising demand for available water resources has resulted in significant increases in the cost of the water. As a result, it has become increasingly important for turfgrass managers to carefully monitor the moisture status of their site and make adjustments in irrigation practices in response to water stress. Conservation techniques to reduce the amount of water required to adequately maintain turfgrass stands have the potential to generate significant financial savings (Devitt et al., 1992). Turfgrass managers have already increased their use of management tools available to them such as on-site weather stations and irrigations scheduling based on calculated ET. However, these methods do not take into account the wide variability in soil characteristics often present on many turfgrass sites. As a result, changes are often made to large areas of the irrigation system to account for localized problems. When using irrigation systems complete with valve-in-head control, it is possible for site-specific modifications to the irrigation system to be made by the turfgrass manager. Remotely sensed data is a powerful graphic tool that can be used in development of management practices to save water (Jackson et al., 1983; Cibula et al., 1992; Kenna, 1995; Fenstermaker-Shaulis et al., 1997). By monitoring changes in moisture stress on a spatial basis it becomes possible to make modifications to the irrigation rate at the individual sprinkler head level. One limitation to the use of traditional remote sensing systems like aerial or satellite photography in turfgrass systems is the presence of shade that is commonly cast across the areas of interest. To address this many handheld systems include some means of compensating for ambient light levels. However, we still feel that the variability induced in the system limits the ability to compare readings collected in full sun to those collected from the shaded areas.

Few studies have been reported in the literature on the use of remote sensing to detect turfgrass moisture stress (Nutter et al., 1991; Horst et al., 1991; Jones et al., 1992; Kenna, 1995; Fenstermaker-Shaulis et al., 1997). The majority of remote sensing literature has focused on detection of growth responses and plant stress in agricultural crops (Deering et al., 1975; Eckardt et al., 1982; Aase et al., 1986; Asrar et al., 1985; Kleman and Fagerlund, 1987; Wanjura and Hatfield, 1987), turf chlorophyll content (Howell, 1999), and turf injury and quality (Trenholm et al., 1999; Bell et al., 2000). Results of these studies indicate that remote sensing can be used to successfully detect plant stress.

Leaf reflectance in the visible portion of the spectrum (400-700 nm) is relatively low due to increased absorption by chlorophyll and is correlated ( $r^2 > 0.97$ ) with concentration of leaf pigments (Gitelson and Merzlyak, 1994; Horler et al., 1983). As plants become stressed, they exhibit decreased reflectance in the near-infrared (NIR) spectral region due to decreased cell layers and increased reflectance in the red spectral region due to decreased chlorophyll content (Guyot, 1990; Carter, 1993). Monitoring these changes in spectral reflectance may reliably indicate changes in plant growth or physiological status (Carter, 1993; Carter and Miller, 1994). Near-infrared reflectance spectroscopy is a rapid analytical method for measuring the chemical composition of materials. Covalent bonds between atoms such as C, N, H, and O absorb energy in the infrared region and have vibrational frequencies and overtones that are detectable in the near-infrared region (400-2500 nm) (Malley et al., 2000; Gillon et al., 1999).

Research often involves the use of controllable variables (factors) to explain or predict other variables (responses). For instance, we may be interested in the influence of N concentration on the biomass production of a particular turfgrass. When these factors are few in number, not highly collinear, and have a well understood relationship to the responses, multiple linear regression (MLR) can be a good way to turn data into useable information (Tobias, 1997). However, in the case of remote sensing, the factors used are the

measurements from the spectrum that can number in the hundreds or thousands and are likely to be highly collinear. When using MLR in cases such as this, it is easy to produce a model that fits the data perfectly from the sample set perfectly while having little use in predicting result from new samples (Tobias, 1997). When this occurs, the model is said to be “over-fitting” the data set. Over-fitting occurs when there are many factors but only a small number of the factors account for most of the variation in the response. Partial least-squares (PLS) is a method developed for constructing predictive models when there are a large number of highly collinear factors (Tobias, 1997). During the calculation of PLS, the X- and Y-scores are chosen so that the relationship between successive pairs of scores are as strong as possible. The PLS factors are computed as linear combinations of spectral amplitudes and the responses are predicted linearly based on these extracted factors. As a result, a PLS regression is not based on a single or even a few frequencies as would be the case with MLR or stepwise regression (Tobias, 1997).

The objectives of this research were (i) to determine if reflectance data can be used to predict the soil moisture status of turfgrass plants, and (ii) to determine the relationship between reflectance data, soil moisture, and visual quality of moisture stressed turfgrass plants.

### **Materials and Methods**

Two studies were conducted at Veenker Memorial Golf Course in Ames, IA to investigate the relationship between soil moisture and remote sensing data collected from the turfgrass canopy with a fiber optic spectrometer.

#### **Fairway Height Study**

A two-year study was conducted on fairways established with a perennial ryegrass (*Lolium perenne* L.) blend on a native soil (fine loamy mixed mesic Cumulic Haplaquoll). Irrigation treatments were applied to nine plots that were 18.3 × 18.3 m in size and located within the perimeter established by four irrigation heads on nine separate fairways. Irrigation

treatments were imposed from 15 July to 21 July 2002, 28 July to 31 July 2002, 23 July to 26 July 2003, and 5 Sep. to 10 Sep. 2003.

Fertilization, mowing, and irrigation were applied uniformly across all plots before the initiation irrigation treatments. All plots received nitrogen at a rate of 48.8 kg ha<sup>-1</sup> and potassium at a rate of 39.2 kg ha<sup>-1</sup> prior to the initiation of treatments. In addition, plots were treated with a growth regulator, Primo Maxx (Trinexapac ethyl), at a rate of 763 g ha<sup>-1</sup> every 28 d as part of the normal golf course maintenance program to reduce clipping production. Turf was mowed 3 d wk<sup>-1</sup> at a height of 12.7 mm with clippings returned to the site. Three irrigation treatments were applied at 0, 32.5, and 65% evapotranspiration as calculated by an onsite automatic weather station (Campbell Scientific, Logan, UT).

### **Greens Height Study**

Treatments were applied to a stand of creeping bentgrass (*Agrostis stolonifera* L.) established on a native soil (fine loamy mixed mesic Cumulic Haplaquoll). Four irrigation treatments (0, 16.25, 32.5, and 48.75 % ET) were applied to four plots that were 9.1 × 9.1 m in size. All treatments were replicated in time after re-randomization and repetition of the study. Irrigation treatments were applied from 25 June to 29 June 2002, 5 July to 9 July 2002, 20 July to 25 July 2002, 1 Aug. to 2 Aug. 2002, 22 July to 26 July 2003, 9 Aug. to 13 Aug. 2003 and 5 Sep. to 10 Sep. 2003.

Fertilization, mowing, and irrigation were applied uniformly across all plots before the initiation of irrigation treatments. All plots received nitrogen at a rate of 48.8 kg ha<sup>-1</sup> and potassium at a rate of 39.2 kg ha<sup>-1</sup> prior to the initiation of treatments. In addition, plots were treated with a growth regulator, Primo Maxx (Trinexapac ethyl), at a rate of 763 g ha<sup>-1</sup> every 28 d as part of the normal golf course maintenance program to reduce clipping production. Turf was mowed 3 d wk<sup>-1</sup> at a height of 6.3 mm and clippings were removed from the site.

### **Data Collection**

Data collection began at the initiation of treatments during each study period and continued on a daily basis until visual symptoms of drought stress became evident on the plots receiving no irrigation (0% ET). Upon expression of drought stress symptoms, the treatments were terminated and the study areas were returned to full irrigation for a minimum of seven days prior to randomizing and reinitiating the treatments. Plots were evaluated for visual quality based on color, shoot density, and uniformity of stand, where 1 equaled no live grass, 6 was acceptable, and 9 equaled dark-green, dense, uniform grass. In addition, plots were rated for drought stress symptoms on a scale of 1 to 5 where 1 equaled no drought stress and 5 equaled severe drought stress (permanent wilt).

### **Reflectance Measurements**

Remotely sensed data was collected with a field portable fiber optic spectrometer fitted with 30 degree field of view optics (Model S2000, Ocean Optics, Inc., Winter Park, FL) daily during the application of irrigation treatments. To reduce variability due to cloud cover and solar zenith angle, the tip of the fiber was mounted inside a rectangular plastic hood that extended down to the turf canopy. Auxiliary lighting was provided by two 12 V halogen lights and resulted in an irradiance of  $2250 \mu\text{mol m}^{-2} \text{s}^{-1}$ . Radiance values were expressed as percent spectral reflectance after standardization with a white standard. The spectrometer has a nominal spectral range from 450 to 1050 nm with approximately 0.3-nm nominal band width. Thus, for each measurement the spectrometer program automatically collects 2500 data points covering the entire spectral range. A linear interpolation routine was used to estimate values at 1-nm interval prior to calculation of indices from the reflectance data. Eight scans were averaged for every measurement and approximately 65 measurements were collected and averaged for each plot. Recalibration of the instrument with the white standard was conducted immediately before collecting measurements from

each plot. Canopy reflectance was measured daily during the period of treatment application between 1400 and 1800 h central standard time (CST).

### **Statistical Analysis**

An analysis of variance (ANOVA) was performed to test treatment effect on soil moisture status and visual quality using PROC ANOVA in SAS (SAS Inst., 1999). Prediction equations for soil moisture content were developed by regressing field data against derived spectra. The procedure for spectral calibration was partial least-squares (PLS) regression as performed by SAS (SAS Inst., 1999). Equations were validated through single sample cross-validation. For the cross-validation, ten percent of the sample was left out for prediction at a time and the number of factors that minimized the predicted residual sum of squares (PRESS) was chosen (Fig. 1). This process was repeated so that every observation was used exactly once for cross-validation.

### **Results and Discussion**

The mean average air temperature, relative humidity, wind speed, and total rainfall for the summer months (June-Sep.) that included the periods when irrigation treatments were imposed in 2002 and 2003 were summarized (Table 1.). Mean average air temperatures were higher for each month in 2002 than the corresponding months in 2003. While there was little difference in the mean relative humidity between the two years, approximately twice as much rainfall fell on the site in 2003 as in 2002.

There was no difference in turf quality or uniformity between plots during the course of treatment applications and quality was maintained above the minimally acceptable level for turfgrass fairways (data not shown). Irrigation treatments had no noticeable impact on turfgrass quality since treatments were stopped as soon as the first signs of wilt appeared. This was necessary to prevent unwanted damage to the golf course setting.

There was no correlation ( $r = -0.20$ ) between visual drought stress ratings and the associated soil moisture content for samples collected one day before the onset of visible

drought stress on the perennial rye grass fairways. However, a weak correlation was observed when drought stress symptoms were visible on some of the plots ( $r = -0.52$ ). In comparison, there was a weak correlation between the visual drought stress ratings and the soil moisture content for data collected from the creeping bentgrass greens height study at both one day before, and on the day of drought stress symptom onset ( $r = -0.60$  and  $-0.52$ , respectively). The design of the experiment dictated that data collection cease at the first sign of wilt in the plots to prevent permanent damage to the golf course fairways. Following these guidelines, wilt was usually only visible on one or two plots in the study when treatments were ceased and normal irrigation was resumed. When considering the value of a remote sensing system for use in management of moisture stress in turfgrass systems, it is essential that it is able to identify plants suffering from moisture stress before the onset of visual symptoms.

As soil moisture decreases, plants exhibit a decrease in tissue moisture content, which in turn influences their reflectance properties (Carter, 1994; Fenstermaker-Shaulis, 1997; Osborne et al., 2002). Regression procedures indicate a weak relationship between volumetric soil moisture content and visual quality ( $r^2 = 0.43$ ). Partial least-squares regression of the leaf reflectance data collected over a two year period yielded strong volumetric soil water content predictive results based on maximum  $r^2$  and minimum SEP values (Table 2) at both one day before the onset of symptoms and on the day symptoms became evident for the perennial ryegrass fairway study. Results indicate a strong relationship between the actual soil moisture content and the predicted soil moisture content as calculated through PLS regression at both one day before symptoms (Fig. 2) and on the day symptoms became evident (Fig. 3).

Results of the creeping bentgrass green height study indicate a weak relationship between visual drought stress ratings and the associated soil moisture content (Table 2). In addition, PLS regression was only able to account for a maximum of 59% of the variation

between actual soil moisture content and predicted soil moisture content for sampling dates one day before the onset of drought stress symptoms (Fig. 4). PLS regression for samples collected the day symptoms were evident only explained 52% of the variability in the data. This response may be due in part to the low mowing height of the plots and infrequent fertilization that resulted in mild chlorosis and necrosis during mid-season. While the decline in quality was not significant enough to be below the minimally acceptable level, it may in fact have had a significant impact on the response of the spectral reflectance properties of the turfgrass plants.

The results of this study indicate that it is possible to predict the soil moisture content based on reflectance data collected from the turfgrass canopy. Models developed for the fairway height perennial ryegrass study produced a better fit than those in the green height creeping bentgrass study. This may have been a function of the cultural practices (low fertility) applied to the creeping bentgrass. Future work should address the relationship between reflectance data, turfgrass species, and mowing height to determine if the results reported here are truly a function of mowing height or if the relationship is species dependent.

Continued development of this remote sensing system will provide an inexpensive tool for the early detection of moisture stress in turfgrass systems. This will facilitate an increase in the site-specific management practices used in turfgrass systems and reduce the risk of over-watering and drought stress.

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Table 1. Weather conditions at the experimental site during June to September of 2002 and 2003.

Month	Mean average air temperature	Mean relative humidity	Mean wind speed	Total Precipitation
	<u>°C</u>	<u>%</u>	<u>m s<sup>-1</sup></u>	<u>mm</u>
-----2002-----				
June	23.1	67.2	2.1	90.9
July	24.3	75.2	1.0	0.2
August	22.5	80.6	1.0	0.2
September	18.5	72.1	1.2	43.4
Total				134.7
-----2003-----				
June	19.8	66.9	1.8	60.1
July	22.5	79.7	2.4	89.0
August	22.9	75.2	2.5	21.8
September	15.6	65.1	3.3	87.4
Total				258.3

Table 2. Summary of partial least-squares regression results for volumetric soil water content with spectral reflectance data sets collected from plots with and without visual signs of drought stress. Data from 2002 and 2003 combined.

Calibration	No. of factors†	$r^2$	SECV‡	<i>N</i>
Perennial Ryegrass Fairway Height Study				
No symptoms	5	0.79	0.0016	36
Symptoms	2	0.83	0.0064	36
Creeping Bentgrass Green Height Study				
No symptoms	6	0.59	0.0010	24
Symptoms	2	0.52	0.0035	36

† The number of factors necessary to achieve a minimum global standard error of prediction for the final partial least-squares regression model.

‡ Standard error of cross validation (the average difference between the actual and predicted values of samples not used to develop the equation).

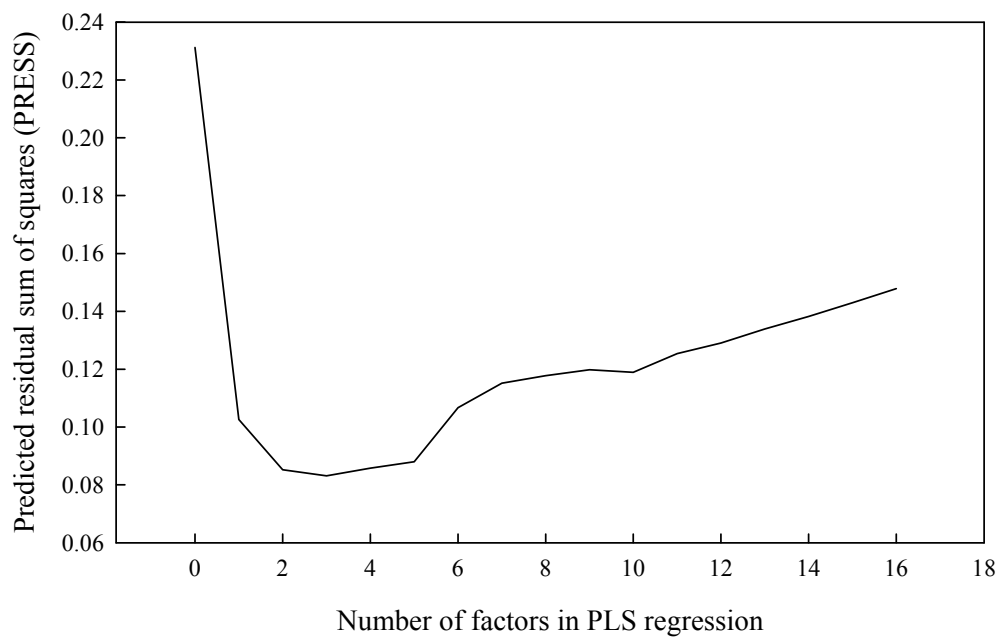


Fig. 1. Graphical illustration of the predicted residual sum of squares vs. the number of factors in the partial least-squares regression model.

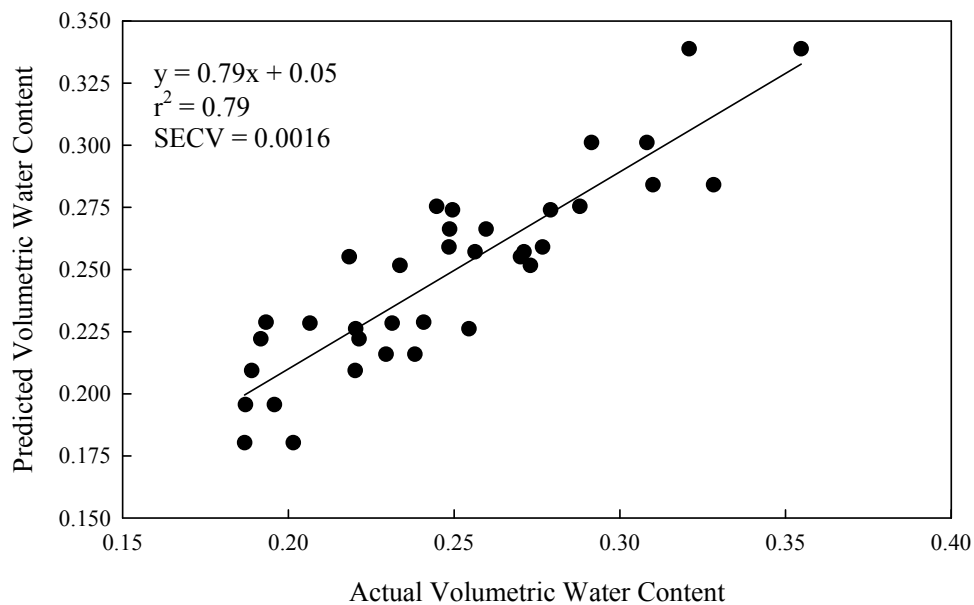


Fig. 2. Predicted versus actual volumetric soil water content for data collected in 2002 and 2003 one day before to onset of visual drought stress symptoms on the perennial ryegrass fairway height study. Volumetric soil water content was predicted by reflectance spectroscopy and regressed against volumetric soil water content as determined by time domain reflectometry.

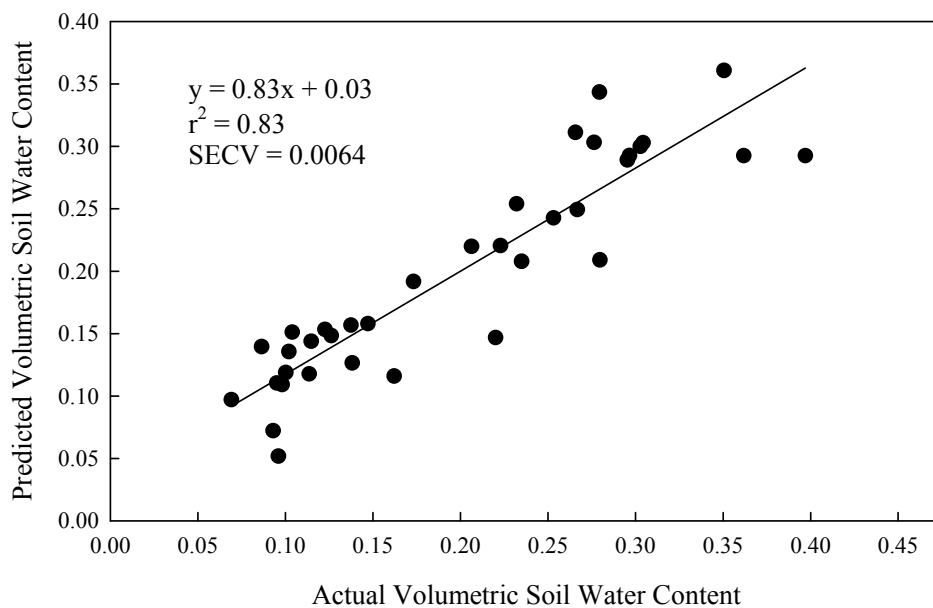


Fig. 3. Predicted versus actual volumetric soil water content for data collected in 2002 and 2003 on the day visual drought stress symptoms were observed for the perennial ryegrass fairway height study. Volumetric soil water content was predicted by reflectance spectroscopy and regressed against volumetric soil water content as determined by time domain reflectometry.

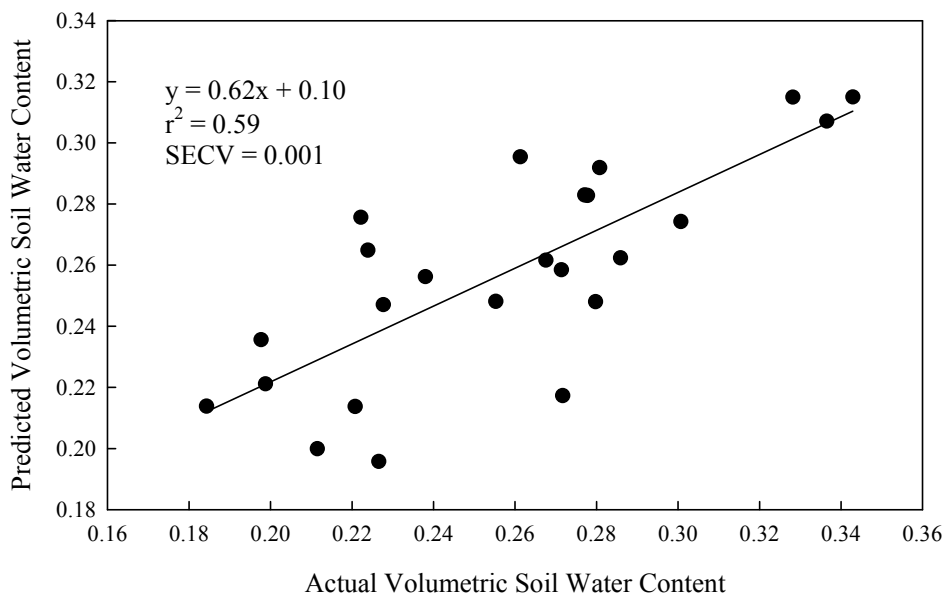


Fig. 4. Predicted versus actual volumetric soil water content for data collected in 2002 and 2003 one day before to onset of visual drought stress symptoms on the Penn A4 creeping bentgrass green height study. Volumetric soil water content was predicted by reflectance spectroscopy and regressed against volumetric soil water content as determined by time domain reflectometry.

## CHAPTER 5. GENERAL CONCLUSIONS

Research investigating the relationship between plant response and remotely sensed data collected from crop canopies has been ongoing for more than two decades. Optical remote sensing techniques have been shown to be valuable tools in quickly and reliably identifying stressed plants through the use of various calculations based on reflectance data collected from the crop canopy. While there has been extensive remote sensing work on agricultural crops, little has been reported on the use of remote sensing in turfgrass systems. The focus of this work was to further investigate the use of a ground-based remote sensing system equipped with an auxiliary light source for use in predicting the nutrient and moisture status of turfgrass plants. The remote sensing system we used in this project is capable of collecting reflectance data on a 1 nm interval from 350 to 1050 nm. This allowed us to collect a complete reflectance spectrum from plants in the visible and near infrared regions of the electromagnetic spectrum. We feel that the complete reflectance spectrum must be analyzed to develop a good prediction model for crop response. Many of the vegetative indices currently reported in literature are based on a very limited portion of the reflectance spectra. While they are capable of identifying plants exhibiting signs of stress, there has been little success in finding indices that are specific to nutrient deficiencies or moisture stress. To address this issue we chose to use stepwise multiple linear regression (MLR) and partial least-squares (PLS) regression to develop the models for predicting nutrient deficiencies and moisture stress. The results suggest that remote sensing systems may be used to accurately predict the nitrogen and moisture stress of turfgrass plants growing in field conditions. While more research needs to be conducted to determine if the models produced through PLS regression and MLR are indeed specific to the deficiency they are calculated for, the results of these studies indicate that MLR and PLS regression provide more consistent results than traditional vegetative indices.

Prediction of the P concentration in plant tissue was best achieved through the use of reflectance values in the blue, yellow, orange, and red regions of the spectrum resulting in an  $R^2 = 0.73$ . These regions correspond with the spectral characteristics of anthocyanin which increase in concentration in the leaf tissue under conditions of P stress. In addition, this study indicates that the physiological changes that result from plants growing in P-deficient conditions reduce the sensitivity of vegetative indices in predicting turfgrass quality, chlorophyll content, and biomass. This is an important consideration for cases where management decisions are based on chlorophyll readings calculated by remote sensing techniques. The results of the handheld chlorophyll meters may only be reliable assuming that the P status of the plant is normal.

When comparing reflectance data to the nitrogen content of turfgrass tissue we found that PLS regression succeeded in developing a predictive model that worked well for all sampling dates throughout the growing season, far exceeding the results produced through the use of NDVI. Vegetative indices such as NDVI are targeted at changes in the chlorophyll content in the plant tissue and the values calculated values do not correlate well across sampling dates. The use of PLS regression allowed us to account for other changes in the spectrum that were related to the N status of the turf, which in turn improved the predictive ability of the model across all sampling dates. It was interesting to note that PLS regression was not able to accurately predict the chlorophyll content of the tissue even though there was a close relationship between the N content and the chlorophyll content.

The results of this study indicate that it is possible to predict the soil moisture content based on reflectance data collected from the turfgrass canopy. Models developed for the fairway height perennial ryegrass study produced a better fit than those in the green height creeping bentgrass study. This may have been a function of the cultural practices (low fertility) applied to the creeping bentgrass. Future work should address the relationship between reflectance data, turfgrass species, and mowing height to determine if the results

reported here are truly a function of mowing height or if the relationship is species dependent. Successful development of a remote sensing system for use in moisture management in turfgrass systems requires that the system be capable of identifying turfgrass areas that have low soil moisture but are not yet to the point of exhibiting visual symptoms of drought.

Continued development of this ground-based remote sensing system will provide an inexpensive tool for the early detection of nutrient and moisture stress in turfgrass systems. As a result, turfgrass managers will be better equipped to incorporate the use of site-specific management practices on their sites which in turn has the potential to reduce fertilizer and irrigation inputs while improving the overall health and quality of the turfgrass.